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Economic fundamentals and cross sectional asset pricing in global financial markets

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Economic Fundamentals and Cross-Sectional Asset Pricing in Global Financial Markets

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Preface

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Victoria Galsband, October 2010

1 Introduction

The recent financial and economic crisis has emphasized the crucial importance of the interplay between the real economy and financial markets. A question about the nature of aggregate macroeconomic risks that drive risk premia in asset markets is among the most fundamental in financial economics (Cochrane, 2005).

This thesis places itself on the intersection between macroeconomics and finance and seeks to contribute to establishing a structural link between the real side of the economy and prices of financial assets. The focus is on the empirical examination of sources of economic risk which account for cross-sectional return differentials and rationalize the time-variation of expected returns on global equity and foreign exchange markets. The objective is here two-fold: first, to identify the macroeconomic aggregate risks which measure "bad" economic times, and second, to explain the mechanism by which these risks move asset prices.

It is generally agreed that investments with risky cash flows should attract higher risk premia. However, how should rational investors assess the risk of an asset and what risk premium should they demand? The standard consumption based capital asset pricing model (C-CAPM) by Rubinstein (1976), Lucas (1978), and Breeden (1979) maintains the assumption that fluctuations in consumption - as a central macroeconomic aggregate - are a major determinant of equilibrium asset prices and expected returns. Specifically, the model predicts that an asset's consumption beta - which gauges asset's systematic risk by its covariance with the marginal utility of consumption - determines its expected return. Yet despite its theoretical purity and intuitive appeal, many early empirical tests have produced very poor results.[1]

Chapter 2 of this dissertation presents further evidence consistent with the implications of the consumption-based asset pricing model. While many papers evaluate exposure to risk by sensitivities of total asset returns to consumption growth - as a single consumption beta, Galsband (2010a) measures risk by comovement of two fundamental asset return components with consumption growth - as two separate consumption betas.

Splitting a consumption beta into a component driven by assets' cash-flow news and a component related to assets' discount-rate news has a number of advantages. Most importantly, the two-beta C-CAPM obtained this way is shown to outperform the single-beta C-CAPM in its general fit while producing lower pricing errors. Capturing the major part of the cross-sectional

[1] See, for instance, Hansen and Singleton (1982), Mankiw and Shapiro (1986), Breeden et al. (1989), Campbell (1996), Cochrane (1996), and Hansen and Jagannathan (1997).

variation of risk premia, empirical tests of the economically motivated two-beta C-CAPM reveal that macroeconomic risks embodied in cash flows can largely account for the cross-sectional return dynamics. Building on the consumption-based models of Abel (1999) and Bansal and Yaron (2004), the recent empirical work by Bansal et al. (2005) and Da (2009) similarly highlights the importance of fundamental cash-flow characteristics in determining the risk exposure of an asset.

In fact, relative importance of cash flow streams and discounting rates is at the heart of the asset valuation theory. Since Gordon (1959) the discounted cash-flow model has been broadly employed both in a theory and in practice as a method for valuing stocks and businesses.

The idea that investors care differently about cash flows and discount rates dates back to Merton (1973). Building on the capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Black (1972) – which argues that stock's risk is summarized by its beta with the market portfolio – the intertemporal capital asset pricing model (ICAPM) of Robert Merton suggests that risk compensation associated with cash flows should exceed the risk compensation associated with discount rates by a factor proportional to the investor's risk aversion. In this ICAPM, investors care more about permanent cash-flow related movements than about temporary discount-rate related changes in the aggregate stock market.

To evaluate this intuitively appealing insight Campbell and Vuolteenaho (2004) break the beta of a stock with the market portfolio into two components, one reflecting news about the market's future cash flows and one reflecting news about the market's discount rates. The authors label the former beta "bad beta", because investors demand a high compensation to bear this risk. The latter beta is called "good beta", because its price of risk is low, in relative terms. In the implementation of this notion the authors rely on the loglinear return approximation by Campbell and Shiller (1988a) which implies the original Gordon model as a special case. The seminal work by Campbell and Shiller (1988a) suggests that unexpected asset returns can be written as a sum of two parts: news about cash flows and (the negative of) news about discount rates. As noted by Chen and Zhao (2009), the cash-flow news is more related to firm fundamentals because of its link to production, and the discount-rate news reflects time-varying risk aversion or investor sentiment. Campbell and Vuolteenaho (2004) show that the failure of the CAPM to explain equity return differentials can be attributed to high discount-rate exposure of low-average-return stocks in the post-1963 period.

Financial economists have employed the Campbell-Shiller framework for analyzing cash-flow and discount-rate components of returns in a number of ways. For instance, Campbell and Vuoteenaho (2004) split the return on the market portfolio to show that high average returns on value and small stocks are largely attributed to their high cash-flow betas. In a similar fashion, Campbell and Mei (1993) break the return on each individual stock portfolio into its cash-flow and discount-rate components. This decomposition reconciles the cross section of average returns, sorted by size and industry, with different exposure of stock's cash-flow and discount-rate news to the fluctuations of the overall stock market. Campbell et al. (2010) further combine the asset-specific beta analysis with the market-level beta dissection for value and growth stocks to show that the cash flows of growth stocks are particularly sensitive to temporary movements in aggregate stock prices, while cash flows of value stocks are particularly sensitive to permanent movements. In a related study, Koubouros et al. (2010) test the asset pricing implications of the four-beta CAPM which links asset-specific cash flows and discount rates to the market permanent and transitory shocks.

Interestingly, until a couple of years ago, the literature has typically utilized the seminal return approximation for models based on market risk. Surprisingly, only very few studies have so far made an effort to deviate from the strict CAPM intuition towards exploring the fundamental components of macroeconomic risks. Such rare examples are the consumption-based models presented by Bansal and Yaron (2004), Bansal et al. (2005), and Da (2009), who demonstrate the great potential of assets'cash-flow exposure to mirror risk compensation. Aiming to fill this gap, chapter 2 of this dissertation examines whether the approximate return decomposition can explain the cross-section of returns within a broader environment of consumption based models that capture individual preferences.

For a variety of consumption-based models, Galsband (2010a) finds that differences in expected excess returns between low book-to-market and high book-to-market portfolios are associated with differences in their cash-flow betas and thus generalizes previous findings of Campbell and Vuolteenaho (2004) for an additional class of asset pricing models based on consumption risk. In line with Bansal et al. (2005) and Da (2009) the empirical findings in chapter 2 support that covariances of permanent shocks to asset returns with consumption earn equilibrium risk premia that are distinguishable from zero. In addition, the results indicate that the risk premium on equity markets is primarily driven by the exposure of assets' cash-flow components to the cyclical variability of durable consumption goods. In particular, while sensitivities of cash-flow shocks to durables account for a great portion of the value premium in the data, the temporary shocks are rather important for models based on aggregate consumption risk. This finding reflects and further corroborates Yogo's (2006) mechanism in which durable goods consumption, in conjunction with nondurable goods consumption, generates a countercyclical risk premium and replicates both the cross-section of expected stock returns and the time variation in the equity premium. Interestingly, the cash-flow beta with durable consumption growth has a much greater potential to convey important information about the differences in risk premia as compared to the cash-flow beta with aggregate consumption growth.

To determine the relative importance of the cash-flow and discount-rate components of an asset return, the empirical studies conventionally employ the approach initiated by Campbell and Vuolteenaho (2004). In this highly influential literature, the discount-rate news is estimated directly by a vector autoregressive model (VAR) relying on a set of common economy-wide state variables; the cash-flow news is then backed out as a residual by subtracting estimated discount-rate news from actual unexpected returns. The robustness of Campbell and Vuolteenaho (2004) results has been disputed by Chen and Zhao (2009), who argue that construction of the cash-flow news is crucial for our understanding of the relative importance of both types of news in driving the time-series and cross-sectional variations of stock returns.

To recognize the permanent and transitory risk components, Galsband (2010a) feeds a number of empirically relevant portfolio-specific micro-level variables into a VAR time series model. This method of computing asset-specific news alleviates the problem of high degree of news correlation driven by a common set state variables. Moreover, the importance of factors related to firm size, book-to-market equity and other financial variables such as leverage, price-to-earnings ratio, value, term, and credit spreads has been highlighted by Fama and French (1989, 1993, 1995), Keim and Stambaugh (1986), Campbell and Shiller (1988a), and Steiner (2009). Similar VARs in Campbell et al. (2010) are successful at replicating the joint dynamics of economic variables and produce economically plausible return estimates.

Extending this analysis, Galsband (2010b) further decomposes the cash-flow and the discount-rate risks into their upside and downside components, respectively. Refining the two-beta model from chapter 2, chapter 3 of this dissertation studies the sensitivities of assets' cash-flow and discount-rate shocks to unexpected upside and downside consumption changes in a framework of a four-beta C-CAPM. Chapter 3 builds on the notion of downside risk which recognizes that investors care differently about downside losses than upside gains. Dating back to Roy (1952) and Markowitz (1959), this idea has led to a voluminous literature across many disciplines, including finance, macro- and microeconomics.

As early as Roy (1952), economists have noted that investors are more sensitive to economic downturns than to periods of economic recovery. An asset which tends to move downward in a bear market more than it moves upward in a bull market should carry a premium because it has particularly low returns at times of high marginal utility. Investors who are sensitive to downside losses, relative to upside gains, require a compensation for holding assets that have a sizable downside covariation with the market. Markowitz (1959) argues that variance considers favorable outcomes to be as important as adverse outcomes and therefore fails to detect asymmetry within asset return distributions. This is a powerful argument for replacing variance - as a pure dispersion measure - with measures of downside risk.

In a mean-semivariance capital asset pricing model (MS-CAPM) of Hogan and Warren (1974) and Bawa and Lindenberg (1977), variance is replaced by semivariance and a standard market beta is replaced by a downside beta - a measure of asset sensitivity to a falling market portfolio. Price et al. (1982) show that there are systematic differences between the regular and historical downside betas of U.S. stocks. In particular, the standard market beta tends to underpredict the risk exposure of low-beta stocks and overpredict the riskiness of high-beta stocks. This finding may help reconcile the fact that the empirical tests of the standard CAPM usually underprice the low-beta stocks and overprice the high-beta stocks (Black et al., 1972 and Reinganum, 1981).

Bawa and Lindenberg (1977) link the empirical failure of the standard CAPM to the market beta which remains constant across periods of bear and bull markets. Gul (1991) studies disappointment averse agents, who place a greater weight on losses versus gains. More recently, Post and van Vliet (2005) and Estrada (2002) argue that investors typically assign greater importance to downside volatility than to upside volatility. To take into account the asymmetric treatment of risk Ang et al. (2006) compute downside (upside) betas over periods when the excess market return is below (above) its mean. Ang et al. (2006) provide empirical evidence on significant reward for bearing downside risk on equity markets and show that stocks with high downside betas have on average high unconditional returns.

Combining the "upside beta - downside beta" decomposition of Ang et al. (2006) with the "bad beta - good beta" approach of Campbell and Vuolteenaho (2004), Botshekan et al. (2010)

develop a four-beta decomposition of the market beta. This framework allows to study the stock return's covariation with market cash-flow and discount-rate news in both up and down markets. Empirical tests of the cross-section of the CRSP stocks in Botshekan et al. (2010) indicate that downside cash-flow and downside discount-rate betas carry the largest premium.

Surprisingly, despite many encouraging findings related to the concept of downside market risk, the intuitive notion of downside consumption risk thus far has not been subjected to rigorous empirical testing. The purpose of chapter 3 of this dissertation is to fill the void by providing an empirical investigation of downside consumption risk measures across different consumption-based models.

Investors who are more sensitive to economic downturns than to periods of economic recovery should require a compensation for holding assets that covary strongly with negative consumption shocks. Hence, assets that tend to do poorly in recessions should have on average higher returns. Building of this economically appealing notion, Polkovnichenko (2010) models aversion to downside risk in consumption to show that downside risk premium exhibits significant variation across portfolios and contributes to value and size premia in the cross-section.

Motivated by this finding, Galsband (2010b) allows for different sensitivities of return innovations to consumption shocks. A conditional version of the two-beta C-CAPM with upside and downside betas consistently generates lower pricing errors and fits the data better than the single-beta C-CAPM. In addition, the economic magnitude of consumption risk in downside betas overweights that of upside betas by roughly 70%. Moreover, differences in assets' exposure to the downside risk succeed to explain more than a half of the cross-sectional return differentials on portfolio returns while there is no significant relation between the value and growth stock returns and their sensitivities to the upside risk. This finding is in line with theoretical models by Gul (1991) and Ang et al. (2006) which suggest that downside risk may be priced cross-sectionally in an equilibrium setting.

Additionally breaking assets' "bad" consumption betas, i.e. the sensitivities of assets' cash-flow components to consumption risk, and assets' "good" consumption betas, i.e. the sensitivities of assets' discount-rate components to consumption risk, into an upside and a downside betas, respectively, yields a four-beta model which distinguishes between upside cash-flow, upside discount-rate, downside cash-flow, and downside discount-rate consumption risk components. The four-beta consumption-based model fits well and generates economically plausible estimates of risk prices. In particular, the results in chapter 3 suggest that different exposures to downside consumption risk are reflected in the cross-section of stock returns. In line with Botshekan et al. (2010), Galsband (2010b) finds that risks associated with the comovement of assets' "good" discount-rate news and assets' "bad" cash-flow news with negative consumption shocks earn a significant premium and go a long way towards explaining cross-sectional return differentials. Hence, both bad and good betas seem to be driven by their high sensitivities to economic downside, or recession, risk.

Froot and Ramadorai (2005) as well as Hoffmann and MacDonald (2009) use methodology similar to Campbell (1991) to study foreign exchange markets. Froot and Ramadorai (2005) decompose the unexpected currency returns into permanent "intrinsic-value" shocks and transitory deviations from intrinsic value, or "expected-return" shocks. Their analysis suggests that intrinsic-value shocks are positively related to forecasted cumulated interest differentials. The findings support the view that institutional-investor currency flows are related to short-term currency returns, while fundamentals better explain long-term returns and values. Hoffmann and MacDonald (2009) explore the real exchange rate-real interest rate relationship in more details. Their results indicate that the real interest rate differential can be used as a reasonable approximation of the expected rate of depreciation over longer horizons.

The relative importance of the cash-flow and discount-rate fundamentals on international equity and foreign exchange markets is explored further in chapter 4 of the thesis. Galsband and Nitschka (2010) employ the "bad beta - good beta" logic of Campbell and Vuolteenaho (2004) to explore systematic risks on currency markets. This investigation is motivated by the observation that carry trades, short positions in low interest rate and long positions in high interest rate currencies, comove with stock markets (Brunnermeier et al., 2008 and Lustig et al., 2009). In contrast to the evidence for value and growth stocks, the authors find that the cross-sectional differences in the forward discount sorted currency portfolio excess returns are explained by their sensitivity to the stock market's discount-rate news. The decomposition of the market return into its cash-flow and discount-rate news driven components reveals that excess returns on low forward discount currency portfolios load positively on "good" news about the stock market's discount rates while high forward discount currencies load negatively on this news. The risk price of the market's discount-rate news component is negative which could be rationalized by the fact that we follow Campbell and Vuolteenaho (2004) in defining discount-rate news as "better than expected". A low sensitivity to this "good" news must be rewarded with a higher risk price than a high sensitivity to the "better than expected" discount-rate news. This pattern has been recently observed in attempts to explain cross-sectional differences in European value and growth stocks with the two-beta variety of the CAPM from a national investor's perspective (Nitschka, 2010). In addition, Galsband and Nitschka (2010) find that the two-beta CAPM is able to price both stock and currency portfolio excess returns. Confirming Campbell and Vuolteenaho (2004), average stock returns, the 25 book-to-market and size sorted portfolios from Fama and French (1993), are priced by the differences in the sensitivity to cash-flow news while at the same time currency excess returns are priced by their different sensitivities to discount-rate news. Moreover, the relation between stock market news and foreign currency returns seems to vary across the two either discount-rate news or both cash-flow and discount-rate news driven stock market booms of the past two decades.

A related study, Galsband and Hoffmann (2010) extend earlier work by Campbell et al. (2010) and Koubouros et al. (2010) to investigate the determinants of global risks on international financial markets. Using bad and good betas as systematic risk measures that are suggested by the ICAPM of Campbell and Vuolteenaho (2004), the authors test the implications of a four-beta CAPM variant for the cross-section of book-to-market, earnings-price, cash earnings-to-price, and dividend yield sorted stock portfolios of G7 countries over the period from 1975 to 2007. Estimating a VAR for the market retuns in the manner of Campbell (1991) and Campbell and Vuolteenaho (2004), and for firm-level returns in the manner of Campbell and Mei (1993) and Galsband (2010a), allows to break market and firm-level stock returns into components driven by cash-flow and discount-rate shocks. To discover systematic risks hidden behind the market beta portfolio-level cash-flow and discount-rate news are regressed on the market's cash-flow and discount-rate components. The failure of the single-beta CAPM to explain the cross-section of value and growth stock returns around the world stands in stark contrast to the empirical success of the four-beta CAPM which separates cash-flow and discount-rate risks for both the global market and individual portfolio returns.

Lustig et al. (2009) show that a carry trade can be a particularly risky investment during global market turbulences. In fact, there are times in which investors are especially concerned that their portfolios not do badly (Cochrane, 2001). They are willing to take into account lower unconditional returns just to make sure that portfolios do not do badly in these particular states of nature. One of the central tasks of asset pricing is to understand and measure economically interpretable variables that forecast such macroeconomic events. A wide class of models suggests that a "recession", "uncertainty" or "financial distress" factor lies behind many asset prices.

The distinction between good and bad times is important for assessing the consumption risk exposure of an asset. A number of recent papers have relied on conditional versions of the asset pricing models to tackle down the issue of separation between "good" and "bad" states. These models emphasize that an asset's risk is determined not by a simple correlation of its return with the market return or consumption growth, but by that correlation conditional on some state variable that reflects time-variation in risk premia. The latter may arise from time variation in risk aversion (as in models with habit persistence, e.g., Campbell and Cochrane, 1999) or time variation in risk itself (as in models with time-varying labour earnings or default risk, e.g. Constantinides and Duffie, 1996). For instance, Lettau and Ludvigson (2001) find that a proxy of consumption-wealth ratio might be a powerful forecaster of the economy state. Their choice of conditioning variable is motivated by its ability to summarize investors' expectations of future returns to the market portfolio. High consumption-wealth ratio signals "bad" periods of high risk or risk aversion; low consumption-wealth ratio signals "good" periods of low risk or risk aversion. The authors show that value stocks, i.e. stocks with high book-to-market value, have higher conditional consumption betas in bad times than their growth counterparts with low book-to-market value. This finding is striking in view of ample evidence that both stock groups have total consumption betas of similar size (Mankiw and Shapiro, 1986; Campbell, 1996; and Cochrane, 1996). A related study of Jagannathan and Wang (1996) includes a proxy for the return on human capital when measuring the return on aggregate wealth. Allowing for time-variation in betas and the market risk premium improves substantially the performance of the static CAPM in explaining the cross-sectional variation in average returns on a large collection of stock portfolios.

The empirical success of scaled factor models is typically attributed to the time variation in parameters stemming from scaling factors (Cochrane, 1996). Cochrane (2001) argues that any intuitively sensible variable which is related to changes in the investment opportunity set can be defended as a state variable even though it does not itself measure "wealth" or the state of the economy. Following the methodology in Cochrane (1996) and Lettau and Ludvigson (2001) chapter 5 of the dissertation explores a conditional version of the C-CAPM which expresses the stochastic discount factor as a conditional, or scaled, factor model with a survey-based measure of inflation uncertainty as a conditioning variable. Uncertainty is central tenet of finance. Financial markets dislike uncertainty because it lowers asset prices, consumption, and wealth. Therefore, asset returns should be sensitive to the time variation in uncertainty. Times of high uncertainty are referred to as "bad" times, times of low uncertainty are labeled as "good" states. Intuitively, an asset that comoves strongly with consumption growth in bad times should offer a premium because it reduces investors' hedging ability in periods of higher uncertainty.

In the asset pricing literature, different models look at different types of uncertainty. For example, Bansal and Yaron (2004) study uncertainty related to fluctuations in conditional consumption volatility. They show that a rise in economic uncertainty, modeled as a time-varying volatility in consumption, lowers asset prices, and fluctuations in economic uncertainty increase the equity risk premium. David (1999) shows how fluctuations in investors' own level of uncertainty can generate a new class of risk and hedging demands in an intertemporal portfolio choice setting. Ozoguz (2009) uses the dynamics of investors' beliefs and Bayesian uncertainty about the state of the economy as state variables that describe the time-variation in investment opportunities. He finds that investors' uncertainty about the state of the economy has a negative impact on asset valuations both at the aggregate market level and at the portfolio level. Early works by Detemple (1986) and Gennotte (1986) analyze the portfolio decision making by investors who can not observe the true state of the economy. These authors show that in such a setting, the conditional expectation of the unobservable state variable replaces the state variable itself and, as in Merton's (1973) ICAPM, hedging demand against changes in this state variable becomes relevant for optimal portfolio choice. Brennan and Xia (2001) argue that uncertainty over fundamentals might be helpful in resolving the equity premium puzzle. Extending the work by Kandel and Stambaugh (1996), Barberis (2000) and Xia (2001) incorporate the effects of uncertainty about return predictability. Finally, David and Veronesi (2001) show that uncertainty about future inflation and earnings growth rates helps explain stock and monthly volatilities and cross-covariances. Lee (1999) finds empirical support for a hypothesis that time-varying inflation uncertainty is related to returns on broad-based portfolios by the negative correlation between ex post real returns and the uncertainty premium.

Galsband (2010c) shows that a scaled multifactor consumption-based asset pricing model with inflation uncertainty can account for a large part of return differentials between low-book-to-market and high-book-to-market portfolios. The remarkable empirical success of the conditional C-CAPM stands in stark contrast to the failure of the standard unconditional C-CAPM which – in spite of its theoretical purity – falls short of accounting for the cross-sectional return differentials. In line with the intuition, assets with high sensitivity to consumption fluctuations in times of high inflation uncertainty tend to have high expected excess returns. This finding is consistent with financial markets which fear economic uncertainty. Moreover, empirical asset pricing tests in Galsband (2010c) suggest that the time-variation in the equity premium is closely related to time-variation in the uncertainty risk: Consumption risk premium increases in bad times, when inflation uncertainty is high, and it decreases in good times, when inflation uncertainty is low.

It is important to note that the choice of inflation uncertainty measure seems to matter to some extent in empirical asset pricing tests. In the literature, there coexist a number of uncertainty measures. On top of this, different models have different predictions about whether it is the level of inflation, inflation uncertainty – as measured by dispersion – or inflation variability which actually matters for asset pricing. The distinction between these three aggregates is not quite easy in the empirical sense because of the strong comovement between these series. In chapter 5, this dissertation seeks to discriminate between inflation uncertainty, inflation variability and inflation to determine the key drivers behind the pricing power of the model. Despite the strong negative relation between inflation and stock returns, the empirical tests fail to discover a significant link between consumption betas and equity excess returns in this case.

2 The Cross-Section of Equity Returns and Assets' Fundamental Cash-Flow Risk

The cross-sectional variation in average returns is naturally justified by differences in exposure to systematic risk across assets.[2] The key insight of intuitively extremely appealing economic theory is that the riskiness of an asset is determined by its ability to insure against consumption fluctuations. Despite the empirical deficits[3] of a standard canonical consumption-based capital asset pricing model (C-CAPM), its theoretical paradigm remains a powerful tool for analyzing asset markets.

This paper studies the cash-flow and discount-rate components of asset returns within a wide environment of consumption-based models. Our main finding is that macroeconomic risks embodied in cash flows can largely account for differences in expected excess returns between low book-to-market and high book-to-market portfolios for a broad class of consumption-based models. In particular, assets whose cash flows have higher consumption risk promise a higher risk premium. In addition, we find that the risk premium on equity markets is primarily driven by the exposure of assets' cash-flow components to the cyclical variability of durable consumption goods.

The starting point here is the approximate return decomposition developed by Campbell and Shiller (1988a). The authors show that unexpected returns can be expressed as a sum of changing cash-flow forecasts and expected future discount rates. This result is obtained by taking a first-order Taylor expansion to an accounting identity and thus independent of the validity of any particular model. Recent literature utilizes the seminal return approximation for models based on market risk in a number of ways. However, only very few papers have so far made an effort to deviate from the strict CAPM intuition towards exploring the fundamental components of macroeconomic risks. Campbell and Vuolteenaho (2004) show that in a standard CAPM framework, stocks with high market cash-flow betas have higher average returns. Similar intuition is captured in consumption-based models presented by Bansal and Yaron (2004), Bansal et al. (2005), and Da (2009), who demonstrate the great potential of assets' cash-flow exposure to mirror risk compensation. Motivated by these common implications, we explore whether assets' cash-flow and discount-rate return components have any bearing on the puzzling value

[2] This chapter of the thesis is based on Galsband (2010a).

[3] See, for instance, Mankiw and Shapiro (1986), Breeden et al. (1989), Campbell (1996), Cochrane (1996), Söderlind (2006), and Hansen and Jagannathan (1997).

premium across various consumption-based models.

Our approach differs from Bansal et al. (2005) who assume a joint dynamics of dividend and aggregate consumption growth rates to measure cash-flow news. To recognize the permanent and transitory risk components, we feed a number of empirically relevant portfolio-specific micro-level variables into a vector autoregressive (VAR) time series model. The importance of factors related to firm size, book-to-market equity and other financial variables such as leverage, price-to-earnings ratio, value, term, and credit spreads has been highlighted by Fama and French (1989, 1995), Keim and Stambaugh (1986), Campbell and Shiller (1988a), and Steiner (2009).

Using data on some commonly applied financial return predicting variables, the model produces reliable forecasts. Conventionally, the cash-flow news is obtained as a residual by subtracting estimated discount-rate news from actual unexpected returns. We show that the cross-sectional dispersion in cash-flow and discount-rate betas explainS up to 80% of the value premium across different models and empirical specifications. Despite the intimate link between fundamental cash flows and expected returns, the two-beta decomposition misses some important aspects of financial market data. Specifically, the model underpredicts average excess returns on Fama-French portfolios and also does a poor job of pricing small growth portfolios. Higher-than-average pricing errors on portfolios with low market equity are, however, common in the empirical tests (Lettau and Ludvigson, 2001 and references therein). Furthermore, the comovement of assets' cash-flow component with macroeconomic, especially consumption-related risks, is sizable, statistically significant and economically plausible.

We take a closer look at this finding by additionally exploring the empirical performance of models based on cash-flow risk only. In line with Bansal et al. (2005) and Da (2009) we find that covariances of permanent shocks to asset returns earn equilibrium risk premia that are distinguishable from zero. The models are capable of replicating the cross-sectional variation in average returns but the predicted returns associated with cash-flow models are somewhat lower than those generated by two-factor models. Moreover, the results of this study suggest that temporary shocks might rather play an important role for models based on aggregate consumption risk than for models relying on durables.

Our further results indicate that the risk premium on equity markets is primarily driven by the exposure of assets' cash-flow components to the cyclical variability[4] of durable consumption

[4] In an international sample consisting of 18 countries, Oertmann (2000) finds that value stocks tend to outperform growth stocks when business conditions and market climate improve.

goods. This finding reflects and further corroborates Yogo's (2006) mechanism in which durable goods consumption, in conjunction with nondurable goods consumption, generates a countercyclical risk premium and replicates both the cross-section of expected stock returns and the time variation in the equity premium. Interestingly, the cash-flow beta with durable consumption growth has a much greater potential to convey important information about the differences in risk premia as compared to the cash-flow beta with aggregate consumption growth. As noted by Bansal et al. (2005), in models that rely on Epstein and Zin (1989) preferences, the standard consumption beta may not be an appropriate measure of asset risk.

Employing the utility index originally proposed by Yogo (2006), this paper examines the empirical success of the intuitive two-beta representation for the following familiar specifications: (a) the standard C-CAPM by Lucas (1978) and Breeden (1979), (b) the durable consumption model used in Dunn and Singleton (1986), Ogaki and Reinhart (1998), (c) the traditional C-CAPM extended to allow for intratemporal Epstein-Zin preferences, and finally (d) a specification with durable goods enriched by the recursive Epstein-Zin feature. To evaluate the cross-sectional implications of the two-beta decomposition, we focus on the standard set of 25 Fama-French benchmark equity portfolios. These test assets have been used extensively to examine the empirical performance of various asset pricing models. To verify the robustness of conclusions, a second portfolio set consisting of 6 book-to-market and size-sorted portfolios is employed.

Another central dimension of this paper concerns timing. Relying on available micro-level portfolio specific financial data, empirical estimation is implemented on an annual basis. This circumstance allows us to take advantage of the fact that the correlation between equity returns and the growth rate in aggregate per-capita consumption increases over longer horizons (Daniel and Marshall, 1997 and Brainard et al., 1991). Working with a one-year horizon also reduces the measurement error in high-frequency consumption data, thus contributing to the success of fundamental cash flows in capturing a large part of the variation in the excess returns. In this respect, the main results of this study are consistent with long-run risk models in Bansal and Yaron (2004), Hansen et al. (2008), Jagannathan and Wang (2007), and Julliard and Parker (2005), who find that long-term consumption growth explains the expected return differentials across assets surprisingly well.

The remainder of the paper is organized as follows. Section 2.1 briefly sketches the approximate return framework and lays out the decomposition of single-factor beta into a cash-flow and a discount-rate beta. Section 2.2 describes the data used in empirical work. Section 2.3 presents results and Section 2.4 concludes.

2.1 The Cash-Flow and Discount-Rate Risk

A standard present-value formula states that changes in asset prices are associated with changes in expected future cash flows or discount rates. The following section briefly sketches a loglinear approximate relationship suggested by Campbell and Shiller (1988a). The return approximation is then used to empirically disentangle a consumption beta of an asset into a cash-flow beta and a discount-rate beta.

2.1.1 The Campbell-Shiller Return Approximation

Using a first-order Taylor expansion, Campbell and Shiller (1988a) approximate the log one-period return, $r_{t+1} = \ln(P_{t+1} + D_{t+1}) - \ln(P_t)$, where P_t is price and D_t is the dividend. The authors show that the log price-dividend ratio is determined by the expected discounted value of future dividend growth and returns

$$p_t - d_t = \frac{k}{1-\rho} + E_t \sum_{j=0}^{\infty} \rho^j \left[\Delta d_{t+1+j} - r_{t+1+j}\right] \tag{2.1}$$

where E_t denotes a rational expectation formed at the end of period t, Δ is a one-period backward difference, k and ρ are parameters in the linearization, and lower-case letters are used for logs. Elaborating on this insight, Campbell (1991) extends the loglinear present-value approach to obtain a decomposition of the unexpected return:

$$\begin{aligned} r_{t+1} - E_t r_{t+1} &= (E_{t+1} - E_t) \left\{ \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - \sum_{j=1}^{\infty} \rho^j r_{t+1+j} \right\} \\ &= N_{CF,t+1} - N_{DR,t+1} \end{aligned} \tag{2.2}$$

The term $N_{CF,t+1} \equiv (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}$ represents the revision in expectations of future discounted dividend growth rates. This expression is referred to as cash-flow news. Analogously, $N_{DR,t+1} \equiv (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j}$ represents the revision in expectations of future returns. It is typically referred to as the discount-rate news.

For the empirical implementation, we assume a first-order[5] autoregressive rule of motion for

[5] As discussed by Campbell and Shiller (1988a), the assumption that the VAR is first-order is not restrictive,

a vector of state variables, $\mathbf{z}_t$:

$$\mathbf{z}_t = \mathbf{a} + \mathbf{\Gamma}\mathbf{z}_{t-1} + \mathbf{u}_t \tag{2.3}$$

where $\mathbf{z}_{t+1}$ is an m-by-1 state vector with r_{t+1} as its first element, $\mathbf{a}$ and $\mathbf{\Gamma}$ are, respectively, an m-by-1 vector and m-by-m companion matrix of constant parameters, and $\mathbf{u}_{t+1}$ is an i.i.d. m-by-1 vector of shocks with $r_{t+1} - E_t r_{t+1}$ as its first element.

It follows immediately that the discount-rate news can be extracted via

$$N_{DR,t+1} = \mathbf{e1}'\boldsymbol{\lambda}\mathbf{u}_{t+1} \tag{2.4}$$

where $\boldsymbol{\lambda} \equiv \rho\mathbf{\Gamma}\left(\mathbf{I} - \rho\mathbf{\Gamma}\right)^{-1}$ and $\mathbf{e1}$ denotes an m-by-1 vector whose first element is unity and the remaining elements are all zero.

The cash-flow news can further be backed out by subtracting the discount-rate news from the total unexpected return,

$$N_{CF,t+1} = \left(\mathbf{e1}' + \mathbf{e1}'\boldsymbol{\lambda}\right)\mathbf{u}_{t+1}. \tag{2.5}$$

2.1.2 Beta Decomposition

This section studies the loglinear return decomposition within a broad environment of consumption-based models. Following Campbell and Mei (1993), Campbell and Vuolteenaho (2004) and Bansal et al. (2005) we define betas by using unconditional variances and covariances of innovations in returns and risk factors.[6] Given the return decomposition in equation (2.2), the consumption beta can be written as

$$\beta^i_{\Delta c} = \beta^i_{CF,\Delta c} + \beta^i_{DR,\Delta c} \tag{2.6}$$

More generally, within a multifactor model, the cash-flow beta

$$\beta^i_{CF,f} \equiv \frac{Cov\left(N^i_{CF}, f\right)}{Var\left(f\right)} \tag{2.7}$$

and the discount-rate beta

$$\beta^i_{DR,f} \equiv \frac{Cov\left(-N^i_{DR}, f\right)}{Var\left(f\right)} \tag{2.8}$$

since this formulation also allows for higher-order VAR models by stacking lagged values into the state vector.

[6] Campbell and Mei (1993) provide a detailed discussion of conditions under which unconditional beta equals a full conditional beta and explain the advantages of beta decomposition.

add up to the total factor beta

$$\beta_f^i = \beta_{CF,f}^i + \beta_{DR,f}^i \tag{2.9}$$

where f represents the fundamental factor(s) used to price assets.

2.1.3 Empirical Linear Factor Models

Motivated by the empirical success of models highlighting the importance of the low-frequency component in consumption data,[7] we adopt the setup by Yogo (2006). This setup not only accounts explicitly for temporal cyclicality in the durability of goods. It also comprises a rich set of commonly used consumption-based models. A further advantage of this framework is that the stockholder's unconditional Euler equation can be conveniently approximated by a linear factor model whose factors are nondurable consumption growth Δc, durable consumption growth Δd, and the return on the optimal market portfolio r^m:

$$E\left[R^{i,e}\right] = b_1 Cov\left(\Delta c, R^{i,e}\right) + b_2 Cov\left(\Delta d, R^{i,e}\right) + b_3 Cov\left(r^m, R^{i,e}\right) \tag{2.10}$$

where $R^{i,e}$ denotes the excess return on portfolio i. Moreover, Yogo (2006) shows that the vector of factor loadings in (2.10) is governed by the structural preference parameters:

$$\begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} = \begin{bmatrix} \kappa\left[1/\sigma + \alpha\left(1/\epsilon - 1/\sigma\right)\right] \\ \kappa\alpha\left(1/\epsilon - 1/\sigma\right) \\ 1-\kappa \end{bmatrix} \tag{2.11}$$

where $\alpha \in (0,1)$ is the weight on durable consumption,[8] $\sigma \geq 0$ is the elasticity of intertemporal substitution (EIS), $\epsilon \geq 0$ is the intratemporal elasticity of substitution between nondurables and

[7] Since Dunn and Singleton (1986), the literature has proposed different possible explanations for delayed adjustment to consumption (Lynch, 1996; Jagannathan and Wang, 1996; Yogo, 2006; Ait-Sahalia et al., 2004; Bansal and Yaron, 2004; Bansal et al., 2005; and Da, 2009).

[8] Following Dunn and Singleton (1986), consumers are assumed to have preferences over the service flows from nondurable and durable goods with one-period utility given by the constant elasticity of substitution function

$$u\left(C_t, D_t\right) = \left[\left(1-\alpha\right) C_t^{1-1/\epsilon} + \alpha D_t^{1-1/\epsilon}\right]^{1/(1-1/\epsilon)}$$

where C_t is the consumption of services from nondurables plus services at date t and D_t is the consumption of services from durable goods at date t. As in Epstein and Zin (1989, 1991), Yogo (2006) allows for possibility of time separability by specifying a recursive intertemporal utility function

$$U_t = \left\{\left(1-\delta\right) u\left(C_t, D_t\right)^{1-1/\sigma} + \delta E_t\left[U_{t+1}^{1-\gamma}\right]^{1/\kappa}\right\}^{1/(1-1/\sigma)},$$

where $\delta \in (0,1)$ denotes the individual time discount factor.

durables, $\gamma > 0$ is the coefficient of relative risk aversion and $\kappa = (1-\gamma)/(1-1/\sigma)$.

Relation (2.10) conveniently nests four familiar consumption-based models as special cases:

(a) The plain-vanilla Consumption-CAPM (C-CAPM) with Δc as the only pricing factor.

(b) The Durable Consumption-CAPM (D-CAPM) with two pricing factors, Δc and Δd.

(c) The Epstein-Zin Consumption-CAPM (EZC-CAPM) which allows for separation of the elasticity of intertemporal substitution from risk aversion as in Epstein and Zin (1991) with two pricing factors, Δc and r^m.

(d) The Epstein-Zin Durable Consumption-CAPM (EZD-CAPM) with Δc, Δd, and r^m as pricing factors.

To further explore the nature of macroeconomic risk, this paper inquires how much of the financial market data can be meaningfully replicated by the comovement of intrinsic cash-flow and discount-rate news with factors f. Empirically, the impact of these sources of risk on the cross-sectional variation of risk premia can be largely captured by the following model:

$$E\left[R^{i,e}\right] = \lambda'_{CF,f}\beta^i_{CF,f} + \lambda'_{DR,f}\beta^i_{DR,f} \tag{2.12}$$

where $\beta^i_{CF,f}$ ($\beta^i_{DR,f}$) denotes a vector of cash-flow (discount-rate) betas of asset i with factors f. The nondurable beta, $\beta_{\cdot,\Delta c}$, measures the comovement of the stock return with the growth rate in nondurable consumption, the durable beta, $\beta_{\cdot,\Delta d}$, measures the comovement of the stock return with the growth rate in durable consumption, and finally, the market return beta, $\beta_{\cdot,r^m}$, is designed to quantify the covariance of a specific stock with the return on the global stock market portfolio. According to this relationship, differences in risk across assets are due to differences in their cash-flow betas, discount-rate betas, or both. Equation (2.12) will be used extensively as the basis of the empirical work, specialized to the particular asset pricing model under consideration.

2.2 Data

This section describes the source and construction of each series used in the empirical work. All variables are measured over the period 1947 to 2007. Since the micro-level portfolio characteristics described below are only available on a year-to-year basis, all empirical tests are conducted on an annual data sample. At the cost of relatively low frequency, an implementation of a VAR system based on extensive panel data is possible. Furthermore, focusing on cumulative (over several quarters) movements in the data allows us to circumvent the measurement error and account for the well-documented slow adjustment property of consumption. In addition, an annual data set is consistent with empirically relevant long-run consumption and portfolio choice decisions.

2.2.1 Consumption

Following earlier work (Hansen and Singleton, 1983), aggregate nondurable consumption is measured as the sum of seasonally adjusted real per-capita consumption expenditure on nondurables and services. Durable consumption is the seasonally adjusted real per-capita consumption expenditure on durables. Real estimates remove the effects of price changes, which can obscure changes in consumption in current dollars. Both series are taken from Table 7.1 of the National Income and Product Accounts (NIPA), available from the U.S. Bureau of Economic Analysis.

Panel A of Table 2.1 reports basic descriptive statistics for nondurable and durable consumption growth. Annual nondurable consumption has a mean of 2.10% and a standard deviation of 1.12%. Annual durable consumption growth has a mean of 4.26% and a standard deviation of 6.76%. Both variables are positively correlated with the stock market and drop substantially at times of recessions.

2.2.2 Benchmark Portfolios

Two sets of portfolios are employed as test assets. The first consists of 25 Fama and French (1992, 1993) value-weighted portfolios. Due to the large and relatively stable pattern of their average returns across different subsamples and frequencies, these portfolios have been used extensively in the literature to examine the performance of various asset pricing models. The portfolio data are available from Kenneth R. French's website. These portfolios are constructed at the end of June of each calendar year as intersections of five size or market equity (ME) portfolios and five book-to-market equity (BE/ME) portfolios on the NYSE, AMEX, and Nasdaq stocks in Compustat. The ME is market capitalization at the end of June. The ratio BE/ME is BE at the last fiscal year end of the prior calendar year divided by ME at the end of December of the prior year. Firms with negative BE are not included in any portfolio. Each portfolio is represented by a two-digit number. The first digit refers to the size quintiles (1 indicating small, 5 large). The second digit refers to the book-to-market quintiles (1 indicating the lowest book-to-market ratio, 5 the highest). For example, the large growth portfolio 51 is comprised of stocks in the biggest ME bin and the lowest BE/ME bin. The second portfolio set is constructed analogously but includes 6 value-weighted portfolios for which equivalent micro-level characteristics are available. The annualized rate of return on a one-month Treasury bill is also available from Kenneth R. French's online data library. Panel B of Table 2.1 provides a brief summary of 25 stock portfolios.

2.2.3 VAR State Variables

Three state variables are employed for the main specification of the VAR. The first is the log value-weighted portfolio return. Following Campbell et al. (2010), we use market-adjusted returns obtained by subtracting the market return from the portfolio return for each time period. The market return is the return on the S&P Composite Stock Price Index from the Robert Shiller online data set. The second state variable is the log BE/ME ratio, measured as a ratio of the sum of BE's to the sum of ME's of all stocks in the portfolio. For robustness purposes, we also use the log BE/ME ratio, measured as a value-weighted average of BE/ME of all stocks in the portfolio. The third state variable is the log BE, measured as the sum of BE's of all stocks in the portfolio. Additionally, the number of firms in portfolios and the average firm size are fed into a VAR in further specifications, implemented mainly to verify our conclusions. As demonstrated in Table 2.1, both portfolio characteristics, BE and BE/ME, strongly follow the pattern in return means, which explains their power to capture their cross-sectional differences.

2.3 Empirical Evidence

Section 2.3.1 briefly describes the VAR estimates used to calculate the impact of today's cash-flow and discount-rate shocks over the discounted infinite future. Section 2.3.2 studies the cross-sectional pricing implications. Finally, Section 2.3.3 provides further extensions and conducts a number of additional robustness tests.

2.3.1 The VAR Dynamics

Despite controversial evidence on return predictability (Lettau and Van Nieuwerburgh, 2008), the literature still relies on past short- and long-term returns, valuation ratios such as book-to-market equity, dividend-price ratio and earnings-price ratio, and company financial fundamentals such as dividends, earnings or cash-flow history as predictors of returns on common stocks.

Table 2.2 reports the basic characteristics of a first-order VAR model for growth and value portfolios,[9] estimated using OLS and employing $\rho = 0.95$ for annual data.[10] The VAR state vector[11] includes a constant, value-weighted stock return (R), book-to-market ratio (BE/ME) and book equity (BE). All three variables are logged. Returns are market-adjusted by subtracting the market return from the portfolio return. BE/ME is calculated as a ratio of the sum of individual firm BE's in the portfolio over the sum of respective ME's. Each row of the table corresponds to a different dependent variable listed in the header of the row. The first three columns report coefficients on the explanatory variables listed in the column header. Together, these coefficients form the VAR companion matrix $\mathbf{\Gamma}$. Huber's robust t-statistics are in parentheses below the coefficient estimates. Panel A of the table presents the estimates for the medium-sized growth portfolio. Panel B presents the estimates for the value portfolio within the same size category.

The first and fourth rows of Table 2.2 give the results of the return forecasting equation when lagged stock market returns, book-to-market ratio, and book equity are applied as regressors. In both regressions, all state variables exhibit some forecasting potential. The reversal property is strongly pronounced for annual returns. Book value is often used as a proxy for a firm's future cash flows. Relating it to the current market price produces a variable that is correlated with future returns. The $\overline{R}^2$ statistic for the return equation is 16.7% for the growth portfolio and 20% for the value portfolio. The remaining rows in Table 2.2 provide evidence of intensive interplay between the state variables. Past returns, the book-to-market ratio, and book equity are strong forecasters of future book-to-market ratio. The autoregressive coefficient of BE is close to unity, but it is also predicted by lagged BE/ME. High persistency in the data might challenge correct statistical inference and coefficient interpretation, leading to spurious results. However, advocates of stock return predictability by financial indicators argue that expected returns contain a slow-moving time-varying component. Its persistence implies that the predicting variables should be persistent as well, with forecastability improving over longer time horizons.

[9] All results retain their validity in 25 portfolio-level VARs. In general, the estimates are more accurate for value as opposed to growth stocks. For comparability, we discuss here the estimates of two VAR systems of medium-sized portfolios and report return forecasting regressions for growth and value portfolios within each size category.

[10] The results do not change qualitatively for other plausible parameter values.

[11] For similar VARs see Campbell (1991), Campbell and Vuolteenaho (2004), and Campbell et al. (2010).

The appendix to Campbell and Vuolteenaho (2004) discusses two well-known biases that might affect the VAR estimates when there is persistency in the data. The first is that estimates of autoregressive coefficients of persistent variables are biased downwards (Kendall, 1954), thus reducing the variability of discount-rate news. The second is that estimates of coefficients of returns on persistent forecasting variables are biased if there is comovement between innovations to forecasting variables and return innovations. In our sample, the average correlation between R and BE is extremely weak, with a correlation for the respective error terms of about -0.03. This implies a restrained Stambaugh (1999) bias for this variable, which seems to antagonize the Kendall (1954) bias with unclear total outcome.

Table 2.3 reports the results from forecasting return regressions for value and growth stocks within each size category from VAR models. Generally, the findings support the assertion that past returns, book-to-market equity, and book equity have some predicting potential for future returns. Note that BE/ME and BE coefficients of value stocks in the predicting regressions generally exceed those of corresponding growth stocks. Similarly, the fit is somewhat higher for stocks with high BE/ME within the same ME group. The reversal property is particularly strongly pronounced for medium-sized and large portfolios. Within each value category, large portfolios tend to have lower pricing errors. The R^2 coefficient is greater for large portfolios than for small portfolios throughout. The value premium is indicated by a significantly positive coefficient on BE/ME. Similarly, when size characteristics are included into the system (not reported), the negative slope coefficient is informative of the well-documented empirical fact that small stocks have higher average returns than big stocks.

2.3.2 Equity Risk Premia in the Cross-Section

This section examines the empirical plausibility of cash-flow and discount-rate betas for the consumption-based specifications compactly captured by (2.10). In each case, the two-beta multifactor representation (2.12) nests the associated empirical model. We compare these models in terms of their ability to explain the pattern of 25 Fama-French portfolios.

The models can be consistently estimated by a two-stage procedure proposed by Fama and MacBeth (1973).[12] For each empirical specification, we briefly discuss the results in terms of factor prices, the goodness of fit, and the mean pricing error. First, we focus on cross-sectional

[12] As noted by Lettau and Ludvigson (2001), the Fama-MacBeth (1973) procedure has important advantages for applications with a moderate number of time-series observations.

asset pricing tests of a two-beta consumption risk model. Next we perform a number of similar pricing exercises for linear factor models with cash-flow risk only.

The Cross-Sectional Fit of the Two-Beta Models Table 2.4 presents results of estimating the empirical specification in (2.12) for the C-CAPM, D-CAPM, EZC-CAPM, and EZD-CAPM. Each column looks at a different model. The table reports the estimated $\lambda_{CF,f}$ and $\lambda_{DR,f}$ coefficients from a cross-sectional regression of average excess returns on a constant and cash-flow and discount-rate betas. The betas are calculated strictly following (2.7) and (2.8) and returns are logged. Below the coefficient estimates we report t-statistics corrected for the generation of regressors (Shanken, 1992). The last three rows give the mean absolute pricing error, the R^2 and the $\overline{R}^2$ adjusted for degrees of freedom.

The results for the standard C-CAPM are presented in the first column of the table. The estimate of $\lambda_{CF,\Delta c}$ is a positive number, consistent with the view that consumption risk carries a positive risk premium. Though positive, the t-statistic for $\lambda_{DR,\Delta c}$ shows that the discount-rate beta on the consumption risk is not a significant determinant of the pattern of average returns. Given the estimated levels of consumption risk, the average return is far too high. The estimated intercept is statistically significant, which implies that average realized excess returns on Fama-French portfolios exceed those predicted by the model by roughly 11 percent per annum. For comparison, contemporaneous consumption risk of the canonical C-CAPM yields significant intercept estimates of about 12 percent per year and the ultimate consumption risk at a horizon of about three years generates intercept term estimates of about 6 to 7 percent per year (Julliard and Parker, 2005). The model explains about 40% of the cross-sectional variation in expected excess returns between low book-to-market and high book-to-market portfolios.

Column 2 of the table reports results for the D-CAPM where both nondurable and durable consumption growth components enter the pricing equation. Compared to the C-CAPM, this specification performs much better in terms of general fit. For the durable consumption model, both the $\overline{R}^2$ as well as the mean average error improve by roughly 20% and 50%, respectively. These results are consistent with what has been reported in the recent literature. Interestingly, taking account of the risk in durables, the coefficient of nondurables drops heavily and loses its statistical significance. Replacing nondurables, the comovement of assets' cash flows with durables plays the key role in capturing the cross-section of returns.

The regression in the third column extends the C-CAPM by bringing together nondurable consumption and market sources of risk. As in the basic C-CAPM, the risk stemming from high sensitivity of cash flows to fluctuations in nondurable consumption growth is priced, even though the $\lambda_{CF,\Delta c}$ estimate is now measured with a lower precision. Furthermore, the results indicate that the market risk is not significantly reflected in the cross-section of returns. Contradicting the prediction of the CAPM theory, λ_{DR,r^m} is estimated with a wrong sign. Using the same returns, Lettau and Ludvigson (2001) and Jagannathan and Wang (2007) estimate various specifications of the CAPM and similarly obtain negative risk estimates on the value-weighted market return. Despite the failure of the market risk to economically explain the differences in size and book-to-market sorted portfolios, taking account of global stock fluctuations slightly improves the general fit of the model. Note that, when risk is measured by Δc alone, the R^2 is 43%, and when risk is measured by Δc and r^m jointly, the R^2 is about 20% higher.

Finally, the last column of the table gives the results of the EZD-CAPM. As before, due to negative coefficient estimates, the market risk is difficult to interpret. However, it still improves the performance of the model compared to the simple D-CAPM. Consistent with previous findings in this study, nondurable betas cease to translate into risk premia once durable betas are additionally included as regressors. The Epstein-Zin durable specification explains more than 70% of the cross-sectional variation in equity risk premia. This number is of a similar order of magnitude to the $\overline{R}^2$ obtained by Lustig and Verdelhan (2007) for the EZD-CAPM confronted with annual returns on eight currency portfolios sorted on interest rate differentials. Compared to other models, the EZD-CAPM approximates 25 Fama-French portfolios best in the least squares sense and produces the lowest mean average error. It is also worth noting that despite implausible estimates of risk premia, taking account of the market risk improves the extent to which the model underpredicts excess returns. For the EZC-CAPM and EZD-CAPM, the magnitude of the intercept drops in economic and statistical terms. This is due to the relatively high estimates of the equity premium associated with durables. For the D-CAPM, $\lambda_{CF,\Delta d}$ is about 7.5% per annum and for the EZD-CAPM it even exceeds the 11% mark.

Graphical evidence of the performance of two-beta models is presented in Figure 2.1. In line with other studies (e.g. Lettau and Ludvigson, 2001; Yogo, 2006; and Jagannathan and Wang, 1998), the model generates the largest pricing error for the small growth portfolio for each specification.

Panel B of Table 2.4 reports the results from the same set of regressions as in Panel A, relying on a larger set of returns. In addition to 25 standard returns, 6 original size and book-to-market sorted portfolios are now included as test assets.[13] Confirming our previous result, nondurables become insignificant when durables enter the regression. Furthermore, the covariances of cash flows with durable consumption risk explain a large part of the cross-sectional return pattern. As in the former pricing test, the R^2 from the EZD-CAPM is almost twice as high as the R^2 from the C-CAPM. As before, the estimation of consumption-based asset pricing models does not provide reliable information about the role of the global market risk factor.

In summary, Table 2.4 transmits two central messages regarding the determination of expected risk premia. The first is the crucial importance of macroeconomic risks embodied in cash flows. The second is the relevance of an asset's exposure to the cyclical fluctuations in durable consumption goods. In particular, the magnitude of the risk price estimates as well as the measurement precision increase substantially once durable consumption expenditure enters the pricing equation. In total, the results indicate that all four considered consumption-based models explain a large share of cross-sectional variation in equity returns. The $\overline{R}^2$ statistics vary from 38% for the C-CAPM to as much as 74% for models that account for durables.

The Cross-Sectional Performance of the Cash-Flow Models To elaborate on results obtained in the previous section, we now evaluate the ability of macroeconomic risks embodied in assets' cash-flow components to fit the data. Specifically, we inquire whether the intrinsic risk conveyed in these cash flows can, on its own, account for differences in expected excess returns between low book-to-market and high book-to-market portfolios. Previous studies[14] suggest that assets' cash-flow exposure should mirror risk compensation.

To evaluate the empirical plausibility of the cash-flow beta model, we consider a cross-sectional regression,

$$E\left[R^{i,e}\right] = \lambda'_{CF,f}\beta^{i}_{CF,f} \tag{2.13}$$

in which the portfolio return is a linear function of its cash-flow betas. Utilizing 25 portfolios, Panel A of Table 2.5 reports the corresponding risk prices. Panel B extends the pool of test assets by additionally including 6 original portfolios. As before, the first column gives the results for the standard C-CAPM, the second estimates the D-CAPM, and the last two columns correspond

[13] For these returns equivalent portfolio characteristics are available.

[14] Bansal et al. (2005) assume joint dynamics of aggregate consumption and growth rates in cash flows to measure the consumption beta of discounted cash flows. Da (2009) links the asset's risk premium to its cash flows as well as to the cash flow's temporal pattern, referred to as cash-flow duration.

to the Epstein-Zin specifications, the EZC-CAPM and the EZD-CAPM, respectively.

The positive estimate of $\lambda_{CF,\Delta c}$ in the first column of the table illustrates that portfolios with high consumption cash-flow betas have, on average, high returns. The D-CAPM significantly prices the comovement of assets' cash flows with the growth rate in durables. Improving the general model fit, the temporary adjustments to the relatively more persistent expenditures for durables provide a better measure of risk, compared to nondurables. This result is true for the D-CAPM versus C-CAPM as well as in the Epstein-Zin framework for the EZD-CAPM against its counterpart EZC-CAPM. Moreover, the economic and statistical significance of the cash-flow risk in nondurables decreases abruptly once the durable consumption growth is additionally considered as a source of risk. In the D-CAPM, $\lambda_{CF,\Delta d}$ is estimated as 8.10% p.a. with a t-statistic of 2.77, and in the EZD-CAPM the estimate of $\lambda_{CF,\Delta d}$ is 11.97% p.a. with a t-statistic of 3.76.

Estimates of the market cash-flow premium are not always intuitively plausible. The estimate of λ_{CF,r^m} is positive but insignificant for the EZC-CAPM and significant but negative for the EZD-CAPM.

Finally, in all four cases, the cash-flow beta model explains a considerable portion of the cross-sectional variation in risk premia, with adjusted $\overline{R}^2$ fluctuating between 32% and 70%. Figure 2.2 provides a visual summary of results presented in Panel A. The findings indicate that measuring risk based on cash flows alone explains a considerable share of the cross-sectional variation in risk premia. A direct comparison of the plots in Figures 2.1 and 2.2 reveals two interesting features of the data. First, the general fit of the C- and EZC-CAPMs declines by about 20% and more than 40%, respectively, for the cash-flow models versus two-beta models. This observation suggests that the risk captured by the transitory component plays an important role in consumption fluctuations of nondurable goods, consistent with the slow adjustment of aggregate consumption to permanent shocks. On the other hand, the corresponding loss in the model fit amounts to negligible 2% and 8% for the D- and EZD-CAPMs, respectively. Moreover, the adjusted $\overline{R}^2$ even goes up slightly for the cash-flow D-CAPM and drops insignificantly in the case of EZD-CAPM. This observation suggests that the majority of fluctuations in durables tend to be accounted for by cash flows, in line with models underpinning the relevance of permanent low-frequency component in long-run consumption expenditure (Jagannathan and Wang, 2007).

2.3.3 Extensions and Further Robustness Checks

We conduct a number of robustness checks in the following dimensions: the magnitude of ρ, other different VAR specifications employing both, pooled and portfolio-specific VAR estimation, other test assets and different sample periods. We report our findings below.

Sensitivity to the Choice of State Variables In order to examine the sensitivity of our main conclusions to the particular choice of state variables, we estimate alternative VAR systems employing micro-level data on the number of firms entering the portfolio, portfolio size and a different measure of book-to-market equity. We find that the parameter estimates do not change much and the conclusions remain qualitatively unchanged. Tables 2.6 and 2.7 repeat the asset pricing tests in Tables 2.4 and 2.5 based on a VAR with market-adjusted returns, BE/ME ratio and average firm size. To determine whether the results depend critically on the estimation method, we evaluated the models relying on pooled and individual portfolio VARs alike. Table 2.8 repeats the asset pricing tests in Table 2.4 based on a pooled VAR.

Additional Test Assets Using our decomposition method based on individual portfolio data, we additionally experiment with alternative Fama-French portfolios with three groups on book-to-market and two groups on size. This is the only sample of stock returns for which an equivalent data set on portfolio-level characteristics is available. Our conclusions remain broadly consistent with the original specification.

Sample Split Fama and French (1993), Julliard and Parker (2005), Campbell et al. (2010), and other earlier studies on conditional and non-conditional asset pricing models choose to split the sample in 1963 in their empirical tests.[15] Following this literature, we perform tests for both, the single- and two-beta model classes in the pre- and post-1963 periods. Due to a low number of observations in the early subperiod, the general fit as well as the precision of some estimates deteriorate somewhat. Our major intuition, however, is not affected, except that the market risk does a better job at explaining expected returns but the comovement of assets' cash flows with aggregate consumption risk is estimated insignificantly. Over the 1963-2007 period, we get the same cross-sectional pattern of coefficients and model fit as in our baseline case. Results are

[15] As discussed by Lettau and Ludvigson (2001) and Campbell and Vuolteenaho (2004), the sample of firms in Fama-French portfolios changed significantly in 1963 due to a limited availability of the data on common equity in the pre-1963 period.

available upon request.

Time Variation in the Equity Premium So far, we have concentrated on the cross-sectional implications of the models implied by (2.12) and (2.13). This subsection completes the analysis by seeking to explain the time-series properties of the equity premium in the stock market. If betas are fixed, time variation in expected returns must reflect time variation in risk compensation.

Allowing for time-varying risk compensation, we obtain time series of $\lambda_{CF,f,t}$ and $\lambda_{DR,f,t}$ by running a cross-sectional regression of excess returns on the betas in each point of time. The average time period t equity premium component due to cash flows

$$E\left[\overline{R}^{e}_{CF,t}\right] = \frac{1}{25}\sum\nolimits_{i=1}^{25}\lambda'_{CF,f,t}\beta^{i}_{CF,f} \tag{2.14}$$

and the component attributed to discount rates

$$E\left[\overline{R}^{e}_{DR,t}\right] = \frac{1}{25}\sum\nolimits_{i=1}^{25}\lambda'_{DR,f,t}\beta^{i}_{DR,f} \tag{2.15}$$

sum up to the total average premium

$$E\left[\overline{R}^{e}_{t}\right] = E\left[\overline{R}^{e}_{CF,t}\right] + E\left[\overline{R}^{e}_{DR,t}\right] \tag{2.16}$$

across 25 Fama-French portfolios. Figure 2.3 plots the time series of the equity premium implied by the EZD-CAPM against the actually realized equity premium. The blue line represents the total equity premium, $E\left[\overline{R}^{e}_{t}\right]$, and the red line represents the part due to cash flows, $E\left[\overline{R}^{e}_{CF,t}\right]$. The difference obviously corresponds to the premium on discount-rate risk. The two lines tend to overlap, implying that the major portion of time variation in the equity premium is driven by the risk embodied in cash flows. The same pattern holds true for other consumption-based specifications explored within the scope of this study, with correlation coefficients varying from 88% to 92%. The two-beta model fits the actual average risk premium on 25 value-weighted Fama-French portfolios represented by the dashed line remarkably well. In the post-war period, the equity premium is, however, excessively volatile compared with its estimated counterparts. Nevertheless, there is a striking comovement between the three time series, increasing particularly since the mid-1960s. The plot clearly visualizes the ability of the model to generate a countercyclical risk premium which reacts strongly to the oil shock in 1968, deep recession of the late 1970s and a severe economic downturn in the early 2000s.

2.4 Conclusions

This paper examines the ability of the cash-flow and discount-rate components of asset returns to reflect economic risks and thus to explain the cross-section of average returns on the 25 Fama-French benchmark equity portfolios within a broad set of consumption-based asset pricing models. Disentangling the consumption beta of an asset into a component driven by assets' cash-flow news and a component related to assets' discount-rate news reveals that macroeconomic, especially consumption-related, risks embodied in cash flows can largely account for the dynamics of average stock returns. Empirically, we find that differences in expected excess returns between low book-to-market and high book-to-market portfolios are associated with differences in their cash-flow betas. In addition, the results indicate that the risk premium on equity markets is primarily driven by the exposure of assets' cash flows to the cyclical variability of durable consumption goods.

The long-term timing dimension, the fundamental nature of cash flows and the cyclical variation in durables are important aspects driving the main conclusions of this study. Consistent with Jagannathan and Wang (2007), Bansal et al. (2005), and Julliard and Parker (2005), the findings in this paper highlight the discretionary power of one-year consumption growth for expected return differentials across assets. Value stocks comove particularly strongly with procyclical durable consumption. This result is in line with a well-known empirical fact that stock return can be predicted by macroeconomic aggregates that are informative about the business cycle. Working with annual time horizons, however, requires long series of low-frequency data for accurate beta estimation.

Despite the strong relationship between cash flows and expected equity returns, we also find evidence indicating that the empirical two-beta specification misses some important features of financial data. First, while the magnitude of the implied risk premium for bearing consumption risk is rather plausible, the estimated market risk premium is often negative. Second, the models are challenged by pricing small growth portfolios. Third, the regressions of excess returns on cash-flow and discount-rate betas yield intercept estimates that are significantly different from zero. This indicates that average excess returns on Fama-French portfolios exceed those postulated by their consumption risk, implying model misspecification. In this respect, beta decomposition does not improve on empirical consumption-based tests in Lettau and Ludvigson (2001), Yogo (2006), and Jagannathan and Wang (1998).

In sum, the empirical evidence in this article supports the view that economic risks in fundamental cash flows are important for understanding differences in risk premia across assets. In particular, there exists a strong link between the cross-sectional pattern in stock returns and the exposure of their cash flows to fluctuations in durable consumption goods.

2.5 Tables and Figures

Table 2.1: Descriptive Statistics

Panel A of the table reports annual means, maxima, minima and standard deviations of log nondurable and durable consumption growth. It also reports the correlations of these variables with the market return and the business cycle, proxied by the NBER recession dummy. Panel B of the table reports annual means, standard deviations, t-statistics, Sharpe ratios, average log book equity and log book-to-market ratio for 25 value-weighted Fama-French portfolios sorted by size and book-to-market equity. The sample period runs from 1947 to 2007.

Panel A: Consumption Growth

	Mean(%)	Max(%)	Min(%)	Std(%)	Mkt	BC
Nondur	2.10	4.17	-0.30	1.12	0.40	-0.47
Dur	4.26	20.35	-10.38	6.76	0.35	-0.50

Panel B: 25 Fama-French Portfolios

	G	2	3	4	V	G	2	3	4	V
	Mean (%)					Std (%)				
S	9.92	16.25	16.17	18.87	21.30	34.40	30.98	25.46	25.23	27.57
2	10.83	14.62	17.37	18.11	19.80	27.46	22.23	22.87	22.72	24.63
3	11.94	14.94	15.66	17.42	18.92	22.78	20.04	19.06	22.10	24.17
4	12.83	13.13	16.26	16.42	17.89	20.87	17.74	19.30	20.50	23.76
L	12.24	12.50	13.75	14.14	15.15	18.27	16.10	16.10	18.32	21.10

Table 2.1: *Continued*

	G	2	3	4	V	G	2	3	4	V
	T-statistic					Sharpe ratio				
S	2.25	4.10	4.96	5.84	6.03	0.29	0.52	0.64	0.75	0.77
2	3.08	5.14	5.93	6.22	6.28	0.39	0.66	0.76	0.80	0.80
3	4.09	5.82	6.42	6.16	6.11	0.52	0.75	0.82	0.79	0.78
4	4.80	5.78	6.58	6.26	5.88	0.62	0.74	0.84	0.80	0.75
L	5.23	6.06	6.67	6.03	5.61	0.67	0.78	0.85	0.77	0.72
	Average BE					Average BE/ME				
S	6.94	7.52	8.00	8.50	9.30	-1.21	-0.54	-0.23	0.05	0.67
2	7.66	8.23	8.60	8.87	9.18	-1.22	-0.59	-0.27	0.02	0.57
3	8.38	8.89	9.22	9.35	9.56	-1.24	-0.62	-0.28	0.02	0.55
4	9.34	9.77	9.87	9.92	10.10	-1.25	-0.61	-0.29	0.03	0.58
L	11.40	11.42	11.42	11.20	11.00	-1.34	-0.63	-0.29	0.02	0.48

Table 2.2: VAR Estimates Based on BE/ME and BE

The table shows the OLS parameter estimates for a first-order VAR model including a constant, value-weighted stock return (R), book-to-market ratio (BE/ME) and book equity (BE). All three variables are logged. Returns are market-adjusted by subtracting the market return from the portfolio return. BE/ME is calculated as a ratio of the sum of individual firm BE's in the portfolio over the sum of respective ME's. Each row corresponds to a different dependent variable. The first three columns report coefficients on the explanatory variables listed in the column header; the last column shows the adjusted $\overline{R}^2$ statistics. Robust t-statistics are in parentheses. Panel A reports the results for medium-sized growth portfolio P31; Panel B reports the results for medium-sized value portfolio P35. The sample period for the dependent variable is 1948 to 2007.

	R_t	$(BE/ME)_t$	BE_t	$\overline{R}^2$(%)
Panel A: Medium Growth P31				
R_{t+1}	-0.306	0.363	0.054	16.71
	(-2.600)	(2.958)	(1.829)	
$(BE/ME)_{t+1}$	-0.301	0.678	-0.061	73.97
	(-3.210)	(7.677)	(-2.360)	
BE_{t+1}	0.069	-0.152	0.962	99.21
	(0.974)	(-2.080)	(61.137)	
Panel B: Medium Value P35				
R_{t+1}	-0.345	0.511	0.121	20.04
	(-2.954)	(3.830)	(3.484)	
$(BE/ME)_{t+1}$	-0.283	0.659	-0.069	74.50
	(-3.283)	(6.641)	(-2.379)	
BE_{t+1}	-0.018	-0.190	0.955	98.06
	(-0.216)	(-1.945)	(35.826)	

Table 2.3: Return Forecasting by BE/ME and BE

The table shows OLS parameter estimates for return forecasting regressions from 25 first-order portfolio-level VAR models including a constant, value-weighted stock return (R), book-to-market ratio (BE/ME) and book equity (BE). All three variables are logged. Returns are market-adjusted by subtracting the market return from the portfolio return. BE/ME is calculated as a ratio of the sum of individual firm BE's in the portfolio over the sum of respective ME's. The first three columns report coefficients on the explanatory variables listed in the column header; the last column shows the adjusted $\overline{R}^2$ statistics. Newey-West (1987) corrected t-statistics are in parentheses. The sample period for the dependent variable is 1948 to 2007.

	R_t	$(BE/ME)_t$	BE_t	$\overline{R}^2(\%)$
$P11$	-0.158	0.361	0.040	5.06
	(-1.301)	(1.965)	(1.292)	
$P15$	-0.186	0.334	0.070	6.52
	(-1.612)	(2.103)	(1.769)	
$P21$	-0.176	0.366	0.055	9.46
	(-1.414)	(2.259)	(1.623)	
$P25$	-0.311	0.487	0.092	15.59
	(-2.648)	(3.644)	(2.720)	
$P31$	-0.306	0.363	0.054	16.71
	(-2.253)	(2.822)	(1.859)	
$P35$	-0.345	0.511	0.121	20.04
	(-2.960)	(3.634)	(3.022)	
$P41$	-0.368	0.239	0.050	15.07
	(-2.886)	(2.221)	(1.707)	
$P45$	-0.426	0.373	0.077	16.66
	(-2.989)	(2.499)	(1.865)	
$P51$	-0.393	0.121	0.012	13.58
	(-3.946)	(1.606)	(0.595)	
$P55$	-0.397	0.332	0.056	18.27
	(-3.324)	(2.767)	(2.444)	

Table 2.4: Tests of Two-Beta Models Based on BE/ME and BE

The table reports the estimated cash-flow and discount-rate risk prices and the measures of fit for the C-CAPM, D-CAPM, EZC-CAPM, and the EZD-CAPM. The test assets are the 25 (31) Fama-French portfolios sorted by size and book-to-market equity in Panel A (B). Estimates are from a cross-sectional regression of average excess returns on an intercept and cash-flow and discount-rate factor betas. Risk prices are expressed in annual percentage terms. Shanken (1992) corrected t-statistics are in parentheses. The underlying VAR system includes market-adjusted returns, BE/ME and BE. All three variables are logged. Returns are market-adjusted by subtracting the market return from the portfolio return. The data cover the period 1947-2007. The last three rows report the mean absolute pricing error, the R^2 and the $\overline{R}^2$ adjusted for the degrees of freedom.

	C-CAPM	D-CAPM	EZC-CAPM	EZD-CAPM
Panel A: 25 Value-Weighted Portfolios				
Constant	11.381	11.618	7.990	5.806
	(4.810)	(5.600)	(2.075)	(1.960)
λ_{CF,r^m}			0.397	-6.278
			(0.110)	(-1.917)
λ_{DR,r^m}			-14.404	-11.234
			(-1.399)	(-1.473)
$\lambda_{CF,\Delta c}$	1.536	0.399	1.185	-0.171
	(2.536)	(0.502)	(1.821)	(-0.249)
$\lambda_{DR,\Delta c}$	0.851	0.442	0.790	0.142
	(1.109)	(0.588)	(1.071)	(0.229)
$\lambda_{CF,\Delta d}$		7.505		11.184
		(2.202)		(3.278)
$\lambda_{DR,\Delta d}$		-0.299		2.217
		(-0.045)		(0.401)
MAE	0.4184	0.3385	0.3820	0.2702
R^2	0.4351	0.6442	0.5286	0.7897
$\overline{R}^2$	0.3837	0.5730	0.4343	0.7196

Table 2.4: *Continued*

	C-CAPM	D-CAPM	EZC-CAPM	EZD-CAPM
Panel B: 31 Value-Weighted Portfolios				
Constant	11.608	11.846	8.063	5.447
	(5.367)	(5.997)	(2.452)	(2.070)
λ_{CF,r^m}			0.085	-6.850
			(0.028)	(-2.382)
λ_{DR,r^m}			-0.143	-12.093
			(-1.613)	(-1.791)
$\lambda_{CF,\Delta c}$	1.591	0.616	1.237	-0.168
	(2.907)	(0.827)	(2.099)	(-0.266)
$\lambda_{DR,\Delta c}$	0.727	0.4161	0.654	0.000
	(1.111)	(0.609)	(1.050)	(0.008)
$\lambda_{CF,\Delta d}$		6.539		11.414
		(2.085)		(3.693)
$\lambda_{DR,\Delta d}$		-1.019		2.824
		(-0.169)		(0.570)
MAE	0.5015	0.4459	0.4459	0.3225
R^2	0.4594	0.6193	0.5495	0.7920
$\overline{R}^2$	0.4208	0.5607	0.4802	0.7400

Table 2.5: Tests of Cash-Flow Models Based on BE/ME and BE

The table reports the estimated cash-flow risk prices and the measures of fit for the C-CAPM, D-CAPM, EZC-CAPM, and the EZD-CAPM. The test assets are the 25 (31) Fama-French portfolios sorted by size and book-to-market equity in Panel A (B). Estimates are from a cross-sectional regression of average excess returns on an intercept and cash-flow factor betas. Risk prices are expressed in annual percentage terms. Shanken (1992) corrected t-statistics are in parentheses. The underlying VAR system includes returns, BE/ME and BE. All three variables are logged. Returns are market-adjusted by subtracting the market return from the portfolio return. The data cover the period 1947-2007. The last three rows report the mean absolute pricing error, the R^2 and the $\overline{R}^2$ adjusted for the degrees of freedom.

	C-CAPM	D-CAPM	EZC-CAPM	EZD-CAPM
Panel A: 25 Value-Weighted Portfolios				
Constant	12.873	12.297	13.226	9.024
	(6.414)	(7.734)	(4.883)	(4.243)
λ_{CF,r^m}			0.786	-6.679
			(0.199)	(-2.024)
$\lambda_{CF,\Delta c}$	1.618	0.339	1.577	0.077
	(2.610)	(0.504)	(2.368)	(0.130)
$\lambda_{CF,\Delta d}$		8.098		11.971
		(2.765)		(3.762)
MAE	0.4384	0.3411	0.4425	0.3034
R^2	0.3720	0.6295	0.3742	0.7334
$\overline{R}^2$	0.3447	0.5958	0.3173	0.6954

Table 2.5: *Continued*

Panel B: 31 Value-Weighted Portfolios				
Constant	13.120	12.446	13.179	8.813
	(7.612)	(8.556)	(5.837)	(4.666)
λ_{CF,r^m}			0.142	-7.603
			(0.042)	(-2.522)
$\lambda_{CF,\Delta c}$	1.736	0.549	1.728	0.200
	(3.185)	(0.862)	(2.941)	(0.362)
$\lambda_{CF,\Delta d}$		7.212		11.979
		(2.645)		(4.035)
MAE	0.5240	0.4547	0.5251	0.3766
R^2	0.4117	0.6077	0.4118	0.7333
$\overline{R}^2$	0.3914	0.5797	0.3697	0.7037

Table 2.6: Tests of Two-Beta Models Based on BE/ME and Size

The table reports the estimated cash-flow and discount-rate risk prices and the measures of fit for the C-CAPM, D-CAPM, EZC-CAPM, and the EZD-CAPM. The test assets are the 25 Fama-French portfolios sorted by size and book-to-market equity. The underlying VAR system includes returns, BE/ME and portfolio size. For further details see notes to Table 2.4.

	C-CAPM	D-CAPM	EZC-CAPM	EZD-CAPM
Constant	10.234	10.106	8.569	6.311
	(6.765)	(6.469)	(1.783)	(1.863)
λ_{CF,r^m}			-2.430	-7.963
			(-0.615)	(-2.188)
λ_{DR,r^m}			-2.226	-0.468
			(-0.213)	(-0.052)
$\lambda_{CF,\Delta c}$	1.290	-0.153	1.412	-0.190
	(2.430)	(-0.194)	(1.602)	(-0.239)
$\lambda_{DR,\Delta c}$	1.109	0.298	1.182	0.512
	(1.611)	(0.381)	(1.463)	(0.782)
$\lambda_{CF,\Delta d}$		8.822		12.432
		(2.358)		(3.579)
$\lambda_{DR,\Delta d}$		5.947		2.478
		(1.188)		(0.442)
MAE	0.4303	0.3617	0.4079	0.2806
R^2	0.3500	0.5843	0.3762	0.7428
$\overline{R}^2$	0.2909	0.5012	0.2515	0.6571

Table 2.7: Tests of Cash-Flow Models Based on BE/ME and Size

The table reports the estimated cash-flow risk prices and the measures of fit for the C-CAPM, D-CAPM, EZC-CAPM, and the EZD-CAPM. The test assets are the 25 Fama-French portfolios sorted by size and book-to-market equity. The underlying VAR system includes returns, BE/ME and portfolio size. For further details see notes to Table 2.5.

	C-CAPM	D-CAPM	EZC-CAPM	EZD-CAPM
Constant	10.380	9.191	9.606	5.606
	(6.322)	(6.005)	(4.616)	(3.212)
λ_{CF,r^m}			-2.567	-9.288
			(-0.611)	(-2.799)
$\lambda_{CF,\Delta c}$	0.760	-0.633	1.022	-0.604
	(1.678)	(-1.818)	(1.633)	(-1.008)
$\lambda_{CF,\Delta d}$		7.952		13.200
		(2.088)		(3.776)
MAE	0.4705	0.4308	0.4479	0.2794
R^2	0.1966	0.4246	0.2230	0.6704
$\overline{R}^2$	0.1617	0.3723	0.1523	0.6234

Table 2.8: Tests of Two-Beta Models Based on Pooled VAR

The table reports the estimated cash-flow and discount-rate risk prices and the measures of fit for the C-CAPM, D-CAPM, EZC-CAPM, and the EZD-CAPM. The test assets are the 25 Fama-French portfolios sorted by size and book-to-market equity. The results are based on a pooled VAR system. For further details see notes to Table 2.4.

	C-CAPM	D-CAPM	EZC-CAPM	EZD-CAPM
Constant	12.277	12.706	5.051	8.673
	(6.541)	(6.001)	(0.800)	(1.689)
λ_{CF,r^m}			-15.158	-11.325
			(-1.877)	(-1.761)
λ_{DR,r^m}			7.164	6.927
			(0.847)	(1.015)
$\lambda_{CF,\Delta c}$	1.394	-0.836	1.694	0.646
	(2.487)	(-0.112)	(2.799)	(0.798)
$\lambda_{DR,\Delta c}$	2.178	1.118	1.222	0.916
	(3.394)	(1.138)	(1.549)	(1.047)
$\lambda_{CF,\Delta d}$		11.007		9.357
		(3.022)		(2.818)
$\lambda_{DR,\Delta d}$		1.569		-1.709
		(0.284)		(-0.326)
MAE	0.3760	0.2847	0.2930	0.2341
R^2	0.5160	0.7474	0.6604	0.8236
$\overline{R}^2$	0.4720	0.6968	0.5925	0.7648

Figure 2.1: Realized versus Predicted Returns for Two-Beta Models

The figure plots realized versus predicted annual returns for the 25 Fama-French portfolios sorted by size and book-to-market equity. The estimated models are the C-CAPM, D-CAPM, EZC-CAPM, and the EZD-CAPM. The horizontal axes correspond to the predicted average excess returns and the vertical axes to the sample average excess returns. The sample period is 1947-2007. The predicted values are from regressions presented in Table 2.4.

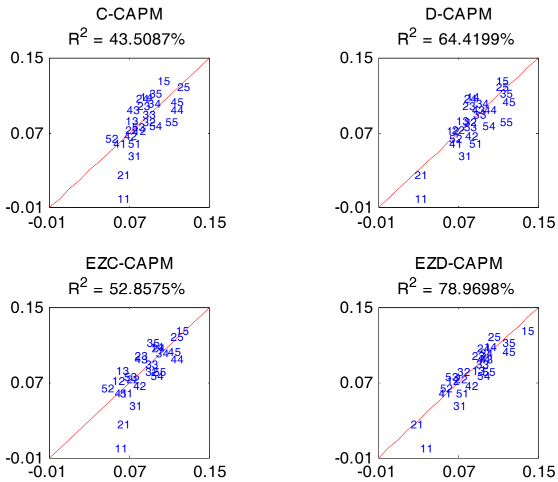


Figure 2.2: Realized versus Predicted Returns for Cash-Flow Models

The predicted values are from regressions presented in Table 5. For further details consult the notes to Figure 2.1.

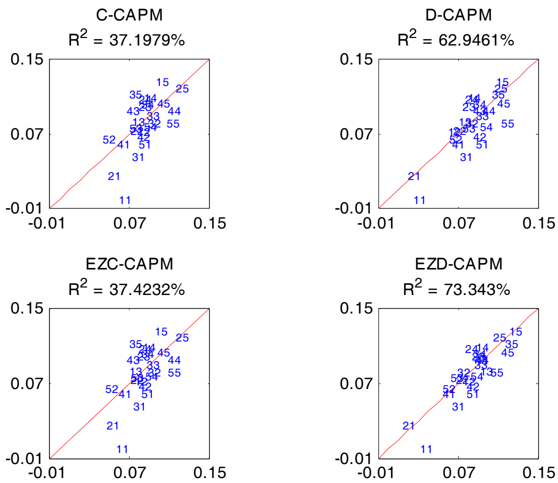
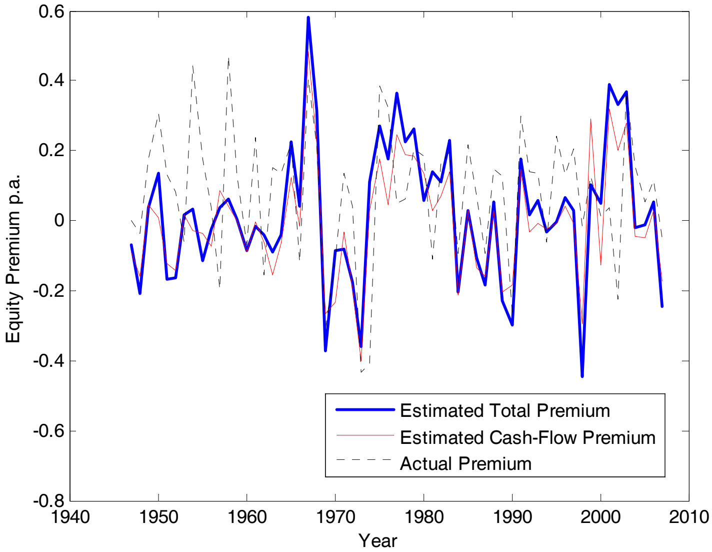


Figure 2.3: Time Variation in Equity Premium

The figure plots time series of total predicted and actually realized equity premium against the predicted premium due to cash flows. The estimated model is the two-beta EZD-CAPM. The sample period is 1947-2007.



3 Downside Risk in Good and Bad Consumption Betas

The idea that investors care differently about downside losses versus upside gains dates back to Roy (1952) and Markowitz (1952).[16] Investors who are more sensitive to economic downturns than to periods of economic recovery, require a compensation for holding assets that covary strongly with negative consumption shocks. Hence, assets that tend to do poorly in recessions should have on average higher returns. This paper provides further evidence on importance of downside risk in consumption for empirical asset pricing. In particular, our results suggest that different exposures to downside consumption risk are reflected in the cross-section of stock returns.

Relying on the consumption-wealth ratio as an indicator of the state of the economy, Lettau and Ludvigson (2001) explore a conditional version of a consumption capital asset pricing model (CCAPM). The authors show that value stocks, i.e. stocks with high book-to-market value, have higher conditional consumption betas in bad times than their growth counterparts with low book-to-market value. This finding is striking in view of ample evidence that both stock groups have total consumption betas of similar size (Mankiw and Shapiro, 1986; Campbell, 1996; and Cochrane, 1996). More recently, Polkovnichenko (2010) provides support for the aversion to downside consumption risk and shows that this result can contribute to our understanding of the value premium.

To investigate this finding we start with a conditional version of the CCAPM which allows for different sensitivities to downside versus upside movements in consumption growth. Our first observation is that the two-beta model consistently generates lower pricing errors and fits the data better than the single-beta CCAPM. In addition, the economic magnitude of consumption risk in downside betas overweights that of upside betas by roughly 70%. Moreover, we find that differences in assets' exposure to the downside risk explain more than a half of the cross-sectional return differentials on portfolio returns while there is no significant relation between the value and growth stock returns and their sensitivities to the upside risk. This finding is in line with theoretical models by Gul (1991) and Ang et al. (2006) which suggest that downside risk may be priced cross-sectionally in an equilibrium setting.

For evaluating the empirical performance of models based on downside consumption risk we focus on the standard set of assets consisting of 25 value-weighted portfolio returns constructed

[16] This chapter of the thesis is based on Galsband (2010b).

by Fama and French based on a double-sorting procedure. Due to the large and relatively stable pattern of average returns across different subsamples and frequencies, these portfolios have been used extensively in the literature to examine the performance of various asset pricing models. We also consider alternative Fama-French portfolios obtained by combining 3 groups of book-to-market sorted stocks and 2 groups of size sorted stocks. We use the two-pass Fama-MacBeth (1973) methodology to obtain risk premia estimates.

An important dimension of this paper is the measurement of assets' cash-flow and discount-rate news. We follow the early studies on the returns decomposition approach initiated by Campbell and Vuolteenaho (2004). In this highly influential literature, the discount-rate news is estimated directly by a VAR relying on a set of common economy-wide state variables; the cash-flow news is then backed out as a residual. The robustness of Campbell and Vuolteenaho (2004) results has been disputed by Chen and Zhao (2009) who argue that construction of the cash-flow news is crucial for our understanding of the relative importance of both types of news in driving the time-series and cross-sectional variations of stock returns. We construct a VAR based on portfolio-specific characteristics. This method of computing asset-specific news alleviates the problem of high degree of news correlation driven by a common set state variables. Following Fama and French (1993), we use variables related to firm size and book-to-market equity to describe the dynamics of returns. Similar VARs in Campbell et al. (2010) and Galsband (2010a) appear successful at replicating the joint dynamics of economic variables and produce economically plausible return estimates.

For better understanding of the relation between the value premium and economy-wide consumption movements, we use the methodology introduced by Campbell and Mei (1993) and Campbell and Vuolteenaho (2004). Pricing assets' cash-flow and discount-rate news' covariances with consumption innovations reveals that a significantly positive premium is attached to both types of news. In our regressions, the estimates of "bad" betas usually exceed those of "good" betas. This result turns out consistent with the intertemporal asset pricing theory by Merton (1973) which suggests that exposure to cash-flow risks should be rewarded with a higher price of risk than an asset's sensitivity to market discount-rate risks.

In a next step, we break assets' "bad" consumption betas, i.e. the sensitivities of assets' cash-flow components to consumption risk, and assets' "good" consumption betas, i.e. the sensitivities of assets' discount-rate components to consumption risk, into an upside and a downside betas, respectively. Thus, we end up with a four-beta model which distinguishes between upside cash-flow, upside discount-rate, downside cash-flow and downside discount-rate consumption risk components. Botshekan et al. (2010) derive a similar decomposition of a standard market beta studying the stock return's covariation with market cash-flow and discount-rate news in both up and down markets. We test whether the four components of the overall consumption beta are priced in the cross-section of stock returns. In line with Botshekan et al. (2010) our results indicate that the risk associated with comovement of assets' "good" discount-rate and "bad" cash-flow news with negative consumption shocks earns a significant premium. Hence, both bad and good betas are driven by their high sensitivities to economic downside, or recession, risk.

We subject our result to a number of robustness checks. We control for non-syncronous and non-frequent stock trading, different sample periods, different test assets, and different model specifications. Although the results deteriorate in the early sample period, the bad downside consumption beta as well as the good downside consumption beta consistently emerge as the major driver of risk premia on equity markets.

The remainder of the paper is organized as follows. Section 3.1 explains the decomposition of stock returns and presents our baseline stock-level VAR results. Section 3.2 further decomposes the "bad" or cash-flow and the "good" or discount-rate risks of value and growth stocks with respect to their sensitivities to positive and negative consumption shocks, and summarizes our main cross-sectional results. Section 3.3 explores the robustness of our findings, and Section 3.4 concludes.

3.1 Decomposing Stock Returns

3.1.1 VAR Methodology

Campbell and Shiller (1988a) show that unexpected stock returns can be approximated by a sum of unexpected future cash-flow news and discount-rate news. Elaborating on this insight, Campbell (1991) extends the loglinear present-value approach to obtain a decomposition of the unexpected return on a dividend paying stock i, $r_{i,t}$:

$$\begin{aligned}
\eta_t^i &= r_t^i - E_{t-1}\left[r_t^i\right] \\
&= (E_t - E_{t-1})\sum_{j=0}^{\infty}\kappa^j \Delta d_{t+j}^i - (E_t - E_{t-1})\sum_{j=0}^{\infty}\kappa^j r_{t+j}^i \\
&= \eta_{CF,t}^i - \eta_{DR,t}^i, \qquad (3.1)
\end{aligned}$$

where E_t is the expectation operator at time t and κ is a constant strictly less than 1. The term $\eta^i_{CF,t} = (E_t - E_{t-1}) \sum_{j=0}^{\infty} \kappa^j \Delta d^i_{t+j}$ represents the revision in expectations of future discounted dividend growth rates. This expression is referred to as cash-flow news. Analogously, $\eta^i_{DR,t} = (E_t - E_{t-1}) \sum_{j=0}^{\infty} \kappa^j r^i_{t+j}$ represents the revision in expectations of future returns. It is typically referred to as the discount-rate news.

For the empirical implementation, we assume a first-order[17] autoregressive rule of motion for a vector of state variables, $\mathbf{z}_t$:

$$\mathbf{z}_t = \mathbf{a} + \mathbf{\Gamma} \mathbf{z}_{t-1} + \mathbf{u}_t \tag{3.2}$$

with r^i_t as the first element of an m-by-1 state vector, $\mathbf{z}_t$, and $r^i_t - E_{t-1}\left[r^i_t\right]$ as the first element of an i.i.d. m-by-1 vector of shocks, $\mathbf{u}_t$. In equation (3.2), $\mathbf{a}$ and $\mathbf{\Gamma}$ are, respectively, an m-by-1 vector and m-by-m companion matrix of constant parameters.

It follows immediately that the discount-rate news can be extracted via

$$\eta^i_{DR,t} = \mathbf{e1}'\boldsymbol{\lambda}\mathbf{u}_t, \tag{3.3}$$

where $\boldsymbol{\lambda} \equiv \kappa\mathbf{\Gamma}\left(\mathbf{I} - \kappa\mathbf{\Gamma}\right)^{-1}$ and $\mathbf{e1}$ denotes an m-by-1 vector whose first element is unity and the remaining elements are all zero.

The cash-flow news can further be backed out by subtracting the discount-rate news from the total unexpected return,

$$\eta^i_{CF,t} = \left(\mathbf{e1}' + \mathbf{e1}'\boldsymbol{\lambda}\right)\mathbf{u}_t. \tag{3.4}$$

3.1.2 State Variables

We implement the main specification of the portfolio-level VAR with three variables. The first is the log value-weighted return on double-sorted portfolios. The data on 25 stock portfolios are readily available from Kenneth R. French's home page. As suggested by Campbell et al. (2010), we use market-adjusted returns obtained by subtracting the market return from the portfolio return for each time period. The market return is the return on the S&P Composite Stock Price Index from the Robert Shiller online data set. The second state variable is the log BE/ME ratio, measured as a ratio of the sum of BE's to the sum of ME's of all stocks in the portfolio. For robustness purposes, we also use the log BE/ME ratio, measured as a value-weighted average

[17] As discussed by Campbell and Shiller (1988a), the assumption that the VAR is first-order is not restrictive, since this formulation also allows for higher-order VAR models by stacking lagged values into the state vector.

of BE/ME of all stocks in the portfolio. We include BE/ME in the state vector to account for the well-known value effect in returns (Fama and French, 1992, 1993 and references therein). The final element of the state vector is assigned to capture the widely discussed size effect in returns. Portfolio size is gauged by the number of firms in the portfolio. Other measures of size, such as average or total book-equity can be applied interchangeably. For the baseline model, we include the number of firms since this variable shows the lowest degree of persistency. For similar VARs see Campbell et al. (2010) and Galsband (2010a).

3.1.3 VAR Dynamics

The table shows the pooled-OLS parameter estimates for a first order firm-level VAR. The total variance of the return is 0.0674, which corresponds to the sum of variance of expected-return news (0.0342), the variance of cash-flow news (0.0037) and twice the covariance between the two news components (0.0002). The two news series are virtually uncorrelated with each other with a correlation coefficient of 0.0065.

The first row of Table 3.1 gives the results of the return forecasting equation when lagged stock market returns, book-to-market ratio and size are applied as regressors. The reversal property is pronounced for annual returns. Parameter estimates imply that expected returns are high when past book-to-market ratio and size are high. Book value is often used as a proxy for a firm's future cash flows. Relating it to the current market price produces a variable that is correlated with future returns.

3.2 Asset Returns and Consumption Risk

Next we study a relation between return innovations and innovations in consumption. To further explore the cash-flow and discount-rate components in unexpected variations of stock returns, it distinguishes between upside and downside movements in consumption growth.

3.2.1 Upside and Downside Consumption Risk

The idea that investors care differently about uncertainty towards unexpected downside versus upside portfolio movements dates back to Roy (1952) and Markowitz (1952). An economic notion of compensation for high sensitivity to downside market movements has a lot of intuitive appeal. Ang et al. (2006) provide empirical evidence on significant reward for bearing downside risk on equity markets. More recently, Polkovnichenko (2010) models aversion to downside risk in consumption to show that downside risk premium exhibits significant variation across portfolios and contributes to value and size premia in the cross-section. Motivated by this finding, we allow for different sensitivities of return innovations to consumption shocks. We measure upside and downside consumption risk by using conditional variances and covariances.

We first define the standard consumption beta or the sensitivity of return innovation, η_t^i, to consumption innovation, η_t^c, as

$$\beta_c^i = \frac{Cov\left(\eta_t^i, \eta_t^c\right)}{Var\left(\eta_t^c\right)} \tag{3.5}$$

and log consumption growth, Δc_t, is assumed to follow a simple AR(1) as in Bansal (2005):

$$\Delta c_t = \rho \Delta c_{t-1} + \eta_t^c. \tag{3.6}$$

For notational convenience, all growth rates are demeaned. The growth rate in consumption is defined as the first difference in log real consumption. Following earlier work, aggregate consumption is measured as the seasonally adjusted real per capita consumption of nondurables and services. The data are taken from the NIPA tables available from the Bureau of Economic Analysis.

The upside consumption beta, $\beta_{c^+}^i$, is then defined as

$$\beta_{c^+}^i = \frac{Cov(\eta_t^i, \eta_t^c \,|\eta_t^c > 0\,)}{Var(\eta_t^c \,|\eta_t^c > 0\,)}. \tag{3.7}$$

This consumption beta is used to measure the sensitivity of unexpected movements in asset return to unexpected upside fluctuations in consumption. A stock with high upside beta tends to payoff when investor's consumption level is already high. Therefore, there should be a discount for stocks with high upside potential (see for comparison Ang et al., 2006).

Similarly, to measure downside consumption risk, a downside beta, $\beta_{c^-}^i$ is conditioned on below-average consumption shocks:

$$\beta_{c^-}^i = \frac{Cov(\eta_t^i, \eta_t^c \,|\eta_t^c < 0\,)}{Var(\eta_t^c \,|\eta_t^c < 0\,)}. \tag{3.8}$$

A stock with high downside beta is a risky investment. Hence, assets that strongly covary with consumption growth, conditional on down movements in the later should have high average returns.

3.2.2 "Good" and "Bad" Consumption Risk

Given the return decomposition in Section 3.1.1, we additionally decompose the total consumption beta in (3.5) into two parts:

$$\begin{aligned}\beta_c^i &= \frac{Cov\left(\eta_{CF,t}^i, \eta_t^c\right)}{Var\left(\eta_t^c\right)} + \frac{Cov\left(-\eta_{DR,t}^i, \eta_t^c\right)}{Var\left(\eta_t^c\right)} \\ &= \beta_{c,CF}^i + \beta_{c,DR}^i, \end{aligned} \tag{3.9}$$

where $\beta_{c,CF}^i$ and $\beta_{c,DR}^i$ are the "bad" or cash-flow and the "good" or discount-rate consumption betas of asset i in sense of Campbell and Vuolteenaho (2004). The "bad" and "good" consumption betas are obtained by projecting innovations in assets' cash flows and discount rates, respectively, on the innovations in consumption growth.

3.2.3 A Four-Fold Decomposition of Consumption Risk

In this subsection, we link the sources of time variation in asset returns with conditional time variation in consumption path. We do so by splitting the upward and downward consumption betas into their "bad" and "good" varieties. Four-beta decompositions have been recently used in a number of empirical studies to explore the cross-sectional properties of asset returns. Some well-known examples are Campbell et al. (2010), Koubouros et al. (2010), and Botshekan et al. (2010). In a similar manner, we introduce four conditional measures of systematic consumption-based risk: upside cash-flow beta, upside discount-rate beta, downside cash-flow beta, and downside discount-rate beta. We define them as

$$\beta_{c^+,CF}^i = \frac{Cov(\eta_{CF,t}^i, \eta_t^c \,|\eta_t^c > 0)}{Var(\eta_t^c \,|\eta_t^c > 0)}, \tag{3.10}$$

$$\beta_{c^+,DR}^i = \frac{Cov(-\eta_{DR,t}^i, \eta_t^c \,|\eta_t^c > 0)}{Var(\eta_t^c \,|\eta_t^c > 0)}, \tag{3.11}$$

$$\beta_{c^-,CF}^i = \frac{Cov(\eta_{CF,t}^i, \eta_t^c \,|\eta_t^c < 0)}{Var(\eta_t^c \,|\eta_t^c < 0)}, \tag{3.12}$$

and

$$\beta^i_{c^-,DR} = \frac{Cov(-\eta^i_{DR,t}, \eta^c_t \,|\eta^c_t < 0\,)}{Var(\eta^c_t \,|\eta^c_t < 0\,)}. \tag{3.13}$$

3.2.4 Cross-Sectional Pricing Implications

The betas introduced above allow us to compare the empirical performance of different consumption-based asset pricing models in terms of their general fit and cross-section performance. In particular, we estimate the single-beta model

$$E[r^{e,i}] = \lambda_0 + \lambda_c \beta^i_c, \tag{3.14}$$

the two-beta model in the spirit of Ang et al. (2006)

$$E[r^{e,i}] = \lambda_0 + \lambda_{c^+}\beta^i_{c^+} + \lambda_{c^-}\beta^i_{c^-}, \tag{3.15}$$

the two-beta model in the spirit of Campbell and Vuolteenaho (2004)

$$E[r^{e,i}] = \lambda_0 + \lambda_{c,CF}\beta^i_{c,CF} + \lambda_{c,DR}\beta^i_{c,DR}, \tag{3.16}$$

and finally a four-beta model which combines (3.15) and (3.16)

$$E[r^{e,i}] = \lambda_0 + \lambda_{c^+,CF}\beta^i_{c^+,CF} + \lambda_{c^-,CF}\beta^i_{c^-,CF} + \lambda_{c^+,DR}\beta^i_{c^+,DR} + \lambda_{c^-,DR}\beta^i_{c^-,DR}. \tag{3.17}$$

We now proceed with asset pricing tests to evaluate the ability of consumption-based models to capture the variation in returns across 25 Fama-French portfolios. To test our conditional and unconditional models we employ the Fama-MacBeth (1973) methodology.

Table 3.2 reports our baseline findings. For each model, the table reports the estimated average pricing error (λ_0), the estimated risk premia along with t-statistics (in parentheses), corrected for the bias in standard errors generated by a two-pass regression (Shanken, 1992), as well as the standard measures of fit of the regression.

All four considered models perform comparably well in fitting the data. The model in column (1) is a one-factor model which differs from the traditional plain-vanilla CCAPM in two important respects: First, in contrary to the standard static CCAPM which is typically estimated on a quarterly data set, our model relies on an annual sample. The analysis is carried out on an annual frequency sample due to the fact that individual portfolios characteristics are only available on a year-to-year basis. The results thus remind us of prominent models highlighting the significance of the low-frequency slow-moving component of consumption growth for financial market data. Second, the betas here are estimated as in (3.5) similar to Campbell and Mei (1993). This measure of riskiness does not correspond to the full traditional beta employed in canonical CCAPM which uses sensitivities of returns themselves rather than innovations in returns.

The two-factor model in column (2) attaches a strongly significant premium to the downside consumption risk. The return comovement with positive consumption shocks is, on the contrary, not priced. Moreover, the constant term drops in economic terms by a factor close to 2 which is evidence of a substantial model improvement compared to (1). In the two-factor model in column (3) the premium associated with assets' cash flows exceeds by roughly 50% the premium associated with assets' discount rates. However, both are significant.

Finally, the four-factor model in column (4) elaborates on models in (2) and (3) and generates highly significant and economically reasonable estimates for downside risk in asset cash flows and discount rates. Furthermore, the pricing error is small in its magnitude and statistically indistinguishable from zero. Overall, the four-beta model performs best in terms of pricing errors. Among the two two-beta specifications, the two-beta model in the spirit of Ang et al. (2006) performs better than the two-beta model in the spirit of Campbell and Vuolteenaho (2004) with respect to the mean pricing errors and general fit.

Figure 3.1 plots the realized average excess returns versus the fitted excess returns of the four models in (3.14)-(3.17). If a model fits perfectly, then the fitted and observed excess returns would line up along the 45° line. As such, these plots provide a visual representation of each model's ability to fit the data. Alternatively, it shows the pricing errors for each of the 25 Fama-French portfolios generated by each of the four models.

3.2.5 Non-Synchronous Trading

To ensure that our sample estimates are not affected by non-frequent and non-synchronous trading, we employ a methodology[18] introduced by Campbell and Vuolteenaho (2004) and Koubouros

[18] For details consult the online appendix to Campbell and Vuolteenaho (2004) as well as the appendix to Campbell et al. (2010).

et al. (2010). Table 3.3 reports the results of Fama-MacBeth (1973) regressions when the empirical measures of betas are extended by two additional lag terms of the fitted values of assets' cash-flow and discount-rate news. For example, betas associated with assets' cash-flow news and consumption growth are computed as follows:

$$\beta^i_{c,CF} = \frac{Cov\left(\eta^i_{CF,t}, \eta^c_t\right)}{Var\left(\eta^c_t\right)} + \frac{Cov\left(\eta^i_{CF,t-1}, \eta^c_t\right)}{Var\left(\eta^c_t\right)} + \frac{Cov\left(\eta^i_{CF,t-2}, \eta^c_t\right)}{Var\left(\eta^c_t\right)}, \tag{3.18}$$

and all remaining betas are constructed accordingly.

3.3 Further Robustness Checks

We conduct a number of robustness checks in the following dimensions: the magnitude of ρ, other plausible VAR specifications employing both, pooled and portfolio-specific estimation, other test assets and different sample periods. We find that changing ρ does not alter the conclusions and that both estimation methods lead to similar results. The choice of a sample size has been a major source of instability. We report our findings below.

3.3.1 Different Subsample Periods

To verify that our main results are not attributed to the specific sample period we study, we consider two alternative subsamples. As Fama and French (1993), Julliard and Parker (2005), Campbell et al. (2010), and other earlier papers on conditional and unconditional asset pricing models we first focus on the post-1963 period. There are at least two reasons to study this sample period: The first is that it is when COMPUSTAT data become available. The second is that most of the evidence on the value premium puzzle comes from this period. We perform tests for both conditional and unconditional models in the post-1963 period. The pattern of empirical estimates of risk premia during the 1963-2007 time span strongly resembles the results from our benchmark estimation. Table 3.4 largely confirms our adhere results. Interestingly, models based on downside risk (the two-beta model in column (2) and the four-beta model in column (4)) have economically low and statistically insignificant pricing errors.

Secondly, we focus on the post-1952 period, a starting period set to match that of Chen and Zhao (2009) and Campbell and Mei (1993). The post-1952 time span is worth examining since Campbell (1991) documents a shift in the relative variability of cash-flow and discount-rate news on the market return after 1952. Table 3.5 shows the respective cross-sectional results.

3.3.2 Sample Split

In Table 3.6 we split our 1947-2007 sample in the middle. Accordingly, Panel A presents the risk premia estimates for the 1947-1976 period and Panel B for the 1977-2007 period. While there is some deterioration in the empirical performance of the single-factor model in column (1) in the second half of the sample in terms of the general fit and average pricing error, the estimate of risk premium (λ_c) is consistently positive and throughout significant.

The performance of the conditional two-beta model in column (2) is surprisingly different in the two panels. The risk premium of downside consumption risk (λ_{c^-}) is estimated with a right sign but highly imprecisely in the early sample; the corresponding R^2 coefficient is close to 8%. By contrast, the standard errors are much lower in the modern sample resulting into an R^2 statistic of about 70%.

The bad and good betas in column (3) explain roughly 60% of the variation in book-to-market and size sorted portfolios over the period 1947-1976. The model performs considerably worse in the post-1977 sample.

Striking is the failure of the four-beta model to explain differences in returns across Fama-French portfolios in the first subsample. Extremely imprecise estimates on "bad" and "good" downside risk prices in column (4) can be attributed to inaccurately measured downside risk exposures in model (2). The R^2 for this regression summarizes this failure: Only about 1.5% of the cross-sectional variation in average returns can be explained by the downside cash-flow and discount-rate betas. The R^2 adjusted for degrees of freedom is even negative, i.e. the model has a larger pricing error than the null hypothesis that all portfolios have constant equal expected returns. Interestingly, the ability of bad and good betas to replicate the cross-sectional differentials in risk exposure vanishes once the downside consumption risk loses its power. By contrast, model (4) explains about 75% of return variation in the modern sample. The success of downside cash-flow and discount-rate betas to capture assets' riskiness is broadly consistent with our benchmark scenario in Table 3.2.

3.3.3 Different Cut-off

Focussing on the unconditional mean of consumption growth as the cut-off gives rise to the downside cash-flow betas computed as:

$$\beta^i_{c^-,CF} = \frac{Cov(\eta^i_{CF,t}, \eta^c_t \,|\eta^c_t < E(\Delta c_t))}{Var(\eta^c_t \,|\eta^c_t < E(\Delta c_t))}, \tag{3.19}$$

where Δc_t is defined as in equation (3.6) and all remaining betas are constructed accordingly. For robustness purposes we repeat all cross-sectional tests with risk measures defined as in (3.19). The respective estimates support that this specification does not change our results qualitatively. Moreover, we find only slight quantitative differences in risk premium estimates compared to our benchmark case.[19]

3.3.4 Alternative Specifications

In what follows we examine the sensitivity of our main conclusions to some natural changes in the specification of the model. In particular, we replace the state variables used in the benchmark case with similar variables and estimate alternative VAR systems. We also consider a different set of test-asset returns and an alternative measure of consumption risk.

First, we follow Koubouros et al. (2010) and assume that asset-specific returns are driven by a common set of economy-wide components. The motivation for this approach comes from the rational asset pricing theory. It is, however, vulnerable to the critique that joint set of predictors might cause a high degree of correlation across the generated news components. In our case, the respective coefficient of correlation takes on a value in a range between 0 and 81 percent with an average of 27 percent. Koubouros et al. (2010) provide further arguments advocating this approach. For our VAR, we use the excess stock return, the ten-year price-earnings ratio, and the value spread as state variables. These variables have been used excessively in the literature on return decomposition since Campbell and Vuolteenaho (2004). As is evident from Table 3.7, the results based on the VAR with common state variables appear to be largely consistent with our benchmark findings in Table 3.2.

Secondly, to ensure that our results do not depend critically on the estimation method, we evaluate the models relying on both pooled and individual portfolio VARs alike. Table 3.8 repeats our benchmark asset pricing regressions, now based on a pooled VAR summarized in Table 3.1.

Next, we experiment with alternative Fama-French portfolios with three groups on book-to-

[19] For consistency with Bansal (2005), the consumption growth Δc_t in (3.6) is demeaned with $E(\Delta c_t)$ being a number very close to zero. An analogous four-beta decomposition cannot be implemented strictly following the definition in (3.19) without demeaning Δc_t, since in this case $\eta^c_t < E(\Delta c_t)$ for any t.

market and two groups on size. This is the only sample of stock returns for which an equivalent data set on portfolio-level characteristics is available. Table 3.9 shows that our conclusions remain broadly consistent with the original specification.

Finally, we exploit Yogo's (2006) finding that there is a tight link between cross-sectional return differentials on Fama-French portfolios and their sensitivity to the durable consumption growth. In Table 3.10, we proxy the consumption risk by the log growth rate in real per capita expenditures on durables. Replacing nondurables with durables results into economically plausible estimates but generally lowers the fit somewhat. The coefficients seem to lie rather on the high side, so do also the pricing errors.

Several other robustness checks were attempted and the results were consistent with the original specification. We considered alternative firm-level state variables employing different measures of size and book-to-market equity. We experimented with a subset of 25 portfolios and a mix of 25 and 6 portfolios. We also repeated the above robustness checks with a shorter sample. We find that the parameter estimates do not change much and appear to be consistent with the previous results. We conclude that the main results of this study are not affected by some plausible changes in the specification of the model, in the sample period and test assets.

3.4 Conclusions

This paper investigates the role of downside risk in consumption for the cross-section of expected returns. The results indicate that returns' comovement with downside, or recession, risk contains a valuable information about the riskiness of an asset. In particular, assets with strong receptiveness to downturns in consumption command a high risk premium. Both the "bad" cash-flow betas as well as the "good" discount-rate betas of stocks with high book-to-market ratio reveal a tendency to react strongly to negative consumption news.

Estimating a two-beta consumption-based model in the spirit of Ang et al. (2006) exhibits that differences in exposure to the downside risk explain more than a half of the cross-sectional return differentials while there is no significant relation between value and growth stock returns and their sensitivities to the upside risk. Pricing these stocks within an alternative two-beta model in the spirit of Campbell and Vuolteenaho (2004) suggests that a significant premium is attached to both, the covariation of asset's "bad" as well as asset's "good" return components with consumption fluctuations.

Finally, we combine these two two-factor models and break assets' "bad" consumption betas, i.e. the sensitivities of assets' cash-flow components to consumption risk, and assets' "good" consumption betas, i.e. the sensitivities of assets' discount-rate components to consumption risk, into an upside and a downside betas, respectively. The four-fold beta decomposition reveals that the risk associated with comovement of assets' "good" discount-rate and "bad" cash-flow news with negative consumption shocks earns a significant premium. Hence, both bad and good betas are driven by their high sensitivities to economic downside risk.

We subject our result to a number of robustness checks and find that bad downside consumption beta as well as good downside consumption beta are priced consistently across different test assets, sample periods and methodologies. In addition, the economic magnitude of downside risk in "bad" betas overweights that of the "good" betas by roughly 50%. This finding is consistent with the intertemporal asset pricing theory by Merton (1973) which suggests that exposure to cash-flow risks should be rewarded with a higher price of risk than an asset's sensitivity to market discount-rate risks.

3.5 Tables and Figures

Table 3.1: Pooled Firm-Level VAR Parameter Estimates

The table shows the OLS parameter estimates for a first-order VAR model including a constant, market-adjusted value-weighted stock return (R), book-to-market ratio (Value) and the number of firms (Size). All three variables are logged. Each row corresponds to a different dependent variable. The first three columns report coefficients on the explanatory variables listed in the column header; the last column shows the adjusted $\overline{R}^2$ statistics. OLS t-statistics are in parentheses. The sample period for the dependent variable is 1948 to 2007.

	R_t	Value_t	Size_t	$\overline{R}^2$(%)
R_{t+1}	-0.256	0.092	0.025	9.85
	(-10.336)	(9.033)	(3.358)	
Value_{t+1}	-0.297	0.968	-0.006	92.49
(Book-to-market ratio)	(-16.315)	(129.011)	(-1.091)	
Size_{t+1}	-0.0045	0.039	0.500	90.74
(Number of firms)	(-3.164)	(6.791)	(117.227)	

Table 3.2: Benchmark Case

The table reports the estimated risk prices (λs) and the measures of fit from cross-sectional Fama-MacBeth regressions using returns on 25 Fama-French portfolios. The regression coefficients are expressed in annual percentage terms. Shanken (1992) corrected t-statistics are in parentheses. The underlying news series are obtained from an asset-specific VAR model including a constant, market-adjusted return, book-to-market ratio and the number of firms. The data cover the period 1947-2007. The last two rows report the R^2 and the $\overline{R}^2$adjusted for the degrees of freedom.

	(1)	(2)	(3)	(4)
λ_0	9.139	4.808	10.098	3.520
	(3.717)	(2.177)	(4.457)	(1.413)
λ_c	1.321			
	(3.563)			
λ_{c^+}		0.002		
		(1.098)		
λ_{c^-}		0.773		
		(3.036)		
$\lambda_{c,CF}$			1.517	
			(3.577)	
$\lambda_{c,DR}$			1.017	
			(2.736)	
$\lambda_{c^+,CF}$				0.090
				(0.656)
$\lambda_{c^-,CF}$				0.678
				(2.969)
$\lambda_{c^+,DR}$				0.145
				(0.808)
$\lambda_{c^-,DR}$				0.885
				(3.264)
R^2	0.5158	0.6048	0.5297	0.6256
adj.-R^2	0.4948	0.5689	0.4869	0.5507

Table 3.3: Controlling for Non-Synchronous Trading

The table reports the estimated risk prices (λs) and the measures of fit from cross-sectional Fama-MacBeth regressions using returns on 25 Fama-French portfolios. The betas are estimated as in equation (3.18). The regression coefficients are expressed in annual percentage terms. Shanken (1992) corrected t-statistics are in parentheses. The underlying news series are obtained from an asset-specific VAR model including a constant, market-adjusted return, book-to-market ratio and the number of firms. The data cover the period 1947-2007. The last two rows report the R^2 and the $\overline{R}^2$ adjusted for the degrees of freedom.

	(1)	(2)	(3)	(4)
λ_0	5.3241	2.389	5.356	1.051
	(2.132)	(0.948)	(2.330)	(0.356)
λ_c	0.600			
	(3.584)			
λ_{c^+}		-0.126		
		(-1.490)		
λ_{c^-}		0.561		
		(4.000)		
$\lambda_{c,CF}$			0.602	
			(3.409)	
$\lambda_{c,DR}$			0.598	
			(2.991)	
$\lambda_{c^+,CF}$				-0.118
				(-1.296)
$\lambda_{c^-,CF}$				0.385
				(3.439)
$\lambda_{c^+,DR}$				-0.189
				(-1.736)
$\lambda_{c^-,DR}$				0.692
				(3.944)
R^2	0.4614	0.5119	0.4614	0.6042
adj.-R^2	0.4380	0.4676	0.4125	0.5251

Table 3.4: Post-1963 Period

The table reports the estimated risk prices (λs) and the measures of fit from cross-sectional Fama-MacBeth regressions using returns on 25 Fama-French portfolios. The regression coefficients are expressed in annual percentage terms. Shanken (1992) corrected t-statistics are in parentheses. The underlying news series are obtained from an asset-specific VAR model including a constant, market-adjusted return, book-to-market ratio and the number of firms. The data cover the period 1963-2007. The last two rows report the R^2 and the $\overline{R}^2$adjusted for the degrees of freedom.

	(1)	(2)	(3)	(4)
λ_0	7.332	0.244	6.917	-1.905
	(2.518)	(0.083)	(2.321)	(-0.548)
λ_c	1.984			
	(3.767)			
λ_{c^+}		0.000		
		(0.114)		
λ_{c^-}		1.066		
		(3.682)		
$\lambda_{c,CF}$			1.850	
			(3.292)	
$\lambda_{c,DR}$			2.091	
			(3.949)	
$\lambda_{c^+,CF}$				0.088
				(0.439)
$\lambda_{c^-,CF}$				0.817
				(3.174)
$\lambda_{c^+,DR}$				0.197
				(0.781)
$\lambda_{c^-,DR}$				1.007
				(3.004)
R^2	0.5838	0.6960	0.5877	0.7347
adj.-R^2	0.5657	0.6684	0.5502	0.6816

Table 3.5: Post-1952 Period

The table reports the estimated risk prices (λs) and the measures of fit from cross-sectional Fama-MacBeth regressions using returns on 25 Fama-French portfolios. The regression coefficients are expressed in annual percentage terms. Shanken (1992) corrected t-statistics are in parentheses. The underlying news series are obtained from an asset-specific VAR model including a constant, market-adjusted return, book-to-market ratio and the number of firms. The data cover the period 1952-2007. The last two rows report the R^2 and the $\overline{R}^2$adjusted for the degrees of freedom.

	(1)	(2)	(3)	(4)
λ_0	8.997	3.389	9.137	2.207
	(3.455)	(1.269)	(3.682)	(0.808)
λ_c	1.360			
	(3.235)			
λ_{c^+}		0.000		
		(0.337)		
λ_{c^-}		0.829		
		(3.328)		
$\lambda_{c,CF}$			1.392	
			(2.960)	
$\lambda_{c,DR}$			1.279	
			(3.216)	
$\lambda_{c^+,CF}$				0.035
				(0.249)
$\lambda_{c^-,CF}$				0.802
				(2.971)
$\lambda_{c^+,DR}$				0.126
				(0.592)
$\lambda_{c^-,DR}$				0.840
				(2.818)
R^2	0.4435	0.6673	0.4446	0.6859
adj.-R^2	0.4193	0.6371	0.3941	0.6231

Table 3.6: Sample Split

The data cover the period 1947-1976 in Panel A and 1977-2007 in Panel B. The last two rows report the R^2 and the $\overline{R}^2$adjusted for the degrees of freedom. For further details see notes to Table 3.2.

	(1)	(2)	(3)	(4)
		Panel A: 1947 - 1976		
λ_0	5.388	8.385	4.628	5.695
	(1.282)	(2.714)	(1.015)	(1.575)
λ_c	0.944			
	(2.505)			
λ_{c^+}		-0.002		
		(-1.001)		
λ_{c^-}		0.105		
		(0.705)		
$\lambda_{c,CF}$			0.930	
			(2.403)	
$\lambda_{c,DR}$			1.356	
			(2.729)	
$\lambda_{c^+,CF}$				-0.053
				(-0.229)
$\lambda_{c^-,CF}$				0.086
				(0.446)
$\lambda_{c^+,DR}$				-0.011
				(-0.054)
$\lambda_{c^-,DR}$				0.072
				(0.348)
R^2	0.5129	0.0792	0.5908	0.0150
adj.-R^2	0.4917	-0.0045	0.5536	-0.1820

Table 3.6: *Continued*

	(1)	(2)	(3)	(4)
		Panel B: 1977 - 2007		
λ_0	11.711	8.324	10.888	7.135
	(4.383)	(3.261)	(3.996)	(2.652)
λ_c	0.741			
	(2.218)			
λ_{c^+}		0.002		
		(1.438)		
λ_{c^-}		0.331		
		(1.854)		
$\lambda_{c,CF}$			0.611	
			(1.438)	
$\lambda_{c,DR}$			0.810	
			(2.435)	
$\lambda_{c^+,CF}$				-0.125
				(-0.574)
$\lambda_{c^-,CF}$				0.321
				(1.785)
$\lambda_{c^+,DR}$				0.047
				(0.222)
$\lambda_{c^-,DR}$				0.357
				(1.934)
R^2	0.3172	0.6707	0.3502	0.7450
adj.-R^2	0.2875	0.6408	0.2911	0.6940

Table 3.7: Economy-Wide State Variables

The table reports the estimated risk prices (λs) and the measures of fit from cross-sectional Fama-MacBeth regressions using returns on 25 Fama-French portfolios. The regression coefficients are expressed in annual percentage terms. Shanken (1992) corrected t-statistics are in parentheses. The underlying news series are obtained from an asset-specific VAR model including a constant, excess return, price-earnings ratio, and the value spread. The data cover the period 1947-2007. The last two rows report the R^2 and the $\overline{R}^2$adjusted for the degrees of freedom.

	(1)	(2)	(3)	(4)
λ_0	4.274	2.837	4.520	2.854
	(1.487)	(1.046)	(1.539)	(1.039)
λ_c	1.178			
	(2.946)			
λ_{c^+}		0.001		
		(0.625)		
λ_{c^-}		0.629		
		(2.383)		
$\lambda_{c,CF}$			1.633	
			(3.558)	
$\lambda_{c,DR}$			0.927	
			(2.225)	
$\lambda_{c^+,CF}$				0.304
				(1.764)
$\lambda_{c^-,CF}$				0.692
				(2.303)
$\lambda_{c^+,DR}$				-0.273
				(-1.922)
$\lambda_{c^-,DR}$				0.599
				(2.769)
R^2	0.2989	0.4318	0.3281	0.6437
adj.-R^2	0.2684	0.3802	0.2670	0.5724

Table 3.8: Pooled VAR Estimates

The table reports the estimated risk prices (λs) and the measures of fit from cross-sectional Fama-MacBeth regressions using returns on 25 Fama-French portfolios. The regression coefficients are expressed in annual percentage terms. Shanken (1992) corrected t-statistics are in parentheses. The underlying news series are obtained from a pooled VAR model including a constant, market-adjusted return, book-to-market ratio and the number of firms. The data cover the period 1947-2007. The last two rows report the R^2 and the $\overline{R}^2$adjusted for the degrees of freedom

	(1)	(2)	(3)	(4)
λ_0	10.041	7.604	8.489	1.908
	(3.735)	(2.355)	(2.355)	(0.755)
λ_c	1.278			
	(3.441)			
λ_{c^+}		0.001		
		(0.478)		
λ_{c^-}		1.063		
		(3.013)		
$\lambda_{c,CF}$			0.9997	
			(2.178)	
$\lambda_{c,DR}$			1.699	
			(3.425)	
$\lambda_{c^+,CF}$				0.078
				(0.723)
$\lambda_{c^-,CF}$				0.806
				(3.220)
$\lambda_{c^+,DR}$				0.209
				(1.531)
$\lambda_{c^-,DR}$				1.521
				(4.983)
R^2	0.4120	0.5704	0.4984	0.6654
adj.-R^2	0.3864	0.5314	0.4528	0.5985

Table 3.9: Different Test Assets

The table reports the estimated risk prices (λs) and the measures of fit from cross-sectional Fama-MacBeth regressions using returns on 6 Fama-French portfolios. The regression coefficients are expressed in annual percentage terms. Shanken (1992) corrected t-statistics are in parentheses. The underlying news series are obtained from a pooled VAR model including a constant, market-adjusted return, book-to-market ratio and the number of firms. The data cover the period 1947-2007. The last two rows report the R^2 and the $\overline{R}^2$adjusted for the degrees of freedom.

	(1)	(2)	(3)	(4)
λ_0	8.328	4.718	15.224	6.378
	(3.507)	(2.255)	(5.501)	(2.030)
λ_c	1.193			
	(3.349)			
λ_{c^+}		0.001		
		(0.447)		
λ_{c^-}		0.891		
		(3.203)		
$\lambda_{c,CF}$			2.901	
			(4.833)	
$\lambda_{c,DR}$			-0.369	
			(-0.854)	
$\lambda_{c^+,CF}$				0.469
				(1.987)
$\lambda_{c^-,CF}$				1.435
				(2.513)
$\lambda_{c^+,DR}$				0.138
				(0.421)
$\lambda_{c^-,DR}$				0.734
				(2.367)
R^2	0.6093	0.8788	0.8889	0.9810
adj.-R^2	0.5117	0.7980	0.8149	0.9049

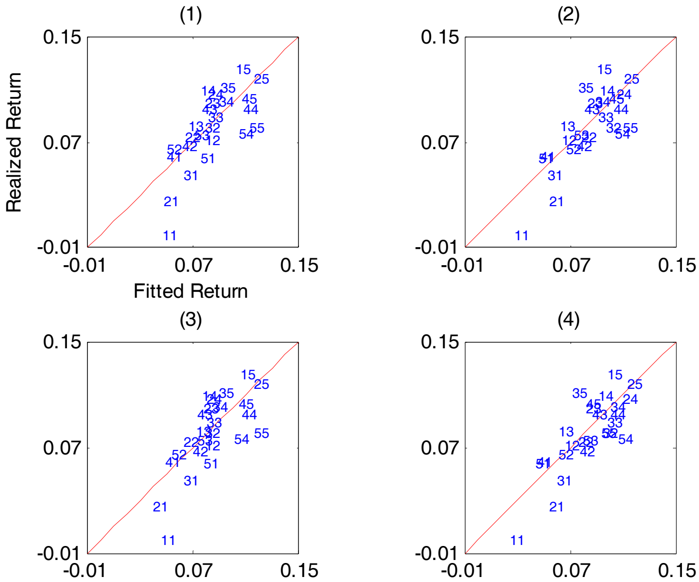
Table 3.10: Durable Consumption Growth

The table reports the estimated risk prices (λs) and the measures of fit from cross-sectional Fama-MacBeth regressions using returns on 25 Fama-French portfolios. The regression coefficients are expressed in annual percentage terms. Shanken (1992) corrected t-statistics are in parentheses. The underlying news series are obtained from a pooled VAR model including a constant, market-adjusted return, book-to-market ratio and the number of firms. Consumption risk is measured by the log growth rate in durables. The data cover the period 1947-2007. The last two rows report the R^2 and the $\overline{R}^2$adjusted for the degrees of freedom.

	(1)	(2)	(3)	(4)
λ_0	10.722	3.816	11.554	5.726
	(4.527)	(0.945)	(5.012)	(2.057)
λ_c	8.023			
	(3.438)			
λ_{c^+}		0.015		
		(1.287)		
λ_{c^-}		4.117		
		(2.946)		
$\lambda_{c,CF}$			9.800	
			(3.737)	
$\lambda_{c,DR}$			2.611	
			(1.166)	
$\lambda_{c^+,CF}$				1.086
				(0.875)
$\lambda_{c^-,CF}$				3.944
				(4.243)
$\lambda_{c^+,DR}$				-1.860
				(-2.267)
$\lambda_{c^-,DR}$				7.124
				(2.507)
R^2	0.5883	0.4261	0.6715	0.4303
adj.-R^2	0.5704	0.3740	0.6417	0.3163

Figure 3.1: Realized versus Predicted Returns

The figure plots realized versus predicted annual returns for the 25 Fama-French portfolios sorted by size and book-to-market equity. The estimated models are (1) the one-factor model, (2) the two-factor model with upside and downside risk, (3) the two-factor model with cash-flow and discount-rate risk, and (4) the four-factor model with upside cash-flow, downside cash-flow, upside discount-rate, and downside discount-rate risk. The horizontal axes correspond to the predicted average excess returns and the vertical axes to the sample average excess returns. The sample period is 1947-2007. The predicted values are from regressions presented in Table 3.2.



4 Foreign Currency Returns and Systematic Risks

The recent financial crisis has shifted attention to the observation that carry trades, short positions in low interest rate and long positions in high interest rate currencies, comove with stock markets during the market turbulences of 2007/2008 (Brunnermeier et al., 2008 and Lustig et al., 2009).[20] Figure 4.1 highlights this stylized fact by plotting the monthly excess return on the S&P500 index against the return on a carry trade strategy[21] for the sample period from December 2006 until April 2008.

Lustig et al. (2009) show that the CAPM (capital asset pricing model) of Sharpe (1964) and Lintner (1965) does a remarkable job in explaining currency excess returns during crisis periods but explains these cross-sectional return differences over a longer sample period only at the cost of implausibly high risk price estimates.

This paper takes a closer look at this finding. Our starting point is the following: Empirical tests of the CAPM rely on stock market returns as a proxy of the market portfolio. We know since Campbell (1991) that stock market returns move because of news about future cash flows or unexpected future returns (discount rates). Campbell and Vuolteenaho (2004) build upon this insight to show that the simple market beta hides more than it reveals. Despite ample evidence that value stocks, i.e. stocks with high book-to-market value, offer higher average returns than their growth counterparts with low book-to-market value, their market betas are of similar size (Fama and French, 1993). Breaking unexpected movements of the market return into cash-flow and discount-rate news components, Campbell and Vuolteenaho (2004) show that differences in the exposure to the market's cash-flow news explain about a half of the cross-sectional differences between value and growth stock portfolio returns while there is no significant relation between the average value and growth stock returns with their sensitivity to the market's discount-rate news. This finding is in line with the intertemporal asset pricing theory by Merton (1973) which suggests that exposure to cash-flow risks should be rewarded with a higher price of risk than an asset's sensitivity to market discount-rate risks.

We assess if this logic can be validated for assets other than stocks and apply the Campbell and Vuolteenaho (2004) "bad" cash-flow and "good" discount-rate beta CAPM version to the forward discount and currency momentum, i.e. past currency return sorted, currency portfolios

[20] This chapter of the thesis is based on Galsband and Nitschka (2010).

[21] The carry trade is calculated as return differential between high forward discount and low forward discount currency portfolios constructed by Lustig et al. (2009). Section 4.2 contains a detailed description of portfolio excess returns.

of Lustig et al. (2009). In contrast to the evidence for value and growth stocks, we find that the cross-sectional differences in the forward discount sorted currency portfolio excess returns are explained by their sensitivity to the stock market's discount-rate news. The risk price of the market's discount-rate news component is negative which could be rationalized by the fact that we follow Campbell and Vuolteenaho (2004) in defining discount-rate news as "better than expected". A low sensitivity to this "good" news must be rewarded with a higher risk price than a high sensitivity to the "better than expected" discount-rate news. This pattern has been recently observed in attempts to explain cross-sectional differences in European value and growth stocks with the two-beta variety of the CAPM from a national investor's perspective (Nitschka (2010)). In addition, we find that the two-beta CAPM is able to price both stock and currency portfolio excess returns. Confirming Campbell and Vuolteenaho (2004), average stock returns, the 25 book-to-market and size sorted portfolios from Fama and French (1993), are priced by the differences in the sensitivity to cash-flow news while at the same time currency excess returns are priced by their different sensitivities to discount-rate news.

Finally, we explore the evolution of foreign currencies' risk exposure to unexpected stock market movements over different time horizons with a particular interest in the past two decades. This exercise is motivated by Campbell et al. (2010), who show that the importance of cash-flow and discount-rate news for movements of the market return varies over time. According to the main results of Campbell et al. (2010), the stock market boom of the middle to late 1990s was driven by news about discount rates while a mix of cash-flow and discount-rate news drove the boom period from 2002 to 2007. We assess if the difference in the driving forces of the U.S. stock market during these periods has any impact on our two-beta CAPM based explanation for cross-sectional differences in currency excess returns. Three findings emerge from this exercise. First, we do not find a significant relationship between stock market news and average currency excess returns for the stock market downturn of the early 2000s. Second, differences in the sensitivity to discount-rate news explain average currency excess returns in the boom period from 2002 to 2007 when both cash-flow and discount-rate news contribute to rising stock market prices. Third, in contrast to the results for the latter boom period and the full sample period, currency excess returns during the boom period in the mid to late 1990s seem to be rationalized by their sensitivities to the market's cash-flow news. This latter finding is particularly interesting as this stock market surge is mainly driven by discount-rate news.

The remainder is organized as follows. Section 4.1 briefly sketches the decomposition of stock returns into cash-flow and discount-rate shocks to break the single CAPM beta of foreign currencies into a cash-flow and a discount-rate beta. Section 4.2 describes the data. Section 4.3 presents our empirical results for the U.S. stock market and foreign currency returns and Section 4.5 concludes.

4.1 Stock Market Return Decomposition

A standard present value relation states that changes in asset prices must be associated with changes in expected future cash flows or discount rates. This section briefly sketches the log-linear approximate relation which allows to empirically break the returns on the market portfolio into cash-flow and discount-rate components.

Using a first-order Taylor expansion, Campbell and Shiller (1988a) approximate the log one-period return, $r_{t+1} = \ln(P_{t+1} + D_{t+1}) - \ln(P_t)$, around the mean log dividend-price ratio, $\overline{(d_t - p_t)}$, where P_t is price, D_t is the dividend, and lower-case letters are used for logs. The resulting log-linear relation can be applied to any asset return:

$$r_{t+1} \approx k + \rho p_{t+1} + (1-\rho) d_{t+1} - p_t \tag{4.1}$$

where k and ρ are parameters[22] in the linearization, and ρ is strictly less than unity.

Using (4.1), one can show[23] that the log price-dividend ratio is determined by the expected value of future discounted dividend growth and returns

$$p_t - d_t = \frac{k}{1-\rho} + E_t \sum_{s=0}^{\infty} \rho^s \left[\Delta d_{t+1+s} - r_{t+1+s}\right] \tag{4.2}$$

where E_t denotes a rational expectation formed at the end of period t and Δ denotes a one-period backward difference. Intuitively, a high stock price today is either associated with high dividends or low returns in the future. Further applying (4.2) to substitute p_t and p_{t+1} out of the approximate equation (4.1), Campbell (1991) shows that the unexpected stock return at any

[22] More specifically, the parameters are defined by $\rho \equiv \frac{1}{1+\exp\overline{(d_t - p_t)}}$ and $k \equiv -\ln\rho - (1-\rho)\ln(1/\rho - 1)$. Interestingly, the interpretation of the discount coefficient ρ should not necessarily be linked to the time-series average of the log dividend yield. For example, Campbell (1993, 1996) links it to the average log consumption-wealth ratio.

[23] Specifically, relation (4.2) results from rearranging (4.1) for the current stock price, solving it forward iteratively, imposing the standard transversality condition, $\lim_{s\to\infty} \rho^s (d_{t+s} - p_{t+s}) = 0$, and subtracting the current dividend.

time can be decomposed into news about future cash flows (i.e., dividends or consumption) and news about future discount rates (i.e., expected returns). Following Campbell (1991), we write the unpredicted component of return on a stock market index as

$$r^M_{t+1} - E_t r^M_{t+1} = (E_{t+1} - E_t) \left\{ \sum_{s=0}^{\infty} \rho^s \Delta d^M_{t+1+s} - \sum_{s=1}^{\infty} \rho^s r^M_{t+1+s} \right\} \tag{4.3}$$

where the cash-flow news

$$N^M_{CF,t+1} \equiv (E_{t+1} - E_t) \sum_{s=0}^{\infty} \rho^s \Delta d^M_{t+1+s} \tag{4.4}$$

corresponds to revision in expectations about future dividend growth and discount-rate news

$$N^M_{DR,t+1} \equiv (E_{t+1} - E_t) \sum_{s=1}^{\infty} \rho^s r^M_{t+1+s} \tag{4.5}$$

corresponds to revision in expectations about future discount rates. Even though equations (4.1)-(4.3) hold only as approximations, we follow the literature[24] and treat them as exact. While an increase in expected cash flows must be associated with a capital gain, a rise in discount rates leads to a capital loss. Furthermore, as argued by Campbell and Vuolteenaho (2004), returns caused by cash-flow news are never reversed since the shock is permanent. By contrast, returns generated by discount-rate news pertain their mean reverting feature due to the transitory nature of a shock. Hence, the cash-flow news component could be interpreted as permanent, the discount-rate component as transitory part of a stock return.

In order to identify market cash-flow and discount-rate news, we follow Campbell (1991) and assume that the data are generated by a first-order[25] vector autoregressive (VAR) model

$$\mathbf{z}_{t+1} = \mathbf{a} + \mathbf{\Gamma} \mathbf{z}_t + \mathbf{u}_{t+1} \tag{4.6}$$

where $\mathbf{z}_{t+1}$ is a m-by-1 state vector with r^M_{t+1} as its first element, $\mathbf{a}$ and $\mathbf{\Gamma}$ are m-by-1 vector and m-by-m companion matrix of constant parameters, and $\mathbf{u}_{t+1}$ is an i.i.d. m-by-1 vector of

[24] Campbell and Shiller (1988a) and Campbell (1991) find that the approximation error is small enough and does not affect the results significantly.

[25] As discussed by Campbell and Shiller (1988a), the assumption that the VAR is first-order is not restrictive, since this formulation also allows for higher-order VAR models by stacking lagged values into the state vector.

shocks. The model in (4.6) produces future market returns forecasts

$$E_t r^M_{t+1+s} = \mathbf{e1}'\mathbf{\Gamma}^{s+1}\mathbf{z}_t \tag{4.7}$$

where $\mathbf{e1}$ denotes a m-by-1 vector whose first element is one and the remaining elements are all zero. Provided that the data are generated by the process in (4.6), the discounted sum of changes in future return expectations (i.e., the discount-rate news) can be written as

$$\begin{aligned} N^M_{DR,t+1} &= \mathbf{e1}'\sum_{s=1}^{\infty}\rho^s\mathbf{\Gamma}^s\mathbf{u}_{t+1} \\ &= \mathbf{e1}'\rho\mathbf{\Gamma}\left(\mathbf{I}-\rho\mathbf{\Gamma}\right)^{-1}\mathbf{u}_{t+1} \\ &= \mathbf{e1}'\boldsymbol{\lambda}\mathbf{u}_{t+1} \end{aligned} \tag{4.8}$$

where $\boldsymbol{\lambda} \equiv \rho\mathbf{\Gamma}\left(I-\rho\mathbf{\Gamma}\right)^{-1}$ and $\mathbf{e1}'\boldsymbol{\lambda}$ captures the effect of each VAR state variable shock on discount-rate expectations.[26] Since the identity $\mathbf{e1}'\mathbf{u}_{t+1} = N^M_{CF,t+1} - N^M_{DR,t+1}$ holds true, $t+1$ cash-flow news can be identified as

$$N^M_{CF,t+1} = \left(\mathbf{e1}' + \mathbf{e1}'\boldsymbol{\lambda}\right)\mathbf{u}_{t+1}. \tag{4.9}$$

The decomposition in equation (4.3) might be useful in several ways. First, it allows us to study the relative importance of permanent and transitory news components of the stock market index. Secondly, it allows us to understand how currency portfolio returns react to equity market news arrival. In particular, we can investigate how currency returns interact with changes in market discount rates and cash flows.

Empirical evidence suggests that the uncovered interest parity condition fails to hold with the exception of high inflation countries (Hansen and Hodrick, 1980; Fama, 1984; and Bansal and Dahlquist, 2000). We therefore define the currency return as $cr^k_t = i^k_t - i_t - \Delta e^k_{t+1}$ where i^k_t denotes country k interest rate, i_t its home country, here United States, equivalent and Δe^k_{t+1} the change in the log spot exchange rate of country k relative to the home currency. Alternatively one could define $cr^k_t = f^k_t - e^k_{t+1}$ exploiting that covered interest rate parity, $f^k_t - e^k_t = \Delta e^k_{t+1}$, holds at daily or lower frequencies (Akram et al., 2008).

At the end of each period t, Lustig et al. (2009) allocate all currencies in a sample of 37

[26] As discussed by Campbell and Vuolteenaho (2004), the weight of the variable in equation (4.8) depends on its persistence and on the absolute value of a variable's coefficient in the first regression of the VAR.

countries to six portfolios on the basis of their forward discounts observed at the end of period t. The receptiveness of currency excess return cr^i_{t+1} of portfolio i to stock market cash-flow news is referred to as cash-flow beta of portfolio i

$$\beta^i_{MCF} \equiv \frac{Cov\left(cr^i_{t+1}, N^M_{CF,t+1}\right)}{Var\left(r^M_{t+1} - E_t r^M_{t+1}\right)}, \tag{4.10}$$

the discount-rate beta is defined analogously

$$\beta^i_{MDR} \equiv \frac{Cov\left(cr^i_{t+1}, -N^M_{DR,t+1}\right)}{Var\left(r^M_{t+1} - E_t r^M_{t+1}\right)}. \tag{4.11}$$

Both betas obviously add up to the traditional CAPM market beta

$$\beta^i = \beta^i_{MCF} + \beta^i_{MDR}. \tag{4.12}$$

4.2 Data

4.2.1 VAR State Variables

Bianchi (2010) points out that the market return decomposition into its news components and the subsequent "bad beta, good beta" analysis of Campbell and Vuolteenaho (2004) depends strongly on the use of the small stock value spread and the extraction of news series over a sample period that includes the stock market crash that preceded the great depression. Bianchi (2010) shows that the value spread inherits important information from the great depression, such that the original VAR of Campbell and Vuolteenaho (2004) can also be described as a two-state Markov-switching process. One regime is closely related to the great depression, the other is not. The former regime receives a large weight when agents form their expectations according to the ICAPM. Hence, as Campbell and Vuolteenaho (2004) exploit basic insights of the ICAPM, their results strongly depend on this great depression regime. Against this backdrop, we follow as closely as possible Campbell and Vuolteenaho (2004) in specifying the VAR model. The state variables are defined as follows. First, the excess market return r^e_M is measured as the log excess return on the CRSP value-weight index. Second, the yield spread ty between long-term and short-term bonds in measured in annualized percentage points. The original yield spread measured as in Campbell and Vuolteenaho (2004) as the difference between the ten-year constant maturity taxable bond yield and the yield on short-term taxable notes is available up to 2001:12. Since 2002 we measure the spread by the difference between the market yield on U.S. Treasury securities at ten-year constant maturity[27], quoted on investment basis from the Federal Reserve[28] and the annualized three-month U.S. Treasury bill rate. Third, the market's smoothed price-earnings ratio is constructed as the log ratio of the S&P 500 price index[29] to a ten year moving average of S&P 500 earnings. Finally, the fourth variable, the small-stock value spread vs, is computed from the Kenneth R. French data library[30] as the difference between the log book-to-market ratios of small value and small growth stocks. Further details on data construction are available in the appendix to Campbell and Vuolteenaho (2004). Our monthly sample period is running from 1928:12 to 2008:05.

4.2.2 Currency Portfolio Returns

We use the monthly data set consisting of six foreign currency portfolio returns from a perspective of a U.S. investor constructed by Lustig et al. (2009).[31] The sample contains 37 countries, including both developed and emerging markets for which forward contracts are traded. At the end of month $t+1$, all currencies in the sample are allocated into six portfolios on the basis of their forward discounts[32] observed at the end of period t, net of transaction costs. The portfolios are rebalanced at the end of every month, so that the first portfolio always contains currencies with smallest forward discounts and portfolio six always contains the largest forward discount currencies. The currency excess return CR^i_{t+1} for portfolio i is computed as the average of the currency excess returns in portfolio i. The currency portfolio returns take into account transaction costs, i.e. bid and ask spreads. Lustig et al. (2009) provide further details on portfolio building methodology. Moreover, Lustig et al. (2009) regard currency portfolios formed according to the previous months' currency excess returns, i.e. momentum. Monthly currency momentum returns are available since December 1983. We thank Adrien Verdelhan for graciously providing us with this data.

Figure 4.2 presents annualized mean returns (in percentage points) as well as Sharpe ratios on

[27] To check how closely our measure of yield spread is related to that of Campbell and Vuolteenaho (2004) we have calculated it also for the period prior to 2002. The correlation between both spread measures for the period 1928-2001 turned out highly significant.

[28] http://www.federalreserve.gov/releases/h15/data.htm

[29] Online data is available on http://www.econ.yale.edu/~shiller/data.htm.

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

[31] Monthly foreign currency excess return data are available on http://hlustig2001.squarespace.com/downloadable-data/.

[32] Under the covered interest rate parity, the forward discount is equal to the interest rate differential. The cross-section of foreign currency portfolio returns formed on the basis of the foreign interest rates has been studied deeply by Lustig and Verdelhan (2007).

six forward discount rates sorted currency portfolios, on the left, and on six momentum sorted currency portfolios, on the right. Portfolio F1(M1) contains currencies with lowest forward discounts (lowest past returns). Portfolio F6(M6) contains currencies with the highest forward discounts (highest past returns). The data are monthly and the sample period is 1983:12-2008:04.

As visualized in Figure 2, average returns on both portfolio sets increase almost monotonically. The pattern in Sharpe ratios strongly resembles the results obtained by Lustig and Verdelhan (2007), who study risk premia across currency portfolios sorted on past interest rates. For forward discount rate sorted portfolios, average returns vary from -1.23 up to 4.33 percent p.a. Similarly, past losers portfolio M1 promises an excess return of about -1 percent per year and past winners portfolio M6 delivers on average an annual return slightly exceeding the 4 percent mark. A short position in low interest rate currencies and a long in high interest rate currencies implies thus an average return of 5.56 percent p.a. which is of comparable order of magnitude as excess return in equity markets. Analogously, a carry trade strategy in momentum portfolios promises on average a return somewhat higher than 5 percent.

4.3 Empirical Results

4.3.1 VAR Dynamics

Table 4.1 reports the basic characteristics of a first-order VAR model, estimated using OLS and employing $\rho = 0.95^{1/12}$ for monthly data. The results do not alter qualitatively for other plausible parameter values. Each row of the table corresponds to a different dependent variable listed in the header of the row. OLS t-statistics are reported in parentheses below the coefficient estimates. The first five columns give coefficients on the explanatory variables listed in the column header; the last column shows the adjusted $\overline{R}^2$ statistics.

The top row of Table 4.1 gives the results of the stock market return forecasting equation when lags of returns, price-earnings ratio, value spread, and term yield are applied as regressors. All four state variables exhibit some forecasting potential. In line with previous findings, the momentum property is strongly pronounced for monthly returns. The past small-stock value spread negatively forecasts the stock market with a t-statistic of 2.34. Consistent with the literature, the coefficient on term yield is positive and statistically significant. Finally, similar to Campbell and Shiller (1988b), Campbell and Vuolteenaho (2004), Campbell et al. (2010), a higher price-earnings ratio is statistically significantly associated with lower returns. The $\overline{R}^2$

statistic for the return equation is 2.19% over the full sample.

The next rows summarize the forecasting power of the VAR system for the remaining state variables. Overall, $\overline{R}^2$ statistics are relatively high and the autoregressive coefficients of the price-earnings ratio, value spread, and term yield are all very close to unity. Several authors have documented and discussed the difficulty of statistical inference and coefficient interpretation resulting from high variable persistence (e.g. Kendall, 1954 and Stambaugh, 1999).[33]

Paying caution to the statistical issues mentioned above, the implied news series are extracted from the VAR system using equations (4.8) and (4.9). The shocks to cash flows are almost uncorrelated with shocks to expected returns with a correlation coefficient of -0.02.

4.3.2 Cash-Flow and Discount-Rate Risks of Foreign Currencies

Many studies use equation (4.3) to investigate equities. Individual stocks as well as broad equity indices have been explored within this framework. To explain the differences in returns across high interest rate and low interest rate currencies, we investigate the interactions between permanent and transitory shocks to the total market wealth, on the one hand, and foreign currency returns, on the other.

Table 4.2 displays the cash-flow and discount-rate betas of the 12 currency portfolio returns as defined in equations (4.10) and (4.11). Panel A delivers the betas for forward discount sorted portfolios, panel B for the currency momentum portfolios.

In line with the results reported in the Lustig et al. (2009) web appendix, the stock market betas, β^i_M, of the currency portfolio excess returns, i.e. the sum of cash-flow and discount-rate betas, are relatively small. In addition, they are mostly negative but do not reveal a clear pattern. This is true for both forward discount and currency momentum sorted currency portfolios.

Campbell and Vuolteenaho (2004) show that differences in cash-flow betas rationalize why value stocks offer higher average returns than growth stocks. Value stocks' cash-flow betas are higher than growth stocks' cash-flow betas. As the ICAPM implies that cash-flow risk should be rewarded with a higher risk price, value stocks have to promise higher returns. This reasoning does not seem to pertain in the context of excess returns on foreign currency portfolios. Neither differences in forward discount nor currency momentum sorted currency portfolio returns seem to be driven by differences in their cash-flow betas.

[33] The appendix to Campbell and Vuolteenaho (2004) discusses the problems associated with persistent forecasting variables and shows that there is little finite-sample bias in the estimated news terms computed using a nonlinear transformation of the companion matrix.

Interestingly, there is a pattern in discount-rate betas of forward discount sorted currency portfolio returns as mirrored in the last line of Panel A of Table 4.2. Moving from the low to high forward discount sorted currency portfolios, discount-rate betas decrease with the exception of portfolio F4. Note that we followed Campbell and Vuolteenaho (2004) in defining discount-rate news as "better than expected" news. The low forward discount portfolio return covaries positively with this good news and hence offers a lower return than its high forward discount counterpart that covaries negatively with the good news. This pattern is also reported in Nitschka (2010) in the context of explaining the cross-section of European value and growth portfolios from the perspective of a national investor. However, we do not find such a pattern for the currency momentum sorted portfolio returns.

In sum, there seems to be a relation between discount-rate betas and excess returns on forward discount sorted currency portfolios. Hence, we should expect the dispersion in the sensitivity to the market's discount-rate news to explain average returns on the forward discount currency portfolios.

4.3.3 Cross-Sectional Pricing Results

Full Sample Period We use the cash-flow and discount-rate betas as well as the market betas from the previous subsection, presented in Table 4.2, to assess the explanatory power of the CAPM and the two-beta version of the CAPM when confronted with returns on foreign currencies. Therefore, we follow Fama and MacBeth (1973) and run cross-sectional regressions of the Lustig et al. (2009) currency portfolio excess returns on either their market betas or their estimated cash-flow and discount-rate betas at each point in time, i.e.

$$cr_t^i = \beta_M^i \lambda_M + v_t, \forall t \tag{4.13}$$

or

$$cr_t^i = \beta_{CF}^i \lambda_{CF} + \beta_{DR}^i \lambda_{DR} + v_t, \forall t \tag{4.14}$$

with cr_t^i the excess return on currency portfolio i as defined in previous sections. We do not consider constant terms in the cross-sectional regressions as we deal with excess returns. Our cross-sectional pricing exercises over the sample period from 1983:11 to 2008:4 are summarized in Table 4.3. Panel A of Table 4.3 provides the results for the single-beta CAPM. Panel B of

Table 4.3 gives the corresponding results for the two-beta CAPM. We confront the two models with four sets of test assets. The results for the different test assets are reported in the columns (1) to (4). Table 4.3 reports second-stage Fama-MacBeth estimates of the risk prices using (1) six forward discount rate sorted, (2) six currency momentum sorted, (3) all twelve currency portfolio, and (4) six forward discount sorted currency portfolio returns together with the 25 Fama and French (1993) size and book-to-market sorted stock portfolios as test assets.

At first glance, the performance of the CAPM does not seem to be particularly bad. As the first column of Panel A of Table 4.3 shows, the CAPM explains about a half of the cross-sectional dispersion in forward discount sorted currency portfolio returns. The risk price of the market return, however, is about seven times larger than the sample average of 5.9% p.a. The second column shows that the CAPM is not able to explain average returns on currency momentum sorted currency portfolios. Considering both forward discount and currency momentum sorted portfolios as test assets, the market return is significantly priced but the risk price is again too high. Additionally including the 25 Fama and French (1993) book-to-market and size sorted stock portfolio returns drives down the risk price but at the expense of very high pricing errors. In sum, our results confirm the point made by Lustig et al. (2009). The CAPM is not a good model for the pricing of foreign currency returns despite its benign performance during the recent crisis period.

Panel B of Table 4.3 gives the corresponding results for the two-beta CAPM. In line with the pattern in cash-flow and discount-rate betas of forward discount sorted currency portfolio returns highlighted above, differences in discount-rate betas explain the cross-sectional dispersion in these currency portfolio returns. The risk price is negative but can be easily explained. Since we follow Campbell and Vuolteenaho (2004) in defining discount-rate news as 'better than expected', the excess returns on the low forward discount currency portfolio loads positively on the market's discount-rate news while the high forward discount currency portfolio covaries negatively with the good news. Hence, the risk price has to be negative. This pattern has been observed by Nitschka (2010), who assesses if the cross-sectional dispersion in European value and growth stock portfolio returns can be explained from a national investor's perspective using two-beta versions of the CAPM. Table 3 additionally reveals that the two-beta variety of the CAPM gives slightly lower pricing errors than the single-beta CAPM but the fit is not much better. It fails to explain the cross-sectional variation in currency momentum sorted currency portfolios (see column (2) of Panel B) which explains its relatively poor performance when confronted with both forward discount and currency momentum sorted currency portfolios (see column (3) of Panel B). It is clear from these findings that the two-beta CAPM is not a perfect description of foreign currency returns' cross-sectional dispersion. The two-factor model by Lustig et al. (2009) currently seems to be the best model for that purpose.

The two-beta CAPM, however, is very useful to reveal that different asset classes react differently to news driving stock market returns. The fourth column of Panel B of Table 4.3 presents the risk price estimates when forward discount sorted currency portfolios and 25 book-to-market and size sorted stock portfolios are jointly considered as test assets. It shows that both cash-flow and discount-rate news are significantly priced. This finding reflects the main result of this paper – forward discount rate sorted currency portfolio returns are explained by differences in their sensitivities to the stock market's discount-rate news – and the seminal contribution of Campbell and Vuolteenaho (2004) showing that cash-flow news drives average returns on value and growth stocks. The two-beta variety of the CAPM allows to price both asset classes while highlighting the different sources of differences in average stock and foreign currency returns at the same time.

Stock Market Booms and Busts So far we have documented that there is a relation between the cross-section of foreign currency returns and news about expected returns on the U.S. stock market. Recently, Campbell et al. (2010) emphasized that stock market booms and crashes in the past two decades had different causes. They find that the stock market boom of the mid-1990s was primarily driven by rational investor's expectation about falling discount rates, while the subsequent bust in 2000 - 2002 reflected an increase in discount rates. The following boom of the early and mid-2000s was fuelled by a mix of cash-flow and discount-rate news, but the latest bust is clearly driven by worse cash-flow prospects.

In this section, we assess if the relation between currency portfolio returns and stock market news that we presented in the previous section is influenced by the particular driving forces of the stock market. Using the forward discount sorted currency portfolio returns as test assets, we therefore assess the performance of the two-beta CAPM for three subsample periods following Campbell et al. (2010): (1) 1995:1 - 2000:2, (2): 2000:3 - 2002:8, and (3) 2002:9 - 2007:8. Table 4.4 summarizes our results. Each column displays the results for one of the three subsample periods. Risk prices and pricing errors are in annualized percentage points.

Campbell et al. (2010) show that the stock market surge from the mid- to end-1990s was primarily driven by lower expected discount rates. Interestingly, the cross-section of forward discount sorted currency portfolio returns seems to be explained by cash-flow news during this period as column (1) in Table 4.4 suggests. This finding stands in marked contrast to our results over the full sample period. The second column of Table 4.4 shows that we cannot relate average currency returns to the stock market's news series during the crash period. The results presented in the third column of Table 4.4 for the stock market boom phase of 2002 - 2007, driven by both cash-flow and discount-rate news according to Campbell et al. (2010), delivers again the pattern observed over the full sample period. Differences in the sensitivity to discount-rate news partly explain cross-sectional dispersion in average foreign currency portfolio returns.

The differences between the pricing results for the two stock market boom periods are striking. A comparison between these two stock market boom periods delivers also interesting differences in terms of average foreign currency returns. As revealed by Table 4.5, while still exhibiting the monotonically increasing pattern from low to high forward discount currencies, average foreign currency returns were all negative during the 1990s stock market surge (see column (1) of Table 4.5) but positive in the 2002 - 2007 boom period.

Taken together, the descriptive statistics and the pricing exercises conducted in this section show that the distinction between expected discount-rate and cash-flow news driven periods matters for the pricing of foreign currency returns. While the basic finding of Lustig and Verdelhan (2007) and Lustig et al. (2009), average excess returns monotonically increase with average forward discounts or interest rate differentials, pertains to both stock market boom periods under study, the explanation of their cross-sectional differences varies. What is even more striking is the marked difference in the level of foreign currency returns during the stock market boom periods. The sign of currency returns does not seem to be only linked to stock market up- and downturns as suggested by Lustig et al. (2009) but also influenced by the kind of news driving the stock market.

4.4 Conclusions

Over long time periods, low interest rate/forward discount currencies typically payoff poorly, whereas high interest rate/forward discount currencies consistently generate positive excess returns. To understand what hides behind profitable carry trade strategies, this paper studies the interaction between aggregate stock and foreign exchange markets. We start by decomposing the market return into its "bad" cash-flow and "good" discount-rate components. This decomposition allows to show that excess returns on low forward discount sorted currency portfolios load positively on "good" news about the market's discount-rate news whereas their high forward discount counterparts load negatively on this "better than expected" news about future returns. In line with this observation, this paper shows that average returns on forward discount sorted currency portfolios are related to differences in their sensitivity to the stock market's discount-rate news. These results also highlight that neither variety of the CAPM, single or two-beta, is a particularly good model for explanations of foreign currency returns compared to the benchmark of the Lustig et al. (2009) two-factor model.

With a focus on the two recent stock market booms in the U.S., we additionally present evidence of a link between the relative dominance of the two stock market's news components and explanations for the cross-sectional dispersion in foreign currency returns. During the stock market boom from 2002 to 2007, driven by a mix of cash-flow and discount-rate news, differences in the sensitivity to discount-rate news explain average returns on forward discount sorted currency portfolio returns. In contrast to this finding and our results over the full sample period, average excess returns on currency portfolios during the stock market surge in the mid- and end-1990s are explained by their exposure to the stock market's cash-flow news. This finding is particularly interesting since this stock market boom period was primarily driven by discount-rate news.

4.5 Tables and Figures

Table 4.1: VAR Characteristics

The table shows the OLS parameter estimates for a first-order VAR model including a constant, the market return (r^M), price-earnings ratio (pe), small-stock value spread (vs) and term yield spread (ty). OLS t-statistics are in parentheses. Each row corresponds to a different dependent variable. The first five columns report coefficients on the explanatory variables listed in the column header; the last column shows the adjusted $\overline{R}^2$ statistics. The sample period is 1928:12-2008:04.

	constant	r_t^M	ty_t	pe_t	vs_t	$\overline{R}^2$(%)
r_{t+1}^M	0.00	0.10	0.01	-0.02	-0.01	2.19
	(3.39)	(2.96)	(1.98)	(-3.03)	(-2.34)	
ty_{t+1}	0.00	0.03	0.89	-0.03	0.08	83.09
	(0.22)	(0.20)	(60.31)	(-1.10)	(3.02)	
pe_{t+1}	0.00	0.52	0.00	0.99	-0.00	99.07
	(1.90)	(23.87)	(0.94)	(296.57)	(-0.96)	
vs_{t+1}	0.00	-0.01	0.00	-0.00	0.99	98.37
	(1.14)	(-0.27)	(0.05)	(-0.37)	(209.16)	

Table 4.2: Cash-Flow and Discount-Rate Betas

The table presents estimated cash-flow and discount-rate betas relative to the total market beta for twelve currency portfolios. Panel A describes forward discount rate sorted currency portfolios. Panel B describes momentum sorted currency portfolios.

Panel A: Forward Discount Date Sorted						
Portfolio	F1	F2	F3	F4	F5	F6
β^i_M	0.04	-0.07	-0.21	-0.02	-0.31	-0.23
β^i_{CF}	-0.14	-0.12	-0.16	-0.10	-0.10	0.04
β^i_{DR}	0.18	0.05	-0.05	0.08	-0.21	-0.27
Panel B: Currency Momentum Sorted						
Portfolio	M1	M2	M3	M4	M5	M6
β^i_M	-0.46	-0.21	0.01	-0.11	-0.07	-0.20
β^i_{CF}	-0.12	-0.20	-0.08	-0.12	-0.05	-0.03
β^i_{DR}	-0.34	-0.01	0.09	0.01	-0.02	-0.17

Table 4.3: Fama-MacBeth Cross-Sectional Regressions

The table reports the Fama-MacBeth estimates of the risk prices using (1) six forward discount rate sorted currency portfolios, (2) six currency momentum sorted currency portfolios, (3) all twelve currency portfolios, and (4) six forward discount rate sorted currency portfolios as well as 25 size and book-to-market sorted stock portfolio returns as test assets. Fama-MacBeth (1973) t-statistics are in parentheses. Panel A reports results from standard CAPM; Panel B reports results from two-beta CAPM. Risk prices, mean squared pricing errors (MSE) and the mean absolute pricing errors (MAE) are reported in percentage points p.a.

	(1)	(2)	(3)	(4)
Panel A: CAPM				
λ_M	42.05	19.32	35.33	8.58
	(2.89)	(1.25)	(2.72)	(2.55)
R^2	0.55	-0.02	0.22	0.20
MSE	2.44	5.47	4.80	12.88
MAE	1.39	1.88	1.61	2.55
Panel B: Two-Beta CAPM				
λ_{CF}	-5.35	-5.27	-3.19	10.97
	(-0.51)	(-0.50)	(-0.32)	(3.30)
λ_{DR}	-11.83	-0.87	-6.62	-1.58
	(-2.77)	(-0.24)	(-1.89)	(-2.21)
R^2	0.51	-0.29	-0.05	0.60
MSE	2.09	5.34	4.55	6.44
MAE	1.10	2.05	1.79	2.02

Table 4.4: Fama-MacBeth Cross-Sectional Regressions

The table reports the Fama-MacBeth estimates of cash-flow and discount-rate news risk prices using six forward discount rate sorted currency portfolios as test assets for the two-beta CAPM. Column (1) reports results for the sample period 1995:1 - 2000:2, column (2) the corresponding results for the sample period 2000:3 - 2002:8, and finally column (3) gives estimates for the period from 2002:9 - 2007:8. Fama-MacBeth (1973) t-statistics are in parentheses. Risk prices, mean squared pricing errors (MSE) and the mean absolute pricing errors (MAE) are reported in percentage points p.a.

	(1)	(2)	(3)
	Two-Beta CAPM		
λ_{CF}	2.01	15.28	25.30
	(2.10)	(0.58)	(0.64)
λ_{DR}	0.36	-4.72	-60.29
	(0.64)	(-0.39)	(-2.97)
R^2	0.31	-0.01	0.43
MSE	4.23	14.27	5.28
MAE	1.84	3.34	1.87

Table 4.5: Average Currency Excess Returns

The table reports average excess returns on forward discount sorted currency portfolios for three subsample periods. Column (1) reports returns for the sample period 1995:1 - 2000:2, column (2) the corresponding excess returns for the sample period 2000:3 - 2002:8, and finally column (3) gives currency portfolio returns for the period from 2002:9 - 2007:8. All returns are reported in percentage points p.a. Portfolio F1 contains currencies with lowest forward discounts. Portfolio F6 contains currencies with the highest forward discounts.

	(1)	(2)	(3)
Average Currency Returns			
F1	-7.56	-7.61	0.98
F2	-4.56	-5.17	1.38
F3	-3.62	-0.44	5.41
F4	-4.91	3.25	5.35
F5	-2.31	-1.71	6.21
F6	-0.02	1.75	9.78

Figure 4.1: Foreign Exchange and Equity Markets

The figure plots monthly excess return on the S&P500 index against the return on a carry trade strategy constructed as a difference on high (F6) and low (F1) forward discount rate currency portfolios for the sample period 2006:12 - 2008:04.

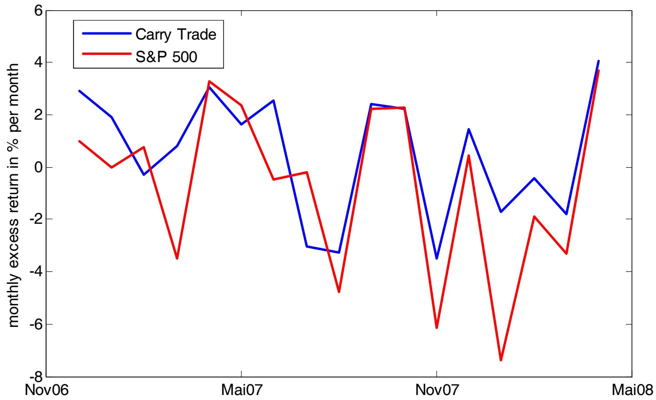
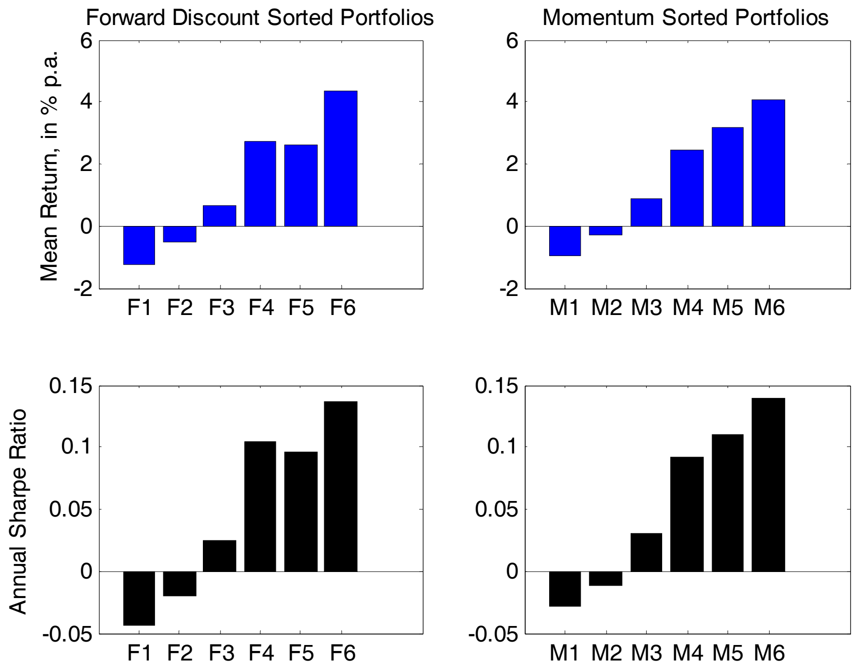


Figure 4.2: Twelve Foreign Currency Portfolios

The figure plots average returns p.a. and annual Sharpe ratios on six forward discount rate and six momentum sorted currency portfolios over the sample period from 1983:12-2008:04.



5 Good Times, Bad Times: Inflation Uncertainty and Equity Returns

Uncertainty is central to asset pricing.[34] Financial markets dislike uncertainty because it lowers asset prices, consumption and wealth. We employ inflation uncertainty as an indicator of the economy state and thus as a factor which can affect risk premia. Times of high uncertainty are referred to as "bad" times, times of low uncertainty are labeled as "good" times. Intuitively, an asset that comoves strongly with consumption growth in bad times should offer a premium because it reduces investors' hedging ability in periods of higher uncertainty. Moreover, this risk premium should go up when inflation uncertainty is high and it should decline when inflation uncertainty is low.

Different models look at different types of uncertainty. For example, Bansal and Yaron (2004) study uncertainty related to fluctuations in conditional consumption volatility. They show that a rise in economic uncertainty, modeled as a time-varying volatility in consumption, lowers asset prices, and fluctuations in economic uncertainty increase the equity risk premium. David (1999) shows how fluctuations in investors' own level of uncertainty can generate a new class of risk and hedging demands in an intertemporal portfolio choice setting. Ozoguz (2009) uses the dynamics of investors' beliefs and Bayesian uncertainty about the state of the economy as state variables that describe the time-variation in investment opportunities. He finds that investors' uncertainty about the state of the economy has a negative impact on asset valuations both at the aggregate market level and at the portfolio level. David and Veronesi (2001) show that uncertainty about future inflation and earnings growth rates helps explain stock and bond monthly volatilities and cross-covariances. Finally, Lee (1999) finds empirical support for a hypothesis that time-varying inflation uncertainty is related to returns on broad-based portfolios by the negative correlation between ex post real returns and the uncertainty premium.

This paper offers three main empirical findings. First, a conditional version of the conventional consumption-based capital asset pricing model (CCAPM) of Lucas (1978) and Breeden (1979) with a survey-based measure of inflation uncertainty as a conditioning variable shows remarkable success in explaining return differentials between low-book-to-market and high-book-to-market portfolios. The success of the conditional CCAPM stands in stark contrast to the

[34] This chapter of the thesis is based on Galsband (2010c). An earlier version of this paper circulated previously under the title "Inflation Uncertainty, Size and Value Premia: Evidence from Survey Data."

failure of the standard unconditional CCAPM which – in spite of its theoretical purity – falls short of accounting for the cross-sectional return differentials.[35] Second, assets with high sensitivity to consumption fluctuations conditional on a survey-based measure of inflation uncertainty tend to have higher expected excess returns. This intuitive finding is consistent with financial markets which fear economic uncertainty. Finally, in asset pricing tests, the equity premium appears to be closely linked to inflation uncertainty. Confirming Veronesi's (1999) prediction that agents demand higher expected returns when uncertainty is high, our results suggest that an increase in economic uncertainty raises average risk compensation: Consumption risk premium increases in bad times, when inflation uncertainty is high, and it decreases in good times, when inflation uncertainty is low.

A number of recent papers have used economically motivated factors as conditioning variables in the (C)CAPM. For instance, Lettau and Ludvigson (2001) find that a proxy of consumption-wealth ratio might be a powerful forecaster of the economy state. Their choice of conditioning variable is motivated by its ability to summarize investors' expectations of future returns to the market portfolio. High consumption-wealth ratio signals "bad" periods of high risk or risk aversion; low consumption-welath ratio signals "good" periods of low risk or risk aversion. The authors show that value stocks, i.e. stocks with high book-to-market value, have higher conditional consumption betas in bad times than their growth counterparts with low book-to-market value. This finding is striking in view of ample evidence that both stock groups have total consumption betas of similar size (Mankiw and Shapiro, 1986; Campbell, 1996; and Cochrane, 1996). A related study of Jagannathan and Wang (1996) includes the return on human capital to explore the ability of the CAPM in a conditional sense. Their specification performs well in explaining the cross-sectional variation in average returns on a large collection of stock portfolios.

The empirical success of scaled factor models is typically attributed to the time variation in parameters stemming from scaling factors (Cochrane, 1996). Cochrane (2001) argues that any intuitively sensible variable which is related to changes in the investment opportunity set can be defended as a state variable. A higher level of inflation uncertaity makes future real earnings on investment more uncertain which in turn reduces current investment and future output (Caballero, 1991). Following the methodology in Cochrane (1996) and Lettau and Ludvigson (2001) we express the stochastic discount factor as a conditional, or scaled, linear factor model

[35] See, for instance, Hansen and Singleton (1982), Mankiw and Shapiro (1986), Breeden et al. (1989), Campbell (1996), Cochrane (1996), and Hansen and Jagannathan (1997).

with a survey-based measure of inflation uncertainty as a conditioning variable. Specifically, to incorporate the conditioning information we interact the fundamental consumption growth with the current inflation uncertainty measure. We then study the cross-sectional properties of the resulting conditional model as a scaled multifactor model.

Two aspects merit particular mention. First, the choice of inflation uncertainty measure seems to matter to some extent in empirical asset pricing tests. Since the proper measure of inflation uncertainty is unknown and there is no commonly accepted economic theory which would provide a function form for it, there coexist a number of uncertainty measures. For example, some authors use the variance of inflation about a moving average estimate of the mean as a proxy for uncertainty. Other authors employ processes based on economic ARIMA, ARCH and other structural forecasting models as proxies for inflation uncertainty. In a strict sense, both are measures of variability rather than uncertainty. A weakness of inflation variability proxies from generalized autoregressive conditional heteroscedasticity models relates to some undesirable empirical properties of these measures.[36] Yet others view the length of the confidence interval the forecaster draws about his point estimate as a measure of uncertainty with regard to inflation. However, this method is also not flawless since the length of that interval may depend upon external events.

Since the highly influential study of Hasbrouck (1984) the literature (see e.g. Zarnowitz and Lambros, 1987 and Golob, 1994) has heavily relied on the cross-forecaster dispersion of expectations as a proxy for uncertainty. Strictly speaking, the cross-sectional variation of individual inflation forecasts is a measure of the dispersion of opinion rather than a measure of misconfidence. Nevertheless, Bomberger and Frazer (1981) argue that it is reasonable to suppose that situations in which future inflation is thought to be more difficult to predict are situations in which individual predictions differ more widely. In line with this argumentation, we proxy inflation uncertainty by the standard deviation of cross-individual forecasts for consumer price index inflation rate. We use inflation forecasts from three best known sources of survey data on inflation expectations – the Michigan Survey, the Livingston Survey, and the Survey of Professional Forecasters.

Second, different models have different predictions about whether it is the level of inflation, inflation uncertainty (as measured by dispersion) or inflation variability (e.g. from a GARCH

[36] In particular, such proxies are known to be often not strongly correlated with the direct survey-based measures, nor with one another. Hence, use of these proxies might lead to incorrect inference about the correlation between inflation and inflation uncertainty (e.g. Batchelor and Dua, 1996).

model) which actually matters for asset pricing. The distinction between these three aggregates is not quite easy in the empirical sense because of the strong comovement between them. This paper seeks to discriminate between inflation uncertainty, inflation variability, and inflation to determine the key drivers behind the pricing power of the model.

We subject our findings to a number of robustness checks. We work with two sets of portfolios as test assets. The first is a standard set of 25 value-weighted returns on portfolios sorted by book-to-market ratio and size constructed by Fama and French. To alleviate the concern that our model spuriously[37] explains the average returns on these portfolios, we employ a second set of 20 portfolios sorted on past risk loadings constructed by Campbell and Vuolteenaho (2004). In a different exercise, we replace nondurable consumption growth with the growth rate in durables. Ever since Yogo (2006) durables are known to be helpful in explaining both the cross-sectional variation in expected stock returns and the time variation in the premium on size and value sorted portfolios. Next, we control for size and value effects, consumption-wealth ratio, and inflation level. We find that a survey-based measure of inflation uncertainty is indicative of the time-varying risk in the economy. Asset's sensitivity to consumption growth conditional on inflation uncertainty risk is informative of its riskiness. We also repeat the above robustness checks with a shorter sample. We find that the parameter estimates do not change much and appear to be consistent with the previous results. We conclude that the main results of this study are not affected by some plausible changes in the specification of the model, in the sample period, and in test assets.

The remainder of the paper is organized as follows. Section 5.1 presents the scaled multi-factor asset pricing model with consumption risk as the only fundamental factor and inflation uncertainty as a single conditioning variable. Section 5.2 describes the data. Section 5.3 summarizes our main cross-sectional results for the scaled CCAPM specification. Section 5.4 performs a sensitivity analysis. And finally, Section 5.5 concludes.

5.1 Scaled Multifactor CCAPM with Inflation Uncertainty

The discussion in this section relies on Cochrane (1996) and Lettau and Ludvigson (2001). We begin by assuming an arbitrage-free environment with a stochastic discount factor M_{t+1} such

[37] Daniel and Titman (1997) argue that testing asset pricing models using only test portfolios sorted by characteristics known to be related to average returns, such as size and value, can yield spurious results.

that for any asset i with a return R^i_{t+1} the following equation holds:

$$1 = E_t \left[M_{t+1} \left(1 + R^i_{t+1} \right) \right], \tag{5.1}$$

where E_t denotes the expectation operator conditional on information available at time t.

In the conditional[38] CCAPM, the implied M_{t+1} is a linear function of a single fundamental factor, consumption growth Δc_{t+1}:

$$M_{t+1} = a_t + b_t \Delta c_{t+1}. \tag{5.2}$$

where a_t and b_t are time-varying coefficients. The statement that the discount factor is a linear factor model is equivalent to the conventional factor pricing representations in terms of betas and factor risk premia (see e.g. Cochrane, 2001). In particular, the conditional model above implies a conditional factor pricing model given by

$$E_t \left[R^i_{t+1} \right] = R^0_t + \beta^i_{\Delta c,t} \lambda_{\Delta c,t}, \tag{5.3}$$

where R^0_t is the return on a zero-beta portfolio uncorrelated with M_{t+1}, the consumption beta is defined as

$$\beta^i_{\Delta c,t} = \frac{Cov_t \left(\Delta c_{t+1}, R^i_{t+1} \right)}{Var_t \left(\Delta c_{t+1} \right)} \tag{5.4}$$

and the risk premium follows

$$\lambda_{\Delta c,t} = -R^0_t Var_t \left(\Delta c_{t+1} \right) b_t. \tag{5.5}$$

More generally, a conditional linear factor model of the form $M_{t+1} = \mathbf{c}'_t \left(1, \mathbf{f}'_{t+1} \right)'$, where $\mathbf{c}_t = (a_t, \mathbf{b}'_t)'$ and $\mathbf{f}_{t+1}$ denotes the vector of fundamental factors, implies a conditional beta representation given by

$$E_t \left[R^i_{t+1} \right] = R^0_t + \widetilde{\boldsymbol{\beta}}^{i\prime}_t \widetilde{\boldsymbol{\lambda}}_t, \tag{5.6}$$

[38] We conventionally refer to a model with constant coefficients, $M_{t+1} = a + b\Delta c_{t+1}$, as unconditional linear factor model.

where

$$\widetilde{\boldsymbol{\beta}}_t^i = Cov_t\left(\mathbf{f}_{t+1}, \mathbf{f}'_{t+1}\right)^{-1} Cov_t\left(\mathbf{f}_{t+1}, R_{t+1}^i\right) \tag{5.7}$$

and $\widetilde{\boldsymbol{\lambda}}_t$ is the vector of period t risk prices of the fundamental prices

$$\widetilde{\boldsymbol{\lambda}}_t = -E\left[R_t^0\right] Cov_t\left(\mathbf{f}_{t+1}, \mathbf{f}'_{t+1}\right)\mathbf{b}_t. \tag{5.8}$$

Taking unconditional expectations, it is straightforward to show that the conditional model in (5.1) does not necessarily imply an unconditional model where a_t and b_t are constant. Similar to Cochrane (1996), Cochrane (2001), Lettau and Ludvigson (2001) and Ozoguz (2009), we rewrite our conditional linear factor CCAPM as a scaled multifactor model by expressing the time-varying coefficients a_t and b_t as linear functions of z_t, $a_t = \gamma_0 + \gamma_1 z_t$ and $b_t = \eta_0 + \eta_1 z_t$. Plugging these equations into (5.1) we obtain a scaled multifactor model with time-invariant coefficients:

$$\begin{aligned} M_{t+1} &= (\gamma_0 + \gamma_1 z_t) + (\eta_0 + \eta_1 z_t)\,\Delta c_{t+1} \\ &= \gamma_0 + \gamma_1 z_t + \eta_0 \Delta c_{t+1} + \eta_1 z_t \Delta c_{t+1}. \end{aligned} \tag{5.9}$$

In vector notation, the model above can be compactly summarized as $M_{t+1} = \mathbf{c}'\mathbf{F}_{t+1}$, where $\mathbf{F}_{t+1} = \left(1, \overline{\mathbf{f}}'_{t+1}\right)'$, $\overline{\mathbf{f}}_{t+1} = \left(z_t, \mathbf{f}'_{t+1}, \mathbf{f}'_{t+1} z_t\right)'$, $\mathbf{c}$ is a constant vector $\mathbf{c} = (\gamma_0, \mathbf{b}')'$, γ_0 is a scalar, $\mathbf{b} = (\gamma_1, \eta'_0, \eta'_1)'$ is a vector of constant coefficients on the scaled factors, $\overline{\mathbf{f}}_{t+1}$. This representation for M_{t+1} is equivalent with an unconditional multifactor beta representation given by

$$E\left[R_{t+1}^i\right] = R_t^0 + \boldsymbol{\beta}^{i\prime}\boldsymbol{\lambda}, \tag{5.10}$$

where $\boldsymbol{\beta}^i$ is a vector of regression coefficients from a multiple regression of returns on asset i on the variable factors, $\overline{\mathbf{f}}_{t+1}$:

$$\boldsymbol{\beta}^i = Cov\left(\overline{\mathbf{f}}_{t+1}, \overline{\mathbf{f}}'_{t+1}\right)^{-1} Cov\left(\overline{\mathbf{f}}_{t+1}, R_{t+1}^i\right) \tag{5.11}$$

and

$$\boldsymbol{\lambda} = -E\left[R_t^0\right] Cov\left(\overline{\mathbf{f}}_{t+1}, \overline{\mathbf{f}}'_{t+1}\right)\mathbf{b}. \tag{5.12}$$

In the case of a single fundamental factor, Δc_{t+1}, and a single scaling variable $z_t = \sigma_t^\pi$ the unconditional multifactor beta representation for asset i with constant betas is given by

$$E\left[R_{t+1}^i\right] = E\left[R_t^0\right] + \beta_z^i \lambda_z + \beta_{\Delta c}^i \lambda_{\Delta c} + \beta_{\Delta cz}^i \lambda_{\Delta cz}, \tag{5.13}$$

where Δc_{t+1} conventionally denotes the current-period log growth rate in nondurables and services and σ_t^π denotes the lagged investors' uncertainty about future inflation. It is important to note that coefficients $\boldsymbol{\lambda}$ in (5.10) do not have the same interpretation as period t risk prices $\widetilde{\boldsymbol{\lambda}}_t$ on the fundamental factors in equation (5.6). Following the literature[39] we estimate a cross-sectional model in (5.13), which delivers estimates of $\boldsymbol{\lambda}$ but not $\widetilde{\boldsymbol{\lambda}_t}$. In this model with uncertainty risk, we would expect assets that covary with consumption growth in times of high inflation uncertainty to have greater returns. These assets would command a higher risk premium because they reduce the hedging ability of a risk averse investor in particularly risky times.

In what follows, we use the unconditional beta representation in (5.13) as the basis for our empirical work. As noted by Ozoguz (2009), a strong advantage of a scaled multifactor representation is that for each asset pricing model under consideration, it nests the corresponding unconditional model in which betas on the scaling variable and the scaling factors are zero. Due to this circumstance, a direct comparison of scaled and unscaled factor models is possible.

5.2 Data

5.2.1 Inflation Uncertainty

This section summarizes and critically examines the inflation uncertainty concept employed in the empirical analysis below. The ongoing literature questions the plausibility of empirical dispersion measures as a valid proxy of inflation uncertainty. The cross-sectional variation of individual inflation forecasts is, strictly speaking, a measure of the dispersion of opinion, or disagreement, rather than a measure of misconfidence. Nevertheless, as argued by Bomberger and Frazer (1981), it is reasonable to suppose that "situations in which future inflation is thought to be more difficult to predict will, in general, be situations in which individual predictions will differ more widely." In line with this argumentation, we follow the literature and proxy inflation uncertainty by the standard deviation across individual forecasts for consumer price index (CPI)

[39] As noted by Lettau and Ludvigson (2001), a straightforward computation of the risk prices for the fundamental factors, $\widetilde{\boldsymbol{\lambda}}_t$, is not possible without making further assumptions.

inflation rate from three best known sources of survey data on inflation expectations: the Survey of Professional Forecasters (SPF), the Michigan Survey (MS), and the Livingston Survey (LS).

The data on the MS is available since 1960Q1. The SPF, conducted by the Federal Reserve Bank of Philadelphia, provides individual inflation expectations since 1981Q3. Finally, the LS is run since 1946 twice a year, in June and December, usually in the middle of the month.

The initial empirical analysis is carried out with the MS data for a number of reasons. First, the available data of the MS expectations start in 1960Q1 and thus provide more than 80 additional time-series observations as compared to the PFS. This number of additional observations might substantially improve the reliability of the statistical inference. Second, the quarterly reported MS inflation dispersion data are rather appropriate for asset pricing tests of quarterly financial market data than the biannual LS. Moreover, the MS is a source of high quality inflation expectations data with a high number of participants. The individual expectations in consumer price changes are accurately reported after adjustment for outliers and biases. Finally, the stationarity propoerties of the MS inflation uncertainty measure make the time-series qualified for asset pricing analysis.

The participants of the MS are asked to estimate the expected change in prices over the next twelve months. Hence, the respective portfolio returns should be measured over a twelve-month horizon in quarterly frequency. Due to significant differences between the surveys, it is difficult to make a quantitative comparison across them. However, we will cross-check the survey evidence qualitatively, using the PFS and LS expectations.

5.2.2 Consumption

Following earlier work (Hansen and Singleton, 1983), aggregate nondurable consumption is measured as the sum of seasonally adjusted real per-capita consumption expenditure on nondurables and services. Real estimates remove the effects of price changes, which can obscure changes in consumption in current dollars. Both series are taken from Table 7.1 of the National Income and Product Accounts (NIPA), available from the U.S. Bureau of Economic Analysis. To match the timing horizon of our state variable, we measure annual nondurable consumption growth at quarterly frequency. The series has a mean of 0.51% and a standard deviation of 0.33%. The stationarity of the data is supported by an the Augmented Dickey-Fuller statistic with a t-statistic of -3.14.

5.2.3 Benchmark Portfolios

Two sets of portfolios are employed as test assets. The first is a standard set of 25 Fama and French value-weighted portfolios sorted by market capitalization (ME) and book-to-market ratio (BE/ME). The portfolio data are available from Kenneth R. French's website. Each portfolio is represented by a two-digit number. The first digit refers to the size quintiles (1 indicating small (S), 5 indicating big (B)). The second digit refers to the book-to-market quintiles (1 indicating the lowest book-to-market ratio or growth (G), 5 indicating the highest book-to-market ratio or value (V)). Table 5.1 provides a brief summary of these 25 annual stock portfolio returns, measured accordingly at quarterly frequency.

The second portfolio set similarly includes annual returns in quarterly frequency on 20 risk-sorted portfolios constructed by Campbell and Vuolteenaho (2004). These data are available until the end of 2001. Using these test assets alleviates the possibility of a beta spread arising not from the comovement with a fundamental risk factor but due to the size and value portfolios sorting (Daniel and Titman, 1997).

5.3 Good Times, Bad Times: A Scaled CCAPM

In this section, we examine the relative performance of the scaled consumption-based asset pricing model given by the equation (5.13) to explain the cross-section of equity risk premia. For this purpose we employ standard cross-sectional regression techniques by Fama and MacBeth (1973) and Jagannathan and Wang (1996). We compare the standard unscaled CCAPM and a scaled CCAPM version with inflation uncertainty as a single scaling variable in terms of their ability to explain the pattern of U.S. equity portfolios.

Table 5.2 presents results of estimating the empirical specification in (5.13). Below the estimated $\boldsymbol{\lambda}$ coefficients we report uncorrected and Shanken-corrected t-statistics. The last two columns give the R^2 and the $\overline{R}^2$ adjusted for degrees of freedom for the cross-sectional regression of average excess returns on a constant and betas. The betas are calculated from a multivariate regression of returns on the factors, $\overline{\mathbf{f}}_{t+1}$.

To form a basis for comparison, we first present the results for the standard unscaled CCAPM. The first row of the table estimates the following cross-sectional specification

$$E\left[R^i_{t+1}\right] = R^0_t + \beta^i_{\Delta c}\lambda_{\Delta c}. \tag{5.14}$$

Consistent with the literature, the static CCAPM fails disastrously to explain portfolio returns. The t-statistic for $\lambda_{\Delta c}$ shows that the consumption beta is not a statistically significant determinant of the cross section of average returns. The $\overline{R}^2$ summarizes this failure: less than 5% of the cross-sectional return variation can be captured by differences in consumption betas of these portfolios. The difficulty of the unconditional CCAPM to explain the cross-section of portfolio returns is displayed graphically in the left plot of Figure 5.1. The figure depicts realized average excess returns against fitted excess returns for the single-beta CCAPM.

By contrast, a specification that includes - in addition to the consumption beta - the scaled consumption beta, performs much better: the cross-sectional $\overline{R}^2$ rises to 55%. The results of the second-pass cross-sectional estimation are summarized in row 2.

Row 3 of the table presents the results for a scaled conditional CCAPM. The three-factor model given by (5.13) relies on consumption growth as the only fundamental factor and a survey-based measure of inflation uncertainty as the single conditioning variable. To test the model, we first obtain the factor loadings β^i_z, $\beta^i_{\Delta c}$, and $\beta^i_{\Delta cz}$ for each portfolios i in a first-pass from a single multivariate regression of the return on portfolio i on the contemporaneous consumption growth, lagged inflation uncertainty, and current consumption growth scaled with lagged inflation uncertainty:

$$R^i_{t+1} = \beta^i_0 + \beta^i_z z_t + \beta^i_{\Delta c}\Delta c_{t+1} + \beta^i_{\Delta cz}\Delta c_{t+1} z_t + \epsilon^i_{t+1}. \tag{5.15}$$

We then estimate a second-pass cross-sectional regression in which average returns across portfolios are regressed on their first-pass factor loadings.

The estimates show that λ_z in (5.13) is not statistically different from zero, implying that the time-varying component of the intercept is not an important determinant of average returns. By contrast, the coefficients on both $\beta^i_{\Delta c}$ and $\beta^i_{\Delta cz}$ are strongly significant and the model fit is relatively high with $\overline{R}^2$ measure of about 74%. A graphical depiction of the model fit is provided in the right plot of Figure 5.1. The model with scaled consumption growth improves substantially the empirical validity of the static CCAPM. When inflation uncertainty varies over time, there are risk premia associated with asset's sensitivity to unanticipated changes in conditional consumption growth. Assets that covary positively with consumption growth when uncertainty risk is high have higher average returns. These assets command a higher risk premium. In line with other studies (e.g. Lettau and Ludvigson, 2001; Yogo, 2006; and Jagannathan and Wang, 1996), the model generates the largest pricing error for the small growth portfolio.

To exclude the possibility that the success of the model is due to the particular portfolio choice, we repeat the estimation with a larger pool of assets which additionally includes the 20 risk-sorted portfolios. Panel B of Table 5.2 presents the respective results. The findings suggest that some portfolios are riskier than others not because their returns are more sensitive to consumption fluctuations in an unconditional sense, but because their returns are more sensitive to consumption fluctuations when times are "bad", i.e. the uncertainty risk is high. We explore this possibility further.

For this purpose, we run the cross-sectional regressions of the type (5.13) for bad and good states separately. For this exercise, a good (bad) state is defined as a quarter during which $z_t = \sigma_t^{\pi}$ is at least one standard deviation below (above) its mean.[40] If time variation in inflation uncertainty is related to time-varying risk premium, the implied risk compensation should be higher during bad states. Tables 5.3 and 5.4 show that this is precisely what we find. Interestingly - in contrast to a specification in Table 5.2 which does not differentiates between states - estimating a simple unconditional CCAPM for good and bad states separately produces significant estimates, consistent with the view that consumption risk carries a positive risk premium. The *t*-statistic for $\lambda_{\Delta c}$ shows that a simple consumption beta is now a significant determinant of the pattern of average returns. The risk premium is at least twice as high in bad times as in good times. Indeed, in good times, the estimated $\lambda_{\Delta c}$ of 0.001 is very low. Given the estimated levels of consumption risk in Table 5.3, the estimated average returns are far too low. The estimated intercept is significantly positive, which implies that average realized excess returns on Fama-French portfolios exceed those predicted by the model by roughly 7 percent per annum. For comparison, contemporaneous consumption risk of the canonical CCAPM yields significant intercept estimates of about 12 percent per year and the ultimate consumption risk at a horizon of about three years generates very similar intercept term estimates of about 6 to 7 percent per year (Julliard and Parker, 2005). The model explains slightly more than 30% of the cross-sectional variation in expected excess returns between low book-to-market and high book-to-market portfolios. This number does not appear unreasonable, provided that there are only about 35 quarters which qualify as good states.

Row 1 of Table 5.4 gives results of a similar regression estimated for bad states, however.

[40] Lettau and Ludvigson (2001) similarly distinguish between good and bad states using, however, the consumption-wealth ratio as a state variable.

Higher risk premium estimates fit actual returns better which results into insignificant intercept estimates and a higher R^2 statistic.

Row 2 in Tables 5.3 and 5.4 further reports results of regressions when two regressors - simple unscaled consumption betas and scaled consumption betas - enter the pricing equation, for good and bad periods, respectively. Compared to the single beta CCAPM, this specification performs somewhat better in terms of general fit. In good states, the model explains about 40% of the cross-sectional return differentials. In bad states, the $\overline{R}^2$ improves to about 50%. As before, bad states are associated with greater risk premia than good states.

The regression in the row 3 in Tables 5.3 and 5.4 estimates the three-factor model in (5.13) again for bad and good states separately. The general model improvement is not substantial in times when inflation uncertainty is low. The respective R^2 statistic increases by another 10% to more than 60% for bad states. Our intuition that consumption risk premium increases in bad times – when inflation uncertainty is high – and decreases in good times – when inflation uncertainty is low – is further supported by the estimates. In both cases, the sensitivity of returns to fluctuations in conditional nondurable consumption growth is significantly reflected in their cross-sectional differentials.

Increasing the number of test assets - as in Panels B of Tables 5.3 and 5.4 - challenges the empirical model fit even more. Both scaled and unscaled consumption betas are, however, significantly related to the cross-section of returns. In sum, our results transmit two central messages regarding the determination of expected risk premia. The first is the crucial importance of conditional consumption risk exposure for rationalizing the return differentials. The second is the distinction of consumption risk exposure in bad versus good states. In particular, the magnitude of the risk price estimates as well as the measurement precision increase substantially when inflation uncertainty goes up. Finally, the results indicate that the considered conditional consumption-based models explain a large share of cross-sectional variation in equity returns.

5.4 Robustness Tests

This section goes through a number of additional robustness tests. First, we replace nondurable consumption growth with the growth rate in durables. Second, we show that despite a high correlation between inflation and inflation uncertainty, it is the latter which helps explain the risk premium on equity markets. We control for size and book-to-market effects, the consumption-wealth ratio and inflation level. And finally, we use inflation forecasts from other surveys to derive an empirical proxy of inflation uncertainty. We find that a survey-based measure of inflation uncertainty is indicative of the time-varying risk in the economy. Asset's sensitivity to conditional consumption growth appears informative of its riskiness.

5.4.1 Durable Consumption Growth

We exploit Yogo's (2006) finding that there is a tight link between cross-sectional return differentials on Fama-French portfolios and their sensitivities to the durable consumption growth. In Table 5.5 the consumption risk is proxied by the log growth rate in real per capita expenditures on durables. Replacing nondurables with durables does not alter the results in a qualitative sense. The coefficients are estimated precisely. However, the point estimates seem to lie rather on the high side. Low pricing errors of the slope estimates and insignificant intercept estimates generate a high model fit. While an unconditional model with durables growth as a single risk factor explains roughly 30% of the cross-sectional return variation, additionally accounting for inflation uncertainty as a conditioning variable increases the model fit up to close to 80%.

5.4.2 Other Scaling Variables

Different models have different predictions about whether it is the level of inflation, inflation uncertainty (as measured by dispersion) or inflation variability (as measured by structural forecasting models) which actually matters for asset pricing. The distinction between these three aggregates is not quite easy in the empirical sense because of the strong comovement between them. This section seeks to discriminate between different scaling variables to determine the key drivers behind the pricing power of the model.

A strong relation between inflation and inflation uncertainty is well documented: the latter goes up when inflation is high. Most prominent explanation of this paradigm involves the response of monetary policy[41] to inflation (Ball, 1992). Holland (1993) argues, furthermore, that inflation uncertainty rises because the policy impact is uncertain. Figure 5.2 displays the actual inflation from the Bureau of Labour Statistics against inflation uncertainty measure based on the MS expectations over the 1960Q1-2009Q4 period. A chart of the twelve-month Michigan forecasts clearly indicates a positive relationship between inflation and inflation uncertainty.

[41] When inflation is low, monetary authority tries to keep it low. To the extent the policy is successful, inflation remains low and hence stable. When inflation is high, however, a disinflationary policy increase inflation variability by lowering the inflation rate.

Both of these variables were highest in the beginning of the 1980s, with inflation rate above 12% and the variability of about 1.1%.

To exclude the possibility that inflation uncertainty finds its reflection in the equity premia because it tracks actual inflation we estimate equation (5.13) with inflation as a state variable. The results of this simple exercise are striking. Despite the strong comovement of both series using inflation as a conditioning variable yields extremely poor cross-sectional results. Table 5.6 summarizes the empirical findings. Scaled CCAPM with actual inflation as a state variable explains just 19% of the cross-sectional return differentials (row 2). The performance of the restricted model in (5.13) with factor loadings $\beta^i_{\Delta c}$ and $\beta^i_{\Delta cz}$ where $z_t = \pi_t$ is even more poor with a respective $\overline{R}^2$ statistic of 2% (row 1).

A number of studies employ the conditional variance of inflation as a measure of inflation uncertainty, even though it is strictly speaking a measure of variability rather than uncertainty. A GARCH specification, which is generally used for inflation and time-varying residual variance as a measure of inflation variability, is as follows:

$$\pi_t = \rho_0 + \sum_{i=1}^{k} \rho_i \pi_{t-i} + \varepsilon_t, \tag{5.16}$$

$$\sigma^2_{\varepsilon_t} = \kappa_0 + \kappa_1 \varepsilon^2_{t-1} + \kappa_2 \sigma^2_{\varepsilon_{t-1}}, \tag{5.17}$$

where ε_t is the residual from regression (5.16) , $\sigma^2_{\varepsilon_t}$ is the conditional variance of the residual term takes as inflation variability at time t, and k is the lag length. Equation (5.16) is an autoregressive representation of inflation. Equation (5.17) is a GARCH (1,1) represenational of the conditional variance.

Table 5.7 represents the cross-sectional pricing results when inflation variability measured as a time-varying conditional variance of a residual term from a GARCH (1,1) process is employed as a scaling variable. The overall model performance is much better than in the case of a standard unconditional CCAPM. The $\overline{R}^2$ statistic is, however, by more than 30% lower than that generated by a conditional model with inflation uncertainty as a scaling variable. The estimate of $\lambda_{\Delta cz}$ remains positive and significant when $z_t = \sigma^2_{\varepsilon_t}$ supporting the view that scaled consumption growth factor is an important driver of the cross-sectional return differentials on value and growth portfolios.

5.4.3 Alternative Scaled Multifactor Models

In this subsection, we estimate a number of specifications of equation (5.13). First, we examine whether the conditional consumption risk with inflation uncertainty as a state variable remains important after the Fama-French factors are controlled for. The estimation results are reported in rows 1-4 of Table 5.8. The risk loadings are estimated similarly in a single multivariate time-series regression of the portfolio returns on the respective risk factors. The addition of the size and book-to-market factors, $(BE/ME)_t$ and BE_t, improves the overall fit of the regression only marginally. The coefficients on both scaled and unscaled factors, $\lambda_{\Delta c}$ and $\lambda_{\Delta cz}$, are still highly significant across all estimated specifications. Even though the SMB and HML factors are helpful in predicting returns, they cannot be reconciled as macroeconomic pricing factors in this setup. The t-statistics in rows 1-4 indicate that the SMB and HML factors are estimated insignificantly but with a right sign.

Rows 5 and 6 of the table report estimates from the scaled CCAPM with inflation uncertainty extended by the log consumption-wealth ratio, cay_t, of Lettau and Ludvigson (2001) as an additional regressor. Two aspects merit particular mention. First, dropping σ_t^π and including cay_t lowers both the t-statistic of $\lambda_{\Delta cz}$ and the R^2 of the regression. The coefficient on cay_t is not statistically distinguishable from zero. Second, an analogous regression with σ_t^π leads to similar results as the original specification.

Finally, we experiment with inflation level as an additional regressor. Rows 7 and 8 of the table support by now well-known negative relation between stock returns and inflation. Controlling for inflation level leaves our previous results unaltered. We conclude that after controlling for size and value effects, consumption-wealth ratio, and inflation level, the positive relation between consumption beta and expected returns remains economically and statistically significant.

5.4.4 Evidence from Other Surveys

Next, we test the robustness of our results with respect to inflation expectations from the Survey of Professional Forecasters and Livingston Survey. Table 5.9 reports the cross-sectional Fama-MacBeth (1973) estimates when inflation uncertainty is proxied by a standard deviation of individual inflation expectations from the Professional Forecasters Survey. The sample period runs from 1981Q3 - 2009Q1.

In Table 5.10, we rely on the LS expectations over the period 1947Q1 - 2009Q4 to measure uncertainty. Reestimating the standard CCAPM over a longer sample period supports the poor ability of unconditional consumption risk to explain the cross-section of equity returns. The corresponding adjusted R^2 of 14.9% in row 1 of Table 5.10 is quite low, and the price of consumption risk, $\lambda_{\Delta c}$, of 0.003 is not strongly significant (t-statistic = 1.61).

As before, we consider next a modified consumption-based asset pricing model, where risk is embodied in scaled consumption growth in addition to the standard unscaled consumption growth. This model implies the following cross-sectional risk premium restriction:

$$E\left[R_{t+1}^{i}\right] = E\left[R_{t}^{0}\right] + \beta_{\Delta c}^{i}\lambda_{\Delta c} + \beta_{\Delta cz}^{i}\lambda_{\Delta cz}, \tag{5.18}$$

where $z_t = \sigma_t^{\pi}$ is the inflation uncertainty scaling factor. As in our previous estimations, the estimates of both, $\lambda_{\Delta c}$ and $\lambda_{\Delta cz}$, in row 2 of the table are positive (0.004 and 0.026, respectively) and the adjusted R^2 exceeds the 40% mark. Estimating the original specification (5.13) yields a better model fit of slightly more than 50%, and statistically precise estimates of $\lambda_{\Delta c}$ and $\lambda_{\Delta cz}$, as before.

As argued in Fama and French (1995), the size and book-to-market factors may proxy for state variables that are not captured by consumption growth. The results in rows 4-7 indicate that controlling for the size and value effects does not diminish the ability of the conditional consumption growth to capture the information about the risk exposure of equity portfolios. The results show that $\lambda_{\Delta cz}$ remains positive and significant. The point estimate of 0.02 is similar to that obtained with the MS proxy of inflation uncertainty. In contrast, the slope estimates of the betas with SMB and HML are imprecisely measured and not significant. The explanatory power of the regressions remains around 50%, suggesting that these additional risk factors add little beyond the explanatory power of conditional consumption growth.

For consistency with our previous analysis, we test the sensitivity of the results when the consumption-wealth ratio of Lettau and Ludvigson (2001) enters the multiple regression of returns on the risk factors. The respective second-stage results are summarized in rows 8 and 9. Further controlling for the inflation level in rows 10 and 11 does not help to explain a larger portion of the cross-sectional return differentials but leaves the estimates on $\lambda_{\Delta cz}$ statistically significant.

Several other robustness checks were attempted and results were consistent with the original specification. We considered other measures of size and book-to-market equity. We experimented with a subset of 25 portfolios and a mix of 25 and 6 portfolios. We also repeated the above robustness checks with a shorter sample. We find that the parameter estimates do not change much and appear to be consistent with the previous results. We conclude that the main results of this study are not affected by some plausible changes in the specification of the model, in the sample period and test assets.

5.5 Conclusions

Uncertainty is central to asset pricing. If investors dislike uncertainty then asset returns will be sensitive to the time variation in the former. This paper investigates a survey-based measure of inflation uncertainty as an indicator of the economy state. Times of high uncertainty are referred to as "bad" times, times of low uncertainty are labeled as "good" states. We argue that the distinction between good and bad times is important for assessing the consumption risk exposure of an asset. Intuitively, assets that comove strongly with consumption growth in bad times should offer a premium because they reduce investors' hedging ability in periods of higher uncertainty. Moreover, this risk premium should go up when inflation uncertainty is high and it should decline when inflation uncertainty is low.

To explore this idea we study a conditional consumption-based capital asset pricing model (CCAPM) with inflation uncertainty as a state variable. Our findings are easily summarized. First, a scaled multifactor CCAPM with a survey-based measure of inflation uncertainty as a conditioning variable can account for a large part of return differentials between low-book-to-market and high-book-to-market portfolios. The remarkable empirical success of the conditional CCAPM stands in stark contrast to the failure of the standard unconditional CCAPM. Second, high sensitivity to conditional consumption fluctuations is typically associated with high excess returns. Third, in asset pricing tests, our results suggest that the equity premium is closely related to inflation uncertainty: The risk premium increases in bad times – when inflation uncertainty is high – and it decreases in good times – when inflation uncertainty is low.

To verify our results we conduct a number of robustness checks. Seeking to determine the driving forces behind the success of the model to explain the cross-section of return differentials, we employ different measures of inflation uncertainty as well as the level of inflation itself as a conditioning variable in asset pricing tests. We use two sets of portfolios as well as smaller subsets as test assets. We replace nondurable consumption growth with the growth rate in durables. We use inflation forecasts from different surveys to derive an empirical proxy of inflation uncertainty. Finally, also after controlling for size and value effects, consumption-wealth ratio and inflation level, the incremental explanatory power of inflation uncertainty does not seem to decline. We conclude that the main results of this study are not affected by some plausible changes in the specification of the model, in the sample period, and in test assets.

5.6 Tables and Figures

Table 5.1: Descriptive Statistics

Panel A of the table reports annual means, maxima, minima, medians and standard deviations of log nondurable consumption growth and inflation uncertainty measures from the Michigan, Livingston and Professional Forecasters Surveys. It also reports the Augmented Dickey-Fuller statistics of these variables with corresponding t-statistics. Panel B of the table reports annual average returns and Sharpe ratios for 25 value-weighted Fama-French portfolios sorted by size and book-to-market equity from 1960Q1 to 2009Q4.

Panel A: Consumption Growth and Inflation Uncertainty							
variable	min	max	mean	median	std	ADF	t-stat
Δc_{t+1}	-0.0043	0.0128	0.0051	0.0052	0.0033	0.5705	-3.1373
$\sigma_t^{\pi,MS}$	3.0000	10.5830	5.6937	5.4772	1.9255	0.2436	-3.8606
$\sigma_t^{\pi,LS}$	0.5959	12.2200	2.5470	1.6487	2.0772	-0.0349	-5.5795
$\sigma_t^{\pi,PFS}$	0.0753	2.2063	0.4621	0.3536	0.3340	-0.0410	-11.0613

Panel B: 25 Fama-French Portfolios						
	G	2	3	4	V	V-G
	Average Excess Return					
S	0.0234	0.0841	0.0881	0.1124	0.1252	0.1018
2	0.0383	0.0734	0.0984	0.1054	0.1149	0.0766
3	0.0431	0.0790	0.0824	0.0942	0.1154	0.0723
4	0.0557	0.0571	0.0775	0.0922	0.0916	0.0359
B	0.0429	0.0527	0.0526	0.0574	0.0692	0.0263
S-B	-0.0195	0.0314	0.0355	0.0551	0.0560	0.0755
	Sharpe Ratios					
S	0.0730	0.3207	0.3813	0.5109	0.5266	0.4537
2	0.1440	0.3504	0.4931	0.5405	0.5746	0.4306
3	0.1798	0.3930	0.4675	0.5035	0.6189	0.4390
4	0.2507	0.3043	0.4193	0.5002	0.4582	0.2075
B	0.2281	0.3154	0.3281	0.3484	0.3849	0.1567
S-B	-0.1552	0.0054	0.0532	0.1625	0.1418	0.2970

Table 5.2: Fama-MacBeth Regressions with Michigan Survey Expectations

Panel A of the table presents $\boldsymbol{\lambda}$ estimates from cross-sectional Fama-MacBeth regressions using returns of 25 Fama-French portfolios: $E\left[R_{t+1}^{i}\right] = R_t^0 + \boldsymbol{\beta}^{i\prime}\boldsymbol{\lambda}$. The individual λ_j estimates from the second stage cross-sectional regressions for the factor j listed in the column head are reported. The betas $\boldsymbol{\beta}$ are computed in a first-stage time-series multiple regressions of returns on the factors, for each portfolio separately. $\sigma_t^{\pi,MS}$ denotes the inflation uncertainty measure from the Michigan Survey calculated as a standard deviation of individual inflation forecasts in each time period, Δc_{t+1} is nondurable consumption growth. The table reports Fama-MacBeth cross-sectional regression coefficients. Two t-statistics are reported for each coefficient estimate in parentheses. The top statistic uses uncorrected standard errors; the bottom statistic uses the Shanken (1992) correction. The last two columns provide the Jagannathan-Wang (1996) unadjusted cross-sectional R^2 statistics and $\overline{R}^2$ adjusted for the degrees of freedom. The sample period is 1960Q1-2007Q4. Panel B of the table additionally employs the 20 risk-sorted Campbell and Vuolteenaho (2004) portfolios as test assets. The sample period is 1960Q1-2001Q4.

Row	Constant	$\sigma_t^{\pi,MS}$	Δc_{t+1}	$\sigma_t^{\pi,MS} \cdot \Delta c_{t+1}$	R^2	$\overline{R}^2$
			Panel A: 25 Fama-French Portfolios			
1	0.036		0.002		0.0892	0.0496
	(1.273)		(1.500)			
	(0.900)		(1.061)			
2	-0.002		0.002	0.030	0.5831	0.5452
	(-0.110)		(1.932)	(4.500)		
	(-0.078)		(1.366)	(3.182)		
3	-0.049	-0.359	0.005	0.043	0.7696	0.7367
	(-2.527)	(-0.471)	(4.643)	(7.207)		
	(-1.787)	(-0.333)	(3.283)	(5.096)		

Table 5.2: *Continued*

Panel B: 25 Fama-French and 20 Campbell-Vuolteenaho Portfolios						
1	0.051		0.001		0.0970	0.0760
	(5.123)		(2.150)			
	(3.623)		(1.520)			
2	0.022		0.001	0.021	0.4583	0.4325
	(2.280)		(2.004)	(5.665)		
	(1.612)		(1.417)	(4.006)		
3	-0.003	0.676	0.003	0.028	0.5453	0.5120
	(-0.244)	(1.179)	(3.387)	(6.409)		
	(-0.173)	(0.834)	(2.395)	(4.532)		

Table 5.3: Fama-MacBeth Regressions in Good States

Good states are defines as a quarter during which the inflation uncertainty measure, $\sigma_t^{\pi,MS}$, is at least one standard deviation below its mean. For further explanation see notes to Table 5.2.

Row	Constant	$\sigma_t^{\pi,MS}$	Δc_{t+1}	$\sigma_t^{\pi,MS} \cdot \Delta c_{t+1}$	R^2	$\overline{R}^2$
			Panel A: 25 Fama-French Portfolios			
1	0.067		0.001		0.3360	0.3072
	(11.221)		(3.412)			
	(7.935)		(2.413)			
2	0.064		0.002	0.007	0.4784	0.4310
	(11.285)		(4.464)	(4.490)		
	(7.980)		(3.157)	(3.175)		
3	0.065	0.002	0.002	0.007	0.4957	0.4237
	(10.815)	(0.035)	(4.515)	(4.513)		
	(7.648)	(0.024)	(3.193)	(3.191)		
			Panel B: 25 Fama-French and 20 Campbell-Vuolteenaho Portfolios			
1	0.069		0.001		0.3091	0.2930
	(18.807)		(4.386)			
	(13.299)		(3.102)			
2	0.068		0.001	0.004	0.3088	0.2759
	(18.000)		(3.846)	(3.644)		
	(12.728)		(2.719)	(2.576)		
3	0.073	-0.036	0.001	0.004	0.3809	0.3356
	(17.633)	(-2.045)	(4.389)	(4.097)		
	(12.469)	(-1.446)	(3.103)	(2.897)		

Table 5.4: Fama-MacBeth Regressions in Bad States

Bad states are defines as a quarter during which the inflation uncertainty measure, $\sigma_t^{\pi,MS}$, is at least one standard deviation above its mean. For further explanation see notes to Table 5.2.

Row	Constant	$\sigma_t^{\pi,MS}$	Δc_{t+1}	$\sigma_t^{\pi,MS} \cdot \Delta c_{t+1}$	R^2	$\overline{R}^2$
Panel A: 25 Fama-French Portfolios						
1	-0.100		0.004		0.4208	0.3957
	(-2.219)		(4.088)			
	(-1.569)		(2.891)			
2	-0.127		0.006	0.043	0.5600	0.5200
	(-3.070)		(5.286)	(5.228)		
	(-2.171)		(3.738)	(3.697)		
3	-0.103	-0.941	0.006	0.048	0.6837	0.6386
	(-2.758)	(-4.286)	(6.296)	(6.523)		
	(-1.951)	(-3.031)	(4.452)	(4.613)		
Panel B: 25 Fama-French and 20 Campbell-Vuolteenaho Portfolios						
1	-0.033		0.002		0.1817	0.1627
	(-1.073)		(3.090)			
	(-0.75)		(2.185)			
2	-0.035		0.002	0.0198	0.1902	0.1516
	(-1.124)		(3.109)	(3.141)		
	(-0.795)		(2.198)	(2.221)		
3	-0.007	-0.518	0.003	0.029	0.4275	0.3857
	(-0.252)	(-2.979)	(4.659)	(4.977)		
	(-0.178)	(-2.107)	(3.294)	(3.520)		

Table 5.5: Fama-MacBeth Regressions with Durables Growth

Δd_{t+1} denotes the log growth rates in durables. Test assets are 25 Fama-French portfolios. For further explanation see notes to Table 5.2.

Row	Constant	$\sigma_t^{\pi,MS}$	Δd_{t+1}	$\sigma_t^{\pi,MS} \cdot \Delta d_{t+1}$	R^2	$\overline{R}^2$
1	-0.001		0.021		0.3190	0.2893
	(-0.036)		(3.282)			
	(-0.025)		(2.321)			
2	-0.010		0.020	0.171	0.7963	0.7778
	(-0.768)		(5.526)	(7.432)		
	(-0.543)		(3.908)	(5.255)		
3	-0.009	0.533	0.019	0.163	0.8000	0.7715
	(-0.664)	(0.813)	(4.343)	(6.127)		
	(-0.469)	(0.575)	(3.071)	(4.333)		

Table 5.6: Fama-MacBeth Regressions with Inflation

π_t denotes the actual annual inflation rate. Test assets are 25 Fama-French portfolios. For further explanation see notes to Table 5.2.

Row	Constant	π_t	Δc_{t+1}	$\pi_t \cdot \Delta c_{t+1}$	R^2	$\overline{R}^2$
1	0.046		0.002	0.008	0.1020	0.0204
	(1.360)		(1.298)	(1.452)		
	(0.962)		(0.918)	(1.027)		
2	-0.001	-2.942	0.004	0.013	0.2887	0.1871
	(-0.021)	(-2.012)	(2.421)	(2.265)		
	(-0.015)	(-1.423)	(1.712)	(1.602)		

Table 5.7: Fama-MacBeth Regressions with Inflation Variability

$\sigma^2_{\varepsilon_t}$ denotes inflation variability measure from the Michigan Survey calculated as a time-varying conditional variance of a residual term from a GARCH (1,1) process. Test assets are 25 Fama-French portfolios. For further explanation see notes to Table 5.2.

Row	Constant	$\sigma^2_{\varepsilon_t}$	Δc_{t+1}	$\sigma^2_{\varepsilon_t} \cdot \Delta c_{t+1}$	R^2	$\overline{R}^2$
1	0.039		0.001	0.009	0.2397	0.1705
	(1.461)		(0.359)	(2.562)		
	(1.033)		(0.254)	(1.812)		
2	-0.033	1.295	0.004	0.020	0.4745	0.3994
	(-1.007)	(2.839)	(2.046)	(4.293)		
	(-0.712)	(2.008)	(1.447)	(3.036)		

Table 5.8: Fama-MacBeth Regressions Including Characteristics

$(BE/ME)_t$ is the book-to-market ratio, BE_t is book equity, cay_t is the consumption-wealth ratio of Lettau and Ludvigson (2001). For further explanation see notes to Tables 5.2 and 5.6.

Row	Constant	$\sigma_t^{\pi,MS}$	Δc_{t+1}	$\sigma_t^{\pi,MS} \cdot \Delta c_{t+1}$	$(BE/ME)_t$	BE_t	R^2	$\overline{R}^2$
1	0.017		0.001	0.024	0.161		0.5810	0.5211
	(0.911)		(1.212)	(3.687)	(1.433)			
	(0.645)		(0.857)	(2.607)	(1.013)			
2	-0.039	-0.418	0.004	0.038	0.066		0.7822	0.7386
	(-1.952)	(-0.608)	(3.911)	(6.518)	(0.789)			
	(-1.380)	(-0.430)	(2.765)	(4.609)	(0.558)			
3	-0.060		0.005	0.040		0.731	0.7182	0.6779
	(-2.513)		(4.015)	(6.391)		(2.312)		
	(-1.777)		(2.839)	(4.519)		(1.635)		
4	-0.075	-0.499	0.006	0.046		0.564	0.8259	0.7911
	(-3.874)	(-0.716)	(5.948)	(8.613)		(2.306)		
	(-2.740)	(-0.506)	(4.206)	(6.090)		(1.630)		

Table 5.8: *Continued*

Row	Constant	$\sigma_t^{\pi,MS}$	Δc_{t+1}	$\sigma_t^{\pi,MS} \cdot \Delta c_{t+1}$	cay_t	π_t	R^2	$\overline{R}^2$
5	0.019		0.001	0.022	0.009		0.4603	0.3832
	(0.581)		(0.624)	(2.223)	(1.511)			
	(0.411)		(0.442)	(1.572)	(1.069)			
6	-0.034	-0.702	0.005	0.040	0.001		0.7933	0.7520
	(-1.464)	(-1.110)	(3.596)	(5.659)	(0.303)			
	(-1.035)	(-0.785)	(2.543)	(4.002)	(0.214)			
7	-0.071		0.004	0.038		-2.095	0.7787	0.7471
	(-3.196)		(4.502)	(7.222)		(-2.633)		
	(-2.260)		(3.183)	(5.107)		(-1.862)		
8	-0.066	0.037	0.005	0.040		-2.045	0.7858	0.7429
	(-2.802)	(0.045)	(4.240)	(6.549)		(-2.542)		
	(-1.982)	(0.032)	(2.998)	(4.631)		(-1.797)		

Table 5.9: Fama-MacBeth Regressions with Professional Forecasters Survey Expectations

$\sigma_t^{\pi,PFS}$ denotes the inflation uncertainty measure from the Professional Forecasters Survey calculated as a standard deviation of individual inflation forecasts in each time period. Test assets are 25 Fama-French portfolios. For further explanation see notes to Table 5.8.

Row	Constant	$\sigma_t^{\pi,PFS}$	Δc_{t+1}	$\sigma_t^{\pi,PFS} \cdot \Delta c_{t+1}$	R^2	$\overline{R}^2$
1	0.0970		-0.001		0.0095	-0.0336
	(2.279)		(-0.469)			
	(1.976)		(-0.331)			
2	0.084		0.000	0.003	0.5230	0.4796
	(3.405)		(0.114)	(3.448)		
	(2.408)		(0.081)	(2.438)		
3	0.081	0.000	0.367	0.003	0.5400	0.4743
	(3.239)	(0.117)	(2.119)	(2.848)		
	(2.291)	(0.083)	(1.498)	(2.014)		

Table 5.10: Fama-MacBeth Regressions with Livingston Survey Expectations

$\sigma_t^{\pi,LS}$ denotes the inflation uncertainty measure from the Livingston Survey calculated as a standard deviation of individual inflation forecasts in each time period. For further explanation see notes to Table 5.8.

Row	Constant	$\sigma_t^{\pi,LS}$	Δc_{t+1}	$\sigma_t^{\pi,LS} \cdot \Delta c_{t+1}$	$(BE/ME)_t$	BE_t	R^2	$\overline{R}^2$
1	0.037		0.003				0.1841	0.1487
	(1.586)		(2.278)					
	(1.122)		(1.611)					
2	-0.001		0.004	0.026			0.4629	0.4141
	(-0.049)		(3.680)	(4.167)				
	(-0.034)		(2.602)	(2.946)				
3	-0.001	-0.070	0.005	0.026			0.5696	0.5081
	(-0.040)	(-0.073)	(4.464)	(4.697)				
	(-0.028)	(-0.052)	(3.157)	(3.322)				
4	0.004		0.002	0.019	0.365		0.5444	0.4793
	(0.180)		(2.290)	(4.137)	(2.394)			
	(0.127)		(1.620)	(2.925)	(1.693)			
5	-0.003	0.0136	0.003	0.019	0.317		0.6498	0.5797
	(-0.144)	(0.147)	(2.957)	(4.700)	(2.316)			
	(-0.102)	(0.104)	(2.091)	(3.324)	(1.638)			

Table 5.10: *Continued*

Row	Constant	$\sigma_t^{\pi,LS}$	Δc_{t+1}	$\sigma_t^{\pi,LS} \cdot \Delta c_{t+1}$	BE_t	cay_t	π_t	R^2	$\overline{R}^2$
6	0.013		0.004	0.023	0.785			0.5490	0.4846
	(0.588)		(3.803)	(4.022)	(1.511)				
	(0.416)		(2.689)	(2.844)	(1.068)				
7	0.008	0.201	0.004	0.024	0.803			0.5895	0.5075
	(0.340)	(0.210)	(4.051)	(4.191)	(1.599)				
	(0.283)	(0.149)	(2.865)	(2.963)	(1.131)				
8	0.027		0.003	0.025		0.003		0.4166	0.3333
	(1.007)		(2.976)	(3.646)		(0.382)			
	(0.712)		(2.104)	(2.578)		(0.270)			
9	0.034	-0.353	0.003	0.020		-0.002		0.6578	0.5894
	(1.607)	(-0.390)	(3.762)	(3.724)		(-0.289)			
	(1.137)	(-0.276)	(2.660)	(2.634)		(-0.204)			
10	-0.021		0.005	0.027			-0.774	0.4760	0.4012
	(-0.590)		(3.238)	(4.112)			(-0.664)		
	(-0.417)		(2.289)	(2.908)			(-0.470)		
11	-0.019	-0.189	0.005	0.028			-1.057	0.5809	0.4971
	(-0.594)	(-0.193)	(3.879)	(4.609)			(-0.983)		
	(-0.420)	(-0.136)	(2.743)	(3.259)			(-0.695)		

Figure 5.1: Realized versus Predicted Returns for Consumption-Based Models

The figure plots realized versus predicted annual returns for the 25 Fama-French portfolios sorted by size and book-to-market equity. The estimated models are the unconditional CCAPM and the conditional CCAPM with inflation uncertainty as a state variable. The horizontal axes correspond to the predicted average excess returns and the vertical axes to the sample average excess returns. The sample period is 1960Q1-2009Q4. The predicted values are from regressions presented in Table 5.2.

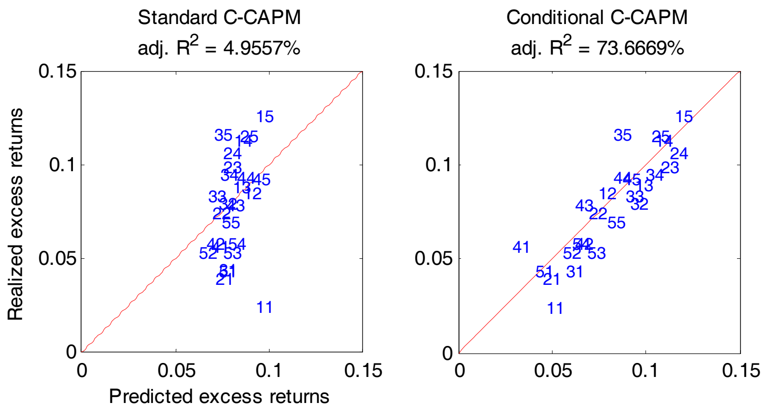
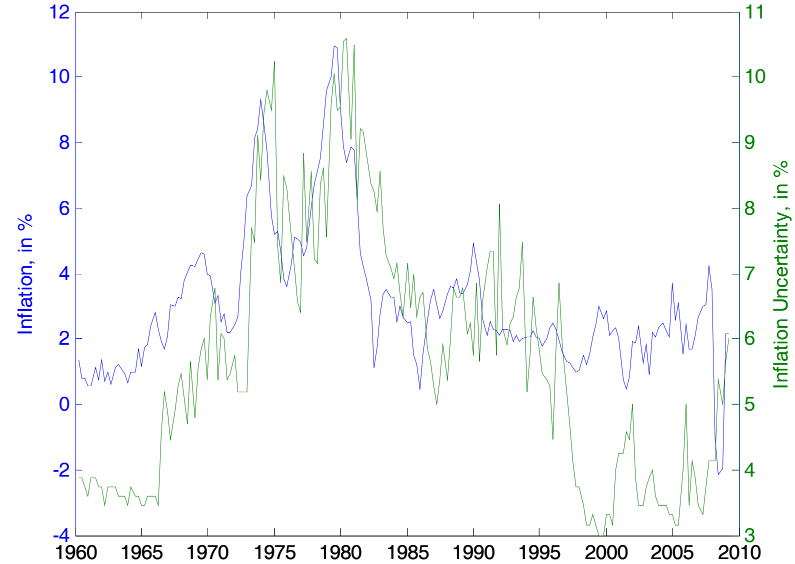


Figure 5.2: Inflation against Inflation Uncertainty

The figure plots the actual annual inflation rate on the left scale against the Michigan Survey measure of inflation uncertainty on the right scale. Inflation uncertainty is calculated as a standard deviation of individual inflation forecasts in each time period. The sample period is quarterly, running from 1960Q1-2009Q4.



6 Summary

This thesis contributes to establishing a structural link between the real side of the economy and prices of financial assets. It focuses on the empirical examination of sources of aggregate risks – or "bad" economic times – which drive the pattern of returns on global equity and foreign exchange markets.

Chapter 2 of the thesis builds on the key insight of intuitively extremely appealing economic theory that the riskiness of an asset is determined by its ability to insure against consumption fluctuations. It decomposes a consumption beta of an asset into a component driven by asset's cash-flow news and a component related to asset's discount-rate news. This approach reveals that macroeconomic risks embodied in cash flows can largely account for the cross-sectional dynamics of average stock returns. Galsband (2010a) finds that differences in expected excess returns between low book-to-market and high book-to-market portfolios tend to be associated with differences in their cash-flow betas and thus reflect macroeconomic, especially consumption-related risks. This result holds true for a broad set of consumption-based asset pricing models. In addition, the results indicate that the risk premium on equity markets is primarily driven by the exposure of assets' cash-flow components to the cyclical variability of durable consumption goods.

Refining this analysis, chapter 3 studies the sensitivities of assets' cash-flow and discount-rate shocks to unexpected upside and downside consumption changes in a framework of a four-beta C-CAPM. Chapter 3 builds on the notion of downside risk which recognizes that investors care differently about downside losses than upside gains. To price a cross-section of Fama-French portfolios, Galsband (2010b) studies the sensitivities of asset-specific cash-flow and discount-rate shocks to unexpected upside and downside consumption changes. The four-beta consumption-based model fits well and generates economically plausible estimates of risk prices. Risks associated with comovement of assets' "good" discount-rate news and assets' "bad" cash-flow news with negative consumption shocks earn a significant premium and go a long way towards explaining cross-sectional return differentials.

The relative importance of the cash-flow and discount-rate fundamentals on international equity and foreign exchange markets is explored further in chapter 4. Galsband and Nitschka (2010) employ the "bad beta - good beta" logic of Campbell and Vuolteenaho (2004) to explore systematic risks on currency markets. This investigation is motivated by the observation that carry trades, short positions in low interest rate and long positions in high interest rate currencies, comove with stock markets (Brunnermeier et al., 2008 and Lustig et al., 2009).

In contrast to the evidence for value and growth stocks, the authors find that the cross-sectional differences in the forward discount sorted currency portfolio excess returns are explained by their sensitivity to the stock market's discount-rate news: Excess returns on low forward discount currency portfolios load positively on "good" news about the stock market's discount rates while high forward discount currencies load negatively on this news. A low sensitivity to the "better than expected" discount-rate news must be rewarded with a higher risk price than a high sensitivity to the "better than expected" discount-rate news. In addition, Galsband and Nitschka (2010) explore the evolution of foreign currencies' risk exposure to unexpected stock market movements over different time horizons with a particular interest in the past two decades. This exercise is motivated by Campbell et al. (2010), who show that the importance of cash-flow and discount-rate news for movements of the market return vary over time.

Finally, chapter 5 explores the ability of a scaled multifactor consumption-based asset pricing model with a survey-based measure of inflation uncertainty as a conditioning variable to account for return differentials between low-book-to-market and high-book-to-market portfolios. Assets with high sensitivity to consumption fluctuations in times of high inflation uncertainty have high expected excess returns. Moreover, the results in Galsband (2010c) suggest that the time-variation in the equity premium is closely related to time-variation in the uncertainty risk: The risk premium increases in bad times – when inflation uncertainty is high – and it decreases in good times – when inflation uncertainty is low.

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