Macroeconomic Determinants of Stock Market Betas

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Abstract

This paper proposes the mixed frequency conditional beta. We employ the MIDAS framework to estimate market betas as a weighted average of a high and low frequency components. Then, we analyze the macroeconomic determinants of stock market betas and the counter- or pro-cyclicality of betas across well-known portfolio sorts. The surplus consumption ratio with time-varying risk aversion and the default premium are the aggregate variables with the higher statistical impact on stock market betas across alternative portfolios. We show the implications of the mixed frequency betas to the term structure of holding-period expected excess returns, and to alternative investment strategies.

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1. Introduction

Understanding the counter-cyclicality of expected excess returns is a key issue of modern asset pricing. From the time-series point of view, the counter-cyclical behavior of aggregate risk aversion, as in Campbell and Cochrane (1999), represents a huge step towards understanding the time-varying behavior of expected returns. At the same time, given the magnitudes of the cross-sectional averages of equity portfolio returns,[1] a key issue of financial economics is to explain the relative degree of counter-cyclicality (or pro-cyclicality) of stock market betas.[2] The objective of this paper is to understand the business cycle behavior of stock market betas. Our main contribution is to decompose stock market betas into high- and low-frequency components using the MIDAS framework. The mixed frequency conditional beta is the weighted average of both components. This decomposition allows us to study the macroeconomic determinants of market betas and how they react to macroeconomic conditions over the economic cycle. It is important to point out that we estimate simultaneously both beta components and the effects of macroeconomic variables. Hence, we avoid the traditional two or three step procedures of previous literature. Moreover, we obtain the relative percentages of the total variability of the time-varying beta across a large sample of portfolios, which is due to the high- and low-frequency components.

The analysis of the macroeconomic determinants of market betas should be a very important step in understanding the cross-sectional differences of expected returns. However, it is surprising how little empirical research is available. Frictionless macroeconomic-based models are the benchmark asset pricing models. They have been extremely useful to describe the temporal behavior of expected returns and their

[1] See, among many others, Fama and French (2015).
[2] The idea of countercyclical betas first appears for small firms in Chan and Chen (1988).

predictability.[3] Indeed, there are three relevant theoretical extensions of the macroeconomic benchmark model to explain the heterogeneity of betas across the business cycle. Using a partial equilibrium two-factor model, Berk, Green, and Naik (1999) argue that the risk of assets in place and the investment decisions affect the business cycle exposure across industries. Gomes, Kogan, and Zhang (2003) construct a dynamic general equilibrium one-factor model, within a production economy, to show that size and book-to-market explain the cross section of average returns because they covariate with conditional betas. The differences in size and growth opportunities explain the exposure of firms to aggregate productivity, so that the dispersion across betas increases during recessions.[4] Finally, Santos and Versonesi (2004) show that time-varying betas depend on the level of the market risk premium, the level of dividend growth, and on the covariation of the firm´s cash flows with the overall market. They argue that the way in which conditional betas change over the business cycle depends on whether the discount beta or the cash flow beta is a more fundamental determinant of conditional betas. Although these papers may guide empirical applications, from our point of view, a comprehensive empirical analysis of stock market betas throughout the business cycle is missing.[5]

This paper provides evidence on the direct relation between stock market betas and the macro economy using eight sets of portfolios sorted by well-known characteristics. We employ a novel statistical approach to estimate simultaneously betas and the impact of macroeconomic variables on them. Note that this is very different

[3] See Cochrane (2007) and Cochrane (2013) for a detailed discussion on macroeconomic-based models and time-varying expected returns.

[4] It is true, however, that in this paper the CAPM would hold if econometricians had continuous time betas. In their paper, the mismeasured betas are correlated with the Fama-French (1993) factors. Hence, this paper may really be a research on mismeasurement of betas rather than about time-varying betas.

[5] As discussed later, the most relevant exception is the paper by Baele and Londono (2013) who perform a detailed empirical analysis of the behavior of industry market betas throughout the business cycle. Andersen, Bollerslev, Diebold, and Wu (2005) also explore the impact of industrial production on market betas but their empirical application is extremely limited being just an illustration of their state space methodology.

from the several step approaches employed by previous papers, and it employs a completely different framework from the state space methodology of Andersen et al. (2005). This statistical procedure decomposes market betas into high- and low-frequency components in the MIDAS statistical framework. We will refer to the resulting estimated betas as the mixed frequency conditional betas. We show that the betas of value, small, low momentum, and low long reversal stocks tend to be counter-cyclical. They tend to go up (down) with bad (good) economic news especially represented by a decreasing (increasing) surplus consumption ratio from Campbell and Cochrane (1999), and by increasing (decreasing) default premium for the cases of value and low momentum stocks. Importantly, it turns out that the betas of growth, big, high momentum, and high long reversals stocks are pro-cyclical. The macroeconomic variables that significantly impact the larger number of portfolios are surplus consumption and the default premium. Out of the eight portfolios used in our sample, the macroeconomic effects are statistically significant in seven and six portfolios for surplus consumption and the default premium respectively. On the other hand, consumption growth, inflation, and dividend yield seem to be the less relevant variables. They are the variables significantly affecting the lower number of portfolios. Therefore, empirical results suggest that variables capturing credit market conditions and the state of the economy, as long as we recognize time-varying risk aversion, are the key aggregate variables determining the temporal behavior of stock market betas. We also argue that time-varying uncertainty proxied by the squared aggregate consumption growth, in the spirit of the long-run risk models of Bansal and Yaron (2004) and Hansen, Heaton, and Li (2008), do not seem to be a significant macroeconomic indicator except for a weak statistical relation with the value portfolio.

It is also important to point out that all portfolios with counter-cyclical betas tend to have large average returns with the key exception of low momentum. Similarly, portfolios with pro-cyclical betas tend to have lower average returns, once again with the exception of high momentum. It seems to be the case that the behavior of betas over the business cycle cannot explain the average historical returns of either low or high momentum stocks. In fact, Daniel and Moskowitz (2012) show in their Figure 5 that rolling betas of the loser decile portfolio, our low momentum portfolio, display a counter-cyclical behavior in the sense of presenting an increasing beta during volatility or stress periods. Although much less dramatically, the betas of their winner decile portfolio tends to be pro-cyclical.[6]

We also show that, across 40 sample portfolios, more than 90% of the variation of the total mixed frequency conditional betas is explained by the variance of the short-term beta. The contribution of the long-term beta to the total variation of beta ranges from 6 to 8%, while the contribution of the covariance between both components is negative.

Finally, we discuss some implications of our framework for the risk-return relation across portfolios, for the term structure of expected returns, and for investment strategies based on the expected excess returns generated by our mixed frequency conditional betas.

This paper is organized as follows. Section 2 reviews the available empirical literature. Section 3 presents the mixed frequency conditional beta, and the statistical framework employed in the estimation. Section 4 explains the data used in the research. Section 5 displays and discusses the empirical results regarding the decomposition of betas and its macroeconomic determinants, and Section 6 contains several relevant

[6] This is also consistent with the time-varying systematic risk of the momentum strategy first reported by Grundy and Martin (2001), who show that momentum has negative betas after stress periods.

implications of the mixed frequency beta framework. Section 7 concludes the paper and points out future research related to the decomposition of betas.

2. Related Empirical Literature on the Macroeconomic Determinants of Market Betas

Before discussing the available empirical evidence, it is important to mention recent papers discussing the macroeconomic determinants of the stock market volatility. The dynamics of volatility seems to be better characterized by the component model introduced by Engle and Lee (1999), and extended by Engle and Rangel (2008). Under this framework, volatility is a product of a slowly changing, low-frequency deterministic component picking up the non-stationary characteristic of the process, and a short-run/high-frequency part described by a GARCH(1,1) process which means-reverts to one. The deterministic component is supposed to be a function of macroeconomic variables, and hence volatility ends up being a combination of macroeconomic effects and time series dynamics.

In addition, econometric methods involving data sampled at different frequencies have been shown to be useful for forecasting volatility in equity assets as well as to explain the relation between conditional variance and expected market returns. This is especially the case relative to the evidence available from the GARCH family. The mixed frequency approach to modeling and predicting volatility known as mixed data sampling (MIDAS hereafter) was introduced in a series of papers by Ghysels, Santa-Clara, and Valkanov (2003, 2005, 2006). The success of MIDAS lies in the additional statistical power that mixed data frequency regressions incorporate from using daily data in estimating conditional variances. In addition, MIDAS allows for a very flexible functional form for the weights to be applied to past squared returns to explain current volatility.

The insight of the MIDAS specification when combining different frequencies motivates Engle, Ghysels, and Sohn (2013) to modify the dynamics of low-frequency volatility methodology employed by Engle and Rangel (2008). They suggest interpreting the long-run/low-frequency volatility component in the spirit of MIDAS so that macroeconomic data, sampled at lower frequency, can directly be employed while maintaining the mean reverting unit GARCH dynamics for the short-run component. Note that in the original two-component model of Engel and Rangel (2008) the low frequency component is deterministic, while in this specification, the low-frequency component is stochastic. This new class of models is called GARCH-MIDAS. The authors show that allowing the long component to be driven by inflation and industrial production growth, the model outperforms other traditional time-series volatility models at long horizons. This insight suggests that macroeconomic variables are also likely to fundamentally drive the low-frequency component of betas. Therefore, a MIDAS approach to estimate the conditional betas seems very reasonable. Unfortunately, the formal statistical methodologies of Engle and Rangel (2008), and Engle et al. (2013) are not available for either covariances or correlations. This is an important point to understand the current state of empirical research regarding the macroeconomic determinants of stock market betas, and our statistical procedure to investigate the macroeconomic determinants of market betas.

To the best of our knowledge, the first empirical study recognizing that macroeconomic variables can explain time-varying market betas is due to Shanken (1990). To allow time-varying betas, the author imposes a linear relation between betas and pre-determined state variables, which has become the standard procedure when testing conditional models. There are two recent papers that are close in spirit to our paper. Baele and Londono (2013) explain the dynamics of market betas for 30 industry US portfolios. They employ a three-step procedure to estimate the effects of macroeconomic variables on betas. They first estimate industry betas using the DCC-MIDAS model proposed by Colacito, Engle, and Ghysels (2009), which combines the DCC model of Engle (2002) with the GARCH-MIDAS techniques of Engle et al. (2013). This procedure estimates the individual and market variance components of betas using the GARCH-MIDAS approach. Then, in a separate estimation, Baele and Londono use the DCC procedure to estimate conditional correlations imposing the previously estimated standardized residuals for each industry and the market from the GARCH-MIDAS approach. In the final step, the authors linearly regress the estimated betas on lagged macroeconomic variables. Note that the key advantage of the GARCH-MIDAS model of Engle et al. (2013) for volatilities is the simultaneous estimation of the model describing the behavior of market volatility, and the impact of macroeconomic variables on volatility. This advantage is lost when applied to covariances or correlations. The extension of this model to systematic risk is not available. Using their three-step procedure, Baele and Londono (2013) show that industry betas display substantial heterogeneity with respect to their business cycle exposure, which is consistent with the models of Berk et al. (1999), Gomes et al. (2003), and Santos and Veronesi (2004). Moreover, they also show that the cross-sectional dispersion on industry betas is larger during recessions, which supports the theoretical predictions of Gomes et. al (2003), but not the theoretical implications from the model of Santos and Veronesi (2004).

The second paper analyzing the macroeconomic determinants of market betas is Andersen et al. (2005) who suggest a state space representation that allows for the extraction and prediction of latent betas from realized betas, and the joint inclusion of macroeconomic variables to analyze the impact of aggregate variables on the behavior of betas. Unfortunately, their empirical application is very limited. They apply their model to three of the 25 Fama-French portfolios sorted by size and book-to-market. They only employ large portfolios for growth, intermediate, and value characteristics. They conclude that the counter-cyclicality of betas is a value stock phenomenon.

In this paper we further explore the impact of macroeconomic variables on market betas across portfolios sorted by characteristics using a much more complete database. In addition, we propose a new statistical procedure that naturally incorporates macroeconomic effects on the low-frequency component of stock market betas.

3. The Mixed Frequency Conditional Beta Estimation Model

There is a vast literature studying the relation between risk and expected returns. Given that our main concern is related to the dynamics of market beta, in this paper we focus in the simple conditional CAPM asset pricing model given by

$$E_t\left(R_{j,t+1}^e\right)=\beta_{jm,t}E_t\left(\lambda_{m,t+1}\right), \tag{1}$$

where $E_t\left(R_{j,t+1}^e\right)$ is the conditional expected excess return on asset j, $E_t\left(\lambda_{m,t+1}\right)$ is the conditional expected market risk premium over the conditional expected return on the zero-beta portfolio, and $\beta_{jm,t}$ is the conditional beta with respect to the market portfolio return.

Let $\beta_{jm,t}^{MF}$ be the mixed frequency conditional beta (MF hereafter) with respect to the market portfolio return,

$$\beta_{jm,t}^{MF}=\frac{Cov_t\left(R_{j,t+1}^e,\lambda_{m,t+1}\right)}{Var_t\left(\lambda_{m,t+1}\right)} \tag{2}$$

The general idea behind MIDAS is to employ mixed frequency data regressions. Under this framework, the MF conditional beta consists of two additive MIDAS components, one interpreted as a short-run or transitory component estimated with daily return data, and a second one identified as the long-run or trend component of beta obtained from macroeconomic state variables:

$$\beta_{jm,t}^{MF} = \phi_j \beta_{jm,t}^{S} + \left(1-\phi_j\right)\beta_{jm,t}^{L} \ , \ \ 0 \le \phi_j \le 1 \ , \tag{3}$$

where ϕ_j is the short-term weight of each of the two components. The short- and long-run MIDAS betas are given by

$$\beta_{jm,t}^{S} = \frac{\sum_{d=1}^{D} \Psi\left(d,\kappa_{j,1},\kappa_{j,2}\right)\times r_{j,t-d}^{e}\ r_{m,t-d}^{e}}{\sum_{d=1}^{D} \Psi\left(d,\kappa_{j,3},\kappa_{j,4}\right)\times r_{m,t-d}^{e^2}} \tag{4}$$

$$\beta_{jm,t}^{L} = \omega_{j,0} + \omega_{j,k} \sum_{h=1}^{H} \Psi\left(h,\kappa_{j,5},\kappa_{j,6}\right)\times F_{k,t-h} \tag{5}$$

where $r_{j,t-d}^{e}$ is the daily lagged excess return of portfolio *j* using data up to month *t* and associated with the following month, $r_{m,t-d}^{e}$ is the daily lagged excess market return up to month *t*, and $F_{k,t-h}$ denotes each of the lagged macroeconomic variables, *k*, relative to month *t*. The number of lags for both the daily returns and the monthly state variables are optimally estimated within the MIDAS procedure according to the beta function weighting scheme given by

$$\Psi\left(s,\kappa_{j,w},\kappa_{j,w+1}\right) = \frac{\left(\frac{s}{S}\right)^{\kappa_{j,w}-1}\left(1-\frac{s}{S}\right)^{\kappa_{j,w+1}-1}}{\sum_{d=1}^{S}\left(\frac{d}{S}\right)^{\kappa_{j,w}-1}\left(1-\frac{d}{S}\right)^{\kappa_{j,w+1}-1}} \quad , \tag{6}$$

which provides many potential shapes to accommodate various lag structures associated with either (past) daily returns or (past) monthly macroeconomic growth rates. The beta function can represent monotonically increasing or decreasing weighting scheme depending upon the values of the two parameters, $\kappa_{j,w}$ and $\kappa_{j,w+1}$.[7]

In order to estimate the MF conditional betas and their macroeconomic determinants, we assume that the monthly return generating process for each portfolio is assumed to be given by

$$R^{e}_{j,t+1} = \lambda_0 + \beta^{MF}_{jm,t}\lambda_{mt+1} + u_{j,t+1} \;\; ; \;\; j = 1,\ldots,N , \tag{7}$$

where $R^{e}_{j,t+1}$ is the monthly excess return of portfolio j during month $t + 1$, $\lambda_{m,t+1}$ is the monthly excess market portfolio return during month $t + 1$, and λ_0 is a constant that may arise due to trading or funding liquidity frictions. The set of parameters to be estimated for each portfolio and for a given macroeconomic variables is given by

$$\Theta = \left(\lambda_0, \lambda_m, \omega_{j,0}, \omega_{j,k}, \phi_j, \kappa_{j,1}, \kappa_{j,2}, \kappa_{j,3}, \kappa_{j,4}, \kappa_{j,5}, \kappa_{j,6}\right) \tag{8}$$

where these parameters are estimated by minimizing the mean squared error defined according to expression (7) as

$$\min_{\{\Theta\}} MSE \equiv \min_{\{\Theta\}} \left[\frac{1}{T} \sum_{t=1}^{T} \left(R^{e}_{j,t+1} - \hat{R}^{e}_{j,t+1} \right)^2 \right] \tag{9}$$

where $\hat{R}^{e}_{j,t+1}$ is the excess return generated by the estimated MF conditional beta given by equation (3). We estimate the parameters by nonlinear least squares and the corresponding standard errors are obtained as described by Judge, Griffith, Hill, and Lutkepohl (1985). A potential concern with the estimation relies on the sensitivity of the results to the initial conditions. For this reason, the initial parameters are obtained by

[7] See Ghysels, Sinko, and Valkanov (2007) for a discussion and comparison among alternative weighting schemes.

Simulated Annealing, a global optimization method which provides a reasonable approximation to the global optimum of a given function in a large search space. Then, we apply the usual quasi-Newton optimization techniques and, in particular, we employ the BFGS method.[8]

It is important to note that, for each macroeconomic variable, we estimate the dynamics of beta for each individual portfolio separately, rather than estimating the model using all portfolios simultaneously. Depending upon the number of portfolios employed in the empirical application, a full estimation would be infeasible given the large number of parameters. Note that our estimation procedure relies on the objective function given by (9) and, therefore, it depends on the assumed generating process given by expression (7). The estimation is not feasible without this equation. At the same time, our empirical results employ the realized excess market return, which has to be the same for all assets in a given sample. This implies the orthogonality between the right hand side variables and the model forecast error, as would be used in heteroskedasticity-consistent standard errors. A constant market risk premium will not capture the key effects of $Cov\left(\beta_{t+1},\lambda_{mt+1}\right)$, which is the relevant insight of conditional asset pricing models. In any case, to minimize the potential disturbing effects of the market risk premium on the empirical results, we employ two alternative empirical strategies regarding the market risk premium. We first impose the realized monthly market risk premium, and secondly we estimate the market risk premium together with the rest of the parameters. We finally note that this is a flexible estimation procedure for conditional betas, since the weights for covariances, variances and lagged macroeconomic variables in expressions (4) and (5) are allowed to be different.

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[8] From Broyden, Fletcher, Goldfarb, and Shanno. This methodology uses the numerical gradient to choose the direction in which the parameter values change and the numerical Hessian to estimate the size of the change. We finally obtain the standard errors using the information matrix, that is, the variance-covariance matrix of the parameters is estimated as the inverse of the numerical Hessian for the optimal values.

4. Data

We want to explore the impact of macroeconomic variables on market betas and the pro-cyclicality or counter-cyclicality of betas across a comprehensive sample of stocks sorted by well-known characteristics. We employ daily and monthly returns from the ten portfolios sorted by book-to-market, size, momentum and long-term reversals available at Kenneth French's website. Panel A of Table 1 contains the historical statistical moments of the two extreme portfolios of these four sets from January 1960 to December 2011. These descriptive statistics display the well-known value, small, high momentum and low long-term reversal premia. These portfolios have high excess kurtosis and negative skewness with the exception of the low momentum portfolio.[9]

Regarding macroeconomic variables, we employ monthly data of eight state variables which have become popular in the macro-finance literature. We obtain nominal consumption expenditures on nondurable goods and services from Table 2.8.5 of the National Income and Product Accounts (NIPA), available at the Bureau of Economic Analysis. Population data are from NIPA's Table 2.6 and the price deflator is computed using prices from NIPA's Table 2.8.4, with the year 2000 as its basis. All this information is used to construct monthly rates of growth of seasonally adjusted real per capita consumption expenditures on nondurable goods and services from January 1959 to December 2011. The corresponding surplus consumption ratio is estimated from the external habit preference model of Campbell and Cochrane (1999) with stochastic discount factor (SDF) given by

$$M_{t,t+\tau} = \rho\left(\frac{S_{t+\tau}}{S_t}\frac{C_{t+\tau}}{C_t}\right)^{-\gamma} \tag{10}$$

[9] Skewness and excess kurtosis are estimated using daily data rather than monthly data.

where γ is the curvature parameter of the utility function that provides a lower bound on the time-varying coefficient of relative risk aversion, ρ is the impatience parameter, C_t is the consumption expenditures on nondurable goods and services described above, X_t is the level of habit, $S_t = C_t - X_t / C_t$ is the surplus consumption ratio, and the counter-cyclical time-varying risk aversion is given by γ / S_t. The aggregate consumption follows a random walk and the surplus consumption process is

$$s_{t+1} = (1-\varphi)\overline{s} + \varphi s_t + \delta(s_t)(c_{t+1} - c_t - g) \tag{11}$$

where g is the mean rate of consumption growth, ϕ is the persistence of the habit shock,[10] and the response or sensitivity coefficient $\delta(s_t)$ is given by

$$\delta(s_t) = \left(1/\sigma_c \sqrt{\gamma/1-\varphi}\right)\sqrt{1-2(s_t - \overline{s})} - 1 \tag{12}$$

where σ_c is the volatility of the consumption growth rate and lower capital letters denote variables in logarithms. It is important to notice that the empirical implementation of the model described by equations (10) to (12) estimates the surplus consumption process using an alternative set of test assets to avoid potential confounding effects. In particular, the surplus consumption is estimated using an iterative generalized method of moment procedure with 25 portfolios sorted by size and book-to-market, which also available in French's website. Figure 1 displays the yearly changes of the resulting time-varying risk aversion given by $\hat{\gamma} / S_t$, with estimated curvature parameter of 2.46. This figure illustrates how risk aversion (surplus consumption) tends to increase (decrease) during bad economic times and especially during the recent great recession. This figure marks recession bars as long as there is a month during the year classified as an NBER official recession date.

[10] The persistence parameter is estimated employing data from the dividend yield obtained from Robert Shiller's website.

We also use aggregate per capita stockholder consumption growth rates. Exploiting micro-level household consumption data, Malloy, Moskowitz, and Vissing-Jorgensen (2011) show that long-run stockholder consumption risk explains the cross-sectional variation in average stock returns better than the aggregate consumption risk obtained from nondurable goods and services. In addition, they report plausible risk aversion estimates. They employ data from the Consumer Expenditure Survey (CEX) for the period March 1982 to November 2004 to extract consumption growth rates for stockholders, the wealthiest third of stockholders, and non-stockholders. To extend their available time period for these series, the authors construct factor-mimicking portfolios by projecting the stockholder consumption growth rate series from March 1982 to November 2004 onto a set of instruments and use the estimated coefficients to obtain a longer time series of instrumented stockholder consumption growth. In this paper, we employ the reported estimated coefficients of Malloy et al. (2011) to obtain a factor-mimicking portfolio with the same set of instruments for stockholder consumption from January 1960 to December 2011.

Additionally, yields-to-maturity for the 3-month Treasury bill, the 10-year government bond and Moody's Baa corporate bond series are obtained from the Federal Reserve Statistical Releases. We then compute two state variables based on these interest rates: a term structure slope, computed as the difference between the 10-year government bond and the Treasury bill rate, and the default premium calculated as the difference between Moody´s yield on Baa corporate bonds and the 10-year government bond yield. Monthly data for the industrial production index are downloaded from the Federal Reserve, with series identifier G17/IP Major Industry Groups. The last macroeconomic indicator is the non-farm employment growth rate, which comes from the Bureau of Labor Statistics, "B" tables of the seasonal adjusted employment situation release. Panel B of Table 1 contains the correlation coefficients among these state variables. A highly positive correlation is reported between surplus consumption growth and consumption growth on nondurable goods and services, while correlations between surplus consumption growth and stockholder consumption growth, industrial production growth and employment growth are also positive but lower in magnitude. A negative correlation is estimated between surplus consumption growth and the default premium, and the expected positive correlations are also obtained between industrial production, consumption and employment growth. Finally, the default premium is particularly negatively correlated with industrial production and employment growth.

5. Empirical Results

5.1 The Effects of Macroeconomic Variables on Mixed Frequency Conditional Betas

As pointed out above, we estimate the MF model separately for each portfolio and macroeconomic variable. We are particularly interested in understanding the reaction of each portfolio's beta to alternative macroeconomic variables. This allows us to discuss the counter- or pro-cyclicality of beta risk for the different portfolios employed in the paper. Hence, the key parameter in this paper is the slope parameter, ω_k, of the low-frequency component of the MF conditional beta given by expression (5):

$$\beta_{jm,t}^{L} = \omega_{j,0} + \omega_{j,k} \sum_{h=1}^{H} \Psi\left(h, \kappa_{j,5}, \kappa_{j,6}\right) \times F_{k,t-h}$$

Table 2 reports the slope parameter for each macroeconomic variable and each portfolio. The first row employs the monthly realized market risk premium, but we also report the results obtained from the simultaneous estimation of the market risk premium with the rest of parameters in the set given by (8). The surplus consumption ratio seems to be the key macroeconomic determinant of portfolio betas. Independently of the market risk premium employed, seven out of the eight portfolios have a statistically significant slope. The only exception is the portfolio composed of largest companies for which betas are explained with consumption growth rather than with consumption relative to habit. Interestingly, aggregate consumption is only statistically significant for big companies. The impact of surplus consumption on the alternative portfolios is different. This is especially relevant because it makes clear the pro- or counter-cyclicality of our sample portfolios. Value, small, low momentum, and low long reversals have strongly counter-cyclical betas with respect to surplus consumption. In other words, the betas of these companies tend to move positively with time-varying risk aversion. On the contrary, growth, high momentum, and high long reversals have pro-cyclical betas. They tend to decrease when surplus consumption decreases. This suggests a hedging behavior, which may explain the low average returns of growth companies relative to value, and the low average return of high long reversal with respect to low long reversal firms. As an example, Figure 2 displays the total MF conditional betas for value and growth portfolios throughout the business cycle measured by surplus consumption. The MF beta of the value portfolio presents a much more volatile behavior than the MF beta of growth companies showing high peaks during financial/industrial economic crisis. It is interesting to note that growth MF betas are higher than value betas at the end of the nineties, that is, during the dot.com crisis.

We must also point out the different behavior of MF betas for the high and low momentum portfolios. We may have expected counter-cyclical betas for the high momentum companies, and pro-cyclical betas for low momentum firms. The results show precisely the opposite behavior, which makes momentum a complex phenomenon. The potential hedging behavior shown by growth and high long reversal stocks does not seem to characterize the low momentum portfolio. It is well-known that it is difficult to rationally explain the pervasive behavior of momentum.[11] Both, Daniel and Moskowitz (2012) and Barroso and Santa-Clara (2015) argue that the impressive performance displayed by momentum is accompanied by occasional but very large crashes. Even more importantly, it seems to take decades for an average risk-averse individual to recuperate the losses associated with the crashes despite the large average momentum premium shown by data. However, Barroso and Santa-Clara (2015) show that momentum risk is time-varying and predictable and explain how to manage this risk. By doing so, the authors find that momentum performance becomes even better than the traditionally recognized risk-adjusted average return. Risk-managed momentum is even harder to explain than in the traditional view because the strategy virtually eliminates the effects of large crashes.

A second relevant macroeconomic variable is the default premium. Six out of our eight portfolios have significant slope coefficients independently of the treatment regarding the market risk premium. Once again, value and low momentum companies show a strong counter-cyclical behavior with higher MF betas during times of increasing the default premium. On the other hand, growth, big, high momentum, and high long reversal firms present a pro-cyclical behavior of their MF conditional betas. Their betas tend to go down with the default premium. It may be surprising the lack of significance of the slope coefficient for small companies. Financial credit constraints should be especially relevant for small companies. However, it is also true that small companies tend to be much more bank-financing dependent than big companies, and

[11] We perform the same analysis using the University of Michigan Consumer Sentiment Index from January 1978 to December 2011. We take the first difference of the Sentiment Index as the macroeconomic indicator. The idea is to check whether there is a different time-varying behavior of the high and low momentum portfolio betas relative to the typical macroeconomic state variable. The results are identical to those reported in Table 2. The high momentum betas tend to increase when the Sentiment Index rises and vice-versa. This implies that, as before, the high momentum betas are pro-cyclical. Similarly, the low momentum betas are counter-cyclical with respect to the Sentiment Index. The analysis using value and growth portfolios also display the same counter-cyclical behavior of value betas and the pro-cyclical behavior of growth systematic risk. The use of the Sentiment Index does not help understanding the time-varying behavior of short-term winners and losers during the business cycle.

our measure of credit restrictions is based on corporate bond financing since it employs yields of low grade-rating corporate bonds relative to riskless government yields.

The term premium tends to present a very similar impact on MF conditional betas across portfolios that the default premium. The results may indicate an impact through long-term financing effects on industrial companies. A higher term premium affects positively the conditional risk of value and low long reversal firms as the default premium does, and negatively to growth and high long reversal stocks as occurs with the default premium.

Stockholder consumption has an overall significant impact on MF conditional betas. Small firms present counter-cyclical betas, but value and low long reversal companies lost significant effects relative to surplus consumption. However, as with surplus consumption, growth, high momentum and high long reversal firms have pro-cyclical MF betas.

Industrial production growth and employment growth are typical business cycle variables with a similar impact on MF betas that surplus consumption. However, the number of portfolios with statistically significant slope coefficients is lower than in those cases. Value companies for industrial growth and small and low long reversal firms for employment growth have counter-cyclical MF betas. Growth and high long reversal stocks have pro-cyclical MF betas with respect to both industrial production and employment growth. Finally, high momentum companies present a weak pro-cyclical behavior with regard to employment growth.

Note that from the results regarding the counter- or pro-cyclicality of betas, we may infer the time-varying behavior of expected returns for our set of portfolios. The main implicit hypothesis that our framework has is that economic activity helps explain the time-varying behavior of expected returns. It turns out that this is closely related to the key idea that motivates the paper by Rossi and Timmermann (2015). Their paper deals with Merton's ICAPM in a time-series framework but they do not discuss the cross-sectional setting. They first develop a daily economic activity index from mixed-frequency data. Then, they construct realized covariances between the market portfolio return and changes in the activity index. From these covariances, and using a nonparametric approach, they estimate a conditional covariance to find a significant and positive relation between this covariance and expected returns. This results suggests that aggregate economic activity explains the market expected returns. Our approach deals with stock market betas and, therefore, it relies on the CAPM rather than in the ICAPM. Moreover, we discuss alternative portfolios with different risk and dynamic characteristics instead of discussing the effects of economic activity on the market portfolio. But, as in Rossi and Timmermann (2015), we argue that a better understanding of the effects of economic activity on time-varying risk and expected returns represents a fundamental step to fully describe the relation between risk and return.

Panels A and B of Figure 3 displays the temporal behavior of MF conditional betas for value and growth portfolios, respectively, and for three alternative macroeconomic variables: surplus consumption, industrial production growth and the default premium. This figure shows the overall consistent impact on macroeconomic variables on the behavior of betas. The MF betas of both value and growth portfolios follow similar patterns over time independently of the state variable employed. As already shown by Figure 2, MF betas of growth companies are much less volatile than value betas. This figure seems to suggest that the mixed frequency beta procedure captures reasonably well the effects of macroeconomic variables on conditional risk through the low-frequency component of betas as long as we employ well-chosen state variable indicators.

Consumption growth, inflation and dividend yield are the state variables with less significant impact on MF conditional betas. The MF betas of big companies tend to increase with consumption growth which suggests a pro-cyclical beta, and low long reversal betas seem to decrease with inflation implying a possible counter-cyclical behavior. These results are consistent with previous results under alternative state variables. Dividend yield has shown to be a key predictor of future returns. A higher dividend yield forecasts higher future market return. This may explain the contemporaneous positive impact on the MF betas of growth stocks, and the negative effect on the MF betas of big companies.

Our results so far seem to favor the effects of time-varying risk aversion with habit preferences. However, a fundamental alternative line of research on the time-varying behavior or expected returns and risk relies on the long-run risk models of Bansal and Yaron (2004), and Hansen, Heaton, and Li (2008). When relative risk aversion is greater than the inverse of the elasticity of intertemporal substitution in the recursive utility framework of Epstein and Zin (1989), a predictable consumption growth component can rationalize the time-series behavior of the aggregate market equity premium without imposing an extraordinarily large risk aversion. This popular approach combines the recursive preferences with an elasticity of intertemporal substitution greater than one, and a specific model of dividend and consumption growth dynamics characterized by long-run risk. Therefore, we should not only recognize the time-varying risk aversion channel but also the uncertainty channel throughout long-run risk. We complete our previous evidence reported in Table 2 with the squared aggregate consumption growth as a way of dealing with time-varying uncertainty. To illustrate the long-run risks related effects, we estimate the model for all eight portfolios using the squared of aggregate consumption growth as the macroeconomic indicator. The impact of time-varying uncertainty in all portfolio betas is positive but estimated with a lot of noise. The *t*-statistics go from 0.08 for big companies to 0.66 for small firms. The only exception is the value stocks with a positive impact on betas of 0.25, and a *t*-statistic of 1.66 when using the realized equity risk premium. Although the statistical relation is quite weak, and we cannot infer any positive and trustable significant effect of the volatility of consumption growth on the betas of value companies, it is at least somehow consistent with the finding of Bansal, Dittmar, and Lundblad (2005) who suggest that value portfolios are more exposed to long-run economic shocks than are growth portfolios. Given this evidence, we conclude that time-varying risk aversion seems to be more relevant than time-varying uncertainty when explaining the time-changing behavior of stock market betas.

Table 3 contains the root mean squared errors (RMSE) in percentage terms for each estimation procedure across portfolios, macroeconomic variables and the two alternative market risk premium assumptions. The lower RMSE across all cases is obtained when we use the realized monthly market risk premium. For a given portfolio and a market risk premium, the RMSE tends to be similar across the macroeconomic variables. However, the RMSE of the estimation for big and growth companies are lower than the RMSE of other portfolios. On the other hand, the RMSE of small and low momentum portfolios seems to be particularly high with respect to the rest of portfolios.

5.2 Short- and Long-Term Weights of Mixed Frequency Conditional Betas

Expression (3) shows that the MF conditional beta is defined as the weighted average of short- and long-term components which reflect the high- and low-frequency aspects of stock market betas. We have no previous evidence about the relative importance of both components and on the potential effects on average returns that these components have. Our estimation framework allows for the estimation of both types of betas and the corresponding weights. On the one hand, these weights are informative about how sensitive market betas are relative to the short-term component of systematic shocks. On the other, the low-frequency weights inform about the smoother business cycle component of beta and, therefore, they reflect how important the returns' responds are to long-term effects of macroeconomic events. These short- and long-term weights may contribute differently to the cross-sectional differences of average returns across and within portfolio sorts.

Table 4 contains the short-term weights across portfolios, macroeconomic variables and the market risk premia.[12] The last row of the table reports the average short-term weights for the eight alternative portfolios across state variables and risk premium estimates. In most cases, the short-term weights are higher when using the realized market risk premium in the estimation. This makes sense, since we measure the return sensitivities with respect to a relatively more volatile market risk premium. At the same time, and for most cases, the weights for a given market risk premium estimation strategy and for a given portfolio, are similar for alternative macroeconomic variables. For example, small and high momentum stocks tend to have large short-term weights for all state variables employed in the estimation. In other words, on average, the long-term component of systematic shocks affects less to small and high momentum stocks

[12] The long-term weight is simple one minus the short-term weight as depicted by expression (3).

than to the rest of the portfolios. Value stocks seem to have a relatively large short-term weight as long as the macroeconomic variable has a significant impact on the portfolio beta. For example, the short-term weight for the value portfolio is large and significant for surplus consumption, industrial production growth, and the default premium, but it is not statistically different from zero for consumption growth, employment, inflation and dividend yield. On the other hand, big and high long reversal portfolios have small short-term weights. Hence, market betas of these portfolios are more affected by the long-term component of systematic macroeconomic dynamics.[13]

Another clarifying analysis consists of estimating the short-term (long-term) weights during recessions relative to the weights in normal economic times. We use the NBER indicators to classify a month as either a recession or a normal month. For this analysis we define the conditional MM beta as

$$\beta_{jm,t}^{MF} = \left[\left(1 - D_t\right) \varphi_{1,j} + D_t \, \varphi_{2,j} \right] \beta_{jm,t}^{S} + \left\{ 1 - \left[\left(1 - D_t\right) \varphi_{1,j} + D_t \, \varphi_{2,j} \right] \right\} \beta_{jm,t}^{L}, \;\; 0 \le \phi_j \le 1$$

$$D_t = \begin{cases} 1 \, if \;\; t \; is \; a \; recession \; NBER \; month \\ 0 \; otherwise \end{cases} \tag{13}$$

The optimization problem is exactly the same as before except that now equation (13) is used instead of expression (3). Table 5 contains the short-term weights for both recession and normal times using the surplus consumption as the macroeconomic variable and the realized market risk premium specification. For an easier comparison, the first row of Table 5 also displays the short-term weights across all portfolios for the full sample period. Among the counter-cyclical beta portfolios, value and low long

[13] Gilbert, Hrdlicka, Kalodimos, and Siegel (2014) show that a stock's market exposure is not the same when measured with different return frequencies. Interestingly, they argue that these effects are relevant over and above the traditional thin trading effects on beta estimation. The additional effects are associated with the uncertainty about the impact of systematic news on firm value, which is different depending upon the degree of transparency that firms have. Their distinction between opaque and transparent firms may be related to the importance that either the short- or long-term beta weights have on a particular portfolio sort.

reversal assets show a higher weight in recessions than in normal times. This suggests that both value and low long reversal portfolios become more sensitive to short-term shocks of systematic risk during bad times. However, not all counter-cyclical beta stocks have a higher short-term weight during recessions. In fact, small and low momentum portfolios have lower short-term weights in bad economic times. The same behavior is reported for high momentum and high long reversal portfolios. Growth and big assets show very stable short-term weighs over the business cycle.[14]

5.3 The Variance Decomposition of the Mixed Frequency Conditional Beta

We argue that using both daily return data and monthly state variable data to estimate a monthly conditional beta may contain more information than classic conditional betas typically estimated using exclusively monthly data such as in Jagannathan and Wang (1996), Ferson and Harvey (1999), and Lettau and Ludvigson (2001), among many others. Indeed, some papers combine both daily and monthly return data when estimating betas. For example, Lewellen and Nagel (2006) estimate a monthly conditional beta by simply regressing daily test asset returns on the market portfolio within each month. In a more involved framework, González, Nave, and Rubio (2012) show that monthly market betas estimated using daily returns in the MIDAS framework produce a positive and significant market risk premium. The implicit assumption in these two papers is that the monthly conditional betas capture all the information in state variables. This implies that conditioning on the state variables is not required. On the contrary, our paper suggests that the short-term betas may not be capturing at least some of the relevant information in the state variable. Therefore, the key difference between this research and previous papers is that we now add long-term betas that are

[14] The results should be interpreted with caution. The NBER business cycle dummies are not measurable at time t when the conditional beta is supposed to be measurable.

estimated using alternative macroeconomic variables, and we investigate the drivers and importance of long-term betas.[15] To conclude, we argue that the combination of the short- and long-run frequency components is the key distinct feature from previous time-varying beta estimation procedures.

We next discuss the relative importance of the two beta components. Our previous discussion on the short- versus long-term weights is a first step to clarify what components of $\beta_{jm,t}^{MF}$ is relevant. A different approach is to examine a variance decomposition of $\beta_{jm,t}^{MF}$ to understand what is driving the underlying movements in $\beta_{jm,t}^{MF}$. We now pay attention to the variation of short- and long-term betas, and not to the relative weights. The percentage breakdown can be estimated using the following expression:

$$1 = \frac{Var\left(\beta_{jm,t}^{S}\right) + Var\left(\beta_{jm,t}^{L}\right) + 2\,Cov\left(\beta_{jm,t}^{S}, \beta_{jm,t}^{L}\right)}{Var\left(\beta_{jm,t}^{MF}\right)} \tag{14}$$

Table 6 shows the results using the surplus consumption and default as the conditioning beta variables. We report the variance decomposition for the extreme portfolios on each set, and also for the average result across the 10 portfolios within a given set. The last row shows the overall average results across all 40 portfolios.[16] The results are very conclusive. Most of the percentage variation of $\beta_{jm,t}^{MF}$ is due to the short-term beta. On average 97.3% and 96.6% is explained by the variation of the short-term beta for surplus consumption and default, respectively. Similarly, most of the variation of $\beta_{jm,t}^{MF}$ for the extreme portfolios is explained by the short-term beta. The

[15] As pointed out before, Rossi and Timmermann (2015) argue that economic activity significantly affects the conditional covariance term in the ICAPM and, therefore, they conclude that economic activity helps explain time variation in the market expected return.

[16] Note that given the estimation procedure of the mixed frequency betas, the first monthly available beta for each portfolio is in February 1961.

only relevant exception is the value portfolio. For these assets, only 61.0% and 77.6% of the variation of $\beta_{jm,t}^{MF}$ is explained by the short-term beta for surplus consumption and default, respectively. On relative terms, the $\beta_{jm,t}^{MF}$ of value firms is strongly influenced by the macroeconomic cycle, especially when we employ surplus consumption (time-varying risk aversion) to describe the business cycle. Figure 4 displays the average short- and long-term betas across all 40 portfolios for both surplus consumption and default. Consistent with the results of Table 6, the variation of the short-term beta component is much stronger than the variation of the long-term component. Note that this is so despite the fact that the long-term beta is on average higher than the short-term beta, which is consistent with the weights reported in Table 4. Moreover, the overall pattern shows an increasing importance of the long-term beta relative to the short-term counterpart especially when we employ default as the state variable. This increasing pattern coincides with the beginning of the great moderation period.

6. Implications of Mixed Frequency Conditional Betas for Expected Returns

In this section, we discuss some relevant implications of our macroeconomic-based conditional betas for the expected returns of our sample portfolios. We first discuss the time-varying behavior of the risk-return relation across the different portfolios. We next analyze the term structure of holding period expected excess returns implied by our mixed frequency betas. Finally, we present the results of simple investment strategies that depend on the expected excess returns estimated with our MIDAS procedure.

6.1 The Risk-Return Relation for Alternative Portfolios

In the previous section, we show that betas of some portfolios are counter-cyclical, whereas others are pro-cyclical. It is also the case that the market expected excess return is counter-cyclical. This simultaneous evidence implies that the expected excess returns for some portfolios are counter-cyclical and pro-cyclical for others. We next analyze whether the same evidence holds for the volatility of these portfolios. Indeed, if (as expected) the conditional volatility of all portfolios is counter-cyclical, then the risk-return relation should be positive form some portfolios and negative for others.

We estimate a simple GARCH (1,1) model to obtain the time-varying monthly conditional volatility of our portfolios using the residuals of expression (7). Then, we run OLS regressions of the conditional volatilities of each portfolio on three macroeconomic variables. We employ the growth rate of industrial production, surplus consumption, and the default premium. We report the results in Table 7. Panel A shows the results when we estimate the mixed frequency betas in equation (7) using surplus consumption. Panel B present the results for conditional betas estimated with default.

In both panels, and for the industrial production index, conditional volatilities are counter-cyclical. The slope coefficients are negative and statistically different from zero except for small stocks. When we employ surplus consumption, the conditional volatilities tend to be significantly counter-cyclical except for growth, big and long low reversal portfolios. In all these three cases, the slope coefficients are not statistically different from zero. Finally, when we employ default to characterize the aggregate economic conditions, and in both panels, the counter-cyclical evidence is robust to all portfolios. The slope coefficients are always positive and statistically different from zero. Overall, it is safe to conclude that conditional volatilities present a counter-cyclical behavior over the business cycle.

We next investigate the risk-return relation across our eight portfolios. Given the previous results, we expect that these portfolios may have a different risk-return relation depending upon the behavior of their expected excess returns over time. We estimate a GARCH (1,1)-in-mean model to estimate the risk-return relation of each portfolio. We report the results in Table 8. Again, we distinguish between the mixed frequency betas estimated with either surplus consumption (Panel A) or default (Panel B). It turns out that the risk-return relation has a different sign depending on the counter- or pro-cyclicality of conditional betas, and expected returns. For those portfolios characterized by a counter-cyclical betas (value, small, low momentum, and low long reversal), the risk-return relation is positive and, in most cases, statistically significant. On the contrary, for portfolios with a pro-cyclical conditional beta (growth, big, high momentum, and long high reversal), the risk-return relation is negative although the statistically significance is slightly weaker especially for big stocks.

6.2 The Term Structure of Holding Period Expected Excess Returns Implied by the Mixed Frequency Conditional Betas

In recent years, there is an increasing literature on the term structure of equity yields that are direct claims to future market-wide dividends. Binsbergen, Brandt, and Koijen (2012) show that, on average, the premium on the short-term dividend claims is higher than the risk premium on the long-term dividend claims. This suggests that the slope of the dividend risk premium is downward sloping. Indeed, this is consistent with the results shown by Lettau and Wachter (2010), and Croce, Lettau, and Ludvigson (2014). Binsbergen, Hueskes, Koijen, and Vrught (2014) extend this initial work by showing that the slope of the term structure of equity yields is pro-cyclical. In other words, long-maturity dividend risk premium is higher than short-term premium during expansions and lower during recessions. More recently, Binsbergen and Koijen (2016) extend this result to several international indices. These authors also show that the volatility of equity yields is downward sloping with maturity.

We next analyze the term structure of holding period expected excess returns implied by our mixed frequency betas model. We realize that the term structure of equity yields discussed in previous literature is not equal to the term structure discussed in this section. However, we argue that both are closely related. The advantage of Binsbergen et al. (2014) is that they do not rely on a cross-section of portfolio returns and additional assumptions about the time-varying behavior of beta risk. They provide a direct evidence on the term structure of dividend strips using dividend futures and, therefore, they are able to measure directly the dividend strip prices at different maturities.

Given our estimated mixed frequency conditional betas, we calculate the annualized expected excess returns of the eight portfolios when those are held during 1, 3, and 6 months, and also during one and two years. Panel A of Table 9 contains the results of different holding period expected excess returns for each portfolio. It turns out that the term structure of expected excess returns is in all cases downward sloping. Moreover, value, small, and big portfolios show a stronger initial decline from one to three months than other portfolios. In Panel B of Table 9, we show that the volatilities of expected excess returns are also declining with maturity for all portfolios. This is consistent with the findings of Campbell and Viceira (2005), who also show that volatilities of expected returns are decreasing with the horizon. As they point out, this behavior is the result of mean-reverting in stock returns induced by the predictability of returns under time-varying expected returns. As a consequence of these two findings, we report in Panel C of Table 9 that, for most cases, Sharpe ratios are increasing with the horizon.

Note that these empirical results are a direct implication of the behavior of our estimated mixed frequency conditional betas. Our main argument in this paper is that these betas can be decomposed into short- and long-term components. We can therefore analyze whether the declining term structure of expected excess returns reported in Table 9 are due to the short- or long-term component of the conditional betas. In Panel A of Table 10, we display the term structure of expected excess returns implied by the long-term beta component. Panel B contains the results for the short-term beta component. The results make clear that the declining behavior of expected excess returns with maturity is entirely due to the long-term beta component, which depends mostly on the macroeconomic conditions of the economic cycle. The short-term beta component does not have significant effects on the term structure despite the fact that most of the variation of the mixed frequency beta depends on the short-term component. Note that the results in Panel A (Panel B) are obtained by shutting down the short-term (long-term) component by making the weight of the high-frequency (low-frequency) beta equals to zero.[17]

6.3 Investment Strategies Conditional on the Expected Excess Returns Estimated by the Mixed Frequency Conditional Betas

As the last implication of our mixed-frequency beta model, we study the performance of alternative out-of-sample investment strategies based on the expected excess returns generated by our model.

[17] The results reported in this section employ mixed frequency betas estimated with surplus consumption. The results using default are practically the same.

For each month of our sample period, we form an overall portfolio composed of the eight portfolios. We weight each portfolio by the ranking this portfolio has according to its expected excess return for a given horizon. The weight of each portfolio in each month for a holding period between *t* and *t* + *τ* is given by

$$\omega_{pt} = \frac{rank\left[E_t\left(R^e_{pt+\tau}\right)\right]^{\theta}}{\sum_{p=1}^{8} rank\left[E_t\left(R^e_{pt+\tau}\right)\right]^{\theta}}; \tau = 1,3,6,12 \tag{15}$$

Expression (15) is proposed by Asness, Moskowitz, and Pedersen (2013). The parameter $\theta \geq 0$ controls for the aggressiveness of the portfolio. When θ is high, we overweight the portfolios with higher expected return. If $\theta = 0$, we have an equally-weighted portfolio. If we impose values for θ of 1 or 2, we have a portfolio, which is different from the equally-weighted portfolios but it also avoids extremes weighting schemes. This is a useful procedures because explicitly avoids short-selling strategies.

Given that we rank expected returns every month during the sample period, we end up with a time series of an optimal portfolio return for a particular investment horizon. We can therefore calculate the overall performance of this optimal portfolio generated by our mixed-frequency beta model. We estimate alphas with respect to the Fama and French (1993) three-factor model augmented with the momentum factor of Carhart (1997). Specifically, these alphas are the intercept from the following OLS regressions for alternative horizons $\tau = 1,3,6,12$:

$$\begin{aligned} R^e_{p,t+\tau} &= \alpha_p + \beta_{pm} R^e_{mt+\tau} + \beta_{psmb} SMB_{t+\tau} + \beta_{phml} HML_{t+\tau} \\ &\quad + \beta_{pmom} MOM_{t+\tau} + \varepsilon_{p,t+\tau} \end{aligned} \tag{16}$$

In addition, we compare the performance of our optimal portfolio with an alternative investment strategy that assumes constant expected returns. For a sample period between January 1948 and January 1961, we estimate the average returns of the eight portfolios. We employ expression (15) to obtain a constant ranking based on this average return during the previous sample period. As before, we also estimate the alphas of this competing portfolio. Note that this is also an out-of-sample analysis because we employ past average returns relative to the sample period used in this part of the analysis.

Panel A of Table 11 contains the results for $\theta = 2$, and Panel B imposes $\theta = 1$, which is a relatively less aggressive strategy. The first column in both panels employs expected excess returns from conditional betas estimated with surplus consumption, and the second column from betas estimated with default. The results of the third column correspond to constant expected excess returns based on past average information. The performance of the time-varying weighting scheme based on monthly rankings has positive and significant alphas for long-enough horizons. For the shortest horizon, alphas are negative, and even statistically different from zero with respect to the less aggressive strategy. On the other hand, we can never reject that alphas based on constant expected returns are equal to zero. We conclude that our mixed frequency conditional betas contain useful information regarding the future behavior of returns. The richness of short- and long-term information in our measure of beta risk seems to be useful for an investment strategy that explicitly incorporates time-varying expected returns.

7. Conclusions

Despite the fact that market beta is the key risk indicator for both portfolio management and asset pricing, we know relatively little about its temporal behavior when compared to volatility. Indeed, we understand the factors driven the high- and low-frequency components of volatility and its macroeconomic determinants. However, similar evidence about stock market betas is scarce. This paper proposes a novel methodology based on MIDAS regression to separate the short- and long-term components of beta. Surplus consumption with time-varying risk aversion and the default premium are key macroeconomic variables driving the time-series behavior of stock market betas across eight well-known characteristic-sorted portfolios. We report intriguing differences over time and across portfolios of the relative weights of the total MF conditional betas. Moreover, we conclude that value, small, low momentum, and low long reversal stocks have counter-cyclical betas, while growth, big, high momentum, and high long reversals have pro-cyclical betas. In addition, value and low long reversal portfolios present higher short-term weights in recessions than in normal times suggesting that they are very sensitive to short-term shocks of systematic risk. Although, these results may help explain well-known asset pricing anomalies under a perspective not fully investigated up to now, it is also true that the results do not seem to facilitate the understanding of the large (small) average return of the high (low) momentum portfolios. We also show that, across all portfolios and on average, most of the variation of the $\beta_{jm,t}^{MF}$ is explained by the variation of the short-term beta rather than from the variation of the long-term beta.

We also study some relevant implications of our mixed frequency beta model. We first show that the risk-return relation of the eight portfolios depends on the counter- or pro-cyclicality of conditional betas. Secondly, we argue that the term structure of holding period expected excess returns implied by our mixed frequency model is declining with maturity. Finally, the investment performance of a portfolio formed according to the time-varying rankings based on the generated expected excess returns from our model, presents positive and significant four-factor alphas for horizons of 3, 6, and 12 months.

To conclude, we think that the distinction between the two beta effects may have relevant implications for factor pricing. Indeed, Gilbert, Hrdlicka, Kalodimos, and Siegel (2014) show that opaque firms have betas estimated with high frequency data that are smaller than their betas estimated with low frequency returns, while the opposite occurs to transparent firms. They argue that factor asset pricing models that might be appropriate at low frequencies will not necessarily explain expected returns correctly when beta risk is estimated at high frequencies. Future research, under our two-beta model, may clarify the importance of the relative exposure of market wealth to short- and long-term risks.

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Table 1
Descriptive Portfolio Statistics and Correlation Coefficients for State Variables:
January 1960-December 2011

Panel A	Historical Moment Returns by Portfolios			
Portfolios	Annualized Monthly Mean %	Annualized Monthly Standard Deviation %	Daily Skewness	Daily Excess Kurtosis
Growth	9.057	17.963	-0.174	10.476
Value	14.873	20.363	-0.470	13.341
Small	13.491	22.147	-0.929	12.285
Big	9.571	14.866	-0.496	18.635
LMom	1.540	27.661	0.419	23.019
HMom	17.850	21.610	-0.505	9.840
LLrev	14.321	22.764	-0.394	12.175
HLrev	9.848	20.841	-0.162	11.866

Panel B	Correlation Coefficients by State Variables							
State Variables	Cons Growth	Stockholder Cons Growth	Industrial Production	Employ Growth	Inflation	Term	Default	Dividend Yield
Surplus Cons	0.930	0.154	0.224	0.268	-0.067	-0.007	-0.213	0.042
Cons Growth	1	0.166	0.205	0.223	-0.140	0.051	-0.118	0.026
Stockholder Cons Growth		1	0.008	0.019	-0.025	0.074	0.028	0.041
Industrial Production			1	0.606	-0.046	0.040	-0.303	-0.110
Employ Growth				1	0.115	-0.130	-0.520	0.008
Inflation					1	-0.288	-0.135	0.421
Term						1	0.462	-0.034
Default							1	-0.038

The numbers reported in Panel A are average sample moments for the full period, and for the 8 extreme portfolios from 4 deciles sorted by value-growth, size, momentum, and long reversals obtained from the web of Kenneth French, where Lmom is low momentum, Hmom is high momentum, LLrev is low long reversals, and HLrev is high long reversals. Sample mean and standard deviations are annualized values from monthly data, while skewness and excess kurtosis are from daily data. Panel B reports the correlation coefficients estimated for the overall sample period using monthly data. Surplus Cons is the surplus consumption ratio with habit persistence and time-varying risk aversion from the Campbell and Cochrane (1999) model, Cons Growth is the monthly growth rate of seasonally adjusted real per capita consumption expenditures on non-durables goods and services; Stockholder Cons Growth is the Malloy, Moskowitz, and Vissing-Jorgensen (2011) measure of consumption growth from stockholders; Industrial Production is downloaded from the Federal Reserve with series identifier G17/IP Major Industry Groups, Employ growth is the non-farm employment growth rate from the Bureau of Labor Statistics, B tables of seasonal adjusted employment situation release, Inflation is the GDP deflator rate, Term is the difference between the 10-year government bond yield, and the 3-month T. bill rate, and Default is the default premium calculated as the difference between Moody´s yield on Baa Corporate Bonds and the 10-year Government Bond Yield.

Table 2
Macroeconomic Determinants of Stock Market Betas: January 1960-December 2011

State Variable	Equity Premium	Growth	Value	Small	Big	LMom	HMom	LLrev	HLrev
Surplus Consumption	Realized	4.976	-17.86	-1.161	-0.009	-5.566	0.960	-2.253	3.498
	ERP	(5.14)	(-4.30)	(-4.38)	(-0.68)	(-4.90)	(2.01)	(-2.53)	(11.59)
	Estimated	3.106	-17.86	-0.705	-0.005	-1.137	0.582	-0.671	2.127
	ERP	(3.34)	(-5.75)	(-2.83)	(-0.78)	(-4.02)	(2.41)	(-2.15)	(5.04)
Consumption Growth	Realized	0.296	-0.102	0.060	3.622	-0.552	0.130	0.000	0.001
	ERP	(0.73)	(-0.23)	(0.10)	(3.74)	(-0.15)	(0.03)	(0.00)	(0.01)
	Estimated	0.111	-0.102	0.022	1.357	-0.176	0.049	0.001	0.000
	ERP	(0.16)	(-0.22)	(0.05)	(4.36)	(-0.22)	(0.16)	(0.03)	(0.00)
Stockholder Consumption Growth	Realized	0.207	-0.560	-0.201	0.006	-4.330	0.832	-0.602	3.853
	ERP	(5.57)	(-1.28)	(-0.57)	(0.95)	(-0.69)	(1.99)	(-0.05)	(15.12)
	Estimated	0.062	-0.156	-0.060	0.002	-1.251	0.250	-0.020	1.155
	ERP	(2.88)	(-0.40)	(-2.33)	(0.24)	(-0.70)	(3.81)	(-0.21)	(2.10)
Industrial Production Growth	Realized	0.214	-38.41	-0.087	-0.003	-0.952	0.083	-0.633	9.407
	ERP	(3.73)	(-2.84)	(-0.52)	(-0.13)	(-0.32)	(0.07)	(-0.10)	(12.76)
	Estimated	0.094	-18.41	-0.038	-0.001	-0.419	0.036	-0.280	4.147
	ERP	(2.22)	(-2.84)	(-0.10)	(-0.01)	(-0.71)	(0.92)	(-0.42)	(5.15)
Employment Growth	Realized	2.032	-0.145	-0.030	-0.004	-0.547	0.073	-4.391	40.350
	ERP	(2.14)	(-0.39)	(-0.20)	(-0.10)	(-0.09)	(0.08)	(-2.04)	(9.15)
	Estimated	1.607	-0.145	-0.023	-0.003	-0.433	0.058	-3.095	31.927
	ERP	(2.18)	(-0.51)	(-2.20)	(-0.00)	(-1.13)	(2.04)	(-5.00)	(3.94)
Inflation	Realized	0.001	0.002	0.027	-0.003	-0.509	0.038	-4.207	0.120
	ERP	(0.00)	(0.19)	(0.06)	(-0.01)	(-0.85)	(0.02)	(-2.06)	(0.25)
	Estimated	0.081	0.002	0.019	-0.002	-0.362	0.027	-3.003	0.086
	ERP	(0.13)	(0.06)	(0.15)	(-0.01)	(-1.56)	(1.25)	(-2.32)	(0.13)
Term	Realized	-5.281	8.916	0.066	0.007	2.505	-0.119	4.344	-4.763
	ERP	(-9.37)	(2.38)	(0.02)	(0.44)	(0.94)	(-0.05)	(13.11)	(-4.00)
	Estimated	-4.065	8.916	0.051	0.051	1.928	-0.092	3.345	-3.667
	ERP	(-3.55)	(4.35)	(0.26)	(0.27)	(0.66)	(-2.24)	(4.56)	(-8-80)
Default	Realized	-5.279	25.96	-0.069	-2.012	3.042	-0.364	2.262	-7.772
	ERP	(-11.3)	(6.93)	(-0.20)	(-7.82)	(2.96)	(-2.55)	(0.02)	(-7.06)
	Estimated	-0.838	5.963	-0.011	-0.319	0.483	-0.058	0.363	-1.234
	ERP	(-2.25)	(3.97)	(-0.04)	(-2.07)	(3.14)	(-3.72)	(1.09)	(-4.24)
Dividend Yield	Realized	0.777	0.247	-0.079	-0.848	-13.97	0.476	-0.667	0.010
	ERP	(8.28)	(0.31)	(-0.29)	(-2.54)	(-0.70)	(0.11)	(-0.59)	(0.04)
	Estimated	0.246	0.033	-0.024	-0.256	-4.215	0.144	-0.490	0.003
	ERP	(2.40)	(0.65)	(-0.49)	(-3.12)	(-1.46)	(0.87)	(-0.86)	(0.03)

This table reports the impact of each the selected macroeconomic determinants on the stock market beta of alternative portfolios using the mixed frequency beta estimation approach. The estimated coefficients depend on the assumption imposed about the equity market risk premium (ERP). We consider the monthly realized market premium and the jointly estimated market premium. In parentheses we report the *t*-statistic.

Table 3

RMSE (%) by State Variables and Portfolios: January 1960-December 2011

State Variable	Equity Premium	Growth	Value	Small	Big	LMom	HMom	LLrev	HLrev
Surplus Consumption	Realized ERP	1.878	3.309	4.012	0.950	4.768	3.290	3.860	2.226
	Estimated ERP	5.146	5.661	6.004	4.460	7.834	6.118	7.147	5.832
Consumption Growth	Realized ERP	1.892	3.400	4.015	0.949	4.802	3.295	3.867	2.231
	Estimated ERP	5.770	6.124	6.712	4.298	8.361	7.066	7.360	6.889
Stockholder Consumption Growth	Realized ERP	1.886	3.400	4.016	0.950	4.791	3.286	3.860	2.228
	Estimated ERP	5.252	6.069	6.128	4.552	7.995	6.245	7.295	5.953
Industrial Production Growth	Realized ERP	1.886	3.290	4.015	0.950	4.798	3.292	3.862	2.215
	Estimated ERP	5.337	5.871	6.760	4.625	8.421	7.116	7.412	6.049
Employment Growth	Realized ERP	1.887	3.400	4.015	0.950	4.803	3.294	3.862	2.201
	Estimated ERP	5.221	6.033	6.613	4.525	8.238	6.207	6.381	5.917
Inflation	Realized ERP	1.892	3.400	4.015	0.950	4.798	3.295	3.862	2.230
	Estimated ERP	5.600	5.939	6.510	4.454	8.109	6.853	6.682	6.282
Term	Realized ERP	1.872	3.362	4.014	0.950	4.795	3.294	3.829	2.215
	Estimated ERP	5.112	5.623	6.475	4.431	7.782	6.816	6.248	5.794
Default	Realized ERP	1.877	3.340	4.015	0.949	4.791	3.290	3.861	2.214
	Estimated ERP	5.118	5.630	6.482	4.151	8.075	6.084	7.108	6.653
Dividend Yield	Realized ERP	1.886	3.400	4.015	0.948	4.804	3.292	3.861	2.230
	Estimated ERP	5.150	5.951	6.009	4.177	8.126	6.867	7.153	6.695

This table reports the RMSE in percentage terms for each selected macroeconomic determinants on the stock market beta and a given portfolio using the mixed frequency beta estimation approach. The estimated coefficients depend on the assumption imposed about the equity market risk premium (ERP). We consider the monthly realized market premium and the jointly estimated market premium.

Table 4
Transitory (Short-Term) Weights for State Variables and Portfolios: January 1960-December 2011

State Variable	Equity Premium	Growth	Value	Small	Big	LMom	HMom	LLrev	HLrev
Surplus Consumption	Realized ERP	0.206	0.431	0.448	0.012	0.071	0.411	0.200	0.041
		(13.40)	(2.47)	(2.35)	(2.67)	(7.64)	(1.99)	(4.63)	(11.91)
	Estimated ERP	0.143	0.431	0.330	0.011	0.042	0.298	0.126	0.089
		(3.43)	(3.12)	(2.22)	(0.94)	(2.62)	(3.35)	(5.77)	(11.50)
Consumption Growth	Realized ERP	0.133	0.004	0.444	0.012	0.321	0.375	0.096	0.076
		(5.30)	(0.46)	(3.35)	(4.16)	(8.68)	(8.78)	(2.33)	(2.43)
	Estimated ERP	0.054	0.004	0.230	0.080	0.170	0.184	0.040	0.030
		(2.26)	(0.02)	(2.02)	(4.05)	(2.14)	(3.60)	(0.13)	(2.46)
Stockholder Consumption Growth	Realized ERP	0.260	0.200	0.448	0.012	0.282	0.411	0.205	0.088
		(2.05)	(1.34)	(3.63)	(15.79)	(0.96)	(11.03)	(1.32)	(4.80)
	Estimated ERP	0.103	0.200	0.195	0.007	0.725	0.173	0.098	0.090
		(2.77)	(1.25)	(2.40)	(0.59)	(0.52)	(2.67)	(1.11)	(3.81)
Industrial Production Growth	Realized ERP	0.259	0.258	0.433	0.012	0.170	0.367	0.214	0.055
		(18.57)	(13.54)	(3.22)	(4.71)	(1.68)	(9.58)	(1.86)	(4.01)
	Estimated ERP	0.152	0.165	0.252	0.092	0.085	0.203	0.117	0.067
		(2.68)	(3.31)	(2.98)	(2.24)	(1.03)	(3.08)	(6.54)	(2.77)
Employment Growth	Realized ERP	0.133	0.001	0.410	0.012	0.325	0.373	0.174	0.051
		(5.13)	(0.57)	(2.71)	(4.42)	(0.51)	(0.58)	(3.37)	(3.46)
	Estimated ERP	0.124	0.001	0.355	0.014	0.268	0.320	0.109	0.041
		(2.04)	(0.18)	(2.79)	(1.51)	(1.86)	(3.66)	(4.66)	(3.48)
Inflation	Realized ERP	0.133	0.000	0.444	0.012	0.308	0.407	0.183	0.076
		(5.21)	(0.00)	(3.20)	(5.53)	(6.61)	(3.14)	(7.55)	(2.65)
	Estimated ERP	0.010	0.000	0.362	0.012	0.228	0.328	0.040	0.050
		(0.15)	(0.00)	(3.22)	(1.25)	(4.71)	(3.07)	(0.57)	(1.33)
Term	Realized ERP	0.200	0.159	0.389	0.013	0.227	0.415	0.310	0.091
		(15.14)	(6.98)	(5.05)	(5.52)	(2.06)	(2.50)	(16.66)	(2.64)
	Estimated ERP	0.163	0.159	0.329	0.133	0.185	0.353	0.258	0.073
		(4.82)	(3.85)	(2.30)	(1.24)	(3.61)	(4.94)	(3.51)	(4.79)
Default	Realized ERP	0.163	0.441	0.392	0.013	0.168	0.405	0.217	0.060
		(12.29)	(3.59)	(0.42)	(2.67)	(11.57)	(4.80)	(0.10)	(7.49)
	Estimated ERP	0.030	0.141	0.093	0.055	0.033	0.098	0.118	0.010
		(2.41)	(5.51)	(0.07)	(3.45)	(10.77)	(3.21)	(0.86)	(2.77)
Dividend Yield	Realized ERP	0.258	0.003	0.425	0.055	0.622	0.426	0.178	0.076
		(3.58)	(0.11)	(2.26)	(9.44)	(0.35)	(0.90)	(0.15)	(4.77)
	Estimated ERP	0.107	0.006	0.182	0.021	0.330	0.183	0.149	0.024
		(2.94)	(0.42)	(2.00)	(9.72)	(1.86)	(1.03)	(0.81)	(0.17)
Average Weight		0.164	0.138	0.385	0.036	0.285	0.358	0.177	0.068

This table reports the transitory weights, ϕ_j, from $\beta^{MF}_{jm,t} = \phi_j \beta^{S}_{jm,t} + \left(1-\phi_j\right)\beta^{L}_{jm,t}$, $0 \le \phi_j \le 1$. This parameter is estimated jointly with the rest of the parameters in the mixed frequency beta procedure. We consider the monthly realized market premium and the jointly estimated market premium. ERP is equity risk premium. In parentheses we report the *t*-statistic. Average weight is the weighted (by the inverse of the SE) average short-term weight across all risk premia and state variables.

Table 5
Transitory (Short-Term) Weights for Surplus Consumption and Portfolios using the Realized Market Equity Premium during Months Classified as Normal and Recession NBER Dates:
January 1960-December 2011

Short-Term Weights	Growth	Value	Small	Big	LMom	HMom	LLrev	HLrev
Full Sample Period	0.206 (13.40)	0.431 (2.47)	0.448 (2.35)	0.012 (2.67)	0.071 (7.64)	0.411 (1.99)	0.200 (4.63)	0.041 (11.91)
Normal NBER Months	0.218 (8.43)	0.268 (3.87)	0.489 (2.07)	0.012 (2.06)	0.294 (2.20)	0.457 (3.67)	0.134 (4.97)	0.083 (9.37)
Recession NBER Months	0.207 (8.40)	0.530 (5.67)	0.355 (5.70)	0.015 (2.05)	0.005 (0.66)	0.265 (1.53)	0.320 (8.45)	0.035 (2.66)

This table reports the transitory weights, ϕ_j, from $\beta^{MF}_{jm,t} = \left[(1-D_t)\varphi_{1,j} + D_t\,\varphi_{2,j}\right]\beta^{S}_{jm,t} + \left\{1-\left[(1-D_t)\varphi_{1,j} + D_t\,\varphi_{2,j}\right]\right\}\beta^{L}_{jm,t}$, $0 \le \phi_j \le 1$, where D_t is the dummy variable whose value is 1 during recessions and zero otherwise. This parameter is estimated jointly with the rest of the parameters in the mixed frequency beta procedure using the monthly realized market premium.

Table 6
Variance Decomposition of Total MIDAS Conditional Betas:
February 1961-December 2011

	Surplus Consumption			Default		
	$\% Var\left(\beta_j^S\right)$	$\% Var\left(\beta_j^L\right)$	$\% 2 Cov\left(\beta_j^S, \beta_j^L\right)$	$\% Var\left(\beta_j^S\right)$	$\% Var\left(\beta_j^L\right)$	$\% 2 Cov\left(\beta_j^S, \beta_j^L\right)$
Growth	88.82	4.96	6.20	91.68	2.92	5.39
Value	61.03	55.55	-16.55	77.58	44.39	-21.94
10 BEME	89.25	21.59	-10.82	95.03	29.02	-24.01
Small	100.32	0.00	-0.32	99.84	0.00	0.16
Big	96.26	0.62	3.12	92.71	0.70	6.60
10 SIZE	100.73	0.14	-0.87	96.69	0.29	3.01
Low Mom	97.88	5.25	-3.12	103.87	1.30	-5.16
High Mom	98.49	0.19	1.31	99.63	0.02	0.35
10 MOM	101.19	2.10	-3.28	102.82	0.49	-3.31
Low Lrev	100.41	0.20	-0.62	100.13	0.26	-0.40
High Lrev	93.30	2.51	4.18	83.55	7.38	9.06
10 LREV	97.94	0.73	1.33	91.73	2.27	5.99
Overall	97.28	6.14	-3.41	96.57	8.02	-4.58

This table shows the percentage of the total MIDAS conditional betas explained by the variances of short-term beta, long-term beta, and the covariance between the short- and long-term betas. It shows the drivers of the underlying movement in the total MIDAS conditional beta. The percentages are given for the extreme portfolios of the 4 sets sorted by book-to-market, size, momentum, and long reversals. It also shows the percentage of the average percentages across all ten portfolios within a give set, and for the overall 40 portfolios. The percentages are obtained from the following decomposition
$1 = \left(Var\left(\beta_{j,t}^S\right) + Var\left(\beta_{j,t}^L\right) + 2\,Cov\left(\beta_{j,t}^S, \beta_{j,t}^L\right)\right) / Var\left(\beta_{j,t}^{MF}\right)$

Table 7
The Time-Varying Behavior of Conditional Volatility for the Excess Return Residuals from Mixed Frequency Betas over the Business Cycle: February 1961-December 2011

Panel A. Slope coefficients from regressing conditional volatility of residuals from MF betas estimated with surplus consumption on macroeconomic variables

	Growth	Value	Small	Big	LMom	HMom	LLrev	HLrev
Industrial Production Index	-0.108 (-5.66) [-2.78]	-0.138 (-2.33) [-1.28]	-0.077 (-1.22) [-0.83]	-0.042 (-3.39) [-1.87]	-0.654 (-5.21) [-3.63]	-0.221 (-4.31) [-2.82]	-0.202 (-2.66) [-1.40]	-0.171 (-6.55) [-2.82]
Surplus Consumption	-0.009 (-0.98) [-0.81]	-0.068 (-2.32) [-1.44]	-0.049 (-1.58) [-1.54]	0.002 (0.26) [0.23]	-0.347 (-5.61) [-2.48]	-0.098 (-3.86) [-2.58]	-0.039 (-1.04) [-0.86]	-0.061 (-4.69) [-1.74]
Default	0.133 (7.59) [2.78]	0.510 (9.82) [3.70]	0.225 (3.83) [1.72]	0.054 (4.64) [1.81]	1.500 (14.40) [4.62]	0.242 (5.07) [2.38]	0.580 (8.58) [4.32]	0.351 (16.76) [6.11]

Panel B. Slope coefficients from regressing conditional volatility of residuals from MF betas estimated with default on macroeconomic variables

	Growth	Value	Small	Big	LMom	HMom	LLrev	HLrev
Industrial Production Index	-0.106 (-5.35) [-2.84]	-0.145 (-2.44) [-1.55]	-0.080 (-1.27) [-0.86]	-0.044 (-3.45) [-1.92]	-0.648 (-5.08) [-3.46]	-0.217 (-4.23) [-2.78]	-0.179 (-2.43) [-1.29]	-0.167 (-6.23) [-2.72]
Surplus Consumption	-0.007 (-0.66) [-0.55]	-0.097 (-3.31) [-1.61]	-0.051 (-1.63) [-1.58]	0.001 (0.20) [0.18]	-0.350 (-5.59) [-2.38]	-0.098 (-3.85) [-2.58]	-0.033 (-0.89) [-0.74]	-0.057 (-4.27) [-1.61]
Default	0.137 (7.52) [2.66]	0.606 (11.95) [4.22]	0.222 (3.76) [1.68]	0.057 (4.75) [1.84]	1.506 (14.22) [4.47]	0.237 (4.95) [2.33]	0.543 (8.23) [4.22]	0.353 (16.32) [6.13]

Panel A of this table shows the slope coefficients from regressing a GARCH (1,1) conditional volatility of residuals from mixed frequency betas estimated with surplus consumption on alternative macroeconomic variables. Panel B shows the slope coefficients when we estimated conditional betas with default. OLS-based *t*-statistics in parentheses, and HAC-based *t*-statistics in brackets.

Table 8
The Risk-Return Relation Implied by the Mixed Frequency Conditional Betas across Portfolios: February 1961-December 2011

Panel A: Results from conditional mixed frequency conditional betas under surplus consumption

	Growth	Value	Small	Big	LMom	HMom	LLrev	HLrev
Estimated slope	-2.098 (-1.62)	1.115 (1.169)	1.982 (2.83)	-1.398 (-0.36)	1.449 (3.11)	-1.373 (1.70)	1.372 (2.02)	-2.416 (-1.43)

Panel B: Results from conditional mixed frequency conditional betas under default

	Growth	Value	Small	Big	LMom	HMom	LLrev	HLrev
Estimated slope	-3.293 (-1.73)	1.037 (1.11)	2.057 (2.92)	-0.910 (-0.24)	1.437 (3.13)	-1.344 (-1.66)	1.204 (1.76)	-2.694 (-1.54)

Panel A of this table shows the slope coefficients of the risk-return trade-off from a GARCH (1,1)-in-mean model using surplus consumption in the estimation of mixed frequency conditional betas. Panel B shows similar results using default in the estimation of conditional betas. The *t*-statistics reported in parentheses are computed using Bollerslev-Wooldridge (1992) standard errors.

Table 9
The Term Structure of Holding Period Annualized Expected Excess Returns Implied by the Mixed Frequency Conditional Betas across Portfolios: February 1961-December 2011

Panel A: Expected returns using mixed frequency conditional betas from surplus consumption

Horizon in months	Growth	Value	Small	Big	Lmom	Hmom	LLrev	HLrev
1	0.0878	0.1486	0.1422	0.0838	0.0189	0.1943	0.1514	0.1007
3	0.0720	0.0943	0.0758	0.0376	-0.0009	0.1665	0.1321	0.0782
6	0.0664	0.0913	0.0724	0.0353	-0.0088	0.1607	0.1307	0.0723
12	0.0604	0.0895	0.0705	0.0341	-0.0113	0.1672	0.1266	0.0784
24	0.0414	0.0917	0.0720	0.0357	-0.0378	0.1347	0.1003	0.0448

Panel B: Volatility of expected returns using mixed frequency conditional betas from surplus consumption

Horizon in months	Growth	Value	Small	Big	Lmom	Hmom	LLrev	HLrev
1	0.1679	0.1676	0.1740	0.1445	0.2222	0.1848	0.1832	0.1939
3	0.1018	0.1035	0.1057	0.0880	0.1365	0.1122	0.1117	0.1183
6	0.0740	0.0767	0.0775	0.0644	0.1005	0.0818	0.0819	0.0866
12	0.0518	0.0533	0.0545	0.0452	0.0706	0.0572	0.0575	0.0609
24	0.0347	0.0347	0.0366	0.0303	0.0473	0.0382	0.0384	0.0411

Panel C: Sharpe ratios using mixed frequency conditional betas from surplus consumption

Horizon in months	Growth	Value	Small	Big	Lmom	Hmom	LLrev	HLrev
1	0.5228	0.8864	0.8174	0.5794	0.0849	1.0513	0.8265	0.5196
3	0.7078	0.9116	0.7168	0.4272	-0.0071	1.4846	1.1819	0.6607
6	0.8968	1.1904	0.9342	0.5482	-0.0871	1.9634	1.5967	0.8355
12	1.3398	1.6776	1.2924	0.7539	-0.1599	2.9212	2.2033	1.2878
24	1.1927	2.6407	1.9689	1.1790	-0.8003	3.5228	2.6097	1.0921

Panel A of this table shows the annualized expected excess return of the alternative portfolios when those are held during 1, 3, 6, 12, and 24 months. The expected excess returns are estimated from the mixed frequency conditional betas obtained with surplus consumption. Panel B reports the corresponding volatility of expected returns for the different holding periods, and Panel C shows the Sharpe ratios for the same holding periods.

Table 10
The Term Structure of Holding Period Annualized Expected Excess Returns Implied by the Long- and Short-Term Mixed Frequency Conditional Betas across Portfolios: February 1961-December 2011

Panel A: Expected returns using mixed frequency long-term conditional betas from surplus consumption

Horizon in months	Growth	Value	Small	Big	Lmom	Hmom	LLrev	HLrev
1	0.1129	0.1499	0.2065	0.0848	0.0269	0.2646	0.1774	0.1050
3	0.0886	0.1401	0.1739	0.0725	0.0058	0.2267	0.1575	0.0822
6	0.0814	0.1303	0.1598	0.0708	-0.0031	0.2106	0.1480	0.0758
12	0.0877	0.1298	0.1635	0.0718	-0.0042	0.2154	0.1480	0.0822
24	0.0510	0.1063	0.1123	0.0482	-0.0346	0.1593	0.1120	0.0474

Panel B: Expected returns using mixed frequency short-term conditional betas from surplus consumption

Horizon in months	Growth	Value	Small	Big	Lmom	Hmom	LLrev	HLrev
1	-0.0009	0.0354	0.0385	-0.0030	-0.1003	0.0725	0.0380	-0.0158
3	-0.0108	0.0395	0.0387	-0.0018	-0.0973	0.0750	0.0410	-0.0132
6	-0.0103	0.0371	0.0421	-0.0014	-0.0972	0.0770	0.0414	-0.0126
12	-0.0091	0.0410	0.0466	0.0001	-0.0985	0.0784	0.0436	-0.0116
24	-0.0096	0.0398	0.0443	0.0003	-0.0989	0.0787	0.0416	0.0111

This table shows the annualized expected excess return of the alternative portfolios when those are held during 1, 3, 6, 12, and 24 months. The expected excess returns are estimated from the mixed frequency conditional betas obtained with surplus consumption. In Panel A, we show the term structure of expected excess returns when we shut down the short-term beta component showing the expected returns over different holding period due to the long-term conditional beta. In Panel B, we report the term structure of expected returns when we shut down the long-term beta component.

Table 11
The Performance of Investment Strategies that Depends on the Expected Excess Returns Estimated with the Mixed Frequency Conditional Beta Model: February 1961-December 2011

Panel A: Four-factor alpha using surplus consumption in the estimation of the mixed frequency conditional beta. Aggressiveness parameter $\theta = 2$

Horizons in months	Time-varying expected excess returns (surplus consumption)	Time-varying expected excess returns (default)	Constant expected excess returns
1	-0.0048 (-0.30)	-0.0211 (-1.41)	0.0004 (0.88)
3	0.1341 (5.96)	0.1457 (6.57)	0.0001 (0.13)
6	0.2262 (6.26)	0.2167 (6.04)	-0.0007 (-1.30)
12	0.2858 (3.60)	0.2814 (3.72)	-0.0011 (-1.27)

Panel B: Four-factor alpha using surplus consumption in the estimation of the mixed frequency conditional beta. Aggressiveness parameter $\theta = 1$

Horizons in months	Time-varying expected excess returns (surplus consumption)	Time-varying expected excess returns (default)	Constant expected excess returns
1	-0.0214 (-1.80)	-0.0292 (-2.45)	0.0003 (0.75)
3	0.0765 (4.01)	0.0791 (4.16)	-0.0001 (-0.28)
6	0.1516 (4.92)	0.1474 (4.76)	-0.0008 (-1.59)
12	0.2096 (3.03)	0.2079 (3.10)	-0.0011 (-1.40)

In this table we show the performance of an investment strategy based on the monthly expected return rankings of the eight portfolios generated by our mixed frequency conditional betas. Panel A reports the results of an investment strategy that weights relatively more heavily those portfolios with higher expected returns. Panel B contains the results for a less aggressive strategy although those portfolios with higher expected returns also receive higher weights. The rankings are time-varying and updated every month. Performance is measures relative to a four-factor model of the three Fama and French portfolios augmented with the momentum factor. The last column reports the results for an investment strategy based on the ranking obtained by the past average returns of the eight portfolios. This strategy maintains this ranking constant throughout the full sample period.

Figure 1
Yearly Changes of Time-Varying Risk Aversion with External Habit Preferences: 1960-2011

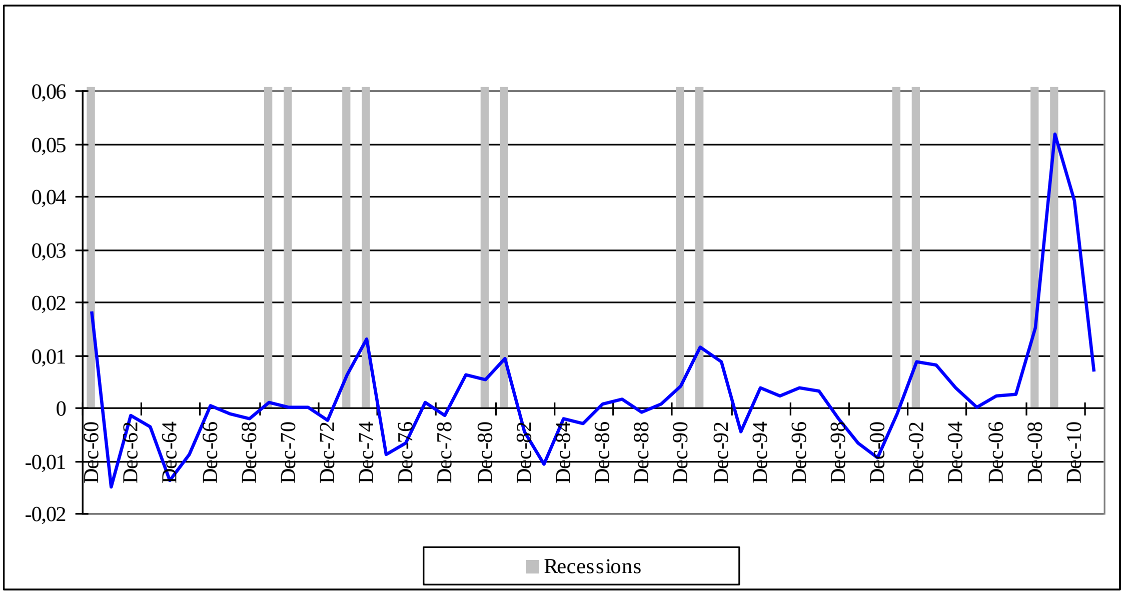


Figure 2
Mixed Frequency Betas for Value and Growth Portfolios with Surplus Consumption and Realized Market Risk Premium: February 1961-December 2011

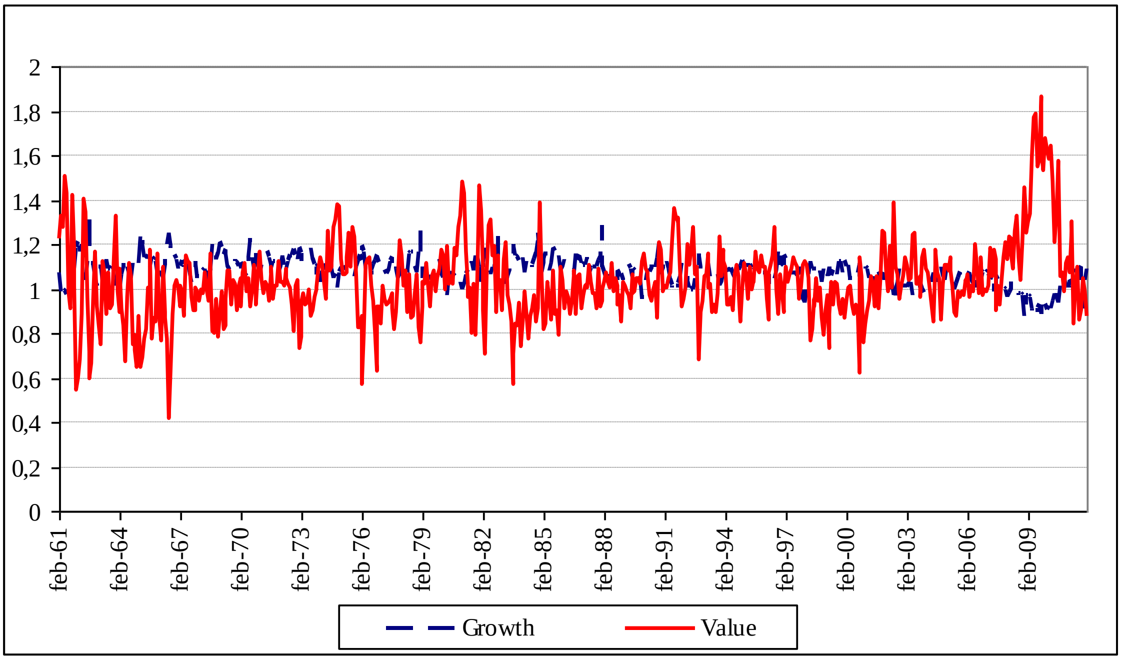
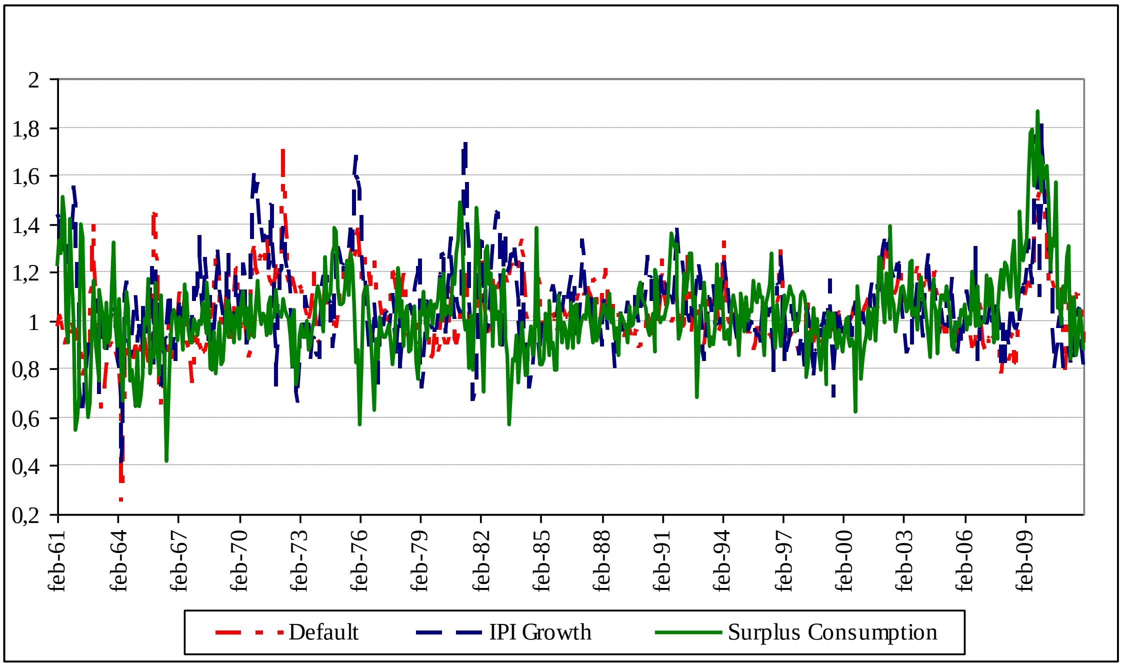


Figure 3

Panel A: Mixed Frequency Betas for the Value Portfolio with Representative State Variables and Realized Market Risk Premium: February 1961-December 2011



Panel B: Mixed Frequency Betas for the Growth Portfolio with Representative State Variables and Realized Market Risk Premium: February 1961-December 2011

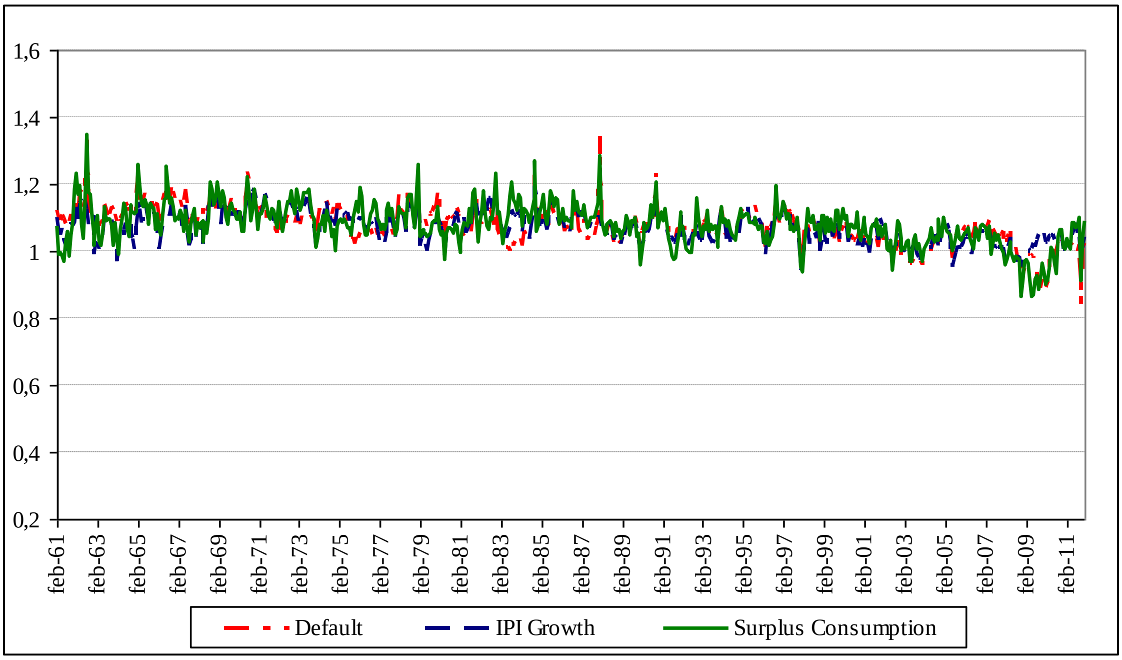
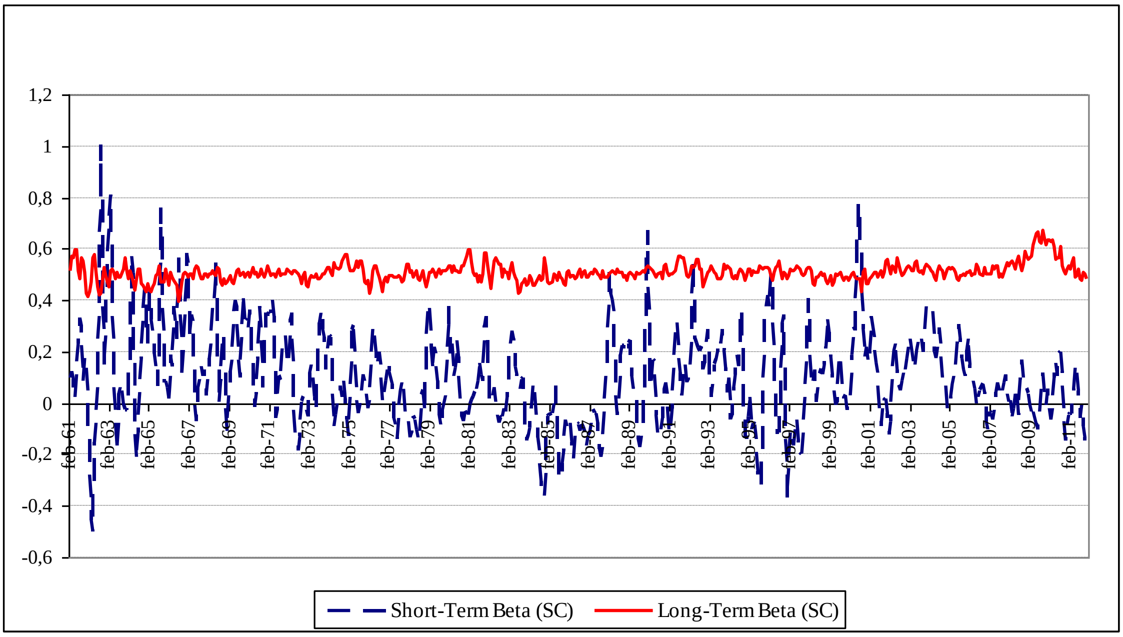


Figure 4

Panel A: Average Short- and Long-Term Betas across 40 Test Assets Sorted by Book-to-Market, Size, Momentum and Long-term Reversals with Surplus Consumption: February 1961-December 2011



Panel B: Average Short- and Long-Term Betas across 40 Test Assets Sorted by Book-to-Market, Size, Momentum and Long-term Reversals with Default: February 1961-December 2011