Title: **MACROECONOMIC DETERMINANTS OF STOCK MARKET BETAS**

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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 decompose market betas into high and low frequency components. The total mixed frequency beta is the weighted average of these two 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.

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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 depicted by models with habit preferences, as in Campbell and Cochrane (1999), represents a huge step towards understanding the time-varying behavior of expected returns over the business cycle. At the same time, given the magnitudes of the cross-sectional averages of equity returns for well-known sets of portfolios,[1] a key issue of financial economics might potentially be 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. In particular, 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 the estimation of both beta components and the effects of macroeconomic variables are simultaneously estimated, avoiding 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.

Despite the fact that the analysis of the macroeconomic determinants of market betas seems to be a very important step in understanding the cross-sectional differences of expected returns across alternative equity returns, it is surprising how little empirical research is available. Frictionless macroeconomic-based models are the benchmark

[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).

asset pricing models. They have been extremely useful to describe the temporal behavior of expected returns and their 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

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[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.

and the impact of macroeconomic variables on them. Note that this is very different 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) in which risk aversion is also counter-cyclical, 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 affecting betas since they are the variables significantly affecting the lower number of portfolios. Our 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 over the business cycle. 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]

Finally, we 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.

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 concludes the paper.

[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.

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). Their proposal consists of two additive GARCH(1,1) components, one interpreted as a short-run or transitory component, and a second one identified as the long-run or trend component of volatility. Recently, however, Engle and Rangel (2008) suggest a multiplicative component structure, the Spline-GARCH model, to accommodate non-stationarity features that are captured by the long run volatility component. Volatility is therefore 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. Engle and Rangel (2008) apply this model to stock market volatilities across 50 countries and conclude that high volatility is explained by high inflation, slow output growth, high volatility of short-term interest rates, high volatility of production growth, and high inflation volatility.

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, especially in comparison with 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) under the Spline-GARCH model. 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. Ferson and Harvey (1998), and Patro, Wald, and Yu (2002) extend this idea to international equity markets. Both papers employ a two-step procedure in which they first estimate worldwide changing betas, and then the authors regress these time-varying betas on a given set of macroeconomic variables. While Ferson and Harvey (1998) show that GDP growth, inflation, overall credit conditions, or the slope of the term structure of interest rates, explain the temporal behavior of equity betas with respect to the global equity portfolio, Patro et al. (2002), employing a panel data model, show that the percentages of exports and imports over GDP are the most relevant factors in explaining the joint behavior of market beta across 16 OCDE countries.

There are two more recent papers that are much closer 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, and 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, and 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

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

where $E_t\left(R^e_{j,t+1}\right)$ 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 $\beta^{MF}_{jm,t}$ be the mixed frequency conditional beta (MF hereafter) with respect to the market portfolio return,

$$\beta^{MF}_{jm,t}=\frac{Cov_t\left(R^e_{j,t+1},\lambda_{m,t+1}\right)}{Var_t\left(\lambda_{m,t+1}\right)} \tag{2}$$

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:

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

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*, and where 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

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

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

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 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

[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.

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 $Cov(\beta_{t+1}, \lambda_{mt+1})$, 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.

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

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

where γ is a parameter of utility curvature, 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

$$s_{t+1} = (1-\phi)\bar{s} + \phi s_t + \lambda(s_t)(c_{t+1} - c_t - g) \tag{11}$$

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

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

$$\lambda(s_t) = \left(1/\sigma_c \sqrt{\gamma/1-\phi}\right)\sqrt{1-2(s_t-\bar{s})}-1 \tag{12}$$

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.

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

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

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

[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.

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 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.

Although the number of portfolios with statistically significant slope coefficients is lower than in the cases of surplus consumption, stockholder consumption growth or the default premium, industrial production growth and employment growth are typical business cycle variables with a similar impact on MF betas that surplus consumption. Value companies for industrial growth and small and low long reversal firms for employment growth have counter-cyclical MF betas, while 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.

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. Of course, 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. The results, either imposing the ex-post market risk premium or the joint estimation of the market risk premium with the rest of parameters, are very similar for all portfolios and macroeconomic variables. 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 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

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

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

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

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

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 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

[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.

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 estimated using alternative macroeconomic variables, and we investigate the drivers and importance of long-term betas. 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.

[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.

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:

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

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. 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 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.

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.

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.

References

Andersen, T., T. Bollerslev, F. Diebold, and J. Wu (2005), A framework for exploring the macroeconomic determinants of systematic risk, *American Economic Review Papers & Proceedings* 95, 398-404.

Baele, L., and J. Londono (2013), Understanding industry betas, *Journal of Empirical Finance* 22, 30-51.

Bansal, R., and A. Yaron (2004), Risks for the long run, *Journal of Finance* 59, 1481-1509.

Bansal, R., R. Dittmar, and C. Lundblad (2005), Consumption, dividends, and the cross-section of equity returns, *Journal of Finance* 60, 1639-1672.

Barroso, P., and P. Santa-Clara (2015), Momentum has its moments, *Journal of Financial Economics* 116, 111-120.

Berk, J., R. Green, and V. Naik (1999), Optimal investment, growth options, and security returns, *Journal of Finance* 54, 1553-1607.

Campbell, J., and J. Cochrane (1999), By force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107, 205-251.

Chan, K., and N.F Chen (1988), An Unconditional Asset-Pricing Test and the Role of Firm Size as an Instrumental Variable for Risk, *Journal of Finance* 43, 309-325.

Cochrane, J. (2007), Financial markets and the real economy, in Rajnish Mehra, Ed. *Handbook of the Equity Premium*, Elsevier, 237-325.

Cochrane, J. (2013), Discount rates, *Journal of Finance* 66, 1047-1108.

Colacito, R., R. Engle, and A. Ghysels (2009), A component model for dynamic correlations, *Journal of Econometrics* 164, 45-59.

Daniel, K., and T. Moskowitz (2012), Momentum crashes, *Swiss Finance Institute*, Research Paper Series no. 13-61.

Engle, R. (2002), Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models, *Journal of Business and Economic Statistics* 20, 339-350.

Engle, R., E. Ghysels, and B. Sohn (2013), Stock market volatility and macroeconomic fundamentals, *Review of Economics and Statistics* 95, 776-797.

Engle, R., and G. Lee (1999), A permanent and transitory component model of stock return volatility. R. Engle and H. White (editors), *Cointegration, causality, and forecasting: A festschrift in honour of Clive W. J. Granger*, Oxford University Press 475-497.

Engle, R., and J. Rangel (2008), The spline GARCH model for low frequency volatility and its global macroeconomic causes, *Review of Financial Studies* 21, 1187-1222.

Epstein, L., and S. Zin (1989), Substitution risk aversion and the temporal behavior of consumption and asset returns: a theoretical framework, *Econometrica* 57, 937-968.

Fama, E., and K. French (1993), Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, E., and K. French (2015), A Five-Factor Asset Pricing Model, *Journal of Financial Economics* 116, 1-22.

Ferson, W., and C. Harvey (1998), Fundamentals determinants of national equity market returns: A perspective on conditional asset pricing, *Journal of Banking and Finance* 21, 1625-1665.

Ferson, W., and C. Harvey (1999), Conditioning variables and cross-section of stock returns, *Journal of Finance* 54, 1325-1360.

Ghysels, E., P. Santa-Clara, and R. Valkanov (2003), The MIDAS touch. Mixed data sampling regression models, *Working Paper*, *University of California, Los Angeles, and University of North Carolina at Chapel Hill*.

Ghysels, E., P. Santa-Clara, and R. Valkanov (2005), There is a risk-return trade-off after all, *Journal of Financial Economics* 76, 509–548.

Ghysels, E., P. Santa-Clara, and R. Valkanov (2006), Predicting volatility: Getting the most out of return data sampled at different frequencies, *Journal of Econometrics* 131, 59–95.

Ghysels, E., A. Sinko, and R. Valkanov (2007), MIDAS regressions: Further results and new directions, *Econometric Reviews* 26, 53-90.

Gilbert, T., Hrdlicka, C., J. Kalodimos, and S. Siegel (2014), Daily Data is Bad for Beta: Opacity and Frequency-Dependent Betas, *Review of Asset Pricing Studies* 4, 78-117.

Gomes, J., L. Kogan, and L. Zhang (2003), Equilibrium cross section of returns, *Journal of Political Economy* 111, 693-732.

González, M., J. Nave, and G. Rubio (2012), The cross-section of expected returns with MIDAS betas, *Journal of Financial and Quantitative Analysis* 47, 115-135.

Grundy, B., and J. Martin (2001), Understanding the nature of the risks and the source of the rewards to momentum investing, *Review of Financial Studies* 14, 29-78.

Hansen, L., J. Heaton, and N. Li (2008), Consumption strikes back?: Measuring long-run risk, *Journal of Political Economy* 116, 260-302.

Jagannathan, R., and Z. Wang (1996), The conditional CAPM and the cross-section of expected returns, *Journal of Finance* 51, 3-53.

Judge, G., W. Griffith, R. Hill, and H. Lutkepohl (1985), The theory and practice of Econometrics, 2nd. Edition, Wiley.

Lettau, M., and S. Ludvigson (2001), Consumption, aggregate wealth, and expected stock returns, *Journal of Finance* 56, 815-849.

Lewellen, J., and S. Nagel (2006), The conditional CAPM does not explain asset pricing anomalies, *Journal of Financial Economics* 82, 289-314.

Malloy, C., T. Moskowitz, and A. Vissing-Jorgensen (2011), Long-run stockholder consumption risk and asset returns, *Journal of Finance* 64, 2427-2479.

Patro, D., J. Wald, and Y. Wu (2002), The impact of macroeconomic and financial variables on market risk: Evidence from international equity returns, *European Financial Management Journal* 8, 421-447.

Santos, T., and P. Veronesi (2004), Conditional betas, *NBER Working Paper* 10413, 1-47.

Shanken, J. (1990), Intertemporal asset pricing: an empirical investigation, *Journal of Econometrics* 45, 99-120.

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 ERP	4.976	-17.86	-1.161	-0.009	-5.566	0.960	-2.253	3.498
		(5.14)	(-4.30)	(-4.38)	(-0.68)	(-4.90)	(2.01)	(-2.53)	(11.59)
	Estimated ERP	3.106	-17.86	-0.705	-0.005	-1.137	0.582	-0.671	2.127
		(3.34)	(-5.75)	(-2.83)	(-0.78)	(-4.02)	(2.41)	(-2.15)	(5.04)
Consumption Growth	Realized ERP	0.296	-0.102	0.060	3.622	-0.552	0.130	0.000	0.001
		(0.73)	(-0.23)	(0.10)	(3.74)	(-0.15)	(0.03)	(0.00)	(0.01)
	Estimated ERP	0.111	-0.102	0.022	1.357	-0.176	0.049	0.001	0.000
		(0.16)	(-0.22)	(0.05)	(4.36)	(-0.22)	(0.16)	(0.03)	(0.00)
Stockholder Consumption Growth	Realized ERP	0.207	-0.560	-0.201	0.006	-4.330	0.832	-0.602	3.853
		(5.57)	(-1.28)	(-0.57)	(0.95)	(-0.69)	(1.99)	(-0.05)	(15.12)
	Estimated ERP	0.062	-0.156	-0.060	0.002	-1.251	0.250	-0.020	1.155
		(2.88)	(-0.40)	(-2.33)	(0.24)	(-0.70)	(3.81)	(-0.21)	(2.10)
Industrial Production Growth	Realized ERP	0.214	-38.41	-0.087	-0.003	-0.952	0.083	-0.633	9.407
		(3.73)	(-2.84)	(-0.52)	(-0.13)	(-0.32)	(0.07)	(-0.10)	(12.76)
	Estimated ERP	0.094	-18.41	-0.038	-0.001	-0.419	0.036	-0.280	4.147
		(2.22)	(-2.84)	(-0.10)	(-0.01)	(-0.71)	(0.92)	(-0.42)	(5.15)
Employment Growth	Realized ERP	2.032	-0.145	-0.030	-0.004	-0.547	0.073	-4.391	40.350
		(2.14)	(-0.39)	(-0.20)	(-0.10)	(-0.09)	(0.08)	(-2.04)	(9.15)
	Estimated ERP	1.607	-0.145	-0.023	-0.003	-0.433	0.058	-3.095	31.927
		(2.18)	(-0.51)	(-2.20)	(-0.00)	(-1.13)	(2.04)	(-5.00)	(3.94)
Inflation	Realized ERP	0.001	0.002	0.027	-0.003	-0.509	0.038	-4.207	0.120
		(0.00)	(0.19)	(0.06)	(-0.01)	(-0.85)	(0.02)	(-2.06)	(0.25)
	Estimated ERP	0.081	0.002	0.019	-0.002	-0.362	0.027	-3.003	0.086
		(0.13)	(0.06)	(0.15)	(-0.01)	(-1.56)	(1.25)	(-2.32)	(0.13)
Term	Realized ERP	-5.281	8.916	0.066	0.007	2.505	-0.119	4.344	-4.763
		(-9.37)	(2.38)	(0.02)	(0.44)	(0.94)	(-0.05)	(13.11)	(-4.00)
	Estimated ERP	-4.065	8.916	0.051	0.051	1.928	-0.092	3.345	-3.667
		(-3.55)	(4.35)	(0.26)	(0.27)	(0.66)	(-2.24)	(4.56)	(-8-80)
Default	Realized ERP	-5.279	25.96	-0.069	-2.012	3.042	-0.364	2.262	-7.772
		(-11.3)	(6.93)	(-0.20)	(-7.82)	(2.96)	(-2.55)	(0.02)	(-7.06)
	Estimated ERP	-0.838	5.963	-0.011	-0.319	0.483	-0.058	0.363	-1.234
		(-2.25)	(3.97)	(-0.04)	(-2.07)	(3.14)	(-3.72)	(1.09)	(-4.24)
Dividend Yield	Realized ERP	0.777	0.247	-0.079	-0.848	-13.97	0.476	-0.667	0.010
		(8.28)	(0.31)	(-0.29)	(-2.54)	(-0.70)	(0.11)	(-0.59)	(0.04)
	Estimated ERP	0.246	0.033	-0.024	-0.256	-4.215	0.144	-0.490	0.003
		(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, the full sample average of the market equity 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, the full sample average of the market equity 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 $\beta^{MF}_{jm,t} = \phi_j \beta^{S}_{jm,t} + (1-\phi_j)\beta^{L}_{jm,t}$, $0 \le \phi_j \le 1$. This parameter is estimated jointly with the rest of the parameters in the mixed frequency beta procedure. We consider the monthly realized market premium, the full sample average of the market equity 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
January 1960-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

$$1 = \left(Var\left(\beta_{j,t}^S\right) + Var\left(\beta_{j,t}^L\right) + 2\, Cov\left(\beta_{j,t}^S, \beta_{j,t}^L\right)\right) / Var\left(\beta_{j,t}^{MF}\right)$$

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

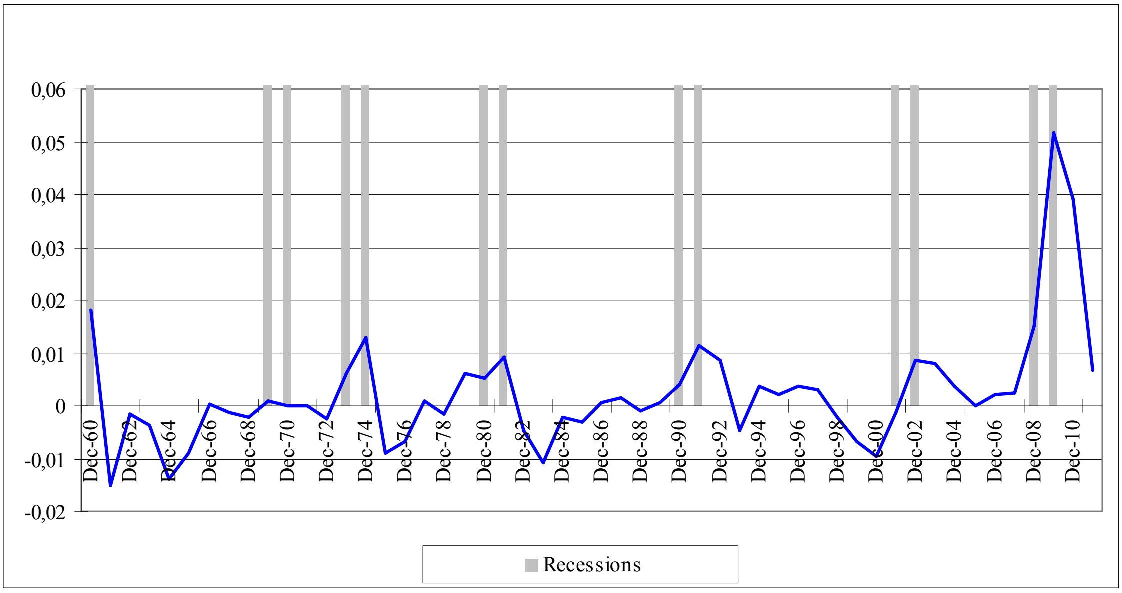


Figure 2
Mixed Frequency Betas for Value and Growth Portfolios with Surplus Consumption and Realized Market Risk Premium: February 1961-December 2011

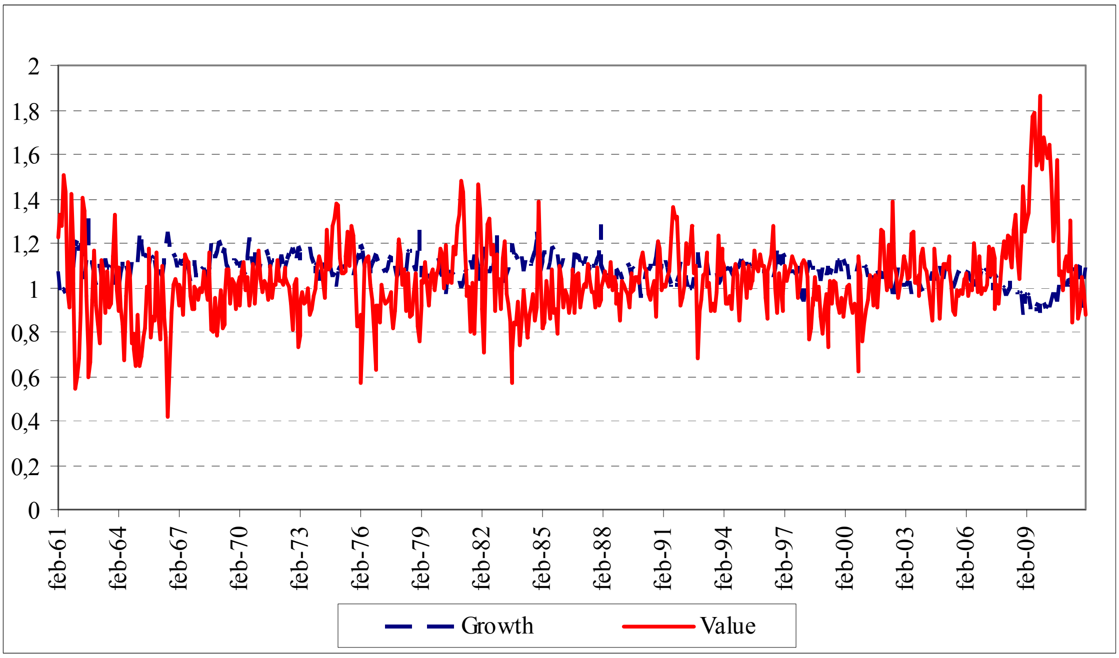
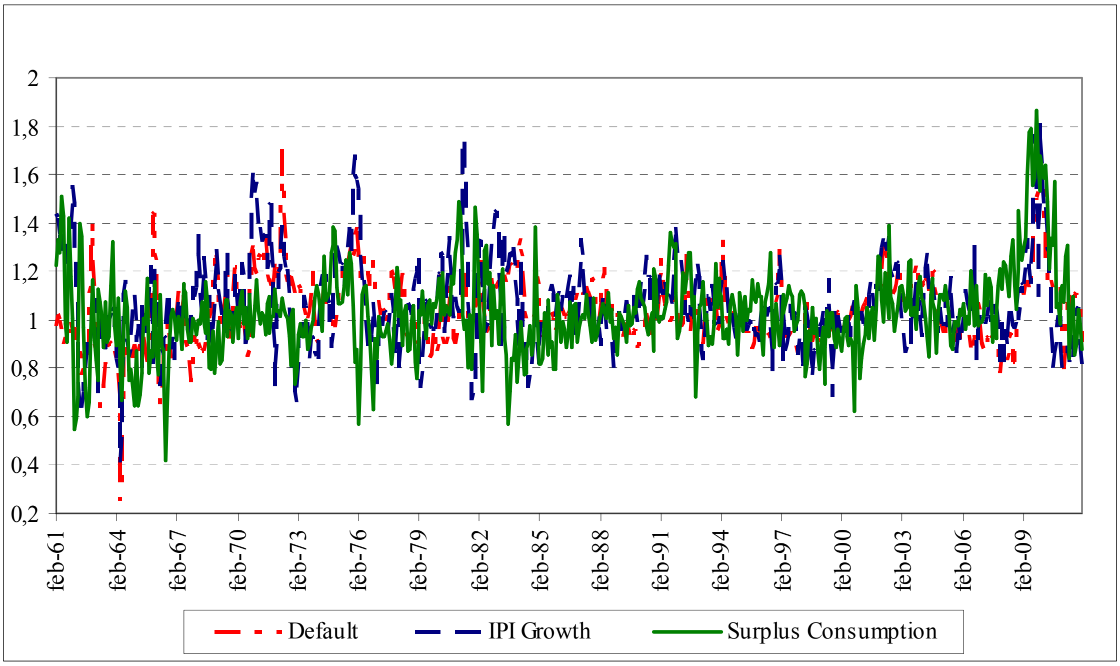


Figure 3
Panel A: Mixed Frequency Betas for the Value Portfolio with Representative State Variables and Realized Market Risk Premium: February 1961-December 2011



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

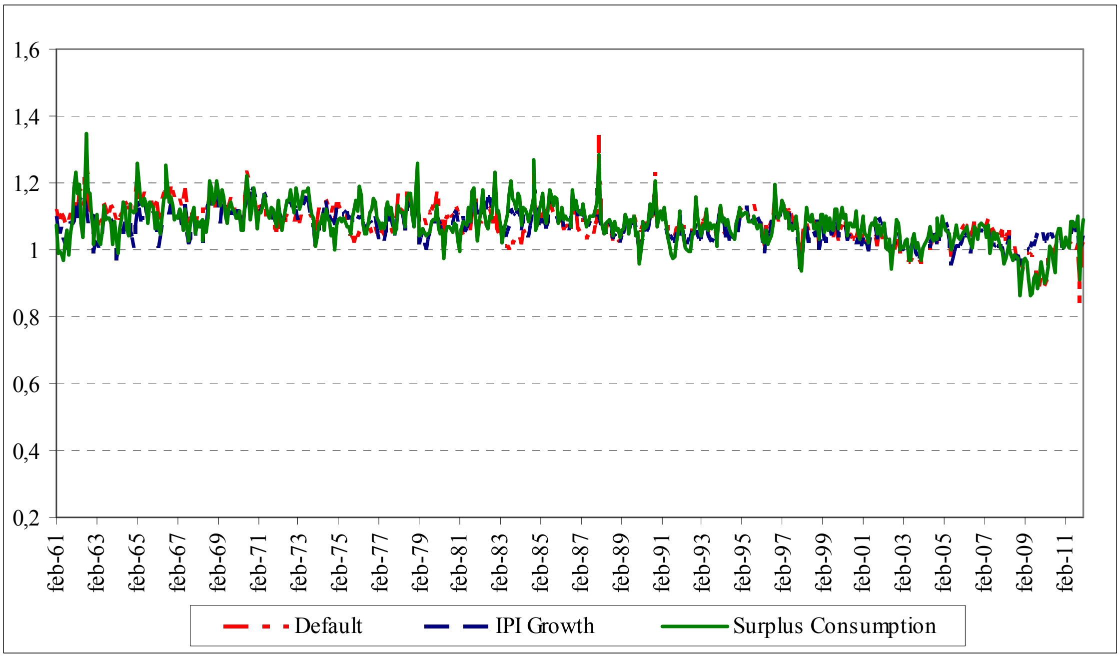
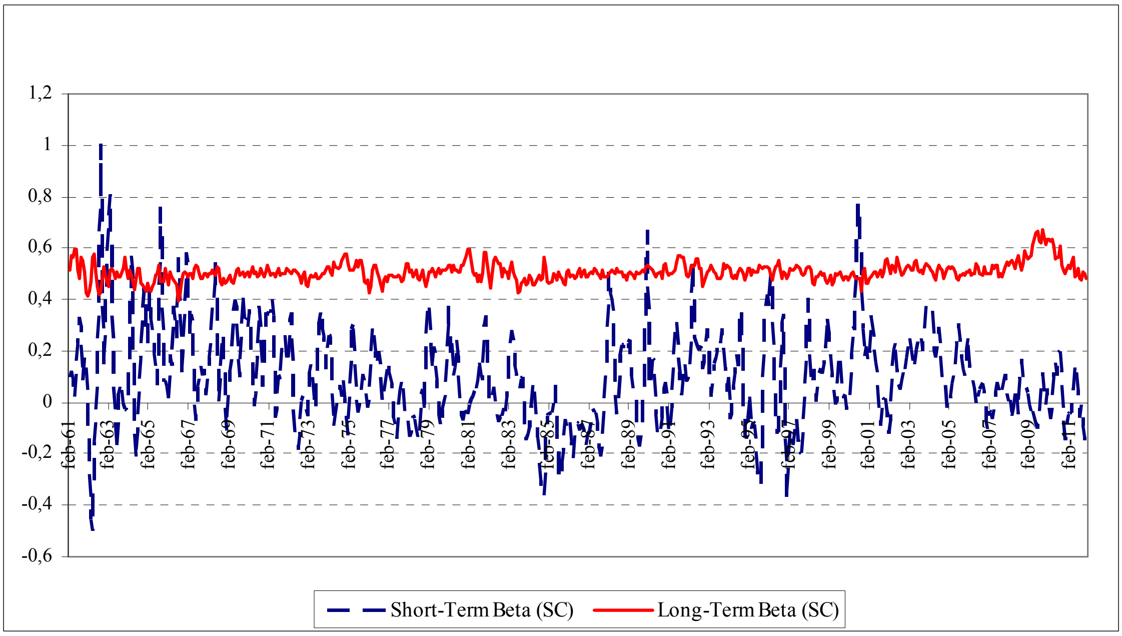


Figure 4

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