FUNDAÇÃO GETÚLIO VARGAS

ESCOLA DE ECONOMIA DE SÃO PAULO

RENATO DALLA COLLETTA

CASH FLOW AND DISCOUNT RATE RISK DECOMPOSITION AND ICAPM FOR THE US AND BRAZILIAN STOCK MARKETS

SÃO PAULO

2012

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Dissertação apresentada à Escola de Economia de São Paulo da Fundação Getulio Vargas (FGV/EESP) como requisito para a obtenção do título de Mestre em Finanças e Economia

Orientador: Prof. Dr. João Filipe Bernardes Volkmann de Mendonça Mergulhão

São Paulo

2012

Colletta, Renato Dalla.

Cash Flow and Discount Rate Risk Decomposition and ICAPM for US and Brazilian Stock Markets / Renato Dalla Colletta. - 2012.

70 f.

Orientador: João Filipe Bernardes Volkmann de Mendonça Mergulhão.

Dissertação (MPFE) - Escola de Economia de São Paulo.

1. Avaliação de riscos. 2. Mercado de capitais. 3. Risco (Economia). 4. Taxa de juros. I. Mergulhão, João de Mendonça. II. Dissertação (MPFE) - Escola de Economia de São Paulo. III. Título.

CDU 336.76

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Campo de conhecimento: Finanças

Data de aprovação:

Banca Examinadora

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DEDICATÓRIA

Ao meu tio, Ronuel Macedo de Mattos, sua vida foi meu exemplo de integridade e generosidade.

AGRADECIMENTOS

Agradeço ao Prof. Dr. Paulo Tenani pelo constante apoio ao meu desenvolvimento acadêmico e profissional, ao meu orientador Prof. Dr. João de Mendonça Mergulhão pelas sempre proveitosas discussões e a toda a minha família pelo suporte incondicional.

Agradeço a todos os colegas e professores do mestrado pelos dois anos de convívio enriquecedor e a todos os colegas da Pragma Patrimônio por sua colaboração durante esses anos. Agradeço especialmente ao João Paulo Improta por ceder os dados das carteiras de Fama-French para o Brasil utilizados nesse trabalho.

Agradeço ainda aos professores John Y. Campbell e Christopher Polk por seus atenciosos esclarecimentos que contribuíram para a elaboração desse trabalho.

RESUMO

Esse trabalho é uma aplicação do modelo intertemporal de apreçamento de ativos desenvolvido por Campbell (1993) e Campbell e Vuolteenaho (2004) para as carteiras de Fama-French 2x3 brasileiras no period de janeiro de 2003 a abril de 2012 e para as carteiras de Fama-French 5x5 americanas em diferentes períodos.

As varíaveis sugeridas por Campbell e Vuolteenaho (2004) para prever os excessos de retorno do mercado acionário americano no period de 1929 a 2001 mostraram-se também bons preditores de excesso de retorno para o mercado brasileiro no período recente, com exceção da inclinação da estrutura a termo das taxas de juros. Entretanto, mostramos que um aumento no *small stock value spread* indica maior excesso de retorno no futuro, comportamento que não é coerente com a explicação para o prêmio de valor sugerida pelo modelo intertemporal. Ainda, utilizando os resíduos do VAR preditivo para definir o risco de choques de fluxo de caixa e de choques nas taxas de desconto das carteiras de teste, verificamos que o modelo intertemporal resultante não explica adequadamente os retornos observados.

Para o mercado norte-americano, concluímos que a abilidade das variáveis propostas para explicar os excessos de retorno do mercado varia no tempo. O sucesso de Campbell e Vuolteenaho (2004) em explicar o prêmio de valor para o mercado norte-americano na amostra de 1963 a 2001 é resultado da especificação do VAR na amostra completa, pois mostramos que nenhuma das varíaveis é um preditor de retorno estatisticamente significante nessa sub-amostra.

Palavras-chave: modelo intertemporal, risco de taxa de desconto, risco de fluxo de caixa, Fama-French Brasil, VAR.

ABSTRACT

This work applies the intertemporal asset pricing model developed by Campbell (1993) and Campbell and Vuolteenaho (2004) to the Brazilian 2x3 Fama-French stock portfolios from January 2003 to April 2012 and to the US 5x5 Fama-French portfolios in dfferent time periods.

The variables suggested by Campbell and Vuolteenaho (2004) to forecast US market excess returns from 1929 to 2001 were also good excess return predictors for the Brazilian market on the recent period, except the term structure yield spread. However, we found that an increase in the small stock value spread predicts a higher market excess return, which is not consistent with the intertemporal model explanation for the value premium. Moreover, using the residuals of the forecasting VAR to define the test portfolios' cash flow and discount rate shock risk sensitivity, we found that the resulting intertemporal model explains little of the variance in the cross section of returns.

For the US market, we conclude that the proposed variables' ability to forecast market excess returns is not constant in time. Campbell and Vuolteenaho's (2004) success in explaining the value premium for the US market in the 1963 to 2001 sub-sample is a result of the VAR specification in the full sample, since we show that none of the variables are statistically significant return predictors in this sub-sample.

Keywords: intertemporal model, discount rate risk, cash flow risk, Fama-French Brazil, VAR.

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1. INTRODUCTION

This work applies the methodology developed in Campbell and Vuolteenaho (2004) to test an intertemporal asset pricing model for Brazilian and US stock market data on different time periods. The results presented here can be divided in three parts: first, we estimate and study a VAR system with variables that should be able to predict aggregate stock market returns. The residuals of this system are then used to calculate a decomposition of market returns into cash flow and discount rate shocks, finally the risk exposure of a set of test portfolios to each of these factors are determined and employed to estimate a specified intertemporal model.

In the original work of Campbell and Vuolteenaho (op.cit.), henceforth refered to as BBGB for short, the authors find that the intertemporal model could explain the value premium found in the US from 1963 to 2001 because value portfolios were more exposed to cash flow shock risk which carries a higher risk premium. Crucial to their achievement was the inclusion of the small stock value spread in the VAR system used to define shocks to the stock market return. Here we found that, even though a much smaller data history is available for Brazil, the same variable is also a statistically significant predictor of market returns from 2003 to April 2012. But the sign of the relationship is the opposite as the one found in the longer US sample. So, if the intertemporal model proposed here holds for Brazil, this finding suggests either that there is no consistent value premium for the Brazilian market or that Brazilian investors have a very low risk aversion coefficient.

All the results presented in BBGB for the US are based on cash flow and discount rate shock series calculated from a VAR determined using data from 1929 to 2001. The authors, however, then divide the asset pricing test in two sub-samples, from 1929 to 1963 and from 1963 to 2001, finding remarkably different results for each sample. Here we repeat their exercise but using each sample separately to determine the VAR and news series. Our main finding is that the predictability reported in the full sample VAR in BBGB is a result of the variables' behavior in the earlier sub-sample. No variable can predict market returns in the sub sample from 1963 to 2001, and the asset pricing models estimated using the news series defined using information uniquely from this period do not explain the value premium. Including more recent data up until 2012, the market return regains some predictability by past market excess returns, an effect of the stock market behavior during the 2008 crash as we show. These evidences relates to a recent work (SUBRAHMANYAM, 2012) which shows that the ability of a series of variables to explain the cross section of single stock returns change in time, therefore time series predictability of the aggregate market would also be time dependent.

In the next section a concise summary of asset pricing literature is provided, along with a brief review of the most cited works published for the Brazilian market. Section three is a full description of the intertemporal asset pricing model tested in the paper, detailing its assumptions and the construction of the variables used in the paper. It seeks to be self-contained and to provide background for the interpretation of the following results. Section 4

describes the data used. Section 5 reports the results of the market return forecasting VAR and section 6 describes the cash flow and discount rate news calculate from the VAR errors. The cash flow and discount rate betas for the test portfolios are calculated in section 7 and section 8 presents the asset pricing model tests. Section 9 concludes.

2.REVIEW

Risk based explanations for differences in the cross section of returns are the core of modern asset pricing theories since the initial empirical sucess of Sharpe's CAPM (SHARPE, 1964). Although not immune to criticism due to simplifying assumptions, both on theory level and on the empirical tests (ROLL, 1977), the CAPM started a rich research area. The idea of using investor's optimizing behavior to link asset prices to sources of systematic risk was first extended to a multiperiod setting in the seminal work of Merton (1973), where the author showed that correlations of prices with changes in the investment opportunity set should be responsible for a part of observable risk premia. Moreover, aggregating portfolio choices across homogeneous agents, an Intertemporal CAPM holds, showing that an asset should be rewarded not just for its exposure to market risk, but also for its behavior during unfavorable changes in the investment opportunity set.

Consumption based models offer a different approach to the pricing problem, relating risk premia to the assets' exposure to consumption risk (BREDEEN, 1979). However, Hansen and Singleton (1982) showed that the model based on standard power utility have a poor empirical performance. Later, Mehra and Prescott (1985) showed that the consumption model could not reproduce the observed equity risk premium for any usual level of risk aversion. The core issue is that agreggate consumption data used to estimate or calibrate the model is simply much less volatile than the stock market. So it would require an unusually high coeficient of risk aversion for the consumption risk to account for the observed stock market behavior (COCHRANE, 2008).

The CAPM also faced a famous rejection in the works of Fama and French (1992). They showed that for more recent data, market risk did not explain much of the observed cross section variation of returns. But adding to the model two long-short equity portfolios returns, constructed by sorting stocks by their market value and book-to-market ratio, would account for most of the risk premium in a large group of portfolios. Therefore, it would be necessary only to explain the risk factors behind the two Fama-French portfolios to have again a complete risk based model for asset pricing (COCHRANE, 2011).

Fama and French were the first to suggest that their two factors portfolios might correspond to intertemporal hedging portfolios in the spirit of Merton's ICAPM (FAMA, FRENCH, 1996) but they make no attempt to identify exactly what variables or changes in the investment set they are a hedge for: "...without knowing why, we have stumbled on explanatatory portfolios that are close to three-factor MMV(minimum-multifactor-variance).(...) We have not identified the two state variables of special hedging concern to investors that lead to three-factor asset pricing."(FAMA, FRENCH, 1996, p.76)). They

suggested, though, that high book-to-market companies are usually those which undergo severe difficulties when the market crashes, so their value is heavily discounted by investors but, on average, most of these companies recover well when conditions improve generating higher returns. The US data, however, display little correlation between the value factor returns and variables indicative of financial distress (COCHRANE, 2001). Lettau and Ludwigson (2001) show alternatively that, although the unconditional correlations are low, the conditional correlations are high during crises, so there is some merit to this explanation for the value premium. In a different argument, Heaton and Lucas (1997) proposed that the average American stock market investor was a small business owner or employee so the size and value factors might be a result of the risk of assets associated with the human wealth component of their portfolio. Small and value companies would be the better available proxy of their non-marketable income, so shorting these stocks is part of their minimum risk portfolio. Liew and Vassalou (1999) showed that the value and size factor portfolio returns could predict GDP growth in the US beyond the market portfolio return, providing an indication that these portfolios' behavior might be related to intertemporal considerations.

Further theoretical advances led to new testable versions both of the intertemporal and consumption asset pricing models. One particularly important breakthrough was the introduction of recursive utility function by Epstein and Zin (1989). This allowed the coefficient of risk aversion and the intertemporal elasticity of substitution to play distinct roles for asset pricing and became the standard framework for a series of models. Another important development was Campbell's alternative to handle the non-linear intertemporal budget constraint (CAMPBELL, 1993). Instead of linearizing it by taking decision time to continuous limit as Merton (1973), Campbell proposes a discrete time version of the intertemporal model where the consumption-wealth ratio is assumed constant. Coupled with Campbell and Shiller log-linearization of returns (1988), Campbell writes an expression for risk premia without consumption data, based only on the asset's systematic risk exposure to the future flow of the investors' wealth returns. Also, if one is able to identify variables that are linked to changes in the investment opportunity set so that they forecast returns as true risk factors, this framework generates an empirically testable version of the ICAPM for the cross section of returns.

One example of such a test was performed in Campbell and Vuolteenaho (2004). These authors employed Campbell-Shiller log-linearization to decompose market returns in a cash-flow shock and a discount rate shock component, so that market risk has, in fact, two different sources. It is argued that assets whose returns are positively correlated to discount rate shocks have intertemporal hedging value to investors with high risk aversion coefficient. The reasoning is that their prices go down in times when it's expected that discount rates will be higher and, therefore, other high yielding investments will be available; but their returns are high when other investment opportunities are expected to be unappealing. Assets highly exposed to cash-flow shocks, however, offer a risk without any intertemporal substituiton compensation, therefore this risk carries a higher premium. This division of market risk was successfull in explaining the value anomaly for post 1963 US data. Consistent with the ICAPM story, Campbell and Vuolteenaho point that the critical point behind their result was

the use of the small stock value spread (difference of book-to-market ratio for the extreme value small Fama-French portfolios) as a forecasting variable for market returns. If growth stocks offer intertemporal advantages, a higher spread should predict lower aggregate market returns, and that is precisely the behavior found in the US data.

Campbell and Vuolteenaho report in BBGB that, although discount rate sensitivity accounts for most of market risk in the portfolios they investigate, it was the small diferences in cash-flow betas that represented much of the cross section variation due to its larger risk premia. The same idea was used by Bansal, Dittmar and Lundblad (2004) in order to sucessfully rehabilitate the empirical validity of the consumption model. They use a VARMA system to evaluate simultaneously dividends and personal consumption growth shocks. But instead of employing aggregate market dividend data, Bansal et. al. estimate each portfolio's dividend growth shock individually, so they can calculate their consumption cash flow beta following Breeden's C-CAPM (op. cit.). These betas fit surprisingly well the cross section premiuns of 30 portfolios sorted by size, value and momentum, with R^2 over 0.6. Further, adding the Fama-French factors SMB and HML did not improve the performance of their model. They argue that time-varying discount rates hide the volatility of each individual portfolio consumption beta, therefore focusing in its cash-flow component results in a much better cross sectional fit. In contrast to Campbell and Vuoteenaho, Bansal et. al. focus on modelling the growth dynamics directly rather than searching for return forecasting variables and rellying on a residual approach to define shocks (BANSAL et. al. 2004).

More recently, Bansal, Kiku, Shaliastovich and Yaron (2012) argue that in a theoretical model based on intertemporal recursive utility function, assuming that the stochastic discount factor and wealth portfolio returns are jointly homoskedastic, as in Campbell (1993), the effect of volatility shocks are not considered by the resulting model, but they actually have major implications for asset pricing. Working with model calibration and a VAR-based shock estimation approach as in BBGB they draw a couple of important conclusions about the data fitting behavior of such models. First, in the homoskedastic model consumption volatility is directly proportional to the wealth portfolio discount rate news. As market and human wealth discount rate news are much more volatile than consumption data, any attempt to calibrate the model will lead to an artificially negative correlation between the two, not the behavior observed in data. The inclusion of the volatily shock corrects this, making the estimate and calibrated series parameters consistent with data. Second, in both versions of the model they work with, it is the cash-flow risk and volatility risk that account for all of the observed equity risk premium; discount rate risk, although more volatile, has virtually no contribution to risk premia also on the heteroskedastic model. Moreover, they propose a volatilty based dynamic CAPM which has a R^2 of 0.96 in the cross section of test portfolios. Their model also imply a value premium of 6.1% and size premium of 6.8% and a positive compensation for volatility risk for all assets in the sample.

For the Brazilian market, asset pricing tests have a much shorter history and the evidences found are much more debatable. To our best knowledge, most works published in the area do not use data from before 1995, claiming that sources are unrealiable and that such data are distorted due to macroeconomic and financial instability (MUSSA et. al., 2011).

Málaga and Securato (2004) found evidence that the 3-factor Fama-French model is superior to the standard CAPM in explaining the cross section of returns in sample, although the size and value premia are not statistically different from zero from 1995 to 2003. Incorporating data up to 2007, Rogers and Securato (2009) also report the superiority of the Fama-French factor for the description of 25 Fama-French portfolios cross section returns in sample, but in their work the value premium is not significant while the size premium plays an important role.

Using the Fama and MacBeth(1973) procedure for pricing model testing with data from 1995 to 2007, Mussa, Rogers and Securato (2009) found, contrary to the evidence of ordinary in-sample test, that the value premium is relevant while the size premium is not. In both studies, they exclude financial services companies from their sample before building the Fama-French portfolios because these are highly levereged which distorts the meaning of book-to-market ratio (MUSSA et. al. op.cit.). However, such a procedure is not commonly adopted in international literature. Finaly, Mussa, Securato, Santos and Famá (2011), test the 4-factors (including momentum) significance splitting the sample (1995 to 2007) in positive and negative market premium periods and tigh and loose monetary policy periods. While whole sample evidence suggests a significant value premium but no size or momentum effects, when the market is low the size premium is high and significant and there is no value premium and momentum. For high market period, value and size are importants, but momentum returns are still zero. For tight monetary policy periods, only value returns are significant. For loose policy periods, no factor has significant return.

3.MODEL DESCRIPTION

3.1 Intertemporal asset pricing with no consumption data

The intertemporal asset pricing model tested in this work was proposed by Campbell and Vuolteenaho (2004) and its main theoretical foundations were laid out by Campbell (1993). The following exposition, based on the works cited above, seeks to clear up the assumptions on which the model is based and to offer possible interpretations for the test results.

The first approach of the intertemporal asset allocation problem by Merton (1973) was to solve its exact version assuming instantaneously continuous stochastic processes for the returns and evolution of investment oportunities and an arbitrary utility function. Although rich in insights about optimal portfolio construction and intertemporal behavior, the ICAPM derived there would require prior knowledge of especific changes in the investment oportunity set (risk factors) and its instantaneous correlations with the assets returns to be tested somehow. Campbell (1993) constructs a more workable, discrete-time version of the model using two building blocks: a log-linearized version of the intertemporal budget constraint and Epstein-Zin recursive utility to substitute out consumption from the model.

Consider that W_t, the representative investor's wealth (including human wealth, assumed tradable in principle), is invested in the market portfolio with return $R_{m,t+1}$ so that the budget constraint is:

$$W_{t+1} = R_{m,t+1}(W_t - C_t) \qquad (3.1)$$

Solving (3.1) forward, it becomes clear that the relation between wealth and consumption depends on a non-linear composition of future returns:

$$W_t = C_t + \sum_{i=1}^{\infty} \frac{C_{t+i}}{\prod_j^i R_{m,t+j}} \qquad (3.2)$$

To avoid this complication, Campbell proposes a log linearized version of the constraint, using a first order Taylor expansion of the log of expression (3.1) around a mean level for the consumption-wealth ratio:

$$\Delta w_{t+1} \cong r_{m,t+1} + k + \left(1 - \frac{1}{\rho}\right)(c_t - w_t) \qquad (3.3)$$

where low-case letters denote log-variables and ρ is a linearization constant, equal to the savings ratio when consumption-wealth ratio is exactly constant. Solving (3.3) forward results now in a simple, linear expression relating wealth and consumption to future portfolio returns and the consumption growth path:

$$c_t - w_t = \sum_{j=1}^{\infty} \rho^j \left(r_{m,t+j} - \Delta c_{t+j}\right) + \frac{\rho k}{1-\rho} \qquad (3.4)$$

Eq. (3.4) is simply a decomposition (approximate to the first order) of the budget constraint, therefore it holds ex-post but also ex-ante if one takes expectations:

$$c_t - w_t = \qquad E_t \sum_{j=1}^{\infty} \rho^j \left(r_{m,t+j} - \Delta c_{t+j}\right) + \frac{\rho k}{1-\rho} \qquad (3.5)$$

Just by virtue of the budget constraint, with no optimal behavior assumptions, eq. (3.5) implies that a higher consumption-wealth ratio today must be a result of either expectation of higher future returns or lower future consumption growth. The same conclusion would follow if one uses eq. (3.5) one step ahead to calculate the expression for consumption surprises:

$$c_{t+1} - E_t c_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j r_{m,t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \Delta c_{t+1+j} \qquad (3.6)$$

Next, Campbell (op.cit.) uses a Epstein-Zin (1989) recursive utility function to derive an asset pricing Euler equation, and, by applying it to the wealth portfolio, to obtain an expression for consumption growth in eq. (3.5) as function of future aggregate market returns. This utility function offers the advantage of giving different roles to the risk aversion and the intertemporal elasticity of substitution, allowing for intertemporal considerations to have a richer role in asset pricing (Campbell, op.cit.). Following his notation, the utility function is given by:

$$U_t = \left[(1-\beta)C_t^{1-\frac{1}{\sigma}} + \beta\left(E_t U_{t+1}^{1-\gamma}\right)^{\frac{1-\frac{1}{\sigma}}{1-\gamma}}\right]^{\frac{1}{1-\frac{1}{\sigma}}} \qquad (3.7)$$

where γ is the coefficient of relative risk aversion, σ is the intertemporal elasticity of substitution and β is the subjective time discount factor. When $\gamma = \sigma^{-1}$ (3.7) becomes the standard power utility function and when γ = σ = 1, (3.7) becomes the time-separable log utility function. To price any asset, an investor demands a return so that his loss of consumption today will be optimally rewarded by the expected improvement in future consumption, leading to the following one-period Euler equation:

$$E_t\left[\beta \frac{\partial U_t}{\partial c_{t+1}} \Big/ \frac{\partial U_t}{\partial c_t} . R_{i,t+1}\right] = 1 \qquad (3.8)$$

The wealth portfolio return defined in eq. (3.1) helps to simplify the lenghty expression that appears on the derivatives of eq. (3.8). Noting that the wealth portfolio is the one that pays the optimized consumption as dividends in each period, from eq. (3.8) one can show that wealth satisfies:

$$W_t = \frac{U_t}{\frac{\partial U_t}{\partial c_t}} \qquad (3.9)$$

Using (3.9) in (3.1) allows one to solve for the complicated expression that result from the derivatives calculation in eq. (3.8) in terms of wealth returns, resulting in a simple looking expression for asset returns:

$$E_t\left[\left[\beta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\sigma}}\right]^{\theta}\left(\frac{1}{R_{m,t+1}}\right)^{1-\theta} R_{i,t+1}\right] = 1 \qquad (3.10)$$

where $\theta=(1-\gamma)/(1-\sigma^{-1})$ is so defined for simplicity. This Euler equation is valid for the wealth portfolio itself, resulting in:

$$E_t\left[\left[\beta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\sigma}} R_{m,t+1}\right]^{\theta}\right] = 1 \qquad (3.11)$$

Expression (3.10) is the basis of the asset pricing model developed by Campbell (1993). In order to derive a testable model without consumption data two further assumptions are made: that asset returns and consumption growth are jointly homoskedastic and lognormally distributed. Actually, the lognormal assumption can be droped and the same

result in eq (3.12) would be obtained if one worked with a second order aproximation for the expectation using the actual distribution. But the homoskedastic assumption is crucial to obtain the pricing equation without consumption data. Using the familiar relationship between the expected value of a lognormal variable and the mean and variance of its log (or a second order aproximation for the expectation given its true probability distribution), equation (3.11) rewrites as:

$$\theta ln\beta - \frac{\theta}{\sigma}E_t\Delta c_{t+1} + \theta E_t r_{m,t+1} + \frac{1}{2}\left[\left(\frac{\theta}{\sigma}\right)^2 \sigma_{cc}^2 + \theta^2\sigma_{mm}^2 - \frac{2\theta^2}{\sigma}\sigma_{cm}\right] = 0 \quad (3.12)$$

where σ^2_{cc} is $Var_t(\Delta c_{t+1})$, σ^2_{mm} is $Var_t(r_{m,t+1})$ and σ_{cm} is $Cov_t(\Delta c_{t+1}, r_{m,t+1})$. With the homoskedastic assumption, a linear relationship between expected consumption growth and expected market returns is derived rearranging terms in eq. (3.12):

$$E_t\Delta c_{t+1} = \mu_{m,t+1} + \sigma E_t r_{m,t+1} \quad (3.13)$$

A higher IES makes the agent postpone consumption when expecting higher returns in his portfolio, increasing the consumption growth. The constant in eq. (3.13) is given by:

$$\mu_{m,t+1} = \sigma ln\beta + \frac{1}{2}\left[\left(\frac{\theta}{\sigma}\right)\sigma_{cc}^2 + \theta\sigma\sigma_{mm}^2 - 2\theta\sigma_{cm}\right]$$
$$= \sigma ln\beta + \frac{1}{2}\left(\frac{\theta}{\sigma}\right)Var_t\left[\Delta c_{t+1} - \sigma r_{m,t+1}\right] \quad (3.14)$$

This relationship shows that a bigger uncertainty about the hability of the market portfolio to pay for future consumption also makes the agent to spend less today if $\theta>1$ (high risk aversion coupled with high IES). Assuming further that consumption growth and any asset returns are jointly homoskedastic and log-normally distributed, the same simplification can be applied to eq. (3.10) generating an expression for expected returns:

$$\theta ln\beta - \frac{\theta}{\sigma}E_t\Delta c_{t+1} + (\theta-1)E_t r_{m,t+1} + E_t r_{i,t+1} + \frac{1}{2}\left[\left(\frac{\theta}{\sigma}\right)^2 \sigma_{cc}^2 + (\theta-1)^2\sigma_{mm}^2 + \sigma_{ii}^2 - \frac{2\theta}{\sigma}(\theta-1)\sigma_{cm} - \frac{2\theta}{\sigma}\sigma_{ic} + 2(\theta-1)\sigma_{im}\right] = 0 \quad (3.15)$$

In order to simplify this lenghty expression we supose the existence of a real risk free asset, whose return is somewhat simplified by the non-existence of some variances and covariances:

$$\theta ln\beta - \frac{\theta}{\sigma}E_t\Delta c_{t+1} + (\theta-1)E_t r_{m,t+1} + E_t r_{f,t+1} + \frac{1}{2}\left[\left(\frac{\theta}{\sigma}\right)^2 \sigma_{cc}^2 + (\theta-1)^2\sigma_{mm}^2 - \frac{2\theta}{\sigma}(\theta-1)\sigma_{cm}\right] = 0 \quad (3.16)$$

Therefore, one can simplify (3.15) by writting the expression for excess returns:

$$E_t r_{i,t+1} - r_{f,t+1} = -\frac{1}{2}\sigma_{ii}^2 + \frac{\theta}{\sigma}\sigma_{ic} + (1-\theta)\sigma_{im} \quad (3.17)$$

The asset's return volatility in eq. (3.17) is a Jensen inequality term that is supressed if the expression is rewritten in simple returns. The two additional terms describe a constant risk premium (a result of homoskedastic assumption) as function of the asset's return covariance with the market and with consumption growth. When θ=1 (time separable power utility case), the market covariance drops out and it results in the Consumption CAPM tested by Hansen and Singleton (1983). When risk aversion is 1 (θ=1), the model colapses to the ordinary CAPM. If θ goes to infinity, i.e. σ = 1 and the coefficient of relative risk aversion is not unity, only the market covariance term will survive too, making the premium expression "myopic". This is because substitution effect exactly balances the income effect when IES is 1. To see this, use expression (3.13) to substitute out consumption growth expectation sin eq. (3.5):

$$c_t - w_t = (1-\sigma)E_t \sum_{j=1}^{\infty} \rho^j r_{m,t+j} + \frac{\rho(k-\mu_m)}{1-\rho} \qquad (3.18)$$

When IES > 1, substitution effect is dominant, the investor is more willing to substitute intertemporally and reduces present consumption at the antecipation of higher future returns. When IES < 1 income effect dominates and consumption rises when higher future returns are expected. If IES = 1 both effects are balanced and the consumption wealth ratio is exactly constant.

Finally, to obtain the expression for risk premia without consumption data, we use (3.13) again to recalculate the expression for consumption shocks (3.6) as a function of market returns only:

$$c_{t+1} - E_t c_{t+1} = r_{m,t+1} - E_t r_{m,t+1} + (1-\sigma)(E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{m,t+1+j} \qquad (3.19)$$

In the simplified homoskedastic log-normal model consumption shocks can be expressed as two components: shocks in market returns and shocks in expected future market returns. With this decomposition, the consumption covariance that appears in eq. (3.17) can be calculated in terms of aggregate market returns:

$$\sigma_{ic} = Cov_t\left(r_{i,t}, \Delta c_{t+1}\right) = E_t\left[\left(r_{i,t} - E_t r_{i,t}\right)\left(c_{t+1} - E_t c_{t+1}\right)\right] = \sigma_{im} + (1-\sigma)\sigma_{ih} \qquad (3.20)$$

Where σ_{ih} is the covariance of asset's i return with future expected shocks to the market returns:

$$\sigma_{ih} = Cov_t\left(r_{i,t}, (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{m,t+1+j}\right) \qquad (3.21)$$

With (3.21) and (3.17), substituting the definition of θ, it is possible to obtain the expression for the risk premium of any asset without consumption data:

$$E_t r_{i,t+1} - r_{f,t+1} + \frac{1}{2}\sigma_{ii}^2 = \gamma\sigma_{im} + (\gamma - 1)\sigma_{ih} \qquad (3.22)$$

Campbell (1993) interprets eq. (3.22) as a discrete time analog of Merton's ICAPM (1973) since it relates an asset expected return with its covariance with market retunrs and its covariance with changes in the investment opportunity set. In this model, it was postulated that the market pays exactly the desired consumption for the invested wealth in each period, so for a high risk averse agent ($\gamma > 1$), an asset that offers higher returns when expectations of future market returns deteriorate ($\sigma_{ih} < 0$) is desirable because it allows the investor to sustain his optimum consumption growth path in this adverse situation. Therefore, an optimizing investor demands a lower risk premium to hold such an asset. If, however, the agent has a low risk aversion ($\gamma < 1$) he would prefer an asset that pays him more when there are better prospect for future market returns ($\sigma_{ih} > 0$) so that he can profit from the possibility to invest more in an environment of higher returns. When using this model for cross sectional tests it is important to mind that the influence of the intertemporal hedging effect depends on the magnitude of the aggregate risk aversion.

Again with the assumption that the assets returns are log-normally distributed, equation (3.22) assumes a simpler form with the left-hand side expressed in simple returns, and the conditional expectation can be substituted by the unconditional one from the homoskedastic assumption:

$$E[R_i - R_f] = \gamma\sigma_{im} + (\gamma - 1)\sigma_{ih} \qquad (3.23)$$

This equation will be used in a cross sectional test for a series of portfolios. In this tests it is important to consider that the market return used to derive this model is that of a portfolio in which total wealth is invested and whose return should be equal to the aggregate consumption at each period. Therefore, the use of a stock market index as a representative of this market portfolio should be understood as a simple proxy, subject to the similar criticism the traditional CAPM tests as pointed by Roll (1977). More recent works use, instead, a portfolio formed by a fixed proportion of stock market and labor income (Bansal et. al. 2012).

3.2 Cash-flow news and discount rate news

To evaluate the intertemporal term in the right hand side of (3.23) this work uses the procedure by Campbell and Vuolteenaho (2004). It follows the ideia first outlined by Campbell (1993) of using a return forecasting VAR to define the shocks to market portfolio returns at each period and then calculate the assets covariance with this shocks. The novelty in Campbell and Vuolteenaho (op.cit.) is the interpretation of the covariances in equation (3.23) as a decomposition of an asset's CAPM beta with market returns. They use Campbell-Shiller (1988) log linearization of returns to derive an identity exactly analogous to (3.6) for market returns, assuming small deviations from an average level of price-dividend ratio:

$$r_{t+1} - E_t r_{t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t)\sum_{j=1}^{\infty}\rho^j r_{t+1+j} \quad (3.24)$$

where Δd_{t+1} is the log dividend growth of the market portfolio and ρ is a log-linearization constant, analogous to the one in eq. (3.3). The content of this identity is straighforward to interpret: surprises in market returns should be caused either by higher than expected dividends or lower than expected future returns given that price-dividend ratio is approximately constant. Campbell and Vuolteenaho (op.cit.) identify each of these terms as a cash-flow news and a discount rate news series:

$$N_{CF,t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} \quad (3.25)$$

$$N_{DR,t+1} = (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j} \quad (3.26)$$

Campbell and Vuolteenaho (op.cit.) suggest using the following market beta estimator to analyse portfolios exposure to each source of market risk:

$$\beta_{i,m} = \frac{Cov\left(r_{i,t}, r_{m,t} - E_{t-1} r_{m,t}\right)}{Var\left(r_{m,t} - E_{t-1} r_{m,t}\right)} \qquad (3.27)$$

This estimator is different from the traditional CAPM ordinary least square regression estimator for betas. It is motivated first by the return decomposition (3.24) and second because it is given a natural interpretation by the intertemporal model as expressed in equation (3.23). One should note that the discount rate news term is exactly the expression whose covariance with returns appears in the intertemporal hedging term in this equation. Substituting market return shocks by its components:

$$\beta_{i,m} = \frac{Cov\left(r_{i,t}, N_{CF,t} - N_{DR,t}\right)}{Var\left(N_{CF,t} - N_{DR,t}\right)} = \beta_{i,CF} + \beta_{i,DR} \qquad (3.28)$$

$$\beta_{i,CF} = \frac{Cov\left(r_{i,t}, N_{CF,t}\right)}{Var\left(N_{CF,t} - N_{DR,t}\right)} \qquad (3.29)$$

$$\beta_{i,DR} = \frac{Cov\left(r_{i,t}, -N_{DR,t}\right)}{Var\left(N_{CF,t} - N_{DR,t}\right)} \qquad (3.30)$$

Taking these definitions in the asset pricing equation (3.23) and assuming that the market portfolio is a good proxy of the wealth portfolio, results in:

$$E\left[R_i - R_f\right] = \gamma Cov\left(r_{i,t+1}, r_{m,t+1} - E_t r_{m,t+1}\right) + (\gamma - 1) Cov\left(r_{i,t+1}, -N_{DR,t+1}\right)$$

$$E\left[R_i - R_f\right] = \gamma \sigma_{m,t}^2 \cdot \beta_{i,CF} + \sigma_{m,t}^2 \cdot \beta_{i,DR} \qquad (3.31)$$

Thus, acording to the intertemporal model proposed, cash-flow risk exposure of an asset should have a risk premium γ times higher than the risk premium for discount rate risk. The explanation proposed by Campbell and Vuolteenaho (2004) is that when discount rates have a negative shock, assets with a high discount rate risk exposure offer a higher return precisely in a moment when expectations of future returns have worsened, so they are valued by investors as intertemporal hedging assets. Assets with high cash-flow beta, on the other hand, are not related to any change in the investment opportunity set, so they go up when there are positive dividend news, go down when the news are negative and offer no intertemporal advantage for the investor to compensate for this risk.

In order to define the shocks for market returns, Campbell and Vuolteenaho (2004) use a first order VAR system with market excess return as the first component and add other *m* state variables that might help predict returns:

$$z_{t+1} = a + \Gamma z_t + u_{t+1} \qquad (3.32)$$

where u_{t+1} is a iid vector of shocks, a is m-by-1 vector of constants and Γ is the m-by-m transition matrix. Defining $e1$ as a m-by-1 vector with 1 in the first component and zeros in all others, the market return at any period can be extracted from the the VAR as:

$$r_{m,t+1+j} = e1'(\mathbb{I} - \Gamma)^{-1}(\mathbb{I} - \Gamma^{j+1})a + e1'\Gamma^j z_t + e1'\sum_{k=0}^{j}\Gamma^{j-k}u_{t+1+k} \qquad (3.33)$$

Using (3.33) and iterated expectations it is clear that only the error terms in u_{t+1} survive in calculating the discount rate news:

$$N_{DR,t+1} = (E_{t+1} - E_t)\sum_{j=1}^{\infty}\rho^j r_{t+1+j} = \sum_{j=0}^{\infty} e1'\rho^j\Gamma^j u_{t+1} = e1'\rho\Gamma(\mathbb{I} - \Gamma)^{-1}u_{t+1}$$
$$= e1'\lambda u_{t+1} \qquad (3.34)$$

Where $\lambda = \rho\Gamma(I - \Gamma)^{-1}$ captures the long run effect of each state variable shock to the discount rate expectations. Using (3.34) in the identity (3.24) one can determine the cash-flow news series without using dividend growth data:

$$N_{CF,t+1} = (e1' + e1'\lambda)u_{t+1} \qquad (3.35)$$

The series so defined are the used to determine the cash-flow and discount rate betas of a series of portfolios which can be used for testing the intertemporal asset pricing model defined by equation (3.31).

4. DATA DESCRIPTION

In order to define the discount rate and cash-flow news series the present work employs the forecasting VAR suggested by Campbell and Vuolteenaho (2004). The variables they chose proved to be statistically significant return predictors for the American market in the sample from 1929 up to 2001 and also sucessfull in accounting for the cross section

behavior of risk premia. The related work of Chen (2003), for instance, using a very similar methodology found no evidence of intertemporal hedge effect in growth stocks even though their variables also yielded a well adjusted time series model for returns.

The first component of the VAR used in this work is the monthly market excess return. It is defined as the difference of the monthly log stock market aggregate return and the log return of the risk free rate. Although not highly persistent, Campbell and Vuolteenaho found a small momentum effect in this variable. Next, they include the yield spread on long and short term sovereign debt. It is measured in percentage points. The term spread is supposed to track the business cycle and so it might help explaining returns in large samples. For constant earnings, a higher price-earnings ratio should indicate lower future returns so a smoothed ratio, to account for quarterly earnings volatility, should aggregate predictive power to the VAR system. It is measured as the end of month price level of aggregate stock market index devided by a trailing moving average of reported earnings per share of stocks in the index. The last variable is the small stock value spread, considered a key factor for the sucessfull cross sectional results in Campbell and Vuolteenaho (op.cit.). The reason it should forecast market returns follows directly from an ICAPM argument: if growth stocks do offer an intertemporal hedging advantage for investors, a higher spread indicates lower expected future returns. The construction of this variable is discussed bellow.

For the US, data from the original work of Campbell and Vuolteenaho (op.cit.) is available at the online appendix at American Economic Review website from December 1928 to December 2001. Their excess log market return (RMe) is calculated from CRSP stock market index and 3 month treasury bill rate. As yield spread (YS) they use data provided by Global Financial Data of the yield on ten-year constant maturity government bonds minus the yield on short term notes. The smoothed price-earnings (PE) is constructed by dividing the price of S&P 500 index by the 10 year moving average of quarterly aggregate earnings of companies in the index. The variable used is the log of this ratio. The small stock value spread (VS) uses data of Fama-French factor portfolios available at professor's Kenneth French website. In June of year t, VS is the difference of the log book-to-market ratio of the small high Fama-French portfolio and the log of the same ratio for the small low Fama-French portfolio. From July of year t to may year t+1, VS is constructed by adding the cumulative log return (since June) of the small low portfolio and adding the cummulative return of the small high portfolio to the VS of June.

To extend US data until April 2012 the following was adopted. From January 2002 to April 2012, RMe is the log return of the S&P 500 index minus the log return of 3-month treasury bill available from Bloomberg. YS is the difference, in percentage points, of the yield on 10 year constant maturity US sovereign bond and the yield on 1 year treasury note, both series available from Bloomberg. PE and VS were calculated exactly as described above, with S&P 500 data from Bloomberg and Fama-French portfolio data from professor's French website. A comparison of the extended series and the original ones in the longest available overlapping period shows the correlations are all above 0.9. Table 1 contains the statistical description of the full series.

Table 1: Descriptive statistics of the VAR state variables – US data – 1929-2012

Variables	Mean	Median	Stdev.	Min	Max	Autocorr.
RMe	0.004	0.009	0.055	-0.344	0.322	0.112
YS	0.811	0.600	0.885	-1.350	3.786	0.947
PE	2.869	2.865	0.355	1.501	3.891	0.991
VS	1.634	1.517	0.358	1.192	2.713	0.991
Correlations	RMe,t+1	YS,t+1	PE,t+1	VS,t+1		
RMe,t+1	1.000	0.043	-0.009	-0.030		
YS,t+1	0.043	1.000	-0.158	0.241		
PE,t+1	-0.009	-0.158	1.000	-0.324		
VS,t+1	-0.030	0.241	-0.324	1.000		
RMe,t	0.112	0.045	0.076	-0.033		
YS,t	0.045	0.947	-0.152	0.237		
PE,t	0.076	-0.152	0.991	-0.322		
VS,t	-0.033	0.237	-0.322	0.991		

Notes: Descriptive statistics of state variables included in the VAR system estimated from the period of december 1928 to april 2012 with monthly sampled data. RMe is the log excess market return calculated from CRSP (1928 to 2001) and S&P 500 (2001 to 2012) indices and three month treasury bill rates. YS is the difference, in percentage points, of yields on 10 year US sovereign bonds and 1 year treasury note. PE is the log smoothed price-earnings ratio of S&P 500 index. VS is the small stock value spread calculated as described in text.

The data available for Brazilian market spans a much shorter period. Most works in the asset pricing only consider stock market data post 1995 because data prior to this period are distorted by macroeconomic instability. Others only use data post 1999 to avoid the fixed exchange rate regime and the market crash that followed its demise. The main difficulty for the Brazilian market, however, was not related to the stock market data, but to the sovereign bond data used to calculate the yield spread. The first Brazilian government bond with 10 years to maturity was issued in 2007, the same year that standardized fixed rate interest swaps (Swap Pré-DI) with 10 year term started to be traded in BMF. Therefore, in order to build the yield spread variable, we used the BMF standardized fixed interest swap rate with 5 years to maturity as the reference long term rate, and the 1 year fixed interest swap rate as the short term rate. YS was calculated as the difference of these rates, in percentage points. RMe is calculated as the difference of the log return on the IBrX index and the BMF 1 month fixed interest swap monthly rate. Aggregate earnings for the IBrX index is only readily available quarterly from 1Q 2001 in the databases of Bloomberg and the consulting company Economática. It would be prohibitive to use a 10 year trailling moving average to smooth price earnings ratio as in Campbell and Vuolteenaho (op.cit.) with such a short series. We opted instead to employ a two year trailling moving average of reported earnings to calculate the PE variable. It could be argued that Brazilian market was still developing in the sample period and that investors would use a shorter past period as a reference of average earnings. However, it is the statistical significance of the variable constructed this way as an excess return predictor in the VAR system that should ultimately validate this choice.

The small stock value spread was calculated exactly as proposed by Campbell and Vuolteenaho (op.cit.). In order to do so, it was necessary to use returns of the 2x3 Fama-French portfolios build for the Brazilian stock market. A description of the portfolios' construction is available on appendix A5. Table 2 shows descriptive statistics for the full sample of Brazilian data used in the VAR, from January 2003 to April 2012. For comparison, table 3 shows the same statistics for the US data in the same period. The mean, standard deviation and autocorrelation of the variables for American and Brazilian data are remarkably similar in the recent period. Yield spread, while smaller on average for Brazil, has much fatter tails, an effect of wild variations in interest rates from 2003 to 2005. As a result, yield spread is negatively correlated with market excess returns in Brazil. The most important change that can be noted for the US is the increase in excess return autocorrelation for the recent sample.

Table 2: Descriptive statistics of the VAR state variables - Brazil data 2003-2012

Variables	Mean	Median	Stdev.	Min	Max	Autocorr.
RMe	0.006	0.009	0.066	-0.301	0.154	0.171
YS	0.837	0.709	2.768	-4.230	14.130	0.867
PE	2.611	2.637	0.168	2.158	2.917	0.918
VS	1.426	1.540	0.334	0.732	2.099	0.893
Correlations	RMe,t+1	YS,t+1	PE,t+1	VS,t+1		
RMe,t+1	1.000	-0.166	0.227	0.103		
YS,t+1	-0.166	1.000	0.090	-0.025		
PE,t+1	0.227	0.090	1.000	0.278		
VS,t+1	0.103	-0.025	0.278	1.000		
RMe,t	0.171	-0.160	0.288	0.169		
YS,t	-0.160	0.867	0.117	-0.047		
PE,t	0.288	0.117	0.918	0.244		
VS,t	0.169	-0.047	0.244	0.893		

Notes: Descriptive statistics of state variables included in the VAR system estimated from the period of January 2003 to April 2012 with monthly sampled data. RMe is the log excess market return calculated from IBrX index and 1 month BMF swap Pre-DI fixed interest rate. YS is the difference, in percentage points, of yields on 5 years and 1 year BMF swap pré-DI rate. PE is the log smoothed price-earnings ratio of IBrX index. VS is the small stock value spread calculated as described in text.

In this work we follow Campbell and Vuolteenaho (2004) and assume all the variables are stationary. Rigorously, the simple VAR system described in eq. (3.32) can only be estimated if this condition is satisfied. Unit root tests, however, have typically low power (BUENO, 2012). It is usual to relly in the economic content of each variable to assert it is stationarity rather than relying on low power tests (COCHRANE, 1991).

Table 3: Descriptive statistics of the VAR state variables - US data 2003-2012

Variables	Mean	Median	Stdev.	Min	Max	Autocorr.
RMe	0.006	0.012	0.046	-0.186	0.115	0.237
YS	1.995	2.276	1.277	-0.564	3.786	0.970
PE	2.852	2.877	0.160	2.310	3.115	0.961
VS	1.502	1.497	0.148	1.232	1.875	0.947
Correlations	RMe,t+1	YS,t+1	PE,t+1	VS,t+1		
RMe,t+1	1.000	0.019	0.024	-0.083		
YS,t+1	0.019	1.000	0.010	0.569		
PE,t+1	0.024	0.010	1.000	-0.623		
VS,t+1	-0.083	0.569	-0.623	1.000		
RMe,t	0.237	0.054	0.285	-0.128		
YS,t	0.054	0.970	0.021	0.528		
PE,t	0.285	0.021	0.961	-0.606		
VS,t	-0.128	0.528	-0.606	0.947		

Notes: Descriptive statistics of state variables included in the VAR system estimated from the period of January 2003 to April 2012 with monthly sampled data. RMe is the log excess market return S&P 500 indices and three month treasury bill rates. YS is the difference, in percentage points, of yields on 10 year US sovereign bonds and 1 year treasury note. PE is the log smoothed price-earnings ratio of S&P 500 index. VS is the small stock value spread calculated as described in text.

5.FORECASTING VAR RESULTS

Table 4 shows coeficients and standard erros of the VAR equations for the full sample of US data. We report OLS standard errors as well as standard errors calculated by a bootstrap method following Campbell and Vuolteenaho's (op.cit.) procedure described in appendix A1. Results for the full sample, as expected, are similar to those reported in the original paper (see appendix A1) for the 1929-2001 sample with one striking difference: the yield spread is not statistically significant in the longer sample, assuming a 5% confidence level. This highlights that recent trends in data might have important implications for the results reported in the original paper. In a first check to determine if this change was caused by a structural break in data due to the financial crash of 2008, the same system was estimated extending the sample only up to december 2007. Results reported in appendix A4 show that even before the outbreak of the financial crisis and the extraordinary monetary policy acommodation that followed, the yield spread had already lost significance due to the inclusion of the five years period from 2002 to 2007.

To investigate further the changes in the predictive behavior of the variabes chosen for the US and how they might affect the the cash-flow and discount rate news series, we propose to split the full sample into two sub-samples each containing the same number of observations and estimate the VAR separetly for each. Such procedure was not used in the Campbell's and Vuolteenaho's work (op.cit.). They estimate the asset pricing models in two different periods and report time evolution of betas estimated in a three-year rolling window in their appendix but all based on news series calculated using the full sample VAR. There is, however, recent

literature (SUBRAHMANYAM, 2012) claiming that variables that could predict short term returns at individual stock level in the past are no longer significant predictors in the more recent period. If such phenomenon is also true for the aggregate market price, it could be reflected in the results of the VAR system we estimate.

Each sub-sample contains 499 monthly data points and covers the periods from 1928:12 to 1970:06 and from 1970:06 to 2011:12. The VAR results for each period are reported in table 5 and table 6. In the first sub-period, all the variables included except the yield spread were significant stock market excess return predictors, with the same sign as those reported in the full sample VAR. Plus, in the earlier period, market returns helped to predict future price-earnings and the small stock value spread helped to predict yield spreads.

Table 4: VAR for US data - full sample

	Constant	RMe(t)	YS(t)	PE(t)	VS(t)	R2	F
RMe(t+1)	0.064*	0.108*	0.002	-0.016*	-0.009**	0.024	6.12
	(0.019)	(0.031)	(0.002)	(0.005)	(0.005)		
	[0.024]	[0.031]	[0.002]	[0.006]	[0.007]		
YS(t+1)	0.010	0.066	0.940*	-0.013	0.047	0.896	2133.71
	(0.101)	(0.166)	(0.011)	(0.027)	(0.027)		
	[0.122]	[0.167]	[0.012]	[0.033]	[0.037]		
PE(t+1)	0.027*	0.555*	0.000	0.991*	-0.002	0.989	22532.58
	(0.013)	(0.022)	(0.001)	(0.004)	(0.004)		
	[0.017]	[0.022]	[0.002]	[0.004]	[0.005]		
VS(t+1)	0.019	-0.017	-0.001	-0.001	0.991*	0.982	13857.04
	(0.017)	(0.028)	(0.002)	(0.004)	(0.005)		
	[0.022]	[0.027]	[0.002]	[0.006]	[0.007]		
	corr/std	RMe(t)	YS(t)	PE(t)	VS(t)		
	RMe(t)	0.054	0.021	0.686	-0.055		
		[0.002]	[0.044]	[0.038]	[0.047]		
	YS(t)	0.021	0.284	-0.042	-0.014		
		[0.044]	[0.014]	[0.070]	[0.031]		
	PE(t)	0.686	-0.042	0.037	-0.082		
		[0.038]	[0.070]	[0.002]	[0.042]		
	VS(t)	-0.055	-0.014	-0.082	0.047		
		[0.047]	[0.031]	[0.042]	[0.003]		

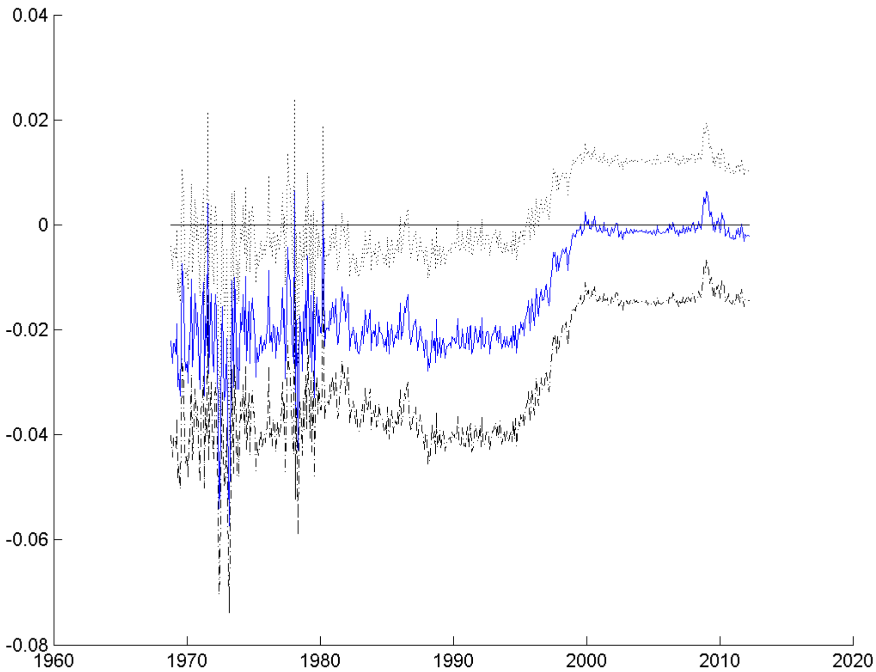
Notes: This table shows the OLS estimate of the first order VAR described in section 2 for US data, full sample from 12:1928 to 04:2012. RMe is excess log market returns, YS is the yield spread, PE the smoothed price-earnings and VS the small stock value spread as described in text. First line of each block shows the OLS estimate of each coefficient, second line reports the OLS standard errors in parentheses, and the third line shows the bootstrap standard errors based on 2500 simulations on square brackets. The last block shows the equations error correlation, with variances in the main diagonal. The standard erros based on 2500 bootstrap simulations is shown bellow in square brackets. *, ** indicates estimate is significant with 5% and 10% confidence level respectively.

In the period from 1970:06 to 2011:12 however, only a small momentum effect of past returns is observable in the monthly VAR, no other variable show any predictive power for

market excess returns. In the modern sub-period market excess returns are still a prediticor of price-earnings and the small stock value spread is still a predictor of yield spreads. Also, the momentum effect is caused by the stock market meltdown in the last quarter of 2008. In appendix A3 we report the VAR for the period 1970:06 to 2007:12 and show that none of the variables can predict stock market returns in this period. We also show that the 5 year rolling window of excess return first autocorrelation has an expressive upward jump in october 2008. It is one rare event that distorts the whole news series because we are using a model which assumes iid shocks.

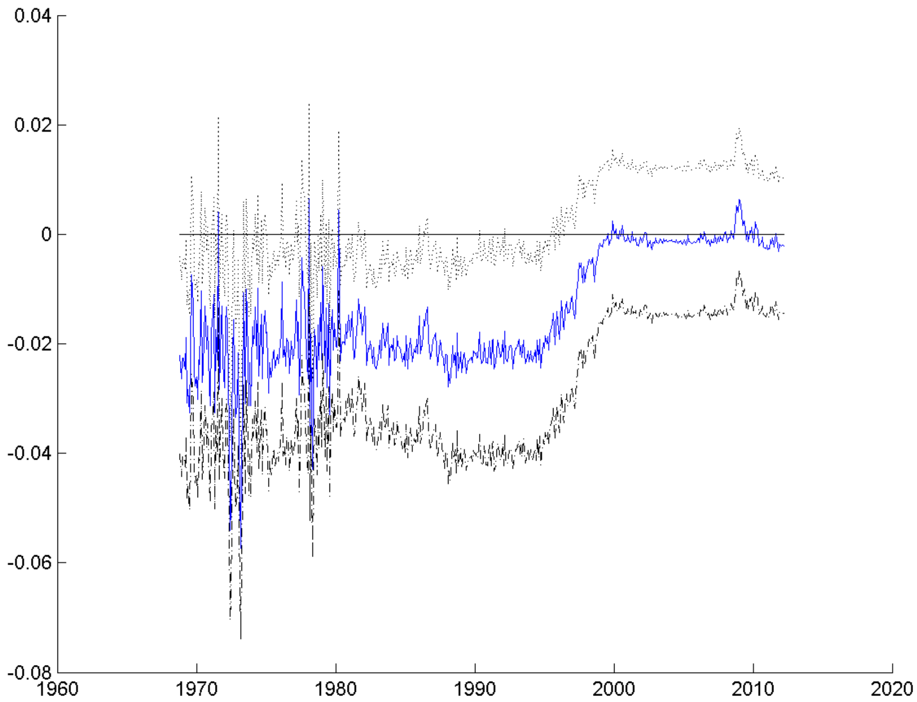
This exercise shows that the history captured by the full sample does not necessarily represent the trends present in a large modern sub-sample, so there can be significant bias in the news series. In the next section, we will present a robustness check, comparing the betas and asset pricing model results for the US considering the news estimated in each subsample in comparison with the same results based on the full sample VAR reported in the original work.

Figure 1: Yield spread coefficient 40 years rolling window



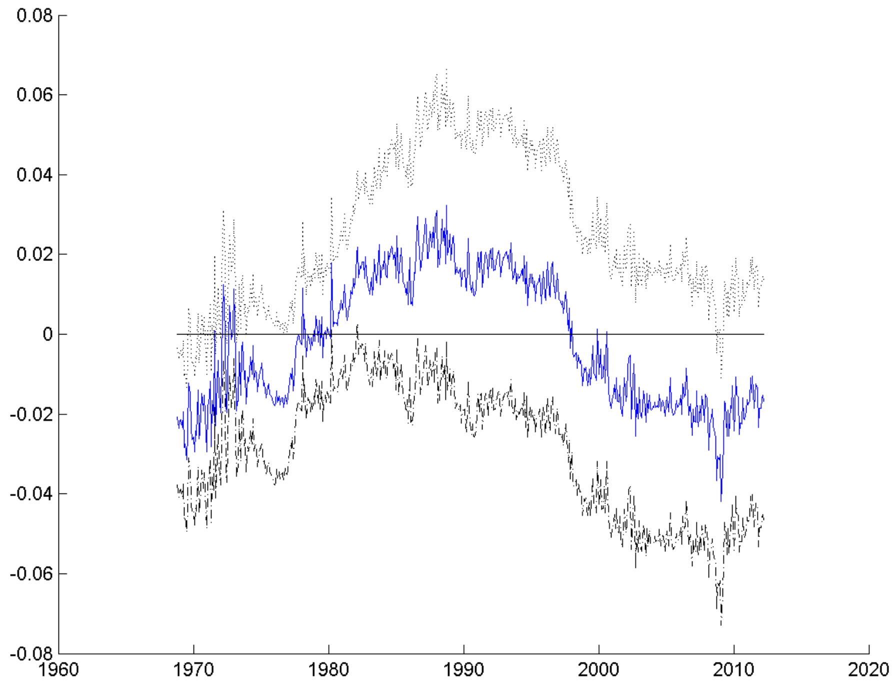
Notes: Yield spread coefficient in the excess market return VAR equation described by eq. (3.32). The dark lines correspond to the OLS two stdev confidence interval.

Figure 2: Smoothed price-earnings coefficient 40 years rolling window



Notes: Smoothed price-earnings ratio coefficient in the excess market return VAR equation described by eq. (3.32). The dark lines correspond to the OLS two stdev confidence interval.

Figure 3: Small stock value spread coefficient 40 years rolling window



Notes: Small stock value spread coefficient in the excess market return VAR equation described by eq. (3.32). The dark lines correspond to the OLS two stdev confidence interval.

As an alternative method to check the changes in the forecasting behavior of the chosen variables, the VAR system was repeatedly estimated in a 40 year monthly rolling window, starting with the period from 1928:12 to 1969:12. Figures 1, 2 and 3 show the estimated coefficients for yield spread, smoothed price-earnings ratio and small stock value spread respectively, as well as the two standard deviations confidence interval for each. It is clear that whatever aggregate market return predictive power displayed by the small stock value spread in the earlier period quickly vanishes in the later sample. This can be one of the main reasons behind the ICAPM poor performance when the market news series are estimated in the modern sample alone, as shown in section 8. The yield spread and price-earnings show an interestingly similar behavior: their predictive power seems to be valid until the middle 90's when they disappear completely.

Table 5: VAR for US data - sample 1928:12 to 1970:06

	Constant	RMe(t)	YS(t)	PE(t)	VS(t)	R2	F
RMe(t+1)	0.134*	0.108*	0.010**	-0.033*	-0.025*	0.047	6.09
	(0.037)	(0.044)	(0.006)	(0.010)	(0.009)		
	[0.053]	[0.044]	[0.007]	[0.014]	[0.015]		
YS(t+1)	0.008	0.151	0.902*	-0.036	0.088*	0.922	1451.89
	(0.102)	(0.121)	(0.018)	(0.028)	(0.025)		
	[0.133]	[0.124]	[0.020]	[0.036]	[0.038]		
PE(t+1)	0.038	0.552*	0.002	0.987*	-0.003	0.984	7605.04
	(0.025)	(0.030)	(0.004)	(0.007)	(0.006)		
	[0.036]	[0.030]	[0.005]	[0.009]	[0.010]		
VS(t+1)	-0.001	-0.005	0.000	0.002	0.997*	0.990	11657.69
	(0.017)	(0.028)	(0.002)	(0.004)	(0.005)		
	[0.041]	[0.032]	[0.006]	[0.010]	[0.012]		
	corr/std	RMe(t)	YS(t)	PE(t)	VS(t)		
	RMe(t)	0.060	-0.125	0.778	-0.333		
		[0.004]	[0.075]	[0.023]	[0.056]		
	YS(t)	-0.125	0.164	-0.112	0.022		
		[0.075]	[0.015]	[0.057]	[0.048]		
	PE(t)	0.778	-0.112	0.040	-0.312		
		[0.023]	[0.057]	[0.002]	[0.052]		
	VS(t)	-0.333	0.022	-0.312	0.044		
		[0.056]	[0.048]	[0.052]	[0.003]		

Notes: This table shows the OLS estimate of the first order VAR described in section 2 for US data, sample from 1928:12 to 1970:06 . RMe is excess log market returns, YS is the yield spread, PE the smoothed price-earnings and VS the small stock value spread as described in text. First line of each block shows the OLS estimate of each coefficient, second line reports the OLS standard errors in parenthesis, and the third line shows the bootstrap standard errors based on 2500 simulations on square brackets. The last block shows the equations error correlation, with variances in the main diagonal. The standard erros based on 2500 bootstrap simulations is shown bellow in square brackets. *, ** indicates estimate is significant with 5% and 10% confidence level respectively.

Since only a short history is available for brazilian data, we first investigate how the VAR specification works for smaller samples in the american data, how the forecastig behavior of the variables evolves over time and how it compares with the behavior displayed in the full sample.

We split the data into a sequency of non-overlapping sub-samples, all with the same size of 9 years (108 monthly observations), which is the same sample size available of brazilian data. This results in 9 sub-samples starting in january 1931 until december 2011. The VAR coefficients for the excess market return equation, with standard errors, for each sub-sample and an estimate of the small sample bias, calculated from a Monte-Carlo exercise described in appendix, are reported in table 7. Full VAR results for each sub-period can be found in the appendix.

Table 6: VAR for US data - sample 1970:06 to 2011:12

	Constant	RMe(t)	YS(t)	PE(t)	VS(t)	R2	F
RMe(t+1)	0.041**	0.090*	0.001	-0.002	-0.021	0.014	1.75
	(0.023)	(0.045)	(0.002)	(0.006)	(0.016)		
	[0.032]	[0.045]	[0.002]	[0.010]	[0.018]		
YS(t+1)	-0.128	-0.035	0.932*	-0.070	0.276*	0.887	964.02
	(0.177)	(0.351)	(0.016)	(0.050)	(0.122)		
	[0.253]	[0.353]	[0.019]	[0.076]	[0.146]		
PE(t+1)	0.027**	0.558*	-0.001	0.994*	-0.007	0.992	14469.51
	(0.016)	(0.032)	(0.001)	(0.005)	(0.011)		
	[0.023]	[0.032]	[0.002]	[0.008]	[0.013]		
VS(t+1)	0.068*	-0.033	0.000	0.011*	0.932*	0.889	991.12
	(0.017)	(0.028)	(0.002)	(0.004)	(0.005)		
	[0.036]	[0.049]	[0.003]	[0.010]	[0.019]		
	corr/std	RMe(t)	YS(t)	PE(t)	VS(t)		
	RMe(t)	0.046	0.119	0.547	0.253		
		[0.002]	[0.059]	[0.074]	[0.052]		
	YS(t)	0.119	0.365	-0.012	-0.016		
		[0.059]	[0.020]	[0.121]	[0.042]		
	PE(t)	0.547	-0.012	0.033	0.159		
		[0.074]	[0.121]	[0.004]	[0.042]		
	VS(t)	0.253	-0.016	0.159	0.050		
		[0.052]	[0.042]	[0.042]	[0.004]		

Notes: This table shows the OLS estimate of the first order VAR described in section 2 for US data, sample from 1970:06 to 2011:12 . RMe is excess log market returns, YS is the yield spread, PE the smoothed price-earnings and VS the small stock value spread as described in text. First line of each block shows the OLS estimate of each coefficient, second line reports the OLS standard errors in parenthesis, and the third line shows the bootstrap standard errors based on 2500 simulations on square brackets. The last blcok show the equations error correlation, with variances in the main diagonal. The standard erros based on 2500 bootstrap simulations is shown bellow in square brackets. *, ** indicates estimate is significant with 5% and 10% confidence level respectively.

As can be seen from table 7, in none of the sub-periods the four variables are jointly statistically significant as return predictors. Also, in none of the isolated sub-samples the small stock value spread is a significant return predictor. This apparently suggests that a longer history is needed to find a consistent pattern among market excess returns and the other predictive variables. The history of coefficients shown in table 7 also indicates that each variable is strongly correlated to returns in a different period of time. Price earnings ratio is a consistently important return predictor since the early sub-samples up to 1985. Yield spread is particularly important in the period from 1994 to 2003, which coincides with the latter period of the so called "great moderation era", when the dominant view was that business cycles were tamed by a combination of fiscal and monetary policy. Curiously, the negative sign indicates that higher yield spread predict lower market returns, what is inconsistent with the business cycle hypothesis. It could, however, be an indication of the market behavior that investors called the "Greenspan Put". It is conjectured that the former head of the Federal Reserve, Alan Greenspan, would loosen monetary policy whenever equity market prices were falling, so the negative sign found in the VAR would be consistent with this anticipation. Market return momentum is important in the most recent period, a direct result of the 2008 crisis as argued before.

Table 7: VAR coefficients in sub-samples for US data

Sub-sample	RMe	YS	PE	VS
2003 - 2012	0.229*	0.003	-0.029	-0.033
	(0.095)	(0.005)	(0.042)	(0.056)
	[0.129]	[0.004]	[0.048]	[0.059]
	-{0.046}	-{0.001}	-{0.027}	{0.009}
1994-2003	-0.021	-0.020*	-0.032	-0.051
	(0.096)	(0.008)	(0.031)	(0.040)
	[0.080]	[0.009]	[0.028]	[0.042]
	-{0.039}	-{0.008}	-{0.024}	-{0.004}
1985-1994	0.051	0.006	-0.053	-0.008
	(0.096)	(0.006)	(0.033)	(0.041)
	[0.132]	[0.007]	[0.044]	[0.046]
	-{0.040}	{0.004}	-{0.027}	-{0.008}
1976-1985	0.002	0.008	-0.104*	-0.027
	(0.095)	(0.006)	(0.043)	(0.029)
	[0.073]	[0.006]	[0.060]	[0.031]
	-{0.032}	-{0.001}	-{0.019}	{0.002}
1967-1976	0.067	0.018	-0.047	0.052
	(0.100)	(0.012)	(0.032)	(0.055)
	[0.102]	[0.013]	[0.036]	[0.051]
	-{0.034}	-{0.011}	-{0.023}	-{0.005}
1958-1967	0.103	0.003	-0.066*	0.075
	(0.094)	(0.013)	(0.025)	(0.048)

	[0.122]	[0.023]	[0.028]	[0.046]
	-{0.037}	-{0.006}	-{0.019}	{0.011}
1949-1958	0.009	0.027	-0.012	0.023
	(0.099)	(0.017)	(0.028)	(0.034)
	[0.095]	[0.020]	[0.030]	[0.032]
	-{0.036}	{0.003}	-{0.017}	{0.004}
1940-1949	0.018	-0.048	-0.087*	0.034
	(0.095)	(0.028)	(0.035)	(0.041)
	[0.111]	[0.035]	[0.061]	[0.047]
	-{0.041}	-{0.017}	-{0.020}	-{0.005}
1931-1940	0.102	0.044	-0.093*	0.049
	(0.093)	(0.027)	(0.034)	(0.094)
	[0.131]	[0.035]	[0.050]	[0.103]
	-{0.043}	{0.047}	-{0.102}	{0.060}

Notes: This table shows the results of the VAR described in section 2 for US data split in 9 years (108 monthly observations) non-overlapping sub-samples from january 1931 to december 2011. First line of each block shows the excess market return OLS coefficient of each variable depicted in the top of the collumn. Second line shows OLS standard errors in parenthesis, the third line is the bootstrap standard errors based on 2500 realizations in square brackets and the fourth shows the small sample bias of each coefficient in curly brackets, calculated with Monte-Carlo simulations with VAR coefficients assumed to be the true data generating process. Starred values indicate coefficients that are statistically signifficant at 5% confidence level based on OLS standard deviation to calculate the t statistic.

Results in table 7 would disencourage any attempt to find a good fit for a market return VAR model for the available brazilian data. Surprisingly, however, using the same set of predictive variables and a short sample of 108 monthly data points from january 2003 to december 2011, it was found that past market excess returns, smoothed price earnings ratio and the small stock value spread are all statistically significant (at 5% confidence level) market return predictors. VAR results are reported in table 8. The R^2 of about 11% in the excess return equation is much higher than the one found in the US for any sample. Only yield spreads have no impact on market returns. This could be attributed to the shorter horizon of typical brazilian investors, but using 2 year term fixed interest swap instead of 5 year yielded no better results (reported in appendix). Instead, it could be argued that the yield curve in Brazil does a poor job in tracking the business cycle. Or simply it would be necessary a longer sample to recognize this effect. For comparison, in the same period of US data the VAR reveals that the only statistically significant variable in the excess return equation is the lagged excess return, an effect of the 2008 meltdown as argued before.

The most remarkable finding is that the small stock value spread does indeed predicts market returns for the brazilian market, but with the opposite sign than the suggested by the intertemporal argument. Moreover, the Monte-Carlo simulation performed to obtain an indication of the small sample bias (reported in appendix) show that this coefficient was probably estimated with a small upward bias, but it would still be statistically significant with a non usual 12% confidence level if one corrects this bias.

For the brazilian market, higher returns for small growth portfolios are followed by higher market returns, this only could be reconciled with the intertemporal argument, considering risk averse investors, if growh stocks offer a higher premium than value stocks. In such case, the value premium would be negative in Brazil. That is, investors expect value stocks to do better when they are surprised by lower expectations of future returns. Alternatively, the value premium could be positive if brazilian investors have a very low risk aversion coefficient so that they enjoy the intertemporal substitution posibility offered by growth stocks to invest more and enhance returns in a up market. Maybe with such high returns for the risk free interest rate in the sample period, brazilian stock market investors are really not much averse to risk after all, this argument may be plausible. Both explanation are different from the more straightforward argument Campbell and Vuolteenaho (op. cit.) use for the US. There, the negative sign in the VAR support the hypothesis that risk averse investors demand a higher premium for value stocks when surprised by lower market returns.

Table 8: VAR for brazilian data – sample 2003:01 to 2012:04

	Constant	RMe(t)	YS(t)	PE(t)	VS(t)	R2	F
RMe(t+1)	0.243*	0.220*	0.001	-0.112*	0.037*	0.110	3.287
	(0.098)	(0.096)	(0.002)	(0.039)	(0.019)		
	[0.113]	[0.111]	[0.002]	[0.044]	[0.031]		
YS(t+1)	-3.129	-1.487	0.789*	1.043	0.345	0.760	84.124
	(1.964)	(1.925)	(0.045)	(0.784)	(0.381)		
	[3.530]	[3.341]	[0.086]	[1.255]	[0.705]		
PE(t+1)	0.276*	0.243*	0.003	0.875*	0.033**	0.856	157.681
	(0.100)	(0.098)	(0.002)	(0.040)	(0.019)		
	[0.174]	[0.201]	[0.004]	[0.070]	[0.033]		
VS(t+1)	0.329	0.391	-0.001	-0.061	0.886*	0.803	108.116
	(0.231)	(0.226)	(0.005)	(0.092)	(0.045)		
	[0.431]	[0.344]	[0.011]	[0.168]	[0.083]		
	corr/std	RMe(t)	YS(t)	PE(t)	VS(t)		
	RMe(t)	0.063	-0.241	0.981	-0.101		
		[0.007]	[0.100]	[0.095]	[0.138]		
	YS(t)	-0.241	1.277	-0.189	0.126		
		[0.100]	[0.350]	[0.149]	[0.175]		
	PE(t)	0.981	-0.189	0.065	-0.089		
		[0.095]	[0.149]	[0.014]	[0.188]		
	VS(t)	-0.101	0.126	-0.089	0.150		
		[0.138]	[0.175]	[0.188]	[0.034]		

Notes: This table shows the OLS estimate of the first order VAR described in section 2 for brazilian data, full sample from 01:2003 to 04:2012. RMe is excess log market returns, YS is the yield spread, PE the smoothed price-earnings and VS the small stock value spread as described in text. First line of each block shows the OLS estimate of each coefficient, second line reports the OLS standard errors in parenthesis, and the third line shows the bootstrap standard errors based on 2500 simulations on square brackets. The last blcok show the equations error correlation, with variances in the main diagonal. The standard erros based on 2500 bootstrap simulations are shown bellow in square brackets. *, ** indicates estimate is significant with 5% and 10% confidence level respectively.

In order to compare with the results obtained for Brazil, we also present all results in this work for the same time period for the US. In table 9 we show the full results for the VAR in the US sample from 2003:01 to 2012:04. As pointed before, in this sample the only statistically significant excess return predictor for the US is lagged returns, an effect entirely caused by the stock market crash in the end of 2008. It is worth noting that lagged market returns can forecast all four variables included in the VAR due to the strong effect of the 2008 crisis in the sample. The small stock value spread can also predict the yield spread and price earnings.

6. CASH FLOW AND DISCOUNT RATE NEWS

The VAR results reported in the last section were used in equations (2.34) and (2.35) to determine cash-flow news and discount rate news series for Brazil and for US. For all the series we use ρ = 0.95 per year as Campbell and Vuolteenaho.

Table 9: VAR for US data - sample 2003:1 to 2012:04

	Constant	RMe(t)	YS(t)	PE(t)	VS(t)	R2	F
RMe(t+1)	0.120	0.223*	0.003	-0.025	-0.033	0.057	1.55
	(0.189)	(0.097)	(0.005)	(0.043)	(0.057)		
	[0.223]	[0.100]	[0.008]	[0.054]	[0.069]		
YS(t+1)	-3.639*	1.385*	0.870*	0.591*	1.464*	0.952	502.14
	(1.192)	(0.614)	(0.032)	(0.271)	(0.360)		
	[1.462]	[0.621]	[0.046]	[0.351]	[0.431]		
PE(t+1)	0.249*	0.905*	0.003*	0.928*	-0.040*	0.994	3931.21
	(0.054)	(0.028)	(0.001)	(0.012)	(0.016)		
	[0.063]	[0.029]	[0.002]	[0.015]	[0.019]		
VS(t+1)	0.199*	-0.175*	0.001	-0.028*	0.921*	0.899	226.18
	(0.017)	(0.028)	(0.002)	(0.004)	(0.005)		
	[0.255]	[0.105]	[0.008]	[0.063]	[0.073]		
	corr/std	RMe(t)	YS(t)	PE(t)	VS(t)		
	RMe(t)	0.045	0.034	-0.039	-0.177		
		[0.004]	[0.126]	[0.120]	[0.111]		
	YS(t)	0.034	0.284	0.214	0.071		
		[0.126]	[0.021]	[0.112]	[0.070]		
	PE(t)	-0.039	0.214	0.013	-0.168		
		[0.120]	[0.112]	[0.001]	[0.066]		
	VS(t)	-0.177	0.071	-0.168	0.046		
		[0.111]	[0.070]	[0.066]	[0.008]		

Notes: This table shows the OLS estimate of the first order VAR described in section 2 for US data, sample from 01:2003 to 04:2012. RMe is excess log market returns, YS is the yield spread, PE the smoothed price-earnings and VS the small stock value spread as described in text. First line of each block shows the OLS estimate of each

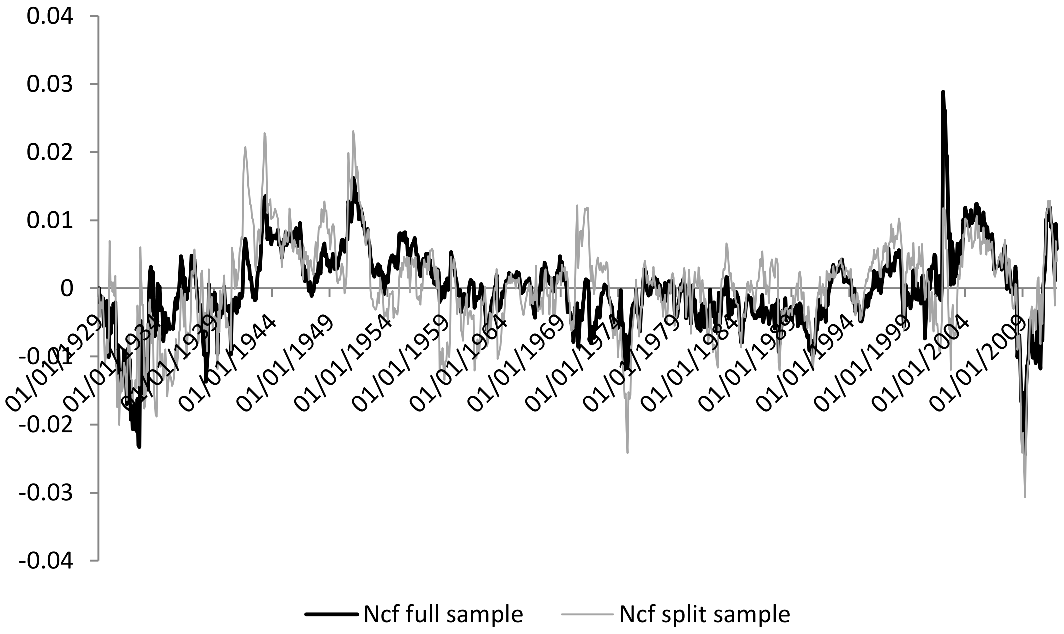
coefficient, second line reports the OLS standard errors in parenthesis, and the third line shows the bootstrap standard errors based on 2500 simulations on square brackets. The last block show the equations error correlation, with variances in the main diagonal. The standard erros based on 2500 bootstrap simulations are shown bellow in square brackets. *, ** indicates estimate is significant with 5% and 10% confidence level respectively.

We first show for the US data how the news terms calculated using tha full sample VAR compares with the series calculated using the VAR estimated from the two split sub-samples as described in the previous section. For a graphical comparison, we show a smoothed exponentially moving average following Campbell and Vuolteenaho (op.cit.). Correlation between the two estimated cash flow news displayed in figure 4 is 0.75, and between the discount rate news series in figure 5 serial correlation is 0.79. This indicates that, although in both cases the series behave very closely during the major shocks, there still can be significant differences which could affect the estimated betas.

In the earlier part of the sample, there is a large period of bad news for cash flow and discount rates until circa 1933 which can be attributed to the 1929 stock market crash and following depression. In the post-war period until the late 50’ there were a series of positive cash-flow shocks, and the series became much more volatile in the 2000’, with almost a decade with positive surprises followed by a major plunge in 2008. The spike in the beginning of 2002 is assumed to be noise due to the change in the series used to calculate the yield spread. The discount rate series is more volatile throughout the full period and the shock in 2008 was comparatively smaller in discount rates than it was for cash-flows.

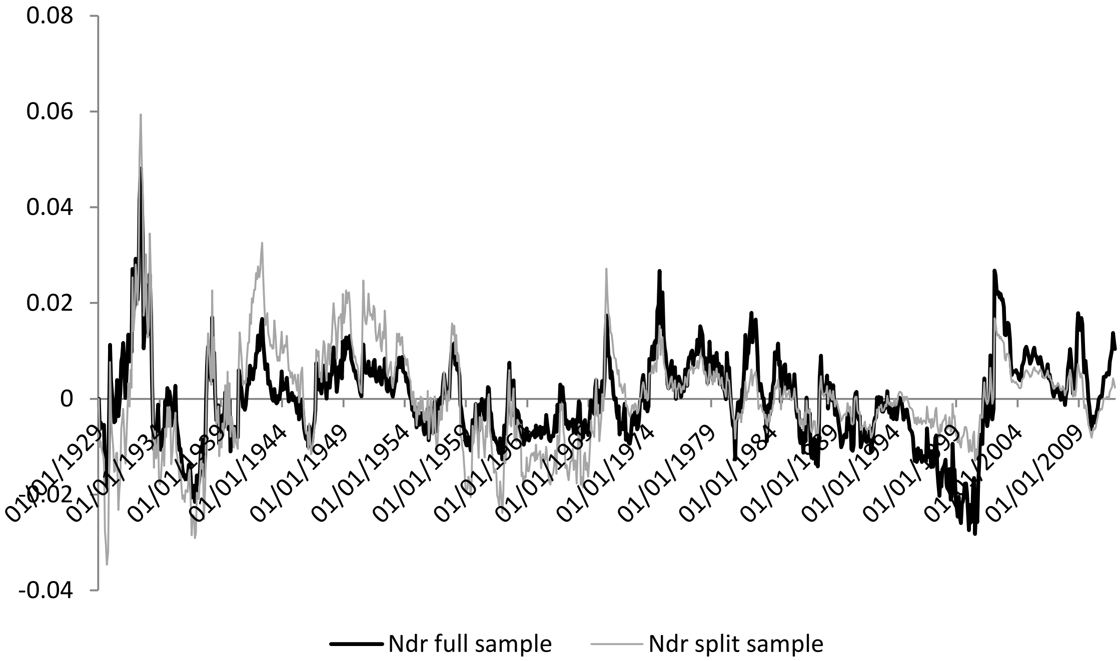
In table 10, we show the estimated functions that relate each shock to a variable included in the VAR to the news series shocks as described by equations (3.34) and (3.35) for the full sample. Adding ten more years from 2002:01 to 2011:12 did little diference for the news series in the full sample comparing to the results of table 3 in Campbell and Vuolteenaho (op.cit.). Higher returns and price earnings ration translate into negative news for future returns (discount rate) while higher returns are positively correlated to cash-flow shocks, indicating that part of the market movement can be accounted by better dividends estimates.

Figure 4: Smoothed Cash-flow news for US data from 1928:12 to 2011:12.



Notes: This figure shows the cash-flow news estimated from the ful sample VAR in black and the same series calculated by two separate VARs using samples from 1928:12 to 1970:06 and 1970:06 and 2011:12 in grey.The series displayed are exponentially weighted moving averages with decay parameter 0.08.

Figure 5: Smoothed Discount Rate news for US data from 1928:12 to 2011:12.



Notes: This figure shows the discount-rate news estimated from the ful sample VAR in black and the same series calculated by two separate VARs using samples from 1928:12 to 1970:06 and 1970:06 and 2011:12 in grey.The series displayed are exponentially weighted moving averages with decay parameter 0.08.

Table 10: Cash-flow and Discount-rate news for the US market - full sample

News covariance	NCF	NDR	News corr/std	NCF	NDR
NCF	0.00096	0.00012	NCF	0.031	0.041
	(0.0004)	(0.0004)		(0.005)	(0.224)
NDR	0.00012	0.00219	NDR	0.041	0.046
	(0.0004)	(0.0007)		(0.224)	(0.007)
Shock correlations	**NCF**	**NDR**	**Functions**	**NCF**	**NDR**
Rme shock	0.507	-0.828	Rme shock	0.642	-0.358
	(0.187)	(0.064)		(0.068)	(0.068)
YS shock	0.242	0.141	YS shock	0.019	0.019
	(0.152)	(0.121)		(0.017)	(0.017)
PE shock	-0.153	-0.895	PE shock	-0.778	-0.778
	(0.229)	(0.059)		(0.110)	(0.110)
VS shock	-0.308	-0.152	VS shock	-0.219	-0.219
	(0.235)	(0.185)		(0.177)	(0.177)

Notes: Cash-flow and discount news description for the US market based on the VAR results in table 4. On the upper left it is shown the covariance matrix of the estimated series, on the upper left it is shown the correlations on the off-diagonal entries and the standard deviations on diagonal entries. The correlations of shocks to the forecasting variables and the news series is on the lower left block. On the lower left block, it is shown the estimated functions relating shocks to the forecasting variables to the news terms as defined in equations (2.34) and (2.35). In parentheses standard errors for each measure based on a bootstrap exercise with 2500 simulations.

Following the same procedure, the news series were estimated for the Brazilian market with the available data from the period of 2003:01 to 2012:04 and for the US, using the VAR estimated in the same period for comparison. As can be seen in table 11, the the news series for the Brazilian market display very similar characteristics to the US series in the full sample since the VAR equations display similar behavior in both cases. Excess returns and PE shocks dominate the dynamics of the news series again and the discount rate news series is more volatile than the cash-flow news also in Brazil in the recent period. The main difference is that in Brazil a positive shock in the small stocks value spread translates into good news for future cash-flows and future returns. This difference was already pointed in the VAR, and if the intertemporal model discussed in section 2 is true it indicates that Brazilian stock market investors are not very much risk averse or that value firms stocks are less risky in Brazil.

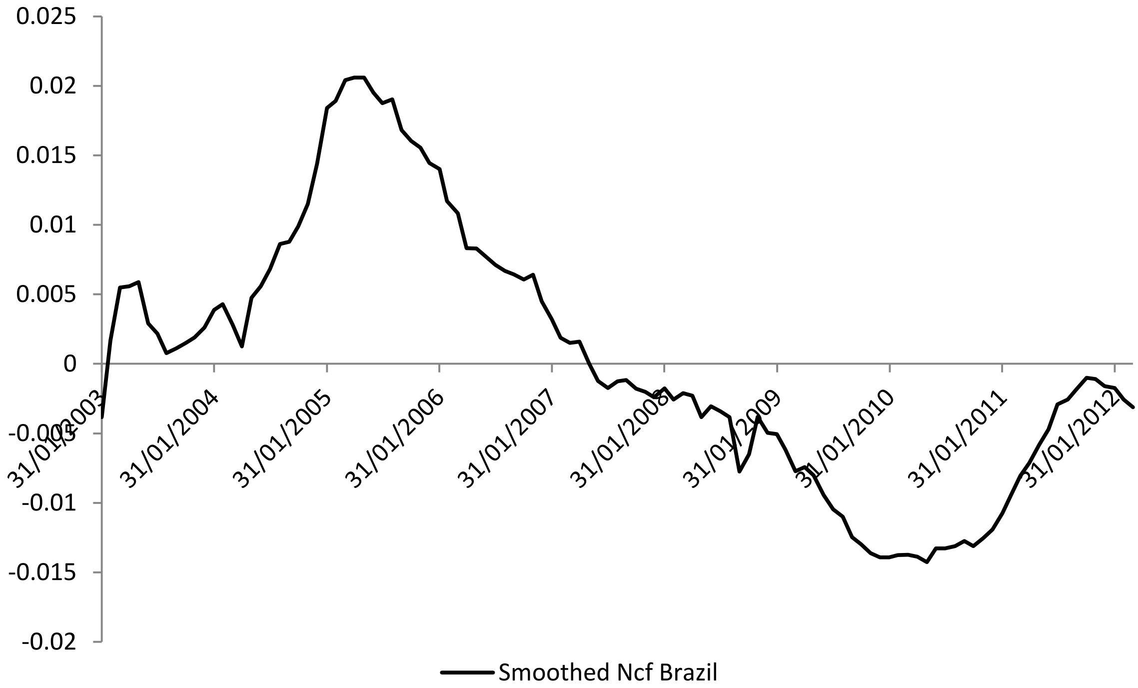
Table 11: Cash-flow and Discount rate news for Brazilian market - 2003:01 to 2012:04 sample.

News covariance	NCF	NDR	News corr/std	NCF	NDR
NCF	0.00037	0.00003	NCF	0.019	0.029
	(0.0001)	(0.0003)		(0.003)	(0.273)
NDR	0.00003	0.00354	NDR	0.029	0.059
	(0.0003)	(0.0008)		(0.273)	(0.007)
Shock correlations	**NCF**	**NDR**	**Functions**	**NCF**	**NDR**
Rme shock	0.284	-0.950	Rme shock	1.013	0.013
	(0.257)	(0.013)		(0.033)	(0.033)
YS shock	-0.789	-0.006	YS shock	-0.010	-0.010
	(0.142)	(0.141)		(0.002)	(0.002)
PE shock	0.134	-0.979	PE shock	-0.963	-0.963
	(0.267)	(0.010)		(0.068)	(0.068)
VS shock	0.044	0.120	VS shock	0.023	0.023
	(0.288)	(0.117)		(0.039)	(0.039)

Notes: Cash-flow and discount news description for the brazilian market based on the VAR results in table 8. On the upper left it is shown the caovariance matrix of the estimated series, on the upper left it is shown the correlations on the off-diagonal entries and the standard deviations on diagonal entries. The correlations of shocks to the forecasting variables and the news series is on the lower left block. On the lower left block, it is shown the estimated functions relating shocks to the forecasting variables to the news terms as defined in equations (2.34) and (2.35). In parenthesis standard errors for each measure based on a bootstrap exercise with 2500 simulations.

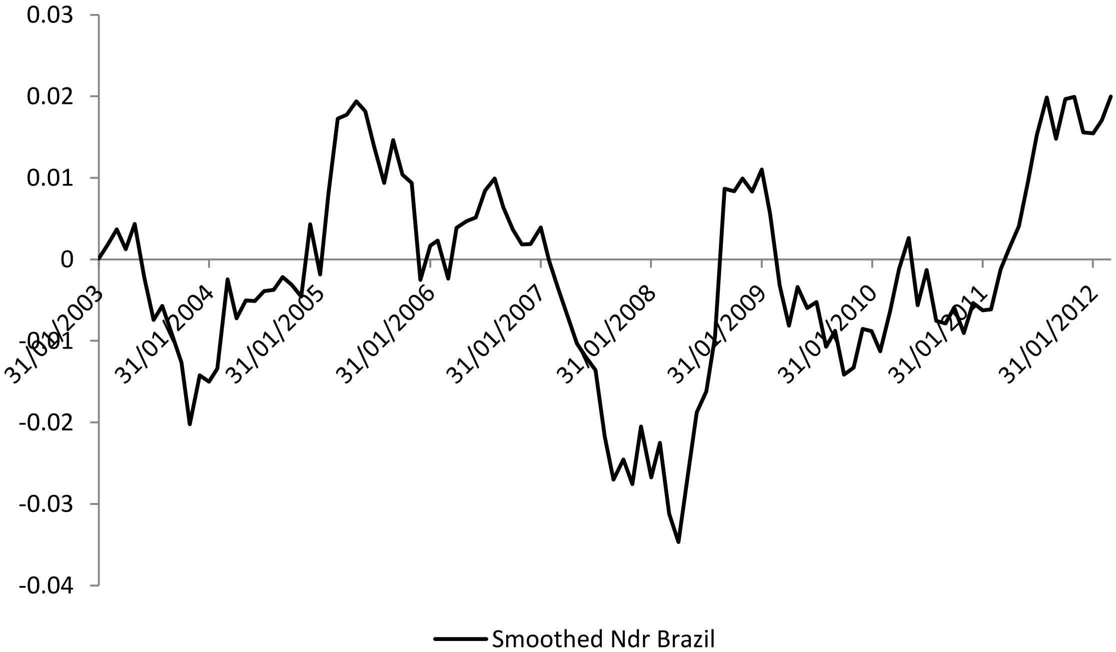
For the US, in the period from 2003:01 to 2012:04, the most striking feature is that the discount rate news are typically an order of magnitude lower than the the cash-flow news and their volatilities are of the same order. This is different than the evidence found in the longer sample by Campbell and Vuolteenaho (op.cit.) and will imply very different betas for the US Fama-French portfolios as will be shown in the next section.

Figure 6: Smoothed Cash Flow news for Brazil data from 2003:01 to 2012:04.



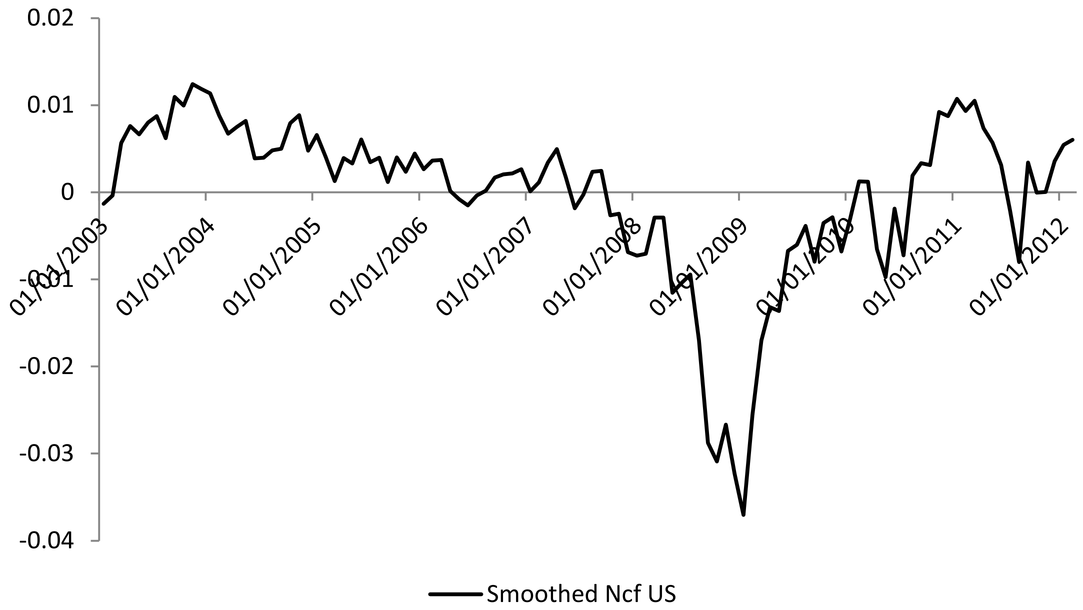
Notes: This figure shows the cash-flow news for brazilian market estimated from the VAR in table 8, using a sample from 2003:01 to 2012:04. The series displayed are exponentially weighted moving averages with decay parameter 0.08.

Figure 7: Smoothed Discount Rate news for Brazil data from 2003:01 to 2012:04.



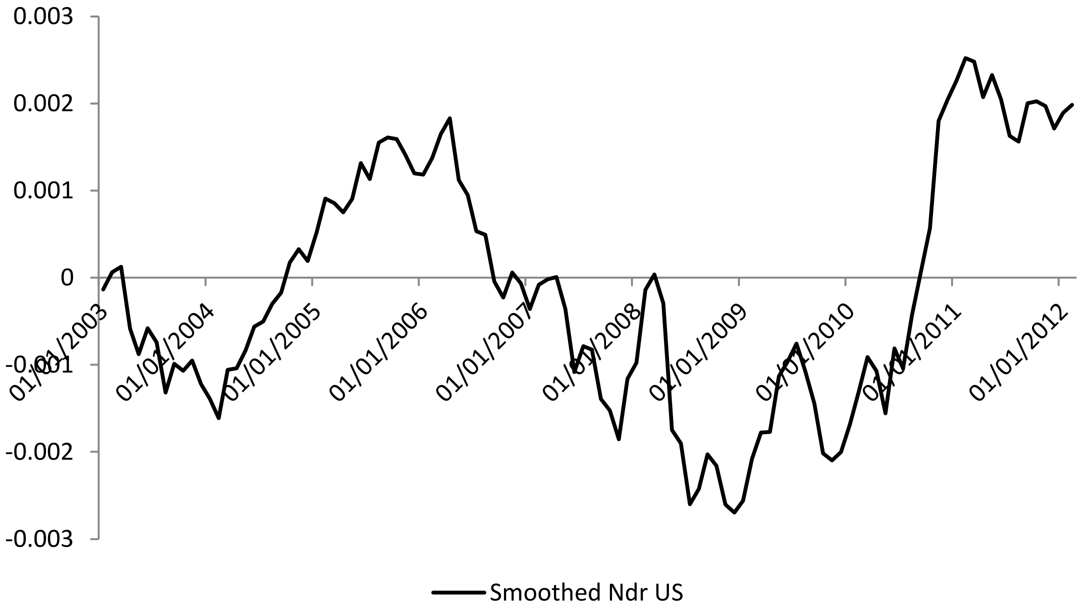
Notes: This figure shows the discount rate news for brazilian market estimated from the VAR in table 8, using a sample from 2003:01 to 2012:04. The series displayed are exponentially weighted moving averages with decay parameter 0.08.

Figure 8: Smoothed Cash Flow news for US data from 2003:01 to 2012:04



Notes: This figure shows the cash flow news for US market estimated from the VAR in table 9, using a sample from 2003:01 to 2012:04. The series displayed are exponentially weighted moving averages with decay parameter 0.08.

Figure 9: Smoothed Discount Rate news for US data from 2003:01 to 2012:04



Notes: This figure shows the discount rate news for US market estimated from the VAR in table 9, using a sample from 2003:01 to 2012:04. The series displayed are exponentially weighted moving averages with decay parameter 0.08.

7. CASH FLOW AND DISCOUNT RATE BETAS

In order to perform the decomposition of market beta in its cash flow and discount rate component, we follow Campbell and Vuolteenaho (op.cit.) and use one additional lag in the numerator of the estimators proposed in (3.29) and (3.30):

$$\hat{\beta}_{i,CF} = \frac{Cov(r_{i,t}, N_{CF,t})}{Var(N_{CF,t} - N_{DR,t})} + \frac{Cov(r_{i,t}, N_{CF,t-1})}{Var(N_{CF,t} - N_{DR,t})} \qquad (7.1)$$

$$\hat{\beta}_{i,DR} = \frac{Cov(r_{i,t}, -N_{DR,t})}{Var(N_{CF,t} - N_{DR,t})} + \frac{Cov(r_{i,t}, -N_{DR,t-1})}{Var(N_{CF,t} - N_{DR,t})} \qquad (7.2)$$

The motivation for such is that we will test portfolios of small stocks in which there is infrequent trading and stale prices as pointed by Scholes and Williams (1977), and Lo and MacKinlay (1990) show that individual stock prices moves in art with a lag to the market movement, with the effect bigger for smaller stocks.

We calculate the betas for 4 sets of portfolios. First we calculate for the 2003:01 to 2012:04 sample for Brazil and the US using the news series reported in the last section. For the US we use the 25 Fama-French portfolios available at professor’s French website and for Brazil we use the 6 2x3 Fama-French porfolios built according to description on appendix. We don’t use all the 25 5x5 Fama French portfolios for Brazil because in such a division we end up with portfolios containing too few stocks or no stocks at all for certain periods. The betas were also calculated for the 16 4x4 Fama-French portfolios and results are reported in appendix. Also, in rder to compare with the resuls presented in Campbel and Vuolteenaho (op.cit.), we calculate the betas for the 25 Fama- French portfolios for the US in two different samples, from 1928:12 to 1963:06 and from 1963:06 to 2001:12 using the VAR estimated in the split samples to calculate the news terms.

We report in table 12 the cash flow and discount rate betas for the Brazilian Fama-French portfolios along with the difference between the extreme portfolios betas. Similarly to the results shown in Campbell and Vuolteenaho (op.cit.) for the US modern sample, for Brazilian portfolios the cash flow beta is much smaller than the discount rate betas. Discount rate betas for small stock are generaly bigger than discount rate betas for big stocks but bithing can be said about the cash flow betas. In the sample, the medium value portofios were the ones with higher average monthly returns in Brazil, and they are the ones with marginally higher discount rate betas. Also, the small stocks had higher avarege returns than the big stocks, and they also present higher discount rate betas. It seems, thus, that cash-flow betas have little information about the cross section of returns which is a setback for the intertemporal model proposed here.

Table 12 - Cash flow and Discount Rate betas for Brazil

βCF	Growth		Medium		Value		Diff	
Small	0.02	[0.07]	0.06	[0.07]	0.06	[0.07]	0.03	[0.04]
Big	0.07	[0.05]	0.12	[0.06]	0.06	[0.06]	-0.01	[0.06]
Diff.	-0.05	[0.05]	-0.07	[0.04]	-0.01	[0.05]		
βDR	Growth		Medium		Value		Diff	
Small	0.88	[0.21]	0.84	[0.20]	0.86	[0.20]	-0.02	[0.13]
Big	0.77	[0.15]	0.90	[0.16]	0.66	[0.18]	-0.12	[0.16]
Diff.	0.11	[0.14]	-0.06	[0.12]	0.20	[0.16]		

Notes: This table reports the cash-flow and discpunt rate betas for the 2x3 Fama-French portfolios of Brazilian stocks. The betas were calculated using estimators (7.1) and (7.2). Diff. indicates the diference between the extreme value or size portfolio betas. In square brackets are shown the standard deviation of each estimator calculated by a bootstrap exercise with 2500 realized simulations.

In table 13 we report the betas for the US in the same period from 2003:01 to 2012:04. Consistent with the previous finding that discount rate news had a much smaller volatility than cash flow news in this sample, we found that cash flow betas are much greater than discount rate betas for all portfolios. All small stocks portfolios have greater cash flow betas than the big stocks portfolios and, with the exception of the medium value one, value portfolios have greater cash flow betas than the growth portfolios. Again, if there is a size and value premium in this period the CAPM might be enough to account for it.

Table 13 - Cash flow and Discount Rate Betas for the US - sample 2003:1 to 2012:04

βCF	Growth		2		3		4		Value		Diff.	
Small	1.43	[0.35]	1.27	[0.29]	1.26	[0.28]	1.15	[0.28]	1.32	[0.36]	-0.11	[0.13]
2	1.24	[0.26]	1.22	[0.27]	1.18	[0.30]	1.19	[0.30]	1.33	[0.38]	0.08	[0.18]
3	1.27	[0.25]	1.24	[0.24]	1.10	[0.23]	1.26	[0.30]	1.17	[0.31]	-0.10	[0.15]
4	1.17	[0.25]	1.22	[0.27]	1.33	[0.28]	1.14	[0.30]	1.29	[0.33]	0.12	[0.14]
Large	0.97	[0.21]	0.95	[0.22]	1.14	[0.21]	1.11	[0.25]	1.27	[0.32]	0.30	[0.16]
Diff.	0.46	[0.19]	0.32	[0.13]	0.13	[0.12]	0.04	[0.11]	0.05	[0.13]		
βDR	Growth		2		3		4		Value		Diff.	
Small	-0.12	[0.31]	-0.12	[0.24]	-0.13	[0.24]	-0.12	[0.24]	-0.14	[0.31]	-0.02	[0.10]
2	-0.11	[0.21]	-0.12	[0.23]	-0.12	[0.26]	-0.13	[0.27]	-0.14	[0.33]	-0.02	[0.16]
3	-0.12	[0.21]	-0.13	[0.20]	-0.11	[0.19]	-0.12	[0.26]	-0.10	[0.28]	0.01	[0.12]
4	-0.11	[0.22]	-0.11	[0.23]	-0.13	[0.24]	-0.11	[0.26]	-0.13	[0.29]	-0.02	[0.11]
Large	-0.08	[0.19]	-0.09	[0.19]	-0.12	[0.19]	-0.11	[0.21]	1.27	[0.29]	1.35	[0.13]
Diff.	-0.04	[0.15]	-0.03	[0.09]	-0.01	[0.09]	-0.01	[0.08]	-1.40	[0.09]		

Notes: This table reports the cash-flow and discpunt rate betas for the 5x5Fama-French portfolios of US stocks, using the VAR in the period from 2003:01 to 2012:04. The betas were calculated using estimators (7.1) and (7.2). Diff. indicates the diference between the extreme value or size portfolio betas. In square brackets are shown the standard deviation of each estimator calculated by a bootstrap exercise with 2500 realized simulations.

Since we found evidence that the forecasting behavior of the variables included in the VAR are very different in the early 1928-1963 and 1963-2001 sub-samples, we

recalculated the betas for the 25 Fama-French portfolios in these periods using the news series calculated by the VAR defined in each sample instead of using the full sample VAR as in Campbell and Vuolteenaho (op.cit.).

The results for the earlier sample are not sensibly different from what is found when using the full sample VAR for the news series. The serial correlation between the cash flow series estimated in the split sample and the one estimated in the full sample is 0.84 and the correlation between both discount rate series is 0.95, therefore no significant differences were expected for the betas reported in table 14 comparing to table 4 in Campbell and Vuolteenaho (op.cit.). Part of the observed difference is due to a revision made by CRSP in its pre 1962 database which affected the Fama-French portfolio returns. In results not reported, we recalculated the betas using the Fama-French portfolios prior to the CRSP correction and the point estimates were generally closer to the results for the full sample VAR in Campbell and Vuolteenaho (op.cit.) but still noticeably different.

For the late sample from 1963:.06 to 2001:12 we observe in table 15 a dramatic change from the betas of the full sample VAR reported in table 5 of Campbell and Vuolteenaho (op.cit.). As we pointed before, in this subsample none of the variables included in the VAR have any predictive power for market excess returns, quiet different from the full sample results. Especially the cash flow news is very distinct from the one calculated using the full sample, the correlation of both series is only 0.60. As observed in table 15, cash flow and discount rate betas have similar magnitudes, whereas in Campbell and Vuolteenaho (op.cit.) they report cash flow betas typically much smaller than discount rate betas for this sub-sample.

Table 14 - Cash Flow and Discount Rate Betas for the US - sample 1928:12 to 1963:06

βCF	Growth		2		3		4		Value		Diff.	
Small	0.39	[0.11]	0.29	[0.09]	0.28	[0.09]	0.29	[0.08]	0.44	[0.09]	0.05	[0.06]
2	0.15	[0.06]	0.17	[0.07]	0.21	[0.07]	0.26	[0.07]	0.39	[0.08]	0.24	[0.04]
3	0.11	[0.07]	0.12	[0.06]	0.15	[0.06]	0.23	[0.07]	0.36	[0.08]	0.25	[0.04]
4	0.02	[0.05]	0.10	[0.06]	0.19	[0.06]	0.24	[0.07]	0.39	[0.09]	0.37	[0.05]
Large	0.01	[0.05]	0.03	[0.04]	0.14	[0.05]	0.19	[0.07]	0.26	[0.07]	0.25	[0.05]
Diff.	0.38	[0.08]	0.25	[0.06]	0.14	[0.05]	0.10	[0.04]	0.18	[0.04]		
βDR	**Growth**		**2**		**3**		**4**		**Value**		**Diff.**	
Small	1.42	[0.19]	1.49	[0.16]	1.39	[0.15]	1.37	[0.15]	1.26	[0.16]	-0.16	[0.12]
2	1.14	[0.11]	1.32	[0.12]	1.18	[0.12]	1.20	[0.13]	1.27	[0.15]	0.13	[0.07]
3	1.27	[0.12]	1.12	[0.10]	1.21	[0.11]	1.13	[0.12]	1.34	[0.15]	0.07	[0.07]
4	1.01	[0.09]	1.09	[0.10]	1.05	[0.11]	1.12	[0.12]	1.42	[0.16]	0.40	[0.09]
Large	1.03	[0.09]	0.96	[0.08]	0.99	[0.08]	1.20	[0.13]	1.05	[0.13]	0.02	[0.08]
Diff.	0.39	[0.15]	0.53	[0.10]	0.40	[0.09]	0.16	[0.07]	0.21	[0.08]		

Notes: This table reports the cash-flow and discpunt rate betas for the 5x5Fama-French portfolios of US stocks using the VAR for period of 1928:12 to 1963:06. The betas were calculated using estimators (7.1) and (7.2). Diff. indicates the diference between the extreme value or size portfolio betas. In square brackets are shown the standard deviation of each estimator calculated by a bootstrap exercise with 2500 realized simulations.

Table 15 - Cash flow and Discount Rate Betas for the US - sample 1963:06 to 2001:12

βCF	Growth		2		3		4		Value		Diff.	
Small	-0.47	[0.08]	0.63	[0.06]	0.58	[0.05]	0.53	[0.05]	0.55	[0.05]	1.02	[0.04]
2	0.73	[0.07]	0.62	[0.05]	0.57	[0.05]	0.55	[0.04]	0.58	[0.05]	-0.15	[0.04]
3	0.69	[0.06]	0.60	[0.05]	0.55	[0.04]	0.52	[0.04]	0.54	[0.05]	-0.14	[0.04]
4	0.63	[0.05]	0.57	[0.04]	0.52	[0.04]	0.50	[0.04]	0.53	[0.04]	-0.09	[0.04]
Large	0.47	[0.04]	0.47	[0.04]	0.43	[0.03]	0.41	[0.03]	0.42	[0.04]	-0.05	[0.03]
Diff.	0.93	[0.06]	0.16	[0.05]	0.15	[0.04]	0.13	[0.04]	0.13	[0.04]		

βDR	Growth		2		3		4		Value		Diff.	
Small	0.78	[0.10]	0.65	[0.09]	0.55	[0.07]	0.49	[0.07]	0.47	[0.07]	-0.31	[0.05]
2	0.80	[0.09]	0.60	[0.07]	0.52	[0.07]	0.46	[0.06]	0.48	[0.07]	-0.32	[0.05]
3	0.78	[0.08]	0.58	[0.07]	0.46	[0.06]	0.43	[0.06]	0.44	[0.06]	-0.33	[0.05]
4	0.70	[0.07]	0.54	[0.06]	0.46	[0.06]	0.42	[0.05]	0.43	[0.06]	-0.27	[0.05]
Large	0.54	[0.06]	0.46	[0.05]	0.38	[0.05]	0.33	[0.05]	0.33	[0.05]	-0.21	[0.05]
Diff.	0.24	[0.07]	0.19	[0.06]	0.17	[0.05]	0.15	[0.05]	0.14	[0.05]		

Notes: This table reports the cash-flow and discpunt rate betas for the 5x5Fama-French portfolios of US stocks using the VAR for period of 1963:06 to 2001:12. The betas were calculated using estimators (7.1) and (7.2). Diff. indicates the diference between the extreme value or size portfolio betas. In square brackets are shown the standard deviation of each estimator calculated by a bootstrap exercise with 2500 realized simulations.

8. ASSET PRICING MODEL TESTS

The cash flow and discount rate betas calculated in the last section will be used to test the cross section intertemporal asset pricing model given by (3.31) whose properties have been discussed in section 2. For comparison, we also test two other models using the betas estimated from the news series: the CAPM with betas given by estimator (3.28) and a two-factor model where cash flow and discount rate beta risk premia can assume irrestricted values. In general, all threem models can be expressed by the single test equation:

$$E\left[R_i - R_f\right] = g_0 + g_1 \cdot \beta_{i,CF} + g_2 \cdot \beta_{i,DR} \qquad (8.1)$$

In the CAPM, we restrict $g_1 = g_2$, for the ICAPM the restriction is $g_2 = \sigma^2_M$, where σ^2_M is the unconditional market monthly return variance. The two-factor model is simply equation (8.1) with no restrictions. Following Campbell and Vuolteenaho (op. cit.) we test the models for the average returns calculated in the same sample in which the betas were determined.

For each sample of interest, the models were estimated with two different especifications: with intercept restricted to be equal to the avarege risk-free rate ($g_0 = E[R_f]$) and with free intercept. The first especification assumes the risk free rate is one available investment for the investor, so the models have to explain, besides the differences in return for each Fama-French portfolio, the unconditional equity premium. With free intercept, the models have to account only for the differences in returns of stock portfolios.

Again we report four sets of results. The tests were performed for the 25 Fama-French US portfolios in the the two sub-samples of 1928:12 to 1963:06 and 1963:06 to 2001:12 with betas given by tables 14 and 15 respectively and for the 6 Fama-French portfolios of Brazilian stocks from 2003:01 to 2012:04 and also for the 25 US portfolios in this same period. In total 6 different regressions were performed for each set of betas, the tables reporting the results identify the model in the top line, the free intercept specification results are shown on the left column and the restricted intercept version in the right column. The first block of rows report the intercept point estimate, its value multiplied by 1200 to give an easier interpretation of results as % per year and the standard error determined by a bootstrap exercise with 2500 simulated realizations fully described in the appendix. For the The second set of rows reports the coefficient of cash flow betas with the same structure and the third the coefficient of discount rate betas. The forth row shows the regressions R^2. Finally, the last row reports a pricing error measure for each model.

The pricing error measure suggested by Campbell and Vuolteenaho (op.cit.) to evaluate the models is given by:

$$\hat{e}'\,\widehat{\Omega}^{-1}\widehat{e} \qquad (8.2)$$

where ê is te vector of residuals from the model and **Ω** is the matrix whose diagonal contains the volatility of each test asset return, in the same order as they appear in the regression. The measure (8.2) is sum of squared residuals weighted by the inverse of volatility, i.e., placing less weight on more noise portfolio returns. The last row of each table reporting results contain this pricing error measure calculated for each model and it 5% critical value calculated using standard deviations from the same bootstrap procedure described in the appendix.

Table 16 - Asset Pricing Tests for US sample 1928:12 to 1963:06

Parameter	Factor Model		Two-beta ICAPM		CAPM	
Constant	0.0178*	0.0013	0.0014	0.0013	0.0093*	0.0013
% per annum	21.31%	1.53%	1.65%	1.53%	11.21%	1.53%
Standard error	(0.0026)	N/A	(11.9243)	N/A	(0.0021)	N/A
βCF premium	0.0090	-0.0021	-0.0052	-0.0049	-0.0028	0.0027
% per annum	10.80%	-2.52%	-6.27%	-5.86%	-3.35%	3.29%
Standard error	(0.0603)	(0.0776)	(0.0511)	(0.0862)	(0.0258)	-(0.1691)
βDR premium	-0.0119	0.0037	0.0043*	0.0043	-0.0028	0.0027
% per annum	-14.30%	4.40%	5.14%	5.14%	-3.35%	3.29%
Standard error	(0.0285)	(0.0603)	(0.0002)	(0.0002)	(0.0258)	-(0.1691)
R2	18.65%	-14.06%	-15.16%	-15.19%	5.56%	-16.91%
Pricing error	0.0136	0.0243	0.0143	0.0366	0.0142	0.0372
5% critical value	0.0037	0.0225	0.0029	0.0397	0.0025	0.0379

Notes: This table reports the the risk premia estimates for a test sample of 25 Fama-French US portofolios for the period from 1928:12 to 1963:06. The models tested are the CAPM, the ICAPM and a two factor model. The betas where calculated using news series as described by equations (7.1) and (7.2). For each model, the first column reports the OLS estimates of the unrestricted intercept version while the second column reports the

estimates for the restricted intercept version. Standard errors are calculated by a bootstrap exercise using 2500 simulated samples. The pricing error is given by expression (8.2). *, ** indicates estimate is significant with 5% and 10% confidence level respectively.

Table 16 shows that no model is very successful in the earlier sample for the 25 US Fama-French portfolios. All the models with restricted intercept have trouble in explaining the unconditional equity premium in this period. Comparing the ICAPM with the two factor model, we see that the discount rate premium should be negative to better account for the cross section of returns, not positive as the market volatility. Note that ICAPM implies a negative risk aversion coefficient in this period. Even the CAPM fails for the FF portfolios in this sample, even though the betas reported in table 14 do not differ much from the ones reported in Campbell and Vuolteenaho (op.cit.). This means that the CAPM was successful in th earlier sample in their work in part due to the inclusion of the 20 risk sorted portfolios in their tests, besides the 25 FF portfolios.

In table 17 we report the results for the same US 25 Fama-French portfolios in the sample from 1963:6 to 2001:12. For this period, using the VAR in sample, we found the betas to differ a lot from those reported in Campbell and Vuolteenaho (op.cit.). Although all models are strictly rejected by the pricing error criteria, the CAPM with unrestricted intercept and the two factor model provid a good fit for the cross section return of the portfolios. Again the ICAPM fails because it imposes positive premium for discount rate beta and, as shown in table 17, the CAPM and the two factor model fit the data with negative premia. The failure of the ICAPM compared to the original paper has two reasons: besides the absence of the 20 risk sorted portfolios in our test, the betas for the FF portfolios are very different because no variable included in the VAR was a good market return predictor in the period. Again, the estimated ICAPM implies a negative risk aversion coefficient.

Table 17 - Asset Pricing Tests for US sample 1963:06 to 2001:12

Parameter	Factor Model		Two-beta ICAPM		CAPM	
Constant	0.0021	0.0052	0.0124*	0.0052	0.0125*	0.0052
% per annum	2.50%	6.21%	14.86%	6.21%	15.02%	6.21%
Standard error	(0.0028)	N/A	(0.0021)	N/A	(0.0021)	N/A
βCF premium	0.0397	0.0300	-0.0146	-0.0019	-0.0066	-0.0001
% per annum	47.62%	36.06%	-17.49%	-2.26%	-7.97%	-0.10%
Standard error	(0.0717)	(0.0559)	(0.0650)	(0.0353)	(0.0323)	-(0.0032)
βDR premium	-0.0358	-0.0315	0.0020*	0.0020*	-0.0066	-0.0001
% per annum	-43.02%	-37.75%	2.42%	2.42%	-7.97%	-0.10%
Standard error	(0.0593)	(0.0429)	(0.0001)	(0.0001)	(0.0323)	-(0.0032)
R2	66.91%	64.89%	8.79%	-9.11%	30.16%	-0.32%
Pricing error	0.0304	0.0347	0.0362	0.0395	0.0362	0.0395
5% critical value	0.0164	0.0149	0.0138	0.0101	0.0137	0.0095

Notes: This table reports the the risk premia estimates for a test sample of 25 Fama-French US portofolios for the period from 1963:06 to 2001:12. The models tested are the CAPM, the ICAPM and a two factor model. The betas where calculated using news series as described by equations (7.1) and (7.2). For each model, the first column reports the OLS estimates of the unrestricted intercept version while the second column reports the

estimates for the restricted intercept version. Standard errors are calculated by a bootstrap exercise using 2500 simulated samples. The pricing error is given by expression (8.2). *, ** indicates estimate is significant with 5% and 10% confidence level respectively.

The results for the asset pricing tests for the 6 brazilian Fama-French portfolios should be regarded as a first exercise because the sample available to estimate a monthly VAR is much shorter than the available for the US. Besides, fewer test portfolios are available because the Fama-French portfolios get too concentrated and illiquid if more quantile divisions are taken. Nonetheless, the models do have some explanatory power over this small cross section. But again, if the ICAPM defined here is to be valid, it implies that Brazilian stock market investors have a negative risk aversion coefficient. Or alternatively, if the stock market is a poor proxy to the Brazilian investors' wealth portfolio, and the actual wealth portfolio returns are much less volatile, the model could then provide a better fit with a still positive cash flow risk premium.

For comparison, using the same period for the US, the results are also not much favorable for any of the tested models even using the 25 Fama-French portfolios. Results in table 19 show that there is little difference between any of the tested models. The main problem lies, then, in the news series estimation, since none of the variables employed in the VAR can help to predict market returns, the news series used are probably not properly specified for this period.

Table 18 - Asset Pricing Tests for Brazil - sample 2003:01 to 2012:04

Parameter	Factor Model		Two-beta ICAPM		CAPM	
Constant	-0.0071	0.0110	0.0087*	0.0110	-0.0044	0.0110
% per annum	-8.49%	13.18%	10.38%	13.18%	-5.26%	13.18%
Standard error	(0.0064)	N/A	(0.0043)	N/A	(0.0041)	N/A
βCF premium	-0.0202	-0.0262	-0.0134	-0.0432	0.0179	0.0007
% per annum	-24.28%	-31.44%	-16.10%	-51.83%	21.42%	0.78%
Standard error	(0.1117)	(0.0690)	(0.0932)	(0.0474)	(0.0275)	(0.0133)
βDR premium	0.0242	0.0028	0.0044*	0.0044	0.0179	0.0007
% per annum	29.00%	3.37%	5.31%	5.31%	21.42%	0.78%
Standard error	(0.0342)	(0.0222)	(0.0002)	(0.0002)	(0.0275)	(0.0133)
R2	26.01%	5.10%	9.18%	3.15%	17.02%	1.05%
Pricing error	0.0097	0.0129	0.0135	0.0159	0.0134	0.0156
5% critical value	0.0091	0.0076	0.0084	0.0057	0.0077	0.0047

Notes: This table reports the the risk premia estimates for a test sample of 6 Fama-French portofolios for Brazil in the period from 2003:01 to 2012:04. The models tested are the CAPM, the ICAPM and a two factor model. The betas where calculated using news series as described by equations (7.1) and (7.2). For each model, the first column reports the OLS estimates of the unrestricted intercept version while the second column reports the estimates for the restricted intercept version. Standard errors are calculated by a bootstrap exercise using 2500 simulated samples. The pricing error is given by expression (8.2). *, ** indicates estimate is significant with 5% and 10% confidence level respectively.

Table 19 - Asset Pricing Tests for US - sample 2003:01 to 2012:04

Parameter	Factor Model		Two-beta ICAPM		CAPM	
Constant	0.0038	0.0015	0.0038	0.0015	0.0042**	0.0015
% per annum	4.59%	1.84%	4.54%	1.84%	5.04%	1.84%
Standard error	(0.0029)	N/A	(0.0022)	N/A	(0.0022)	N/A
βCF premium	-0.0018	0.0001	0.0033	0.0052	0.0031	0.0055
% per annum	-2.16%	0.12%	4.00%	6.21%	3.72%	6.63%
Standard error	(0.0253)	(0.0461)	(0.0194)	(0.0532)	(0.0143)	(0.0388)
βDR premium	-0.0505	-0.0502	0.0019*	0.0019*	0.0031	0.0055
% per annum	-60.56%	-60.28%	2.31%	2.31%	3.72%	6.63%
Standard error	(0.0491)	(0.0892)	(0.0000)	(0.0000)	(0.0143)	(0.0388)
R2	4.19%	3.58%	1.48%	0.89%	1.33%	0.51%
Pricing error	0.0416	0.0700	0.0479	0.1213	0.0476	0.1232
5% critical value	0.0172	0.0471	0.0152	0.1635	0.0149	0.1638

Notes: This table reports the the risk premia estimates for a test sample of 25 Fama-French US portfolios in the period from 2003:01 to 2012:04. The models tested are the CAPM, the ICAPM and a two factor model. The betas where calculated using news series as described by equations (7.1) and (7.2). For each model, the first column reports the OLS estimates of the unrestricted intercept version while the second column reports the estimates for the restricted intercept version. Standard errors are calculated by a bootstrap exercise using 2500 simulated samples. The pricing error is given by expression (8.2). *, ** indicates estimate is significant with 5% and 10% confidence level respectively.

One last exploratory exercise was performed with the US data. In all the previous asset pricing tests presented in this section, as well as in the ones presented in Campbell and Vuolteenaho's work, the news series were calculated using errors from a VAR system estimated using a fixed sample. This implies that, to calculate the betas of each portfolio investors are using a fixed relationship (the VAR transition matrix) estimated based on information they could not have had access to at each time.

In an attempt to solve this issue we propose to estimate the VAR using a moving window, in such way that investors would identify the shocks to each state variable and determine the discount rate and cash-flow news with information available at the time. With this procedure, it is hoped that the betas obtained better represent the investors' contemporaneous views of each portfolio.

We used a 40 year rolling window, starting with the period from 1928:12 to 1969:12. The VAR thus estimated in this first window was used to calculate the news series from 1963:06 to 1969:12, as we seek to compare the asset pricing model results with the ones in table 17. Then, for each month included a new transition matrix is estimated and used, together with the VAR error in this month, to calculate a new point for the discount rate and cash flow news series. The procedure is repeated until 2001:12. With the news series so determined, the cash-flow and discount rate betas of the 25 Fama-French portofolios are calculated and the factor model, ICAPM and CAPM are tested in the same way as described above.

The results reported in table 20 show that, as expected the overall fit of the models measured by their adjusted R^2 is worse than the ones reported in table 17, with betas calculated using the fixed sample. This was expected, since the tests in table 17 were performed with betas and average returns calculated in the same sample and results in table 20 are closer to a truly out-of-sample test. What is interesting, however, is that among the models out of sample, the ICAPM with fixed risk free rate is the better performing model measured by the adjusted R^2. A more careful analysis, however, is required before this result can be interpreted as as indication that intertemporal considerations played an important role for American investors in this period.

Table 20 - Asset Pricing Tests for US - rolling window news series

Parameter	Factor Model		Two-beta ICAPM		CAPM	
Constant	0.0023	0.0052	0.0046*	0.0052	0.0051*	0.0052
% per annum	2.76%	6.21%	5.49%	6.21%	6.12%	6.21%
Standard error	(0.0014)	N/A	(0.0008)	N/A	(0.0019)	N/A
βCF premium	0.0118*	0.0051	0.0051*	0.0060*	0.0002	0.0002
% per annum	14.15%	6.12%	6.11%	7.24%	0.29%	0.21%
Standard error	(0.0056)	(0.0041)	(0.0021)	(0.0011)	(0.0021)	(0.0005)
βDR premium	0.0056*	0.0017	0.0020	0.0020	0.0002	0.0002
% per annum	6.66%	2.04%	2.42%	2.42%	0.29%	0.21%
Standard error	(0.0024)	(0.0012)	N/A	N/A	(0.0021)	(0.0005)
R2	6.34%	3.57%	5.46%	7.31%	-4.25%	0.09%

Notes: This table reports the the risk premia estimates for a test sample of 25 Fama-French US portfolios in the period from 1963:06 to 2001:12. The models tested are the CAPM, the ICAPM and a two factor model. The betas where calculated using news series as described by equations (7.1) and (7.2) using a rolling window VAR as described in the text. Standard errors are OLS estimates and R2 represents the adjusted R^2.

9. CONCLUSION

Following the methodology of Campbell and Vuolteenaho (2004), this work rebuilds the cash flow and discount rate news series for the aggregate stock market returns for the US using different data periods. We found that, in accordance with recent publication by Subrahmanyam (2012), variables that could predict market returns in the earlier sample are no longer statistically meaningful predictors in a monthly VAR in the period from 1963 to 2001. Also, extending the period up until 2012, we verify that market returns display some short term momentum, according to the methodology employed, due to the stock market crash of 2008. We showed that the news series are sensitive to the sample period used to estimate the return forecasting VAR, which affects the calculated betas and gives different results for the asset pricing tests. Particularly for the 1963-2001 sample, the betas for the 25 Fama-French portofolios calculated using the in-sample VAR based news series are very different from the ones reported in BBGB, and the ICAPM doesn’t show the same success in accounting for the value premium in this period.

In all, the results obtained here for the US point that it is the relationship established among the predictive variables and market returns in the 1930's and 1940's that are crucial to the explanation of the value premium in the post 1963 sample. If one uses only the in-sample data to define shocks to market returns in this later period the news series found do not support the intertemporal model so strongly because the state variables are not good market return predictors. Using a rolling window VAR to simulate the news series determined by a contemporaneous forecaster, however, despite a worst overall fit of all the models, the ICAPM seems to be superior to the traditional CAPM and the factor model in the same period.

For Brazilian stock market data, past market excess returns, smoothed price earnings ratio and the small stock value spread were all good aggregate market excess return predictors in the period from 2003 to April 2012. Only the interest rate term spread did not show any correlation to stock market returns in the period. But for the Brazilian market a increase in the small stock value spread predicts higher market returns, which should imply, if the ICAPM developed here is true, that either Brazilian stock market investors are risk averse and simply there is no value premium in the Brazilian market or there is a value premium because Brazilian investors are very low risk averse and prefer to have resources to profit from improved future market returns. A third option within the model's framework that wasn't empirically explored here is that the stock market is a poor proxy for Brazilian investors' wealth portfolio. In this case the results found here could be improved if the VAR and the news could be calculated using, for instance, a combination of stocks, bonds and human capital (BANSAL et. al., 2012). This possibility could be explored in future researches.

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LIST OF APPENDICES

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A.1 Forecasting VAR Bootstrap and Small Sample Bias

Standard errors reported for the estimated VARs, news series, betas and pricing models were all calculated based on a bootstrap exercise proposed by Campbell and Vuolteenaho (2004).

Initially the VAR (3.32) is estimated from the actual sample and the m x 1 vector of residuals u_{t+1} is saved. Then, assuming that the VAR transition matrix is the true data generating process, a pseudo sample is created using the estimated transition matrix, the initial value of each series and a m x 1 vector of residuals bootstrapped from the original vector u_{t+1}. Using this pseudo sample, we estimate a new VAR, calculate again the news series, the cash flow and discount rate betas of each test asset, estimate again each of the cross sectional asset pricing model presented and calculate the pricing error according to expression (8.2). This procedure is repeated 2500 times, generating a series of bootstrapped values for each statistic of interest. The standard error of these series is the reported bootstrap standard deviation in the text.

The VAR coefficients may be affected by two kinds of small samples biases. First, as pointed by Stambaugh (1999), when return innovations are positively correlated to innovations in the forcasting variable, the respective coefficient in the VAR equation is biased downward. The opposite happens when returns and forecasting variables innovations are negatively correlated. Also, according to the work of Kendall (1954), the estimates of coefficients of persistent autoregressive processes are biased downward when the means of the processes are also estimated.

In order to provide an estimate of this bias for each of VAR systems reported in this work, we follow Campbell and Vuolteenaho (2004), presenting the results of a Monte Carlo simulation. We take again the transition matrix of the VAR system estimated with the sample as the true data generating process. With this coeeficient and assuming i.i.d. errors, we generate 2500 sets of the forecasting variables series samples. For each of of this samples a new VAR is estimated, we obtain thus a series for each statistic of interest. The difference between the mean value of this series and the value of the statistic determined in the original sample is an indicative of the total small sample bias.

As expected, the bias for some coefficients in the short sample of Brazilian data is quiet large. Table A1 shows the small bias for Brazilian data. In the first row is shown the estimated coefficients from the original VAR, the second row shows the mean of the Monte Carlo simulation and the third row is the indicated bias. The most noteworthy bias in table A1 for the conclusions presented in this work is the donward bias in the small stock value spread coefficient in the excess return forecasting equation. If the true value of the coefficient is taken to be 0.03 as indicated by the simulation, it would still be different from zero with a non usual 12% confidence level.

Table A1 - Small sample bias Brazil data 2003:01 to 2012:04

	Constant	rme(t)	ys(t)	pe(t)	vs(t)	Function CF	Function DR
rme(t+1)	0,243	0,220	0,001	-0,112	0,037	1,013	0,013
	0,304	0,181	0,001	-0,130	0,030	0,990	-0,010
	{0,062}	-{0,039}	{0,000}	-{0,019}	-{0,007}	-{0,023}	-{0,023}
ys(t+1)	-3,129	-1,487	0,789	1,043	0,345	-0,010	-0,010
	-3,141	-1,493	0,786	1,049	0,344	-0,002	-0,002
	-{0,012}	-{0,005}	-{0,002}	{0,006}	-{0,001}	{0,008}	{0,008}
pe(t+1)	0,276	0,243	0,003	0,875	0,033	-0,963	-0,963
	0,356	0,244	0,001	0,837	0,049	-0,822	-0,822
	{0,081}	{0,001}	-{0,002}	-{0,038}	{0,016}	{0,140}	{0,140}
vs(t+1)	0,329	0,391	-0,001	-0,061	0,886	0,023	0,023
	0,366	0,388	-0,009	-0,052	0,849	-0,007	-0,007
	{0,037}	-{0,004}	-{0,008}	{0,009}	-{0,037}	-{0,030}	-{0,030}

Notes: This table shows an indication of the small sample bias in the coefficients of VAR reported in table 8 for the Brazilian data from 2003:01 to 2012:04 on the left block and the same indication for each coefficient of the functions defining cash flow and discount rate shocks on the right block. On each set of results, the first line shows the coefficients estimated from the original sample, the second line shows the mean value of each coefficient obtained from 2500 pseudo samples and the third line shows the diference of both values.

We report the results from the same Monte Carlo exercise for the three US samples: from 20003:01 to 2012:04 in table A2, from 1928:12 to 1963:06 in table A3 and from 1963:06 to 2001:12 in table A4.

Table A2 - Small Sample Bias for US sample 2003:01 to 20012:4

	Constant	rme(t)	ys(t)	pe(t)	vs(t)	Function CF	Function DR
rme(t+1)	0,133	0,229	0,003	-0,029	-0,033	1,01	0,01
	0,201	0,183	0,002	-0,057	-0,024	0,83	-0,17
	{0,068}	-{0,046}	-{0,001}	-{0,027}	{0,009}	-{0,177}	-{0,177}
ys(t+1)	-3,671	1,362	0,871	0,609	1,449	0,01	0,01
	-3,676	1,361	0,870	0,609	1,455	0,00	0,00
	-{0,005}	-{0,001}	-{0,001}	{0,000}	{0,006}	-{0,009}	-{0,009}
pe(t+1)	0,247	0,900	0,004	0,930	-0,041	-0,28	-0,28
	0,338	0,902	0,004	0,901	-0,048	-0,38	-0,38
	{0,092}	{0,002}	{0,000}	-{0,029}	-{0,007}	-{0,102}	-{0,102}
vs(t+1)	0,205	-0,170	0,000	-0,031	0,923	-0,07	-0,07
	0,275	-0,169	-0,004	-0,033	0,887	-0,05	-0,05
	{0,070}	{0,001}	-{0,005}	-{0,002}	-{0,036}	{0,019}	{0,019}

Notes: This table shows an indication of the small sample bias in the coefficients of VAR reported in table 9 for the US data from 2003:01 to 2012:04 on the left block and the same indication for each coefficient of the functions defining cash flow and discount rate shocks on the right block. On each set of results, the first line shows the coefficients estimated from the original sample, the second line shows the mean value of each coefficient obtained from 2500 pseudo samples and the third line shows the diference of both values.

Table A3 - Small Sample Bias US sample 1928:12 to 1963:06

	Constante	rme(t)	ys(t)	pe(t)	vs(t)	Function CF	Function DR
rme(t+1)	0,063	0,108	0,002	-0,016	-0,009	0,50	-0,50
	0,056	0,082	0,000	-0,008	-0,021	0,82	-0,18
	-{0,008}	-{0,026}	-{0,002}	{0,008}	-{0,011}	{0,323}	{0,323}
ys(t+1)	0,015	0,071	0,941	-0,014	0,046	0,04	0,04
	-0,128	-0,035	0,930	-0,072	0,280	0,02	0,02
	-{0,142}	-{0,106}	-{0,011}	-{0,058}	{0,234}	-{0,026}	-{0,026}
pe(t+1)	0,026	0,555	0,000	0,991	-0,002	-1,01	-1,01
	0,052	0,556	-0,002	0,985	-0,007	-0,45	-0,45
	{0,025}	{0,000}	-{0,002}	-{0,006}	-{0,005}	{0,558}	{0,558}
vs(t+1)	0,019	-0,017	-0,001	-0,001	0,991	-0,40	-0,40
	0,084	-0,032	-0,003	0,011	0,925	-0,11	-0,11
	{0,065}	-{0,015}	-{0,002}	{0,013}	-{0,066}	{0,288}	{0,288}

Notes: This table shows an indication of the small sample bias in the coefficients of VAR reported in table 9 for the US data from 1928:12 to 1963:06 on the left block and the same indication for each coefficient of the functions defining cash flow and discount rate shocks on the right block. On each set of results, the first line shows the coefficients estimated from the original sample, the second line shows the mean value of each coefficient obtained from 2500 pseudo samples and the third line shows the diference of both values.

Table A4 - Small Sample Bias for US sample from 1963:06 to 2001:12

	Constant	rme(t)	ys(t)	pe(t)	vs(t)	Function CF	Function DR
rme(t+1)	0,063	0,108	0,002	-0,016	-0,009	0,73	-0,27
	0,056	0,082	0,000	-0,008	-0,021	0,82	-0,18
	-{0,008}	-{0,026}	-{0,002}	{0,008}	-{0,011}	{0,090}	{0,090}
ys(t+1)	0,015	0,071	0,941	-0,014	0,046	0,01	0,01
	-0,128	-0,035	0,930	-0,072	0,280	0,02	0,02
	-{0,142}	-{0,106}	-{0,011}	-{0,058}	{0,234}	{0,009}	{0,009}
pe(t+1)	0,026	0,555	0,000	0,991	-0,002	-0,69	-0,69
	0,052	0,556	-0,002	0,985	-0,007	-0,45	-0,45
	{0,025}	{0,000}	-{0,002}	-{0,006}	-{0,005}	{0,238}	{0,238}
vs(t+1)	0,019	-0,017	-0,001	-0,001	0,991	-0,11	-0,11
	0,084	-0,032	-0,003	0,011	0,925	-0,11	-0,11
	{0,065}	-{0,015}	-{0,002}	{0,013}	-{0,066}	-{0,003}	-{0,003}

Notes: This table shows an indication of the small sample bias in the coefficients of VAR reported in table 9 for the US data from 1963:06 to 2001:12 on the left block and the same indication for each coefficient of the functions defining cash flow and discount rate shocks on the right block. On each set of results, the first line shows the coefficients estimated from the original sample, the second line shows the mean value of each coefficient obtained from 2500 pseudo samples and the third line shows the diference of both values.

Appendix A.2 - Forecasting VAR for the US 9 year sub samples

Table A5: VAR for US data - sample 1994:01 to 2003:12

	Constant	RMe(t)	YS(t)	PE(t)	VS(t)	R2	F
RMe(t+1)	0,207	-0,021	-0,020	-0,032	-0,051	0,096	2,70
	(0,091)	(0,096)	(0,008)	(0,031)	(0,040)		
	[0,140]	[0,094]	[0,011]	[0,048]	[0,053]		
YS(t+1)	-0,027	0,063	0,969	-0,049	0,148	0,910	256,85
	(0,538)	(0,568)	(0,045)	(0,181)	(0,237)		
	[0,853]	[0,574]	[0,071]	[0,297]	[0,332]		
PE(t+1)	0,134	0,500	-0,007	0,984	-0,049	0,969	809,91
	(0,091)	(0,096)	(0,008)	(0,031)	(0,040)		
	[0,137]	[0,097]	[0,011]	[0,049]	[0,055]		
VS(t+1)	0,087	-0,043	-0,005	0,060	0,812	0,802	103,26
	(0,017)	(0,028)	(0,002)	(0,004)	(0,005)		
	[0,207]	[0,138]	[0,016]	[0,068]	[0,070]		
	corr/std	RMe(t)	YS(t)	PE(t)	VS(t)		
	RMe(t)	0,046	0,113	0,388	0,414		
		[0,004]	[0,095]	[0,147]	[0,095]		
	YS(t)	0,113	0,267	-0,494	0,101		
		[0,000]	[0,058]	[0,263]	[0,093]		
	PE(t)	0,388	-0,494	0,044	0,180		
		[0,000]	[0,000]	[0,014]	[0,092]		
	VS(t)	0,414	0,101	0,180	0,065		
		[0,000]	[0,000]	[0,000]	[0,009]		

Notes: This table shows the OLS estimate of the first order VAR described in section 2 for US data, sample from 1994:01 to 2003:12. RMe is excess log market returns, YS is the yield spread, PE the smoothed price-earnings and VS the small stock value spread as described in text. First line of each block shows the OLS estimate of each coefficient, second line reports the OLS standard errors in parenthesis, and the third line shows the bootstrap standard errors based on 2500 simulations on square brackets. The last blcok show the equations error correlation, with variances in the main diagonal. The standard erros based on 2500 bootstrap simulations are shown bellow in square brackets.

Table A6: VAR for US data - sample 1985:01 to 1994:12

	Constant	RMe(t)	YS(t)	PE(t)	VS(t)	R2	F
RMe(t+1)	0,172	0,051	0,006	-0,053	-0,008	0,038	1,01
	(0,090)	(0,096)	(0,006)	(0,033)	(0,041)		
	[0,127]	[0,094]	[0,008]	[0,046]	[0,066]		
YS(t+1)	-1,104	-0,975	0,864	0,275	0,294	0,799	101,32
	(0,710)	(0,763)	(0,049)	(0,259)	(0,322)		
	[1,035]	[0,777]	[0,065]	[0,371]	[0,517]		
PE(t+1)	0,097	0,425	0,001	0,968	0,000	0,973	903,34
	(0,053)	(0,057)	(0,004)	(0,019)	(0,024)		
	[0,075]	[0,057]	[0,005]	[0,027]	[0,039]		
VS(t+1)	0,080	0,101	-0,006	-0,003	0,957	0,914	272,65

	(0,017)	(0,028)	(0,002)	(0,004)	(0,005)		
	[0,104]	[0,077]	[0,006]	[0,037]	[0,055]		
	corr/std	RMe(t)	YS(t)	PE(t)	VS(t)		
	RMe(t)	0,044	0,026	0,834	0,345		
		[0,004]	[0,039]	[0,045]	[0,045]		
	YS(t)	0,026	0,353	0,062	-0,024		
		[0,039]	[0,033]	[0,077]	[0,077]		
	PE(t)	0,834	0,062	0,026	0,321		
		[0,045]	[0,077]	[0,014]	[0,103]		
	VS(t)	0,345	-0,024	0,321	0,035		
		[0,045]	[0,077]	[0,103]	[0,015]		

Notes: This table shows the OLS estimate of the first order VAR described in section 2 for US data, sample from 1985:01 to 1994:12. RMe is excess log market returns, YS is the yield spread, PE the smoothed price-earnings and VS the small stock value spread as described in text. First line of each block shows the OLS estimate of each coefficient, second line reports the OLS standard errors in parenthesis, and the third line shows the bootstrap standard errors based on 2500 simulations on square brackets. The last blcok show the equations error correlation, with variances in the main diagonal. The standard erros based on 2500 bootstrap simulations are shown bellow in square brackets.

Table A7: VAR for US data - sample 1976:01 to 1985:12

	Constant	RMe(t)	YS(t)	PE(t)	VS(t)	R2	F
RMe(t+1)	0,303	0,002	0,008	-0,104	-0,027	0,064	1,73
	(0,117)	(0,095)	(0,006)	(0,043)	(0,029)		
	[0,157]	[0,096]	[0,007]	[0,059]	[0,055]		
YS(t+1)	-0,136	-0,163	0,734	0,229	-0,234	0,570	33,84
	(1,379)	(1,118)	(0,073)	(0,503)	(0,345)		
	[1,870]	[1,147]	[0,085]	[0,690]	[0,629]		
PE(t+1)	0,210	0,390	0,005	0,919	-0,004	0,933	356,57
	(0,076)	(0,062)	(0,004)	(0,028)	(0,019)		
	[0,104]	[0,062]	[0,005]	[0,038]	[0,036]		
VS(t+1)	0,202	-0,069	0,012	-0,058	0,959	0,911	261,35
	(0,017)	(0,028)	(0,002)	(0,004)	(0,005)		
	[0,172]	[0,100]	[0,007]	[0,064]	[0,054]		
	corr/std	RMe(t)	YS(t)	PE(t)	VS(t)		
	RMe(t)	0,041	0,235	0,747	0,478		
		[0,004]	[0,039]	[0,045]	[0,045]		
	YS(t)	0,235	0,483	0,252	-0,146		
		[0,039]	[0,033]	[0,077]	[0,077]		
	PE(t)	0,747	0,252	0,027	0,312		
		[0,045]	[0,077]	[0,014]	[0,103]		
	VS(t)	0,478	-0,146	0,312	0,041		
		[0,045]	[0,077]	[0,103]	[0,015]		

Notes: This table shows the OLS estimate of the first order VAR described in section 2 for US data, sample from 1976:01 to 1985:12. RMe is excess log market returns, YS is the yield spread, PE the smoothed price-earnings

and VS the small stock value spread as described in text. First line of each block shows the OLS estimate of each coefficient, second line reports the OLS standard errors in parenthesis, and the third line shows the bootstrap standard errors based on 2500 simulations on square brackets. The last blcok show the equations error correlation, with variances in the main diagonal. The standard erros based on 2500 bootstrap simulations are shown bellow in square brackets.

Table A8: VAR for US data - sample 1967:01 to 1976:12

	Constant	RMe(t)	YS(t)	PE(t)	VS(t)	R2	F
RMe(t+1)	0,056	0,067	0,018	-0,047	0,052	0,050	1,35
	(0,071)	(0,100)	(0,012)	(0,032)	(0,055)		
	[0,127]	[0,098]	[0,015]	[0,048]	[0,077]		
YS(t+1)	0,439	2,105	0,692	-0,035	-0,157	0,616	40,89
	(0,384)	(0,538)	(0,064)	(0,175)	(0,299)		
	[0,639]	[0,540]	[0,083]	[0,247]	[0,417]		
PE(t+1)	0,039	0,480	0,009	0,974	0,021	0,978	1138,34
	(0,045)	(0,063)	(0,008)	(0,021)	(0,035)		
	[0,079]	[0,064]	[0,010]	[0,030]	[0,048]		
VS(t+1)	0,067	0,008	0,017	0,030	0,888	0,868	168,36
	(0,017)	(0,028)	(0,002)	(0,004)	(0,005)		
	[0,117]	[0,091]	[0,014]	[0,045]	[0,065]		
	corr/std	RMe(t)	YS(t)	PE(t)	VS(t)		
	RMe(t)	0,047	0,198	0,740	0,328		
		[0,004]	[0,039]	[0,045]	[0,045]		
	YS(t)	0,198	0,255	0,085	0,044		
		[0,039]	[0,033]	[0,077]	[0,077]		
	PE(t)	0,740	0,085	0,030	0,225		
		[0,045]	[0,077]	[0,014]	[0,103]		
	VS(t)	0,328	0,044	0,225	0,043		
		[0,045]	[0,077]	[0,103]	[0,015]		

Notes: This table shows the OLS estimate of the first order VAR described in section 2 for US data, sample from 1967:01 to 1976:12. RMe is excess log market returns, YS is the yield spread, PE the smoothed price-earnings and VS the small stock value spread as described in text. First line of each block shows the OLS estimate of each coefficient, second line reports the OLS standard errors in parenthesis, and the third line shows the bootstrap standard errors based on 2500 simulations on square brackets. The last blcok show the equations error correlation, with variances in the main diagonal. The standard erros based on 2500 bootstrap simulations are shown bellow in square brackets.

Table A9: VAR for US data - sample 1958:01 to 1967:12

	Constant	RMe(t)	YS(t)	PE(t)	VS(t)	R2	F
RMe(t+1)	0,091	0,103	0,003	-0,066	0,075	0,114	3,27
	(0,096)	(0,094)	(0,013)	(0,025)	(0,048)		
	[0,122]	[0,093]	[0,016]	[0,032]	[0,056]		
YS(t+1)	0,481	0,544	0,789	-0,164	0,051	0,699	59,23
	(0,426)	(0,417)	(0,059)	(0,109)	(0,212)		
	[0,527]	[0,418]	[0,070]	[0,142]	[0,262]		
PE(t+1)	0,044	0,435	0,000	0,958	0,056	0,966	729,95

	(0,074)	(0,073)	(0,010)	(0,019)	(0,037)		
	[0,093]	[0,073]	[0,012]	[0,025]	[0,042]		
VS(t+1)	0,374	-0,049	0,025	-0,017	0,786	0,680	54,16
	(0,017)	(0,028)	(0,002)	(0,004)	(0,005)		
	[0,143]	[0,112]	[0,018]	[0,037]	[0,065]		
	corr/std	RMe(t)	YS(t)	PE(t)	VS(t)		
	RMe(t)	0,031	-0,021	0,841	-0,028		
		[0,004]	[0,039]	[0,045]	[0,045]		
	YS(t)	-0,021	0,136	-0,008	-0,059		
		[0,039]	[0,033]	[0,077]	[0,077]		
	PE(t)	0,841	-0,008	0,024	0,000		
		[0,045]	[0,077]	[0,014]	[0,103]		
	VS(t)	-0,028	-0,059	0,000	0,036		
		[0,045]	[0,077]	[0,103]	[0,015]		

Notes: This table shows the OLS estimate of the first order VAR described in section 2 for US data, sample from 1958:01 to 1967:12. RMe is excess log market returns, YS is the yield spread, PE the smoothed price-earnings and VS the small stock value spread as described in text. First line of each block shows the OLS estimate of each coefficient, second line reports the OLS standard errors in parenthesis, and the third line shows the bootstrap standard errors based on 2500 simulations on square brackets. The last blcok show the equations error correlation, with variances in the main diagonal. The standard erros based on 2500 bootstrap simulations are shown bellow in square brackets.

Table A10: VAR for US data - sample 1949:01 to 1958:12

	Constant	RMe(t)	YS(t)	PE(t)	VS(t)	R2	F
RMe(t+1)	0,000	0,009	0,027	-0,012	0,023	0,067	1,84
	(0,099)	(0,099)	(0,017)	(0,028)	(0,034)		
	[0,172]	[0,096]	[0,023]	[0,047]	[0,064]		
YS(t+1)	0,645	0,061	0,845	-0,220	0,024	0,877	181,43
	(0,264)	(0,264)	(0,045)	(0,074)	(0,090)		
	[0,419]	[0,257]	[0,061]	[0,110]	[0,164]		
PE(t+1)	-0,012	0,464	0,012	0,995	0,011	0,969	798,78
	(0,079)	(0,079)	(0,014)	(0,022)	(0,027)		
	[0,139]	[0,079]	[0,019]	[0,038]	[0,052]		
VS(t+1)	0,155	0,001	-0,009	-0,027	0,944	0,904	239,19
	(0,017)	(0,028)	(0,002)	(0,004)	(0,005)		
	[0,151]	[0,090]	[0,023]	[0,042]	[0,058]		
	corr/std	RMe(t)	YS(t)	PE(t)	VS(t)		
	RMe(t)	0,032	-0,114	0,742	-0,107		
		[0,004]	[0,039]	[0,045]	[0,045]		
	YS(t)	-0,114	0,084	-0,036	0,003		
		[0,039]	[0,033]	[0,077]	[0,077]		
	PE(t)	0,742	-0,036	0,025	-0,123		
		[0,045]	[0,077]	[0,014]	[0,103]		
	VS(t)	-0,107	0,003	-0,123	0,029		
		[0,045]	[0,077]	[0,103]	[0,015]		

Notes: This table shows the OLS estimate of the first order VAR described in section 2 for US data, sample from 1949:01 to 1958:12. RMe is excess log market returns, YS is the yield spread, PE the smoothed price-earnings and VS the small stock value spread as described in text. First line of each block shows the OLS estimate of each coefficient, second line reports the OLS standard errors in parenthesis, and the third line shows the bootstrap standard errors based on 2500 simulations on square brackets. The last blcok show the equations error correlation, with variances in the main diagonal. The standard erros based on 2500 bootstrap simulations are shown bellow in square brackets.

Table A11: VAR for US data - sample 1940:01 to 1949:12

	Constant	RMe(t)	YS(t)	PE(t)	VS(t)	R2	F
RMe(t+1)	0,217	0,018	-0,048	-0,087	0,034	0,087	2,44
	(0,122)	(0,095)	(0,028)	(0,035)	(0,041)		
	[0,171]	[0,092]	[0,037]	[0,050]	[0,056]		
YS(t+1)	-0,225	0,248	0,906	0,039	0,104	0,974	972,98
	(0,185)	(0,144)	(0,043)	(0,053)	(0,062)		
	[0,250]	[0,145]	[0,056]	[0,076]	[0,082]		
PE(t+1)	0,107	0,460	-0,028	0,951	0,024	0,955	535,94
	(0,086)	(0,067)	(0,020)	(0,025)	(0,029)		
	[0,121]	[0,067]	[0,026]	[0,036]	[0,039]		
VS(t+1)	-0,025	0,234	0,034	0,030	0,948	0,984	1600,49
	(0,017)	(0,028)	(0,002)	(0,004)	(0,005)		
	[0,135]	[0,082]	[0,030]	[0,041]	[0,044]		
	corr/std	RMe(t)	YS(t)	PE(t)	VS(t)		
	RMe(t)	0,044	-0,024	0,809	-0,463		
		[0,004]	[0,039]	[0,045]	[0,045]		
	YS(t)	-0,024	0,067	-0,113	0,127		
		[0,039]	[0,033]	[0,077]	[0,077]		
	PE(t)	0,809	-0,113	0,031	-0,477		
		[0,045]	[0,077]	[0,014]	[0,103]		
	VS(t)	-0,463	0,127	-0,477	0,038		
		[0,045]	[0,077]	[0,103]	[0,015]		

Notes: This table shows the OLS estimate of the first order VAR described in section 2 for US data, sample from 1940:01 to 1949:12. RMe is excess log market returns, YS is the yield spread, PE the smoothed price-earnings and VS the small stock value spread as described in text. First line of each block shows the OLS estimate of each coefficient, second line reports the OLS standard errors in parenthesis, and the third line shows the bootstrap standard errors based on 2500 simulations on square brackets. The last blcok show the equations error correlation, with variances in the main diagonal. The standard erros based on 2500 bootstrap simulations are shown bellow in square brackets.

Table A12: VAR for US data - sample 1931:01 to 1940:12

	Constant	RMe(t)	YS(t)	PE(t)	VS(t)	R2	F
RMe(t+1)	0,054	0,102	0,044	-0,093	0,049	0,119	3,44
	(0,243)	(0,093)	(0,027)	(0,034)	(0,094)		
	[0,314]	[0,094]	[0,030]	[0,048]	[0,113]		
YS(t+1)	-1,302	0,019	0,778	0,152	0,501	0,833	127,20
	(0,583)	(0,224)	(0,064)	(0,081)	(0,227)		
	[0,753]	[0,229]	[0,069]	[0,116]	[0,269]		

PE(t+1)	0,073	0,560	0,033	0,941	0,011	0,967	752,41
	(0,152)	(0,058)	(0,017)	(0,021)	(0,059)		
	[0,203]	[0,058]	[0,020]	[0,030]	[0,073]		
VS(t+1)	0,338	-0,054	0,017	0,009	0,846	0,844	138,38
	(0,017)	(0,028)	(0,002)	(0,004)	(0,005)		
	[0,181]	[0,054]	[0,018]	[0,028]	[0,065]		
	corr/std	RMe(t)	YS(t)	PE(t)	VS(t)		
	RMe(t)	0,096	-0,185	0,768	-0,471		
		[0,004]	[0,039]	[0,045]	[0,045]		
	YS(t)	-0,185	0,229	-0,146	0,112		
		[0,039]	[0,033]	[0,077]	[0,077]		
	PE(t)	0,768	-0,146	0,060	-0,459		
		[0,045]	[0,077]	[0,014]	[0,103]		
	VS(t)	-0,471	0,112	-0,459	0,055		
		[0,045]	[0,077]	[0,103]	[0,015]		

Notes: This table shows the OLS estimate of the first order VAR described in section 2 for US data, sample from 1931:01 to 1940:12. RMe is excess log market returns, YS is the yield spread, PE the smoothed price-earnings and VS the small stock value spread as described in text. First line of each block shows the OLS estimate of each coefficient, second line reports the OLS standard errors in parenthesis, and the third line shows the bootstrap standard errors based on 2500 simulations on square brackets. The last blcok show the equations error correlation, with variances in the main diagonal. The standard erros based on 2500 bootstrap simulations are shown bellow in square brackets.

Appendix A3 – Results for the US in the 1928:12 to 2001:12 period

Table A13: VAR for US data - sample 1928:12 to 1963:06

	Constant	RMe(t)	YS(t)	PE(t)	VS(t)	R2	F
RMe(t+1)	0.155	0.105	0.012	-0.041	-0.027	0.054	5.84
	(0.042)	(0.049)	(0.007)	(0.012)	(0.010)		
	[0.062]	[0.047]	[0.009]	[0.016]	[0.017]		
YS(t+1)	-0.003	0.002	0.920	-0.024	0.070	0.934	1456.23
	(0.102)	(0.117)	(0.017)	(0.030)	(0.024)		
	[0.152]	[0.118]	[0.021]	[0.038]	[0.043]		
PE(t+1)	0.049	0.557	0.003	0.982	-0.004	0.979	4810.47
	(0.028)	(0.033)	(0.005)	(0.008)	(0.007)		
	[0.043]	[0.032]	[0.006]	[0.011]	[0.012]		
VS(t+1)	-0.011	-0.010	-0.002	0.005	0.998	0.989	9441.19
	(0.017)	(0.028)	(0.002)	(0.004)	(0.005)		
	[0.051]	[0.035]	[0.006]	[0.012]	[0.015]		
	corr/std	RMe(t)	YS(t)	PE(t)	VS(t)		
	RMe(t)	0.004	0.085	0.024	0.055		
		[0.002]	[0.059]	[0.074]	[0.052]		
	YS(t)	0.085	0.018	0.063	0.048		
		[0.059]	[0.020]	[0.121]	[0.042]		
	PE(t)	0.024	0.063	0.003	0.054		
		[0.074]	[0.121]	[0.004]	[0.042]		
	VS(t)	0.055	0.048	0.054	0.003		
		[0.052]	[0.042]	[0.042]	[0.004]		

Notes: This table shows the OLS estimate of the first order VAR described in section 2 for US data, sample from 1928:12 to 1963:06 used in the asset pricing tests in section 8. RMe is excess log market returns, YS is the yield spread, PE the smoothed price-earnings and VS the small stock value spread as described in text. First line of each block shows the OLS estimate of each coefficient, second line reports the OLS standard errors in parenthesis, and the third line shows the bootstrap standard errors based on 2500 simulations on square brackets. The last blcok show the equations error correlation, with variances in the main diagonal. The standard erros based on 2500 bootstrap simulations are shown bellow in square brackets.

Table A14: VAR for US data - sample 1963:06 to 2011:12

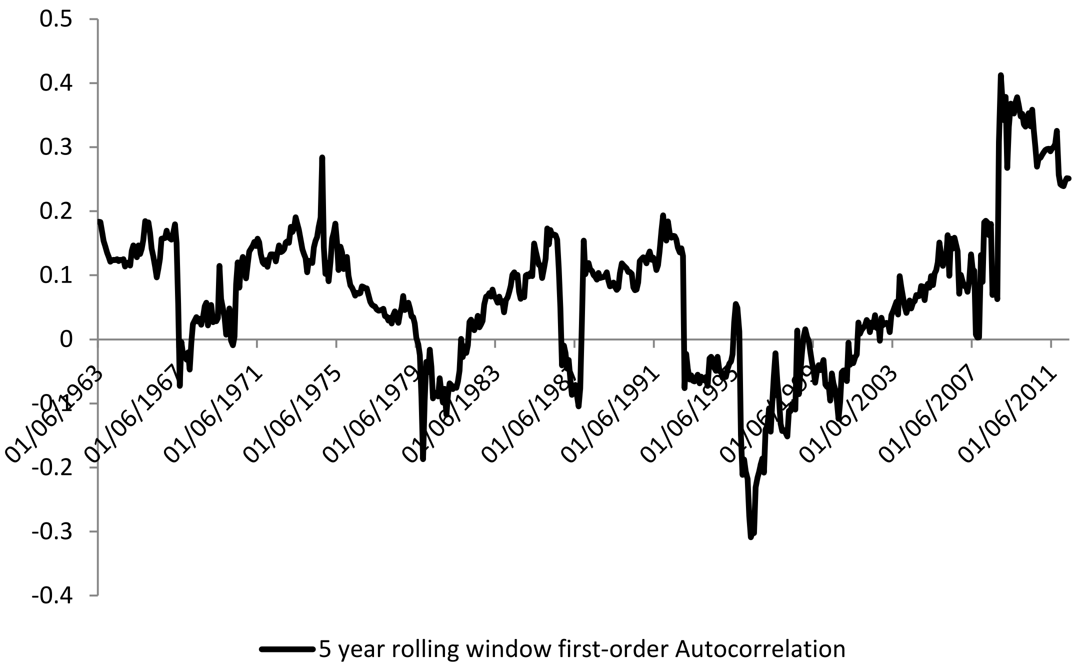
	Constant	RMe(t)	YS(t)	PE(t)	VS(t)	R2	F
RMe(t+1)	0.034	0.058	0.004	-0.001	-0.021	0.012	1.39
	(0.023)	(0.047)	(0.003)	(0.007)	(0.018)		
	[0.037]	[0.047]	[0.003]	[0.012]	[0.020]		
YS(t+1)	0.146	0.154	0.857	-0.031	0.016	0.736	317.93
	(0.173)	(0.357)	(0.024)	(0.052)	(0.136)		
	[0.257]	[0.362]	[0.027]	[0.080]	[0.161]		
PE(t+1)	0.015	0.447	0.001	0.998	-0.007	0.994	19266.18
	(0.014)	(0.030)	(0.002)	(0.004)	(0.011)		
	[0.024]	[0.030]	[0.002]	[0.008]	[0.013]		

VS(t+1)	0.070	0.023	0.001	0.017	0.917	0.890	922.87
	(0.017)	(0.028)	(0.002)	(0.004)	(0.005)		
	[0.037]	[0.050]	[0.004]	[0.012]	[0.021]		
	corr/std	RMe(t)	YS(t)	PE(t)	VS(t)		
	RMe(t)	0.045	0.121	0.772	0.351		
		[0.002]	[0.063]	[0.022]	[0.046]		
	YS(t)	0.121	0.339	0.106	-0.038		
		[0.063]	[0.018]	[0.057]	[0.046]		
	PE(t)	0.772	0.106	0.028	0.250		
		[0.022]	[0.057]	[0.001]	[0.047]		
	VS(t)	0.351	-0.038	0.250	0.047		
		[0.046]	[0.046]	[0.047]	[0.004]		

Notes: This table shows the OLS estimate of the first order VAR described in section 2 for US data, sample from 1963:06 to 2001:12 used in the asset pricing tests in section 8. RMe is excess log market returns, YS is the yield spread, PE the smoothed price-earnings and VS the small stock value spread as described in text. First line of each block shows the OLS estimate of each coefficient, second line reports the OLS standard errors in parenthesis, and the third line shows the bootstrap standard errors based on 2500 simulations on square brackets. The last blcok show the equations error correlation, with variances in the main diagonal. The standard erros based on 2500 bootstrap simulations are shown bellow in square brackets.

Appendix A4- Effect of October 2008 in the US sample

Figure A1: First order autocorrelation of US market excess return



Notes: This figure shows the five-year rolling window of the first order autocorrelation of US stock market monthly excess return form 1963:06 to 2012:04. Returns calculated using CRSP value weighted stock index CRSP Treasury Bills with 3 months to maturity.

Appendix A5 – Fama-French Portfolios

The 5x5 Fama French portfolio returns for the US used in this work were obtained from professor's Kenneth French website. They are calculated with data from CRSP and constructed following the exact methodology proposed in Fama and French (1993). As pointed in the text, the data previous then 1962 was revised by CRSP in 2012, so the portfolio returns used in this work in this periods are different than the ones in Campbell and Vuolteenaho. Table A15 shows the average monthly excess returns of the 25 Fama-French US portfolios in all the periods used to test the asset pricing models in this work:

Table A15 - 5x5 Fama French Portfolios for the US - Monthly Average Returns

Portfolio	1928:12 to 1963:06	1963:06 to 2001:12	2003:01 to 2012:04
11	-0.0052	-0.0009	0.0042
12	-0.0007	0.0054	0.0085
13	0.0050	0.0063	0.0077
14	0.0071	0.0084	0.0074
15	0.0089	0.0091	0.0110
21	0.0029	0.0011	0.0090
22	0.0074	0.0047	0.0100
23	0.0073	0.0073	0.0109
24	0.0072	0.0080	0.0084
25	0.0075	0.0085	0.0099
31	0.0049	0.0017	0.0080
32	0.0062	0.0055	0.0096
33	0.0077	0.0058	0.0107
34	0.0071	0.0072	0.0094
35	0.0053	0.0086	0.0128
41	0.0047	0.0032	0.0088
42	0.0060	0.0034	0.0083
43	0.0068	0.0057	0.0061
44	0.0060	0.0071	0.0091
45	0.0056	0.0072	0.0066
51	0.0046	0.0031	0.0046
52	0.0043	0.0036	0.0062
53	0.0060	0.0038	0.0041
54	0.0043	0.0048	0.0020
55	0.0080	0.0051	0.0042

Notes: This table shows the average monthly aritimetic excess returns of the 25 US Fama French portfolios in three different periods: from 1928:12 to 1963:06, from 1963:06 to 2001:12 and from 2003:01 to 2012:04. The nomenclature of the portfolios follows the convention: first index refers to size and the second to the value quantile of the stocks classification. All data used available from professor's Kenneth French website.

The Fama French portfolios from Brazil were constructed according to the Fama and French (1993) procedure with data from the provider Economática. The universe of elegible stocks were all public traded companies registered in BM&F Bovespa (excluding ETFs and listed mutual funds) which have had at least one trade every week in the year previuos to the formation of the portfolio. After this initial liquidity filter, the 2x3 portfolios are formed as follows: By the end of June of year t, all elegible stocks are ranked by their

market value, all stocks bellow the median are classified as *small* stocks, the one above the median are *big* stocks. In the same date, stocks are also ranked by their book-to-market value. Stocks in the third lowest quantile are labeled *low*, the one in the middle quantile are named *medium* and stocks in the highest third quantile are named *high*. The intersection of the size and value labels split stocks into six portfolios: small low(11), small medium (12), small high (13), big low (21), big medium (22) and big high (23). Next, weighting each stock by its market value, monthly returns of these portfolios are calculated through may of year t+1. The whole procedure is repeated every June. Table A16 shows the avarege monthly excess returns of each portfolio used to test the asset pricing models in this work.

Table A16 - 2x3 Fama French Portfolios Brazil - 2003:01 to 2012:04

Portfolio	Average Monthly Excess Returns
Small Low	0.0101
Small Medium	0.0183
Small High	0.0143
Big Low	0.0067
Big Medium	0.0112
Big High	0.0078

Notes: This table shows the average monthly aritimetic excess returns of the 2x3 Brazil Fama French portfolios in the period from 2003:01 to 2012:04. The portfolios were built using data from Economatica, following the procedure of Fama and French (1993) adding a liquidity filter, narrowing the elegible set of stocks to those which have had at least one trade every week in the year preceeding the formation of the portfolios.