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EQUITY YIELDS AND BETA TERM STRUCTURE. AN ANALYSIS IN TIME-FREQUENCY DOMAIN♣

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Abstract

Recent financial literature has found empirical evidence for the existence of a term structure of equity yields. There are several empirical studies that show that the behavior of asset returns, with respect to the risk factors, change over time and therefore a dynamic beta. This work uses discrete wavelet transform to obtain a decomposition of the time series in orthogonal factors for different frequencies and time horizons. In this way, we apply this methodology to a sample of portfolios and different risk factors. The results show that for some portfolios and factors, there is a term structure of betas, since even the sign of the effect changes with the time horizon.

Keywords: term structure, time-scale beta, wavelets, factorial CAPM, time-frequency decomposition.

JEL Classification: C32; C38; G12.

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1. INTRODUCTION

According to the seminal work by Fama and MacBeth (1973), the CAPM assumes a constant beta risk, however, Klemkosky and Martin (1975), Bollerslev, et al. (1988) and Harvey (1989) argued that the expectations of economic agents for future returns are conditional and therefore random variables rather than constant, implying that the beta of a risky asset should be time-varying. Several works find empirical evidence about variation in the conditional betas of equity portfolios (Jagannathan and Wang, 1996; Lewellen and Nagel, 2006; Bali, 2008; Bali and Engle, 2010; Bali and Engle, 2012).

Additionally, recent financial literature (see among others Binsbergen et al., 2012 and Croce et al., 2014) finds that the premium on the short-term dividend claims is higher than the risk premium on the long-term dividend claims, suggesting that the slope of the dividend risk premium is downward. In this way, the so-called term structure of risk premium appears.

In this context, our aim is to study this structure risk premium and whether the term structure is a result of the beta coefficient variations associated with each asset.

To test this hypothesis, we resort to a methodology recently applied in the financial field, the wavelet decomposition of a time series. The assumption is that economic and financial phenomena may exhibit different characteristics over different time scales as economic agents make decisions about consumption, saving and investing with heterogeneous time horizons. Then, from an original series of returns, this procedure extracts different orthogonal tendencies in a time-frequency domain, which allows for simultaneous analysis of the different terms of yields from a single series.

Wavelet analysis is relatively new in economics and finance, although the literature on wavelets is growing rapidly (see Chakrabarty, et al., 2015 for a survey of the wavelet analysis applied to financial markets). The use of wavelet decomposition in finance has been extended for different purposes. Rua & Nunes (2012) use wavelet to calculate the market beta according to the CAPM theory. Yi et al. (2013) use wavelets to detect jumps in high-frequency financial time series. Galleti (2012) and Saiti et al. (2016) analyze contagion, the first during the US subprime crisis of 2007, and the second among Islamic and non-Islamic Asian stock markets. Malagon et al. (2015) use wavelet decomposition to explain the idiosyncratic risk puzzle with the existence of market participants with different investment horizons and Faria & Verona (2018) propose a method defined in the joint time-frequency domain to forecast stock market returns by wavelet decomposition which significantly improves upon previous work. In this study, our focus is on time-scale CAPM.

Gençay et al. (2003, 2005) estimated CAPM models for discrete wavelet decomposition and found that the relationship between the return of a portfolio and its beta becomes stronger as the wavelet scale increases. Fernandez (2006), Rhaeim et al. (2007), Aktan et al. (2009), Masih et al. (2010), Dajčman et al. (2013) and Alaouia et al. (2015) found evidence that the fraction of systematic risk at lower frequencies has a higher association with lower frequencies of the market portfolio. Kang et al. (2017) presented a paper based on a wavelets framework that broke down the explanatory power of different time-scale betas, but unlike our work, they only apply this methodology to the explanatory factors of the returns, not to the portfolios or assets.

In short, the financial literature on wavelets and CAPMs analyze the temporal effect of the factors but not the temporal structure of the asset beta for different risk factors simultaneously. Additionally, important parts of these studies show the wavelet methodology as an analytical tool without looking closer at the effects of its results, so that methodological issues might condition the empirical results. Some relevant problems arise which this empirical study aims to answer: Is the wavelet filter (Daubechies) applied by most of the financial literature optimal? What is the statistical behavior of each component (from low to high frequency) extracted from original data by wavelet decomposition? Moreover, what is the requirement and the explanatory power of the selected components on which the empirical studies are carried out?

This paper is organized as follows. Section 2 reviews the literature. Section 3 presents the methodology applied in the paper. Section 4 describes the data. Section 5 goes through the main empirical results. Section 6 offers a conclusion.

2. LITERATURE REVIEW ON TIME-VARIANT BETAS

Harvey (1989), Ferson and Harvey (1991, 1993) and Saleem and Vaihekoski (2010) suggested that a constant beta estimated using OLS does not capture the dynamics of the beta.

Fama and French (1997, 2006), Jagannathan and Wang (1996), Ghysels (1998), Reyes (1999), Lettau and Ludvigson (2001), Wang (2003), Lewellen and Nagel (2006), Ang and Chen (2007) and Kim and Kim (2017), among others, have considered the possibility that the beta-coefficient may indeed vary over time.

Groenewold and Fraser (1999) found that the instability of betas over time leads to important practical problems. Besides those posed by the interpretation of betas which change over time, there are estimate problems both for practical use and for use in testing the CAPM.

In addition, Jagannathan and Wang (1996), Lettau and Ludvigson (2001) and Beach (2011) concluded that the conditional CAPM with a time-varying beta outperforms the unconditional CAPM with a constant beta.

Part of the recent literature on asset pricing has focused on studying the behavior of the term structure of returns of risky assets. Campbell and Viceira (2005) showed that the volatility of equity yields and the volatilities of expected returns are downward sloping over time. Binsbergen et al.

(2012), Lettau and Wachter (2011) and Croce et al. (2014) showed that the slope of the dividend risk premium is downward.

Binsbergen et al. (2013) extended this conclusion showing that the long-maturity dividend risk premium is higher than the short-term premium during expansions and lower during recessions. These results were extended to several international indices in Binsbergen and Koijen (2017).

Bali et al. (2016) analyzed the time-varying sensitivity of an asset to the market portfolio and to shifts in future investment opportunities.

González et al. (2018) reported differences over time and across portfolios of the relative weights of the total mixed-frequency conditional betas, concluding that value, small, low momentum and low long reversal stocks have counter-cyclical betas, while growth, big, high momentum and high long reversal stocks have pro-cyclical betas. Also, value and low long reversal portfolios present higher short-term weights in recessions than in normal times, suggesting that they are very sensitive to short-term shocks of systematic risk.

According to McNevin and Nix (2018), estimating is not straightforward, since the assumptions place restrictions on time horizons and frequency changes and the specific information does not remain stable over time and therefore a complete description of the systematic risk of investments in sectors requires estimates that capture time-varying behavior at different frequencies.

In short, from the arguments of Bansal and Yaron (2004), Bansal et al. (2005) and Parker and Julliard (2005), only part of the information in the standard betas is relevant for pricing risky assets and the relevant part is concentrated in certain time-scale betas. To study the domain of time and frequency at the same time is an opportunity to apply other less usual methodologies and, extending the previous arguments, we go one step further in the research on equity yields and beta term structures or time-scale betas.

3. METHODOLOGY

Our methodological proposal has two stages. First, we extract time-scale orthogonal signals for different frequencies and from portfolio returns and risk factors. Later, we estimate the term structure of the betas from wavelet signals for each time horizon.

3.1. Discrete Wavelet Decomposition

To study time-scale components and the beta term structure we use a wavelet decomposition. The main feature of wavelet analysis is that it can break a variable down into its constituent components. So a wavelet transform represents a general function in terms of simple, fixed building blocks at different scales and positions. Then, a dyadic grid in the timescale plane samples the time-scale parameters to form orthogonal bases with optimal time-frequency localization properties.

Conceptually, a discrete wavelet transform (DWT) decomposing of time series X with N dimension supposes extracting the scale (W) and smooth (V) vectors. These elements show the high frequency and low frequency behavior, respectively. Thus, for a maximum frequency J,[1] the original series can be represented as:

$$X = \sum_{j=1}^{J} W_j^T \cdot \mathbb{W}_j + V_J^T \cdot \mathbb{V}_J = \sum_{j=1}^{J} D_j + S_J \tag{1}$$

Where,

$$\begin{aligned} \mathbb{W}_j &= W_j \cdot X \\ \mathbb{V}_j &= V_j \cdot X \end{aligned} \tag{2}$$

[1] According to Percival and Walden (2000) and dispensing with the assumption of circularity, this requires the condition $J < log_2\left(\frac{N}{L-1}\right)$, where L is the width of the wavelet filter.

Expression (1) is called multiresolution analysis and shows the original time series as the sum of a constant or mean value of reversion (S) and variations of X for different scales (D). The contribution of each scale factor D_j is defined as energy and represents the contribution to the sample variance of X due to changes in this factor.

$$\hat{\sigma}_X^2 = \frac{1}{N}\|X\|^2 - \bar{X} = \frac{1}{N}\sum_{j=1}^{J}\|\mathbb{W}_j\|^2 \qquad (3)$$

Each element in the sub-matrix W_j, with $(N \times L)$ dimension, is a filter wavelet coefficient ($h_{t,l}$) and with $L \leq N$ depends on selected filter type. Similarly, the sub-matrix V_j, with $(N \times L)$ dimension, is a filter wavelet coefficient ($g_{t,l}$). Both types of coefficients are related as $g_{t,l} = (-1)^{l+1} \cdot h_{L-l-1}$.

Different wavelet families have a trade-off between the degree of symmetry (i.e., linear phase characteristics of wavelets) and the degree to which ideal high-pass filters are approximated (Percival and Walden, 2000). The degree of symmetry in a wavelet is important in reducing the phase shift of features during the wavelet decomposition. In this work, unlike the aforementioned studies, the following filters (see Percival and Walden, 2000) are tested:

- Haar: The simplest wavelet with a filter of length L=2. The Haar wavelet has compact support, however, it has just one vanishing moment and is piecewise constant. Furthermore, the resulting wavelet basis functions have the significant additional disadvantage of being discontinuous.
- Daubechies: To overcome the disadvantage of the Haar wavelet, this wavelet filter has compact support and has also identified two sets of filters, namely, the extremal phase (D) and the least asymmetric (LA) or symmlets. These filters have even lengths L (between 2 and 20).
- Best Localized: This family refines the LA idea and penalizes low frequency. The usual lengths are between 14 and 20.

– Coiflet: In this family of wavelets the scaling function is vanishing moments. The wavelet is near symmetric. The usually lengths are between 6 and 30.

So, DWT is useful in decomposing time series data into an orthogonal set of components with different frequencies by checking the relationship between high frequency fluctuations in stock prices obtained from the reconstruction of the series by wavelet crystals. MODWT (Maximal Overlap Discrete Wavelet Transform) is a variant of DWT that can handle any sample size when $N-2^J \neq 0$. The smooth and detail coefficients of MODWT multiresolution analysis are associated with zero phase filters and produces a more asymptotically efficient wavelet variance estimator than the DWT. However, the MODWT loses orthogonality. Then we apply MODWT, but, unlike previous empirical studies, we select the most appropriate filter according to the orthogonality problem. We use a double criterion or requirement: first, we select the filter with the most orthogonal signals, or determinant of the correlation matrix among signals close to 1; and second, as we use only signals with accumulated energy over 95%, we select the filter with the lowest RSME (Root Square Mean Error) of the original time series.

3.2. Term Structure of Betas

Unlike Trimech, et al. (2009) and Kang et al. (2017), this paper does not examine the relationship between stock returns and Fama-French risk factors at different time-scales but analyses the relationship between time-scale portfolio returns and time-scale risk factors to estimate the term structure of betas.

The general multi-factor model for M portfolios and K risk factors is:

$$\forall i = 1,\dots,M$$
$$R_{i,t} - Rf_t = r_{i,t} = \alpha_{0,i} + \sum_{k=1}^{K} \beta_{k,i} \cdot f_{k,t} + \varepsilon_{i,t} \tag{4}$$

Where R is daily return, Rf is the daily risk-free rate and f is the daily risk factor value. The premium risk factor for each factor is:

$$\mathrm{E}\left(r_{i,t}\right)=\sum_{k=1}^{K}\lambda_k\cdot\beta_{i,k}+\upsilon_i \tag{5}$$

But, if we express the above model in time-scale format and replace the daily value for wavelet decomposition in the time-frequency domain then:

$$\begin{aligned}&\forall i=1,\ldots,M\\&\forall j=1,\ldots,J\\&w_{i,j,t}=\alpha_{0,i,j}+\sum_{k=1}^{K}\beta_{k,j,i}\cdot w_{k,j,t}+\xi_{i,j,t}\end{aligned} \tag{6}$$

Where $\beta_{k,j,i}$ is the beta value for portfolio-i with respect to factor-k and time-horizon-j and the vector $\mathrm{B}_{i,k}=\left[\beta_{i,1,k}\quad\ldots\quad\beta_{i,J,k}\right]$ is the term structure of betas for factor-k. Then $\mathfrak{B}_i=\left[\mathrm{B}_{i,1}\quad\ldots\quad\mathrm{B}_{i,K}\right]$ is the surface of risky portfolio-i betas for all factors.

Additionally, we estimate the term structure of risk premium for each factor as:

$$\mathrm{E}\left(r_{i,t}\right)=\sum_{j=1}^{J}\lambda_{j,k}\cdot\beta_{i,j,k}+\nu_{i,k} \tag{7}$$

4. DATA

In this research, we use daily data from March 1, 1984 until October 31, 2017. First, we select risk factors (10 in total):

- QMJ factor, obtained from AQR Capital Management Database[2] (QMJ) and we employ Frazzini and Pedersen (2014)'s Betting Against Beta (BAB) factor as the main proxy for funding liquidity.
- Fama and French 5-factors[3]: Excess Return Market Portfolio (Mkt), Small Minus Big portfolio returns (SMB), High Minus Low portfolio

[2] www.aqr.com

returns (HML), Robust Minus Weak portfolio returns (RMW), Conservative Minus Aggressive portfolio returns (CMA), Momentum (MOM), Short Term Reversal Factor (STR) and Long Term Reversal Factor (LTR).

Our portfolios sample (10 portfolios) is obtained from the Kenneth French database. To achieve a representative sample of the market, we extract the first and last percentile for each category in French's portfolio: Long Term Reversal portfolio (LT_low and LT_high), Short Term Reversal portfolio (ST_low and ST_high), Momentum portfolio (MOM_low and MOM_high), Size portfolios (SIZE_low and SIZE_high) and Book to Market portfolios (BtM_low and BtM_high).

First, we apply 25 filters for wavelet transform, described above, and we report in Table-1 the selected filter for each factor and portfolio. The selection is made looking for the wavelets to be as orthogonal as possible among signals extracted (the determinant of the correlation matrix is close to 1) and also with the selected wavelets that explain at least 95% of the covariance matrix, so they incur in the smallest RSME (Root Square Mean Error) when rebuilding the original series (high and low pass filter).

[Insert Table-1 here]

From Table-1 we obtain the first contributions of this paper. First, in all cases up to the quarterly trend we explain more than 95% of the behavior of the original series. The study of the term structure of the betas has this time limit in our case. Second, unlike other empirical works that apply wavelets to financial data[4] (see Reboredo et al. 2017), we found that not all series require the same type of filter, and this can condition the subsequent results. Third, Fernandez (2006) and Masih et al. (2010) showed the contribution of each scale to total value at risk, but unlike this work, they do

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

[4] Daubechies least asymmetric filter with a wavelet filter length of 8 is a common wavelet filter in other empirical studies of financial markets (among others, Gençay et al. 2005; Fernandez, 2006; Rhaeim et al. 2007).

not report the contribution of each wavelet or scale to the total stock systematic risk.

Next, in Table-2 we show a statistics summary for the original series and wavelets.[5] Panel-A shows the factors and Panel-B the portfolios.

[Insert Table-2. Panel-A and B here]

Table-2's results show that returns are stationary, heteroskedastic, leptokurtic and in a few cases also autoregressive. However, wavelets display the same statistical properties as the original series but are more autoregressive in all cases.

An important question that arises from these results, and one not studied in the previous literature, is whether the wavelets are heteroskedastic from inheriting the original data or by construction. This is important because this characteristic must be taken into account in subsequent modeling, since as is well-known, standard OLS errors are not consistent and should be corrected for autocorrelation and heteroskedasticity (for example, by Newey-West).

To solve this question we simulated Gaussian series, not autocorrelated and not heteroskedastic, and then we applied the wavelet decomposition to these simulated series. Finally, we performed a statistical analysis of the scales obtained. In the Annex, we provide an example of the simulations. In all cases, the wavelets showed autocorrelation and heteroskedasticity, so it is clear that these statistical characteristics are not inherited from the original series but result from the methodology itself.

5. EMPIRICAL RESULTS

[5] Only the first and last wavelet are reported by table size. The rest of the statistics for the intermediate wavelets were very similar and are available upon request.

First, we show the empirical results for multi-factor model for daily excess return of portfolios (Table-3) to allow comparison with the results obtained from wavelets.

[Insert Table-3 here]

From Table-4 to Table-9, we report the term structure of betas obtained from wavelet decomposition.

[Insert Table-4, 5, 6, 7, 8 and Table-9 here]

The estimates have interesting results:

- The constant for wavelet model is always null or non-significant, so it is not reported, whilst for daily return data there are no cases with constant not null: MOM_high, ST_low and LT_high.
- Regarding the level of goodness of fit (R^2), we observe how the two days wavelet is similar to the wavelet obtained with the daily returns, but the goodness of adjustment begins to decrease when the time horizon increases. This result is the opposite of Gençay et al.'s (2003, 2005), and we believe it to be more coherent, since if the term increases, the wavelet energy is lower, as we verified above, that is, its weight in the explanation of the sample variance of daily returns decreases.

Also, there are other results by risk factor:

- The market factor beta for daily returns and two day wavelets are very similar for all portfolios. Only for SIZE_low and SIZE_high portfolios are the market time-scale beta values stable for all horizons. For BtM_low, MOM_low, MOM_high, ST_low, ST_high and LT_high, the market factor has a lower effect on the wavelet as the term increases. Finally, the portfolios with the highest market effect over the time horizon are BtM_high and LT_low.

— SMB factor show daily return betas similar to two day wavelet betas. These values are only stable across all horizons for SIZE_low and BtM_high. When the horizon increases the value decreases for BtM_low, ST_low and LT_low, and the value increases for SIZE_high. For others portfolios the time-scale beta SMB does not show a relationship with time horizons.
— Daily beta HML factors for returns are similar to wavelet betas for two days. There are no portfolios with a stable effect over time with respect to this factor. When the time horizon increases, the HML effect grows for SIZE_high, BtM_high and LT_low and decreases for ST_low and LT_high. For the other portfolios, there is no relationship with the time horizon.
— The RMW factor is significant for the two day wavelet for all portfolios despite not being significant in some cases of daily returns. When the time horizon increases, the RMW effect is higher for all portfolios but is only positive for BtM_high and LT_low. In the rest of portfolios the beta is negative.
— The CMA factor shows a special case for the SIZE_low portfolio, since the daily return beta is significant while only monthly beta wavelets are not null. The LT_low show the CMA factor's erratic effect with respect to time-horizon. When the term increases, the CMA effect is higher for BtM_low, MOM_low, MOM_high, ST_low, ST_high and LT_high; conversely, this effect is lower for SIZE_high and BtM_high.
— The MOM factor presents daily beta returns very similar to wavelet betas for two days. But beta behavior for SIZE_low and ST_low is erratic. We discard two groups of portfolios depending on whether the effect is higher and positive (BtM_low, ST_high and LT_high) or it is maintained over time (SIZE_high, BtM_high and LT_low). Portfolios MOM_low and MOM_high show an effect that decreases over time, negatively and positively respectively.
— The STR factor has daily beta returns similar to two day wavelets. The term structure of beta STR shows three types: increases with

time horizon (BtM_low, MOM_low, MOM_high, ST_low and LT_high); increases and changes sign of the STR effect (SIZE_low, SIZE_high and BtM_high); and decreases (ST_high and LT_low).

— The LTR factor shows similar betas for daily returns and two day wavelets. We observe that SIZE_low, SIZE_high and BtM_low have an erratic behavior regarding this factor. BtM_high, LT_low and LT_high show a term structure beta-LTR decreasing when the time horizon increases. Finally, MOM_low, MOM_high, ST_low and ST_high present an increasing term structure of beta-LTR, even the sign changes of negative to positive for ST portfolios.

— The BAB factors show a higher effect in the long term. ST_low, ST_high, LT_low and LT_high present significant and higher monthly betas. SIZE_low, BtM_low and MOM_low show a decreasing term structure of BAB-beta. BtM_high and MOM_high have an increasing term structure of BAB-beta.

— The QMJ-beta value of daily returns are very similar to two day wavelet betas. There are two groups of portfolios: the first group shows portfolios with negative and increasing term structure of QMJ-beta (MOM_low, MOM_high, ST_low, ST_high and LT_high); the second shows a change in the beta sign with time horizon increases (from positive to negative, SIZE_high and BtM_low, and from negative to positive, BtM_high and LT_low).

In short, the beta term structure of factors shows a wealth of behaviors not usually observed in empirical finance work. Figure-1, as an example, represents the term structure of beta market risk for each portfolio.

[Insert Figure-1 here]

Table-10 shows the term structure of risk premium for each factor.

[Insert Table-10 here]

Two results stand out: first, the statistical significance of the market risk premium (positive and growing with the time horizon) for all terms; and second, the remaining significant premiums, CMA and QMJ factors are in the longer terms (1-3 months), while STR factor is negative for shorter terms (2 days) and positive for longer horizons (1-3 months).

6. CONCLUSIONS

There is some consensus in the financial literature on the dynamics of betas. In addition, recent empirical studies have shown the existence of a term structure of risky asset returns. This empirical study aims to demonstrate the existence of a term structure of the betas associated with each risky asset.

To do so, a novel methodology called wavelet decomposition is used, which can extract (daily) explanatory and orthogonal signals in the time-frequency domain from an original series in a frequency.

In this regard, this work has proven that the wavelet filter applied for such decomposition must be chosen to maximize the orthogonality and minimize the prediction error of the original series with the number of scales needed to reach an explanatory power or energy over 95%. Likewise, the behavior of these scales has been studied, reaching the conclusion that their statistical characteristics are intrinsic to their construction and, consequently, any analysis must consider them, so in this work the estimated standard errors are Newey-West.

We found in the analysis of the time-scale betas that the results of the two day scale are very similar to the estimate with the original data (daily returns), as would be expected, since it is the frequency most similar to that of the original data.

Also, we found that the degree of adjustment of the models decreases as the time horizon increases, which contradicts the results of Gençay et al. (2003, 2005), and our results are supported by an optimal prior selection based on wavelet energy, so that for the longer term there is less information.

The time-scale market betas are the most stable. For the rest of the factors we found that the behavior is diverse and in most cases more significant for the longer terms. The significant risk premiums in different time horizons, in addition to the market, were the CMA, STR and QMJ factors.

The CMA factor shows an upward slope for BtM_low, MOM_low, MOM_high, ST_low, ST_high and LT_high, and a downward slope for SIZE_high and BtM_high.

For the STR factor we find three groups of portfolios: the first with upward slopes (BtM_low, MOM_low, MOM_high, ST_low and LT_high); the second with downward slopes (ST_high and LT_low); and the third with inconstant signs (SIZE_low, SIZE_high and BtM_high).

For the QMJ factor we find two groups of portfolios: the first with a downward slope (MOM_low, MOM_high, ST_low, ST_high and LT_high); and the second group with portfolios with a beta sign change with time horizon increases (from positive to negative, SIZE_high and BtM_low, and from negative to positive, BtM_high and LT_low).

Overall, this study provides a new approach to the term structure of equity returns and their time-scales betas and will allow for future research to find ideal factors for asset pricing depending on the time horizon of the investment.

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TABLES

TABLE 1. WAVELET FILTER SELECTION

Risk Factors	Filter	Determ(correl)	RSME	Energy 2 days	Energy 1 week	Energy 2 weeks	Energy 1 month	Energy 2 months	Energy 3 months
Mkt	Least Asymmetric-16	0.99274	0.8001%	50.65%	76.51%	89.52%	94.94%	97.45%	98.81%
SMB	Least Asymmetric-20	0.99636	0.4230%	49.85%	74.86%	87.11%	92.92%	96.12%	98.05%
HML	Least Asymmetric-16	0.99606	0.4365%	45.99%	70.93%	85.98%	92.35%	95.12%	97.50%
RMW	Best Localized-18	0.99816	0.3447%	42.44%	68.73%	83.28%	90.73%	94.53%	97.10%
CMA	Least Asymmetric-20	0.99371	0.3121%	43.19%	71.22%	85.22%	92.42%	95.90%	97.66%
MOM	Least Asymmetric-16	0.99185	0.6592%	39.39%	65.84%	82.61%	90.67%	94.51%	97.67%
STR	Least Asymmetric-20	0.99679	0.6453%	38.48%	69.09%	84.77%	92.59%	96.66%	97.97%
LTR	Least Asymmetric-20	0.99504	0.3670%	43.48%	70.64%	83.96%	90.85%	94.91%	97.06%
BAB	Least Asymmetric-16	0.99444	0.5184%	55.84%	79.64%	89.22%	94.09%	96.51%	97.95%
QMJ	Least Asymmetric-20	0.99750	0.3740%	46.04%	69.61%	83.85%	91.51%	94.69%	97.28%
Portfolios	Filter	Determ(correl)	RSME	Energy 2 days	Energy 1 week	Energy 2 weeks	Energy 1 month	Energy 2 months	Energy 3 months
SIZE_low	Best Localized-18	0.99614	0.7649%	44.43%	67.81%	81.60%	88.92%	93.18%	96.22%
SIZE_high	Least Asymmetric-16	0.99273	0.7997%	52.72%	78.50%	90.76%	95.63%	97.89%	99.05%
BtM_low	Least Asymmetric-20	0.99608	0.8793%	49.60%	76.50%	89.49%	94.88%	97.36%	98.74%
BtM_high	Least Asymmetric-16	0.99259	1.0647%	49.14%	73.90%	87.62%	93.71%	96.31%	98.41%
MOM_low	Least Asymmetric-20	0.99591	1.4341%	45.39%	70.64%	85.54%	92.94%	95.89%	98.13%
MOM_high	Least Asymmetric-20	0.99330	1.0735%	46.31%	73.71%	88.80%	94.79%	97.52%	98.63%
ST_low	Least Asymmetric-20	0.99490	1.4204%	45.46%	72.44%	87.36%	94.21%	97.34%	99.03%
ST_high	Least Asymmetric-20	0.99640	0.9843%	49.28%	75.84%	89.11%	94.56%	96.69%	98.19%
LT_low	Least Asymmetric-16	0.99604	1.0781%	47.86%	72.64%	86.34%	92.81%	96.01%	97.97%
LT_high	Least Asymmetric-20	0.99552	1.0360%	49.20%	76.03%	89.17%	94.92%	97.41%	98.66%

TABLE 2. SUMMARY OF STATISTICS. Panel-A. Factors and their wavelets

Factors/wavelets	#obs	min	mean	max	std.dev	Skew.	Exc Kurtosis	Q test AR(2) on data	ARCH (2) test	Q test AR(2) on square data	ADF test
Mkt	8342	-0.1744	0.0003	0.1135	0.0109	-0.6563	16.162	2.58 [0.274]	479.56 [0.000]**	951.18 [0.000]**	-54.52
2d_Mkt	8342	-0.0771	0.0000	0.0665	0.0074	0.0421	11.03	494.62 [0.000]**	1890.1 [0.000]**	3452.80 [0.000]**	-182.14
3m_Mkt	8342	-0.0021	0.0000	0.0021	0.0005	-0.0103	0.9809	2096.78 [0.000]**	11217000 [0.000]**	16001.9 [0.000]**	-4.43
SMB	8342	-0.1121	0.1242	0.0611	0.0058	-0.8977	21.362	0.01 [0.996]	369.68 [0.000]**	681.40 [0.000]**	-52.42
2d_SMB	8342	-0.0701	0.0000	0.0636	0.0039	-0.0986	24.325	299.45 [0.000]**	3378.0 [0.000]**	3362.71 [0.000]**	-181.85
3m_SMB	8342	-0.0015	0.0000	0.0017	0.0003	0.0027	2.6505	1476.78 [0.000]**	11212000 [0.000]**	16046.1 [0.000]**	-4.38
HML	8342	-0.0422	0.0001	0.0483	0.0057	0.4331	9.7542	7.72 [0.021]*	895.85 [0.000]**	2009.68 [0.000]**	-50.96
2d_HML	8342	-0.0377	0.0000	0.0331	0.0036	-0.1766	13.187	463.94 [0.000]**	2628.1 [0.000]**	3646.88 [0.000]**	-182.17
3m_HML	8342	-0.0017	0.0000	0.0018	0.0003	-0.0794	4.6611	1089.32 [0.000]**	13443000 [0.000]**	16126.8 [0.000]**	-4.46
RMW	8342	-0.0303	0.0002	0.0452	0.0043	0.309	9.238	34.39 [0.000]**	786.97 [0.000]**	1738.59 [0.000]**	-48.52
2d_RMW	8342	-0.027	0.0000	0.024	0.0027	-0.1092	9.1017	579.82 [0.000]**	1636.3 [0.000]**	2763.64 [0.000]**	-178.83
3m_RMW	8342	-0.002	0.0000	0.0018	0.0003	-0.0173	12.264	547.85 [0.000]**	15420000 [0.000]**	16192.3 [0.000]**	-4.38
CMA	8342	-0.0593	0.0001	0.0253	0.004	-0.4591	11.93	39.018 [0.000]**	321.30 [0.000]**	692.387 [0.000]**	-51.52
2d_CMA	8342	-0.0314	0.0000	0.0253	0.0025	-0.3633	10.381	533.62 [0.000]**	1591.1 [0.000]**	2566.63 [0.000]**	-184.28
3m_CMA	8342	-0.0013	0.0000	0.0014	0.0002	0.0005	5.233	1013.10 [0.000]**	10714000 [0.000]**	16060.9 [0.000]**	-4.51
MOM	8342	-0.082	0.0003	0.0701	0.008	-0.9462	12.948	52.564 [0.000]**	507.39 [0.000]**	1144.06 [0.000]**	-49.01
2d_MOM	8342	-0.0548	0.0000	0.0509	0.0048	-0.0577	13.013	452.23 [0.000]**	2202.4 [0.000]**	3413.53 [0.000]**	-182.76
3m_MOM	8342	-0.003	0.0000	0.0029	0.0006	0.0039	3.7157	1243.15 [0.000]**	12586000 [0.000]**	16103.3 [0.000]**	-4.36
STR	8342	-0.0717	0.0009	0.1122	0.0079	1.7421	27.377	38.84 [0.000]**	324.09 [0.000]**	721.056 [0.000]**	-52.26
2d_STR	8342	-0.0439	0.0000	0.0483	0.0046	0.4196	18.392	340.91 [0.000]**	1915.5 [0.000]**	3149.14 [0.000]**	-186.56
3m_STR	8342	-0.0026	0.0000	0.0025	0.0004	0.0034	7.2083	817.37 [0.000]**	9998900 [0.000]**	16053.1 [0.000]**	-4.45
LTR	8342	-0.0562	0.3197	0.0337	0.0047	-0.477	8.8983	29.65 [0.000]**	426.91 [0.000]**	948.009 [0.000]**	-50.38
2d_LTR	8342	-0.0387	0.0000	0.0294	0.0029	-0.313	10.964	512.75 [0.000]**	1751.5 [0.000]**	2746.27 [0.000]**	-182.5
3m_LTR	8342	-0.0011	0.0000	0.0012	0.0003	-0.0021	1.4708	1866.54 [0.000]**	10239000 [0.000]**	15981.0 [0.000]**	-4.33
BAB	8342	-0.1876	0.0004	0.1404	0.0075	-1.4599	74.647	2.68 [0.261]	999.18 [0.000]**	1430.85 [0.000]**	-54.87
2d_BAB	8342	-0.1377	0.0000	0.1264	0.0054	-0.5556	108.56	76.44 [0.000]**	3823.1 [0.000]**	3457.34 [0.000]**	-181.94
3m_BAB	8342	-0.0023	0.0000	0.0022	0.0004	-0.001	5.4613	985.87 [0.000]**	11425000 [0.000]**	16083.1 [0.000]**	-4.4
QMJ Factor	8342	-0.0455	0.0002	0.054	0.0049	0.0962	12.115	14.93 [0.000]**	569.06 [0.000]**	1296.71 [0.000]**	-48.83
2d_QMJ	8342	-0.0391	0.0000	0.0353	0.0032	-0.0609	19.821	338.02 [0.000]**	3340.2 [0.000]**	4383.09 [0.000]**	-186.68
3m_QMJ	8342	-0.0013	0.0000	0.0013	0.0003	0.0022	2.6511	1478.37 [0.000]**	14225000 [0.000]**	16117.7 [0.000]**	-4.31

TABLE 2. SUMMARY OF STATISTICS. Panel-B. Portfolios and their wavelets

Portfolios and wavelet	#obs	min	mean	max	std.dev	Skew.	Exc. Kurt.	Q test AR(2) on data		Q test AR(2) on square data	ADF test
SIZE_low	8342	-0.1026	0.0003	0.0783	0.0098	-0.8927	11.481	17.99 [0.000]**	1139.0 [0.000]**	2424.00 [0.000]**	-46.45
2 d SIZE_low	8342	-0.0648	0.0000	0.0647	0.0062	0.1036	14.281	428.17 [0.000]**	2565.3 [0.000]**	3889.17 [0.000]**	-184.8
3 m SIZE_low	8342	-0.0026	0.0000	0.0029	0.0006	0.0053	1.3118	1937.09 [0.000]**	12715000 [0.000]**	16049.6 [0.000]**	-4.35
SIZE_high	8342	-0.1969	0.0003	0.1175	0.0112	-0.6968	19.535	6.80 [0.033]*	401.01 [0.000]**	873.290 [0.000]**	-56.05
2 d SIZE_high	8342	-0.107	0.0000	0.0672	0.0077	-0.0472	13.439	426.052 [0.000]**	1841.8 [0.000]**	3175.23 [0.000]**	-181.6
3 m SIZE_high	8342	-0.0021	0.0000	0.0021	0.0005	-0.0082	1.1191	2025.43 [0.000]**	10473000 [0.000]**	15983.0 [0.000]**	-4.42
BtM_low	8342	-0.168	0.0003	0.1324	0.0119	-0.3218	12.21	4.43 [0.108]	516.16 [0.000]**	1039.92 [0.000]**	-55.3
2 d BtM_low	8342	-0.0682	0.0000	0.0847	0.008	0.1625	9.0505	574.825 [0.000]**	1721.6 [0.000]**	3115.82 [0.000]**	-185.9
3 m BtM_low	8342	-0.0027	0.0000	0.0026	0.0006	-0.0017	1.6696	1787.00 [0.000]**	11170000 [0.000]**	16015.5 [0.000]**	-4.43
BtM_high	8342	-0.1615	0.0004	0.1324	0.0144	-0.5307	14.985	0.45 [0.795]	665.40 [0.000]**	1465.25 [0.000]**	-52.37
2 d BtM_high	8342	-0.1027	0.0000	0.1054	0.0096	-0.0116	13.594	477.627 [0.000]**	13064. [0.000]**	7257.11 [0.000]**	-183.2
3 m BtM_high	8342	-0.0044	0.0000	0.0044	0.0008	-0.0202	4.2782	1150.25 [0.000]**	17520000 [0.000]**	16196.3 [0.000]**	-4.37
MOM_low	8342	-0.1776	0.1481	0.2143	0.0187	0.3601	17.992	8.64 [0.0132]*	539.23 [0.000]**	1221.84 [0.000]**	-50.66
2 d MOM_low	8342	-0.125	0.0000	0.1489	0.0121	0.0613	18.095	338.596 [0.000]**	2178.1 [0.000]**	3283.43 [0.000]**	-190.9
3 m MOM_low	8342	-0.0051	0.0000	0.0048	0.001	-0.0084	3.984	1195.89 [0.000]**	13158000 [0.000]**	16116.9 [0.000]**	-4.31
MOM_high	8342	-0.1937	0.0005	0.1077	0.0141	-0.5881	9.8107	9.76 [0.007]**	439.61 [0.000]**	923.687 [0.000]**	-54.78
2 d MOM_high	8342	-0.0763	0.0000	0.0686	0.0092	0.0716	7.0597	716.052 [0.000]**	2096.2 [0.000]**	3403.84 [0.000]**	-182
3 m MOM_high	8342	-0.0025	0.0000	0.0025	0.0006	-0.0017	0.9078	2136.41 [0.000]**	10761000 [0.000]**	15971.0 [0.000]**	-4.43
ST_low	8342	-0.1773	0.0013	0.2513	0.0186	0.7583	23.422	8.20 [0.016]*	755.13 [0.000]**	1466.65 [0.000]**	-52.67
2 d ST_low	8342	-0.1389	0.0000	0.1393	0.0119	0.0499	21.42	290.51 [0.000]**	2203.7 [0.000]**	3558.42 [0.000]**	-187.4
3 m ST_low	8342	-0.0054	0.0000	0.005	0.001	-0.0017	5.2481	1012.05 [0.000]**	11980000 [0.000]**	16097.5 [0.000]**	-4.33
ST_high	8342	-0.13	-0.0004	0.1274	0.0133	-0.6378	9.238	4.77 [0.091]	413.79 [0.000]**	940.027 [0.000]**	-54.65
2 d ST_high	8342	-0.0816	0.0000	0.1103	0.0089	0.066	11.322	516.247 [0.000]**	2355.8 [0.000]**	3373.63 [0.000]**	-185.6
3 m ST_high	8342	-0.0023	0.0000	0.0023	0.0006	-0.0031	0.9538	2111.13 [0.000]**	11948000 [0.000]**	16012.9 [0.000]**	-4.32
LT_low	8342	-0.1753	0.0004	0.1259	0.0144	-0.515	10.4	2.34 [0.309]	971.85 [0.000]**	2115.94 [0.000]**	-51.32
2 d LT_low	8342	-0.0915	0.0000	0.1135	0.0095	0.1889	11.75	518.67 [0.000]**	2976.1 [0.000]**	4147.22 [0.000]**	-184.3
3 m LT_low	8342	-0.003	0.0000	0.0028	0.0008	-0.0116	0.3524	2491.48 [0.000]**	11914000 [0.000]**	15986.5 [0.000]**	-4.39
LT_high	8342	-0.1532	0.0004	0.1704	0.014	-0.2398	12.34	4.65 [0.097]	838.79 [0.000]**	1615.85 [0.000]**	-54.36
2 d LT_high	8342	-0.0788	-0.0033	0.1022	0.0094	0.2827	12.348	443.735 [0.000]**	1636.4 [0.000]**	3169.24 [0.000]**	-185
3 m LT_high	8342	-0.0029	0.0000	0.0028	0.0006	-0.0026	1.7297	1764.31 [0.000]**	11038000 [0.000]**	16013.9 [0.000]**	-4.45

Table 3. BETA ESTIMATE RESULTS FOR DAILY RETURNS

Portolios	Estimate	Const	Mkt	SMB	HML	RMW	CMA	MOM	STR	LTR	BAB	QMJ	R^2
SIZE_low	beta	0.0000	0.7389	0.7965	0.0604	-0.0172	0.0543	0.0281	0.0291	0.0657	0.1313	-0.2519	90.08%
	t-value NW	-0.38	81.28(**)	83.58(**)	4.79(**)	-0.93	2.91(**)	2.89(**)	3.18(**)	4.31(**)	6.59(**)	-14.55(**)	
SIZE_high	beta	0.0000	1.0104	-0.2587	-0.0152	0.0332	0.0347	-0.0172	-0.0025	0.0024	-0.0177	0.0863	99.14%
	t-value NW	-1.68	302.01(**)	-21.56(**)	-2.21(*)	5.68(**)	3.08(**)	-4.10(**)	-0.52	0.26	-2.21(*)	16.02(**)	
BtM_low	beta	0.0000	1.0123	-0.0498	-0.3405	0.0069	-0.2213	-0.0264	-0.0044	0.0360	-0.0227	0.1411	95.61%
	t-value NW	1.11	169.96(**)	-6.141(**)	-29.18(**)	0.52	-14.67(**)	-4.27(**)	-0.64	2.98(**)	-2.89(**)	10.65(**)	
BtM_high	beta	0.0000	1.1014	0.2487	0.8872	-0.1478	-0.1746	-0.0586	0.0127	0.2111	-0.0099	-0.1175	88.92%
	t-value NW	0.53	107.1749(**)	14.98(**)	37.75(**)	-5.84(**)	-6.58(**)	-5.07(**)	1.06	9.58(**)	-0.73	-4.36(**)	
MOM_low	beta	0.0000	1.0514	0.3462	0.1343	-0.0638	-0.4963	-0.9962	0.0823	0.1449	-0.0045	-0.5059	89.21%
	t-value NW	0.10	78.3779(**)	15.54(**)	3.05(**)	-1.50	-12.54(**)	-59.33(**)	3.64(**)	4.52(**)	-0.23	-10.17(**)	
MOM_high	beta	0.0001	1.0763	0.2042	-0.0609	-0.0701	-0.3841	0.6743	0.0323	0.0272	-0.0288	-0.2895	91.53%
	t-value NW	1.98(*)	120.0601(**)	15.31(**)	-3.76(**)	-3.03(**)	-14.95(**)	55.61(**)	2.82(**)	1.27	-2.51(**)	-11.86(**)	
ST_low	beta	0.0002	1.0108	0.2500	0.1045	-0.0738	-0.3799	-0.1516	0.9942	-0.0997	-0.0616	-0.3541	90.65%
	t-value NW	3.18(**)	66.7583(**)	10.07(**)	3.13(**)	-2.29(*)	-8.92(**)	-9.59(**)	48.65(**)	-2.97(**)	-3.01(**)	-10.57(**)	
ST:high	beta	0.0000	1.0677	0.2163	-0.0241	-0.1164	-0.2122	-0.0623	-0.7080	-0.0852	-0.0550	-0.3481	89.93%
	t-value NW	0.7600	117.0066(**)	16.01(**)	-1.02	-4.51(**)	-6.98(**)	-5.19(**)	-48.01(**)	-4.07(**)	-4.28(**)	-12.71(**)	
LT_low	beta	0.0001	1.0578	0.4265	-0.0807	-0.0127	0.1018	-0.0777	0.0719	0.8329	-0.0031	-0.3091	87.05%
	t-value NW	0.89	96.0097(**)	20.17(**)	-3.03(**)	-0.47	3.31(**)	-5.88(**)	4.56(**)	29.82(**)	-0.19	-11.21(**)	
LT_high	beta	0.0001	1.1124	0.1222	-0.0789	0.1131	-0.2933	0.0305	0.0214	-0.5513	-0.0395	-0.1610	93.02%
	t-value NW	2.43(**)	123.08(**)	7.84(**)	-4.43(**)	5.45(**)	-12.87(**)	3.06(**)	1.94(*)	-26.67(**)	-3.27(**)	-8.24(**)	

TABLE 4. TERM STRUCTURE OF BETAS FOR 2 DAY WAVELETS

Portolios	Estimate	Mkt	SMB	HML	RMW	CMA	MOM	STR	LTR	BAB	QMJ	R^2
SIZE_low	beta	0.7326	0.7470	0.1244	0.0435	0.0259	0.0649	0.0309	0.0578	0.0880	-0.2205	89.57%
	t-value NW	87.07(**)	78.16(**)	9.01(**)	2.37(**)	1.25	6.19(**)	3.31(**)	3.59(**)	5.36(**)	-12.65(**)	
SIZE_high	beta	10233	-0.2610	-0.0120	0.0411	0.0347	-0.0167	-0.0084	0.0063	-0.0149	0.0785	99.17%
	t-value NW	348.52(**)	-20.89(**)	-1.65(*)	4.97(**)	2.88(**)	-3.59(**)	-2.02(*)	0.71	-2.94(**)	12.52(**)	
BtM_low	beta	1.0118	-0.0470	-0.3429	-0.0332	-0.2380	-0.0401	-0.0172	0.0383	-0.0229	0.1374	95.76%
	t-value NW	171.57(**)	-4.73(**)	-28.25(**)	-2.45(**)	-14.52(**)	-5.83(**)	-2.31(*)	2.85(**)	-3.07(**)	10.45(**)	
BtM_high	beta	1.0881	0.2335	0.8687	-0.1806	-0.1519	-0.0404	-0.0026	0.2307	-0.0134	-0.0963	89.06%
	t-value NW	95.81(**)	14.98(**)	37.95(**)	-6.8(**)	-5.71(**)	-3.47(**)	-0.18	9.71(**)	-1.114	-3.41(**)	
MOM_low	beta	1.0517	0.3584	0.142	-0.0502	-0.5231	-0.9931	0.0473	0.1776	-0.0375	-0.4161	89.31%
	t-value NW	72.21(**)	18.20(**)	3.42(**)	-1.35	-12.61(**)	-52.64(**)	2.21(*)	5.09(**)	-2.31(*)	-9.94(**)	
MOM_high	beta	1.0702	0.1683	-0.0737	-0.1338	-0.4367	0.6999	0.0318	0.0452	-0.0415	-0.2425	91.43%
	t-value NW	129.41(**)	12.60(**)	-4.28(**)	-5.58(**)	-17.78(**)	55.11(**)	2.54(**)	2.15(*)	-3.66(**)	-10.46(**)	
ST_low	beta	1.0079	0.2423	0.0635	-0.0710	-0.4193	-0.1696	1.0143	-0.0550	-0.0419	-0.3947	89.96%
	t-value NW	59.53(**)	11.46(**)	1.94(*)	-2.18(*)	-9.64(**)	-9.44(**)	42.73(**)	-1.64	-2.96(**)	-10.43(**)	
ST_high	beta	1.071	0.2368	-0.0510	-0.1230	-0.2550	-0.0688	-0.7339	-0.0566	-0.0432	-0.3508	90.28%
	t-value NW	124.06(**)	15.40(**)	-1.91(*)	-4.86(**)	-8.66(**)	-5.81(**)	-50.44(**)	-2.36(**)	-3.76(**)	-12.49(**)	
LT_low	beta	1.0567	0.4157	-0.1319	-0.0424	0.1109	-0.0845	0.0744	0.8534	0.0040	-0.2892	86.41%
	t-value NW	81.21(**)	15.61(**)	-4.46(**)	-1.39	2.77(**)	-5.74(**)	4.54(**)	25.31(**)	0.28	-10.06(**)	
LT_high	beta	1.1183	0.0987	-0.1026	0.0929	-0.3181	0.0236	0.0142	-0.5328	-0.0388	-0.1499	93.36%
	t-value NW	139.85(**)	5.30(**)	-6.01(**)	4.92(**)	-12.68(**)	2.12(*)	1.25	-27.04(**)	-3.57(**)	-7.75(**)	

TABLE 5. TERM STRUCTURE OF BETAS FOR 1 WEEK WAVELETS

Portolios	Estimate	Mkt	SMB	HML	RMW	CMA	MOM	STR	LTR	BAB	QMJ	R^2
SIZE_low	beta	0.6334	0.5934	-0.1741	-0.1763	-0.0164	-0.0855	-0.0806	-0.0155	-0.0567	0.2282	80.58%
	t-value NW	72.67(**)	41.77(**)	-12.48(**)	-7.12(**)	-0.72	-7.66(**)	-6.63(**)	-0.69	-4.71(**)	10.82(**)	
SIZE_high	beta	1.0226	-0.1837	-0.0394	-0.1559	0.0045	-0.0220	0.0015	0.0202	0.0048	0.0267	98.31%
	t-value NW	346.55(**)	-28.59(**)	-6.66(**)	-17.38(**)	0.55	-5.13(**)	0.45	3.01(**)	0.86	3.65(**)	
BtM_low	beta	0.5233	-0.3609	-0.1286	-0.2457	-0.8092	0.0704	0.2000	0.0307	-0.1003	-0.5543	64.05%
	t-value NW	31.67(**)	-12.75(**)	-5.64(**)	-7.43(**)	-18.01(**)	4.30(**)	7.77(**)	0.62	-5.23(**)	-14.70(**)	
BtM_high	beta	1.1035	0.1566	0.9412	0.2474	-0.1432	-0.0653	-0.0236	0.1459	-0.0465	-0.0296	88.64%
	t-value NW	109.10(**)	11.24(**)	54.21(**)	10.41(**)	-5.91(**)	-6.25(**)	-1.96(*)	7.01(**)	-3.62(**)	-1.20	
MOM_low	beta	0.5177	-0.0766	0.0246	-0.3771	-0.8928	-0.5232	0.3265	0.0811	-0.0067	-1.8223	65.17%
	t-value NW	22.32(**)	-2.18(*)	0.49	-6.42(**)	-12.47(**)	-17.02(**)	8.32(**)	12596	-0.21	-23.15(**)	
MOM_high	beta	0.5807	-0.0663	0.0299	-0.1188	-0.8744	0.5931	0.2175	0.0406	-0.1398	-0.8381	62.08%
	t-value NW	28.90(**)	-2.05(*)	1.18	-3.17(**)	-18.43(**)	31.20(**)	8.14(**)	0.77	-6.43(**)	-22.27(**)	
ST_low	beta	0.5302	-0.1098	0.0852	-0.3213	-0.7284	0.0128	1.2105	-0.1281	-0.1211	-1.2567	77.48%
	t-value NW	25.49(**)	-3.61(**)	2.82(**)	-7.66(**)	-11.86(**)	0.64	38.51(**)	-2.06(*)	-5.05(**)	-26.55(**)	
ST_high	beta	0.5494	-0.1392	-0.0083	-0.2098	-0.6653	0.0756	-0.4850	-0.1574	-0.0744	-1.3455	62.53%
	t-value NW	27.47(**)	-4.55(**)	-0.29	-5.25(**)	-11.72(**)	4.04(**)	-16.17(**)	-2.58(**)	-3.44(**)	-28.94(**)	
LT_low	beta	0.9928	0.2845	0.2596	0.3450	-0.0549	0.0251	0.0440	0.4894	-0.1126	-0.1064	80.57%
	t-value NW	76.18(**)	15.33(**)	10.05(**)	11.53(**)	-1.96(*)	1.51	3.21(**)	17.24(**)	-6.18(**)	-3.75(**)	
LT_high	beta	0.5807	-0.2400	-0.0032	-0.3283	-0.7257	0.1264	0.2539	-0.6330	-0.0915	-0.9736	66.77%
	t-value NW	28.82(**)	-8.35(**)	-0.12	-8.85(**)	-12.49(**)	7.24(**)	8.63(**)	-9.86(**)	-4.22(**)	-22.85(**)	

TABLE 6. TERM STRUCTURE OF BETAS FOR 2 WEEK WAVELETS

Portolios	Estimate	Mkt	SMB	HML	RMW	CMA	MOM	STR	LTR	BAB	QMJ	R^2
SIZE_low	beta	0.6606	0.6305	-0.0939	-0.1817	-0.0022	-0.0503	-0.0597	-0.0463	-0.1329	0.2269	81.48%
	t-value NW	86.64(**)	49.92(**)	-6.69(**)	-7.59(**)	-0.10	-4.25(**)	-5.61(**)	-2.64(**)	-9.35(**)	12.23(**)	
SIZE_high	beta	1.0058	-0.1917	-0.0367	-0.1021	0.0100	-0.0183	0.0073	0.0205	0.0140	0.0190	98.30%
	t-value NW	347.54(**)	-47.39(**)	-8.71(**)	-12.95(**)	1.28	-4.61(**)	2.18(*)	3.36(**)	3.21(**)	3.43(**)	
BtM_low	beta	0.5249	-0.3078	-0.0996	-0.3239	-0.9477	0.0933	0.1077	0.0805	-0.0101	-0.5728	63.05%
	t-value NW	41.91(**)	-14.48(**)	-4.63(**)	-10.01(**)	-29.22(**)	6.51(**)	6.58(**)	2.60(**)	-0.49	-19.22(**)	
BtM_high	beta	1.1401	0.1849	0.9280	0.3593	-0.1531	-0.0452	-0.0132	0.1500	-0.0034	-0.0052	88.00%
	t-value NW	115.71(**)	12.54(**)	56.58(**)	13.46(**)	-6.69(**)	-3.83(**)	-1.41	7.75(**)	-0.23	-0.19	
MOM_low	beta	0.4976	-0.1376	0.2150	-0.4295	-0.8742	-0.5580	0.2010	0.0864	0.0481	-19862	69.54%
	t-value NW	19.73(**)	-3.23(**)	4.56(**)	-7.36(**)	-14.31(**)	-22.56(**)	6.49(**)	1.50	1.23	-30.38(**)	
MOM_high	beta	0.5808	0.0272	0.0619	-0.2280	-11693	0.5063	0.0840	0.2055	0.0780	-0.9736	61.80%
	t-value NW	41.45(**)	1.12	2.50(**)	-5.59(**)	-26.37(**)	27.295**)	4.01(**)	5.19(**)	3.32(**)	-23.92(**)	
ST_low	beta	0.4952	-0.0332	0.0100	-0.4067	-0.9121	-0.0381	1.1425	0.0501	-0.0485	-1.2884	80.24%
	t-value NW	31.21(**)	-1.15	0.32	-9.35(**)	-20.90(**)	-2.033*)	53.32(**)	1.25	-1.75	-28.27(**)	
ST_high	beta	0.5526	-0.0600	0.0726	-0.4048	-0.8662	0.0455	-0.5833	0.0298	0.0063	-1.3109	62.85%
	t-value NW	37.55(**)	-2.31(*)	2.84(**)	-11.10(**)	-22.84(**)	2.76(**)	-28.79(**)	0.81	0.26	-35.92(**)	
LT_low	beta	1.0903	0.3815	0.2266	0.2859	0.1269	0.0360	0.0196	0.4882	-0.1613	0.1153	80.77%
	t-value NW	89.94(**)	20.34(**)	9.05(**)	8.77(**)	4.46(**)	2.342**)	1.41	18.45(**)	-7.75(**)	4.20(**)	
LT_high	beta	0.5589	-0.1155	0.0147	-0.5511	-0.9431	0.0861	0.1346	-0.5457	-0.0471	-1.0641	68.05%
	t-value NW	40.36(**)	-4.87(**)	0.59	-14.44(**)	-25.35(**)	5.23(**)	6.96(**)	-15.11(**)	-1.99(*)	-29.49(**)	

TABLE 7. TERM STRUCTURE OF BETAS FOR 1 MONTH WAVELETS

Portolios	Estimate	Mkt	SMB	HML	RMW	CMA	MOM	STR	LTR	BAB	QMJ	R^2
SIZE_low	beta	0.6685	0.6825	-0.1241	-0.3338	0.2108	0.0358	-0.0323	-0.1049	-0.1972	0.2346	82.21%
	t-value NW	95.77(**)	57.90(**)	-11.17(**)	-16.44(**)	10.79(**)	4.07(**)	-3.27(**)	-6.81(**)	-16.03(**)	14.11(**)	
SIZE_high	beta	0.9617	-0.2054	-0.0230	-0.1131	0.0577	-0.0098	0.0212	-0.0200	-0.0076	-0.0134	98.18%
	t-value NW	335.30(**)	-46.91(**)	-6.71(**)	-18.78(**)	9.31(**)	-4.04(**)	8.19(**)	-3.45(**)	-1.29	-2.85(**)	
BtM_low	beta	0.4797	-0.1677	-0.2568	-0.3175	-0.8069	0.0671	0.1468	0.0605	0.0155	-0.6657	65.92%
	t-value NW	45.49(**)	-9.66(**)	-15.10(**)	-12.08(**)	-28.06(**)	6.57(**)	12.20(**)	2.23(*)	0.91	-25.93(**)	
BtM_high	beta	1.1662	0.3161	0.9746	0.1953	-0.1367	-0.0434	0.0248	0.0613	-0.1199	0.0652	87.61%
	t-value NW	128.98(**)	20.63(**)	69.30(**)	8.90(**)	-5.99(**)	-4.75(**)	2.61(**)	2.49(**)	-6.25(**)	3.40(**)	
MOM_low	beta	0.4241	0.2822	-0.0082	-0.5121	-0.9861	-0.6139	0.3387	0.1331	0.0156	-2.0808	75.83%
	t-value NW	23.53(**)	11.05(**)	-0.29	-10.75(**)	-22.59(**)	-30.14(**)	12.02(**)	3.53(**)	0.53	-34.76(**)	
MOM_high	beta	0.5819	0.1411	-0.1386	-0.1798	-0.7836	0.5180	0.1444	0.1431	-0.0439	-0.9723	65.30%
	t-value NW	38.77(**)	6.07(**)	-6.43(**)	-5.16(**)	-20.06(**)	34.96(**)	9.68(**)	3.67(**)	-1.63	-27.51(**)	
ST_low	beta	0.4750	0.1348	0.0142	-0.3606	-0.6090	-0.0595	1.1036	-0.1452	-0.1499	-1.4154	80.88%
	t-value NW	29.94(**)	5.68(**)	0.58	-10.26(**)	-16.97(**)	-4.13(**)	50.70(**)	-4.48(**)	-6.09(**)	-38.45(**)	
ST_high	beta	0.4626	0.0527	-0.1390	-0.2595	-0.7236	0.0641	-0.5537	0.1328	-0.0625	-1.3289	66.03%
	t-value NW	36.28(**)	2.39(**)	-6.56(**)	-8.72(**)	-20.55(**)	5.07(**)	-31.47(**)	4.03(**)	-3.01(**)	-43.26(**)	
LT_low	beta	1.1361	0.3587	0.3349	0.4161	-0.0099	-0.0320	0.0135	0.3492	-0.0858	0.0543	80.13%
	t-value NW	90.56(**)	19.76(**)	15.49(**)	14.27(**)	-0.36	-2.20(*)	1.02	13.16(**)	-3.82(**)	2.16(*)	
LT_high	beta	0.5623	0.0671	-0.0683	-0.4720	-0.8328	0.1090	0.1473	-0.4821	-0.0725	-1.0289	68.72%
	t-value NW	45.36(**)	3.36(**)	-3.18(**)	-15.47(**)	-23.72(**)	9.26(**)	9.32(**)	-15.17(**)	-3.53(**)	-35.19(**)	

TABLE 8. TERM STRUCTURE OF BETAS FOR 2 MONTH WAVELETS

Portolios	Estimate	Mkt	SMB	HML	RMW	CMA	MOM	STR	LTR	BAB	QMJ	R^2
SIZE_low	beta	0.7354	0.7198	-0.0727	-0.4089	0.0540	0.0297	-0.0657	-0.1047	-0.1779	0.1260	84.79%
	t-value NW	107.61(**)	57.02(**)	-5.65(**)	-16.95(**)	2.60(**)	2.54(**)	-5.50(**)	-7.01(**)	-14.10(**)	5.72(**)	
SIZE_high	beta	0.9655	-0.1875	-0.0211	-0.1273	-0.0061	-0.0151	0.0047	-0.0315	-0.0002	-0.0473	98.16%
	t-value NW	342.29(**)	-45.18(**)	-5.42(**)	-18.23(**)	-1.03	-4.53(**)	1.58	-6.30(**)	-0.04	-8.16(**)	
BtM_low	beta	0.5350	-0.0765	-0.1705	-0.3851	-0.8109	0.0457	0.2278	0.0534	0.0938	-0.5896	67.67%
	t-value NW	59.81(**)	-4.40(**)	-9.80(**)	-16.05(**)	-25.55(**)	4.44(**)	19.94(**)	1.86	5.66(**)	-23.65(**)	
BtM_high	beta	1.1245	0.1773	0.8122	0.2731	-0.2005	-0.1072	-0.0417	0.3663	-0.1705	0.1842	89.21%
	t-value NW	155.26(**)	12.71(**)	50.67(**)	13.70(**)	-10.04(**)	-12.04(**)	-3.63(**)	20.32(**)	-14.25(**)	9.12(**)	
MOM_low	beta	0.4564	0.2881	0.0253	-0.4464	-0.8319	-0.5686	0.4537	0.1475	0.1249	-15705	74.15%
	t-value NW	31.66(**)	9.31(**)	0.88	-9.73(**)	-19.78(**)	-26.90(**)	20.17(**)	4.09(**)	4.68(**)	-31.50(**)	
MOM_high	beta	0.5990	0.2527	-0.0737	-0.2717	-0.7299	0.4488	0.2034	0.2609	0.0763	-0.8662	65.26%
	t-value NW	54.03(**)	11.37(**)	-3.22(**)	-8.86(**)	-18.78(**)	28.88(**)	14.74(**)	7.60(**)	3.62(**)	-27.71(**)	
ST_low	beta	0.5179	0.2064	0.1758	-0.4542	-0.6364	0.0072	1.2880	-0.1393	0.0236	-13684	86.00%
	t-value NW	52.02(**)	9.76(**)	8.99(**)	-16.01(**)	-18.06(**)	0.60	78.80(**)	-4.83(**)	1.26	-41.37(**)	
ST_high	beta	0.5293	0.0860	0.0381	-0.3864	-0.5015	0.0213	-0.3691	0.0765	0.0815	-1.0954	59.72%
	t-value NW	55.72(**)	4.68(**)	1.99(*)	-14.86(**)	-14.62(**)	1.83(*)	-29.26(**)	2.44(**)	4.69(**)	-39.05(**)	
LT_low	beta	11031	0.2517	0.2525	0.4173	-0.0660	-0.0446	0.0068	0.7098	-0.1408	0.1158	82.32%
	t-value NW	113.17(**)	16.07(**)	11.41(**)	15.29(**)	-2.71(**)	-3.43(**)	0.55	35.06(**)	-7.56(**)	4.42(**)	
LT_high	beta	0.6114	0.1293	-0.0820	-0.5315	-0.6979	0.0376	0.2911	-0.3935	0.0843	-0.9425	71.71%
	t-value NW	59.13(**)	6.73(**)	-4.02(**)	-19.53(**)	-20.18(**)	3.11(**)	22.64(**)	-12.33(**)	4.54(**)	-33.49(**)	

TABLE 9. TERM STRUCTURE OF BETAS FOR 3 MONTH WAVELETS

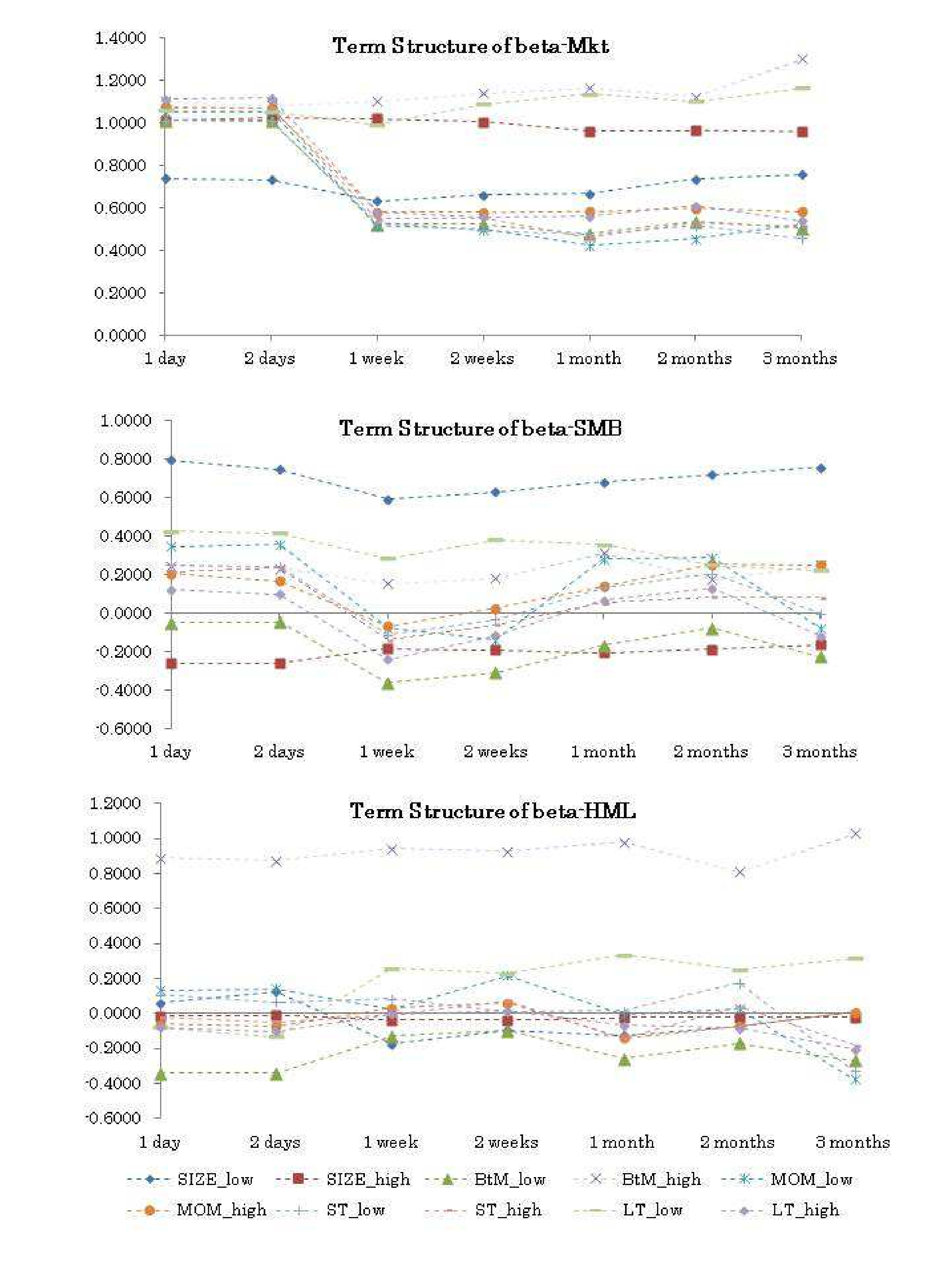
Portolios	Estimate	Mkt	SMB	HML	RMW	CMA	MOM	STR	LTR	BAB	QMJ	R^2
SIZE_low	Beta	0.7570	0.7569	0.0085	-0.8173	-0.0399	0.0188	-0.1163	-0.0705	-0.2491	-0.1071	86.30%
	t-value NW	120.34(**)	53.76(**)	0.87	-48.19(**)	-2.22(*)	2.89(**)	-11.05(**)	-5.52(**)	-26.91(**)	-6.63(**)	
SIZE_high	Beta	0.9608	-0.1640	-0.0258	-0.2228	0.0182	-0.0114	0.0119	-0.0073	-0.0387	-0.0611	97.90%
	t-value NW	448.25(**)	-43.99(**)	-7.14(**)	-36.41(**)	3.38(**)	-5.54(**)	5.12(**)	-1.62	-13.04(**)	-12.86(**)	
BtM_low	Beta	0.5059	-0.2268	-0.2684	-0.2151	-0.8044	0.0734	0.1467	0.2325	0.0327	-0.4174	63.54%
	t-value NW	57.65(**)	-12.19(**)	-14.46(**)	-8.86(**)	-26.60(**)	8.28(**)	15.37(**)	10.88(**)	2.105(*)	-17.27(**)	
BtM_high	Beta	1.3054	0.2496	1.0274	0.3248	-0.0374	-0.0610	-0.0462	-0.1043	-0.1313	0.1069	91.56%
	t-value NW	198.70(**)	20.56(**)	97.73(**)	23.07(**)	-2.26(*)	-11.68(**)	-7.28(**)	-7.81(**)	-13.11(**)	6.83(**)	
MOM_low	beta	0.5254	-0.0764	-0.3755	-0.9340	-0.3927	-0.4890	0.5454	0.4171	0.1588	-1.868	70.64%
	t-value NW	37.46(**)	-2.36(**)	-10.83(**)	-18.61(**)	-8.05(**)	-30.65(**)	22.78(**)	12.62(**)	5.65(**)	-35.27(**)	
MOM_high	beta	0.5839	0.2497	0.0083	-0.1965	-0.6800	0.4820	0.0609	0.2671	-0.1456	-0.4925	65.83%
	t-value NW	55.48(**)	12.87(**)	0.46	-8.51(**)	-22.57(**)	53.47(**)	6.87(**)	11.61(**)	-8.20(**)	-20.43(**)	
ST_low	beta	0.4592	0.0005	-0.3320	-0.0303	-0.5626	0.0668	1.2055	0.1847	0.0536	-1.0513	79.84%
	t-value NW	33.23(**)	0.02	-9.58(**)	-0.91	-13.27(**)	5.19(**)	76.52(**)	6.39(**)	2.15(*)	-32.27(**)	
ST_high	beta	0.5143	0.0810	-0.1807	-0.2812	-0.5002	0.1025	-0.4079	0.2408	-0.1940	-0.9549	66.22%
	t-value NW	49.61(**)	4.04(**)	-8.09(**)	-10.84(**)	-15.85(**)	10.44(**)	-34.97(**)	10.64(**)	-10.51(**)	-31.61(**)	
LT_low	beta	1.1656	0.2229	0.3162	0.8459	0.1563	-0.0719	0.0312	0.4294	0.0206	0.1227	82.10%
	t-value NW	127.34(**)	12.09(**)	22.02(**)	37.39(**)	6.97(**)	-8.54(**)	1.99(*)	24.01(**)	1.44	5.15(**)	
LT_high	beta	0.5410	-0.1178	-0.2055	-0.4291	-0.6739	0.1031	0.1461	-0.1807	-0.0134	-0.7073	61.02%
	t-value NW	48.63(**)	-5.41(**)	-9.11(**)	-15.38(**)	-19.75(**)	9.80(**)	13.73(**)	-7.29(**)	-0.69	-25.35(**)	

TABLE 10. TERM STRUCTURE OF RISK PREMIUM

Factors	Estimate	1 day	2 days	1 week	2 weeks	1 month	2 months	3 months
Mkt	parameter	0.04%	0.10%	0.18%	0.33%	0.52%	1.16%	1.85%
	t-value	2.73(**)	2.88(**)	2.89(**)	3.65(**)	7.588(**)	12.73(**)	2.45(**)
SMB	parameter	0.07%	-0.30%	-0.46%	0.47%	0.22%	0.28%	-0.15%
	t-value	1.43	-1.08	-1.58	1.31	0.57	0.79	-0.64
HML	parameter	0.04%	0.00%	0.43%	-0.25%	-0.16%	0.15%	-0.10%
	t-value	0.61	-0.02	0.81	-0.74	-0.46	0.34	-0.71
RMW	parameter	-0.16%	0.00%	0.00%	0.39%	-0.46%	-0.24%	0.21%
	t-value	-0.71	0.02	0.01	1.61	-1.08	-0.78	2.49(**)
CMA	parameter	-0.11%	0.05%	0.34%	-0.33%	0.44%	0.69%	0.22%
	t-value	-1.96(*)	0.23	0.86	-1.04	3.36(**)	2.09(*)	0.94
MOM	parameter	0.01%	0.13%	-0.42%	0.86%	-1.07%	-0.49%	1.10%
	t-value	0.19	0.28	-0.41	0.57	-0.76	-0.45	0.88
STR	parameter	0.11%	-0.12%	0.06%	0.47%	0.11%	0.12%	0.12%
	t-value	3.63(**)	-2.51(**)	0.90	8.38(**)	2.95(**)	3.17(**)	4.32(**)
LTR	parameter	0.02%	0.20%	-0.10%	-0.33%	0.20%	0.43%	-0.31%
	t-value	0.28	0.61	-0.27	-0.64	0.53	1.53	-1.49
BAB	parameter	-0.26%	0.25%	-0.48%	0.40%	-0.46%	-0.14%	0.31%
	t-value	-0.76	0.46	-1.66	1.36	-1.81	-0.81	2.32(*)
QMJ	parameter	-0.09%	-0.09%	-0.09%	0.09%	-0.04%	0.01%	0.02%
	t-value	-1.59	-1.31	-0.61	0.61	-1.71	2.88(**)	3.86(**)

FIGURE

FIGURE 1. TERM STRUCTURE OF THREE FACTOR FAMA-FRENCH BETA



ANNEX

Variable	#obs	min	mean	max	std.dev	Skewness	Excess Kurtosis	Ljung-Box Q-Statistics raw data		ARCH 1-2 test	Box-Pierce Q-Statistics Squared data		ADF Test
Simulated daily return	8342	-3,5822	0,0010	4,3768	1,0000	0,0003	-0,0246	1.15	[0.378]	0.0689 [0.9334]	0.13806	[0.933]	-52,79
2 days	8342	-2,4349	0,0000	2,5825	0,6836	-0,0106	0,0363	2441.81	[0.000]**	1350.3 [0.000]**	1611.24	[0.000]**	-182,9
1 week	8342	-0,7782	0,0000	0,8341	0,2080	0,0003	-0,0512	2676.62	[0.000]**	10968. [0.000]**	6045.08	[0.000]**	-87,89
2 weeks	8342	-0,4834	0,0000	0,4700	0,1301	0,0004	-0,0128	2784.58	[0.000]**	2022.0 [0.000]**	2050.84	[0.000]**	-37,57
1 months	8342	-0,4078	0,0000	0,4364	0,0992	-0,0013	0,4069	2445.40	[0.000]**	47898 [0.000]**	8522.48	[0.000]**	-18,27
2 months	8342	-0,3293	0,0000	0,3140	0,0718	-0,0004	0,0095	2769.43	[0.000]**	658680 [0.000]**	13711.5	[0.000]**	-8,82
3 months	8342	-0,1825	0,0000	0,1837	0,0487	-0,0011	0,2034	2605.36	[0.000]**	110040 [0.000]**	15929.0	[0.000]**	-4,55