Master of Science in Finance, Double Degree

Stockholm School of Economics / Bocconi University

Master of Finance Thesis

# Factor Sensitivities to Alternative Macroeconomic Environments


## Abstract

In this thesis, we examine how different factors are exposed to alternative macroeconomic environments. We apply a range of different approaches in order to explore these relationships. Firstly, we analyse mean excess returns and Sharpe ratios of factors in different macroeconomic regimes. We define the regimes by taking the median of macroeconomic indicators, and, alternatively, by applying a Markov switching model to the indicators. Secondly, we apply a two-state Markov switching model to excess returns, including macroeconomic indicators as explanatory variables. We cover all major factors in our research – size, value, momentum, quality and high dividend yield – as well as the main risk-efficient factor strategies, such as minimum volatility and risk weighted. We find that momentum, mid cap and large cap are pro-cyclical factors, which benefit significantly from favourable macroeconomic environments, while small cap, quality, high dividend yield, minimum volatility and risk weighted are relatively more resilient to negative macroeconomic developments. Finally, we construct a dynamic, rule-based factor allocation strategy and show that it significantly outperforms market and equally weighted factor portfolios over different investment horizons.



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**Key words:** Smart beta, factor investing, Markov switching models, dynamic portfolios

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## 1. Introduction

After the global financial crisis of 2007-2008, a growing number of institutional investors have been questioning their approach to asset allocation. Traditionally, investors diversified their portfolios with multiple asset classes and geographies. However, during the global financial crisis, correlations between asset classes increased significantly, and portfolios turned out to be not as well diversified as assumed, causing dramatic negative returns. After the publication of the paper by Ilmanen and Kizer (2009), who show that diversification across factors is more effective than diversification across asset classes, a factor-based, or risk-based, allocation approach has gained traction. In 2017, 46% of global asset owners have had allocations to smart beta strategies, up from 26% in 2015.[1]

In addition, nowadays, institutional investors are facing more challenging macroeconomic environment than before the crisis. Ultra-low yields, caused by unconventional monetary policies, suppressed the expected returns and prompted investors to include more risky assets in their portfolios. For instance, in February 2017, Norwegian Sovereign Wealth Fund increased its target allocation into equities from 60% to unprecedented 70%. The investors have also increasingly started to take into account macroeconomic considerations when allocating assets in order to make timely investments and harvest the highest possible returns.

In this thesis, we examine how different factors are exposed to alternative macroeconomic environments. We use different approaches to explore these relationships. Firstly, we analyse how mean excess returns and Sharpe ratios of factors change in alternative macroeconomic regimes compared to their all-time means and Sharpe ratios. Secondly, we apply Markov switching models to factor excess returns, including macroeconomic indicators as explanatory variables in the model.

Our research covers all main smart beta factors – from the most common, such as size, value and momentum, to risk-efficient strategies, such as minimum volatility and risk parity.

Originally, factors were constructed as self-financing portfolios, meaning that long positions were financed by shorting assets. For instance, in size factor, buying stocks of companies with small capitalization is financed by selling stocks of companies with large

[1] FTSE Russel, Smart beta: 2017 global survey findings from asset owners.

capitalization. In our research, we focus on long only factors, and we are using MSCI smart beta indices as proxies for the factors. Since these indices are typically used as benchmarks for smart beta ETFs, our research, in fact, explores how passive smart beta strategies respond to different macroeconomic regimes.

As a starting point, for constructing macroeconomic indicators, we replicate the methodology, set up by Ilmanen, Maloney and Ross (2014). Following their example, we construct five key macroeconomic indicators – growth, inflation, real yields, volatility and illiquidity. By taking the median of each indicator, we define five pairs of binary environments. We focus on comparing Sharpe ratios and risk premia across different regimes when drawing conclusions.

We further extend Ilmanen et al. (2014) framework by applying a two-state Markov switching (MS) model to macroeconomic indicators to define regimes, instead of simply taking the median. Then, we apply Markov switching models to excess factor returns, and include macroeconomic indicators as factor variables.

We find that Mid Cap, Large Cap and Momentum factors are very sensitive to macroeconomic indicators – they significantly benefit from growth up, inflation down, volatility down and illiquidity down regimes. On the other hand, Small Cap, Quality, High Dividend Yield, Minimum Volatility and Risk Weighted factors show some defensive properties to particular macroeconomic indicators. For instance, the returns of Minimum Volatility and Risk Weighted factors decrease the least when the growth goes down; Quality and High Dividend Yield factors are the most resilient to inflation up; and Small Cap and High Dividend Yield are the most resilient to volatility up and illiquidity up.

Finally, based on our findings, we construct five dynamic factor portfolios: growth, inflation, real yields, volatility and illiquidity. When the respective macroeconomic indicator is in a favourable regime, we invest in factors, which benefit the most from these macroeconomic environments.[2] When the respective macroeconomic indicator is in an unfavourable regime, we invest in factors, which are the most resilient to these

[2] Under favourable regime, or favourable macroeconomic conditions, we mean an environment, in which equity returns are expected to increase – growth up, inflation down, volatility down and illiquidity down regimes. On the other hand, under unfavourable regime, or unfavourable macroeconomic conditions, we mean an environment, in which equity returns are expected to decrease – growth down, inflation up, volatility upand illiquidity up regimes. We assume that impact of real yields on equity returns is uncertain, therefore, it is hard to decide if real yield up / down is a favourable or unfavourable regime.

macroeconomic developments. In the end, we show that dynamic portfolios, constructed in such a way, significantly outperform MSCI World index and equally weighted static factor portfolio over 5-year, 10-year and all-sample investment horizons.

While allocation to different factors helps to diversify strategic portfolios, understanding factor exposures to different macroeconomic environments provides valuable insights on how to harvest excess returns. Dynamic factor allocation strategy helps to exploit a return upside arising from favourable macroeconomic conditions and limit downside caused by unfavourable macroeconomic environments.

The rest of the paper is organised in the following way. Chapter 2 discusses the relevant literature on the topic. Chapter 3 explains methodology. Chapter 4 describes the data used in the thesis. Chapter 5 discusses the results, and finally, Chapter 6, presents conclusions.

## 2. Literature Review

Literature that aims to explain asset returns can be traced back to Sharpe (1964) and Lintner (1965), who develop the capital asset pricing model (CAPM). According to CAPM, the market premium is the only risk premium available to investors. However, this was later challenged by Fama and French (1992), who introduce additional factors, size and value. Fama and French (1992) define size factor as difference between returns of companies with small and large market capitalization, and value as difference between returns of companies with low and high price to book ratio. Fama and French (1992) find that their three-factor model is better at explaining returns of diversified portfolios than CAPM, and, therefore, these factors also carry a significant risk premium, in addition to market premium.

Later on, the model was extended by Carhart (1997), who add a momentum factor, difference between returns of "winner" and "loser" portfolios, to the model. Momentum factor means that stocks, which outperformed during the last 12 months, will outperform in the future, while stocks, which underperformed during the last 12 months, will underperform in the future. This factor is also a zero-cost portfolio, where buying winner companies is financed by selling loser companies.

Since then, many additional factors, such as quality (Piotroski, 2000), low beta (Black, 1972), high dividend yield, profitability, investment (Fama and French, 2015; Hou et al., 2015a) and others have been introduced. Overall, Harvey and Liu (2014) identify more than 300 factors in the literature.

Though empirical evidence for factor investing existed before 2000, it was not until the global financial crisis that it caught broad attention of institutional investors. Potential of smart beta strategies for asset management attracted an interest after the release of the report by Ang et al. (2009) at the request of the Norwegian sovereign wealth fund GPFG.[3] The report assesses performance of active fund management and emphasizes the benefits of factor investing. It also concludes that active management does not significantly contribute to the portfolio performance.

Ilmanen and Kizer (2012) also contributed to promotion of smart beta strategies among institutional investors. They argue that during 2007-2009 global financial crisis, when asset class correlation increased, factor investing still provided significant diversification benefits. They show that diversification across the factors have been much more effective in reducing volatility of the portfolio than asset class diversification. This prompted some investors to reconsider their investment approaches toward factor diversification rather than asset class diversification.

Asness et al. (2013) extend the usage of factors to other asset classes. In addition to stocks, they find value and momentum risk premia in currencies, bonds and commodities.

Zhang et al. (2009) explore the link between macroeconomic factors and style returns. They employ two different approaches – discrete state analysis and threshold regression – to identify how GDP growth, inflation innovations, 3-month Treasury bill rates, term spread and credit spread affect size and value factors. They find that both factors perform significantly better in the period of higher GDP growth and lower short-term rates. They also document positive exposure of value factor to unexpected inflation, negative exposure of size factor to unexpected inflation and positive exposure of both factors to term spread.

Russo (2015) explores how factor investing strategy can be implemented according to a macroeconomic environment. He focuses on equity-related factors and develops a factor investing model, based on the macroeconomic cycles. In Russo's framework, the macroeconomic cycle is characterized by four phases – expansion, deceleration, weakness

[3] Government Pension Fund Global.

and recovery. Then, he establishes a rule-based approach for assessing the current phases and implements factor allocation. He finds that in the recovery phase value and mid cap should be overweighted, min volatility and quality should be underweighted; in expansion phase quality and momentum – overweighted, min volatility – underweighted; in deceleration min volatility and high dividend should be overweighted, and in recession momentum should be underweighted and min volatility and quality overweighted. Finally, he shows that this rule-based dynamic factor allocation consistently outperforms MSCI benchmark.

Finally, since we apply Markov switching models (MSM) to explain factor returns, it is necessary to mention literature, which covers this class of models. The pioneering researcher who started to apply widely Markov switching models to time series is Hamilton (1989). Later, Krolzig (1996) extended Hamilton's univariate model to multivariate case, so called Markov switching vector autoregressive model (MS-VAR). Literature, which combines both application of a Markov switching model and factors analysis is not as extensive.

## 3. Methodology

### *3.1 General framework*

Following Ilmanen et al.(2014) approach, we define 10 different macroeconomic environments based on five indicators and explore indices mean excess returns and Sharpe ratios in each of the environments.

Firstly, we construct macroeconomic indicators, which are growth, inflation, real yields, volatility and illiquidity. Then, by taking the median of each indicator, we define binary states – up, if data point is higher than median, and down otherwise. The resulting ten regimes are growth up, growth down, inflation up, inflation down, real yield up, real yield down, volatility up, volatility down, illiquidity up and illiquidity down. Finally, we sort excess returns by regimes and calculate their means and Sharpe ratios in each specific macroeconomic environment. In addition, for each time-series we calculate differences between the all-time mean and the mean in each macroeconomic state to measure the change and sensitivity of factors to each macroeconomic environment.

We repeat the exercise, but instead of taking median to define binary regimes, we apply a two-state Markov switching model to macroeconomic indicators. The model specification is the following:

$$y_t = \mu_{S_t} + \sigma_{S_t} \cdot \varepsilon_t,$$

where $y_t$ is macroeconomic indicator at time t, $\mu$ – mean, $\sigma$ – variance, $\varepsilon_t$ – error term ($\varepsilon_t \sim$ IID(0,1)). Subscription $s_t$ means that the estimate is state-switching, therefore, in this model specification we allow both mean and variance to be different in states.

The outputs from the model are estimates of means and variances in two states, as well as constant transition probabilities and expected durations of states. It is also possible to calculate smoothed and filtered probabilities for the states, where smoothed probability is the probability of being in a certain state taking into account all sample observations, and filtered probability is the probability of being in a certain state taking into account only previous sample observations. If filtered probability of the state with the higher mean is larger than 0.5 at a certain point of time, we define the regime to be up, otherwise – down.

Again, we sort all of the excess returns by up and down regimes, and calculate their means and Sharpe ratios in each macroeconomic environment.

Finally, we want to measure exposure of each asset class to macroeconomic indicators and explore if the exposure changes depending on the state of the returns. We apply a two-state Markov switching model with the following specification

$$y_t = \alpha_{S_t} + \sum \beta_{S_t} \cdot \Delta X_t + \sigma_{S_t} \cdot \varepsilon_t,$$

where $y_t$ is excess asset return at time t, $X_t$ – macroeconomic indicator at time t, $\alpha$ – intercept, $\beta$ – estimate of the exposure to indicators, $\sigma$ – variance of excess returns, $\varepsilon_t$ – error term ($\varepsilon_t \sim$ IID(0,1)). All five macroeconomic indicators are included as explanatory variables into the model. Also, all estimates of the model – intercepts, variances and five beta estimates – are state-switching.

*3.2 Markov switching models*

Since we extensively apply Markov switching models throughout our research, both to macroeconomic indicators and excess returns, we would like to explain briefly the underlying theory behind this family of models.

Markov switching models belong to the class of regime switching models. Regime switching models also include threshold models (TM) and smooth transition models (STM). Threshold models assume that state variable $s_t$ depends on the value of some exogenous threshold variable at time *t*. In smooth transition models, state variable takes value depending on some discrete probability distribution function. In MSMs $s_t$ is unobservable from a discrete, first-order, irreducible, ergodic Markov chain. The difference between threshold and Markov switching models is obvious – in TMs, the state variable is defined exogenously, while in MSMs it is latent. Regarding the difference between STMs and MSMs, Markov switching can be considered as a special case of smooth transition, where the cumulative distribution function is defined as a logistic function. However, MSMs received wider application in literature, since they are more flexible and easier to estimate. In addition, it is easier to extend MSMs to multivariate cases.

Under MSM specification, the dependent variable $y_t$ switches regimes according to some unobservable variable $s_t$, which takes on integer values. For simplicity, we assume two regimes. Therefore, $s_t$ can take on values 1 or 2. Markov process governs the state variable between the regimes in such a way that

$$P(a < y_t \leq b \mid y_1, y_2, \dots, y_{t-1}) = P(a < y_t \leq b \mid y_{t-1}).$$

This means that Markov process is not path-dependent and probability distribution of the state at time t depends only on the state at time t-1. The simplest form of Markov switching model is called 'Hamilton's filter'. If to denote unobserved state variable $z_t$, a first order Markov process is the following

$$\begin{aligned}
&p(z_t = 1 \mid z_{t-1} = 1) = p_{11};\\
&p(z_t = 2 \mid z_{t-1} = 1) = 1 - p_{11};\\
&p(z_t = 2 \mid z_{t-1} = 2) = p_{22};\\
&p(z_t = 2 \mid z_{t-1} = 1) = 1 - p_{22},
\end{aligned}$$

where $p_{11}$ is the probability of being in regime 1 at t given that the variable was in regime 1 at t-1, (1 - $p_{11}$) – probability of being in regime 2 at t given that the variable was in regime 1 at t-1, $p_{22}$ – probability of being in regime 2 at t given that the variable was in regime 2 at t-1, (1 - $p_{22}$) – probability of being in regime 2 at t given that the variable was in regime 1 at t-1. $p_{11}$ and $p_{22}$ are called transition probabilities.

State variable $z_t$ evolves as the following AR(1) process:

$$z_t = (1 - p_{11}) + (p_{11} + p_{22} - 1) \cdot z_{t-1} + \eta_t.$$

The dependent variable evolves as:

$$y_t = \mu_1 + \omega z_t + (\sigma_1^2 + \varphi z_t)^{1/2} u_t,$$

where $\mu_1$and $\mu_2 = \mu_1 + \omega$ are expected values in states 1 and 2 respectively, $\sigma_1^2$ and $\sigma_2^2 = \sigma_1^2 + \varphi$ are variances in states 1 and 2 respectively, $u_t$ – error term ($u_t \sim$ N(0,1)). The unknown parameters $(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, p_{11}, p_{22})$ are estimated using maximum likelihood.

Engel and Hamilton (1990) provide comprehensive details on estimating Markov switching models.

With population parameters summarized in the vector,

$$\theta = (\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, p_{11}, p_{22})',$$

the unconditional distribution of the state of the first observation can be written in the following way:

$$p(s_1 = 1; \theta) = \frac{(1 - p_{22})}{(1 - p_{11}) + (1 - p_{22})};$$
$$p(s_2 = 2;\ \theta) = 1 - p.$$

The joint probability distribution function of the series with a sample size T $T(y_1, \dots, y_T)$ and unobserved states $(s_1, \dots, s_T)$ can then be written as:

$$p(y_1, \dots, y_T, s_1, \dots, s_T; \theta) =$$
$$= p(y_T|s_T; \theta) \cdot p(s_T|s_{T-1}; \theta) \cdot p(y_{T-1}|s_{T-1}; \theta) \cdot p(s_{T-1}|s_{T-2}; \theta) \cdot \dots \cdot\cdot\, p(y_2|s_2; \theta) \cdot$$
$$p(s_2|s_1; \theta) \cdot p(y_1|s_1; \theta) \cdot p(s_1; \theta).$$

Finally, the likelihood function to be maximized is the summation of joint probability distribution functions over all possible values of $(s_1, \dots, s_T)$:

$$p(y_1, \dots, y_T; \theta) = \sum_{s_1=1}^{2} \cdots \sum_{s_1=1}^{2} p(y_1, \dots, y_T, s, \dots, s_T; \theta).$$

When estimating parameters, the singularity in likelihood function may sometimes arise if, for example, the mean of regime 1 equals the value of the first observation in the sample and the variance of regime 1 is permitted to go to zero. This problem is addressed by applying the Bayesian prior to the parameters of the two regimes.

## 4. Data

*4.1 Macroeconomic indicators*

To construct growth indicator, we take the Chicago Fed National Activity Index (CFNAI), which is the monthly index designed to gauge overall economic activity in the US. Since the return is a forward looking measure,[4] and CFNAI relates to the past, it is necessary to include growth forecast into indicator to reflect investors' expectations about the economy. Therefore, we also use quarterly forecasts for the growth of industrial production index from Survey of Professional Forecasters (SPF). We standardize CFNAI and IP growth forecast, and define the growth indicator as an average of the standardized series.

For the inflation indicator, we use yearly changes in the Consumer Price Index for All Urban Consumers, and quarterly forecasts for the change in the GDP Price Index as a forward looking metric. Likewise, we standardize both series and take their average to construct the inflation indicator.

For the real yield indicator, we take the average of standardized long-term and short-term real yields. Long-term real yield is defined as the 10-year US Treasury bond yield minus the 10-year inflation forecast, short-term real yield as the 3-month US Treasury bill yield minus the 1-year inflation forecast respectively. For 1-year inflation rate we use the same series as in inflation indicator – GDP Price index growth from SPF, however, for the 10-year CPI forecast, the data is available only since 1991. Prior to 1991, as a 10-year CPI proxy we use GDP Price Index forecast plus the average of differences between 1- and 10-year inflation forecasts from 1991 to 2016.

In constructing the volatility indicator, we only take into account equity market volatility. Equity volatility is calculated as volatility of the S&P daily returns over the past year. The CBOE Volatility Index (VIX Index) may be considered as a forward looking measure for equity volatility, however, we do not use it because its history is shorter than our sample period.

As an illiquidity indicator, we use standardized aggregate liquidity measure developed by Pastor and Stambaugh (2003). The liquidity measure is constructed using individual daily stock returns and volumes from NYSE and AMEX.

[4] The returns are considered to be forward looking, since they might reflect the change in the investors' views on company's future cash flows.

### *4.2 Smart beta indices*

As a representation of the global economy and a benchmark for our analysis, we use MSCI World Index, which captures 85% of free float market capitalization in 23 developed markets. As factor proxies, we use smart beta indices developed by MSCI. MSCI World Small Cap, MSCI World Mid Cap and MSCI World Large Cap indices represent the behavior of size factor. MSCI World Value, MSCI World Momentum, MSCI World Minimum Volatility, MSCI World Risk Weighted, MSCI World Quality and MSCI World High Dividend Yield are used as value, momentum, minimum volatility, minimum risk, quality and high dividend yield factors. The data are of monthly frequency and span from July 1988 to November 2016. MSCI Small, Mid and Large Cap are the only indices which span from July 1995 to November 2016 due to unavailability of earlier data.

### *4.3 Descriptive statistics*

Over the sample period, all factors have positive mean excess returns (see Table 1). Quality and Momentum factors performed the best, with the risk premia of 0.94% and 0.88% respectively, while Large Cap and Value performed the worst, with the risk premia of 0.44% and 0.47% respectively. As expected, the defensive smart beta strategies, Min Volatility and Risk Weighted, had the lowest volatility, 2.44% and 2.90% respectively, while Small Cap and Mid Cap had the highest volatility of 3.77% and 3.53% respectively. All indices have negative skewness, meaning that the distribution of the data is asymmetric and returns higher than the mean occur more than 50% of the time. All series have excess kurtosis higher than zero, and none of the series are normally distributed according to the Jarque-Bera test.

The common argument for the implementation of the smart beta strategies is that they are weakly correlated, therefore, they provide additional diversification when included in the portfolio. This is true for factors constructed using both short and long legs. However, since we assume no short selling and use broad equity indices for factor replication, our series are strongly correlated. The most correlated pairs are MSCI World and Large Cap Indices (0.997), MSCI World and Value Indices (0.975) and Mid Cap and Small Cap Indices (0.970). The least correlated pairs are Momentum and High Div Yield (0.773), Small Cap and Min Vol (0.775), Momentum and Min Vol (0.787) and Momentum and Value (0.790).

## 5. Results

### *5.1 Macroeconomic environments*

As already indicated above, we apply two methodologies to define macroeconomic states. Firstly, we apply the median to macroeconomic indicator – if a data point is higher than the median of the macroeconomic time-series, the regime is called to be up, otherwise down. Secondly, we apply a two-state Makov switching model to macroeconomic indicators, with the following specification

$$y_t = \mu_{S_t} + \sigma_{S_t} \cdot \varepsilon_t,$$

where $y_t$ is macroeconomic indicator at time t, $\mu$ – mean, $\sigma$ – variance, $\varepsilon_t$ – error term ($\varepsilon_t \sim$ IID(0,1)).

By using a median of macroeconomic indicators to define the environments we enforce equal numbers of observations in up and down regimes. For all indicators, we have 170 observations in up regime and 171 observations in down regime. Since macroeconomic indicators are standardized, their means in up and down regimes are always nearly symmetric relative to zero (see Table 3). This imposes a restriction that on average, over the sample period, magnitude of down regime is always nearly the same as magnitude of up regime. However, negative shocks, e.g. growth down or illiquidity up, are usually larger in magnitude than positive shocks and last for shorter periods of time. In addition, one of the regimes, either up or down, may be prevailing over the sample period, meaning that it occurs more frequently than the other regime.

These issues are addressed when we apply a two-state MS model with state-switching mean and variance. This model distinguishes between states, in which macroindicator has different first two moments – mean and variance. As a result, we obtain binary macroeconomic regimes, which have different number of observations and different means, so that they are no longer symmetric around zero. Therefore, we consider MS model as a more systemic way to distinguish between macroeconomic environments.

The details of regime parameters, obtained from MS model, are presented in Table 4. We report mean, variance, transition probability, expected duration and number of observations for all 10 binary macroeconomic regimes. The dynamics of macroindicators, as well as regime realizations for both median and MS methods, are presented in Figures 1-6 and commented below.

Applying MS model to growth indicator reveals that over 1988-2016 sample period up regime was indeed more common (301 observations in up vs 40 observations in down regime), more persistent (transition probability is higher by 7% in up regime) and had higher expected duration (98.5 months in up vs 12.6 months in down regime). Overall, MS model defines that the economy was in growth up regime for 88% of the time versus 50% defined by median. Down regimes, in their turn, correspond specifically to periods of economic crisis and market crashes, like early 1990s economic recession in the US, dot-com bubble collapse in 2001-2002 and global financial crisis in 2008-2009. Also, the mean for down regime is low, -2.798, while the mean of up regime is 0.383. This clearly shows that while positive growth was on average modest but occurred frequently, negative shocks were rare and drastic.

The means of inflation, real yield and volatility up and down regimes are almost symmetric around all-time average zero – inflation means in up and down regimes are 1.00 and -0.84 respectively, real yield means in up and down regimes are 0.96 and -0.94 respectively, and volatility means in up and down regimes are 0.92 and -1.00 respectively. Up and down regimes of these macroindicators also have nearly same transition probabilities, expected durations and frequency of occurrence. Therefore, whether we use median or MS model, this should not substantially affect the resulting average excess returns of smart beta indices in those macro states.

Likewise growth, illiquidity up and down regimes have asymmetric means around zero. Also, down state is more persistent (transition probability of 99% vs 96% in down state), have higher expected duration (71 months vs 27 months) and occurs more frequently over the sample period – 70% of the time or in 237 observations out of 341.

We mentioned the benefits of MS model over the median approach – it does not impose equal number of observations in binary regimes and symmetry of state means around zero. However, MS approach also has pitfalls. If MS model is applied to a short sample, some regimes may result having very few observations. Then, mean excess returns in up and down regimes will be incomparable due to the large standard error of mean in the regime with few observations. In such case, median approach will be preferable.

*5.2 Factor sensitivities to macroeconomic environments*

As mentioned above, to measure factor sensitivities to macroeconomic environments, we apply two alternative approaches. Firstly, we define macroeconomic environments, sort factor returns according to the environments and compare factor risk premia and Sharpe ratios in different regimes. Secondly, we apply a two-state Markov switching model to the factor excess returns to understand if macroeconomic indicators have power in explaining variance in factor excess returns.

*5.2.1 Approach I: comparing risk premia and Sharpe ratios in alternative macroeconomic environments*

In this section, we discuss how factors are exposed to different macroeconomic environments, based on application of a median and Markov switching models to macroeconomic indicators. Firstly, we discuss the results from application of a median.

Since all factors we investigate are equity indices, as equities in general, they are all positively exposed to growth, negatively exposed to inflation, volatility and illiquidity. For most factors, mean excess returns in real yield up and down regimes are not very different from all-time means, therefore, based on this approach, we conclude that smart beta indices are not sensitive to real yields.

No factor significantly outperforms the MSCI World Index in growth up regime (see Figures 7 and 8 for details). However, some indices show defensive properties in growth down regime comparing to MSCI – these are Small Cap and Quality, which outperform the world index by 0.42% and 0.58% respectively.

All factors are sensitive to inflation. Small Cap, Mid Cap and Large Cap benefit from inflation down regime the most – they increase by 0.87%, 0.70% and 0.57% respectively comparing to their all-time means, while Quality and High Yield are defensive against rising inflation – their returns decrease by 0.30% and 0.27% respectively, which is the smallest decrease from all-time means among all indices.

Most indices do not have significant differences in mean excess returns and Sharpe ratios in real yield up and down regimes. Moreover, all factors have positive risk premia and Sharpe ratios in both regimes. However, in the up regime, Quality and High Yield factor risk premia increase comparing to the all-time average, by 0.12% and 0.08% respectively, while Min Volatility and Risk Weighed significantly increase in down regime, by 0.15% and 0.20%. This finding suggests that in order to exploit real yield changes optimally, one should always invest in factors, which are generally believed to be defensive – in Quality and High Yield when real yields are up and Min Volatility and Risk Weighted when real yields are down.

All factors are negatively exposed to volatility changes. Momentum, Quality and High Yield benefit the most from volatility down regime – they increase by 0.41%, 0.40% and 0.40%, while Min Volatility and Small Cap show some defensive properties against volatility up – their risk premia decrease the least comparing to all-time averages when volatility goes up, by 0.25% and 0.15% respectively.

Likewise, all smart beta indices are significantly and negatively exposed to illiquidity indicator. Mid and Large Cap benefit from illiquidity down the most, carrying the largest relative excess premia and Sharpe ratios, 0.73% and 0.71% respectively, while all factors suffered from illiquidity up regime.[5]

To sum up, these findings show that in general Momentum, Mid Cap and Large Cap tend to be pro-cyclical and sensitive to multiple macroeconomic indicators – while they benefit the most from favourable macroeconomic environments, they also suffer from macroeconomic shocks. On the other hand, Quality, High Dividend Yield and Small Cap have defensive properties against some negative shocks, like high inflation and high volatility. However, by applying median to macroindicators we were not able to identify clearly, which factors outperform in growth up regime or provide protection in an illiquidity up regime, due to the above-mentioned limitations of this approach.

Since some of the results from applying median to the economic indicators were not very clear, for instance, which factors are the best to invest in growth up regime and which in illiquidity up regime, let us take a look and try to explain exposures, which arise from application of a two-state Markov model to macroeconomic indicators.

As already mentioned, when we apply a Markov switching model to growth indicator, growth up regime is prevailing, though it indicates rather modest average growth rate. On the other hand, growth down regime is rare, but growth rates in this regime are dramatically negative. Therefore, all factors result to be very sensitive to growth indicators with positive mean returns in up regime and very negative mean returns in down regime. Mid Cap, Large Cap and Momentum are the most sensitive to growth, with the highest relative risk premia in up regime, 0.27%, 0.30% and 0.28%, and the lowest relative risk

[5] By relative excess returns (or premia) we mean the difference between all-time mean of excess returns and the mean in a specific regime.

premia in down regime, -1.99%, -2.21% and -2.08% respectively. Small Cap, Min Volatility and Risk Weighted are the least sensitive to growth, meaning that they limit downside in comparison to other factors in down regime. Their excess means in growth down decrease by 1.36%, 1.17% and 1.15% comparing to their all-time means. These strategies are defensive in the case of negative growth shocks.

All factors are negatively exposed to inflation. Small Cap, Mid Cap and Momentum benefit from inflation down regime the most (0.52%, 0.53% and 0.48% respectively), while Quality and High Dividend Yield provide protection against rising inflation. Their risk premia decrease by 0.37% and 0.31%, which is the smallest decrease among all indices.

Likewise in case of an application of a median to real yield indicator, application of a MS model reveals that there is no unidirectional exposure of smart beta indices to real yields. Both in real yield up and down regimes factor mean excess returns are positive. However, Small Cap and Risk Weighted mean excess returns significantly decrease in real yield up (by 0.28% and 0.21%) and increase in real yield down regime comparing to all-time average of excess returns (by 0.47% and 0.21%). On the contrary, Quality and High Dividend Yield risk premia increase in real yield up (by 0.13% and 0.08%) and decrease in real yield down regime (by 0.13% and 0.09%).

All smart beta strategies are sensitive to volatility indicator. Mid Cap and Large Cap benefit the most from volatility down state. Their relative excess risk premia are 0.41% and 0.52% respectively. Small Cap and Minimum Volatility are the most resilient to volatility up, their risk premia decrease by 0.17% and 0.20% comparing to all-time means.

All factors are significantly exposed to illiquidity indicator. Mid Cap, Large Cap and Momentum have the highest relative returns in illiquidity down regime (0.43%, 0.43% and 0.37% respectively) and the lowest relative returns in illiquidity up regime (-0.67%, -0.67% and -0.85%), meaning that these factors have the strongest exposure to illiquidity. Small Cap and High Dividend Yield have the highest relative return in illiquidity up regime (0.56% and -0.31%), meaning that these strategies can be a protection in illiquidity up states.

Overall, findings from applying MS model to macroeconomic indicators go in line with the findings from applying the median. In addition, they confirm that Mid Cap, Large Cap, Momentum are very sensitive to macroeconomic indicators, including growth, and benefit the most from favourable conditions. Quality, High Dividend Yield, Min Volatility, Risk Weighted and Small Cap clearly belong to the category of the defensive factor strategies, which provide some degree of resilience in challenging macroeconomic environment. Surprisingly, value factor does not show neither pro-cyclical, nor defensive properties compared to other factors, which makes it difficult to conclude in what portfolios it should be included when one wants to exploit macroeconomic changes to harvest yield.

### *5.2.2 Approach II: Markov switching models application to factor excess returns*

Applying a two-state MS model to factor excess returns is a fundamentally different approach than applying MS model to macroeconomic indicators. While the latter distinguishes between two states of macroeconomic indicators, the former distinguishes between two states of each factor excess returns and aims to identify if changes in levels of macroeconomic indicators explain the excess returns in each state.

To start with, all smart beta indices have significant negative exposure to illiquidity indicator (see Table 6 for details) in one of the states. In addition, both in up and down states most factors have significant negative exposure to volatility. It means that changes in illiquidity and volatility explain factor price movements in either one or both states. These findings are consistent with the findings from the former approach.

By sorting the returns according to the macroeconomic environment, we find that factor indices are not sensitive to real yields. However, applying the MS model to excess returns shows that changes in real yields can explain excess returns of some factors. Min Volatility, Risk Weighted and High Dividend Yield are negatively exposed to real yields in either up or down regime, the respective coefficients are -0.085, -0.041 and -0.055. These are defensive smart beta strategies, therefore, when yields go down they may be seen as a substitute for low yielding bond investments, and consequently the return on these strategies increase. On the other hand, Mid Cap is positively exposed to real yields in down regime with beta coefficient of 0.085. Possible explanation is that when real yields go up, which usually signals the end of expansionary monetary policies and the recovery in the economy, Mid Cap benefits from relocation of investments to equities. Small Cap, Large Cap and Momentum change the sign of exposure to real yields in up and down states: Small Cap and Momentum are positively exposed to real yields in up regimes and negatively exposed to real yields in down regimes. Large Cap is negatively exposed to real yields in up regimes and positively exposed in down regimes. Based on these different exposures in up and down states, a specific investment strategy can be created: when Small Cap, Momentum and Large Cap are in their down states and real yields are expected to increase – sell Small Cap, sell Momentum and buy Large Cap; and vice versa if the real yields are expected to decrease. Otherwise, when Small Cap, Momentum and Large Cap are in their up states and real yields are expected to increase – buy Small Cap, buy Momentum and sell Large Cap, and vice versa if the real yields are expected to decrease. From an economic point of view, these results are difficult to interpret, therefore, they should be further examined before implementing the above investment strategy.

For most factors, changes in inflation levels does not have a significant power in explaining the excess returns. However, Small Cap is negatively exposed to inflation in up state (-0.034), while Min Volatility is negatively exposed to inflation in down state (-0.058). For Small Cap it means that in up state Small Cap benefits from decrease of inflation. This is consistent with the findings from the former approach. For Min Volatility it means that it suffers from increase of inflation in its down state. This is an unexpected result, since we perceive Min Volatility to be a defensive factor.

Most factors excess returns are not explained by growth indicator – beta coefficients in most cases are insignificant. However, Small Cap is significantly and positively exposed to growth indicator in down state (0.016 beta coefficient) – it means that Small Cap returns are plummeting when they are in down state and growth is slowing down. Min Volatility is exposed negatively to growth indicator in down state (-0.20) – it means that in down state Min Volatility is resilient to slowing growth, confirming defensive properties of this factor.

To sum up, all of the equity factors are significantly and negatively exposed to volatility and illiquidity. Though the former approach suggested that factors are not sensitive to real yields, we find that changes in real yields have power in explaining factor excess returns. Moreover, some of the factors change the sign of their exposure to real yields in their up and down states, suggesting an investment strategy based on Markov switching models. Changes in inflation and growth cannot explain excess returns of all factors but Small Cap and Min Volatility – Small Cap is found to be sensitive to both inflation and growth, while Min Volatility is sensitive to inflation but defensive to growth.

### *5.3 Dynamic factor allocation according to macroeconomic regimes*

Based on the results following from the first approach, we create dynamic factor allocation strategies and test their performance from July 1995 to November 2016.

### *5.3.1 Portfolio construction*

In each macroeconomic environment, we are able to identify factors, which are the most and least sensitive to a specific macroeconomic indicator. Therefore, we can create dynamic macroeconomic portfolios, which benefit the most from favourable environments – growth up, inflation down, volatility down and illiquidity down regimes, and are the most resilient to negative developments – growth down, inflation up, volatility up and illiquidity up regimes. When the regime switches from up to down, we divest factors, which are the most sensitive to an indicator and invest in factors, which are the most resilient to an indicator. That is why we refer to the strategy as dynamic, since the composition of the portfolio changes entirely in case the economy switches to another regime.

The regimes of the macroeconomic environments are defined by a two-state Markov switching model, applied to an indicator. Therefore, the strategy is rule-based, and does not require significant cost. An investor has to choose what sample length to use to define the regimes, as well as the frequency of data as it may affect the effectiveness of the strategy. In our case, we test the performance of five dynamic factor allocation strategies since July 1995 to November 2016 on a monthly basis. The factors are equally weighted when they are included in the portfolio.

Five dynamic factor allocation strategies we examine are:

- Growth portfolio: when growth is in up regime, invest in Mid Cap, Large Cap and Momentum, when growth is down – in Small Cap, Risk Weighted and Min Volatility;
- Inflation portfolio: when inflation is up, invest in Quality and High Dividend Yield, when down – Small Cap, Mid Cap and Momentum;
- Real yields portfolio: when real yields are in up regime, invest in Quality and High Dividend Yield, when down – Small Cap, Min Volatility and Risk Weighted;
- Volatility portfolio: when volatility is up, invest in Small Cap and Min Volatility, when volatility is down – in Mid Cap, Large Cap and Quality.
- Illiquidity portfolio: when illiquidity is up, invest in Small Cap, Min Volatility and High Dividend Yield, when down – in Mid Cap, Large Cap and Momentum.

It is necessary to highlight that we study the performance of the dynamic portfolios "in-sample", therefore, we expect the portfolios to perform relatively well. However, in reality, investors in 1995 did not know in which factors to invest to harvest the best returns. On the other hand, since we use monthly data and have only 12 data points per year, and do not have very long historic sample, "out-of-sample" testing is limited.

*5.3.2 Portfolio performance*

We measure the performance of these five dynamic factor allocation strategies against MSCI World Index, which is our benchmark. In addition, we construct an equally weighted all factors portfolio (EW all-factor hereinafter) and compare its performance with the performance of the benchmark and five dynamic portfolios. The idea is to understand if dynamic factor allocation according to the macroeconomic environments brings additional value for the investors in comparison to investing in MSCI World Index or static equally weighted factor portfolio.

All five dynamic factor strategies outperformed the MSCI World Index and EW all-factor since July 1995 to November 2016 (see Figure 15). Real yields dynamic portfolio performed the best, followed by inflation, growth, volatility and illiquidity portfolios. Real yields, inflation and growth outperformed the benchmark by more than 100% by the end of 2016, while volatility and illiquidity outperformed the benchmark by more than 75% by the end of 2016. In fact, this means that our dynamic factor allocation strategies indeed work for this sample period and bring higher returns to an investor than investing in the market.

Further, we compare the performance of dynamic factor strategies and EW all-factor portfolio to the benchmark over three time horizons – all sample, 10-year and 5-year. We choose these horizons to see how the performance of different dynamic strategies changes over time relative to the benchmark. We also use 5-year and longer horizons, because a full economic cycle usually lasts from five to ten years, and we would like to test our strategies over the full or almost full economic cycle, where switching off an indicator to another regime takes place.

Over the whole sample period, real yields strategy yielded the highest annualized excess returns as well as the highest Sharpe ratio, 7.79% and 0.76 (see Table 7 for details). At the same time, all dynamic macroeconomic strategies have significantly higher Sharpe ratios than the benchmark and higher Sharpe ratios than equally weighted factor portfolio. We also calculate tracking errors, a standard deviation of strategy performance to the benchmark, and information ratios (IRs), which effectively measure how much return an investor gets for an extra unit of active risk. Over the whole sample period, growth, inflation and real yield strategies had the highest information ratios (1.33, 1.24 and 1.46 respectively), while IRs of volatility and illiquidity have been smaller than equally weighted factor strategy (0.95 and 0.92 vs 1.09 of EW portfolio). It means that since 1995, investing in EW all-factor portfolio would bring more alpha, than investing in volatility or illiquidity dynamic strategies.

Over 10-year horizon, all dynamic factor strategies outperform the benchmark and EW all-factor portfolio both in terms of returns and Sharpe ratios. In addition, all strategies have better information ratios than EW all-factor portfolio (1.06). It means that over the most recent 10-year horizon, all dynamic macroeconomic strategies bring higher active returns than both market and factor portfolio. Over 10-year horizon, growth portfolio have yielded the highest information ratio (1.52), followed by volatility portfolio (1.40).

Over the most recent 5-year horizon, all strategies returns and Sharpe ratios were superior to the benchmark and EW all-factor portfolio. Inflation portfolio had the highest Sharpe ratio out of all dynamic factor strategies – 1.20. When it comes to information ratio, IRs of all dynamic strategies have been higher than both market benchmark and EW factor portfolio. This means that all dynamic strategies yield better returns per unit of active risk than simple static all factor strategy. Volatility portfolio have had the highest IR over the recent five years – 1.14.

To sum up, we clearly see that in most cases dynamic factor strategies have better performance than MSCI World Index and equally weighted all-factor portfolio. In addition, the performance of dynamic factor strategies have been different for different investment horizons. For instance, over the whole sample period, real yields have shown the best performance measured by information ratio, over 10-year horizon growth portfolio performed the best, while over 5-year horizon volatility portfolio performed the best. In terms of Sharpe ratio, real yields perform the best over the whole sample period, while volatility perform the best over 10-year investment horizon, and real yields portfolio perform the best over 5-year period. This suggests that in order to better diversify macroeconomic risks and harvest better returns, one should invest in multiple dynamic macroeconomic portfolios simultaneously rather than one.

## 6. Conclusions

In this paper, we examine how different factors are exposed to alternative macroeconomic environments. We apply several different approaches in order to explore these relationships. Firstly, we sort excess returns according to binary macroeconomic regimes, calculate their risk premia and Sharpe ratios in each macroeconomic regime and compare them with all-time means and Sharpe ratios. Secondly, we apply a two-state Markov switching model to factor excess returns, including macroeconomic indicators as explanatory variables in the model.

The second approach we use to examine asset excess returns exposure to macroeconomic indicators is fundamentally different from the first one. In the former approach, we impose binary regimes on macroeconomic indicators and look at excess returns in the defined regimes. In the latter, we impose binary regimes on factor returns. We apply a two-state Markov switching model to each factor excess returns including changes in macroeconomic factors as explanatory variables in the model.

Both approaches reveal that smart beta strategies are particularly vulnerable to volatility and illiquidity – when volatility or illiquidity goes up, factor returns fall significantly. Though the first approach does not seem to capture sensitivity to real yields, the second one clearly suggests that an increase in real yields decreases factor returns. For specific factors, such as Small Cap, Momentum and Large Cap, the exposure of returns to real yields changes a sign (from positive to negative or vice versa) in up and down states, meaning that specific investment strategies can be created to exploit these properties.

As equity indices in general, all factors are positively exposed to growth and negatively exposed to inflation. Some of them, such as Mid Cap, Large Cap, and Momentum, are pro-cyclical and found to be very sensitive to macroeconomic changes, while others, such as Small Cap, Quality, High Dividend Yield, Minimum Volatility and Risk Weighted have defensive properties against changes in certain macroeconomic environments.

We create five dynamic factor portfolios, based on their sensitivities to macroeconomic environments, and show that all of the portfolios outperform global market index and equally-weighted all-factors portfolio for the "in-sample" period. This means that is possible to exploit factor sensitivities to harvest better than market returns and achieve some active risk reward.

Understanding factor returns exposure to alternative macroeconomic environments has very valuable practical implications. Firstly, it provides insights on how allocations should change if the investor wants to increase its exposure to certain macroeconomic variables to get higher returns. Secondly, it helps to hedge against macroeconomic changes and construct diversified portfolios, which would perform well in any of the environment.

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**Table 1**

**Summary statistics for factor returns**

The following table shows the main statistics for monthly factor indices returns over the sample period from July 1988 to November 2016. Jarque-Bera is a test statistics used to assess whether a series is normally distributed. P-value close to zero suggests that the null hypothesis, a series is normally distributed, is rejected.

| | **Mean** | **Med.** | **Min.** | **Max.** | **St. Dev.** | **Skew** | **Kurt.** | **Jarque-Bera** | **p** |
|---|---|---|---|---|---|---|---|---|---|
| **MSCI World** | 0,49% | 0,99% | -19,04% | 11,13% | 3,28% | -0,58 | 1,37 | 46,01 | 0,00 |
| **Small Cap** | 0,66% | 0,92% | -22,71% | 16,30% | 3,77% | -0,62 | 2,06 | 61,88 | 0,00 |
| **Mid Cap** | 0,58% | 0,88% | -23,38% | 14,03% | 3,53% | -0,87 | 2,82 | 117,95 | 0,00 |
| **Large Cap** | 0,44% | 0,95% | -18,26% | 10,35% | 3,31% | -0,70 | 1,34 | 40,14 | 0,00 |
| **Value** | 0,47% | 0,74% | -18,64% | 13,35% | 3,27% | -0,57 | 1,57 | 53,35 | 0,00 |
| **Momentum** | 0,88% | 1,23% | -16,70% | 18,16% | 3,39% | -0,44 | 1,44 | 40,39 | 0,00 |
| **Min Vol** | 0,68% | 0,95% | -15,86% | 9,91% | 2,44% | -0,71 | 2,30 | 103,97 | 0,00 |
| **Risk Weighted** | 0,79% | 1,20% | -19,34% | 12,61% | 2,90% | -0,75 | 2,64 | 131,14 | 0,00 |
| **Quality** | 0,94% | 1,05% | -15,09% | 12,20% | 3,00% | -0,41 | 0,98 | 23,21 | 0,00 |
| **High Div Yield** | 0,54% | 0,57% | -19,12% | 13,51% | 3,01% | -0,67 | 2,31 | 101,58 | 0,00 |

**Table 2**

**Factor indices sample correlations**

The following table presents full-sample pairwise correlations between factor indices for the period from July 1988 to November 2016.

| | MSCI World | Small Cap | Mid Cap | Large Cap | Value | Momen tum | Min Vol | Risk Weight ed | Quality | High Div Yield |
|---|---|---|---|---|---|---|---|---|---|---|
| **MSCI World** | 1,000 | | | | | | | | | |
| **Small Cap** | 0,889 | 1,000 | | | | | | | | |
| **Mid Cap** | 0,952 | 0,970 | 1,000 | | | | | | | |
| **Large Cap** | 0,997 | 0,880 | 0,947 | 1,000 | | | | | | |
| **Value** | 0,975 | 0,867 | 0,921 | 0,963 | 1,000 | | | | | |
| **Momentum** | 0,855 | 0,794 | 0,851 | 0,868 | 0,790 | 1,000 | | | | |
| **Min Vol** | 0,906 | 0,775 | 0,844 | 0,885 | 0,908 | 0,787 | 1,000 | | | |
| **Risk Weighted** | 0,943 | 0,906 | 0,935 | 0,925 | 0,956 | 0,796 | 0,925 | 1,000 | | |
| **Quality** | 0,929 | 0,796 | 0,877 | 0,957 | 0,874 | 0,857 | 0,839 | 0,858 | 1,000 | |
| **High Div Yield** | 0,910 | 0,801 | 0,866 | 0,921 | 0,938 | 0,773 | 0,898 | 0,933 | 0,883 | 1,000 |

**Table 3**

**Parameters of macroeconomic environments defined by applying median**

The following table contains parameters, mean, standard deviation and number of observation for each macroeconomic defined by applying median.

| | | Mean | Log of standard deviation | No. of obs. in the regime |
|---|---|---|---|---|
| **Growth** | *Up* | 0.845 | -1.209 | 170 |
| | *Down* | -0.840 | -0.023 | 171 |
| **Inflation** | *Up* | 0.923 | -0.258 | 170 |
| | *Down* | -0.918 | -0.883 | 171 |
| **Real yield** | *Up* | 0.960 | -1.049 | 170 |
| | *Down* | -0.954 | -0.606 | 171 |
| **Volatility** | *Up* | 0.978 | -0.192 | 170 |
| | *Down* | -0.972 | -1.339 | 171 |
| **Illiquidity** | *Up* | 0.990 | -0.097 | 170 |
| | *Down* | -0.984 | -0.674 | 171 |

**Table 4**

**Markov switching model estimates for macroeconomic environments**

The following table contains estimates from the two-state heteroskedastic Markov switching model applied to macroeconomic indicators. Model specification is the following

$$y_t = \mu_{S_t} + \sigma_{S_t} \cdot \varepsilon_t,$$

where $y_t$ is macroeconomic indicator at time t, $\mu$ – mean, $\sigma$ – variance, $\varepsilon_t$ – error term ($\varepsilon_t \sim$ IID(0,1)). Number of observations in each regime is calculated based on filtered probabilities inferred from the model. Filtered probability of 0.5 or higher indicates up regime and vice versa.

| | | **Mean** | **Log sigma** | **Transition probability** | **Expected duration** | **No. of obs. in the regime** |
|---|---|---|---|---|---|---|
| **Growth** | *Up* | 0.383<br>(0.038) | -0.433<br>(0.042) | 0.990 | 98.543 | 301 |
| | *Down* | -2.798<br>(0.272) | 0.465<br>(0.114) | 0.921 | 12.638 | 40 |
| **Inflation** | *Up* | 0.999<br>(0.109) | -0.009<br>(0.058) | 0.977 | 44.250 | 155 |
| | *Down* | -0.835<br>(0.065) | -0.497<br>(0.058) | 0.981 | 51.818 | 186 |
| **Real yield** | *Up* | 0.963<br>(0.042) | -0.862<br>(0.071) | 0.985 | 67.299 | 171 |
| | *Down* | -0.944<br>(0.058) | -0.465<br>(0.062) | 0.985 | 68.420 | 170 |
| **Volatility** | *Up* | 0.920<br>(0.101) | 0.204<br>(0.054) | 0.978 | 45.131 | 178 |
| | *Down* | -0.990<br>(0.031) | -1.174<br>(0.072) | 0.973 | 36.710 | 163 |
| **Illiquidity** | *Up* | 0.719<br>(0.230) | 0.754<br>(0.076) | 0.963 | 26.961 | 104 |
| | *Down* | -0.305<br>(0.057) | -0.203<br>(0.059) | 0.986 | 71.425 | 237 |

**Table 5**

**Summary table of factor sensitivities to macroeconomic environments**

The following table contains factors, which are the most and least exposed to each macroeconomic environment. Sensitivities are defined as the difference from the all-sample mean excess return and Sharpe ratio for each factor in each environment.

| | | Median approach | | Markov Switching model | |
|---|---|---|---|---|---|
| | | **Return** | **SR** | **Return** | **SR** |
| **Growth** | *Most exposed* | Value<br>Risk Weighted | Min Vol<br>Risk Weighted | Mid Cap<br>Large Cap<br>Momentum | Mid Cap<br>Large Cap<br>Momentum |
| | *Least exposed* | Small Cap<br>Quality | Small Cap | Min Vol<br>Risk Weighted | Small Cap |
| **Inflation** | *Most exposed* | Small Cap<br>Mid Cap<br>Large Cap | Small Cap<br>Mid Cap<br>Momentum | Small Cap<br>Mid Cap | Mid Cap<br>Momentum |
| | *Least exposed* | Quality<br>High Div Yield<br>Min Volatility | Quality<br>High Div Yield | Quality<br>High Div Yield | Quality<br>High Div Yield<br>Value |
| **Real yield** | *Most exposed* | Small Cap<br>Min Vol<br>Risk Weighted | Min Vol<br>Risk Weighted | Small Cap<br>Risk Weighted | Small Cap<br>Min Vol<br>Risk Weighted |
| | *Least exposed* | Quality<br>High Div Yield | Quality<br>High Div Yield | Quality<br>High Div Yield | Quality<br>High Div Yield |
| **Volatility** | *Most exposed* | Momentum<br>Quality<br>High Div Yield | Risk Weighted<br>Quality<br>High Div Yield | Mid Cap<br>Large Cap | Mid Cap<br>Large Cap<br>Quality |
| | *Least exposed* | Small Cap<br>Min Vol | Small Cap | Small Cap<br>Min Vol | Small Cap<br>Value |
| **Illiquidity** | *Most exposed* | Mid Cap<br>Large Cap<br>Momentum | Mid Cap<br>Large Cap | Mid Cap<br>Large Cap<br>Momentum | Mid Cap<br>Large Cap<br>Momentum |
| | *Least exposed* | Min Vol<br>Risk Weighted | | Min Vol<br>High Div Yield | Small Cap<br>High Div Yield |

**Table 6**

**Markov switching models estimates for excess returns of the factors**

The following table contains estimates from the two-state heteroskedastic Markov switching model applied to factor excess returns. Model specification is $y_t = \alpha_{S_t} + \sum \beta_{S_t} \cdot \Delta X_t + \sigma_{S_t} \cdot \varepsilon_t$, where $y_t$ is excess facto return at specific point of time, $X_t$ – macroeconomic indicator, $\alpha$ –intercept, $\beta$ – estimate for the exposure to indicators, $\sigma$ – variance of excess returns, $\varepsilon_t$ – error term ($\varepsilon_t \sim$ IID(0,1)).

| | Intercept | Growth | Inflation | Real yields | Volatility | Illiquidity |
|---|---|---|---|---|---|---|
| MSCI World | -0.0030 | 0.0003 | -0.0026 | 0.0402 | **-0.0609*****| -0.0004 |
| | **0.0067***** | -0.0038 | -0.0183 | -0.0208 | **-0.0566***** | **-0.0044***** |
| Small Cap | -0.0015 | **0.0160***** | 0.0343 | **-0.0470*** | **-0.1351***** | **-0.0093***** |
| | **0.0087**** | -0.0038 | **-0.0339*** | **0.1572***** | **-0.0452**** | 0.0025 |
| Mid Cap | 0.0004 | 0.0028 | 0.0145 | **0.0853**** | **-0.0583**** | -0.0001 |
| | **0.0080***** | 0.0011 | -0.0165 | 0.0282 | **-0.0766***** | **-0.0038***** |
| Large Cap | 0.0049 | -0.0025 | -0.0125 | **0.1528***** | -0.0125 | 0.0006 |
| | **0.0114***** | 0.0062 | 0.0089 | **-0.0643***** | **-0.1519***** | **-0.0036**** |
| Value | -0.0041 | 0.0018 | -0.0034 | 0.0345 | **-0.0553***** | -0.0014 |
| | **0.0066***** | -0.0026 | -0.0104 | -0.0262 | **-0.0574***** | **-0.0045***** |
| Momentum | 0.0088 | -0.0045 | -0.0431 | **-0.0878**** | **-0.1949***** | 0.0026 |
| | **0.0085***** | 0.0011 | -0.0044 | **0.0667***** | **-0.0294**** | **-0.0033***** |
| Min Vol | -0.0017 | **-0.0204***** | **-0.0576***** | **-0.0851***** | **-0.1790***** | 0.0035 |
| | **0.0063***** | 0.0039 | -0.0046 | -0.0037 | **-0.0170*** | **-0.0023***** |
| Risk Weighted | 0.0056 | 0.0017 | -0.0089 | 0.0320 | **-0.1046***** | 0.0008 |
| | **0.0082***** | -0.0014 | -0.0134 | **-0.0407**** | **-0.0334***** | **-0.0041***** |
| Quality | 0.0065 | -0.0010 | -0.0116 | 0.0164 | **-0.0722**** | -0.0002 |
| | **0.0092***** | -0.0027 | -0.0100 | -0.0207 | **-0.0247*** | **-0.0042**** |
| High Yield | -0.0010 | 0.0072 | 0.0023 | 0.0268 | **-0.0785**** | 0.0013 |
| | **0.0067***** | -0.0024 | -0.0111 | **-0.0552***** | **-0.0268**** | **-0.0046***** |

***significant at 1% level; **significant at 5% level; *significant at 10% level

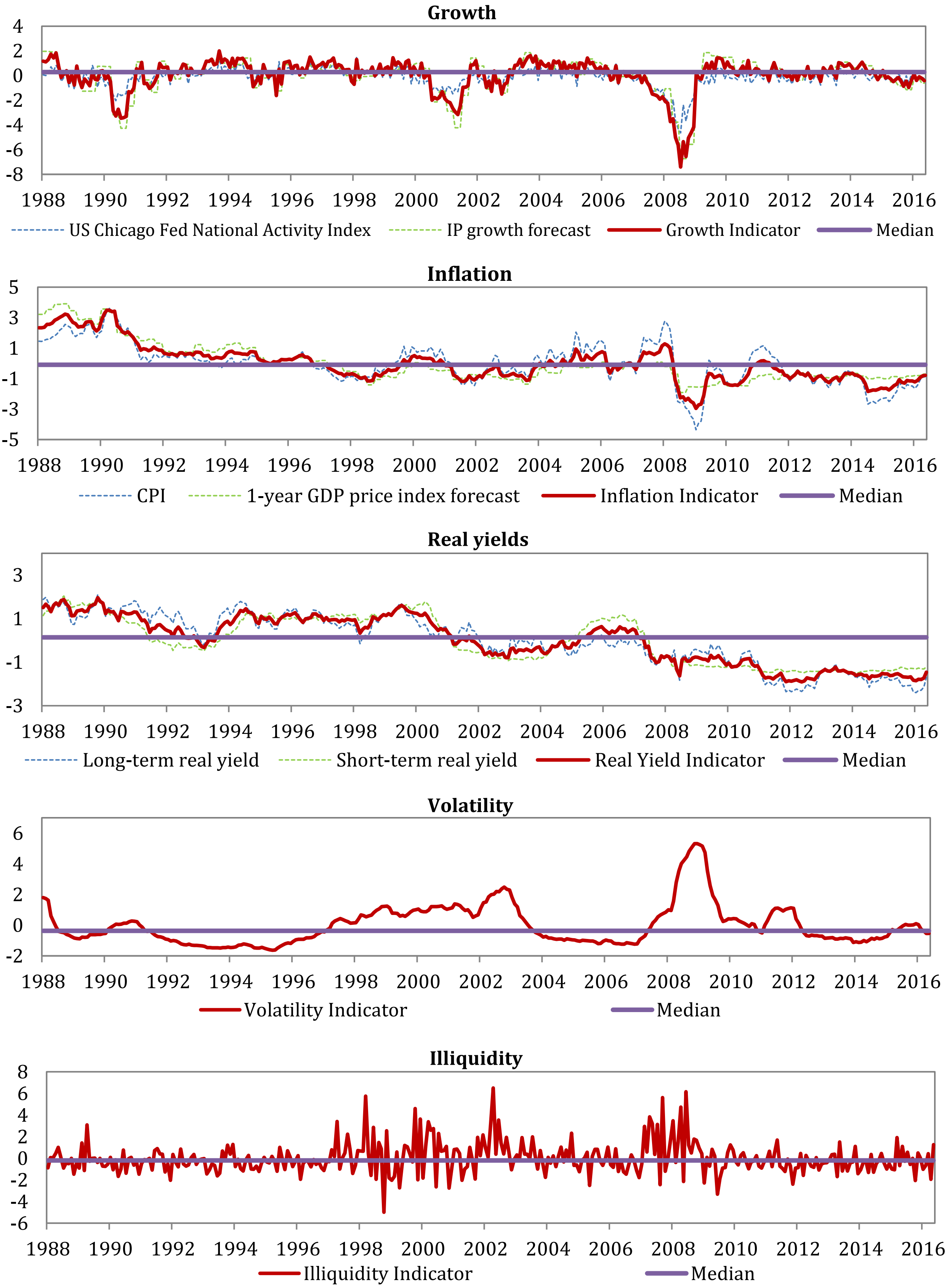
**Table 7**

**Dynamic strategies annualized performance**

| | MSCI World | EW All Factors | Growth | Inflation | Real yield | Volatility | Illiquidity |
|---|---|---|---|---|---|---|---|
| | | | | ***1995-2016*** | | | |
| **Return** | 3.23% | 5.26% | 6.50% | 7.46% | 7.79% | 6.17% | 5.71% |
| **Sharpe Ratio** | 0.28 | 0.50 | 0.58 | 0.66 | 0.76 | 0.61 | 0.54 |
| **Tracking Error** | - | 1.86% | 2.47% | 3.40% | 3.12% | 3.08% | 2.68% |
| **Information Ratio** | - | 1.09 | 1.33 | 1.24 | 1.46 | 0.95 | 0.92 |
| | | | | ***10-year*** | | | |
| **Return** | 2.31% | 3.83% | 5.04% | 5.45% | 5.46% | 5.54% | 4.38% |
| **Sharpe Ratio** | 0.19 | 0.33 | 0.43 | 0.44 | 0.50 | 0.51 | 0.37 |
| **Tracking Error** | - | 1.44% | 1.80% | 2.31% | 2.85% | 2.32% | 1.79% |
| **Information Ratio** | - | 1.06 | 1.52 | 1.36 | 1.11 | 1.40 | 1.16 |
| | | | | ***5-year*** | | | |
| **Return** | 7.96% | 8.92% | 9.28% | 10.06% | 9.85% | 9.81% | 9.28% |
| **Sharpe Ratio** | 0.92 | 1.14 | 1.13 | 1.20 | 1.32 | 1.26 | 1.13 |
| **Tracking Error** | - | 1.49% | 1.54% | 2.29% | 2.69% | 1.62% | 1.54% |
| **Information Ratio** | - | 0.64 | 0.86 | 0.92 | 0.70 | 1.14 | 0.86 |

**Figure 1**

**Macroeconomic indicators (standardized)**



## Figure 2

## Markov switching filtered regime probabilities for growth

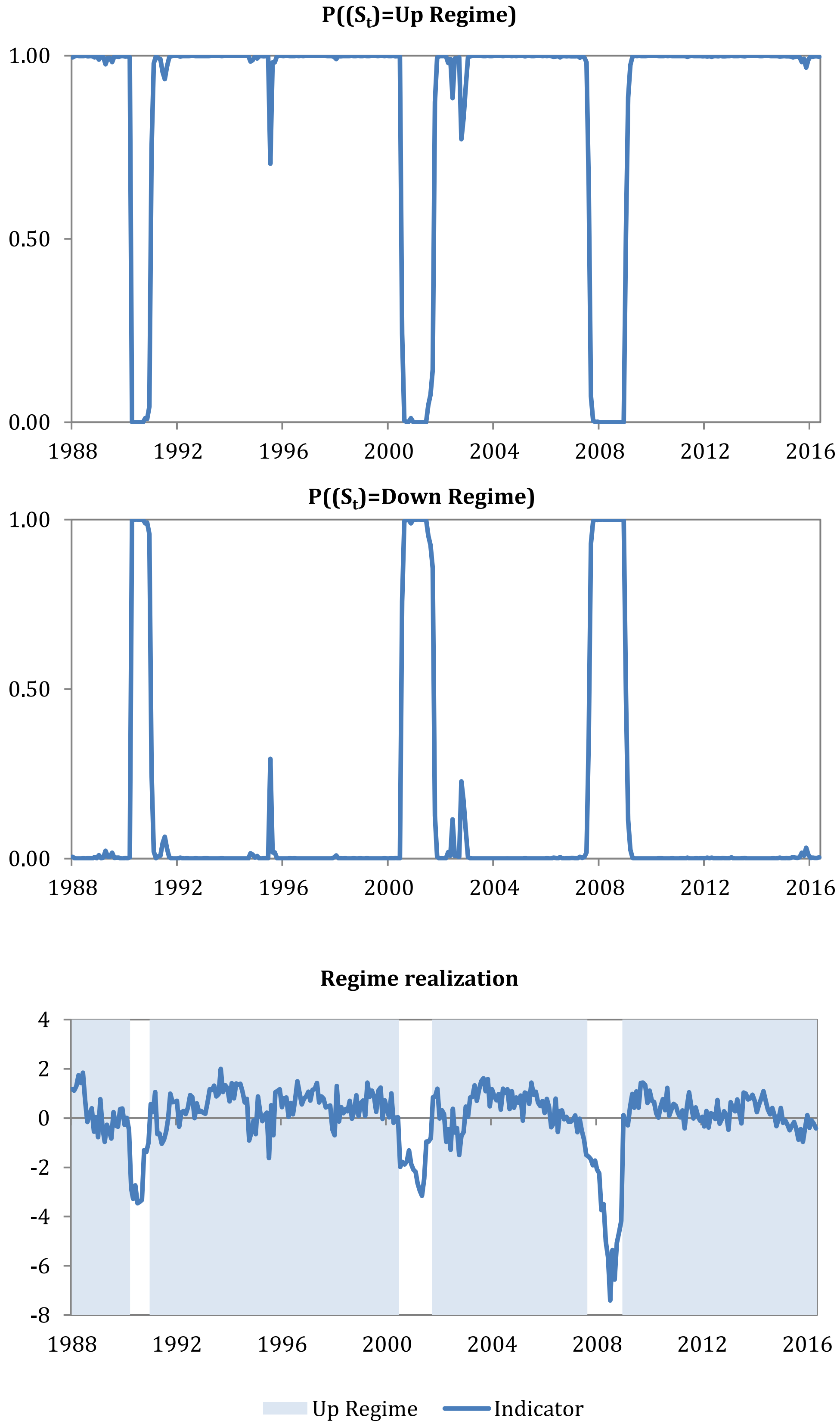
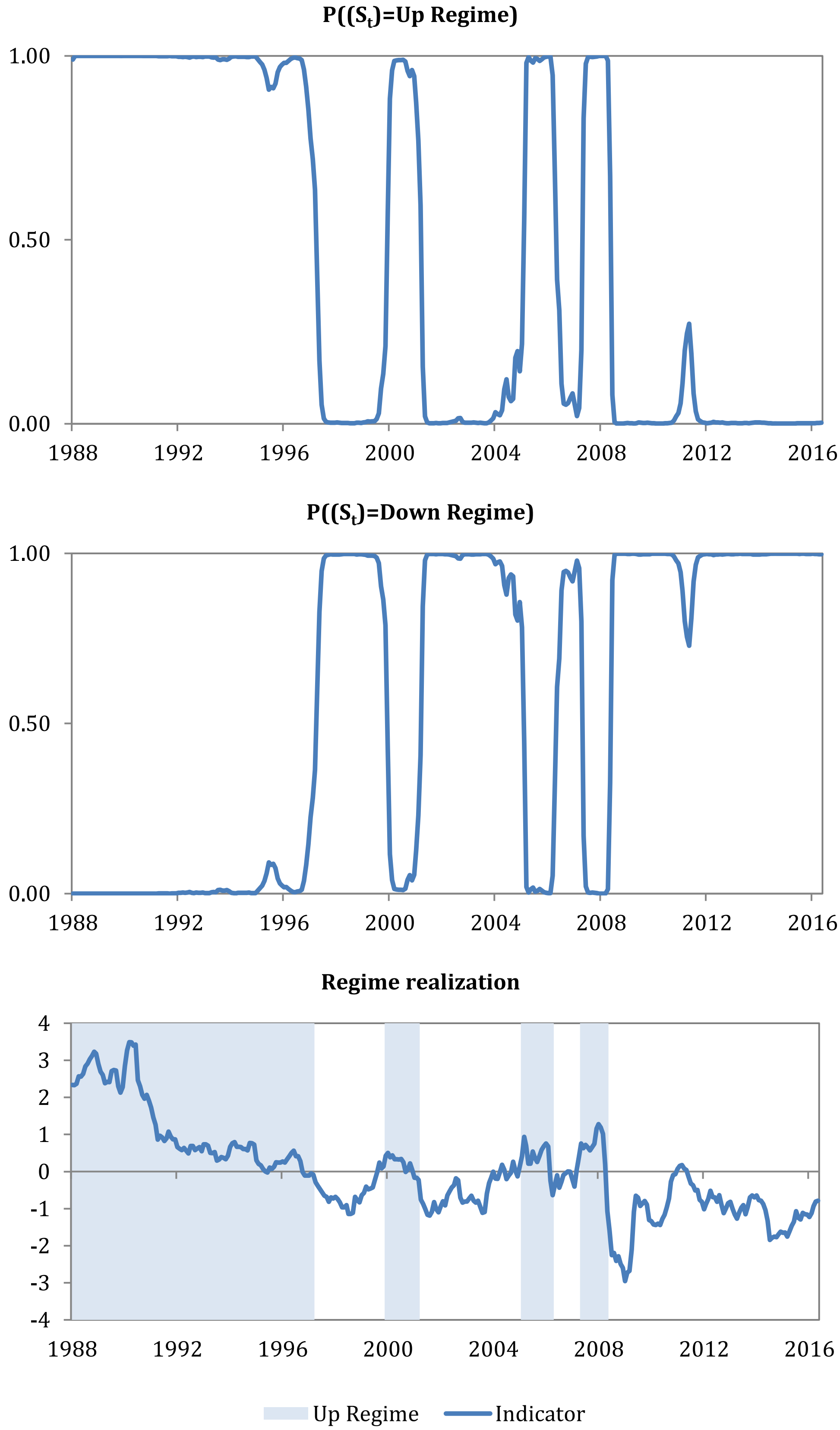


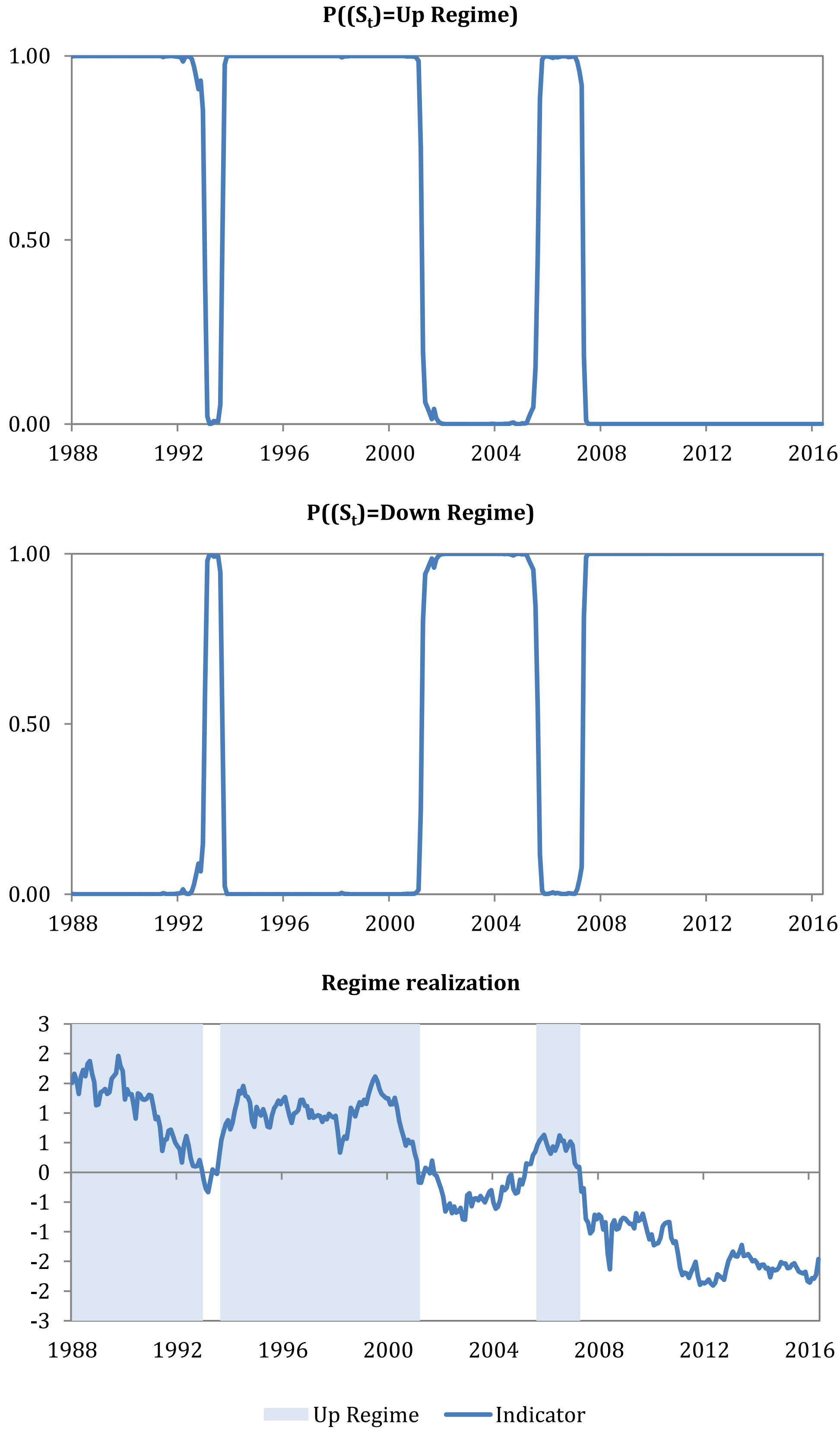
**Figure 3**

**Markov switching filtered regime probabilities for inflation**



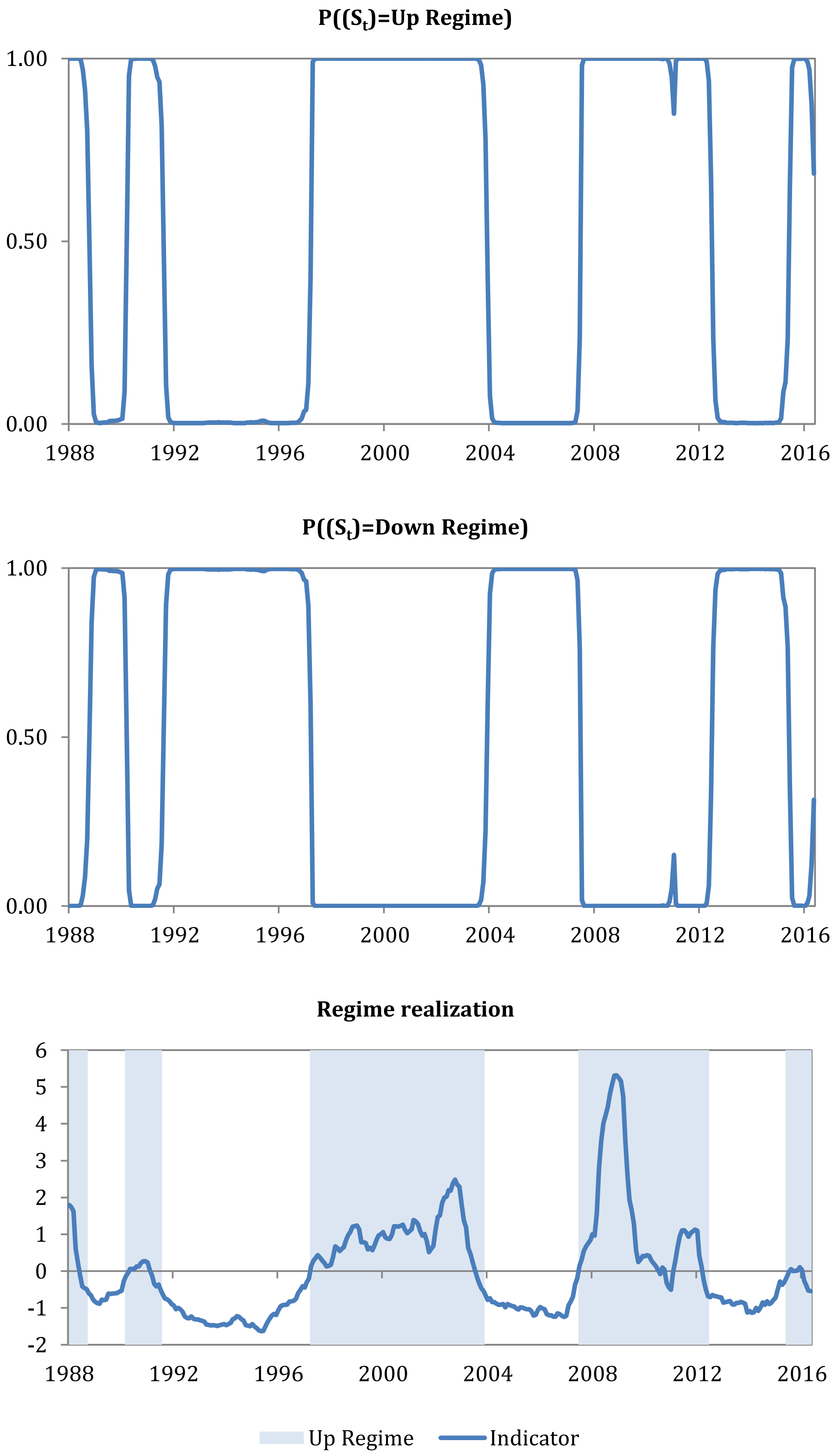
## Figure 4

## Markov switching filtered regime probabilities for real yields



## Figure 5

**Markov switching filtered regime probabilities for volatility**



## Figure 6

## Markov switching filtered regime probabilities for illiquidity

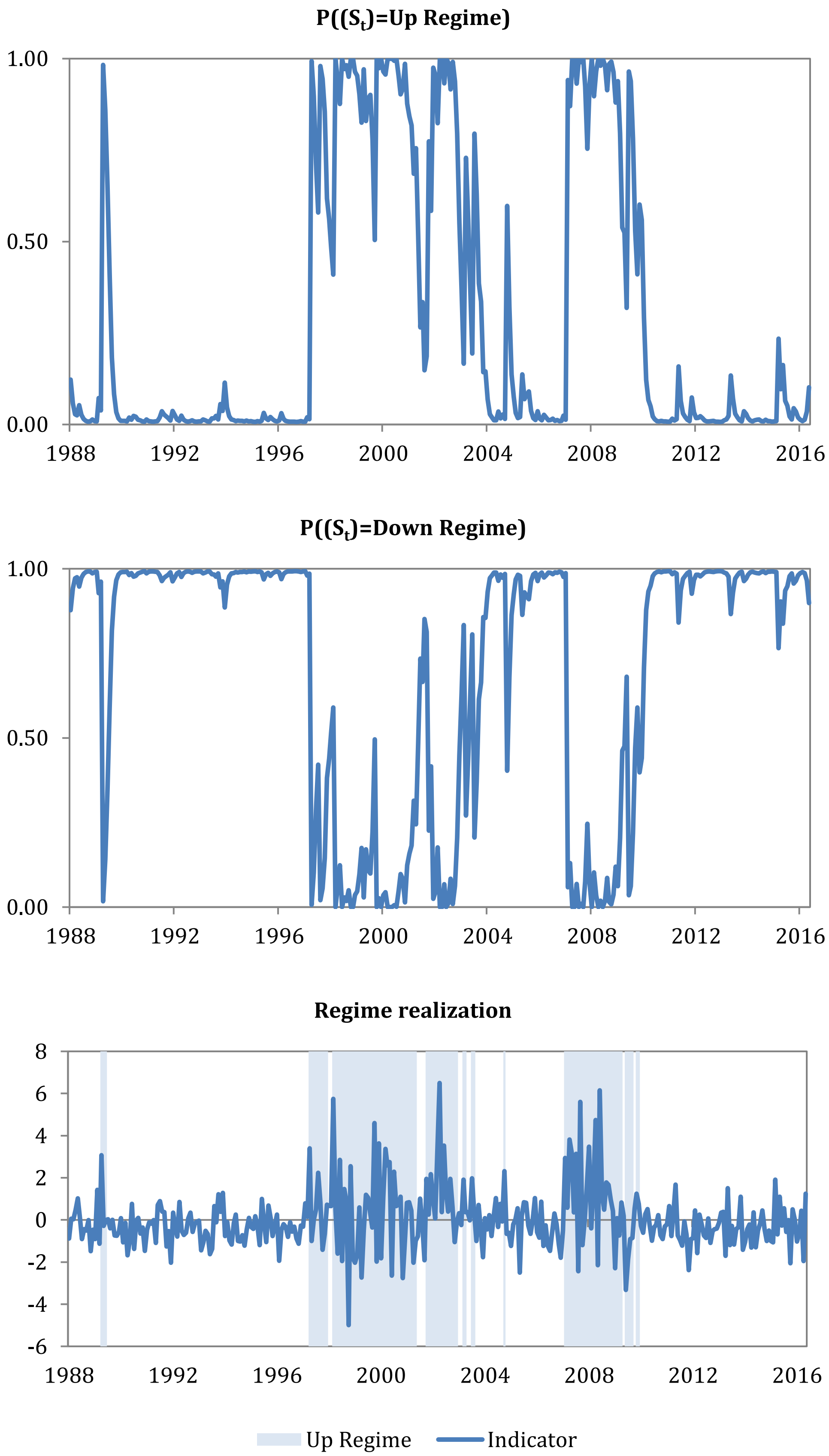


**Figure 7**

**Mean excess returns in each macroeconomic environment defined by median**

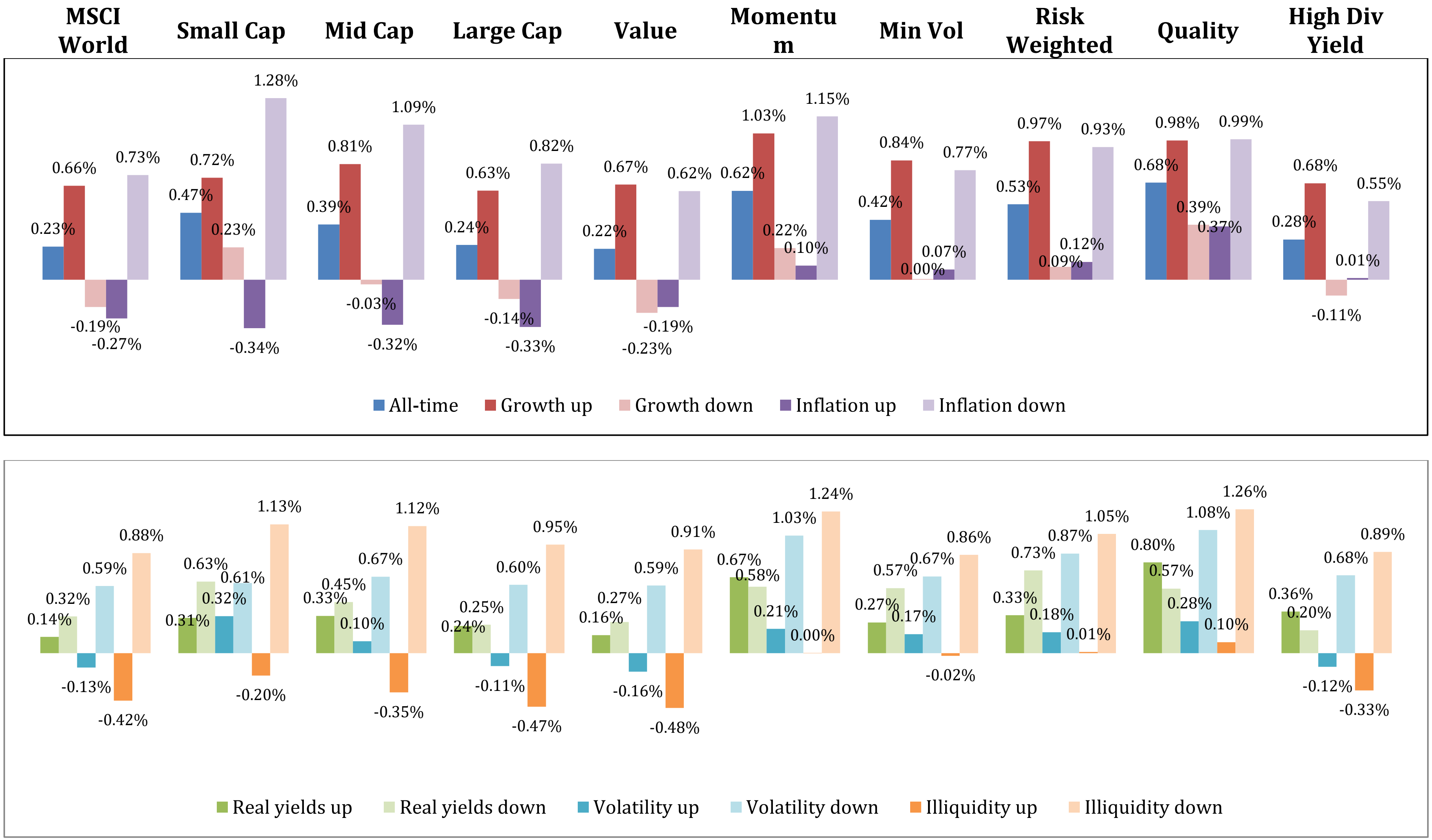


**Figure 8**

**Differences from all-sample mean excess returns in each macroeconomic environment defined by median**

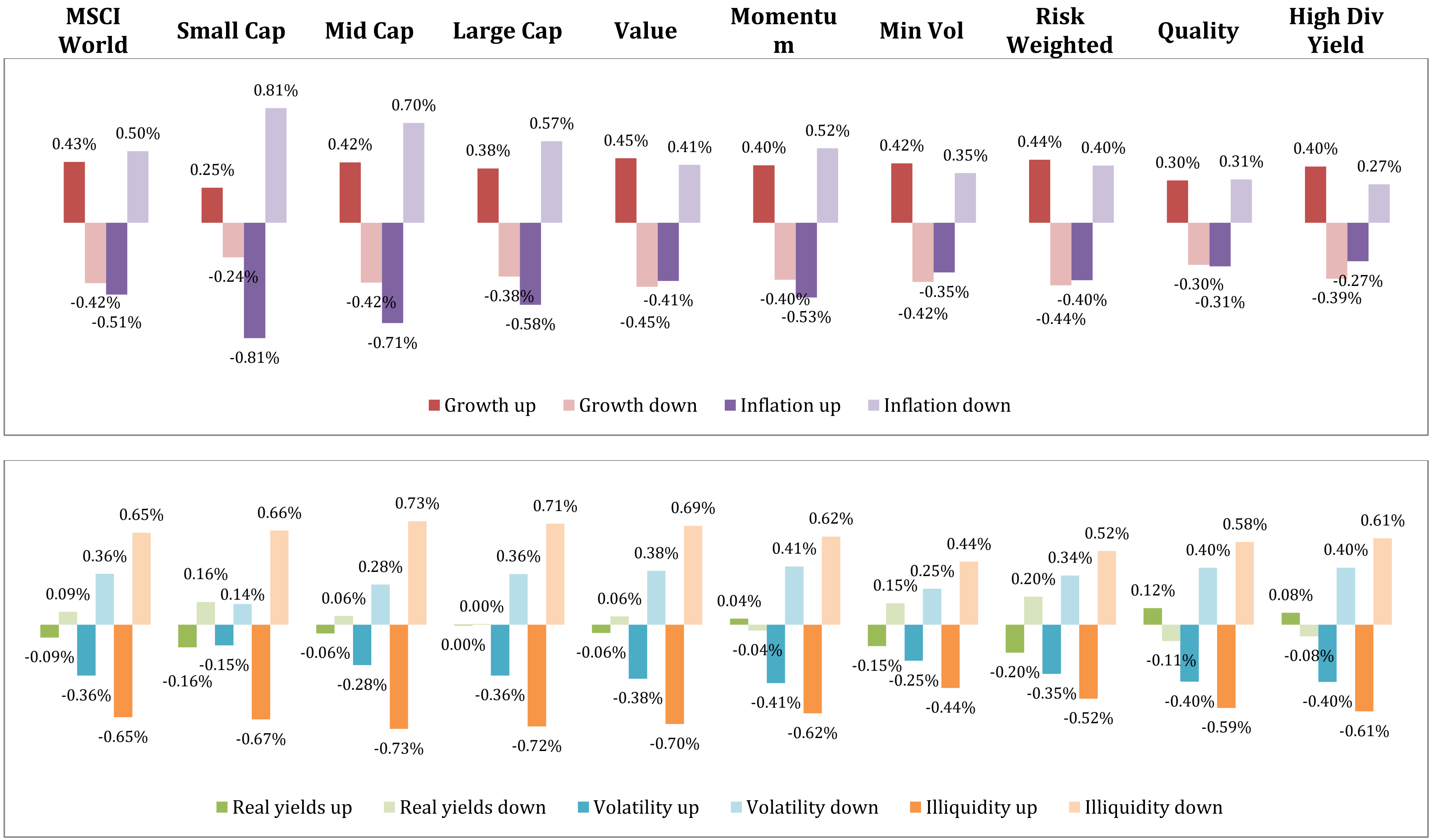


**Figure 9**

**Sharpe ratios in each macroeconomic environment defined by median**

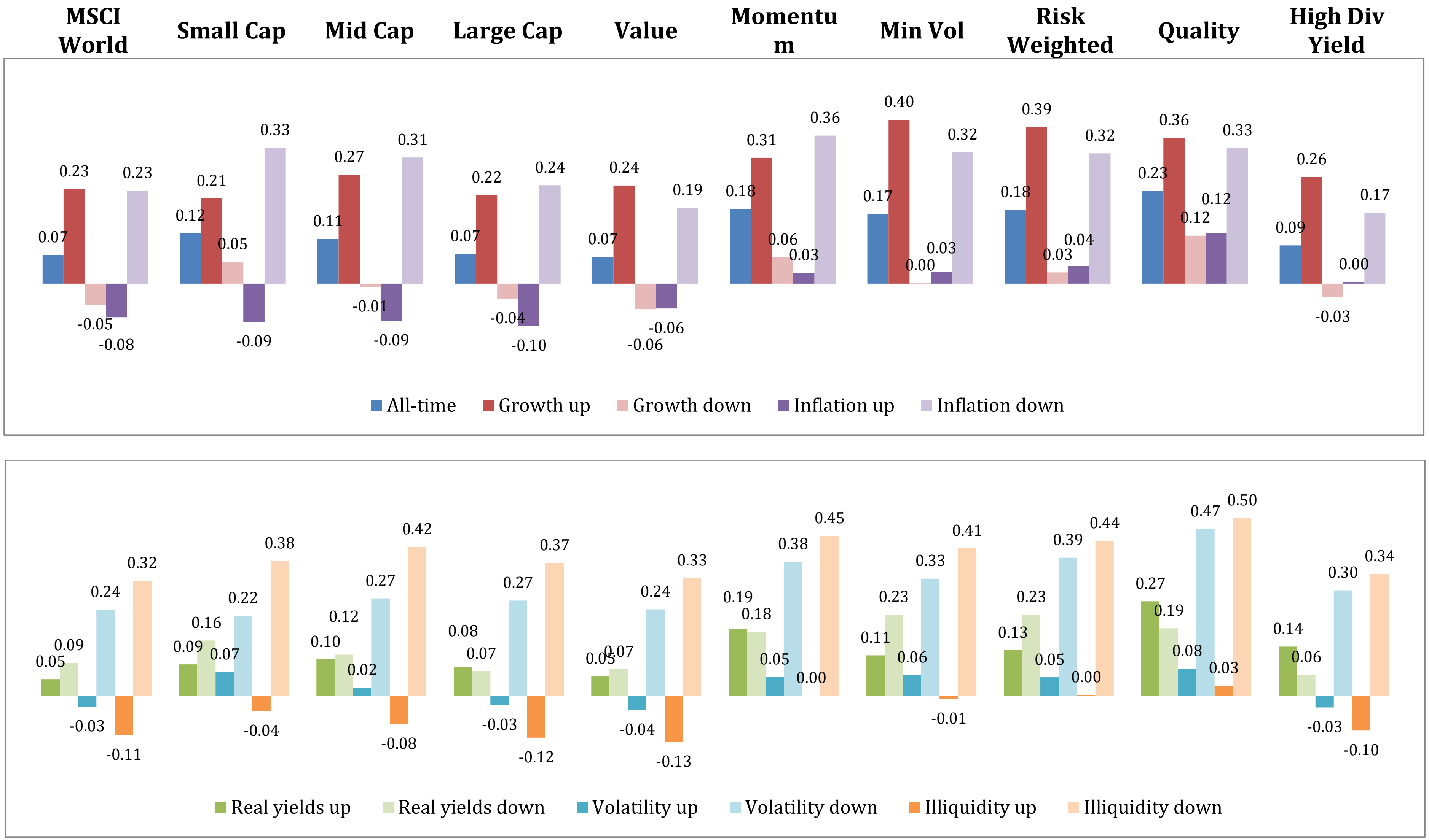


**Figure 10**

**Differences from all-sample Sharpe ratios in each macroeconomic environment defined by median**

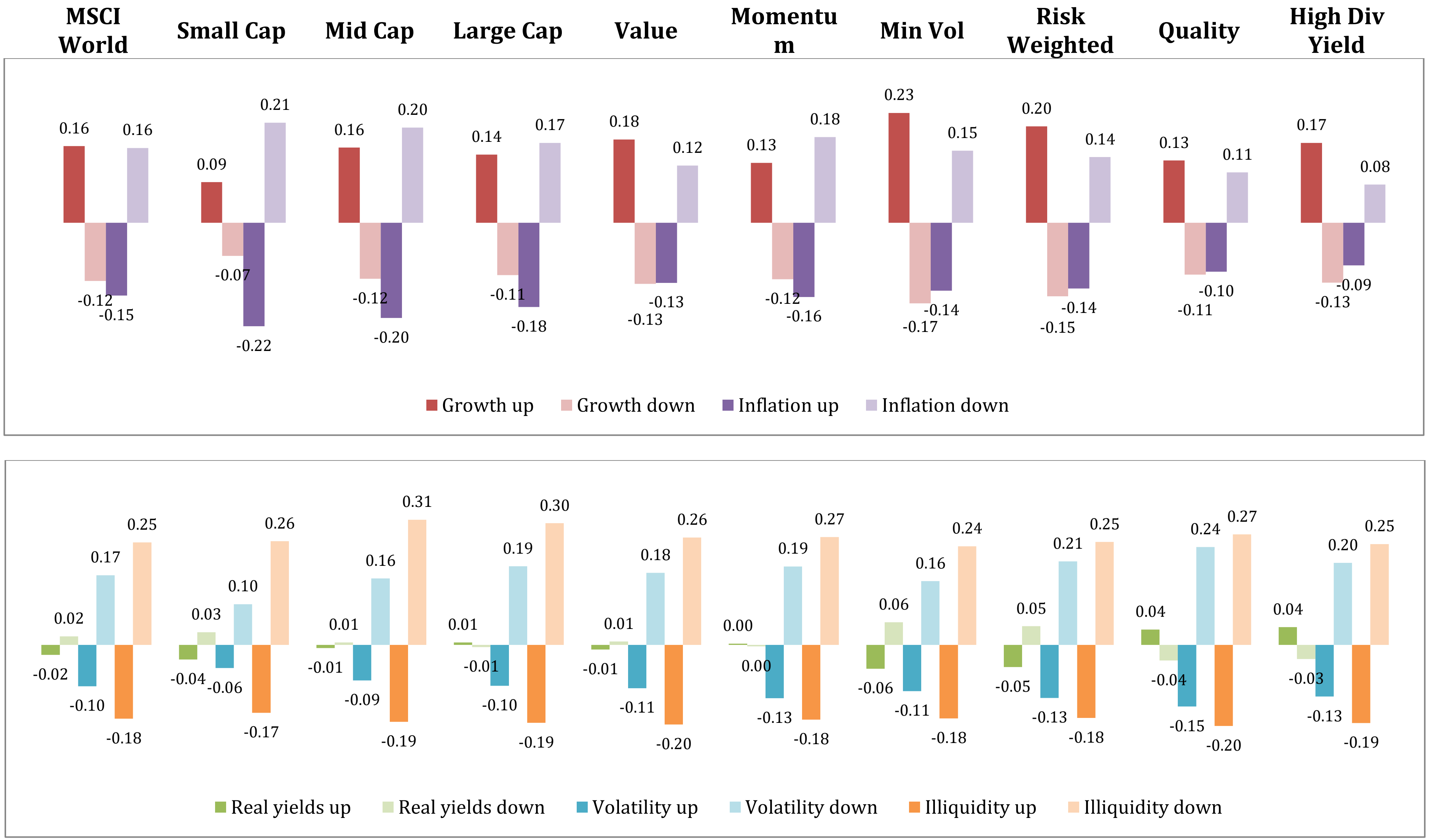
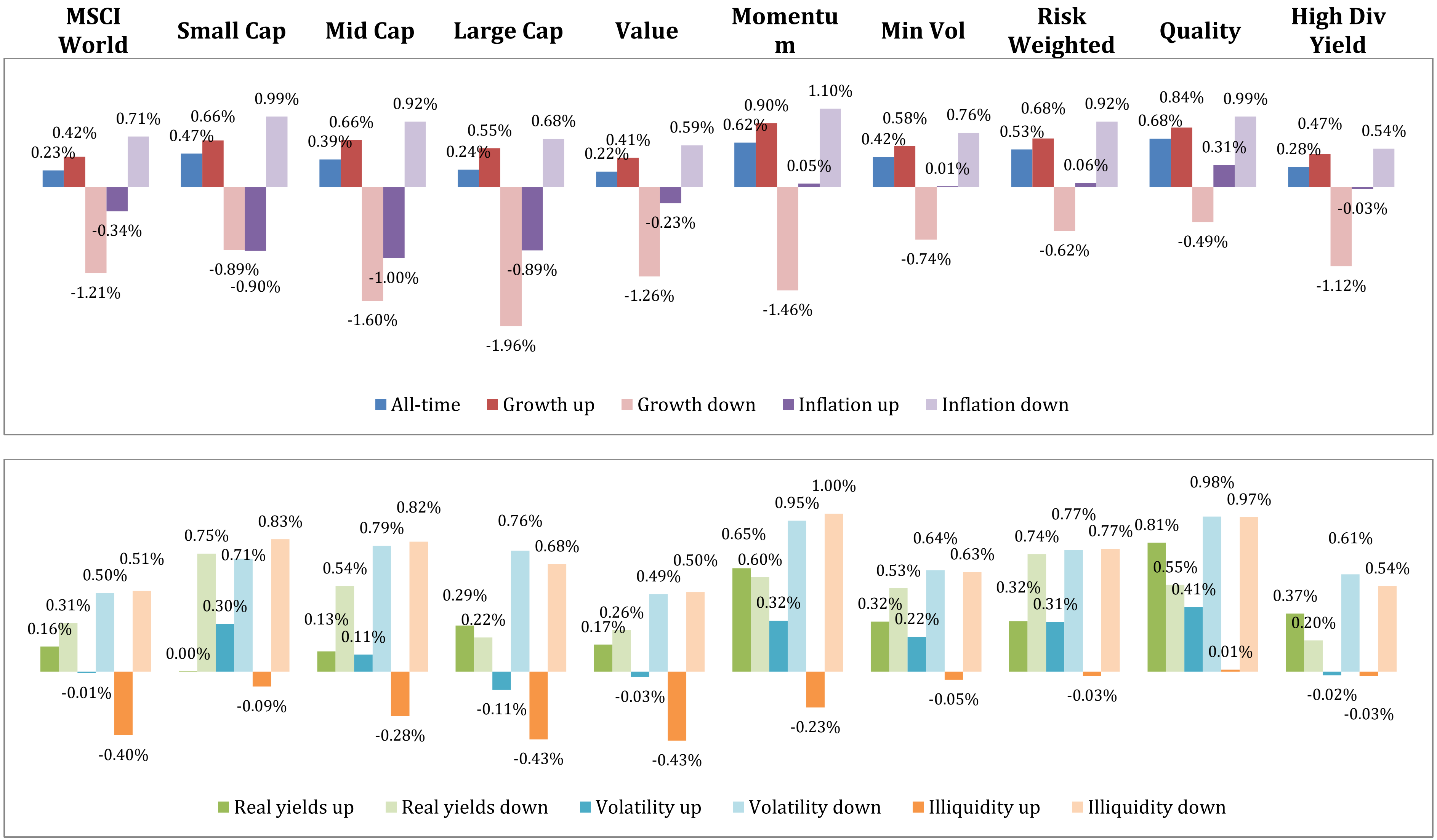


**Figure 11**

**Mean excess returns in each macroeconomic environment defined by MS**



## Figure 12

**Differences from all-sample mean excess returns in each macroeconomic environment defined by MS**

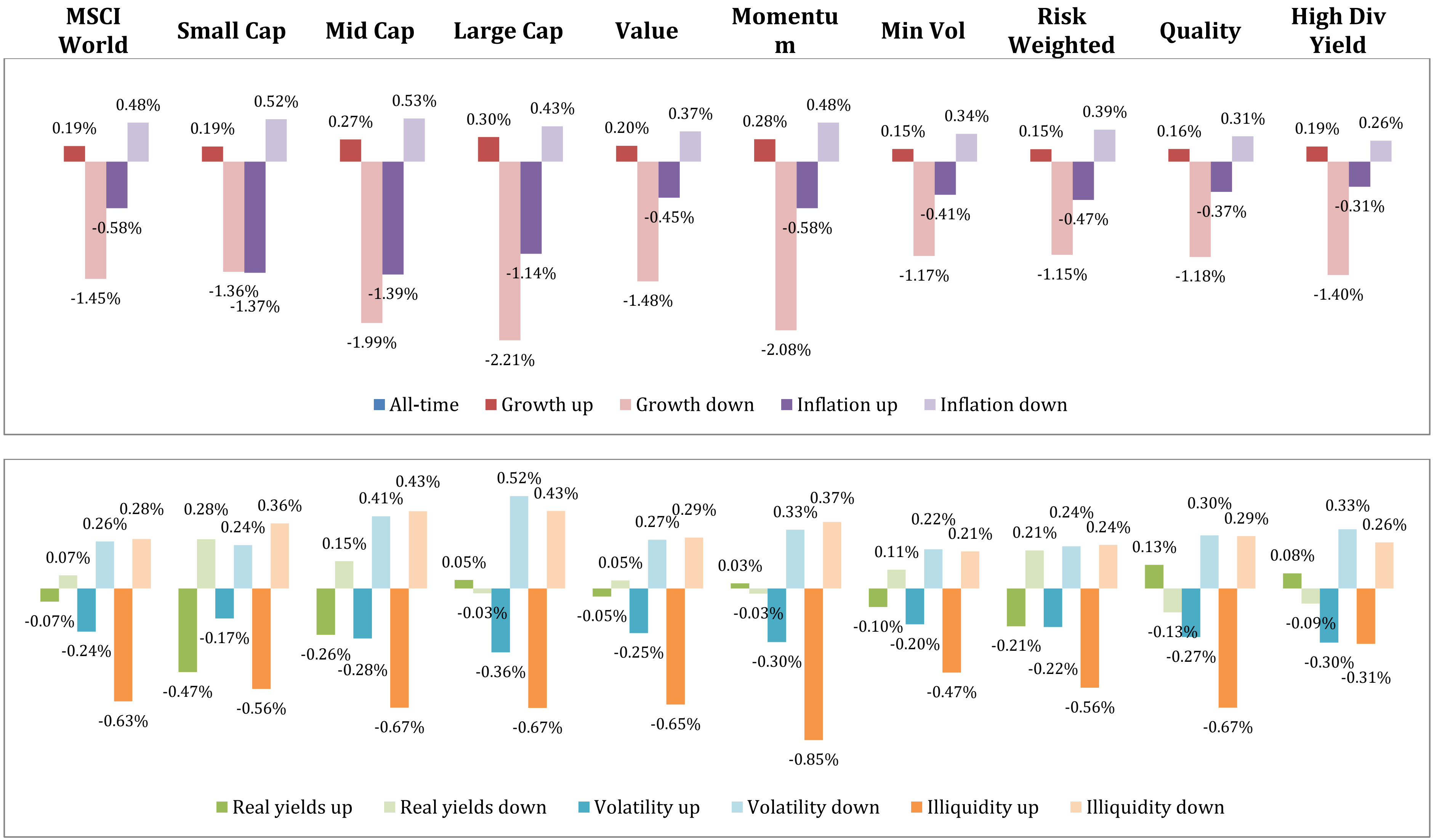


**Figure 13**

**Sharpe ratios in each macroeconomic environment defined by MS**

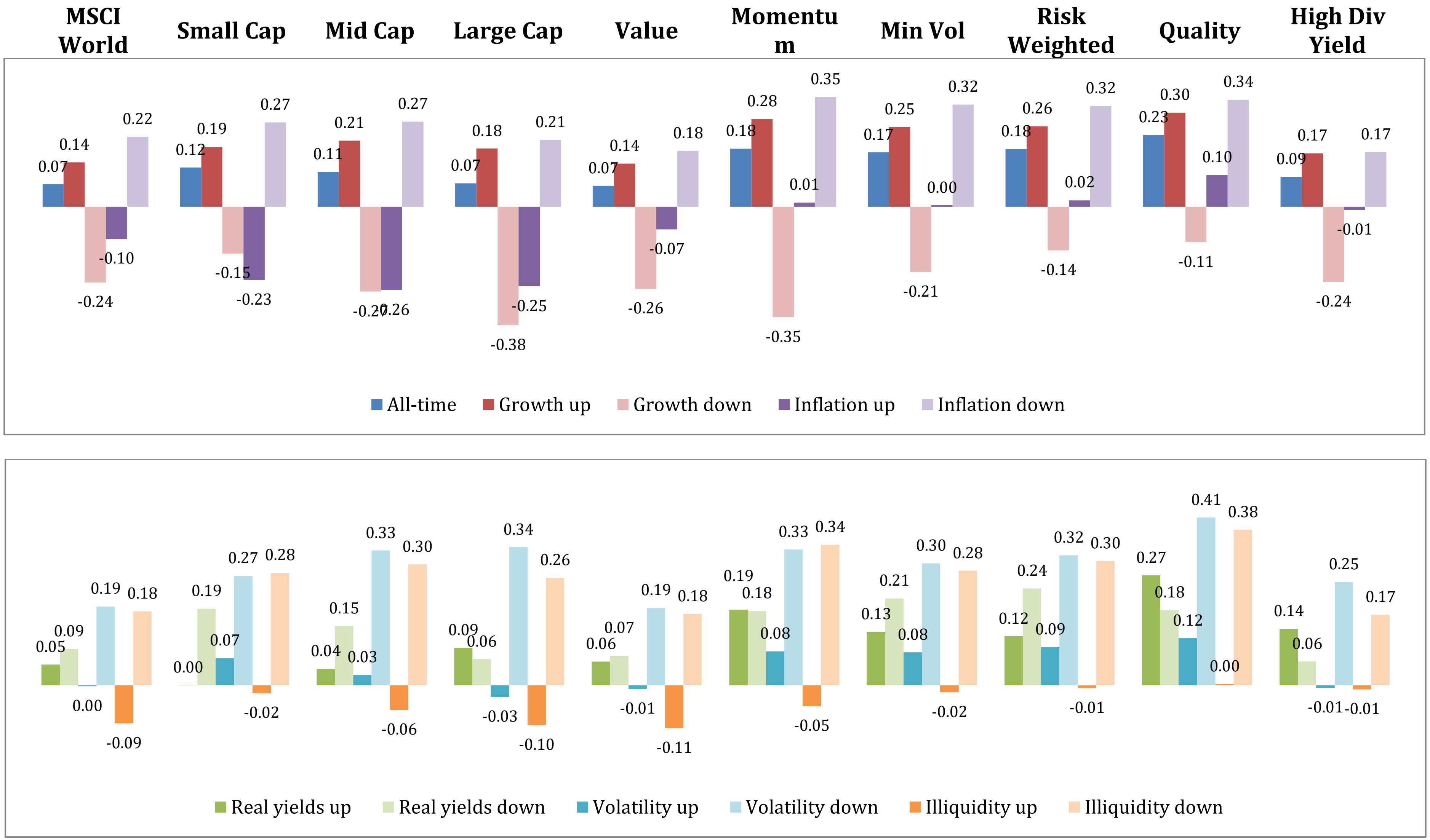


**Figure 14**

**Differences from all-sample Sharpe ratios in each macroeconomic environment defined by MS**

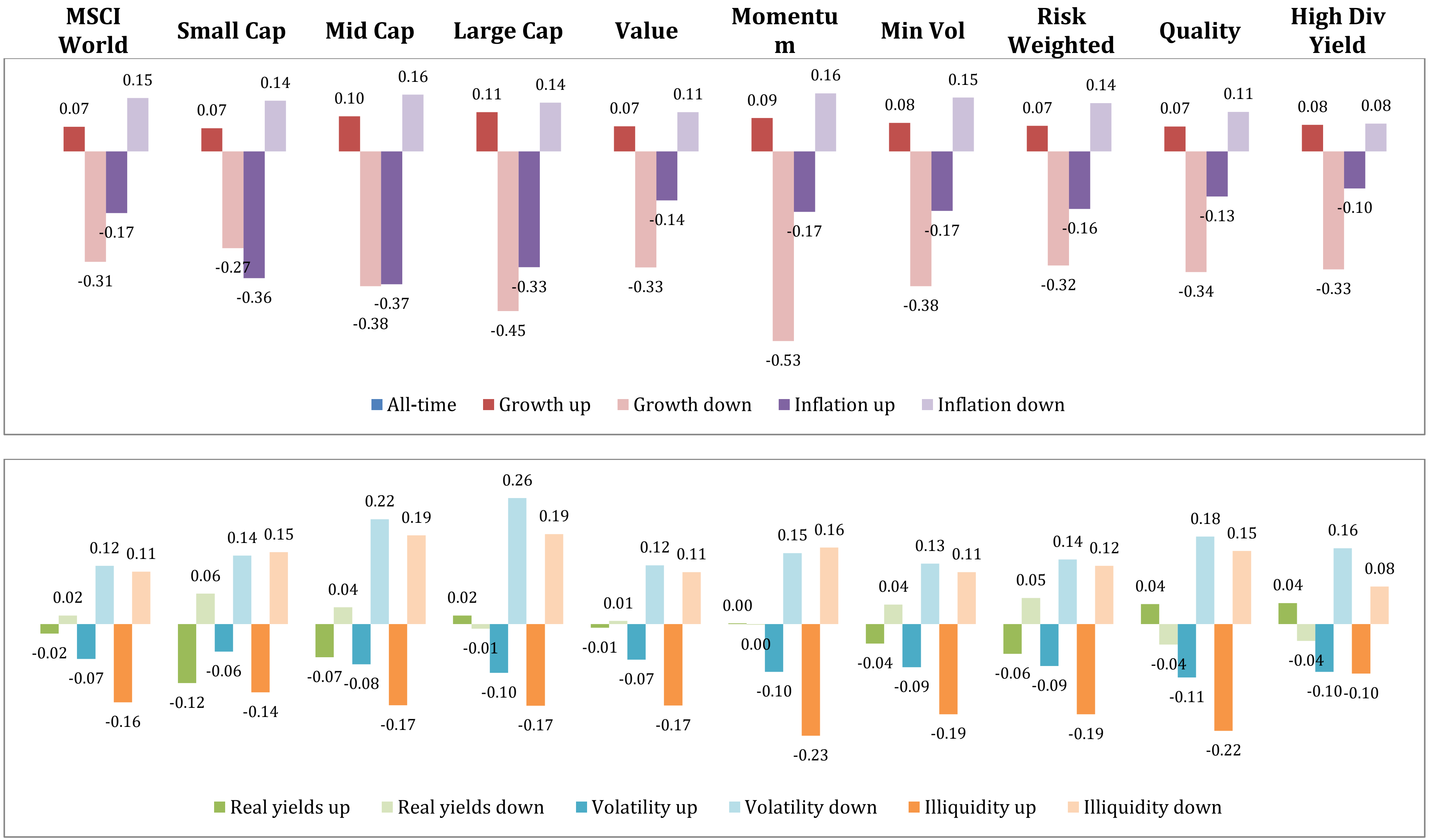
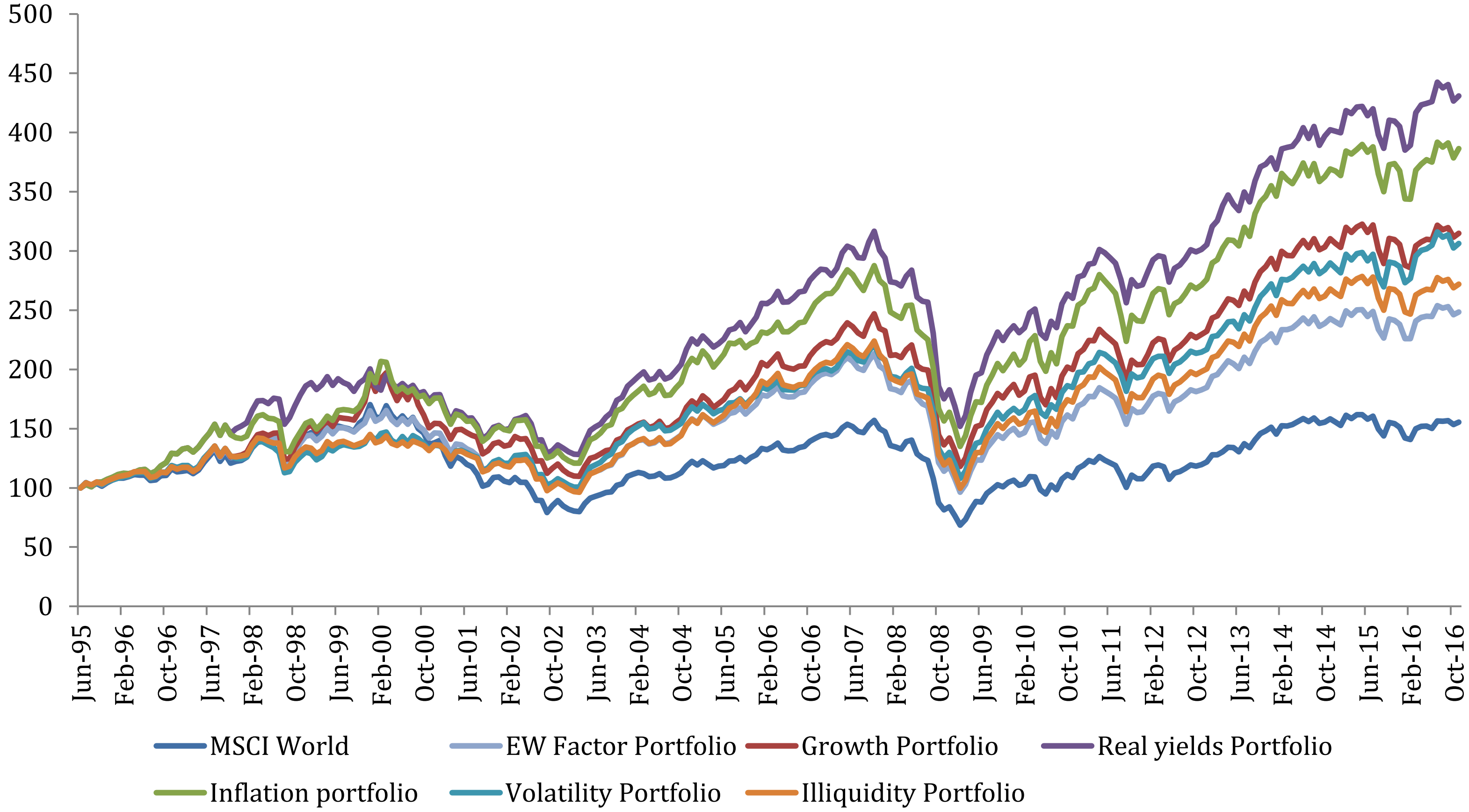


**Figure 15**

**Dynamic factor allocation strategies performance (1995-2016)**



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Master of Science in Finance, Double Degree

Stockholm School of Economics / Bocconi University

Master of Finance Thesis

# Asset Class Returns Exposure to Alternative Macroeconomic Environments

[The following part of the thesis was submitted and defended at Bocconi University on April 21, 2017]

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**Discussant:** Milena Tacheva Petrova

## Contents

**Tables and Figures**

**Abstract**

In this thesis, we examine how different asset classes are exposed to alternative macroeconomic environments. We apply a range of different approaches in order to explore these relationships. Firstly, we analyse mean excess returns (risk premia) and Sharpe ratios of asset classes in different macroeconomic regimes. We define the regimes by taking the median of macroeconomic indicators, and, alternatively, by applying a Markov switching model to the indicators. Secondly, we apply a two-state Markov switching model to excess returns, including macroeconomic indicators as explanatory variables in the model. We cover a broad range of asset classes in our research – traditional assets, alternatives, style factors, industry portfolios and REIT sectors, and we find empirical evidence of their significant exposures to macroeconomic regimes. For instance, equities are found to be sensitive to multiple macroindicators, namely, growth, inflation, real yields, volatility and illiquidity. Treasury bonds are found to be exposed to real yield and inflation. Commodities are sensitive to inflation, and REITs are the most resilient to different macroeconomic regimes.

## 1. Introduction

A growing number of institutional investors have started explicitly taking into account macroeconomic conditions when making decisions about asset allocation. In particular, an extended period of low interest rates has had a negative impact on pension funds, putting them at risk of underfunding, and oil-fuelled sovereign wealth funds have suffered from the slump in oil prices. These circumstances push investors to chase after higher returns and shake their traditional approaches to investing.[1]

In the thesis, we examine how different asset classes are exposed to alternative macroeconomic environments. We use different approaches to explore these relationships. Firstly, we compare mean excess returns and Sharpe ratios in multiple macroeconomic regimes. Secondly, we apply Markov switching models to asset excess returns, including macroeconomic indicators as explanatory variables in the model.

Our research covers a broad range of asset classes – from traditional assets, such as stocks and bonds, to alternative assets, such as commodities and real estate investment trusts (REITs), and style portfolios, such as size, value and momentum. We also cover twelve industry portfolios and seven REIT sectors. So far, this is the most extensive coverage of asset classes in the existing literature on the topic.

As a starting point, we replicate the analysis, set up by Ilmanen, Maloney and Ross (2014). Following their example, we construct five key macroeconomic indicators – growth, inflation, real yields, volatility and illiquidity. By taking the median of each indicator, we define five pairs of binary environments as well as four extra regimes as the intersection of binary growth and inflation regimes. We focus on comparing Sharpe ratios and risk premia across different regimes when drawing conclusions.

We further extend Ilmanen et al. (2014) framework by applying two-state Markov switching (MS) model to macroeconomic indicators to define regimes, instead of simply taking the median. Though Markov switching techniques are rightfully believed to be more sophisticated, we find that both median and MS are similarly able to capture asset classes sensitivities to alternative environments.

[1] In February 2017, Norwegian Sovereign Wealth Fund increased its target allocation into equities from 60 to unprecedented 70 per cent.

Finally, we apply Markov switching model to asset excess returns, and include macroeconomic indicators as factor variables.

In our thesis, we provide empirical evidence that all equities are significantly exposed to multiple macroeconomic indicators: growth, inflation and illiquidity if applying the first approach; moreover, also inflation, real yields, volatility and illiquidity if applying the second approach. Treasuries are exposed to inflation and real yields, while commodities are exposed only to inflation. Application of different approaches to style factors, unfortunately, does not provide consistent results.

For industry portfolios, the second approach better captures industry sensitivities to indicators. Non Durables, Healthcare and Business Equipment are found to be defensive, meaning that they are the most resilient to negative developments in growth. Durables, Chemicals and Other are found to be the most pro-cyclical portfolios, meaning that they benefit the most from higher economic growth. Energy is the only industry portfolio with significant positive exposure to inflation, while among the remaining, Utilities are the least sensitive and Shops are the most sensitive to inflation.

REIT equity sectors excess returns, in contrast to other equities, are explained only by variation in volatility. We interpret this finding as evidence that REITs are less sensitive to macroeconomic indicators than other equities. In their turn, among REIT equity sectors, Healthcare and Self-storage are the most resilient, since they performe well across all macroeconomic environments.

Finally, we have identified several asset classes, which change the sign of their exposure to specific macroeconomic indicators depending on their state. The value style portfolios change their exposure to inflation, Business Equipment and Shops change their exposures to real yields, and Energy changes its exposure to volatility. Identifying these types of relationships is very important, since they help to time the investments into specific assets more effectively.

Understanding the asset class exposures to different macroeconomic environments provides valuable insights to rationalize asset allocation decisions. In addition, it helps to identify assets, which are the most resilient to macroeconomic changes, and construct well-diversified and effective portfolios.

The rest of the paper is organised in the following way. Chapter 2 discusses the relevant literature on the topic. Chapter 3 explains our methodology. Chapter 4 describes the data used in the thesis. Chapter 5 discusses the results, and finally, Chapter 6, presents our conclusions.

## 2. Literature Review

The literature that aims at explaining asset returns can be traced back to Sharpe (1964) and Lintner (1965), who developed capital asset pricing model (CAPM). In this model, expected stock returns depend on a single factor – market. Later, the model was challenged by Ross (1986), who developed arbitrage pricing theory (APT), which allows to identify multiple factors explaining asset returns.

Fama and French (1993) extended CAPM by adding two more risk factors to the model – size and book-to-market (or value) – and show that an extended model better explains the returns of stocks. In addition, they show that factors related to bond markets, such as term structure and default risk, also capture some variation in stock and bond returns.

Chen, Roll and Ross (1986) focus specifically on macroeconomic and financial market variables in explaining US stock market returns. Their macroeconomic variables include industrial production, inflation, risk premium, term structure, market index, consumption and oil prices. They found that industrial production, unexpected change in risk premium, unexpected inflation and unexpected change in term structure are the most significant factors in explaining stock returns.

To analyse the affect of macroeconomic variables on stock returns, McElroy and Burmeister (1988) modified the APT into multivariate nonlinear regression model. Their five macroeconomic factors are risk premium, term structure, unexpected deflation, unexpected growth in sales and the residual market factor. In this nonlinear specification, the authors found that all five macroeconomic factors significantly affect stock returns.

In general, the vast majority of literature, which uses macroeconomic factors to explain asset returns, focuses on stocks and bonds, while fewer researchers focus on other asset classes. However, there are some findings for commodities and style factors as well.

Daskalaki, Kostakis and Skiadopoulus (2014) employ several families of models to explain cross-section in individual commodity futures returns. They use macroeconomic, tradable and specific commodity-related factors, such as hedging pressure and inventory. Their macroeconomic factors are industrial production growth shocks, inflation shocks, consumption growth shocks, interest rate shocks and GDP growth shocks. The authors found that none of the models can explain cross-section returns, and they conclude that commodity markets are very heterogeneous.

Zhang et al. (2009) explored the link between macroeconomic factors and style returns. They employ two different approaches – discrete state analysis and threshold regression – to identify how GDP growth, inflation innovations, 3-month Treasury bill rates, term spread and credit spread affect size and value factors. The found that both factors perform significantly better in the period of higher GDP growth and lower short-term rates. They also documented positive exposure of value factor to unexpected inflation, negative exposure of size factor to unexpected inflation and positive exposure of both factors to term spread.

All of the literature mentioned above focuses on some specific asset class. Ilmanen et al. (2014) cover a broader range of asset classes when exploring their sensitivities to macroeconomic environments. They include equities, bonds, commodities as well as five style factors – value, momentum, carry, defensive and trend. As macroeconomic indicators, they use growth, inflation, real yields, volatility and illiquidity. Ilmanen et al. (2014) found that equities have positive exposure to growth, bonds have negative exposure to real yields, commodities have positive exposure to inflation and style factors perform well in all macroeconomic environments. They also conclude that adding style factors to portfolios provide significant diversification benefits and improve Sharpe ratios of the portfolios in every macroeconomic environment. In our paper, we replicate the approach of Ilmanen et al. (2014) when we construct macroeconomic indicators and define the regimes.

Finally, since we apply Markov switching models (MSM) to explain asset returns, it is necessary to mention literature, which covers this class of models. The pioneering researcher who started to apply widely Markov switching models to time series was Hamilton (1989). Later, Krolzig (1996) extended Hamilton's univariate model to multivariate case, so called Markov switching vector autoregressive model (MS-VAR). Literature, which combines both Markov switching model and macroeconomic factors as predictors, is not very extensive. One of the papers is by Guidolin and Ono (2006), where they examine if the dynamic linkages between the macroeconomy and asset prices are time-varying. Macroeconomic variables used in the model include inflation, real industrial production growth and a measure of real money growth. The authors concluded that linkages between macroeconomy and asset prices have been stable over time.

## 3. Methodology

### *3.1 General framework*

Following Ilmanen et al. (2014) approach, we define 14 different macroeconomic environments based on five indicators and explore asset classes mean excess returns and Sharpe ratios in each of the environments.

Firstly, we construct macroeconomic indicators, which are growth, inflation, real yields, volatility and illiquidity. Then, by taking the median of each indicator, we define binary states – up, if data point is higher than median, and down otherwise. The resulting ten regimes are growth up, growth down, inflation up, inflation down, real yields up, real yields down, volatility up, volatility down, illiquidity up and illiquidity down. We also apply growth and inflation indicators simultaneously to define extra four macroeconomic environments: growth up & inflation up, growth up & inflation down, growth down & inflation up, growth down & inflation down. Finally, we sort excess returns by regimes and calculate their means and Sharpe ratios in each specific macroeconomic environment.

We repeat the exercise, but instead of taking median to define binary regimes, we apply a two-state Markov switching model to macroeconomic indicators. The model specification is the following

$$y_t = \mu_{S_t} + \sigma_{S_t} \cdot \varepsilon_t,$$

where $y_t$ is macroeconomic indicator at time t, $\mu$ – mean, $\sigma$ – variance, $\varepsilon_t$ – error term ($\varepsilon_t \sim$ IID(0,1)). Subscription $s_t$ means that the estimate is state-switching, therefore, in this model specification we allow both mean and variance to change depending on state.

The outputs from the model are estimates of means and variances in two states, as well as constant transition probabilities and expected durations of states. It is also possible to calculate smoothed and filtered probabilities for the states, where smoothed probability is the probability of being in a certain state taking into account all sample observations, and filtered probability is the probability of being in a certain state taking into account only previous sample observations. If filtered probability of the state with the higher mean is larger than 0.5 at a certain point of time, we define the regime to be up, otherwise – down.

Again, we sort all of the excess returns by up and down regimes, and calculate their means and Sharpe ratios in each macroeconomic environment.

We also calculate standard errors of mean excess returns and Sharpe ratios in each specific regime. If the calculation of standard error of mean excess return is straight-forward – it is the sample standard deviation divided by the root of number of observations in the sample – calculation of standard errors of Sharpe ratios is more tricky. Lo (2002) derives the formula to be

$$SE(SR) = \sqrt{\left(1 + \frac{1}{2}SR^2\right)/T},$$

where SR is Sharpe ratio and T is the number of observations. Application of this formula assumes that excess returns are independently and identically distributed, otherwise generalized method of moments should be applied.

Finally, we want to measure exposure of each asset class to macroeconomic indicators and explore if the exposure changes depending on the state of the returns. We apply two-state Markov switching model with the following specification

$$y_t = \alpha_{S_t} + \sum \beta_{S_t} \cdot \Delta X_t + \sigma_{S_t} \cdot \varepsilon_t,$$

where $y_t$ is excess asset return at time t, $X_t$ – macroeconomic indicator at time t, $\alpha$ – intercept, $\beta$ – estimate for the exposure to indicators, $\sigma$ – variance of excess returns, $\varepsilon_t$ – error term ($\varepsilon_t \sim$ IID(0,1)). All five macroeconomic indicators are included as explanatory variables into the model. Also, all estimates of the model – intercepts, variances and five beta estimates – are state-switching.

*3.2 Markov switching models*

Since we extensively apply Markov switching models throughout our research, both to macroeconomic indicators and excess returns, we would like to explain briefly the underlying theory behind this family of models.

Markov switching models belong to the class of regime switching models. Regime switching models also include threshold models (TM) and smooth transition models (STM). Threshold models assume that state variable $s_t$ depends on the value of some exogenous threshold variable at time *t*. In smooth transition models, state variable takes value depending on some discrete probability distribution function. In MSMs $s_t$ is unobservable from a discrete, first-order, irreducible, ergodic Markov chain. The difference between threshold and Markov switching models is obvious – in TMs, state variable is defined exogenously, while in MSMs it is latent. Regarding the difference between STMs and MSMs, Markov switching can be considered as a special case of smooth transition, where cumulative distribution function is defined as logistic function. However, MSMs received wider application in literature, since they are more flexible and easier to estimate. In addition, it is easier to extend MSMs to multivariate cases.

Under MSM specification, the dependent variable $y_t$ switches regimes according to some unobservable variable $s_t$, which takes on integer values. For simplicity, we assume two regimes. Therefore, $s_t$ can take on values 1 or 2. Markov process governs the state variable between the regimes in such a way that

$$P(a < y_t \leq b \mid y_1, y_2, \dots, y_{t-1}) = P(a < y_t \leq b \mid y_{t-1}).$$

This means that Markov process is not path-dependent and probability distribution of the state at time t depends only on the state at time t-1. The simplest form of Markov switching model is called 'Hamilton's filter'. If to denote unobserved state variable $z_t$, a first order Markov process is the following

$$\begin{aligned} p(z_t = 1 \mid z_{t-1} = 1) &= p_{11}; \\ p(z_t = 2 \mid z_{t-1} = 1) &= 1 - p_{11}; \\ p(z_t = 2 \mid z_{t-1} = 2) &= p_{22}; \\ p(z_t = 2 \mid z_{t-1} = 1) &= 1 - p_{22}, \end{aligned}$$

where $p_{11}$ is the probability of being in regime 1 at t given that the variable was in regime 1 at t-1, (1 - $p_{11}$) – probability of being in regime 2 at t given that the variable was in regime 1 at t-1, $p_{22}$ – probability of being in regime 2 at t given that the variable was in regime 2 at t-1, (1 - $p_{22}$) – probability of being in regime 2 at t given that the variable was in regime 1 at t-1. $p_{11}$ and $p_{22}$ are called transition probabilities.

State variable $z_t$ evolves as the following AR(1) process

$$z_t = (1 - p_{11}) + (p_{11} + p_{22} - 1) \cdot z_{t-1} + \eta_t.$$

The dependent variable evolves as

$$y_t = \mu_1 + \omega z_t + (\sigma_1^2 + \varphi z_t)^{1/2} u_t,$$

where $\mu_1$and $\mu_2 = \mu_1 + \omega$ are expected values in states 1 and 2 respectively, $\sigma_1^2$ and $\sigma_2^2 = \sigma_1^2 + \varphi$ are variances in states 1 and 2 respectively, $u_t$ – error term ($u_t \sim$ N(0,1)). The unknown parameters $(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, p_{11}, p_{22})$ are estimated using maximum likelihood.

Engel and Hamilton (1990) provide comprehensive details on estimating Markov switching models.

With population parameters summarized in the vector

$$\theta = (\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, p_{11}, p_{22})',$$

the unconditional distribution of the state of the first observation can be written in the following way

$$p(s_1 = 1; \theta) = \frac{(1 - p_{22})}{(1 - p_{11}) + (1 - p_{22})};$$
$$p(s_2 = 2;\ \theta) = 1 - p.$$

The joint probability distribution function of the series with a sample size T $T(y_1, \dots, y_T)$ and unobserved states $(s_1, \dots, s_T)$ can then be written as

$$p(y_1, \dots, y_T, s_1, \dots, s_T; \theta) =$$
$$= p(y_T|s_T; \theta) \cdot p(s_T|s_{T-1}; \theta) \cdot p(y_{T-1}|s_{T-1}; \theta) \cdot p(s_{T-1}|s_{T-2}; \theta) \cdot \dots \cdot\cdot p(y_2|s_2; \theta) \cdot$$
$$p(s_2|s_1; \theta) \cdot p(y_1|s_1; \theta) \cdot p(s_1; \theta).$$

Finally, the likelihood function to be maximized is the summation of joint probability distribution functions over all possible values of $(s_1, \dots, s_T)$:

$$p(y_1, \dots, y_T; \theta) = \sum_{s_1=1}^{2} \cdots \sum_{s_1=1}^{2} p(y_1, \dots, y_T, s, \dots, s_T; \theta).$$

When estimating parameters, the singularity in likelihood function may sometimes arise if, for example, the mean of regime 1 equals the value of the first observation in the sample and the variance of regime 1 is permitted to go to zero. This problem is addressed by applying the Bayesian prior to the parameters of the two regimes.

## 4. Data

### *4.1 Macroeconomic indicators*

To construct growth indicator, we take the Chicago Fed National Activity Index (CFNAI), which is the monthly index designed to gauge overall economic activity in the US.

Since the return is a forward looking measure, and CFNAI relates to the past, it is necessary to include growth forecast into indicator to reflect investors' expectations about the economy. Therefore, we also use quarterly forecasts for the growth of industrial production index from Survey of Professional Forecasters (SPF). We standardize CFNAI and IP growth forecast, and define growth indicator as an average of standardized series.

For the inflation indicator, we used yearly change of Consumer Price Index for All Urban Consumers and quarterly forecast for the change in the GDP Price Index as a forward looking metric. Likewise, we standardize both series and take their average to construct inflation indicator.

For the real yield indicator, we take the average of standardized long-term and short-term real yields. Long-term real yield is defined as 10-year US Treasury bond yield minus 10-year inflation forecast, short-term real yield as 3-month US Treasury bill yield minus 1-year inflation forecast respectively. For 1-year inflation rate we use the same series as in inflation indicator – GDP Price index growth from SPF, however, for 10-year CPI forecast, the data is available only since 1991. Prior to 1991, as a 10-year CPI proxy we use GDP Price Index forecast plus the average of differences between 1- and 10-year inflation forecasts from 1991 to 2016.

Constructing volatility indicator, we want to take into account both equity and bond markets volatilities. Equity volatility is calculated as volatility of S&P daily returns over the past year. Bond volatility is calculated as volatility of 10-year US Treasury Bond monthly returns over the last year. Since we standardize both series, the fact that we use daily returns for equity volatility and monthly returns for bond volatility does not have significant material impact on volatility indicator.

As an illiquidity indicator, we use standardized aggregate liquidity measure developed by Pastor and Stambaugh (2003). The liquidity measure relates to equity markets since it is constructed using individual daily stock returns and volumes from NYSE and AMEX. Also, unlike other indicators, which continue to November 2016, illiquidity indicator is limited to December 2015.

*4.2 Asset classes*

To make the research easier to follow and more comprehensive, we group analyzed asset classes into three categories: main assets, industry portfolios and REIT equity sectors.

#### *4.2.1 Main assets*

Main assets include asset classes with different characteristics and risk-return profiles. They are stocks, bonds, commodities, REIT equities, REIT mortgages and three factors – size, value and momentum. We use monthly excess returns of MSCI World Index for equities, 30-year US Treasury bonds for treasuries, S&P Goldman Sachs Commodities Index for commodities, FTSE NAREIT US Real Estate Index for REIT equities and mortgages, and Fama-French factors for size, value and momentum. Size and Value factors are constructed from six value-weighted portfolios based on size and book-to-market ratios. Two portfolios are made by ranking market capitalization of the firms, three portfolios are made by ranking their book-to-market ratios. These give six portfolios in intersection. Size factor (SMB) is the average return of three small portfolios minus average return of three large portfolios. Value factor (HML) is the average return of two portfolios with high book-to-market ratios minus average return of two portfolios with low book-to-market ratios. This excludes value neutral stocks. Momentum factor (MOM) is constructed from six value-weighted portfolios based on size and prior returns. Again, two portfolios are created by ranking size, three by ranking prior returns over the last twelve months. Momentum is the average return of two "winner" portfolios minus average return of two "loser" portfolios. Unlike the rest of the assets in Main assets category, factors are zero-cost portfolios, meaning that investments in certain stocks (for example, value) are funded by shorting others (for example, growth). Finally, the data used to construct factors, include all stocks from NYSE, AMEX and NASDAQ. All data series, except Treasuries, span from January 1972 to November 2016. Data for monthly Treasury returns is available until December 2015.

#### *4.2.2 Industry portfolios*

The same stocks as in Fama-French factors are used to form twelve industry portfolios: Consumer Non Durables, Consumer Durables, Manufacturing, Energy, Chemistry, Business Equipment (computers and software), Telecoms, Utilities, Shops (wholesale, retail and some services), Healthcare, Money and Other. Portfolio of Other includes mines, construction, building materials, transportation, hotels, bus services and entertainment.

#### *4.2.3 REIT equity sectors*

We analyse monthly excess returns of eight FTSE NAREIT US Real Estate Index sectors. They are Office, Industrial, Retail, Residential, Diversified, Healthcare, Lodging / Resorts and Self-Storage. The data for REIT sectors start from January 1994. Some sectors, such as Timber, Infrastructure, Data Centres and Specialty, were left out, because their prices are available no earlier than since December 2010 and they have low number of constituents.

### *4.3 Descriptive statistics*

Summary statistics for all assets are presented in Tables 1-4. Among main asset classes, mean returns of the assets as well as volatilities are very different. REIT equities have the highest mean return over the sample period, while size factor has the lowest mean return. Commodities and HML are the most and the least volatile assets respectively. All industry portfolios performed relatively well during the sample period with Other yielding the smallest mean return and Non-Durables yielding the biggest mean return. Volatilities of all portfolios are higher than 4%, with Non Durables being the least volatile and Business Equipment being the most volatile industries. Among REIT equity sectors, Self-storage has the smallest mean return and Industrial has the highest mean return. REIT equity sectors are the most volatile group of assets, with Industrial being its most volatile and Residential being the least volatile. All of the assets have skewness and excess kurtosis significantly different from zero, and Jarque-Bera test confirms that none of the asset returns is normally distributed.

All three categories of assets have positive pairwise correlations between all their assets. Main assets have the weakest comovement, with SMB and MOM being the least correlated and Commodities and REIT mortgages being the most correlated. Industry portfolios show higher correlations between each other than main assets, with Business Equipment and Utilities being the least correlated and Manufacture and Other being the most correlated. REIT equity sectors tend to move together even more than industries, with correlation between Healthcare and Lodging / Resorts being the smallest and correlation between Office and Diversified being the biggest.

## 5. Results

### *5.1 Macroeconomic environments*

Using a median of macro indicators to define the environments enforces equal number of observations in up and down regimes. However, this enforcement may be restrictive, since one of the regimes may be prevailing during the sample period. Applying MS model with state-switching mean and variance solves the issue, as it distinguishes between states, in which macro indicator has different moments, without imposing an equal number of observations in states. The dynamics of macroindicators, as well as regime realizations, are presented in Figures 1-6.

Applying MS model to growth indicator reveals that over 1972-2016 sample period up regime was more common, more persistent and had higher expected duration (See Table 5 for details). Overall, MS model defines that the economy was in growth up regime for 65% of the time versus 50% defined by median. Down regime rather corresponds to periods of market crashes and crises, like ones in 70s, early 80s, early 1990s, 2000s and 2007-2009.

Inflation up regime is less common state than inflation down when MS specification is applied. It also has lower persistence and lower expected duration. Inflation up regime occurs in 1973-1986 and 1988-1992, meaning that since 1992 all the observations are considered to be in inflation down state.

Real yields and volatility up and down regimes are roughly of equal frequency, persistency and duration.

Illiquidity up regime occurs in 27% of the sample time. As in the case of growth, it corresponds to the periods of market crashes when liquidity is drought up. Illiquidity down regime is more persistent and has higher expected duration.

### *5.2 Asset class performance*

Generally, whether we apply Markov-switching model or median to define the regimes, mean excess returns and Sharpe ratios show similar differences in binary states in most cases. Whenever Markov-switching and median approaches result in different average excess returns or Sharpe ratios, we will highlight and comment it. Mean excess returns and Sharpe ratios of all asset classes in each of the regimes are presented in Figures 7-18.

#### *5.2.1 Main assets*

Both MS and median sorting show that equities tend to be sensitive to growth, inflation and illiquidity indicators – they perform well in growth up, inflation down and illiquidity down states, and poorly in growth down, inflation up and illiquidity up. Equities are especially strong when growth up is combined with inflation down simultaneously – in this regime equities average excess return, as well as Sharpe ratio, is the second highest among all asset classes of the group (after REIT equities).

Since US Treasuries have very solid creditworthiness, they tend to perform well in all economic environments. The biggest difference in average excess returns is observable in real yield regimes – they are lower when real yield is up and higher when real yield is down. This is consistent with the common logic – tightening monetary policy of the Federal Reserve System often signals confidence in future economic growth, therefore, investors relocate portion of their money from bonds into riskier asset classes.

Commodity excess returns tend to be sensitive to inflation macroeconomic indicator – when inflation is high, risk premia are high, and vice versa. This makes sense, since investors, expecting high inflation rates, turn to commodities and other real assets as safe havens, pushing prices up. Though MS model captures some exposure to growth indicator, when sorted by median, commodities do not show any significant exposure to growth.

REIT equities, having the highest average excess return and Sharpe ratio over the sample period among all assets, tend to perform well in all economic environments. The only factor to which REIT equities have significant exposure is illiquidity – likewise in case of stocks, high liquidity is associated with high returns and vice versa. Median sorting finds some exposure to growth indicator, however, when sorted by MS model, Sharpe ratios in growth up and down regimes are similar.

Some interesting results are found for REIT mortgages – they are negatively exposed to growth, inflation, real yields and illiquidity indicators, meaning that in up regimes excess returns tend to be low or negative, while in down regimes they are positive and high. It is important to highlight that REIT mortgages are exposed to growth in an opposite manner to equities, which means that they are a good hedge if low economic growth is expected. Moreover, REIT mortgages are an excellent hedge when low growth is combined with low inflation, yielding the highest Sharpe ratio among all explored asset classes in this regime. Also, it is not surprising that REIT mortgages are exposed to real yields, since they are bond-like asset class.

Size factor has an exposure to growth, real yields, volatility and illiquidity, but in an opposite way to equities. This means that size factor is a good hedge for equity portfolios. Indeed, in growth up periods, when markets are bullish, large cap companies tend to get overvalued, and their valuations suffer the most when economic outlook becomes negative and markets turn bearish. Therefore, small cap minus large cap returns perform poorly in the growth up regime and well in growth down. The same logic applies to real yields – when real yields are up and investors tend to have higher allocations to equities, prices for large cap stocks are pushed up more than prices for small cap stocks, and size factor perform poorly. Size factor performed significantly better in volatility and illiquidity up regimes than in volatility and illiquidity down regimes, meaning that it is resilient to market prices fluctuations and unexpected market crashes. Moreover, size factor is the only asset class, which has better excess returns in illiquidity up environment than illiquidity down environment.

Though size seems to be a good hedge against low growth, low real yields, volatility and illiquidity, its average excess return over taken sample period is negative. Therefore, the properties of size factor should be explored for the shorter and more recent samples to justify the reasonability of investing into it.

When we apply median to define regimes, we do not find any visible exposure of value factor to any macroeconomic environment, meaning that it is a good portfolio diversifier across all regimes. MS captures some degree of value's negative exposure to inflation. Since value investing can be interpreted as a contrarian strategy, makes sense that it better withstands macroeconomic changes than other asset classes. However, as in the case of size factor, average excess return of value over the sample period is close to zero. Therefore, some additional research should be done to justify the investments into value factor.

Momentum factor is found to be exposed to growth and volatility indicators. MS model application also captures its exposure to real yields and illiquidity. Momentum favours growth up, real yields up, volatility down and illiquidity down regimes. Therefore, we see that its exposure to market indicators reminds the exposure of equities. It makes sense, since momentum follows market sentiments and has better returns when markets have positive outlook for macroeconomic indicators and past performance of stocks tend to persist in the near future.

To sum up, all of the assets are found to be exposed to at least one macroeconomic indicator. REIT equities and value factor have the most stable performance across all regimes, with REIT yielding significantly high mean excess returns in each regime but illiquidity up, and value factor yielding near-zero mean excess returns. Equities are found to be the most vulnerable to macroeconomic changes, since they are sensitive to at least three macroeconomic factors. REIT mortgages are found to be a perfect hedge in simultaneous growth down & inflation down regime, yielding significantly higher risk premium and Sharpe ratio than all other asset classes.

*5.2.2 Industry portfolios*

In general, findings from sorting returns by regimes show that industry portfolios are sensitive to growth, inflation and illiquidity indicators. Since industry portfolios are equities, this is consistent with the findings in our previous section. In most cases, industry mean excess returns are higher in growth up, inflation down and illiquidity down regimes. Some of the industries are also exposed to volatility.

By applying MS model to define regimes, we find that Telecoms, Utilities, Healthcare and Others are exposed to growth indicator the most. These industries have the biggest differences in Sharpe ratios in growth down and growth up regimes. In contrast, Shops, Non Durables and Durables are the least exposed to economic growth.

Telecoms, Utilities and Others tend to be the most resilient industries to inflation, yielding roughly similar risk premia in inflation up and down regimes. Contrary to them, Manufacture, Chemicals and Business Equipment tend to show the biggest differences in mean excess returns in binary inflation states, suggesting that they are the most sensitive to inflation indicator.

All industries are significantly exposed to illiquidity indicator. It is possible to highlight which are the most and least sensitive to illiquidity. Non Durables, Durables, Telecoms and Others turned out to have the biggest differences in Sharpe ratios in illiquidity up and down regimes, while Energy, Business Equipment and Utilities turned out to be the most resilient to illiquidity among other industries.

Most of the industries do not show any significant differences in Sharpe ratios for volatility up and down regimes but Money and Energy. In volatility down regime Money and Energy have high mean excess returns, while in volatility up their returns are significantly lower.

Though we were able to draw some conclusions based on the differences in Sharpe ratios in binary regimes, some of these results seem to be counterintuitive. For instance, we would not expect Utilities and Healthcare to be dependent on growth more than Manufacturing, since they provide products and services consumed by population disregarding the economic cycle. On the other hand, some of the results are perfectly supported by common sense. For instance, we found Utilities to be among the most resilient to inflation, and we know that utility services are often inflation-hedged. Non Durables are found to be the least exposed to growth, which is explained by the fact that people always consume foods and beverages disregarding the economic situation. The interesting finding is Money and Energy's significant exposure to volatility. When markets are volatile, financial companies' earnings are more uncertain, therefore, stock prices of such companies fall. Prices for products of energy companies are often determined daily in the open market, therefore, makes sense that high volatility has negative impact on the returns of these companies.

*5.2.3 REIT equity sectors*

In general, REIT equity sectors tend to have positive exposure to growth indicator. Office, Industrial and Residential have the biggest difference in Sharpe ratios in growth up and down regimes, suggesting that they are the most sensitive to growth. Healthcare was the only sector yielding higher Sharpe ratio in growth down regime than in growth up.

REIT equity sectors do not show unidirectional exposure to inflation, with Diversified, Healthcare and Self-storage yielding higher mean excess returns in inflation up regime and all others yielding higher mean premiums in inflation down regime.

REIT equity sectors show substantial exposure to illiquidity indicator. They yield lower or negative risk premia when illiquidity is up, and higher premia when illiquidity is down. Residential and Lodging / Resorts have the lowest mean excess returns in illiquidity up regime and the highest mean excess returns in illiquidity down regime among all other REIT sectors, suggesting that they are the most sensitive to illiquidity. In contrast, Healthcare and Self-storage risk premiums are almost the same in illiquidity up and down regimes, suggesting that they are resilient to illiquidity.

All REIT equity sectors have slightly higher Sharpe ratios in volatility down regime, however Office, Industrial, Residential and Lodging / Resorts have substantially higher Sharpe ratios in volatility down than volatility up, suggesting that these are more sensitive to volatility than others.

The important general finding is that Healthcare and Self-Storage tend to have relatively stable mean excess returns and Sharpe ratios in any macroeconomic environment, meaning that they are the most resilient to changes in the economy and are good portfolio hedgers.

Though we are able to spot differences in REIT equities mean excess returns and Sharpe ratios in alternative macroeconomic environments, it is important to keep in mind that shorter sample is available for this asset class – from January 1994 to November 2016. Therefore, statistical standard errors of means of these asset excess returns are higher, meaning that the results are less credible. The problem of high standard errors is explained in the following section.

*5.3 Standard errors*

In general, whether we choose median or Markov switching model to define the regimes, the resulting average excess returns and Sharpe ratios respond similarly to different macroeconomic indicators. For instance, in both cases equities perform well in growth up regime and poorly in growth down regime. However, the choice between median and MS affects standard errors of the mean returns and Sharpe ratios a lot.

The statistical standard errors of mean returns and Sharpe ratios depend on number of observations in each macroeconomic environment. Therefore, when Markov switching results in a small number of observations for the specific regime, high standard errors of the mean undermine the credibility of the result. For instance, by applying MS, we have 32 observations in growth down regime for REIT sectors versus 243 in growth up. Though mean excess returns for some sectors are very negative, due to large standard errors we cannot claim that they are statistically different from zero.

This is particularly important when we are interested to look at the returns not only in binary states, but at the intersections of states, like we do when we calculate means and Sharpe ratios in growth up & inflation up, growth up & inflation down, growth down & inflation up and growth down & inflation down regimes. When we apply MS to growth and inflation to define four regimes in intersection, we result having only 49 observations in growth down & inflation down regime. Therefore, mean excess returns in this regime are hard to compare to returns in other regimes due to their high standard error. See Figures 19-20 for standard errors of mean excess returns and Sharpe ratios in different regimes resulting from MS and median.

Therefore, applying Markov switching to define the regimes is generally very useful for large samples as it does not impose an equal number of observation in states and better captures the changes in the regimes. However, if the sample period is short, or if one is interested in looking at the intersections of the regimes, applying median may make more sense as it results in smaller standard errors of the mean returns.

### *5.4 Markov switching models applied to asset excess returns*

By applying a two-state Markov switching model with macro indicators as explanatory variables to each asset class, we want to examine if macro factors are able to explain the variations in asset excess returns. We also want to find out if some assets have different exposures to same macroeconomic indicator in their up and down states. This can be particularly valuable for timing the investments. See Tables 6-8 for estimates of all models parameters.

#### *5.4.1 Main assets*

Generally, for most assets beta exposures to indicators are significant in one state, either up or down. MS model finds that equities are negatively exposed to inflation, real yields, volatility and illiquidity in up state, and only to volatility in down state. It means that when equity excess returns tend to be down, they are explained only by changes in volatility, when in up state, equity returns are also explained by movements in other indicators.

Treasuries are significantly exposed only to inflation and real yields, both in down and up states. Beta exposures to these indicators are negative in both states, meaning that higher inflation and higher real yields always decrease Treasury returns. The results for Treasuries make perfect economic sense – since Treasury pays a fixed coupon, higher inflation will decrease real future cash flows from the coupon, and therefore, price for the bond will fall. Higher real yield already imply lower prices for Treasury bonds, since real yields are in fact inferred from prices for treasuries.

MS model applied to commodity returns captures strong positive exposure of commodities to inflation – though the exposure is significant only in down state, the beta is relatively high and very significant. Being real assets, commodities are known to be safe havens in times of high inflation.

REIT equities and mortgages are found to be negatively exposed to inflation, real yields, volatility and illiquidity in one of the states, either up or down.

Beta exposures found in factors are rather surprising and partly contradict our findings from sorting the returns according to defined macroeconomic environments. Size factor, which is supposed to have an opposite exposure to indicators than equities, in fact show positive exposure to growth, negative exposure to inflation and negative exposure to volatility exactly as equities. Unlike equities, they are positively exposed to real yields.

The important finding is that value factor changes the sign of its exposure to inflation in up and down regimes – in up regime beta is positive, while in down regime it is negative. It means that investor can effectively time its investment into value factor. If the returns are in up regime and inflation is high, one should invest in value, if returns are in up regime and inflation is low – divest. Likewise, if returns are in down regime and inflation is low – invest, returns are in down regime and inflation is high – divest.

Momentum factor is negatively exposed only to growth and inflation in its up state, meaning that changes in other factors do not explain momentum's returns. This is somehow unexpected result since sorting returns by median and MS, showed significant equity-like exposure to almost all indicators.

To sum up, application of MS model to assets returns reveals that equities, REIT equities and REIT mortgages excess returns are not explained by growth macro indicator, but rather by real yields and volatility in addition to inflation and illiquidity. Application of MS confirms that Treasuries are negatively exposed to real yields and commodities are positively exposed to inflation. It also finds that Treasuries are negatively exposed to inflation. Findings for size and momentum style factors contradict the findings from sorting the returns according to the regime. Value factor is found to change its exposure to inflation depending if it is up or down regime.

*5.4.2 Industry portfolios*

Two-state MS models applied to industry portfolios finds that changes in macroeconomic indicators are good in explaining industry excess returns. As in case of aggregate equities above, we find that industry portfolios risk premia are explained by inflation, real yields, volatility, illiquidity and sometimes growth.

Non Durables, Business Equipment and Healthcare are negatively exposed to changes in growth in their down regimes. Durables, Chemicals and Other are positively exposed to growth in their up regimes. This finding confirms that Non Durables, Business Equipment and Healthcare are the most resilient to low growth, and Durables, Chemical and Other are the most pro-cyclical. Therefore, in expectation of high growth, one should increase their allocation to Durables, Chemicals and Others, while in expectation of low growth allocations should be increased into Non Durables, Business Equipment and Healthcare.

Almost all industries are negatively exposed to inflation in up states and don't have significant exposure to inflation in down states. However, Energy turns out to be a good hedge against high inflation, since it is found to be the only industry with positive exposure to inflation. Moreover, though Utilities are found to be negatively exposed to inflation, they have the least exposure to inflation among all industry portfolios. Shops are negatively and significantly exposed to inflation in both states, suggesting that this industry is the most vulnerable to the negative effects of inflation.

Most of the industries are negatively exposed to real yields in either up or both up and down states. Two industries, Business Equipment and Shops, have positive exposure to real yields in down regime, and negative exposure to real yields in up regime. This is a valuable finding for timing the investments into Business Equipment and Shops. If real yields are high and returns are in down regime, one should invest in these industries. If real yields are low and returns are in down regime, one should divest Business Equipment and Shops. The same logic applies to up regimes of the returns – long if real yields are low and short if real yields are high.

Most of the industries are negatively exposed to volatility in at least one of the states. Energy has negative exposure to volatility in up regime and positive exposure to volatility in down regime. As in case with Business Equipment and Shops, this finding helps to time the investment into Energy depending on the regime of the excess returns and level of volatility. All of the industries are negatively exposed to changes in illiquidity in at least one of the regimes.

### *5.4.3 REIT equity sectors*

REIT equity sectors returns are the best explained by changes in volatility – all sectors are negatively exposed to volatility in up states. Office, Industrial and Healthcare are negatively exposed to volatility both in up and down states, and in down states the magnitude of exposure is bigger. Therefore, an investor who expects volatility to increase, should decrease her allocation to the mentioned three sectors.

In general, changes in levels of inflation, as well as real yields and growth, do not explain REIT sectors returns. Only Retail and Healthcare have negative exposures to inflation in up and down states respectively. Only Healthcare and Self-storage have negative exposures to real yields in down regimes, and no REIT equity subsector is significantly exposed to growth in this model specification.

In general, changes in macroeconomic factors explain REIT equity sectors returns much worse than they explain returns of industry portfolios. This can be interpreted as evidence that REIT equity sectors are more resilient to changing macroeconomic conditions than other equities, as it was suggested by findings from sorting excess returns according to Markov switching regimes.

## 6. Conclusions

In this paper, we examine how different asset classes are exposed to alternative macroeconomic environments. We applied several different approaches in order to explore these relationships. Firstly, we sorted excess returns according to binary macroeconomic regimes and compared their means and Sharpe ratios. Secondly, we applied two-state Markov switching model to excess returns, including macroeconomic factors as explanatory variables in the model.

When we sort excess returns according to the regimes defined by median and MS, we find that they both capture asset class sensitivities to macroeconomic environments in a similar way. Equities are found to have significant positive exposure to growth, negative exposure to inflation and negative exposure to illiquidity. Treasuries have negative exposure to real yields, and commodities have positive exposure to inflation. REIT equities perform very well in all macroeconomic environments but illiquidity up, REIT mortgages are negatively exposed to all macroeconomic indicators but volatility and are an exceptionally good hedge in simultaneous growth down and inflation down regime. Style factors – size, value and momentum – all behave differently. Size factor is exposed to macroeconomic indicators in an opposite way to equities, suggesting that it is a good hedge for equities against macroeconomic changes. Value factor has relatively stable performance in all macroeconomic regimes but inflation up if defined by MS. Momentum factor is very sensitive to all but inflation macroeconomic indicator, and its exposure to growth and illiquidity is the same as the exposure of equities.

We find that most of the industry portfolios have positive exposure to growth, negative exposure to inflation and negative exposure to illiquidity. This is not surprising, since industry portfolios are equities. Based on differences in Sharpe ratios in binary regimes, we try to identify industries, which are the most and the least sensitive to these macroeconomic environments. Though some findings are hard to comment, we find that Non Durables are among the most resilient to growth, Utilities are among the most resilient to inflation. We also find that, unlike other industries, Money and Energy are sensitive to volatility, which makes perfect economic sense.

REIT equity sectors have positive exposure to growth and negative exposure to illiquidity. The most valuable takeaway from analysing average excess returns and Sharpe ratios of REITs is that Healthcare and Self-storage performed very well in all macroeconomic environments, suggesting that they are the most resilient to macroeconomic changes.

The second approach we used to examine asset excess returns exposure to macroeconomic indicators is fundamentally different. In the first approach, we imposed binary regimes on macroeconomic indicators and looked at excess returns in the defined regimes. In the latter, we imposed binary regimes on asset returns. We applied two-state Markov switching model to each asset class excess returns including changes in macroeconomic factors as explanatory variables in the model.

Firstly, Markov switching model suggests that equities, REIT equities and REIT mortgages have no significant exposure to growth, instead they have significant negative exposure to real yields and volatility in addition to inflation and illiquidity. The model confirms our previous findings that Treasuries are negatively exposed to real yields and commodities are positively exposed to inflation. In addition, it finds significant negative exposure of Treasuries to inflation.

The results for style factors contradict our previous findings from binary macroeconomic environments. Size factor is positively exposed and momentum is negatively exposed to growth according to this model, though previous results suggested the opposite.

Industry portfolios returns are well explained by movements in inflation, real yields, volatility and illiquidity. A few industries are significantly exposed to growth. Non Durables, Business Equipment and Healthcare have negative growth exposure in their down regimes, suggesting that they are defensive, and Durables, Chemicals and Others have positive growth exposure in the up regimes, suggesting that they are pro-cyclical. Energy is found to be the only industry with a positive exposure to inflation, with Utilities being the least exposed to inflation among the remaining industries. Shops returns are found to be the most sensitive to changes in inflation.

The only significant factor which captures the variation in returns of all REIT equity sectors is volatility. We interpret it as a suggestion that REIT equity sectors are more resilient to different macroeconomic environments than other asset classes, in particular equities.

Another important conclusion from the model is that almost all of the beta exposures are unidirectional and coefficients do not change signs depending on the regime of the asset. Only value factor changes the sign of its exposure to inflation, Business Equipment and Shops change the signs of their exposures to real yields and Energy changes the sign of its exposure to volatility. This evidence is particularly valuable for timing the investments into these assets.

Overall, as we already mentioned, two approaches are different so we did not expect them to produce exactly the same results. Though there are some minor contradictions in the findings, we believe that the results obtained from both approaches complement each other and help better understand the relationships between asset class returns and macroeconomic regimes.

Understanding asset class returns exposure to alternative macroeconomic environments has very valuable practical implications. Firstly, it provides insights on how asset allocation should change if the investor wants to increase its exposure to certain macroeconomic variables to get higher returns. Secondly, it helps to hedge against macroeconomic changes and construct diversified portfolios, which would perform well in any of the environment.

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**Table 1**

**Summary statistics for asset returns**

The following table shows the main statistics for monthly asset returns over the sample period from January 1972 to November 2016. Jarque-Bera is a test statistics used to assess whether a series is normally distributed. P-value close to zero suggests that the null hypothesis, a series is normally distributed, is rejected.

| | Mean | Med. | Max. | Min. | St. Dev. | Skew | Kurt. | Jarque-Bera | p |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | **Main assets** | | | | |
| **Equities** | 0.60% | 0.83% | 14.27% | -19.05% | 4.26% | -0.535 | 4.66 | 88 | 0.00 |
| **Treasuries** | 0.68% | 0.64% | 17.41% | -14.74% | 3.53% | 0.417 | 5.44 | 146 | 0.00 |
| **Commodities** | 0.70% | 0.73% | 25.77% | -28.20% | 5.89% | 0.030 | 5.25 | 114 | 0.00 |
| **REIT equities** | 1.06% | 1.26% | 31.02% | -31.67% | 4.92% | -0.678 | 10.81 | 1412 | 0.00 |
| **REIT mortgages** | 0.60% | 0.87% | 38.40% | -24.11% | 5.76% | -0.264 | 8.34 | 646 | 0.00 |
| **SMB** | 0.17% | 0.10% | 22.08% | -17.17% | 3.10% | 0.559 | 9.69 | 1033 | 0.00 |
| **HML** | 0.39% | 0.30% | 12.91% | -11.25% | 2.93% | 0.049 | 5.09 | 99 | 0.00 |
| **MOM** | 0.67% | 0.77% | 18.38% | -34.58% | 4.42% | -0.139 | 13.45 | 2626 | 0.00 |
| | | | | | **Industry portfolios** | | | | |
| **Non-Durables** | 1.10% | 1.10% | 18.88% | -21.03% | 4.32% | -0.285 | 5.28 | 124 | 0.00 |
| **Durables** | 0.86% | 0.87% | 42.63% | -32.63% | 6.51% | 0.110 | 7.85 | 530 | 0.00 |
| **Manufacture** | 1.02% | 1.30% | 21.08% | -28.58% | 5.38% | -0.537 | 5.91 | 217 | 0.00 |
| **Energy** | 1.07% | 0.92% | 24.56% | -18.33% | 5.64% | 0.062 | 4.17 | 31 | 0.00 |
| **Chemicals** | 0.97% | 1.10% | 20.22% | -24.59% | 4.73% | -0.242 | 5.33 | 127 | 0.00 |
| **Business Equip.** | 0.97% | 0.92% | 20.78% | -26.07% | 6.64% | -0.198 | 4.35 | 45 | 0.00 |
| **Telecoms** | 0.99% | 1.21% | 21.34% | -16.22% | 4.75% | -0.269 | 4.33 | 46 | 0.00 |
| **Utilities** | 0.92% | 1.04% | 18.84% | -12.65% | 4.07% | -0.166 | 4.22 | 36 | 0.00 |
| **Shops** | 1.00% | 1.00% | 25.86% | -28.25% | 5.24% | -0.278 | 5.72 | 173 | 0.00 |
| **Healthcare** | 1.03% | 1.10% | 29.52% | -20.46% | 4.96% | 0.068 | 5.64 | 157 | 0.00 |
| **Money** | 1.00% | 1.33% | 21.10% | -22.10% | 5.51% | -0.417 | 4.92 | 99 | 0.00 |
| **Other** | 0.82% | 1.08% | 19.35% | -29.24% | 5.39% | -0.532 | 5.65 | 184 | 0.00 |
| | | | | | **REIT equity subsectors** | | | | |
| **Office** | 1.08% | 1.56% | 32.46% | -31.80% | 6.18% | -0.452 | 8.97 | 418 | 0.00 |
| **Industrial** | 1.17% | 1.25% | 70.48% | -56.19% | 8.70% | 0.279 | 26.43 | 6296 | 0.00 |
| **Retail** | 1.10% | 1.51% | 43.52% | -36.78% | 6.41% | -0.315 | 15.45 | 1780 | 0.00 |
| **Residential** | 1.09% | 1.36% | 22.24% | -26.66% | 5.58% | -0.732 | 6.95 | 203 | 0.00 |
| **Healthcare** | 0.87% | 1.30% | 39.69% | -31.43% | 6.02% | -0.216 | 12.95 | 1135 | 0.00 |
| **Lodging/Resorts** | 1.12% | 1.12% | 27.73% | -25.48% | 5.98% | -0.281 | 6.31 | 129 | 0.00 |
| **Self-storage** | 0.79% | 0.59% | 67.53% | -33.43% | 8.77% | 0.954 | 16.29 | 2064 | 0.00 |

**Table 2**

**Main assets sample correlations**

The following table presents full-sample pairwise correlations between main assets for the sample period Jan 1972 – Nov 2016.

| | **Equities** | **Treasuries** | **Commodity** | **REIT equities** | **REIT mortgages** | **SMB** | **HML** | **MOM** |
|---|---|---|---|---|---|---|---|---|
| **Equities** | 1.000 | | | | | | | |
| **Treasuries** | 0.632 | 1.000 | | | | | | |
| **Commodities** | 0.756 | 0.851 | 1.000 | | | | | |
| **REIT equities** | 0.457 | 0.456 | 0.620 | 1.000 | | | | |
| **REIT mortgages** | 0.808 | 0.730 | 0.869 | 0.580 | 1.000 | | | |
| **SMB** | 0.555 | 0.675 | 0.779 | 0.439 | 0.635 | 1.000 | | |
| **HML** | 0.613 | 0.602 | 0.649 | 0.411 | 0.571 | 0.632 | 1.000 | |
| **MOM** | 0.603 | 0.405 | 0.487 | 0.541 | 0.499 | 0.286 | 0.471 | 1.000 |

**Table 3**

**Industry portfolios sample correlations**

The following table presents full-sample pairwise correlations between industry portfolios for the sample period Jan 1972 – Nov 2016.

| | Non Dur. | Dur. | Manuf. | Energy | Chem. | Bus. Equip. | Telec. | Utilities | Shops | Health. | Money | Other |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Non Durables** | 1.000 | | | | | | | | | | | |
| **Durables** | 0.632 | 1.000 | | | | | | | | | | |
| **Manuf.** | 0.756 | 0.851 | 1.000 | | | | | | | | | |
| **Energy** | 0.457 | 0.456 | 0.620 | 1.000 | | | | | | | | |
| **Chemicals** | 0.808 | 0.730 | 0.869 | 0.580 | 1.000 | | | | | | | |
| **Business Equipment** | 0.555 | 0.675 | 0.779 | 0.439 | 0.635 | 1.000 | | | | | | |
| **Telecoms** | 0.613 | 0.602 | 0.649 | 0.411 | 0.571 | 0.632 | 1.000 | | | | | |
| **Utilities** | 0.603 | 0.405 | 0.487 | 0.541 | 0.499 | 0.286 | 0.471 | 1.000 | | | | |
| **Shops** | 0.821 | 0.748 | 0.816 | 0.402 | 0.765 | 0.700 | 0.640 | 0.441 | 1.000 | | | |
| **Healthcare** | 0.744 | 0.504 | 0.649 | 0.407 | 0.710 | 0.589 | 0.543 | 0.450 | 0.662 | 1.000 | | |
| **Money** | 0.768 | 0.755 | 0.817 | 0.527 | 0.768 | 0.631 | 0.654 | 0.543 | 0.783 | 0.662 | 1.000 | |
| **Other** | 0.765 | 0.801 | 0.921 | 0.588 | 0.829 | 0.781 | 0.671 | 0.506 | 0.836 | 0.670 | 0.840 | 1.000 |

**Table 4**

**REIT equity sectors sample correlations**

The following table presents full-sample pairwise correlations between REIT equity sectors for the sample period Jan 1994 – Nov 2016.

| | Office | Industrial | Retail | Residential | Diversified | Healthcare | Lodging / Resorts | Self-storage |
|---|---|---|---|---|---|---|---|---|
| **Office** | 1.000 | | | | | | | |
| **Industrial** | 0.814 | 1.000 | | | | | | |
| **Retail** | 0.882 | 0.845 | 1.000 | | | | | |
| **Residential** | 0.840 | 0.697 | 0.817 | 1.000 | | | | |
| **Diversified** | 0.898 | 0.772 | 0.885 | 0.831 | 1.000 | | | |
| **Healthcare** | 0.759 | 0.742 | 0.803 | 0.712 | 0.741 | 1.000 | | |
| **Lodging / Resorts** | 0.767 | 0.681 | 0.777 | 0.696 | 0.810 | 0.587 | 1.000 | |
| **Self-storage** | 0.751 | 0.668 | 0.785 | 0.744 | 0.745 | 0.752 | 0.600 | 1.000 |

**Table 5**

**Markov switching model estimates for environments**

The following table contains estimates from the two-state heteroskedastic Markov switching model applied to macroeconomic indicators. Model specification is the following

$$y_t = \mu_{S_t} + \sigma_{S_t} \cdot \varepsilon_t,$$

where $y_t$ is macroeconomic indicator at time t, $\mu$ – mean, $\sigma$ – variance, $\varepsilon_t$ – error term ($\varepsilon_t \sim$ IID(0,1)). Number of observations in each regime is calculated based on filtered probabilities inferred from the model. Filtered probability of 0.5 or higher indicates up regime and vice versa.

| | | Mean | Log sigma | Transition probability | Expected duration | No. of obs. in the regime |
|---|---|---|---|---|---|---|
| **Growth** | *Up* | 0.187<br>(0.028) | -0.729<br>(0.040) | 0.987 | 74.184 | 354 |
| | *Down* | -0.345<br>(0.156) | 0.740<br>(0.054) | 0.976 | 42.528 | 185 |
| **Inflation** | *Up* | 1.243<br>(0.088) | 0.138<br>(0.049) | 0.989 | 93.928 | 209 |
| | *Down* | -0.799<br>(0.023) | -1.022<br>(0.045) | 0.995 | 193.406 | 330 |
| **Real yield** | *Up* | 0.916<br>(0.047) | -0.351<br>(0.045) | 0.980 | 50.566 | 277 |
| | *Down* | -0.974<br>(0.039) | -0.580<br>(0.047) | 0.982 | 56.925 | 262 |
| **Volatility** | *Up* | 0.785<br>(0.061) | -0.194<br>(0.044) | 0.978 | 44.969 | 268 |
| | *Down* | -0.775<br>(0.031) | -1.068<br>(0.068) | 0.981 | 53.359 | 271 |
| **Illiquidity** | *Up* | 0.872<br>(0.208) | 0.747<br>(0.067) | 0.909 | 11.026 | 144 |
| | *Down* | -0.360<br>(0.050) | -0.229<br>(0.057) | 0.962 | 26.615 | 384 |

**Table 6**

**Markov switching models estimates for main assets**

The following table contains estimates from the two-state heteroskedastic Markov switching model applied to main assets excess returns. Model specification is the following

$$y_t = \alpha_{S_t} + \sum \beta_{S_t} \cdot \Delta X_t + \sigma_{S_t} \cdot \varepsilon_t,$$

where $y_t$ is excess asset return at specific point of time, $X_t$ – macroeconomic indicator, $\alpha$ –intercept, $\beta$ – estimate for the exposure to indicators, $\sigma$ – variance of excess returns, $\varepsilon_t$ – error term ($\varepsilon_t \sim$ IID(0,1)).

| | Intercept | Growth | Inflation | Real yields | Volatility | Illiquidity |
|---|---|---|---|---|---|---|
| Equities | -0.0057 | -0.0039 | 0.0164 | -0.0034 | **-0.0465**** | -0.0025 |
| | **0.0079***** | 0.0020 | **-0.0423**** | **-0.0338***** | **-0.0242*** | **-0.0044***** |
| Treasuries | 0.0007 | -0.0003 | **-0.0699***** | **-0.0730***** | -0.0028 | 0.0001 |
| | **0.0050***** | -0.0038 | **-0.0927***** | **-0.2330***** | 0.0038 | -0.0005 |
| Commodities | 0.0004 | -0.0032 | **0.2206***** | 0.0208 | -0.0161 | -0.0011 |
| | 0.0040 | 0.0014 | 0.0375 | 0.0085 | **-0.0253*** | 0.0002 |
| REIT equities | 0.0009 | 0.0046 | 0.0424 | -0.0085 | **-0.0733**** | 0.0002 |
| | **0.0087***** | 0.0024 | **-0.0449***** | **-0.0306***** | -0.0072 | **-0.0020**** |
| REIT mortgages | -0.0416 | -0.0075 | -0.0534 | -0.0958 | 0.0624 | **-0.0086*** |
| | **0.0058***** | 0.0006 | **-0.0660***** | **-0.0559***** | **-0.0364***** | -0.0014 |
| SMB | **-0.0030**** | **0.0035**** | **-0.0183*** | **0.0101**** | **-0.0179***** | -0.0007 |
| | 0.0090 | -0.0568 | -0.0391 | -0.1021 | -0.1491 | 0.0065 |
| HML | 0.0038 | 0.0101 | **-0.2003**** | **-0.1569***** | -0.0029 | **-0.0043*** |
| | -0.0010 | 0.0000 | **0.0369***** | 0.0026 | -0.0056 | 0.0010 |
| MOM | -0.0020 | 0.0050 | 0.0748 | 0.0118 | 0.0107 | 0.0009 |
| | **0.0051***** | **-0.0034**** | **-0.0102**** | -0.0159 | -0.0024 | 0.0013 |

***significant at 1% level; **significant at 5% level; *significant at 10% level

**Table 7**

**Markov switching models estimates for industry portfolios**

The table contains estimates from the two-state heteroskedastic Markov switching model applied to industry portfolios excess returns.

| | Intercept | Growth | Inflation | Real yields | Volatility | Illiquidity |
|---|---|---|---|---|---|---|
| Non Durables | -0,0084 | **-0,0431**** | -0,0191 | -0,0314 | **-0,1040**** | -0,0008 |
| | **0,0091***** | 0,0033 | **-0,0506***** | **-0,0381***** | **-0,0223**** | **-0,0043***** |
| Durables | 0,0070 | -0,0042 | -0,0211 | 0,0291 | **-0,1048**** | 0,0012 |
| | **0,0051*** | **0,0076**** | **-0,0594**** | **-0,0252**** | **-0,0544***** | **-0,0073***** |
| Manufacture | 0,0001 | -0,0040 | 0,0308 | -0,0047 | **-0,0579**** | -0,0025 |
| | **0,0088***** | 0,0044 | **-0,0460*** | **-0,0228*** | **-0,0403***** | **-0,0074***** |
| Energy | -0,0064 | 0,0037 | -0,0337 | 0,0324 | **-0,2144***** | 0,0010 |
| | **0,0128***** | -0,0018 | **0,0987***** | -0,0119 | **0,0428**** | **-0,0056***** |
| Chemicals | -0,0096 | -0,0219 | 0,0409 | -0,0513 | -0,0753 | -0,0015 |
| | **0,0077***** | **0,0053*** | **-0,0447**** | **-0,0196**** | **-0,0240*** | **-0,0055***** |
| Business Equipment | 0,0072 | **-0,0460**** | 0,1302 | **0,2134**** | **-0,1101*** | 0,0018 |
| | **0,0072***** | 0,0046 | **-0,0731***** | **-0,0199*** | **-0,0298**** | **-0,0048***** |
| Telecoms | -0,0010 | -0,0036 | 0,0124 | 0,0624 | **-0,0570*** | 0,0001 |
| | **0,0094***** | -0,0035 | **-0,0683***** | **-0,0332***** | 0,0053 | **-0,0051***** |
| Utilities | -0,0003 | 0,0041 | -0,0043 | **-0,0307**** | -0,0082 | **-0,0040**** |
| | **0,0075***** | -0,0046 | **-0,0375*** | **-0,0896***** | **-0,0291***** | -0,0016 |
| Shops | -0,0149 | 0,0052 | **-0,1492***** | **0,0754***** | **-0,2186***** | **-0,0085***** |
| | **0,0113***** | 0,0019 | **-0,0981***** | **-0,0494***** | -0,0022 | -0,0010 |
| Healthcare | 0,0022 | **-0,0529***** | 0,0243 | 0,0472 | 0,0254 | **-0,0175***** |
| | **0,0087***** | 0,0031 | **-0,0444**** | **-0,0428***** | **-0,0395***** | 0,0008 |
| Money | -0,0100 | -0,0058 | -0,0016 | -0,0221 | -0,0398 | -0,0014 |
| | **0,0114***** | 0,0034 | **-0,0541**** | **-0,0485***** | -0,0185 | **-0,0061***** |
| Other | -0,0017 | -0,0029 | 0,0343 | -0,0167 | -0,0355 | **-0,0069**** |
| | **0,0058**** | **0,0073**** | **-0,0844**** | **-0,0228*** | **-0,0509***** | **-0,0024*** |

***significant at 1% level; **significant at 5% level; *significant at 10% level

**Table 8**

**Markov switching models estimates for REIT equity sectors**

The table contains estimates from the two-state heteroskedastic Markov switching model applied to REIT equity sectors excess returns.

| | Intercept | Growth | Inflation | Real yields | Volatility | Illiquidity |
|---|---|---|---|---|---|---|
| Office | **0,0923*** ** | 0,0169 | 0,0872 | -0,2229 | **-0,4467** ** | 0,0125 |
| | **0,0091*** | 0,0067 | -0,0239 | 0,0008 | **-0,0415*** | -0,0025 |
| Industrial | 0,1825 | -0,0325 | -0,1091 | -0,3556 | **-0,8005** ** | **0,0465*** ** |
| | **0,0099*** ** | 0,0012 | -0,0098 | -0,0009 | **-0,0350*** | -0,0006 |
| Retail | 0,0018 | 0,0299 | 0,2305 | -0,1730 | -0,0871 | 0,0119 |
| | **0,0110** ** | -0,0002 | **-0,0532*** | -0,0258 | **-0,0572*** ** | -0,0003 |
| Residential | -0,0039 | 0,0355 | -0,0453 | 0,1039 | -0,1507 | 0,0077 |
| | **0,0082** ** | 0,0105 | -0,0524 | 0,0009 | **-0,0616** ** | **-0,0034** ** |
| Diversified | 0,0064 | 0,0173 | 0,0510 | -0,0115 | -0,1046 | 0,0049 |
| | **0,0094*** ** | 0,0018 | -0,0247 | -0,0399 | **-0,0443** ** | **-0,0025*** |
| Healthcare | **0,0112*** ** | 0,0022 | **-0,0829** ** | **-0,0737*** ** | **-0,0329*** | -0,0013 |
| | **0,0771*** | 0,0115 | -0,3301 | -0,1420 | **-0,5745** ** | **0,0244*** ** |
| Lodging / | -0,0028 | 0,0355 | -0,0451 | 0,1025 | -0,1505 | 0,0078 |
| Resorts | **0,0105*** ** | 0,0102 | -0,0527 | 0,0008 | **-0,0600** ** | **-0,0034*** ** |
| Self-storage | -0,0018 | -0,0069 | 0,1117 | -0,1508 | -0,0876 | 0,0113 |
| | **0,0181*** ** | 0,0033 | -0,0444 | **-0,0679** ** | -0,0301 | -0,0013 |

***significant at 1% level; **significant at 5% level; *significant at 10% level

## Figure 1

## Macroeconomic indicators (standardized)

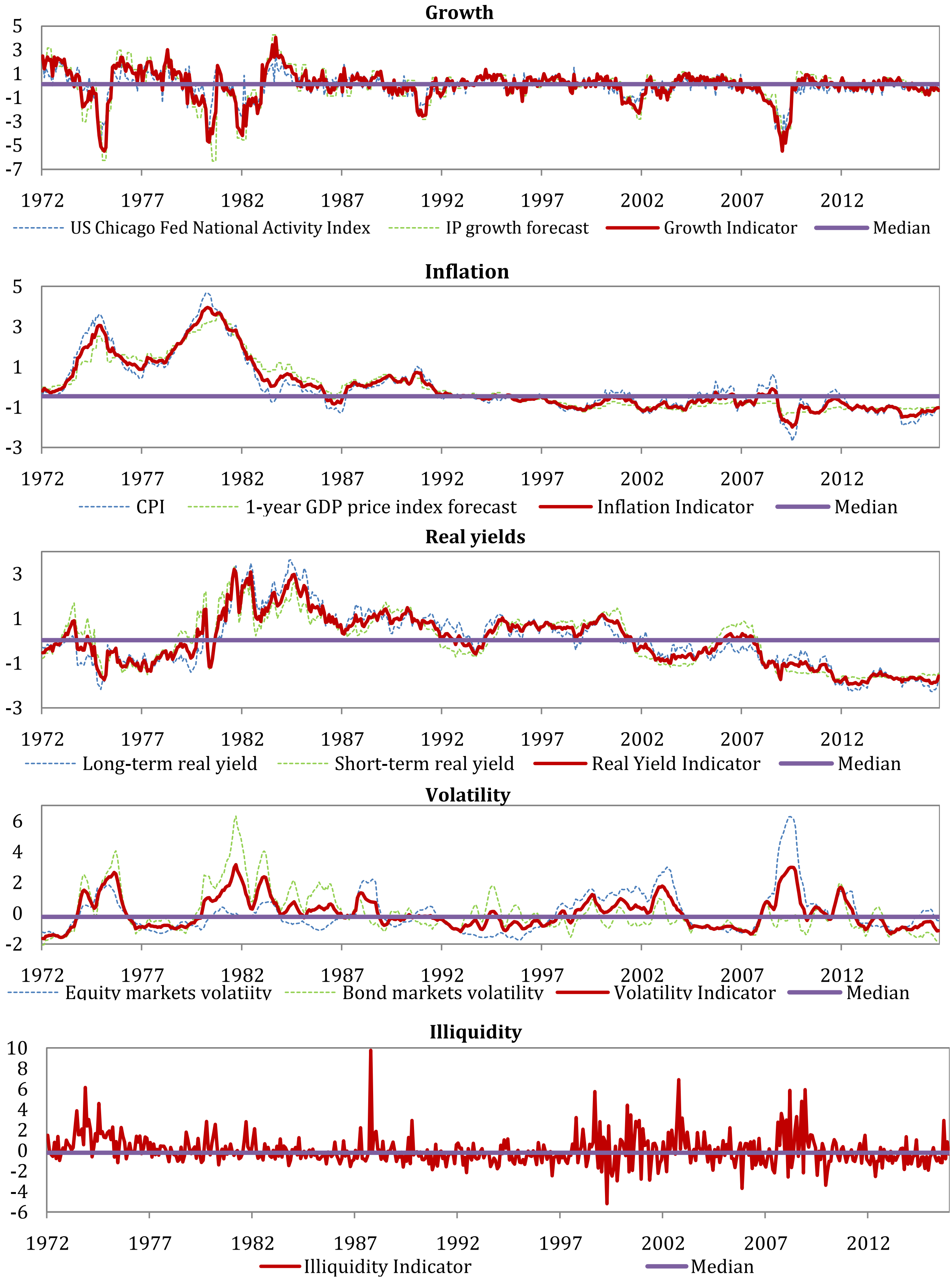
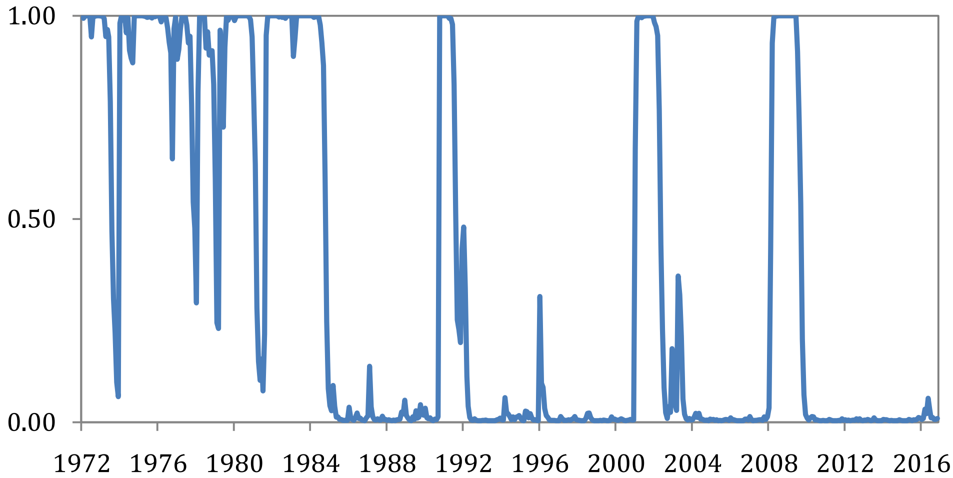


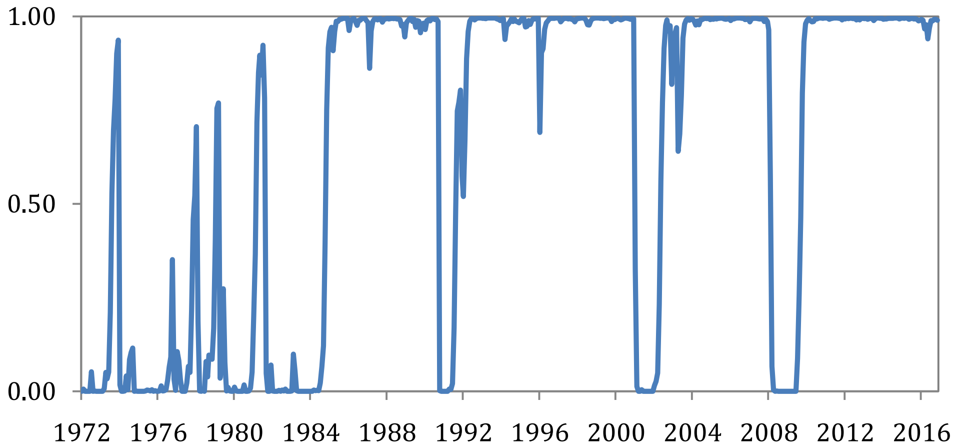
**Figure 2**

**Markov switching filtered regime probabilities for growth**

**P(($S_t$)=Down Regime)**




**P(($S_t$)=Up Regime)**




**Regime realization**

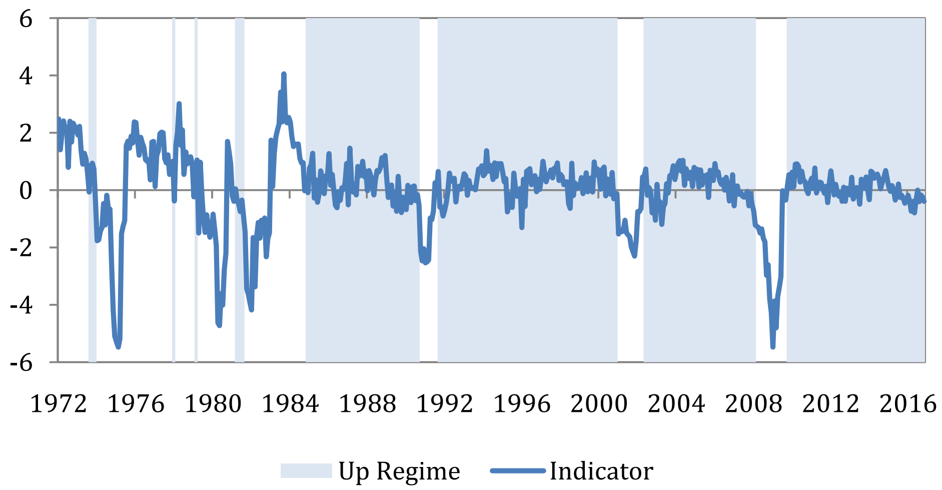
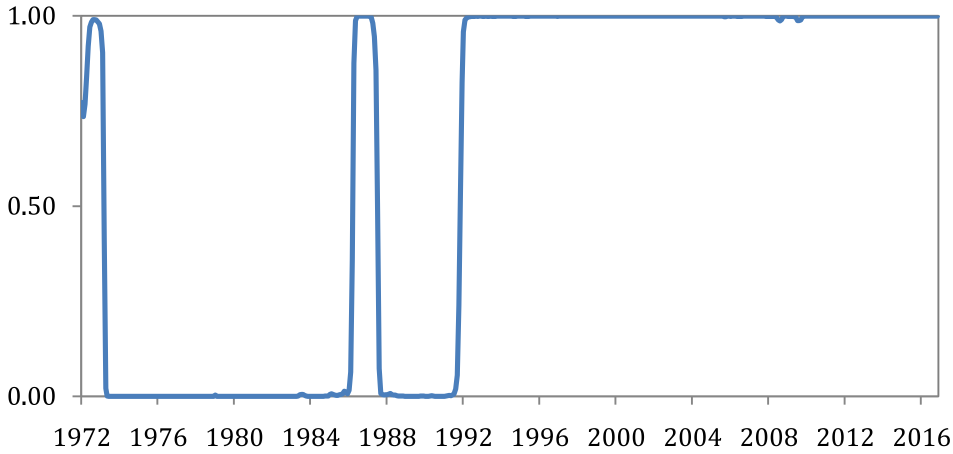


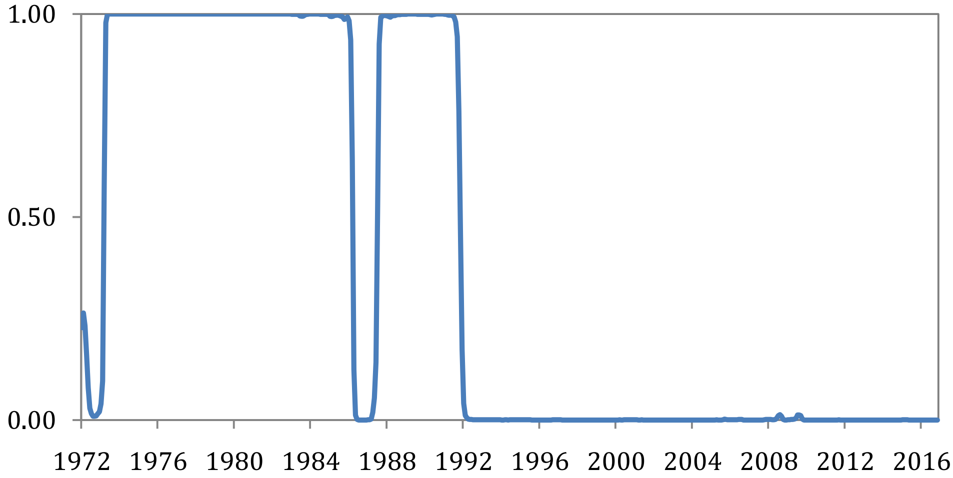
**Figure 3**

**Markov switching filtered regime probabilities for inflation**

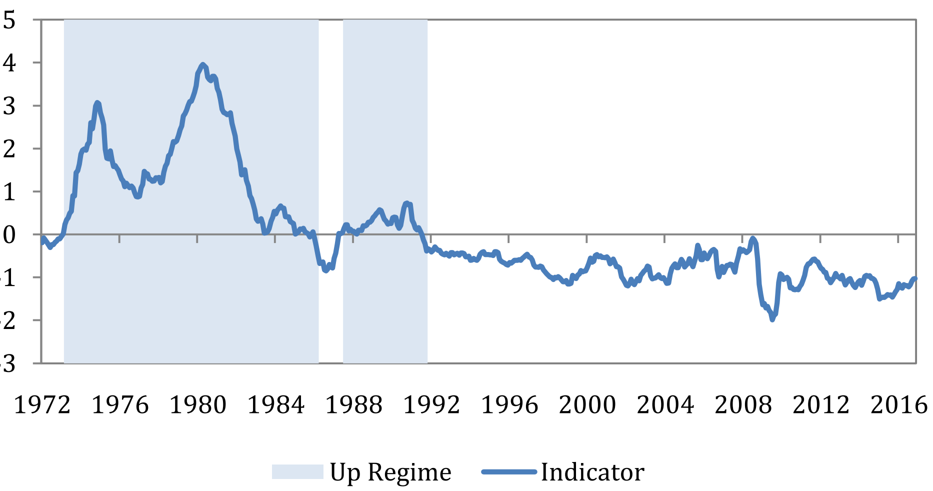
**P(($S_t$)=Down Regime)**




**P(($S_t$)=Up Regime)**

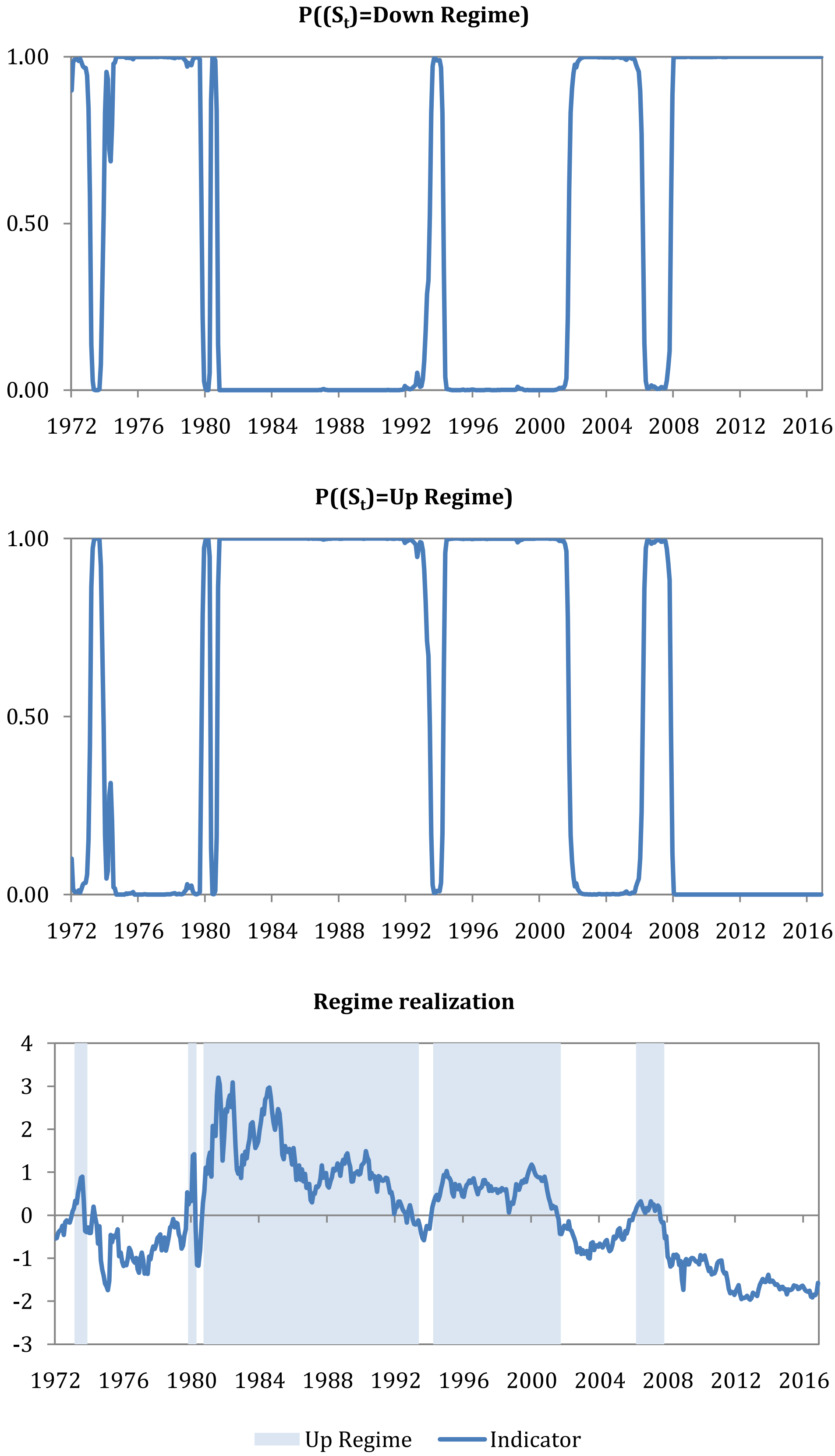



**Regime realization**



## Figure 4

## Markov switching filtered regime probabilities for real yields



## Figure 5

## Markov switching filtered regime probabilities for volatility

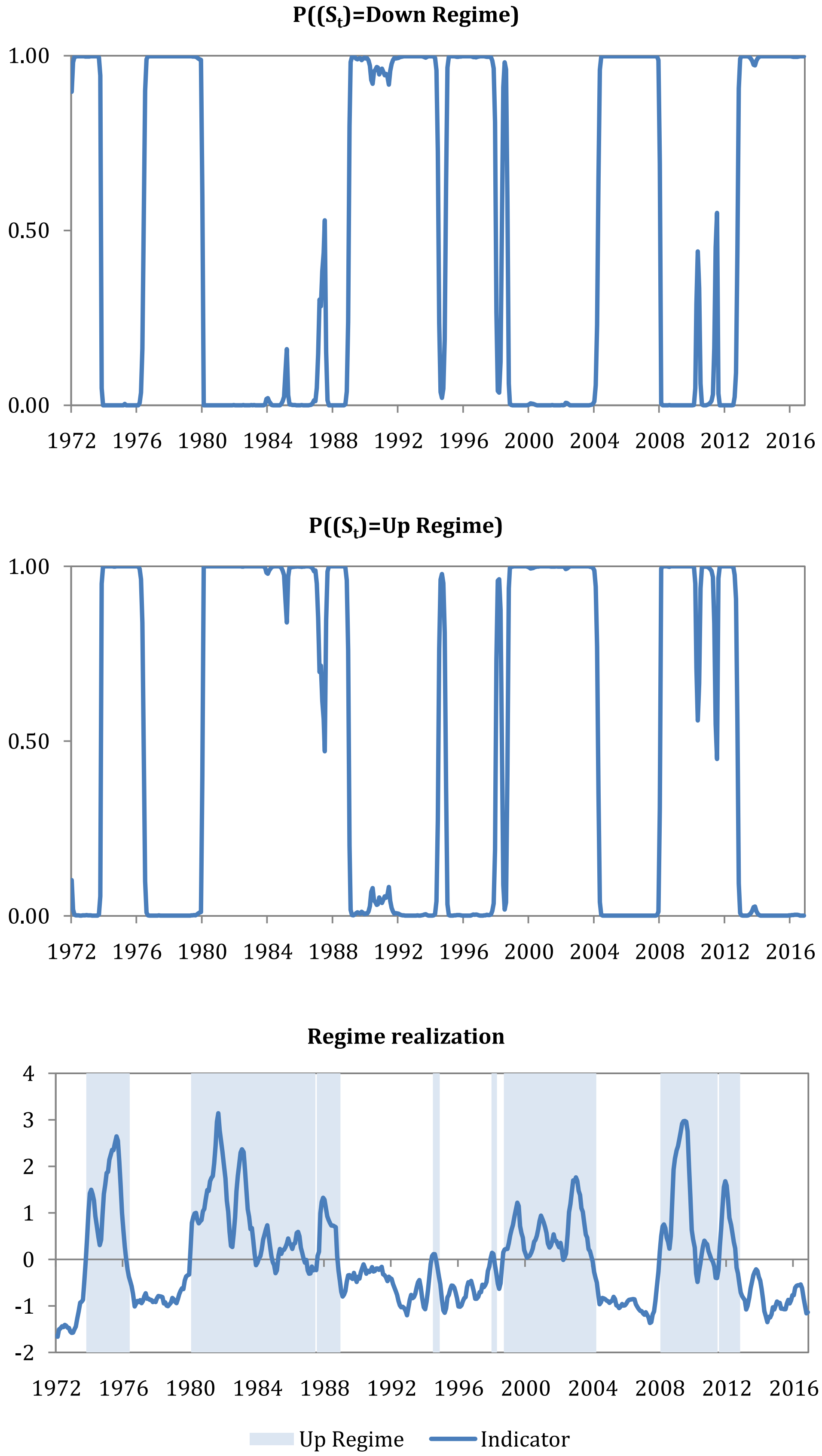
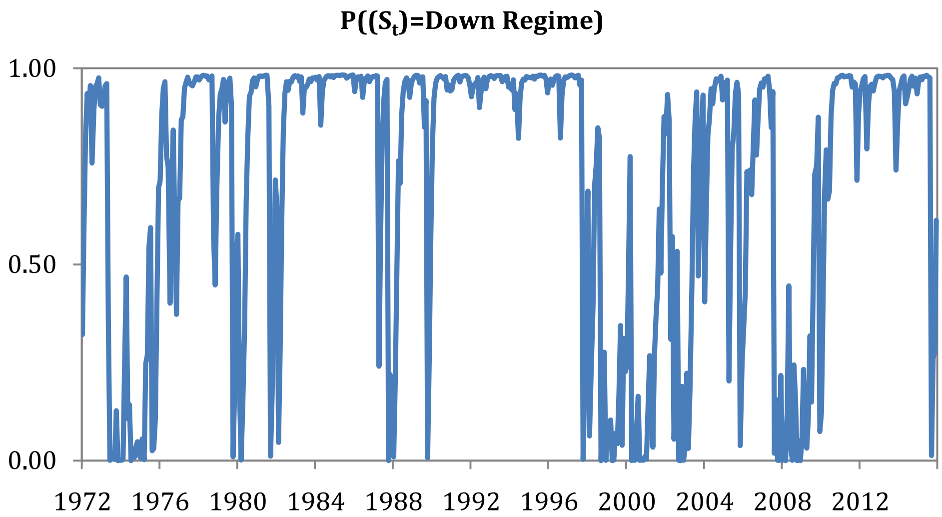
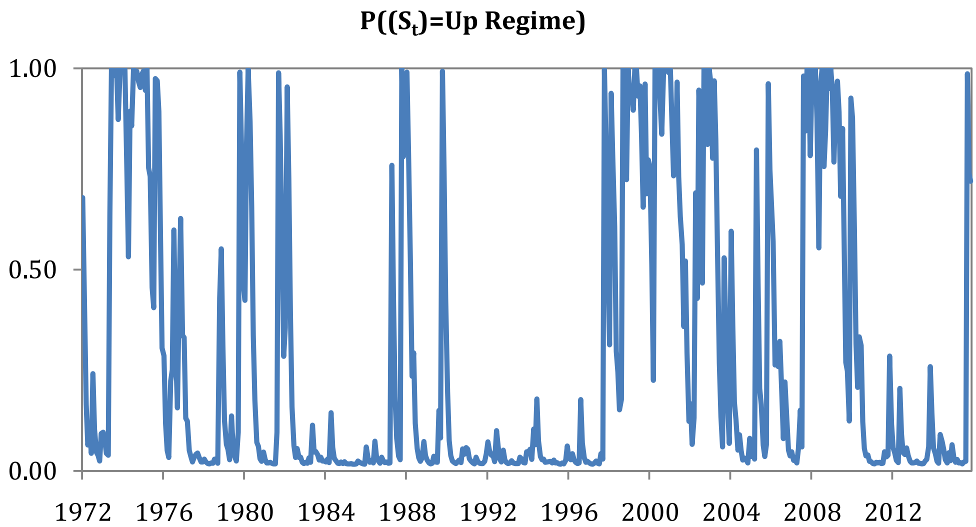
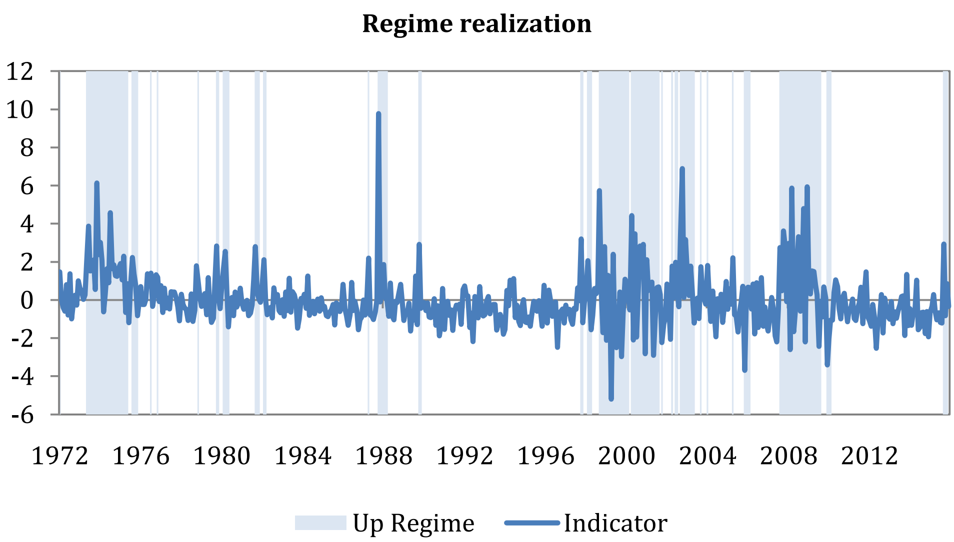


**Figure 6**

**Markov switching filtered regime probabilities for illiquidity**

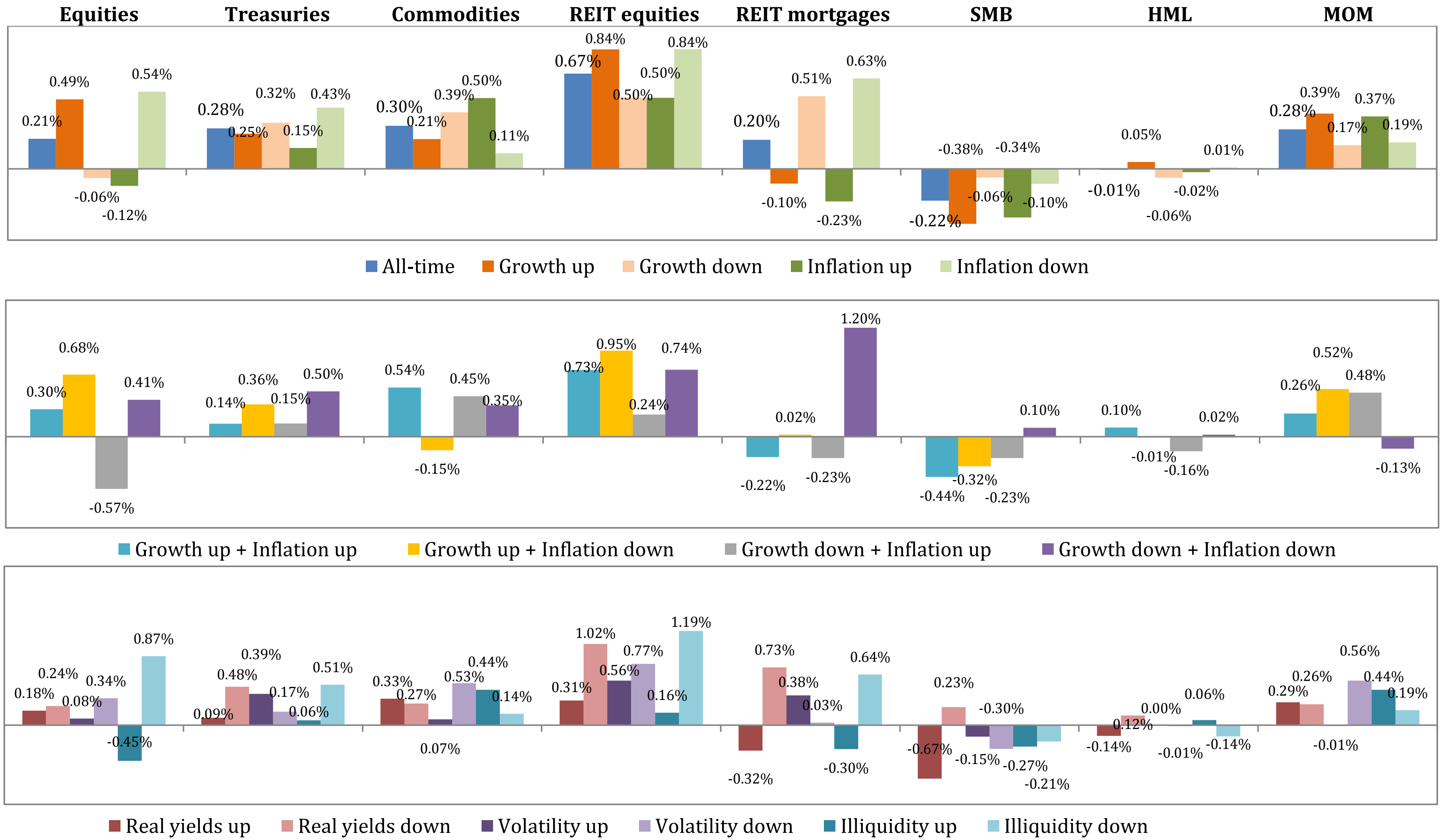


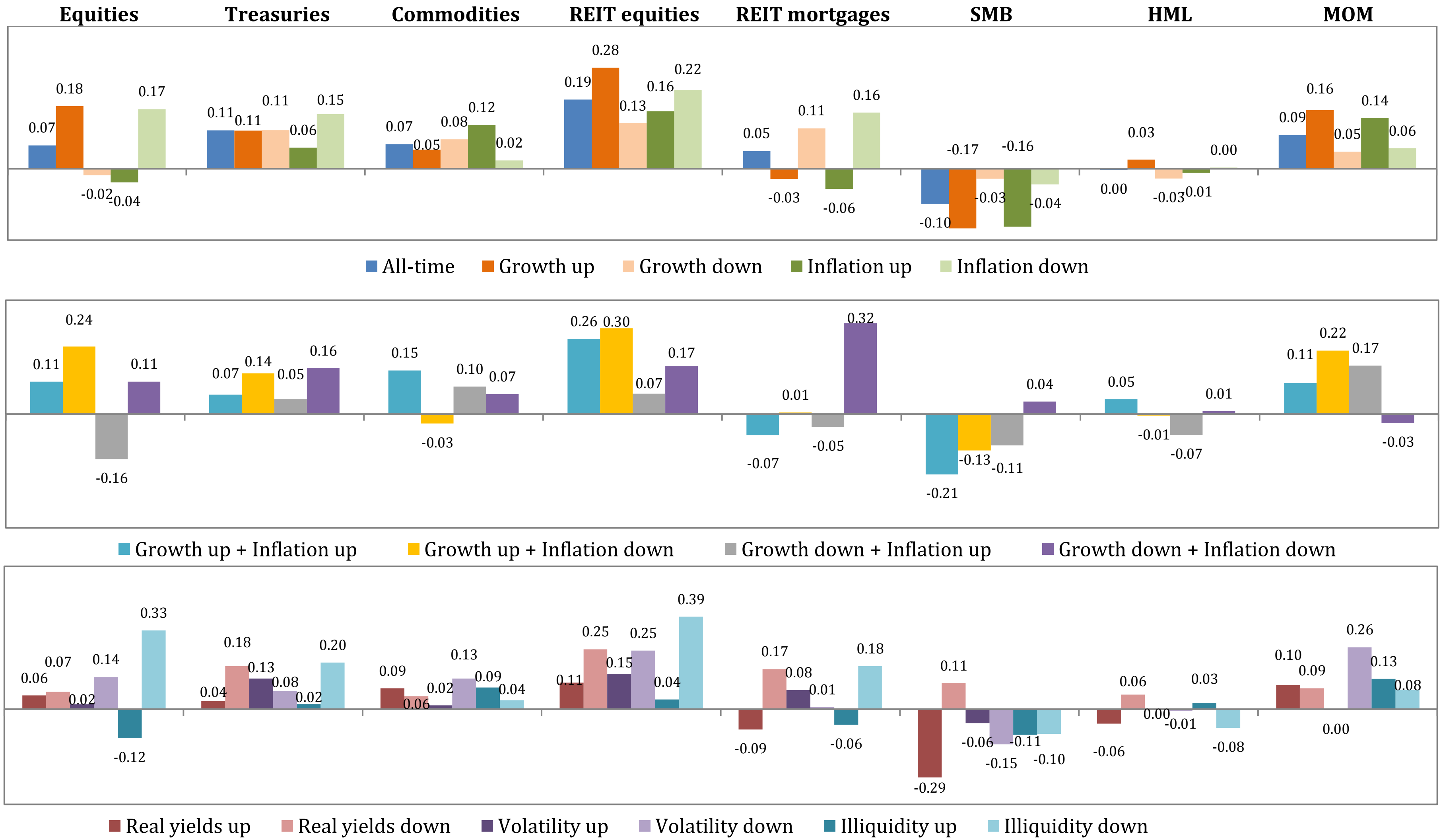
## Figure 7

## Mean excess returns of main assets in each macroeconomic environment defined by median



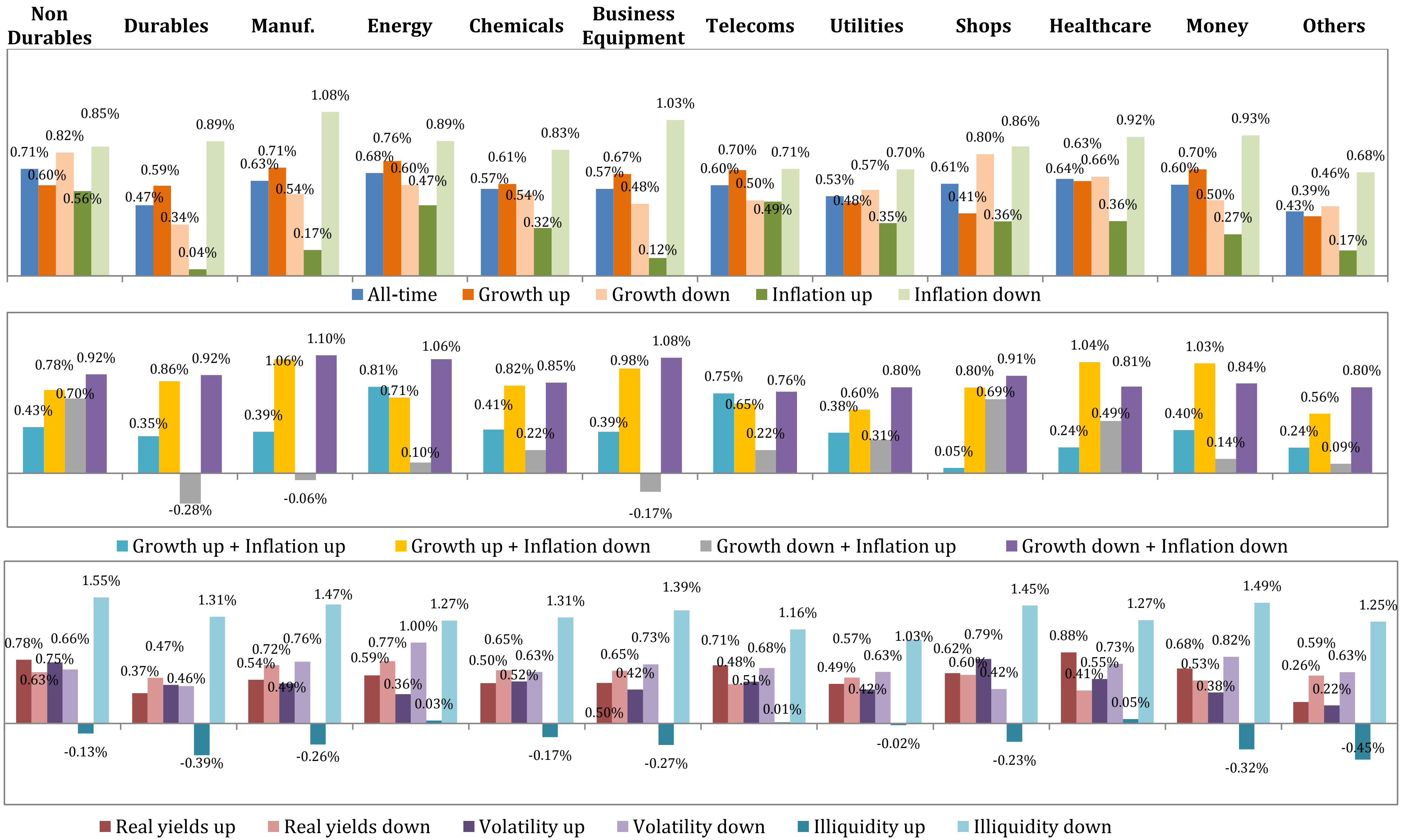
## Figure 8

## Sharpe ratios of main assets in each macroeconomic environment defined by median



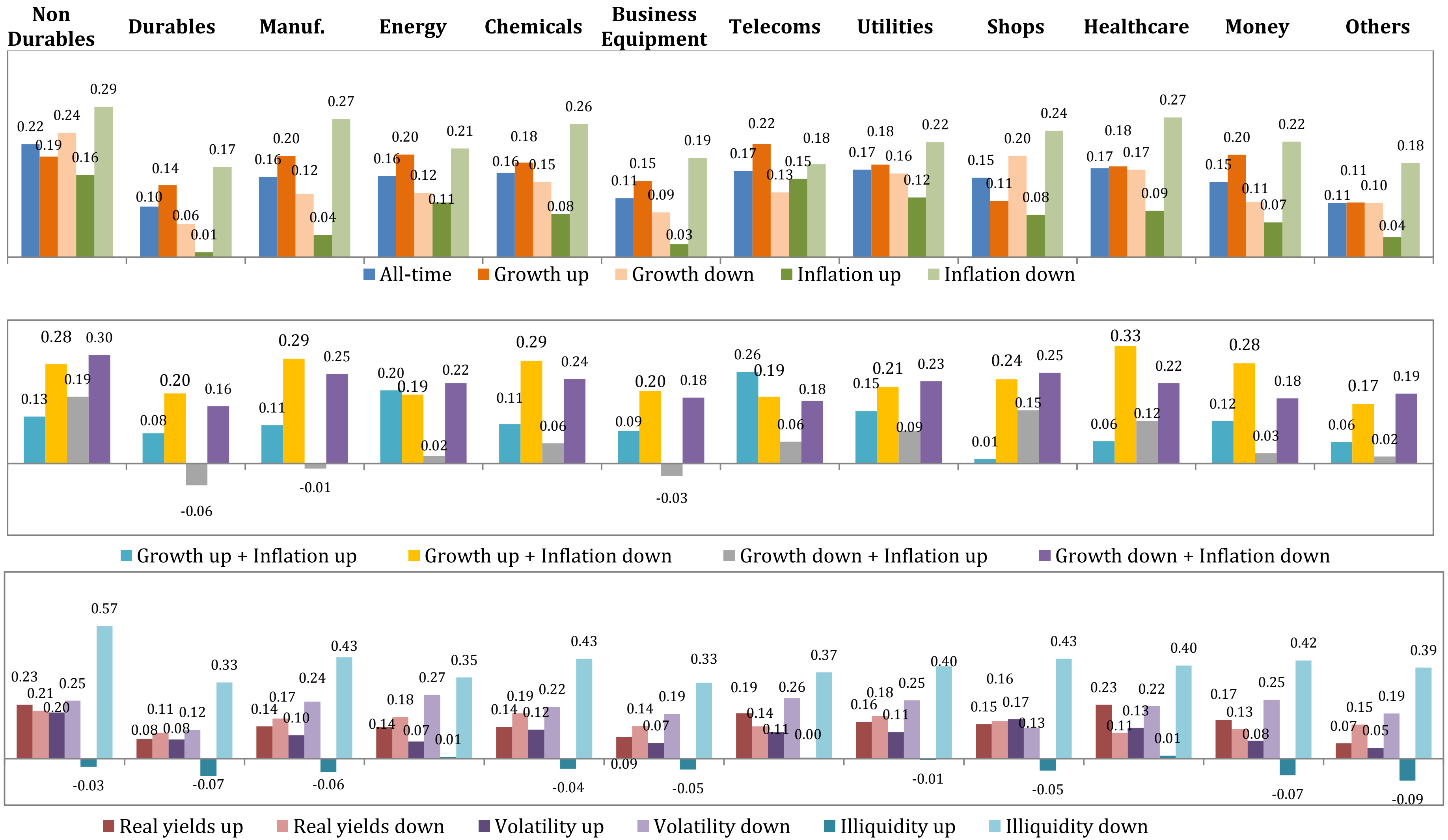
## Figure 9

## Mean excess returns of industry portfolios in each macroeconomic environment defined by median



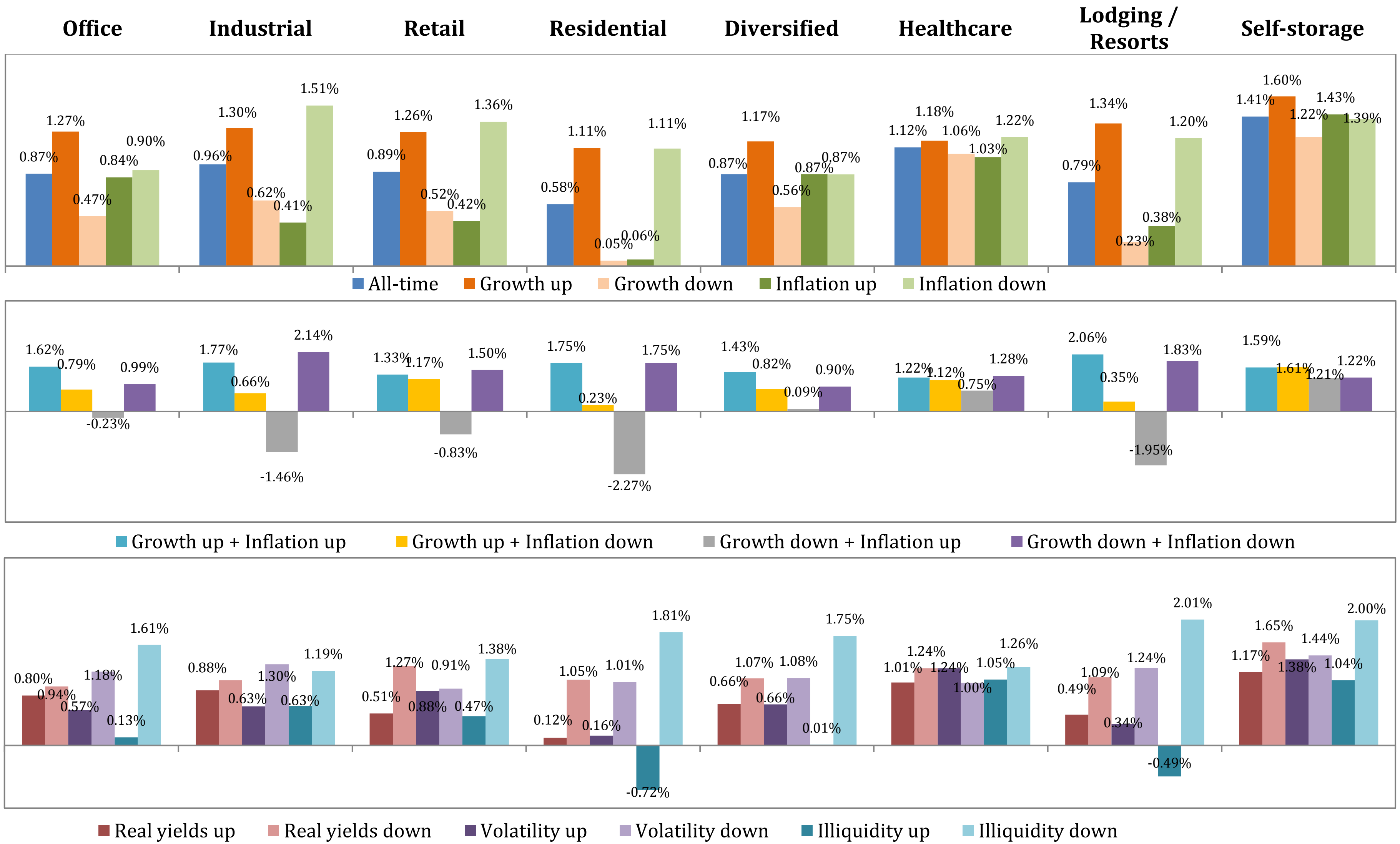
## Figure 10

**Sharpe ratios of industry portfolios in each macroeconomic environment defined by median**



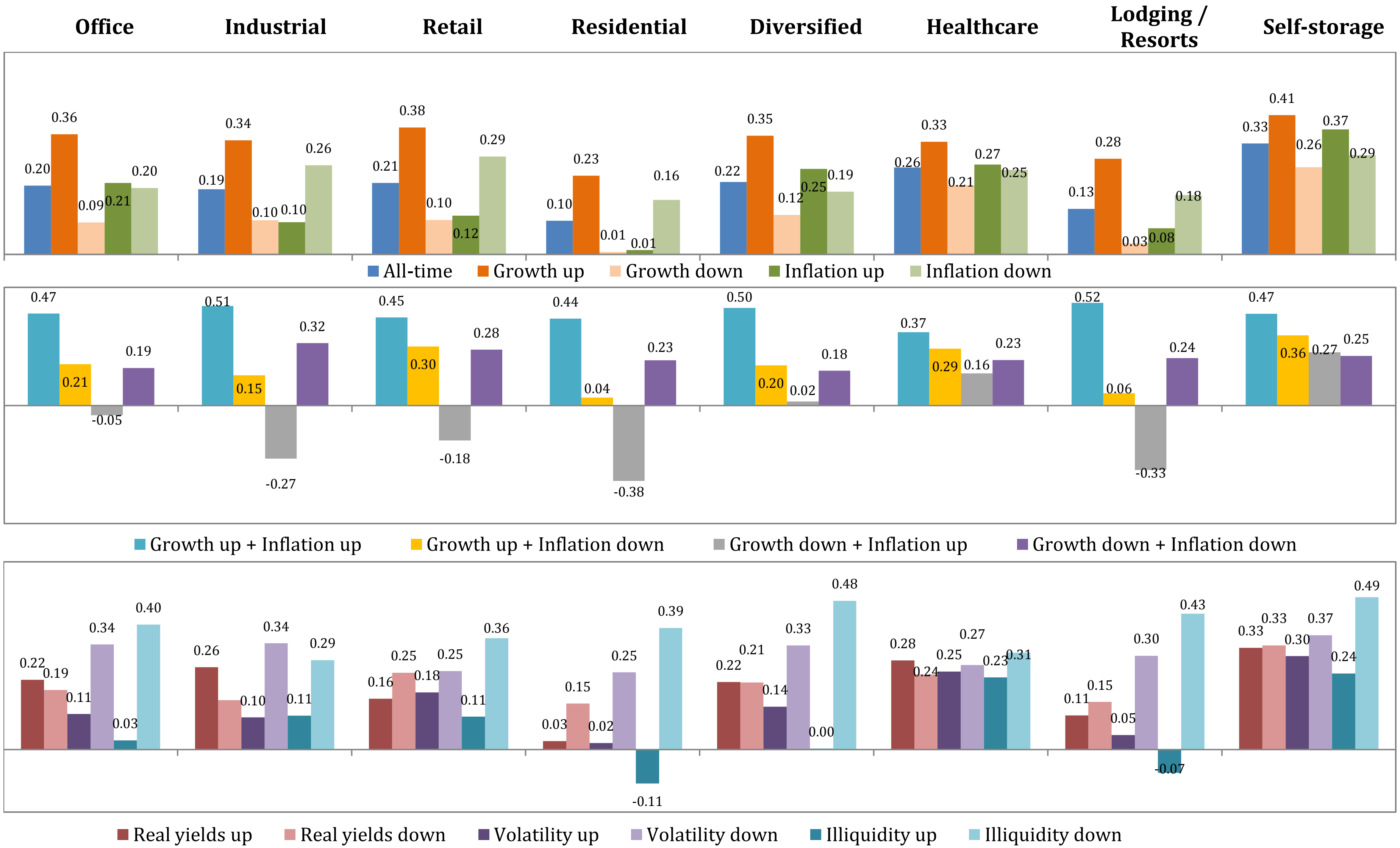
## Figure 11

**Mean excess returns of REIT equity sectors in each macroeconomic environment defined by median**



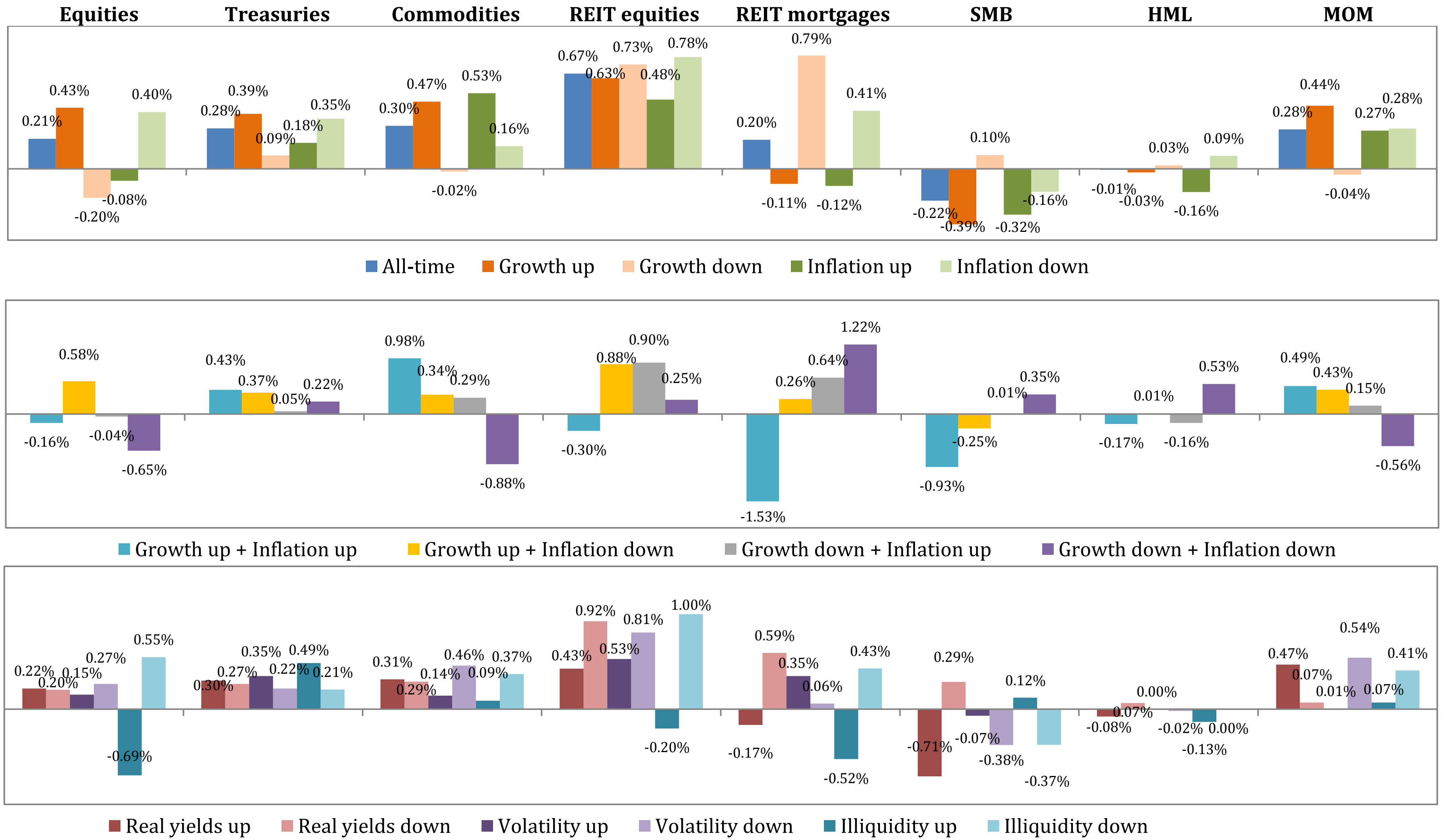
## Figure 12

**Sharpe ratios of REIT equity sectors in each macroeconomic environment defined by median**



# Figure 13

## Mean excess returns of main assets in each macroeconomic environment defined by MS



## Figure 14

### Sharpe ratios of main assets in each macroeconomic environment defined by MS

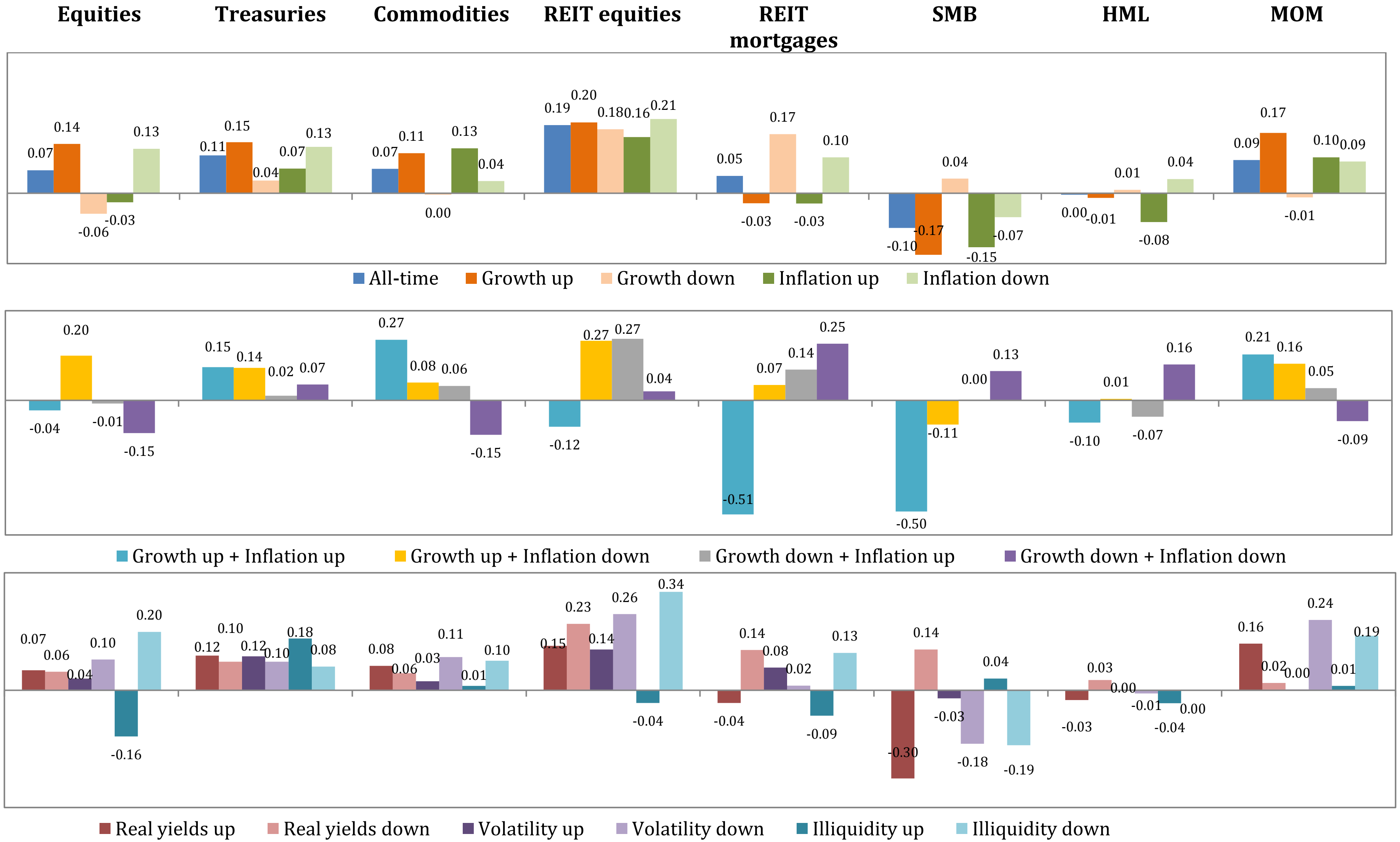
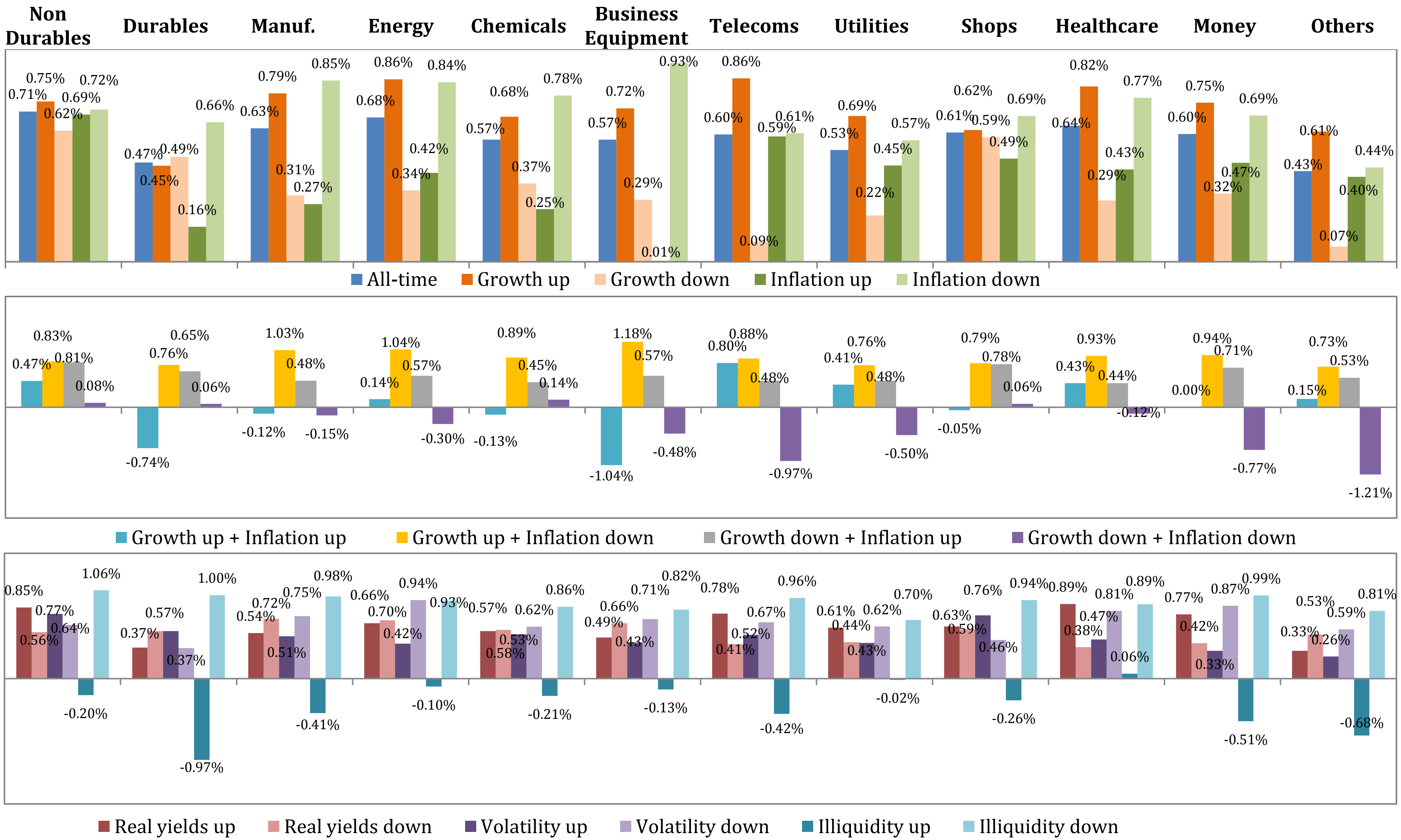


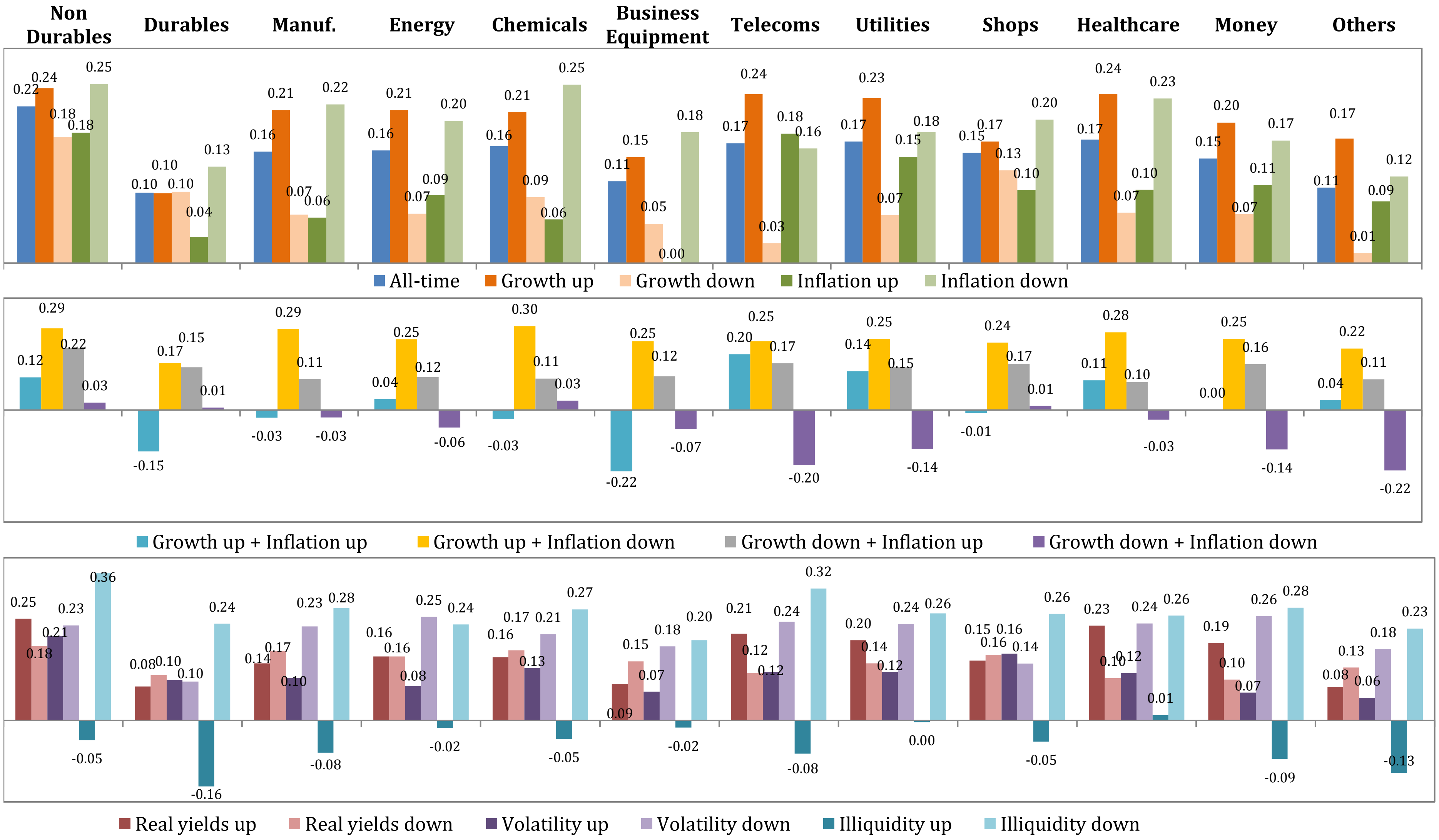
**Figure 15**

**Mean excess returns of industries in each macroeconomic environment defined by MS**



## Figure 16

## Sharpe ratios of industry portfolios in each macroeconomic environment defined by MS



## Figure 17

### Mean excess returns of REIT equity sectors in each macroeconomic environment defined by MS

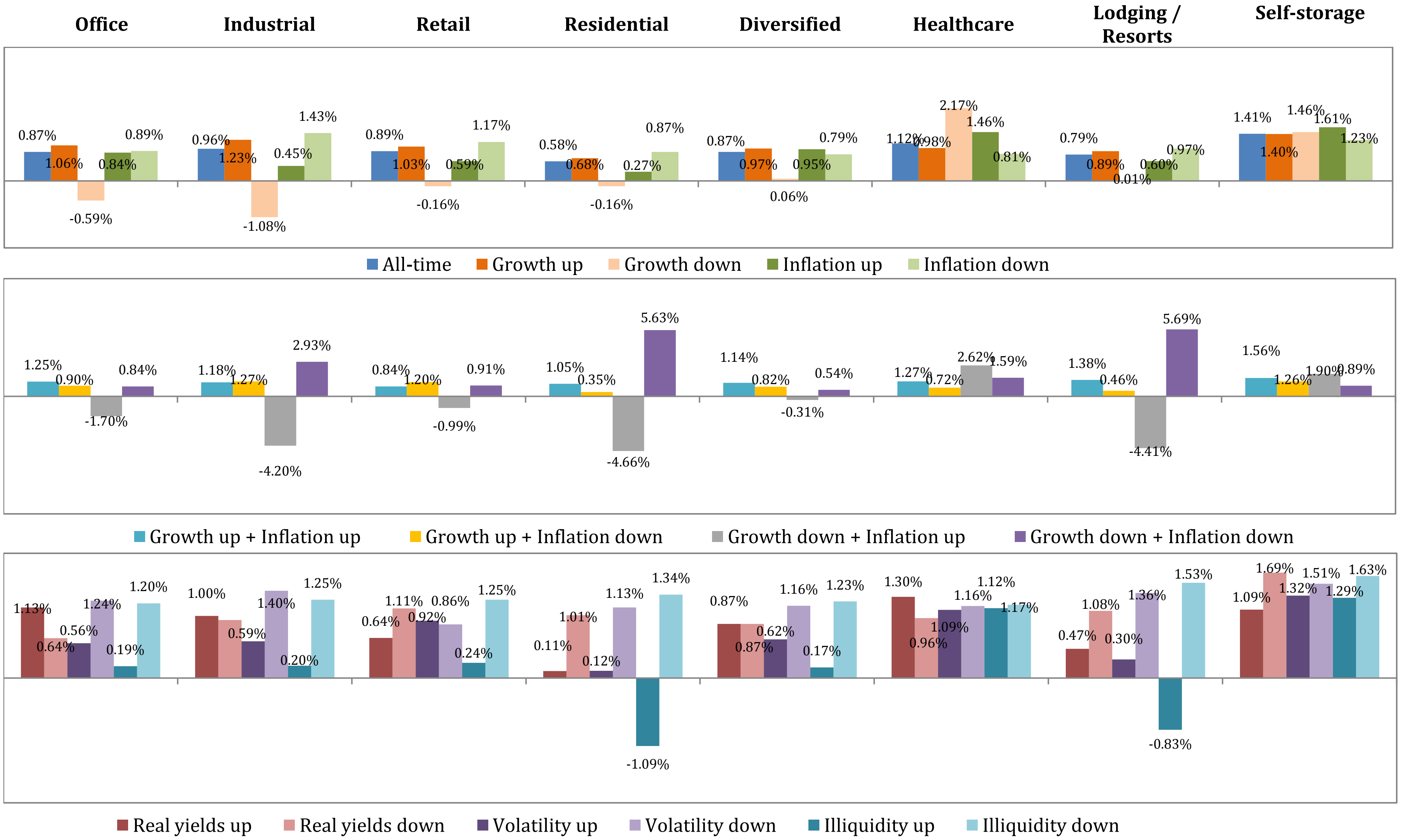
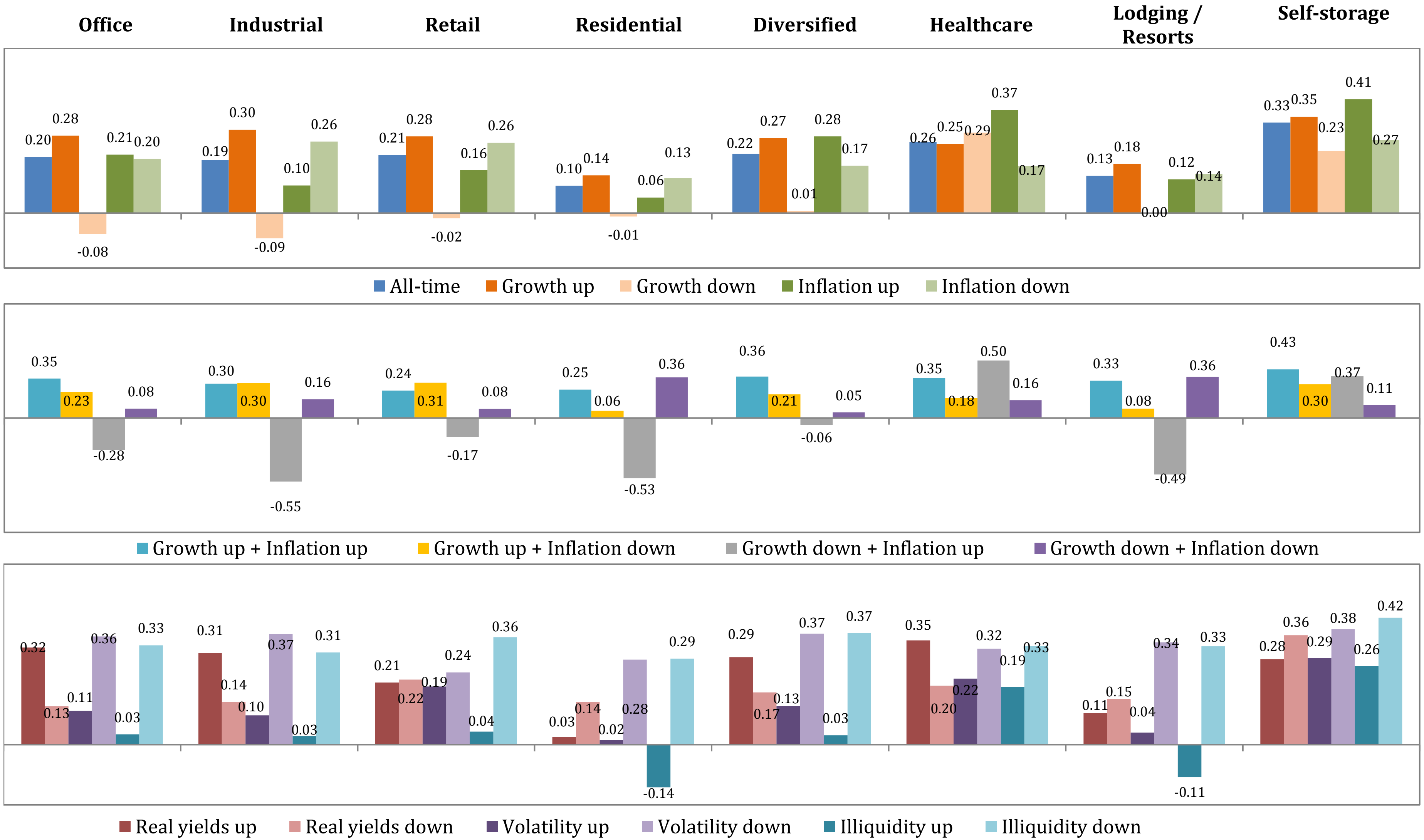


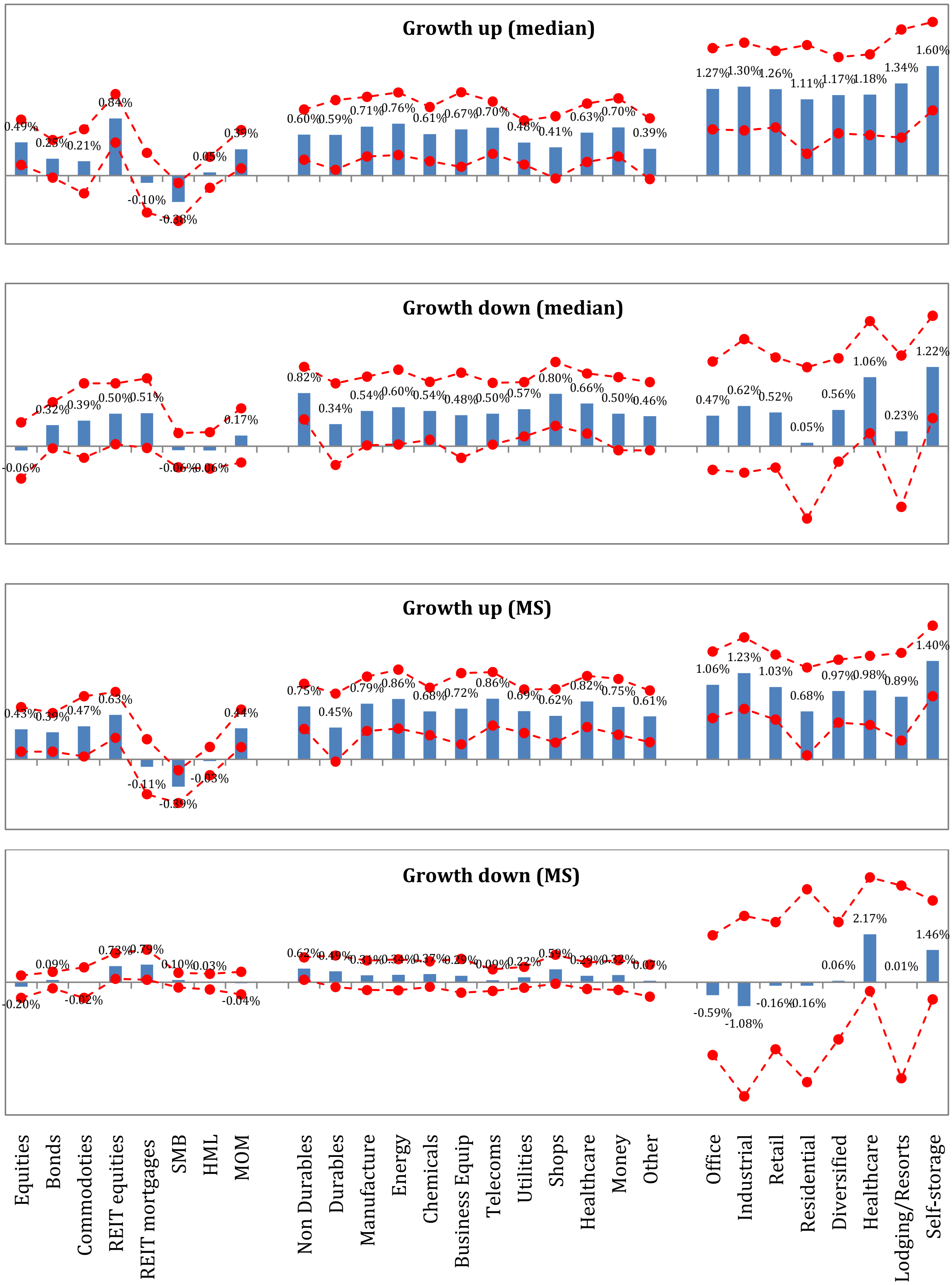
**Figure 18**

**Sharpe ratios of REIT equity sectors in each macroeconomic environment defined by MS**

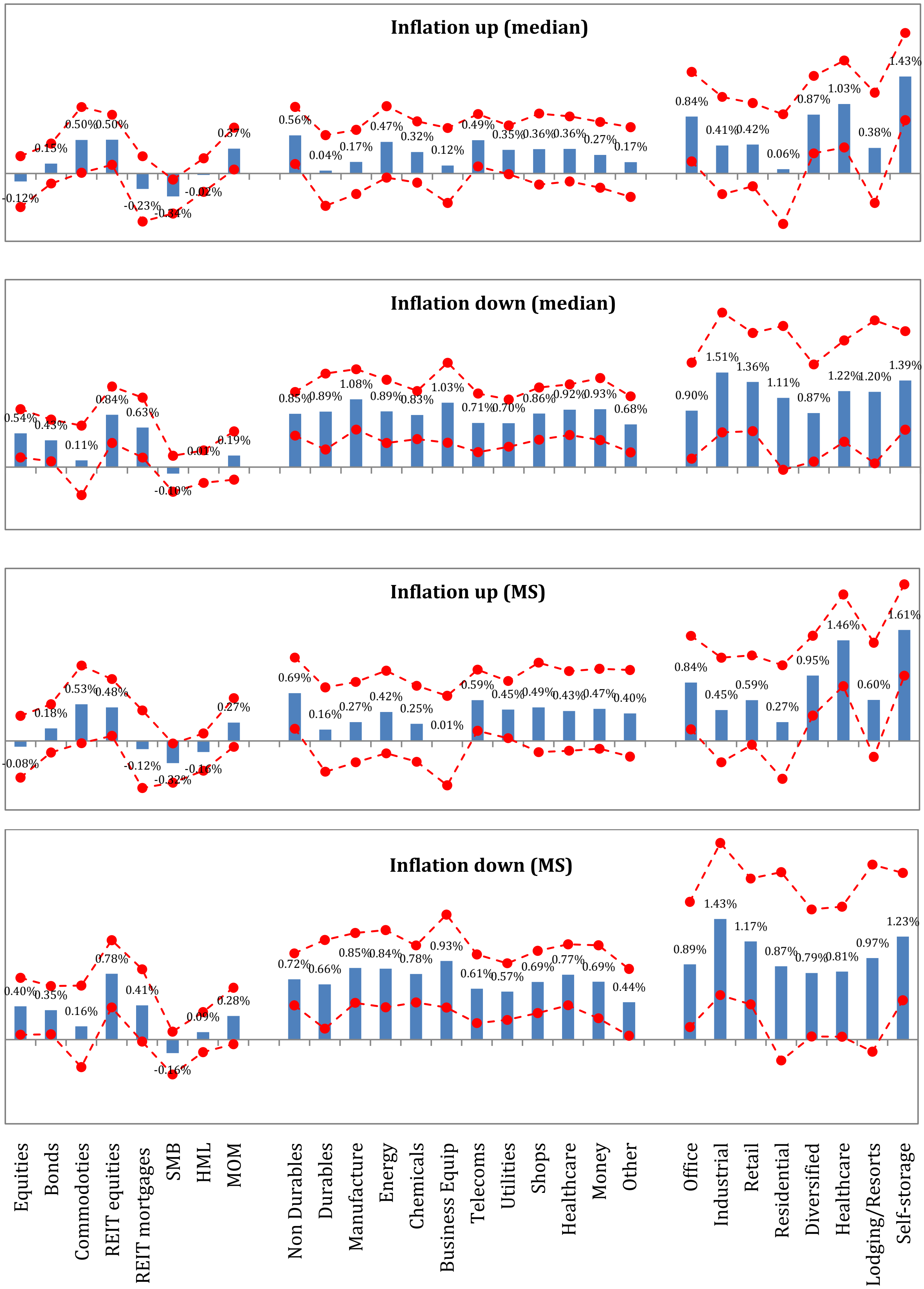


## Figure 19

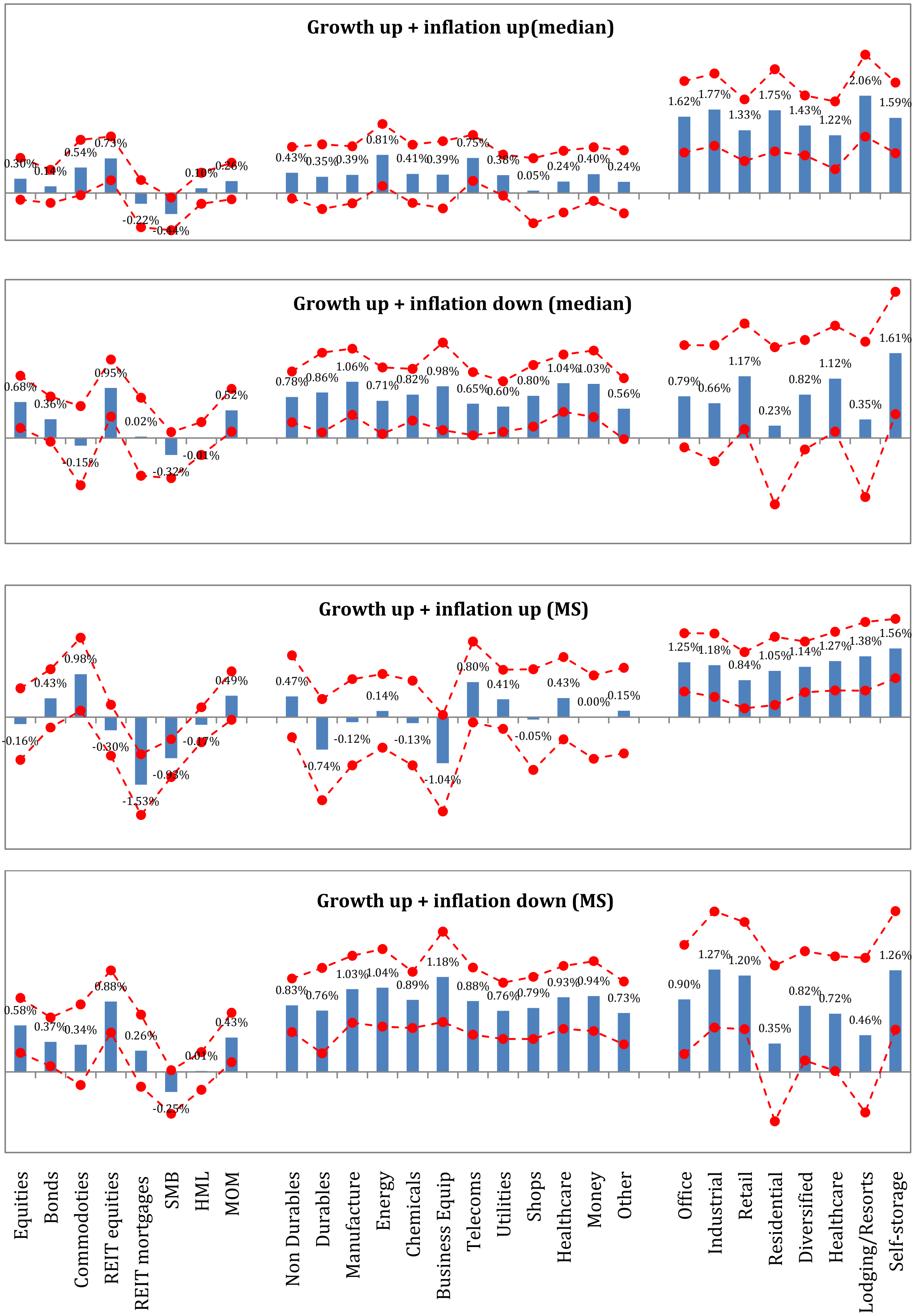
## Mean excess returns and their 95% upper and lower bounds



## Figure 19 (continue)



## Figure 19 (continue)



## Figure 19 (continue)

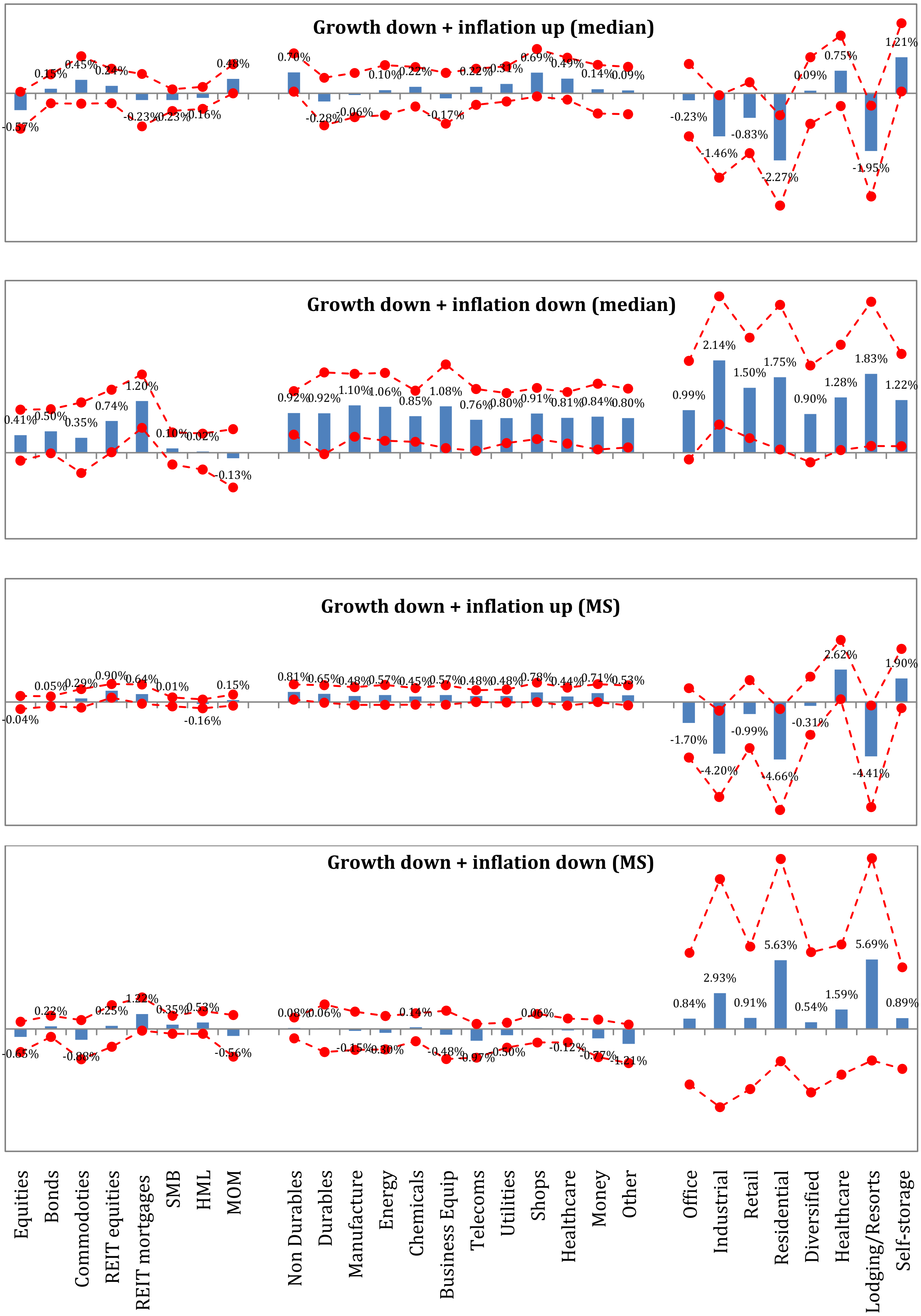


**Figure 19 (continue)**

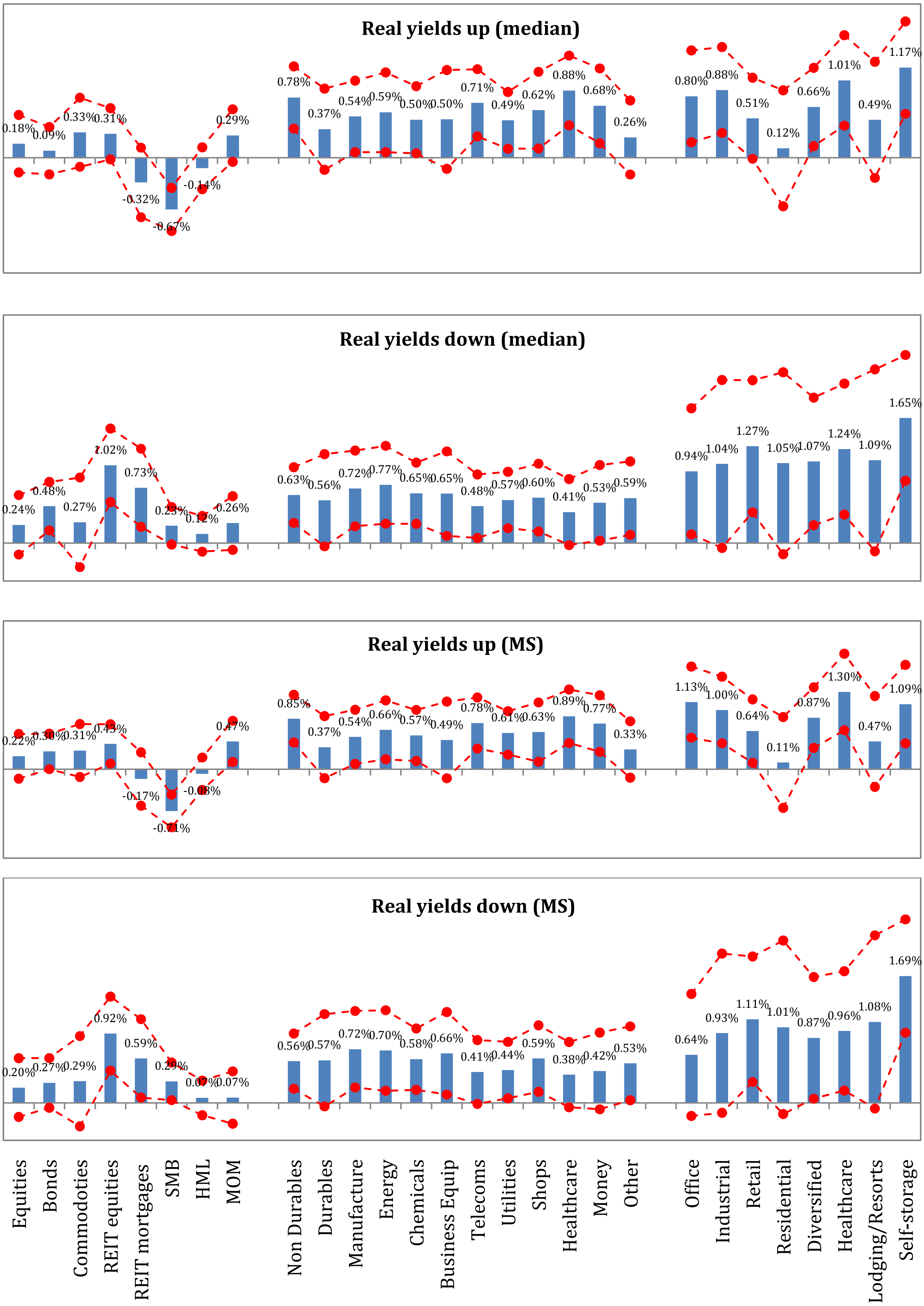
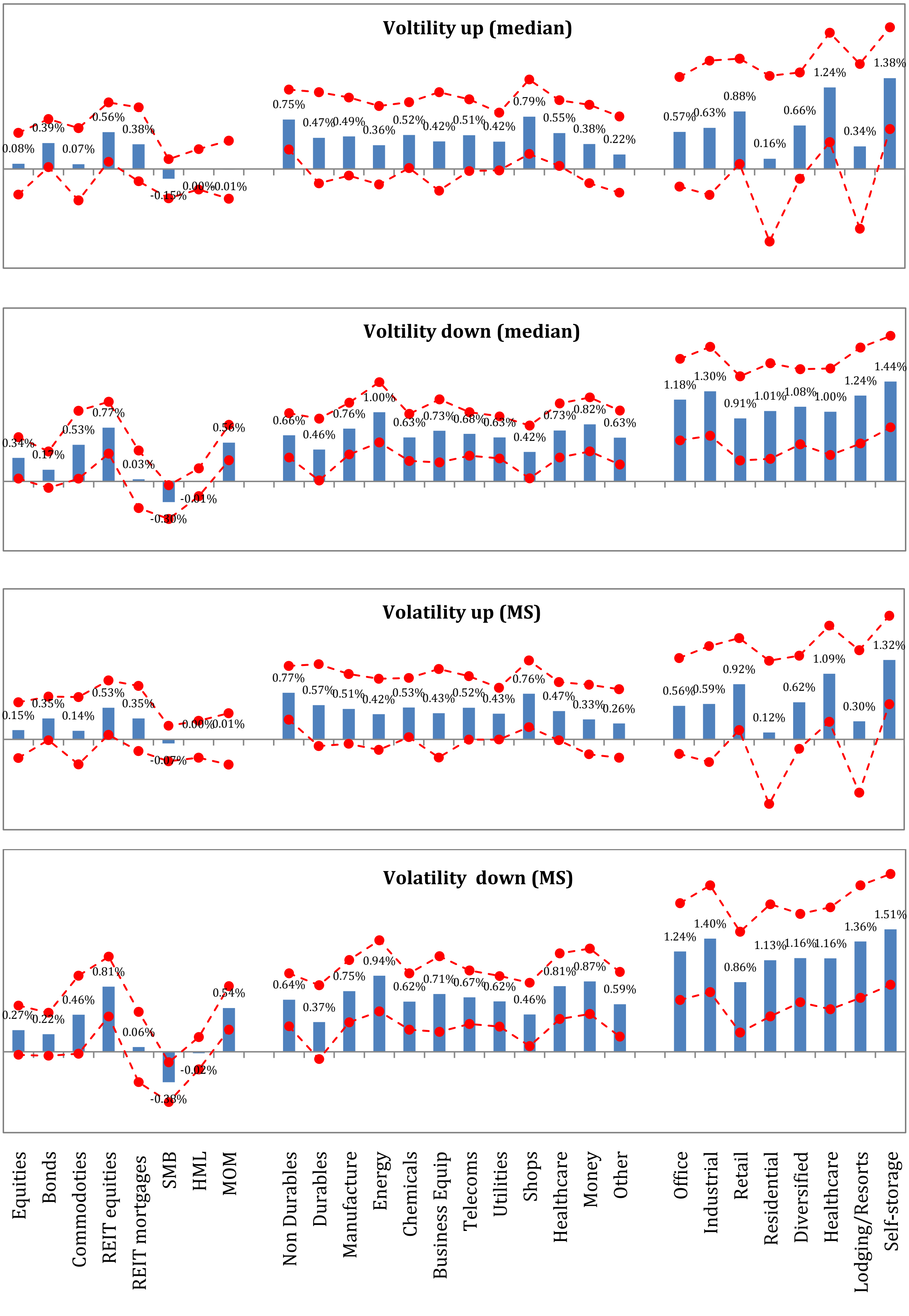
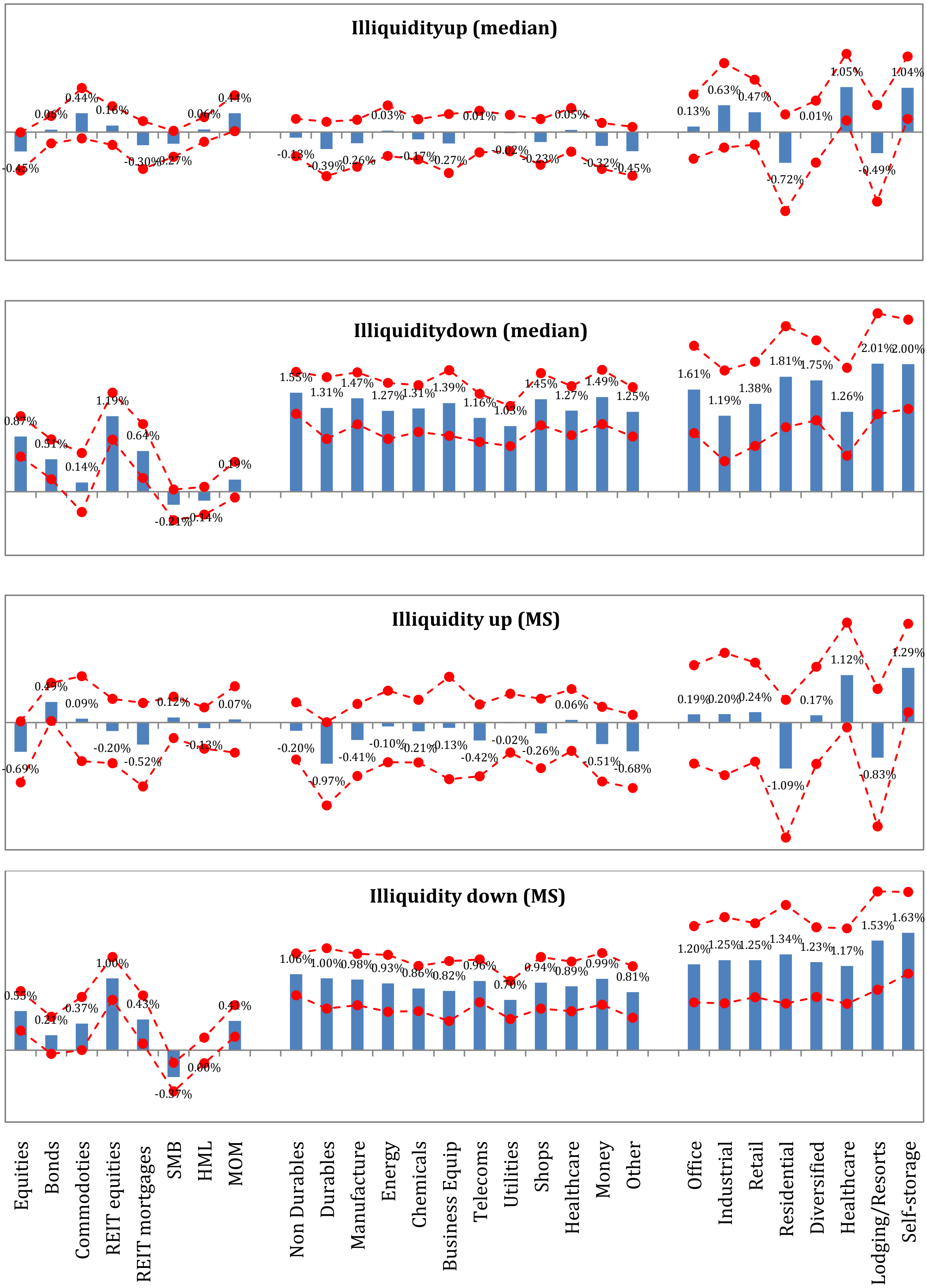


**Figure 19 (continue)**

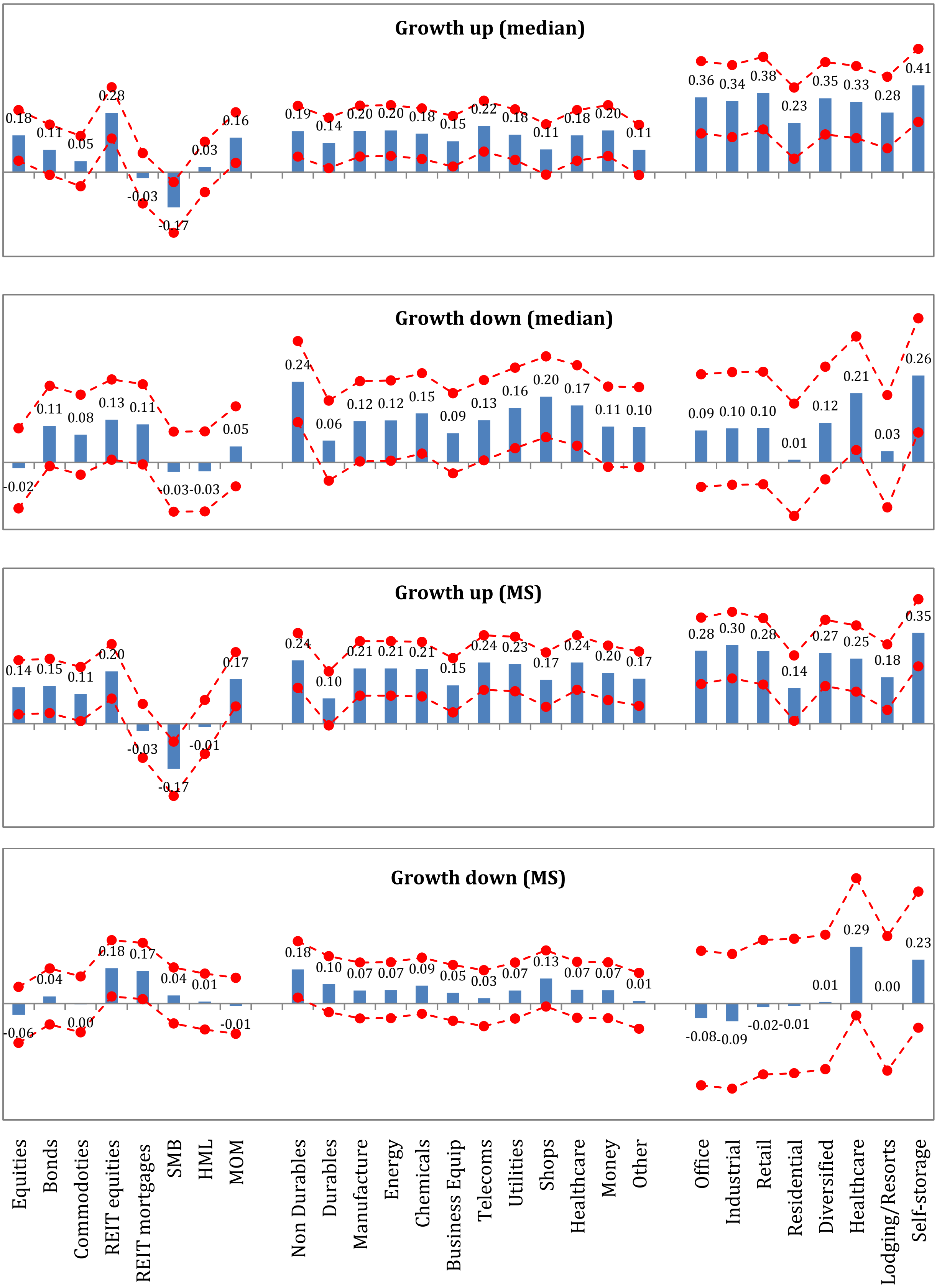


## Figure 19 (continue)

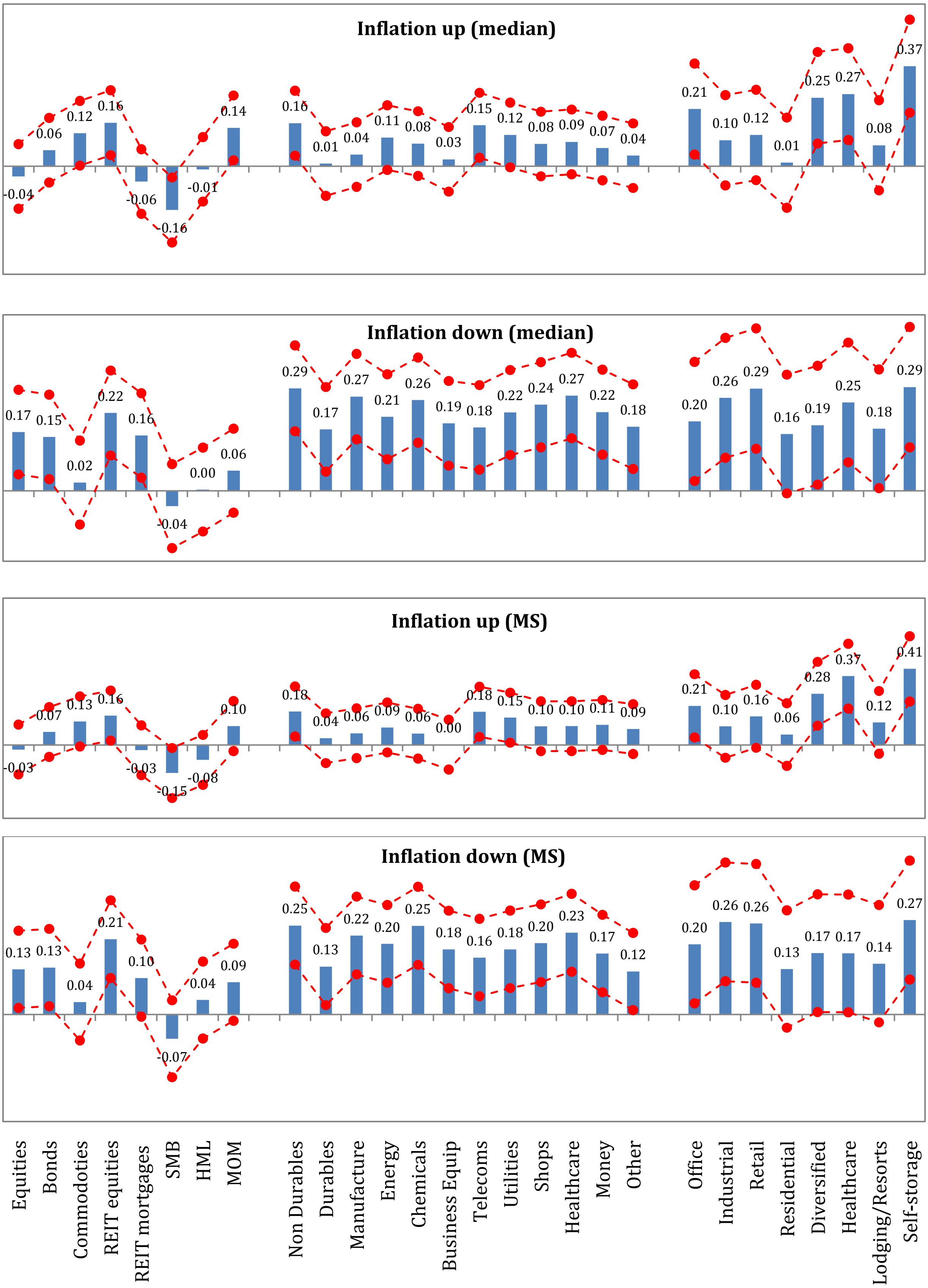


## Figure 20

## Sharpe ratios and their 95% upper and lower bounds



## Figure 20 (continue)



## Figure 20 (continue)

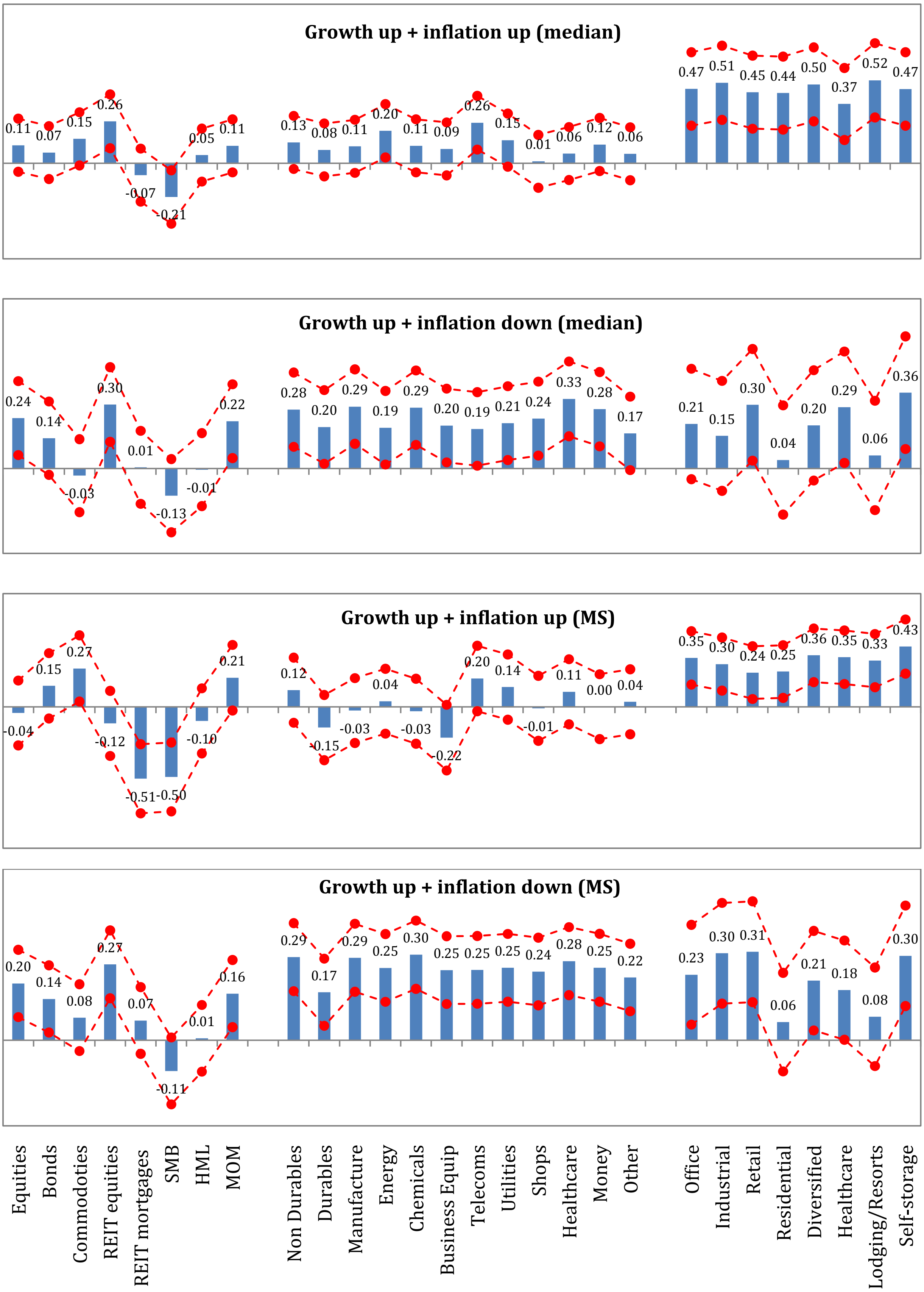
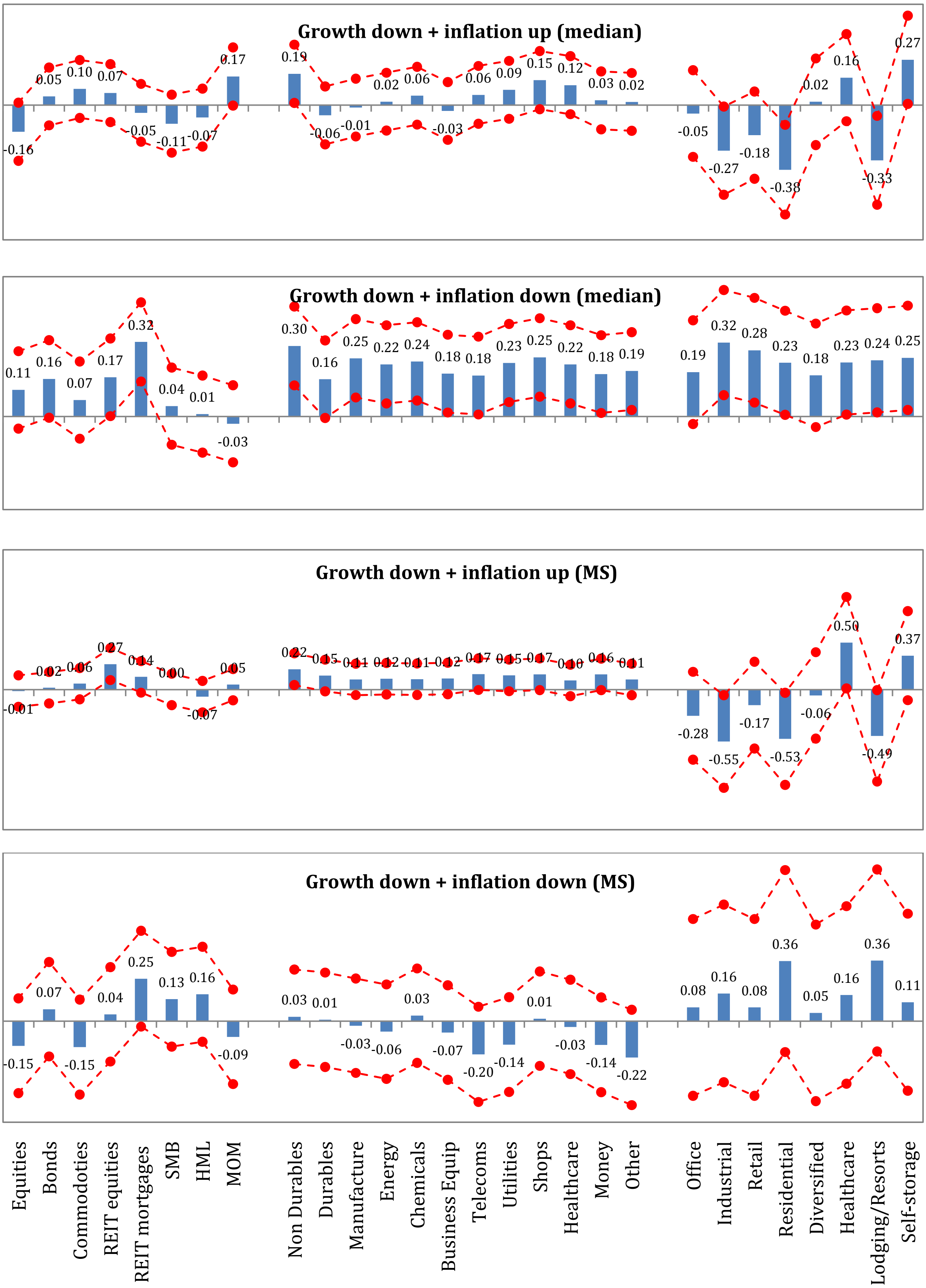
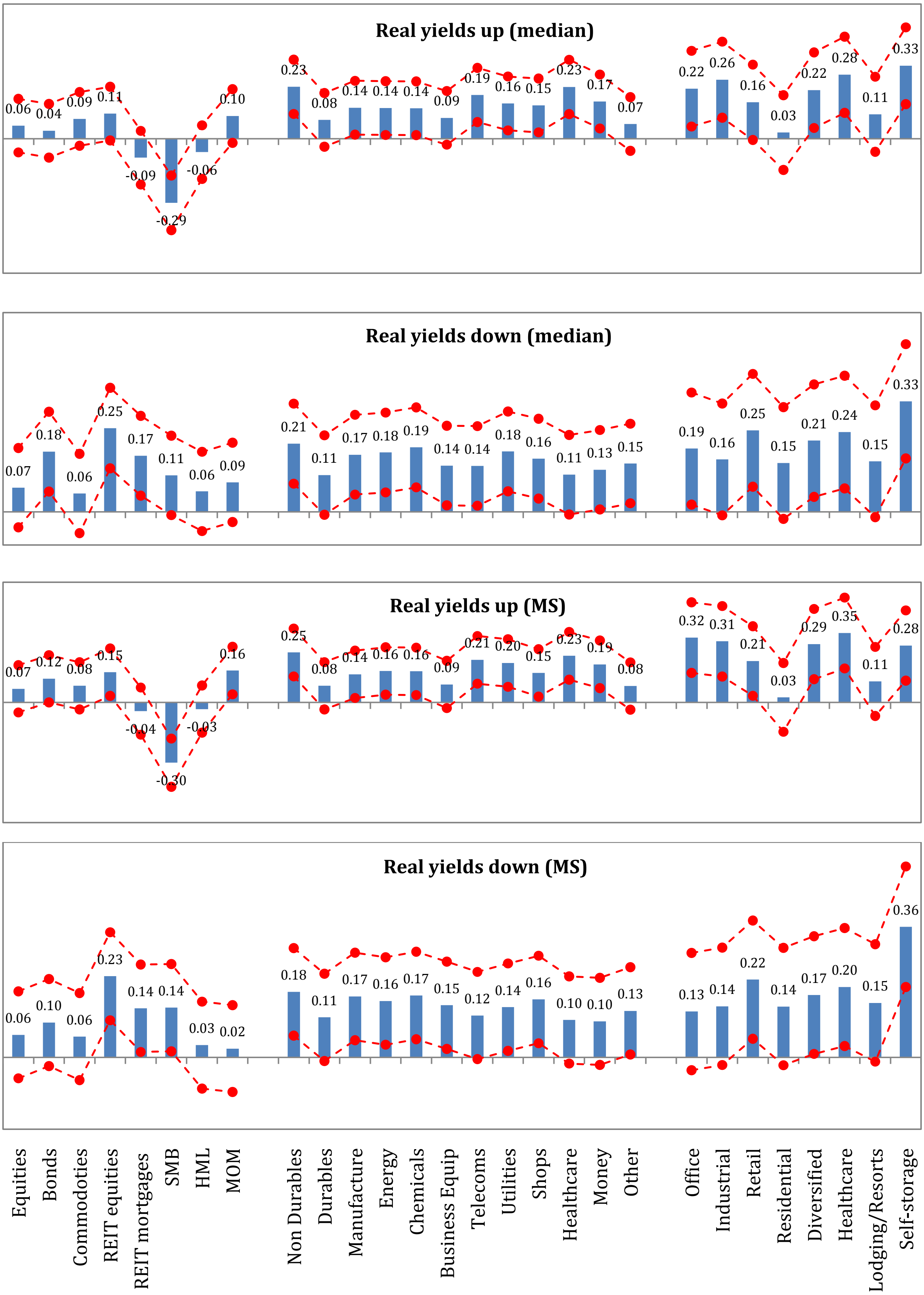


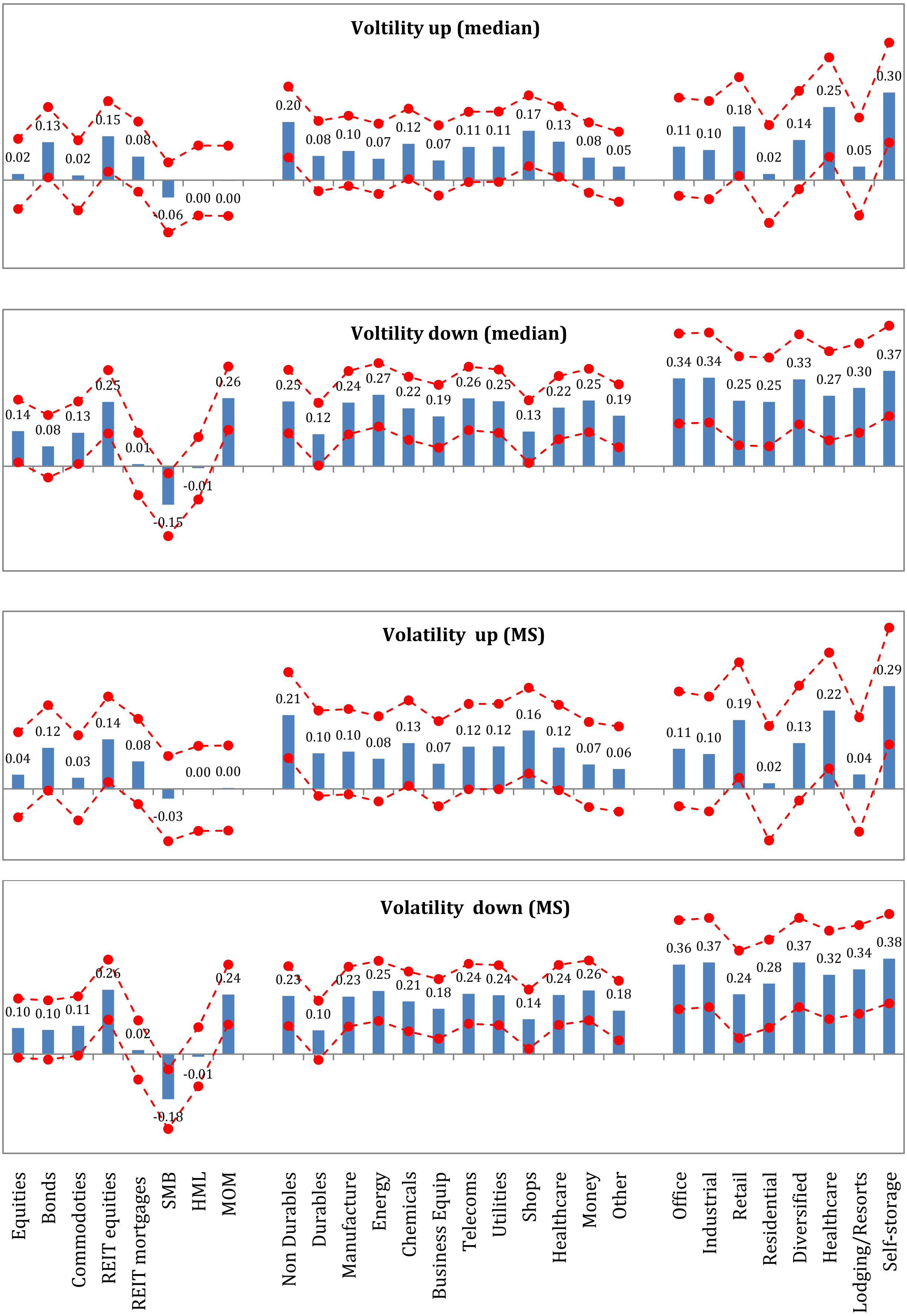
**Figure 20 (continue)**



## Figure 20 (continue)



## Figure 20 (continue)



## Figure 20 (continue)