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# CASMEF Working Paper Series

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Working Paper No. 6
November 2017

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# Can hedge funds time the market?

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**Abstract**

We answer the somewhat narrower question of whether hedge funds adjust their conditional market exposure in response to real-time changes in macroeconomic conditions, and whether doing so improves their performance. We find that hedge funds differ substantially in their responsiveness to macroeconomic data. The most pro-cyclical market timers outperform their less active and counter-cyclical peers by over four percent annualized with a risk adjusted alpha of 5.5 percent.

**JEL classification:** E32, G11, G20
**Keywords:** nowcasting, business cycle, hedge funds, market timing

# 1 Introduction

Hedge funds represent the most sophisticated, in terms of information processing, as well as flexible, with regard to mandate, institutional investors today. Even so, there is an ongoing debate about whether the risk-adjusted performance of hedge funds warrants their relatively high fees. We contribute to this debate by evaluating empirically whether equity focused hedge funds, as a whole or certain subgroups, tactically vary their equity market exposure in response to real-time information about changes in macroeconomic conditions, and whether doing so improves their performance.

We combine two recent literatures – research on the market timing ability of hedge funds with research on "nowcasting" changes in macroeconomic conditions. Chen and Lian (2007) find evidence of market timing ability focusing on a restricted group of hedge funds that are self-proclaimed market timers. Chen (2007) instead evaluates market timing ability for the "focus market" of hedge funds, defined as the single security a given hedge fund trades most actively.[1][2] Both studies consider market timing based on private and public information, where the latter is proxied by the usual suspects (e.g., dividend yield, term spread, credit spread). We study the whole cross-section of equity hedge funds and focus on a very specific set of public information – real-time economic data releases.

We use the economic nowcasting approach of Beber et al. (2015) to summarize the real-time information content of the cross-section of economic data releases for the United States. Their economic growth index is based on principal component analysis and aggregates information concerning macroeconomic activity. Specifically, it combines news about output, employment and macroeconomic sentiments (it excludes data on inflation, trade, public policy, and real estate). More importantly for the interpretation of our results, the economic growth index does not include revised data but it is based entirely on the flow of information as it becomes available in real time. Beber et al. (2015) show that the index has predictive power for future GDP releases and, despite being based exclusively on macroeconomic information, is correlated with financial markets.

We interpret this economic growth index as a proxy for the information a sophisticated data analyzer, such as today's hedge funds, could extract from the flow of economic data releases. We then adopt the conditional performance evaluation framework of Ferson and Schadt (1996) (see also Christopherson et al., 1998) to assess the economic value generated by hedge funds that modify their market exposure on the basis of this public but not trivial technique to process information. Our methodology consists of two steps. First, we estimate in rolling samples a conditional market beta model to measure the sensitivity of each hedge fund's market exposure to changes in macroeconomic conditions. Second, we sort funds into groups based on their measured market timing intensity to evaluate forward looking (and hence out-of-sample) whether hedge funds that are more responsive to

[1] More recently, Cao et al. (2013) provide evidence that hedge funds can time market liquidity.

[2] There is also a comparatively vast literature investigating the market timing ability of mutual fund managers (e.g., Treynor and Mazuy, 1966, Henriksson, 1984, Jiang et al., 2007).

economic data outperform others, controlling for the standard hedge fund risk factors of Fung and Hsieh (2004).

Our results are based on a sample of 2224 equity hedge funds (dead and alive funds). We find that about 17 (9) percent of the funds exhibit a positive (negative) and statistically significant market exposure sensitivity to economic data releases. This finding implies that a sizable number of hedge funds in our sample take into consideration economic data before tactically positioning their portfolio, consistent with conventional wisdom that hedge funds are sophisticated investors. Furthermore, we find that the most pro-cyclical market timers (high exposure) outperform their less active and counter-cyclical peers (low exposure) with a risk adjusted alpha of 5.5 percent annualized.

## 2 Data

We use the Hedge Fund Research (HFR) data. In order to deal with survivorship bias, we merge the HFR database, which only contains data for live hedge funds, with the HFR Dead Funds database, which contains data for funds that no longer exist. HFR classifies hedge funds according to four main investment strategies, namely Equity Hedge, Event Driven, Macro and Relative Value. We focus on the first category of funds, i.e. Equity Hedge, because this is the category in which managers have the highest exposure to the stock market. It is also the most representative of the hedge fund industry as most of the hedge funds trade mainly in equity markets. To make our study comparable to other studies in the hedge fund literature, we apply some date filters. First, we focus on the period from January 1994 onwards; second, we restrict our sample to those funds that report returns and AUM in US$; third, we consider only funds that report net-of-fee returns on a monthly basis and having average AUM of at least $10 million. Finally, to be included in our dataset, we require to a fund to have at least 36 months of observations. After this filtering process, our final dataset contains 2224 funds over the sample period January 1994-December 2014. Out of these 2224 funds, 747 are alive at the end of the sample period while 1477 cease to exist during the sample period.

Table 1 shows that the number of funds in our data grows until the financial crisis in 2008 and then starts to decline afterwards. This is coherent with the development of the hedge fund industry that experienced a boom started in the 1990s which was then interrupted by the financial crisis. The impact of the financial crisis on the hedge fund industry is also evident by looking at distribution of the monthly excess returns. Indeed, 2008 is the year associated to the lowest average excess returns.

We use the real-time economic growth index of Beber et al. (2015) to summarize the information content of the cross-section of economic data releases for the United States. Their index aggregates data releases concerning output, employment and macroeconomic sentiment. It is available at the daily frequency, and we compute a 20-day moving average to capture the information that has become available to hedge fund managers throughout the month. We plot the real-time economic growth

index (GI) in Figure 1 with the shaded periods representing NBER dated recessions. Table 2 shows the correlations between GI and common hedge fund risk factors.

Following Fung and Hsieh (2001, 2004), we consider the following hedge fund risk factors: market excess returns (Mkt), small minus big return premium (SMB), the monthly change of the yield of the 10-year US government bond (D10Y), the monthly change between the BAA yield and the 10-year US government bond yield (BAA-10Y), the bond trend following factor (BDTF), the currency trend following factor (FXTF) and the commodity trend following factor (CMTF).[3]

# 3 Empirical analysis

## 3.1 Empirical framework

To assess the potential variation in market exposure of hedge funds due to changes in macroeconomic conditions measured in real time, we rely on the conditional beta model used by, among others, Ferson and Schadt (1996) and Christopherson et al. (1998). More specifically, for each fund we estimate the following regression model:

$$R_{i,t+1} = \alpha_i + \beta_{i,t} Mkt_{t+1} + \sum_{j=1}^{J} \gamma_j f_{j,t+1} + u_{i,t+1}, \tag{1}$$

where $R_{i,t+1}$ is the excess return of fund $i$ in month $t+1$ and $Mkt_{t+1}$ is the excess return on the market portfolio. The risk-free rate is proxied by the one-month Treasury bill rate. We label as $f$ the other hedge fund risk factors listed above.

We specify the fund's $\beta_{i,t}$ as:

$$\beta_{i,t} = \beta_0 + \beta_1 GI_t, \tag{2}$$

where $GI_t$ is the indicator of the current macroeconomic conditions, e.g., the US economic growth index measured at the end of month $t$.[4] Hence, $\beta_{i,t}$ is decomposed into two components. The first, $\beta_0$, captures the unconditional exposure of the fund to the stock market, while the second, $\beta_1 GI_t$, measures the market exposure that the manager takes after observing macroeconomic conditions at $t$. When we substitute equation (2) into equation (1), the model becomes:

$$R_{i,t+1} = \alpha_i + \beta_0 Mkt_{t+1} + \beta_1 Mkt_{t+1} GI_t + \sum_{j=1}^{J} \gamma_j f_{j,t+1} + u_{i,t+1}. \tag{3}$$

[3] We thank David Hsieh for making the data om bond, currency and commodity trend-following factors available from `http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls`. The data for the risk-free rate, Mkt and SMB are from the Kenneth French's website `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html` while the data for the BAA-rated corporate bond yields and the 10-year constant maturity Treasury yields are from the Federal Reserve database.

[4] Results do not change if we consider an unconditionally demeaned index $GI_t - \overline{GI}$.

To evaluate the economic value generated by investing in hedge funds that adjust their market exposure according to real-time changes in macroeconomic conditions, we proceed as follows: First, for each month $t$ starting in January 1997, we use 36-month rolling window of past returns to estimate equation (3) for each fund to obtain the coefficient $\beta_1$. We then form 10 deciles portfolios of hedge funds on the basis of these estimated market timing coefficients. Portfolio 1 (P1) contains funds associated to the lowest estimated $\beta_1$ and portfolio 10 (P10) contains funds associated to the highest estimated $\beta_1$. Next, for each portfolio we track the out-of-sample performance in month $t+1$ by equally weighting individual hedge fund returns. We rebalance the portfolios every month. Furthermore, in line with the existing literature (e.g., Cao et al., 2013), we adjust portfolio returns for risk using Fung and Hsieh's (2004) seven-factor model.

### 3.2 Results

The results are reported in Table 3. The estimates of the parameter $\beta_1$ across funds suggest that there are obvious differences in the conditional market exposure of the hedge funds in our sample. In particular, the proportion of funds that have positive (about 17 percent of the sample) or negative (about 9 percent of the sample) statistically significant conditional beta is high.

The performance of the portfolio strategy based on the value of the parameters $\beta_1$ is reported in Table 4. Pro-cyclical market timers (P10) characterized by the highest conditional betas outperform their counter-cyclical peers (P1) with the lowest conditional betas and generate a risk adjusted alpha of 5.5 percent annualized. These results are corroborated by Figure 2 where the cumulative returns from an investment of 1$ in P1 and in P10 in 1997 are plotted. Investing in the group P10 was about five times more remunerative than investing in the group P1 although P10 funds suffered higher losses during the recession that followed the financial crisis. The negative performance of P10 during this period should not be too surprising as P10 includes those funds that have a positive conditional market exposure despite the underlying macroeconomic conditions. In particular, these can be funds that could have predicted a recession shorter or milder than the actual one and, as a consequence, failed to fully adjust their positive exposure to the stock market.

Finally, we address the reasonable concerns that our results may be driven i) by the inclusion of the 2008-2009 financial crisis in the sample, and/or ii) by the inclusion of funds that have ceased to exist. More specifically, in Table 5 we report the results obtained when we apply our analysis to the shorter period from January 1997 to December 2007, while in Table 6 we report the results for the alive funds and for the funds that have ceased to exist, respectively. The results show that: i) if we exclude the financial crisis from the sample, then we observe a even stronger difference in the performance of pro-cyclical market timers (P10) with respect to their counter-cyclical peers (P1); and ii) the difference in the performance of pro-cyclical market timers (P10) with respect to their counter-cyclical peers (P1)

is not driven by the inclusion in the sample of funds that no longer exist. Indeed, we find that even if we focus only on alive funds, the most pro-cyclical market timers still outperform their less active and counter-cyclical peers. The same pattern, but weaker, emerges also if we focus only on funds that have ceased to exist.

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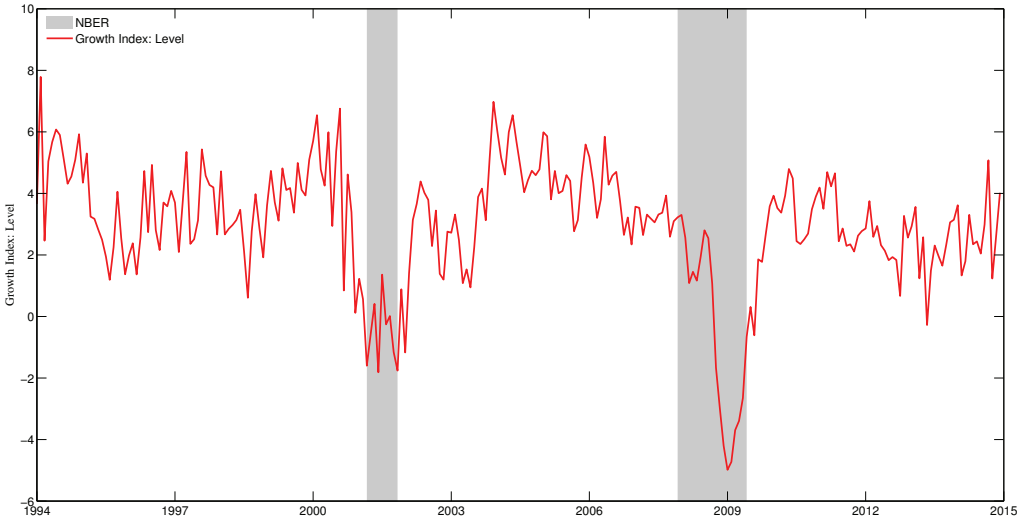
# Figures:

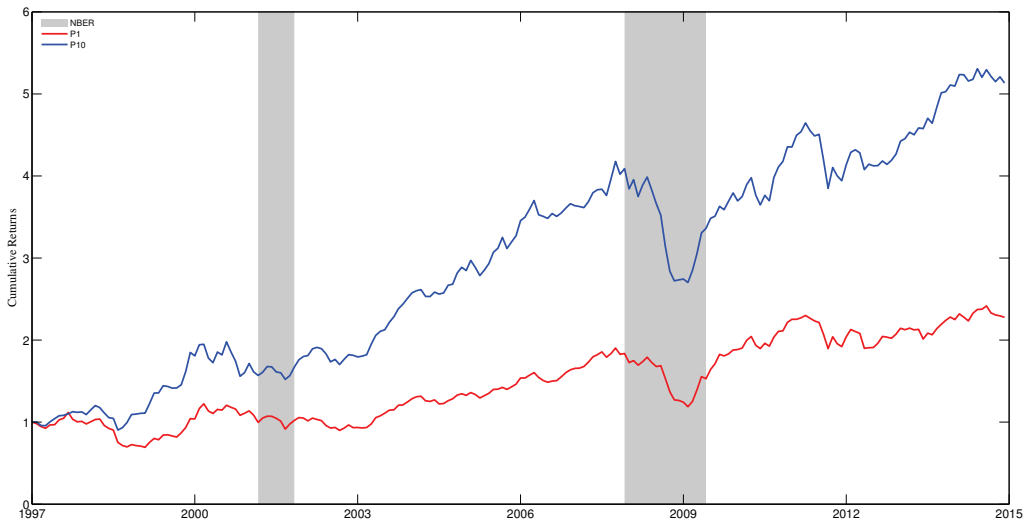
## Figure 1: Economic Growth Index

The figure shows the economic growth index during the sample period 1994-2014.




## Figure 2: P1 vs P10: cumulative returns

The figure shows the cumulative returns from investing 1$ in 1997 in P1 (lowest conditional market exposure) and in P10 (highest conditional market exposure) along with the NBER dated recessions.



# Tables:

### Table 1: Hedge fund descriptive statistics

This table presents descriptive statistics about the hedge funds in our sample. For each year, column two contains the number of funds available, while columns from thee to seven provide information (average, standard deviation, median, percentile 25 and percentile 75) about the distribution of funds' excess returns.

| Year | n | Average | St. Dev | Med | perc25 | perc75 |
|---|---|---|---|---|---|---|
| 1994 | 242 | 0.13 | 4.89 | 0.03 | -2.16 | 2.02 |
| 1995 | 308 | 1.47 | 4.92 | 1.15 | -0.69 | 3.42 |
| 1996 | 389 | 1.69 | 5.10 | 1.34 | -0.56 | 3.74 |
| 1997 | 469 | 1.32 | 6.08 | 1.01 | -1.43 | 4.17 |
| 1998 | 562 | 0.13 | 8.70 | 0.63 | -2.64 | 4.08 |
| 1999 | 651 | 2.85 | 8.12 | 1.52 | -1.25 | 5.44 |
| 2000 | 760 | 0.57 | 8.41 | 0.23 | -3.00 | 3.57 |
| 2001 | 850 | 0.32 | 6.05 | 0.32 | -1.84 | 2.56 |
| 2002 | 959 | -0.23 | 4.81 | 0.00 | -2.06 | 1.75 |
| 2003 | 1068 | 1.81 | 4.09 | 1.10 | -0.25 | 3.16 |
| 2004 | 1178 | 0.83 | 3.51 | 0.62 | -0.74 | 2.24 |
| 2005 | 1327 | 0.78 | 3.67 | 0.61 | -0.98 | 2.39 |
| 2006 | 1405 | 0.85 | 3.66 | 0.65 | -0.83 | 2.39 |
| 2007 | 1452 | 0.82 | 4.26 | 0.61 | -0.98 | 2.48 |
| 2008 | 1455 | -2.13 | 7.42 | -0.91 | -4.76 | 1.57 |
| 2009 | 1351 | 2.10 | 5.90 | 1.35 | -0.78 | 4.24 |
| 2010 | 1291 | 0.94 | 4.48 | 0.78 | -1.28 | 3.17 |
| 2011 | 1244 | -0.46 | 4.83 | -0.17 | -2.20 | 1.51 |
| 2012 | 1133 | 0.72 | 3.98 | 0.70 | -0.88 | 2.40 |
| 2013 | 996 | 1.26 | 5.74 | 1.17 | -0.43 | 2.87 |
| 2014 | 892 | 0.19 | 4.04 | 0.33 | -1.44 | 1.92 |

### Table 2: Correlation among the Fung and Hsieh (2004) risk factors and the economic growth index (GI)

| | **Mkt** | **SMB** | **D10Y** | **BAA-10Y** | **BDTF** | **FXTF** | **CMTF** | **GI** |
|---|---|---|---|---|---|---|---|---|
| **Mkt** | 1.00 | | | | | | | |
| **SMB** | 0.25 | 1.00 | | | | | | |
| **D10Y** | 0.10 | 0.09 | 1.00 | | | | | |
| **BAA-10Y** | -0.28 | -0.19 | -0.51 | 1.00 | | | | |
| **BDTF** | -0.25 | -0.07 | -0.18 | 0.20 | 1.00 | | | |
| **FXTF** | -0.19 | -0.02 | -0.17 | 0.28 | 0.27 | 1.00 | | |
| **CMTF** | -0.17 | -0.07 | -0.12 | 0.19 | 0.19 | 0.35 | 1.00 | |
| **GI** | 0.04 | -0.06 | 0.09 | -0.02 | -0.11 | 0.07 | 0.01 | 1.00 |

## Table 3: $\beta_1$ descriptive statistics

The table presents descriptive statistics about the estimated coefficient $\beta_1$ measuring fund's market exposure conditional on the current macroeconomic conditions. Panel A shows the percentage of equity hedge funds below or above a specified t-statistic threshold. Panel B presents the t-statistics of the bottom and top percentiles of the distribution. The sample runs from January 1994 to December 2014.

| Panel A: Percentage of the funds | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $t <= -2.326$ | $t <= -1.960$ | $t <= -1.645$ | $t <= -1.282$ | $t >= 1.282$ | $t >= 1.645$ | $t >= 1.960$ | $t >= 2.326$ |
| | 6.79 | 8.86 | 11.92 | 15.69 | 28.73 | 22.26 | 17.31 | 12.59 |
| Panel B: bottom and top t-statistics | | | | | | | | |
| | 1% | 3% | 5% | 10% | 90% | 95% | 97% | 99% |
| | -4.25 | -3.15 | -2.70 | -1.81 | 2.70 | 3.36 | 3.97 | 4.77 |

## Table 4: Average portfolio returns and out-of-sample alphas (full sample)

The table presents monthly average excess returns (percent) of portfolios of hedge funds sorted according to the estimated coefficient $\beta_1$ measuring fund's market exposure conditional on the current macroeconomic conditions. The second part of the table presents the estimated monthly $\alpha$ (percent) from a regression of portfolio returns on the Hsieh and Fung (2004) seven factors. The sample runs from January 1997 to December 2014. T-statistics (in parenthesis) are calculated based on Newey and West heteroskedasticity and autocorrelation-consistent standard errors with four lags. * indicates the 10% significance level, ** indicates the 5% significance level, *** indicates the 1% significance level.

| | *P1* | *P2* | *P3* | *P4* | *P5* | *P6* | *P7* | *P8* | *P9* | *P10* | *P10-P1* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Returns | 0.48 | 0.44 | 0.42 | 0.53 | 0.50 | 0.45 | 0.41 | 0.47 | 0.55 | 0.86 | 0.38 |
| | (1.37) | (1.67*) | (1.93*) | (2.68***) | (2.88***) | (2.30**) | (2.07**) | (2.34**) | (2.14**) | (2.68***) | (1.97**) |
| *alpha* | 0.09 | 0.12 | 0.11 | 0.26 | 0.26 | 0.19 | 0.14 | 0.19 | 0.22 | 0.46 | 0.37 |
| | (0.46) | (0.90) | (1.02) | (2.74***) | (2.94***) | (1.75*) | (1.31) | (2.32**) | (2.14**) | (2.60**) | (2.05**) |

## Table 5: Average portfolio returns and out-of-sample alphas (1997-2007)

The table presents monthly average excess returns (percent) of portfolios of hedge funds sorted according to the estimated coefficient $\beta_1$ measuring fund's market exposure conditional on the current macroeconomic conditions. The second part of the table presents the estimated monthly $\alpha$ (percent) from a regression of portfolio returns on the Hsieh and Fung (2004) seven factors. The sample runs from January 1997 to December 2007. T-statistics (in parenthesis) are calculated based on Newey and West heteroskedasticity and autocorrelation-consistent standard errors with four lags. * indicates the 10% significance level, ** indicates the 5% significance level, *** indicates the 1% significance level.

| | *P1* | *P2* | *P3* | *P4* | *P5* | *P6* | *P7* | *P8* | *P9* | *P10* | *P10-P1* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Returns | 0.56 | 0.61 | 0.52 | 0.73 | 0.61 | 0.56 | 0.44 | 0.54 | 0.70 | 1.18 | 0.62 |
| | (1.31) | (2.01**) | (2.19***) | (3.41***) | (3.10***) | (2.42**) | (1.92*) | (2.23**) | (2.44**) | (3.15***) | (2.34**) |
| *alpha* | 0.25 | 0.33 | 0.21 | 0.48 | 0.37 | 0.30 | 0.15 | 0.25 | 0.39 | 0.77 | 0.52 |
| | (0.98) | (2.06**) | (1.56) | (4.08***) | (3.04***) | (2.09**) | (1.07) | (2.72***) | (3.21***) | (3.53***) | (2.16**) |

## Table 6: Average portfolio returns and out-of-sample alphas (alive versus ceased funds)

The table presents monthly average excess returns (percent) of portfolios of alive hedge funds sorted according to the estimated coefficient $\beta_1$ measuring fund's market exposure conditional on the current macroeconomic conditions. The second part of the table presents the estimated monthly $\alpha$ (percent) from a regression of portfolio returns on the Hsieh and Fung (2004) seven factors. The sample runs from January 1997 to December 2014. T-statistics (in parenthesis) are calculated based on Newey and West heteroskedasticity and autocorrelation-consistent standard errors with four lags. * indicates the 10% significance level, ** indicates the 5% significance level, *** indicates the 1% significance level.

Panel A: Alive Funds

| | *P1* | *P2* | *P3* | *P4* | *P5* | *P6* | *P7* | *P8* | *P9* | *P10* | *P10-P1* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Returns | 0.70 | 0.67 | 0.57 | 0.83 | 0.62 | 0.71 | 0.56 | 0.62 | 0.80 | 1.56 | 0.85 |
| | (1.96**) | (2.16**) | (2.28**) | (3.54***) | (2.82***) | (3.31***) | (2.81***) | (2.76***) | (3.37***) | (4.71***) | (2.83***) |
| *alpha* | 0.37 | 0.32 | 0.23 | 0.57 | 0.31 | 0.47 | 0.32 | 0.30 | 0.47 | 1.19 | 0.81 |
| | (1.35) | (1.83*) | (1.67*) | (4.62***) | (2.84***) | (3.69***) | (2.95***) | (1.99**) | (4.35***) | (5.74***) | (2.62***) |

Panel B: Ceased Funds

| | *P1* | *P2* | *P3* | *P4* | *P5* | *P6* | *P7* | *P8* | *P9* | *P10* | *P10-P1* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Returns | 0.26 | 0.31 | 0.27 | 0.33 | 0.34 | 0.20 | 0.29 | 0.19 | 0.40 | 0.42 | 0.16 |
| | (0.71) | (1.38) | (1.31) | (1.75*) | (2.13**) | (1.09) | (1.46) | (1.00) | (1.58) | (1.26) | (0.82) |
| *alpha* | -0.13 | 0.03 | -0.01 | 0.09 | 0.11 | -0.02 | 0.03 | -0.07 | 0.11 | 0.03 | 0.16 |
| | (-0.66) | (0.28) | (-0.09) | (0.83) | (1.22) | (-0.18) | (0.25) | (-0.71) | (0.95) | (0.14) | (0.85) |