Regime Shifts: Implications for Dynamic Strategies

Sundar Jayavelmurugan
Sundarau.j@gmail.com

Abstract

Long-term investors can often bear the risk of outsized market movements or tail events more easily than the average investor; for bearing this risk, they hope to earn significant excess returns. Rebalancing periodically to a fixed benchmark allocation, however, is not the way to do this. In the presence of time-varying investment opportunities, portfolio weights should be adjusted as new information arrives to take advantage of favourable regimes and reduce potential drawdowns.

Regime shifts present significant challenges for investors because they cause performance to deviate significantly from the ranges implied by long-term averages and covariances. Regime-switching models can match financial markets' tendency to change their behaviour abruptly and the phenomenon that the new behaviour often persists for several periods after a change. Therefore, it is important to study how these changing regimes could be used to guide the active investor in tactically changing his portfolio allocation. To that effect, the effect of different regimes on different allocation strategies are taken up for study in this report.

Keywords: *Hidden Markov Model, Regime Shift*

1. Proposal

In this project, I would like to like to study how different allocation strategies work under shifting regimes. In order to determine the regimes, a hidden markov model is used to categorize the shifts. Four different factors are used for detecting the regime change. Two based on the financial markets, one based on economic change and another based on inflation. For the different dynamic strategies, the EDHEC Risk Alternative Indexes are used [4]. The idea behind this work comes primarily from the seminal work of Kritzman Et al. [1]

After an initial in sample testing, depending on how successful the different strategies were affected by the changing regimes, an out of sample testing was also carried out for one particular allocation style. This whole paper is about the discussion about the methods employed and the outcomes.

The important contribution of this work would be that it would go a long way in understanding how Hidden Markov Models could be put to use for dynamic allocation of assets.

2. A simple introduction to Hidden Markov Model

Assume a simplified coin toss game with a fair coin. Under the assumption of conditional dependence (the coin has memory of past states and the future state depends on the sequence of past states) we must record the specific sequence that lead up to the 11th flip and the joint probabilities of those flips. So, imagine after 10 flips we have a random sequence of heads and tails. The joint probability of that sequence is 0.5^10 = 0.0009765625. Under conditional dependence, the probability of heads on the next flip is 0.0009765625 * 0.5 = 0.00048828125.

Is that the real probability of flipping heads on the 11th flip? No. We know that the event of flipping the coin does not depend on the result of the flip before it. The coin has no memory. The process of successive flips does not encode the prior results. Each flip is a unique event with equal probability of heads or tails, aka conditionally independent of past states. This is the Markov property.

2.1. What is a Markov Model?

A Markov chain (model) describes a stochastic process where the assumed probability of future state(s) depends only on the current process state and not on any the states that preceded it (shocker).

Assume you want to model the future probability that your dog is in one of two states given its current state. To do this we need to specify the state space, the initial probabilities, and the transition probabilities.

Imagine you have a very lazy fat dog, so we define the state space as sleeping, eating, We will set the initial probabilities to 65% and 35% respectively.

Since at any point the dog can be in either state and can switch to the other state this is a classic example of Markov switching. To define the process, we need then to describe the transition probability matrix. This matrix tells what the probability is to persist in a particular state (persistence) and what is the probability to shift to another state (transition).

$$\Pr(X_1 = \ i) = \ p_i$$

This is the initial probability of being in a regime i, where X_1 us the first regime in the Markov chain. The Transition matrix is denoted by Γ.

$$\Gamma = \begin{pmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{pmatrix}$$

Where $\gamma_{ij} = \Pr(X_t = \ j \mid X_{t-1} = \ i \ )$

It denotes the probability of transition to a state j when the previous state is i. Over time the Markov chain can be either in regime 1 or regime 2. Each regime generates observations which are consistent with the state. For example, a person sleeping heart rate will be different from the person exercising heart rate. The observations themselves can come from particular distributions. Let's say Y_t are the observations generated. Y_t could be from a normally distributed distribution with mean μ_i and standard deviation σ_i

In practise we cannot observe the underlying states X_t. We can only observe the data Y_t . For example, the heart rate is spiking without knowing what is the state he is. Hidden Markov models are used to infer the states from the underlying observations.

So, in our case of trading, why go through all trouble when one could have decided the regime based on thresholds. Markov Switching models perform better than simple partitions in correctly identifying regimes and capturing persistence of regimes.

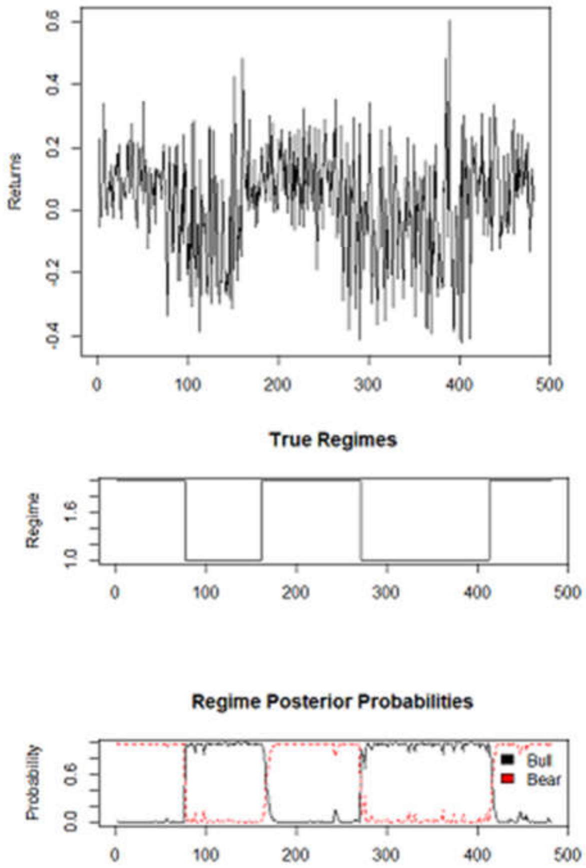


Fig 1. Simulated Markov Switching Process

3. Regime Variables

The regime variables are based on time series for financial market turbulence, inflation, economic growth.

For financial market turbulence, I used the S&P 500 returns for equity and the G9 currencies for FX. The S&P 500 were downloaded from yahoo and stored as a csv as of late pandas is having a problem to get data using Yahoo API.

The G9 currencies are obtained automatically by the program from FRED website [5].

For economic turbulence the economic growth using quarter over quarter percentage growth in seasonally adjusted US real national product from the second quarter of 1947 is used. This is again obtained from Fred.

For inflation turbulence, the US Consumer Price Index is used. This is also obtained from Fred.

For testing of different strategies, unlike the authors of the original paper ([1]), I used the EDHEC data set [4]. This is only available for manual download from this website. I have manually downloaded and kept the returns for usage in the Python code.

These are simply returns on various hedge fund strategies as opposed to deliberately constructed risk premia that are expected to respond to different states across economic/financial regime variables. A snapshot of the strategies follows, along with their most recent summary results:

Indexes and Benchmarking

EDHEC-Risk Alternative Indexes

Hedge Fund Strategies	October 2017	YTD	Annual Average Return since January 2001	Annual Std Dev since January 2001	Sharpe Ratio
Convertible Arbitrage	0.60%	5.24%	5.83%	6.17%	0.30
CTA Global	3.67%	0.94%	4.64%	7.98%	0.08
Distressed Securities	0.00%	3.83%	8.82%	5.77%	0.84
Emerging Markets	1.37%	14.00%	8.80%	9.41%	0.51
Equity Market Neutral	0.72%	3.65%	4.20%	2.62%	0.07
Event Driven	0.18%	6.59%	7.07%	5.54%	0.55
Fixed Income Arbitrage	0.31%	3.79%	5.57%	3.74%	0.42
Global Macro	1.28%	1.90%	5.49%	4.04%	0.37
Long/Short Equity	1.44%	9.84%	5.71%	6.48%	0.26
Merger Arbitrage	0.23%	4.51%	4.91%	2.92%	0.31
Relative Value	0.65%	5.18%	6.29%	4.12%	0.55
Short Selling	-9.90%	-32.17%	-5.27%	13.11%	-0.71
Funds of Funds	1.13%	6.40%	3.60%	4.53%	-0.09

Fig 2. EDHEC Indexes performance

In terms of the data used in this project, it is useful to make a distinction at the outset between economic regime variables which are used to partition history into different states in a meaningful way) and risk premia (simple returns in my case) which are used to assess performance across states for each economic regime variable.

3.1. Turbulence definition

The paper [1]. defines this variable as a condition in which asset prices behave in an unusual fashion given historical patterns of behaviour and proposes to measure it using the Mahalanobis distance:

$$d_t = (y_t - \mu)\Sigma^{-1}(y_t - \mu)^t$$

where

$y_t = vector\ of\ asset\ returns\ for\ period\ t$

$\mu = sample\ average\ vector\ of\ historical\ returns$

$\Sigma =$ sample covariance martrix of historical returns

The Equity Turbulence Index uses S&P 500 daily returns estimating mean and covariances using equally weighted historical returns for the past 10 years and averaging the daily turbulence scores within each month. The Currency Turbulence Index (CTI)was constructed by using currency returns (vs.USD) for 8 of the G-10 countries, estimating mean and covariances using equally weighted historical returns for the past 3 years and averaging the daily turbulence scores within each month

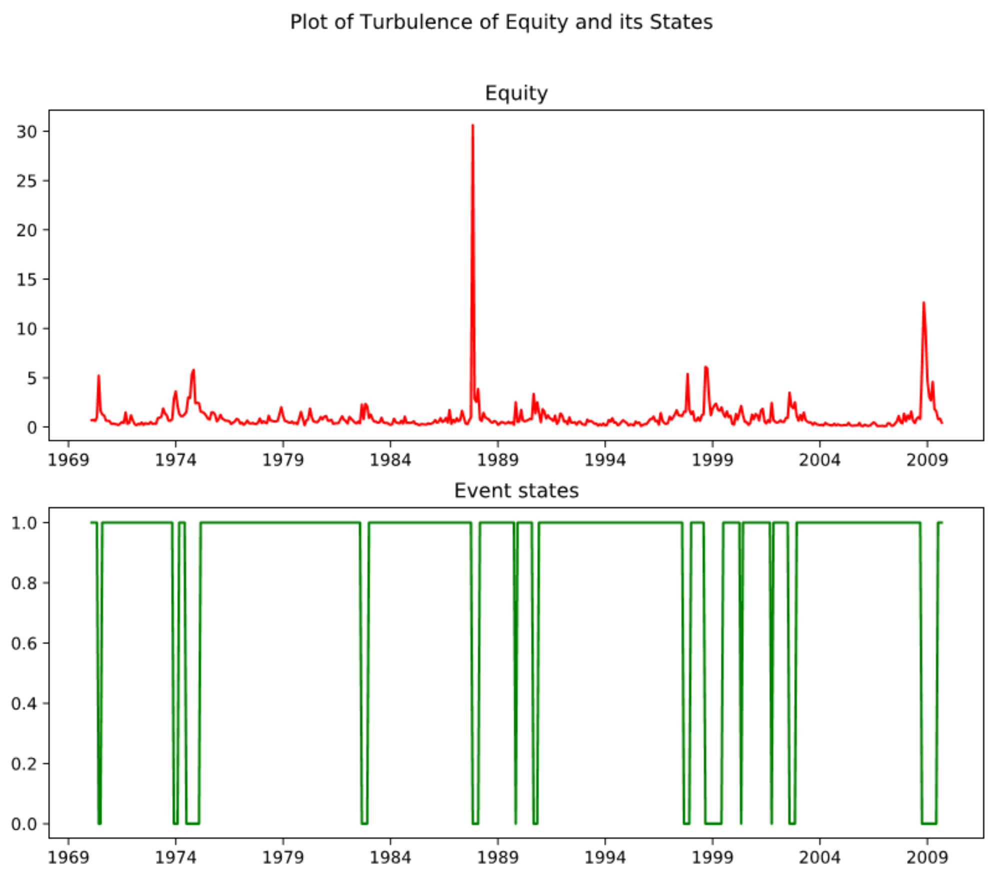


Fig 3. Turbulence and Event State for Equity

4. Fitting the hidden markov model:

There are different ways to fit the parameter of the hidden markov model. Some of the methods are Baum-Welch algorithm, the Viterbi algorithm and the Expectation Maximization. I am not going into the details of the algorithm. But it should be noted that the Python HMM library uses the expectation maximization. I also separately implemented the whole thing in R. I used depmixS4 package. I found that the R version is much more robust than the Python version. For example, in S&P 500, the Black Friday (1987) skews the Python model such that it paints everything as a different state than the 1987 October returns. Maybe this is because I am using a 2-state model whereas probably higher states should be used to capture the markovian models. I used 2 as used in the paper [1]. as well as 2 states are easy to code and the data is also easy to analyse. So, for S&P 500 alone, I had to use the R model estimated parameters. There are 2 states in this exercise. One is the normal state and the other one is the event state. It is up to us to denote the different states. The parameters are estimated from the model. These are the mean observation, the standard deviation and the persistence and transition probabilities.

Some results are shown in the Appendix. A number of graphs had to be removed to fall within the submission size.

In the Appendix the turbulence and the markov states are shown from Pages 17 – 20, whereas the estimates are tabulated as well as plotted from Pages 21 - 28.

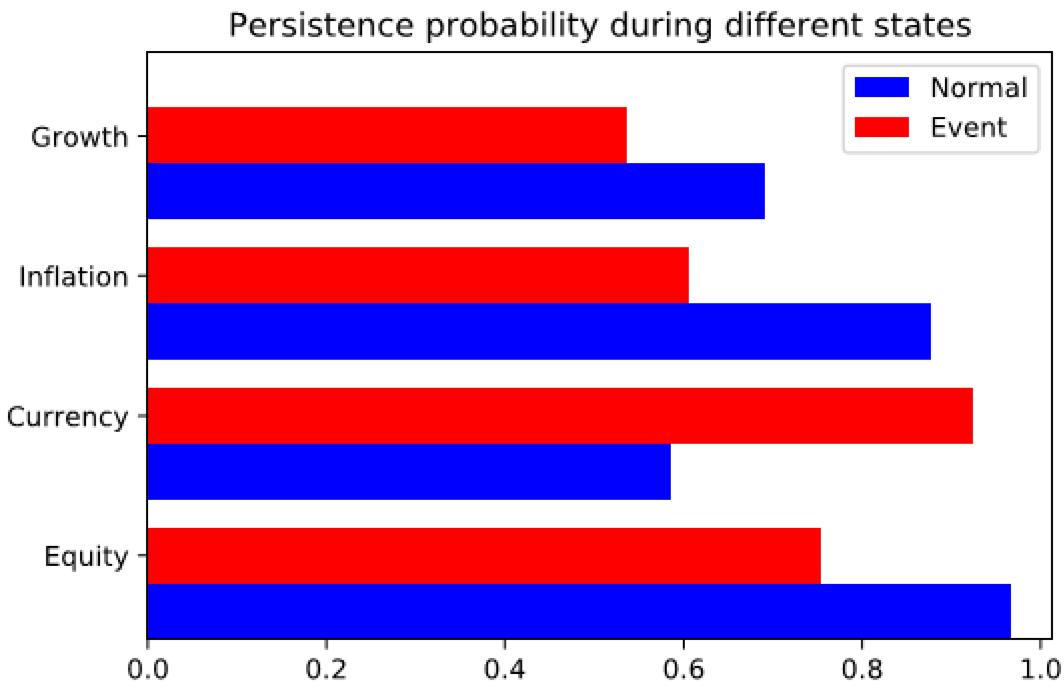


Fig 4. Persistence Probability for different regimes under Normal and Event States

4.1. Aligning the Risk Premia returns and the regime variable time series.

The next step in the process would be to align the risk premia returns with the regime states. For example, I would want to know how the Convertible Arbitrage Strategy worked when the Equity regime was in a particular state.

4.2. In sample performance

Now that we have the aligned results we could then see the standard deviation scaled difference state means. This was defined as (event mean – normal mean) / standard deviation in the paper. Event mean is calculated as the mean of the returns obtained by investing only in the event state. Normal mean is the mean of the returns obtained by investing only in the normal state. Standard deviation is the standard deviation of all returns. Here I reversed the formula, I calculated (normal mean – event mean)/standard deviation. This is because I expected the normal events to be more than the event mean. It turned out to be the opposite. The scaled differences are in the last few pages under Appendix. For equity and currency, the events were favourable whereas in growth and inflation it was opposite.

For example, Equity the following is the performance of different strategies under Normal state. These are the mean returns:

Table 1. The performance of various strategies

under Normal State for Equity Regime

Convertible Arbitrage	0.005815
CTA Global	0.005064
Distressed Securities	0.008442
Emerging Markets	0.010674
Equity Market Neutral	0.005584
Event Driven	0.007708
Fixed Income Arbitrage	0.004928
Global Macro	0.007682
Long/Short Equity	0.007547
Merger Arbitrage	0.005949
Relative Value	0.006458
Short Selling	0.001495
Funds of Funds	0.006420

These are the returns under Event state for Equity:

Table 2. The performance of various strategies

under Event State for Equity Regime

Convertible Arbitrage	0.000593
CTA Global	0.001426
Distressed Securities	-0.000489
Emerging Markets	-0.002428
Equity Market Neutral	0.000418
Event Driven	-0.000086
Fixed Income Arbitrage	-0.000697
Global Macro	-0.000009
Long/Short Equity	0.000213
Merger Arbitrage	0.000836
Relative Value	0.000243
Short Selling	0.002666
Funds of Funds	-0.000501

4.3. The Cumulative returns and drawdowns when states are known versus unknown

In addition to the in-sample scaled performance score calculated above, I also tried to look at how cumulative returns varied depending on one's knowledge of the estimated states in each regime. I simply multiplied the chosen fund return by the state map for each economic regime variable (so that fund returns are multiplied by 1 in the case of a normal state and 0 of an event state), calculated the cumulative return as well as drawdowns for that and compared the results to the case where states are unknown.

The other results (Fund returns are multiplied by 0 for normal state and 1 for event state, Fund returns are multiplied by -1 for normal state and 1 for event state, Fund returns multiplied by 1 for normal state and -1 for event state) are also attached. This was just to experiment and see how the different strategies behaved. The cumulative returns and the drawdowns are calculated and compared with those where the markov states are not used for decision making (whether to invest or not). These are found in pages 29 – 44 under Appendix. Also, the performance of different strategies under different regimes under different states are also given in these pages.

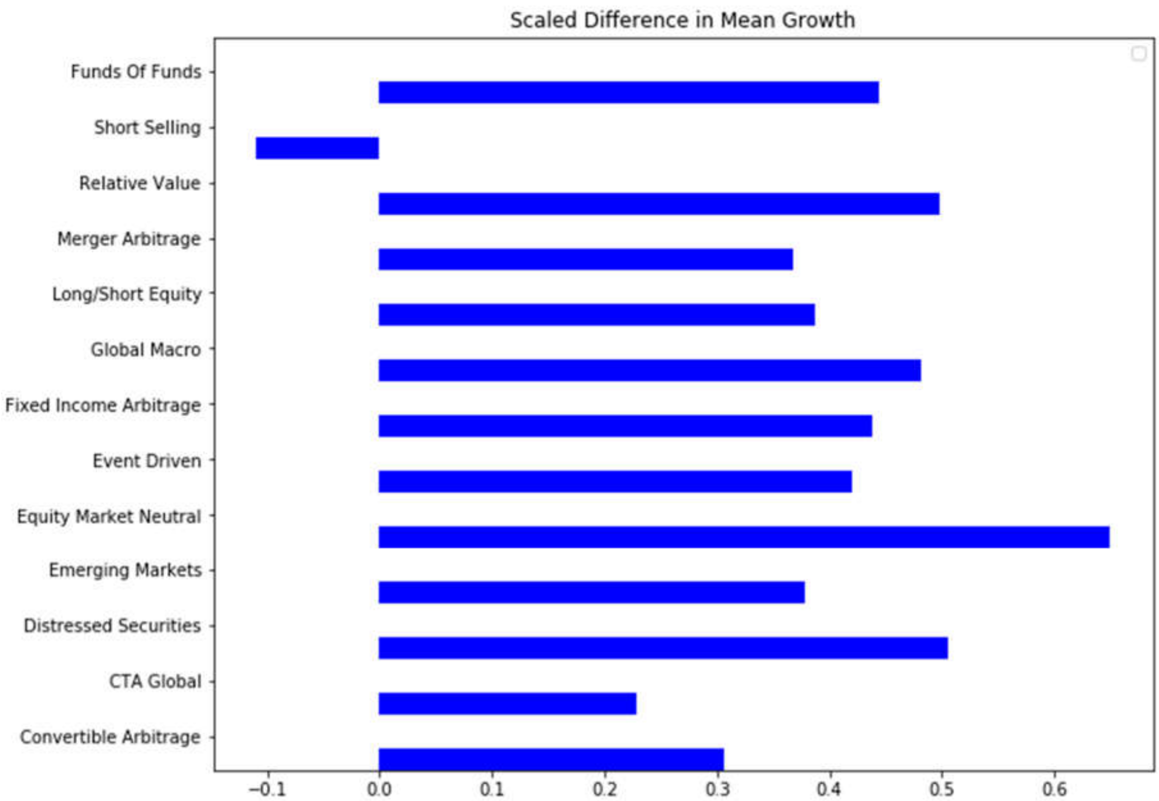


Fig 5. Scaled Difference in mean under different strategies for Growth Factor (A comparison between Normal and Event State)

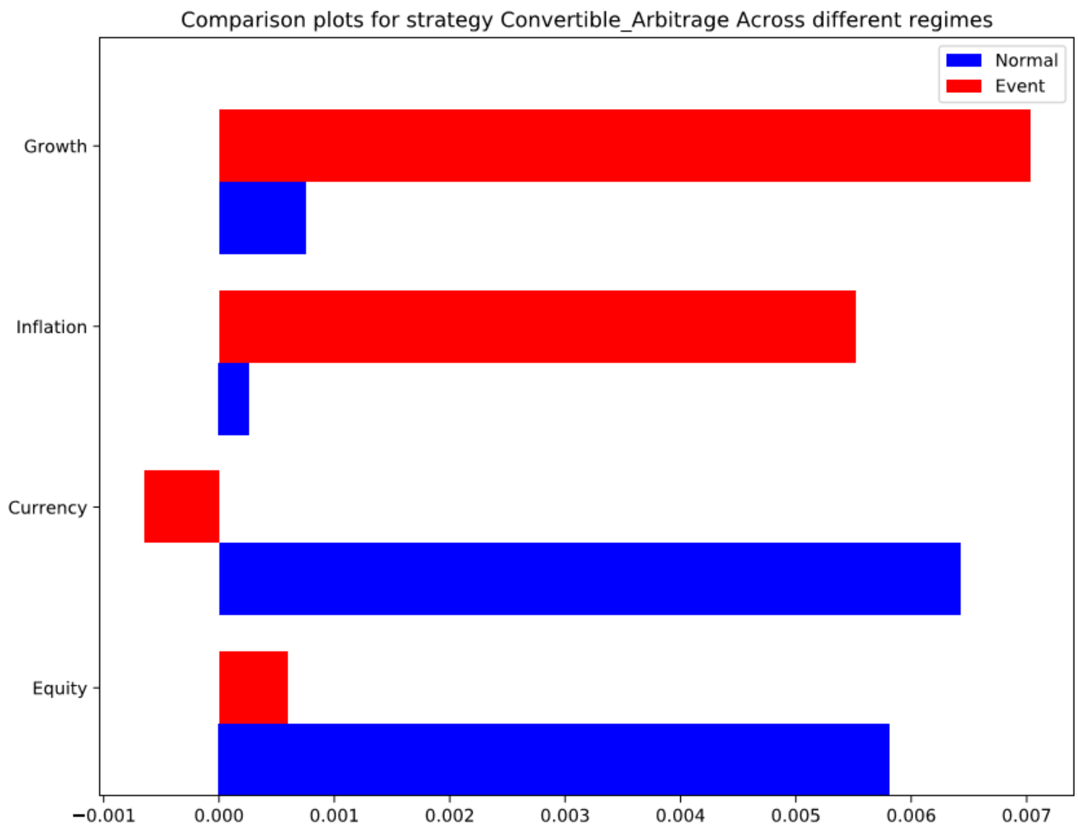


Fig 6. Comparison plots for strategy Convertible Arbitrage under different regimes

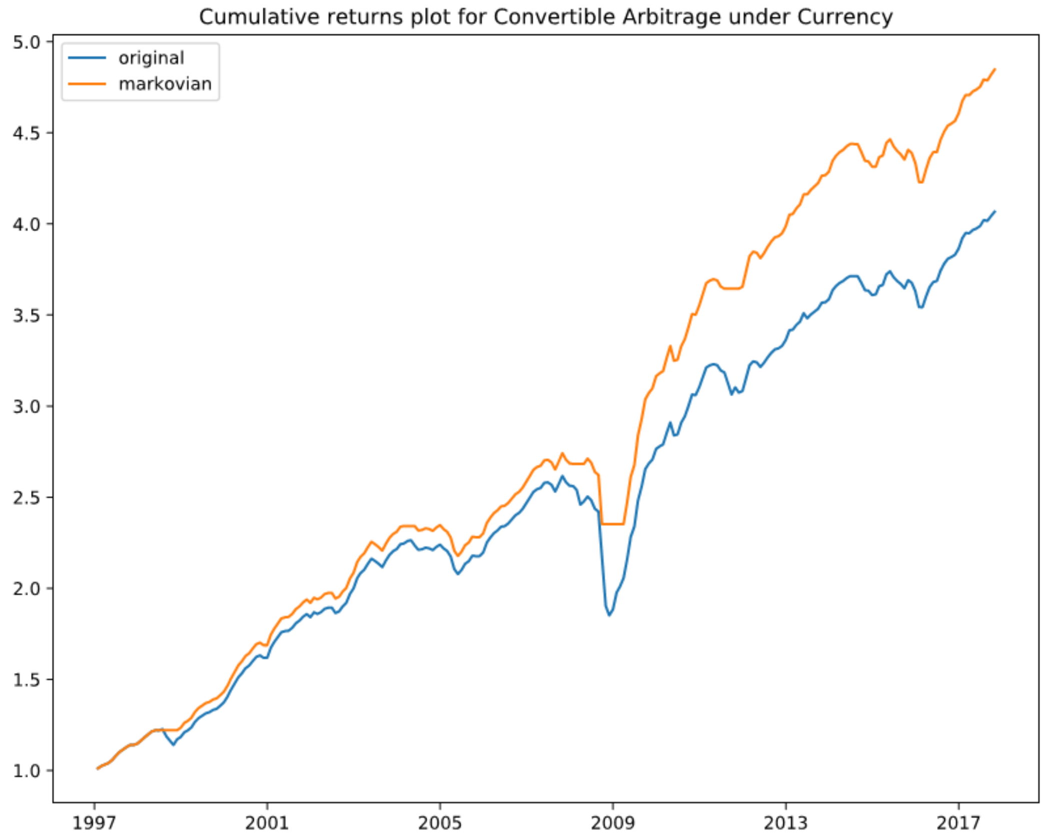


Fig 7. In sample cumulative returns for Convertible Arbitrage when using Markovian State information and when not using Markovian (Invest during Normal, don't invest during Event state of Currency Regime)

4.4. Observations

These are some of my observations.

- The Inflation and Equity economic regime variable begins in the normal state, with a high probability of remaining in this state and a low probability of transitioning to the event state
- The Event state for all regime variable is characterised by generally higher estimated sigmas and means than corresponding values for the normal state.
- The persistence of normal states across economic regime variables is generally higher than that that of event states. The corollary is found in transition estimates where we are more likely to transition from the event state to the normal state than from the normal state to the event state for all regime variables.
- This is the most significant observation of all. The in-sample performance shows that different regimes have different effects when they are in different states i.e. for example the Convertible Arbitrage performs very well under Normal regime for Equity but fairs worse in the case of Event state.

- The Event performance was much better for Equity and Currency regime (when compared to Normal state performance). The converse is true wrt to Growth and Inflation regime.

- For the case where we invest during the Normal state but don't invest in Event State the performance vis a vis without knowledge of the states was a mixed bag. In some cases, there were good performance and, in some cases, it was very worse.

When I look at the cumulative returns only a few strategies have performed well using the Markovian information under investing during normal state and abstaining during event. These for example, convertible arbitrage under currency regime and emerging markets under equity/currency.

5. Out of sample Testing

For the out of sample testing, I used the QSTrader to simulate the strategies [6]. It provides a good framework for testing strategies focussing on the design of the strategies without worrying about coding for the results visualization and back testing and this is especially helpful for fast prototyping of strategies. I used the IShares MSCI Emerging Markets ETF (EEM henceforth) and the Vanguard FTSE Emerging Markets ETF (VVO henceforth) to simulate the emerging markets strategy. Amongst the very few strategies that showed promise, the emerging markets is the easiest to simulate (when compared to vis-à-vis the Fixed Income Arbitrage for example) given the data constraints. I used the currency as well as the S&P 500 regimes. I employed two different methods to fit the HMM model. One was the same method used in the in-sample testing i.e. to use the turbulence information to generate the HMM model. In the second method the returns were directly used to generate the HMM model. For fitting the second model two different time periods were chosen. One was from 1993 to 2010 (to get a long period for fitting) and the second was to use a shorter period (2005 to 2010, so as to not get influenced by whatever happened in far away history). For fitting the first model, only one-time period was chosen. This was between 1974 and 2004. The following section describes the various results obtained while doing the tests.

Basically, I used three variants of risk management. In the first case, there was no consideration of the Markovian states. In the second, if the regime is volatile, don't send long orders. The short orders are passed through if already stock is held. The back tests were done from 2011 to 2018. Basically, all the strategies use a simple moving average crossover strategy with additional risk management as described above. The SMA uses 30 days for long term and 10 days for short term windows.

5.1. Results

When I used either the currency/SPY fitted HMM model for Vanguard FTSE Emerging Markets ETF (VWO hereafter), the performance of the strategy improved after using regime state information.

Here are the tear-sheets with and without Markovian information

Monthly Returns (%)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2011	0.0	-4.0	1.9	0.0	2.0	15.6	8.7	-40.4	-38.2	95.0	0.0	-27.1
2012	0.1	28.0	0.0	-15.4	-39.7	0.9	-0.1	33.6	7.8	0.0	12.9	20.2
2013	3.3	3.6	-1.8	0.2	-14.7	-36.3	-28.3	14.3	60.9	14.5	10.6	-8.4
2014	6.6	12.1	12.2	7.1	-1.9	1.9	7.3	7.5	-25.9	1.2	0.0	-10.0
2015	-13.3	10.6	12.1	13.4	-1.7	-17.8	-19.8	-5.0	-2.0	0.0	-5.8	-23.3
2016	-3.0	-28.3	0.0	-0.3	7.2	40.3	10.2	-21.3	7.2	0.0	-19.3	10.3
2017	-0.1	0.0	29.2	-0.1	4.8	5.8	34.2	0.0	12.9	19.1	0.6	-0.6
2018	22.4	-10.0	-1.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Curve vs. Benchmark

Total Return	6%	-3%
CAGR	0.76%	-0.47%
Sharpe Ratio	0.55	0.08
Sortino Ratio	0.53	0.11
Annual Volatility	106.93%	20.75%
R-Squared	0.08	0.09
Max Daily Drawdown	85.17%	43.70%
Max Drawdown Duration	1680	1701
Trades per Year	9.9	

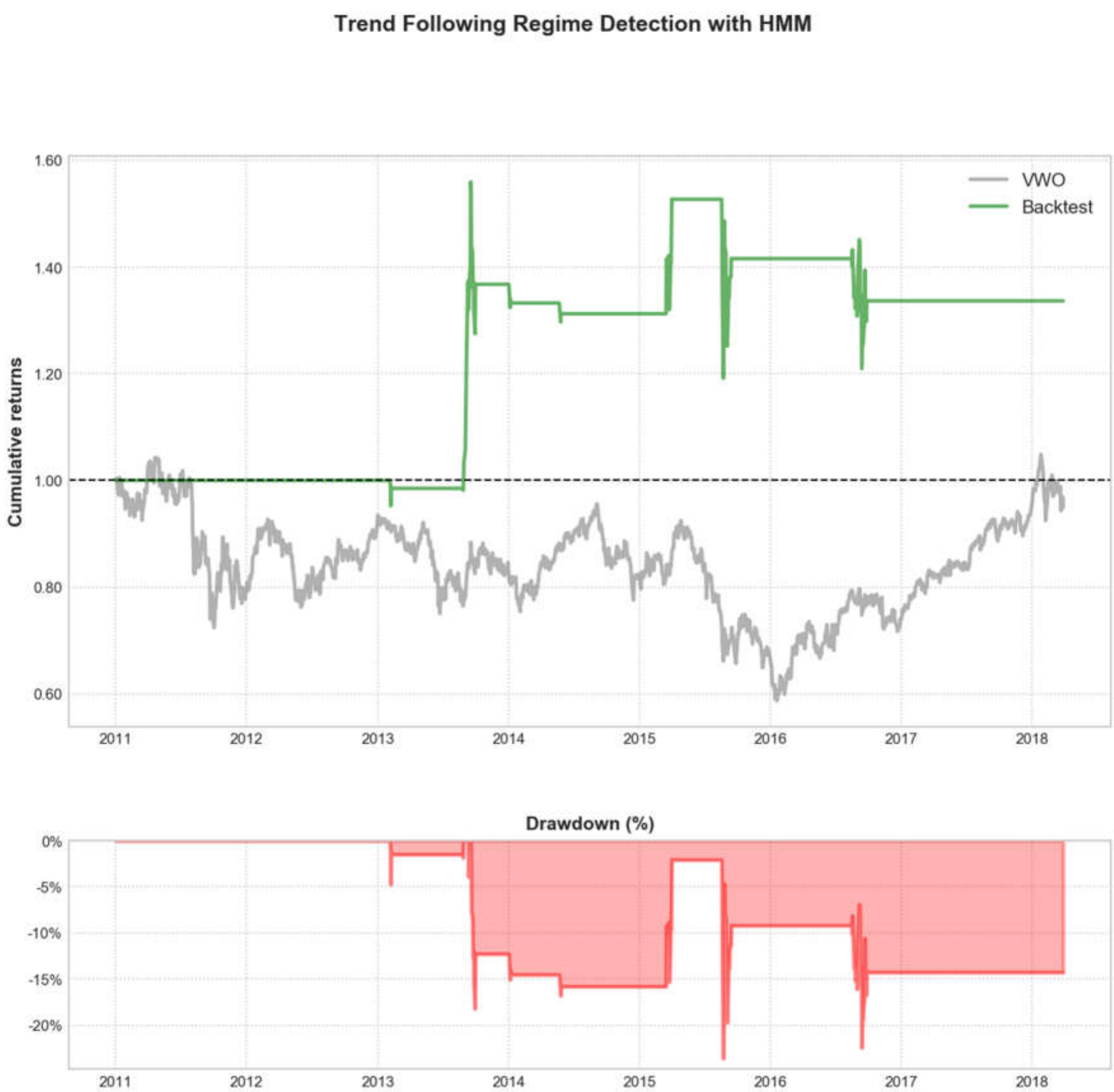
Trade

Trade Winning %	58%
Average Trade %	0.08%
Average Win %	2.22%
Average Loss %	-2.92%
Best Trade %	10.32%
Worst Trade %	-11.62%
Worst Trade Date	TBD
Avg Days in Trade	0.0
Trades	72

Time

Winning Months %	62%
Average Winning Month %	11.67%
Average Losing Month %	-14.11%
Best Month %	95.02%
Worst Month %	-40.43%
Winning Years %	50%
Best Year %	157.86%
Worst Year %	-46.82%

Fig 8. Out of Sample Backtesting performance without HMM information



Monthly Returns (%)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2011	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2012	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2013	0.0	-1.5	0.0	0.0	0.0	0.0	0.0	5.0	23.3	7.3	0.0	0.0
2014	-2.6	0.0	0.0	0.0	-1.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2015	0.0	0.0	7.3	8.4	0.0	0.0	0.0	-6.5	-0.9	0.0	0.0	0.0
2016	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-7.6	2.2	0.0	0.0	0.0
2017	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2018	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Curve vs. Benchmark

Total Return	34%	-3%
CAGR	4.10%	-0.47%
Sharpe Ratio	0.33	0.08
Sortino Ratio	0.11	0.11
Annual Volatility	15.87%	20.75%
R-Squared	0.63	0.09
Max Daily Drawdown	23.60%	43.70%
Max Drawdown Duration	1140	1701
Trades per Year	1.0	

Trade

Trade Winning %	29%
Average Trade %	1.28%
Average Win %	7.85%
Average Loss %	-1.35%
Best Trade %	10.32%
Worst Trade %	-3.10%
Worst Trade Date	TBD
Avg Days in Trade	0.0
Trades	7

Time

Winning Months %	93%
Average Winning Month %	0.66%
Average Losing Month %	-3.41%
Best Month %	23.30%
Worst Month %	-7.59%
Winning Years %	75%
Best Year %	36.80%
Worst Year %	-5.58%

Fig 9. Out of Sample Backtesting performance with HMM information from S&P 500

This is very much in line with the In-Sample results.

When I used EEM, the results were quite counterintuitive. The performance deteriorated when using the regime information provided by either the currency or the S&P 500 data.

Fig 10. Out of Sample Backtesting performance with HMM information from S&P 500 for EEM

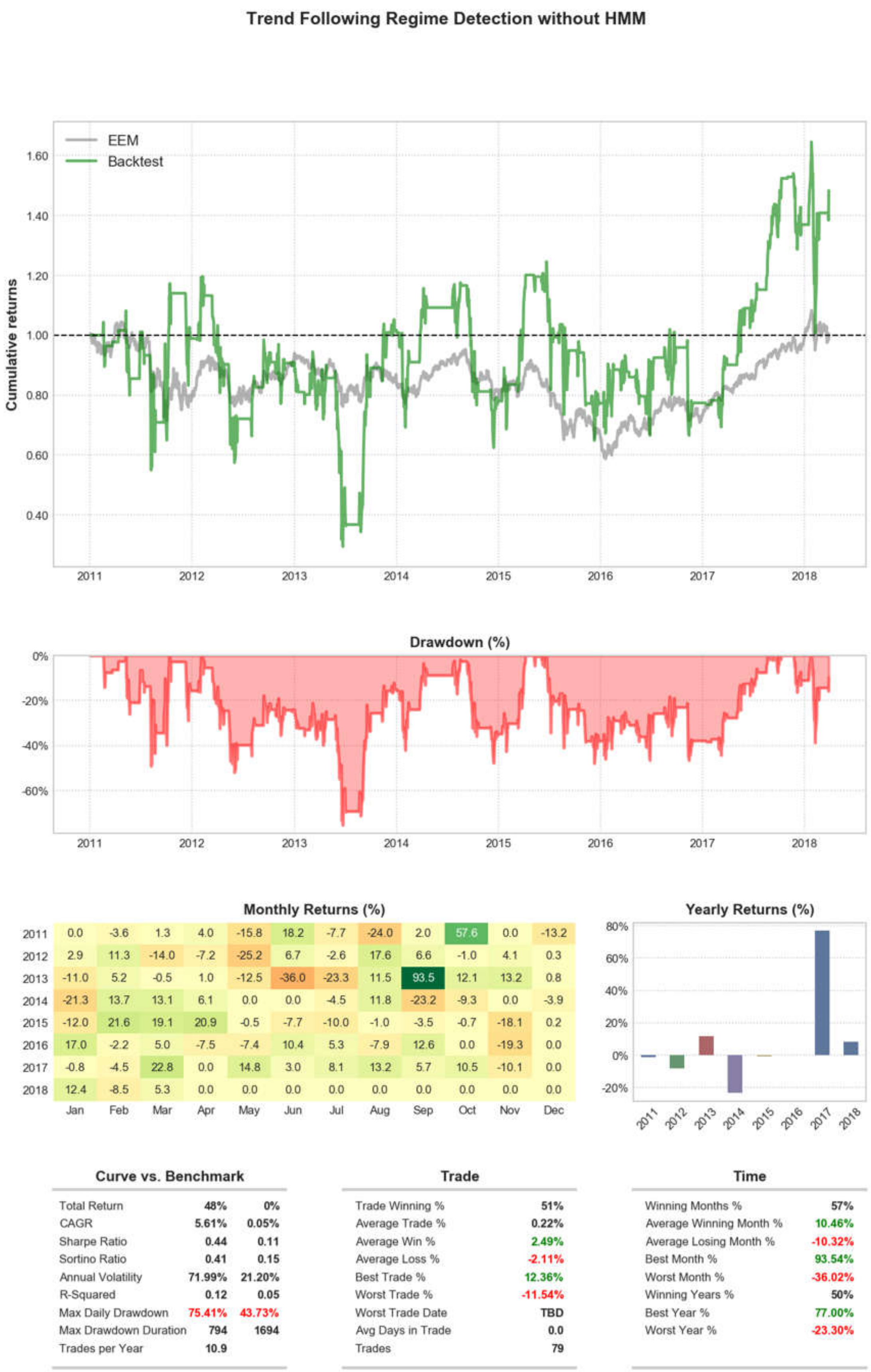


Fig 11. Out of Sample Backtesting performance without HMM information for EEM

As for using the HMM model using the direct SPY returns it didn’t prove to be quite useful. So, the results are mixed in that the out of sample testing are in line for VVO but not so for EEM when compared to the in-sample testing.

I tied various combination of HMM models, time periods and instruments. And I have shown the most pertinent results. Also, there are other exogenous parameters that needs to be tuned. For example, the SMA strategy uses 30 and 10 for long and short window durations. This perhaps plays a major role in the performance.

6. Conclusion

The out of sample testing was inconclusive. I used only two instruments to test 1 strategy for lack of time and data resources. Maybe this work could be further extended by using a wider variety of data sets confirming to different strategies. So, this quite premature to conclude whether the regime based tactical allocation strategy worked or not. Based on those strategies that work and that do not work the different strategies could be combined to help in designing quite a dynamic allocation for investing. Nevertheless, this project made me to work outside the comfort zone. In the process I learnt about the Hidden Markov Models, its implementation using different algorithms like Expectation Maximization.
This work could be further extended by incorporating Gaussian mixture models. These work on a similar principle to the Hidden Markov Models. It would be interesting study by itself.

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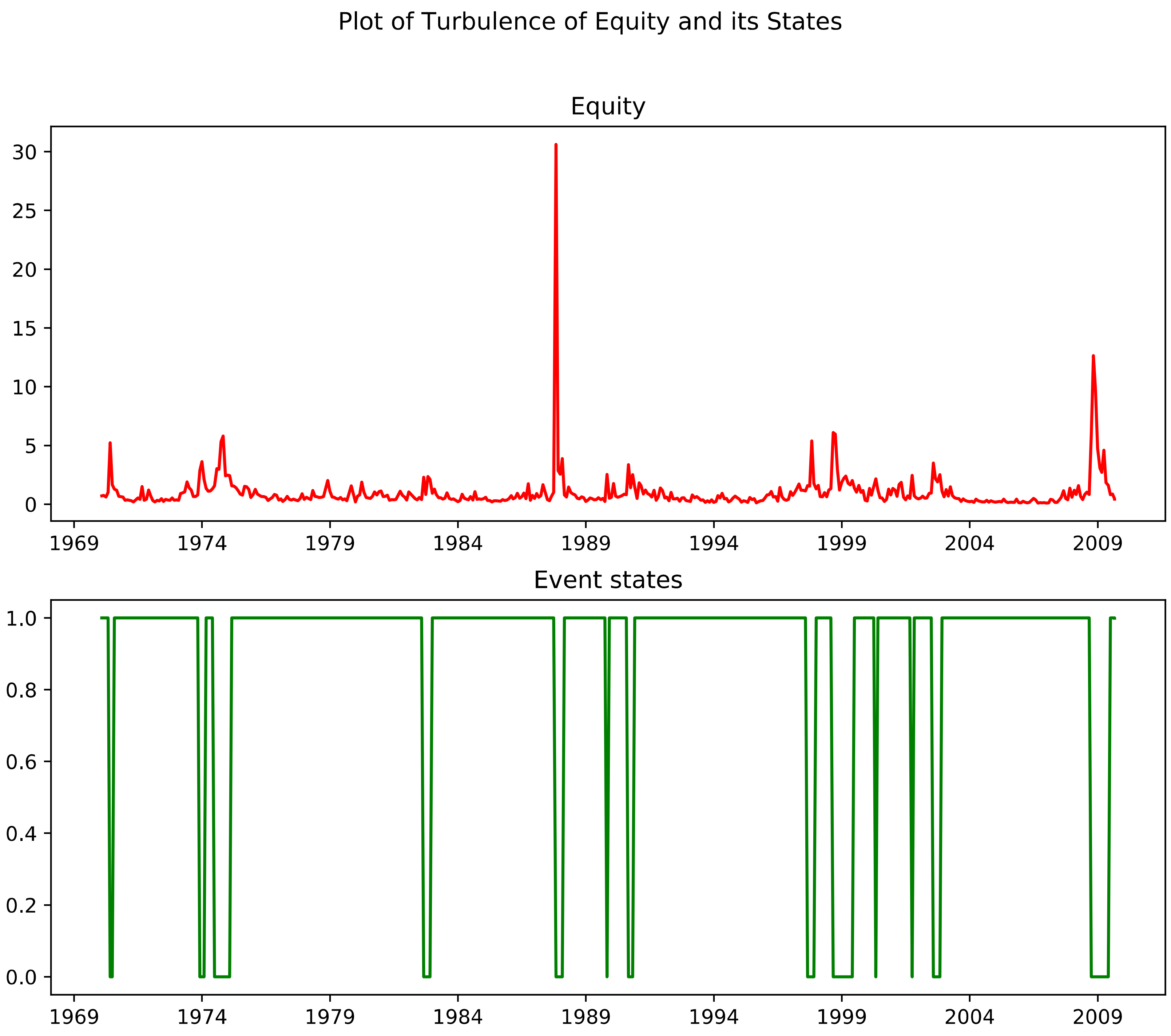
Appendix



Plot of Turbulence of Equity and its States
Equity
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1994
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Event states
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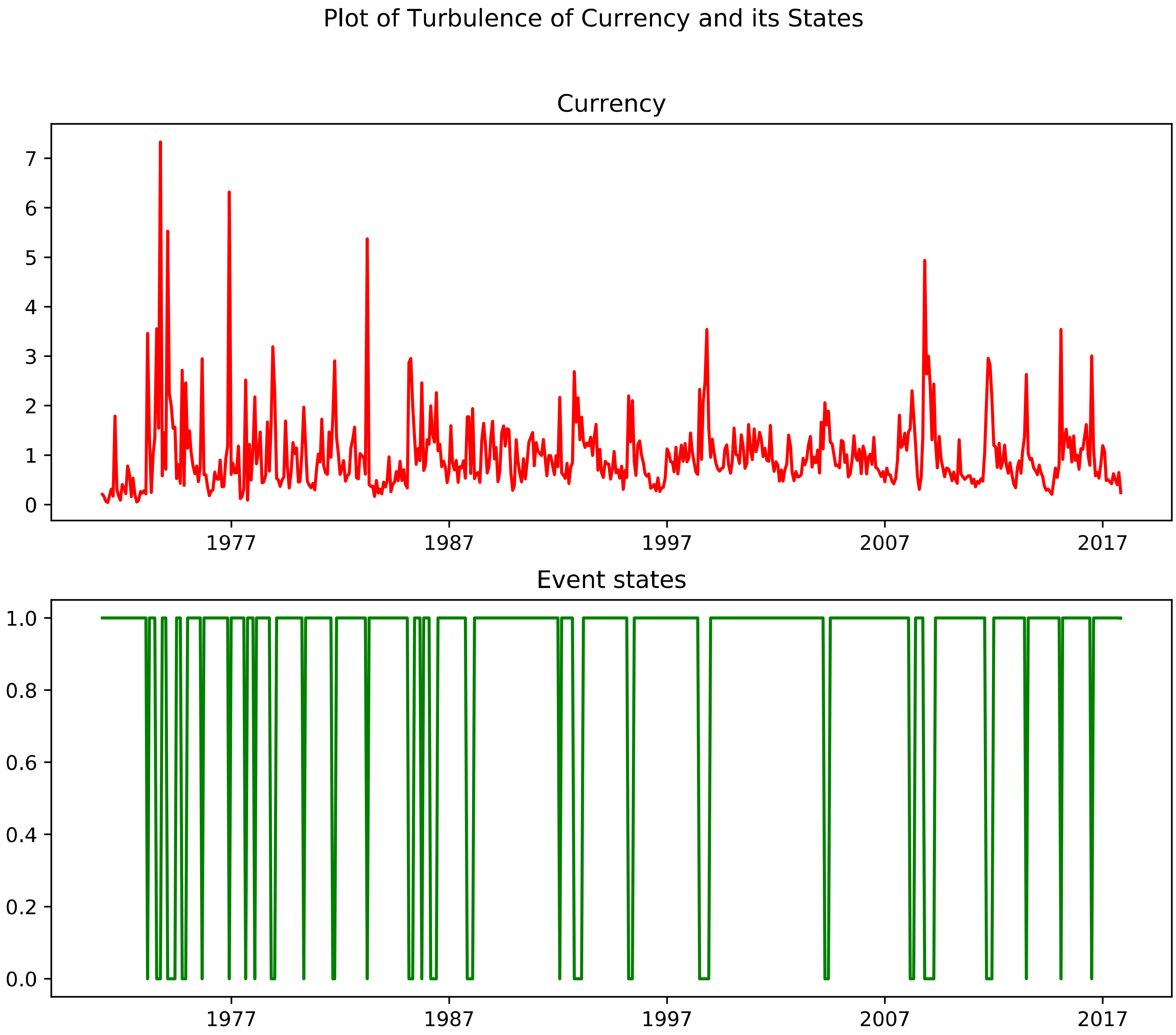

Plot of Turbulence of Currency and its States
Currency
7
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1987
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Event states
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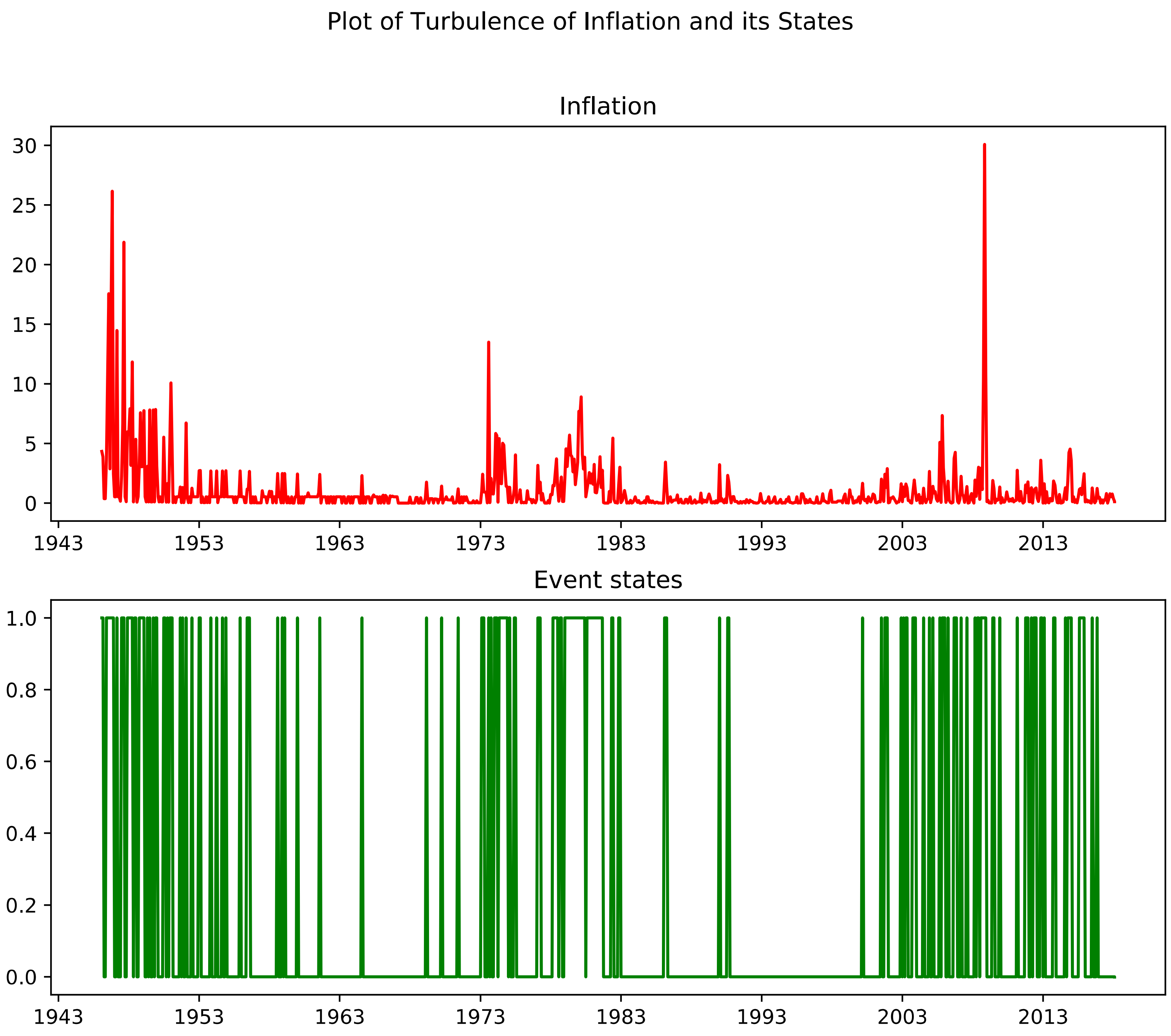

Plot of Turbulence of Inflation and its States
Inflation
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Event states
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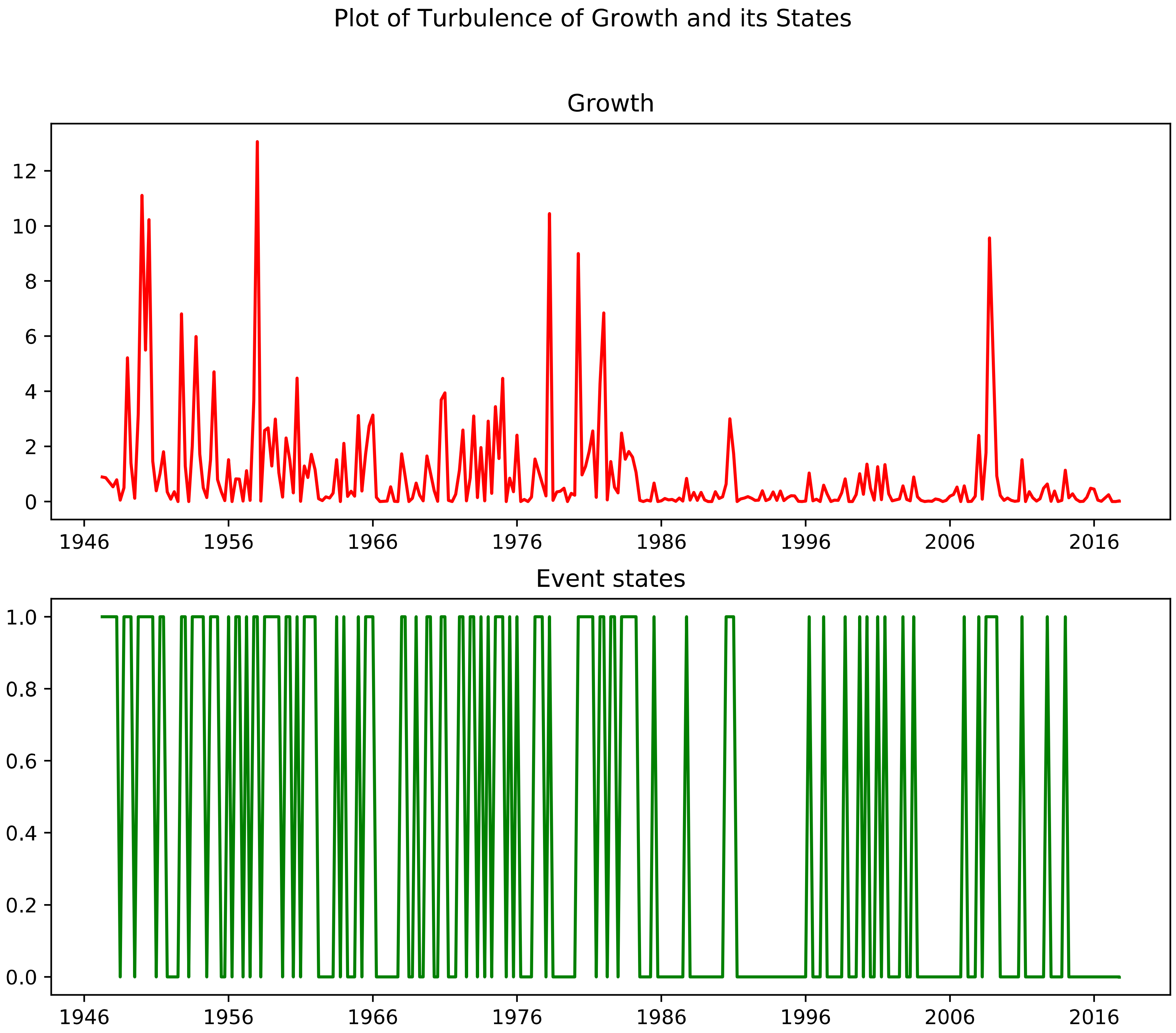
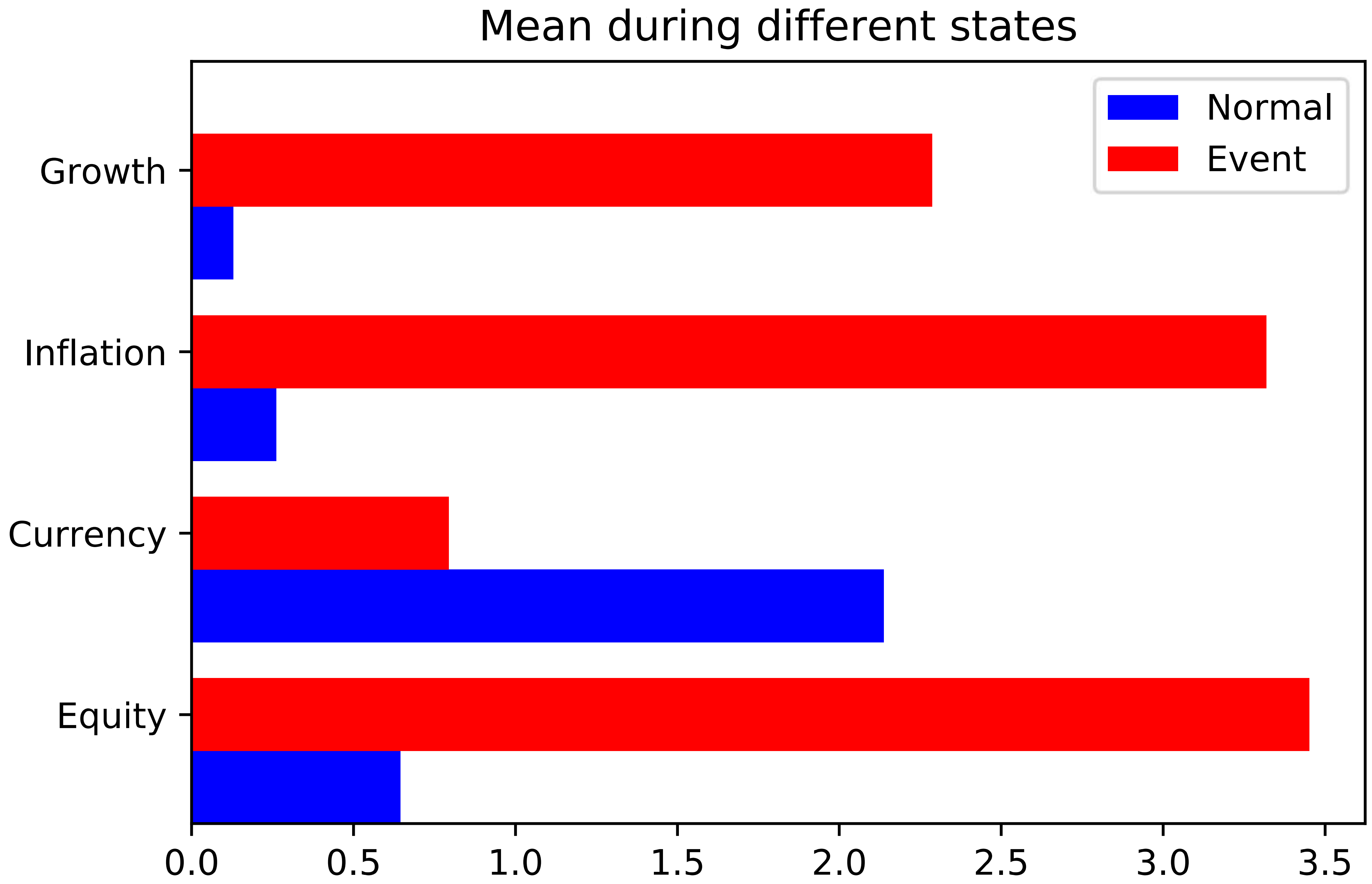
2003
2013


Plot of Turbulence of Growth and its States
Growth
Event states
0
2
4
6
8
10
12
0.0
0.2
0.4
0.6
0.8
1.0
1946
1956
1966
1976
1986
1996
2006
2016

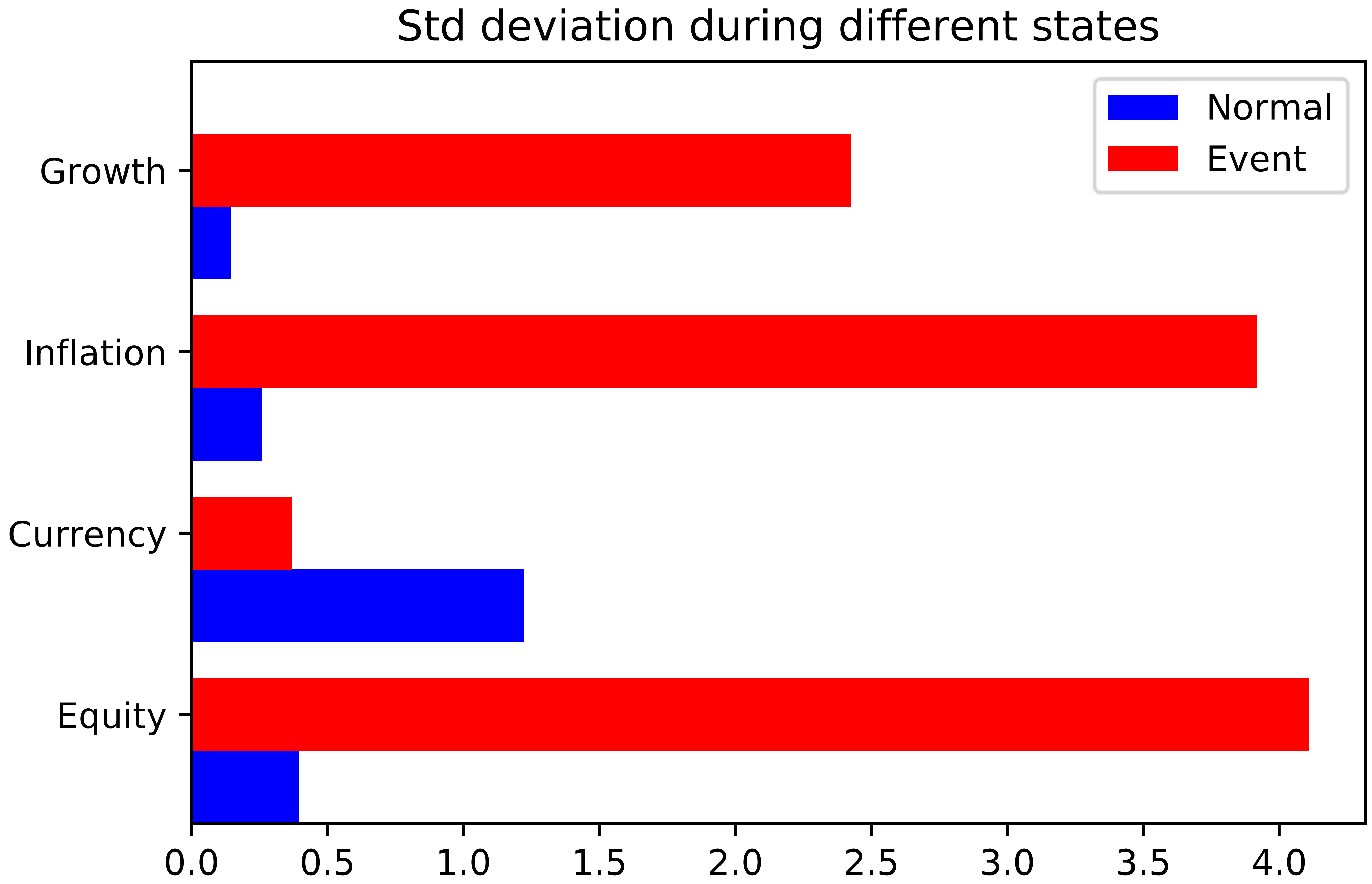
Mean Estimates in different regimes

Regime	Normal	Event
Equity	0.644	3.451
Currency	2.13717397952	0.793916328159
Inflation	0.261734583751	3.31843725792
Growth	0.128534891405	2.28641873559


Mean during different states
Normal
Event
Growth
Inflation
Currency
Equity
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5

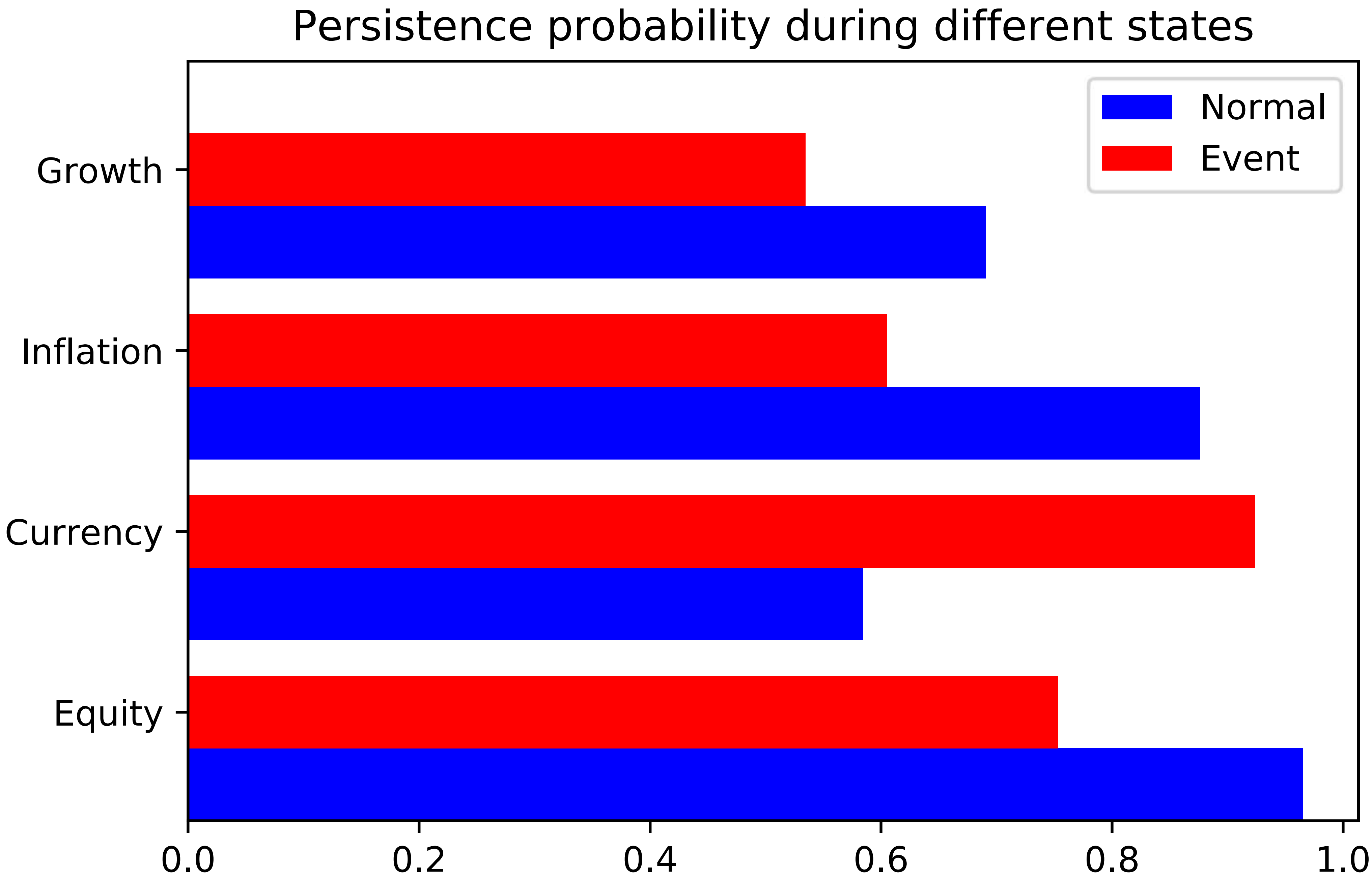
Standard_Deviation Estimates in different regimes

Regime	Normal	Event
Equity	0.393	4.11
Currency	1.22003680083	0.367763933001
Inflation	0.2606383895	3.91703864423
Growth	0.142891671145	2.42498095372


Std deviation during different states
Normal
Event
Growth
Inflation
Currency
Equity
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0

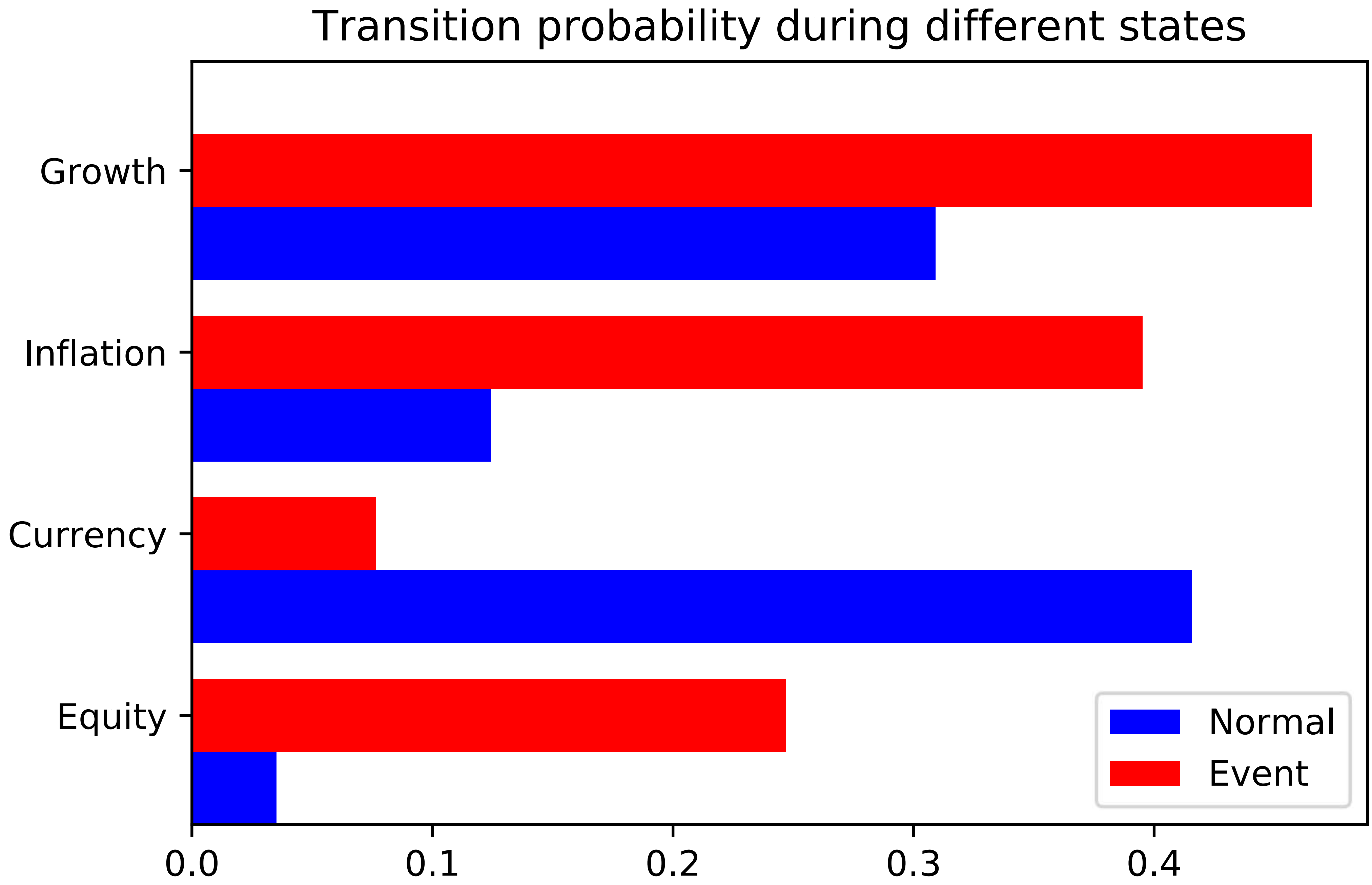
Persistence_Probability Estimates in different regimes

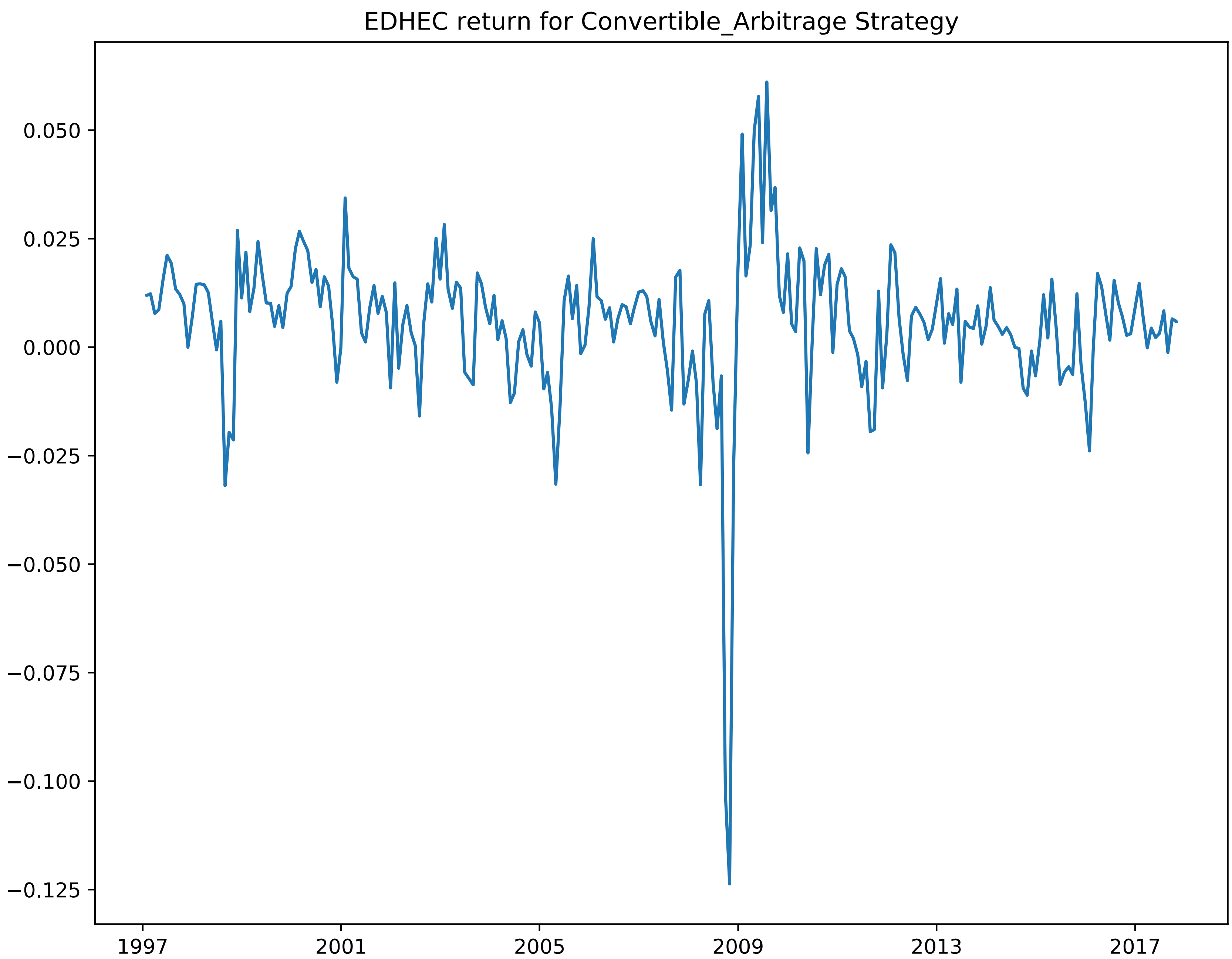
Regime	Normal	Event
Equity	0.965	0.753
Currency	0.584321214197	0.923617753202
Inflation	0.875782045613	0.604914677786
Growth	0.690878329631	0.534546407737


Persistence probability during different states
Normal
Event
Growth
Inflation
Currency
Equity
0.0
0.2
0.4
0.6
0.8
1.0

Transition_Probability Estimates in different regimes

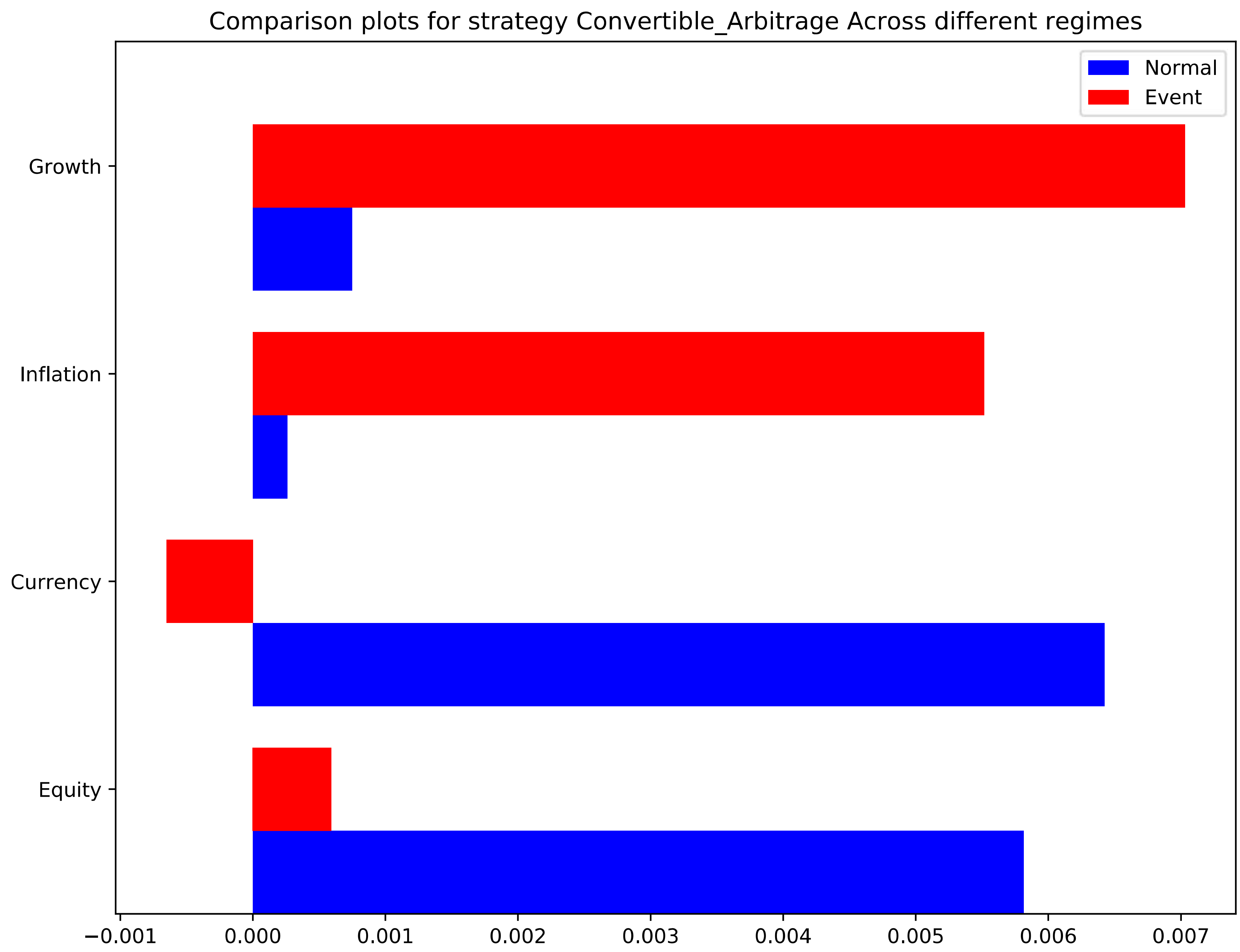
Regime	Normal	Event
Equity	0.035	0.247
Currency	0.415678785803	0.0763822467984
Inflation	0.124217954387	0.395085322214
Growth	0.309121670369	0.465453592263

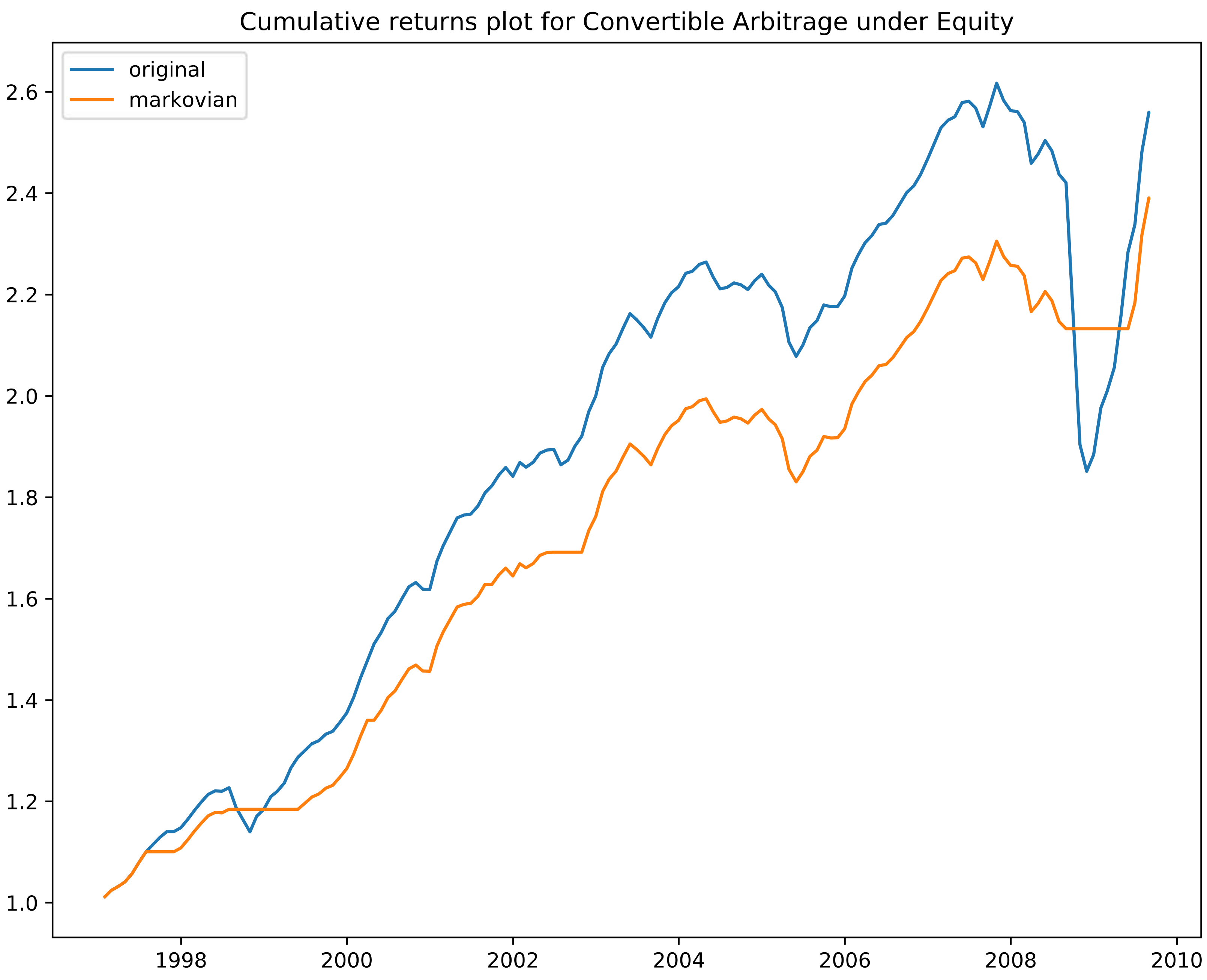

Transition probability during different states
Growth
Inflation
Currency
Equity
0.0
0.1
0.2
0.3
0.4
Normal
Event


EDHEC return for Convertible_Arbitrage Strategy
0.050
0.025
0.000
−0.025
−0.050
−0.075
−0.100
−0.125
1997
2001
2005
2009
2013
2017

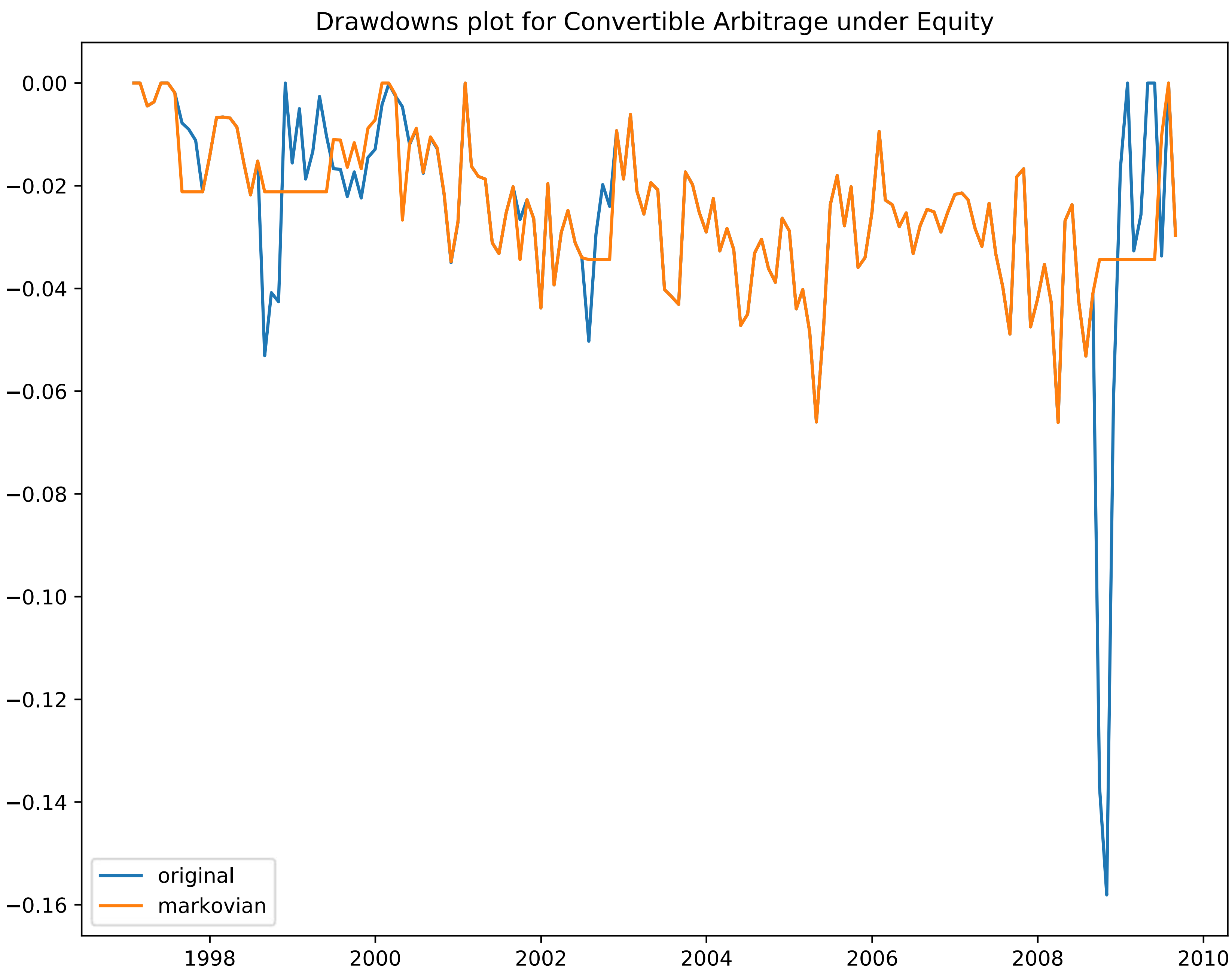
Convertible_Arbitrage Estimates in different regimes

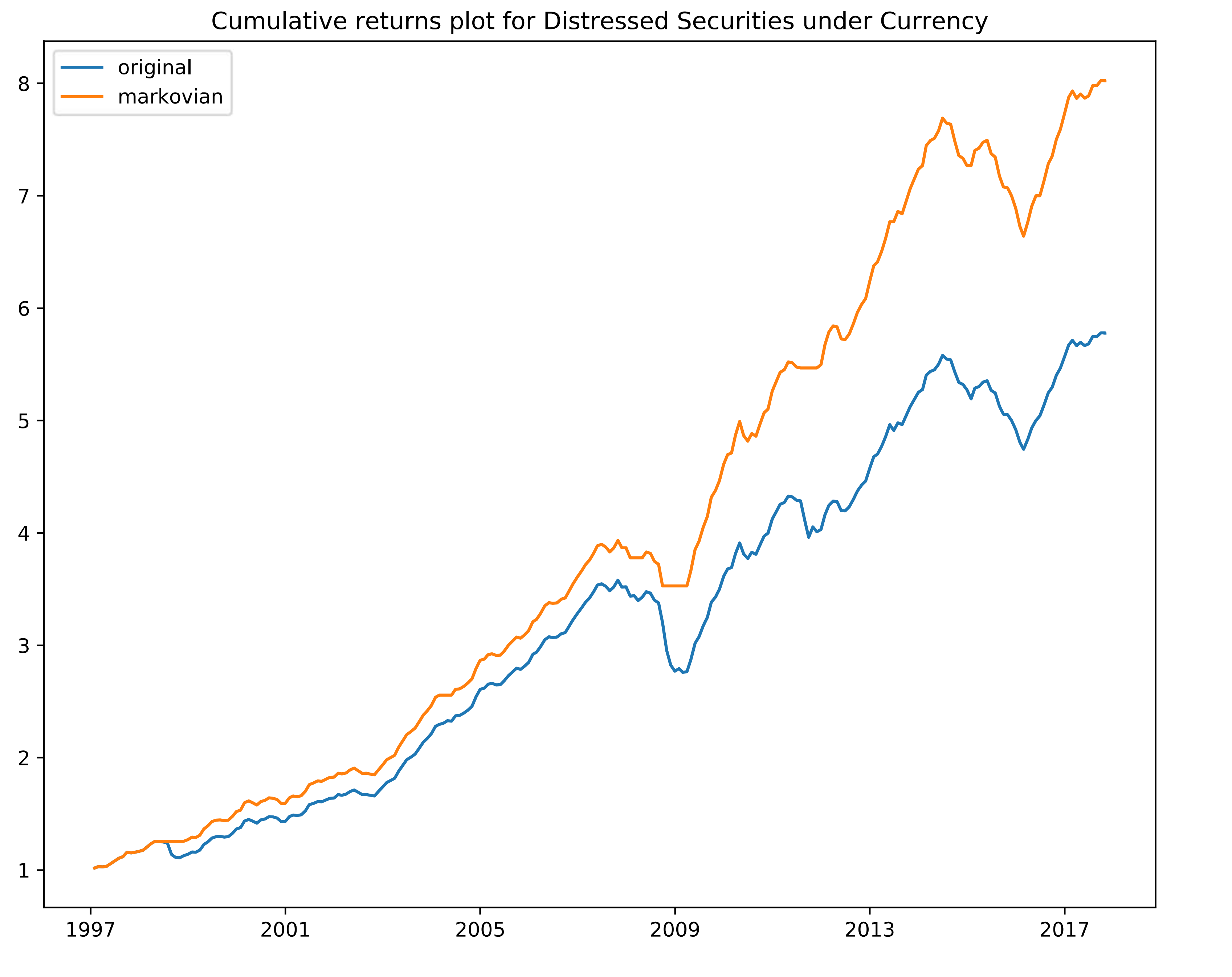
Regime	Normal	Event
Equity	0.00581513157895	0.000593421052632
Currency	0.006424	-0.00065
Inflation	0.0002596	0.0055144
Growth	0.000748809523810	0.00702976190476

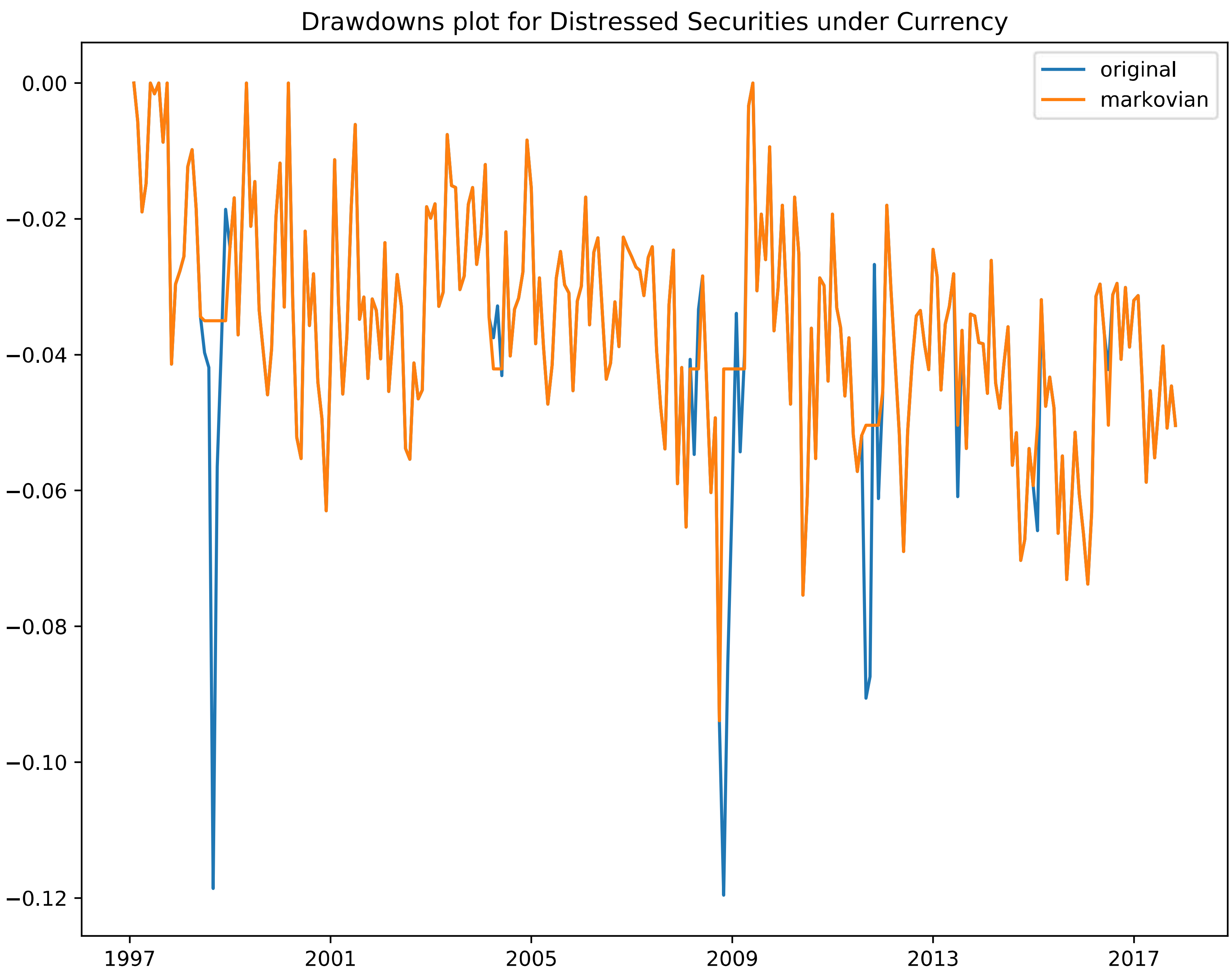

Comparison plots for strategy Convertible_Arbitrage Across different regimes
Normal
Event
Growth
Inflation
Currency
Equity
−0.001
0.000
0.001
0.002
0.003
0.004
0.005
0.006
0.007



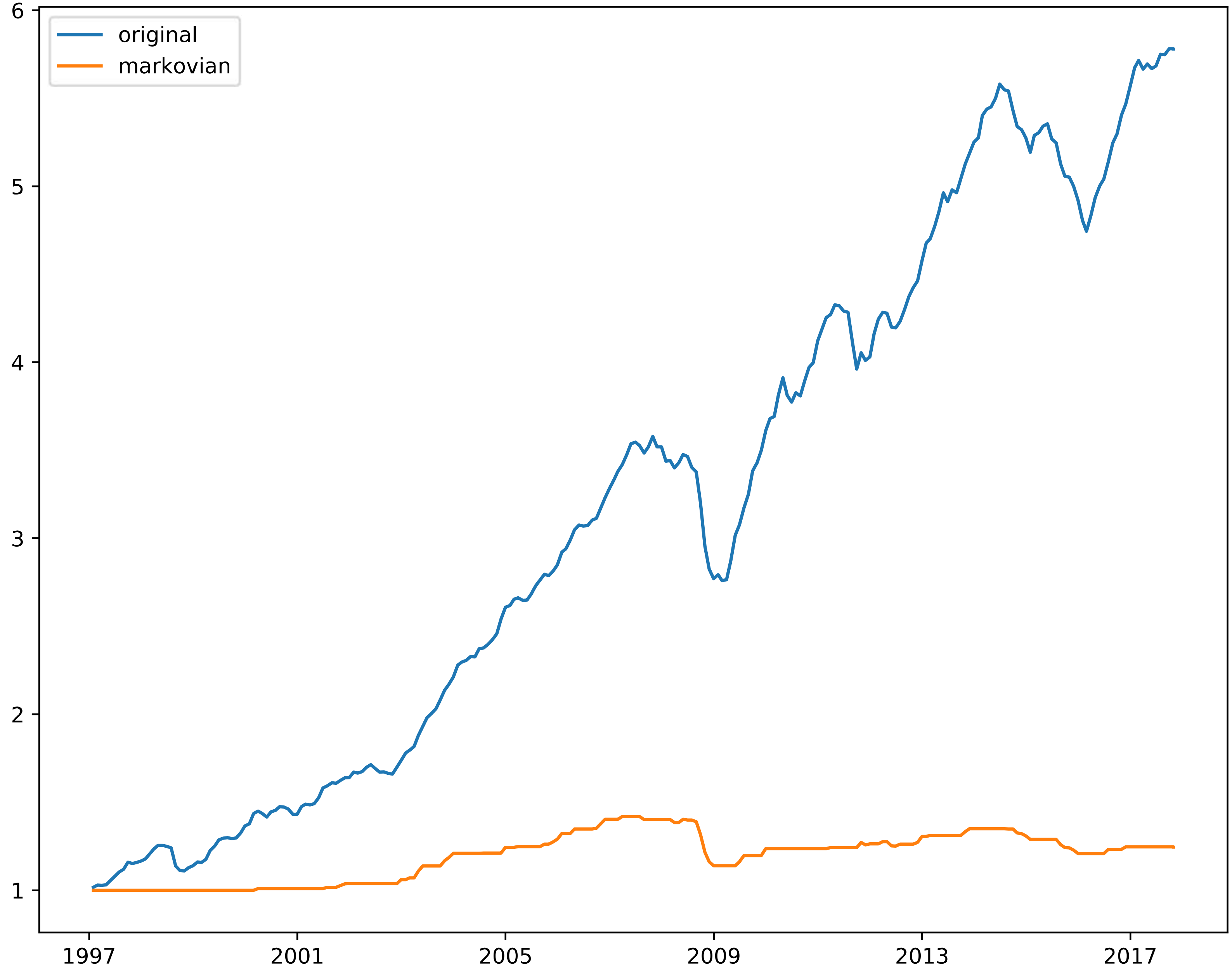
Cumulative returns plot for Convertible Arbitrage under Equity
original
markovian
2.6
2.4
2.2
2.0
1.8
1.6
1.4
1.2
1.0
1998
2000
2002
2004
2006
2008
2010

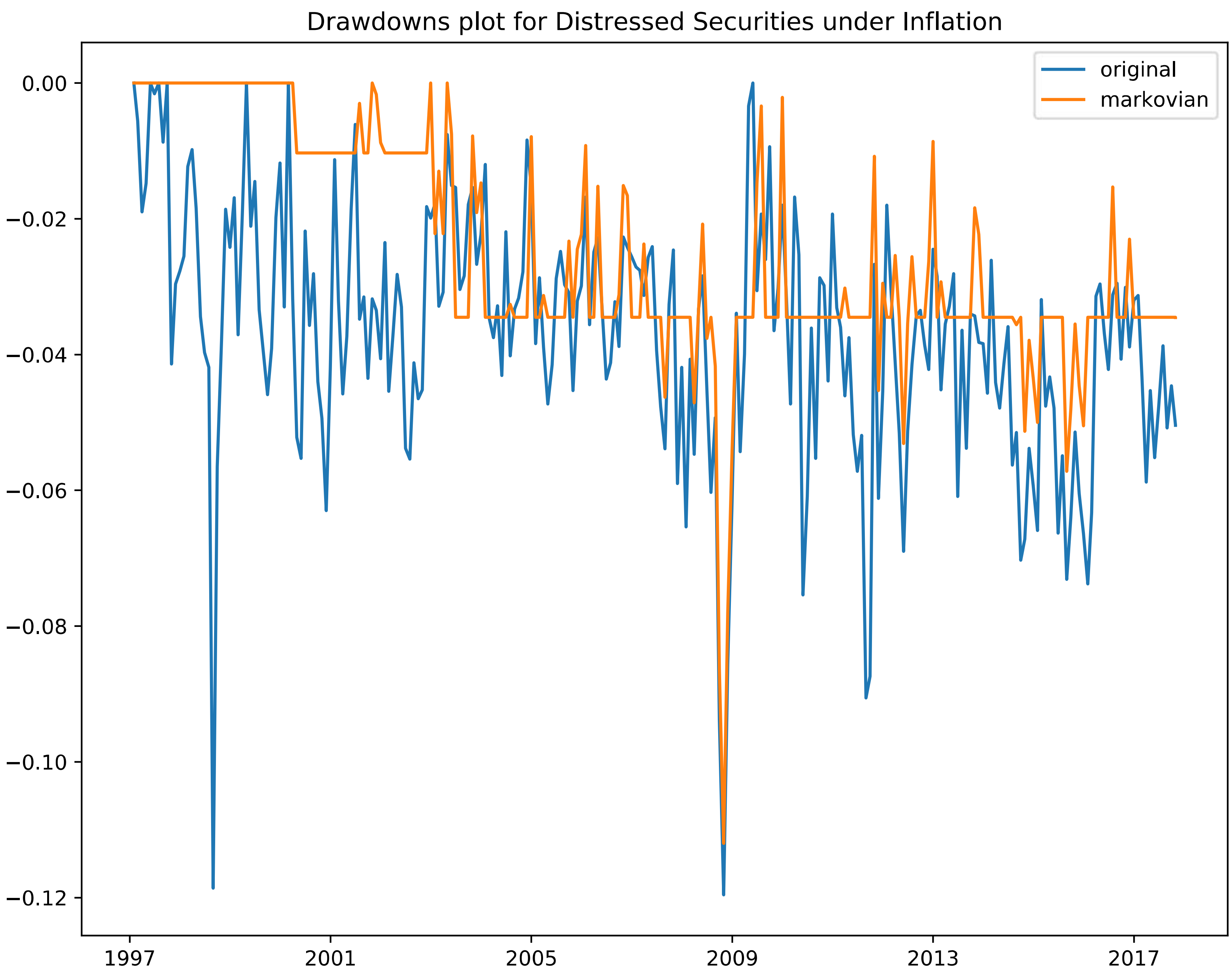

Drawdowns plot for Convertible Arbitrage under Equity
0.00
−0.02
−0.04
−0.06
−0.08
−0.10
−0.12
−0.14
−0.16
1998
2000
2002
2004
2006
2008
2010
original
markovian

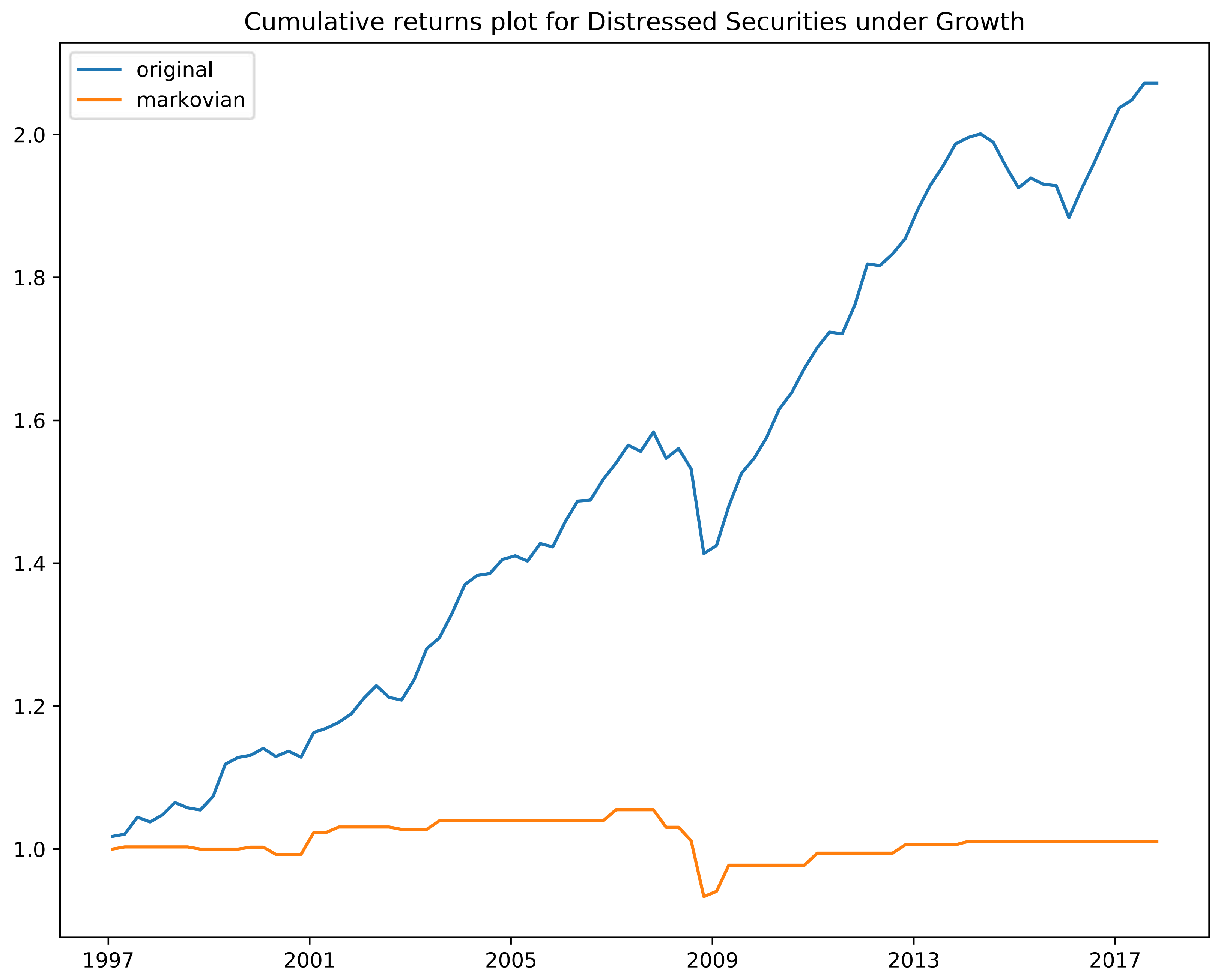

Cumulative returns plot for Distressed Securities under Currency
original
markovian
1
2
3
4
5
6
7
8
1997
2001
2005
2009
2013
2017


Drawdowns plot for Distressed Securities under Currency
original
markovian
0.00
−0.02
−0.04
−0.06
−0.08
−0.10
−0.12
1997
2001
2005
2009
2013
2017

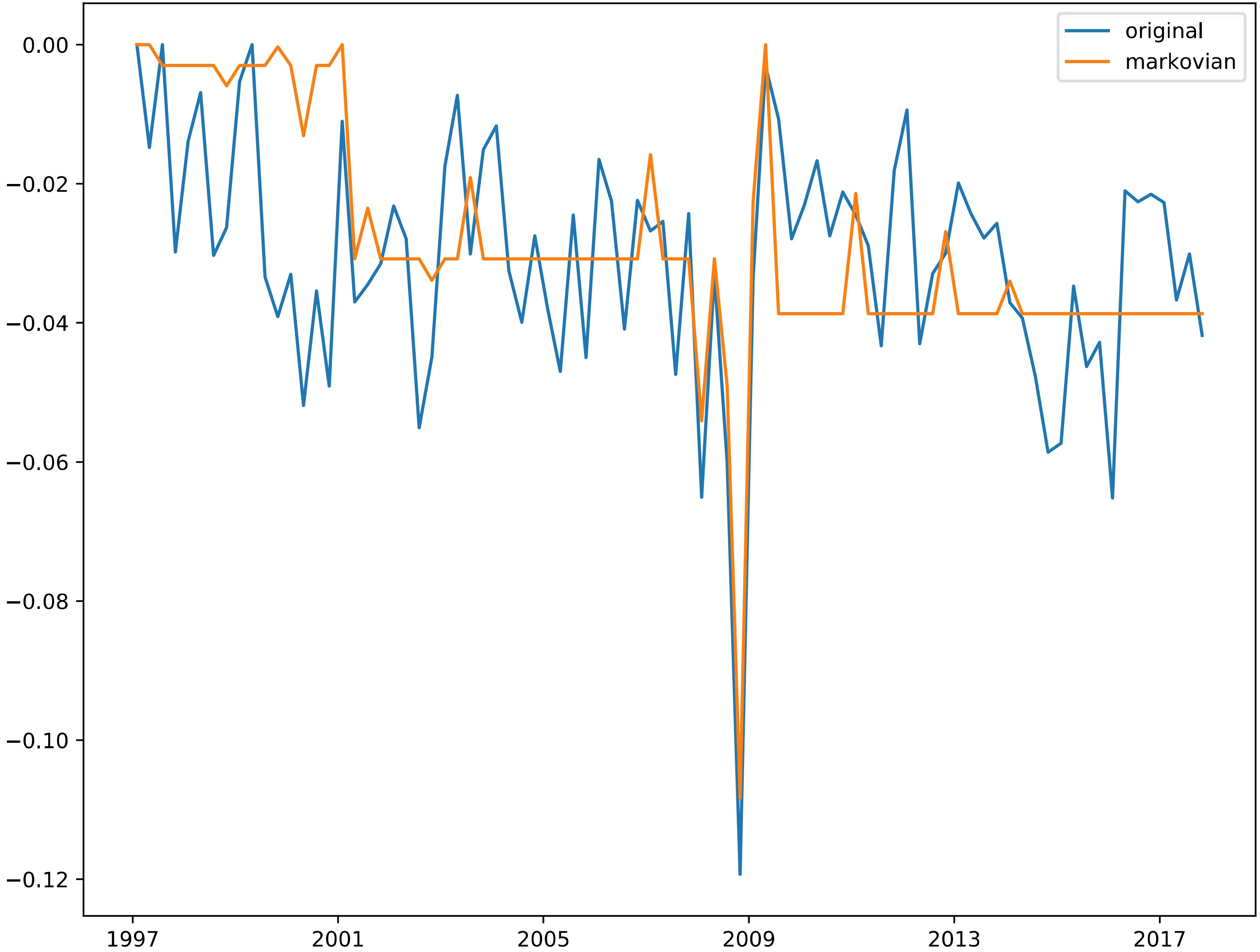
Cumulative returns plot for Distressed Securities under Inflation

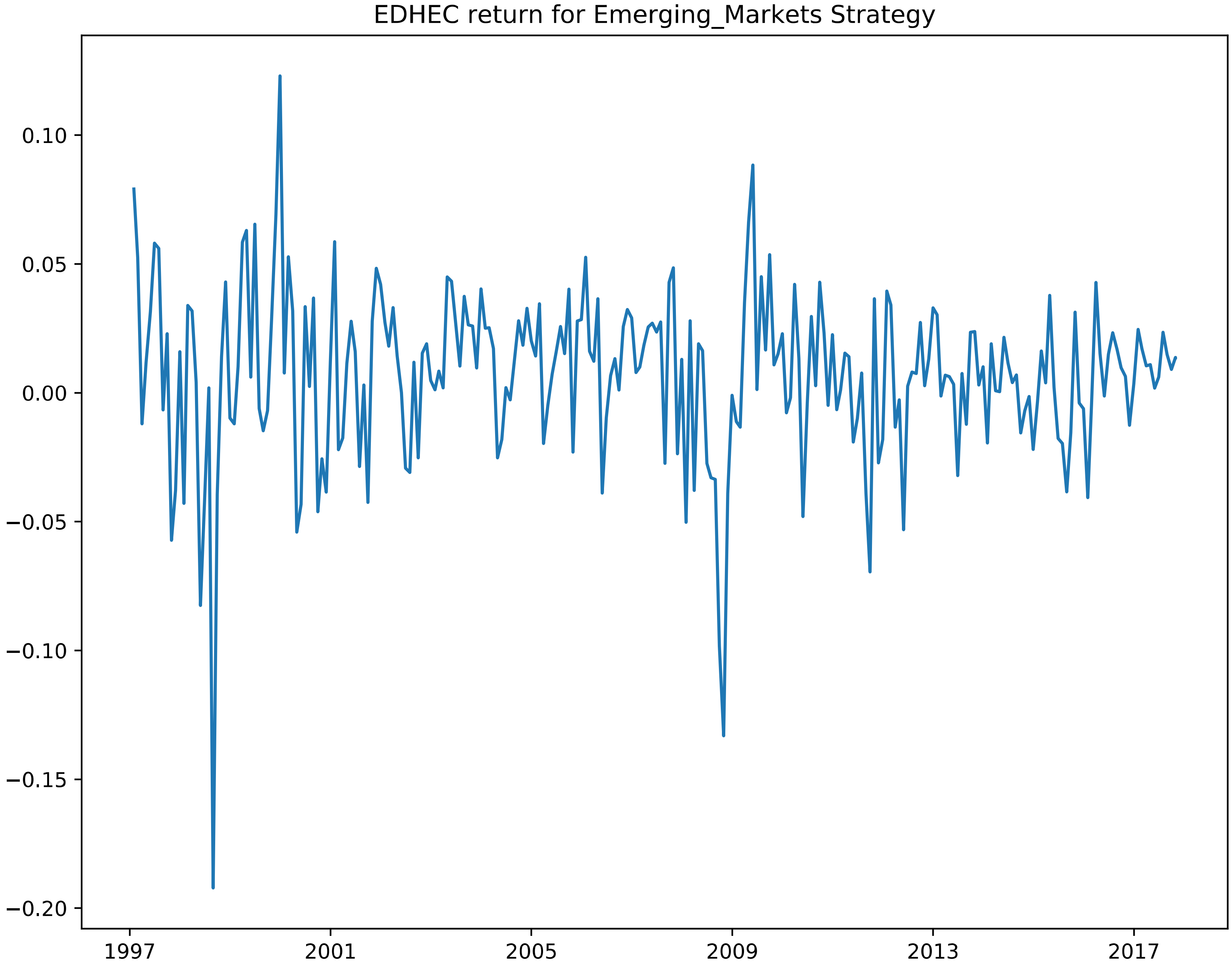



Drawdowns plot for Distressed Securities under Inflation
original
markovian
0.00
−0.02
−0.04
−0.06
−0.08
−0.10
−0.12
1997
2001
2005
2009
2013
2017


Cumulative returns plot for Distressed Securities under Growth
original
markovian
2.0
1.8
1.6
1.4
1.2
1.0
1997
2001
2005
2009
2013
2017

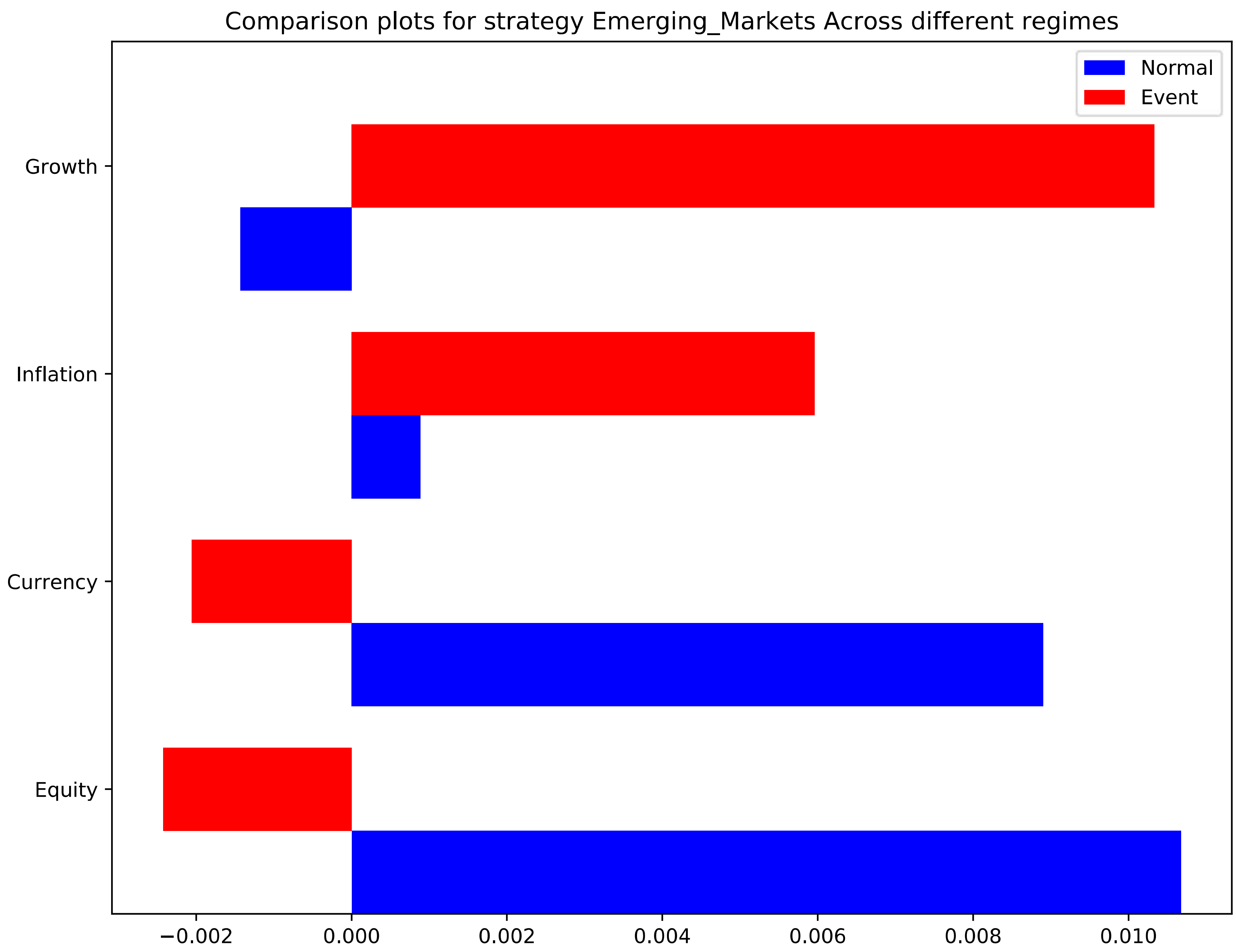
Drawdowns plot for Distressed Securities under Growth

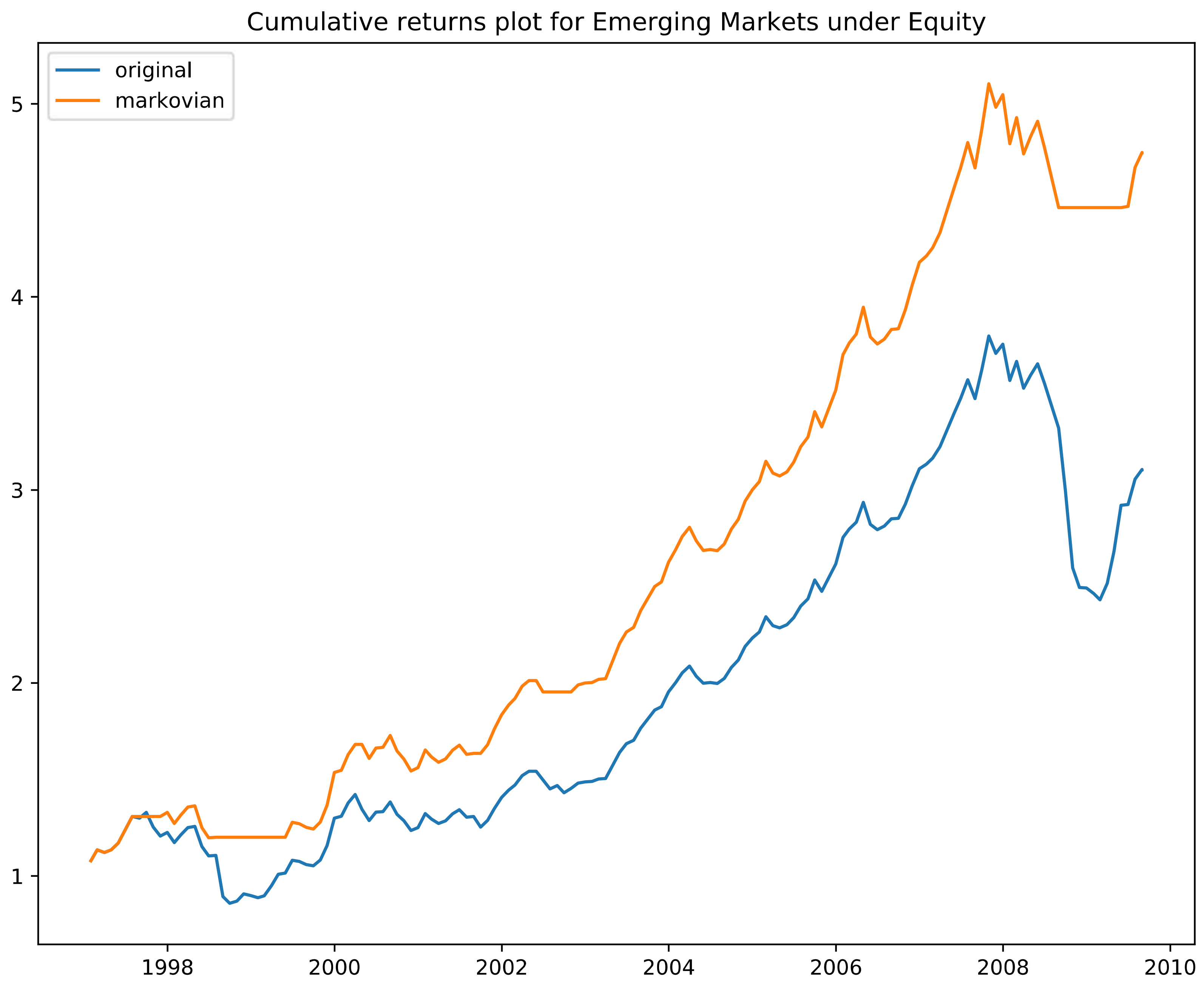



EDHEC return for Emerging_Markets Strategy
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.20
1997
2001
2005
2009
2013
2017

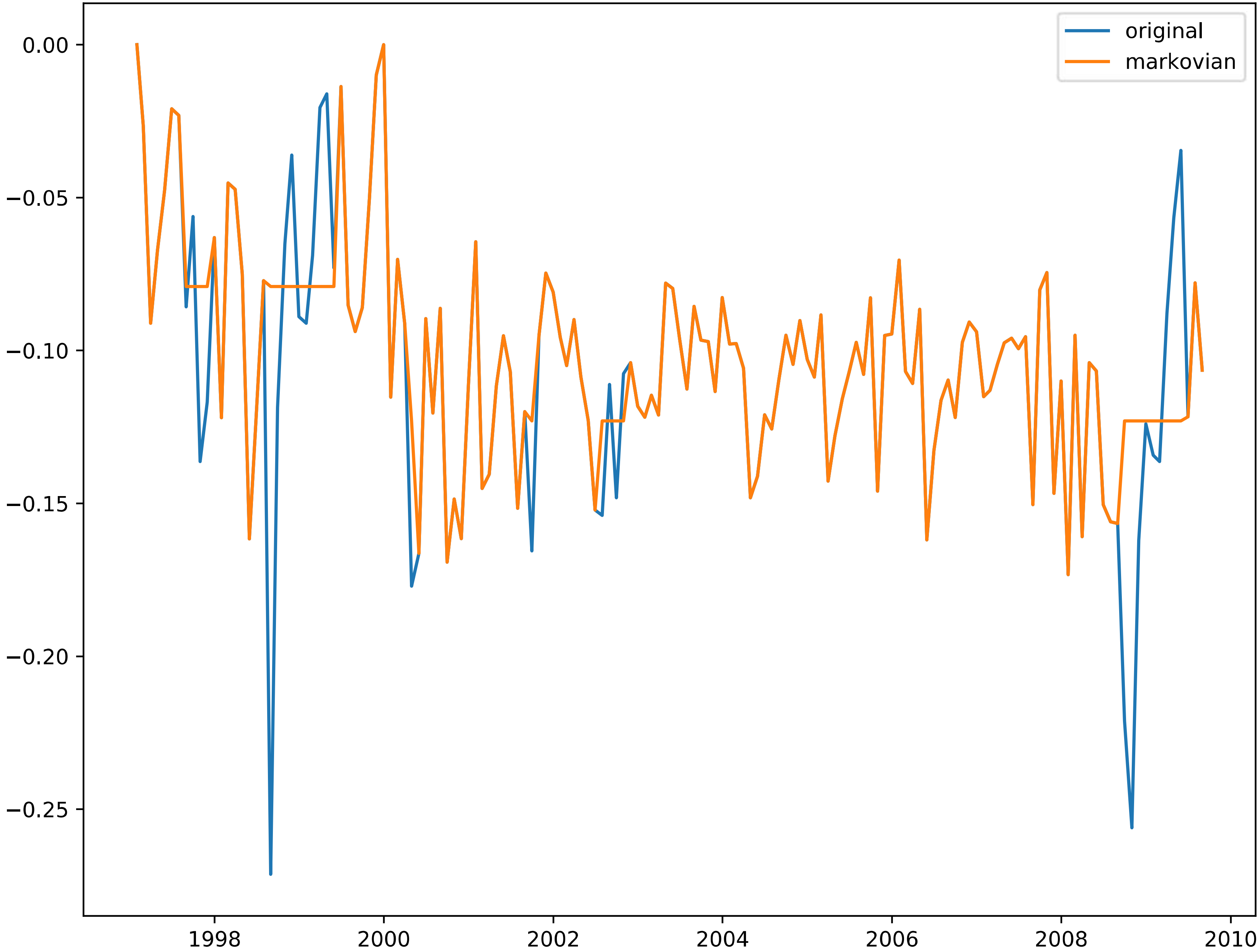
Emerging_Markets Estimates in different regimes

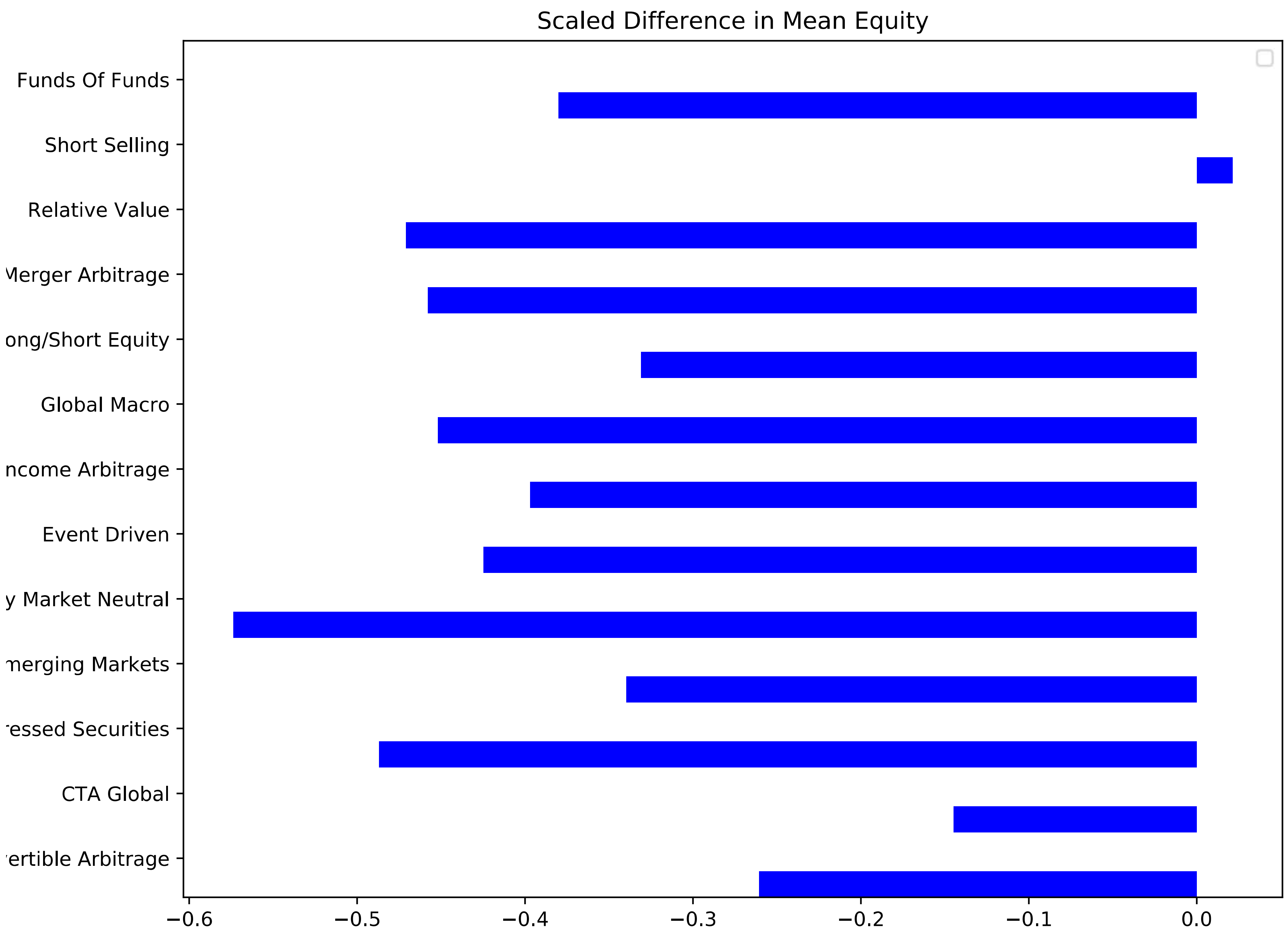
Regime	Normal	Event
Equity	0.0106736842105	-0.00242763157895
Currency	0.0089024	-0.002058
Inflation	0.0008852	0.0059592
Growth	-0.00143095238095	0.0103333333333

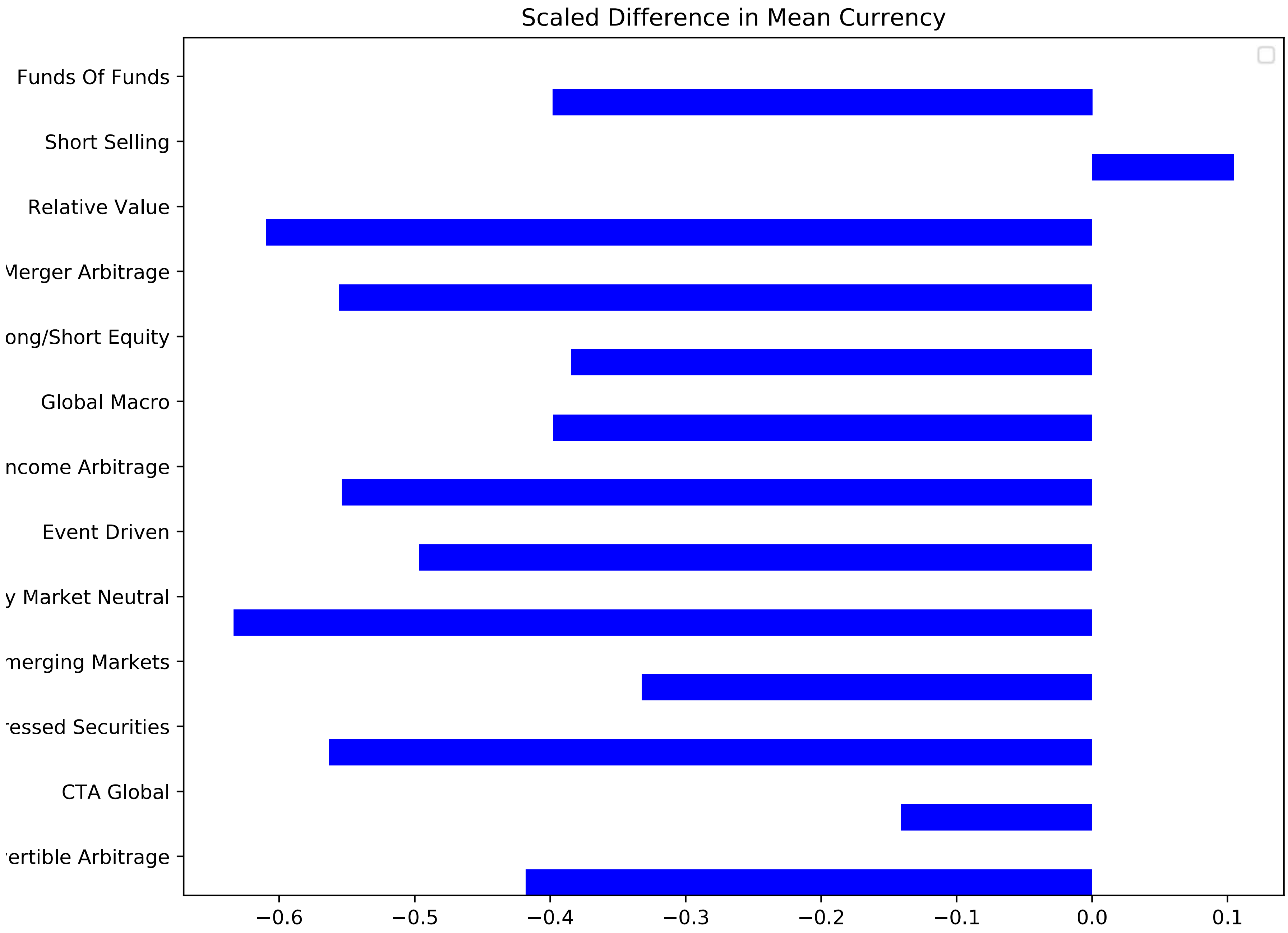

Comparison plots for strategy Emerging_Markets Across different regimes
Normal
Event
Growth
Inflation
Currency
Equity
−0.002
0.000
0.002
0.004
0.006
0.008
0.010

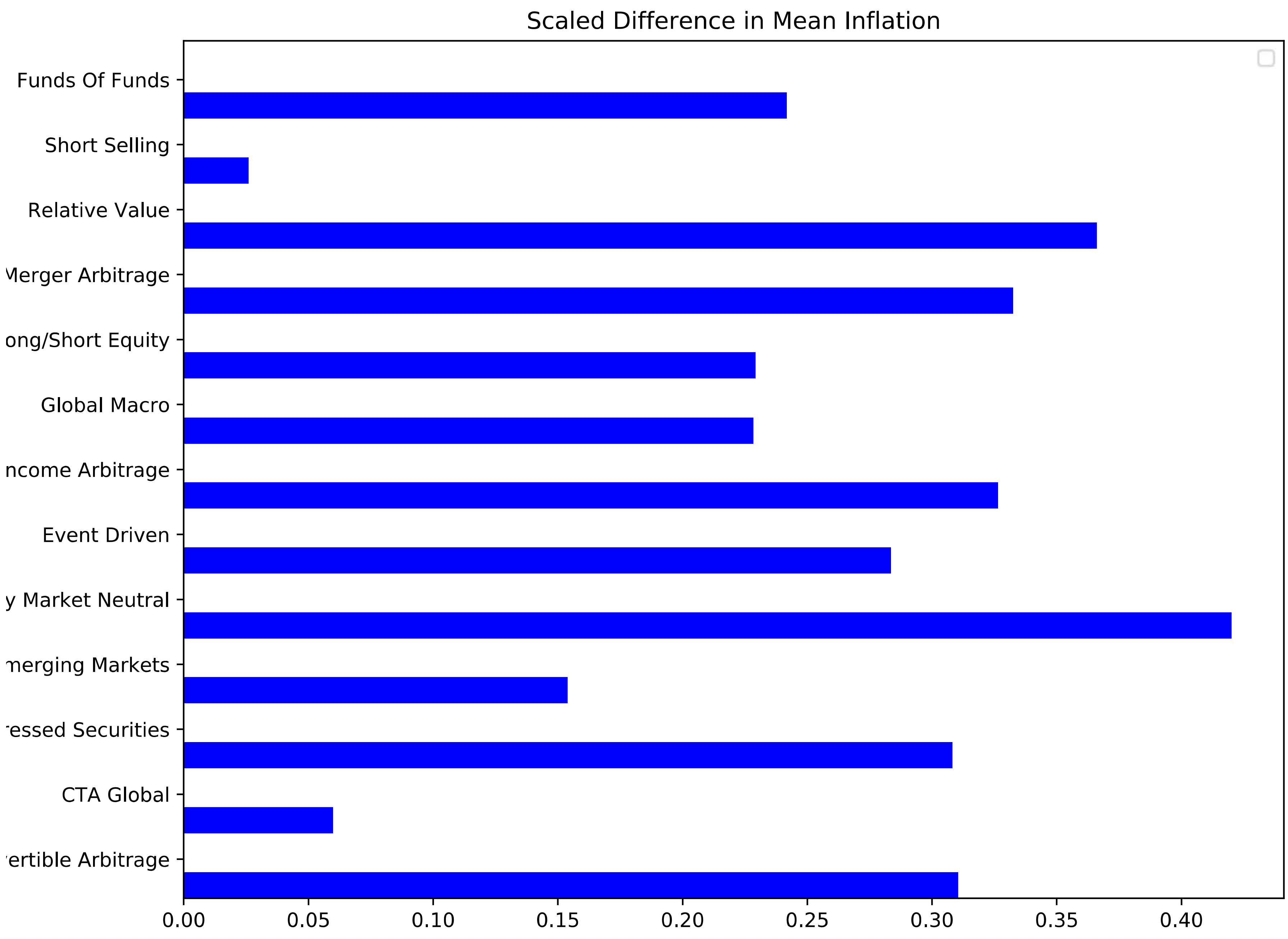

Cumulative returns plot for Emerging Markets under Equity
original
markovian
1
2
3
4
5
1998
2000
2002
2004
2006
2008
2010

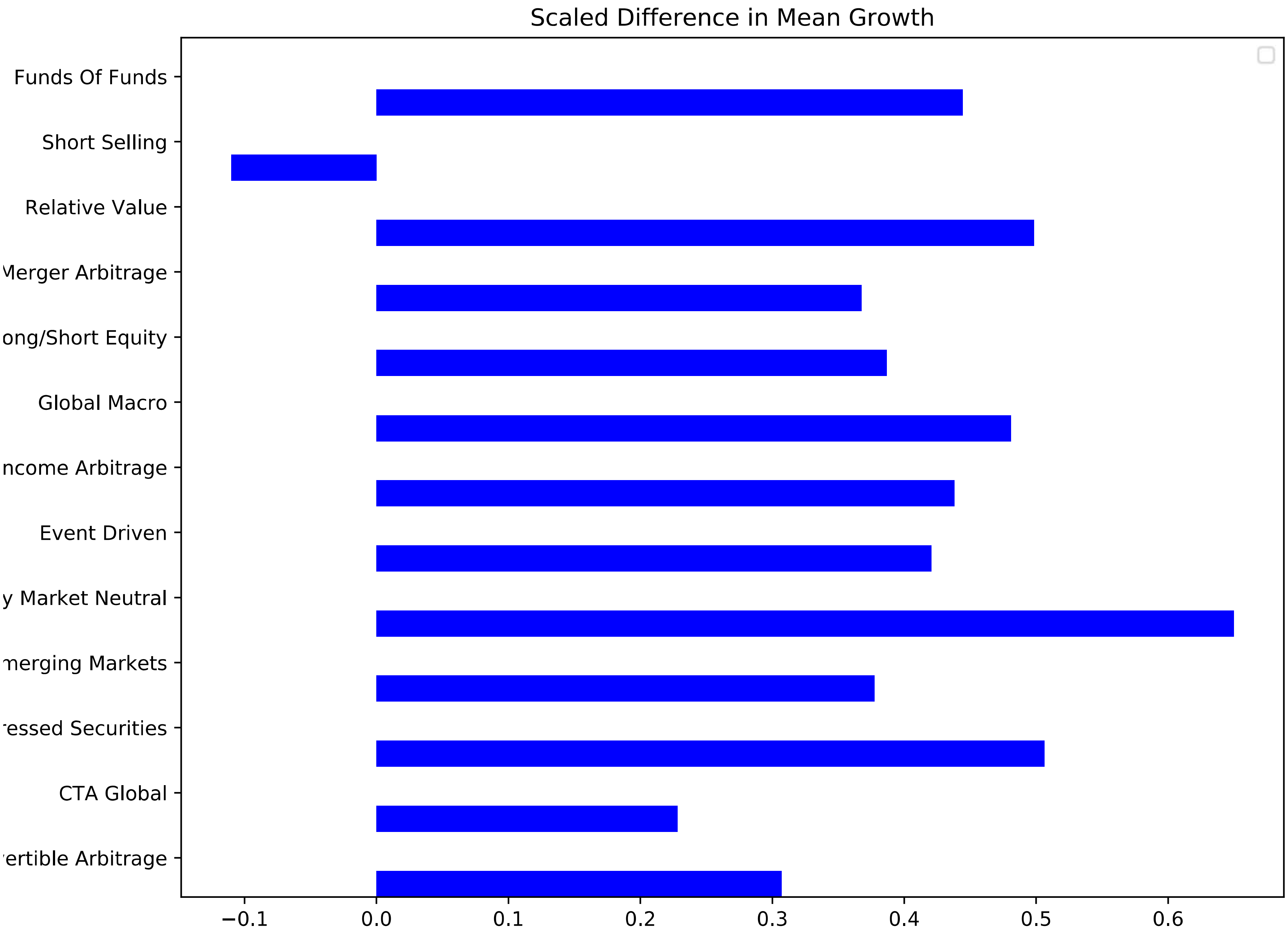
Drawdowns plot for Emerging Markets under Equity




Scaled Difference in Mean Equity
Funds Of Funds
Short Selling
Relative Value
Merger Arbitrage
ong/Short Equity
Global Macro
ncome Arbitrage
Event Driven
y Market Neutral
merging Markets
ressed Securities
CTA Global
ertible Arbitrage
−0.6
−0.5
−0.4
−0.3
−0.2
−0.1
0.0


Scaled Difference in Mean Currency
Funds Of Funds
Short Selling
Relative Value
Merger Arbitrage
ong/Short Equity
Global Macro
ncome Arbitrage
Event Driven
y Market Neutral
merging Markets
ressed Securities
CTA Global
ertible Arbitrage
−0.6
−0.5
−0.4
−0.3
−0.2
−0.1
0.0
0.1


Scaled Difference in Mean Inflation
Funds Of Funds
Short Selling
Relative Value
Merger Arbitrage
ong/Short Equity
Global Macro
ncome Arbitrage
Event Driven
y Market Neutral
merging Markets
ressed Securities
CTA Global
ertible Arbitrage
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40


Scaled Difference in Mean Growth
Funds Of Funds
Short Selling
Relative Value
Merger Arbitrage
ong/Short Equity
Global Macro
ncome Arbitrage
Event Driven
y Market Neutral
merging Markets
essed Securities
CTA Global
ertible Arbitrage
−0.1
0.0
0.1
0.2
0.3
0.4
0.5
0.6