DALLASFED

Occasional Paper

Dynamic Methods for Analyzing Hedge-Fund Performance: A Note Using Texas Energy-Related Funds

Jiaqi Chen and Michael L. Tindall

Federal Reserve Bank of Dallas
Financial Industry Studies Department

Occasional Paper 16-02
July 2016

Dynamic Methods for Analyzing Hedge-Fund Performance: A Note Using Texas Energy-Related Funds

by

Jiaqi Chen and Michael L. Tindall
Financial Industry Studies Department
Federal Reserve Bank of Dallas*

July 2016

Abstract

We apply dynamic regression to Texas energy-related hedge funds to track changes in portfolio structure and manager performance in response to changing oil prices. We apply hidden Markov models to compute shifts in portfolio performance from boom to bust states. Using these dynamic methods, we find that, in the recent oil-price decline, these funds raised their exposure to high-grade energy-related bonds in a bet that the spread to low-grade energy bonds would widen. When the high-grade bonds eventually fell, the hedge funds entered into a bust state.

Keywords: dynamic regression, Kalman filter, hidden Markov models.

Hedge-fund performance is typically measured statically over a specified period using various measures, such as efficiency and the Sharpe ratio, that purport to summarize performance in a single number for an entire period. However, a much more interesting picture emerges where dynamic methods of performance measurement are used. Dynamic methods provide a narrative rather than a single number. They make it possible to observe hedge-fund performance over time and manager skill level and to analyze underlying causes of changes. In this paper, we study the effects on energy-related hedge funds of the precipitous decline in energy prices in 2014–15. Whereas conventional performance measures would simply inform us with a single number that these funds performed poorly, a much richer picture emerges where we use dynamic analysis. With dynamic methods, we find that hedge funds investing in the energy sector responded to declines in oil prices by switching between key energy-related asset classes. We find that these hedge funds achieved only partial success and that manager skill levels fell over the period. We apply hidden Markov models to track and analyze the movement of energy-related asset classes and hedge funds from boom to bust states in the period.

* Please direct correspondence to jiaqi.chen@dal.frb.org or michael.tindall@dal.frb.org. The views expressed herein are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System.

DATA

We exclusively use monthly data in our analysis. Our analysis is based on four key total-return indexes:

1. A low-grade corporate energy bond index.
2. A high-grade corporate energy bond index.
3. An index of stock prices of companies involved in energy exploration and production.
4. An index of Texas-based hedge funds specializing in energy markets.

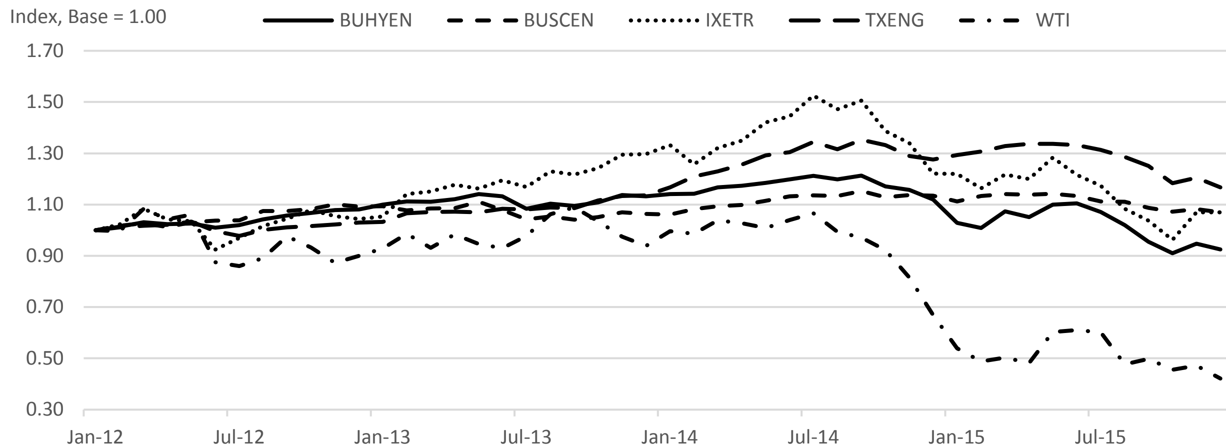
For the low-grade energy bond index, we use the Bloomberg US-dollar "high yield" corporate energy bond index, Bloomberg symbol BUHYEN. For the high-grade energy bond index, we use the Bloomberg US-dollar corporate energy bond index, Bloomberg symbol BUSCEN. BUHYEN is a market value-weighted index of non-investment-grade fixed-rate taxable corporate bonds. BUSCEN is a market value-weighted index of investment-grade fixed-rate taxable corporate bonds. To be included in either index, a security must have a minimum par amount of $250 million. For the energy equity market, we use the S&P Energy Select Sector Total Return Index, Bloomberg symbol IXETR. This is a capitalization-weighted index intended to track the movement of companies involved in petroleum development and/or production.

We construct an index of hedge funds located in Texas that invest primarily in the energy sector. Our index includes Texas-based hedge funds listed under the "Sector-Energy/Basic Materials," "Yield Alternatives-Energy Infrastructure," and "Commodity-Energy" categories of the Hedge Fund Research, Inc. database. There are 34 hedge funds in these three categories. To this, we add four more Texas-based hedge funds whose detailed descriptions in the database indicate that they invest primarily in the energy sector. The average assets under management of these funds are $80 million. The funds are combined using equal weights to create our Texas energy fund index, denoted as TXENG.

INDEX PERFORMANCE

Exhibit 1 shows the performance of the four indexes from January 2012 to December 2015. The West Texas Intermediate crude oil spot price, WTI, is included as a reference to show the general behavior of energy prices. The exhibit shows that energy-related markets experienced substantial declines beginning at about mid-2014.

Exhibit 1
Performance of Energy-related Indexes
January 2012 - December 2015



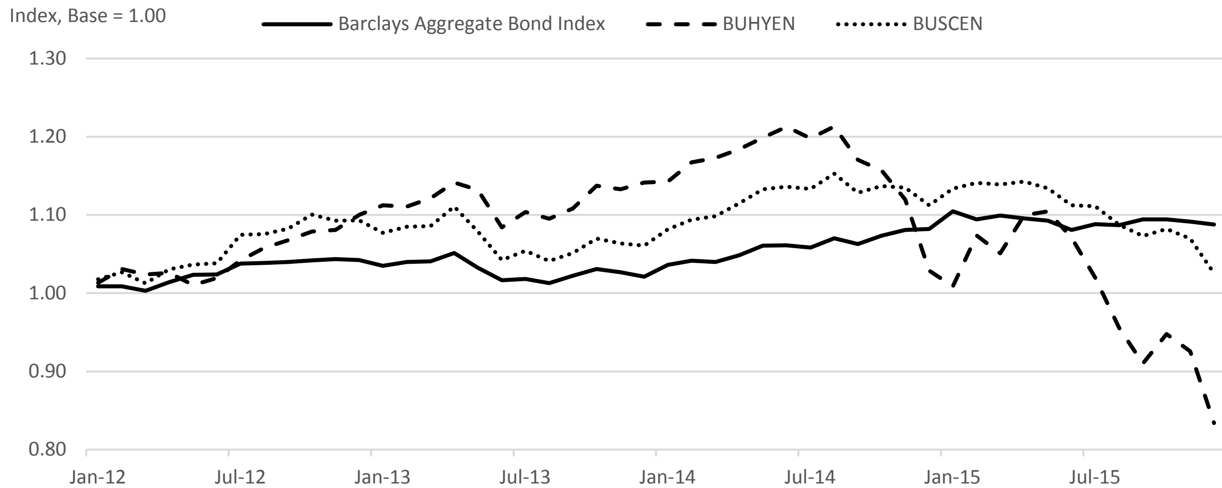
Using July 2014 as the separating point, the basic performance statistics for the four indexes are presented in Exhibit 2. The Texas energy fund index, TXENG, experienced the greatest deterioration in risk-adjusted performance of the four indexes. In the January 2012-July 2014 period, its Sharpe ratio was 2.56, which fell to -1.48 in the August 2014-December 2015 period. The energy-related equity index, IXETR, experienced the sharpest decline in annual return, falling 45.12 percentage points from the first period to the second period.

Exhibit 2
Performance Statistics for the Energy-related Indexes

	January 2012 - July 2014			August 2014 – December 2015		
Symbol	Annual Return	Volatility	Sharpe Ratio	Annual Return	Volatility	Sharpe Ratio
BUHYEN	8.02%	4.72%	1.70	-22.08%	14.78%	-1.49
BUSCEN	5.24%	5.18%	1.01	-6.62%	5.36%	-1.23
IXETR	18.40%	13.58%	1.35	-26.72%	19.87%	-1.34
TXENG	13.58%	5.30%	2.56	-11.87%	8.03%	-1.48

The downturns in the energy-related bond indexes beginning at mid-2014 were not generally driven by a decline in bond prices. Rather, they reflected the energy price decline. Exhibit 3 shows the performance of Barclays US Aggregate Total Return Bond Index and the two energy-related bond indexes. The exhibit shows that the Barclays aggregate bond index was stable during the energy-price slide, while the two energy-related bond indexes turned lower.

Exhibit 3
Barclays Aggregate US Bond Index, BUHYEN, and BUSCEN, January 2012 - December 2015



RISK EXPOSURE OF THE TEXAS ENERGY HEDGE-FUND INDEX

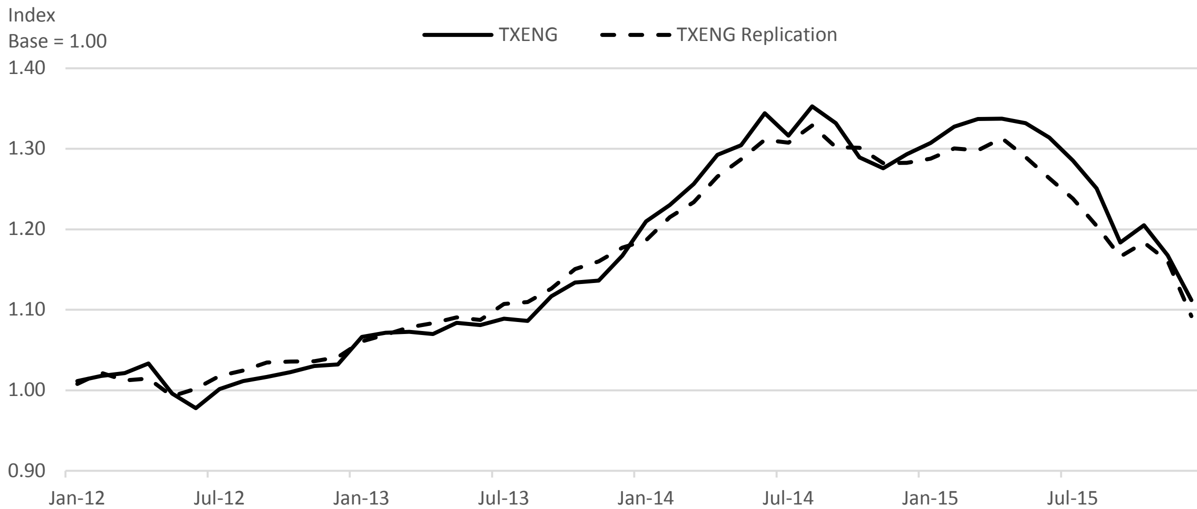
To analyze the performance of our Texas energy fund index, we model its return as a function of the returns of the two energy-related bond indexes and the energy stock index in a multi-factor model:

$$R_t^{TXENG} = \alpha + \beta^{BUHYEN} R_t^{BUHYEN} + \beta^{BUSCEN} R_t^{BUSCEN} + \beta^{IXETR} R_t^{IXETR} + \varepsilon_t$$

where R_t^i is the return of index i in month t and β^i is the factor exposure for index i. We use dynamic analysis as described in Appendix A to allow the α and β^i to vary over time. This allows us to capture the dynamic nature of hedge-fund investing. Exhibit 4 shows the results where we apply dynamic analysis to construct a replication of the Texas energy fund index. In the exhibit, we see that, despite the simplicity of our dynamic multi-factor model—it employs just three factors—the replication tracks the original TXENG index very well. This suggests that, although the funds are actively trading various instruments, we can replicate their performance with a dynamic combination of the three assets in our model, excluding oil prices explicitly as a factor.

Exhibit 4

Texas Energy-related Hedge-fund Index and Replication, January 2012 - December 2015



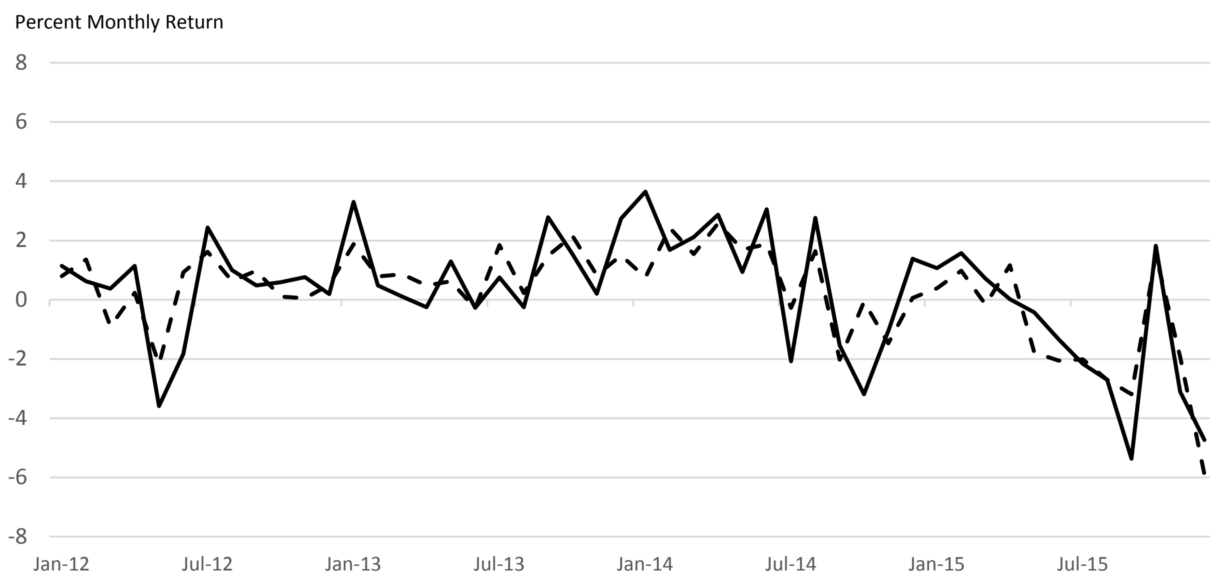
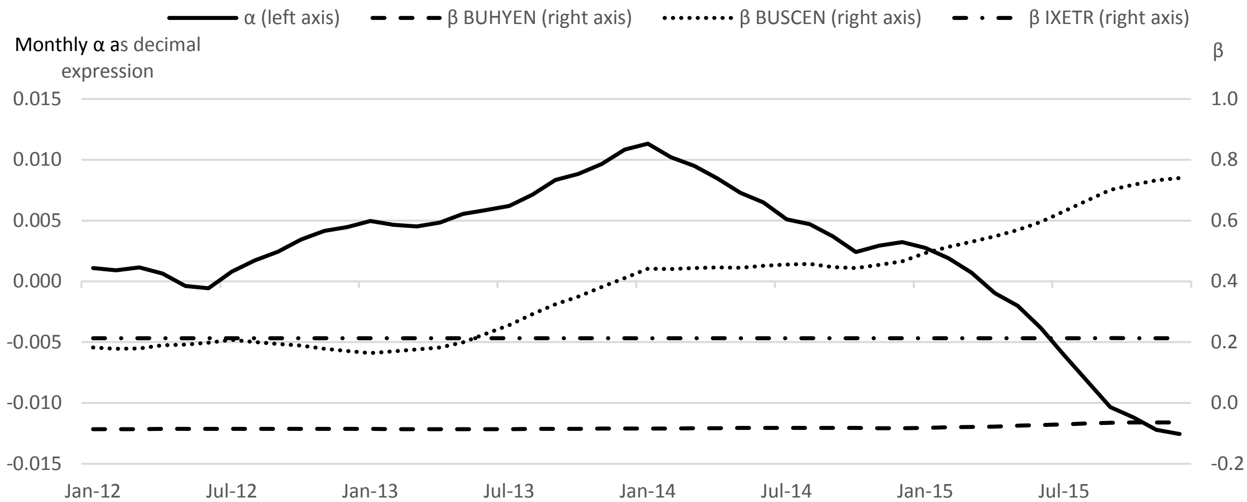


Exhibit 5 shows the behaviors of the α and β^i over the period. The overall decline in α over the sample period implies that hedge-fund manager skill was decreasing in the time frame. The factor exposures, i.e., the β^i of the low-grade energy bond index and the energy equity index remained stable over the sample period, while the exposure of the high-grade energy bond index increased noticeably. With the negative factor exposure of the low-grade energy bond and the increasingly positive exposure of the high-grade energy bond, Texas energy hedge funds were essentially betting on both the widening of the spread between the two bonds and the recovery of the high-grade bonds. As it turned out, the bet on the spread worked, i.e., the spread widened, but the anticipated recovery in high-grade bonds failed to materialize, and that damaged hedge fund performance.

Exhibit 5

Texas Energy Fund Index Time-varying Alpha and Betas, January 2012 - December 2015



MONITORING ENERGY MARKET CYCLES

Boom-bust states in market cycles can be computed using a hidden Markov model (HMM). The mathematics of HMMs are discussed in Appendix B. In our application, the premise is that index returns have distinctive distributions in each of the two states and that the probability of being in either state can be estimated using observed returns. We applied HMM for each individual index separately for the January 2012-December 2015 period. Exhibit 6 shows the mean returns and standard deviations of returns in each state and the transition probability, which is the probability that the index switches states in a given month. As expected, for each index, mean returns are positive (negative) in the boom (bust) state, and variance of return is higher in the bust period.

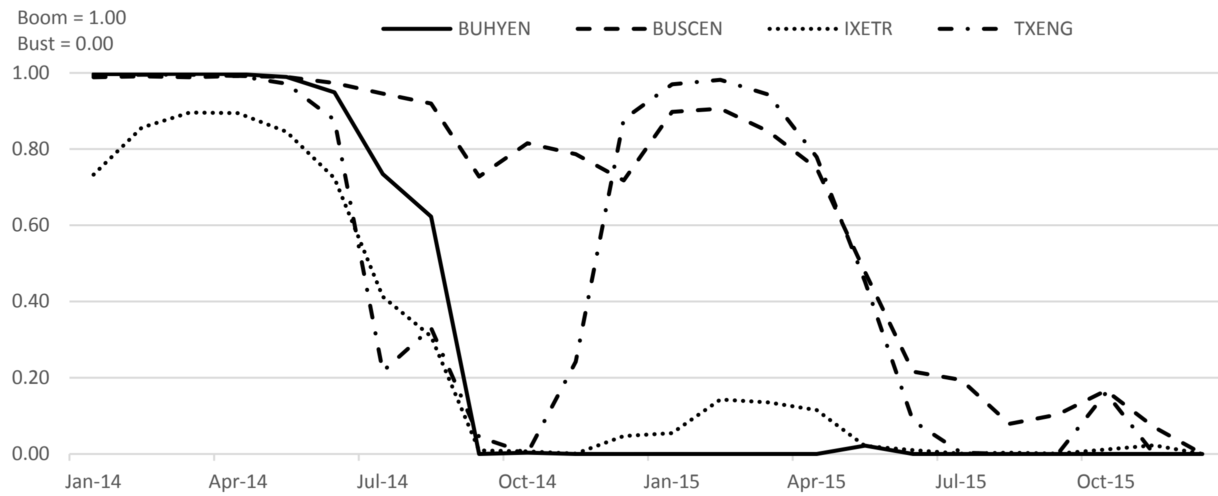
Exhibit 6
Hidden Markov Model Monthly Return Statistics

	Boom State	Bust State
BUHYEN:		
Mean	0.80%	-2.03%
Standard Deviation	1.01%	4.92%
Transition Probability	7.35%	6.14%
BUSCEN:		
Mean	0.62%	-0.70%
Standard Deviation	1.03%	1.73%
Transition Probability	8.80%	11.52%
IXETR:		
Mean	1.96%	-2.22%
Standard Deviation	3.16%	5.66%
Transition Probability	10.84%	8.47%
TXENG:		
Mean	1.18%	-1.77%
Standard Deviation	1.08%	2.24%
Transition Probability	11.17%	18.70%

Exhibit 7 shows the results for each index where we use HMMs to compute the probability of being in a boom or bust state during the January 2014-December 2015 period. According to the exhibit, low-grade energy bonds and energy equities entered a bust state in September 2014. High-grade energy bonds did not enter a bust state until the later part of 2015. That is, the initial drop in energy prices in 2014 put pressure on less well-funded energy companies in the second half of 2014. Then, as oil prices slumped further in 2015, well-funded energy companies came under pressure, and high-grade energy bonds started to fall. Interestingly, Texas energy-related hedge funds entered a bust state in September 2014, came out in late 2014, and then re-entered a bust state in mid-2015. This is understandable from our risk-factor exposure analysis in the dynamic multi-factor model. That is, in the latter part of the cycle, as low-grade energy bond prices fell more rapidly than high-grade energy bond prices, hedge funds benefitted because they were essentially betting on the widening of the spread, shorting low-grade bonds. Finally, however, even high-grade bonds fell, and the performance of energy-related hedge funds deteriorated.

Exhibit 7

Boom-Bust Indexes, January 2014 - December 2015



CONCLUSION

In this paper, we apply dynamic methods to analyze the performance of energy-related hedge funds. Compared with conventional techniques, these methods enable us to provide a rich narrative about hedge-fund performance, letting us observe fund performance over time and analyze the underlying causes of those changes. We examine how the energy-price slide affected energy-related low-grade bonds, high-grade bonds, equities, and hedge funds. We decompose the performance of the Texas energy hedge-fund index and find that manager skill at those funds decreased during the price slide and that energy-related hedge funds were essentially betting on 1) the widening of the yield spread between the high-grade and low-grade bonds and 2) a recovery of high-grade bonds. The first bet worked, but the second bet failed, leading to the hedge funds' poor performance.

Using hidden Markov models, we examine the transitions between boom and bust in energy-related asset classes and funds. We find that high-grade bonds held up relatively well during the energy-price slide. These bonds did not enter a bust state until mid-2015, almost a year after low-grade bonds and energy equities entered bust states. Like low-grade bonds and energy equities, the hedge funds we examined entered a bust state quickly, but the funds adjusted their portfolios, adding to their holdings of high-grade energy bonds, and rallied out of a bust state while low-grade bonds and equities did not. Eventually, as high-grade bonds entered a bust state, hedge funds had no way out and moved again into a bust state.

Unlike hedge funds, which can quickly adjust their portfolios, energy-related companies could not rapidly restructure their businesses in response to the sliding energy prices, and their shares fared poorly. Low-grade energy bonds performed even worse. According to our analysis, at the December 2015 end of our sample period, energy-related low-grade bonds, investment-grade bonds, equities, and hedge funds were all in or near bust states.

APPENDIX A

Kalman Filter Estimation

A dynamic linear model, or Kalman filter, provides an alternative way to estimate dynamic α and β compared to static regression or rolling regression. Our setup follows Chen and Tindall [2013] where the state equation follows a random walk:

$$\beta_t = \beta_{t-1} + \boldsymbol{w}_t. \tag{A-1}$$

The $p * 1$ state vector β_t is generated from the previous state vector $\beta_{\boldsymbol{t-1}}$ for $t = 1,2,3, \ldots, n$. The vector $\boldsymbol{w}_t$ is a $p * 1$ independent and identically distributed zero-mean normal vector having a covariance matrix of Q. The starting state vector β_0 is assumed to have mean $\boldsymbol{\mu}_0$ and a covariance matrix of Π_0. The state process is a Markov chain, but we do not have direct observation of it. We can only observe a linear transformation of β_t with added noise which is the monthly return of the TXENG index. Thus, we have the following observation equation:

$$\boldsymbol{y}_t = \boldsymbol{x}_t \beta_t + \boldsymbol{v}_t, \tag{A-2}$$

where $\boldsymbol{x}_t$ is a $1 * p$ matrix representing the intercept and returns from the factors in the multi-factor model, the observed data $\boldsymbol{y_t}$, and $\boldsymbol{v}_t$ is white Gaussian noise with a covariance R. We also assume $\boldsymbol{v}_t$ and $\boldsymbol{w}_t$ are uncorrelated. Our primary interest is to produce the estimator for the underlying unobserved β_t given the data $\boldsymbol{Y}_s = \{\boldsymbol{y}_1, \ldots, \boldsymbol{y}_s\}$. In the literature, where $s < t$, this is referred to as forecasting; where $s = t$, this is Kalman filtering; and where $s > t$, this is Kalman smoothing. With the definitions $\beta_t^s = E(\beta_t | \boldsymbol{Y}_s)$ and $\boldsymbol{P}_t^s = E[(\beta_t - \beta_t^s)(\beta_t - \beta_t^s)]$ and the initial conditions $\beta_0^0 = \beta_0 = \boldsymbol{\mu}_0$ and $P_0^0 = \Pi_0$, we have the recursive Kalman filter equations as follows:

$$\beta_t^{t-1} = \beta_{t-1}^{t-1}, \tag{A-3}$$

$$\boldsymbol{P}_t^{t-1} = \boldsymbol{P}_{t-1}^{t-1} + Q \qquad , \tag{A-4}$$

for $t = 1,2,3, \ldots, n$ with:

$$\beta_t^t = \beta_t^{t-1} + K_t(\boldsymbol{y}_t - \boldsymbol{x}_t \beta_t^{t-1}), \tag{A-5}$$

$$\boldsymbol{P}_t^t = [I - K_t \boldsymbol{x}_t]\boldsymbol{P}_t^{t-1}, \tag{A-6}$$

$$K_t = \boldsymbol{P}_t^{t-1} \boldsymbol{x}_t' [\boldsymbol{x}_t \boldsymbol{P}_t^{t-1} \boldsymbol{x}_t' + \boldsymbol{R}]^{-\boldsymbol{1}}\boldsymbol{.} \tag{A-7}$$

The Q and R are estimated using maximum likelihood.

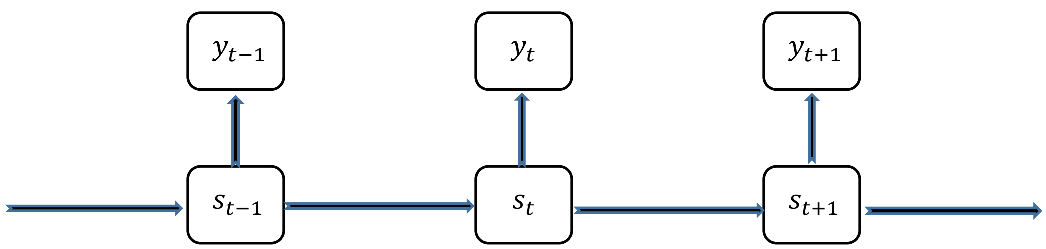
APPENDIX B

Hidden Markov Model for Bust and Boom Estimation

HMMs were introduced by Baum and Petrie [1966], foreshadowed by work on the forward-backward algorithm by Stratonovich [1960]. HMMs have found a multitude of uses spanning such fields as speech recognition, cryptanalysis, and various forms of probabilistic DNA sequencing. They were popularized in the field of econometrics by Hamilton [1989] in his seminal work on business-cycle analysis.

In a simple Markov model, the states of a system are observable. In contrast, in HMMs the states are not observable, but something else is observed, and HMMs extract the hidden states from these observations. For example, in speech-recognition applications, the observed outcomes are waveforms of the audio signals, and the hidden states extracted from the waveforms appear as the text of the spoken words. In cryptanalysis, the observed outcomes are the encrypted message, and the hidden states extracted from the encryption are the text of the decoded message.

The diagram below illustrates the structure of a simple HMM. The random variable y_t is the observation at time t, and the random variable s_t is the hidden state at t. The arrows represent conditional linkages. For example, the conditional probability distribution of the hidden variable s_t at time t depends only on the value of s_{t-1}, and the observed y_t depends only on s_t.



Typically, the hidden state variables are discrete. The observations may be discrete or continuous. There are two types of parameters in HMMs: 1) transition probabilities and 2) emission probabilities. For each of the possible hidden states at t, there is a transition probability to each of the hidden states at $t + 1$. The transition probabilities from a given state sum to 1. The set of emission probabilities governs the distribution of the observed variable for each of the states at a particular time. The size of this set of state variables depends on the nature of the observed variable.

In our analysis, there are two states: boom and bust. The observations are continuous. The conditional distribution is normal for each state: $N(u_1, \sigma_1^2)$ for the boom state and $N(u_2, \sigma_2^2)$ for the bust state. The system can be expressed as follows:

$$y_t|s_t \sim N\left(u_{s_t}, \sigma_{s_t}^2\right);\ s_t = 1, 2 \tag{B-1}$$

$$p(y_t|z_t) = \frac{1}{\sqrt{2\pi}\sigma_{s_t}} e^{-(y_t - u_{s_t})^2/2\sigma_{s_t}^2} \tag{B-2}$$

where the information set $z_t = (s_t, s_{t-1}, \dots s_1, y_{t-1}, y_{t-2}, \dots, y_1)$. The transition probability between the two states is $p(s_t = j|s_{t-1} = i) = p_{ij}$, and the HMM is estimated by maximizing the likelihood function:

$$p(y_1, y_2, \dots, y_T, s_1, s_2, \dots, s_T) = p(s_1) * p_{s_1 s_2} * \dots * p_{s_{T-1} s_T} * \prod_{i=1}^{T} p(y_i | i) \tag{B-3}$$

using the Baum–Welch algorithm. What interests us is to determine the hidden state s_t given the observations $y_T, \dots y_1$. If $T > t$, we have the smoothed probability; if $T = t$, it is the filtered probability. The smoothed probability is non-causal as it contains future information. Meanwhile, it is very helpful to study the historical event.

REFERENCES

Baum, Leonard E., and Ted Petrie (1966), "Statistical Inference for Probabilistic Functions of Finite State Markov Chains," *The Annals of Mathematical Statistics*, 37 (6): 1554–1563.

Chen, Jiaqi, and Michael L. Tindall (2013), “Hedge Fund Dynamic Market Sensitivity,” *Journal of Alternative Investments*, 16 (1): 118-129.

Hamilton, James D. (1989), "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle," *Econometrica*, 57 (2): 357–384.

Stratonovich, Ruslan L. (1960), “Conditional Markov Processes," *Theory of Probability and its Applications*, 5 (2): 156–178.