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Gathering Insights on the Forest from the Trees: A New Metric for Financial Conditions

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Abstract

By incorporating the Harvey accumulator into the large approximate dynamic factor framework of Doz et al. (2006), we are able to construct a coincident index of financial conditions from a large unbalanced panel of mixed frequency financial indicators. We relate our financial conditions index, or FCI, to the concept of a "financial crisis" using Markov-switching techniques. After demonstrating the ability of the index to capture "crisis" periods in U.S. financial history, we present several policy-geared threshold rules for the FCI using Receiver Operator Characteristics (ROC) curve analysis.

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Keywords: financial crisis, financial conditions, dynamic factor, EM algorithm, Harvey accumulator, ROC curve, Markov-switching

1 Introduction

Financial innovation over the course of the past 40 years has made it difficult to capture broad financial conditions in a small number of variables covering just a few traditional financial markets. Recent research has instead focused on capturing financial conditions from variables that span several traditional as well as more recently developed markets. Here, we take this approach a step further applying the large approximate dynamic factor methods of Doz et al. (2006) to a data set of 100 financial indicators capturing a broad array of information on financial markets.

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The information in these indicators is distilled in a single high frequency index, the Financial Conditions Index, or FCI. What separates the FCI from other similar indexes is that it allows for real-time examination of financial conditions from an unbalanced panel of mixed frequency indicators. We show that increasing values of the FCI capture rising risk premia, declining credit volumes, and deleveraging across the financial system.

To illustrate its usefulness, we relate the FCI to the concept of a "financial crisis", using differences in the mean and volatility in the index over time to identify a Markov-switching process. Our results demonstrate that the FCI accurately captures the major events in U.S. financial history over the past 37 years. Based on these major events, we then develop threshold rules for the index using methods of analysis common to medical statistics to derive a framework that balances the costs and benefits of identifying financial crises in real-time.

2 Literature

Measures of financial conditions generally involve a weighted average of a number of financial indicators. Some prominent examples are the indexes of Illing and Liu (2006), Nelson and Perli (2007), Hakkio and Keeton (2009) and Hatzius et al. (2010). Several of these indexes use a method called "principal components analysis" (PCA) to estimate the weight placed on each series. PCA interprets the importance of movements in any number of data series based on their relative historical correlations. In this fashion, contradictory movements are sorted out in a way that is consistent with the historical importance of individual indicators to the broader financial system.

Typically, these PCA-based measures are constructed as the first principal component of a set of underlying financial indicators, where "first" signifies that it is the element common to all of the indicators that explains the largest amount of the total variation among them. Standardizations vary, but often a positive index value is associated with deteriorating financial conditions with the magnitude measured in standard deviations from the sample mean of the index.

This form of index construction has an equivalent representation as a restricted least squares problem given a latent factor F_t and factor loadings Λ such that $\varepsilon_t'\varepsilon_t = \hat{N} I_{\hat{N}}$ where $\hat{N}$ is the number of data series. Consider the linear model below, where Y_{it} is a vector of stationary variables that have been demeaned and standardized to have a unit variance:

$$Y_{it} = \Lambda_i F_t + \varepsilon_{it} \tag{1}$$

Given a panel of sufficient size, Bai and Ng (2002) show that PCA estimates of the latent factors are consistent.

Indexes of this kind also have the advantage of capturing the interconnectedness of financial indicators. The more interrelated an indicator is with its peers, the higher the weight it receives in the index. This opens up the possibility that a small deterioration in a highly weighted indicator may mean more for the state of financial conditions than a large deterioration in an indicator that receives little weight. In this way, PCA assigns a relative ranking consistent with an indicator's systemic importance.

The PCA method of index construction has become commonplace in the measurement of business cycles. A prominent example is the Chicago Fed National Activity Index based on the work of Stock and Watson (1999) which captures a single latent factor extracted from 85 variables describing U.S. economic activity. More recently, it has also begun to be applied to financial variables. For instance, Hakkio and Keeton (2009) estimate their Kansas City Fed Financial Stress Index, or KCFSI, from a sample of U.S. financial indicators on the health of the banking system, debt, equity and money markets.

Variation in the frequency or availability of data, however, makes the PCA decomposition above infeasible without alteration. For financial variables where higher frequency data is generally available, the typical alteration consists of using only those variables with consistent time series and/or moving to a monthly or even quarterly frequency of measurement. The KCFSI fits this description, focusing on a small sample of indicators at a monthly frequency.

In contrast, Stock and Watson (2002) show how this problem can instead be addressed by introducing an iterative estimation strategy. Their algorithm relies on the fact that PCA reduces to ordinary least squares (OLS) estimation when F_t is known. From an initial balanced subset of the data, one produces an initial guess for F_t by means of PCA, followed by Λ by OLS projection onto this guess. Missing values are then replaced by their expectation conditional on the observed data and estimates of F_t and Λ are updated until the sum of squared errors for the complete data converges to some criterion.

As the size of the cross-section grows, Stock and Watson (2002) demonstrate that this strategy produces a consistent estimate of F_t robust to weak serial correlation between the idiosyncratic errors and within them across time. Furthermore, Bai and Ng (2004) show that this is also true for dynamic factor models in the sense that the static factors estimated by PCA can potentially span the same space as the true dynamic factors.

Hatzius et al. (2010) employ this "cross-sectional averaging" strategy to construct the USMPFFCI, stretching the index history back to the early 1970's compared with the early 1990's for the KCFSI. They demonstrate that this method also has the advantage of incorporating information in a manner consistent with the development of financial markets that have grown in importance over time, i.e. securitized debt, repo, and derivatives markets. By doing so, they are able to compare the level of financial conditions during many known periods of crisis while still taking account of financial innovation.

A shortcoming of their work, however, is that it, too, requires an initial balanced panel in order to use PCA. Hatzius et al. (2010) relax this constraint by estimating a quarterly index. The potential usefulness of high frequency financial indicators in a real-time setting where decisions must be made is a feature we would like to retain in our FCI. Therefore, the model we describe below will incorporate an unbalanced panel of mixed frequency indicators. Here, we build off the work of Aruoba et al. (2009) in their measurement of business conditions at a weekly frequency.

3 The model

Fundamentally, the model for the Financial Conditions Index is similar to any coincident index model where the variation in a number of indicators is governed by one common source (a factor) and an idiosyncratic term. In a purely static sense, equation (1) represents the model, with $t = 1, \ldots, \hat{T}$ and $i = 1, \ldots, \hat{N}$ where in our particular baseline model $\hat{T}$ is the time series length of the longest available indicator and $\hat{N}$ is the number of variables. Here, F_t represents the common source of variation, or factor, in Y_{it}. For our purposes, this factor will serve as a proxy for the state of financial conditions.

In this model, each indicator can have different sensitivities to the common factor (controlled by the heterogenous Λ_i), however, the overall responsiveness of each indicator to changes in the factor remains constant over time.[1] A unique characteristic of Y_{it} in our particular context is not only its size (in both the cross section and frequency domain) but also that it contains series of varying reported frequencies and series that start and end at different times within the sample.[2]

Where we depart from the previous literature is that our estimate of the unobserved factor will take into account both the cross-sectional correlations in the data as well as any dynamic correlations. In our model, any dynamic correlations will be absorbed in the dynamics of F_t. Adding dynamics of some finite order ($p^\star$) to the unobserved factor moves the model above into the standard state space representation:

$$
\begin{aligned}
y_t &= Z_t \alpha_t + \epsilon_t && (2) \\
\alpha_{t+t} &= T_t \alpha_t + R_t \eta_t, && (3)
\end{aligned}
$$

where $\epsilon_t \sim N(0, H)$ and $\eta_t \sim N(0, Q)$.[3]

This model can be estimated using the EM algorithm outlined by Shumway and Stoffer (1982) and Watson and Engle (1983) in order to obtain maximum likelihood estimates of the system matrices and subsequently the unobserved factor. In general, the EM algorithm requires one pass through the Kalman filter and smoother, and then re-estimation of the state-space parameters using ordinary least squares estimation at each iteration.[4] The resulting sequence of log-likelihood function valuations is non-decreasing, and convergence of the algorithm is governed by its stability.[5]

[1]This restriction can be relaxed. Consistency requires only that the factor loadings "change slowly" over time. For further details, see Stock and Watson (2002).

[2]In what follows, we restrict our attention to the period from 1973 onward during which at least 25 percent of the series in the index have complete time series.

[3]For a more descriptive formulation of the the system matrices and the state variables see section A.2.

[4]A small alteration in the least squares step is required to account for the fact that the unobserved components of the model must first be estimated.

[5]For more details on the particular log-likelihood function and the methods used to implement the EM algorithm see section A.3.

The EM algorithm proves advantageous in this setting because it allows for a complete characterization of the data-generating process using incomplete data and combines two easy to implement statistical methods. In addition, the typical critique of the algorithm, its slow convergence rate, is not problematic in this setting due to the size of both the frequency and cross section dimensions which allow for consistent initial estimates using the standard or iterative PCA techniques described in Stock and Watson (2002).

4 Estimating the model

As described above, the EM algorithm utilizes the Kalman filter and smoother in order to obtain the sufficient statistics necessary to re-estimate the system's matrices using standard ordinary least squares techniques. Due to the irregular observation of the data in our framework, two extensions to the standard Kalman recursion equations need to be made. The first alteration involves setting up the Kalman filter to deal with missing values as discussed by Durbin and Koopman (2001). The second modification involves including additional state variables that evolve deterministically to properly adjust for the varying temporal aggregation properties of the mixed frequency data. Next, we give a brief summary of both of these extensions to the standard filter as well as a more explicit formulation of the state-space system matrices and the EM algorithm.

4.1 Missing Value Kalman Filter

Because of the aforementioned irregularity of observation in our data-set, as one moves through time, the vector of observables (denoted y_t), changes size from period to period. Figure 1 summarizes this pattern of data availability. The early part of the sample is dominated by quarterly and monthly variables. The number of weekly variables grows steadily from the mid-1980's through the end of the sample. Nineteen series span the entire sample period (1971–2010), while the shortest series begins in 2009.

Consequently, as one proceeds through the Kalman filter and smoother, to accommodate the partially observed vector $y_t^\star$ in the data one must use the known matrix W_t whose rows are a subset of the rows of $I(\hat{N})$ (such that $y_t^\star = W_t y_t$) to alter the system matrices at that particular point in time. Taking this W_t as given, the system matrices Z and H become $Z^\star = W_t Z$ and $H^\star = W_t H W_t'$, respectively. Substituting these matrices into the standard filter and smoother equations allows one to proceed as usual through the recursive equations outlined in the appendix.

4.2 Temporal aggregation and the Harvey Accumulator

Another unique characteristic that results from the irregular frequency of observation is the different temporal aggregations inherent in our data-set. By applying the accumulator of Harvey (1989), one can manage this data irregularity with relative ease. The goal of the accumulator is to augment the state with a deterministically evolving indicator that is a summary of all past values of the unobserved factor aggregated in such a way as to correspond with the nature of the series observed at a frequency differing from the base frequency.

More specifically, variables viewed as a "stock", or a *snap shot* in time, will not need such aggregation of past realizations of the factor. Variables that correspond to sums or averages over the higher base frequency, however, will need to accumulate all the higher frequency factor realizations over that period in order to properly account for the contemporaneous factor's contribution to what is being observed.[6] Any "stocks" that are differenced can be interpreted as sum variables and treated as such.

Our data-set includes both variables that resemble "sums" as well as "averages," in addition to indicators that are first differenced. Combining this with the weekly, monthly and quarterly frequencies of observations, our particular model will need three Harvey accumulators in the state.[7]

Sum Variables Accumulator

For both the monthly and quarterly sums accumulator we follow Aruoba et al. (2009)'s implementation of the Harvey (1989) accumulator. The accumulators for sum variables will be denoted S_t. By construction, any sum accumulator should represent the current sum of all of the factor realizations (base frequency) that have occurred within the current period of the lower frequency of observation. Additionally, the accumulator should be defined recursively so as to be included in the state space equations of (2)-(3). Analytically, the sum accumulator evolves each period by the following equation:

$$S_t = s_t S_{t-1} + \alpha_t$$

where s_t is a calendar determined indicator that evolves according to:

$$s_t = \begin{cases} 0 & \text{if } t \text{ is the first period (base frequency) within the lower frequency} \\ 1 & \text{otherwise} \end{cases}$$

For notational purposes, it is assumed in what follows that α_t is an AR(1) process defined by $\alpha_{t+1} = \rho\alpha_t + R\eta_t$. Incorporating this representation of the accumulator into the state space model follows from a simple substitution of the contemporaneous factor as outlined by Aruoba et al. (2009).

[6] Variables have different interpretations of how they are accumulated over the period of time they are observed. Some, such as monthly corporate bond issuance, represent *sums* of the higher frequency (in this case weekly issuance). Other variables, like Citigroup's monthly asset-backed security yield spread, represent *averages* of the higher frequency (weekly spreads). Ultimately, this difference will lead to a different construction of the accumulator.

[7] One does not need a Harvey accumulator for series that are observed at a weekly (the base) frequency, as well as any series that are stocks. In our data-set we have an accumulator for (1) monthly averages (2) monthly sums and (3) quarterly sums.

Average Variables Accumulator

For the purposes of exposition, we will denote the desired accumulator for the average variables with M_t, and derive it as though we are aggregating from a weekly base frequency to monthly observations of the financial indicators.[8] By construction, this accumulator should represent the *current* average of all of the factor realizations (occurring every week) that have occurred within the current month (frequency that is being observed) and be defined recursively for seamless addition to the state space equations of (2)-(3). Analytically, the average accumulator evolves each period by the following equation:

$$M_t = \frac{(m_t - 1)M_{t-1} + \alpha_t}{m_t}$$

where m_t is a calendar determined indicator that evolves:

$$m_t \quad = \quad \begin{cases} 1 & \text{if } t \text{ is the first week of the month} \\ 2 & \text{if } t \text{ is the second week of the month} \\ \textit{etc.} & \end{cases}$$

Explicitly including the accumulator in the state requires augmenting the state and some substitution. The resulting formulation is given by:

$$\begin{bmatrix} \alpha_t \\ M_t \end{bmatrix} \quad = \quad \begin{bmatrix} \rho & 0 \\ \frac{\rho}{m_t} & \frac{m_t - 1}{m_t} \end{bmatrix} \begin{bmatrix} \alpha_{t-1} \\ M_{t-1} \end{bmatrix} + \begin{bmatrix} R \\ \frac{R}{m_t} \end{bmatrix} \eta_{t-1}$$

4.3 EM Algorithm

At each iteration of the EM algorithm, one pass through the Kalman filter and smoother is made using the system matrices Z, H, T, Q, P_1 and a_1 as well as the Harvey accumulator and missing observation extensions. By utilizing both the smoothed estimates and their covariance matrices, one can update the expectation of the conditional loglikelihood function; the (E) step. Then, using OLS techniques, the system matrices are re-estimated; the (M) step. This process will yield a non-decreasing sequence of log-likelihood values. A concise version of the log-likelihood, and the one that can be computed at each iteration, is as follows:

$$\log L \quad = \quad -\frac{1}{2} \sum_{t=1}^{\hat{T}} (\log |F_t^{\star}| + v_t^{\star\prime} F_t^{\star^{-1}} v_t^{\star}) \tag{4}$$

[8] All methods outlined in this section generalize fully to any particular combination of base and observation frequencies that one might encounter with the only necessary modifications occurring in the evolution of the calendar indicator m_t or s_t.

Now that the (E) and (M) steps have been completely defined, one can iterate between the two steps until (4) becomes stable.[9] Further details of the algorithm can be found in the appendix.

5 What is the FCI Capturing?

Table 2 lists all of the 100 financial indicators in our FCI along with their stationary transformations and estimated weights. The weights, or factor loadings, are a useful way of interpreting the systemic relationship between the indicators in the index. With the large approximate dynamic factor method as with PCA, the resulting index and weights are only identified up to scale. To make the weights comparable to PCA, we have scaled each according to the PCA convention that $E(\Lambda'\Lambda) = I$.

5.1 Contributions to the FCI

Credit risk measures tend to be positive contributors to the index, while money and credit aggregates and measures of leverage tend to be negative contributors. This pattern of increasing risk premia and declining credit volumes and leverage is consistent with tightening financial conditions and provides the basis for the FCI's interpretation. The way in which leverage enters the index may seem counterintuitive, but is in line with the findings of Adrian and Shin (2009) that leverage is procyclical. In this way, the process of deleveraging appears in the FCI as an indicator of deteriorating financial conditions.

Without index dynamics, it is not possible to fully capture the risk inherent in the build-up of leverage. Our dynamic framework relaxes this constraint allowing the procyclical nature of leverage to be reflected in the estimated dynamic process for the index. A large build-up of leverage that pushes the index well below its sample mean will generate a tendency to reverse this decline that depends on the estimated degree of mean reversion.

Taking into account the financial markets represented in our FCI, we have segmented our 100 financial indicators into three categories: Money Markets (28), Debt/Equity Markets (27), and the Banking System (45). Measures of the health of the banking system capture 41 percent of the variation in the data explained by the FCI, followed by money market measures at 30 percent and debt and equity markets at 28 percent.

The Money Markets category is comprised mostly of interbank, repo, swap, and commercial paper spreads and is the basis of most other financial conditions indices. These measures primarily capture credit risk and liquidity. Some of the biggest contributors to the FCI in this category include the 2-year swap and TED spreads as well as the 1-month nonfinancial A2P2/AA commercial paper credit spread and repo market volume. The latter two variables

[9] As a convergence criterion we used $|\log L(k) - \log L(k-1)/((\log L(k) + \log L(k-1))/2)| < 10^{-6}$. Important to note, though, is that because the initial estimates are consistent, the EM algorithm converges rather quickly; within 150 iterations.

are fairly unique to our FCI, as are the measures of open interest in money market derivatives that we include in this category.

In the Debt/Equity Markets group are mostly equity and bond price measures. In terms of equity prices, the largest weights are given to the index of volatility for the S&P 500, the VIX, and the relative price of financial stocks in the S&P 500. Like Hatzius et al. (2010), we also include here residential and commercial real estate prices and measures of stock market capitalization. In terms of bond prices, the index covers corporate, municipal, and asset-backed bond markets. Bond spreads like the high yield/Baa corporate and financial/corporate enter strongly here with large positive weights, but so do non-mortgage, mortgage, and commercial mortgage asset-backed bond spreads and credit default swap spreads tied to corporate bonds.

The Banking system category is comprised mainly of survey-based measures of credit availability and the assets and liabilities of commercial and "shadow" banks. The Senior Loan Officer Opinion Survey questions on commercial bank loan spreads and standards all enter strongly into the index as do several other measures of business and consumer credit conditions. The Credit Derivatives Research Counterparty Risk index measured as the average of the credit default swap spreads of the largest 14 issuers of CDS contracts also receives a large weight in this category, with the remaining weight split roughly evenly between measures of asset quality and measures of commercial and "shadow" bank lending and leverage.

5.2 Comparisons with other indexes

It is important to keep in mind that the estimated factor loadings are not unique. The same estimated index may have more than one set of weights that are consistent with it. Therefore, to make comparisons it is best to compare the indices, themselves. To establish a reference scale for the index, in what follows we have expressed it relative to its sample mean and standard deviation. A zero value is, thus, equivalent to the sample mean, and deviations from zero are measured in standard deviation units.

Figure 2 compares our FCI against the USMPFFCI and KCFSI. All three indexes tell a similar overall story: the 1970's and 80's were a particularly stressful period for financial markets that only recent years can match in magnitude. Compared to the USMPFFCI, the differences with the FCI are most considerable in the recent period with much of this attributable to the FCI's broader coverage of high frequency data on securitized debt, repo, and derivatives markets.

In contrast, the KCFSI is more similar to the FCI in the recent period, but with higher peaks and valleys. This stems mostly from the fact that it weights more highly recent events given the generally lower volatility of the index and its financial indicators post-1984. To see this, consider figure 3 which depicts the KCFSI and the initial PCA estimate of the FCI beginning in 1997. The initial estimate resembles the KCFSI to a high degree, although the difference in data coverage is apparent even here at times.

5.3 Comparisons across time

Our method obtains a significant time series for the FCI just as Hatzius et al. (2010) do for the UMPFFCI. One side effect of this is a much higher mean due to the volatility in the 1970's and 80's that the longer indexes capture. This suggests that comparisons across time using indices of shorter duration like the KCFSI may be biased. However, in some ways they may also be more relevant. Financial markets since the early 1980's have undergone significant transformations. If the relationships between financial indicators have changed, i.e. the weights have changed, then a shorter sample makes sense.

To test this hypothesis, we also constructed the FCI using only data from the post-1984 period. Figure 4 plots both the shorter sample and full sample FCI.[10] As with the KCFSI and the FCI, for the period of time in which the two overlap most of the difference appears in their levels. This suggests that it is primarily the lower volatility of the post-1984 period that is driving what differences we do see, and is line with broader findings on the "Great Moderation."

The factor loadings in table 2 confirm this with small differences between indexes for most variables. However, the post-1984 index does shift around weight between the three broad groups of financial indicators. Figure 5 displays the contribution of each of the these groups to the total variance of the 100 financial indicators explained by the full and post-1984 sample indexes. One can see from this figure that the money market variables explain much more of the post-1984 index with the extra weight shifted almost entirely from the banking system group.

5.4 Comparisons across indicators

An alternative to using a shorter sample period is to instead focus only on the subset of financial indicators whose history extends back over most of the sample. In this way, we can judge if it is possible to consistently capture financial conditions over an extended period without incorporating information from more recently developed financial markets. Figure 6 plots the FCI computed from the 39 financial indicators in our data-set that extend back to 1978 against the 100-variable index over the same time period.

One can see from both figure 6 and the factor loadings in table 2 that the smaller-variable index is capturing something very different than the larger one. Except for the most recent period where both indexes demonstrate large positive values, the two are highly negatively correlated. Well-known periods of deterioration in financial conditions, such as the late 1970's and early 1980's, appear in the narrower index as very loose periods for financial conditions. In fact, looking at the factor loadings in table 2, many of them are of the opposite sign compared to the weight given to the same variable in the 100-variable index.

The above suggests several explanations for what may be confounding the estimation of the smaller variable index in a way that does not appear in our larger variable FCI. First,

[10] Just as with the full sample index, we do not consider the first two years of estimates so that the shorter sample index begins in 1987. At this point, over 50 percent of the indicators have complete time series.

the 100-variable index appears to be spanning a space that is larger than the 39-variable index. This is not surprising given what we know about financial development over the past 40 years and the greater inclusion of these financial markets in the larger index. Second, the subset of indicators we have chosen for the smaller variable index contains a bias towards those also more likely to be affected by the change in volatility post-1984. This can be seen in the fact that many of the same indicators in the 39-variable index also show large changes in their factor loadings in the post-1984 100-variable index.

5.5 Stability of the FCI

As an example of where the smaller index seems to be going awry, consider the Treasury yield curve indicators. Measures from both the short and long end of the curve get large positive weights in the 39-variable index, meaning that as the yield curve steepens the index rises. In contrast, the weight they receive in the larger 100-variable index is much smaller and negative, meaning that as the yield curve steepens financial conditions tend to improve. However, even this relationship is not stable over time. In the shorter sample 100-variable index, the long end of the curve receives a large positive weight while the short end receives a smaller negative weight.

This pattern suggests to us that the instability over time and indicators described above is due to changes in the level and volatility of economic growth and inflation. The high inflation, high negative growth periods of the late 1970's and early 1980's suggest a correlation pattern in the data that is counterintuitive to the low inflation, high negative growth period of the recent crisis. The fact that the larger 100-variable index does not exhibit to the same degree these problems over time suggests to us that it is spanning a space that is less sensitive to the level of economic growth and inflation. However, it does still appear to be somewhat influenced by the change in volatility post-1984.

6 Identifying "Financial Crises"

The measure of financial conditions that we have constructed is not unlike a temperature in a person. Consequently, one might expect to have to address some of the same issues faced by medical practitioners in utilizing a patient's temperature in a diagnosis. Specifically, (1) what is a "normal" level and subsequently a level that would warrant concern?; (2) are the risks associated with both extremely low values and high values the same? ; and (3) how well does this measure predict the true underlying state of the patient? By implementing Markov-swithcing and receiver operator characteristics (ROC) curve techniques, we will attempt to address each of these issues.

What proves to be a "normal" temperature in a person often tends to be a range rather then a particular value. Similarly, it makes sense to consider that what constitutes a "normal" value for financial conditions could also be a range as well as something that might change over time. In practice, redefining normal for every person, or in this context point in time, would be counterproductive. Instead, the average across the population is usually a suitable starting point.

Because we have already standardized the FCI to have a mean of zero and unit variance, a value of zero seems a reasonable place to initially deem as normal. It captures the average level of financial conditions in our sample, and corresponds to a weighted average of measures of risk, liquidity, and leverage all expressed relative to their average levels over the same time period. In an attempt to build a "range of normal," it is common to simply select some number of standard deviations from the sample mean, or, equivalently, "build the range" by including everything that falls within a desired percentage of the population.

A possible source of bias in this kind of reasoning, however, might result if a priori we believe that some members of that population are in fact "really sick" and their temperatures are skewed as a result. Including these members when calculating the average will reduce the power of this metric to distinguish between states of the world, i.e. a "healthy state" and a "sick state". For us, the "really sick state" conforms with the notion of a financial crisis, where a number of financial indicators are deviating substantially from their historical norms. Ideally, we would want to develop the concept of normal for the FCI with some sort of reference to these different segments of the population.

If we envision every week in our sample as many different patients, some "sick" and some "normal," and their particular value of the FCI as their "temperature" we can begin to build the intuition behind an optimal range or value for normal. Ideally, we would have a professional consensus on which of these patients turned out to be in fact "sick" and "normal", much like NBER produces for recessions and expansions. Unfortunately, what we have to resort to is the historical accounts of various financial events in U.S. history over the sample period we examine.

Table 3 provides a list of 5 financial crisis episodes in U.S. financial history over the last 40 years along with some of the major events that occurred during each of them. It will be these episodes that we take as given as the "sick" members of the population. In general, they are associated with periods of high risk premia, low liquidity, and declining leverage. To arrive at these episodes, we conducted a survey of the literature on banking and financial crises over the past 40 years. The dating of each of the five episodes is our interpretation of the consensus in the literature as to the beginning and ends of each crisis.[11]

As a robustness check on the validity of these episodes, we begin by using a Markov-switching model to estimate a two state model of financial conditions and the probabilities of each state. Ultimately, the interpretation of the two states estimated by the Markov-switching model is ambiguous, but the identifying restrictions we impose will help to characterize one state as a "crisis period." Because we avoid using the state probabilities estimated to define our financial episodes explicitly, similarity in the dates of high crisis probability to the ones used to define our crisis episodes lend some credibility to the threshold policy analysis that will follow.

[11]Some examples include: FDIC (1984), FDIC (1997), Laeven and Valencia (2008), Reinhart and Rogoff (2008), Minsky (1986), Spero (1999), Schreft (1990), Cameron (2008), and El-Gamal and Jaffe (2008)

	μ_{S_t}	ς_{S_t}
State 1	-0.01	0.00
State 2	0.18	0.01
State 3	-0.01	0.01

Table 1: Estimated parameters from Markov-switching model

6.1 Markov-switching model of financial conditions

Taking the estimated FCI as given, we estimate a variant of the Markov-switching model of Hamilton (1989) to characterize changes over time in the mean and variance of the index. It will be assumed that there are three states of the world, denoted by $S_t \sim \{S_t = 1, S_t = 2, S_t = 3\}$. Equation (5) defines the univariate time series specification used in our estimation of the Markov-switching model

$$F_t(I - A(L)) = \mu_{S_t} + \varepsilon_t \tag{5}$$

where $\varepsilon_t \sim N(0, \varsigma_{S_t})$ and S_t denotes the three states of the world. In this particular specification, the FCI (F_t) will have some finite ordered dynamics that are *state in-variant*, $A(L)$, while the mean and variance of the errors of the FCI will vary by state, μ_{S_t} and ς_{S_t}, respectively.[12]

As noted earlier, our interpretation of the state that represents "really sick" patients is characterized by periods of high risk premia, low liquidity, and deleveraging. In the context of the Markov-switching model, we would expect that if in fact the states that the model is distinguishing conform with this interpretation, a "high mean, high variance" state would emerge. In terms of estimation, there is no restriction that these parameters would have to be grouped in this way. Given what we found above concerning the reduction in volatility post-1984, we also want to allow for a third state that could potentially be a combination of the other two.

Table 1 displays the mean and variance estimated for each of the three states. In fact, with a mean of -0.01 and variance of 0.00 for state 2, and a mean of 0.18 and variance of 0.01 for state 1, the Markov-switching model separately identifies a high mean, high variance and a low mean, low variance state. The third state has the same mean as state 1 and the same variance as state 2 consistent with the notion of a high volatility state at a lower mean due to the overall lower volatility in the post-1984 period.

Figure 7 plots the FCI in panel A where the shading indicates the particular crisis episodes found in table 3. The estimated probability of what we refer to as the crisis state, state 2, is shown through the entire sample in panel B. It is clear from figure 7 that what we are calling

[12] We use three lags of the FCI in the estimation that follows, although results are qualitatively similar with four lags instead. Substantial loss of degrees of freedom prevents the use of more than four lags.

a crisis state coincides closely with the crisis episodes of table 3. During the majority of these episodes, the probability of a crisis state is quite high, particularly surrounding their peak events. The prominent exception is the fourth episode where volatility was higher, but at a lower level. This episode should, however, be picked up by the third state that accommodates this possibility.

Panel C displays the combined probability of states 2 and 3 through the entire sample. The fourth episode is indeed classified as a crisis period under this broader definition. However, so are several other periods outside of the episodes we consider.[13] Almost all of these instances occur in the period post-1984 as one would expect given the parameter estimates above and our previous subsample results for the index.

A particularly interesting period where states 2 and 3 receive a high probability is the 2002-2007 period. State 2's probability during this period is essentially zero, but state 3 receives a very high probability on more than one occasion despite the fact that the index during this period changes very little over time. This period, in other words, confounds our model. The persistently negative values of the FCI during this time are consistent with state 3 in that they have a similar mean to state 1, and the variance during this period is only marginally different than several other instances of where there is a high probability of state 2.

This result is interesting in two respects. First, because it may indicate that state invariant dynamics are not reasonable in this case. More interesting, however, is the fact that this is the period leading up to the most recent crisis. The model may be signaling something very different about this period, i.e. that financial conditions below their historical average for a significant period of time may contain information on future crises. It would not be unreasonable to imagine a "sickness" that was instead linked closer to periods of low risk, high liquidity, and increasing leverage. This particular interpretation we leave to future research.

6.2 Receiver Operator Characteristics (ROC) curve analysis

The above results provide some justification for the broad categorical descriptions of different periods in U.S. financial history in table 3. Here, we develop a unique threshold rule that will be used to identify the "crisis" state of financial conditions in real-time based on past instances of U.S. financial crises. To do so, we follow the approach used by Berge and Òscar Jordà (2009) in estimating optimal threshold values for common business cycle indicators including the Chicago Fed National Activity Index.

The Social Planner's Utility Function

The nonparametric estimation strategy of Berge and Òscar Jordà (2009) requires that we categorize each observed value of the FCI as a "crisis" or "non-crisis" period as in table 3

[13]Most of these instances include major events that were excluded from the other episodes for various reasons. In fact, it would be rather easy to group the mid 1980's and early 1990's with the third episode encompassing the S&L crisis.

and then place relative weights on the utility from correctly predicting each of these states and the disutility from making a false positive versus false negative evaluation of the state of financial conditions. By varying these relative utility and disutility weights, we can develop boundaries for the index corresponding with competing alternatives for addressing the state of future financial conditions.

Keep in mind, however, that this analysis remains subject to the Lucas critique in that it holds fixed both the reaction of financial markets to past policy and past policy to past financial market events. At best, what it can answer is only what level of the index has been associated with crisis conditions in the past. Only a fully articulated model of the financial system and the policy process can tell you how both policymakers and financial market participants may respond to current and future events. Presumably, however, even such a model would take account of past responses which is what we detail here.

Consider the derivation in Berge and Òscar Jordà (2009),

$$
\begin{aligned}
TP(c) &= P[F_t \geq c || S_t = 1] && (6)\\
FP(c) &= P[F_t \geq c || S_t = 0] && (7)
\end{aligned}
$$

with $S_t \in \{0, 1\}$ indicating the non-crisis and crisis states of financial conditions, respectively. $TP(c)$ is typically referred to as the true positive, sensitivity, or recall rate, and $FP(c)$ is known as the false positive or 1-specificity rate. The relationship between the two is described by the receiver operating characteristics (ROC) curve. With the Cartesian convention, this curve is given by

$$
\{ROC(r), r\}_{r=0}^{1} \qquad (8)
$$

where $ROC(r) = TP(c)$ and $r = FP(c)$. Figure 8 depicts this curve and calculates the area under the curve for the FCI using the crisis periods in table 3. The closer to one the area under the curve the more predictive the index is of these periods.

The social planner's utility function for the classification of the FCI at each point in time as a crisis or non-crisis period is expressed as in Baker and Kramer (2007),

$$
U = U_{11}ROC(r)\pi + U_{01}(1 - ROC(r))\pi + U_{10}r(1 - \pi) + U_{00}(1 - r)(1 - \pi) \qquad (9)
$$

where U_{ij} is the utility (or disutility) associated with the prediction i given that the true state is j, $i, j \in \{0, 1\}$ and π is the unconditional probability of observing a crisis episode in the sample. Utility maximization implies that the optimal threshold value c is given by,

$$
\frac{\partial ROC}{\partial r} = \frac{U_{00} - U_{10}}{U_{11} - U_{01}} \frac{1 - \pi}{\pi} \qquad (10)
$$

that is the point where the slope of the ROC curve equals the expected marginal rate of substitution between the net utility of accurate crisis and non-crisis episode prediction.

Essentially, in this type of policy analysis one is weighing the costs of a Type I versus Type II error relative to the benefits of correctly predicting the true state. This intuitively amounts to deciding on whether one wants to put more emphasis (in utility terms) on correctly identifying either state, or possibly equal weight to both. An example of assigning equal weight to both identifying crisis and non-crisis episodes would be assigning $U_{00} = U_{11} = 1, U_{01} = U_{10} = -1$.

On the other hand, if one wanted to put all the emphasis on correctly identifying financial crises, and subsequently no emphasis on the likely error of identifying the other state as a crisis, we could assign the utilities this way: $U_{00} = 0, U_{11} = 1, U_{01} = -1, U_{10} = -\epsilon$ where ϵ needs to be small but non-zero in order to prevent the policy utility function from being degenerate. Finally, a threshold rule that puts more emphasis on identifying non-crisis periods could be identified by using a utility function defined this way: $U_{00} = 1, U_{11} = 0, U_{01} = -\epsilon, U_{10} = -1$.

The optimal thresholds defined above form a particular subset of the estimated index values consistent with three parameterizations of the level sets of the social planner's utility function. Graphically, each policy attempts to find the unique intersection of the linear utility function with the convex ROC curve. A policy placing a very steep penalty on missing an occurrence of a financial crisis thus looks to intersect the upward sloping portion of the ROC curve. A policy that places a relatively larger penalty on missing an occurrence of a non-crisis period does the opposite and instead intersects the flatter portion of the ROC curve. The equal weight, or "unbiased", policy falls somewhere in between the other two on the ROC curve.

Alternatively, consider the following thought experiment with regard to the FCI depicted in figure 9. Draw a horizontal line across the graph at the highest value of the index that does not fall in a period categorized as a crisis period. This defines the threshold for the index that puts a very large weight on correctly identifying non-crisis episodes and avoiding false positives. Similarly, draw a horizontal line across the graph at the lowest value of the index that falls in a period of financial crisis. This defines a threshold which puts a very large weight on correctly identifying non-crisis periods and avoiding false negatives.

With relatively equal weight on all four utilities (disutilities), Berge and Òscar Jordà (2009) derive a threshold value that balances the need to catch financial crisis periods in advance with the desire to avoid assigning movements in the FCI at low levels to a financial crisis. In essence, this derivation "rebases" the index based on the historical financial crises we have identified so that the optimal threshold now takes on a similar meaning for the probability of a crisis period that a zero value of the index does for historical financial conditions. It will, however, be sensitive as to how we date periods of past financial crisis.

We have found through trial and error that this sensitivity is not very high as long as the beginning and end of the episodes are liberally defined. Small changes in the dating of crisis episodes can have a big impact on the upper and lower thresholds defined above, but the equal weighting method tends to balance out these changes so that the optimal threshold produced varies very little when the unconditional probability of a crisis is well defined. This is somewhat reassuring given that in real-time it may be difficult to assess the beginning and end of a new episode.

Interpreting the ROC thresholds

Interestingly, a policy which equally weights the costs and benefits of identifying a crisis episode suggests that even financial conditions slightly below their historical trend can be associated with a financial crisis. The resulting threshold for the index in this case is a negative number (-0.4). This result makes sense intuitively as it is very apparent in figure 9 that the transition in many cases into and out of a crisis episode is characterized by a sudden and sharp deviation from below trend, often greater than a standard deviation in size. Furthermore, as the index is currently defined, several of these episodes are preceded by periods of persistently negative index values.

In essence, the ROC analysis above suggests that the relevant baseline for financial conditions based on historical crisis episodes is not necessarily the sample mean of the FCI. Given what we found above in relation to the change in the mean of the FCI over time, this is not surprising. However, one could also imagine a policy that puts more weight on avoiding severe crises and less weight on crisis episodes like the third and the fourth in table 3. Here, even though it remains sensitive to the dating of crisis episodes, the upper threshold value may be a more relevant benchmark.

Alternatively, one could consider the range between the equal weighted and upper threshold as an early indicator of crisis financial conditions. We refer to this range in figure 9 as a "Reactionary" policy for classifying financial conditions as it puts progressively more weight on avoiding incorrectly classifying increasing levels of the FCI as indicating a crisis. A similar definition can also be applied to the range of values between the lower and equal-weighted thresholds. In this case, a "Pre-emptive" policy for classifying financial conditions would put progressively more weight on avoiding missing the early signs of a financial crisis at low levels of the FCI. The union of the two ranges can be considered as a "range of normal" in the sense above that most instances of crisis and non-crisis weeks fall outside this range.

It is helpful to consider what each of the above policies would have meant in hindsight for the most recent crisis compared to others in the past. An unbiased policy first signals the development of crisis conditions in August 2007 nearly in step with our dating. This is a feature common to several of the crises we consider, although both the late 1970's and 90's would have registered some false positives using this policy. In contrast, a reactive policy would not have signaled concern until the summer of 2008, and not consistently until the post-Lehman period. It also would have entirely avoided classifying the the 1998-2002 period as a crisis. The latter is the only instance of a crisis where this would have been the case.

Conversely, in the post-Lehman era the FCI remained in the region between the reactive and unbiased policy until late 2009. Most recently, it has fluctuated within a small range around this policy threshold suggesting financial conditions have returned to levels consistent in the past with non-crisis periods. For a brief period following the spring 2010 European debt crisis, it once again breached this threshold, but subsequently has returned below it. However, in contrast to the aftermath of all of the other episodes, it remains above its level just prior to the crisis. As such, a pre-emptive policy would still classify its most recent behavior as characteristic of crisis conditions.

The "range of normal" interpretation, on the other hand, accords well with the Markov-switching analysis. The periods of highest probability for both types of crises tend to fall above a reactionary and below a pre-emptive policy. Not much is gained from the former, but the latter is instructive. For instance, such a policy would have raised red flags several times during the period from 2002-2007. The same can be said of the late 1970's and early 1980's, although it applies just as well to the mid-1990's. Thus, although ROC analysis is not very well suited for more than two states of financial conditions, it appears a case could be made based on our results that they are consistent with the three states considered above.

7 Conclusion

In this paper, we outlined the econometric methods needed to incorporate the most general set of indicators necessary to build a real-time metric of financial conditions. To provide evidence of its applicability, Markov-switching methods were used to evaluate the index's ability to capture well known financial crises in U.S history. Then, using ROC analysis threshold rules were developed to help predict future crises based on the level of the index during past crises and subjective utility weights.

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A Appendix

A.1 Kalman Filter and Smoother Recursive Equations

The Kalman filter and smoother equations are a standard tool for producing forecasts and smoothed estimates of state-space models. Combined with the assumption of Gaussian errors, it can be shown that the recursive equations of the filter will yield the minimum mean-squared error estimate within the class of linear estimators. In this paper, we will adopt the notation of Durbin and Koopman (2001) and define the Kalman filter equations as follows.[14]

With a_1 and P_1 given, the filter equations are

$$\begin{array}{ll} v_t = y_t - Za_t & F_t = ZP_tZ' + H \\ K_t = T_tP_tZ'F_t^{-1} & L_t = T_t - K_tZ \\ a_{t+1} = T_ta_t + K_tv_t & P_{t+1} = T_tP_tL_t' + RQR' \end{array}$$

The equations for the backwards smoother are given by[15]:

$$\begin{array}{ll} r_{t-1} = Z'F_t^{-1}v_t + L_t'r_t & N_{t-1} = Z'F_t^{-1}Z + L_t'N_tL_t \\ \tilde{\alpha}_t = a_t + P_tr_{t-1} & V_t = P_t - P_tN_{t-1}P_t \\ J_t = P_{t-1}L_{t-1}'(I - N_{t-1}P_t) & \end{array}$$

with $r_{\hat{T}} = 0$, and $N_{\hat{T}} = 0$.

A.2 Building the state

This section gives a more detailed explanation of how to build the system matrices of the state space, as well as how to obtain the initial estimates needed to begin the EM algorithm. The unobserved factor is assumed to have some finite order dynamics $p^\star$. Using standard OLS techniques on a PCA estimated version of the factor F_t°, an initial guess of these dynamics are generated and described by vector ρ°.[16] Augmenting the state to include $p^\star$ lags of F_t yields the following state equation, with $\alpha_t = [F_{t-i}]$ for $i = 0, \ldots, p^\star - 1$:

$$\alpha_{t+1} = \begin{bmatrix} \multicolumn{2}{c}{\rho} \\ I(p^\star - 1) & 0_{p^\star-1\times 1} \end{bmatrix} \alpha_t + \begin{bmatrix} 1 \end{bmatrix} \eta_t$$

Now, specifying

[14] For more details on the derivation of these equations, see (Durbin and Koopman, 2001, 64–73).

[15] It should be noted that the additional matrix J_t, is being calculated so that the maximization step in the EM algorithm can be defined more easily.

[16] The BIC criterion was used on the initial guess of the factor from the cross-sectional PCA method to determine the number of lags to be 15.

$$\tilde{T} = \begin{bmatrix} & \rho \\ I(p^\star - 1) & 0_{p^\star-1\times 1} \end{bmatrix}$$

one can augment the state (currently a $p^\star$ long vector), by the additional states needed for each of the accumulators derived in section (4.2) to yield the state equation (taking the ρ dynamics above as given):

$$\begin{bmatrix} \alpha_t \\ M_t \\ S_t \end{bmatrix} = \begin{bmatrix} \tilde{T} & 0 & 0 & 0 \\ \frac{\rho}{m_t} & \frac{m_t-1}{m_t} & 0 & 0 \\ \rho & 0 & s_t & 0 \end{bmatrix} \begin{bmatrix} \alpha_{t-1} \\ M_{t-1} \\ S_{t-1} \end{bmatrix} + \begin{bmatrix} 1 \\ 0_{p^\star-1\times 1} \\ \frac{1}{m_t} \\ 1 \end{bmatrix} \eta_{t-1} \tag{11}$$

It should be noted that as written above the $\tilde{T}$ *within* the general transition system matrix, T, here is time invariant, and subsequently the dynamics being estimated (essentially a re-estimation of ρ) at each iteration of the EM algorithm are from a *time invariant* system. However, our (accumulator augmented) state transition system matrix (as well as the coefficient matrix on the η_t) *does vary over time* due to the different number of weeks in a given month, m_t, or quarter, q_t, which also must be carried in the state vector for our purposes.

Moving to the measurement equation, assume that a priori the vector of factor loadings for each series Λ is known.[17] Then, taking the state equation (11) as given, the Z measurement system matrix is simply a $\hat{N}$ by $p^\star + 3$ matrix, where each row has the particular loading λ_i in either the first column (if it corresponded with a weekly or stock variable) or one of the last three columns (corresponding to one of the accumulators i.e. monthly average, monthly sum, or quarterly sum) and zeros everywhere else. The initial guess of H is the diagonal matrix of the variances of the residuals from the initial PCA estimate of the factor, $\sigma_i I(\hat{N})$.[18]

A.3 The EM Algorithm defined

Now that the system matrices have all been defined, the EM algorithm's updates of each of these system matrices can be explicitly defined. With initial estimates of Z, H, and T, we can begin to run algorithm to obtain the maximum likelihood estimates of each. The log-likelihood function for the complete set of data $\alpha_1, \ldots, \alpha_{\hat{T}}, y_1, \ldots, y_{\hat{T}}$ can be written in the form[19]

[17]The initial guess of these loadings, Λ°, will in fact be the loadings obtained from the PCA estimate of the factor mentioned above.

[18]The lack of identification that is common to these models requires that we restrict the scale of either the factor loadings, as in PCA, or the factor. We use the normalization of Doz et al. (2006) and restrict the variance of the state disturbances to be 1 to set the scale of the factor.

[19]In what follows, we drop the R matrix in the notation of the log-likelihood for notational convenience. Due to the fact that there is only one factor and that one is not estimating the dynamics or variances of the deterministic accumulators, this has no substantive implications.

$$
\begin{aligned}
\log L &= -\frac{1}{2}\log|P_1| - \frac{1}{2}(\alpha_1 - a_1)' P_1 (\alpha_1 - a_1) \\
&\quad -\frac{\hat{T}-1}{2}\log|Q| - \frac{1}{2}\sum_{t=2}^{\hat{T}}(\alpha_t - T\alpha_{t-1})' Q^{-1}(\alpha_t - T\alpha_{t-1}) \\
&\quad -\frac{\hat{T}}{2}\log|H| - \frac{1}{2}\sum_{t=1}^{\hat{T}}(y_t - Z\alpha_t)' H^{-1}(y_t - Z\alpha_t) \qquad (12)
\end{aligned}
$$

In order to calculate the conditional expectation defined in the log-likelihood function, it is convenient to define the conditional mean and covariance of the state given all of the observed data from the Kalman smoother recursive equations: the covariance matrix of α_t and α_{t-1} being the additional equation in the Kalman smoother mentioned before.

$$
\begin{aligned}
E(\alpha_t | y_1, \ldots, y_{\hat{T}}) &= \tilde{\alpha}_t \qquad (13) \\
\text{cov}(\alpha_t | y_1, \ldots, y_{\hat{T}}) &= V_t \qquad (14) \\
\text{cov}(\alpha_t, \alpha_{t-1} | y_1, \ldots, y_{\hat{T}}) &= J_t' \qquad (15)
\end{aligned}
$$

Now, taking conditional expectations yields:

$$
\begin{aligned}
G(a_1, P_1, T, Z, Q, H | y_1, \ldots, y_{\hat{T}}) &= -\frac{1}{2}\log|P_1| - \frac{1}{2}\text{tr}\left\{P_1(V_1 + (\tilde{\alpha}_1 - a_1)(\tilde{\alpha}_1 - a_1)')\right\} \\
&\quad -\frac{\hat{T}-1}{2}\log|Q| - \frac{1}{2}\text{tr}\left\{Q^{-1}(C - BT' - TB' + TAT')\right\} \\
&\quad -\frac{\hat{T}}{2}\log|H| - \frac{1}{2}\text{tr}\left\{H^{-1}(F - EZ' - ZE' + ZDZ')\right\} \qquad (16)
\end{aligned}
$$

where tr denotes trace and

$$
\begin{array}{ll}
A = \sum_{i=1}^{\hat{T}-1}(V_i + \tilde{\alpha}_i \tilde{\alpha}_i') & D = \sum_{i=1}^{\hat{T}}(V_i + \tilde{\alpha}_i \tilde{\alpha}_i') \\
B = \sum_{i=2}^{\hat{T}}(J_t' + \tilde{\alpha}_i \tilde{\alpha}_{i-1}') & E = \sum_{i=1}^{\hat{T}}(y_i^\star \tilde{\alpha}_i^\star) \\
C = \sum_{i=2}^{\hat{T}}(V_i + \tilde{\alpha}_i \tilde{\alpha}_i') & F = \sum_{i=1}^{\hat{T}}(y_i^\star y_i^{\star\prime})
\end{array}
$$

It should be noted that $y_i^\star$ and $\tilde{\alpha}_t^\star$ denotes only using periods in which y_t is observed. Now taking the partial derivative with respect to each of the system matrices T, Z and H of the conditional expectation log-likelihood yields the following updating equations for each of the system matrices.

EM Updating Equation 1. *The new estimate for the transition matrix T' that maximizes the conditional loglikelihood function in (16) is given by:*

$$T' = BA^{-1}$$

EM Updating Equation 2. *The new estimate for the observation equation matrix Z' that maximizes the conditional loglikelihood function in (16) is given by:*

$$Z' = ED^{-1}$$

While the above equations derive estimates for an unrestricted coefficient matrix, in our particular model every indicator only loads onto one particular element in the state; either the contemporaneous value of the factor or one of the accumulators. Subsequently, one can estimate each particular loading in Z' by running individual OLS regressions. If one selects the particular row in both the $y_t^\star$ and $\tilde{\alpha}_t^\star$ matrices when constructing E and D, which become scalars, then the particular loading λ_{ij} for indicator i which loads onto the j state variable that gets put into Z will be $\frac{E_{ij}}{D_j}$.

For the purposes of defining the new estimate H', taking into account this restriction on the coefficient matrix Z, it will make sense to define each of the $\hat{N}$ elements along the diagonal of H separately. With new estimates of λ_{ij}, the expected log-likelihood with respect to H can be separated into $\hat{N}$ different equations with the optimal value of H_i for the indicator i that loads onto state variable j defined as:

EM Updating Equation 3. *The new estimates for each of the elements in the diagonal matrix H' that maximizes the conditional loglikelihood function in (16) is given by:*

$$H_i' = \frac{1}{\hat{T}^\star}(y_i^\star - \lambda_i \tilde{\alpha}_{j,t}^\star)^2$$

Where the $\star$ denotes one only includes observations and estimates of the state for periods that the indicators are observed and adjusts the scalar $\hat{T}$ accordingly.

Finally, for a_1 the loglikelihood is maximized by updating this parameter to the smoothed estimate $\tilde{\alpha}_1$. For the update of P_1, we follow Shumway and Stoffer (1982) by initializing it at some reasonable baseline level. Now, the EM algorithm for our dynamic factor model is complete with the extensions of handling missing observations and temporal aggregation issues in the underlying data.

(all of the financial indicators are in basis points or percentages)

LV: Level
LVMA: Level relative to MA
DLV: First Difference
DLN: Log First Difference
DLNQ: 13-week Log Difference

1: Money Markets
2: Debt/Equity Markets
3: Banking System

Financial Indicator	**Transformation**	**Frequency**	**Haver/Bloomberg*/Call Report^ Mnemonic**	**Start**	**Category**	**Full Sample**	**Post-1984**	**39-variable Index**
1-month Nonfinancial CP A2P2/AA credit spread	LV	W	FAP1M-FCP1M	1997w2	1	2.255	2.213	
2-year Swap/Treasury yield spread	LV	W	T111W2-R111G2	1987w14	1	2.229	2.424	
3-month TED spread (LIBOR-Treasury)	LV	W	FLOD3-FTBS3	1980w23	1	1.825	3.066	
1-month Merrill Lynch Options Volatility Expectations (MOVE)	LV	W	SPMLV1	1988w15	1	1.690	1.551	
3-month Merrill Lynch Swaption Volatiltiy Expectations (SMOVE)	LV	W	SPMLSV3	1996w49	1	1.678	1.008	
3-month/1-week AA Financial CP spread	LV	W	FFP3M-FFP7D	1997w2	1	1.582	1.783	
1-month Asset-backed/Financial CP credit spread	LV	W	FAB1M-FFP1M	2001w1	1	1.581	1.996	
3-month Eurodollar spread (LIBID-Treasury)	LV	W	FDB3-FTBS3	1971w2	1	1.522	3.200	-1.851
On-the-run vs. Off-the-run 10-year Treasury liquidity premium	LV	W	FYCEPA-FCM10	1985w1	1	0.974	0.494	
10-year Swap/Treasury yield spread	LV	W	T111WA-R111GA	1987w14	1	0.845	0.947	
3-month Financial CP/Treasury bill spread	LV	W	FFP3-FTBS3	1971w1	1	0.619	2.919	-0.430
Fed Funds/Overnight Treasury Repo rate spread	LV	W	FFED-RPGT01D*	1991w21	1	0.495	1.041	
3-month OIS/Treasury yield spread	LV	W	T111W3M-R111G3M	2003w38	1	0.452	1.148	
Agency MBS Repo Delivery Failures Rate	DLNQ	W	FDDM/(FDDM+FDTM)	1994w40	1	0.426	0.326	
1-year/1-month LIBOR spread	LV	W	FLOD1Y-FLOD1	1986w2	1	0.368	0.004	
Treasury Repo Delivery Fails Rate	DLNQ	W	FDDG/(FDDG+FDTG)	1994w40	1	0.307	0.542	
Agency Repo Delivery Failures Rate	DLNQ	W	FDDS/(FDDS+FDTS)	1994w40	1	0.168	0.289	
Fed Funds/Overnight Agency Repo rate spread	LV	W	FFED-RPAG01D*	1991w21	1	0.150	0.545	
Corporate Securities Repo Delivery Failures Rate	DLNQ	W	FDDC/(FDDC+FDTC)	2001w40	1	0.103	0.122	
Fed Funds/Overnight MBS Repo rate spread	LV	W	FFED-RPMB01D*	1991w21	1	0.037	0.215	
10-year Constant Maturity Treasury yield	DLV	W	FCM10	1971w2	1	-0.050	-0.126	-0.105
Broker-dealer Debit Balances in Margin Accounts	DLN	M	SPMD	1971w5	1	-0.122	-0.267	0.061
3-month/1-week Treasury Repo spread	LV	W	RPGT03M*-RPGT01W*	1991w21	1	-0.141	0.141	
2-year/3-month Treasury yield spread	LV	W	FYCEP2-FTBS3	1971w1	1	-0.237	0.242	1.264
Commercial Paper Outstanding	DLN	W	FCPT	1995w45	1	-0.482	-0.486	
10-year/2-year Treasury yield spread	LV	W	FYCEPA-FYCEP2	1971w34	1	-0.706	-0.375	3.704
3-month Eurodollar, 10-year/3-month swap, 2-year and 10-year Treasury Optic	DLNQ	W	COPED3P+COPTN2P+COPT10P+COPIRSP	2002w7	1	-1.024	-0.802	
Total Repo Market Volume (Repurchases+Reverse Repurchases)	DLNQ	W	FDFR+FDFV	1994w40	1	-1.331	-1.078	
Citigroup Global Markets ABS/5-year Treasury yield spread	LV	M	SYCAAB-FCM5	1989w52	2	2.487	2.708	
Bloomberg 5-year AAA CMBS spread to Treasuries	LV	W	CMBSAAA5*	1996w27	2	2.234	1.574	
Merrill Lynch High Yield/Moody's Baa corporate bond yield spread	LV	W	FMLHY-FBAA	1997w2	2	2.116	1.252	
CBOE S\&P 500 Volatility Index (VIX)	LV	W	SPVIX	1990w1	2	2.074	1.811	
Credit Derivatives Research North America Investment Grade Index	LV	W	S009LIG	2006w1	2	1.528	1.015	
Credit Derivatives Research North America High Yield Index	LV	W	S009LHY	2006w1	2	1.516	0.972	
Citigroup Global Markets Financial/Corporate Credit bond spread	LV	M	SYCF-SYCT	1979w52	2	1.179	1.826	
Citigroup Global Markets MBS/10-year Treasury yield spread	LV	M	SYMT-FCM10	1979w52	2	0.848	1.706	
Bond Market Association Municipal Swap/20-year Treasury yield spread	LV	W	SBMAS-FCM20	1989w27	2	0.818	1.480	
20-year Treasury/State \& Local Government 20-year General Obligation Bon	LV	W	FSLB-FCM20	1971w1	2	0.502	-0.587	-2.143
Moody's Baa corporate bond/10-year Treasury yield spread	LV	W	FBAA-FCM10	1971w1	2	0.348	1.097	1.897
Total Money Market Mutual Fund Assets/Total Long-term Fund Assets	LV	M	ICMMA/ICIA	1974w52	2	0.231	0.217	-0.293
Nonfinancial business debt Outstanding/GDP	DLN	Q	XL14TCRE5/GDP	1971w13	2	0.025	0.105	-0.115
Federal, state, and local debt Outstanding/GDP	DLN	Q	(XL31CRE5+XL21CRE5)/GDP	1971w13	2	0.024	0.098	0.140
Total MBS Issuance (Relative to 12-month MA)	LVMA	M	N/A	2000w52	2	-0.022	-0.108	
S\&P 500, NASDAQ, and NYSE Market Capitalization/GDP	DLN	Q	(SPSP5CAP+SPNYCAPH+SPNACAP)/GDP	1971w13	2	-0.041	-0.090	0.022
New US Corporate Equity Issuance (Relative to 12-month MA)	LVMA	M	FNSIPS	1987w52	2	-0.047	0.005	
Wilshire 5000 Stock Price Index	DLN	M	SPWIE	1971w5	2	-0.052	-0.149	0.026
Loan Performance Home Price Index	DLN	M	USLPHPIS	1976w9	2	-0.066	-0.349	-0.137
New State \& Local Government Debt Issues (Relative to 12-month MA)	LV	M	FNSIS	2004w9	2	-0.108	-0.133	
MIT Center for Real Estate Transactions-Based Commercial Property Price Inc	DLN	Q	MTBIP	1984w26	2	-0.111	-0.106	
Nonmortgage ABS Issuance (Relative to 12-month MA)	LVMA	M	N/A	2000w52	2	-0.130	-0.127	
S\&P 500, S\&P 500 mini, NASDAQ 100, NASDAQ mini Options and Futur	DLNQ	W	COPSPMP+COPSP5P+COPNAMP+COPNASP	2000w12	2	-0.134	0.047	
CMBS Issuance (Relative to 12-month MA)	LVMA	M	N/A	1990w52	2	-0.157	-0.195	
New US Corporate Debt Issuance (Relative to 12-month MA)	LVMA	M	FNSIPB	1987w52	2	-0.179	-0.269	
Net Notional Value of Credit Derivatives	DLN	W	D001TOTH	2008w45	2	-0.256	-0.474	
S\&P 500 Financials/S\&P 500 Price Index (Relative to 2-year MA)	LVMA	W	S5N40I/SPN5COM	1989w37	2	-1.860	-2.040	
Sr Loan Officer Opinion Survey: Tightening Standards on Small C\&I Loans	LV	Q	FTCIS	1990w13	3	2.501	1.591	
Sr Loan Officer Opinion Survey: Increasing spreads on Small C\&I Loans	LV	Q	FSCIS	1990w13	3	2.467	1.471	
Sr Loan Officer Opinion Survey: Tightening Standards on CRE Loans	LV	Q	FTCRE	1990w26	3	2.418	1.628	
Sr Loan Officer Opinion Survey: Tightening Standards on Large C\&I Loans	LV	Q	FTCIL	1990w13	3	2.416	1.513	
Sr Loan Officer Opinion Survey: Increasing spreads on Large C\&I Loans	LV	Q	FSCIL	1990w13	3	2.364	1.314	
30-year Jumbo/Conforming fixed rate mortgage spread	LV	W	ILMJNAVG*-ILM3NAVG*	1998w23	3	2.220	1.776	
Credit Derivatives Research Counterparty Risk Index	LV	W	S000CRI	2006w1	3	1.361	0.859	
National Federation of Independent Business Survey: Credit Harder to Get	LV	M	NFIB20	1973w44	3	1.228	0.779	0.368
30-year Conforming Mortgage/10-year Treasury yield spread	LV	W	FCM-FCM10	1978w35	3	1.154	1.260	-0.574

Table 2: Financial Indicators in the FCI

(all of the financial indicators are in basis points or percentages)

LV: Level
LVMA: Level relative to MA
DLV: First Difference
DLN: Log First Difference
DLNQ: 13-week Log Difference

1: Money Markets
2: Debt/Equity Markets
3: Banking System

Financial Indicator	**Transformation**	**Frequency**	**Haver/Bloomberg*/Call Report^ Mnemonic**	**Start**	**Category**	**Full Sample**	**Post-1984**	**39-variable Index**
Ameican Bankers Association Value of Delinquent Home Equity Loans/Total	DLV	M	USHWODA	1999w9	3	0.284	0.252	
Ameican Bankers Association Value of Delinquent Consumer Loans/Total Lo	DLV	M	USSUMDA	1999w9	3	0.264	0.235	
Ameican Bankers Association Value of Delinquent Credit Card Loans/Total L	DLV	M	USBKCDA	1999w9	3	0.220	0.176	
S\&P US Credit Card Quality Index 3-month Delinquency Rate	DLV	M	CCQID3	1992w9	3	0.157	0.153	
Noncurrent/Total Loans at Commercial Banks	DLN	Q	(RCFD1407^+RCFD1403^)/RCFD2122^	1984w26	3	0.139	0.138	
Ameican Bankers Association Value of Delinquent Non-card Revolving Credit	DLV	M	USREVDA	1999w9	3	0.139	0.140	
C\&I Loans/Total Assets	DLNQ	W	FABWCA/FAA	1973w9	3	0.068	0.159	-0.415
Mortgage Bankers Association Serious Delinquencies	DLV	Q	USL14FA+USL149A	1972w26	3	0.028	0.116	0.078
Total Assets of Funding Corporations/GDP	DLN	Q	OA50TAO5/GDP	1971w13	3	0.022	0.076	-0.019
Mortgage Bankers Association Mortgage Applications Volume Market Index	DLN	W	MBAM	1990w2	3	0.020	-0.043	
Total Assets of Agency and GSE backed mortgage pools/GDP	DLN	Q	OA41MOR5/GDP	1971w13	3	0.011	0.029	-0.069
Total Assets of ABS issuers/GDP	DLN	Q	OA67TAO5/GDP	1983w39	3	0.005	-0.004	
FDIC Volatile Bank Liabilities	DLN	Q	RCON2604^+RCFN2200^+RCFD2800^+MAX(RCFD2890^,RCFD3190^)+RCFD3548^	1978w26	3	0.000	-0.031	-0.052
Deposits/Total Assets	DLNQ	W	FBDA/FAA	1973w9	3	0.000	-0.091	0.083
Fed funds and Reverse Repurchase Agreements w/ nonbanks and Interbank L	DLNQ	W	(FAIFFA+FABWORA)/FAA	1973w9	3	-0.005	-0.105	-0.108
Total Assets of Finance Companies/GDP	DLN	Q	OA61TAO5/GDP	1971w13	3	-0.009	0.009	-0.024
Total Unused C\&I Loan Commitments/Total Assets	DLN	Q	RCON3423^/RCON2170^	1984w26	3	-0.011	-0.019	
Total REIT Assets/GDP	DLN	Q	OA64TAO5/GDP	1971w13	3	-0.012	-0.065	0.030
Total Assets of Broker-dealers/GDP	DLN	Q	OA66TAO5/GDP	1971w13	3	-0.013	-0.075	-0.007
Real Estate Loans/Total Assets	DLNQ	W	FABWRA/FAA	1973w9	3	-0.019	-0.100	-0.030
Total Assets of Pension Funds/GDP	DLN	Q	OA57TAO5/GDP	1971w13	3	-0.023	-0.072	0.006
MZM Money Supply	DLN	M	FMZM	1974w9	3	-0.028	0.060	0.102
Total Assets of Insurance Companies/GDP	DLN	Q	(OA51TAO5+OA54TAO5)/GDP	1971w13	3	-0.029	-0.054	0.053
Commercial Bank 48-month New Car Loan/2-year Tteasury yield spread	LV	Q	FK48NC-FCM2	1976w26	3	-0.033	-0.010	0.209
Consumer Credit Outstanding	DLN	M	FOT	1971w5	3	-0.039	-0.063	-0.138
Securities in Bank Credit/Total Assets	DLNQ	W	FABYA/FAA	1973w9	3	-0.052	-0.089	0.216
Commercial Bank 24-month Personal Loan/2-year Treasury yield spread	LV	Q	FK24P-FCM2	1976w26	3	-0.083	-0.073	0.218
S\&P US Credit Card Quality Index Receivables Outstanding	DLN	M	CCQIO	1992w9	3	-0.095	-0.022	
S\&P US Credit Card Quality Index Excess Rate Spread	LV	M	CCQIX	1992w5	3	-0.109	-0.193	
Finance Company Receivables Outstanding	DLN	M	FROT	1985w31	3	-0.149	-0.092	
Finance Company New Car Loan interest rate/2-year Treasury yield spread	LV	M	FFINC-FCM2	1976w26	3	-0.150	0.196	0.857
Sr Loan Officer Opinion Survey: Willingness to Lend to Consumers	LV	Q	FWILL	1971w13	3	-0.538	-1.085	0.926
UM Household Survey: Auto Credit Conditions Good/Bad spread	LV	M	N/A	1978w5	3	-1.354	-1.178	1.948
UM Household Survey: Mortgage Credit Conditions Good/Bad spread	LV	M	N/A	1978w5	3	-1.487	-1.619	2.033
UM Household Survey: Durable Goods Credit Conditions Good/Bad spread	LV	M	N/A	1978w5	3	-1.543	-1.611	1.613
National Association of Credit Managers Index	LV	M	CMI	2002w9	3	-2.004	-1.374	

1973-74 Bear Market, Petrodollar Recyling, and International Banking Crisis (1973-1975)	1973w2	January 11, 1973	Dow peaks above 1000 and then begins to decline ushering in 73-74 "bear" market
	1973w19	May 11-13, 1973	Bildenberg meeting to discuss developing pressures in "petrodollar" market
	1973w42	October 18, 1973	United States National Bank of San Diego declared insolvent, first billion dollar bank failure
	1973w44	October, 1973	Arab Oil Embargo begins, intensifying petrodollar market problems
	1974w13	March, 1974	Oil embargo is lifted, but money center banks and REITS continue to experience problems
	1974w19	May 10, 1974	Regulatory agencies step in with financial assistance for Franklin National Bank
	1974w23	June 8, 1974	Saudia Arabia agrees to keep price of oil denominated in US $
	1974w41	October 8-9, 1974	Franklin National Bank collapses and is acquired by European American Bank
	1974w49	December 6, 1974	1973-74 bear market ends with the Dow down 45%
	1975w3	January 19, 1975	Merger of Security National Bank of New York with Chemical National Bank to avoid failure
	1975w21	May 23, 1975	Regulatory agencies assist Bank of the Commonwealth to keep it afloat
Dollar Crisis, Mutual Savings Bank Crisis, Penn Square, LDC Crisis, and Continental Illinois (1978-1984)	1978w31	August 1, 1978	Dollar begins steep decline against major foreign currencies
	1978w44	November 1, 1978	Carter announcement of a dollar defense program
	1978w51	December 17, 1978	OPEC decides to keep its US dollar reserves, but increase oil prices in 1979
	1980w11	March 14, 1980	Carter announcement of imposition of credit controls
	1980w13	March 26, 1980	Regulatory agencies step in with financial assistance for First Pennsylvania National Bank
	1980w27	July 3, 1980	Federal Reserve announces phase out of credit controls
	1981w44	November 4, 1981	FDIC assists merger of Greenwich Savings Bank, first in a series of mutual savings bank assisted mergers
	1982w27	July 5, 1982	Penn Square Bank fails
	1982w32	August 12, 1982	Mexico defaults on their debt, beginning of LDC crisis
	1982w45	November 8, 1982	Mexico and IMF reach accord on loan plan
	1984w19	May 9-11,1984	Run on Continental Illinois begins, bank borrows $3.6 billion through discount window
	1984w27	July 1, 1984	Regulators develop plan to take over Contintental's bad loans
	1984w39	September 26, 1984	Resolution of Continental completed
Savings & Loan Crisis and "Black Monday" (1986-1991)	1986w52	December 31, 1986	Federal Savings and Loan Insurance Corporation becomes insolvent
	1987w42	October 19,1987	"Black Monday": DJIA -22.6%, SP500 -20.4%
	1989w32	August 9, 1989	Financial Institutions Reform Recovery and Enforcement Act (FIRREA) signed into law
	1989w35	September 1, 1989	Stock market returns to pre-crash levels
	1991w12	March 23, 1991	RTC Funding Act of 1991 signed into law
Asian Financial Crisis, Russian Debt Default and LTCM, Y2K, Dot-com Bubble, 9/11, and Accounting Scandals (1997-2002)	1997w27	July 2, 1997	Thai government announces a "managed float" of the baht, which devalued by 15%
	1997w32	August 11, 1997	IMF approves a stand-by credit for Thailand
	1998w33	August 17, 1998	Russia defaults on its debt
	1998w38	September 23, 1998	Collapse of LTCM (Federal Reserve steps in with support to financial markets)
	1999w30	July 27, 1999	IMF approves stand-by credit for Russian Federation
	1999w40	October 1, 1999	Fed establishes Century Date Change Special Liquidity Facility
	2000w1	January 1, 2000	Y2K passes
	2000w10	March 10, 2000	NASDAQ peaks then loses 31% of its value within 4 weeks and 50% within 6 months
	2001w37	September 11, 2001	Terrorist attack on the World Trade Center
	2001w50	December 13, 2001	SEC enforcement action against Enron
	2002w28	July 15, 2002	Arthur Anderson indicted
	2002w31	July 30, 2002	Sarbanes-Oxley Act passed
Subprime Mortgage Crisis and Subsequent Events (2007-Current)	2007w31	July 31, 2007	Bear Stearns liquidates two hedge funds investing in MBS
	2008w11	March 14, 2008	Bear Stearns sold to JPMorgan Chase with NY Fed support
	2008w28	July 13-15,2008	Fannie Mae and Freddie Mac receive government assistance
	2008w36	September 7, 2008	FHFA places Fannie Mae and Freddie Mac into conservatorship
	2008w37	September 14-16, 2008	Lehman Brothers files for bankruptcy, AIG requires government assistance, Reserve Fund "breaks the buck"
	2008w40	October 3, 2008	Emergency Economic Stabilization Act passed (TARP)
	2008w47	November 23, 2008	Citigroup requires government assistance
	2009w3	January 16, 2009	Bank of America requires government assistance
	2009w48	December 2, 2009	Bank of America announces plans to repay TARP assistance
	2009w49	December 9, 2009	TARP extended to Oct. 3 2010
	2009w50	December 14, 2009	Citigroup reaches agreement to repay TARP assistance
	2010w19	May 9-10, 2010	EU, ECB, and IMF announce $1 trillion aid package after Greek debt crisis

Table 3: Recent Crises in U.S. Financial History

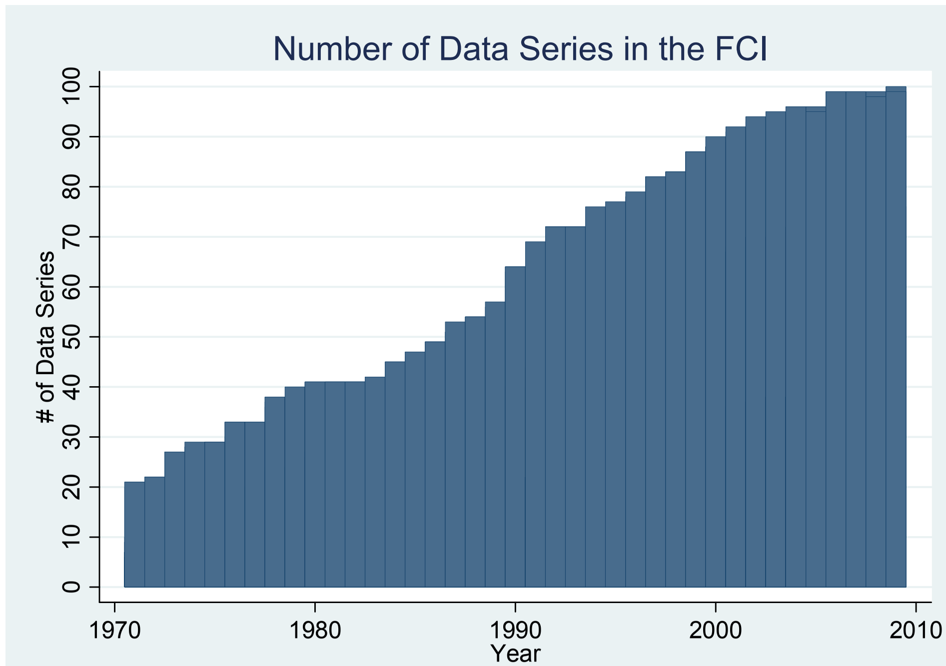

Figure 1: Pattern of Data Availability

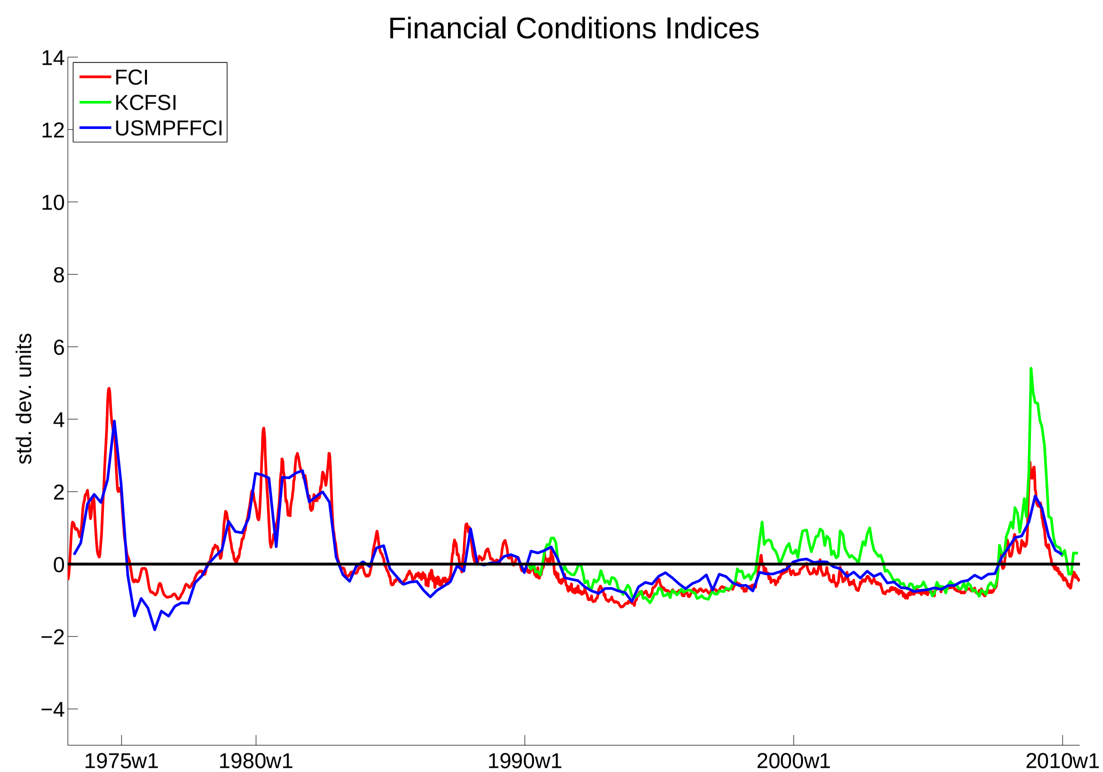

Figure 2: Financial Conditions Index vs. USMPFFCI and KCFSI

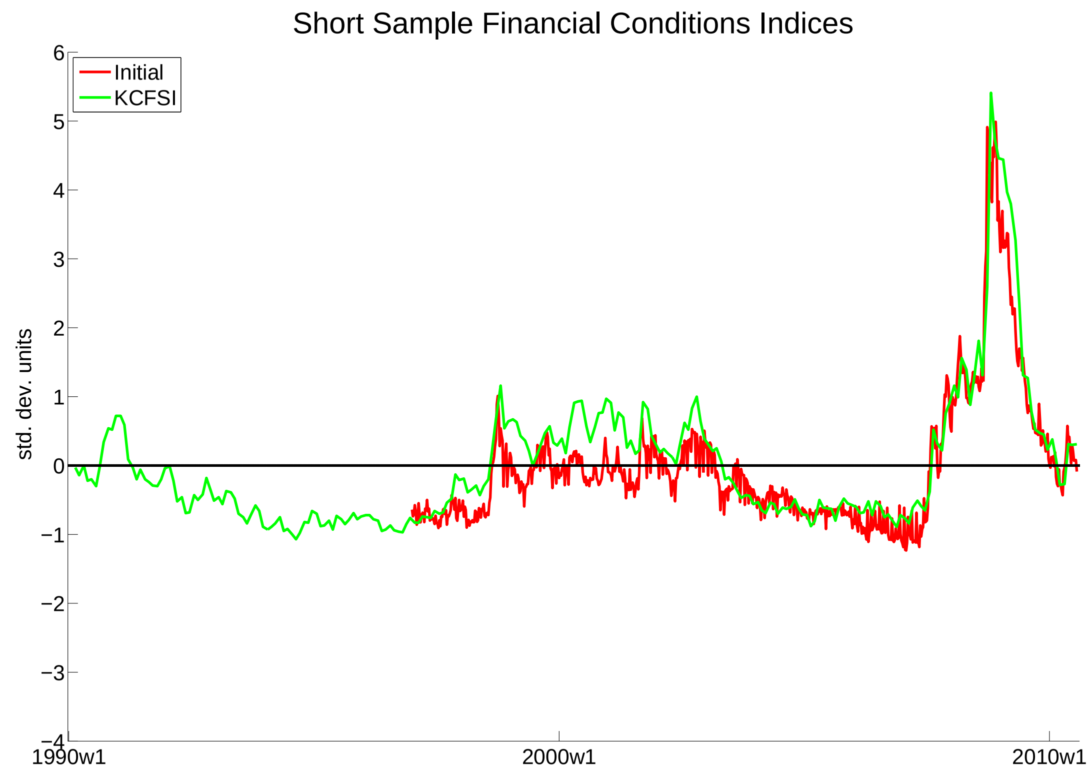

Figure 3: PCA-estimated Indexes

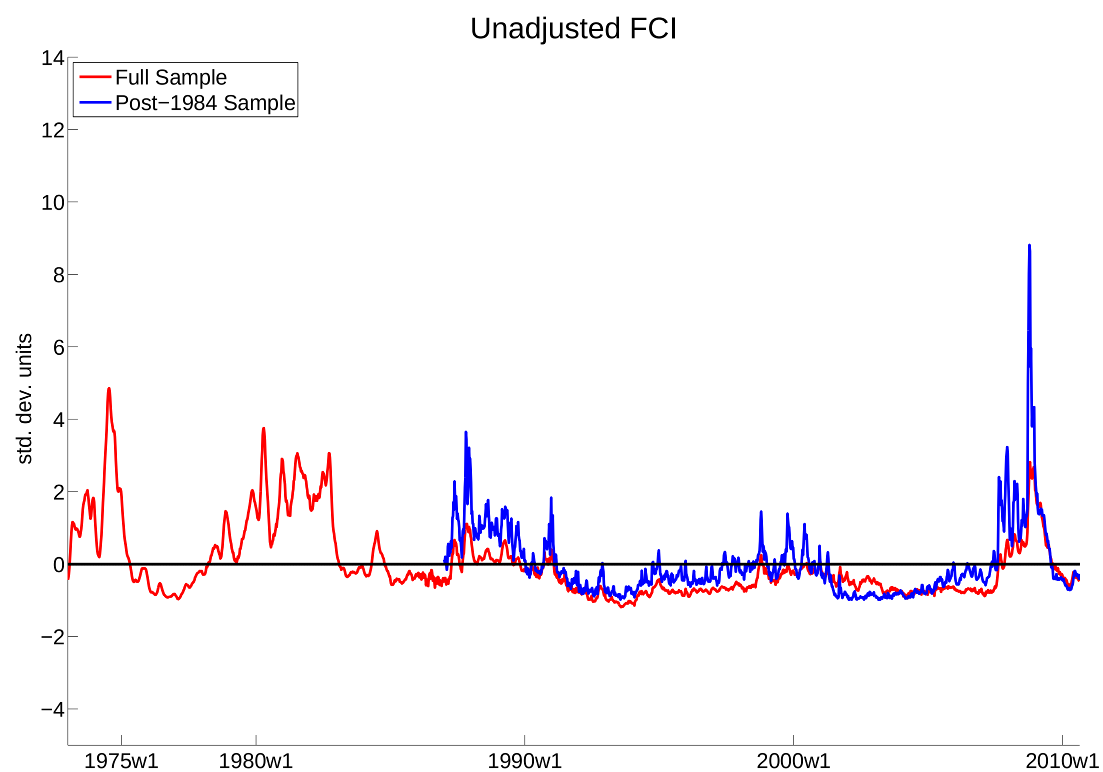

Figure 4: Full Sample vs. Post-1984

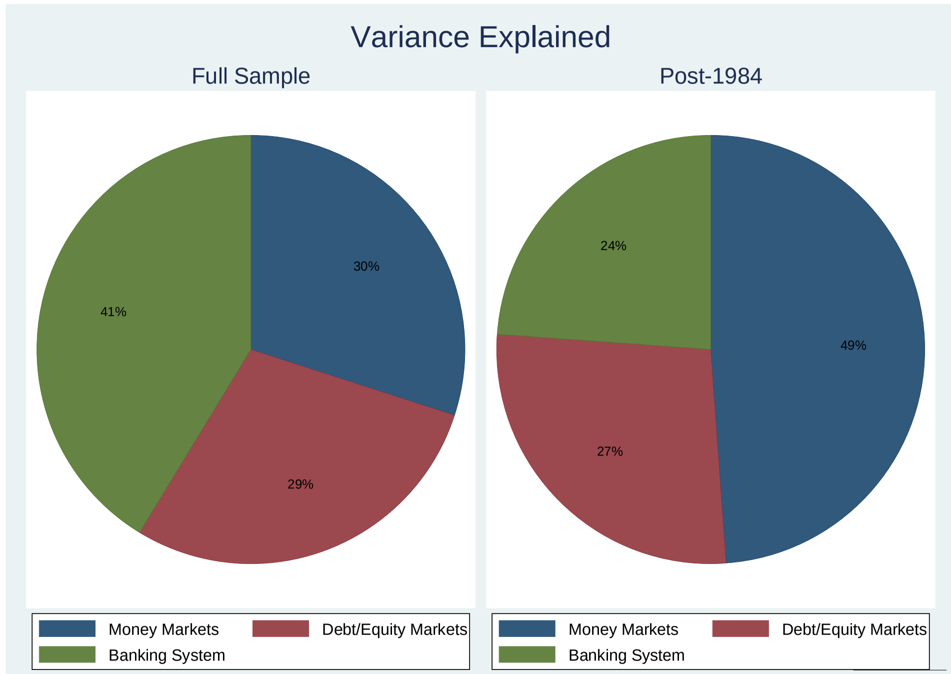

Figure 5: Decomposition of Variance Explained by the FCI

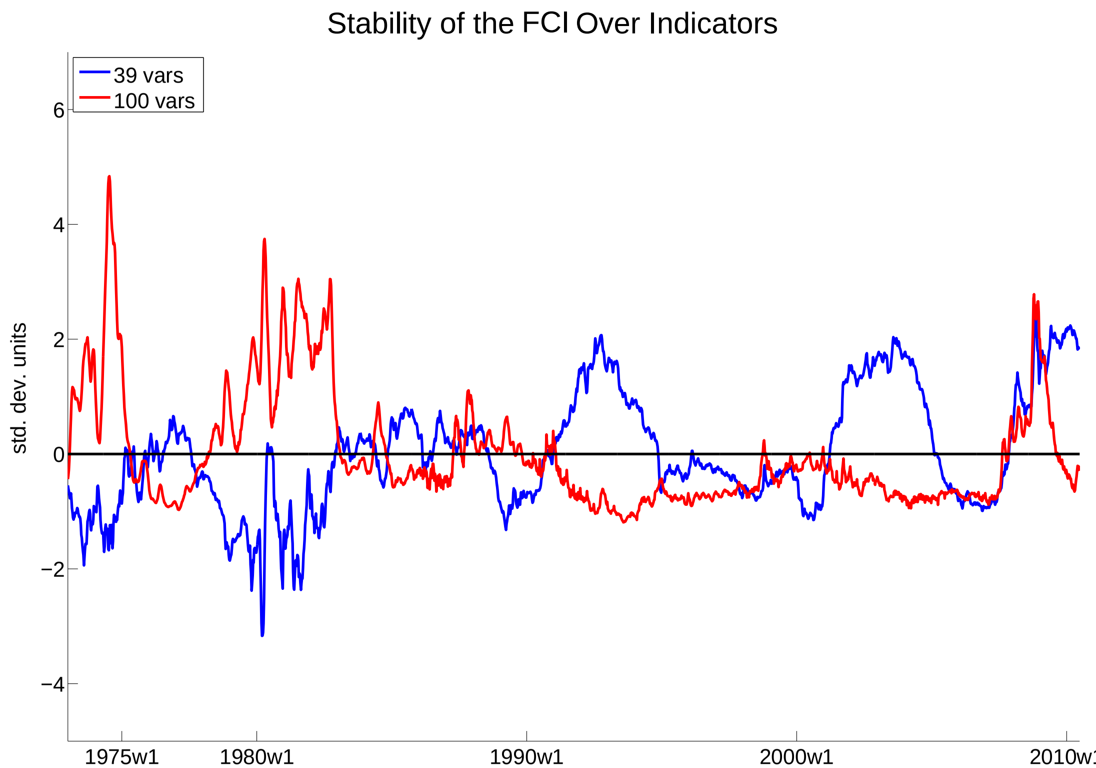

Figure 6: 100 vs. 39-variable Indexes

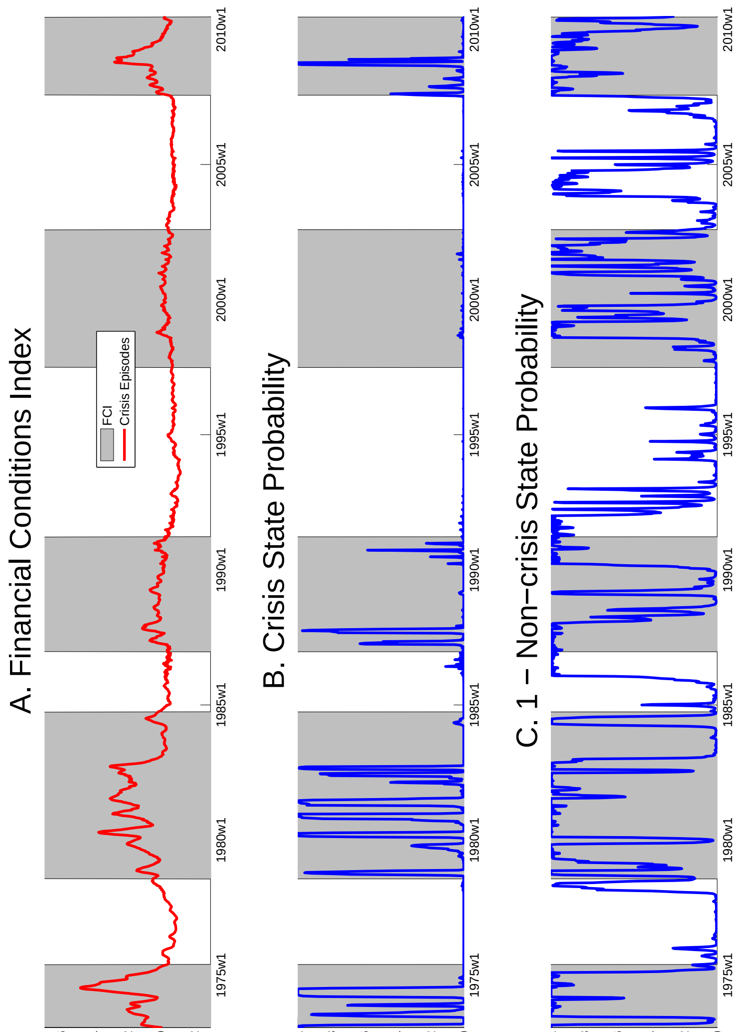

Figure 7: Markov-Switching Model for the FCI

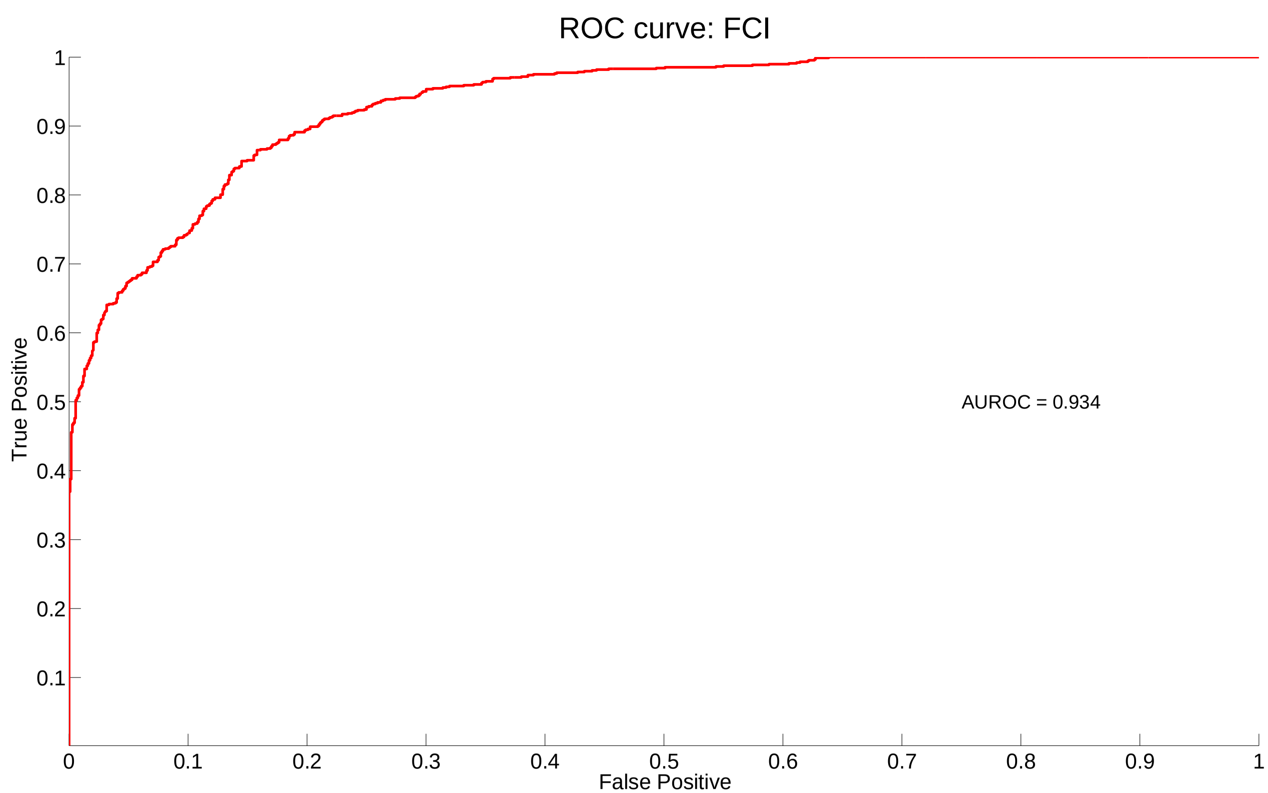

Figure 8: Receiver Operator Characteristics curve for the FCI

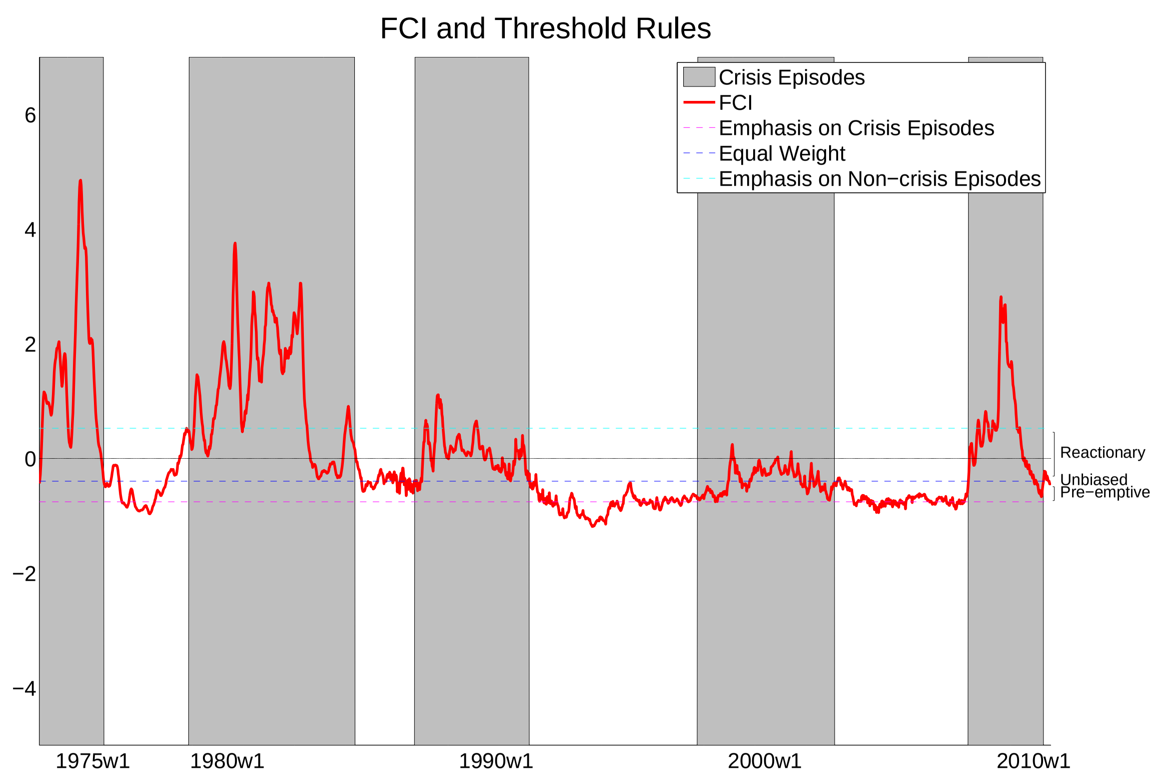

Figure 9: Optimal ROC thresholds for the FCI

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