Monitoring financial stability: A financial conditions index approach

Scott Brave and R. Andrew Butters

Introduction and summary

One of the key observations to come out of the recent crisis is that financial innovation has made it difficult to capture broad financial conditions in a small number of variables covering just a few traditional financial markets. The network of financial firms outside the traditional commercial banking system—that is, the so-called shadow banking system—was at the forefront of many of the major events of the crisis, as were newer financial markets for derivatives and asset-backed securities.

In the wake of the crisis, policymakers, regulators, financial market participants, and researchers have all affirmed the importance of the interconnections between traditional and newly developed financial markets, as well as their linkages to the nonfinancial sectors of the economy. The Dodd–Frank Wall Street Reform and Consumer Protection Act of 2010 sets forth a financial stability mandate built on this widespread affirmation.

Monitoring financial stability, thus, now explicitly requires an understanding of both how traditional and evolving financial markets relate to each other and how they relate to economic conditions. Indexes of financial conditions are an attempt to quantify these relationships. Here, we describe two new indexes that expand on the work of Illing and Liu (2006), Nelson and Perli (2007), Hakkio and Keeton (2009), and Hatzius et al. (2010).

In what follows, we first describe our method of index construction. The novel contribution of our method is that it takes into account both the cross-correlations of a large number of financial variables and the historical evolution of the index to derive a set of weights for each element of the index. We also develop an alternative index that separates the influence of economic conditions from financial conditions. We then highlight the contribution of different sectors of the financial system to our indexes, as well as the systemically important indicators among them.

Next, we show that the indexes of financial conditions we produce are useful tools in gauging financial stability. Major events in U.S. financial history are well captured by the history of our indexes, as is the interdependence of financial and economic conditions. To further demonstrate the latter, we establish that it is possible to use our indexes to improve upon forecasts of measures of economic activity over short and medium forecast horizons.

Measuring financial conditions

Indexes of financial conditions are typically constructed as weighted averages of a number of indicators of the financial system's health. Commonly, a statistical method called principal component analysis, or PCA, is used to estimate the weight given each indicator (see box 1 for details). The benefit of PCA is its ability to determine the individual importance of a large number of indicators so that the weight each receives is consistent with its historical importance to fluctuations in the broader financial system.

Indexes of this sort have the advantage of capturing the interconnectedness of financial markets—a desirable feature allowing for an interpretation of the systemic importance of each indicator. The more correlated an indicator is with its peers, the higher the weight it receives. This allows for the possibility that a small deterioration in a heavily weighted indicator may mean more for financial stability than a large deterioration in an indicator of little weight.

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The authors thank Hesna Genay, Spencer Krane, Alejandro Justiniano, Gadi Barlevy, Jeff Campbell, Douglas Evanoff, and Lisa Barrow for their helpful comments.

BOX 1

What is principal component analysis?

Here, we explain the mathematics behind PCA.[1] In our explanation, x_t denotes the $1\times N$ element row vector of data at time t. The first step is to form the stacked matrix of data vectors X_T, where each column of this vector contains T observations of a financial indicator normalized to have a mean of zero and a standard deviation of one. The eigenvector–eigenvalue decomposition of the variance–covariance matrix $X_T^{'}X_T$ then produces a set of weights referenced by the $N\times 1$ vector W corresponding to the eigenvector associated with the largest eigenvalue of this matrix.[2] These weights are used to construct a weighted sum of the x_t at each point in time such that the resulting index is given by $I_t = X_T W$.

In a general setting, variation in the frequency or availability of data makes PCA infeasible. To circumvent this issue, many indexes restrict the set of financial indicators and the time period examined at the cost of losing coverage of more recently developed financial markets and longer historical comparisons. Alternatively, Stock and Watson (2002) show how this issue can be addressed by an iterative estimation strategy that relies on the incomplete data methods of the expectation-maximization (EM) algorithm of Watson and Engle (1983). As the number of indicators becomes large, this strategy produces an index estimate with the same desirable statistical properties as PCA.

The EM algorithm uses the information from the complete, or "balanced," panel of indicators to make the best possible prediction of the incomplete, or "unbalanced," panel of indicators. Stock and Watson's (2002) EM algorithm begins with estimation by PCA on a balanced subset of the data to obtain an initial estimate of the index. Data for each of the financial indicators are then regressed on this estimate of the index, and the results of each regression are used to predict missing data. The index is then reestimated by PCA on both the actual and predicted data. This process continues until the difference in the sum of the squared prediction errors between iterations reaches a desired level of convergence.

Stock and Watson's (2002) EM algorithm is, however, a purely static estimation method and does not incorporate information along the time dimension into the construction of the index. In addition, it, too, is restricted by the need for an initial balanced panel of the highest-frequency indicators, given its reliance on PCA. Because most high-frequency financial indicators are not readily available prior to the mid-1980s, this constraint is not trivial. We, instead, use this method as a starting point, but then rely on the alternative estimation procedure of Doz, Giannone, and Reichlin (2006). Their method allows us to also incorporate information along the time dimension into our index, and is a form of what is referred to as dynamic factor analysis.

[1]For further details on PCA, see Theil (1971), pp. 46–48.

[2]Underlying the normalization of the data is the concept of "stationarity," or the notion that the mean and variance of each indicator do not vary over time. For this to be true, some indicators must first be altered with a stationarity-inducing transformation prior to estimation. The stationarity-inducing transformations we used can be found in table A1 in the appendix.

The PCA method also has its limitations, however. For instance, often the choice of which financial indicators to include is restricted by the frequency of data availability, as well as the length of time for which data are available. Work by Stock and Watson (2002) and others have shown how to relax some of these constraints, and we pursue this direction further so as to construct a richer and longer time series for our indexes.

Our goal is to be able to construct high-frequency indexes with broad coverage of measures of risk, liquidity, and leverage. By risk, we mean both the premium placed on risky assets embedded in their returns and the volatility of asset prices. In terms of liquidity, our measures capture the willingness to both borrow and lend at prevailing prices. Measures of leverage, in turn, provide a reference point for financial debt relative to equity.

To allow for historical comparisons and financial innovation, our method must also be able to incorporate time series of varying lengths and different frequencies. To do so, we apply the methods of Doz, Giannone, and Reichlin (2006) and Aruoba, Diebold, and Scotti (2009) (see box 2 for details). This framework allows us to make use of weekly, monthly, and quarterly financial indicators with histories that potentially begin and end at different times.

To briefly describe our method, we add a second dimension to the averaging process—namely, the time-series dimension of the index. At each point in time, all of the available indicators are used to construct the index, ignoring those that are unavailable. The historical time-series dynamics of the index are then used to smooth its history; and when these indicators again

BOX 2

Estimating our financial conditions indexes

Our FCI is constructed in a similar fashion to many coincident indicator models where the variation in a panel of time series is governed linearly by an unknown common source and an idiosyncratic error term. The static measurement equation these models all have in common is of the following form:

$$X_t = \Gamma F_t + \varepsilon_t,$$

where F_t represents a $1 \times T$ latent factor capturing a time-varying common source of variation in the $N \times T$ matrix of standardized and stationary financial indicators X_t and Γ represents its $N \times 1$ loadings onto this factor. A defining characteristic of X_t for our FCI is its large size in both the cross section (N) and time domain (T).

Adding dynamics of some finite order to the latent factor moves the model into the large approximate dynamic factor framework of Doz, Giannone, and Reichlin (2006). The state-space representation of this model is given by:

$$X_t = \Gamma F_t + \varepsilon_t,$$

$$F_t = AF_{t-1} + \nu_t,$$

where Γ are factor loadings estimated off the cross section of financial indicators and A is the transition matrix describing the evolution of the latent factor over time. The latent factor's dynamics, p, as expressed in the transition matrix A are assumed to be of finite order: $p = 15$ weeks. Fifteen lags correspond roughly with one quarter's worth of data.

With the model in state-space form and initial estimates of the system matrices, the EM algorithm outlined by Shumway and Stoffer (1982) can be used to estimate the latent factor F_t. At each iteration of the algorithm, one pass of the data through the Kalman filter and smoother is made, followed by reestimation of the system matrices by linear regression.[1] The log-likelihood function that results is nondecreasing, and convergence is governed by its stability.

We use the PCA-based EM algorithm of Stock and Watson (2002) to provide consistent initial estimates of Γ and $\frac{\varepsilon_t^{'}\varepsilon_t}{N}$, and we use linear regression on the subsequent estimate of F_t to obtain consistent initial estimates of A and $\frac{\nu_t^{'}\nu_t}{T}$. It is worth emphasizing, however, that these initializations are more restrictive than necessary and serve in this framework only to considerably reduce the required number of iterations of the EM algorithm. For instance, PCA normalizes the factor loadings to satisfy $\frac{\Gamma^{'}\Gamma}{N} = I$ and assumes that $\frac{\varepsilon_t^{'}\varepsilon_t}{N} = \sigma^2 I$. The large approximate dynamic factor

become available, the history is updated to reflect the information gained.

Using this method, we construct our weekly financial conditions index (FCI) that takes into account both the cross-correlations of the indicators and the historical evolution of the index itself in determining the appropriate weights. The latter serves to smooth changes to the index over time, leaving behind more persistent contributions from the indicators. This feature is desirable, particularly in real time, because it avoids putting too much emphasis on potentially temporary factors influencing financial conditions.

Following Hatzius et al. (2010), we also consider adjusting the indicators for current and past economic activity and inflation prior to construction of the index. Our "adjusted" FCI, described in box 2, is motivated by the observation that financial and economic conditions are highly correlated. Removing the variation explained by the latter addresses potential asymmetries in the response of one to the other. For instance, a deterioration in financial conditions when economic growth is high and inflation low may have different effects on the real economy than a deterioration in financial conditions when economic growth is low and inflation high.

Our adjusted FCI is, thus, likely relevant for isolating the source of the shock to financial conditions.[1] That said, our FCI is a broader metric of financial stability because it captures the interaction of financial conditions and economic conditions. Combined, the two indexes could serve as useful policy tools by providing a sense of how tight or loose financial markets are operating relative to historical norms.

Figure 1 plots our FCI and adjusted FCI. Interpreting the level of both requires a reference to some historical norm. The norm considered in figure 1 is the sample mean of each index, which provides a sense of the average state of financial conditions, or its long-term historical trend. In this sense, a zero value for our FCI in figure 1 corresponds with a financial system operating

BOX 2 (CONTINUED)

Estimating our financial conditions indexes

model framework relaxes this assumption, instead using the normalization that $\frac{v_t' v_t}{T} = I$ and accommodating cross-sectional heteroskedasticity, that is,

$$\frac{\varepsilon_t' \varepsilon_t}{N} = \sigma_i^2 I.$$

Because of the varying frequencies of observation of the data in our FCI, we must also make two extensions to the EM algorithm prior to estimation. The first 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 adjust for the temporal aggregation issues caused by the varying frequencies of data observation. Here, we follow Aruoba, Diebold, and Scotti (2009) in their application of Harvey (1989) to data of varying frequencies of observation to augment the transition dynamics of the state-space model accordingly.

Our adjusted FCI requires pretreatment of the data before application of the routine we just described. Each of the 100 financial variables is first regressed on current and lagged values of a measure of the business cycle—that is, the three-month moving average of the Chicago Fed National Activity Index (CFNAI-MA3)—and inflation—that is, three-month total inflation as measured by the Personal Consumption Expenditures (PCE) Price Index—with the number of current and lagged values in each regression chosen for each variable using the Bayesian Information Criterion. The independent variables of these regressions were transformed so as to match the frequency of observation of the dependent variable. For weekly variables, we assumed only lagged values enter the regression and that these values are constant over the weeks of the month because of the monthly frequency of observation for the CFNAI-MA3 and total PCE inflation. The standardized residuals from these regressions are then used to construct our adjusted FCI.

Our 100 financial indicators consist of 47 weekly, 29 monthly, and 24 quarterly variables. The longest time series extends back to 1971, while the shortest begins in 2008. We estimate the EM algorithm on the unbalanced panel from the first week of 1971 through 2010. However, we only consider the estimates from the first week of 1973 onward. At this point, over 25 percent of the financial indicators we examine have complete time series. Because of the number of high-frequency indicators we examine, it is not until 1987 that 50 percent have complete time series.

[1]In addition, 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. See Brave and Butters (2010a) for more information on the construction of the index.

at the historical average levels of risk, liquidity, and leverage. For our adjusted FCI, a zero value indicates a financial system operating at the historical average levels of risk, liquidity, and leverage consistent with economic conditions.

In general, risk measures receive positive weights in each index, whereas liquidity and leverage measures tend to have negative weights. This pattern of increasing risk premiums and declining liquidity and leverage is consistent with tightening financial conditions, and provides us a basis for interpreting both indexes: Positive index values indicate tighter conditions than on average, and negative index values indicate looser conditions than on average.

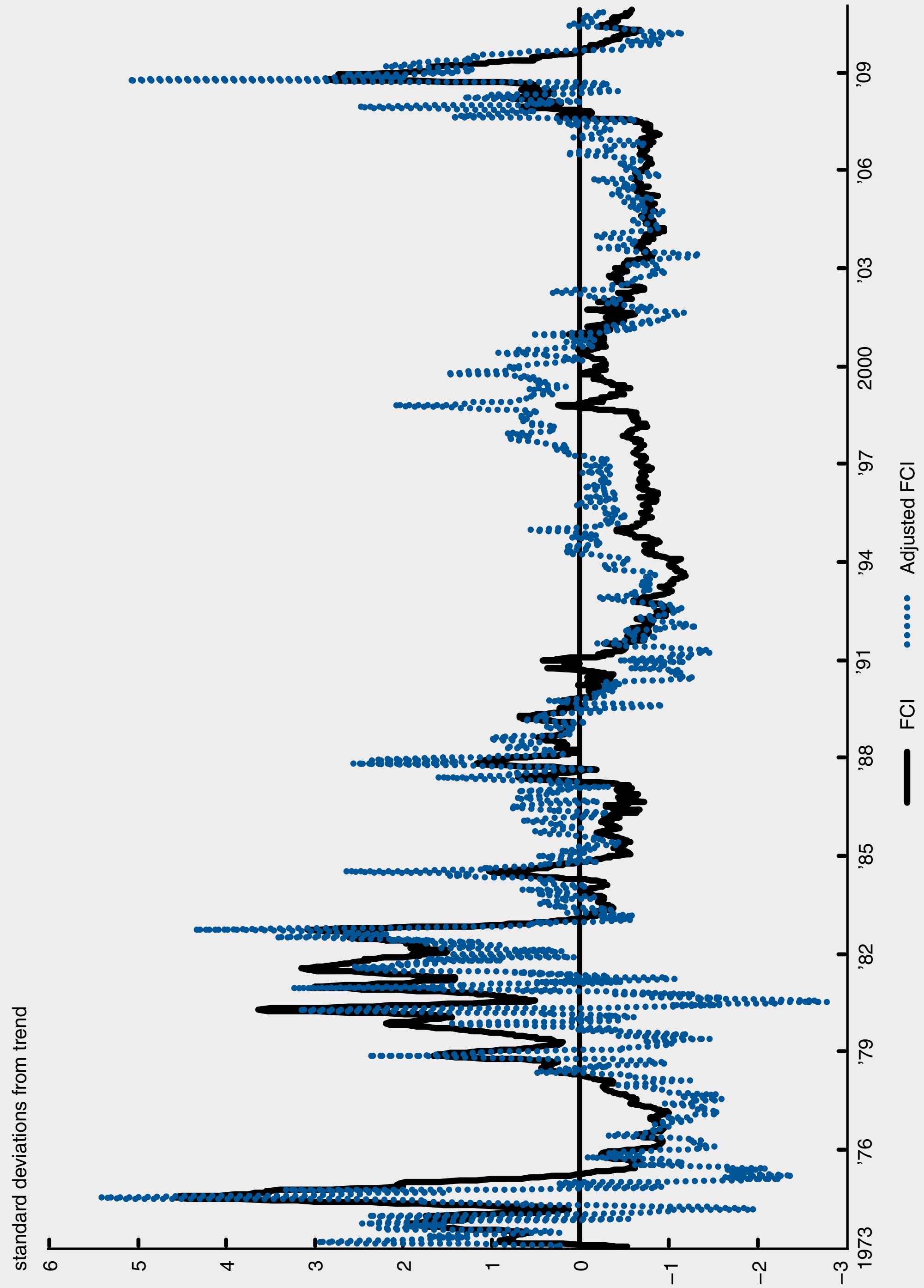
In addition, it is common for financial conditions indexes to be expressed relative to their sample standard deviations. We follow this approach to establish a scale for our FCI and adjusted FCI in figure 1. Measured in this way, an index value of 1.0 is associated with financial conditions that are tighter than on average by one standard deviation. Similarly, an index value of –1.0 indicates that financial conditions are looser than on average by one standard deviation.

It is important to note, however, that given the transformations described previously, direct comparisons across the two indexes are *not* valid. Instead, comparisons must be made with respect to how each captures financial conditions over time. For instance, our adjusted FCI is much less persistent, moving above and below its average value more frequently than our FCI. It is also the case that our adjusted FCI gives more emphasis to recent financial market disruptions, often putting them on par with the more volatile 1970s and 1980s.

Instances can occur where adjusting for economic conditions produces a different interpretation of financial conditions than our FCI. Periods of high economic growth, such as the mid-1980s and late 1990s, often lead to an above-average adjusted FCI when our FCI is below average. Conversely, periods of high

FIGURE 1

Financial conditions indexes (FCI and adjusted FCI), 1973–2010



inflation, such as the 1970s and early 1980s, often lead to a below-average adjusted FCI when our FCI is above average.

Systemically important indicators

There are two ways to view the systemic relationship expressed in each indicator's weight: by its sign and by its magnitude. Risk measures with their generally positive weights and liquidity and leverage measures with their generally negative weights imply that increasingly positive values of the index capture periods of above-average risk and below-average liquidity and leverage. Conversely, increasingly negative values of the index capture periods where risk premiums are below average and liquidity and leverage are above average.

The way in which leverage enters our indexes is in line with Adrian and Shin (2010), who find leverage is often procyclical (that is, it is positively correlated with the overall state of the economy). In this way, the process of deleveraging appears in the indexes as an indicator of deteriorating financial conditions. Unlike other methods, however, our estimation framework can potentially take into account that a buildup of leverage generates a tendency to reverse itself that depends on the degree of mean reversion that our FCI and adjusted FCI have shown over time.

Taking into account the financial markets represented, we have segmented the financial indicators in our FCI and adjusted FCI into three categories: money markets (28 indicators), debt and equity markets (27), and the banking system (45). Table A1 in the appendix summarizes all 100 financial indicators in the form they enter both indexes; the indicators are listed in this order—from those with the largest positive weights to those with the largest negative weights within each category for our FCI. Because in our estimation method the weights are only identified up to scale, we have scaled them to have a unit variance in the table for ease of comparison.

The money markets category is made up mostly of interest rate spreads that form the basis of most other financial conditions indexes.[2] However, unlike for many of these indexes, we also include in this category measures of implied volatility and trading volumes of several money market financial products. Interest rate spreads and measures of implied volatility tend to receive positive weights, whereas trading volumes tend to receive negative weights. The implication of this pattern is that widening spreads, increasing volatility, and declining volumes all constitute a tightening in money market conditions.

Some of the interest rate spreads given the greatest positive weights in our FCI include the one-month nonfinancial A2P2/AA commercial paper credit spread, as well as the two-year interest rate swap and the three-month Libor spreads relative to Treasuries. The first captures the risk premium for issuing short-term commercial paper to less creditworthy borrowers. The remaining two indicators capture elements of liquidity and credit risk in the interest rate derivative and interbank lending markets, respectively. The Merrill Lynch implied volatility measures for options and swaptions (MOVE and SMOVE) also receive large positive weights, whereas open interest in money market derivatives and repo market volume receive sizable negative weights. The former two indicators are, in a sense, measures of risk, while the latter two can be viewed as measures of liquidity and leverage.

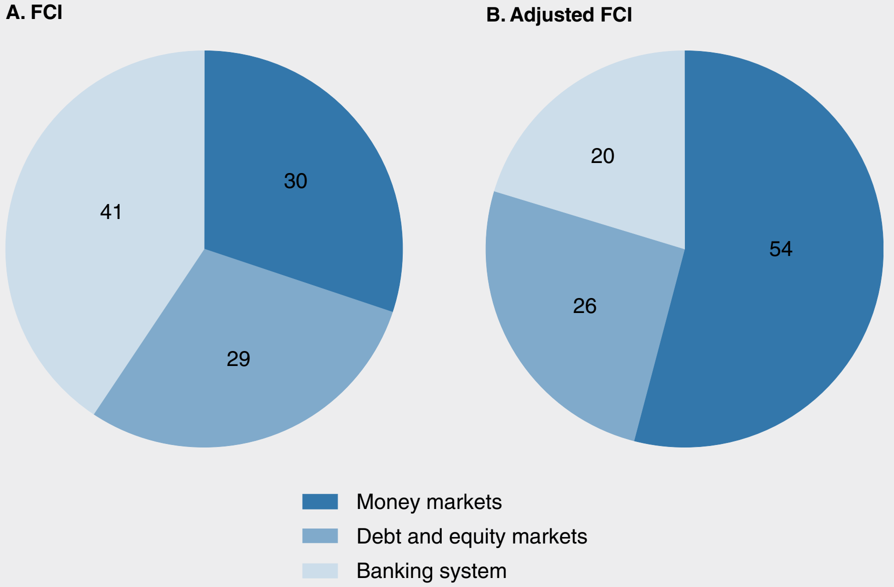
The debt and equity markets category comprises mostly equity and bond price measures capturing volatility and risk premiums in their various forms. In addition to stock and bond market prices, we include in this category residential and commercial real estate prices, as well as municipal and corporate bond, stock, asset-backed security, and credit derivative market volumes. The latter measures capture elements of both market liquidity and leverage. In general, the indicators in this category follow the same pattern as the money market category, so that widening credit spreads, increasing volatility, and declining volumes denote tightening debt and equity market conditions.

In terms of equities, the largest positive weight in our FCI is given to the Chicago Board Options Exchange (CBOE) Market Volatility Index, commonly referred to as the VIX, which measures the implied volatility of the Standard & Poor's (S&P) 500; the largest negative weight is given to the relative valuation of financial stocks in the S&P 500 (S&P Financials/S&P 500). In terms of bonds, credit spreads such as the high yield/Baa corporate and financial/corporate enter strongly here with large positive weights; so do spreads relative to Treasuries or swaps for nonmortgage asset-backed securities (ABS), mortgage-backed securities (MBS), and commercial-mortgage-backed securities (CMBS). Swap spreads on credit derivatives for investment grade and high-yield corporate bonds—or credit default swaps (CDS), a measure of insurance protection tied to default—are also given sizable positive weights.

The banking system category contains mainly survey-based measures of credit availability as well as accounting-based measures for commercial banks and so-called shadow banks, but a few interest rate spreads also appear in this category. The former indicators are primarily measures of liquidity and leverage, but they also capture the risk tied to deteriorations in

FIGURE 2

Decomposition of variance explained by financial conditions indexes (FCI and adjusted FCI)



Note: All values are in percent.

credit quality. Of the interest rate spreads, the difference between the 30-year jumbo and conforming fixed-rate mortgages receives the largest positive weight, followed by the 30-year conforming mortgage/10-year Treasury yield spread.

The Federal Reserve Board's Senior Loan Officer Opinion Survey questions on loan spreads and lending standards all enter strongly into our FCI (mostly with large positive weights so that widening spreads and tighter standards reflect tighter conditions in the banking system), as do several other survey measures of business and consumer credit availability. Depending on how these survey measures are expressed, some receive large negative weights; but in each case, declining availability coincides with tighter banking system conditions.

The Credit Derivatives Research Counterparty Risk Index, measured as the average of the CDS spreads of the largest 14 issuers of CDS contracts, also receives a large positive weight, with the remaining weight split roughly evenly between measures of credit quality and commercial and shadow bank lending and leverage. All of these measures capture the inherent risks to the stability of the financial system posed by the potential collapse of commercial and shadow bank entities.

Differences arise in the relative systemic importance of several indicators when considering the impact of economic conditions in the estimation of the indicator weights. Figure 2 helps to explain these differences. Measures of the health of the banking system capture 41 percent of the variation explained by our FCI, followed by money market measures at 30 percent and debt and equity market measures at 29 percent. After performing the same calculation on our adjusted FCI, we note that money market measures now dominate at 54 percent, with debt and equity market measures accounting for 26 percent and the banking system measures accounting for 20 percent.

Thus, the primary effect of adjusting for economic conditions appears to be the reduction in importance of banking system measures. The survey-based indicators within the banking system category, in particular, show the largest declines in weight. A lower weight in this case indicates that much of the variation in these indicators can be explained by changes in either economic activity or inflation over time. A secondary effect, visible in table A1 in the appendix, is the addition of weight to certain measures of liquidity and leverage—that is, corporate bond and asset-backed security issuance, the net notional value of credit derivatives, and several commercial and shadow bank leverage measures.

It is likely that some of this result, shown in figure 2, stems from the fact that most of the previously mentioned measures are available at a weekly frequency. Our adjustment for economic conditions is more likely to account for medium-frequency rather than high-frequency variation. However, an examination of the weights in table A1 suggests that this cannot be the sole explanation. Several weekly money market measures receive greater weight—for example, the three-month London interbank bid (Eurodollar) and offered (TED) rate spreads; but there are also a number of weekly debt and equity market measures that receive less—for example, the high yield/Baa corporate bond, CMBS, and various credit derivative swap spreads, as well as the VIX.

Gauging financial stability

One way to judge the validity of our indexes as measures of financial stability is to follow the narrative approach and link their values to significant events in U.S. financial history. To illustrate this point, we plot our FCI and adjusted FCI in figure 3, highlighting prominent historical events.[3] Each panel of figure 3 depicts a decade of the index. Events are labeled with text boxes and arrows directed toward a specific week of both indexes denoted by a circle marker.

Overall, significant periods of crisis in financial history are well captured by both indexes, as are periods of relative calm. There are subtle differences, however, between the indexes around the time of several of the major events marked in figure 3. The first is clearly seen in panel A of figure 3 during the 1973–75 period that saw disruptions in equity markets and the failures of several large banks. In general, our adjusted FCI is quicker than our FCI to note both the onset and end of pressures—as financial conditions began to deteriorate prior to the 1973–75 recession and as they began to recover sooner than the real economy.

For most of the rest of the 1970s, both indexes indicate very similar financial conditions. However, by the end of the decade and into the early 1980s, as shown in panels A and B of figure 3, differences again emerge. The large swings in economic activity and inflation during these periods lead the adjusted FCI to be much more volatile, often swinging from well below zero to well above it very quickly. At their peak levels, both indexes are still very similar, capturing very well the major events of this period.

From the mid-1980s through the end of the decade, differences between the two indexes are much smaller (panel B of figure 3). Two events, however, stand out during this period of strong growth and disinflation: the resolution of Continental Illinois National Bank and Trust Company and the "Black Monday" stock market crash of 1987; the adjusted FCI puts more weight relative to earlier events on each compared with the FCI. The adjusted FCI is also quicker to note above-average tightness in response to the U.S. savings and loan crisis and quicker to recover from the crisis after accounting for the 1990–91 recession (see panels B and C of figure 3).

From the mid-1990s through the end of the decade (panel C of figure 3), the adjusted FCI consistently indicates financial conditions relative to economic conditions either about average or tighter than on average. In contrast, only after the Russian debt default, the subsequent collapse of Long-Term Capital Management, and the run-up to Y2K (the year 2000 software problem) does the FCI indicate financial conditions that are tighter than on average. During this period, the adjusted FCI additionally picks up the relative tightening in financial markets surrounding the Mexican peso devaluation and Asian financial crisis (around the time of the devaluation of the Thai baht).

Despite small differences surrounding the crash of the NASDAQ Stock Market and the corporate accounting scandals of the early 2000s (panel D of figure 3), both indexes generally indicated conditions looser than on average through the early part of the previous decade. Beginning in late 2005, the adjusted FCI moved closer to its average, while the FCI remained well below its average. The recent financial crisis appears at about the same time in both indexes, from mid-2007 through mid-2009, while the recovery registers a little later in the adjusted FCI.

More recently, as seen in figure 1 (p. 26), both indexes demonstrate that the financial system has healed significantly. Financial conditions by either measure, however, remain tighter than they were before the crisis. They have also been responsive to the European sovereign debt concerns that began in the spring of 2010 and the slowdown in economic activity throughout the summer months of 2010. In fact, our adjusted FCI breached its average level in the summer of 2010 before easing again during the rest of 2010.

Our historical analysis shows that persistent deviations in the interpretation of our two indexes contain useful information. The adjusted FCI is, in some sense, a forward-looking indicator of the FCI. When financial conditions are out of balance with economic conditions for an extended period, a correction in the FCI tends to result. Whether or not this result is due to the influence of the policy actions taken during these periods or other economic forces is beyond the scope of the analysis here. However, we refer the reader to Brave and Butters (2010a) and Brave and

FIGURE 3

Financial conditions indexes (FCI and adjusted FCI) and prominent historical events, 1973–2009

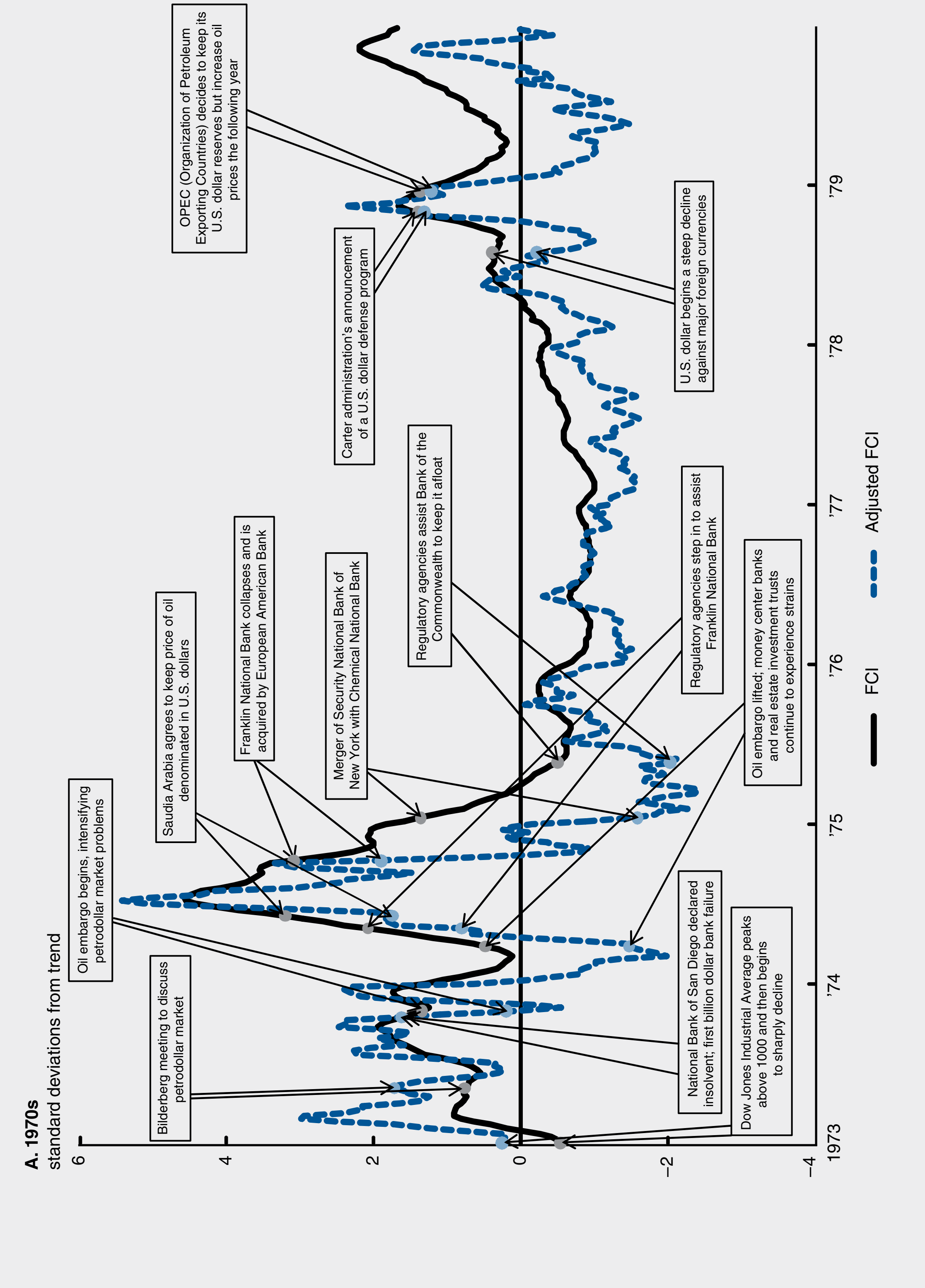


FIGURE 3 (CONTINUED)

Financial conditions indexes (FCI and adjusted FCI) and prominent historical events, 1973–2009

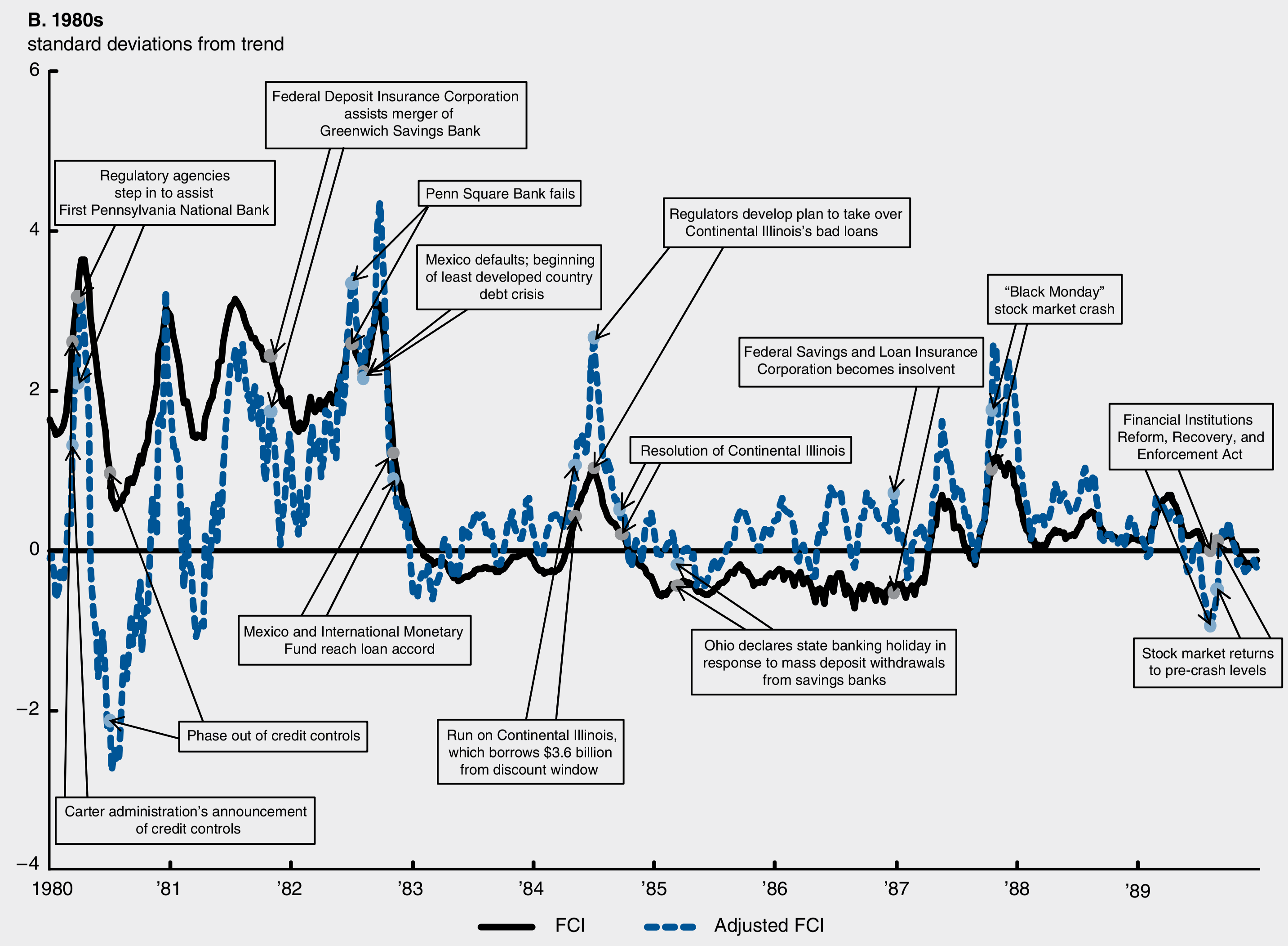


FIGURE 3 (CONTINUED)

Financial conditions indexes (FCI and adjusted FCI) and prominent historical events, 1973–2009

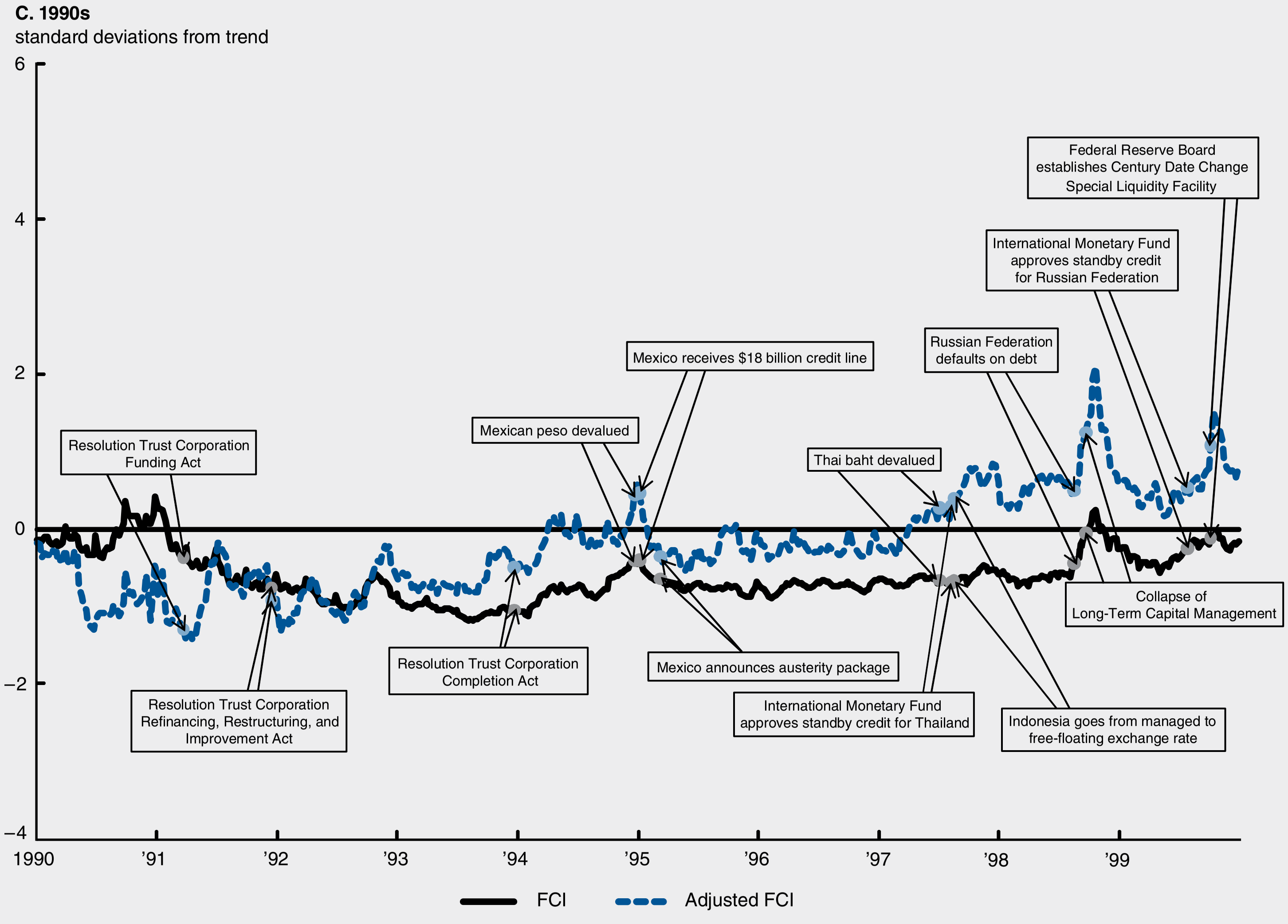
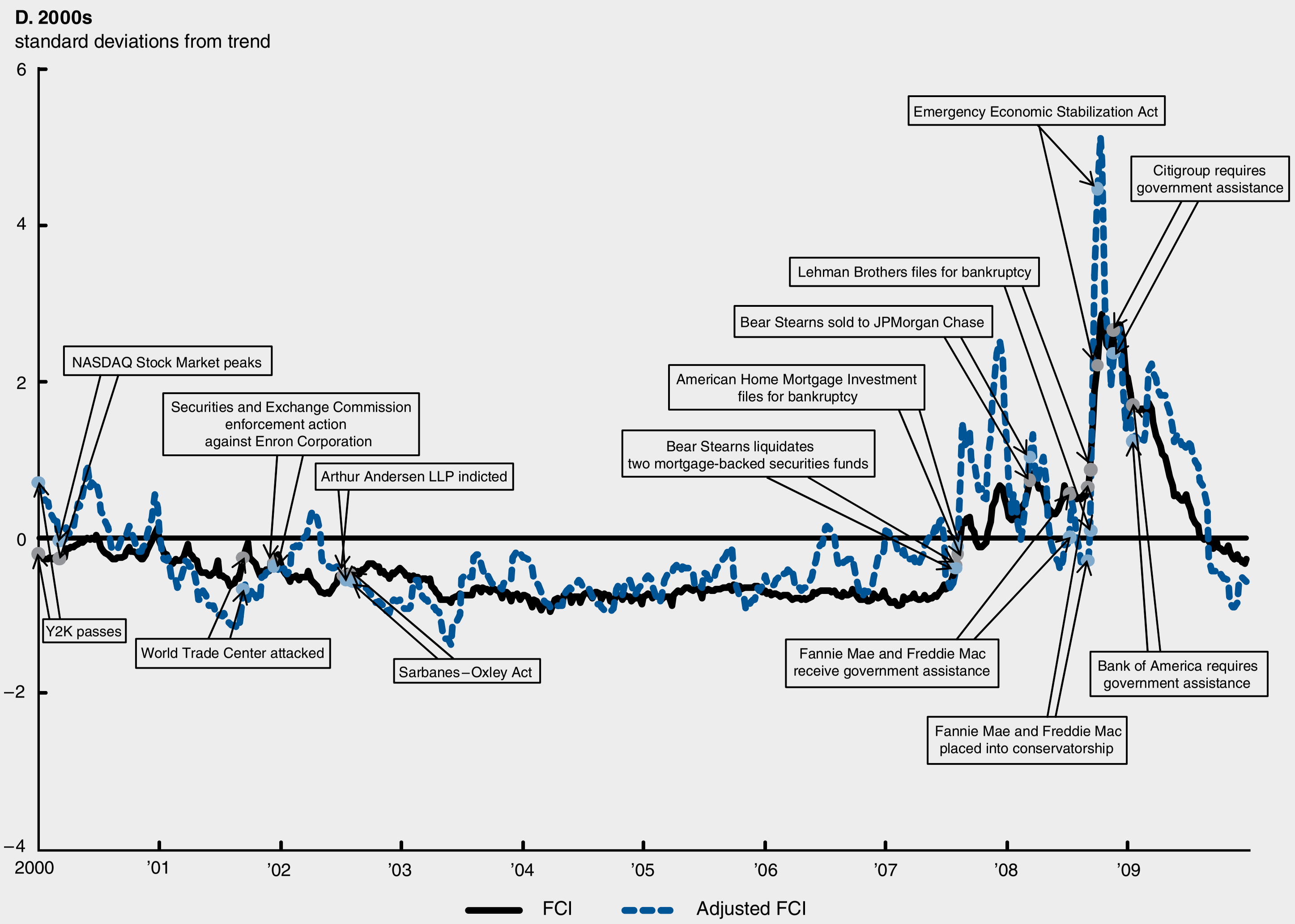


FIGURE 3 (CONTINUED)

Financial conditions indexes (FCI and adjusted FCI) and prominent historical events, 1973–2009



Genay (2011) for more rigorous analyses of the FCI and adjusted FCI.

Forecasting economic conditions

Another test of our indexes is their ability to predict the impact of changes in financial conditions on future economic activity. We follow the forecasting framework of Hatzius et al. (2010); but we refine their approach in two ways: 1) by concentrating on the portion of our FCI that cannot be explained by its historical dynamics and 2) by including as explanatory variables high-frequency nonfinancial measures of economic activity, such as the Chicago Fed National Activity Index (CFNAI).[4]

We refer to the portion of our FCI that cannot be predicted based on its historical dynamics as the FCI residual. The FCI residual corresponds with the error term, ν_t, from the transition equation of our dynamic factor model (described in detail in box 2), where we follow the convention described previously for our FCI and scale it by its sample standard deviation. Because the FCI captures an element of financial conditions that also depends on economic conditions, systematic changes in the FCI over time reflect the historical response of financial conditions to past changes in financial and economic conditions. The FCI residual, therefore, reflects the deviation of financial conditions from this historical pattern.

It is this aspect of the FCI residual that we find appealing as an explanatory variable for future economic activity; in this regard, we prefer the FCI residual over the adjusted FCI, which captures only the deviation of financial conditions from economic conditions. Hatzius et al. (2010) frame the use of their adjusted index as a method of focusing purely on the impact of financial shocks on economic activity. We, instead, use our FCI because it also contains information on economic shocks. We then control for whether this information is in addition to that found in high-frequency nonfinancial measures of economic activity.

To demonstrate the ability of the FCI residual to predict future economic conditions and for the sake of comparison with the adjusted FCI, we conducted a pseudo out-of-sample forecasting exercise. Our mixed-frequency forecasting regressions incorporated lagged values of quarterly forecast variables taken from the U.S. Bureau of Economic Analysis's national income and product accounts (NIPA), as well as current and lagged values of the three-month moving average of the CFNAI alone or in combination with the 13-week moving average of one of the following sampled at the end of each month: the FCI residual, adjusted FCI, or adjusted FCI residual (which is the portion of the adjusted FCI unexplained by its historical dynamics).[5]

The CFNAI's three-month moving average serves as our reference point in evaluating the marginal information content of our measures of financial conditions over high-frequency nonfinancial measures of economic activity. It is a summary measure of 85 indicators constructed using PCA on data for production and income; employment, unemployment, and hours; personal consumption and housing; and sales, orders, and inventories.[6] The CFNAI has been used in the past to forecast economic growth and inflation by Stock and Watson (1999) and Brave and Butters (2010b), among others.

Our forecasting regression takes the following form:

$$Y_{t+h} - Y_t = \alpha + \sum_{i=1}^{I} \beta_i \Delta Y_{t+1-i} + \sum_{j=1}^{J} \gamma_j CFNAI_{t+1-j} + \sum_{k=1}^{K} \delta_k FCI_{t+1-k} + \varepsilon_{t+h},$$

where Y refers to the natural log of a particular NIPA data series, *CFNAI* indicates the three-month moving average of the CFNAI, and *FCI* is the 13-week moving average of either the FCI residual, adjusted FCI, or adjusted FCI residual. The explanatory variables were aligned with the NIPA data in the last month of each quarter (t) to match frequencies so that the index i represents a quarter (or three months) and the indexes j and k both represent months.

To construct forecasts, we began with data from 1973:Q1 through 1984:Q4.[7] One quarter's worth of data was then added on a recursive basis and forecasts made at a horizon (h) of one, two, four, and six quarter(s) ahead until the end of our data in 2010:Q2. The advantage of this framework is that it mimics the production of forecasts in real time (minus the impact of data revisions). In this way, we can account for model uncertainty. To allow for the further possibility of a change in lag structure over time, we had each recursive regression incorporate the Bayesian Information Criterion lag selection method.[8]

For an evaluation criterion, we used the mean-squared forecast error (MSFE) statistic computed from our sample of forecasts from 1985:Q1 through 2010:Q2 expressed relative to the similar statistic based on forecasts computed using only lagged quarterly growth rates of the NIPA variables. This ratio provides a test of model fit, so that a value less than 1 indicates an improvement in forecast accuracy relative to an autoregressive baseline for each NIPA variable. The MSFE statistic summarizes two elements in our pseudo out-of-sample context: the improvement in fit from incorporating the CFNAI

TABLE 1

Pseudo out-of-sample relative MSFE ratios

h	CFNAI	FCI residual	Adjusted FCI	Adjusted FCI residual	h	CFNAI	FCI residual	Adjusted FCI	Adjusted FCI residual
A. Gross domestic product					**B. Gross domestic purchases**				
1	0.88	0.81	0.88	0.85	1	1.06	0.98	1.01	1.00
2	0.98	0.82	1.06	0.96	2	1.14	0.90	1.14	1.06
4	1.05	0.90	1.07	1.00	4	1.14	0.98	1.15	1.08
6	1.06	0.88	1.07	1.01	6	1.17	1.05	1.19	1.11
C. Final sales					**D. Nonfarm private inventories**				
1	1.06	0.91	1.03	0.96	1	0.59	0.58	0.58	0.60
2	1.07	0.88	1.06	0.97	2	0.37	0.37	0.37	0.37
4	1.16	0.94	1.17	1.10	4	0.47	0.40	0.46	0.44
6	1.18	1.02	1.20	1.11	6	0.64	0.56	0.63	0.61
E. Nonresidential investment					**F. Residential investment**				
1	0.78	0.76	0.79	0.78	1	1.13	0.92	0.93	0.96
2	0.76	0.67	0.81	0.73	2	1.17	0.91	1.19	1.00
4	0.86	0.75	0.90	0.85	4	1.06	0.97	1.11	1.07
6	0.91	0.79	0.89	0.84	6	1.01	0.95	1.03	1.01
G. PCE: Durables					**H. PCE: Nondurables**				
1	1.13	0.92	1.11	1.13	1	0.95	0.87	1.00	0.91
2	1.18	0.99	1.19	1.18	2	1.02	0.87	1.15	0.98
4	1.32	1.23	1.29	1.33	4	1.00	0.89	1.05	0.98
6	1.33	1.30	1.37	1.35	6	1.03	0.94	1.07	1.00
I. PCE: Services									
1	1.12	1.03	1.10	1.07					
2	1.01	0.97	1.01	1.01					
4	1.01	0.94	0.98	0.99					
6	1.00	0.97	1.03	1.02					

Notes: The table displays mean-squared forecast error (MSFE) ratios expressed relative to an autoregressive baseline model. The forecasted variable is listed at the top of each panel. Column headings for each panel denote the additional variable added to the baseline model: The CFNAI is the three-month moving average of the Chicago Fed National Activity Index and is included in all four specifications. The FCI residual is the 13-week moving average of the portion of the financial conditions index unexplained by its historical dynamics, the adjusted FCI is the 13-week moving average of the financial conditions index adjusted for economic conditions, and the adjusted FCI residual is the 13-week moving average of the portion of the adjusted financial conditions index unexplained by its historical dynamics—these three individually serve to augment the model including the CFNAI. The rows in each panel denote the forecast horizon (*h*) measured in quarters beyond the end of the sample period. The sample period is recursive beginning in 1973:Q1 and rolling forward from 1985:Q1 through 2010:Q2. PCE denotes personal consumption expenditures.
Source: Authors' calculations based on data from the U.S. Bureau of Economic Analysis, *National Income and Product Accounts of the United States*, from Haver Analytics.

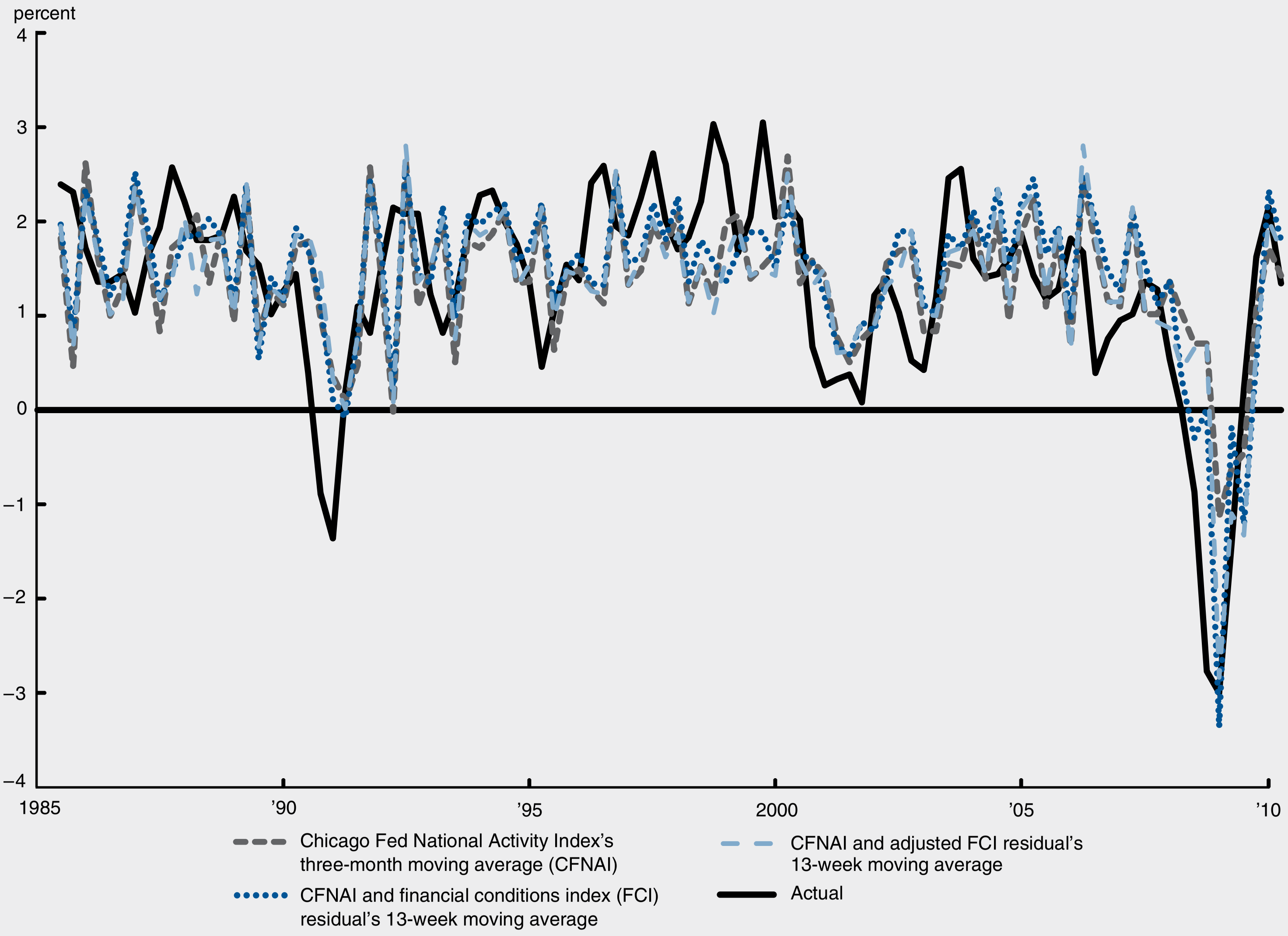
alone or from incorporating the CFNAI along with the FCI residual, adjusted FCI, or adjusted FCI residual to the forecasting regression, balanced against the added parameter uncertainty from estimating additional regression coefficients.

Table 1 summarizes the results for nine NIPA variables all expressed in real, or constant price, terms. Gross domestic product (GDP) in panel A is the broadest measure we consider, but we also examine several of its components. Gross domestic purchases (panel B) exclude exports, and thus solely capture domestic demand. Final sales (panel C) remove the influence of changes in inventories. Nonfarm private inventories, nonresidential investment, and residential investment (panels D, E, and F) form the basis of the investment component of GDP we consider, and personal expenditures on durables, nondurables, and services (panels G, H, and I) account for consumption. We do not directly consider government spending or exports.

A few observations are readily apparent from this table. First, including the CFNAI in our forecasting regressions on NIPA data results in a substantial improvement in forecast accuracy (MSFE ratios less than 1) for GDP and measures of business investment, particularly at shorter horizons. Adding the FCI residual improves upon these initial forecasts at every horizon and for every variable, with the magnitude of improvement ranging from just less than 1 percent to 22 percent.[9] In contrast, adding the adjusted FCI rarely improves on the forecasts based on the CFNAI alone; and the

FIGURE 4

Two-quarter-ahead forecasts of real gross domestic product growth



Source: Authors’ calculations based on data from the U.S. Bureau of Economic Analysis, *National Income and Product Accounts of the United States*, from Haver Analytics.

forecasts augmented with the adjusted FCI are less accurate than the forecasts augmented with the FCI residual in nearly every case.

The FCI-residual forecasts are also superior when compared with the adjusted-FCI-residual forecasts in nearly every case. However, the adjusted-FCI-residual forecasts are often superior to the forecasts based on the CFNAI alone and those augmented with the adjusted FCI. In this respect, our results suggest how to improve the ability of the adjusted FCI to forecast future economic activity—the key is to focus on the portion of the adjusted FCI that is not explained by its historical dynamics. This potential improvement is made by our extension of the index construction methodology of Hatzius et al. (2010) to a dynamic framework.

The results in table 1 also suggest that the FCI residual contains information on future economic activity in addition to that found in high-frequency nonfinancial measures of economic activity. There is, however, considerable variation in the forecasting performance of the FCI residual over time not shown in table 1. Much of the gains in forecast accuracy are concentrated in the recent period. Despite this fact, the inclusion of the FCI residual in our forecasting regressions rarely significantly worsens the forecast based on the CFNAI alone, so that it comes with little cost but potentially large benefits.

Figure 4 captures an instance of the small cost, large reward nature of including the FCI residual in our forecasting regression. It depicts actual real GDP growth at a two-quarter horizon and the forecasts for this measure based on the CFNAI's three-month moving average, as well as these forecasts including the 13-week moving average of the FCI residual or adjusted FCI residual. Differences prior to the recent crisis tend to be small. During these periods, sometimes the forecast including the FCI residual is marginally superior and sometimes it is not.

The forecast series begin to consistently deviate from one another in the second half of 2007, when the crisis started to unfold. Throughout the recent recession and recovery, the forecast including the FCI residual has more consistently tracked actual real GDP growth than any of the other forecasts we consider. At times during this period, however, the adjusted-FCI-residual forecast has been superior. The FCI-residual forecast's dominance over the adjusted-FCI-residual forecast over the entire period is due in large part to it more quickly picking up the beginning of the recent recession and the magnitude of the subsequent recovery.

Conclusion

Our newly constructed financial conditions indexes can serve as tools for both policymakers and financial market participants in gauging the current state of financial markets. Computed over a long time horizon and from a large sample of financial indicators of different frequencies, these indexes provide a timely assessment of how tightly or loosely financial markets are operating relative to historical financial and economic conditions.

As a measure of financial stability, our indexes exhibit several essential characteristics. Known periods of financial crisis correspond closely with peak periods of tightness in each index, and the turning points of each index coincide with well-known events in U.S. financial history. Furthermore, our indexes contain information on future economic activity beyond that found in nonfinancial measures of economic activity.

Our indexes are also unique in that they derive from an estimation method that captures both the systemic importance of traditional and new financial markets and the dynamic evolution of overall financial conditions. In the future, we plan to develop this framework further in order to better understand the channels through which changes in financial conditions affect economic activity.

NOTES

[1]Hatzius et al. (2010) also construct a similar version of their index of financial conditions and relate it to changes in the federal funds rate over time. We have found very similar results to theirs; our adjusted FCI is significantly correlated with measures of monetary policy, though we have not documented this here. See Brave and Genay (2011), who relate monetary policy during the recent crisis to the adjusted FCI, for more information.

[2]Most of our 100 financial indicators have become standard fare in the financial press as a result of the recent financial crisis. Rather than describe each in further detail, we refer interested readers to the useful summaries found in Nelson and Perli (2007), Hakkio and Keeton (2009), and Hatzius et al. (2010).

[3]The literature on financial crises is quite extensive. The following works are a few of those that were instrumental in constructing our timeline of events: Federal Deposit Insurance Corporation (1984, 1997), Reinhart and Rogoff (2008), Schreft (1990), Minsky (1986), Spero (1999), Laeven and Valencia (2008), Carron (1982), and El-Gamal and Jaffe (2008).

[4]Hakkio and Keeton (2009) also use the CFNAI to make similar comparisons.

[5]We use smoothed measures of the explanatory variables when appropriate to approximate the quarterly frequency of the NIPA variables being forecasted.

[6]For more details on the CFNAI, including its 85 indicators, see www.chicagofed.org/digital_assets/publications/cfnai/background/cfnai_background.pdf.

[7]To be technically correct, we varied the endpoint of the initial sample based on the forecast horizon so that the first forecast always began at 1985:Q1.

[8]Maximums of $I = 5$ quarters and J, $K = 6$ months were used in its calculation.

[9]In the case of nonfarm private inventories, there is one instance in table 1 where the improvement is not apparent because of the rounding in this table.

TABLE A1

Financial indicators in the financial conditions indexes (FCI and adjusted FCI)

Financial indicator	Transformation	Frequency	Haver/Bloomberg*/ Call Report^ mnemonic	Start	Category	FCI	Adjusted FCI
1-month Nonfinancial CP A2P2/AA credit spread	LV	W	FAP1M-FCP1M	1997w2	1	2.255	2.308
2-year Swap/Treasury yield spread	LV	W	T111W2-R111G2	1987w14	1	2.229	2.975
3-month TED spread (Libor-Treasury)	LV	W	FLOD3-FTBS3	1980w23	1	1.825	3.606
1-month Merrill Lynch Options Volatility Expectations (MOVE)	LV	W	SPMLV1	1988w15	1	1.690	1.566
3-month Merrill Lynch Swaption Volatility Expectations (SMOVE)	LV	W	SPMLSV3	1996w49	1	1.678	0.564
3-month/1-week AA Financial CP spread	LV	W	FFP3M-FFP7D	1997w2	1	1.582	2.037
1-month Asset-backed/Financial CP credit spread	LV	W	FAB1M-FFP1M	2001w1	1	1.581	2.064
3-month Eurodollar spread (LIBID-Treasury)	LV	W	FDB3-FTBS3	1971w2	1	1.522	3.048
On-the-run vs. Off-the-run 10-year Treasury liquidity premium	LV	W	FYCEPA-FCM10	1985w1	1	0.974	0.916
10-year Swap/Treasury yield spread	LV	W	T111WA-R111GA	1987w14	1	0.845	1.189
3-month Financial CP/Treasury bill spread	LV	W	FFP3-FTBS3	1971w1	1	0.619	1.741
Fed Funds/Overnight Treasury Repo rate spread	LV	W	FFED-RPGT01D*	1991w21	1	0.495	1.084
3-month OIS/Treasury yield spread	LV	W	T111W3M-R111G3M	2003w38	1	0.452	1.352
Agency MBS Repo Delivery Failures Rate	DLNQ	W	FDDM/(FDDM+FDTM)	1994w40	1	0.426	0.430
1-year/1-month Libor spread	LV	W	FLOD1Y-FLOD1	1986w2	1	0.368	0.378
Treasury Repo Delivery Failures Rate	DLNQ	W	FDDG/(FDDG+FDTG)	1994w40	1	0.307	0.474
Agency Repo Delivery Failures Rate	DLNQ	W	FDDS/(FDDS+FDTS)	1994w40	1	0.168	0.045
Fed Funds/Overnight Agency Repo rate spread	LV	W	FFED-RPAG01D*	1991w21	1	0.150	0.592
Corporate Securities Repo Delivery Failures Rate	DLNQ	W	FDDC/(FDDC+FDTC)	2001w40	1	0.103	0.051
Fed Funds/Overnight MBS Repo rate spread	LV	W	FFED-RPMB01D*	1991w21	1	0.037	0.173
10-year Constant Maturity Treasury yield	DLV	W	FCM10	1971w2	1	−0.050	−0.208
Broker–dealer Debit Balances in Margin Accounts	DLN	M	SPMD	1971w5	1	−0.122	−0.203
3-month/1-week Treasury Repo spread	LV	W	RPGT03M*-RPGT01W*	1991w21	1	−0.141	0.858
2-year/3-month Treasury yield spread	LV	W	FYCEP2-FTBS3	1971w1	1	−0.237	0.167
Commercial Paper Outstanding	DLN	W	FCPT	1995w45	1	−0.482	−0.231
10-year/2-year Treasury yield spread	LV	W	FYCEPA-FYCEP2	1971w34	1	−0.706	−0.979
3-month Eurodollar, 10-year/3-month swap, 2-year and 10-year Treasury Options and Futures Open Interest	DLNQ	W	COPED3P+COPTN2P+COPT10P+COPIRSP	2002w7	1	−1.024	−0.075
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	2.865
Bloomberg 5-year AAA CMBS spread to Treasuries	LV	W	CMBSAAA5*	1996w27	2	2.234	1.647
Merrill Lynch High Yield/Moody's Baa corporate bond yield spread	LV	W	FMLHY-FBAA	1997w2	2	2.116	0.659
CBOE S&P 500 Volatility Index (VIX)	LV	W	SPVIX	1990w1	2	2.074	1.815
Credit Derivatives Research North America Investment Grade Index	LV	W	S009LIG	2006w1	2	1.528	0.477
Credit Derivatives Research North America High Yield Index	LV	W	S009LHY	2006w1	2	1.516	0.495
Citigroup Global Markets Financial/Corporate Credit bond spread	LV	M	SYCF-SYCT	1979w52	2	1.179	1.959
Citigroup Global Markets MBS/10-year Treasury yield spread	LV	M	SYMT-FCM10	1979w52	2	0.848	1.568
Bond Market Association Municipal Swap/20-year Treasury yield spread	LV	W	SBMAS-FCM20	1989w27	2	0.818	1.561
20-year Treasury/State & Local Government 20-year General Obligation Bond yield spread	LV	W	FSLB-FCM20	1971w1	2	0.502	−0.189

TABLE A1 (CONTINUED)

Financial indicators in the financial conditions indexes (FCI and adjusted FCI)

Financial indicator	Transformation	Frequency	Haver/Bloomberg*/ Call Report^ mnemonic	Start	Category	FCI	Adjusted FCI
Moody's Baa corporate bond/10-year Treasury yield spread	LV	W	FBAA-FCM10	1971w1	2	0.348	0.936
Total Money Market Mutual Fund Assets/Total Long-term Fund Assets	LV	M	ICMMA/ICIA	1974w52	2	0.231	0.177
Nonfinancial business debt outstanding/GDP	DLN	Q	XL14TCRE5/GDP	1971w13	2	0.025	0.091
Federal, state, and local debt outstanding/GDP	DLN	Q	(XL31CRE5+XL21TCR5)/GDP	1971w13	2	0.024	0.010
Total MBS Issuance (Relative to 12-month MA)	LVMA	M	N/A	2000w52	2	−0.022	−0.106
S&P 500, NASDAQ, and NYSE Market Capitalization/GDP	DLN	Q	(SPSP5CAP+SPNYCAPH+SPNACAP)/GDP	1971w13	2	−0.041	−0.079
New US Corporate Equity Issuance (Relative to 12-month MA)	LVMA	M	FNSIPS	1987w52	2	−0.047	0.027
Wilshire 5000 Stock Price Index	DLN	M	SPWIE	1971w5	2	−0.052	−0.108
Loan Performance Home Price Index	DLN	M	USLPHPIS	1976w9	2	−0.066	−0.146
New State & Local Government Debt Issues (Relative to 12-month MA)	LV	M	FNSIS	2004w9	2	−0.108	−0.185
MIT Center for Real Estate Transactions-Based Commercial Property Price Index	DLN	Q	MTBIP	1984w26	2	−0.111	−0.128
Nonmortgage ABS Issuance (Relative to 12-month MA)	LVMA	M	N/A	2000w52	2	−0.130	−0.184
S&P 500, S&P 500 mini, NASDAQ 100, NASDAQ mini Options and Futures Open Interest	DLNQ	W	COPSPMP+COPSP5P+COPNAMP+COPNASP	2000w12	2	−0.134	−0.250
CMBS Issuance (Relative to 12-month MA)	LVMA	M	N/A	1990w52	2	−0.157	−0.184
New US Corporate Debt Issuance (Relative to 12-month MA)	LVMA	M	FNSIPB	1987w52	2	−0.179	−0.279
Net Notional Value of Credit Derivatives	DLN	W	D001TOTH	2008w45	2	−0.256	−0.522
S&P 500 Financials/S&P 500 Price Index (Relative to 2-year MA)	LVMA	W	S5N40I/SPN5COM	1989w37	2	−1.860	−2.007
Sr Loan Officer Opinion Survey: Tightening standards on Small C&I Loans	LV	Q	FTCIS	1990w13	3	2.501	1.366
Sr Loan Officer Opinion Survey: Increasing spreads on Small C&I Loans	LV	Q	FSCIS	1990w13	3	2.467	1.312
Sr Loan Officer Opinion Survey: Tightening standards on CRE Loans	LV	Q	FTCRE	1990w26	3	2.418	1.442
Sr Loan Officer Opinion Survey: Tightening standards on Large C&I Loans	LV	Q	FTCIL	1990w13	3	2.416	1.274
Sr Loan Officer Opinion Survey: Increasing spreads on Large C&I Loans	LV	Q	FSCIL	1990w13	3	2.364	1.060
30-year Jumbo/Conforming fixed-rate mortgage spread	LV	W	ILMJNAVG*-ILM3NAVG*	1998w23	3	2.220	2.078
Credit Derivatives Research Counterparty Risk Index	LV	W	S000CRI	2006w1	3	1.361	0.644
National Federation of Independent Business Survey: Credit Harder to Get	LV	M	NFIB20	1973w44	3	1.228	0.668
30-year Conforming Mortgage/10-year Treasury yield spread	LV	W	FRM30F-FCM10	1978w35	3	1.154	1.491
American Bankers Association Value of Delinquent Home Equity Loans/Total Loans	DLV	M	USHWODA	1999w9	3	0.284	0.169
American Bankers Association Value of Delinquent Consumer Loans/Total Loans	DLV	M	USSUMDA	1999w9	3	0.264	0.106
American Bankers Association Value of Delinquent Credit Card Loans/Total Loans	DLV	M	USBKCDA	1999w9	3	0.220	0.090
S&P US Credit Card Quality Index 3-month Delinquency Rate	DLV	M	CCQID3	1992w9	3	0.157	0.024
Noncurrent/Total Loans at Commercial Banks	DLN	Q	(RCFD1407^+RCFD1403^)/RCFD2122^	1984w26	3	0.139	0.146
American Bankers Association Value of Delinquent Non-card Revolving Credit Loans/Total Loans	DLV	M	USREVDA	1999w9	3	0.139	0.197
Commercial Bank C&I Loans/Total Assets	DLNQ	W	FABWCA/FAA	1973w9	3	0.068	0.191
Mortgage Bankers Association Serious Delinquencies	DLV	Q	USL14FA+USL149A	1972w26	3	0.028	0.078

TABLE A1 (CONTINUED)

Financial indicators in the financial conditions indexes (FCI and adjusted FCI)

Financial indicator	Transformation	Frequency	Haver/Bloomberg*/ Call Report^ mnemonic	Start	Category	FCI	Adjusted FCI
Total Assets of Funding Corporations/GDP	DLN	Q	OA50TAO5/GDP	1971w13	3	0.022	0.022
Mortgage Bankers Association Mortgage Applications Volume Market Index	DLN	W	MBAM	1990w2	3	0.020	−0.086
Total Assets of Agency and GSE backed mortgage pools/GDP	DLN	Q	OA41MOR5/GDP	1971w13	3	0.011	0.031
Total Assets of ABS issuers/GDP	DLN	Q	OA67TAO5/GDP	1983w39	3	0.005	0.025
FDIC Volatile Bank Liabilities	DLN	Q	RCON2604^+RCFN2200^+RCFD2800^ +MAX(RCFD2890^,RCFD3190^)+RCFD3548^	1978w26	3	0.000	0.017
Commercial Bank Deposits/Total Assets	DLNQ	W	FBDA/FAA	1973w9	3	0.000	−0.026
Fed funds and Reverse Repurchase Agreements w/ nonbanks and Interbank Loans/Total Assets	DLNQ	W	(FAIFFA+FABWORA)/FAA	1973w9	3	−0.005	−0.060
Total Assets of Finance Companies/GDP	DLN	Q	OA61TAO5/GDP	1971w13	3	−0.009	0.012
Total Unused C&I Loan Commitments/Total Assets	DLN	Q	RCON3423^/RCON2170^	1984w26	3	−0.011	−0.036
Total REIT Assets/GDP	DLN	Q	OA64TAO5/GDP	1971w13	3	−0.012	0.071
Total Assets of Broker–dealers/GDP	DLN	Q	OA66TAO5/GDP	1971w13	3	−0.013	−0.035
Commercial Bank Real Estate Loans/Total Assets	DLNQ	W	FABWRA/FAA	1973w9	3	−0.019	−0.026
Total Assets of Pension Funds/GDP	DLN	Q	OA57TAO5/GDP	1971w13	3	−0.023	−0.053
MZM Money Supply	DLN	M	FMZM	1974w9	3	−0.028	−0.076
Total Assets of Insurance Companies/GDP	DLN	Q	(OA51TAO5+OA54TAO5)/GDP	1971w13	3	−0.029	−0.067
Commercial Bank 48-month New Car Loan/2-year Treasury yield spread	LV	Q	FK48NC-FCM2	1976w26	3	−0.033	−0.135
Consumer Credit Outstanding	DLN	M	FOT	1971w5	3	−0.039	0.057
Commercial Bank Securities in Bank Credit/Total Assets	DLNQ	W	FABYA/FAA	1973w9	3	−0.052	−0.159
Commercial Bank 24-month Personal Loan/2-year Treasury yield spread	LV	Q	FK24P-FCM2	1976w26	3	−0.083	−0.172
S&P US Credit Card Quality Index Receivables Outstanding	DLN	M	CCQIO	1992w9	3	−0.095	−0.013
S&P US Credit Card Quality Index Excess Rate Spread	LV	M	CCQIX	1992w5	3	−0.109	−0.387
Finance Company Receivables Outstanding	DLN	M	FROT	1985w31	3	−0.149	0.041
Finance Company New Car Loan interest rate/2-year Treasury yield spread	LV	M	FFINC-FCM2	1976w26	3	−0.150	−1.130
Sr Loan Officer Opinion Survey: Willingness to Lend to Consumers	LV	Q	FWILL	1971w13	3	−0.538	−0.334
UM Household Survey: Auto Credit Conditions Good/Bad spread	LV	M	N/A	1978w5	3	−1.354	−1.321
UM Household Survey: Mortgage Credit Conditions Good/Bad spread	LV	M	N/A	1978w5	3	−1.487	−1.802
UM Household Survey: Durable Goods Credit Conditions Good/Bad spread	LV	M	N/A	1978w5	3	−1.543	−1.668
National Association of Credit Managers Index	LV	M	CMI	2002w9	3	−2.004	−0.130

Transformations
LV: Level
LVMA: Level relative to moving average
DLV: First difference
DLN: Log first difference
DLNQ: 13-week log difference

Categories
1. Money markets
2. Debt and equity markets
3. Banking system

Notes: All of the financial indicators are in basis points or percentages. N/A means not applicable; the relevant series are taken from Inside Mortgage Finance Publications, CRE Finance Council, and University of Michigan data. For more information on the indicators, please contact the authors.

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