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Abstract

We evaluate the short horizon predictive ability of financial conditions indexes for stock returns and macroeconomic variables. We find reliable predictability only when the sample includes the 2008 financial crisis, and we argue that this result is driven by tailoring the indexes to the crisis and by non-synchronous trading. Financial conditions indexes are based on a variety of constituent variables and aggregation methods, and we discuss a simple procedure for consolidating the growing number of different indexes into a single proxy for financial conditions.

Keywords: Financial conditions indexes, stock returns predictability, forecasting.

JEL Classification: E32, G01, G17.

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1 Introduction

The severity and the economic impact of the 2008 financial crisis have led to a proliferation of indexes that proxy for financial conditions or financial stress, which we collectively refer to as financial conditions indexes (FCIs). In this paper we evaluate whether FCIs can predict stock returns or innovations to macroeconomic variables over a one-month or a one-quarter horizon. We focus on predictability over relatively short horizons in order to capture the effect that the health of the financial system has on the broader economy, rather than longer run predictability arising from business cycle fluctuations. In addition, we suggest a simple procedure for aggregating the various FCIs into a single proxy for financial conditions.

We find that most FCIs can predict monthly and quarterly returns on the S&P 500 and on a portfolio of financial companies, and also innovations to a number of macroeconomic variables - but only if the period around the 2008 financial crisis is included (2007-2012). Such narrow predictability could be the result of threshold effects, in that financial conditions matter only after they deteriorate sufficiently.[1] A second possibility is that the FCIs we consider have predictive power because they typically include variables that, like the TED spread, had unusually large movements during the 2008 crisis, and such variables were included in the FCIs precisely because of their pronounced fluctuations in 2007 and 2008. Figure 1 shows the times series of the TED spread from 1986 onwards, and it clearly highlights the uniquely high level that characterized the 2008 financial crisis. A third possibility is that some of the predictive power is the result of non-synchronous data: most FCIs, for instance, include VIX, an implied volatility index derived from options on the S&P 500. These options trade for 15 minutes after trading on the underlying index ends (4:15pm versus 4:00pm Eastern Time), with the consequence that VIX on day t contains information that will be reflected in stock prices only on day $t+1$ – a fact that can generate spurious

[1] In Kashyap, Lamont, and Stein (1994), for instance, financing constraints at the firm level only become binding in tight-money environments. Hubrich and Tetlow (2012) find that macroeconomic dynamics crucially depend on financial stress, with stress being "of negligible importance in 'normal' times, but of critical importance when the economy is in a high-stress [...] state." (page 30).

predictability.

FCIs are typically designed to measure whether broad financial conditions are loose or tight by historical standards (for instance, the Bloomberg and Chicago Fed indexes), or whether the financial system is experiencing historically unusual stress (e.g., the Carlson, Lewis, and Nelson (2012) index). The importance of a well-functioning financial system to the broad economy is highlighted by the results in Bernanke and Blinder (1992), Kashyap, Stein, and Wilcox (1993), Peek and Rosengren (1997), Kashyap, Lamont, and Stein (1994), and Paravisini (2008), who show that tight monetary policy, binding capital ratios, and bank financing constraints can reduce the supply of credit. The effect is stronger in the case of small banks with less liquid assets (Kashyap and Stein (2000)), and the impact is felt more directly by small firms (Gertler and Gilchrist (1994), Khwaja and Mian (2008)) and bank-dependent borrowers (Chava and Purnanandam (2011)). A tight credit supply ultimately affects investment (Campello, Graham, and Harvey (2010)), inventories (Kashyap, Lamont, and Stein (1994)), and the broader economy (Bernanke (1983), Peek and Rosengren (1997), Peek and Rosengren (2000), Calomiris and Mason (2003)).

The existing evidence is mixed on whether FCIs should be thought of as coincident indicators, or early warning indicators. While some studies suggest that FCIs can predict selected economic variables, the results are often unstable across sub-periods, which could be due to the FCIs including variables that have prominently characterized recent crises. In addition, the results may point to predictive power only at business-cycle frequency, which means that FCIs could be proxying for periodic changes in economic activity, rather than for the state of the financial system. As an example, Hatzius, Hooper, Mishkin, Schoenholtz, and Watson (2010) focus on predicting macroeconomic variables over one and two quarters, and they find that the FCIs they study seldom have better predictive power than stock market returns. The authors note on page 21 that:

> "the better performance during the most recent five years (relative to both the

average of the alternative FCIs and KC Fed's index as representative of one of the better performing FCIs) may reflect selection bias in our choice of variables to include in the index: naturally, our selection was governed in part by an understanding of the types of financial variables that were used for monitoring and measuring the recent financial crisis. In this sense, we did not seek to mitigate observer bias."

Our predictability analysis relies on simple predictive regressions of a set of stock returns or innovations to macroeconomic variables on lagged FCI values. We keep the indexes in levels, instead of using changes, because the authors uniformly emphasize that their FCIs are ordinal measures of financial conditions/stress. Relative to Hatzius, Hooper, Mishkin, Schoenholtz, and Watson (2010), who also evaluate the predictive power of several FCIs, we study predictability at a monthly as well as quarterly horizon, in order to minimize the risk that we find predictability arising from business cycle effects. Second, we study a larger number of FCIs and a larger number of financial and macroeconomic variables. Third, we explicitly discuss whether the predictability that arises in coincidence with the 2008 financial crisis is hard-wired in the FCIs, in the sense that the variables included in the FCIs may have been chosen on the basis of whether they experienced large fluctuations in 2007 and 2008. Finally, as described in the next paragraph, we assess the statistical significance of predicability with a methodology that is robust to biases generated by the high persistence that typically characterizes FCIs.

As is clear from the time series plots in Figure 2, FCIs tend to be quite persistent. The high autocorrelation that characterizes the FCIs is also evident in the confidence intervals for the autoregressive roots shown in Table 2.[2] We report confidence intervals, rather than point estimates, to highlight that, after accounting for statistical uncertainty, the FCIs plausibly have autoregressive roots very close to one. In 5 cases, we are actually unable to reject the

[2] The procedure for calculating the confidence intervals in Table 2 is described in the online appendix to Campbell and Yogo (2006).

hypothesis that the FCIs have a unit root. The high persistence of the indexes is important to us because we use them as predictors, and relying on standard asymptotics when testing the null of no predictability in the presence of a highly persistent predictor can be inappropriate, if other conditions detailed in Section 2 are met. Specifically, it can lead to a rejection rate that is inconsistent with the nominal size of the test. We therefore use, where applicable, the local-to-unit asymptotics procedure of Campbell and Yogo (2006), which corrects for this rejection bias.

In the second part of our analysis we discuss a simple two-step methodology for combining the different FCIs into a single proxy for financial conditions. The large number of FCIs is itself indicative of the uncertainty that surrounds the measurement of financial conditions, and aggregating the individual indexes can help average out model uncertainty and identify a cleaner proxy.

We first identify the five indexes that best summarize the information provided by the remaining FCIs. As detailed in Section 3, we do so on the basis of the adjusted R^2 from regressions of changes in the principal component of all indexes – except for index i – on changes in index i. While it is possible that a low R^2 is the result of an index being a unique and more accurate measure of financial conditions, the broad nature and the overlap of the variables included in the FCIs (like Treasury yields, or the implied volatility index VIX) renders such a possibility unlikely. In the second step we form all combinations of the five indexes, and select the "best" combination on the basis of how well it summarizes the information in the remaining FCIs, again on the basis of the adjusted R^2 from regressions that, in order to minimize overfitting concerns, we run on several subsamples.

In Section 2 we evaluate the predictive power of a comprehensive selection of FCIs, using stock returns and macroeconomic quantities as dependent variables. In Section 3 we discuss the merits of combining a subset of FCIs into a composite FCI. Section 4 concludes.

2 Assessing the Predictive Ability of FCIs

The set of 12 FCIs that we consider includes indexes that (1) focus on the United States, (2) are available at a monthly or higher frequency, and (3) have a sufficiently long history (see Table 1, which also reports data sources and lists the abbreviated names we use in the paper).[3] The FCIs are largely based on financial market variables, including implied volatilities, Treasury yields, yield spreads, commercial paper rates, stock returns, and exchange rates (see Kliesen, Owyang, and Vermann (2012) for a detailed list of variables that underlie a range of the FCIs we study here). Some FCIs only include a relatively small set of variables, as in the case of the St. Louis Fed Financial Stress Index. Other indexes, such as the Chicago Fed Adjusted National Financial Conditions Index, contain over one hundred variables. The constituents are aggregated either with a principal component analysis or through a weighted sum. In the latter case, weights are typically assigned subjectively by the authors, although a few of the indexes use more sophisticated methods. The Cleveland Financial Stress Index (CFSI), for instance, calculates weights dynamically based on the relative dollar flow observed in the Federal Reserve Board's Flow of Funds statistical release (Z.1).[4] All the indexes are expressed in terms of z-scores, with the exception of the Financial Stress Index of Carlson, Lewis, and Nelson (2012), which is expressed in terms of probabilities.

Table 2 reports summary statistics for the FCIs, together with their value at the end of September 2008. For most FCIs, the September 2008 value was in the worst 10% of the 1995-2012 sample, with the exception of the Morgan Stanley index, which mainly deteriorated into October 2008. Pairwise correlations among the FCIs (see Table 3) range between 22% and 96%, with the majority being above 70%.

[3] In order to increase the power of our test, we require that the FCIs cover the stressful episodes that characterized the late 1990s (the Asian and Russian financial crises, LTCM collapse). For this reason, we do not include the HSBC Financial Clog Index (Bloomberg ticker *HSCLOG Index*) or the Westpac U.S. Financial Stress Index (Bloomberg ticker *WRAISTRS Index*) whose series start in 2007 and 1998, respectively.

[4] See Oet, Eiben, Bianco, Gramlich, and Ong (2011) for details.

We evaluate the predictive power of the 12 FCIs we study with a series of monthly and quarterly predictive regressions of the form:

$$y_t = \alpha + \beta \times FCI_{t-1} + \epsilon_t$$

The FCIs enter the predictive regressions in levels, instead of changes, because financial conditions are likely to have real effects when they are unusually tight or unusually loose, rather than when they move within their normal range. We do not control for the predictive power of other variables, like the variance risk premium (Bollerslev, Tauchen, and Zhou (2009)), because the results from regressions in which FCIs are the only predictor already suggest that they lack reliable predictive power at the horizons we focus on.

The FCI coefficient is estimated with OLS, and we assess its statistical significance with either heteroskedasticity consistent standard errors, or with the local-to-unity asymptotics procedure of Campbell and Yogo (2006). Local-to-unity asymptotics is useful in evaluating the statistical significance of *persistent* predictors, because, in such cases, the standard t-test can give a rejection rate that is inconsistent with its nominal size.

In practice, we assume that each of the FCIs follows an AR(1) process, and use local-to-unity asymptotics unless the autoregressive root of the FCI is sufficiently distant from one, in a sense defined below, or unless there is no correlation between the innovations to the FCI's autoregressive process and the innovations in a regression of the predicted variable on the FCI. Note that both a persistent predictor and a non-zero correlation are necessary for the standard OLS asymptotics to be inappropriate. Using the notation in Campbell and Yogo (2006), we rely on heteroskedasticity consistent standard errors if the DF-GLS statistic is less than -5 (a more negative DF-GLS statistic shifts the confidence interval for the autoregressive root of the predictor away from one), or if the parameter $\hat{\delta}$ (which measures the correlation between the innovations) is equal to 0.[5]

The dependent variables in our predictive regressions are (a) returns on a broad market index and on various industry portfolios, and (b) autoregressive residuals of several economic variables. We consider monthly and quarterly returns on the S&P 500 and on seven equally weighted industry portfolios: finance, construction, manufacturing, transportation, wholesale trade, retail trade, and services. The macroeconomic variables we consider measure the availability of credit (total consumer credit, and commercial and industrial loans), the state of the housing market (housing starts), and manufacturing activity (durable goods orders, industrial production, and total manufacturing inventory).[6]

We first present the results that focus on whether FCIs can predict stock returns in Tables 5 through 9. For each portfolio/FCI combination we report the coefficient on the FCI (β_{FCI}) and the regression root mean squared error (RMSE). We show an asterisk next to a coefficient when the coefficient is statistically significant, that is when the Campbell and Yogo (2006) 90% confidence interval does not include zero. Table 5 shows results for the 1995-2012 sample, and it indicates that 11 of the 12 FCIs can predict returns on the finance industry portfolio, that four can predict the S&P 500, and that the Morgan Stanley index can predict returns on the finance and three additional industry portfolios. There is noticeable dispersion in the RMSEs across industry portfolios for a given FCI, with the construction and services portfolios generally showing the largest RMSE and the finance the lowest, but the RMSEs are remarkably similar across FCIs for a given portfolio. The statistically significant coefficients have the expected negative sign, indicating that higher financial stress is followed by lower returns.

One potential source of predictability is non-synchroneity across markets: many FCIs,

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5 When needed, we linearly interpolate the values obtained from the lookup tables in the online appendix to Campbell and Yogo (2006), which only provide a discrete set of values for $\hat{\delta}$ and of the DF-GLS statistic.

6 Stock returns are from CRSP through Wharton Research Data Services. The macroeconomic data are from the FRED database of the St. Louis Federal Reserve. See Table 4 for summary statistics and additional details on the construction of the industry portfolios.

for instance, include the S&P 500 option implied volatility index VIX, which is based on options whose trading ends 15 minutes after the trading for stocks does - a fact that could cause spurious predictability (see Atchison, Butler, and Simonds (1987) for a discussion of the effects of non-synchronous trading on the autocorrelation of equity index returns). We explore this possibility by running predictive regressions on monthly industry returns that skip the first day of each month. Table 6 shows that now only 5 of the 12 FCIs have statistically significant predictive power for the "Finance" portfolio, down from 11 in Table 5, suggesting that non-synchroneity does play a role, but is not the sole driver of predictability.

The severity of the 2008 financial crisis naturally raises the question of whether the predictive power of the FCIs mainly arises from the events that started in early 2007, or whether it is also present in the broader sample. In Table 7 we report the coefficients and RMSEs estimated over the 1995-2006 sample, and the results highlight that, essentially, there is no predictability left. Later in this section we discuss whether the lack of predictive power outside of the 2008 crisis is due to predictability only being there during periods of financial stress, or whether it is the result of the FCIs being tailored to the recent financial crisis.

The conclusions that we can draw from monthly returns also carry over to quarterly returns, for which results are reported in Tables 8 and 9. The number of FCIs with predictive power for returns on the S&P 500 or on the financial industry portfolio in the 1995-2012 sample is 5. Similar to the monthly analysis, returns on the remaining industry portfolios are not predictable. Excluding the first day of each quarter when computing the returns (untabulated results) does not change the statistical significance of the coefficients, although restricting the sample to the pre-crisis period (1995-2006, Table 9) all but eliminates the predictability, with the exception of the Morgan Stanley index, which can now predict returns on 5 portfolios. Note that the coefficients for the Morgan Stanley index are positive, while they were negative at the monthly horizon in the full sample (Table 5). The positive sign is consistent with the possibility that, already at the quarterly horizon, the predictive power of the Morgan Stanley index may be due to business cycle predictability – poor current financial conditions imply that, over a medium/long horizon, economic and financial conditions are more likely to improve than to further deteriorate, and stock returns will likely be positive.

We now discuss whether the FCIs are informative about future innovations to the macroeconomic variables we mentioned earlier in this section. In order to implement the Campbell and Yogo (2006) procedure, the only covariate we include in the predictive regressions is one of the FCIs, and we account for autocorrelation in macroeconomic variable changes by using the residuals from log-change autoregressions as the dependent variable, where the number of lags is chosen on the basis of the Schwarz Bayesian information criterion.[7]

The first set of results, reported in Table 10, focuses on one-month ahead predictability, with the sample running from 1995 to 2012.[8] The Chicago Fed, St. Louis Fed, Kansas City Fed, and IMF FCI indexes predict all the variables. Most other indexes predict at least 3 of the 6 variables, with only IMF FSI having statistically insignificant coefficients throughout. When the sample excludes the 2008 financial crisis (Table 11), however, the evidence in favor of predictability is weak, with most indexes being able to predict only one macroeconomic variable - typically industrial production. Similar conclusions can be drawn when focusing on quarterly horizons, as shown in Tables 12 and 13 (only the Morgan Stanley index can predict more variables in the short sample than in the full sample).

One possible reason why the predictability we find in the 1995-2012 sample is not robust to the exclusion of 2007-2012 is that it is subject to threshold effects, in that only

[7] At the monthly frequency, we use two lags for total consumer credit, commercial and industrial loans, industrial production, and total manufacturing inventory, and one lag for durable goods orders and housing starts. At the quarterly frequency, we use two lags for total consumer credit and total manufacturing inventory, one lag for commercial and industrial loans and industrial production, and zero lags for durable goods orders and housing starts.

[8] While we expect a negative relation between a worsening of current financial conditions and future economic activity, some coefficients in Tables 3 and 4 are positive. The reason is that the Campbell and Yogo (2006) procedure requires a negative correlation between current innovations to the dependent variable and the predictor, hence we sometimes need to multiply the FCI by -1. We systematically check that the sign of the estimated coefficient is as expected: positive if the FCI (multiplied by -1 as applicable) signals stress when low, negative otherwise.

poor financial conditions can predict future returns or macroeconomic conditions. In Figure 3 we show a scatter plot of innovations to log-changes of total inventory against the St. Louis FCI, where observations for which the index is above its 80^{th} percentile are highlighted in color. Red triangles indicate an observation from between 2007 and 2012 and green squares indicate an observation from outside that range.

The evidence in Figure 3 is not supportive of a threshold effect, in that the negative relationship between FCI and log-changes in inventories is only evident in the observations from the recent crisis. We argue that the "recent financial crisis effect" arises either (1) because predictability is only present when investors expect that large dislocations are approaching (for instance, correlations can change, and FCIs ultimately measure correlations); or (2) because the variables underlying the many FCIs constructed after the 2008 crisis were chosen based on their movements during the crisis.[9] It is difficult to empirically assess the merit of (1) and (2) above, not least because only one major financial crisis is included in the sample.

Our opinion is that the empirical evidence in favor of the FCIs having reliable predictive power is weak, especially in light of the fact that the FCIs are built by combining public data for typically highly liquid financial instruments - hence they can hardly be characterized as containing privileged information.

3 Efficiently Combining FCIs

In the previous section we established that the FCIs we study have weak predictive power for broad economic developments. We now turn to the question of how to consolidate the increasingly large number of indexes into a single proxy for financial conditions. The implicit assumption in searching for the "best" combination is that the FCIs we focus on

[9] Figure 3 is representative of other index/variable combinations. The unreported figures are available upon request from the authors.

provide broadly similar information, and that no FCI stands out by virtue of measuring financial conditions with greatly superior accuracy. We believe such assumption is validated by the largely comparable performance of the different indexes in the predictability analysis discussed above, and by the fact that the FCIs mostly include variables that capture broad macroeconomic trends (for example, Treasury yields, or S&P 500 option implied volatility).

We propose a simple methodology to combine the various FCIs into a single proxy for financial conditions, which entails calculating the first principal component of a subset of appropriately chosen indexes. The FCIs themselves are already an aggregation of underlying variables, often based on a principal component analysis. The procedure we describe below can be seen as a higher level consolidation that aggregates across different variable sets and methodologies, with the objective of smoothing out transitory fluctuations and extracting a more informative proxy for financial conditions.

First, we sort the individual indexes on the basis of how well they capture the information contained in the remaining FCIs. We measure this ability to capture information using the adjusted R^2 from regressions[10] of changes in the first principal component of all indexes except for index i on changes in index i. Letting i denote the FCI of interest, with $i = 1, ..., 12$, and "fpc" the calculation of the first principal component:

$$\begin{aligned} PC_{-i} &= \text{fpc}(\{FCI_j\}_{j \neq i}) \\ \Delta PC_{-i} &= \gamma + \delta \times \Delta FCI_i + \varepsilon_t \end{aligned}$$

In the interest of robustness, we also run a second set of regressions where the dependent and independent variables are one-lag autoregressive residuals of, respectively, ΔPC_{-i} and ΔFCI_i.

It is, of course, possible for these regressions to yield a low R^2 if index i does not span the remaining FCIs because it is a radically better proxy for financial conditions. As noted

[10] We use robust regressions (Hamilton (1991)), which reduce the influence of outliers.

above, the overlap and the encompassing nature of the variables that underlie the different indexes makes such a possibility unlikely. Table 14 reports the adjusted R^2s of the regressions described above, which we run on two different samples, 1995-2006 and 1995-2012. The rankings in the two samples are quite similar, with the St. Louis FCI, in particular, having a noticeable margin on the other indexes. We use the ranking to select the five FCIs with the highest adjusted R^2 for further aggregation. The two Bloomberg FCIs are ranked among the top five when the sample includes the period surrounding the 2008 financial crisis, however, given that the two indexes are built in a similar way, and that BFCI+ ranks noticeably worse than BFCI in the shorter sample, we exclude BFCI+ from the set of best-performing indexes. We replace BFCI+ with the Kansas City index, which ranks sixth in the 1995-2012 sample, and fifth when excluding the years around the 2008 financial crisis.

In the second step we form all combinations of the five indexes selected above,[11] calculate each combination's first principal component, and regress[12] changes in the first principal component of the FCIs (out of the 12 we study) that are not in the combination under consideration on changes in the first principal component of the combination. Letting **C** denote the combination of interest:

$$\begin{aligned} PC_{\notin \mathbf{C}} &= \mathrm{fpc}(\{FCI_j\}_{j \notin \mathbf{C}}) \\ PC_{\in \mathbf{C}} &= \mathrm{fpc}(\{FCI_j\}_{j \in \mathbf{C}}) \\ \Delta PC_{\notin \mathbf{C}} &= \gamma + \delta \times \Delta PC_{\in \mathbf{C}} + \varepsilon_t \end{aligned}$$

In order to minimize the risk of overfitting, the regressions are run on several subsamples, and we use the resulting set of adjusted R^2 to select the "best" combination of FCIs. Specifically, we calculate, for each combination and in each subsample, the squared deviation of the combination's adjusted R^2 relative to the highest adjusted R^2 in each sub-

11 We form 31 different combinations: five individual indexes, ten sets of two indexes, ten sets of three indexes, five sets of four indexes, and one set of five indexes.

12 We again use robust regressions (see Hamilton (1991)).

sample. We then average, for each combination, the squared deviations across time periods, and use the averages to identify the "best" composite FCI. Table 15 reports five averages: the first (column A) shows arithmetic averages; in the second (B) the average is weighted by the ratio of daily S&P 500 return volatility in each subsample over the volatility in the full sample; in the third (C) it is weighted by the ratio of the average VIX level in each subsample over the average VIX level in the full sample; in the fourth (D) weights are based on the volatility of daily VIX changes; in the fifth (E) the arithmetic average is calculated on the four non-overlapping samples (7/95-12/98 through 1/06-6/12).

The criterion we use to rank the FCIs is, of course, one of potentially many. For example, we could have selected the FCIs with the lowest volatility. Such choice would have implied an assumption on the way financial conditions change over time, namely that they evolve smoothly. Choosing the FCIs with the highest volatility would have implied that we assume financial conditions can change rapidly, and that we are looking for a more reactive proxy. Precisely to avoid imposing strong assumptions on the nature of the process for financial conditions, we have adopted a criterion that focuses on making efficient use of the available data, and that only assumes that (1) all the indexes we study provide some information about financial conditions, and that (2) none of the indexes is likely to contain uniquely accurate information about financial conditions.

The results in Table 15 show that the first principal component of the St. Louis Fed, Bloomberg, Chicago Fed, and Citi indexes has the lowest average squared deviations in all columns (A) to (E): hence we consider such combination as our Composite FCI (CFCI). Figure 4 highlights that the CFCI follows the general pattern of the individual FCIs, but its volatility exhibits different regimes depending on whether financial conditions are loose or tight. The three panels of Figure 5 show the CFCI against three alternative proxies for financial conditions: the St. Louis Fed index, which is the best performing individual FCI, the first principal component of the St. Louis Fed and of the index with the lowest correlation with STLFSI (the MS FCI), and the implied volatility index VIX, which is one of the variables underlying many FCIs. The CFCI tracks the STLFSI closely, although the latter is less volatile in the years following the bull market of the late 1990s. The first principal component of STLFSI and of MS FCI is more volatile than the CFCI, especially in the earlier part of the sample, and it points to much more improved conditions than the CFCI in early 2008, just before the crisis gained full traction.

A comparison of VIX and the CFCI shows that the two track each other quite well, with the exception of the period between mid-2007 and late 2008, when VIX remains stable, and the CFCI shows a largely steady deterioration in financial conditions. In addition, the CFCI points to loose financial conditions in the second half of the 1990s until late 1998, while, over the same period, VIX points to slowly deteriorating conditions starting in 1995. In Figure 6 we plot the 24-month exponentially-weighted rolling correlation between VIX changes and changes in the CFCI, where observations are weighted so that the weight decays by 50% every 12 months (see Figure 6 for details). The correlation is initially low, but it jumps to about 80% with the Russian default in August 1998. With the exception of two relatively short periods in late 2000 and 2005/2006, it stays mostly above 50%, and it has been around 80-90% since the events of the late summer of 2008.

4 Conclusion

We provide an assessment of the one-month and one-quarter ahead predictive power that a selection of indexes of financial conditions and financial stress (to which we collectively refer as FCIs) have for returns on a broad equity index and a set of equity industry portfolios, and for innovations to log-changes in macroeconomic variables that proxy for the state of consumer and business credit, manufacturing, and housing. The evidence for predictive power at the horizons we consider is weak – unless the financial crisis is included – and it highlights the role of non-synchronous trading and, potentially, data mining.

We also suggest a procedure for combining the various FCIs into a single proxy for financial conditions, which summarizes the different variable sets and aggregation methods used in building the individual FCIs. The composite FCI follows the pattern of the individual FCIs, but it clearly exhibits different volatility regimes according to whether financial conditions are tighter or looser than the historical norm, a feature that can be useful when evaluating the current state of financial conditions.

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Figure 1: Time series of the TED spread.

The graph shows the time series of the spread, in basis points, between the three-month USD LIBOR and the three month U.S. Treasury yield, which is commonly referred to as "TED spread". Data are from the British Bankers' Association and the Federal Reserve H.15 Statistical Release. The vertical lines highlight five events that range from the Asian crisis in 1997 to the European debt crisis in 2010.

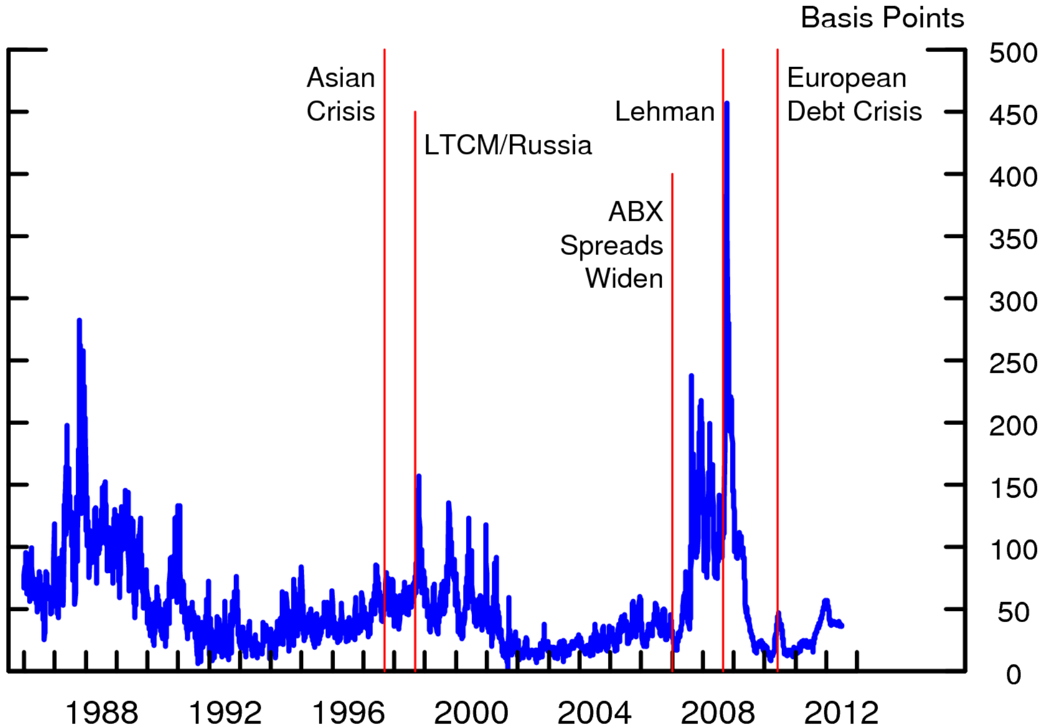

Figure 2: Time series plots of the 12 financial conditions indexes.

The three panels show the time series of the 12 FCIs we study. For scale reasons, the IMF U.S. Financial Stress Index and the natural logarithm of the Carlson, Lewis, and Nelson (2012) Financial Stress Index are shown separately in, respectively, the middle and bottom panels. See Table 1 for a list of FCI acronyms.

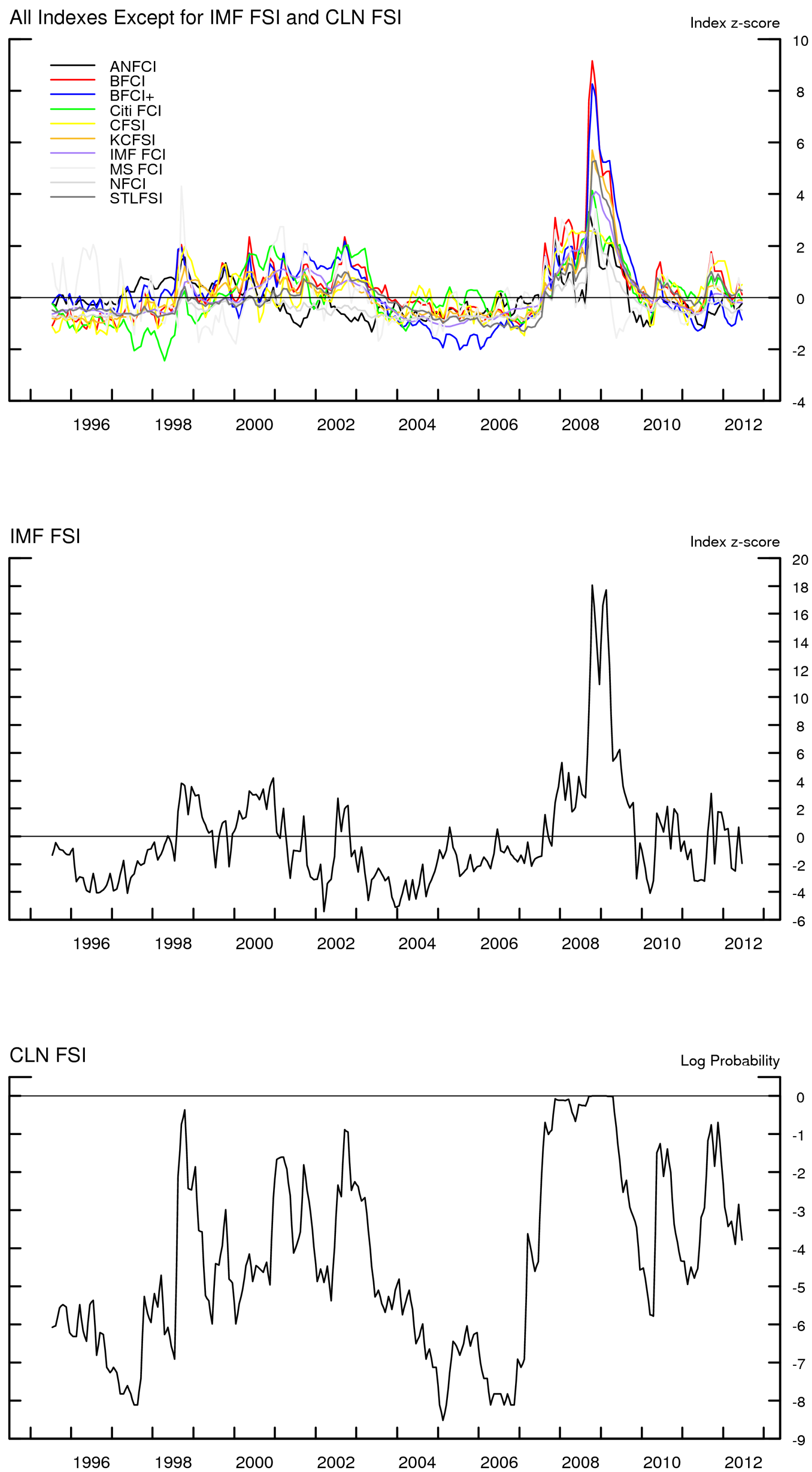

Figure 3: Threshold effects.

The plot shows a scatter of innovations to log-changes in total inventories against the St. Louis Fed's Financial Stress Index. The green squares and red triangles correspond to observations for which the index is above its 80^{th} percentile, with the red triangles indicating an observation from between 2007 and 2012 and the green squares indicating an observation from oustide that range. July 1995 to June 2012.

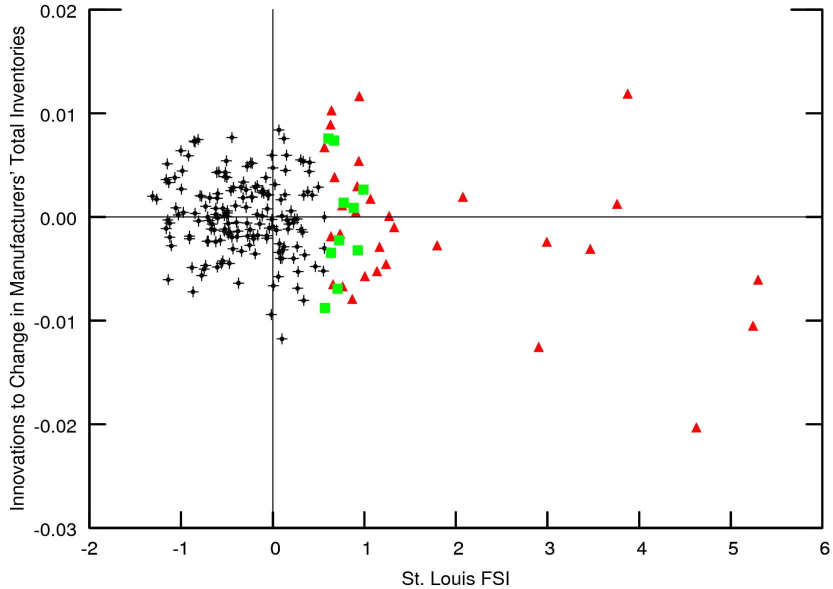

Figure 4: The Composite FCI.

The Composite FCI is the first principal component of four indexes: STLFSI, BFCI, NFCI, and Citi FCI. The four indexes are selected on the basis of the procedure described in Section 3.

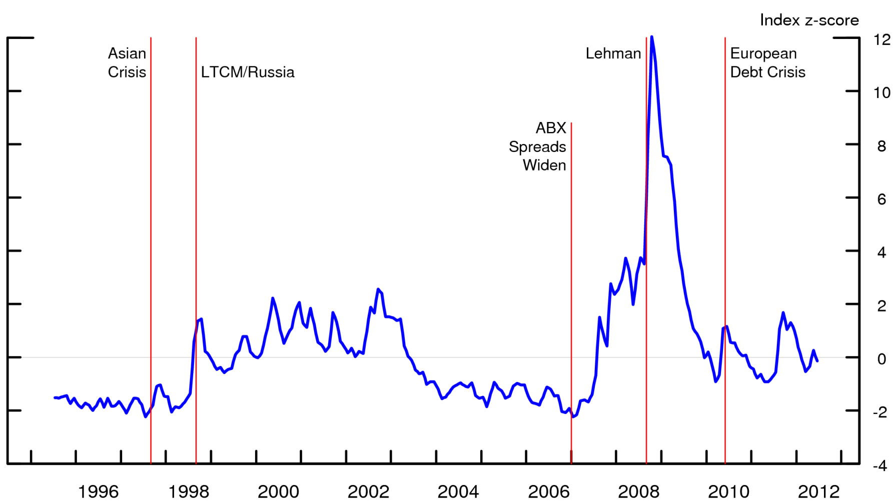

Figure 5: The Composite FCI and other proxies of financial conditions.

Each of the three panels show the Composite FCI (CFCI, blue line) against one of three alternative proxies for financial conditions: the St. Louis Fed index (top panel), which is the individual FCI that best summarizes the information in the remaining FCIs (see Table 14); the first principal component of the St. Louis Fed index and of the index that is least correlated with the St. Louis Fed index (the Morgan Stanley FCI – middle panel); and the implied volatility index VIX (bottom panel). VIX data are from the CBOE.

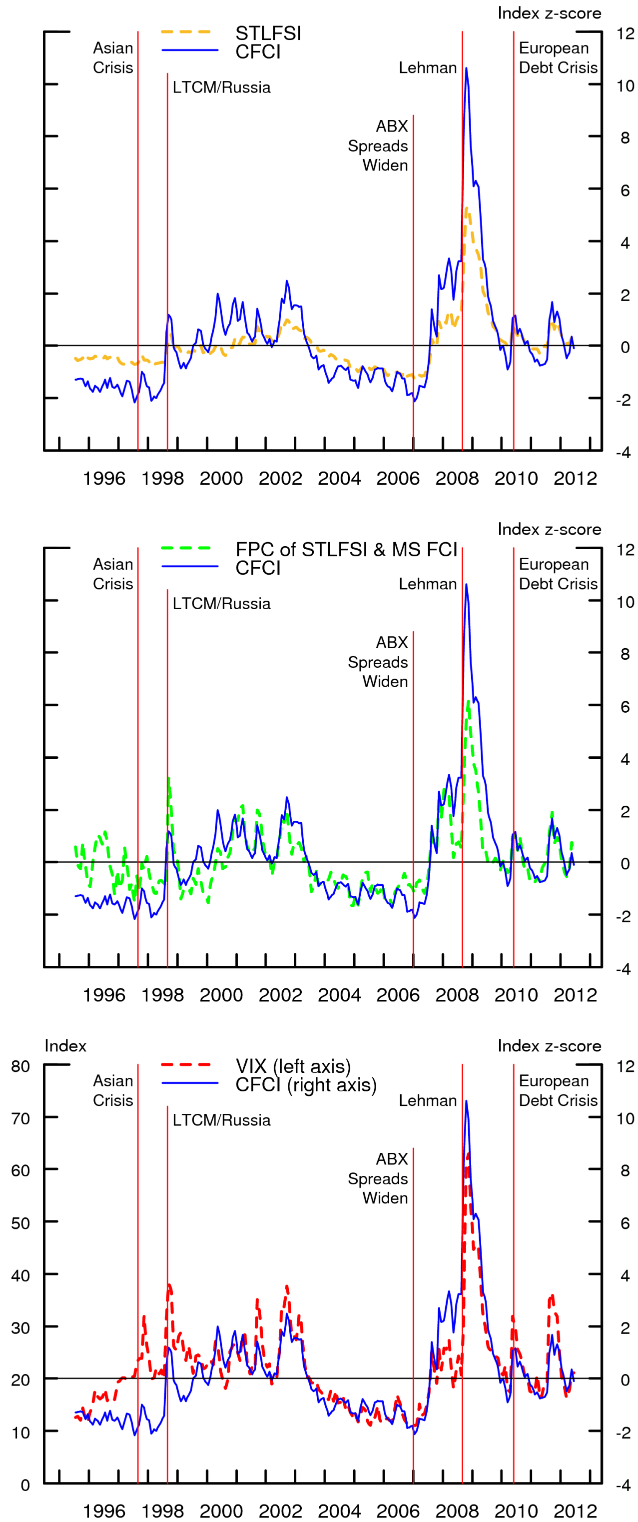

Figure 6: Exponentially-weighted correlation between VIX changes and changes in the Composite FCI.

The graph shows the exponentially-weighted correlation (black dotted line) between monthly changes in the volatility index VIX and monthly changes in the Composite FCI, together with the VIX index, which is standardized for scale reasons (red dashed line), and the Composite FCI (CFCI, blue solid line). The correlation is calculated on the basis of a 24-month rolling window, where the weights decay by 50% every 12 months. Specifically, the weights assigned to observations $\{t-i\}_{i=0}^{23}$ are given by: $\frac{1}{0.75} \cdot \alpha \cdot (1-\alpha)^i$, where $\alpha = 1 - e^{\frac{-ln(4)}{24}}$.

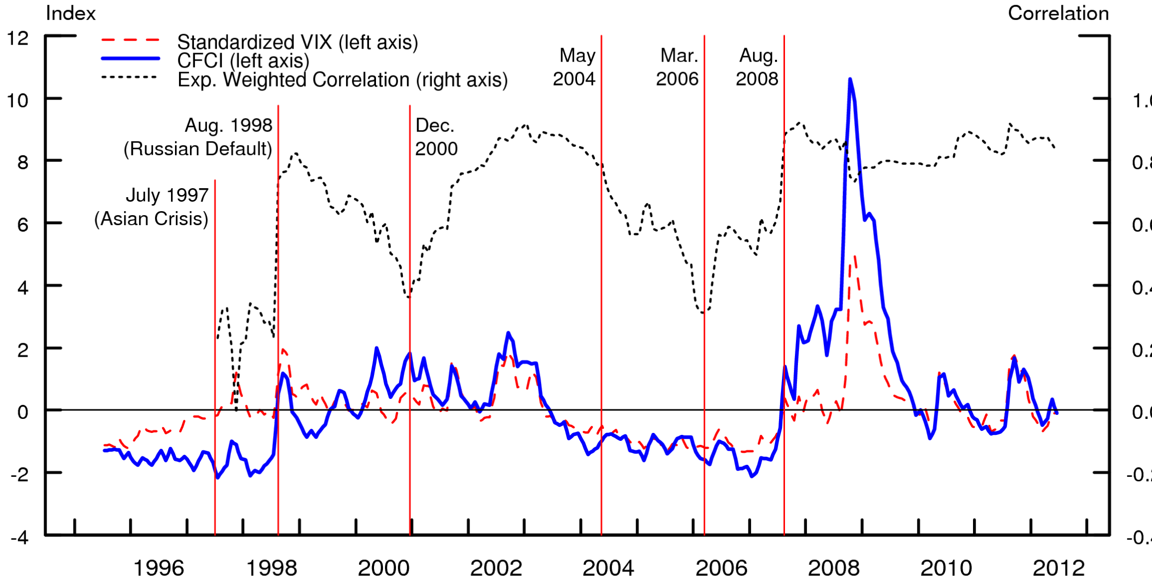

Table 1: Summary descriptions of the 12 FCIs.

The table provides summary information on the 12 FCIs we study. The abbreviations in the "Frequency & Aggregation" column indicate whether the frequency of the index is daily (D), weekly (W), or monthly (M), and whether the variables underlying the index are aggregated with a weighted average (WA), first principal component (FPC), or dynamic factor model (DFM). The FCI in Carlson, Lewis, and Nelson (2012) is based on an index developed in 2003. All indexes are expressed as z-scores, with the exception of the CLN FSI, which is a probability. In the empirical analysis we replace the CLN FSI with its natural logarithm (the index never is exactly zero in our sample).

Full Name	Short Name	Frequency & Aggregation	Start Year	Year Est.	Reference	Data Source
Bloomberg U.S. Financial Conditions Index	BFCI	D-WA	1994	2009	Rosenberg (2009)	Bloomberg
Bloomberg U.S. Financial Conditions Index Plus	BFCI+	D-WA	1994	2009	Rosenberg (2009)	Bloomberg
Cleveland Financial Stress Index	CFSI	D-WA	1991	2009	Oet et al. (2011)	Cleveland Fed
Morgan Stanley Financial Conditions Index U.S.	MS FCI	D-WA	1995	N/A		Bloomberg
Financial Market Stress Index	CLN FSI	W-FPC	1994	2003	Carlson et al. (2012)	Authors
National Financial Conditions Index	NFCI	W-FPC	1973	2006	Brave and Butters (2010)	Chicago Fed
Adjusted National Financial Conditions Index	ANFCI	W-FPC	1973	2006	Brave and Butters (2010)	Chicago Fed
St. Louis Fed Financial Stress Index	STLFSI	W-FPC	1993	2009	Kliesen and Smith (2010)	St. Louis Fed
Kansas City Financial Stress Index	KCFSI	M-FPC	1990	2009	Hakkio and Keeton (2009)	Kansas City Fed
Citi Financial Conditions Index	Citi FCI	M-WA	1983	2000	D'Antonio (2008)	Citi Research
I.M.F. U.S. Financial Conditions Index	IMF FCI	M-DFM	1994	2009	Matheson (2011)	Author
I.M.F. U.S. Financial Stress Index	IMF FSI	M-WA	1980	2011	Cardarelli et al. 2011	Authors

Table 2: Summary statistics of the 12 FCIs.

The table shows the mean, median, 10th and 90th percentiles, peak crisis value (September 2008), total observations, and 90% confidence interval for the AR(1) autoregressive root (see Campbell and Yogo (2006)). July 1995 to June 2012.

Daily	**Mean**	**Median**	**10th**	**90th**	**Value on Sept. 2008**	**# obs**	**90% CI for AR root**	
BFCI	0.426	0.060	-0.887	1.910	7.651	4435	0.922	0.996
BFCI+	0.264	-0.057	-1.237	1.782	5.980	4435	0.901	0.986
CFSI	0.138	0.024	-1.065	1.613	2.592	4435	0.939	1.004
MS FCI	0.075	-0.139	-1.144	1.718	0.764	4429	0.834	0.947
Weekly	**Mean**	**Median**	**10th**	**90th**	**Value on Sept. 2008**	**# obs**	**90% CI for AR root**	
CLN FSI	-4.311	-4.625	-7.264	-0.660	-0.001	887	0.923	0.997
NFCI	-0.361	-0.534	-0.783	0.229	1.847	887	0.936	1.002
ANFCI	-0.030	-0.224	-0.815	0.923	3.310	887	0.757	0.898
STLFSI	0.050	-0.127	-0.905	0.909	2.904	887	0.936	1.002
Monthly	**Mean**	**Median**	**10th**	**90th**	**Value on Sept. 2008**	**# obs**	**90% CI for AR root**	
KCFSI	0.132	-0.115	-0.800	1.010	2.730	204	0.945	1.006
Citi FCI	0.137	0.013	-1.172	1.694	3.224	204	0.916	0.993
IMF FCI	0.078	-0.189	-0.781	1.100	2.930	204	0.974	1.015
IMF FSI	-0.216	-1.065	-3.425	3.393	8.930	204	0.807	0.930

Table 3: Monthly FCI correlations.

The table shows linear correlations among the 12 FCIs, measured at monthly frequency. For weekly and daily FCIs we take the latest observation in a calendar month. July 1995 to June 2012.

	ANFCI	BFCI	BFCI+	Citi FCI	CFSI	IMF FSI	KCFSI	IMF FCI	MS FCI	NFCI	CLN FSI	STLFSI
ANFCI	100											
BFCI	60.44	100										
BFCI+	64.85	90.31	100									
Citi FCI	23.89	78.48	65.67	100								
CFSI	51.41	79.82	68.43	69.42	100							
IMF FSI	65.79	82.83	78.78	66.97	70.20	100						
KCFSI	60.24	92.95	90.60	76.09	78.53	88.98	100					
IMF FCI	51.16	89.35	91.51	76.45	75.24	78.74	93.57	100				
MS FCI	22.09	46.63	45.83	39.05	32.85	38.18	38.03	45.02	100			
NFCI	67.91	93.76	89.62	72.24	79.02	88.59	95.71	92.09	41.32	100		
CLN FSI	38.41	76.28	69.51	68.99	80.96	62.97	74.50	77.95	48.65	72.52	100	
STLFSI	49.23	91.57	89.88	73.45	74.51	79.29	92.94	90.48	39.70	91.75	76.07	100

Table 4: Summary statistics of industry stock returns and log-changes of macro variables.

The table reports summary statistics for the returns on the S&P 500 index and on industry portfolios, and for log-changes in selected macroeconomic variables. The industry portfolios are equally-weighted, and built using CRSP data on the basis of SIC code (finance: 6000 to 6231 and 6712 to 6726; construction: 1521 to 1799; manufacturing: 2011 to 3999; transportation: 4011 to 4971; wholesale trade: 5012 to 5199; retail trade: 5211 to 5999; services: 7011 to 8999). The macroeconomic variables are (with the St. Louis Fed's FRED mnemonic in parentheses): commercial and industrial loans at all commercial banks (BUSLOANS), total consumer credit owned and securitized (TOTALSL), manufacturers' new orders for durable goods (DGORDER), housing starts (HOUST), industrial production (INDPRO), and value of manufacturers' total inventories (AMTMTI). July 1995 to June 2012.

Stock returns	**Mean**	**Std. Dev.**	**Median**	**10th**	**90th**	**# obs**
S&P 500	0.006	0.046	0.010	-0.060	0.059	204
Finance	0.009	0.046	0.012	-0.033	0.059	204
Constr.	0.012	0.080	0.016	-0.085	0.100	204
Manuf.	0.012	0.073	0.015	-0.081	0.099	204
Transp.	0.009	0.061	0.017	-0.071	0.072	204
Whol. Trade	0.012	0.067	0.020	-0.070	0.085	204
Ret. Trade	0.011	0.072	0.009	-0.066	0.078	204
Services	0.012	0.084	0.020	-0.086	0.101	204
Macro variables	**Mean**	**Std. Dev.**	**Median**	**10th**	**90th**	**# obs**
C&I	0.004	0.010	0.005	-0.011	0.015	204
Cons. Credit	0.005	0.006	0.004	-0.003	0.009	204
Dur. Goods	0.002	0.042	0.003	-0.047	0.049	204
Hous. Starts	-0.003	0.069	-0.007	-0.089	0.080	204
Ind. Prod.	0.002	0.007	0.002	-0.006	0.009	204
Tot. Invent.	0.002	0.007	0.002	-0.008	0.010	204

Table 5: Predictive regressions: monthly stock returns, 1995-2012.

The table reports the coefficients and root mean squared errors (both in %) of predictive regressions of one-month ahead stock returns on FCI levels. See Tables 1 and 4 for more details on the FCIs and for the definition of industry portfolios. Asterisks indicate significance at the 90% level. Statistical significance is evaluated on the basis of heteroskedasticity-consistent standard errors, or, where appropriate, with the local-to-unity asymptotics procedure of Campbell and Yogo (2006) (see Section 2 for details). July 1995 to June 2012.

	BFCI		**BFCI+**		**CFSI**		**MS FCI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	-0.432*	4.604	-0.288	4.629	-0.180	4.649	0.022	4.652
Finance	-0.624*	4.517	-0.420*	4.569	-0.778*	4.550	-0.241*	4.611
Constr.	-0.164	8.079	-0.054	8.082	0.291	8.077	-0.227	8.079
Manuf.	-0.263	7.265	-0.055	7.276	0.186	7.274	-0.415*	7.262
Transp.	-0.315	6.122	-0.119	6.138	0.005	6.141	-0.369*	6.127
Whol. Trade	-0.303	6.676	-0.100	6.690	0.115	6.691	-0.301*	6.684
Ret. Trade	-0.194	7.227	0.029	7.233	0.114	7.232	0.016	7.233
Services	-0.108	8.393	0.111	8.393	0.481	8.380	-0.182	8.392

	NFCI		**ANFCI**		**STLFSI**		**CLN FSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	-1.239*	4.596	-0.069	4.652	-0.511	4.622	-0.117	4.644
Finance	-1.843*	4.491	-1.068*	4.545	-0.660*	4.567	-0.271*	4.573
Constr.	-0.500	8.077	-0.205	8.081	0.230	8.079	-0.027	8.082
Manuf.	-0.575	7.269	0.020	7.276	0.076	7.276	0.035	7.276
Transp.	-0.840	6.121	0.042	6.141	-0.116	6.139	-0.057	6.139
Whol. Trade	-0.697	6.680	-0.368	6.686	0.080	6.692	0.074	6.690
Ret. Trade	-0.223	7.232	-0.417	7.226	0.444	7.218	0.100	7.229
Services	-0.393	8.391	0.279	8.392	0.275	8.390	0.179	8.384

	KCFSI		**Citi FCI**		**IMF FCI**		**IMF FSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	-0.583*	4.608	-0.566	4.608	-0.920*	4.565	-0.041	4.650
Finance	-0.766*	4.542	-0.406	4.595	-0.770*	4.557	-0.200*	4.558
Constr.	0.063	8.082	0.030	8.083	-0.170	8.081	0.078	8.077
Manuf.	-0.013	7.276	-0.007	7.276	-0.328	7.269	0.039	7.275
Transp.	-0.201	6.137	-0.281	6.132	-0.587	6.114	0.000	6.141
Whol. Trade	-0.048	6.692	-0.060	6.692	-0.186	6.690	0.000	6.692
Ret. Trade	0.282	7.226	-0.071	7.232	0.167	7.231	0.107	7.222
Services	0.130	8.393	-0.122	8.393	-0.209	8.392	0.078	8.389

Table 6: Predictive regressions: monthly stock returns excluding the first day of the month, 1995-2012.

The table reports the coefficients and root mean squared errors (both in %) of predictive regressions of one-month ahead stock returns on FCI levels. Returns are calculated after excluding the first day of each month. See Tables 1 and 4 for more details on the FCIs and for the definition of industry portfolios. Asterisks indicate significance at the 90% level. Statistical significance is evaluated on the basis of heteroskedasticity-consistent standard errors, or, where appropriate, with the local-to-unity asymptotics procedure of Campbell and Yogo (2006) (see Section 2 for details). July 1995 to June 2012.

	BFCI		**BFCI+**		**CFSI**		**MS FCI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	-0.230	4.620	-0.110	4.630	-0.027	4.633	0.308	4.621
Finance	-0.453*	4.581	-0.263	4.615	-0.634*	4.589	0.007	4.634
Constr.	0.071	8.295	0.198	8.289	0.438	8.283	0.192	8.293
Manuf.	-0.060	7.146	0.124	7.144	0.314	7.139	-0.039	7.146
Transp.	-0.156	6.067	0.013	6.072	0.117	6.070	-0.057	6.071
Whol. Trade	-0.091	6.529	0.091	6.529	0.238	6.526	0.086	6.530
Ret. Trade	0.062	7.190	0.247	7.180	0.278	7.185	0.448	7.174
Services	0.075	8.149	0.273	8.139	0.579	8.129	0.216	8.147
	NFCI		**ANFCI**		**STLFSI**		**CLN FSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	-0.670	4.617	0.113	4.633	-0.193	4.629	-0.041	4.632
Finance	-1.349*	4.567	-0.922*	4.580	-0.386	4.616	-0.197	4.610
Constr.	0.188	8.295	0.039	8.295	0.602	8.271	0.078	8.293
Manuf.	-0.081	7.146	0.131	7.146	0.355	7.137	0.121	7.140
Transp.	-0.422	6.067	0.129	6.071	0.103	6.071	0.008	6.072
Whol. Trade	-0.186	6.530	-0.199	6.529	0.361	6.520	0.147	6.521
Ret. Trade	0.364	7.187	-0.175	7.189	0.762	7.147	0.187	7.177
Services	0.042	8.150	0.369	8.145	0.521	8.132	0.258	8.127
	KCFSI		**Citi FCI**		**IMF FCI**		**IMF FSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	-0.329	4.619	-0.318	4.619	-0.633*	4.592	0.050	4.630
Finance	-0.540*	4.596	-0.260	4.625	-0.547	4.603	-0.121	4.612
Constr.	0.360	8.286	0.189	8.293	0.160	8.294	0.183	8.267
Manuf.	0.192	7.143	0.173	7.144	-0.085	7.146	0.125	7.131
Transp.	-0.041	6.071	-0.139	6.070	-0.399	6.059	0.067	6.066
Whol. Trade	0.159	6.528	0.089	6.530	0.054	6.531	0.078	6.524
Ret. Trade	0.531	7.167	0.155	7.188	0.424	7.179	0.204	7.151
Services	0.296	8.144	0.048	8.150	0.003	8.150	0.147	8.132

Table 7: Predictive regressions: monthly stock returns, 1995-2006.

The table reports the coefficients and root mean squared errors (both in %) of predictive regressions of one-month ahead stock returns on FCI levels. See Tables 1 and 4 for more details on the FCIs and for the definition of industry portfolios. Asterisks indicate significance at the 90% level. Statistical significance is evaluated on the basis of heteroskedasticity-consistent standard errors, or, where appropriate, with the local-to-unity asymptotics procedure of Campbell and Yogo (2006) (see Section 2 for details). July 1995 to December 2006.

	BFCI		**BFCI+**		**CFSI**		**MS FCI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	0.147	4.277	0.038	4.279	0.718	4.245	0.436	4.253
Finance	0.180	3.392	0.279	3.384	-0.040	3.395	0.512	3.350
Constr.	0.524	6.737	0.057	6.751	1.080	6.703	-0.027	6.751
Manuf.	0.979	6.980	0.351	7.019	1.739	6.907	0.045	7.028
Transp.	0.625	5.983	0.209	6.002	1.291	5.928	0.119	6.004
Whol. Trade	0.715	6.170	0.210	6.196	1.192	6.135	0.310	6.190
Ret. Trade	0.444	6.140	0.154	6.149	0.911	6.113	0.707	6.104
Services	1.474	8.853	0.861	8.895	2.400	8.757	0.327	8.932
	NFCI		**ANFCI**		**STLFSI**		**CLN FSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	-0.070	4.279	1.117*	4.228	-0.331	4.275	0.045	4.278
Finance	0.214	3.395	-0.547	3.380	0.889	3.366	0.156	3.382
Constr.	1.120	6.746	0.096	6.751	1.149	6.726	0.242	6.735
Manuf.	3.335	6.981	0.856	7.010	1.724	6.974	0.434	6.978
Transp.	1.169	5.999	1.027	5.975	0.773	5.993	0.242	5.988
Whol. Trade	1.695	6.185	0.053	6.199	1.529	6.151	0.428	6.144
Ret. Trade	1.015	6.146	-0.107	6.151	1.347	6.113	0.389	6.105
Services	3.748	8.891	1.542	8.892	2.440	8.853	0.732	8.825
	KCFSI		**Citi FCI**		**IMF FCI**		**IMF FSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	-0.493	4.268	-0.451	4.253	-0.929	4.239	0.177	4.260
Finance	-0.029	3.395	0.218	3.388	0.590	3.375	-0.069	3.392
Constr.	0.421	6.746	0.089	6.751	0.265	6.749	0.029	6.751
Manuf.	1.005	7.001	0.401	7.016	0.396	7.024	0.267	7.003
Transp.	0.373	6.001	-0.063	6.005	-0.371	6.001	0.248	5.980
Whol. Trade	0.575	6.189	0.222	6.195	0.606	6.188	0.084	6.196
Ret. Trade	0.479	6.144	-0.020	6.151	0.838	6.129	0.029	6.151
Services	1.252	8.905	0.145	8.937	0.560	8.932	0.369	8.900

Table 8: Predictive regressions: quarterly stock returns, 1995-2012.

The table reports the coefficients and root mean squared errors (both in %) of predictive regressions of one-quarter ahead stock returns on FCI levels. See Tables 1 and 4 for more details on the FCIs and for the definition of industry portfolios. Asterisks indicate significance at the 90% level. Statistical significance is evaluated on the basis of heteroskedasticity-consistent standard errors, or, where appropriate, with the local-to-unity asymptotics procedure of Campbell and Yogo (2006) (see Section 2 for details). July 1995 to June 2012.

	BFCI		**BFCI+**		**CFSI**		**MS FCI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	-1.099*	8.882	-0.668	8.989	-0.650*	9.027	0.800	9.005
Finance	-1.401*	9.046	-0.960	9.188	-2.191*	9.043	0.041	9.314
Constr.	-0.006	15.616	0.203	15.612	1.144	15.572	0.481	15.606
Manuf.	-0.025	15.042	0.565	15.016	1.181	14.994	0.436	15.034
Transp.	-0.498	12.529	0.165	12.551	0.141	12.553	0.196	12.552
Whol. Trade	0.179	14.199	0.714	14.156	0.919	14.171	1.210	14.135
Ret. Trade	0.620	14.885	1.278	14.778	1.101	14.875	1.897	14.760
Services	0.462	17.074	1.090	17.002	1.927	16.977	2.035	16.932
	NFCI		**ANFCI**		**STLFSI**		**CLN FSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	-3.647*	8.787	-0.946	9.019	-1.171	8.972	-0.175	9.042
Finance	-4.615*	8.900	-3.325*	8.917	-1.387	9.206	-0.611	9.197
Constr.	-1.267	15.597	-1.657	15.558	1.217	15.566	0.432	15.581
Manuf.	-0.726	15.036	-1.195	15.011	1.479	14.966	0.567	14.980
Transp.	-2.066	12.493	-1.208	12.515	0.559	12.540	0.187	12.545
Whol. Trade	-0.311	14.200	-1.626	14.140	1.882	14.071	0.713	14.097
Ret. Trade	1.256	14.898	-1.265	14.882	3.085	14.580	0.871	14.769
Services	-0.701	17.085	-1.424	17.051	1.947	16.974	0.981	16.926
	KCFSI		**Citi FCI**		**IMF FCI**		**IMF FSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	-1.467*	8.918	-1.408	8.903	-2.324*	8.756	-0.078	9.047
Finance	-1.665*	9.147	-0.630	9.286	-1.743	9.154	-0.494	9.148
Constr.	0.602	15.603	1.202	15.553	-0.173	15.615	0.232	15.594
Manuf.	1.092	14.998	1.201	14.978	0.034	15.042	0.384	14.981
Transp.	0.054	12.553	0.050	12.553	-0.921	12.521	0.206	12.532
Whol. Trade	1.456	14.118	1.122	14.142	0.653	14.187	0.448	14.113
Ret. Trade	2.559	14.671	1.309	14.839	1.777	14.813	0.650	14.739
Services	1.339	17.032	0.861	17.061	0.235	17.088	0.440	17.019

Table 9: Predictive regressions: quarterly stock returns, 1995-2006.

The table reports the coefficients and root mean squared errors (both in %) of predictive regressions of one-quarter ahead stock returns on FCI levels. See Tables 1 and 4 for more details on the FCIs and for the definition of industry portfolios. Asterisks indicate significance at the 90% level. Statistical significance is evaluated on the basis of heteroskedasticity-consistent standard errors, or, where appropriate, with the local-to-unity asymptotics procedure of Campbell and Yogo (2006) (see Section 2 for details). July 1995 to December 2006.

	BFCI		**BFCI+**		**CFSI**		**MS FCI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	0.375	8.351	0.168	8.355	1.122	8.316	2.058*	7.984
Finance	1.338	6.788	1.173	6.776	-0.921*	6.853	1.698*	6.579
Constr.	3.094	13.512	1.314	13.707	2.639	13.638	1.062	13.717
Manuf.	4.004	13.913	1.732	14.225	5.299	13.799	1.906	14.157
Transp.	2.077	11.938	1.020	12.025	2.769	11.899	1.734	11.893
Whol. Trade	3.342	12.132	1.416	12.385	2.961	12.281	2.681*	12.052
Ret. Trade	3.199	12.507	1.841	12.665	2.178	12.710	3.560*	12.080
Services	5.677	17.299	3.557	17.595	7.327	17.157	3.757*	17.412
	NFCI		**ANFCI**		**STLFSI**		**CLN FSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	-3.303	8.308	-1.628	8.301	-0.956	8.342	0.257	8.341
Finance	1.664	6.871	-2.247	6.756	3.035	6.705	0.398	6.841
Constr.	2.746	13.755	-2.492	13.696	4.777	13.552	0.958	13.644
Manuf.	5.456	14.262	-1.420	14.315	6.194	13.977	1.710	13.933
Transp.	-1.532	12.065	-0.722	12.065	2.813	11.985	0.990	11.912
Whol. Trade	2.633	12.452	-2.846	12.358	5.263	12.172	1.509	12.109
Ret. Trade	2.919	12.786	-2.431	12.730	4.964	12.551	1.540	12.442
Services	4.453	17.944	-1.607	17.960	8.253	17.471	2.613*	17.222
	KCFSI		**Citi FCI**		**IMF FCI**		**IMF FSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	-1.730	8.284	-1.548	8.186	-2.812	8.161	0.073	8.355
Finance	0.438	6.881	0.939	6.810	2.134	6.750	-0.399	6.814
Constr.	1.901	13.723	1.388	13.693	1.514	13.742	-0.299	13.755
Manuf.	2.813	14.229	1.877	14.195	1.485	14.309	0.197	14.331
Transp.	0.500	12.069	0.076	12.073	-0.890	12.059	0.095	12.070
Whol. Trade	1.673	12.428	1.257	12.398	1.710	12.425	-0.125	12.469
Ret. Trade	1.745	12.763	0.851	12.778	2.553	12.707	-0.185	12.803
Services	3.291	17.864	1.385	17.922	1.847	17.947	0.428	17.953

Table 10: Predictive regressions: innovations to monthly log-changes in macroeconomic variables, 1995-2012.

The table reports the coefficients and root mean squared errors (both in %) of predictive regressions of one-month ahead innovations to log-changes in macroeconomic variables on FCI levels. See Tables 1 and 4 for more details on the FCIs and on the macroeconomic variables. Asterisks indicate significance at the 90% level. Statistical significance is evaluated on the basis of heteroskedasticity-consistent standard errors, or, where appropriate, with the local-to-unity asymptotics procedure of Campbell and Yogo (2006) (see Section 2 for details). July 1995 to June 2012.

	BFCI		**BFCI+**		**CFSI**		**MS FCI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
C&I	0.078*	0.662	0.105*	0.652	0.072	0.669	-0.051	0.671
Cons. Credit	-0.034	0.519	-0.032	0.519	-0.047	0.519	0.018	0.521
Dur. Goods	-0.883*	3.733	-0.765*	3.781	-0.920*	3.860	-0.667*	3.905
Hous. Starts	-1.184*	6.241	-0.895*	6.344	-0.759*	6.456	-0.764*	6.448
Ind. Prod.	-0.120*	0.645	-0.094*	0.654	-0.167*	0.649	-0.126*	0.657
Tot. Invent.	-0.059*	0.437	-0.054*	0.438	-0.043	0.444	-0.071*	0.439
	NFCI		**ANFCI**		**STLFSI**		**CLN FSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
C&I	0.240*	0.658	0.059	0.672	0.180*	0.647	-0.038	0.667
Cons. Credit	-0.129*	0.516	-0.025	0.521	-0.073*	0.516	-0.017	0.520
Dur. Goods	-2.366*	3.725	-1.147*	3.875	-1.153*	3.786	-0.317*	3.900
Hous. Starts	-2.984*	6.265	-1.875*	6.342	-1.220*	6.376	-0.321*	6.457
Ind. Prod.	-0.321*	0.645	-0.051	0.670	-0.162*	0.650	0.072*	0.649
Tot. Invent.	-0.143*	0.438	-0.050	0.444	-0.073*	0.439	-0.021	0.443
	KCFSI		**Citi FCI**		**IMF FCI**		**IMF FSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
C&I	0.168*	0.647	0.119*	0.660	0.183*	0.649	0.034	0.661
Cons. Credit	-0.061*	0.517	-0.034	0.520	-0.068*	0.517	-0.013	0.519
Dur. Goods	-1.247*	3.731	-0.834*	3.860	-1.356*	3.746	-0.335	3.772
Hous. Starts	-1.282*	6.349	1.162*	6.369	-1.390*	6.359	-0.414	6.317
Ind. Prod.	0.177*	0.643	0.180*	0.640	-0.213*	0.638	-0.044	0.651
Tot. Invent.	-0.071*	0.439	-0.075*	0.438	-0.106*	0.434	-0.017	0.442

Table 11: Predictive regressions: innovations to monthly log-changes in macroeconomic variables, 1995-2006.

The table reports the coefficients and root mean squared errors (both in %) of predictive regressions of one-month ahead innovations to log-changes in macroeconomic variables on FCI levels. See Tables 1 and 4 for more details on the FCIs and on the macroeconomic variables. Asterisks indicate significance at the 90% level. Statistical significance is evaluated on the basis of heteroskedasticity-consistent standard errors, or, where appropriate, with the local-to-unity asymptotics procedure of Campbell and Yogo (2006) (see Section 2 for details). July 1995 to December 2006.

	BFCI		**BFCI+**		**CFSI**		**MS FCI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
C&I	-0.085	0.583	-0.087*	0.580	0.042	0.586	-0.041	0.586
Cons. Credit	0.030	0.332	0.040	0.331	0.005	0.333	-0.029	0.332
Dur. Goods	0.339	3.683	0.309	3.681	0.420	3.681	-0.170	3.690
Hous. Starts	0.225	5.249	0.382	5.238	0.414	5.244	0.455	5.230
Ind. Prod.	0.138*	0.547	0.059	0.556	-0.092	0.555	-0.082*	0.552
Tot. Invent.	-0.040	0.383	-0.052	0.380	-0.022	0.384	-0.075*	0.375
	NFCI		**ANFCI**		**STLFSI**		**CLN FSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
C&I	0.217	0.585	-0.058	0.586	-0.221*	0.576	-0.057*	0.577
Cons. Credit	-0.118	0.332	-0.058	0.332	-0.016	0.333	0.015	0.332
Dur. Goods	2.128	3.657	0.179	3.693	0.667	3.679	-0.185	3.677
Hous. Starts	0.465	5.251	0.120	5.252	-0.827	5.236	0.145	5.245
Ind. Prod.	0.363*	0.552	-0.054	0.559	0.153	0.554	0.058*	0.548
Tot. Invent.	-0.179	0.382	0.048	0.383	-0.098	0.381	-0.033*	0.379
	KCFSI		**Citi FCI**		**IMF FCI**		**IMF FSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
C&I	0.128	0.582	0.076	0.582	0.227*	0.570	0.009	0.587
Cons. Credit	0.058	0.332	0.021	0.333	0.055	0.332	0.020	0.330
Dur. Goods	0.876	3.655	-0.274	3.683	-0.807	3.659	0.187	3.670
Hous. Starts	0.144	5.252	-0.256	5.246	0.490	5.244	-0.091	5.249
Ind. Prod.	0.169*	0.550	0.132*	0.542	-0.147*	0.552	0.041	0.552
Tot. Invent.	-0.079	0.381	0.052	0.380	-0.149*	0.373	-0.016	0.383

Table 12: Predictive regressions: innovations to quarterly log-changes in macroeconomic variables, 1995-2012.

The table reports the coefficients and root mean squared errors (both in %) of predictive regressions of one-quarter ahead innovations to log-changes in macroeconomic variables on FCI levels. See Tables 1 and 4 for more details on the FCIs and on the macroeconomic variables. Asterisks indicate significance at the 90% level. Statistical significance is evaluated on the basis of heteroskedasticity-consistent standard errors, or, where appropriate, with the local-to-unity asymptotics procedure of Campbell and Yogo (2006) (see Section 2 for details). July 1995 to June 2012.

	BFCI		**BFCI+**		**CFSI**		**MS FCI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
C&I	0.406*	1.229	0.477*	1.161	0.571*	1.260	-0.414*	1.305
Cons. Credit	-0.099	1.003	-0.122	0.996	-0.121	1.007	-0.029	1.014
Dur. Goods	-1.858*	5.308	-1.637*	5.483	-1.413*	5.896	-1.450*	5.840
Hous. Starts	-1.373*	8.645	-0.803	8.822	-1.077*	8.846	0.781	8.870
Ind. Prod.	-0.248*	1.291	-0.167	1.324	-0.371*	1.296	-0.348*	1.290
Tot. Invent.	-0.285*	1.112	-0.257*	1.128	-0.238*	1.175	-0.197	1.179
	NFCI		**ANFCI**		**STLFSI**		**CLN FSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
C&I	1.238*	1.176	0.548*	1.314	0.752*	1.155	0.204*	1.298
Cons. Credit	-0.329	0.996	-0.064	1.014	-0.174	0.999	-0.014	1.014
Dur. Goods	-4.935*	5.311	-2.643*	5.679	-2.278*	5.604	-0.708*	5.824
Hous. Starts	-4.171*	8.562	-2.657	8.651	-0.784	8.878	-0.386	8.865
Ind. Prod.	-0.657*	1.292	-0.061	1.349	-0.289*	1.317	-0.163*	1.291
Tot. Invent.	-0.578*	1.150	0.420*	1.151	-0.258*	1.171	-0.101*	1.175
	KCFSI		**Citi FCI**		**IMF FCI**		**IMF FSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
C&I	0.780*	1.117	0.526*	1.246	0.812*	1.132	0.201	1.191
Cons. Credit	-0.145	1.003	-0.089	1.010	-0.208*	0.994	-0.038	1.006
Dur. Goods	-2.415*	5.508	-1.635*	5.765	-2.866*	5.369	-0.635	5.637
Hous. Starts	-1.163	8.829	-1.025	8.834	-2.011*	8.690	-0.375	8.815
Ind. Prod.	-0.393*	1.285	-0.384*	1.274	-0.430*	1.281	-0.117	1.285
Tot. Invent.	-0.282*	1.163	0.334*	1.136	-0.375*	1.141	-0.094	1.153

Table 13: Predictive regressions: innovations to quarterly log-changes in macroeconomic variables, 1995-2006.

The table reports the coefficients and root mean squared errors (both in %) of predictive regressions of one-quarter ahead innovations to log-changes in macroeconomic variables on FCI levels. See Tables 1 and 4 for more details on the FCIs and on the macroeconomic variables. Asterisks indicate significance at the 90% level. Statistical significance is evaluated on the basis of heteroskedasticity-consistent standard errors, or, where appropriate, with the local-to-unity asymptotics procedure of Campbell and Yogo (2006) (see Section 2 for details). July 1995 to December 2006.

	BFCI		**BFCI+**		**CFSI**		**MS FCI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
C&I	0.431*	1.111	0.399*	1.095	0.436	1.127	-0.292	1.118
Cons. Credit	0.058	0.607	0.028	0.609	0.094	0.606	-0.065	0.605
Dur. Goods	0.956	4.426	-0.960	4.389	0.748	4.469	-0.768*	4.408
Hous. Starts	1.513	5.349	1.758*	5.190	1.210	5.434	1.506*	5.203
Ind. Prod.	-0.261	1.097	-0.096	1.115	-0.087	1.118	-0.216*	1.089
Tot. Invent.	-0.364*	0.876	-0.374*	0.845	-0.232	0.915	-0.316*	0.851
	NFCI		**ANFCI**		**STLFSI**		**CLN FSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
C&I	1.375*	1.110	0.061	1.172	0.761*	1.104	-0.191*	1.109
Cons. Credit	-0.352	0.602	-0.176	0.601	0.027	0.609	0.030	0.607
Dur. Goods	3.930	4.372	0.480	4.494	-1.337	4.450	-0.492*	4.396
Hous. Starts	2.044	5.478	0.501	5.499	2.546	5.347	-0.336	5.467
Ind. Prod.	-0.693	1.103	-0.160	1.116	-0.310	1.108	-0.118	1.095
Tot. Invent.	-1.189*	0.872	0.009	0.931	-0.625*	0.873	-0.165*	0.872
	KCFSI		**Citi FCI**		**IMF FCI**		**IMF FSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
C&I	0.699*	1.085	0.344*	1.111	0.810*	1.052	0.137	1.121
Cons. Credit	0.191	0.597	0.050	0.607	-0.066	0.608	-0.047	0.598
Dur. Goods	1.607	4.386	-0.413	4.481	-2.054*	4.308	-0.320	4.432
Hous. Starts	0.515	5.497	0.255	5.500	1.043	5.467	-0.085	5.503
Ind. Prod.	-0.426*	1.087	0.362*	1.049	-0.303	1.103	-0.142	1.062
Tot. Invent.	0.523*	0.870	0.317*	0.865	-0.605*	0.847	0.142	0.861

Table 14: Explanatory power of FCIs.

The table reports the adjusted R^2s (in %) of robust regressions (Hamilton (1991)) of changes in the first principal component of all the FCIs (aside from the one indicated in each row) on changes in the indicated FCI (columns "ΔPC"), and of one-lag autoregressive residuals of changes in the first principal component of all the FCIs (aside from the one indicated in each row) on one-lag autoregressive residuals of the changes in the indicated FCI (columns "Res.Δ").

	July 1995 - Dec. 2006				**July 1995 - June 2012**			
	ΔPC	**Res.Δ**	**Average**	**Rank**	**ΔPC**	**Res.Δ**	**Average**	**Rank**
BFCI	48.10	44.33	46.22	2	56.99	52.98	54.98	4
BFCI+	34.99	30.76	32.88	6	58.35	54.20	56.27	3
Citi FCI	34.43	37.18	35.81	4	44.62	45.39	45.00	5
CFSI	32.49	29.44	30.97		24.70	21.89	23.30	
NFCI	44.36	41.34	42.85	3	65.07	60.79	62.93	2
ANFCI	15.85	11.62	13.74		35.92	29.30	32.61	
IMF FSI	22.33	27.99	25.16		33.35	35.60	34.48	
KCFSI	35.44	31.61	33.52	5	42.23	36.41	39.32	6
IMF FCI	14.04	19.18	16.61		29.36	38.77	34.06	
MS FCI	17.79	17.78	17.79		21.34	24.40	22.87	
CLN FSI	29.96	27.70	28.83		33.61	30.96	32.28	
STLFSI	63.72	60.01	61.86	1	75.63	73.82	74.72	1

Table 15: Explanatory power of the first principal component of FCI combinations

The first six columns report the adjusted R^2 of robust regressions (Hamilton (1991)) of changes in the first principal component of all the FCIs (aside from those indicated in each row) on changes in the first principal component of the indicated FCI combination (the results for individual FCIs are untabulated). The last five columns show the averages, across sub-periods, of the squared deviations of each combination's adjusted R^2 from each time period's largest adjusted R^2. Column A shows simple averages across the six sub-periods. Columns B through D report weighted averages, where the weights assigned to each sub-period are based on the volatility of daily S&P 500 returns (B), on the average implied volatility index VIX (C), and on the volatility of daily changes in VIX (D). The weights are calculated by normalizing the volatilities/averages in each sub-period with the volatility/average over the full sample. Column E shows simple averages across the four non-overlapping sub-periods (7/95-12/98 through 1/06-6/12).

	7/95-	**7/95-**	**7/95-**	**1/99-**	**1/02-**	**1/06-**	**Average Sq. Deviation**				
Combination	**6/12**	**12/06**	**12/98**	**12/01**	**12/05**	**6/12**	**A**	**B**	**C**	**D**	**E**
STLFSI - BFCI	70.36	58.68	56.74	63.44	49.81	76.69	1.48	1.41	1.46	1.43	1.80
STLFSI - NFCI	76.12	62.17	60.36	63.24	53.72	81.68	0.84	0.80	0.84	0.79	1.14
STLFSI - KCFSI	70.27	57.41	51.55	52.77	63.80	71.02	2.41	2.41	2.49	2.39	3.11
STLFSI - Citi FCI	73.31	54.23	63.40	53.77	50.30	83.16	1.72	1.69	1.77	1.57	1.97
BFCI - NFCI	62.43	53.95	48.65	58.89	45.55	67.20	3.45	3.39	3.43	3.46	3.99
BFCI - KCFSI	66.10	61.43	59.81	64.21	56.65	71.91	1.30	1.35	1.33	1.36	1.44
BFCI - Citi FCI	70.96	57.93	65.49	51.25	51.55	77.34	1.80	1.85	1.91	1.69	2.26
NFCI - KCFSI	61.03	48.32	48.91	48.74	47.14	63.46	4.76	4.80	4.85	4.77	5.34
NFCI - Citi FCI	64.41	48.97	52.43	42.64	40.08	77.58	4.64	4.53	4.72	4.31	5.48
Citi FCI - KCFSI	58.78	45.10	40.34	39.41	42.36	65.57	7.11	7.00	7.22	6.90	8.29
STLFSI - BFCI - NFCI	71.32	61.96	60.88	70.83	50.99	76.04	0.91	0.88	0.88	0.90	1.12
STLFSI - BFCI - KCFSI	73.73	66.84	68.00	71.86	61.51	73.02	0.41	0.48	0.43	0.49	0.56
STLFSI - BFCI - Citi FCI	77.09	64.29	70.55	62.94	55.97	81.66	0.48	0.49	0.50	0.44	0.65
STLFSI - NFCI - KCFSI	69.66	59.32	54.66	56.15	63.33	72.18	1.85	1.86	1.91	1.85	2.35
STLFSI - NFCI - Citi FCI	78.31	62.22	72.37	57.62	55.16	86.07	0.77	0.79	0.83	0.69	1.04
STLFSI - Citi FCI - KCFSI	71.36	58.55	52.90	52.85	54.60	78.65	2.09	2.03	2.15	1.98	2.74
BFCI - NFCI - KCFSI	67.96	64.93	63.85	70.14	56.97	68.97	0.98	1.08	1.01	1.11	1.16
BFCI - NFCI - Citi FCI	71.05	62.86	67.08	60.44	55.34	75.32	0.94	0.99	0.99	0.93	1.18
BFCI - Citi FCI - KCFSI	74.89	63.92	72.16	58.57	57.04	79.65	0.72	0.76	0.78	0.68	0.99
NFCI - Citi FCI - KCFSI	69.52	54.51	55.68	48.79	47.95	75.87	2.83	2.80	2.92	2.67	3.53
STLFSI - BFCI - NFCI - KCFSI	72.80	68.44	69.11	76.10	59.18	71.79	0.46	0.53	0.48	0.55	0.61
STLFSI - BFCI - NFCI - Citi FCI	75.70	67.11	71.43	68.03	57.75	81.43	**0.23**	**0.24**	**0.24**	**0.22**	**0.32**
STLFSI - BFCI - Citi FCI - KCFSI	74.75	67.53	73.34	63.24	60.31	79.45	0.39	0.43	0.43	0.39	0.55
STLFSI - NFCI - Citi FCI - KCFSI	74.28	62.26	61.22	56.73	57.17	80.84	1.09	1.09	1.15	1.02	1.48
BFCI - NFCI - Citi FCI - KCFSI	76.26	67.30	73.28	62.83	57.98	79.01	0.44	0.48	0.48	0.43	0.65
STLFSI - BFCI - NFCI - Citi FCI - KCFSI	75.45	68.96	72.45	68.46	60.12	77.55	0.26	0.29	0.28	0.28	0.36