Assessing and Combining Financial Conditions Indexes*

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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. In addition, we suggest a simple procedure for aggregating the various indexes into a single proxy for financial conditions, which can help to reduce the uncertainty faced by policymakers when monitoring financial conditions.

JEL Codes: E32, G01, G17.

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). An open question in the literature is

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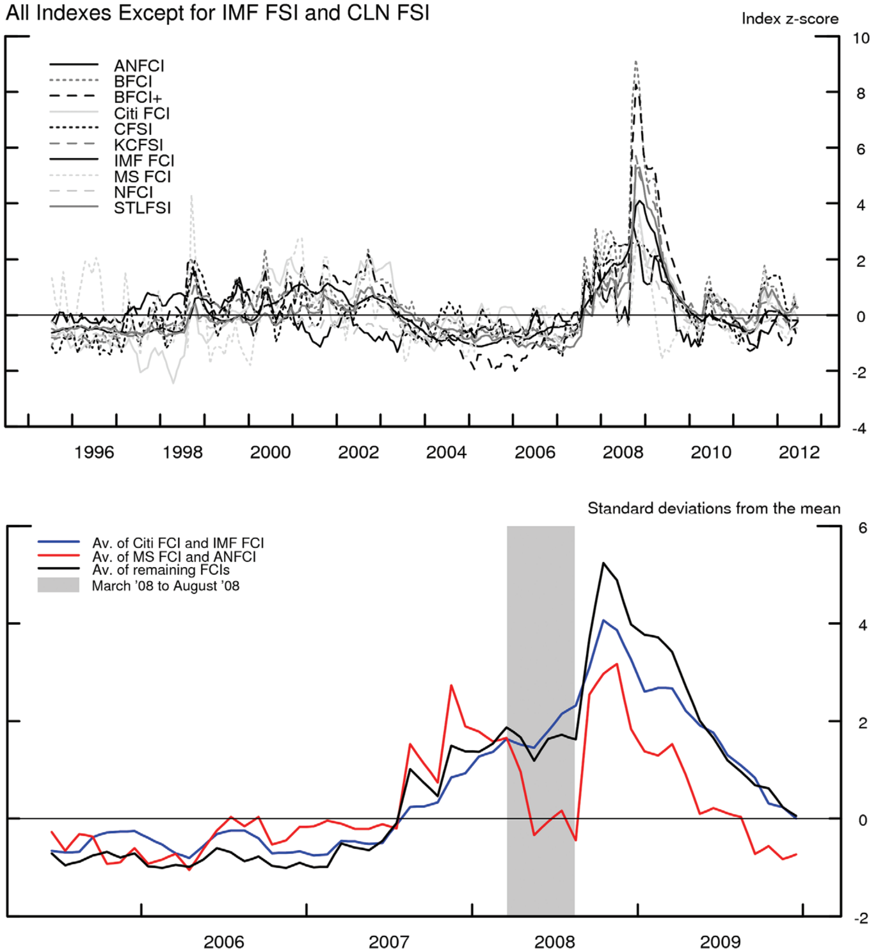
whether these indexes should be used as indicators of current financial conditions, or whether they also have predictive power for future financial and economic activity and could be used as early-warning indicators. In this paper we evaluate whether FCIs can predict stock returns or innovations to macroeconomic variables over a one-month or a one-quarter horizon. In addition, we study the Granger causality relation between the FCIs and several measures of credit availability that we use as proxies for the "financial cycle" (Borio 2014). Finally, 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. However, this predictability is not robust to excluding the period around the 2008 financial crisis (2007–12). We posit three possible explanations for this pattern. The first is threshold effects, in the sense that financial conditions may matter only after deteriorating beyond a certain threshold. The second is data mining, because most of the FCIs were introduced after the financial crisis, and they are built using variables that displayed significant movements during the crisis. And the third is non-synchronous data, given that most FCIs include one variable derived from the prices of options that trade after equity markets close, hence FCIs include, by construction, information that will be incorporated in stock prices the next day. We provide evidence that all three effects are present, but we argue that predictability is mainly driven by data mining and by non-synchronous trading.

The FCIs we study measure financial conditions in one of two ways. The first approach is to evaluate whether broad financial conditions are loose or tight by historical standards (e.g., the Bloomberg and Chicago Fed indexes). Alternatively, other indexes purport to measure whether the financial system is experiencing historically unusual stress (e.g., the Carlson, Lewis, and Nelson 2014 index). Despite these and other methodological differences that we detail in section 2, the FCIs exhibit a large amount of common variation, as can be seen in the top graph in figure 1. Such a result is expected because, while the concept of "financial conditions" is often only loosely defined by the articles that build the various FCIs, changes in the state of the financial system directly affect many of the variables used to build the FCIs. However, the top graph in figure 1

Figure 1. Time-Series Plots of the Twelve Financial Conditions Indexes



Notes: The graphs show the time series of the twelve FCIs we study. For scale reasons, the International Monetary Fund (IMF) U.S. Financial Stress Index and the Carlson, Lewis, and Nelson (2014) Financial Stress Index are not shown. The bottom graph focuses on the years surrounding the 2008 financial crisis, and it shows the averages of standardized versions of (i) Citi FCI and IMF FCI, (ii) MS FCI and ANFCI, and (iii) the remaining FCIs. See table 1 for a list of FCI acronyms.

shows that, at certain points in time, different indexes provide a conflicting reading of financial conditions. This was the case, for instance, in 1997–98 for the Citi FCI and 2004–05 for one of the Bloomberg FCIs. In section 3, we propose a method to extract a single and more precise measure of financial conditions from the set of indexes we consider.

Having a reliable measure of financial conditions is important for policymakers because, as the literature has shown, financial conditions matter in a variety of ways. 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), Kashyap, Lamont, and Stein (1994), Peek and Rosengren (1997), and Paravisini (2008), who show that tight monetary policy, binding capital ratios, and bank financing constraints can reduce the supply of credit, especially in the case of small banks with less liquid assets (Kashyap and Stein 2000). A reduced credit supply has particularly negative effects for 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, 2000; Calomiris and Mason 2003).

We assess predictability using simple predictive regressions of a set of stock returns or innovations to macroeconomic variables on lagged FCI values. Our analysis differs from Hatzius et al. (2010), who also evaluate the predictive power of several FCIs, in a few important ways. First, we only consider FCIs that are updated at least monthly (we should emphasize that, as shown in figure 1, the FCIs still have meaningful monthly variation), and we study their predictive power for stock returns and innovations to macroeconomic variables one month and one quarter ahead. By using such horizons, our predictability results are unlikely to reflect business-cycle effects, especially in the case of one-month-ahead regressions. 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.[1] Finally, as described in more detail in section 2, we assess the statistical significance of predictability with a methodology that is robust to biases generated by the high persistence that typically characterizes FCIs, which we found had noticeable effects on the results discussed in section 2.

Our conclusions differ from those of English, Tsatsaronis, and Zoli (2005), who focus on four- and eight-quarter horizons, and consider a longer sample than we do. They aggregate financial variables with principal component analysis and find that the resulting proxies for financial conditions have some predictive power for macroeconomic variables. Our conclusions, however, are more in line with those of Hatzius et al. (2010), because we find limited value in using FCIs as reliable early-warning indicators, especially when (i) excluding the period surrounding the 2008 financial crisis from the sample, and (ii) acknowledging that the choice of the variables that enter many FCIs may have been influenced by knowing, in hindsight, what precipitated the financial crisis.

In the second part of our paper, we discuss a simple two-step methodology for combining the various 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. In the top graph in figure 1, one can see that the FCIs generally move together in the long run, but they can provide conflicting assessments at a given point in time—even shortly before a major financial crisis. For instance, the bottom graph in figure 1 shows the averages of three sets of (standardized) FCIs between 2006 and 2009. The shaded area highlights the period between March and August 2008, which corresponds to the months between the purchase of The Bear Stearns Companies, Inc. by JPMorgan Chase & Co. (March 16, 2008) and the bankruptcy filing of Lehman Brothers Holdings Inc. on September 15, 2008. The chart clearly shows that

[1]For example, Hatzius et al. (2010) develop their own FCI in addition to evaluating others. They note on page 21 that "the better performance during the most recent five years ... 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."

different FCIs give conflicting readings of the state of the financial system in the second and third quarters of 2008, ranging from a noticeable deterioration to a large improvement.

Aggregating the individual indexes can help average out model uncertainty and provide policymakers with a single variable that reflects the information available in all of the FCIs. We first identify the indexes that best summarize the information provided by the remaining FCIs. In the second step we form all combinations of the identified indexes and select the "best" combination on the basis of how well it summarizes the information in the remaining FCIs. This procedure is discussed in detail in section 3.

2. Assessing the Predictive Ability of FCIs

We consider twelve FCIs that (i) focus on the United States, (ii) are updated at least every month, and (iii) have a sufficiently long history.[2] Table 1 contains a detailed list of data sources and includes the abbreviated FCI names we use in the paper.

The construction of the FCIs varies considerably, although all of them 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 small set of variables, as in the case of the Bloomberg Financial Conditions Index, which is based on ten underlying variables. One index, the Chicago Fed Adjusted National Financial Conditions Index, has more than 100 underlying variables.

In general, the constituent variables are aggregated using principal component analysis or simple weighted sums. Principal component analysis is used extensively in the literature to extract information from a large set of macroeconomic or financial variables for forecasting purposes. For example, Ludvigson and Ng (2007) rely

[2]In order to increase the power of our test, we require that the FCIs cover the stressful episodes that characterized the late 1990s (the Long-Term Capital Management collapse, and the Asian and Russian financial crises). 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.

Table 1. Summary Descriptions of the Twelve FCIs

Full Name	Short Name	Availability and 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, Lewis, and Nelson (2014)	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
IMF U.S. Financial Conditions Index	IMF FCI	M-DFM	1994	2009	Matheson (2012)	Author
IMF U.S. Financial Stress Index	IMF FSI	M-WA	1980	2011	Cardarelli, Elekdag, and Lall (2011)	Authors

Notes: The table provides summary information on the twelve FCIS we study. The abbreviations in the "Availability and Aggregation" column indicate whether the index is updated 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 (2014) 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).

on dynamic factor analysis to summarize a broad cross-section of variables, and find that several of the resulting factors can predict one-quarter-ahead excess stock returns. Stock and Watson (2002) use principal component analysis to build factors used to predict several macroeconomic variables in the medium run (six, twelve, and twenty-four months ahead).

For indexes constructed as weighted sums, 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) (Oet et al. 2011). All the indexes are expressed in terms of z-scores, with the exception of the Financial Stress Index of Carlson, Lewis, and Nelson (2014), which is expressed in terms of probabilities.

2.1 Predictive Regressions

We evaluate the predictive power of the twelve FCIs 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 regression in levels, rather than changes, because the developers of most of the FCIs emphasize that their indexes are ordinal measures of financial conditions/stress.

We focus on one-month-ahead and one-quarter-ahead regressions because our predictability results might in part reflect business-cycle effects if the dependent variable were measured over longer horizons. In particular, many FCIs include the implied volatility index VIX as a constituent variable. Bollerslev, Tauchen, and Zhou (2009) find that the variance risk premium, which is the difference between the squared value of VIX and a measure of realized variance, can predict stock returns about three to six months out, with the associated adjusted R^2 peaking at a five-month horizon and declining gradually at longer horizons. The variance risk premium is driven by the dynamics of both volatility risk and risk aversion; the latter is embedded in VIX, and its evolution over time has a business-cycle component. Note that we do not control for the predictive power of other variables, like the variance risk premium, because the results from regressions in which FCIs are the only predictor already suggest a lack of 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 the local-to-unity asymptotics procedure of Campbell and Yogo (2006). Local-to-unity asymptotics are 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.

As is clear from the time-series plots in figure 1, 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.[3] 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 five cases, we are actually unable to reject the hypothesis that the FCIs have a unit root. Given the nature of the problem we study, asymptotic standard errors would normally be biased against finding predictability, and the local-to-unit asymptotics procedure of Campbell and Yogo (2006) corrects for this bias. Our results show that the Campbell and Yogo (2006) procedure finds predictability 25 percent more often than OLS for innovations to macroeconomic variables, and six times as often for stock returns.[4]

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

[4]The direction and severity of the bias depend on the persistence of the predictor, on the correlation between the innovations to the predictor and to the predicted variable (δ), and on the sign of the predictive relation (see the discussion on the skewness of the t-statistic distribution in section 3.2 of Campbell and Yogo 2006). Given the persistence of the FCIs, and assuming that poor financial conditions lead to negative returns/innovations to macroeconomic variables, OLS should find predictability less often than the Campbell and Yogo (2006) procedure for FCIs that increase in value when financial conditions deteriorate. In order to run the Campbell and Yogo (2006) procedure, we need to make sure that the correlation δ is negative, and we do so by multiplying an FCI by –1 if needed. The figures mentioned in the text refer to predictive regressions based on the full sample and where the FCIs, after being multiplied by –1 if needed, increase in value when financial conditions deteriorate. This is the case for all the full-sample regressions that predict returns, and for 78 percent of the full-sample regressions that predict innovations to macroeconomic variables.

Table 2. Summary Statistics of the Twelve FCIs

	Mean	Median	10th	90th	Value on Sept. 2008	# Obs.	90% CI for AR Root	
Daily								
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								
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								
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

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

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 in footnote 5, 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.[5] Note that both a persistent predictor and a non-zero correlation are necessary for the standard OLS asymptotics to be inappropriate.

The dependent variables in our predictive regressions are (i) returns on a broad market index and on various industry portfolios, and (ii) autoregressive residuals of log-changes in several economic variables; we study residuals because, unlike returns, changes in macroeconomic variables can be autocorrelated. 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 present the results for the predictability of stock returns in tables 4 through 7. 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 at the 90 percent confidence level.

[5]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 zero. 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 the Center for Research in Security Prices (CRSP) through Wharton Research Data Services. The macroeconomic data are from the Federal Reserve Economic Data (FRED) database of the Federal Reserve Bank of St. Louis. See table 3 for summary statistics and additional details on the construction of the industry portfolios.

Table 3. Summary Statistics of Industry Stock Returns and Log-Changes of Macro Variables

	Mean	Std. Dev.	Median	10th	90th	# Obs.
			Stock Returns			
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
Construction	0.012	0.080	0.016	−0.085	0.100	204
Manufacturing	0.012	0.073	0.015	−0.081	0.099	204
Transportation	0.009	0.061	0.017	−0.071	0.072	204
Wholesale Trade	0.012	0.067	0.020	−0.070	0.085	204
Retail 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			
C&I	0.004	0.010	0.005	−0.011	0.015	204
Consumer Credit	0.005	0.006	0.004	−0.003	0.009	204
Durable Goods	0.002	0.042	0.003	−0.047	0.049	204
Housing Starts	−0.003	0.069	−0.007	−0.089	0.080	204
Ind. Production	0.002	0.007	0.002	−0.006	0.009	204
Total Inventory	0.002	0.007	0.002	−0.008	0.010	204

Notes: 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 vairables. The industry portfolios are equally weighted and are built using CRSP data on the basis of Standard Industrial Classification (SIC) codes (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 Federal Reserve Bank of St. Louis'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). Time period: July 1995 to June 2012.

Table 4 shows results for the 1995–2012 sample, and it indicates that eleven of the twelve 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 portfolios 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 levels of financial stress (or tighter financial conditions) tend to be followed by lower returns.

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 5 we report the coefficients and RMSEs estimated over the 1995–2006 sample, and the results highlight that, essentially, there is no meaningful 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 (tables 6 and 7). Five FCIs have predictive power for returns on the S&P 500 or on the financial industry portfolio in the 1995–2012 sample. Similar to the monthly analysis, returns on the remaining industry portfolios are not predictable.

Restricting the sample to the pre-crisis period (1995–2006, table 7) all but eliminates the predictability, with the exception of the Morgan Stanley index, which can now predict returns on five 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 4). This difference is consistent with the possibility that measuring returns over longer horizons captures the early signs of a turning business cycle. The Morgan Stanley index may signal poor financial conditions when the business cycle is close to its trough, and, while one-month-ahead returns may still be negative as the economy bottoms out, one-quarter-ahead returns may already capture the initial pickup in economic activity.

Table 4. Predictive Regressions: Monthly Stock Returns, 1995–2012

	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
Construction	−0.164	8.079	−0.054	8.082	0.291	8.077	−0.227	8.079
Manufacturing	−0.263	7.265	−0.055	7.276	0.186	7.274	−0.415*	7.262
Transportation	−0.315	6.122	−0.119	6.138	0.005	6.141	−0.369*	6.127
Wholesale Trade	−0.303	6.676	−0.100	6.690	0.115	6.691	−0.301*	6.684
Retail 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
	ANFCI		**NFCI**		**CLN FSI**		**STLFSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	−0.069	4.652	−1.239*	4.596	−0.117	4.644	−0.511	4.622
Finance	−1.068*	4.545	−1.843*	4.491	−0.271*	4.573	−0.660*	4.567
Construction	−0.205	8.081	−0.500	8.077	−0.027	8.082	0.230	8.079
Manufacturing	0.020	7.276	−0.575	7.269	0.035	7.276	0.076	7.276
Transportation	0.042	6.141	−0.840	6.121	−0.057	6.139	−0.116	6.139
Wholesale Trade	−0.368	6.686	−0.697	6.680	0.074	6.690	0.080	6.692
Retail Trade	−0.417	7.226	−0.223	7.232	0.100	7.229	0.444	7.218
Services	0.279	8.392	−0.393	8.391	0.179	8.384	0.275	8.390

(*continued*)

Table 4. (Continued)

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

Notes: 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 3 for more details on the FCIs and for the definition of industry portfolios. Asterisks indicate significance at the 90 percent level. Statistical significance is evaluated on the basis of heteroskedasticity-consistent standard errors or, where appropriate, with the local-to-unity asymptotics of Campbell and Yogo (2006) (see section 2 for details). Time period: July 1995 to June 2012.

Table 5. Predictive Regressions: Monthly Stock Returns, 1995–2006

	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
Construction	0.524	6.737	0.057	6.751	1.080	6.703	−0.027	6.751
Manufacturing	0.979	6.980	0.351	7.019	1.739	6.907	0.045	7.028
Transportation	0.625	5.983	0.209	6.002	1.291	5.928	0.119	6.004
Wholesale Trade	0.715	6.170	0.210	6.196	1.192	6.135	0.310	6.190
Retail 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
	ANFCI		**NFCI**		**CLN FSI**		**STLFSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	1.117*	4.228	−0.070	4.279	0.045	4.278	−0.331	4.275
Finance	−0.547	3.380	0.214	3.395	0.156	3.382	0.889	3.366
Construction	0.096	6.751	1.120	6.746	0.242	6.735	1.149	6.726
Manufacturing	0.856	7.010	3.335	6.981	0.434	6.978	1.724	6.974
Transportation	1.027	5.975	1.169	5.999	0.242	5.988	0.773	5.993
Wholesale Trade	0.053	6.199	1.695	6.185	0.428	6.144	1.529	6.151
Retail Trade	−0.107	6.151	1.015	6.146	0.389	6.105	1.347	6.113
Services	1.542	8.892	3.748	8.891	0.732	8.825	2.440	8.853

(continued)

Table 5. (Continued)

	Citi FCI		IMF FSI		KCFSI		IMF FCI	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	−0.451	4.253	0.177	4.260	−0.493	4.268	−0.929	4.239
Finance	0.218	3.388	−0.069	3.392	−0.029	3.395	0.590	3.375
Construction	0.089	6.751	0.029	6.751	0.421	6.746	0.265	6.749
Manufacturing	0.401	7.016	0.267	7.003	1.005	7.001	0.396	7.024
Transportation	−0.063	6.005	0.248	5.980	0.373	6.001	−0.371	6.001
Wholesale Trade	0.222	6.195	0.084	6.196	0.575	6.189	0.606	6.188
Retail Trade	−0.020	6.151	0.029	6.151	0.479	6.144	0.838	6.129
Services	0.145	8.937	0.369	8.900	1.252	8.905	0.560	8.932

Notes: 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 3 for more details on the FCIs and for the definition of industry portfolios. Asterisks indicate significance at the 90 percent level. Statistical significance is evaluated on the basis of heteroskedasticity-consistent standard errors, or, where appropriate, with the local-to-unity asymptotics of Campbell and Yogo (2006) (see section 2 for details). Time period: July 1995 to December 2006.

Table 6. Predictive Regressions: Quarterly Stock Returns, 1995–2012

	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
Construction	−0.006	15.616	0.203	15.612	1.144	15.572	0.481	15.606
Manufacturing	−0.025	15.042	0.565	15.016	1.181	14.994	0.436	15.034
Transportation	−0.498	12.529	0.165	12.551	0.141	12.553	0.196	12.552
Wholesale Trade	0.179	14.199	0.714	14.156	0.919	14.171	1.210	14.135
Retail 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
	ANFCI		**NFCI**		**CLN FSI**		**STLFSI**	
	β_{FCI}	**RMSE**	β_{FCI}	**RMSE**	β_{FCI}	**RMSE**	β_{FCI}	**RMSE**
S&P 500	−0.946	9.019	−3.647*	8.787	−0.175	9.042	−1.171	8.972
Finance	−3.325*	8.917	−4.615*	8.900	−0.611	9.197	−1.387	9.206
Construction	−1.657	15.558	−1.267	15.597	0.432	15.581	1.217	15.566
Manufacturing	−1.195	15.011	−0.726	15.036	0.567	14.980	1.479	14.966
Transportation	−1.208	12.515	−2.066	12.493	0.187	12.545	0.559	12.540
Wholesale Trade	−1.626	14.140	−0.311	14.200	0.713	14.097	1.882	14.071
Retail Trade	−1.265	14.882	1.256	14.898	0.871	14.769	3.085	14.580
Services	−1.424	17.051	−0.701	17.085	0.981	16.926	1.947	16.974

(*continued*)

Table 6. (Continued)

	Citi FCI		IMF FSI		KCFSI		IMF FCI	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	−1.408	8.903	−0.078	9.047	−1.467*	8.918	−2.324*	8.756
Finance	−0.630	9.286	−0.494	9.148	−1.665*	9.147	−0.743	9.154
Construction	1.202	15.553	0.232	15.594	0.602	15.603	−0.173	15.615
Manufacturing	1.201	14.978	0.384	14.981	1.092	14.998	0.034	15.042
Transportation	0.050	12.553	0.206	12.532	0.054	12.553	−0.921	12.521
Wholesale Trade	1.122	14.142	0.448	14.113	1.456	14.118	0.653	14.187
Retail Trade	1.309	14.839	0.650	14.739	2.559	14.671	1.777	14.813
Services	0.861	17.061	0.440	17.019	1.339	17.032	0.235	17.088

Notes: 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 3 for more details on the FCIs and for the definition of industry portfolios. Asterisks indicate significance at the 90 percent level. Statistical significance is evaluated on the basis of heteroskedasticity-consistent standard errors or, where appropriate, with the local-to-unity asymptotics of Campbell and Yogo (2006) (see section 2 for details). Time period: July 1995 to June 2012.

Table 7. Predictive Regressions: Quarterly Stock Returns, 1995–2006

	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
Construction	3.094	13.512	1.314	13.707	2.639	13.638	1.062	13.717
Manufacturing	4.004	13.913	1.732	14.225	5.299	13.799	1.906	14.157
Transportation	2.077	11.938	1.020	12.025	2.769	11.899	1.734	11.893
Wholesale Trade	3.342	12.132	1.416	12.385	2.961	12.281	2.681*	12.052
Retail 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
	ANFCI		**NFCI**		**CLN FSI**		**STLFSI**	
	β_{FCI}	**RMSE**	β_{FCI}	**RMSE**	β_{FCI}	**RMSE**	β_{FCI}	**RMSE**
S&P 500	−1.628	8.301	−3.303	8.308	0.257	8.341	−0.956	8.342
Finance	−2.247	6.756	1.664	6.871	0.398	6.841	3.035	6.705
Construction	−2.492	13.696	2.746	13.755	0.958	13.644	4.777	13.552
Manufacturing	−1.420	14.315	5.456	14.262	1.710	13.933	6.194	13.977
Transportation	−0.722	12.065	−1.532	12.065	0.990	11.912	2.813	11.985
Wholesale Trade	−2.846	12.358	2.633	12.452	1.509	12.109	5.263	12.172
Retail Trade	−2.431	12.730	2.919	12.786	1.540	12.442	4.964	12.551
Services	−1.607	17.960	4.453	17.944	2.613*	17.222	8.253	17.471

(*continued*)

Table 7. (Continued)

	Citi FCI		IMF FSI		KCFSI		IMF FCI	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	−1.548	8.186	0.073	8.355	−1.730	8.284	−2.812	8.161
Finance	0.939	6.810	−0.399	6.814	0.438	6.881	2.134	6.750
Construction	1.388	13.693	−0.299	13.755	1.901	13.723	1.514	13.742
Manufacturing	1.877	14.195	0.197	14.331	2.813	14.229	1.485	14.309
Transportation	0.076	12.073	0.095	12.070	0.500	12.069	−0.890	12.059
Wholesale Trade	1.257	12.398	−0.125	12.469	1.673	12.428	1.710	12.425
Retail Trade	0.851	12.778	−0.185	12.803	1.745	12.763	2.553	12.707
Services	1.385	17.922	0.428	17.953	3.291	17.864	1.847	17.947

Notes: 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 3 for more details on the FCIs and for the definition of industry portfolios. Asterisks indicate significance at the 90 percent level. Statistical significance is evaluated on the basis of heteroskedasticity-consistent standard errors or, where appropriate, with the local-to-unity asymptotics of Campbell and Yogo (2006) (see section 2 for details). Time period: July 1995 to December 2006.

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 (table 8) 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 International Monetary Fund (IMF) FCI indexes predict all the variables; most other indexes predict at least three of the six variables. When the sample excludes the 2008 financial crisis (table 9), 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 10 and 11 (only the Morgan Stanley index can predict more variables in the short sample than in the full sample).[9]

[7]For the monthly series, 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. For the quarterly series, 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 8 and 9 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, and negative otherwise.

[9]In an unreported analysis, we obtain similar results when, instead of excluding the period around the financial crisis, we orthogonalize the innovations relative to the appropriately lagged Chicago Fed National Activity Index, which is a proxy for the current state of the economy. The similarity of the results when (i) excluding the crisis and (ii) controlling for the state of the economy is not surprising, especially in a relatively short sample like ours, because the financial crisis also coincided with a severe recession, which exerts a strong leverage effect.

Table 8. Predictive Regressions: Innovations to Monthly Log-Changes in Macroeconomic Variables, 1995–2012

	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
Consumer Credit	−0.034	0.519	−0.032	0.519	−0.047	0.519	0.018	0.521
Durable Goods	−0.883*	3.733	−0.765*	3.781	−0.920*	3.860	−0.667*	3.905
Housing Starts	−1.184*	6.241	−0.895*	6.344	−0.759*	6.456	−0.764*	6.448
Ind. Production	−0.120*	0.645	−0.094*	0.654	−0.167*	0.649	−0.126*	0.657
Total Inventory	−0.059*	0.437	−0.054*	0.438	−0.043	0.444	−0.071*	0.439
	ANFCI		**NFCI**		**CLN FSI**		**STLFSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
C&I	0.059	0.672	0.240*	0.658	−0.038	0.667	0.180*	0.647
Consumer Credit	−0.025	0.521	−0.129*	0.516	−0.017	0.520	−0.073*	0.516
Durable Goods	−1.147*	3.875	−2.366*	3.725	−0.317*	3.900	−1.153*	3.786
Housing Starts	−1.875*	6.342	−2.984*	6.265	−0.321*	6.457	−1.220*	6.376
Ind. Production	−0.051	0.670	−0.321*	0.645	0.072*	0.649	−0.162*	0.650
Total Inventory	−0.050	0.444	−0.143*	0.438	−0.021	0.443	−0.073*	0.439

(continued)

Table 8. (Continued)

	Citi FCI		IMF FSI		KCFSI		IMF FCI	
	β_{FCI}	**RMSE**	β_{FCI}	**RMSE**	β_{FCI}	**RMSE**	β_{FCI}	**RMSE**
C&I	0.119*	0.660	0.034*	0.661	0.168*	0.647	0.183*	0.649
Consumer Credit	−0.034	0.520	−0.013	0.519	−0.061*	0.517	−0.068*	0.517
Durable Goods	−0.834*	3.860	−0.335*	3.772	−1.247*	3.731	−1.356*	3.746
Housing Starts	1.162*	6.369	−0.414*	6.317	−1.282*	6.349	−1.390*	6.359
Ind. Production	0.180*	0.640	−0.044*	0.651	0.177*	0.643	−0.213*	0.638
Total Inventory	−0.075*	0.438	−0.017*	0.442	−0.071*	0.439	−0.106*	0.434

Notes: 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 3 for more details on the FCIs and on the macroeconomic variables. Asterisks indicate significance at the 90 percent level. Statistical significance is evaluated on the basis of heteroskedasticity-consistent standard errors or, where appropriate, with the local-to-unity asymptotics of Campbell and Yogo (2006) (see section 2 for details). Time period: July 1995 to June 2012.

Table 9. Predictive Regressions: Innovations to Monthly Log-Changes in Macroeconomic Variables, 1995–2006

	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
Consumer Credit	0.030	0.332	0.040	0.331	0.005	0.333	−0.029	0.332
Durable Goods	0.339	3.683	0.309	3.681	0.420	3.681	−0.170	3.690
Housing Starts	0.225	5.249	0.382	5.238	0.414	5.244	0.455	5.230
Ind. Production	0.138*	0.547	0.059	0.556	−0.092	0.555	−0.082*	0.552
Total Inventory	−0.040	0.383	−0.052	0.380	−0.022	0.384	−0.075*	0.375
	ANFCI		**NFCI**		**CLN FSI**		**STLFSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
C&I	−0.058	0.586	0.217	0.585	−0.057*	0.577	−0.221*	0.576
Consumer Credit	−0.058	0.332	−0.118	0.332	0.015	0.332	−0.016	0.333
Durable Goods	0.179	3.693	2.128	3.657	−0.185	3.677	0.667	3.679
Housing Starts	0.120	5.252	0.465	5.251	0.145	5.245	−0.827	5.236
Ind. Production	−0.054	0.559	0.363*	0.552	0.058*	0.548	0.153	0.554
Total Inventory	0.048	0.383	−0.179	0.382	−0.033*	0.379	−0.098	0.381

(*continued*)

Table 9. (Continued)

	Citi FCI		IMF FSI		KCFSI		IMF FCI	
	β_{FCI}	**RMSE**	β_{FCI}	**RMSE**	β_{FCI}	**RMSE**	β_{FCI}	**RMSE**
C&I	0.076	0.582	0.009	0.587	0.128	0.582	0.227*	0.570
Consumer Credit	0.021	0.333	0.020*	0.330	0.058	0.332	0.055	0.332
Durable Goods	−0.274	3.683	0.187	3.670	0.876	3.655	−0.807	3.659
Hous. Starts	−0.256	5.246	−0.091	5.249	0.144	5.252	0.490	5.244
Ind. Production	0.132*	0.542	0.041*	0.552	0.169*	0.550	−0.147*	0.552
Total Inventory	0.052	0.380	−0.016	0.383	−0.079	0.381	−0.149*	0.373

Notes: 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 3 for more details on the FCIs and on the macroeconomic variables. Asterisks indicate significance at the 90 percent level. Statistical significance is evaluated on the basis of heteroskedasticity-consistent standard errors or, where appropriate, with the local-to-unity asymptotics of Campbell and Yogo (2006) (see section 2 for details). Time period: July 1995 to December 2006.

Table 10. Predictive Regressions: Innovations to Quarterly Log-Changes in Macroeconomic Variables, 1995–2012

	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
Consumer Credit	−0.099	1.003	−0.122	0.996	−0.121	1.007	−0.029	1.014
Durable Goods	−1.858*	5.308	−1.637*	5.483	−1.413*	5.896	−1.450*	5.840
Housing Starts	−1.373*	8.645	−0.803	8.822	−1.077*	8.846	0.781	8.870
Ind. Production	−0.248*	1.291	−0.167	1.324	−0.371*	1.296	−0.348*	1.290
Total Inventory	−0.285*	1.112	−0.257*	1.128	−0.238*	1.175	−0.197	1.179
	ANFCI		**NFCI**		**CLN FSI**		**STLFSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
C&I	0.548*	1.314	1.238*	1.176	0.204*	1.298	0.752*	1.155
Consumer Credit	−0.064	1.014	−0.329	0.996	−0.014	1.014	−0.174	0.999
Durable Goods	−2.643*	5.679	−4.935*	5.311	−0.708*	5.824	−2.278*	5.604
Housing Starts	−2.657	8.651	−4.171*	8.562	−0.386	8.865	−0.784	8.878
Ind. Production	−0.061	1.349	−0.657*	1.292	−0.163*	1.291	−0.289*	1.317
Total Inventory	0.420*	1.151	−0.578*	1.150	−0.101*	1.175	−0.258*	1.171

(*continued*)

Table 10. (Continued)

	Citi FCI		IMF FSI		KCFSI		IMF FCI	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
C&I	0.526*	1.246	0.201*	1.191	0.780*	1.117	0.812*	1.132
Consumer Credit	−0.089	1.010	−0.038	1.006	−0.145	1.003	−0.208*	0.994
Durable Goods	−1.635*	5.765	−0.635*	5.637	−2.415*	5.508	−2.866*	5.369
Housing Starts	−1.025	8.834	−0.375	8.815	−1.163	8.829	−2.011*	8.690
Ind. Production	−0.384*	1.274	−0.117*	1.285	−0.393*	1.285	−0.430*	1.281
Total Inventory	0.334*	1.136	−0.094*	1.153	−0.282*	1.163	−0.375*	1.141

Notes: 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 3 for more details on the FCIs and on the macroeconomic variables. Asterisks indicate significance at the 90 percent level. Statistical significance is evaluated on the basis of heteroskedasticity-consistent standard errors or, where appropriate, with the local-to-unity asymptotics of Campbell and Yogo (2006) (see section 2 for details). Time period: July 1995 to June 2012.

Table 11. Predictive Regressions: Innovations to Quarterly Log-Changes in Macroeconomic Variables, 1995–2006

	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
Consumer Credit	0.058	0.607	0.028	0.609	0.094	0.606	−0.065	0.605
Durable Goods	0.956	4.426	−0.960	4.389	0.748	4.469	−0.768*	4.408
Housing Starts	1.513	5.349	1.758*	5.190	1.210	5.434	1.506*	5.203
Ind. Production	−0.261	1.097	−0.096	1.115	−0.087	1.118	−0.216*	1.089
Total Inventory	−0.364*	0.876	−0.374*	0.845	−0.232	0.915	−0.316*	0.851
	ANFCI		**NFCI**		**CLN FSI**		**STLFSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
C&I	0.061	1.172	1.375*	1.110	−0.191*	1.109	0.761*	1.104
Consumer Credit	−0.176	0.601	−0.352	0.602	0.030	0.607	0.027	0.609
Durable Goods	0.480	4.494	3.930	4.372	−0.492*	4.396	−1.337	4.450
Housing Starts	0.501	5.499	2.044	5.478	−0.336	5.467	2.546	5.347
Ind. Production	−0.160	1.116	−0.693	1.103	−0.118	1.095	−0.310	1.108
Total Inventory	0.009	0.931	−1.189*	0.872	−0.165*	0.872	−0.625*	0.873

(continued)

Table 11. (Continued)

	Citi FCI		IMF FSI		KCFSI		IMF FCI	
	β_{FCI}	**RMSE**	β_{FCI}	**RMSE**	β_{FCI}	**RMSE**	β_{FCI}	**RMSE**
C&I	0.344*	1.111	0.137*	1.121	0.699*	1.085	0.810*	1.052
Consumer Credit	0.050	0.607	−0.047	0.598	0.191	0.597	−0.066	0.608
Durable Goods	−0.413	4.481	−0.320	4.432	1.607	4.386	−2.054*	4.308
Housing Starts	0.255	5.500	−0.085	5.503	0.515	5.497	1.043	5.467
Ind. Production	0.362*	1.049	−0.142*	1.062	−0.426*	1.087	−0.303	1.103
Total Inventory	0.317*	0.865	0.142*	0.861	0.523*	0.870	−0.605*	0.847

Notes: 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 3 for more details on the FCIs and on the macroeconomic variables. Asterisks indicate significance at the 90 percent level. Statistical significance is evaluated on the basis of heteroskedasticity-consistent standard errors or, where appropriate, with the local-to-unity asymptotics of Campbell and Yogo (2006) (see section 2 for details). Time period: July 1995 to December 2006.

2.2 Granger Causality Tests

In the final part of our predictability analysis, we study the relation between each of the FCIs and selected measures of credit availability. Borio (2014) highlights that the financial cycle can amplify macroeconomic fluctuations and contribute to significant economic dislocations, and that one key component of the financial cycle is credit availability. Borio (2014) also suggests that peaks in the financial cycle are closely associated with financial crises, which implies that the results of our tests in this section can provide additional evidence on whether FCIs are a useful signal for an upcoming financial crisis. The measures of credit availability that we consider are consumer credit, mortgage credit, and the issuance of commercial mortgage-backed securities (CMBS), all expressed as a fraction of nominal gross domestic product. The last two variables are directly related to the real estate boom that set the stage for the 2008 financial crisis, with one of them also measuring the importance of credit provision through the securitization channel.[10]

We depart from the methodology of Campbell and Yogo (2006) when studying the relation between the FCIs and the measures of credit availability, and we conduct a series of Granger causality tests instead. The reason is that it is the overall level of credit availability, rather than its changes or innovations, that contributes to the buildup of financial vulnerabilities during financial booms and that sets the stage for future financial crises (see the discussion in Borio 2014). By using Granger causality tests based on quarterly vector autoregressions with an appropriate number of lags, we can focus on levels and still account for the persistence of both the FCIs and the credit availability variables. We use the procedure described in Toda and Yamamoto (1995) to account for the fact that the FCIs and the credit availability variables may not only be persistent but also potentially integrated in small samples.

[10]The consumer credit and mortgage credit data is from the Federal Reserve's Z.1 release. Consumer credit is series LA153166000.Q (household and non-profit organizations; consumer credit), while mortgage credit is series LA153165105.Q (household and non-profit organizations; home mortgages). CMBS issuance is total issuance less Fannie Mae/Freddie Mac, resecuritized, and foreign property issuance, and it is provided by Commercial Mortgage Alert. Nominal gross domestic product is the series GDP from the FRED database of the Federal Reserve Bank of St. Louis.

For each FCI/credit variable pair, we select the optimal number of vector autoregression lags (m) with the Schwarz Bayesian information criterion. We then use augmented Dickey-Fuller tests to determine each series' order of integration, and define n as the maximum order of integration for the two series. Next, we estimate a vector autoregression with $m + n$ lags. Using heteroskedasticity-consistent standard errors, we construct Wald test statistics to determine the joint statistical significance of the coefficients on the first m lags of the FCI in the equation for the credit availability variable, and the joint statistical significance of the coefficients on the first m lags of the credit availability variable in the equation for the FCI. These are the Granger causality tests, and the null hypothesis is that the coefficients are jointly zero. Table 12 reports the resulting p-values.

The top panel of table 12 shows the p-values of tests of whether the FCIs Granger-cause the indicated credit availability measure, and the bottom panel shows the results of tests that the credit availability measures Granger-cause the FCIs. In the left panels we use the full sample, which runs from 1995 to 2012. In the right panels we evaluate to what extent the results are affected by observations corresponding to the financial crisis by setting the 2008 observations of the dependent variables to missing.[11] We assess the robustness of the results to the financial crisis by excluding only one year (2008), because the credit availability variables have a strong trend before the crisis and only after 2007 do they exhibit significant variation (Borio 2014 highlights that the financial cycle evolves more slowly than the economic cycle). Truncating the sample after 2007 would have eliminated the variation that is likely most important for identifying the effect we are interested in.

In the full sample, consumer credit, mortgage credit, and CMBS issuance are Granger-caused by five, four, and three FCIs, respectively. After setting the 2008 observations of the credit availability measures to missing, no FCIs Granger-cause CMBS issuance, and three out of twelve still Granger-cause consumer credit and mortgage credit. Focusing on whether the FCIs are Granger-caused by credit availability, only six tests of the seventy-two that we report

[11] We set the observations to missing rather than dropping them to avoid using 2007:Q4 as the first lag for 2009:Q1.

Table 12. FCIs and Measures of Credit Availability: Granger Causality Tests

	Full Sample			Excluding 2008		
	CCR/GDP	**MTG/GDP**	**CMBS/GDP**	**CCR/GDP**	**MTG/GDP**	**CMBS/GDP**
FCIs Granger-Causing Credit Availability						
BFCI	0.12	0.17	0.34	0.36	0.20	0.66
BFCI+	0.20	0.16	0.69	0.72	0.62	0.75
CFSI	0.62	0.51	0.06*	0.68	0.57	0.16
MS FCI	0.65	0.74	0.98	0.87	0.80	0.59
CLN FSI	0.21	0.90	0.56	0.21	0.93	0.71
NFCI	0.03**	0.06*	0.10	0.07*	0.20	0.23
ANFCI	0.04**	0.40	0.07*	0.27	0.06*	0.30
STLFSI	0.13	0.02**	0.21	0.20	0.16	0.16
KCFSI	0.07*	0.06*	0.16	0.13	0.15	0.33
Citi FCI	0.01***	0.43	0.23	0.02**	0.26	0.73
IMF FCI	0.01***	0.14	0.09*	0.01***	0.08*	0.11
IMF FSI	0.34	0.06*	0.51	0.46	0.05**	0.61

(*continued*)

Table 12. (Continued)

	Full Sample			Excluding 2008		
	CCR/ GDP	**MTG/ GDP**	**CMBS/ GDP**	**CCR/ GDP**	**MTG/ GDP**	**CMBS/ GDP**
Credit Availability Granger-Causing FCIs						
BFCI	0.42	0.19	0.93	0.17	0.27	0.63
BFCI+	0.23	0.09*	0.66	0.07*	0.32	0.45
CFSI	0.27	0.82	0.33	0.39	0.73	0.56
MS FCI	0.11	0.80	0.78	0.07*	0.56	0.34
CLN FSI	0.17	0.72	0.25	0.19	0.54	0.12
NFCI	0.61	0.30	0.81	0.41	0.78	0.84
ANFCI	0.95	0.44	0.18	0.77	0.92	0.50
STLFSI	0.29	0.14	0.61	0.15	0.36	0.52
KCFSI	0.98	0.06*	0.50	0.27	0.71	0.70
Citi FCI	0.10	0.72	0.34	0.10*	0.94	0.65
IMF FCI	0.56	0.05**	0.33	0.41	0.16	0.26
IMF FSI	0.75	0.40	0.73	0.80	0.53	0.89

Notes: The table shows p-values from tests that the given FCI Granger-causes the indicated measure of credit availability (top panel) and that the given credit availability measure Granger-causes the indicated FCI (bottom panel). The measures are consumer credit over nominal GDP (CCR/GDP), mortgage credit over nominal GDP (MTG/GDP), and issuance of commercial mortgage-backed securities over nominal GDP (CMBS/GDP). We choose the number of lags for the vector autoregressions underlying the tests by summing the optimal lag chosen with the Schwarz Bayesian information criterion and the maximum order of integration of the two series in the vector autoregression chosen with augmented Dickey-Fuller tests (Toda and Yamamoto 1995). We conclude that there is Granger causality if a Wald test rejects the null hypothesis that the lagged values of the independent variable are equal to zero. Note that, following Toda and Yamamoto (1995), we only test that the first m lags are equal to zero, where m is the number of lags identified as optimal with the Schwarz criterion. The symbols ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

in the bottom panel reject the null of no Granger causality. These results suggest that, if we exclude 2008, neither the FCIs nor the credit availability measures Granger-cause each other. The reason is that only six tests out of thirty-six (16.7 percent) reject the null that the FCIs do not Granger-cause the credit variables, and the number drops to three out of thirty-six (8.3 percent) when we test whether the credit variables Granger cause the FCIs. In both cases, the incidence of rejections is roughly in line with the expected number of false positives for tests that have a significance level of 10 percent. In the full sample, the evidence is less clear on whether the FCIs Granger-cause the credit variables, because twelve tests out of thirty-six (33.3 percent) reject the null of no Granger causality. The number of tests that reject the null that the credit variables do not Granger-cause the FCIs remains three out of thirty-six.

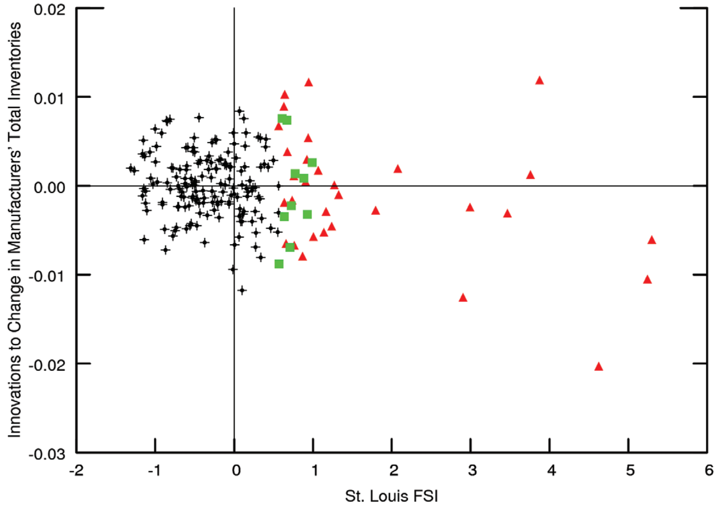
2.3 Interpreting Our Results

Overall, our opinion is that the empirical evidence in favor of the FCIs having reliable predictive power is weak. Given that the FCIs are built by combining public data for typically highly liquid financial instruments, they can hardly be characterized as containing privileged information. We discuss three possible explanations for the predictability we find in some of our results: threshold effects, data mining, and non-synchronous trading. We ultimately conclude that those results are mainly driven by data mining and by non-synchronous trading.

The predictability could be the result of threshold effects, in that financial conditions matter only after they deteriorate sufficiently.[12] In figure 2 we show a scatter plot of innovations to log-changes of total inventories against the St. Louis FCI, where observations for which the index is above its 80th percentile are highlighted by different shapes. Triangles indicate an observation from between

[12] 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).

Figure 2. Threshold Effects



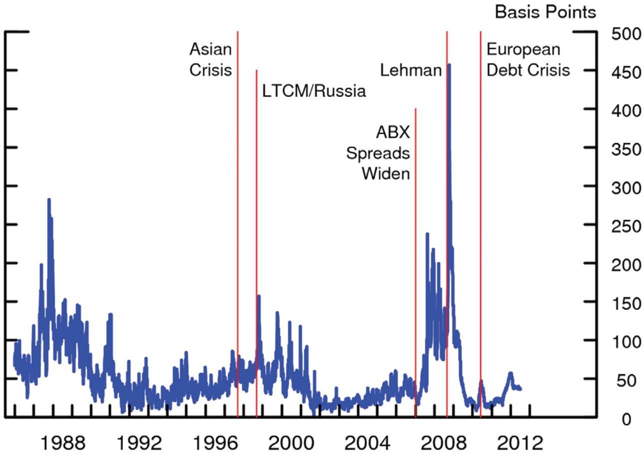
Notes: The plot shows a scatter of innovations to log-changes in total inventories against the Federal Reserve Bank of St. Louis's Financial Stress Index. The squares and triangles correspond to observations for which the index is above its 80th percentile, with the triangles indicating an observation from between 2007 and 2012 and the squares indicating an observation from outside that range. Time period: July 1995 to June 2012.

2007 and 2012, and squares indicate an observation from outside that range.[13]

The evidence in figure 2 does not clearly point to a threshold effect. There is indeed a negative relationship between the FCI and log-changes in inventories; however, this negative relationship is strong only in the observations from the recent crisis. One possible explanation is that the variables underlying the many FCIs constructed after the 2008 crisis were chosen based on their movements during the crisis. For instance, the FCIs typically include variables like the spread between three-month LIBOR and the three-month Treasury-bill rate (the TED spread), which had unusually large movements during the 2008 crisis. Figure 3 shows the time series of

[13]Figure 2 is representative of other index/variable combinations. The unreported figures are available upon request from the authors.

Figure 3. Time Series of the TED Spread



Notes: 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 the "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.

the TED spread from 1986 onwards, and it highlights the unusually high level of the TED spread that was a feature of the 2008 financial crisis. Unfortunately, in practice it is difficult to distinguish a threshold effect from possible data mining, not least because only one major financial crisis is included in the sample.

Another potential source of predictability is non-synchronous trading across markets. Many FCIs, for instance, include the implied volatility index VIX, which is derived from the prices of S&P 500 index options. These options trade for fifteen minutes after trading in the underlying index ends (4:15 p.m. versus 4:00 p.m. eastern standard time)[14] 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 predictability (see Atchison, Butler, and Simonds 1987 for a discussion of the effects of non-synchronous

[14]Details on the trading hours of S&P 500 index options can be found at http://www.cboe.com/products/indexopts/spx_spec.aspx

trading on the autocorrelation of equity index returns). We explore this possibility by running predictive regressions on returns that exclude the first day of each holding period.

Table 13 shows that now only five of the twelve FCIs have statistically significant predictive power for the finance portfolio, down from eleven in table 4, suggesting that non-synchronous trading does play a role but is not the sole driver of predictability. In unreported results, we find that excluding the first day of each quarter does not change the significance patterns of tables 6 and 7; most likely, the effect of non-synchronous trading is diluted by the larger variation of returns measured over longer horizons.

The notion that FCIs only have weak predictive power is also supported by a series of Granger causality tests. These tests focus on the dynamic relation between the FCIs and a set of measures for the availability of consumer credit, mortgage credit, and CMBS issuance. Two of these variables are closely related to the housing boom that characterized the 2000s, and CMBS issuance also measures the importance of the securitization channel for the provision of commercial real estate credit. Even though both the variables of interest and the statistical approach are different than in the predictive regression analysis, this additional set of results supports our main conclusion that the FCIs do not have predictive power if one excludes the 2008 financial crisis from the sample.

Finally, we should emphasize that we do not conduct an out-of-sample analysis, which would be a more stringent test of predictability, because our in-sample analysis already finds a lack of reliable predictive power.

3. Combining FCIs

We now turn to the question of how to consolidate the increasingly large number of indexes into a single proxy for financial conditions. The FCIs themselves are already an aggregation of underlying variables, and 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 reducing model uncertainty for policymakers. As discussed in the introduction, the various FCIs follow similar long-run trends, but they can give significantly different readings on financial conditions at a given point in time (e.g.,

Table 13. Predictive Regressions: Monthly Stock Returns Excluding the First Day of the Month, 1995–2012

	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
Construction	0.071	8.295	0.198	8.289	0.438	8.283	0.192	8.293
Manufacturing	−0.060	7.146	0.124	7.144	0.314	7.139	−0.039	7.146
Transportation	−0.156	6.067	0.013	6.072	0.117	6.070	−0.057	6.071
Wholesale Trade	−0.091	6.529	0.091	6.529	0.238	6.526	0.086	6.530
Retail 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
	ANFCI		**NFCI**		**CLN FSI**		**STLFSI**	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	0.113	4.633	−0.670	4.617	−0.041	4.632	−0.193	4.629
Finance	−0.922*	4.580	−1.349*	4.567	−0.197	4.610	−0.386	4.616
Construction	0.039	8.295	0.188	8.295	0.078	8.293	0.602	8.271
Manufacturing	0.131	7.146	−0.081	7.146	0.121	7.140	0.355	7.137
Transportation	0.129	6.071	−0.422	6.067	0.008	6.072	0.103	6.071
Wholesale Trade	−0.199	6.529	−0.186	6.530	0.147	6.521	0.361	6.520
Retail Trade	−0.175	7.189	0.364	7.187	0.187	7.177	0.762	7.147
Services	0.369	8.145	0.042	8.150	0.258	8.127	0.521	8.132

(*continued*)

Table 13. (Continued)

	Citi FCI		IMF FSI		KCFSI		IMF FCI	
	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE	β_{FCI}	RMSE
S&P 500	−0.318	4.619	0.050	4.630	−0.329	4.619	−0.633*	4.592
Finance	−0.260	4.625	−0.121	4.612	−0.540*	4.596	−0.547	4.603
Construction	0.189	8.293	0.183	8.267	0.360	8.286	0.160	8.294
Manufacturing	0.173	7.144	0.125	7.131	0.192	7.143	−0.085	7.146
Transportation	−0.139	6.070	0.067	6.066	−0.041	6.071	−0.399	6.059
Wholesale Trade	0.089	6.530	0.078	6.524	0.159	6.528	0.054	6.531
Retail Trade	0.155	7.188	0.204	7.151	0.531	7.167	0.424	7.179
Services	0.048	8.150	0.147	8.132	0.296	8.144	0.003	8.150

Notes: 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 3 for more details on the FCIs and for the definition of industry portfolios. Asterisks indicate significance at the 90 percent level. Statistical significance is evaluated on the basis of heteroskedasticity-consistent standard errors or, where appropriate, with the local-to-unity asymptotics of Campbell and Yogo (2006) (see section 2 for details). Time period: July 1995 to June 2012.

see figure 1). When aggregating the FCIs, we first select a smaller subsample of indexes, and then search for the "best" combination.

In the first step, 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[15] 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 $i = 1, \ldots, 12$ and "fpc" the first principal component,

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

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 over 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.

Three aspects of our setup warrant further discussion. First, the ranking criterion does not compare the FCIs with a benchmark, because financial conditions are an unobservable factor. We also do not use forecasting errors to select or optimally combine the various predictors (e.g., Timmermann 2006), because in the first part of the paper we find that FCIs are not particularly reliable at forecasting either returns or macroeconomic variables. Second, it is in principle possible that a regression yields a low R^2 because index i is a radically better proxy for financial conditions and does not span the remaining FCIs. However, the overlap and the encompassing nature

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

Table 14. Explanatory Power of FCIs

	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

Notes: The table reports the adjusted R^2s (in %) of robust regressions (Hamilton 1991) of (i) 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 labeled "ΔPC"), and of (ii) 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 labeled "Res.Δ").

of the variables that underlie the different indexes make such a possibility unlikely. Third, we choose to select *five* FCIs, and the choice of this number is admittedly arbitrary, but the key point is that we are able to reduce the number of combinations we consider, thus lowering the likelihood that our results are driven by data mining.

In the second step we form all combinations of the five indexes selected above,[16] calculate each combination's first principal component, and regress[17] changes in the first principal component of the FCIs that are not in the combination under consideration (out of the twelve we study) 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 subsample. 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

[16]We form thirty-one 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.

[17]We again use robust regressions (see Hamilton 1991).

Table 15. Explanatory Power of the First Principal Component of FCI Combinations

Combination	7/95–6/12	7/95–12/06	7/95–12/98	1/99–12/05	1/02–12/05	1/06–6/12	Average Squared Deviation				
							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

(continued)

Table 15. (Continued)

Combination	7/95–6/12	7/95–12/06	7/95–12/98	1/99–12/05	1/02–12/05	1/06–6/12	Average Squared Deviation				
							A	B	C	D	E
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

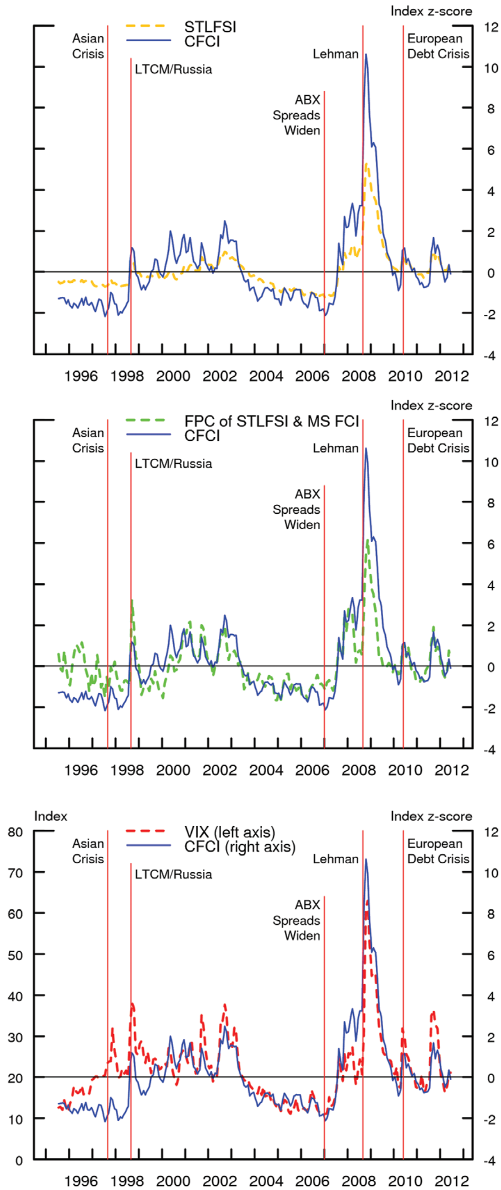
Notes: The first six columns report the adjusted R^2s (in %) of robust regressions (Hamilton 1991) of (i) changes in the first principal component of all the FCIs (aside from those indicated in each row) on changes on the first principal component of the indicated FCI combination (the results for individual 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–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).

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 only assumes that (i) all the indexes we study provide some information about financial conditions, and (ii) none of the indexes is likely to contain uniquely accurate information about financial conditions.

The results in table 15 show (in bold) 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)–(E): hence we consider such combination 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 graphs in figure 4 show the CFCI against three alternative proxies for financial conditions: STLFSI, which is the best-performing individual FCI; the first principal component of STLFSI and of the index with the lowest correlation with STLFSI (MS FCI); and the implied volatility index VIX, which is one of the variables underlying many FCIs. The CFCI tracks 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.

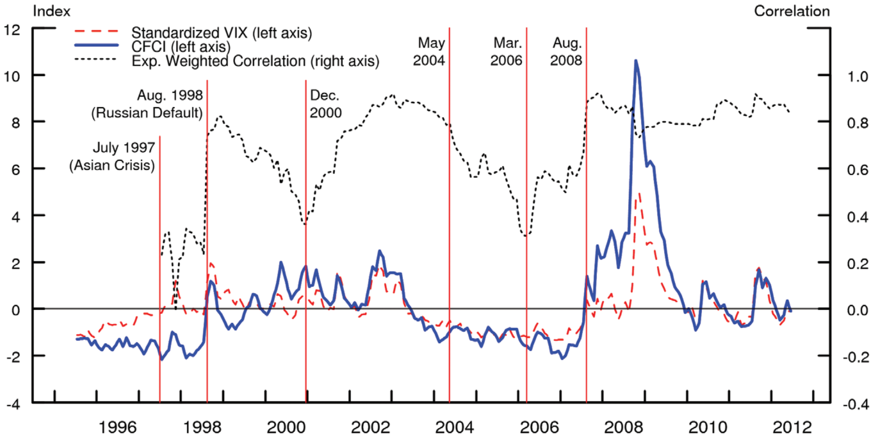
A comparison of VIX and the CFCI shows that the two track each other quite well, with the exception of the period between mid-2007 and late 2008, when VIX remains stable, and the CFCI shows a largely steady deterioration in financial conditions. In addition, the CFCI points to loose financial conditions 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 5, we plot the twenty-four-month exponentially weighted rolling correlation between VIX changes and changes in the CFCI, where observations are weighted so that the weight decays by 50 percent every twelve months (see figure 5 for details). The correlation is initially

Figure 4. The Composite FCI and Other Proxies of Financial Conditions



Notes: Each of the three graphs shows the composite FCI (CFCI, solid line) against one of three alternative proxies for financial conditions: the STLFSI (top graph), which is the individual FCI that best summarizes the information in the remaining FCIs (see table 14); the first principal component of the STLFSI and of the index that is least correlated with the STLFSI (the MS FCI—middle graph); and the implied volatility index VIX (bottom graph). VIX data are from the Chicago Board Options Exchange.

Figure 5. Exponentially Weighted Correlation between VIX Changes and Changes in the Composite FCI



Notes: The graph shows exponentially weighted correlation (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 (dashed line), and the composite FCI (CFCI, solid line). The correlation is calculated on the basis of a twenty-four-month rolling window, where the weights decay by 50 percent every twelve 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 $\alpha = 1 - e^{\frac{-ln(4)}{24}}$.

low, but it jumps to about 80 percent with the Russian default in August 1998. With the exception of two relatively short periods in late 2000 and 2005/06, it stays mostly above 50 percent, and it has been around 80–90 percent since the events of the late summer of 2008.

4. Conclusion

We provide an assessment of the one-month-ahead and one-quarter-ahead predictive power that a selection of financial conditions indexes (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. Our analysis is based on local-to-unity asymptotics, which allows for accurate statistical inference in the presence of persistent predictors. We find that the evidence for predictive power at the horizons we consider is generally weak, unless the financial crisis is included. Further, part of the predictive power is driven by the effects of non-synchronous trading and, potentially, data mining. We also study the relation between the FCIs and consumer credit, mortgage credit, and the issuance of commercial mortgage-backed securities, and find only limited evidence that the FCIs Granger-cause these variables. Based on these results, we conclude that FCIs are better used as aggregate indicators of current financial conditions.

We also observe that, even in the months leading to the 2008 financial crisis, different FCIs can provide conflicting assessments of financial conditions. We suggest a procedure for combining the various FCIs into a single proxy, which can help reduce the uncertainty facing policymakers when monitoring financial conditions. Our procedure builds on the modest assumptions that all the FCIs we study provide some information about financial conditions, yet no index contains uniquely accurate information.

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