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Abstract

Financial conditions indexes (FCIs) may be useful tools for policymakers because they may have the ability to summarize overall financial conditions for households and companies and at the same time provide timely information on real economic activity. A monthly FCI for Norway is constructed by using principal components based on 13 financial variables. Real-financial linkages are examined by correlation analyses and by analyzing in- and out-of-sample fit of a regression model. Through this exercise the FCI is found to be a useful leading indicator of Norwegian GDP growth. Alternative FCIs are also considered, in particular an FCI based on variables purged of business cycle effects.

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1 Introduction

The recent financial crisis and the economic downturn that followed have brought to the fore the importance of financial conditions and how they may affect the overall economy. As financial markets develop and come to play a greater role, the information set available to policymakers expands as new financial products emerge. At the same time, it becomes harder to gauge the overall state of financial conditions, with individual variables possibly giving mixed signals. This poses a challenge for monetary policy.

In preparing for policy decisions, Norges Bank analyzes the state of the economy. This work is partly guided by models. The financial sector and financial factors are, however, far from adequately captured in models used for policy (Woodford, 2010). Furthermore, a number of indicators of financial conditions are observed and subject to discretionary judgment. As the information set is vast, it can be useful to follow summary statistics capturing a broader picture in a few single measures. A financial conditions index (FCI) may be suitable in this respect. Springing out from the literature on monetary conditions indexes (MCIs), intended to capture the overall stance of monetary policy, the more comprehensive FCIs are created to provide information about the broader financial conditions and their impact on economic activity. As methods and financial variables differ between FCIs, the exact focus, use and interpretation varies across indicators. In some cases FCIs measure the tightness/accommodativeness of financial factors relative to their historical average, while other indexes illustrate financial conditions' contribution to growth. Some indexes are closely related to policy making in as much as index values can be interpreted in terms of interest rate equivalents (see e.g. Beaton, Lalonde and Luu (2009)). Other indexes are more oriented towards forecasting and may be used as leading indicators as they can provide timely information about economic activity. Whether an FCI mainly captures financial variables' response to economic activity, or if it is more of an indicator of financial conditions' impact on real activity, depends on how it is constructed, although this distinction is not always made clear. However, in both instances an FCI can provide early and leading information as financial data typically are available well in advance of quarterly national statistics.

A number of FCIs have already been constructed, both by central banks, international organizations and private institutions. However, no such indicator has so far been developed for the Norwegian economy. Inspired by existing FCIs for other economies and adapting to a Norwegian framework, the construction of a financial conditions index for Norway is thus the main focus of this paper.[1,2] Several methods have been used to construct FCIs. Here, an underlying factor is estimated by using the method of principal components. This procedure allows for the inclusion of a large number of financial variables, yet a parsimonious model is retained. The estimated factor is taken as a measure of financial conditions, which in turn are expected to provide information about real economic activity. To examine the possible real-financial linkages, correlation analyses and analyses of in- and out-of-sample fit of a regression model are performed and supplemented with graphical inspections. The FCI is found to be a useful leading indicator of real economic activity: It is easy to estimate and available on a monthly basis. An alternative version of the index is also considered, where the FCI is based on financial variables purged of business cycle effects. This adjustment is done in order to create an FCI reflecting financial variables' impact on economic growth, without including their endogenous response to real economic activity. Although both versions of the index can be used, the unpurged version is chosen as the preferred FCI for Norway.

The rest of the paper is organized as follows: Further motivation for and discussion of an FCI is provided in section 2, while the method is presented in section 3. Data and related issues are discussed in section 4. In section 5 principal components are estimated and real-financial linkages are examined through correlation analysis and by analyzing in-and out-of-sample fit of a regression model. In section 6 the preferred FCI for Norway is presented, together with an alternative FCI purged of business cycle effects. A few words of caution are noted in section 7, before a short conclusion is provided in section 8.

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[1] This paper provides a summary of the work presented in Vonen (2011).

[2] Work related to the role of financial conditions in Norway does however exist, see e.g. Langbraaten (2001) and Bjørnland and Jacobsen (2010) on the role of asset prices for monetary policy, Gerdrup, Hammersland and Naug (2006), Aastveit and Trovik (2010) and Næs, Skjeltorp and Ødegaard (2011) on the relationship between financial variables and the real economy, and Brubakk and Natvik (2010) for the inclusion of financial frictions in a policy model.

2 The importance of financial conditions and the role of FCIs

As monetary policy makes itself felt by altering financial conditions, an FCI can be expected to be useful for policymakers. Following Hatzius et al. (2010, p. 1), financial conditions can be defined as “(...) the current state of financial variables that influence economic behavior and (thereby) the future state of the economy.” Descriptions of the monetary transmission mechanism are thoroughly covered elsewhere; see e.g. Boivin, Kiley and Mishkin (2010) and Norges Bank (2004). To put it shortly, a wide range of variables may have a bearing on households’ and firms’ spending and investment behavior. In addition to interest and exchange rate effects, asset prices such as house and stock prices are of importance. Furthermore, credit availability, risk premiums and liquidity conditions in various financial markets are also relevant features of the overall financial conditions. Data for such measures are thus relevant components of an FCI.

There are several reasons to believe that asset prices (and other financial variables) can provide valuable information about current and future economic activity (see Gerdrup, Hammersland and Naug (2006), among several others). First of all, asset prices reflect expectations about future economic developments, and thus they are often said to be forward-looking. Second, asset prices may affect the economy with a lag, and finally, asset prices are updated frequently with a rather short time lag, and are seldom subject to revisions.

Financial variables are both affected by and have an impact on the real economy. What is less obvious is how to assess the quantitative effects and strengths of the various links. Complicating things further, there are also other factors than monetary policy that affect financial conditions. And finally, the links between the policy rate and financial conditions, as well as those between financial conditions and real activity, are likely to vary (Hatzius et al., 2010). In light of the possible interactions and effects mentioned above, the policymaker’s task of deciding on the appropriate level of the policy rate, or on the use of less conventional policy instruments for that matter, may seem daunting. A lot of information is subject to discretionary judgment. Individual variables may give mixed signals, and the appropriate weight given to various aspects is not necessarily known.

This is where a financial conditions index (FCI) may be introduced as a helpful, albeit crude tool. A single indicator capturing the overall financial conditions may provide a useful guideline when making policy decisions. FCIs have already been constructed for several countries, based on various methodologies and taking on different interpretations and uses. The literature on FCIs may be seen as springing out from the work on the more narrow monetary conditions indexes (MCIs) during the 1990s (Hatzius et al. (2010). These MCIs were weighted averages of an interest rate and an exchange rate, attempting to capture the overall stance of monetary policy. Over time, more variables have been included, and other methodological approaches have been employed in order to construct broader indicators, known as financial conditions indexes. The methods most commonly used can be divided in two broad groups: (i) A weighted-sum approach and a (ii) principal components (PC) approach (Hatzius et al., 2010).

(i) In the first approach, each variable is given a weight in the FCI according to the relative impact of a change in that variable on real economic activity. These weights are in turn determined in one of three different ways: By estimating a structural/large scale macro model, by using reduced form demand equations or by use of vector autoregressions (VAR).

(ii) In the second approach, one or several underlying factors are estimated from a larger set of variables. As these factors are unknown, they need to be estimated, and this is often done by use of the principal components method. The first such principal component captures the largest share of variation among the included variables, and this primary principal component is often used as an FCI in itself.

For construction of the Norwegian FCI, the latter approach is chosen, and this method is briefly described in the following section.

3 Methodology – estimating factors by principal components

A number of the most recently published papers on FCIs make use of factor estimation for FCI construction, using one or combinations of several estimated factors as an FCI. Relevant examples are Hatzius et al. (2010), Brave and Butters (2010) and Skaarup, Duschek-Hansen and Nielsen (2010), among others. One attractive feature of this approach is that it allows for the incorporation of a broad number of variables in a parsimonious way. This contrasts the weighted-sum approach mentioned above, where only a small number of varibles can be included.

The approach taken in paper is closely related to the work of Hatzius et al. (2010) and Skaarup, Duschek-Hansen and Nielsen (2010). For a more in-depth and technical derivation of factor models and the use of principal components, see e.g. Stock and Watson (2002a); here, a brief description is provided.[3]

Many macroeconomic time series tend to co-vary over time, and this has been exploited in business cycle analysis for several decades (Stock and Watson, 2002b). One may hypothesize that a few underlying factors govern the movement in a larger number of series. Assuming such a factor representation of the data is appropriate, factors are related to the observable variables (in this case a set of financial variables) in the following way: Let N be the number of variables x_i, $i = 1, \dots N$, and T be the number of time period observations included in the analysis, $t = 1, \dots T$. The time t observation of a given variable x_i can then be expressed as

$$\begin{aligned} x_{it} &= \lambda_i F_t + e_{it} \\ &= C_{it} + e_{it} \end{aligned} \qquad (3.1)$$

where F is the underlying factor. The relationship between a given factor and an observable variable is given by the so called factor loadings, λ_i.These loadings will in general differ between the variables, and for each variable there is one factor loading associated with each of the underlying factors. $C_{it} = \lambda_i F_{it}$ is referred to as the common component of the model. e_{it} is the idiosyncratic or variable specific component reflecting the "uniqueness" in each variable, that is, the part of the variation in a series which is *not* common to all the included variables.

The underlying factors are not observable themselves, and therefore they need to be estimated. As for several other FCIs, principal components are used for this purpose. The first principal component accounts for the largest share of total variance in the data. The next principal components are labeled according to the declining share of variance accounted for. Note that all the principal components are orthogonal to each other; a given principal component is uncorrelated with all the other principal components. In total, the number of principal components is equal to the number of original variables in the dataset.[4] However, a substantial

[3] The following paragraphs are largely based on Stock and Watson (2002a), Johnson and Wichern (1992) and Theil (1971).
[4] In order to make the variables comparable, they are standardized before being transformed to principal components. Standardization implies that the variance of each variable equals one, and therefore the total variance in the dataset is equal to the number of variables N.

share of the total variance can usually be accounted for by only a few principal components, and the method is thus an efficient way of reducing the data dimension.[5]

In the classical factor model, the factors and the idiosyncratic components are assumed to be cross-sectionally and serially uncorrelated. These assumptions are not likely to be fulfilled for the variables used in macroeconomic time series analysis. However, so-called approximate factor models allows the idiosyncratic terms to be "weakly" correlated both cross-sectionally and over time, and these models are also more suitable for large N and T. Given the appropriate assumptions, consistent estimates of the underlying factors can still be obtained. Furthermore, it can be shown that principal components are sufficiently accurate estimates for these to be included in subsequent regression analysis (Hatzius et al., 2010). Before principal components are calculated and analyzed, data series and related issues are presented and discussed in the following section.

4 Data

The choice of which data to include in an FCI is both a question of economic and financial structure, data availability and limitations posed by the econometric method. The 13 variables included in the Norwegian FCI are listed in table 4.1. For details on data sources and transformations, see table A1 at the end of the paper.[6]

Ideally, the FCI should provide a broad coverage of the Norwegian financial market, and the list of variables thus includes data both from the stock market, money market, bond market and the foreign exchange market. Furthermore, the list contains variables concerning both firms' and households' behavior. During recent years, financial innovation has been an important feature of many economies. This is reflected in the vast number of financial series used by Hatzius et al. (2010) and Brave and Butters (2010), who use 45 and 100 series respectively in constructing their FCIs. Even though the Norwegian financial sector also has grown during recent years, this expansion has come more along traditional lines of credit to households and businesses and less

[5] This requires however that there is some correlation between the variables. If the included variables are completely uncorrelated, each of the principal components will account for the same amount of variation (the variance of each equals one), and thus the original variables are only expressed in terms of a different set of coordinates, while nothing is gained in terms of parsimony.

[6] As calculation of principal components usually requires stationary data, the series have been transformed to induce stationarity where relevant.

as a consequence of financial innovation in terms of securitization etc. (Norwegian Official Report, 2011). This fact may indicate that the relevant range of variables for the Norwegian case is somewhat narrower. But more importantly, as any “new” variables in principle are interesting to include in an FCI, some series are left out due to the limitation imposed by the rather simple econometric framework employed. In constructing the Norwegian FCI, a balanced data panel is used such that all data series need to be of the same length, and they should also be available as far back as from 1993. Furthermore, a high-frequent FCI is desirable, and therefore series of no lower than monthly frequency are included.[7]

Table 4.1: Financial variables included in the principal components.

Financial variables	**Short name**
Spread between interest rates on 10 year govt. bonds – 3 month govt. bills	10yr3mth
Trade weighted real exchange rate (TWI)	TWI
Stock market index	Stock
House prices	House
Oil price	Oil
Credit (C1), general public	C1 gp
Credit (C2), non-financial enterprises	C2 nfe
Credit (C2), from commercial banks	C2 bank
Money supply (M1)	M1
Money supply (M2), non-financial enterprises	M2 nfe
Relative spread (stock market illiquidity measure)	RS
Amihuds’ illiquidity ratio (stock market illiquidity measure)	Amihud
Three month NIBOR	NIBOR

In addition to its role as an indicator of financial conditions, the FCI should also be able to provide information about real economic activity. Both these features affect the choice of data. With these aims in mind, the included series are chosen based on both theoretical considerations as well as being empirically guided. For example, interest rates, exchange rates, house and stock prices are important components of the monetary transmission mechanism, and are thus relevant aspects of financial conditions. Furthermore, a number of asset prices are found to have predictive ability for real economic activity, such as the term spread and stock prices (see e.g.

[7] Admittedly, it is possible to estimate factors based on an *unbalanced* data panel with series of *mixed* frequencies, such as in Brave and Butters (2010). However, these possible extensions are left for future work.

Stock and Watson (2003) for a broad survey). In a related manner, both money supply and credit variables may carry information about real economic activity; see e.g. Gerdrup, Hammersland and Naug (2006) for a survey of Norwegian data. Furthermore, empirical work on both Norwegian and US data indicates that stock market illiquidity measures may function as leading indicators of developments in real activity (Næs, Skjeltorp and Ødegaard, 2011). Two such measures, the relative spread and Amihud's illiquidity ratio, are therefore included in the Norwegian FCI.

Some potentially relevant variables are left out due to too short data series. Among these are credit surveys, various credit spreads, the LIBOR-OIS spread for the money market and a VIX-index for the stock market. In particular, credit surveys are found to be important components of other FCIs, see e.g. Swiston (2008) and Hatzius et al. (2010). Norges Bank's Survey of Bank Lending could have served a purpose similar to that of the US SLOOS data, but the former is only available from 2007.[8] These excluded variables, as well as other, more recent series, will be even more relevant to include as time passes by, if the data sample starts at a later date or if an unbalanced panel is used.

Summing up, the list of included variables may not seem very long, especially when considering the fact that a large number of variables in principle can be used. However, the number of series is higher than what could easily have been included in a VAR. Furthermore, as pointed out by Boivin and Ng (2006), more data need not be better for factor estimation, as additional series may contain a lot of noise without contributing much to the common variance in the data. Actually, at the onset of the work with the Norwegian FCI a larger dataset was used. However, this dataset gave a rather unbalanced picture of financial conditions in Norway, with too much weight given to stock market variables. Moreover, the resulting principal components were less informative of real economic activity. This example may illustrate the need for careful consideration of which data to include even though the use of a large number of series is possible. On this note it may be worth mentioning that the preferred choice among two alternative FCIs in Gomez, Murcia and Zamudio (2011) is the one based on a smaller set of variables.

[8] Furthermore, it is only available on a quarterly basis.

5 Principal components and regression results

The dual purpose of the FCI – that is, the wish to capture some broad notion of financial conditions, which in turn can provide information about real economic activity – naturally leads to a two-step empirical procedure. First, factors are estimated using the method of principal components as explained above. This is done based on the assumption that one or several of these principal components can serve as a useful proxy for financial conditions. However, the potential relationship between financial variables and real economic activity does not in itself affect the principal components; these PCs are calculated based on the financial variables alone, in a sense without any knowledge about real economic activity. Therefore, the possible link between the principal components and real economic activity is examined in a second step. This is done by performing both in-sample regressions and pseudo out-of-sample forecasts where one or several PCs are used as explanatory variables, while quarterly growth in GDP Mainland[9] Norway (seasonally adjusted, sa) is the variable to be explained. The results are compared to those of a simple benchmark autoregressive (AR) model, as well as to results using individual financial series as independent variables.

As the monthly principal components will be related to quarterly GDP series, the financial variables are filtered before the principal components are calculated in order to ensure a quarterly interpretation. More specifically, monthly measures of three month aggregates are constructed by filtering the data using the lag operator in the following way: $(1 + 2L + 3L^2 + 2L^3 + L^4)X_t$ where X_t is assumed to be a stationary variable, for example the monthly change in some variable. The observation corresponding to the third month of every quarter thus represents a quarterly quantity, which in turn can be compared to quarterly data for GDP. This is the same procedure as the one followed by Aastveit and Trovik (2010).

5.1 Principal components, loadings and variance explained

Due to various transformations, some observations are lost.[10] The principal components time series therefore cover the period 1994M1 to 2010M12. The first among these principal components is plotted in figure 5.1.

[9] All GDP data used in this paper are series for Mainland Norway.
[10] Some further observations are left out as comparison will be made to a purged version where some further degrees of freedom are used, see section 6.2.

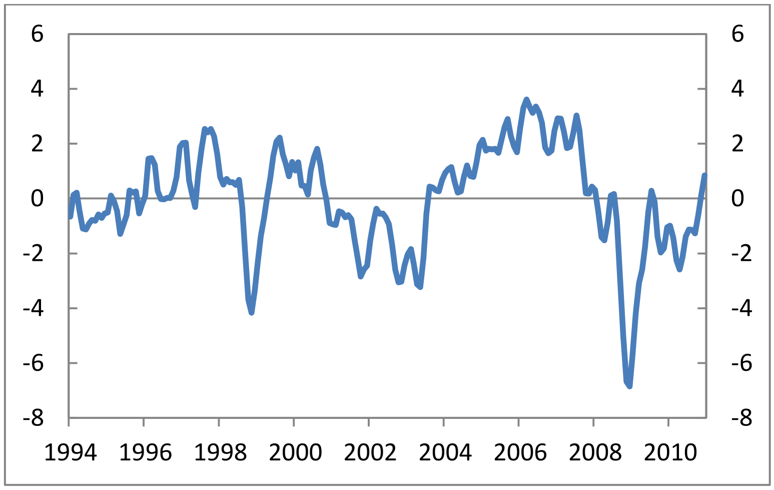

Figure 5.1: First principal component, monthly series. 1994M1-2010M12

This first principal component accounts for 26.9 percent of the total variance in the dataset. The share of variance accounted for by the first six principal components is listed in table 5.1. The same is illustrated in the pareto plot in figure 5.2, where bars show the share of variance explained by the first ten principal components, and the curve indicates the cumulative variance accounted for by a given number of principal components.

Table 5.1: Variance explained by each of the first six principal components. Per cent of total variance.

	Variance explained. Per cent of total variance.
PC1	26.9
PC2	19.4
PC3	10.3
PC4	8.9
PC5	7.4
PC6	7.0
Sum, first *four* PCs	65.5

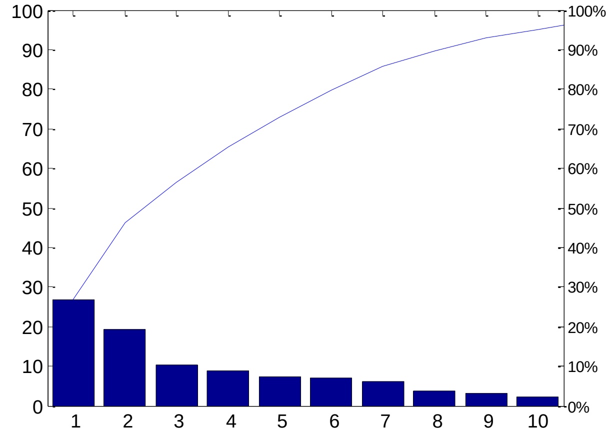

Figure 5.2.: Per cent of total variance explained by each of the first 10 principal components and cumulative variance accounted for by the same 10 principal components.

This pattern for the principal components based on Norwegian data is quite similar to the variance explained by the various principal components reported in Skaarup, Duschek-Hansen and Nielsen (2010). They construct a factor-based FCI for Denmark using 13 financial variables, the same number of series as in the Norwegian case.[11] The Danish FCI is based on the first principal component which accounts for 24.7 % of the total variance in the dataset. It is useful to see that other FCIs are based on principal components with similar statistical "properties." In addition to the share of variance accounted for, it is also of interest to assess the link between a given principal component and the various financial variables, as indicated by the factor loadings. The loadings for the first principal component is shown in figure 5.3.

[11] Both a VAR-based FCI and an FCI based on the principal components approach are examined.

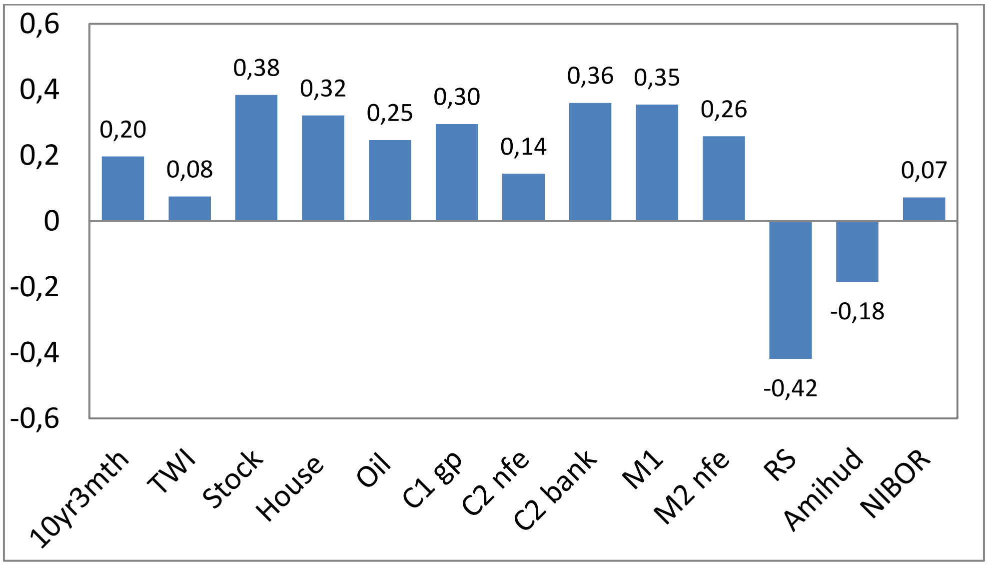

Figure 5.3: Factor loadings, first principal component.

Most of the variables have positive factor loadings, while the two illiquidity measures have negative loadings. As the factor representation in itself gives no information about the relationship between the financial variables and economic growth, it may be hard to give an economic interpretation of the factor estimates and the corresponding loadings. However, anticipating the course of events, the regression results reported below reveal a significant positive relationship between the first principal component and quarterly growth in GDP. This finding will facilitate the interpretation of the factor loadings. If a given factor loading is positive, an increase in the corresponding variable is positively associated with an increase in the underlying factor, this factor being represented by the first principal component. As this principal component is positively related to growth, one can argue in favour of a positive relationship between the corresponding variable and growth.

- The magnitude of the factor loadings varies substantially between the variables, but qualitatively, the signs of the loadings are possible to reconcile with the expected relationship between the financial variables and GDP growth. For example, stock and house prices are likely to be positively related to growth, even though causation can go in both directions. A depreciated currency may stimulate growth through an increase in net exports, and money and credit measures are also expected to be positively related to growth, even though the question of timing may be a relevant issue. The positive loading on the NIBOR rate may be more surprising. Higher interest rates are often seen to have a dampening effect on growth. On the other hand, stronger growth calls for higher interest rates, and hence the association between growth rates and interest rates can be both positive and negative. Unfortunately, the method does not allow for a detailed interpretation of exactly which effects that are captured by the principal components, and causation cannot be established.

- The two illiquidity measures have negative loadings. This is in line with what is expected, as stock market illiquidity may be an indication of a future economic downturn. Such empirical findings and possible explanations are described in detail in Næs, Skjeltorp and Ødegaard (2011).

As has been mentioned already, causal effects can go in several directions and exactly which mechanisms that are captured by the principal component(s) and what effects are reflected in the loadings is not clear. However, the considerations behind the variables chosen, the signs of the estimated factor loadings and the regression results reported below indicate a positive link between the first principal component and real economic activity. Therefore, this first principal component may provide a useful basis for an FCI.

Before a more formal investigation of the relationship between the first principal component and growth is carried out, some graphical plots are provided. As mentioned above, quarterly series of the principal components are needed for comparison with GDP figures. When every third observation is used, the following quarterly series for the first principal component is obtained:

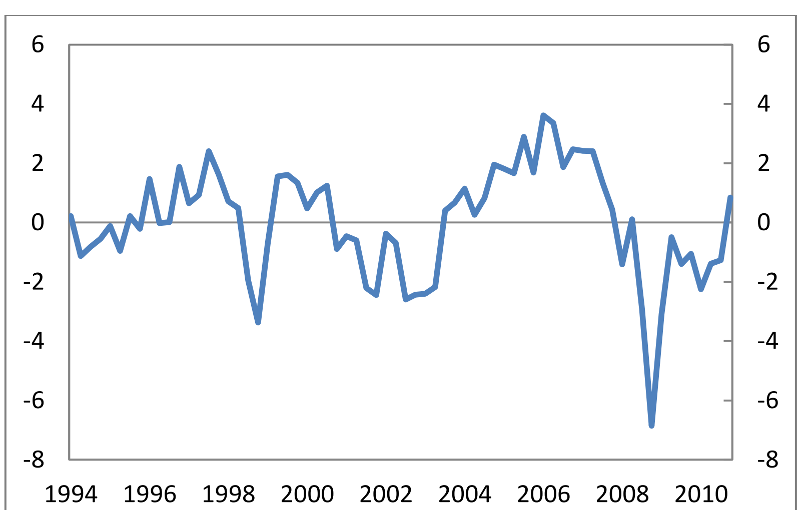

Figure 5.4: First principal component (PC1Q), quarterly series. 1994Q1-2010Q4.

Naturally, this quarterly series is less smooth than the original monthly series, but the overall picture is retained. In figure 5.5a the quarterly principal component is plotted together with quarterly growth in seasonally adjusted GDP. The two series do not track each other particularly well. However, the latter series is very volatile and development in this series is thus rather hard to predict.

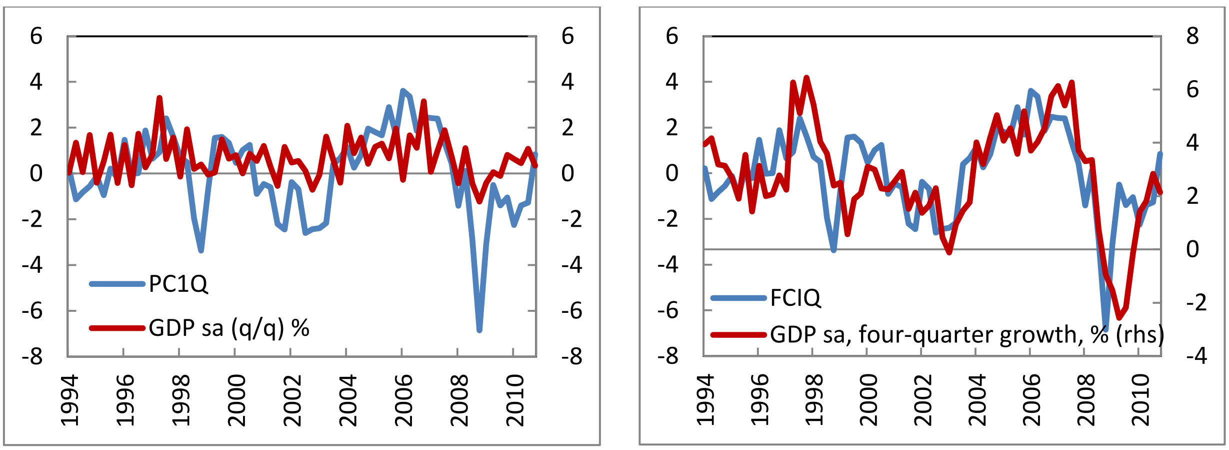

Figure 5.5a and b: First quarterly principal component (PCQ1) and a) quarterly GDP growth, sa (%) b) four-quarter GDP growth, sa (%).1994Q1-2010Q4

However, the PCQ1 and four-quarter growth in the same GDP series follow a more similar pattern, as seen in panel b of figure 5.5. This may indicate that the first principal component picks up a more cyclical pattern of lower frequency. This issue will be further examined in section 6.1.

So far the discussion has been concentrated on the first principal component (and its quarterly counterpart). The next principal components, more specifically PC2-PC4, exhibit quite different patterns compared to PC1. This is only to be expected as principal components are orthogonal to each other by construction. However, as they may carry relevant information about real economic activity, these PCs are included in the regressions described below.

5.2 The predictive power of the financial factor(s) – how close is the link between financial conditions and real economic activity?

In order to assess the link between financial conditions – as captured by the principal components - and GDP growth more formally, both in-sample and pseudo out-of sample regressions are performed. Quarterly growth in seasonally adjusted GDP is regressed on one lag of itself and on one or more of the quarterly principal components, which are also lagged relative to the quarterly observation being explained. A constant term is also included in all the regressions. The general model being estimated is given by the following equation

$$\Delta y_{t+h} = \beta_0 + \sum_{j=1}^{4} \beta_{1j} X_{tj} + \beta_2 \Delta y_t + \varepsilon_{t+1} \qquad (j=1,\dots4,\ h=1,\dots5) \qquad (5.1)$$

where Δy is quarterly GDP growth, X_{tj} is the time t observation of principal component j and h is the quarterly forecast horizon. As seen from table 5.1 above, the first four principal components account for the bulk of the variation in the dataset. Therefore, these four PCs are used as explanatory variables by including one, two, three or four principal components.[12] Regressions are first done for the whole sample period (in-sample), after which a recursive pseudo out-of-sample forecast is done. Results are initially compared to those of a simple autoregressive model. At a later stage, results will also be compared to those from regressions using individual financial variables, see section 5.2.3. In the remaining part of this chapter, regression results are provided and briefly commented on.

5.2.1 In-sample regressions using principal components

R^2 and p-values for the overall regressions are reported in table 5.2.[13] The autoregressive model, where GDP is regressed on one lag of itself and a constant term hardly has any explanatory power and is not significant.[14] This is not surprising, bearing in mind the high volatility of quarterly GDP growth in Norway, and that only one lag of the dependent variable is considered.[15] By including principal component(s) in the model, the results are significantly improved, with the best result found for the model where only the first principal component is included, predicting growth one quarter ahead (h=1). Admittedly, R^2 is still not very large, but all models are significant at a 5 % level, both for one and two quarters ahead.

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[12] Either the first, the two first, the three first or the four first. Results are only provided for h=1 and h=2.

[13] The rows of the table refer to different models: E.g. “3 PC” indicates the model including the three first principal components. This pattern is followed throughout the paper.

[14] Here “significant” refers to p-values below 0.05.

[15] One lag is used for all the regressions (except when purging the financial variables in section 6.2, see equation 6.1). A higher number of lags could have been included, either a fixed number or determined by some information criterion.

Table 5.2: In-sample regression results for AR and PC models. h=1 and h=2.

Horizon: h=1	R^2	p-value
AR	0.0185	0.2726
1 PC	0.2447	0.0001
2 PC	0.2460	0.0005
3 PC	0.2460	0.0014
4 PC	0.2864	0.0008
Horizon: h=2	**R^2**	**p-value**
AR	0.0516	0.0665
1 PC	0.1540	0.0051
2 PC	0.1899	0.0043
3 PC	0.2065	0.0063
4 PC	0.2102	0.0127

5.2.2 Pseudo out-of-sample forecasting

Next, pseudo out-of-sample forecasting is performed.The models are estimated recursively, with forecasts starting in 2001Q1. The forecast period is further split into two sub-periods: 2001Q1-2005Q4 and 2006Q1-2010Q4. The models are evaluated in terms of root mean square errors (RMSEs) and relative RMSEs with the simple AR-model as a benchmark. Forecast results are reported in table 5.3.

Table 5.3: Pseudo out-of-sample forecast results for AR and PC models, h=1 and h=2. The lowest relative RMSEs for the whole forecast period are highlighted.

h=1	RMSE			Relative RMSE		
Period	2001Q1-2010Q4	2001Q1-2005Q4	2006Q1-2010Q4	2001Q1-2010Q4	2001Q1-2005Q4	2006Q1-2010Q4
AR	0.9461	0.8356	1.0451	1	1	1
1 PC	0.7985	0.7511	0.8432	**0.8440**	0.8989	0.8068
2 PC	0.8128	0.7608	0.8616	0.8591	0.9105	0.8244
3 PC	0.8846	0.8882	0.8809	0.9350	1.0629	0.8429
4 PC	0.8666	0.8651	0.8652	0.9160	1.0353	0.8279
h=2	**RMSE**			**Relative RMSE**		
Period	**2001Q1-2010Q4**	**2001Q1-2005Q4**	**2006Q1-2010Q4**	**2001Q1-2010Q4**	**2001Q1-2005Q4**	**2006Q1-2010Q4**
AR	0.8920	0.8210	0.9577	1	1	1
1 PC	0.8507	0.7738	0.9212	**0.9537**	0.9425	0.9619
2 PC	0.8556	0.7870	0.9190	0.9592	0.9586	0.9596
3 PC	0.8942	0.8842	0.9041	1.0025	1.0770	0.9440
4 PC	0.9343	0.9358	0.9329	1.0474	1.1398	0.9741

The best forecast result in terms of relative RMSE for the whole forecast period is found for the model including the first principal component. This is true both for one and two quarters ahead, even though results for the former is better. There are some differences between the two sub-periods. For one quarter ahead, the absolute RMSEs are quite similar across the two sub-periods. The change in relative RMSE can thus be traced back to the particular poor AR forecast for one period ahead. Results for the whole forecast period indicate that the models with either the first or the two first principal components are more relevant for predicting GDP growth.

5.2.3 Comparison with individual financial series

An autoregressive model with only one lag may seem like a somewhat sparse basis for comparison. Therefore, similar regressions are performed where the principal components are replaced with individual financial variables. More specifically, the X_j in equation 5.1 is now taken to represent a single financial variable rather than one of the estimated PCs. Models are estimated for all the 13 financial variables listed in table 4.1. As noted above, attempts at predicting real activity using financial data abound. Since the principal components are derived from the same financial series, the relevant question here is whether there is something to gain from pooling the information compared to the performance of forecasts based on individual financial series. There is reason to believe, and empirical evidence shows that this may indeed be the case, as idiosyncratic variation in the included series in a sense is averaged away (Stock and Watson, 2002b). In- and out-of-sample results are reported in tables 5.4a and b, with the AR and PC1 results included for ease of comparison.

For one quarter ahead, the “best” individual financial variable is the relative spread (RS), with in-sample results similar to those of the PC1 model. The relative spread is also the best single series out-of-sample for the whole forecast period taken together. However, the PC1 model has a lower relative RMSE than any of forecasts based on individual financial series. In total, five variables are significant explanatory variables in-sample (highlighted in the table), and these are also among the best-performing variables out-of-sample. For two quarters ahead, table 5.4b reveals that house prices is the best single series, marginally outperforming the PC1 model both in- and out-of-sample. M1 yields results similar to the PC1 model, but for the other individual series results are somewhat poorer.

Table 5.4a: In- and out-of-sample results for individual financial variables, h=1.

	In-sample		**Out-of-sample – different periods**					
h =1			**RMSE**			**Relative RMSE**		
	R^2	**p-value**	**2001Q1-2010Q4**	**2001Q1-2005Q4**	**2006Q1-2010Q4**	**2001Q1-2010Q4**	**2001Q1-2005Q4**	**2006Q1-2010Q4**
10yr3mth	0.1572	0.0042	0.8857	0.7326	1.0160	0.9362	0.8767	0.9722
TWI	0.0199	0.5259	1.0860	1.1175	1.0535	1.1479	1.3374	1.0080
Stock	0.1657	0.0030	0.8834	0.7221	1.0195	0.9337	0.8642	0.9755
House	0.0791	0.0715	0.9146	0.8434	0.9806	0.9667	1.0093	0.9383
Oil	0.0335	0.3356	0.9603	0.8516	1.0578	1.0150	1.0191	1.0122
C1 gp	0.0583	0.1465	0.9389	0.8440	1.0250	0.9924	1.0101	0.9808
C2 nfe	0.0209	0.5080	0.9570	0.8430	1.0587	1.0115	1.0089	1.0130
C2 bank	0.1157	0.0195	0.9199	0.8398	0.9936	0.9723	1.0050	0.9507
M1	0.1145	0.0204	0.8812	0.8158	0.9420	0.9314	0.9763	0.9013
M2 nfe	0.0579	0.1484	0.9340	0.8537	1.0079	0.9872	1.0217	0.9644
RS	**0.2172**	**0.0004**	0.8667	0.7786	0.9466	**0.9161**	0.9318	0.9058
Amihud	0.0190	0.5411	0.9741	0.8243	1.1040	1.0296	0.9865	1.0564
NIBOR	0.0189	0.5431	0.9707	0.8546	1.0744	1.0260	1.0227	1.0280
AR	0.0185	0.2726	0.9461	0.8356	1.0451	1	1	1
PC1	0.2447	0.0001	0.7985	0.7511	0.8432	0.8440	0.8989	0.8068

Table 5.4b: In- and out-of-sample results for individual financial variables, h=2.

	In-sample		**Out-of-sample – different periods**					
h =2			**RMSE**			**Relative RMSE**		
	R^2	**p-value**	**2001Q1-2010Q4**	**2001Q1-2005Q4**	**2006Q1-2010Q4**	**2001Q1-2010Q4**	**2001Q1-2005Q4**	**2006Q1-2010Q4**
10yr3mth	0.1090	0.0264	0.8561	0.7889	0.9184	0.9598	0.9609	0.9590
TWI	0.0560	0.1630	0.9554	0.9442	0.9665	1.0711	1.1501	1.0092
Stock	0.0895	0.0521	0.8797	0.7995	0.9531	0.9862	0.9738	0.9952
House	**0.1869**	**0.0015**	0.8424	0.8391	0.8456	**0.9444**	1.0220	0.8829
Oil	0.0628	0.1297	0.9024	0.8052	0.9901	1.0117	0.9808	1.0338
C1 gp	0.0517	0.1880	0.9083	0.8414	0.9706	1.0183	1.0248	1.0135
C2 nfe	0.0517	0.1880	0.9044	0.8247	0.9777	1.0139	1.0045	1.0209
C2 bank	0.0625	0.1311	0.9009	0.8248	0.9710	1.0100	1.0046	1.0139
M1	0.1426	0.0079	0.8556	0.8313	0.8792	0.9592	1.0125	0.9180
M2 nfe	0.0725	0.0935	0.8955	0.8392	0.9484	1.0039	1.0222	0.9903
RS	0.1017	0.0341	0.8778	0.8012	0.9482	0.9841	0.9759	0.9901
Amihud	0.1030	0.0326	0.8979	0.8118	0.9764	1.0066	0.9888	1.0195
NIBOR	0.1036	0.0319	0.9297	0.8325	1.0177	1.0423	1.0140	1.0627
AR	0.0516	0.0665	0.8920	0.8210	0.9577	1	1	1
PC1	0.1540	0.0051	0.8507	0.7738	0.9212	0.9537	0.9425	0.9619

Summing up, the best individual financial variables yield similar results to those from models including one or several principal components, although which variable is better depends on the forecast horizon. Somewhat unstable results across forecast periods are also present for the forecasts based on individual financial series, and this problem is therefore not just confined to the models based on principal components. However, no formal in-sample test for structural instability is made, and it is therefore hard to do any further formal comparison between the PC models and models including individual financial series in this respect. However, combining the in- and out-of-sample results, the overall impression is that there seems to be something to gain from pooling information by using estimated factors. Even though individual variables occasionally perform better, one could claim that it is more robust to make use of the estimated factors as these yield better results "on average."

6 An attempt at an FCI for Norway

The analysis described above indicates a significant positive relationship between the first principal component and GDP growth. Furthermore, there may be useful information in some of the other principal components as well, and so it remains to be decided exactly how the FCI should be constructed. Most FCIs based on estimated factors only include the first estimated factor/principal component. However, in some studies FCIs are constructed by weighing together several principal components, such as in Gomez, Murcia and Zamudio (2011) and English, Tsatsaronis and Zoli (2005). However, as most of the relevant information for Norwegian GDP growth seems to be captured by the first principal component, this series alone is taken to be the FCI for Norway. This also facilitates the interpretation of the index, as indicated in the discussion of the factor loadings. Moreover, it is conceivable that the other principal components pick up rather different developments as these are orthogonal to the first principal component.

The time series plotted in figure 5.1 is thus taken to be the preferred FCI for Norway. It is easy to calculate and it can be updated every month. There is a positive relation between the FCI and GDP growth, hinting at its possible use as a leading indicator of real economic activity. However, the indicator probably captures *both* impacts from financial factors to the real economy, as well as the financial variables' endogenous response to economic activity. Further comments on this distinction is made in section 6.2 where an alternative index is presented.

6.1 Use and interpretation of the FCI

The preferred FCI for Norway provides a summary measure of the broad financial conditions, and can further be indicative of developments in the real economy. However, as already mentioned, quarterly growth in Norwegian GDP is particularly volatile and therefore hard to predict. In a final attempt to establish a link between the FCI and real economic activity, the FCI is related to alternative measures of real activity. In particular, the quarterly FCI (as seen in figure 5.4) is plotted together with growth (both quarterly and four-quarter growth) in trend GDP, a smoother time series.[16] In general, the trend version of a series may be more informative than the seasonally adjusted version if there is a lot of random variation in the raw data. In addition to graphical plots, as seen in figures 6.1 and 6.2, correlation coefficients between the FCIQ and the trend growth series are calculated, see table 6.1. This is done both for the contemporaneous relationship between the variables, as well as including leads, where the time t value of the FCIQ is related to growth in future quarters (t+1, t+2 etc).

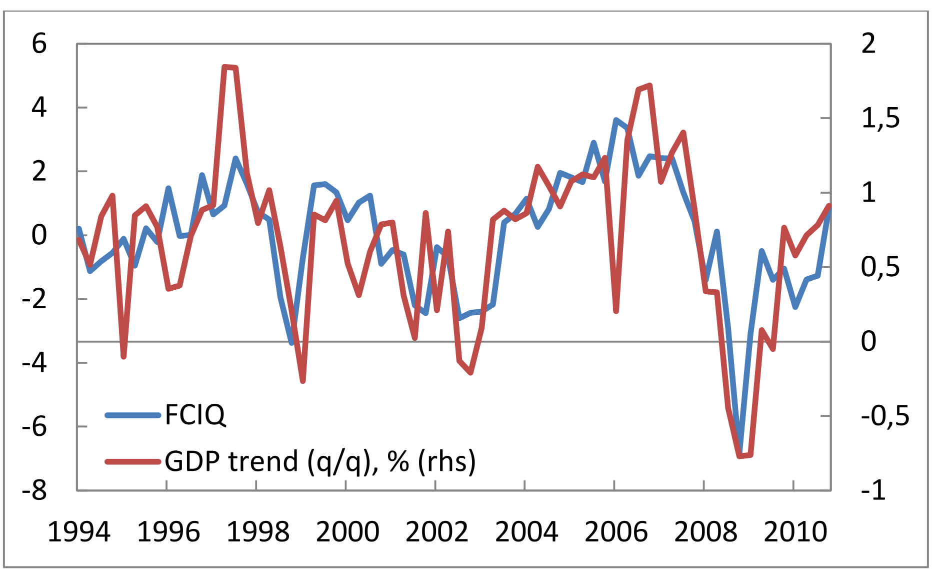

Figure 6.1: Quarterly FCI and quarterly growth in trend GDP (%). 1994Q1-2010Q4.

[16] Time series are often seasonally adjusted to remove variations in the series related to seasonal effects – fluctuations in the series that typically occur around the same time every year. One way of adjusting a time series it to decompose the series into three parts (after a pre-treatment of the data): A seasonal component (S), a trend component (T) and an irregular component (I). The seasonal component contains the variation in the time series that occurs within one year, and a seasonally adjusted series (A) thus only contains the trend and irregular components (A=T+I). The trend component is a smoother series reflecting a more underlying tendency in the data. This measure may be more informative if the original series contains a lot of random/ irregular variation. For further details, see http://www.ssb.no/english/metadata/methods/seasonal_adjustment.pdf.

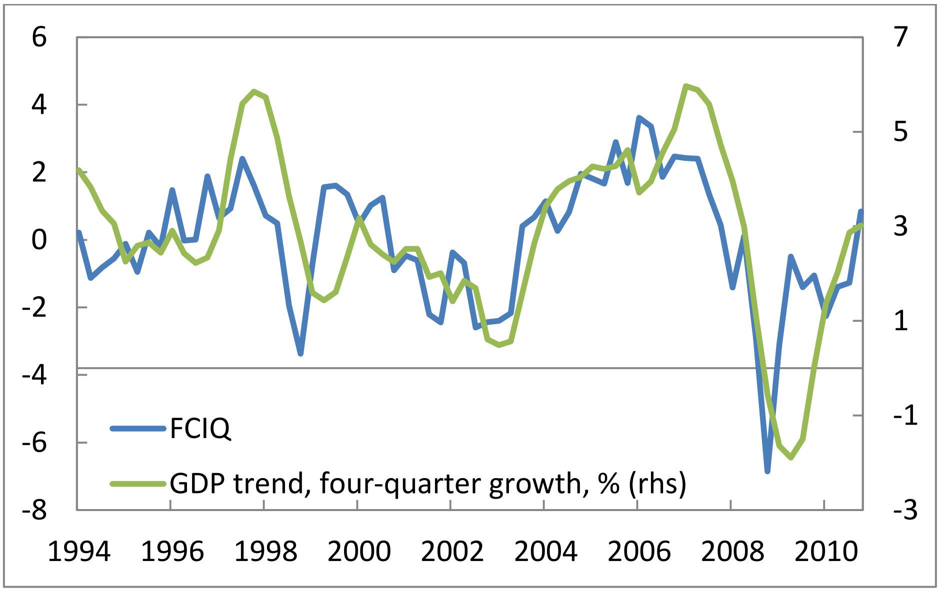

Figure 6.2: Quarterly FCI and four-quarter growth in trend GDP (%). 1994Q1-2010Q4.

Table 6.1: Correlations between quarterly FCI and trend growth in GDP (the highest value for each variable is highlighted).

	Correlations with FCIQ						
	t	t+1	t+2	t+3	t+4	t+5	t+6
GDP trend (q/q)	**0.69**	0.65	0.50	0.35			
GDP trend (y/y)	0.64	0.76	**0.78**	0.71			

Both the graphs and correlation coefficients lend support to the interpretation of the FCI being a leading indicator of real economic activity.[17] Admittedly, for quarterly trend growth, the FCI is more of a coincident than a leading indicator, as the contemporaneous correlation coefficient is the highest one. Still, it would in practice be leading as the financial data on which it is based are available well in advance of actual GDP data. On the other hand, the FCI is clearly leading developments in four-quarter trend growth, with the highest correlation coefficient found for two quarters ahead. A correlation of around 0.8 indicates a rather close relationship between the FCI and trend growth in GDP. This is quite remarkable bearing in mind that the FCI is estimated on financial variables only. Some studies using principal components make an attempt at identifying or characterizing the estimated factors. One example is seen in Martinsen (2010, p. 19), where the results indicate that "(...) the first factors for the regions pick up the developments in real activity,

[17] When relating the FCI to quarterly measures of real activity, the quarterly FCI, FCIQ, is used. However, the results are taken to be representative for the monthly FCI as well.

and may thus be suitable for forecasting GDP growth (...).” One could speculate that the first estimated factor in this analysis may serve a similar purpose.[18]

In viewing the FCI as a leading indicator for Norway, it is reassuring to notice that the index bears close resemblance to other leading indicators for the Norwegian real economy. This can be seen in figure 6.3 where the quarterly FCI is plotted together with the confidence indicator from Statistics Norway’s Business tendency survey for comparison.

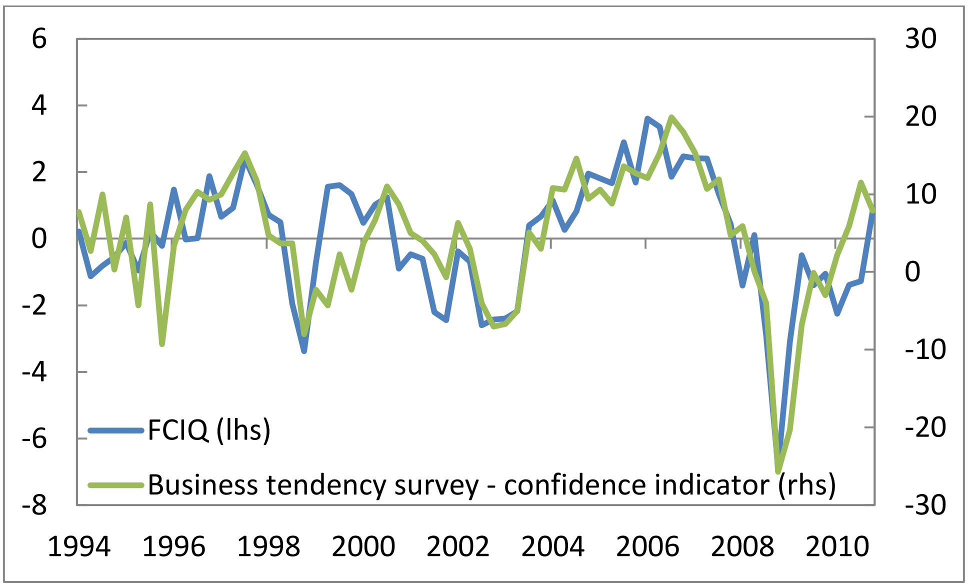

Figure 6.3: FCI and the Business tendency survey confidence indicator, unadjusted. Quarterly series. 1994Q1-2010Q4.

The two indicators are based on rather different sources and types of information, and yet they reveal a similar overall picture.[19] The correlation coefficient between the series (for the period in question) is as high as 0.77. As the pool of available leading indicators for Norway is quite small, the FCI can be seen as a useful supplement. In particular, it has the advantage of being available

[18] In Vonen (2011) the FCIQ is also related to an estimate of the output gap. For this measure, the real-financial relationship seems less tight and the FCI is more leading - with the highest correlation coefficient found for five quarters ahead.

[19] The Business tendency survey is a qualitative survey assessing business managers’ view on the current economic situation and the future outlook. The series plotted in figure 6.3 is a composite indicator derived from answers to several of the questions in the survey. See http://www.ssb.no/emner/08/05/10/rapp_200310/rapp_200310.pdf for details on the survey.

at a monthly frequency as well as being based on financial data which are released with rather short time lags.

6.2 An alternative FCI – adjusted for business cycle effects.

As noted above, the FCI does not shed light on the difference between the financial variables' impact on growth and their endogenous response to real economic activity. Even though this fact does not impair its possible role as a leading indicator, it would still be of interest to have a measure of some sort of "exogenous" financial factors; an indicator incorporating the financial variables' impact on growth, but without their endogenous response to real activity. Some FCIs are constructed with the aim of including only the former effect, see e.g. Hatzius et al. (2010) and Skaarup, Duschek-Hansen and Nielsen (2010). Inspired by these indicators, a similar approach is taken in this paper in an attempt to create an FCI purged of business cycle effects. More precisely, each financial variable is regressed on current and lagged values of GDP growth.[20] Using quarterly series of the financial variables,[21] each series is regressed on current and two lags of quarterly GDP growth:

$$x_{it} = \beta_0 + \beta_1 \Delta y_t + \beta_2 \Delta y_{t-1} + \beta_3 \Delta y_{t-2} + v_{it} \qquad (6.1)$$

The residuals, v_{it}, or rather, the estimates of these, $\hat{v}_{\mathrm{it}}$, are in turn used as measures of financial variables purged of the effect of GDP growth, and the calculation of the principal components is now based on these, $\hat{v}_{\mathrm{it}}$s. Apart from this change, the procedure is identical to that of the original FCI: Principal components are calculated and then subsequently used in regressions and correlation analysis. These steps are thoroughly documented and discussed in Vonen (2011), and thus only a brief summary is provided in the following. Just as the first principal component is used as an FCI in the original setup, the first principal component based on purged financial variables is chosen as the FCI purged of business cycle effects.

[20] In the two papers mentioned, the inflation rate is also included as a regressor. Furthermore, Skaarup, Duschek-Hansen and Nielsen (2010) also include an interest rate.
[21] Constructed in the same way as the quarterly FCI series as described in section 5.1.

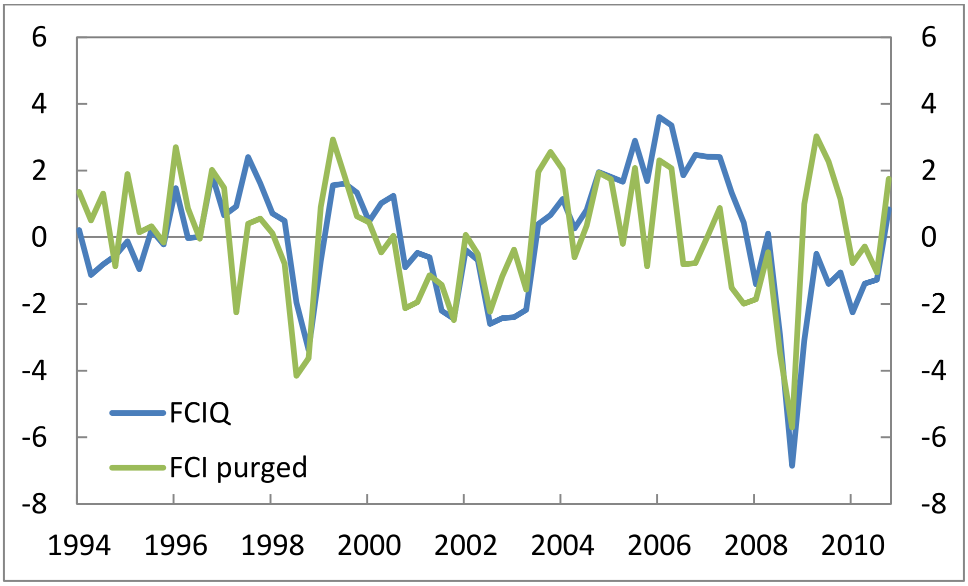

Figure 6.4: Comparison of FCIs, purged and unpurged quarterly series. 1994Q1-2010Q4.

As seen in figure 6.4, the purged and unpurged FCIs track each other fairly well, but the purged version is somewhat more volatile. There are also some fairly large discrepancies between the two series. For example, in mid-1997 the purged series indicates somewhat tighter financial conditions than the impression given by the unpurged index. This difference between the series probably reflects the relatively high GDP growth around the same period, e.g. as seen in figure 6.2. Even though a significant positive relationship was found between GDP growth and the purged FCI, this link seems to be less tight compared to the results using the unpurged FCI. This impression is confirmed by examining correlation coefficients between the purged FCI and the trend growth series, see table 6.2.

Table 6.2: Correlations between quarterly FCI based on purged financial variables and trend growth in GDP (the highest value for each variable is highlighted).

	Correlations with FCI based on purged variables					
	t	t+1	t+2	t+3	t+4	t+5
GDP trend (q/q)	0.15	**0.48**	0.44	0.37		
GDP trend (y/y)	-0.01	0.19	0.35	0.46	**0.48**	0.43

These correlation coefficients are lower than the corresponding numbers for the unpurged FCI. Furthermore, the purged FCI is more leading, with the highest correlation found one to three quarters later than for the unpurged version. This is however only to be expected as much of the contemporaneous correlation between GDP and the financial variables is removed in the purged version.

6.3 Returning to the original FCI – an example

The purged FCI has a theoretical appealing feature as it can be interpreted as the "exogenous" impact from financial conditions to GDP growth. At the same time, the additional regression step introduces yet another source of uncertainty, and to what extent a "pure" exogenous measure of financial conditions is obtained in practice is not really clear.[22] Furthermore, as long as a quarterly GDP series is used for business cycle adjustment (as shown in equation 6.1), the purged index will only be available every quarter, and with a longer lag. Alternatively, a forecast of GDP could have been used for the most recent observation (Δy_t) in equation 6.1, but the FCIs' advantage of being a high-frequent measure would still be lost. Finally, for the purpose of being a leading indicator, the unpurged version is clearly a better measure, even though the distinction between exogenous impact and endogenous response is lost. Bearing these trade-offs in mind, the unpurged version was chosen as the preferred FCI for Norway, and therefore the remaining part of this paper will be focused on this measure.

A possible use of the Norwegian FCI can be illustrated by a recent historical example. In the autumn of 2008, the financial crisis hit the world economy with full force. Most people, including policy makers, were caught off guard; at least the exact timing and magnitude of the downturn was rather unanticipated. As the crisis unfolded, central banks, including Norges Bank, responded by reducing policy rates in large and frequent steps (Norges Bank, 2009). This period was characterized by a high degree of uncertainty concerning the future economic outlook. In this situation, an FCI could have served as a useful guideline. By end of October/beginning of November, the low FCI value of -2.9 for September would have been known. Furthermore, well ahead of the policy meeting in December, the until then lowest value of the index ever, -5.0 based on October data, would have provided valuable information on where the economy could be heading. These details are illustrated in figure 6.5, where the FCI is plotted together with the policy rate.

[22] Financial conditions and GDP growth are endogenous to each other, and a more sophisticated econometric procedure may be required in order to capture the actual "exogenous" financial forces.

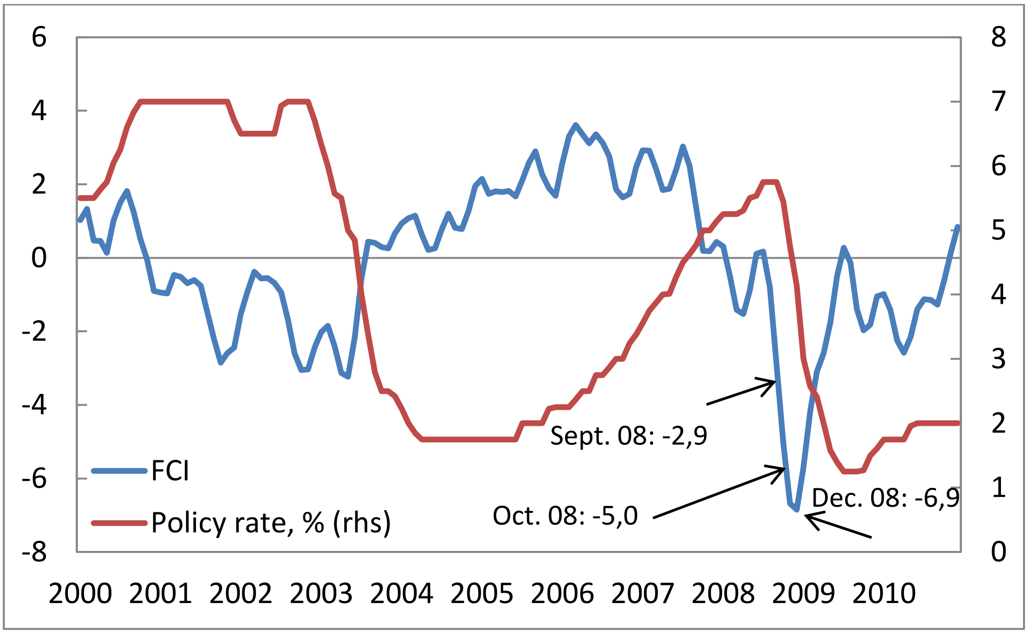

Figure 6.5: FCI and the key policy rate (%), monthly series. 2000M1-2010M12.

This example is just one suggestion of how to make use of the FCI. Of course, the interpretation of the index is subject to discretion. It does not translate into interest rate equivalents, nor is it intended to elicit any mechanical action from the central bank. The use of MCIs as operational targets has been controversial, and the same goes for a similar use of an FCI. Furthermore, relating the FCI to a mechanical policy rule would touch upon the debate on how and if the central bank should respond to asset prices, see e.g. Gauthier, Graham and Liu (2004). Leaving this debate aside, it seems reasonable to view this FCI as a useful first step towards a summary statistic serving two purposes: Capturing broad financial conditions and at the same time providing timely and leading information on real economic activity.

7 Robustness checks and further alternatives

Results from alternative estimations and robustness checks are reported in Vonen (2011). Here, a brief overview is provided, along with a few words of caution that are worth emphasizing. These are issues related to the data included and the interpretation of the FCI.

As the principal components are dependent on the overall variation in the dataset, the principal components – and thereby the FCI itself – will change as the dataset and thereby the variance composition is changed. Therefore, every time the FCI is updated, the whole time series is affected. As long as these changes are small this should not impair the use of the index. To assess the FCIs' sensitivity to the amount of data included, the index was re-estimated on various subsets of the data sample. Indeed, even though small changes are found, such as seen in figure 6.6, the overall picture is retained and the FCI can thus be used for historical comparisons.

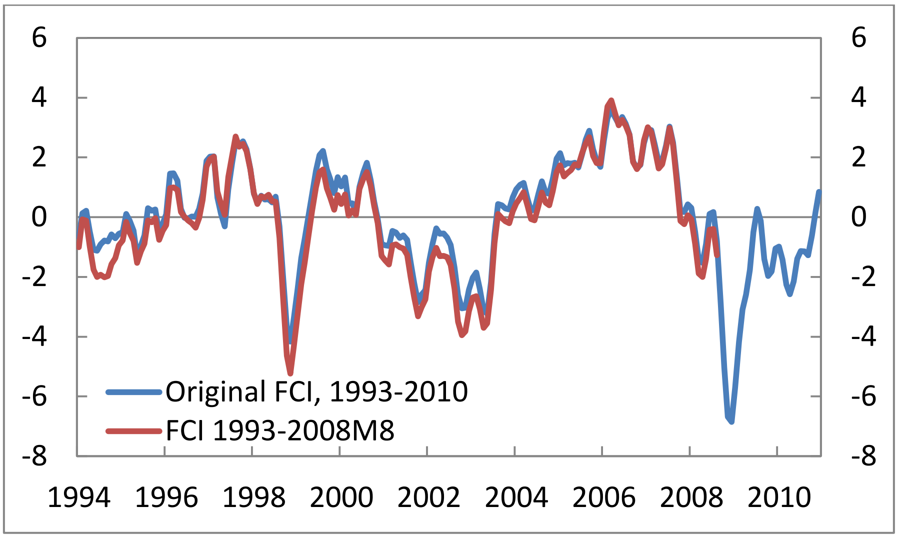

Figure 6.6: Original FCI and FCI based on data from 1993M1-2008M8, monthly series. 1994M1-2010M12. (The periods indicated in the legend refer to the data periods covered).

However, as can be seen from figure 6.6, adding a few more years of data changes the level of the index at any given time. For example, by including the period covering the financial crisis, former downturns seem less severe. This is of importance when interpreting the index. The fact that index values – the levels – change as history evolves may be part of the reason behind Murray's (2009) warning on how FCIs should be used. He advises that a given *level* of an FCI should not be given too much weight. Rather, large *changes* in index values may indicate substantial financial easing or tightening. In a related manner, Guichard, Haugh and Turner (2009, p. 5) find the FCIs to be significant explanatory variables in regressions explaining output gaps, yet "(...) direct interpretations of the levels of the indicators should be made with great caution." One alternative would be to compare the level of an FCI to its level during historical periods where financial conditions were known to be particularly tight or loose. Even though the exact index value/level for a given time period will change with the addition of new data, its position relative to the value in other periods would be retained. This way of reading an FCI could also be seen as more intuitive than e.g. an interpretation in terms of standard deviations (Hakkio and Keeton, 2009).

Finally, in interpreting the index the inherent lack of structural foundation of FCIs based on the principal components method should be kept in mind. Movements in the index can be traced back to changes in the underlying financial variables. However, even though attempts have been made to interpret the FCI and to establish correlation and to some extent causation, neither the exact economic mechanisms nor a fine-tuned picture can be revealed. This is not to undermine the potential usefulness and benefit of the FCI, but rather to emphasize that its value should be judged based on what it really is – a “rough and ready” summary statistic.

8 Summing up

The work on a financial conditions index for Norway is summarized in this paper, while a broader coverage is provided in Vonen (2011). The first principal component from a dataset of 13 monthly financial variables is used as the preferred FCI for Norway. Even though the lack of structural foundation may complicate interpretations, the index is found to carry information about real economic activity. Two different versions of the index are suggested: One based on financial variables purged of the impact of GDP growth, while the other one is calculated without such adjustments. Even though the latter is given the most attention and is chosen as the preferred FCI, both versions can in principle be put to use, as long as the distinction between them is made clear: While the purged version may be interpreted as financial conditions’ impact on the real economy, the unpurged version also contains financial variables’ response to real economic activity. However, for the purpose of a leading indicator, the unpurged version is clearly a better measure.

The real-financial linkages are examined both in-and out-of-sample. Even if quarterly growth in seasonally adjusted GDP is hard to predict, the FCI generally outperforms the alternative models examined. Furthermore, the link appears to be stronger when relating the FCI to slower-moving measures such as trend growth in GDP, especially four-quarter trend growth. Taken together, the FCI may be useful for policy making in providing a comprehensive measure of financial conditions and at the same time being a leading indicator of real economic activity. Furthermore, the FCI is easy to estimate and can be updated every month. Several changes and improvements are possible and should definitely be pursued. However, the current FCI is seen as a useful initial step and can easily be put to use as a readily available summary statistic and leading indicator.

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Data documentation

The following transformations are used: First difference = 2, differences in logarithms =5. The remaining series enter in levels =1.

Table A.1: Variables included in the FCI.

Series number	Description	Short name	Source	Transformation
1	Spread between the interest rates on 10 year government bonds and three month government bills	10yr3mth	Thomson Reuters	1
2	Trade weighted real exchange rate (TWI). Real exchange rate between NOK and the currencies of 25 trading partners	TWI	Norges Bank	1
3	Stock market index for the Oslo Stock Exchange. Total return, total market.	Stock	Thomson Reuters	5
4	House prices, seasonally adjusted. Price per square meter.	House	NEF, NFF, Finn.no and EconPöyry. The series is extended with a data series from the RIMINI database (RIMINI is a macro model formerly used in Norges Bank).	5
5	Oil price (Brent Blend), USD/barrel.	Oil	Thomson Reuters	5
6	Credit (C1) to the general public. Domestic credit in NOK.	C1 gp	Statistics Norway	5
7	Credit (C2) to non-financial enterprises. Domestic credit in NOK and foreign currency.	C2 nfe	Statistics Norway	5
8	Credit (C2) from commercial banks. Domestic credit in NOK and foreign currency provided by commercial banks.	C2 bank	Statistics Norway	5
9	M1. Narrow money stock.	M1	Statistics Norway	5
10	M2 non-financial enterprises. Broader money stock.	M2 nfe	Statistics Norway	5
11	Relative spread. Stock market illiquidity measure	RS	Norges Bank	1
12	Amihud’s stock market illiquidity measure	Amihud	Norges Bank	5
13	Three month NIBOR.	NIBOR	Norges Bank	2

Table A.2: Additional data series

Description	Source
GDP Mainland Norway, seasonally adjusted	Statistics Norway
GDP Mainland Norway, trend component	Statistics Norway
Key policy rate	Norges Bank
The Business tendency survey – confidence indicator. Unadjusted.	Statistics Norway