Financial Conditions Indices for Canada

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Abstract

In this paper, we construct several FCIs for Canada based on three approaches: an IS-Curve-based model, generalized impulse response functions and factor analysis. Each approach is intended to address one or more criticisms applied to MCIs and existing FCIs. We evaluate our various FCIs based on their weights, dynamic correlation with output and inflation, their in-sample fit in explaining output and their out-of-sample forecast performance. Based on the IS-Curve method with monthly data, we find that housing prices, equity prices and bond yield risk premia, in addition to short- and long-term interest rates and the exchange rate, are significant in explaining output from 1981 to 2000. In both the HP-filter and first difference specifications, housing prices have a higher or comparable absolute-value coefficient than that of the exchange rate. Finally, we find that the FCI outperforms the MCI in many criteria considered in this paper.

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1. Introduction

The transmission of monetary policy has traditionally been explained by the interest rate channel and exchange rate channel. Recent debates in the literature, however, have implied that property and equity prices may also play an important role in the transmission mechanism through a wealth effect (e.g. Modigliani, 1971) and a credit channel (e.g. Bernanke and Gertler, 1989). A wealth effect occurs when a change in asset prices affects the financial wealth of individuals and subsequently leads to a change in their consumption decisions. A credit channel exists when a rise in asset prices increases the borrowing capacity of individuals and firms by expanding the value of their collateral. This increase in available credit allows households and businesses to make additional purchases of goods and services and, thus, boost aggregate demand.

The usefulness of asset prices in determining aggregate demand and inflation has long been a controversial debate. While there seems to be a strong case for a role of asset prices in the transmission mechanism from a theoretical point of view, the empirical evidence is somewhat mixed. Many studies find that stock returns possess little predictive content for future output (e.g. Fama (1981), Harvey (1989), Stock and Watson (1989, 1999), Estrella and Mishkin (1998)). Goodhart and Hofmann (2000) find that stock prices have no marginal predictive content for *inflation* in their international data set of seventeen developed countries. Using a backward-looking IS-Phillips Curve model for the G7 countries, however, Goodhart and Hofmann (2001) suggest that both housing and share prices have a significant impact on the *output gap*. They also find that the effect of housing prices is larger than that of stock prices and in most cases, including Canada, also larger than the effect of the exchange rate.

Research at the Bank of Canada also suggests that asset prices, especially property prices, may possess important information about future inflationary pressure. Clinton (1999) studies three periods in which Canada's monetary policy is deemed to have been too easy (1972-1973, 1980-1981 and 1988-1989). In all three episodes, the author notes that strongly rising property prices were evident from an early stage. Furthermore, Clinton argues that a real estate boom might precede a generalized inflation, not only because of its impact on loans via higher collateral, but also because:

- it reflects the impact of excess liquidity before other markets characterised by more a elastic supply curve.
- it quickly captures inflation expectations (land is a classic inflation edge).

The author also documents that, usually, a bull stock market is evident as inflationary pressures start to build. However, he suggests that its volatility makes the market index less reliable as an indicator, since it flashes too many signals. The bull market of the 1990s is an example where the housing market provided mixed signals about inflation.[2]

Another Bank of Canada study by Zhang (2002) suggests that bond risk premia may have strong predictive power for future output. Using U.S. data from 1997 to 2001, the author finds that the high-yield bond spread and the investment-grade spread can explain 68 percent and 42 percent, respectively, of output variations one year ahead, while the term spread can explain only 12 per cent. For output forecasts up to one year ahead, corporate bond spreads also outperform popular indicators such as the commercial paper-treasury bill spread, fed funds rate, consumer sentiment index, Conference Board leading indicator, and the Standard & Poor's index both in-sample and out-of-sample. The forecasts from the high-yield spread are found to be more accurate than those from the investment-grade spreads[3]. Applying the methodology to Canadian data, Djoudad and Wright (2002) also find that the U.S. high-yield spread has a strong predictive power for Canadian output.

A look at the composition of Canadian household total assets (see Table 1) also suggests that housing prices, equity prices and relative bond yields may play an important role in the transmission mechanism. Property assets account for a third of total household assets in Canada. Stocks also account for a significant portion of total assets and its importance has gradually increased over the last 20 years. While the direct holding of bonds has slightly decreased, the importance of life insurance and pensions has significantly risen. This may suggest that households hold more bonds indirectly through an investment vehicle. The actual composition of bonds in the investment vehicle portfolio may have in fact increased[4].

Aiming at capturing these possible effects of asset prices on the real economy, several authors and institutions have included them in constructing new measures of monetary policy stance. These measures, often called Financial Conditions Indices (FCIs), expand on the traditional measures of policy stance by

2. It was, however, a clear indicator of output growth during that period.
3. Nevertheless, these results need to be interpreted with caution given the small sample from which these findings are drawn.
4. Although the wealth effect from an increase in the value of an insurance policy or a pension plan on consumption may not be significant.

including other indicators of the degree of tightness of financial conditions faced by economic agents and affected by monetary policy. FCIs normally contain measures of interest rates, exchange rates and housing and equity market conditions weighted according to an economic model. Studies show that these indices outperform the traditional Monetary Conditional Index (MCI), a weighted average of the short-term interest rate and the exchange rate, in tracing and predicting output and inflation.[5] (see e.g. Goodhart and Hofmann 2002, Lack 2002) Nevertheless, FCIs still suffer from certain criticisms applied to MCIs, such as *model dependency, ignored dynamics, parameter inconstancy* and *non-exogeneity of regressors*.[6]

In this paper, we provide a review of these existing indices and propose several FCIs for Canada based on different approaches. Our contribution to the literature is that each approach is intended to address one or more criticisms applied to the MCI and existing FCIs. Our first approach derives component weights from an IS-Phillips Curve framework in two ways: the first uses the sum of coefficients on the lags of variables, the second includes individual lags in the FCI to take into account the *dynamics* of variables over time. Our second and third approaches are focused on the criticism of *non-exogeneity of regressors* and *model dependency,* deriving weights based on generalized impulse response functions from a VAR and factor analysis, respectively. For all three methods, we experiment with one set of variables detrended with an HP filter and a second version detrended by first differencing. We then evaluate our different FCIs according to their weights, dynamic correlation with output and inflation, their in-sample fit in explaining output, and their out-of-sample forecast performance. While common practice in the literature is to use quarterly data starting from the 1960's, we use monthly data from 1981 to 2000. This way, we avoid potential structural breaks caused by oil prices in the 1970's and thus marginally address the problem of *parameter inconstancy.* Furthermore, the higher data frequency is more analyticcally useful given the Bank of Canada's adoption of a fixed policy action date schedule (eight times yearly).

Based on the IS-Curve method, we find that housing prices, equity prices and bond risk premia, in addition to short and long-term interest rates and the exchange rate, are significant in explaining output from 1981 to 2000. In both the HP-filter and first-difference specifications, housing prices have a higher or comparable absolute-value coefficient than that of the exchange rate. The long-term interest rate is found to carry the highest weight among the variables in the two specifications. We also find that our FCIs using a U.S. high-yield bond spread perform better than our FCIs that include a Canadian invest-

5. Section 5 provides a more detailed comparison between the MCI and our FCIs
6. see e.g. Eika, Ericsson and Nymoen, 1996 and Ericsson, Jansen, Kerbeshian and Nymoen, 1998.

ment bond spread. Out of the eight FCIs based on all three approaches, two specifications have particularly well-rounded attributes according to our chosen criteria. The FCI deriving its weights from summed coefficients of an IS Curve using first-differenced data serves best as a short-term (less than one year) predictor of output growth, while that deriving its weights from VAR impulse-response functions using first-differenced data serves best to predict output over the longer term (one to two years). Our FCIs also largely outperform the MCI in many criteria considered in this paper.

The rest of the paper is organized as follows. Section 2 provides a critical review of existing FCIs in the literature. Section 3 presents the methodology of our three approaches to constructing FCIs. Section 4 discusses the properties and performance of our FCIs. Section 5 compares the FCI with the Bank of Canada's MCI. Section 6 discusses the interpretation of our FCIs as a measure of financial stance and Section 7 concludes with suggestions for future research.

2. The Literature on FCIs

Researchers from central banks and various private organizations have developed different versions of FCIs to complement existing measures of policy stance. Table 2 provides a summary of the variables, detrending methods and weighting schemes used in these FCIs.

2.1 Variables Included in an FCI

All FCIs known so far contain a short-term interest rate and an exchange rate, implying that all FCIs are extensions of MCIs. The short-term interest rate is sometimes considered a measure of stance in itself, since it is highly correlated with the policy instrument, the overnight rate, and has been found by numerous studies to bear some predictive power for output and inflation. (e.g. Sims (1981) and Bernanke and Blinder (1992)). The exchange rate provides additional information about the exchange rate channel, through which aggregate demand is affected by the relative price of imports and exports.

Some FCIs also include a long-term interest rate or a corporate bond risk premium. While long-term rates are affected less directly by monetary policy than the short-term rate, they are more relevant to the financing decisions of businesses and households. It is also interesting that Goldman Sachs and JP Morgan also include the term spread in their FCI for Canada. While many studies have suggested that the term spread has more predictive power for inflation than the short-term interest rate in Canada[7], the use of both these variables may imply overlapping information.

Existing FCIs differ most in terms of their choice of variables to represent equity market conditions. While stock prices are most intuitive, some private institutions also use measures of stock valuation, the equity market capitalization-to-GDP ratio, the dividend price ratio and a measure of household equity wealth. Macroeconomic Advisers reports that the idea behind their choice of the dividend price ratio and household equity wealth is that the wealth channel can be divided into two parts, that which affects households directly and that which affects businesses through the equity-cost of capital. Apart from that, there is insufficient information on how the other institutions chose their particular measures of stock market conditions over other alternatives.

Property prices are used in the FCIs of Goodhart and Hofmann (2001) and, subsequently, Mayes and Virén (2001). Both studies find that property prices have stronger explanatory and predictive power for inflation than do equity prices. The former study also finds that the impact of housing prices on the output gap is larger than that of the exchange rate in Canada. However, the authors acknowledge that the timeliness of housing price data remains a challenge for the purposes of an FCI.

JP Morgan's FCI is the only one in Table 2 that includes monetary aggregates. It should be noted, however, that the construction of this index may be considered somewhat *ad hoc*. The only criterion placed on the variables included in their index was that they were, "monetary and financial indicators that the Bank of Canada has emphasized at various times in the past [or] well known financial market indicators that reflect the cost of funds to Canadian businesses."[8] Furthermore, JP Morgan assign equal weights to all components in their index as opposed to weighting the variables by some estimated relative importance.

2.2 Detrending the Variables

Detrending of variables is an important issue because it is directly related to the way these variables are modelled and the interpretation of the FCI. The primary reason for detrending is to deal with non-stationarity in many economic series for the purpose of econometric modelling. Depending whether the series has a stochastic trend or a deterministic trend, first differencing the variables and taking the

7. See Macklem (1992) and Macklem (1995) for a more detailed discussion.
8. Quotation taken from correspondence with Ted Carmichael of JP Morgan. (Mar. 25, 2002)

deviation from a trend can be applied, respectively. Goodhart and Hofmann (2001) define all four of their chosen variables in deviation from some trend. The trend for the short-term interest rate is its sample mean and that for the exchange rate and housing prices is their linear trend. In the case of equity prices, due to the time-varying nature of expectations for future dividend growth, a Hodrick-Prescott Filter with a high smoothing parameter of 10,000 is used. The deviation of each variable from its trend is then used in the construction of the index.[9]

An advantage of deriving a long-run trend or equilibrium value for all the variables is that a positive deviation of the FCI from its equilibrium value can be interpreted as a relatively tight stance, and vice versa. This interpretation of the FCI is particularly important if the policy maker wants to use the FCI as an operational target. However, finding a time-varying equilibrium value for these variables, just like for any other economic variable, is difficult and usually involves extensive modelling work.

A popular method to derive a time-varying trend is to use the HP filter. Despite its simplicity, this method is subject to some criticism. One prominent criticism is that the filter is two-ended, implying that the calculated trend this period must depend on data from next period. This causes practical problems when generating timely analysis and forecasts.[10] Another potential drawback of the HP-filter is that it may not be able to remove the stochastic trend of the series, even if the filtered series is stationary.

2.3 Weighting of the Variables

There are mainly two methods used in the literature to determine and weight the component variables of an FCI. The first is to try to explain the role of asset prices in the transmission mechanism through economic modelling. As mentioned in Goodhart and Hofmann (2000), there are three ways of doing this:

- simulation in a large scale macro-econometric models
- reduced-form aggregate demand equations
- Vector Autoreggression (VAR) impulse response functions

9. In a similar later study (2002), recognizing the need for a time-varying trend for all variables, the authors apply HP filters to all four series.
10. See Guay and St-Amant (1996) for a more detailed explanation of the HP filter and its drawbacks.

Large-scale models are designed to capture structural features of the economy and take into account the interaction of all variables. Therefore, they might be more appropriate than reduced-form aggregate demand equations and VAR impulse response functions. Goldman Sachs and Macroeconomic Advisers use this approach to construct an FCI for the U.S. In reality, however, stock and other asset prices play a limited role in many large scale macro-models currently used by central banks and other organizations. This is partly due to the lack of consensus in the theoretical literature on the channels through which asset prices affect aggregate demand and inflation. As a result, reduced-form equations and VAR impulse response functions serve as a useful alternative to estimate such an effect from empirical data.

A typical reduced-form model consists of an IS equation relating the output gap to interest rates, exchange rates and other asset prices, and a Phillips Curve relating inflation to the output gap. Generally the choice of explanatory variables depends on their statistical significance in the model. The coefficient estimates then determine the weight of each variable. This methodology is perhaps the most widely used in the construction of FCIs (see Table 2). However, its simple assumption that all asset prices are exogenous to each other and to the real economy may lead to estimation bias.

Goodhart and Hofmann (2001) also extend the reduced-form approach to an identified VAR, which includes all variables in the reduced-form model and one-period lagged world oil prices as an exogenous variable.[11] The relative weights between the endogenous variables are then calculated based on the average impact of a one-unit shock to each asset price on inflation over the following 12 quarters. Compared to the reduced-form model, the approach of using VAR impulse response functions imposes less economic theory and allows for more interactions between variables. The authors find that FCIs from both approaches yield similar results, while housing prices have a higher weight under the VAR approach, implying an additional indirect effect on CPI via housing prices.

The second main approach to determining FCI components and weights is largely atheoretic. It is based on the abilities of various leading indicators and their different combinations to forecast output or inflation.[12] This approach is motivated by Stock and Watson (2000) who calculate the median and trimmed mean (removing largest and smallest outliers) of the forecasts by 38 individual indicators from a

11. It is, however, difficult to justify the assumptions made by the authors to identify their VAR.
12. An extreme case of an atheoretic approach is taking the simple average of all components, e.g. JP Morgan and Goldman Sachs for Canada.

bivariate model. The authors find that the performance of the combined forecasts exceeds that of many univariate benchmarks as well as individual bivariate models. While the median or trimmed mean of individual forecasts already implicitly weights the indicators according to their coefficient in the bivariate regression, this approach, as Mayes and Virén (2001) noted, does not allow time-varying weights and is oversimplified if it is adopted in the construction of an FCI.

2.4 FCIs as Tools

Private institutions (GS, JP Morgan, MA) link their FCIs with output growth several quarters ahead and often gauge the future course of monetary policy based on the current level of their FCI. They have used graphs to show that their FCI foreshadows future output growth better than the Bank of Canada's MCI. While these external organizations use FCIs to guess monetary policy actions, the use of such indices can be more diverse for the central bank itself. As analysed in Mayes and Virén (2001), the FCI can serve a central bank in at least two ways. First, when there is a shock to the economy, changes in the FCI can give an indication of the market's interpretation of the shock and their expectation of future monetary policy. Second, the central bank can obtain leading information on the impact of market conditions and expectations on the future economic outlook.

A more aggressive use of the FCI is to derive a policy rule by normalising on the interest rate. Using a similar model to the one developed in their earlier studies (2000, 2001), Goodhart and Hofmann (2002) show that the optimal policy reaction function is such that the interest rate should not only react to current and lagged values of CPI inflation and the output gap, but also to the real exchange rate, real house prices, real share prices and the change in world oil prices. This is similar to an "MCI-based" rule suggested by Ball (1999), in which exchange rate targeting plays a role in setting monetary policy. This use of an FCI or MCI is controversial. Opponents of this view include Bernanke and Gertler (1999) and Gertler et al. (1998). Goodhart and Hofmann (2002) also denounce mechanical policy response to asset prices and advise that policy makers proceed with caution when interpreting information in asset prices.

2.5 Criticisms of FCIs

Although many of these studies argue that their FCIs are an improvement over MCIs, they are still subject to many of the same main criticisms levied against the MCI. In particular, many FCIs fail to address the following technical issues:

A) model dependency

Like those of an MCI, weights of existing FCIs are usually derived from a model, be it a single equation IS Curve or a large scale macroeconomic model. Therefore, the ability of the FCI to capture the impact of financial variables on aggregate demand is only as good as the assumptions underlying the model. This argument is particularly true in the case of an FCI, since asset prices, especially housing prices, do not play an explicit role in many macro models (Goodhart and Hofmann, 2001).

B) ignored dynamics

FCIs contain variables that affect output and inflation with varying speed. While a rise in the short-term interest rate lowers inflation in six to eight quarters, for example, a change in housing prices could have an impact on inflation instantaneously. Thus, looking at the components of the FCI at any period ignores these dynamics across time. A common treatment of this problem is to include a lag structure in the IS Curve or model from which the weights are derived. The contemporaneous value of each component in the index is simply multiplied by the sum of the coefficients on the lags. This is obviously an oversimplified approach (See Batini and Turnbull 2002 for a more detailed discussion).[13]

C) parameter inconstancy

Often FCIs are derived from an estimated model or equation covering the last twenty to thirty years. It is most likely that there have been regime changes and other structural breaks within the sample period. Some FCIs, especially those from the private sector, do not address this problem. Even in the cases where this problem is addressed, only simple breakpoint tests are applied.

D) non-exogeneity of regressors

In models or equations where weights are derived, the variables in the index are usually modelled as exogenous variables. However, it is likely that they are simultaneously affected by the dependent variables (output and inflation), so a simultaneity bias may be present. Moreover, housing and equity prices are often characterised as forward-looking variables, namely depending on future output and inflation outlooks. Thus, even in a VAR, where all variables are simultaneously determined by lags of itself and other variables, some parameters may still be difficult to interpret.

13.The FCI from Macroeconomic Advisers is the only one surveyed that includes individual lags of the components.

3. Three Ways to Derive an FCI for Canada

In an effort to improve some of the aforementioned weaknesses of MCIs and existing FCIs, we propose three methods to construct an FCI for Canada. The first method derives weights from a reduced-form IS-Phillips Curve framework. The weights are derived in two ways: we first use the sum of coefficients on the lags of the variables, and second we include individual lags in the FCI to take into account the *dynamics* of these variables over time. Our second and third approaches are focused on the criticisms of *non-exogeneity* and *model dependency*, deriving weights based on generalized impulse response functions from a VAR or factor analysis, respectively. For each of these versions, we experiment with a dataset detrended with an HP filter and a dataset detrended by first differencing. Finally, while common practice in the literature is to use quarterly data starting from the 1960's, we use monthly data from 1981 to 2000. This way, we avoid the potential structural breaks caused by oil prices in the 1970's and, thus, marginally improve the problem of *parameter inconstancy.*

3.1 FCIs Based on a Reduced-Form Model

Despite being subject to the validity of its assumptions, the advantage of deriving an FCI from a structural model is that it is more likely to identify the effect of each potential transmission channel on the real economy. Besides monetary policy actions, other shocks that may have an impact on the economy, such as fiscal shocks, external shocks, supply shocks and market sentiment can also be modelled in such a framework.

This method was adopted in the construction of the Bank of Canada's MCI (see Duguay, 1994) and is a popular methodology in the construction of FCIs (see Table 2). Models used for this purpose usually consist of an IS Curve and a Phillips Curve. For example, in Duguay (1994) the IS Curve relates the components of the MCI (the interest rate and the exchange rate) to output growth, controlling for external output, commodity prices and fiscal policy. The Phillips Curve then links the output gap to inflation, controlling for inflation expectations (assumed to be formed adaptively) and the effects of oil prices, tax rates and the changes in real exchange rate. All explanatory variables are modelled as moving averages.

Goodhart and Hofmann (2000, 2001, 2002) use a framework proposed by Rudebusch and Svensson (1998). Their IS Curve contains the output gap as the dependent variable and the components of their FCI in addition to lagged output gap and an external (OECD) output gap for some countries. Their

Phillips Curve, on the other hand, relates the output gap to inflation, controlling for oil prices and lags of inflation.

We adopt a framework similar to that of Goodhart and Hofmann (2000, 2001, 2002). Our model consists of a backward-looking IS Curve and a backward-looking Phillips Curve (equations 1 and 2, respectively). We estimate two versions of our IS-PC model, one using HP-filtered data and one using first-differenced data.[14] The IS Curve includes lagged values of output, asset prices and commodity prices. The lagged values of output are expected to take into account other types of shocks such as US output and fiscal shocks. The Phillips curve contains lagged values of inflation and output, and contemporaneous and lagged values of oil prices.[15] The two equations are defined as follows:

$$y_t = \alpha_1 + \sum_{i=1}^{n} \sum_{j=1}^{n_i} \lambda_{i,j} x_{i,t-j} + \sum_{k=1}^{p} \gamma_k y_{t-k} + \sum_{l=0}^{q} \theta_l pcom_{t-l} + \varepsilon_t \tag{1}$$

$$\pi_t = \alpha_2 + \sum_{i=1}^{m1} \beta_{1i} \pi_{t-i} + \sum_{j=1}^{m2} \beta_{2j} y_{t-j} + \sum_{k=0}^{m3} \beta_{3k} poil_{t-k} + \varepsilon_t \tag{2}$$

where *y* is the output gap in our HP-filtered specification (i.e. the percentage gap between real monthly gross domestic product and its potential level, calculated as its HP-filtered trend) or monthly growth of real gross domestic product in our first-differenced specification.[16] x_i is component *i* of the FCI, where x = {real 90-day commercial paper rate, real 10-year government bond rate, C6 real exchange rate, real residential housing prices, real S&P 500 stock price index and AA corporate bond risk premium or the US high yield bond spread}[17]; *pcom* is the real Bank of Canada commodity price index. In our Phillips Curve, π is year-over-year core inflation (CPI excluding its 8 most volatile components and effects of indirect taxes) and *poil* is monthly growth in crude oil prices.

14. HP filters typically use a smoothing parameter of 1600 for quarterly data, but there exists no consensus on the appropriate value for monthly data. We use a relatively high parameter of 129 600 based on Ravn & Uhlig (2002).
15. Thus far, the Phillips Curve does not play a role in our analysis beyond ensuring theoretically desirable properties of our observed data. However, it does serve as a platform upon which to extend our research.
16. A constant is included in equation (1) when using first-differenced data, but not when using HP-filtered data.
17. The US high-yield spread is considered based on the results of Djoudad & Wright (2002) suggesting a strong relationship between this spread and Canadian real GDP growth.

3.2 FCIs Based on Generalised Impulse Response Functions

The IS-PC framework suffers from a specification problem: the implicit (false) assumption that the variables in the FCI are exogenous to output and inflation (and to each other). A natural way to address this problem is to base our FCI weights on the impulse responses of an atheoretic VAR. This approach also has pitfalls, however, since the traditional procedure, suggested by Sims (1981), is to use a Cholesky decomposition to orthogonalize the shocks (see, for example, Goodhart and Hofmann [2001]). In doing so, the orthogonalized impulse response functions are dependent on assumptions regarding the order in which each variable affects the others. In the case of an FCI including many financial variables all reacting instantaneously to shocks in the economy, there is no clear guidance as to what set of assumptions should be made.

An appealing alternative is to base the weights on generalised impulse response functions. While orthogonalized impulse responses are not invariant to the reordering of the variables in the VAR, generalised impulse responses are. The generalised impulse responses are unique and fully take into account the historical patterns of correlations observed amongst different shocks. An FCI can then be constructed by weighting the variables according to their relative average impact on output over the following 18 to 24 months, the period of time over which monetary policy is thought to have its full impact on output and inflation.

Here is a simple illustration of the generalized impulse response function. Consider the VAR model,

$$X_t = \sum_{i=1}^{p} \Phi_i X_{t-i} + \varepsilon_t , \quad t = 1, 2, \ldots, T \tag{3}$$

where $X_t = (x_{1t}, x_{2t}, \ldots, x_{mt})'$ is an $m \times 1$ vector of jointly determined, dependent, stationary variables and ϕ_i is an $m \times m$ coefficient matrix. Under standard assumptions on the residuals, equation (3) can be rewritten as the infinite moving average representation,

$$X_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} , \quad t = 1, 2, \ldots, T \tag{4}$$

with $A_0 = I_m$ and $A_i = 0$ for $i < 0$.

An impulse response function measures the effects of shocks at given point in time on the (expected) future values of variables in a dynamic system. The best way to describe an impulse response is to view it as the outcome of an experiment in which the time profile of the effect of a hypothetical $m \times 1$ vector of shocks of size $\delta = (\delta_1, \delta_2, \ldots, \delta_m)'$ hitting the economy at time t, is compared with a base-line profile at time $t + n$ given the economy's history.

Denoting the known history of the economy up to time $t - 1$ by the non-decreasing information set Ω_{t-1}, the generalised impulse response function of X_t at horizon n, is defined by

$$GI_X(n, \delta, \Omega_{t-1}) = E(X_{t+n} | \varepsilon_t = \delta, \Omega_{t-1}) - E(X_{t+n} | \Omega_{t-1}) \qquad (5)$$

Substituting equation (4) into (5), we have $GI_X(n, \delta, \Omega_{t-1}) = A_n \delta$, which is independent of Ω_{t-1}, but depends on the composition of shocks defined by δ.

Clearly, the appropriate choice of the hypothesized vector of shocks, δ, is central to the properties of the impulse response function. The traditional approach, suggested by Sims (1981), is to resolve the problem surrounding the choice of δ by using a Cholesky decomposition of the variance-covariance matrix of the residuals, Σ,

$$PP' = \Sigma,$$

where P is a $m \times m$ lower triangular matrix. It is then easy to show that the $m \times 1$ vector of the orthogonalized impulse response function of a unit shock to the jth equation on X_{t+n} is given by $OI_X(n, e_j, \Omega_{t-1}) = A_n P e_j$, where e_j is an $m \times 1$ selection vector with unity as its jth element and zeros elsewhere. As already mentioned, these orthogonalized impulse response functions vary with the reordering of variables.

An alternative approach, and the one we follow in this paper, is to use (4) directly, but instead of shocking all the elements of ε_t, we could choose to shock only one element, say its jth element, and integrate out the effects of other shocks using the historically observed distribution of the errors. In this case, it is easily shown that the effect of one standard error shock to the jth equation at time t on expected values of X at time $t + n$ is

$$GI_X(n, \delta, \Omega_{t-1}) = \sqrt{\sigma_{jj}} A_n \Sigma e_j \qquad (6)$$

where $\delta = E(\varepsilon_t | \varepsilon_{jt} = \sqrt{\sigma_{jj}})$.

3.3 FCIs Based on Factor Analysis

A third option in developing an FCI is to derive a linear weighted combination of financial variables through factor analysis. The basic idea of factor analysis is to extract weighted linear combinations (factors) from a number of variables. This helps to detect the common structure in these variables and remove "noise" created by irregular movements of certain variables at certain times. In a two-variable example, the principal factor of the two variables is the least-squared regression line between them. An advantage of this approach is that it does not depend on any model, while a disadvantage is that weights on individual variables are unknown.

Many studies have applied factor analysis to a large number of explanatory variables in forecasting models. For example, Stock and Watson (1989, 1999) forecast GDP with a few factors derived from 215 monthly indicators and find the factor model outperforms various benchmark models. Combining the information content in 334 Canadian and 110 U.S. macroeconomic variables into a few representative factors, Gosselin and Tkacz (2001) find that factor models perform as well as more elaborate models in forecasting Canadian inflation.

We apply factor analysis to a set of financial variables and derive our FCI from their primary factor. We can express these variables as a function of the unknown factors:

$$X_{it} = \lambda_i(L) F_t + e_{it} \qquad (7)$$

where X_{it} is the ith variable, $F_t = (f_t, ..., f_{t-q})$ is a $r \times 1$ vector, q is the maximum number of lags, $r = (q+1)\bar{r}$, $\bar{r}$ is the number of factors we would like to extract and is set to ten[18], and $\lambda_i(L)$ is a lag polynomial. The factors f_t and disturbances e_{it} are assumed to be mean-zero stochastic processes. The factor F_t is estimated by the method of principal components. This involves minimizing the sum of squared residuals of equation (7), which can be expressed as a non-linear objective function:

$$V(F, \Lambda) = \frac{\sum_{i=1}^{N}\sum_{t=1}^{T}(X_{it} - \lambda_i' F_t)^2}{NT} \tag{8}$$

where N is the number of variables and T is the sample length. After reorganizing F to the left-hand side of equation (8), minimization is equivalent to maximizing $tr[\Lambda'(X'X)\Lambda]$, subject to $\frac{(\Lambda'\Lambda)}{N} = I_r$, where $\Lambda = (\lambda_0, \ldots, \lambda_q)$ and each λ is of dimension $N \times 1$ (see Stock and Watson 1999). The principal-components estimator of F is thus

$$\hat{F} = \frac{(X\hat{\Lambda})}{N} \tag{9}$$

$\hat{\Lambda}$ is obtained by setting it equal to $N^{\frac{1}{2}}$ times the eigenvectors of the $N \times N$ matrix X'X corresponding to its r largest eigenvalues.

4. Properties of our FCIs

In order to compare properties across our three methodologies as explained in Section 3 and various specifications of each, we composed a list of six properties or performance criteria.[19] Namely, for a given FCI we look at the estimated weights on its components, its graphical presentation and dynamic correlation versus the output gap (or monthly growth in real GDP), its dynamic correlation with year-over-year core inflation as well as its in and out-of-sample performance in a simple forecasting exercise.

18.The marginal information content decreases rapidly after the first three to four factors. Ten factors are usually sufficient to capture the common variance of the entire data set.

19.Several combinations of variables were estimated within each methodology, the best of which are reported in this paper. The results of alternative formulations are available upon request.

4.1 FCIs Based on a Reduced-Form Model

Referring back to Section 3.1, our IS-PC equations (1) and (2) are estimated separately using OLS over sample period 1981m1-2000m12[20]. The lag structure for each variable includes all sequential time periods between *t-1* and the last significant lag, up to a maximum of 12 lags.

We then proceed to derive the weights for the FCI in two ways. Following Goodhart and Hofmann (2001, 2002), we apply coefficients summarized across lags to each contemporaneous component in the FCI. Despite making for a technically simple FCI, this approach is subject to the criticism that different asset prices have an impact on the real economy with varying lags, and by multiplying the weights with the contemporaneous value of these variables, the dynamics over time are ignored. In response to this criticism, we also construct a separate version of our FCI allowing for the full dynamics of individual lags. This is similar to Batini and Turnball (2002), who construct a dynamic MCI for the UK using this methodology.

Table 3 reports the estimated weights and p-values on our “summarized-weight” FCIs, one using HP-filtered data and one using first-differenced data. Likewise, Table 4 shows the equivalent information for our two “individual-lag” FCIs.

As described regarding our general IS Curve specification (equation 1), each of our four IS-based FCIs include the real commercial paper rate, the real 10-year Government of Canada bond rate, the real C6 exchange rate, real housing prices and the real S&P 500 stock price index. However, they differ somewhat in their use of variables to measure the corporate bond risk premium. Our HP-filter *individual*-lag FCI contains the Canadian AA long-term corporate bond spread, whereas our first-difference *individual*-lag FCI and both our *summarized*-coefficient FCIs use the U.S. high-yield spread.

Further inspection of Table 3 reveals that both our summarized-coefficient FCIs have estimated weights that are consistent with economic theory. The traditional policy transmission channels upon which MCIs are built dictate that a higher short-term interest rate or higher exchange rate (appreciation of domestic currency) indicate a tighter policy stance. Indeed, in our summarized-coefficient FCIs, both of these variables carry a negative coefficient. The long-term interest rate is often interpreted as a proxy for

20. Our estimation period ends in 2000 for the purpose of performing an out-of-sample forecast exercise over 2001m1 to 2002m6, the results of which are reported later in this section.

future output growth: a higher long-term interest rate for a given short-term interest rate, or a steeper yield curve, is well known to be a good indicator of higher future output growth. Accordingly, our FCIs have a positive summarized weight on the long-term interest rate. Alternatively, a higher corporate bond risk premium, for a given long-term interest rate, suggests a rising cost of external financing for high risk businesses and ensuing weakness in output via the credit channel. Thus we expect a negative weight on this variable in our FCIs.[21] In fact, this is the case. Our FCIs also lend credence to the existence of some combination of a wealth channel and/or credit channel for monetary policy in that both housing and stock prices hold positive estimated coefficients. Relatively speaking, the long-term government bond rate and the corporate bond risk premium respectively carry the first and second largest absolute weights in both our summarized-coefficient FCIs, followed by the short-term interest rate. Housing prices and the exchange rate are the fourth and fifth largest for our HP-filtered summarized-coefficient FCI, whereas the ordering of these two variables is reversed for the first-differenced version. Finally, stock prices take the smallest relative absolute weight in both our summarized-coefficient FCIs.

Table 5 displays the summarized coefficients on our backward-looking Phillips Curves. Although HP-filtered data provide a more intuitive measure of the output gap than does first-differenced output, we estimate equation (2) using each measure. Again, the lag structure of each variable includes all lags between the first lag and the last significant lag (up to a maximum of 12 lags). Both Phillips Curves estimate the output gap (or output growth) with a positive sign, which is consistent with theory wherein a higher output gap exerts more inflationary pressure on the economy. The HP-filtered output gap is statistically significant at a 5% margin, while its first-differenced counterpart is not quite significant at a 15% level. Theoretically, for a net commodity exporter like Canada, an increase in oil prices should lead to more inflation through increased domestic spending. This positive relationship does not hold up in our HP-filtered Phillips Curve. Furthermore, in both curves, the summarized coefficient of crude oil prices is very small.

Our second criteria by which to judge the adequacy of our FCI is visual inspection vis-a-vis the output gap (or output growth). Ideally, the FCI will perform as a leading indicator and effectively signify business cycle turning points. Figure 1 illustrates our HP-filter summarized-coefficient FCI against the

21. We also constructed a version of our FCI without the long-term interest rate in order to investigate the possibility of multicolinearity between the long rate and the risk premium. In both the HP-filter version and the first-difference version of this alternative specification, the weights on the short-term interest rate are positive and are no longer in line with theory.

output gap. This FCI appears to follow the output gap fairly closely and often catches turning points in advance (e.g. upturns in 1986 and 1991, downturns in 1994 and 1999). Tables 6 and 7 contain dynamic correlations, our third criterion, of all four IS-based FCIs versus the output gap/output growth and year-over-year inflation, respectively, for various lag lengths. This table provides further evidence of the leading indicator property of our HP-filter summarized-coefficient FCI, with a solid dynamic correlation peaking at 0.604 two and three months in advance of the output gap. The correlation of this FCI with year-over-year inflation peaks at 0.176, leading by nineteen months. This is roughly consistent with the view that monetary policy typically affects the real economy with a lag of about two years.

Figure 2 presents a similar graph of our first-difference summarized-coefficient FCI (in annualized terms) against year-over-year real GDP growth. Visually, this FCI also generally performs well as a leading indicator. Various turning points are clearly predicted in advance (e.g. upturns in 1995 and 2001, downturns in 1983, 1987, 1994 and 1998). The correlation of this index with output growth peaks at 0.609 four months in advance. Its correlation with inflation is consistently strong, with a peak of 0.512 thirty eight and thirty nine months ahead. Figure 3 illustrates the relationship with this FCI and core inflation.

Our HP-filter individual lag FCI is displayed in Figure 4 against the output gap. This index is significantly more volatile than the other three IS-Curve-based FCIs owing primarily to its dynamic lag structure as well as its particular weights and the competing movements of its components. Nonetheless, it is able to follow the output gap fairly closely and does well in leading some turning points (e.g. upturns in 1982, 1986, 1992 and 2001, downturns in 1989, 2000). This FCI has a slightly lower correlation with the output gap, peaking at 0.459 at a lead of four months. In terms of its correlation with inflation, it reaches a high of 0.123 twenty-six months in advance.

Our final FCI based on the reduced-form methodology, the one featuring first-differenced data and an individual, dynamic lag structure, is shown in Figure 5 (in annualized terms) against year-over-year real GDP growth. Similar to the preceding FCIs, this index follows output growth quite well over some periods. This FCI also appears to lead various turning points (e.g. upturns in 1991 and 1996, downturns in 1988 and 1999-2000). However, the maximum correlation of this FCI with output growth occurs contemporaneously at a level 0.592. In this respect, its leading indicator property is not as strong as our other three IS-Curve-based FCIs. On the other hand, this index does have a solid positive correlation with inflation peaking at 0.570 at a lead of 35 months.

The final two criteria by which we compare our FCIs are the in and out-of-sample properties of a simple forecasting exercise. The exercise utilizes a rolling estimation of the form:

$$y_t = \alpha_3 + \beta FCI_{t-k} + \varepsilon_t \tag{10}$$

where y is the output gap (or year-over-year growth of real output), *FCI* is the particular FCI under consideration and k takes the value of {6, 9, 12, 18, 24}. In other words, this forecast is a simple way of determining whether or not a given FCI helps explain y 6, 9, 12, 18 or 24 periods ahead.

The length of the estimation sample for equation (10) is constant throughout the rolling process, initially beginning in the early 1980s and ending at the last available observation so as to provide a one-step-ahead forecast of the output gap (or output growth) k-steps ahead from our incorporated FCI data. In the end, forecasted observations are obtained for each month from January 2001 to June 2002, regardless of the value of k in equation (6).[22] Thus, this method of forecasting allows strict comparison of results between FCIs for any particular value of k, but not across values of k (since the number of observations used in estimation varies). Recall also that the weights for our FCIs are estimated from 1981 to 2000 to ensure the “out-of-sample” properties of our forecast over 2001 and the first half of 2002.

Table 8 reports the in-sample properties (coefficient on the FCI, its p-value and the adjusted R^2) as well as the mean squared forecast error for the forecasts using our reduced-form based FCIs. As one would expect, it is generally true that the size of the coefficient on a given FCI, and the R^2 value fall as k increases. Conversely, the p-value of the coefficient on the FCI and the mean squared forecast error both increase as k grows larger. A general message is told by these numbers: the further ahead one looks, the less information today’s value of the FCI provides in explaining the output gap (or output growth). As noted above, however, comparisons across values of k must be treated with caution on account of differing estimation sample sizes for each k.

22. For example, when k = 24, estimation begins over 1983m1 to 2000m12, forecasting a value for 2001m1. In the last iteration of the rolling regression, the estimation sample is 1984m6 to 2002m5, forecasting a value for 2002m6. When k = 6, the initial estimation period is 1981m6 to 2002m12 and the final period is 1982m11 to 2002m5. Forecast values are still generated from 2001m1 through to 2002m6.

Our FCI based on HP-filtered data and using summarized coefficients shows up statistically significant at the 10% level when explaining the output gap six, nine, twelve and eighteen months ahead. However, it is insignificant when looking 24 months ahead. The largest coefficient on the FCI is 1.91 when k = 6. In this case, a one-point increase in the FCI translates into about a 1.91 percentage point increase in the output gap. This lag length also provides the maximum R^2 of 0.311 for this FCI. Subsequent values of k give an R^2 level that peters off fairly linearly to a value of approximately zero when k = 24. Our first-difference summarized-coefficient FCI performs quite well in-sample, showing up statistically significant at all observed horizons (6, 9, 12, 18 and 24 months). Its maximum coefficient is 1.20 at a horizon of six months, suggesting that the year-over-year growth rate of real output half a year in the future will move 1.2 percentage points with each 1 point increase in today's FCI value. The six-month horizon also gives the strongest R^2 for this FCI at a level of 0.310.

When looking at our individual-lag FCI based on HP-filtered data, it shows up statistically significant if k = 6, 9, 12 and 18, but not when k = 24. This FCI also has a stronger coefficient when it is significant. For example, its largest coefficient, 2.83, comes at k = 6, suggesting that a one point change in this FCI translates to a 2.83 percentage point increase in the output gap half a year later. The coefficient on this variable drops off quickly once k reaches 18 and is insignificantly different from zero when k =24. Turning to our other individual-lag-coefficient FCI, based on first-differenced data, we find that it is statistically significant throughout our relevant horizon of six to 24 months. The strongest coefficient on this FCI suggests that a one point increase in the FCI translates to a 1.33 percentage point increase in the year-over-year growth of real output six months ahead.

Refer again to Table 8 for the reported mean squared forecast errors of our out-of-sample forecast exercise. These results are also presented in graphical form for each FCI in Figures 6 through 9. Keeping in mind that mean squared forecast errors can only be compared between FCIs that forecast the same dependent variable, our summarized-coefficient FCIs perform best (i.e. have the lowest mean squared forecast error) overall using both HP-filter and first-difference definitions. The HP-filtered summarized-coefficient FCI performed better at the 9, 12 and 18 month horizon in comparison with the HP-filtered individual-lag FCI. At 6 and 24 months ahead, the individual-lag FCI performed slightly better. Likewise, the first-difference summarized-coefficient FCI performed better at all relevant lags, 6 through 24 compared to its individual-lag counterpart.

4.2 FCIs Based on Generalized Impulse Response Functions

Our VAR models are estimated with an 18-order lag structure[23] and our FCI weights have been defined as the cumulative impact of a typical shock to each component on output over 24 months, the period of time over which monetary policy is believed to have most of its impact. The resulting FCI based on first-differenced data includes the short-term interest rate, the long-term interest rate, the exchange rate, the TSX index, housing prices and the U.S. high-yield risky spread. Its HP-filter counterpart is composed of the same 6 variables with the exception of the stock market which is measured using the S&P 500. Figures 10 and 11, respectively, plot these two indices with output.

These FCIs can be viewed using the same six criteria presented in Section 4.1. Weights for both impulse-response-function FCIs are given in Table 9 and the impulse response functions themselves are illustrated in Figures 12 and 13. Both FCIs have large positive weights on housing prices. These weights are consistent with expectations that high housing prices are a signal of excess demand and a leading indicator of strong construction activity. It is worth noticing however that, in the long run, output is adversely affected by an increase in new housing prices (see Figure 13). This suggests that high housing prices may divert too much capital from more-productive sectors of the economy, therefore depressing potential output.

Both FCIs also place strong negative weights on the U.S. high-risk premium. A higher risky spread in the US means tighter credit conditions and lower growth in the US going forward, which, given the strong economic links between Canada and the US, is an indicator of lower growth in Canada as well. Our FCIs also both have a negative weight on the short-term interest rate which is consistent with the impact of monetary policy. The weights on the three remaining variables are of different signs in the different indices; this deserves some discussion.

The negative weight on the stock market in the first-difference FCI is relatively quite small and, accordingly, should not be given much importance. This same FCI places a positive weight on the long-term interest rate, suggesting that a positive surprise in this interest rate, or a steepening yield curve, is an

23. AIC and Schwarz criteria contradict each other. Schwarz's criteria suggested only one lag while AIC's suggested too many lags. This could be attributed to the presence of cointegration between the variables. Eighteen lags (six quarters) was in between the AIC and Schwarz suggestions.

indication of stronger economic growth going forward. This weight is negative in the HP-filter index, but can be explained such that a higher long-term interest rate increases potential output still more than it increases short-run output. This is consistent with the impulse response function in Figure 13. The positive weight on the exchange rate in the first-difference index is consistent with the expected trade-balance effect of an appreciation. Its positive weight in the HP-filter FCI is plausible since a higher exchange rate may decrease potential output, via higher cost of imported machinery and equipment, by more than it decreases actual demand. This again is consistent with the impulse response function in Figure 13.

Tables 6 and 7 include the dynamic correlations of our impulse-response-function FCIs with output and inflation, respectively. Both the HP-filter and first-difference FCIs have relatively strong correlations with output. The same can be said for the first-difference specification's correlation with inflation. However, the HP-filter version is somewhat less strongly correlated with inflation.

The in-sample fit of our two impulse-response-function FCIs are presented in Table 10 and can be visually examined in Figures 10 and 11. On the whole, these FCIs perform fairly well according to these criteria. In particular, the first-difference index leads the 1988, 1994 and 1999 downturns. The HP-filter index is disappointing over the late 1990s.

Both indices also perform competitively out-of-sample at a longer forecast horizon (Table 10). Figures 14 and 15 illustrate the forecast performance of our HP-filter and first-difference impulse-response-function FCIs, repsectively.

4.3 FCIs Based on Factor Analysis

Our factor-analysis FCI based on HP-filtered data contains the short-term interest rate, long-term interest rate, exchange rate, housing prices, S&P/TSX Composite index and the AA corporate spread. Its first-difference counterpart replaces the last two variables with the S&P 500 index and the US high-yield bond spread. Table 11 gives the percentage of common variance explained by each of the first four factors for these two indices. 80-90 percent of the common variance of output is captured by the first factor; thus, we specify our FCIs according to this factor.

Our two factor-analysis FCIs can be viewed using five of the six performance criteria utilized earlier in Section 4.[24] Figures 16 and 17, respectively, plot these two FCIs with their comparable GDP measures. The HP-filter version leads the recovery in 1982, 1986, 1993, 1995 and the downturn in 1989 and 1994 by about one to three months, and coincides with the recession in 1982 and the most recent economic downturn. On the other hand, the first-difference version with US equity and bond variables leads the boom in 1982, 1991, 1995, the bust in 1987, 1999 and the pick-up in 2002. On average, the latter appears to pick up more economic turning points and predict them with a longer lead than the former.

Tables 6 and 7, respectively, show the dynamic correlation between our factor-analysis FCIs and output and inflation. The HP-filter version performs better according to this property. It has a higher correlation with both output and inflation at almost all horizons than the first-difference version. Moreover, the latter is negatively correlated with lagged inflation at certain horizons, which is counterintuitive.

Table 10 shows the in-sample and out-of-sample performance of our two FCIs based on factor analysis. The first-difference version is statistically significant in explaining future output at all horizons, while the HP-filter version performs worse, with an insignificant coefficient at the 12, 18 and 24 month horizons. The forecast-equation coefficients of all FCIs based on factor analysis are relatively high compared to other methods of FCI weighting. In terms of the out-of-sample forecast over 2001m1 to 2002m6, both versions perform better at a shorter horizon, with the HP-filter FCI yielding smaller forecast errors overall than the first-difference version. Figures 18 and 19 illustrate the out-of-sample forecast performance of our HP-filter and first-difference factor-analysis FCIs.

4.4 Comparison of our Various FCIs

While each of our FCIs performs well in some respects, two specifications have particularly well-rounded attributes according to our six properties/performance criteria. These two FCIs are the summarized-coefficient IS-based FCI and the impulse-response based FCI both constructed using first-differenced data.

Both these FCIs roughly appear to do equally well at picking up turning points in output growth. They also both have estimated weights that are consistent with theory, although the weights and variables used between the two are somewhat different. Both FCIs include the short-term interest rate, the long-

24.In a factor analysis, weights are changing over time and are unknown.

term interest rate, the C6-exchange rate, housing prices and the U.S. corporate bond risk premium. However, the IS-based FCI contains the S&P 500 stock index, while the impulse-response based FCI utilizes the TSX composite index. The IS-based FCI places a relatively high weight on the 10-year government bond yield and a relatively low weight on the US high-yield bond spread and housing prices in comparison with the impulse-response based FCI (see Tables 3 and 9, respectively).

The IS-based FCI is comparatively more highly correlated with output and inflation than the impulse-response based FCI. It also performs better in terms of in-sample significance in the forecasting equation and in short-term forecasting 6 and 9 months ahead. On the other hand, the impulse-response based FCI performed better in longer-term forecasts, at 12, 18 and 24-month horizons.

Thus, both of these specifications are useful depending on the task at hand. The IS-based FCI is more valuable for predicting near-term output growth, while the impulse response-based FCI is more helpful for predicting longer-term output growth.

5. Comparing the IS-based FCI with the MCI

At a first glance, an FCI resembles a traditional MCI in several ways. They share a similar name and they contain similar variables. In fact, the former includes all the variables in the latter. They are also similar in that their weights are usually derived using an IS-Curve-based model to reflect the relative impact of the variables on aggregate demand. Nevertheless, the two indices bear significant differences.

The Bank of Canada's MCI was created mainly as a measure of the bearing of monetary policy on the economy, i.e. the policy stance.[25] The concept of an MCI is based on the belief that monetary policy affects aggregate demand (and thus inflation via the output gap) mainly through interest rate and exchange rate channels. On the other hand, the FCI contains asset prices that are only partially affected by monetary policy and yet may have an important impact on aggregate demand. As discussed earlier, this potential impact can take place through the wealth effect or the credit channel. In a sense, the FCI is a much broader measure of policy stance, which can be call a "financial stance."

25. While the Bank of Canada (Freedman, 1995) refers to "using the MCI as an operational target of monetary policy", the importance of the MCI in setting monetary policy has been largely de-emphasized.

Another important difference between the two indices is the way their variables are detrended. In the HP-filtered and first-difference versions of our FCI, we assume that the variables have a deterministic and stochastic trend, respectively. These assumptions are intended to take care of the non-stationarity of the data.[26] The MCI, in contrast, assumes that the interest rate and the exchange rate are stationary.[27] One can only compare today's MCI with that of the MCI in the base period, which is January 1987 in the case of the Bank of Canada's MCI. It is hard to believe that the economy was in equilibrium during the base period and that the nature of equilibrium has not changed since.

Despite its desirable features, the FCI has to at least outperform the MCI empirically in order to be a useful tool in the conduct of monetary policy. To investigate the properties of the MCI we perform a similar set of exercises as we did for our FCIs to investigate the performance of the MCI. Graph 20 plots the MCI and our best IS-Curve-based FCI against year-over-year GDP growth. Our FCI seems to do a much better job at tracing the dynamics of GDP growth and at capturing the turning points in the economy.

Table 12 to 13 show the dynamic correlation between the MCI and GDP growth and inflation, respectively. The MCI yields a slightly lower correlation with output growth compared to our FCIs at their respective peak month. However, the peak correlation between output and the MCI occurs with a longer lead than that of the FCI. Its peak correlation implies that the MCI leads the output gap by 18 months and year-over-year output by eleven, while the peak correlation between our FCIs and output takes place at a much shorter horizon. On the other hand, the MCI is positively correlated with inflation across all horizons, wrongly suggesting that the tighter monetary policy is, the higher will be inflation. However, this finding likely reflects the downward trend of both inflation and the components of the MCI over the 1990's, suggesting the positive correlation is spurious.

Table 14 presents the results of the MCI-based forecast of the output gap and year-over-year GDP growth. In both specifications, the MCI yields a correct sign and is significant at most of the relevant horizons. Compared with our FCIs, the MCI is generally less statistically significant, but produces a slightly higher adjusted-R^2. In terms of the out-of-sample forecast, the FCI unambiguously outperforms

26. A series of unit-root tests suggest that all our variables are integrated of order one. Unit root tests results are available upon request.

27. In practice, however, more emphasis is usually placed on the change of the MCI instead of its level. The problem of non-stationarity is in a sense addressed this way. See next section.

the MCI. The latter produces much larger forecast errors than any of our FCIs in forecasting output growth.

6. Interpretation of the FCI as a Measure of “Financial Stance”

Given that our best FCIs are a weighted sum of the first differences of our chosen variables, their interpretation as a measure of stance is not clear *a priori*. In this section we argue that, because the first difference of a series is simply its deviation from its stochastic trend or its equilibrium value, the higher is the FCI, the looser is the “financial stance” and the higher is expected growth.

Decomposing each variable in our FCI into its permanent and transitory component, we obtain:

$$x_t = x_t^e + tc_t$$

where the permanent component is the equilibrium value of the variable, x_t^e, and tc_t is its transitory component or its deviation from equilibrium. Take the first difference of x_t:

$$\Delta x_t = (x_t^e - x_{t-1}^e) + tc_t + tc_{t-1}.$$

Now assume that the equilibrium changes very slowly, so that we can approximate the monthly change, Δx_t, as:

$$\Delta x_t = tc_t + tc_{t-1}.$$

This assumption cannot be made if Δt is large. So is it more complicated to compare the value of the FCI 2 years ago with its value today in terms of stance, since the equilibrium values have probably changed over that period.[28] But from one fixed policy action date to another, it seems reasonable to assume that equilibrium levels of the variables have not changed much, if they have changed at all.

Under this assumption, a positive change in the short-term interest rate for example, means a tighter money market; Since the short-term interest rate is negatively weighted, it decreases the FCI, which implies lower expected output growth. Symmetrically, an increase in housing prices, directly stimulates housing supply, and indirectly, through the credit channel, increases the borrowing capacity of consumers and firms which stimulates investment and consumption. Since housing prices are positively weighted in the FCI, they are indicative of a looser “financial stance” and signal higher output growth.

7. Conclusion

In this paper, we provide a survey of the existing FCIs and propose several FCIs for Canada based on three different approaches. Each approach is intended to address one or more criticisms applied to the

28.The same critique applies to the MCI.

MCI and existing FCIs. For each approach, we experiment with one set of data detrended using an HP filter and a second set of data detrended by first differencing. We then evaluate the different versions of our FCIs based on six criteria: estimated weights of its components, its graphical presentation and dynamic correlation versus the output gap (or monthly growth in real GDP), its dynamic correlation with year-over-year core inflation as well as its in and out-of-sample performance in a simple forecasting exercise.

Our first approach derives its weights from an IS-Phillips Curve framework in two ways: first, using the sum of the coefficients on the lags of the variables, and, second, including individual lags in the FCI to take into account the dynamics of these variables over time. Using monthly data from 1981 to 2000, we find that housing prices, equity prices and bond risk premia, in addition to the short and long-term interest rates and the exchange rate, are significant in explaining output. In both the HP-filter and first-difference specifications, housing prices have a higher or comparable absolute-value coefficient compared to that of the exchange rate. The long-term interest rate carries the highest weight among the variables in both specifications. We also find that the FCIs using U.S. stock prices and high-yield bond spreads perform better than the ones including the Canadian stock prices and investment bond spreads.

Our second and third approaches are focused on the criticism of model dependency and non-exogeneity of regressors, deriving the weights based on generalized impulse response functions from a VAR and a factor analysis, respectively. Using first-differenced data, the weights derived from the second approach are comparable to those derived from the first approach.

Out of our eight FCIs based on all three approaches, two specifications have particularly well-rounded attributes considering several different criteria. The FCI deriving its weights from summed coefficients of an IS Curve using first-differenced data serves best as a short-term (less than one year) predictor of output growth, while that deriving its weights from VAR impulse-response functions using first-differenced data serves best to predict output over the longer term (one to two years). Our FCIs also outperform the MCI in many of the criteria considered in this paper.

Future research can further investigate the properties of this FCI by comparing its forecasting performance with benchmark univariate models. It may also be possible to derive the weights of the FCI from a large-scale macro model in which financial variables play an important role.

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Table 1: Composition of Canadian Household Total Asset[a]

Years	Property	Equity[b]	Bonds	Life insurance and pension	Others
1981-1985	36%	10%	5%	14%	35%
1986-1990	36%	10%	5%	17%	32%
1991-1995	36%	11%	4%	19%	30%
1996-2000	34%	14%	3%	22%	27%

a. Source, Statistics Canada Cansim matrix 751.
b. Including mutual funds.

Table 2: MCI and FCIs by Organizations and Academic Studies

Organizations/ Studies	Short-term rates	Long-term rates	Exchange rates	Equity market	Other variables	detrending	Weights
Bank of Canada	nominal 90 CP		nominal C6			change from a base period	from IS Curve
Banque de France for G7	real 3-month market rate	real 10-year government	real effective			“similar” to the BOC index	from IMF and OECD’s macro models
Myers and Virén, (2001) for 17 countries	real 3-month market rate		real bilateral vs. US	real stock price	real house price	level of real interest and exchange rate; first difference for the rest	from IS Curve (single equation)
Goldman Sachs for Canada [a]	real 3-month market rate		real effective	measure of stock valuation	yield curve	unknown	simple average
Goldman Sachs (2000) for U.S. [b]	real 3-month LIBOR	real A-rated corporate indexed	real trade-weighted	Equity mkt cap/ GDP ratio		deviations from historic mean for interest rates and exchange rate	from Fed macro model
JP Morgan for Canada (2002) [c]	nominal 3-month market	10-year corporate spread	nominal C6	nominal TSE 300	(1) yield curve (2) M1 (3) M2++	deviation from mean divided by variance	simple average[d]
Macroeconomic Advisers for the U.S. (1998)	real fed funds rate	real 10-year Treasury yield	real	(1) dividend/ price ratio (2) household equity wealth		not specified; referred to as “technical adjustment”	from the Washington University Macro Model (WUMM)
Goodhart and Hofmann (2001) for G7	real 3-month market rate		real effective	real stock price	real property price	deviation from trend, which is long-run mean for interest rate; linear trend for exchange rate and house price; HP filter for stock price[e]	(1) from reduced-form IS and PC model (2) from IRF of a VAR
Lack (2002)	real 3-month LIBOR		real trade-weighted		real property price	first difference	responses to shocks to a (1) restricted and a (2) structural macro model

a. Information provided by Phillipe Muller from FMD, who had previously spoken with Mark Chandler about this subject.
b. See Dudley and Hatzius (2000).
c. See Carmichael (2002).
d. Short term interest rate and exchange rate are combined as one component to mimic the MCI of the Bank of Canada.
e. Goodhart and Hofmann (2002) construct an FCI only for the UK, in which all variables are detrended using the HP filter.

Table 3: Specification of FCIs Based on IS Curve with Summarized Lags[a]

Variable	FCI - HP Filter	FCI - 1st Diff.
	Weight	Weight
Constant	-	0.137
Real 90-day Commercial Paper Rate$_t$	-0.118	-0.164
Real 10-year Government of Canada Bond Rate$_t$	0.288	0.554
Real C6 Exchange Rate$_t$	-0.044	-0.111
Real Housing Price Index$_t$	0.073	0.108
Real S&P 500 Stock Index$_t$	0.019	0.067
US High-Yield Risky Spread$_t$	-0.224	-0.194
Adjusted R^2	94.0	21.8

a. Both regressions contained contemporaneous and lagged values of commodity prices, as well as lags of the output gap. Neither of these variables are included in the calculation of the FCIs.

Table 4: Specification of FCIs Based on IS Curve with Individual Lags[a]

Variable	FCI - HP Filter	FCI - 1st Diff.
	Coefficient (p-value[b])	Coefficient (p-value[a])
Constant	-	0.138 (0.001)
Real CP90$_{t-1}$	-0.071 (0.317)	-0.067 (0.289)
Real CP90$_{t-2}$	-0.035 (0.735)	-0.078 (0.154)
Real CP90$_{t-3}$	0.009 (0.899)	-0.087 (0.020)
Real CP90$_{t-4}$	0.028 (0.657)	-0.017 (0.765)
Real CP90$_{t-5}$	0.089 (0.228)	0.031 (0.436)
Real CP90$_{t-6}$	-0.007 (0.872)	0.050 (0.255)
Real CP90$_{t-7}$	-0.094 (0.037)	-0.064 (0.175)

Table 4: Specification of FCIs Based on IS Curve with Individual Lags[a]

Variable	FCI - HP Filter	FCI - 1st Diff.
	Coefficient (p-value[b])	Coefficient (p-value[a])
Real CP90$_{t-8}$		0.012 (0.804)
Real CP90$_{t-9}$		-0.009 (0.754)
Real CP90$_{t-10}$		-0.081 (0.015)
Real CP90$_{t-11}$		0.027 (0.389)
Real CP90$_{t-12}$		0.124 (0.012)
Real 10-year Gov't Yield$_{t-1}$	0.054 (0.661)	-0.021 (0.820)
Real 10-year Gov't Yield$_{t-2}$	0.057 (0.741)	0.057 (0.421)
Real 10-year Gov't Yield$_{t-3}$	0.074 (0.645)	0.189 (0.069)
Real 10-year Gov't Yield$_{t-4}$	-0.200 (0.203)	-0.016 (0.877)
Real 10-year Gov't Yield$_{t-5}$	0.187 (0.209)	0.110 (0.204)
Real 10-year Gov't Yield$_{t-6}$	-0.098 (0.476)	-0.050 (0.554)
Real 10-year Gov't Yield$_{t-7}$	0.262 (0.127)	0.291 (0.001)
Real 10-year Gov't Yield$_{t-8}$	-0.367 (0.005)	
Real 10-year Gov't Yield$_{t-9}$	0.165 (0.009)	
Real C6 Exchange Rate$_{t-1}$	-0.092 (0.000)	
Real C6 Exchange Rate$_{t-2}$	0.059 (0.002)	-0.108 (0.000)
Real Housing Price Index$_{t-1}$	0.138 (0.022)	0.122 (0.090)
Real Housing Price Index$_{t-2}$	-0.155 (0.128)	-0.029 (0.637)
Real Housing Price Index$_{t-3}$	0.088 (0.493)	0.026 (0.756)
Real Housing Price Index$_{t-4}$	-0.028 (0.804)	-0.012 (0.838)
Real Housing Price Index$_{t-5}$	0.150 (0.075)	0.185 (0.000)
Real Housing Price Index$_{t-6}$	-0.334 (0.001)	-0.183 (0.003)
Real Housing Price Index$_{t-7}$	0.167 (0.027)	
Real Housing Price Index$_{t-8}$	-0.023 (0.765)	

Table 4: Specification of FCIs Based on IS Curve with Individual Lags[a]

Variable	FCI - HP Filter	FCI - 1st Diff.
	Coefficient (p-value[b])	Coefficient (p-value[a])
Real Housing Price Index$_{t-9}$	-0.038 (0.644)	
Real Housing Price Index$_{t-10}$	-0.035 (0.628)	
Real Housing Price Index$_{t-11}$	0.104 (0.024)	
Real S&P 500 Stock Index$_{t-1}$	0.013 (0.001)	0.015 (0.055)
Real S&P 500 Stock Index$_{t-2}$		0.020 (0.001)
Real S&P 500 Stock Index$_{t-3}$		-0.006 (0.445)
Real S&P 500 Stock Index$_{t-4}$		0.005 (0.412)
Real S&P 500 Stock Index$_{t-5}$		0.013 (0.187)
Real S&P 500 Stock Index$_{t-6}$		0.001 (0.791)
Real S&P 500 Stock Index$_{t-7}$		0.007 (0.257)
Real S&P 500 Stock Index$_{t-8}$		0.013 (0.024)
US High-Yield Risky Spread$_{t-1}$		-0.113 (0.089)
US High-Yield Risky Spread$_{t-2}$		-0.011 (0.873)
US High-Yield Risky Spread$_{t-3}$		-0.229 (0.002)
US High-Yield Risky Spread$_{t-4}$		0.173 (0.073)
Cdn AA Long-Term Spread$_{t-1}$	-0.163 (0.093)	
Cdn AA Long-Term Spread$_{t-2}$	0.014 (0.926)	
Cdn AA Long-Term Spread$_{t-3}$	-0.180 (0.267)	
Cdn AA Long-Term Spread$_{t-4}$	0.031 (0.797)	
Cdn AA Long-Term Spread$_{t-5}$	0.011 (0.931)	
Cdn AA Long-Term Spread$_{t-6}$	-0.137 (0.177)	
Cdn AA Long-Term Spread$_{t-7}$	-0.304 (0.001)	
Cdn AA Long-Term Spread$_{t-8}$	-0.006 (0.965)	
Cdn AA Long-Term Spread$_{t-9}$	0.286 (0.033)	

Table 4: Specification of FCIs Based on IS Curve with Individual Lags[a]

Variable	FCI - HP Filter	FCI - 1st Diff.
	Coefficient (p-value[b])	Coefficient (p-value[a])
Cdn AA Long-Term Spread$_{t-10}$	-0.079 (0.417)	
Cdn AA Long-Term Spread$_{t-11}$	-0.152 (0.084)	
Cdn AA Long-Term Spread$_{t-12}$	0.143 (0.325)	
Cdn AA Long-Term Spread$_{t-13}$	0.217 (0.010)	
Adjusted R^2	93.3	21.2

a. Both regressions contained contemporaneous and lagged values of commodity prices, as well as lags of the output gap. Neither of these variables are included in the calculation of the FCIs.
b. Based on standard errors adjusted for autocorrelation.

Table 5: Phillips Curve - Summarized Coefficients

Variable	HP-Filtered Data	First-Differenced Data
	Coefficient (p-value[a])	Coefficient (p-value[a])
Constant	0.046 (0.058)	-0.002 (0.936)
Year-Over-Year Inflation	0.979 (0.000)	0.990 (0.000)
Real GDP	0.032 (0.020)	0.080 (0.165)
Monthly Growth in Crude Oil Prices	-0.001 (0.749)	0.001 (0.535)
Adjusted R^2	99.2	99.4

a. Based on standard errors adjusted for autocorrelation.

Table 6: Dynamic Correlations Between our FCIs and the Output Gap (or Year-Over-Year Real GDP Growth)[a]

	Financial Conditions Index							
	IS (Summarized Coefficients)		IS (Individual Lag Coefficients)		Impulse Response Function		Factor Analysis	
FCI leads (months)	HP-Filtered	First-Differenced	HP-Filtered	First-Differenced	HP-Filtered	First-Differenced	HP-Filtered	First-Differenced
3	0.604	0.604	0.448	0.582	0.598	0.521	0.537	0.233
6	0.559	0.585	0.436	0.533	0.589	0.527	0.496	0.249
9	0.488	0.491	0.397	0.486	0.553	0.510	0.323	0.241
12	0.419	0.422	0.320	0.419	0.465	0.480	0.111	0.204
18	0.288	0.356	0.175	0.406	0.253	0.361	-0.078	0.263

a. Correlations calculated between the output gap and our HP-filtered FCIs, as well as year-over-year real output growth and our first-differenced FCIs.

Table 7: Dynamic Correlations Between our FCIs and Year-Over-Year Inflation

	Financial Conditions Index							
	IS (Summarized Coefficients)		IS (Individual Lag Coefficients)		Impulse Response Function		Factor Analysis	
FCI leads (months)	HP-Filtered	First-Differenced	HP-Filtered	First-Differenced	HP-Filtered[a]	First-Differenced	HP-Filtered	First-Differenced
18	0.175	0.209	0.084	0.345	-0.006	0.387	0.258	-0.150
24	0.167	0.303	0.107	0.444	-0.127	0.414	0.208	-0.186
30	0.120	0.378	0.121	0.524	-0.247	0.442	0.086	-0.210
36	0.032	0.480	-0.067	0.567	-0.314	0.417	0.073	-0.044

a. HP-filtered Impulse-Response FCI does lead year-over-year inflation with a small positive correlation in the range of 1 to 17 months (peak 0.129 at 1 month).

Table 8: Properties of FCI-based Forecasting Exercise (IS-Based FCIs)

FCI based on	Steps Ahead	Coefficient on FCI[a,b]	Adjusted R^2 [b]	MSFE[b,c]
IS Curve HP-Filtered Data Summed Coefficients	6	1.91 (0.00)	0.311	0.814
	9	1.62 (0.00)	0.223	0.315
	12	1.40 (0.00)	0.170	0.578
	18	0.97 (0.06)	0.099	1.363
	24	0.23 (0.64)	0.002	1.098
IS Curve First-Differenced Data Summed Coefficients	6	1.20 (0.00)	0.310	0.783
	9	0.97 (0.00)	0.206	1.111
	12	0.84 (0.00)	0.156	1.514
	18	0.73 (0.01)	0.121	2.180
	24	0.60 (0.02)	0.083	2.505
IS Curve HP-Filtered Data Indiv. Lag Coefficients	6	2.83 (0.00)	0.183	0.578
	9	2.63 (0.00)	0.160	0.847
	12	2.10 (0.00)	0.105	1.145
	18	1.24 (0.05)	0.043	1.401
	24	0.48 (0.50)	0.003	1.097
IS Curve First-Differenced Data Indiv. Lag Coefficients	6	1.33 (0.00)	0.256	1.233
	9	1.20 (0.00)	0.213	1.274
	12	1.05 (0.01)	0.162	1.526
	18	1.04 (0.01)	0.167	2.207
	24	0.92 (0.04)	0.134	2.624

a. Values in parentheses denote t-test statistical significance.
b. Estimated over entire sample: 1981 to 2000.
c. RMSE calculated using a rolling forecast with an initial sample beginning in 1981. Output gap (or real GDP growth) is forecast over 2001m1 to 2002m6.

Table 9: FCI Weights as Derived From VAR Generalized Impulse Response Function

Variable	FCI - HP Filter	FCI - 1st Diff.
	Coefficient	**Coefficient**
Real 90-day Commercial Paper Rate $_t$	-2.089	-0.15
Real 10-Year Government of Canada Bond Rate $_t$	-1.75	0.249
Real C6 Exchange Rate $_t$	0.066	-0.21
Real Housing Price Index $_t$	7.95	0.38
Real S&P 500 Stock Index	0.54	
Real TSX Composite Index $_t$		-0.02
US High-Yield Risky Spread $_t$	-9.22	-0.74

Table 10: Properties of FCI-based Forecasting Exercise (Impulse Response & Factor Analysis FCIs)

FCI based on	Steps Ahead	Coefficient on FCI[a,b]	Adjusted R^2 [b]	MSFE[b,c]
Impulse Response HP-Filtered Data	6	0.28 (0.00)	0.210	1.305
	9	0.25 (0.02)	0.174	1.312
	12	0.2 (0.09)	0.112	1.275
	18	0.08 (0.49)	0.016	1.117
	24	-0.06 (0.57)	0.006	0.938
Impulse Response First-Differenced Data	6	0.48 (0.00)	0.274	4.389
	9	0.46 (0.00)	0.256	2.202
	12	0.43 (0.00)	0.226	1.373
	18	0.32 (0.01)	0.126	1.838
	24	0.1 (0.42)	0.006	2.354
Factor Analysis HP-Filtered Data	6	14.2 (0.00)	0.267	0.768
	9	11.49 (0.00)	0.175	1.206
	12	8.28 (0.01)	0.098	1.321
	18	5.29 (0.10)	0.045	1.309
	24	4.62 (0.19)	0.035	1.157
Factor Analysis First-Differenced Data	6	2.25 (0.20)	0.033	1.574
	9	2.43 (0.12)	0.040	1.874
	12	2.25 (0.10)	0.034	2.282
	18	3.15 (0.03)	0.073	2.810
	24	4.86 (0.00)	0.186	4.084

a. Values in parentheses denote t-test statistical significance.
b. Estimated over entire sample: 1981 to 2000.
c. RMSE calculated using a rolling forecast with an initial sample beginning in 1981. Output gap (or real GDP growth) is forecast over 2001m1 to 2002m6.

Table 11: Factor Analysis FCIs: Percentage of Common Variance Explained by Each Factor

	Based on HP-Filtered Data[a]	Based on First-Differenced Data[b]
Factor 1	81.8%	88.3%
Factor 2	8.2%	5.8%
Factor 3	7.3%	2.9%
Factor 4	2.4%	1.8%

a. Contains short-term interest rate, long-term interest rate, exchange rate, housing price, S&P/TSX Composite Index and AA corporate bond spread.
b. Contains short-term interest rate, long-term interest rate, exchange rate, housing price, S&P500 index and US high yield bond spread.

Table 12: Dynamic Correlations Between the MCI and Year-Over-Year GDP and the Output Gap

MCI leads (months)	Output Gap	Output Growth
3	-0.066	-0.433
6	-0.155	-0.493
9	-0.248	-0.532
12	-0.332	-0.528
18	-0.438	-0.432

Table 13: Dynamic Correlations Between the MCI and Year-Over-Year Inflation,

MCI leads (months)[a]	Inflation
18	0.644
24	0.588
30	0.520
36	0.455

a. Peak correlation with inflation is 0.758 at a lead of 6 months.

Table 14: Forecasts Based on MCI

Forecasted Variable	Steps Ahead	Coefficient on FCI[a]	Adjusted R^2	MSFE
Output Gap	6	-0.04 (0.41)	0.017	0.821
	9	-0.07 (0.11)	0.079	1.047
	12	-0.10 (0.02)	0.162	1.233
	18	-0.13 (0.00)	0.262	1.533
	24	-0.11 (0.01)	0.239	1.942
12-Month Output Growth	6	-0.22 (0.00)	0.300	7.631
	9	-0.24 (0.00)	0.355	7.837
	12	-0.23 (0.00)	0.339	7.586
	18	-0.18 (0.02)	0.211	7.118
	24	-0.09 (0.29)	0.061	7.160

a. Values in parentheses denote t-test statistical significance.

Figure 1
IS-Based HP-Filter FCI and the Output Gap - Summarized Coefficients

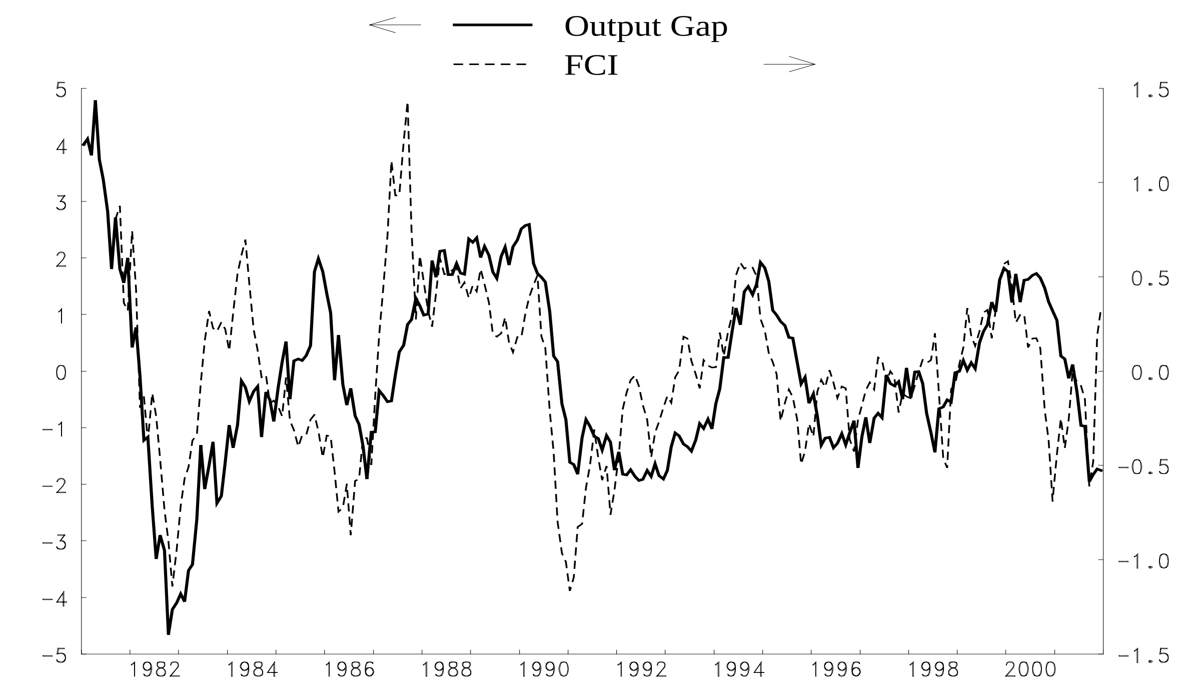


Figure 2
IS-Based First-Difference FCI and Real Output Growth - Summarized Coefficients

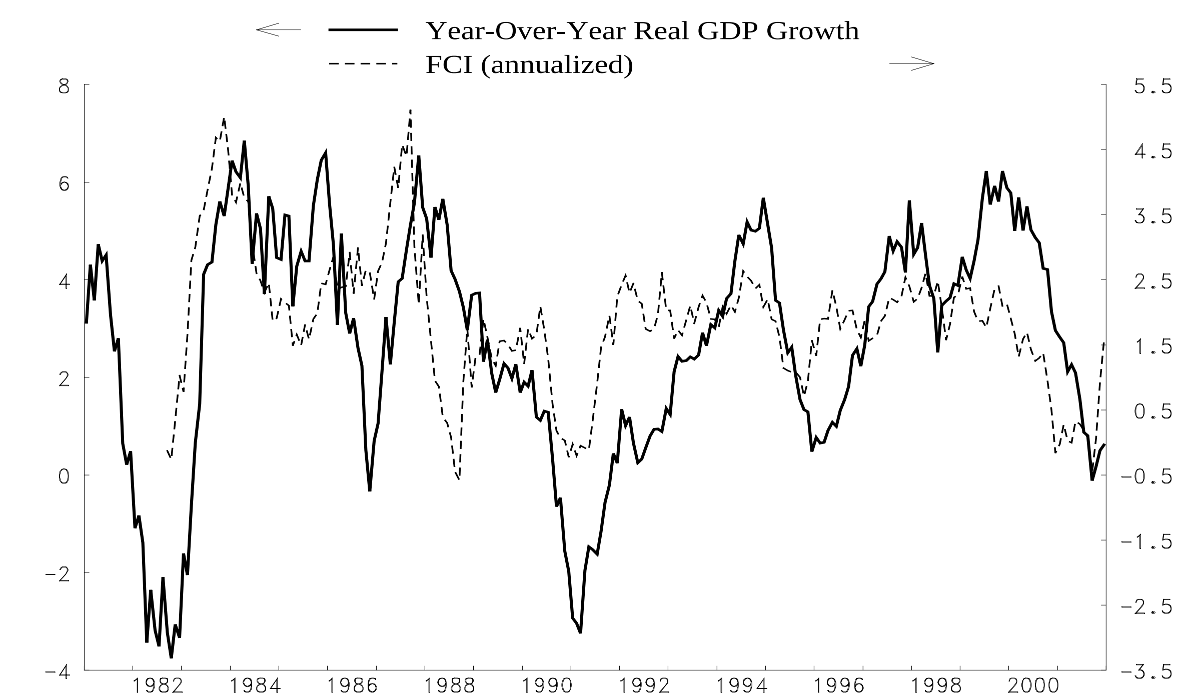


Figure 3
IS-Based First-Difference FCI and Inflation - Summarized Coefficients

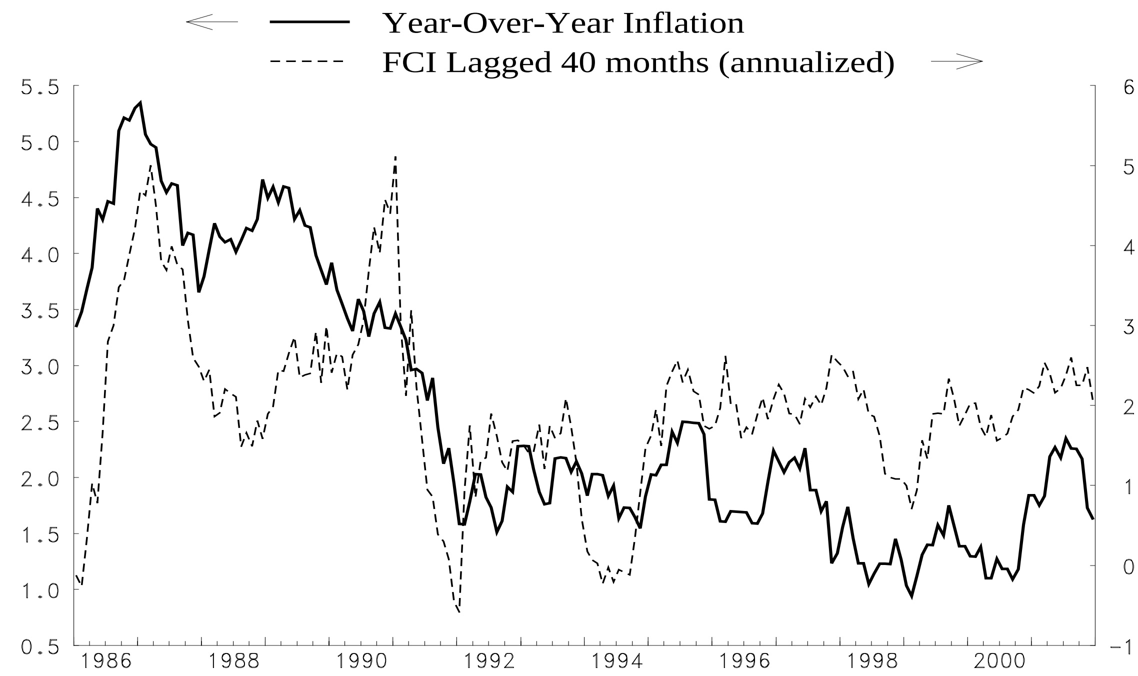


Figure 4
IS-Based HP-Filter FCI and the Output Gap - Individual Lag Coefficients

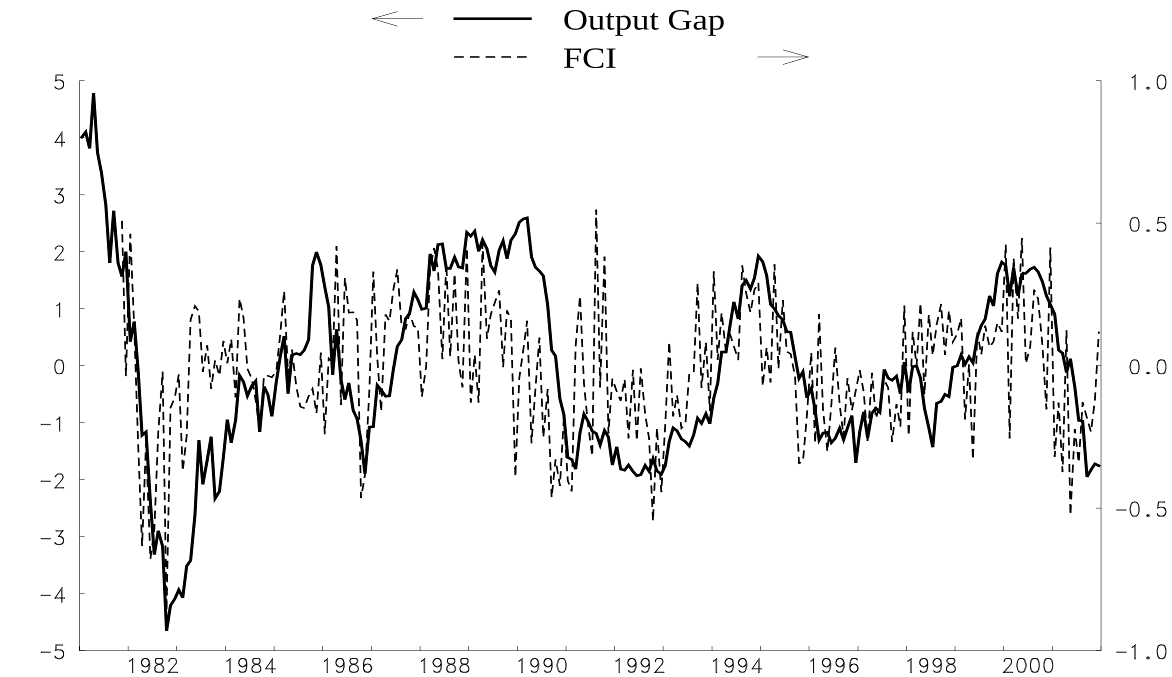


Figure 5
IS-Based First-Difference FCI and Real Output Growth - Individual Lag Coefficients

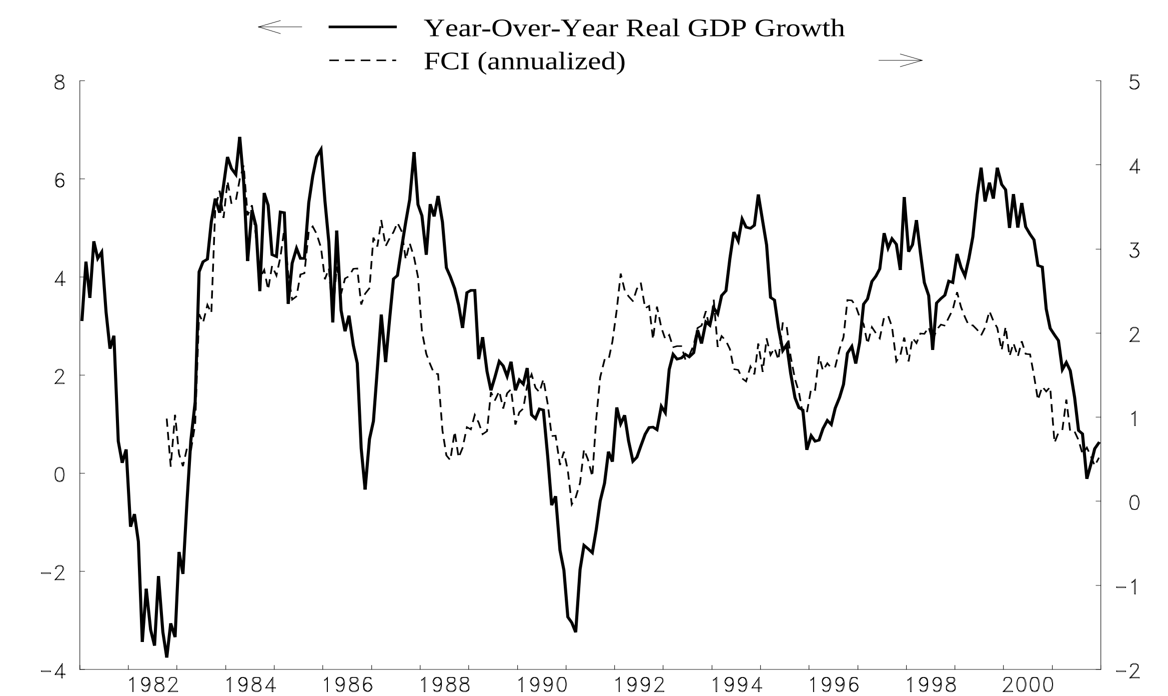


Figure 6
Forecast (based on HP-Filter Summarized-Coefficient IS-Curve FCI) Versus Actual Output Gap
(solid line - HP Filtered Real GDP; dashed line - forecast)

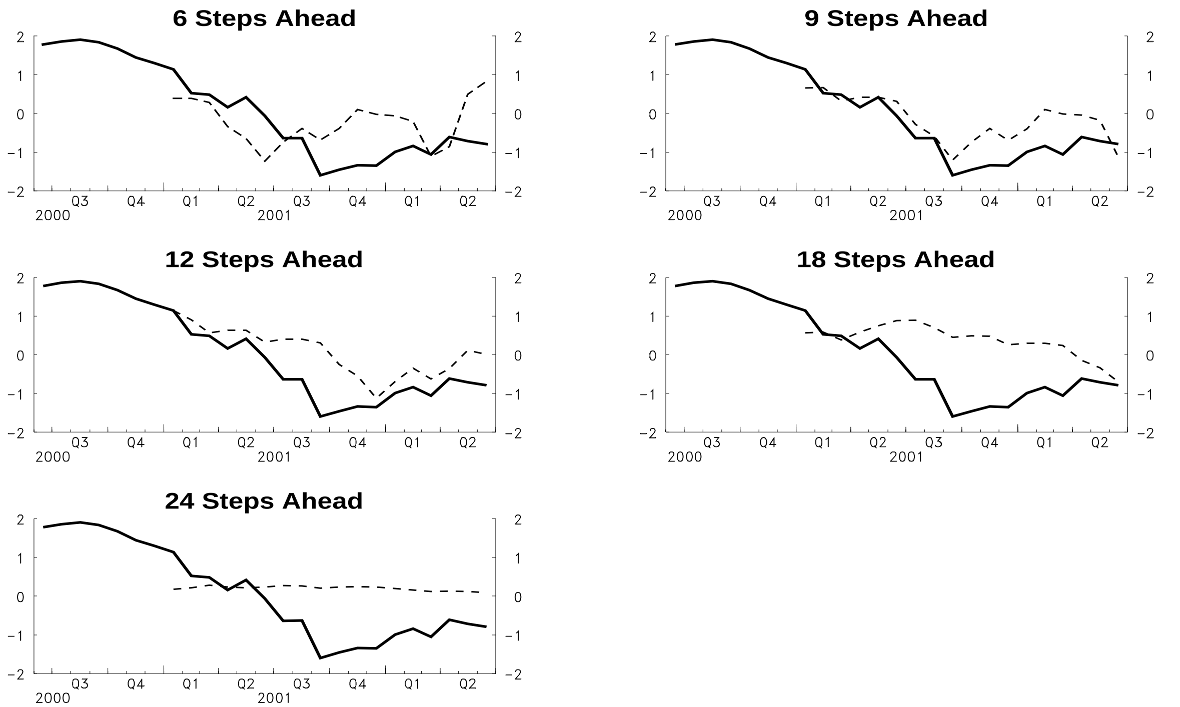


Figure 7
Forecast (based on First-Difference Summarized-Coefficient IS-Curve FCI) Versus Actual Real Output Growth
(solid line - year-over-year real GDP growth ; dashed line - forecast)

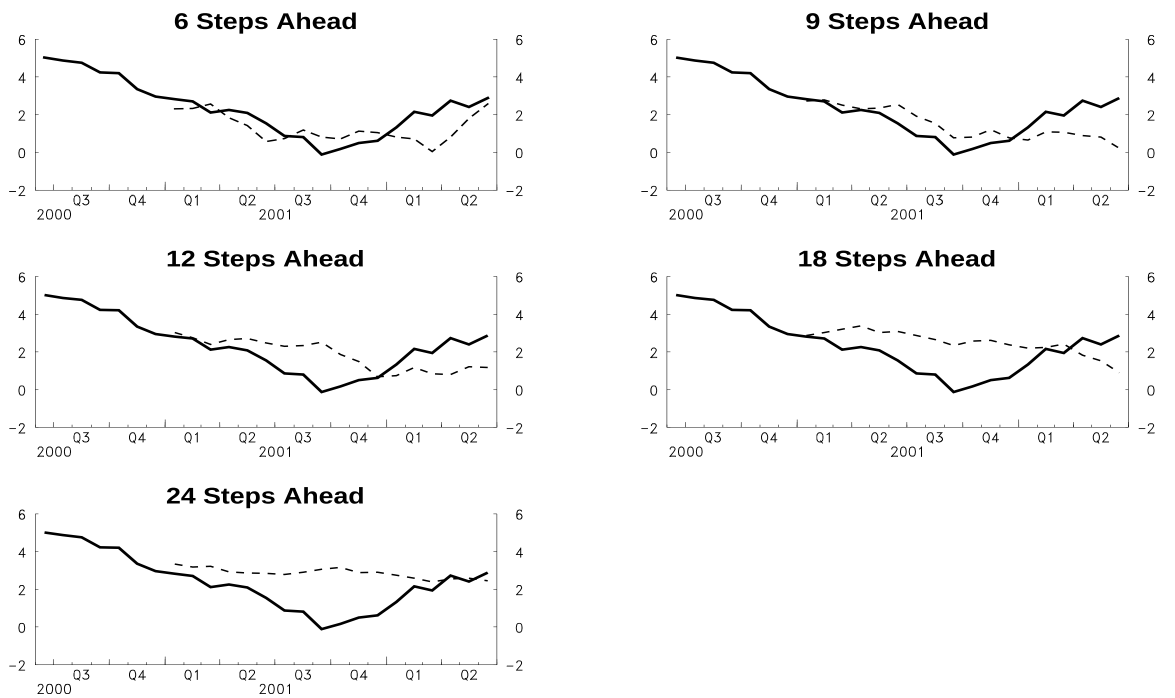


Figure 8
Forecast (based on HP-Filter Individual-Lag-Coefficient IS-Curve FCI) Versus Actual Output Gap
(solid line - HP Filtered Real GDP; dashed line - forecast)

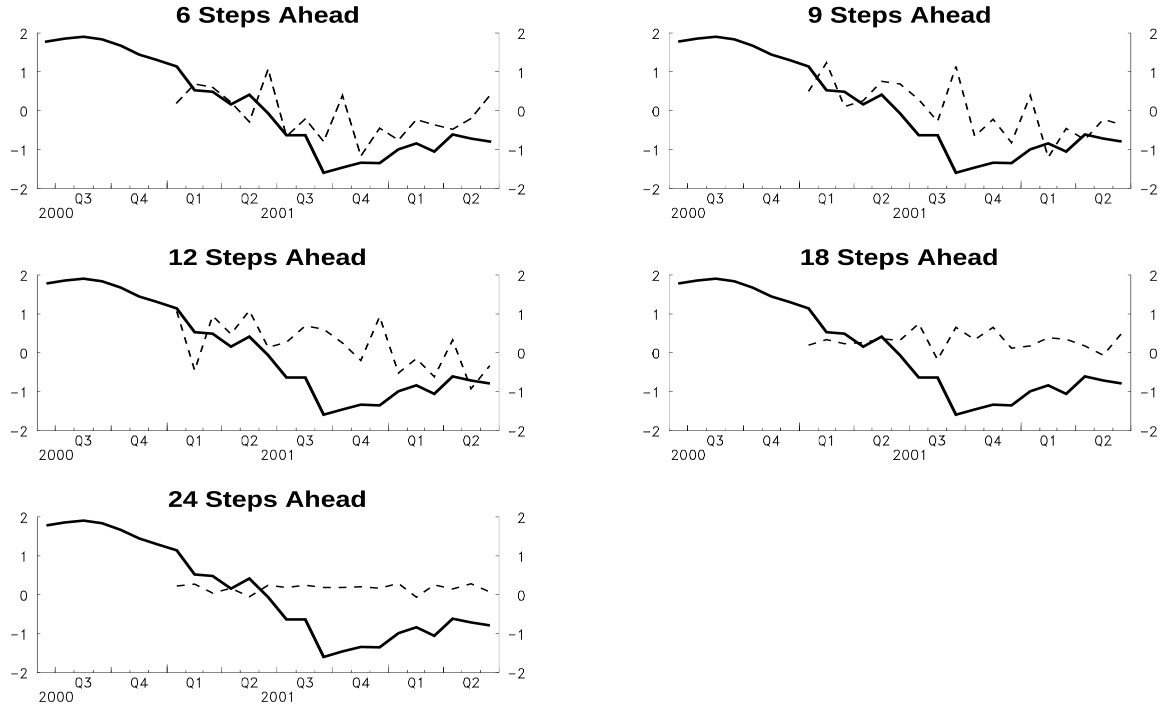


Figure 9
Forecast (based on First-Difference Individual-Lag-Coefficient IS-Curve FCI) Versus Actual Real Output Growth
(solid line - year-over-year real GDP growth ; dashed line - forecast)

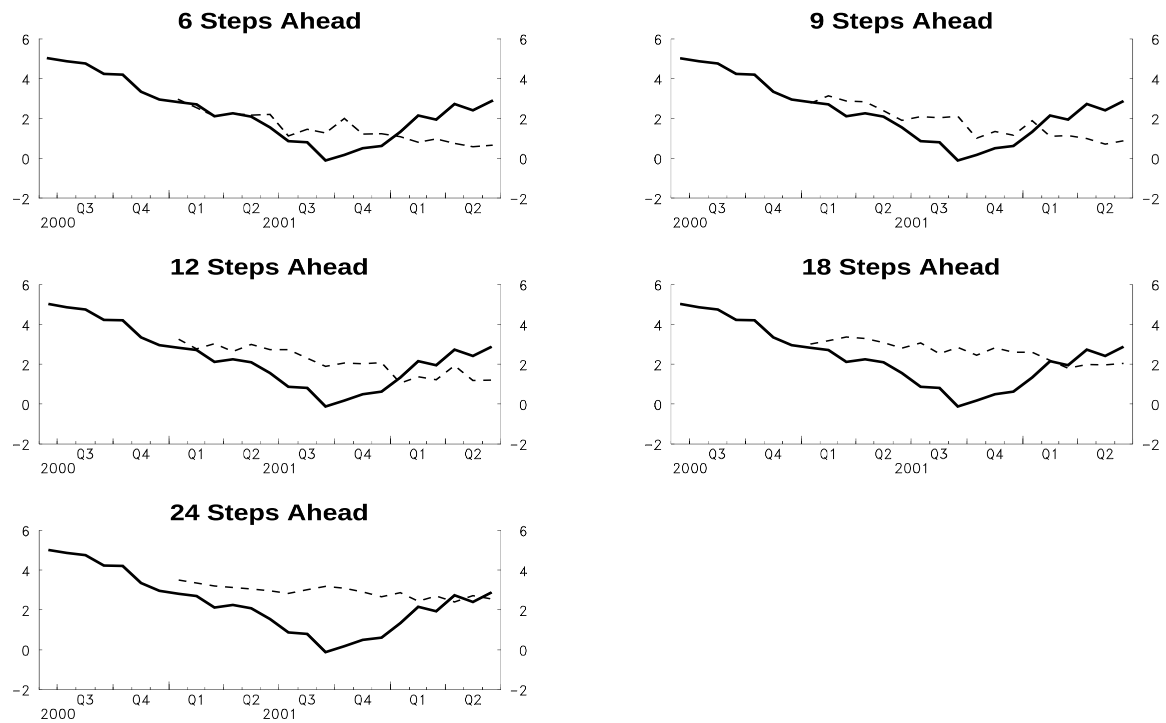


Figure 10
Impulse-Response-Based HP-Filter FCI and the Output Gap

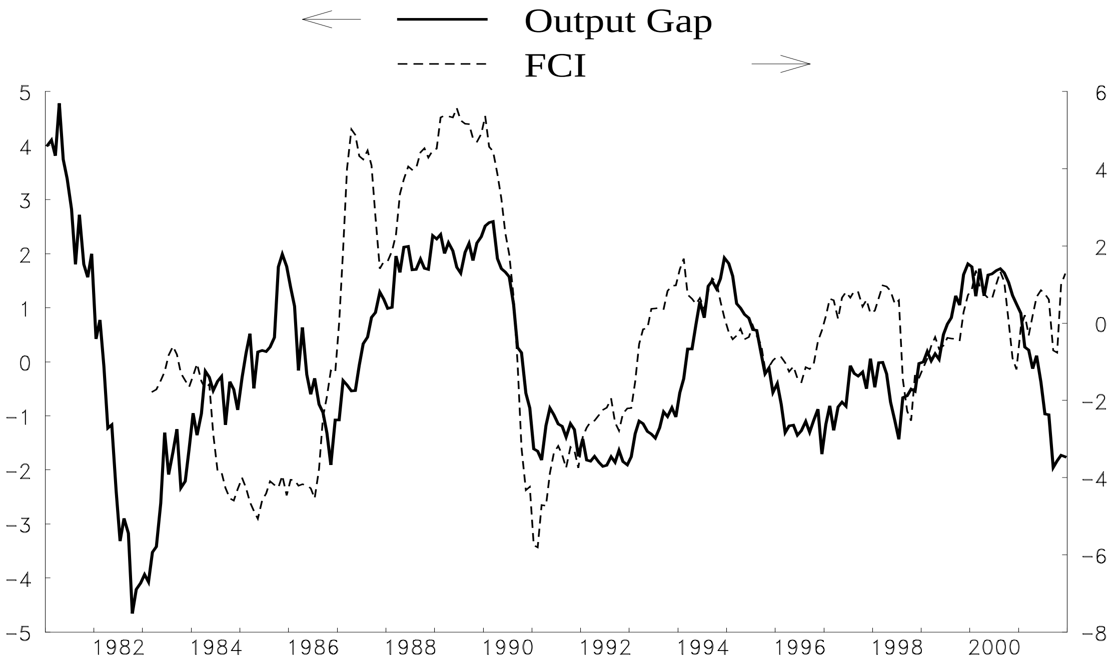


Figure 11
Impulse-Response-Based First-Difference FCI and Real Output Growth

Figure 12
Impulse Response of Output - Real HP-Filtered Data
(solid line - year-over-year real GDP growth ; dashed line - forecast)

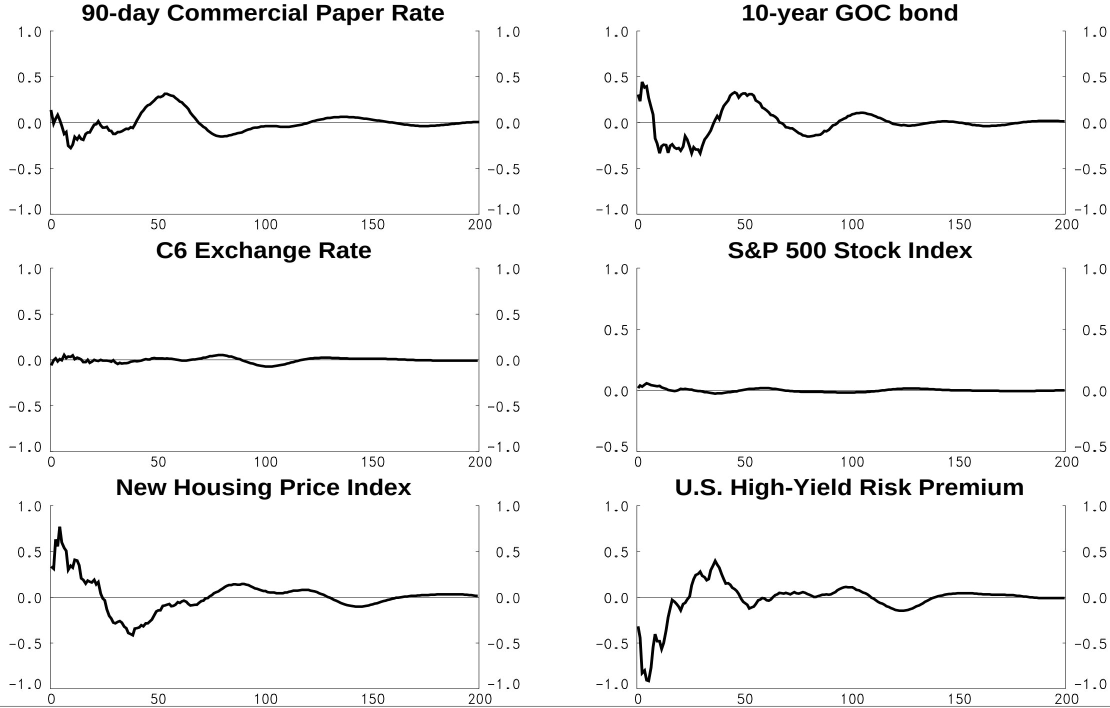


Figure 13
Impulse Response of Output - Real First-Differenced Data
(solid line - year-over-year real GDP growth ; dashed line - forecast)

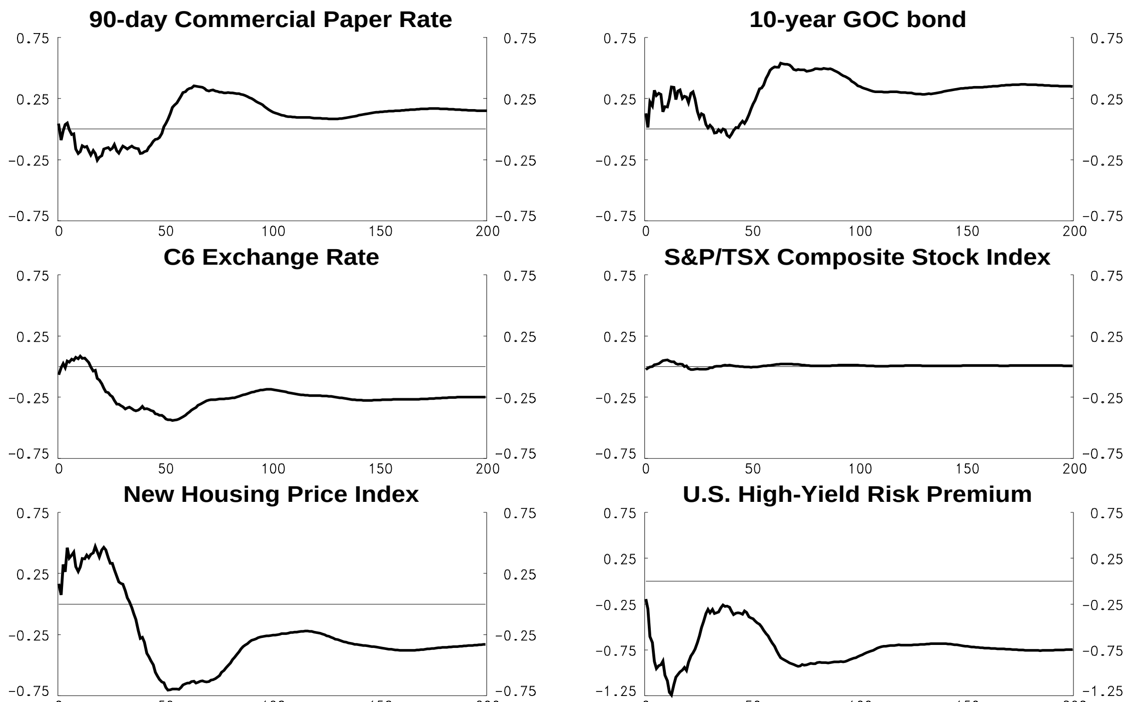


Figure 14

Forecast (Based on HP-Filter Impulse-Response FCI) Versus Actual Output Gap
(solid line - HP Filtered Real GDP; dashed line - forecast)

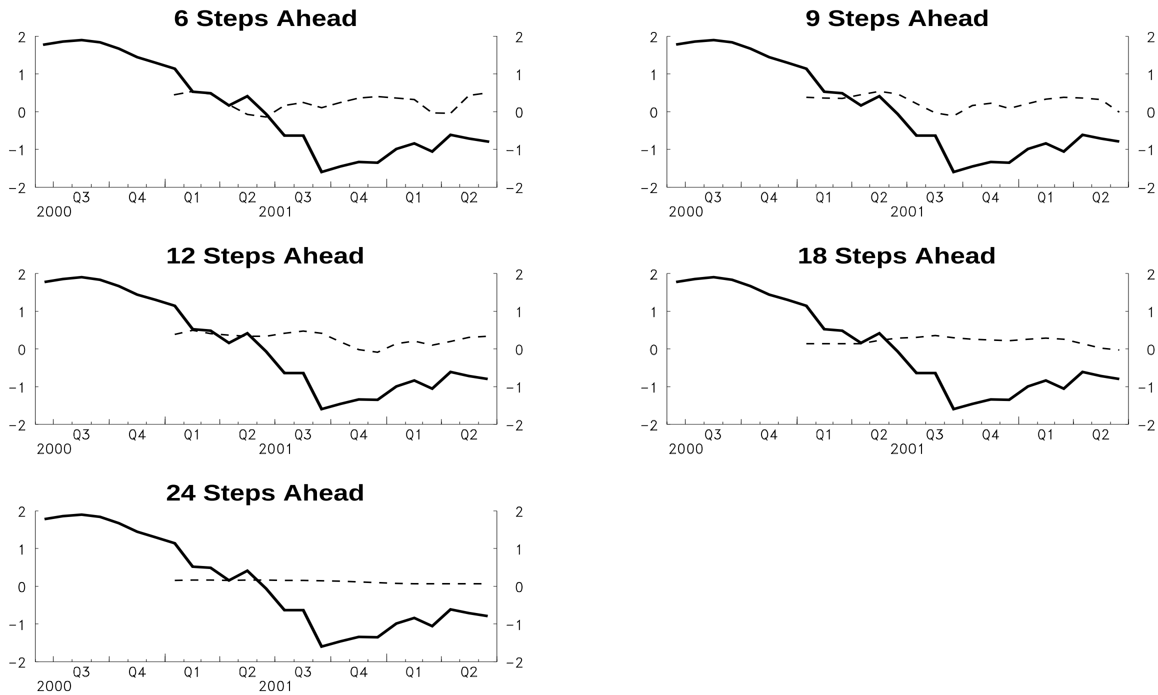


Figure 15

Forecast (Based on First-Difference Impulse-Response FCI) Versus Actual Real Output Growth
(solid line - year-over-year real GDP growth ; dashed line - forecast)

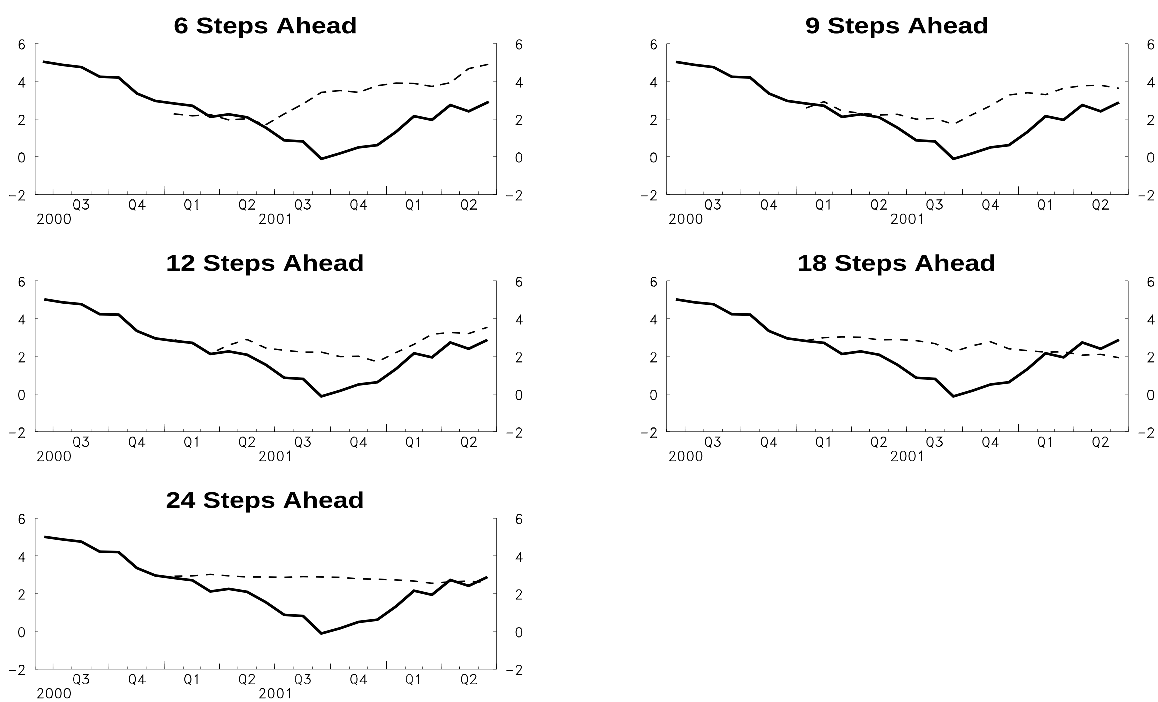


Figure 16
Factor-Analysis-Based HP-Filter FCI and the Output Gap

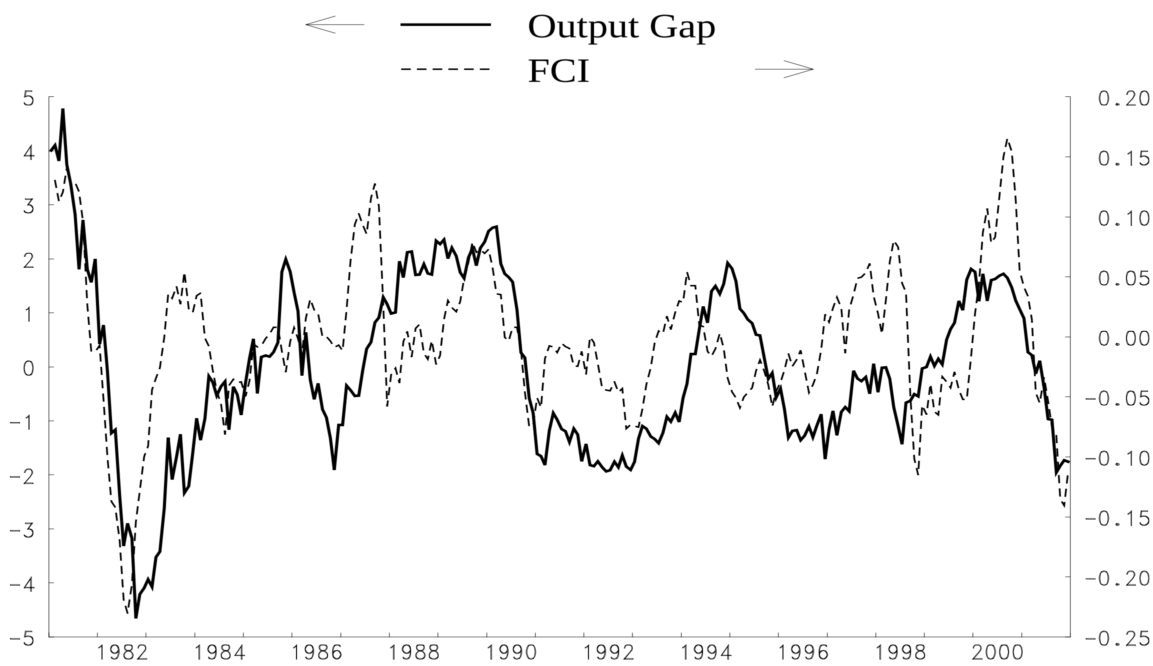


Figure 17
Factor-Analysis-Based First-Difference FCI and Real Output Growth

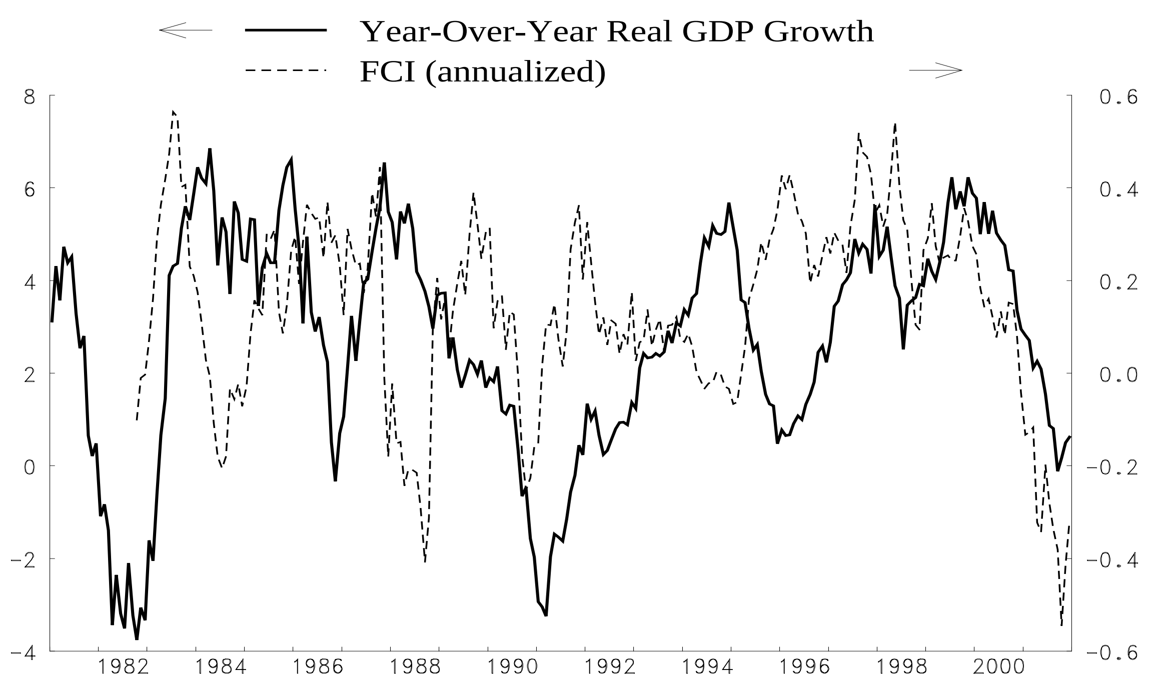


Figure 18

Forecast (Based on HP-Filter Factor-Analysis FCI) Versus Actual Output Gap
(solid line - HP Filtered Real GDP; dashed line - forecast)

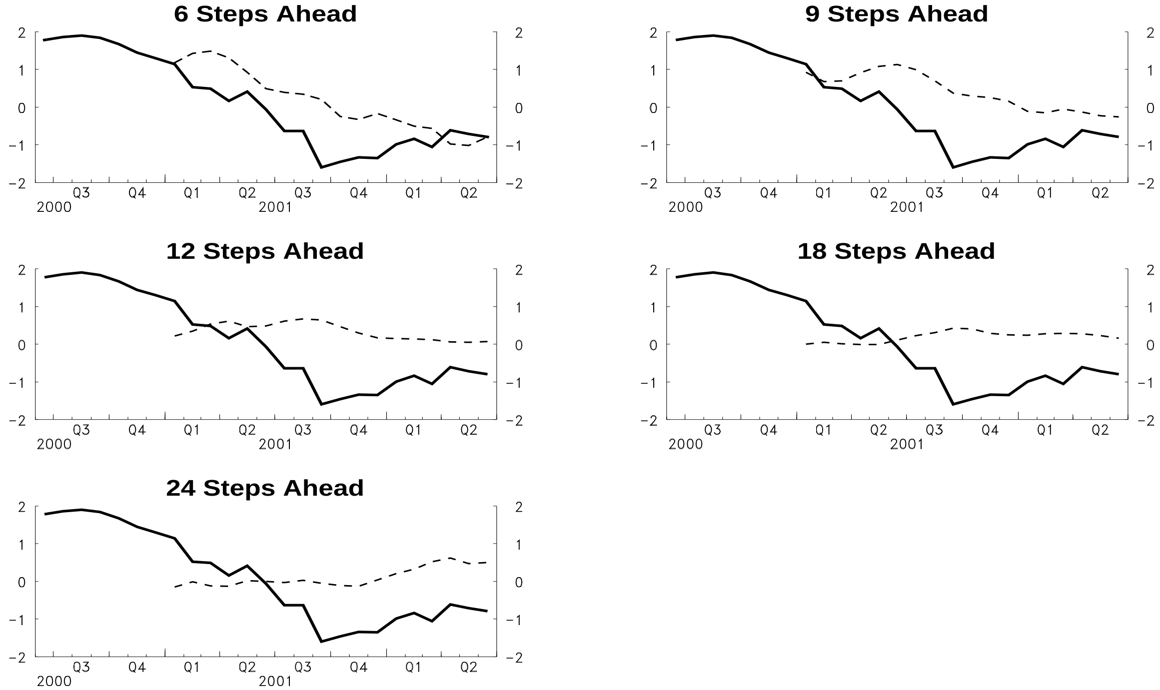


Figure 19

Forecast (Based on First-Difference Factor-Analysis FCI) Versus Actual Real Output Growth
(solid line - year-over-year real GDP growth ; dashed line - forecast)

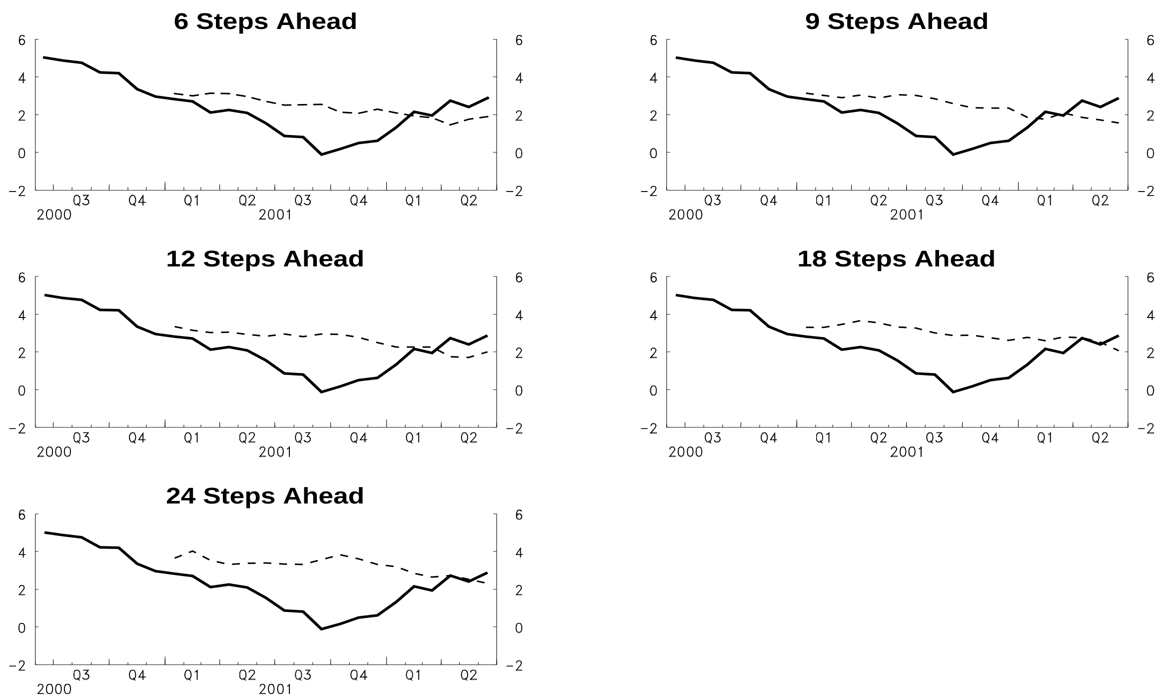
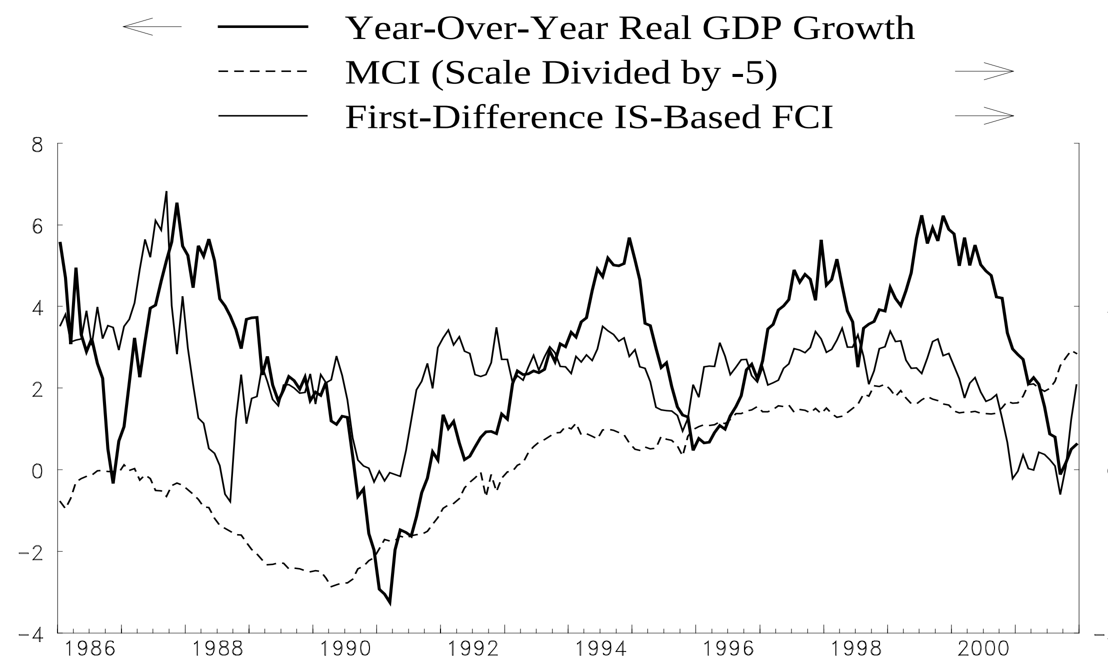


Figure 20
MCI, FCI and Output Growth



MCI, FCI and Inflation