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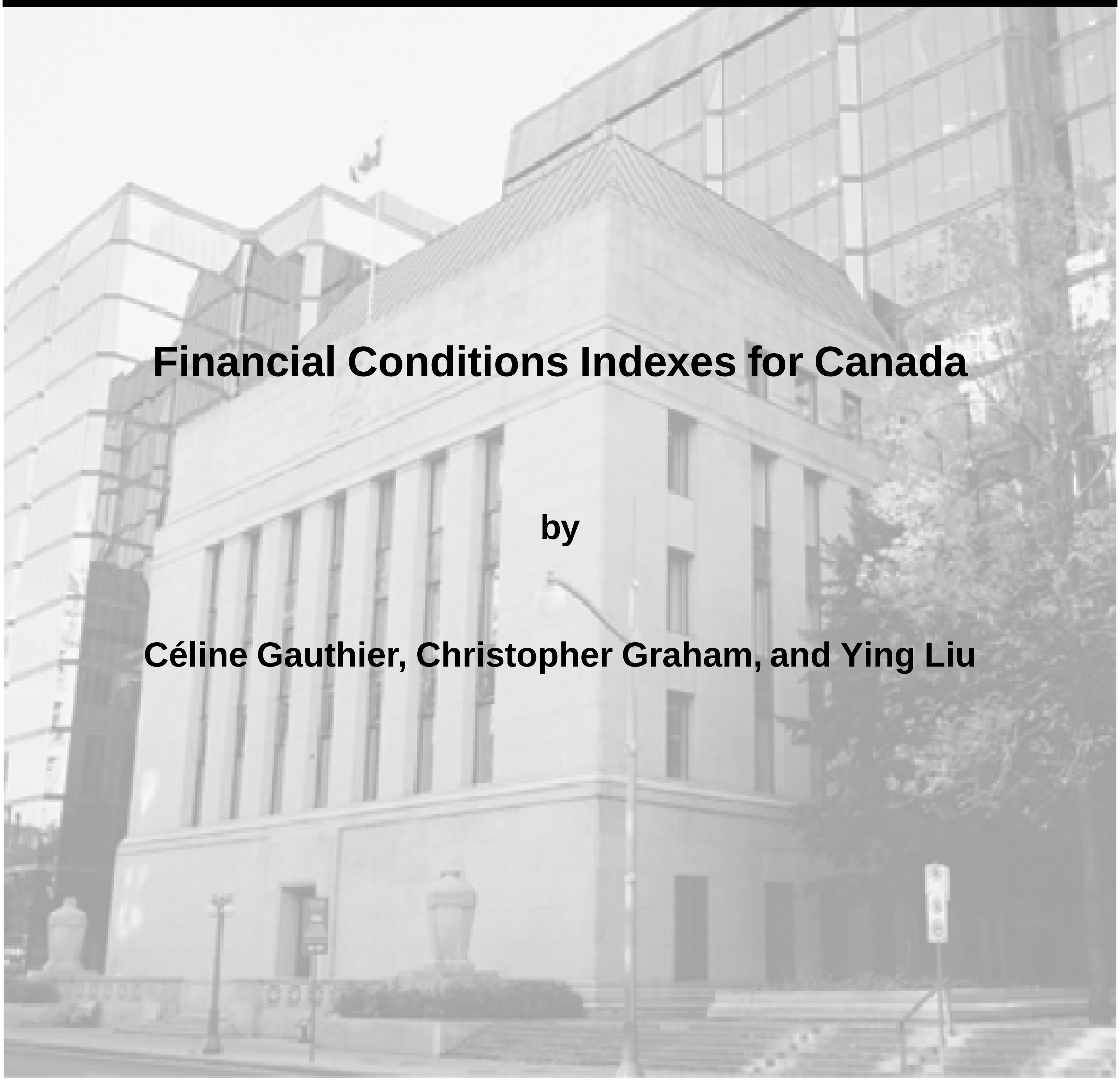

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Abstract

The authors construct three financial conditions indexes (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 of the monetary conditions index (MCI) and existing FCIs. To evaluate their three FCIs, the authors consider five performance criteria: the consistency of each FCI's weight with economic theory, its graphical ability to predict turning points in the business cycle, its dynamic correlation with output, its in-sample fit in explaining output, and its out-of-sample performance in forecasting output. Using monthly data, the authors find, in general, that housing prices, equity prices, and bond yield risk premiums, in addition to short- and long-term interest rates and the exchange rate, are significant in explaining output from 1981 to 2000. They also find that the FCIs outperform the Bank of Canada's MCI in many areas.

JEL classification: E44, E52
Bank classification: Monetary and financial indicators; Monetary conditions index

Résumé

Les auteurs élaborent trois nouveaux indices des conditions financières au Canada. Le premier est fondé sur la courbe IS, le second sur l'établissement de courbes de réaction généralisées et le troisième sur l'analyse factorielle. Les méthodes retenues pour la construction de ces indices visent à répondre à l'un ou plusieurs des reproches adressés à l'indice des conditions monétaires de la Banque du Canada et aux autres indices en usage. Les trois nouveaux indices sont évalués à l'aune des cinq critères suivants : la conformité de leur pondération à la théorie économique, leur capacité à prévoir les points de retournement du cycle économique, leur corrélation dynamique avec la production, leur capacité à expliquer la production à l'intérieur de l'échantillon et à la prévoir hors échantillon. Travaillant avec des données mensuelles, les auteurs constatent, de manière générale, que le prix des logements, les cours boursiers et les primes de risque relatives aux obligations, tout comme les taux d'intérêt à court et à long terme et le taux de change, permettent d'expliquer l'évolution que la production a connue entre 1981 et 2000. Ils relèvent également que leurs indices surpassent, à de nombreux égards, l'indice des conditions monétaires de la Banque.

Classification JEL : E44, E52
Classification de la Banque : Indicateurs monétaires et financiers; Indice des conditions monétaires

1. Introduction

The transmission of monetary policy has traditionally been explained using an interest rate channel and an exchange rate channel. Some research, however, implies 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 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, therefore, boost aggregate demand.

The usefulness of asset prices in determining aggregate demand and inflation has long been controversial. Although, from a theroretical viewpoint, asset prices seem to play a significant role in the transmission mechanism, the empirical evidence is 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 G-7 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 that of Canada—also larger than the effect of the exchange rate.[1]

Research at the Bank of Canada suggests that asset prices, especially property prices, may possess important information about future inflationary pressure. Pichette and Tremblay (2003) examine the link between consumption and disaggregate wealth in Canada. Using a vector-error-correction model, the authors find evidence of a significant housing wealth effect for Canada. Conversely, the evidence regarding the stock market wealth effect is weak. In terms of policy implications, other things being equal, Pichette and Tremblay suggest that more weight should be put on fluctuations in housing prices than on fluctuations in stock prices. On the other hand, using the same methodology to examine the links between financial markets and the real economy, Gauthier and Li (2004) find that real stock prices and output are cointegrated one for one, which

1. Because Goodhart and Hofmann obtain similar weights when using the impulse responses from a structural vector autoregression (VAR), these weights can be considered to be structural as long as their identification assumptions are considered reasonable.

suggests that stock price movements at low frequency are closely linked to potential output changes.

In another Bank of Canada study, Zhang (2002) suggests that bond risk premiums may have strong predictive power for future output. Using U.S. data from 1988 to 2001, Zhang finds that the high-yield bond spread and the investment-grade spread can explain 68 per cent and 42 per cent, respectively, of employment 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, federal funds rate, consumer sentiment index, Conference Board leading indicator, and the Standard & Poor's (S&P) 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.

The composition of Canadian household total assets (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 account for a significant portion (more than 10 per cent) of total assets and their importance has gradually increased over the past 20 years. While the direct holding of bonds has decreased slightly, the importance of life insurance and pensions has risen significantly. This suggests that so many households hold more bonds indirectly through an investment vehicle that the actual composition of bonds in the investment vehicle portfolio may have in fact increased.[2]

In an attempt to capture these possible effects of asset prices on the real economy, several authors and institutions include them when they construct new measures of the monetary policy stance. These measures, often called financial conditions indexes (FCIs), expand on traditional measures of policy stance by including other indicators of the tightness of financial conditions that economic agents face and that are 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 indexes generally outperform the traditional monetary conditions index (MCI), a weighted average of the short-term interest rate and the exchange rate, in tracing and predicting output and inflation (see, for example, Goodhart and Hofmann 2002, Lack 2002).[3] Nevertheless, FCIs still suffer from certain criticisms that also apply to the MCI, such as *model dependency, ignored dynamics, parameter inconstancy,* and *non-exogeneity of regressors* (see, for example, Eika, Ericsson, and Nymoen 1996; Ericsson et al. 1998).

2. The wealth effect from an increase in the value of an insurance policy or a pension plan on consumption may not be significant.

3. Section 5 provides a more detailed comparison between the MCI and our FCIs.

In this paper, we review these existing indexes 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 of the MCI and existing FCIs. Our first approach derives component weights from an IS-Phillips curve framework in two ways: using the sum of coefficients on the lags of variables, and including individual lags in the FCI to take into account the *dynamics* of variables over time. Our second and third approaches focus 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. For all three methods, we experiment with one set of variables detrended with a Hodrick and Prescott (HP) (1980) filter and a second set detrended by first-differencing. We then evaluate our different FCIs according to the consistency of their weights with economic theory, their graphical ability to predict turning points in the business cycle, their dynamic correlation with output, their in-sample fit in explaining output, and their out-of-sample performance in forecasting output. Although it is common practice to use quarterly data starting from the 1960s, we use monthly data from 1981 to 2000. We thereby avoid potential structural breaks caused by the oil-price shocks of the 1970s, and partly address the problem of *parameter inconstancy*. Furthermore, the higher data frequency is more analytically useful for the Bank's yearly fixed schedule of eight dates for announcing decisions on its key policy interest rate.

Based on the IS-curve method, we find that housing prices, equity prices, and bond risk premiums, in addition to short- and long-term interest rates and the exchange rate, are significant in explaining output from 1981 to 2000. We also find that our FCIs that use a U.S. high-yield bond spread perform better than our FCIs that include a Canadian investment-grade bond spread. Out of the eight FCIs that are based on all three approaches, two have particularly well-rounded attributes, according to our criteria. The best short-term (less than one year) predictor of output growth is the FCI that derives its weights from summed coefficients of an IS curve using first-differenced data; the best longer-term (one to two years) predictor of output growth is the FCI that derives its weights from VAR impulse-response functions using first-differenced data. Our FCIs also largely outperform the MCI in many criteria considered in this paper.

The rest of this paper is organized as follows. Section 2 provides a critical review of the literature on FCIs. Section 3 describes the three approaches we use to construct FCIs. Section 4 discusses the properties and performance of our FCIs. Section 5 compares the IS-based FCI with the Bank'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 FCIs to complement existing measures of policy stance. Table 2 summarizes the variables, detrending methods, and weighting schemes used in these FCIs.

2.1 Variables included in an FCI

All FCIs, so far as we can ascertain, include a short-term interest rate and an exchange rate, which implies that all FCIs are extensions of the MCI. As Freedman (1995) illustrates, the two variables contain important information about the stance of monetary policy. The short-term interest rate is sometimes considered a measure of this stance in itself, since it is highly correlated with the policy instrument—the overnight rate—and has been found in numerous studies to bear some predictive power for output and inflation (see, for example, Sims 1980 and Bernanke and Blinder 1992). The inclusion of the exchange rate captures the exchange rate channel, through which the relative price of imports and exports affects aggregate demand. This channel is particularly important for a small open economy like Canada.

Some FCIs 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 interesting that Goldman Sachs and J.P. Morgan include the term spread in their FCI for Canada. While many studies suggest that the term spread has more predictive power for inflation than the short-term interest rate in Canada, the use of both these variables may imply overlapping information (see, for example, Cozier and Tkacz 1994).

Existing FCIs differ most in the variables they use 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 (1998) 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 other institutions in Table 2 chose their particular measures of stock market conditions over 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. Goodhart and Hofmann also find that the impact of housing prices on the output gap is larger than that of the exchange rate in Canada. However, they acknowledge that the timeliness of data on housing prices remains a challenge for the purposes of an FCI.

In Table 2, only J.P. Morgan's FCI includes monetary aggregates. The variables were chosen so that the index includes "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."[4]

2.2 Detrending the variables

Detrending of variables is an important issue because it is directly related to the way the variables are modelled and the FCI interpreted. Detrending is mainly used to deal with non-stationarity in many economic series for the purpose of econometric modelling. Depending on whether the series has a stochastic trend or a deterministic trend, first-differencing the variables and taking the deviation from a linear trend can be applied, respectively. A time-varying trend or a deviation from an estimated equilibrium value can also be used.

The HP filter is a popular method of deriving a time-varying trend. Despite its simplicity, however, the filter is subject to some criticism, particularly that it is two-sided. This fact implies that the calculated trend in a given period depends on data from the next period, which causes practical problems when generating timely analysis and forecasts.[5] One way to reduce this problem would be to complete the observed data with mechanical projections, such as those obtained from a univariate process.

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 accommodative stance, and vice versa. This interpretation is particularly important if a policy-maker wants to use the FCI as an operational target. However, finding a time-varying equilibrium value for these variables, as for any other economic variable, is difficult and usually involves extensive modelling work.

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 of the exchange rate and housing prices is their linear trend. In the case of equity prices, because of the time-varying nature of the expectations for future dividend growth, an HP filter with a high smoothing

4. This quotation is taken from correspondence with Ted Carmichael, of J.P. Morgan (25 March 2002).
5. See Guay and St-Amant (1996) for a more detailed explanation of the HP filter and its drawbacks.

parameter of 10,000 is used. The deviation of each variable from its trend is then used in the construction of the index.[6]

2.3 Weighting the variables

In the literature, two main methods are used 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 Goodhart and Hofmann (2000) state, there are three ways to do this:

- simulation in a large-scale macroeconometric model
- reduced-form aggregate-demand equations
- VAR impulse-response functions

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 United States. 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 that relates the output gap to interest rates, exchange rates, and other asset prices, and a Phillips curve that relates 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 (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 and/or identification problems.

Goodhart and Hofmann (2001) also extend the reduced-form approach to a VAR technique that includes all variables in the reduced-form model and one-period lagged world oil prices as an exogenous variable. The relative weights between the endogenous variables are calculated based on the average impact of a one-unit shock to each asset price on inflation over the following 12 quarters.[7] Compared with the reduced-form model, the use of VAR impulse-response functions

6. In a later study, Goodhart and Hofmann (2002) recognize the need for a time-varying trend for all variables and apply the HP filter to all four series.

7. Goodhart and Hofmann (2001) identify the shocks using a standard Cholesky factorization with orderings of variables supported by economic assumptions. We argue, however, that these assumptions are hard to justify. See section 3.2 for a discussion.

imposes less economic theory and allows for more interaction between variables. The authors find that FCIs from both approaches yield similar results, whereas housing prices have a higher weight under the VAR approach.

The second main method used to determine and weight the component variables of an FCI is based on the abilities of various leading indicators and their different combinations to forecast output or inflation.[8] This method is motivated by Stock and Watson (2000), who calculate the median and trimmed mean (removing the largest and smallest outliers) of the forecasts by 38 individual indicators from a bivariate model. They find that the performance of the combined forecasts exceeds that of many univariate benchmarks, as well as individual bivariate models. The median or trimmed mean of individual forecasts already implicitly weights the indicators according to their coefficient in the bivariate regression. This approach, however, as Mayes and Virén (2001) note, does not allow for time-varying weights.

2.4 FCIs as tools

Private institutions (Goldman Sachs, J.P. Morgan, Macroeconomic Advisers) 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 use 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 predict monetary policy actions, the use of such indexes can be more diverse for the central bank itself. First, when there is a shock to the economy, changes in the FCI can give the policy-maker an indication of the market's interpretation of the shock and expectations regarding future monetary policy. Second, the central bank can obtain leading information on the impact of market conditions and expectations of the future economic outlook. Third, the FCI can be used as a synthetic measure of the financial conditions that economic agents face and thus constitutes a broad assessment of the "financial" stance.[9]

A more aggressive use of the FCI would be to derive a policy rule by normalizing the interest rate. Using a model similar 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 housing 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

8. An extreme case of an atheoretic approach is to take the simple average of all components (e.g., J.P. Morgan and Goldman Sachs) for Canada.
9. Section 6 discusses this function of the FCI in greater detail.

plays a role in setting monetary policy. This use of an FCI or MCI is, however, controversial; it is opposed by Bernanke and Gertler (1999) and Gertler et al. (1998). Goodhart and Hofmann (2002) also denounce the mechanical policy response to asset prices, and advise that policy-makers should proceed with caution when they interpret information in asset prices.

2.5 Criticisms of FCIs

Although many of the studies argue that their FCIs are an improvement over the MCI, they are subject to many of the same main criticisms. In particular, many FCIs fail to address the four technical issues identified below.

(i) Model dependency

Like those of an MCI, the weights of existing FCIs are usually derived from a model, whether it be 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 that underlie 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).

(ii) Ignored dynamics

FCIs contain variables that affect output and inflation with varying speed. While a rise in the short-term interest rate lowers inflation within 6 to 8 quarters, for example, a change in housing prices could have an instantaneous impact on inflation. Thus, an examination of the components of the FCI at a given period would ignore these dynamics across time. A common solution to this problem is to include a lag structure in the IS curve or the model from which the weights are derived. The contemporaneous value of each component in the index can then be multiplied by the sum of the coefficients on the lags, although this is obviously an oversimplified approach (see Batini and Turnbull 2002 for a detailed discussion).[10]

(iii) Parameter inconstancy

Often, FCIs are derived from an estimated model or equation that covers the past 20 to 30 years. There have likely 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.

10. In the survey, only Macroeconomic Advisers have an FCI that includes individual lags of the components.

(iv) Non-exogeneity of regressors

In models or equations where weights are derived, the variables in the index are usually modelled as exogenous variables. It is probable, however, that they are simultaneously affected by each other and by the dependent variables (output and inflation), which leads to simultaneity bias. One simple way to overcome this problem is to estimate a reduced-form VAR, but it introduces an identification problem. Moreover, housing and equity prices are often characterized as forward-looking variables; namely, they depend on future output and inflation outlooks. This further complicates the identification problem.

3. Three Ways to Derive an FCI for Canada

In an effort to improve some of the aforementioned weaknesses of the MCI 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 by using the sum of coefficients on the lags of the variables, and by including individual lags in the FCI to take into account the *dynamics* of those variables over time. Our second and third methods focus 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 using an HP filter and a dataset detrended by first-differencing.[11] Although it is common practice in the literature to use quarterly data starting from the 1960s, we use monthly data from 1981 to 2000; we thereby avoid the potential structural breaks caused by oil prices in the 1970s and marginally improve the problem of *parameter inconstancy.*

3.1 FCIs based on a reduced-form model

The advantage of deriving an FCI from a reduced-form model is that the effect of each potential transmission channel on the real economy can be identified under a sufficient number of identification restrictions. 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 (Table 2). Models used for this purpose

11. A series of unit-root tests suggest that all our variables are integrated of order one. Results of the unit-root tests are available upon request.

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 links the output gap to inflation, controlling for inflation expectations (assumed to be formed adaptively) and the effects of oil prices, tax rates, and changes in the 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 (1999). Their IS curve contains the output gap as the dependent variable and the components of their FCI, in addition to the 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-Phillips curve (IS-PC) model: one using HP-filtered data and the other using first-differenced data.[12] 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 U.S. output and fiscal shocks. The Phillips curve contains lagged values of inflation and output, and contemporaneous and lagged values of oil prices.[13] Oil prices are also assumed to be exogenous to Canadian inflation.[14] The two equations are defined as follows:

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

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

12. HP filters typically use a smoothing parameter of 1600 for quarterly data, but there is no consensus on the appropriate value for monthly data. We use a relatively high parameter of 129,600 based on Ravn and Uhlig (2002).

13. Thus far, the Phillips curve does not play a role in our analysis, beyond ensuring theoretically desirable properties of our observed data. It does, however, serve as a platform upon which to extend our research. Results are available upon request.

14. Exogeneity cannot be rejected under both the Granger causality test and Geweke-Meese-Dent two-sided tests.

where *y* is the output gap in our HP-filtered specification (i.e., the percentage gap between real monthly GDP and its potential level, calculated as its HP-filtered trend) or the monthly growth of real GDP in our first-differenced specification.[15] x_i is component *i* of the FCI, where *x* = {real 90-day commercial paper rate, real 10-year government bond rate, C-6 real exchange rate, real residential housing prices, real S&P 500 stock price index, and AA corporate bond risk premium or the U.S. high-yield bond spread}.[16] *pcom* is the real Bank of Canada commodity price index. In our Phillips curve, π is year-over-year core inflation (CPI excluding its eight most volatile components and the effects of indirect taxes) and *poil* is the monthly growth in crude oil prices.

3.2 FCIs based on generalized impulse-response functions

The IS-PC framework discussed in section 3.1 has 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 solve this problem is to base our FCI weights on the impulse responses of an atheoretic VAR in which all the variables are treated as endogenous. This approach has pitfalls, however, since the traditional procedure, suggested by Sims (1980), 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 that includes 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 generalized impulse-response functions. Although orthogonalized impulse responses are not invariant to the reordering of the variables in the VAR, generalized impulse responses are. They are unique and take into full account the historical patterns of correlations observed among different shocks. An FCI can 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.

The generalized impulse-response function can be illustrated simply. Consider the VAR model,

15. A constant is included in equation (1) when using first-differenced data, but not when using HP-filtered data.

16. The U.S. high-yield spread is considered based on the results of Djoudad and Wright (2002), which suggest a strong relationship between this spread and Canadian real GDP growth.

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

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 a given point in time on the (expected) future values of variables in a dynamic system. It can best be described 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 baseline profile at time $t + n$, given the economy's history.

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

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

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 (1980), 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 an $m \times m$ 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 stated earlier, these orthogonalized impulse-response functions vary with the reordering of variables.

The alternative approach we follow in this paper was first suggested by Pesaran and Shin (1998). They propose 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 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

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

where σ_{jj} is the variance of e_j and $\delta = E(\varepsilon_t | \varepsilon_{jt} = \sqrt{\sigma_{jj}})$.

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. Factor analysis extracts 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; 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 that 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. English, Tsatsaronis, and Zoli (2003) construct an FCI by extracting factors (called financial factors) from around 50 financial and real variables for the United States, Germany, and the United Kingdom. They find that the financial factors provide considerable information about output and investment, but are not very informative about future 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:

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

where X_{it} is the ith variable, $F_t = (f_t,..., f_{t-q})$ is an $r \times 1$ 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 10, and $\lambda_i(L)$ is a lag polynomial.[17] 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

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

where $\hat{\Lambda}$ 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

To evaluate our three FCIs, we consider five desirable properties or performance criteria[18]: the consistency of each FCI's estimated weight with economic theory, its graphical ability to predict turning points in the business cycle, its dynamic correlation with the output gap (or monthly growth in real GDP), its in-sample econometric fit with the output gap (or output growth), and its out-of-sample performance in forecasting the output gap (or output growth).

17. 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.
18. Several combinations of variables were estimated within each of our three methodologies. The best of these are reported herein. The results of alternative formulations are available upon request.

4.1 FCIs based on a reduced-form model

In section 3.1, our IS-PC equations (1) and (2) are estimated separately using ordinary least squares (OLS) over the sample period 1981m1–2000m12.[19] The lag structure for each variable has been chosen by a general-to-specific strategy that begins with twelve lags and keeps all lags between the first and the last significant lag.

We use two methods to derive the weights for the FCI. Following Goodhart and Hofmann (2001, 2002), we apply coefficients summarized across lags to each contemporaneous component in the FCI. In other words, the coefficients on each lag of a particular explanatory variable are added together and taken as the weight on that variable at time *t*. This method is subject to the criticism that different asset prices have an impact on the real economy with varying lags, and that by multiplying the summarized weights by the contemporaneous value of those variables, the dynamics over time are ignored. In response to this criticism, we construct a separate version of our FCI, allowing for the full dynamics of individual lags. This is similar to Batini and Turnbull (2002), who use this method to construct a dynamic MCI for the United Kingdom.

In either case, we cannot make comparative statements regarding the size of the estimated coefficients, because they are based on a reduced-form model and therefore partly reflect contemporaneous relationships between explanatory variables. We find it desirable, however, to obtain weights and signs consistent with economic intuition, for communication purposes. As such, Table 3 reports the estimated weights and *p*-values on our "summarized-weight" FCIs, using alternatively HP-filtered data and first-differenced data.

As described for our general IS curve specification (equation (1)), each of our four IS-based FCIs includes the real 90-day commercial paper rate, the real 10-year Government of Canada bond rate, the real C-6 exchange rate, real housing prices, and the real S&P 500 stock price index. Each of these FCIs, however, differs somewhat in its 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.[20]

Regarding the first criterion by which we judge the performance of our FCI, further inspection of Table 3 reveals that both our summarized-coefficient FCIs have estimated weights that are

19. 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.
20. Recall that both the Canadian AA corporate spread and the U.S. high-yield spread were tried as alternative measures of the risk premium in each FCI. The FCIs with the most desirable properties are reported here.

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 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 government bond yield, 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. In fact, this is the case. Our FCIs suggest some combination of a wealth channel and/or credit channel for monetary policy, in that both housing and stock prices hold positive estimated coefficients. Furthermore, the test statistic put forth by Andrews (1993) suggests that our estimated parameters, using either HP-filtered data or first-differenced data, are stable over our sample.[21] The estimation results for the specification of the FCI based on the IS curve with individual lags and for the Phillips curve are also consistent with economic intuition and are available upon request.

The second criterion by which we judge the performance of our FCI is visual inspection vis-à-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 compares our HP-filter summarized-coefficient FCI with the 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). Table 4 reports dynamic correlations, our third criterion, of all four IS-based FCIs versus the output gap/output growth 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 0.606 two and three months in advance of the output gap.

Figure 2 compares our first-difference summarized-coefficient FCI (in annualized terms) with 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.

21. Specifically, a SupF statistic of 2.4 using HP-filtered data, and 2.2 using first-differenced data, implies that we cannot reject the null hypothesis of parameter stability at the 99 per cent level over our sample.

Figure 3 compares our HP-filter individual lag FCI with the output gap. This index is significantly more volatile than the other three IS-curve-based FCIs, primarily because of its dynamic lag structure. 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 and 2000). This FCI has a slightly lower correlation with the output gap, peaking at 0.459 at a lead of four months.

Figure 4 compares (in annualized terms) our final FCI based on the reduced-form methodology—featuring first-differenced data and an individual, dynamic lag structure—with 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 1987 and 1999–2000). However, the maximum correlation of this FCI with output growth occurs with a lead of only one month, at a level of 0.583. In this respect, its leading-indicator property is not as strong as in our other three IS-curve-based FCIs.

The final two criteria by which we judge the performance of our FCIs are their in- and out-of-sample properties in 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 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, beginning in the early 1980s and ending at the last available observation, thereby providing a one-step-ahead forecast of the output gap (or output growth) k-steps ahead from our incorporated FCI data. Forecast observations are obtained for each month from January 2001 to June 2002, regardless of the value of k in equation (6).[22] 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 the estimation varies). Recall that the weights for our FCIs are estimated

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.

from 1981 to 2000, to ensure the “out-of-sample” properties of our forecast over 2001 and the first half of 2002.

Table 5 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 (MSFE) for the forecasts using our FCIs based on a reduced-form model. 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. The message behind these numbers is that the further ahead one looks, the less of an explanation today’s value of the FCI provides regarding the output gap (or output growth). As noted above, however, comparisons across values of *k* must be treated with caution, because of differing estimation sample sizes for each *k*.

Our HP-filtered summarized-coefficient FCI shows up statistically significant at the 10 per cent level when explaining the output gap 6, 9, 12, and 18 months ahead. It is insignificant, however, 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 in a fairly linear fashion 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, which suggests that the year-over-year growth rate of real output half a year in the future will move 1.2 percentage points with each one-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.

Our individual-lag FCI based on HP-filtered data 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 $k = 6$, which suggests that a one-point change in this FCI translates into 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. Our other individual-lag-coefficient FCI, based on first-differenced data, is statistically significant throughout our relevant horizon of 6 to 24 months. The strongest coefficient on this FCI suggests that a one-point increase in the FCI translates into a 1.33 percentage point increase in the year-over-year growth of real output six months ahead.

Referring again to Table 5 for the reported MSFEs of our out-of-sample forecast exercise, and keeping in mind that they can be compared only between FCIs that forecast the same dependent variable, our summarized-coefficient FCIs perform best (i.e., have the lowest MSFE) overall using both HP-filter and first-difference definitions. The HP-filtered summarized-coefficient FCI performs 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 performs slightly better. Likewise, the first-difference summarized-coefficient FCI performs better at all relevant lags, 6 through 24, compared with 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] 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 risk spread. Its HP-filter counterpart is composed of the same six variables, except for the stock market, which is measured using the S&P 500. In Figure 5, the HP-filter FCI is plotted with the output gap. In Figure 6, the first-difference FCI is plotted with the output growth.

These FCIs can be viewed using the same five criteria described in section 4.1. Table 6 lists the weights for both impulse-response-function FCIs, and Figures 7 and 8 illustrate the impulse-response functions themselves. Both FCIs have positive weights on housing prices, consistent with expectations that high housing prices are a signal of excess demand and a leading indicator of strong construction activity. In the long run, however, output is adversely affected by an increase in new housing prices (Figure 8). 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 negative weights on the U.S. high-risk premium. A higher risk spread in the United States means tighter credit conditions and lower growth in that country going forward, which, given the strong economic links between Canada and the United States, 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 indexes; this deserves some discussion.

23. Akaike's information criteria (AIC) and Schwarz's criteria contradict each other. Schwarz's criteria suggest only one lag, whereas AIC suggests too many lags. This could be attributed to the presence of cointegration between the variables. Eighteen lags (six quarters) is in-between the AIC and Schwarz suggestions.

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, which suggests that a positive surprise in this interest rate, or a steepening yield curve, means stronger economic growth going forward. This weight is negative in the HP-filter index, but may be explained as a higher long-term interest rate increasing potential output still more than it increases short-run output. This is consistent with the impulse-response function shown in Figure 8. The negative 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, because a higher exchange rate may decrease potential output, via the higher cost of imported machinery and equipment, by more than it decreases actual demand. This again is in line with the impulse-response function shown in Figure 8.

Table 4 shows that both the HP-filter and first-difference impulse-response function FCIs have relatively dynamic correlations with output. This fact is also reflected in the in-sample fit of these two FCIs (Table 7 and Figures 5 and 6). Overall, 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 indexes also perform competitively out-of-sample at a relatively long forecast horizon (Table 7).

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 U.S. high-yield bond spread, respectively. Table 8 reports the percentage of common variance explained by each of the first four factors for these two indexes. The first factor captures 80 to 90 per cent of the common variance of output; thus, we specify our FCIs according to this factor.

Our two factor-analysis FCIs can be evaluated using four of the five performance criteria used in section 4.[24] Figures 9 and 10 plot these two FCIs with their comparable GDP measures. The HP-filter version (Figure 9) 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 (Figure 10) with U.S. equity and bond variables leads the boom in 1982, 1991, 1995, the busts in 1987 and 1999, and

24. Recall that, in a factor analysis, weights change over time and are unknown.

the pickup in 2002. On average, the first-difference FCI appears to pick up more economic turning points and predict them with a longer lead than the HP-filter version.

Table 4 shows that the HP-filter version has a higher correlation with output than the first-difference version at almost all horizons.

Table 7 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; 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 with other methods of weighting. In terms of the out-of-sample forecast, both versions perform better at a shorter horizon, with the HP-filter FCI yielding smaller forecast errors overall than the first-difference version.

4.4 Comparison of our FCIs

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

Both of these FCIs feature estimated weights and signs that are consistent with theory (Tables 3 and 6, respectively). While they each share several variables (the short-term interest rate, long-term interest rate, C-6 exchange rate, housing prices, and U.S. corporate bond risk premium), the IS-curve-based FCI contains the S&P 500 index as a measure of stock prices, whereas the impulse-response-based FCI utilizes the TSX composite index. Overall, the two indexes appear to pick up roughly the same number of turning points in output growth.

The IS-curve-based FCI is more highly correlated with output at shorter horizons 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 performs 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-curve-based FCI is better for predicting near-term output growth and the impulse-response-based FCI is better for predicting longer-term output growth.

5. Comparing the IS-Curve-Based FCI with the MCI

At first glance, an FCI resembles a traditional MCI in several ways. They share a similar name and they contain similar variables. In fact, the FCI includes all of the variables of the MCI. 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 indexes have significant differences.

The Bank of Canada's MCI was created mainly to measure the effect of the Bank's monetary policy stance on the economy.[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 in section 1, 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 the policy stance, and can be called the "financial stance."

Another important difference between the two indexes is the way in which their variables are detrended. In the HP-filter and first-difference versions of our FCI, we assume that the variables are non-stationary. The MCI, in contrast, implicitly assumes that the interest rate and the exchange rate are stationary. The MCI is expressed as the weighted average of the change in the interest rate from its value in January 1987 and the change in the exchange rate from its value in the same time period. 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.[26]

In addition, the signs of the MCI and the FCI are interpreted differently. The MCI is defined such that a higher value means a tighter monetary policy, whereas a higher FCI signifies a more accommodative financial stance.

Despite its desirable features, the FCI must outperform the MCI empirically to be a useful tool in the conduct of monetary policy. To investigate the properties and performance of the MCI, we perform a set of exercises similar to those we performed for our FCIs. Specifically, we explore the MCI's graphical representations, correlations, and forecasting ability with respect to output. It is

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.
26. In practice, however, more emphasis is usually placed on the change in the MCI instead of its level. The problem of non-stationarity is, in a sense, addressed in this way. See also section 6.

important to note, however, that we focus on the MCI's first-difference as opposed to its level, given that changes in policy stance are more clearly reflected in the former measure. Figure 11 plots the first-differenced MCI and our IS-curve-based FCI against year-over-year GDP growth. Graphically, our FCI seems to do much better at tracing the dynamics of GDP growth and capturing the turning points in the business cycle. The first-differenced MCI, in contrast, seems to capture excessive quarter-over-quarter noise.

Table 9 shows the dynamic correlation between the MCI and GDP growth. The MCI yields the wrong sign in the correlation with output growth, except for the correlation with output growth at 12 and 18 months. Even at those two horizons, the dynamic correlation with output growth is much lower than that between our FCIs and output growth.

Table 10 shows the results of the MCI-based forecast of the output gap and year-over-year GDP growth. The MCI yields the wrong sign in forecasting the output gap at all horizons and output growth 6 and 9 months ahead. Compared with our FCIs, the MCI is generally less statistically significant, and produces a lower adjusted R^2. In terms of forecasting the output gap, our first-difference IS-curve-based FCI outperforms the MCI 6, 9, and 12 months ahead, but not 18 and 24 months ahead. Nevertheless, our FCI that uses weights from the impulse-response functions, which has been found to forecast better in longer horizons, produces a smaller MSFE than the MCI 24 months ahead. Similarly, our IS-curve-based FCI does better in forecasting output growth than the MCI in shorter horizons (6 to 18 months ahead), whereas the impulse-response-based FCI does better in the longer horizon (24 months ahead). Overall, our FCIs outperform the MCI under our set of criteria.

6. Interpreting 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 I(1) series is simply its deviation from its stochastic trend or its equilibrium value, the higher the FCI, the looser the “financial stance” and the higher the 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:

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

Then 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. It is more complicated to compare the value of the FCI two years ago with its value today in terms of monetary policy stance, since the equilibrium values have probably changed over that period.[27] But from one monetary policy fixed announcement date to another, it seems reasonable to assume that equilibrium levels of the variables have not changed much, if 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, it increases the borrowing capacity of consumers, which stimulates consumption. Because housing prices are positively weighted in the FCI, a higher level is indicative of a looser “financial stance” and signals higher output growth.

7. Conclusion

We have provided a survey of the existing FCIs and proposed several FCIs for Canada based on three different approaches. Each approach is intended to address one or more criticisms of the MCI and existing FCIs. For each approach, we experimented with one set of data detrended using an HP filter and a second set detrended by first-differencing. We then evaluated the different versions of our FCIs based on five criteria: estimated weights on components that are consistent with theory, graphical leading-indicator properties with respect to business cycle turning points, strong dynamic correlation versus the output gap (or monthly growth in real GDP), and in- and out-of-sample performance in a simple forecasting exercise of the output gap (or output growth).

Our first approach derived its weights from an IS-Phillips curve framework in two ways: using the sum of the coefficients on the lags of the variables, and including individual lags in the FCI to take into account the dynamics of those variables over time. Using monthly data from 1981 to 2000, we found that housing prices, equity prices, and bond risk premiums, 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, estimated parameters are consistent with theoretical

27. The same critique applies to the MCI.

expectations. Consistent with Djoudad and Wright (2002), we also found that the FCIs that use U.S. stock prices and high-yield bond spreads perform better than the ones that include Canadian stock prices and investment bond spreads.

Our second and third approaches derived weights based on generalized impulse-response functions from a VAR and a factor analysis, respectively.

Out of our eight FCIs based on all three approaches, two specifications showed particularly well-rounded attributes considering several different criteria. The FCI that derived its weights from the summed coefficients of an IS curve using first-differenced data served the best as a short-term (less than one year) predictor of output growth, whereas the FCI that derived its weights from VAR impulse-response functions using first-differenced data served the best to predict output over the longer term (one to two years). Our FCIs also outperformed the MCI in most of the criteria we considered.

Future research can further investigate the properties of these FCIs by comparing their forecasting performance with benchmark univariate models. It may also be possible to derive the weights of the FCIs 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 Assets

Years	Property (per cent)	Equity[a] (per cent)	Bonds (per cent)	Life insurance and pension (per cent)	Others (per cent)
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. Including mutual funds.
Source: Statistics Canada Cansim matrix 751

Table 2: MCI and FCIs Constructed by Orgarizations and Academic Studies

Organizations/studies	Short-term rates	Long-term rates	Exchange rates	Equity market	Other variables	Detrending	Source of weights
Bank of Canada	Nominal 90 CP		Nominal C-6			Change from a base period	IS curve
Banque de France for G-7	Real 3-month market rate	Real 10-year government rate	Real effective			“similar” to the BoC index	IMF’s and OECD’s macro models
Mayes and Virén, (2001) for 17 countries	Real 3-month market rate		Real bilateral vs. U.S.	Real stock price	Real house prices	Level of real interest and exchange rate; first-difference for the rest	IS curve (single equation)
Goldman Sachs for Canada	Real 3-month market rate		Real effective	Measure of stock valuation	Yield curve	Unknown	Simple average
Goldman Sachs (2000) for U.S.[a]	Real 3-month LIBOR	Real A-rated corporate, indexed	Real trade-weighted	Equity mkt cap/ GDP ratio		Interest and exchange rates (deviation from historic mean)	Fed macro model
J.P. Morgan for Canada (2002)[b]	Nominal 3-month market rate	10-year corporate spread	Nominal C-6	Nominal TSX index	(1) Yield curve (2) M1 (3) M2++	Deviation from mean divided by variance	Simple average[c]
Macroeconomic Advisers (1998) for the U.S.	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”	Washington University Macro Model (WUMM)
Goodhart and Hofmann (2001) for G-7	Real 3-month market rate		Real effective	Real stock price	Real property prices	Deviation from trend: long-run mean for interest rate; linear trend for exchange rate and house prices; HP filter for stock prices[d]	1) Reduced-form IS and PC model 2) Impulse-response functions of a VAR
Lack (2002)	Real 3-month LIBOR		Real trade-weighted		Real property prices	First-difference	Shocks to a: 1) Restricted 2) Structural macro model

a. See Dudley and Hatzius (2000).
b. See Carmichael (2002).
c. The short-term interest rate and exchange rate are combined as one component to mimic the Bank of Canada’s MCI.
d. Goodhart and Hofmann (2002) construct an FCI only for the U.K., 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—First-difference
	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 C-6 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
U.S. high-yield risk spread$_t$	-0.224	-0.194
Adjusted R^2	94.0	21.8

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

Table 4: 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	0.600	0.448	0.580	0.598	0.521	0.537	0.233
6	0.559	0.580	0.436	0.538	0.589	0.527	0.496	0.249
9	0.488	0.500	0.397	0.496	0.553	0.510	0.323	0.241
12	0.419	0.433	0.320	0.428	0.465	0.480	0.111	0.204
18	0.288	0.368	0.175	0.413	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 5: 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 6: FCI Weights as Derived From VAR Generalized Impulse-Response Function

Variable	FCI—HP filter	FCI—First-difference
	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 C-6 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
U.S. high-yield risk spread_t	-9.22	-0.74

Table 7: 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	0.10 (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 8: Factor-Analysis FCIs: Percentage of Common Variance Explained by Each Factor

	Based on HP-filtered data[a] (per cent)	Based on first-differenced data[b] (per cent)
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 U.S. high-yield bond spread.

Table 9: Dynamic Correlations Between the MCI and Year-Over-Year GDP and the Output Gap

MCI leads (months)	Output gap	Output growth
3	0.029	0.244
6	0.313	0.166
9	0.290	0.042
12	0.265	-0.089
18	0.022	-0.193

Table 10: Forecasts Based on First-Difference of MCI

Forecasted variable	Steps ahead	Coefficient on FCI[a]	Adjusted R^2	MSFE
Output gap	6	0.75 (0.00)	0.092	0.834
	9	0.67 (0.00)	0.077	0.831
	12	0.54 (0.02)	0.050	0.883
	18	0.28 (0.27)	0.009	1.053
	24	0.07 (0.67)	-0.003	0.977
12-month output growth	6	0.64 (0.04)	0.023	2.547
	9	0.13 (0.68)	-0.003	2.624
	12	-0.24 (0.46)	-0.000	2.674
	18	-0.57 (0.04)	0.019	2.333
	24	-0.65 (0.07)	0.033	2.133

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

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

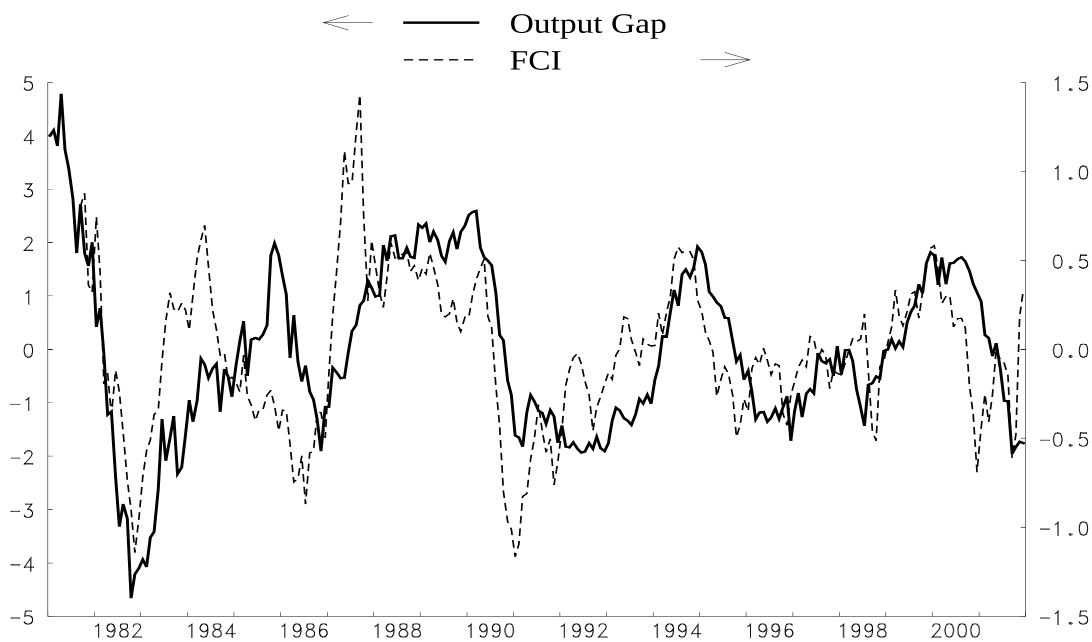


Figure 2
IS-Based First-Difference FCI and Real Output Growth - Summarized Coefficients

Figure 3
IS-Based HP-Filter FCI and the Output Gap - Individual Lag Coefficients

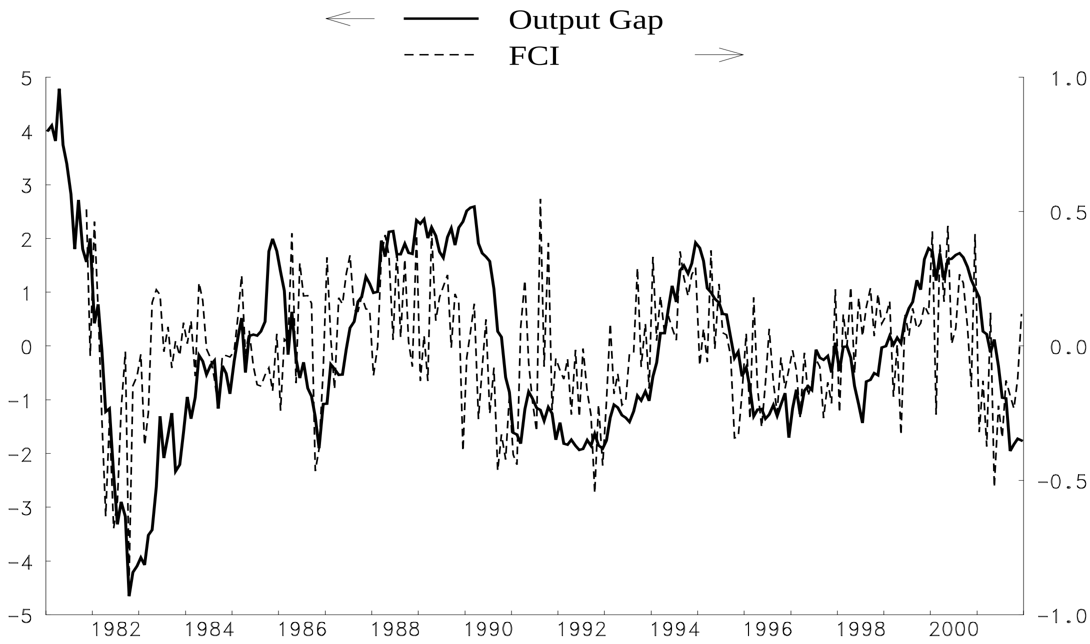


Figure 4
IS-Based First-Difference FCI and Real Output Growth - Individual Lag Coefficients

Figure 5
Impulse-Response-Based HP-Filter FCI and the Output Gap

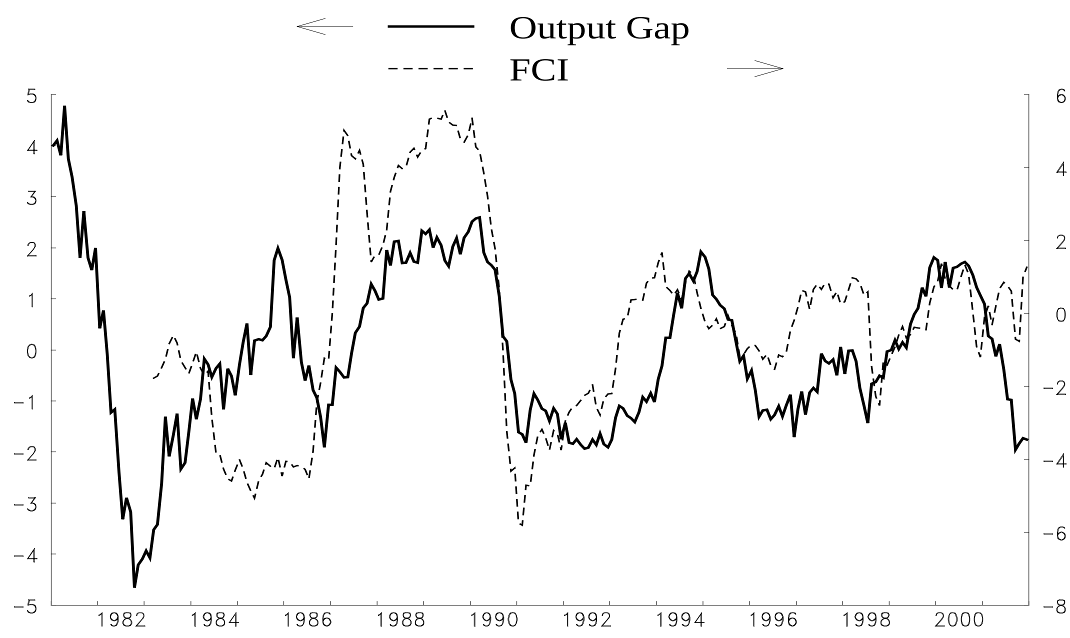


Figure 6
Impulse-Response-Based First-Difference FCI and Real Output Growth

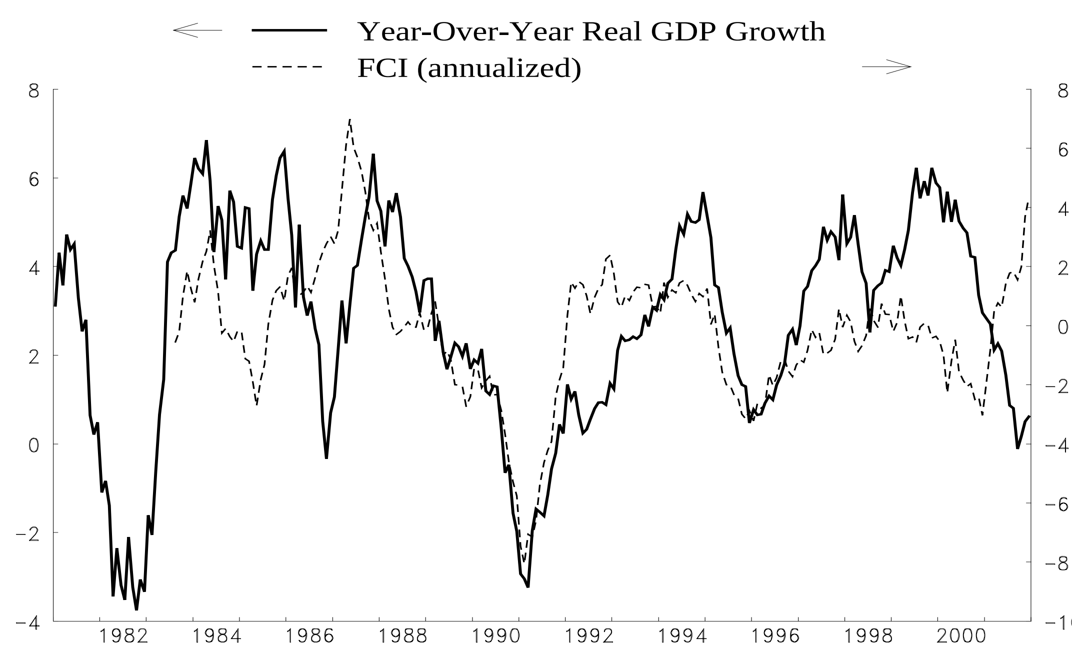


Figure 7

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

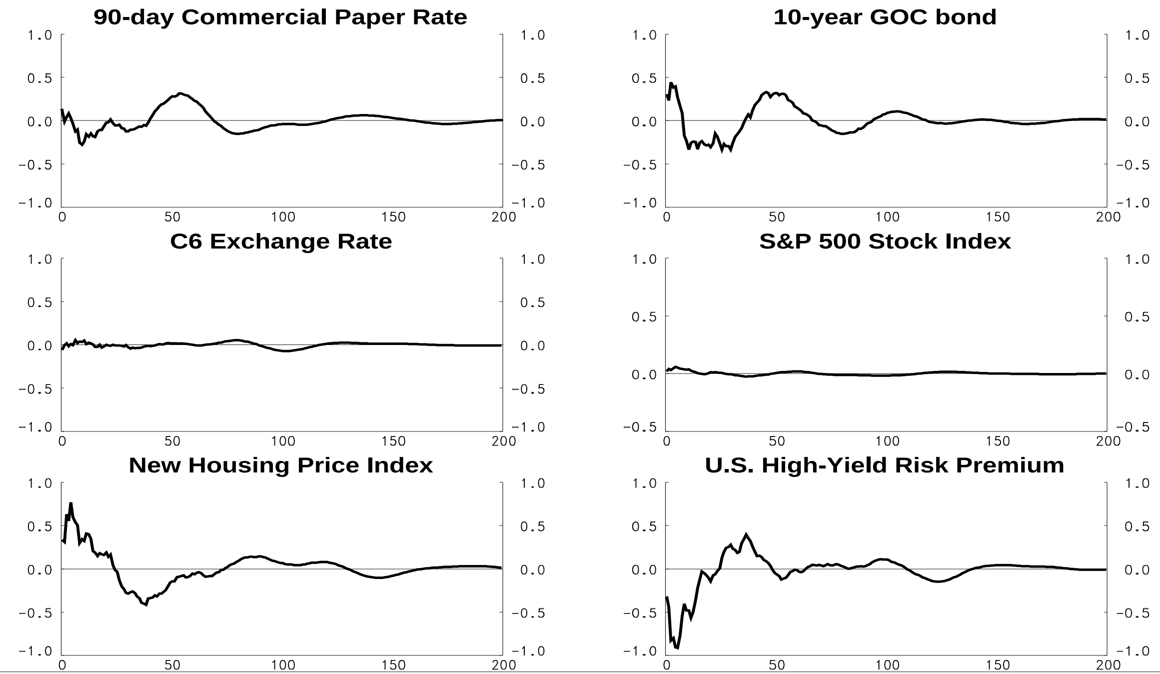


Figure 8

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

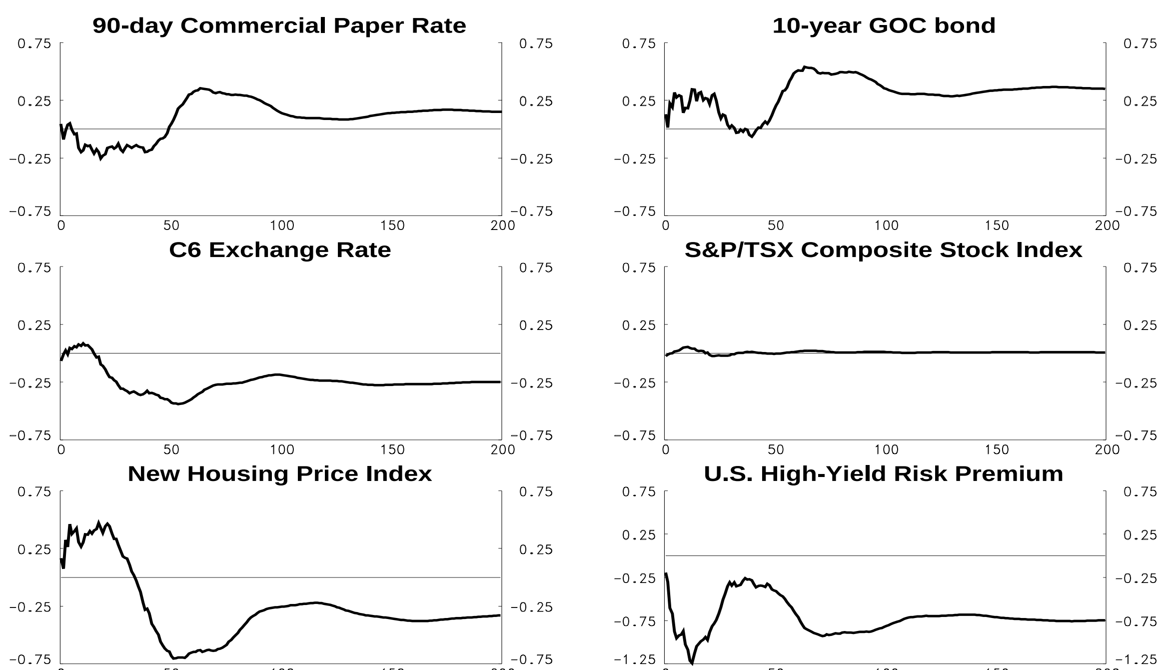


Figure 9
Factor-Analysis-Based HP-Filter FCI and the Output Gap

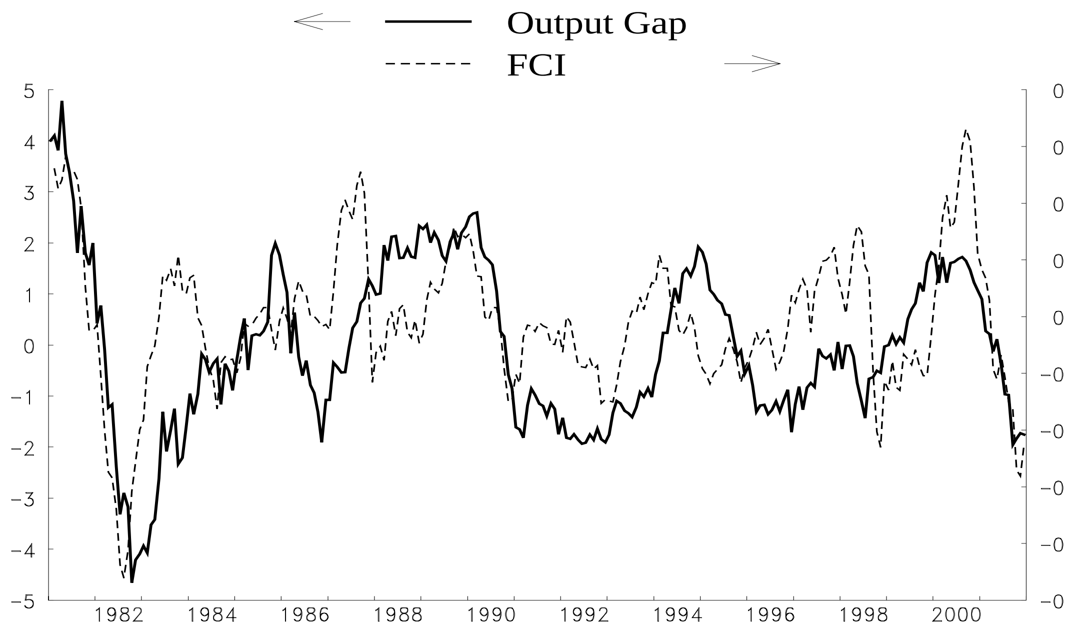
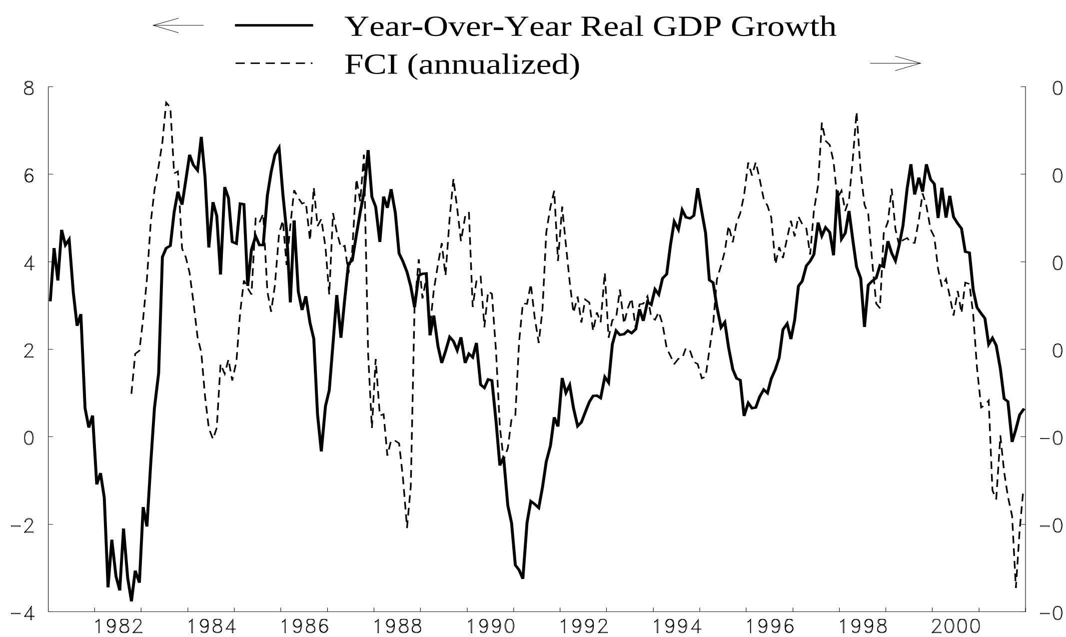


Figure 10
Factor-Analysis-Based First-Difference FCI and Real Output Growth



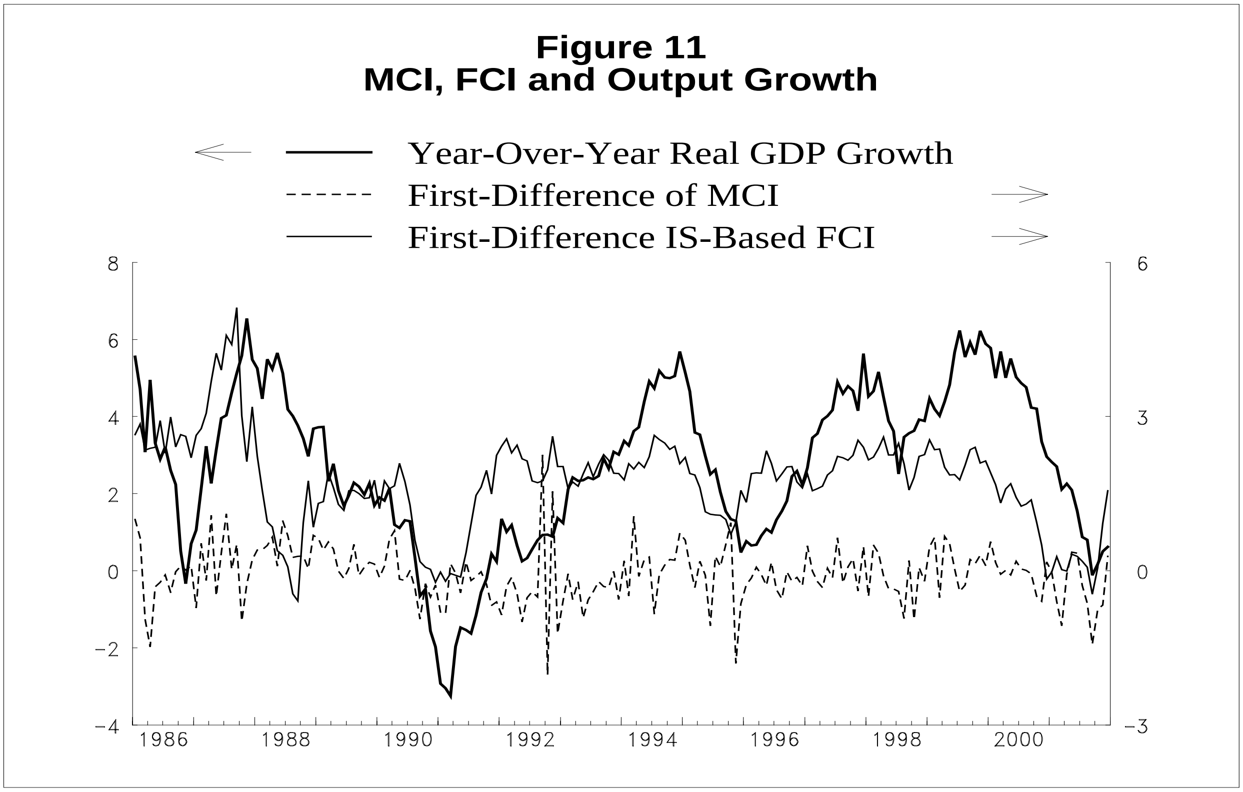


Figure 11
MCI, FCI and Output Growth
Year-Over-Year Real GDP Growth
First-Difference of MCI
First-Difference IS-Based FCI
8
6
4
2
0
−2
−4
6
3
0
−3
1986
1988
1990
1992
1994
1996
1998
2000

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