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Predictive Macro-Impacts of PLS-based Financial Conditions Indices: An Application to the USA

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Predictive Macro-Impacts of PLS-based Financial Conditions Indices: An Application to the USA

Duo Qin and Qing-chao Wang*

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Abstract

This investigation seeks to construct financial conditions indices (FCIs) by the partial least squares (PLS) method with the aims (i) that the FCIs should outperform interest rate, which is conventionally used in small VAR (Vector Auto-Regression) models to present the predictive macro-impacts of the financial markets, and (ii) that the FCIs are adequately invariant during regular updates to resemble non-model based aggregate indices. Both aims are shown to be attainable as long as the FCIs are tailor-made with carefully selected components and suitably targeted macro variables of forecasting interest. The positive outcome sheds light on why the widely used principal component analysis (PCA) approach is ill-suited to the tasks here whereas why the PLS route promises a fruitful way forward.

Keywords: Partial Least Squares, financial conditions index, concatenation, forecasting

JEL classification: E17, C22, C53

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1. Introduction

The 2008 financial crisis has drawn macroeconomists' attention onto a major weakness of extant macro models – lack of variables adequately representative of broad financial market conditions which must have exerted non-negligible predictive impact on key macro variables, e.g. see Barnett (2011), Ng (2011) and Borio (2013). Correspondingly, there is a visible growth in the construction of various financial conditions indices (FCI). Since there lacks a clear matrix to weigh up indicators and indices across different financial markets, most of these aggregate FCIs are model-based and essentially based on the method principal component analysis (PCA) and/or augmented by dynamic factor analysis (DFA), e.g. see Hatzius *et al* (2010), Brave and Butters (2011), Qin and He (2012), Paries *et al* (2014).

Evaluation of the predictive macro impacts of existing FCIs has yielded mixed results, e.g. see Aramonte *et al* (2013). Many of these FCIs suffer from a lack of historical invariance when the models from which they have been derived are updated with incoming new data. Although it is shown in Stock and Watson (2011) that factor invariance is theoretically achievable if the chosen indicator set is sufficiently large, this is virtually unachievable in practice, because available financial indicators which are potentially relevant for macro forecasting purposes fall well below this 'sufficiently large' requirement. Moreover, financial indicators are often found to be most prone to weight shifts as compared to non-financial indicators, e.g. see Stock and Watson (2009). If indicator sets are artificially extended by inclusion of many other irrelevant indicators, the predictive capacity of the resulting factors dwindles. Consequently, FCIs which are shown to exhibit certain macro predictive capacity tend to suffer from frequent historical variations during model updates and hence cannot be used in the same manner as those non-model based aggregate indices, such as CPI (consumer price indices).

This weakness may be circumvented by an alternative method – partial least squares (PLS), a method which has been rarely used in econometrics since its invention about half a century ago, see Wold (1966, 1975). Since the forecasting variables of interest are explicitly imposed as a targeting condition or a constraint in the PLS procedure, the probability should be greater to find the resulting component weights more constant than those PCA-based ones. Meanwhile, the predictive capacity of PLS-based indices cannot be inferior, and is likely to be superior, to those comparable PCA-based ones since the PLS method can be seen as an extension of the PCA method. Indeed, this point has already been verified in a few econometric studies emerging in the recent decade, e.g. Lin and Tsay (2005), Groen and Kapetanios (2008), Eickmeier and Ng (2011), Lannsjö (2014), Kelly and Pruitt (2015), Fuentes *et al* (2015).

The present investigation builds on the above finding and delves into the possibility of constructing PLS-based FCIs which resemble commonly used aggregate indices and also outperform monetary variables in conventional macro models in forecasting major macro variables. Our investigation is carried out on the US case. Following the common practice, we set our experiments within the simple framework of small-scaled vector-auto-regression (VAR) models. Specifically, we choose inflation, annual growth rates of industrial production (IP) and GDP as our macro variables of forecasting interest and interest rate to represent the conventionally used monetary variables. It should be noted that four of the six previous studies cited in the previous paragraph are also on the US case, but none has been focused on the construction of FCIs, nor on the issue of historical invariance of the resulting aggregate factors during data updates so as to make them comparable to non-model based aggregate indices.

Our investigation has yielded encouraging results. It is indeed possible to construct PLS-based FCIs which resemble commonly used non-model based aggregate indices and also outperform the interest rate variable in our comparative forecasting exercises. Moreover, such FCIs have to be tailor-made, with carefully selected components and specifically targeted macro variables of forecasting interest. The outcome of our experiments helps shed light on why the PCA route is ill-suited to the task here whereas why the PLS route promises a fruitful way forward (see section 5). But before describing these findings in more detail (section 4), we need to outline first the forecasting methods (section 2), as well as financial indicator selection and classification principles (section 3).

2. Forecasting Methods

We design our experiments on the basis of a prototype VAR model of output (year-on-year) growth, (annual) inflation and interest rate, following the seminal works by Stock and Watson, e.g. (1989; 2002). Two output variables are considered – IP and GDP, due mainly to the lack of published monthly GDP time-series. Here, monthly GDP are interpolated from quarterly time series using the monthly weights of total retail sales, which is taken as a proxy of private consumption, the largest component (over 2/3) of the US GDP series.[1] Data series of these four variables are plotted in Figure 1 and their sources are listed in Appendix. Since the forecasting adequacy of conventionally used monetary variable is our focal interest, we regard the interest rate, i_t, as an exogenous variable. Specifically, denote the dataset of the three macro variables of forecasting interest as $Y_{3\times t}$, we have:

(1) $$Y_t = \beta'(L)Y_{t-1} + \alpha'(L)i_t + e_t.$$

Now, let us denote $X_{t\times n}$ as a dataset of financial variables which have been standardised following the PCA convention. Let $F_{k\times t}$ be the latent FCI set corresponding to $X_{t\times n}$, with $k \ll n$. In the PCA setting:

(2) $$X_t = F_t P' + U_t,$$

[1] We have also experimented with a compound weights of the sum of retail sales and net foreign trade, but the results differ little.

these latent factors are derived by their maximum capacity of representing data variance in terms of the covariance matrix, $X'X$. The resulting PCA-factor based model as an alternative to (1) is:

(3) $Y_t = \beta'(L)Y_{t-1} + \phi'(L)F_{t-1} + \varepsilon_t.$

As mentioned in the previous section, the constancy in P' tends to be poor when (2) is re-estimated as new data observations become available, to the extent that the PCA-based F_t suffers from frequent historical revisions during regular updates. Consequently, F_t cannot be treated in an equivalent manner as i_t making model (3) less credible than model (1). In order to circumvent this weakness, we turn to the PLS method. The method effectively extends (2) by adding a constraint on the choice of component weights with respect to the targeted forecasting variables:

(4) $\mathrm{y}_{j,t} = G_{j,t-1}B_j' + V_{j,t}, \quad j = 1,2,3.$

In contrast to PCA, PLS factors are derived by the principle of maximising the covariance matrix, $X'YY'X$. The PLS method is executed by means of a nonlinear iterative algorithm on (2) and (4) to estimate matrices, P and B, so as to produce PLS-based F_t. The algorithm is commonly known as NIPALS, following H. Wold's seminal work (1966, 1975, 1980), see also Wegelin (2010) and Sanchez (2013).

Currently, we limit our experiments to the first PLS factor only so as to keep the investigation as practical and focused as possible.[2] Monthly data of the period 1980M1-2014M12 are collected, and the first sub-period of 1980-2000 is kept for model estimation. The estimated models are then used for forecasts up to two years (24 months) before they are updated. This allows us to carry out seven rounds of comparative forecasting trials. Within each round, the predicted part of the FCIs is derived using the estimated component weights

[2] There is noticeable desire from many central banks for single aggregate financial sector indices, e.g. see Gadanecz and Jayaram (2009).

from the latest update. In correspondence to the FCIs from each update, a set of concatenated FCIs are also produced and used in the forecasting trials. In order to highlight the differences between the concatenated FCIs from those FCIs derived simply from various rounds of estimation, we sometimes refer to the latter as the un-concatenated FCIs. An illustration of how concatenated FCI series are constructed is given in Figure 2.

Since over-parameterisation is a well-known weakness of VAR models, we adopt the general-to-specific approach (see Hendry, 1995) during the estimation stage of the first sub-sample as well as the subsequent updates to reduce (1) and (3) into parsimonious models.[3]

3. Selection of Financial Variables as Indicators

The selection is driven mainly by two concerns: market coverage and dynamics. The first has been widely acknowledged. We thus follow the recent literature in making our choice of the financial series, e.g. Hatzius *et al* (2010) and Paries *et al* (2014). A detailed list of these series is given in the Appendix.

The second concern, however, has been far less heeded than the first. In the present investigation, we deal with the dynamic selection issue in two stages. The first stage follows a classification proposed by Qin and He (2012), i.e. processing and dividing financial series into two types – the short-run versus the long-run indicators. The former consists of growth rates or changes of individual variables whereas the latter various ratios or differences between series, such as various interest rate spreads. Since the latter type embodies the disequilibrium effects of financial markets in a much concentrated manner, it is expected to capture what has been identified as main transmission channels between the financial and real sectors, see BCBS (2011). From the time-series perspective, this set of disequilibrium indicators exhibits distinctly lower frequency dynamics than the short-run sets, dynamics which matches better

[3] It is shown in Qin *et al* (2008) that parsimonious reduction of dynamic models raises the forecasting capacity significantly.

with those exhibited from macro time series. Such match is substantively important as it corresponds to what applied economists have tried to emphasise, e.g. see Drehmann *et al* (2012) and Borio (2014) as a recent effort. In a subsequent study, Wang (2016) experiments with the PLS-based FCIs extracted from indicator sets by Qin and He's classification. His experiments reveal that the indicators which play significant roles to the formation of FCIs are dominantly from the disequilibrium set while short-run indicators can be largely screened out. This finding confirms to the conventional wisdom that everyday volatilities from financial markets are mostly noise to the real sectors unless they accumulate into disequilibrium signals too large to be ignored at a macro level. Following Wang's finding, our indicator set is solely built on disequilibrium financial variables, see Table 1. Through careful scrutiny of the dynamic movements of individual variables, we find a few exhibiting distinctly greater persistence than others, such as bank lending to deposit ratio and the ratio of bond market index to equity market index. We therefore include their first-differences into the set as well.

The second stage is to allow for the possibility that indicators from various financial markets do not move with the same dynamic pulse. It should be noted that almost all the available factor-based aggregate indices in the literature are derived from large time-series panels of indicators arranged homogeneously timewise. This amounts to imposing simultaneity or regular cross-market synchronisation on all indicators, an assumption which is obviously over-restrictive here. We therefore try to relax this assumption by exploring the screening capacity of the PLS method, e.g. see Wold *et al* (2010). Specifically, we allow each indicator, $x_{i,t-m}$, to differ in lags up to six months: $m = 1, \cdots ,6$, and select the lag with the largest loading using the PLS sparse method. As a result, the filtered set, X_n, contains indicators with heterogeneous lag lengths between 1 and 6 months. Clearly, the longer of the indicator lags, the greater the predictive value of the corresponding indicators is in terms of leading information provision.

4. Empirical Results

First of all, it is clearly shown in Figure 3 that different forecast targets result in different FCI series by the PLS method. Similarity of the IP-targeted FCI and the GDP-targeted FCI reflects the fact that industrial production forms a sizeable part of GDP, but the difference of these two series from the inflation-targeted FCI is too striking to ignore. The forecasting constraint expressed by Eq. (4) is indeed binding on Eq. (2). An immediate implication of this is that an unconstrained and universal FCI based on the PCA approach should be inferior to these FCIs as far as the predictive capacity with respect to targeted variables is concerned.

In addition to those FCIs illustrated in Figure 3, a set of concatenated FCIs are also constructed from each update (see Figure 2 for the concatenation method). The two sets are used in model (3) alternatively in our comparative analysis of the relative forecasting performance of models (3) versus (1). The analysis is based on two commonly used statistics: (i) ratio of the mean squared errors (RMSE) of (3) to (1) and (ii) *p*-value of a forecasting encompassing test known as the modified Diebold-Mariano (MDM) test, with the null hypothesis postulating that (3) encompasses (1).[4] Since the sample size of individual rounds of forecasting trials is relatively small (24 months), we also report the two test statistics using accumulated foregoing samples from the 2nd round onwards. The statistics based on trials using the concatenated FCIs are also reported from the 2nd round onwards. All these test statistics are reported in Table 2. To cut through the details of this table, a summary diagram is plotted in Figure 4 using the average RMSEs of all individual rounds categorised by forecasting horizon from Table 2.

Key results of Table 2 and Figure 4 can be drawn from four different perspectives. First, model (3) outperforms model (1) at a broad level, the majority of the RMSE is smaller than

[4] It should be noted that results from the RMSE do not always agree with the MDM test results because the two are based on different statistical criteria, see Harvey *et al* (1998).

unit and most of the *p*-values are larger than 5%. Second and from the perspective of forecasting horizons, the predictive supremacy of (3) over (1) becomes unquestionably evident when the horizon extends beyond 6 months. We deduce two explanations for this. There must be valuable leading information content in the FCIs which is missing in the interest rate variable. Meanwhile, the dynamics of the three targeted variables are dominantly explained by their own first lag in both models. In other words, these variables exhibit a strong unit-root dynamic tendency, see Figure 1, and the simple VARs with a single financial variable, be it interest rate or FCI, are inadequate in explaining that dynamics.[5] We shall come back to this point later. Third and from the angle of three target variables, the IP-targeted FCIs are the most effective in raising the predictive capacity of (3) over (1) while the inflation-targeted FCIs are the least effective. This suggests that IP is more susceptive to general financial market conditions than GDP whereas inflation the least susceptive of the three. Indeed, both the interest rate variable and the FCI are dropped out as insignificant from the parsimonious VAR reduction process in the last two rounds of the post-crisis period, resulting in those not available (N/A) entries in Table 2.[6] Interestingly, the concatenated FCI has survived model reduction of these two rounds although the resulting predictive value-added looks marginal. A comparison of the concatenated versus un-concatenated FCIs forms the fourth perspective. On the whole, we find it viable to concatenate PLS-based FCIs regularly in two-year intervals, with predictive results on a slightly favourable side in the IP case, no noticeable difference in the GDP case, and on a marginally unfavourable side in the inflation case. If we look at the time-series plots of un-concatenated versus concatenated FCIs in Figure 5, we find that the two sets are much closer prior to the 2008 crisis than the post-crisis period and that, in the inflation case, the crisis

[5] The estimated results of parsimonious VARs in various rounds of comparative forecasting trials are not reported here to save space. Nevertheless, the basic dynamic structure of these VARs is similar to what has been reported in the relevant literature.

[6] In all the reduced VAR models, the own lags of inflation exhibit strongest unit-root tendency whereas the own lags of IP the weakest of the three.

has resulted in a rather permanent gap between the two series. In order to further illustrate how the crisis affects concatenation, we disaggregate, in Figure 6, the summary RMSEs of the concatenated version used in Figure 4 into two parts: one for the pre-crisis subsample and the other the post-crisis subsample. Figure 6 shows clearly that, during financial market turmoil, concatenation helps maintaining the predictive capacity of those FCIs which have been empirically verified for suitably targeted variables, e.g. IP in the present case. The practical significance of this finding is two-fold at least. (i) Concatenation of model-based FCIs is achievable only when they are carefully customised for suitably targeted macro variables, and it is virtually impossible to construct one FCI which possesses adequate predictive power for all key macro variables and remain practically invariant during model update; and (ii) The goal of concatenation offers us an additional handle of selection. It helps us to identify which macro variable is more susceptive to overall financial market disequilibrium shocks than others, and moreover how varied these shocks are from different financial market components in terms of both magnitude and dynamics.

The latter aspect leads us to the next issue of examination – the PLS component weights and lag lengths of the FCIs. These are listed in Tables 3, 4 and 5 from three sub-sample estimations – the base round plus two rounds corresponding to Figure 5. Tables 6 is a condensed version of these three tables in combination. The first and foremost noticeable evidence from these tables is lack of cross-market synchronisation as far as the component lags are concerned. Meanwhile, a sizeable part of the components have relatively constant weights over time, as shown by the grey-shaded blocks, especially before the 2008 financial crisis. If we compare the weights for the three targeted variables, we notice that there are more insignificant or small weights in the inflation case than the other two cases. This reflects why the predictive power of inflation-targeted FCI is the weakest. Now, let us compare the lags and weights across different markets. It is discernible that weights of the indicators from forex markets and/or equity markets are smaller on the whole than those of the indicators from the fixed-income markets as well as the banking sector. This implies that disequilibrium shocks from the forex and equity markets play a relatively minor role to our macro variables of forecasting interest. Overall, indicators of the fixed-income markets provide greater leading information content than those of the banking sector by having relatively longer lags. On the other hand, most of the weights of those differenced indicators in the banking sector are either relatively small or insignificant, a result in partial confirmation to Wang's earlier finding (2016) about the general irrelevance of short-run indicators as a category. Another point worth special scrutiny is indicator, x15, interest rate premium in the banking sector, since this indicator is closest to the interest rate variable in benchmark model (1). The impacts of this indicator remain relatively stable for all three macro variables, albeit with longer lag lengths in the IP and GDP cases than what we find in the benchmark model. Nevertheless, there is no sign of its weights dominating, in absolute magnitude, the weights of other significant indicators, a sign which reflects clearly financial information deficiency of the benchmark model.

One issue which deserves further scrutiny is the forecasting performance of model (3) versus model (1) with respect to the oncoming of the 2008 financial crisis. It is already shown in the mid-column block of Table 2 that (3) outperforms (1) during the 2007M1-08M12 period for forecasting horizon longer than 3 months, indicating that the FCIs have brought in more relevant and earlier signals than what the interest rate variable contains, especially when we take into consideration those relatively long lags of significant indicators listed in Tables 3-5. Table 7 provides the absolute mean squared errors (MSE) of forecasting by the two models for three sub-sample periods: a seven-year pre-crisis period, a 12-month period leading into the crisis and a 24-month crisis period. It is evident from the table that model (3) provides marginally better forecasts than model (1) of the oncoming crisis (2nd period), although both models forecast poorly during the crisis period (much larger MSEs of the 3rd period than those of the 1st period). If we compare the MSEs across different forecasting targets, we see that IP is the most affected by the crisis while inflation the least. This is actually already shown in both Figure 2 and Tables 3-5, where the crisis has resulted in least variations in the inflation case as compared to the other two cases as far as shifts between the concatenated and un-concatenated FCIs and also in the indicator weight compositions are concerned. This finding confirms to our earlier observation that inflation is the least sensitive of the three to financial market conditions.

Finally, it is worth pointing out a major limitation of the VAR model framework in predicting the impact of major external shocks, since these models rely dominantly on the explanatory power of the own lags, i.e. the lagged dependent variables. This is partially discernible from Table 6, where improvements by FCIs are rather small as compared to the scale of deteriorating MSEs as the forecasting horizons rise, especially during the crisis period. It is evident that a better designed model framework to include major co-trending and/or co-shifting variables or factors is desirable before further experiments on FCIs are carried out.

5. Concluding Remarks

The experimental results are encouraging. We find it possible to produce model-based FCIs which can be updated in the similar manner as non-model based aggregate indices are updated. Such FCIs have to be tailor-made, with carefully selected components and specifically targeted macro variables of forecasting interest. The positive outcome sheds us light on why PCA-based FCIs are inappropriate for the task here. It is too naïve not only to aim at constructing one aggregate FCI which should have predictive impacts on a wide range of macro variables, but also to assume synchronisation of all the financial indicators from which the PCA-based FCIs are extracted. Furthermore, the need to go for tailor-made FCIs using the PLS method tells us the importance of assessing carefully the substantive distances of targeted macro variables to general financial market conditions. Specifically in the present case, we find that IP is the most vulnerable while inflation is the least responsive of the three to aggregate financial market disequilibrium shocks. This finding suggests to us that the PLS-based FCIs may exhibit greater predictive potential if they are applied to conventionally built structural models instead of small VAR models. In other words, the PLS route should not be regarded narrowly as another data-mining tool in a data-rich situation with as little dependence on substantive knowledge as possible.

Indeed, experiments on how to utilise PLS-based FCIs to improve conventional structural models are on the top of our future research agenda. Meanwhile, much refinement is also highly desirable of the simple PLS method we have tried so far. One particular area is to seek ways to improve the PLS weight screening procedure by an appropriate mixture of mode A (reflective model) and mode B (formative model), e.g. see Wold (1980) and Esposito Vinzi *et al* (2010). All the existing econometric studies that we know of have adopted mode A, including ours. However, this mode is clearly over-simplistic when it comes to the screening of various financial indicators, especially to the case of dynamic selection of the indicators. Last but not least, more systematic investigations are needed into the conditions required for concatenating model-based FCIs during routine data updating processes, so as to enhance the practical significance of this research well beyond the academic arena.

Appendix: Variable definitions and data sources

Variable	Description	Source (CEIC)
O1	3-month market interest rate of US	Euro Dollar Deposits Rate: London: 3-Month Month Average
O2	3-month market interest rate of UK	Sterling Interbank Rate: Last Fri of the Period: 3 Months
O3	3-month market interest rate of Canada	CA: Money Market Rate
O4	3-month market interest rate of Sweden	SE: Money Market Rate
O5	exchange rate of UK	UK: Official Rate; End of Period
O6	Exchange rate of Canada	CA: Official Rate; End of Period
O7	Exchange rate of Sweden	SE: Official Rate: End of Period
O8	forward exchange rate of UK	UK: Forward Exchange Rate: 3 Months
O9	forward exchange rate of Canada	CA: Forward Exchange Rate: 3 Months
O10	Forward exchange rate of Sweden	SE: Forward Exchange Rate: 3 Months
O11	Stock market index of US	Index: Standard & Poors: 500
O12	Stock market index of Canada	CA: Index: Share Price (End of Period)
O13	Stock market index of Germany	Equity Market Index: Month End: DAX
O14	Stock market index of Japan	Index: TSE 1st Section Composite
O15	Stock market index of UK	UK: Index: Share Price
O16	Low yield corporate bond	Corporate Bonds Yield: Moody's Seasoned: Aaa Rated
O17	High yield corporate bond	Corporate Bonds Yield: Moody's Seasoned: Baa Rated
O18	1-year to mature government bond	Treasury Bills Yield: Constant Maturity: Nominal: Monthly Average: 1 Year
O19	10-year to mature government bond	Treasury Notes Yield: Constant Maturity: Nominal: Monthly Average: 10 Years
O20	20-year to mature government bond	State and Local Government Bonds Yield: 20 Years to Maturity
O21	3-month T bill	Treasury Bills Rate: Secondary Market: Monthly Average: 3 Months
O22	6-month T bill	Treasury Bills Rate: Secondary Market: Monthly Average: 6 Months
O23	Overnight interest rate	US: Deposit Rate: LIBOR: USD: Overnight
O24	1-year market rate	US: Deposit Rate: LIBOR: USD: 1 Year
O25	Deposit rate	US: Deposit Rate: LIBOR: USD: 3 Months
O26	Lending rate	US: Lending Rate
O27	Mortgage rate	Mortgage Fixed Rate: Monthly Average: 30 Year
O28	Mortgage volume of the banking sector	Commercial Banks: Credit: LL: Real Estate
O29	Loan volume of the banking sector	Commercial Banks: Credit: Loans and Lease (LL)

O30	Total liabilities of the banking sector	Commercial Banks: Total Liabilities
O31	Equity of the banking sector	Commercial Banks: Residual
O32	Deposit volume of the banking sector	Commercial Banks: Deposits
O33	M1	US: Money Supply: M1: Seasonally Adjusted
O34	Real effective exchange rate	US: Real Effective Exchange Rate Index: Based on Consumer Price Index
O35	Consumer Price Index	US: All items; from OECD
O36	Industrial Production Index	US: Total industry; from OECD
O37	GDP (quarterly)	US: Gross domestic production in constant price; from OECD
O38	Total retail sales	US: Total retail trade; from OECD

References

Aramonte, Sirio, Samuel Rosen and John W. Schindler (2013) Assessing and combining financial conditions indexes. *Finance and Economics Discussion Series*, Divisions of Research & Statistics and Monetary Affairs, Federal Reserve Board, Washington, D.C. No. 2103-39.

Barnett, William A. (2011) Getting it Wrong: How Faulty Monetary Statistics Undermine the Fed, the Financial System, and the Economy, the MIT Press.

Borio, Claudio (2013) The great financial crisis: Setting priorities for new statistics, *BIS Working Paper*, No. 408.

Borio, Claudio (2014) The international monetary and financial system: the Achilles heels and what to do about it. *BIS Working Paper*, No. 456.

Brave, Scott and R. Andrew Butters (2011) Monitoring financial stability: A financial conditions index approach, *Economic Perspectives*, Federal Reserve Bank of Chicago.

BCBS (2011) The transmission channels between the financial and real sectors: a critical survey of the literature, Basel Committee on Banking Supervision Working Papers, BIS No 18, http://www.bis.org/publ/bcbs_wp18.htm .

Drehmann, M, Borio, C. and Tsatsaronis, K. (2012). Characterising the financial cycle: don't lose sight of the medium term! *BIS working paper No. 380*.

Eickmeier, Sandra and Tim Ng (2011) Forecasting national activity using lots of international predictors: An application to New Zealand, *International Journal of Forecasting*, 27, 496-511.

Esposito Vinzi, Vincenzo, Laura Trinchera and Silvano Amato (2010) PLS path modelling: From foundations to recent developments and open issues for model assessment and improvement, in V. Esposito Vinzi et al eds., *Handbook of Partial Least Squares*, Chapter 2, Springer-Verlag.

Fuentes, Julieta, Pilar Poncela and Julio Rodriguez (2015) Sparse partial least squares in time series for macroeconomic forecasting, *Journal of Applied Econometrics*, 30, 576-95.

Gadanecz, Blaise and Kaushik Jayaram (2009) Measures of financial stability – a review, *IFC Bulletin no 31*, Bank of International Settlement.

Groen, Jan J.J. and George Kapetanios (2008) Revisiting useful approaches to data-rich macroeconomic forecasting, *Federal Reserve Bank of New York Staff Report*, No. 327.

Harvey D., Leybourne, S.T. and Newbold, P. (1998) Tests for forecasting encompassing, *Journal of Business and Economic Statistics*, 16, 254-9.

Hatzius, J., Hooper, P., Mishkin, F., Schoenholtz, K. and Watson, M. (2010). Financial conditions indexes: a fresh look after the financial crisis, *NBER Working Papers*, no 16150.

Hendry, D.F. (1995) Dynamic Econometrics. Oxford University Press, Oxford.

Kelly, Bryan and Seth Pruitt (2015) The three-pass regression filter: A new approach to forecasting using many predictors, *Journal of Econometrics*, 186, 294-316.

Lin, Jin-Lung and Ruey S. Tsay (2005) Comparison of forecasting methods with many predictors, mimeo, http://econ.ccu.edu.tw/academic/master_paper/051205seminar.pdf

Lannsjö, Fredrik (2014) Forecasting the business cycle using partial least squares, Department of Mathematics, KTH, Stockholm, Sweden; weblink

McIntosh, Cameron N., Jeffrey R. Edwards and John Antonakis (2014) Reflections on partial least squares path modelling. Organizational Research Methods, 17(2), 210-51.

Qin, D., Cagas, M.A., Ducanes, G., Magtibay-Ramos, N. and Quising, P. (2008). Automatic leading indicators versus macroeconometric structural models: A comparison of inflation and GDP growth forecasting, *International Journal of Forecasting*, 24, 399-413.

Qin, Duo and Xinhua He (2012) Modelling the impact of aggregate financial shocks external to the Chinese economy. *BOFIT Discussion Papers* 52/2012.

Paries, Matthieu Darracq, Laurent Maurin and Diego Moccero (2014) Financial conditions index and credit supply shocks for the Euro area, *European Central Bank Working Paper Series*, No. 1644.

Sanchez, G. (2013) PLS Path Modeling with R. Trowchez Editions. Berkeley, 2013.

Stock, James H. and Mark W. Watson (1989) New indexes of coincident and leading economic indicators, *NBER Macroeconomics Annual*, 4, 351-409.

Stock, James H. and Mark W. Watson (2002) Macroeconomic forecasting using diffusion indexes. *Journal of Business and Economic Statistics*, 20, 147-62.

Stock, J., and Watson, M. (2009) Forecasting in dynamic factor models subject to structural instability. The Methodology and Practice of Econometrics. A Festschrift in Honour of David F. Hendry, pp. 173-205.

Stock, J. H., and Watson, M. W. (2011) Dynamic factor models. Oxford Handbook of Economic Forecasting. Oxford University Press, USA, pp. 35-59.

Wang, Qing-Chao (2016) Testing a new approach to construct international financial market indices: An application to Asian-Pacific economies (PhD thesis), Department of Economies, SOAS, University of London.

Wegelin, Jacob A. (2010) A survey of partial least squares (PLS) methods, with emphasis on the two-block case, *Department of Statistics Technical Report* No. 371, University of Washington.

Wold, Herman (1966) Estimation of principal component and related models by iterative least squares, in P.R. Krishnaiah ed., Multivariate Analysis, New York: Academic Press, pp. 391-420.

Wold, Herman (1975) PLS path models with latent variables: the NIPALS approach, in H. M. Blalock, A. Aganbegian, F. M. Borodkin, R. Boudon, and V. Cappecchi (eds.), Quantitative Sociology: International Perspectives on Mathematical and Statistical Modeling. New York: Academic Press.

Wold, Herman (1980) Model construction and evaluation when theoretical knowledge is scarce: Theory and application of partial least squares, in J. Kmenta and J.B. Ramsey eds. Evaluation of Econometric Models, New York: Academic Press Inc., pp. 47-74.

Wold, Svante, Lennart Eriksson, and Nouna Kettaneh (2010) PLS in data mining and data integration, in V. Esposito Vinzi *et al* eds., *Handbook of Partial Least Squares*, Chapter 15, Springer-Verlag.

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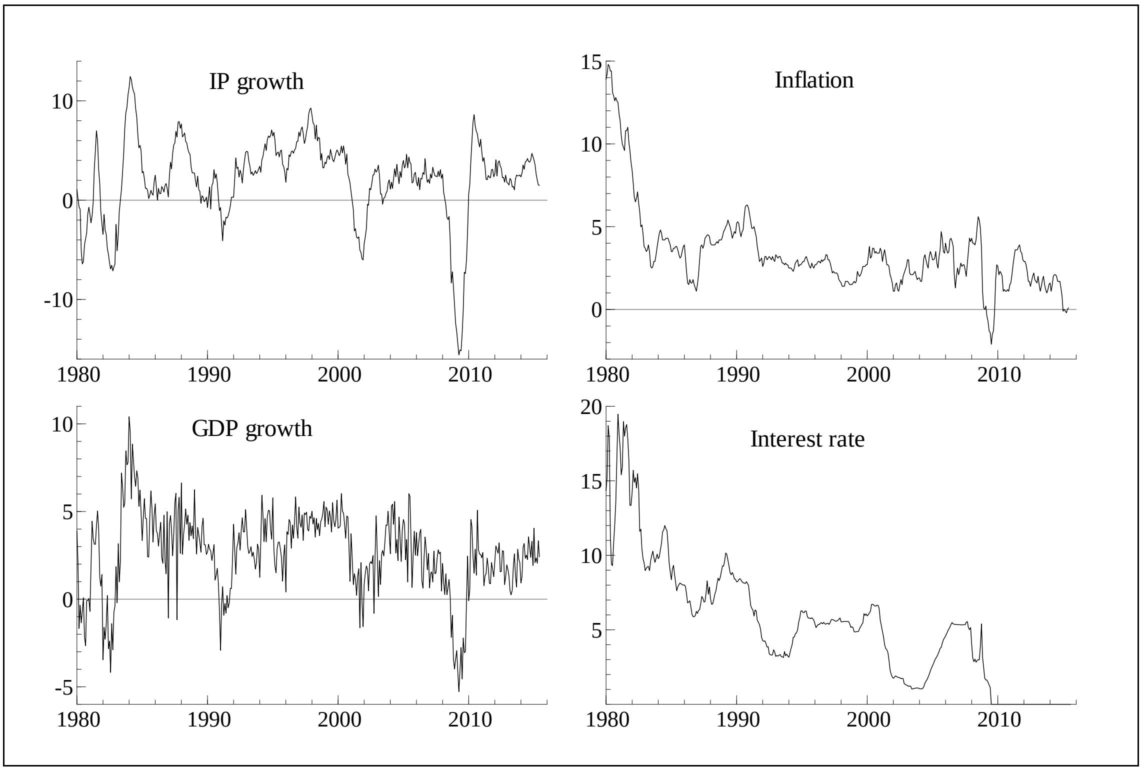
Figure 1. Data Series of Variables in Model (1)



Note: See Appendix for data source.

Figure 2. Illustrations of concatenated FCIs

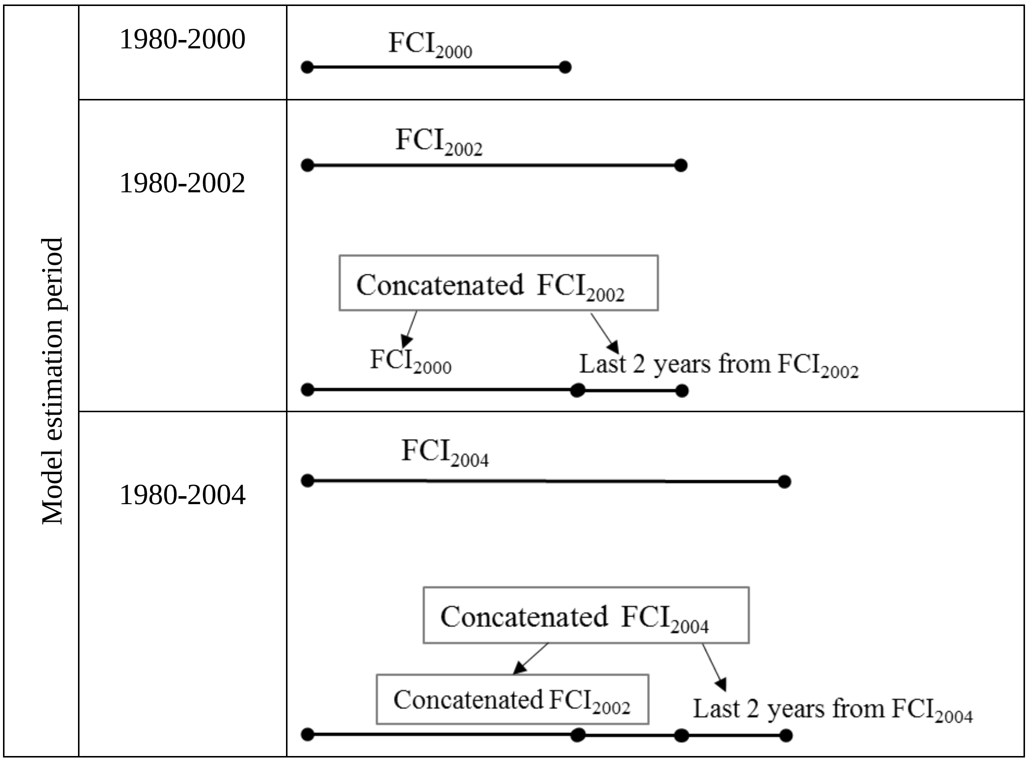
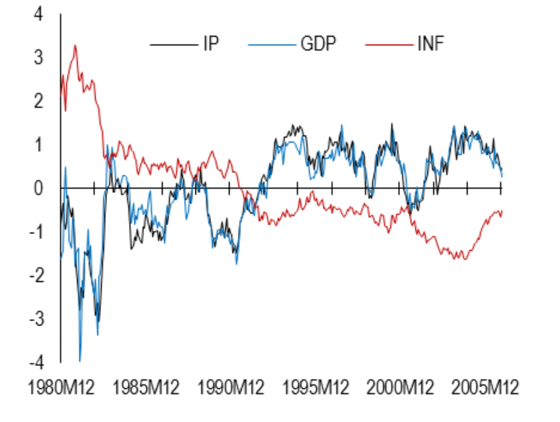


Figure 3. FCIs: black curve – targeted at IP growth; blue curve –targeted at GDP growth; red curve – targeted at inflation

1980M8-2006M12	1980M8-2012M12



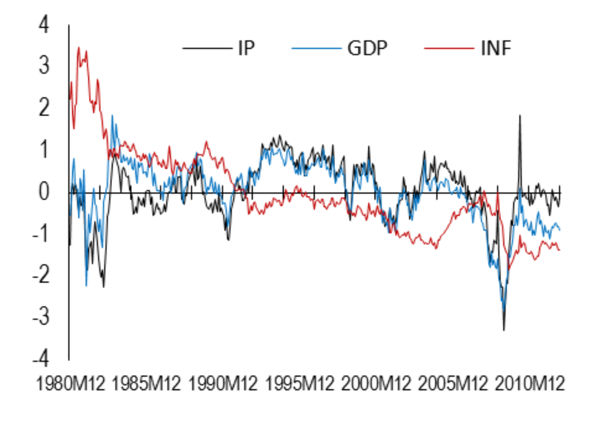
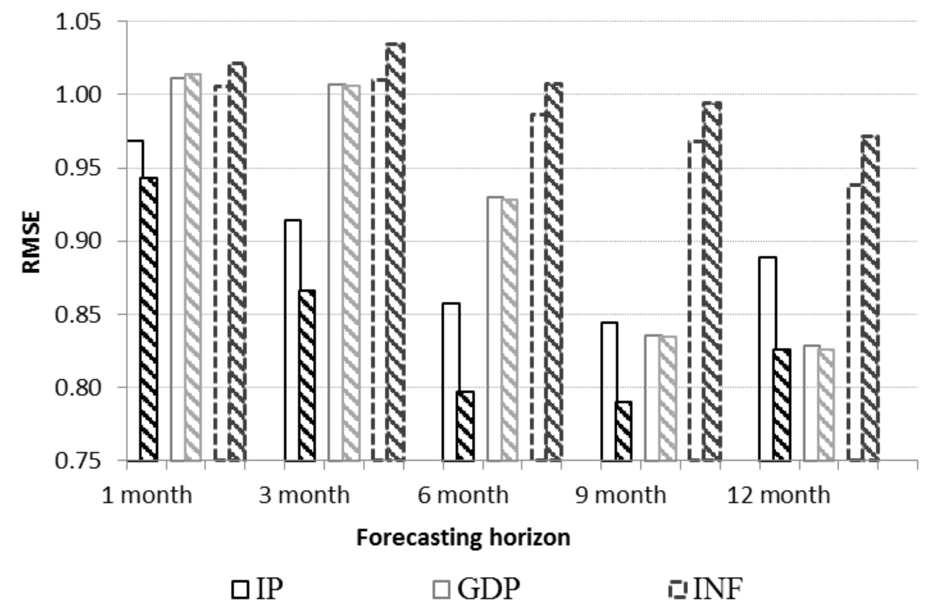


Figure 4. Average RMSEs of Individual Rounds by Forecasting Horizon from Table 2



Note: Model (3) outperforms (1) when RMSE<1.

Figure 5. FCIs (solid curve) versus Concatenated FCIs (dotted grey curve)

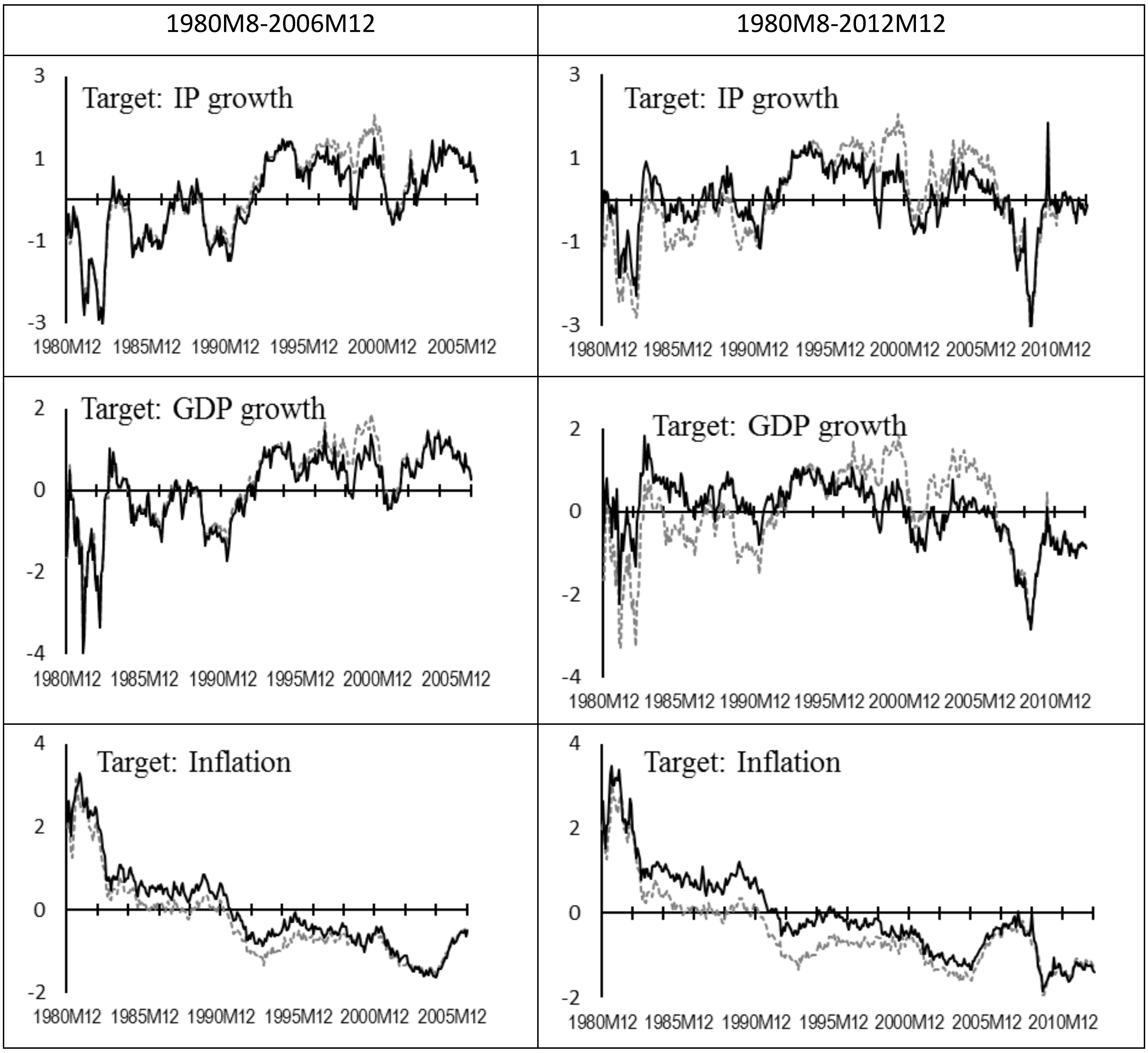


Figure 6. Subsample Average RMSEs of the Concatenated Version in Table 2

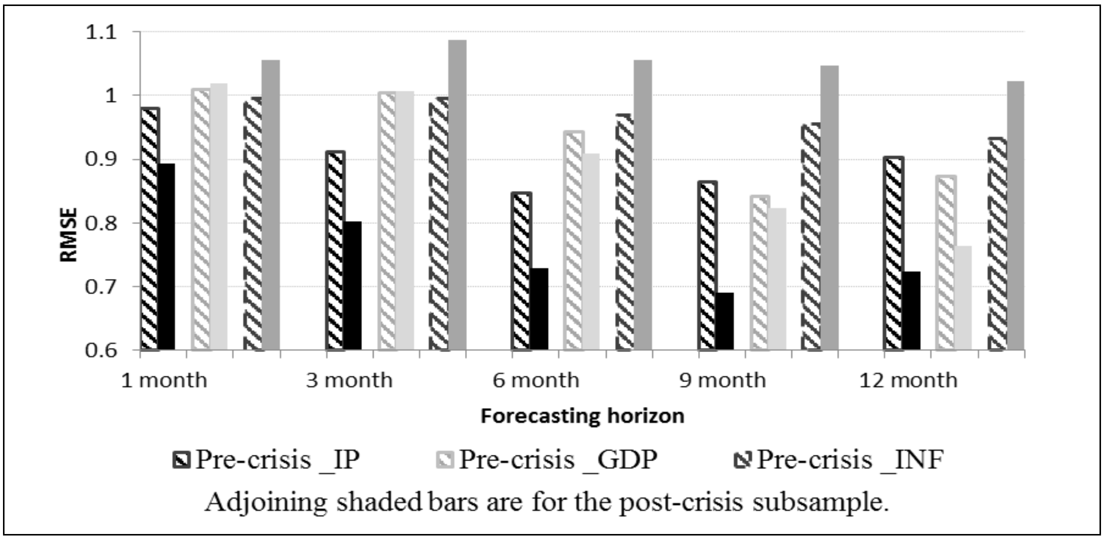


Table 1. Financial variables processed from the data series in Appendix

Variable	Definition	Calculation method (see Appendix)
x1	Covered interest rate parity (CIP) vis-à-vis UK sterling	O2-O1-(1/O8-O5)
x2	CIP vis-à-vis Canadian dollar	O3-O1-(1/O9-O6)
x3	CIP vis-à-vis Sweden krona	O4-O1-(1/O10-O7)
x4	Real effective rate (RER) of US dollar	O34
x5	Ratio of stock market indices (SMI): USA/Canada	O11/O12
x6	Ratio of SMI: USA/Germany	O11/O13
x7	Ratio of SMI: USA/Japan	O11/O14
x8	Ratio of SMI: USA/UK	O11/O15
x9	Corporate bond yield spread: AAA versus BAA ratings	O16/O17
x10	Treasury bond (TB) yield spread: 10-to-1 years	O19-O18
x11	TB spread: 20-to-10 years	O20-O19
x12	TB spread: 20-to-1 years	O20-O18
x13	TB spread: 6-to-3 months	O22-O21
x14	TED: interbank loan to TB rates	O24-O23
x15	Interest rate (IR) premium: money market rate (MMR) net of T-bill rate	O1 - O21
x16	IR spread: lending-to-deposit rates	O26-O25
x17	IR spread: Mortgage-to-corporate rates	O27-O26
x18	Total liability to equity ratio of the banking sector	O30/O31
x22	First difference of above	
x19	Total lending to deposit ratio of the banking sector	O29/O32
x23	First difference of above	
x21	Bank lending: mortgage to loan ratio	O28/O29
x25	First difference of above	
x20	Debt to liquidity ratio of the banking sector: M1 to liquidity	O33/O30
x24	First difference of above	

Table 2. RMSE and *p*-value of Forecasting Encompassing Test from Comparative Forecasts

	01M1-02M12	03M1-04M12		05M1-06M12		07M1-08M12		09M1-10M12		11M1-12M12		13M1-14M12	
h	Target: IP growth; model (3) versus model (1)												
1	1.00 [0.25]	0.97 [0.62]	1.00 [0.50]	1.03 [0.11]	0.98 [0.43]	1.01 [0.18]	0.99 [0.17]	0.81 [0.66]	0.93 [0.45]	0.95 [0.54]	0.93 [0.47]	1.01 [0.16]	0.93 [0.46]
3	0.98 [0.40]	0.91 [0.73]	1.00 [0.60]	0.98 [0.34]	0.96 [0.65]	0.96 [0.52]	0.95 [0.59]	0.60 [0.97]	0.77 [0.98]	0.97 [0.33]	0.78 [0.98]	1.00 [0.28]	0.78 [0.98]
6	0.92 [0.82]	0.90 [0.54]	0.93 [0.86]	0.87 [0.82]	0.92 [0.82]	0.88 [0.86]	0.90 [0.95]	0.52 [0.98]	0.67 [0.99]	1.05 [0.18]	0.68 [0.99]	0.86 [0.58]	0.68 [0.99]
9	0.90 [0.83]	1.07 [0.16]	0.91 [0.82]	0.79 [0.88]	0.93 [0.82]	0.83 [0.88]	0.88 [0.98]	0.42 [0.96]	0.59 [0.99]	1.17 [0.17]	0.59 [1.00]	0.73 [0.88]	0.59 [1.00]
12	0.94 [0.56]	1.22 [0.42]	0.94 [0.45]	0.80 [0.63]	0.98 [0.44]	0.84 [0.62]	0.89 [0.96]	0.40 [0.70]	0.55 [0.99]	1.29 [0.41]	0.56 [0.99]	0.73 [0.65]	0.56 [0.99]
	Alternative: model (3) using concatenated FCI versus model (1)												
1		0.93 [0.75]	0.96 [0.63]	0.97 [0.70]	0.97 [0.72]	1.02 [0.21]	0.99 [0.25]	0.82 [0.47]	0.93 [0.31]	0.89 [0.73]	0.92 [0.34]	0.97 [0.56]	0.93 [0.34]
3		0.84 [0.82]	0.92 [0.73]	0.89 [0.69]	0.92 [0.79]	0.94 [0.45]	0.93 [0.67]	0.58 [0.92]	0.75 [0.92]	0.87 [0.62]	0.76 [0.92]	0.96 [0.51]	0.76 [0.92]
6		0.86 [0.82]	0.91 [0.78]	0.77 [0.44]	0.89 [0.72]	0.84 [0.84]	0.86 [0.93]	0.45 [0.96]	0.63 [0.99]	0.91 [0.42]	0.63 [0.99]	0.83 [0.70]	0.63 [0.99]
9		1.17 [0.12]	0.93 [0.60]	0.62 [0.48]	0.88 [0.57]	0.77 [0.87]	0.81 [0.97]	0.31 [0.93]	0.52 [0.99]	1.02 [0.23]	0.53 [0.99]	0.74 [0.87]	0.53 [0.99]
12		1.33 [0.36]	0.99 [0.20]	0.56 [0.48]	0.90 [0.17]	0.78 [0.62]	0.81 [0.94]	0.28 [0.66]	0.48 [0.99]	1.16 [0.40]	0.48 [0.99]	0.73 [0.65]	0.48 [0.99]
	Target: GDP growth; model (3) versus model (1)												
1	1.01 [0.09]	0.97 [0.74]	0.99 [0.45]	1.00 [0.21]	1.00 [0.26]	1.06 [0.18]	1.01 [0.12]	1.00 [0.26]	1.00 [0.09]	1.05 [0.04]*	1.01 [0.05]	0.99 [0.36]	1.01 [0.05]
3	1.07 [0.03]*	0.89 [0.98]	0.97 [0.49]	0.97 [0.49]	0.97 [0.48]	1.08 [0.12]	1.00 [0.15]	0.92 [0.51]	0.98 [0.18]	1.13 [0.00]*	0.99 [0.09]	0.99 [0.36]	0.99 [0.08]
6	1.00 [0.31]	0.83 [0.97]	0.90 [0.89]	0.98 [0.26]	0.93 [0.62]	0.96 [0.49]	0.94 [0.61]	0.69 [0.90]	0.86 [0.86]	1.25 [0.01]*	0.88 [0.86]	0.80 [0.96]	0.87 [0.90]
9	0.99 [0.40]	0.81 [0.88]	0.88 [0.90]	0.71 [0.41]	0.85 [0.80]	0.87 [0.78]	0.85 [0.94]	0.55 [0.86]	0.72 [0.99]	1.15 [0.14]	0.74 [0.99]	0.77 [0.86]	0.74 [0.99]
12	1.06 [0.44]	0.76 [0.60]	0.88 [0.71]	0.82 [0.47]	0.86 [0.53]	0.85 [0.57]	0.86 [0.77]	0.47 [0.63]	0.66 [0.98]	1.08 [0.42]	0.68 [0.98]	0.76 [0.59]	0.68 [0.99]
	Alternative: model (3) using concatenated FCI versus model (1)												
1		0.97 [0.69]	0.99 [0.42]	1.00 [0.18]	1.01 [0.22]	1.06 [0.16]	1.01 [0.10]	1.00 [0.26]	1.01 [0.07]	1.06 [0.03]*	1.01 [0.04]*	1.00 [0.33]	1.01 [0.04]*
3		0.89 [0.98]	0.97 [0.48]	0.97 [0.45]	1.01 [0.45]	1.09 [0.10]	1.00 [0.12]	0.91 [0.55]	0.99 [0.18]	1.12 [0.00]*	0.99 [0.10]	0.99 [0.38]	0.99 [0.09]
6		0.83 [0.96]	0.90 [0.89]	0.98 [0.24]	0.98 [0.59]	0.96 [0.45]	0.94 [0.55]	0.68 [0.85]	0.87 [0.88]	1.24 [0.00]*	0.87 [0.79]	0.81 [0.96]	0.87 [0.84]
9		0.80 [0.87]	0.88 [0.90]	0.72 [0.38]	0.97 [0.77]	0.86 [0.76]	0.85 [0.91]	0.54 [0.83]	0.74 [0.98]	1.15 [0.13]	0.74 [0.98]	0.78 [0.88]	0.74 [0.98]
12		0.76 [0.60]	0.88 [0.71]	0.82 [0.46]	0.99 [0.50]	0.85 [0.57]	0.86 [0.74]	0.44 [0.62]	0.67 [0.98]	1.08 [0.41]	0.67 [0.98]	0.77 [0.60]	0.68 [0.99]
	Target: inflation; model (3) versus model (1)												
1	1.01 [0.24]	0.99 [0.65]	1.00 [0.35]	0.99 [0.85]	0.99 [0.68]	0.99 [0.69]	0.99 [0.74]	1.05 [0.05]	1.00 [0.21]	N/A	N/A	N/A	N/A
3	1.01 [0.24]	1.00 [0.44]	1.00 [0.25]	0.99 [0.76]	0.99 [0.53]	0.97 [0.71]	0.98 [0.73]	1.08 [0.01]*	1.02 [0.10]	N/A	N/A	N/A	N/A
6	0.98 [0.48]	0.96 [0.64]	0.98 [0.56]	0.97 [0.95]	0.97 [0.88]	0.96 [0.72]	0.96 [0.84]	1.06 [0.05]	1.02 [0.16]	N/A	N/A	N/A	N/A
9	0.97 [0.52]	0.96 [0.62]	0.97 [0.59]	0.95 [0.87]	0.96 [0.83]	0.93 [0.82]	0.94 [0.97]	1.03 [0.26]	0.99 [0.67]	N/A	N/A	N/A	N/A
12	0.94 [0.53]	0.90 [0.64]	0.92 [0.84]	0.93 [0.59]	0.93 [0.97]	0.95 [0.61]	0.94 [0.99]	0.97 [0.52]	0.96 [0.96]	N/A	N/A	N/A	N/A
	Alternative: model (3) using concatenated FCI versus model (1)												
1		0.99 [0.74]	1.00 [0.40]	0.99 [0.82]	1.00 [0.70]	0.99 [0.59]	1.00 [0.67]	1.10 [0.02]*	1.02 [0.05]	1.01 [0.22]	1.02 [0.04]*	1.06 [0.00]*	1.02 [0.03]*
3		1.00 [0.51]	1.00 [0.28]	0.99 [0.73]	1.00 [0.57]	0.98 [0.64]	1.00 [0.67]	1.15 [0.00]*	1.05 [0.02]*	1.02 [0.24]	1.05 [0.01]*	1.09 [0.00]*	1.04 [0.01]*
6		0.97 [0.62]	1.00 [0.55]	0.97 [0.94]	0.97 [0.88]	0.96 [0.73]	0.97 [0.86]	1.12 [0.03]*	1.05 [0.03]*	0.97 [0.83]	1.05 [0.03]*	1.08 [0.10]	1.05 [0.03]*
9		0.96 [0.62]	0.97 [0.59]	0.96 [0.87]	0.96 [0.82]	0.93 [0.84]	0.96 [0.97]	1.08 [0.09]	1.01 [0.14]	0.93 [0.95]	1.01 [0.19]	1.13 [0.05]	1.01 [0.15]
12		0.90 [0.64]	0.94 [0.84]	0.94 [0.59]	0.93 [0.97]	0.95 [0.62]	0.94 [0.99]	1.02 [0.47]	0.98 [0.76]	0.94 [0.57]	0.98 [0.80]	1.11 [0.44]	0.97 [0.77]

Note: *h* denotes forecasting horizon. The 2nd column in the last six sub-samples are based on enhanced samples by foregoing forecasts; *p*-values smaller than 5% are marked by *; N/A means not available

Table 3: Selected Indicator lags and Estimated Weights for FCIs Targeted at IP Growth

Market Type	Subsample size	1980m8-2000m12		1980m8-2006m12		1980m8-2012m12	
	Indicator	lag	weight	lag	weight	lag	weight
Forex market	CIP vis-à-vis UK sterling	2	-0.062	**1**	-0.072	**2**	***-0.037***
	CIP vis-à-vis Canadian dollar	3	0.127	3	0.143	3	0.064
	CIP vis-à-vis Sweden krona	1	0.067	1	0.063	1	0.049
	RER US dollar	5	***-0.015***	**4**	-0.044	**3**	***-0.005***
Equity market	Ratio of SMI: USA/Canada	6	0.091	6	0.077	6	0.093
	Ratio of SMI: USA/Germany	6	0.062	6	0.095	6	0.138
	Ratio of SMI: USA/Japan	1	0.076	**6**	***-0.009***	6	-0.040
	Ratio of SMI: USA/UK	5	***0.012***	**1**	-0.048	**6**	-0.064
Fixed income market	Corporate bond yield spread	1	0.143	1	0.168	**2**	0.226
	TB spread: 10-to-1 years	6	0.115	6	0.144	6	0.103
	TB spread: 20-to-10 years	6	0.123	6	0.093	**1**	***-0.024***
	TB spread: 20-to-1 years	6	0.154	6	0.148	6	0.059
	TB spread: 6-to-3 months	2	-0.093	2	-0.139	**3**	-0.135
	TED: interbank loan to TB rates	4	0.050	4	0.069	**6**	***0.018***
Banking sector	IR premium: MMR net of T-Bill rate	5	-0.130	**6**	-0.120	6	-0.163
	IR spread: lending-to-deposit rates	1	0.076	1	0.070	**2**	0.049
	IR spread: Mortgage-to-corporate rates	5	-0.140	5	-0.115	**6**	-0.060
	Total liability to equity ratio	1	-0.104	1	-0.053	**6**	***0.037***
	First difference of above	3	-0.076	3	-0.086	**6**	-0.064
	Total lending to deposit ratio	1	0.089	1	0.047	**6**	***-0.066***
	First difference of above	1	0.069	1	0.119	1	0.136
	Lending: mortgage to loan ratio	6	0.071	6	***0.023***	**1**	-0.047
	First difference of above	1	0.018	1	0.041	1	0.075
	Debt to liquidity ratio: M1 to liquidity	1	***0.000***	**6**	0.080	6	0.124
	First difference of above	1	-0.065	1	-0.091	1	-0.087
	Absolute Average	3.14	0.08	3.17	0.09	4.1	0.08

Note: Bold lags indicate lag shifts; the weights in bold italics are insignificant at 5%; the grey shaded row blocks indicate relatively constant weights of unchanging lagged indicators over samples.

Table 4: Selected Indicator lags and Estimated Weights for FCIs Targeted at GDP growth

Market Type	Subsample size	1980m8-2000m12		1980m8-2006m12		1980m8-2012m12	
	Indicator	lag	weight	lag	weight	lag	weight
Forex market	CIP vis-à-vis UK sterling	3	-0.064	3	-0.062	3	***-0.013***
	CIP vis-à-vis Canadian dollar	3	0.149	3	0.153	3	0.058
	CIP vis-à-vis Sweden krona	1	0.064	1	0.056	1	***0.025***
	RER US dollar	3	0.088	3	0.077	**6**	0.105
Equity market	Ratio of SMI: USA/Canada	6	0.086	6	0.079	6	0.091
	Ratio of SMI: USA/Germany	6	0.074	6	0.126	6	0.163
	Ratio of SMI: USA/Japan	6	0.082	6	***0.013***	**1**	-0.072
	Ratio of SMI: USA/UK	2	***0.008***	**3**	***-0.027***	**6**	-0.068
Fixed income market	Corporate bond yield spread	2	0.125	**1**	0.141	1	0.183
	TB spread: 10-to-1 years	5	0.147	**6**	0.168	6	0.092
	TB spread: 20-to-10 years	3	0.092	3	0.066	**1**	-0.062
	TB spread: 20-to-1 years	5	0.153	5	0.146	**1**	***-0.017***
	TB spread: 6-to-3 months	3	-0.119	3	-0.156	3	-0.135
	TED: interbank loan to TB rates	6	0.089	6	0.106	6	0.046
Banking sector	IR premium: MMR net of T-Bill rate	5	-0.143	5	-0.133	5	-0.136
	IR spread: lending-to-deposit rates	3	0.068	**2**	0.054	**3**	***0.017***
	IR spread: Mortgage-to-corporate rates	5	-0.142	5	-0.120	**1**	***0.011***
	Total liability to equity ratio	1	-0.068	1	***-0.026***	**6**	0.102
	First difference of above	1	-0.118	1	-0.129	1	-0.087
	Total lending to deposit ratio	1	0.062	1	***0.024***	**6**	***-0.065***
	First difference of above	2	0.078	2	0.101	**1**	0.111
	Lending: mortgage to loan ratio	6	***0.016***	**1**	***-0.017***	1	-0.100
	First difference of above	1	***0.009***	**3**	***-0.038***	3	***-0.026***
	Debt to liquidity ratio: M1 to liquidity	1	***-0.032***	**6**	***0.038***	6	0.132
	First difference of above	3	-0.053	3	-0.068	3	-0.074
	Absolute Average	3.36	0.09	3.42	0.08	3.78	0.08

Note: Bold lags indicate lag shifts; the weights in bold italics are insignificant at 5%; the grey shaded row blocks indicate relatively constant weights of unchanging lagged indicators over samples.

Table 5: Selected Indicator lags and Estimated Weights for FCIs Targeted at Inflation

Market Type	Subsample size	1980m8-2000m12		1980m8-2006m12		1980m8-2012m12	
	Indicator	lag	weight	lag	weight	lag	weight
Forex market	CIP vis-à-vis UK sterling	1	-0.061	1	-0.056	1	***-0.033***
	CIP vis-à-vis Canadian dollar	3	-0.035	3	-0.034	3	-0.051
	CIP vis-à-vis Sweden krona	6	0.077	6	0.058	6	0.049
	RER US dollar	6	***-0.018***	6	***-0.027***	**1**	***0.012***
Equity market	Ratio of SMI: USA/Canada	1	-0.122	1	-0.127	1	-0.108
	Ratio of SMI: USA/Germany	1	***0.000***	**6**	***-0.016***	**3**	***0.022***
	Ratio of SMI: USA/Japan	1	-0.081	1	-0.094	1	-0.102
	Ratio of SMI: USA/UK	6	0.057	**1**	***-0.015***	1	***-0.028***
Fixed income market	Corporate bond yield spread	1	-0.126	1	-0.115	1	-0.054
	TB spread: 10-to-1 years	6	-0.131	**5**	-0.119	5	-0.124
	TB spread: 20-to-10 years	3	-0.069	3	-0.085	3	-0.106
	TB spread: 20-to-1 years	4	-0.128	4	-0.125	4	-0.136
	TB spread: 6-to-3 months	6	***-0.040***	6	***-0.042***	6	***-0.044***
	TED: interbank loan to TB rates	6	-0.133	**4**	-0.123	**6**	-0.135
Banking sector	IR premium: MMR net of T-Bill rate	1	0.165	1	0.166	1	0.140
	IR spread: lending-to-deposit rates	1	***0.018***	1	***0.009***	**6**	***-0.022***
	IR spread: Mortgage-to-corporate rates	4	0.140	4	0.142	**1**	0.152
	Total liability to equity ratio	1	0.059	1	0.075	1	0.094
	First difference of above	2	0.033	2	0.032	**1**	0.034
	Total lending to deposit ratio	1	-0.105	1	-0.109	**6**	-0.103
	First difference of above	4	***-0.023***	4	***-0.007***	**1**	***0.027***
	Lending: mortgage to loan ratio	1	-0.106	1	-0.101	1	-0.117
	First difference of above	1	***-0.010***	1	***-0.023***	1	***-0.020***
	Debt to liquidity ratio: M1 to liquidity	6	***0.006***	6	0.047	6	0.076
	First difference of above	4	***-0.011***	**5**	***-0.013***	**4**	***-0.027***
	Absolute Average	2.72	0.07	2.65	0.07	2.94	0.07

Note: Bold lags indicate lag shifts; the weights in bold italics are insignificant at 5%; the grey shaded row blocks indicate relatively constant weights of unchanging lagged indicators over samples.

Table 6: Tables 3-5 in Combination

Target: IP growth						Target: GDP growth						Target: Inflation					
1980m8-2000m12		1980m8-2006m12		1980m8-2012m12		1980m8-2000m12		1980m8-2006m12		1980m8-2012m12		1980m8-2000m12		1980m8-2006m12		1980m8-2012m12	
X1(-2)	-0.062	**X1(-1)**	-0.072	**X1(-2)**	***-0.037***	X1(-3)	-0.064	X1(-3)	-0.062	X1(-3)	***-0.013***	X1(-1)	-0.061	X1(-1)	-0.056	X1(-1)	***-0.033***
X2(-3)	0.127	X2(-3)	0.143	X2(-3)	0.064	X2(-3)	0.149	X2(-3)	0.153	X2(-3)	0.058	X2(-3)	-0.035	X2(-3)	-0.034	X2(-3)	-0.051
X3(-1)	0.067	X3(-1)	0.063	X3(-1)	0.049	X3(-1)	0.064	X3(-1)	0.056	X3(-1)	***0.025***	X3(-6)	0.077	X3(-6)	0.058	X3(-6)	0.049
X4(-5)	***-0.015***	X4(-4)	-0.044	**X4(-3)**	***-0.005***	X4(-3)	0.088	X4(-3)	0.077	**X4(-6)**	0.105	X4(-6)	***-0.018***	X4(-6)	***-0.027***	**X4(-1)**	***0.012***
X5(-6)	0.091	X5(-6)	0.077	X5(-6)	0.093	X5(-6)	0.086	X5(-6)	0.079	X5(-6)	0.091	X5(-1)	-0.122	X5(-1)	-0.127	X5(-1)	-0.108
X6(-6)	0.062	X6(-6)	0.095	X6(-6)	0.138	X6(-6)	0.074	X6(-6)	0.126	X6(-6)	0.163	X6(-1)	***0.000***	**X6(-6)**	***-0.016***	**X6(-3)**	***0.022***
X7(-1)	0.076	**X7(-6)**	***-0.009***	X7(-6)	-0.040	X7(-6)	0.082	X7(-6)	***0.013***	**X7(-1)**	-0.072	X7(-1)	-0.081	X7(-1)	-0.094	X7(-1)	-0.102
X8(-5)	***0.012***	**X8(-1)**	-0.048	**X8(-6)**	-0.064	X8(-2)	***0.008***	**X8(-3)**	***-0.027***	**X8(-6)**	-0.068	X8(-6)	0.057	**X8(-1)**	***-0.015***	X8(-1)	***-0.028***
X9(-1)	0.143	X9(-1)	0.168	**X9(-2)**	0.226	X9(-2)	0.125	**X9(-1)**	0.141	X9(-1)	0.183	X9(-1)	-0.126	X9(-1)	-0.115	X9(-1)	-0.054
X10(-6)	0.115	X10(-6)	0.144	X10(-6)	0.103	X10(-5)	0.147	**X10(-6)**	0.168	X10(-6)	0.092	X10(-6)	-0.131	**X10(-5)**	-0.119	X10(-5)	-0.124
X11(-6)	0.123	X11(-6)	0.093	**X11(-1)**	***-0.024***	X11(-3)	0.092	X11(-3)	0.066	**X11(-1)**	-0.062	X11(-3)	-0.069	X11(-3)	-0.085	X11(-3)	-0.106
X12(-6)	0.154	X12-6)	0.148	X12(-6)	0.059	X12(-5)	0.153	X12(-5)	0.146	**X12(-1)**	***-0.017***	X12(-4)	-0.128	X12(-4)	-0.125	X12(-4)	-0.136
X13(-2)	-0.093	X13(-2)	-0.139	**X13(-3)**	-0.135	X13(-3)	-0.119	X13(-3)	-0.156	X13(-3)	-0.135	X13(-6)	***-0.040***	X13(-6)	***-0.042***	X13(-6)	***-0.044***
X14(-4)	0.050	X14(-4)	0.069	**X14(-6)**	***0.018***	X14(-6)	0.089	X14(-6)	0.106	X14(-6)	0.046	X14(-6)	-0.133	**X14(-4)**	-0.123	**X14(-6)**	-0.135
X15(-5)	-0.130	**X15(-6)**	-0.120	X15(-6)	-0.163	X15(-5)	-0.143	X15(-5)	-0.133	X15(-5)	-0.136	X15(-1)	0.165	X15(-1)	0.166	X15(-1)	0.140
X16(-1)	0.076	X16(-1)	0.070	**X16(-2)**	0.049	X16(-3)	0.068	**X16(-2)**	0.054	**X16(-3)**	***0.017***	X16(-1)	***0.018***	X16(-1)	***0.009***	**X16(-6)**	***-0.022***
X17(-5)	-0.140	X17(-5)	-0.115	**X17(-6)**	-0.060	X17(-5)	-0.142	X17(-5)	-0.120	**X17(-1)**	***0.011***	X17(-4)	0.140	X17(-4)	0.142	**X17(-1)**	0.152
X18(-1)	-0.104	X18(-1)	-0.053	**X18(-6)**	***0.037***	X18(-1)	-0.068	X18(-1)	***-0.026***	**X18(-6)**	0.102	X18(-1)	0.059	X18(-1)	0.075	X18(-1)	0.094
X22(-3)	-0.076	X22(-3)	-0.086	**X22(-6)**	-0.064	X22(-1)	-0.118	X22(-1)	-0.129	X22(-1)	-0.087	X22(-2)	0.033	X22(-2)	0.032	**X22(-1)**	0.034
X19(-1)	0.089	X19(-1)	0.047	**X19(-6)**	***-0.066***	X19(-1)	0.062	X19(-1)	***0.024***	**X19(-6)**	***-0.065***	X19(-1)	-0.105	X19(-1)	-0.109	**X19(-6)**	-0.103
X23(-1)	0.069	X23(-1)	0.119	X23(-1)	0.136	X23(-2)	0.078	X23(-2)	0.101	**X23(-1)**	0.111	X23(-4)	***-0.023***	X23(-4)	***-0.007***	**X23(-1)**	***0.027***
X21(-6)	0.071	X21(-6)	***0.023***	**X21(-1)**	-0.047	X21(-6)	***0.016***	**X21(-1)**	***-0.017***	X21(-1)	-0.100	X21(-1)	-0.106	X21(-1)	-0.101	X21(-1)	-0.117
X25(-1)	***-0.018***	X25(-1)	-0.041	X25(-1)	-0.075	X25(-1)	***0.009***	**X25(-3)**	***-0.038***	X25(-3)	***-0.026***	X25(-1)	***-0.010***	X25(-1)	***-0.023***	X25(-1)	***-0.020***
X20(-1)	***0.000***	**X20(-6)**	0.080	X20(-6)	0.124	X20(-1)	***-0.032***	**X20(-6)**	***0.038***	X20(-6)	0.132	X20(-6)	***0.006***	X20(-6)	0.047	X20(-6)	0.076
X24(-1)	-0.065	X24(-1)	-0.091	X24(-1)	-0.087	X24(-3)	-0.053	X24(-3)	-0.068	X24(-3)	-0.074	X24(-4)	***-0.011***	**X24(-5)**	***-0.013***	**X24(-4)**	***-0.027***

Note: Refer to Table 1 for indicators' definition. Bold lags indicate lag shifts; Weights in bold italics are insignificant at 5%; unchanging indicators with relatively constant weights across samples are marked in grey shade.

Table 7. Absolute MSEs from Model (1) and Model (3) Using Concatenated FCIs: Forecasting Performance Leading into the 2008 Crisis

Forecasting period	2001M1-2007M12		2007M6-2008M6		2008M1-2010M12	
Model	(1)	(3)	(1)	(3)	(1)	(3)
h	Target: IP					
1	0.828	0.822	0.748	0.663	1.688	1.503
3	1.368	1.304	1.519	1.128	4.053	2.905
6	1.920	1.738	1.952	1.637	7.052	4.437
9	2.247	1.982	N/A	N/A	9.422	5.151
12	2.200	1.963	N/A	N/A	11.132	5.821
	Target: GDP					
1	1.339	1.377	0.872	0.774	1.457	1.539
3	1.308	1.371	0.884	0.804	1.686	1.747
6	1.335	1.494	0.952	0.858	2.441	2.084
9	1.289	1.512	N/A	N/A	3.201	2.273
12	1.312	1.568	N/A	N/A	3.850	2.302
	Target: Inflation					
1	0.415	0.413	0.502	0.510	0.669	0.699
3	0.784	0.775	1.049	1.012	1.654	1.781
6	0.795	0.773	1.449	1.320	2.267	2.436
9	0.846	0.819	N/A	N/A	2.561	2.636
12	0.897	0.838	N/A	N/A	2.844	2.810