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Is the 'Great Recession' really so different from the past?

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Abstract

Based on the decline in real GDP growth, many economists now believe that the 'Great Recession', the output contraction the world experienced in 2008–09, is the deepest global economic contraction since the Great Depression. But as real-time real GDP data are typically revised, we investigate if the decline in, and total output loss (severity) of, G-7 real GDP during the 'Great Recession' is really so different from the past. We use a GDP weighted average of, as well as a dynamic common factor extracted from, real-time G-7 real GDP data to verify if this is the case. Furthermore, we use a Mincer-Zarnowitz (1969) forecast efficiency regression to predict the revision to G-7 real GDP growth during the 'Great Recession', based on outturns of unrevised variables. In real-time data, the depth and intensity of the 'Great Recession' are similar to the mid-1970s recession. The Mincer-Zarnowitz (1969) model predicts a revision to G-7 real GDP growth of about 1.9%. Tentatively these facts imply that G-7 real GDP growth during the 2008–09 period may yet be revised to be in line with past deep recessions, but this conclusion is subject to the caveat that the revisions process may have changed over time.

Key words: Real-time data, international business cycle, dynamic common factor model, Great Recession.

JEL classification: F44.

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'…The US economy remains almost comatose. The slump already ranks as the longest period of sustained weakness since the Depression. The economy is staggering under many 'structural' burdens, as opposed to familiar 'cyclical' problems. The structural faults represent once-in-a-lifetime dislocations that will take years to work out. Among them: the job drought, the debt hangover, the banking collapse, the real estate depression, the health-care cost explosion, and the runaway federal deficit…'

- Time Magazine (1992)

'...On the question of GDP data revisions, I well remember the experience of the early 1990s recovery, when I was working as Economics Director at the CBI. Initial estimates of GDP growth were much weaker than the picture that we now have of that recovery...'.

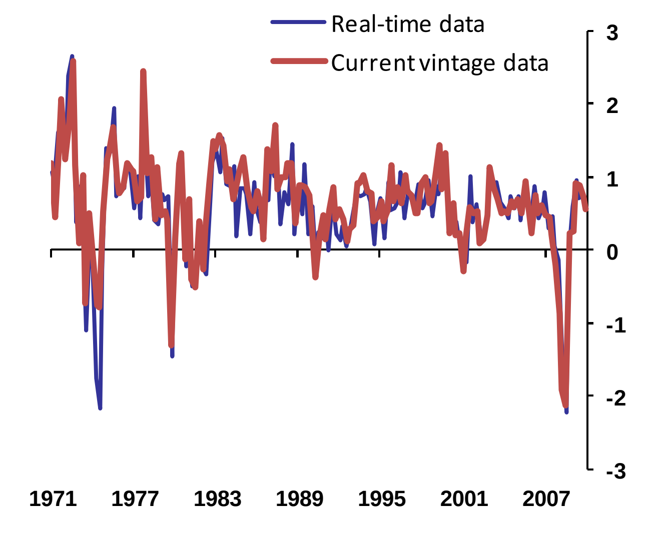
- Andrew Sentance, Former External Member of the MPC (2011)

1. Introduction

The 2008 – 2009 global recession is now frequently referred to as the 'Great Recession', reflecting a consensus among both policy makers (IMF, 2009) and academic economists (Eichengreen and O'Rourke, 2009; Kose, Loungani and Terrones, 2011) that, in terms of depth and severity[1], this was the most significant global economic contraction since the Great Depression. Indeed, the current vintage of GDP-weighted[2] G-7 real GDP quarterly growth rates supports this conclusion (figure 1). But as the quote from Time Magazine in 1992 highlights, even the fairly mild recession in the 1990s felt like a 'slump' at the time.[3] This should not be surprising since initial estimates of real GDP are often subject to revision, a fact first documented by Zellner (1958)[4], many years after the first estimate has been published (Siklos, 2008). Since cyclical fluctuations are greater during recessions, measurement errors are probably larger then too.[5]

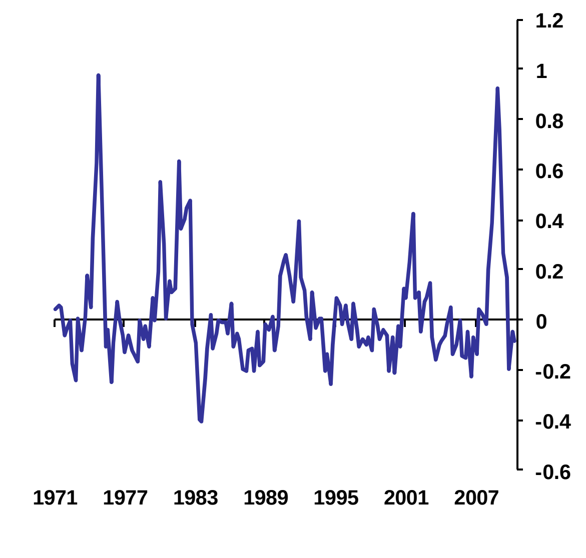
[1] Depth is defined as the maximum decline in real GDP growth, and severity as the total output loss, experienced during a recession.
[2] Our weights are fixed and computed as an average over the period 1970-1980. This is the weighting scheme we use for all G-7 aggregates throughout the paper. Fixed weights obtained over a longer horizon do not make a difference to our results.
[3] Indeed, real-time estimates of US real GDP growth during the 1990s recovery were substantially revised upwards later.
[4] The body of literature studying this phenomenon has grown quickly in the past decade. See Croushore (2008a) for a recent survey.
[5] Chiu and Wieladek (2012) provide some evidence for this assertion. In contrast to their general exploration of revisions during recessions, here we are only interested in revisions to G-7 real GDP growth during the 'Great Recession'.

Figure 1: Real-time data and current vintage data of G-7 real GDP growth



Source: OECD Main Economic indicators.

Figure 2: Change in G-7 unemployment rate



Source: OECD Main Economic indicators.

Indeed, in real-time data, the decline in G-7 real GDP growth, as well as the total output loss, during the ‘Great Recession’ does not appear to be so different from the 1970s recession (figure 1).[6] On the other hand, the rise in the unemployment rate, which is not revised, is not dissimilar to previous recessions (figure 2). It is of course important to note that the relationship between real GDP growth and changes in the unemployment rate may be unstable over time: Indeed, if labour productivity declines for exogenous reasons, the change in the unemployment rate may be proportionately smaller than the decline in real GDP growth. Bearing this caveat in mind, the apparent contradiction between the current vintage of G-7 real GDP and unemployment rate data led us to ask: ‘Is the ‘Great Recession’ really so different from the past?’ This is an important policy question, as one of the main justifications for the unconventional monetary and fiscal policy measures, following the onset of the ‘Great Recession’, was precisely the belief that the depth and intensity of this economic contraction was different from the past.[7]

To answer this question, we first examine if the fall in real GDP growth the G-7 experienced during the ‘Great Recession’ is unusually deep and severe, when compared to

[6] For the G-7 aggregate, the real-time depth and total output loss (severity) during the 1970s recession were 2 and 5.2, compared to 2.2 and 3.75 for the ‘Great Recession’.

[7] This is of course not to say that monetary policy makers take initial releases of real GDP data at face value. Indeed, to which extent a given data release will be revised is typically an important matter of debate within a central bank.

real GDP data that was available at the time of previous recessions.[8] Second we use a Mincer-Zarnowitz (1969) forecast efficiency regression[9] to forecast the revision to real GDP growth[10] for the 'Great Recession' period based on outturns of the following contemporaneously known variables: the growth rate of the real equity, house and oil price as well as the change in the unemployment rate, the real long-term interest, the real short-term interest rate, CPI inflation and the preliminary estimate of real GDP growth.

In the first part of this study, we explore if, in real-time data, the depth and severity of the 'Great Recession' are similar to previous recessions. We have already shown that, when expressed as a GDP-weighted average, the evolution of real-time G-7 real GDP growth rates experienced during the 'Great Recession' is not that different from the 1970s recession. To verify that this conclusion is robust across econometric methods, we follow recent work and also use a dynamic common factor model to extract the international business cycle from quarterly real-time real GDP growth rates for the G-7. In previous applications, such methods have been employed to study and identify the international business cycle from domestic investment, consumption and output data across a range of countries.[11] We estimate the common factor with Bayesian methods from quarterly real-time real GDP growth data, as in Del Negro and Otrok (2008), and also permit for stochastic volatility[12] in our model as the decline in the volatility of G-7 macroeconomic time series over time has been extensively documented by previous work (Stock and Watson, 2005).

Of course, the size of past revisions does not have to be a good guide to the present or future. Faust, Rogers and Wright (2005) examine real GDP revisions for the G-7

[8] We will refer to data which was available at the time of previous recessions as 'real-time' data for the rest of this paper.
[9] We would like to stress that this is, of course, not the only way to attempt and forecast revisions. For example Ashley, Driver, Hayes and Jeffrey (2005) propose a simple methodology that relies on business surveys to predict revisions. Similarly, Cunningham, Eklund, Jeffrey, Kapetanios and Labhard (2007) propose a more sophisticated state-space approach for this purpose. As our work is explicitly focused on the G-7 and it may be difficult to obtain internationally comparable business surveys, we choose to follow previous work and use the Mincer-Zarnowitz (1969) approach.
[10] Throughout this paper, we will refer to the current vintage of real GDP data as 'revised' data.
[11] See Gregory, Head and Raynauld (1997) and Kose, Otrok and Whiteman (2008) for previous work for the G-7.
[12] Del Negro and Otrok (2008) also introduce time-varying coefficients in addition to stochastic volatility into their dynamic common factor model to study the time-varying evolution of business cycles in 19 countries. We abstain from time-varying coefficients as Del Negro and Otrok (2008) find little role this type of time-variation, it does not affect the factor estimate in their sample and for reasons of parsimony.

covering data up until 1997Q4 and find that while contemporaneous information has minimal predictive power for real GDP revisions in the US, predictability cannot be rejected for remaining G-7 countries. But, in 1993, international statistical agencies adopted a new international standard for compilation of national account statistics - the System of National Accounts 1993 (United Nations Statistics Division, 1993), making their findings, quite possibly, inapplicable today. We therefore repeat their exercise for real GDP growth revisions between 1993Q1 and 2005Q4.[13][14] Our analysis is therefore based on data that have been constructed with the same methodology, most probably containing similar types of measurement error, as the preliminary real GDP data that are available for the 'Great Recession' period today. Real GDP revisions during recessions could, of course, be different from those in normal times. For all but the UK and Canada, the only two countries not to experience a recession during our sample period, we therefore include an interaction of all the proposed predictors with a dummy variable taking the value of one during recessions and zero otherwise, as well as the dummy variable itself, as additional explanatory variables. The downside of this strategy is that we only have 52 time series observations and up to 17 possible explanatory variables, leaving any regression estimates subject to the curse of dimensionality. We use Bayesian Model Averaging to address this problem and objectively select the best predictors of the real GDP revision for each country. Only the variables with the highest posterior probabilities enter the Mincer-Zarnowitz (1969) forecast efficiency regressions. The estimated coefficients are then used to test for predictability and to forecast real GDP revisions country by country for the 'Great Recession' period. Finally, an important caveat of our approach is that the methodology underlying national accounting is constantly, albeit slowly, evolving and may have therefore changed beyond our estimation horizon. This is something that we cannot account for and is exactly the reason for why our regression results should be treated as the forecasts that they are.

[13] One stylised fact about real GDP revisions, as argued by Jacobs and Van Norden (2011) and Siklos (2008), is that they may occur many years after the initial estimate has been published, which is why we choose 2005Q4 as a cut-off point.
[14] Different countries implemented SNA1993 at different times; for the sake of simplicity, here we treat the implementation date as 1993 for all countries in our sample. In section 5, we run a robustness analysis treating the implementation as 1995 for all countries.

Our results suggest that, in real-time data, the depth and severity associated with the mid-1970s recession was similar to that experienced during the 'Great Recession'. To assess if the depth/severity of the extracted international business cycle factor are statistically similar across episodes, we compare their joint distribution during the 'Great Recession' and 1970s recession. With real-time data, only about 81%/76% of the points in the distribution suggest that the 'Great Recession' is deeper/more severe than the 1970s recession. Based on past data outturns, the estimated Mincer-Zarnowitz (1969) regressions confirm that, real GDP revisions are predictable in all of the G-7 but Canada and the US. Our out-of-sample forecast of the revision shows that current vintage real GDP growth in Italy, the UK[15], Japan and Germany may be subject to substantial revision going forward. For the UK, forecasts and backcasts of data revisions used by the MPC will not necessarily be consistent with the results presented here, as our analysis is completely independent of that framework.[16] In contrast, most of the revision to G-7 real GDP growth in the 1970s was driven by the US. As a GDP-weighted average, our findings imply that G-7 real GDP growth during the 'Great Recession' could be revised upwards by about 1.9%, bringing the real-time data depth (2.1%) and output loss (3.75%) closer to the current vintage data depth (0.85%) and output loss (1.94%) of the early 1970s recession.

In summary, we find that in real-time real GDP data, the depth and severity of the 'Great Recession' is similar to that of the mid-1970s recession. Despite a methodological change in national income accounting, our results suggest that revisions for some G-7 countries are still predictable. Based on the evolution of the unrevised variables during the 'Great Recession', a weighted average of country-by-country forecasts implies a revision of about 1.9% to GDP-weighted G-7 real GDP growth. These results support the tentative conclusion that, in revised data, the depth and severity of the 'Great Recession' may not look too different from previous post World War II economic contractions.

[15] But note that other analysis of revisions on the most recent UK data suggest that UK revisions are not statistically different from zero [See http://www.ons.gov.uk/ons/dcp171778_307982.pdf].
[16] See the Box on page 39 of the November 2007 Inflation Report and associated references http://www.bankofengland.co.uk/publications/Documents/inflationreport/ir07nov.pdf for a discussion.

The rest of this paper is structured as follows. Section 2 describes the data and section 3 the empirical methodology. Section 4 presents the results and section 5 examines robustness. Section 6 concludes.

2. Data

In this section, we describe the sources of the data in detail and show that changes in the unemployment rate are typically not revised.

Data for the G-7 real-time real GDP growth rates and changes in the unemployment rate are obtained from several sources. The OECD provides real-time data for a variety of economic series and OECD countries, including the G-7, in an on-line database for vintages starting in 1999.[17] For time periods before this, Faust, Rogers and Wright (2005) provide real-time real GDP growth starting in the 1960s until 1997Q4. Their data series starts in 1965 for Canada, the UK and the US; in 1970 for Japan; in 1979 for Germany; in 1979 for Italy; and in 1988 for France. There is also a small gap of three quarters in 1998 between these two datasets, which we have covered by obtaining the vintage GDP data from the appropriate print edition of the OECD Main Economic Indicators publication. For Germany, we were able to extend the real-time data series with real GNP growth rates back to Q3 1971 which we obtained from Gerberding, Kaatz, Worms and Seitz (2005). To cover a timespan that is as long as possible and include all of the G-7, our data start in Q3 1971, when German data become available. For France and Italy, we use annual real-time real GDP data from past editions of the OECD economic outlook to fill in missing quarterly data. There are several ways to do this. One way would be to attribute one fourth of the annual real GDP growth to each quarter, but this would ignore important quarterly growth rate variation. Instead we take the within-year distribution of quarterly growth rates in the current vintage of data and apply it to the annual real-time real GDP growth rates. As an example, suppose that the current vintage of data shows a country's current vintage annual real GDP growth rate is 4% and is distributed as 2%, 1%. ,.5% and .5% in quarter 1, 2, 3 and 4, respectively. If the

[17] http://stats.oecd.org/mei/default.asp?rev=1

corresponding real-time annual real GDP growth rate is 8%, then the corresponding real-time quarterly distribution would be 4%, 2%, 1% and 1% in quarter 1, 2, 3 and 4, respectively. We apply this procedure to fill in the missing data for Italy and France, as it is presumably unrealistic to assume constant quarterly growth rates. As for 'final' data from the current vintage, we have simply taken the real GDP series for each country from the 2010Q4 vintage of the OECD's Economic outlook database. For Germany, we obtain the 'final' real GDP data from the 2010Q4 vintage of the IMF's International Financial Statistics.

We use the change in the unemployment rate as one of the possible predictors of the real GDP revision. This relies on the assumption that revisions to the unemployment rate are minimal. For the US, Aruoba (2008) notes that the revisions to the unemployment rate are small and confined to changes in seasonal factors. To further establish the veracity of this claim for the remaining G-7 countries, we obtain real-time unemployment rate data, and compare them to the current vintage of this variable. Real-time unemployment rate data for Canada, France, Germany, Italy, Japan and the UK are taken from past print editions of the OECD Main Economic Indicators (MEI) publication. In almost every case, the latest annual readings of these two series are taken from the June editions of the MEI.[18] From 1999 onwards, the equivalent real-time data are taken from the OECD's real-time database. For the US, we take advantage of the comprehensive real-time database first collected by Croushore and Stark (2001) and now maintained by the Federal Reserve Bank of Philadelphia, which provides real-time industrial production data since 1962, and real-time unemployment rates since 1965.[19]

Figures A1-A7 in appendix A compare the change in the unemployment rate at annual frequency in both current vintage and real-time data. The G-7 GDP-weighted average is only subject to minimal revision. While there are some revisions in the change to the unemployment rate in individual countries, they do not appear to be large relative to the overall magnitude of the series. Given this absence of revision, we will use the

[18] The 2009 data is taken from the April 2010 edition of the OECD Main Economic Indicators.
[19] http://www.philadelphiafed.org/research-and-data/real-time-center/real-time-data/

outturns of this variable together with quarterly CPI inflation and financial market variables, in particular stock market and house price indices as well as the oil price and the short-term and long-term interest rates, to predict the revision to real GDP in the later section of this paper. Stock market price indices are obtained from the OECD Main Economic Indicator database. These are not revised and converted to real stock market indices by dividing the nominal values by the corresponding CPI[20] for each country, which is not revised either.[21] We seasonally adjust each CPI index with the X12 procedure. Similarly, the OECD also provides real house price data, based on national sources.[22] Nominal short-term and long-term rates are also taken from the OECD Main Economic Indicators database and we construct real rates by subtracting year-on-year CPI inflation from these variables. For the oil price, we use the 'Spot Oil Price: West Texas Intermediate' series provided by the Federal Reserve Bank of St Louis database, converted to a real oil price series by dividing the nominal value by the US CPI. All data start in 1971 Q3 and finish in 2010 Q3.

3. Methodology

In this study we aim to assess if the evolution of real GDP growth the G-7 experienced during the 'Great Recession' is really so different from the past. In the introduction we have already shown that when expressed as a GDP-weighted average, the evolution of the G-7 real-time real GDP growth rate during the 'Great Recession' is similar to that experienced during the mid-1970s recession. This is, of course, not the only way to measure international business cycles. Our second measure, popular in recent empirical work, is a common factor extracted from a panel of G-7 quarterly real GDP growth rates with a Bayesian dynamic common factor model. One approach to assess if the troughs in the international business cycle factor are statistically different across recessions is to compare their marginal distributions at these points in time. But in a recent paper, Cogley, Primiceri and Sargent (2010) argue that this procedure confounds

[20] For the UK we use the RPI.
[21] Croushore (2008b) notes that in the US, the CPI index is not revised. We assume that the same applies for the rest of the G-7.
[22] Our implicit assumption is that real house prices are not revised, but our results are robust to excluding this variable.

uncertainty about the level of the common factor with uncertainty about the change in the common factor between two periods of time. They suggest an analysis of the joint distribution of the common factor at the two points under consideration, to assess statistical significance, instead. Indeed, this is the procedure that we adopt to assess whether the trough (depth) in the estimated international business cycle factor in the 'Great Recession' and the 1970s recession are significantly different from each other. We also use this procedure to assess if the severity, that is the sum of negative common factor observations during the recession, is greater during the 'Great Recession' than previous recessions.

But past measurement mistakes do not have to be a good guide to the present or future. In their examination of real GDP revisions between the 1970s and 1997Q4, Faust, Wright and Rogers (2005) cannot reject predictability for all of the G-7, but the US. In light of methodological changes in national income accounting since then, it is unclear how applicable their results are for recent data outturns. In particular, the OECD, IMF, United Nations and the World Bank adopted the 'System of National Accounts 1993' as 'the international standard for compilation of national account statistics and for the international reporting of comparable national accounts data' (United Nations Statistics Division, 1993) in 1993. We therefore test if revisions are still predictable following this methodological change using the Mincer-Zarnowitz (1969) regression approach on data starting in 1993Q1. As one stylised fact about real revisions is that they occur many years after the initial estimate has been published (Jacobs and Van Norden, 2011), our last observation is 2005Q4. Our regression model is therefore estimated on data that have been calculated with the same national income accounting methodology, most probably containing similar measurement errors, as the preliminary real GDP data that is available for the 'Great Recession' today. [23]

[23] The reporting convention for international statistics has recently been updated to 'System of National Accounts 2008'. However, according to the OECD (2010), the implementation of these new guidelines has been delayed and even our most recent vintage of data (2010Q4) was still compiled according to the 'System of National Accounts 1993' standards.

It is, of course, unclear if a model estimated on real GDP revisions in normal times is appropriate to forecast revisions during recessions. To address this issue we include interactions of the proposed predictors with a dummy variable taking a value of one in recessions and zero otherwise, as well as the dummy variable itself, as additional explanatory variables for countries that experienced a recession during the proposed sample period. But this leaves us with only 52 time series observations and up to 17 possible predictors for each country. Any inference based on standard regression techniques will thus clearly be constrained by limited degrees of freedom. The economic growth literature used Bayesian Model Averaging to address this problem (Doppelhoffer, Sala-i-Martin and Miller, 2004; Fernandez, Ley and Steel, 2001). We follow this approach here and only retain the predictors with the highest posterior probabilities as the explanatory variables in our Mincer-Zarnowitz (1969) regressions. These estimated models are then used to test for predictability of real GDP revisions and forecast them for the 'Great Recession', based on the outturns of the unrevised predictors.

3.1 Dynamic common factor model

Dynamic common factor methods have been widely used in previous work to study international business cycles. Gregory, Head and Raynauld (1997) was one of the first studies to use a dynamic common factor model to extract a common factor from G-7 growth rates of consumption, investment and output. They refer to their common factor as the 'world business cycle'. Kose, Otrok and Whiteman (2003) use annual growth rates of these three variables to identify a world business cycle in 60 countries covering seven regions of the world, while Kose, Otrok and Whiteman (2008) use a similar technique to study the evolution of G-7 business cycles. More recently, Del Negro and Otrok (2008) introduce time-varying coefficients and stochastic volatility into the standard dynamic common factor model to account for these features of the data. They apply their model to the real GDP growth rates of 19 OECD countries. We follow this approach to extract the international business cycle from a panel of the G-7 countries quarterly real-time real GDP growth rates. As documented by Stock and Watson (2005) the volatility of G-7 real

GDP growth rates seems to have declined over time, while there is less evidence for an increase in synchronization. Modelling the variances as constant, in a world where they are time-varying, might result in the estimate of the factor compensating for this misspecification. This in turn would affect the interpretation of our results.[24] To answer the question posed in this study credibly, it therefore seems important to permit the variances of the error terms to vary over time.

We thus propose to implement the following model:

$$Y_{i,t} = \gamma_i w_t + e_{i,t} \tag{1}$$

$$e_{i,t} = \rho_i e_{i,t-1} + \sigma_i e^{\frac{h_{i,t}}{2}} v_{i,t} \qquad v_{i,t} \sim N(0,1) \tag{2}$$

$$w_t = \varphi w_{t-1} + \sigma_0 e^{\frac{h_{0,t}}{2}} v_{0,t} \qquad v_{0,t} \sim N(0,1) \tag{3}$$

$$h_{i,t} = h_{i,t-1} + \mu_{i,t} \qquad \mu_{i,t} \sim N(0, \omega_i) \tag{4}$$

$$E\left[v_{i,t} v_{j,t}\right] = 0,\ E\left[\mu_{i,t} \mu_{j,t}\right] = 0\ \ \forall\, i\ \neq j\ , \tag{5}$$

where $Y_{i,t}$ is the quarterly real GDP growth rate in country i at time t, $e_{i,t}$ is an autocorrelated error term. w_t is a common factor which drives time series in all of the countries and γ_i is the country-specific factor loading relating the factor to the individual country time series. The variance-covariance matrices of the error terms in equation (**2**) and (**3**) evolve according to a stochastic volatility term. These are modelled as following a log-normal distribution in order to ensure that all of the variances are positive. $\mu_{i,t}$ follows a normal distribution.

[24] In preliminary estimations, with a model that assumed fixed variances, the estimate of the factor during periods of greater volatility was indeed larger.

For simplicity of notation we will refer to this model in the following state space form for the rest of the paper:

$$Y_t = HW_t \tag{6}$$

$$W_t = \Phi W_{t-1} + g_t \qquad g_t \sim N(0, \Sigma_t) \tag{7}$$

where $W_t = [w_t;\ e_{i,t} \dots e_{k,t}]'$ and $\Phi = [\varphi;\ \rho_i \dots \rho_k]'$ where k is the number of countries. The matrix H contains the corresponding factor-loadings as well as an identity matrix to account for the fact that the $e_{i,t}$'s enter the measurement equation in levels directly. Σ_t is a square matrix with the corresponding $e^{h_{i,t}}\sigma_i^2$ on its diagonal. Our previous assumptions imply that this is a diagonal matrix, which permits us to draw the stochastic volatility terms equation by equation.

3.1.1 Dynamic common factor model – Identification

From a purely statistical point of view, the above model is subject to two distinct identification problems. Neither the scales nor the signs of the factor and the factor loadings are identified.

Like most dynamic common factor models, our model is subject to the problem that the relative scale of the model is indeterminate. One can multiply the vector of factor loadings, Γ, by a constant d for all i, which gives $\hat{\Gamma} = d\Gamma$. We can also divide the factor by d, which yields $\widehat{w_t} = \frac{w_t}{d}$. The scale of the model $\hat{\Gamma}\widehat{w_t}$ is thus observationally equivalent to the scale of the model Γw_t. In order to solve this problem, we follow the approach presented in Del Negro and Otrok (2008) and set the initial condition of the stochastic volatility term associated with the factor, $h_{0,0}$, as well as σ_0, to 1. We also set ω_0, the variance of the error term associated with the stochastic volatility of the factor to 1. As in Del Negro and Otrok (2008), to factor each σ_i^2 separately from the corresponding $e^{h_{i,t}}$, it is necessary to set $h_{i,0}$ to 0 for each i.

In addition, the model is subject to the rotational indeterminacy problem (Harvey, 1993). For any $k\ x\ k$ orthogonal matrix F there exists an equivalent specification such that the rotations $\Gamma^* = F\Gamma$ and $w_t^* = Fw_t$ produce the same distribution for Y_t as in the original model. This implies that the signs of the factor loadings and the common factor are not separately identified. This can be easily seen when setting F=-1, as in this case $\Gamma^* w_t^*$ and Γw_t are observationally equivalent. In order to solve this problem we follow Del Negro and Otrok (2008) and impose one of the factor loadings to be positive, as this permits the identification of the sign of the factor and thus the rest of the model.

From an economic point of view, we follow previous work and interpret the common factor as the international business cycle.

3.1.2 Dynamic common factor model - Implementation

Dynamic factor models can be estimated with maximum likelihood methods (Gregory, Head and Raynauld, 1997). But if the model is complex, because of the presence of stochastic volatility terms for example, estimating the joint density directly by maximising the likelihood function may prove to be difficult. Alternatively, one can use the forward filter, backward smoother introduced in Carter and Kohn (1994) to estimate the model via Gibbs sampling. In our application, Gibbs sampling permits us to break down the estimation of this complex model into several stages, which reduces the difficulty of this task drastically. Following previous work, we demean the data and standardise the variance of each series to unity prior to econometric analysis. Details of the sampling algorithm we use to approximate the posterior are presented in appendix C.

Testing for convergence

We replicate the algorithm presented in appendix C 100,000 times with Gibbs sampling and discard the first 90,000 replications as burn-in, keeping only every 10th draw in order to reduce auto-correlation among the draws. We then obtain the parameter estimates of the posterior distribution from the last 1,000 replications by taking the median and constructing 68% posterior coverage bands around it.[25] We follow previous work and try various length of the iterative process. The results do not change, whether we replicate the model 100,000 times and retain 10,000 draws or replicate it 10,000 times and retain the final 1,000 draws for inference. Similarly, our results do not change if we use estimates from a principal component, or a dynamic common factor model with time-invariant variances, to initialise the Gibbs sampling procedure.

3.2 Mincer-Zarnowitz regression model

In the second part of this study, we examine the predictability of real GDP revisions and forecast them for the 'Great Recession' period. We follow previous work (Faust, Wright and Rogers, 2005; Mankiw, Runkle and Shapiro, 1984) and use the Mincer-Zarnowitz (1969) regression approach for this purpose. As mentioned earlier, we use data that has been compiled using the same national income accounting methodology as the 'Great Recession' preliminary real GDP growth outturns.[14] Our coefficient estimates will therefore reflect revisions that stem from the availability of greater information over time, rather than changes in the definitions of national income accounts.[26]

Revisions to preliminary estimates of real GDP growth can reflect the subsequent inclusion of two types of information: information available at the time (*the noise view*), or additional information available only after *(the news view*), the real-time estimates have been made. Formally, the preliminary estimate of real GDP growth, X_t^p, can be decomposed as the sum of final, revised, data X_t^f and an error term ε_t, i.e. $X_t^p = X_t^f + \varepsilon_t$. Under the noise view, subsequent revisions to preliminary estimates of real GDP are a result of omitted contemporaneous information, meaning that they are predictable and that X_t^f is orthogonal to ε_t. On the other hand, if revisions are a result of 'news', they will not be predictable and X_t^p will be orthogonal to ε_t. In intermediate cases ε_t will, of course,

[25] The choice of this particular posterior coverage band interval follows recent work that estimates dynamic common factor models with Bayesian methods. See for example Mumtaz and Surico (2011) or Kose, Otrok and Whiteman (2003).
[26] New information can emerge a long time after the preliminary real GDP estimate has been recorded. For example, following the 2001 census in the UK, it emerged that the total population grew by only 1 million in the 1990s, rather than the two million previously assumed (Dorling, 2007).

be correlated with both. As in Faust, Rogers and Wright (2005), we run a Mincer-Zarnowitz (1969) regression to distinguish between these two views. If news explains all of the measurement error, then the revision, i.e. the difference between X_t^p and X_t^f, should in theory be uncorrelated with any information available at time t. But if revisions at least in part were to reflect noise, ε_t and X_t^p would be correlated. In particular, X_t^p would predict the revisions. Formally, the regression is:

$$R_t = \alpha + \beta X_t^p + u_t \tag{8}$$

where $\boldsymbol{\alpha}$ is a constant and $\mathbf{R_t} = \mathbf{X_t^f} - \mathbf{X_t^p}$. $\mathbf{u_t}$ is a normally distributed error term. The Mincer-Zarnowitz (1969) procedure is in essence an F-test of the null-hypothesis that $\boldsymbol{\alpha} = \boldsymbol{\beta} = \mathbf{0}$. Failure to reject this null hypothesis would imply that real GDP growth revisions are not predictable and vice versa. Following this test, we then use the estimated regression coefficients to forecast the real GDP growth revision country by country out-of-sample for the period between 2006Q1 and 2010Q3.

Of course, the preliminary estimate of real GDP growth is not the only variable that is likely to contain relevant information for the revision. We therefore also use the following variables as potential predictors of the real GDP growth revision: quarterly CPI inflation, real equity price growth, real house price growth, real oil price growth, the quarterly change in unemployment and the real short-term and long-term interest rate. In addition, a model estimated on revisions to real GDP during 'normal times' may not be appropriate for forecasting revisions during recessions. During our proposed time period, all but the UK and Canada experienced as least one recession. According to the business cycle dates provided by the Economic Cycle Research Institute[27], which uses the NBER recession dating methodology, France experienced a recession from 02/1992 to 08/1993 and 08/2002 to 05/2003; Germany from 01/1991 to 04/1994 and 01/2001 to 08/2003; Italy from 02/1992 to 10/1993; Japan from 04/1992 to 02/1994, 03/1997 to 07/1999 and 08/2000 to 04/2003 and the US from 03/2001 to 11/2001. This allows us to explore if revisions do indeed react to different predictors during recessions for these countries. We therefore

[27] http://ecri-prod.s3.amazonaws.com/reports/samples/1/BC_0211.pdf

add interactions of the predictors listed above with a dummy variable taking the value of one during recessions and zero otherwise, as well as the dummy variable itself, to the above list of explanatory variables.

3.3 Bayesian Model Averaging

As explained in section 3.2, we have up to 17 (k) possible predictors of the real GDP revision, but only 52 (N) time series observations for each country. Given the limited degrees of freedom, the inclusion of all these variables in a standard regression would lead to biased inference. The economic growth literature has proposed Bayesian Model Averaging to determine objectively which variable has the highest explanatory power in this case. We follow this approach here to select the best predictors of real GDP growth revisions based on their posterior inclusion probabilities.

The idea underlying Bayesian Model Averaging is to consider the results for all the models which include all possible combinations of the regressors and average them. In our case there are 2^k or up to 131072 models. The weights in the averaging are given by the posterior model probabilities $p(M|y)$ where M is the model and y is the data. In order to compute the posterior model probabilities by means of Bayes rule, two elements are required. First, we need the posterior distribution of the parameters in each model M, which is used to derive the marginal likelihood $p(y|M)$. Second, we need to specify the prior distribution of the models $p(M)$. With marginal likelihood and model prior distributions at hand, the model posterior probabilities can be derived as

$$p(M|y) \propto p(y|M)p(M) \tag{9}$$

As to the setup of the priors, we follow Fernandez, Ley and Steel (2001). In particular, for each model, we compute the posterior probability distribution of the parameters by assuming an uninformative prior on the variance of the residuals and on the intercept. For the remaining regression coefficients we use the g-prior of Zellner (1986), setting

$g = \frac{1}{\max(N,k^2)}$ .We set a uniform prior for the distribution of the models.[28] Since we only have up to 131072 models, we follow Magnus, Powel and Pruefer (2010) and evaluate each one of them to obtain the exact likelihood, without having to rely on MCMC methods for approximation. High posterior inclusion probabilities indicate that, irrespective of which other explanatory variables are included, the regressor has a strong explanatory power. We argue that this is therefore an efficient and objective way to select the best predictors of the real GDP growth revision for each country.

4. Results

4.1 Dynamic common factor model

We present all of the results from the dynamic common factor model below. Figure 6 depicts the international business cycle factor, estimated from quarterly real-time real GDP growth rates for the G-7, together with the 68% posterior coverage bands. Clearly, both the mid-1970s and the most recent recession seem to be the deepest G-7 recessions over this sample period. The posterior coverage bands around both of these recessions are quite wide and overlap. Figure 7 shows the joint distribution of the international business cycle factor troughs for the 1970s and the 'Great Recession' with values for the 'Great Recession' on the y-axis and those for the 1970s recession on the x-axis. Any combination above the red 45 degree line suggests that the trough of the 'Great Recession' is deeper than that of the 1970s recession. Roughly 81 percent of the combinations are above, with a substantial number clustered along, this line. Similarly, figure 8 shows the joint distribution of the severity, defined as the sum of negative outturns of the international business cycle factor, for the 1970s and 'Great Recession'. In this case, roughly 76 percent of the combinations are above the 45 degree line. According to the criteria set out in Cogley, Primiceri and Sargent (2010), this is not enough evidence to conclude that either the trough or severity of the international business cycle during

[28] In practical terms, Bayesian Model Averaging is implemented with the STATA BMA function documented in De Luca and Magnus (2011).

the 'Great Recession' is deeper than that of the 1970s recession. In other words, with real-time data, there is not enough statistical evidence to suggest that the 'Great Recession' is so different from the past.

This finding is clearly in contrast to the evidence presented in Aruoba, Diebold, Kose and Terrones (2011). They use a similar econometric methodology to extract a G-7 real activity factor from the current vintage of data and find that the 'Great Recession' is the most severe recession, the G-7 experienced, since 1970. As we shown below, once we apply our methodology to the current vintage of data, we come to the same conclusion. As the current vintage of data for the 'Great Recession' will most likely be revised, it is therefore probably too early to provide a definitive conclusion on the depth and severity of the 'Great Recession' compared to other recessions.

Figure 6: Dynamic common factor estimated on real-time real GDP data

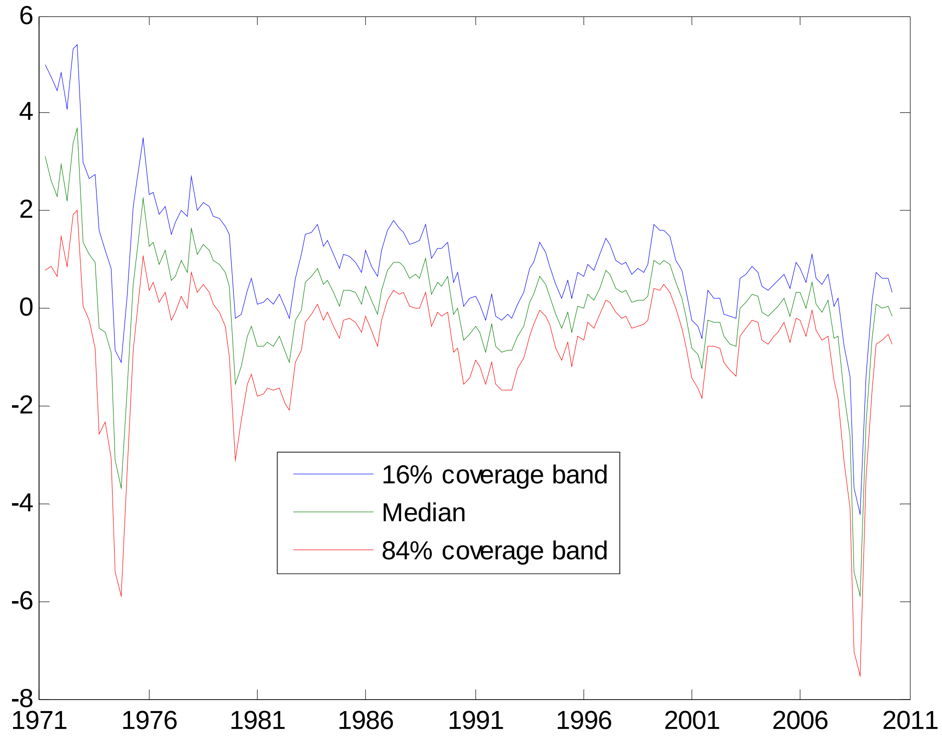


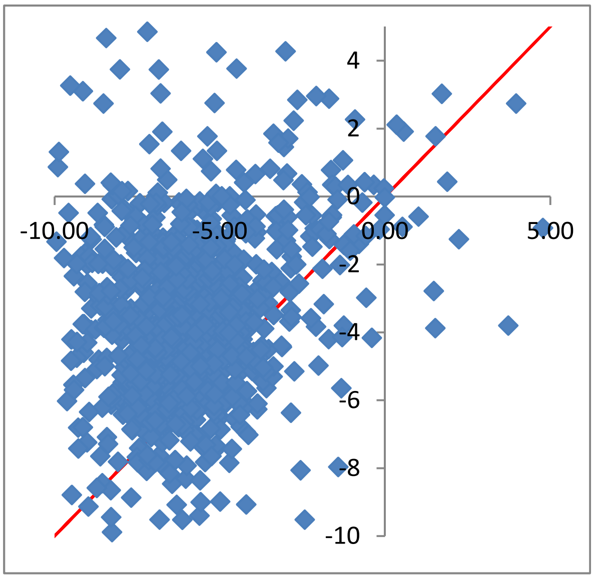
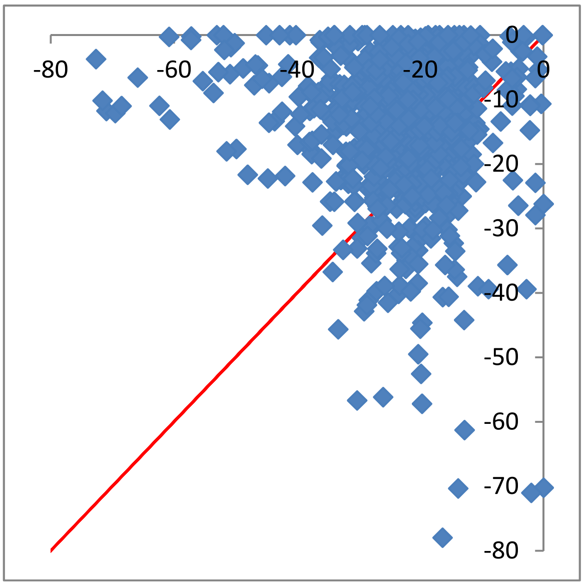
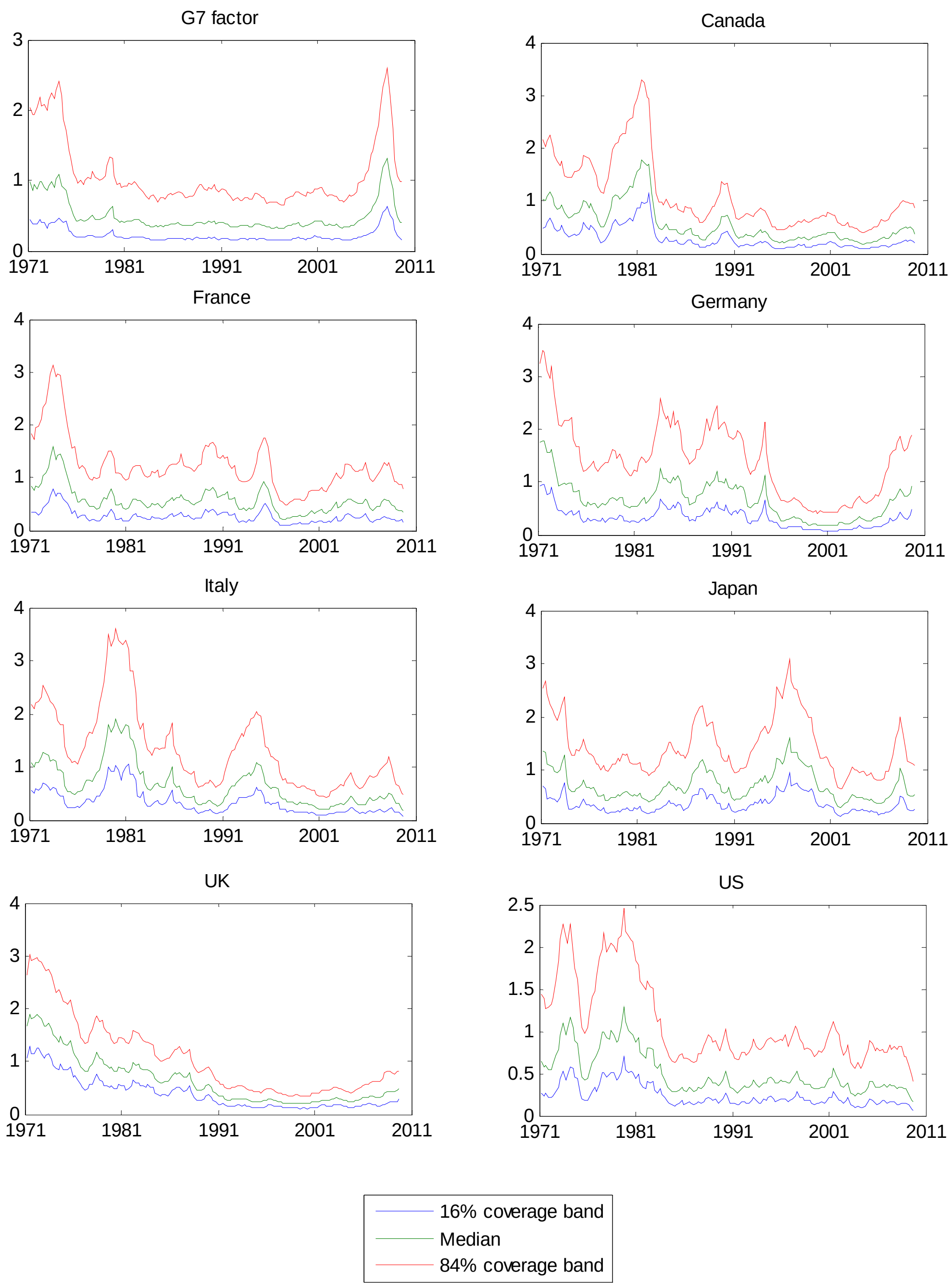
Figure 7: Joint distribution of the common factor trough for the 1974/2008 recession, real-time real GDP data	Figure 8: Joint distribution of the common factor severity for the 1974/2008 recession, real-time vintage real GDP data
	

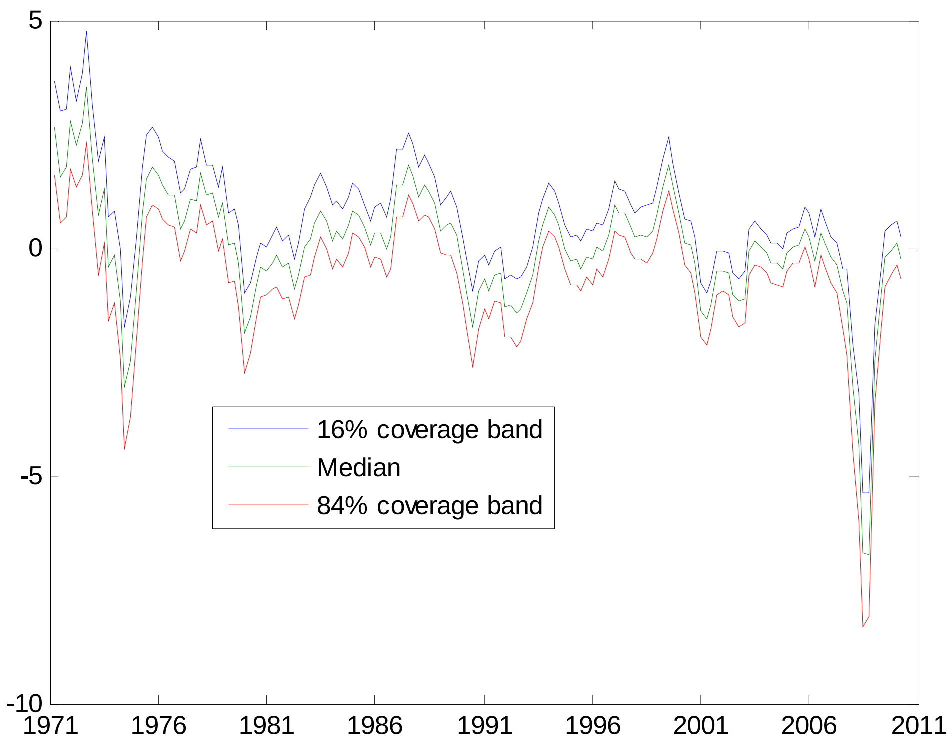
Figure 9 displays the evolution of the stochastic volatility terms estimated from this model. The stochastic volatility term of the factor appears to be elevated both in the 1970s and 2000s. Similarly, even with real-time data, there appears to be a decline in the volatility of US GDP innovations in the early 1980s and in the UK starting in the 1990s. Both of these results are consistent with the conventional view that these periods have been characterised by low volatility of macroeconomic aggregates in these countries, commonly referred to as the 'Great Moderation' and the 'Great Stability', respectively.

Figure 9: Stochastic volatilities estimated on real-time real GDP data



On the other hand, when the same model is estimated on the current vintage of quarterly growth rates of G-7 real GDP data, the decline in the international business cycle factor is much greater during the 'Great Recession' than during previous post war recessions (figure 10). Figures 11 and 12 show the joint distribution of the international business cycle factor troughs and severity for the 1970s and the 'Great Recession' with values for the 'Great Recession' on the y-axis and those for the 1970s recession on the x-axis, respectively. Any combination above the red 45 degree line indicates that the 'Great Recession' is deeper/more severe the 1970s recession. Unlike with real-time real GDP data, 99% of the combinations are above, with few combinations clustered long, the red line in either case. This provides strong statistical support for the notion that in the current vintage of data the trough/severity of the international business cycle factor experienced during the 'Great Recession' is deeper/larger than that experienced in the 1970s recession.

Figure 10: Dynamic common factor estimated on current vintage real GDP data



The stochastic volatility terms also differ across these two data types. In particular, with the current vintage of real GDP data, the decline in UK real GDP volatility occurred in the early 1980s rather than the 1990s. Canada, on the other hand, experienced its decline in the volatility of the idiosyncratic component of GDP much later than in real-time data. Germany and Japan look similar across both datasets (figure 13).

Figure 11: Joint distribution of the common factor trough for the 1974/2008 recession, current vintage real GDP data

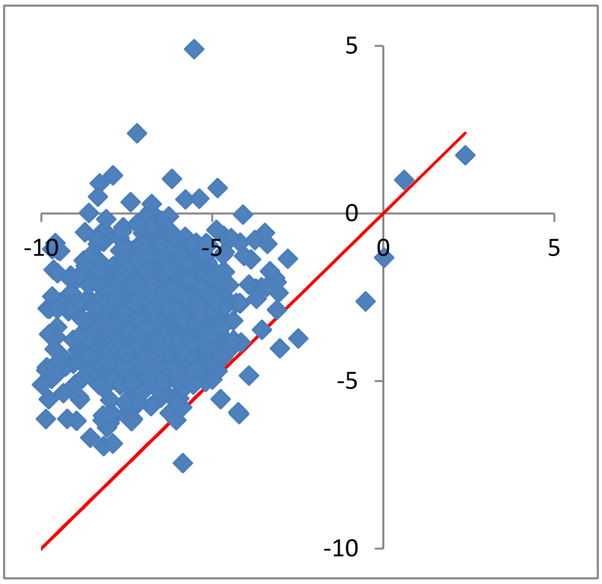


Figure 12: Joint distribution of the common factor severity for the 1974/2008 recession, current vintage real GDP data

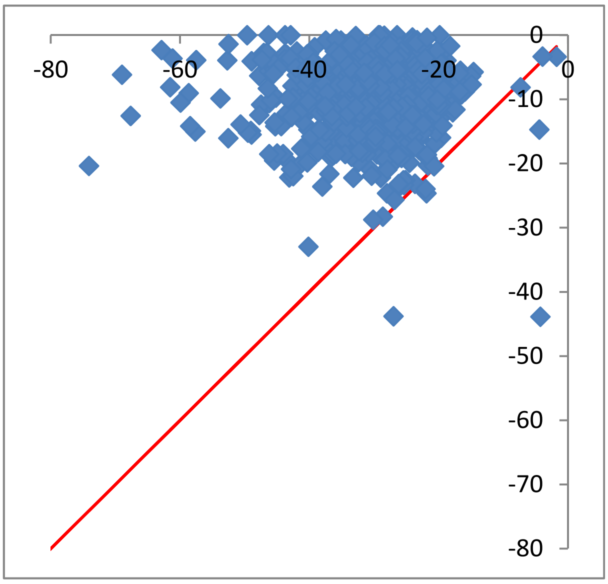
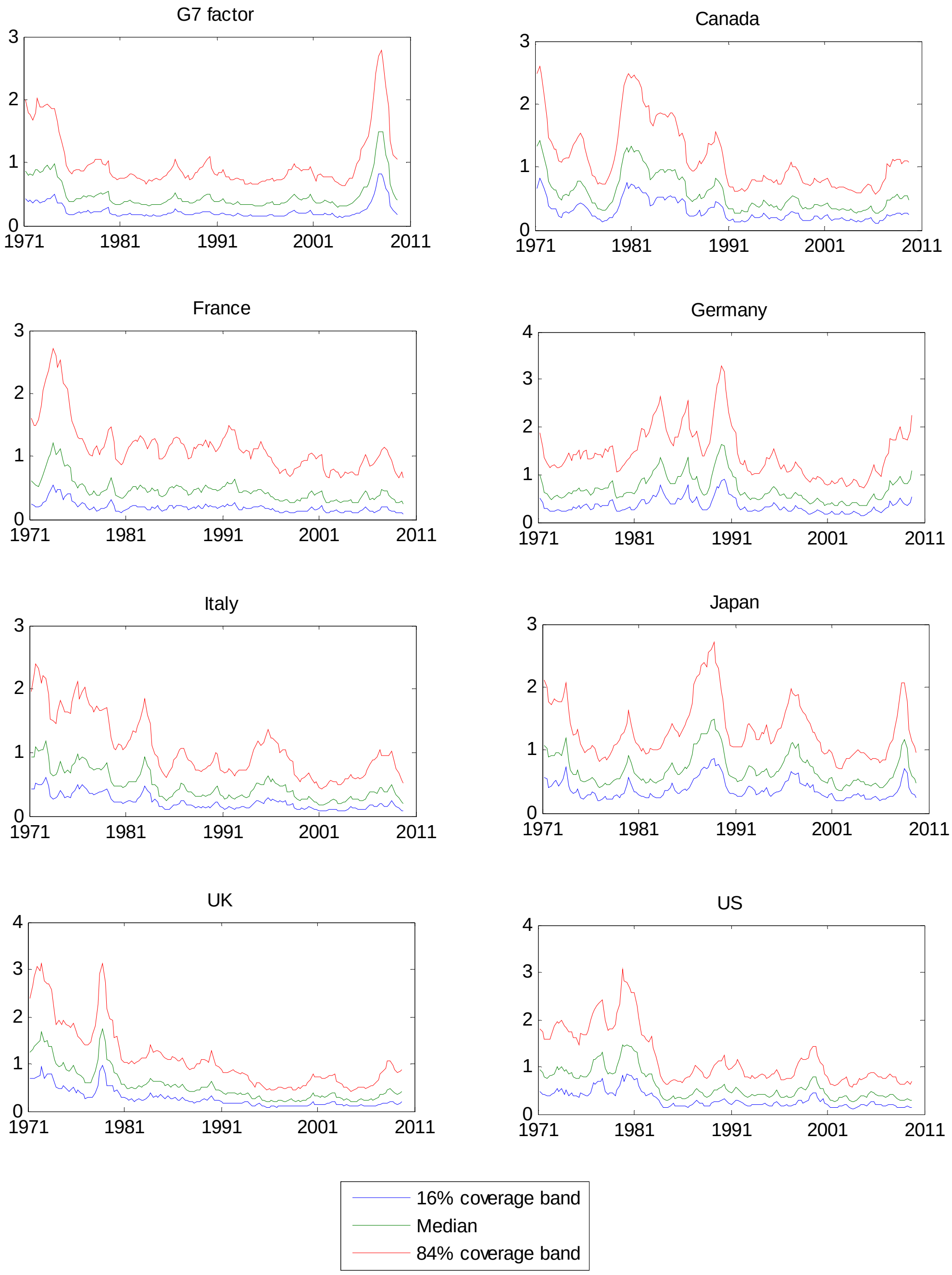


Figure 13: Stochastic volatilities estimated on current vintage real GDP data



4.2 Bayesian Model Averaging results

Table 1 presents the posterior inclusion probabilities for each possible predictor of the revision. We only retain variables that have a posterior probability of at least .7.[29] By this criterion, only the preliminary real GDP growth rate, apart from the constant which is included in every model by definition, should be retained for the US. None of the variables for Canada match this threshold and hence we only include the change in the real long-term rate, since this variable has the highest posterior probability. For the UK and Germany, the preliminary estimate of real GDP growth has the highest posterior probability and is therefore the predictor with the highest explanatory power. The change in the unemployment rate, interacted with the dummy variable for recessions, is an additional important predictor for Japan. For France and Italy, the change in unemployment and the short-term real interest rate have high posterior probabilities, in addition to the preliminary estimate of real GDP growth, respectively.

Table 1

VARIABLES	US	UK	France	Japan	Italy	Germany	Canada
Constant	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Prelim. GDP Growth	0.70	0.99	0.88	1.00	1.00	1.00	0.14
Unemp. Change	0.10	0.34	0.86	0.08	0.08	0.37	0.44
Stock Price Growth	0.08	0.11	0.59	0.06	0.13	0.07	0.44
Short Rate	0.36	0.12	0.07	0.06	0.86	0.16	0.17
Long Rate	0.27	0.12	0.24	0.07	0.09	0.39	0.50
House Price Growth	0.15	0.11	0.07	0.06	0.09	0.61	0.12
Inflation	0.09	0.12	0.08	0.08	0.09	0.11	0.32
Oil Price Growth	0.08	0.11	0.10	0.12	0.08	0.07	0.32
Prelim. GDP Growth (R)	0.17		0.17	0.06	0.11	0.13	
Unemp. Change (R)	010		0.07	0.84	0.10	0.09	
Stock Price Growth (R)	0.21		0.17	0.06	0.12	0.08	
Short Rate (R)	0.12		0.07	0.07	0.14	0.13	
Long Rate (R)			0.08	0.07		0.15	
House Price Growth (R)			0.08	0.09		0.11	
Inflation (R)			0.09	0.06		0.18	
Oil Price Growth (R)				0.07		0.20	
Recession Dummy				0.17		0.21	

Note: All nominal growth rates above were deflated with the corresponding CPI inflation.
(R) indicates the interacted value of a variable with the recession dummy.
Empty cells reflect variables that were collinear and have been dropped.

[29] The subsequent results are not affected if we adopt a threshold of .9 instead.

4.3 Mincer-Zarnowitz regression results

For each country, we estimate the Mincer-Zarnowitz (1969) forecast efficiency regression with the variables that have the highest posterior inclusion probabilities. The estimates from these regressions are shown in table 2. The F-test statistics indicate that we can reject the null hypothesis that all of the estimated coefficients are jointly equal to 0 at the 5% level, in all of the G-7, but not the US and Canada. This suggests that revisions are predictable in all but these two countries, which is consistent with the findings of Faust, Wright and Rogers (2005) for the US.

Table 2

VARIABLES	US	UK	France	Japan	Italy	Germany	Canada
Prelim. Growth	-0.26*	-0.59***	-0.33***	-0.69***	-0.54***	-0.62***	
	(0.13)	(0.14)	(0.099)	(0.083)	(0.10)	(0.15)	
Unemp. Change			-0.68***				
			(0.18)				
Unemp. Change (R)				-2.59***			
				(.94)			
Short Rate					0.31***		
					(0.09)		
Long Rate							-.08*
							(.043)
Constant	0.19*	0.52***	0.20***	0.33**	0.28***	0.24***	0.10**
	(0.10)	(0.095)	(0.055)	(0.094)	(0.076)	(0.086)	(0.039)
Observations	52	52	52	52	52	52	52
R-squared	0.081	0.225	0.255	0.61	0.448	0.568	0.05
F test	3.86*	16.4***	8.95**	34.77***	14.49***	16.55***	3.41*

Note: All nominal growth rates above were deflated with the corresponding CPI inflation. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Subsequently, we use the estimated regression models to forecast real GDP revisions during 2006Q1 to 2010Q3 country by country. These results are shown in figures 14-20. This exercise suggests that revisions are likely to be largest in Germany and Japan, followed by the UK and Italy. For the remainder of the countries, the real GDP revision forecast is not statistically significant at the 5% level. Finally, Figure 21 shows the G-7 GDP-weighted average of the country-by-country forecasts. This suggests a revision of .81 (1.08) in 2009Q1 (2008Q4) with a one standard deviation confidence band of .34 (.58) and 1.24 (1.57) and a two standard deviation confidence band of .037 (-.13) and 2.11 (1.76), respectively. Together these two quarters, which are contained in the one-standard deviation confidence band and hence statistically different from zero[30], suggest an expected revision of about 1.9%. A revision of this size would be sufficient to make the real-time depth (2.1%) and output loss (3.75%) of the 'Great Recession' comparable to the current vintage depth (0.85%) and output loss (1.94%) of the 1970s recession. Yet there is an important difference. In the 1970s, most of the revision to G-7 real GDP growth was the result of a substantial revision to US data. On the other hand, our analysis suggests that this time the revision will probably result from revisions in Germany, Japan, the UK and Italy.

Figure 14: Real GDP growth revision forecast – Canada

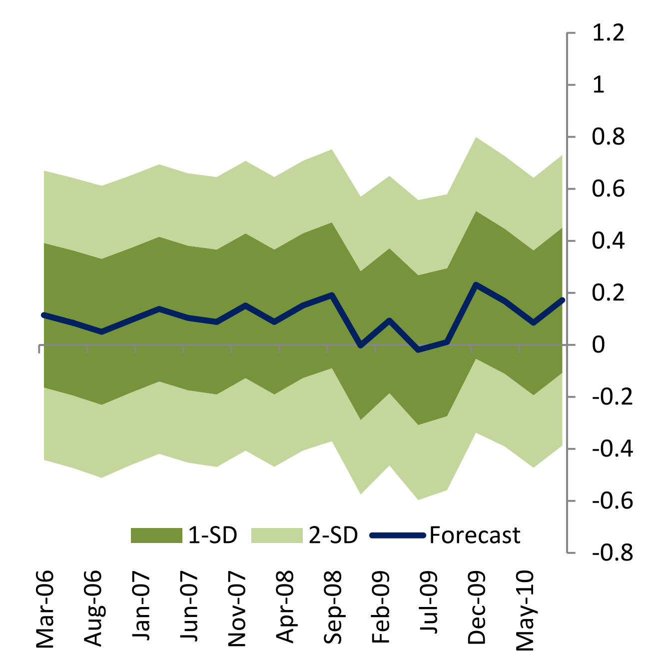
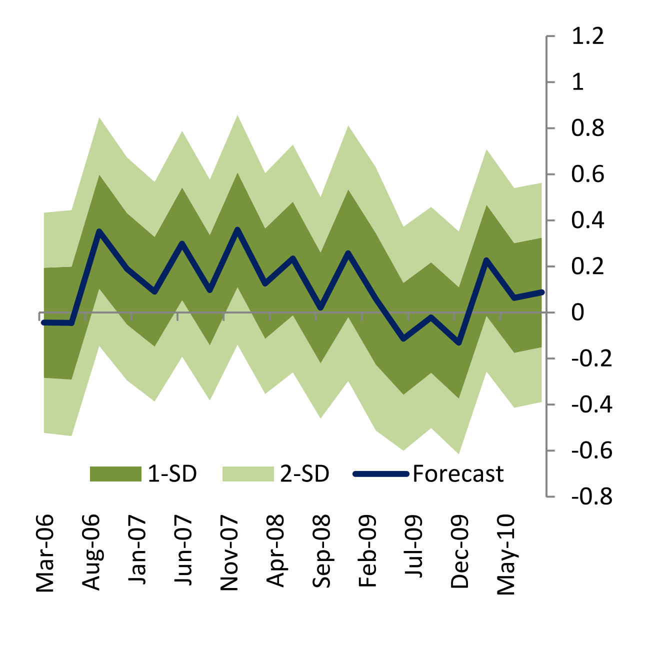


Figure 15: Real GDP growth revision forecast –France



[30] Strictly speaking, the weighted forecast for both 2008Q4 is not statistically significant at the 5% level, since the lower bound includes zero. Nevertheless, a large mass of the forecast distribution for 2008Q4 still points to a positive revision for this point in time. As a result there is still a substantial likelihood that the revision at this point in time is statistically different from zero and this is the interpretation we choose to follow.

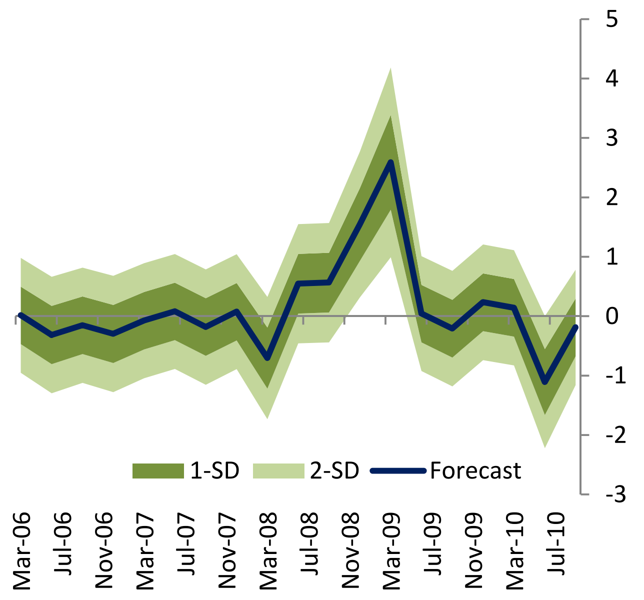
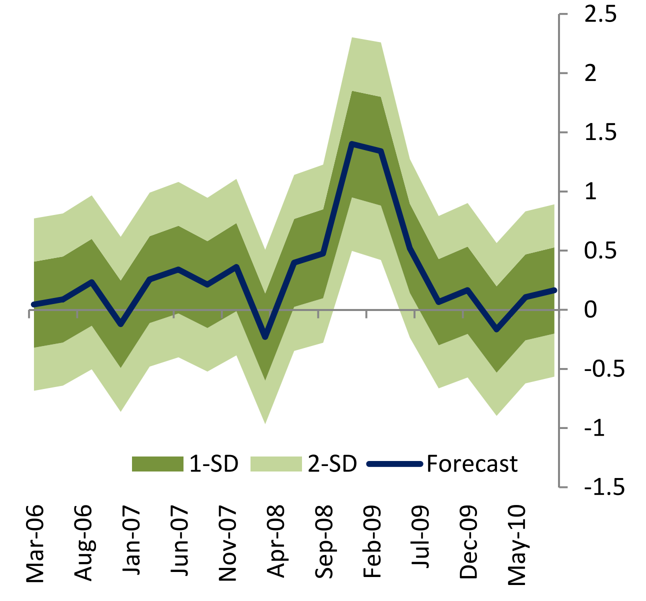
Figure 16: Real GDP growth revision forecast – Germany	Figure 17: Real GDP growth revision forecast - Italy
	

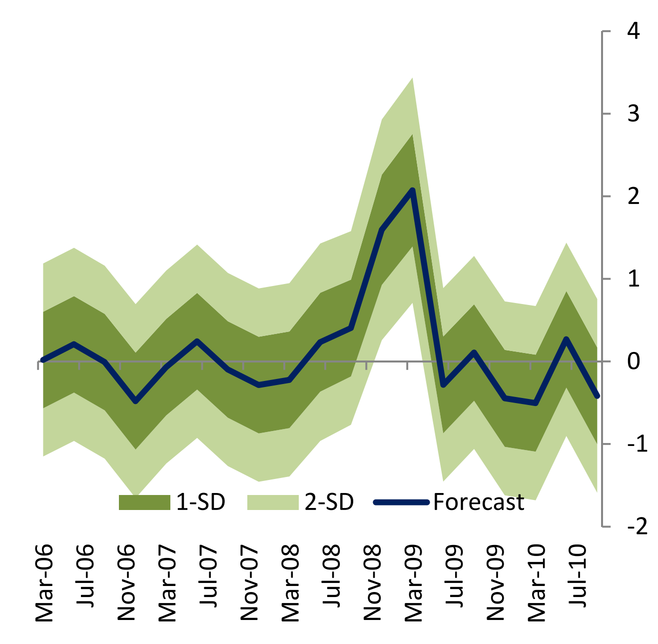
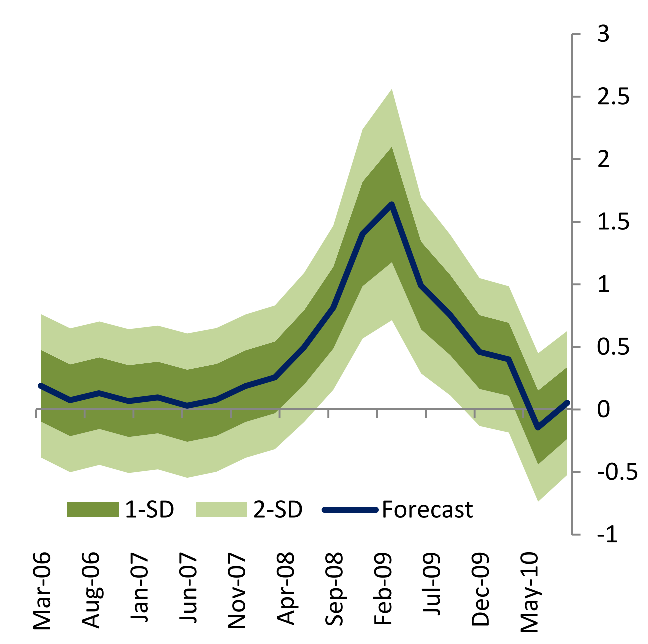
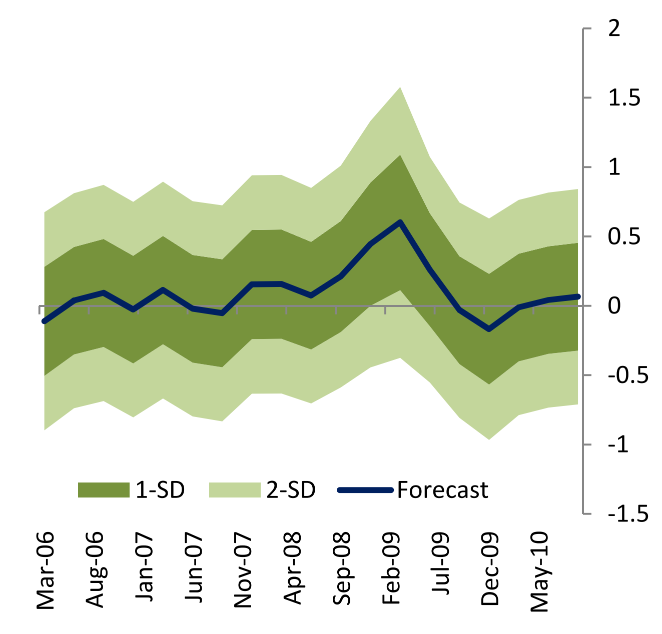
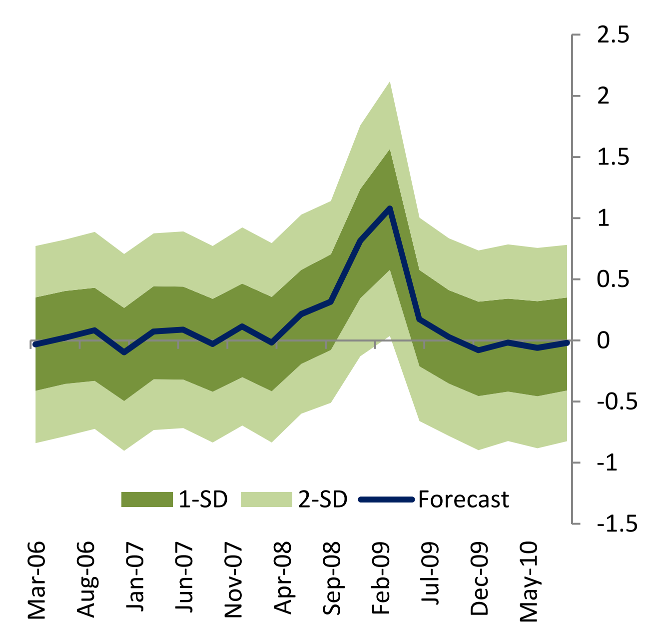
Figure 18: Real GDP growth revision forecast - Japan	Figure 19: Real GDP growth revision forecast - UK
	

Figure 20: Real GDP growth revision forecast - US	Figure 21: Real GDP growth revision forecast – G-7
	

5. Robustness

5.1 Choice of estimation window

In this section we explore the robustness of the estimates in table 2 to the choice of estimation window. A stylised fact about real GDP revisions is that they may occur many years after the initial estimate has been published (Jacobs and Van Norden, 2011; Siklos, 2008). This is why we truncate our sample at 2005Q4, since data thereafter may still be subject to substantial revision. In practice it is of course impossible to know at which point all revisions have been incorporated. To see how robust our previous results to the choice of this date are, we re-estimate table 1 with 2002Q4 as the cut-off date. These results are shown in table 4. Similarly, the full implementation of the 'System of National Accounts 1993' may, quite possibly, have been delayed in some countries. To address this concern, we re-estimate table 1 on data starting in 1995Q1[31]. These results are shown in table 5. Most of the results reported in either table 4 or 5 are similar to table 1, perhaps with the exception that predictability cannot rejected for Canada in table 5. Overall, however, the choice of start or end date does not seem to make much of a difference to our results.

[31] The majority of G7 countries had implemented SNA1993 by 1995.

Table 4

VARIABLES	US	UK	France	Japan	Italy	Germany	Canada
Prelim. Growth	-0.25	-0.56***	-0.33***	-0.71***	-0.60***	-0.62***	
	(0.15)	(0.16)	(0.12)	(0.09)	(0.11)	(0.15)	
Unemp. Change			-0.78***				
			(0.18)				
Unemp. Change (R)				-2.67***			
				(.96)			
Short Rate					0.33***		
					(0.09)		
Long Rate							-.092*
							(.05)
Constant	0.20	0.53***	0.18**	0.35***	0.35***	0.29***	0.11**
	(0.12)	(0.11)	(0.07)	(0.11)	(0.10)	(0.10)	(0.05)
Observations	40	40	40	40	40	40	40
R-squared	0.07	0.21	0.30	0.65	0.49	0.59	0.06
F test	2.77	11.86***	9.13**	30.44***	14.03***	16.02***	3.18*

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5

VARIABLES	US	UK	France	Japan	Italy	Germany	Canada
Prelim. Growth	-0.27	-0.74***	-0.38***	-0.71***	-0.48***	-0.68***	
	(0.14)	(0.13)	(0.09)	(0.09)	(0.12)	(0.15)	
Unemp. Change			-0.68***				
			(0.22)				
Unemp. Change (R)				-2.78***			
				(.99)			
Short Rate					0.47***		
					(0.16)		
Long Rate							-.10**
							(.05)
Constant	0.20	0.58***	0.21**	0.35***	0.26***	0.24***	0.12***
	(0.11)	(0.09)	(0.06)	(0.11)	(0.08)	(0.09)	(0.04)
Observations	44	44	44	44	44	44	44
R-squared	0.09	0.33	0.27	0.65	0.43	0.59	0.08
F test	3.71*	30.01***	9.56***	35.13***	10.16***	20.73***	4.50**

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6. Conclusion

At present there appears to be a consensus among both policymakers and academic economists that the 'Great Recession' is the deepest economic contraction of G-7 output since the Great Depression. But unemployment data tell a different story. One explanation for this inconsistency is a decline in productivity (output per worker) in most of the G-7. On the other hand, since it is well known that real GDP data are revised, in this paper we therefore ask: 'Is the 'Great Recession' really so different from the past?'

We show that the fall in the quarterly growth rate of G-7 real GDP reached during the 'Great Recession' is not that different from the mid-1970s recession in real-time data. Similarly, there does not appear to be sufficient statistical evidence to conclude that the trough/severity of the international business cycle (dynamic common) factor, estimated on real-time data, in the mid-1970s recession is different from that reached during the 'Great Recession'.

But of course, past real GDP measurement mistakes need not be a good guide to the present, let alone the future. This is particularly so, given the change in national income accounting methodology following the adaption of the 'System of National Accounts 1993' by the OECD, IMF, UN and World Bank (United Nations Statistics Division, 1993). In the second part of this study we therefore examine revisions to real GDP data after this date and test if revisions are still predictable following this change in methodology. For this purpose we follow previous work and use the Mincer-Zarnowitz (1969) forecast efficiency regression approach to forecast revisions during the 'Great Recession'. To avoid the 'curse of dimensionality' with up to 17 possible predictors and only 52 time-series observations for each country, we use Bayesian Model Averaging to objectively select the predictors with the highest explanatory power. Only variables with the highest posterior inclusion probability are retained as explanatory variables in the actual Mincer-Zarnowitz (1969) regressions. But even then, it is important to point out that national accounting methodologies are constantly evolving and that therefore our regression results based on past data may not necessarily be applicable to future revisions.

This is exactly the reason why they should be treated as what they are: economic forecasts based on the estimates from past revision patterns. We find that real GDP revisions are still predictable for all of the G-7 but the US and Canada. Our revision forecasting exercise suggests a revision of approximately 1.9% to aggregate G-7 real GDP growth during the 'Great Recession' period, mostly driven by revisions in Japan, Germany, Italy and the UK[32]. A revision of this size would bring the real-time depth (2.1%) and output loss (3.75%) of the 'Great Recession' in line with the current vintage depth (0.85%) and output loss (1.94%) of the 1970s recession.

As the quotation at the beginning of the paper demonstrates, economic contractions can always draw comparisons to the Great Depression when they first occur, but subsequent revisions may reveal a much milder downturn than initially perceived. Since important revisions to real GDP can take many years (Jacobs and Van Norden (2011) and Siklos (2008)), only time will tell whether history is repeating itself. Yet as we have shown here, it is perfectly plausible that a substantial fraction of the 'Great Recession' will be eventually revised away. Both academic researchers and policy makers may thus want to place larger weight, than is currently the case, on this possible outcome.

[32] In the UK, the Office of National Statistics (ONS) periodically reviews the causes and scale of past revisions in the UK's national accounts [http://www.ons.gov.uk/ons/dcp171778_307982.pdf]. It is therefore entirely possible that our predictions are not as reliable for the UK. Nevertheless, this is not a substantial issue for our results, since the weight of UK in G-7 revisions is not very large.

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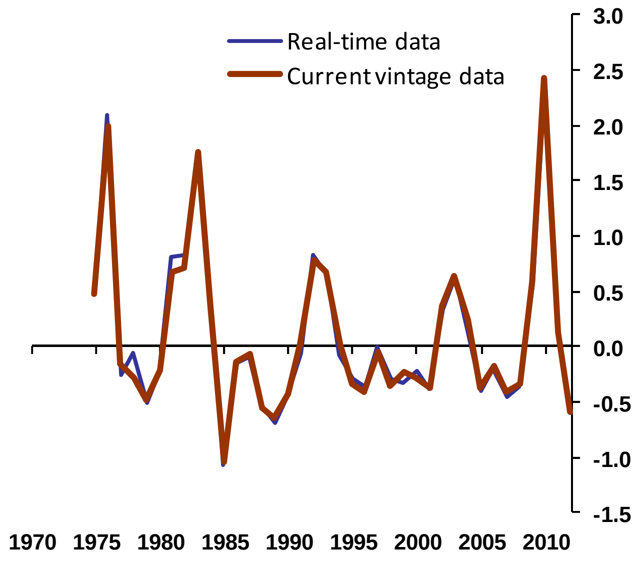
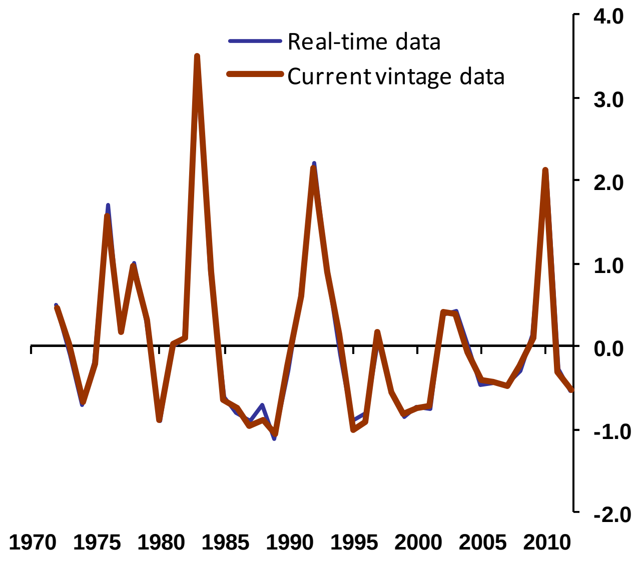
Appendix A – Data

Figure A1: Unemployment rate change for the G-7 excluding France



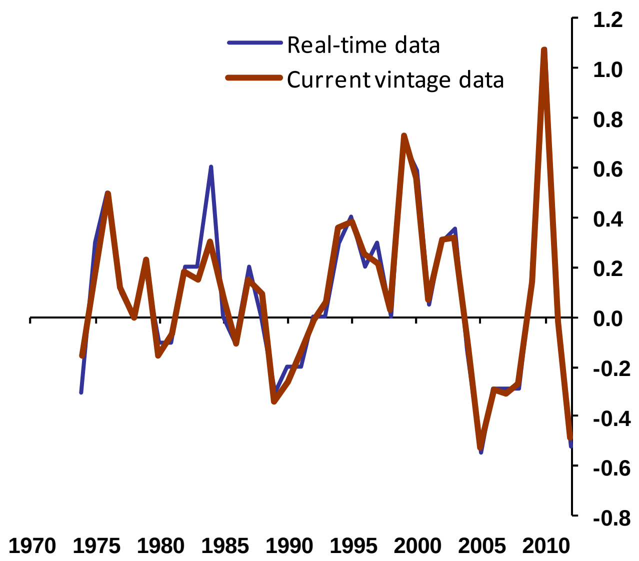
Source: Past and latest editions of OECD MEI.

Figure A2: Unemployment rate change for Canada



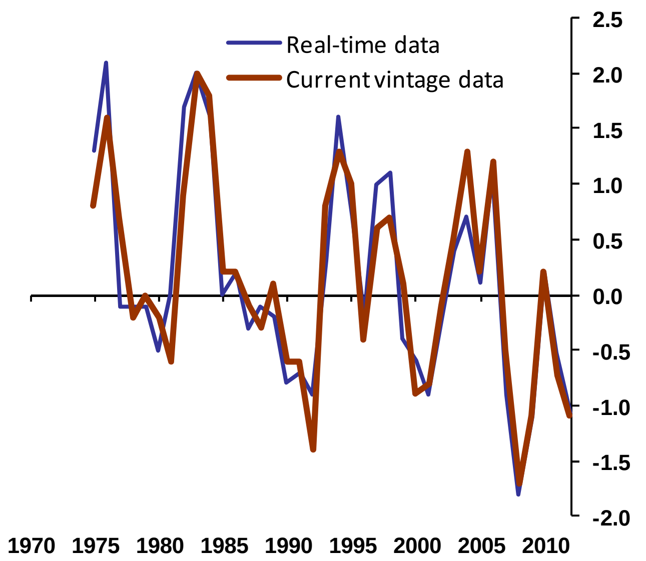
Source: Past and latest editions of OECD MEI.

Figure A3: Unemployment rate change for Japan



Source: Past and latest editions of OECD MEI.

Figure A4: Unemployment rate change for Germany



Source: Past and latest editions of OECD MEI.

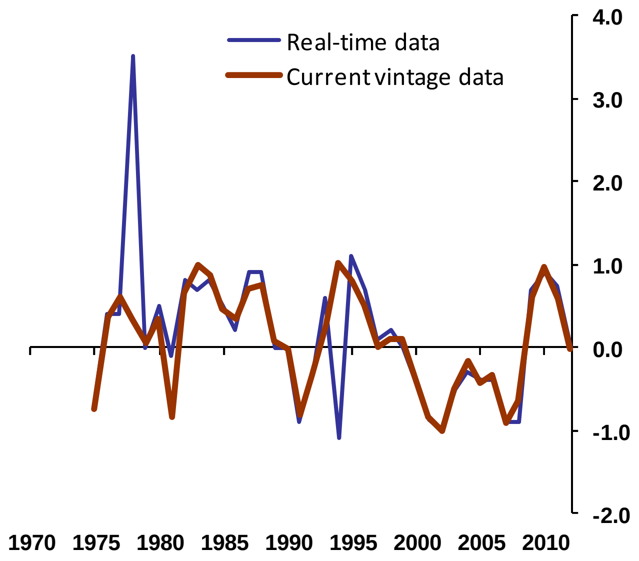
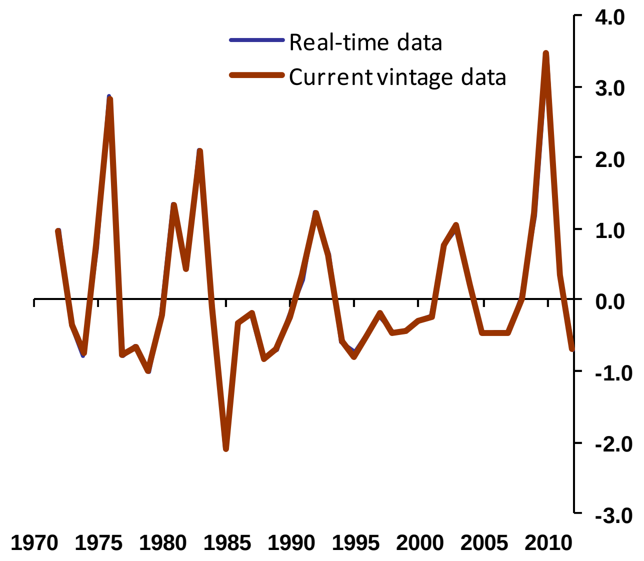
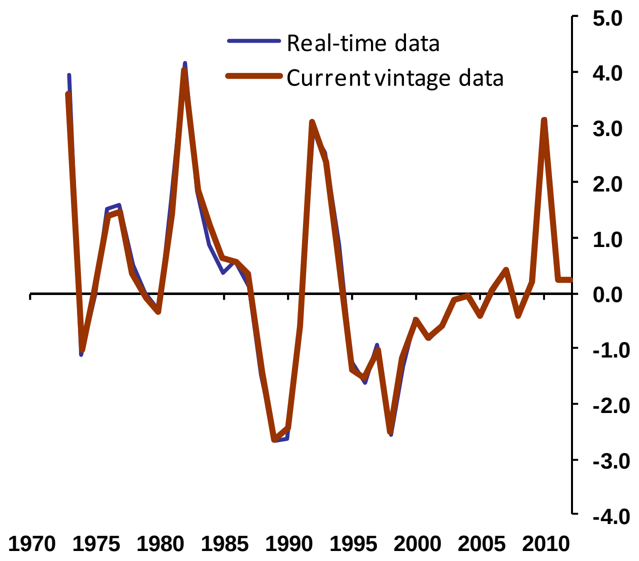
Figure A5: Unemployment rate change for Italy	Figure A6: Unemployment rate change for the US
	
Source: Past and latest editions of OECD MEI.	Source: Past and latest editions of OECD MEI.

Figure A7: Unemployment rate change for the UK

Source: Past and latest editions of OECD MEI.

Appendix B

Dynamic Common Factor model - Estimation

Estimation with Gibbs sampling permits us to break the estimation down into several steps, reducing the difficulty of implementation drastically. For instance, if the unobserved dynamic common factor in equation (4) would be known, then the estimation of the factor loadings, γ_i, would only involve a simple OLS regression. Similarly, if the factor loadings and the time-varying variances are known, then the estimation of the unobserved factors only involves the application of the Kalman filter to the state space form of the model in equation (6). Furthermore, given the knowledge of the error terms in equation (3) and (4), one can estimate the stochastic volatility component by applying the Kalman filter to equation (5). Finally, given knowledge of the dynamic common factor, the estimation of the autoregressive parameter in equation (4) can be performed through a simple regression of the lagged factor on itself. For this purpose we employ a Gibbs sampling algorithm that approximates the posterior distribution and describe each step of the algorithm below.

Step 1 - Estimation of the factor-loadings on all other parameters

Conditional on a draw of W_t, we draw the factor loadings γ_i and the associated covariance matrix. With knowledge of all the other parameters we can estimate each factor loading γ_i via OLS regression equation by equation. The posterior densities which we use to achieve this are:

$$\gamma_i \mid Y_{i,t}, W_t, \Sigma_t \quad \sim \mathrm{N}(\gamma_i^*, \Delta_i^*) \tag{11}$$

where $\gamma_i^* = (w_t^{*\prime} w_t^*)^{-1} w_t^{*\prime} Y_{i,t}$ and $\Delta_i^* = (w_t^{*\prime} w_t^*)^{-1} \frac{1}{(1-\rho_i)^2}$, where $w_t^* = \frac{w_t}{\sigma_i e^{\frac{h_{i,t}}{2}}}$.

Step 2 - Estimation of the dynamic common factor and the autoregressive error terms

We can now obtain an estimate of W_t with the forward-filter, backward smoother'.[33] We draw the unobservable factor W_t conditional on all other parameters from

$$W_T \mid Y_T, \mathrm{H}, \Sigma_t \quad \sim \mathrm{N}(W^*_{T|T,Y_T,\mathrm{H},G}, \mathrm{P}^*_{T|T,Y_T,\mathrm{H},G}) \tag{12}$$

$$W_t \mid Y_t, \mathrm{H}, \Sigma_t \quad \sim \mathrm{N}(W^*_{t|\mathrm{t},Y_t,\mathrm{H},G}, \mathrm{P}^*_{t|t,Y_t,\mathrm{H},G}) \tag{13}$$

We first iterate the Kalman filter forward through the sample, in order to calculate $W^*_{T|T,Y_T,\mathrm{H},G,R_i} = E(W_T \mid Y_T, \mathrm{H}, \mathrm{G}, R_i)$ and the associated variance-covariance matrix $\mathrm{P}^*_{T|T,Y_T,\mathrm{H},G,R_i} = \mathrm{Cov}(W_T \mid Y_T, \mathrm{H}, G, R_i)$ at the end of the sample, namely time period *T*. The calculation of these parameters permits sampling from the posterior distribution in (12). We then use the last observation as an initial condition and iterate the Kalman filter backwards through the sample and draw W_t from the posterior distribution in (13) at each point in time.

Step 3 - Estimation of the stochastic volatility components

We follow the approach presented in Kim, Sheppard and Chib (1998) to draw the stochastic volatility terms. To do this we first write the residual of each equation as $z_{i,t} = \frac{e_{i,t}-\rho_i e_{i,t-1}}{\sigma_i}$ or $z_{i,t} = \frac{w_{i,t}-\varphi w_{i,t-1}}{\sigma_0}$, in case of the factor. We express $z_{i,t}$ as $z^*_{i,t} = \log(z^2_{i,t} + c)$, where c is small offset constant, to ensure that we do not take the log of 0. This transformation yields:

$$z^*_{i,t} = h_{i,t} + v^*_{i,t} \tag{14}$$

Where $v^*_{i,t} = \log(v^2_{i,t})$. If $v^*_{i,t}$ were normally distributed, then $h_{i,t}$ could be drawn using the standard Carter and Kohn (1994) algorithm with (14) as the measurement and (5) as the transition equation. But $v^*_{i,t}$ is distributed as a $\log(\chi^2)$. We follow the solution suggested in Kim, Sheppard and Chib (1998) and approximate this distribution as a

[33] See Carter and Kohn (1994) for derivation and further description.

mixture of 7 normal distributions. Conditional on a draw from this distribution, we can now draw $h_{i,t}$ using (14) as the measurement and (5) as the transition equation. In particular:

$$h_T \mid z^*_{i,T}, w_T, v^*_{i,T}, \omega_i \;\sim \mathrm{N}(h^*_{T|T,z^*_{i,T},w_T,v^*_{i,T},\omega_i}, \mathrm{P}^*_{T|T,z^*_{i,T},w_T,v^*_{i,T},\omega_i}) \tag{15}$$

$$h_{i,t} \mid z^*_{i,t}, w_t, v^*_{i,t}, \omega_i \;\sim \mathrm{N}(h^*_{t|t,z^*_{i,t},w_t,v^*_{i,t},\omega_i}, \mathrm{P}^*_{t|t,z^*_{i,t},w_t,v^*_{i,t},\omega_i}) \tag{16}$$

We first iterate the Kalman filter forward through the sample, in order to calculate $h_T \mid z^*_{i,T}, w_T, v^*_{i,T}, \omega_i = E(h_T \mid z^*_{i,T}, w_T, v^*_{i,T}, \omega_i)$ and the associated variance-covariance matrix $\mathrm{P}^*_{T|T,Y_T,\mathrm{H},G,R_i} = \mathrm{Cov}(h_T \mid z^*_{i,T}, w_T, v^*_{i,T}, \omega_i)$ at the end of the sample, namely time period *T*. The calculation of these parameters permits sampling from the posterior distribution in (15). We then use the last observation as an initial condition and iterate the Kalman filter backwards through the sample to draw $h_{i,t}$ from the posterior distribution in (16) at each point in time. This procedure is performed equation by equation, consistent with the assumption that the error terms are uncorrelated across equations.

Step 4 – Estimation of φ, σ_i^2 and ω_i

We draw the variance-covariance matrix σ_i^2 from an inverse Gamma distribution:

$$\sigma_i^2 \;\sim\; IG(\tfrac{\delta_2}{2}, \tfrac{z_2}{2}) \;, \tag{17}$$

where z_2 is the number of time-series observations and $\delta_2 = (e^*_{i,t} - \rho_i e^*_{i,t-1})'(e^*_{i,t} - \rho_i e^*_{i,t-1})$, where $e^*_{i,t} = \frac{e_{i,t}}{e^{\frac{h_{i,t}}{2}}}$. The AR coefficient φ is obtained through a standard regression of $w_t\varphi$ on its own lagged value and the coefficients are sampled from a normal distribution. We only retain draws with roots inside the unit circle. σ_0 is set to 1 in order to identify the scale of the model. The posterior density in this case is:

$$\varphi \mid Y_{i,t}, W_t, G \quad \sim \mathrm{N}(\varphi^* , \Delta_i^*) \tag{18}$$

where $\varphi^* \;= (\, w_{t-1}^*{}' w_{t-1}^*)^{-1}\, w_{t-1}^*{}' w_t^*$ and Δ_i^*= $(\, w_{t-1}^*{}' w_{t-1}^*)^{-1}$, where $w_t^* = \frac{w_t}{e^{\frac{h_{i,t}}{2}}}$.

Similarly, the individual ρ_i's are sampled from

$$\rho_i \mid Y_{i,t}, W_t, G \quad \sim \mathrm{N}(\rho_i^*, \Delta_i^*) \tag{19}$$

where $\rho_i^* = (\, e_{i,t-1}^*{}' e_{i,t-1}^*)^{-1}\, e_{i,t-1}^*{}' e_{i,t}^*$ and Δ_i^*= $(\, e_{i,t-1}^*{}' e_{i,t-1}^*)^{-1} \sigma_i^2$, where $e_{i,t}^* = \frac{e_{i,t}}{e^{\frac{h_{i,t}}{2}}}$. ω_i is drawn from an inverse Gamma distribution:

$$\omega_i \;\sim\; IG(\frac{\delta_3}{2}, \frac{z_3}{2}) \;, \tag{20}$$

where z_3 is *T+1* and $\delta_2 = .0001 + (h_{i,t} - h_{i,t-1})'(h_{i,t} - h_{i,t-1})$.

Step 5 - Go to step 1