Nowcasting US GDP: The role of ISM Business Surveys*

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Abstract

We study the role of the well-known monthly diffusion indices produced by the Institute for Supply Management (ISM) in nowcasting current quarter US GDP growth. In contrast to the existing literature on ISM surveys, we investigate their marginal impact on these nowcasts when large unbalanced (jagged edge) macroeconomic data sets are used in real time to generate them. We find evidence that these ISM indices are helpful in improving the nowcasts when new ISM information becomes available in the beginning of the month, ahead of other monthly indicators. Furthermore, and while the existing literature has focused almost exclusively on manufaturing information, here we establish the increasingly significant role of the recently created non-manufacturing ISM diffusion indices in such nowcasting contexts.

JEL Classification: C33, C53.

KEYWORDS: Forecasting, ISM, PMI, NMI, factor models, Kalman filter, Real time data.

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1 Introduction: ISM variables and their role in nowcasting

The *Institute for Supply Management* (ISM) produces a well known monthly report on business conditions based on firms' responses to a questionnaire it sends out every month. Supply chain managers and business executives are asked about their firms's production, employment, inventory levels, and other important information during the preceding month and their responses are then used to construct *diffusion*, or summary indices of business activity. These diffusion indices can be useful tools in assessing the current state of various sectors and of the economy in general. Most prominently, their *Purchasing Managers' Index* (PMI) for the manufacturing sector is a very well known economic indicator that regularly receives media attention and is closely watched by policy makers and others aiming to get a head start in forecasting the economy's movements in real time.

As Koenig (2002) points out, PMI and other ISM diffusion indices have two main advantages: First, and most importantly, it's timeliness: New ISM manufacturing information comes out on the first business day of every month (and the ISM non-manufacturing variables shortly afterwards) and it contains the reports based on the previous month's questionnaires. No other economic variable of such importance becomes available first thing every month, on a consistent basis. Second, because of their nature as survey responses, ISM data are typically subject to at most small revisions. As such, they preserve most of the real-time nature that is crucial in many estimation and forecasting exercises (see, inter alia, Orphanides (2002), Koenig et al (2003), etc.)

Furthermore, ISM variables and the PMI in particular have been shown to have forecasting power for GDP and the business cycle. For instance, Dasgupta and Lahiri (1993) have shown that the PMI can be useful in forecasting GDP changes; similar results on the performance of the PMI as a leading indicator include Klein and Moore (1991), Dasgupta and Lahiri (1992), Kauffman (1999), Koenig (2002), Lindsey and Pavur (2005), and Banerjee and Marcellino (2006).

While this literature has had a long and interesting history, there has been intense interest over the last few years in *nowcasting*, which is the task of predicting the present, the very recent past, or the very near future of GDP, and some other macro variables as well. Some important recent contributions in this area are Evans (2005), Giannone et al (2008, 2010), Banbura et al (2011), Barhoumi et al (2010), Camacho and Perez-Quiros (2010), Frale et al. (2010, 2011), Foroni and

Marcellino (2011), and Kuzin et al (2011)[1].

Much of this nowcasting literature takes advantage of recent advances in factor models and related techniques that allow researchers to extract useful information from large data sets with many predictors and thus deliver forecasting gains. However, directly employing a large model with many variables would require estimating a large number of parameters, which may compromise the estimated model's forecasting performance. Factor models, that the nowcasting literature employ, manage to deal successfully with that issue.

An additional challenge that comes with this task of extracting the maximum amount of useful information from these large data sets in real time is that as new data releases arrive throughout the quarter they are incorporated at various times into these panels, which are thus unbalanced panels, or have *jagged edges*. The nowcasting literature often employs standard Kalman filtering techniques to deal with this issue of different variables having different endpoints at any given point in time.

This paper brings together the extant literature on ISM and the PMI with the new literature on nowcasting. In particular, while in the past the PMI has been studied as a potential nowcasting tool largely in isolation from other concurrently available macroeconomic variables[2], this paper revisits the PMI and other ISM variables within the context of the large jagged data sets employed in nowcasting. After all, it is not just the PMI that can be expected to have forecasting/nowcasting power for GDP growth, but potentially many other variables as well. For instance, payroll information is released by the Labor Department on the first Friday of every month. Thus, an interesting question that has not received much, if any, attention, is *to what extent the PMI and other ISM indicators have added value when they are part of a much larger information set that is used to produce the nowcasts*. Investigating this issue is the paper's first goal; for that purpose, we adopt the approach of the seminal paper of Giannone, Reichlin, and Small (2008) - henceforth GRS. They employ a dynamic factor model and the Kalman smoother to nowcast US GDP. We revisit some of their work, while paying closer attention to individual ISM variables and their role in nowcasting GDP.

Another gap in the existing literature is that it is mostly the PMI (and associated manufacturing

[1] This literature covers both the U.S. and the Euro Area, and also some of these papers pay particular attention, like we do here, to the role that surveys play in nowcasting.

[2] See, for example, Koenig (2002), Pelaez (2003a, 2003b), Cho and Ogwang (2006).

indicators) that has been studied, largely to the exclusion of non-manufacturing ISM data, despite the well-known fact that the non-manufacturing share in the economy has been steadily increasing, cf. Cho and Ogwang (2007). The paper's second goal is thus to focus on non-manufacturing ISM indicators too, and to investigate their added value in nowcasting as well.

The paper's two central findings are, first, that ISM information does have added value for nowcasting GDP, even when the nowcasts are generated using large information sets, and second, that non-manufacturing ISM indicators are at least as important as their manufacturing counterparts.

The paper is organized as follows: Section 2 provides some historical background and more details on the ISM and the diffusion indices it produces. Section 3 investigates, in a more traditional way, the bivariate relationship between ISM indicators and GDP growth. The rest of the paper then studies the role of ISM indicators in nowcasting GDP growth from large panels. In particular, section 4 summarizes the econometric approach of GRS that we employ and section 5 presents results from our nowcasting exercises with various ISM variables. Finally, Section 6 offers some concluding remarks.

2 ISM data: A closer look

Except for a four-year interruption during World War II, the ISM (formerly known as NAPM, the National Association of Purchasing Management) has been sending every month since 1933 a national survey to a sample of purchasing and supply executives of more than 400 companies in 20 manufacturing industries across the U.S. The resulting report containing the data compiled from the survey responses is the Manufacturing ISM Report on Business (ROB). These survey responses reflect the change in the current month over the previous one for 10 indicators which are new orders, production, employment, supplier deliveries, inventories, customers' inventories, prices, backlog of orders, exports, and imports.

Diffusion indexes are then created based on the responses to these survey questions. For instance, for production, the possible responses to the question "What is the trend for production?" are positive, neutral or negative (compared to the preceding month). The resulting diffusion index is created by adding the percentage of positive responses to half the percentage of the neutral responses. This number varies between 0 and 100 and represents the percent of companies that increased their production during the month. Basically, a level above 50 indicates that more executives are reporting increase for that variable than are reporting decrease. Diffusion indices are then seasonally adjusted[3].

The Purchasing Managers' Index (PMI) is an equally weighted (0.20 each)[4] composite index of five of these seasonally adjusted diffusion indexes: New Orders, Production, Employment, Supplier Deliveries and Inventories. The composite index PMI again ranges from 0 to 100, with 50 again being the critical reference. ISM specifies a reading above (below) 50 as indicating that the manufacturing sector is in expansion (contraction). Furthermore, as Koenig (2002) estimates, a PMI above 41 indicates an expansion of the overall economy. Other studies, including our own results in this paper, obtain similar estimates for the threshold value for the overall economy, but always suggest a higher threshold value (Koenig reports a 48) for manufacturing.

The index is released at 10:00 a.m. EST on the first business day of each month, requires little revision, and is widely recognized by many economists and business practitioners as a reliable short-term barometer of economic activity (www.ism.ws/ISMReport; Dasgupta and Lahiri 1993). While, and as discussed earlier, these are clearly desirable features, there are disadvantages to the PMI as well: One such drawback is simply a result of the PMI being a diffusion index: Its increases or decreases do not capture the intensity with which business conditions are changing. Furthermore, the PMI does not account for size differences across firms. As such, it may miss important shifts in business conditions if, for instance, such shifts are primarily concentrated in a few large firms.

For our purposes the ultimate criterion is to what extent the PMI helps nowcast GDP, especially

[3] The details of this seasonal adjustment are available in:
http://www.ism.ws/about/mediaroom/newsreleasedetail.cfm?ItemNumber=19992

[4] When the PMI was first introduced in 1980 by Thedore Torda, then a senior economist of the US Department of Commerce, it was constructed as an equally weighted composite index of five of the ten seasonally adjusted diffusion indexes: new orders, production, employment, supplier deliveries and inventories. The PMI was back-calculated prior to 1980, and is available starting in 1948. In 1982, the US Department of Commerce changed the weights of these five diffusion indexes in order to maximize the relationship between the PMI and the GDP. The new weights were 0.30 for New Orders, 0.25 for production, 0.20 for Employment, 0.15 for Supplier deliveries and 0.10 for Inventories (Torda 1985). Several studies have discussed the plausibility of using fewer components and different weights which can improve the PMI. Pelaez (2003a) proposed an alternative to PMI, which is based on regressions of the growth rate of GDP and industrial production index on current and lagged values of PMI components. The weights were allowed to evolve over time in one version and remained fixed in another. Pelaez (2003b) used an index composed of three of the PMI components (new orders, employment and supplier deliveries). Cho and Ogwang (2006) used only the employment component of PMI. Cho and Ogwang (2007) applied principal component analysis using six of the ten non-manufacturing diffusion indexes to compose a non-manufacturing PMI. In 2008, ISM eventually returned to equal weights.

in the context of the many other variables that can be used for that purpose. Figure 1 plots the PMI and we can clearly see that there is a strong, yet far from perfect relationship between the PMI and the business cycle.

In addition to these manufacturing indices, the ISM has begun composing non-manufacturing indices as well. While services is not as cyclical as the manufacturing sector is, it is well known that the share of manufacturing in the economy has dropped dramatically over the last half century. In that context, non-manufacturing diffusion indices seem central to achieving better coverage of the economy. The non-manufacturing Report on Business becomes available on the third business day of each month soon after the manufacturing ROB, and it is again based on survey questions (asked of 375 executives in 16 non-manufacturing industries across the country). There are 10 non-manufacturing seasonally adjusted ISM diffusion indices: business activity, new orders, employment, supplier deliveries, backlog of orders, new export orders, inventory change, inventory sentiment, imports and prices. There is also a composite Non-Manufacturing Index (NMI) which is available only since 2008, however. This NMI is based on business activity, new orders, employment, and supplies deliveries, so we use the entire time series of these four indices to back-calculate the NMI. Figure 1 also illustrates this NMI and it again suggests that there is some relationship between the NMI and the business cycle. The correlation between the PMI and the NMI during 1997:07-2011:11 is 0.786 - far away from unity. Our task in what follows is to investigate more explicitly the importance of all these manufacturing and non-manufacturing ISM indices in nowcasting GDP growth.

3 ISM indicators and GDP growth: A bivariate investigation

Our goal in this section, much in line with the existing literature on ISM surveys and the PMI, is to study through standard regressions the bivariate relationship between PMI, or the NMI, and GDP growth. An obvious issue in a context such as this one is the different frequencies of the target variable and its predictors: The GDP growth rate is a quarterly quantity, whereas ISM variables are monthly indices. One way of addressing this issue is to employ a simple and intuitive approach such as that of Koenig (2002) coming from the existing ISM literature. Another approach that is specifically designed for mixed frequency contexts is the methodology of Mixed Data Sampling

(MIDAS). In the rest of this section we employ each of these two approaches in turn.

3.1 Koenig's Regression

Koenig's specification includes GDP growth (ΔY_t) as the dependent variable, which he regresses on a quarterly PMI series ($PMI_{q,t}$), based on the following transformation of the standard monthly PMI index: $PMI_{q,t} \equiv (1/9)PMI(t-1,2)+(2/9)PMI(t-1,3)+(3/9)PMI(t,1)+(2/9)PMI(t,2)+(1/9)PMI(t,3)$, where $PMI(t,i)$ is the level of the PMI in the ith month of quarter t. So, $PMI_{q,t}$ is a weighted average of the levels of the monthly PMI index coming from this quarter and last quarter - an intuitive transformation given that GDP growth measures the percent change from last quarter to this one. Following Koenig (2002), the model that we estimate here is:

$$\Delta Y_t = c_1(PMI_{q,t} - c_2) + c_3 \Delta PMI_{q,t} + u_t$$

where u_t is the usual regression error term. $PMI_{q,t}$ is as defined above, a weighted average of levels this quarter and last quarter, and $\Delta PMI_{q,t}$ is the difference between this quarter and last quarter. The advantage of estimating in this non-linear form is that it will yield an estimate of the threshold parameter c_2: a PMI value above it suggests the economy is expanding.

Using observations on the PMI and real-time GDP growth over 1965:03 - 2011:11[5], the estimated equation was

$$\underset{(8.22)}{}\Delta Y_t = \underset{(8.22)}{0.22}((PMI_{q,t} - \underset{(26.56)}{41.29}) + \underset{(7.56)}{0.36}\Delta PMI_{q,t}, \qquad adj.R^2 = 0.486; \quad DW = 1.67$$

t-values are reported in parentheses. The estimates are quite similar to those in Koenig (2002), who uses revised GDP figures and a different estimation sample (1948:Q3-2002:Q1). The explanatory power (0.486) is reasonably good but of course far from perfect, and the in-sample root mean square error is 2.25. The threshold value of 41.29 for expansion is about the same as Koenig's figure.

We also examine the nowcasting capability of the respective non-manufacturing index (NMI) that we obtain using non-manufacturing ISM data that are available since 1997:07. Using the composite quarterly NMI values, that is $NMI_{q,t}$, which is defined in the same way as with the

[5] Employing early estimates of GDP results in an estimation sample that only starts in 1965. We opted for real-time GDP figures to make the results more directly comparable with those of some exercises that come next. However, the results here are quite similar to the ones we obtained with experiments using revised GDP figures, and also to the results obtained by Koenig (2002), who uses revised figures. See, inter alia, Koenig, Dolmas and Piger (2003) for a discussion on this issue.

PMI, the following non-linear regression was estimated:

$$\Delta Y_t = \underset{(5.55)}{0.31}(NMI_{q,t} - \underset{(27.96)}{45.6}) + \underset{(3.79)}{0.42}\Delta NMI_{q,t}, \qquad adj.R^2 = 0.515; \quad DW = 1.95$$

The explanatory power here is similar to that with the PMI and the estimates suggest a higher value (45.6) of the threshold while using NMI compared to PMI to signal GDP growth.

Overall the results for PMI are similar to those of the existing literature and suggest that PMI has reasonably good explanatory power in nowcasting GDP growth. Furthermore, the results for NMI suggest that non-manufacturing ISM information is as useful for such nowcasting tasks as the more widely known manufacturing index.

Of course, these results using Koenig's model utilize one particular prescription regarding the issue of creating a quarterly index from its monthly counterpart, where the relative contributions of the individual monthly ISM indices have been pre-specified. In what follows, we address this issue in a more complete and general way by drawing on MIDAS techniques:

3.2 A MIDAS Approach

Mixed Data Sampling, or MIDAS, regressions are a recently developed framework (see, inter alia, Ghysels et al. (2004), Andreou et al. (2010, 2011) and Sinko et al (2010)) for handling regressions where the dependent variable is of a different (lower) frequency than the explanatory variable(s). It can be applied to a context such as ours, where monthly variable(s) (ISM indices, and possibly other variables) are used to forecast or nowcast GDP growth, a quarterly quantity. Indeed, MIDAS models have already been employed and showed promise in nowcasting and forecasting contexts (see, for example, interesting work by Kuzin et al (2011), Foroni and Marcellino (2011) for the Euro Area and Marcellino and Schumacher (2010) for Germany).

MIDAS can be viewed as a way to deal with the mixed frequency problem that is both parsimonious and data-driven. For example, using the notation developed above, suppose we are interested in studying the relationship between (quarterly) ΔY_t and the (monthly) PMI (or the NMI). The simplest thing to do is to construct quarterly averages using the three observations on PMI during the quarter: $PMI_{q,t} \equiv (PMI(t,1) + PMI(t,2) + PMI(t,3))/3$, and then just regress ΔY_t on $PMI_{q,t}$: $\Delta Y_t = \mu + \beta PMI_{q,t} + \varepsilon_t$. Imposing such equal weights can be quite restrictive, however, and Andreou et al (2010) indeed illustrate the ensuing econometric issues. An alternative approach is to regress ΔY_t on each of the quarter's three monthly PMI indices separately: $\Delta Y_t = \mu + \beta_1 PMI(t,1) + \beta_2 PMI(t,2) + \beta_3 PMI(t,3) + \varepsilon_t$. While there is little problem with this in our context, this approach can be quite problematic in cases where the high frequency variable is, say, daily, because of parameter proliferation. It can also suffer from dynamic misspecification without further refinement of the equation. Given this, MIDAS models can be quite appealing because they are parsimonious while also allowing for data-driven weights. In our context, MIDAS offers a flexible and encompassing framework with which we can investigate the separate contributions of the monthly PMI (or NMI) values every quarter to the nowcasts.

A benchmark, static "MIDAS with leads" regression model that's appropriate for our specific nowcasting task is as follows:

$$\Delta Y_t = \mu + \beta \sum_{i=0}^{2} w_{3-i}(\theta) \Delta PMI(t, 3-i) + \varepsilon_t$$

where ΔPMI here denotes (monthly) differences, ε_t is the error term, the w's are the weights, that are a function of parameter(s) θ, and the unknown parameters (μ, θ, β) are to be estimated by Nonlinear Least Squares. Its dynamic, Autoregressive Distributed Lag extension, with lags of both the dependent and explanatory variables, that we estimate here is:

$$\Delta Y_t = \mu + \sum_{i=0}^{p_Y^Q - 1} \mu_i Y_{t-1-i} + \beta[\sum_{i=0}^{2} w_{3-i}(\theta)\Delta PMI(t, 3-i) + \sum_{j=0}^{p_{PMI}^M - 1} \sum_{i=0}^{2} w_{6-i+j*3}(\theta) \Delta PMI(t-1-j, 3-i)] + \varepsilon_t$$

The existing MIDAS literature (see, for instance, Sinko et al (2010)) discusses various choices for parameterizing the MIDAS polynomial weights, including beta, exponential almon, polynomial almon, and step weights. We did several experiments with different lag lengths for the explanatory variables and different specifications for the weights. As examples, below we present some of the results for a specification with one lag of the dependent variable and no lags for the explanatory variables:

Beta weights: $w_i^{beta}(\theta_1, \theta_2, \theta_3) = \frac{(\frac{i-1}{N-1})^{\theta_1 - 1}(1-(\frac{i-1}{N-1}))^{\theta_2 - 1}}{\sum_{i=1}^{N}(\frac{i-1}{N-1})^{\theta_1 - 1}(1-(\frac{i-1}{N-1}))^{\theta_2 - 1}} + \theta_3$, where N is the total number of MIDAS lags. The PMI results are as follows: The dependent variable lag coefficient, μ_0 is 0.603, the intercept, μ is 0.983, $\beta = 0.213$, 1st monthly weight ($\equiv \beta \times w_1$) = 0.22, 2nd monthly weight ($\equiv \beta \times w_2$) = 0.433, 3rd monthly weight ($\equiv \beta \times w_3$) = 0.22, $R^2 = 0.447$. The respective results for NMI are: $\mu_0 = 0.564$, $\mu = 1.031$, $\beta = 111.27$, 1st monthly weight = 0.189, 2nd monthly weight = 0.367, 3rd monthly weight = 0.267, $R^2 = 0.367$.

Exponential Almon weights: $w_i^{almon}(\theta_1, \theta_2) = \frac{e^{\theta_1 i + \theta_2 i^2}}{\sum_{i=1}^{N} e^{\theta_1 i + \theta_2 i^2}}$. For PMI, we have: $\mu_0 = 0.598$, $\mu = 0.988$, $\beta = 0.867$, 1st monthly weight = 0.277, 2nd monthly weight = 0.423, 3rd monthly weight = 0.168, $R^2 = 0.45$. For NMI, the figures are: $\mu_0 = 0.564$, $\mu = 1.031$, $\beta = 0.831$, 1st monthly weight = 0.19, 2nd monthly weight = 0.369, 3rd monthly weight = 0.272, $R^2 = 0.367$.

In general, the results tend to be similar across weight parameterizations, the 2nd monthly weight tends to be higher than the other two weights, and the explanatory power of the MIDAS models with PMI and NMI is not as high as with the regressions reported in section 3.1.

The MIDAS model's explanatory power does increase if additional MIDAS lags are introduced; for instance, specifications with additional MIDAS lags coming from the last two quarters has substantially higher adjusted R^2's. Table 1 reports the manufacturing and non-manufacturing results from a specification with one dependent variable lag, 2 quarter PMI (or NMI) lags, and step function weights, which are as follows: $\beta w_i^{step}(\theta_1, ..., \theta_P) = \theta_1 I_{i \in [a_0, a_1]} + \sum_{p=2}^{P} \theta_p I_{i \in (a_{p-1}, a_p]}$, with $a_0 = 1 < a_1 < ... < a_P = N$, and $I_{i \in [a_{p-1}, a_p]} = \begin{cases} 1, & a_{p-1} \leq i \leq a_p \\ 0, & \text{otherwise} \end{cases}$.

This specification allows for equality restriction(s) for subsets of the MIDAS-lag coefficients (for instance, we can introduce a restriction where the same step-weight applies to several lags). Here, however, we estimate one parameter per each monthly sampling of the PMI (or the NMI). Thus, in Table 1, we have a total of 9 slope coefficients (as there are three quarters, the current one plus the previous two), which are also the monthly weights.

As we can see in Table 1, the MIDAS lag coefficients are positive and significant, for both the PMI and NMI models, except for a few cases from past quarters. Again as before, the current quarter 2nd month MIDAS lag coefficient is higher than the other two months for both PMI and NMI. Model fits are better than with the MIDAS models without the extra lags discussed above, and are comparable to those we obtained with Koenig's regressions, and about the same for both PMI and NMI (the adjusted R^2's are 0.514 and 0.495, respectively).

Of course, one must be cautious when comparing PMI and NMI results; the two estimation time periods are quite different (1965:03 to 2011:11 for manufacturing, and 1997:07 to 2011:11 for non-manufacturing). In fact, when the PMI model is estimated over the NMI sample the adjusted R^2 is only 0.35, suggesting that over this later period NMI does a better job than PMI.

Furthermore, we have strong prior reasons to suspect temporal instability. For instance, simple correlations between the PMI and GDP variables over subsamples can be quite different, and this correlation is indeed much lower (0.44) during the relatively stable period 1984-2000 than during either earlier periods or the period since 2001. We gain some insight into temporal stability issues more generally by running recursive regressions of the MIDAS model discussed in the previous paragraph. Figure 2 presents the adjusted R^2's, starting in 1977, for PMI, and Figure 3 has the adjusted R^2's, starting in 2004, for NMI. The contrast between the two figures is striking: There is a clear, almost monotonic decrease in the PMI model fit for most of the time[6], which contrasts starkly with an equally clear increase in the NMI model fit for much of the time. Thus, we consider the main conclusion of this exercise to be a strengthening of the message of the previous section regarding the increasingly important role of non-manufacturing ISM indices, which however, have not received as much attention as the PMI.

Over all, the main findings of this section are, first, the evidence of the increasingly central role of non-manufacturing information, and second that both PMI and NMI by themselves have significant explanatory power in nowcasting current quarter GDP growth. Whereas the first finding is new, the second one is consistent with results from numerous previous studies, and it suggests that the media and the policy makers' interest in ISM is understandable. However, ISM indicators exist together with many others in the economy with which the ISM indices are expected to be highly correlated. So the question is: how significant is the marginal contribution of ISM indicators given other indicators, and how important is the fact that PMI and NMI are announced ahead of other indicators at the beginning of each month. We attempt to answer this question in what comes next.

[6]Note that while the R^2 drops for most of the time, the drop tapers off and there is even an increase during the second half of the last decade, and also in the late seventies/early eighties. This pattern is not consistent with the hypothesis that correlation of PMI with GDP has diminished after 1984 due to better inventory control practices (McConnell and Perez-Quiroz 2000). One explanation of our finding is that during crisis periods, the factors that PMI represents (e.g., supplier deliveries, Inventories, etc.) tend to have closer relationship with the economy. During prolonged periods of stable growth PMI may possibly lose its relative advantage.

4 Nowcasting GDP growth using the framework of Giannone, Reichlin, and Small

The approach of GRS that we employ combines a dynamic factor framework with the Kalman smoother. It thus deals not only with the mixed frequency issue discussed above, but also with the other two central challenges associated with nowcasting using large data sets, (as discussed in the introduction, namely the large number of variables with a potential proliferation of parameters, and the jagged edges of the data set)[7]. Furthermore, it has the potential to capture essential dynamics in the various time series of the panel. The rest of this section summarizes the GRS approach, keeping their notation intact. The reader is referred to their paper for more detailed information.

It is assumed that the information included in the large number of explanatory variables is captured by a few common factors:

$$x_{t|\nu_j} = \mu + \Lambda F_t + \xi_{t|\nu_j} \tag{1}$$

where $x_{t|\nu_j}$ is an $n \times 1$ vector of observed explanatory variables[8] available in vintage ν_j ($j = 1, ..., J$), in month ν. In practice GRS create 15 vintages per month (so 45 in a quarter) based on their analysis of the pattern of data releases every month (this pattern is about the same across months, which justifies this approach). F_t is an $r \times 1$ vector of the common factors and Λ is an $n \times r$ matrix of factor loadings. The dynamics of the common factors are modeled as follows:

$$F_t = AF_{t-1} + Bu_t \tag{2}$$

where u_t is a $q \times 1$ white noise vector of shocks to the common factors and B is an $r \times q$ matrix of rank q. A is an $r \times r$ matrix with all roots of $\det(I_r - Az)$ lying outside the unit circle. GRS parameterize (and make a robustness case for) their benchmark specification with $r = q = 2$ and

[7]Note that alternative ways have been proposed in the literature for the task of estimating and forecasting using large data sets with mixed frequencies and jagged edges. For instance, an interesting study by Marcellino and Schumacher (2010) proposes an approach that applies MIDAS techniques on factors obtained from data sets of many higher frequency variables. By combining MIDAS with a factor model, it consequently handles all the estimation challenges discussed here.

[8]These variables have been transformed to induce stationarity. We keep GRS's transformations intact, and we thus refer the reader to (the appendix to) GRS for the details.

we keep the same parameterization in what follows. Note that the idiosyncratic error terms $\xi_{t|\nu_j}$ are assumed to be cross-sectionally orthogonal white noises and also orthogonal to shocks u_t.

Note that with equations (1) and (2) we have a state space framework and we can thus apply standard Kalman filtering techniques to estimate the common factors, given parameter estimates. GRS proceed with the estimation as follows: First, they apply principal components to a balanced-panel subset of the original jagged-edge data set[9] and estimate the parameters above by OLS regressions on these principal components. Then the common factors are estimated by running the Kalman smoother using the entire (thus unbalanced) data set, where parameter estimates replace true parameter values in the state space specification above. Given such estimates of the common factors, GDP nowcasts emerge simply as the fitted values from OLS regressions of the quarterly GDP series on these quarterly estimated factors[10].

The jagged edge data set that GRS have put together consists of close to 200 macro variables for the US economy starting in January of 1982. These variables, most of which are at the monthly frequency, and which include real and monetary quantities, prices, surveys, are grouped into blocks, or vintages, 15 per month, on the basis of a stylized calendar of monthly data releases that remains (mostly) unchanged across months. This data set (of the original GRS paper) was collected at a single point in time, and thus cannot be used to take into account data revisions and their possible effect on the nowcasts. We employ this "pseudo real-time" data set in parts of the analysis that follows. However, we also put to use in the next section a *true* real-time version of the GRS data set, which enables us to account for data revisions as well. This data set[11] is updated every Friday with any and all releases that are available at that point. Therefore we essentially have a series of overlapping, real-time sets with any later data set differing from previous ones for one or both of two possible reasons: updated figures for a given observation(s) of one or more variables in the data set, and/or more recent observations for one or more variables in the data set.

The GRS data that we use in what follows does include the five ISM manufacturing variables

[9] This balanced panel is created by discarding observations that are not available for all the variables.

[10] As discussed earlier, and unlike the GDP series, most of the observables in the GRS data set come at the monthly frequency. GRS thus further transform them by applying a filter (Mariano and Murasawa 2003) that converts the monthly series to an (approximately) quarterly quantity when observed at the end of a quarter. Thus the OLS regressions are run at the quarterly frequency for both the dependent variable and the regressors. This is GRS's approach to the more simplistic *bridge regressions* of standard nowcasting practice.

[11] The data, which were kindly provided to us by David Small, are the series used in Giannone et al (2010), minus a few proprietary series.

discussed earlier that are used to construct the PMI, but not the ISM non-manufacturing series. We thus augment the GRS data set with non-manufacturing information and with any additional ISM manufacturing indices that could be potentially beneficial. We thus end up considering materials buying prices (in addition to PMI and its five indices) on the manufacturing side, and six non-manufacturing indices: inventories, new orders, deliveries, employment, prices, and business activity.

5 Assessing the Nowcasting Performance of ISM variables

Our goal in this section is to evaluate the performance of the ISM variables (both when considered in isolation and when bundled together) in nowcasting GDP, always in the context of an environment where many macro variables are part of our information set at any point in time within any quarter. Other recent work (for instance, and in addition to GRS, see Banbura et al (2011) and Camacho and Perez-Quiros (2010)) has stressed the importance of the timeliness issue when it comes to survey data's impact on nowcasts. Timeliness must certainly be a central factor when it comes to the ISM data in particular; as discussed earlier, the ISM manufacturing indices become available first thing every month and their non-manufacturing counterparts come out soon after that.

We thus probe deeper into both of these issues, namely the marginal impact of the ISM variables on the nowcasts and the timeliness factor, with a view to gaining some insight on the following three questions: Suppose you are located at the end of month $\nu - 1$ or the beginning of month ν, and your task is to nowcast (or forecast, if month $\nu - 1$ is the last month of the previous quarter) GDP for the quarter in which month ν belongs. First, do ISM data help in this task? Second, which (any or all) ISM variables do help and what's the role of PMI in this task? Third, what's the added value, if any, of non-manufacturing ISM data?

Our first take in attempting to answer these questions is by looking at the time series of the nowcasts, and by assessing how their in-sample fit is affected by the various ISM indices (together or in isolation). However, this simple exercise does not capture the timeliness issue discussed above, nor does it account for forecast uncertainty. We therefore proceed, in a second step, to compute out-of-sample Mean Square Forecast Errors, while again focusing on the effect of the ISM variables. Finally, we conduct a true real-time analysis (using the real-time vintages described in the previous section) of various quarters in isolation (corresponding to the periods before, during, and after the Great Recession of 2007-2009); for each of these quarters we consider different scenarios where we nowcast using information available in real time at the very beginning of a month, and then add one or more observations from ISM indices to our information set and see how this affects the nowcasts of quarterly GDP growth rates.

5.1 The marginal impact of ISM indices on nowcast accuracy

We first compute the "nowcasts", or more precisely, the fitted values of GDP growth rates obtained using the factors F_t, (estimated using the state-space approach of equations (1) and (2)), over the entire historical period. We repeat this several times, each time leaving out one (or more) ISM indices from the raw data used to estimate the factors. These exercises produce a series of figures, two of which are included in Figures 4a and 4b. These figures, which plot realized GDP growth, nowcasts obtained without using any ISM indices, and nowcasts obtained using one or more ISM indices[12], enable us to assess how well the nowcasts track realized GDP growth, with or without ISM information. These figures lead us to two immediate conclusions:

First, we confirm the GRS observation that their approach leads to good in sample fits - the nowcasts track the realized GDP growth rates well. Second, it seems that ISM variables do not make a big difference, when it comes to in-sample fit: the nowcast lines obtained with and without ISM indices are largely congruent[13].

One might be tempted then to cast doubt on the importance of these ISM indices altogether. However, this would be premature: As discussed above, the exercise here ignores (being in-sample) the timeliness issue, the real-time nature of the data, as well as nowcast uncertainty. All of these issues of course are of paramount importance from the perspective of a policy maker or of an econometrician seeking to assess the evolution of GDP in real time and in a timely manner.

[12] The full set of figures is available from the authors. Here we include two examples: The first one includes all the ISM manufacturing variables, and the second one includes nowcasts produced using the five non-manufacturing ISM indices.

[13] As discussed earlier, the data are transformed into "quarterly equivalents" using the approximation introduced by the Mariano and Murasawa filter (Mariano and Murasawa 2003). As a robustness check, we also computed in sample fits using factors estimated using data without applying the filter; the results were very similar and the conclusions reached (regarding the role of ISM variables in sample) are the same. Note that the RMSE from this exercise (using all three months' factors) was found to be 32.4% less than the RMSE using only the PMI series (see MIDAS results in Table 1). This is one way of illustrating the value of the GRS approach to nowcasting using many indicators, compared to univariate benchmarks.

In the exercises that follow, we thus seek to replicate more closely the actual environment faced by a nowcaster in real time. To assess the marginal impact of ISM indices on the accuracy of the nowcasts, we perform an exercise similar to the "pseudo" real-time exercise of GRS, replacing their 15 "stylized monthly" data releases by various ISM variables, considered either jointly or in isolation.

More specifically, we first produce a nowcast of current-quarter GDP growth using observations that approximate the information set available at the very beginning of the month, that is even before the ISM manufacturing release of the first business day of the month. Then we repeat this exercise using an expanded information set that includes the extra observation on the PMI that becomes available in the beginning of the month. Subsequently we repeat this exercise six times, each time augmenting the information set with an extra observation coming from one of the five ISM indices that are part of the PMI (New Orders, Production, Employment, Supplier Deliveries and Inventories) or from Prices. Finally, we produce another nowcast using all the new observations coming from all of the five indices that enter the PMI together[14]. Then we repeat, for all the subsequent months[15]; that is, we compute a series of nowcasts recursively, and we measure (out-of-sample) nowcast uncertainty by estimating Mean Square Forecast Errors (MSFE). The results of this recursive exercise are depicted in Figure 5a, which shows both the evolution of MSFE across months through a quarter, and the marginal impact of ISM information within a month. Several conclusions emerge from this figure:

First, we confirm the conclusion of GRS that forecast accuracy increases precipitously as the quarter progresses and more information (from accumulating data releases) gathers.

Second, and for any month, one or more ISM variables help in increasing accuracy; while most ISM indices help, it is hard to identify a specific index that clearly outperforms the rest (in reducing uncertainty).

Third, incorporating the PMI and/or all the indices together always results in reduced MSFE.

[14] Note that this is different than using the PMI: The PMI is a composite index that imposes equal weights, whereas with this approach we allow the weights to be estimated. Indeed they are essentially weights based on the dynamic factor estimation as discussed earlier; This is pretty much in the spirit of Carriero and Marcellino (2011) who study survey indicators in the context of the European Union.

[15] We also include a fourth month in our figures; that is, we compute the nowcasts obtained using the information set available at the very end of a quarter, with and without the extra ISM information coming in the very beginning of the following quarter (and thus well before any GDP figures on the quarter that just ended become available by the BEA).

Clearly, the last two conclusions taken together suggest that the nowcaster should pay attention to the latest ISM manufacturing information as soon as it gets released in the beginning of the month as it always has a role in reducing MSFE.

We then focus on the role of the Non-Manufacturing ISM indices in a similar way: Figure 5b shows MSFEs for each of the months of the quarter (that is, the three months of the quarter plus the fourth month as discussed before) corresponding to nowcasts that are obtained as follows: First, before the ISM release at the beginning of the month; second, using the new PMI observation only (i.e., as the sole addition to the information set available at the very beginning of the month); third, using extra observation(s) coming from the non-manufacturing indices only, first individually, and then jointly[16]. The main observation that one can make using this exercise (in addition to the ones obtained with the manufacturing exercise) is that non-manufacturing information is useful in reducing nowcast uncertainty, and indeed more so than the PMI, as introducing the non-manufacturing indices together ("All") reduces the MSFEs more so than the PMI does[17]. One important caveat that must be added here though is that the period over which the MSFEs are computed is much shorter, as, non-manufacturing indices, and in contrast to their manufacturing counterparts, are only available starting in July of 1997.

In light of this, and also in light of the earlier discussion on temporal stability, it would be useful to investigate to what extent the observations and conclusions stated above are temporally stable and also statistically significant. We thus repeat the manufacturing MSFE exercise for the shorter non-manufacturing forecast evaluation sample, thus making the manufacturing/non-manufacturing results more directly comparable; we further break the longer manufacturing forecast evaluation sample into three subsamples (1986:01-1993:09, 1993:10-2001:06, and 2001:07-2009:12), and we also consider an additional exercise where the earlier two of these three subsamples are merged. We then do, for all these samples, standard Diebold-Mariano tests[18] for comparing predictive accuracy (Diebold and Mariano (1995)) where we compare the nowcasts obtained before the latest ISM release (as described above) to those obtained when we incorporate the latest ISM information,

[16] Specifically, these non-manufacturing diffusion indices are: The non-manufacturing Business Activity Index, Employment, Inventories, New Orders, and Supplier Deliveries.

[17] We also conducted an exercise where we compared MSFEs associated with nowcasts obtained by completely removing (or adding) ISM variables from the information set. We reached similar results and conclusions.

[18] We also repeat these tests using the small sample modification of Diebold-Mariano proposed by Harvey et al (1997). The results are about the same, so here we report the Diebold-Mariano p-values.

coming, first, from the 5 manufacturing indices, and second, from the 5 non-manufacturing indices (again as described above).

The full-sample p-values for the manufacturing vs "no ISM" test are 0.4563, 0.1817, 0.6436, and 0.5246, for the 1st, 2nd, 3rd, and 4th months, respectively, thus none are statistically significant. The respective non-manufacturing p-values are: 0.2743, 0.0918, 0.0048, and 0.0584. When it comes to the manufacturing p-values for the subsamples, it is only the nowcast improvements over the second subperiod (i.e., 1993:10-2001:06) that are statistically significant; in particular, the improvements over the third subperiod (for which we also have the non-manufacturing information) are not significant. Finally, and for the case of manufacturing vs no ISM using the first two evaluation subsamples (i.e., 1986:01-2001:06), it is only the 4th month for which the improvement is statistically significant at the 5% level.[19]

These results clearly cast some doubt on the statistical significance of nowcast improvements one gets by incorporating the latest manufacturing information. However, they also provide statistical support to the picture suggested by Figure 5b and outlined above, namely that non-manufacturing ISM information is useful, and at a very minimum at least as useful as manufacturing information, in improving the GDP nowcast in the beginning of the month. We regard this finding, which also adds to the results on the importance of non-manufacturing obtained in the bivariate context of Section 3, as important. It is especially significant in the context of the existing academic literature on surveys and the ISM that has largely ignored the non-manufacturing indices and has studied mostly manufacturing information and the PMI.

Of course, and as discussed above, all these observations of this section are made using a pseudo-real time data set. The exercise that follows aims to get even closer to actual nowcasting conditions by employing the sequence of real time data sets discussed in the previous section, thus also taking into account the role of data revisions.

5.2 Nowcasting with ISM in real time during the Great Recession

We consider nineteen quarters in isolation starting in 2007 Q1 and ending in 2011 Q3, that is the periods before, during, and after the latest recession (2007 Q4 to 2009 Q2), which is arguably a

[19] Note that for recursive MSFE comparisons in nested model situations, as in our case, the standard Diebold-Mariano approach tends to be conservative. Thus, the true contribution of the ISM indicators could be higher than that suggested by these p-values, see Clark and McCracken (forthcoming).

challenging period from a nowcasting perspective (Figures 6a and 6b). For each of these quarters, and in a manner similar to before, we do the following exercises:

First, we produce a forecast for quarterly GDP growth rate at the beginning of the first month of the quarter, say month ν, on the basis of the information set that would have been available in real time at the very end of month $\nu - 1$, or early in the morning of the first business day of month ν; that is, right before month ν's ISM manufacturing release becomes available[20].

Second, and as before, we generate additional five nowcasts by augmenting the information set just described with the new observation from each of the five diffusion indices (one at a time) that are part of the PMI: New Orders, Production, Employment, Supplier Deliveries and Inventories.

Third, we continue again as above: we repeat this exercise introducing all five indices at the same time, and the PMI on its own. Thus, on the horizontal axis, "No ISM" denotes dynamic factor model forecasts generated in real time using the large set of predictors without the latest information from any of the ISM indicators. Each of the other seven categories (e.g., Prod. only, Empl. only, All 5, etc.) denotes forecasts generated by 'No ISM' plus (the latest observation(s) of) ISM production, employment, all five ISM indicators together, etc. Successive panels also indicate how these large set of indicators were performing in nowcasting quarterly GDP growth in real time as the recession was progressing quarter by quarter.

We thus have eight nowcasts in total per month ("No ISM", "Production only", "Employment only", "Inventories only", "New Orders only", "Supplier Deliveries only", "All 5", and "PMI only") which are to be assessed in terms of how far they are from the real time GDP growth figure. The results for the first eighteen quarters are summarized in the eighteen separate panels (nine in each page) of Figure 6a[21], which contain a straight dotted line (the preliminary GDP growth figure) and four additional lines for the four months corresponding to a quarter. The eight nowcasts are on the horizontal axis of these graphs. Looking at these figures, we can reach some interesting conclusions, several of which are qualitatively similar to the ones we reached above:

There is clear evidence that some ISM information almost always helps improve the nowcasts

[20] Then we produce similar nowcasts for months $\nu+1$, $\nu+2$, and $\nu+3$. Given that the survey solicits information for month-over-month changes, nowcasts for $\nu+1$, $\nu+2$, and $\nu+3$ relate directly to the quarter in question. As discussed earlier, we have a sequence of sets that contain real-time data as they are available on Fridays. Since the lag between the first business day of the month and the closest real-time Friday data release differs from month to month, we painstakingly had to do some adjustments to these Friday data sets on a case by case basis, according to the calendar of data releases to create the information sets we needed for our purposes.

[21] To fit in two pages, we do not include the 2011Q3 panel in Figure 6a, but it is available upon request.

in the beginning of the month, even if only by a little, as in 97.4% of cases (74 out of $19 \times 4 = 76$) at least one of the 7 nowcasts obtained when incorporating the latest ISM observation(s) is better (closer to the GDP line) than its "No ISM" counterpart.

When it comes to nowcasts obtained with the 5 individual ISM indices, 3 out of 5 on average per quarter outperform the "No ISM" nowcasts. However, it is not possible to securely identify any individual indices that consistently overperform, as good performance by a given index in some months or quarters tends to be offset by relatively poor performance at other times. When it comes to underperformers though, the supplier deliveries index does tend to produce nowcasts that are worse than the other four[22].

Given the above result, one would expect that bundling the 5 indices together, either in the PMI, or with different weights as in "All 5" would be a strategy that is likely to yield better nowcasts than the "No ISM" approach, and that is indeed the case (57.9% of the time with the PMI, and 63.2% of the time with "All 5"). Furthermore, in bilateral comparisons between the PMI and "All 5", these two fare about the same, with the latter only having a slight edge (as it outperforms the PMI 52.6% of the time).

Additionally, in bilateral comparisons between, on the one hand, the better of PMI and "All 5", and, on the other hand, the best of the 5 individual indices, which, as discussed above, typically changes from month to month, the (switching) best of the 5 indicators outperforms the indices taken together (either in the PMI or in "All 5") 61.8% of the time. This finding, in conjunction with the one before, suggests that the issue of equal vs freely estimated weights in combined ISM indices may not be that consequential after all. As pointed out earlier, this is an issue that the existing ISM literature has considered. Rather, one could explore alternative approaches that allow for evolving weights, as opposed to the fixed weights resulting from the GRS model with time-invariant factor loadings.

Furthermore, and consistent with our earlier findings and with the nowcasting literature, nowcasts do get better (i.e., tend to move closer to the target GDP growth estimate) as we progress to later months within a quarter. Indeed, two thirds of the time on average within a quarter a given month's nowcast is better than the previous month's nowcast, and in half of all quarters there is

[22] It is interesting to note here that the Conference Board very recently removed ISM Supplier Deliveries from their Leading Economic Index (and replaced it with the ISM New Orders Index).

nowcast improvement monotonically throughout the quarter.

We also investigate the role of non-manufacturing ISM indices in a similar manner: We generate nowcasts using information at the beginning of the month without the new ISM data, and then we see how these nowcasts change when we introduce new observations coming from non-manufacturing ISM indices - or the new observation coming from the PMI. Results for the 18 quarters are provided in the 18 panels of Figure 6b. The conclusions reached are similar to the ones already discussed in the previous case - both non-manufacturing information and the PMI tend to help nowcasts over the factor model nowcasts without the latest ISM observations. The relative contribution of NMI over PMI is not consistent over all quarters examined, however. In terms of relative performance, the non-manufacturing nowcasts are the best 39.5% of the time, the PMI nowcasts are best 35.5% of the time, and the "No ISM" nowcasts win 25% of the time. Thus, our conclusion from this exercise is similar to the one from the MSFE exercise of the previous section: Despite the little attention non-manufacturing ISM information has gotten so far, non-manufacturing nowcasts are at least as good as PMI nowcasts, or even better.

It would be interesting to note here that since we cover in real time the periods before, during, and after the latest NBER recession, we may be able to get some insight on the issue of whether ISM information tends to be more or less helpful in recessionary periods compared to more "normal" times. We did not observe any robust changes in the patterns discussed in the exercises above between the recession and the short periods before/after the recession. However, we also computed MSFEs for the recession/non-recession periods, both for the manufacturing and non-manufacturing cases. These figures are: 4.724 for the "No ISM" nowcasts, and 4.428 for the "PMI" nowcasts over the entire period, 2007 Q1 - 2011 Q3; so we get a 6.27% improvement in the MSFE when we utilize the latest observation on the PMI to generate the nowcasts (as opposed to when we do not). These figures are higher for the recession period: 6.940 and 6.419, with the improvement thus being somewhat higher: 7.52%. The respective MSFE improvements in the non-manufacturing exercise are higher, for both periods: 6.5% (entire period) and 10.2% (recession). This analysis leads us to two conclusions: First, ISM indicators seem to have been at least as useful in nowcasting during the last recession as in the quarters immediately before and after. The second conclusion is the same as that discussed in the previous paragraph: non-manufacturing nowcasts are at least as good as those based on the PMI.

In a nutshell, a few useful prescriptions that emerge from the results of section 5.2, specifically as they pertain to the role of ISM in GDP nowcasts in real time, are: First, ISM information should be part of the information set used for the nowcasts, especially in the beginning of each month. Second, ISM indices, should be combined, possibly with time-varying weights. Third, and in contrast to much traditional practice, non-manufacturing ISM information should play a central role in generating these nowcasts.

6 Conclusions

The diffusion indices produced by the Institute for Supply Management are well known and highly publicized as they are generally thought to contain useful information about the economy's direction. As such, they have been studied extensively by various researchers. Much of the existing literature, nevertheless, tends to consider the ISM indices, and the PMI in particular, in isolation. However, what may be more interesting from, say, a policy maker's perspective who tries to assess the usefulness of ISM indices in nowcasting GDP (given the plethora of variables that could be used for that purpose), is the marginal impact of the ISM variables given all the other information that is available in real time. In this paper, we focus on this issue: we study the importance of ISM variables within the context of a large data set that is used to nowcast GDP growth. For this purpose, we employ the approach to nowcasting from large data sets developed by Giannone, Reichlin, and Small (2008).

We find evidence that the emphasis on ISM indices (both manufacturing and non-manufacturing) is in a sense well placed: Even in a context where many other variables are available, ISM indicators help us improve the nowcasts of current quarter GDP growth, as the quarter unfolds in real time. This is primarily because they become available first thing in the month and ahead of other indicators. Furthermore, we also find that the non-manufacturing indices have significant added value in nowcasting GDP. Thus, in contrast to existing practice of focusing on manufacturing ISM surveys, their non-manufacturing counterparts should play a central role in such nowcasting exercises.

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Table 1: MIDAS Model for Nowcasting Real GDP Growth

Variable	***Manufacturing (PMI)***			***Non-Manufacturing (NMI)***		
	Coefficient	*Std. Err.*	*p-value*	*Coefficient*	*Std. Err.*	*p-value*
Intercept	1.454	0.229	0.000	1.312	0.389	0.002
GDP growth-lag	0.417	0.065	0.000	0.450	0.125	0.001
Current quarter Month 1	0.291	0.075	0.000	0.226	0.115	0.056
Current quarter Month 2	0.314	0.074	0.000	0.418	0.137	0.004
Current quarter Month 3	0.135	0.073	0.064	0.310	0.167	0.070
Last quarter Month 1	0.102	0.076	0.184	0.254	0.125	0.049
Last quarter Month 2	0.065	0.073	0.372	0.440	0.135	0.002
Last quarter Month 3	0.324	0.074	0.000	0.311	0.168	0.071
2 quarters ago Month 1	0.153	0.076	0.046	0.269	0.136	0.054
2 quarters ago Month 2	0.025	0.072	0.725	-0.088	0.153	0.397
2 quarters ago Month 3	0.209	0.077	0.007	-0.093	0.162	0.570
Adjusted R-sq	0.514			0.495		
RMSE	2.190			1.643		
DW statistic	2.193			2.208		

Notes: The regressors are MIDAS lags corresponding to PMI (1965:03 – 2011:11) and NMI (1997:07 – 2011:11).

Figure 1: PMI and NMI

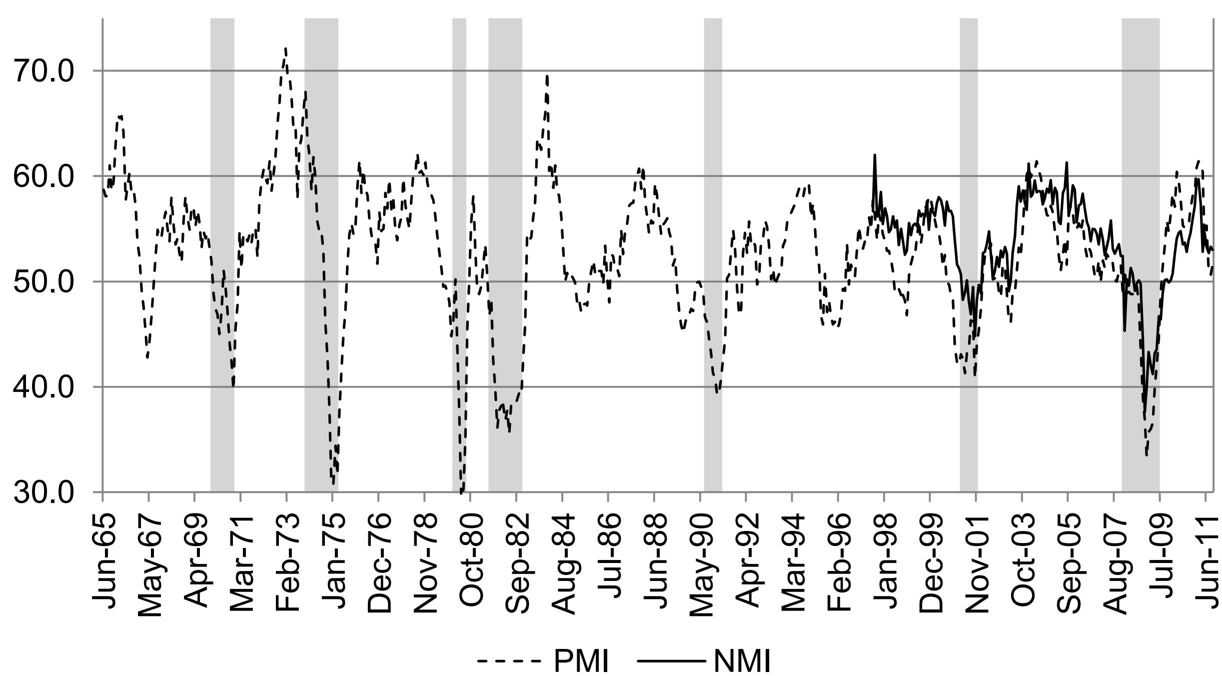

Figure 2: Adj. R^2 from Recursive PMI MIDAS Regressions

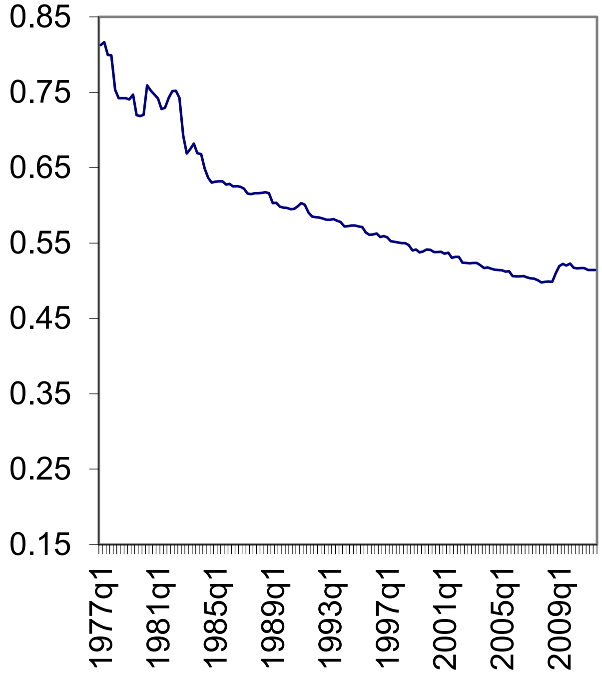

Figure 3: Adj. R^2 from Recursive NMI MIDAS Regressions

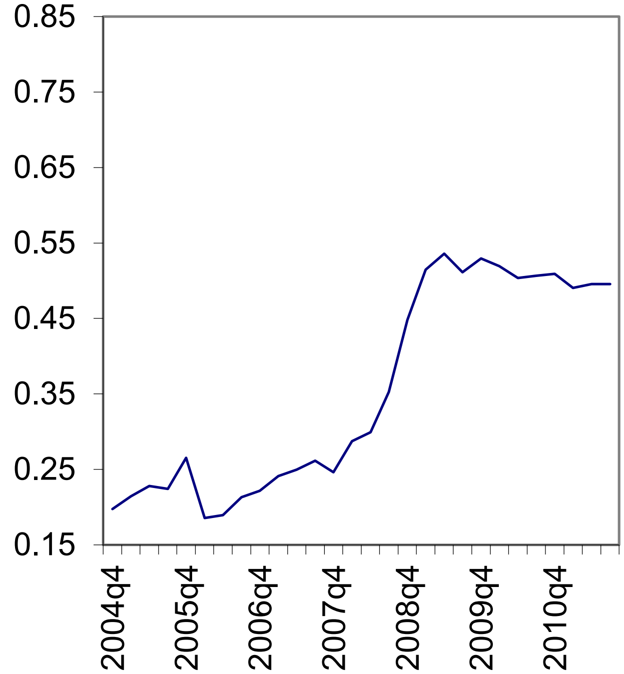

Figure 4a: In sample results (PMI only vs no ISM variables)

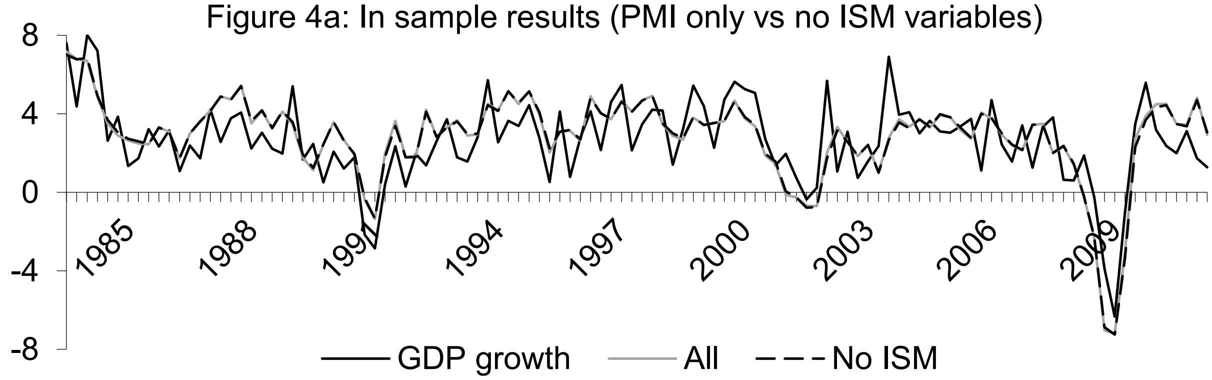

Figure 4b: In sample results (Non-Manufacturing vs Manufacturing ISM variables)

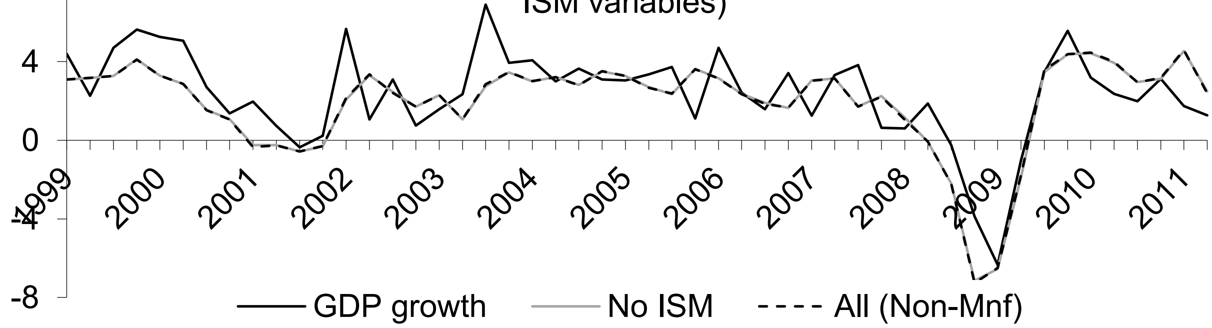

Figure 5a: MSFE for Various Manufacturing ISM Variables

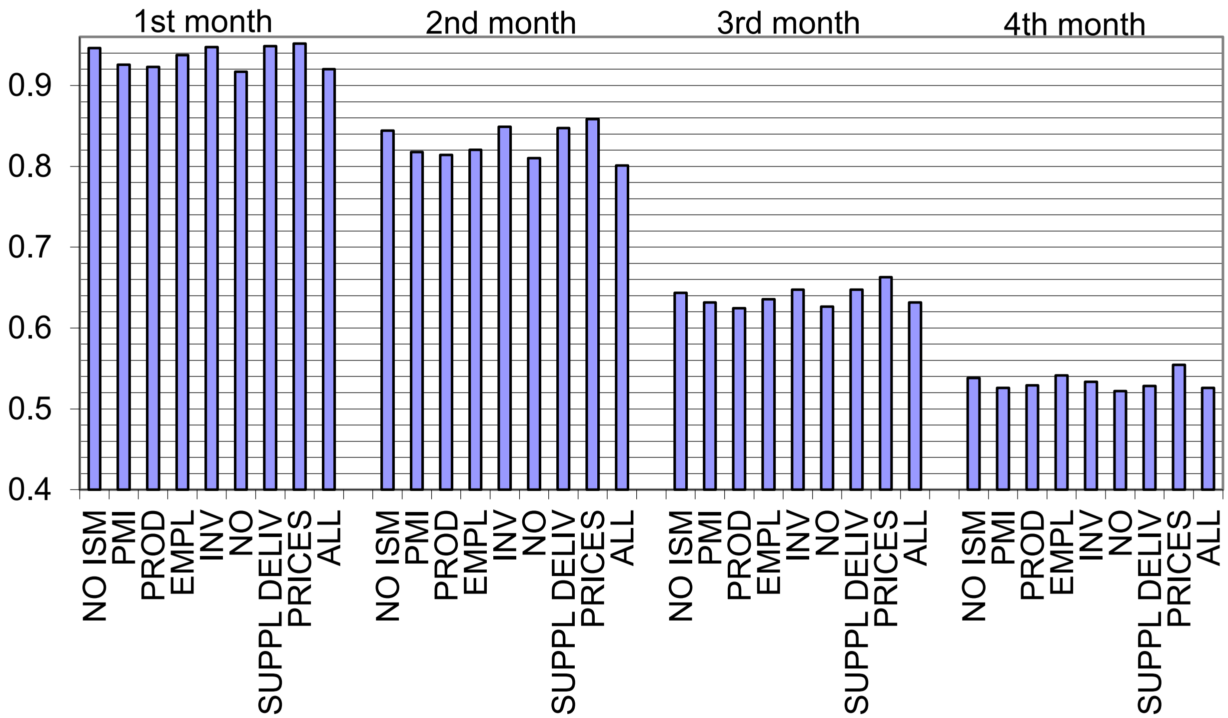

Figure 5b: MSFE for Non-Manufactuting ISM Variables and the PMI

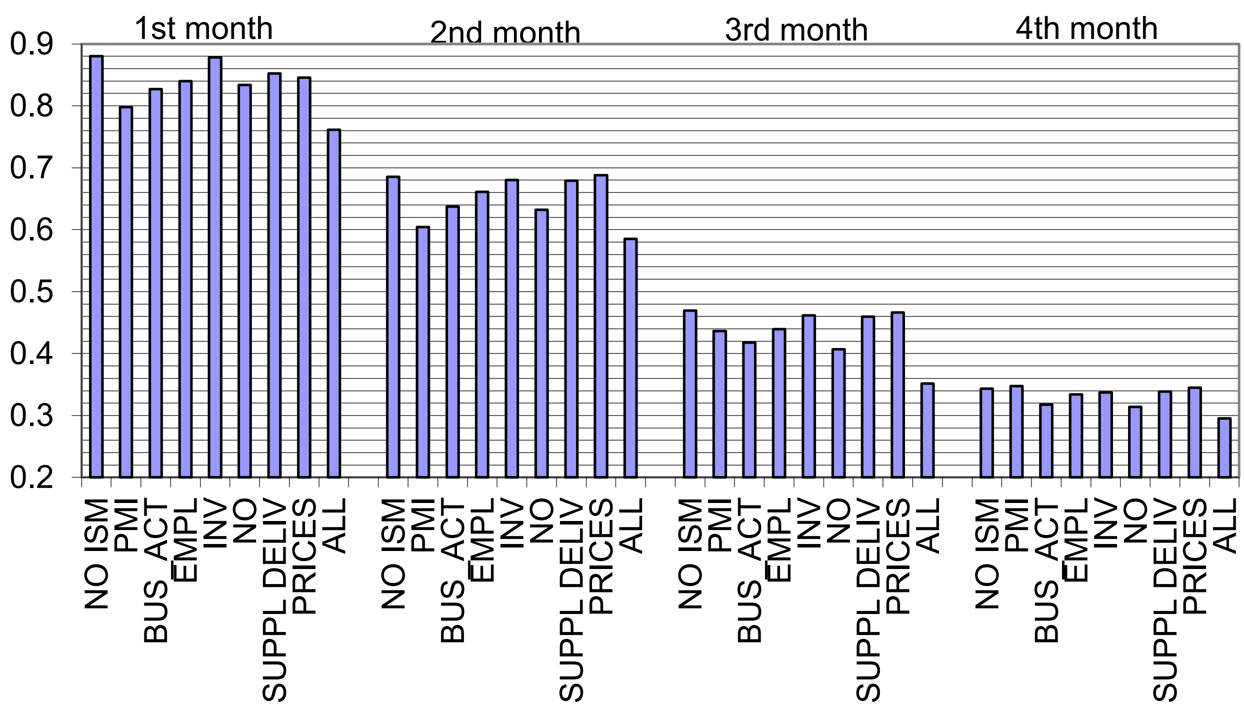

Figure 6a: Nowcasts in Real Time and the Great Recession

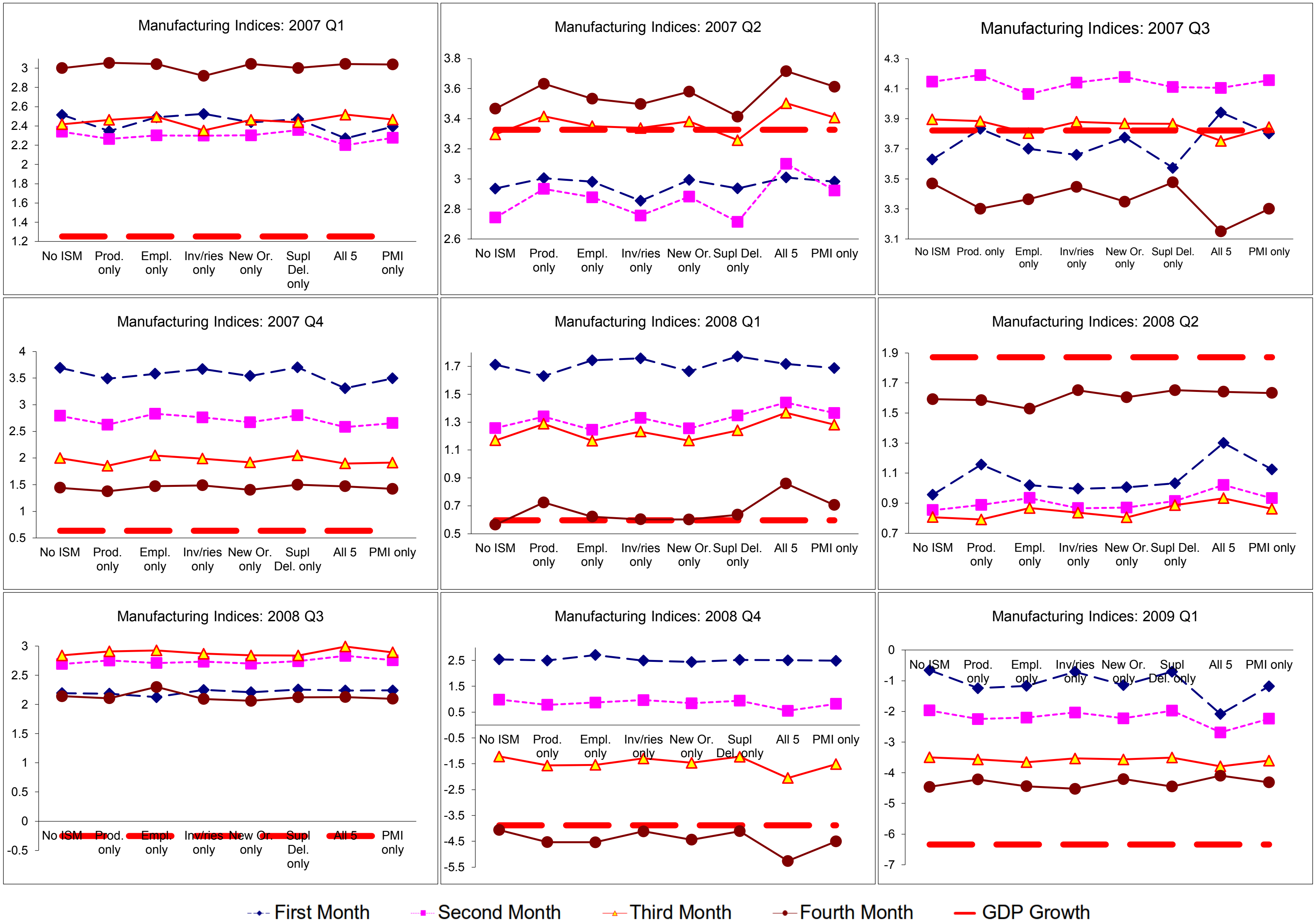

Figure 6a (continued): Nowcasts in Real Time and the Great Recession

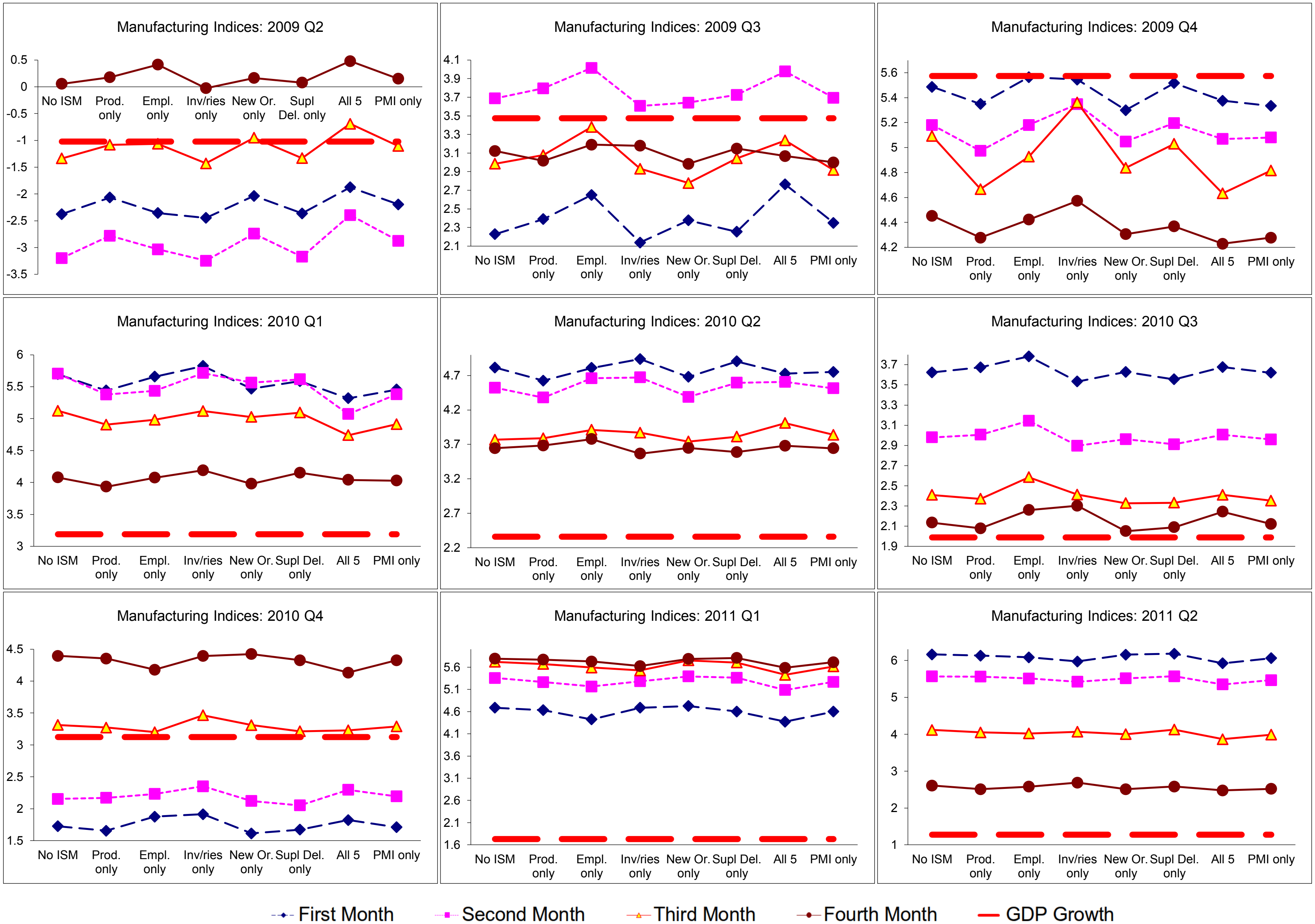

Figure 6b: Nowcasts in Real Time and the Great Recession

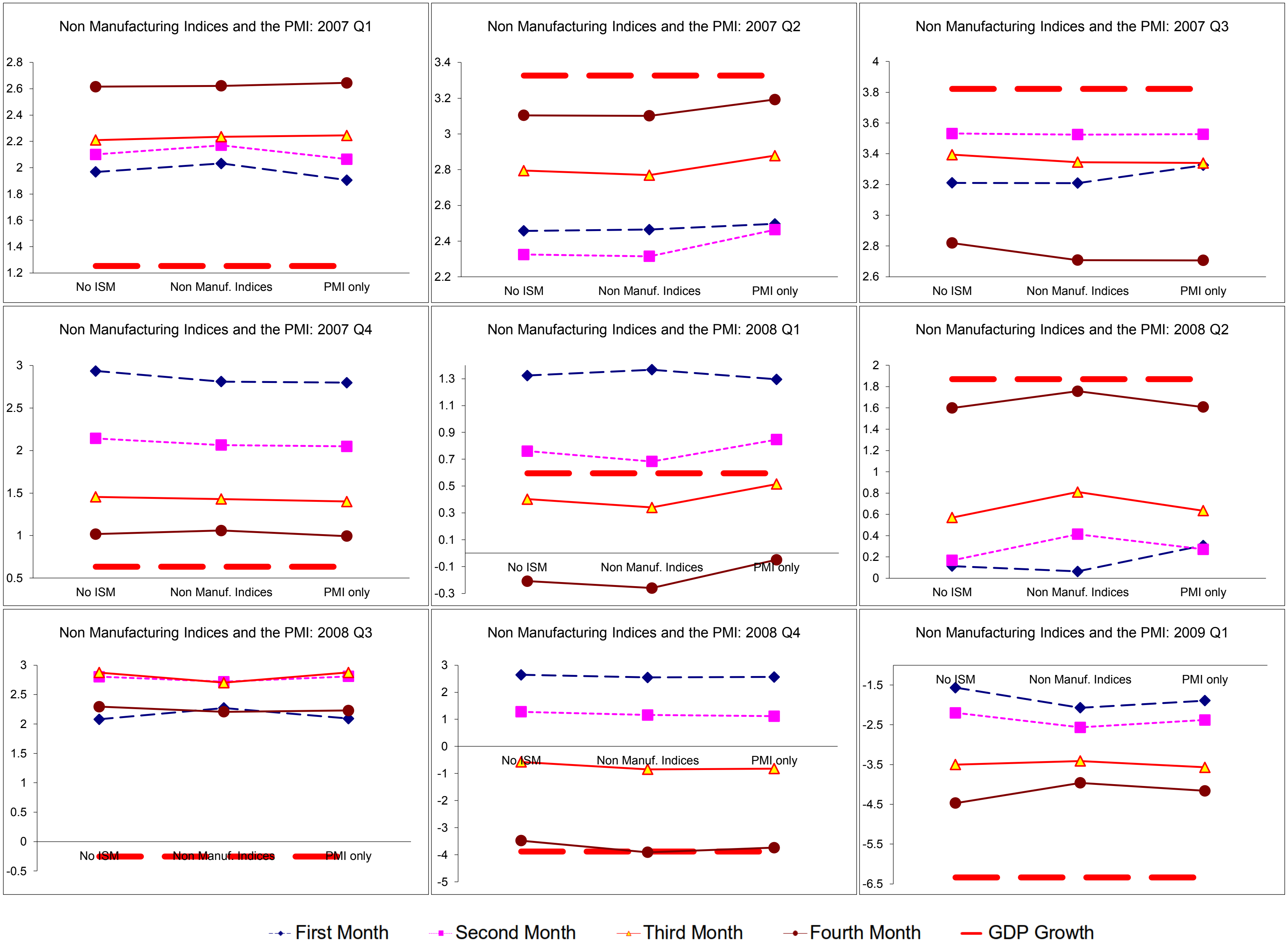

Figure 6b (continued): Nowcasts in Real Time and the Great Recession