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Learning About Informational Rigidities from Sectoral Data and Diffusion Indices

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Abstract

This paper uses sectoral data to study survey-based diffusion indices designed to capture changes in the business cycle in real time. The empirical framework recognizes that when answering survey questions regarding their firm's output, respondents potentially rely on infrequently updated information. The analysis then suggests that their answers reflect considerable information lags, on the order of 16 months on average. Moreover, because information stickiness leads respondents to filter out noisy output fluctuations when answering surveys, it helps explain why diffusion indices successfully track business cycles and their consequent widespread use. Conversely, the analysis shows that in a world populated by fully informed identical firms, as in the standard RBC framework for example, diffusion indices would instead be degenerate. Finally, the data suggest that information regarding changes in aggregate output tends to be sectorally concentrated. The paper, therefore, is able to offer basic guidelines for the design of surveys used to construct diffusion indices.

JEL classification: E32, C42, C43
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1 Introduction

Data provided by statistical agencies regarding the state of the economy typically lag current conditions. For example, manufacturing data are released with a one month lag by the Federal Reserve Board, revised up to three months after their initial release, and further subject to an annual revision. At the monthly frequency, this data is also quite noisy in a way that partially masks underlying business cycle conditions. Thus, in an alternative attempt to track the business cycle in real time, and to confirm initial Board data releases, information is also compiled by many institutions and government agencies from qualitative data. The Institute for Supply Management (ISM), for example, constructs a widely used monthly diffusion index of manufacturing production, based on nationwide surveys, that will be the focus of the analysis. In addition, several Federal Reserve Banks including Atlanta, Dallas, Kansas City, New York, Philadelphia, and Richmond, produce similar indices that are meant to capture real time changes in economic activity at a more regional level.[1]

A central issue pertaining to these surveys is that gathering information on a large number of sectors in a timely fashion is costly and, given time and resource constraints, the scope of the questions must necessarily be limited. Thus, diffusion indices constructed by the ISM and Federal Reserve Banks rely on simple trichotomous classifications whereby respondents are asked whether a variable, say production for that respondent's firm, is "up," "the same," or "down" relative to the previous period. The number of respondents can vary over time and the respondents themselves need not be the same from survey to survey. Individual responses are aggregated into proportions of respondents reporting a rise, no change, or a fall in output. Diffusion indices are then constructed by further converting these proportions into aggregate time series meant to track economic activity. The methods typically used in performing these conversions are discussed in detail in Section 2.

While various properties of diffusion indices, sometimes also referred to as balance statistics, have been studied in some detail, this work has been limited because firm-level data underlying individual survey responses are either not systematically recorded or not publicly available. It has proven challenging, therefore, to say much about the nature of survey responses, and whether they reflect informational rigidities. It has also been difficult to explain why converting qualitative answers in the way suggested by diffusion indices has proven useful in following economic activity in real time.[2]

[1] Other examples of popular national diffusion indices include the Employment Diffusion index constructed by the Bureau of Labor Statistics, and the Diffusion Index for Industrial Production constructed by the Board of Governors.

[2] Diffusion indices, however, have been used to investigate the extent to which expectations can be considered rational as well as to help forecast economic activity. See Pesaran and Weale (2006) for a comprehensive

In this paper, I use sectoral manufacturing data to construct an empirical framework composed of hypothetical survey respondents. Each respondent acts as a spokesperson for a firm whose output reflects both aggregate conditions and conditions specific to the sector in which it operates. Methods used to construct diffusion indices are then applied to these hypothetical respondents to create a synthetic diffusion index of manufacturing production that can be directly compared to that published by the Institute for Supply Management.

The analysis makes two key assumptions. First, information is costly to acquire so that survey respondents are not necessarily aware of their firm's exact output at each date. Specifically, I allow respondents to update their information set infrequently in the manner suggested by Mankiw and Reis (2002, 2006). Second, as noted in Pesaran and Weale (2006), respondents recognize that some changes in their firm's output are not necessarily meaningful so that increases or decreases are reported only when exceeding given thresholds. Under the maintained assumptions, a primary objective of the analysis is to provide estimates of i) the degree of information stickiness, and ii) the thresholds that define perceptions of rises and falls in output, that best describe the ISM manufacturing production index.

Using data on manufacturing production in 124 sectors over the period 1972-2009, I estimate that survey respondents update their expectations on average every 16 months. Furthermore, the data also suggest that the degree of information stickiness has fallen over time. Thus, using the onset of the Great Moderation to split the sample, the empirical work estimates an average information lag of 20 months prior to the Great Moderation compared to 13 months during the latter period. These findings, therefore, are consistent with a fall in the cost of acquiring information over time. For comparison, previous studies relying on non-truncated surveys and aggregate data have found average information stickiness of roughly 12 months, as presented in Carroll (2003) based on data from the Michigan Survey of Consumers and the Survey of Professional Forecasters (SPF), and 12.5 months, as calculated in Mankiw, Reis and Wolfers (2003) using similar information as well as the Livingston Survey. In a different vein, Mankiw and Reis (2006), and Reis (2009), use quantitative models to calibrate the degree of information stickiness by targeting different aspects of the cyclicality of aggregate variables or their responses to shocks. This work finds that information lags of 6 to 16 months are generally most consistent with salient features of the data. Most recently, Coibion and Gorodnichenko (2009) present evidence against the hypothesis of full information based on a variety of survey forecasts. Their findings suggest that forecast errors are persistent with a half-life of up to 16 months. More important, the dynamics of these forecast errors are consistent with predictions of models with informational rigidities. None

treatment of survey expectations. See also Ivaldi (1992), as well as Jeong and Maddala (1996), for studies of the rationality of survey data.

of these studies, however, include the detailed level of disaggregation exploited here.

A key implication of this paper is that informational rigidities provide a foundation for the widespread use of diffusion indices as contemporaneous economic indicators. In particular, these rigidities mean that a considerable fraction of respondents answer surveys based on what they expect their firm's output to be given their most recent information rather than actual production. Therefore, high frequency output fluctuations that are unrelated to business cycles tend to be filtered out. Accordingly, around 60 percent of the variation in the monthly ISM production diffusion index is located at business cycle frequencies compared to just 23 percent of the variance in monthly aggregate manufacturing. Information stickiness, therefore, in effect lets respondents abstract from "noisy" movements in sectoral production. The analysis further shows that in a world populated by identical firms that are always fully informed, as in the standard Real Business Cycle (RBC) environment for example, diffusion indices become degenerate and thus cease to be useful.[3]

As mentioned earlier, information on individual survey responses that underlie the construction of diffusion indices is either not recorded systematically or not made publicly available. In contrast, because the empirical framework involves the modeling of hypothetical survey respondents, it allows for the tracking, as a counterfactual of sort, of the proportions of "up," "same," and "down" responses over past business cycles. The empirical work then shows some notable differences in the historical behavior of these proportions. Prior to the Great Moderation, the proportion of "optimists" (those reporting expected output increases) and "pessimists" (those reporting expected output decreases) play an equal role in driving the diffusion index. Hence, recessions and expansions are reflected by corresponding spikes in the measure of "optimists" and "pessimists.' However, after the onset of the Great Moderation, while recessions are still marked by sharp increases in the proportion of "pessimists," movements in the proportion of "optimists" are considerably more subdued. Therefore, from this standpoint, the Great Moderation period is not only associated with a noticeable decline in volatility but also with an asymmetry in sectoral output fluctuations.

Finally, drawing on previous work in Foerster, Sarte and Watson (2008), the analysis suggests that information regarding changes in overall manufacturing tends to be concentrated in relatively few sectors. Hence, taking as given the methods by which qualitative survey responses are converted into a quantitative diffusion index, the empirical framework offers

[3] There is also a large literature that examines the pitfalls associated with ignoring the distinction between real time and revised data. These problems motivate in part the interest in creating diffusion indices. See Croushore (2009) for a recent and comprehensive survey of real-time data analysis. See also Runkle (1998), Croushore and Stark (2001), and Fernald and Wang (2005), for the challenges posed by data revisions to the making of policy in real time.

some basic lessons regarding the design of surveys that underlie these indices. First, contrary to standard practice at some Federal Reserve Banks, it is not necessary for surveys to try to capture a representative sample of all manufacturing. The intuition is straightforward. In some sectors, variations in output are driven almost entirely by aggregate factors while, in other sectors, output movements reflect mostly sector-specific considerations. Therefore, to gain insight into current aggregate business cycle conditions, surveys should emphasize the former sectors and largely disregard the latter sectors. Second, having identified sectors whose variations reflect mostly factors driving aggregate changes, I show that a useful diffusion index may be produced using as few as 15 sectors instead of all 124 sectors in the data set.

The rest of this paper is organized as follows. Section 2 describes the methods typically used to construct the ISM and other diffusion indices based on qualitative surveys. Section 3 highlights key differences between sectoral manufacturing production data and the ISM manufacturing production index. Section 4 then presents an empirical framework aimed at reconciling these differences under the assumption that survey respondents update their expectations only infrequently. The estimation methods and findings are reviewed in section 5. Section 6 performs a series of counterfactuals that illustrate how the usefulness of diffusion indices relates to different aspects of the economic environment. Section 7 offers concluding remarks.

2 Description of the ISM and other Production Diffusion Indices

The Institute for Supply Management is a large U.S. trade association comprising approximately 40,000 supply management professionals. As part of a broader mandate, it compiles a monthly Manufacturing Report on Business based on questions asked of purchasing executives. To keep the survey process straightforward, and to limit the burden on respondents, questions are posed in a format such that they reply with only one of three answers to indicate a change relative to the previous month. The spirit of the survey, therefore, is very much to capture some notion of changes in output otherwise reflected more formally in growth rates. In this case, answers regarding production are limited to "up," "the same," or "down," and an index is then constructed from the responses. Because this simplification lets respondents answer more quickly than if a precise answer regarding production changes (rather than a general assessment) were required, it is crucial to the timeliness of the index. The ISM calculates its index by adding the percentage of positive responses to half of the percentage of "same" responses.

Formally, let M represent the number of manufacturing sectors that make up total manufacturing as classified by the U.S. Census Bureau. Let x_t^{ij} denote the output of a given firm i working in a sector j at date t, and Δx_t^{ij} denote its growth rate relative to the previous period. Consider a survey that asks a sample of N respondents in each of these M manufacturing sectors whether their firm's output is "up" (u_t^{ij}), "the same" (s_t^{ij}), or "down" (d_t^{ij}), relative to the previous period. Following Pesaran and Weale (2006), the ISM surveying process would then typically be described as cataloging respondents' perception of changes in their firm's output at t relative to $t-1$ in the following manner:

$$\begin{aligned} &\text{if } \Delta x_t^{ij} > \tau, \text{ respondent } i \text{ reports "up"}; \; u_t^{ij}(\tau) = 1, \; s_t^{ij}(\tau) = d_t^{ij}(\tau) = 0, \\ &\text{if } -\tau \leq \Delta x_t^{ij} \leq \tau, \text{ respondent } i \text{ reports "same"}; \; s_t^{ij}(\tau) = 1, \; u_t^{ij}(\tau) = d_t^{ij}(\tau) = 0, \\ &\text{if } \Delta x_t^{ij} < -\tau, \text{ respondent } i \text{ reports "down"}; \; d_t^{ij}(\tau) = 1, \; u_t^{ij}(\tau) = s_t^{ij}(\tau) = 0. \end{aligned} \tag{1}$$

The interval $[-\tau, \tau]$ defines an indifference region that represents respondents' latent perceptions of rises and falls in output. It captures the idea that changes in output may not always be substantive enough to convey meaningful information, or that respondents may not be certain that they are, and therefore may not worth reporting as "up" or "down." An immediate implication is that whether an output change is considered "up," "same," or "down," depends intrinsically on the threshold that defines the bounds of the indifference interval. This dependence is made explicit by writing $u_t^{ij}(\tau)$, $s_t^{ij}(\tau)$, and $d_t^{ij}(\tau)$ in equation (1).

Given the structure of the surveys, the fraction of "optimists" in the sample is given by

$$U_t = M^{-1} N^{-1} \sum_{j=1}^{M} \sum_{i=1}^{N} u_t^{ij}(\tau). \tag{2}$$

Similarly, the fractions of "same" respondents and "pessimists" are given by

$$S_t = M^{-1} N^{-1} \sum_{j=1}^{M} \sum_{i=1}^{N} s_t^{ij}(\tau) \tag{3}$$

and

$$D_t = M^{-1} N^{-1} \sum_{j=1}^{M} \sum_{i=1}^{N} d_t^{ij}(\tau), \tag{4}$$

respectively. The value of the ISM diffusion index at t, denoted $\mathcal{I}_t$, is then defined as

$$\begin{aligned} \mathcal{I}_t &= \left(U_t + \frac{1}{2} S_t \right) \times 100 \\ &= M^{-1} N^{-1} \sum_{j=1}^{M} \sum_{i=1}^{N} \left(u_t^{ij}(\tau) + \frac{1}{2} s_t^{ij}(\tau) \right) \times 100. \end{aligned} \tag{5}$$

The resulting index values range from 0 to 100, with numbers above 50 generally indicating an expansion of economic activity.

In the case of the Federal Reserve Banks (FRB) surveys, the respondents are also asked to report only "increases," "decreases," and "no change" in output relative to the previous month, but the form of the index varies slightly relative to the ISM index. The FRB Richmond survey, for example, calculates its index by subtracting the percentage of negative responses from the percentage of positive responses, producing the so-called "balance statistic" motivated by the probability approach of Carlson and Parkin (1975). Hence, in this case, we have that

$$\begin{aligned} \mathcal{I}_t &= (U_t - D_t) \times 100 \\ &= M^{-1} N^{-1} \sum_{j=1}^{M} \sum_{i=1}^{N} \left(u_t^{ij}(\tau) - d_t^{ij}(\tau) \right) \times 100, \end{aligned} \tag{6}$$

which is bounded between -100 and 100 and takes on a value of zero when an equal number of respondents reports increases and decreases.

It is useful to note that actual changes in aggregate manufacturing output, denoted Δx_t, are given by

$$\Delta x_t = \sum_{j=1}^{M} w_t^j \Delta x_t^j, \tag{7}$$

where $\Delta x_t^j = \sum_i w_t^{ij} \Delta x_t^{ij}$ represents output growth in sector j, w_t^{ij} is the share (or weight) of firm i's production in sector j, and w_t^j is the share of sector j's output in aggregate production. Foerster, Sarte and Watson (2008) show that movements in Δx_t are relatively invariant to the exact sectoral weighting scheme so that the expression in (7) is well approximated by $M^{-1} \sum_{j=1}^{M} \Delta x_t^j = M^{-1} \sum_{j=1}^{M} \sum_i w_t^{ij} \Delta x_t^{ij}$. Therefore, if the sample of respondents, N, is large enough, the diffusion indices in (5) and (6) rely on approximately the same aggregation used to arrive at manufacturing output growth. A key difference, of course, is that the variables being aggregated in the diffusion indices are truncated reports of individual firm output changes (in the sense of being translated to 0s and 1s) rather than actual output growth.

Some key questions that the analysis will address are: i) How well does the ISM diffusion index of manufacturing production capture variations at business cycle frequencies and, moreover, how does it compare to actual manufacturing output growth? ii) How is the diffusion index's ability to track movements at business cycle frequencies related to various features of the environment, in particular the degree of information stickiness characterizing survey respondents? iii) Given an upper bound on the number of sectors that can feasibly be surveyed in a given period, how does one choose which sectors to survey? Put another way, how does one distinguish between sectors that are informative about the state of aggregate manufacturing and those that are not?

3 Basic Properties of Sectoral Manufacturing Data and the ISM Diffusion Index

Because Federal Reserve Banks' diffusion indices reflect regional rather than national conditions, and given that manufacturing data is unavailable at the state level, the analysis uses nation-wide sectoral manufacturing data and the corresponding ISM manufacturing production diffusion index. As explained above, the diffusion index is a monthly series obtained from the Institute for Supply Management constructed as in equation (5). Monthly data on manufacturing production are obtained from the Board of Governors over the period 1972-2009. The manufacturing sector is disaggregated into 124 industries according to the North American Industry Classification System (NAICS), which corresponds roughly to a six-digit level of disaggregation. The raw output data are used to compute sectoral growth rates as well as the relative shares of different sectors in aggregate manufacturing. Monthly growth rates (in percentage points) in sectoral output are computed as $\Delta x_t^j = \ln(X_t^j / X_{t-1}^j) \times 1200$, where X_t^j denotes production in the j^{th} sector at date t. The main properties of the data are described in Table A1.

Figures 1A and 1B show the behavior of manufacturing production growth, computed according to equation (7), and that of the monthly ISM manufacturing production index over the period 1972-2009. The intervals defined by the dashed vertical lines depict recessions dated by the National Bureau of Economic Research (NBER). Looking at Figure 1A, monthly growth rates in manufacturing productions are quite volatile, exceeding 8 percentage points (at an annual rate) over the whole sample period. The fall in volatility associated with the Great Moderation is also evident in Figure 1A; the standard deviation of manufacturing production growth declines essentially by half after 1984. Aside from having a large standard deviation, observe also that the manufacturing production series is relatively "choppy," with growth in a given month bearing little relationship to growth in the previous or subsequent months. In stark contrast, despite also reflecting monthly reported changes, the ISM manufacturing production diffusion index shown in Figure 1B is much smoother with high frequency fluctuations that are much less apparent. At the same time, the ISM series evidently picks up recessions quite well, with the index falling considerably below 50, the neutral threshold in equation (5), in each recession since that of 1973. Given that the ISM manufacturing diffusion index is meant to capture economic activity in real time, Figure

1B makes clear why it is a popular contemporaneous economic indicator.[4]

To gain additional insight into the two measures of manufacturing production illustrated in Figures 1A and 1B, Figures 2A and 2B show the power spectra of manufacturing output growth and the diffusion index (up to frequency $\pi/2$). On the whole, the spectral shapes shown in Figure 2 are typical of growth rate spectra for real macroeconomic variables, as documented for example in King and Watson (1996); the spectra are low at low frequencies, increase to a peak at a cycle length of approximately 50 months, and then decline sharply at high frequencies. King and Watson (1996) refer to this shape as the "typical spectral shape for growth rates" and it is noteworthy that, despite being based on truncated qualitative responses, the spectral shape of the diffusion index conforms closely to that benchmark.

To interpret the shapes shown in Figures 2A and 2B more specifically, it is helpful to recall some key concepts of frequency domain analysis. The *Spectral Representation Theorem* states than any covariance-stationary series, for example Δx_t in this case, can be expressed as a weighted sum of periodic functions of the form $\cos(\omega t)$ and $\sin(\omega t)$,

$$\Delta x_t = \mu + \int_0^\pi \alpha(\omega)\cos(\omega t)d\omega + \int_0^\pi \delta(\omega)\sin(\omega t)d\omega, \tag{8}$$

where ω denotes a particular frequency and the weights $\alpha(\omega)$ and $\delta(\omega)$ are random variables with zero means. The variance of Δx_t can then be subsequently decomposed as

$$var(\Delta x_t) = 2\int_0^\pi f(\omega)d\omega, \tag{9}$$

where the power spectrum, $f(\omega)$, gives the extent of frequency ω's contribution to the total variance of the series. Each frequency, ω, is in turn associated with cycles of period $p = 2\pi/\omega$.

Following King and Watson (1996), business cycle frequencies are defined in this paper as those associated with cycles of periods ranging from 24 to 96 months.[5] Thus, the dashed vertical lines in Figures 2A and 2B correspond to frequencies, ω, ranging from $0.065 = (2\pi)/96$ to $0.26 = (2\pi)/24$.

Two observations stand out in Figures 2A and 2B. First, the business cycle interval indeed contains the peak of the spectrum of manufacturing output growth and, remarkably, that of the ISM manufacturing production index as well. More importantly, consistent with Figures 1A and 1B, it is unmistakable that business cycle frequencies explain a much

[4]The ISM series, however, is subject to a minor adjustment each year to reflect changes in seasonal factors used to construct the index.

[5]This definition is in turn based on earlier work by NBER researchers using the methods described in Burns and Mitchell (1947).

larger fraction of the variance in the diffusion index than in manufacturing output growth. In particular, compared to the manufacturing diffusion index, a substantially greater fraction of the variation in manufacturing output growth is located at high frequencies, thus accounting for the "noisy" aspect of output growth relative to the diffusion index. The power spectra in Figure 2 imply that the business cycle interval contains close to 60 percent of the overall variance in the diffusion index compared to just 23 percent of the variance in monthly manufacturing output growth. In that sense, month to month, the manufacturing diffusion index performs considerably better than actual manufacturing output growth in tracking variations at business cycle frequencies.

Of course, it is always possible to use quarterly growth rates of manufacturing output, or filter the series in some other way, to follow its movements at business cycle frequencies. However, the question then is: why does this issue not arise with the diffusion index which, similarly to output growth, is based on monthly aggregated reports of individual changes in output?[6] The next sections will argue that the answer lies not in the truncating and averaging used in equation (5), but follows from having differentially informed survey respondents.

While month-to-month variations in manufacturing output growth shown in Figure 1A are large, variations in growth rates at the sectoral level are even more pronounced. This follows from the fact that, in equation (7), some of the sectoral variation "averages out" in aggregation. Figure 3A indeed shows that, at the six-digit level of disaggregation, the standard deviations of sectoral growth rates can easily exceed 100 percent and, on average, are on the order 43 percent compared to a standard deviation of 8.5 percent in aggregate manufacturing growth. Although firm-level data are not available, the same reasoning suggests that firm-level variations in output might be even larger. From that standpoint, therefore, it is unclear that surveying individual firms in the way carried out by the ISM would produce a useful economic indicator. In fact, the ISM production index not only performs well in capturing downturns and upturns in manufacturing generally, but the magnitude of the diffusion index is also suggestive of the strength in these cyclical swings. Thus, looking at Figure 3B, most index values are clustered between 45 and 55 as expected, but index values of 35 and below are clearly associated with the most significant falls in output growth in Figures 1A and 1B (i.e. the recessions in the 1970s and 1980s as well as the most recent recession).

Tables 1 and 2 summarize the main observations made in this section. Table 1 gives the

[6] In addition, since monthly manufacturing output is released with a lag and subject to several revisions, the problem of not having the information available for real time analysis persists. This problem is compounded by the fact that, even if an output measure were available in real time, conventional filters that successfully isolate business cycle frequencies are two-sided.

standard deviations of manufacturing output growth and of the ISM index, as well as the fractions of variance explained by business cycle and higher frequencies in the two series. Table 2 shows the autocorrelations in output growth and the diffusion index, as well as the cross correlations between the two series at different leads and lags. Observe the distinct difference between the first and second row of Table 2. Consistent with the "choppiness" of the manufacturing series shown in Figure 1A, manufacturing output growth in a given month bears little relationship to growth in previous months. In contrast, this is clearly not so for the manufacturing diffusion index, whose index values in a given month are highly correlated with index values in previous months. In addition, observe also that manufacturing output growth leads the manufacturing diffusion index in that the correlations between output growth and the diffusion index are larger for future values, rather than past values, of the index. An objective of the paper will be in part to explain all of these observations.

Given the nature of sectoral output growth in manufacturing, the next section sets up an empirical framework that helps explain the key differences between aggregate manufacturing output growth and the manufacturing diffusion index discussed in Figures 1 through 3 and Tables 1 and 2. The framework exploits the fact that the diffusion index derives from aggregated reports of monthly manufacturing output changes. Thus, one of its a central assumption is to allow for a distribution of hypothetical respondents with differentially updated information. The paper then explores what degree of information stickiness helps best reconcile the two series.

4 The Empirical Framework

Let output growth of a firm i operating in a sector j evolve according to

$$\Delta x_t^{ij} = \Delta x_t^j + u_t^i, \tag{10}$$

where $E_{t-1}(u_t^i) = 0 \ \forall i$. In other words, changes in output for a firm working in sector j reflect in part changes in that sector's conditions and in part firm-level idiosyncratic disturbances that have zero mean. Each firm is associated with a spokesperson who reports on changes in her firm's output. As in Mankiw and Reis (2002), however, I assume that at any given date, it is costly to determine exactly what a firm's production changes are, or for the purpose of the surveys, what portion of a firm's production changes are actually informative about the current state. The presumption is that information flows from the factory floor, production process, and other relevant sectoral considerations are imperfect and that the firm representative responding to the surveys is only infrequently apprised of the exact state of output growth. Formally, at each date and in each sector, a fraction $\alpha \in (0,1)$ of representatives are able to update their information set. This implies that in each time period, a fraction α of spokepersons have current information, a fraction $\alpha(1-\alpha)$ of spokepersons have one-period old information, a fraction $\alpha(1-\alpha)^2$ of spokepersons have two-period old information, and so on.[7]

As discussed above, survey designers ask a sample of N representatives in each of M sectors whether their firm's output increased, decreased, or stayed the same at t relative to $t-1$. Because of informational rigidities, respondents' answers cannot always reflect their firm's current output growth. Instead, for respondents who do not have current information, answers to the surveys are based on what they expect current output changes to be conditional on their most recent information, $E_{t-k}(\Delta x_t^{ij})$, where $t-k$ is the date at which they last updated their information set.

Because some respondents base their answers on expected output changes, $E_{t-k}(\Delta x_t^{ij})$, rather than actual output changes, Δx_t^{ij}, a basic element of the empirical framework concerns their perceptions of sectoral output growth, Δx_t^j, in equation (10). To this end, I model changes in sectoral output as

$$\begin{aligned} \Delta x_t^j &= \lambda^j F_t + e_t^j,\ j = 1, ..., M, \\ F_t &= \Phi(L) F_{t-1} + \eta_t, \end{aligned} \tag{11}$$

where F_t represents a set of latent dynamic factors common to all manufacturing sectors, η_t is a common disturbance such that $E_{t-1}(\eta_t) = 0$, λ^j is a factor loading specific to sector j, and e_t^j is a sector-specific shock such that $E_{t-1}(e_t^j) = 0\ \forall j$. In vector notation, the dynamic factor model in (11) can be expressed as

$$X_t = \Lambda F_t + e_t, \tag{12}$$

where X_t is an $M \times 1$ vector of sectoral growth rates, $(\Delta x_t^1, ..., \Delta x_t^M)'$, Λ is an $M \times r$ matrix of factor loadings, F_t is an $r \times 1$ vector of manufacturing-wide factors, and e_t is an $M \times 1$ vector of sectoral shocks, $(e_t^1, ..., e_t^M)'$, that are cross-sectionally weakly correlated with variance-covariance matrix Σ_{ee}. The number of time series observations is denoted by T.

As discussed in Stock and Watson (2010), the dynamic factor model in (12) has proven a valuable approach to handling, and modeling simultaneously, large data sets where the number of series approaches or exceeds the number of time series observations, as in this paper's application. Aside from this strict statistical interpretation, however, Foerster, Sarte, and Watson (2008) also show that equation (12) can be derived as the reduced form solution

[7] See Reis (2006) for the microfoundations of this approach to modeling information stickiness.

to a canonical multisector growth model of the type first developed in Long and Plosser (1983), and further studied in Horvath (1998, 2000), Dupor (1999), and Carvalho (2007). Because these models explicitly take into account input-output linkages across sectors, the "uniquenesses," e_t, may not satisfy weak cross-sectional dependence. In particular, while F_t in (12) can generally be identified with common shocks to sectoral total factor productivity (TFP), the e_t's reflect linear combinations of the underlying structural sector-specific shocks. By ignoring the comovement in "uniquenesses," the factor model (12) can then overstate the degree of comovement in sectoral output that is attributed to common TFP shocks. Using sectoral data on U.S. industrial production and matching input-output tables, Foerster et al. (2008) show that the internal comovement stemming from input-output linkages is relatively small. Therefore, for the remainder of the analysis, I interpret F_t as reflecting aggregate sources of variation in sectoral TFP.

With the dynamic factor model (12) in hand, it is now possible to create a "synthetic" manufacturing production diffusion index. The synthetic index is analogous to that discussed in section 2 but makes explicit that not all respondents have up-to-date information when answering surveys.

As a simple example, suppose that $F_t = \phi F_{t-1} + \eta_t$, $\phi < 1$. Then, in each sector j, αN respondents know their firm's current production change exactly, $E_t(\Delta x_t^{ij}) = \Delta x_t^{ij} = \lambda^j F_t + e_t^j + u_t^i$. Furthermore, under the maintained assumptions, $\alpha(1-\alpha)N$ respondents last updated their information set in the previous period and, for these respondents, survey answers reflect what they expect current output growth to be given that period's information, $E_{t-1}(\Delta x_t^{ij}) = \lambda^j \phi F_{t-1}$. Similarly, $\alpha(1-\alpha)^2 N$ respondents' answers will reflect $E_{t-2}(\Delta x_t^{ij}) = \lambda^j \phi^2 F_{t-2}$, and so on.

Observe that, except for the respondents who have current information, only fixed sector-specific characteristics and aggregate factors end up playing a role in the construction of the synthetic index. This is because $E_{t-k}(\Delta x_t^{ij}) = \lambda^j \phi^k F_{t-k}$, $j = 1, ..., M$, and $k = 1, 2, ...$ so that only the sector-specific factor loadings, λ^j, and the factor components and their lags, $\phi^k F_{t-k}$, are ultimately relevant. Thus, for the majority of firms (assuming that α is small), variability arising either from firm-level shocks or from sectoral shocks tends to be filtered out as $E_{t-k}(u_t^i) = 0$ and $E_{t-k}(e_t^j) = 0$ $\forall i$, j and $k = 1, 2, ...$. Put another way, as a result of information stickiness, some firm representatives can only report what they expect output growth to be instead of actual output growth. It follows that for these respondents, month to month shocks affecting changes in firm output will not be fully reflected in the diffusion index. However, since the goal of diffusion indices is precisely to capture aggregate business cycles, this implication of infrequent updating turns out to be particularly useful for this purpose. In addition, because answers based on expected output growth reflects past information through $\lambda^j \phi^k F_{t-k}$, information stickiness may help explain not only the smooth nature of the diffusion index in Figure 1B, but also why manufacturing output growth leads the index in Table 2.

Since individual firm level data is not available, Δx_t^{ij} cannot be computed for the fraction of firms whose respondents have current information. In that case, I assume that $\Delta x_t^{ij} = \Delta x_t^j = \lambda^j F_t + e_t^j$. In other words, currently informed respondents are assumed to represent firms whose output growth mimics the sector in which they operate. This allows the empirical framework to abstract from individual firm variability entirely. However, as made clear by Figure 2A, sectoral output remains quite volatile. Therefore, if firm-level output volatility is considerably more pronounced than sectoral volatility, then the empirical framework only provides a lower bound for the degree of information stickiness. Put another way, more informational rigidity would then be necessary to filter out high frequency fluctuations in output growth in order to obtain the smooth diffusion index shown in Figure 1B.

Analogously to equation (1), the synthetic ISM surveying process described in this section can be characterized as recording, for each sector j, differentially informed perceptions of changes in output according to the following conditions:

$$\begin{array}{l} \text{if } E_{t-k}(\Delta x_t^{ij}) > \tau, \text{ then } u_t^{kj}(\tau) = 1,\ s_t^{kj}(\tau) = d_t^{kj}(\tau) = 0,\ k = 0, 1, ... \\ \text{if} - \tau \leq E_{t-k}(\Delta x_t^{ij}) \leq \tau \text{ , then } s_t^{kj}(\tau) = 1,\ u_t^{kj}(\tau) = d_t^{kj}(\tau) = 0,\ k = 0, 1, ... \\ \text{if } E_{t-k}(\Delta x_t^{ij}) < -\tau, \text{ then } d_t^{kj}(\tau) = 1,\ u_t^{kj}(\tau) = s_t^{kj}(\tau) = 0,\ k = 0, 1, ..., \end{array} \tag{13}$$

where, at each date t and in each sector j, $E_{t-k}(\Delta x_t^{ij}) = \lambda^j \phi^k F_{t-k}$ for $\alpha(1-\alpha)^k N$ respondents.

The proportions of "up," "down," and "same" respondents now depend not only on the threshold that defines perceptions of rises and falls in output, τ, but also on the degree of information stickiness, α. Given the empirical set-up, the number of "optimists" and "same" respondents in the survey is given by

$$U_t(\alpha, \tau) = M^{-1} \sum_{j=1}^{M} \sum_{k=0}^{\infty} \alpha(1-\alpha)^k u_t^{kj}(\tau) \tag{14}$$

and

$$S_t(\alpha, \tau) = M^{-1} \sum_{j=1}^{M} \sum_{k=0}^{\infty} \alpha(1-\alpha)^k s_t^{kj}(\tau), \tag{15}$$

respectively. Therefore, similarly to equation (5), the synthetic diffusion index for manufacturing production, denoted $\widetilde{\mathcal{I}}_t(\alpha, \tau)$, takes the form

$$
\begin{aligned}
\widetilde{\mathcal{I}}_t(\alpha,\tau) &= \left(U_t(\alpha,\tau)+\frac{1}{2}S_t(\alpha,\tau)\right)\times 100 \\
& M^{-1}\sum_{j=1}^{M}\sum_{k=0}^{\infty}\alpha(1-\alpha)^k\left(u_t^{kj}(\tau)+\frac{1}{2}s_t^{kj}(\tau)\right)\times 100.
\end{aligned} \tag{16}
$$

Given this synthetic diffusion index, the natural question is: what degree of information stickiness, α, and indifference threshold, τ, best describe the actual manufacturing production index created by the ISM? Thus, a and τ are chosen to satisfy

$$
\min_{\alpha,\ \tau}\ \mathcal{S}(\alpha,\tau)=\sum_{t=1}^{T}\left(\mathcal{I}_t-\widetilde{\mathcal{I}}_t(\alpha,\tau)\right)^2. \tag{17}
$$

Before moving on to the estimation and findings, it is worth summarizing the two key elements of the empirical framework set out in this section. First, respondents who do not have current information answer survey questions based on expected output growth, conditional on their most recent information, rather than actual output growth. Hence, since $E_{t-k}(u_t^i) = 0$ and $E_{t-k}(e_t^j) = 0\ \forall i,j$, and $k = 1,2...$, this feature of information stickiness helps filter out high frequency fluctuations that arise through shocks. Second, to the extent that respondents' answers reflect past information through $\lambda^j\phi^k F_{t-k}$, and because equation (17) is a weighted sum of these information lags, one expects the resulting diffusion index to be smoother than manufacturing output growth. It is also precisely this mechanism that may allow manufacturing output growth to lead the ISM diffusion index as shown in Table 2.

5 Estimation and Empirical Findings

The estimation of the empirical framework described in the previous section proceeds in two steps. The first step involves estimation of the dynamic factor model (12). The second step uses the resulting model estimates to construct a synthetic diffusion index according to equations (13) through (16) and solves equation (17).

In the first step, the number of factors in (12) are estimated using the Bai and Ng (2002) ICP1 and ICP2 estimators. The factors themselves and the loadings are then estimated by principle component methods. When M and T are large, as they are in this paper's application, Stock and Watson (2002) show that principle components provide consistent estimates of the factors. In addition, the estimation error in the estimated factors is sufficiently small that it can be ignored when carrying out variance decompositions or conducting inference about Λ. In other words, $\widehat{F}_t$, can be treated as data in a second-stage regression or subsequent investigation. In the second step, therefore, estimates of the factors obtained in this way are used in the construction of the synthetic diffusion index, $\widetilde{\mathcal{I}}_t(\alpha, \tau)$, according to the rules given by (13). Equation (17) is then solved for the degree of informational rigidity, α, and the indifference threshold, τ, that best characterize the actual manufacturing diffusion index.

The Bai and Ng (2002) ICP1 and ICP2 estimators yield 2 factors in the full sample (1972-2009), and the findings in this section are based on this 2-factor model. However, for robustness, the analysis was also carried out using 1 and 3-factor models with similar results (not shown).

Given equation (12), the factor analysis centers on two main results that will help develop intuition for the behavior of the diffusion index. First, I denote by $R^2(F)$ the fraction of aggregate manufacturing variability that is explained by common shocks. In particular, letting $\mathbf{w}$ denote the $M \times 1$ vector of constant mean shares, $\Delta x_t = \mathbf{w}'\Lambda F_t + \mathbf{w}'e_t$ so that $R^2(F) = \mathbf{w}'\Lambda\Sigma_{FF}\Lambda'\mathbf{w}/\sigma^2_{\Delta x}$, where $\sigma^2_{\Delta x}$ is the variance of aggregate manufacturing output growth. Second, I also highlight the extent to which the common factors explain output growth variability in individual sectors, $R^2_j(F) = \lambda^j\Sigma_{FF}\lambda^{j\prime}/\sigma^2_{\Delta x_j}$, where $\sigma^2_{\Delta x_j}$ is the variance of sector j's output growth. The purpose of this last calculation is to show that in some sectors, fluctuations in output growth reflect in part aggregate factors while, in other sectors, changes in output result mostly from idiosyncratic considerations. This feature of sectoral data will be key in providing guidelines regarding which sectors to survey in the construction of a manufacturing diffusion index.

The factor model implies a volatility of aggregate manufacturing output growth that is nearly identical to that found in the data, 8.47 percent. More important, the common factors explain 85 percent or the bulk of the variability in aggregate manufacturing output growth. Figure 4A further illustrates this point by plotting manufacturing output growth, Δx_t, and the model's fitted values of the factor component, $\mathbf{w}'\Lambda F_t$. Consistent with the factors' dominant role in driving aggregate variability, the two series track each other closely over the full sample period. It immediately follows that, in order to build a diffusion index that reflects aggregate manufacturing output growth, a practical step involves focusing on particular sectors whose output variability is largely driven by the common factors.

To help distinguish sectors along this dimension, Figure 4B depicts the distribution of $R^2_j(F)$ statistics. The figure shows that, in fact, common factors typically account for a small fraction of the variability in sectoral output growth (the mean and median $R^2_j(F)$ are 0.17 and 0.13 respectively). Simply put, sector-specific shocks tend to drive sectoral variability.

However, Figure 4B also shows that this is not the case of all sectors. The factor component explains more than 40 percent of the variations in output growth in approximately 15 sectors, and $R_j^2(F)$ is as high as 0.65 in this exercise. It is those sectors, therefore, that are likely to be most informative to surveys used to construct a diffusion index of manufacturing production.

Given these findings, equation (17) yields estimates of 0.06 for α and 3.04 for τ.[8] In other words, respondents update their information set every 16 and a half months on average, and changes in output are reported as "up" or "down" if they exceed 3 percent. Recall that Figure 2 implied a median standard deviation of 31.7 percent for monthly sectoral output growth. Therefore, relative to that benchmark, the indifference interval for which respondents report "no change" appears remarkably narrow, approximately one tenth of the median sectoral standard deviation. In addition, the extent of information stickiness suggested by this experiment is somewhat longer than that found in previous work, mainly with aggregate inflation data. For instance, Carroll (2003) uses the Michigan Survey, a quarterly series on households' inflation expectations, as well as the Survey of Professional Forecasters over the period $1981-2000$, to estimate individuals' degree of information stickiness in forming inflation expectations. He finds that on average, individuals update their expectations once a year. Similarly, Mankiw, Reis and Wolfers (2003) use the Livingston Survey and the Michigan Survey to estimate the rate of information updating that maximizes the correlation between the interquartile range of inflation expectations from the survey data with that predicted by the model in Mankiw and Reis (2002). In this exercise, a vector autoregression (VAR) is estimated using monthly aggregate U.S. data to generate forecasts of future annual inflation. The authors then find that on average, the general public updates their expectations once every 12.5 months. In other work, Mankiw and Reis (2006), as well Mankiw and Reis (2007), estimate that a rate of information updating that generally ranges from 6 to 16 months helps best match key aspects of business cycle fluctuations. Finally, Coibion and Gorodnichenko (2009) use various macroeconomic survey forecasts to show that forecast errors are persistent, with a half-life of up to 16 months, and are consistent with predictions of models with informational rigidities.

[8] Since the number of time series observations is finite in practice, the horizon for k in equation (16) must be truncated at some value, $k_{\max}$. In this case, $k_{\max}$ is set to 35 which can be thought of as an upper bound on information lags. That is, respondents with potentially older information in (13) form expectations according to the information set defined by $k_{\max}$, $E_{t-k}(\Delta x_t^{ij}) = E_{t-k_{\max}}(\Delta x_t^{ij})\ \forall k > k_{\max}$. However, note that when $\alpha = 0.06$, only 10 percent of respondents have information lags that excced 35 months. Thus, increasing $k_{\max}$ does not materially affect the findings, although this can only be checked to a point since observations are lost as $k_{\max}$ increases. Finally, the number of lags, L, used in equation (11) to model respondents' expectations is folded into problem (17). Solving this problem gives that $L = 2$ helps best decribe the ISM diffusion index in the sense of minimizing the overall sum of squares, $\mathcal{S}$.

Tables 3 and 4 describe basic properties of the synthetic diffusion index estimated from sectoral data. Looking at Table 3, the synthetic index is not quite as volatile as that actually produced by the Institute for Supply Management. However, the proportions of variance of the synthetic index explained by business cycles and higher frequencies almost exactly match those of the ISM diffusion index. Recall that the monthly sectoral data at the base of the empirical work reflect mainly high frequency, or "noisy," fluctuations (Table 2 and Figure 3A). Therefore, information stickiness in essence filters out these fluctuations to produce an index that instead moves mostly with the business cycle. As indicated in Table 4, the autocorrelations of the synthetic diffusion index at different lags, $\rho(\widetilde{\mathcal{I}}_t, \widetilde{\mathcal{I}}_{t-k})$, closely match those of the actual index created by the ISM, $\rho(\mathcal{I}_t, \mathcal{I}_{t-k})$. Furthermore, because some survey respondents rely on expectations of output changes conditional on information that has not been updated, information stickiness also helps explain why manufacturing output growth leads the ISM diffusion index. Thus, Table 4 shows that the cross-correlations between manufacturing output growth and the synthetic index at different leads and lags, $\rho(\Delta x_t, \widetilde{\mathcal{I}}_{t+k})$, are generally quite close to those between manufacturing output growth and the actual ISM index, $\rho(\Delta x_t, \mathcal{I}_{t+k})$.

Figure 5 summarizes these findings graphically. Looking at Figure 5A, the synthetic diffusion index moves relatively closely with the actual ISM index apart from two notable exceptions. First, the synthetic diffusion index mostly misses the depth of the recessions of the early 1980s. In contrast, the fall in economic activity associated with these recessions is reflected in a large decline in the ISM index. Second, the economic expansion that followed the 1991 recession is marked by particularly large values of the ISM index by historical standards, but is more subdued according to the synthetic index. These two key differences between the synthetic and actual ISM indices explain in large part the lower volatility of the synthetic diffusion index. Comparing Figures 3B and 5B, the distributions of the synthetic and ISM index values are remarkably alike although, as just indicated, the synthetic index does not quite reproduce extreme values of the actual index at either end of the support. Finally, note that the shape of the synthetic diffusion index's power spectrum in Figure 5C closely resembles that of the ISM index in Figure 2B. Not surprisingly, therefore, the proportions of variance in the two series that are explained by specific frequencies are remarkably close (as in Table 3).

Diffusion indices, in practice, do not systematically record or make public individual survey responses on which they are based. However, as indicated earlier, the proportions of "optimists" (those reporting expected production increases), and "pessimists," (those reporting expected production decreases) in the empirical framework are simply given by $U_t(\alpha, \tau) = M^{-1} \sum_{j=1}^{M} \sum_{k=0}^{\infty} \alpha(1-\alpha)^k u_t^{kj}(\tau)$ and $D_t(\alpha, \tau) = M^{-1} \sum_{j=1}^{M} \sum_{k=0}^{\infty} \alpha(1-\alpha)^k d_t^{kj}(\tau)$, respectively. Similarly, the proportion of respondents reporting no change is given by $S_t(\alpha,\tau) = M^{-1}\sum_{j=1}^{M}\sum_{k=0}^{\infty}\alpha(1-\alpha)^k s_t^{kj}(\tau)$. Figures 6A and 6B show the model-implied behavior of these proportions over past business cycles. Two features are worth highlighting. First, at any given time, most respondents typically report no change. Second, the proportions of "optimists" and "pessimists" behave differently before and after the Great Moderation. Thus, prior to 1984, recessions are marked by spikes in the proportion of "pessimists" while expansions are marked by similar spikes in the proportion of "optimists." However, after the onset of the Great Moderation, while the recessions of 1991, 2001, as well as the current recession, are still marked by sharp increases in the fraction of respondents reporting expected output declines, increases in the proportion of respondents reporting an expected rise in output is more subdued. From this standpoint, therefore, the Great Moderation period is not only associated with a sharp decline in volatility (Figure 1A) but also an asymmetry in sectoral output fluctuations. A conjecture that would be interesting to explore is whether this reduction in "optimism" post 1984 may be indirectly to the slow employment recoveries that followed the 1991 and 2001 recessions, or other notable changes in business cycles.

6 Deconstructing the ISM Diffusion Index

Having described the ISM index and its implications for the degree of information stickiness characterizing survey respondents, this section further deconstructs the index according to various components of the empirical framework. In particular, it asks four questions related to the construction of diffusion indices: i) how does the extent of informational rigidity among survey respondents affect the behavior of the ISM diffusion index? ii) how important is the degree of heterogeneity across sectors in producing a qualitative index that helps track the business cycle? iii) is it possible to more efficiently construct a diffusion index by steering the underlying survey's efforts towards key relevant sectors? iv) Does the Great Moderation have implications for potential changes in the types of sectors that are most informative about aggregate manufacturing and the degree of informational rigidity inferred from the ISM index?

6.1 Fully Informed Survey Respondents

Figure 7 shows how changes in the degree of informational rigidity, α, and the indifference threshold, τ, affect the behavior of the synthetic diffusion index relative to that produced by the ISM. Looking at Figure 7A, assuming that α is as estimated in section 5 but that $\tau = 0$, the synthetic diffusion index becomes considerably more volatile than that estimated in the previous section. Its standard deviation is now 16.8, more than twice as volatile as that of the actual ISM. This finding reflects the fact that all changes in output, no matter how immaterial, are now always reported as "up" or "down." Moreover, in this case, the synthetic index with $\tau = 0$ is considerably less correlated with manufacturing production growth, with a correlation of 0.25, compared to the actual correlation of 0.45 which the synthetic index was able to match in section 5.

More interesting is the effect of relaxing the information stickiness assumption. Figure 7B illustrates the estimated synthetic index that obtains when τ is set as in section 5 but all respondents are always fully informed, $\alpha = 1$. In that case, equations (13) and (16) become

$$\begin{aligned} &\text{if } \Delta x_t^j > \tau, \text{ then } u_t^j(\tau) = 1,\ s_t^j(\tau) = d_t^j(\tau) = 0 \\ &\text{if} - \tau \leq \Delta x_t^j \leq \tau \text{ , then } s_t^j(\tau) = 1,\ u_t^j(\tau) = d_t^j(\tau) = 0, \\ &\text{if } \Delta x_t^j < -\tau, \text{ then } d_t^j(\tau) = 1,\ u_t^j(\tau) = s_t^j(\tau) = 0, \end{aligned} \tag{18}$$

and

$$\widetilde{\mathcal{I}}_t(1,\tau) = M^{-1} \sum_{j=1}^{M} \left(u_t^j(\tau) + \frac{1}{2} s_t^j(\tau) \right) \times 100, \tag{19}$$

respectively. When all respondents are fully informed, the empirical framework is one where answers of "up," $u_t^j(\tau)$, and "same," $s_t^j(\tau)$, are independent of information lags, k. In essence, the synthetic diffusion index (19) now reflects contemporaneous sectoral output changes up to the truncation rules described by equation (18). One effect of these truncation rules is to transform what would be an overall measure of manufacturing output growth, $M^{-1} \sum_{j=1}^{M} \Delta x_t^j$, into an index bounded between 0 and 100.

Figure 7B depicts the diffusion index that obtains under this scenario. Two observations are worth noting. First, the synthetic diffusion index is considerably more volatile than that produced by the ISM. More striking, the time series properties of this synthetic index now more closely match those of manufacturing output growth instead of the ISM index. The correlation between the synthetic index and changes in manufacturing production is 0.85 instead of 0.45. Furthermore, as indicated in Table 5, the proportions of variance of $\widetilde{\mathcal{I}}_t(1,\tau)$ that are attributable to business cycles (as well as shorter frequency fluctuations) are essentially identical to those of manufacturing output growth. Finally, Table 6 shows that the autocorrelation properties of $\widetilde{\mathcal{I}}_t(1,\tau)$ are now much closer to those of manufacturing output growth than those of the ISM index (as shown in Table 4). In sum, without information stickiness, movements in the synthetic diffusion index essentially mimic those of manufacturing output growth despite the truncation rules defined by (18). This finding is reminiscent of the work in Kashyap and Gourio (2007) who show that it is not necessary to keep track of exact changes in a series, in their case aggregate investment, to capture some of its most salient features. Given the differences between Figures 1A and 1B, I interpret this finding as *prima facie* evidence that survey respondents do not report current actual changes in output but rather some notion of changes that incorporates past information.[9]

Figure 8 illustrates the role of sectoral heterogeneity in the construction of diffusion indices. In particular, it asks: is it important for sectors to behave differently in order to construct meaningful diffusion indices? Thus, Figure 8A reflects a scenario where all sectors have the same factor loadings, equal to the mean factor loading, and sectoral shocks are shut down. In terms of the notation introduced earlier, $\lambda^j = \overline{\lambda} = M^{-1}\sum_{j=1}^{M}\lambda^j \;\forall j.$ [10] Therefore, expectations of current output changes, $E_{t-k}(\Delta x_t^{ij})$, are no longer sector dependent and the only source of differences across respondents resides in information lags,

$$E_{t-k}(\Delta x_t^{ij}) = \overline{\lambda}\phi^k F_{t-k} \forall\ i,\ j \text{ and } k = 1, 2, ... \tag{20}$$

By and large, Figure 8A shows that heterogeneity in information lags alone goes a long way towards producing a synthetic diffusion index that is close to the actual ISM index. This is in spite of what essentially amounts to a representative firm assumption. In that sense, informational heterogeneity appears at least as important as heterogeneity in production. The fraction of the synthetic diffusion index variance explained by business cycle frequencies is now somewhat lower than that of the ISM index, 0.45 instead of 0.58, but still considerably higher than that of manufacturing output growth, 0.23. In addition, the autocorrelation structure of the synthetic index series shown in Figure 8A resembles more closely that of the ISM index than that of manufacturing output growth (not shown).

Suppose now that, in addition to firms behaving identically across sectors, respondents are always fully apprised of current conditions and always able to report changes as either "up" or "down." In this frictionless environment with a representative firm, typical of many RBC models for example, we have that either $u_t^j = 1$ and $d_t^j = 0\ \forall j$ or vice versa so that, at any date, everyone simultaneously reports "up" or "down." Hence, the ISM diffusion index can now only take on two values, 100 or -100, and thus becomes degenerate. As shown in Figure 8B, without heterogeneity of any kind, the standard diffusion index described in section 2 ceases to be useful. Given that the nature of production is the same in Figures 8A and 8B, the contrast between the two figures only serves to underscore the importance of heterogeneous information lags across respondents.

[9] In addition, to the extent that firm level output growth is even more idiosyncratic than sectoral output growth, a diffusion index that reflects real time output changes would be even less useful.

[10] Under this assumption, the factor component becomes an exact proxy for aggregate output growth in manufacturing, $\overline{\lambda}F_t = M^{-1}\sum_{j=1}^{M}\Delta x_t^j$.

6.2 Choosing Which Sectors to Survey in Creating Diffusion Indices

Section 5 presented estimates from the factor model such that i) the factor component, $\mathbf{w}'\Lambda F_t$, accounted for most of the variation in manufacturing output growth, Δx_t, (recall Figure 4A), and ii) sectors differed in the degree to which they were driven by common factors rather than idiosyncratic considerations, (recall Figure 5B). These two observations suggest that information regarding the state of overall manufacturing is likely to be located in some sectors more than others. In fact, Figure 5B suggests that many sectors in the data set likely contribute very little information to a diffusion index meant to track overall changes in manufacturing in real time. To explore this notion further, it is useful to rank sectors according to their $R_j^2(F)$ statistic. Output variations in sectors where $R_j^2(F)$ is close to zero are almost entirely driven by idiosyncratic considerations while those with higher $R_j^2(F)$ reflect in part the effects of common factors. Figure 9 then plots diffusion indices constructed as in section 5 (i.e. with $\alpha = 0.06$ and $\tau = 3.04$) but using only the top and bottom 15 sectors ranked by $R_j^2(F)$.

Remarkably, Figure 9A shows that surveying only 15 sectors where the common factors have the greatest role is enough to produce a diffusion index that is nearly identical to that constructed using all sectors in section 5. This finding reflects the fact that information regarding changes in aggregate manufacturing tends to be concentrated in relatively few sectors.[11] Conversely, Figure 9B indicates that a diffusion index constructed using 15 sectors where the common factors are least important would have a noticeably more difficult time tracking expansions and contractions in economic activity. Because the factor component does not dominate variations in sectoral output in this case, the implied diffusion index is relatively uniform and varies little over time. That said, even in this scenario, information stickiness remains useful in filtering out high frequency fluctuations resulting from idiosyncratic shocks. Therefore, whatever variation is left in the diffusion index still tends to move with the business cycle.

Tables 7 and 8 give the 15 sectors with highest and lowest $R_j^2(F)$ statistics used to construct the synthetic diffusion indices in Figures 9A and 9B, as well as their share or weight in overall manufacturing. Interestingly, Table 7 suggests that a fairly large proportion of the most informative sectors involve metal work in one way or another (e.g. Metal Valves, Architectural and Structural Metal Products, Fabricated Metals: Forging and Stamping, Foundries, Metalworking Machinery, Coating and Engraving, etc.). At the opposite ex-

[11] See Foerster, Sarte, and Watson (2008) for alternative calculations that highlight this feature of sectoral data.

treme, Table 8 indicates that many of the least useful sectors in the diffusion index involve food-related industries (e.g. Fluid Milk, Coffee and Tea, Animal Food, Seafood Product and Preparation, Wineries and Distilleries, Soft Drinks and Ice, etc.). That said, one should be cautious in interpreting Figure 9A. While it suggests that using only 15 sectors, chosen according to their $R_j^2(F)$ statistic, is enough to replicate the diffusion index created using all sectors in section 5, the empirical framework assumes that enough firms are surveyed in each sector to recover the entire distribution of information lags across respondents. Given time and resource constraints in the surveying process, this is potentially far from the case. Finally, Tables 7 and 8 indicate that sectors that may be most informative in the construction of a diffusion manufacturing index tend to represent a larger share of manufacturing. However, this relationship is far from tight so that some of the most informative sectors, such Metalworking Machinery or Coating, Engraving, and Allied Activities, have small weights at 0.05 and 0.08, respectively. In fact, virtually all of the least informative sectors in Table 8 have larger weights. This observation points to the pitfall of assuming that sectors that represent a small share of overall manufacturing must necessarily be uninformative about its state.

6.3 The ISM Manufacturing Production Diffusion Index and The Great Moderation

Of course, the sectoral rankings shown in Tables 7 and 8 are not exact and will change somewhat as the estimation is carried out over different sample periods. One of the most studied aspects of Figure 1 is the break in the volatility of aggregate manufacturing output growth around 1984, and it is natural to ask whether structural changes in U.S. manufacturing over time have led to changes in the way that information is concentrated across sectors. In fact, when the factor model (12) is estimated before and after the Great Moderation, in particular over the periods $1972-1983$ and $1984-2009$, the sectors that are most and least informative about aggregate manufacturing tend not to change much. Specifically, out of the 30 sectors with the highest $R_j^2(F)$ statistics over the full sample period, 22 of those sectors can be found in the pre Great Moderation period while 23 are found in the post 1984 sample. Similarly, of the bottom 30 least informative sectors, 18 are found in the pre 1984 period while 25 of those sectors are found post Great Moderation.

Finally, section 5 pointed out that the rate of information updating estimated in this paper, around 16 months, is somewhat higher than that estimated in other studies using more aggregated survey work, for instance around 12 months in Carroll (2003). Because the latter paper relies on inflation and employment expectations measured by the Michigan Survey of Consumers, the sample period in that work reflects mostly the post Great Moderation period, in particular $1981 - 2000$ for inflation expectations. Now, observe that the ISM manufacturing diffusion index in Figure 1B does not experience the dramatic decline in volatility that characterizes manufacturing output growth around 1984. It follows that after that date, all else equal, less information stickiness is needed in order to smooth out high frequency output fluctuations (since those are less pronounced) and match the diffusion index in Figure 1B. Consistent with this observation, estimating the empirical model in section 5 over the $1972 - 1983$ period yields $\alpha = 0.05$ compared to $\alpha = 0.076$ over the $1984 - 2009$ period. In other words, the rate of information updating averages approximately 20 months prior to the Great Moderation and falls to around 13 months after 1984. Because the variability of the ISM index remains approximately unchanged throughout the entire sample, this finding follows almost mechanically from having to smooth larger manufacturing output growth fluctuations in the 1970s which are mostly absent starting in the early 1980s (apart from the most recent recession). Therefore, when estimated over separate subsamples, the empirical model suggests, somewhat intuitively, that the cost of acquiring information has fallen over time.

7 Concluding Remarks

This paper has used disaggregated manufacturing data to study survey-based diffusion indices that aim to capture changes in the business cycle in real time. To keep surveys straightforward, and to limit the burden on respondents, these diffusion indices are generally constructed from questions that require only one of three qualitative answers to indicate changes in a variable relative to the previous month. The empirical framework then recognizes that in answering these survey questions, respondents potentially use infrequently updated information.

The analysis suggests that survey answers underlying the ISM manufacturing production diffusion index reflect considerable information lags, on the order of 16 months on average. Furthermore, it underscores that informational rigidities, in essence, lead respondents to filter out high frequency output fluctuations when answering surveys. The resulting index, therefore, is better able to isolate variations at business cycle frequencies. In that sense, informational rigidities provide a foundation for the widespread use of diffusion indices as a contemporaneous economic indicators. The analysis further shows that in a world populated by fully informed identical firms, as in the standard RBC environment for instance, diffusion indices become degenerate.

Finally, the empirical work highlights the fact that information regarding changes in aggregate manufacturing output tends to be concentrated in relatively few sectors. Hence, contrary to standard practice, it is not necessary for surveys to try to capture a representative sample of all manufacturing sectors in order to track changes in aggregate activity. The intuition is straightforward. In some sectors, changes in output reflect to a significant extent factors that drive aggregate changes while, in other sectors, output variations are mostly explained by idiosyncratic considerations. The analysis then uses factor analytic methods to provide a ranking of the most and least informative sectors in constructing a diffusion index of manufacturing production. In particular, it shows that a useful index may be produced using as few as 15 sectors instead of all 124 sectors that make up U.S. manufacturing.

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Table A1
Summary Statistics of Sectoral Growth Rates by NAICS Industry Classification, 124 Sectors

Sector	Weight	St. Dev.	Min	Max
Animal Food	0.42	20.34	-77.95	73.41
Grain and Oilseed Milling	0.77	24.63	-102.10	97.04
Sugar and Confectionery Products	0.55	42.61	-164.10	218.06
Fruit and Vegetable Preserving and Specialty Foods	1.03	30.45	-105.55	126.93
Fluid Milk	0.38	7.08	-26.48	21.94
Creamery Butter	0.01	59.67	-267.00	214.20
Cheese	0.17	19.99	-82.90	97.03
Dry, Condensed, and Evaporated Dairy Products	0.16	52.57	-231.36	193.13
Ice Cream and Frozen Desserts	0.11	36.50	-138.26	160.08
Animal Slaughtering and Meat Processing Ex Poultry	0.88	24.45	-102.78	157.19
Poultry Processing	0.45	24.69	-89.13	109.23
Seafood Product Preparation and Packaging	0.14	64.90	-183.23	194.39
Bakeries and Tortilla	1.23	10.99	-46.35	46.64
Coffee and Tea	0.18	67.55	-482.59	256.91
Other Food Except Coffee and Tea	0.98	18.70	-70.06	79.24
Soft Drinks and Ice	0.59	23.06	-84.53	147.10
Breweries	0.45	50.06	-263.55	161.54
Wineries and Distilleries	0.27	85.54	-341.73	487.06
Tobacco	1.07	56.86	-193.63	240.72
Fiber, Yarn, and Thread Mills	0.22	47.96	-243.22	173.63
Fabric Mills	0.67	19.04	-78.45	83.48
Textile and Fabric Finishing and Fabric Coating Mills	0.30	25.15	-113.25	75.18
Textile Furnishings Mills	0.35	43.20	-186.23	126.54
Other Textile Product Mills	0.20	21.38	-92.27	122.51
Apparel	1.76	16.98	-80.86	60.69
Leather and Allied Products	0.33	23.46	-147.29	72.74
Sawmills and Wood Preservation	0.43	59.18	-360.33	244.06
Veneer and Plywood	0.16	61.58	-439.26	292.12
Engineered Wood Member and Truss	0.07	42.19	-216.46	140.13
Reconstituted Wood Products	0.09	47.19	-207.97	144.84
Millwork	0.34	24.25	-119.46	72.95
Wood Containers and Pallets	0.09	21.81	-76.67	105.69
Manufactured Homes [Mobile Homes]	0.13	57.06	-217.45	392.50
Prefabricated Wood Building and All Other Miscellaneous Wood Products	0.15	26.65	-117.69	68.15
Pulp Mills	0.08	29.73	-198.33	126.75
Paper and Paperboard Mill	1.58	25.73	-93.49	98.47
Paperboard Containers	0.71	22.66	-124.69	119.40
Paper Bags and Coated and Treated Paper	0.38	35.37	-156.42	141.08
Other Converted Paper Products	0.37	25.59	-104.31	113.58
Printing and Related Support Activities	2.28	13.66	-42.62	50.30
Petroleum Refineries	1.79	26.00	-144.77	177.58
Paving, Roofing, and Other Petroleum and Coal Products	0.34	27.19	-158.31	89.93
Organic Chemicals	1.43	37.32	-396.50	243.72
Industrial Gas	0.21	31.99	-187.49	151.15
Synthetic Dyes and Pigments	0.15	77.57	-297.87	295.62
Other Basic Inorganic Chemicals	0.57	54.49	-448.42	337.87

Sector	Weight	St. Dev.	Min	Max
Plastics Materials and Resins	0.70	48.01	-405.72	367.90
Synthetic Rubber	0.10	65.28	-243.86	287.58
Artificial and Synthetic Fibers and Filaments	0.33	55.83	-326.64	215.32
Pesticides, Fertilizers, and Other Agricultural Chemicals	0.50	28.60	-121.31	171.54
Pharmaceuticals and Medicines	2.63	14.88	-64.87	48.83
Paints and Coatings	0.40	40.25	-217.57	147.49
Adhesives	0.13	31.46	-113.83	167.52
Soap, Cleaning Compounds, and Toilet Preparation	1.41	25.74	-72.81	98.71
Other Chemical Product and Preparation	0.93	25.69	-99.87	88.83
Plastics Products	2.29	16.00	-102.16	68.43
Tires	0.43	72.31	-458.82	730.97
Rubber Products Ex Tires	0.40	26.67	-177.39	132.57
Pottery, Ceramics, and Plumbing Fixtures	0.11	26.62	-178.58	76.15
Clay Building Materials and Refractories	0.15	40.23	-238.86	173.10
Flat and Brown Glass and Other Glass Manufacturing	0.44	23.55	-92.92	94.66
Glass Container	0.18	48.81	-226.22	236.17
Cement	0.19	53.02	-292.85	236.65
Concrete and Products	0.68	28.01	-103.06	84.81
Lime and Gypsum Products	0.12	71.19	-448.70	247.56
Other Nonmetallic Mineral Products	0.37	31.89	-111.52	125.19
Iron and Steel Products	1.67	63.15	-311.12	232.73
Alumina Refining	0.05	34.00	-234.00	216.92
Primary Aluminum Production	0.14	24.54	-192.40	68.39
Secondary Smelting and Alloying of Aluminum	0.04	71.18	-217.41	566.08
Miscellaneous Aluminum Materials	0.19	93.97	-699.29	517.89
Aluminum Extruded Products	0.09	95.80	-715.36	528.85
Primary Smelting and Refining of Copper	0.06	135.37	-1285.13	743.14
Primary Smelting/Refining of Nonferrous Metal [Ex Cu and Al]	0.07	84.11	-405.04	394.53
Copper and Nonferrous Metal Rolling, Drawing, Extruding, and Alloying	0.35	71.67	-327.73	269.51
Foundries	0.77	24.05	-122.17	72.36
Fabricated Metals: Forging and Stamping	0.50	19.59	-89.44	62.80
Fabricated Metals: Cutlery and Handtools	0.34	19.44	-83.68	103.95
Architectural and Structural Metal Products	1.16	13.70	-54.41	43.04
Boiler, Tank, and Shipping Containers	0.58	24.56	-79.38	111.19
Fabricated Metals: Hardware	0.29	26.47	-89.19	91.05
Fabricated Metals: Spring and Wire Products	0.20	20.49	-95.10	57.73
Machine Shops; Turned Products; and Screws, Nuts, and Bolts	1.05	22.07	-79.57	77.58
Coating, Engraving, Heat Treating, and Allied Activities	0.41	17.86	-138.55	48.19
Metal Valves Except Ball and Roller Bearings	1.15	13.18	-57.14	38.84
Ball and Roller Bearings	0.17	32.17	-190.44	147.70
Farm Machinery and Equipment	0.39	100.40	-808.88	543.35
Lawn and Garden Tractor and Home Lawn and Garden Equipment	0.10	70.30	-281.26	249.34
Construction Machinery	0.44	112.71	-696.01	704.18
Mining and Oil and Gas Field Machinery	0.29	35.46	-137.09	133.41
Industrial Machinery	0.73	26.89	-147.88	73.05
Commercial and Service Industry Mach/Other Gen Purpose Mach	2.17	13.04	-55.75	42.24

Sector	Weight	St. Dev.	Min	Max
Ventilation, Heating, Air-cond & Commercial Refrigeration eq	0.71	58.57	-161.66	251.32
Metalworking Machinery	0.84	18.21	-97.69	38.33
Engine, Turbine, and Power Transmission Equipment	0.78	36.79	-164.35	153.17
Computer and Peripheral Equipment	1.50	23.36	-51.56	76.46
Communications Equipment	1.54	26.44	-208.02	205.26
Audio and Video Equipment	0.18	143.23	-538.96	782.25
Semiconductors and Other Electronic Components	2.32	27.57	-159.64	83.97
Navigational/Measuring/Electromedical/Control Instruments	2.34	12.95	-37.83	56.63
Magnetic and Optical Medi	0.19	41.36	-133.44	161.54
Electric Lighting Equipment	0.33	28.23	-157.19	115.86
Small Electrical Household Appliances	0.15	42.18	-194.91	218.19
Major Electrical Household Appliances	0.36	70.30	-500.84	428.10
Electrical Equipment	0.88	21.65	-62.60	58.28
Batteries	0.16	59.40	-213.32	268.63
Communication and Energy Wires and Cables	0.21	27.62	-107.21	99.73
Other Electrical Equipment	0.47	21.28	-82.05	79.85
Automobiles and Light Duty Motor Vehicles	2.28	96.68	-667.76	628.14
Heavy Duty Trucks	0.15	187.80	-1736.24	1509.01
Motor Vehicle Bodies	0.21	64.98	-417.67	212.83
Truck Trailers	0.08	98.98	-627.44	550.81
Motor Homes	0.05	133.18	-857.31	650.42
Travel Trailers and Campers	0.08	96.89	-687.25	374.34
Motor Vehicle Parts	3.04	36.06	-196.79	191.45
Aircraft and Parts	2.40	36.34	-306.70	241.50
Guided Missile and Space Vehicles and Propulsion	0.76	36.14	-187.51	229.34
Railroad Rolling Stock	0.23	42.62	-161.57	151.64
Ship and Boat Building	0.51	31.09	-151.82	127.32
Other Transportation Equipment	0.16	50.94	-309.80	248.16
Household and Institutional Furniture and Kitchen Cabinets	0.86	19.70	-81.92	65.33
Office and Other Furniture	0.62	21.73	-67.72	77.00
Medical Equipment and Supplies	1.22	11.99	-39.71	59.57
Other Miscellaneous Manufacturing	1.36	13.66	-54.00	49.97

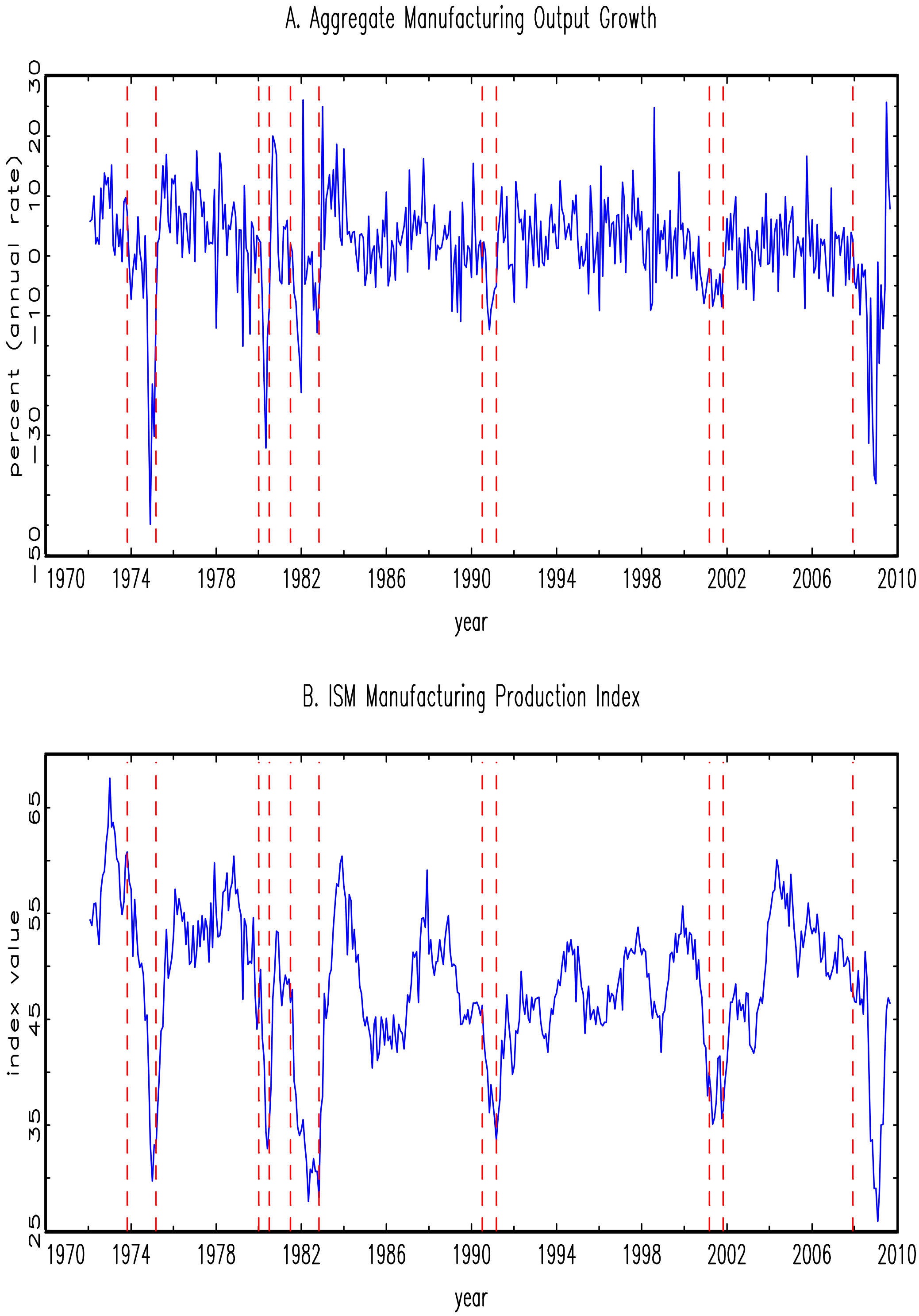


Figure 1. Aggregate Variations in Manufacturing

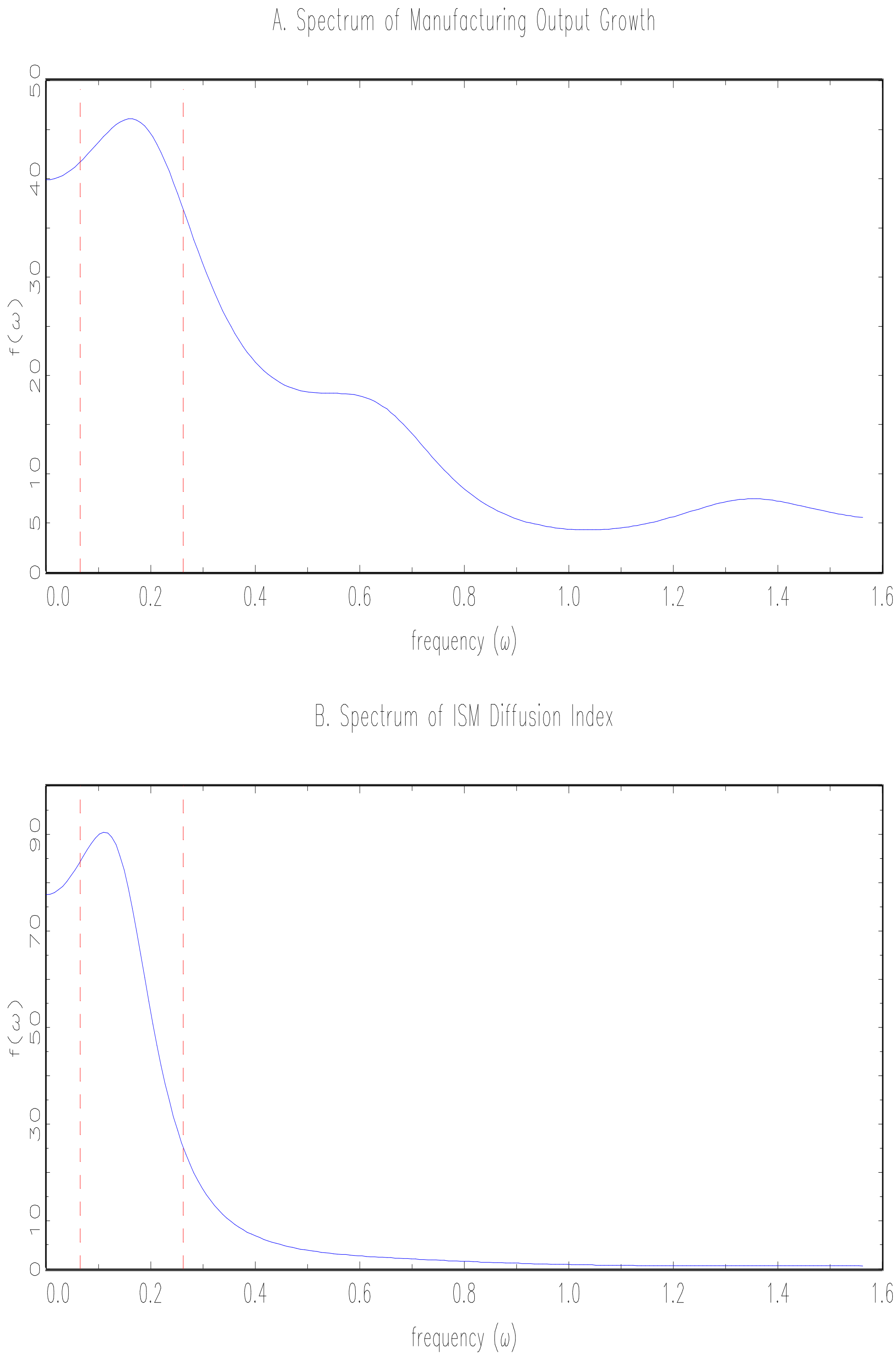
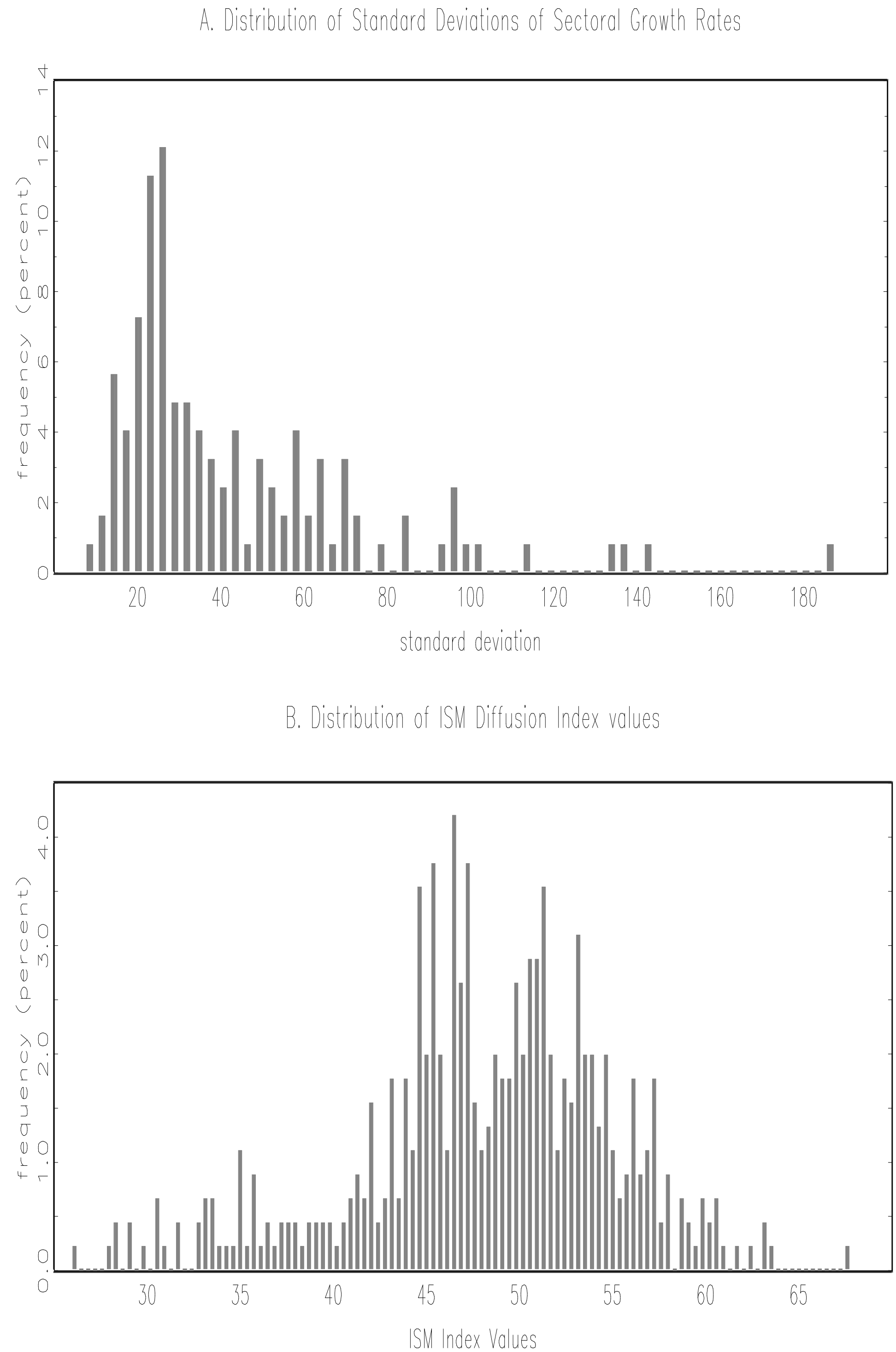


Figure 2. Frequency Decomposition of Manufacturing Variations



Figuer 3. Individual Sector Variations and the Distribution of ISM indices

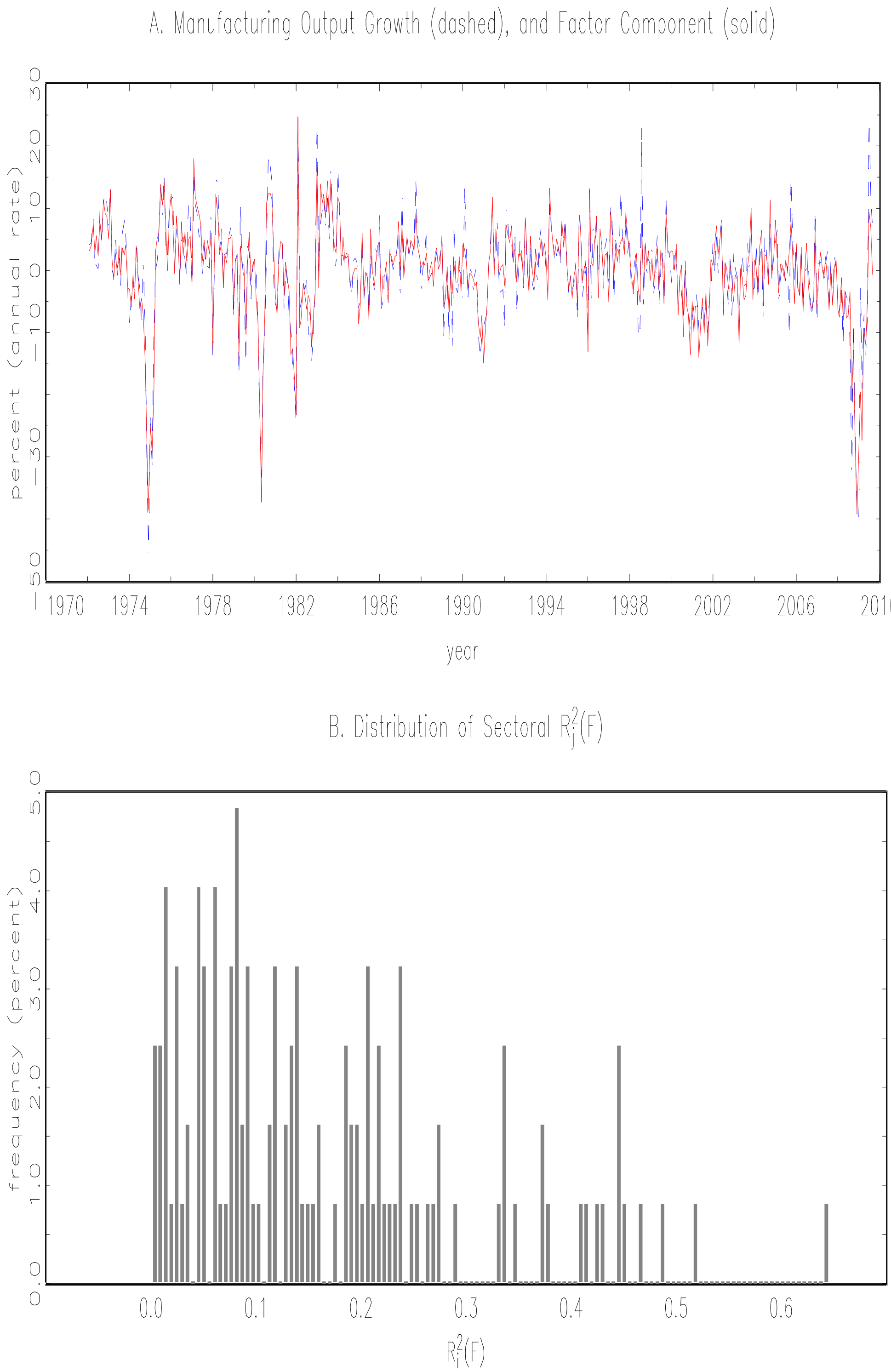


Figure 4. Accounting for Manufacturing Variations Using Common Factors

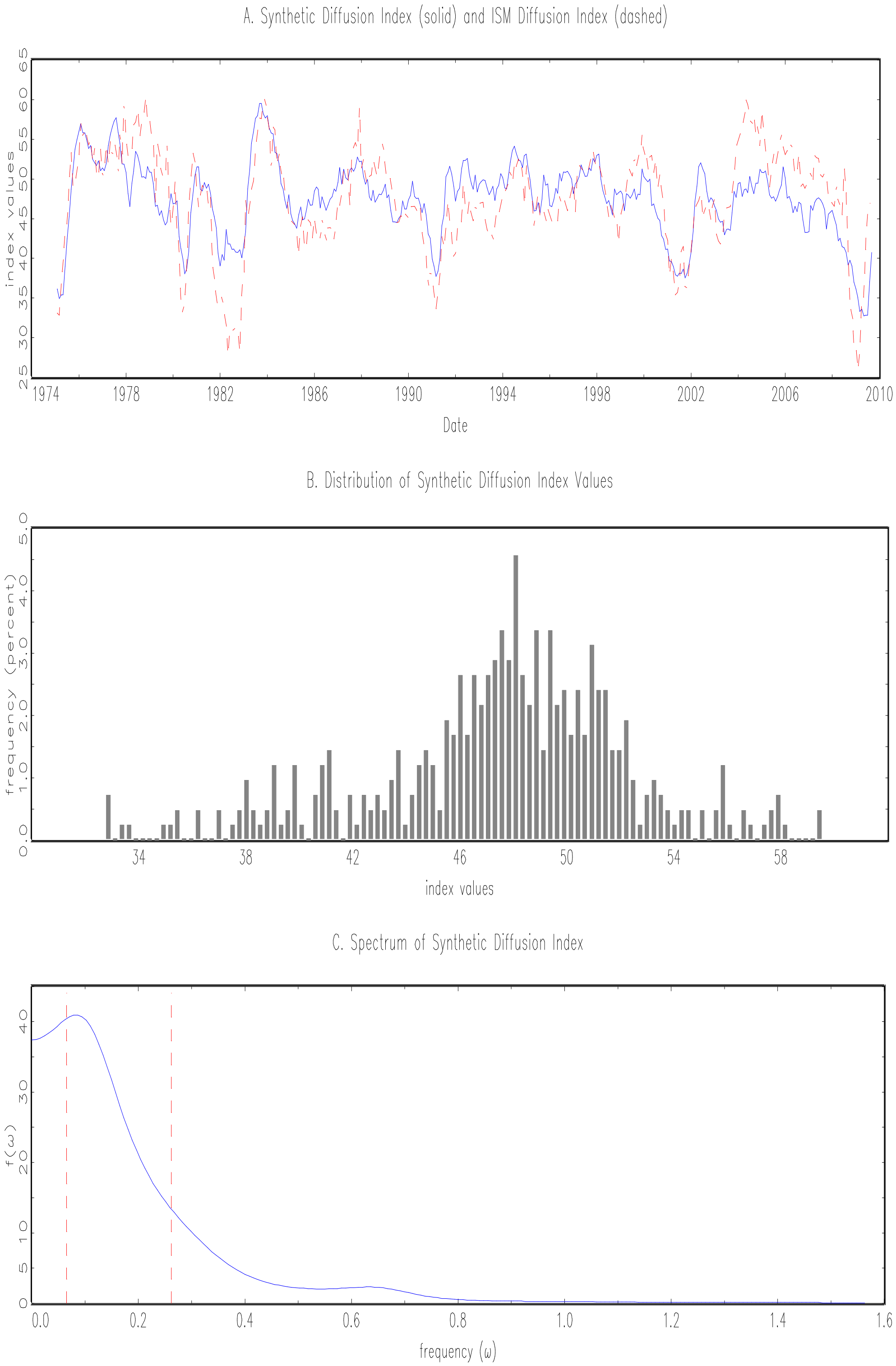


Figure 5. Properties of the Synthetic Diffusion Index

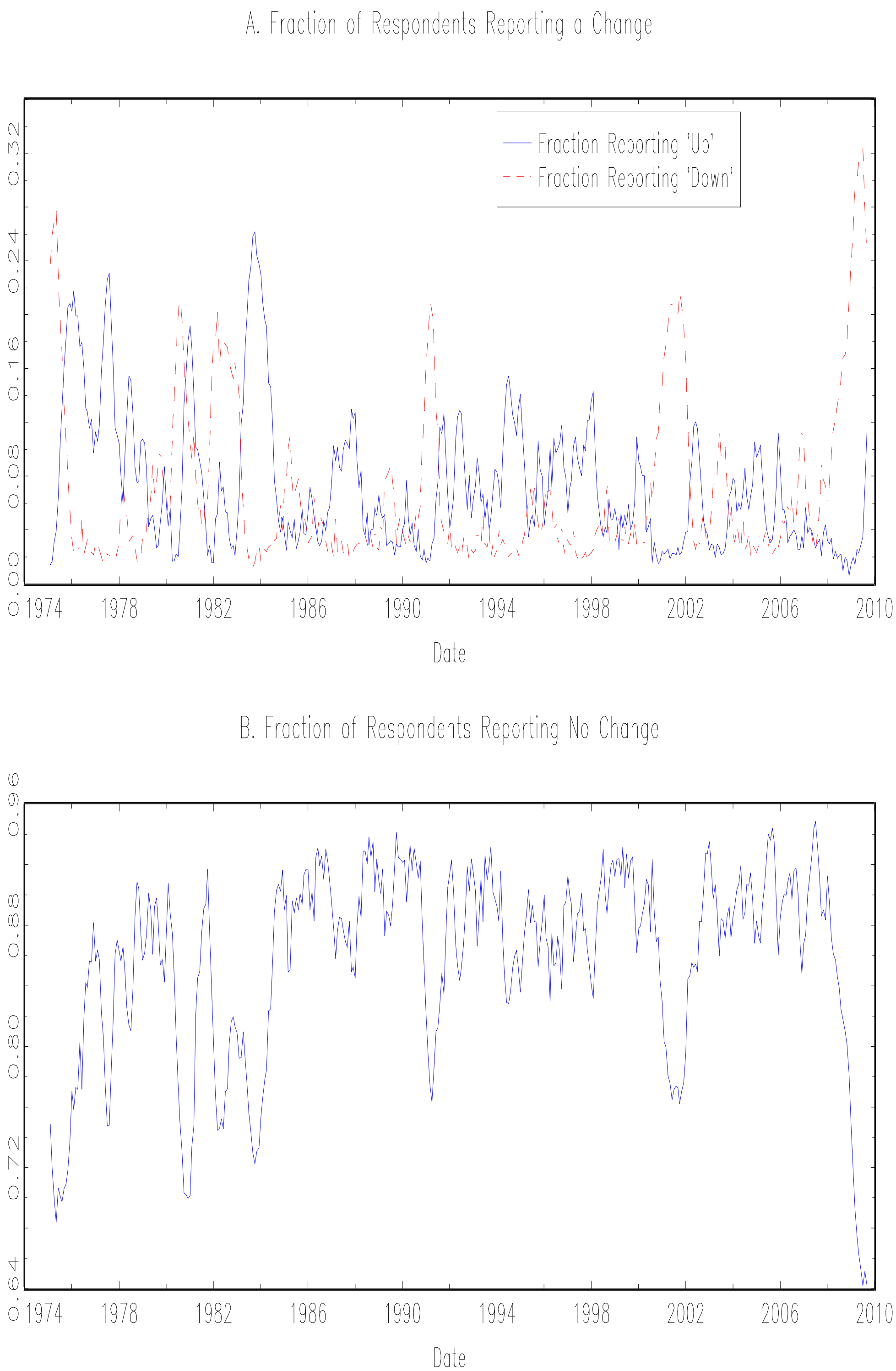


Figure 6. Historical Behvavior of the Proportions of "Optimists" and "Pessimists"

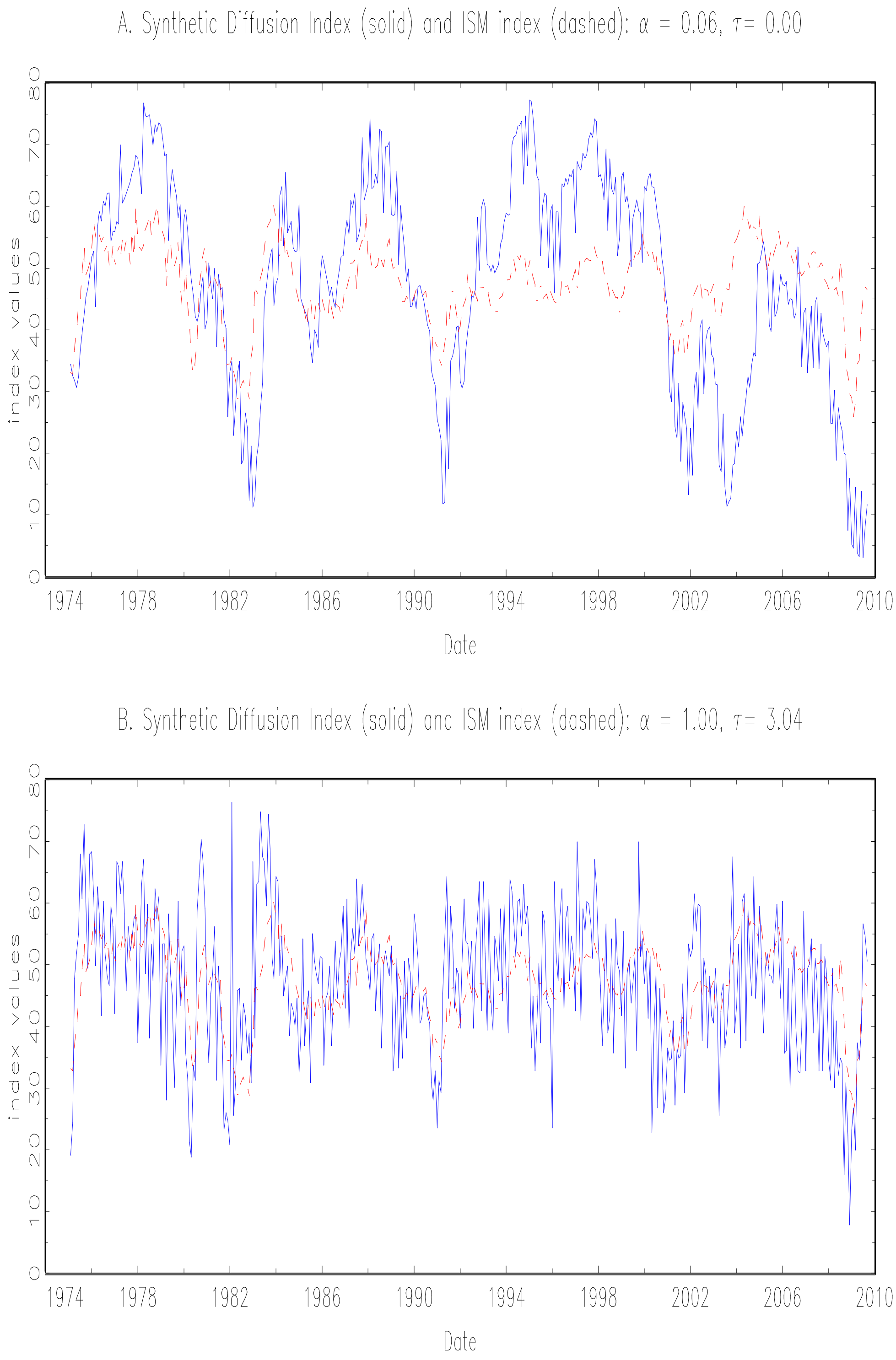
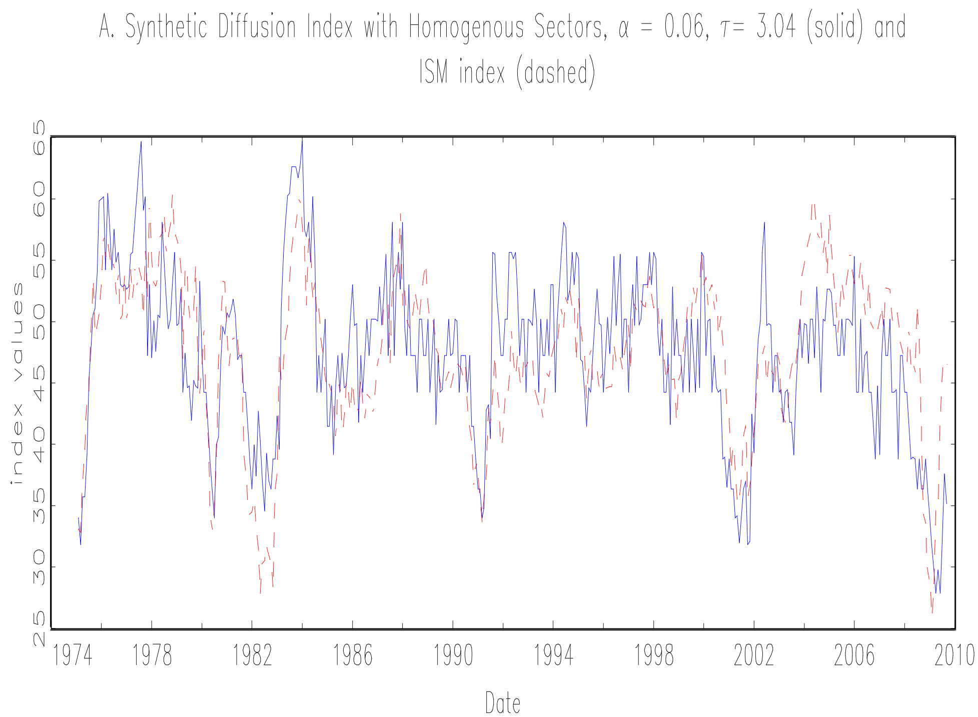


Figure 7. Removing Informational Rigidities with Heterogenous Sectors



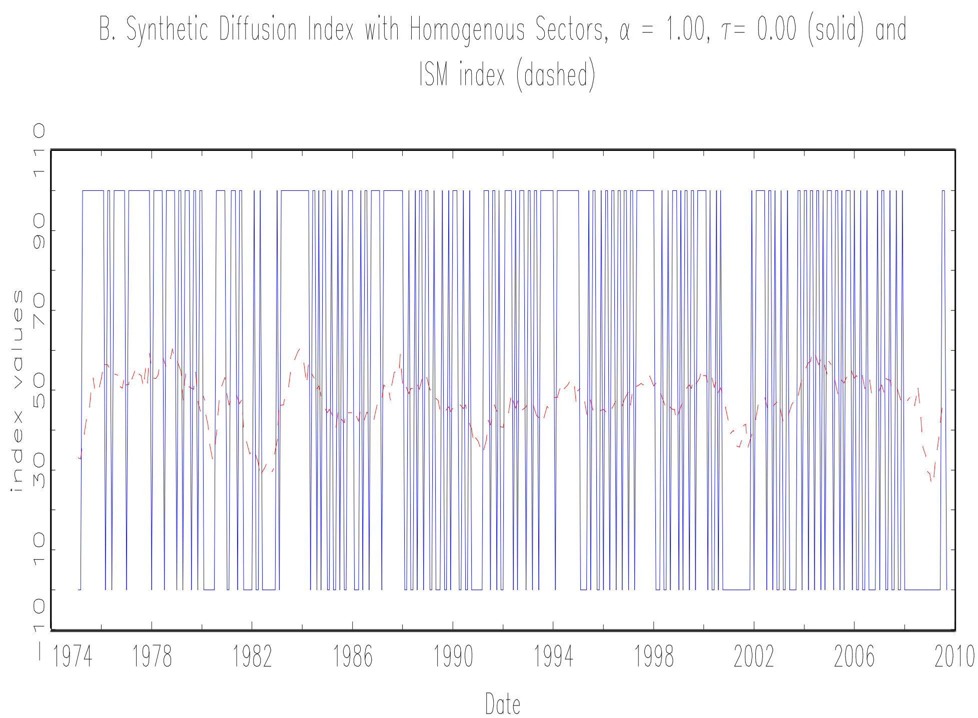


Figure 8. Removing Informational Rigidities with Homogenous Sectors

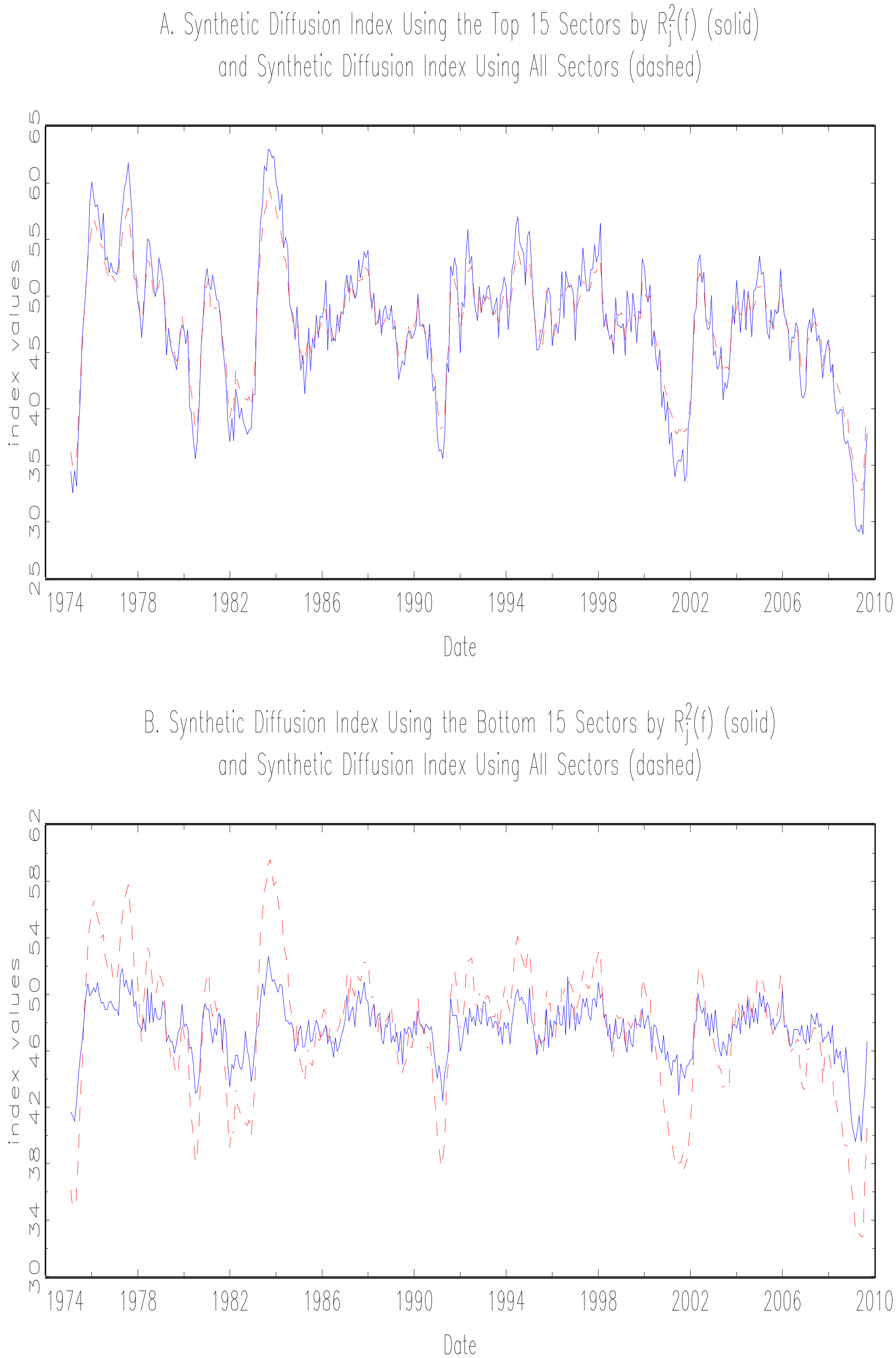


Figure 9. Information Concentration and the Construction of Diffusion Indices

Table 1
Volatility of Output Growth and the ISM Diffusion Index in Manufacturing

	Standard Deviation	*1972-2009* Fraction of Variance at Business Cycle Frequencies $2\ years \le p \le 8\ years$	Fraction of Variance at High Frequencies $p < 2\ years$
Output Growth	8.48	23.39	69.37
Diffusion Index	6.91	57.91	19.27

Table 2
Autocorrelation and Cross-correlation Structure of Output Growth and the ISM index

	Autocorrelations (1972-2009)						
k	0	1	2	3	4	5	6
$\rho(\Delta x_t, \Delta x_{t-k})$	1.00	0.35	032	0.27	0.15	0.10	0.10
$\rho(\mathcal{I}_t, \mathcal{I}_{t-k})$	1.00	0.92	0.85	0.77	0.68	0.60	0.51
	Cross-Correlations (1972-2009)						
k	-3	-2	-1	0	1	2	3
$\rho(\Delta x_t, \mathcal{I}_{t+k})$	0.15	0.22	0.31	0.45	0.51	0.50	0.48

Table 3
Volatility of the Manufacturing ISM Diffusion and Synthetic Diffusion Indices

	Standard Deviation	*1972-2009* Fraction of Variance at Business Cycle Frequencies $2\ years \le p \le 8\ years$	Fraction of Variance at High Frequencies $p < 2\ years$
Diffusion Index	6.91	57.91	19.27
Pseudo Diffusion Index	4.79	54.10	21.66

Table 4

Autocorrelation and Cross-correlation Structure of the ISM Diffusion and Synthetic Diffusion indices

	Autocorrelations (1972-2009)						
k	0	1	2	3	4	5	6
$\rho(\mathcal{I}_t, \mathcal{I}_{t-k})$	1.00	0.92	0.85	0.77	0.68	0.60	0.51
$\rho(\widetilde{\mathcal{I}}_t, \widetilde{\mathcal{I}}_{t-k})$	1.00	0.95	0.88	0.78	0.67	0.56	0.47
	Cross-Correlations (1972-2009)						
k	-3	-2	-1	0	1	2	3
$\rho(\Delta x_t, \mathcal{I}_{t+k})$	0.15	0.22	0.31	0.45	0.51	0.50	0.48
$\rho(\Delta x_t, \widetilde{\mathcal{I}}_{t+k})$	0.24	0.25	0.30	0.45	0.52	0.64	0.64

Table 5

Volatility of Manufacturing Output Growth and the Synthetic Diffusion Index with Fully Informed Respondents, $\alpha = 1$

		1972-2009	
	Standard Deviation	Fraction of Variance at Business Cycle Frequencies $2 \text{ years} \leq p \leq 8 \text{ years}$	Fraction of Variance at High Frequencies $p < 2 \text{ years}$
Output Growth	8.48	23.39	69.37
Pseudo Diffusion Index	11.60	25.74	63.88

Table 6

Autocorrelations of Manufacturing Output Growth and the Synthetic Diffusion Index with Fully Informed Respondents, $\alpha = 1$

	Autocorrelations (1972-2009)						
k	0	1	2	3	4	5	6
$\rho(\Delta x_t, \Delta x_{t-k})$	1.00	0.35	032	0.27	0.15	0.10	0.10
$\rho(\widetilde{\mathcal{I}}_t, \widetilde{\mathcal{I}}_{t-k})$	1.00	0.39	0.38	0.41	0.21	0.17	0.21

Table 7

Most Informative Sectors Ranked According to $R_j^2(F)$

Sector	$R_j^2(F)$	Weight
1. Plastic Products	0.65	1.36
2. Household and Institutional Furniture	0.52	1.22
3. Metal Vales Except Balls and Roller Bearings	0.49	0.62
4. Architectural and Structural Metal Products	0.47	0.86
5. Commercial and Service Industry Machinery	0.45	0.17
6. Other Miscellaneous Manufacturing	0.45	0.51
7. Reconstituted Wood Products	0.45	0.23
8. Fabricated Metals: Forging and Stamping	0.45	0.76
9. Foundries	0.43	2.40
10. Fabricated Metals: Spring and Wire	0.43	3.04
11. Sawmills and Wood Preservation	0.42	0.08
12. Metalworking Machinery	0.41	0.05
13. Coating, Engraving, and Allied Activities	0.39	0.08
14. Textile Furnishings Mills	0.37	0.21
15. Other Electrical Equipment	0.37	0.15

Table 8

Least Informative Sectors Ranked According to $R_j^2(F)$

Sector	$R_j^2(F)$	Weight
1. Aircraft and Parts	0.00	0.42
2. Guided Missile and Space Vehicles	0.00	0.77
3. Fluid Milk	0.00	0.55
4. Coffee and Tea	0.01	1.03
5. Dry, Condensed, and Evaporated Dairy Products	0.01	0.38
6. Primary Smelting/Refining of Nonferrous Metals	0.01	0.01
7. Farm Machinery and Equipment	0.01	0.17
8. Animal Food	0.01	0.16
9. Seafood Product Preparation and Packaging	0.01	0.11
10. Heavy Duty Trucks	0.01	0.88
11. Wineries and Distilleries	0.01	0.45
12. Soft Drinks and Ice	0.02	0.14
13. Copper and Nonferrous Metal Rolling	0.02	1.23
14. Grain and Oilseed Milling	0.02	0.18
15. Mining and Oil and Gas Field Machinery	0.02	0.98