When Is Sticky Information More Information?

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Abstract

This paper uses sectoral data to study survey-based balance 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 notable information lags, on the order of 7 and half months on average. Moreover, information stickiness implies that noisy output fluctuations will be attenuated in survey answers and, consequently, helps explain why balance indices successfully track business cycles. Conversely, in an environment populated by fully informed identical firms, as in the standard RBC framework for example, balance indices instead become degenerate. Finally, information regarding changes in aggregate output tends to be sectorally concentrated. The paper, therefore, illustrates how this feature of the data may be relevant for the construction of balance indices.

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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 business cycles 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 balance index of manufacturing production, based on nationwide surveys, that will be the focus of this 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.

A central issue pertaining to these surveys is that gathering information on a large number of sectors is costly in time and resources. Therefore, to be timely, the scope of the questions must necessarily be limited. Thus, balance 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. Balance 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 balance 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 into balance indices has proven useful in following economic activity in real time.[1]

In this paper, I use sectoral manufacturing data to construct an empirical framework with hypothetical survey respondents. In particular, data on manufacturing production are disaggregated into 124 sectors according to the North American Industrial Classification System (NAICS) and obtained from the Board of Governors of the Federal Reserve System. Each respondent acts as a spokesperson for a firm whose production reflects both aggregate conditions and conditions specific

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

to the sector in which it operates. Methods used to construct balance indices are then applied to these hypothetical respondents to create a synthetic balance 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 first noted by Theil (1952), 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, one 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 sectoral output data over the period 1972-2010, I estimate that survey respondents update their expectations on average every 7 and half months. For comparison, Mankiw and Reis (2006) rely on non-truncated surveys and aggregate data and find average information stickiness of roughly 4 to 6 months for firms, and up to a year for consumers. Most recently, Coibion and Gorodnichenko (2009) present evidence that suggests information lags of around 6 to 7 months on average. No previous work, however, includes 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 balance 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 54 percent of the variation in the monthly ISM production balance index is located at business cycle frequencies compared to less than half that number, just 24 percent, for the variance in monthly aggregate manufacturing production. Information stickiness, therefore, in effect lets respondents abstract from "noisy" movements in sectoral production. In a world populated by identical firms that are always fully informed, as in the standard Real Business Cycle (RBC) environment for example, balance indices would instead be degenerate.[2]

Drawing on previous work in Foerster, Sarte and Watson (2011), 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 balance index, the empirical framework offers 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

[2] 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 balance 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.

of all manufacturing. The intuition is that 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, it is useful to survey the former sectors while largely disregarding the latter sectors. Second, having identified sectors whose variations reflect mostly factors driving aggregate changes, I show that a useful balance index may be produced using considerably fewer sectors than those tracked in the full data set.

The rest of this paper is organized as follows. Section 2 describes the methods typically used to construct the ISM and other balance 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 presents a series of robustness checks on the reasonableness of obtained estimates of information stickiness. Section 7 offers concluding remarks.

2 Description of the ISM and other Production Balance Indices

The Institute for Supply Management is a large U.S. trade association that comprises supply management professionals. As part of a broader mandate, it compiles a monthly Manufacturing Report on Business based on questions asked of purchasing executives in approximately 400 companies. 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 about their state of production. It is easiest for now to consider a balanced panel but this assumption is relaxed in section 6. A firm may answer that its output is "up" (u_t^{ij}), "the same" (s_t^{ij}), or "down" (d_t^{ij}), relative to the previous period. As first motivated by Theil (1952), and comprehensively reviewed in Pesaran and Weale (2006), surveying processes such as that underlying the ISM can be described as cataloging respondents' perception of changes in their firm's output at t relative to $t-1$ in the following manner:

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

In first attempting to take a quantitative approach to qualitative information, Theil (1952) immediately recognized that not all output changes would be considered meaningful enough by respondents to report as increases or decreases. In particular, consistent with Theil's original framework, 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 not worth reporting as "up" or "down." A direct 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.[3] This dependence is made explicit by writing $u_t^{ij}(\tau)$, $s_t^{ij}(\tau)$, and $d_t^{ij}(\tau)$ in equation (1).

Questions asked in surveys underlying the ISM index, as well as in several Federal Reserve Bank surveys, are not released to the public. It is not immediately clear, therefore, that they explicitly distinguish between changes in real business conditions and changes in nominal output otherwise induced by an increase in overall prices. However, from the context of the surveys, and perhaps other communication with ISM membership, it appears understood that spurious changes in production stemming from an increase in overall prices are of limited interest, and the performance of the ISM historically supports this notion. In this paper, I assume that respondents focus on real changes characterizing their firm's output.

Given the structure of the surveys, the fraction of "up" respondents 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 "down" respondents are given by

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

and

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

[3] Theil (1952) writes: " ... it is not correct to think that any increase in production, however small, will be reported by the entrepreneurs as an increase. It is more plausible that changes, either positive or negative, that are proportionally small will not be regarded as increases or decreases but as cases of no change. (...) The interval $(-p, p)$ will be called an indifference interval." I'd like to thank an anonymous referee for pointing me to this quote.

respectively. The value of the ISM balance 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 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 (2011) 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 balance indices in (5) and (6) rely on approximately the same aggregation used to arrive at manufacturing output growth. A notable difference is that the variables being aggregated in the balance 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 balance 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 balance 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) 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 Balance Index

Because Federal Reserve Banks' balance 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 balance index. As explained above, the balance index is a monthly series obtained from the Institute for Supply Management constructed as in equation (5). Monthly data on sectoral manufacturing production and sectoral shares are obtained from the Board of Governors over the period 1972-2010. 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 of the different sectors. 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 and that of the monthly ISM manufacturing production index over the period 1972-2010.[4] 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 production are quite volatile, with a standard deviation 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 balance 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 1973. Given that the ISM manufacturing balance index is meant to capture economic activity in real time, Figure 1B makes clear why it is a popular contemporaneous economic indicator.[5]

[4] Aggregate manufacturing production is calculated from disaggregated sectoral data according to equation (7) but using constant mean weights for simplicity.

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

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 balance 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 balance 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.[6] 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 larger fraction of the variance in the balance index than in manufacturing output growth. In particular, compared to the manufacturing balance 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 balance index. The power spectra in Figure 2 imply that the business cycle interval contains close to 54 percent of the overall variance in the balance index compared to just 24 percent of the variance in monthly manufacturing output growth. In that sense, month to month, the manufacturing balance index performs considerably better than actual manufacturing output growth in tracking variations at business cycle frequencies.

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

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 balance index which, similarly to output growth, is based on monthly aggregated reports of individual changes in output?[7] 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 of 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 balance index is also suggestive of the strength in these cyclical swings. Thus, looking at Figure 3B, most index values are clustered between 50 and 60 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 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 balance 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 balance 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 balance index in that the correlations between output growth and the balance 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

[7] 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.

growth and the manufacturing balance index discussed in Figures 1 through 3 and Tables 1 and 2. The framework exploits the fact that the balance index derives from aggregated reports of monthly manufacturing output changes. Thus, one of its 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.[8]

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

[8] Reis (2006) provides microfoundations for this approach to modeling information stickiness based on an explicit resource cost of acquiring information. Carroll (2003) also shows that this reduced form approach to information stickiness can be rationalized using epidemiological-based models of information transmission.

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. Aside from this strict statistical interpretation, however, Foerster, Sarte, and Watson (2011) also show that equation (12) can be derived as the reduced form solution 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. (2011) 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 balance 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 balance index. However, since the goal of balance 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 balance 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 3A, 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 balance 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

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

and

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

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

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

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

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

Before moving on to estimation and findings, it is worth summarizing the two key elements of the empirical framework set out in this section.[9] 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 (16) is a weighted sum of these information lags, one expects the resulting balance index to be smoother than manufacturing output growth. It is also precisely this mechanism that may allow manufacturing output growth to lead the ISM balance 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

[9] Although not explicitly written to simplify notation, the number of lags, L, used in equation (11) to model respondents' expectations is also folded into problem (17).

resulting model estimates to construct a synthetic balance 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, Stock and Watson (2002) show that principal components provide consistent estimates of the factors. In the second step, estimates of the factors and loadings obtained in this way are used in the construction of the synthetic balance 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 balance index.

The Bai and Ng (2002) ICP1 and ICP2 estimators yield 2 factors in the full sample (1972-2010), and the findings in this section are based on this 2-factor model. 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 balance index. First, I denote by $R^2(F)$ the fraction of aggregate manufacturing variability that is explained by common shocks. In particular, letting w denote the $M \times 1$ vector of constant mean shares, $\Delta x_t = w'\Lambda F_t + w'e_t$ so that $R^2(F) = w'\Lambda\Sigma_{FF}\Lambda'w/\sigma^2_{\Delta x}$, 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 has natural implications for which sectors might be most informative in the construction of a manufacturing balance index.

The factor model implies a volatility of aggregate manufacturing output growth that is nearly identical to that found in the data, 8.35 percent. More important, the common factors explain 84 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, $w'\Lambda F_t$. 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 balance index that reflects aggregate manufacturing output growth, a practical step might focus 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 0.16 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 for 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. Those 15 sectors, therefore, are likely to be most informative in the construction of a balance index for manufacturing production.

Given these findings, equation (17) yields estimates of 0.134 for α and 3.10 for τ.[10] In other words, respondents update their information set every 7 and half months on average (i.e. $1/0.134 = 7.46$), and changes in output are reported as "up" or "down" if they exceed 3 percent. Recall that Figure 3 implied a median standard deviation of 31.85 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 using disaggregated data is generally consistent with previous work based on aggregate data. For instance, Mankiw and Reis (2006, 2007) estimate that a rate of information updating of about 6 months helps best describe the behavior of firms. Coibion and Gorodnichenko (2009) use various macroeconomic survey forecasts to show that forecast errors are persistent in a way consistent with models embodying informational rigidities, and reflect information lags of 6 to 7 months on average. 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, indicating a degree of information stickiness somewhat longer than our estimates suggest. 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.

Tables 3 and 4 describe basic properties of the synthetic balance 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 balance index. Recall that the monthly sectoral data at the base of the empirical work reflect mainly high

[10] 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 $\alpha = 0.134$, only 3 percent of respondents have information lags that exceed 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. The solution to (17) also gives that $L = 2$ best decribes the ISM diffusion index in the sense of minimizing the overall sum of squares, S.

frequency, or "noisy," fluctuations (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 balance 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, $\rho(I_t, I_{t-k})$. 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 balance 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, $\rho(\Delta x_t, I_{t+k})$.

Figure 5 summarizes these findings graphically. Looking at Figure 5A, the synthetic balance index moves relatively closely with the actual ISM index, albeit with some exceptions. The synthetic balance 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. 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. Finally, the synthetic index does not fully reflect the rise in the ISM coming out of the 2001 recession nor does it fully capture the fall in the index around 2009 following the financial crisis. These differences between the synthetic and actual ISM indices explain in large part the lower volatility of the synthetic balance index. Comparing Figures 3B and 5B, the distributions of the synthetic and ISM index values largely overlap 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 balance index's power spectrum in Figure 5C closely matches 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 also close (as in Table 3).

6 Robustness and Additional Aspects of the ISM Index

Having illustrated the significance of information stickiness for survey answers pertaining to the ISM index, this section provides a series of exercises aimed at acquiring a sense of robustness for the estimates obtained in the previous section. In addition, this section highlights some notable features of balances indices uncovered by our empirical framework.

6.1 Robustness

The estimation exercise in section 5 yielded a degree of information stickiness of approximately 7 and half months, which is in the range of other estimates in a literature that, to this point, is largely based on aggregate data. A question that then arises is: what is the sense of tightness around this estimate given the underlying sectoral data?

The estimation process described in the previous section relies on two distinct steps. First, expectations of production growth reflecting differential information sets, $E_{t-k}(\Delta x_t^{ij})$, must be constructed for all sectors. These expectations depend on estimates of Λ and F from the approximate factor model so that, as first underscored by Pagan (1984), some variation in the estimates of α and τ is expected from having generated regressors, $\widehat{\lambda}^j \widehat{F}_{t-k}$, in each sector, j, and for different information sets, $t-k$. Second, estimates of α and τ solve the least square problem (17) where $\widetilde{I}_t(\alpha,\tau)$ reflects in part an information-weighted averaging of the truncated expectations, $E_{t-k}(\Delta x_t^{ij})$, according to equation (16) and the rules set out in (13) trough (15). It may, therefore, have been more appropriate to write $\widetilde{I}_t(\alpha,\tau;\widehat{\Lambda},\widehat{F})$ in problem (17).

The empirical framework in this paper is guided to a large degree by the structure of information stickiness proposed by Mankiw and Reis (2002, 2006), and Reis (2006). This structure, however, does not extend to having clear implications for the nature of the error that is ultimately associated with the observed index, $v_t = I_t - \widetilde{I}_t(\alpha,\tau)$, or how to arrive at standard errors for the estimates of α and τ. Thus, to construct confidence intervals for $\widehat{\alpha}$ and $\widehat{\tau}$, I follow a two-stage bootstrap approach analogous to that followed by Gonçalves and Perron (2010) with respect to factor-augmented regression models. In this approach, both the observed residuals $\widehat{e}_t = (\widehat{e}_t^1, ..., \widehat{e}_t^N)$ from the approximate factor model (12), and observed residuals $\widehat{v}_t$ from the least square problem (17), are used to represent the unobserved distributions $e_t = (e_t^1, ..., e_t^N)$ and v_t under the residual resampling bootstrap procedure.

The bootstrap algorithm proceeds as follows:

1. Let $\widehat{e}_t^*$ represent a resampled version of $\widehat{e}_t = X_t - \widehat{\Lambda}\widehat{F}_t$ in (12) and construct

$$X_t^* = \widehat{\Lambda}\widehat{F}_t + \widehat{e}_t^*, \tag{18}$$

where $\widehat{\Lambda}$ and $\widehat{F}_t$ are treated as true in the bootstrap world.

2. Estimate the bootstrap factors $\widehat{F}_t^*$ and bootstrap loadings $\widehat{\Lambda}^*$ using X_t^*.
3. Let $\widehat{v}_t^*$ denote a resampled version of $\widehat{v}_t = I_t - \widetilde{I}_t(\widehat{\alpha},\widehat{\tau};\widehat{\Lambda},\widehat{F}_t)$ and construct $I_t^* = I_t + \widehat{v}_t^*$.
4. Solve equation (17) using I_t^* and the bootstrap factors, $\widehat{F}_t^*$, and loadings, $\widehat{\Lambda}^*$,

$$\min_{\alpha,\, \tau} \ \mathcal{S}(\alpha,\tau) = T^{-1}\sum_{t=1}^{T}\left(\mathcal{I}_t^* - \widetilde{\mathcal{I}}_t(\alpha,\tau;\widehat{\Lambda}^*,\widehat{F}_t^*)\right)^2, \tag{19}$$

to yield bootstrap estimators $\widehat{\alpha}^*$ and $\widehat{\tau}^*$.

Figure 6 illustrates the empirical distribution of information stickiness, $1/\widehat{\alpha}^*$, and indifference thresholds, $\widehat{\tau}^*$, obtained from this bootstrap procedure using 2000 Monte Carlo trials. These distributions suggest 95 percent confidence intervals of $[6.10, 8.51]$ months for the degree of information stickiness, and $[2.43, 3.78]$ for the indifference thresholds. Thus, the degree of information stickiness depicted in Figure 6A is consistent with estimates of 6 to 7 months suggested in Coibion and Gorodnichenko (2009), but does not quite stretch to a situation where information is updated only once a year as in Mankiw and Reis (2002). Interestingly, the empirical distribution in Figure 6A also suggests that a rate of information updating faster than 5 months is distinctly unlikely given our sectoral data.

Without assuming that v_t is gaussian, an alternative approach to (17) would have been to solve a least absolute deviations problem, $\min_{\alpha,\ \tau}\ S^d(\alpha,\tau) = \sum_{t=1}^{T} |I_t - \widetilde{\mathcal{I}}_t(\alpha,\tau)|$, although least squares typically offers a more stable solution. In fact, carrying out the least absolute deviations problem gives an estimate of information stickiness of 7.75 months which is close to the benchmark estimate of 7.46 months. The indifference threshold is now estimated to be 3.00 percent compared to 3.10 percent in the benchmark case.

Thus far, I have proceeded as though the ISM were based on a balanced panel with N respondents in each of M sectors. In practice, however, membership in the ISM Business Survey Committee is initially based on each industry's contribution to GDP. Depending on the particular survey and whether it targets, say, manufacturing or services, these weights are then adjusted to reflect that survey's importance in GDP. For example, in the case of manufacturing production, the weight of each industry included in manufacturing must be divided by the total share of manufacturing in GDP so that the adjusted weights sum to one. This amounts to each manufacturing industry's representation being proportional to its share in total manufacturing production, denoted w^j.

To see the implication of this alternative weighting scheme for the empirical framework, let $\overline{N}$ denote the total number of respondents across all sectors and information sets, and N_j the number of respondents in industry j. Specifically, $\overline{N} = \sum_{j=1}^{M}\sum_{k=0}^{\infty} N_j\alpha(1-\alpha)^k$ so that, with a balanced panel, $\overline{N} = MN$. Averaging all respondents' answers, once truncated appropriately according to (13) through (15), yields

$$\widetilde{I}_t(\alpha,\tau) = (\overline{N})^{-1}\sum_{j=1}^{M} N \sum_{k=0}^{\infty}\alpha(1-\alpha)^k \left(u_t^{kj}(\tau) + \frac{1}{2}s_t^{kj}(\tau)\right) \times 100, \tag{20}$$

or equation (16), with each sector having equal weight, $N/\overline{N} = 1/M$, in the index. When the number of survey respondents in a given sector is instead weighted according to that sector's share in aggregate production, so that $N_j/\overline{N} = w^j$, we have that $\sum_{j=1}^{M}\sum_{k=0}^{\infty} N_j\alpha(1-\alpha)^k = \sum_{j=1}^{M}\sum_{k=0}^{\infty} w_j\overline{N}\alpha(1-\alpha)^k$, and averaging the responses gives

$$\begin{aligned} \widetilde{I}_t^u(\alpha,\tau) &= (\overline{N})^{-1}\sum_{j=1}^{M} N_j \sum_{k=0}^{\infty}\alpha(1-\alpha)^k \left(u_t^{kj}(\tau) + \frac{1}{2}s_t^{kj}(\tau)\right) \times 100 \\ &= \sum_{j=1}^{M} w^j \sum_{k=0}^{\infty}\alpha(1-\alpha)^k \left(u_t^{kj}(\tau) + \frac{1}{2}s_t^{kj}(\tau)\right) \times 100, \end{aligned} \tag{21}$$

where the superscript "u" stands for "unbalanced." Put simply, each sector now has weight w^j in the index rather than $1/M$. Using this alternative formulation for the synthetic index, the empirical exercise yields estimates of information stickiness of 7.30 months, compared to our benchmark of 7.46 months, and the same indifference threshold, 3.10 percent. These findings are consistent with the observation in Foerster et al. (2011) that when aggregating sectoral data, whether one uses constant mean weights, time varying weights, or uniform weights does not appear to play a material role.

The degree of information stickiness estimated under either weighting scheme (20) or (21) involves the full set of sectors in manufacturing. One might alternatively inquire about the extent of informational rigidities in subsets of industries. One natural segmentation of manufacturing, that nevertheless still leaves a large number of sectors for the factor analysis, distinguishes between non-durable and durable goods. Following the procedure described in section 4, the non-durable goods sector yields an estimate of information stickiness of 7.60 months, with an indifference threshold of 2.00 percent. In the durable goods sector, the estimated degree of informational rigidities is 6.70 months, associated with an indifference threshold of 4.90 percent. While these estimates are relatively close to our benchmark estimates, the more narrow industry findings presented here are indicative of equilibrium outcomes that add some range to the set of results presented thus far, rather than provide a more structural interpretation of cross-industry differences in informational rigidities. Information stickiness ultimately reflects deliberate decisions on the part of economic agents regarding how fast to update their information sets. These decisions depend in turn on the benefits of updating, which are presumably greater in more volatile industries, and on the costs which may also vary by industries because of differences in production processes.

Alternatively, one might also ask about how the extent of informational rigidities may have changed over time. One of the most studied aspects of Figure 1 is the break in the volatility of aggregate manufacturing output growth around 1984, and a question arises as to its implications for estimates of information stickiness within our empirical framework. Foerster et al. (2011) document that the sharp decline in the volatility of aggregate manufacturing production in the mid 1980s applies at the disaggregated sectoral level as well. In terms of the ISM manufacturing balance index, Figure 1B shows a decline in volatility that is not quite as dramatic as that characterizing output growth around 1984, although the overall amplitude of the index does nevertheless fall. Because manufacturing production becomes less volatile after 1984, less smoothing of high frequency output fluctuations are necessary relative to pre-1984 to match the balance index in Figure 1B. In the empirical framework, less smoothing is achieved in part by way of a higher α, and thus less information stickiness, in the moving average of current and past information captured in equation (16). At the same time, this moving average is carried out given the distribution of respondents across "optimists" and those who are "indifferent" in the index, which is governed by τ in (13). In particular, a higher indifference threshold means that more responses are counted as "no change" which, all else equal, reduces the amplitude of the synthetic index. Estimating the empirical model in section 4 over the $1972 - 1983$ period yields an estimate 0.11 for α, or an average rate of information updating of 9 months, with an indifference threshold of 2 percent. In contrast, over the $1984 - 2009$ period, the rate at which firms update their information set falls to 5 months on average, with an estimate of 0.22 for α, and an associated indifference threshold of 4.70 percent. While the quicker rate of information updating in the more recent period is consistent with a falling cost of acquiring information over time, the same caveat underscored in the case of our industry results applies. Since the benefits of updating information are presumably also smaller in the less volatile environment of post 1984, these findings are more narrowly interpreted as indicative of equilibrium outcomes rather than of structural changes in information acquisition.

In summary, estimates of informational rigidities derived from an application of the models in Mankiw and Reis (2002,2006), and Reis (2006), to sectoral manufacturing data suggests a rate of information updating ranging between 5 months and 9 months, depending on the set of industries and the time period under consideration.

6.2 Additional Aspects of Balance Indices

One key lesson from the empirical framework is that informational rigidities help explain the relatively smooth behavior of the ISM index given the relatively noisy fluctuations of the underlying disaggregated data. However, even absent informational rigidities, in converting survey reports into simple trichotomous classifications and averaging them, the underlying sectoral data are already truncated into an index, but it is not clear how well this "full information" alternative series might perform in capturing business cycle frequencies.

To isolate the effects of sticky information on our synthetic index, suppose that respondents are all fully informed, $\alpha = 1$. Two key findings emerge. First, the proportions of variance of $\widetilde{\mathcal{I}}_t(1, \tau)$ that are attributable to business cycles (as well as shorter frequency fluctuations) become similar to those of manufacturing output growth. Only 28 percent of the variation in the synthetic index is now explained by business cycle frequencies, compared to 50.34 percent in the benchmark case and 24 percent for manufacturing output growth. Second, the autocorrelation properties of $\widetilde{\mathcal{I}}_t(1, \tau)$ turn out to be much closer to those of manufacturing output growth than the ISM index, thus reproducing the "choppiness" of manufacturing growth. In sum, without information stickiness, movements in the synthetic index essentially mimic those of manufacturing output growth despite the truncation rules defined by (13). In that sense, with fully informed respondents, the resulting balance index is no more useful in capturing business cycle conditions than aggregate manufacturing production.[11] 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, whether through informational rigidities or otherwise.

Estimates from the factor model presented in section 5 indicated that i) the factor component, $w'\Lambda F_t$, 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 industries more than others. In fact, Figure 5B suggests that many industries in the data set likely contribute very little

[11] 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.

information to a balance index meant to track overall changes in manufacturing in real time. In particular, output variations in industries where $R_j^2(F)$ is close to zero are almost entirely driven by idiosyncratic considerations. Figure 7 plots a balance index constructed as in section 4 but using only the top 15 sectors ranked by $R_j^2(F)$. The figure shows that surveying only 15 sectors where the common factors have the greatest role is enough to produce a balance index that is close to that constructed using all sectors. This finding illustrates the potential relevance of factor analytic methods, and importance of sectoral concentration of information, for the construction of balance indices.[12] In addition, focusing on fewer sectors might allow for more detailed surveying of firms, which in turn can make it possible to more systematically address pitfalls associated with firm size or intensity of changing conditions noted in Koenig (2002).

Finally, the proportions of "optimists" (those reporting expected production increases), and "pessimists," (those reporting expected production decreases) in the empirical framework are given by $\widetilde{U}_t(\alpha,\tau) = M^{-1}\sum_{j=1}^{M}\sum_{k=0}^{\infty}\alpha(1-\alpha)^k u_t^{kj}(\tau)$ and $\widetilde{D}_t(\alpha,\tau) = M^{-1}\sum_{j=1}^{M}\sum_{k=0}^{\infty}\alpha(1-\alpha)^k d_t^{kj}(\tau)$, respectively. The proportion of respondents reporting "no change" is simply the residual $1 - \widetilde{U}_t(\alpha,\tau) - \widetilde{D}_t(\alpha,\tau)$. Figures 8A and 8B depict the model-implied behavior of these proportions over past business cycles when compared to their counterparts reported by the ISM. The fraction of model-implied "pessimists" in Figure 8A tracks ISM "down" responses well, with a correlation of 0.79. The fraction of model-implied "optimists" in Figure 8B, although commoving relatively well with ISM "up" responses with a correlation of 0.66, appears generally below the corresponding ISM-reported percentages, especially towards the latter part of the sample. Over the full sample period, "up" responses represent 27 percent of all responses in the ISM index on average while the model counterpart proportion is 15 percent.

As indicated in Pesaran and Weale (2006), the assumption of a symmetric indifference threshold $[-\tau,\tau]$ seems natural and is often convenient in setting up an empirical exercise around balance indices. However, Figures 8A and 8B suggest that survey respondents may in part have somewhat different thresholds for "up" responses and "down" responses, and understanding why is a potentially interesting question for future research.[13] More generally, both the upper and lower indifference thresholds could independently vary with the specific industry being surveyed or even over time. This added flexibility, however, comes at the cost of having to estimate additional parameters. In the case where these thresholds are both industry-specific and time varying, potentially implying a very large number of parameters, sectoral production data of the kind used in this

[12] The choice of 15 sectors here is somewhat arbitrary. In Figure 4B, the factor component explains more than 40 percent of the variations in output in 15 sectors. Additional sectors help bring the "narrow" synthetic index closer to the benchmark synthetic index that uses all sectors but it is clear that most of the work is being done by sectors where the factor component plays a large role.

[13] In the empirical model, "optimists" and "pessimists" are represented in approximately equal proportions, at around 14 percent, although the symmetry of the underlying data also matters. McQueen and Thorley (1993), and Acemoglu and Scott (1997), suggest asymmetric elements of business cycles. Note also in Figure 8 that the proportion of "pessimists" displays pronounced spikes around recessionary periods while the proportion of "optimists" tends to be more uniform.

paper may no longer be sufficient but having access to individual firm responses could prove a way forward.[14]

7 Concluding Remarks

This paper has used disaggregated manufacturing data to study survey-based balance 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 balance 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 balance index reflect notable information lags, on the order of 7 and a half 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 balance indices as economic indicators.

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 capturing 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 shows how factor analytic methods may be used to distinguish between the most and least informative sectors in constructing a balance index of manufacturing production.

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[14] The Census Bureau's Monthly Manufacturing Survey (M3 Survey) contains firm level data on shipments and new orders, among other things, although access procedures are onerous. This data can only be accessed through one of the regional data centers with an approved research proposal. Once obtained, M3 survey firm level data could potentially be matched by name, address, and industry, with respondents to regional Fed surveys. The match rate is likely to be well below 100 percent, but the resulting integrated data may nonetheless be quite helpful in further investigating informational rigidities using survey data.

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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

Table 1

Volatility of Output Growth and the ISM balance Index in Manufacturing

		1972-2010	
	Standard Deviation	Fraction of Variance at Business Cycle Frequencies $2\ years \leq p \leq 8\ years$	Fraction of Variance at High Frequencies $p < 2\ years$
Output Growth	8.35	23.90	68.57
Balance Index	7.85	54.15	30.03

Table 2

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

				Autocorrelations (1972-2010)			
k	0	1	2	3	4	5	6
$\rho(\Delta x_t, \Delta x_{t-k})$	1.00	0.36	033	0.27	0.16	0.10	0.10
$\rho(\mathcal{I}_t, \mathcal{I}_{t-k})$	1.00	0.89	0.78	0.66	0.54	0.44	0.35
				Cross-Correlations (1972-2010)			
k	-3	-2	-1	0	1	2	3
$\rho(\Delta x_t, \mathcal{I}_{t+k})$	0.23	0.34	0.47	0.58	0.62	0.56	0.47

Table 3

Volatility of the Manufacturing ISM balance and Synthetic balance Indices

		1972-2010	
	Standard Deviation	Fraction of Variance at Business Cycle Frequencies $2\ years \leq p \leq 8\ years$	Fraction of Variance at High Frequencies $p < 2\ years$
Balance Index	7.85	54.15	30.03
Synthetic Balance Index	6.08	50.34	32.95

Table 4

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

	Autocorrelations (1972-2010)						
k	0	1	2	3	4	5	6
$\rho(\mathcal{I}_t, \mathcal{I}_{t-k})$	1.00	0.89	0.78	0.66	0.54	0.44	0.35
$\rho(\widetilde{\mathcal{I}}_t, \widetilde{\mathcal{I}}_{t-k})$	1.00	0.90	0.76	0.61	0.47	0.36	0.28
	Cross-Correlations (1972-2010)						
k	-3	-2	-1	0	1	2	3
$\rho(\Delta x_t, \mathcal{I}_{t+k})$	0.23	0.34	0.47	0.58	0.62	0.56	0.47
$\rho(\Delta x_t, \widetilde{\mathcal{I}}_{t+k})$	0.22	0.31	0.40	0.59	0.73	0.67	0.58

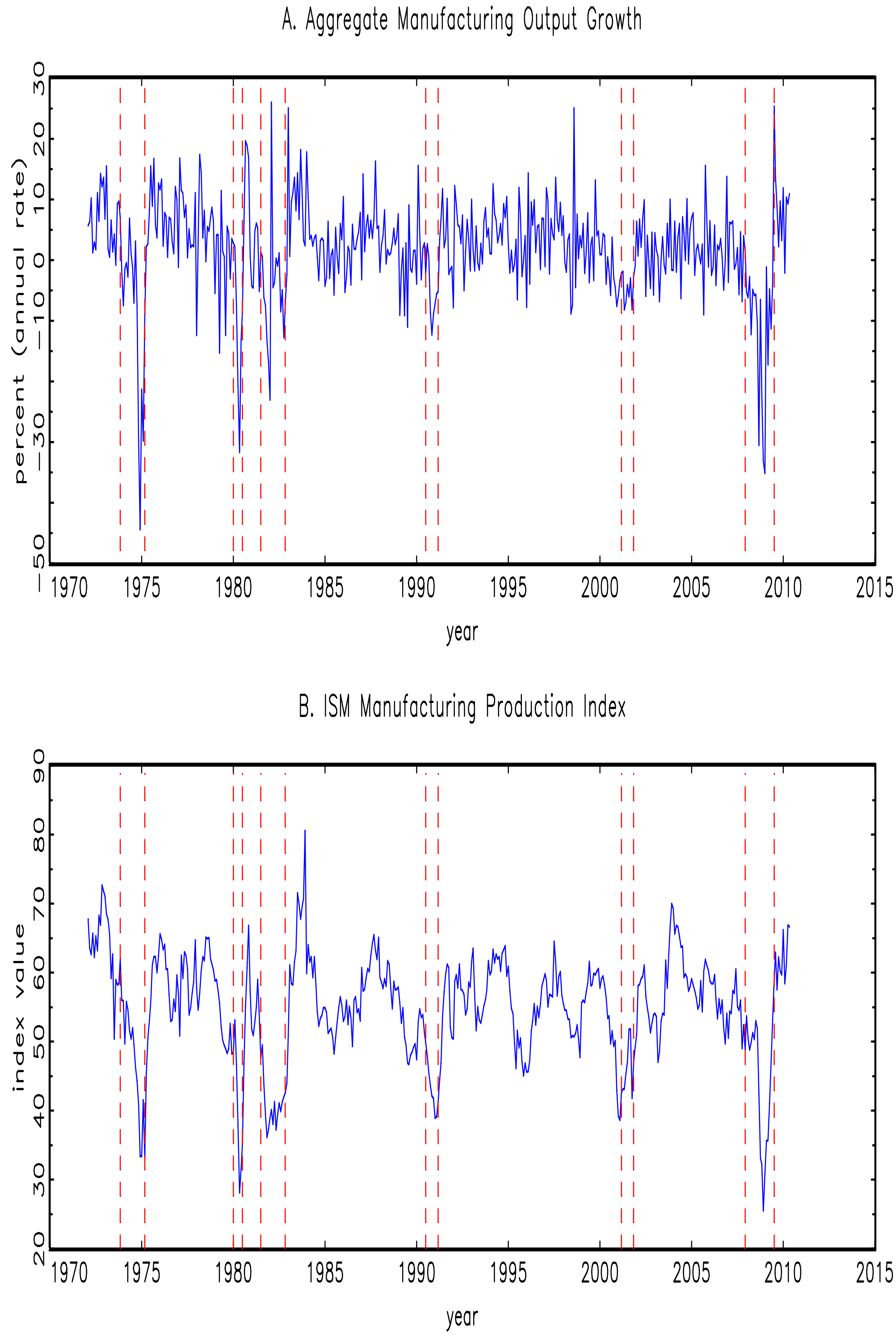

Figure 1: Aggregate Variations in Manufacturing

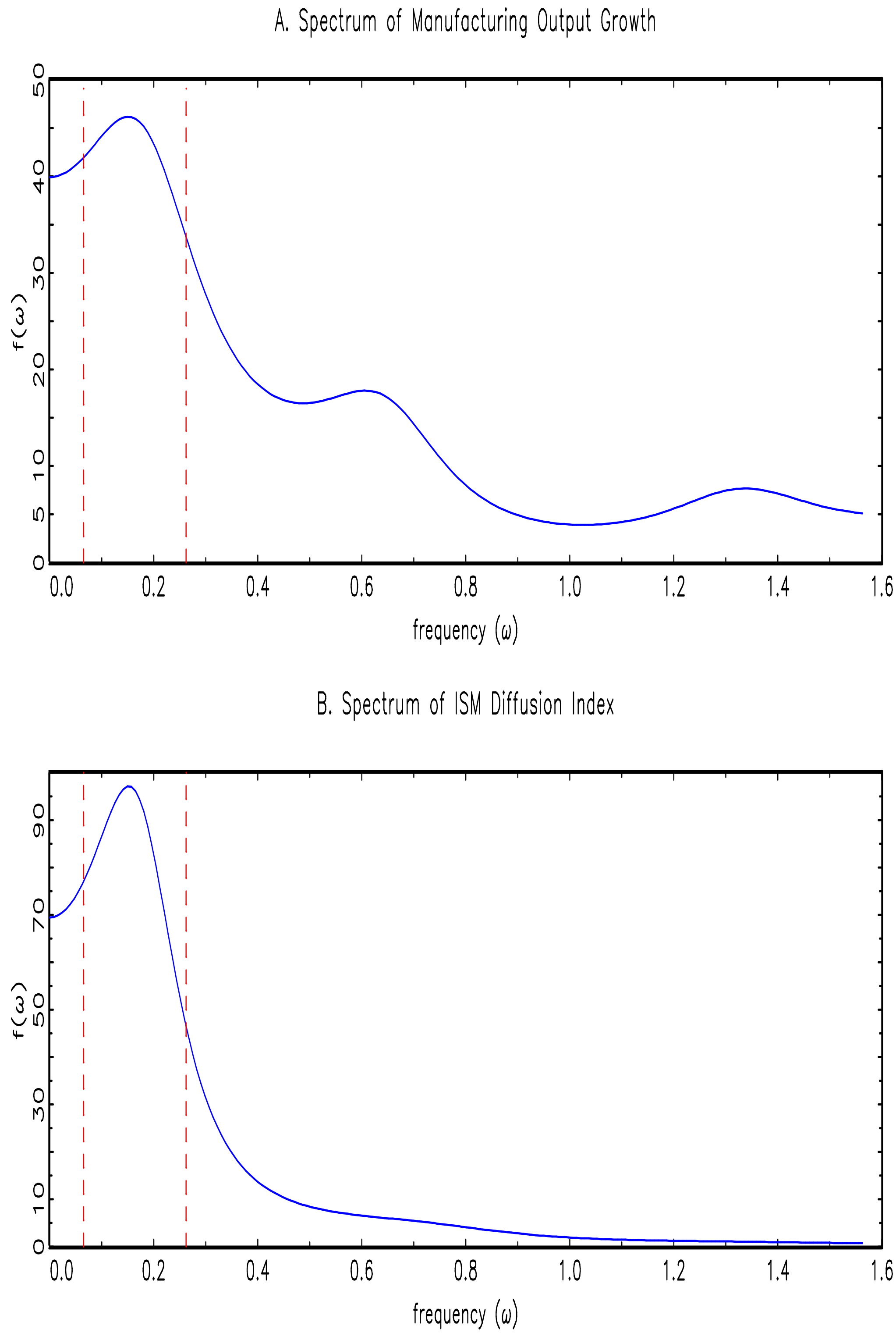

Figure 2: Frequency Decomposition of Manufacturing Variations

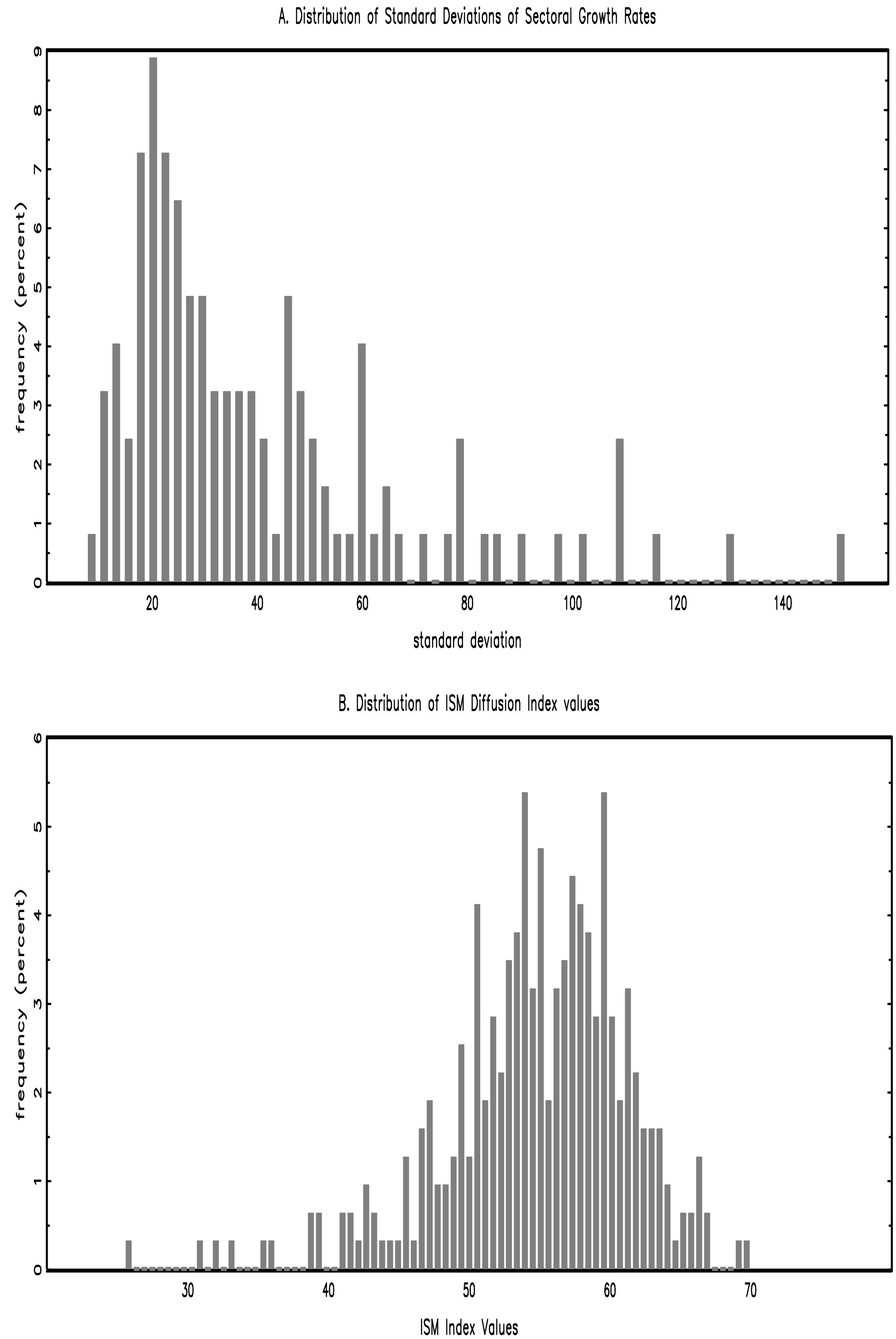

Figure 3: Individual Sector Variations and the Distribution of ISM Indices

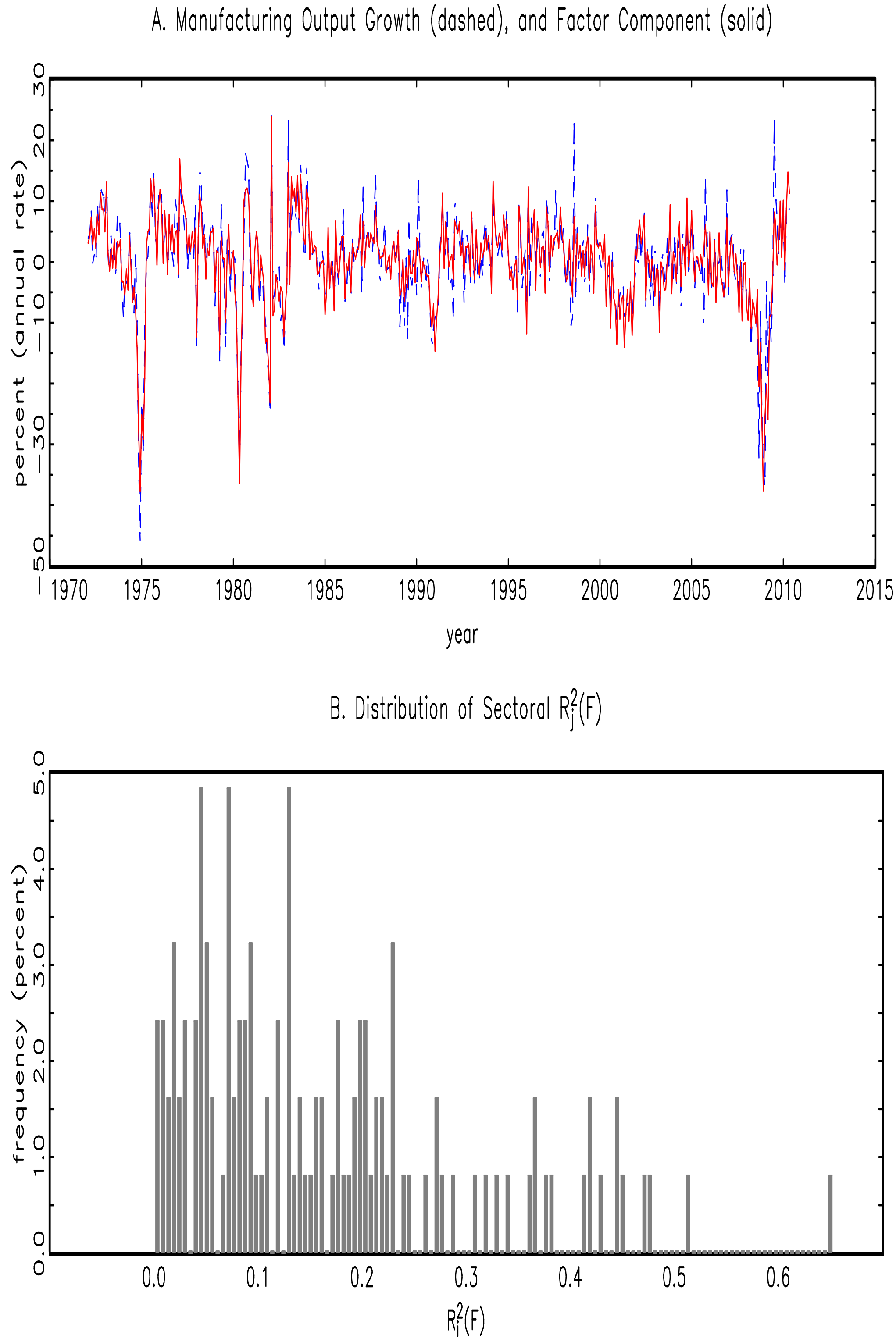

Figure 4: Accounting for Manufacturing Variations Using Common Factors

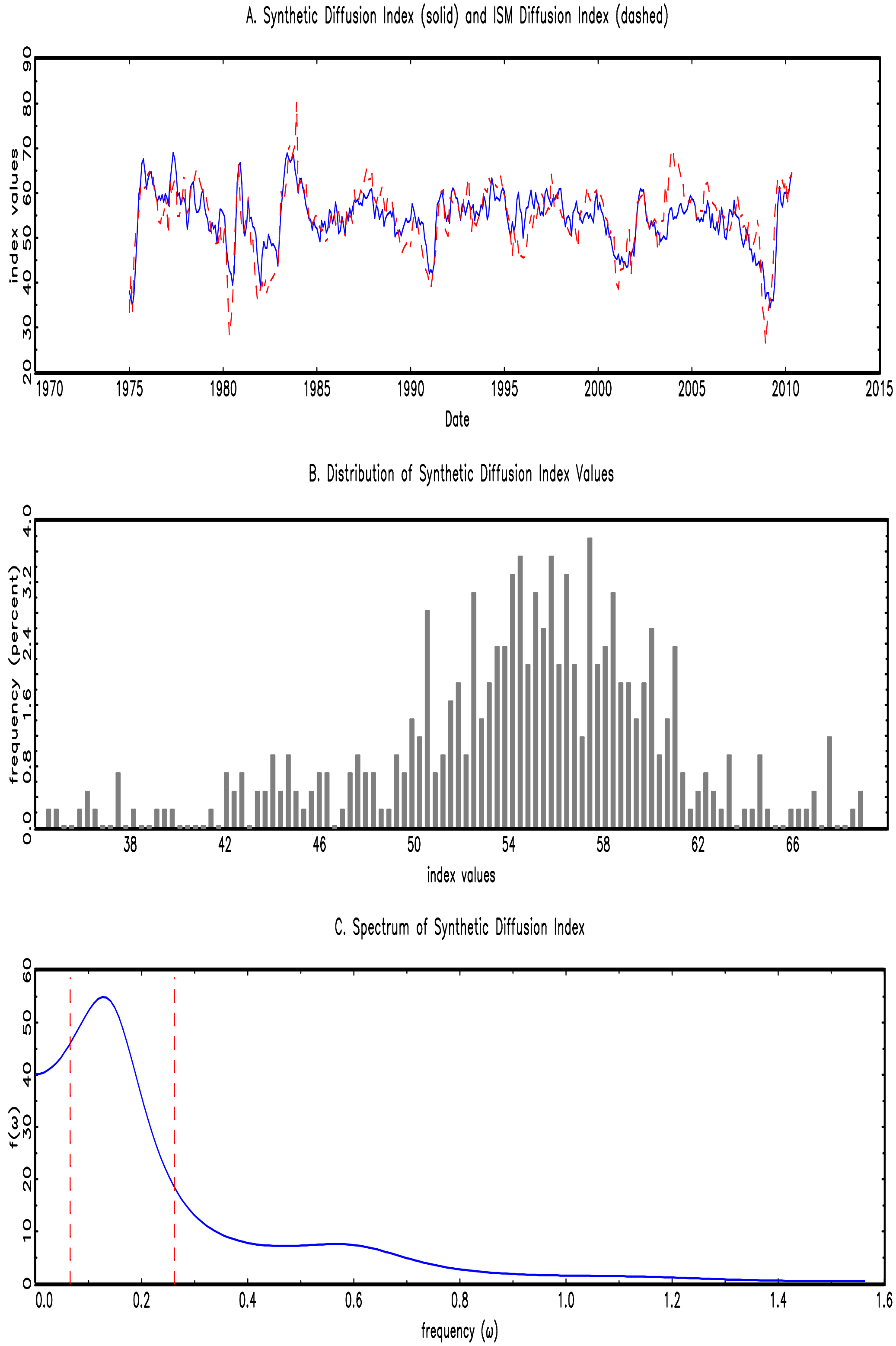

Figure 5: Properties of the Synthetic Diffusion Index

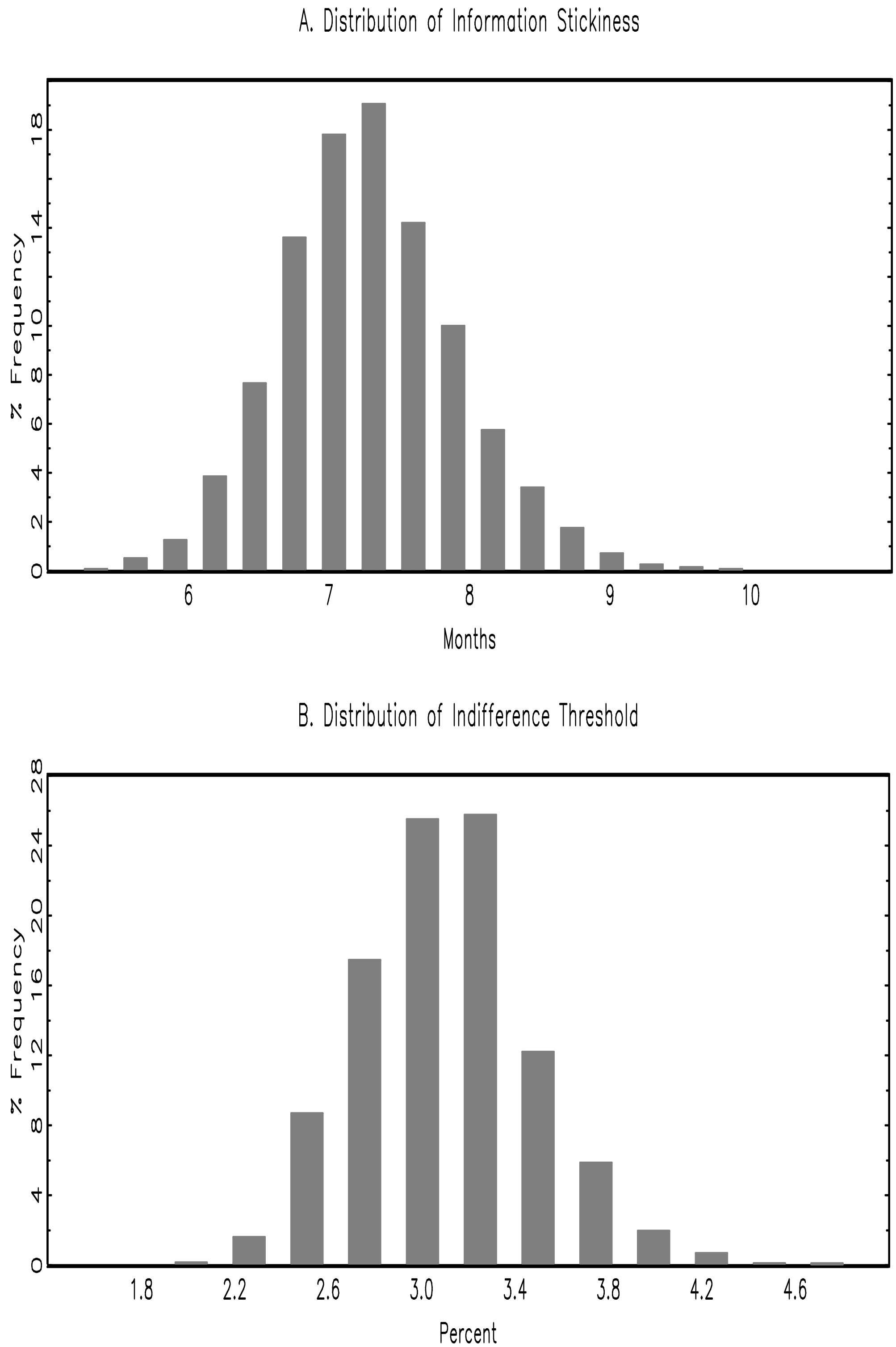

Figure 6: Empirical Distributions of Informational Rigidities

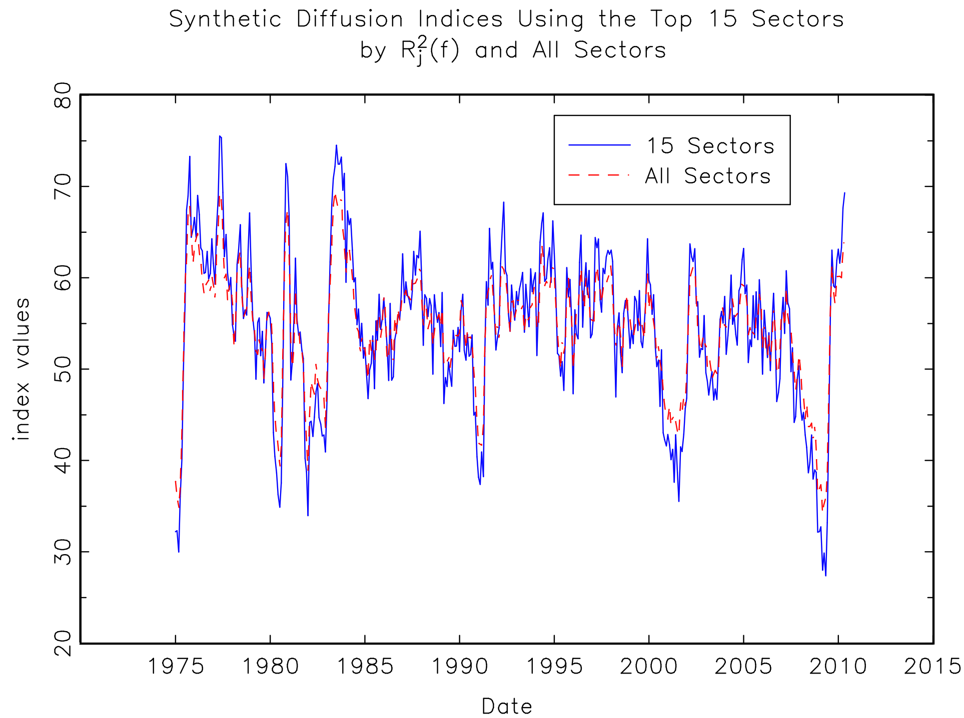

Figure 7: Sectoral Information Concentration and Balance Indices

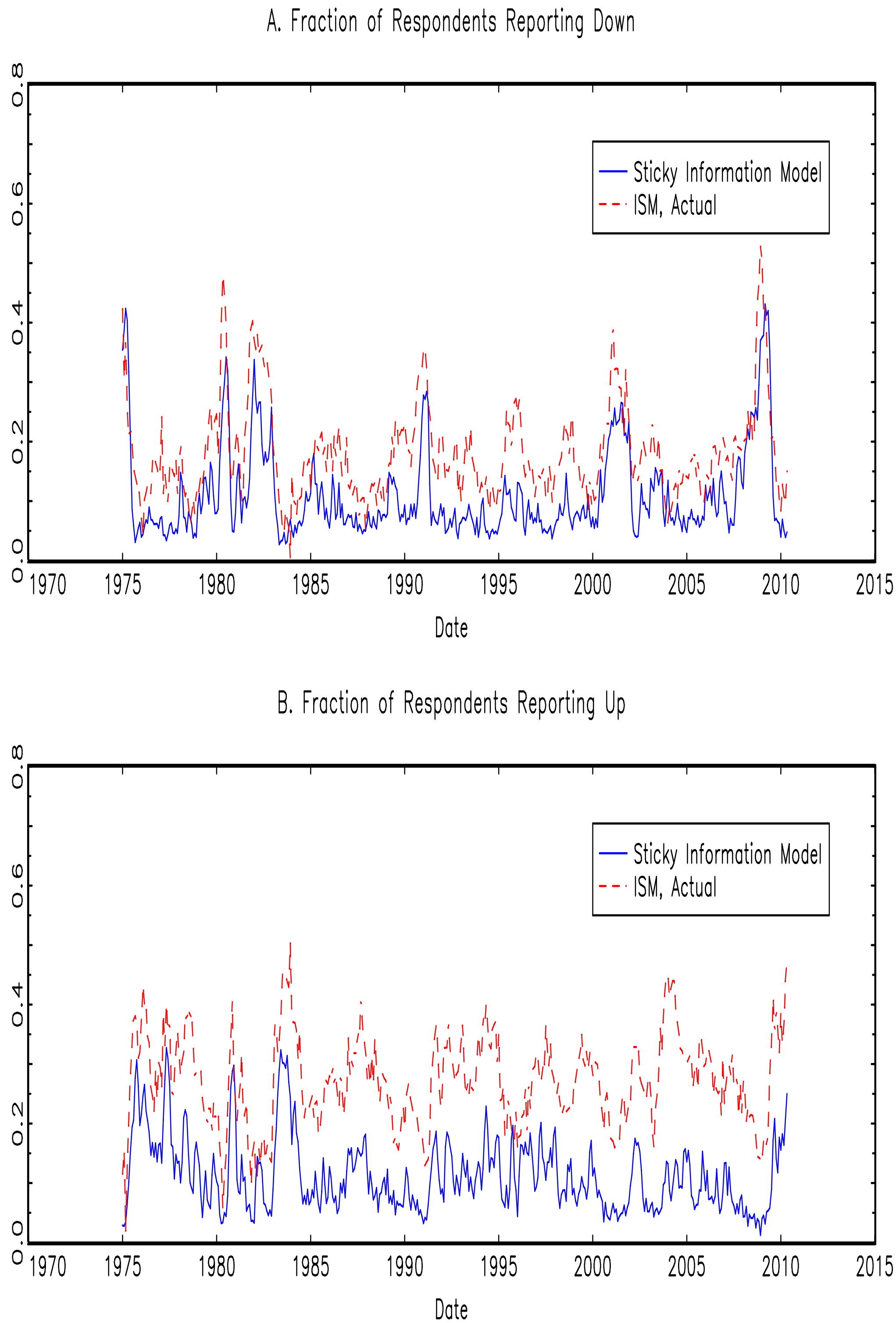

Figure 8: Proportions of Pessimists and Optimists in the Balance Index