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QUANTIFYING THE QUALITATIVE RESPONSES OF THE OUTPUT PURCHASING MANAGERS INDEX IN THE US AND THE EURO AREA

by Philip Vermeulen

In 2012 all ECB publications feature a motif taken from the €50 banknote.

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Abstract

The survey based monthly US ISM production index and Eurozone manufacturing PMI output index provide early information on industrial output growth before the release of the official industrial production index. I use the Carlson and Parkin probability method to construct monthly growth estimates from the qualitative responses of the US ISM production index and the Eurozone manufacturing PMI output index. I apply the method under different assumptions on the cross-sectional distribution of output growth using the uniform, logistic and Laplace distribution. I show that alternative distribution assumptions lead to very similar estimates. I also test the performance of the different growth estimates in an out of sample forecasting exercise of actual industrial production growth. All growth estimates beat a simple autoregressive model of output growth. Distribution assumptions again matter little most of the time except during the financial crisis when the estimates constructed using the Laplace distributional assumption perform the best. My findings are consistent with recent findings of Bottazzi and Sechi (2006) that the distribution of firm growth rates has a Laplace distribution.

Key words: diffusion index, forecasting, Purchasing managers' surveys, ISM, PMI, Qualitative response data, Carlson-Parkin method

JEL:C18, E27

Non-technical summary

Industrial production growth is an important business cycle indicator which is however released with a considerable lag. Policymakers and practioners regularly look for indicators that reveal information on output growth before its release. For the US, probably the most prominent information is released as a set of indicators by the Institute for Supply Management (ISM). For the euro area the information services company Markit provides a similar set of indicators. I investigate two indicators which theoretically have the closest link with industrial production, the 'ISM production index' in the US and 'Markit Eurozone manufacturing PMI output index' in the euro area. For the construction of these indices a representative sample of firms are asked each month whether output went 'up', 'down', or remained 'unchanged'. The indices that are released are diffusion indices, namely simple weighted averages of the aggregate 'up' and "unchanged" response shares in the population, i.e. with weights 1 and 0.5 respectively.

I quantify these indices to construct estimates of output growth which I then compare with growth rates calculated from the official industrial production data. I construct different estimates under different assumptions on the cross-sectional distribution of output growth using the uniform, logistic and Laplace distribution. I show that alternative distribution assumptions lead to very similar estimates. I also test the performance of the different growth estimates in an out of sample forecasting exercise of actual industrial production growth. All growth estimates beat a simple autoregressive model of output growth. Distribution assumptions again matter little most of the time except during the financial crisis when the estimates constructed using the Laplace distributional assumption perform the best. This finding is consistent with the literature on the cross sectional distribution of growth rates in an economy.

1 Introduction

Monthly industrial production growth is an important business cycle indicator. Unfortunately it is released with a considerable lag. This has led observers, policy makers and practioners to look for indicators that reveal information on output growth before its release. For the US, probably the most prominent information is released as a set of indicators by the Institute for Supply Management (ISM). For the euro area the information services company Markit provides a similar set of indicators. Both organizations release every month a range of indices covering a wide set of variables, such as output, employment, inventories and new orders which they then release together with an aggregate composite index commonly referred to as 'purchasing managers index' on both sides of the Atlantic. The indices of the ISM and Markit are released at the beginning of the month. So they provide the first information on the previous month useful for business cycle analysis. The indices are the result of business surveys where purchasing managers are asked the direction of change (i.e. "up", "down" or "unchanged") of particular economic variables at the firm level. As purchasing managers generally should have a good knowledge of what is happening with their own firm, answering a simple 'direction of change' question should give reliable answers.

The indices that are released are diffusion indices, namely simple weighted averages of the aggregate "up" and "no change" response shares in the population, i.e. with weights 1 and 0.5 respectively.[2] Say if 50 percent of the managers answer that output has increased and 10 percent that it has remained unchanged the index would be 55.

For the output index, termed officially as 'ISM production index' in the US and 'Markit Eurozone manufacturing PMI output index' in the euro area, a representative sample of industrial firms in both economies is asked whether output (at the firm level) went up, down or remained unchanged relative to the previous month. In principle therefore the output index data should reveal information about the direction and strength of monthly industrial production growth.

This paper constructs estimates of monthly output growth for the US and the euro area using the ISM production index and the Markit Eurozone manufacturing PMI output index. The estimated series tracks actual industrial production growth rather well. For the US I use the time series of response shares of "up", "down" and "unchanged". For the euro area I only use the index as the response shares are not made public.

[2]The ISM explains on its web-site: *All the ISM indexes are "diffusion indexes" and are indicators of month-to-month change. The percent response to the "Better," "Same," or "Worse" question is difficult to compare to prior periods; therefore, we diffuse the percentages for this purpose. A diffusion index indicates the degree to which the indicated change is dispersed or diffused throughout the sample population. Respondents to ISM surveys indicate each month whether particular activities (e.g., new orders) for their organizations have increased, decreased, or remained unchanged from the previous month. The ISM indexes are calculated by taking the percentage of respondents that report that the activity has increased ("Better") and adding it to one-half of the percentage that report the activity has not changed ("Same") and adding the two percentages.*

I use the well known Carlson-Parkin method to quantify the data. The idea of quantifying qualitative business survey data goes back to Anderson (1952) and Theil (1952). Carlson and Parkin (1975) rediscovered the findings by Theil (1952) and developed the probability method to quantify qualitative survey data. The method by Carlson and Parkin consists in making a parametric assumption on the underlying distribution for the answers of the survey and applying that distribution to the aggregate response shares to provide an estimate of the mean of the distribution. In the Carlson-Parkin method it is assumed that respondents answer that a variable (say output) shows "no change" when the actual change is in a certain (small) range say $[-\delta, \delta]$. Likewise, respondents answer by "down" when the actual change is in the range $]-\infty, -\delta[$ and similarly for up when the actual change is in $]\delta, \infty[$. The aggregate response shares of actual responses "up", "down" and "unchanged" are then taken as maximum likelihood estimates of the respective probabilities of these intervals. In other words, if D is the response share of "down" in the population then D is taken as an estimate of $F(-\delta)$, with $F(.)$ the parametric cumulative distribution function. Similarly for the "up"(U) and "no change" answer which are estimates of respectively $1 - F(\delta)$ and $F(\delta) - F(-\delta)$. Under this assumption, Carlson and Parkin show that the mean of the distribution is given by $\delta\frac{F^{-1}(D)+F^{-1}(1-U)}{F^{-1}(D)-F^{-1}(1-U)}$ with F^{-1} the inverse CDF.

I use the Carlson-Parkin method to quantify the output index data in the US for which I have the time series of response shares available. However for the euro area the response shares are not released. I therefore have to make some further assumptions and adjust the Carlson-Parkin method to apply it on the index itself. One of the determining factors of the Carlson-Parkin method is the parametric choice of the cumulative distribution function $F(.)$. Different choices will give different numerical estimates. Recently however Bottazzi and Sechi (2003, 2006) have shown that the industry distribution of firm growth rates follows a Laplace distribution. This finding seems robust across industries and across countries. I include the Laplace distribution among two other distributions that I use, the uniform and the logistic. I find that the distributional assumption has little effect on the estimated growth rates.

Ultimately the Carlson-Parkin estimates of growth are useful because they provide an early estimate of true growth before official data is released. To check their performance I also perform an out of sample forecasting exercise over the period 2002 to 2010. I test whether the Carlson-Parkin estimated growth series are better forecasters than a simple benchmark autoregressive model for industrial production. I find that this is the case. I also find that the simple diffusion index as released by ISM and Markit performs equally well for forecasting as the Carlson-Parkin estimates except during times of serious turmoil such as the financial crisis. Then, and only then, the Carlson-Parkin estimates perform better. This can be explained by the fact that the nonlinear transformation of the data that the Carlson-Parkin method entails deviates from the simple diffusion index the most the further out the index is to its outliers. During the financial crisis the Laplace distribution provides the best estimates.

The main findings in this paper are threefold. First, the Carlson-Parkin estimates of growth based on the US ISM production index and the Eurozone manufacturing PMI output index provide useful early information for output growth. They beat a simple autoregressive forecasting model. Second,the underlying distributional assumptions in the construction of the Carlson Parkin estimates however are less important, at least during normal times as they lead to very similar growth estimates. Third, the Carlson-Parkin estimates when used for real time forecasting provide an improvement on the simple diffusion index when the output index is in the tails of its distribution. Furthermore the somewhat better performance of the Carlson-Parkin method under the Laplace distribution assumption is consistent with the IO-literature on the distribution of firm growth rates.

The rest of the paper proceeds as follows. Section two puts the paper into the literature. Section three describes the data. Section four explains the Carlson-Parkin method and shows how it can be used when only the index is available. Section five contains the empirical analysis. Section six concludes.

2 Related literature

A distinction has to be made between survey questions as they pertain to the recent past as observed by the firm versus the expected future. This is an important distinction, as in the first case firms reply on their own observations (e.g. if they increased output relative to the month before), whereas in the second case firms are asked to reveal intentions (will output be increased) or are asked to forecast something. This paper is focused on the usefulness of recent observed experience questions when official data on the recent experience is not yet available. Most of the literature however have used the Carlson-Parkin method on questions related to the expected future. This literature has mostly focused on the question whether the expectations are formed rationally and whether the forecasts made are unbiased.

Carlson and Parkin (1975) initially developed their probability method to estimate inflation expectations of households using qualitative response shares of consumer surveys. In those surveys consumers are often asked forward-looking questions on whether prices will rise or fall. A large literature on inflation expectation measurement and tests of rationality using this method has followed. An alternative method is developed in Pesaran (1984,1987). It uses a regression approach on the proportion of 'up' and 'down' answers. As the proportion of 'up'and 'down' are not available for the euro area, this paper does not consider Pesaran's method. Both methods are reviewed in Nardo (2003).

Dasgupta and Lahiri (1992) were the first to quantify the ISM purchase price data using the Carlson-Parkin method. They compare their Carlson-Parkin estimates to the producer price index and find that they match each other nicely. Their study is complementary to this paper. They focus on the question about prices faced by the firm in the previous month, i.e. past experience, and not on a forecast of the firm. This paper focuses on the past output experience.

Hanssens and Vanden Abeele (1987) use the EC surveys on production expectations on the month ahead and show how useful they are for forecasting. They conclude that expectations data does not perform better than actual past output data. However they do not analyze the forecasting performance of recent output trends is I do here. Smith and MCaleer (1995) quantify five series of an Australian survey of which one is output. Cunningham (1997) discusses the application of the method on the UK CBI's survey of the British Chambers of Commerce.

The indices of the ISM have a long tradition in being useful for forecasting output. For instance, Marcellino et al. (2006), Stock and Watson (2002a) and Stock and Watson (2002b) use the indices [3] for production, new orders, supplier deliveries and inventories for forecasting industrial production growth. However all these studies ignore transformations of the data and simply use the indices as provided by ISM. Harris et al. (2004) show that the output index tracks developments in GDP closely. However, they also ignore possible manipulations to the index. In the euro area there is much less literature on the Markit data due its relatively young age. Banbura et al. (2010) include the euro area purchasing managers index and the employment sub-index in a set of variables used to now-cast euro area GDP.

3 The data

The ISM and Markit data are relatively well known and need little introduction. Both ISM and Markit advertise the usefulness of the data for policymakers and their early release dates. For instance Markit writes in their releases: *They are the most closely-watched business surveys in the world, favored by central banks, financial markets and business decision makers for their ability to provide up-to-date, accurate and often unique monthly indicators of economic trends.* Indeed the European Central Bank regularly comments and interprets the evolution of different Markit indices in its 'Monthly Bulletin'. The ISM web-site reports quotes by Alan Greenspan, Michael Boskin and Joseph Stiglitz about the importance of the data.

In this paper I use the ISM production index and the Eurozone Manufacturing PMI output index. The ISM reports that the data is based on monthly interviews with more

[3] Note, in their paper the US indices were still known under the former name NAPM.

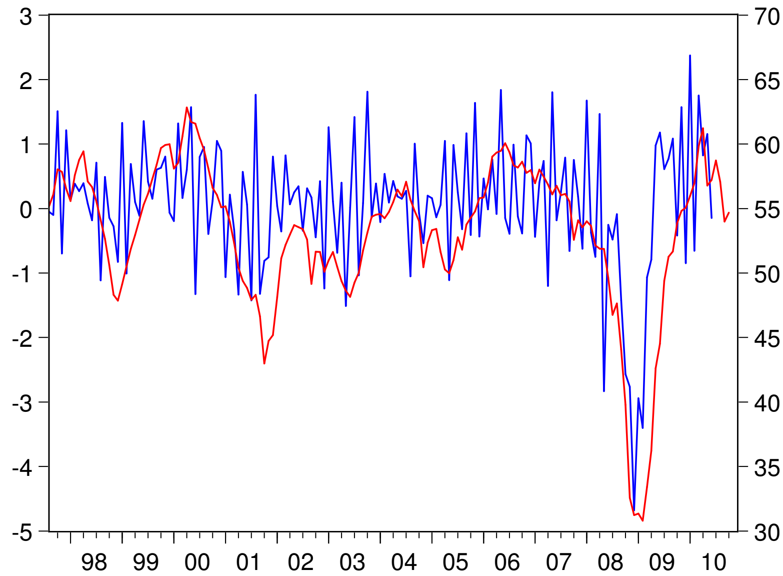


Figure 1: Euro area Industrial production month on month growth (dark shade/blue) and Markit Eurozone PMI output index (light shade/red)

then 400 industrial companies. Markit claims answers from more than 3000 manufacturing firms. The ISM production index data for the US is available from the ISM web-site. I use the share data from January 1948 to June 2010. The percentage "up", "down", "unchanged" always sum up to 100 percent. The ISM reports that to achieve a valid, weighted sample, participants are selected based on the contribution of each industry to gross domestic product (GDP). I obtain the Eurozone Manufacturing PMI output index from Markit. Markit does not release the share data. I use the index since its inception from July 1997. Both the US and euro area data are usually released the first Monday after the end of the month.

I further use the monthly growth rate of the official industrial production data, as released from the Federal Reserve and Eurostat. For the forecasting exercise I use the shorter time period from January 2002 to June 2010. This is due to the fact that I use vintage data for industrial production. For the euro area they start from the vintage January 2001. To easier compare US and euro area forecasting results I restrict the analysis to this period. To match the output index data as closely as possible with the real data, for the euro area the Total production index excluding construction is taken, for the US the Manufacturing index is used.[4] I use the euro area Real-Time Database and the US-real time database from the Federal Reserve Bank of Philadelphia to construct forecasts. These data-sets provide real-time monthly data vintages for US and euro area industrial production. Each vintage describes the data as it was available at that particular time point. A full description of these data-sets is given in Giannone et

[4]Coded IPM in the database

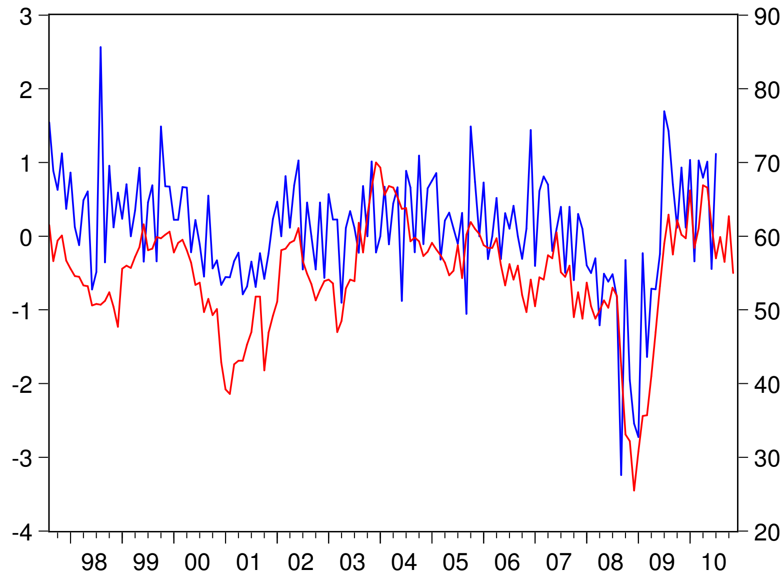


Figure 2: US Industrial production month on month growth (dark shade/blue) and ISM production index (light shade/red) (since July 1997)

al. (2010) and Croushore and Stark (2001). Both the US and euro area output index data are not part of these databases, but given their regular release time, they are matched with the timing of these databases.

Figure 1 shows the euro area month on month industrial production growth together with the Eurozone Manufacturing PMI output index. Figures 2 and 3 show the US month on month industrial production growth together with the ISM production index.

An important observation that can be readily drawn from this figures is that industrial production month on month growth both in the US and the euro area are very volatile and much more so than the survey indices. This is a typical finding. Cunningham (1997) provides a few reasons for the often found smoothness of surveys relative to the index the survey is trying to match. One possibility is that the official data is too erratic and contains measurement error. Another possibility is that respondents smooth their responses. Trying to find out where the relative smoothness stems from is beyond the scope of this paper.

4 The Carlson-Parkin method

In this section I explain the Carlson-Parkin method. To put the method in perspective, I develop a small model of how true output growth, official industrial production growth (which I consider to be an estimate of the truth) and qualitative survey data are all interrelated. I show how I apply it to the US and euro area data. The Carlson-Parkin

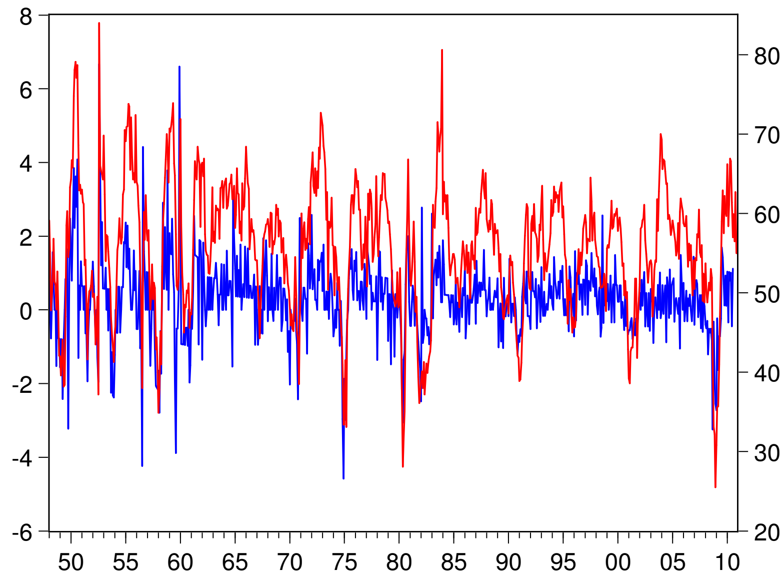


Figure 3: US Industrial production month on month growth (dark shade/blue) and ISM production index (light shade/red) (since 1948)

method can be used for surveys on actual changes (as here in this paper) as well as on expectations of future changes. The interpretation of the answers to the survey is of course different whether respondents are answering questions on past events or future expected events. Explanations of the Carlson-Parkin method as it pertains to expectations can be found among others in Carlson and Parkin (1975) and Nardo (2003). The model I develop in this section (or some closely related relative) is often implicitly assumed in the application of the Carlson-Parkin method on actual changes. See also Cunningham (1997) on the interpretation of surveys on actual changes.

4.1 The probability method

Define true (forever unobserved) monthly industry output growth as g_t. Growth measured by the official industrial production index denoted by $\overline{g_t}$ is effectively an estimate of true industry output growth. I assume that the relationship between the two growth rates is given by

$$\overline{g}_t = g_t + \nu_t \tag{1}$$

with ν_t a zero mean measurement error (potentially autocorrelated). So the official statistics are here assumed as unbiased estimates of true growth. Indeed as Cunningham (1997) notes : *the official and survey data are both usually based on samples of the firms in the economy.* One should therefore not assume that industrial production is measurement error free.

Consider now the output purchasing managers survey with N firms. Firm i's actual output growth g_{it} at time t is defined as the sum of average output growth of the firms in the survey sample g_t^s and an idiosyncratic shock ϵ_{it}.

$$g_{it} = g_t^s + \epsilon_{it} \tag{2}$$

where ϵ_{it} has mean zero and variance σ_t. The cumulative distribution function of ϵ_{it} is assumed to be $F_t(.)$. All firms in the survey sample draw shocks from the same distribution, so $F_t(.)$ does not have a subscript i. The subscript t on the CDF indicates that σ_t potentially varies over time but not across firms. The relationship between the unobserved industry output and average output growth of the firms in the survey sample is considered to be governed by:

$$g_t - g_t^s = \alpha + \eta_t \tag{3}$$

with α being a systematic constant bias (possibly zero) and η_t a temporary deviation of both growth rates with mean zero, but potentially autocorrelated. The bias α reflects the sample selection, if e.g. only larger firms are in the sample and if larger firms grow systematically differently than the aggregate industry. η_t could be related to the business cycle.

Respondents are the purchasing managers of the random survey sample of N firms. They are asked whether in their individual firm output went up, remained unchanged or increased. A respondent answers that output in firm i went up when $g_{it} \geq \delta$, i.e. each respondent knows the realization of its own firm g_{it}, and has the indifference threshold δ. The indifference threshold accounts for the fact that often people don't perceive very small changes. In the literature this is sometimes known as threshold of perception or 'just noticeable difference'. A large psychology literature shows that indeed people do not respond to small changes or perceive small changes identical to no change at all (see e.g. Batchelor (1986).) Similarly respondents answer that output went down when $g_{it} \leq -\delta$, and answer with "no change" when $-\delta < g_{it} < \delta$.

The share of up answers in the random sample is then $UP_t = \sum_{i=1}^{N} \frac{I(g_{it} \geq \delta)}{N}$ with I(x) the indicator function being 1 when x is true and zero otherwise. Similarly $DOWN_t = \sum_{i=1}^{N} \frac{I(g_{it} \leq -\delta)}{N}$. So UP_t and $DOWN_t$ are random variables (because they depend on the realizations of the ϵ_{it}). It is easy to see that they have the following expectation:

$$\begin{aligned} E(UP_t) &= E(\sum_{i=1}^{N} \frac{I(g_{it} \geq \delta)}{N}) && (4) \\ &= P[g_{it} \geq \delta] = P[g_{it} - g_t^s \geq \delta - g_t^s] && (5) \\ &= P[\epsilon_{it} \geq \delta - g_t^s] = 1 - F_t(\delta - g_t^s) && (6) \end{aligned}$$

$$\begin{aligned} E(DOWN_t) &= E(\sum_{i=1}^{N} \frac{I(g_{it} \leq -\delta)}{N}) && (7) \\ &= P[g_{it} \leq -\delta] = P[g_{it} - g_t^s \leq -\delta - g_t^s] && (8) \\ &= P[\epsilon_{it} \leq -\delta - g_t^s] = F_t(-\delta - g_t^s) && (9) \end{aligned}$$

Using the inverse of the CDF of ϵ_{it} these equations can be written as:

$$F_t^{-1}(1 - E(UP_t)) = \delta - g_t^s \tag{10}$$

$$F_t^{-1}(E(DOWN_t)) = -\delta - g_t^s \tag{11}$$

These can be solved for g_t^s as

$$g_t^s = \delta \frac{F_t^{-1}(E(DOWN_t)) + F_t^{-1}(1 - E(UP_t))}{F_t^{-1}(E(DOWN_t)) - F_t^{-1}(1 - E(UP_t))} \tag{12}$$

Define x_t

$$x_t \equiv \frac{F_t^{-1}(E(DOWN_t)) + F_t^{-1}(1 - E(UP_t))}{F_t^{-1}(E(DOWN_t)) - F_t^{-1}(1 - E(UP_t))} \tag{13}$$

so that $g_t^s = \delta x_t$. One can call x_t the true unscaled growth rate (in the sample).

Now the actual time series of up and down shares in the data $\overline{UP_t}$ and $\overline{DOWN_t}$, with the bar indicating data, can be used as maximum likelihood estimates of the expected values.

Define the unscaled estimates of sample output growth as:

$$\overline{x}_t \equiv \frac{F_t^{-1}(\overline{DOWN_t}) + F_t^{-1}(1 - \overline{UP_t})}{F_t^{-1}(\overline{DOWN_t}) - F_t^{-1}(1 - \overline{UP_t})} \tag{14}$$

using a parametric assumption on $F_t(.)$. Define the sampling error υ_t caused by replacing expectations by the realized shares, i.e. $\upsilon_t \equiv \delta x_t - \delta \overline{x_t}$. Note that $\overline{x_t}$ provides an estimate of sample output growth up to the scaling factor δ.

Combining equation (12) and definition (14) with equations (1) and (3) the officially measured industrial production growth rate and the unscaled sample output growth estimates are related trough:

$$\overline{g_t} = \alpha + \delta \overline{x_t} + s_t \tag{15}$$

with $s_t = \nu_t + \eta_t + \upsilon_t$.

The indifference threshold δ and the systematic bias α are then estimated trough ordinary least squares of the above regression. The Carlson-Parkin estimates of output growth are then given by $\hat{\alpha} + \hat{\delta}\overline{x_t}$. Note that $\overline{x_t}$ will be negatively correlated with s_t due to the negative correlation with υ_t leading to a traditional measurement error bias in the

OLS regression. This bias is usually ignored in the literature as it is expected that with a large enough sample on which the survey is done, measurement error υ_t should be rather small.

4.2 Assumptions for the cumulative distribution function

The cumulative distribution function $F_t(.)$ has to be chosen a priori. In the model above this distribution is equal to the cross-sectional distribution of monthly firm growth rates in the economy. Ideally, one would consider functional forms for the CDF $F_t()$ that match the cross-sectional distribution of monthly growth rates in the data. However this data is generally not available (if it was available one wouldn't have to use Carlson-Parkin estimates in the first place as one would know the mean of the distribution.) A small IO-literature has investigated the distribution of growth rates, mostly for annual data. Bottazzi and Sechi (2006) show that the cross-sectional distribution of firm growth rates follows a Laplace distribution. I consider three distributions, the uniform, the logistic and the Laplace.

The uniform is useful as a simple benchmark. It also has a CDF whose inverse is linear. The inverse CDF for a zero mean uniform random variable is given by:

$$F_t^{-1}(y) = \sigma_t\sqrt{3}(2y-1) \tag{16}$$

Applying this inverse CDF to (14) leads to the following estimate of unscaled sample output growth:

$$\overline{x_t} = \frac{\overline{UP_t} - \overline{DOWN_t}}{1 - \overline{UP_t} - \overline{DOWN_t}} \tag{17}$$

This estimate is closely related, but not identical, to the popular balance statistic $\overline{UP_t} - \overline{DOWN_t}$. The denominator of $\overline{x_t}$ just rescales the balance statistic with the variable share of "unchanged" responses. (Because that's what $1 - \overline{UP_t} - \overline{DOWN_t}$ is.) It is also closely related to the diffusion index, which is the sum of the percentage of up and one halve the percentage of unchanged, which can be shown to be identical as $0.5(1 + \overline{UP_t} - \overline{DOWN_t})$, a linear transformation of the balance statistic. So when people naively use the balance statistic or diffusion index and relate it to official data one could say that they implicitly assume the uniform distribution for the shock process combined with a constant "unchanged" share. Note that the variance σ_t drops out of the calculation of $\overline{x_t}$. So one doesn't need a separate assumption on the value of σ_t even if the variance of the distribution varies over time. This will also be true for the logistic and Laplace distribution.

The second distribution I consider is the logistic. The logistic is taken for two reasons. First it also has an analytical inverse CDF. Second it is also appealing because the logistic is close to a normal distribution, which does not have a closed form inverse CDF. The inverse CDF of the logistic distribution is given by:

$$F_t^{-1}(y) = -\sigma_t \frac{\sqrt{3}}{\pi} \ln \frac{1-y}{y} \tag{18}$$

I also provide estimates using the Laplace distribution. This choice is inspired by the findings of Bottazzi and Sechi (2006). They show that the cross-sectional distribution of firm growth rates follows a Laplace distribution. If this is the case also for the sample of firms used in the Purchasing managers survey than this distribution should be the correct one to use and should give the best estimates. The inverse cumulative distribution functions of the Laplace distribution is given by

$$\begin{aligned} F_t^{-1}(y) &= \frac{\sigma_t}{\sqrt{2}} \ln 2y, y \leq 0.5 \\ &= -\frac{\sigma_t}{\sqrt{2}} \ln 2(1-y), y > 0.5 \end{aligned} \tag{19}$$

4.3 The adapted Carlson-Parkin method

For the euro area, the $\overline{UP_t}$ and $\overline{DOWN_t}$ shares are not available. The Carlson-Parkin method has therefore to be adapted to be used on index value themselves. Assume again that equations (1)(2)(3) hold.

The index value $\overline{I_t}$ as released by Markit is defined by one times the share of up answers plus a halve time the share of unchanged answers i.e. it is equal to $\overline{UP_t} + 0.5\overline{UNC_t}$ with both $\overline{UP_t}$ and $\overline{UNC_t}$ unobserved. I make the simplifying assumption that the indifference threshold is zero, i.e. $\delta = 0$. So firms answers "up" when $g_{it} \geq 0$. Firms answer "down" when $g_{it} < 0$. This assumption implies that firms never answer "unchanged". Under this assumption the index is equal to $\overline{UP_t}$. We have

$$E(I_t) = E(\sum_{i=1}^{N} \frac{I(g_{it} \geq 0)}{N}) \tag{20}$$

$$= P[g_{it} \geq 0] = P[g_{it} - g_t^s \geq 0 - g_t^s] \tag{21}$$

$$= P[\epsilon_{it} \geq 0 - g_t^s] = 1 - F_t(-g_t^s) \tag{22}$$

$$\tag{23}$$

This can again be solved for g_t^s:

$$g_t^s = -F_t^{-1}(1 - E(I_t)) \tag{24}$$

Now the actual index in the data $\overline{I_t}$, can be used as maximum likelihood estimate of the expected value. Combining equation (24) with equations (1) and (3) we get:

$$\overline{g_t} = \alpha - F_t^{-1}(1 - \overline{I_t}) + s_t \tag{25}$$

How this relationship is used is best shown with an example. Consider the logistic distribution. For this we have

$$-F_t^{-1}(1 - \overline{I_t}) = \sigma_t \frac{\sqrt{3}}{\pi} \ln \frac{\overline{I_t}}{1 - \overline{I_t}} \tag{26}$$

So that the regression becomes:

$$\overline{g_t} = \alpha + \sigma_t \overline{z_t} + s_t \tag{27}$$

with $\overline{z_t} = \frac{\sqrt{3}}{\pi} \ln \frac{\overline{I_t}}{1-\overline{I_t}}$ Now only if one assumes σ_t to be constant over time, the Carlson-Parkin estimates are given by: $\hat{\alpha} + \hat{\sigma}\overline{z_t}$

In a similar fashion, Carlson-Parkin estimates can be derived for the uniform and Laplace distribution. Note however that for the uniform distribution we have $\overline{z_t} = \sqrt{3}(2\overline{I_t} - 1)$, which is just a linear transformation of the index. This linear transformation in equation (27) will obviously have the same fit as using the index itself. So using the index or assuming the uniform distribution will lead to the same Carlson-Parkin estimates (with however different levels of α and σ). This is not the case when one has the share data available and can apply the full Carlson-Parkin method. As shown above the scaling of the balance statistic is variable. Obviously the absence of the share data comes at considerable cost in terms of two extra assumptions which are likely violated, $\delta = 0$ and $\sigma_t = \sigma$. Essentially the adapted Carlson-Parkin method just implies the use of nonlinear transformations of the index value to provide estimates of output growth whereas the Carlson-Parkin method uses nonlinear transformations of the up and down shares (and therefore contains more information). The choice of the nonlinear transformations are governed by the assumptions made on the cross-sectional distribution of growth rates in the sample.

4.4 The non-linear relationship between growth and the diffusion index

The model above shows that true growth is non-linearly related to the diffusion index. Equation (25) shows the theoretical relationship between industrial production growth $\overline{g_t}$ and the diffusion index I_t. Figure 4 demonstrates this equation for F being the logistic distribution, assuming a constant σ_t and zero error s_t .The striking feature of this relationship is that at low levels and high levels of growth the relationship is highly nonlinear. However over a wide range of growth rates, the relationship is nearly linear.

Essentially what the Carlson-Parkin method does is undo the non-linear relationship and make it linear again through the transformation with F^{-1}. What happens at low or high levels of the index is particularly interesting as the transformations of the index data for the Carlson-Parkin estimates are highly non-linear the lower or higher is the index. The picture looks similar for F being the Laplace distribution and is a straight line for F being the uniform distribution.

In tranquil times therefore, using the diffusion index directly or the Carlson-Parkin estimates should likely be irrelevant. Note that the level indices by definition move between zero and hundred, and in reality in an even smaller interval. A transformation of values around 50 almost behaves like a linear transformation so that little effect of the functional form of F should be expected from transforming a variable that hovers around 50. However as the index drops closer to zero, the Carlson-Parkin transformations (except the uniform) does not any longer behave like a linear transformation. It is at these instances that one should expect an effect of the transformation. Although this reasoning strictly applies to the euro area where I use the index, the same idea also holds for the US where I use the share data. The closer the diffusion index is to zero, the closer the up-share has to be to zero as well and the more nonlinear the transformation through F^{-1} becomes.

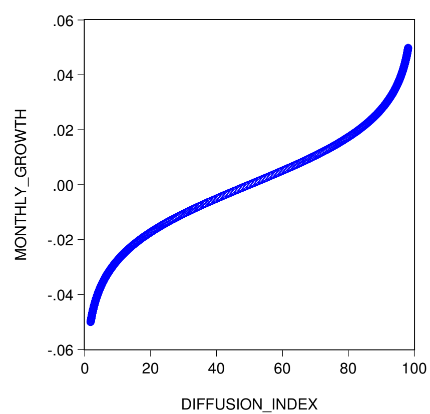


Figure 4: Theoretical relationship diffusion index and monthly industrial production growth: example

5 Empirical analysis

In this section I discuss how the estimated output growth using the output index data relates to the actual industrial production growth series.

5.1 Empirical comparison of different Carlson-Parkin estimates

I first estimate equations (15) and (27) by OLS. For the US the time period is 1948:01-2010:06. For the euro area the time period is restricted to 1997:08-2010:06. Over these sample periods the mean of monthly industrial production growth $\overline{g_t}$ is 0.07 percent for the euro area versus 0.25 percent for the US. The standard deviations are equal to 1.05 percent in both economies. Monthly industrial production is therefore very volatile. The results are presented in Table 1. The different Carlson-Parkin estimates perform very similar in terms of explanatory power over the entire period both in the euro area and the US. All estimates explain around one third of the variation in the industrial production index.

Importantly the Carlson-Parkin-estimates seem to track the cyclical movement in industrial production growth rather well. See Figures 5 and 6. Since there is little visible difference between the different Carlson-Parkin estimates I show the Laplace ones. An interesting feature is also that the Carlson-Parkin estimates are much smoother than the industrial production growth series. Again this smoothness is coming from the smoothness of the survey data itself.

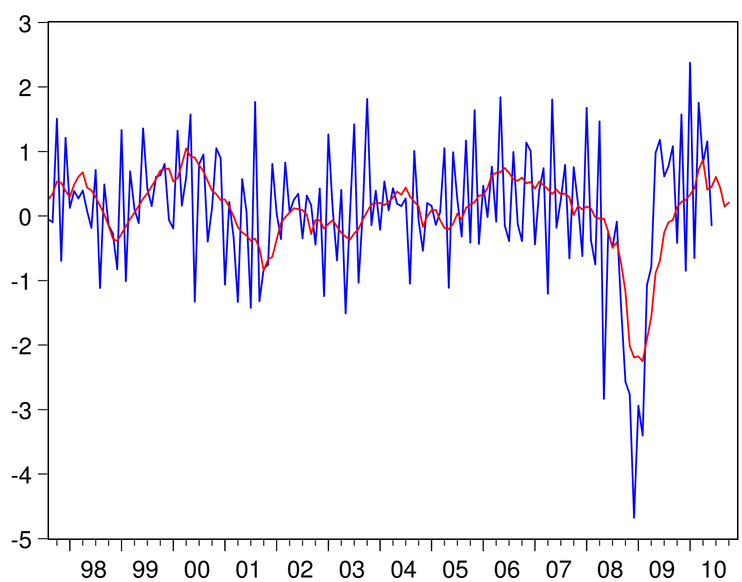


Figure 5: Euro area Industrial production month on month growth and Carlson-Parkin estimates (using the Laplace distribution)

The estimated coefficient on unscaled growth in the euro area regression can be interpreted as an estimate of the cross-sectional variance of growth rates in the sample. It ranges from 2.57 percent for the uniform distribution to 5.97 percent for the Laplace.

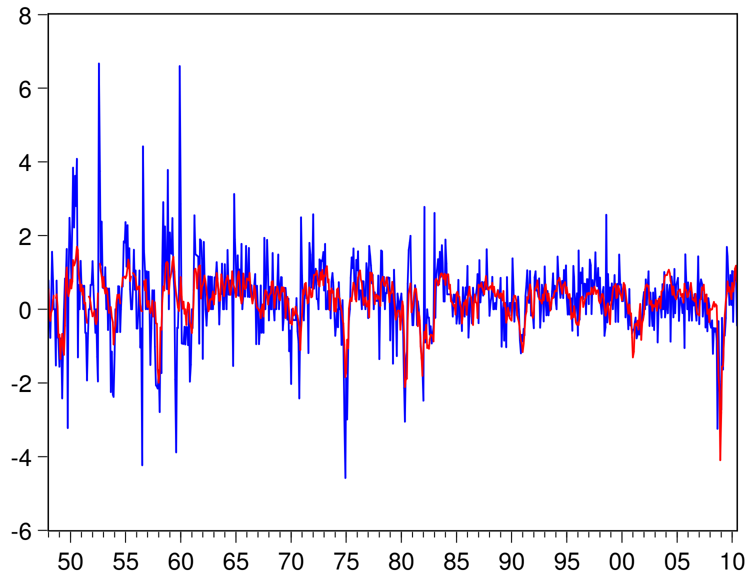


Figure 6: US Industrial production month on month growth and Carlson-Parkin estimates (using the Laplace distribution)

In the US regression the estimated coefficient on unscaled growth is an estimate of the indifference threshold δ. It is estimated to be in a narrow range from 1.45 percent for the logistic to 1.68 for the Laplace distribution.

Does the survey contain useful information? To test this I ran an autoregressive model for industrial production growth $\overline{g_t}$. The Akaike criterion suggests an AR(3) for both the US and the euro area. The standard error of the regression is 0.92 for the US and 0.99 for the euro area, both higher than those of the models presented in Table (1) which are around 0.89 for the euro area and 0.87 in the US. So the survey data fits better than the fitted values of a benchmark autoregressive process.

However the Carlson-Parkin estimates fit equally well compared to fitted values from a linear regression of growth on the simple diffusion index. For the euro area the standard error of the regression of growth on the diffusion index is obviously identical to the one of the uniform model (as the uniform is just a linear transformation of the diffusion index). For the US using the diffusion index the standard error of the regression is also 0.87, identical to the other models. From these results one could argue that the assumptions on the underlying distribution matter very little and that knowledge of the share data for the US does not lead to improved estimates above the diffusion index itself. However the performance of the different estimates could change over time. As argued above the transformation by F^{-1} should be most relevant when the index is far away from 50. This is investigated in the out of sample forecasting exercise.

Table 1: Carlson-Parkin regressions: for US (1948:01-2010:06) and euro area (1997:08-2010:06)

Model	Intercept	σ and δ	R^2	DW	SER
		euro area			
uniform	-0.23	2.75	0.29	2.50	0.89
	(-2.81)	(7.84)			
logistic	-0.22	4.24	0.29	2.51	0.89
	(-2.77)	(7.92)			
Laplace	-0.21	5.97	0.30	2.54	0.88
	(-2.63)	(8.10)			
		USA			
uniform	-0.09	1.52	0.31	1.69	0.87
	(-2.40)	(18.33)			
logistic	-0.13	1.45	0.32	1.71	0.87
	(-3.34)	(18.49)			
Laplace	-0.54	1.68	0.32	1.70	0.87
	(-10.16)	(18.61)			

Ordinary least squares results from equations (15) and (27)
Number of observations for US is 743, for euro area 155.
Values in monthly percentages. DW is Durbin Watson. SER is standard error of regression.
t statistics in parentheses

5.2 Forecasting exercise

5.2.1 The forecasting models

In this section I test the forecasting performance of the Carlson-Parkin estimates of growth. I compare them with a benchmark autoregressive model for industrial production growth and with a model that uses the diffusion index.

The forecasting experiment is meant to track the real life experience of an observer at the beginning of a month t. The experiment should help in deciding what that observer should do to obtain an estimate of industrial production growth during month t-1. Ignore the index and just estimate an autoregressive process on growth? Use the diffusion index as it is provided? Or use the share data for the US and transform the index in the euro area to obtain Carlson-Parkin estimates that then can be used in a forecasting regression?

The index data is received in the beginning of the month before the industrial production index is released. I focus on the one-step ahead output growth forecast (which are essentially forecasts of the output growth of the previous month) as this one coincides with the information contained in the output purchasing managers index data. Denote the time of the vintage by superscript v. At time v the forecaster re-estimates the model using the available vintage at time v. At time v the latest release of the output purchasing managers index data in both the US and the euro area is the index for the month $v-1$. At time v industrial production growth is known, i.e. available in the vintage data, up to (including) $t = v - 2, i.e. \overline{g}^v_{v-2}$[5]. Every time v one-month ahead forecasts of industrial production growth are produced, i.e $\hat{g}_{v-1}$. The out-of sample window is January 2002 to June 2010. All models are estimated with a rolling window of 8 years.

The benchmark model is the univariate autoregressive AR(p) model using only lags of the monthly growth rate of industrial production. This benchmark model is estimated with one, two and three lags ($p = 1, 2, 3$).

$$\overline{g}^v_t = \mu^v + \sum_{j=1}^{p} \phi^v_j \overline{g}^v_{t-j} + \epsilon^v_t \tag{28}$$

with $t = v - 2 - 12 * 8, ..., v - 2$. The one-step ahead forecast is then simply $\hat{g}_{v-1} = \hat{\mu}^v + \sum_{j=1}^{p} \hat{\phi}^v_j \overline{g}^v_{v-1-j}$.The benchmark model is compared with bivariate models. Each bivariate model is the univariate AR(p) with an additional variable being the unscaled output growth estimate $\overline{x_t}$ (or $\overline{z_t}$ for the Euro Area). The model in equation 29, with the

[5]This timing implies that v occurs in the beginning of the month for the US, because at mid-month, industrial production of month $v-1$ is released. For the euro area v is mid-month, i.e. right after the release of industrial production of $v-2$

unscaled growth estimate $\overline{x_t}$ is estimated.

$$\overline{g}_t^v = \mu + \sum_{j=1}^{p} \phi_j^v \overline{g}_{t-j}^v + \sum_{j=0}^{p} \rho_j^v \overline{x}_{t-j} + \epsilon_t^v \tag{29}$$

with $t = v - 2 - 12 * 8, ..., v - 2$. Similarly as above the one-step ahead forecast is $\hat{g}_{v-1} = \hat{\mu}^v + \sum_{j=1}^{p} \hat{\phi}_j^v \overline{g}_{v-1-j}^v + \sum_{j=0}^{p} \hat{\rho}_j^v \overline{x}_{v-1-j}$.

The unscaled growth estimates are constructed using consecutively the uniform, the logistic and the Laplace distribution. I call those the Carlson-Parkin models. An alternative benchmark to the autoregressive model is simply replacing $\overline{x_t}$ by the diffusion index itself. I call this the diffusion index model. Note that as the euro area output index is only available since August 1997, this implies that for the first 3 years of forecasts the models don't have an eight year window but a gradually increasing window up to eight years. From August 2008 onwards there is then a full 8 years of euro area data available. The benchmark and US models always are estimated on full 8 year windows. The models are referred to with the respective transformation UNIF, LOGI, LAPL. The DIFF model stands for the model using the diffusion index. As for the euro area the transformation of the diffusion index for the uniform distribution is linear, the forecasting performance will be identical for those two models.

Output growth is measured on a monthly basis. That is $\overline{g}_t^v$ is measured as IP index time t/IP index time (t-1)-1.

5.2.2 Global forecasting accuracy over 2002-2010

In this section I test the forecasting performance in the US and the euro area of the different estimates of output growth . First I present the empirical results for the entire out of sample period 2002:01-2010:06. In the section that follows I discuss the empirical results of the local forecasting performance, first focusing on periods when the indices are low, then discussing the results of Giacomini and Rossi tests.

In the euro area, average monthly output growth $\bar{g}_t^v$ over the period 2002:01-2010:06 is a meagre 0.02 percent, with a standard deviation of 1.15 percent. Growth was somewhat higher and less volatile in the US. Over the same period, in the US average monthly output growth was 0.05 percent with a standard deviation of 0.83 percent. All in all, in both economies industrial production almost didn't grow.

Table 2 presents the root mean squared forecast errors (RMSFE) of the benchmark, the diffusion index model and the Carlson-Parkin models over the entire out of sample period 2002:01-2010:06. First I test whether the benchmark model is outperformed by the diffusion index model and the Carlson-Parkin models. Note that the benchmark model is nested within the diffusion index and Carlson-Parkin model. Therefore I use the test proposed in Clark and West (2007) to compare the parsimonious benchmark model with

Table 2: Root Mean squared forecast errors: period 2002.01-2010.06

euro area

lag	AR	DIFF	UNIF	LOGI	LAPL
1	1.20	0.91	0.91	**0.90**	**0.88**
2	1.15	0.89	0.89	0.88	0.85
3	1.10	0.87	0.87	**0.86**	**0.84**

USA

lag	AR	DIFF	UNIF	LOGI	LAPL
1	0.81	0.71	0.70	0.70	0.67
2	0.79	0.71	0.70	0.70	0.67
3	0.80	0.73	0.72	0.72	**0.69**

Values in monthly percentages
RMSFEs of Carlson-Parkin models that are significantly lower then their respective diffusion index model at the 10 percent level are in bold. Using modified Diebold-Mariano test.

respectively the diffusion index and Carlson-Parkin models. To perform this test one first constructs adjusted forecast error differences as

$$\hat{f}_t = (\overline{g}_t - \hat{g}_{1t})^2 - (\overline{g}_t - \hat{g}_{2t})^2 + (\hat{g}_{1t} - \hat{g}_{2t})^2 \tag{30}$$

where $\overline{g}_t$ is output growth, $\hat{g}_{1t}$ is the forecast of output growth from the benchmark model, and $\hat{g}_{2t}$ is the forecast of output growth of the diffusion index or Carlson-Parkin model. The Clark and West test is then:

$$CW = \frac{p^{-1} \sum_{t=1}^{p} \hat{f}_t}{\sqrt{\sigma^2}} \tag{31}$$

where p is the out of sample size and σ^2 is an HAC estimate of the variance of $\hat{f}_t$. I use the following Newey-West (1994) estimate of the variance

$$\sigma^2 = \frac{1}{p-1} \sum_{v=0}^{q} 2(1 - \frac{v}{q+1}) \sum_{t=v+1}^{p} (\hat{f}_t - \bar{f})(\hat{f}_{t-v} - \bar{f}) \tag{32}$$

with q=4.

Table 3 shows the results of the Clark and West-test. The null hypothesis of this test is equal expected mean squared prediction error. The results in Table 3 show that for all models the tests reject the null hypothesis between the benchmark models and the diffusion index or Carlson-Parkin models. This implies that both in the US and the euro area output index data contains information useful in forecasting output growth.

Table 3: Clark and West test for equal predictive accuracy between AR and other models: period 2002.01-2010.06

euro area

lag	DIFF	UNIF	LOGI	LAPL
1	1.82**	1.82**	1.80**	1.76**
2	1.92**	1.92**	1.89**	1.82**
3	2.36**	2.36**	2.31**	2.20**

USA

lag	DIFF	UNIF	LOGI	LAPL
1	1.93**	1.78**	1.89**	1.56*
2	2.02**	1.81**	1.97**	1.56*
3	2.14**	1.97**	2.10**	1.76**

Values in percentages.
* significant at the 10 percent level.
** significant at the 5 percent level.

Table 2 shows that the gains in reducing the RMSFE are very similar across all models, indicating that it doesn't matter much if one uses the diffusion index directly or one of the Carlson-Parkin estimates.

Next I test whether the Carlson-Parkin models outperform the diffusion index models. Forecasters not only want to know whether using the output index data is useful, they also want to know if using the transformations of the data are improving on simply using the diffusion index. As the diffusion index and Carlson-Parkin models are non-nested I compare both types of models using the modified Diebold-Mariano test as in Harvey et al. (1997). First, forecast error differences are constructed as

$$\hat{d}_t = (\overline{g}_t - \hat{g}_{1t})^2 - (\overline{g}_t - \hat{g}_{2t})^2 \tag{33}$$

where $\overline{g}_t$ is output growth, $\hat{g}_{1t}$ is the forecast of output growth from the diffusion index model, and $\hat{g}_{2t}$ is the forecast of output growth of the Carlson-Parkin model. The modified Diebold-Mariano test is then:

$$DM = \frac{p^{-1}\sum_{t=1}^{p}\hat{d}_t}{\sqrt{\sigma^2}} \tag{34}$$

with p the out of sample size and σ^2 is an HAC estimate of the variance of $\hat{d}_t$, constructed as in equation 32 using $\hat{d}_t$ and $\bar{d}$ instead of $\hat{f}_t$ and $\bar{f}$. Critical values are taken from the t-distribution with p-1 degrees of freedom.

The test results are indicated in table 2. Numbers in bold indicate that the Carlson-Parkin model outperforms the diffusion index model. In the euro area the Laplace model (with lag 1 and 3) shows statistically significant improvement relative to the diffusion index model with a reduction around 3 percent of the level of the RMSFE. However such an improvement is small economically, representing around 0.03 percent measured in terms of monthly output growth. In the US the Laplace model with three lags improves on the diffusion model with a 0.04 percent. All in all, using the diffusion index or any Carlson-Parkin estimate proves to be superior above a simple autoregressive process for industrial production growth. If one has to choose among Carlson-Parkin estimates the results show some slight preference for the Laplace model but using the diffusion index does almost as good.

5.3 Local forecasting accuracy over 2002-2010

The global accuracy tests presented above ignore possible instability in the performance of the models over time.

In particular a global test masks what happens when indices are very low. During the 2008-2009 period the financial crisis caused many indices to reach unprecedented low levels. As reasoned above, the diffusion index is non-linearly related to the growth rate, so that the Carlson-Parkin transformations should become more relevant during times of very low growth, i.e. very low diffusion index levels.

I first focus on the 15th percentile lowest values of each of the indices. Of course in many case this overlaps substantially with the financial crisis period.

Table 4 shows the RMSFE of the models conditional on the index being below the 15th percentile. First, notice that the RMSFE of all models increases dramatically. For instance, in the euro area the RMSFE of the benchmark AR(3) model over the entire period 2002:01-2010:06 is 1.10 percent, whereas it is 2.36 when the diffusion index is below the 15 percentile. The 15th percentile of the diffusion index is 47.5. For the US the numbers are 0.80 versus 1.41, with a diffusion index of 48.7 at the 15th percentile. The large increase in RMSFE is essentially due to the dramatic increase in volatility of output growth during the financial crisis. Output growth became more volatile and less predictable.

Second, I perform the modified Diebold-Mariano test on this sub-sample of observations. Now the test results reveal that the diffusion index model is outperformed by the Carlson-Parkin models in all instances. Table 5 shows the differences in RMSFE between the diffusion index model and the Carlson-Parkin models. The largest reduction takes place for the Laplace model with a reduction of the RMSFE in both the euro area and the US of around 10 percent (or between 0.11 and 0.17 percentage points in terms of monthly growth rates).

An alternative to checking periods of low index values is to analyze the relative performance of the diffusion index versus the Carlson-Parkin models at each point in time.

Table 4: Root Mean squared forecast errors conditional on low index values (below the 15th percentile): variable periods

euro area

lag	AR	DIFF	UNIF	LOGI	LAPL
1	2.35	1.51	1.51	1.48	1.40
2	2.29	1.56	1.56	1.52	1.43
3	2.13	1.52	1.52	1.48	1.38

USA

lag	AR	DIFF	UNIF	LOGI	LAPL
1	1.50	1.13	1.07	1.10	0.99
2	1.38	1.15	1.07	1.11	0.99
3	1.41	1.22	1.15	1.18	1.05

Table 5: Differences in Root Mean squared forecast errors between diffusion index model and Carlson Parkin models conditional on low index values (below the 15th percentile): variable periods

Differences in RMFSE with DIFF

euro area

lag	UNIF	LOGI	LAPL
1	-	**0.03**	**0.11**
2	-	**0.04**	**0.13**
3	-	**0.04**	**0.14**

USA

lag	UNIF	LOGI	LAPL
1	**0.08**	**0.03**	**0.14**
2	**0.08**	**0.04**	**0.16**
3	**0.07**	**0.04**	**0.17**

Values in monthly percentages

Numbers in bold indicate that RMSFE of Carlson Parkin models is significantly lower then their respective diffusion index model (one-sided modified Diebold-Mariano test at the 5 percent level)

I use the fluctuation test of Giacomini and Rossi (2010) to do this. The null hypothesis is that $E(d_t) = 0$ for all t, t in 2002:01-2010:06. The test, consist in calculating the time path of the Diebold and Mariano statistic over centered rolling windows of size m and checking whether it breaches a threshold. The test is constructed as follows:

$$DM_{t,m} = \frac{(1/p)\sum_{j=t-m/2}^{t+m/2-1} \hat{d}_j}{\sqrt{\frac{\sigma^2}{m}}} \tag{35}$$

with σ^2 the HAC estimate of the variance of $\hat{d}_t$, constructed as in equation 32. The null hypothesis is rejected against a one sized alternative $E(d_t) > 0$ when $max|DM_{t,m}| > k$ with k depending on the significance level and on the window size m relative to the out-of-sample window p. Giacomini and Rossi (2010) provide the critical values (see Table 1 of their article). I use a rolling window m of 12 observations, with p=102. I use a small window as the indices are only at the extremes for a relatively short time period. The one-sided test with a nominal size of 5 (10) percent has a critical value of 3.18 (2.92). So if $DM_{t,m} > 3.18$ the Carlson-Parkin model outperforms the diffusion index model.

Figures 4 and 5 report the results of the Giacomini and Rossi fluctuation test. In all figures the comparison of the diffusion model is with its Carlson-Parkin counterpart. Each figure reports the test statistic and the 5 and 10 percent critical values, shown as the horizontal lines. So when the test statistic is below the horizontal lines, then the diffusion index and Carlson-Parkin model are performing equally well. We cannot reject the null hypothesis of equal forecasting performance. When the test statistic moves between the two upper lines the Carlson-Parkin model is statistically significantly better then the level model at the 10 percent level, when it moves above the upper line it is significantly better at the 5 percent level. Table 6 reports the maximum value of the test statistic and the time point when it is reached.

The findings are the following. In the euro area, the test statistic shows that the logistic and Laplace Carlson-Parkin models significantly outperformed the diffusion index model in the midst of the financial crisis. (Obviously the uniform model is identical to the diffusion model). Table 6 shows that the maximum was reached in the first quarter of 2009. It is significant at the 5 pct level for lags 1, 2 and 3. The US results are similar. Here also the uniform model (which is based on the share data) outperforms the diffusion index model.Table 6 shows that the maxima of the test statistics all lay in the first or second quarter of 2009.

One should conclude that the Carlson-Parkin estimates are reasonable relative to the diffusion index. However they only improve forecasting performance in the tails of the distribution of the index. In addition the gains in forecasting performance are small. So is it worth it? Well, the transformations are easy to do and basically costless. More importantly one can not be certain that in the future, a deep recession might bring these

Table 6: Maximum value of Giacomini and Rossi fluctuation test

euro area

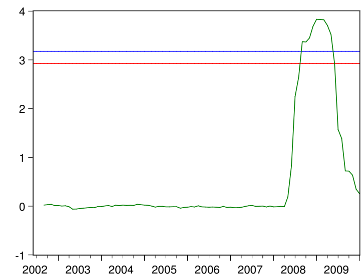
lag	UNIF	Midpoint Window	LOGI	Midpoint Window	LAPL	Midpoint Window
1	-	-	**3.83**	09M01	**3.95**	09M01
2	-	-	**3.61**	09M02	**3.66**	09M02
3	-	-	**3.70**	09M03	**3.69**	09M02

USA

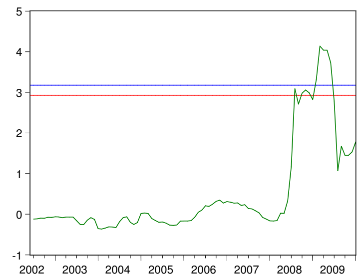
lag	UNIF	Window	LOGI	Window	LAPL	Window
1	**3.32**	09M05	**4.14**	09M03	3.07	09M02
2	**3.50**	09M05	**4.11**	09M03	3.14	09M02
3	**3.73**	09M05	**4.35**	09M03	**3.36**	09M03

Test of local outperformance of diffusion model by Carlson-Parkin model.
** number in bold are significant at the 5 percent level (critical value 3.18).
Window size m is 12 months.

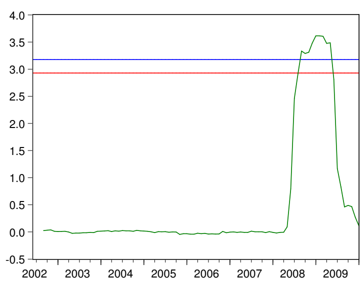
indicators back or even below the levels seen in the financial crisis. Forecasters should be warned then, replacing diffusion indices by Carlson-Parkin estimates are likely to improve forecasts.



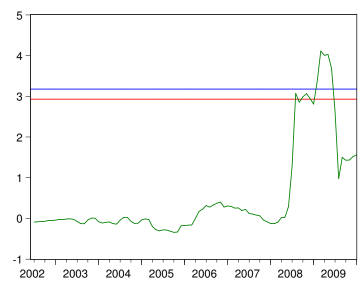
(a) Euro Area lag 1



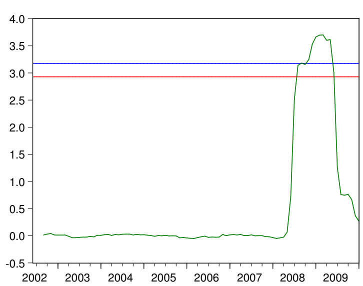
(b) US lag 1



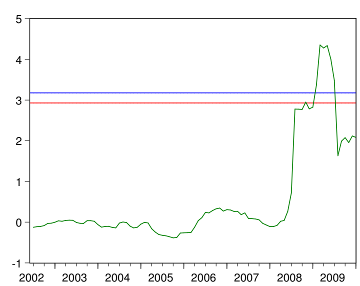
(c) Euro Area lag 2



(d) US lag 2

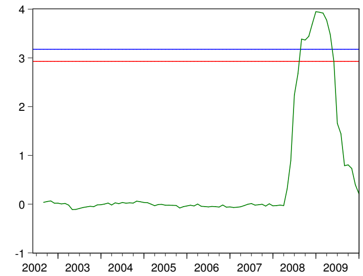


(e) Euro Area lag 3

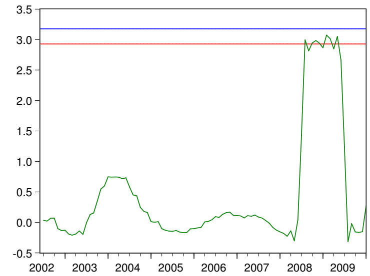


(f) US lag 3

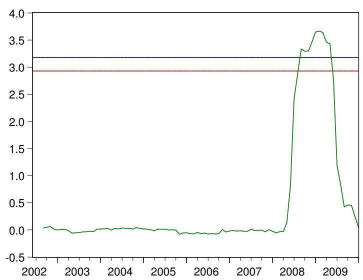
Figure 7: Fluctuation test: diffusion index models versus logistic Carlson-Parkin models



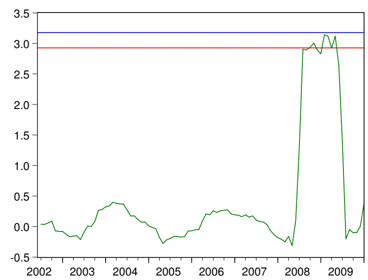
(a) Euro Area lag 1



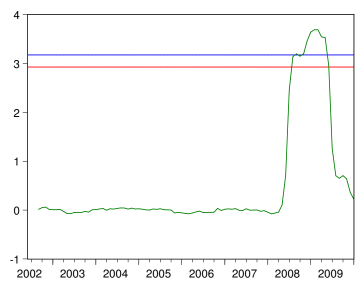
(b) US lag 1



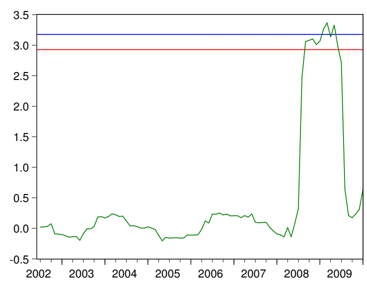
(c) Euro Area lag 2



(d) US lag 2



(e) Euro Area lag 3



(f) US lag 3

Figure 8: Fluctuation test: Diffusion index models versus Laplace Carlson-Parkin models

6 Conclusion

I have constructed Carlson-Parkin estimates of monthly output growth using the ISM production index and the Markit Eurozone manufacturing PMI output index. These estimates follow closely industrial production growth. When the output index is low using the Carlson-Parkin method to provide estimates of industrial production growth rather then the diffusion index itself improves forecasting performance. I find somewhat better performance of the Carlson-Parkin method under the Laplace distribution assumption. This is consistent with the IO-literature on the distribution of firm growth rates.

The results in this paper has wider implications. How should business survey results be optimally translated into useful numbers? Many survey indicators of growth in employment, inventories, orders etc are released as diffusion indices. Commentators and analysts often only use these diffusion indices when relating them to official statistics. However a good match between official statistics and diffusion indices is based on the implicit assumption that the fraction of unchanged answers remains constant and that the distribution of the underlying variable is uniform. Only under these conditions the diffusion index can be justified. Alternatively quantitative estimates of growth rates can be obtained using the Carlson-Parkin method using different distributional assumptions. The question that imposes itself is what are the cross-sectional distributions of employment growth rates, inventory growth rates etc? Using these distributions to translate the answers of business surveys might lead to better quantification then using the diffusion index. How much this is the case is for further research.

References

Anderson O., The business test of the IFO institute for economic research, Munich, and its theoretical model,Revue de lnstitut international de statistique, 20 1-17

Banbura M., Giannonr, D. and L. Reichlin, 2010, "Nowcasting", ECB Working Paper series 1275.

Batchelor R.A., 1986, "The psychophysics of inflation", Journal of Economic Psychology, 7 , 269-290

Batchelor R.A., Orr, A.B., 1988, "Inflation expectations Revisited", Economica, 55 (219), 317-331

Bottazzi G., Secchi A., 2003, "Why are distributions of firm growth rates tent-shaped?, Economics letters 80 , 415-420.

Bottazzi G., Secchi A., 2006, "Explaining the distribution of firms growth rates, The Rand Journal of Economics 37 , 23-263.

Carlson J., Parkin, M., 1975, "Inflation Expectations", Economica, 42(166) 123-138

Clark T.E., West, K.D., 2007, "Approximately normal tests for equal predictive accuracy in nested models", Journal of Econometrics 138 291-311

Croushore D., Stark T., "A Real-Time Data Set for Macroeconomists", 2001, Journal of Econometrics, 105, 111-30.

Cunningham A., 1997, "Quantifying survey data", Bank of England Quarterly Bulletin: Agust 1997 292-300

Dasgupta S., Lahiri K., 1992, A comparative study of alternative methods of quantifying qualitative survey responses using NAPM data, Journal of business & economic statistics, Vol 10 (4) 391-400

Diebold F.X., Mariano, R.S., 1995,"Comparing predictive accuracy", Journal of Business and Economic Statistics 13, 253-263.

Giacomini R., Rossi, B., 2010,"Forecast comparisons in unstable environments", Journal of Applied Econometrics 25 595-620.

Giannone D., Henry, J., Lalik, M., and Modugno M., 2010,"An area-wide real-time database for the euro area", European Central Bank Working Paper Series, no 1145.

Hanssens D.E., Vanden Abeele, P.M, 1987, "A Time-series study of the formation and predictive performance of EEC production survey expectations", Journal of Business & Economic Statistics, Vol 5 (4) 507-519

Harris M., Owens R.E.,Sarte P-D.G., 2004, "Using manufacturing surveys to assess economic conditions, Federal Reserve Bank of Richmond Economic Quarterly Volume 90/4 Fall.

Harvey D., Leybourne, S., and Newbold P., 1997, "Testing the equality of prediction mean squared errors", International Journal of Forecasting 13, 281-291.

Marcellino M., Stock, J.H., Watson M.W., 2006, "A Comparison of Direct and Iterated Multistep AR Methods for Forecasting Macroeconomic Time Series", Journal of Econometrics.

Nardo M., 2003, "The quantification of qualitative survey data: a critical assessment", Journal of Economic Surveys, 17(5) 645-668

Pesaran M.H., 1984, "Expectations formations and macro-econometric modelling", in Malgrange, P and Muet, P.A. (eds.), Contemporary Macroeconomic Modelling, Basil Blackwell, Oxford.

Pesaran M.H., 1987, The limits to rational expectations, Blackwell.

Stock J.H., Watson M.W., 2002a, "Macroeconomic Forecasting Using Diffusion Indexes", Journal of Business & Economic Statistics, April, Vol 20 n2, 147-162.

Stock J.H., Watson M.W., 2002b, "Forecasting Using principal components from a large number of predictors", Journal of the Stastistical Association, December, Vol 97 n460, 1167-1179.

Theil H., 1952, "On the time shape of economic microvariables and the Munich Business test", Revue de lnstitut international de statistique, 20 105-120