Uncertainty in UK manufacturing: evidence from qualitative survey data*

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Abstract

This paper generalizes the probability method of quantification [Carlson and Parkin, *Economica*, 1975] to the variance facilitating the quantification of business survey data which ask individuals whether or not they are uncertain. In an application to UK manufacturing traditional time-series and cross-sectional measures of uncertainty are then evaluated and the effect of uncertainty on investment considered.

Keywords: Uncertainty; Quantification; Qualitative Survey Data; Disagreement; Dispersion; Investment

JEL classification: C8; C42; D8

1 Introduction

Economic uncertainty is discussed widely as an influence on the behaviour of macroeconomic aggregates, such as investment. But our understanding of uncertainty and what it means for the economy is impeded by the difficulties involved in measuring it empirically. Popular approaches to measuring uncertainty include "cross-sectional" measures, based on the dispersion of individuals' expectations or forecasts in surveys. There are also "time-series" measures, based on relating uncertainty to specific macroeconomic aggregates such as inflation or output growth. These define uncertainty as the squared difference or error between the actual value of the aggregate and its expected value measured from surveys or using a forecasting model. GARCH methods model uncertainty by letting the conditional variance of this error change over time. But a more satisfactory approach than either of these indirect methods is to measure uncertainty directly by exploiting micro-level (*ex ante*) subjective measures of uncertainty obtained from surveys.

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While time-series measures are only as reliable as the model on which they are based, we know that conventional cross-sectional measures only characterize disagreement or dispersion. This is only one component of total uncertainty.[1] Nevertheless there remains an empirical debate about how good a proxy disagreement is for uncertainty; cf. Zarnowitz & Lambros (1987) and Giordani & Söderlind (2003).

However, surveys rarely deliver quantitative measures of uncertainty and when they do typically only a small number (fewer than fifty or so) of forecasters are asked for their probability distributions for the aggregates of concern. For example, the Survey of Professional Forecasters (SPF) asks at present around 30 forecasters their opinions about future inflation and output growth in the US. From these density forecasts measures of uncertainty, typically based on the variance, can be extracted although there has recently been discussion about whether this is best achieved from the aggregate (mean) density forecast or from the average of the variances from the individual density forecasts; see Zarnowitz & Lambros (1987), Diebold et al. (1999), Giordani & Söderlind (2003) and Clements (2005).

In this paper we consider how to extract a measure of uncertainty from qualitative survey data which simply indicate whether or not individuals are uncertain. We extend the well-known probability method of quantification [Carlson & Parkin (1975) [CP]] from the first to second moment in order to extract a quantitative measure of uncertainty from these qualitative data. Uncertainty estimates are then obtained for UK manufacturing using survey data published by the Confederation of British Industry (CBI). The CBI each quarter ask over 1100 firms, representing over a third of total employment in the sector, whether or not they are uncertain, specifically when planning their investments in buildings and plant and machinery. As far as we are aware, these CBI data are the only source of firm-specific information on uncertainty in the UK and any empirical study of the way in which uncertainty affects business behaviour is therefore dependent on the coherent analysis of them. In common with many studies of the SPF data, we then evaluate popular cross-sectional and time-series measures of uncertainty in relation to the direct measure. We thus contribute to the continuing debate over whether disagreement is a good proxy for uncertainty empirically. Finally we examine the effect of uncertainty on investment behaviour, with the possibility of identifying the link between macroeconomic stability and investment.

The plan of this paper is as follows. In Section 2 we outline the CBI survey and in Section 3 we extend the probability method of CP to quantify uncertainty data. Section 4 reviews traditional measures of uncertainty, Section 5 presents the empirical results and Section 6 concludes.

[1] The variance of the aggregate distribution equals average individual uncertainty ("within" model variance) plus disagreement ("between" model variance). See also equation (5) below.

2 The CBI Survey

The *Industrial Trends Survey* of the CBI, a leading independent employers' organization, is conducted on a quarterly basis and offers qualitative opinion from UK manufacturing firms on past and expected trends in output, exports, prices, costs, investment intentions, business confidence and capacity utilisation. The survey is the UK's longest running business tendency survey. The survey receives replies from about 1100 firms each quarter. The firms are asked a range of questions including whether or not capital expenditure was constrained by uncertainty about demand. Firms provide categorical answers indicating, for example, whether or not they are uncertain. On investment they are asked: "Do you expect to authorize more or less capital expenditure in the next twelve months than you authorized in the past twelve months on: (a) buildings and (b) plant and machinery (P&M)".

Responses from the survey are available in January, April, July and October, which we match to q4, q1, q2 and q3, respectively. For example, the January survey represents information formed before any first quarter information became available to firms and is therefore matched to the fourth quarter of the previous year.

3 Use of categorical data on uncertainty

Qualitative survey data are often quantified to facilitate their interpretation and analysis. The CP approach takes the aggregate findings of such surveys, say the proportion of firms reporting that output has risen, stayed the same or fallen, and relates them to official output data. It is related to the regression method of Pesaran (1987); see Pesaran & Weale (2005) for a discussion of these and related approaches.

When quantifying these categorical data using the probability method it is usually assumed that there is an underlying variable which is normally distributed and that the category reported depends on the value of the underlying latent variable. Respondents change from one category to another as the latent variable crosses a threshold whose value can be determined econometrically, given suitable data and an appropriate identifying restriction. Plainly it cannot be assumed that responses to a question on uncertainty are driven directly by a latent variable and that this latent variance is normally distributed with mean zero, since this does not rule out the possibility of negative variances. Below we therefore suggest a simple extension to the probability method which uses the uncertainty, second-moment, information directly. Previous work has considered first moment information only (e.g. the aggregate responses to questions where firms are asked whether they expect output growth/inflation to rise, stay the same or fall), and computed uncertainty as the cross-sectional dispersion around the traditional CP quantified estimate; see Demetriades (1989).

3.1 Quantification of uncertainty: extending the probability method

Consider a survey that asks a sample of firms whether or not they are uncertain. Let P_t $(t = 1, ..., T)$ denote the proportion of firms in the sample that report they are uncertain. Quantification of uncertainty is based on u_t, the aggregate shocks that hit the economy. Quantitative estimates of uncertainty can be derived from P_t given the following conditions.

Condition 1 *Firm i's $(i = 1, ..., N)$ answer to the uncertainty question derives from its subjective probability density function for u_t, $f_i(u_t \mid \Omega^i_{t-1})$, conditional on the information set available to it Ω^i_{t-1}, such that $u^2_{it} = \mathsf{Var}(u_t \mid \Omega^i_{t-1})$.*

Condition 2 *The responses of firm i are classified as uncertain if:*

$$u^2_{it} \geq \lambda_{it}, \tag{1}$$

where λ_{it} is a subjectively imposed threshold value. If $u^2_{it} < \lambda_{it}$ the firm is not uncertain.

Condition 3 *Firms are independent and the structure of $f_i(u_t \mid \Omega^i_{t-1})$ is the same and known across firms, i.e. $f_i(u_t \mid \Omega^i_{t-1}) = f(u_t \mid \Omega^i_{t-1})$.*

Condition 4 *The aggregate density $f(.)$ is normal with mean zero and variance σ^2_t.*

Condition 5 *The response thresholds λ_{it} are invariant across firms and time, $\lambda_{it} = \lambda$.*

Conditions 1 and 2 follow the spirit of the probability approach of CP. u^2_{it} represents the extent to which firm i is uncertain about the future and should be distinguished from a measure of disagreement (across firms), which is what the traditional CP approach delivers given its focus on the variance of the sample (cross-sectional) mean rather than u^2_{it}; see Pesaran & Weale (2005).

Condition 3 is again familiar from CP. In our context it implies that the random variable u_{it} is an independent draw from the aggregate density $f(u_t \mid \Omega_{t-1})$, where Ω_{t-1} is the union of Ω^i_{t-1}. For CP with their focus on some central tendency of respondents' subjective probability densities (e.g. a firm expects output to rise if the mean of their density for output growth is greater than some threshold value) a central limit theorem then implies that the aggregate density is normal, or less restrictively stable; see Batchelor (1981). In our case without interpreting u_{it} as the mean, normality of $f(.)$ must be imposed. Nevertheless some support for Condition 4 is offered again invoking a central limit theorem if we view the aggregate shocks u_t to be the weighted sum of independent, or less restrictively stationary, firm-level shocks. Under Condition 4, the standardized sample variance $(u^2_{it}/\ \sigma^2_t)$ can be considered as a random draw from a $\chi^2(1)$ density.

Condition 5, again parallelling CP, then implies that the proportion of uncertain firms P_t provides a consistent (as $N \to \infty$) estimate of the population proportion:

$$P_t \xrightarrow{p} \Pr(u^2_t \geq \lambda \mid \Omega_{t-1}) = 1 - F\left(\frac{\lambda}{\sigma^2_t}\right), \tag{2}$$

where $F(.)$ denotes the cumulative distribution function of the $\chi^2(1)$ density.

$b_t = \frac{\lambda}{\sigma_t^2}$ can be calculated as the abscissa of the distribution corresponding to the cumulative probability of $1 - P_t$. As in the CP approach one can then estimate σ_t^2 given a scaling parameter λ:[2]

$$\sigma_t^2 = \lambda \frac{1}{b_t}. \tag{3}$$

Thus we can measure uncertainty σ_t^2 consistently up to a linear transformation: since λ is a constant its role is merely to scale σ_t^2. Interpretation of σ_t^2 should be conducted independently of its scale, for example by using correlation rather than root mean squared error statistics.

Additional guidance about what σ_t^2 represents can be seen by interpreting $f(u_t \mid \Omega_{t-1})$ as a combined density, with (without loss of generality) firms' individual densities receiving an equal weight in the combination:

$$f(u_t \mid \Omega_{t-1}) = (1/N) \sum_{i=1}^{N} f_i(u_t \mid \Omega_{t-1}^i) \tag{4}$$

It follows from the properties of a finite mixture density that

$$\sigma_t^2 = \mathsf{E}_c(u_{it}^2) + \mathsf{Var}_c(\mathsf{E}(u_t \mid \Omega_{t-1}^i)) \tag{5}$$

where E_c denotes that expectations are taken with respect to the cross-sectional distribution. Since $\mathsf{E}(u_t \mid \Omega_{t-1}^i) = 0$ for all i, aggregate uncertainty, σ_t^2, equals average firm-level uncertainty, u_{it}^2.

Figure 1 plots σ_t from 1979, when survey data on uncertainty were first published, to the present day. Figure 1 shows that uncertainty appears to have been fluctuating around a higher mean value since 1990. Uncertainty peaked in the early 1980s and the early 1990s which were both recessionary periods. There was also a sharp peak in 2001 q4 in the aftermath of the attacks in New York. However, uncertainty was no higher in the period after 2001, when manufacturing output was generally falling, than it had been in the second half of the 1990s when output was rising.

4 Time-series and cross-sectional uncertainty estimates

It is important to understand how different measures of uncertainty are related both to σ_t^2 and to each-other given their use in empirical work, for example as an explanatory variable in investment equations; see Carruth et al. (2000). Different empirical studies use different uncertainty estimates and this may be affecting results. Although we expect σ_t^2 to be better related to output than inflation, reflecting the fact that firms are asked a question about demand rather than inflationary uncertainty, we do also consider some measures of inflationary uncertainty where inflation is calculated using the producer price index for manufactured output.

[2] As $P_t \to 0, 1$ the behaviour of P_t and σ_t^2 will diverge.

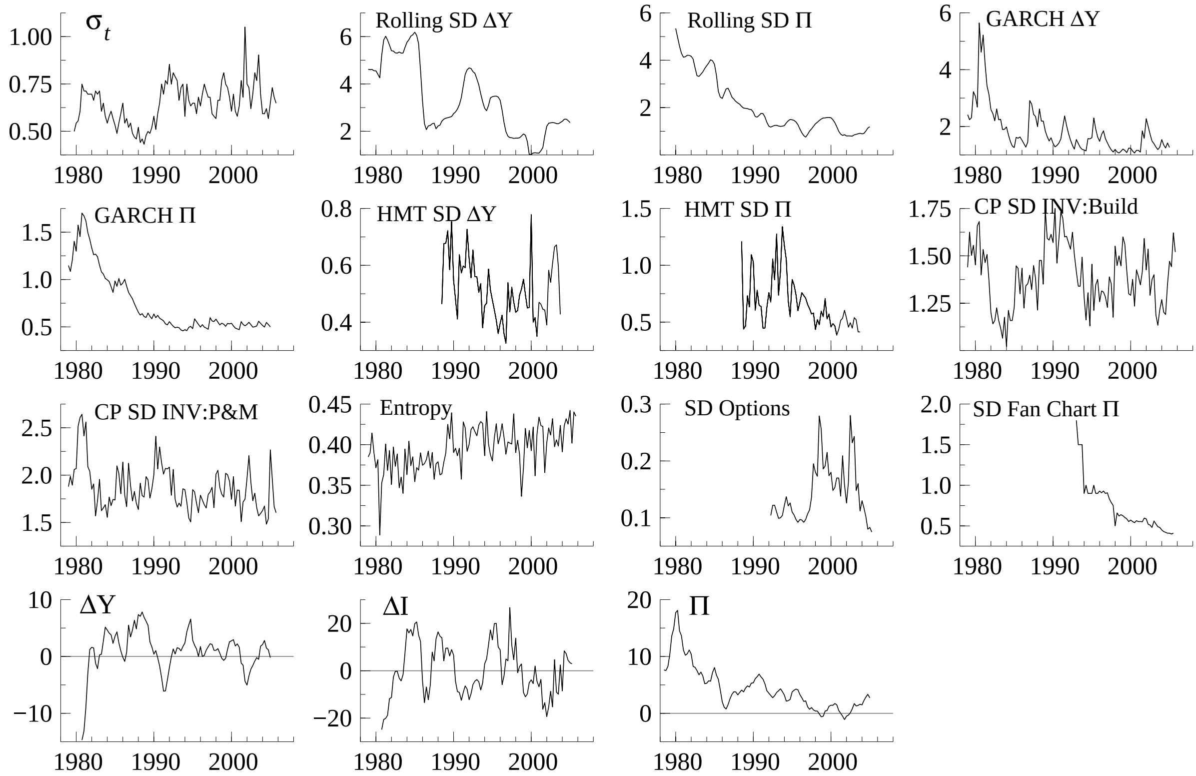

Figure 1: Measures of uncertainty and other indicators

We examine two popular time-series measures of uncertainty, the unconditional and conditional standard deviation of output growth and inflation. Specifically we consider a twenty quarter rolling standard deviation of quarterly manufacturing output growth as a measure of unconditional volatility. The conditional variance is estimated using a GARCH(1,1) model for quarterly inflation and output growth, with the mean modelled as an AR(4).

Three cross-sectional measures are considered, the first of which we explain in some detail given the lack of attention given to the underlying panel data-set.

First, we rely on the dispersion or standard deviation (SD) of macroeconomic forecasts in the tabulations published by HM Treasury ("Forecasts for the UK economy: a comparison of independent forecasts"). Over our sample period HMT sampled each month, in total, 60 independent City (43) and non-City (17) forecasters, although there are on average only 34 firms present in a given sample with a range from 13 firms (at the beginning of the sample) to 46 firms (towards the end of the sample). We consider the standard deviation across this panel of the year ahead point forecasts of inflation and output growth as tabulated by HMT in March, June, September and December. The four forecasts made during a given calendar year are for inflation in q4 of the next year and output growth in the next calendar year. They are therefore fixed-event forecasts; as the information set available to the forecaster increases during the year we should expect, *ceteris paribus*, uncertainty (and forecast errors) to decline.

Secondly, we extract a measure of dispersion from the CP method following Demetriades (1989) applied to the two investment questions from the CBI survey. Thirdly, a cross-sectional entropy measure is defined as $-\sum_{j=1}^{3} P_{jt}\log(P_{jt})$, where P_{jt} is the proportion of firms who give the j-th response ($j = 1, 2, 3$), corresponding to "down", "the same" and "up", respectively, to the CBI question: 'Are you more or less optimistic than you were four months ago about the general business situation in your industry'.

In addition to these time-series and cross-sectional measures we consider two alternative direct estimates. First, as estimated from prices of options in financial markets and tabulated on a daily basis by the Bank of England; see Clews et al. (2000). Specifically, we consider the standard deviation from the logarithmic returns implied probability density function for the FTSE 100 equity index in six months time.[3] From these daily data we take (as close as possible to) the end of quarter standard deviation estimates. This provides a measure of 'market' uncertainty. It is however only available from 1992. Secondly, we consider the standard deviation of the Bank of England's fan chart of year ahead inflation, which was first published in 1993. The standard deviation is taken as a measure of the Bank of England's subjective uncertainty; see Britton et al. (1998). We follow Wallis (2004) and correct earlier confusion about what the published uncertainty measure represents.

5 How good are different measures of uncertainty?

The cross-sectional and time-series measures of uncertainty are evaluated according to their ability to match σ_t. Figure 1 plots these alternative estimates and Table 1 shows their correlation against σ_t.

σ_t is only weakly correlated with both the time-series and cross-sectional measures of uncertainty, with correlation often lower than 0.1. While σ_t appears to have risen over the last 25 years, the time-series methods all suggest, albeit with some cyclical dynamics, that uncertainty has fallen. In contrast to the time-series methods, the cross-sectional measures do not indicate such a decline and are more volatile. In fact the entropy measure correctly suggests that uncertainty has risen over the sample-period, however correlation against σ_t remains weak at just 0.17.

These results are consistent with related work that has shown both how misleading disagreement can be as a measure of uncertainty (see Zarnowitz & Lambros (1987) - but inconsistent with Giordani & Söderlind (2003)) and that time-series models do not capture uncertainty as measured in the SPF survey (see Giordani & Söderlind (2003)). Indeed our results suggest that traditional measures of uncertainty do a bad job at proxying

[3]These are available from: http://www.bankofengland.co.uk/statistics/impliedpdfs/index.htm

uncertainty, as actually perceived by firms. This is consistent with the view that the time-series measures do not pick up idiosyncratic uncertainty, and are inherently backward looking, and that the cross-sectional measures only capture disagreement.

Table 1 also shows that σ_t is only weakly correlated with the direct measures of uncertainty implied by the options data and the fan chart. While the Bank of England since 1993 has become increasingly certain about the prospects for inflation, the options data do pick up the peaks in σ_t in 2001, after 9-11, and the earlier but less pronounced peak in 1999.

But Table 1 does show that σ_t is strongly negatively correlated with both investment and output growth, with correlations higher than 0.5 in absolute value. Higher uncertainty is associated with lower output growth; this result is consistent with the cross-country evidence presented by Ramey & Ramey (1995). σ_t is only correlated -0.22 with inflation reinforcing our impression that σ_t is best related to output, reflecting the fact that firms are asked a question about demand rather than inflationary uncertainty.

Table 1: Correlation of aggregate uncertainty, σ_t, with other indicators and measures of uncertainty

Measure of Uncertainty		σ_t	ΔI
σ_t		1.000	-0.530
Time-Series	Rolling SD ΔY	0.005	0.042
	Rolling SD Π	-0.299	0.024
	GARCH ΔY	-0.089	-0.288
	GARCH Π	-0.161	-0.192
Cross-Sectional	HMT SD ΔY	-0.058	-0.115
	HMT SD Π	-0.024	0.192
	CP SD INV:Build	0.059	-0.271
	CP SD INV:P&M	-0.002	-0.418
	Entropy	0.170	-0.053
Direct	SD Options	0.082	-0.323
	SD Fan Chart	0.077	0.161
Macro-aggregates	ΔY	-0.588	0.678
	ΔI	-0.530	1.000
	Π	-0.224	-0.049

Notes: Correlations are computed across the maximum available sample period. SD denotes standard deviation; ΔY is output growth; Π is inflation; ΔI is investment growth; INV:Build is investment in buildings; INV:P&M is investment in plant and machinery; HMT SD is the standard deviation of the point forecasts across the forecasters in the HMT panel; CP SD is the standard deviation measure from the traditional Carlson-Parkin method.

Table 1 also lists the correlation of σ_t and the alternative uncertainty estimates against investment growth. Economic theory, perhaps despite first impressions, is ambiguous about the sign of the relationship between uncertainty and investment; e.g. see Abel et al. (1996) and Guiso & Parigi (1999). While the majority of the uncertainty estimates are negatively related with investment growth, σ_t exhibits a much stronger negative relationship. This suggests that the mixed findings over the sign of the relationship found in previous work, albeit with focus on the partial correlation coefficient, may be due to their use of less satisfactory proxies of uncertainty. It is also interesting to relate a popular concern for policy-makers in the UK, namely the apparently low level of investment, to the fact that the trend appears to have been for increased uncertainty σ_t over the past 25 years.

6 Conclusion

We propose an extension of the probability method of quantification to the variance and provide quantitative uncertainty estimates for the UK manufacturing sector. These estimates are derived from a unique data set which provides categorical information on uncertainty at the firm-level.

More resources need to be devoted to the collection of subjective measures of uncertainty. It is not clear that popular time-series and cross-sectional proxies are satisfactory. By estimating uncertainty directly using the disaggregated results of surveys, perhaps at a sectoral level, it would be possible to break uncertainty down into its microeconomic and macroeconomic components. Future work might then better understand the link between investment, and in turn economic growth, and macroeconomic stability.

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