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Working Paper 20/12

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Kevin Lee, Michael Mahony and Paul Mizen

Produced By:

Centre for Finance, Credit and Macroeconomics
School of Economics
Sir Clive Granger Building
University of Nottingham
University Park
Nottingham
NG7 2RD

Output Expectations, Uncertainty and the UK Business Cycle; Evidence from the CBI's Suite of Business Surveys*

by

Kevin Lee, Michael Mahony and Paul Mizen†

Abstract

Novel methods are used to produce quantitative measures of output expectations and output uncertainties in the UK based on the information provided by the CBI business surveys since 2000. These are employed alongside actual output data in an analysis of the source of innovations and propagation mechanisms underlying output dynamics. The coverage of the surveys (conducted separately for the manufacturing, distributive trade and service sectors) and the sample length (covering the periods before and after the Financial Crisis and through the Brexit period) means the analysis provides a compelling characterisation of UK business cycle experiences over the last twenty years.

Keywords: Business Cycles, Survey Data, Expectations, Uncertainty.
JEL Classification: C32, E32, E71.

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*†University of Nottingham, UK. Version dated October 2020. We are grateful to Nicola Grimwood, Ben Jones and Anna Leach at the CBI for help and advice on accessing the CBI Suite of Business Surveys. Financial support from the ONS through the Economic Statistics Centre of Excellence is gratefully acknowledged. Corresponding author: Michael Mahony, School of Economics, University of Nottingham, Nottingham NG7 2RD, UK. E-mail: michael.mahony@nottingham.ac.uk.

1 Introduction

Expectation formation is understood to play a key role in macroeconomics, having taken centre-stage during the Rational Expectations Revolution of the seventies and thereafter. But there has been a recent surge of interest in the way that individuals acquire and process information and the impact this has on output dynamics. For example, as discussed below, authors have explored the role of learning and information rigidities in business cycle dynamics, attempted to distinguish the effects on output of news on fundamentals from sentiment, and considered the role of psychological factors and cognitive limitations in output determination.[1] At the same time, there has also been a related focus on the role of uncertainty as a potential source of business cycle fluctuations and/or a contributor to the propagation of innovations from other sources.[2]

Given this interest, it is surprising that relatively little use is made of direct measures of expectations, as obtained from surveys, in modelling business cycle dynamics. Of course, there is a long tradition of using direct measures to study the expectation formation process itself,[3] and there are important papers deriving measures of uncertainty from survey responses. But, for example, few of the VAR models used to investigate the effect of uncertainty on output include direct measures of expectations in the VAR,[4] and survey-based measures of uncertainty, if they are used at all, are typically considered as just one among many alternative measures. But the failure to use survey data is not just a lost opportunity for gaining direct insights on firms' expectations, sentiments and uncertainties. The omission of direct measures of expectations from business cycle analysis makes it difficult to distinguish the contributions to the cycle of firms' fundamentals and their use of information without employing potentially contentious identifying assumptions, and can introduce model misspecifcation that obscures or perverts these behavioural insights.

[1] The introduction of the new code "E7 Macro-Based Behavioural Economics" to the JEL Classification System in 2017 is an obvious sign of the growth of interest in the area.

[2] Bloom (2014) and Castelnuovo (2019) provide excellent overviews of this literature.

[3] See Pesaran and Weale (2006) and Croushore (2010) for a useful overview.

[4] Aristidou et al (2019) note that it is unusual to find direct measures of output expectations even in models that are used to forecast future output levels.

This paper provides a time series model of actual output, expected output and output uncertainties in the UK drawing on the data provided in the Confederation of British Industry's (CBI) suite of business surveys. We briefly review the advantages of using direct measures in empirical work on the business cycle (and the potential dangers of omitting them) and we introduce a novel method of deriving quantitative measures of expectations and uncertainty from the qualitative CBI survey responses. We then use these quantitative measures in a simple VAR model to capture UK business cycle dynamics between 2000q1-2020q1.[5] The analysis provides a compelling characterisation of UK business cycle experiences over the last twenty years showing, for example, that output uncertainty does provide a negative source of shocks to output outcomes and, although these are usually small, they caused relatively large permanent drops in output in the years following the Global Financial Crisis (GFC) and sovereign debt crisis and in during the period of UK discussions on leaving the EU.

1.1 Related Literature

The literature on macro-based behavioural economics has expanded in many different dimensions. The focus in many papers has been the role of agents' use of information in generating macro dynamics. So, Evans and Honkopohja (2001), Eusepi and Preston (2011) and Bordalo et al. (2020), for example, emphasise the role of learning in expectation formations and business cycle fluctuations, while the influential papers by Mankiw and Reis (2002), Sims (2003) and Woodford (2001) explore the consequences of various forms of information rigidity in rational expectations models. In the latter, agents are assumed rational but are either slow to take account of macroeconomic information even when it is publicly available ('sticky information models') or are only able to observe the fundamentals on which decisions are based with error ('noisy information'). The divergence between agents' perceptions of the economy and reality can generate short-run fluctuations in output that are quite separate from their long-run time-paths in these

[5]We end the analysis before the effects of the coronavirus pandemic to focus attention on the modelling strategy and the usefulness of direct measures in this. The advantages of the measures in producing real-time output nowcasts as the effects of the pandemic play out are described in Lee et al (2020).

circumstances. Empirical evidence on the nature and extent of learning and information rigidities, based on the analysis of survey responses of professional forecasters, has been provided in Branch and Evans (2006), Coibion and Gorodnichenko (2011, 2012), and Dovern et al (2012, 2015), inter alia, to establish that these influences are important in practice.

At the same time, interest in the role of uncertainty in business cycle dynamics has been studied extensively since Bloom's (2009) seminal piece outlining how a temporary increase in uncertainty can elicit a 'wait and see' response to investing firms resulting in an initial contraction and subsequent expansion in economic activity. An enormous literature developed in response suggesting various alternative measures of uncertainty[6] and exploring the extent to which this sort of macro dynamic is observed in practice, typically including the uncertainty measure in a VAR and identifying the effects of uncertainty shocks on output through an impulse response analysis. Prominent examples include Bloom (2009) itself, Caggiano et al. (2014), Jurado et al. (2015), Barrero et al. (2017), and Ludvigson et al. (2020), and papers which make reference to measures of uncertainty based on survey responses include Lahiri and Liu (2006), Lahiri and Sheng (2008, 2010), Boero et al. (2015), Bachmann et al. (2016), Clements (2017), Garratt et al. (2019), and Jo and Sekkel (2019), for example.

Interest in macro-based behavioral economics has extended well-beyond the extensions provided by the more nuanced approach to the use of information and the acknowledgement of the potential role of uncertainty though. For example, Akerlof and Shiller's (2019) text and de Grauwe and Ji's (2020) text, emphasise the role of fear, concern for fairness, cognitive limitations and other psychological and social factors in decision-making and macroeconomic dynamics, noting that these influences can operate independently of underlying economic fundamentals. The distinction between the effects on output exerted by news on fundamentals and that exerted by autonomous movements in sentiment has been explored in Beaudry and Portier (2006, 2014), Barsky and Sims (2011, 2012) and Bachmann and Sims (2012), inter alia. The inclusion of forward-looking variables in the

[6] Altig et al. (2020), for example,discusses ten popular alternative measures of uncertainty relating to the UK macroeconomy.

empirical work (sometimes including surveys of expectations and confidence) plays a key role in capturing the various influences that might impact on macroeconomic dynamics and, through carefully chosen identification assumptions, in testing the validity of these alternative hypotheses. In short, direct measures of expectations has been a recurring element in much of the recent work investigating macro-based behavioural economics, although they have not been used as systematically and widely as they might have been.

2 The Use of Direct Measures of Expectations in Modelling the Business Cycle

The primary purpose of the paper is to provide an empirical analysis of the UK business cycle making use of the direct measures of expectations obtained from the CBI surveys. But it is worth briefly rehearsing some of the advantages of using the direct measures in modelling output movements as well as the potential dangers of omitting them. Stated simply, in the very likely situation in which individuals recognise that some part of the innovations in today's output are only short-lived, measures of uncertainty based on actual output data alone will overstate the true extent of the uncertainty surrounding output, and models estimated using only actual data are likely to overstate the long-term consequences of output movements. Further, if the relative importance of the short-lived element of output change varies over time, the typical univariate model of actual output considered alone will be misspecified, and misspecified in such a way that it will suggest a role for uncertainty on output dynamics even if one does not exist or overstate the role if one does exist. These points hold even where there is Full Information Rational Expectations (FIRE), and the presence of information rigidities or more nuanced cognitive processes introduces an even more straightforward role for using direct measures of expectations in modelling output dynamics.

To illustrate these points, denote output growth $x_t = y_t - y_{t-1}$, where y_t is (the logarithm of) output at time t, and consider a simple model in which growth is determined according to the following

$$x_t = v_t + \omega_t - \omega_{t-1} \tag{2.1}$$

depending on two types of shock, v_t and ω_t, the latter of which is known to have only short-lived effects and will be offset in the next period. If the two types of shock are independent and have variance σ_v^2 and σ_ω^2 respectively, then the variance of x_t is $\sigma_v^2 + 2\sigma_\omega^2$. Assuming that expectations are formed with FIRE and are captured by the direct survey measures, then the expected value of x_{t+1} formed in time t is the offset of the short-lived shock experienced in t

$$ {}_t x_{t+1}^e = E\ (\ v_{t+1} + \omega_{t+1} - \omega_t \mid \text{-}\ {}_t) = -\omega_t\ . \tag{2.2}$$

The advantage of having direct measures of expectations from a survey is immediately apparent: the short-lived shocks are observed directly through the survey responses, and the other shocks are recoverable from the 'adjusted' actual series obtained by subtracting the effects of the short-lived shocks from the original actual series:

$$x_t + {}_t x_{t+1}^e - {}_{t-1}x_t^e = v_t. \tag{2.3}$$

The 'news' arriving on x_t at time t is reflected in the expectational error $x_t - {}_{t-1}x_t^e = v_t + \omega_t$ and the uncertainty surrounding growth - describing the extent to which output in t is not known in $t-1$, i.e. $\sigma_v^2 + \sigma_\omega^2$ - can be readily calculated and split into its component parts. This will be important if, for example, we believe that the uncertainty surrounding the short-lived shocks σ_ω^2 play a less important role in decision-making than the uncertainty captured by σ_v^2.

In the absence of direct measures of expectations, modelling may be based on the actual output series alone which, in this illustration, can be captured by the moving average (MA) process

$$x_t = u_t + \theta u_{t-1} \tag{2.4}$$

where θ and the variance of u_t, σ_u^2, are obtained matching the variance and covariance terms of the two characterisations; i.e. the solution to $\sigma_v^2 + 2\sigma_\omega^2 = (1+\theta^2)\sigma_u^2$ and $-\sigma_\omega^2 = \theta\sigma_u^2$. Solving we find that $\theta \in [-1, 0]$ with the value depending on the relative size of the two types of shock (tending to 0 when the permanent shocks dominate and $\frac{\sigma_v^2}{\sigma_\omega^2} \to \infty$, and tending to -1 when the short-lived shocks are relatively important and $\frac{\sigma_v^2}{\sigma_\omega^2} \to 0$). Since $(1+\theta+\theta^2)\sigma_u^2 = \sigma_v^2 + \sigma_\omega^2$, we know $\sigma_u^2 > \sigma_v^2 + \sigma_\omega^2$ and the uncertainty associated with the expectational error obtained from the univariate MA specification overstates the uncertainty surrounding expectational error observed when the direct measures are available (and obviously cannot be used in a decomposition to measure the sizes of the uncertainties surrounding the two types of shock).

The problems arising from the unsatisfactory treatment of the short-lived shocks when modelling actual output alone are compounded in the case where the MA representation is approximated with a finite autoregressive process (AR) as is typical in the literature. This is exemplified by measures of 'persistence' which show the long-run effect of a shock to the output *level.* When output growth is characterised by the MA representation in (2.4), a 1% shock to growth will leave expected growth unchanged in the long run but will cause the output level to be $(1+\theta)\%$ higher than it would have been in the absence of the shock. Obviously, if the short-lived shocks dominate and θ tends to -1, the measure can be arbitrarily close to zero (reflecting the fact that output levels are stationary in this case). However, if the MA process is approximated by an AR(2) model $x_t = \rho_1 x_{t-1} + \rho_2 x_{t-2} + u_t$ for example, then the restrictions on ρ_1 and ρ_2 required to ensure stationarity mean that the persistence measure $\frac{1}{1-\rho_1-\rho_2} \geq \frac{1}{3}$.[7] This illustrates the idea that the type of (low order) AR model of output typically reported in the literature - without reference to direct measures of expectations - imposes a lower threshold on persistence so that it will also overstate the long-run effects of shocks to output if the effects of the transitory shocks are important.

Perhaps even more importantly in the context of the recent discussions of business cycle dynamics, the time series representation of actual output considered alone will be badly misspecified if the relative importance of the two types of shock vary over time. This would be the situation if, for example, there are occasional periods of crisis associated with increased volatility in the permanent shocks (with the size of the short-lived shocks unchanged). This heteroskedasticity means the parameters of the univariate model - θ and σ_u^2 in (2.4) or the corresponding parameters in the AR approximation - are actually time-varying and a simple time-invariant univariate model would be misspecified. Further, the

[7]See Hamilton (1994, p17) for details. Note too that, in the AR(1) case, where $\rho_1 \in [-1, 1]$ for stationarity, persistence cannot be less than $\frac{1}{2}$.

nature of the misspecification is such that the misspecified errors of an estimated time-invariant specification will be correlated over time with the volatility in the errors so that the addition in the growth equation of an uncertainty variable that reflects this volatility would show as important even if uncertainty actually has no effect on output growth.

The limitations of the univariate model of actual output arise because the single model is being used to capture the outcomes of two processes: the process determining output and the expectation formation process. A bivariate model of actual and expected growth - making use of direct measures of expectations - is able to characterise the two processes and their interactions properly and would avoid the econometric issues raised above. For example, consider the first-order model

$$\begin{bmatrix} x_t \\ {}_t x^e_{t+1} \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} x_{t-1} \\ {}_{t-1}x^e_t \end{bmatrix} + \begin{bmatrix} \xi_{1t} \\ \xi_{2t} \end{bmatrix}. \tag{2.5}$$

This model can clearly accommodate the illustrative example of (2.1), with $b_{12} = 1$ and $b_{11} = b_{21} = b_{22} = 0$, and with $\xi_{1t} = v_t + \omega_t$ and $\xi_{2t} = -\omega_t$. In practice, the two types of shocks - and associated uncertainties - could be obtained through an orthoganalisation of the estimated residuals (regressing the reduced form residuals $\widehat{\xi_{1t}}$ on $\widehat{\xi_{2t}}$ with the residuals from this regression interpreted as observations of the $\widehat{v}_t$'s). Measures of the persistence of shocks to the bivariate model - based on the 'variance of the long-differences' in this multivariate setting[8] - can deliver values that are arbitrarily close to zero, and estimated regression parameters - and associated impulse response analyses - remain unbiased even in the presence of heteroskedasticity in the ξ's. The FIRE assumption of the illustrative model is embedded within (2.5) by imposing the restriction that $b_{12} = 1$ and $b_{11} = 0$, but more sophisticated assumptions on the expectation formation process could be captured through an appropriate set of (less-rigid) restrictions, while leaving the relationship unrestricted would give maximum flexibility in representing the expectation formation process.[9] Equally, more complex models of output determination would be accommodated if no coefficient restrictions are imposed and/or higher order lags are included in

[8]See Lee, Pesaran and Pierse (1992) and Pesaran, Pierse and Lee (1993) for discussion of persistence measures in multivariate systems.

[9]The model in (2.5) implicitly assumes expectational errors are stationary: actual growth $x_t = y_t - y_{t-1}$ and expected growth ${}_{t-1}x^e_t = {}_{t-1}y^e_t - y_{t-1}$ are both assumed to be stationary, so their difference $x_t -$

the VAR model. And, given that the danger of finding a spurious relationship between growth and uncertainty is avoided when the direct measures of expectations are included in the analysis, the addition of measures of uncertainty in the VAR would allow for an uncorrupted analysis of the effects of uncertainty in growth dynamics.

3 Measuring Expectations and Uncertainty Using the CBI Survey

The discussion above is based on the idea that *quantitative* measures of expected output and the uncertainty surrounding output are readily available. As is often the case, however, the CBI surveys provide only *qualitative* information on individuals' expectations. The first step in the analysis is the derivation of quantitative measures from the qualitative responses, therefore, and in this section, we describe a novel approach to this derivation which accommodates the possibility that the relationship between growth and the reported survey responses may change over time. We also describe two measures of uncertainty based on the survey responses that can capture different aspects of individuals' lack of knowledge about growth.

3.1 Deriving quantitative measures of expectations

The CBI Survey provides qualitative information on the question "Excluding seasonal variations, what has been the trend over the past three months and what are the expected trends for the next three months, with regard to volume of output (i.e. production)?". Survey participants can respond that the trend has been one of 'Up', 'Same', 'Down' or 'n/a' over the two time frames. Then

$$R_t = \frac{n_{Rt}}{n_t} = \text{ prop. individuals saying in } t \text{ that trend was 'Up' over the previous 3 months}$$
$$S_t = \frac{n_{St}}{n_t} = \text{ prop. individuals saying in } t \text{ that trend was 'Same' over the previous 3 months}$$
$$F_t = \frac{n_{Ft}}{n_t} = \text{ prop. individuals saying in } t \text{ that trend was 'Down' over the previous 3 months}$$

while the corresponding variables referring to the expected trend over the next three months are denoted ${}_tR^e_{t+1}$, ${}_tS_{t+1}$ and ${}_tF^e_{t+1}$.

${}_{t-1}x^e_t = y_t - {}_{t-1}y^e_t$ is also stationary. If output has a unit root, this means actual and expected output *levels* are cointegrated with cointegrating vector $(1, -1)$ and shocks to the system have the same long run effect on these two series. See Garratt, Lee and Shields (2018) for further discussion.

There have been a number of methods proposed for converting the information contained in these proportions into a time series for a quantitative measure of expectations.[10] Many are based on the recognition that, if the average percentage increase in output for those individuals reporting a rise is α and the average decrease in output for those individuals reporting a fall is $-\beta$, then the average increase in output across all individuals is

$$\begin{aligned} x_t &= \frac{1}{n_t} \left[\sum^{n_{Rt}} \alpha + \sum^{n_{St}} 0 - \sum^{n_{Ft}} \beta \right] \\ &= \frac{1}{n_t} \left[(n_{R_t} \times \alpha) + (n_{S_t} \times 0) - (n_{S_t} \times \beta) \right] \\ &= (R_t \times \alpha) - (F_t \times \beta). \end{aligned} \tag{3.6}$$

Further, if the average increases and decreases, α and β, remain relevant in expectation, then the expected future growth is given by

$${}_t x^e_{t+1} = ({}_t R^e_{t+1} \times \alpha) - ({}_t F^e_{t+1} \times \beta). \tag{3.7}$$

The 'regression method' for converting qualitative survey outcomes to a quantitative series is based on (3.6) and (3.7) where estimated values for α and β can be obtained by treating (3.6) as a relationship that holds over time with error and regressing $\overline{x}_t$ on R_t and F_t.The estimated values can then be applied to (3.7) to obtain a time series for expected growth.[11]

3.1.1 Accommodating structural change

The assumption that the average percentage increase of output among those experiencing a rise and the average percentage decrease in output among those experiencing a fall are both constant over time is extremely unlikely to hold true in practice; more realistically, α will be higher and β will be lower in good times, and vice versa in recessions. However, the formula at (3.6)-(3.7) remain relevant even if these averages change over time so long

[10] See Pesaran (1987) for a more detailed discussion.

[11] These expressions also provide the motivation for using the *balance statistic* $B_t = R_t - F_t$ as an indicator of growth since, in the special case where $\alpha = \beta$, (3.7) simplifies to $\overline{x}_t = \alpha \times B_t$ and ${}_t\overline{x}_{t+1} = \alpha \times {}_t B_{t+1}$ and actual and expected growth move proportionately with the backward-looking and forward-looking balance statistics respectively.

as we replace α and β with time-varying α_t and β_t. Two possibilities for estimating values for α_t and β_t based on (3.6) are as follows:

1. use a rolling sample window of, say, s periods and obtain time-varying values for α and β for at each point in time T by estimating the models $M_{s,T}$ defined by.

$$M_{s,T}: \quad x_t = \alpha_{s,T}\ R_t - \beta_{s,T}\ F_t + \varepsilon_{s,T} \qquad \text{for} \quad t = T-s, ..., T. \tag{3.8}$$

   so that the coefficient attached to each period are based on the regression estimated over the most recent s periods; and

2. use a 'meta model', again based on a set of rolling regressions, but allow the data to choose an appropriate sample window at each point to balance the advantages of longer samples (which provide more accuracy in estimated relationships) versus short samples (which are less vulnerable to the effects of structural breaks).

Both of these approaches will capture time variation in the α and β coefficients and improve the scaling in quantification. The simple rolling window approach is more straightforward but makes an arbitrary choice on the size of the sample window. As explained below, the 'meta model' is based on a more systematic choice of window size and is able to capture both smoothly evolving relationships and abrupt changes in the relationship between growth and the survey responses.

The 'meta' modelling approach is described in detail in Lee et al. (2015), where it is applied to the estimation of a Taylor rule, and Aristidou et al. (2019), where it applied in the context of forecasting output growth and the probability of recessions. The approach deals with the uncertainty over the appropriate sample window through model averaging, assuming that there are S possible models that can be used to characterise output growth at time T. The models are all of the form in (3.6) but estimated over various sample windows $T - s_{\max}, ..., T - s_{\min}$ with $S = s_{\max} - s_{\min} + 1$. Hence each model $M_{s,T}$ links output growth to the backward-looking qualitative survey responses over the period $T - s, ..., T$, but we contemplate models that might be relevant only for the most recent $s_{\min}$ periods or back to $s_{\max}$ periods in the past.

The 'meta model' explaining $\overline{x}_t$ over the full sample $\underline{T}, ..., \overline{T}$ is then defined by

$$\overline{M}_{.,.} = \{M_{s,T}, \ \ w_{s,T} \quad \text{for} \quad s = s_{\min}, .., s_{\max}, \quad T = \underline{T}, ..., \overline{T}\} \tag{3.9}$$

with weights $w_{s,T}$ capturing the relevance of the different candidate model at each point over the sample.[12] A pragmatic approach to deriving model weights is to allow these to evolve over time, updating the weights in each period to reflect new evidence on whether the previously-held model continues to be valid or whether an alternative new-born model is now appropriate. The approach can be formalised by writing, for any T and for $s = s_{\min}, ..., s_{\max} - 1$,

$$w_{s,T-1} \quad \rightarrow \quad \begin{cases} w_{s+1,T} & \text{if the null } M_{s+1,T} \text{ is not rejected in favour of } M_{r,T} \text{ for } r = s_{\min},...,s \ , \\ w_{r,T} & \text{if the null } M_{s+1,T} \text{ is rejected in favour of } M_{r,T} \text{ for } r = s_{\min},...,s \end{cases} \tag{3.10}$$

Here, the weight assigned at time $T-1$ to the model based on data $T-1-s$ to $T-1$ is either transferred to the model with one additional observation - i.e. using data $T-1-s$ to T - or to a new model based on the shorter sample of data $T-r$ to T. If a model is rejected in favour of more than one shorter alternative, the weight can be split equally among the alternative models. In transferring the weights, the tests should be conducted comparing the null to successively shorter samples so the weights can be shifted down sequentially where the evidence is that a model based on a shorter sample outperforms a model based on a longer one. Given that the shorter models are all nested within the longer model, the validity of the null can be tested using standard F-tests of structural stability.

The estimated weights of the meta model show which of the individual models, distinguished by the sample length, provide the most likely characterisation of the relationship between x_t.and the qualitative survey responses. The importance of the various models is reflected in the averaged coefficients

$$\alpha_T = \sum_s \alpha_{s,T} \times w_{s,T} \quad \text{and} \quad \beta_T = \sum_s \beta_{s,T} \times w_{s,T} \ ,$$

[12]The motivation for the meta modelling approach is the Bayesian Modelling Average formula described in Hoeting et al. (1999) and discussed in detail in Lee et al. (2003).

and changes in the size of the weights over time provide useful information on how the relationship has evolved. For example, the *duration statistic*

$$D_T = \sum_s s \times w_{s,T} \tag{3.11}$$

provides a time-T indication of the average duration of the relationship in place at that time. The use of model weights provides considerable flexibility in capturing the time-variation in the nature of the relationship between growth and the survey responses which can evolve smoothly over time, with weights shifted to progressively longer samples during periods of stability for example, or can change very abruptly if, for example, the weights all shift to a short sample following a significant structural break.

3.2 Deriving measures of output uncertainty

Uncertainty refers to the extent to which something is not known and different types of uncertainty can be defined depending on the event of interest and the perspective from which the event is considered. As noted previously, many measures of uncertainty have been proposed in the literature but these are often based on an outside metric - stock price volatility or newspaper coverage, for example[13] - which may be only tangentially related to the event of interest. In the case of output uncertainty, for example, this can introduce a disconnect between the uncertainty measure and output fluctuations, with the measures reflecting uncertainties about events that may have little or no connection with the current or future values of output. There are also potential problems where the measure is obtained from a first-stage econometric model of the variable of interest - e.g. based on the errors from a forecasting model as in Jurado et al (2015) and Ludvigson et al. (2020) - since the measures implicitly assume an underlying expectation formation process that may or may not be applicable. For example, the sort of information rigidities highlighted by Coibion and Gorodnichenko (2019) generate expectational errors that reflect genuine uncertainty about the variable - in that agents have not collected the information necessary to form FIRE even though it is available - but which then introduce a

[13] Examples include Bloom (2009), Caggiano et al. (2014), Baker et al. (2016), and Barrero et al. (2017), inter alia.

systematic component into the size of expectational errors which would be omitted from a measure of uncertainty based on forecast errors. In contrast, uncertainty measures based on individuals' stated understanding of output growth, as reflected in surveys, unambiguously relate to 'uncertainty about output growth' and automatically take into account individuals' use of information without any underlying assumptions being made.

Two potentially useful measures of uncertainty about output growth can be obtained from the survey data on output expectations reported in the CBI surveys. The first is derived directly from the average expected future growth series of (3.7) and is based on the size of the average expectational error, $\sqrt{(x_{t+1} - \ _{t}x^{e}_{t+1})^2}$. This provides a natural measure of the extent of what is not known about x_{t+1} as reflected in the the (one-period-ahead) expectational error and as revealed at time $t+1$. The measure is common to all survey respondents and is often termed 'ex post consensus uncertainty'. The disadvantage of using this measure is that it involves the actual outcome - hence the descriptor 'ex post' - which is unknown at the time expectations are formed and so does not properly capture the uncertainty surrounding the reported expectation at the time it was reported. Lahiri and Sheng (2008) therefore suggest constructing a measure of 'ex ante consensus uncertainty' $_{t}x^{uc}_{t+1}$ based on a GARCH model in which

$$x_{t+1} - \ _{t}x^{e}_{t+1} = c + \epsilon_{t+1} \tag{3.12}$$

and, for example,

$$\epsilon_{t+1} \sim N(0, \sigma^2_{t+1}) \ \text{ and } \ \sigma^2_{t+1} = \phi_0 + \phi_1\sigma^2_t + \phi_2\epsilon_t$$

so that the size of the expectational error in time $t+1$ is driven by the innovations observed at time t. The ex ante consensus uncertainty measure is $_{t}x^{uc}_{t+1} = \widehat{\sigma_{t+1}}$, the estimated standard deviation of the innovations to the (de-meaned) expectational error at time $t+1$ conditioned on the information available at t.

A second useful measure of uncertainty on output growth is provided by the dispersion of opinion among the survey respondents at t over outcomes at time $t+1$. As highlighted in Kozeniauskas et al (2018), this dispersion measure will depend on a number of different elements including the cross-section variability in firm-level actual outcomes, the public information on these outcomes and firms' private information about their own and other firms' prospects. Disagreement will occur even in the absence of uncertainty when firms' responses are driven by differences in micro circumstances. But disagreement will also reflect differences in information across firms and the relative weight firms place on public and private signals. Reverting back for a moment to the case where α and $-\beta$ are time-invariant measures of the average growth among those firms reporting 'Up' and those reporting 'Down' respectively, the cross-section variance of responses on expected growth is given by

$$\begin{aligned}
\left({}_t x^{ud}_{t+1}\right)^2 &= \frac{1}{n_t}\left(\sum^{n_{R^e_{t+1}}} \alpha^2 + \sum^{n_{S^e_{t+1}}} 0 - \sum^{n_{F^e_{t+1}}} \beta^2\right) - \left({}_t x^e_{t+1}\right)^2 \\
&= \frac{1}{n_t}\left[(n_{R^e_{t+1}} \times \alpha^2) + (n_{S^e_{t+1}} \times 0) - (n_{F^e_{t+1}} \times \beta^2)\right] - \left({}_t x^e_{t+1}\right)^2 \\
&= ({}_t R^e_{t+1} \times \alpha^2) + ({}_t F^e_{t+1} \times \beta^2) - \left[({}_t R^e_{t+1} \times \alpha) - ({}_t F^e_{t+1} \times \beta)\right]^2 \qquad (3.13)
\end{aligned}$$

The estimated values of α and β discussed above (including those taking into account any potential time-variation in the parameters) can be used with (3.13) to obtain a time series for this 'disagreement-based uncertainty' assuming that the time-variation is dominated by information flows rather than changing variation in micro circumstances. This is the measure - assuming time-invariant parameters - used by Bachmann et al. (2016) in their study of the effects of uncertainty on the business cycle in the US and Germany.

4 Actual Output, Expected Output and Output Uncertainty in the UK, 2000q1-2020q1

The empirical work of the paper is conducted using actual quarterly output data provided by Office for National Statistics (ONS) and expectations data reported quarterly through the CBI's suite of business surveys. The CBI suite constitutes four surveys completed by businesses operating in the UK and traces its origins back to 1958 with the introduction of the Industrial Trends Survey (ITS) covering the UK manufacturing sector. Since then the survey suite has expanded with the addition of the Distributive Trades Survey (DTS), the Services Sector Survey (SSS) and the Financial Services Survey (FSS) in 1983, 1998 and 1989 (respectively) with each survey covering their eponymous industrial sectors.[14]

Our analysis focuses on the period 2000q1 - 2020q1 and on the output of the sectors covered by the ITS, DTS and SSS which constitute more than 90% of UK private sector activity.[15] Activity as referenced in the ITS, DTS and SSS relates to the volume of 'output', 'sales' and 'business' respectively. The corresponding actual output series are obtained from the ONS and represent the Gross Value Added series for our '*Manufacturing sector'* (i.e. Sections B, C, and F of the UK's Standard Industrial Classification [SIC] 2007 covering the production industries excluding Energy and Water), our '*Distribution sector*' (i.e. Sections G and H of SIC2007 covering Wholesale and Retail Trades and Transportation and Storage Services) and our '*Service sector*' (i.e. Sections I-T excluding K of SIC2007 covering other services apart from Financial Services).[16]

Figure 1 introduces the raw output data for the Manufacturing, Distribution and Service sectors, showing the evolution over time of the (logarithm of the) output level, y_t. The UK Manufacturing Sector was broadly the same size in 2020 as in 2000, with quarterly growth over the sample period averaging just -0.04% per annum. The slowdown associated with the Global Financial Crisis [GFC] of 2008/9 clearly played a considerable role in this, seeing output fall by 12% in the year from 2008q3. Output growth in Distribution and Services was a little more healthy, averaging 0.54% and 0.44% per annum respectively, but these too suffered considerable downturn in the period following the GFC. Figure 2(a)-(c) plots the corresponding quarterly output growths $y_t - y_{t-1}$ alongside the survey responses R_t and F_t published in the three surveys in t. The broad co-movements in the data are apparent, with the proportions of firms reporting 'Up' and 'Down' rising and falling as output growth rises and falls, and are reflected in the simple correlations

[14]A detailed description of the questions posed in the surveys, the sample frame, the characteristics of the firm participants and a summary of the properties of the data relating to some key business cycle features is provided in Lee et al. (2020).

[15]Financial services are excluded as the sample of firms surveyed is smaller than the others.

[16]The data used in here are the most recently published,' final vintage' measures. An alternative would be to use measures of output as published in real time and to accommodate data revisions in the analysis, as in Garratt et al. (2008) or Aristidou et al. (2019), for example. Our view is that this is important for nowcasting and forecasting but is less so for in-sample business cycle modelling.

between quarterly output growth and R_t and F_t which are, respectively, 0.43 and -0.54 in Manufacturing, 0.51 and -0.61 in Distribution and 0.35 and -0.52 in Services.

Figure 3(a)-(c) describes the quantitative expectations series obtained adopting the three alternative approaches for converting the qualitative survey expectations series into quantitative series discussed above. These are: the 'whole sample' regression approach, assuming α and β in (3.6) and (3.7) are constant over time; the 'rolling modelling' approach in which α and β are allowed to vary over time with their estimates based on a rolling regression analysis of fixed length; and the 'meta modelling' approach in which α and β vary over time with their estimates based on estimated model averages. The derived quantitative expectations series for the methods, ${}_ty^e_{t+1} - y_t$, are plotted against the actual outcome, $y_{t+1} - y_t$, in the figure and the expectations series for the different conversion methods show the relative benefits of the more sophisticated quantification methods in each case. To provide a little detail, we note that estimates of the α and β in the 'whole sample' regression model are $\alpha = 4.77$ (0.85) and $-\beta = -4.53$ (0.75) for Manufacturing (with standard errors in parentheses), $\alpha = 4.26$ (0.54) and $-\beta = -3.18$ (0.55) for Distribution and $\alpha = 2.58$ (0.40) and $-\beta = -1.07$ (0.34) for Services.[17] Applying these parameters to the forward-looking survey responses, provides a series for expected growth that has a statistically significant correlation with actual outcomes of 0.51, 0.58 and 0.43 in Manufacturing, Distribution and Services respectively, so the estimated relationships are certainly useful. But the relatively large standard errors of the coefficients reflects some considerable residual variability in these relationships and suggests that it might be useful to take into account possible time-variation in the parameters. Figures 3(a)-(c) show the relationships based on the rolling-window and meta-modelling approaches are indeed better able to capture the more extreme periods of output growth and contraction than the other series, with the correlation with actual outcomes being 0.65, 0.65 and 0.68 in the meta models for Manufacturing, Distribution and Services, for example.[18] Figure 4(a)-(c) plots the duration statistics defined in (3.11) that lie behind the meta models'

[17]The estimated parameters are broadly consistent with the simple balance statistic assumption that α and β are equal in Manufacturing then, but this is clearly not the case for Distribution and Services.

[18]The various rolling regressions were estimated subject to the restriction that α and β remain positive. In practice, this meant restricting $\beta = 0.01$ on those occasions when the unrestricted β became negative.

expectations series, highlighting in the Manufacturing results for example, four or five distinct periods during which the preferred sample period increased period-by-period - indicating model stability - to be replaced abruptly by shorter preferred sample lengths at specific break-points.[19]

The two uncertainty measures described at (3.13) and (3.12) can be obtained based on the estimated parameters and derived expectations series found using the parameters obtained through the meta modelling approach and these are plotted in Figure 5(a)-(c). The ex ante consensus uncertainty measure is obtained from an estimated GARCH model applied to the expectation errors allowing for a fourth-order ARCH in the variance for Manufacturing and a first-order ARCH in the variance for the Distribution and Service sectors.[20] In Manufacturing, the two most pronounced episodes of high consensus uncertainty are the period covering the GFC and its aftermath and in 2019, perhaps associated with the UK's negotiations on leaving the EU. These episodes also show in the measures of disagreement-based uncertainty for Manufacturing, although there are also high values associated in the early 2000's at which time a global slowdown was threatening UK manufacturing.

[19]The shortest sample length considered reasonable for estimation was two years. This is also the minimum length of time assumed to be required for a break to be recognised (so that breaks occur 8 periods before the shift in weight). Break points were identified by rejecting the null of no break described in (3.10) based on F-tests operating at the 1% significance level.

[20]The inclusion of a lagged σ_{t-1} term was not helpful so the models had an ARCH form in every sector. For example, the estimated model for the variance for Manufacturing was $\sigma_t = 0.62 + 0.35\epsilon_{t-1}^2 + 0.28\epsilon_{t-2}^2 - 0.13\ \epsilon_{t-3}^2 - 0.23\ \epsilon_{t-4}^2$.

4.1 Capturing the Effects of Expectations and Uncertainty on the Business Cycle

The interplay between actual and expected output growth and the associated uncertainties can be captured in a relatively straightforward VAR model:

$$\begin{bmatrix} {}_t y^{uc}_{t+1} \\ {}_t y^{ud}_{t+1} \\ y^{e}_{t+1} - y_t \\ y_t - y_{t-1} \end{bmatrix} = \mathbf{B}_0 + \sum_{k=1}^{p} \mathbf{B}_k \begin{bmatrix} {}_{t-k} y^{uc}_{t-k+1} \\ {}_{t-k} y^{ud}_{t-k+1} \\ {}_{t-k} y^{e}_{t-k+1} - y_{t-k} \\ y_{t-k} - y_{t-k-1} \end{bmatrix} + \begin{bmatrix} \xi_{1t} \\ \xi_{2t} \\ \xi_{3t} \\ \xi_{4t} \end{bmatrix} \tag{4.14}$$

for $t = 1, ..., T$ where the $\mathbf{B}$'s are matrices of parameters and the ξ's are mean zero innovations. The model explains four stationary series: the size of the observed 'consensus uncertainty' relating to ${}_t y^{e}_{t+1}$ and dated at t; the size of the disagreement uncertainty surrounding expectations of ${}_t y^{e}_{t+1}$; the expected growth in output published in the survey dated at time t; and the growth in actual output at time t All the dependent variables are dated at time t so the vectors of shocks $\boldsymbol{\xi}_t = (\xi_{1t}, ..., \xi_{4t})'$, $t = 1, .., T$, fully characterise the news arriving on these variables in each period. The interdependencies between actual and expected outputs and the uncertainties surrounding expectations that are captured by the model in (4.14) are consistent with any number of structural models in which output outcomes depend on lagged and expected future outputs and any number of assumptions on expectations formation, information rigidities and the role of sentiment.[21]

Models of the form in (4.14) were estimated for the Manufacturing, Distribution and Service sectors and VAR's of order 3, 2, and 2 were found to be sufficient to capture the dynamics of the system in each case. The underlying regressions had good explanatory power in all cases[22] and showed strong interdependence between all four variables. The system dynamics are best illustrated and interpreted through an impulse response analysis and in what follows we impose a causal ordering of the shocks through a Choleski decomposition. This can be motivated by the assumptions that, for example, output decisions are made against a backdrop of uncertainty, so that the uncertainty variables

[21] As noted earlier, the model does incorporate the assumption that expectational errors are stationary.

[22] The average R^2's over the three sectors for the uncertainty, disagreement, expected output growth and actual output growth equations were 0.43, 0.76, 0.89 and 0.39 respectively.

are determined prior to the output variables. Similarly, we might assume that current decisions are based on expectations on the future so that ${}_ty^{uc}_{t+2}$ precedes ${}_ty^{ud}_{t+2}$ and y^e_{t+2} precedes y_t. This would allow us to identify the separate effects of consensus uncertainty shocks, disagreement shocks, shocks to expected future output and, finally, shocks to current output. Figure 6(a)-9(a) through to Figure 6(c)-9(c) provide a picture of the system dynamics in the three sectors, setting out the response of the four variables to shocks to, respectively, uncertainty, disagreement, expected output and actual output., under this Choleski ordering. The shocks in each case are taken to be of a 'typical' (one standard deviation) size so the effects of the shocks on output, say, are comparable across the Figures. For example, Figures 6(a) and 6(b) show that both 'consensus uncertainty' shocks and 'disagreement uncertainty' shocks have a negative impact on actual and expected output in the Manufacturing sector, with a typical uncertainty shock causing output to be 0.5% lower than it would have been in the absence of the shock for the consensus uncertainty and similarly for a typical disagreement shock, with adjustment taking two or three years. The impact effects on output of a typical shock to expected output are around 0.5%, but there is then a relatively prolonged build-up of an effect over the subsequent three years, leaving output around 1.2% higher than it would have been in the absence of the shock. In each case, the actual and expected output series converge to the same levels - by construction - but this convergence is not monotonic and can take up to 18 months, providing little support for a Full-Information Rational Expectations interpretation of the model (in which the output response would mirror that of the expectations response after one quarter). The impact effect of a typical shock to actual output is around 0.7% and also initiates adjustments over the subsequent two years, although the ultimate effect remains at around 0.7%.

Similar patterns show in the impulse responses for Distribution and Services in Figures 6(b)-9(b) and Figures 6(c)-9(c). Typical uncertainty and disagreement shocks cause expected and actual outputs to fall, again in the region of -0.3% to -0.2%, although the uncertainty and disagreement responses are more protracted than in the Manufacturing sector and take four or five years to have their full impact. The effects of shocks to expected and actual output show over a much shorter time frame (of one or two years) and in both cases, it is the shocks to expected output that have the most persistent effect. The time paths of the actual and expected series are again complicated, providing little or no support for the patterns of adjustment suggested by FIRE for example, and illustrating the complexities of business cycle dynamics introduced by firms' use of information, sentiment and uncertainty.

While these impulse responses are useful in describing the dynamics of the estimated model, the implications for the macroeconomy are better captured in Figures 10(a)-(c) which plots the output series alongside the Beveridge-Nelson trend output series in each sector. The Beveridge-Nelson trends show, at each point in time, the output level that will be achieved when all current and past shocks have played out and assuming that no further shocks occur.[23] The trend is readily-interpreted as the steady-state output level therefore and reflects the size of the shocks actually observed in the data as well as the infinite horizon effects captured by the impulse responses. For ITS, for example, Figure 10(a) shows output falling some 2.5% below trend during the GFC but broadly tracking the trend from 2012/13.[24] However, Figure 10(a) also plots the BN trend that would have been observed if there had been no shocks to uncertainty or our disagreement measure after 2007q4, denoted 'BN excl. U and D'. This trend lies above the original BN trend throughout the period, showing that the shocks to uncertainty and disagreement caused trend output to be some 2.5%-4.5% lower than it would have been in the absence of shocks through 2008-2012 and some 1%-2% lower at the end of the sample. Comparably large effects for uncertainty and disagreement are observed in the Service and the Distributive Trade sectors in Figures 10(b) and 10(c), although the timing of the largest effects - during

[23]The estimated model provides measures of the actual shocks experienced and, based on the estimated parameters, their accumulated effect which drives the *change* in the BN trend. The *level* of the BN trend is obtained assuming actual output was at steady state in 2007q4, arbitrarily chosen at a point just prior to the GFC. For expositional purposes, the plotted BN trend is the average value over the previous 4 quarters.

[24]It is worth noting that, while actual output fell more than BN trend, the latter itself dropped around 7% from peak to trough in the GFC. This might explain why the downward pressure on prices - exerted by a negative gap - was not as large as expected by some commentators at that time considering the actual output drop alone.

2011/12 and 2014/15 - are a little later than observed in Manufacturing and coincide more with the timing of the sovereign debt crisis and the UK's discussions on whether to leave the EU.

5 Concluding remarks

We have argued that surveys of firms' expectations provide reliable measures and direct insights on the processes underlying expectation formation and the uncertainty surrounding the process. Omitting these measures from empirical work on output dynamics not only wastes an important source of information but also leads to potentially serious misinterpretation of results, including overstatements of the uncertainty surrounding shocks and of the persistent effect, and finding a spurious (or over-stated) causal relationship from uncertainty to output growth. One potential reservation in the use of surveys is that many surveys provide only qualitative responses, but we have described a novel 'meta modelling' approach that provides a relatively straightforward means of translating these into quantitative series taking into account the changing nature of the relationship between survey responses and outcomes. The expectations and uncertainty series that are derived can then be employed in a relatively straightforward VAR model that captures the interplay between these series and actual outcomes. Based on the data produced by the CBI for the UK, we find that these interactions are complex, out-of-line with those suggested by simple models embodying Rational Expectations, instead requiring more nuanced explanations of firms' use of information and of cognitive limitations and other psychological and social factors in decision-making. We do find a role for uncertainty and disagreement shocks in influencing business cycle dynamics, with these having relatively substantial effects of up to 4% in different sectors during GFC and sovereign debt crisis and during the UK's discussions over Brexit.

Figure 1
Evolution Over Time of the (Logarithm of the) Output Level

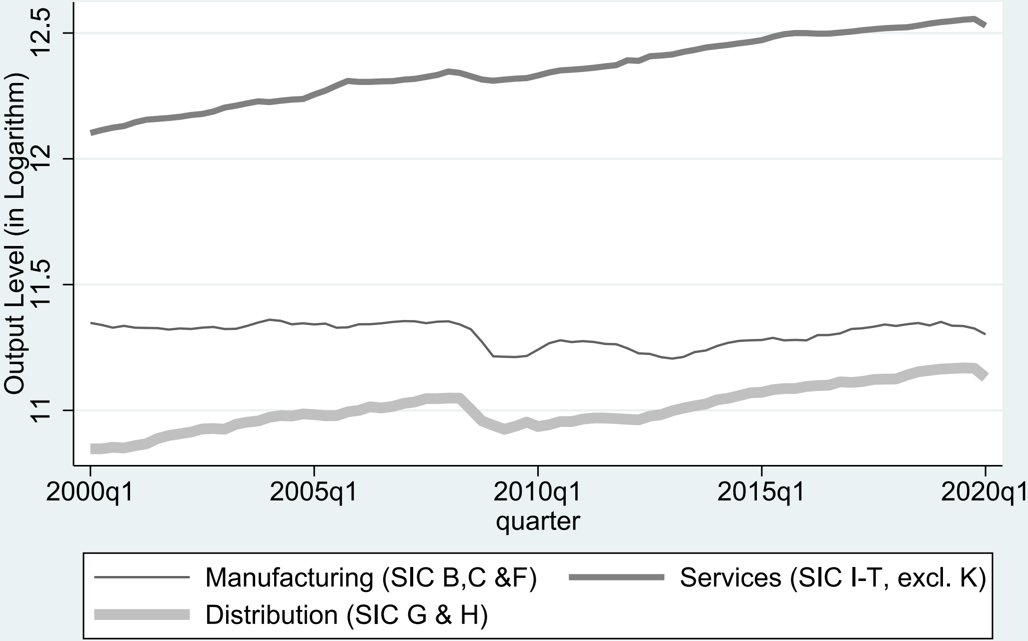


Figure 2(a)
Quarterly Output Growth and Survey Responses (ITS)

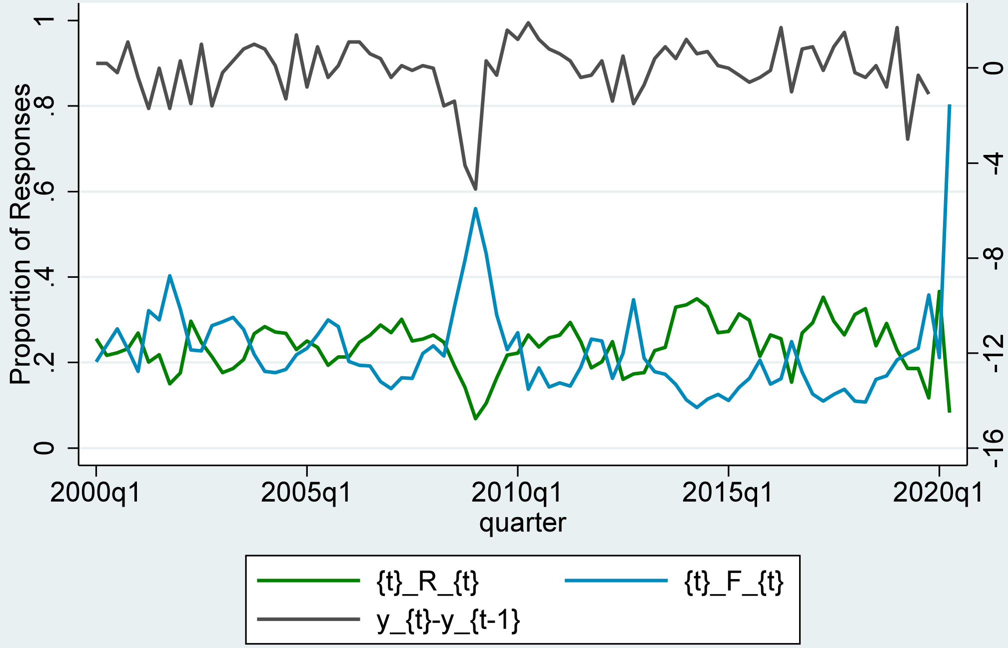


Figure 2(b)
Quarterly Output Growth and Survey Responses (SSS)

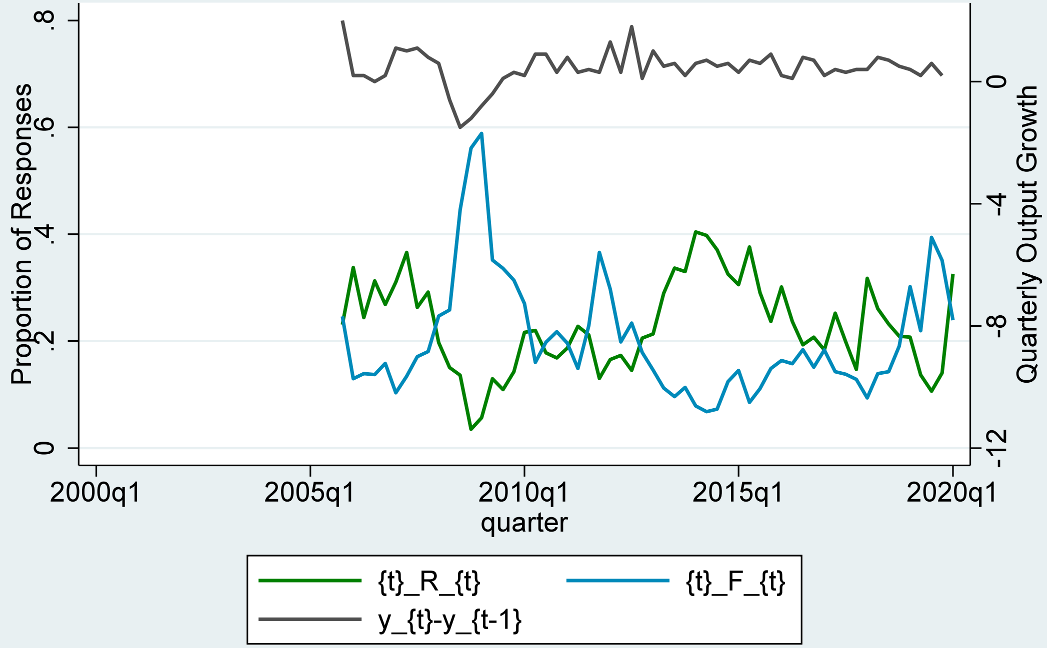
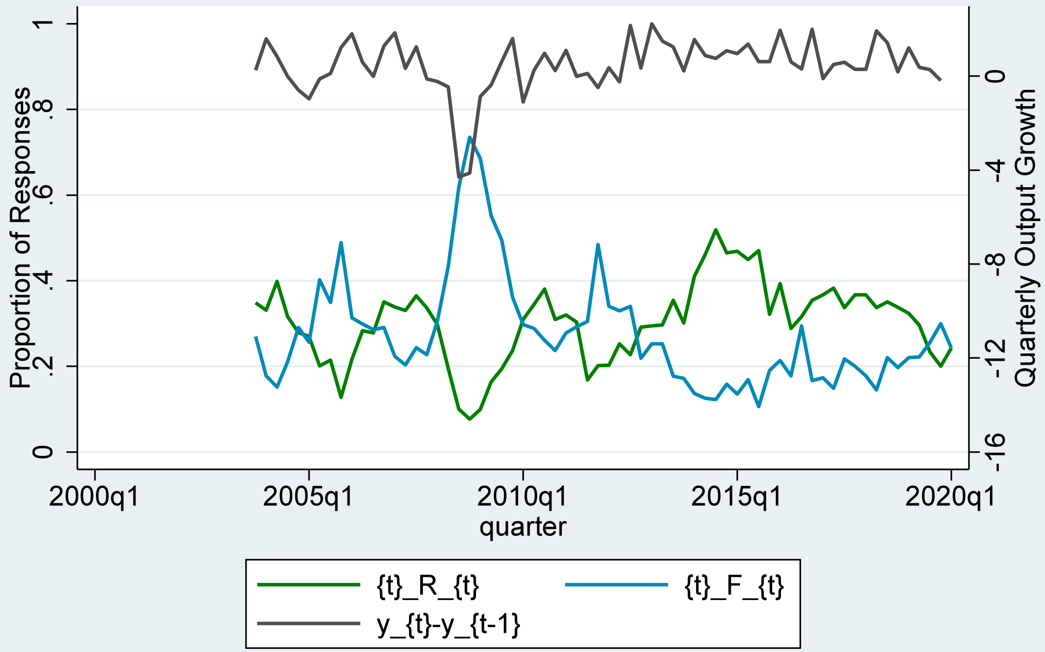


Figure 2(c)
Quarterly Output Growth and Survey Responses (DTS)



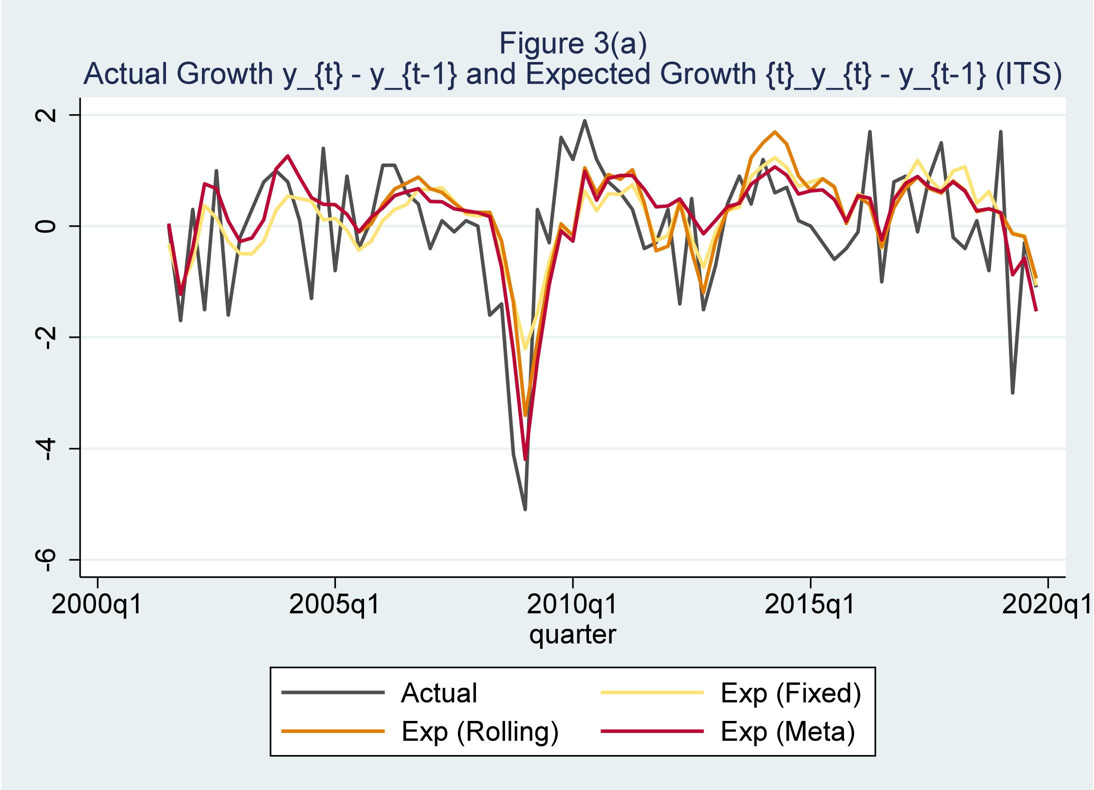


Figure 3(a)
Actual Growth y_{t} - y_{t-1} and Expected Growth {t}_y_{t} - y_{t-1} (ITS)
2
0
-2
-4
-6
2000q1
2005q1
2010q1
2015q1
2020q1
quarter
Actual
Exp (Fixed)
Exp (Rolling)
Exp (Meta)

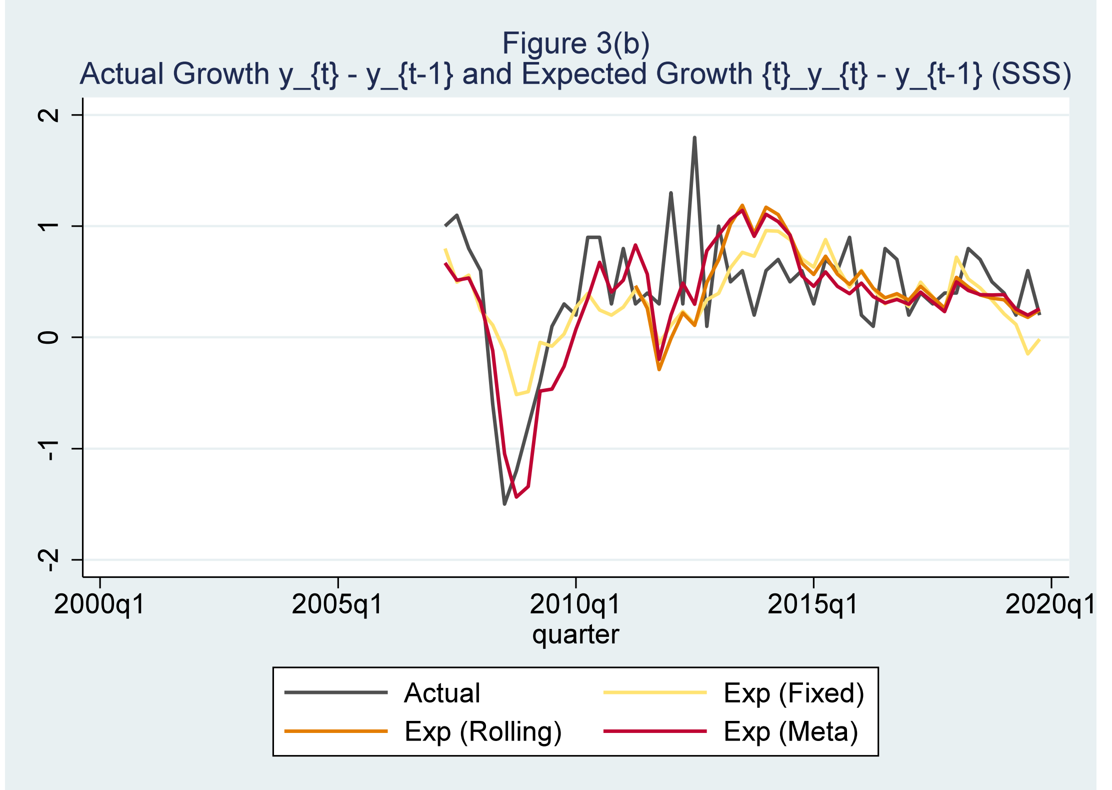


Figure 3(b)
Actual Growth y_{t} - y_{t-1} and Expected Growth {t}_y_{t} - y_{t-1} (SSS)
2
1
0
-1
-2
2000q1
2005q1
2010q1
2015q1
2020q1
quarter
Actual
Exp (Fixed)
Exp (Rolling)
Exp (Meta)

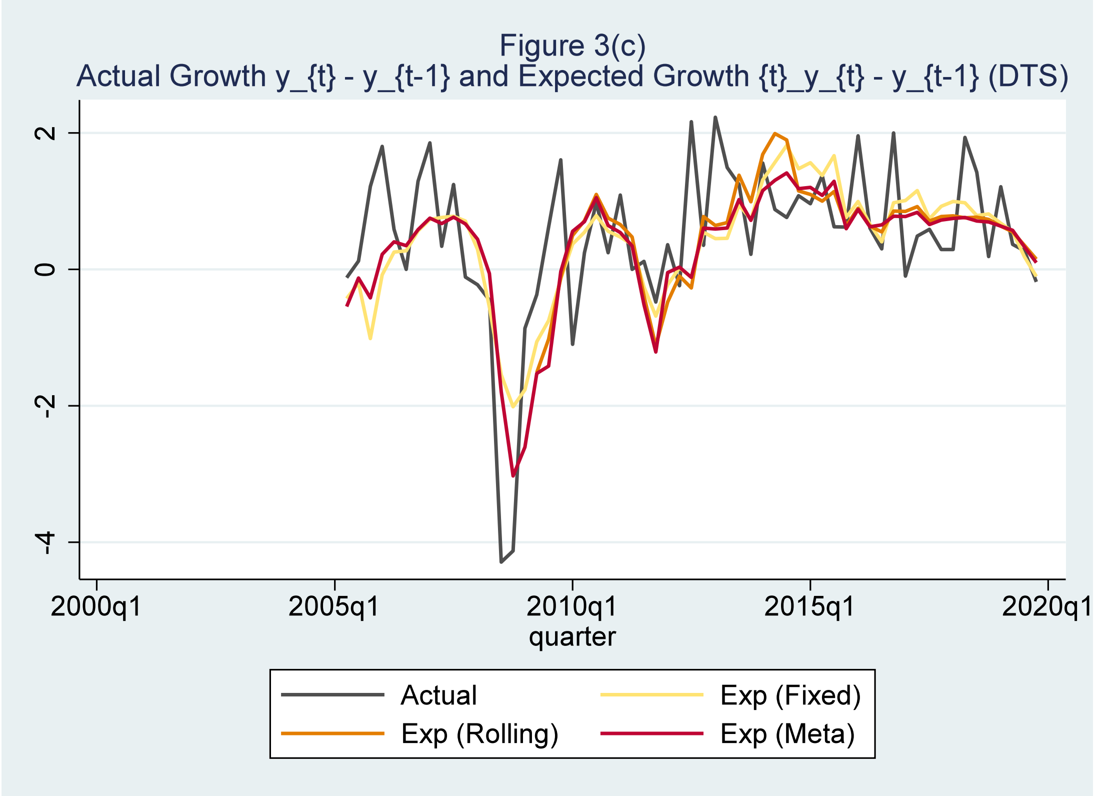


Figure 3(c)
Actual Growth y_{t} - y_{t-1} and Expected Growth {t}_y_{t} - y_{t-1} (DTS)
2
0
-2
-4
2000q1
2005q1
2010q1
2015q1
2020q1
quarter
Actual
Exp (Fixed)
Exp (Rolling)
Exp (Meta)

Figure 4(a)
Sample Duration and Differences in Time-Varying Parameters (ITS)

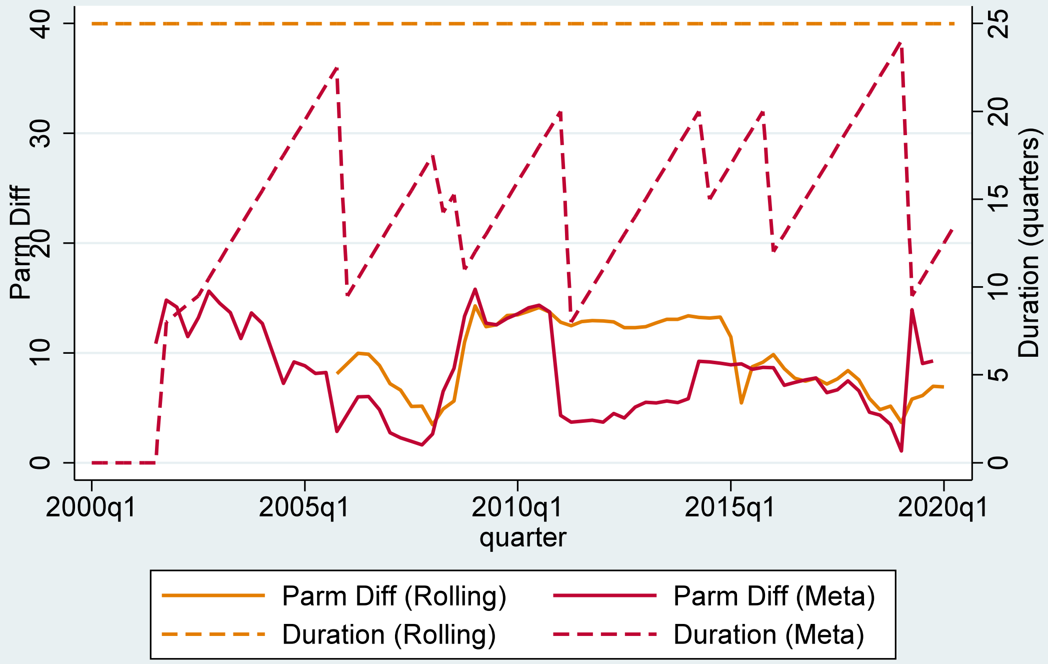


Figure 4(b)
Sample Duration and Differences in Time-Varying Parameters (SSS)

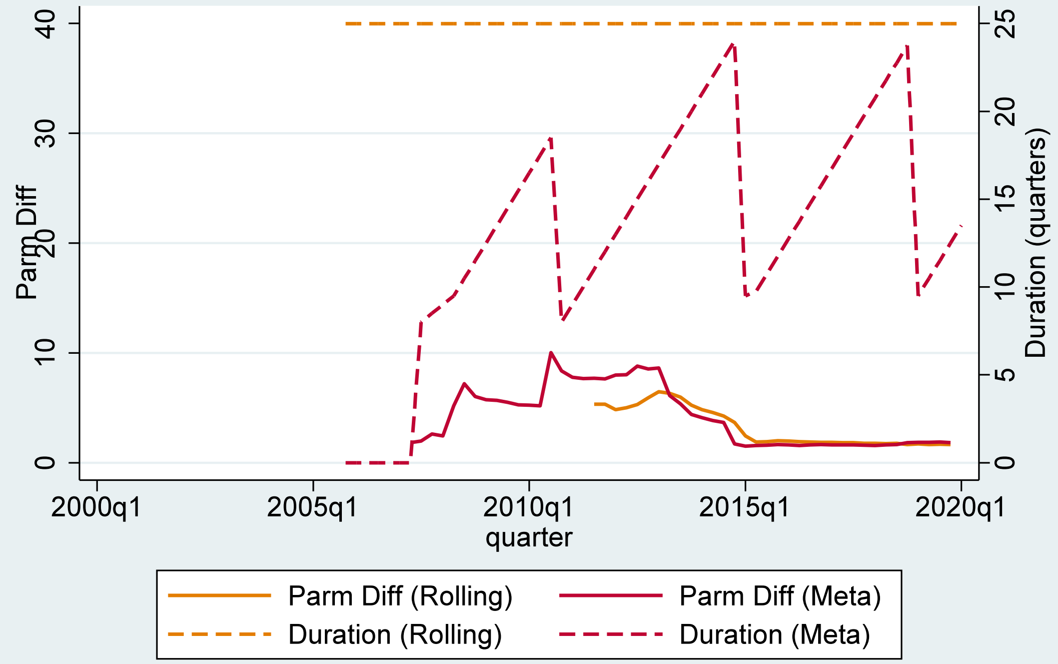


Figure 4(c)
Sample Duration and Differences in Time-Varying Parameters (DTS)

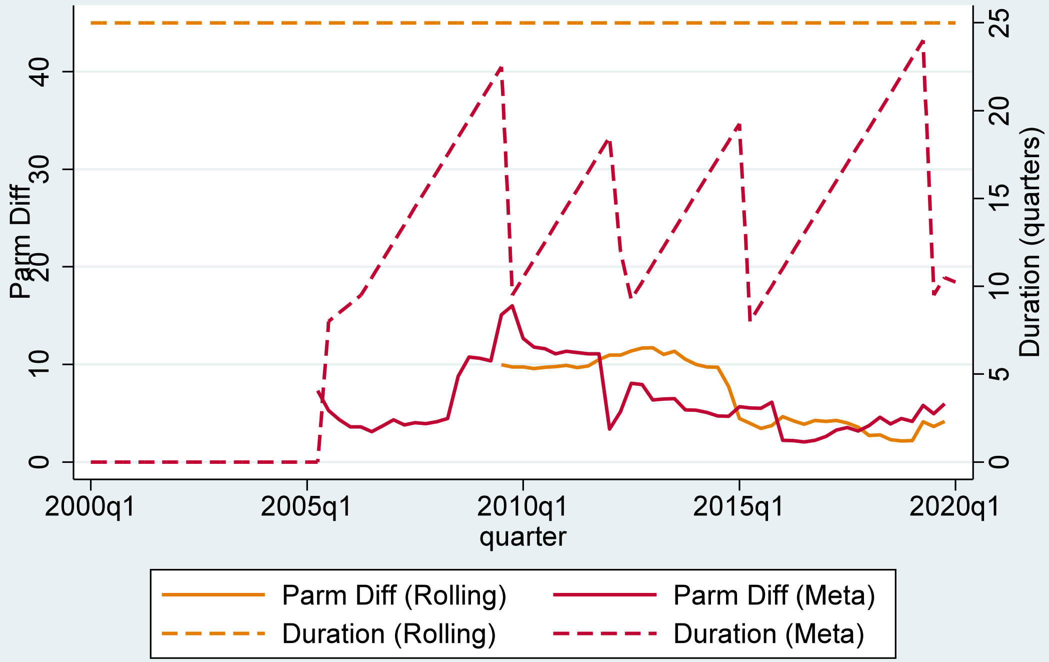


Figure 5(a)
Uncertainty and Disagreement (ITS)

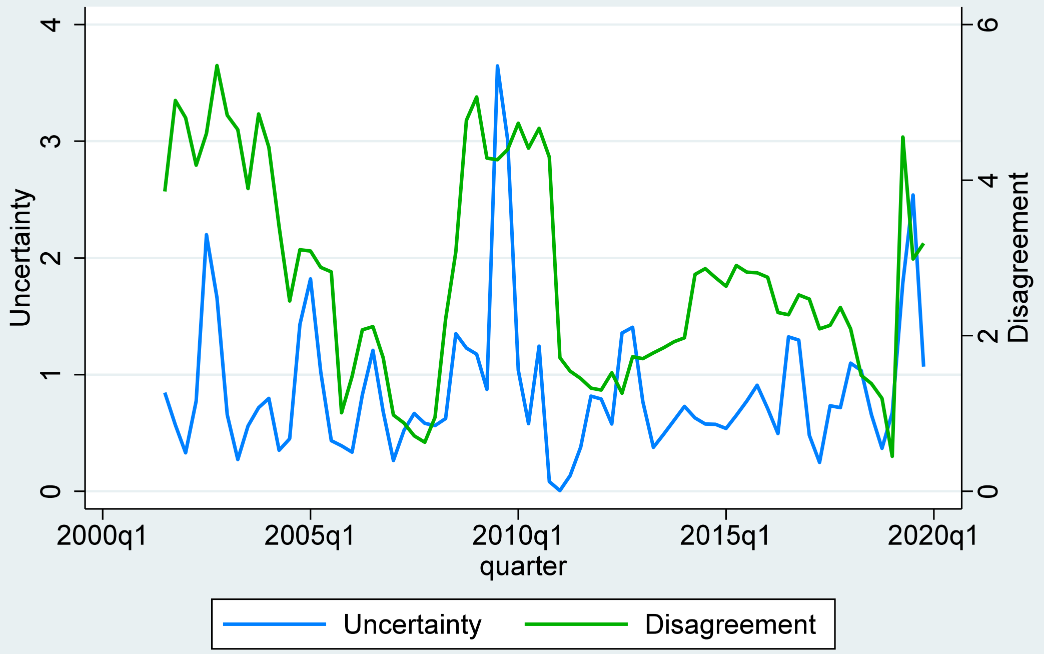


Figure 5(b)
Uncertainty and Disagreement (SSS)

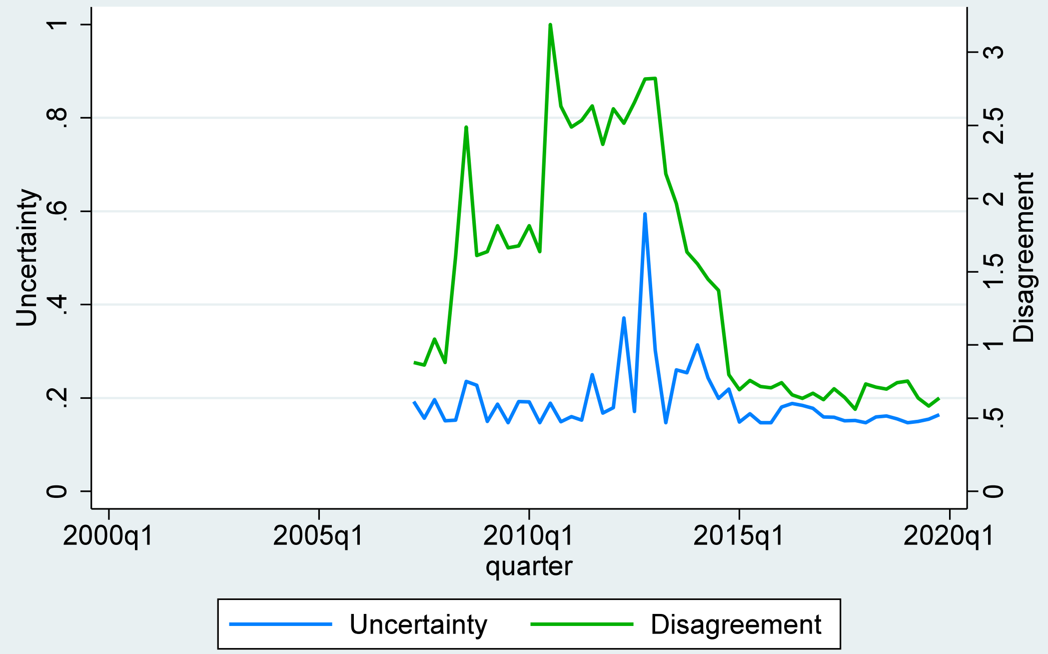


Figure 5(c)
Uncertainty and Disagreement (DTS)

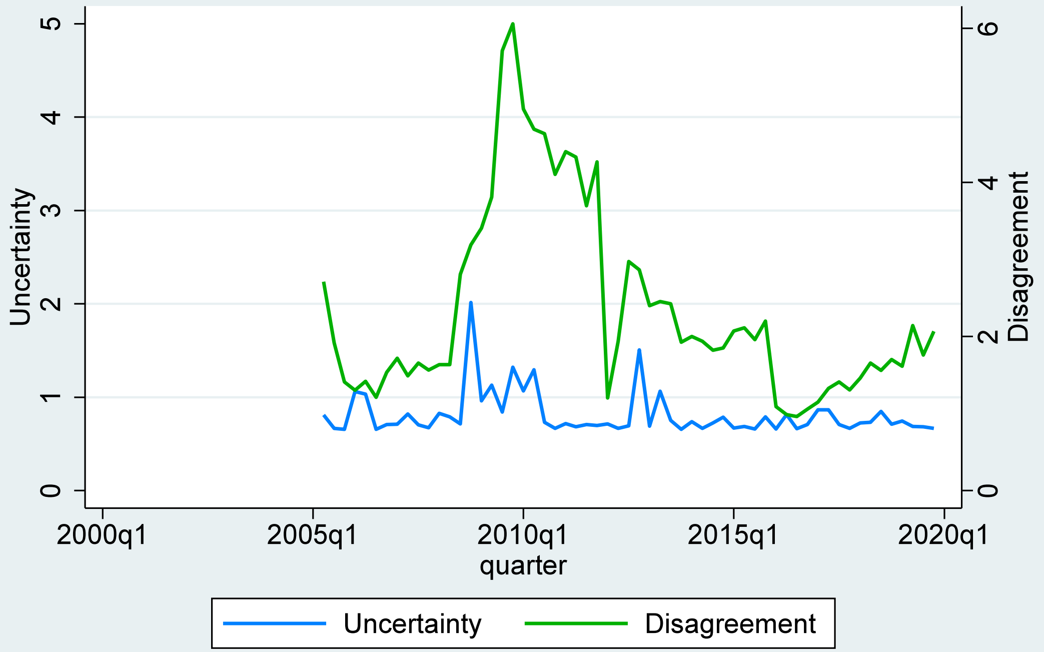


Figure 6(a)
Response to (one st. dev.) Uncertainty Shock (ITS)

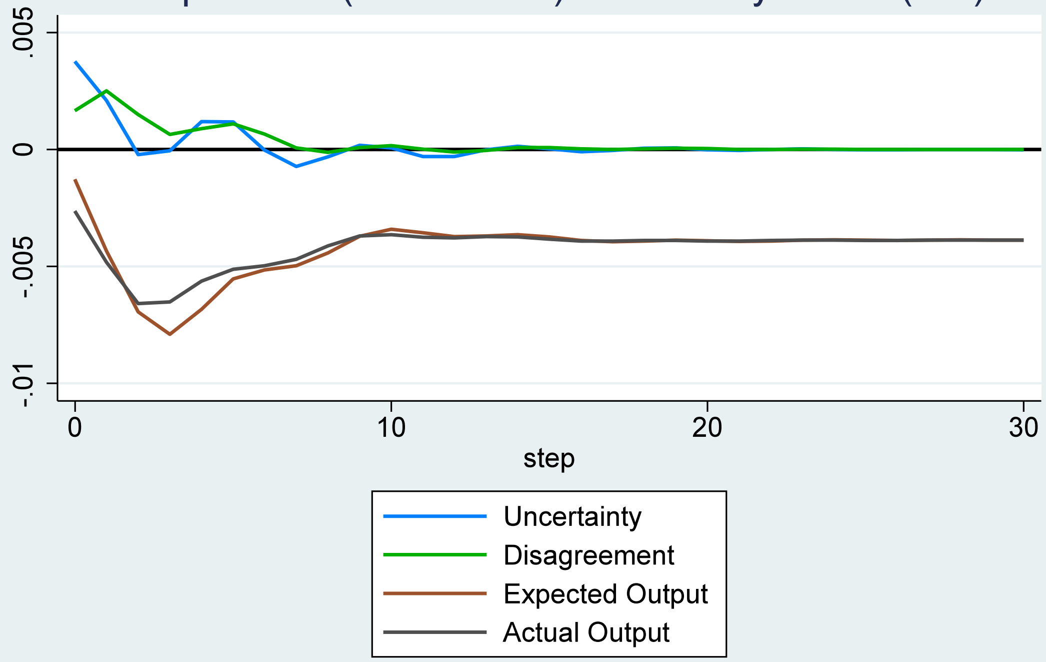


Figure 7(a)
Response to (one st. dev.) Disagreement Shock (ITS)

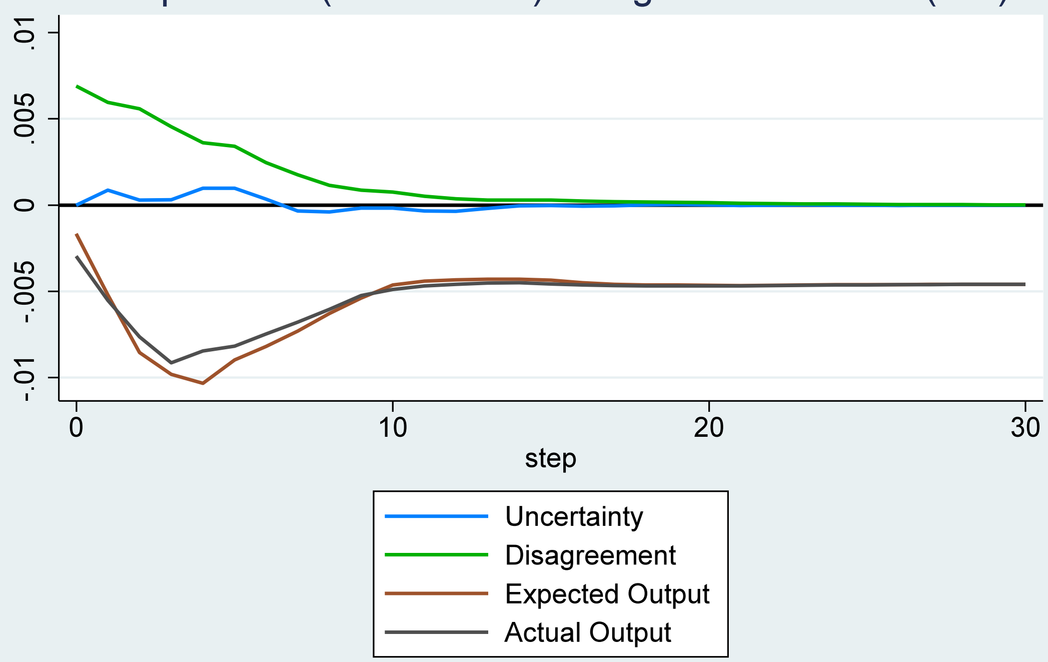


Figure 8(a)
Response to (one st. dev.) Expected Output Shock (ITS)

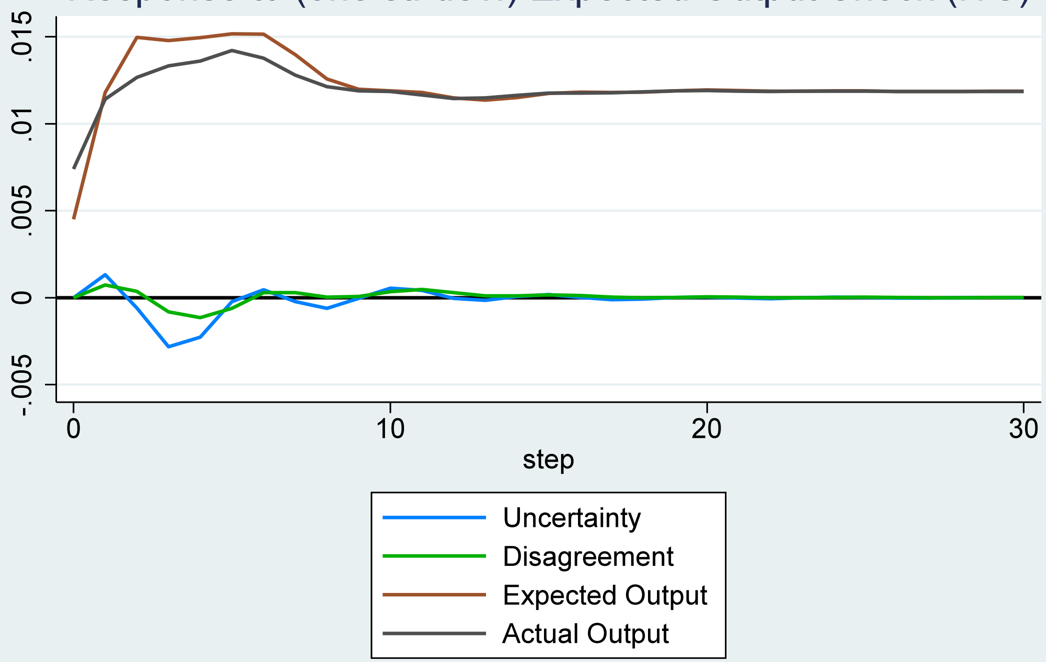


Figure 9(a)
Response to (one st. dev.) Actual Output Shock (ITS)

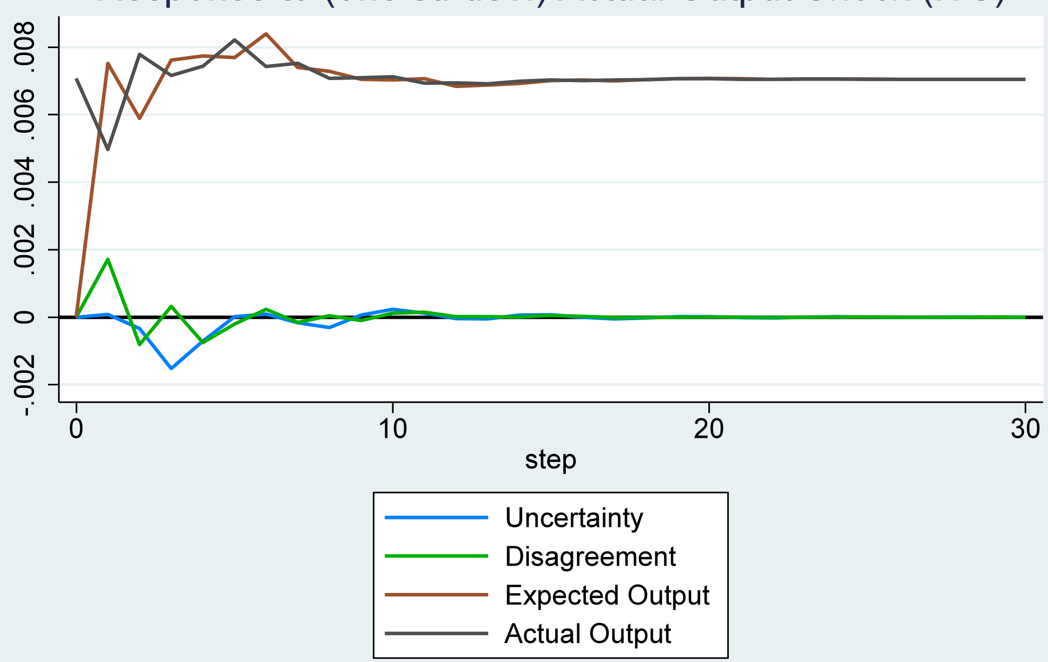


Figure 6(b)
Response to (one st. dev.) Uncertainty Shock (SSS)

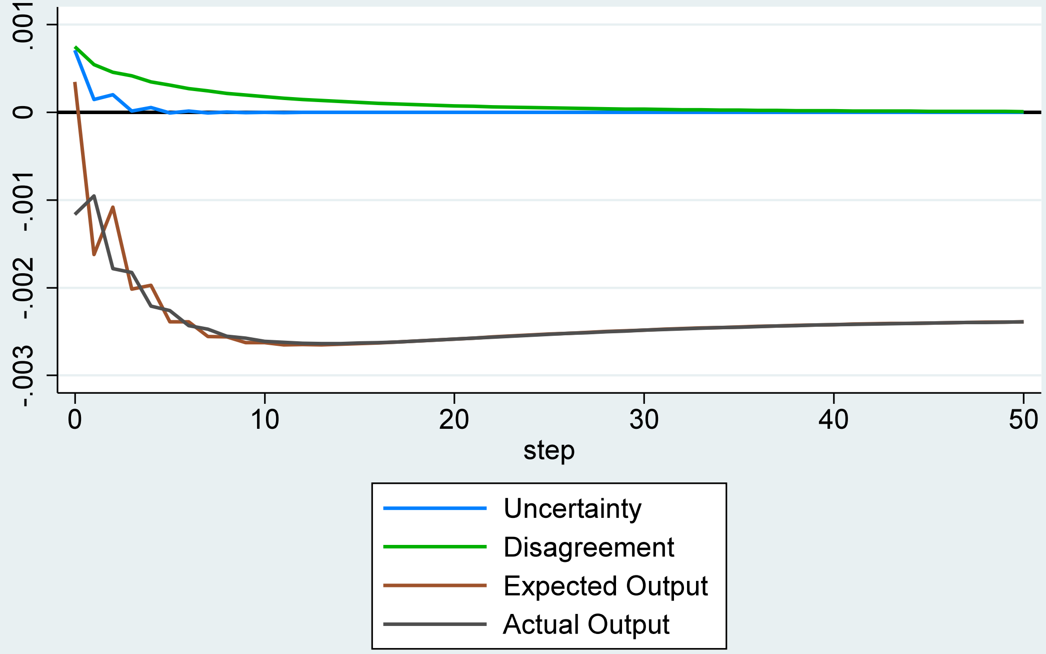


Figure 7(b)
Response to (one st. dev.) Disagreement Shock (SSS)

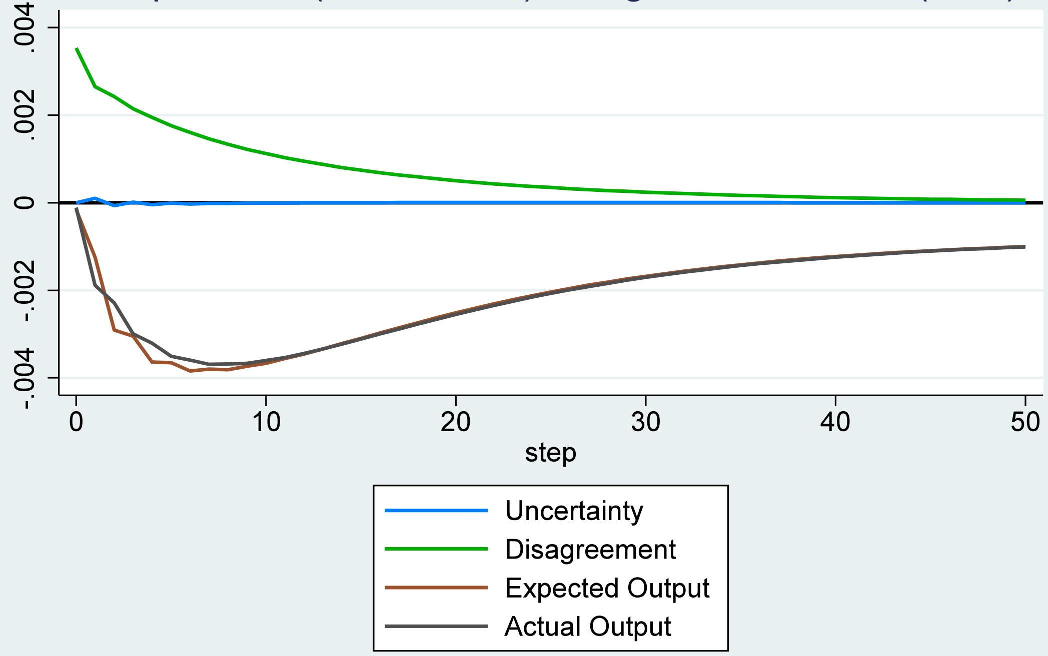


Figure 8(b)
Response to (one st. dev.) Expected Output Shock (SSS)

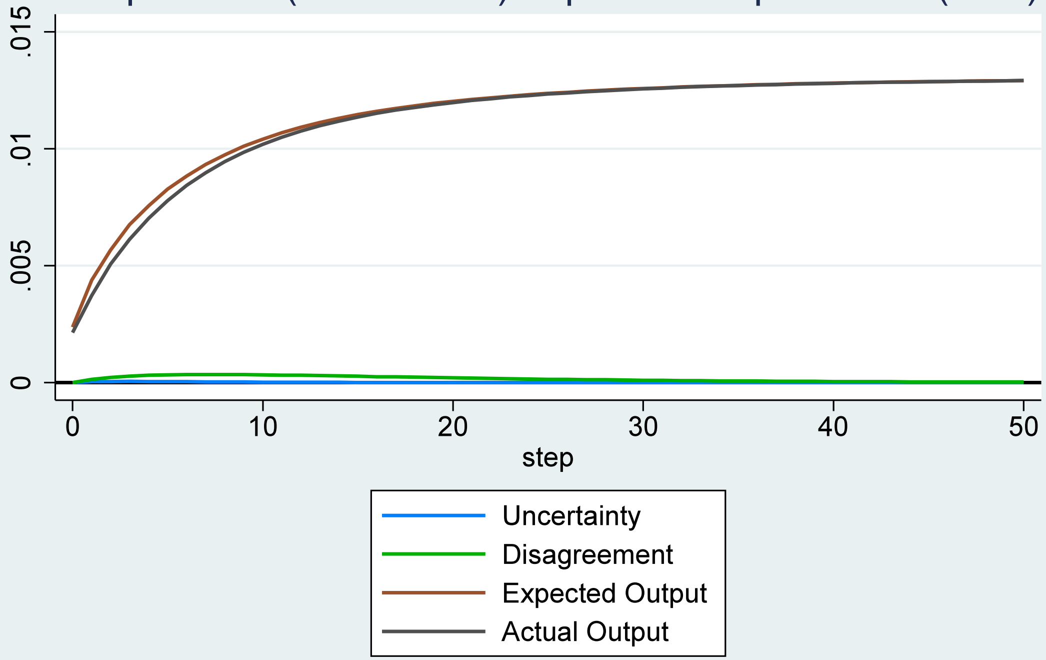


Figure 9(b)
Response to (one st. dev.) Actual Output Shock (SSS)

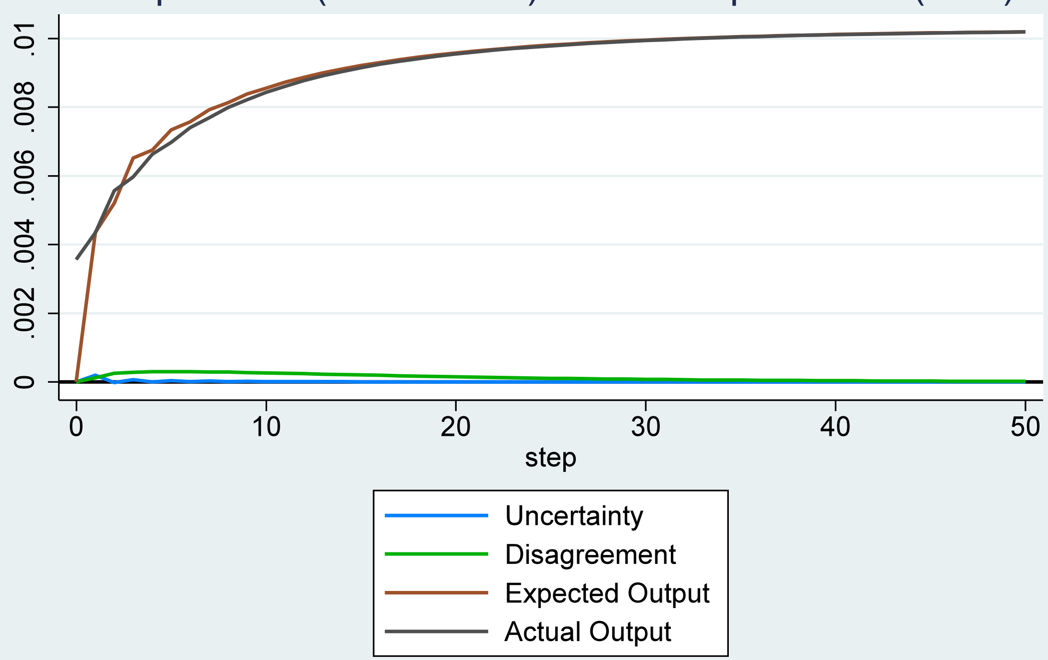


Figure 6(c)
Response to (one st. dev.) Uncertainty Shock (DTS)

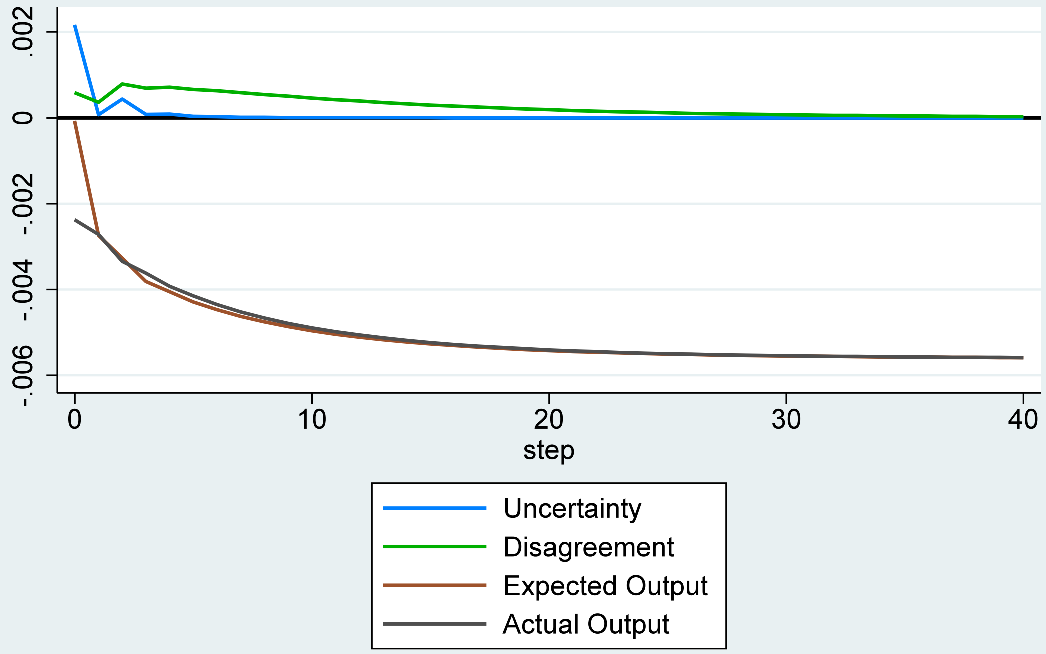


Figure 7(c)
Response to (one st. dev.) Disagreement Shock (DTS)

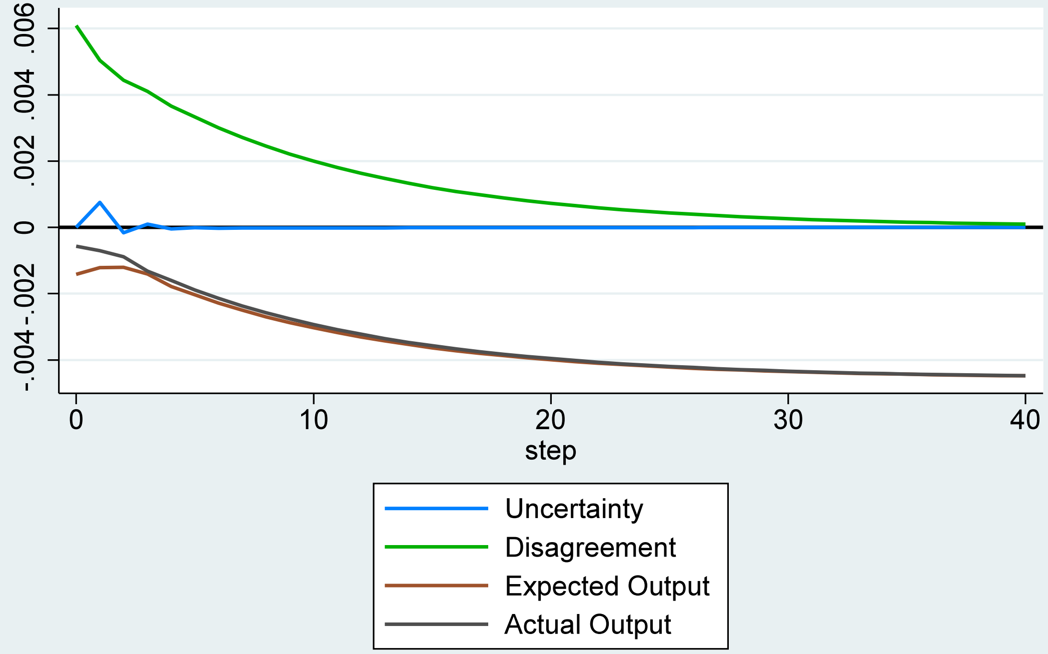


Figure 8(c)
Response to (one st. dev.) Expected Output Shock (DTS)

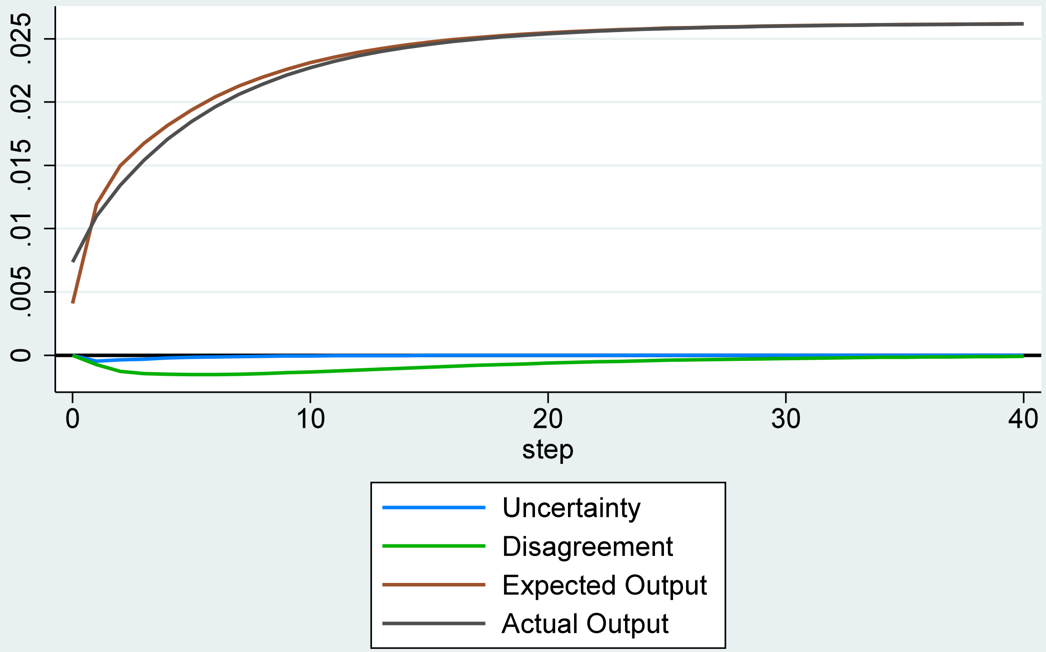
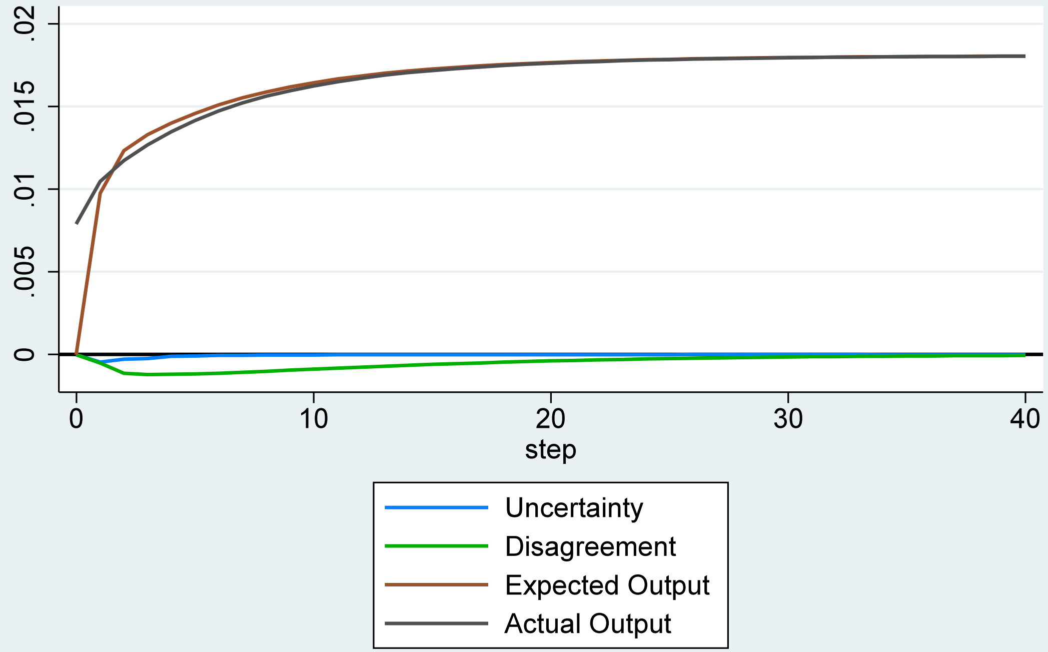


Figure 9(c)
Response to (one st. dev.) Actual Output Shock (DTS)



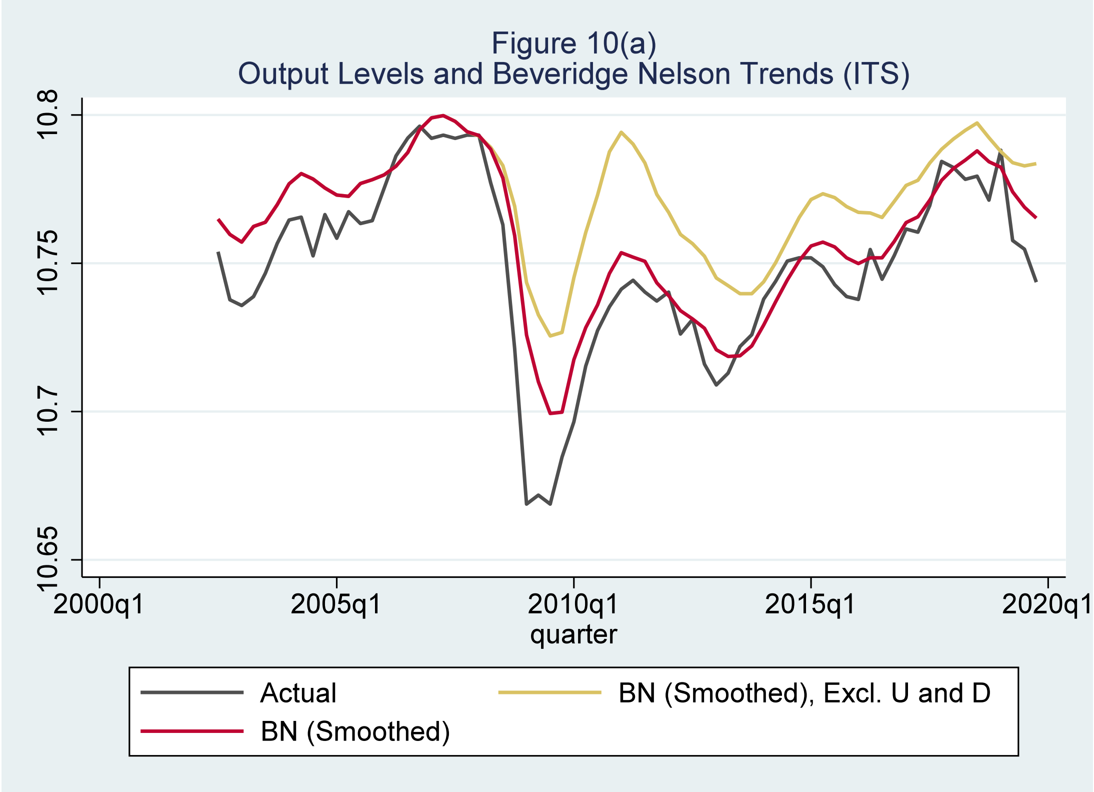


Figure 10(a)
Output Levels and Beveridge Nelson Trends (ITS)
10.8
10.75
10.7
10.65
2000q1
2005q1
2010q1
2015q1
2020q1
quarter
Actual
BN (Smoothed)
BN (Smoothed), Excl. U and D

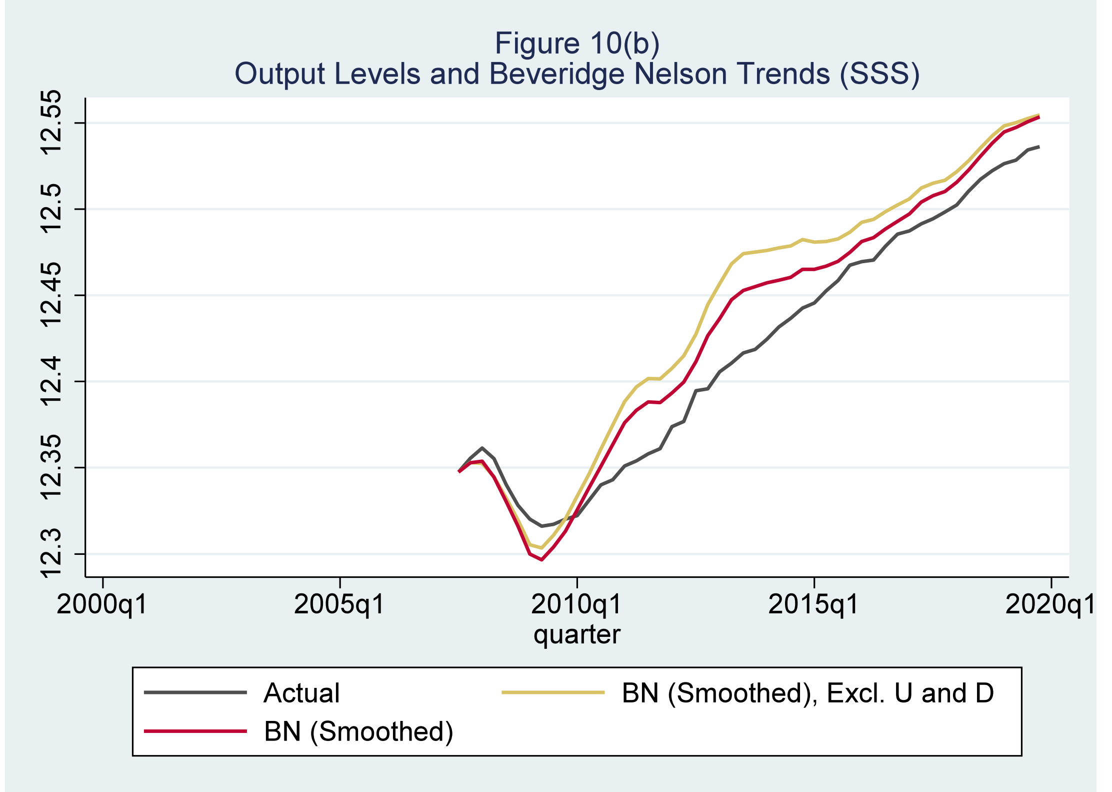


Figure 10(b)
Output Levels and Beveridge Nelson Trends (SSS)
12.55
12.5
12.45
12.4
12.35
12.3
2000q1
2005q1
2010q1
2015q1
2020q1
quarter
Actual
BN (Smoothed)
BN (Smoothed), Excl. U and D

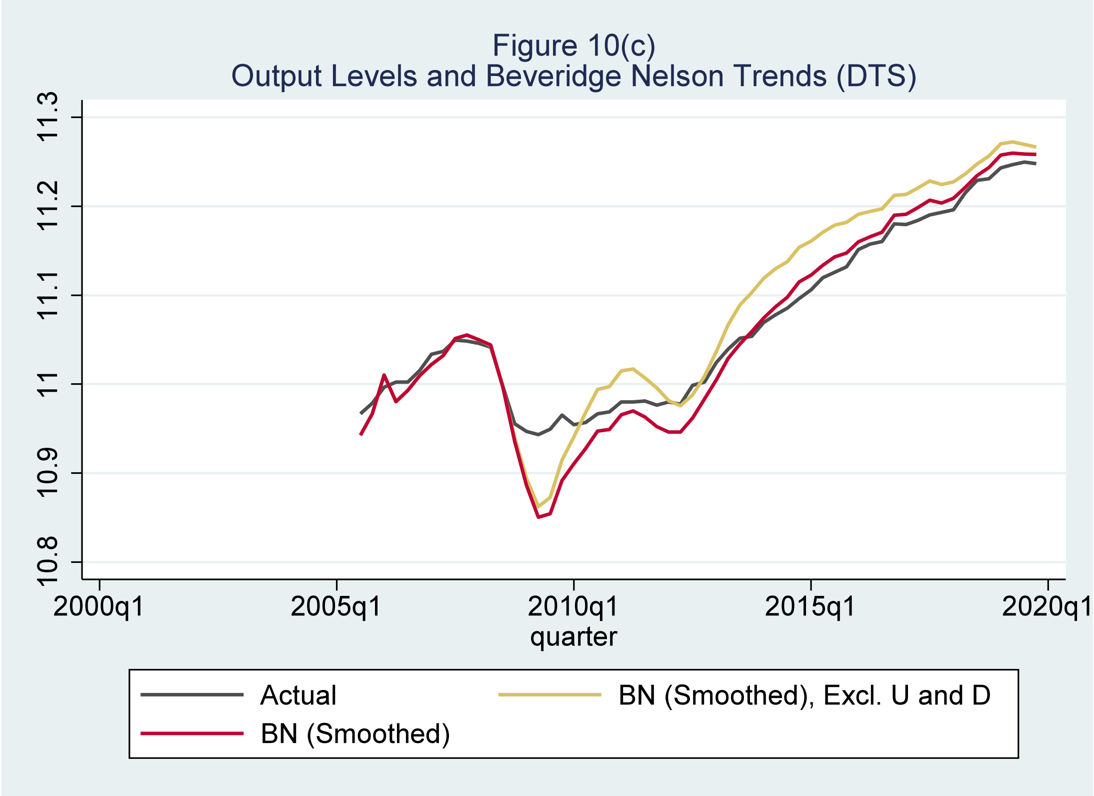


Figure 10(c)
Output Levels and Beveridge Nelson Trends (DTS)
11.3
11.2
11.1
11
10.9
10.8
2000q1
2005q1
2010q1
2015q1
2020q1
quarter
Actual
BN (Smoothed)
BN (Smoothed), Excl. U and D

References

Akerlof, G.A. and R. J. Shiller (2009), *Animal Spirits: How Human Psychology Drives the Economy, and Why it Matters for Global Capitalism*, Princeton University Press.

Altig, d., S. Baker, J.M. Barrero, N. Bloom, P. Bunn, S. Chen, S.J. Davis, J. Leather, B. Meyer, E. Mihaylov, P. Mizen, N.Parker, T Renault, P. Smietanka and G. Thwaites (2020)m, Economic Uncertainty before and during the COVID-19 Pandemic, *Journal of Public Economics*

Aristidou, C., K.C. Lee and K. Shields, (2019), Evaluating the Use of Real-Time Data in Forecasting Output Levels and Recessionary Events in the US, *Journal of the Royal Statistical Society A*, 182, 131-163.

Bachmann, R. and E. R. Sims (2012), Confidence and the Transmission of Government Spending Shocks, *Journal of Monetary Economics*, Elsevier, 59(3), 235-249.

Bachmann, R., S. Elstner, and E.R. Sims. (2013). Uncertainty and Economic Activity: Evidence from Business Survey Data, *American Economic Journal: Macroeconomics*, 5, 217–249.

Barsky, R.B. and E. R. Sims (2011),."News, Shocks and Business Cycles," *Journal of Monetary Economics*, 58(3), 273-289.

Barsky R.B. and E.R. Sims (2012), "Information, Animal Spirits, and the Meaning of Innovations in Consumer Confidence," *American Economic Review*, 102(4), 1343-77.

Beaudry, P. and F. Portier (2006), "Stock Prices, News, and Economic Fluctuations.", *American Economic Review* 96, pp. 1293-1307.

Baker, S.R., N. Bloom, and S.J. Davis, (2016) Measuring Economic Policy Uncertainty, *Quarterly Journal of Economics*, 131, 1593-1636.

Barrero, J.M., N. Bloom and I, Wright (2017), Short and Long Run Uncertainty, *NBER Working paper* 23676

Bloom, N. (2009), The Impact of Uncertainty Shocks, *Econometrica*, 77, 3, 623-685.

Bloom, N. (2014), Fluctuations in Uncertainty, *Journal of Economic Perspectives*, 28, 2, 153-76.

Boero, G., J. Smith, and K.F. Wallis, (2015), The Measurement and Characteristics of Professional Forecasters' Uncertainty, *Journal of Applied Econometrics*, 30, 7, 1029-1046.

Bordalo, P., N. Gennaioli, Y. Ma, and A. Shleifer (2020), Overreaction in Macroeconomic Expectations, *American Economic Review*, 110(9), 2748-2782.

Castelnuovo, E. (2019), Domestic and Global Uncertainty: A Survey and Some New Results, *Melbourne Institute Working Paper,* no. 13/19.

Clements, M. P. (2017). Assessing Macro Uncertainty in Real-Time when Data are Subject to Revision, *Journal of Business and Economic Statistics*, 35(3), 420-433.

Coibion, O. and Y. Gorodnichenko (2012) What Can Survey Forecasts Tell Us about Information Rigidities? *Journal of Political Economy*,. 120, 1, 116-159.

Coibion, O. and Y. Gorodnichenko, (2015). Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts, *American Economic Review* 105 (8): 2644–78.

Coibion, O.,Y Gorodnichenko and R Kamdar, (2018) The formation of expectations, inflation, and the phillips curve, Journal of Economic Literature 56 (4), 1447-91

Croushore, D. (2010),. "Philadelphia Fed Forecasting Surveys: Their Value for Research," *Business Review*, Federal Reserve Bank of Philadelphia, issue Q3, 1-11.

De Grauwe, P. and Y. Ji, (2019), *Behavioural Macroeconomics: Theory and Policy*, Oxford University Press

Dovern, J., U. Fritsche, P. Loungani, and N. Tamirisa, (2015), Information Rigidities: Comparing Average and Individual Forecast for a Large International Panel, *International Journal of Forecasting*, 31, 14-154.

Dovern, J., U. Fritsche and J. Slacalek, (2012), Disagreement among Forecasters in G7 Countries, *Review of Economics and Statistics*, 94(4), 1081-1096.

Eusepi, S. and B. Preston. (2011). Expectations, Learning, and Business Cycle Fluctuations, *American Economic Review*, 101(6), 2844-2872.

Evans, G and S Honkapohja (2001), Learning and Expectations in Macroeconomics, Princeton University Press.

Garratt, A., K.C. Lee, M.H. Pesaran and Y. Shin, (2003), Forecast Uncertainties in Macroeconometric Modelling: An Application to the UK Economy, *Journal of the American Statistical Association*, 98, 464, 829-838.

Garratt, A., K.C. Lee, and K. Shields, (2018), The Role of Uncertainty, Sentiment and Cross-Country Interactions in G7 Output Dynamics, *Canadian Journal of Economics*, 51, 391-418

Jo, S. and R. Sekkel, (2019), Macroeconomic Uncertainty through the Lens of Professional Forecasters, *Journal of Business and Economic Statistics,* 37, 3, 436-446.

Jurado, K,. S C. Ludvigson and S. Ng, (2015) Measuring Uncertainty, *American Economic Review*, 105, 1177-1216.

Hamilton, J. (1994), *Time Series Analysis*, Princeton University Press.

Kozeniauskas, N., A. Orlik and L. Veldkamp (2018), What are Uncertainty Shocks?, *Journal of Monetary Economics*, 100, 1-15.

Lahiri, K. and F. Liu (2006), Modelling multi-period inflation uncertainty using a panel of density forecasts, *Journal of Applied Econometrics*, 21, 1199-1219.

Lahiri, K. and X. Sheng (2008), Evolution of forecast disagreement in a Bayesian learning model, *Journal of Econometrics*, 144, 325-340.

Lahiri, K. and F. Sheng (2010) Measuring forecast uncertainty by disagreement: The missing link, *Journal of Applied Econometrics*, 25, 514-538.

Lee, K.C. (1994), Formation of Price and Cost Inflation Expectations in British Manufacturing Industries: A Multi-Sectoral Analysis, *The Economic Journal*, 104(423), pp.372-385.

Lee, K.C., M. Mahony and P. Mizen, (2020), Nowcasting Output Movements and Recessionary Events Using the CBI's Suite of Business Surveys; A Technical Note, *Working Paper*, University of Nottingham.

Lee, K.C, J. Morley and K. Shields, (2015), The Meta Taylor Rule, *Journal of Money, Credit and Banking*, 47, 1, 73-98.

Ludvigson, S., S. Ma and S.Ng (2020) "Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response?". *American Economic Journal: Macroeconomics*, forthcoming.

Lui, S., Mitchell, J., and Weale, M. (2010), Qualitative Business Surveys: Signal or Noise?, *Journal of the Royal Statistical Society*, 174, pp.327-348.

Lui, S., Mitchell, J., and Weale, M. (2011), The Utility of Expectational Data: Firm-level Evidence using Matched Qualitative-Quantitative UK Surveys, *International Journal of Forecasting*, 27, pp.1128-1146.

Mankiw, N.Gregory, Ricardo Reis, (2002). Sticky Information Versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve, *Quarterly Journal of Economics* 117(4), 1295-1328.

Mitchell, J., Smith, R. J. and Weale, M. R. (2002), Aggregate versus Disaggregate Survey-Based Indicators of Economic Activity, *National Institute of Economic and Social Research Discussion Paper*, no. 194.

Mitchell, J., Mouratidis, K. and Weale, M. (2004), The Impact of Survey Aggregation Methods on the Quality of Business Survey Indicators, *ECFIN/2003/A3-04*.

Mitchell, J., Mouratidis, K. and Weale, M. (2007), Uncertainty in UK manufacturing: evidence from qualitative survey data, *Economics Letters*, 94(2), pp.245-252.

Mitchell, J., Smith, R.J. and Weale, M. (2013), Efficient Aggregation of Panel Qualitative Survey Data, *Journal of Applied Econometrics*, 28, pp. 580-603.

Pesaran, M.H. (1987), *The Limits to Rational Expectations*, Oxford: Basil, Blackwell.

Pesaran, M.H. and Weale, M. (2006), Survey expectations, *Handbook of Economic Forecasting*, Elsevier.

Sims, C. A., (2003), Implications of Rational Inattention, *Journal of Monetary Economics*, 50(3), 665-690