Centre for Economic Policy Research

STUDY CENTER GERZENSEE

European Summer Symposium in International Macroeconomics (ESSIM) 2011

Hosted by
Study Center Gerzensee

Gerzensee, Switzerland; 31 May – 3 June 2011

Man-bites-dog Driven Business Cycles

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MAN-BITES-DOG
DRIVEN BUSINESS CYCLES

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ABSTRACT. The newsworthiness of an event is partly determined by how unusual it is and this paper investigates the business cycle implications of this fact. We present a tractable model that features an information structure in which some types of signals are more likely to be observed after unusual events. The proposed information structure can help us understand why we observe (i) large changes in macro economic aggregate variables without a correspondingly large change in underlying fundamentals (ii) persistent periods of high macroeconomic volatility and (iii) a positive correlation between absolute changes in macro variables and the cross-sectional dispersion of expectations as measured by survey data. These results are consequences of optimal updating by agents when the availability of some signals are positively correlated with tail-events. The model is estimated by likelihood based methods using raw survey data and a quarterly time series of total factor productivity along with standard aggregate time series. The estimated model suggests that there have been episodes in recent US history when the impact on output of innovations to productivity of a given magnitude were up to 30 per cent larger than normal.

1. Introduction

A well-known journalistic dictum states that "*dog-bites-man* is not news, but *man-bites-dog* is news". That is, unusual events are more likely to be considered newsworthy than events that are commonplace. This paper investigates the business cycle implications of this aspect of news reporting. Particularly, we will demonstrate that a single and relatively simple mechanism can help us understand three features of business cycles. First, there can be large changes in aggregate variables like CPI inflation and GDP growth, but without an easily identifiable change in fundamentals of comparable magnitude. Second, there appears to be persistent episodes of increased macroeconomic volatility in the data. Third, measures of uncertainty as well as measures of cross-sectional dispersion of expectations are positively correlated with absolute magnitudes of changes in macro economic aggregates. These features can be explained by Bayesian agents optimally updating to signals that are more likely to be available about unusual events.

Date: May 24, 2011 (preliminary draft). The author thanks Emre Ozdenoren, Martin Schneider, Jaume Ventura, Mirko Wiederholt and participants at the LBS workshop on *The Macroeconomics of Incomplete Information: Empirical and Policy Perspectives* for useful comments. Financial support from Ministerio de Ciencia e Innovacion (ECO2008-01665), Generalitat de Catalunya (2009SGR1157), Barcelona GSE Research Network and the Government of Catalonia is gratefully acknowledged.
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Conceptually, one can divide information about the current state of the world into two categories. *Statistics* are signals that are reported regardless of the realized values of the variable that they refer to while *news* are signals that are more likely to be available about unusual events. In order to distinguish our terminology from the one used by the literature studying how information about future productivity affect the economy today (e.g. Beaudry and Portier 2006 and Jaimovich and Rebelo 2009) "news" in the sense meant here will be referred to as man-bites-dog signals. A prime example of man-bites-dog news reporting is the *Movers* segment on Bloomberg Television. In a typical segment, the price movements of a few stocks are reported with short statements on the probable causes of these movements. The stocks in question is a small sub-sample of all stocks traded and are selected on the basis of having had the largest price movements during the day. Unusual price movements are thus more likely to be reported than more common price movements. Similar effects are also at work in the news about macroeconomic events. Carroll (2003) and Doms and Morin (2004) report that the volume of news about macroeconomic events are positively correlated with the magnitude of the events in question. Doms and Morin further find that the content of news has an effect on the macro economy, even at times when the picture of the economy painted by news media is not accurately reflecting underlying fundamentals.

That some types of signals are more likely to be available about unusual events may suggest that we should be better informed about unusual events. However, the flip-side of this argument is that the distribution of events conditional on there being a man-bites-dog signal available is different from the unconditional distribution in ways that may undo the effect of having more information. Observing a man-bites-dog signal can actually increase uncertainty about an event. To see why, consider again the example of the *Movers* segment. If you were told that a certain stock had been mentioned in the *Movers* segment, but not told if its price had risen or fallen, how would you revise your expectations about the dividend process of the stock in question? If you are a Bayesian, your conditional variance of expected future dividends should arguably increase. Stated differently, the fact that the stock was mentioned in the *Movers* section tells you something about the second moment of the dividend process. After observing the actual price change, you may of course also revise your conditional mean and again update your conditional variance. This example illustrates the two effects at work: Conditioning only on the *availability* of a man-bites-dog signal increases uncertainty, while observing the actual contents of the signal decreases the uncertainty. Below we show in a tractable setting that the former effect can dominate so that the posterior uncertainty after observing a man-bites dog signal is larger than when no such signal is observed.

In a dynamic setting, a larger posterior uncertainty in period t translates into a larger prior uncertainty in period $t+1$. By embedding a man-bites-dog information structure in a simple business cycle model similar to that of Lorenzoni (2009), we show that the propagation of uncertainty through time endogenously generates persistent periods of higher volatility in the endogenous variables. The mechanism is the following. In a given period, the weight agents put on new information is inversely related to the precision of their priors. If a man-bites-dog signals is generated in period t, this may increase the prior uncertainty in period $t+1$. Agents will then put more weight on all signals in period $t+1$ relative to the case when there was no man-bites-dog episode in period t. The increased sensitivity to new information can persist for several periods and implies that the impact of an exogenous disturbance of a given magnitude can also be larger than usual for several periods. This mechanism can endogenously generate periods of higher volatility of macro economic aggregates as observed in the data and documented by Engle (1982) and Fernandez-Villaverde and Rubio-Ramirez (2010) among others.

In the business cycle model presented below, man-bites-dog signals are public signals. This means that information about unusual events will be more correlated across agents than information about common events. For a signal to be public in the strong common knowledge sense of the word, it is not enough that a signal is publicly available. Instead, the signal must not only be observed by everybody, but the fact the everybody observes the signal must also be common knowledge. The concept of a public signal in this sense is thus much stronger than the everyday meaning of the term "public information". Arguably, while the theoretical dichotomy between purely private or purely public signals is somewhat artificial, information about unusual events are more likely to be closer to the theoretical ideal of a public signal than information about more commonplace events. For instance, in a segmented news market where different news outlets cater to partially different audiences, there are some events that all news organizations will report. Though there are many aspects of an event that determines how newsworthy it is judged to be, everything else equal, the more unusual an event is, the larger is the number of news organizations that will consider it newsworthy.

As mentioned above, observing a man-bites-dog signals can increase the posterior uncertainty relative to the case when no man-bites-dog signal is observed. The same parameter restrictions that ensures that posterior variances increases after a man-bites-dog signal also implies that the cross-sectional dispersion of expectations increases. This holds even if the man-bites-dog signal is public (in the strong common knowledge sense of the word). In the data, we observe a positive correlation between the cross-sectional dispersion of forecasts (as measured by the Survey of Professional Forecaster) and the absolute magnitudes of changes in macro aggregates. Interpreted through the lens of the model, this suggest that the empirically relevant specification of the model may be one where the increase in uncertainty from conditioning on the availability of a man-bites-dog signal is dominating the increased precision due to the content of the signal.

In order to quantify the importance of the the man-bites-dog aspect of news reporting I estimate the model on US data. In addition to standard macro variables like GDP, CPI inflation and the Federal Funds rate, I also use the quarterly time series of Total Factor Productivity constructed by John Fernald (2010) as well as raw survey data from the *Survey of Professional Forecasters.* Using raw survey data has at least two advantages. First, and as documented by Mankiw, Reis and Wolfers (2004) and Swanson (2006) there is significant time variation in the dispersion of forecasts reported by survey respondents. Since the model can potentially fit this fact, raw survey data (i.e. without averaging across respondents) can be exploited when estimating the model allowing for a sharper inference about the precision of signals observed by agents. The second advantage of using raw survey data rather than a median or mean expectation stems from the fact that the number of survey respondents varies over time. For instance, the number of respondents forecasting nominal GDP growth and CPI inflation varies between 9 (1990:Q2) and 50 (2005:Q4) in a sample that covers the period 1981:Q3 to 2010Q4. Using raw survey data and likelihood based estimation methods naturally incorporates that we have a (presumably) more representative sample of the population with 50 observations than with 9.

Most existing macro models imply that the dispersion of cross-sectional expectations is either zero, as in the full information rational expectations models, or non-zero but constant as in models with private but time invariant information structures, e.g. Mackowiak and Wiederholt (2009), Graham and Wright (2009), Nimark (2008, 2010) or Melosi (2011). One exception is the sticky information models of Mankiw and Reis (2002) and Reis (2006a, 2006b). In these models, only a fraction of agents update their information in each period and those who update, all observe the state perfectly. This results in a cross-sectional distribution of expectations that is a mixture of a degenerate and a dispersed distribution. It is because the cross-sectional dispersion of expectations in the model presented here is time varying but continuous that it it possible to estimate the structural parameters of the model using likelihood based methods and "raw" survey data. One methodological contribution of the paper is to demonstrate how dynamic models with a time varying information structure can be solved. As far as I know, this is the first paper to solve such a model and this may be of independent interest to some readers.

The paper is structured as follows. In the next section, the concept of man-bites-dog signals is introduced formally. In the static setting of that section, many results can be derived analytically and it is demonstrated that the implications of man-bites-dog signals crucially depend on two parameters (i) the parameter governing how unusual an event has to be to significantly increase the probability of observing a signal (ii) the variance of the noise in the generated signal. The larger either of these parameters are, the more likely it is that the economy will display the features described here in the introduction. Section 3 presents a simple business cycle model similar to that of Lorenzoni (2009), but with a man-bites-dog type of information structure. Section 4 discusses how the model is solved and how the parameters are estimated. Section 5 contains the main empirical results of the paper. Section 6 describes some robustness exercises and Section 7 concludes.

2. Signals and unusual events

This section presents a simple and tractable framework for thinking about signals that are more likely to be available when something unusual has happened. There are no economic decisions made by agents beyond forming an expectation about a latent variable. The purpose of the section is to build intuition for how the filtering problems of Bayesian agents change when the availability of some signals is positively correlated with tail events. These insights also carry over to the business cycle model presented in a later section.

2.1. **Reverse engineering the conditional probability of observing a signal.** Agents indexed by $j \in (0,1)$ want to form an expectation about the latent variable x. Its unconditional probability density function is denoted $p(x)$ and x has zero mean and unconditional variance σ_x^2. The indicator variable S takes the value 1 when the signal y about x is available and zero otherwise. We want to find a specification such that the conditional probability of observing a signal is increasing in the distance of the realized value of x from its mean. That is, we want to find a joint distribution of x and S such that the inequality

$$\frac{\partial p\left(S=1 \mid x\right)}{\partial\left|x\right|} \geq 0 \tag{2.1}$$

holds. The main idea is illustrated in Figure 1. There, the unconditional distribution $p(x)$ of x is plotted (solid line) together with the probability $p(S = 1 \mid x)$ of observing the signal y conditional on the realization of x. At the mean, there is approximately a 40% chance

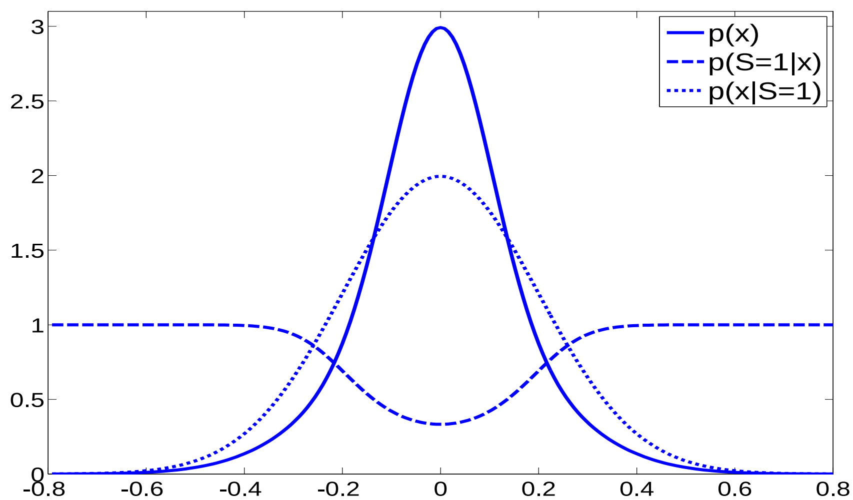

FIGURE 1. Unconditional distribution of x and conditional probability of observing the signal y.

of observing the signal y. As realizations of x further from the mean are considered, the conditional probability of observing a signal increases towards 1 so that a signal is generated almost surely when the realization of x is far enough away from the mean.

It turns out to be easier to maintain tractability by instead of directly specifying the conditional probability of observing a signal $p\left(S=1 \mid x\right)$ in the numerator of (2.1) to instead specify the distribution of x conditional on $S = 1$. By Bayes' rule, we have that the conditional probability of observing a signal is given by

$$p\left(S=1 \mid x\right) = \frac{p\left(x \mid S=1\right)}{p\left(x\right)} p\left(S=1\right). \tag{2.2}$$

Since $p(x)$ is uniformly decreasing in $|x|$ for any symmetric unimodal distribution $p(x)$, we can ensure that the inequality (2.1) holds by choosing a conditional distribution $p\left(x \mid S=1\right)$ that is decreasing at a slower rate than $p(x)$ in $|x|$. For unimodal symmetric distributions $p(x)$ and $p(x \mid S = 1)$ we thus need to choose a $p(x \mid S = 1)$ that is more dispersed than $p(x)$.

The link between the conditional and unconditional distributions of x and the conditional probability of observing a signal is perhaps easiest to illustrate in a graph. In Figure 1 the dotted line is the probability of x conditional on $S = 1$. The relationship (2.2) implies that the conditional probability of observing the signal y is the ratio of the dotted line and the solid line times the normalizing constant $p(S = 1)$. To ensure that the probability of observing a signal increases as values of x further from its mean are considered, we thus need to choose a conditional probability $p(x \mid S = 1)$ that decreases at a slower rate than $p(x)$ in $|x|$. Visually, this is obvious if the more peaked distribution (solid curve) is compared to the flatter distribution (dotted curve). At the points where the solid and the dotted curves cross, the ratio on the right hand side of (2.2) is one, implying that the unconditional probability of observing a signal in this example can be read off the dashed line on a straight line downward from the point of the crossing curves. In the particular example used to construct Figure 1, $p(S = 1)$ is 50%.

One specification that delivers a conditional probability of observing the signal y that is increasing in $|x|$ and maintains tractability of agents' filtering problem is to let x be distributed as the mixture normal

$$x \sim (1 - \omega) N \left(0, \sigma^2\right) + \omega N \left(0, \gamma\sigma^2\right) \tag{2.3}$$

where ω is the unconditional probability of observing y, i.e. $\omega = p(S = 1)$ so that

$$p(x \mid S = 0) = N\left(\mu_x, \sigma^2\right) \tag{2.4}$$

$$p(x \mid S = 1) = N\left(\mu_x, \gamma\sigma^2\right) \tag{2.5}$$

The parameter ω determines how unusual the outcomes associated with the signal y are in the unconditional sense. The parameter γ determines how the conditional probability of observing a public signal depends the realizations of x. Setting $\gamma > 1$ ensures that the conditional probability $p(S = 1 \mid x)$ is increasing in the deviation of x from its mean, i.e. that the inequality (2.1) holds. Intuitively, the inequality (2.1) will hold since a more dispersed distribution is "flatter" at all points of the support except at the mean, than a more concentrated distribution. Note that this argument works in both directions: Bayes' rule implies that *any* conditional distribution of the probability of observing a signal that is uniformly increasing in $|x|$ must be associated with a conditional distribution $p(x \mid S = 1)$ that has relatively more probability mass further out in the tails compared to the unconditional distribution of x.

The advantage of modeling the information structure this way is that since the conditional distributions (2.4) and (2.5) are Gaussian, the expectations of x conditional on S are known in closed form. In the set up of this paper, agents will never need to evaluate the unconditional distribution $p(x)$ since whether S equals 1 or 0 will always be known to agents. So while it is easier to maintain tractability by directly specifying the conditional distributions $p(x \mid S = 0)$ and $p(x \mid S = 1)$ we may still want to treat the unconditional distribution of x as the primitive, perhaps because it corresponds to a particular data moment. For a given unconditional variance σ_x^2 and parameters ω and γ we can back out the implied σ^2 by using that the variance of the mixture normal distribution (2.3) is given by

$$\sigma_x^2 = \omega\gamma\sigma^2 + (1 - \omega)\sigma^2 \tag{2.6}$$

so that

$$\sigma^2 = \frac{\sigma_x^2}{\omega\gamma + (1-\omega)} \tag{2.7}$$

For a given unconditional variance σ_x^2 we can thus adjust the slope and level of the dashed line $p(S = 1 \mid x)$ by choosing different values of ω and γ while holding the variance of the unconditional distribution $p(x)$ fixed by letting σ^2 be determined by (2.7).[1]

2.2. **The filtering problem.** Agents indexed by j form an estimate of x conditional on all available information. When $S = 0$, agent j observes only a private signal x_j which is the sum of the true x plus an idiosyncratic noise term

$$x_j = x + \varepsilon_j : \varepsilon_j \sim N\left(0, \sigma_\varepsilon^2\right) \ \forall \ \ j. \tag{2.8}$$

where the variance of the idiosyncratic noise is common across agents. When $S = 1$ agents also observe the public signal y

$$y = x + \eta : \varepsilon \sim N\left(0, \sigma_\eta^2\right). \tag{2.9}$$

The information set of agent j is thus given by

$$\Omega_j^0 = x_j, S \tag{2.10}$$

if $S = 0$ and

$$\Omega_j^1 = y, x_j, S \tag{2.11}$$

if $S = 1$. The fact that all agents observe y when $S = 1$ is common knowledge (though this does not really matter until later). The conditional expectations of x are then given by the standard formulas for multiple signals with independent Gaussian noise processes

$$E\left(x \mid \Omega_j^0\right) = \frac{\sigma_\varepsilon^{-2}}{\sigma_\varepsilon^{-2} + \sigma^{-2}} x_j \tag{2.12}$$

and

$$E\left(x \mid \Omega_j^1\right) = \frac{\sigma_\varepsilon^{-2}}{\sigma_\varepsilon^{-2} + \sigma_\eta^{-2} + \gamma^{-1}\sigma^{-2}} x_j + \frac{\sigma_\eta^{-2}}{\sigma_\varepsilon^{-2} + \sigma_\eta^{-2} + \gamma^{-1}\sigma^{-2}} y \tag{2.13}$$

That is, the conditional expectations of x are linear functions of the signals where the weights are determined by the relative precision of the individual signals. The posterior variances are also standard for normally distributed signals with independent noise processes and given by

$$E\left[x - E\left(x \mid \Omega_j^0\right)\right]^2 = \left(\sigma_\varepsilon^{-2} + \sigma^{-2}\right)^{-1} \tag{2.14}$$

and

$$E\left[x - E\left(x \mid \Omega_j^1\right)\right]^2 = \left(\sigma_\varepsilon^{-2} + \sigma_\eta^{-2} + \gamma^{-1}\sigma^{-2}\right)^{-1} \tag{2.15}$$

[1]In settings where higher unconditional moments matter, one need to be careful since some values of ω and γ may introduce kurtosis in the unconditional distribution of x.

2.3. **The implications of *man-bites-dog* signals.** The set up described above allows us to prove two results that at first may appear counter intuitive. First, the posterior uncertainty can be larger after the signal y has been observed, compared to when it has not. Secondly, the dispersion of expectations about x may increase after y is observed, even though y is a public signal.

Proposition 1. *The posterior uncertainty about x can be larger when the signal y is observed relative to when it is not. I.e. there are parameter values such that the inequality*

$$E\left[x - E\left(x \mid \Omega_j^0\right)\right]^2 < E\left[x - E\left(x \mid \Omega_j^1\right)\right]^2 \tag{2.16}$$

holds.

Proof. Directly comparing the posterior variances (2.14) and (2.15) implies that the proposition holds if

$$\sigma_\varepsilon^{-2} + \sigma^{-2} > \sigma_\varepsilon^{-2} + \sigma_\eta^{-2} + \gamma^{-1}\sigma^{-2} \tag{2.17}$$

Rearranging this expression gives

$$\sigma_\eta^2 > \frac{\sigma^2}{(1-\gamma^{-1})} \tag{2.18}$$

so that if $\gamma > 1$ there exists some $\sigma_\eta^2 > \sigma^2$ such that the inequality in the proposition holds. □

Proposition 1 states that if the signal y is noisy enough and $\gamma > 1$, the posterior variance may be larger when y is observed compared to when it is not. This is possible due to the conditional nature of the probability of observing y. The fact that y is observed indicates that something unusual is more likely to have happened, in the sense that larger deviations of x from its mean are more likely if $\gamma > 1$. When y is very noisy, this effect dominates. Conversely, if γ is large so that only very unusual events are more likely to generate a signal y, the signal y need not be very noisy for the increased uncertainty to dominate. However, since the right hand side of (2.18) has a minimum of σ^2 when $\gamma \to \infty$, that $\sigma_\eta^2 > \sigma^2$ is a necessary condition for the posterior uncertainty to be larger. Recognizing that the fact that a signal is available tells agents something about the (second moments of the) state can thus cause posterior uncertainty to be larger after a public signal is observed as compared to when it is not.

Corollary 1. *When the inequality*

$$\sigma_\eta^2 > \frac{\sigma^2}{(1-\gamma^{-1})} \tag{2.19}$$

holds, the cross sectional dispersion of expectations about x is larger when y is observed than when it is not.

The proof, which is given in the Appendix, follows directly from that the denominator in the weight on the private signal is the same as the denominator in the posterior variances. The cross sectional dispersion is increasing in the weight on the private signal, holding the variance of the idiosyncratic noise constant. The same conditions that deliver a higher posterior variance thus also deliver more weight on the private signal and the intuition is also similar. If the public noise variance is high and the conditional likelihood of a tail event is high, agents will put more weight on other (e.g. private) sources of information.

It is straight forward to show that the total weight agents put on all signals increases when $S = 1$.

Proposition 2. *The average expectation of x responds stronger to x when S=1 than when S=0.*

Proof. In the Appendix. □

The proof of Proposition 2 simply entails verifying that the sum of the coefficients on the two signals when $S = 1$ is larger than the coefficient on the single private signal when $S = 0$. The result is a direct consequence of the decrease in precision of agents beliefs "posterior" to observing $S = 1$ but "prior" to observing y. The weight agents put on y and x_j is inversely related to this precision and the sum of these weights thus go up unambiguously.

This section demonstrated that Bayesian updating to signals that are more likely to be available after an unusual event can have quite different properties compared to Bayesian updating to signals whose availability is uncorrelated with the underlying variable. Particularly, it was demonstrated that both posterior uncertainty and the cross-sectional dispersion of posterior beliefs can increase when a man-bites-dog signal is observed. It was also shown that on average, agents expectations of the latent variable respond stronger to a given deviation of the latent variable from its mean when there is a man-bites-dog signal available. In the next section, the man-bites-dog information structure will be embedded in a simple business cycle model in order to illustrate the dynamic consequences of having signals whose availability is positively correlated with tail events.

3. A business cycle model

In this section I present a simple business cycle model, following closely that of Lorenzoni (2009) but with a man-bites-dog information structure. In the model, there is both private and public information and the man-bites-dog signal is specified as a public signal about aggregate productivity. This means that information about large changes to productivity will be more correlated across agents than information about small changes. The model also features strategic complementarities. It is well-known that strategic complementarities tend to increase the importance of public signals, e.g. Morris and Shin (2002). In the model presented here, this effect will be further reinforced by the man-bites-dog mechanism, generating an amplification mechanism implying that aggregate variables may respond more than proportionally to larger productivity shocks.

3.1. Preferences and technology.

There is a continuum of islands indexed by $j \in (0, 1)$. On each island there is a continuum of households. Households are indexed by $i \in (0, 1)$ and consume goods and supply labor. A household on island j maximizes

$$E \sum_{s=0}^{\infty} \beta^s \left[\exp(d_{j,t}) \ln C_{j,t} - \frac{N_{j,t}^{1+\varphi}}{1+\varphi} \mid \Omega_t(j) \right] \tag{3.1}$$

where $C_{j,t}$ is the consumption bundle consumed by island j households

$$C_{j,t} = \left(\int_{\mathcal{B}j,m} C_{j,m,t}^{(\delta-1)/\delta} dm \right)^{\delta/(1-\delta)} \tag{3.2}$$

As in Lorenzoni (2009), households only consume a subset $\mathcal{B}_{j,m}$ of the available goods in the economy. This assumption ensures that local economic interactions on an individual island do not perfectly reveal the aggregate state. The shock $d_{j,t}$

$$d_{j,t} = d_t + \xi_{j,t} : \xi_{j,t} \sim N\left(0, \sigma_\xi^2\right) \tag{3.3}$$

is a demand disturbance that is correlated across islands. The common component d_t follows an AR(1) process

$$d_t = \rho_d d_{t-1} + u_t^d \tag{3.4}$$

Households on island j own the firms located on island j that produce good j using the technology

$$Y_{j,t} = A_{j,t} N_{j,t} \tag{3.5}$$

where (the log of) productivity $a_{j,t}$ is the sum of a common component a_t and the island specific component $\varepsilon_{j,t}$

$$a_{j,t} = a_t + \varepsilon_{j,t} : \varepsilon_{j,t} \sim N\left(0, \sigma_{\varepsilon a}^2\right) \ \forall \ \ j, t. \tag{3.6}$$

The common productivity component a_t follows an AR(1) process

$$a_t = \rho_a a_{t-1} + u_t^a \tag{3.7}$$

Firms on island j are owned by island j households and set prices $P_{j,t}$ to maximize discounted expected profits $\Pi_{j,t}$

$$E\left[\sum_{\tau=t}^{\infty} \theta^\tau \beta^\tau \frac{C_{j,t}}{C_{j,t+\tau}} \Pi_{j,t} \mid \Omega_t^j \right] = E\left[\sum_{\tau=t}^{\infty} \theta^\tau \beta^\tau \frac{C_{j,t}}{C_{j,t+\tau}} \left(P_{j,t+\tau} Y_{j,t+\tau} - W_{j,t+\tau} N_{j,t+\tau} \right) \mid \Omega_t^j \right] \tag{3.8}$$

where θ is the probability of changing prices of a given good in a given period. The budget constraint of households on island j is thus given by

$$\frac{B_{j,t+1}}{R_t} + \int_{\mathcal{B}j,m} C_{j,m} dj \ dm = B_{j,t} + W_{j,t} N_{j,t} + \Pi_{j,t} \tag{3.9}$$

where the (log of the) nominal one period interest rate R_t follows a Taylor rule

$$r_t = \phi_\pi \pi_t + \phi_y y_t + \phi_r r_{t-1} + u_t^r \tag{3.10}$$

3.2. **Linearized equilibrium conditions.** The model presented above can be log linearized around a non-stochastic steady state, yielding the following equilibrium conditions. An Euler equation determining the optimal intertemporal allocation of consumption

$$c_{j,t} = E\left[c_{j,t+1} \mid \Omega_t^j \right] - r_t + E\left[\overline{\pi}_{j,t+1} \mid \Omega_t^j \right] + \varepsilon_{j,t} \tag{3.11}$$

where $\overline{\pi}_{j,t+1}$ is the inflation of the goods basket consumed on island j in period $t+1$.

A labor supply condition equating marginal disutility of labor supply with the marginal utility of consumption multiplied by the real wage

$$w_{j,t} - \overline{p}_{j,t} = c_{j,t} + \varphi n_{j,t}. \tag{3.12}$$

A demand schedule for good j depending on aggregate output and the relative price of good j

$$y_{j,t} = y_t - \delta\left(p_{j,t} - \overline{p}_{\mathcal{C}j,t}\right) + \xi_{j,t}. \tag{3.13}$$

where $\overline{p}_{\mathcal{C}j,t}$ is the log of the relevant price sub index for consumers from other islands buying goods from island j. The island j Philips curve relating inflation on island j to the nominal marginal cost on island j and expected future island j inflation is given by

$$\begin{aligned} p_{j,t} - p_{j,t-1} &= \lambda\left(\overline{p}_{\mathcal{B}j,t} + c_{j,t} - p_{j,t} - a_{j,t}\right) + \lambda\delta\left(y_{j,t} - \varphi p_{j,t} - a_{j,t}\right) \\ &\quad + \beta E\left(p_{j,t+1} - p_{j,t} \mid \Omega_t^j\right) \end{aligned} \tag{3.14}$$

where $\overline{p}_{\mathcal{B}j,t}$ is the relevant price subindex for consumers on island j. More details on the derivation of the log linearized equilibrium conditions are given in the Appendix.

3.3. **The joint distribution of signals and shocks.** The man-bites-dog signal structure is embedded in the business cycle model in a similar way as in the static setting discussed above. The unobservable variable of interest is the common component of productivity a_t and I will specify a joint distribution of the indicator variable s_t and the innovations u_t^a in (3.7) such that a man-bites-dog signal is more likely to be generated when there has been a large (in absolute terms) innovation to the common productivity process a_t. The indicator variable s_t takes the value 1 when a man-bites-dog signal is generated in period t which occurs with unconditional probability ω. (Some alternative specifications are discussed in the robustness section below.) Similar to the static setting of Section 2, a mixture normal density for u_t^a will be used to keep the filtering problem tractable

$$u_t^a \sim (1-\omega) N\left(0, \sigma^2\right) + \omega N\left(0, \gamma\sigma^2\right). \tag{3.15}$$

so that the unconditional variance of the productivity innovations u_t^a is given by

$$E\left(u_t^2\right) = (1-\omega)\sigma^2 + \omega\gamma\sigma^2 \tag{3.16}$$

To complete the description of the joint distribution of innovations and signals, it is further assumed that when $s_t = 1$ all households observe an additional public signal $z_{a,t}$ given by

$$z_{a,t} = a_t + \eta_t : \eta_t \sim N\left(0, \sigma_\eta^2\right) \tag{3.17}$$

The vector of observables $\mathbf{z}_{j,t}$ available to households and firms on island j in period t then is

$$\mathbf{z}_{j,t} = \left[a_{j,t}, d_{j,t}, y_{j,t}, \overline{p}_{j,t}, r_t, s_t\right] \quad \text{if} \quad s_t = 0 \tag{3.18}$$

$$\mathbf{z}_{j,t} = \left[a_{j,t}, d_{j,t}, y_{j,t}, \overline{p}_{j,t}, r_t, s_t, z_{a,t}\right] \quad \text{if} \quad s_t = 1 \tag{3.19}$$

The information set $\Omega_{j,t}$ of firms and households on island j evolves as

$$\Omega_{j,t} = \{\mathbf{z}_{j,t}, \Omega_{j,t-1}\} \tag{3.20}$$

This completes the description of the model.

4. Solving and estimating the model

There are two features of the model presented above that make standard solution methods for linear rational expectations models inapplicable. First, there is island specific information about variables of common interest to all islands. Natural state representation then tend to become infinite, due to the well-known problem of the infinite regress of expectations that arises when agents need to "forecast the forecasts of others" (see Townsend 1983 and Sargent 1991). Secondly, the precision of agents' information is a function of the realized history of s_t and thus varying across time. In this section, I first describe how the method proposed in Nimark (2011) can be modified to solve a model with a time varying information structure. The solved model is in a standard state space form, albeit with time varying parameters. The section ends with describing how to evaluate the likelihood of the model conditional on a given set of parameters and a given history of s_t. It also describes how a posterior estimate of the joint distribution of the parameters of the model and the history of s_t can be constructed using a version of the Metropolis-Hasting algorithm.

4.1. **Solving dynamic models with private information.** In Nimark (2011) it is demonstrated that if the variance of the the unobservable exogenous state is finite, the equilibrium dynamics of a model with privately informed agents can be approximated to an arbitrary accuracy by a finite dimensional representation. There are two parts to deriving this result. The first step puts structure on higher order expectations, i.e. expectation about other agents expectations, by exploiting that it is common knowledge that agents form model consistent expectations. The second step uses the structure imposed by common knowledge of rational expectations to show that the impact of orders of expectations is decreasing in the order of expectation. This second step is somewhat involved, and interested readers are referred to the original reference. Here we briefly describe how common knowledge of model consistent expectations help put structure on the dynamics of higher order expectations.

Let $\mathbf{x}_t$ denote a vector containing the exogenous state variables a_t and d_t so that

$$\mathbf{x}_t \equiv \begin{bmatrix} a_t \\ d_t \end{bmatrix} \tag{4.1}$$

The solution method then delivers a law of motion of the state X_t of the form

$$X_t = MX_{t-1} + N\mathbf{u}_t : \mathbf{u}_t \sim N(0, I) \tag{4.2}$$

where

$$X_t \equiv \begin{bmatrix} \mathbf{x}_t \\ \mathbf{x}_t^{(1)} \\ \vdots \\ \mathbf{x}_t^{(\overline{k})} \end{bmatrix} \tag{4.3}$$

and

$$\mathbf{x}_t^{(k+1)} \equiv \int E\left[\mathbf{x}_t^{(k)} \mid \Omega_t(j)\right] \tag{4.4}$$

The state thus consists of average higher order expectations of current productivity a_t and the common demand shock d_t. The constant $\overline{k}$ is the maximum order of expectation considered.

The intuition for how common knowledge of model consistent expectations puts structure on higher order expectations is the following: As usual in rational expectations models, first order expectations $\mathbf{x}_t^{(1)}$ are optimal, i.e. model consistent estimates of the actual state $\mathbf{x}_t$. The knowledge that other islands have model consistent estimates allow inhabitants of an individual island to treat average first order expectations as a stochastic process with known properties when they form second order expectations. Common knowledge of the model thus implies that second order expectations $\mathbf{x}_t^{(2)}$ are optimal estimates of $\mathbf{x}_t^{(1)}$ given the law of motion for $\mathbf{x}_t^{(1)}$. Imposing this structure on all orders of expectations allows us to find the law of motion (4.2) for the complete hierarchy of expectations as functions of the structural parameters of the model.

For a given law of motion (4.2), the endogenous variables can be computed as a linear function of higher order expectations about the current state $\mathbf{x}_t$ and the aggregate shocks $\mathbf{u}_t$ by using that the the structural equations of the linearized model can be written in the form

$$\begin{bmatrix} \pi_t \\ y_t \end{bmatrix} = A \int E \left(\begin{bmatrix} \pi_{t+1} \\ y_{t+1} \end{bmatrix} \mid \Omega_{j,t} \right) + B\mathbf{x}_t$$

Conjecturing (and verifying) a solution of the form

$$\begin{bmatrix} \pi_t \\ y_t \end{bmatrix} = GX_t + g\mathbf{u}_t \tag{4.5}$$

together with method of undetermined coefficients then implies that matrix G must satisfy the equation

$$G = AGMH + \begin{bmatrix} B & \mathbf{0} \end{bmatrix} \tag{4.6}$$

where H is a matrix defined so that

$$\int E\left[X_t \mid \Omega_t(j)\right] = HX_t \tag{4.7}$$

i.e. H moves a vector of average higher order expectations one step "up" in orders of expectations. For a given A and M, the equation (4.6) can be solved for G by function iteration.

The fact that the state of the model is made up of expectations and higher order expectations means that the law of motion of the state in a given period is a function of the precision of agents priors as well as the precision of period t signals. Since these quantities will depend on the history of s_t, the law of motion of the state will be time varying. That the law of motion will be time varying then in turn implies that the function mapping the current state into endogenous variables will also be time varying.

4.2. **Regimes and endogenous time varying dynamics.** Changes in the regimes s_t will in general have persistent effects on the dynamics of the model. The reason is that if, for example, we are in a regime that increases posterior uncertainty in period t then that will translate into an increase in prior uncertainty in period $t+1$. How much weight agents put on signals observed in period $t+1$ depends on the precision of the signals relative to the precision of the prior. A large posterior uncertainty in period t translates in to more weight being put on signals observed in period $t+1$. This makes the model more interesting and allow us to potentially fit more facts in the data. It also allows us to exploit the variation in the cross-sectional dispersion of forecasts as measured by the SPF to make stronger inference about the precision of agents information at different points in time. But since a period t regime s_t has persistent effects we need to keep track of the history of s_t (which we denote s^t) to determine period t equilibrium dynamics. Here we describe how this is done in practice.

As long as the filtering errors of agents are a stable process, we do not need to keep track of the entire history but only the most recent realizations of s_t. How far back in time the realizations of s_t matter of course depends on the parameters of the model. More specifically, it will depend on the eigenvalues of the process that propagates filtering errors through time. If the underlying processes are not very persistent, or if information is very accurate, filtering errors do not tend to be long lived and only a few of the past realizations of s_t influences current dynamics. We will proceed by assuming that there is a maximum lag of s_t, say $s_{t-\mathcal{T}}$ that matters for current dynamics. This strategy implies that if there are 2 different exogenous regimes (i.e. $s_t \in \{0, 1\}$) we have $2^{\mathcal{T}}$ relevant different histories s^t of regimes and we need to somehow keep track of these. We will use the following indexing strategy. Each finite history of s_t which we will denote s^t can be expressed uniquely by a decimal number using the mapping between binary and decimal numbers. The history

$$s^t = \{0, 0, 0, 1\} \tag{4.8}$$

will be assigned the index number 1 since the binary number 0001 equals 1 in the decimal system. Similarly, the history

$$s^t = \{1, 1, 0, 1\} \tag{4.9}$$

is given the index number 14 since the binary number 1101 equals 13 in the decimal system and so on. The number of relevant histories of s_t equals 16 in this case where it is assumed that the last last 8 periods of s_t are relevant for current dynamics, we then have that the number of endogenous regimes equals $2^8 = 256$. In the latter case we need to use 8 bit binary numbers to keep tack of the relevant histories of s_t and so on. We will denote the number of different relevant histories $\mathcal{S}$ and so that $\mathcal{S} = 2^{\mathcal{T}}$.

4.3. **Solving the model with time varying information sets.** As mentioned above, the fact that the state of the model is made up of expectations and higher order expectations means that how agents update their state estimates determines the actual law of motion of the very same state that agents form estimates about. In the static setting of Section 2 it was demonstrated that the availability of a man-bites-dog signal affect how agents update their state estimates and their uncertainty about these estimates. Particularly, if there is a man-bites-dog signal available, uncertainty may increase so that agents put more weight on new information. In a dynamic setting that means that the law of motion of the state will be time-varying. Still, a method similar to the one used for the time invariant case can also be applied when information sets and conditional variances are time varying. Here a brief overview of how this is done is given, though the details are relegated to the Appendix.

First, with time varying information sets, the law of motion now depends on the history of regimes s^t so that

$$X_t = M(s^t)X_{t-1} + N(s^t)\mathbf{u}_t : \mathbf{u}_t \sim N(0, I) \tag{4.10}$$

The endogenous variables can still be written as linear functions of the state, but now with time varying parameters

$$\begin{bmatrix} \pi_t \\ y_t \end{bmatrix} = G(s^t)X_t + g(s^t)\mathbf{u}_t \tag{4.11}$$

The matrices $G(s^t)$ and $g(s^t)$ can be computed by noting that for given conjectured law of motion (4.10) and linear function (4.11) we have that

$$\begin{aligned} \begin{bmatrix} \pi_t \\ y_t \end{bmatrix} &= A \int E\left(\begin{bmatrix} \pi_{t+1} \\ y_{t+1} \end{bmatrix} \mid \Omega_{j,t} \right) + B\mathbf{x}_t \\ &= \omega AG\left(s^t, 1\right) M\left(s^t, 1\right) HX_t \\ &\quad (1-\omega) AG\left(s^t, 0\right) M\left(s^t, 0\right) HX_t + \\ &\quad +B\mathbf{x}_t \end{aligned}$$

When forming expectations about future inflation and consumption agents will take into account that the next period state s_{t+1} will be 1 with probability ω and 0 with probability $(1-\omega)$

$$\begin{aligned} G\left(s^t\right) &= \omega AG\left(s^t, 1\right) M\left(s^t, 1\right) H \\ &\quad + (1-\omega) AG\left(s^t, 0\right) M\left(s^t, 0\right) H \\ &\quad + \begin{bmatrix} B & \mathbf{0} \end{bmatrix} \end{aligned}$$

where $M\left(s^t, 0\right) = M\left(s^{t+1} \mid s_{t+1} = 0\right)$ etc.

The solution algorithm is a fixed point problem over the $\mathcal{S}$ relevant histories of s_t which can be solved by function iteration. For given $G(s^t)$ and $g(s^t)$ the algorithm computes the matrices $M(s^t)$ and $N(s^t)$. For a given $M(s^t)$ and $N(s^t)$, it computes new values of $G(s^t)$ and $g(s^t)$, and so on. Nimark (2010) uses a version of Brouwer's fixed point theorem to prove for the time invariant case that a solution to this iteration exists and that there is a finite maximum order of expectation $\overline{k}$ that results in equilibrium dynamics that are arbitrarily close to the dynamics of the limit $\overline{k} \to \infty$. For these results to apply it is sufficient that the variance of the exogenous state $\mathbf{x}_t$ is finite and no explicit use is made of the constancy of parameters.

4.4. **Estimating the model.** The solved model is a state space system with time varying parameters and standard likelihood based methods are applicable to estimate the parameters of the model. In addition to the 18 structural parameters of the model, which we denote

$$\Theta = \{\rho_a, \rho_\xi, \sigma_a, \sigma_d, \sigma_r, \sigma_\varepsilon, \sigma_{\zeta 1}, \sigma_{\zeta 2}, \sigma_\eta, \delta, \eta, \phi_\pi, \phi_y, \phi_r, \theta, \beta, \omega, \gamma\} \tag{4.12}$$

we also want to construct a posterior estimate of the indicator variable s_t that keeps track of whether there was a man-bites-dog signal available in period t or not. Below we describe how this can be done by sampling from the two conditional distributions $p\left(\Theta \mid s^T, Z^T\right)$ and $p\left(s^T \mid \Theta, Z^T\right)$. Dividing the sampling from the joint posterior distribution of Θ and s^T into two blocks also lets us get around the problem that unlike the agents inside the model, we as econometricians do not observe the regimes s_t. Conditional on a draw from s^T, the model is linear-Gaussian and it is easy to evaluate the likelihood.

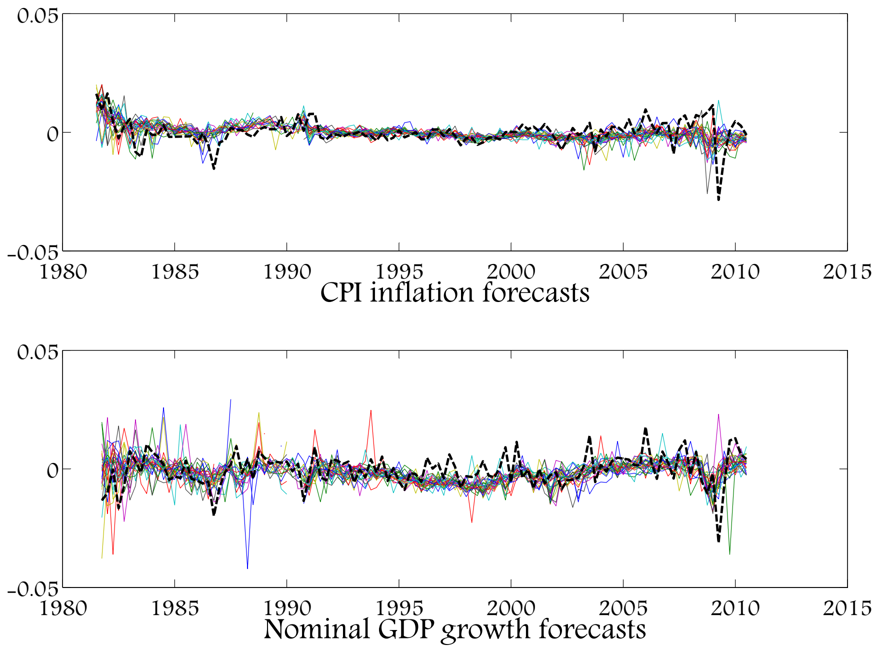

FIGURE 2. Actual and SPF Forecasts of CPI inflation and Nominal GDP growth

4.5. **The data.** The time series used to estimate the model are US CPI inflation, the Federal Funds rate, US real GDP, the quarterly time series of total factor productivity constructed by John Fernald (2010) and raw survey data from the Survey of Professional Forecasters (SPF). The data is quarterly and the sample ranges from 1981:Q3 to 2010:Q4. The start date is chosen based on the availability of survey data for inflation forecasts and the end date is the date of the most recent data on real GDP and total factor productivity. CPI inflation is de-trended using a linear trend and the same trend is taken out of the Federal Funds rate. Real GDP is de-trended using the HP-filter with a smoothing coefficient of 1400. The raw survey data is one quarter ahead forecasts of CPI inflation and nominal GDP growth taken from the Survey of Professional Forecasters available from the web site of the Federal Reserve Bank of Philadelphia. Inflation forecasts are de-trended using the CPI inflation trend and nominal GDP growth forecasts are de-trended by subtracting the inflation trend and the growth in the real GDP (HP-filter) trend. We denote the vector of observables in period t Z_t. All elements in Z_t have natural counterparts in the model. Specifically, TFP will be taken as a noisy measure of the common productivity component and the vectors of survey forecasts $\mathbf{f}'_\pi$ and $\mathbf{f}'_{\pi+\Delta y}$ are taken to be representative of the expectations of the privately informed agents in the model. The observables in period t are thus given by

$$Z_t = \left[\begin{array}{cccccc} a_t & \pi_t & y_t & r_t & \mathbf{f}'_\pi & \mathbf{f}'_{\pi+\Delta y} \end{array} \right]' \tag{4.13}$$

and linked to the state of the model by the measurement equation

$$Z_t = D(s^t)X_t + R(s^t)u_t \tag{4.14}$$

Due to the fact that the number of survey respondents is not constant in the sample, the dimensions of both D and R are varying across time. More interestingly, the entries of D and R also varies over time. The matrix D is time varying since the function mapping the state into endogenous variables is time varying. The matrix R is time varying since the cross-sectional dispersion of forecasts are time varying in the model and each survey entry can be viewed as a noisy measure of the average expectation where the variance of the "noise" is the cross-sectional variance of forecasts implied by the model. The cross-sectional variance will vary across time and be a function of the structural parameters Θ as well as the history s^t. The (de-trended) survey data is plotted in Figure 2 along with the actual outcomes of CPI inflation and Nominal GDP growth.

There are four observable variables in Z_t that map into aggregate variables in the theoretical model, but in most periods there are only three aggregate disturbances. To avoid stochastic singularity when evaluating the likelihood function, we treat the the TFP series as well as the in CPI inflation and real GDP growth as being measured with (very small) noise.[2]

4.6. **Estimation Algorithm.** The posterior distribution of Θ and s^T are estimated using an Adaptive Multiple-Block Metropolis algorithm (see Chib 2001 and Haario et al 2001). It exploits that conditional on a history of man-bites-dog regimes s^T, the model is in linear-Gaussian state space form. The estimation algorithm can be described as follows.

(1) Specify and initial values Θ_0 and s_0^T.
(2) Repeat for $j = 1, 2, ..., J$
  (a) Block 1: Draw from $p\left(\Theta \mid s^T, Z^T\right)$
    (i) Propose $\Theta^* \sim N\left(\Theta_{j,1}, c\Sigma_{\Theta,j}\right)$ where c is a (small) constant and $\Sigma_{\Theta,j}$ is the covariance of the Markov chain $[\Theta_0 \; \Theta_1 \; \cdots \; \Theta_j]$
    (ii) Calculate $\alpha_j^\Theta = \min\left\{\frac{L\left(Z^t|s_{j-1}^T,\Theta^*\right)}{L\left(Z^t|s_{j-1}^T,\Theta_{j-1}\right)}, 1\right\}$
    (iii) Set $\Theta_{j+1} = \Theta^*$ if $U(0,1) \leq \alpha_j^\Theta$ and $\Theta_{j+1} = \Theta_j$ otherwise.
  (b) Block 2: Draw from $p\left(s_\tau \mid s^{-\tau}, \Theta, Z^T\right)$
    (i) Draw a time period τ uniformly from the set $\{1, 2, ...T\}$
    (ii) Set $s^* = s_{j-1}^T$
    (iii) Propose $s_t^* = 1$ if $U(0,1) \leq \omega$ and $t = \tau$.
    (iv) Calculate $\alpha_j^s = \min\left\{\frac{L\left(Z^t|s_{j-1}^T,\Theta_j\right)p(s^*)}{L\left(Z^t|s_{j-1}^T,\Theta_j\right)p(s_{j-1}^T)}, 1\right\}$
    (v) Set $s_{j+1}^T = s^*$ if $U(0,1) \leq \alpha_j^s$ and $s_{j+1}^T = s_j^T$ otherwise.
(3) Return values $\{\Theta_0, \Theta_1,...,\Theta_J\}$ and $\{s_0^T, s_1^T,...,s_J^T\}$

[2]The variances of the measurement errors are about $1/100^{th}$ of the variance of the actual time series.

4.7. **Posterior parameter estimates.** The posterior estimates of Θ from 100 000 draws from the Metropolis algorithm[3] are reported in Table 1.

Table 1 (Preliminary)

Posterior Parameter Estimates 1981:Q3-2010:Q3

Θ	Mode $\widehat{\Theta}$	Prior dist.	Posterior 2.5%-97.5%
	Preferences etc		
φ	1.01	$U(0,10)$	(0.81-0.89)
δ	1.03	$U(0,10)$	(0.78-0.87)
β	0.98	$U(0,10)$	(0.98-0.99)
θ	0.64	$U(0,10)$	(0.60-0.69)
	Exogenous aggregate processes		
ρ_a	0.85	$U(0,0.99)$	(0.84-0.85)
ρ_d	0.31	$U(0,0.99)$	(0.29-0.32)
σ_a	0.008	$U(0,0.99)$	(0.006-0.010)
σ_d	0.007	$U(0,1)$	(0.004-0.012)
σ_r	0.10	$U(0,1)$	(0.07-0.12)
	Island specific processes		
σ_ε	0.28	$U(0,1)$	(0.26-0.31)
$\sigma_{\zeta 1}$	0.32	$U(0,1)$	(0.27-0.36)
$\sigma_{\zeta 2},$	0.30	$U(0,1)$	(0.22-0.40)
$\sigma_\xi,$	0.21	$U(0,1)$	(0.18-0.24)
	Man-bites-dog parameters		
ω	0.05	$U(0,1)$	(0.04-0.05)
γ	3.9	$U(0,10)$	(3.8-4.1)
σ_η	0.57	$U(0,10)$	(0.50-0.65)
	Bond supply shocks		
ϕ_r	0.09	$U(0,1)$	(0.07-0.13)
ϕ_π	1.52	$U(0,10)$	(1.43-1.62)
ϕ_y	0.2	$U(0,10)$	(0.15-0.26)
Log likelihood at $\widehat{\theta}$: 3402.2			

5. Estimated Man-bites-dog Dynamics

The estimated model can be used to quantify the contribution of the man-bites-dog mechanism to business cycle dynamics.

5.1. **The impact of innovations to productivity.** Figure 3 illustrates the impulse response function of output and inflation to a one (unconditional) standard deviation innovation to the common productivity shock a_t. The dashed black lines are the responses when there is no man-bites-dog signal, the solid blue lines are the responses when there is a man bites dog signal in the impact period. It is clear from the figure that the response of output

[3]I am aware that this is rather few draws for a Metropolis algorithm and the results should be considered preliminary. 100 000 draws take several days to complete and I am currently waiting for longer chains to finish.

to a productivity shock of a given magnitude is much larger if it coincides with the generation of a man-bites-dog signal.

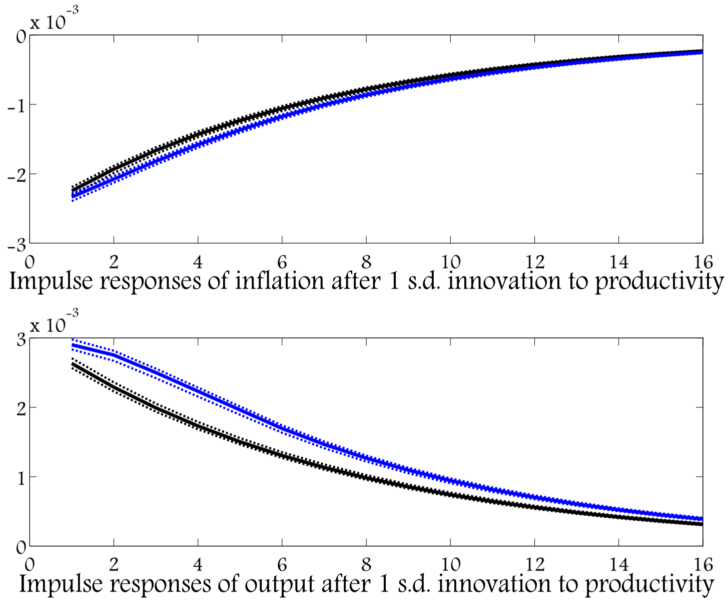

Figure 3. Impulse responses of inflation (top panel) and output (bottom panel) to a 1 s.d. innovation to productivity. Blue lines are for man-bites-dog signal in period 1, i.e. $s^t = 1, 0, 0, 0, 0$ and black lines for no man-bites-dog signal. Dotted lines show the 95 per cent posterior credible intervals.

Since the probability of generating a man-bites-dog signal is increasing in the absolute size of the shock, the larger a shock is, the more likely is it that the response will be described by the blue impulse responses. Small shocks on the other hand are more likely to generate the weaker responses illustrated by the black line. This conditionality of the magnitude of the impulse responses is further illustrated in Figure 4, where the expected impact (y-axis) of a productivity shock on output is plotted for different ratios (x-axis) of the size of the shock relative to its standard deviation. We can see in the figure that for the expected impact is larger for larger shocks. The man-bites-dog information structure thus introduces a non-linearity in the endogenous variables responses to exogenous shocks.

The stronger responses of endogenous variables to an innovation of given magnitude are caused by two conceptually different effects that both work to amplify the responses when there is a man-bites-dog signal available. First, since the man-bites-dog signal is a public signal in the strong common knowledge sense of the word, higher order expectations will respond stronger than they do to private signals. In a setting with strategic complementarities, this translates into a stronger endogenous response. This is the "coordination effect" identified by Morris and Shin (2002) implying that public signals can appear to be overly influential on affecting equilibrium outcomes as they work as "focal points" for expectations.

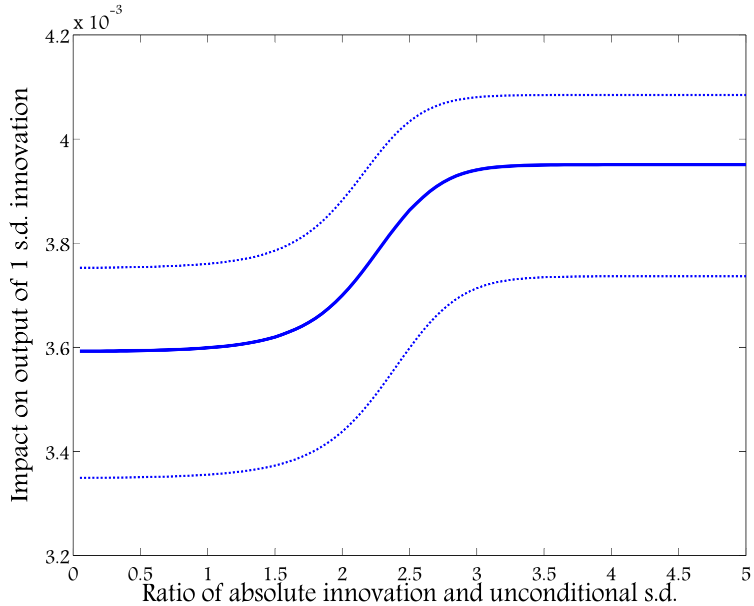

FIGURE 4. Expected output multiplier on innovation to productivity conditional on magnitude of innovation.

Secondly, the stronger updating effect identified in the static setting in Section 2 is also at work in a dynamic setting. That is, within the period, agents always respond stronger to new information when a man-bites-dog signal is available since this implies that tail events are more likely.

5.2. **Historical man-bites-dog episodes.** In the top panel of Figure 5 the posterior probabilities of man-bites-dog events are plotted against the sample dates. There are four episodes in which the posterior probability of the economy being in a man-bites-dog state are close to 1. They correspond to the end of the Volcker disinflation, the recession in the early 1990s, the short downturn that followed the dot com boom and the current recession that began in 2008. It thus appears that there is certain asymmetry in the data: The man-bites-dog events identified by the model are all recession or down turns. This may suggest that the model should be amended so that a man-bites-dog event not only increases the conditional second moment of innovations, but also on average is more likely to occur when there is negative shock. This is investigated in the robustness section below.

5.3. **Endogenous persistence in volatility.** The model estimates suggest that man-bites-dog events are associated with stronger responses to innovations to productivity and estimated history of the output multiplier on productivity innovations is plotted in the in the bottom panel of Figure 5. There it can be seen that when there is man-bits-dog event, the impact multiplier increases sharply, but only returns to normal levels gradually. That is, a

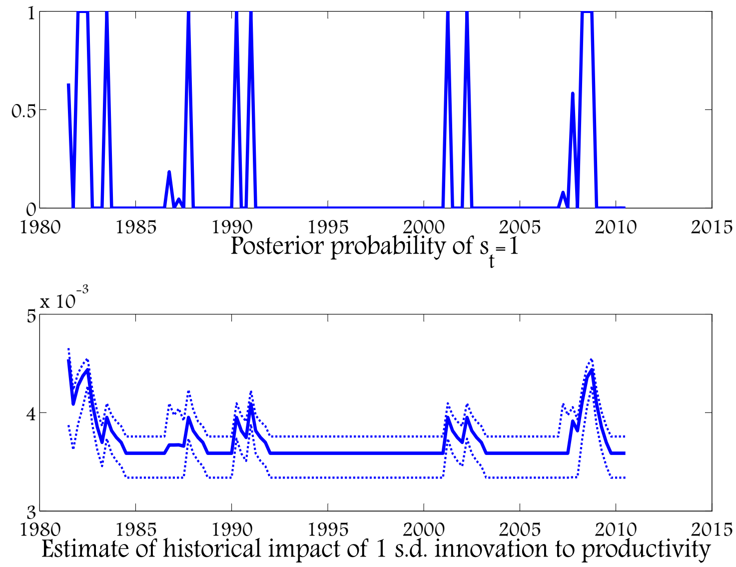

FIGURE 5. Estimated histories.

man-bites-dog signal increases the sensitivity of output to productivity shocks for several periods. The reason is that if a man-bites-dog signal is observed in period t then this will affect the posterior covariance of the state estimation error in period t. The posterior covariance in period t translates into the prior covariance in period $t+1$ implying that the man-bites-dog signal in period t has persistent effects on the law of motion of the state (and not only on the state itself). These effects can be quite persistent, depending on the parameters and generally increase when uncertainty is relatively large and when the persistence of the exogenous state is high. Figure 6 illustrates the output multiplier on a productivity shock the periods after a man-bites-dog signal is observed. That is, figure 6 plots the posterior estimate of the relevant elements of

$$G(s^t)N(s^t) : t = 1, 2, ... \tag{5.1}$$

for

$$s^t = 1, 0, 0, 0, 0, ... \tag{5.2}$$

That is, Figure 6 plots an impulse response of the time varying parameter that governs how much output increases after a one standard deviation innovation to productivity. As can be seen from the figure, the impact a productivity shock has when a man-bites-dog signal is generated is persistently higher after the impact period. The man-bites-dog information structure thus generates something similar to ARCH or stochastic volatility dynamics in the endogenous variables even though no such persistence is present in the volatility of the productivity process. (A picture similar to Figure 6 can be plotted for the inflation multiplier.)

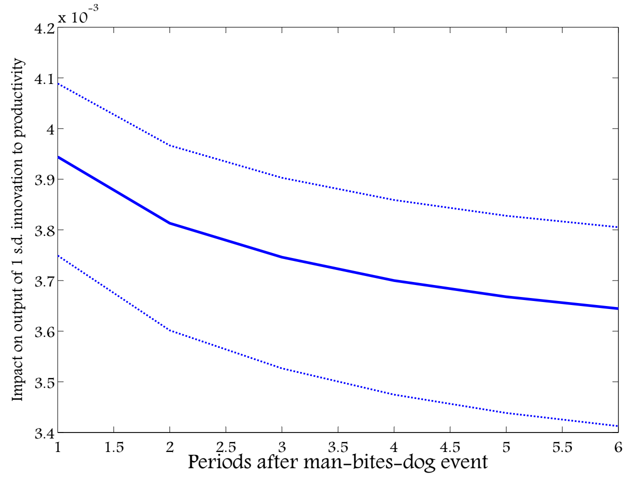

FIGURE 6. Illustrating the man-bites-dog signal induced ARCH dynamics of output.

5.4. **Man-bites-dog signals and the cross-sectional dispersion of expectations.** As was shown in the static setting of Section 2, uncertainty can either increase or decrease when a man-bites-dog signal is observed relative to when it is not. Whether this effect is present depends on the value of the parameter γ governing how unusual an event has to be to significantly increase than probability of observing a man-bites-dog signal and how noisy the man-bites-dog signal is when it is observed. When γ is large or the man-bites-dog signal is very noisy, uncertainty is more likely to increase after a man-bites-dog signal and the cross-sectional dispersion of first order expectations increases. In Figure 7 we have plotted how the cross-sectional dispersion of first order expectations changes after a man-bites-dog signal at the posterior mode of the estimated model. It can be seen that at the mode, the uncertainty effect of a man-bites-dog signal appear to dominate and the cross-sectional dispersion increases at the time of the man-bites-dog signal. Afterwards, the dispersion gradually returns to the more concentrated distribution associated with periods when there are no man-bites-dog events in the relevant history of s_t.

These results can be contrasted to those of Kondor (2010). He shows that in a setting where two classes of agents are constrained in what type of private information they can acquire, a public signal may increase the dispersion between first and second order expectations. In the model presented here, a man-bites-dog signal decreases dispersion between different order of expectation (not shown) but increases the cross sectional dispersion of first order expectations.

5.5. **A counter factual business cycle history.** In this section I use smoothed estimates of the state X^T to compute a counter factual history of output and inflation when no man-bites-dog signals are generated.

[TBC]

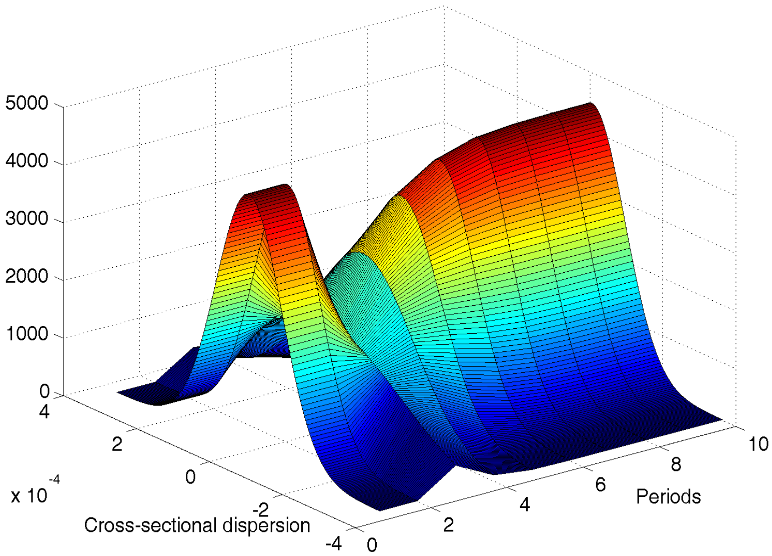

FIGURE 7. Impulse response of cross sectional distribution of expectations after a man-bites-dog signal, i.e. $s^t = 0, 1, 0, 0, 0, ...$ (Cross sectional dispersion increases (widens) in period 2 when $s_2 = 1$.)

6. Robustness

[TBC]

7. Conclusion

That some types of signals are more likely to be available about unusual events may suggest that we should be better informed about unusual events. However, in this paper we have showed that the flip-side of this argument is that the distribution of events conditional on there being a man-bites-dog signal available is different from the unconditional distribution in ways that may undo the effect of having more information. It was demonstrated that conditioning only on the *availability* of a man-bites-dog signal increases uncertainty, while observing the actual contents of the signal decreases uncertainty. If the likelihood of observing the signal only increases substantially after very unusual events or if the signal is sufficiently noisy, the former effect may dominate so that the posterior uncertainty after observing a man-bites-dog signal is larger than it would be if no such signal was available. We also showed that even though the the man-bites-dog signal is public, the cross-sectional dispersion of (first order) expectations may increase.

In the second part of the paper, a simple business cycle model was presented and estimated in which large innovations to productivity is more likely to generate a public signal. The model was then used to demonstrate that some macro economic phenomena can be explained by economic agents optimally updating their beliefs after observing man-bites-dog signals. Particularly, we showed that the model can explain why apparently small negative productivity shocks sometimes trigger sharp downturns and why there are persistent periods of high volatility in macro economic aggregates like GDP growth. Arguably, these features of the model describes a type of "crisis mentality" in which there is an intense media focus on the economy with more information produced and broadcast, yet uncertainty and sensitivity to new information appears to increase.

It may be worth pointing out some differences between the mechanism proposed here and models featuring stochastic volatility. In a stochastic volatility model, the variance of the exogenous shocks hitting the economy is a persistent time-varying process. In the model presented here, the sensitivity of endogenous variables to a given magnitude of shocks varies over time. While the man-bites-dog mechanism is more likely to be triggered by a large exogenous shock, the persistent increase in sensitivity of the endogenous variables to exogenous shocks is entirely endogenous. To the extent that we can observe the exogenous shocks directly, this distinction is a testable difference between the two approaches.

The model was estimated by likelihood based methods using both the quarterly total factor productivity time series constructed by Fernald (2010) and "raw" survey data from the Survey of Professional Forecasters along with more standard macro indicators. Using a time series of TFP as an observable variable has obvious advantages in terms of disciplining the model, especially since one of the aims of the paper has been to quantify the extent of time variation in the impact of TFP shocks on other variables. Using raw survey data allow us incorporate the information in the second moments of the survey responses into the posterior estimates of the parameters of the model and achieve a sharper handle on the implied precision of the information available to economic agents. Particularly, we could use the time-variation in the cross-sectional dispersion of survey responses to identify man-bites-dog events sharply in the data. We found that such events appear to be more likely to be associated with recession and downturns than booms, though the model is flexible enough to also allow for man-bites-dog driven booms.

Finally, the paper makes a methodological contribution by demonstrating how a model with time varying information sets can be solved. This may be of separate interest to some readers.

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Appendix A. Additional proofs

Proposition 2. *The average expectation of x responds stronger to x when S=1 than when S=0.*

Proof. We need to show that the sum of the coefficients on the private signal x_j and public signal y in the conditional expectation

$$E\left(x \mid \Omega_j^1\right) = \frac{\sigma_\varepsilon^{-2}}{\sigma_\varepsilon^{-2} + \sigma_\eta^{-2} + \gamma^{-1}\sigma^{-2}} x_j + \frac{\sigma_\eta^{-2}}{\sigma_\varepsilon^{-2} + \sigma_\eta^{-2} + \gamma^{-1}\sigma^{-2}} y \tag{A.1}$$

when $S = 1$ is larger than the coefficient on the private signal

$$E\left(x \mid \Omega_j^0\right) = \frac{\sigma_\varepsilon^{-2}}{\sigma_\varepsilon^{-2} + \sigma^{-2}} x_j \tag{A.2}$$

when $S = 0$. Simply comparing the expected average expectation conditional on x for $S = 0$

$$\int E\left[x \mid \Omega_j^0\right] dx = \int \frac{\sigma_\varepsilon^{-2}}{\sigma_\varepsilon^{-2} + \sigma^{-2}} x_j dj \tag{A.3}$$

$$= \left(1 - \frac{\sigma^{-2}}{\sigma_\varepsilon^{-2} + \sigma^{-2}}\right) x \tag{A.4}$$

and $S = 1$

$$E\left[\int E\left(x \mid \Omega_j^1\right) dx \mid x\right] = \int \frac{\sigma_\varepsilon^{-2}}{\sigma_\varepsilon^{-2} + \sigma_\eta^{-2} + \gamma^{-1}\sigma^{-2}} x_j dj \tag{A.5}$$

$$+ \frac{\sigma_\eta^{-2}}{\sigma_\varepsilon^{-2} + \sigma_\eta^{-2} + \gamma^{-1}\sigma^{-2}} x \tag{A.6}$$

$$= \left(1 - \frac{\gamma^{-1}\sigma^{-2}}{\sigma_\varepsilon^{-2} + \sigma_\eta^{-2} + \gamma^{-1}\sigma^{-2}}\right) x \tag{A.7}$$

$$+ \frac{\sigma_\eta^{-2}}{\sigma_\varepsilon^{-2} + \sigma_\eta^{-2} + \gamma^{-1}\sigma^{-2}} \eta \tag{A.8}$$

means that the proposition is true if the inequality

$$\left(1 - \frac{\sigma^{-2}}{\sigma_\varepsilon^{-2} + \sigma^{-2}}\right) < \left(1 - \frac{\gamma^{-1}\sigma^{-2}}{\sigma_\varepsilon^{-2} + \sigma_\eta^{-2} + \gamma^{-1}\sigma^{-2}}\right) \tag{A.9}$$

holds. The last expression can with a little algebra be rearranged to

$$\gamma^{-1} < 1 + \sigma_\eta^{-2} \tag{A.10}$$

which is always true since $\gamma > 1$ and $\sigma_\eta^{-2} > 0$. □

Appendix B. Deriving the linearized equilibrium conditions

[TBC]

Appendix C. Solving the model

[TBC]