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“Noisy Fiscal Policy”

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Abstract

This paper investigates the macroeconomic effects of fiscal policy in a setting in which private agents receive noisy signals about future shocks to government expenditures. We show how to empirically identify the relative weight of news and noise shocks to government spending and compute the level of noise for Canada, the UK and the US. We then investigate the quantitative implications of imperfect fiscal policy information using a medium-scale DSGE model. We find that when the government seeks to implement a persistent change in expected public spending, the existence of noise (as estimated using actual data) implies a sizable difference in fiscal multipliers compared to the perfect fiscal foresight case.

Keywords: Government spending, Noisy Information, DSGE Models

1. Introduction

A recent stream of literature has investigated the role of foresight in fiscal policy, which implies that the implementation of fiscal policy measures is lagged with respect to their announcement (see, e.g., Leeper, Walker,

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and Yang, 2013). This literature is concerned with the macroeconomic effects implied by the presence of fiscal policy news. For example, Schmitt-Grohé and Uribe (2012), Khan and Tsoukalas (2012) and Born, Peter, and Pfeifer (2013) find that news shocks explain a major portion of government spending fluctuations. Moreover, these studies find that news on government spending propagates significantly through the real economy: if one abstracts from other sources of aggregate fluctuations and considers government spending shocks in isolation, the expected components of government policies (i.e., news shocks) account for between 40% and 100% of the variance of GDP, and the remaining variance is attributable to unexpected government spending shocks.

News shocks are introduced in this literature by assuming that agents have perfect foresight about the size and the timing of future policy. However, recent influential contributions in macroeconomics have highlighted the role of imperfect information in business cycles. In particular, such findings are found in Lorenzoni (2009), which shows that imperfect information about aggregate productivity is a key source of cyclical fluctuation.

Given the considerable uncertainty surrounding the implementation of fiscal policy, it seems natural to extend the setup to imperfect information about news to the case of government spending. In this paper, we thus focus on the macroeconomic effects of noisy fiscal policy announcements. By noisy announcements, we mean the following: A policymaker announces a fiscal policy measure at a particular point in time that is supposed to come into effect at a future date, while private agents in the economy believe that the announcement may not be fully implemented. Partial implementation may be due to amendments that occur during the legislative process or to incomplete information about future states of the economy. As a consequence, the information structure we examine is different from previous papers in which future fiscal policy is fully predictable.

Thus, the main contribution of this paper is twofold: i) we quantify the size of noisy news using data from both forecasts and realizations of government spending; ii) we assess the effect of noise and its propagation through the economy using a medium-scale DSGE model with real frictions.

The main result of this paper is that a "noisy" announcement leads to an under-reaction of macroeconomic variables to the announcement itself. The values of the fiscal multipliers drastically fall compared to the full information case. We make use of the official government spending forecasts from the annual budgets of three countries (Canada, the United Kingdom and the United States) for which we were able to obtain enough information. We find that the amount of noise observed for these three countries is rather significant: the share of noise in these official government spending forecasts ranges from 28% in the US to 84% in the UK. When embedding these estimates into a full-fledged DSGE model, we find that in a "noisy" scenario, before news events are realized, the value of government spending multipliers, compared to the full information case, falls proportionally to the level of noise. Additionally, the effect of noise does not vanish with the occurrence of the fiscal shock. For example, in the UK, for which the relevance of noise is most compelling, we obtain a loss in the output multiplier of approximately 10% one year after the materialization of the news compared to the perfect information case. Such an effect is more pronounced for investment, even in economies in which the role of noise is limited; for example, for the US, which is the country with the lowest share of noise among those considered, we find that the loss in the investment multiplier one year after the realization of a news event remains at approximately 12%, a non-negligible figure.

Our work can thus be seen as an attempt to connect several bodies of literature. First, our paper is an extension of the literature on fiscal foresight. Notably, papers such as Ramey (2011) and Leeper, Walker, and Yang (2013) show the relevance of fiscal foresight and the perils econometricians face from ignoring it.[1] Such findings have been recently reinforced by Born, Peter, and Pfeifer (2013), which shows that all of the output variance generated by fiscal policies arises from news about government spending. We show that when imperfect information is included, the effects of fiscal foresight are drastically reduced.[2]

Other studies (Ellahie and Ricco, 2014; Ricco, 2014) introduce informa-

[1] An earlier attempt to introduce anticipated fiscal policy in an SVAR framework can be found in Tenhofen and Wolff (2007).

[2] A slightly different approach is pursued in Hollmayr and Matthes (2015), wherein uncertainty stems from the fact that agents learn whether shocks are temporary or permanent over time. This, of course, leads to an increase in the volatility of the macro variables over the short run compared with the case in which agents perfectly know the nature of the shock that is affecting the economy. A similar result can be found in our paper when the economy experiences a permanent fiscal shock. For a model of fiscal consolidation in which agents need to learn whether restrictive fiscal shocks are temporary or permanent over time, see Lemoine and Lindé (2015).

tional frictions in SVAR models, although no microfoundations for such frictions are provided. In particular, Ricco (2014) introduces a shock to agents' expectations, a so-called "misexpectation shock", into a rather standard fiscal VAR model. Such a shock is aimed at capturing "the differences between the agents' expectations about the current state of the economy and the ex-post revealed value of macroeconomic variables" (Ricco 2014, p.4). This shock is due to information frictions. The author finds that macroeconomic variables react to such shocks, albeit more moderately than to fundamental fiscal shocks. In our paper, we recover similar findings and provide a structural interpretation of agents' misexpectations.

Our approach is also partly related to a set of papers on fiscal policy uncertainty. One of these papers recently revived interest in fiscal uncertainty, Bloom, Baker, and Davis (2013), which empirically demonstrates the detrimental effects of fiscal uncertainty on macroeconomic variables. Fernández-Villaverde et al. (2011) instead develops a model in which the volatility of fiscal policy is assumed to be changing over time. Such a feature of fiscal policy leads to an increase in uncertainty and implies detrimental effects on both output and consumption. When monetary policy is stuck at the zero lower bound, such effects are reinforced. These findings are also shown in a New Keynesian model by Johannsen (2014). There are, however, three main differences between this strand of literature and our approach. First, from a methodological point of view, we provide a structural interpretation of fiscal uncertainty (i.e., for the lack of full information), whereas in the above-mentioned papers, uncertainty is modeled as an exogenous time variation in the volatility of model disturbances. Second, we focus on government spending rather than on taxes because introducing (distortionary) taxes would make our arguments slightly more opaque and because of the lower comparability of tax schedules across countries.[3] Third, the detrimental effects of uncertainty obtained in the above-mentioned papers are mainly related to precautionary savings motives that arise from the time-varying nature of the shocks' volatility. In the current paper, we instead focus on the first-order effects of uncertainty.

The idea that noise pollutes the impact of news shocks is not new in

[3]In an extension of our model (available upon request) with distortionary taxes on capital, we show that an announced increase in taxes on capital negatively affects both output and consumption. However, contrary to Fernández-Villaverde et al. (2011), the lack of information on news shocks in our model mitigates this negative effect.

macroeconomics. Indeed, a recent stream of literature has highlighted the problems with the identification of these two shocks, although the focus of this literature is on TFP shocks (Blanchard, L'Huillier, and Lorenzoni, 2013; Barsky and Sims, 2012 and Forni et al., 2014). With respect to this literature, our contribution is related not only to the introduction of noise in government spending but also to the identification procedure, which relies on the comparison of forecasts and realizations of the government spending process.

This paper proceeds as follows. In Section 2, we introduce the quantitative model and highlight its key items. In Section 3, we introduce our empirical methodology, while in Section 4, we estimate the amount of news and noise in the data. In Section 5, the results of the quantitative exercise are shown and discussed. Finally, Section 6 concludes.

2. The model

To investigate the quantitative properties of noisy fiscal policy we rely on a model with real frictions, along the lines of Mertens and Ravn (2011) and Chahrour, Schmitt-Grohé, and Uribe (2012). The main features of the model are described in the following sections.

2.1. Household and firm

There is a representative household maximizing

$$\hat{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{m_t^{1-\sigma}}{1-\sigma} - \omega \frac{n_t^{1+\kappa}}{1+\kappa} z_t^{1-\sigma} \right],$$

where $\beta \in (0,1)$ is the discount factor, $\sigma > 0$ is a parameter governing the elasticity of intertemporal substitution ($\frac{1}{\sigma}$), $\omega > 0$ is a scale parameter, and $\kappa \geq 0$ is the inverse of the Frisch elasticity of labor supply.

The variable z_t is an exogenous, deterministic process representing a labor augmenting technology that evolves according to

$$z_t = \gamma_z z_{t-1}.$$

The variable n_t represents hours worked, while m_t is a composite good made of both durable and nondurable goods

$$m_t = c_t^{\nu} v_t^{1-\nu} - b c_{t-1}^{\nu} v_{t-1}^{1-\nu},$$

where c_t and v_t are non-durable and durable goods, respectively, and $\nu \in [0,1]$ is a share parameter.

In each period the household budget constraint writes

$$c_t + x_t + d_t = w_t n_t + r_t u_t k_t + T_t,$$

where x_t and d_t are new purchases of capital and of durable goods, respectively.[4] Real wages are denoted w_t, returns on capital r_t and capital utilization u_t. Taxes T_t are levied in a lump-sum fashion. The respective laws of motion of capital and of durable goods are given by

$$k_{t+1} = \left[1 - \delta_k - \Psi_k\left(u_t\right)\right] k_t + x_t \left[1 - \Phi_k\left(\frac{x_t}{x_{t-1}}\right)\right]$$

and

$$v_{t+1} = \left(1 - \delta_v\right) v_t + d_t \left[1 - \Phi_v\left(\frac{d_t}{d_{t-1}}\right)\right].$$

We assume that Φ_k, Φ_v and Ψ are zero at the non-stochastic steady state and that Φ_k', Φ_v', Φ_k'', Φ_v'' and Ψ' are greater than or equal to zero.[5]

The firm maximizes its profits under a standard Cobb-Douglas production function

$$\begin{aligned} &\max_{n_t, k_t} y_t - w_t n_t - r_t u_t k_t \\ s.t. \quad & y_t = a\left(u_t k_t\right)^{\theta}\left(z_t n_t\right)^{1-\theta}. \end{aligned}$$

Given that the focus of this paper is on government spending shocks, we keep – without loss of generality – TFP, denoted a, fixed.

2.2. Government sector

The government budget is assumed to be balanced (i.e., $T_t = g_t$), with a government spending process that is exogenous and driven by news.[6]

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[4]In our model, durable goods do not play a specific role. We introduce them to keep our model as in line as possible with Mertens and Ravn (2011) and Chahrour, Schmitt-Grohé, and Uribe (2012).

[5]The functional forms we choose are $\Phi_k = \frac{\omega_i}{2}\gamma_z^2\left(\frac{x_t}{x_{t-1}} - 1\right)^2$, $\Phi_d = \frac{\omega_d}{2}\gamma_z^2\left(\frac{d_t}{d_{t-1}} - 1\right)^2$, and $\Psi = \psi_1\left(\nu_t - 1\right) + \frac{\psi_2}{2}\left(\nu_t - 1\right)^2$.

[6]As Ricardian equivalence holds in this setup, one could also introduce government debt, with the results being unaffected.

The process can be then written (in log-deviations from the steady state) as

$$\widehat{g}_t = \rho \widehat{g}_{t-1} + \varepsilon_{t-q} \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon^2), \tag{1}$$

where $|\rho| \leq 1$, and ε_t is a white noise shock to government spending with mean zero and variance equal to σ_ε^2. The exogenous fiscal policy shock is a news shock that appears with a lag equal to q periods.

Notice that government spending is modeled as a rather persistent AR(1) process. This modeling choice replicates the findings of several estimated DSGE models, where the autoregressive parameter for government spending found is very close to unity (e.g., Smets and Wouters (2007), Mertens and Ravn (2011), Khan and Tsoukalas (2012) and Schmitt-Grohé and Uribe (2012)), and is reinforced by the findings discussed in Section 3.

For sake of simplicity, we focus here on the case with a single news shock to government spending. More general representations (including multiple news shocks) are discussed in Leeper et al. (2013) and Beaudry and Portier (2014).[7]

Let us assume for simplicity that $q = 1$. Then, the timing of the shock is such that the new policy is known one period in advance. Such timing is used to illustrate the presence of noisy news. We will relax this assumption later by considering longer lags in the announced government spending policy and a more complex information structure. The new government policy expected in period $t+1$ is then given by

$$\hat{E}_t \widehat{g}_{t+1} = \rho \widehat{g}_t + \hat{E}_t \varepsilon_t.$$

If the change in government spending is perfectly anticipated by private agents, this equation reduces to

$$\hat{E}_t \widehat{g}_{t+1} = \rho \widehat{g}_t + \varepsilon_t \equiv \widehat{g}_{t+1}.$$

Thus, the expected change in government policy, represented by a news shock, is perfectly forecasted by private agents, i.e., they know the new government policy in advance. Here, we depart from this setup by assuming that private agents observe a noisy signal of ε_t (i.e., noisy news about government spending) from

$$s_t = \varepsilon_t + \nu_t, \tag{2}$$

[7] See also, the discussion about identification with multiple news events in the next section.

where ν_t represents a noise shock. This variable is assumed to be a zero mean white noise with variance σ_ν^2, and it is uncorrelated with ε_t for any time index. If the endogenous variables of the model react to noise, then the economy displays sunspot-like fluctuations, as it is affected by shocks that are unrelated to fundamentals. This noise shock is of central interest in the following sections. It represents how the private sector anticipates the way that government policy is conducted.

Such noise is meant to capture the complex political process that leads to policy changes, as well as political economy considerations. For example, such a setting could capture a situation wherein a policymaker announces measures that can be partially eliminated during the legislative process (for example, because of a different majority in parliament).

If the volatility of ν_t is negligible with respect to ε_t, private agents would react immediately to news in the government policy. In this case, the private sector perfectly foresees how an announced government spending policy will be conducted. If the signal is noisy, this is no longer the case. Indeed, expectations of the new policy are corrupted because private agents do not react perfectly to the announcement about government spending in such an environment.

In this imperfect information case, the conditional expectations of private agents are given by

$$\hat{E}_t \varepsilon_t = \alpha s_t \equiv \alpha \left(\varepsilon_t + \nu_t \right),$$

where the parameter α is obtained from a linear projection of ε_t on s_t (see Hamilton 1994a)

$$\alpha = \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_\nu^2}.$$

When information is perfectly transmitted to private agents in the economy ($\alpha = 1$ and $\sigma_\nu = 0$), they fully incorporate the announced government policy in the next period, so they can immediately adjust their consumption and labor supply decisions to the new economic conditions. Conversely, when the announced policy is completely noisy ($\sigma_\varepsilon / \sigma_\nu \to 0$ and $\alpha \to 0$), they will not react, as their expectations are insensitive to the new policy.

Before calibrating and solving the model, we describe the methodology used to extract both news and noise from the data, we then discuss the results of our estimation.

3. Identifying news and noise from government spending forecasts

In this section, we will discuss our empirical methodology for recovering the relative contributions of news and noise using both realizations and expectations of government spending. Instead of using a full information estimation technique that requires us to solve and estimate a DSGE model with noisy news shocks and other disturbances, we propose a simple limited information approach that only exploits data for actual realizations and forecasts of government spending. In addition to its simplicity, an advantage of this procedure is that the estimation does not depend on the specification of the whole DSGE model. As most of the data we consider are available at an annual frequency, we will also propose a method to recover the parameters at a quarterly frequency.

3.1. Methodology

The methodology we rely on for recovering α is an application of the method of moments, with targeted moments being derived by comparing the agents' forecasts and actual government spending.

To start, assume that government spending obeys process (1) with $q \geq 1$. Also suppose that agents observe $\widehat{g}_t$ and a signal as in (2) from which they infer the value of ε_t. Regardless of the value of q, the econometrician has enough information to estimate ρ and σ_ε^2 from the observation of $\widehat{g}_t$.

Additionally, the agents' forecasts will be

$$\hat{E}_t \widehat{g}_{t+1} = \rho \widehat{g}_t + \hat{E}_t \left[\varepsilon_{t-q+1} | S_t \right] \equiv \rho \widehat{g}_t + \alpha s_{t-q+1},$$

where

$$\alpha = \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_\nu^2}$$

and

$$S_t = \left\{ s_t, s_{t-1,\ldots} \right\}.$$

We can then make use of these forecasts to estimate the variance of noise by computing the one-period-ahead forecast net of the autoregressive component

$$\hat{E}_t \widehat{g}_{t+1} - \rho \widehat{g}_t = \alpha \left(\varepsilon_{t-q+1} + \nu_{t-q+1} \right) \tag{3}$$

and then taking the variance of such an object

$$V_1 \equiv V \left(\hat{E}_t \widehat{g}_{t+1} - \rho \widehat{g}_t \right) = \alpha^2 \left(\sigma_\varepsilon^2 + \sigma_\nu^2 \right) = \frac{\sigma_\varepsilon^4}{\sigma_\varepsilon^2 + \sigma_\nu^2} \tag{4}$$

from which we derive σ_ν^2

$$\sigma_\nu^2 = \frac{\sigma_\varepsilon^2 \left(\sigma_\varepsilon^2 - V_1\right)}{V_1}.$$

From the inspection of (4), notice that $\sigma_\varepsilon^2 > V_1$. Note that this moment does not depend on the lag q of the announcement: this property allows us to recover α.[8] Once we have α and ε_t, we can directly recover the noise ν_t from (3).

An equivalent way to estimate α relies on performing a linear projection of the forecast error in (3) on the realization of the shock $\widehat{g}_{t+1} - \rho \widehat{g}_t = \varepsilon_{t-q+1}$

$$\frac{Cov\left(\varepsilon_t, \alpha s_t\right)}{Var(\varepsilon_t)} = \alpha,$$

where the residual of this OLS regression of αs_t over ε_t is equal to $\alpha \nu_t$, so the time series of ν_t is also easily recovered. An interesting observation comes from the fact that the R^2 of the regression is equal to α. This means that when the signal is not very noisy (i.e., $\sigma_\nu \to 0$), a good inference can be made concerning the fundamentals of the economy. However, when the signal is extremely noisy (i.e., $\sigma_\nu \to \infty$), no inference can be made.

3.2. Discussion

Two remarks on the suggested methodology are in order. First, note that the above identification strategy crucially relies on the fact that the information set of the agents and that of the econometrician do not coincide. On the one hand, the econometrician does not directly observe the signal and therefore has to recover it indirectly from agents' expectations. On the other hand, the econometrician observes the future realizations from the actual government spending process, which are unknown data when the agents produce their forecasts. Hence, by comparing the outcome with the agents' forecasts, the econometrician is able to recover α.

Second, note that the estimation procedure for α can be polluted by model misspecification. We discuss three types of misspecification in the following paragraphs.

[8] We acknowledge, however, that this is not a general result. This property is obtained here because we consider a single news shock. With multiple news shocks and signals, the estimated α is polluted by the signals. See the discussion below.

Expected and unexpected fiscal shocks. A first type of misspecification may arise if the true government spending process includes an expected and an unexpected component

$$\widehat{g}_t = \rho \widehat{g}_{t-1} + \epsilon_{t-q} + \eta_t,$$

with $\eta_t \sim N(0, \sigma_\eta^2)$. We will prove that ignoring the unexpected component of government spending leads to estimating an upper (lower) bound for the role of noise (news).

Suppose that the econometrician mistakenly ignores η_t and instead tries to estimate the model as in (1): she will then mistakenly treat the two shocks $\eta_t + \varepsilon_{t-q}$ as a single shock (denoted w_t). The variance of estimated news will be $\sigma_w^2 = \sigma_\eta^2 + \sigma_\varepsilon^2$. However the variance of the forecast, net of the autoregressive component, $\hat{E}_t \widehat{g}_{t+1} - \rho \widehat{g}_t = \alpha s_{t-q+1}$ is equal to $\alpha \sigma_\varepsilon^2$. Dividing this variance by the variance of estimated news yields the misestimated level of α

$$\tilde{\alpha} \equiv \frac{\alpha \sigma_\varepsilon^2}{\sigma_w^2} \equiv \alpha \frac{\sigma_\varepsilon^2}{\sigma_\eta^2 + \sigma_\varepsilon^2} \leq \alpha,$$

where it can be seen that the lower the relative share of the expected component in government expenditure, the smaller the estimated α and the more relevant the misspecification bias.

Such misspecification, however, should not be troublesome in practice because Born, Peter, and Pfeifer (2013) show that the quantitative relevance of unexpected shocks to government spending is extremely limited, while almost all of its variance is due to expected shocks (and thus, $\tilde{\alpha}$ is very close to the true noise-to-signal ratio).

Multiple noisy news. A different misspecification issue arises in if there are multiple noisy news. For clarity, we restrict our attention here to the case of two noisy news, although the argument can be easily made more general. Consider the government spending process

$$\hat{g}_t = \rho \hat{g}_{t-1} + \varepsilon_{1,t-1} + \varepsilon_{2,t-2},$$

where $\varepsilon_{1,t-1}$ and $\varepsilon_{2,t-1}$ have mean zero and variances $\sigma_{\varepsilon,1}^2$ and $\sigma_{\varepsilon,2}^2$, respectively. They are also uncorrelated. Private agents receive a noisy signal ($s_{1,t}$, $s_{2,t}$) for each news shock. The challenge here is to identify five parameters: ρ, $\sigma_{\varepsilon,1}$, $\sigma_{\varepsilon,2}$, α_1 and α_2 (or equivalently, $\sigma_{\nu,1}$ and $\sigma_{\nu,2}$). However, identifying all the parameters is not possible: our limited information approach has the advantage of being able to identify noisy news without specifying a whole model, but with the disadvantage that it uses too little information to estimate a richer specification of government spending. Identification can be achieved only if we impose some restrictions on the noise parameters.[9]

Also of interest is the case when the true model is composed of two noisy news shocks but the econometrician attempts to estimate the process as in (1). Direct computations yield

$$\tilde{\alpha} = \alpha_1 \omega + \alpha_2 (1 - \omega),$$

where

$$\omega = \frac{\sigma^2_{\varepsilon,1}}{\sigma^2_{\varepsilon,1} + \sigma^2_{\varepsilon,2}}$$

is the fraction of the variance of government spending explained by the news shock $\varepsilon_{1,t-1}$. It appears that our procedure correctly identifies the true noisy news if $\omega \to 1$ (i.e., the news shock $\varepsilon_{1,t-1}$ explains most of the variance of government spending) and/or $\alpha_1 \simeq \alpha_2$. Conversely, if the noisy structures are significantly different ($\alpha_1 \neq \alpha_2$) and the news shock $\varepsilon_{2,t-2}$ is the main driver ($\omega \to 0$), the procedure will correctly identify the value of α_2 but will fail to identify the true number of lags. However, note that the estimation results in Born, Peter, and Pfeifer (2013) indicate that among the news shocks, only the news shock with the longest delay matters, meaning that we can reasonably restrict our analysis to a single news shock.

Misspecification of the Autoregressive Process. Thus far, we assumed that the AR(1) process for government spending is the true process. One may wonder how our estimate of α is affected by a misspecification of the autoregressive process. Let us then assume that the true data generating process (DGP) is an AR(2) process

$$\hat{g}_t = \rho_1 \hat{g}_{t-1} + \rho_2 \hat{g}_{t-2} + \varepsilon_{t-1},$$

[9] For example, if we assume the same signal structure for both news processes ($\sigma^2_{\varepsilon,1} = \sigma^2_{\varepsilon,2} = \sigma^2_{\varepsilon}$ and $\sigma_{\nu,1} = \sigma_{\nu,2} = \sigma_{\nu,}$), then it is possible to retrieve the model parameters using our simple method of moments for realizations and expectations.

where $\rho_1+\rho_2<1$, $\rho_2-\rho_1<1$ and $|\rho_2|<1$ to satisfy stationarity conditions. Suppose that we wrongly assume that government spending follows an AR(1) process. Some tedious calculations[10] yield the estimated value of α in the misspecified AR(1) model under the true DGP

$$\widetilde{\alpha}=\mu_1\left(\mu_0+\alpha\right),$$

where

$$\begin{aligned}
\mu_0 &= \frac{\rho_2^2}{1-\rho_2^2};\\
\mu_1 &= \left(\frac{1+\rho_2}{1-\rho_2}\right)\left(1-\rho_2\left(\frac{1-\rho_1-\rho_2}{1-\rho_2}\right)\right)\left(1-\rho_2\left(\frac{1+\rho_1-\rho_2}{1-\rho_2}\right)\right).
\end{aligned}$$

The estimated value $\widetilde{\alpha}$ is a biased estimate of the true α unless $\rho_2\neq 0$. When $\rho_2\to 0$, $\mu_0\to 0$ and $\mu_1\to 1$, the bias tends to zero. There is no trivial characterization of this bias with respect to ρ_1 and ρ_2, but we can consider a simple illustrative example[11] that highlights the consequence of misspecification for the estimation of α. We set $\rho_1=0$, and then, ρ_2 can vary between -1 and 1. In this case, the estimation of α from the misspecified AR(1) model is given by

$$\widetilde{\alpha}=\rho_2^2+(1-\rho_2^2)\alpha.$$

When $\rho_2\to\pm 1$, the estimated value tends to one, and thus, we will incorrectly conclude that there is no noise in government spending policy. For any value of $\rho_2\neq 0$, the estimation of the misspecified AR(1) model can yield $\widetilde{\alpha}>\alpha$; thus, we wrongly underestimate the size of the noise.

To address this misspecification issue, in what follows, we model government spending as an AR(1) process. As discussed, such a choice is not only in line with the literature but also with the evidence at our disposal. Indeed, if one takes the quarterly detrended log-series of real per capita government spending in the US (from 1952Q1 to 2014Q1), the AR(1) will be, among the ARMA(*p*,*q*) processes, selected using the Bayesian Information and Hannan-Quinn criteria.[12] The above evidence is also supported

[10]See Appendix A.

[11]See Appendix A.2 for another illustration of misspecification.

[12]If one were to use the Akaike Information Criterion (AIC), the chosen process would

by the shape of the partial autocorrelation function, where the strong autocorrelation that emerges at a one-quarter lag suddenly disappears from two lags on, whereas the same function computed on Δg_t shows that this latter process has no significant autocorrelation at any lag (see Figure B.9 in Appendix B).

3.3. Recovering quarterly series

Most of the series we address are available at a yearly frequency, while most of the literature examines quarterly frequency data. Thus, a further step is needed to convert our annual data into quarterly data. To do so, once the yearly parameters have been recovered, we make use of an indirect inference algorithm (Smith, 1993) to obtain comparable moments at a quarterly frequency.[13] The algorithm essentially generates simulated quarterly series for actual (with news) and expected (with news and noise) government spending whose moments, aggregated at a yearly frequency, yield the the same moments observed in the data. The outcome of the algorithm is a so-called "binding function" that links the α computed at a yearly frequency with parameters computed at a quarterly frequency. The function, reported in Figure B.10 in Appendix B, is increasing in both the autoregressive parameter and in the share of news in the signal. Note, however, that the higher the value of ρ, the flatter the function becomes in the value of α at an annual frequency. This implies that in such a case, two close annual estimates of α may lead to significantly different quarterly estimates of α.

In what follows, we apply the methodology described above to Canada, the United Kingdom and the United States.

4. Estimation results

In this section, we identify the relative importance of noise and news in the data, making use of the official government spending forecasts reported in the annual budgets of Canada, United Kingdom and United

be the ARMA(5,2). The AIC function, however, is very flat for processes with autoregressive parameters between 1 and 5. Additionally, the AIC results should be treated with caution given the well-known fact that this criterion is not consistent (see Lütkepohl 2005).

[13]Note that if we were to resort to usual temporal disaggregation techniques, we would obtain smooth time series in which the role of noise is significantly reduced.

States as the primary data sources. For the US case, we also refer to another source of government spending forecasts, the Survey of Professional Forecasters (SPF), as a robustness check[14]. The output of our moments comparison exercise for these three countries is summarized in Table 1.

Country	Annual		Quarterly	
	ρ	α	ρ	α
Canada (Budget)	0.86	0.70	0.95	0.23
	(0.016)	*(0.039)*	*(0.011)*	*(0.010)*
UK (Budget)	0.84	0.66	0.94	0.16
	(0.017)	*(0.024)*	*(0.012)*	*(0.007)*
US (Budget)	0.85	0.89	0.94	0.72
	(0.018)	*(.045)*	*(0.012)*	*(0.032)*
US (SPF)	0.97	0.84	0.99	0.52
	(0.009)	*(0.036)*	*(0.007)*	*(0.055)*

Table 1: Estimated values of α and ρ at annual and quarterly frequencies.

Note: Bootstrapped standard errors based on 1000 replications of the residuals are reported in parentheses.

4.1. Canada

For Canada, we collect data from the annual federal budgets from 1968 to 2012. In Canada, the budget - which defines the budget plan for the next fiscal year (FY) - is usually presented to parliament between January and June. The FY in Canada starts on April 1st and ends on March, 31st of the next calendar year. The variable that we track was called "Budgetary Expenditures" until 1982. Since 1987, it has been called "Program Expenditures" (data from 1983 to 1986 are missing and have thus been interpolated via cubic splines). This broad item includes all government outlays net of servicing or repayment of debt.[15] We complement such series with their one-year-ahead forecasts, as reported by the government in its budget.

[14] See Appendix F for the data sources.

[15] It would have been desirable to analyze more narrow series for government consumption and investment, but the lack of available data led us to use the above-described series.

We divide both series by population and by the GDP implicit price deflator and then detrend them with a linear trend. The population series was first disaggregated at a quarterly frequency using standard disaggregation techniques[16] and then aggregated at a FY frequency. The resulting series of actual expenditures along with the one-year-ahead forecasts are reported in Figure B.11 in Appendix B.

The estimated process is fairly persistent ($\rho = 0.86$), while the share of news in the signal is approximately 70%. When translated into quarterly frequency, we obtain $\rho = 0.95$ and $\alpha = .23$. The dynamics of news and noise are reported in Figure 1. A reduction in news and noise volatility is observed during the 90s in conjunction with the start of the so-called "Great Moderation", while no significant increase in volatility is recorded at the time of the global financial crisis. Such a result is consistent with the narrative that Canada was among the few developed countries not significantly impacted by the global financial crisis. Thus, no specific fiscal actions (i.e., neither stimulus nor austerity measures) were implemented by policymakers due to the crisis.

4.2. United Kingdom

To identify the contribution of news and noise in government spending for the UK, we use the historical official forecasts database made available by the Office for Budget Responsibility.[17] This database collects the forecasts made for each year's budget as presented by the government, which usually occurs in March for the following FY.[18] We focus on forecasts for total managed expenditures (TME), which is a broad measure of total government spending in the UK that includes public sector current expenditures, public sector net investment and depreciation, transfers and debt servicing. The forecasts are available for FY 1989-90 to FY 2012-13.

We also collect data on actual TME. This series is available at annual frequency from FY 1946-47 to FY 2012-13.

We first divide this series by a price index to obtain the variables expressed in real terms.[19] Then, we detrend them by a linear trend and

[16] We use the "tempdisagg" package in R using the Denton-Cholette disaggregation method.

[17] See http://budgetresponsibility.org.uk/data.

[18] In the UK, the FY starts in April and ends in March of the next calendar year.

[19] We make use of the GDP deflator from 1955 to 2012, while from 1946 to 1954, we make

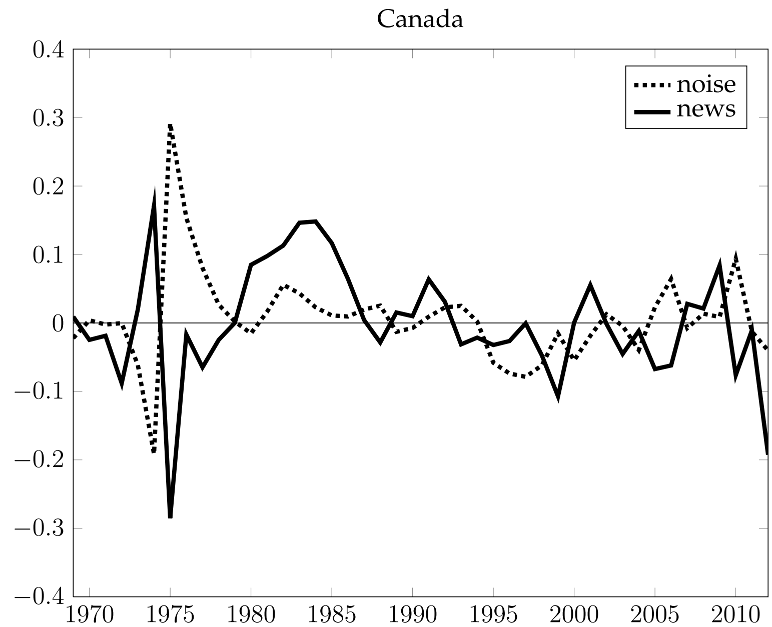

Figure 1: Dynamics of news and noise in Canada

Note: This figure plots the estimated dynamics of news and noise in the Canadian data.

compute the autoregressive parameter and the variance. The estimated autoregressive parameter is 0.84, a value that is very similar (0.94), when converted to quarterly frequency, to the value obtained for Canada. The value of α at an annual frequency is estimated to be 0.66, thus implying a higher share of noise in the signal than in the Canadian data. This implies an even smaller value for α at a quarterly frequency (0.16). It should be stressed, however, that such a value may also be affected by the short series available (23 years). This limitation notwithstanding, a reduction in news and noise can be observed from 2000 to 2009 (see Figure 2), while an increase in volatility can be observed more recently, possibly related to the adoption of tighter fiscal policy by the UK government.

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use of the long-term indicator of consumer goods and services prices (source: ONS).

United Kingdom

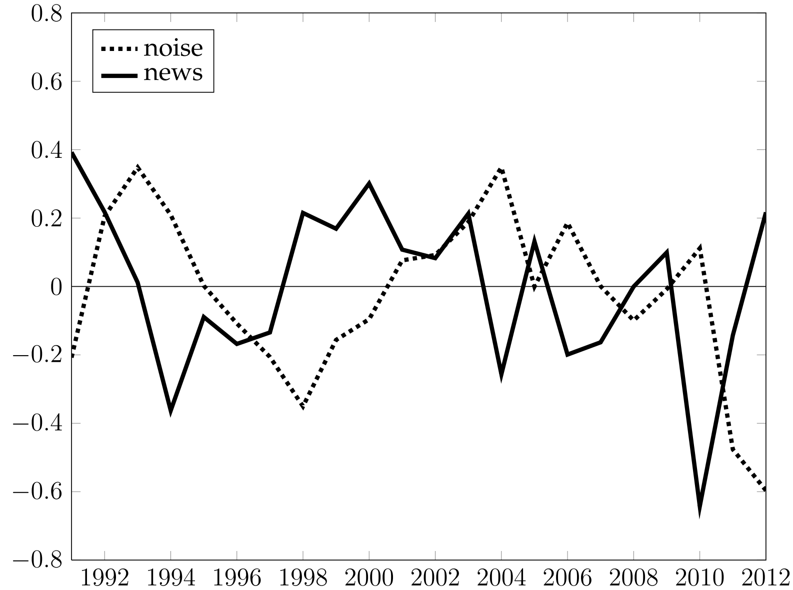

Figure 2: Dynamics of news and noise in the United Kingdom

Note: This figure plots the estimated dynamics of news and noise in the UK data.

4.3. United States

To estimate news and noise in US government spending, we use two distinct datasets. Our main reference will be the annual federal budgets, but we also use SPF data, which allows to perform some robustness checks.

4.3.1. Budget data

We first gather data on actual and forecasted "Total Budget Outlays" extracted from the US federal budgets from 1968 to 2013. The series displays a degree of persistence broadly in line with that observed for Canada and the UK ($\rho = 0.85$ at an annual frequency, $\rho = .94$ at a quarterly frequency). However, the share of news in the signal the agents receive is higher than in the previous cases, approximately 0.89 at an annual frequency, which implies $\alpha = 0.72$ at a quarterly frequency. As can be observed in Figure 3, the volatility of news and noise sharply has increased in recent years, especially in 2009 (possibly due to the enactment of the American Recovery and Reinvestment Act), 2010 and 2012.

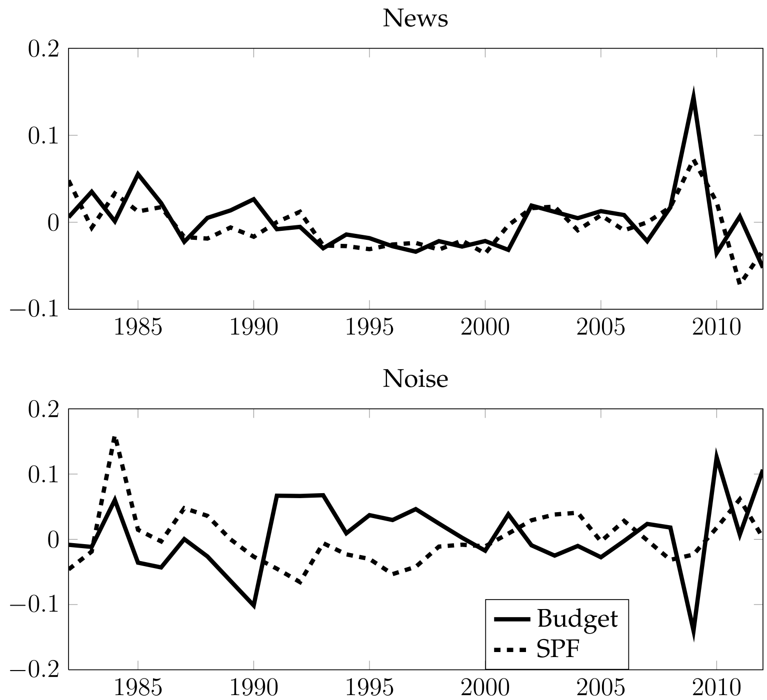

Figure 3: Dynamics of news and noise in the US

Note: This figure plots the estimated dynamics of news and noise in US budget data and annualized SPF data.

4.3.2. Survey of Professional Forecasters

We complement the above findings using an alternative source of quarterly government spending data, the SPF. The item we focus on is the median forecast of real federal government consumption expenditures and gross investment (the variable RFEDGOV). The information structure of the SPF is as follows. Forecasters are provided with information about the realization in the preceding quarter; hence, they know g_{t-1}. They receive a questionnaire at the end of the first month of quarter t, which they submit by the middle of the second month of period t. It is fair to assume that they have noisy information about g_t, whose preliminary estimate will only be available in the future, that is, at the end of t. Therefore, we consider forecasts of g_t that are made in period t to be noisy. In this way, we access forecasts up to five periods ahead.

As the government spending series in the SPF has been subject to several revisions, we rebase the series on the NIPA federal government current receipts and expenditures series divided by the CPI. Both the actual series and the forecasts are then detrended by a linear trend. Table 1 reports the results of the estimation procedure. The autoregressive parameter is very persistent and close to 1 (it is .987). The variances of the news and noise shocks are very close, thus implying that $\alpha = 0.52$. Compared to the estimates obtained from budget data, the degree of persistence is higher, while the share of news in the signal is lower. This suggests that agents in the economy perceive fiscal policy as being more noisy than it really is. Overall, the SPF data confirm the robustness of our findings. In Figure 3, we plot the annualized series of news and noise shocks as identified using the budget data and the SPF data. The news series is very similar across these two datasets. For the noise series, notice that they qualitatively capture the same dynamics, especially during the 80s. Such a result seems to confirm the robustness of the estimation exercise, taking into account that the datasets are related to different time series, computed at different frequencies and over time spans that only partially overlap.

On the rational expectations hypothesis. As an aside, it is worth noting that implicit in our methodology is an assumption of rational expectations. In other words, we assume that forecasts are unbiased and efficient.[20] To support this assumption, we checked our dataset to determine whether the forecast errors ($E_{t-1}g_t - g_t$) indeed have a zero mean and whether their distribution is not skewed or normal. If forecast errors have zero mean, then the forecasts are, on average, unbiased. The results of these tests are reported in Table D.3 in Appendix D. The hypothesis of a zero mean for the forecast errors is confirmed across all countries at a 95 percent confidence interval. The skewness of distribution of the forecast errors is examined using the D'Agostino skewness test, whose null hypothesis implies that the data are not skewed. The results of the test confirm that the UK and US data do not display a significant degree of skewness, whereas the null

[20]We are aware of potential issues related to bias in both forecasts and data revisions, but we decided to rely on the assumption of rational expectations for two reasons. First, we deem the costs of departing from this hypothesis (in terms of both the number of degrees of freedom for the underlying assumptions and the complexity of the empirical approach) to outweigh the benefits. Second, as discussed next in the text, our dataset seems to satisfy, overall, the rational expectations hypothesis, which is in line with the findings of Pesaran and Weale (2006).

hypothesis for Canada is rejected.[21] The normality test performed via the Jarque-Bera test, indicates that the forecast errors computed on UK and US budget data are normally distributed, while the errors for Canadian budget data and US SPF data are not. Overall, these findings suggest that the distribution of forecast errors is centered at zero and not skewed. Therefore, at a minimum, they imply that the rational expectations hypothesis cannot be discarded.

4.3.3. Robustness checks using SPF data

The quarterly frequency of the SPF data allows us to perform further robustness checks on the possible endogeneity of noise. Indeed, one may claim that what we have labeled "noise" so far could be mere model misspecification that arises from ignoring the endogenous response of fiscal policy to macro variables. Therefore, we assume that the government spending rule is of the kind

$$g_t = \rho g_{t-1} + \gamma X_t + \varepsilon_{t-q}, \tag{5}$$

where X_t is a measure of economic activity such as real per capita GDP (in log-deviation from a linear trend) or the level of detrended TFP.[22]. Alternatively, X_t may be a dummy for NBER recession dates or for the political party in power during period t. The former aims to control for structural differences in the path of government spending during recessions, while the latter aims to control for different political spending styles. To estimate news and noise in such a model, we need to observe $\hat{E}_t X_{t+1}$. To maintain tractability, we use the realization of X_{t+1} (thus assuming perfect foresight of this variable).

We then estimate both OLS regressions and IV regressions (using the one-period lag of X_t as the instrumental variable) for equation (5) and

[21] More precisely, the forecast errors for Canada display negative skewness, thus indicating that realizations of government spending tend to outperform forecasts – although, on average, the forecast error is zero. However, a close inspection of the Canadian time series reveals that the skewness is due to two data points (related to the years 1974 and 1975). If one removes these two points from the series, the null hypothesis for skewness is confirmed.

[22] The source for this GDP data is the US Bureau of Economic Analysis, while for TFP, the source is the Federal Reserve of San Francisco (see http://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/)

report the results in Table 2. In all these cases, we obtain a level of noise that is similar to the process without an endogenous component. These findings thus confirm that the source of noise in the data is outside the model.

Endogenous component	GDP		TFP		NBER recessions	Democrat Republican
	OLS	IV	OLS	IV	OLS	OLS
ρ	0.9862	0.9858	0.9856	0.9856	0.9859	0.9860
	(0.0095)	*0.0095)*	*(0.0108)*	*(0.0108)*	*(0.0095)*	*(0.0095)*
γ	0.1084	-0.0569	0.0004	0.0004	-0.0039	0.0008
	(0.0748)	*(0.0831)*	*(0.000)*	*(0.0002)*	*(0.0035)*	*(0.0056)*
α	0.52	0.54	0.56	0.56	0.51	0.53
	(0.0463)	*(0.0563)*	*(0.0582)*	*(0.0567)*	*(0.0505)*	*(0.0543)*

Table 2: Estimates of α with endogenous components in the spending rule.

Note: In the IV regressions, we use lagged realizations of X_t as instruments. Standard errors are reported in parentheses. Standard errors for the α parameter are obtained through a bootstrapping procedure based on 1000 replications of the residuals.

To check the goodness of fit of our approach, we also simulated data (see Table D.4 in Appendix D). More precisely, we modified our DSGE model by introducing an endogenous government spending rule as in (5) with the log of detrended GDP on the right-hand side. The parameters were calibrated on the IV regression with GDP.[23] We then generated simulated data for 1000 periods from the model assuming that news and noise shocks were the only sources of economic fluctuation and estimated the regressions using these simulated data to determine whether the true parameters could be recovered. The results reported in Table D.4 show that the values of the parameters estimated via an IV approach are close to the values of the true parameters. Interestingly, given that the feedback coefficient is found to be non-significant in the IV regression, a simple AR(1) estimation would be able to generate values for ρ and α that are very close to the true values.

[23]Therefore, the parameters were set as follows: $\rho = 0.9858$, $\gamma = -0.0569$ and $\alpha = 0.54$.

5. Quantitative results from the DSGE model

The model is log-linearized around the non-stochastic steady state and solved using standard methods. The values of the parameters, which are reported in Appendix C, are taken from Mertens and Ravn (2011) and Chahrour, Schmitt-Grohé, and Uribe (2012), with the notable exception of the parameters related to government spending and information flows. Although the parameters in the original Mertens and Ravn (2011) paper were estimated using US data, we apply the same calibration to the UK and Canada to compare their output with that of the US model. Furthermore, to make the results comparable across countries, and because the augmented Dickey-Fuller and Phillips-Perron tests do not reject the unit root hypothesis, we conduct simulations for these countries setting the autoregressive parameter of government spending equal to 1. Note, however, than none of our qualitative results is due to the fact that we assume that $\rho = 1$ in the government spending process. The quantitative results do not change significantly as long as the government spending process displays enough persistence.[24] Lastly, for comparability we set $q = 4$ for all countries, a fairly conservative value in line with the literature on fiscal news (Born et al. 2013,Leeper et al. 2013, Mertens and Ravn 2011 and Schmitt-Grohé and Uribe 2012).

5.1. Inspecting the mechanism

Before comparing the outcomes of the model under the estimated values of α, Figure 4 plots the IRFs for output, non-durables, durable goods and investment reactions to a news and a noise shock in a fictitious case wherein the amount of noise is equivalent to the amount of news (i.e., $\alpha = .5$). Note that output jumps up in period 4 only if the announced increase in government spending actually takes place; if the announcement turns out to be pure noise it means that no actual spending occurs. As expected, the shapes of the IRFs are the same for noise and news until the shock actually occurs. This similarity is due to the fact that agents in this economy are not able to identify the source of the variation in the signal. An important corollary is that choice variables also react to a noise shock until the news event is realized. Moreover, noise shocks affect real

[24] For a discussion of the macroeconomic role of government spending persistence, see Dupaigne and Fève (2015).

variables even after their non-fundamental nature is revealed. In other words, when an announcement is at least partially noisy (i.e., $\alpha > 0$), an announced increase in government spending is able to generate a positive response of output even if the positive signal is due entirely to noise.

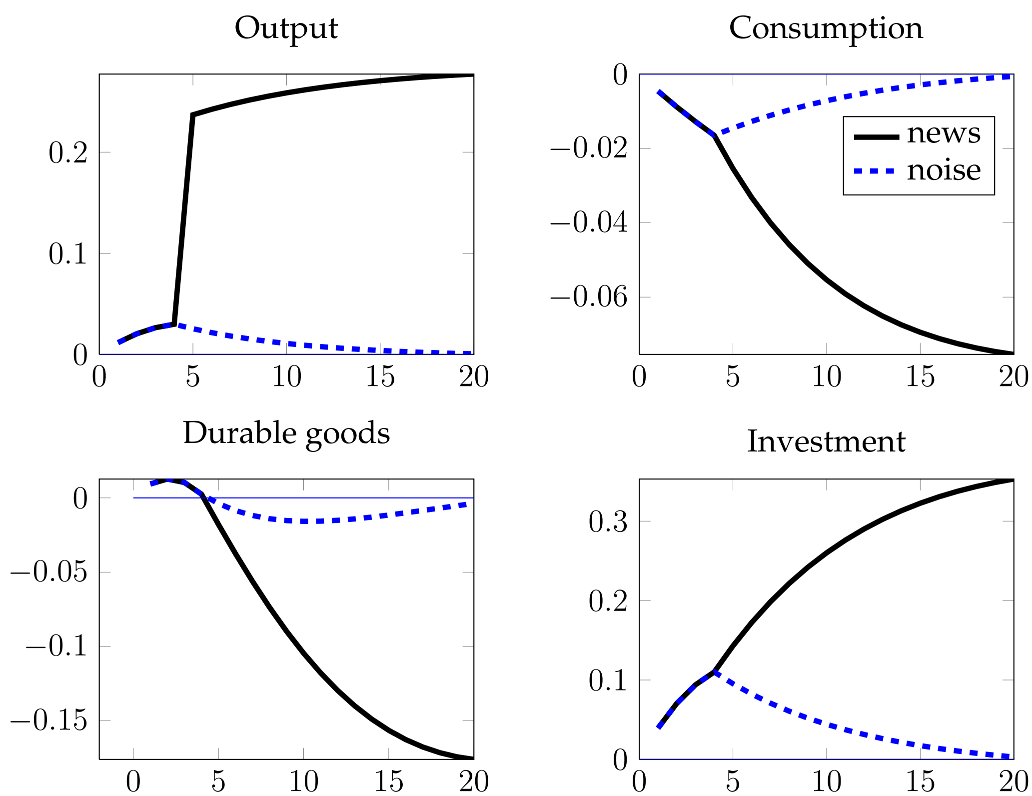

Figure 4: IRFs for output, consumption, durable goods and investment to a noise and a news shock

Note: This figure plots the IRFs for output, non-durables consumption, durable goods consumption and investment (as percentages) to a 1 percent shock to government spending under a mild level of noise ($\alpha = 0.5$).

The long-lasting effect of noise can be gauged by performing a variance decomposition of news and noise shocks at different horizons for the above variables. These results are plotted in Figure 5. Noise still explains approximately 20 percent of the investment variance after 10 periods while the percentage is a bit lower for consumption of both non-durable and durable goods. The variance of output is much less affected by noise after that noise is revealed. This pattern is due to the fact that output is the sum of consumption, durables, investment and government spending, and this latter variable (which exhibits no variance before period 5) is not affected by noise.

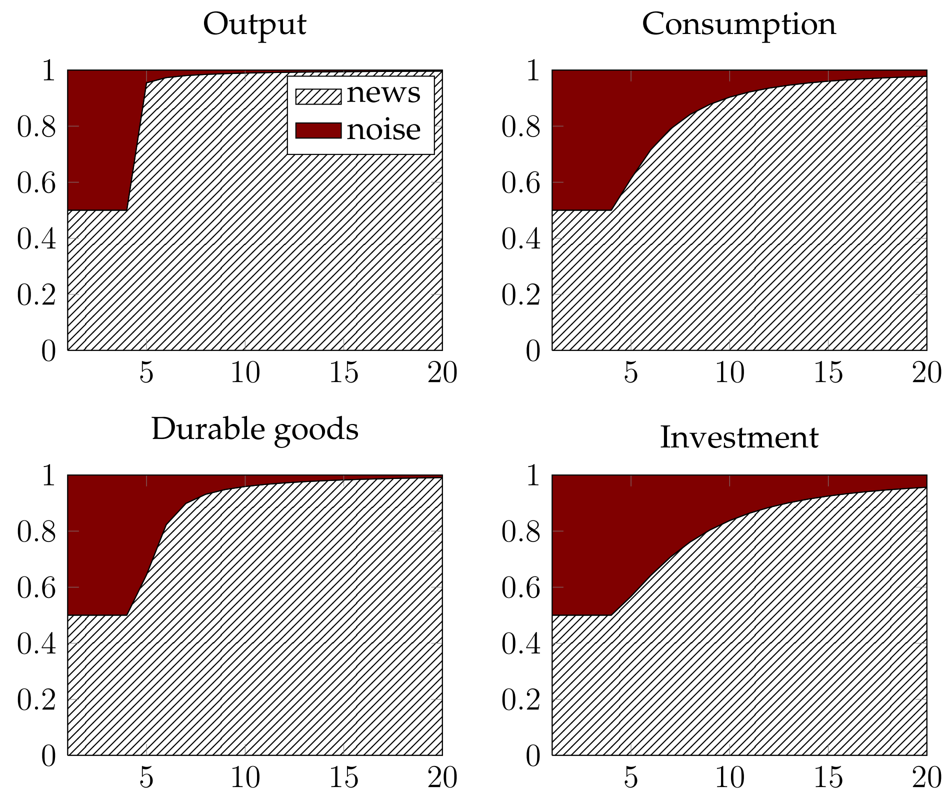

Figure 5: Conditional variance decomposition of news and noise shocks at different horizons

Note: This figure plots the conditional variance decomposition of news and noise shocks at different horizons for output, consumption of non-durables, consumption of durable goods and investment under a mild level of noise ($\alpha = 0.5$).

5.2. Quantifying the effect of noisy news

We investigate the quantitative impact of noise by comparing the IRFs for a news shock under different assumptions about the information flow.

More precisely, we compare the outcome of an economy under perfect information about government spending ($\alpha = 1$) to one under the parametrization implied by the estimated noise to signal ratio in Table 1. For the value of α in the US, we rely on budget data for consistency with the UK and Canada datasets, which are also based on budget data. The results of this exercise are reported in Figure 6.

Note that the main role played by noise is to mitigate the dynamics of the variables. Additionally, due to real rigidities, even after the shock is realized, agents' reactions tend to lag behind the reaction observed under perfect information. Comparing the outcomes under partial information, the response of the UK and Canada are similar, while as expected, the reaction of the US is closer to the full information benchmark.

In Figure 6, the variable that reacts the most is investment. This result is much in line with the view of news shocks as an inducer of "animal spirits" (see Beaudry and Portier 2014) and is related to the fact that investment is a forward-looking variable mainly because it cannot immediately adjust to external shocks. However, the presence of noise dampens the adjustment of investment. As for consumption and durable goods, investment under-reacts until the uncertainty is resolved (in period 5), and then, a phase of gradual catch-up to the perfect information case occurs.

We now address the issue of quantifying the impact of noise on some measures of fiscal multipliers. First, note that over the long run, the economy is not affected by imperfect information: the long-run multiplier for output, defined as the relative variation in the steady states of output and government spending after a persistent government spending shock, is equal to 1.35, irrespective of the severity of the information issue because when the news shock is realized, agents will be able to infer it from the dynamics of government spending and will thus gradually adjust their choices. Over the short to medium run, however, the picture can substantially change due to the frictions generated by imperfect information.

To quantify the impact of information frictions on the transmission of fiscal policy shocks, we compute two measures of the government spending multipliers for output, consumption and investment.[25] The first one is

[25]Multipliers for durable goods are reported in Appendix B.

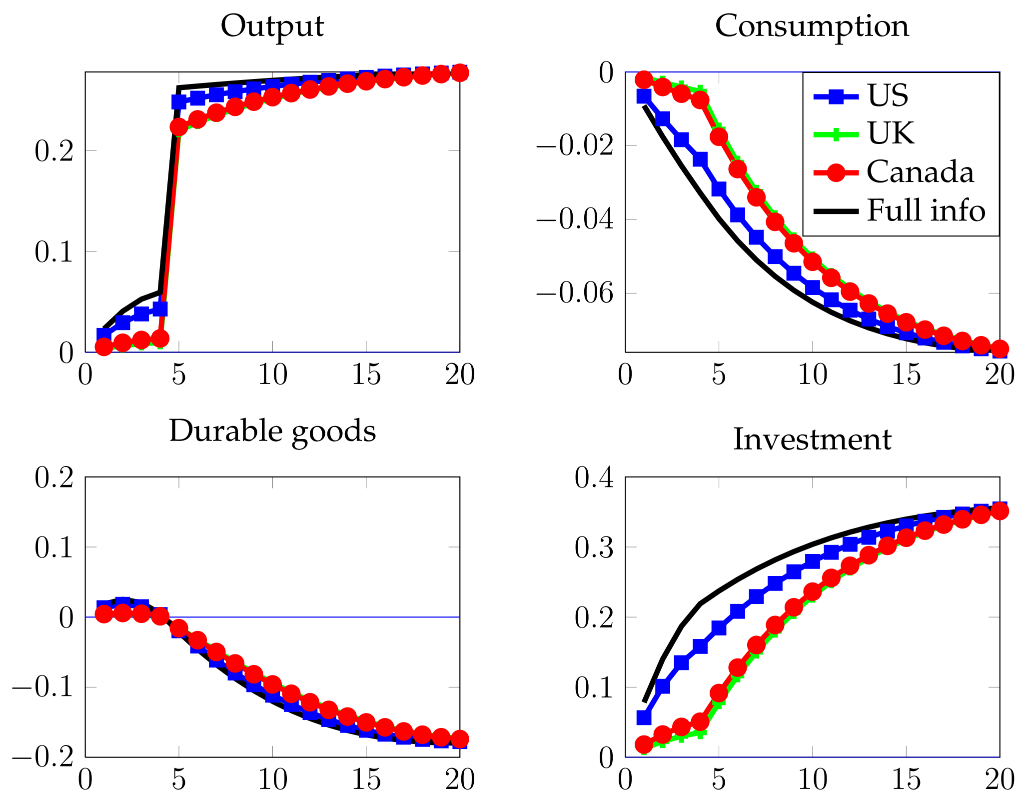

Figure 6: IRFs for a news shock

Note: This figure plots the IRFs for output, non-durable consumption, durable goods consumption and investment (as percentages) reactions to a 1 percent shock in government spending under the assumption of perfect information ($\alpha = 1$) vs the estimated level of noise for Canada, the UK and the US.

computed as

$$GSM_t = \frac{\widehat{X_t}}{\widehat{g_q}} \frac{X}{G}$$

for $t = 1, ..., T$, where X_t is alternatively output, consumption or investment, while X and G denote the steady state values, and variables with a hat are log-deviations from the steady state.

The second measure is the net present value of the multiplier (Mountford and Uhlig, 2009), which is computed according to the formula

$$NPV_t = \frac{\sum_{j=0}^{k} \beta^j \widehat{X}_{t+j}}{\sum_{j=0}^{k} \beta^j \widehat{g}_{t+j+q}} \frac{X}{G}.$$

Note that in the first case, the denominator is lagged forward as the news shock occurs in period $t+q$. In the upper panels of Figure 7, the values of GSM_t and NPV_t for output are reported for the three economies considered along with the full information benchmark.

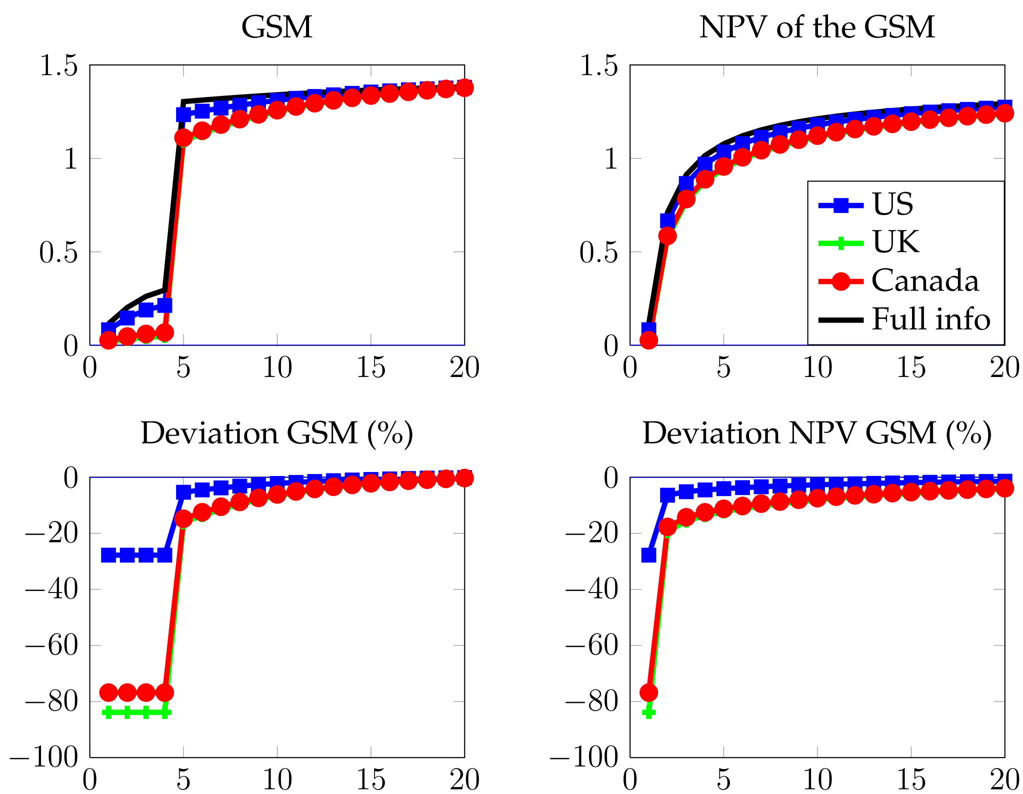

Figure 7: Output multipliers and deviation from the full information multipliers

Note: This figure plots the multipliers for output and the deviation (as a percentage) under partial information compared to the full information case. The figures in the bottom panel are computed as $\frac{X_t^i - X_t^{FI}}{X_t^{FI}}$, where X is alternatively the GSM and the NPV of the GSM, and $i = CA, UK, US$.

In both cases, the values of the multipliers under partial information are consistently lower than in the case of perfect information. To gain a quantitative insight into the loss for each economy due to information frictions, we compute the distance in percentage terms of the multiplier for each economy from the corresponding full information multiplier. The results are reported in the lower panels of the figure and expressed in percentage terms. Note that if one considers the GSM, the losses for the UK and Canada are well above 80% until the news is realized. In fact, the loss from the full information multiplier is exactly equal to $1 - \alpha$ and is not dependent on the value of the parameters or on the frictions in the model.[26] After the realization of the news shock, the loss falls to approximately 15 percent or less, while the multiplier gradually converges to its long-run value. The loss for the US is less severe on impact (28 percent), but still notable.

If we consider the multipliers for consumption and investment (Figure 8), we note that the negative effect on consumption is fairly small (up to -0.15 over the long run). The effect on investment, however, is significant. The potential of investment is dampened by noise: the investment multiplier soon after the shock is realized (period 5) is approximately 0.4 under full information. This value drops significantly to 0.2 or less in all three cases when imperfect information is considered. In contrast to the multiplier on output, such a multiplier loss is not rapidly recovered after the realization of the shock. For example, in period 10, both consumption and investment multipliers in noisy environments are still approximately 20 percent less than the level one would have observed under full information.

[26]We also performed the above exercises using alternative specifications of the model (results available upon request). More precisely, we removed durable goods and introduced nominal frictions in the form of Calvo pricing to a model *à la* Smets and Wouters. All of the above results hold, and for a reasonable calibration of the parameters related to price stickiness and monetary policy reaction, we quantitatively obtain very similar values for multipliers from period 5 on.

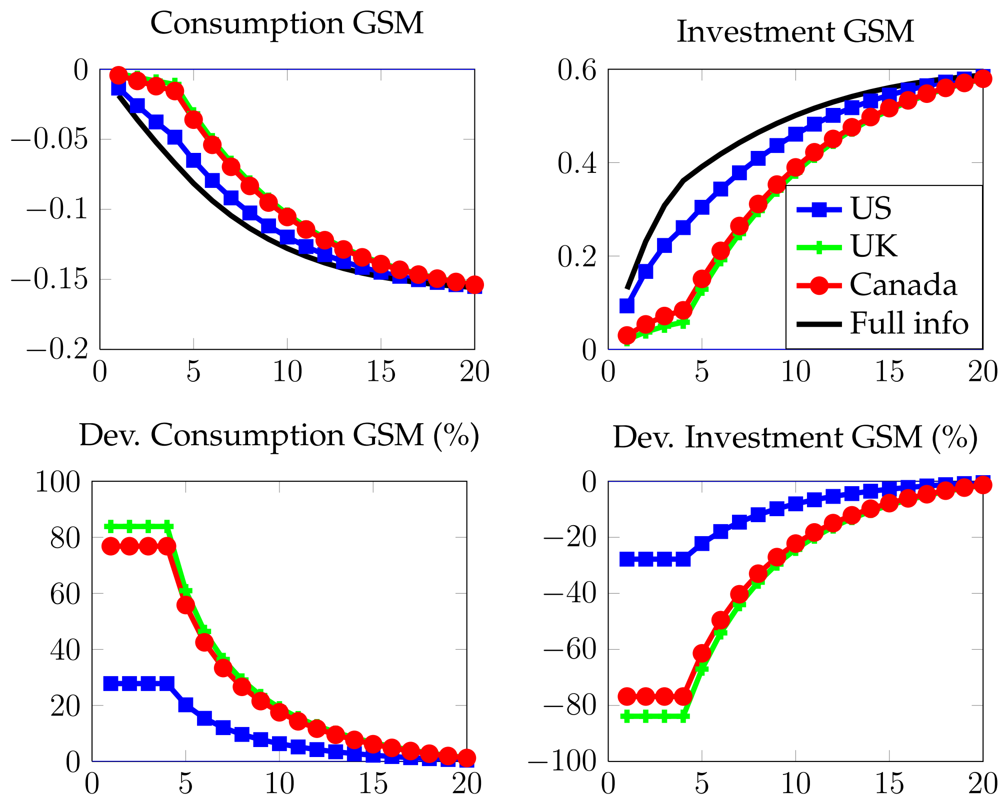

Figure 8: Consumption and investment multipliers and deviation from full information multipliers

Note: This figure plots the multipliers for consumption and investment and the deviation under partial information compared to the full information case. The figures in the bottom panel are computed as $\frac{X_t^i - X_t^{FI}}{X_t^{FI}}$ where X is alternatively the GSM and the NPV of the GSM and $i = CA, UK, US$.

6. Conclusion

The role of imperfect information in business cycles is one of the most promising research paths recently explored in macroeconomics. In this paper, we highlighted the relationship between imperfect or "noisy" information and the conduct of fiscal policy.

Using official forecasts of government spending as reported in the annual budgets of Canada, the UK and the US, we demonstrated the implementation of a limited information approach (a simple method of moments) to identify news and noise. The amount of noise observed for these three countries is significant: on average, the percentage of noise in official government spending forecasts ranges from 28% to 84%. Using these values in a richer DSGE setting, we highlighted the detrimental effects on fiscal multipliers, particularly on investment multipliers.

Our approach can be fruitfully extended to other policy settings in which announcements play crucial roles, such as monetary policy (forward guidance) or banking regulations and structural reforms implemented with lags.

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Appendix

Appendix A. Further results on misspecification

Appendix A.1. Estimation of $\widetilde{\alpha}$

The true data generating process (DGP) is an AR(2) process

$$\hat{g}_t = \rho_1 \hat{g}_{t-1} + \rho_2 \hat{g}_{t-2} + \varepsilon_{t-1}$$

and the misspecified AR(1) model is written

$$\hat{g}_t = \rho \hat{g}_{t-1} + \tilde{\varepsilon}_{t-1}$$

Under the AR(2), we first estimate the parameter ρ in the AR(1) model. From the first order autocorrelation of an AR(2) process (see Hamilton 1994b), we deduce

$$\rho = \frac{\rho_1}{1-\rho_2}$$

To obtain an estimate of α in the misspecified AR(1) model, we linearly project $E_t\hat{g}_{t+1} - \rho\hat{g}_t$ on $\hat{g}_{t+1} - \rho\hat{g}_t$. We deduce

$$\begin{aligned}
\tilde{\alpha} &= \frac{Cov\left(E_t\hat{g}_{t+1} - \rho\hat{g}_t, \hat{g}_{t+1} - \rho\hat{g}_t\right)}{V\left(\hat{g}_{t+1} - \rho\hat{g}_t\right)} \\
&= \frac{Cov\left((\rho_1-\rho)\hat{g}_t + \rho_2\hat{g}_{t-1} + \alpha(\varepsilon_t + \nu_t), (\rho_1-\rho)\hat{g}_t + \rho_2\hat{g}_{t-1} + \varepsilon_t\right)}{V\left((\rho_1-\rho)\hat{g}_t + \rho_2\hat{g}_{t-1} + \varepsilon_t\right)} \\
&= \frac{((\rho_1-\rho)^2 + \rho_2^2)V(\hat{g}_t) + 2(\rho_1-\rho)\rho_2 Cov(\hat{g}_t, \hat{g}_{t-1}) + \alpha\sigma_\varepsilon^2}{V\left((\rho_1-\rho)\hat{g}_t + \rho_2\hat{g}_{t-1} + \varepsilon_t\right)} \\
&= \frac{\left(\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2} + \rho_2^2\right)V(\hat{g}_t) - 2\frac{\rho_1\rho_2^2}{1-\rho_2}Cov(\hat{g}_t, \hat{g}_{t-1}) + \alpha\sigma_\varepsilon^2}{V\left((\rho_1-\rho)\hat{g}_t + \rho_2\hat{g}_{t-1} + \varepsilon_t\right)}
\end{aligned}$$

Using the autocovariances (at orders 0 and 1), we deduce

$$\begin{aligned}
V(\hat{g}_t) &= \frac{(1-\rho_2)\sigma_\varepsilon^2}{(1+\rho_2)((1-\rho_2)^2 - \rho_1^2)} \\
Cov(\hat{g}_t, \hat{g}_{t-1}) &= \frac{\rho_1}{1-\rho_2}\frac{(1-\rho_2)\sigma_\varepsilon^2}{(1+\rho_2)((1-\rho_2)^2 - \rho_1^2)} \\
V\left((\rho_1-\rho)\hat{g}_t + \rho_2\hat{g}_{t-1} + \varepsilon_t\right) &= \frac{(1-\rho_2)\sigma_\varepsilon^2}{(1+\rho_2)\left((1-\rho_2)^2 - \frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}\right)}
\end{aligned}$$

After replacement into $\tilde{\alpha}$, we deduce

$$\begin{aligned}
\tilde{\alpha} &= \frac{\left(\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}+\rho_2^2\right)\frac{(1-\rho_2)\sigma_\varepsilon^2}{(1+\rho_2)((1-\rho_2)^2-\rho_1^2)}-2\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}\frac{(1-\rho_2)\sigma_\varepsilon^2}{(1+\rho_2)((1-\rho_2)^2-\rho_1^2)}+\alpha\sigma_\varepsilon^2}{\frac{(1-\rho_2)\sigma_\varepsilon^2}{(1+\rho_2)\left((1-\rho_2)^2-\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}\right)}} \\
&= \frac{\left(\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}+\rho_2^2\right)\frac{(1-\rho_2)}{(1+\rho_2)((1-\rho_2)^2-\rho_1^2)}-2\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}\frac{(1-\rho_2)}{(1+\rho_2)((1-\rho_2)^2-\rho_1^2)}+\alpha}{\frac{(1-\rho_2)}{(1+\rho_2)\left((1-\rho_2)^2-\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}\right)}} \\
&= \frac{\frac{\rho_2^2}{1-\rho_2^2}+\alpha}{\frac{(1-\rho_2)}{(1+\rho_2)\left((1-\rho_2)^2-\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}\right)}} \\
&= \frac{\rho_2^2}{1-\rho_2^2}\frac{1+\rho_2}{1-\rho_2}\left((1-\rho_2)^2-\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}\right)+\frac{1+\rho_2}{1-\rho_2}\left((1-\rho_2)^2-\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}\right)\alpha \\
&= \left(\frac{\rho_2^2}{1-\rho_2^2}\right)\left(\frac{1+\rho_2}{1-\rho_2}\right)\left(1-\rho_2\left(\frac{1-\rho 1-\rho_2}{1-\rho_2}\right)\right)\left(1-\rho_2\left(\frac{1+\rho 1-\rho_2}{1-\rho_2}\right)\right) \\
&\quad+\left(\frac{1+\rho_2}{1-\rho_2}\right)\left(1-\rho_2\left(\frac{1-\rho 1-\rho_2}{1-\rho_2}\right)\right)\left(1-\rho_2\left(\frac{1+\rho 1-\rho_2}{1-\rho_2}\right)\right)\alpha
\end{aligned}$$

Appendix A.2. A simple illustration of misspecification

Let us assume that the true data generating process (DGP) is an AR(1), but we wrongly assume that government spending does not display serial correlation. To obtain an estimate of α in the misspecified AR(1) model, we linearly project $E_t\hat{g}_{t+1}$ on $\hat{g}_{t+1}$ and use the true stochastic process of government spending. The estimated value for α in the misspecified model under the true DGP is given by

$$\widetilde{\alpha} = \rho + \alpha(1-\rho^2)$$

Assume that $\rho \in [0, 1]$, i.e., government spending can display serial correlation. This implies that $\widetilde{\alpha} \geq \alpha$, so we will underestimate the size of the noise. For example, if $\rho \to 1$, the estimated value tends to one. Thus, we will incorrectly conclude that there is no noise in government spending policy.

Appendix B. Additional graphs

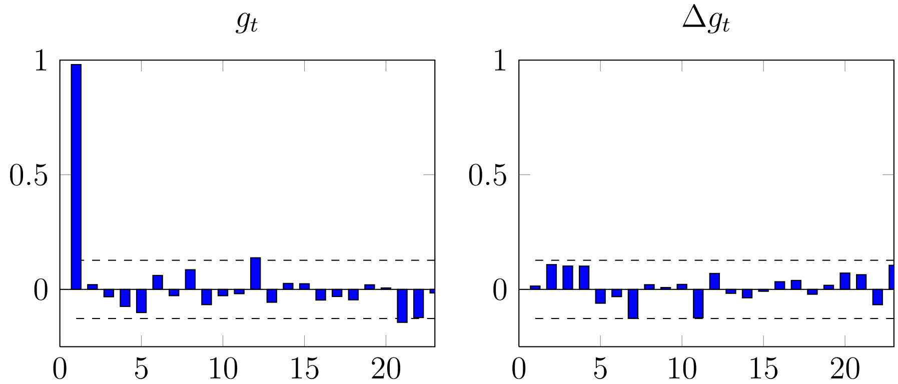

Figure B.9: Partial autocorrelation of government spending in the US

Note: In this figure, the autocorrelation functions for the quarterly log-series of real per capita government spending in the US (linearly detrended from 1952Q1 to 2014Q1, left panel) and for its first difference (Δg_t, right panel) are plotted. Confidence intervals are at 95% level. Series: "Real Government Consumption Expenditures and Gross Investment" (id: GCEC96), source: U.S. Bureau of Economic Analysis; "Total Population: All Ages including Armed Forces Overseas", source: U.S. Department of Commerce, Census Bureau.

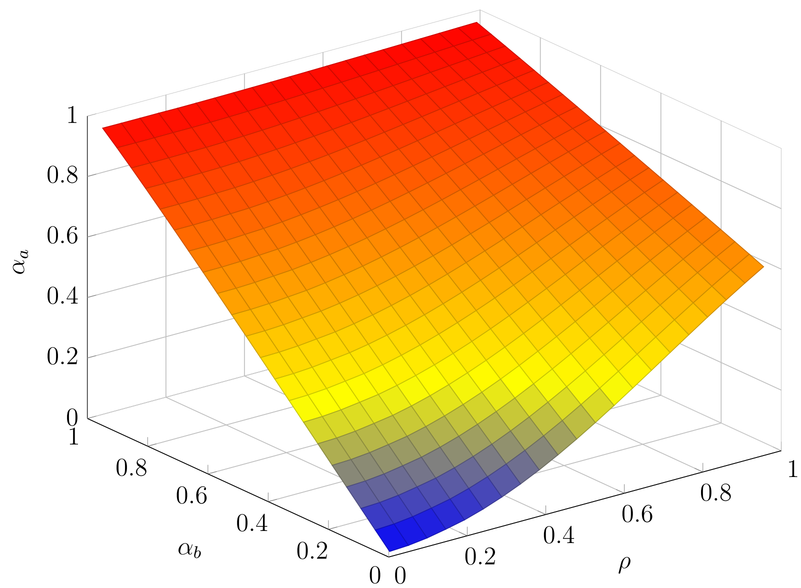

Figure B.10: The binding function

Note: This figure plots the binding function that yields the share of news at a yearly frequency (α_a) as a function of the share of news and the autoregressive parameter of the quarterly series (α_b and ρ).

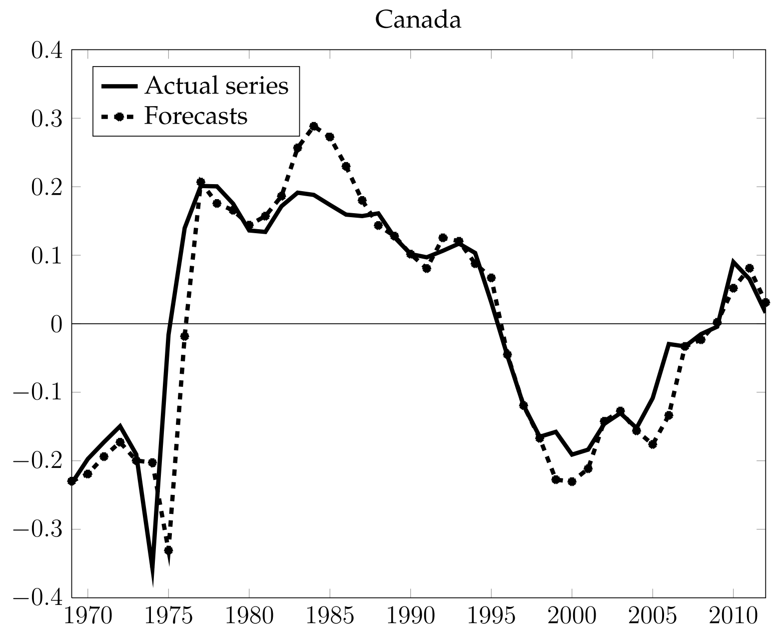

Figure B.11: Log of detrended per capita real government spending in Canada

Note: This figure plots actual realizations and one-step-ahead forecasts of the log of detrended per capita real government spending in Canada.

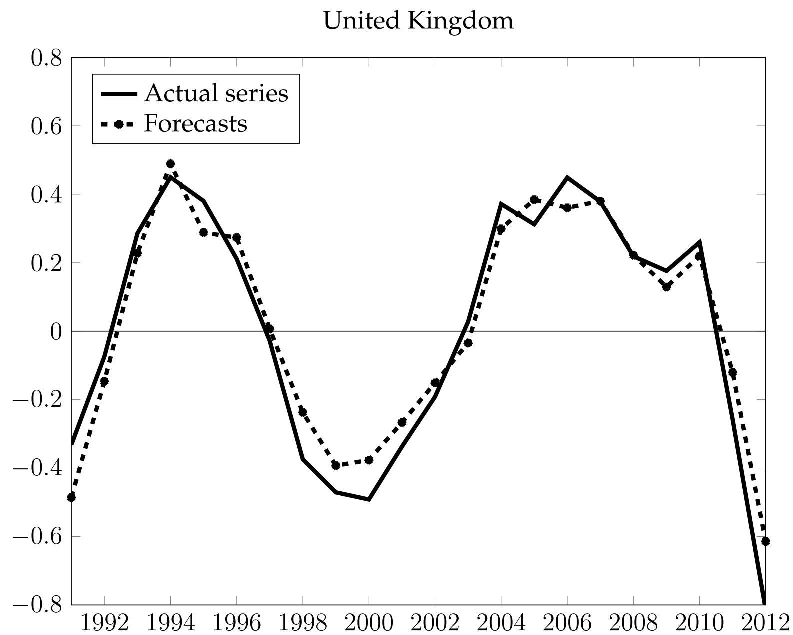

Figure B.12: Log of detrended per capita real government spending in the UK

Note: This figure plots realizations and one step ahead forecasts of the log of detrended per capita real government spending in the United Kingdom.

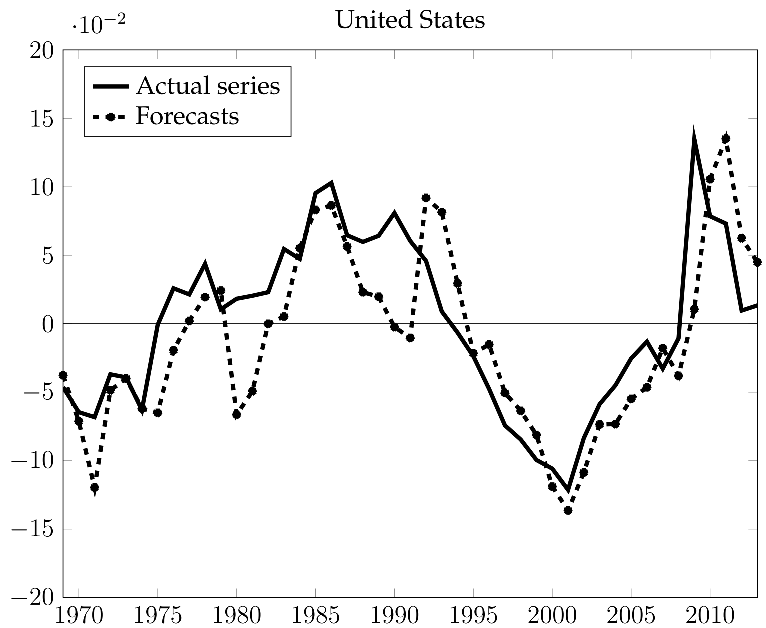

Figure B.13: Log of detrended per capita real government spending in the US

Note: This figure plots realizations and one-step-ahead forecasts of the log of detrended per capita real government spending in the United States.

Appendix C. Calibrated values

Parameter	Value	Description
γ_z	1.005	Trend
θ	.36	Capital share
Y	1	Steady state output
$\frac{G}{Y}$	0.201	Share of government spending
ν	1	Capital utilization at steady state
N	.25	Labor at steady state
$\frac{C}{D}$	7.4034	Consumption to durables
σ	3.7621	Elasticity of intertemporal substitution
b	0.8804	Habit formation
β	0.9742	Discount factor
κ	0.9759	Disutility of labor
ω_i	8.488	Adjustment cost for investment
ω_d	7.795	Adjustment cost for durables
ρ_g	1	Persistence of government spending shock
σ_g	.0548	Std dev of government spending shock

Note: The values of the parameters are taken from Mertens and Ravn (2011), except for the parameters related to the government spending process (ρ_g and σ_g).

Appendix D. Additional tables

Country	t-test ($\mu = 0$)	D'Agostino skewness test	Jarque-Bera test
Canada	-0.0073	Skew=-1.8754	χ^2_2= 144.6786
	[-0.0283; 0.0137]	*(0.0050)*	*(0.0000)*
UK	0.0014	Skew=0.1623	χ^2_2=0.6364
	[-0.0026; 0.0054]	*(0.804)*	*(0.7274)*
US (Budget)	-0.0125	Skew = -0.2756	χ^2_2=0.5967
	[-0.0248; -0.0002]	*(0.5802)*	*(0.7421)*
US (SPF)	-0.0016	Skew=-0.1480	χ^2_2=36.6799
	[-0.0043; 0.0011]	*(0.6335)*	*(0.0000)*

Table D.3: Zero mean, skewness and normality tests on forecast errors.

In the t-test column, the lower and upper bounds of the 95 percent confidence intervals are reported in brackets. The D'Agostino skewness test and Jarque-Bera test p-values are reported in parentheses. The null hypothesis for the D'Agostino skewness test is that data have no skewness. The null hypothesis for the Jarque-Bera test is that data are normally distributed.

	True parameters	AR(1)	IV
ρ	0.9858	0.9779	0.9786
		(0.0064)	*(0.0064)*
γ	-0.0569		-0.1047
			(0.1727)
α	0.54	0.55	0.55
		(0.0243)	*(0.0248)*

Table D.4: Estimates of simulated data with endogenous components in the spending rule.

Note: In the IV regression we use the lagged realizations of GDP as the instrument. Standard errors are reported in parentheses. Standard errors for the α parameter are obtained through a bootstrapping procedure based on 1000 replications of the residuals.

Appendix E. Durable goods multipliers and NPV GSM for consumption and investment

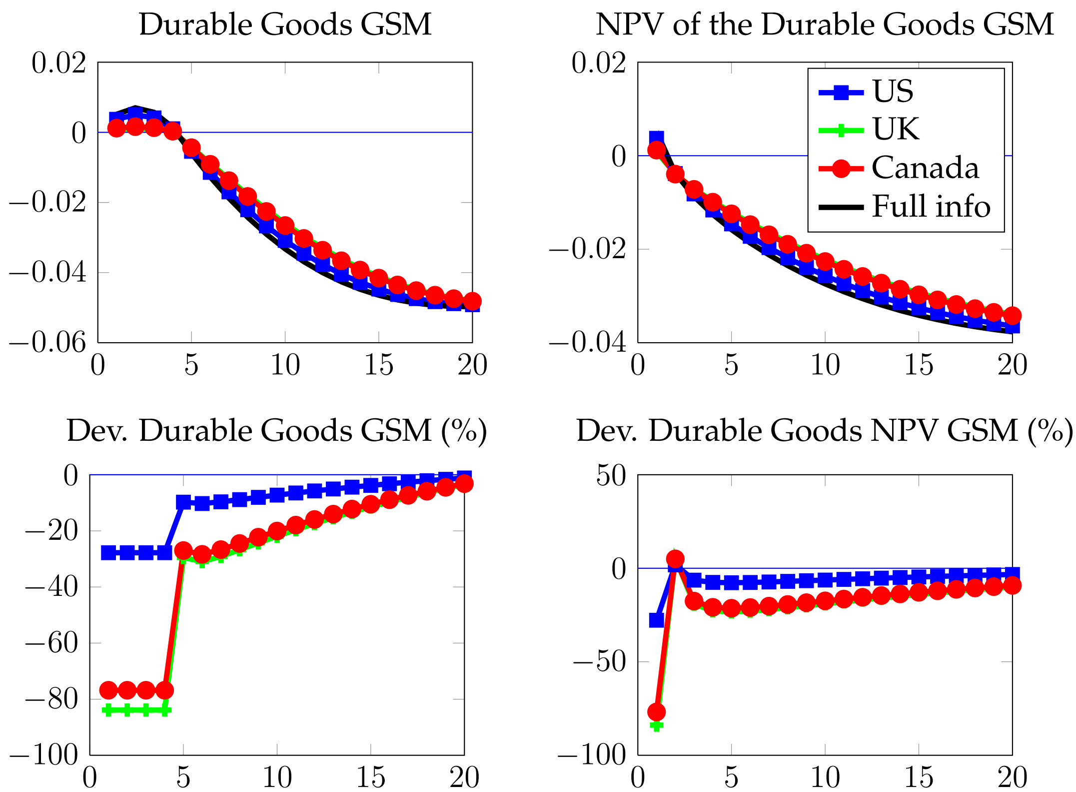

Figure E.14: Durable goods multiplier and deviation from full information

Note: This figure plots the multipliers for durable goods and the deviation under partial information compared to the full information case. The figures in the bottom panel are computed as $\frac{X_t^i - X_t^{FI}}{X_t^{FI}}$ where X is alternatively the GSM and the NPV of the GSM and $i = CA, UK, US$.

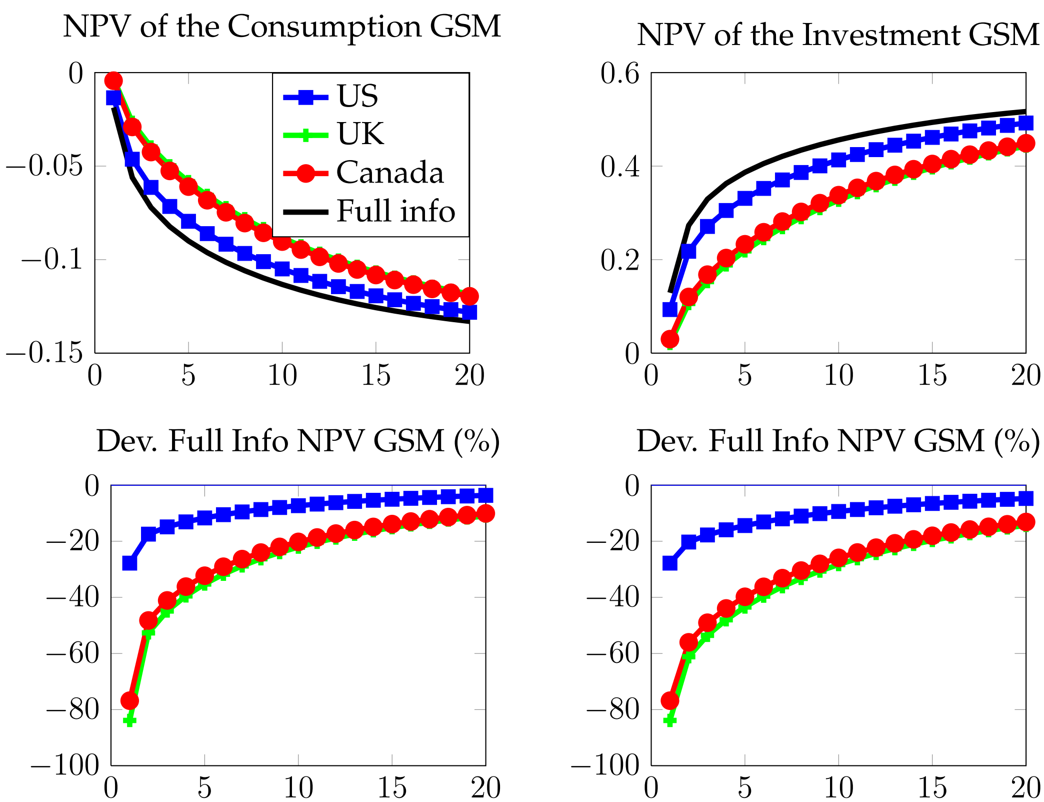

Figure E.15: NPV multipliers of consumption and investment and deviation from full information

Note: This figure plots the NPV multipliers for consumption and investment and the deviation under partial information compared to the full information case. The figures in the bottom panel are computed as $\frac{X_t^i - X_t^{FI}}{X_t^{FI}}$ where X is alternatively the GSM and the NPV of the GSM and $i = CA, UK, US$.

Appendix F. Data sources

Appendix F.1. Canada

The following are the series for Canada:

- Government Spending: "Budget Expenditures" (up to 1982) and "Program Expenses" (from 1987). Source: Budget Speech and Budget Plan, various years.
- Population: "Total population". Source: World Bank (series id: SP.POP.TOTL)

- Price deflator: "GDP Implicit Price Deflator". Source: OECD.

Appendix F.2. United Kingdom

The following are the series for the UK:

- Government Spending: "Total managed expenditure". Source: UK Budget, various years.
- Population: "Mid-year population estimates". Source: ONS.
- Price deflator: "GDP Implicit Price Deflator". Source: OECD.

Appendix F.3. United States

The following are the series for the US:

- Government Spending (Budget): "Total budget outlays". Source: Federal Budget, various years.
- Government Spending (SPF): "Real Federal Government Consumption Expenditures and Gross Investment". Source: Survey of Professional Forecasters (series id: RFEDGOV).
- Population: "Total Population: All Ages including Armed Forces Overseas". Source: U.S. Department of Commerce: Census Bureau.
- Price deflator: "Consumer Price Index for All Urban Consumers: All Items". Source: U.S. Department of Labor: Bureau of Labor Statistics.