The Role of Expectation Formation for Macroeconomic Policy

by

Vania Prabayajnya Philia Esady

Thesis submitted to

City, University of London

in partial fulfillment for the degree of

Doctor of Philosophy

in Economics

Department of Economics

November 2020

Contents

List of Tables

List of Figures

Acknowledgments

I am filled with gratitude to my first supervisor, Joseph Pearlman, who have provided me with many opportunities since the beginning. Each conversation we have is enlightening as he shares his vast knowledge: directing me to the state-of-the-art research topics and long-established literature. I am indebted to my second supervisor, Michael Ben-Gad, for the hours of discussions that successfully untangle the knots in my thinking. His optimism boosted my confidence of being a researcher and graduate teaching assistant, as well as when I went through the job market. I shall be forever grateful that both of them constantly believed in me.

A special thanks to Herakles Polemarchakis, my MSc thesis supervisor, whose eternal kindness (even long after my MSc) and brilliance motivated me to follow a research career and pursue a PhD.

I am grateful to Saqib Jafarey who kindly read early versions of my work and provided excellent feedback. I would also like to mention Giulia Faggio, Mireia Jofre-Bonet, Victoria Serra-Sastre, and Agne Suziedelyte, who have become role models for me as a woman in economics.

This journey would not have been the same without Salma Ben-Lalouna and Iris Lopes-Rafegas, my main support system for the first-year courses, APRs, teaching questions, and many more. I am happy to have the "Asian Women in Macro" group: Amanah Ramadiah, Ivy Sabuga and Aruhan Shi. I am also grateful for the camaraderie of Zamid Aligishiev, Alessandro Cantelmo, Anna Kaliciak, Yi Mu, and many others during the PhD years.

I appreciate the financial support from City, University of London and the Department of Economics.

I would like to thank Nikoleta Anesti, Nick Bate, Marco Del Negro, Ana Galvao, Alistair Macaulay, Junior Maih, Kristoffer Nimark, Galina Potjagailo, and Tiziano Ropele, as well as seminar participants at the Bank of England, CESifo, Norges Bank and RES 2018 for their insightful comments and suggestions.

I am lucky to have found Jessica Halim, Cininta Meirinda and Adelita Siregar — who have always been supportive and excited for my academic and career choices.

A very special thanks goes to my parents, Eddy Isworo and Threesia Katoppo, for their eternal patience, help, support and prayers, especially during the PhD.

I am inspired by the strength of my grandmother who despite only having early formal education, has successfully brought up her children to complete higher-education degrees. She never doubted my choice and ability to do a PhD. I believe that my late mother, Esther Bhakti, would have had the same faith in me.

Words would not suffice my gratitude to and for Boromeus Wanengkirtyo, my partner from the start to the end. Thank you for your guidance, discussions, feedback and constant support.

Vania Esady

November 2020

Commit to the Lord whatever you do, and He will establish your plans. Proverbs 16:3 NIV

Abbreviations

BP	Blanchard and Perotti (2002)
DSGE	Dynamic Stochastic General Equilibrium
ECB	European Central Bank
FAVAR	Factor-Augmented Vector Autoregression
FFR	Federal Funds Rate
FOMC	Federal Open Market Committee
FRED	Federal Reserve Economic Data
GDP	Gross Domestic Product
GI	Great Inflation
GIRF	Generalised Impulse Response Function
GM	Great Moderation
GNP	Gross National Product
HANK	Heterogeneous Agents New Keynesian
IQR	Interquartile Range
IRF	Impulse Response Function
IS-LM	Investment-Savings Liquidity Preference-Money Supply
MR07	Mankiw and Reis (2007)
NBER	National Bureau of Economic Research
NIPA	National Income and Product Accounts
OLS	Ordinary Least Squares
PSID	Panel Study of Income Dynamics
QE	Quantitative Easing

RBC	Real Business Cycle
RR	Romer and Romer (2004)
SD	Standard Deviation
SIGE	Sticky Information General Equilbrium
SPF	Survey of Professional Forecasters
ST	Smooth Transition
VAR	Vector Autoregression
VIX	Chicago Board Options Exchange (CBOE) Volatility Index
ZLB	Zero Lower Bound

Introduction

The overarching theme of this thesis is how information frictions affect expectations formation, and its implications for monetary and fiscal policymaking. Why is that important? Economic agents, such as firms and households, attempt to infer the current state of the economy when making decisions, which is typically not observable in real-time. If their ability to assess current economic conditions (or in economic terms, nowcasts) vary over time, it may affect the way they respond to various shocks, such as monetary and fiscal shocks.

I answer this broad question empirically and theoretically. Empirically, I use several methodologies and proxy the degree of information frictions with the Survey of Professional Forecasters — in particular, the dispersion of their nowcasts ('disagreement'). How can one think of this proxy? A significant amount of disagreement by professional forecasters on a near-term forecast indicates a period of when it is difficult to observe the current state of the economy, or in other words, there is high information rigidities. Theoretically, I explore two styles of information friction models (rational inattention and sticky information) for firms' price-setting and households' consumption-saving behaviour.

In Chapter 1, I investigate the heterogeneity of monetary policy transmission under time-varying disagreement. Empirically, I establish that during high disagreement periods, prices respond more sluggishly in response to (various measures of) monetary shocks. These stickier prices cause a flatter Phillips curve, leading to the empirical result that monetary policy has stronger real (output) effects. I also develop a tractable theoretical model that show rationally inattentive price-setters produce this result. The rational inattention model contains two theoretical predictions. One, how disagreement across of rationally inattentive price-setters changes when various parameters (that models information frictions) change. Two, how the response of rationally inattentive price-setters to a monetary shock changes when the same parameters change. The rational inattention model also highlights the fundamental differences between uncertainty and disagreement, bridging the results of this chapter with the literature on uncertainty.

While there are many models on information frictions to explain its effects on the transmission of monetary shocks, there is surprisingly little on its role on fiscal shocks. In Chapters 2 and 3, I investigate the effects of fiscal shocks on macroeconomic variables and the role of information frictions. Currently, there is still a lack of consensus on how consumption responds to a government spending shock. Typical neoclassical real business cycle (RBC) models predict that consumption should fall to an expansionary government spending shock, but other (more Keynesian) models suggest that consumption rises instead. A key takeaway from this debate is that the forward-lookingness of households is an important determinant of how a government spending shock propagates, as it influences how Ricardian the households are.

In Chapter 2, I empirically show that the effects of fiscal policy can be state-dependent due to changes in information frictions. I document a novel result that reconciles the Keynesian and neoclassical predictions of fiscal policy. I use a non-linear local projections framework and combine it with the insights of the previous chapter — using professional forecasters' disagreement as a measure of information frictions. The key finding is that during periods of high information frictions, households act less Ricardian (as they are less forward-looking), and thus government spending co-moves with consumption. In contrast, during low information frictions, households act sufficiently Ricardian such that consumption falls in response to a government spending rise. Another important result highlights that firms and households pay heterogeneous attention to different components of government spending and transfer payment shocks. Thus, fiscal policymakers will benefit from understanding how information frictions affect the decision making process of firms and households in order to use different tools that best achieve their policy goals.

In Chapter 3, I provide a theoretical quantitative framework to the empirical findings of Chapter 2, on how information frictions could affect the consumption response to a government spending shock. In particular, I build on a general equilibrium model with sticky information, and add households with limited asset market participation ('rule-of-thumb' or 'hand-to-mouth' households). When information frictions are not severe, many households are able to identify a government spending shock and thus, their Ricardian effects dominate the rule-of-thumb households leading to a fall in aggregate consumption. In contrast, when information frictions impede their ability to identify the shock, only few households save in advance of higher future taxes and therefore, aggregate consumption rises.

What can policymakers take away from this thesis? Lower disagreement across agents is ideal when implementing disinflationary monetary policies. Improved central bank communication may help reduce disagreement among economic agents that could lead to a reduction of the sacrifice ratio. In other words, it helps reduce output losses for a given fall in inflation. In addition, expectations formation gives rise to a novel channel of monetary and fiscal policy interaction. Monetary policy has long used communications to shape expectations on future economic conditions. For example, most advanced economy central banks publish some kind of forecast for both inflation and real output. If these communications are successful in influencing expectations — and in particular, *decreasing* disagreement on future economic conditions — monetary policy communications could reduce the stimulative power of an expansionary fiscal policy shock (and likewise, reduce the output losses of a contractionary fiscal shock).

However, note that this is purely a positive, rather than normative, question. If central banks do not communicate sufficiently, it may reduce the effectiveness of monetary policy, which could remain the primary demand-management tool for advanced economies. Additionally, even without the monetary policy benefits, keeping information frictions high could still be welfare sub-optimal. For example, it makes it more difficult for households to smooth consumption in anticipation to all other economic shocks, including fiscal policy.

Chapter 1

Real and Nominal Effects of Monetary Shocks under Time-Varying Disagreement

"Much of the dispersion in beliefs can be explained by firms' incentives to collect and process information, i.e. rational inattention motives."
— Olivier Coibion, Yuriy Gorodnichenko, Saten Kumar (2015)

"... the literature has convincingly shown that disagreement is not uncertainty. They are conceptually different."
— Ricardo Reis, *ECB Forum in Central Banking*, Sintra (June 2018)

1.1 Introduction

A noticeable feature of survey data is the remarkable range of disagreement on various forecasts of macroeconomic variables across different economic agents.[1] Andrade et al. (2016) find these disagreement to be time-varying at all horizons. The intuition behind the stylised facts is that economic agents are not fully informed all the time, and thus, naturally creates heterogeneity in beliefs that inherently changes over time. The literature highlights this observation is consistent with the predictions arising from information frictions model (Andrade et al., 2016; Falck et al., 2019; Mankiw et al., 2004).

[1]As noted by Ricardo Reis in ECB Forum in Central Banking, Sintra (June 2018) during his discussion on "Inflation expectations – a policy tool?" (Coibion et al., 2018b).

This paper's primary research question examines how varying degrees of disagreement affect the transmission mechanism of monetary policy. Economic agents are not only forward-looking, but in reality, households and firms also try to infer the current state of the economy when making decisions. If their ability to assess the current economic conditions (nowcasts) varies over time, it may affect their ability to respond to various shocks, including monetary shocks. A period of significant nowcast disagreement across agents indicates of when it is difficult to observe the current economic state – in other words, when there is high information rigidities. I examine *real output* nowcast disagreement because people often think about economic growth prospects when making decisions.[2] For example, households worry about their (un)employment chances, and firms optimise prices given demand conditions. Consequently, current output expectations would also matter to monetary policymakers.

The contribution of this paper is two-fold. The main contribution is, using various empirical approaches and a measure of disagreement across professional forecasters, to empirically document how during heightened disagreement, monetary policy has *smaller* effect over inflation, yet *more* influence over output. But first, I design a tractable rational-inattention model to examine how price-setting might change with varying information frictions. The model also dissects the relationship between disagreement and uncertainty – two fundamentally different concepts – to highlight how they distinctly affect monetary transmission, and when there is a positive link between them (or when they break down).

What differentiates disagreement and uncertainty measures? Heightened uncertainty since the global financial crisis has spurred a large collective effort in measuring economic uncertainty. A previous and established literature proxied uncertainty with the disagreement of individual forecasts in surveys (Bomberger, 1996; Lahiri and Sheng, 2010). However, the contemporary literature considers uncertainty and disagreement as fundamentally different concepts, as I also show in the tractable model. Empirically, various measures of macroeconomic uncertainty and disagreement have positive, but weak, correlations (Kozeniauskas et al., 2018).[3]

[2]This paper complements the literature that has largely focused on how *inflation expectations* disagreement affect monetary transmission as discussed in Section 1.2.

[3]'Disagreement' in this paper is close to the Kozeniauskas et al. (2018) definition of '*higher-order uncertainty*'.

I utilise the tractable model to examine how uncertainty and disagreement concepts affect price-setting behaviour of firms, and thus, the effect of monetary policy on central banks' goal variables. While uncertainty has been looked at extensively, the question remains, how does disagreement about current economic conditions amongst agents affect their response to monetary shocks? As with many other imperfect information models, the rational inattention model suggests that when firms are only able to imperfectly observe factors that affect their optimal prices, they attach a positive (but less than unity) weight to the signals they receive (the 'Kalman gain') on these factors. This implies that their prices respond sluggishly to aggregate monetary shocks. The slower prices respond, the more 'sticky' prices appear, leading to a flatter Phillips curve. Thus output would correspondingly react by more to the monetary shock.

A novel insight from the rational inattention model is that plausible causes of the variation in disagreement has different effects on how price-setters respond to monetary shocks, in comparison to uncertainty. For example, a reduction in firms' information processing capacity worsens the quality of information available, leading firms to attach less weight to signals they receive.[4] Prices would then be more sluggish and disagreement increases. Note that this is the case even when the fundamental uncertainty on macroeconomic outcomes has *not* changed, illustrating one of the cases where uncertainty and disagreement do not co-move together.

Another insight from the rational inattention model is that endogenous optimal attention allocation could cause disagreement to change non-monotonically in response to fluctuations in aggregate uncertainty. In particular, an *increase* in demand uncertainty raises the benefits to monitoring demand conditions. Firms could optimally re-allocate much more attention to monitoring demand, and actually *decrease* disagreement of the assessment of demand across different firms.

These results also shed light on how increased communication by monetary policymakers can affect their ability to deliver on their stabilisation objectives. There is a recent trend of vastly increased central bank transparency — from releasing detailed minutes of monetary policy deliberations, increased frequency of speeches, to developing material more easily accessible to the general public (for example, the Bank

[4]For example, the reduction of information available to a firm from the bankruptcy of a supplier or customer.

of England's *Monetary Policy Report* infographics).[5] However, much of the literature focuses on how inflation expectations helps anchoring inflation. The mechanism that explains the empirical results in this paper suggests that, in addition, communicating aggregate *real* conditions can help central banks achieve their objectives. As improved communication helps economic agents form expectations about current and future conditions, this reduces the disagreement of agents and potentially lowers the sacrifice ratio. With disinflationary monetary policies, inflation can be reduced with smaller output losses.

Empirically, I employ non-linear methods to answer the research question. In the baseline exercise, I use a threshold vector autoregression that allows macroeconomic variables to have different response given varying disagreement. The general idea of the empirical threshold VAR methodology is to pick an endogenous 'threshold variable' that contains information about the different regimes (Tsay, 1998) — in this case, high and low disagreement. It is important to note that the threshold variable in this paper is endogenous, and thus allows for endogenous regime switching. As will be discussed in greater detail, the threshold variable (disagreement) is the dispersion of the cross-sectional real GDP nowcasts from the U.S. Survey of Professional Forecasters (SPF).

Furthermore, the main results are robust to alternative monetary policy shock identification schemes. I construct a narratively-identified monetary policy shock series, by extending Romer and Romer (2004) up to 2013 (when the Greenbook forecasts have been published). The shock identification allows for non-linearities in the monetary policy reaction function according to disagreement. I apply the narrative monetary policy shocks with a threshold VAR approach, as well as state-dependent local projections.

This paper is structured as follows. Section 1.2 summarises the related literature. Section 1.3 presents the theoretical model that elucidates the fine distinction between uncertainty and disagreement, and their implications for pricing behaviour. Section 1.4 describes the data, measure of disagreement and econometric methodology, and highlights the main empirical results. The extension in Sections 1.5 and 1.6 explores

[5] Following Geraats (2002), the literature distinguishes various types of central bank transparency. Recently, Dincer et al. (2019) illustrate how prominent central banks, including the U.S. Federal Reserve, have deployed greater transparency as a policy tool in the aftermath of the financial crisis.

the narratively-identified monetary policy shocks, and local projections as an alternative empirical methodology. In Section 1.7, I conclude and provide policy implications of the results.

1.2 Literature Review

This paper contributes to three strands of literature. First, it contributes to the vast and growing empirical literature on state-dependent effects of monetary policy shocks. Second, it complements the literature on disagreement about expectations, that has largely focus on inflation expectations. Third, it builds on the literature in explaining time-varying disagreement through the lens of a theoretical model with information frictions (in particular, rational inattention).

The main empirical results of this paper sit in between the argument about the strength of monetary policy in different economic regimes, such as time-varying uncertainty, and booms and recessions. Caggiano et al. (2014) and Tenreyro and Thwaites (2016) find that monetary shocks have less impact on output and prices in *recessions*, while others such as Peersman and Smets (2001) and Lo and Piger (2005) find the opposite — i.e. there appears little agreement across the literature. Similarly, the literature on monetary transmission under uncertainty also find monetary policy could either be less or more effective in affecting output (and prices) in *high uncertainty* (Castelnuovo and Pellegrino, 2018; Aastveit et al., 2017) or, it may have stronger impact on real output (Park, 2019).

In terms of empirical methodology, this paper closest to Castelnuovo and Pellegrino (2018) and Park (2019) in using threshold VAR to study the state-dependent effects of monetary policy shocks. However, a key difference with my paper is that their threshold variable (or the interaction term in Aastveit et al. (2017)) are treated as an exogenous variable — such that their uncertainty measures cannot react to monetary policy shocks. In practice, as shown by Pellegrino (2018), uncertainty can indeed respond to monetary policy shocks — indicating the importance of allowing the threshold variable to be endogenous.[6]

Specifically, this paper complements the literature looking at the effects of mone-

[6]In line with the literature, I also compute the impulse responses using GIRFs which accounts for the endogenous threshold variable that creates non-linearities in the threshold model.

tary policy shocks under time-varying disagreement, that has largely focus on *inflation expectations* disagreement. Falck et al. (2019) examine disagreement in forecasts about future inflation and its interaction with monetary policy effectiveness. Using one-quarter ahead inflation forecasts in the SPF, they find that in the high disagreement regime, inflation and inflation expectations respond relatively weakly to monetary policy shocks — showing a large 'price-puzzle', while the response of output are not statistically different in the two regimes.

Moreover, the literature on disagreement presents stylised facts about main macroeconomic variables, including output, in long- and short-run predictions (Andrade et al., 2016; Dovern et al., 2012; Patton and Timmermann, 2010). It also offers various theoretical explanations for the time-varying disagreement using models with different information frictions. Andrade et al. (2016) and Falck et al. (2019) show that their empirical observation is consistent with predictions from dispersed information models, while Mankiw et al. (2004), Andrade and Le Bihan (2013) and Coibion et al. (2018a) use recent models of inattention due to sticky information á la Mankiw and Reis (2002) and rational inattention á la Sims (2003).

The disagreement (cross-sectional forecast dispersion) measure is related to recent empirical work that measure aggregate volatility. This approach builds on a long literature, for example Baker et al. (2016) and D'Amico and Orphanides (2008), to study the *direct* effect of uncertainty shocks (rather than the *indirect* impact on monetary transmission). It is important to note, as I highlight in the next section, the relationship between uncertainty and disagreement is not always monotonic, and thus, the results from the uncertainty literature do not necessarily conflict with the disagreement results in this paper. Kozeniauskas et al. (2018) emphasise the importance in distinguishing the different uncertainty measures. In the recent uncertainty literature in understanding monetary policy transmission, authors most often use *'macro uncertainty'* — uncertainty about aggregate variable such as Jurado et al. (2015) or VIX. Whereas the disagreement measure in this paper is related closer to the concept of *'higher-order uncertainty'* that is defined as the uncertainty (shocks) about others' beliefs arising when forecasts differ. Although they are positively correlated, as shown later in the paper, their relationship could break down.[7]

[7] The other category of uncertainty in Kozeniauskas et al. (2018) is '*micro dispersion*', as dispersion of firm outcomes often proxies for micro uncertainty (an increase in the variance of idiosyncratic shocks

The analysis of this paper is closest to Zhang (2017) who investigates endogenous information processing capacity (rational inattention) as a channel through which *uncertainty* affects pricing dynamics, and empirically tests it with a Markov-switching FAVAR. The key mechanism of the model is that with higher uncertainty, firms would exert more effort into monitoring the economic state. The higher degree of attentiveness lets firms detect (monetary) shocks more promptly and more accurately, thus allowing the effects of the shocks to be less persistent. Theoretically, I expand on her model to examine the implications on disagreement on the allocation of attention, and its links with aggregate uncertainty. In Zhang's setup, the attention paid to a particular variable only depends on the prior uncertainty of the variable itself, and the aggregate marginal cost of attention. In contrast, in my tractable model, because the agent has to allocate its finite attention, the relative variance across different variables also matter. Empirically, the main difference of this paper's threshold VAR methodology and Markov-switching approach is that the latter examine the whole model for structural breaks. The threshold variable pins down the regimes, which enables the threshold VAR to specifically differentiate across disagreement regimes. Zhang shows the Markov-switching model picks up the large regime change from the Great Inflation to the Great Moderation period, but I show that there is variation in disagreement regimes even *within* the Great Moderation period.

Naturally, this paper contributes to the rational inattention literature to study the effects of monetary shocks. For example, Menkulasi (2009) considers a dynamic general equilibrium model in which firms optimally allocate their limited attention across aggregate and idiosyncratic states. The model shows an increase in the volatility of aggregate shocks causes an optimal re-allocation of attention to the aggregate environment. Additionally, there is a fast growing literature on *designing* rational inattention models to understand monetary policy transmission (amongst many, Sims (2010), Maćkowiak and Wiederholt (2009) and Maćkowiak and Wiederholt (2015)). However, these mechanisms have not been utilised much to explain the empirical evidence of state-dependent monetary transmission. Thus, this paper narrows the gap in the lit-

to firm). Vavra (2013) finds expansionary monetary policy leads to an increase in aggregate price flexibility and is less effective at increasing real output during periods of higher volatility — measured using firm-specific or micro uncertainty. The different measures of 'state' between this paper and Vavra's explain the different findings, and thus called for distinct mechanisms (he focuses on (S,s) price-setting models).

erature by applying the mechanisms from rational inattention models to analyse the non-linear effects of monetary policy.

1.3 Stylised Rational Inattention Model

To illustrate the mechanisms that generate the empirical results, I present a stylised price-setting model with rational inattention, with closed-form solutions that allow me to compute comparative statics. I analyse how disagreement endogenously evolve to changes in information processing of firms and various uncertainties relevant for pricing decisions, and how that relates to how monetary shocks affect optimal prices.[8]

In this model, the price-setters in the firms face an unobserved aggregate demand y_t, composed of a normally-distributed demand shock b_t, and a 'monetary policy' component $c \cdot r_t$. The demand shock has a variance σ_b^2, which I refer to as fundamental demand uncertainty.[9] For tractability, without the loss of generality, the demand shock is assumed to be mean-zero. The monetary policy component is fully known: price-setters observe the policy rate r_t and the interest-elasticity of demand $c > 0$.

$$y_t = b_t - c \cdot r_t, \qquad \text{where} \quad b_t \sim N(0, \sigma_b^2) \tag{1.1}$$

In this simple model, I assume demand is insensitive to prices, leading to a flat demand curve. The full-information optimal price p_{it}^* purely depends on the marginal costs, which is increasing with respect to demand y_t, and decreasing to an unobserved, stochastic firm-specific productivity term a_{it} where i represents a firm.

$$p_{it}^* = \varphi y_t - a_{it}, \qquad \text{where} \quad a_{it} \sim N(0, \sigma_a^2) \tag{1.2}$$

This simple structure can be micro-founded by a profit-maximising firm with decreasing returns to scale (thus marginal costs are increasing in output) that is common with rational inattention models, or a firm that faces labour market rigidities (thus needs

[8]The model is partially based on the simple model in Zhang (2017), but I add more economic structure and different informational structure to aid interpretation. The analysis focuses on the behaviour of disagreement to changes in uncertainty and how rationally inattentive price-setters respond to monetary shocks.

[9]The simplifying assumption that the shock is white noise, enabling us to get analytical solutions, as the optimal information decision is independent across time periods. We abstract away from dynamics, as we are interested in the intratemporal attention allocation.

to pay higher wages to produce more output).

To help set optimal prices, firms receive the signals $s_{it} = \{s_{it}^y, s_{it}^a\}$ on key variables:

$$
\begin{aligned}
s_{it}^y &= y_t + \varepsilon_{it}^y, & \varepsilon_{it}^y &\sim N(0, \sigma^2_{\varepsilon_{y,t}}) & (1.3)\\
s_{it}^a &= a_{it} + \varepsilon_{it}^a, & \varepsilon_{it}^a &\sim N(0, \sigma^2_{\varepsilon_{a,t}}) & (1.4)
\end{aligned}
$$

The firms choose the variance of the noise on the two signals, but this decision is subject to an information constraint:[10]

$$I\left(p_{it}^*; s_{it}\right) = H\left(p_{it}^*\right) - H\left(p_{it}^* \mid s_{it}\right) \leq K \tag{1.5}$$

where the firms are limited to how much entropy $H(\cdot)$ they could reduce on the two state variables b_t and a_{it} after observing the signal s_{it}. Given that the signals are uncorrelated and Gaussian, this can be simplified to and have the functional form of Eq (1.6):[11]

$$\underbrace{\frac{1}{2}\log_2\left(\frac{\sigma_y^2}{\sigma^2_{\varepsilon_{y,t}}} + 1\right)}_{K_{it}^y} + \underbrace{\frac{1}{2}\log_2\left(\frac{\sigma_{a_i}^2}{\sigma^2_{\varepsilon_{a,t}}} + 1\right)}_{K_{it}^a} \leq K \tag{1.6}$$

where K_{it}^y and K_{it}^a are the entropy reduction to the uncertainty on the two unobserved state variables. Hereafter, I will refer to K_{it}^y and K_{it}^a as the 'attention' firm i allocates to monitoring y_t and a_{it}, which will be chosen optimally.

Rearranging Eq (1.6), the attention allocations imply the following perceived volatility of the tracking noises:

$$
\begin{aligned}
\sigma^2_{\varepsilon_{y,t}} &= \frac{1}{2^{2K_{it}^y} - 1}\sigma_y^2 & (1.7)\\
\sigma^2_{\varepsilon_{a,t}} &= \frac{1}{2^{2K_{it}^a} - 1}\sigma_{ai}^2 & (1.8)
\end{aligned}
$$

In other words, the more attention paid to each variable, the associated variance of the noise on the signals would be lower. As the signals are i.i.d., and the only source of information on y_t is s_{it}^y, any dispersion in the expectations of y_t across firms i

[10]Notice that the firms do not receive signals about other firms idiosyncratic shocks, or public signals, and thus do not create higher-order signal extraction problems.

[11]I leave the details of the derivation in Appendix A.1.

is captured by $\sigma^2_{\varepsilon_{y,t}}$. Thus, $\sigma^2_{\varepsilon_{y,t}}$ is a sufficient summary statistic of demand nowcast disagreement.

In the Zhang (2017) model, K is pinned down by ensuring the marginal benefit of information equates to a fixed marginal cost of information, as the firms 'purchase' information with a linear cost in K. This model has a small, but important, departure by assuming maximum information gain constraint K is exogenous to the firm. This makes it more tractable to see the impact of changes in uncertainty of different variables, as well as changes in the information capacity, on attention allocation and price-setting.

1.3.1 Optimal Pricing and Attention Allocation

Each firm i minimises the expected profit losses due to mispricing by setting prices given its information choice, subject to the maximum information gain constraint:

$$\min_{\{K^y_{it}, K^a_{it}\} \in \mathcal{R}^+} E\left[(p_{it} - p^*_{it})^2 | s_{it}\right] \qquad \text{subject to } K^y_{it} + K^a_{it} \leq K \tag{1.9}$$

As Maćkowiak and Wiederholt (2009) show, minimising the quadratic loss around the full-information optimal price subject to information constraints is equivalent to profit-maximisation. The quadratic loss function is symmetric, so it is trivial to show that the optimal price is the firms' best guess of what the true optimal price is given the signal it receives:

$$p_{it} = E\left[p^*_{it} \mid s_{it}\right] = \varphi E\left[y_t \mid s^y_{it}\right] - E\left[a_{it} \mid s^a_{it}\right] \tag{1.10}$$

As in Zhang (2017), the model is solved by a backward two-step procedure. Firstly, the optimal price is solved for a given attention allocation $\{K^y_{it}, K^a_{it}\}$. Secondly, I use the result from the first step to substitute for the profit loss (from the optimal profit) in the firm's objective as a function of the information choice. The attention allocation decision can then be solved by optimising the objective.

The optimal price setting decision for a given attention allocation can be inferred from standard Bayesian updating and the pricing rule Eq (1.10). Rearranging it, we get Eq (1.12) which can be attained using noise volatilities from Eq (1.7) and Eq (1.8):

$$p_{it} = \varphi \frac{\sigma_y^2}{\sigma_y^2 + \sigma_{\varepsilon_{y,t}}^2} s_{it}^y - \frac{\sigma_a^2}{\sigma_a^2 + \sigma_{\varepsilon_{a,t}}^2} s_{it}^a \tag{1.11}$$

$$= \varphi \left(1 - 2^{-2K_{it}^y}\right) s_{it}^y - \left(1 - 2^{-2K_{it}^a}\right) s_{it}^a \tag{1.12}$$

This optimal pricing behaviour substituted into the expected profit loss due to mis-pricing, noting the independence of fundamental and noise shocks, results in:

$$E\left[(p_{it} - p_{it}^*)^2 \mid s_{it}\right] = \varphi^2 2^{-2K_{it}^y} \sigma_y^2 + 2^{-2K_{it}^a} \sigma_a^2 \tag{1.13}$$

$$= \varphi^2 2^{-2K_{it}^y} \sigma_b^2 + 2^{-2K_{it}^a} \sigma_a^2 \tag{1.14}$$

where the last equality (1.14) results from the prior variances $\sigma_y^2 = \sigma_b^2$, as the monetary policy component of demand $c \cdot r_t$ is observable. Substituting the maximum information gain constraint, it is trivial to show the expected profit loss is strictly convex for any finite and strictly positive combination of $\{\sigma_b^2, \sigma_a^2\}$. Thus, there exists a unique interior solution for the optimal attention allocation:[12]

$$K_{it}^{y*} = \frac{1}{2} \log_2 \left(\frac{\varphi \sigma_b}{\sigma_a}\right) + \frac{1}{2} K \tag{1.15}$$

$$K_{it}^{a*} = \frac{1}{2} \log_2 \left(\frac{\sigma_a}{\varphi \sigma_b}\right) + \frac{1}{2} K \tag{1.16}$$

The optimal attention allocation results are very intuitive: the attention paid to demand is increasing with the total attention available K and the uncertainty surrounding demand σ_b (as higher demand uncertainty increases the benefits to monitoring demand conditions y_t), while decreasing in productivity uncertainty σ_a. The last result suggests that an increase in productivity uncertainty would make firms reallocate attention away from monitoring demand conditions. This contrasts to Zhang (2017), where in that model the attention paid to a variable depends only on the prior variance of the variable itself and the marginal cost of attention.[13]

[12] See Appendix A.1 for details of the derivation.

[13] In Zhang (2017) model, an increase in (the equivalent of) demand uncertainty would mean firms increase K, to ensure that the marginal benefit of attention equates the exogenous marginal cost.

1.3.2 Comparative Statics: Disagreement

As we have now solved for the optimal attention allocation, in this subsection, we examine how disagreement of demand conditions $\sigma^2_{\varepsilon_{y,t}}$ responds to changes in: (1) total attention available K, (2) productivity uncertainty σ^2_a, and (3) demand uncertainty σ^2_b. In the next subsection, we examine the price reaction to monetary policy shocks in response to changes in the aforementioned parameters.

Firstly, for demand disagreement, we revisit Eq (1.7). From this equation, it is clear that disagreement is a function of (exogenous) fundamental uncertainty, but also related to the endogenous decision of attention allocation:

$$\sigma^2_{\varepsilon_{y,t}} = \frac{1}{2^{2K^y_{it}} - 1}\sigma^2_y$$

Substituting in the optimal attention allocation and differentiating it with respect to K, σ^2_a and σ^2_b results in:

$$\frac{d\sigma^2_{\varepsilon_{y,t}}}{dK} = -\sigma^2_b \ln(2) 2^{2K^y_{it}} \left(\frac{1}{2^{2K^y_{it}} - 1}\right)^2 < 0 \tag{1.17}$$

$$\frac{d\sigma^2_{\varepsilon_{y,t}}}{d\sigma^2_a} = \frac{1}{2}\frac{\sigma^2_b}{\sigma^2_a} 2^{2K^y_{it}} \left(\frac{1}{2^{2K^y_{it}} - 1}\right)^2 > 0 \tag{1.18}$$

$$\frac{d\sigma^2_{\varepsilon_{y,t}}}{d\sigma^2_b} = \frac{-2 + 2^{2K^y_{it}}}{2(2^{2K^y_{it}} - 1)^2} \gtrless 0 \tag{1.19}$$

The first two derivatives, Eq (1.17) and (1.18), are simple and fairly intuitive: changes in total information processing available to firms K and productivity uncertainty σ^2_a only affect demand disagreement only through the endogenous response of attention K^y_{it}. A lowering of the total information processing capacity of firms lead firms to pay less attention to aggregate demand (as well as productivity), leading to a poorer quality of information and thus increased disagreement across firms. Similarly, an increase of fundamental idiosyncratic productivity uncertainty lead firms to reallocate attention away from monitoring aggregate demand conditions, which also increase demand disagreement.

The more interesting case is what happens when fundamental demand uncertainty σ^2_b rises. The sign of the derivative in Eq (1.19) is ambiguous: it is positive when $K^y_{it} > \frac{1}{2}$ and negative when $K^y_{it} < \frac{1}{2}$. In other words, when attention on aggregate demand is relatively high, fundamental demand uncertainty *positively* co-moves with demand disagreement, but when attention is relatively low, uncertainty and disagreement *negatively* co-move. This is because there are two opposing forces: a direct effect of an increase in fundamental uncertainty, and an indirect effect from the endogenous re-allocation of attention towards monitoring demand. When attention is relatively low, the re-allocation of attention towards aggregate demand conditions could be strong enough that it overturns the direct effect (as the marginal benefits of re-allocating attention towards demand is high).

Maćkowiak and Wiederholt (2009) argue that to explain the sluggish response of prices to aggregate monetary shocks, it must be that idiosyncratic productivity matters a lot more for firm profits than demand uncertainty ($\sigma_a^2 \gg \sigma_b^2$), implying that firms pay little attention to aggregate conditions. While my model is clearly not quantitative, the Maćkowiak and Wiederholt (2009) result at least points to the plausibility of negative co-movement between uncertainty and disagreement. Empirically, Kozeniauskas et al. (2018) document that the correlation between various uncertainty and disagreement measures are quite low.

1.3.3 Comparative Statics: Price Setting

This subsection returns to the key research question: how do prices respond to monetary shocks under different conditions? By combining Eq (1.10) and $s^y_{it} = y_t + \varepsilon^y_{it} = b_t - cr_t + \varepsilon^y_{it}$, we arrive at:

$$\frac{dp_{it}}{dr_t} = \frac{dp_{it}}{ds^y_{it}} \cdot \frac{ds^y_{it}}{dr_t} = \left(1 - 2^{-2K^y_{it}}\right) \cdot (-c)\varphi < 0 \tag{1.20}$$

$$= -\varphi c \left(1 - \frac{\sigma_a}{\sigma_b \varphi} 2^{-K}\right) \tag{1.21}$$

where we derive the second line by substituting in K^{y*}_{it} from Eq (1.15). Intuitively, firms set lower prices as demand falls (as full-information optimal prices also fall). However, the extent that this occurs depends on the level of attention on aggregate demand conditions.

Taking the second-order comparative statics of Eq (1.21) with respect to the same parameters in the previous subsection:

$$\frac{d^2 p_{it}}{dr_t dK} = -\ln(2)\frac{\sigma_a}{\varphi\sigma_b}2^{-K}\varphi c < 0 \tag{1.22}$$

$$\frac{d^2 p_{it}}{dr_t \sigma_a} = \frac{1}{\varphi\sigma_b}2^{-K}\varphi c > 0 \tag{1.23}$$

$$\frac{d^2 p_{it}}{dr_t d\sigma_b} = -\frac{\sigma_a}{\varphi}\frac{1}{\sigma_b^2}2^{-K}\varphi c < 0 \tag{1.24}$$

These results are also fairly intuitive: prices are less responsive to monetary shocks when firms pay less attention. This could be generated by: (1) a reduction in total information processing capacity, (2) an *increase* in productivity uncertainty, or (3) a *decrease* in aggregate demand uncertainty.

The key takeaway from this simple model is that the mechanisms of increased disagreement and uncertainty to the monetary transmission mechanism can be very different, and thus explain why the results with disagreement regimes contrast with those in the literature on uncertainty. For example, a reduction of information processing capability of agents raises disagreement and weakens monetary policy, but this change has no effect on fundamental uncertainty. Meanwhile, an increase in productivity uncertainty also increases demand disagreement, and the same time, reduces the effectiveness of monetary policy. But a *decrease* in demand uncertainty could cause an endogenous attention response, that is an *increase* in disagreement, but also weakens monetary transmission.

1.4 Empirical Analysis

1.4.1 Data

I obtained quarterly data of real GDP, GDP deflator, commodity price index and effective Federal Funds Rate from the Federal Reserve Economic Data (FRED) database, for the sample period of 1970Q1 to 2018Q4. Real GDP and GDP deflator are measures of economic activity and prices, sourced from the Bureau of Economic Analysis, and are seasonally adjusted. I include a commodity price index to control for energy and food price shocks, and capture supply side factors that may influence output and prices. This data is from the Bureau of Labour Statistics, and is originally not seasonally adjusted.[14] The choice of these variables is standard in the empirical literature studying monetary policy transmission as noted by Christiano et al. (1996), Sims (1992), and Bernanke and Gertler (1995). I transform real GDP, GDP deflator and commodity price index with log first-differences.

I replaced the effective Federal Funds Rates (FFR) from 2009Q1 to 2015Q3 with the Wu and Xia (2016) shadow rate to account for the zero lower bound (ZLB) and quantitative easing. To overcome this issue, Wu and Xia (2016) propose a non-linear term structure model to construct a shadow interest rate that captures the effect of unconventional monetary policies on the overall stance of monetary policy.[15] During these periods, the FFR was between 0 and 0.25 percent. Thus, the 'Wu-Xia shadow interest rate' captures the overall monetary policy stance better than the FFR on its own.

1.4.2 Measuring Disagreement

Following a line of literature that uses survey data to measure information frictions, I calculate *disagreement* among forecasters from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters (SPF). In particular, the SPF's *cross-sectional forecast dispersion* that is defined as the difference between the 75^{th} percentile and the 25^{th} percentile of the projections in levels or growth at a point in time. Following this, I define the benchmark *disagreement measure* among forecasters by calculating the interquartile range of *real* GDP for the *current* quarter (nowcast), divided by the median of the current quarter as a normalisation.[16] Interquartile range is widely used in the literature to ensure that any outliers do not unfairly influence the variable of interest — the measure of disagreement.[17]

[14] I have seasonally adjusted commodity price index using the Census Bureau's X-13 ARIMA-SEATS, with near identical results.

[15] In response to the global financial crisis, the Federal Open Market Committee (FOMC) took drastic measures that took the FFR in to the effective lower bound from December 2008 to 2015, as they set the target range for the FFR at 0 to 25 basis points. Additionally, the Fed took unconventional measures, such as quantitative easing, to further ease credit conditions and lower long-term interest rates. Thus, after December 2008, the FFR is less likely to describe the monetary policy stance well. The 'Wu-Xia shadow interest rate' is updated only if the target range for the FFR is at or above 25 to 50. On December 16, 2015, the FOMC raised the target range for the FFR to 25 to 50 basis points.

[16] As a robustness check, I also calculated the 2-quarter and 1-year ahead forecast disagreement of the nominal GDP in Figure A.1 in Appendix A.3.1.

[17] This is similar to using standard deviation as a measure of disagreement. However, as Sill (2014) shows, the standard deviation in cross-sectional forecasts is clearly more volatile, though tracks the interquartile range measure fairly closely. In line with the literature, I measure disagreement using

SPF is a quarterly survey of approximately 50 professional forecasters (on average) across many different macroeconomic variables.[18] It is one of the longest standing macroeconomic surveys, starting in 1968Q4. Thus, it covers a variety of episodes in U.S. macroeconomic history, including important economic events in the 1970s.

Furthermore, as professional forecasters are some of the most informed agents in the economy, SPF serves as a conservative benchmark for information frictions in their forecasts' cross sectional variation. Such that, if there was an increase of information frictions that reduces a professional forecaster's ability to predict macroeconomic aggregates — despite all publicly available information and forecasting techniques — then, we could expect there would be higher information frictions among other economic agents, such as households and firms.

I focus on the variable that is representative of the business cycle — *real GDP* (nowcast) — as the aim of this paper is to study the responses of output and prices to a monetary shock Rossi and Sekhposyan (2015).[19] Additionally, as Bok et al. (2018) highlight, forecasts are most helpful to understand where the economy is now. They show there is little predictability of real GDP SPF forecasts beyond the current and next quarter.

Figure 1.1 plots the disagreement measure — interquartile range of individual responses divided by the median — for the current quarter (nowcasts) real GDP.[20] The estimated value of the threshold parameter, as will be explained in the following subsection, is the solid red line. High disagreement periods are defined as the periods where the disagreement variable is above the threshold (as estimated by the model) — depicted in the red shaded area. Grey shaded areas indicate the NBER business cycle contraction dates. The delay parameter is set to 1, hence the regimes change with a lag of one period, after crossing the threshold.

interquartile range.

[18] At its current format, each forecaster provide the same set of baseline variables for the current quarter and up to four quarters ahead, as well as annualised values for the following 2 years for certain variables. SPF also asks special variables and special questions with different horizons.

[19] To re-emphasise, this paper complements the literature looking at the effects of monetary policy shock under time-varying disagreement, that has largely focused on *inflation expectations* disagreement, such as Falck et al. (2019). See Section 1.2 for more details.

[20] The SPF provides individual forecasts for the quarterly and annual level of chain-weighted real GDP. The dataset is seasonally adjusted. Prior to 1992, these are forecasts for real GNP. Note that there was a consensus for the official measure of output to be GDP rather than GNP in 1991. The change from GNP to GDP can also be observed in other macroeconomic forecast surveys such as Blue Chips. In Figure A.7 in Appendix A.3.5, I show that real and nominal GNP tracks real and nominal GDP very well. Annual forecasts are for the annual average of the quarterly levels.

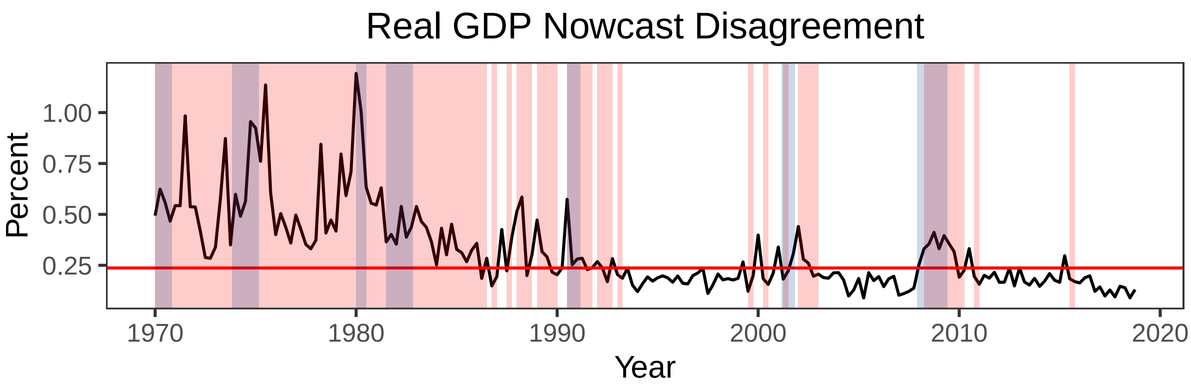

Figure 1.1. Time-Varying Real GDP Nowcast Disagreement

Note: Time series of the real GDP disagreement index based on the dispersion (interquartile range) of SPF nowcast. The grey shaded areas indicate NBER-dated recessions. The red shaded areas indicate high disagreement periods. The red line indicate the estimated threshold. The y-axis is the interquartile range as a percentage of the median. It is simply a measure of dispersion, much like a standard deviation.

Eyeballing Figure 1.1, we see that disagreement tends to be higher in the early years of the survey (pre-early 1990) in comparison with the latter half of the sample. As a check, a Wald structural break test point to 1980Q2 as the structural break in the disagreement variable, rather than early 1990s.[21] The shaded area in the chart shows that 1980 is in the midst of the first portion of high disagreement period, thus the results here is not solely due to a structural break in the sample period.[22]

This pattern of declining disagreement also tracks the period known as the Great Moderation from 1984 to 2008, when the overall volatility of the economic data was lower than in the pre-1984 period. However, it is important to emphasise that the fall in disagreement is not just a consequence of the Great Moderation. We can still observe high disagreement regimes, especially in the late 1980s to early 1990s, and around business cycle recession dates. While high disagreement is (weakly) correlated with recessions, high disagreement episodes are more prolonged after recessions, and disagreement regime changes typically occur at a higher frequency than business cycles.

[21]The output of the Supremum Wald (test for a structural break at an unknown break date, with symmetric trimming of 15%) indicates to reject the null hypothesis of no structural break at the 5% level, with a test statistic of 157.4213.

[22]Additionally, in Chapter 2, I show various robustness of using different structural changes (by dates), and show that it produces different impulse response of various macroeconomic variables when using disagreement of real GDP nowcasts.

The rational inattention model in the previous section provides a plausible explanation for the decline in disagreement in the latter half of the sample. Total attention K may have increased as there is a generally greater effort in forecasting GDP and other macroeconomic variables in the past 30 years. Moreover, during this time, forecasting methods and information available may have significantly improved, and thus creates a lower disagreement among professional forecasters.

1.4.3 Methodology

Estimation of the Threshold Variable

The estimation of the threshold uses conditional maximum likelihood, following Galvão (2006). If the threshold is known, it is possible to simply split the sample (above and below the threshold variable) and estimate the parameters with OLS, as well as the variance-covariance matrix Σ of the residuals U_t in each of the two regimes. Thus, a numerical optimiser iterates across the threshold values, to find the optimal threshold θ^*.

$$\theta^* = \min_{\theta} \left[\frac{T_1}{2} \log |\widehat{\Sigma}^{(1)}(\theta)| + \frac{T_2}{2} \log |\widehat{\Sigma}^{(2)}(\theta)| \right] \tag{1.25}$$

where $|\widehat{\Sigma}^{(i)}(\theta)|$ is the determinant of the covariance matrix of the residuals U_t in regimes $i = 1, 2$ (low and high disagreement regimes).

Threshold Vector Autoregression Model

The baseline methodology of this paper is a threshold VAR that allows the model to capture potentially different effect of monetary policy shocks in high and low disagreement regimes. The VAR model parameters are allowed to differ across (disagreement) regimes, and the transition between the regimes being governed by the evolution of a single *endogenous* variable of the VAR crossing a threshold (the 'threshold variable').[23] Therefore, this makes it possible that regime switches may occur after the shock to each variable. Because of this, the magnitude (and even the sign) of the impulse response may be affected by: (1) the state of the system at the time of the shock, (2) the sign of the shock, and (3) the magnitude of the shock.

[23] There are other non-linear methodologies, including smooth-transition VARs, interacted VARs, and Markov-switching approaches. The choice of appropriate non-linear methodology depends on the specific research question.

The threshold VAR model is described below. The first term in on the right hand side of the equation is analogous to a linear VAR. The non-linearity of the model comes from introducing different regimes on the second term of the right hand side.

$$Y_t = \left[c_1 + \sum_{j=1}^{p} \gamma_1(L)Y_{t-j}\right] + \left[c_2 + \sum_{j=1}^{p} \gamma_2(L)Y_{t-j}\right] I(y^*_{t-d} > \theta^*) + U_t \tag{1.26}$$

where Y_t is a vector of endogenous (stationary) variables as mentioned in the previous section. I is an indicator function that takes the value of 1 when the threshold variable is higher than the *estimated* threshold parameter θ^*, and 0 otherwise, with time lag d set to 1. U_t are reduced-form disturbances. $\gamma_1(L)$ and $\gamma_2(L)$ are lag polynomial matrices with order p. The lag order selection by Akaike information criteria marginally chose 4 lags in the linear VAR, and to maintain consistency I estimate the threshold VAR with the same number of lags.

The specific identification — real GDP, GDP deflator, commodity price index, FFR and disagreement — reflects some assumptions about the links in the economy. The ordering of the first four variables associated with the Cholesky decomposition of the covariance matrix of U_t is widely used, such as in Bernanke and Gertler (1995).[24] Ordering SPF dispersion last implies that it reacts contemporaneously to all other variables. The results are robust to other orderings.

As this is a non-linear model, I use the generalised impulse response (GIRF) approach of Tsay (1998). The full algorithm, including the computation of bootstrap confidence intervals, is described in Appendix C of Caggiano et al. (2015).

1.4.4 Baseline Results

The impulse responses in Figure 1.2 and 1.3 correspond to a 1 standard deviation positive shock to FFR, while the shaded area corresponds to a 68% bootstrapped confidence interval. Figure 1.2 shows the impulse response functions (IRFs) of *linear* vector autoregressive — i.e. without differentiating the level of disagreement in economy. Figure 1.3 shows the generalised impulse responses (GIRFs) of the baseline threshold VAR, allowing for a shock that occurs initially in a low disagreement

[24] The Cholesky decomposition I use in this paper assumes lower triangular matrix, such that monetary policy shocks do not affect real GDP, GDP deflator and commodity price index within the same quarter.

regime (blue line) and high (red-dash line) disagreement regime. It is important to note that the linear IRF in Figure 1.2 does not necessarily lie between the high and low disagreement GIRFs. This is because the GIRFs allow regime switching after a shock.

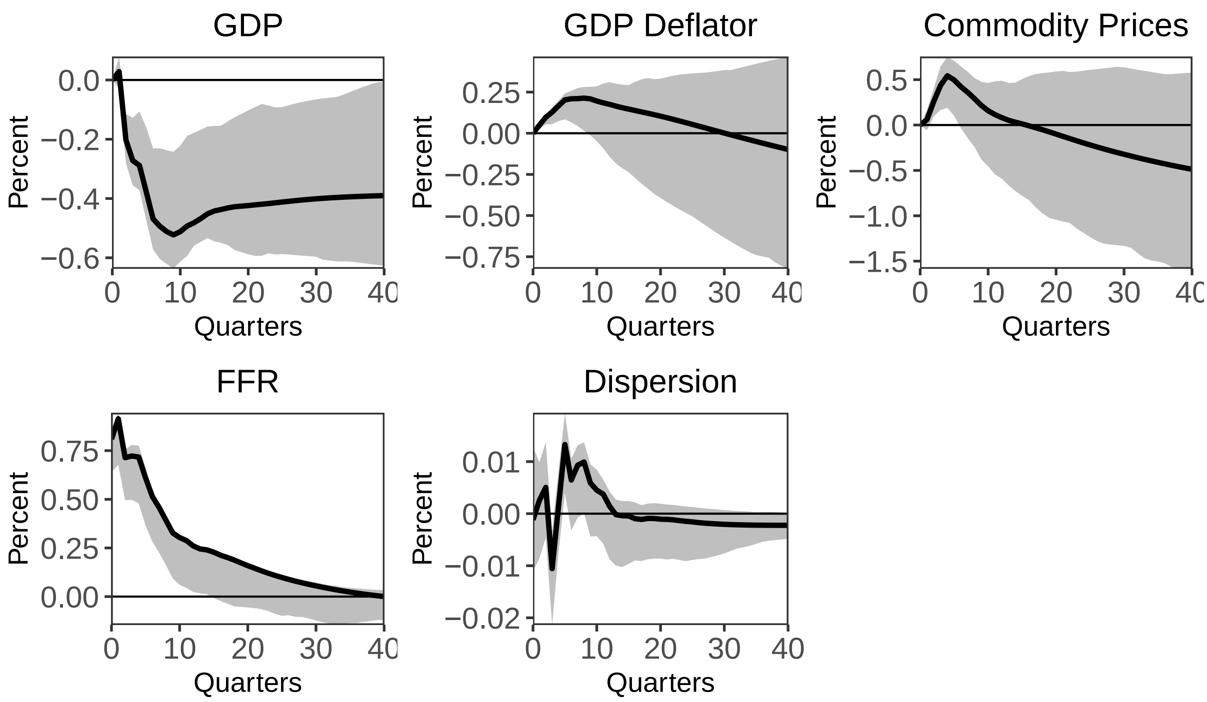

Figure 1.2. VAR Impulse Responses to a Monetary Policy Shock

Note: The shock corresponds to a positive one standard deviation change in the FFR. The IRFs are generated with 68% bootstrapped confidence intervals using (linear — without the distinction between high and low disagreement) Cholesky-identified structural VAR. Sample period is 1970Q1-2018Q4.

In the linear VAR, the peak effect on real GDP is 0.5% after around 8 quarters or 2 years, which is a typical horizon in the literature for output to respond to a contractionary monetary shock. The commodity price index drops more quickly than GDP deflator as expected by Bernanke and Gertler (1995). The sluggish responses in real GDP and price level, as well as the persistent decline in GDP deflator is fairly consistent with the literature, for example Galí (2015) and Christiano et al. (1999). The GDP deflator depiction of a weak 'price-puzzle' — prices increase after an increase in FFR — is a common finding for monetary shocks identified with a recursive VAR.

The generalised impulse responses (GIRFs) in Figure 1.3 show the main result — that there is heterogeneity in the effects of monetary policy shocks in the two disagreement regimes. In high disagreement periods (red lines), monetary policy shocks have a strong impact on real activity yet a weak impact on nominal variable. In contrast, during low disagreement (blue lines), monetary policy is more powerful in affecting prices.

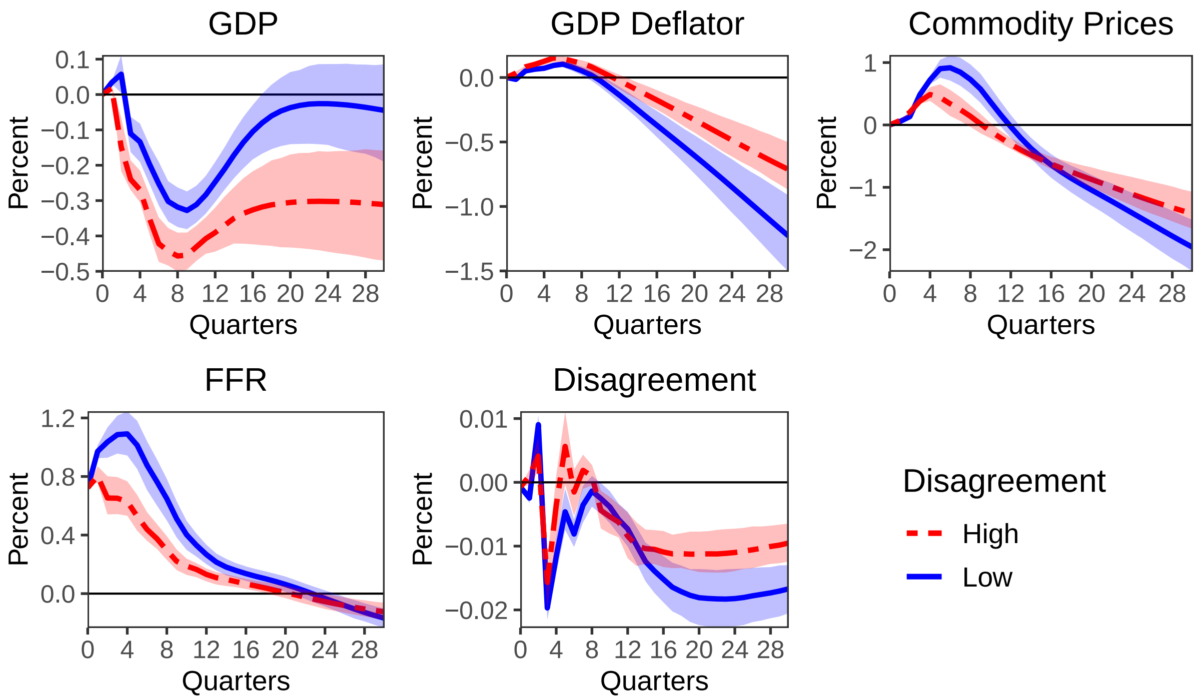

Figure 1.3. Threshold VAR Generalised Impulse Responses to a Monetary Policy Shock

Note: The shock corresponds to a positive one standard deviation change in the FFR. The GIRFs are generated with 68% bootstrapped confidence intervals using threshold VAR. The threshold is estimated using SPF disagreement of the nowcasts of **real** GDP. Red dashed-line indicate high disagreement period and blue solid-line low disagreement period. Sample period is between 1970Q1 and 2018Q4.

There is a long debate in the literature on the predictions of monetary policy transmission in different economic regimes. When looking at recessions or higher uncertainty, the typical intuition would be that agents becomes more cautious, and therefore, respond more slowly. Tenreyro and Thwaites (2016) find strong evidence that the effects of monetary policy on real and nominal variables are less powerful in recessions. Castelnuovo and Pellegrino (2018) and Aastveit et al. (2017) also point to a weak impact of monetary policy shocks on real activity under high uncertainty — the period they relate with recessions.

In contrast, I show that in high disagreement periods, a positive shock to FFR is more powerful in controlling output, yet less powerful in affecting prices.[25] The peak

[25]Notice that these shocks are monetary policy shocks rather than monetary policy changes. The

impact of the contractionary monetary policy shocks reduces GDP by approximately 0.3% in the low disagreement regime. Whereas, an equivalent sized shock reduces GDP by 0.45% in high disagreement regime — a sizeable increase of around half. Furthermore, the real effects of monetary policy is much more persistent under high disagreement, in addition to falling faster on impact. Correspondingly, the impact of monetary policy under low disagreement is *stronger*. At the end of the GIRFs horizon, the impact on prices is -1.2%, almost twice lower than the effect of -0.7% under high disagreement.

Therefore, the presence of heightened disagreement, the trade-off between output and inflation worsens, as output falls faster after a positive monetary policy shock. This means inflation-output trade-off is even trickier to deal with when disagreement is high, which I discuss in more detail later in the discussion of policy implications.

The rational inattention model offers three explanations for the empirical findings. All explanations have a common theme that to produce the more sluggish response of prices to a monetary shock, attention paid by price-setters to aggregate conditions must be lower. Thus, firms react less to monetary shocks, making prices more 'sticky'. A standard New Keynesian model with stickier prices would predict that output would respond more to a monetary shock.

Firstly, the information processing capacity of firms could be lower, leading firms to reduce attention to aggregate conditions (and others). This could be caused by a variety of reasons — for example, the exit of firms over the business cycle break down existing supplier-customer relationships that facilitate information flows across the supply chain. This would also reduce the quality the information that the firm processes, leading to higher disagreement, which is consistent with the empirical finding.

Secondly, higher uncertainties in state variables other than aggregate conditions (in the model, idiosyncratic productivity was one example), lead firms to re-allocate attention away from aggregate conditions. This has the same effect in increasing disagreement and stickier prices. This result also holds in larger general equilibrium

monetary policy shocks is relative to what the Taylor rule implies should happen, and the Taylor rule is implicit in the (threshold) VAR in Eq (1.26). Thus, in times of weak growth, it is perfectly feasible to have a positive monetary policy shock (that is, monetary policy could have loosened but not as much as the implicit Taylor rule suggests). On another note, a negative shock (reduction in) FFR is not exactly symmetric, but only for extremely large shocks. It does not change the main results of the paper.

models. Maćkowiak and Wiederholt (2009) show that by increasing the variance of idiosyncratic productivity shocks, rationally inattentive firms pay very little attention to monetary shocks, resulting in prices reacting slowly and by a small amount to a monetary shock.

Thirdly, a *decrease* in aggregate demand uncertainty could potentially make prices more sticky. A rationally inattentive firm would respond to this by reducing attention allocated to monitoring aggregate conditions. As the model shows, in some parameter regions, the endogenous response of attention allocation has the potential to increase disagreement by reducing the information quality used to monitor on aggregate conditions. These regions typically occur when the overall variance of aggregate conditions is low compared to idiosyncratic shocks, thus the marginal benefits of paying attention are high. This is exactly the parameter space that Maćkowiak and Wiederholt (2009) suggest is plausible to create the effect that prices respond sluggishly to monetary shocks.

These theoretical results bridge the disagreement results with the broader literature on the effect of uncertainty on monetary transmission, which typically finds that monetary policy has a weaker effect on prices and output during heightened uncertainty. The effect of rising uncertainty on the responsiveness of prices is potentially non-monotonic, and the three different posited mechanisms could be more important at different times. As discussed earlier, Kozeniauskas et al. (2018) measure of 'macro uncertainty' is positively but not strongly correlated with 'higher-order uncertainty' measured in dispersions in forecasts.[26]

Lastly, the response of the FFR is higher for longer in the low disagreement regime. An explanation for this is, in high disagreement regime, output falls significantly by more and thus the endogenous monetary policy component is forced to relax monetary policy. On the other hand, as this does not occur under the low disagreement regime, this enables the central bank to keep monetary policy tight for longer to lower inflation. This suggests that, at least empirically, the inflation expectations channel does not operate by as much as the fall in inflation created by the drag on output gap.

[26]The 'cross-sectional disagreement' among forecasters I use in this paper is closer to the 'higher-order uncertainty' measure rather than 'macro uncertainty' measures such as Jurado et al. (2015) or VIX used in many uncertainty papers.

1.5 Non-Linear Narrative Shocks

In this section, I consider alternative ways to empirically identify monetary policy shocks, with a focus on the narrative identification. The 'narrative' approach refers to the use of historical documents to reconstruct the intended policy target rate and the information set of the policymakers (Cloyne and Hürtgen, 2016; Champagne and Sekkel, 2018; Miranda-Agrippino and Ricco, 2020). I extend the narrative identification by Romer and Romer (2004) as the narrative monetary shocks, and estimate it non-linearly. I apply the non-linearly narratively identified monetary shocks to both the threshold VAR framework, as well as local projections (which I will explore in Section 1.6).

I consider the effects of the monetary policy shocks as the residuals from an estimated reaction function following Romer and Romer (2004) (henceforth, RR). RR identify innovations to monetary policy by accounting for Federal Reserve's information set. I follow their orthogonalisation procedure by regressing the Federal Funds target rate changes on Greenbook forecasts (and its revisions) at each FOMC meeting.[27] The original RR regression is:

$$\Delta FFR_t = \beta^b \mathbf{X}_t + \varepsilon_t \tag{1.27}$$

where $\mathbf{X}_t$ are the control variables employed by RR, and the estimated residuals are the identified monetary policy shocks.[28] As the premise of this paper is that the behaviour of the economy is characterised by forms of non-linearity and state-dependent, it is possible that the FOMC's monetary policy reaction function may has also been state-dependent. In other words, estimating shocks with standard linear framework may include state-dependent measurement error (Tenreyro and Thwaites, 2016). To account for this possibility, I estimate the narrative shock analogue to the original RR, corresponding to each definition of the economic state. For exposition here, I focus using a dummy state variable $F(z_t)$ where $F(z_t) = 1$ when in a high disagreement

[27] In the zero lower bound periods, I regress the changes in the Wu and Xia (2016) shadow rate instead of the target rate. This is explained later in this section.

[28] The control variables are lags of Greenbook forecasts for GDP growth and GDP deflator, as well as their revisions since the last FOMC meeting. As with Romer and Romer (2004), I match the Greenbook used for the particular FOMC meeting.

(H) state (defined as when z_t is above its median), and $F(z_t) = 0$ when in a low disagreement (L) state.[29]

Augmenting the original RR regression for state-dependence, the identification scheme is

$$\Delta FFR_t = F(z_{t-1})\beta^{(H)'}\mathbf{X}_t + (1 - F(z_{t-1}))\beta^{(L)'}\mathbf{X}_t + \tilde{\varepsilon}_t \quad (1.28)$$

where $\mathbf{X}_t$ are the control variables employed by RR and the estimated residuals $\tilde{\varepsilon}_t$ are the *non-linearly* identified monetary policy shocks.

The original RR series provides narrative monetary shocks up to 1996. I extend the series up to 2013. The literature has extended the series up to the financial crisis, such as Wieland and Yang (2020), Coibion et al. (2017), Miranda-Agrippino and Ricco (2020), and Tenreyro and Thwaites (2016). I extend the series using the extended dataset provided by Wieland and Yang (2020) up to 2007, and to 2008 using Coibion et al. (2017). To complete the dataset to 2013, I hand-matched the Greenbook forecasts, which are published with a five-year lag.

As noted in RR, the particular reason to analyse the Federal Reserve's intentions through the Federal Funds Rate (FFR) is, for much of the sample the Federal Reserve targeted the FFR. Therefore, the *change* in the intended FFR captures best what the Federal Reserve was aiming to do. This also deals with the concern of the periods where FOMC was not explicitly targeting the FFR, as well as serving as the easiest indicator of FOMC's intentions to deduce accurately over a long period of time and over a variety of monetary regimes. To maintain consistency, I also use this approach after the financial crisis. However, where the FFR has been near the zero lower bound, the target FFR would give zero variation in this period. In addition, the target FFR does not capture the true monetary policy stance, due to the use of unconventional monetary policies, such as quantitative easing (QE) and forward guidance. As in the baseline exercise, I use the Wu and Xia (2016) shadow rate to capture the additional features of unconventional monetary policy that have noticeable impact on the macroeconomy (Ramey, 2016).

[29] In Appendix A.3.4, I also define a smooth transition state using a logistic transformation as in Tenreyro and Thwaites (2016). This is then used for the smooth transition local projections. For consistency (across the baseline and the smooth transition local projection) in this section, I use $F(z_t)$ to refer to the dummy state variable. Note that $F(z_t) = 1$ is equal to $I_t = 1$ in Eq (1.26) and (2.2).

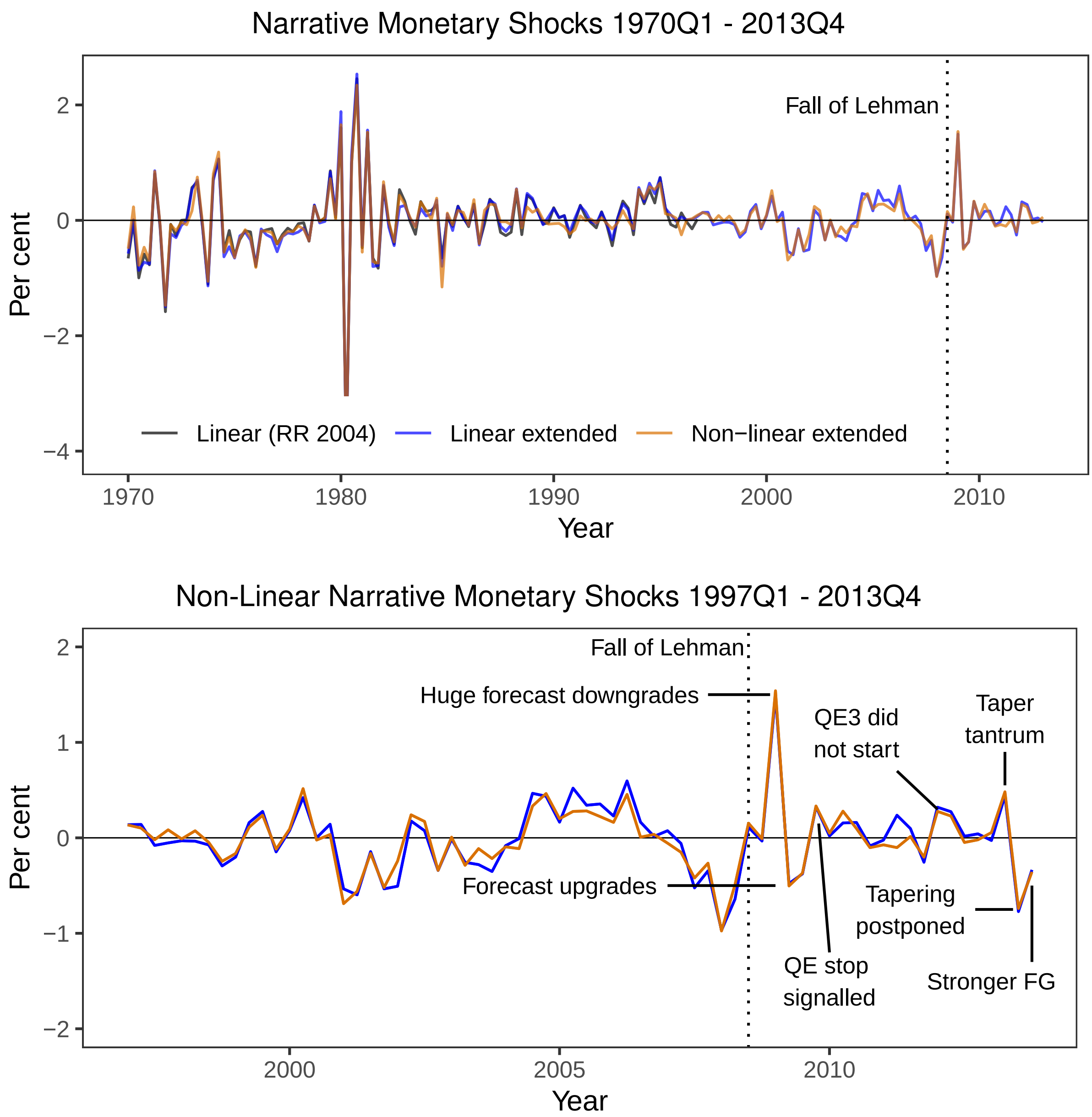

Figure 1.4. Narrative Monetary Shocks. Top: Whole Sample, Bottom: Recent Sample.

Note: I extend the narrative monetary shocks of Romer and Romer (2004) up to 2013Q4. The top figure shows the RR original shocks (black line), the extended linear narrative shock (blue line), and the extended non-linear narrative shocks (orange line). The bottom figure zooms in to show how the narrative approach with shadow rates neatly captures unexpected movements in unconventional monetary policies since the global financial crisis.

The standard in the literature for post-crisis monetary policy shock identification uses high frequency data around monetary policy announcements (Cochrane and Piazzesi, 2002; Gertler and Karadi, 2015; Nakamura and Steinsson, 2018). The high frequency identification literature often refers to the changes in futures contracts around key monetary events. They use a tight window around these events, in order to isolate monetary policy news from other types of shocks (Cesa-Bianchi et al., 2020). However, data for high frequency identification only goes back to the 1990s, as these financial instruments were not actively traded before then, it at all. While this is sufficient for monthly estimation, this paper uses the Survey of Professional Forecasters which is performed quarterly. Using the narrative monetary policy shock identification (instead of high frequency) allows me to use the full sample from the 1970s.

Figure 1.4 shows how the narrative approach with shadow rates neatly captures unexpected movements in unconventional policies since the financial crisis.[30] We observe a large positive shock in the first quarter of 2009. In March, the FOMC observed an increasing economic slack and this was reflected in a significant downgrade of economic forecasts — real GDP growth at two quarters ahead was downgraded to -0.5% instead of +1.8% — indicating that the FOMC realised that the U.S. economy was in a deep recession. This led their decision of announcing additionally large QE. However, the QE was not strong enough to overcome the contractionary effect of the Delphic forward guidance (Campbell et al., 2012). By 2009Q2, the FOMC saw a modest improvement in the economic outlook since the March meeting, reflected in their forecasts upgrades, which partly reflected some easing of financial market conditions. However, economic activity was likely to remain weak for a time, thus the magnitude was smaller than the preceding quarter. By the end of the 2009, in light of ongoing improvements in the financial markets, the FOMC signalled that the special liquidity facilities will expire in 2010Q1. Nonetheless, they communicated that they were prepared to modify plans if necessary to support financial stability and economic growth, which helps explain the small positive (contractionary) shock.

Another example of how the narrative approach captures monetary policy shocks is shown in the first half of 2012, where there is a sequence of positive shocks. In these

[30]My notation focuses on the events after the financial crisis. Economic events in periods between 1997 and 2007 have been discussed in the aforementioned papers.

periods, the FOMC did not start QE3, as the market had hoped multiple times. There was a relatively dovish statement, but was largely expected by markets. Combined, this is reflected in the modest contractionary shocks in the periods.

Moreover, in June 2013, there were discussions of 'tapering' QE purchases, contingent on a continuation of good economic data.[31] These discussions surprised financial markets, and in effect, producing what would be widely known as the "taper tantrum". However, in September 2013, the FOMC held off from scaling back asset purchases — again, surprising market participants, but in the opposite direction. Correspondingly, these two unexpected announcements generated a positive shock (contractionary) in June 2013, and a negative shock (expansionary) in September 2013 in the generated RR shocks in Figure 1.4.

1.5.1 Threshold VAR using Narrative Monetary Shocks

The next step in the analysis is to use the new non-linear narrative monetary shocks to estimate the effects on real and nominal variables. In order to be consistent with the baseline specification in Section 1.4.4 and standard literature, I follow Romer and Romer (2004) in using the narrative shocks instead of the FFR, but keeping the Cholesky ordering of the variables the same.[32]

Figure 1.5 shows the responses of output and prices to a positive one standard deviation shock to the narrative monetary shock. Quantitatively, it is difficult to compare the narratively identified monetary shock to the Cholesky identified. One standard deviation shock in the narrative identified monetary shock (which is in changes-space) is not equal to the one standard deviation shock to FFR in levels. Additionally, because the GIRFs are inherently non-linear, we cannot simply scale the responses. Hence, I focus on the qualitative differences between the high and low disagreement responses of output and prices.

Qualitatively, using a different shock identification (narrative shocks), the main results still hold. The results here also demonstrates the heterogeneity in the effect

[31] Specifically, the FOMC plan to reduce the pace of purchases of Treasuries from \$85 billion per month to \$65 billion by the second half of 2013, and further possibility of completely stopping asset purchases in 2014.

[32] I also removed commodity prices as a control because as Romer and Romer (2004) discussed, the narrative identification sufficiently avoids endogenous and anticipatory movements unlike the FFR, and therefore does not produce a large price-puzzle.

of monetary policy shock across the high and low disagreement regimes. In high disagreement periods, prices respond weakly to monetary policy shock, but output responds strongly. In low disagreement, the opposite is true. Thus, the main result and mechanism as previously explained – that prices are more sticky in high disagreement periods due to higher information frictions, leading to larger real effects of monetary shocks – holds with narratively identified monetary shocks á la Romer and Romer (2004).

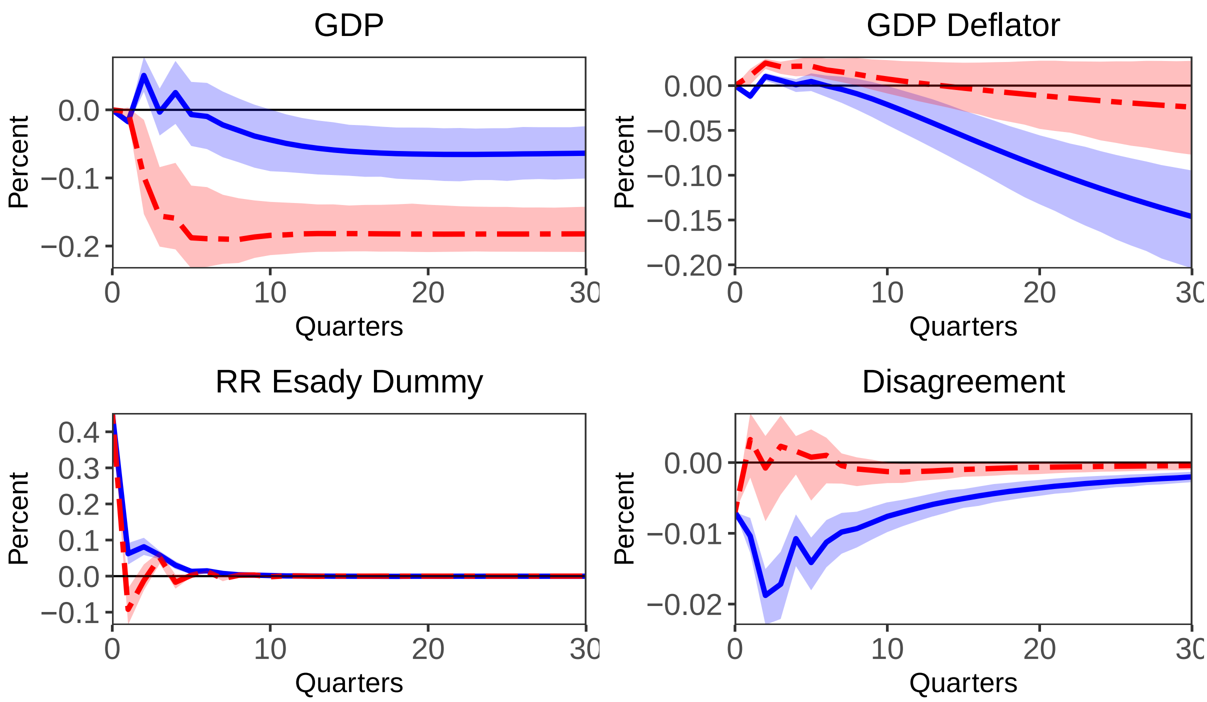

Figure 1.5. Threshold VAR Generalised Impulse Responses to a Narrative Monetary Shock

Note: The shock corresponds to a positive one standard deviation change in the narrative monetary shocks. The GIRFs are generated with 68% bootstrapped confidence intervals using threshold VAR. The threshold is estimated using SPF disagreement of the nowcasts of real GDP. Red-dash (blue-solid) lines indicate high (low) disagreement period. Sample period is 1970Q1-2013Q4.

In a more quantitative detail, we see in Figure 1.5 that at peak impact (around six-quarter horizon), the contractionary monetary policy reduces real GDP by approximately 0.2%, and similarly until the end of the horizon. During low disagreement periods, output eventually reduces by 0.07%, which is three times weaker compared to the response during high disagreement periods. Overall, the responses in the two regimes are significantly different from zero, and from each other. During high disagreement periods, output become immediately statistically significant from zero, while there is a lag during low disagreement periods. This is also observed in the generalised impulse response of output in Figure 1.3. In high disagreement, the peak response of output to the narrative monetary shocks is about half of the peak effect to the Cholesky identified monetary shocks.

The difference in magnitude is even more apparent in the response of prices to the two shocks. In low disagreement, the response of GDP deflator to the narrative monetary shock is -0.15%. More importantly, here we also observe the difference between the responses in high and low disagreement periods using the two shocks identification. Prices respond more strongly in low disagreement periods, and that it is significantly different from the response during high disagreement in the latter horizon. This suggests that both shocks identification strategies are able to pick up the heterogeneity in the responses of macroeconomic variables during different disagreement periods.

1.6 Local Projections

In this section, I explore the robustness of the main results by applying the non-linearly narratively identified monetary shocks to the local projections method.[33] The innovation of narratively identified monetary shocks has allowed for the possibility of using direct projections method to study the effects of monetary policy shocks on macroeconomic variable. Local projections method has more recently been applied to study the state-dependent effects of monetary policy as it can be easily adapted for estimating a state-dependent model (Tenreyro and Thwaites (2016); Coibion et al. (2017); Aastveit et al. (2017); Falck et al. (2019)).

I use Jordà's (2005) local projections method to estimate the impulse response to estimate the response of output and inflation for each horizon h. The linear model is as follows:

$$x_{t+h} = \alpha_h + \psi_h(L)X_{t-1} + \beta_h \text{shock}_t + \varepsilon_{t+h} \quad \text{for} \quad h = 0, 1, 2, ..., \tag{1.29}$$

[33] In understanding propagation of structural shocks, an often asked question is how to choose between SVAR and LP estimators of impulse responses. A conventional wisdom is that SVARs are more efficient (Ramey, 2016), while LPs are more robust to model misspecification (Jordà, 2005). However, many of these remarks are not based on formal analysis. Plagborg-Møller and Wolf (2020) prove that LPs and VARs estimate the same impulse responses, as well as showing that the two are not conceptually different methods.

Similarly, for the model that allows state-dependence, I estimate a set of regressions for each horizon h as follows:

$$x_{t+h} = F(z_{t-1})[\alpha_{A,h} + \psi_{A,h}(L)X_{t-1} + \beta_{A,h}\text{shock}_t]$$
$$+ (1 - F(z_{t-1}))[\alpha_{B,h} + \psi_{B,h}(L)X_{t-1} + \beta_{B,h}\text{shock}_t] + \varepsilon_{t+h}$$

where x is the variable of interest, X is a vector of control variables, $\psi_h(L)$ is a polynomial in the lag operator, $F(z_{t-1})$ denotes the state, and shock$_t$ is the narratively-identified shock. The control variables include a linear and a quadratic trend, and lag of x. I set the lag to 4 quarters to maintain consistency. The coefficient β_h gives the response of x at time $t+h$ to the shock at time t. The impulse responses are constructed as sequences of the β_h's estimated in a series of single regressions for each horizon. The state variable $F(z_{t-1})$ equals 1 when the economy is in regime A (high disagreement periods) and 0 when in regime B (low disagreement periods).[34] The interactions with the indicator variable allows all coefficients to vary according to the state of the economy. The set of coefficients $\beta_{A,h}$ and $\beta_{B,h}$ are used to construct the impulse responses for each regime A and B, respectively. Furthermore, as is standard in the literature, I use the Newey-West standard error correction to address the potential autocorrelation in the residuals (Newey and West, 1994).

1.6.1 Local Projection Impulse Responses

Figure 1.6 shows the state-dependent local projections impulse responses to a 1% narrative monetary shock. Much like comparing the narratively identified threshold VAR, it is tricky to compare these local projections to the Cholesky identified (baseline) threshold VAR. In this subsection, I compare these local projections impulse responses to the narrative threshold VAR. This allows for a focus on the different methodologies, rather than shock identification. However, this is also tricky because while Figure 1.6 are state-dependent impulse responses, they are linear *within* a state (unlike GIRFs in the threshold VAR, which allow switching between the states).

Thus, due to this intricacy, the focus of the analysis remains on the *qualitative* comparison between the responses in high and low disagreement regime, given the

[34] In the appendix, I also define a smooth transition state using a logistic transformation as in Tenreyro and Thwaites (2016).

methodologies. The main results and mechanism apparent in both threshold VARs are also present in the local projections, illustrating the robustness of the result to estimation procedures. In high disagreement periods, output responds fairly quickly to the monetary shocks. Whereas in the low disagreement regime, output is statistically insignificant from zero for more than twelve quarters. This result arises from the higher stickiness of prices during the high disagreement periods, as apparent from the magnitude of the impulse responses towards the end of the profile. As for prices, in low disagreement periods, the impact of monetary policy shocks is twice stronger than in high disagreement periods. The responses in the high and low disagreement regimes are significantly different in the latter part of the horizon — in line with the findings of the threshold VARs.

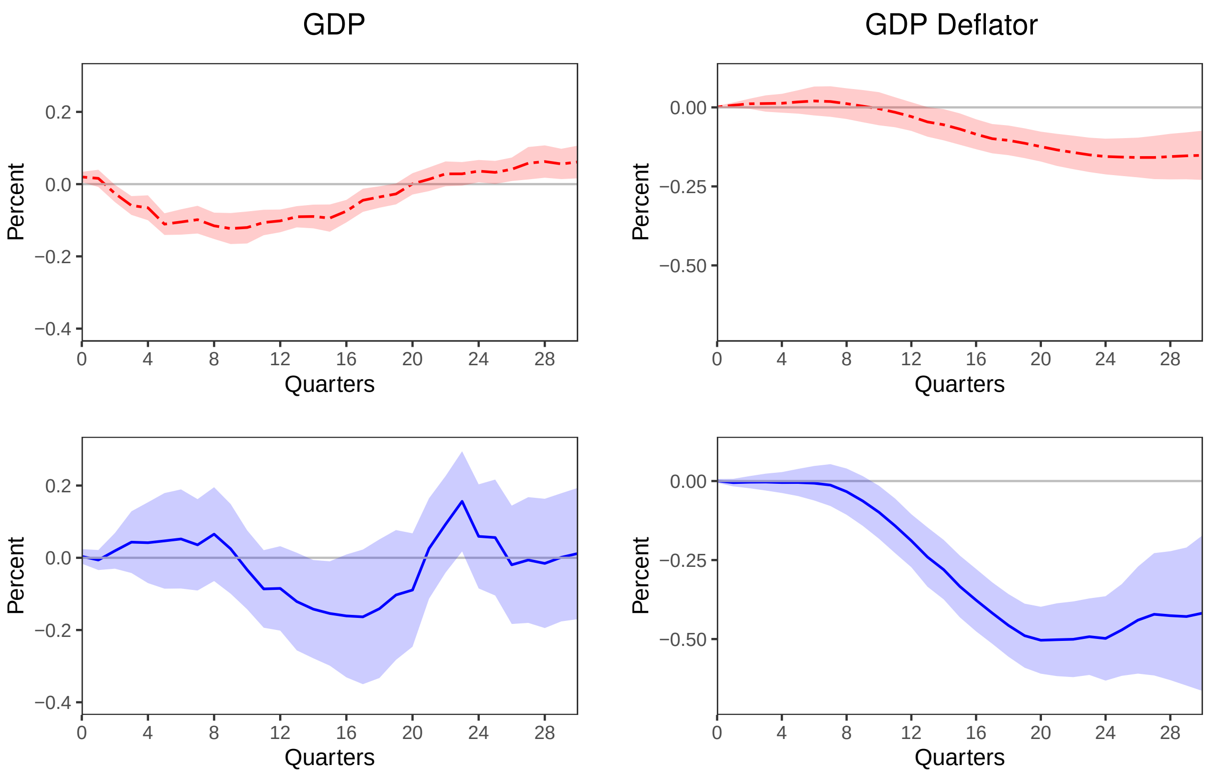

Figure 1.6. Local Projection Impulse Responses to a Narrative Monetary Shock

Note: The first and second column shows the response of real output and prices to a 1% narrative monetary shock. The first and second rows show the responses under high (red-dash lines) and low (blue-solid lines) disagreement periods, respectively. The shaded area is the 68% confidence interval. The sample period is from 1970Q1 to 2013Q4.

In order to be able to quantitatively compare it with Figure 1.5, notice that the size of the shocks is not exactly the same. In the threshold VAR, the shock corresponds to a positive one standard deviation change in the narrative monetary shocks — equivalent to approximately 0.45% shock to narrative monetary shocks. With this consideration, in high disagreement regime, the peak response of output is twice larger when using the threshold VAR. Meanwhile, the response of prices is much stronger (about 4 times) with local projections. In low disagreement, IRFs in Figure 1.6 also show a larger reduction, although only by twenty percent by the end of the horizon. Thus, in response to a narrative monetary shock, state-dependent local projections seems to capture stronger effect in prices (than in comparison to the results using threshold VAR).

1.7 Conclusion and Policy Implications

The main contribution of the paper is to empirically document the state-dependent effects of monetary policy with regard to real output nowcast disagreement using threshold VARs and non-linear local projections. In periods of heightened disagreement, monetary policy has smaller effects on inflation, but larger on output. This is robust to both Cholesky and narratively identified monetary shocks. This result complements Falck et al. (2019) where they find monetary policy is weaker on inflation during high *inflation expectations* disagreement, but no heterogeneous effects on output. Additionally, my findings contrast to the literature on the effects of uncertainty on monetary transmission (where they find weaker response of both output and inflation during higher uncertainty periods). A by-product of the model dissects the relationship between uncertainty and disagreement, and how they distinctly affect state-dependent monetary transmission under varying degree of information frictions.

The intuition of the main result is that price-setters respond less in periods with higher information frictions, and thus prices become stickier. These stickier prices lead to smaller price adjustments, but also because of the higher nominal rigidities, it causes a flatter Philips curve, leading to larger output effects for the given monetary shock. Another insight from the rational inattention model is that endogenous optimal attention allocation could cause disagreement to change non-monotonically in response to fluctuations in aggregate uncertainty.

The key policy takeaway from these results is the role of central bank communication. The results show that during periods of low disagreement, contractionary monetary policy (that intends to reduce inflation, "disinflationary policy") is able to reduce inflation significantly with relatively little output loss. This raises the potentially important role of central bank in communicating aggregate conditions to economic agents, enabling them to internalise the disinflationary (contractionary) policy that effectively makes prices more flexible. Thus, the sacrifice ratio is lower and enables an inflation-targeting central bank to better achieve its objective. This mechanism complements the literature results in having a credible central bank moving inflation expectations down during a disinflationary policy episode, which further reduces the sacrifice ratio.

Similarly, if inflation is below target but output is at potential, it is also optimal for the central bank to communicate. The increased in price flexibility allows it to increase inflation to target more quickly, while avoiding large and unsustainable positive output gaps (which are associated with undesirable effects, such as misallocation and credit booms). However, if a dual-mandate central bank objective is to raise economic growth rather than to stabilise inflation, it is not necessarily optimal either to *not* communicate. In a world of low interest rates, forward guidance could be a potent tool for expansionary monetary policy. Naturally, communication is an integral part of forward guidance. Thus, improving communication during such an episode, and achieving the benefits of forward guidance may outweigh the cost of increased price flexibility in terms of a reduction of the real effects of monetary policy.

Chapter 2

Reconciling the Effects of Government Spending: The Role of Information Frictions

2.1 Introduction

Since the 2008 financial crisis and the large fiscal stimulus surrounding it, there has been a reinvigoration in understanding the variations of how government spending influence the business cycle. Standard neoclassical models have long emphasised the importance of forward-looking expectations in the effectiveness of fiscal policy. With Ricardian equivalence, households consumption falls in response to a positive government spending shock as households save in anticipation of a future tax rise. Yet, a broad empirical literature finds a positive response of consumption, which is more in line with the predictions of Keynesian models. This paper empirically reconciles the Keynesian and neoclassical predictions on the effects of fiscal policy, through emphasising the importance of information frictions.

I estimate the state-dependent responses in high and low information friction regimes with non-linear local projections. I use a popular identification strategy of government spending shocks following Blanchard and Perotti (2002) (henceforth, BP). I find that the effect of a positive government spending shock increases output in both high and low information friction regimes, but only increases consumption in the high information friction regime. This leads to the *magnitude* of the stimulatory effect on output to be higher during periods of high information frictions, despite the paths of government spending under both regimes being remarkably similar. Thus, in high information frictions periods, consumption behaves similarly to the Keynesian prediction. In contrast, in the other regime, the consumption fall is more akin to the neoclassical prediction.

How do information frictions reconcile these results? Information frictions affect how forward-looking households and firms can be. In particular, the Ricardianness of the households (anticipating current or future tax rises in response to a government spending increase) could be influenced by information frictions. In turn, the ability of households to form accurate expectations on future income and economic conditions varies along with to these frictions. Consequently, households' response to a government spending shock could vary over time.

Specifically, if households find it more difficult to predict the future path of taxes (in response to a government spending shock, which may not be easily observable in real-time), it is plausible that households behave in a non-Ricardian way as they do not anticipate higher future taxes. This leads to more Keynesian effects of government spending. Conversely, a low information frictions regime enable households to be highly forward-looking, and thus, close to fully Ricardian. In turn, they observe the shock and save ahead in anticipation of higher future taxes to smooth their consumption, resulting in the usual neoclassical prediction.

Following an extensive literature, I measure information frictions through disagreement of professional forecasters: in particular, nowcasts of real output. When information frictions are highly prevalent, forecasts of the aggregate economy are more difficult to form — even by those best placed to make forecasts, such as those in the *Survey of Professional Forecasters* — and thus, they are more likely to be dispersed. On the other hand, take the extreme case of zero information frictions where all forecasters would use all available information perfectly, and they would all make the same forecast (zero disagreement).

The key contribution of this paper is the reconciliation of the (theoretical and empirical) debate on the behaviour of consumption after a government spending shock. While both sides agree output rises following an unanticipated expansion in government spending, Ramey and Shapiro (1998) find that consumption falls, yet BP find that consumption rises. Reis (2018) attribute their differences owing to their identification strategies. BP uses structural assumptions on the formation of fiscal policy to identify exogenous spending shocks, while Ramey and Shapiro (1998) uses war build-ups as the source of the shocks. Here, I find that *even with* the BP identification strategy, consumption can fall after a government spending shock, if households are given the chance to be sufficiently Ricardian (during low information frictions). If not, more Keynesian effects take hold, and thus consumption rises after the expansion in government spending.

These results guide further research into different microfoundations for fiscal policy dynamic models. For instance, Galí et al. (2007) emphasise the need for not only nominal rigidities, but also a large group of non-Ricardian households to achieve a positive co-movement of consumption and government spending. The latter is modelled as hand-to-mouth households that consume their entire disposable income. In this paper, the main result suggests information frictions should be a part of the transmission channel.

A second contribution of this paper is on the state-dependent transmission channel of the different components of government spending (government consumption and government investment), as well as transfer payments. The key takeaway for fiscal policymakers is that information frictions affect the ability of economic agents, such as firms and households, to respond to various fiscal shocks. This highlights that economic agents pay heterogeneous attention to the different types of government spending, and may respond differently to the specific type of shock.

Specifically, information frictions affect the behaviour of households (private consumption) the most in response to shocks in government consumption and transfer payments. The state-dependency of private consumption in response to these two shocks is particularly distinct. The short-term effect of transfer payment is stronger and statistically significant across low and high disagreement periods. Whereas, the medium-run private consumption impact of a government spending shock is *twice* that of the effect on transfer payments when information frictions are high.

These findings are consistent with disparate transmission channels of the two shocks. Transfer payments — such as social security and unemployment benefits — work more directly through increasing the current income of households with high marginal propensity to consume. This is consistent with the main results where rule-of-thumb households choose to consume more in the current period than to save for future tax rise. On the other hand, government consumption works through indirect, general equilibrium channels. The purchase of domestically produced goods and services by the government leads to the standard Keynesian amplification channels through increased aggregate demand and hiring.

Moreover, the responses of private investment to a government spending shock show fewer heterogeneities between the high and low information frictions regimes. Broadly, the results are similar to the empirical literature where private investment falls during both regimes after an expansionary government spending shock, due to crowding out effects.[1] However, this is not observed in the responses of private investment to government investment and transfer payment shocks. Government investment crowds-in private investment but only in low disagreement regime, whereas transfer payments more strongly crowds-out private investment in the same regime. This is consistent with the channel of complementarities between public and private productive investment — where productive government investment crowds-in private investment, and 'non-productive' transfers crowds-out private investment.

The fiscal policy literature is vast and has little agreement. As previously highlighted, even though most macroeconomic models predict that an expansionary effect on output, those models often differ on the implied effects on consumption. Galí et al. (2007) discuss how the textbook IS-LM (Keynesian) and the standard RBC (neoclassical) models provide an example of such stark heterogeneous qualitative predictions on private consumption. The Keynesian model predicts that consumption should rise as consumers behave in a non-Ricardian way, with their consumption being a function of their current disposable income and not of their lifetime resources. On the other hand, the neoclassical model of macroeconomic fluctuations is based on economic agents who optimise intertemporally with an increase in the present value of lump-sum taxes. This negative wealth effect induced by the fiscal expansion through an unproductive government spending results in the lowering of private consumption. The New Keynesian model that incorporates nominal rigidities into the neoclassical framework exhibits the same wealth effect that crowds out consumption after an

[1]An exception to this is the first few quarters after the shock, where under low disagreement, investment rises initially falling.

expansionary fiscal shock. In the more recent theoretical models, replicating the empirically relevant 'crowding-in' comovement within a DSGE framework is possible by adding extra elements, although it remains challenging (Jacob, 2015).[2]

Similarly, the empirical evidence on private consumption to a shock in government spending can support either theoretical view above.[3] Several authors have found that government spending shocks cause private consumption to rise (a non-exhaustive list includes Fatás and Mihov (2001); Blanchard and Perotti (2002); Galí et al. (2007); Perotti et al. (2007)), although these findings are challenged by Ramey and Shapiro (1998); Edelberg et al. (1999); Burnside et al. (2004); Ramey (2008). Often, the different findings depend on the methodologies and identification strategies. The most common identification methods are narrative techniques (Ramey and Shapiro, 1998; Ramey and Zubairy, 2018) and various structural vector autoregressive approaches with Cholesky decomposition following Blanchard and Perotti (2002).[4] More recently the local projections approach (Auerbach and Gorodnichenko, 2013; Ramey, 2016) that I use here have gained popularity, where the shock identification can use either the narrative (news shocks) or BP shocks.

The 'non-linearity' in this paper is in line with many papers in the empirical fiscal policy literature that looks at the state-dependent effects of fiscal policy shocks, such as Auerbach and Gorodnichenko (2013) and Ramey and Zubairy (2018).[5] Auerbach and Gorodnichenko (2013) find that multipliers are large in recessions, arguing that when there is more slack, crowding out effects are less likely, and the Keynesian effects become more likely. On the other hand, Ramey and Zubairy (2018) find that multipliers are below unity, regardless of slack (with an exception to the zero lower bound period, where spending multipliers are around 1.5).[6] In relation to this paper, if high disagreement periods purely contain recessions, the results here could merely

[2]See Chapter 3 for a more thorough literature review on the theoretical models on positive private consumption multiplier.

[3]There is an equivalently large literature on tax shocks that I do not discuss here. Ramey (2016) has a detailed discussion on identification methods. While papers such as Mertens and Ravn (2013) and Leeper et al. (2013) discuss fiscal foresight, in particular, the difficulties of identifying anticipated shocks to tax.

[4]There are various application of the VAR such as sign restriction VAR (Mountford and Uhlig, 2009), Bayesian VAR (d'Alessandro et al., 2019) and Panel VAR (Ravn et al., 2007).

[5]There are, of course, other types of nonlinearities such as asymmetries like those explored in Brinca et al. (2019).

[6]Using military spending to identify government spending shock, Biolsi (2017) find higher slack threshold produce higher multiplier, but still below unity.

show the standard slack channels (rather than the effect of information frictions).[7] The correlation between the disagreement state variable in this paper and indicators of recession (or slack) is only mildly positive. The correlation with the slack state of Ramey and Zubairy (2018) is 0.2, and with NBER-dated recessions is below 0.4. In other words, the disagreement variable I describe in this paper captures variation in both, recessions (or slack) and expansions.

Furthermore, the results here are robust to numerous robustness checks. The placebo tests with different time, such as Great Inflation and Great Moderation periods, confirms that the distinct responses of macroeconomic variables to the disaggregated government spending shocks is indeed due to the varying degree of information frictions, not a specific time period. I also find the results to be robust to alternative measurements of disagreement.

The rest of the paper is structured as follows. In Section 2.2, I describe the macroeconomic data. I present the measurement of state using the cross-sectional disagreement among forecasters in Section 2.2.2. I explain the econometric methodology and shock identification in Section 2.3. I present the linear and state-dependent impulse responses, as well as multipliers to a government spending shock in Section 2.4, and to the disaggregated shocks in Section 2.5. The robustness checks using placebo test can be found in Section 2.6. Section 2.7 concludes.

2.2 Data Description

I obtained quarterly data of the macroeconomic variables from Federal Reserve Economic Data (FRED). All variables are seasonally adjusted. The sample period is between 1970Q1 and 2018Q4. It starts on 1970Q1 because the measure for disagreement — discussed in the next section — is derived from the Survey of Professional Forecasters (now run by the Federal Reserve Bank of Philadelphia) which starts in 1970. This sample period includes a wide variety of economic dynamics: ranging from the unstable Great Inflation, the Great Moderation, but in particular, the Great Recession. This was a time where government spending played an important role, with a significant fiscal stimulus package (American Recovery and Reinvestment Act of 2009)

[7] Although, note that it does not preclude information frictions as another mechanism of why multipliers are large in recessions.

being implemented. Indeed, the concerted fiscal policy reaction to counteract the Great Recession, sparked a renaissance in fiscal policy research.

2.2.1 Log vs Level

I transform real GDP, real consumption, real investment, real wage and real government spending using the Gordon and Krenn's (2010) transformation (dividing the variables by an estimate of the potential GDP), and then taking the logarithms. In this way, one can interpret the IRFs as responses to a 1% changes in government spending.

When estimating the multiplier, I also divide all NIPA variables by an estimate of the potential GDP but do not take logarithms of the variables. As discussed in Ramey and Zubairy (2018), this puts all NIPA variables in the same units, such that one can estimate the multiplier directly. For example, an output multiplier of 1.5 means an increase of 1 U.S. dollar of government spending increases output by 1.5 U.S. dollars.[8] This remark on the data transformation would be particularly crucial in Section 2.5 where I compare the responses of macroeconomic variables to disaggregated government spending shocks.

2.2.2 Measurement of State

As in the previous chapter, I use survey data to measure the time-varying information frictions. I also measure the state of the economy using disagreement of real GDP nowcasts from the Survey of Professional Forecasters. I choose (the dispersions of) professional forecasters to construct the disagreement variable in this chapter for three reasons. Firstly, the data availability of professional forecasts is excellent. The Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters (SPF) is a quarterly survey of approximately 50 professional forecasters (on average) across many macroeconomic variables.[9] Secondly, this particular survey goes back to the 1970s, covering a variety of episodes in U.S. macroeconomic history, as previously mentioned. Thirdly, professional forecasters are some of the most informed agents

[8] Ramey and Zubairy (2018) note the use of Gordon and Krenn's (2010) transformation in their paper is for both the calculation of multiplier and analysing the IRFs. However, the IRFs plot the responses of output and government spending to a **1%** increase of government spending.

[9] At its current format, each forecaster provides the same set of variables for the current quarter to four quarters ahead, as well as annualised values for the following 2 years for certain variables.

in the economy. They therefore provide a conservative benchmark for information frictions in their forecasts' cross sectional variation. This is because if there was any informational friction increase that reduces their ability to forecast macroeconomic aggregates — despite all the information and knowledge the professional forecasters have access to — it would be highly likely that the rise in information frictions affect economic agents who make real economy decisions, such as consumption and investment.

I also use economic output (real GDP) forecasts as the main variable because it is a relevant variable of interest to different economic agents. For example, current real GDP informs households of their current real income and potentially employment prospect, and thus helps inform their current consumption plan. Likewise, current real GDP partly determines a firm's future demand schedule. This is a crucial element in their investment decisions, as firms often need time to invest into building production capacity to meet future demand.

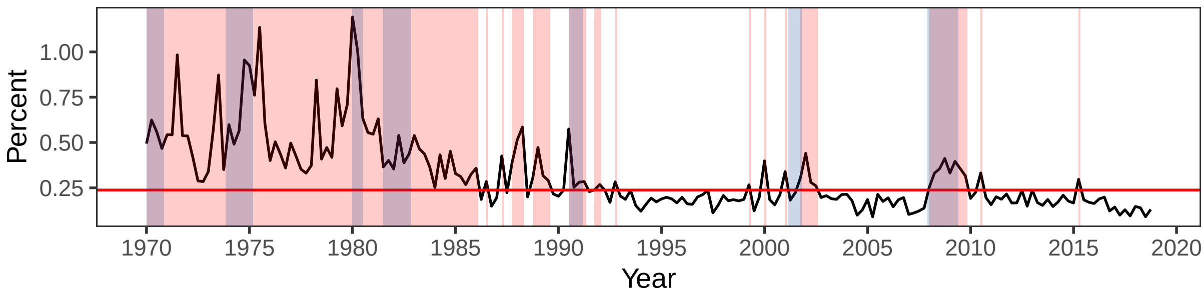

Figure 2.1. Real GDP Nowcast Disagreement

Note: Time series of real GDP disagreement index based on the dispersion (interquartile range) of Survey of Professional Forecasters nowcast. The red shaded areas indicate high disagreement periods. The red line indicate the sharp transition threshold given by the median disagreement. The grey shaded areas indicate NBER-dated recessions.

Figure 2.1 plots the Survey of Professional Forecaster cross-sectional disagreement, interquartile range of individual responses (dispersion) divided by the median, for the current quarter (nowcast) of real GDP.[10] Higher cross-sectional disagreement

[10]Figure 2.1 and Figure 1.1 are similar but with one difference. In Figure 2.1, the SPF's real GDP nowcast disagreement regimes are split by the *median*, whereas in Figure 1.1, it is split using a threshold value estimated using a constrained conditional maximum likelihood.

among forecasters represents an economy under high information frictions. High information friction periods are defined as the periods where the disagreement is above the threshold — depicted in the red shaded area. And vice versa, lower cross sectional disagreement among forecasters represents an economy under low information frictions, below the (red line) threshold. Grey shaded areas indicate the NBER business cycle contraction dates. The threshold parameter is chosen such that each regime contains half of the disagreement data (median disagreement), ensuring consistency across different disagreement measures in the robustness in Appendix B.2.1.

The chart shows that disagreement generally tend to be higher in the survey early years compared with the latter half of the sample. Broadly speaking, this pattern of declining disagreement tracks the period known as the Great Moderation from 1984 to 2008, when the overall volatility of the economic data was lower than in the pre-1984 period. Although we could still observe high disagreement regimes during the Great Moderation, especially around business cycle contraction dates. While high disagreement is correlated with recessions, high disagreement episodes are more prolonged than recessions, and disagreement regime changes typically occur at a higher frequency than business cycles. The correlation between the disagreement state variable in this paper and indicators of recession (or slack) is only mildly positive. The correlation with the slack state of Ramey and Zubairy (2018) is 0.2, and with NBER-dated recessions is below 0.4.

2.3 Econometric Methodology

2.3.1 Local Projections

I use Jordà's (2005) local projections to estimate the impulse responses. This method estimates a series of regression for each horizon h for each variable. The linear model is as follows

$$x_{t+h} = \alpha_h + \psi_h(L) z_{t-1} + \beta_h \text{shock}_t^G + \varepsilon_{t+h} \quad \text{for} \quad h = 0, 1, 2, ..., H \tag{2.1}$$

where x is the variable of interest, z is a vector of control variables, $\psi_h(L)$ is a polynomial in the lag operator, and shock is the identified shock. The vector of baseline control variables, z, contains lags of government spending and variable of interest (for example, consumption). The term $\psi_h(L)$ is a lag polynomial of order 4, as I use quarterly data. The identification of the shock is discussed in the next subsection. $\textbf{shock}_t^G$ in Eq (2.1) is the shocks identified in Eq (2.3). ε_{t+h} is the residual term.

The coefficient β_h gives the response of x at time $t+h$ to the shock at time t. The impulse responses are constructed as sequences of the β_h's estimated in a series of single regressions for each horizon. This method stands in contrast to the standard method of estimating the parameters of the VAR for horizon 0 and then using them to iterate forward to construct the impulse response functions.

The local projections method is easily adapted to estimating a state-dependent model. While Auerbach and Gorodnichenko (2013) were the first to employ this method to estimate state-dependent fiscal policy, the model used in this paper is closer to Ramey and Zubairy (2018). Similar to the linear model, for the model that allows state-dependence, I estimate a set of regressions for each horizon h as follows

$$\begin{aligned} x_{t+h} &= I_{t-1}[\alpha_{A,h} + \psi_{A,h}(L)z_{t-1} + \beta_{A,h}\text{shock}_t^G] \\ &\quad + (1 - I_{t-1})[\alpha_{B,h} + \psi_{B,h}(L)z_{t-1} + \beta_{B,h}\text{shock}_t^G] + \varepsilon_{t+h} \end{aligned} \tag{2.2}$$

The indicator variable I equals 1 when the economy is in regime A (high information frictions) and 0 when is in regime B (low information frictions). The interactions with the indicator variable allows all coefficients to vary according to the state of the economy. The set of coefficients $\beta_{A,h}$ and $\beta_{B,h}$ are used to construct the impulse responses for each regime A and B, respectively. $\textbf{shock}_t^G$ in Eq (2.2) is the shocks that will be identified in Eq (2.4) which allows for the non-linearity (high and low information frictions). As is standard in the literature, I use the Newey-West standard errors to allow for potential autocorrelation in the residuals (Newey and West, 1994).[11]

2.3.2 Shock Identification

In the fiscal policy literature, there are two common ways to identify government spending shock: Blanchard-Perotti (Cholesky) and military spending news. In this pa-

[11]Newey-West standard errors require a choice to be made on the bandwidth of the maximum periods of autocorrelation of the regressions' residuals ε_{t+h}. While Jordà (2005) uses the bandwidth $H+1$, I follow Ramey and Zubairy (2018) instead which uses the automatic bandwidth selection in Newey and West (1994).

per, the government spending shock corresponds to the Blanchard and Perotti (2002) (BP) identification. BP identification rely on the institutional information about the tax and transfer systems, to exploit the lag of government spending and tax collections to identify the shocks to fiscal policy. The decision and implementation lags imply that at a sufficiently high frequency (in this case within a quarter), there is little or no discretionary response of fiscal policy to unexpected contemporaneous movements in economic activity. Using these shocks, it is possible to trace the dynamic effects of fiscal policy shocks on GDP and its components.

The BP approach orthogonalises current government spending by lags of real government spending, real net tax and real GDP.[12] For the non-linear case, I allow the coefficients to vary in both regimes. I modify the methodology from Ramey and Zubairy (2018) slightly to accommodate the IRFs estimation more than output. To identify the BP shock consistently for all of the variables, I identify the shock prior to the IRFs estimation.[13] In the linear case, this is done by orthogonalising government spending with lags of itself, as well as output and taxes as follows[14]

$$G_t = \beta_G(L)G_{t-1} + \beta_T(L)T_{t-1} + \beta_Y(L)Y_{t-1} + \text{shock}_t^G \tag{2.3}$$

Similarly for the model that allows state-dependence, where I equals 1 when the economy is in the high disagreement regime and 0 in low disagreement regime. The *interactions* with the indicator variable allows the shock to vary according to the state of the economy.

$$\begin{aligned} G_t = {} & I_{t-1}[\beta_G(L)G_{t-1} + \beta_T(L)T_{t-1} + \beta_Y(L)Y_{t-1}] \\ & + (1 - I_{t-1})[\beta_G(L)G_{t-1} + \beta_T(L)T_{t-1} + \beta_Y(L)Y_{t-1}] + \text{shock}_t^G \end{aligned} \tag{2.4}$$

[12]In the Cholesky identification, government spending is ordered first because of the aforementioned lags of the setting of discretionary fiscal policy. Additionally, I follow Ramey and Zubairy (2018) to use lags of average tax rate (tax revenue as a ratio of GDP), instead of real net tax.

[13]Because Ramey and Zubairy (2018) only studies output effects, they can use government spending directly in the local projections regression. By the Frisch-Waugh-Lovell theorem, this is identical to orthogonalising the shock first (Frisch and Waugh, 1933; Lovell, 1963).

[14]For clarity, the VAR identification of the linear shock is as follows, with a lower triangular Cholesky decomposition matrix:

$$\begin{bmatrix} G_t \\ T_t \\ Y_t \end{bmatrix} = B(L) \begin{bmatrix} G_{t-1} \\ T_{t-1} \\ Y_{t-1} \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ A_{21} & 1 & 0 \\ A_{31} & A_{32} & 1 \end{bmatrix} \begin{bmatrix} u_t^G \\ u_t^T \\ u_t^Y \end{bmatrix}$$

The shock identified from this procedure is then taken to the IRFs estimation. For the non-linear estimation, the orthogonalisation regression is allowed to take different coefficients in the two regimes. This is very similar to Blanchard and Perotti (2002), and the narrative identification in the monetary policy literature (Romer and Romer, 2004) (in the non-linear setting, see Tenreyro and Thwaites (2016)).

An often used narrative identification strategy for fiscal policy shocks is to use news to military spending. Ramey and Zubairy (2018) use this to complement BP identification. However, as Ramey (2011) noted, there is little variation in this series after the Korean War. While this is perfectly fine for Ramey and Zubairy (2018) whose sample starts in the late 19th century, the disagreement series starts in 1970 (discussed in Section 2.2.2) — therefore, the narrative identification of military news would be unsuitable for this paper. As a cross-check, instrumenting the BP identified shock with the military news variable, results in a first-stage F-statistic between 2-3 for the BP orthogonalised government spending, or at 3-4 for the non-orthogonalised (raw) government spending (Table 2.1). This is far below the usual rule-of-thumb of F-statistic of 10 for a strong instrument.

	Output	Consumption	Investment
Orthogonalised g	2.96	2.87	2.08
Non-orthogonalised g	3.25	3.90	3.47

Table 2.1. First Stage F-statistics of Military News on Government Spending

2.4 Results

The impulse responses in Figure 2.2, 2.3 and 2.4 show the responses of output, government spending, consumption, investment, real wage, and unemployment to a 1% government spending shock. The bands are 68 percent confidence bands that are based on Newey-West standard errors to account for serial correlation (Jordà, 2005).

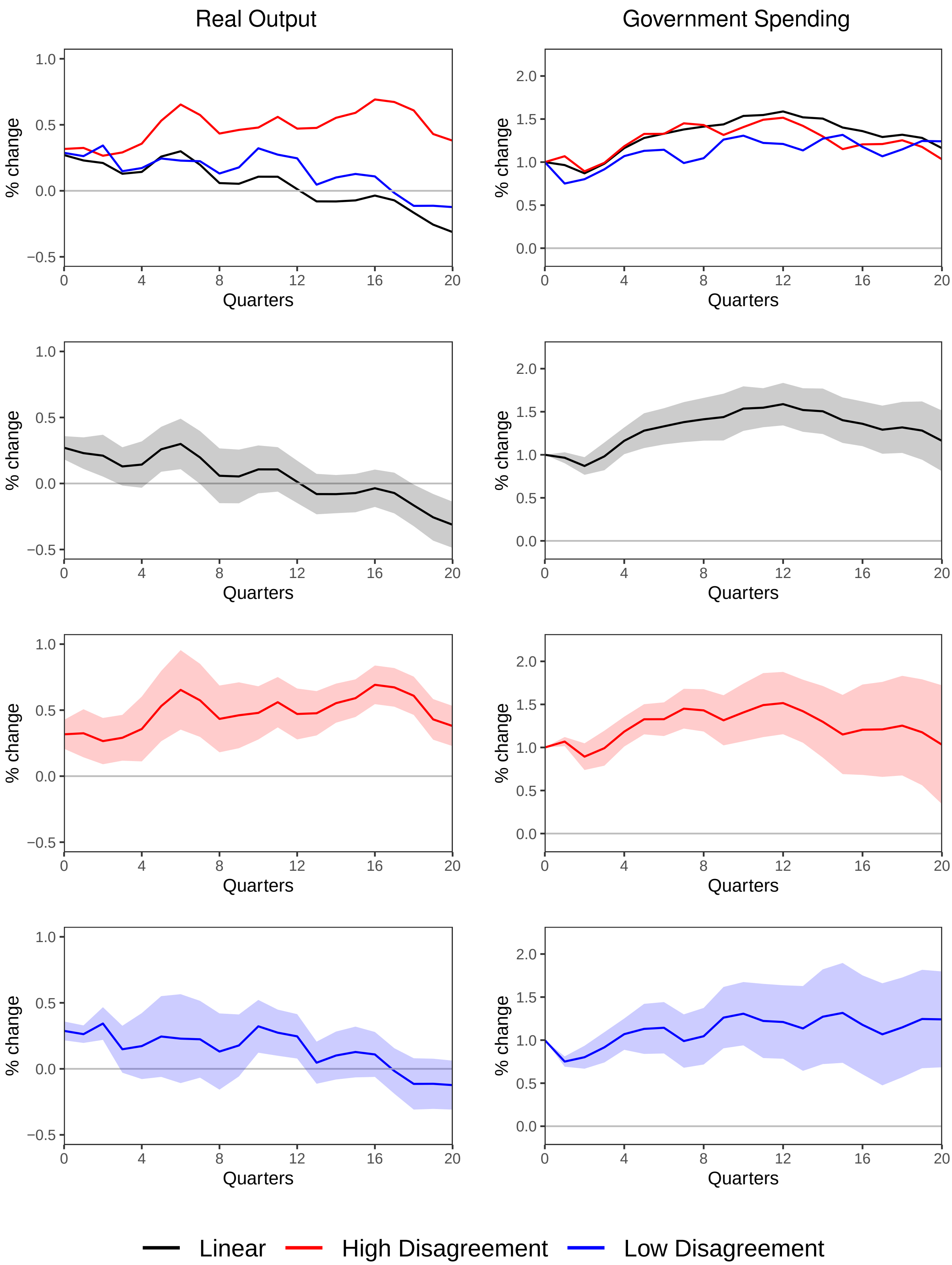

Figure 2.2. Local Projection Impulse Responses of GDP and Government Spending to a Government Spending Shock

Note: Response of output and government spending to a 1% government spending (Blanchard-Perotti) shock. The black-lines show the response in a linear model. The red- and blue-lines show the state-dependent responses in high and low disagreement regimes, respectively. The shaded area is 68 percent confidence interval around the responses. The sample period is from 1970Q1 to 2018Q4.

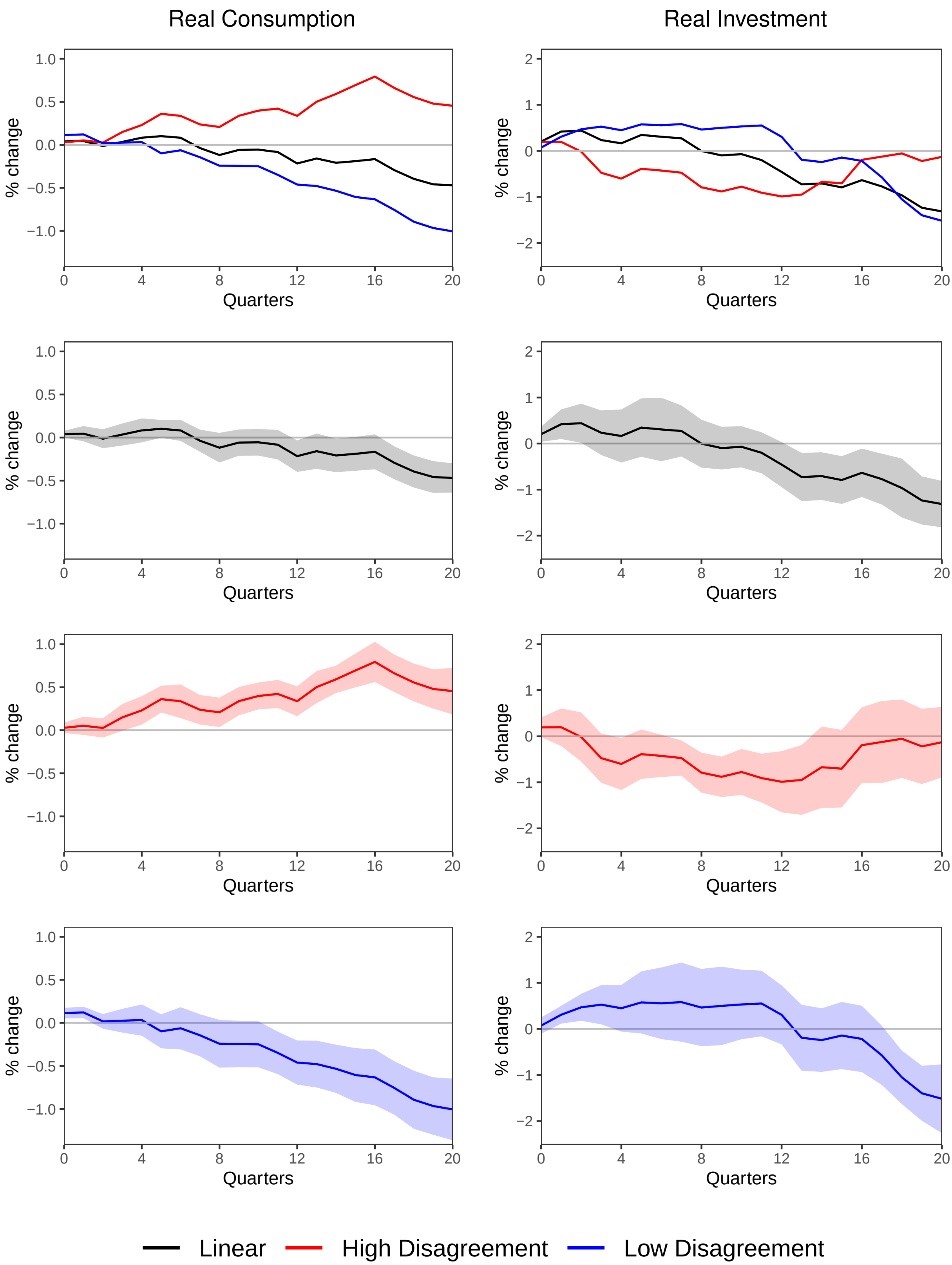

Figure 2.3. Local Projection Impulse Responses of Consumption and Investment to a Government Spending Shock

Note: Response of consumption and investment to a 1% government spending (Blanchard-Perotti) shock. The black-lines show the response in a linear model. The red- and blue-lines show the state-dependent responses in high and low disagreement regimes, respectively. The shaded area is 68 percent confidence interval around the responses. The sample period is from 1970Q1 to 2018Q4.

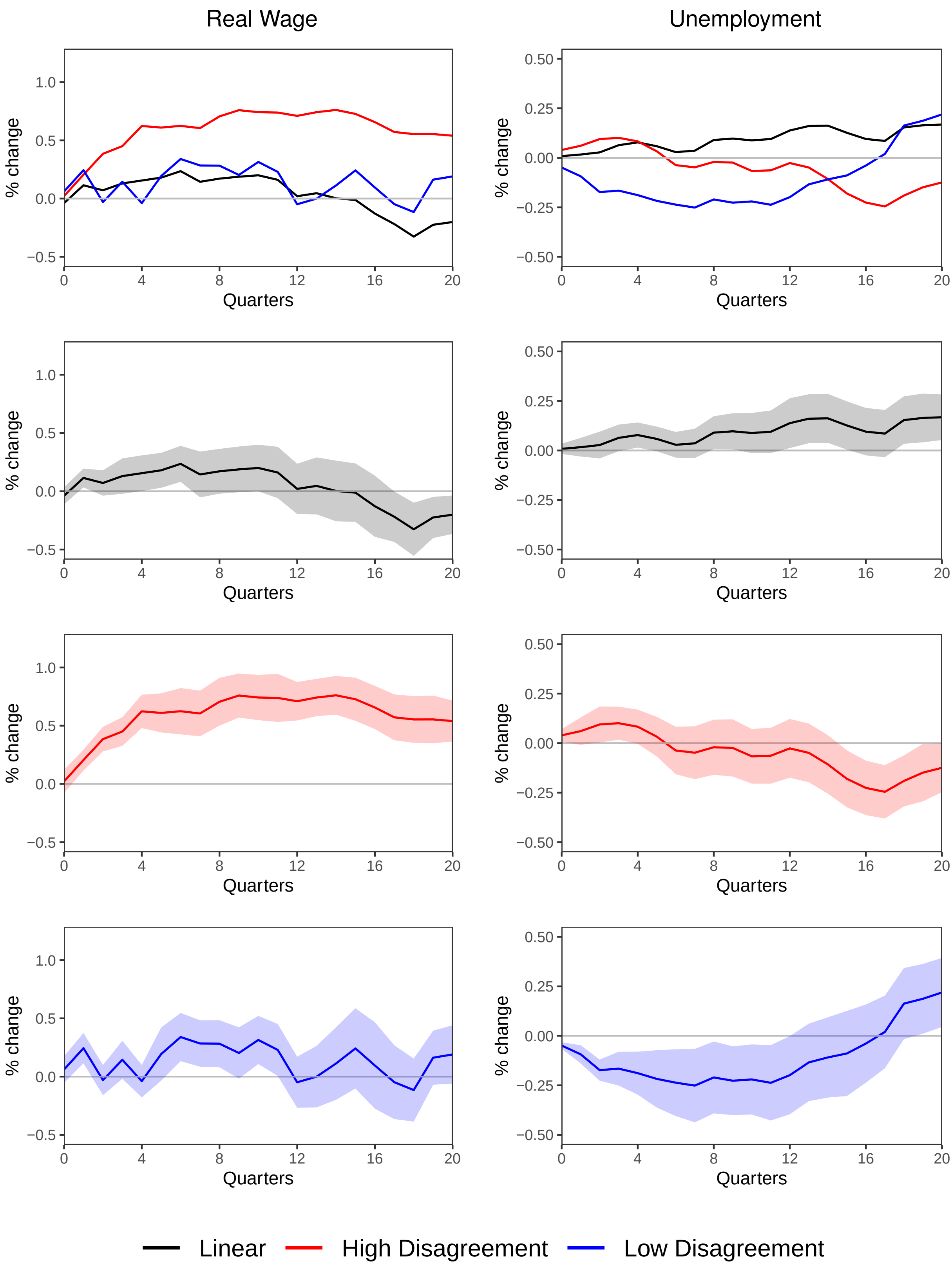

Figure 2.4. Local Projection Impulse Responses of Real Wage and Unemployment to a Government Spending Shock

Note: Response of real wage and unemployment to a 1% government spending (Blanchard-Perotti) shock. The black-lines show the response in a linear model. The red- and blue-lines show the state-dependent responses in high and low disagreement regimes, respectively. The shaded area is 68 percent confidence interval around the responses. The sample period is from 1970Q1 to 2018Q4.

2.4.1 Linear Effects

A useful starting point to examine how the responses of macroeconomic variables to government spending shocks may vary with information frictions is to use a linear method (which assumes that responses are invariant to the state of the economy), and compare it to the literature.

Overall, the results here are similar to Ramey (2011) who, using various identification methods, finds that private spending falls after a government spending expansion. [15] The response of consumption is muted — it is mainly zero but becomes slightly negative in the later horizons. Mountford and Uhlig (2009) also find negative or no significant effect on consumption using a sign restrictions identified VAR. As Ramey (2016) noted, this is consistent with evidence from estimated DSGE models (such as Smets and Wouters (2007) and Cogan et al. (2010)) with results close to the neoclassical model. In both cases, a government spending shock lowers consumption and leads to multipliers below unity.

Output initially increases in response to an increased government spending but becomes mostly zero in the medium run, and then becomes negative in the fourth year. This linear response of output is closer to Auerbach and Gorodnichenko (2013) than to Ramey and Zubairy (2018) that shows strong positive output response. We can likely reconcile this difference with the sample period, with the former looking at the period between 1985-2010, while the latter has a much longer sample period (1889-2015).

While the neoclassical and Keynesian models have clear predictions on the responses of output and consumption to a government spending shock, the implications on private investment is largely unsettled. The two theoretical models may predict an increase or fall of private investment, depending on various conditions (Blanchard and Perotti, 2002). For example, in the neoclassical model, a government spending shock can raise private investment if the shock is sufficiently persistent (and taxes are sufficiently nondistortionary). My results suggest, investment initially rises, where the peak response of the central tendency rises to around 0.5%, but then falls to around -1%. The initial crowding-in of private investment could be explained by the persistent response of government spending, as shown in Figure 2.2. Other papers such as

[15] Ramey (2011) defines private spending as GDP minus government consumption and investment.

Ramey and Zubairy (2018), Blanchard and Perotti (2002) and Galí et al. (2007) also show a persistent response of government spending to its own shock. Meanwhile, the magnitude of the crowding-out effect in the later horizons is similar to Auerbach and Gorodnichenko (2013) on the response of real private investment of OECD countries, and Blanchard and Perotti (2002) who find the peak response of investment in the United States to be -1%.

2.4.2 Non-Linear Effects

The non-linear responses to a government spending shock in Figure 2.2, 2.3 and 2.4 show how the linear results could mask the very different behaviour in the two states — high and low information frictions (measured by disagreement).[16] It is important to re-emphasise at this point that I identify the shock the non-linearly, to be consistent with non-linear local projections.[17] This implies that the linear estimates, with linearly identified shocks, should *not* necessarily lie between the two non-linear estimates.

The responses of consumption has the most conspicuous difference across the two states. Under high disagreement, there is a persistent positive effect of a positive 1% government spending shock. Consumption rises to its peak of 0.7% at around four years' horizon, whereas the linear model largely stays slightly below zero. This also contrasts to the low disagreement regime, where consumption falls significantly to around -0.5%.

The non-linear responses of output are alike in the two states, specifically in the short-term (up to two quarters) at around 0.3% — similar to the linear IRF. But after the first year, the positive response of output in high disagreement period is much more persistent than in low disagreement, remaining above zero for at least 20 quarters. Under low disagreement, the output goes to zero fairly quickly — becoming statistically insignificant after 4 quarters, and the central tendency goes to zero after 7 quarters.

Investment falls almost immediately in high information frictions periods, with a peak response of around -1%. While in low disagreement periods, there is a crowding-in effect of investment in the first year, which goes to zero in the medium run and

[16] These results are robust to using alternative measure of disagreement in Appendix B.2.1.
[17] For example, see Tenreyro and Thwaites (2016) for the equivalent for monetary shocks.

eventually is crowded-out after the fourth year.

In Figure 2.2, the responses of government spending to the shock are not statistically significantly different in the two states, and in comparison to the linear response. This indicates that the dynamics of government spending do not depend on the informational frictions of the agents in the economy, and thus, the results that on other macroeconomic aggregates, are not driven by different behaviour of government spending in the two regimes.

In this paper, I highlight that a positive government spending shock is expansionary (output rises), but the responses of consumption go in the opposite directions due to the varying Ricardianness of households. The different behaviour of consumption we observe during high and low disagreement regimes is attributed to information frictions, and reconciles the predictions of both Keynesian and neoclassical models. When there is high disagreement amongst professional forecasters — indicating large information frictions at the time — households are less able to anticipate higher future (distortionary) taxes. Furthermore, given that there are lags in the release of information on government spending (for example, as part of GDP releases), it is also plausible that households were not able to detect the rise in government spending in real time. For instance, they could misattribute the rise of their disposable income due to a positive productivity shock (which raises real wages), instead of a government spending shock.

The labour market responses in the two regimes are also more suggestive of a role of information frictions, rather than just credit or liquidity constraints. If credit or liquidity constraints bind, creating the rule-of-thumb households of Galí et al. (2007), it would suggest a very strong link between household income and consumption. For example, as household incomes rise, this should relax the constraints, enabling households to consume more. However, real wages under high disagreement rises much more quickly than consumption, and does not fall under low disagreement (unlike consumption).

On the other hand, the classic Ricardian equivalence (and its breaking due to informational frictions) is more difficult to see in investment behaviour. There are two competing effects. The standard neoclassical effect is the crowding out effect of higher interest rates (as government spending is a positive demand shock, monetary policy should tighten to keep inflation under control) leading to higher borrowing rates, and thus discourages investment. Alternatively, if agents anticipate higher capital taxes, the marginal return to investing into an additional unit of capital is lower, and hence, also discourages investment. On the other hand, firms need to invest into production capacity in the future, as capital investments typically take some time to be converted to production capacity. Basu and Kimball (2003) emphasise the need for costly investment planning in a DSGE model, to get investment to rise after a positive government spending shock. Under low disagreement, investment rises in the beginning. Perhaps this is due to confidence effects: firms anticipate greater future demand, but in the longer run, crowding out dominates. With high disagreement, investment falls immediately, suggesting firms do not anticipate higher future demand (despite output and consumption increasing persistently in this regime). The crowding out effect due to higher interest rates is easier to observe, and thus this effect dominates.

2.4.3 Multiplier

Table 2.2 shows the estimates of multipliers in different horizons for the linear model and the state dependent model. As noted earlier, I use the Gordon and Krenn's (2010) transformation — dividing NIPA variables by an estimate of potential GDP such that all NIPA variables are in the same unit, and so the multipliers can be calculated directly. In this paper, I define the cumulative multipliers as the cumulative gain of GDP, private consumption, or private investment, relative to the cumulative government spending. As Ramey and Zubairy (2018) argue, the integral (sum) of multipliers address relevant policy question.[18]

In the linear model, the output multiplier is positive, but decreasing, until at least 20 quarters. The consumption and investment multipliers are slightly positive in the first 1–2 years and then it becomes negative. The output and consumption multipliers are estimated to be higher in the high disagreement than in the low disagreement regime. The stark difference in estimates across the two states imply that

[18]There are other definitions of a multiplier in a dynamic setting. Mountford and Uhlig (2009) and Uhlig (2010) also calculate the multiplier as the integral of output response divided by the integral of government spending response. Blanchard and Perotti (2002) define the multiplier as the ratio of the peak response of NIPA variables to the initial government spending shock. Auerbach and Gorodnichenko (2012, 2013) define the multiplier as the average response of output and its components to the initial government.

the multipliers of output and consumption are more positively persistent in the high disagreement regime.[19]

Meanwhile, the estimates of investment multipliers in the high and low disagreement regime are not as significantly different as much as output and consumption. In fact, we observe the multipliers to be low, with small variation. Similar to the IRFs in Figure 2.3, these multipliers suggest crowding out effect on investment during high information frictions period.

	1-quarter	1-year	2-year	3-year	4-year	5-year
Output						
Linear	1.26	0.97	0.82	0.57	0.35	0.13
High Disagreement	1.50	1.47	1.68	1.66	1.80	1.89
Low Disagreement	1.66	1.44	1.26	1.21	1.02	0.74
Consumption						
Linear	0.12	0.08	-0.01	-0.13	-0.24	-0.42
High Disagreement	0.13	0.30	0.47	0.59	0.84	0.96
Low Disagreement	0.46	0.24	-0.09	-0.36	-0.67	-1.05
Investment						
Linear	0.19	0.15	0.11	0.03	-0.07	-0.17
High Disagreement	0.09	-0.13	-0.20	-0.28	-0.30	-0.27
Low Disagreement	0.14	0.29	0.34	0.33	0.24	0.07

Table 2.2. Estimates of Multipliers Using Local Projections to a Government Spending Shock

Note: These are the cumulative multipliers defined as $M_h^x = \frac{\sum_{i=0}^{h} x_h}{\sum_{i=0}^{h} g_h}$ where x_h is the dollar effect on variable x of a one dollar increase in government spending at h quarters after the shock.

2.4.4 Policy Implications of Government Spending Shocks

A possible challenge to information frictions as an explanation of fiscal policy transmission is the traditional Keynesian channels on why fiscal policy multipliers vary during recessions and expansions. In recessions, there is more slack in the economy, and thus crowding out effects (if any) are minimised. If times of severe information

[19]One may notice that the linear multipliers are sometimes not in between the high and low disagreement multipliers. A conjecture for the source of this behaviour is the identification of non-linear shocks in the state-dependent model.

frictions is highly correlated with a slack measure, the result that expansionary power of government spending is larger during high disagreement could be only picking up these Keynesian effects.

However, as Table 2.3 shows, the correlation between the disagreement measures and various measures of slack is only mildly positive.[20] This suggests that high disagreement episodes are somewhat more prevalent in recessions than expansions, but recessions are certainly not the sole cause of high disagreement. Therefore, the responses of macroeconomic variables in the high and low disagreement regimes are unlikely to be caused solely by (the lack of) crowding out effects, pointing towards the role of time-varying information frictions instead.

	Recession	Slack
Disagreement	0.3773	0.2304

Table 2.3. Correlation of State Variables

Note: Disagreement is the baseline state variable in this paper, measured by the Survey of Professional Forecasters current quarter (nowcast) of real GDP cross-sectional dispersion divided by median. Recession is defined by NBER-dated recessions dates. Slack is defined as in Ramey and Zubairy (2018) where unemployment is above or equal to 6.5%.

This also reflects the mixed takeaways from the literature on fiscal multipliers. On one hand, Auerbach and Gorodnichenko (2013) find that multipliers are large in recessions, and significantly larger than in expansions. On the other hand, with a much longer sample going back to the 19th century, Ramey and Zubairy (2018) find that multipliers are below unity, regardless of slack (with an exception to the zero lower bound period, where spending multipliers are around 1.5). While there is indeed a positive correlation between disagreement and slack, not all recessions are accompanied with severe information frictions. Thus, the results suggest multipliers are not necessarily larger in *all* recessions relative to expansions, but it may be the case if the recession also brought on severe information frictions.

Another way to define the state of the business cycle is by looking at economic

[20] To ensure consistency with the local projections estimation, both the disagreement and slack measures are converted into an indicator variable.

regimes under different uncertainty. Alloza (2017) estimate the impact of government spending shock on economic activity in high and low uncertainty regimes, and recession and boom. His results suggest that government spending is expansionary in times of boom or low uncertainty, but contractionary in recession or high uncertainty (unusually high stock market volatility) periods. This is in contrast to other existing empirical results, for example Auerbach and Gorodnichenko (2012). Uncertainty is frequently used in the empirical monetary policy literature to measure different state, and is sometimes proxied by the cross-sectional dispersion in surveys of expectations. However, disagreement and uncertainty are conceptually different (Reis, 2018). Additionally, Kozeniauskas et al. (2018) show the correlation between cross-sectional dispersion in the Survey of Professional Forecasters and other measures of macroeconomic uncertainty (for example, Jurado et al. (2015)) is at best weak. For this reason, I do not draw a close analogy between the results of this paper and that of Alloza (2017).

The key theme of this paper is that expectations formation matters, and in particular, how that determines the ability of households to monitor current economic conditions and anticipate future future taxes. Monetary policymakers have long paid attention to (inflation) expectations, which if anchored, helps the policymakers meet their inflation targets. But typically, fiscal policymakers historically did not emphasise the extent of information frictions as an important pillar of fiscal policy. The results of this paper suggest the setting of fiscal policy should also consider households' ability to form expectations to determine its effectiveness.

2.5 Disaggregated Shocks

Similar to the variety of monetary policy instruments (ranging from policy interest rates, asset purchases, and bank funding schemes), fiscal policy also has different tools. In this section, I focus on the analysis of the responses of total output, private consumption and private investment to an increase in government consumption, government investment and transfer payments. Just as the responses of macroeconomic variables to a shock in government spending could differ according to the regime in which they occur, they may also differ for different components of government spending (Auerbach and Gorodnichenko, 2012; Perotti et al., 2007). In particular, these authors discuss how government consumption (government spending on goods and services) and government investment operate through different mechanisms. Meanwhile, the response of macroeconomic variables to transfer payment shocks is relatively unknown in the fiscal policy literature, despite its substantial size in the United States (Romer and Romer, 2016; Oh and Reis, 2012). The heterogeneous mechanisms I discuss here provide insights to policymakers when designing strategies to achieve a particular desired outcome (for example, whether boosting consumption or investment is preferred), for a given state of the world.

At this point, it is important to note that the NIPA definition of total government spending excludes transfer payments, as transfer payments are not purchases of goods or services. During the sample period (1970-2018), nominal government consumption accounts for 79% of total government spending on average, with gross investment accounting for the other 21%, as illustrated in Figure B.2. Transfer payments accrue to the equivalent of 66% of total government spending (translating to 83% of government consumption). Figure B.3 shows the time series of government spending, its components, and transfer payment in log dollars.

The first result to highlight is the response of private consumption to the disaggregated government shocks, and then how it compares to each other, as well as to the baseline results of an overall government spending shock. Figure 2.5 shows that private consumption rises to an increase of government consumption. The impulse responses are similar to the response to a government spending shock. This is not surprising as government consumption (government spending on goods and services) accounts the largest part of non-transfer spending — on average, 80% of government spending. A similar pattern can be seen in the response of consumption to transfer payment shocks in Figure 2.7. It is intriguing that transfer payments, mostly composed of social security benefits, also pushes up private consumption, persistently under high information friction but not in the other regime.[21]

[21] Figure 2.9 shows the shock to transfer payment is much less persistent than government consumption shocks.

However, there are two notable differences between the effects of government consumption and transfer payments shocks on private consumption. First, in high disagreement periods, an increase of transfer payments has an immediate and persistent positive effect on consumption, but in low disagreement, it has an insignificant effect. This is perhaps because transfer payments are more predictable than government spending or government consumption. Indeed in response to a 1% government consumption shock, it takes about half-a-year for the state-dependent responses to be statistically significantly different from zero during high disagreement, but during low disagreement, the fall in private consumption becomes statistically significant from zero after 1.5 years. Second, the magnitudes of the responses to the two shocks are strikingly different. Given its average nominal size, a 1% transfer payments shock is around 20% smaller than a 1% government consumption shock.[22] Yet, the medium-run private consumption impact of a government spending shock is more than *twice* of transfer payments under high disagreement.[23]

A possible explanation for these two differences is through the different channels the shocks operate through. Transfer payments work directly through increasing the current income of households, often to lower-income households with likely high marginal propensity to consume.[24] This is consistent with the assumption of many fiscal policy models where rule-of-thumb households choose to consume more in the current period than to save for future tax rise (Galí et al., 2007). On the other hand, government consumption works through indirect, general equilibrium channels. The purchase of domestically produced goods and services by the government leads to the standard Keynesian amplification channels through increased aggregate demand and hiring.

[22] Table 2.4 shows, during high information frictions periods, a one dollar government consumption increase leads to 2.95 dollars increase in private consumption, but only 0.71 cents to a one dollar increase in transfer payment in Table 2.6. The IRFs for the shocks and dollar-change effects comparison can be found in Figure 2.9 and Figure 2.8, respectively.

[23] As noted previously, Figure 2.9 shows the different shocks persistence, so it is more difficult to compare the exact magnitude.

[24] In the United States, much of transfer payments is accounted by pensions. A lower-income households could also include those whose *current* income is lower due to retirement.

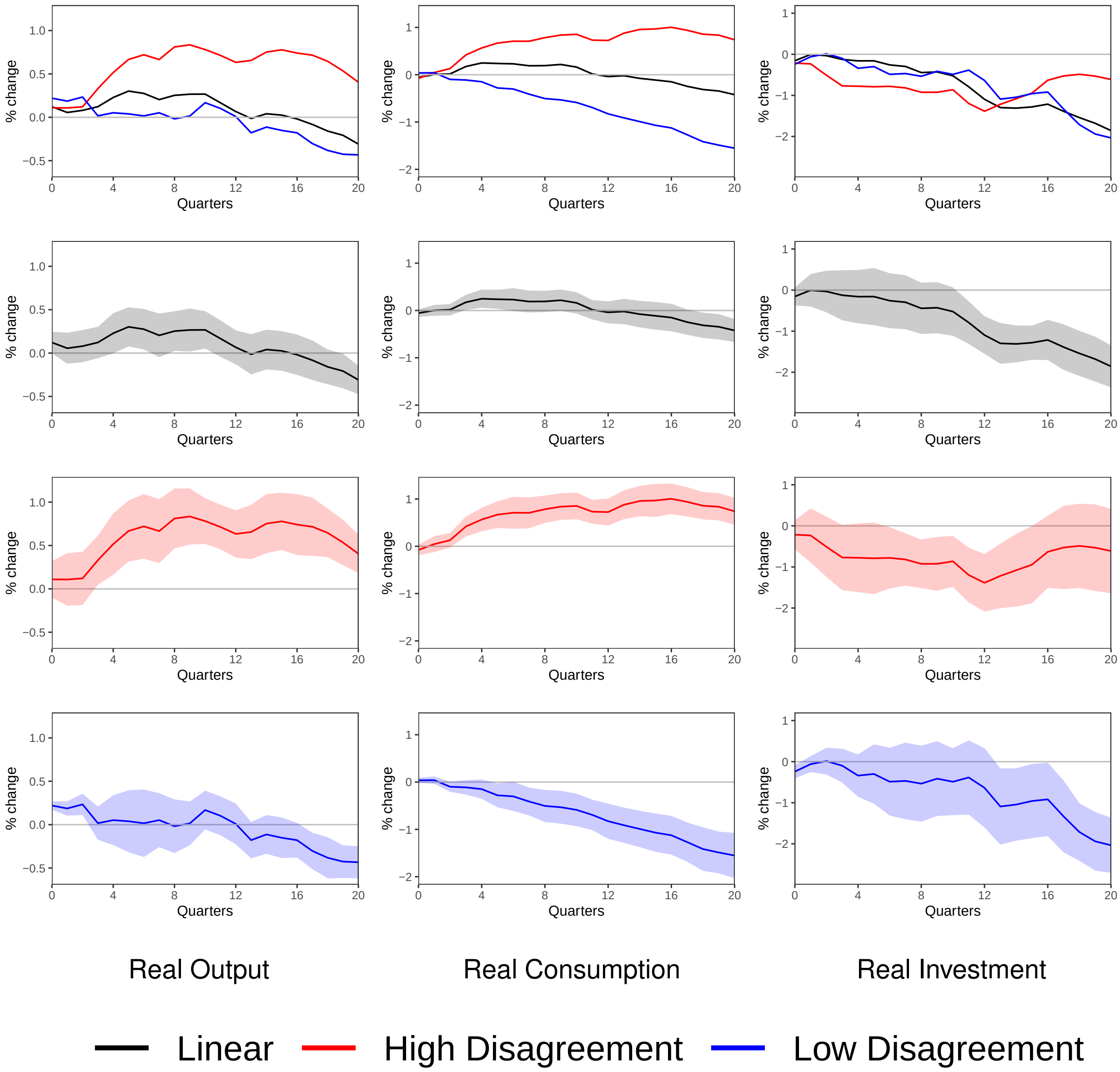

Figure 2.5. Local Projection Impulse Responses to a 1% Government Consumption Shock

Note: The columns shows the response of output, private consumption, and private investment to a 1% positive shock of government consumption. In the first row, the black lines show the response in a linear model, the red (blue) lines show the responses in the high (low) disagreement regimes. The second, third and fourth row shows a 68% confidence interval. The sample period is 1970Q1-2018Q4.

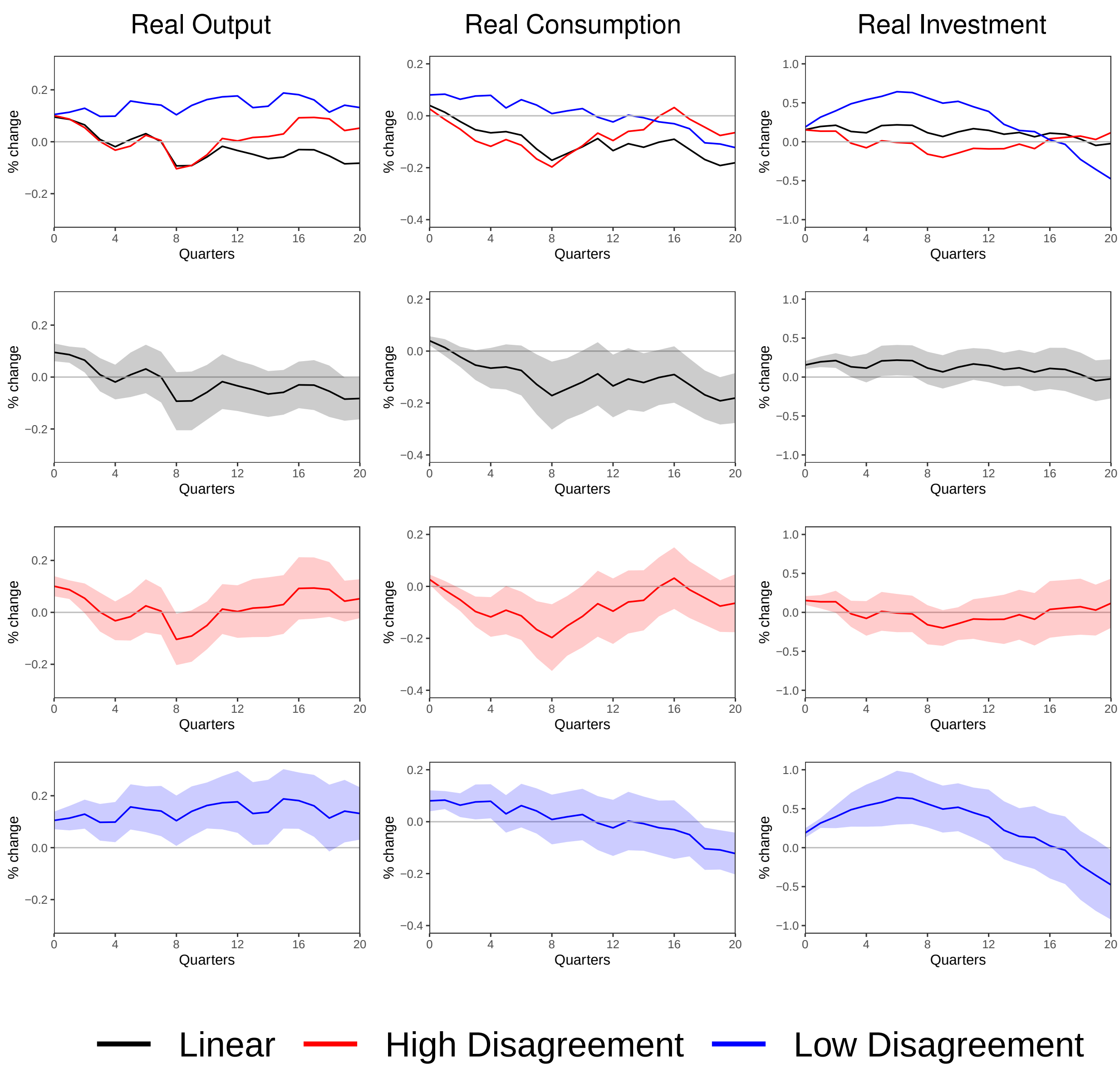

Figure 2.6. Local Projection Impulse Responses to a 1% Government Investment Shock

Note: The columns shows the response of output, private consumption, and private investment to a 1% positive shock of government investment. In the first row, the black lines show the response in a linear model, the red (blue) lines show the responses in the high (low) disagreement regimes. The second, third and fourth row shows a 68% confidence interval. The sample period is 1970Q1-2018Q4.

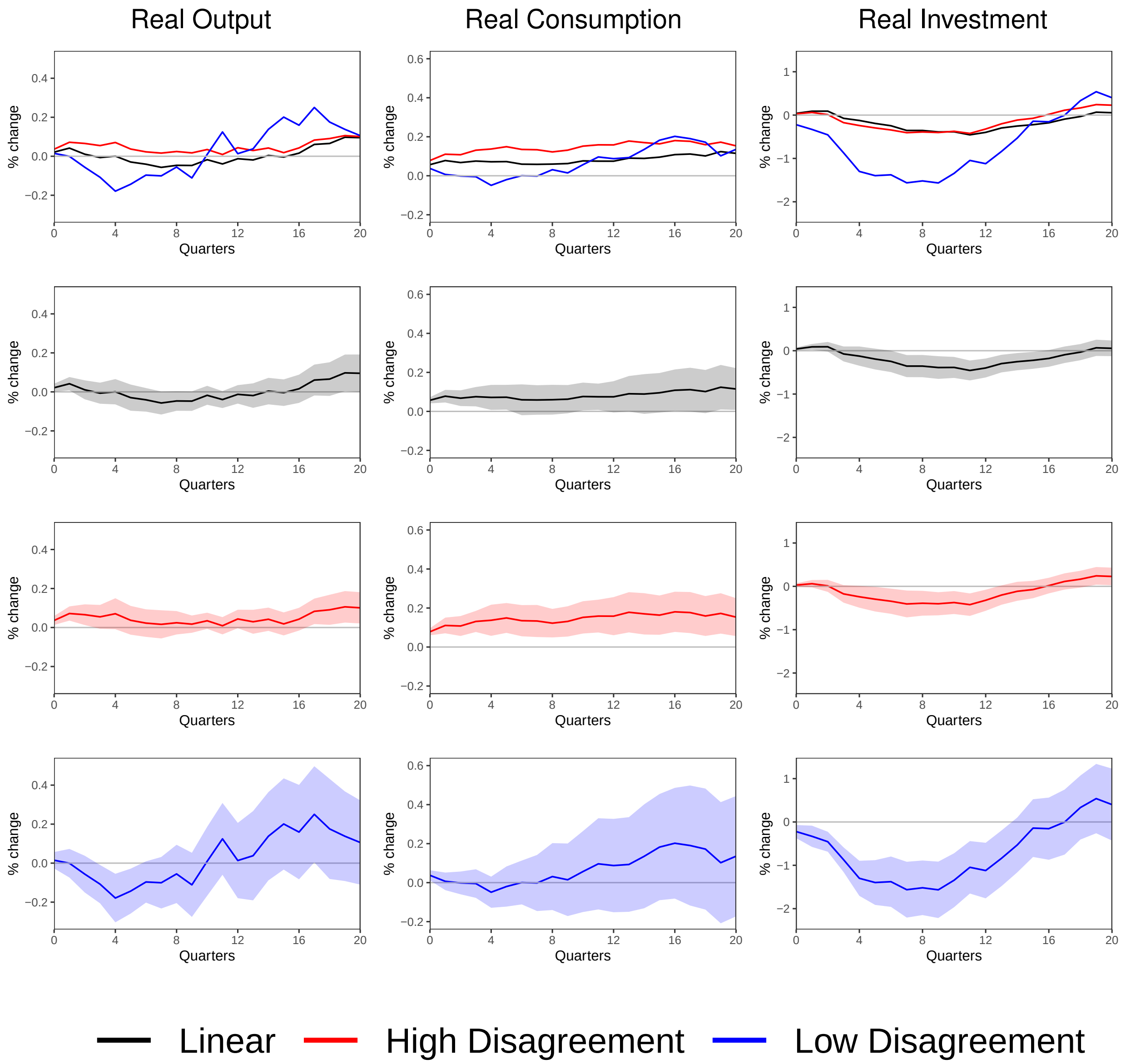

Figure 2.7. Local Projection Impulse Responses to a 1% Transfer Payment Shock

Note: The columns shows the response of output, private consumption, and private investment to a 1% positive shock of transfer payment. In the first row, the black lines show the response in a linear model, the red (blue) lines show the responses in the high (low) disagreement regimes. The second, third and fourth row shows a 68% confidence interval. The sample period is 1970Q1-2018Q4.

This contrasts with the behaviour of private investment. In the main result, with a government spending shock, investment rises a little initially under low disagreement, while it falls under high disagreement. However, to a government consumption shock, private investment quickly falls under both regimes. Interestingly, it is clear to see that the a 1% increase to government *investment* crowds-out consumption in the linear case, as well as in high and low disagreement (thus, the response of consumption is not state-dependent following government investment shocks). Yet, the same shock crowds-*in* private investment during low disagreement periods for first three years, and in the medium run, it crowds out private investment to about 0.5pp. In high disagreement periods, an increase of government investment does not affect private investment.

An explanation consistent with these results is the balancing role of supply (crowding out) and demand (firms under imperfect information that has to plan investment in advance). Under low information frictions, firms could quickly identify the increase in government investment spending (e.g. in infrastructure), increasing the marginal returns of their own private investment (crowding in). This is the mechanism underlying in models with complementarities between public and private investment. With high information frictions in contrast, this effect is not powerful enough to counteract the crowding out effect of resources going towards government spending, and thus private investment falls. This crowding out effect also dominates in response to a government consumption increase in both regimes, further underlining the importance of the public-private investment complementarities channel.

This exercise also brings to light how the disaggregated shocks have different transmission mechanism in comparison to the baseline exercise with *total* government spending shock. In Figure 2.8, I compare the response of output, private consumption and private investment in terms of dollar changes. The comparison in dollar changes is more comparable across the different shocks than the previous responses in logs because the graphs compare the different types of government spending shocks. This is because a 1% shock to government consumption is much larger than a 1% shock to government investment, simply because the former is larger on average.

These results show the macroeconomic impact depends on the type of government spending. Overall, the disaggregated results are consistent with the channels suggested by the main results, and seem to suggest different mechanisms are at work across firms and households. Government consumption and transfer payments influences households' behaviour the most, with only small effects on firms' private investment. The response of private investment to overall government spending is primarily driven by the behaviour to government investment shocks. This indicates that firms and households pay different attention to the different types of government spending, and hence they react differently. Therefore, fiscal policymakers will benefit from understanding the decision making process of firms and households to best accomplish their objectives.

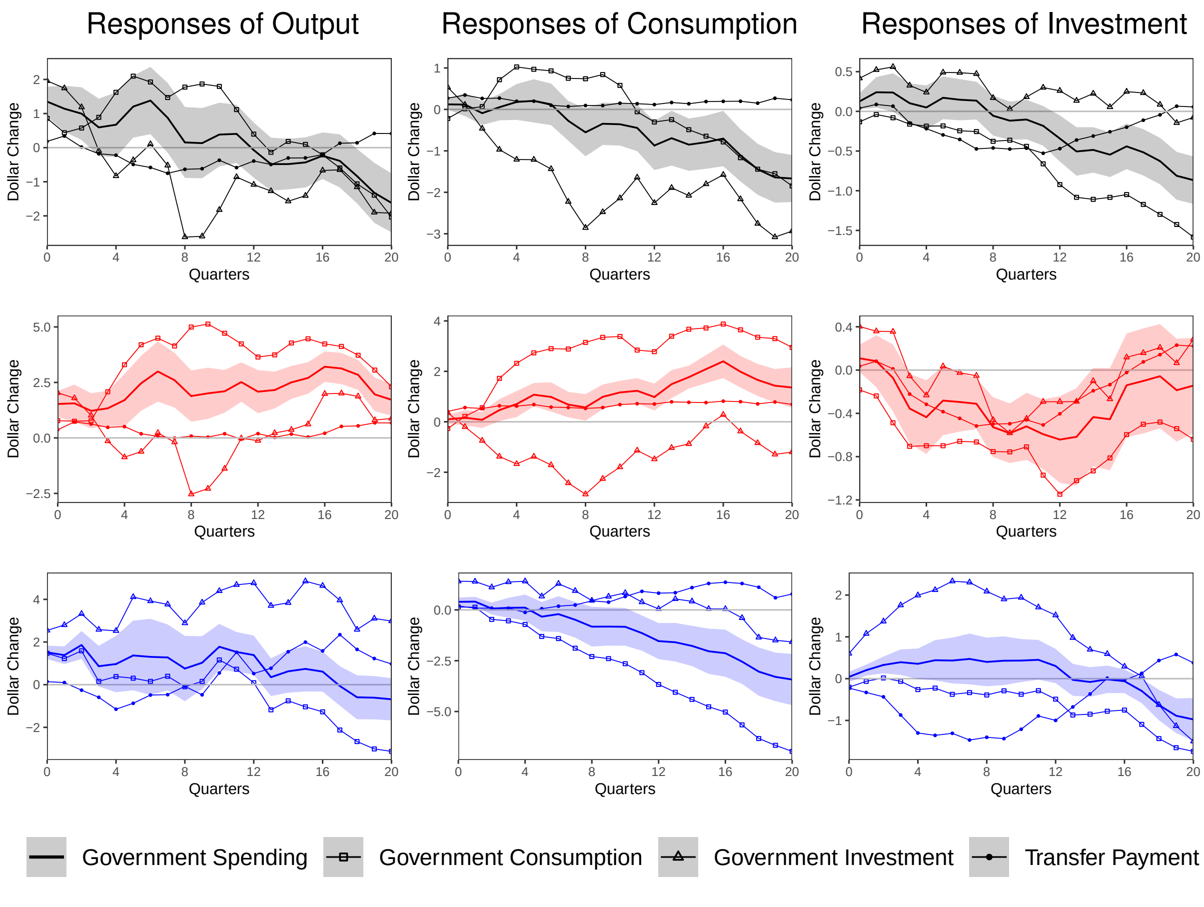

Figure 2.8. Local Projection Impulse Responses in Dollar Change

Note: The first row exhibit the linear responses, and the second and third row the state-dependent responses (high and low information frictions, respectively) to a **1 dollar change** in government spending shock, government consumption shock, government investment shock, or transfer payment shock. The sample period is 1970Q1-2018Q4.

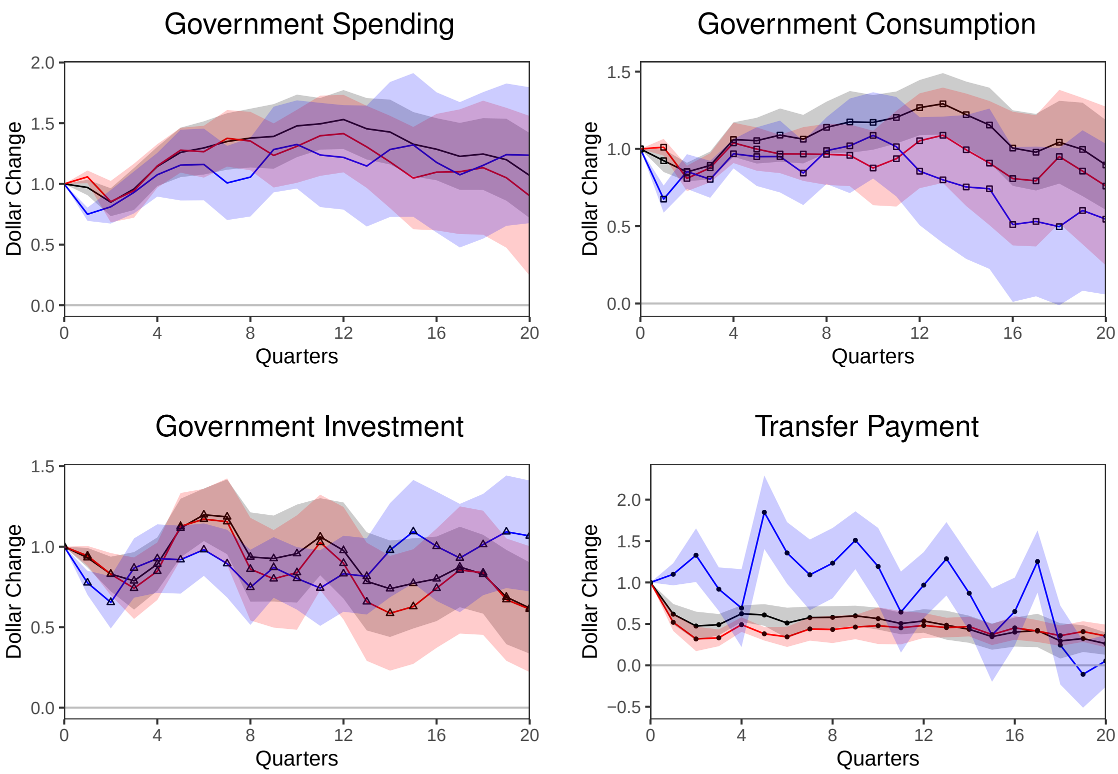

Figure 2.9. Impulse Responses of Various Government Spending to Own Shocks

Note: Each chart shows the linear response black lines, and the state-dependent – high disagreement and low disagreement – responses. The top left shows the response of government spending to a 1 dollar change in government spending, and similarly to government consumption, government investment and transfer payment. The sample period is 1970Q1-2018Q4.

	1-quarter	1-year	2-year	3-year	4-year	5-year
Output						
Linear	0.67	0.93	1.28	1.21	0.90	0.52
High Disagreement	0.76	1.62	2.95	3.47	3.69	3.73
Low Disagreement	1.61	1.12	0.69	0.64	0.23	-0.44
Consumption						
Linear	-0.11	0.34	0.55	0.44	0.21	-0.09
High Disagreement	-0.03	0.96	1.88	2.29	2.66	2.88
Low Disagreement	0.16	-0.34	-1.04	-1.68	-2.59	-3.77
Investment						
Linear	-0.09	-0.13	-0.18	-0.29	-0.45	-0.62
High Disagreement	-0.21	-0.49	-0.59	-0.70	-0.74	-0.72
Low Disagreement	-0.16	-0.13	-0.24	-0.28	-0.44	-0.74

Table 2.4. Multipliers Using Local Projection to a Government Consumption Shock

	1-quarter	1-year	2-year	3-year	4-year	5-year
Output						
Linear	1.92	0.89	0.06	-0.45	-0.67	-0.86
High Disagreement	1.97	0.88	0.08	-0.25	0.01	0.32
Low Disagreement	3.01	3.26	3.66	4.19	4.24	3.99
Consumption						
Linear	0.33	-0.45	-1.10	-1.43	-1.61	-1.93
High Disagreement	0.08	-0.83	-1.39	-1.53	-1.38	-1.36
Low Disagreement	1.58	1.59	1.30	1.09	0.87	0.43
Investment						
Linear	0.49	0.47	0.42	0.35	0.32	0.28
High Disagreement	0.39	0.19	0.04	-0.11	-0.12	-0.06
Low Disagreement	0.94	1.61	2.01	2.06	1.70	1.16

Table 2.5. Multipliers Using Local Projection to a Government Investment Shock

	1-quarter	1-year	2-year	3-year	4-year	5-year
Output						
Linear	0.32	0.04	-0.42	-0.56	-0.60	-0.42
High Disagreement	0.72	1.01	0.71	0.55	0.49	0.67
Low Disagreement	0.11	-0.35	-0.35	-0.10	0.24	0.54
Consumption						
Linear	0.38	0.42	0.33	0.30	0.32	0.36
High Disagreement	0.64	1.04	1.20	1.27	1.39	1.48
Low Disagreement	0.13	0.06	0.12	0.27	0.48	0.64
Investment						
Linear	0.08	-0.05	-0.32	-0.48	-0.52	-0.46
High Disagreement	0.08	-0.15	-0.53	-0.67	-0.60	-0.43
Low Disagreement	-0.26	-0.63	-0.82	-0.89	-0.79	-0.66

Table 2.6. Multipliers Using Local Projection to a Transfer Payment Shock

Note: These are the cumulative multipliers defined as $M_h^x = \frac{\sum_{i=0}^{h} x_h}{\sum_{i=0}^{h} g_h}$ where x_h is the dollar effect on variable x of a one dollar increase in government spending at h quarters after the shock.

2.6 Robustness

2.6.1 Placebo Test: Responses to Government Spending Shocks

Given that I use purely time-series variation in disagreement, I investigate the plausible role of structural change in the economy driving the results across the two regimes. To do so, I create a placebo test — where I divide the 'regime' into two time periods — and see whether these artificial pseudo-regimes also create meaningful differences that could account for the results I find. I focus on three different time periods as threshold to reflect possible changes in the economy: 1983Q3 (Placebo 1), 1989Q1 (Placebo 2), and 1992Q1 (Placebo 3). Here, I focus on the responses to a government spending shock, but for completeness, I also include the impulse responses to the disaggregated shocks in the next subsection.

First, I examine the role of the Great Inflation (GI) of the 1970s and the Great Moderation (GM) (including the Great Recession periods, post Global Financial Crisis) periods. There is a well-known large literature around the causes of the Great Moderation, so I place the most weight of importance on Placebo 1. The threshold is the start of Great Moderation in 1983Q3 (Stock and Watson, 2002). I compare the responses of output, government spending, consumption and investment in Figure 2.10 to the baseline responses in Figure 2.2 and 2.3.

In the baseline case, much of high disagreement periods coincide with the GI period, and vice versa, periods of low disagreement coincide with the GM period. In the IRFs, the responses in the high disagreement and Great Inflation period is shown by the red line, and the responses in the low disagreement and Great Moderation period is shown by the blue dotted-line.

One of the key differences between the baseline exercise in the previous sections and in these placebo tests is the response of *government spending* to its own shock. In the main result, the response of government spending is similar in the high and low disagreement regime (and in the linear estimation). Meanwhile, for example, here the response during GI is much less persistent (goes to zero by the fourth year) and this is significantly different to the response in the GM period. This supports the main analysis that the overlapping responses of government spending in the two disagreement regimes indicate that the path of government spending is independent to expectation formation of economic agents, albeit the *effects* of government spending on macroeconomic variables can be affected by expectations formation.

The dynamic responses of output during the GM and low disagreement regime are both significantly positive only up to one year and becomes zero afterwards. The peak positive output response during GI is similar to the positive peak response during high disagreement period (around 1%), but it quickly goes back to zero (even slightly negative at -0.75%). This strongly contrasts to the behaviour under high disagreement in the main result, even when most of the GI period is classified as a high disagreement regime. This suggests that the high disagreement dynamics is *not* driven purely by the GI period.

The central tendencies of the consumption response in GM and low disagreement period are similar — slightly positive but becomes negative after one year. But, while the main result shows significant negative response of consumption after 2 years, the response of consumption during Great Moderation is statistically insignificant from zero at all periods. The pattern of the response of investment is also similar in the baseline and placebo test, but only up to 15 quarters.

The more notable difference comes from the responses of consumption and investment during GI and the high disagreement period. In the main result, the response of consumption is persistently positive throughout all 20 quarters. However, in the placebo test, the consumption response is slightly negative for 2 years (quarters 6 to 14). Moreover, where in the main result the response of investment is mostly negative, in the placebo test it is positive from quarter 4 to 8. Thus, like output, I conclude that the behaviour of consumption in the high disagreement regime is not purely due to the GI period.[25]

Second, I look at the responses of the same variables as above, but for the time period of pre- and post-1989. Throughout the year 1989 and 1990, the US economy was weakening, and entered a short recession. The early 1990s recession saw limited expansion, oil price shock, and sluggish employment recovery. This highlights one of the analysis in the paper that high disagreement periods are only weakly correlated with recession. As we see in Figure 2.10, the periods in early 1990, saw mostly periods

[25]The non-monotonic response of output during the Great Inflation period can perhaps be explained by the responses of consumption and investment in the same period, and also the larger response of investment during Great Inflation period.

of low disagreement.

Third, I examine the responses of macroeconomic variables for the time period of pre- and post- 1992. The choice to divide the sample period in this way is due to the history of the Survey of Professional Forecasters. The Federal Reserve Bank of Philadelphia took over the SPF since 1990, and in 1992, they started to survey for the forecasts of GDP instead of GNP.[26] If GDP was more predictable and/or less volatile than GNP, then that would naturally create lower disagreement across forecasters. However, as seen in Figure A.3.5, GNP tracks GDP extraordinarily closely. This eliminates the possibility that the change (lessening) in disagreement is due to forecasters finding it easier to forecast GDP than GNP.

The state-dependent responses of the macroeconomic variables using Placebo 2 and Placebo 3, are in general similar. To recall, many of the high disagreement periods happened at the beginning of the sample. Thus, the similarities in some of these responses are mechanical. For example, we observe a slightly more expansionary effects of a 1% government spending shock in latter half of the sample. We also observe similar patterns of the responses of real private consumptions as in the baseline exercise. However, upon a closer look, we see more differences in the responses of government spending and real private investment. This indicates that the information frictions channel provide additional explanation to the state-dependent responses of some macroeconomic variables following an increase in government spending. Therefore, while Placebos 2 and 3 are not as useful as Placebo 1, it is particularly important that Placebo 1 suggests that the transition to the Great Moderation did not contribute to the main results. This explicitly tests out for the structural change in the United States that is well-documented by the huge literature on the Great Moderation (Stock and Watson, 2003).

[26]The SPF began in 1968 and was conducted by the American Statistical Association and the National Bureau of Economic Research.

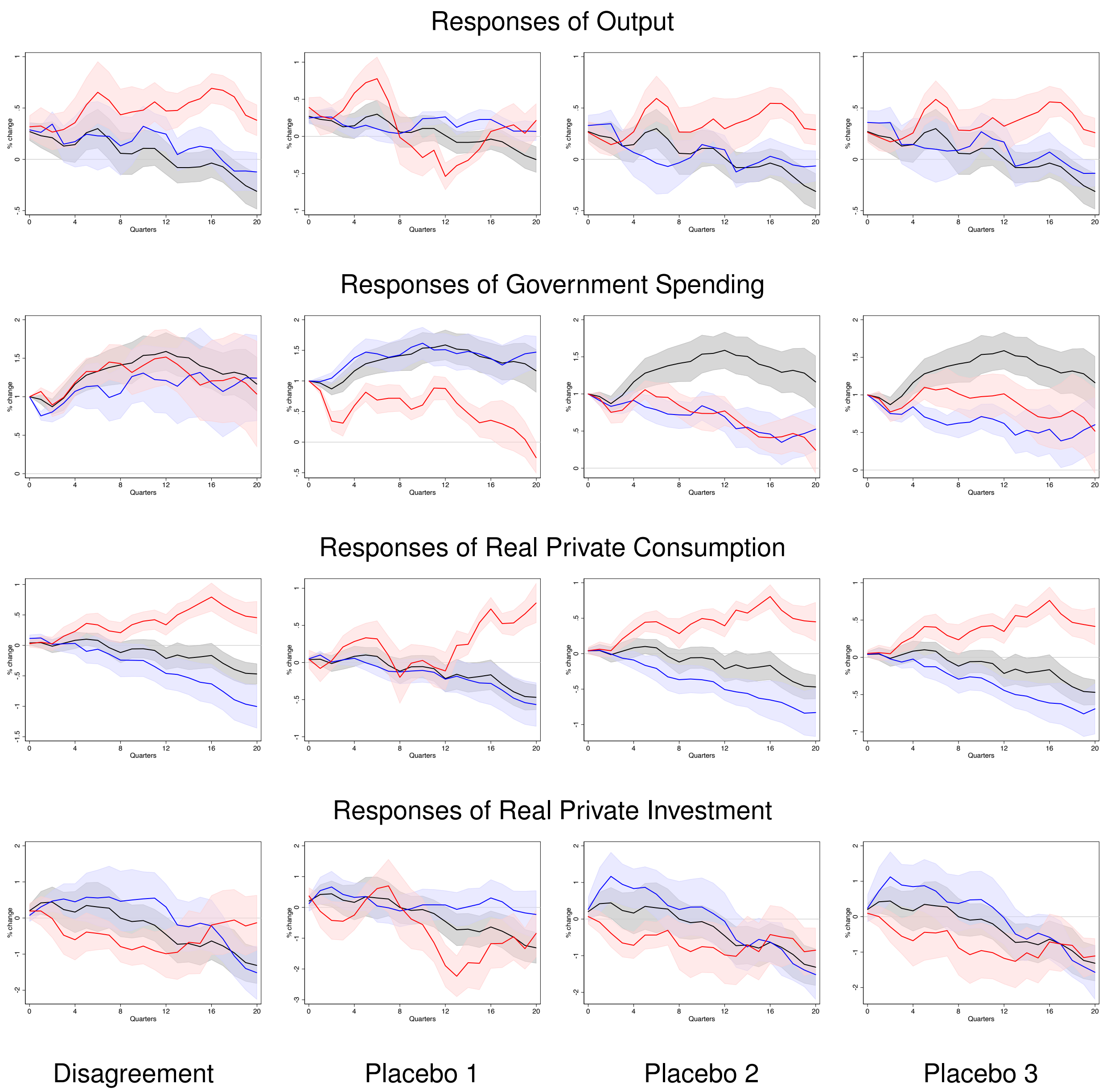

Figure 2.10. Impulse Responses to a 1% Government Spending Shock with Placebo States

Note: Responses to a 1% **government spending** shock. Each column corresponds to different definition of 'state' – Disagreement, Placebo1, Placebo 2 and Placebo 3. The red lines show the responses in high information frictions, the Great Inflation period, before 1989Q1, and before 1992Q1, respectively. The blue lines show the responses in low information frictions, after 1983Q2 (Great Moderation), after 1989Q1, and after 1992Q1, respectively. The black lines are the linear response (central tendency). The shaded region is 68% confidence interval. The sample period is 1970Q1-2018Q4.

Placebo Test 1: **Great Inflation vs Great Moderation**						
	1-quarter	**1-year**	**2-year**	**3-year**	**4-year**	**5-year**
Output						
Great Inflation	1.02	1.10	1.29	0.18	0.05	0.63
Great Moderation	1.37	1.08	0.76	0.77	0.70	0.56
Consumption						
Great Inflation	-0.36	-0.17	-0.06	-0.21	0.33	1.06
Great Moderation	0.42	0.42	0.34	0.30	0.22	0.05
Investment						
Great Inflation	0.06	-0.37	-0.28	-0.58	-0.94	-1.12
Great Moderation	0.27	0.34	0.29	0.29	0.31	0.28
Placebo Test 2						
	1-quarter	**1-year**	**2-year**	**3-year**	**4-year**	**5-year**
Output						
1970Q1-1983Q2	0.50	-0.03	0.47	0.62	0.96	1.45
1983Q3-2018Q4	2.12	1.91	1.27	1.00	0.43	-0.04
Consumption						
1970Q1-1983Q2	-0.05	0.14	0.54	0.83	1.29	1.70
1983Q3-2018Q4	0.46	0.48	0.25	0.01	-0.35	-0.73
Investment						
1970Q1-1983Q2	-0.07	-0.53	-0.72	-0.94	-1.15	-1.33
1983Q3-2018Q4	0.40	0.59	0.46	0.25	0.02	-0.19
Placebo Test 3						
	1-quarter	**1-year**	**2-year**	**3-year**	**4-year**	**5-year**
Output						
1970Q1-1991Q4	1.21	1.21	1.61	1.59	1.82	1.97
1992Q1-2018Q4	2.03	1.75	1.40	1.45	1.17	0.81
Consumption						
1970Q1-1991Q4	0.20	0.45	0.71	0.86	1.19	1.34
1992Q1-2018Q4	0.16	-0.06	-0.49	-0.89	-1.45	-1.99
Investment						
1970Q1-1991Q4	0.01	-0.23	-0.29	-0.43	-0.52	-0.58
1992Q1-2018Q4	0.34	0.62	0.65	0.58	0.36	0.07

Table 2.7. Estimates of Multipliers using Local Projection to a Government Spending Shock with Time Placebo as Threshold

Note: These are the cumulative multipliers defined as $M_h^x = \frac{\sum_{i=0}^h x_h}{\sum_{i=0}^h g_h}$ where x_h is the dollar effect on variable x of a one dollar increase in government spending at h quarters after the shock.

2.6.2 Placebo Test: Responses to Disaggregated Shocks

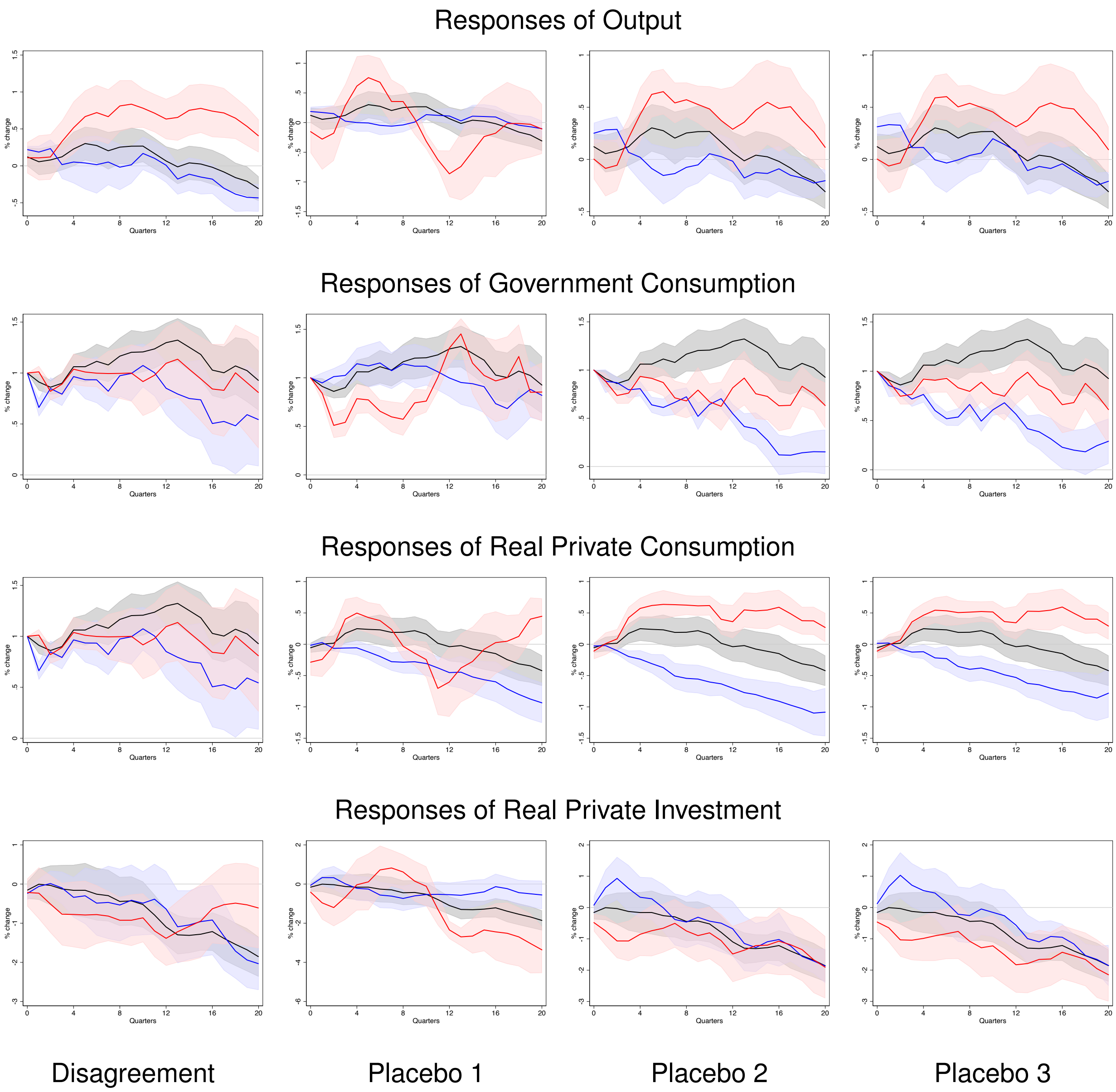

Figure 2.11. Impulse Responses to a 1% Government Consumption Shock with Placebo States

Note: Responses to a 1% **government consumption** shock. Each column corresponds to different definition of 'state' — Disagreement, Placebo1, Placebo 2 and Placebo 3. The red lines show the responses in high information frictions, the Great Inflation period, before 1989Q1, and before 1992Q1, respectively. The blue lines show the responses in low information frictions, after 1983Q2 (Great Moderation), after 1989Q1, and after 1992Q1, respectively. The black lines are the linear response (central tendency). The shaded region is 68% confidence interval. The sample period is 1970Q1-2018Q4.

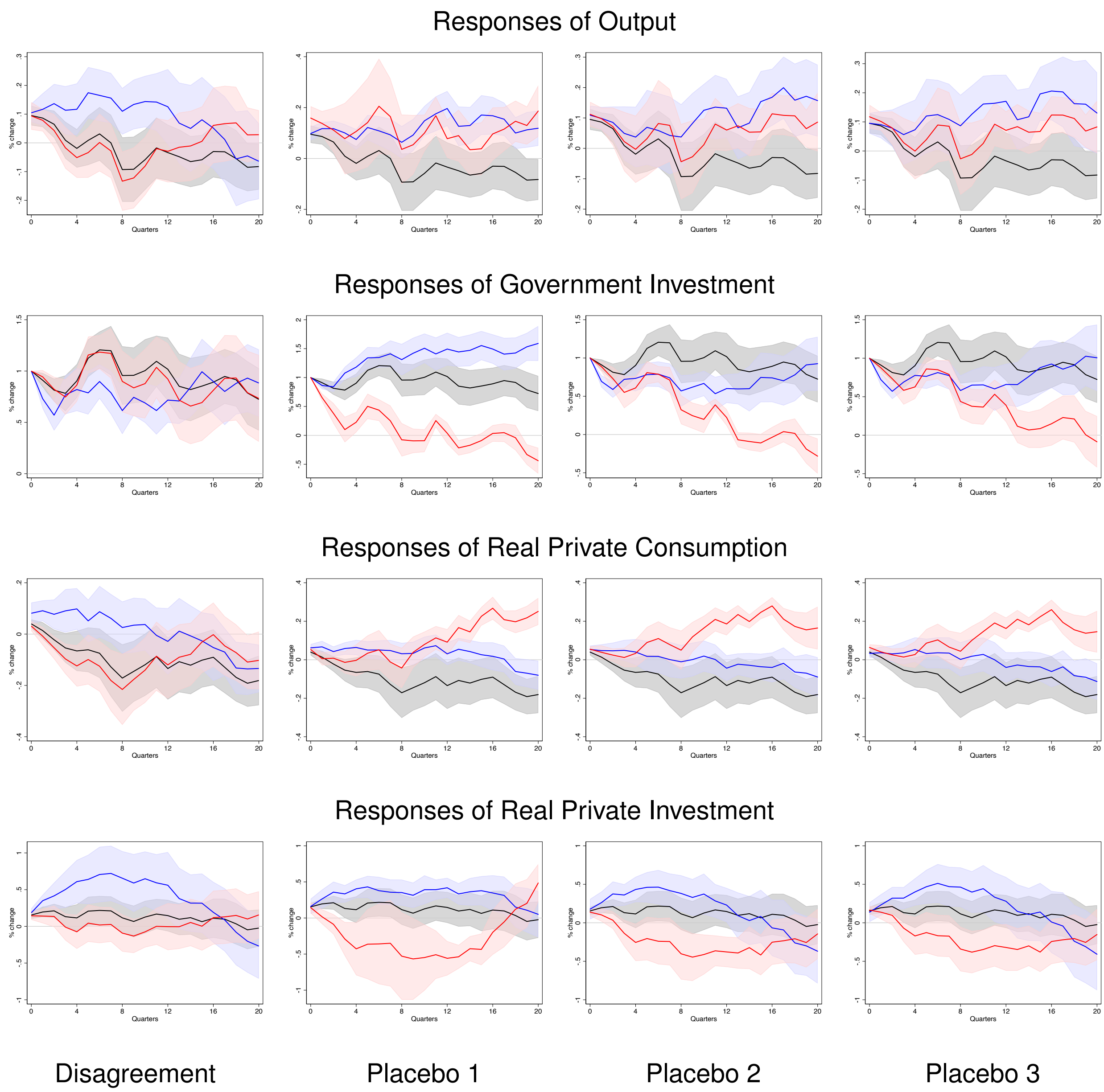

Figure 2.12. Impulse Responses to a 1% Government Investment Shock with Placebo States

Responses to a 1% **government investment** shock. Each column corresponds to different definition of 'state' — Disagreement, Placebo1, Placebo 2 and Placebo 3. The red lines show the responses in high information frictions, the Great Inflation period, before 1989Q1, and before 1992Q1, respectively. The blue lines show the responses in low information frictions, after 1983Q2 (Great Moderation), after 1989Q1, and after 1992Q1, respectively. The black lines are the linear response (central tendency). The shaded region is 68% confidence interval. The sample period is 1970Q1-2018Q4.

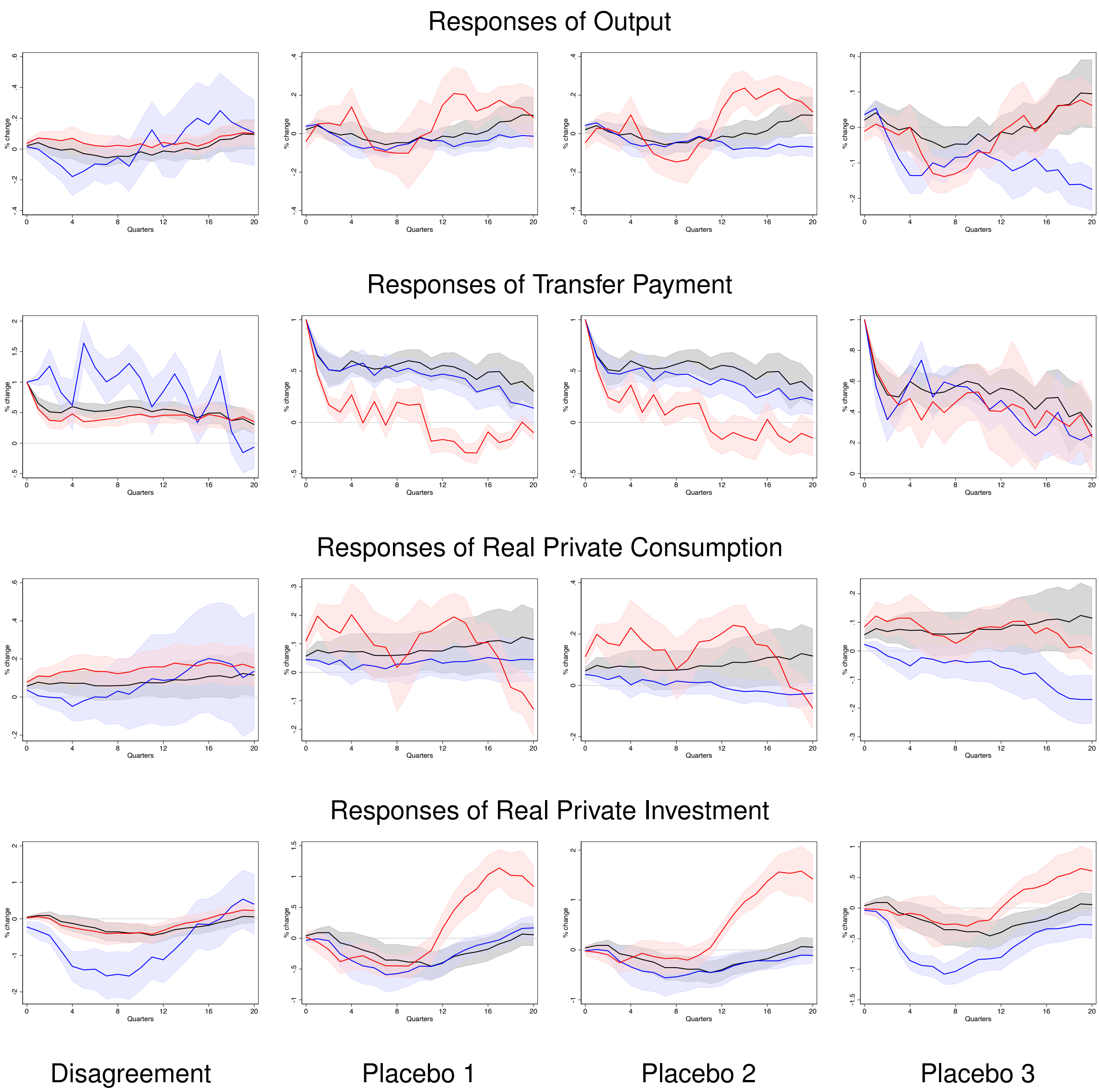

Figure 2.13. Impulse Responses to a 1% Transfer Payment Shock with Placebo States

Responses to a 1% **transfer payment** shock. Each column corresponds to different definition of 'state' — Disagreement, Placebo1, Placebo 2 and Placebo 3. The red lines show the responses in high information frictions, the Great Inflation period, before 1989Q1, and before 1992Q1, respectively. The blue lines show the responses in low information frictions, after 1983Q2 (Great Moderation), after 1989Q1, and after 1992Q1, respectively. The black lines are the linear response (central tendency). The shaded region is 68% confidence interval. The sample period is 1970Q1-2018Q4.

2.7 Conclusion

Do information frictions affect the transmission of government spending shocks? Yes. The results across the two regimes — high and low disagreement of real output nowcasts by professional forecasters, which I use to proxy the degree of information frictions – can be summarised as follows. In response to an increase in government spending, consumption rises strongly and persistently in times of high information frictions. This contrasts with the low information frictions regime, where consumption falls to the same government spending shock.

The key intuition of the empirical results is that when households are less able to identify economic shocks — including government spending — in real time, and forecast future tax rates, households' consumption respond positively to the government spending increase. In addition to the greater consumption response in magnitude, the rise in consumption also persists for longer. I also show evidence from labour market variables that suggest credit or liquidity constraints are less likely to explain the dynamic heterogeneities across the two regimes, relative to the information-frictions based explanation. The lack of a strong correlation between the disagreement state variable, and slack variables suggests that the identification of the regimes are not likely to be driven by recessionary times, which are likely to bring other channels.

This result bridges the Keynesian and neoclassical theoretical literature together (and their respective supporting empirical literature). I show evidences that channels from the two strands operate, but which dominates appear to depend on the extent of information frictions at a given time. This creates time-variation in the Ricardianness of agents, and as a result, agents can appear both Keynesian and neoclassical at different regimes.

Lastly, to shed more light on the transmission channels, I examine the responses to shocks of the disaggregated components of government spending (consumption and investment) as well as transfer payments. Information frictions affect the behaviour of household (consumption) the most in response to shocks in government consumption and transfer payment. On the other hand, these two shocks only have small effects on firms (investment) but government investment shocks influence it more, shaping its overall response to total government spending. These results indicate that firms and households pay heterogeneous attention to the different types of government spending, and hence, they react differently. Therefore, fiscal policymakers benefit from understanding the decision making process of firms and households in order to use different tools that best achieve their policy goals.

Chapter 3

Sticky Information and the Effects of Government Spending Shocks

3.1 Introduction

How do government spending shocks transmit to the real economy? This is an age-old question in macroeconomics. It is also ever more important in a low interest rate environment, where fiscal policy is expected to be more active to compensate for the reduced effectiveness of monetary policy close to the zero lower bound (Bernanke, 2020). There is still little agreement in the literature of how government spending shocks propagate through the economy. Empirically, in the previous chapter of this thesis, I reconcile the Keynesian and neoclassical predictions of fiscal policy — with a focus on explaining the varying response of private consumption to a government spending shock. I do this by emphasising the importance of information frictions.

While there are many models on information frictions to explain its effects on the transmission of monetary shocks, there is surprisingly little on its role on fiscal shocks. In this chapter, I build on the sticky information setup in Mankiw and Reis (2007) to provide a quantitative framework on how information frictions could affect the response of consumption to a government spending shock, and thus the associated fiscal multipliers. In this setup, only a fraction of the agents in the economy update their information about the state of the economy in that period (in effect, acting as the Calvo fairy in typical New Keynesian models). This friction creates nominal and real rigidities, as the agents that do not update correspondingly do not react to shocks occurring in that period.

I merge this setup with the seminal work of Galí et al. (2007) — in particular, the addition of 'rule-of-thumb' households.[1] These households cannot participate in asset markets to borrow or save, and thus simply consume their after-tax labour income. How does this help explain the empirical results in my previous chapter — that in periods of severe information frictions, consumption rise after a positive government spending shock, and contrarily, consumption falls when information frictions are not prevalent? The intuition is that, in this setup, there are effectively three types of households *in the period* of a positive government spending shock: (1) 'optimising' households that update, (2) optimising households that do *not* update (and thus, do not realise the shock has occurred), and (3) rule-of thumb households.[2] The rule-of-thumb households behave in a similar way as in Galí et al. (2007) — the increase in labour demand correspondingly increases their labour income, and thus their consumption rises.

The information frictions primarily act upon the optimising households.[3] When information frictions are prevalent — few optimising households update — then few households identify the shock. Correspondingly, few households save in advance of higher future taxes (optimising households that do not update their information also do not update their consumption plans). Therefore, *aggregate* consumption *rises* as the increase in the rule-of-thumb households' consumption dominate. In contrast, when information frictions are less important, the effect of the Ricardian optimising households dominate as many households save after the government spending shock, and thus aggregate consumption *falls*.

I explore the mechanisms of the model through various sensitivity analyses in Section 3.3.1 and demonstrate how variations in information frictions could produce different directions of consumption responses. I find that all three forms of information frictions (i.e. the inattentive consumers, workers and firms) contribute to

[1] In the recent heterogeneous agent New Keynesian (HANK) literature, these type of households are also known as hand-to-mouth consumers.

[2] The model in the next section clearly identifies the set of households that update in the same period as the government spending shock (household type (1)), as well as the optimising households that do not update contemporaneously following a government spending shock (household type (2)). The latter set of households will update their information in the future periods with some probability.

[3] The rule-of-thumb households are not directly affected by the information stickiness per se, but are of course affected by general equilibrium effects through factor markets.

producing the heterogeneity in consumption responses. The information friction that appears to have the largest effect on consumption behaviour is the consumers, as could be expected. This determines the proportion of Ricardian households who are able to observe and respond contemporaneously. Additionally, information rigidities on Ricardian households' *workers* prevent real wages from falling, which helps the consumption boom. Also, sticky information on price-setting slows down price adjustment, which dampens the crowding out effect of rising real interest rates so that Ricardian households do not reduce their consumption by too much. Moreover, it turns out that at least some information frictions in all three agents are necessary to reproduce the empirical consumption response in the previous chapter. But I also observe that the effects of each of these information frictions do not compound off one another.

The existing literature show New Keynesian models that incorporate nominal rigidities into the neoclassical framework exhibit the same wealth effect as a neoclassical model that crowds out consumption after an expansionary fiscal shock. However, in the more recent theoretical models, replicating the empirically relevant 'crowding-in', co-movement of consumption with government spending within a DSGE framework is possible by adding extra elements, although it remains challenging (Jacob, 2015). These elements include rule-of-thumb households (Galí et al., 2007; Furlanetto, 2011), deep habit formation (Ravn et al., 2007; Jacob, 2015), government-in-utility specification (Linnemann and Schabert, 2004), and non-separability between consumption and leisure (GHH preferences) (Monacelli and Perotti, 2008; Christiano et al., 2011; Bilbiie, 2011). Other papers also combine some of these methods, for example, combining a complementarity between private and public spending with habit formation (Bouakez and Rebei, 2007), or with GHH preferences (Ganelli and Tervala, 2009). However, there is limited work on explaining how government spending can stimulate consumption using information frictions. An exception to this is Murphy (2015), who builds on the imperfect information framework of Lucas (1972) and Lorenzoni (2009) to provide an alternative explanation of the positive consumption multiplier based on a positive wealth effect.

In Reis (2006a), the role of rule-of-thumb households is reflected by inattentive consumers and inattentive savers. Households differ by costs-to-planning and income risk, and self-select to either plan consumption, or plan savings. Those who choose to plan savings ('inattentive savers') rationally choose not to plan consumption (as it is costly to update plan) and absorb all of their income fluctuations in consumption. In other words, they live hand-to-mouth. In contrast, 'inattentive consumers' rationally choose to plan consumption as the cost-to-planning is relatively low, similar to the Ricardian households in my model (they sporadically update). The Reis (2006a) 'inattentive consumer' model implies one-third of U.S. population chooses to never plan — that is, the rule-of-thumb households.

Hurst (2003) uses data from the Panel Study of Income Dynamics (PSID) and finds that households who reach retirement with low wealth also have a larger drop in consumption at retirement (consistent with inadequate planning for retirement). The panel component of the PSID show that these households had consumption growth that responded to predictable increases and declines in income during their working years, while no such behaviour found among other pre-retired households. He finds this behaviour to be inconsistent with liquidity constraints, precautionary savings or habit formation, but can be explained by rule-of-thumb behaviour (where they follow a near-sighted consumption plans during their working lives). This evidence also supports the role of rule-of-thumb behaviour and inattentive households in this paper.

This paper is organised as follows. Section 3.2 sets up the sticky information general equilibrium model with rule-of-thumb households. It also provides details on the optimising behaviour, as well as assumptions on information of each agent in the economy. Section 3.3 describes the parameter calibrations and the main results, including the sensitivity analysis. I include some fiscal policy discussion in Section 3.4, and the final section concludes.

3.2 Model Setup

The sticky information general equilibrium (SIGE) model of Mankiw and Reis (2007) and Reis (2009) is similar to the neoclassical (full-information rational expectations) model, but with one different assumption on the information structure. In SIGE, while the expectations of each 'inattentive agent' are formed rationally, they do not necessarily act upon all the available information *at each point in time*. It implicitly assumes that there are fixed costs of acquiring, absorbing and processing information, such that agents optimally choose to only update their information sporadically (Reis, 2006a,b). The key difference between this paper and the SIGE model is the addition of rule-of-thumb households á la Galí et al. (2007).

In this section, I set out the assumptions on information of each agent in the economy, as well as their optimising behaviour. However, it would be useful to first understand how the agents meet at every period in three sets of markets as described in Reis (2009). There are three markets: the goods market, the bond market and the labour market. Information frictions — in the form of sticky information — exist in each of these markets, but not all agents are inattentive. The mathematical detail of the remaining 'attentive agents' is left to Appendix C.1.

One, in the goods market, monopolistically-competitive firms sell varieties of goods to households. The pricing department of these firms face information friction. These *inattentive price-setters* update their information set with a probability λ. The equilibrium in the goods market leads to Phillips curve (or aggregate supply) with sticky information:

$$p_t = \lambda \sum_{j=0}^{\infty} (1-\lambda)^j p_{t,j}$$

where p_t is the aggregate price and $p_{t,j}$ is the price of firm j at time t, *which was last updated at* $t-j$. In other words, $p_{t,j}$ reflects the optimal price at time t that the firm expects at time $t-j$. The higher the λ, the more current prices reflect the expectations of firms that updated recently.[4] On the other hand, the purchasing consumer ('purchasers' who buy from the continuum of firms and responsible for aggregating up the consumption basket) do not face information frictions — that is, she is an attentive agent.

Two, in the bond market (a market for savings), the saver-planner consumers ('consumers' who dictate how much overall to consume and save) trade bonds and interest rates change to balance borrowing and lending. In this paper, the bonds also finance government budget deficits. These *inattentive consumers* update their informa-

[4]Note that the Phillips curve, the IS curve and the wage curve is carefully derived later in this section and in Appendix C. See Eq (3.41) for the details of the optimal price $p_{t,j}$, Eq (3.25) for optimal consumption $c_{t,j}$, and Eq (3.31) for optimal wages $w_{t,j}$ — where "optimal" means that the agent has the latest information set.

tion set with a probability δ. The equilibrium in the bond market leads to an IS curve (of the optimising households) with sticky information:

$$c_t^o = \delta \sum_{j=0}^{\infty} (1-\delta)^j c_{t,j}^o$$

where c_t^o is the aggregate consumption of the Ricardian households, and $c_{t,j}^o$ is the consumption of Ricardian households j at time t, *which was last updated at* $t-j$. The higher the δ, the larger is the proportion of informed (and optimising) consumers who respond to shocks immediately.

Three, the labour market features workers on the supply side, and the labour packer and firms on the demand side. The labour packer bundles the differentiated labour input into a homogeneous labour input available for production by the firms. The labour packer and the hiring department of a firm are 'attentive agents'. On the supply side, there are monopolistically-competitive households who sell varieties of labour to the labour packer. These *inattentive workers* update their information set with a probability ω. The equilibrium in the labour market leads to a wage curve (of the optimising households) with sticky information:

$$w_t^o = \omega \sum_{j=0}^{\infty} (1-\omega)^j w_{t,j}^o$$

where w_t^o is the aggregate wage of the Ricardian households, and $w_{t,j}^o$ is the wage of Ricardian households j at time t, *which was last updated at* $t-j$. The higher the ω, the larger is the proportion of informed (and optimising) workers who respond to shocks immediately.

3.2.1 Households

I assume a continuum of infinitely-lived households. A fraction $(1-\chi)$ of households have access to the bond markets where they can trade a full set of contingent securities. I use the term *optimising* or *Ricardian* interchangeably to refer to this subset of households. These households face information frictions in the form of sticky information. The remaining fraction χ of households do not own any assets or have any debt, and just consume their current labour income net of taxes. I refer to them as *rule-of-thumb* households.[5]

If all (inattentive) agents are fully informed, the model structure collapses to Galí et al. (2007) with no nominal rigidities. Here, nominal rigidites arise from the sticky information on firms (creating sticky prices) and on workers (creating sticky nominal wages).

The period preferences of both types of households (optimising and rule-of-thumb) are

$$U(C_{t,j}, L_{t,j}) = \frac{C_{t,j}^{1-\frac{1}{\theta}}}{1-\frac{1}{\theta}} - \frac{L_{t,j}^{1+\frac{1}{\psi}}}{1+\frac{1}{\psi}} \tag{3.1}$$

$C_{t,j}$ and $L_{t,j}$ is the consumption and labour supply by agent j at time t. θ is the intertemporal elasticity of substitution and ψ is the Frisch elasticity of labour supply. This utility function will be subject to a budget constraint that would be specific to the optimising household and the rule-of-thumb household, which I describe in detail in the following subsections.

Optimising Households

The optimising household seeks to maximise

$$E_{t-j} \sum_{t=0}^{\infty} \beta^t U(C^o_{t,j}, L^o_{t,j}) \tag{3.2}$$

subject to the (optimising households') budget constraint

$$C^o_{t,j} + \frac{B^o_{t+1,j}}{R_{t+1}} = B^o_{t,j} + \frac{W_{t,j}L^o_{t,j}}{P_t} - T^o_{t,j} \tag{3.3}$$

where β is the discount factor, $C^o_{t,j}$ is the consumption of the *optimising* household j, $\frac{W_{t,j}}{P_t}$ is the real wage for $L^o_{t,j}$ labour supply of the *optimising* household j, and R_t is the real interest rate factor.

Saver-planners

The saver-planner j enters the period with real bonds $B^o_{t,j}$, uses some of it to consume, earns labour income and pays lump-sum taxes $T^o_{t,j}$. Included in this lump-sum taxes

[5] Galí et al. (2007) describe different interpretations for that behaviour include myopia, lack of access to capital markets, fear of saving, ignorance of intertemporal trading opportunities.

are also profits and losses from firms, and payments from an insurance contract that all households signed at date $t = 0$, which ensures that at every period they are all left with the same wealth. Moreover, $j = 0$ denotes the agent (here, saver-planner) who forms expectations rationally based on up-to-date information.

The dynamic program that characterises the saver-planner's problem is tedious and is therefore covered in Appendix C.3. The optimality conditions of the saver-planners from their optimisation are:

$$
\begin{aligned}
(C^o_{t,0})^{-\frac{1}{\theta}} &= \beta E_t \left[(C^o_{t+1,0})^{-\frac{1}{\theta}} R_{t+1} \right] && (3.4) \\
(C^o_{t,j})^{-\frac{1}{\theta}} &= E_{t-j} \left[(C^o_{t,0})^{-\frac{1}{\theta}} \right] && (3.5)
\end{aligned}
$$

The first equation above is the standard Euler equation for an agent that updates at that point in time ('well-informed'). It states that the marginal utility of consuming today is equal to the expected discounted marginal utility of consuming tomorrow multiplied by the return on savings. The second equation notes that agents who do not update at that point (rather, their information set was updated j periods ago) set their marginal utility of consumption to what they expect it would be with full information.

Workers

The optimising workers supply labour input to a 'labour packer firm' (see Subsection 3.2.3), who will then combine it with the labour supply from the rule-of-thumb households. The Ricardian workers' aim is to minimise their expected discounted disutility of labour. The dynamic program that characterises the workers' problem is even more tedious, and is covered in Appendix C.4. The optimality conditions of the optimising workers are

$$
\frac{\gamma_t}{\gamma_t - 1} \frac{P_t \left(L^o_{t,0} \right)^{\frac{1}{\psi}}}{W^o_{t,0}} = \beta E_t \left(R_{t+1} \frac{\gamma_{t+1}}{\gamma_{t+1} - 1} \frac{P_{t+1} \left(L^o_{t+1,0} \right)^{\frac{1}{\psi}}}{W^o_{t+1,0}} \right) \tag{3.6}
$$

$$
W^o_{t,j} = \frac{E_{t-j} \left[\gamma_t \left(L^o_{t,j} \right)^{\frac{1}{\psi}} \right]}{E_{t-j} \left[\gamma_t L^o_{t,j} \left(L^o_{t,0} \right)^{\frac{1}{\psi} - 1} / W^o_{t,0} \right]} \tag{3.7}
$$

Eq (3.6) is the *inter*temporal labour supply Euler equation for a well-informed worker. If the elasticity of substitution across labour varieties γ_t is fixed, the marginal disutility of supplying labour today (divided by the real wage today) equates the discounted marginal disutility tomorrow (divided by the the real wage tomorrow) times the interest rate. This is much akin to the standard labour supply condition under full information, combined with the consumption Euler equation. With time-varying γ_t, the labour supply Euler equation takes into account the change in the mark-up charged by the monopolistic worker.[6]

Inattentiveness of Optimising Households

There is a fraction δ of consumers (saver-planners) and a fraction ω of workers in the optimising households who update their information. Thus, every period, there are δ consumers who have current information, $\delta(1-\delta)$ with one-period-old information, $\delta(1-\delta)^2$ with two-period-old information, and so on. Because agents only differ on the date at which they last updated, we can group them and let j denote how long ago the optimising consumers last updated. Likewise, ω of workers update their information set, and they can be grouped into groups of j of size $\omega(1-\omega)^j$.

Rule-of-Thumb Households

The rule-of-thumb households are assumed to behave in a 'hand-to-mouth' fashion, fully consuming their current after-tax labour income. These agents differ from the optimising agents because they cannot smooth consumption through bond holdings. Thus, they do not smooth their consumption path in the face of fluctuations in labour income, nor do they intertemporally substitute in response to changes in interest rates. Following Galí et al. (2007), I abstract from the sources of that behaviour. The literature, for instance, attribute it to a combination of lack of access to financial markets, or (continuously) binding borrowing constraints. Their period utility is given by

$$U(C_t^r, L_t^r)$$

[6] The left-hand side of this Eq (3.6) reflects the *intra*temporal problem, substituted into the consumption Euler equation in Eq (3.4).

subject to the (rule-of-thumb households') budget constraint

$$C_t^r = \frac{W_t^r L_t^r}{P_t} - T_t^r$$

where the lump-sum taxes paid by the rule-of-thumb households T_t^r can differ from those paid by the optimising households T_t^o. Under the assumption of a competitive labour market, the labour supply of the rule-of-thumb household satisfy

$$\frac{W_t^r}{P_t} = (C_t^r)^\theta (L_t^r)^{\frac{1}{\psi}}$$

Aggregation of Households

Aggregate consumption and labours are given by a weighted average of the corresponding variable for each household type

$$C_t \equiv \chi C_t^r + (1-\chi) C_t^o \tag{3.8}$$

$$L_t \equiv \chi L_t^r + (1-\chi) L_t^o \tag{3.9}$$

3.2.2 Firms

There is a monopolistically-competitive firm that produces each variety of good i. Each of these firms, indexed by j, operates a technology that uses labour input $L_{t,j}$ supplied by the labour packer at a single cost W_t to produce good i under diminishing returns to scale $\alpha \in (0,1)$ and a common technology shock A_t. The firm's pricing department (the price-setters) is in charge of setting the price $P_{t,j}$ and selling the output $Y_{t,j}$ to maximise real after-tax profits subject to the technology and the demand for good i:

$$\max_{P_{t,j}} E_{t-j} \left[\frac{P_{t,j} Y_{t,j}}{P_t} - \frac{W_t L_{t,j}}{P_t} \right] \tag{3.10}$$

The $E_{t-j}(.)$ expectations operator of the pricing department of firm j depends on its information. This is subject to the production function

$$Y_{t,j} = A_t L_{t,j}^\alpha \tag{3.11}$$

and the total demand for variety good i

$$Y_{t,i} = \left(\frac{P_t(i)}{P_t}\right)^{-\nu_t} (G_t + C_t) \quad \text{where} \quad C_t = \int_0^1 C_{t,j}(i)dj \tag{3.12}$$

where $C_{t,j}(i)$ is the consumption of variety i by household j at time t, and G_t is the exogenous government spending. $Y_{t,i}$ is the total production of good i at time t. In equilibrium $Y_{t,i} = Y_{t,j}$, and $P_t(i) = P_{t,j}$ as each good is produced by a unique firm.

After some rearranging, the first-order condition of firm j is

$$P_{t,j} = \frac{E_{t-j}\left[\frac{\nu_t W_t L_{t,j}}{P_t}\right]}{E_{t-j}\left[\frac{\alpha(\nu_t-1)Y_{t,j}}{P_t}\right]} \tag{3.13}$$

I leave the mathematical details in Appendix C.2.

3.2.3 Labour Packer

The labour packer receives a supply of differentiated labour input from the optimising and rule-of-thumb households. They bundle these differentiated labour input into a homogeneous labour input available for production by the firms. Their profit maximisation is

$$\max_{\{L_{t,j}(i)\}_{i\in[0,1]}} W_t L_t - W_t^o L_t^o - W_t^r L_t^r \tag{3.14}$$

$$\text{subject to} \quad L_t = \left[(1-\chi)^{\frac{1}{\sigma}} (L_t^o)^{\frac{\sigma-1}{\sigma}} + (\chi)^{\frac{1}{\sigma}} (L_t^r)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

σ is the elasticity of substitution across the two household types. This should be contrasted to γ which is the elasticity of substitution across households but *within* a household type. The first-order condition of this optimisation problem gives the labour demand schedule for the optimising and rule-of-thumb household, respectively:

$$L_t^o = (1-\chi)\left(\frac{W_t^o}{W_t}\right)^{-\sigma} L_t \tag{3.15}$$

$$L_t^r = \chi\left(\frac{W_t^r}{W_t}\right)^{-\sigma} L_t \tag{3.16}$$

and this gives the wage index

$$W_t = \left[(1-\chi)(W_t^o)^{1-\sigma} + \chi(W_t^r)^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \tag{3.17}$$

While Ricardian and rule-of-thumb households can have different wages, the monopolistic firms will face a single wage to pay to the labour packer. Therefore, this retains the tractability of the SIGE model with only one type of household. The complete derivation can be found in Appendix C.1.1.

3.2.4 Market Clearing

The market clearing condition is

$$Y_t \quad = \quad G_t + C_t \tag{3.18}$$

Here, government spending behaves exogenously as the government spending shock. This is slightly different to Mankiw and Reis (2007) where government spending is a proportion of consumption, which they interpret broadly as an aggregated demand shock.

3.2.5 Monetary Policy

Monetary policy is set according to a Taylor rule

$$i_t = \phi_\pi \log\left(\frac{P_t}{P_{t-1}}\right) - \varepsilon_t \tag{3.19}$$

where $\phi_\pi > 1$ and a positive ε_t corresponds to an expansionary shock.

3.2.6 Fiscal Policy

The government budget constraint is

$$T_t + \frac{B_{t+1}}{R_{t+1}} = B_t + G_t \tag{3.20}$$

where $T_t \equiv \chi T_t^r + (1-\chi)T_t^o$. I set the steady-state zero net supply of bonds (and thus, a balanced primary budget). The fiscal policy rule takes the following form

$$t_t = \phi_b b_t + \phi_g g_t \tag{3.21}$$

where $t_t \equiv \frac{T_t - T}{Y}$, $b_t \equiv \frac{B_t - B}{Y}$, and ϕ_b and ϕ_g are positive constants.

3.2.7 The Log-Linearised Economy and Shocks

I log-linearise the equilibrium conditions around the non-stochastic steady state. Small caps denote the log-deviations of the respective large capitalised variable from this steady state, with a few exceptions: $\tilde{\nu}_t$ and $\tilde{\gamma}_t$ which are the log-deviations of ν_t and γ_t. $\tilde{r}_t$ which is the log-deviation of the short rate $E_t R_{t+1}$ and for clarity, r_t is the log-deviation of the *long* rate:

$$r_t = \sum_{k=0}^{\infty} \tilde{r}_{t+k} \tag{3.22}$$

Lastly, as noted before, $t_t \equiv \frac{T_t - T}{Y}$ and $b_t \equiv \frac{B_t - B}{Y}$.

From the inattentive saver-planner's problem of the Ricardian households:

$$c_{t,0}^o = E_t(c_{t+1}^o - \theta \tilde{r}_t) \tag{3.23}$$

$$c_{t,j}^o = E_{t-j}(c_{t,0}^o) \tag{3.24}$$

Iterating the two equations above, we get the first equation below. The second equation below is the log-linearised IS curve of the optimising households:

$$c_{t,j}^o = E_{t-j}(-\theta r_t) \tag{3.25}$$

$$c_t^o = \delta \sum_{j=0}^{\infty} (1-\delta)^j c_{t,j}^o \tag{3.26}$$

From the problem of the rule-of-thumb households, and the aggregation of the two households types:

$$(1-\eta)c_t^r = \eta \frac{1+\psi}{\psi} l_t^r - \frac{1}{\theta_C} t_t \tag{3.27}$$

$$c_t = \chi c_t^r + (1-\chi)c_t^o \tag{3.28}$$

where $\eta = \frac{\nu-1}{\nu}\frac{\alpha}{\theta_C}$.

Similarly from the inattentive worker's problem:

$$w_{t,0}^o - p_t - \frac{l_{t,0}^o}{\psi} + \frac{\tilde{\gamma}_t}{(\gamma-1)} = E_t\left[-\tilde{r}_t + w_{t+1,0}^o - p_{t+1} - \frac{l_{t+1,0}^o}{\psi} + \frac{\tilde{\gamma}_{t+1}}{(\gamma-1)}\right] \tag{3.29}$$

$$w_{t,j}^o = E_{t-j}(w_{t,0}^o) \tag{3.30}$$

Combining and iterating the two equations above, we get the first equation below. The second equation below is the log-linearised wage curve of the optimising households:

$$w_{t,j}^o = E_{t-j}\left[p_t + \frac{\gamma}{\gamma+\psi}(w_t^o - p_t) + \frac{1}{\gamma+\psi}(l_t^o) - \frac{\psi}{\gamma+\psi}r_t - \frac{\psi}{\gamma+\psi}\frac{\tilde{\gamma}_t}{\gamma-1}\right] \tag{3.31}$$

$$w_t^o = \omega\sum_{j=0}^{\infty}(1-\omega)^j w_{t,j}^o \tag{3.32}$$

From the problem of the rule-of-thumb worker's problem results in their labour supply equation

$$w_t^r = c_t^r + \frac{1}{\psi}l_t^r \tag{3.33}$$

The labour packer production function (setting the elasticity of substitution $\sigma = 1$), and the resulting optimisation results in the following linearised equations:

$$l_t = \chi l_t^r + (1-\chi)l_t^o \tag{3.34}$$

$$l_t^o = l_t + \sigma(w_t - w_t^o) \tag{3.35}$$

$$l_t^r = l_t + \sigma(w_t - w_t^r) \tag{3.36}$$

$$w_t = \chi w_t^r + (1-\chi)w_t^o \tag{3.37}$$

From the inattentive firm's problem results in these linearised price-setting equations

$$y_{t,j} = a_t + \alpha l_{t,j} \tag{3.38}$$

$$y_{t,j} = y_t - \nu(p_{t,j} - p_t) \tag{3.39}$$

$$p_{t,j} = E_{t-j}\left[w_t - y_{t,j} - l_{t,j} - \frac{\tilde{\nu}_t}{(\nu-1)}\right] \tag{3.40}$$

$$= E_{t-j}\left[p_t + \frac{\alpha(w_t - p_t) + (1-\alpha)y_t - a_t - \alpha\frac{\tilde{\nu}_t}{(\nu-1)}}{\alpha + \nu(1-\alpha)}\right] \quad (3.41)$$

$$p_t = \lambda\sum_{j=0}^{\infty}(1-\lambda)^j p_{t,j} \quad (3.42)$$

Finally, log-linearising the market clearing conditions and monetary policy rules leads to (the fiscal rule in Eq (3.21) is already linearised)

$$y_t = \theta_G g_t + \theta_C c_t \quad (3.43)$$

$$i_t = \phi_\pi \pi_t - \varepsilon_t \quad (3.44)$$

$$i_t = \tilde{r}_t + E_t\pi_{t+1} \quad (3.45)$$

There are five source of shocks in the model: government spending, monetary policy, aggregate productivity growth, goods markups and labour markups. Each of these shock follow an independent AR(1) process:

$$g_t = \rho_g g_{t-1} + e_t^g \quad (3.46)$$

$$\varepsilon_t = \rho_\varepsilon \varepsilon_{t-1} + e_t^\varepsilon \quad (3.47)$$

$$a_t = \rho_z a_{t-1} + e_t^a \quad (3.48)$$

$$\tilde{\nu}_t = \rho_\nu \tilde{\nu}_{t-1} + e_t^\nu \quad (3.49)$$

$$\tilde{\gamma}_t = \rho_\gamma \tilde{\gamma}_{t-1} + e_t^\gamma \quad (3.50)$$

where the shocks $e_t^s\ N(0,\sigma_s^2)$ are i.i.d over time. However, for the purpose of this paper, I will focus purely on the government spending shock.

I solve the model using perturbations, and truncate the lags of Eq (3.26), (3.32) and (3.42) to 24 lags. I have also compared the solution to when I truncate the lags up to 64 lags, but this does not make any quantitatively significant differences to the solution truncated to 24 lags.[7]

[7] Verona and Wolters (2014) follow a similar strategy, but with 16 lags. Therefore, I have a more accurate solution. Similarly, Lorenzoni (2009) checks his truncation method by also increasing the number of lags.

3.3 Results

Each period is assumed to correspond to a quarter — setting the discount factor β to the standard 0.99. Then, I calibrate the following parameters to the estimated posterior mean of Reis (2009), setting $\nu = 10.09, \gamma = 9.09, \psi = 5.15$ and $\theta = 1$. As in the baseline calibration of Galí et al. (2007), I set $\phi_\pi = 1.5, \theta_G = 0.2, \rho_g = 0.9, \phi_g = 0.1$ and $\phi_b = 0.33$. The proportion of rule-of-thumb households λ is set to 0.25.[8] The labour share α is set to $2/3$, and $\sigma = 1$ indicates a Cobb-Douglas input to the labour packer. The baseline setting for the sticky information parameters follows the estimated parameter values in Mankiw and Reis (2007) (MR07) with $\delta = 0.176, \omega = 0.21$ and $\lambda = 0.657$, and I will explore the behaviour of the model under various degrees of inattentiveness.[9]

Next, as a starting point, I change the three inattentiveness parameters equally under different calibrations. Note that $\delta = \omega = \lambda = 1$ indicate full attentiveness or full information, and $\delta = \omega = \lambda = 0$ is when agents are fully inattentive. In the next section, I will explore the role of individual parameters. The parameters governing the inattentiveness of the optimising consumers δ, workers ω and firms λ are set to vary in impulse responses in Figure 3.1, Figure 3.2 and Figure 3.3.

The response of consumption to a 1% government spending shock varies in the sign across different degrees of inattentiveness. When $\delta = \omega = \lambda = 0.65$ (agents updating relatively quickly — on average every 1.5 quarters), Ricardian households strongly reduce their consumption, in line with the neoclassical effects. This is because the rise in aggregate demand increases inflation, resulting in a monetary policy response that raises the real interest rate. By the consumption Euler equation, optimising households' consumption falls, and drives the overall reduction in aggregate consumption.

In contrast, when agents are highly inattentive $\delta = \omega = \lambda = 0.125$ (updating less often — on average every 2 years), aggregate consumption rises instead. This is due to relatively muted effects of the Ricardian households, as only a few of them

[8] Galí et al. (2007) and Furlanetto (2011) set the proportion of rule-of-thumb households to 0.5 in their baseline calibration, but their analysis find that 0.25 to be a more plausible percentage of rule-of-thumb households. It is also closer to the predictions of the heterogeneous agents (HANK) literature.

[9] Carroll (2003), Mankiw et al. (2004) and Nunes (2009) estimate that households update their expectations (of inflation) around once per year. This translates to sticky information parameters of households, δ and ω, equal to 0.25.

realise the shock has happened. This allows Keynesian multiplier-like effects to take place. As output rises after the expansionary shock, labour demand increases. This simultaneously increases hours worked and real wages of both households, including the rule-of-thumb households. This raises their labour income which mechanically increases their consumption. The boost in consumption also leads to an increase in aggregate demand, which further stimulates labour demand, and thus the Keynesian multiplier effects take hold.

Relating the results here to the empirical results of the previous chapter, the model manages to capture most of the key results in aggregate behaviour. Firstly, aggregate consumption in Figure 3.1 has different signs depending on the degree of information frictions, at least for the first few quarters. When information frictions are severe, consumption in aggregate behaves like a rule-of-thumb household — in that, it increases to a rise in government spending. On the other hand, when agents frequently update, the household sector as a whole behaves like those in standard neoclassical models.

When the model is calibrated to 1-year inattentiveness ($\delta = \omega = \lambda = 0.25$), as expected, the results mainly lie between the 2-years and 1.5-quarter calibrations. Given that the 1-year calibration is similar to the MR07 estimated posterior means, with the exception of more flexible prices in MR07 (1.5 quarters average price duration), it is interesting to compare the two calibrations to examine the role of price rigidities in the model. The most obvious difference lies in the inflation response in Figure 3.3, with inflation rising significantly more under the MR07 calibration. This leads to a monetary policy response that raises the real interest rate by more, and via the consumption Euler equation, Ricardian households consumption also falls farther (at least, in the short term). In addition, the higher inflation in MR07 calibration leads to lower real wages (of both households). This reduces the real labour income of households, reducing the rule-of-thumb households consumption.

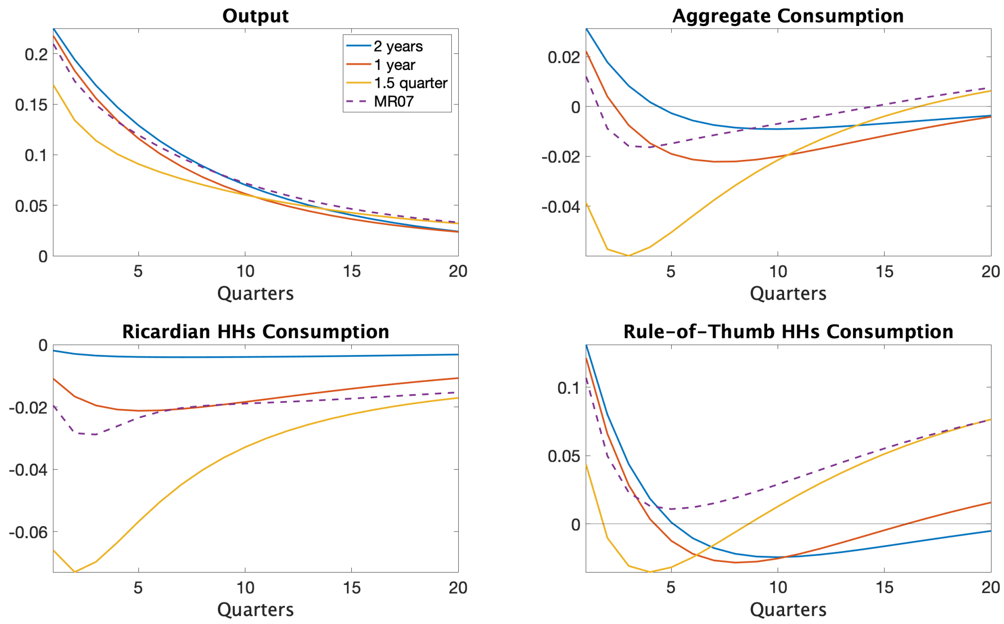

Figure 3.1. Impulse Responses of Output and Consumption with Varying Degree of Inattentiveness

Note: Responses to a 1% government spending shock. The blue lines show the responses when $\delta = \omega = \lambda = 0.125$ (indicating agents update infrequently, every 2 years), the red lines when $\delta = \omega = \lambda = 0.25$ (updating every 1 year), and yellow lines when $\delta = \omega = \lambda = 0.65$ (updating every 1.5 quarters). The dashed lines correspond to the MR07 calibration: $\delta = 0.176$, $\omega = 0.21$ and $\lambda = 0.657$.

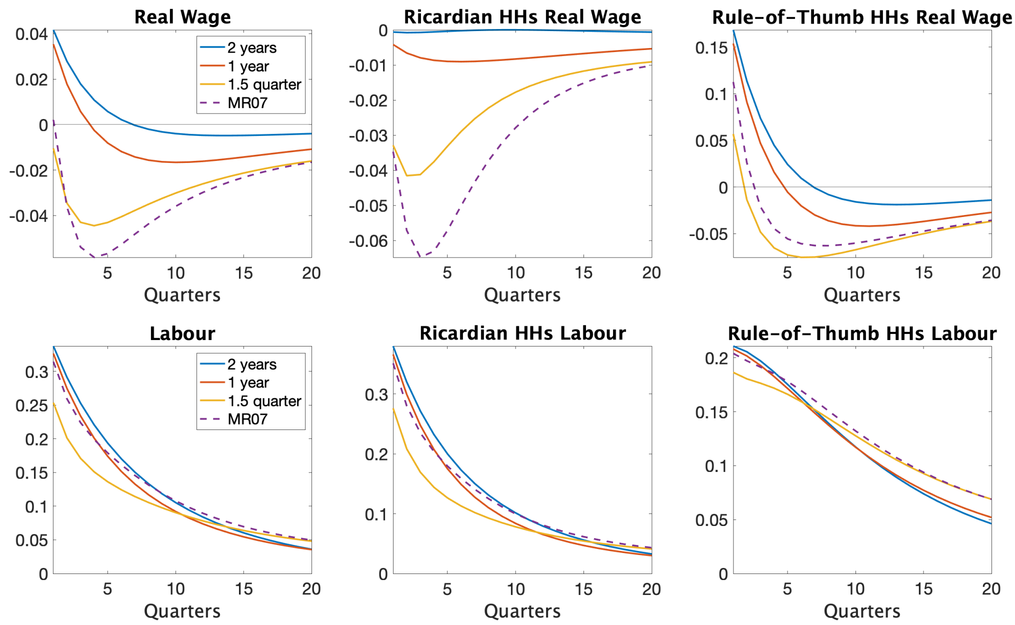

Figure 3.2. Impulse Responses of Labour Market Variables with Varying Degree of Inattentiveness

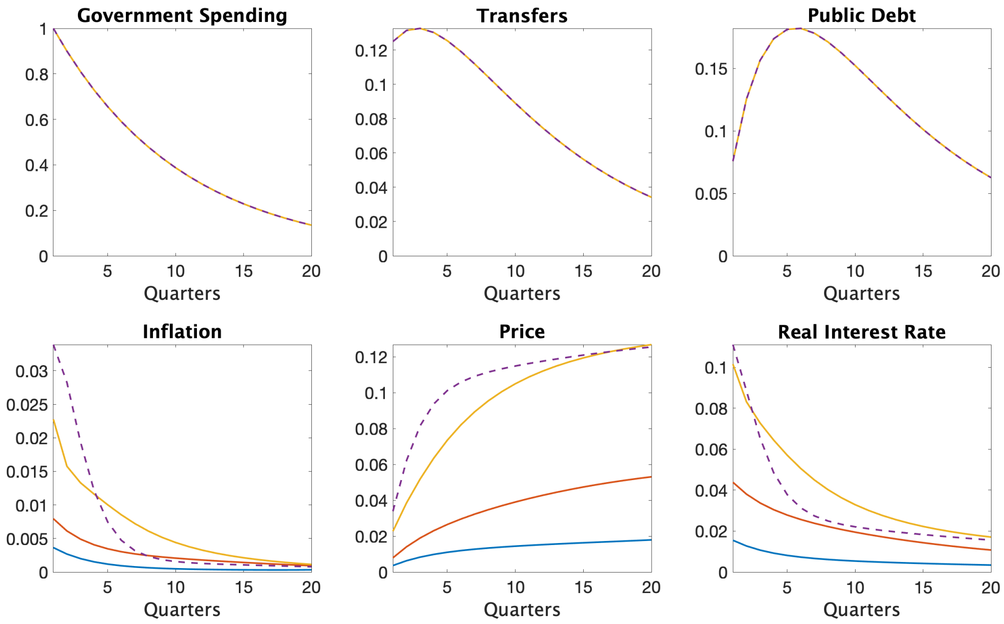

Figure 3.3. Impulse Responses of Other Key Variables with Varying Degree of Inattentiveness

Note: Figure 3.2 and Figure 3.3 show the responses to a 1% government spending shock. The blue lines show the responses when $\delta = \omega = \lambda = 0.125$ (indicating agents update infrequently, every 2 years), the red line when $\delta = \omega = \lambda = 0.25$ (updating every 1 year), and the yellow lines when $\delta = \omega = \lambda = 0.65$ (updating every 1.5 quarters). The dashed lines correspond to the MR07 calibration: $\delta = 0.176$, $\omega = 0.21$ and $\lambda = 0.657$.

Furthermore, the role of information rigidities on labour supply is also apparent in helping produce a positive consumption co-movement with a government spending shock. Figure 3.2 shows that hours worked of both types of households rise but real wages only rise on impact for the rule-of-thumb households. This could be explained by the following. Labour demand increases for both types of workers, but there is a much larger shift in labour supply of the Ricardian households via a wealth effect, leading to a fall in their real wages. This effect is reduced when the workers pay less attention, for example, in the 2 years calibration.

There is also a spillover effect from the Ricardian real wages to the rule-of-thumb households. As the price of Ricardian labour do not fall by as much when agents are more inattentive, firms do not substitute away from rule-of-thumb labour by as much. This keeps rule-of-thumb real wages higher, enhancing the boost to their labour income, and therefore consumption.

In order to understand how government spending affect the income of the two types of households in this model, I calculate their pre-tax income. From the Ricardian households' budget constraint, we find that their (pre-tax) income net of bond sales/purchases:

$$\text{income}^o = \left(\theta_C + \theta_T^o\right)\left(\alpha\frac{\nu-1}{\nu}\left[w_t^o + l_t^o - p_t\right] + b_t - \beta b_{t+1}\right) \tag{3.51}$$

where $\theta_T^o \equiv \frac{T}{Y} = \left[\frac{1}{1-\chi}\right]\left[\theta_G - \chi\left(\alpha\frac{\nu-1}{\nu} - \theta_C\right)\right]$. Similarly, from the rule-of-thumb households' budget constraint we have:

$$\text{income}^r = l_t^r + w_t^r - p_t \tag{3.52}$$

I plot these equations in Figure 3.4, using the parameters as above, with the sticky information parameters following the MR07.

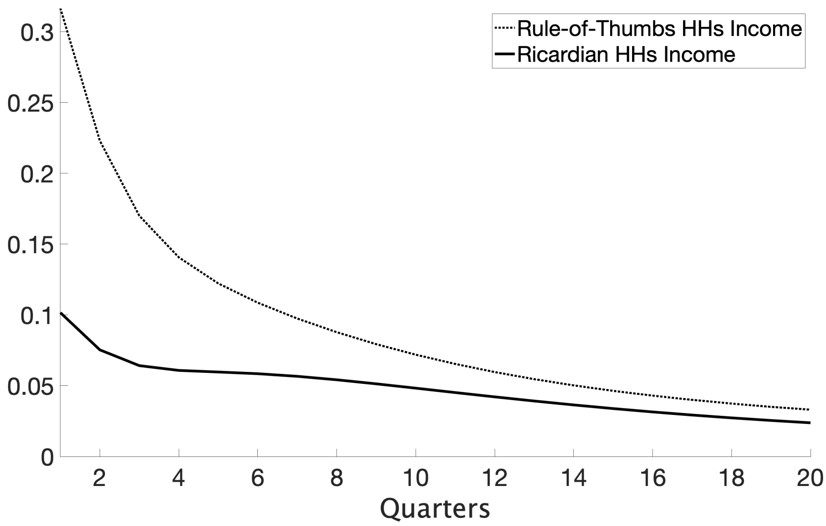

Figure 3.4. Impulse Responses of Households' Income

Note: The figure shows the response of Ricardian (solid line) and rule-of-thumb (dotted line) households income to a 1% government spending shock. Total household income is defined in Eq (3.51) and Eq (3.52). The proportion of rule-of-thumb households is $\chi = 0.25$. The sticky information parameters follow MR07 where $\delta = 0.176$, $\omega = 0.21$ and $\lambda = 0.657$.

Figure 3.4 shows that an increase in government spending is able to raise the *total* income of rule-of-thumb households more — around three-fold that of optimising households. However, the increase in *labour* income across the two household types is exactly the same. This is a consequence of the Cobb-Douglas production function of the labour packer, which allocates an equal expenditure for each component. The difference in total income can be explained by the saving behaviour of the Ricardian households. That is, they save and invest into government bonds which in turn finances the rise in government spending.

This also relates to the finding of Galí et al. (2007) that labour market frictions are important in gaining a positive consumption response to an increase in government spending. In fact, they only manage to get a positive consumption response in the model with a labour union, which effectively creates rigidities in wage-setting. Here the frictions in the labour market is microfounded through information frictions.

3.3.1 Sensitivity Analysis

So far, I only had a blunt instrument in analysing how information frictions affect the consumption response to a government spending shock, as I varied all sticky information parameters at the same time. In this subsection, I dissect the contribution of each of the sticky information parameters, as well as the role of rule-of-thumb households, in driving how aggregate consumption responds. To do this, I analyse the contemporaneous response of output and consumption (normalised by steady state output) to a positive government spending shock, as a function of various information stickiness and fraction of rule-of-thumb consumers specific to each figure in this subsection.[10] The remaining parameters are kept at their baseline values, and where the sticky information parameters are not varied, it follows MR07. The size of the shock is 1% of steady state output, such that the plotted values of these figures can be interpreted as impact multipliers. Moreover, I also show the impact responses of the real wage to further understand the responses of the rule-of-thumb and Ricardian households.

To recap, varying δ (forward-lookingness of consumers) could affect the consumption multiplier as it determines the proportion of consumers that respond to the crowding-out effects of the government spending shocks. ω (forward-lookingness of wage-setters) also influence the consumption multiplier by influencing the rigidities in the labour market and the associated wealth effect of labour supply that the previous section discussed. λ (price-stickiness of firms) contributes to the consumption multiplier as more rigid prices lead to a smaller inflation response to the government

[10] Galí et al. (2007) also have a similar exercise where they focus on the impact multiplier.

spending shock, and thus a smaller monetary policy response such that consumption of Ricardian households fall by less (as according to the consumption Euler equation). Lastly, χ (the proportion of the rule-of-thumb households) changes the extent of the Keynesian multiplier effects that produces a positive consumption multiplier, which typically eludes neoclassical models. Of course, there will be interactions between these parameters too, which I explore below.

Figure 3.5 shows the impact multiplier of output and consumption as a function of consumers' inattentiveness $(1-\delta)$.[11] The different lines depict the various level of workers' inattentiveness – from very inattentive $(1-\omega=0.9)$ (updating every 10 quarters) to more frequent updating $(1-\omega=0.1)$ (around almost every quarter).

The first result of these charts suggests that both lower δ (that is, more inattentive consumers) and lower ω (that is, more inattentive workers) contribute to a larger government spending impact multiplier. As the inattentiveness of consumers increases, the lower the impact multipliers are on output and consumption. Likewise, as the inattentiveness of workers ω increases, each line is lower in the output and consumption charts. This implies that both the consumer and worker channels are operating qualitatively. As δ decreases, consumers are less Ricardian in aggregate, and as ω is lower, the labour supply effect — that Ricardian workers supply more labour upon realising that the shock has happened via a wealth effect — is weaker, and thus supports the results in consumption and real wage in the previous section.

The second result is that these two channels do not complement one another. This could be seen by comparing the increase in the output and aggregate consumption impact multiplier when changing ω when moving across δ (in the left and right of the charts). The increase in the impact multiplier when lowering ω is larger when δ is high (when the consumers are close to fully attentive, and thus the consumer channel is relatively weak). Note that this result is fully driven by Ricardian households' consumption, as the gap between $\omega=0.1$ and $\omega=0.9$ varies with δ only in the Ricardian consumption and not in the rule-of-thumb consumption. This suggests that indeed it is an information friction effect that operates.

[11] For the equivalent figures of real wages and labour, see Figure C.1.

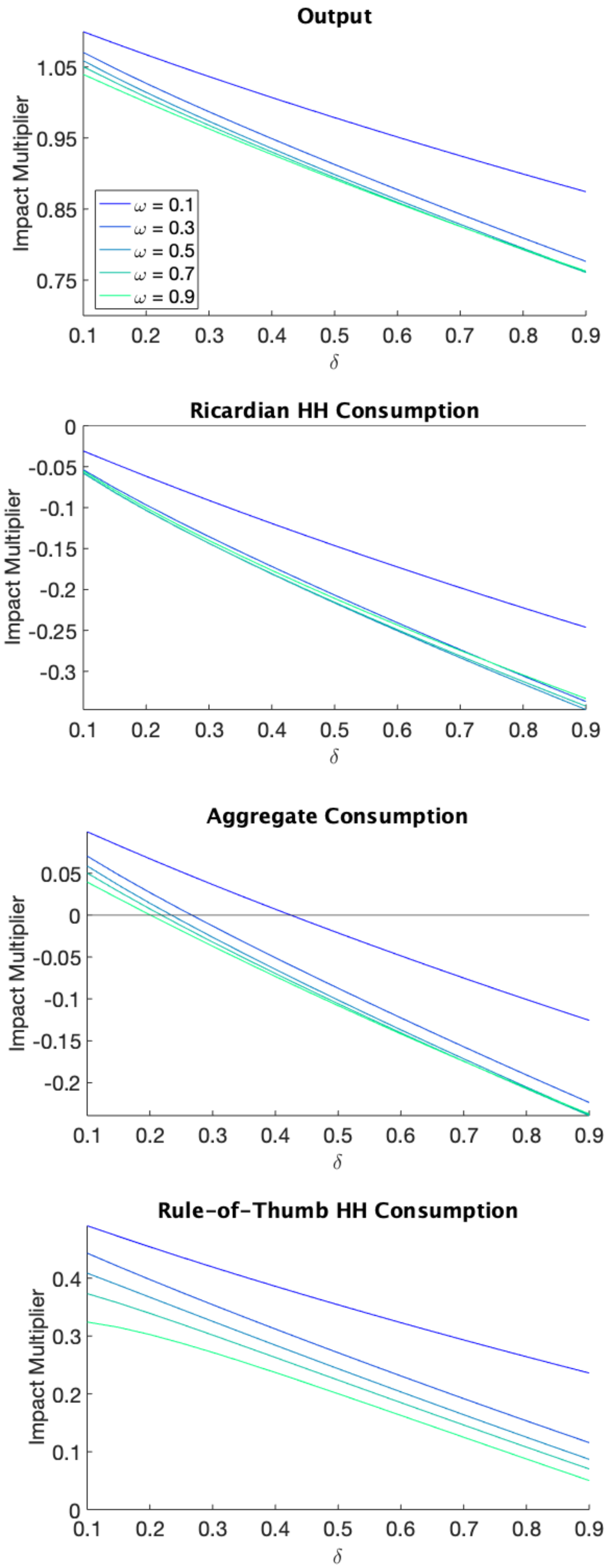

Figure 3.5. Impact Multipliers of Output and Consumption as a Function of Varying Inattentiveness of Consumers δ and Workers ω

Note: A value of δ and ω closer to 0 indicate more sticky information.

The third result is that a quantitative horse-race between the role of δ and ω in creating a larger government spending multiplier, δ appears to be more important. For a given ω, as δ is lowered (making consumers more inattentive), the impact multiplier is larger by 0.3. In contrast, for a given δ, as ω falls from 0.9 to 0.1 (making workers more inattentive), the impact multiplier only increases by 0.1 on average.

Furthermore, a crucial ingredient of this model is the role of limited asset market participation (rule-of-thumb households), which was the key insight from Galí et al. (2007). So, a pertinent question is how does the proportion of rule-of-thumb households affect the impact multiplier and how it interacts with the consumer and worker channels.

The first takeaway from Figures 3.6 to 3.8 is, as expected, the larger the proportion rule-of-thumb households, the higher is the output and aggregate consumption multipliers. This is because the higher χ is the stronger the Keynesian multiplier effects are through the rule-of-thumb households. Ricardian households' consumption falls by more when χ is higher, because of the larger output impact leads to higher inflation, inducing a stronger monetary policy response to tighten, and thus lower the Ricardian consumption through the consumption Euler equation. However, this is more than offset by the larger response of the rule-of-thumb households consumption, leading to an overall larger aggregate consumption multiplier when χ is higher. Additionally, the output and consumption charts are negatively sloped as before, indicating that the consumer and worker channels are more prominent when information rigidities are stronger, no matter the level of χ.

The second takeaway is that limited asset market participation interacts with sticky information parameters to create larger impact multipliers. This can be seen in the figures as the effect of increasing χ is much more pronounced when information rigidities are severe (for example, when $\delta = \omega = 0.1$). This is because when a large proportion of Ricardian consumers and workers respond to the government spending shock (i.e. when δ or ω are large), the reduction in Ricardian consumption dampens the Keynesian multiplier effects from taking hold.

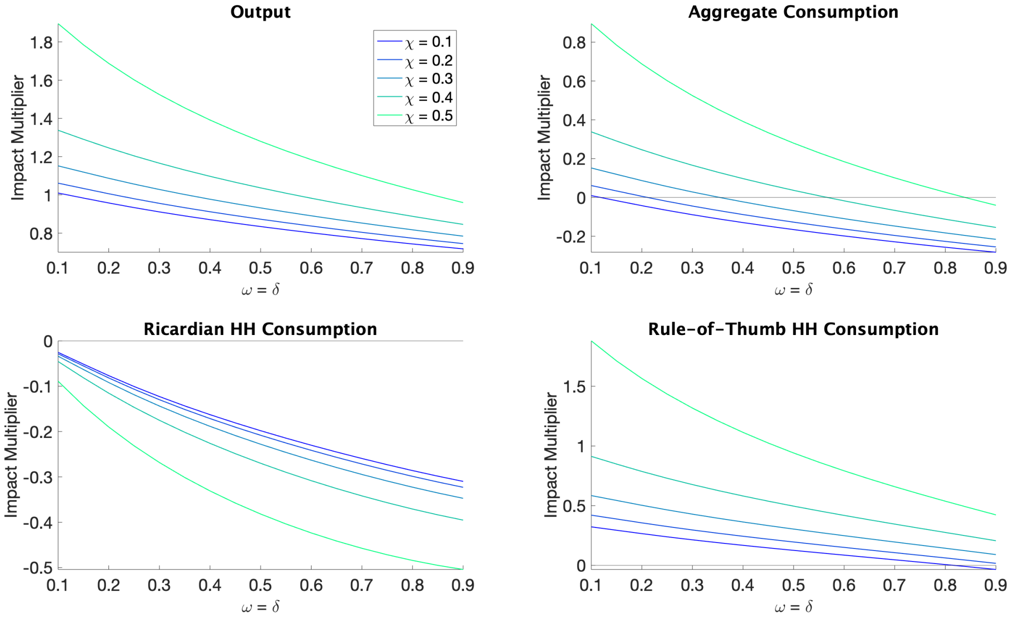

Figure 3.6. Impact Multipliers of Output and Consumption as a Function of Varying Inattentiveness of Households and χ the Fraction of Rule-of-Thumb Households

Note: δ and ω closer to 0 indicate more sticky information.

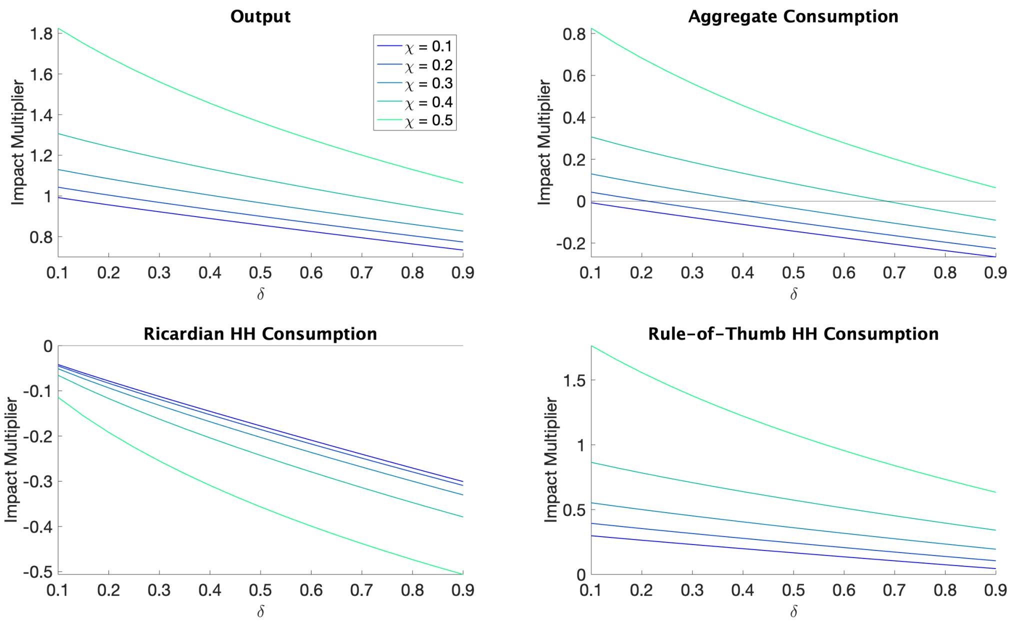

Figure 3.7. Impact Multipliers of Output and Consumption as a Function of Varying Inattentiveness of Consumers and χ the Fraction of Rule-of-Thumb Households

Note: δ closer to 0 indicate more sticky information.

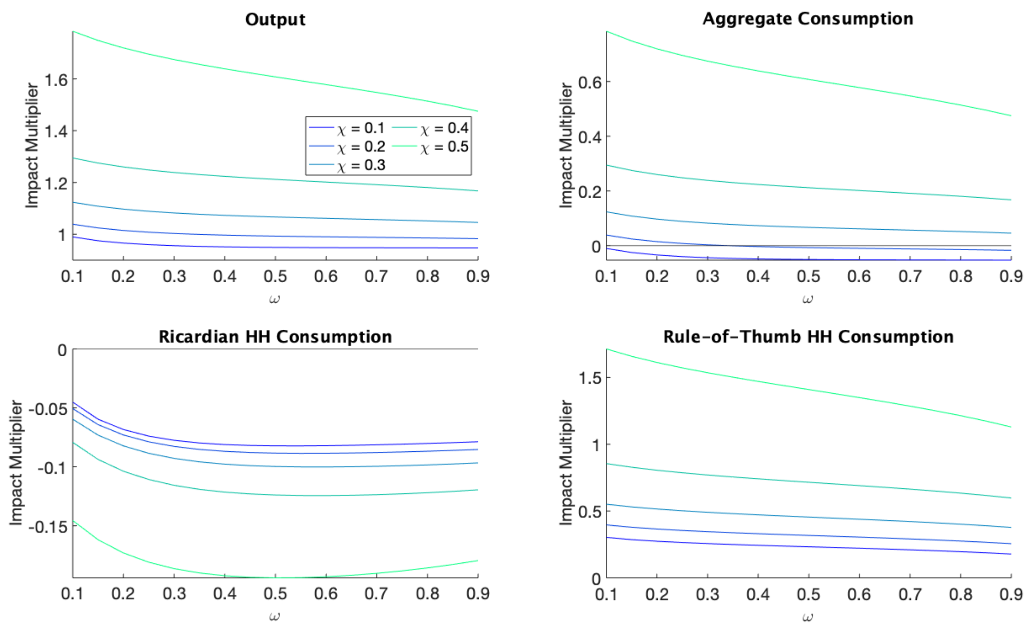

Figure 3.8. Impact Multipliers of Output and Consumption as a Function of Varying Inattentiveness of Workers and χ the Fraction of Rule-of-Thumb Households

Note: ω closer to 0 indicate more sticky information.

Galí et al. (2007) emphasise the role of nominal rigidities in achieving co-movement between consumption and government spending. This remains the case in the information friction setup here. The intuition of why price rigidities help large multipliers is as follows. If prices are very sticky, inflation does not rise by much in response to a demand shock. As such, the monetary policy response is relatively muted, and therefore the Ricardian households consumption does not fall by much. This allows for an amplification to aggregate consumption via the Keynesian multiplier effects.

This can be seen in Figure 3.9 where I vary the information rigidities on price-setters to show that as prices become more sticky, the impact multipliers are also larger. Likewise, in Figure 3.10, reducing price flexibility λ increases the impact multipliers, and especially so when χ is large. As χ increases, the reduction in Ricardian consumption is only marginally increased when prices are sticky, but is substantial when prices are relatively flexible.

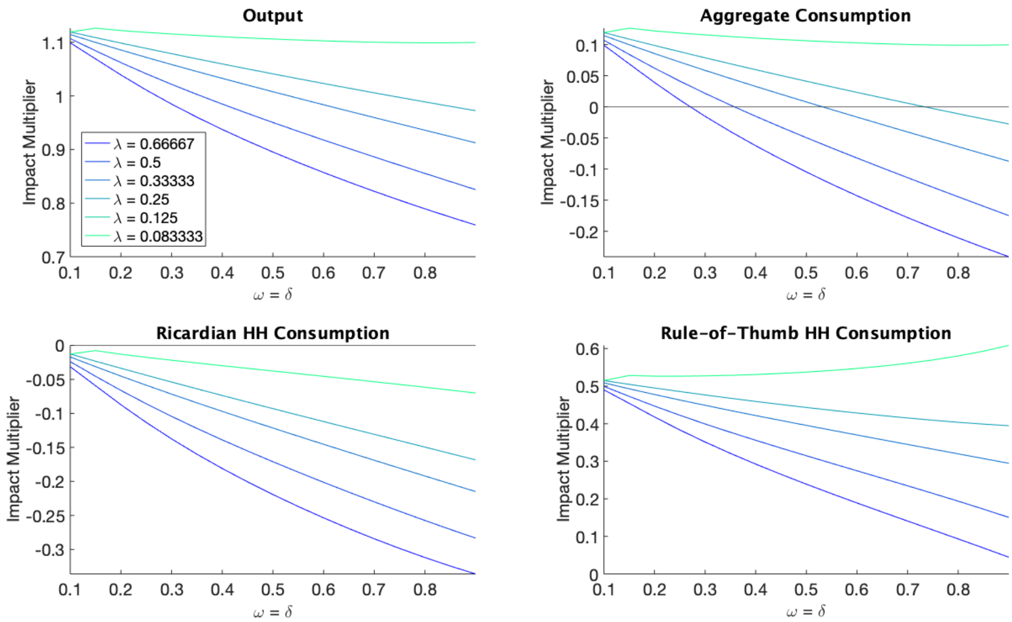

Figure 3.9. Impact Multipliers of Output and Consumption as a Function of Varying Inattentiveness of Households $\delta = \omega$ and Firms λ

Note: A value of δ, ω and λ closer to 0 indicate more sticky information.

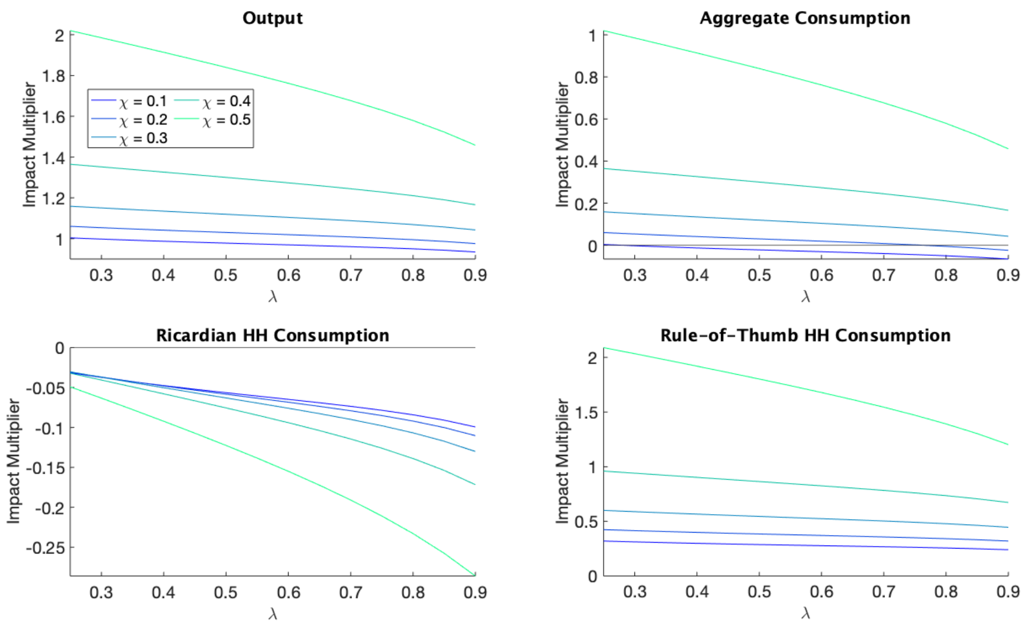

Figure 3.10. Impact Multipliers of Output and Consumption as a Function of Varying Inattentiveness Firms and Fraction of Rule-of-Thumb Households

Note: λ closer to 0 indicate more sticky information. χ is the fraction of rule-of-thumb households.

Previously, it was shown that rigidities in consumers are partially substitutable in workers in producing a large multiplier. Here, the substitution is much stronger — the inattentiveness of firms can make up for frequently updating households ($\delta = \omega$). Even when households (both consumers and workers) update very frequently, as long prices are very rigid, a positive consumption impact multiplier is still feasible. However, the price rigidities here would imply extremely long price durations, much longer than what the literature suggests (Bils and Klenow, 2004; Klenow and Kryvtsov, 2008; Nakamura and Steinsson, 2008). The micro evidence shows that price changes occur between 3 to 9 months, on average. Therefore, in empirically-sensible calibrations, it is likely that information rigidities in the household sector play an important role in explaining large government spending multipliers.

3.4 Fiscal Policy Discussions

Much of the discussion in the previous sections revolves around the role of monetary policy. This is of course not unique to this model – even the textbook IS-LM model predicts that the monetary policy response affect the equilibrium outcome of government spending. However, it should be emphasised that while the real interest rate is mostly determined by the Taylor rule (the central bank sets the nominal rate but does not pin down expected inflation), it still plays a crucial role in the clearing of the bond market. If the government increases spending but does not raise sufficient taxes, it has to issue government bonds. In the model, the Ricardian households are the sole buyers of government bonds. Therefore, the real interest rate must rise to incentivise these households to save. This operates through the consumption Euler equation that reduces consumption, and thus increases the demand for government bonds.

In this paper, I focus exclusively on lump-sum taxes. This is an important first step as it allows us to cleanly examine the role of information frictions, which will be more difficult under distortionary taxes. The reason is, combined with the fiscal rule specification that the path of government spending, taxes and public debt are exactly the same no matter the degree of information frictions, as shown in Figure 3.3. This implies that the fiscal stimulus *over time* from the 1% government spending shock are identical across the different calibrations. In addition, this implicit assumption is somewhat supported by the empirical results in Chapter 2, where I show that the path of a government spending shock is very similar in the high and low information frictions regimes (alongside the linear estimates too).

3.5 Conclusion

There is little agreement in the literature on how consumption responds to government spending shocks. In Chapter 2, I empirically reconciled the Keynesian and neoclassical predictions on the contrasting response of private consumption to a government spending shock, by emphasising the importance of information frictions. Here, I provide a quantitative framework on how information frictions could affect consumption response to a government spending shock, and thus the associated fiscal multipliers.

I use a standard sticky information general equilibrium model á la (Mankiw and Reis, 2007) with the addition of rule-of-thumb households á la Galí et al. (2007). In this setup, only a fraction of the households (optimising households) in the economy update their information about the state of the economy that period. This friction creates nominal and real rigidities as agents update to shocks with a lag. The rule-of-thumb households fully consume their current after-tax labour income. These households differ from the optimising households (those who update their consumption plan sporadically) as they cannot smooth consumption through bond holdings.

When there are many optimising households who save in advance of higher future taxes, consumption falls in line with neoclassical effects and in line with empirical results in Chapter 2 under low information rigidities. On the other hand, when agents are highly inattentive and that the proportion of rule-of-thumb households is sufficiently high, the effects of the Ricardian households are relatively muted. This allows for aggregate consumption to rise, as Keynesian multiplier-like effects take place, as with the empirical results under significant information frictions.

Furthermore, I examine the contribution of each of the sticky information parameters in the model, as well as the role of the rule-of-thumb households, in producing the overall behaviour of aggregate consumption. I find that all three forms of information frictions contribute to producing the heterogeneity in consumption responses, but that the information friction on consumers has the largest effect on consumption behaviour.

A key takeaway from this paper is that all considered forms of information frictions – consumers, labour supply and price-setting – contribute to a more positive/less negative consumption multiplier, but that the information frictions on consumers seem to be the most important among the three. In this paper, I focus exclusively on lump-sum taxes and government spending shocks for important reasons described in the previous section. Future work that includes distortionary taxes could provide insights how various fiscal policy instruments interact with information frictions in two dimensions. Firstly, when distortionary taxes are used instead of lump-sum taxes to repay public debt. Secondly, distortionary taxes open new fiscal policy instruments for a government to achieve their objectives.

Appendix A

Real and Nominal Effects of Monetary Shocks under Time-Varying Disagreement

A.1 Rational Inattention Model Details

Optimal price setting decision:

$$p_{it} = E\left[p^*_{it} \mid s_{it}, I_{i,t-1}\right] = \varphi E\left[y_t \mid s^y_{it}, I_{i,t-1}\right] - E\left[a_{it} \mid s^a_{it}, I_{i,t-1}\right] \tag{A.1}$$

Information constraint:

$$I\left(p^*_{it}; s_{it} \mid I_{i,t-1}\right) = H\left(p^*_{it} \mid I_{i,t-1}\right) - H\left(p^*_{it} \mid s_{it}, I_{i,t-1}\right) \leq K \tag{A.2}$$

Note that for Gaussian distributed random variable X, the unconditional and conditional entropy is:

$$H\left(X\right) = \frac{1}{2}\log_2\left[2\pi e Var\left(X\right)\right] \tag{A.3}$$

$$H\left(X \mid I\right) = \frac{1}{2}\log_2\left[2\pi e Var\left(X \mid I\right)\right] \tag{A.4}$$

So:

$$\underbrace{H\left(y_t \mid I_{i,t-1}\right) - H\left(y_t \mid s^y_{it}, I_{i,t-1}\right)}_{K^y_{it}} + \underbrace{H\left(a_{it} \mid I_{i,t-1}\right) - H\left(a_{it} \mid s^a_{it}, I_{i,t-1}\right)}_{K^a_{it}} \leq K \tag{A.5}$$

Taking the profit maximising price and signals (where the noises of the signals follow unit-variance Gaussian processes and independent of one another), the information constraint becomes:

$$\underbrace{\frac{1}{2}\log_2\left[2\pi e Var\left(y_t \mid I_{i,t-1}\right)\right] - \frac{1}{2}\log_2\left[2\pi e Var\left(y_t \mid s^y_{it}, I_{i,t-1}\right)\right]}_{K^y_{it}}$$
$$+ \underbrace{\frac{1}{2}\log_2\left[2\pi e Var\left(a_{it} \mid I_{i,t-1}\right)\right] - \frac{1}{2}\log_2\left[2\pi e Var\left(a_{it} \mid s^a_{it}, I_{i,t-1}\right)\right]}_{K^a_{it}} \leq K$$

$$\underbrace{\frac{1}{2}\log_2\left[2\pi e \sigma^2_y\right] - \frac{1}{2}\log_2\left[2\pi e \frac{\sigma^2_{\varepsilon y}}{\sigma^2_{\varepsilon y} + \sigma^2_y}\sigma^2_y\right]}_{K^y_{it}}$$
$$+ \underbrace{\frac{1}{2}\log_2\left[2\pi e \sigma^2_{ai}\right] - \frac{1}{2}\log_2\left[2\pi e \frac{\sigma^2_{\varepsilon ai}}{\sigma^2_{\varepsilon ai} + \sigma^2_{ai}}\sigma^2_{ai}\right]}_{K^a_{it}} \leq K$$

$$\underbrace{-\frac{1}{2}\log_2\left[\frac{\sigma^2_{\varepsilon y}}{\sigma^2_{\varepsilon y} + \sigma^2_y}\right]}_{K^y_{it}} \underbrace{- \frac{1}{2}\log_2\left[\frac{\sigma^2_{\varepsilon ai}}{\sigma^2_{\varepsilon ai} + \sigma^2_{ai}}\right]}_{K^a_{it}} \leq K \tag{A.6}$$

$$\underbrace{\frac{1}{2}\log_2\left(\frac{\sigma^2_y}{\sigma^2_{\varepsilon y}} + 1\right)}_{K^y_{it}} + \underbrace{\frac{1}{2}\log_2\left(\frac{\sigma^2_{ai}}{\sigma^2_{\varepsilon ai}} + 1\right)}_{K^a_{it}} \leq K \tag{A.7}$$

Based on the previous equation, an attention allocation implies the following perceived volatility of the tracking noises

$$\sigma^2_{\varepsilon y} = \frac{1}{2^{2K^y_{it}} - 1}\sigma^2_y \tag{A.8}$$

$$\sigma_{\varepsilon ai}^2 = \frac{1}{2^{2K_{it}^a} - 1}\sigma_{ai}^2 \tag{A.9}$$

A.1.1 Optimal Pricing Rule and Attention allocation

For a given attention choice, Kalman filtering equation, pricing rule, and the noise volatility above, the optimal price setting decision is

$$\begin{aligned} p_{it} &= E\left[p_{it}^* \mid s_{it}, I_{i,t-1}\right] \\ &= \varphi E\left[y_t \mid s_{yit}, I_{i,t-1}\right] - E\left[a_{it} \mid s_{ait}, I_{i,t-1}\right] \end{aligned}$$

$$p_{it} = \varphi\left(1 - 2^{-2K_{it}^y}\right)s_{it}^y - \left(1 - 2^{-2K_{it}^a}\right)s_{it}^a \tag{A.10}$$

Conditional profit loss due to mispricing becomes:

$$\begin{aligned}
&E\left[\left(p_{it} - p_{it}^*\right)^2 \mid I_{i,t-1}\right] && \text{(A.11)}\\
&= E\left[\varphi\left(1 - 2^{-2K_{it}^y}\right)s_{it}^y - \left(1 - 2^{-2K_{it}^a}\right)s_{it}^a - \left(\varphi y_t - a_{it}\right)\right]^2 && \text{(A.12)}\\
&= E\left[\varphi\left(-2^{-2K_{it}^y}y_t + \left(1 - 2^{-2K_{it}^y}\right)\varepsilon_{it}^y\right) - \left(-2^{-2K_{it}^a}a_{its} + \left(1 - 2^{-2K_{it}^a}\right)\varepsilon_{it}^a\right)\right]^2 && \text{(A.13)}\\
&= E\left[\varphi^2\left(2^{-4K_{it}^y}y_t^2 + \left(1 - 2^{-2K_{it}^y}\right)^2\varepsilon_{it}^{y2}\right) + \left(2^{-4K_{it}^a}a_{it}^2 + \left(1 - 2^{-2K_{it}^a}\right)^2\varepsilon_{it}^{a2}\right)\right] && \text{(A.14)}
\end{aligned}$$

taking expectations and substituing $\sigma_{\varepsilon y}^2$ and $\sigma_{\varepsilon a}^2$

$$\begin{aligned}
&E\left[\left(p_{it} - p_{it}^*\right)^2 \mid I_{i,t-1}\right] && \text{(A.15)}\\
&= \left[\varphi^2\left(2^{-4K_{it}^y}\sigma_y^2 + \left(1 - 2^{-2K_{it}^y}\right)^2\sigma_{\varepsilon y}^2\right) + \left(2^{-4K_{it}^a}\sigma_{ai}^2 + \left(1 - 2^{-2K_{it}^a}\right)^2\sigma_{\varepsilon ai}^2\right)\right] && \text{(A.16)}\\
&= \left[\varphi^2\left(2^{-4K_{it}^y}\sigma_y^2 + \frac{\left(1 - 2^{-2K_{it}^y}\right)^2}{2^{2K_{it}^y} - 1}\sigma_y^2\right) + \left(2^{-4K_{it}^a}\sigma_{ai}^2 + \frac{\left(1 - 2^{-2K_{it}^a}\right)^2}{2^{2K_{it}^a} - 1}\sigma_{ai}^2\right)\right] && \text{(A.17)}\\
&= \left[\varphi^2\left(\frac{1 - 2^{-2K_{it}^y}}{2^{2K_{it}^y} - 1}\right)\sigma_y^2 + \left(\frac{1 - 2^{-2K_{it}^a}}{2^{2K_{it}^a} - 1}\right)\sigma_a^2\right] && \text{(A.18)}\\
&= \varphi^2 2^{-2K_{it}^y}\sigma_y^2 + 2^{-2K_{it}^a}\sigma_a^2 && \text{(A.19)}\\
&= \varphi^2 2^{-2K_{it}^y}\sigma_b^2 + 2^{-2K_{it}^a}\sigma_a^2 && \text{(A.20)}
\end{aligned}$$

The objective function becomes

$$\min_{K_{it}^{y}} \varphi^2 2^{-2K_{it}^{y}} \sigma_b^2 + 2^{-2(K-K_{it}^{y})} \sigma_a^2 \tag{A.21}$$

first-order conditions:

$$\varphi^2(-2)\ln(2)2^{-2K_{it}^{y*}} \sigma_b^2 + 2\ln(2)2^{-2(K-K_{it}^{y*})} \sigma_a^2 = 0 \tag{A.22}$$

$$\varphi^2 2^{-2K_{it}^{y*}} \sigma_b^2 = 2^{-2(K-K_{it}^{y*})} \sigma_a^2 \tag{A.23}$$

taking $\log_{(2)}$ of everything:

$$-2K_{it}^{y*} + \log_2(\varphi^2\sigma_b^2) = -2K_{it} + 2K_{it}^{y*} + \log_2 \sigma_a^2 \tag{A.24}$$

$$K_{it}^{y*} = \frac{1}{4}\log_2\left(\varphi^2\frac{\sigma_b^2}{\sigma_a^2}\right) + \frac{1}{2}K \tag{A.25}$$

$$K_{it}^{y*} = \frac{1}{2}\log_2\left(\varphi\frac{\sigma_b}{\sigma_a}\right) + \frac{1}{2}K \tag{A.26}$$

A.1.2 Comparative Statics: Disagreement

Using the perceived volatility of the tracking noises and optimal attention allocation

$$\sigma_{\varepsilon y}^2 = \frac{1}{2^{2K_{it}^{y}} - 1}\sigma_y^2, \quad K_{it}^{y*} = \frac{1}{4}\log_2\left(\varphi^2\frac{\sigma_b^2}{\sigma_a^2}\right) + \frac{1}{2}K$$

Differentiating it with respect to σ_b^2:

$$\frac{d\sigma_{\varepsilon y}^2}{d\sigma_b^2} = \frac{1}{2^{2K_{it}^{y}} - 1} + \sigma_b^2\frac{d}{dK_{it}^{y}}\left(\frac{1}{2^{2K_{it}^{y}} - 1}\right)\frac{dK_{it}^{y}}{d\sigma_b^2}$$

where

$$\frac{d}{dK_{it}^{y}}\left(\frac{1}{2^{2K_{it}^{y}} - 1}\right) = \frac{(-2)\ln(2)2^{2K_{it}^{y}}}{(2^{2K_{it}^{y}} - 1)^2}$$

$$\frac{d}{d\sigma_b^2}\left(\frac{1}{4}\log_2\left(\varphi^2\frac{\sigma_b^2}{\sigma_a^2}\right)+\frac{1}{2}K\right)=\frac{1}{4}\frac{1}{\sigma_b^2\ln(2)}$$

therefore,

$$\begin{aligned}
\frac{d\sigma_{\varepsilon y}^2}{d\sigma_b^2} &= \frac{1}{2^{2K_{it}^y}-1}+\sigma_b^2\frac{(-2)\ln(2)2^{2K_{it}^y}}{(2^{2K_{it}^y}-1)^2}\frac{1}{4}\frac{1}{\sigma_b^2\ln(2)}\\
&= \frac{1}{2^{2K_{it}^y}-1}-\frac{1}{2}\frac{2^{2K_{it}^y}}{(2^{2K_{it}^y}-1)^2}\\
&= \frac{2(2^{2K_{it}^y}-1)-2^{2K_{it}^y}}{2(2^{2K_{it}^y}-1)^2}\\
&= \frac{-2+2^{2K_{it}^y}}{2(2^{2K_{it}^y}-1)^2}\gtrless 0
\end{aligned}$$

Differentiating it with respect to K and σ_a^2 results in:

$$\begin{aligned}
\frac{d\sigma_{\varepsilon y}^2}{dK} &= \frac{d\sigma_{\varepsilon y}^2}{dK_{it}^y}\frac{dK_{it}^y}{dK}\\
&= \sigma_b^2(-1)\frac{d2^{2K_{it}^y}}{dK_{it}^y}\left(\frac{1}{2^{2K_{it}^y}-1}\right)^2\frac{dK_{it}^y}{dK}\\
&= \sigma_b^2(-1)2\ln(2)2^{2K_{it}^y}\left(\frac{1}{2^{2K_{it}^y}-1}\right)^2\frac{dK_{it}^y}{dK}\\
&= -\sigma_b^2 2\ln(2)2^{2K_{it}^y}\left(\frac{1}{2^{2K_{it}^y}-1}\right)^2\frac{1}{2}\\
&= -\sigma_b^2\ln(2)2^{2K_{it}^y}\left(\frac{1}{2^{2K_{it}^y}-1}\right)^2<0
\end{aligned}$$

$$\begin{aligned}
\frac{d\sigma_{\varepsilon y}^2}{d\sigma_a^2} &= \frac{d\sigma_{\varepsilon y}^2}{dK_{it}^y}\frac{dK_{it}^y}{d\sigma_a^2}\\
&= \sigma_b^2(-1)2\ln(2)2^{2K_{it}^y}\left(\frac{1}{2^{2K_{it}^y}-1}\right)^2\frac{dK_{it}^y}{d\sigma_a^2}\\
&= \sigma_b^2(-1)2\ln(2)2^{2K_{it}^y}\left(\frac{1}{2^{2K_{it}^y}-1}\right)^2\left(-\frac{1}{4\ln(2)\sigma_a^2}\right)\\
&= \frac{1}{2}\frac{\sigma_b^2}{\sigma_a^2}2^{2K_{it}^y}\left(\frac{1}{2^{2K_{it}^y}-1}\right)^2>0
\end{aligned}$$

A.1.3 Comparative Statics: Price Setting

$$p_{it} = \varphi\left(1 - 2^{-2K_{it}^y}\right) s_{it}^y - \left(1 - 2^{-2K_{it}^a}\right) s_{it}^a \tag{A.27}$$

where

$$s_{it}^y = y_t + \varepsilon_{it}^y = b_t - cr_t + \varepsilon_{it}^y$$

$$\frac{ds_{it}^y}{dr_t} = -c \tag{A.28}$$

$$\frac{dp_{it}}{dr_t} = \frac{dp_{it}}{ds_{it}^y}\frac{ds_{it}^y}{dr_t} = \varphi\left(1 - 2^{-2K_{it}^y}\right)(-c) < 0 \tag{A.29}$$

Which means that as r $\uparrow$, $p_{it} \downarrow$

Then, we can replace $2^{-2K_{it}^y}$ using

$$K_{it}^{y*} = \frac{1}{2}\log_2\left(\varphi\frac{\sigma_b}{\sigma_a}\right) + \frac{1}{2}K$$

such that

$$2^{-2K_{it}^y} = \frac{\sigma_a}{\sigma_b\varphi}2^{-K}$$

and thus

$$\frac{dp_{it}}{dr_t} = \left(1 - 2^{-2K_{it}^y}\right)(-c) = -\varphi c\left(1 - \frac{\sigma_a}{\sigma_b\varphi}2^{-K} < 0\right)$$

again, an expansionary monetary policy shock, price

$$\frac{d}{dK_{it}}\left(\frac{dp_{it}}{dr_t}\right) = -\ln(2)\frac{\sigma_a}{\sigma_b\varphi}2^{-K}\varphi c < 0 \tag{A.30}$$

$$\frac{d}{d\sigma_a}\left(\frac{dp_{it}}{dr_t}\right) = \frac{1}{\sigma_b\varphi}2^{-K}\varphi c > 0 \tag{A.31}$$

$$\frac{d}{d\sigma_b}\left(\frac{dp_{it}}{dr_t}\right) = \frac{\sigma_a}{\varphi}(-1)\frac{1}{\sigma_b^2}2^{-K}\varphi c < 0 \tag{A.32}$$

A.2 GIRF Bootstrap Algorithm

I follow the algorithm in Koop et al. (1996):

1. Pick a history and Ω_{t-1} contains the sequence of lagged data up to time $t-1$, which defines the history of the model at date t. Also, pick a structural shock of size δ.

2. Use Monte-Carlo integration to compute the *conditional* response for: variable y, shock size δ, history Ω_{t-1} and horizon $h = 0, 1, \ldots, H$

3. Then average out over each regime's set of random histories Ω^r, to get the *unconditional* responses for each regime

4. Subtract the **second** from **first** time path. The difference is the estimate of GIRF.

5. However, Step 4 is a noisy estimate. To eliminate the random variation in the GIRF, repeat steps **2 - 4** many times and take the mean of the resulting impulse responses as the central tendency. I also take the empirical quantiles from these draws to compute the confidence intervals.

A.3 Robustness

A.3.1 Time-Varying Disagreement: Real GDP Forecasts Horizons

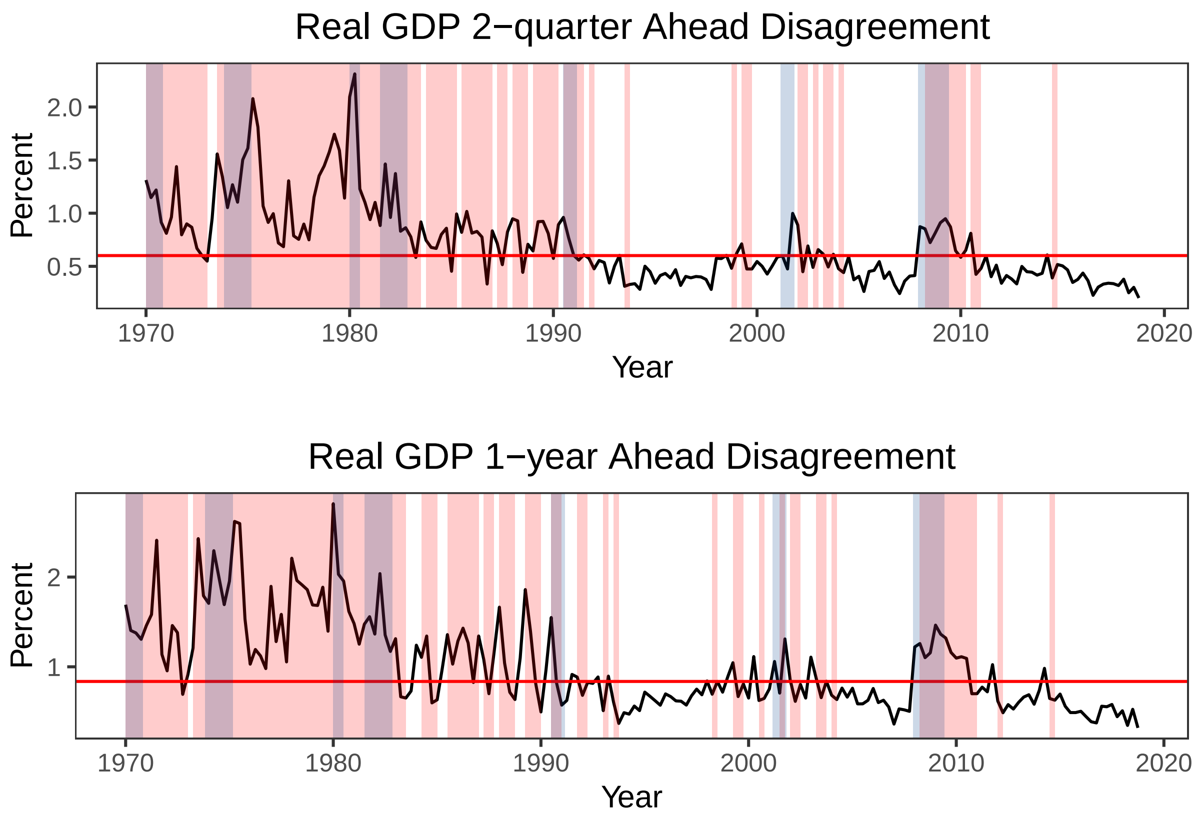

Figure A.1. Time-Varying Disagreement: Real GDP Forecasts: 2- and 4-Quarter Ahead

Note: Time series of the real GDP disagreement index based on the dispersion (interquartile range) of SPF 2-quarter ahead and 1-year (4 quarters) ahead forecasts. The grey shaded areas indicate NBER-dated recessions. The red shaded areas indicate high disagreement periods. The red line indicate the estimated threshold. The sample period is 1970Q1-2018Q4.

A.3.2 GIRFs: Real GDP Forecasts Horizons

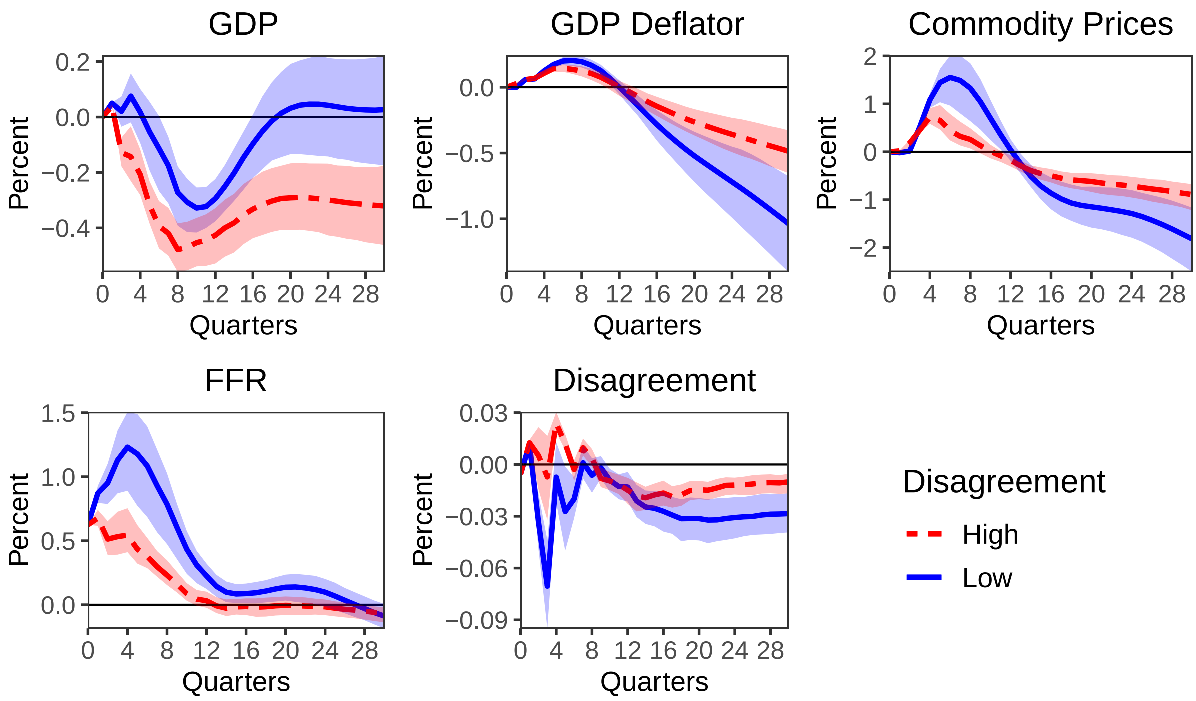

Figure A.2. Threshold VAR Generalised Impulse Responses: 2-quarter Ahead

Note: The shock corresponds to a positive one standard deviation change in the FFR. The GIRFs are generated with 68% bootstrapped confidence intervals using threshold VAR with a lag of 4 quarters. The threshold is estimated using SPF disagreement of the **2-quarter ahead** of real GDP. Red lines (dashed) indicate high disagreement period and blue lines (solid) indicate low disagreement period. The sample period is 1970Q1-2018Q4.

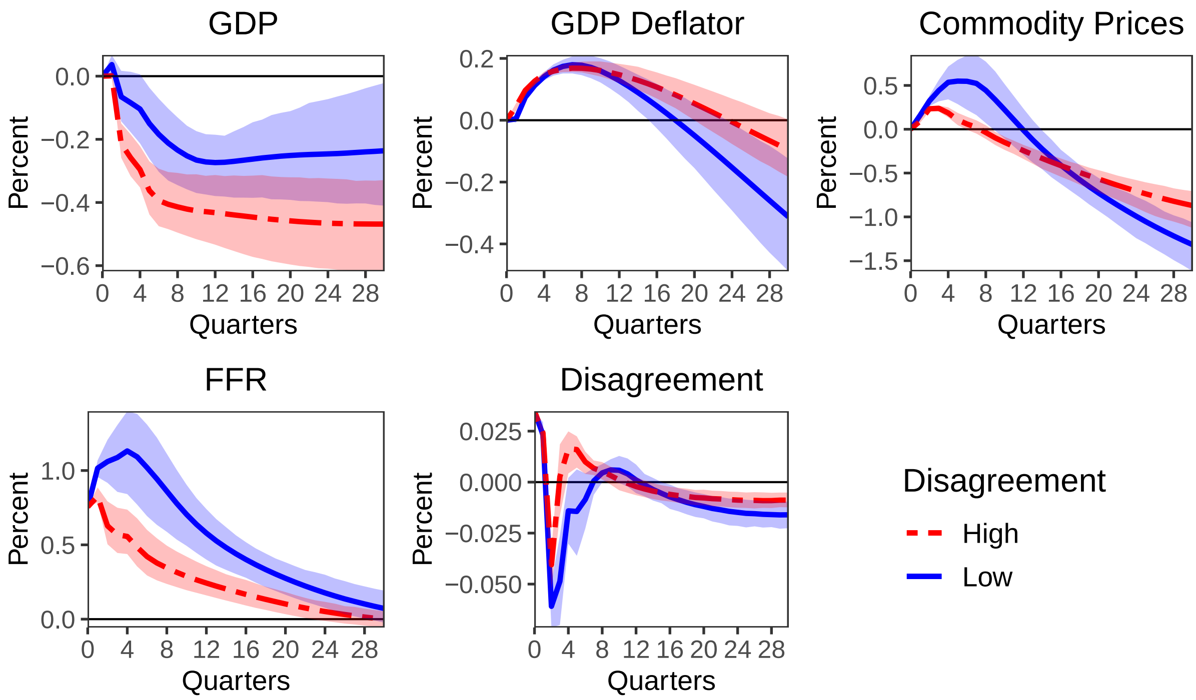

Figure A.3. Threshold VAR Generalised Impulse Responses: 1-year Ahead

The shock corresponds to a positive one standard deviation change in the FFR. The GIRFs are generated with 68% bootstrapped confidence intervals using threshold VAR with a lag of 4 quarters. The threshold is estimated using SPF disagreement of the **1-year ahead** of real GDP. Red lines (dashed) indicate high disagreement period and blue lines (solid) indicate low disagreement period. The sample period is 1970Q1-2018Q4.

A.3.3 GIRFs: Pre-Global Financial Crisis

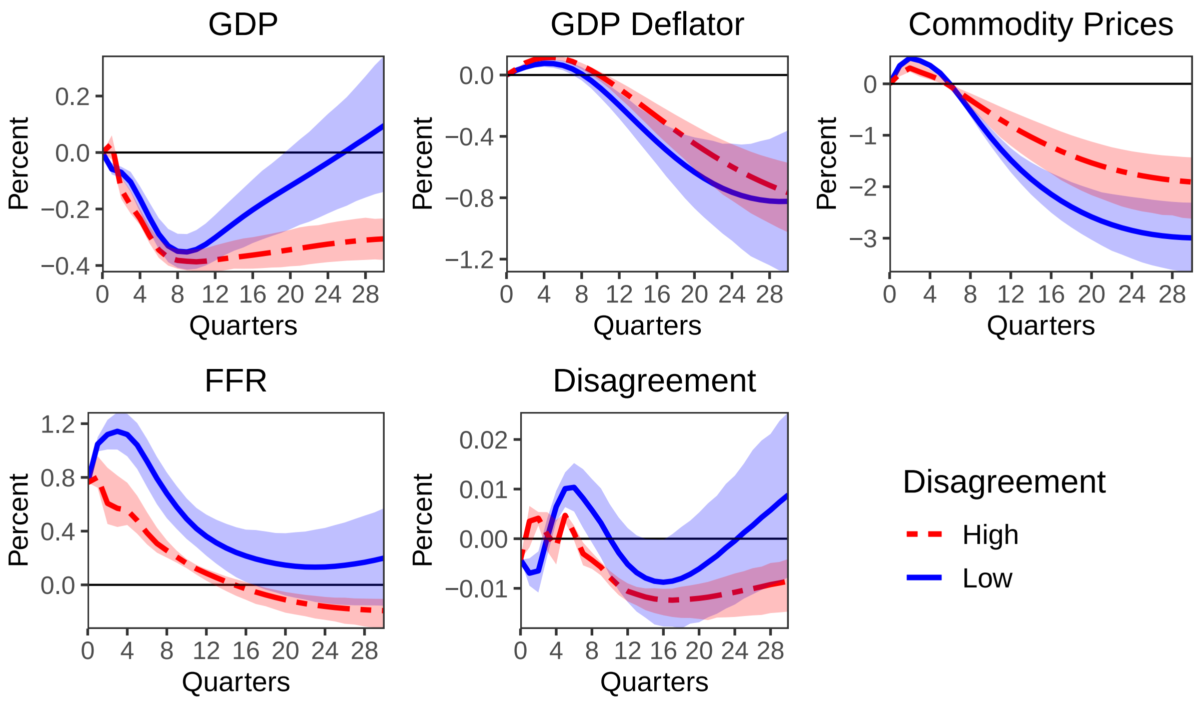

Figure A.4. Threshold VAR Generalised Impulse Responses: Pre-GFC

The shock corresponds to a positive one standard deviation change in the FFR. The GIRFs are generated with 68% bootstrapped confidence intervals using threshold VAR with a lag of 3 quarters. The threshold is estimated using SPF disagreement of the **nowcasts** of real GDP. Red lines (dashed) indicate high disagreement period and blue lines (solid) indicate low disagreement period.The sample period is 1970Q1-2007Q4.

A.3.4 Smooth Transition Local Projections

The reasons to use a dummy variable in the local projections in the main section is to allow for the nature of the disagreement variables that may change each period, that is also consistent with the threshold VAR. But, I show here that using the smooth transition local projections — which has been utilised in the literature to estimate the effects monetary and fiscal policy shocks in recession and expansion periods — the main results also hold. Figure A.5 plots the narrative shock series, but for the non-linearly narratively identified monetary policy shocks, I use a smooth-transition method of regimes-switching.

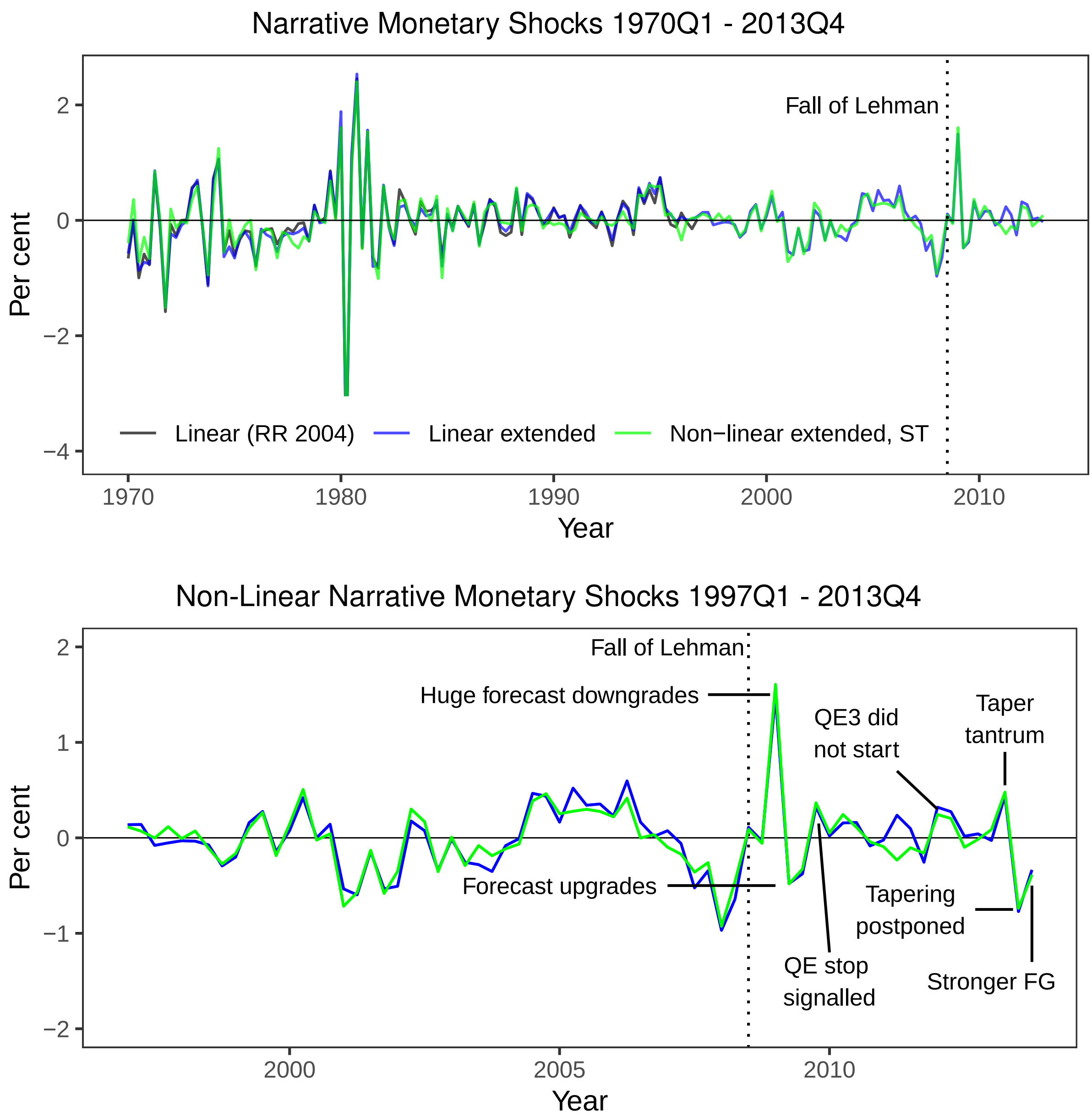

Figure A.5. Smooth Transition Local Projections Narrative Monetary Shocks

I extend the narrative monetary shocks of Romer and Romer (2004) up to 2013Q4. The top figure shows the RR original shocks (black line), the extended linear narrative shock (blue line), and the extended non-linear narrative shocks (green line). I use smooth-transition to identify the disagreement regimes for the non-linearly narratively identified monetary shocks. The bottom figure shows how the narrative approach with shadow rates neatly captures unexpected movements in unconventional monetary policies since the financial crisis.

As in Section 1.6, I estimate a set of regressions for each horizon h as follows

$$\begin{aligned} x_{t+h} = & F(z_{t-1})[\alpha_{A,h} + \psi_{A,h}(L)X_{t-1} + \beta_{A,h}\text{shock}_t] \\ & + (1 - F(z_{t-1}))[\alpha_{B,h} + \psi_{B,h}(L)X_{t-1} + \beta_{B,h}\text{shock}_t] + \varepsilon_{t+h} \end{aligned}$$

Instead here, $F(z_t)$ is a smooth increasing function of an indicator of the state of the economy z_t. Following Granger and Terasvirta (1993) and Tenreyro and Thwaites (2016), I employ the logistic function

$$F(z_t) = \frac{\exp\left(\theta \frac{(z_t - c)}{\sigma_z}\right)}{1 + \exp\left(\theta \frac{(z_t - c)}{\sigma_z}\right)}$$

where c is a parameter that controls what proportion of the sample the economy spends in either state and σ_z is the standard deviation of the state variable $F(z_t)$. The parameter θ determines how violently the economy switches from high to low disagreement when z_t changes. Higher values of θ mean that $F(z_t)$ spends more time close to the $0, 1$ bounds of the process, moving the model closer to a discrete regime-switching setup. Smaller values of θ mean that more of the observations are taken to contain some information about behaviour in both high and low disagreement regimes. I calibrate the parameter value to $\theta = 3$, as in Tenreyro and Thwaites (2016), to give an intermediate degree of intensity to the regime switching.

Impulse Responses to a 1% Narrative Monetary Shock

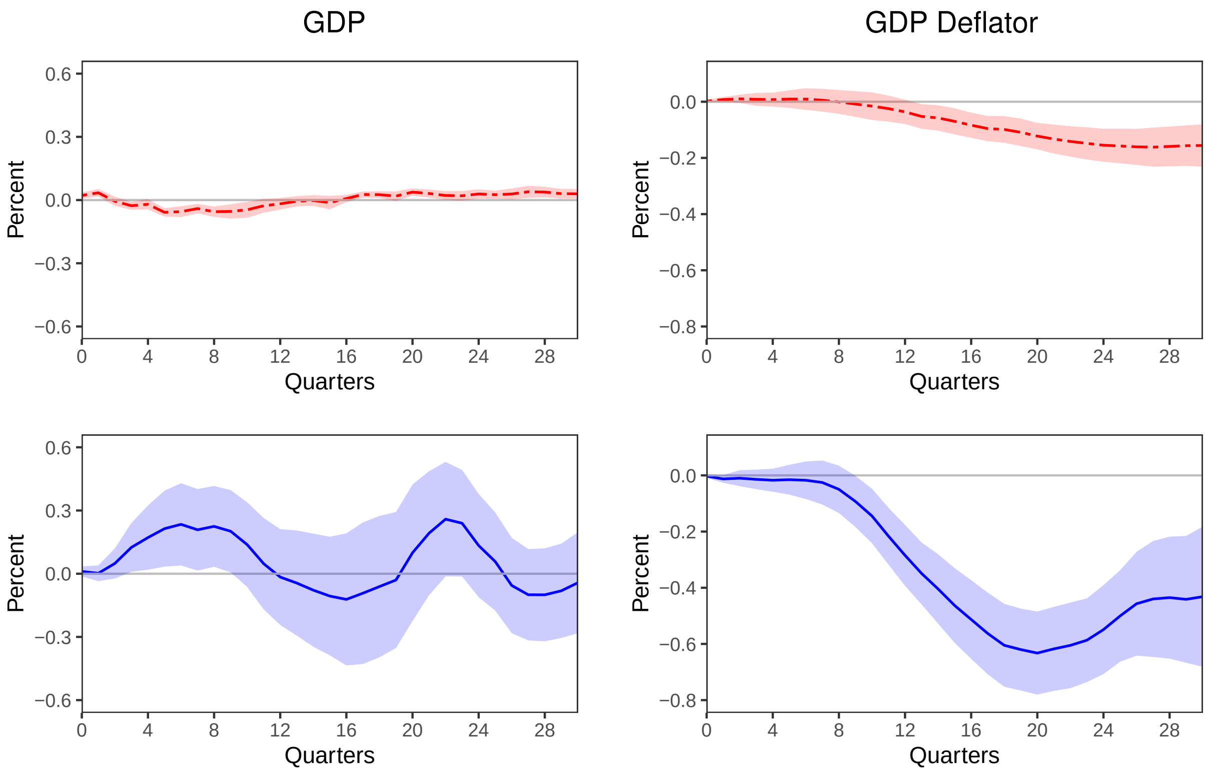

Figure A.6. Smooth Transition Local Projections Impulse Responses

The first and second column shows the response of real output and prices to a 1% narrative monetary shock, respectively. The first and second rows show the responses under high and low disagreement periods, respectively. The shaded area is the 68% confidence interval. The sample period is 1970Q1-2018Q4.

A.3.5 GDP vs GNP

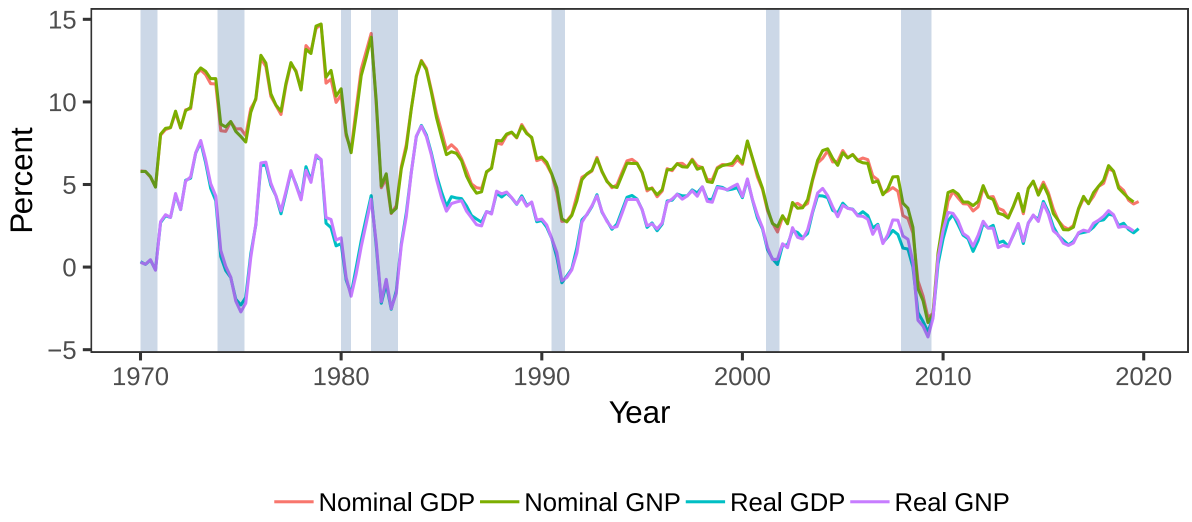

Figure A.7. GNP and GDP 4-Quarter Growth

The figure shows the percent change from a year ago of GPD and GNP. The red line depicts Nominal GDP and the blue line depicts the Real GDP. The green line depicts Nominal GNP and the purple line depicts the Real GNP. The sample period is 1970Q1-2018Q4.

Appendix B

Reconciling the Effects of Government Spending: The Role of Information Frictions

B.1 Survey of Professional Forecasters: GNP and GDP Nowcast

As an additional robustness check, I investigate another possible structural breaks in the collection of the surveys. I conduct the same analysis as the baseline exercise but restricting the sample period I use here to (a) 1970Q1-1991Q4 and (b) 1992Q1-2018Q4. I keep the same definition of state as in the main analysis: disagreement (IQR) of the real GDP nowcasts. An important point to note here is that even though the threshold is still at the median of the disagreement time series, there is much less variation in the disagreement series between 1992 and 2018. Thus, when comparing the high and low disagreement regime, we are in effect comparing 'low' and 'lower' disagreement regime, respectively. Similarly there when comparing the regimes between 1970 and 1991, it would be comparing 'high' and 'higher' disagreement regimes. Moreover, the baseline disagreement series shows that the moderation of disagreement starts earlier than 1992Q1. This is more in line with 'Placebo1' in the Placebo tests, a period around the Great Moderation period in the mid-1980s.

For this analysis, it is perhaps worth noting again the history of the Survey of

Professional Forecasters. Since 1992, forecasters were asked forecasts of GDP instead of GNP in the previous years.[1] If GDP was more predictable and/or less volatile than GNP, then that would naturally create lower disagreement across forecasters. However, as GNP tracks GDP extraordinarily closely, it eliminates the possibility that the change (lessening) in disagreement is due to forecasters finding it easier to forecast GDP than GNP.

In Figure B.1, some of the output responses may not be very intuitive. However, examining the components of output (government spending, consumption and investment) is more insightful. The responses of the macroeconomic variables during 1992 to 2018 approximately coincide with the baseline results. The response of consumption is qualitatively the same as the baseline results, only that it takes more time for consumption to rise under the high disagreement regime. This could be because the *'high'* disagreement regime in this restricted sample only indicates marginally high levels of information frictions, but still low levels in absolute terms.

Furthermore, investment also behaves qualitatively similar as the baseline results. The minor difference is the magnitudes of the responses: under low disagreement, consumption and investment falls by twice as much as the baseline results. This strength in the consumption and investment response is sufficient to cancel out the rise in government spending itself, explaining why output falls. It is worth repeating the point that the variation in disagreement in this restricted sample is very limited. Indeed, one of the main reason why Ramey and Zubairy (2018) extend their sample to the 19^{th} century is to gain sufficient number of slack and non-slack states to get enough variation. Thus, it is not a surprise that magnitudes of the results here differ to the baseline sample, but nevertheless, it supports the main analysis as the key results hold qualitatively.

[1] The SPF began in 1968 and was conducted by the American Statistical Association and the National Bureau of Economic Research. The Federal Reserve Bank of Philadelphia took over the survey since 1990.

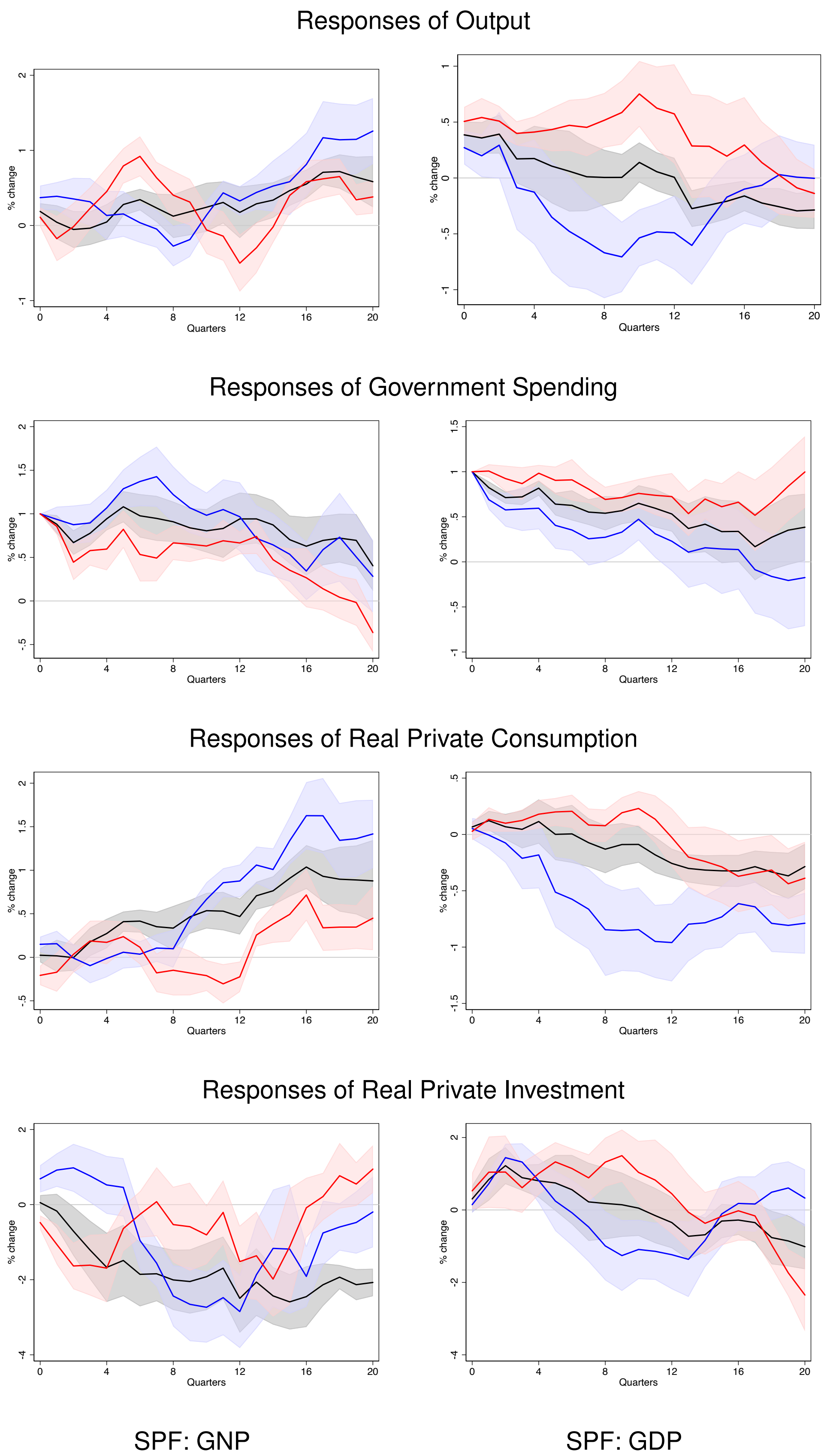

Figure B.1. Impulse Responses to a 1% Government Spending Shock: GNP and GDP

Note: The first column shows the responses from when forecasters were asked to forecast GNP (**sample period: 1970Q1-1991Q4**) and the second column shows when they forecasted GDP (**sample period: 1992Q1-2018Q4**). The threshold is real GDP Nowcast (IQR normalised with median) disagreement.

Sample Period: 1970Q1-1991Q4						
	1-quarter	**1-year**	**2-year**	**3-year**	**4-year**	**5-year**
Output						
Linear	0.12	0.04	0.14	0.18	0.25	0.37
High Disagreement	-0.04	0.17	0.56	0.34	0.35	0.55
Low Disagreement	0.39	0.33	0.14	0.15	0.27	0.50
Consumption						
Linear	0.02	0.11	0.24	0.34	0.50	0.64
High Disagreement	-0.20	0.00	0.01	-0.10	0.09	0.24
Low Disagreement	0.16	0.04	0.05	0.24	0.51	0.76
Investment						
Linear	-0.06	-0.87	-1.33	-1.64	-1.94	-2.13
High Disagreement	-0.83	-1.86	-1.31	-1.27	-1.48	-1.27
Low Disagreement	0.83	0.81	-0.06	-0.80	-1.06	-1.05

Sample Period: 1992Q1-2018Q4						
	1-quarter	**1-year**	**2-year**	**3-year**	**4-year**	**5-year**
Output						
Linear	0.41	0.36	0.26	0.21	0.10	0.01
High Disagreement	0.52	0.49	0.52	0.61	0.58	0.47
Low Disagreement	0.28	0.16	-0.32	-0.61	-0.75	-0.84
Consumption						
Linear	0.10	0.10	0.03	-0.05	-0.16	-0.26
High Disagreement	0.08	0.12	0.14	0.15	0.04	-0.06
Low Disagreement	0.03	-0.12	-0.64	-1.09	-1.44	-2.10
Investment						
Linear	0.63	1.00	0.90	0.62	0.34	0.04
High Disagreement	0.78	0.89	1.10	1.15	0.89	0.42
Low Disagreement	0.52	1.29	0.67	-0.26	-0.56	-0.35

Note: These are the cumulative multipliers defined as $M_h^x = \frac{\sum_{i=0}^h x_h}{\sum_{i=0}^h g_h}$ where x_h is the dollar effect on variable x of a one dollar increase in government spending at h quarters after the shock.

Table B.1. Estimates of Multipliers using Forecast of GNP and GDP

B.2 Government Spending and Transfer Payment in Log Dollars

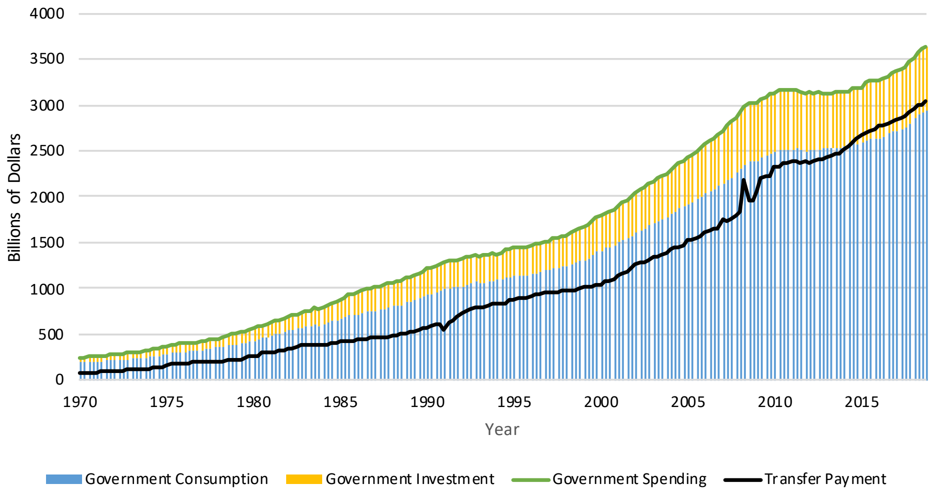

Figure B.2. Nominal Government Spending and Transfer Payment Time Series

Note: The proportion of nominal government consumption (blue bars) and investment (yellow bars) nominal government spending (green line), as well as transfer payments (black line).

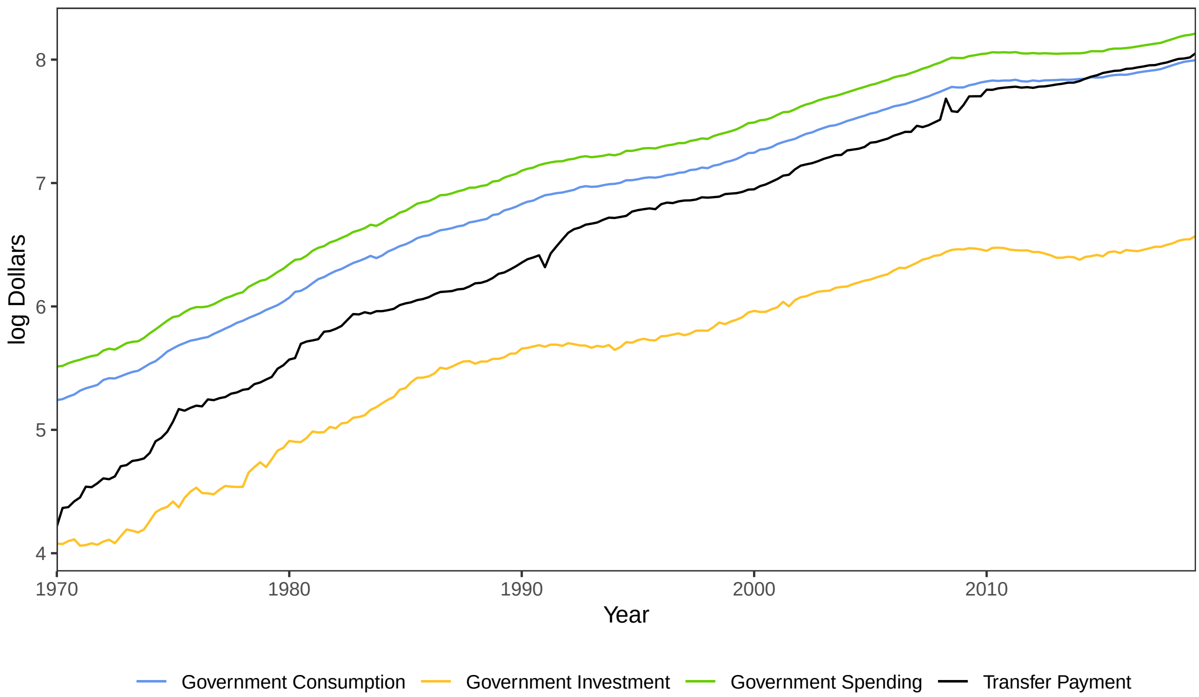

Figure B.3. Government Spending and Transfer Payment in Log Dollars

B.2.1 Alternative Measurements of Disagreement

The third robustness check is to look at various alternative ways to measure disagreement, as follows:

Quasi IQR : The first alternative is, instead of using the interquartile range $25^{th} - 75^{th}$, I use a range between 16^{th} and 84^{th} percentile.[2]

IQR SD : The second (IQR SD) and third (IQR Winsor SD) alternative is to treat the outlier using statistical treatment. In this case, the outliers are data point that lower than $25^{th} percentile + 1.5 * IQR$ and higher than $75^{th} percentile + 1.5 * IQR$. The difference between the second and third alternative is the way I treat the outliers: either I simply drop the outliers, or in the latter alternative, I winsorise the outliers (instead of dropping the data, I replace outliers lower than the 25^{th} percentile to the value of the 25^{th} percentile, and likewise with outliers above the 75^{th} percentile).

Outlier SD : The fourth (Outlier SD) and fifth alternative (Outlier Winsor SD) is to treat the outlier using statistical treatment where observations beyond the *median value* $\pm$ *3*σ are outliers. The difference between the two alternatives is as above.

SD : The last alternative is to simply take the standard deviation from the whole sample period.

[2] This allows for a more lenient outlier treatment. Giordani and Söderlind (2003), Boero et al. (2015), and Grimme et al. (2014) have used quasi standard deviation to treat their survey data. The idea is that for a normal distribution, this interval is equal to the mean $\pm$ 1 standard deviation. Since I do not use the standard deviation for this specific measurement, I call it the Quasi IQR.

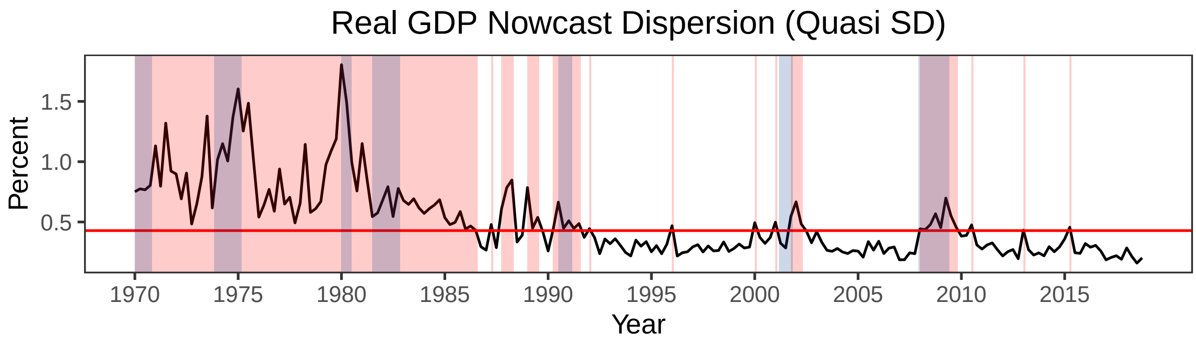

Figure B.4. Alternative Measurement of Disagreement: Quasi SD

Note: Time series of the disagreement index based on the **range between** 84^{th} **and** 16^{th} **percentile** normalised with median of Survey of Professional Forecasters real GDP nowcast. The red shaded areas indicate high disagreement periods.

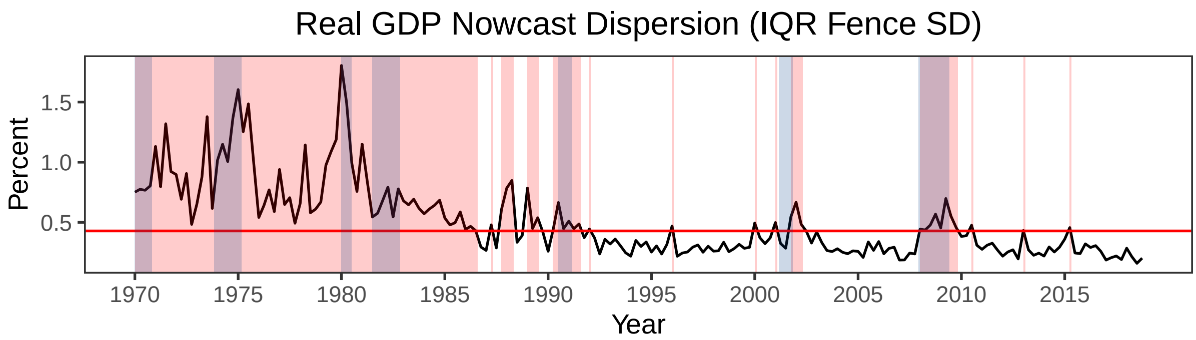

Figure B.5. Alternative Measurement of Disagreement: IQR Fence SD

Note: Time series of the disagreement index based on the standard deviation of Survey of Professional Forecasters real GDP nowcast after the **outlier treatment** of trimming observations outside of a *'fence'* defined as $25^{th} percentile + 1.5 * IQR$ and $75^{th} percentile + 1.5 * IQR$.

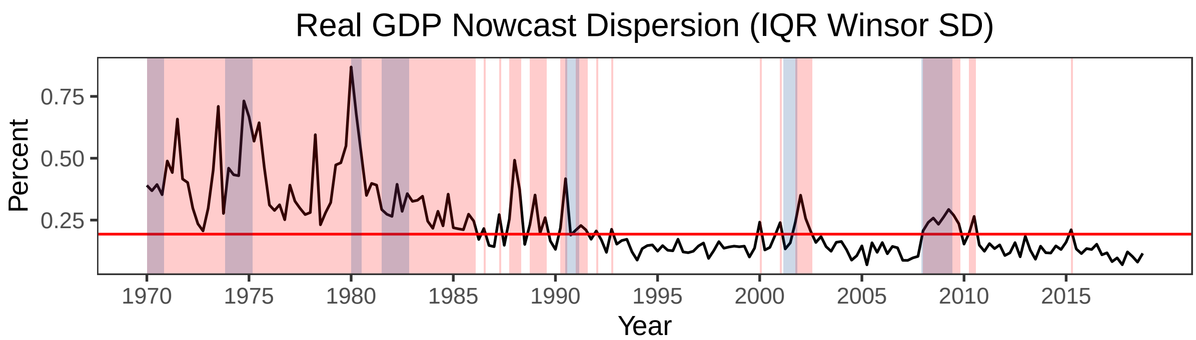

Figure B.6. Alternative Measurement of Disagreement: IQR Winsor SD

Note: Time series of the disagreement index based on the standard deviation of Survey of Professional Forecasters real GDP nowcast after the **outlier treatment of winsorising** variables outside of a *'fence'* defined as $25^{th} percentile + 1.5 * IQR$ and $75^{th} percentile + 1.5 * IQR$.

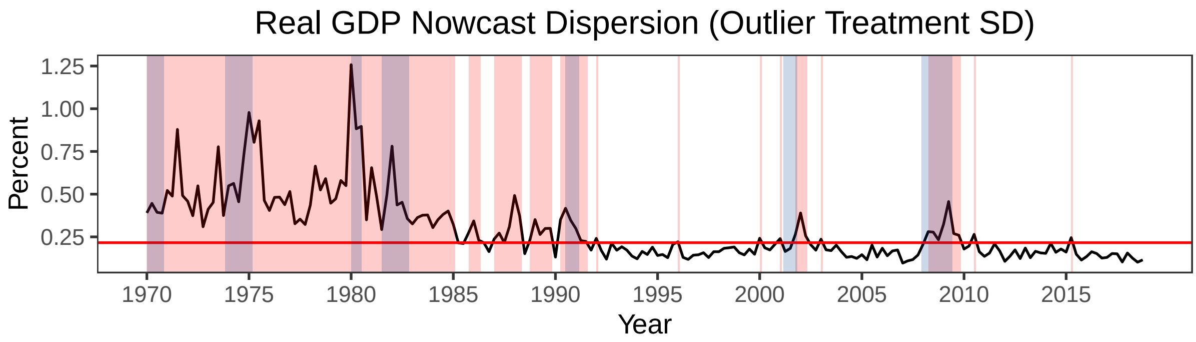

Figure B.7. Alternative Measurement of Disagreement: Outlier Treatment SD

Note: Time series of the disagreement index based on the standard deviation (after an **outlier treatment** by trimming the observations beyond the *median value* $\pm$ *3σ* normalised with the median) of the of Survey of Professional Forecasters real GDP nowcast.

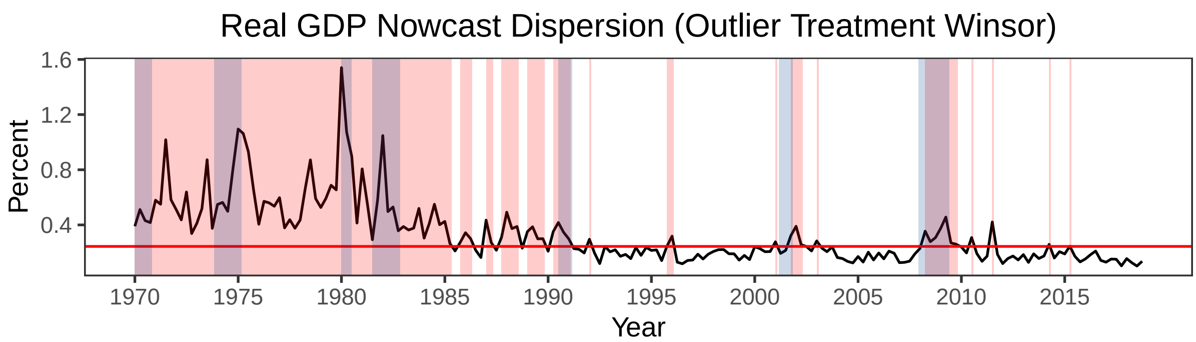

Figure B.8. Alternative Measurement of Disagreement: Outlier Treatment Winsor

Note: Time series of the disagreement index based on the standard deviation (after an **outlier treatment by winsorising** the observations beyond the *median value* $\pm$ *3σ* normalised with the median) of the of Survey of Professional Forecasters real GDP nowcast.

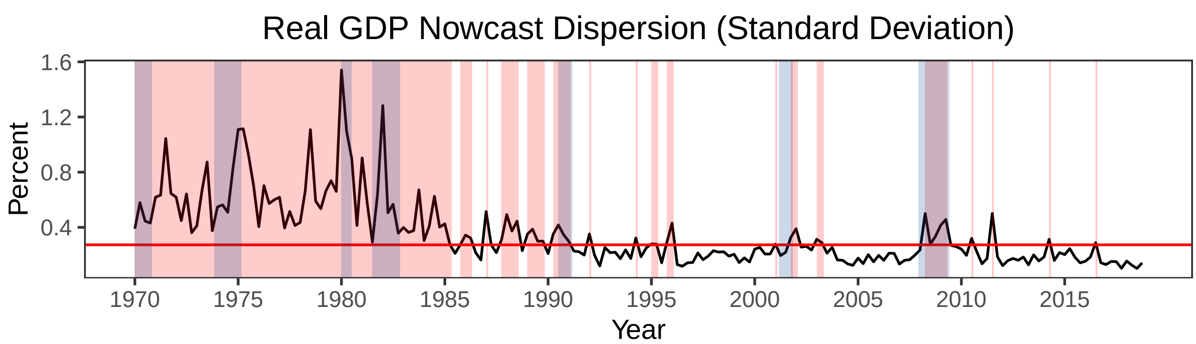

Figure B.9. Alternative Measurement of Disagreement: Standard Deviation

Note: Time series of the disagreement index based on **the standard deviation** of Survey of Professional Forecasters real GDP nowcast.

Table B.10 compares the impulse responses of high and low disagreement regimes, for alternative disagreement measures as described above. As in the main result, government spending responses under the two regimes are statistically different. This is reassuring that government spending do not respond differently whether firms and households are in the low or high information frictions, echoing the main results that government spending is not affected by household or firms' expectations formation. It also makes comparisons of the two states easier.

The response of output corresponds to main result where it is persistently above zero in high disagreement regime, and that this is statistically different to responses under low disagreement regime – where response of output is initially positive and then dips towards zero and can become negative. There is only one disagreement measure that do not reproduce the main result: the pure *standard deviation*. The responses in the two regimes are not statistically different in the two regimes, because even under low disagreement, output has mostly positive response. But with surveys, it is very important to treat for outliers. Using measures of standard deviation with either trimming or winsorising, I arrive at the same results as the baseline disagreement measure.

The response of consumption is in general consistent with the main findings: (1) in high information friction regime, households might become non-Ricardian and (2) the responses between the two regimes are different — in low information frictions, consumers expect that higher future taxes to finance the increase in government spending. But again, with the exception of the *standard deviation* disagreement measure where in low disagreement regime, the response of consumption is very weakly negative.

Lastly, the response of investment across the various alternative disagreement measures is also broadly consistent with the baseline results. The minor differences occur at the longer horizons with some measures, where under low disagreement investment is not statistically significant from zero (in the baseline, there is some crowding out of private investment). The responses under high disagreement periods is qualitatively the same as the baseline result for all of the alternative measures.

Table B.2 displays the estimates of the government spending multipliers for the alternative disagreement measures. As Figure B.10 show closely similar impulse responses, I show the multipliers for three of the alternative measures.

Disagreement: Quasi IQR						
	1-quarter	**1-year**	**2-year**	**3-year**	**4-year**	**5-year**
Output						
High Disagreement	1.03	0.66	0.74	0.67	0.84	0.91
Low Disagreement	2.15	2.30	2.25	2.06	1.34	0.71
Consumption						
High Disagreement	0.01	-0.02	-0.01	-0.01	0.15	0.18
Low Disagreement	0.69	0.92	1.06	0.90	0.50	0.00
Investment						
High Disagreement	0.17	-0.01	-0.08	-0.17	-0.23	-0.26
Low Disagreement	0.28	0.60	0.65	0.52	0.28	-0.01

Disagreement: Outlier Treatment SD						
	1-quarter	**1-year**	**2-year**	**3-year**	**4-year**	**5-year**
Output						
High Disagreement	1.34	1.36	1.70	1.66	1.76	1.79
Low Disagreement	1.54	1.04	0.44	0.30	0.15	0.01
Consumption						
High Disagreement	0.09	0.25	0.43	0.53	0.76	0.82
Low Disagreement	0.35	0.18	-0.16	-0.47	-0.79	-1.14
Investment						
High Disagreement	0.12	-0.11	-0.17	-0.25	-0.31	-0.32
Low Disagreement	0.13	0.21	0.13	0.04	-0.06	-0.16

Disagreement: Standard Deviation						
	1-quarter	**1-year**	**2-year**	**3-year**	**4-year**	**5-year**
Output						
High Disagreement	1.16	0.93	0.99	0.89	0.93	0.90
Low Disagreement	1.90	1.78	1.48	1.46	0.84	0.24
Consumption						
High Disagreement	-0.02	0.04	0.10	0.12	0.21	0.18
Low Disagreement	0.47	0.50	0.21	-0.12	-0.86	-1.67
Investment						
High Disagreement	0.11	-0.10	-0.25	-0.42	-0.53	-0.62
Low Disagreement	0.11	0.26	0.29	0.28	0.12	-0.12

Note: These are the cumulative multipliers defined as $M_h^x = \frac{\sum_{i=0}^{h} x_h}{\sum_{i=0}^{h} g_h}$ where x_h is the dollar effect on variable x of a one dollar increase in government spending at h quarters after the shock.

Table B.2. Estimates of Multipliers with Alternative Disagreement Measures

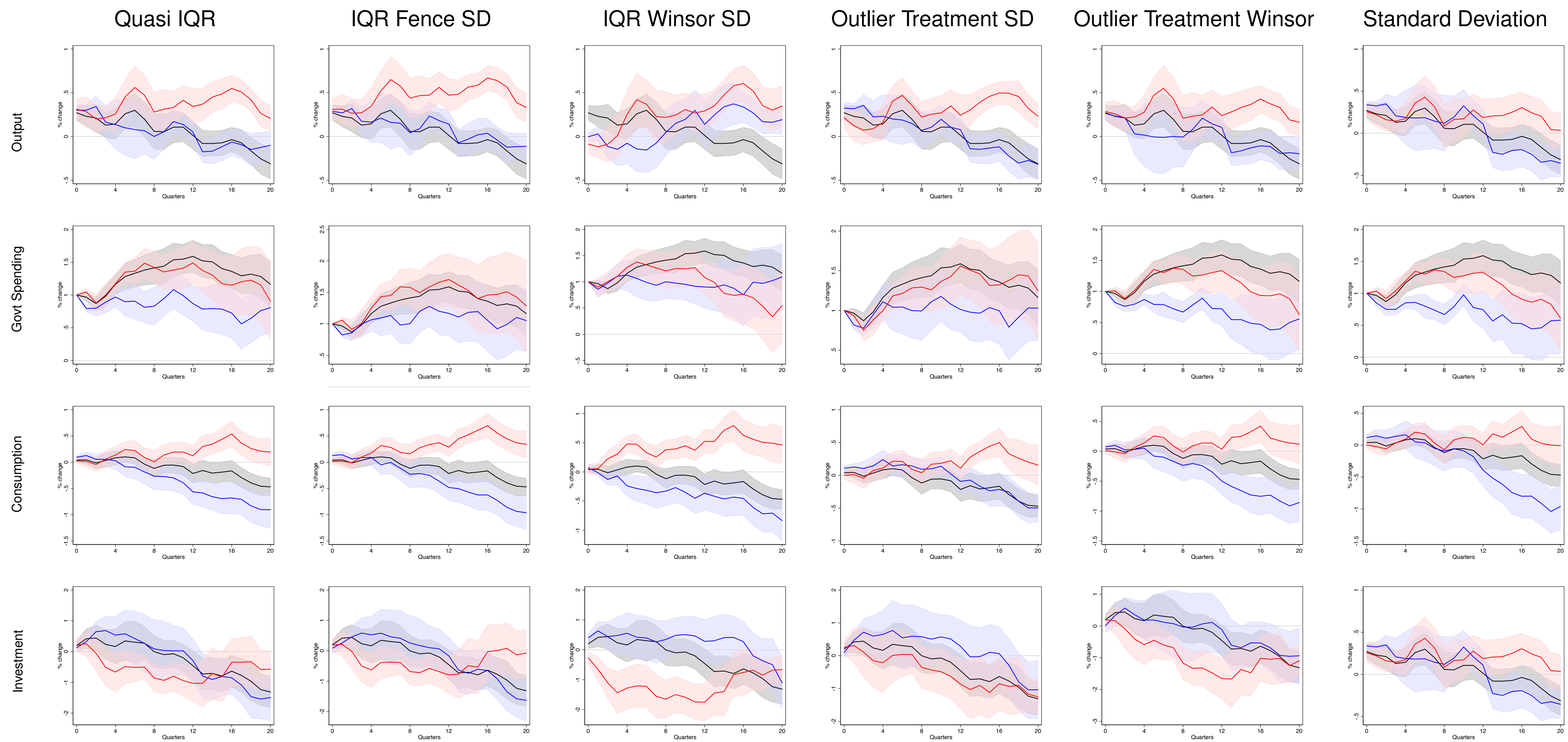

Figure B.10. Impulse Responses to a 1% Government Spending Shock using Alternative Disagreement Measures

Note: The row shows responses of output, government spending, consumption and investment, respectively, to a 1% government spending shock. Government spending is the (real) government consumption expenditure and gross investment in Ramey and Zubairy (2018) dataset. The columns show the various ways to measure disagreement. The sample period is 1970Q1-2018Q4.

Appendix C

Sticky Information and the Effects of Government Spending Shocks

C.1 Attentive Agents

In the sticky information model setup (Mankiw and Reis, 2007; Reis, 2009), some agents in the economy are attentive – they do not face any information frictions problems. These attentive agents are the consumer's shoppers of the households who purchase goods from the goods market, and the hiring department of a firm j demands workers $L_{t,j}$ from the labour packer (see Section C.1.1) and pays the labour packer the aggregate wage W_t. Note that these agents are different to the agents who are inattentive (face information frictions) – the consumer's saver-planner and worker in the households, and price-setter in the firms.

Consumer's shopper j at date t choose to consume a continuum of varieties of goods i

$$\max_{\{C_{t,j}(i)\}_{i\in[0,1]}} C_{t,j} = \left[\int_0^1 C_{t,j}(i)^{\frac{\nu_t}{\nu_t-1}} di\right]^{\frac{\nu_t-1}{\nu_t}}$$

subject to $\int_0^1 P_{t,i}C_{t,j}(i) < P_t C_{t,j}$.

$P_{t,i}$ is the price of each variety of good i, and the consumer values them according to a Dixit-Stiglitz utility function, with a stochastic elasticity of substitution ν_t. The solution to this problem is

$$C_{t,j}(i) = C_{t,j}\left(\frac{P_{t,i}}{P_t}\right)^{-\nu_t}$$

where the aggregate price index P_t is defined as

$$P_t = \left(\int_0^1 P_{t,i}^{1-\nu_t} di \right)^{\frac{1}{1-\nu_t}}$$

Integrating over the continuum of shoppers gives the total demand for variety i:

$$\int_0^1 C_{t,j}(i) dj = \left(\frac{P_{t,i}}{P_t} \right)^{-\nu_t} \int_0^1 C_{t,j} dj.$$

C.1.1 Labour Packer

The labour packer receives a supply of differentiated labour input from the optimising and rule-of-thumb households. They bundle the differentiated labour from Ricardian households (which each supply a labour variety i) with a Dixit-Stiglitz aggregator that minimises the wage bill

$$\max_{\{L_{t,j}^o(i)\}_{i \in [0,1]}} \int_0^1 W_{t,j}^o L_{t,j}^o(i) di$$

subject to

$$L_{t,j}^o = \left(\int_0^1 L_{t,j}^o(i)^{\frac{\gamma_t - 1}{\gamma_t}} di \right)^{\frac{\gamma_t}{\gamma_t - 1}}$$

This creates labour supply L_t^o, which then combined with L_t^r (from the rule-of-thumb households) by another Dixit-Stiglitz aggregator. I assume that the elasticity substitution is 1, resulting in a Cobb-Douglas production function. This simplifying assumption allows greater tractibility so that we can keep the Galí et al. (2007) assumption that steady-state labour $L = L^o = L^r$.

Production function of the labour packer

$$L_t = (L_t^r)^{\chi} (L_t^o)^{(1-\chi)}$$

where $\chi + (1 - \chi) = 1$.

The labour packer maximises

$$\max_{\{L_{t,k}(i)\}_{i \in [0,1]}} W_t L_t - W_t^o L_t^o - W_t^r L_t^r$$

subject to

$$L_t = \left[(1-\chi)^{\frac{1}{\sigma}}(L_t^o)^{\frac{\sigma-1}{\sigma}} + (\chi)^{\frac{1}{\sigma}}(L_t^r)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

Solving for

$$\mathcal{L} = W_t L_t - W_t^o L_t^o - W_t^r L_t^r + \lambda_t \left[-L_t + \left((1-\chi)^{\frac{1}{\sigma}}(L_t^o)^{\frac{\sigma-1}{\sigma}} + (\chi)^{\frac{1}{\sigma}}(L_t^r)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}\right]$$

FOC:

$$\begin{aligned}
L_t &: \quad W_t - \lambda_t = 0 \\
L_t^o &: \quad -W_t^o + \lambda_t (L_t^o)^{-\frac{1}{\sigma}}(1-\chi)^{\frac{1}{\sigma}}\left((1-\chi)^{\frac{1}{\sigma}}(L_t^o)^{\frac{\sigma-1}{\sigma}} + (\chi)^{\frac{1}{\sigma}}(L_t^r)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{1}{\sigma-1}} = 0 \\
\text{Note} &: \quad L_t^{\frac{1}{\sigma}} = \left((1-\chi)^{\frac{1}{\sigma}}(L_t^o)^{\frac{\sigma-1}{\sigma}} + (\chi)^{\frac{1}{\sigma}}(L_t^r)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{1}{\sigma-1}} \text{ so,} \\
&: \quad -W_t + \lambda_t (L_t^o)^{\frac{\sigma-1}{\sigma}}(1-\chi)^{\frac{1}{\sigma}} L_t^{\frac{1}{\sigma}} = 0 \\
W_t &= W_t \left(\frac{L_t^o}{L_t}\right)^{-\frac{1}{\sigma}} (1-\chi)^{\frac{1}{\sigma}}
\end{aligned}$$

Rearrange to get:

$$\begin{aligned}
L_t^o &= (1-\chi)\left(\frac{W_t^o}{W_t}\right)^{-\sigma} L_t \\
L_t^r &= \chi \left(\frac{W_t^r}{W_t}\right)^{-\sigma} L_t
\end{aligned}$$

Wage Index

$$\begin{aligned}
L_t &= \left[(1-\chi)^{\frac{1}{\sigma}}(L_t^o)^{\frac{\sigma-1}{\sigma}} + (\chi)^{\frac{1}{\sigma}}(L_t^r)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \\
&= \left[(1-\chi)^{\frac{1}{\sigma}}\left((1-\chi)\left(\frac{W_t^o}{W_t}\right)^{-\sigma} L_t\right)^{\frac{\sigma-1}{\sigma}} + (\chi)^{\frac{1}{\sigma}}\left(\chi\left(\frac{W_t^r}{W_t}\right)^{-\sigma} L_t\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \\
&= \left[(1-\chi)\left(\frac{W_t^o}{W_t}\right)^{1-\sigma} L_t^{\frac{\sigma-1}{\sigma}} + \chi\left(\frac{W_t^r}{W_t}\right)^{1-\sigma} L_t^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \\
L_t &= L_t \left[(1-\chi)\left(\frac{W_t^o}{W_t}\right)^{1-\sigma} + \chi\left(\frac{W_t^r}{W_t}\right)^{1-\sigma}\right]^{\frac{\sigma}{\sigma-1}}
\end{aligned}$$

Rearrange for W_t:

$$W_t = \left[(1-\chi)(W_t^o)^{1-\sigma} + \chi(W_t^r)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$$

C.1.2 Log-linearisation

Labour demand

$$\begin{aligned} l_t^o &= -\sigma(w_t^o - w_t) + l_t \\ l_t^r &= -\sigma(w_t^r - w_t) + l_t \end{aligned}$$

Wage Index

$$\begin{aligned} w_t &= \frac{1}{W}\Bigg[(1-\chi)(1-\sigma)(W^o)^{-\sigma}\frac{1}{1-\sigma}\left[(1-\chi)(W^o)^{1-\sigma} + \chi(W^r)^{1-\sigma}\right]^{\frac{1}{1-\sigma}-1}(W_t^o - W^o) \\ &+ \chi(1-\sigma)(W^r)^{-\sigma}\frac{1}{1-\sigma}\left[(1-\chi)(W^o)^{1-\sigma} + \chi(W^r)^{1-\sigma}\right]^{\frac{1}{1-\sigma}-1}(W_t^r - W^r)\Bigg] \\ &= \frac{1}{W}\left[(1-\chi)(W^o)^{-\sigma}W^oW^\sigma\frac{W_t^o - W^o}{W^o} + \chi(W^r)^{-\sigma}W^rW^\sigma\frac{W_t^r - W^r}{W^r}\right] \\ &= \frac{1}{W}\left[(1-\chi)(W^o)^{1-\sigma}W^\sigma w_t^o + \chi(W^r)^{-\sigma}W^\sigma w_t^r\right] \\ w_t &= (1-\chi)\left(\frac{W^o}{W}\right)^{1-\sigma} w_t^o + \chi\left(\frac{W^r}{W}\right)^{1-\sigma} w_t^r \end{aligned}$$

C.2 Sticky Information Phillips Curve – Firms

Consider the maximisation problem faced by the pricing department of a firm that last updated its information j periods ago. In each period, a randomly drawn fraction of firms λ updates their information, so there are $\lambda(1-\lambda)^j$ firms in this situation. The firms choose a nominal price to maximise expected real profits:

$$\max_{P_{t,j}} E_{t-j}\left[\frac{P_{t,j}Y_{t,j}}{P_t} - \frac{W_{t,j}L_{t,j}}{P_t}\right] \tag{C.1}$$

subject to its production function

$$Y_{t,j} = A_t L_{t,j}^{\alpha} \tag{C.2}$$

and the total demand for variety of goods i

$$Y_{t,i} = \left(\frac{P_t(i)}{P_t}\right)^{-\nu_t} C_t + \left(\frac{P_t(i)}{P_t}\right)^{-\nu_t} G_t, \quad \text{where} \quad C_t \equiv \int_0^1 C_{t,j} dj \tag{C.3}$$

Notice that in equilibrium $Y_{t,i} = Y_{t,j}$, and $P_t(i) = P_{t,j}$ as each good is produced by a unique firm.

$$\begin{aligned}
\mathcal{L} \;\; = \;\; & E_{t-j}\Bigg\{ \frac{P_{t,j}Y_{t,j}}{P_t} - \frac{W_{t,j}L_{t,j}}{P_t} \\
& + \lambda_1 \left[-Y_{t,j} + A_t L_{t,j}^{\alpha} \right] \\
& + \lambda_2 \left[-Y_{t,j} + \left(\frac{P_{t,j}}{P_t}\right)^{-\nu_t} C_t + \left(\frac{P_{t,j}}{P_t}\right)^{-\nu_t} G_t \right] \Bigg\}
\end{aligned}$$

Note: the $\lambda_{\{1,2\}}$ use for the Langragian is different to the λ for firms' inattentiveness.

FOC

$$P_{t,j}: \quad E_{t-j}\frac{Y_{t,j}}{P_t} - E_{t-j}\nu_t\lambda_2 \left(\frac{P_{t,j}}{P_t}\right)^{-\nu_t} \frac{1}{P_{t,j}}(C_t + G_t) = 0 \tag{C.4}$$

$$Y_{t,j}: \quad E_{t-j}\frac{P_{t,j}}{P_t} - E_{t-j}\lambda_1 - E_{t-j}\lambda_2 = 0 \tag{C.5}$$

$$L_{t,j}: \quad -E_{t-j}\frac{W_t}{P_t} + E_{t-j}\lambda_1 \alpha A_t L_{t,j}^{\alpha-1} = 0 \tag{C.6}$$

From the first-order condition with respect to $L_{t,j}$, we get that:

$$E_{t-j}\frac{W_t}{P_t} = E_{t-j}\lambda_1 \alpha A_t L_{t,j}^{\alpha} \frac{1}{L_{t,j}} \implies E_{t-j}\frac{1}{\alpha}\frac{W_t L_{t,j}}{P_t}\frac{1}{Y_{t,j}} = E_{t-j}\lambda_1$$

Then, inserting λ_1 into the second FOC, we get λ_2:

$$\implies E_{t-j}\frac{P_{t,j}}{P_t} - E_{t-j}\frac{1}{\alpha}\frac{W_t L_{t,j}}{P_t}\frac{1}{Y_{t,j}} = E_{t-j}\lambda_2$$

We can then plug the expression of λ_1 and λ_2 into the FOC with respect to $P_{t,j}$

$$
\begin{aligned}
E_{t-j}\frac{Y_{t,j}}{P_t} &= E_{t-j}\left[\nu_t\left(\frac{P_{t,j}}{P_t}\right)^{-\nu_t}\frac{1}{P_{t,j}}(C_t+G_t)\left(\frac{P_{t,j}}{P_t}-\frac{1}{\alpha}\frac{W_t L_{t,j}}{P_t}\frac{1}{Y_{t,j}}\right)\right] \\
& E_{t-j}\left[\nu_t\frac{1}{P_{t,j}}Y_{t,j}\frac{1}{P_t}\left(P_{t,j}-\frac{1}{\alpha}\frac{W_t L_{t,j}}{Y_{t,j}}\right)\right] \\
& E_{t-j}\left[\frac{\nu_t}{P_{t,j}}\left(Y_{t,j}-\frac{1}{\alpha}\frac{W_t L_{t,j}}{P_{t,j}}\right)\right]
\end{aligned}
$$

Rearrange to get an expression $P_{t,j}$:

$$
\begin{aligned}
E_{t-j}\frac{1}{\alpha}\frac{\nu_t}{P_t}\frac{W_t L_{t,j}}{P_{t,j}} &= E_{t-j}\frac{\nu_t}{P_t}Y_{t,j}-E_{t-j}\frac{Y_{t,j}}{P_t} \\
&= E_{t-j}(\nu_t-1)\frac{Y_{t,j}}{P_t}
\end{aligned}
$$

Hence, we find that the first-order condition of the optimisation problem of the firm is:

$$
P_{t,j}=\frac{E_{t-j}\left[\frac{\nu_t W_t L_{t,j}}{P_t}\right]}{E_{t-j}\left[\alpha(\nu_t-1)\frac{Y_{t,j}}{P_t}\right]} \tag{C.7}
$$

Log-linearisation

$$
p_{t,j}=p_t+\frac{\alpha(w_t-p_t)+(1-\alpha)y_t-a_t-\alpha\frac{\hat{\nu}_t}{\nu-1}}{\alpha+\nu(1-\alpha)} \tag{C.8}
$$

C.3 Sticky Information IS Curve – Consumers

Here we consider the problem of an inattentive consumer. For simplicity, I drop the 'o' notation, for example, C_t here is actually C_t^o. If she updates her plan at date t, she chooses a plan for current and future consumption to solve:

$$
V(B_t)=\max_{C_{t+i,i}}\left\{\sum_{i=0}^{\infty}\beta^i(1-\delta)^i\frac{C_{t+i,i}^{1-\frac{1}{\theta}}-1}{1-\frac{1}{\theta}}+\beta\delta\sum_{i=0}^{\infty}\beta^i(1-\delta)^i E_t[V(B_{t+1+i})]\right\} \tag{C.9}
$$

subject to her budget contraint

$$B_{t+1+i} = \Pi_{t+1+i}\left(B_{t+i} - C_{t+i,i} + \frac{W_{t+1+i,i}L_{t+1+i,i} - T_{t+1+i,i}}{P_{t+i}}\right) \text{ for i = 0, 1, ...} \quad \text{(C.10)}$$

and a no-Ponzi scheme condition. $V(.)$ is the value function of the agent that depends on her wealth B_t with a δ is the probability at each date t that the *consumer* updates her plan. β is the discount factor and θ is the intertemporal elasticity of substitution so preferences are iso-elastic. Notice that preferences are also additively separable in consumption and leisure, but since the consumer does not control labor supply, the term in leisure drops out of her problem. The budget constraint assumes that wages are received at the beginning of the period so they earn interest Π_t (which is equal to the real return of government bonds R_t) before the next period. Finally T_t denote both lump-sum taxes as well as the payments from an insurance contract that all agents sign at the beginning of time that ensures that they all have the same wealth at the start of each period. This is a standard assumption in these models to avoid tracking the wealth distribution over time. The optimality conditions are:

$$\beta^i(1-\delta)^i C_{t+i,i}^{-\frac{1}{\theta}} = \beta\delta\sum_{k=i}^{\infty}\beta^k(1-\delta)^k E_t\left[V'(B_{t+1+k})\bar{\Pi}_{t+i,t+1+k}\right] \quad \text{for i = 0,1,2,} \quad \text{(C.11)}$$

$$V'(B_t) = \beta\delta\sum_{k=i}^{\infty}\beta^k(1-\delta)^k E_t\left[V'(B_{t+1+k})\bar{\Pi}_{t,t+1+k})\right] \quad \text{(C.12)}$$

We denote by $\bar{\Pi}_{t+i,t+1+k} = \prod_{z=t+i}^{t+k}\Pi_{z+1}$ the compound return between $t+i$ and $t+1+k$.

Combining Eq (C.11) for $i = 0$ with Eq (C.12) we get that $C_{t,0}^{-\frac{1}{\theta}} = V'(B_t)$. Writing Eq (C.12) recursively and using these results, we get the first result in Eq (C.13). Equation (C.13) is the standard Euler equation for a well-informed agent, who update their information in the current period. It reads that the marginal utility of consuming today is equal to the expected discounted marginal utility of consuming tomorrow times the return on savings. Condition Eq (C.11) for $i = j$ and Eq (C.12) for date $t+j$ imply our second result in Eq (C.14). Equation (C.14) notes that agents who are not very well informed (those who do not update in the current period) set their marginal utility of consumption to what they expect it would be with full information.

$$C_{t,0}{}^{-\frac{1}{\theta}} = E_t\left(R_{t+1}C_{t+1,0}^{-\frac{1}{\theta}}\right) \tag{C.13}$$

$$C_{t+j,j}{}^{-\frac{1}{\theta}} = E_t\left(C_{t+j,0}^{-\frac{1}{\theta}}\right) \tag{C.14}$$

For interested readers, I elaborate the steps to obtain these optimality conditions of the consumer's plan in the following subsection.

Derivations in detail

Getting the first result (Euler equation). The first optimality condition, Eq (C.11), is the first-order condition from the value function of Eq (C.9). The next step is to take the FOC of the value function, by taking Eq (C.9) recursively

$$V(B_t) = \max_{C_{t+i,i}}\left\{\frac{C_{t+i,i}^{1-\frac{1}{\theta}}-1}{1-\frac{1}{\theta}} + +\beta\delta E_t\left[V(B_{t+1})\right] \quad + \beta(1-\delta)\frac{C_{t+i,i}^{1-\frac{1}{\theta}}-1}{1-\frac{1}{\theta}} + \beta\delta\beta(1-\delta)E_tV(B_{t+2}) + \ldots\right\} \tag{C.15}$$

where:

$$\begin{aligned}
B_{t+1} &= \Pi_{t+1}\left(B_t - C_{t,i} + \ldots\right)\\
B_{t+2} &= \Pi_{t+2}\left(B_{t+1} - C_{t+1,i} + \ldots\right)\\
B_{t+2} &= \Pi_{t+2}\left(\Pi_{t+1}\left(B_t - C_{t,i} + \ldots\right) - C_{t+1,i} + \ldots\right)
\end{aligned}$$

The first-order condition of the value function is

$$\begin{aligned}
V'(B_t) &= \beta\delta E_t\left[V'(B_{t+1})\Pi_{t+1})\right] +\\
&\quad \beta\delta\beta(1-\delta)E_t\left[V'(B_{t+2})\Pi_{t+2}\Pi_{t+1})\right] +\\
&\quad \beta\delta\beta^2(1-\delta)^2E_t\left[V'(B_{t+3})\Pi_{t+3}\Pi_{t+2}\Pi_{t+1})\right] + \ldots\\
V'(B_t) &= \beta\delta\sum_{k=0}^{\infty}\beta^k(1-\delta)^kE_t\left[V'(B_{t+1+k})\bar{\Pi}_{t,t+1+k}\right]
\end{aligned}$$

Similarly for $V'(B_{t+1})$,

$$\begin{aligned}
V'(B_{t+1}) &= \beta\delta E_{t+1}\left[V'(B_{t+2})\Pi_{t+2})\right] +\\
&\quad \beta\delta\beta(1-\delta)E_{t+1}\left[V'(B_{t+3})\Pi_{t+3}\Pi_{t+2})\right] + \ldots
\end{aligned}$$

Multiply both sides of $V'(B_{t+1})$ with $\beta(1-\delta)\Pi_{t+1}$

$$\begin{aligned} \beta(1-\delta)V'(B_{t+1})\Pi_{t+1} &= \beta(1-\delta)\beta\delta E_{t+1}\left[V'(B_{t+2})\Pi_{t+2}\Pi_{t+1})\right] + \\ &\quad \beta\delta\beta^2(1-\delta)^2 E_{t+1}\left[V'(B_{t+3})\Pi_{t+3}\Pi_{t+2}\Pi_{t+1})\right] + \dots \end{aligned}$$

By the Law of Iterative Expectations: $E_t[E_{t+1}X_{t+2}] = E_t[X_{t+2}]$ i.e. today's expectations of tomorrow's expectations of a day after variable is equal to today's expectations of day after variable.

Thus, when we multiply both sides with E_t, we get

$$\begin{aligned} \beta(1-\delta)E_t[V'(B_{t+1})\Pi_{t+1}] &= \beta(1-\delta)\beta\delta E_t\left[V'(B_{t+2})\Pi_{t+2}\Pi_{t+1})\right] + \\ &\quad \beta\delta\beta^2(1-\delta)^2 E_t\left[V'(B_{t+3})\Pi_{t+3}\Pi_{t+2}\Pi_{t+1})\right] + \dots \end{aligned}$$

and we can see that the RHS of the above equation correspond the second terms onwards of the $V'(B_t)$ equation, such that we have

$$\begin{aligned} V'(B_t) &= \beta\delta E_t\left[V'(B_{t+1})\Pi_{t+1})\right] + \beta(1-\delta)E_t[V'(B_{t+1})\Pi_{t+1}] \\ V'(B_t) &= \beta E_t\left[V'(B_{t+1})\Pi_{t+1})\right] \end{aligned}$$

As noted previously, combining Eq (C.11) for $i = 0$ with Eq (C.12)

$$\beta^0(1-\delta)^0 C_{t+i,i}^{-\frac{1}{\theta}} = \beta\delta\sum_{k=i}^{\infty}\beta^0(1-\delta)^0 E_t\left(V'(B_{t+1+k})\bar{\Pi}_{t+0,t+1+0}\right) \tag{C.16}$$

$$C_{t,0}^{-\frac{1}{\theta}} = V'(B_t) \tag{C.17}$$

and we also get that $C_{t+1,0}^{-1/\theta} = V'(B_{t+1})$. Then, writing Eq (C.12) recursively and using these results, we get Eq (C.13).

$$\begin{aligned} V'(B_t) &= \beta E_t\left[V'(B_{t+1})\Pi_{t+1}\right] \\ C_{t,0}^{-\frac{1}{\theta}} &= \beta E_t\left[C_{t+1,0}^{-1/\theta}R_{t+1}\right] \end{aligned}$$

where $\Pi_{t+1} = R_{t+1}$ as it is only for one period.

Getting the second result. To re-cap, let's note the equations we need to get to second result, as shown in (Eq C.14). (i) setting $i = j$ in Eq (C.11). (ii) from the equality we find where $C_{t,0}^{-\frac{1}{\theta}} = V'(B_t)$. (iii) combining (i) and (ii) for date $t+j$.

$$
\begin{aligned}
(i) \quad & \beta^j(1-\delta)^j C_{t+j,j}^{-\frac{1}{\theta}} = \beta\delta \sum_{k=j}^{\infty} \beta^k (1-\delta)^k E_t \left(V'(B_{t+1+k})\bar{\Pi}_{t+j,t+1+k}\right) \\
(ii) \quad & C_{t+j,0}^{-\frac{1}{\theta}} = V'(B_{t+j}) \\
(iii) \quad & V'(B_{t+j}) \ = \beta\delta \sum_{k=0}^{\infty} \beta^k (1-\delta)^k E_{t+j}\left[V'(B_{t+j+1+k})\bar{\Pi}_{t+j,t+j+1+k}\right] \\
& \qquad = \beta\delta E_{t+j}\left[V'(B_{t+j+1})\bar{\Pi}_{t+j,t+j+1}\right] + \\
& \qquad \quad \beta\delta\beta(1-\delta)E_{t+j}\left[V'(B_{t+j+1+1})\bar{\Pi}_{t+j,t+j+1+1}\right] + \dots
\end{aligned}
$$

Note: $\bar{\Pi}_{t+j,t+j+1} = \Pi_{t+j+1}$ and $\bar{\Pi}_{t+j,t+j+2} = \Pi_{t+j+1}\Pi_{t+j+2}$ so,

$$
\begin{aligned}
(iii) \quad V'(B_{t+j}) \ &= \beta\delta E_{t+j}\left[V'(B_{t+j+1})\Pi_{t+j+1}\right] + \\
& \quad \beta\delta\beta(1-\delta)E_{t+j}\left[V'(B_{t+j+2})\Pi_{t+j+1}\Pi_{t+j+2}\right] + \dots
\end{aligned}
$$

Therefore (i) becomes:

$$
\begin{aligned}
(i) \quad \beta^j(1-\delta)^j C_{t+j,j}^{-\frac{1}{\theta}} = \ & \beta\delta\beta^j(1-\delta)^j E_t\left(V'(B_{t+1+j})\bar{\Pi}_{t+j,t+1+j}\right) + \\
& \beta\delta\beta^{j+1}(1-\delta)^{j+1}E_t\left(V'(B_{t+1+j+1})\bar{\Pi}_{t+j,t+1+j+1}\right) + \dots \\
= \ & \beta\delta\beta^j(1-\delta)^j E_t\left(V'(B_{t+1+j})\Pi_{t+j+1}\right) + \\
& \beta\delta\beta^{j+1}(1-\delta)^{j+1}E_t\left(V'(B_{t+1+j+1})\Pi_{t+j+1}\Pi_{t+j+2}\right) + \dots
\end{aligned}
$$

Dividing both sides with $\beta^j(1-\delta)^j$, Eq (i) becomes

$$
C_{t+j,j}^{-\frac{1}{\theta}} = \beta\delta E_t\left(V'(B_{t+1+j})\Pi_{t+j+1})\right) + \beta\delta\beta(1-\delta)E_t\left(V'(B_{t+j+2})\Pi_{t+j+1}\Pi_{t+j+2}\right) + \dots \tag{C.18}
$$

Taking the expectation E_t for Eq (iii) we get

$$
E_t(V'(B_{t+j})) = \beta\delta E_t\left[V'(B_{t+j+1})\Pi_{t+j+1}\right] + \beta\delta\beta(1-\delta)E_t\left[V'(B_{t+j+2})\Pi_{t+j+1}\Pi_{t+j+2}\right] + \dots \tag{C.19}
$$

We can see that the RHS of Eq (C.18) is equal to the RHS of Eq (C.19) , thus

$$
E_t(V'(B_{t+j})) = C_{t+j,j}^{-\frac{1}{\theta}}
$$

As we have established earliner (and noting taking the expectations at time t) that

$$E_t\left(C_{t+j,0}^{-\frac{1}{\theta}}\right) = E_t\left(V'(B_{t+j})\right)$$

Finally, we have the second condition in Eq (C.14)

$$C_{t+j,j}^{-\frac{1}{\theta}} = E_t\left(C_{t+j,0}^{-\frac{1}{\theta}}\right) \tag{C.20}$$

C.4 Sticky Information Wage Curve – Labours

Here we consider the problem of an inattentive worker from the optimising households, who solve a similar problem to optimising consumers in the previous section. For simplicity, I drop the *'o'* notation, for example, L_t here is actually L_t^o.

$$\hat{V}(B_t) = \max_{W_{t+i,i}^o}\left\{-\sum_{i=0}^{\infty}\beta^i(1-\omega)^i E_t\left(\frac{L_{t+i,i}^{1+\frac{1}{\varphi}}+1}{1+\frac{1}{\varphi}}\right) + \beta\omega\sum_{i=0}^{\infty}\beta^i(1-\omega)^i E_t[\hat{V}(B_{t+1+i})]\right\} \tag{C.21}$$

subject to the budget constraint (that is identical to the consumer's)

$$B_{t+1+i} = \Pi_{t+1+i}\left(B_{t+i} - C_{t+i,i} + \frac{W_{t+1+i,i}L_{t+1+i,i} + T_{t+1+i,i}}{P_{t+i}}\right) \text{ for i = 0, 1, ...} \tag{C.22}$$

and labour demand

$$L_{t,i} = \left(\frac{W_t(i)}{W_t}\right)^{-\gamma_t} L_t, \quad \text{where} \quad L_t \equiv \int_0^1 L_{t,j}dj \tag{C.23}$$

where $\hat{V}(.)$ is the value function perceived by the worker with ω as the probability at each date t that the *worker* updates her information. β is the discount factor and ψ is the Frisch elasticity of labour supply in the iso-elastic utility function.

Then, setting this up:

$$\hat{V}(B_t) \;=\; \max_{W_{t+i,i}}\left\{-\sum_{i=0}^{\infty}\beta^i(1-\omega)^i E_t\left[\frac{\left(\left(\frac{W_t(i)}{W_t}\right)^{-\gamma_t}L_t\right)^{1+\frac{1}{\varphi}}+1}{1+\frac{1}{\varphi}}\right]\right.$$

$$+\beta\omega\sum_{i=0}^{\infty}\beta^i(1-\omega)^i E_t\left[V\left(\Pi_{t+1+i}\left(B_{t+i}-C_{t+i,i}+\frac{T_{t+1+i,i}}{P_{t+i}}\right.\right.\right.$$

$$\left.\left.\left.\left.\frac{W_{t+1+i,i}\left(\frac{W_{t+1+i,i}}{W_{t+1+i}}\right)^{-\gamma_{t+1+i}}L_{t+1+i}}{P_{t+i}}\right)\right)\right]\right\}$$

FOC

$$\beta^i(1-\omega)^i E_t L_{t+i,i}^{\frac{1}{\varphi}}(-\gamma_{t+i})\overbrace{\frac{W_{t+i,i}{}^{-\gamma_{t+i}-1}}{W_{t+i}^{-\gamma_{t+i}}}L_{t+i}}^{=\frac{L_{t+i,i}}{W_{t+i,i}}}$$

$$+\beta\omega\sum_{k=i}^{\infty}\beta^k(1-\omega)^k E_t\left[\hat{V}'(B_{t+1+k})\bar{\Pi}_{t+i,t+1+k}\right.$$

$$\left.\frac{(1-\gamma_{t+1+i})\overbrace{\left(\frac{W_{t+1+i,i}}{W_{t+1+i}}\right)^{-\gamma_{t+1+k}}L_{t+1+i}}^{=L_{t+1+i}}}{P_{t+i}}\right]=0$$

This gives us the first optimality condition

$$\beta^i(1-\omega)^i E_t\gamma_{t+i}\frac{L_{t+i,i}^{1+\frac{1}{\varphi}}}{W_{t+i,i}}=\beta\omega\sum_{k=i}^{\infty}\beta^k(1-\omega)^k E_t\left[\hat{V}'(B_{t+1+k})\bar{\Pi}_{t+i,t+1+k}\frac{(\gamma_{t+i}-1)L_{t+i,i}}{P_{t+i}}\right] \tag{C.24}$$

As the budget constraint is identical to the consumer's, then we get the second optimality condition

$$\hat{V}'(B_t)=\beta\omega\sum_{k=i}^{\infty}\beta^k(1-\omega)^k E_t\left[\hat{V}'(B_{t+1+k})\bar{\Pi}_{t,t+1+k}\right] \tag{C.25}$$

Combining Eq (C.24) for $i=0$ with Eq (C.25), we get

$$W_{t,0}=\frac{\gamma_t}{\gamma_t-1}\frac{P_t L_{t,0}^{\frac{1}{\varphi}}}{\hat{V}'(B_t)} \tag{C.26}$$

Taking Eq (C.25) recursively

$$\hat{V}'(B_t)=\beta\omega E_t\hat{V}'(B_{t+1})\Pi_{t+1}+$$

$$
\begin{aligned}
& \beta\omega\beta(1-\omega)E_t\hat{V}'(B_{t+2})\Pi_{t+1}\Pi_{t+2} + \dots \\
\hat{V}'(B_{t+1}) &= \beta\omega E_{t+1}\hat{V}'(B_{t+2})\Pi_{t+2} + \dots \\
\beta(1-\omega)E_t\hat{V}'(B_{t+1})\Pi_{t+1} &= \beta\omega\beta(1-\omega)E_{t+1}\hat{V}'(B_{t+2})\Pi_{t+1}\Pi_{t+2} + \dots \\
\hat{V}'(B_t) &= \beta\omega E_t\hat{V}'(B_{t+1})\Pi_{t+1} + \beta(1-\omega)E_t\hat{V}'(B_{t+1})\Pi_{t+1} \\
&= E_t\hat{V}'(B_{t+1})\Pi_{t+1}\left[\beta\omega + \beta - \beta\omega\right] \\
&= \beta E_t\hat{V}'(B_{t+1})\Pi_{t+1}
\end{aligned}
$$

and using Eq (C.26) we get

$$
\begin{aligned}
\hat{V}'(B_t) &= \frac{\gamma_t}{\gamma_t - 1}\frac{P_t L_{t,0}^{\frac{1}{\varphi}}}{W_{t,0}} \\
\hat{V}'(B_{t+1}) &= \frac{\gamma_{t+1}}{\gamma_{t+1} - 1}\frac{P_{t+1} L_{t+1,0}^{\frac{1}{\varphi}}}{W_{t+1,0}}
\end{aligned}
$$

So $\hat{V}'(B_t)$ is:

$$
\hat{V}'(B_t) = \beta E_t\left[\frac{\gamma_{t+1}}{\gamma_{t+1} - 1}\frac{P_t L_{t+1,0}^{\frac{1}{\varphi}}}{W_{t+1,0}}\Pi_{t+1}\right]
$$

Rearranging this gives us (note that since it is only one period ahead, $\Pi_{t+1} = R_{t+1}$)

$$
\frac{\gamma_t}{\gamma_t - 1}\frac{P_t L_{t,0}^{\frac{1}{\varphi}}}{W_{t,0}} = \beta E_t\left(R_{t+1}\frac{\gamma_{t+1}}{\gamma_{t+1} - 1}\frac{P_t L_{t+1,0}^{\frac{1}{\varphi}}}{W_{t+1,0}}\right) \tag{C.27}
$$

To define $W_{t+i,i}$ we set Eq (C.24) for $i = j$ and Eq (C.25) for date $t + j$. Setting Eq (C.24) for $i = j$ we have

$$
\begin{aligned}
\beta^j(1-\omega)^j E_t\gamma_{t+j}\frac{L_{t+j,j}^{1+\frac{1}{\varphi}}}{W_{t+j,j}} &= \beta\omega\sum_{k=j}^{\infty}\beta^k(1-\omega)^k E_t\left[\hat{V}'(B_{t+1+k})\bar{\Pi}_{t+j,t+1+k}\frac{(\gamma_{t+j} - 1)L_{t+j,j}}{P_{t+j}}\right] \\
&= \beta\omega\beta^j(1-\omega)^j E_t\left[\hat{V}'(B_{t+1+j})\Pi_{t+j+1}\frac{(\gamma_{t+j} - 1)L_{t+j,j}}{P_{t+j}}\right] \\
&\quad + \beta\omega\beta^{j+1}(1-\omega)^{j+1}E_t\left[\hat{V}'(B_{t+2+j})\Pi_{t+j+1}\Pi_{t+j+2}\frac{(\gamma_{t+j+1} - 1)L_{t+j+1,j}}{P_{t+j}}\right] + \dots
\end{aligned}
$$

Divide both sides by $\beta^j(1-\omega)^j$:

$$E_t\gamma_{t+j}\frac{L_{t+j,j}^{1+\frac{1}{\varphi}}}{W_{t+j,j}} = \beta\omega E_t\left[\hat{V}'(B_{t+1+j})\Pi_{t+j+1}\frac{(\gamma_{t+j}-1)L_{t+j,j}}{P_{t+j}}\right]$$
$$+\beta\omega\beta(1-\omega)E_t\left[\hat{V}'(B_{t+2+j})\Pi_{t+j+1}\Pi_{t+j+2}\frac{(\gamma_{t+j+1}-1)L_{t+j+1,j}}{P_{t+j}}\right]+\dots$$

Next, we set Eq (C.25) for $t+j$:

$$\begin{aligned}\hat{V}'(B_{t+j}) &= \beta\omega\sum_{k=i}^{\infty}\beta^k(1-\omega)^k E_{t+j}\left[\hat{V}'(B_{t+j+1+k})\bar{\Pi}_{t+j,t+j+1+k}\right]\\ &= \beta\omega E_{t+j}\left[\hat{V}'(B_{t+j+1})\Pi_{t+j+1}\right]\\ &\quad+\beta\omega\beta(1-\omega)E_{t+j}\left[\hat{V}'(B_{t+j+2})\Pi_{t+j+1}\Pi_{t+j+2}\right]+\dots\end{aligned}$$

Taking E_t on both sides:

$$E_t\hat{V}'(B_{t+j}) = \beta\omega E_t\left[\hat{V}'(B_{t+j+1})\Pi_{t+j+1}\right]+\beta\omega\beta(1-\omega)E_t\left[\hat{V}'(B_{t+j+2})\Pi_{t+j+1}\Pi_{t+j+2}\right]+\dots$$

We can see that the RHS of the above equation is part of the RHS of Eq (C.24) (and setting j = i) it becomes:

$$\beta^i(1-\omega)^iE_t\gamma_{t+i}\frac{L_{t+i,i}^{1+\frac{1}{\varphi}}}{W_{t+i,i}} = E_t\hat{V}'(B_{t+i})\frac{(\gamma_{t+i}-1)L_{t+i,i}}{P_{t+i}}$$

where

$$\hat{V}'(B_{t+i}) = \frac{\gamma_{t+i}}{\gamma_{t+i}-1}\frac{P_{t+i}L_{t+i,0}^{\frac{1}{\varphi}}}{W_{t+i,0}}$$

so

$$E_t\gamma_{t+i}\frac{L_{t+i,i}^{1+\frac{1}{\varphi}}}{W_{t+i,i}} = E_t\left[\frac{\gamma_{t+i}}{\cancel{\gamma_{t+i}-1}}\frac{\cancel{P_{t+i}}L_{t+i,0}^{\frac{1}{\varphi}}}{W_{t+i,0}}\frac{\cancel{(\gamma_{t+i}-1)}L_{t+i,i}}{\cancel{P_{t+i}}}\right]$$

We find that

$$W_{t+i,i} = \frac{E_t\left(\gamma_{t+i} L_{t+i,i}^{\frac{1}{\varphi}}\right)}{E_t\left(\gamma_{t+i} L_{t+i,i} L_{t+i,0}^{\frac{1}{\varphi}-1} / W_{t+i,0}\right)} \tag{C.28}$$

C.5 Sensitivity Analysis: Responses of Wage and Labour

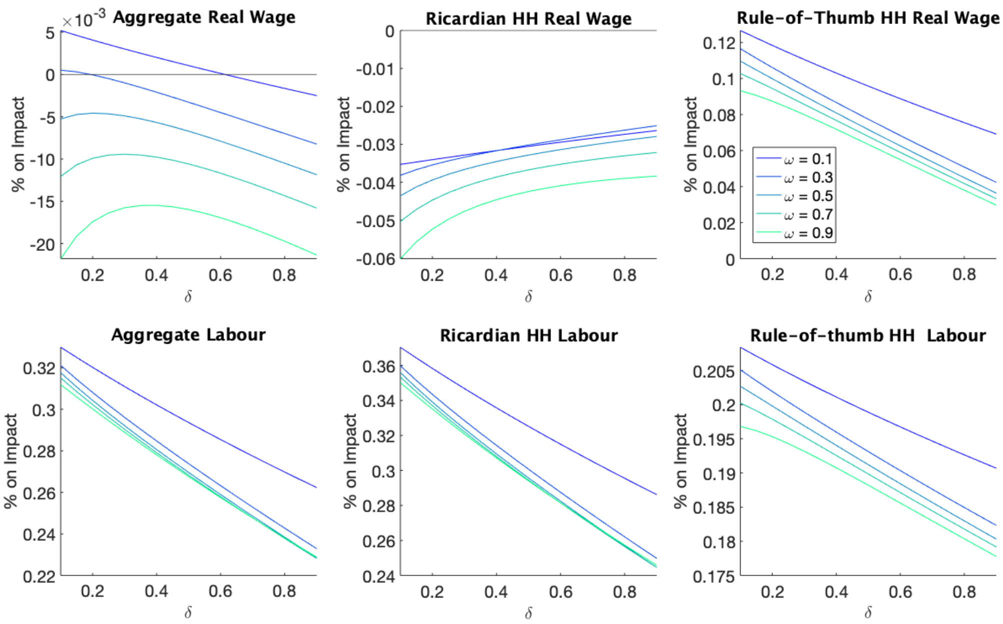

Figure C.1. Response of Wage as a Function of Varying Inattentiveness of Consumers δ and Workers ω

Note: A value of δ and ω closer to 0 indicate more sticky information.

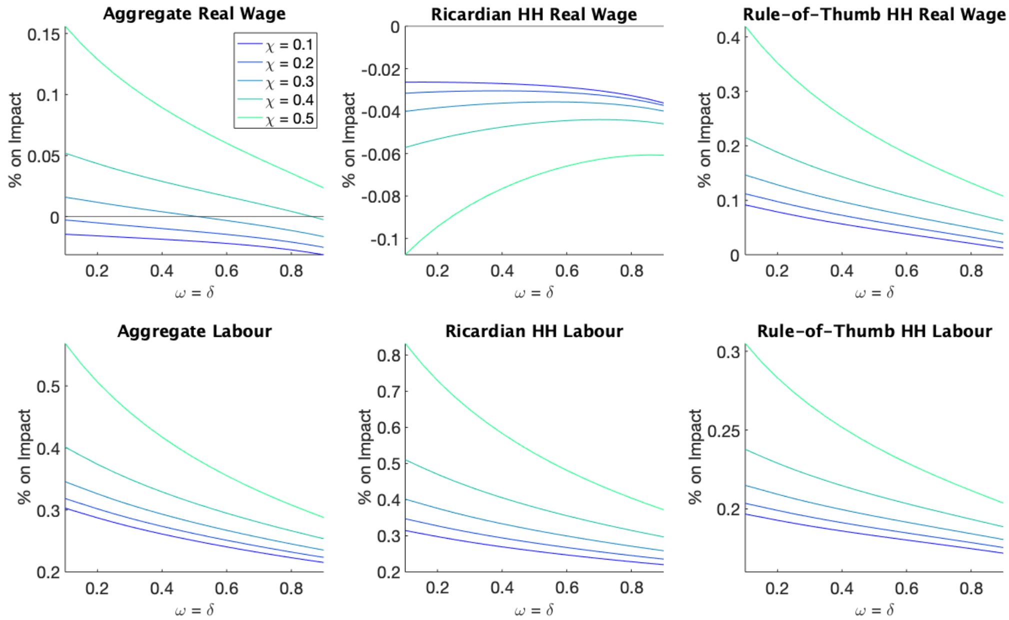

Figure C.2. Response of Wage as a Function of Varying Inattentiveness of Households and χ the Fraction of Rule-of-Thumb Households

Note: δ and ω closer to 0 indicate more sticky information.

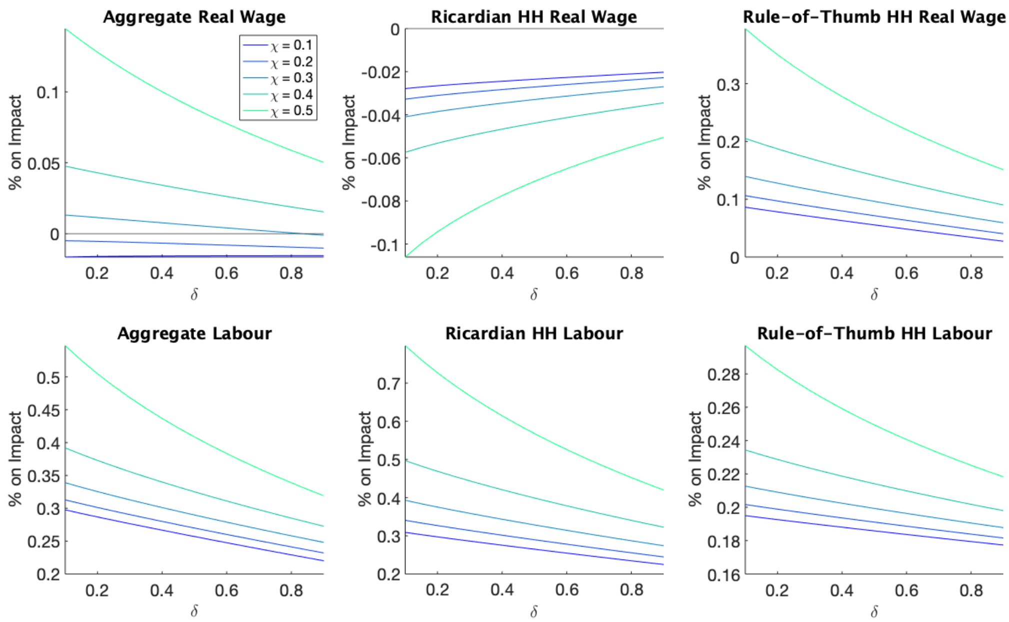

Figure C.3. Response of Wage as a Function of Varying Inattentiveness of Consumers and χ the Fraction of Rule-of-Thumb Households

Note: δ closer to 0 indicate more sticky information.

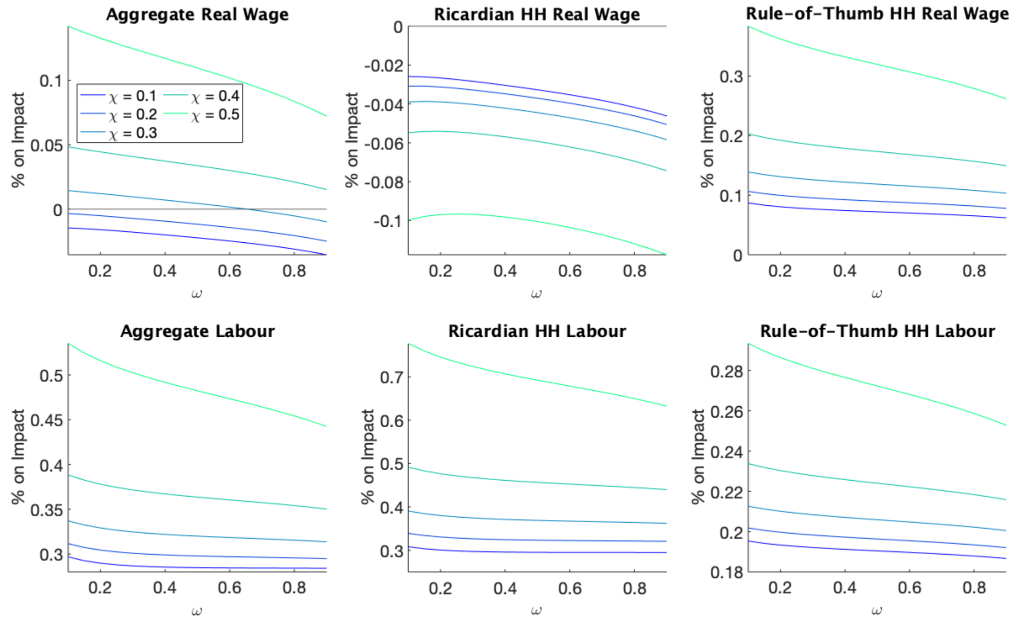

Figure C.4. Response of Wage as a Function of Varying Inattentiveness of Workers and χ the Fraction of Rule-of-Thumb Households

Note: ω closer to 0 indicate more sticky information.

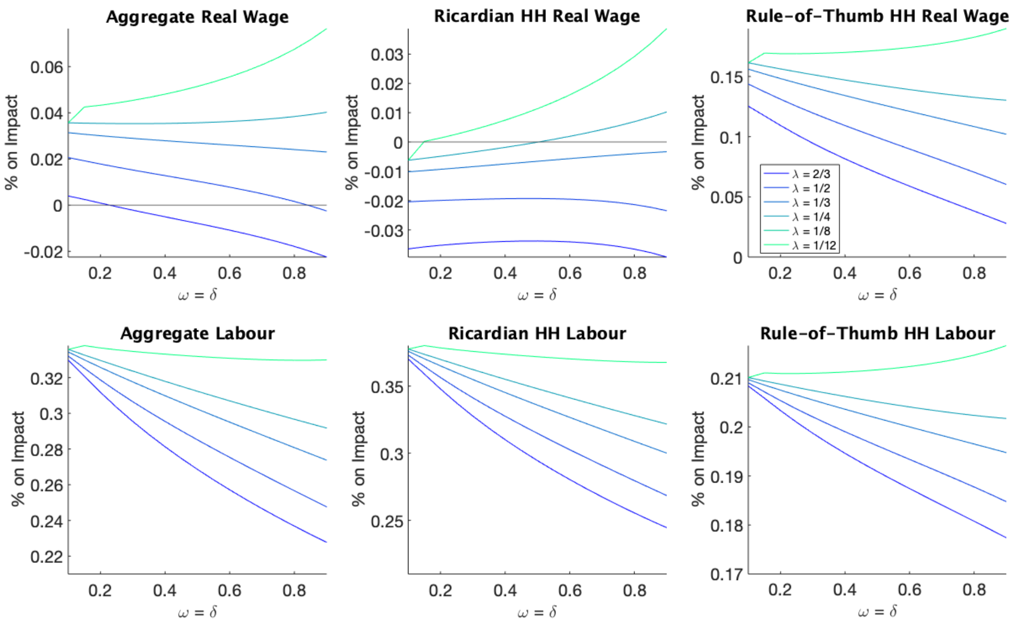

Figure C.5. Response of Wage as a Function of Varying Inattentiveness of Households $\delta = \omega$ and Firms λ

Note: A value of δ, ω and λ closer to 0 indicate more sticky information.

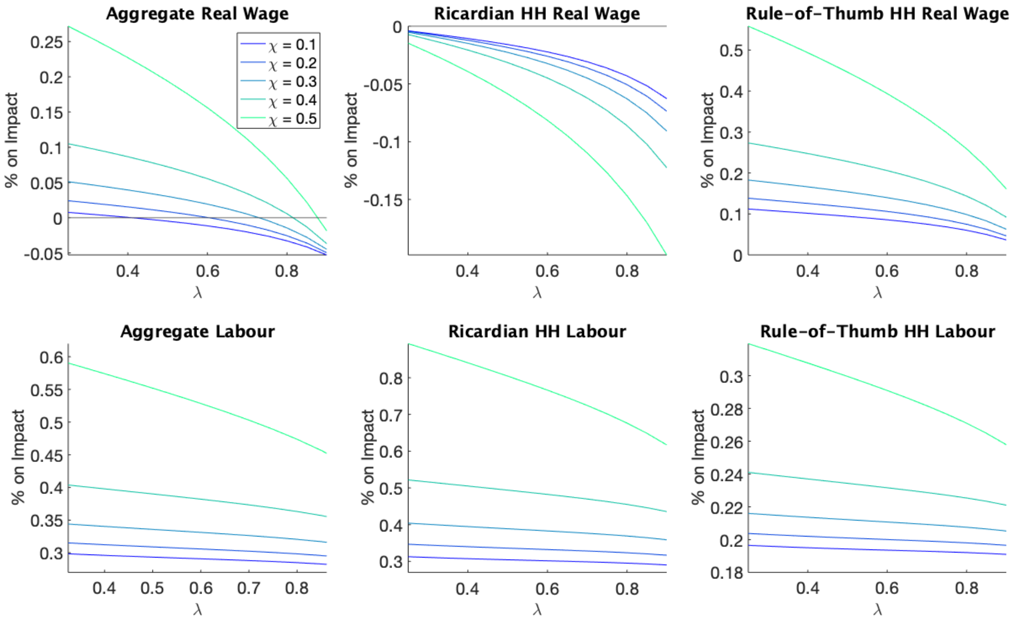

Figure C.6. Response of Wage as a Function of Varying Inattentiveness Firms and Fraction of Rule-of-Thumb Households

Note: λ closer to 0 indicate more sticky information. χ is the fraction of rule-of-thumb households.

Bibliography

Aastveit, K. A., Natvik, G. J., and Sola, S. (2017). Economic Uncertainty and the Influence of Monetary Policy. *Journal of International Money and Finance*, 76:50–67.

Alloza, M. (2017). Is Fiscal Policy More Effective in Uncertain Times or During Recessions? *Banco de Espana Working Paper No. 1730*.

Andrade, P., Crump, R. K., Eusepi, S., and Moench, E. (2016). Fundamental Disagreement. *Journal of Monetary Economics*, 83:106–128.

Andrade, P. and Le Bihan, H. (2013). Inattentive Professional Forecasters. *Journal of Monetary Economics*, 60(8):967–982.

Auerbach, A. J. and Gorodnichenko, Y. (2012). Measuring the Output Responses to Fiscal Policy. *American Economic Journal: Economic Policy*, 4(2):1–27.

Auerbach, A. J. and Gorodnichenko, Y. (2013). Fiscal Multipliers in Recession and Expansion. *Fiscal Policy after the Financial Crisis*, page 63.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics*, 131(4):1593–1636.

Basu, S. and Kimball, M. (2003). Investment Planning Costs and the Effects of Fiscal and Monetary Policy. *University of Michigan manuscript*.

Bernanke, B. S. (2020). The New Tools of Monetary Policy. *American Economic Review*, 110(4):943–83.

Bernanke, B. S. and Gertler, M. (1995). Inside the Black Box: The Credit Channel of Monetary Policy Transmission. *Journal of Economic Perspectives*, 9(4):27–48.

Bilbiie, F. O. (2011). Nonseparable Preferences, Frisch Labor Supply, and the Consumption Multiplier of Government Spending: One Solution to a Fiscal Policy Puzzle. *Journal of Money, Credit and Banking*, 43(1):221–251.

Bils, M. and Klenow, P. J. (2004). Some Evidence on the Importance of Sticky Prices. *Journal of Political Economy*, 112(5):947–985.

Biolsi, C. (2017). Nonlinear Effects of Fiscal Policy over the Business Cycle. *Journal of Economic Dynamics and Control*, 78:54–87.

Blanchard, O. and Perotti, R. (2002). An Empirical Characterization of the Dynamic Effects of Changes in Government Spending and Taxes on Output. *the Quarterly Journal of Economics*, 117(4):1329–1368.

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

Bok, B., Caratelli, D., Giannone, D., Sbordone, A. M., and Tambalotti, A. (2018). Macroeconomic Nowcasting and Forecasting with Big Data. *Annual Review of Economics*, 10:615–643.

Bomberger, W. A. (1996). Disagreement as a Measure of Uncertainty. *Journal of Money, Credit and Banking*, 28(3):381–392.

Bouakez, H. and Rebei, N. (2007). Why does Private Consumption Rise after a Government Spending Shock? *Canadian Journal of Economics/Revue Canadienne d'économique*, 40(3):954–979.

Brinca, P., Faria-e Castro, M., Homem Ferreira, M., and Holter, H. (2019). The Nonlinear Effects of Fiscal Policy. *FRB St. Louis Working Paper*, (2019-15).

Burnside, C., Eichenbaum, M., and Fisher, J. D. (2004). Fiscal Shocks and Their Consequences. *Journal of Economic Theory*, 115(1):89–117.

Caggiano, G., Castelnuovo, E., Colombo, V., and Nodari, G. (2015). Estimating Fiscal Multipliers: News from a Non-Linear World. *The Economic Journal*, 125(584):746–776.

Caggiano, G., Castelnuovo, E., and Groshenny, N. (2014). Uncertainty Shocks and Unemployment Dynamics in US Recessions. *Journal of Monetary Economics*, 67:78–92.

Campbell, J. R., Evans, C. L., Fisher, J. D., Justiniano, A., Calomiris, C. W., and Woodford, M. (2012). Macroeconomic Effects of Federal Reserve Forward Guidance [with Comments and Discussion]. *Brookings Papers on Economic Activity*, pages 1–80.

Carroll, C. D. (2003). Macroeconomic Expectations of Households and Professional Forecasters. *The Quarterly Journal of Economics*, 118(1):269–298.

Castelnuovo, E. and Pellegrino, G. (2018). Uncertainty-Dependent Effects of Monetary Policy Shocks: A New-Keynesian Interpretation. *Journal of Economic Dynamics and Control*.

Cesa-Bianchi, A., Thwaites, G., and Vicondoa, A. (2020). Monetary Policy Transmission in the United Kingdom: A High Frequency Identification Approach. *European Economic Review*, 123:103375.

Champagne, J. and Sekkel, R. (2018). Changes in Monetary Regimes and the Identification of Monetary Policy Shocks: Narrative Evidence from Canada. *Journal of Monetary Economics*, 99:72–87.

Christiano, L., Eichenbaum, M., and Rebelo, S. (2011). When is the Government Spending Multiplier Large? *Journal of Political Economy*, 119(1):78–121.

Christiano, L. J., Eichenbaum, M., and Evans, C. (1996). The Effects of Monetary Policy Shocks: Some Evidence from the Flow of Funds. *The Review of Economics and Statistics*, 78(1):16–34.

Christiano, L. J., Eichenbaum, M., and Evans, C. L. (1999). Monetary Policy Shocks: What Have We Learned and to What End? *Handbook of Macroeconomics*, 1:65–148.

Cloyne, J. and Hürtgen, P. (2016). The Macroeconomic Effects of Monetary Policy: A New Measure for the United Kingdom. *American Economic Journal: Macroeconomics*, 8(4):75–102.

Cochrane, J. H. and Piazzesi, M. (2002). The Fed and Interest Rates – A High-Frequency Identification. *American Economic Review*, 92(2):90–95.

Cogan, J. F., Cwik, T., Taylor, J. B., and Wieland, V. (2010). New Keynesian versus Old Keynesian Government Spending Multipliers. *Journal of Economic Dynamics and control*, 34(3):281–295.

Coibion, O., Gorodnichenko, Y., Kueng, L., and Silvia, J. (2017). Innocent Bystanders? Monetary Policy and Inequality. *Journal of Monetary Economics*, 88:70–89.

Coibion, O., Gorodnichenko, Y., and Kumar, S. (2018a). How do Firms Form Their Expectations? New Survey Evidence. *American Economic Review*, 108(9):2671–2713.

Coibion, O., Gorodnichenko, Y., Kumar, S., and Pedemonte, M. (2018b). Inflation Expectations as a Policy Tool? Technical report, National Bureau of Economic Research.

d'Alessandro, A., Fella, G., and Melosi, L. (2019). Fiscal Stimulus with Learning-by-Doing. *International Economic Review*, 60(3):1413–1432.

D'Amico, S. and Orphanides, A. (2008). Uncertainty and Disagreement in Economic Forecasting. *Finance and Economics Discussion Series 2008-56, Board of Governors of the Federal Reserve System (U.S.), revised 2008.*

Dincer, N., Eichengreen, B., and Geraats, P. (2019). Transparency of Monetary Policy in the Postcrisis World. *The Oxford Handbook of the Economics of Central Banking*, page 287.

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

Edelberg, W., Eichenbaum, M., and Fisher, J. D. (1999). Understanding the Effects of a Shock to Government Purchases. *Review of Economic Dynamics*, 2(1):166–206.

Falck, E., Hoffmann, M., and Hürtgen, P. (2019). Disagreement about Inflation Expectations and Monetary Policy Transmission. *Journal of Monetary Economics*.

Fatás, A. and Mihov, I. (2001). The Effects of Fiscal Policy on Consumption and Employment: Theory and Evidence. *CEPR Discussion Paper*, 2760.

Frisch, R. and Waugh, F. V. (1933). Partial Time Regressions as Compared with Individual Trends. *Econometrica: Journal of the Econometric Society*, pages 387–401.

Furlanetto, F. (2011). Fiscal Stimulus and the Role of Wage Rigidity. *Journal of Economic Dynamics and Control*, 35(4):512–527.

Galí, J. (2015). *Monetary Policy, Inflation, and the Business Cycle: An Introduction to the New Keynesian Framework and its Applications*. Princeton University Press.

Galí, J., López-Salido, J. D., and Vallés, J. (2007). Understanding the Effects of Government Spending on Consumption. *Journal of the European Economic Association*, 5(1):227–270.

Galvão, A. B. C. (2006). Structural Break Threshold VARs for Predicting US Recessions Using the Spread. *Journal of Applied Econometrics*, 21(4):463–487.

Ganelli, G. and Tervala, J. (2009). Can Government Spending Increase Private Consumption? The Role of Complementarity. *Economics Letters*, 103(1):5–7.

Geraats, P. M. (2002). Central Bank Transparency. *The Economic Journal*, 112(483):F532–F565.

Gertler, M. and Karadi, P. (2015). Monetary Policy Surprises, Credit Costs, and Economic Activity. *American Economic Journal: Macroeconomics*, 7(1):44–76.

Giordani, P. and Söderlind, P. (2003). Inflation Forecast Uncertainty. *European Economic Review*, 47(6):1037–1059.

Gordon, R. J. and Krenn, R. (2010). The End of the Great Depression: VAR Insight on the Roles of Monetary and Fiscal Policy. *NBER Working paper*, 16380:183–231.

Granger, C. W. and Terasvirta, T. (1993). Modelling Non-Linear Economic Relationships. *Oxford University Press*.

Grimme, C., Henzel, S. R., and Wieland, E. (2014). Inflation Uncertainty Revisited: A Proposal for Robust Measurement. *Empirical Economics*, 47(4):1497–1523.

Hurst, E. (2003). Grasshoppers, Ants, and Pre-Retirement Wealth: A Test of Permanent Income. *NBER Working Papers*, 10098.

Jacob, P. (2015). Deep Habits, Price Rigidities, and the Consumption Response to Government Spending. *Journal of Money, Credit and Banking*, 47(2-3):481–510.

Jordà, Ò. (2005). Estimation and Inference of Impulse Responses by Local Projections. *American Economic review*, 95(1):161–182.

Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring Uncertainty. *The American Economic Review*, 105(3):1177–1216.

Klenow, P. J. and Kryvtsov, O. (2008). State-Dependent or Time-Dependent Pricing: Does It Matter for Recent US Inflation? *The Quarterly Journal of Economics*, 123(3):863–904.

Koop, G., Pesaran, M. H., and Potter, S. M. (1996). Impulse Response Analysis in Nonlinear Multivariate Models. *Journal of Econometrics*, 74(1):119–147.

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

Lahiri, K. and Sheng, X. (2010). Measuring Forecast Uncertainty by Disagreement: The Missing Link. *Journal of Applied Econometrics*, 25(4):514–538.

Leeper, E. M., Walker, T. B., and Yang, S.-C. S. (2013). Fiscal Foresight and Information Flows. *Econometrica*, 81(3):1115–1145.

Linnemann, L. and Schabert, A. (2004). Can Fiscal Spending Stimulate Private Consumption? *Economics Letters*, 82(2):173–179.

Lo, M. C. and Piger, J. M. (2005). Is the Response of Output to Monetary Policy Asymmetric? Evidence from A Regime-Switching Coefficients Model. *Journal of Money, Credit, and Banking*, 37(5):865–886.

Lorenzoni, G. (2009). A Theory of Demand Shocks. *American Economic Review*, 99(5):2050–84.

Lovell, M. C. (1963). Seasonal Adjustment of Economic Time Series and Multiple Regression Analysis. *Journal of the American Statistical Association*, 58(304):993–1010.

Lucas, R. E. (1972). Expectations and the Neutrality of Money. *Journal of Economic Theory*, 4(2):103–124.

Maćkowiak, B. and Wiederholt, M. (2009). Optimal Sticky Prices under Rational Inattention. *The American Economic Review*, 99(3):769–803.

Maćkowiak, B. and Wiederholt, M. (2015). Business Cycle Dynamics under Rational Inattention. *The Review of Economic Studies*, 82(4):1502–1532.

Mankiw, N. G. and Reis, R. (2002). Sticky Information versus Sticky Prices: a Proposal to Replace the New Keynesian Phillips Curve. *The Quarterly Journal of Economics*, 117(4):1295–1328.

Mankiw, N. G. and Reis, R. (2007). Sticky Information in General Equilibrium. *Journal of the European Economic Association*, 5(2-3):603–613.

Mankiw, N. G., Reis, R., and Wolfers, J. (2004). Disagreement about Inflation Expectations. *NBER Macroeconomics Annual 2003*, 18:209–248.

Menkulasi, J. (2009). Rational Inattention and Changes in Macroeconomic Volatility. *University of Maryland, Working Paper*.

Mertens, K. and Ravn, M. O. (2013). The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States. *American Economic Review*, 103(4):1212–47.

Miranda-Agrippino, S. and Ricco, G. (2020). The Transmission of Monetary Policy Shocks. *American Economic Journal: Macroeconomics (Forthcoming)*.

Monacelli, T. and Perotti, R. (2008). Fiscal Policy, Wealth Effects, and Markups. *NBER Working Papers*, 14584.

Mountford, A. and Uhlig, H. (2009). What are the Effects of Fiscal Policy Shocks? *Journal of Applied Econometrics*, 24(6):960–992.

Murphy, D. P. (2015). How can Government Spending Stimulate Consumption? *Review of Economic Dynamics*, 18(3):551–574.

Nakamura, E. and Steinsson, J. (2008). Five Facts about Prices: A Reevaluation of Menu Cost Models. *The Quarterly Journal of Economics*, 123(4):1415–1464.

Nakamura, E. and Steinsson, J. (2018). High-Frequency Identification of Monetary Non-Neutrality: The Information Effect. *The Quarterly Journal of Economics*, 133(3):1283–1330.

Newey, W. K. and West, K. D. (1994). Automatic Lag Selection in Covariance Matrix Estimation. *The Review of Economic Studies*, 61(4):631–653.

Nunes, R. (2009). On the Epidemiological Microfoundations of Sticky Information. *Oxford Bulletin of Economics and Statistics*, 71(5):643–657.

Oh, H. and Reis, R. (2012). Targeted Transfers and the Fiscal Response to the Great Recession. *Journal of Monetary Economics*, 59:S50–S64.

Park, K. (2019). Uncertainty, Attention Allocation and Monetary Policy Asymmetry. *Bank of Korea Working Paper*, 5.

Patton, A. J. and Timmermann, A. (2010). Why do Forecasters Disagree? Lessons from the Term Structure of Cross-Sectional Dispersion. *Journal of Monetary Economics*, 57(7):803–820.

Peersman, G. and Smets, F. (2001). The Monetary Transmission Mechanism in the Euro Area. *ECB Working Paper 91*.

Pellegrino, G. (2018). Uncertainty and Monetary Policy in the US: A Journey into Non-Linear Territory. *Melbourne Institute Working Paper Series*.

Perotti, R., Reis, R., and Ramey, V. (2007). In Search of the Transmission Mechanism of Fiscal Policy [with comments and discussion]. *NBER Macroeconomics Annual*, 22:169–249.

Plagborg-Møller, M. and Wolf, C. K. (2020). Local Projections and VARs Estimate the Same Impulse Responses. *Econometrica (Forthcoming)*.

Ramey, V. A. (2008). Comment on" In Search of the Transmission Mechanism of Fiscal Policy". In *NBER Macroeconomics Annual 2007, Volume 22*, pages 237–246. University of Chicago Press.

Ramey, V. A. (2011). Identifying Government Spending Shocks: It's All in the Timing. *The Quarterly Journal of Economics*, 126(1):1–50.

Ramey, V. A. (2016). Macroeconomic Shocks and Their Propagation. In *Handbook of Macroeconomics*, volume 2, pages 71–162. Elsevier.

Ramey, V. A. and Shapiro, M. D. (1998). Costly Capital Reallocation and the Effects of Government Spending. In *Carnegie-Rochester Conference Series on Public Policy*, volume 48, pages 145–194. Elsevier.

Ramey, V. A. and Zubairy, S. (2018). Government Spending Multipliers in Good Times and in Bad: Evidence from US Historical Data. *Journal of Political Economy*, 126(2):850–901.

Ravn, M. O., Schmitt-Grohé, S., and Uribe, M. (2007). Explaining the Effects of Government Spending Shocks on Consumption and the Real Rate. *NBER Working Papers*, 13328.

Reis, R. (2006a). Inattentive Consumers. *Journal of Monetary Economics*, 53(8):1761–1800.

Reis, R. (2006b). Inattentive Producers. *The Review of Economic Studies*, 73(3):793–821.

Reis, R. (2009). A Sticky-Information General Equilibrium Model for Policy Analysis. *Documentos de Trabajo (Banco Central de Chile)*, (495):1.

Reis, R. (2018). Comment on "Inflation Expectations – a Policy Tool?" by Olivier Coibion, Yuriy Gorodnicheko, Saten Kumar and Mathieu Pedemonte.

Romer, C. D. and Romer, D. H. (2004). A New Measure of Monetary Shocks: Derivation and Implications. *American Economic Review*, 94(4):1055–1084.

Romer, C. D. and Romer, D. H. (2016). Transfer Payments and the Macroeconomy: The Effects of Social Security Benefit Increases, 1952-1991. *American Economic Journal: Macroeconomics*, 8(4):1–42.

Rossi, B. and Sekhposyan, T. (2015). Macroeconomic Uncertainty Indices Based on Nowcast and Forecast Error Distributions. *American Economic Review*, 105(5):650–55.

Sill, K. (2014). Forecast Disagreement in the Survey of Professional Forecasters. *Business Review*, (Q2):15–24.

Sims, C. A. (1992). Interpreting the Macroeconomic Time Series Facts: The Effects of Monetary Policy. *European Economic Review*, 36(5):975–1000.

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

Sims, C. A. (2010). Rational Inattention and Monetary Economics. *Handbook of Monetary Economics*, 3:155–181.

Smets, F. and Wouters, R. (2007). Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach. *American Economic review*, 97(3):586–606.

Stock, J. H. and Watson, M. W. (2002). Has the Business Cycle Changed and Why? *NBER Macroeconomics Annual*, 17:159–218.

Stock, J. H. and Watson, M. W. (2003). Has the Business Cycle Changed? Evidence and Explanations. *Monetary Policy and Uncertainty: Adapting to a Changing Economy*, pages 9–56.

Tenreyro, S. and Thwaites, G. (2016). Pushing on a String: US Monetary Policy is Less Powerful in Recessions. *American Economic Journal: Macroeconomics*, 8(4):43–74.

Tsay, R. S. (1998). Testing and Modeling Multivariate Threshold Models. *Journal of the American Statistical Association*, 93(443):1188–1202.

Uhlig, H. (2010). Some Fiscal Calculus. *American Economic Review*, 100(2):30–34.

Vavra, J. (2013). Inflation Dynamics and Time-Varying Volatility: New Evidence and an Ss Interpretation. *The Quarterly Journal of Economics*, 129(1):215–258.

Verona, F. and Wolters, M. H. (2014). Sticky Information Models in Dynare. *Computational Economics*, 43(3):357–370.

Wieland, J. F. and Yang, M.-J. (2020). Financial Dampening. *Journal of Money, Credit and Banking*, 52(1):79–113.

Wu, J. C. and Xia, F. D. (2016). Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound. *Journal of Money, Credit and Banking*, 48(2-3):253–291.

Zhang, F. (2017). Rational Inattention in Uncertain Business Cycles. *Journal of Money, Credit and Banking*, 49(1):215–253.