Essays on Monetary Economics and Applied Macroeconomics

Donghai Zhang

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DIRECTORS DE LA TESI
Davide Debortoli i Barbara Rossi

Departament d'Economia i Empresa

To my parents.

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Abstract

This thesis consists three chapters on topics in monetary economics and applied macroeconomics. In the first chapter, I consider a framework where the central bank has private information about future economic conditions. Agents update their beliefs according to Bayes' theorem. Policy actions play a signaling role, and may therefore have an impact on both short and long-term interest rates. I discuss the implications of information frictions for the design of optimal simple rule. In the second chapter, I explore the role of market power for the optimal choice of inflation index for a central bank to stabilize In a framework with cross-sector heterogeneities in both nominal rigidity and market power. The optimal weight attached to inflation in a sector is increasing in this sector's: i) price stickiness (stickiness channel) and ii) degree of market competition (competition channel). Moreover, if firms in a more competitive sector adjust their price more frequently as predicted by costly price adjustment models, the competition channel offsets the stickiness channel. In the third chapter, I show that for short horizon exchange rate predictability, the simple random walk model outperforms professional forecasts. A new puzzle arises: why do professional forecasters not adopt the simple random walk model to provide a more accurate estimate? I provide an explanation based on ambiguity averse forecasters.

Resum

Aquesta tesi està compresa per tres capítols que tracten temes en economia monetària i macroeconomia aplicada. En el primer capítols considero un marc teòric en el qual el banc central té informació privada respecte les condicions econòmiques futures. Els agents econòmics actualitzen les seves creences en base al teorema de Bayes. Les accions del banc tenen un paper senyalador, i poden tenir un impacte en els tipus d'interès a curt i llarg termini. En aquest marc, discuteixo el paper de les friccions de la informació a l'hora de dissenyar una regla monetària simple. En el segon capítols exploro el paper del poder de mercat en l'elecció òptima de l'índex de preus a ser estabilitzat. En aquest cas considero un marc teòric en el qual les rigideses nominals i el poder de mercat difereixen entre sectors. El pes òptim assignat a la inflació d'un sector és creixent en la rigidesa dels preus (efecte rigidesa) i en el nivell de competició (efecte competició) d'aquest sector. Si les empreses en un sector competitiu ajusten els preus més freqüentment, tal com prediuen els models que consideren un ajust de preus costós, l'efecte competició contrarestarà l'efecte rigidesa. Finalment, en el tercer capítols , demostro que per a predir els tipus de canvi a curt termini, un simple model random walk supera les prediccions professionals. D'aquesta observació sorgeix una nova incògnita: per què els professionals no adopten un model random walk per oferir unes prediccions més encertades? En aquest capítols mostro com tal incògnita es pot explicar en base a l'aversió a l'ambigüitat dels professionals.

Preface

This thesis consists three chapters on topics in monetary economics and applied macroeconomics. The first chapter of the thesis studies the information channel of monetary policy in a model where the central bank has superior information regarding news shock. Monetary policy shocks affect interest rates at long horizons (10 years or more). Furthermore, the private sector's real GDP forecasts are revised upward in response to a monetary tightening. These facts challenge the prevailing theories in academic and policy circles, which are based on the paradigm that monetary policy has limited long-run effects and a monetary policy tightening should depress agents? beliefs about real GDP. In this paper, I propose a micro-founded model to rationalize those facts, based on the information channel of monetary policy. I consider a framework where the central bank has private information about future economic conditions. Agents update their beliefs according to Bayes' theorem. Policy actions play a signaling role, and may therefore have an impact on both short and long-term interest rates. Moreover, I provide novel empirical facts that the aforementioned responses are stronger when monetary shocks are expansionary. An extension of the model with ambiguity averse agents and ambiguous signals rationalizes such an asymmetry. Finally, I discuss the implications of information frictions for the design of optimal simple rule.

The second chapter explores the role of market power for the design of the optimal monetary policy. Existing empirical evidence suggest cross-sector heterogeneities in both nominal rigidity and market power. This paper studies the optimal choice of inflation index for a central bank to stabilize in a framework that embeds those features. The optimal weight attached to inflation in a sector is increasing in this sector's: i) price stickiness (stickiness channel) and ii) degree of market competition (competition channel). Moreover, if firms in a more competitive sector adjust their price more frequently as predicted by costly price adjustment models, the competition channel offsets the stickiness channel. The finding challenges the conventional wisdom that the central bank should attach a higher weight to a sector with a higher degree of nominal rigidity, and supports the current practice of central banks around the world (CPI targeting).

In the third chapter, I propose and rationalize puzzles related to the professional forecasts of exchange rates. For short horizon exchange rate predictability, the simple random walk model outperforms professional forecasts. A new puzzle arises: why do professional forecasters not adopt the simple random walk model to provide a more accurate estimate? This paper provides an explanation. In this framework, the forecaster faces model uncertainty and reports the forecast that minimizes the forecast error under the worst-case scenario. Therefore professional forecasts are intentionally suboptimal. Estimation results show that the model matches the empirical puzzle. In addition, the model predicts that the forecaster substantially underreacts to current news, which is consistent with empirical facts provided in this paper. Moreover, the null of ”rationality” is rejected using simulated data confirming existing findings even though forecasters in the model perform optimally.

Contents

Chapter 1

TERM STRUCTURE, FORECAST REVISION AND THE INFORMATION CHANNEL OF MONETARY POLICY

1.1 Introduction

I emphasize two facts that are inconsistent with the predictions of a standard New Keynesian (NK thereafter) model. **Fact 1**: monetary policy shocks affect long-term interest rates (10 years or more). And **Fact 2**: the private sector's real GDP forecasts are revised upward in response to a monetary tightening.[1] Since the long-term rate is the weighted average of the current and expected future short-term rate, the significant impacts of monetary shocks on long-term rates imply that monetary policy shocks have highly persistent effects on the real economy for more than 10 years! Clearly, this is contradictory to NK models, which are based on the paradigm that monetary policy has limited long-run impacts. Moreover, NK models predict that agents' expected real GDP is revised downward in response to a monetary tightening. A sign that is the opposite of what we observe in data!

The goal of this paper is to provide a micro-founded model that rationalizes those facts. I consider a framework where the central bank has private information about future economic conditions. Agents update their beliefs according to Bayes' rule. Policy actions play a signaling role, and may thus generate the aforementioned empirical facts. I can then discuss policy implications.

In the first part of the paper, I present the empirical framework. I employ monetary surprises, constructed using High Frequency Identification (HFI thereafter) strategy,[2] as instrumental variables (IV). The basic idea behind the HFI strategy is that financial contracts reflect the market's beliefs about future monetary actions. Thus, the tick-by-tick data on Federal Funds futures and Eurodollar futures enable us to construct monetary surprises within 30-minute surrounding the FOMC announcements. The tight window (30 minutes) ensures that those identified measures are true

[1] See Romer and Romer (2000), Gürkaynak, Sack and Swanson (2005*b*), Hanson and Stein (2015), Nakamura and Steinsson (2017) Gilchrist, López-Salido and Zakrajšek (2015), Campbell et al. (2012) and Hubert (2015) for similar results derived using alternative identification strategies.

[2] See the seminal work of Kuttner (2001) and Gürkaynak, Sack and Swanson (2005*a*) for the construction of monetary surprises.

surprises to the market.

However, monetary surprises are not necessarily monetary shocks. A monetary action might turn out as a surprise to the market when the central bank observes/anticipates a change in economic condition that is not fully understood by the market. Whereas, a monetary shock is defined as the central bank's exogenous deviation from a monetary policy rule that is unrelated to economic conditions. Thus, the HFI monetary surprises are subject to the endogeneity problem.

To address this endogeneity problem, I control for two sets of variables in the IV approach. The first set of variables are Greenbook forecasts[3], which is a proxy for the central bank's information set. The second set of variables are factors that are constructed from more than 100 macroeconomic time series, which are good representations of fundamental shocks yet orthogonal to monetary policy.[4] The identification assumption is that, once those variables are controlled for, the HFI monetary surprises are exogenous.

In the baseline empirical framework, I obtain the following results. In response to a monetary shock that increases the monetary instrument by 100 basis points, the nominal interest rate with a maturity of 10 years increases by 50 basis points on impact. And, the private sector's real GDP forecasts are revised upward in response to a monetary tightening. From the NK perspective, the first fact is a quantitative puzzle and the second puzzle a qualitative one.

[3]The Fed's internal forecasts that are only available with a lag of five years. A similar approach is taken by Romer and Romer (2004) to construct R&R monetary shocks from fed funds rate and by Miranda-Agrippino (2016), Lakdawala (2016) and Campbell et al. (2016) to clean HFI monetary surprise.

[4]In Loria et al. (2017), we project HFI monetary surprises on those factors to address the endogeneity problem.

In the second part of the paper, I propose a novel framework to rationalize the aforementioned empirical facts. I consider a simple NK model where the central bank has private information about the productivity trend,[5] which is not perfectly observed by private agents. As a result, private agents might interpret an expansionary (negative) monetary surprise in two different ways. First, it can be interpreted as the Fed's endogenous response to a worse than expected long-term productivity trend. If this is the case, private expectation regarding the productivity trend decreases and, consequently, the market's expectation regarding the natural real interest rate drops. If the productivity trend is persistent, which is the case empirically, the expectations regarding the natural real rate in the far future decreases. Thus, the long-term rate responds proportionally to a monetary surprise. Alternatively, an expansionary monetary surprise can be interpreted as a pure monetary shock. If this is the case, it contains no information about the unobserved productivity trend, and therefore expectations about the trend and the natural real interest rate are not affected. In my framework, since private agents cannot distinguish a shock to productivity trend from a monetary policy shock, optimal belief updating (Bayes' rule) requires that agents assign weights to both interpretations. Thus, in response to a negative monetary surprise (driven by a pure monetary shock or a shock to productivity trend) both the perceived trend and the perceived natural real rate drop. Hence long-term interest rates decrease and expected real GDP in the next quarters drop. The model is estimated using the Bayesian method.

Three main results stand out. First, the model with asymmetric information rationalizes both Fact 1 and Fact 2. Second, the information

[5]Shocks to the productivity trend can be interpreted as news shocks as discussed in Barsky and Sims (2012).

channel dampens the traditional effect of monetary policy via an intertemporal substitution effect. On the one hand, via the conventional channel, a higher interest rate leads to a higher saving rate by reducing the aggregate consumption. On the other hand, a positive monetary shock is partially interpreted, as the future economic condition will be better than previously expected. Through the second channel, consumers have the desire to consume more. Overall, the aggregate impact of a monetary shock is smaller as compared to an NK model with perfect information. Third, information asymmetry does not change the optimal simple rule. In this model, the welfare lost under the optimal simple rule is 1.04% (as a fraction of steady state consumption). Whereas, the welfare loss is 1.05% if the central bank follows a "naive" optimal simple rule — the optimal rule derived under the assumption that the private market has perfect information. The difference is minimal.

In addition, I uncover novel empirical facts that the aforementioned effects of monetary shocks on long-term rates and real GDP forecasts are asymmetric. The responses are more pronounced (more puzzling) when the monetary shocks are expansionary. A simple extension of the baseline model rationalizes those asymmetric facts, based on signals of uncertain qualities and ambiguity averse agents. Moreover, the model predicts the asymmetric effects of monetary shocks on output and inflation, which are consistent with empirical facts discovered in the empirical literature[6].

Related Literature The empirical part of the paper is related to the literature that studies the impacts of FOMC announcements on the yield curve and private agents' forecasts. See for example Romer and Romer

[6]See for example Barnichon and Matthes (2016).

(2000), Gürkaynak, Sack and Swanson (2005*b*), Hanson and Stein (2015), Nakamura and Steinsson (2017), Gilchrist, López-Salido and Zakrajšek (2015) and Campbell et al. (2012). Unlike in the existing literature, I employ relevant control variables to address the potential endogeneity problem discussed above[7]. This allows us to interpret the estimated responses as the market's reactions to exogenous monetary shocks (actions).

This paper contributes to the literature on the information channel of monetary policy actions. Earlier works include Cukierman and Meltzer (1986), Ellingsen and Soderstrom (2001). Erceg and Levin (2003), Kozicki and Tinsley (2005) and Gürkaynak, Sack and Swanson (2005*b*). And recent studies include Baeriswyl and Cornand (2010), Tang (2015), Melosi (2017) and Falck, Hoffmann and Hurtgen (2017). In contrast to previous studies, this paper introduces asymmetric information about news shocks and argues that consumers extract information about the future economic condition from a monetary policy action. This is crucial to rationalize the empirical facts that I discuss in this paper. In another closely related paper, Nakamura and Steinsson (2017) emphasize the information effects of FOMC statements. Unlike in their work, I build a model that endogenizes the signal extraction process and I use it to assess the role of the signaling channel of monetary actions in explaining the two empirical puzzles. Moreover, this micro-foundation allows us to study extensions of the model such as the one presented in the last part of this paper.

More broadly, this paper adds to the literature that has focused on money non-neutrality arising from imperfect information. In his island

[7]Miranda-Agrippino (2016), Lakdawala (2016), Campbell et al. (2016) and Loria et al. (2017) also clean those HFI monetary surprises in their VAR analysis that studies the impacts of monetary shocks on real activities such as industrial production and inflation.

model, Lucas (1972) shows that money non-neutrality arises from the imperfect knowledge regarding those nominal disturbances. Woodford (2002), Sims (2003), Mackowiak and Wiederholt (2009) and Mankiw and Reis (2002) provide alternative frameworks in which the real effect of a monetary shock emerges from information friction. In contrast, in this paper, money non-neutrality arises from price stickiness and the presence of information asymmetry dampens the impacts of monetary shocks.

The last part of the paper relates to the recent literature that studies the implications of ambiguity and signals of uncertain qualities in macroeconomics and finance. Epstein and Schneider (2008) provide the first argument that ambiguity averse agents react to signals of uncertain qualities asymmetrically. Based on the same ambiguity structure, recent applications include Ilut (2012), Ilut, Kehrig and Schneider (2015), Baqaee (2017) and Michelacci and Paciello (2017). This paper adapts the same idea to a framework in which the central bank's action plays a signaling role. And I study the implications for the dynamics of economic activities to monetary shocks.

The remainder of the paper is organized as follows. Section (1.2) presents empirical facts. Section (1.3) introduces the baseline model. Section (1.4) estimates the model and discusses implications of the model as compared to the basic New Keynesian model. Section (1.5) analyzes the implication for the design of optimal simple rule and central bank communication policy. Section (1.6) extends the model by introducing ambiguous signals and ambiguity averse agents. Section (1.7) presents the theoretical predictions of the extended model. And Section (1.8) concludes.

1.2 Empirical Facts

This section discusses empirical facts in details. Section 3.2.1 presents the impact effects of monetary shocks on the yield curve. Section 1.2.2 discusses the impact effects of monetary policy shocks on real GDP forecasts.

1.2.1 Fact 1: Impact Effect of Monetary Policy on Yield

In the baseline, I estimate regressions of the following form:

$$\triangle Y_t^h = \alpha^h + \beta^h \triangle MP_t + \gamma^h X_t + \epsilon_{h,t}, \tag{1.1}$$

where, $\triangle Y_t^h$ is the daily changes in nominal yield taken from Gürkaynak, Sack and Wright (2007). The superscript h denotes the maturity of the yield. $\triangle MP_t$ is the daily changes in the monetary policy instrument, two-year nominal yield nominal yield, surrounding the monetary policy decision date. The use of two-year nominal yield as a policy instrument is consistent with Gilchrist, López-Salido and Zakrajšek (2015), Gertler and Karadi (2015) and Hanson and Stein (2015). This is the common practice in the High Frequency Identification (HFI) literature to include forward guidance. It is debatable whether the daily change in the monetary instrument or the change in a tighter window (ex: 30-minute window surrounding FOMC announcement) is a better proxy for monetary surprise. Hanson and Stein (2015) argue in favor of the daily change to allow for the market to have sufficient time to digest the new information. Gürkaynak, Sack and Swanson (2005*a*) argue that the use of a tighter window (30 minutes) surrounding the FOMC announcement is desirable to minimize the noise. To combine the advantages of those two, I instrument the daily changes of $\triangle MP_t$ by monetary surprises constructed within a 30-minute window surrounding the FOMC announcements using data on the financial future[8]. [9]

However, due to the asymmetric information of the central bank and private agents, the HFI monetary surprises are subject to an endogeneity problem. To see this, in a world with asymmetric information, a non-monetary shock that is observed by the central bank but is not seen by private agents will be included in the HFI monetary surprises because the central bank's reaction to this unobserved shock comes as a surprise to private agents.

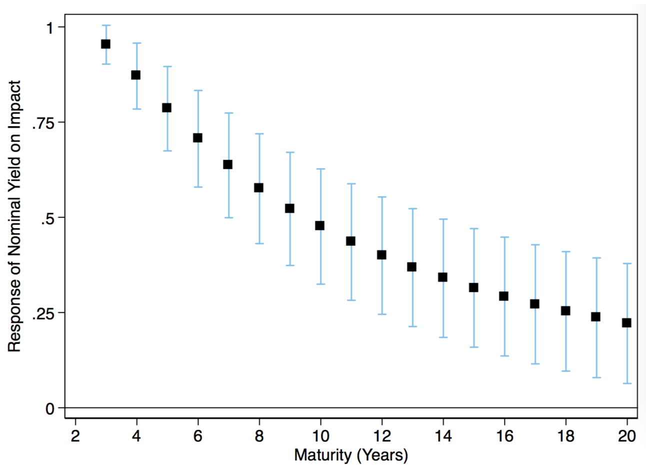
To address this endogeneity problem, I control for two sets of variables in the IV approach. The first set of variables are Greenbook forecasts, which is a proxy for the central bank's information set. Following Romer and Romer (2004), the Fed's internal forecasts of inflation, real output growth, and the unemployment rate are included in vector X_t. The second set of variables are real-time factors that are constructed from more than 100 macroeconomic time series, which are good representations of fundamental shocks yet orthogonal to monetary policy. Those are also included in vector X_t in order to ensure the exogeneity assumption of instruments. The underlying identification assumption is that those HFI monetary surprises are exogenous once controlled for Greenbook forecasts and factors. Intuitively, this approach is equivalent to the two-step approach: first, clean those HFI monetary surprises using Greenbook forecasts and factors; and second, use those cleaned monetary surprises

[8]I thank Refet Gurkaynak for providing the updated 30-minute window HFI monetary surprises.

[9]Gertler and Karadi (2015) use those HFI monetary surprises, the raw data, as instruments in a Structural Vector Autoregressive model.

as instruments. The one-step approach employed in this paper has the advantage that the standard errors are free of construction error, which would arise in the two steps approach. The construction of the factors is discussed in appendix (1.9.7). The baseline specification controls for five factors. The same number of factors are used in Ramey (2016). However, the results are robust to the use of different numbers of factors.

Figure 1.1: Responses of Nominal Yields at Different Maturities to Monetary Shocks



Note: The square dots represent the estimated $\hat{\beta}^h$ from separated regressions: $\triangle Y_t^h = \alpha^h + \beta^h \triangle MP_t + \gamma^h X_t + \epsilon_{h,t}$ using HFI monetary surprises as instruments for the variable of interest $\triangle MP_t$. The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 1990M2 to 2010M12.

For each h, I estimate a regression of the form (1.1) using HFI monetary surprises as instruments for the variable of interest $\triangle MP_t$. In the baseline, I employ eight instruments. These are: surprises in the current month's fed funds futures (FF1), in the one month, two month and three month ahead monthly fed funds futures (FF2, FF3, FF4), and in the three month, six month, nine month and year ahead futures on three month Eurodollar deposits (ED1, ED2, ED3, ED4). Results are robust to the use of smaller instrument sets. The F-statistics from the first-stage regression is reported in Table (1.6). As can be seen, the F-statistics from the first-stage regression for the baseline is 28.7 which is greater than the rule-of-thumb value 10 proposed by Stock and Yogo (2005). This suggests strong relevance of these instruments. The sample ranges from 1990M2 to 2010M12 due to the availability of HFI monetary surprises and Greenbook forecasts. Note that I exclude dates when there were large-scale asset purchasing announcements. However, the results are not affected if those are included.

Figure (1.1) plots the estimates of $\hat{\beta}$s from estimating separate regressions. The lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. As one can see, monetary shocks have persistent positive and significant effects on the entire yield curve. For instance, the nominal rate with maturity of 20 years increases by roughly 0.25 basis points in response to a 1 basis point exogenous increase in monetary instrument.

Asymmetric effect of monetary shock on the yield curve Next, I test whether the effects of monetary shocks on the yield curve are symmetric. To address this question, I estimate regressions of the following form:

$$\triangle Y_t^h = \alpha_1^h + \alpha_2^h I_{\text{-}negative} + \beta_1^h \triangle MP_t + \beta_2^h \triangle MP_t \times I_{\text{-}negative} + \gamma^h X_t + v_{h,t}, \tag{1.2}$$

where $I_{\text{-}negative}$ is the indicator variable that equals to 1 if $\triangle MP_t < 0$ and 0 otherwise. Again, $\triangle MP_t$ and $\triangle MP_t \times I_{\text{-}negative}$ are instrumented by HFI monetary surprises[10] and those interacting with $I(HFI < 0)$, the latter is the indicator variable that equals to 1 if the HFI monetary surprise is smaller than zero and 0 otherwise. The F-statistics from the first-stage regression is reported in the second and the third rows of Table (1.6). As can be seen, the F-statistics from the first-stage regression for the baseline is 84.7 for $\triangle MP_t$ and 75.3 for the interacting term $\triangle MP_t \times I_{\text{-}negative}$ suggesting strong relevance of these instruments.

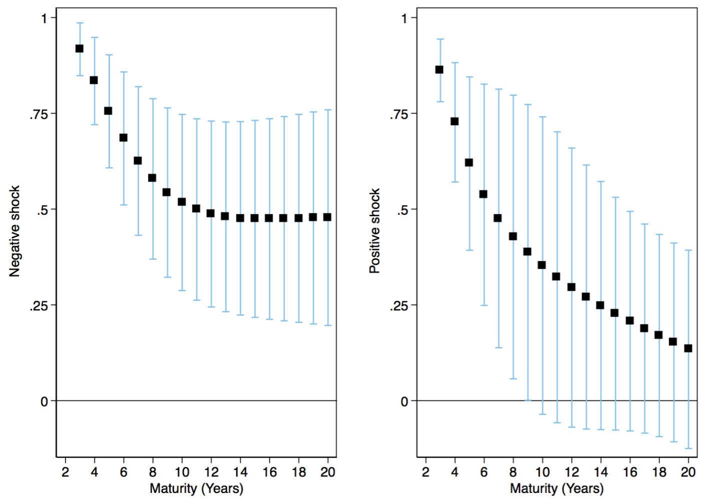
Surprisingly, as one can see from Figure (1.2), while a negative (expansionary) monetary shock has a significant effect on long-term yield, a positive monetary shock only affects yields with short maturities (up to 8 years).

Robustness Checks The results discussed in this section are robust to: i) the use of alternative instrument sets ii) excluding the recession periods, iii) excluding factors, iv) excluding Greenbook forecasts, v) excluding all control variables, vi) the use of inflation indexed forward rate (TIPSF) and vii) the use of Romer and Romer (2004) (R&R thereafter) monetary shocks. See Appendix 1.9.3 for detailed explanations and figures.

I emphasize that the results are robust to the use of R&R monetary shocks: an alternative measure of monetary shock that is often used in the literature. Those shocks are identified at monthly frequencies and are perceived as aggregate exogenous monetary shocks. Therefore, I use

[10]There are few episodes where there were more than one monetary announcement in a month, I sum up the monetary surprises to get the monthly data.

Figure 1.2: The Asymmetric Impact Effects of Monetary Shocks on Nominal Yields



Note: The square dots on the left panel represent the estimated $\hat{\beta}_1^h + \hat{\beta}_2^h$ and the square dots on the right panel represent the estimated $\hat{\beta}_1^h$, where $\hat{\beta}^h$s are estimated from separated regressions: $\triangle Y_t^h = \alpha_1^h + \alpha_2^h I_{\text{-}negative} + \beta_1^h \triangle MP_t + +\beta_2^h \triangle MP_t \times I_{\text{-}negative} + X_t + v_{h,t}$ using HFI monetary surprises and those interacted with $I(HFI < 0)$ as instruments for the variable of interest $\triangle MP_t$ and $\triangle MP_t \times I_{\text{-}negative}$. The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 1990M2 to 2010M12.

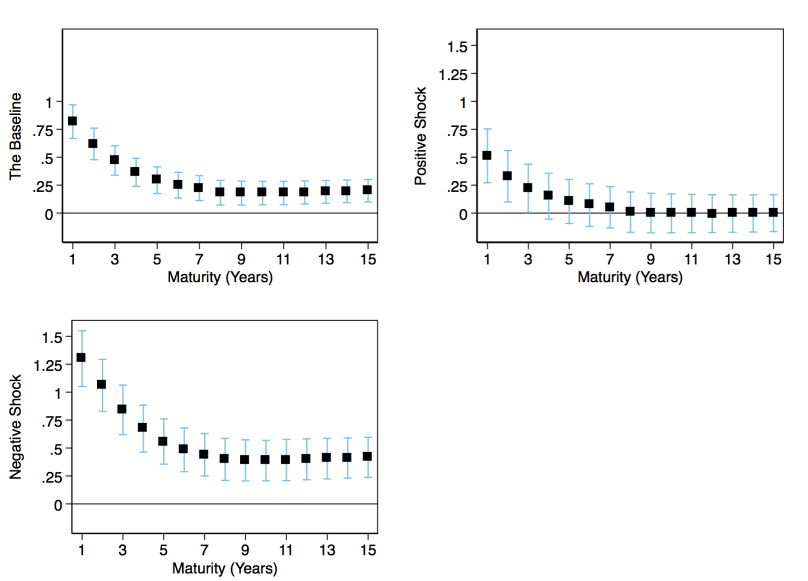
those shocks directly and estimate regressions of the following forms:

$$\text{Linear case: } \triangle Y_t^h = \alpha^h + \beta^h RR_t + \gamma^h X_t + \epsilon_{h,t}, \tag{1.3}$$

$$\text{Asymmetry: } \triangle Y_t^h = \alpha_1^h + \alpha_2^h I_{\text{-}negative} + \beta_1^h RR_t + \beta_2^h RR_t \times I_{\text{-}negative} + \gamma^h X_t + v_{h,t}, \tag{1.4}$$

with RR_t denotes the R&R monetary shocks and $\triangle Y_t^h$ is the monthly changes in nominal yield with maturity h. Figure (1.3) plots the estimation results: in the baseline regression, an R&R monetary shock has a big impact on yields at the long horizon. And the effect is sign dependent: the impact is more pronounced when the sign of a monetary shock is negative (expansionary). The sample ranges from 1969M1 to 2007M12 due to the availability of R&R monetary shocks.

Figure 1.3: Impact Effect on Yield Robustness Check: R&R Monetary Shocks



Note:The top left panel reports the results from estimating the baseline regressions: $\triangle Y_t^h = \alpha^h + \beta^h RR_t + \gamma^h X_t + \epsilon_{h,t}$, where RR_t denotes the R&R Monetary Shocks. The square dots on the bottom panel represent the estimated $\hat{\beta}_1^h + \hat{\beta}_2^h$ and the square dots on the top right panel represent the estimated $\hat{\beta}_1^h$, where $\hat{\beta}^h$s are estimated from separated regressions: $\triangle Y_t^h = \alpha_1^h + \alpha_2^h I_{\text{-}negative} + \beta_1^h RR_t + \beta_2^h RR_t \times I_{\text{-}negative} + \gamma^h X_t + \upsilon_{h,t}$. The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 1969M1 to 2007M12.

1.2.2 Fact 2: Expected Real GDP and Monetary Policy

One interpretation of the first set of facts is that monetary surprise is perceived as news about future growth rate in consumption. The second set of facts provides evidence that is consistent with this hypothesis. Following Romer and Romer (2000), I estimate regressions of the following form:

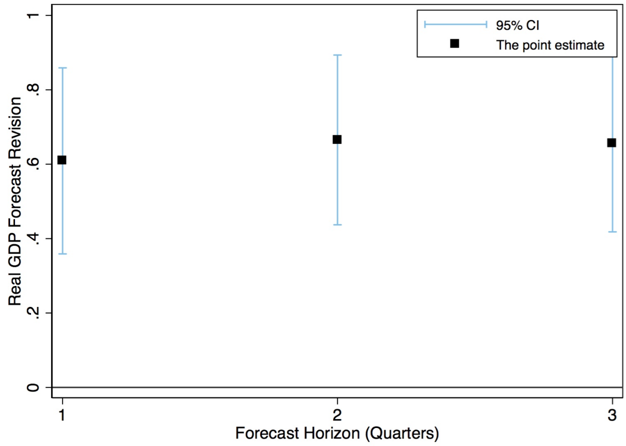
$$y_{t+j|t} - y_{t+j|t-1} = \alpha^j + \beta^j \triangle MP_t + \gamma^j X_t + v_{j,t}, \tag{1.5}$$

where $\triangle MP_t$ is instrumented by HFI monetary surprises. I add the following control variables, denoted as X_t: the lagged real GDP, price deflator, monetary instrument and both contemporaneous and lagged factors and Greenbook forecasts. According to information criteria, it has been decided to use two lags. $y_{t+j|t}$ denotes expected log real GDP at j quarters ahead that I take from the Survey of Professional Forecasters (SPF). In order to correctly identify the effect of monetary shock on forecast revision, one needs to adjust HFI monetary surprise as it occurred between the current survey ($y_{t+j|t}$) and the previous survey ($y_{t+j|t-1}$). This is possible since the exact dates of SPF and FOMC meetings are publicly available.

The F-statistics from the first-stage regression is reported in the second panel of Table (1.6). As can be seen, the F-statistics from the first-stage regression for the baseline is 15.2 suggesting strong relevance of these instruments.

Figure (1.4) plots the instantaneous effect of monetary shock on real GDP forecast revision at 1 quarter, 2 quarters and 3 quarters ahead. In response to a monetary shock that increases the monetary instrument by 100 basis points, professional forecasters revise their real GDP forecasts for

Figure 1.4: The impact effect of a monetary shock on real GDP forecast revision



Note: The square dots represent the estimated $\hat{\beta}_j$s from separated regressions: $y_{t+j|t} - y_{t+j|t-1} = \alpha^j + \beta^j \triangle MP_t + \gamma^j X_t + v_{j,t}$. The forecast horizons are denoted in quarters and $y_{t+j|t}$ denotes the forecast made at time t about the real GDP at quarter $t+j$. The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 1990Q1 to 2010Q4.

the next quarters raising them by roughly 60 basis points. Qualitatively, this is the opposite of what the standard NK model predicts: monetary tightening should depress the expected real GDP.

Asymmetric effect of monetary shock on real GDP forecast revision

Next, I test whether the effect of monetary shock on the real GDP forecast revision is symmetric. To address this question, I estimate regressions of the following form:

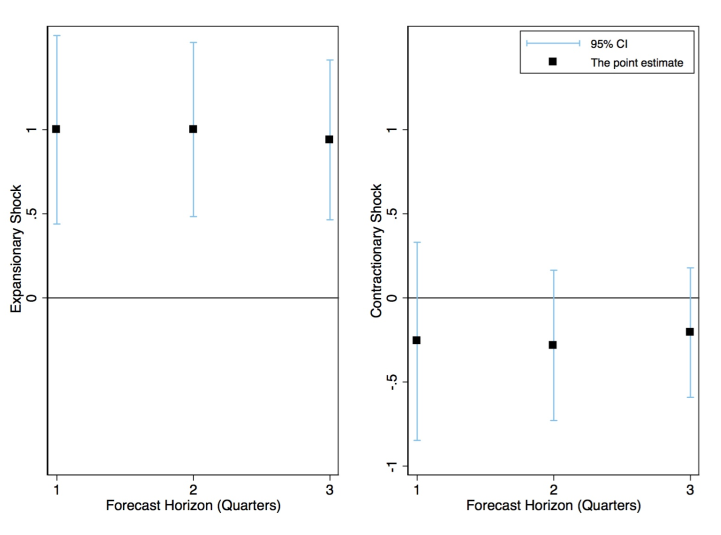
$$y_{t+j|t} - y_{t+j|t-1} = \alpha^j + \beta_1^j \triangle MP_t + \beta_2^j \triangle MP_t \times I_{\text{-}negative} + \gamma^j X_t + v_{j,t}.$$

Again, $\triangle MP_t$ and $\triangle MP_t \times I_{\text{-}negative}$ are instrumented by HFI monetary surprises and monetary surprises interacting with $I(HFI < 0)$. These instruments are relevant as is evidenced by the second panel of Table (1.6). Figure (1.5) plots the estimation results: $\hat{\beta}_1^j + \hat{\beta}_2^j$ on the left panel and $\hat{\beta}_1^j$ on the right panel. Similar to the case for the yield curve, in response to an expansionary monetary shock, agents revise their real GDP forecast downwards — the opposite of what a standard NK model predicts. And in contrast, a positive monetary shock does not affect real GDP forecast revision.

Robustness Checks The results discussed in this section are robust to: i) the use of alternative instrument set, ii) excluding the recession periods, iii) excluding factors, iv) excluding Greenbook forecasts, v) excluding all controls and vi) the use of R&R monetary shocks. See Appendix 1.9.3 for detailed explanations and figures.

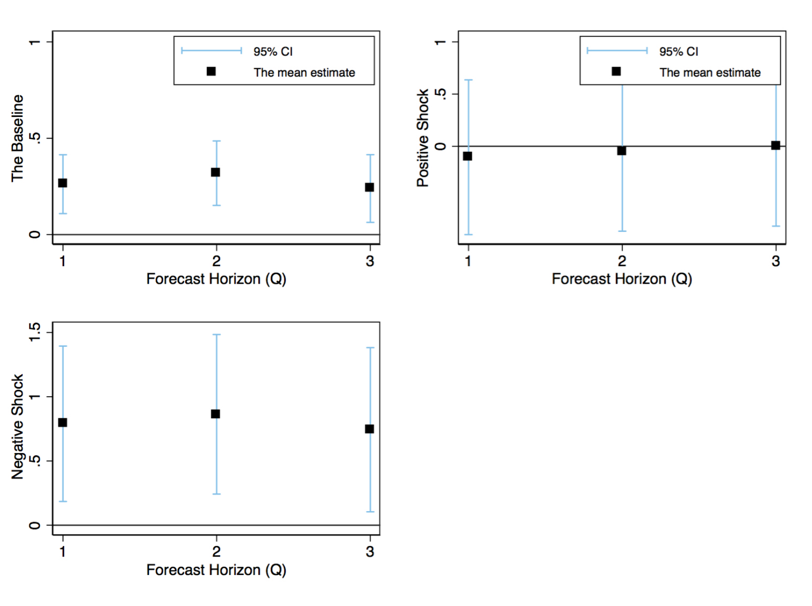
I emphasize that the results are robust to the use of R&R monetary shocks. As is evidenced by Figure (1.6), the use of R&R monetary shocks as identified exogenous shocks generates the same puzzle. Moreover, the impact of an R&R monetary shock on real GDP forecast revisions is sign dependent. While in response to a negative (expansionary) monetary shock agents revise their real GDP forecasts downwards, positive (contractionary) monetary shocks have limited impacts on real GDP forecast revisions and the effects are statistically insignificant.

Figure 1.5: The asymmetric effect of a monetary shock on real GDP forecast revision



Note: The square dots on the left panel represent the estimated $\hat{\beta}_1^j + \hat{\beta}_2^j$ and the square dots on the right panel plot the estimated $\hat{\beta}_1^j$, where the coefficients are estimated from separated regressions: $y_{t+j|t} - y_{t+j|t-1} = \alpha^j + \beta_1^j \triangle MP_t + \beta_2^j \triangle MP_t \times I_{\text{-}negative} + \gamma^j X_t + v_{j,t}$. The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 1990Q1 to 2010Q4.

Figure 1.6: Impact Effect on Forecast Revision Robustness Check IV: R&R Monetary Shocks



Note: The top left panel reports the results from estimating the baseline regressions: $y_{t+j|t} - y_{t+j|t-1} = \alpha^j + \beta^j RR_t + \gamma^j X_t + v_{j,t}$ using HFI monetary surprises as instruments for $\triangle MP_t$. The square dots on the bottom panel represent the estimated $\hat{\beta}_1^j + \hat{\beta}_2^j$ and the square dots on the top right panel represent the estimated $\hat{\beta}_1^j$, where $\hat{\beta}^j$s are estimated from separated regressions: $y_{t+j|t} - y_{t+j|t-1} = \alpha^j + \beta_1^j RR_t + \beta_2^j RR_t \times I_{\text{-}negative} + \gamma^j X_t + v_{j,t}$. The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 1969Q1 to 2007Q4.

1.3 The Model

These facts challenge different varieties of NK models, which are based on the paradigm that monetary policy has limited long-run effects and a monetary policy tightening should depress agents' expectations regarding real GDP.

Figure (1.11) plots the impact effects of monetary shocks on nominal yields at different maturities and real GDP forecast revisions at different horizons predicted by a standard NK model with perfect information (a special case of the model discussed below). The circles and intervals are the mean estimates and 95% confidence intervals constructed based on posterior parameters' distributions. Details regarding the estimation of the model will be discussed in Section (1.4). As can be seen, the effect of a monetary shock on expected real GDP growth is clearly at odds with the Fact 2 discussed above. And quantitatively, a monetary policy shock has limited effect on long-term yield, which is inconsistent with Fact 1.

In this section, I build a model to rationalize the baseline (linear) facts. The model extends the basic NK model discussed in Galí (2008a) with a stochastic trend in productivity, which is not fully observed by private agents. Shocks to the stochastic trend can be interpreted as a news shock as in Barsky and Sims (2012).

1.3.1 Households

A representative household $j \in (0,1)$ seeks to maximize the following utility function:

$$\mathbb{E}\sum_{t=0}^{\infty}\beta^t e^{\delta_t}U(C(j)_t,N(j)_t),\ \text{with}\ U(C(j)_t,N(j)_t)=\left[log(C(j)_t)-\frac{N(j)_t^{1+\varphi}}{1+\varphi}\right],$$

where δ_t is the preference shock that follows:

$$\delta_t = \rho_\delta \delta_{t-1} + \epsilon_t^\delta \text{ with } \epsilon_t^\delta \sim N(0, \sigma_\delta^2)$$

N_t denotes labour supply and C_t is a consumption index given by:

$$C_t = \left(\int_0^1 C_{j,t}^{(\gamma-1)/\gamma} \mathrm{d}j \right)^{\gamma/(\gamma-1)}$$

I have assumed a continuous supply of consumption goods [0,1] with elasticity of substitution γ among them. The representative consumer faces a standard budget constraint:

$$\int_0^1 P_t(j) C_t(j) \mathrm{d}j + Q_t B_{t+1} \leq B_t + W_t N_t + T_t$$

where, $P_t(j)$ denotes the price of good j, Q_t denotes the price at time t of one period bond that pays B_{t+1} at time $t+1$, W_t the wage and T_t the lump-sum transfer including profit from firms. Solving the consumer's optimization problem leads to the following Euler equation:

$$Q_t = \beta \mathbb{E} \left\{ \frac{\Lambda_{t+1}}{\Lambda_t} \frac{P_t}{P_{t+1}} \right\}$$

where, $P_t = \left(\int_0^1 P_{j,t}^{1-\gamma} \mathrm{d}j \right)^{1/(1-\gamma)}$ is the aggregate price index and $\Lambda_t = U_{c,t} e^{\delta_t}$.

1.3.2 Firms

There is a continuum of firms indexed by $j \in [0,1]$ whicj produce differentiated goods in a monopolistic competitive market according to the following production function:

$$Y_{t,j} = e^{a_t} N_{t,j}$$

I assume that firms have access to the same technology with the latter follows the following process:

$$a_t = a_{t-1} + g_t + \epsilon_t^a \text{ with } \epsilon_t^a \sim N(0, \sigma_a^2)$$
$$g_t = \rho_g g_{t-1} + (1 - \rho_g) g^* + \epsilon_t^g \text{ with } \epsilon_t^g \sim N(0, \sigma_g^2).$$

Firms are subject to nominal rigidity *à la* Calvo (1983). Each period a fraction θ of firms cannot reset prices optimally, but choose their price according to the following indexation rule:

$$P_t(i) = P_{t-1}(i) \pi_{t-1}^{\omega} \pi^{1-\omega},$$

where π_{t-1} is the lagged inflation and π the steady state inflation. The fraction $1-\theta$ of firms can reset their prices freely and will do so optimally to maximize the following equation:

$$\mathbb{E} \left[\sum_{k=0}^{\infty} \theta^k \beta^k \frac{\Lambda_{t+k}}{\Lambda_t} (P_t(i) \Pi_{t,t+k} - MC_t) Y_{t+k}(i) \right],$$

subject to constraint:

$$Y_{t+k}(i) = \left(\frac{P_{t+k}(i) \Pi_{t,t+k}}{P_{t+k}} \right)^{-\gamma} Y_{t+k},$$

where $\Pi_{t,t+k} \equiv \prod_{s=1}^{k} (\pi_{t+s-1}^{\omega} \pi^{(1-\omega)})$.

1.3.3 Log-linearized equilibrium conditions

I have log linearized the Euler equation around the steady state to get the dynamic IS equation:

$$\hat{y}_t = \mathbb{E}\hat{y}_{t+1} - [\hat{i}_t - \mathbb{E}\hat{\pi}_{t+1} - \rho_g \mathbb{E}\hat{g}_t + (\mathbb{E}\delta_{t+1} - \delta_t)]. \tag{1.6}$$

Since the model has a stochastic trend, to solve the model around a stationary steady state, I rescale the non-stationary variable by level productivity A_t. The variable with hat denotes its deviation from its steady state.

The log linearized Phillips curve is derived from firms' problem:

$$\hat{\pi}_t = \frac{\beta}{1+\omega\beta}\mathbb{E}\hat{\pi}_{t+1} + \frac{\omega}{1+\omega\beta}\hat{\pi}_{t-1} + \kappa\hat{y}_t + \epsilon_t^{\pi}, \tag{1.7}$$

where $k \equiv \frac{(1-\theta\beta)(1-\theta)}{\theta(1+\omega\beta)}(\varphi + 1)$. Note that I have introduced shock to the Phillips curve: ϵ_t^{π} with mean 0 and variance σ_{π}.

1.3.4 Monetary policy

The central bank sets the interest rate following a version of the Taylor rule that keeps track of the efficient real interest rate — the one that would prevail without frictions (Wicksell (1989)). Cúrdia et al. (2015) show that the interest rate tracks an efficient rate of return that fits the U.S.'s data well. Formally, Woodford (2001) shows, in a framework without information friction, that such a rule is optimal.

I assume a Taylor rule of the following form:

$$\hat{i}_t = \rho_m \hat{i}_{t-1} + (1-\rho_m)(\phi_r r_t^e + \phi_{\pi}\hat{\pi}_t + \phi_y \hat{y}_t) + \epsilon_t^m, \text{ with } \epsilon_t^m \sim i.i.d\ N(0, \sigma_m^2). \tag{1.8}$$

The persistent component $\rho_m \hat{i}_{t-1}$ is introduced to generate persistent impacts of monetary shocks. The theoretical argument for introducing this component is the following: in a framework with the presence of an output gap and inflation tradeoff, such as the current one, it is optimal for the central bank to conduct monetary policy with commitment in order to smooth the welfare loss over time. Consequently, the current policy rate depends on the previous one. Thus the lagged interest rate in the Taylor rule allows the simple policy rule to be able to approximate the optimal monetary policy under commitment.

The variable r_t^e denotes the efficient real interest rate.[11] In this framework, the efficient real interest rate is the one that would prevail if the market were perfectly competitive and if there were no information frictions. To determine the efficient real interest rate, I solve the social planner's problem in this economy. The social planner makes intra-temporal consumption and labor decisions according to:

$$-\frac{U_{N,t}}{U_{C,t}} = MPN_t. \tag{1.9}$$

The inter-temporal optimality condition under efficient allocation is:

$$R_t = \beta \mathbb{E}^e \Big\{ \frac{\Lambda_t}{\Lambda_{t+1}} \Big\}. \tag{1.10}$$

[11] An alternative interpretation of r_t^e in the taylor rule is that the central bank reacts to its expected future economy or financial conditions, for instance the expected real GDP growth in the next period. The latter is proportional to the trend of the economy and is therefore similar to r_t^e.

Combine (1.9) with (2.9) and log-linearize :

$$r_t^e = \mathbb{E}^e g_{t+1} - \mathbb{E}^e \triangle \delta_{t+1}, \tag{1.11}$$

Lastly, ϵ_t^m in the Taylor rule is the exogenous monetary shock. In the literature, there are two main interpretations of these monetary policy shocks. First, ϵ_t^m reflects shocks in the FOMC's preference as committee members may prefer to respond more to inflation on one day than on another. Second, ϵ_t^m captures measurement error in the real time data that the FOMC has during the day of policy making. My preferred interpretation is the second: although the central bank aims to keep track of r_t^e, due to information friction the policy rate fluctuates around the intended one.[12] What matters is the assumption that ϵ_t^m is exogenous to policy decision and private agents do not observe monetary shocks. In the presence of unobserved monetary shocks, the central bank's action does not provide perfect information regarding the unknown g_t therefore agents' learning is persistent.

1.3.5 Belief updating and solution of the model

Private agents make decisions based on an uncertain environment. Namely, they do not observe the productivity trend g_t perfectly and cannot distinguish trend shocks (ϵ_t^g) from level productivity shocks (ϵ_t^a). Moreover, agents do not observe monetary shocks (ϵ_t^m). Since the trend is relevant for their optimal decisions, agents will infer g_t from observable variables. Let us denote agents' estimate of g_t by $g_{t|t} \equiv E(g_t|Z^t)$, where Z^t is the history of variables that are relevant for inference about g_t that agents

[12]That is $\epsilon_t^m \equiv (1-\rho_m)\rho_g(g_t - \mathbb{E}^{Fed} g_t)$.

observe up to time t.

I assume that agents understand the model and know the distributions of shocks as well as the parameters of the model. To update $g_{t|t}$, agents use the up-to-date history of $Z_t = [a_t \; \hat{i}_t \; s_t]$ those are: the level of productivity, the policy rate and additional private signals about g_t summarized in s_t:

$$s_t = g_t + \epsilon_t^p \text{ with } \epsilon_t^p \sim i.i.d \; N(0, \sigma_p^2). \tag{1.12}$$

I introduce s_t for two reasons. First, it is more realistic to assume, apart from monetary action and level productivity, that agents receive additional information about the future development of the economy. For example, by reading newspapers. Second, with the introduction of s_t the NK model with perfect information is nested in this model by setting σ_p equal to zero. Thus, one approach to assess whether the information channel of monetary policy is empirically relevant or not is to check if the estimated σ_p is different from zero.

It is worth emphasizing that the realized short-run interest rate i_t provides information about the underlying trend g_t, because agents know the central bank's reaction function. Moreover, due to the fact that agents do not observe monetary shocks, they cannot infer g_t perfectly from monetary actions.

The signal extraction problem of agents is subject to a simultaneity problem. The monetary policy signal responds to endogenous variables $\hat{\pi}_t$, $\hat{y}_t$, and those are determined based on agents' posterior belief about g_t, which in turn depends on monetary policy. Svensson and Woodford (2004) provide a solution for optimal filtering under these settings.

The model's solution is derived in Appendix (1.9.4). In the model, agents update their beliefs about the unknown process $\hat{g}_t$ and ϵ_t^m using

kalman filter. And naturally $g_{t|t}$ and $\epsilon^m_{t|t}$ are state variables. Define $X_t \equiv \begin{pmatrix} \epsilon^m_t & \hat{g}_t & \hat{\delta}_t & \epsilon^\pi_t & \hat{i}_{t-1} & \hat{\pi}_{t-1} & \epsilon^m_{t|t} & \hat{g}_{t|t} \end{pmatrix}'$,
$U_t \equiv \begin{pmatrix} \epsilon^g_t & \epsilon^\delta_t & \epsilon^\pi_t & \epsilon^m_t & \epsilon^a_t & \epsilon^p_t \end{pmatrix}'$ and $X^f_t \equiv \begin{pmatrix} \hat{y}_t & \pi_t \end{pmatrix}'$ then the state space representation of the model's solution is:

$$X_{t+1} = AX_t + BU_{t+1}, \tag{1.13}$$

$$X^f = FX_t, \tag{1.14}$$

with matrix A, B and F specified in Appendix (1.9.4).

1.3.6 Term structure

This section describes the term structure implied by the model. Following Bekaert, Cho and Moreno (2010) and Nimark (2008), yields of different maturities are derived based on the following four equations together with the assumption that shocks are normal. The first equation characterizes the short-run yield, which is basically the monetary policy rule:

$$i_t = M_I X_t \tag{1.15}$$

The second equation relates yields at different maturities with corresponding prices:

$$i^n_t = -\frac{1}{n} log(P^n_t) \tag{1.16}$$

In the third equation, I assume that there is no arbitrage condition:

$$P^{n+1}_t = E_t(M_{t+1} P^n_{t+1}) \tag{1.17}$$

The fourth equation derives the stochastic discount factor from consumers' optimization problem:

$$M_{t+1}^{n} = \beta \frac{\Lambda_{t+1} P_t}{\Lambda_t P_{t+1}} \tag{1.18}$$

Combining these equations one can write the yields in terms of state variable X_t as[13]:

$$\begin{bmatrix} i_t \\ i_t^2 \\ . \\ . \\ i_t^n \end{bmatrix} = \begin{bmatrix} -A_1 \\ -\frac{1}{2}A_2 \\ . \\ . \\ -\frac{1}{n}A_n \end{bmatrix} + \begin{bmatrix} -B_1 \\ -\frac{1}{2}B_2 \\ . \\ . \\ -\frac{1}{n}B_n \end{bmatrix} X_t \tag{1.19}$$

where i_t^n denotes the yield with maturity n at time t. A_n and B_n are derived recursively in Appendix (1.9.4). There are three key features that are absent in the previous literature. First in this model, agents' belief about trend $\hat{g}_{t|t}$ enters as a state variable and therefore affects the whole yield curve. Second, monetary policy acts as one of the signals, and as a consequence, monetary surprises affect the long end of the yield through their effects on $\hat{g}_{t|t}$ that standard models cannot capture. And third, if the process for g_t is highly persistent, which is verified in our estimation exercise shown later in this paper, current shocks would affect the yield curve at long horizons.

[13] See Appendix (1.9.4) for the detailed derivations.

1.4 Model Estimation and Results

I estimate the model using a Bayesian approach with quarterly data from the U.S. ranging from the first quarter of 1982 to the last quarter of 2016. Real GDP per capita, inflation, nominal yields with maturities of two, five and ten years are included in the measurement equations, see Appendix (1.9.8) for detailed data descriptions.

Identification It is well known that many DSGE models are subject to local identification issues, see Canova and Sala (2009) for potential reasons. Iskrev (2010) and Komunjer and Ng (2011) provide algorithms to check for identification prior to estimation. It is standard practice in the literature that unidentified parameters are then calibrated. I follow Komunjer and Ng (2011)'s procedure and all parameters are verified to be locally identified.

Priors and Posteriors Tables (1.1) and (1.7) report the prior and posterior estimates. Priors are reported in the first three columns. They are taken from the literature, see for example An and Schorfheide (2007). I estimate posteriors using the Random Walk Metropolis-Hastings algorithm. Posterior means and standard errors for both the model with asymmetric information and the one with perfect information (in which σ_p is imposed as zero) are reported. The key parameters that drive the main results are reported in Table (1.1): variances of monetary, level productivity, trend and private signal shocks — these are not only a measure of volatility but also a measure of precision of signals. In the model with asymmetric information, the posterior mean of σ_p — the private signal noise is much larger than monetary shock volatility (σ_m). This suggests that the information is indeed not perfect. In addition, σ_a, the noise of another source of private information, is relatively big and determines the magnitude of the information channel of monetary policy.

Table (1.7) reports the posterior estimates of other parameters. With few exceptions, estimated parameters between a model with asymmetric information and a model with perfect information are similar. The results discussed below are not driven by those differences.

Table 1.1: Prior and Posterior: key parameters

	Priors			Asymmetric Information		Perfect Information	
	Mean	s.d	Distribution	Mean	s.d	Mean	s.d
σ_m	2×10^{-3}	4	InvGamma	1.2×10^{-3}	0.8×10^{-4}	1.7×10^{-3}	1.2×10^{-4}
σ_a	2×10^{-3}	4	InvGamma	6.7×10^{-3}	4.9×10^{-4}	7.1×10^{-3}	4.1×10^{-4}
σ_g	2×10^{-3}	4	InvGamma	1.6×10^{-3}	0.1×10^{-3}	1.6×10^{-3}	0.1×10^{-3}
σ_p	2×10^{-3}	4	InvGamma	1.9×10^{-2}	0.9×10^{-2}	–	–

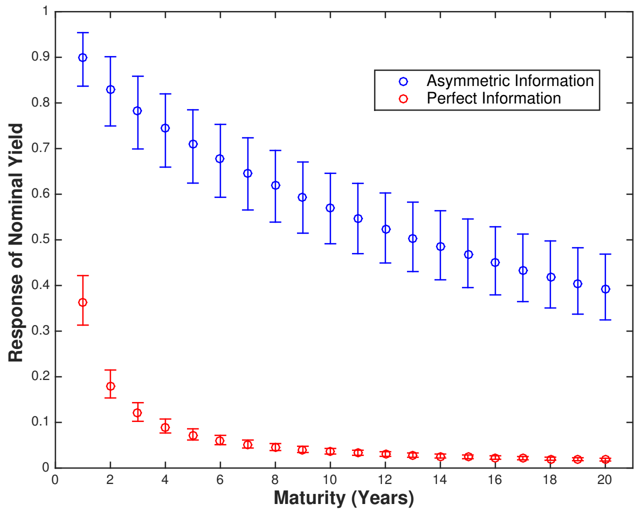
Note: Posterior means and standard deviations are estimated using the Random Walk Metropolis-Hastings algorithm

1.4.1 Results

Rationalizing Fact 1: the Impact Effects of Monetary Shocks on Long-term Yield Figure (1.7) plots one of the main facts that I aim to capture: the impact effects of monetary shocks on nominal yields. Those should be compared to their empirical counterpart: Figure (1.1).

The circles and intervals are the mean estimates and 95% confidence intervals constructed based on posterior parameters' distributions. The

Figure 1.7: Prediction of the Model: the Impact Effects of Monetary Shocks on Nominal Yields



Note: This figure depicts the impact effects of monetary shocks on nominal yield at different maturities predicted by the models. The circles and intervals are the mean estimates and 95% confidence intervals constructed based on posterior parameters' distributions. The blue lines plot the predictions of the model under asymmetric information. The red ones plot those for the perfect information case: all parameters are set to be the same as for the asymmetric case except for the private signal volatility σ^p, which is imposed as zero.

blue lines plot the predictions of the model under asymmetric information. The red ones plot those for the perfect information case: all parameters are set to be the same as for the asymmetric case except for private signal volatility σ^p, which is imposed as zero. This choice of comparison is made to ensure that the information channel is the key mechanism driving the model's success. [14]

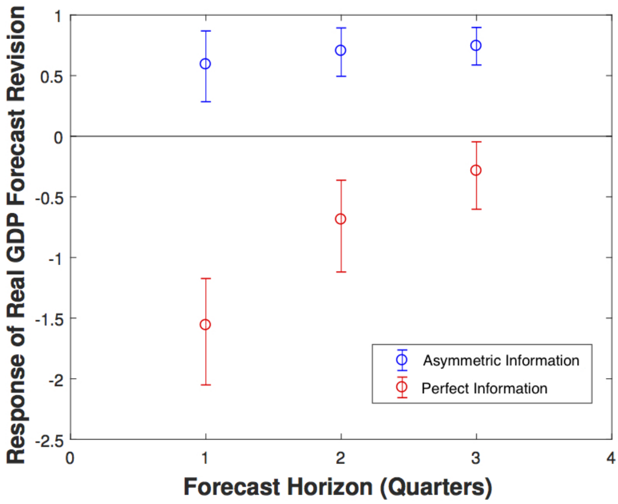
[14] Alternatively, one can compare the predictions of the two models based on separate

As one can see, while the model with perfect information fails to reproduce the empirical facts, the model with information asymmetry reflects the facts very well. As observed in the data, the model predicts that on impact nominal yields at all horizons respond to monetary shocks positively and significantly. In the model, private agents cannot distinguish a monetary shock from the central bank's endogenous response to the bank's information about the news shock. And agents know that the monetary policy responds positively to a news shock. As a result, a positive monetary surprise that originates from a pure positive monetary shock is partially interpreted as the central bank has received good news about the economy's future development. Hence, the perceived natural real interest rate increases. Notice that the natural real interest rate is highly persistent ($\rho_g = 0.98$) in this economy, a magnitude that is shared in the long-run risk literature (Bansal and Yaron (2004)), and therefore the expected natural real interest rate in the far future also increases. Consequently, the long-term yield, which is the weighted average of the current and expected future policy rate, increases in response to a positive monetary shock.

Rationalizing Fact 2: the Impact Effects of Monetary Shocks on Real GDP Forecast Revisions Figure (1.8) shows the second fact that I aim to rationalize: the impact effects of monetary shocks on real GDP forecast revisions. These should be compared to their empirical counterparts: Figure (1.4). Again, the figure plots the mean estimates and 95% confidence intervals both for the model with information asymmetry (in blue) and with perfect information (in red). In contrast to the prediction of the

parameter estimates. The results are unchanged.

Figure 1.8: Prediction of the Model: the Impact Effects of Monetary Shocks on Real GDP Forecast Revisions



Note: This figure depicts the impact effects of monetary shocks on real GDP forecast revision at different horizons predicted by the models. The circles and intervals are the mean estimates and 95% confidence intervals constructed based on posterior parameters' distributions. The blue lines plot the predictions of the model under asymmetric information. The red ones plot those for the perfect information case: all parameters are set to be the same as for the asymmetric case except for the private signal volatility σ^p, which is imposed as zero.

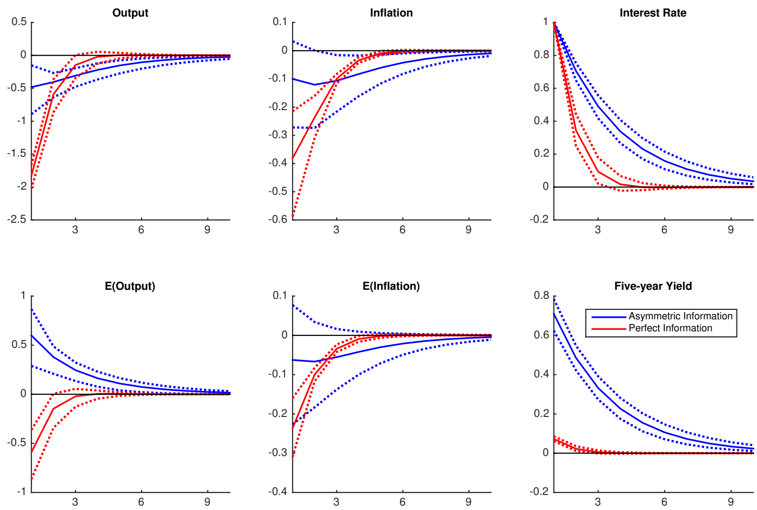
standard NK model (the red lines), the model with asymmetric information fits the data well. In response to a positive monetary shock, agents, both in the model and data, revise upward their forecasts of log real GDP in the next quarters. This is due to the information channel of monetary policy. A positive monetary shock is partly interpreted as the arrival of a positive news shock. As a result, agents become more optimistic.

Implication: the Information Channel Dampens the Conventional Effect of Monetary Policy Figure (1.9) compares the IRFs of endogenous variables to a positive monetary shock in the model with asymmetric information with those in the model with perfect information. The solid and dashed lines are the mean estimates and 95% confidence interval of IRFs of the models constructed based on the posterior parameters' distributions. The ones in blue plot the predictions of the model under asymmetric information. The red ones plot those for the perfect information case: all parameters are set to be the same as for the asymmetric case except for the private signal volatility σ^p, which is imposed as zero.

The bottom left panel and bottom right panel confirm the previous findings (on impact): while the model with asymmetric information reproduces both Fact 1 and Fact 2 as discussed above, the model with perfect information fails to match the data. Moreover, those impulse responses suggest that agents misinterpret a monetary surprise at the beginning and only fully learn the truth after roughly two years.

More interesting results are shown on the top left and middle panels. As compared to the case with perfect information, the effects of monetary policy shock to output and inflation in the model with asymmetric information are more silent. Unlike in the perfect information case, in which monetary policy affects output only through the consumer's Euler equation and inflation adjusts according to the Phillips curve, with asymmetric information the information channel of monetary policy emerges. A contractionary monetary policy is perceived as a good news shock, thus agents become more optimistic and, as a result, they consume more. The information channel of monetary policy dampens the traditional channel. As a result, monetary policy shocks in the model with asymmetric information are less disturbing. Moreover, in contrast to a model with perfect information, with asymmetric information the actual GDP path does not coincide with expected GDP.

Figure 1.9: IRFs: Asymmetric Information vs Perfect Information



Note: This figure plots IRFs after a positive monetary shock. E(Output) and E(Inflation) denote the expected log real output and inflation in one quarter ahead. The solid and dashed lines are the mean estimates and 95% confidence interval of IRFs of the models constructed based on the posterior parameters' distributions. The ones in blue plot the predictions of the model under asymmetric information. The red ones plot those for the perfect information case: all parameters are set to be the same as for the asymmetric case except for the private signal volatility σ^p, which is imposed as zero.

The analyses in Figure (1.9) are conducted based on parameters that are estimated using the model with asymmetric information. While it is useful to cleanly pin down the information channel of monetary shock on economic activities, one cannot answer the question of whether ignoring information asymmetry would lead to biased estimates for the effectiveness of monetary shocks. To address this question, Figure (1.12) depicts

IRFs for both the model with asymmetric information (in blue) and perfect information (in red) based on separately estimated parameters. As one can see, to the extent that the true model features information asymmetry ($\sigma^p > 0$), estimating a model with perfect or symmetric information ($\sigma^p = 0$) would lead to significantly biased estimates regarding the effectiveness of monetary shocks on output and inflation.

Discussion: How Plausible is the Estimated Degree of Information Frictions? The previous analysis shows that the estimated degree of information asymmetry is capable of rationalizing the aforementioned empirical puzzles. Yet we have not discussed whether the implied information asymmetry is reasonable or not. The fact that the model-implied responses of real GDP forecast revisions to monetary shocks (Figure (1.8)) matches the empirical Fact 2 suggests that the underlying information asymmetry is reasonable. In the next exercise, I provide additional evidence.

Romer and Romer (2000) show that the FOMC staff's internal forecasts dominate commercial forecasts based on the estimation of the following regressions:

$$y_{t+h} = \alpha + \beta^P E_t^P(y_{t+h}) + \beta^F E_t^F(y_{t+h}) + e_t, \tag{1.20}$$

where $E_t^P(y_{t+h})$ denotes commercial forecasts (private agents' forecasts) at time t about variable y at h horizons ahead, and $E_t^F(y_{t+h})$ denotes the Fed's internal forecasts. They do the exercise both for real GDP forecasts and inflation forecasts. The null hypothesis is whether $\beta^F = \beta^P$. Under the null both private and the Fed's internal forecasts are equally precise. With $\beta^F > \beta^P$ meaning the Fed's information is superior to that of private agents. Estimation results are reported in Table (3) and Table (5) and I have copied those numbers to the last two columns of Table (1.2)[15]: overall $\hat{\beta}^P$ is not statistically different from zero and $\hat{\beta}^F$ is close to one. Those results suggest that the Fed has superior information about future inflation and real GDP and for the predictability of those variables it is enough to use solely the Fed's internal forecasts as predictors.

Using the structure model in this paper, I replicate their empirical results using the estimated parameters. I simulate the model 10 000 times for 65 periods each (the same sample size as in Romer and Romer (2000) regressions using SPF survey data). In each simulation, I construct the realized variables y_{t+h}: real GDP and Inflation; the private agents' forecasts of the corresponding variables at different horizons h denoted as $E_t^P(y_{t+h})$; and the central bank's forecasts denoted as $E_t^F(y_{t+h})$. For each simulation, I estimate the regressions of the form (1.20). The mean estimates are reported in Table (1.2), and the standard deviations are reported in parentheses. Those should be compared to the empirical results discovered by Romer and Romer (2000), i.e. the numbers contained in the fourth and fifth columns. As one can see, the model successfully replicates Romer and Romer (2000)'s empirical results not only qualitatively but also quantitatively.

In addition, in each simulation, I calculate the ratio of mean square forecast error (RMSFE). The averages square forecast error (MSFE) is calculated as the average squared difference between the expected and actual GDP/inflation. The RMSFE is then obtained by taking the ratio between the MSFE of the Fed's forecasts and the MSFE of the private forecasts. An RMSFE smaller than one suggests that the Fed's inter-

[15]The parameters are estimated using SPF data.

nal forecasts are more precise than the private's forecasts. The means of simulated RMSFE are reported in the third column and the standard deviations are reported in parentheses. These should be compared to their empirical counterparts discovered by Romer and Romer (2000) that are reported in the last column. The simulated RMSFE are greater than their empirical counterparts, suggesting that the degree of the central bank's information advantage assumed in this model is smaller to that implied by the actual data. In practice, the central bank may have information advantage regarding other shocks in the economy and/or its monetary policy reaction function. Those features, that are assumed away in the current model[16], may explain the gap between the simulated and actual RMEFE.

Overall, I interpret those as evidence suggesting that the implied information asymmetry in the model is realistic.

[16]These information advantages cannot rationalize the aforementioned facts, therefore those features are assumed away for simplicity.

Table 1.2: Model Simulation: Romer and Romer (2000) Regressions

$$y_{t+h} = \alpha + \beta^P E_t^P(y_{t+h}) + \beta^F E_t^F(y_{t+h}) + e_t$$

	Model Simulations			Romer and Romer (2000)		
Forecast Horizon h	$\hat{\beta}^P$	$\hat{\beta}^F$	RMSFE	$\hat{\beta}^P$	$\hat{\beta}^F$	RMSFE
Real GDP						
1 Quarter	-0.01 (0.10)	1.00 (0.13)	0.79 (0.03)	0.56 (0.53)	0.81 (0.52)	-
2 Quarters	-0.02 (0.24)	1.00 (0.26)	0.94 (0.03)	0.66 (0.53)	1.07 (0.66)	-
3 Quarters	-0.03 (0.44)	1.00 (0.40)	0.97(0.02)	0.40 (0.28)	0.99 (0.44)	-
4 Quarters	-0.02 (0.71)	0.99 (0.57)	0.98 (0.01)	-1.07 (0.55)	2.33 (0.46)	-
Inflation						
1 Quarter	-0.01 (0.20)	1.00 (0.23)	0.94 (0.02)	0.39 (0.42)	0.57 (0.38)	0.72
2 Quarters	-0.02 (0.34)	1.01 (0.36)	0.97 (0.02)	-0.48 (0.33)	1.33 (0.29)	0.76
3 Quarters	-0.03 (0.46)	1.01 (0.47)	0.98 (0.01)	-0.65 (0.31)	1.55 (0.29)	0.74
4 Quarters	-0.05 (0.60)	1.01 (0.58)	0.99 (0.01)	-0.72 (0.36)	1.53 (0.32)	0.70

Notes: I simulate the model 10 000 times for 65 periods each. In each simulation, I construct the realized variables y_{t+h}: real GDP and Inflation; the private agents' forecasts of the corresponding variables at different horizons h denoted as $E_t^P(y_{t+h})$; and the central bank's forecasts denoted as $E_t^F(y_{t+h})$. In each simulation, I estimate Romer and Romer (2000)'s regressions: $y_{t+h} = \alpha + \beta^P E_t^P(y_{t+h}) + \beta^P E_t^F(y_{t+h}) + e_t$. The mean estimates are reported in the first two columns of the table, and the standard deviations are reported in parentheses. In addition, in each simulation, I calculate the ratio of mean square forecast error (RMSFE). The means of simulated RMSFE are reported in the third column and the standard deviations are reported in parentheses. The last three columns report empirical results discovered by Romer and Romer (2000).

1.4.2 Robustness Checks

An Alternative Taylor Rule The estimation results discussed above are based on a Taylor rule that responds to the efficient real interest rate. While keeping track of the efficient real rate is optimal, as I will discuss below, it is less clear how the central bank constructs the efficient real rate in practice. A more realistic assumption is to assume a monetary rule in which the central bank reacts to macroeconomic variables, such as current and expected inflation and output growth. In fact, Romer and Romer (2004) construct monetary shocks based on the assumption that the Fed reacts to current inflation and Real GDP growth as well as the Fed's internal forecasts of those variables. This section conducts a robustness exercise based on a rule of this type. In particular, I assume that the central bank reacts to inflation and expected real GDP growth:

$$\hat{i}_t = \rho_m \hat{i}_{t-1} + (1-\rho_m)(\phi_\pi \hat{\pi}_t + \phi_y E^{Fed}(y_{t+1} - y_t) + \epsilon_t^m, \qquad (1.21)$$

where $E^{Fed}(y_{t+1} - y_t)$ denotes the Fed's internal forecast of real GDP growth in the next quarter. In practice, those are the FOMC staff's internal forecasts contained in the Greenbook, which is only available to the public with a lag of five years. Thus, according to this rule, the central bank reacts to its private information: the expected real GDP growth, which in turn depends on the underlying unobserved trend shock. Therefore policy action provides a signal regarding g_t.

The model with this alternative Taylor rule is estimated separately. Figure (1.13) plots the predictions of the model. Similar to the baseline, monetary shocks have significant impacts on long-term yield. And contractionary monetary shocks have expansionary impacts on private agents' real GDP expectations.

Replicating Empirical Facts using Simulated Data Previously, the impacts of monetary shocks on the yield curve and real GDP forecasts are derived using the state representation of the model. Thus, those are the exact responses of endogenous variables to exogenous monetary shocks.

However, this is not the case in the empirical framework. In this section, I construct the model-implied impacts of monetary shocks closely following the empirical framework discussed in section (1.2).

To this end, I simulate the following variables: monetary surprises, R&R monetary shocks, yields with different maturities, real GDP forecast revisions and the central bank's internal forecasts of real GDP and inflation. Note that R&R monetary shocks are constructed as the residuals from projecting the monetary instrument on the current real GDP, Inflation, the central bank's forecast of real GDP and inflation, and the lagged short-term interest rate.

I construct the model-implied empirical evidence by estimating the empirical frameworks discussed in section (1.2) using those simulated variables. Figure (1.14) plots the simulated results by estimating regressions of the form (1.1) using monetary surprises as the instrumental variable and the central bank's forecast of real GDP and inflation as control variables. I simulate the model 10 000 times for 160 periods each (same as the empirical sample size). In each simulation, parameters of the model are drawn randomly from posterior parameters' distributions. The circles in Figure (1.14) report the simulated impacts of monetary shocks on the yield curve using the median of the posterior parameters' distributions and the lines plot the 95% probability intervals constructed based on posterior parameters' distributions. Similarly, Figure (1.15) plots the simulated results by estimating regressions of the form (1.3).

As one can see from Figure (1.14) and Figure (1.15), the model is capable of replicating the two empirical facts discussed in section (1.2): monetary shocks affect interest rates at long horizons and the private sector's real GDP forecasts are revised upward in response to a monetary tightening.

1.5 Welfare Analysis and Monetary Policy

This section discusses the optimal central bank communication and optimal monetary policy simple rule under the current framework.

The Welfare Loss Function The welfare loss function can be derived as the second order approximation of a household's welfare[17]:

$$W = \frac{1}{2} E_0 \sum_{t=0}^{\infty} \beta^t \Big[(1+\varphi)\hat{y}_t^2 + \frac{\epsilon}{\lambda}\hat{\pi}_t^2 \Big], \tag{1.22}$$

where the welfare loss W is expressed in terms of the consumption loss as a fraction of steady state consumption. Note that the deep parameters φ, ϵ and λ, those that characterize the relative importance between the variances of output gap and inflation, were not estimated due to the identification issue. The analyses conducted below are based on the same parameterization as in Galí (2008*a*): $\varphi = 1$, $\epsilon = 6$, $\lambda = 0.17$.

Central Bank Communication Given the superior information that the central bank holds regarding the news shock, a natural question arises: would it be optimal for the central bank to release its private information? With full central bank transparency, the information channel of monetary policy would vanish.

Let us remember that, previously, I have assumed that the private agent observes a private signal about g_t:

$$s_t = g_t + \epsilon_t^p \text{ with } \epsilon_t^p \sim i.i.d\ N(0, \sigma_p^2).$$

[17] See Galí (2008*a*) for detailed derivations.

If σ_p^2 equals zero, the information would be perfect. Following Baeriswyl and Cornand (2010), the central bank's communication policy can be measured by σ_p^2. A fully transparent central bank would release everything and therefore the private signal, which includes information released by the central bank, would be perfect, i.e. $\sigma_p^2 = 0$. An the other extreme, with a fully opaque central bank, the one that is assumed in this paper, the noise of the private signal would continue to be the estimate reported in Table (1.1): 1.9 ($\times 10^{-2}$).

To see whether central bank transparency is beneficial or detrimental to welfare, I calculate the welfare loss (measured as a fraction of steady state consumption) for different values of σ_p^2 that ranges from 0 to 1.9. Figure (1.16) plots the result. The vertical axis denotes the welfare loss and the horizontal axis denotes the degree of opacity measured by σ_p^2 . Note that the degree of opacity equal to zero corresponds to a fully transparent central bank and the other extreme corresponds to a fully opaque one. As is shown in the figure, opacity regarding the news shock improves welfare. The intuition behind this is as follows. In an NK framework with sticky prices, a positive news shock today would lead to a boom in aggregate consumption due to individual consumption smoothing decisions. But current technology has not yet increased. Therefore, the output gap will be positive. In addition, inflation arises. Both volatility in the output gap and inflation is detrimental to welfare. Hence, the representative agent would be better off if information regarding the increase in technology in the future can be hidden from them.

Optimal Simple Rule I now turn to the discussion of the optimal simple monetary policy rule given the parameters' estimates. The optimal simple rule is the solution to the following problem:

$$\min_{\rho_m,\phi_r,\phi_\pi,\phi_y} W = \frac{1}{2}E_0 \sum_{t=0}^{\infty} \beta^t \Big[(1+\varphi)\hat{y}^2 + \frac{\epsilon}{\lambda}\hat{\pi}_t^2\Big],$$

Subject to the dynamics of the economy. Let us remember that the control variables are the parameters (weights) in the simple Taylor rule:

$$\hat{i}_t = \rho_m \hat{i}_{t-1} + (1-\rho_m)(\phi_r r_t^e + \phi_\pi \hat{\pi}_t + \phi_y \hat{y}_t) + \epsilon_t^m.$$

Panel A of Table (1.3) reports the optimal simple rule under both the asymmetric information and perfect information model. Both are calculated based on the medians of the posterior distributions of parameters estimated using the asymmetric information model, with the exception of σ_p, which is imposed as zero for the case with perfect information.

The optimal simple rule is qualitatively similar when information asymmetry is introduced. It is optimal to respond to the lagged interest rate due to commitment. It is efficient to keep track of the efficient real rate. Woodford (2001) shows that the optimal Taylor rule is the one that responds to the natural real interest rate one-to-one, the same result carrying over to the current setup in which the central bank has superior information regarding the news shock. In a standard NK model with perfect information, it is optimal for the policy rate to respond aggressively to inflation. The same result holds for the model with asymmetric information. Moreover, even though both models feature a tradeoff between stabilization of output gap and inflation, the optimal weight of the output gap is zero. This is the case because the response to efficient real rates already manages the stabilization of the output gap.

Quantitatively, in the presence of information frictions, the optimal simple rule responds less to the efficient real interest rate via a bigger ρ_m and a smaller ϕ_r. A monetary rule that reacts more to the efficient real interest rate reveals more information about the productivity trend, in other words, the information channel is stronger (which is detrimental to welfare as discussed above). Thus, in the presence of the information channel the central bank chooses to react less to the productivity trend strategically.

The fifth column reports the welfare loss, as fraction of steady state consumption, under optimal simple rule of the corresponding models. The welfare loss in the model with perfect information is 1.09%, bigger than the one associated with the asymmetric information model (1.04%). This confirms the optimal communication conducted above: revealing that information is detrimental to welfare even under the optimal simple rule. One interesting question is: if the central bank conducts the optimal simple rule ignoring the information asymmetry, how big is the welfare loss? The last column provides an answer; it reports the welfare loss associated with the optimal simple rule derived from the model with perfect information. If the true model were the one with asymmetric information, a central bank that ignores this feature would commit to a welfare loss of 1.05%: a 0.01 percentage point higher than the one associated with the optimal simple rule.

The previous analyses are conducted in the presence of a cost-push shock, σ_π. The existence of such a shock leads to a policy trade-off: the full stabilization of both inflation and the output gap is not feasible. On Panel B of Table (1.3), I analyze the optimal simple rule in the absence of cost-push shocks ($\sigma_\pi = 0$). In this case, it is well-known that the full stabilization of both inflation and the output gap can be achieved by following a strict inflation targeting Taylor rule ($\phi_\pi = \infty$). This can be seen in the last row, the optimal coefficient on inflation is infinite and the other coefficients are irrelevant in order to achieve a welfare loss of zero. As is shown in the first row on Panel B, the same result holds when the assumption of asymmetric information is made. This is because information frictions do not introduce a new policy trade-off.

Table 1.3: The Optimal Simple Rule

					Welfare Loss	
	ρ_m	ϕ_r	ϕ_π	ϕ_y	Optimal rule	Naive rule
Panel A: The Baseline Model						
Asymmetric Information	0.65	0.98	3.70	0	1.04%	1.05 %
Perfect Information	0.57	1.00	3.72	0	1.09%	1.09%
Panel B: Without Cost-push Shock						
Asymmetric Information	-	-	∞	-	0	0
Perfect Information	-	-	∞	-	0	0

Note: Panel A reports the optimal simple rule under both the asymmetric information and perfect information model. Both are calculated based on the medians of the posterior distributions of parameters estimated using the asymmetric information model, with the exception of σ_p, which is imposed as zero for the case with perfect information. On Panel B, I conduct the same exercise without the cost-push shock, i.e. $\sigma_\pi = 0$.

In sum, despite the minor quantitative differences in the optimal ϕ_m and ϕ_r, the policy implication for the design of optimal simple monetary rule is unaffected by the introduction of information asymmetry.

A Joint Analysis of the Central Bank Communication and the Optimal Simple Rule Previously, the optimal communication and simple rule are discussed separately. In the next exercise, I consider both policies jointly.

In Table (1.4), I calculate the optimal simple rule under different degrees of central bank opacity. The later is measured by σ_p. The last row corresponds to the full transparent case, in which case, the model is equivalent to a one with perfect information. As can be seen from the second and third columns, the more transparent the central bank is, the weaker is the information channel of the monetary policy action. As a result, the closer the optimal simple rule is to the one under perfect information (the last row). Moreover, at all those levels of transparency considered, a central bank that conducts a ”ignorant rule” commits to a welfare loss that is very close to the optimal one, the difference is less than 0.01 percentage point.

Figure (1.17) plots the welfare loss under different degrees of central bank opacity and the corresponding optimal simple rule. The welfare loss is decreasing in opacity. Qualitatively, the result is the same as in Figure (1.16), in the latter, the analysis was conducted based on a suboptimal monetary simple rule. Crucial to this result is the presence of a cost-push shock. In the absence of the policy trade-off, a strict inflation target will always be able to fully stabilize inflation and close the output gap independent to the degree of transparency.

Table 1.4: **The Optimal Simple Rule**

					Welfare Loss	
Degree of Opacity σ_p	ρ_m	ϕ_r	ϕ_π	ϕ_y	Optimal rule	Naive rule
1.9×10^{-2}	0.65	0.98	3.70	0	1.04%	1.05 %
1×10^{-2}	0.64	0.98	3.70	0	1.04%	1.05 %
0.5×10^{-2}	0.63	0.99	3.63	0	1.05%	1.06 %
0.1×10^{-2}	0.58	1.00	3.66	0	1.08%	1.08 %
0.01×10^{-2}	0.57	1.00	3.72	0	1.09%	1.09 %
0	0.57	1.00	3.72	0	1.09%	1.09%

Note: Each row reports the optimal simple rule under different degrees of central bank opacity. The later is measured by σ_p.

1.6 A Model with Ambiguity Averse Agents

The previous sections present a baseline model that rationalizes the baseline (linear) facts. However, the model predicts symmetric effects of monetary policy on the yield curve and forecast revision, which are inconsistent with the novel (asymmetry) facts I introduced in section (1.2), namely Figure (1.2) and Figure (1.5). In order to generate the asymmetry in the same family of model, I introduce the following additional assumptions: the first, the volatilities of shocks are uncertain; and the second, agents are ambiguity averse. To illustrate this, I show the extension in which monetary policy as a signal is ambiguous i.e. the exact distribution of monetary shock is not known, in the sense that the volatility of monetary shock is unknown. It is known that it lies in between $[\overline{\sigma}_m, \underline{\sigma}_m]$. However, results are robust if one or more of the following volatilities are uncertain: level productivity shock, trend productivity shock, private signal shock and monetary shock. This is because, ambiguity in those shocks leads to an ambiguous Kalman gain in agents' belief updating equation. The latter is crucial for rationalizing the asymmetric facts.

Household A representative household $j \in [0,1]$ which is ambiguity averse solves the following optimization problem:

$$\max_{C(j)_t, N(j)_t} \min_{\sigma_m^t \in \Gamma^t} \mathbb{E}_t \sum_{t=0}^{\infty} \beta^t e^{\delta_t} \left[logC(j)_t - \frac{N(j)_t^{1+\varphi}}{1+\varphi} \right].$$

I have assumed that agents have multiple priors regarding the quality of the monetary policy signal. This Knightian uncertainty is axiomatized by Gilboa and Schmeidler (1989) and Epstein and Schneider (2003). Due to ambiguity, agents believe that σ_m can potentially be time varying. σ_m^t denotes the perceived variance of monetary shock up to time t. $\Gamma^t = \{ \underbrace{\Gamma \times ... \times \Gamma}_{\text{t times}} \}$ with $\Gamma = [\underline{\sigma}_m, \overline{\sigma}_m]$. Ambiguity averse agents behave according to their worse case belief, denoted as $\tilde{\mathbb{E}}_t$. Therefore, one can simplify a household's optimization problem as:

$$\max_{C(j)_t, N(j)_t} \tilde{\mathbb{E}}_t \sum_{t=0}^{\infty} \beta^t e^{\delta_t} \left[logC(j)_t - \frac{N(j)_t^{1+\varphi}}{1+\varphi} \right]$$

with the choice of prior σ_m^t that enters in belief $\tilde{\mathbb{E}}_t$ yet to be determined. To solve the consumer's optimization problem, I have found the following

Euler equation:

$$Q_t = \beta \tilde{\mathbb{E}}_t \Big\{ \frac{\Lambda_{t+1}}{\Lambda_t} \frac{P_t}{P_{t+1}} \Big\}$$

Log-linearized equilibrium conditions The model is solved by taking the following steps: i) guess a σ_m^t that $\min_{\sigma_m^t \in \Gamma^t} \mathbb{E}_t \sum_{t=0}^{\infty} \beta^t e^{\delta_t} U(c_t, n_t)$; ii) solve the log-linearized model under the conjectured worse-case belief and iii) verify the initial guesses.

Given an initial guess of utility minimizing σ_m^t, the log-linearized Euler equation around a steady state[18] to get the dynamic IS equation:

$$\hat{y}_t = \tilde{\mathbb{E}}_t \hat{y}_{t+1} - [\hat{i}_t - \tilde{\mathbb{E}}_t \hat{\pi}_{t+1} - \rho_g \tilde{\mathbb{E}}_t \hat{g}_t + (\tilde{\mathbb{E}}_t \delta_{t+1} - \delta_t)]. \tag{1.23}$$

The log-linearized Phillips curve is derived from firms' problem:

$$\hat{\pi}_t = \frac{\beta}{1+\omega\beta} \tilde{\mathbb{E}}_t \hat{\pi}_{t+1} + \frac{\omega}{1+\omega\beta} \hat{\pi}_{t-1} + \kappa \hat{y}_t, \tag{1.24}$$

Note that since the households own the firms, they share the same worst-case belief. Equations (1.23) and (1.24) are similar to those derived in the baseline model except that now the expectation is taken under the worst-case belief.

Belief updating and solution of the model The fact that the monetary signal is ambiguous, complicates agents' belief updating. Given signals, agents choose a $\sigma_m \in [\overline{\sigma}_m, \underline{\sigma}_m]$ that leads to the worst-case belief. In

[18] Ilut and Schneider (2014) log-linearize around the worst-case steady state. This is not the case here because the fact that signals are uncertain does not distort the steady state: in the steady state information is perfect.

the setup of this paper, the choice of σ_m depends on the sign of monetary surprise. It is apparent that households' utility is higher if the unknown productivity trend g increases. Thus facing an ambiguous monetary signal, the natural initial guess of the worse-case scenario for private agents is the σ_m leading to a lower posterior $g_{t|t}$. Hence the perceived volatility of the monetary signal ($\tilde{\sigma}_m$) is kinked:

$$\tilde{\sigma}_m = \begin{cases} \overline{\sigma}_m, & \text{if monetary surprise } > 0 \\ \underline{\sigma}_m, & \text{if monetary surprise } < 0 \end{cases}. \tag{1.25}$$

Intuitively, a negative (positive) surprise is partially perceived as a bad (good) news shock, thus the worst case, up to the first order, is associated with a smaller (bigger) σ_m leading to larger (smaller) drop (rise) in expected trend.[19]

The equation (1.25) results in a kinked belief updating equation:

$$\tilde{\mathbb{E}}_t(.) = \begin{cases} \mathbb{E}(.|\Omega_t, \overline{\sigma}_m), & \text{if monetary surprise } > 0 \\ \mathbb{E}(.|\Omega_t, \underline{\sigma}_m), & \text{if monetary surprise } < 0 \end{cases}. \tag{1.26}$$

With an ambiguous monetary signal, the dynamics of the model change depending on the type and sign of the shocks. In response to perfectly observed shocks: ϵ_t^δ and ϵ_t^π, the dynamic of the model is characterized by equation (1.13) and equation (1.14) i.e. the same as in the baseline model. In response to unobserved shocks: ϵ_t^g, ϵ_t^a and ϵ_t^m, the dynamic of the model depends on the signs of the shocks. Below, I discuss the dy-

[19]I have kept the analysis to a first-order approximation because solving the model beyond the first order would require a nonlinear filter for the belief updating equation. Solving such a model in general is still an open question.

namics of the economy in response to monetary shocks. The results can be easily generalized to any shocks.

Case 1 ($\epsilon_t^m > 0$): a positive monetary shock (contractionary) results in positive monetary surprise at time t. This is partly perceived as a good news shock. Thus agents revise their beliefs about g_t upwards. But since they are max-minimizers, they choose to distrust the monetary signal and update their beliefs using the monetary signal precision under the worst-case scenario i.e. $\overline{\sigma}_m$. As a result, agents have made a mistake and have become over-optimistic. In the next period and all the following periods, over-optimistic agents will be"shocked" by negative monetary surprises and slowly realize that there was no shock to g at time t. This correction process from $t+1$ on, which that is accompanied by negative monetary surprises is linked to a worst-case scenario prior $\underline{\sigma}_m$. In sum, the solution of the model in this case is summarized in Proposition (1).

Proposition 1. *if* $\epsilon_t^m > 0$ *the solution of the model is as follows:*

$$X_{t+j} = \begin{cases} \overline{A}X_{t+j-1} + \overline{B}U_{t+j}, & for\, j = 0 \\ \underline{A}X_{t+j-1} + \underline{B}U_{t+j}, & for\, j > 0 \end{cases}, \tag{1.27}$$

$$X^f_{t+j} = \begin{cases} \overline{F}X_{t+j}, & for\, j = 0 \\ \underline{F}X_{t+j}, & for\, j > 0 \end{cases}. \tag{1.28}$$

where $\overline{A}$, $\overline{B}$ *and* $\overline{F}$ *are parameters associated with* $\overline{\sigma}_m$ *and* $\underline{A}$, $\underline{B}$ *and* $\underline{F}$ *are parameters associated with* $\underline{\sigma}_m$. *The agents choose to commit to their choices of* $\sigma_{m,t}$ *made in the past.*

Proof. see Appendix (1.9.6). ■

Case 2 ($\epsilon_t^m < 0$): similarly to case 1, a negative monetary shock results in a negative monetary surprise at time t and a positive surprise afterwards. The solution of the model in this case is summarized in Proposition (2).

Proposition 2. *if ($\epsilon_t^a < 0$ or $\epsilon_t^m < 0$) the solution of the model is as follows:*

$$X_{t+j} = \begin{cases} \underline{A}X_{t+j-1} + \underline{B}U_{t+j}, & for\, j = 0 \\ \overline{A}X_{t+j-1} + \overline{B}U_{t+j}, & for\, j > 0 \end{cases}, \tag{1.29}$$

$$X_{t+j}^f = \begin{cases} \underline{F}X_{t+j}, & for\, j = 0 \\ \overline{F}X_{t+j}, & for\, j > 0 \end{cases}. \tag{1.30}$$

1.7 Estimation and Results

Estimation Procedure I set the majority of the parameters to be the median estimates of the baseline model, except for $\underline{\sigma}_m$ and $\overline{\sigma}_m$, which were not present in the linear model. I estimate those key parameters by minimizing the distance between the impact effects of monetary policy shock on real GDP forecast revisions generated from simulations of the model and those from actual data, i.e. those reported in Figure (1.5). As is discussed in Proposition (1) and Proposition (2), the response to a positive monetary shock (the right panel in Figure (1.5)) is used to estimate $\overline{\sigma}_m$ and the left panel in Figure (1.5) is useful for the estimation of $\underline{\sigma}_m$. The key parameters to be estimated are stacked in vector $\Theta \equiv \begin{bmatrix} \underline{\sigma}_m & \overline{\sigma}_m \end{bmatrix}$.

Let $\mathbf{M}^*$ denote the six moments from data: three forecast revision horizons and two sets of estimates in response to positive and negative shocks. For a given parameter vector Θ, I simulate those moments $\mathbf{M}(\Theta)$ using the model. For each parameter in Θ, the distance between the actual data and the simulation of the model is:

$$\Big(\frac{\mathbf{M}^*(i) - \mathbf{M}(\Theta)(i)}{\mathbf{M}^*(i)}\Big)^2.$$

My estimator is the solution to the following problem:

$$\hat{\Theta} = argmin \sum_{i=1}^{6} \Big(\frac{\mathbf{M}^*(i) - \mathbf{M}(\Theta)(i)}{\mathbf{M}^*(i)}\Big)^2.$$

Parameter estimates are reported in Table (2.3), in which the first column reports the mean estimate (σ_m) that is taken from Table (1.1) and second and third columns report the lower bound ($\underline{\sigma}_m$) and upper bound ($\overline{\sigma}_m$) respectively. While the estimated $\underline{\sigma}_m$ is merely slightly smaller than the mean estimate, $\overline{\sigma}_m$ is double the size of σ_m. This is the case because empirically the responses of real GDP forecast revisions to negative monetary shocks are similar to those estimated in the baseline model and responses to positive monetary shocks are much smaller.

Table 1.5: Estimated Parameters

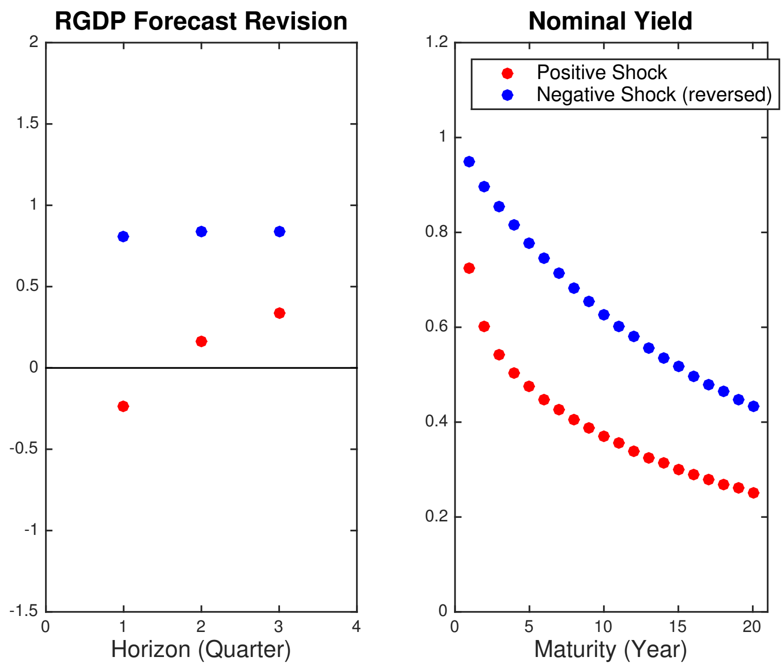
The Mean Estimate σ_m	The Lower Bound $\underline{\sigma}_m$	The Upper Bound $\overline{\sigma}_m$
1.2×10^{-3}	1.0×10^{-3}	2.0×10^{-3}

Notes: The mean estimate is taken from Table (1.1), the lower bound and upper bound reported in the second and third columns are estimated using the simulated method of moments.

Results: the Asymmetric Effects of Monetary Shocks The left panel in Figure (1.10) depicts the impact effects of monetary shocks on real GDP forecast revision at different horizons. The right panel reports the impact responses of nominal yield with different maturities to monetary shocks. The red circles report the responses to a positive monetary shock and blue ones correspond to the responses to a negative monetary shock. The asymmetry is apparent and this figure successfully replicates the empirical fact that we have seen in Figure (1.5). The intuition is the following: a negative (positive) monetary shock is perceived by private agents as an ambiguous signal about a bad (good) news shock therefore they become more pessimistic (optimistic), yet the correct amount of belief updating is ambiguous. Since they are ambiguity averse, they update as much (little) as possible, in other words the information channel is strong (weak). Therefore the puzzling facts are more (less) pronounced when the monetary shock is negative (positive). The right panel in Figure (1.10) confirms that the same asymmetric patterns hold for the yield curve: in absolute value, a negative monetary shock affects the yield curve more than the effects of a positive shock.

Figure (1.18) plots the impulse response functions of output and inflation to a positive (in red) and negative (in blue) monetary shock. As one can see, a contractionary monetary policy shock is more effective (disturbing) than an expansionary one. This is consistent with empirical studies, such as, for example, Barnichon and Matthes (2016). This is a result of the information channel and ambiguity aversion. The information channel offsets the transitional channel of monetary policy. Together with the assumptions of an ambiguous signal and ambiguity averse agent, the information channel is stronger when the monetary action sends a bad news (negative monetary shock). Since the traditional channel of monetary shock is sign independent, overall the total effect is asymmetric.

Figure 1.10: Model Result I: Rationalizing Asymmetric Facts



Note: Plots of the model implied responses of real GDP forecast revisions at different horizons and nominal yield with different maturities to monetary shocks.

Robustness Checks The results discussed above are based on a model in which monetary policy as a signal is ambiguous. However, this is not a necessary condition. The key to the success of the model is the kinked belief updating equation, which arises as long as one or more of the following volatilities are uncertain: level productivity shock, trend productivity shock, private signal shock and monetary shock. Figure (1.19) plots the estimation results of a model in which the volatility of the level productivity shock is uncertain, Figure (1.20) plots the results in the case where volatility of the trend productivity shock is uncertain, and in Figure (1.21) both private signal shock and monetary shock feature uncertain volatilities. In all of those cases, the model generates asymmetric effects of monetary shocks on real GDP forecast revision and the yield curve in a way that is consistent with empirical findings.

An interesting feature arises in Figure (1.19) and (1.21): the impulse responses of real GDP and inflation to a negative monetary shock are hump-shaped. The theoretical literature rationalizes the hump-shape IRFs by introducing capital or habit formation to the basic NK model. This paper provides an alternative mechanism: the information channel. Through the information channel, a negative monetary shock has expansionary effects while through the standard channel the impacts are contractionary. After a pure monetary shock, in the beginning, the information channel is strong and it nearly offsets the standard channel. The total effect is small on impact. Over time, agents learn the truth and the information channel diminishes faster than the conventional effect. As a result, even though the realized interest rates are not as high as in the first period, the total effects of monetary policy are stronger in the subsequent periods.

1.8 Conclusion

I have provided a micro-founded model based on the information channel of monetary policy that rationalizes: first, monetary policy shocks have an impact on interest rates at long horizons (10 years or more) and second, a contractionary monetary policy has an expansionary effect on agents' forecasts of real GDP. In the framework, the central bank holds superior information about future economic conditions. Policy actions partially reveal that information to the public, and thus the model is capable of generating the aforementioned facts. In the presence of the information channel, the impacts of monetary shocks on output and inflation are mitigated. I have also discussed the optimal central bank communication and the design of optimal monetary simple rule: it is optimal to be fully opaque about trend shocks; the information asymmetry studied in this paper does not affect the design of optimal simple rule.

In addition, I have uncovered novel empirical facts that the aforementioned effects of monetary shocks on long-term rates and real GDP forecasts are asymmetric. The responses are more pronounced (more puzzling) when the monetary shocks are expansionary. A simple extension of the baseline model rationalizes these asymmetric facts, based on signals of uncertain qualities and ambiguity averse agents. Moreover, the model predicts the asymmetric effects of monetary shocks on output and inflation, which are consistent with empirical facts discovered in empirical literature.

There are two lessons to be learned from this paper. First, in a world where the central bank has private information, the HFI monetary surprises are not necessary monetary shocks, and the former are subject to the endogeneity problem. Thus, researchers, who are interested in identifying the impacts of monetary shocks using HFI monetary surprises, should clean those measures beforehand. Second, a deviation from the monetary policy rule that intends to stimulate real GDP is not fruitful. In particular, an exogenous drop in the monetary instrument has a limited impact on real GDP due to the presence of the information channel.

An interesting extension of this paper could be to combine the current framework with time-varying volatilities. Since the seminal work by Bloom (2009), there is a growing literature that allows for a time varying second moment and studies the impacts of macroeconomic uncertainty shocks. Many indexes, such as those provided by Jurado, Ludvigson and Ng (2015), Rossi and Sekhposyan (2015) and Baker, Bloom and Davis (2016), show evidence of time-varying volatilities. In this framework, volatilities are the deep parameters that characterize the degree of information frictions. Therefore, time-varying second moments will lead to a time-varying information channel of monetary policy. Consequently, the impacts of monetary shocks on actual economic activities will be varying over time.

1.9 Appendix

1.9.1 Tables

Table 1.6: Instrument Relevance : F-statistics from the First-stage Regression

	Baseline	FFR Futures	G&K	FF4&ED4
		The Yield Curve		
Linear Framework				
$\triangle MP$	28.7	27.3	30.2	42.3
Allow for Asymmetry				
$\triangle MP$	84.7	22.3	28.5	26.2
$\triangle MP_t \times I_{-negative}$	75.3	32.7	24.2	15.5
		Forecast Revisions		
Linear Framework				
$\triangle MP$	15.2	1.3	13.4	2.3
Allow for Asymmetry				
$\triangle MP$	28.3	7.7	15.0	1.1
$\triangle MP_t \times I_{-negative}$	16.9	2.3	21.3	0.4

Notes: This table reports the F-statistics from the first-stage regression. In the baseline, the instrument set consists of HFI monetary surprises constructed from four fed funds futures and four futures on three month eurodollar deposits. The second column reports the F-statistics when only HFI monetary surprises constructed from four fed funds futures are used as instrument. In the third column, I employ the same instrument set as in Gertler and Karadi (2015), namely: surprises in the current month's fed funds futures (FF1), in the three month ahead monthly fed funds futures (FF4), and in the six month, nine month and year ahead futures on three month Eurodollar deposits (ED2, ED3, ED4). The last column reports the results using only FF4 and ED4 as instruments.

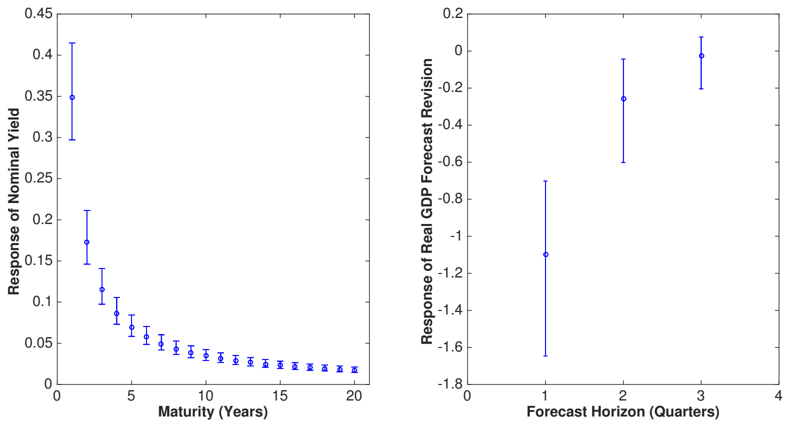
Table 1.7: Prior and Posterior: others

	Priors			Asymmetric Information		Perfect Information	
	Mean	s.d	Distribution	Mean	s.d	Mean	s.d
σ_π	2×10^{-3}	4	InvGamma	2.5×10^{-3}	0.2×10^{-3}	3.0×10^{-3}	0.3×10^{-3}
σ_d	2×10^{-3}	4	InvGamma	1.2×10^{-2}	0.3×10^{-2}	3.7×10^{-2}	0.4×10^{-2}
σ^e_{y2}	2×10^{-3}	4	InvGamma	5.5×10^{-5}	4.1×10^{-5}	6.4×10^{-5}	6.3×10^{-5}
σ^e_{y5}	2×10^{-3}	4	InvGamma	4.3×10^{-5}	3.2×10^{-5}	5.0×10^{-5}	4.3×10^{-5}
σ^e_{y10}	2×10^{-3}	4	InvGamma	6.8×10^{-4}	4.8×10^{-5}	2.0×10^{-4}	4.7×10^{-5}
g^*	0.5×10^{-2}	0.5×10^{-2}	Gamma	0.4×10^{-2}	0.7×10^{-2}	0.4×10^{-2}	0.6×10^{-2}
π^*	0.5×10^{-2}	0.5×10^{-2}	Gamma	0.6×10^{-2}	0.4×10^{-2}	0.6×10^{-2}	0.3×10^{-2}
β	0.99	0.01	Beta	0.99	0.01	0.99	0.01
k	0.3	0.1	Beta	0.12	0.04	0.36	0.07
ω	0.3	0.1	Beta	0.34	0.08	0.30	0.07
ρ_g	0.5	0.2	Beta	0.98	0.003	0.99	0.003
ρ_m	0.5	0.2	Beta	0.78	0.02	0.81	0.03
ρ_d	0.5	0.2	Beta	0.89	0.02	0.94	0.01
ϕ_π	1.5	0.25	Gamma	1.1	0.05	1.6	0.13
ϕ_y	0.25	0.05	Gamma	0.35	0.06	0.31	0.06
ϕ_r	1	0.05	Gamma	0.90	0.02	0.97	0.03

Note: Posterior means and standard deviations are estimated by Random Walk Metropolis-Hasting algorithm

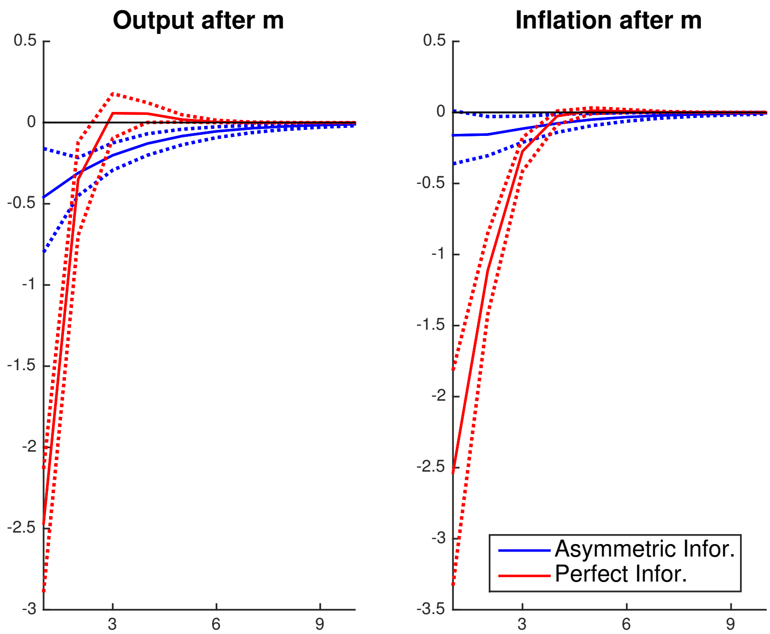
1.9.2 Figures

Figure 1.11: Predictions of a Standard NK Model: Responses to Positive Monetary Shocks



Note: This figure depicts the impact effects of monetary shocks on nominal yield at different maturities and real GDP forecast revisions at different horizons predicted by a standard NK model with perfect information. The circles and intervals are the mean estimates and 95% confidence intervals constructed based on posterior parameters' distributions.

Figure 1.12: Asymmetric Information v.s Perfect Information: Separate Estimations



This figure plots the IRFs for both the model with asymmetric information (in blue) and perfect information (in red). Both models are estimated separately. The solid and dashed lines are the mean estimates and 95% confidence interval of IRFs of the models constructed based on the posterior parameters' distributions.

Figure 1.13: Robustness Check: an Alternative Taylor rule

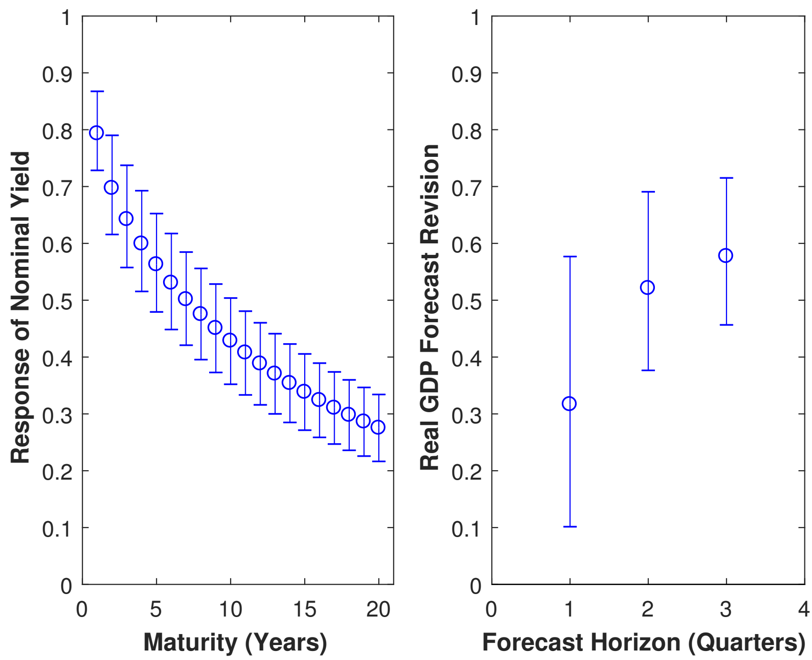


Figure 1.14: Robustness Check: Simulated Responses using the HFI Approach

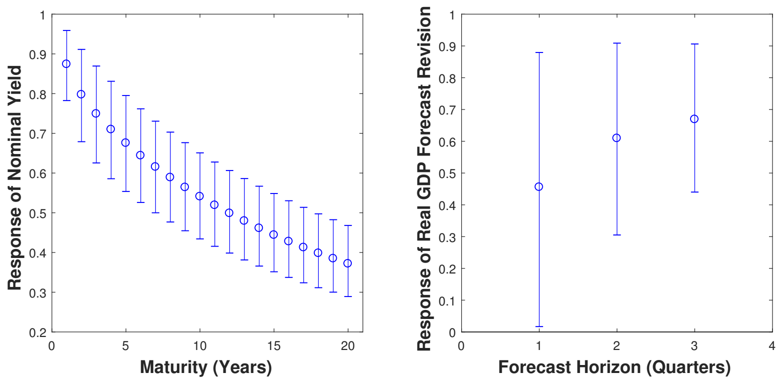


Figure 1.15: Robustness Check: Simulated Responses using the R&R Approach

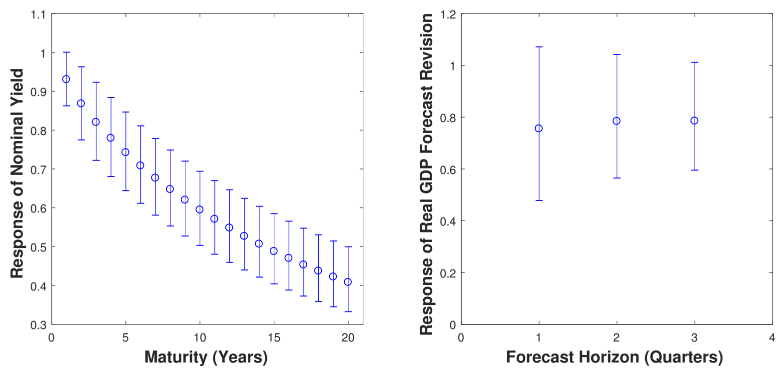
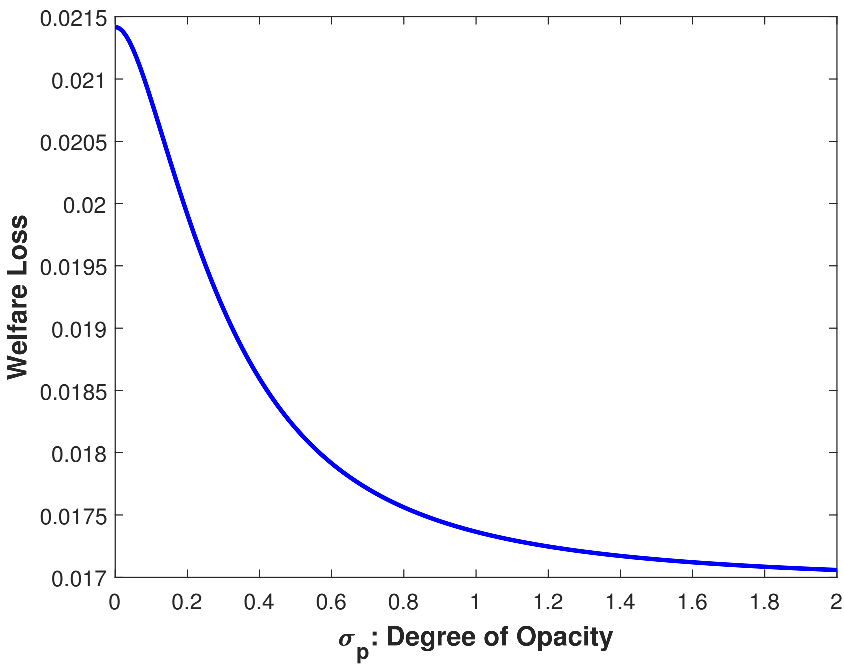
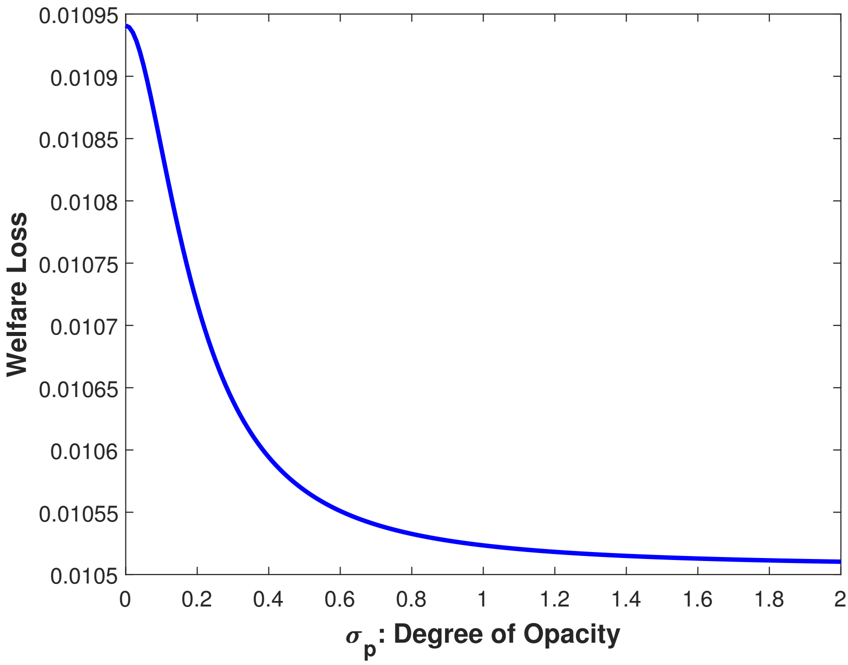


Figure 1.16: Optimal Central Bank Communication



Note: This figure plots the welfare loss associate to different degrees of central bank transparency. The latter is negatively related to σ_p, with $\sigma_p = 0$ corresponding to the full transparent case. All the other parameters are fixed at their means of the corresponding posterior parameter's distributions.

Figure 1.17: Optimal Central Bank Communication under Optimal Simple Rule



Note: This figure plots the welfare loss associate to different degrees of central bank transparency under the corresponding optimal simple rule. For each value of σ_p, the welfare loss is calculated under the corresponding optimal simple rule. All the other parameters are fixed at their means of the corresponding posterior parameter's distributions.

Figure 1.18: Model Result II: the Asymmetric Effect on Economic Activities

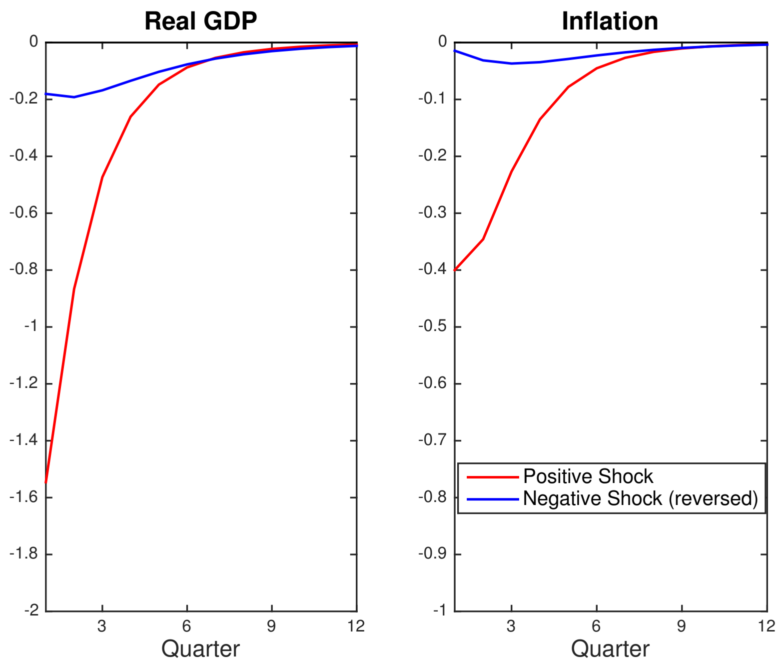


Figure 1.19: Model Robustness Check I: Ambiguous Productivity Volatility

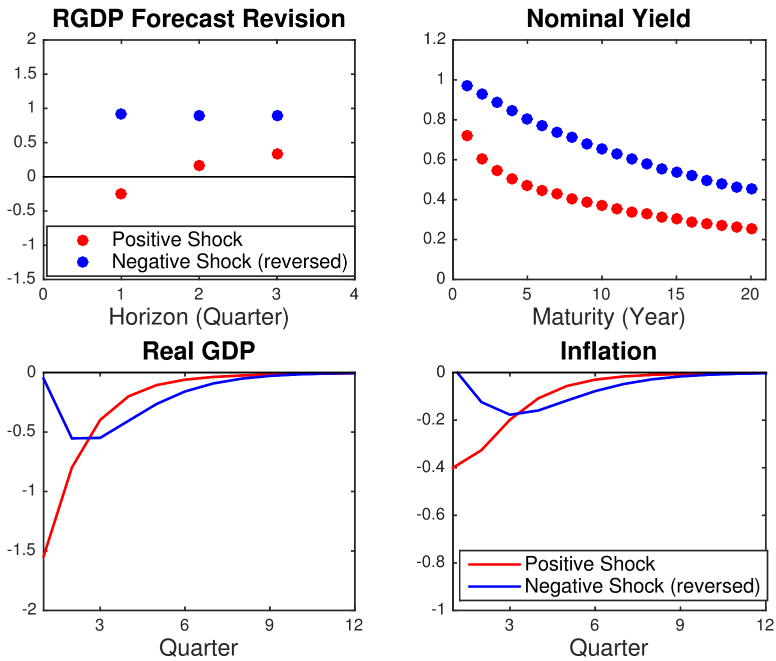
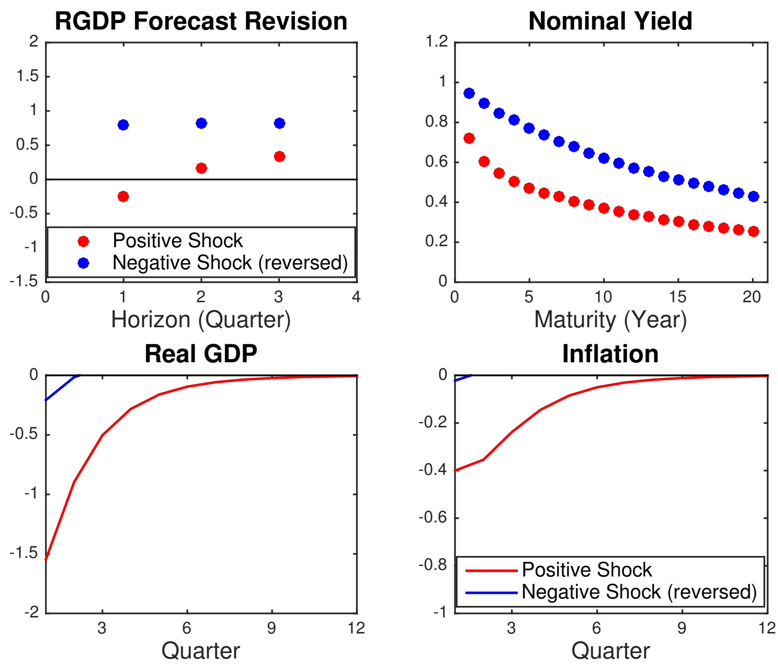


Figure 1.20: Model Robustness Check II: Ambiguous Growth Volatility

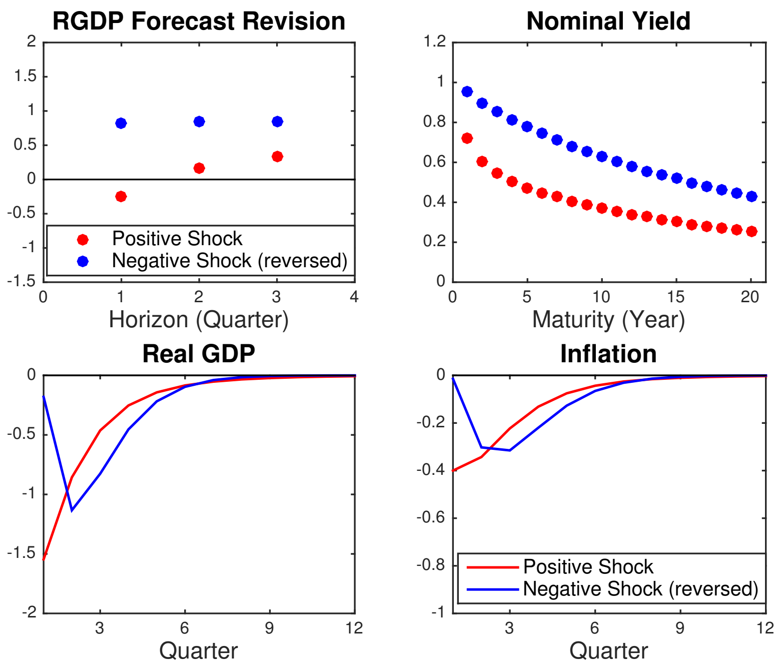


1.9.3 Empirical Results: Robustness Checks

Monetary Shocks and the Yield Curve This section shows that the empirical evidences presented in section (1.2) are robust to: i) the use of alternative instrument sets ii) excluding the recession periods; iii) excluding factors; iv) excluding Greenbook forecasts; v) excluding all control variables; and vi) the use of inflation indexed rate.

The results are robust to the use of alternative instrument sets. Table (1.6) reports F-statistics from the first-stage regressions using alternative instrument sets. The second column reports the F-statistics when only

Figure 1.21: Model Robustness Check III: Ambiguous Monetary and Private Signal Volatilities



HFI monetary surprises constructed from four fed funds futures are used as instrument. In the third column, I employ the same instrument set as in Gertler and Karadi (2015), namely: surprises in the current month's fed funds futures (FF1), in the three month ahead monthly fed funds futures (FF4), and in the six month, nine month and year ahead futures on three month Eurodollar deposits (ED2, ED3, ED4). The last column reports the results using only FF4 and ED4 as instruments. As can be seen, these alternative instrument are relevant. Figure (1.22), Figure (1.23) and Figure (1.24) plot the estimated results using those alternative instruments: monetary shocks affect interest rate at long horizon and the impacts are more pronounced when the shocks are negative.

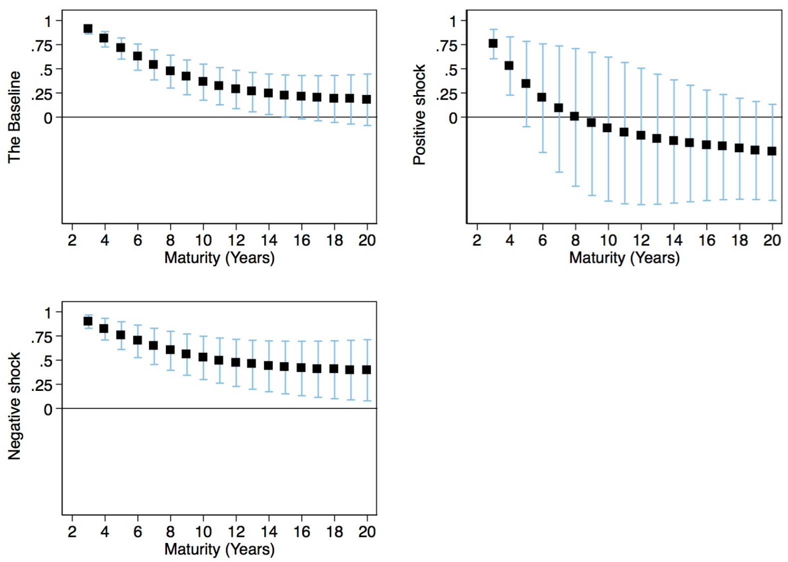
Figure (1.25) shows the estimation results for the sample excluding the deep recession periods: namely the second half of 2008 and the first half of 2009. The asymmetry is not driven by the state of the economy.

Figure (1.26), Figure (1.27) and Figure (1.28) show that with or without control variables do not affect the results. This suggests that both the endogenous and exogenous components of monetary surprises affect long-term interest rates, a feature that is consistent with the model presented in this paper. Moreover, monetary shocks affect inflation indexed rates at long horizon, which are proxies for real interest rate, and the impacts are sign dependent.

Monetary Shocks and Forecast Revisions I conduct the same set of robustness checks for the puzzles related to monetary shocks and forecast revisions.[20] See Figure (1.30), Figure (1.31), Figure (1.32), Figure (1.33) and Figure (1.34) for estimation results. As it is evidenced by those figures, the impact of monetary shock on real GDP forecast revision is sign dependent. While in response to a negative (expansionary) monetary shock agents revise their real GDP forecast downwards and economically significant, a positive (contractionary) monetary shock has little impact on real GDP forecast revisions and the effect is statistically insignificant.

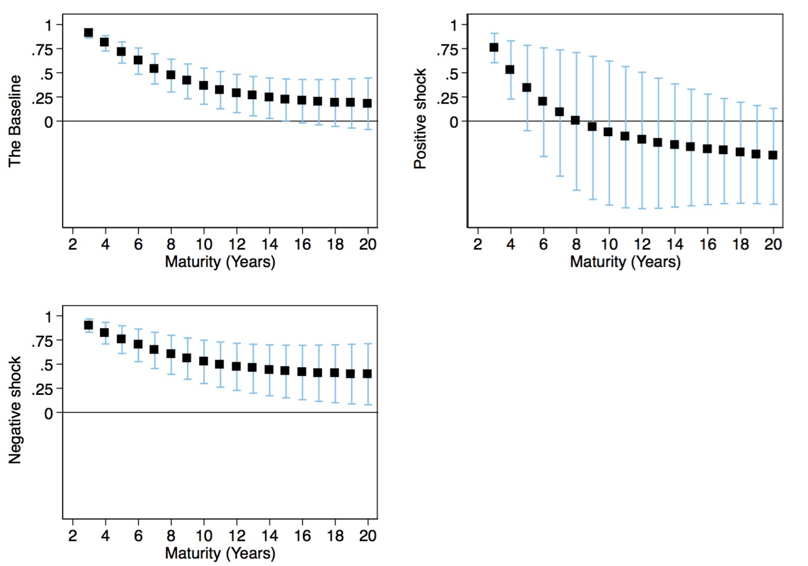
[20]However, I skip the use of alternative instrument sets that have no explanatory power in the first stage.

Figure 1.22: Impact Effect on Yield Robustness Check: FFR Futures as Instruments



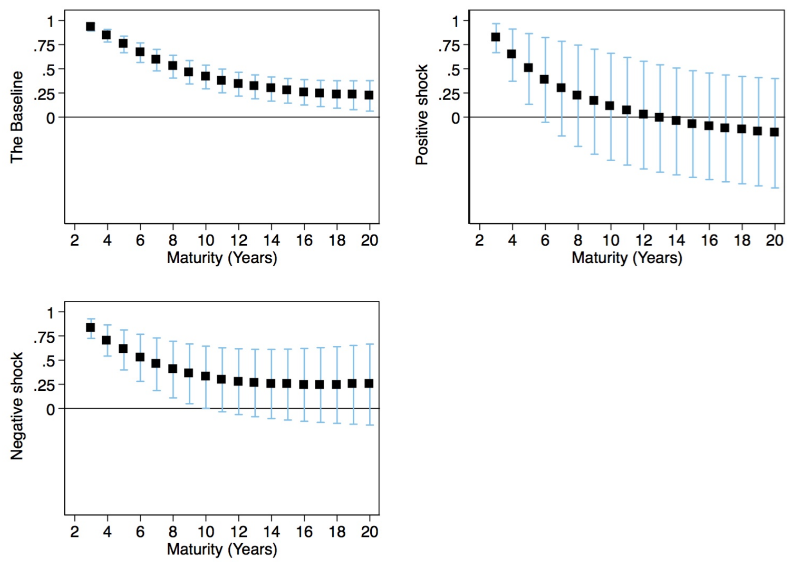
Notes: The top left panel reports the results from estimating the baseline regressions: $\triangle Y_t^h = \alpha^h + \beta^h \triangle MP_t + \gamma^h X_t + \epsilon_{h,t}$ using HFI monetary surprises as instruments for $\triangle MP_t$. The square dots on the bottom panel represent the estimated $\hat{\beta}_1^h + \hat{\beta}_2^h$ and the square dots on the top right panel represent the estimated $\hat{\beta}_1^h$, where $\hat{\beta}^h$s are estimated from separated regressions: $\triangle Y_t^h = \alpha^h + \beta_1^h \triangle MP_t + \beta_2^h \triangle MP_t \times I_{\text{-}negative} + \gamma^h X_t + \upsilon_{h,t}$ using HFI monetary surprises and those interacting with $I(HFI < 0)$ as instruments for the variables of interest $\triangle MP_t$ and $\triangle MP_t \times I_{\text{-}negative}$.The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 1990M2 to 2010M12.

Figure 1.23: Impact Effect on Yield Robustness Check: FF4&ED4 as Instruments



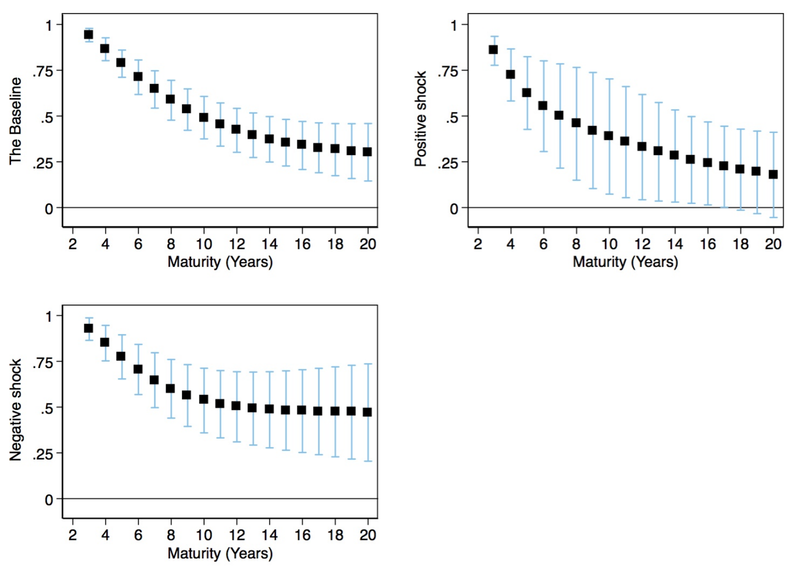
Notes: The top left panel reports the results from estimating the baseline regressions: $\triangle Y_t^h = \alpha^h + \beta^h \triangle MP_t + \gamma^h X_t + \epsilon_{h,t}$ using HFI monetary surprises as instruments for $\triangle MP_t$. The square dots on the bottom panel represent the estimated $\hat{\beta}_1^h + \hat{\beta}_2^h$ and the square dots on the top right panel represent the estimated $\hat{\beta}_1^h$, where $\hat{\beta}^h$s are estimated from separated regressions: $\triangle Y_t^h = \alpha^h + \beta_1^h \triangle MP_t + \beta_2^h \triangle MP_t \times I_{\text{-}negative} + \gamma^h X_t + \upsilon_{h,t}$ using HFI monetary surprises and those interacting with $I(HFI < 0)$ as instruments for the variables of interest $\triangle MP_t$ and $\triangle MP_t \times I_{\text{-}negative}$.The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 1990M2 to 2010M12.

Figure 1.24: Impact Effect on Yield Robustness Check: G&K Instrument Set



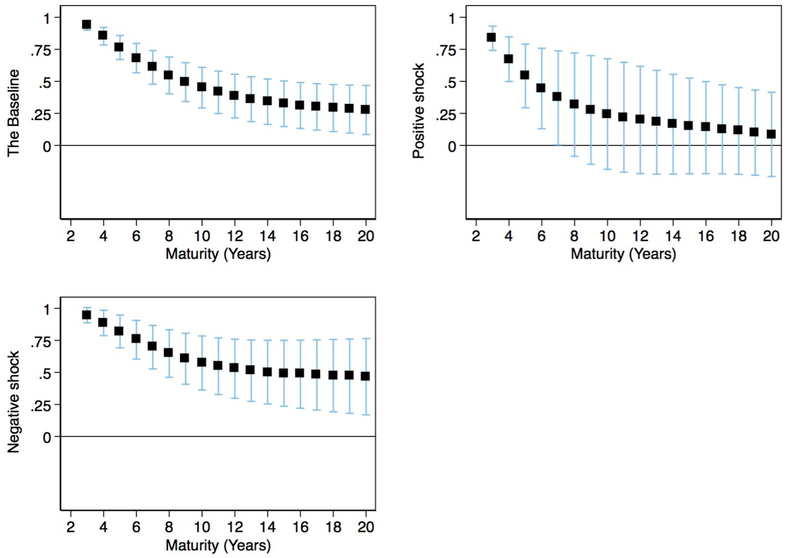
Notes: The top left panel reports the results from estimating the baseline regressions: $\triangle Y_t^h = \alpha^h + \beta^h \triangle MP_t + \gamma^h X_t + \epsilon_{h,t}$ using HFI monetary surprises as instruments for $\triangle MP_t$. The square dots on the bottom panel represent the estimated $\hat{\beta}_1^h + \hat{\beta}_2^h$ and the square dots on the top right panel represent the estimated $\hat{\beta}_1^h$, where $\hat{\beta}^h$s are estimated from separated regressions: $\triangle Y_t^h = \alpha^h + \beta_1^h \triangle MP_t + \beta_2^h \triangle MP_t \times I_{\text{-}negative} + \gamma^h X_t + v_{h,t}$ using HFI monetary surprises and those interacting with $I(HFI < 0)$ as instruments for the variables of interest $\triangle MP_t$ and $\triangle MP_t \times I_{\text{-}negative}$.The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 1990M2 to 2010M12.

Figure 1.25: Impact Effect on Yield Robustness Check: Excluding Recession Periods



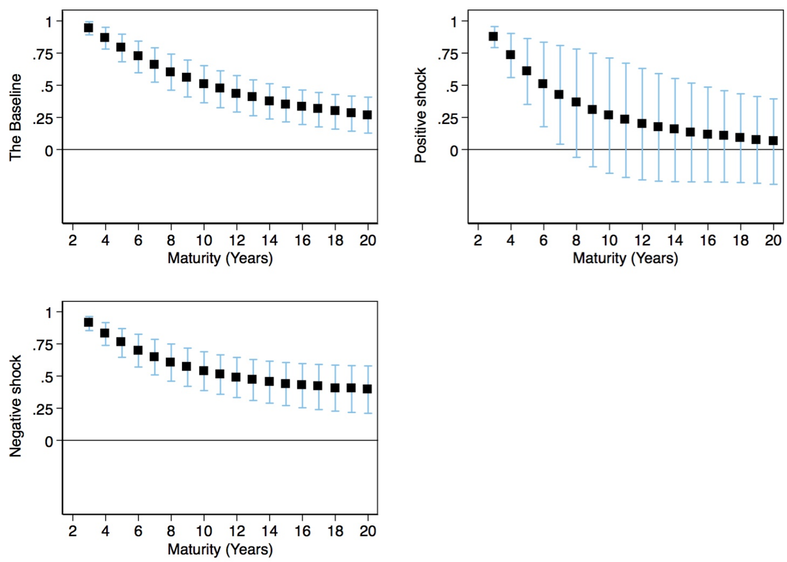
Notes: The top left panel reports the results from estimating the baseline regressions: $\triangle Y_t^h = \alpha^h + \beta^h \triangle MP_t + \gamma^h X_t + \epsilon_{h,t}$ using HFI monetary surprises as instruments for $\triangle MP_t$. The square dots on the bottom panel represent the estimated $\hat{\beta}_1^h + \hat{\beta}_2^h$ and the square dots on the top right panel represent the estimated $\hat{\beta}_1^h$, where $\hat{\beta}^h$s are estimated from separated regressions: $\triangle Y_t^h = \alpha^h + \beta_1^h \triangle MP_t + \beta_2^h \triangle MP_t \times I_{\text{-}negative} + \gamma^h X_t + \upsilon_{h,t}$ using HFI monetary surprises and those interacting with $I(HFI < 0)$ as instruments for the variables of interest $\triangle MP_t$ and $\triangle MP_t \times I_{\text{-}negative}$.The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 1990M2 to 2010M12.

Figure 1.26: Impact Effect on Yield Robustness Check: Excluding Factors



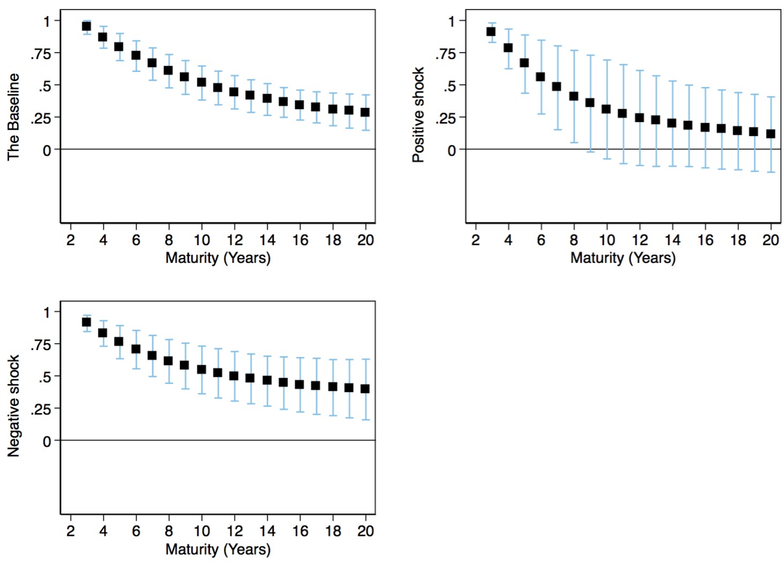
Note: The top left panel reports the results from estimating the baseline regressions: $\triangle Y_t^h = \alpha^h + \beta^h \triangle MP_t + X_t + \epsilon_{h,t}$ using HFI monetary surprises as instruments for $\triangle MP_t$. The control variables X_t contains only Greenbook forecasts. The square dots on the bottom panel represent the estimated $\hat{\beta}_1^h + \hat{\beta}_2^h$ and the square dots on the top right panel represent the estimated $\hat{\beta}_1^h$, where $\hat{\beta}^h$s are estimated from separated regressions: $\triangle Y_t^h = \alpha^h + \beta_1^h \triangle MP_t + \beta_2^h \triangle MP_t \times I_{\text{-}negative} + X_t + v_{h,t}$ using HFI monetary surprises and those interacting with $I(HFI < 0)$ as instruments for the variables of interest $\triangle MP_t$ and $\triangle MP_t \times I_{\text{-}negative}$.The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 1990M2 to 2010M12.

Figure 1.27: Impact Effect on Yield Robustness Check: Excluding Greenbook Forecasts



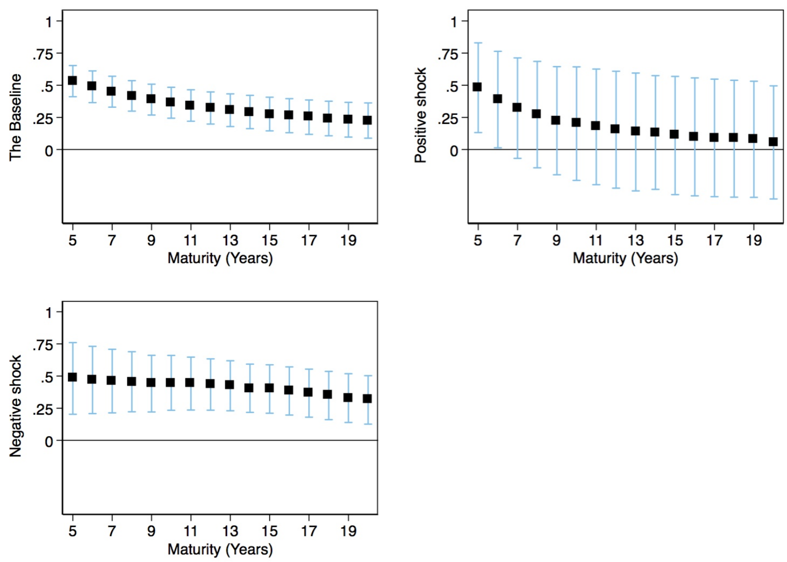
Note: The top left panel reports the results from estimating the baseline regressions: $\triangle Y_t^h = \alpha^h + \beta^h \triangle MP_t + \gamma^h X_t + \epsilon_{h,t}$ using HFI monetary surprises as instruments for $\triangle MP_t$. The control variables X_t contains only factors. The square dots on the bottom panel represent the estimated $\hat{\beta}_1^h + \hat{\beta}_2^h$ and the square dots on the top right panel represent the estimated $\hat{\beta}_1^h$, where $\hat{\beta}^h$s are estimated from separated regressions: $\triangle Y_t^h = \alpha^h + \beta_1^h \triangle MP_t + \beta_2^h \triangle MP_t \times I_{\text{-}negative} + \gamma^h X_t + \upsilon_{h,t}$ using HFI monetary surprises and those interacting with $I(HFI < 0)$ as instruments for the variables of interest $\triangle MP_t$ and $\triangle MP_t \times I_{\text{-}negative}$.The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 1995M1 to 2015M12.

Figure 1.28: Impact Effect on Yield Robustness Check: Excluding Control Variables



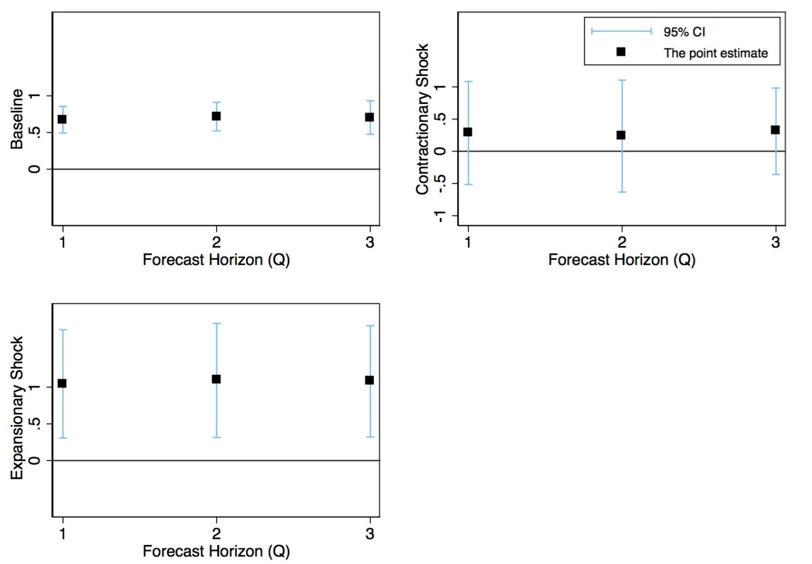
Note: The top left panel reports the results from estimating the baseline regressions: $\triangle Y_t^h = \alpha^h + \beta^h \triangle MP_t + \epsilon_{h,t}$ using HFI monetary surprises as instruments for $\triangle MP_t$. The square dots on the bottom panel represent the estimated $\hat{\beta}_1^h + \hat{\beta}_2^h$ and the square dots on the top right panel represent the estimated $\hat{\beta}_1^h$, where $\hat{\beta}^h$s are estimated from separated regressions: $\triangle Y_t^h = \alpha^h + \beta_1^h \triangle MP_t + \beta_2^h \triangle MP_t \times I_{\text{-}negative} + v_{h,t}$ using HFI monetary surprises and those interacting with $I(HFI < 0)$ as instruments for the variables of interest $\triangle MP_t$ and $\triangle MP_t \times I_{\text{-}negative}$.The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 1990M2 to 2015M12.

Figure 1.29: Impact Effect on Yield Robustness Check: Inflation Indexed Yields



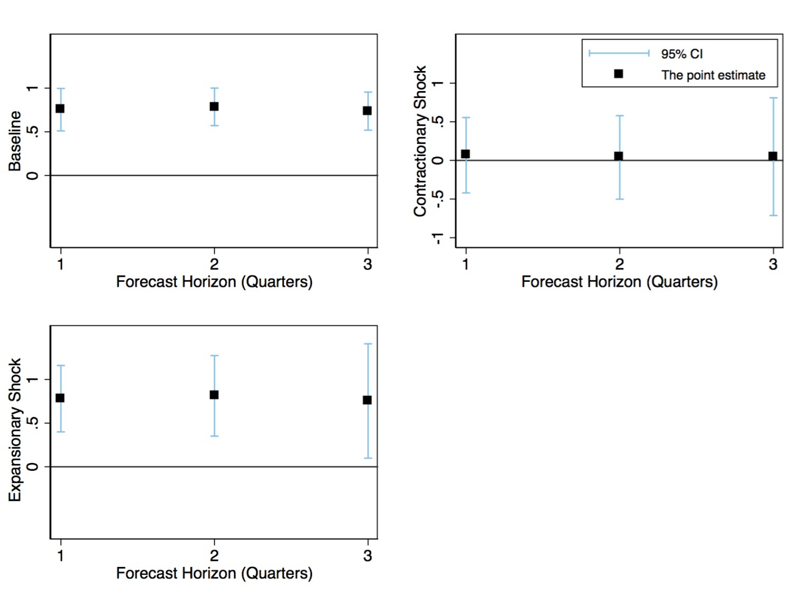
Note: The top left panel reports the results from estimating the baseline regressions: $\triangle Y_t^h = \alpha^h + \beta^h \triangle MP_t + \gamma^h X_t + \epsilon_{h,t}$ using HFI monetary surprises as instruments for $\triangle MP_t$. $\triangle Y_t^h$ is the daily change around FOMC event in the inflation indexed yield. The square dots on the bottom panel represent the estimated $\hat{\beta}_1^h + \hat{\beta}_2^h$ and the square dots on the top right panel represent the estimated $\hat{\beta}_1^h$, where $\hat{\beta}^h$s are estimated from separated regressions: $\triangle Y_t^h = \alpha^h + \beta_1^h \triangle MP_t + \beta_2^h \triangle MP_t \times I_{\text{-}negative} + \gamma^h X_t + \upsilon_{h,t}$ using HFI monetary surprises and those interacting with $I(HFI < 0)$ as instruments for the variables of interest $\triangle MP_t$ and $\triangle MP_t \times I_{\text{-}negative}$.The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 2004M1 to 2010M12.

Figure 1.30: Impact Effect on Forecast Revision Robustness Check: G&K Instrument Set



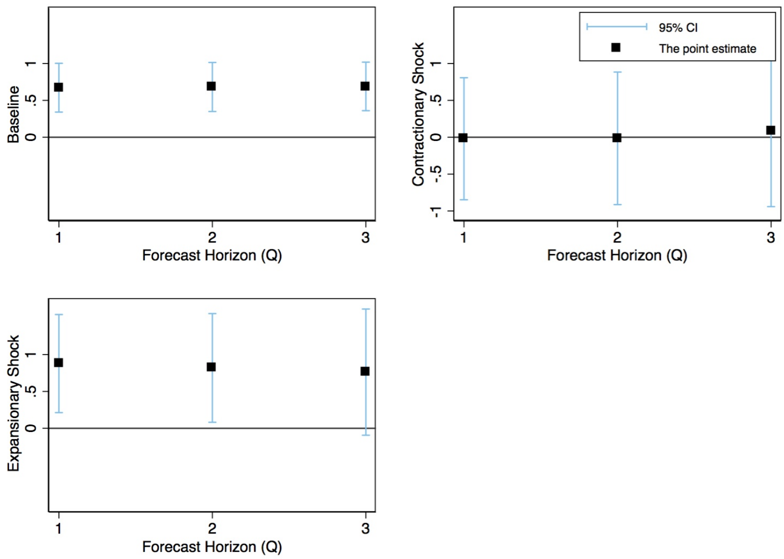
Note: The top left panel reports the results from estimating the baseline regressions: $y_{t+j|t} - y_{t+j|t-1} = \alpha^j + \beta^j \triangle MP_t + \gamma^j X_t + v_{j,t}$ using HFI monetary surprises as instruments for $\triangle MP_t$. The square dots on the bottom panel represent the estimated $\hat{\beta}_1^j + \hat{\beta}_2^j$ and the square dots on the top right panel represent the estimated $\hat{\beta}_1^j$, where $\hat{\beta}^j$s are estimated from separated regressions: $y_{t+j|t} - y_{t+j|t-1} = \alpha_1 + \beta_1^j \triangle MP_t + \beta_2^j \triangle MP_t \times I_{\text{-}negative} + \gamma^j X_t + v_{j,t}$ using HFI monetary surprises and those interacting with $I(HFI < 0)$ as instruments for the variables of interest $\triangle MP_t$ and $\triangle MP_t \times I_{\text{-}negative}$. The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 1990Q1 to 2010Q4.

Figure 1.31: Impact Effect on Forecast Revision Robustness Check: Excluding Recession Periods



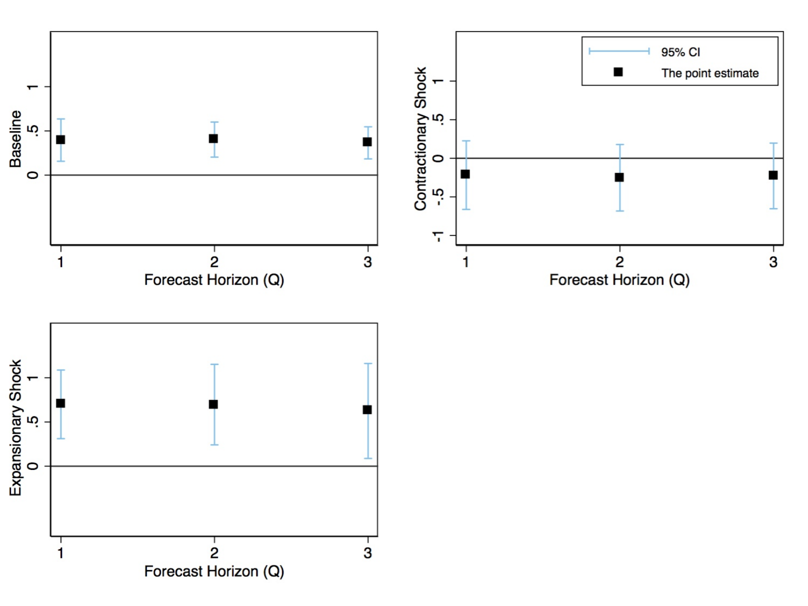
Note: The top left panel reports the results from estimating the baseline regressions: $y_{t+j|t} - y_{t+j|t-1} = \alpha^j + \beta^j \triangle MP_t + \gamma^j X_t + v_{j,t}$ using HFI monetary surprises as instruments for $\triangle MP_t$. The square dots on the bottom panel represent the estimated $\hat{\beta}_1^j + \hat{\beta}_2^j$ and the square dots on the top right panel represent the estimated $\hat{\beta}_1^j$, where $\hat{\beta}^j$s are estimated from separated regressions: $y_{t+j|t} - y_{t+j|t-1} = \alpha_1 + \beta_1^j \triangle MP_t + \beta_2^j \triangle MP_t \times I_{-negative} + \gamma^j X_t + v_{j,t}$ using HFI monetary surprises and those interacting with $I(HFI < 0)$ as instruments for the variables of interest $\triangle MP_t$ and $\triangle MP_t \times I_{-negative}$. The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 1990Q1 to 2010Q4.

Figure 1.32: Impact Effect on Forecast Revision Robustness Check: Excluding Factors



Note: The top left panel reports the results from estimating the baseline regressions: $y_{t+j|t} - y_{t+j|t-1} = \alpha^j + \beta^j \triangle MP_t + \gamma^j X_t + v_{j,t}$ using HFI monetary surprises as instruments for $\triangle MP_t$. The square dots on the bottom panel represent the estimated $\hat{\beta}_1^j + \hat{\beta}_2^j$ and the square dots on the top right panel represent the estimated $\hat{\beta}_1^j$, where $\hat{\beta}^j$s are estimated from separated regressions: $y_{t+j|t} - y_{t+j|t-1} = \alpha^j + \beta_1^j \triangle MP_t + \beta_2^j \triangle MP_t \times I_{\text{-}negative} + \gamma^j X_t + v_{j,t}$ using HFI monetary surprises and those interacting with $I(HFI < 0)$ as instruments for the variables of interest $\triangle MP_t$ and $\triangle MP_t \times I_{\text{-}negative}$. The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 1990Q1 to 2010Q4.

Figure 1.33: Impact Effect on Forecast Revision Robustness Check: Excluding Greenbook Forecasts



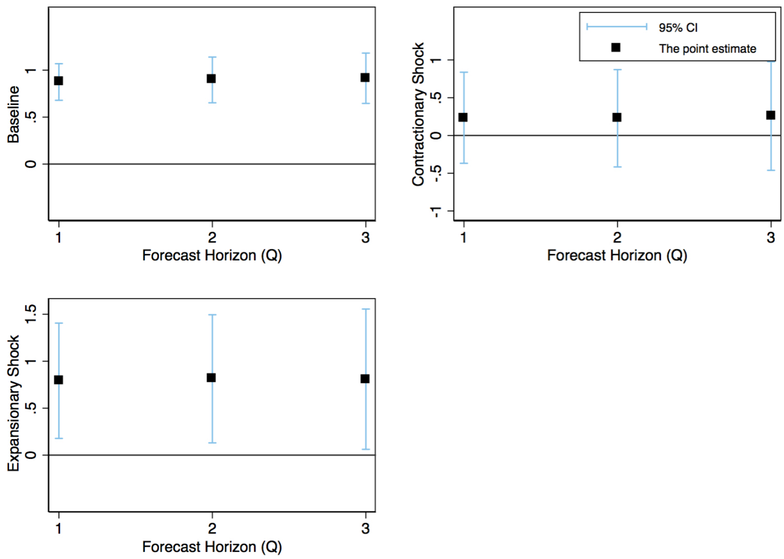
Note: The top left panel reports the results from estimating the baseline regressions: $y_{t+j|t} - y_{t+j|t-1} = \alpha^j + \beta^j \triangle MP_t + \gamma^j X_t + v_{j,t}$ using HFI monetary surprises as instruments for $\triangle MP_t$. The square dots on the bottom panel represent the estimated $\hat{\beta}_1^j + \hat{\beta}_2^j$ and the square dots on the top right panel represent the estimated $\hat{\beta}_1^j$, where $\hat{\beta}^j$s are estimated from separated regressions: $y_{t+j|t} - y_{t+j|t-1} = \alpha^j + \beta_1^j \triangle MP_t + \beta_2^j \triangle MP_t \times I_{\text{-}negative} + \gamma^j X_t + v_{j,t}$ using HFI monetary surprises and those interacting with $I(HFI < 0)$ as instruments for the variables of interest $\triangle MP_t$ and $\triangle MP_t \times I_{\text{-}negative}$. The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 1990Q1 to 2015Q4.

1.9.4 Model Solution

Define: $X_t^b = (\epsilon_t^m, \hat{g}_t, \delta_t, \epsilon_t^\pi, \hat{i}_{t-1}, \hat{\pi}_{t-1})'$ and $X_t^f = (\hat{y}_t, \hat{\pi}_t)'$. The model can be summarized as:

$$M^0 \begin{bmatrix} X_{t+1}^b \\ X_{t+1|t}^f \end{bmatrix} = M^1 \begin{bmatrix} X_t^b \\ X_t^f \end{bmatrix} + M^2 \begin{bmatrix} X_{t|t}^b \\ X_t^f \end{bmatrix} + M^3 u_{t+1} \tag{1.1}$$

Figure 1.34: Impact Effect on Forecast Revision Robustness Check: Excluding Control Variables



Note: The top left panel reports the results from estimating the baseline regressions: $y_{t+j|t} - y_{t+j|t-1} = \alpha^j + \beta^j \triangle MP_t + v_{j,t}$ using HFI monetary surprises as instruments for $\triangle MP_t$. The square dots on the bottom panel represent the estimated $\hat{\beta}_1^j + \hat{\beta}_2^j$ and the square dots on the top right panel represent the estimated $\hat{\beta}_1^j$, where $\hat{\beta}^h$s are estimated from separated regressions: $y_{t+j|t} - y_{t+j|t-1} = \alpha^j + \beta_1^j \triangle MP_t + \beta_2^j \triangle MP_t \times I_{\text{-}negative} + v_{h,t}$ using HFI monetary surprises and those interacting with $I(HFI < 0)$ as instruments for the variables of interest $\triangle MP_t$ and $\triangle MP_t \times I_{\text{-}negative}$. The blue lines are the 95% confidence interval constructed using standard errors that are robust to serial correlation and heteroskedasticity. Sample: 1990Q1 to 2015Q4.

or explicitly:

$$M^0 \begin{bmatrix} \epsilon^m_{t+1} \\ \hat{g}_{t+1} \\ \delta_{t+1} \\ \epsilon^\pi_{t+1} \\ \hat{i}_t \\ \hat{\pi}_t \\ \hat{y}_{t+1|t} \\ \hat{\pi}_{t+1|t} \end{bmatrix} = M^1 \begin{bmatrix} \epsilon^m_t \\ \hat{g}_t \\ \delta_t \\ \epsilon^\pi_t \\ \hat{i}_{t-1} \\ \hat{\pi}_{t-1} \\ \hat{y}_t \\ \hat{\pi}_t \end{bmatrix} + M^2 \begin{bmatrix} \epsilon^m_{t|t} \\ \hat{g}_{t|t} \\ \delta_t \\ \epsilon^\pi_t \\ \hat{i}_{t-1} \\ \hat{\pi}_{t-1} \\ \hat{y}_t \\ \hat{\pi}_t \end{bmatrix} + M^3 \begin{bmatrix} \epsilon^g_{t+1} \\ \epsilon^\delta_{t+1} \\ \epsilon^\pi_{t+1} \\ \epsilon^m_{t+1} \end{bmatrix},$$

where

$$M^0 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & -1 & 0 & \frac{\beta}{1+\omega\beta} \end{bmatrix} M_3 = \begin{bmatrix} 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$M^1 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \rho_g & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \rho_\delta & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & (1-\rho_m)\rho_g & (1-\rho_m)\rho_\delta & 0 & \rho_m & 0 & (1-\rho_m)\phi_y & (1-\rho_m)\rho_\pi \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & (1-\rho_\delta) & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & -1 & 0 & -\frac{\omega}{1+\omega\beta} & -\kappa(1+\varphi) & 0 \end{bmatrix}$$

$$M^2 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -\rho_g & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Transform (1.1) into:

$$\begin{bmatrix} X_{t+1}^b \\ X_{t+1|t}^f \end{bmatrix} = A^1 \begin{bmatrix} X_t^b \\ X_t^f \end{bmatrix} + A^2 \begin{bmatrix} X_{t|t}^b \\ X_t^f \end{bmatrix} + A^3 u_{t+1} \tag{1.2}$$

where $A^1 \equiv (M^0)^{-1} M^1$, $A^2 \equiv (M^0)^{-1} M^2$ and $A^3 \equiv (M^0)^{-1} M^3$

Variables that are observable to private agent and relevant for belief updating are summarized in vector Z_t :

$$Z_t = C \begin{bmatrix} X_t^b \\ X_t^f \end{bmatrix} + v_t \tag{1.3}$$

or explicitly:

$$\begin{bmatrix} i_t \\ \triangle a_t \\ s_t^p \end{bmatrix} = C \begin{bmatrix} \epsilon_t^m \\ \hat{g}_t \\ \delta_t \\ \epsilon_t^\pi \\ \hat{i}_{t-1} \\ \hat{\pi}_{t-1} \\ \hat{y}_t \\ \hat{\pi}_t \end{bmatrix} + \begin{bmatrix} 0 \\ \epsilon_t^a \\ \epsilon_t^p \end{bmatrix} \tag{1.4}$$

where:

$$C = \begin{bmatrix} 1 & (1-\rho_m)\rho_g & (1-\rho_m)\rho_\delta & 0 & \rho_m & 0 & (1-\rho_m)\phi_y & (1-\rho_m)\rho_\pi \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Take expectation on (1.2):

$$\begin{bmatrix} X^b_{t+1|t} \\ X^f_{t+1|t} \end{bmatrix} = W \begin{bmatrix} X^b_{t|t} \\ X^f_t \end{bmatrix} \tag{1.5}$$

where $W \equiv A^1 + A^2$. The Schur decomposition of matrix W is HUH^{-1}. Pre-multiply the previous equation by H^{-1} and define $Y_t \equiv H^{-1}X_{t|t}$ we get:

$$Y_{t+1} = UY_t \tag{1.6}$$

Solving the 2nd block of Y_{t+1} first, where $|\lambda_i| > 1$. Eliminating explosive equilibrium implies:

$$\begin{aligned} Y_{f,t} &= 0 \\ \Rightarrow X^f_t &= GX^b_{t|t}, \end{aligned} \tag{1.7}$$

where $G \equiv -(H^{inv}_{22})^{-1}H^{Inv}_{21}$. Note that through out the paper the matrix $H \equiv \begin{bmatrix} H_1 \\ H_2 \end{bmatrix} \equiv \begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix}$, similar notations apply to other matrixes. The 2nd block of (1.5) together with (1.7) implies:

$$X^b_{t+1|t} = J^b X^b_{t|t} \tag{1.8}$$

$$X^f_{t+1|t} = J^f X^b_{t|t}, \tag{1.9}$$

where $J^b \equiv (W_{11} + W_{12}G)$, $J^f \equiv G(W_{11} + W_{12}G)$.

(1.2) - (1.5):

$$\begin{bmatrix} X^b_{t+1} - X^b_{t+1|t} \\ 0 \end{bmatrix} = A^1 \begin{bmatrix} X^b_t - X^b_{t|t} \\ 0 \end{bmatrix} + A^3 u_{t+1}$$

The first block implies that:

$$X^b_{t+1} = HX^b_t + JX^b_{t|t} + A^3_1 u_{t+1} \tag{1.10}$$

where $J \equiv W_{11} + W_{12}G - A^1_{11}$ and $H \equiv A_{11}$.

Notice that in the belief matrix $X^b_{t|t}$, only two variables are not perfectly observed by agents, those are ϵ^m_t, and g_t. Denote $x_t \equiv [\epsilon^m_t, g_t]'$ and $x_{t|t} \equiv [\epsilon^m_{t|t}, g_{t|t}]'$. The remaining variables are perfectly observable, therefore equal to their counter-parts in matrix X^b_t. Next, we will find law of motion for $x_{t|t}$.

Rewrite (1.3):

$$\begin{aligned} Z_t &= C_1 X^b_t + C_2 X^f_t + v_t \\ &= C_1 X^b_t + C_3 X^b_{t|t} + v_t \\ &= C_b X^b_t + M x_{t|t} + v_t, \end{aligned}$$

where $C_3 = C_2 G$, $C_b \equiv C_1 + [0_{3,2}\ C_3(:, 3 : end)]$, $M \equiv C_3(:, 1 : 2)$. The above signal equation can be transform to:

$$Z^x = Lx_t + Mx_{t|t} + v_t, \tag{1.11}$$

where $Z^x \equiv Z_t - [0_{3,2}\ C_b(:, 3 : 6)]X^b_t$, $L = C_b(:, 1 : 2)$. Note that:

$$x_t = J^x x_{t-1} + u^x_t, \tag{1.12}$$

where $J^x = \begin{bmatrix} 0 & 0 \\ 0 & \rho_g \end{bmatrix}$ and $u_t^x = \begin{bmatrix} \epsilon_t^m \\ \epsilon_t^g \end{bmatrix}$. Now, results derived in Svensson and Woodford (2003) applies directly.

$$x_{t|t}^b = x_{t|t-1}^b + K(L(x_t - x_{t|t-1}) + v_t) \tag{1.13}$$

$$K = PL'(LPL' + \Sigma_{vv})^{-1} \tag{1.14}$$

$$P = J^x[P - PL'(LPL' + \Sigma_{vv})^{-1}LP]J^{x'} + \Sigma_{ux}^2 \tag{1.15}$$

State Space representation $X_t \equiv \begin{bmatrix} X_t^b \\ x_{t|t} \end{bmatrix}$ and $V_t \equiv \begin{bmatrix} \epsilon_t^g \\ \epsilon_t^\delta \\ \epsilon_t^\pi \\ \epsilon_t^m \\ \epsilon_t^a \\ \epsilon_t^p \end{bmatrix}$. We collect the relevant equations into one state space representation.

$$X_{t+1} = AX_t + BV_{t+1}, \tag{1.16}$$

$$X_t^f = FX_t \tag{1.17}$$

$$X_{t+1|t}^f = F_1 X_t \tag{1.18}$$

with

$$
\begin{aligned}
A &= \begin{bmatrix} A_b \\ A_{bb} \end{bmatrix} B = \begin{bmatrix} B_b \\ B_{bb} \end{bmatrix} \\
A_b &= \begin{bmatrix} H & 0_{nb\times 2} \end{bmatrix} + \begin{bmatrix} 0_{nb\times 2} & J(:, 3:end) & J(:, 1:2) \end{bmatrix}, \\
B_b &= A_1^3 L^u, L^u = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix} \\
A_{bb} &= \begin{bmatrix} 0_{2\times nb} & J^x - KLJ^x \end{bmatrix} + \begin{bmatrix} KLJ^x & 0_{2\times 6} \end{bmatrix} \\
B_{bb} &= KLL^x + KL^v, L^v = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}, L^x = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \\
F &= \begin{bmatrix} 0_{nf\times 2} & G(:, 3:end) & G(:, 1:2) \end{bmatrix} \\
F_1 &= \begin{bmatrix} 0_{nf\times 2} & J^f(:, 3:end) & J^f(:, 1:2) \end{bmatrix} \\
F_2 &= \begin{bmatrix} 0_{nf\times 2} & J^{f2}(:, 3:end) & J^{f2}(:, 1:2) \end{bmatrix}, J^{f2} = J^b J^f
\end{aligned}
$$

1.9.5 Term structure

This section derives term structure implied by the model discussed above. The goal is to write down the term structure in terms of our state vector X_t. i_t enters as the fourth element in vector X_{t+1}, therefore:

$$i_t = M_I X_t, \tag{1.19}$$

where $M_I \equiv A(5, :)$.

The stochastic discount factor, both nominal (M^n_{t+1}) and real (M^r_{t+1}) can be derived from consumer's first order condition:

$$M^n_{t+1} = \beta \frac{U_{c,t+1} P_t}{U_{c,t} P_{t+1}}$$
$$M^r_{t+1} = \beta \frac{U_{c,t+1}}{U_{c,t}}$$

Given the utility function specified in this paper, $m_{t+1} \equiv log M_{t+1}$ is defined as:

$$m^n_{t+1} = log\beta - y_{t+1} + y_t - \pi_{t+1} + (\rho_\delta - 1)\delta_t - g_t \tag{1.20}$$
$$m^r_{t+1} = log\beta - y_{t+1} + y_t + (\rho_\delta - 1)\delta_t - g_t \tag{1.21}$$

Consider the nominal discount factor, rewrite in terms of state variable:

$$m^n_{t+1} = log\beta + \begin{bmatrix} -1 & -1 \end{bmatrix} X^f_{t+1} + \begin{bmatrix} 1 & 0 \end{bmatrix} X^f_t + \begin{bmatrix} 0 & -1 & \rho_\delta - 1 & 0_{5\times 1} \end{bmatrix} X_t$$

Recall that $X^f_t \equiv F X_t$, $X^f_{t+1} = FAX_t + FBV_{t+1}$, plug them in:

$$m^n_{t+1} = \overline{m} + M_n X_t + M_{vn} V_{t+1}, \tag{1.22}$$

where $\overline{m} \equiv log\beta$, $M_n \equiv \begin{bmatrix} -1 & -1 \end{bmatrix} FA + \begin{bmatrix} 1 & 0 \end{bmatrix} F + \begin{bmatrix} 0 & -1 & \rho_\delta - 1 & 0_{1\times 5} \end{bmatrix}$ and $M_{vn} \equiv \begin{bmatrix} -1 & -1 \end{bmatrix} FB$.

Similarly:

$$m^r_{t+1} = \overline{m} + M_r X_t + M_{vr} V_{t+1} \tag{1.23}$$

where $M_r \equiv \begin{bmatrix} -1 & 0 \end{bmatrix} FA + \begin{bmatrix} 1 & 0 \end{bmatrix} F + \begin{bmatrix} 0 & -1 & \rho_\delta - 1 & 0_{5\times 1} \end{bmatrix}$ and

$M_{vr} \equiv \begin{bmatrix} -1 & 0 \end{bmatrix} FB.$

The no arbitrage condition:

$$P_t^{n+1} = E_t(M_{t+1} P_{t+1}^n) \tag{1.24}$$

The relation between yield and price of zero coupon bond:

$$i_t^{(n)} = -n^{-1} log(P_t^n) \tag{1.25}$$

With (1.19) (1.22) (1.23) (1.24) (1.25) we can derive the yield curve as linear function of state variable X_t. Let's begin with the nominal yield and the real yield curve is derived similarly. Note that $i_t^{(1)} \equiv i_t$. From (1.19) (1.25) and let $n = 1$ we get:

$$\begin{aligned} P_{t+1}^1 &= exp(-i_{t+1}) \\ &= exp(-M_I X_{t+1}) \\ &= exp(-M_I A X_t - M_I B V_{t+1}) \end{aligned} \tag{1.26}$$

Plug (1.23) and (1.26) into (1.25):

$$\begin{aligned} P_t^2 &= v_{h,t}(M_{t+1} P_{t+1}^1) \\ &= v_{h,t}[exp(\overline{m} + M_n X_t + M_{vn} U_{t+1} - M_I A X_t - M_I B V_{t+1})] \\ &= v_{h,t}[exp(\overline{m} + (M_n - M_I A) X_t + (M_{vn} - M_I B) V_{t+1})] \end{aligned}$$

Under the assumption that shocks are normally distributed, the previous equation follows a log-normal distribution[21]. Therefore:

$$P_t^2 = exp(\overline{m} + (M_n - M_I A)DX_t + 0.5Var_2), \tag{1.27}$$

we have used the fact that $X_{t|t} = DX_t$ with $D \equiv \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$.
Var_2 depends on parameters and are remained to be determined. By (1.25)

$$\begin{aligned} i_t^{(2)} &= -0.5log(P_t^2) \\ &= -0.5\overline{m} - 0.25Var_2 - 0.5(M_n - M_I A)DX_t \end{aligned} \tag{1.28}$$

We have derived the expression for yield of a zero-coupon bond with maturity of 2. We will show in general for $n \geq 2$:

$$logP_t^n = A_n + B_n X_t \tag{1.29}$$

For $n = 1$, $logP_t^1 = -M_I X_t$. And we have shown for $n = 2$:

$$\begin{aligned} A_2 &= \overline{m} + 0.5Var_2 \\ B_2 &= (M_n - M_I A)D \end{aligned}$$

[21] If x follows a log-normal distribution, $E(e^x) = e^{E(x)+0.5\sigma_x^2}$

In order to find the general rule, let's take one more step and set $n = 3$:

$$P_t^3 = v_{h,t}(M_{t+1}P_{t+1}^2)$$

(1.29) implies that $P_{t+1}^2 = exp(A_2 + B_2AX_t + B_2BV_{t+1})$. Therefore:

$$\begin{aligned} P_t^3 &= v_{h,t}[exp(\overline{m} + M_nX_t + M_{vn}V_{t+1} + A_2 + B_2AX_t + B_2BV_{t+1}] \\ &= v_{h,t}[exp(\overline{m} + A_2 + (M_n + B_2A)X_t + (M_{vn} + B_2B)V_{t+1}] \end{aligned}$$

Hence:

$$logP_t^3 = A_3 + B_3X_t,$$

with

$$\begin{aligned} A_3 &= \overline{m} + A_2 + 0.5Var_3 \\ B_3 &= (M_n + B_2A)D \end{aligned}$$

The recursive relations for A_n and B_n are:

$$A_n = A_{n-1} + \overline{m} + 0.5Var_n \tag{1.30}$$

$$B_n = (M_n + B_{n-1}A)D \tag{1.31}$$

The expressions for $Vars$ are:

$$\begin{aligned}
Var_2 &= [B_2 D^{-1}]^b P [B_2 D^{-1}]^{b'} + (M_{vn} + M_I B)\Sigma_{VV}(M_{vn} + M_I B)' \\
&\quad + \sigma^2 \Psi^2 (\sigma_g^2 + \sigma_a^2 + \sigma_m^2) \\
Var_3 &= [B_3 D^{-1}]^b P [B_3 D^{-1}]^{b'} + (M_{vn} + B_2 B)\Sigma_{VV}(M_{vn} + B_2 B)' \\
&\quad + \sigma^2 \Psi^2 (\sigma_g^2 + \sigma_a^2 + \sigma_m^2) \\
Var_n &= [B_n D^{-1}]^b P [B_n D^{-1}]^{b'} + (M_{vn} + B_{n-1} B)\Sigma_{VV}(M_{vn} + B_{n-1} B)' \\
&\quad + \sigma^2 \Psi^2 (\sigma_g^2 + \sigma_a^2 + \sigma_m^2)
\end{aligned}$$

Thus the yield curve with different maturities can be collected in:

$$\begin{bmatrix} i_t \\ i_t^2 \\ . \\ . \\ i_t^n \end{bmatrix} = \begin{bmatrix} -A_1 \\ -\frac{1}{2}A_2 \\ . \\ . \\ -\frac{1}{n}A_n \end{bmatrix} + \begin{bmatrix} -B_1 \\ -\frac{1}{2}B_2 \\ . \\ . \\ -\frac{1}{n}B_n \end{bmatrix} X_t + e_t^i \tag{1.32}$$

1.9.6 Proof of Proposition 1

Proof: At time t, a positive monetary shock leads to a positive monetary surprise, thus the agent updates $g_{t|t}$ upwards as less as possible using $\sigma_{m,t} = \overline{\sigma}_m$. Note that $E_t(i_{t+1})$ is positively related to $g_{t|t}$ with the coefficient θ_g.

At time $t+1$, the misinterpretation committed at time t leads to a negative monetary surprise $-\theta_g g_{t|t}$, thus the agent updates $g_{t+1|t+1}$ downwards. The exact amount of forecast revision depends on the choice of $\sigma_{m,t}$ and $\sigma_{m,t+1}$. It is apparent that $\sigma_{m,t+1} = \underline{\sigma}_m$ leads to a maximum downward revision of $g_{t+1|t+1}$ (worse-case) independent with the choice of $\sigma_{m,t}$.

The $\sigma_{m,t}$ chosen at $t+1$ continue to be the same as before, i.e. $\overline{\sigma}_m$. To see this, by contradiction, assume that the agent revises her choice of $\sigma_{m,t}$ downward such that $g_{t|t+1} - g_{t|t} = \triangle$. As a result, $g_{t+1|t+1}$ would be $(1-(k_{t,t}-k_{t,t+1})\theta_g)\triangle$ higher than the one associated with $\sigma_{m,t} = \overline{\sigma}_m$, thus this is not the worse-case. The latter contradicts that the agent is a max-minimizer. Note that I have used the fact that under the worse case choice of $\sigma_{m,t}$ the belief updating equation is $g^*_{t+1|t+1} = g_{t|t} - k_{t,t}\theta_g g_{t|t}$ and under the alternative case $g_{t+1|t+1} = g_{t|t+1} - k_{t,t+1}\theta_g g_{t|t+1}$, with $(k_{t,t} - k_{t,t+1}) < 0$.

Similarly, at time $t+j$ for $j > 1$, the agent keeps being shocked by negative monetary surprise until she fully learned the truth, i.e there was merely a pure monetary shock at t. And the worse case belief is associated with $\{\underbrace{\overline{\sigma}_m, ..., \underline{\sigma}_m}_{j \text{ times}}\}$.

The same arguments hold for a negative monetary shock Proposition 2. The choice of $\sigma_{m,t}$ made at time t is not revised at future periods. ■

1.9.7 Data

Construction of factors

The goal is to construct factors (principal components) that represent state of the economy but are orthogonal to the monetary instrument. Many DSGE model, such as the one presented in this paper, has the solution that takes the following form:

$$Y_t = FX_t + e_t,$$

where X_t is a N by T vector that includes all state variables that evolve exogenously and Y_t is a M by T vector that contains observable variables. In practice M is large and in theory N is small. Using the realtime 110 monthly macroeconomics time series from FRED-MD, I construct the first N principal components denoted as $F_{all,t}$ with N equal to five for the baseline regressions and N equal to eight for the robustness check represented in the paper. I have used realtime data, i.e $F_{all,t}$ are constructed using data up to time t, in order to excluding future information. Those principal components are good representation of the state of the economy (X_t). However since those will be used to "clean" (as controls) the HFI monetary surprises, it is important to remove the state variable related to monetary shock from $F_{all,t}$. To this end, I follow Bernanke, Boivin and Eliasz (2004)'s approach. I construct the first N principal components from slow-moving variables (those do not respond to monetary shock on impact) denoted as $F_{slow,t}$, then estimate regression of the following form:

$$F_{all,t} = c + \beta_1 F_{slow,t} + \beta_1 FFR_t + \beta_2 Y2Y_t + u_t \tag{1.33}$$

where FFR_t and $Y2Y_t$ denote the fed funds rate and two year nominal yields: those are the proxies for monetary instruments. This regression aims to determine the part in $F_{all,t}$ that originate from monetary shocks. $F_{slow,t}$ is included to ensure unbiased estimates for β_1 and β_2. The desired factors F_t are thus constructed as the difference between the $F_{all,t}$ and those originate from monetary shocks:

$$F_t = F_{all,t} - \hat{\beta}_1 FFR_t - \hat{\beta}_2 Y2Y_t. \tag{1.34}$$

In Loria et al. (2017), we show that the constructed F_t have predictive power on the HFI monetary surprises suggesting the information asymmetry between the central bank and private agent. And it is thus important to control for F_t in order to identify the pure monetary shocks from the HFI monetary surprises.

1.9.8 Bayesian Estimation

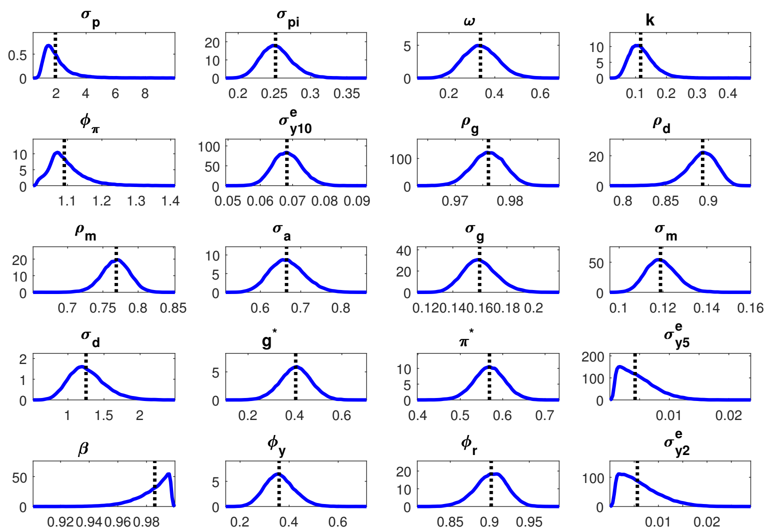
Measurement equations The measurement equations are:

$$\begin{aligned} log(RGDP_t/POP_t) - log(RGDP_{t-1}/POP_{t-1}) &= g^* + \hat{y}_t - \hat{y}_{t-1} + \hat{g}_t + \epsilon_t^a \\ Inflation_t &= \hat{\pi}_t + \pi^* \\ Y2Y_t/4 &= \hat{i}_t + e_t^{y2} \\ Y5Y_t/4 &= -\frac{1}{20} B_{20} X_t + e_t^{y5} \\ Y10Y_t/4 &= -\frac{1}{40} B_{40} X_t + e_t^{y10}, \end{aligned}$$

where $RGDP_t/POP_t$ denotes the per capita real GDP, Inflation is the GDP price deflator, $Y2Y_t$, $Y5Y_t$ and $Y10Y_t$ are the demeaned nominal yields with maturity of two, five and ten years respectively. By demeaning the yield I forgo testing the model's ability to match the average slope of yield curve. Matching the empirical slope of the yield curve would require additional features such as liquidity premium, which is beyond the scope of this paper. Nimark (2008) take the same data transformation. Similar to the empirical exercises conducted above, I have used the quarterly return of the two-year nominal yield as policy instrument. This is a short-cut to allow me to interpret the monetary shock in the model as a mix of conventional monetary shock (shock to the fed funds target) and the forward guidance shock (shock to interest rate at longer horizon). Moreover, using two years yields as policy instrument makes estimation using data beyond 2008 (zero lower bound) possible[22]. Note that I have add measurement errors to the yields to allow for potential time varying risk premium that are not captured in the model.

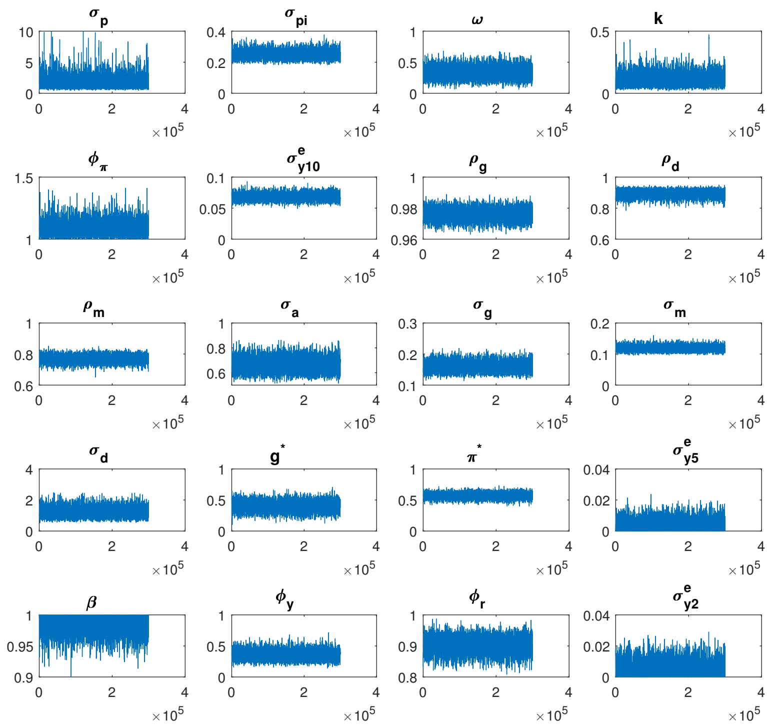
Posterior Convergence Check Figure (1.35) provides a visual representation of posterior distributions. Both the trace plots (see Figure (1.36)) and the recursive average of parameters (see Figure (1.37)) suggest the convergence of posterior distributions.

Figure 1.35: Posterior Distributions



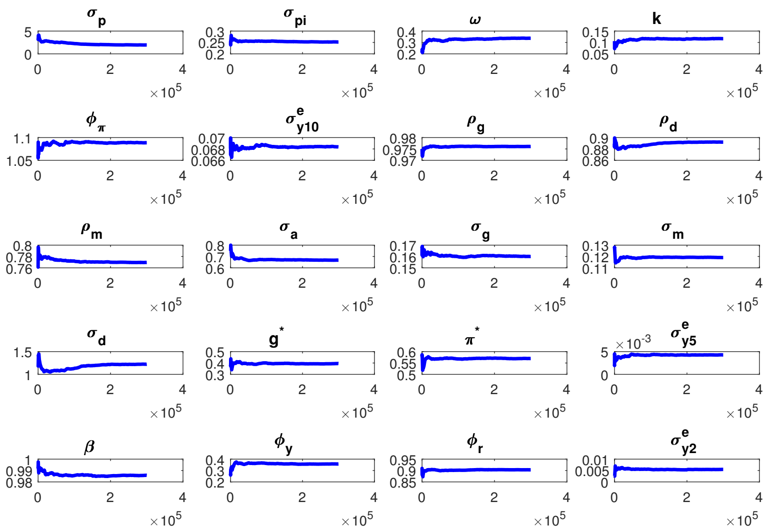
[22]However, results are robust if the two-year nominal yields enter in the measurement.equation as yield with maturity of eight periods.

Figure 1.36: Convergence Check I: Traceplots



Note: A traceplot is a plot of the value of the draw of the parameter at each iteration against the iteration number

Figure 1.37: Convergence Check II: Recursive Average



Chapter 2

WHICH INFLATION INDEX TO STABILIZE? THE ROLE OF MARKET POWER

2.1 Introduction

As of early 2011, there were 27 central banks around the world adopted inflation targeting as their policy objectives.[1] In a historical shift, on 25 January 2012, the former U.S. Federal Reserve Chairman Ben Bernanke set a formal inflation target of 2%, making the total number of inflation targeting countries to 28. All those central banks employ the consumer price index (CPI) as their policy instruments except for the U.S., in which the personal consumption expenditure (PCE) is chosen to be the operational target. While there exist minor differences in the construction of those two indexes, both of them are constructed as the weighted average of sectorial inflation using the shares of consumption as the weights.

[1]See Hammond (2012).

Although it is convenient for a central bank to target CPI/PCE because statistical agencies, such as the Bureau of Labor Statistics in the U.S., collect and publish those measures. However, it is not clear whether such a practice is optimal. Should the central bank stabilize an inflation index that is constructed using alternative weights other than their consumption shares? This paper addresses this question.

To answer this question, I build a multi-sector New Keynesian model, in which sectors differ in their degrees of price stickiness and price elasticities of demand in addition to sectorial technology shocks. In a setup with monopolistic competition, the price elasticity of demand is positively related to the degree of competition and negatively correlated with market power (markup). Thereafter, I will use those terms interchangeably. Existing literature has mainly focused on the implications of relative price stickiness. Denote this as **Stickiness Channel**, see Aoki (2001), Benigno (2004) and Mankiw and Reis (2003). However, little is known about the impact of heterogeneity in sectorial market power (**Competition Channel**) on the choice of the optimal inflation index.

Allowing for this additional feature is necessary for two reasons. First, for its empirical relevance. Loecker and Eeckhout (2017) show significant cross-sector heterogeneities in markup in the U.S. and using different data and method, Christopoulou and Vermeulen (2012) find similar results for both the U.S. and the Euro Area. Second, costly price adjustment models developed by Barro (1972), Sheshinski and Weiss (1977) and Golosov and Lucas (2007) predict more flexible price in a sector with higher competition. Therefore, analyzing the stickiness channel without considering the origin of the relative frequency of price adjustment might be misleading.

The main contribution of this paper is to fill this gap in the literature.

Two results stand out. First, the more competitive (lower market power) a sector is, the higher is the optimal weight for that sector. In the extreme case when a market is infinitely close to a perfect competition market (flat demand curve), the optimal inflation index is the one that only consists inflation in that sector. The intuition is the following. In a more competitive market, firms face a flatter demand curve. Consequently, a given change in price leads to a more significant movement in quantity. In the presence of price stickiness, this results in a more significant dispersion in output, which is welfare detrimental due to consumers' love of variety. In sum, inflation in a more competitive sector creates a bigger distortion. Therefore, stabilizing inflation in that sector is relatively more important, hence the higher weight. Second, interestingly, when the model is calibrated to data, the competition channel offsets the stickiness channel. As a result, targeting CPI (weighted by the size of the market) dominates the stabilization of an inflation index that is merely based on the relative price stickiness. This finding challenges the conventional wisdom that the central bank should attach a higher weight to a sector with a higher degree of nominal rigidity, and supports the current practice of central banks around the world (CPI targeting).

The framework enables us to calculate the optimal inflation index by taking into account sectorial heterogeneities both in price stickiness and market power. The optimal weight is not necessary increasing in relative price stickiness as suggested by Aoki (2001), Benigno (2004) and Mankiw and Reis (2003) if competition and frequency of price adjustment are positively correlated.

Previous literature on the optimal inflation index is abundant, but most conclusions are drawn based on frameworks that introduce nominal rigidity into different markets. Erceg, Henderson and Levin (2000)[2] show that in the presence of nominal wage rigidity, the optimal monetary policy index includes wage inflation. Huang and Liu (2005) demonstrate that with price stickiness in intermediate sectors, it is optimal for the central bank to respond to both CPI inflation and PPI inflation. By introducing nominal rigidity to the investment goods sector, Basu and Leo (2016) conclude that the optimal policy reacts to inflations in both consumption goods and investment goods. Different from those papers, the current paper investigates a factor — market power that is a source of sectorial heterogeneity in nominal rigidity. And study the interaction between competition and nominal rigidity for the design of optimal monetary policy. Anand, Prasad and Zhang (2015) consider the optimal inflation targeting policy for developing countries. They show that with a significant fraction of hand-to-mouth workers in the food sector, stabilizing headline CPI is welfare improving as compared to maintaining core CPI.

More broadly, this paper is related to the literature that studies the optimal monetary policy with a dynamic price elasticity originating from firm entry and exit. See, for example, Bilbiie, Ghironi and Melitz (2008), Bilbiie, Fujiwara and Ghironi (2014), Bergin and Corsetti (2008), Cooke (2016), Etro and Rossi (2015), Faia (2012) and Lewis (2013). In contrast to those studies, this paper focuses on the heterogeneity in price elasticity across sectors. In another closely related paper, Andrés, Ortega and Vallés (2008) rely on cross-country heterogeneity in competition to explain inflation differentials in the EMU. While the current framework shares similar features, this paper focuses on the interaction between price stickiness and market competition and studies the implication for the design of optimal

[2] See also Galí (2008*b*) Chapter 6 for a textbook treatment.

monetary policy.

The remainder of the paper is organized as follows. Section (2) introduces the model. Section (3) discusses the central bank's problem. Section (4) presents the main results. And Section (5) concludes.

2.2 Model

I consider a multi-sector New Keynesian model as the one discussed in Woodford (2011), which is a closed economy version of Benigno (2004). Different from the existing literature, I allow for heterogeneity in the degree of market power across sectors.

2.2.1 Households

A representative household seeks to maximize the following utility function:

$$\mathbb{E}\sum_{t=0}^{\infty}\beta^t\left[\frac{C_t^{1-\sigma}}{1-\sigma}-\sum_{k=1}^{K}\frac{N_{k,t}^{1+\varphi}}{1+\varphi}di\right],$$

subject to budget constraint:

$$P_tC_t+Q_tB_{t+1}\leq B_t+\sum_{k=1}^{K}W_{kt}N_{kt}+\sum_{k=1}^{K}T_{kt}$$

where P_t denotes the aggregate price defined below, Q_t denotes the price at time t of a one period bond that pays B_{t+1} at time $t+1$, W_{kt} the sectorial wage and T_{kt} the lump-sum transfer including profit from firms. There are K sectors in the economy, each of those sectors requires a sector-specific labor N_k. The aggregate consumption that enters utility function is a CES aggregate of K subindices:

$$C_t \equiv \left[\sum_{k=1}^{K} n_k^{1/\eta} C_{kt}^{(\eta-1)/\eta} \right]^{\eta/(\eta-1)}, \tag{2.1}$$

with the elasticity of substitution across sectors $\eta > 0$ and n_k denotes the size of the sector k with $\sum_{k=1}^{K} n_k = 1$. Each subindices C_{kt} is a CES aggregate of the following form:

$$C_{kt} \equiv \left[n_k^{-1/\epsilon_k} \int_0^{n_k} C_{kt}(i)^{(\epsilon_k-1)/\epsilon_k} di \right]^{\epsilon_k/(\epsilon_k-1)} \tag{2.2}$$

with an elasticity of substitution ϵ_k that varieties across sectors.

The implied sectorial prices index are:

$$P_{kt} \equiv \left[n_k^{-1} \int_0^{n_k} p_{kt}(i)^{1-\epsilon_k} di \right]^{1/(1-\epsilon_k)}, \tag{2.3}$$

The implied aggregate price index is:

$$P \equiv \left[\sum_{k=1}^{K} n_k P_{kt}^{1-\eta} \right]^{1/(1-\eta)} \tag{2.4}$$

Solving the consumers' problem regarding the optimal allocation of demand across varieties yields the following demand functions:

$$C_{kt}(i) = \frac{1}{n_k} C_{kt} \left(\frac{P_{kt}(i)}{P_{kt}} \right)^{-\epsilon_k}, \qquad C_{kt} = n_k C_t. \left(\frac{P_{kt}}{P_t} \right)^{-\eta} \tag{2.5}$$

The former is the demand function faced by an individual firm i in sector k and the one on the right is the sectorial demand faced by sector k. It is worth to emphasize that the price elasticity of demand faced by firm i in sector k is $-\epsilon_k$, the same magnitude as the elasticity of substitution with the opposite sign (downward sloping). This is intuitive: the higher is the elasticity of substitution the easier it is for a consumer to substitute goods i by another goods j in the same sector. Hence, the more elastic is the demand hence more competitive this sector is. In the limiting case of $\epsilon_k \to \infty$, the market is perfectly competitive.

2.2.2 Firms

There are K sectors in the economy, with a continuous of monopolistic competitive firms operate in each of those sectors. All sectors share the production function of the same functional form but are subject to different shocks:

$$Y_{kt} = e^{a_{kt}} L_{kt}^{1-\alpha}, \tag{2.6}$$

Firms are subject to nominal rigidity *à la* **?**: each firm may reset its price with probability $1 - \theta_k$. Hence, the log level price at sector k, p_{kt}, evolves as the following:

$$p_{kt} = \theta_k p_{k,t-1} + (1 - \theta_k) p_{kt}^*$$

where p^*_{kt} is the optimal price that a reoptimizing firm at sector k would set, which is the solution to the following problem:

$$\max_{P^*_{kt}} \sum_{h=0}^{\infty} \theta_k^h \mathbb{E}_t \Big\{ Q_{t,t+h} \big(P^*_{kt} Y_{k,t+h|t} - \Psi_{k,t+h}(Y_{k,t+h|t}) \big) \Big\} \tag{2.7}$$

subject to its demand constraints specified in (2.5). Where $Q_{t,t+h} \equiv \beta^k (C_{t+h}/C_t)^{-\sigma}(P_t/P_{t+h})$ denotes the stochastic discount factor, $\Psi_{k,t+h}$ denotes the cost function and $Y_{k,t+h|t}$ is the output for a firm in sector k that last reset its price in period t.

The optimality condition implied by the firm's problem is:

$$\sum_{h=0}^{\infty} \theta_k^h \mathbb{E}_t \Big\{ Q_{t,t+h} Y_{k,t+h|t} \big(P^*_{kt} - \frac{\epsilon_k}{\epsilon_k - 1} \Psi'_{k,t+h}(Y_{k,t+h|t}) \big) \Big\} = 0$$

Thus, the desired markup, defined as the markup under flexible price, is equal to $\frac{\epsilon_k}{\epsilon_k - 1}$. The frictionless markup is decreasing in ϵ_k: the monopolistic competitive firm charges a lower markup in a more competitive market.

2.2.3 Equilibrium

Solve the household's problem and log-linearize to obtain the dynamic IS equation:

$$\widetilde{y}_t = \mathbb{E}\widetilde{y}_{t+1} - \frac{1}{\sigma}[i_t - \mathbb{E}\pi_{t+1} - r_t^N)], \tag{2.8}$$

where

$$\widetilde{y}_t \equiv y_t - y_t^N, \qquad y_t^N = \psi^a \sum_{k=1}^{K} n_k a_{kt}, \qquad r_t^N \equiv \sigma \psi^a \sum_{k=1}^{K} n_k \mathbb{E}_t \triangle a_{k,t+1}$$

with $\psi^a \equiv \frac{(1+\varphi)}{\sigma(1-\alpha)+\varphi+\alpha}$. Throughout this paper, a variable with tilde denotes this variable in deviation from its natural level. And a variable with hat denotes this variable in deviation from its steady state. Solve the firms' optimization problem and log-linearize, I obtain the New Keynesian Philipps Curve (NKPC) for each sector k:

$$\pi_{kt} = \lambda_k(\widehat{mc}_{kt} - \widehat{p}_{R,kt}) + \beta \mathbb{E}_t \pi_{k,t+1} \tag{2.9}$$

where $\lambda_k \equiv \frac{(1-\beta\theta_k)(1-\theta_k)}{\theta_k}\Theta_k$, $\Theta_k \equiv \frac{1-\alpha}{1-\alpha+\alpha\epsilon_k}$, $p_{R,kt}$ is the sector k's relative price (relative to aggregate price), defined as $p_{kt} - p_t$. And $\widehat{mc}_{kt}$ is the real marginal cost in sector k, which is defined as:

$$\widehat{mc}_{kt} = \sigma(\widehat{y}_t - \widehat{y}_t^N) + \frac{\alpha+\varphi}{1-\alpha}(\widehat{y}_{kt} - \widehat{y}_{kt}^N) + \eta^{-1}(\widehat{y}_t^N - \widehat{y}_{kt}^N). \tag{2.10}$$

In the derivations of $\widehat{mc}_{kt}$, I have used household's labor supply equations and the fact that $\widehat{mc}_{kt}^N = -\eta^{-1}(\widehat{y}_{kt}^N - \widehat{y}_t^N)$ as it is implied by the sectorial demand function. Plug (2.10) into (2.9) and replace $p_{R,kt}$ by $-\eta^{-1}\widehat{y}_{R,kt}$, where $\widehat{y}_{R,kt} \equiv \widehat{y}_{kt} - \widehat{y}_t$, I obtain the following sectorial NKPC:

$$\pi_{kt} = k_k \widetilde{y}_t + \gamma_k \widetilde{y}_{R,kt} + \beta \mathbb{E}_t \pi_{k,t+1} \tag{2.11}$$

where $k_k \equiv \lambda_k(\sigma + \frac{\varphi+\alpha}{1-\alpha})$ and $\gamma_k \equiv \lambda_k(\eta^{-1} + \frac{\varphi+\alpha}{1-\alpha})$. Alternatively, the NKPC can be rewritten as:

$$\pi_{kt} = k_k \widetilde{y}_t - \eta\gamma_k \widetilde{p}_{R,kt} + \beta \mathbb{E}_t \pi_{k,t+1} \tag{2.12}$$

As it is the case in standard multi-sector NK models, sectorial heterogeneities give birth to relative price (or quantity) dispersion across sectors, therefore a full stabilization of both inflation and output gap is no longer feasible. Moreover, while a positive aggregate output gap arises inflation in all sectors, an increase in relative price (or quantity) in one sector has a disinflationary impact in that sector and increases inflation pressure in other sectors.

2.3 Central Bank

2.3.1 Welfare Loss Function

Before moving to the central bank's problem, I will derive the welfare loss function, which is the objective of the central bank. Following Rotemberg and Woodford (1997, 1999) and **?**, the second order approximation of the representative consumer's period welfare loss expressed in consumption equivalent variation (CEV) is:

$$L = \sum_{k=1}^{K} \frac{\epsilon_k}{\lambda_k} n_k var(\pi_{kt}) + (\sigma + \frac{\varphi+\alpha}{1-\alpha}) var(\widetilde{y}_t)$$
$$+ (\eta^{-1} + \frac{\varphi+\alpha}{1-\alpha}) \sum_{k=1}^{K} n_k var(\widetilde{y}_{R,kt}) \tag{2.13}$$

where $\lambda_k \equiv \frac{(1-\beta\theta_k)(1-\theta_k)}{\theta_k}\Theta_k$ defined as above. Normalize the weights on π_{kt} such that $\sum \phi_k = 1$:

$$L = \sum_{k=1}^{K} \phi_k var(\pi_{kt}) + \lambda_y var(\widetilde{y}_t) + \lambda_{R_y} \sum_{k=1}^{K} n_k var(\widetilde{y}_{R,kt}) \qquad (2.14)$$

where

$$\phi_k = \frac{n_k \epsilon_k \lambda}{\lambda_k}, \qquad \lambda_y = (\sigma + \frac{\varphi + \alpha}{1-\alpha})\lambda, \qquad \lambda_{Ry} = (\eta^{-1} + \frac{\varphi + \alpha}{1-\alpha})\lambda$$

and λ is defined as:

$$\lambda \equiv (\sum_{0}^{K} n_k \epsilon_k \lambda_k^{-1})^{-1}$$

See Appendix (2.6) for the derivations.

Similar to a standard multi-sector NK model, volatilities in sectorial inflation, aggregate output gap, and the relative output gap are welfare detrimental. More interestingly, by allowing for sectorial heterogeneity in market power, inflation is a sector with a higher elasticity of demand enters in the welfare loss function with a bigger relative weight, i.e. $\frac{\partial \phi_k}{\partial \epsilon_k} > 0$.

2.3.2 Monetary Policy

The central bank adopts inflation targeting as the means of conducting monetary policy. This is the case for many central banks around the world. I assume that the target rate is always 0 (the steady-state inflation rate) and the goal is always achieved. This is equivalent to a Taylor rule with strict inflation index targeting. The monetary instrument is the ex-ante choice of an inflation index that the central bank stabilizes ex-post. In other words, I ask the question: which measure of inflation index should the central bank stabilize and announce it to the public? This question can be formulated as the following:

$$\min_{\{\omega_k\}} L = \min_{\{\omega_k\}} \sum_{k=1}^{K} \phi_k var(\pi_{kt}) + \lambda_y var(\widetilde{y}_t) + \lambda_{R_y} \sum_{k=1}^{K} n_k var(\widetilde{y}_{R,kt}) \tag{2.15}$$

subject to:

NKPC: $\pi_{kt} = k_k \widetilde{y}_t + \gamma_k \widetilde{y}_{R,kt} + \beta \mathbb{E}_t \pi_{k,t+1}, \forall k$

Dynamic IS: $\widetilde{y}_t = \mathbb{E}\widetilde{y}_{t+1} - \frac{1}{\sigma}\left(i_t - \mathbb{E}\pi_{t+1} - r_t^N\right)$

Monetary Policy : $\sum_{k=1}^{K} \omega_k \pi_{kt} = 0$

sectorial Demand: $y_{k,t} = y_t - \eta(p_{1,t} - p_t), \forall k$

Relative Output Gap: $\widetilde{y}_{R,kt} = y_{k,t} - y_t - n_2 * \Psi_{ak} * (a_1 - a_2), \forall k$

Aggregate Inflation CPI: $\pi_t = \sum_{k=1}^{K} n_k \pi_{kt}$

sectorial Inflation: $\pi_{kt} = p_{k,t} - p_{k,t-1}, \forall k$

Aggregate Price: $p_t = \sum_{k=1}^{K} n_k p_{k,t}$

Natural Real Interest Rate: $r_t^N = \sigma \psi^a \sum_{k=1}^{K} n_k \mathbb{E}_t \triangle a_{k,t+1}$

Previous studies have uncovered two main results. First, if sectors share the same degrees of nominal rigidities and market competition, CPI targeting is optimal. Second, it is optimal to give higher weight to the sector with a higher degree of nominal rigidity. The remaining of this paper is to investigate the role of market power and in particular how it might interact with the stickiness channel.

2.3.3 Special Cases

I begin with analyzing a liming case in which one sector is infinitely close to perfect competition[3], i.e., $\epsilon_k \to \infty$. In this case, the loss function collapses to:

$$L \to var(\pi_k).$$

It follows immediately that:

Proposition 1. *If $\epsilon_k \to \infty$ and $\theta_k \neq 0$, the optimal monetary policy is to set $\pi_k = 0$.*

This does not mean that the welfare loss under the optimal monetary policy is zero. In fact, due to asymmetric shocks, the aggregate and the relative output gap, and inflation in the remaining sectors fluctuate, which give rise welfare loss. It means that if goods in sector k are almost perfect substitutes then, in terms of welfare loss, stabilizing inflation in this sector is infinitely more valuable than stabilizing any other variables. This is the case because, with a flat demand curve and nominal rigidity, price

[3]It only makes sense to talk about the infinitely close case, because in the limiting case with perfect competition firms are price takers. Therefore the firm's problem discussed in the previous section, price setter firms, would not carry over.

dispersion that arises from inflation leads to an infinitely big dispersion in output.

Next, I investigate whether the competition channel affects the optimality of core inflation stabilization suggested by Aoki (2001) and Benigno (2004).

Proposition 2. *If price is flexible in sector k, independent of the relative market power, the optimal weight for this sector is zero.*

Proof: see Benigno (2004).
If the price is flexible, inflation does not lead to price dispersion. Therefore welfare loss originating from inflation is trivial no matter how competitive the market is.

A more interesting interaction between market power and nominal rigidity rises in the general case. This is left for the next section.

2.4 Quantitative Analysis

Unless otherwise specified, the model's parameters are calibrated to be those reported in Table (2.1). Most parameters are calibrated to values that are frequently used in the literature. $\sigma = 2$ implies that inter-temporal elasticity of substitution equal to 0.5. The Frisch elasticity of labor supply ($1/\varphi$) is set to be 1/3. I set the discount factor $\beta = 0.99$, which corresponds to a steady-state annual interest rate of 4%. The production function has decreasing return to scale with $\alpha = 1/3$, a value that is commonly used in business cycle literature. I consider a two sectors model with equal size, i.e. $n_1 = n_2 = 0.5$, While sectors are subject to different productivity shocks, the process for the productivity is the same: $a_{kt} = 0.95 a_{k,t-1} + \epsilon_{kt}$, ϵ_{kt} is normally distributed with mean 0

and variance 0.002. Hobijn and Nechio (2017) provide an estimate of the elasticity of substitution across sectors $\eta = 1$.

Table 2.1: Calibration

Utility function	$\sigma = 2, \varphi = 3$
Discount factor	$\beta = 0.99$
Production function	$\alpha = 1/3$
Size of sectors	$n_1 = 0.5, n_2 = 0.5$
Exogenous shocks	$\rho_1 = \rho_2 = 0.95, \sigma^2_{a1} = \sigma^2_{a2} = 0.02$
Nominal rigidity	$\theta_1 = 0.63, \theta_2 = 0.73$
Elasticity of substitution	$\eta = 1, \epsilon_1 = 11/3, \epsilon_2 = 7/3$

The sectorial nominal rigidities and elasticities of substitution are calibrated to match their counterpart in the manufacturing (sector 1) and service (sector 2) sectors in the U.S. $\theta_1 = 0.63$ and $\theta_2 = 0.73$ matches the frequency of price adjustment reported in Gorodnichenko and Weber (2016) [4] for the manufacturing and service sectors. The sectorial elasticities of substitution are calibrated to be $\epsilon_1 = 11/3$ and $\epsilon_2 = 7/3$ that match markups in manufacturing (1.375) and service sectors (1.75) estimated by Loecker and Eeckhout (2017) for 2014. Those markups are higher than the values that are typically assumed in the literature: 1.1 or 1.2. I provide a robustness check using those commonly used values, and qualitatively

[4] Gorodnichenko and Weber (2016)'s estimates are based on the method discussed in Nakamura and Steinsson (2008), I take the values from the former because Gorodnichenko and Weber (2016)'s classifications of sectors matches the ones used in Loecker and Eeckhout (2017), which I based on to calibrate sectorial markups.

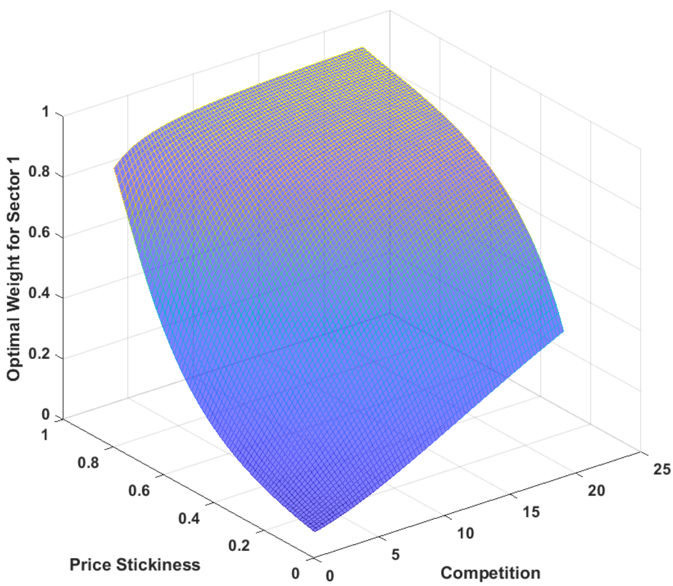
results are unchanged. What matters is the markup in the service sector is higher than manufacturing, which is confirmed by Christopoulou and Vermeulen (2012) in their estimates of markups for both the U.S. and the Euro Area.

2.4.1 Results

In the previous section, we have seen that in the limiting case when a sector is infinitely close to perfect competition, the optimal monetary policy fully stabilize inflation in this sector, i.e., the optimal weight for this sector is 1. Figure (2.1) shows that the optimal weight attached to the inflation in a sector is strictly increasing in both the degree of competition (stickiness channel) and its degree of price stickiness (competition channel). While the former is well known, the later is new to the literature. The intuition for the competition channel is the following. In a more competitive monopolistic market, firms face a flatter demand curve. Consequently, a given change in price leads to a larger movement in quantity. In the presence of price stickiness, this results in a bigger dispersion in output, which is welfare detrimental due to consumers' love of variety. In sum, inflation in a more competitive sector creates a bigger distortion. Therefore, stabilizing inflation in that sector is relatively more important, hence the higher weight.

Next, I conduct welfare analysis under alternative inflation index stabilization policies: optimal inflation index, CPI and inflation index based only on price stickiness. Again, the welfare comparison is done for different values of markup in sector 1. The other parameters are calibrated to be those reported in Table (2.1). Recall that the sector 2 is calibrated to be the stickier sector. Figure (2.2) and Table (2.3) report the results.

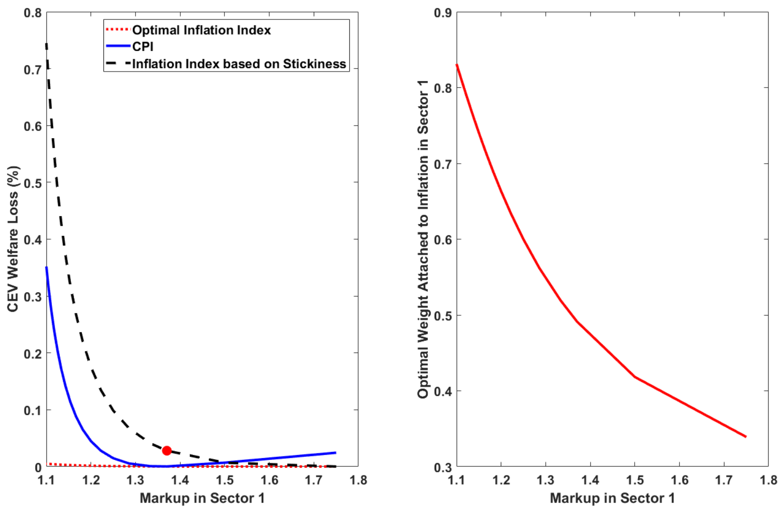
Figure 2.1: Optimal Inflation Index to Stabilize



Note: The optimal inflation index to stabilize as a function of markup and price stickiness. Calibration: $\theta_2 = 0.73$ and $\epsilon_2 = 7/3$ i.e. markup in sector 2 equals to 1.75.

The reported welfare loss is the CEV defined above in deviation from the CEV under the optimal monetary policy. The left panel shows that the stabilization of an optimal inflation index that is calculated based on both competition and nominal rigidity (red dotted line) dominates policies that stabilize CPI (solid blue line) or an inflation index only based on nominal rigidity (dashed black line). The inflation index solely based on nominal rigidity is calculated by solving the central bank's problem assuming that the central bank's perceived markups in both sectors are the same and equal to the markup in sector 2.[5] The associated welfare loss is then calculated by evaluating this policy in the true model with different markups.

Figure 2.2: Welfare Analysis: Alternative Policies



Note: Welfare loss as a function of markup in sector 1 under alternative policies. The welfare loss is the corresponding CEV in deviation from the CEV under optimal monetary policy. Calibration: $\theta_1 = 0.63$, $\theta_2 = 0.73$ and $\epsilon_2 = 7/3$ i.e. markup in sector 2 equals to 1.75. The red dot corresponds to the point where markup in sector 1 equal to 1.37 — the empirically relevant one.

Interesting results arise when comparing the performance of CPI stabilization with the inflation index based on stickiness. When markup in sector 1 is big enough, greater than 1.5 as indicated by the second raw of Table (2.3), stabilizing the inflation index based on stickiness as rec-

[5]Similar results hold if the perceived markups are calibrated to the markup in sector 1 or the average markup. Because as long as the perceived markups are equal, the optimal weight only depends on the relative stickiness.

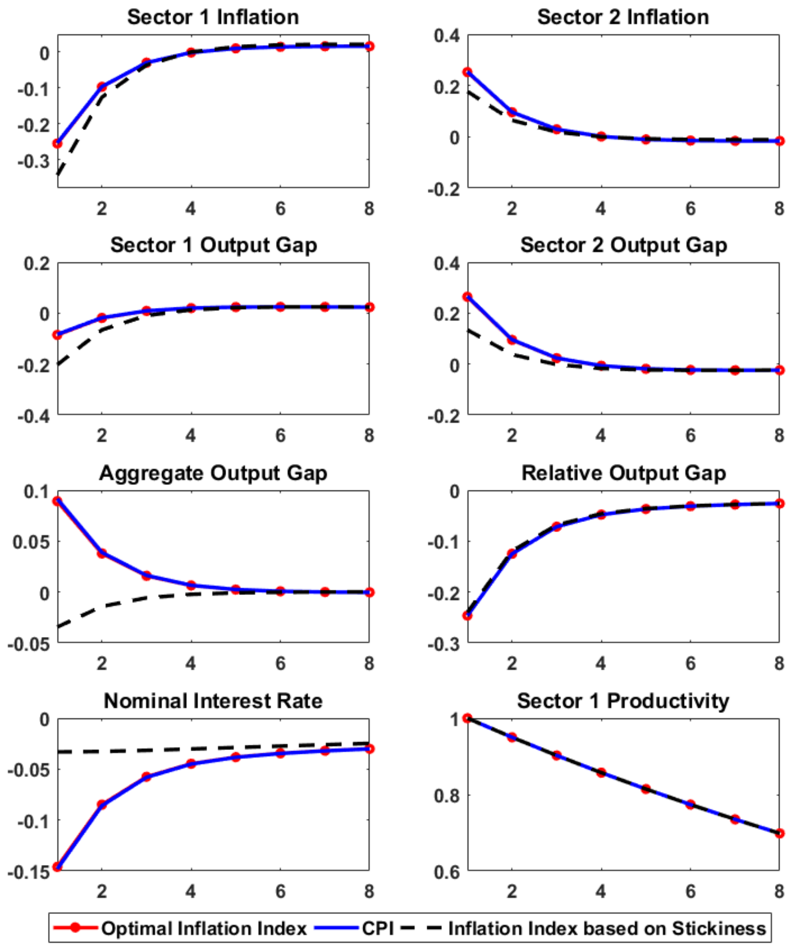
ommended by Benigno (2004) and Mankiw and Reis (2003) is welfare improving as compared to the stabilization CPI. However, if sector 1 is competitive with a markup less than 1.5, stabilizing CPI is superior. Costly price adjustment models developed by Barro (1972), Sheshinski and Weiss (1977) and Golosov and Lucas (2007) predict more flexible price in a sector with higher competition. This suggests that the competition channel offsets the stickiness channel. This is verified in the data. Sector 1 is calibrated to match the manufacturing sector ($\theta_1 = 0.63 < \theta_2$), which corresponds a markup of 1.37 (smaller than markup in sector 2: the service sector) in the data. This point is plotted as the red dot in the figure. In this case, CPI is very close to the optimal inflation index as one can see from the third row of Table (2.3). The optimal weight for sector 1 is 0.49, merely 0.01 smaller than CPI's weight (0.5) and 0.15 higher than the inflation index that only based on stickiness (0.34). Stabilizing CPI almost replicates the allocations under the optimal monetary policy, whereas setting the inflation index that only based on stickiness equal to zero would lead to a welfare loss that is 0.03 percentage points higher than the optimal allocation.

Table 2.2: Welfare Analysis: Alternative Policies

		CEV Welfare Loss (%)		
Markup in Sector 1	Optimal Weight ω_1^*	Optimal Inflation Index	CPI	Inflation Index based on Stickiness
1.75	0.34	0.00	0.02	0.00
1.50	0.42	0.00	0.01	0.01
1.37	0.49	0.00	0.00	0.03
1.20	0.66	0.00	0.04	0.18

Note: The welfare loss is the corresponding CEV in deviation from the CEV under optimal monetary policy. The analysis is based on the following calibration: $\theta_1 = 0.63$, $\theta_2 = 0.73$ and $\epsilon_2 = 7/3$ i.e. markup in sector 2 equals to 1.75.

Figure 2.3: Effects of Productivity Shock in Sector 1 under Alternative Monetary Policies



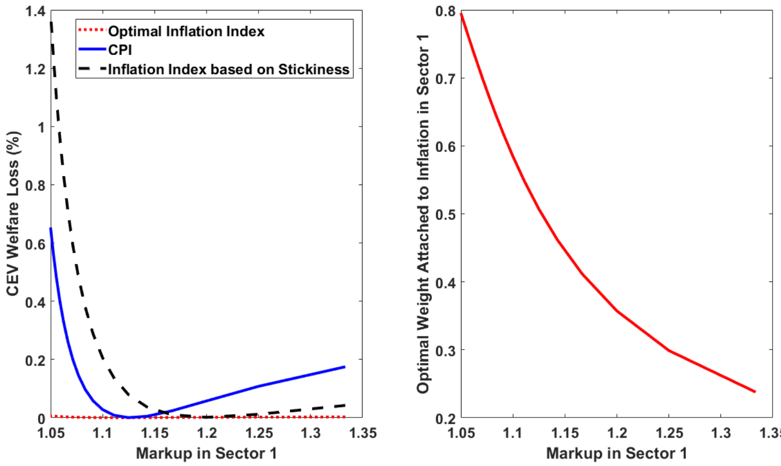
To understand better the intuition why stabilizing CPI dominates the stabilization of the inflation index that only based on stickiness. Figure (2.3) reports the impulse responses to a technology shock in sector 1 under different policies: optimal inflation (in red with circles), CPI (solid blue line) and the inflation index that only based on stickiness (dasheded black line). As one can see, the responses to sector 1 productivity shock are similar under optimal inflation index and CPI stabilization policies. This verifies the results we have seen before. The results are different under the policy that maintains the inflation index that only based on stickiness equal to zero. Under this policy, the responses of all the other variables are smaller as compared to the those under the optimal inflation index policy, except for inflation in sector 1. Under the optimal inflation index policy, the central bank is willing to bring higher volatilities to variables such as output gap and inflation in sector 2 to reduce the volatility in inflation in sector 1. This is the case, because the welfare loss associated with inflation in sector 1 is higher once the competition channel is taken into account.

We turn to investigate the mechanism how the central bank achieves the optimal allocation. A positive technology shock in sector 1 leads to a decrease in sector 1's inflation as the marginal cost is reduced. Since the welfare cost of a change in inflation in sector 1 is substantial, As compared to a policy that is suboptimal (dashed black lines), under the optimal policy the central bank reduces interest rate more to mitigate the reduction in sector 1's inflation. Consequently, inflation and output gap in sector 2 rises more, in addition to the direct impact of the technology shock.

2.4.2 Robustness Check

In this section, I conduct the welfare analysis with an alternative calibration of markup in sector 2 (service sector): $\epsilon_2 = 6$, i.e., the markup is

Figure 2.4: Robustness Check: Sector 2 Markup $= 1.2$



equal to 1.2. Figure (2.4) and Table (2.3) report the results. Qualitatively similar results hold as before. Quantitatively, the breakeven markup in sector 1 is 1.16 (the required markup in sector 1 such that the stabilization of CPI and stickiness based inflation index are equivalent in terms of welfare loss), merely 0.04 points less than markup in sector 2. If the markup in the manufacturing sector is 0.1 less than the service sector, ignoring the competition channel leads to a welfare loss that is 0.21 percentage point higher the optimal inflation index policy and 0.18 percentage point higher than stabIlizing CPI.

Table 2.3: Robustness Check: Sector 2 Markup $= 1.2$

		CEV Welfare Loss (%)		
Markup	Optimal Weight ω_1^* in Sector 1	Optimal Inflation Index	CPI	Inflation Index based on Stickiness
1.25	0.30	0.00	0.16	0.02
1.16	0.43	0.00	0.01	0.01
1.10	0.58	0.00	0.03	0.21

Note: The welfare loss is the corresponding CEV in deviation from the CEV under optimal monetary policy. The analysis is based on the following calibration: $\theta_1 = 0.63$, $\theta_2 = 0.73$ and $\epsilon_2 = 6$ i.e. markup in sector 2 equals to 1.2.

2.5 Conclusion

Which inflation index should a central bank stabilize? This paper addresses this question in a multi-sector model, in which sectors differ in their degrees of nominal rigidity and competition. The optimal inflation targeting policy depends on both the nominal rigidity and competition. The optimal weight attached to inflation in a sector is increasing in this sector's price stickiness (stickiness channel) and degree of market competition (competition channel). The paper shows the interaction between the stickiness and competition channel. In particular, if firms operating in a market with greater competition adjust their prices more frequently as predicted by costly price adjustment models, the competition channel offsets the stickiness channel. When the model is calibrated to the service and manufacturing sectors in the US, I show that stabilizing CPI is welfare improving as compared to stabilizing an inflation index based on stickiness. This finding challenges the conventional wisdom in academic circle and supports the current practice of central banks around the world.

2.6 Appendix: Derivation of the Welfare Loss Function

The second order Taylor expansion of the representative household's utility U_t around a steady-state (C, L) in terms of log deviations can be written as:

$$U_t - U \approx U_c C\Big(\widehat{y}_t + \frac{1-\sigma}{2}\widehat{y}_t^2\Big) + \sum_{k=1}^{K} U_{L_k} L_k \Big(\widehat{l}_{kt} + \frac{1+\varphi}{2}\widehat{l}_{kt}^2\Big) di.$$

Note that

$$(1-\alpha)\widehat{l}_{kt} = \widehat{y}_{kt} - a_{kt} + d_{kt}$$

where $d_{kt} \equiv (1-\alpha) log(\frac{P_{kt}(i)}{P_{kt}})^{-\frac{\epsilon_k}{1-\alpha}}$.

***Lemma* 1.** *$d_{kt} = \frac{\epsilon_k}{2\Theta} var_i\{p_{kt}(i)\}$, with $\Theta_k \equiv \frac{1-\alpha}{1-\alpha+\alpha\epsilon_k}$*

Proof: Gali (2008, chapter 4)

Therefore,

$$U_t - U \approx U_c C\Big(\widehat{y}_t + \frac{1-\sigma}{2}\widehat{y}_t^2\Big) + \sum_{k=1}^{K} \frac{U_{L_k} L_k}{1-\alpha}\Big(\widehat{y}_{kt} + \frac{\epsilon_k}{2\Theta_k} var_i\{p_{kt}(i)\} + \frac{1+\varphi}{2(1-\alpha)}(\widehat{y}_{kt} - a_{kt})^2\Big) + t.i.p.$$

where $t.i.p$ denotes the terms independent of policy. Under the assumption that cost of employment is subsidized optimally at sectorial level to eliminate distortions originate from monopolistic competition, the steady-state is efficient and $-\frac{U_{L_k}}{U_c} = MPN$.

Approximate the CES aggregate C_t defined in (2.1) around $c_k = c + log(n_k)$:

$$\sum_{k=1}^{K} n_k \widehat{y}_{kt} \approx \widehat{y}_t - \frac{1-\eta^{-1}}{2} \sum_{k=1}^{K} n_k \widehat{y}_{R,kt}^2$$

with $\sum_{k=1}^{K} n_k \widehat{y}_{R,kt}^2 \equiv \sum_{k=1}^{K} n_k (\widehat{y}_{kt} - \widehat{y}_t)^2$. Using the fact that $MPN =$

$(1-\alpha)(Y_k/L_k), Y = C$, it follows that:

$$\frac{U_t - U}{U_c C} \approx -\frac{1}{2}\Big[\sum_{k=1}^{K}\Big(\frac{\epsilon_k n_k}{\Theta_k} var_i\{p_{kt}(i)\}\Big) - (1-\sigma)\widehat{y}_t^2 - (1-\eta^{-1})\sum_{k=1}^{K} n_k \widehat{y}_{R,kt}^2$$

$$+ \frac{1+\varphi}{1-\alpha}\sum_{k=1}^{K} n_k(\widehat{y}_{kt} - a_{kt})^2\Big] + t.i.p$$

$$= -\frac{1}{2}\Big[\sum_{k=1}^{K}\Big(\frac{\epsilon_k n_k}{\Theta_k} var_i\{p_{kt}(i)\}\Big) - (1-\sigma)\widehat{y}_t^2 - (1-\eta^{-1})\sum_{k=1}^{K} n_k \widehat{y}_{R,kt}^2$$

$$+ \frac{1+\varphi}{1-\alpha}\sum_{k=1}^{K} n_k(\widehat{y}_{kt}^2 - 2\widehat{y}_{kt}a_{kt})\Big] + t.i.p$$

$$= -\frac{1}{2}\Big[\sum_{k=1}^{K}\Big(\frac{\epsilon_k n_k}{\Theta_k} var_i\{p_{kt}(i)\}\Big) + (\sigma + \frac{\varphi+\alpha}{1-\alpha})\widehat{y}_t^2 + (\eta^{-1}$$

$$+ \frac{\varphi+\alpha}{1-\alpha})\sum_{k=1}^{K} n_k \widehat{y}_{R,kt}^2 - 2\frac{1+\varphi}{1-\alpha}\sum_{k=1}^{K} n_k \widehat{y}_{kt} a_{kt}\Big] + t.i.p$$

$$= -\frac{1}{2}\Big[\sum_{k=1}^{K}\Big(\frac{\epsilon_k n_k}{\Theta_k} var_i\{p_{kt}(i)\}\Big) + (\sigma + \frac{\varphi+\alpha}{1-\alpha})\widehat{y}_t^2$$

$$+ (\eta^{-1} + \frac{\varphi+\alpha}{1-\alpha})\sum_{k=1}^{K} n_k \widehat{y}_{R,kt}^2$$

$$- 2\frac{1+\varphi}{1-\alpha}\sum_{k=1}^{K} n_k(\widehat{y}_t + \widehat{y}_{kt} - \widehat{y}_t)a_{kt})\Big]$$

$$= -\frac{1}{2}\Big[\sum_{k=1}^{K}\Big(\frac{\epsilon_k n_k}{\Theta_k} var_i\{p_{kt}(i)\}\Big) + (\sigma + \frac{\varphi+\alpha}{1-\alpha})\widehat{y}_t^2$$

$$+ (\eta^{-1} + \frac{\varphi+\alpha}{1-\alpha})\sum_{k=1}^{K} n_k \widehat{y}_{R,kt}^2 - 2(\sigma + \frac{\varphi+\alpha}{1-\alpha})\widehat{y}_t y^N$$

$$- 2(\eta^{-1} + \frac{\varphi+\alpha}{1-\alpha})\sum_{k=1}^{K} n_k(\widehat{y}_{kt} - y_t)(\widehat{y}_{kt}^N - y_t^N)\Big] + t.i.p$$

$$= -\frac{1}{2}\Big[\sum_{k=1}^{K}\Big(\frac{\epsilon_k n_k}{\Theta_k} var_i\{p_{kt}(i)\}\Big) + (\sigma + \frac{\varphi+\alpha}{1-\alpha})\widetilde{y}_t^2$$

$$+ (\eta^{-1} + \frac{\varphi+\alpha}{1-\alpha})\sum_{k=1}^{K} n_k \widetilde{y}_{R,kt}^2\Big] + t.i.p$$

where $\widetilde{y}_t \equiv y_t - y_t^N$. From line 2 to line 3, I have used the fact that $\sum_{k=1}^K n_k \widehat{y}_{kt}^2 = \sum_{k=1}^K n_k \widehat{y}_{R,kt}^2 + (\sum_{k=1}^K n_k \widehat{y}_{kt})^2 \approx \sum_{k=1}^K n_k \widehat{y}_{R,kt}^2 + \widehat{y}_t^2$. From line 4 to line 5, where the fact was used that $a_{kt} = \frac{\sigma(1-\alpha)+\alpha+\varphi}{1+\varphi} y_t^N$ and $a_{kt} - \sum_{k=1}^K a_{kt} = \frac{\eta^{-1}(1-\alpha)+\alpha+\varphi}{1+\varphi} \widehat{(} y_{kt}^N - y_t^N)$.

To summarize, the second order approximation of the representative consumer's welfare loss as a fraction of steady-state consumption is:

$$\begin{aligned} W &= \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \Big(\frac{U_t - U}{U_c C} \Big) \\ &= -\frac{1}{2} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \Big[\sum_{k=1}^{K} \Big(\frac{\epsilon_k n_k}{\Theta_k} var_i\{p_{kt}(i)\} \Big) \\ &+ (\sigma + \frac{\varphi+\alpha}{1-\alpha}) \widetilde{y}_t^2 + (\eta^{-1} + \frac{\varphi+\alpha}{1-\alpha}) \sum_{k=1}^{K} n_k \widetilde{y}_{R,kt}^2 \Big] + t.i.p. \end{aligned}$$

***Lemma* 2.** $\sum_{t=0}^{\infty} \beta^t var_i\{p_{kt}(i)\} = \frac{\theta_k}{(1-\beta\theta_k)(1-\theta_k)} \sum_{t=0}^{\infty} \beta^t \pi_{kt}^2$

Proof: Woodford (2003, chapter 6)

Thus we obtain the following welfare loss function:

$$\begin{aligned} W = -\frac{1}{2} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \Big[\sum_{k=1}^{K} \frac{\epsilon_k}{\lambda_k} n_k \pi_{kt}^2 + (\sigma + \frac{\varphi+\alpha}{1-\alpha}) \widetilde{y}_t^2 \\ + (\eta^{-1} + \frac{\varphi+\alpha}{1-\alpha}) \sum_{k=1}^{K} n_k \widetilde{y}_{R,kt}^2 \Big] + t.i.p. \end{aligned}$$

where $\lambda_k \equiv \frac{(1-\beta\theta_k)(1-\theta_k)}{\theta_k} \Theta_k$ defined as above. Normalize the weights on

π_{kt} such that $\sum \omega_k = 1$:

$$W = -\frac{1}{2}\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \Big[\sum_{k=1}^{K} \phi_k \pi_{kt}^2 + \lambda_y \widetilde{y}_t^2 + \lambda_{R_y} \sum_{k=1}^{K} n_k \widetilde{y}_{R,kt}^2 \Big] + t.i.p. \quad (2.1)$$

where

$$\phi_k = \frac{n_k \epsilon_k \lambda}{\lambda_k}, \qquad \lambda_y = (\sigma + \frac{\varphi + \alpha}{1-\alpha})\lambda, \qquad \lambda_{Ry} = (\eta^{-1} + \frac{\varphi + \alpha}{1-\alpha})\lambda$$

and λ is defined as:

$$\lambda \equiv (\sum_{0}^{K} n_k \epsilon_k \lambda_k^{-1})^{-1}$$

From the sectorial demand equation, one can rewrite sectorial output dispersion as a function of sectorial price dispersion:

$$W = -\frac{1}{2}\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \Big[\sum_{k=1}^{K} \frac{\epsilon_k}{\lambda_k} n_k \pi_{kt}^2 + (\sigma + \frac{\varphi + \alpha}{1-\alpha}) \widetilde{y}_t^2 + \eta(1 + \frac{\varphi + \alpha}{1-\alpha}\eta) var_k(\widetilde{p}_{kt}) \Big] + t.i.p.$$

Normalize the weights on π_{kt}:

$$W = -\frac{1}{2}\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \Big[\sum_{k=1}^{K} \phi_k \pi_{kt}^2 + \lambda_y \widetilde{y}_t^2 + \lambda_{R_p} var_k(\widetilde{p}_{kt}) \Big] + t.i.p. \quad (2.2)$$

where

$$\lambda_{Rp} = \eta(1 + \frac{\varphi + \alpha}{1-\alpha}\eta)\lambda$$

Chapter 3

THE RANDOM WALK BEATS PROFESSIONAL FORECAST: FACTS, PUZZLES AND EXPLANATIONS

3.1 Introduction

It is a well-known fact since Meese and Rogoff (1983*a*,*b*, 1988) that exchange rates are very difficult to predict using macro variables. This is especially true for predicting exchange rates in the near future (next few months). Economists have struggled for decades to find the macro variables that beat the simple random walk for out-of-sample forecasts. Few, if any, have succeeded and many well-known international macroeconomic models fail to compete with the random walk. See Rossi (2013) for an excellent updated survey. In this literature, one variable that is well appreciated by the private sector, yet few academic studies have been done based on it, is the professional forecasts of exchange rates.

This paper contributes to filling this gap. Empirically, I compare the forecasting performance of the professional forecasts (PF), those provided by the Consensus Economics, [1] with the prediction of the Random Walk model (RW). Four results stand out.

First, the random walk beats the professional forecasts according to the mean square forecast error (MSFE), the mean absolute forecast error (MAFE) and the mean absolute percentage forecast error (MAPFE) criteria. For three-months-ahead exchange rate forecasts, the forecast errors based on the professional forecasts are significantly bigger, both economically and statistically, than those constructed using the random walk model. Second, the professionals' forecasting model deviates from the random walk model substantially. Their current forecast depends, roughly, half on the current level of exchange rate. Note that a forecaster whose forecasts are based on the random walk model would update their current estimate depending wholly on the current exchange rate. Third, in a counter-factual exercise, I show that the higher the weight that the professional forecasters attached to the random walk model, the better it predicts the future exchange rate. Fourth, professional forecasts fail to pass the rationality test.

Overall, empirical facts suggest that professional forecasters underreact to the current exchange rate levels and that this is sub-optimal. A new puzzle arises: why do professional forecasters not adopt the simple random walk model to provide a more accurate estimate?

In the second half of this paper, I provide an explanation. In the model, the forecaster faces model uncertainty and reports the forecast that minimizes the forecast error in the worst-case scenario. Therefore profes-

[1] The empirical part was conducted while I was visiting the ECB. I am grateful for their hospitality and support in data collection.

sional forecasts are intentionally suboptimal. The model is estimated using the maximum likelihood method. Estimation results show that the model matches the puzzle raised above and, besides, the model predicts that the forecaster substantially underreacts to current news, which is consistent with empirical facts provided in this paper. Moreover, I conduct rationality tests using simulated data. The null of "rationality" is rejected according to the model, which is consistent with the existing empirical literature and the tests presented in the current paper. Note that this result is obtained in a framework where professional forecasters perform optimally.

The empirical part of the paper contributes to the literature that test the rationality of professional forecasts of the exchange rate, see for example Frankel and Froot (1987), Ito (1990) and Dominguez (1986). Different from the literature, this paper focuses on forecast accuracy comparison between the PF and the RW.

The literature on model uncertainty and ambiguity averse agent is vast. See Hansen and Sargent (2008) for a textbook treatment of the robust control approach, and Epstein and Schneider (2008) for the multiple priors approach. This paper follows the second approach and rationalizes the empirical findings discussed above based on ambiguity averse forecasters. In a closely related paper, Ellison and Sargent (2012) defend the forecast performance of the Federal Reserve Open Market Committee (FOMC) by assuming that the FOMC members make policy decisions maximizing social welfare under the worst-case scenario and report their forecasts using the corresponding worse-case beliefs. This paper provides an empirical application of ambiguity aversion that rationalizes empirical puzzles related to professional forecasts of exchange rates.

The paper is structured as follows. Section (3.2) presents empirical evidence for exchange rate forecast. Section (3.3) models exchange rate, and a professional forecaster's forecast formation. Section (3.4) estimates the model and discuss the estimation results. Section (3.5) concludes.

3.2 Empirical Analysis

In this section, I provide evidence that the Random Walk model beats the professional forecast regarding exchange rate predictability. For the professional forecasts, I use the data collected by the Consensus Economics. I conduct the empirical analysis for twelve countries: Canada, Egypt, Eurozone, Israel, Japan, Nigeria, South Africa, U.K, Denmark, Norway, Sweden and Switzerland.

3.2.1 The Random Walk Model Beats Professional Forecast

A direct criterion for comparing the forecast accuracy is to calculate and compare the ratio of mean square forecast error (RMSFE):

$$MSFE = \frac{1}{T}\sum_{t=1}^{T}(\epsilon_{t+h|t})^2, \tag{3.1}$$

where $\epsilon_{t+h|t}$ denotes the forecast error. RMSFE is obtained as MSFE of professional forecast divided by the MSFE of the random walk model. The second column in Table (3.1) reports the results. A value greater than 1 suggests that the professional forecast makes more significant forecast errors. The third column in Table (3.1) reports p-values of the Diebold and Mariano (1995) test of the null hypothesis that the forecast accuracy is equal according to the MSFE criterion. As one can see, the random walk outperforms the professional forecast for the majority of countries considered.

Columns 4 to 6 in Table (3.1) compare the forecast accuracy between the random walk and professional forecast using mean absolute forecast error (MAFE) and mean absolute percentage forecast error (MAPFE). Those criteria are constructed as the following.

$$MAFE = \frac{1}{T}\sum_{t=1}^{T} \left|\epsilon_{t+h|t}\right|, \tag{3.2}$$

$$MAPFE = \frac{1}{T}\sum_{t=1}^{T} \left|\frac{\epsilon_{t+h|t}}{y_{t+h}}\right| \tag{3.3}$$

where y_{t+h} is the actual exchange rate at time $t+h$. The p-value is calculated for the test of the null hypothesis that the professional forecast and random walk model's forecast accuracy is equal. Again, the null is rejected and the RW model is the better forecast for most countries.

3.2.2 Expectation Formation

Previously, we have seen that the random walk model outperforms the professional forecast. In other words, professional forecasters deviate from the RW model and yet perform worse. In this subsection, I investigate by how much professional forecasters deviate from the RW. For simplicity, and to be consistent with the model that I introduce in the next section, I assume that they only respond to their prior belief (the forecast made in the previous month) and current new information (current exchange rate). Thus, it is natural to estimate regressions of the following

Table 3.1: Comparison of Forecast Accuracy

Country	MSFE		MAFE		MAPFE	
	RMSFE	DM p-value	$RMAFE$	DM p-value	$RMAPFE$	DM p-value
Canada	1.20	0.01	1.13	0.00	1.20	0.16
Egypt	0.97	0.77	1.25	0.00	1.26	0.00
EURO	1.23	0.09	1.12	0.06	1.10	0.49
Israel	1.08	0.54	1.09	0.19	1.10	0.15
Japan	1.23	0.00	1.14	0.00	1.14	0.00
Nigeria	1.42	0.01	1.47	0.00	1.46	0.00
South Africa	1.27	0.01	1.18	0.00	1.18	0.00
U.K	0.98	0.80	1.05	0.23	1.06	0.14
Denmark	1.79	0.05	1.32	0.03	1.32	0.03
Norway	1.30	0.10	1.11	0.13	1.10	0.13
Sweden	1.28	0.04	1.19	0.02	1.19	0.02
Switzerland	1.10	0.16	1.15	0.02	1.14	0.06

Notes: $MSFE = \frac{1}{T}\sum_{t=1}^{T}(\epsilon_{t+h|t})^2$, $MAFE = \frac{1}{T}\sum_{t=1}^{T}\left|\epsilon_{t+h|t}\right|$ and $MAPFE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{\epsilon_{t+h|t}}{y_{t+h}}\right|$, where $\epsilon_{t+h|t}$ denotes the forecast error. RMSFE is the ratio between the MSFE of the professional forecasts and the RW model. p-values are calculated according to Diebold and Mariano (1995),

form:

$$y^{pro}_{c,t+3|t} = \alpha + \kappa_1 y^{pro}_{c,t+2|t-1} + \kappa_2 y_{c,t} + e_{c,t}. \tag{3.4}$$

where, $y_{c,t+h}$ denotes the log of the actual exchange rate of country c at h months after time t. And $y^{pro}_{c,t+h|t}$ means the professional forecasts of $y_{c,t+h}$ in month t. However, running this regression is problematic since $y^{pro}_{c,t+3|t}$ has a unit root. It is well known that with a unit root the OLS estimation of the autoregressive coefficient (κ_1 in this case) is biased and the t-statistic doesn't have a standard normal distribution in a finite sample. To handle this issue, I take the first difference of those variables and estimate the regressions of the following form:

$$\triangle y^{pro}_{c,t+3|t} = \alpha + \kappa_1 \triangle y^{pro}_{c,t+2|t-1} + \kappa_2 \triangle y_{c,t} + u_{c,t} \tag{3.5}$$

The parameter of interest is κ_2, in particular, we are interested in how much it deviates from 1 (the case if professional forecasters adopt the RW model). Table (3.2) reports the results. Standard errors that are robust to serial correlation and heteroskedasticity are reported in parentheses. Across almost all countries, the weights that a professional forecaster assigns on the current exchange rate are close to 0.5. Note that, if professional forecasters were using a random walk model to make forecasts, the κ_2 would be equal to 1. This is rejected for all countries, suggesting that professionals' forecasting model deviate from the random walk model substantially,

Table 3.2: The Expectation Formation

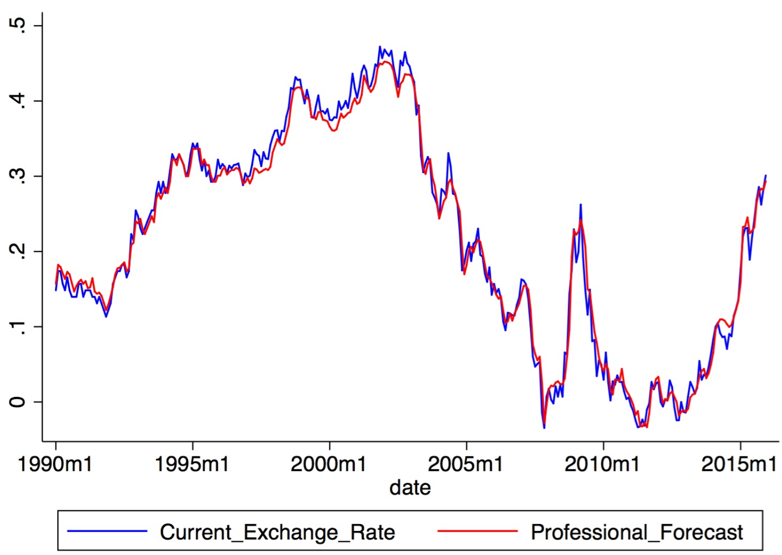
$$\triangle y^{pro}_{c,t+3|t} = \alpha + \kappa_1 \triangle y^{pro}_{c,t+2|t-1} + \kappa_2 \triangle y_{c,t} + u_{c,t}$$

	Can	Egy	Eur	Isr	Jap	Nig	S.A	U.K	Den	Nor	Swe	Swi
κ_1	0.346***	0.035	0.343***	0.057	0.374***	-0.460***	0.271***	0.281***	-0.585***	0.497***	0.388***	0.080
	(0.068)	(0.086)	(0.045)	(0.070)	(0.034)	(0.138)	(0.059)	(0.049)	(0.118)	(0.067)	(0.059)	(0.118)
κ_2	0.457***	0.695***	0.597***	0.454***	0.515***	0.692***	0.494***	0.346***	0.222**	0.429***	0.461***	0.707***
	(0.036)	(0.048)	(0.034)	(0.052)	(0.029)	(0.151)	(0.049)	(0.117)	(0.113)	(0.035)	(0.036)	(0.157)
α	-0.001	0.006***	0.000	0.005***	0.001	0.017***	0.006***	-0.003**	0.000	-0.003***	-0.005***	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Observations	311	210	203	210	311	203	270	311	181	203	203	202
R-squared	0.684	0.668	0.738	0.597	0.758	0.335	0.740	0.720	0.132	0.777	0.790	0.772

Notes: $y_{c,t+3}$ denotes the log of the actual exchange rate, of country c, 3 months after month t. And $y^{pro}_{c,t+h|t}$ denotes the professional forecasts of $y_{c,t+h}$ in month t. Each column reports results from separate regressions. Standard errors that are robust to serial correlation and heteroskedasticity are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The same conclusion can be drawn by comparing the plot of the current exchange rate ($y_{c,t}$) with the professional forecasts about future exchange rate made at time t ($y^{pro}_{c,t+h|t}$). Figure (3.1) makes such a comparison for Canada. Indeed, the professional forecasts deviate from the RW. And more interestingly, consistent with the regression results, professional forecasts are smoother as compared to the actual exchange rate. Similar results are found for other countries, see Figure (3.4), Figure (3.5) and Figure (3.6).

Figure 3.1: A Plot of the Current Exchange rate and Professional Forecast: Canada



This figure plots the current exchange rate, y_t in blue, together with the current professional forecast of exchange rate at 3-month ahead, $y^{pro}_{c,t+3|t}$ in red.

3.2.3 Counter-factual Analysis

We have seen in section (3.2.2) that professional forecaster's model deviate substantially from the random walk (as measured by κ_2). In this subsection, I investigate whether professional forecasters' performances would improve if they had used a model that is closer to the RW.

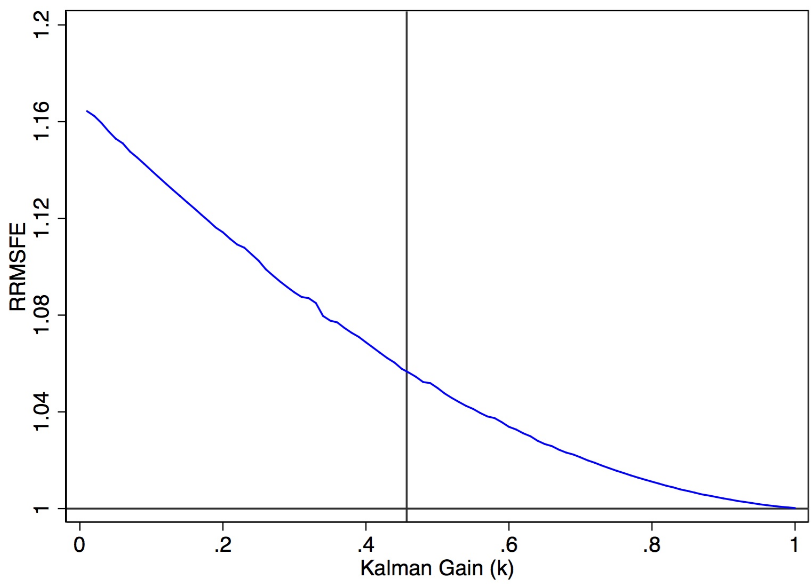
To address this question, I construct synthetic forecasts using different values of κ_2 from 0 to 1. Again, to be consistent with the model introduced blow, the synthetic professional forecast is created based on the following equation:

$$y^{syn}_{c,t+3|t} = (1-\kappa_2)y^{pro}_{c,t+2|t-1} + \kappa_2 y_{c,t} \tag{3.6}$$

For each value of κ_2, I calculate RMSFE between the synthetic professional forecast and the RW. Figure (3.2) plots the RMSFE for Canada, recall that the ratio greater than one suggests that the synthetic forecast is worse than the random walk. The solid vertical line denotes the RMSFE under the estimated κ_2 reported in Table (3.2). Interestingly, not only the forecast performance is the best when the random walk model ($\kappa_2 = 1$) is used, the RMSFE is monotonically decreasing in κ_2. Similar results hold for the other countries, see in Figure (3.3).

This exercise rules out the possibility that professional forecasters avoid the use of the RW model to look more sophisticated. If this were the case, they would have chosen a κ_2 closer to 1 (for example 0.9 rather than 0.5).

Figure 3.2: The RMSFE(κ) of Synthetic Forecasts for Canada



The synthetic forecast are constructed using $y^{syn}_{c,t+3|t} = (1-\kappa)y^{pro}_{c,t+2|t-1} + \kappa y_{c,t}$. The solid vertical line denotes the RMSFE under the κ_2 estimated in Table (3.2).

3.2.4 Rationality Test

It is well known since Frankel and Froot (1987), Ito (1990) and Dominguez (1986) that exchange rate forecasts do not pass the rationality test:

$$y_{c,t+3} - y_{c,t} = \alpha + \beta(y^{pro}_{c,t+3|t} - y_{c,t}) + e_{c,t}, \tag{3.7}$$

where $y_{c,t+h}$ denotes the log of the actual exchange rate, of country c, h months after month t. And $y^{pro}_{c,t+h|t}$ denotes the professional forecasts of $y_{c,t+h}$ in month t. Under the full rationality: $\alpha = 0$ and $\beta = 1$.

Estimation results are reported in Table (3.3). Standard errors that are

Table 3.3: Rationality Test: $y_{c,t+3} - y_{c,t} = \alpha + \beta^p(y^{pro}_{c,t+3|t} - y_{c,t}) + e_{c,t}$

	Can	Egy	Eur	Isr	Jap	Nig	S.A	U.K	Den	Nor	Swe	Swi
β^p	-0.055	0.248	-0.045	0.401**	-0.108	0.047	-0.307**	0.583**	0.180***	0.083	0.365**	0.292
	(0.148)	(0.241)	(0.145)	(0.183)	(0.120)	(0.121)	(0.128)	(0.243)	(0.059)	(0.144)	(0.155)	(0.287)
Constant	0.001	0.009***	-0.000	-0.003	-0.001	0.011**	0.018***	0.002	0.000	0.002	0.005**	-0.006***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)	(0.003)	(0.000)	(0.002)	(0.002)	(0.002)
Observations	309	208	201	208	309	201	268	309	177	201	201	200
R-squared	0.001	0.011	0.000	0.032	0.002	0.001	0.018	0.061	0.040	0.002	0.029	0.017

Notes: $y_{c,t+3}$ denotes the log of the actual exchange rate, of country c, 3 months after month t. And $y^{pro}_{c,t+h|t}$ denotes the professional forecasts of $y_{c,t+h}$ in month t. Each column reports results from separate regressions. Standard errors that are robust to serial correlation and heteroskedasticity are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

robust to serial correlation and heteroskedasticity are reported in parentheses. The estimated β is statistically different from 1. In fact, most countries feature a β that is statistically insignificant.

3.2.5 Summary

To summarize the empirical findings: i) the random walk model beats the professional forecast, ii) professional's forecasting model deviates far away from the random walk model iii) moving towards the random walk model, the professional forecasts' performance would improve monotonically and iv) professional forecasts do not pass the rationality test.

Naturally, a puzzling question arises: why would not they, the professional forecasters, use the simple random walk model to provide a more accurate forecast? In the next section, I provide a simple model to rationalize the behavior of forecasters.

3.3 Model

Section (3.3.1) provides the benchmark model with information friction. Section (3.3.2) introduces the model uncertainty.

3.3.1 The Benchmark Model: Information Friction and Model Certain

This section writes down the benchmark model in which the model is certain. Assume that the exchange rate y_t is composed of a permanent component x_t and a temporary component ϵ_t.

$$y_t = x_t + \epsilon_t, \tag{3.8}$$

where $\epsilon_t \sim N(0, \sigma_\epsilon^2)$. The permanent component x_t is not perfectly observed, and it follows:

$$x_t = x_{t-1} + u_t, \tag{3.9}$$

where $u_t \sim N(0, \sigma_u^2)$. I have assumed that the permanent component x_t follows a random walk without drift to match the fact that the exchange rate has a unit root. Furthermore, I assume that the current exchange rate y_t contains all the relevant information about x_t, no other signals are relevant/needed for the forecaster's belief updating. This is, of course, assumed for simplicity. Nevertheless, this is consistent with the well known Meese and Rogoff (1983*a*,*b*, 1988) puzzle that exchange rate is very difficult to predict using other macro variables. This assumption is most likely to hold for forecast at short horizons.

Agent updates belief about x_t, denoted as $x_{t|t}$, according to the Kalman

Filter. The problem of the forecaster is thus:

$$\max_{y_{t+1|t}} -E_t(y_{t+1|t} - y_{t+1})^2, \tag{3.10}$$

subject to the data generating process (3.8) and (3.9). Where $y_{t+1|t}$ denotes her posterior belief (forecast). Agent's belief updating equation follows:

$$x_{t|t} = (1 - k_t)x_{t|t-1} + k_t y_t \tag{3.11}$$

$$k_t = p_{t|t-1}(p_{t|t-1} + \sigma_\epsilon^2)^{-1} \tag{3.12}$$

$$p_{t+1|t} = (p_{t|t-1} - p_{t|t-1}^2(p_{t|t-1} + \sigma_\epsilon^2)^{-1}) + \sigma_u^2. \tag{3.13}$$

In practice, the $p_{t|t-1}$ in the Riccati equation (3.13) converges to its steady-state variable quickly. Therefore, it is sensible to drop the time subscript of k_t and $p_{t|t-1}$ whenever necessary. Note that the pure random walk model is a special case when $\sigma_\epsilon = 0$ and consequently $k = 1$.

The solution to this problem is thus:

$$y_{t+1|t} = x_{t|t} \tag{3.14}$$

with $x_{t|t}$ updating according to equations (3.11) (3.12) and (3.13).

3.3.2 Information Friction and Model Uncertain

Based on the benchmark model discussed above, this section introduces model uncertainty. In the spirit of Epstein and Schneider (2008), I assume that the forecaster faces Knightian uncertainty regarding the volatility of temporary shock:

$$y_t = x_t + \epsilon_t, \tag{3.15}$$

where ϵ_t is i.i.d normally distributed with mean 0 and standard error σ_ϵ. However, the forecaster is uncertain about σ_ϵ, and she believes that σ_ϵ belongs to the interval $[\underline{\sigma}_\epsilon, \overline{\sigma}_\epsilon]$. This Knightian uncertainty is axiomatized by Gilboa and Schmeidler (1989) and Epstein and Schneider (2003). This model nests the previous one in case $\underline{\sigma}_\epsilon = \overline{\sigma}_\epsilon = \sigma_\epsilon$. The distance between $\overline{\sigma}_\epsilon$ (or $\underline{\sigma}_\epsilon$) and σ_ϵ measures the degree of model uncertainty.

Facing the model uncertainty, an ambiguity averse forecaster reports a forecast by solving:

$$\max_{y^{pro}_{t+1|t}} \min_{\{\sigma_{\epsilon,i}\}_{i=0}^{t}} -E_t(y^{pro}_{t+1|t} - y_{t+1})^2 \tag{3.16}$$

subject to constraint (3.9). One motivation for this objective function is that professional forecasters concern their reputations. While the damage to one's reputation is minimal when she commits a small forecast error, the drop in reputation is significantly bigger when one makes a big forecast error. Thus to avoid big forecast error, the forecaster maximizes the reverse of expected square forecast error under the worst case scenario. Similar to the benchmark case, the forecast error minimizing agent chooses k_t and uses an updating rule of the form:

$$y^{pro}_{t+1|t} = x_{t|t} = (1 - k_t)x_{t|t-1} + k_t y_t, \tag{3.17}$$

where it remains to determine the process for $x_{t|t-1}$ and k_t.

Solving the Inner Problem

$$\min_{\{\sigma_{\epsilon,i}\}_{i=0}^{t}} -E_t(y^{pro}_{t+1|t} - y_{t+1})^2 \tag{3.18}$$

Plug (3.9) and (3.17) in and omit the terms that are irrelevant for the minimization:

$$\min_{\{\sigma_{\epsilon,i}\}_{i=0}^{t}} -E_t\left[(1-k_t)(x_{t|t-1} - x_t) + k_t\epsilon_t\right]^2$$

The inner problem is thus simplified to choose $\{\sigma_{\epsilon,i}\}_{i=0}^{t}$ such that posterior uncertainty about x_t, denoted as $P_{t|t}$, is maximized given the constraint that $\sigma_{\epsilon,i} \in [\underline{\sigma}_\epsilon, \overline{\sigma}_\epsilon], \forall\, i$.

$$\min_{\{\sigma_{\epsilon,i}\}_{i=0}^{t}} -P_{t|t} = -\left[(1-k_t)^2 P_{t|t-1} + k_t^2\sigma_\epsilon^2\right] \tag{3.19}$$

The posterior uncertainty $P_{t|t}$ is increasing in $\sigma_{\epsilon,i}, \forall\, i$ since the drop in the precision of any signal in the past would lead to a more uncertain prior thus a bigger posterior uncertainty today. the solution to the this problem is thus a corner solution: $\sigma_{\epsilon,i} = \overline{\sigma}_\epsilon, \forall i$.

The Outer Problem The outer problem is:

$$\max_{k_t} \left[(1-k_t)^2 P_{t|t-1} + k_t^2(\sigma_\epsilon^2 + \eta^2)\right].$$

The solution to this problem is (3.17) with k_t defined recursively as:

$$k_t = P_{t|t-1}(P_{t|t-1} + \overline{\sigma}_\epsilon^2)^{-1}. \tag{3.20}$$

$$P_{t|t-1} = P_{t-1|t-2} - P^2_{t-1|t-2}(P_{t-1|t-2} + \overline{\sigma}_\epsilon^2)^{-1}) + \sigma_u^2 \tag{3.21}$$

Compare this to the Kalman gain derived in the benchmark model (3.12), with model uncertainty the ambiguity averse forecaster under-reacts to the current signal. Although she knows that, as compared to standard Kalman filter, this is sub-optimal in terms of expected squared forecast error. This solution is the one that minimizes squared forecast error under the worst case scenario.

3.4 Model Estimation

3.4.1 State Space Representation

The state space representation of the model of the robust forecaster is:

$$Z_t = Dx_t + Cu_t \tag{3.22}$$

$$x_t = Ax_{t-1} + BU_t, \tag{3.23}$$

with $Z_t \equiv \begin{bmatrix} y^{pro}_{t+h|t} & y_t \end{bmatrix}'$, $x_t \equiv \begin{bmatrix} x_t & x_{t|t-1} & y_t \end{bmatrix}'$, $v_t \equiv \begin{bmatrix} v_{jt} \end{bmatrix}'$ and $U_t \equiv \begin{bmatrix} u_{jt} \end{bmatrix}'$ are vectors with u_{jt}, $u_{jt} \sim N(0, 1)$. And

$$A \equiv \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 - k^U & k^U \\ 1 & 0 & 0 \end{bmatrix} B \equiv \begin{bmatrix} \sigma_u & 0 & 0 \\ 0 & 0 & 0 \\ \sigma_u & 0 & \sigma_\epsilon \end{bmatrix}$$

$$D \equiv \begin{bmatrix} 0 & 1 - k^U & k^U \\ 0 & 0 & 1 \end{bmatrix} C \equiv \begin{bmatrix} \sigma_e & 0 \\ 0 & 0 \end{bmatrix},$$

where:

$$k^U = p(p + \overline{\sigma}_\epsilon^2)^{-1},$$
$$p = (p - p^2(p + \overline{\sigma}_\epsilon^2) + \sigma_u^2.$$

Note that the state space representation of the benchmark model is obtained by replacing k^U by k that is pinned down by the convergence version of (3.12) and (3.13). Given the state space representation, it is easy to construct the likelihood function using the standard Kalman filter. The parameters are estimated using the maximum likelihood method. For each country, I use the log of the actual exchange rate (y_t), the log of professional's forecast of the exchange rate at three months ahead ($y_{t+3|t}^{pro}$) as the measurement equations. Note that I have included a measurement error ϵ_e to the professional forecast data in order to capture anything else that is in the survey but not explained by the simple model. I estimate the following four parameters separately for each country: σ_u, σ_ϵ, σ_e and $\overline{\sigma}_\epsilon$.

3.4.2 Simulation Results

Estimated Parameters Table (3.4) reports the parameters estimated by MLE. the parameters are estimated for each country separately. The Kalman gains are then computed using $k^U = p(p + \sigma_\epsilon^2 + \eta^2)^{-1}$with the corresponding $p = (p - p^2(p + \overline{\sigma}_\epsilon^2)^{-1}) + \sigma_u^2$. And $k = p(p + \sigma_\epsilon^2)^{-1}$ with the corresponding $p = (p - p^2(p + \sigma_\epsilon^2)^{-1}) + \sigma_u^2$.

The degree of information friction is small if the model is certain: this can be seen from the signal noise ratio of σ_ϵ/σ_u as well as the implied Kalman gain if the model were certain. The Kalman gain under the filter without model uncertainty is very close to unity suggesting that without

Table 3.4: MLE Parameter Estimates

	Parameter Estimates				Implied Kalman Gain	
					Model Certain	Model Uncertain
Country	σ_ϵ	σ_u	$\overline{\sigma}_\epsilon$	σ_e	k	k^U
Canada	0.002	0.020	0.021	0.011	0.988	0.610
Egypt	0.000	0.018	0.000	0.019	1.000	1.000
EURO	0.000	0.029	0.025	0.021	1.000	0.671
Israel	0.000	0.023	0.029	0.017	1.000	0.534
Japan	0.000	0.033	0.033	0.020	1.000	0.616
Nigeria	0.000	0.023	0.000	0.039	1.000	1.000
South Africa	0.000	0.043	0.060	0.022	1.000	0.502
U.K	0.013	0.028	0.025	0.019	0.846	0.618
Denmark	0.000	0.001	0.003	0.001	0.904	0.219
Norway	0.004	0.018	0.025	0.014	0.947	0.506
Sweden	0.007	0.015	0.019	0.015	0.853	0.516
Switzerland	0.006	0.011	0.009	0.010	0.811	0.625

Notes: the parameters are estimated using MLE, for each country separately. The Kalman gains are then computed using $k^U = p(p + \overline{\sigma}_\epsilon^2)^{-1}$ with the corresponding $p = (p - p^2(p + \overline{\sigma}_\epsilon^2)^{-1}) + \sigma_u^2$. And $k = p(p + \sigma_\epsilon^2)^{-1}$ with the corresponding $p = (p - p^2(p + \sigma_\epsilon^2)^{-1}) + \sigma_u^2$.

max-min preference, the professional forecaster would report a forecast that is very close to the current exchange rate. However, due to the high degree of model uncertainty $\overline{\sigma}_\epsilon$, which is on average close to the volatility of the permanent component σ_u, the ambiguity averse forecaster would take this into consideration and the implied Kalman gain with model uncertainty is far less than 1.

The Failure of the Benchmark Model I replicate the forecast accuracy comparison exercise as it is done in section (3.2.1) for the benchmark model using simulated data. I take parameter estimates from Table (3.4), [2] simulate the benchmark model for 10000 times. The length of the time series is the same as its empirical counterpart studies in section (3.2). For each simulation, I compute the RMSFE, the RMAFE and the RMAPFE. I report median estimates and the numbers in Low and High columns correspond to the 5th and the 95th percentiles respectively. As one can see, both the professional forecaster and the random walk model under the benchmark model predict the future exchange rate equally well. This is clearly inconsistent with the empirical findings discussed above,

The Random Walk Beats Professional Forecast Table (3.6) reports the forecast accuracy test for the framework in which the model is uncertain. The random walk beats the professional forecast according to the all of the criteria studied. This is consistent with the empirical results displayed above. This is the case because professional forecaster underacts to the current news, as it is implied the computed Kalman gain reported in Table (3.4), to avoid big forecast error in the worst case scenario. The intuition is the following. Due to information friction, when the forecaster

[2]Simulation results are identical if the benchmark model is estimated separately.

Table 3.5: Prediction of the Benchmark Model

	RMSFE			RMAFE			RMAPFE		
		90% Interval			90% Interval			90% Interval	
Country	Median	Low	High	Median	Low	High	Median	Low	High
Canada	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Egypt	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
EURO	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Israel	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Japan	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Nigeria	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
South Africa	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
U.K	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Denmark	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Norway	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Sweden	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Switzerland	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

Notes: I simulate the model for 10000 times. For each simulation, I compute the RMSFE, RMAFE and RMAPFE. The Low and High columns correspond to the 5 and the 95 percentiles respectively.

observes the current exchange rate, she cannot tell whether this is due to movement in the permanent or temporary component. She forms expectation using the Bayes' rule. However, the current exchange rate as a signal is ambiguous. The variance of expected forecast error is the largest when the model uncertainty in the signal is the biggest, therefore the forecaster as a max-minimizer reports her forecast by distrusting the signal as much as possible.

The Shorter the Forecasting Horizon the Worse the Professional Forecasts Table (3.8) ,Table (3.9) and Table (3.10) repeat the exercises for forecast horizon at 1, 12 and 24 months ahead respectively. For 1-month horizon forecast, the robust forecaster does a much worse job than the random walk model, However, as the forecast horizon increases, the discrepancy between those two decreases. For forecasts of exchange rate at 24 months ahead, both the robust forecaster's forecast is as "good" as the random walk model.

Implication: Rationality Test We have seen in Table (3.3) that the professional forecasts do not pass the rationality test. For comparison, those results are reported again in the last three columns in Table (3.7). The model is capable of reproducing those results. I estimate the same regressions using data simulated from the model. The first three columns in Table (3.7) report simulation results. Surprisingly, the prediction of the model matches the empirical counterpart both qualitatively and qualitatively. This paper agrees with the literature that survey forecasts do not pass the rationality test. However, it proposes different rationale: professional forecasters face model uncertainty and they are ambiguity averse. As a result, they report a survey answer that minimizes forecast error un-

Table 3.6: Prediction of the Model with Model Uncertain: $h = 3$

	RMSFE			RMAFE			RMAPFE		
		90% Interval			90% Interval			90% Interval	
Country	Median	Low	High	Median	Low	High	Median	Low	High
Canada	1.05	1.00	1.11	1.03	1.00	1.06	1.03	0.99	1.06
Egypt	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
EURO	1.04	0.99	1.08	1.02	0.99	1.05	1.02	0.99	1.05
Israel	1.09	1.01	1.17	1.05	1.00	1.09	1.05	1.00	1.09
Japan	1.06	1.00	1.11	1.03	1.00	1.06	1.03	0.99	1.07
Nigeria	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
South Africa	1.11	1.02	1.19	1.05	1.01	1.10	1.05	0.99	1.15
U.K	1.01	0.96	1.05	1.00	0.97	1.03	1.00	0.97	1.04
Denmark	1.44	1.19	1.74	1.20	1.08	1.34	1.20	1.08	1.34
Norway	1.09	1.00	1.17	1.04	1.00	1.09	1.04	1.00	1.09
Sweden	1.04	0.97	1.12	1.02	0.98	1.06	1.02	0.98	1.06
Switzerland	0.99	0.95	1.03	1.00	0.97	1.02	1.00	0.97	1.02

Notes: I simulate the model for 10000 times. For each simulation, I compute the RMSFE, RMAFE and RMAPFE. The Low and High columns correspond to the 5 and the 95 percentiles respectively.

der the worst-case scenario. Thus the rejection of null of rationality does not imply professional forecasts are irrational. Moreover, the answers contained in the survey are not necessarily the expectations that those professionals have when making investment decisions.

3.4.3 Robustness Check: Introducing Model Uncertainty to the State Equation

In the baseline, professional forecasters only face model uncertainty in the measurement equation. Now. assume that both the observable equation and state equation are subject to model uncertainty:

$$y_t = x_t + \epsilon_t,$$
$$x_t = x_{t=1} + u_t,$$

where both ϵ_t and u_t are i.i.d normally distributed with mean 0 with unknown standard errors that are perceived to belongs to the intervals $[\underline{\sigma}_\epsilon, \overline{\sigma}_\epsilon]$ and $[\underline{\sigma}_u, \overline{\sigma}_u]$ with $\overline{\sigma}_\epsilon = \sigma_\epsilon + \eta_1$ and $\overline{\sigma}_u = \sigma_u + \eta_2$.

The solution (Kalman Gain) to this model is:

$$k_t = P_{t|t-1}(P_{t|t-1} + \sigma_\epsilon^2 + \eta_1^2)^{-1}. \tag{3.24}$$
$$P_{t|t-1} = P_{t-1|t-2} - P_{t-1|t-2}^2(P_{t-1|t-2} + \sigma_\epsilon^2 + \eta_1^2)^{-1}) + \sigma_u^2 + \eta_2^2 \tag{3.25}$$

Now it is unclear whether the forecaster would over-react or under-react to the current news. The bias depends on the relative model uncertainty between: η_1 and η_2. Parameters estimates and the implied Kalman gains are reported in Table (3.11). The estimated η_1 is bigger than η_2 for most countries driving the overall Kalman gain bias downward. The implied k_u

Table 3.7: The Rationality Test

$y_{c,t+3} - y_{c,t} = \alpha + \beta(y^{pro}_{c,t+3|t} - y_{c,t}) + e_{c,t}$

	Model Simulations			Empirical Regressions		
		90% Interval			90% Interval	
Country	$\hat{\beta}^{model}$	Low	High	$\hat{\beta}^{data}$	Low	High
Canada	0.07	-0.41	0.55	-0.06	-0.30	0.17
Egypt	-	-	-	0.25	-0.64	0.15
EURO	0.06	-0.53	0.62	-0.05	-0.30	0.20
Israel	0.04	-0.37	0.46	0.40	0.10	0.70
Japan	0.04	-0.46	0.53	-0.11	-0.31	0.09
Nigeria	-	-	-	0.05	0.15	0.25
South Africa	0.04	-0.34	0.42	-0.31	-0.52	-0.09
U.K	0.48	-0.02	0.95	0.58	0.18	0.98
Denmark	0.09	-0.11	0.32	0.18	0.08	0.28
Norway	0.13	-0.25	0.51	0.08	-0.15	0.31
Sweden	0.32	-0.06	0.69	0.37	0.11	0.63
Switzerland	0.63	0.11	1.11	0.29	-0.19	0.77

Notes: $y_{c,t+3}$ denotes the log of the actual exchange rate, of country c, 3 months after month t. And $y^{pro}_{c,t+h|t}$ denotes the professional forecasts of $y_{c,t+3}$ in month t. The first three columns report estimation results calculated from simulated data. The last three columns report results from separate regressions using survey data. The empirical confidence intervals are constructed based on standard errors that are robust to serial correlation and heteroskedasticity.

is close to those estimated from the baseline specification. Table (3.12) reports the simulation results. Again, the same results hold: the random walk model beats the professional forecasts.

3.5 Conclusion

This paper shows that for short-horizon exchange rate predictability the simple random walk model outperforms professional forecasts. A new puzzle arises: why do professional forecasters not adopt the simple random walk model to provide a more accurate estimate? This paper provides an explanation. In the framework, the forecaster faces model uncertainty and she reports the forecast that minimizes the forecast error under the worst case scenario. Therefore professional forecasters provide suboptimal forecast intentionally. The ability of the model to match the empirical facts is tested through a Maximum Likelihood estimation exercise. Estimation results show that the model matches the empirical puzzle and in addition, the model predicts that the forecaster under-react to current news substantially for exchange rate predictability. The later is consistent with empirical facts provided in this paper. Moreover, the null of "rationality" is rejected using simulated data confirming existing findings even though forecasters in the model perform optimally.

3.6 Appendix

3.6.1 Tables

Table 3.8: Prediction of the Model with Model Uncertain: $h = 1$

	RMSFE			RMAFE			RMAPFE		
		95% Interval			95% Interval			95% Interval	
Country	Median	Low	High	Median	Low	High	Median	Low	High
Canada	1.23	1.12	1.36	1.11	1.05	1.17	1.11	1.05	1.17
Egypt	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
EURO	1.24	1.13	1.36	1.11	1.06	1.17	1.11	1.05	1.18
Israel	1.28	1.15	1.41	1.13	1.07	1.20	1.13	1.07	1.20
Japan	1.17	1.08	1.27	1.08	1.03	1.13	1.08	1.03	1.15
Nigeria	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
South Africa	1.33	1.19	1.49	1.16	1.09	1.23	1.16	1.06	1.29
U.K	1.00	0.94	1.06	1.00	0.97	1.04	1.00	0.96	1.04
Denmark	9.35	5.12	17.49	3.09	2.27	4.32	3.09	2.27	4.32
Norway	1.25	1.12	1.39	1.12	1.05	1.19	1.12	1.05	1.19
Sweden	2.03	1.61	2.59	1.43	1.26	1.63	1.43	1.26	1.63
Switzerland	0.97	0.93	1.01	0.98	0.96	1.01	0.98	0.96	1.01

Notes: I simulate the model for 10000 times. For each simulation, I compute the RMSFE, RMAFE and RMAPFE. The Low and High columns correspond to the 5 and the 95 percentiles respectively.

Table 3.9: Prediction of the Model with Model Uncertain: $h = 12$

	RMSFE			RMAFE			RMAPFE		
		95% Interval			95% Interval			95% Interval	
Country	Median	Low	High	Median	Low	High	Median	Low	High
Canada	1.02	0.98	1.05	1.01	0.99	1.03	1.01	0.99	1.03
Egypt	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
EURO	1.02	0.98	1.05	1.01	0.99	1.03	1.01	0.98	1.03
Israel	1.02	0.98	1.06	1.01	0.99	1.03	1.01	0.98	1.03
Japan	1.01	0.98	1.04	1.01	0.99	1.02	1.01	0.99	1.03
Nigeria	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
South Africa	1.03	0.97	1.07	1.01	0.98	1.04	1.01	0.98	1.06
U.K	1.00	0.97	1.02	1.00	0.98	1.01	1.00	0.98	1.01
Denmark	1.79	1.07	2.97	1.35	1.03	1.79	1.35	1.03	1.79
Norway	1.02	0.97	1.06	1.01	0.98	1.03	1.01	0.98	1.04
Sweden	1.11	0.95	1.27	1.06	0.97	1.14	1.06	0.97	1.14
Switzerland	0.99	0.97	1.01	1.00	0.99	1.01	1.00	0.99	1.01

Notes: I simulate the model for 10000 times. For each simulation, I compute the RMSFE, RMAFE and RMAPFE. The Low and High columns correspond to the 5 and the 95 percentiles respectively.

Table 3.10: Prediction of the Model with Model Uncertain: $h = 24$

	RMSFE			RMAFE			RMAPFE		
		95% Interval			95% Interval			95% Interval	
Country	Median	Low	High	Median	Low	High	Median	Low	High
Canada	1.01	0.97	1.03	1.00	0.99	1.02	1.01	0.99	1.02
Egypt	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
EURO	1.01	0.98	1.03	1.00	0.99	1.02	1.01	0.99	1.02
Israel	1.01	0.97	1.03	1.01	0.98	1.02	1.01	0.98	1.02
Japan	1.01	0.98	1.02	1.00	0.99	1.01	1.00	0.99	1.02
Nigeria	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
South Africa	1.01	0.97	1.04	1.01	0.98	1.02	1.01	0.98	1.04
U.K	1.00	0.98	1.01	1.00	0.99	1.01	1.00	0.99	1.01
Denmark	1.38	0.86	2.11	1.19	0.92	1.52	1.19	0.92	1.52
Norway	1.01	0.97	1.04	1.01	0.98	1.02	1.01	0.98	1.02
Sweden	1.05	0.92	1.16	1.03	0.95	1.09	1.03	0.96	1.09
Switzerland	1.00	0.98	1.01	1.00	0.99	1.01	1.00	0.99	1.01

Notes: I simulate the model for 10000 times. For each simulation, I compute the RMSFE, RMAFE and RMAPFE. The Low and High columns correspond to the 5 and the 95 percentiles respectively.

Table 3.11: Robust Check: MLE Parameter Estimates

	Parameter Estimates					Implied Kalman Gain	
						Benchmark	Model Uncertain
Country	$\hat{\sigma}_\epsilon$	$\hat{\sigma}_u$	$\hat{\eta}_1$	$\hat{\sigma}_e$	$\hat{\eta}_2$	$\hat{K}$	$\hat{K}_u$
Canada	0.002	0.020	0.025	0.011	0.013	0.988	0.612
Egypt	0.000	0.018	0.000	0.019	0.092	1.000	1.000
EURO	0.000	0.029	0.035	0.021	0.028	1.000	0.671
Israel	0.000	0.023	0.029	0.017	0.000	1.000	0.534
Japan	0.000	0.033	0.033	0.020	0.002	1.000	0.616
Nigeria	0.000	0.023	0.000	0.039	0.098	1.000	1.000
South Africa	0.000	0.043	0.061	0.022	0.006	1.000	0.502
U.K	0.013	0.028	0.022	0.019	0.007	0.846	0.659
Denmark	0.000	0.001	0.017	0.001	0.004	0.904	0.220
Norway	0.004	0.018	0.025	0.014	0.004	0.947	0.511
Sweden	0.007	0.015	0.064	0.015	0.048	0.853	0.536
Switzerland	0.006	0.011	0.007	0.010	0.000	0.811	0.685

Notes: the parameters are estimated using MLE, for each country separately. The Kalman gains are then computed using $k_u = p_u(p_u + \sigma_\epsilon^2 + \eta_1^2)^{-1}$ and $p_u = (p_u - p_u^2(p_u + \sigma_\epsilon^2 + \eta_1^2)^{-1}) + \sigma_u^2 + \eta_2^2$. And $k = p(p + \sigma_\epsilon^2)^{-1}, p = (p - p^2(p + \sigma_\epsilon^2)^{-1}) + \sigma_u^2$.

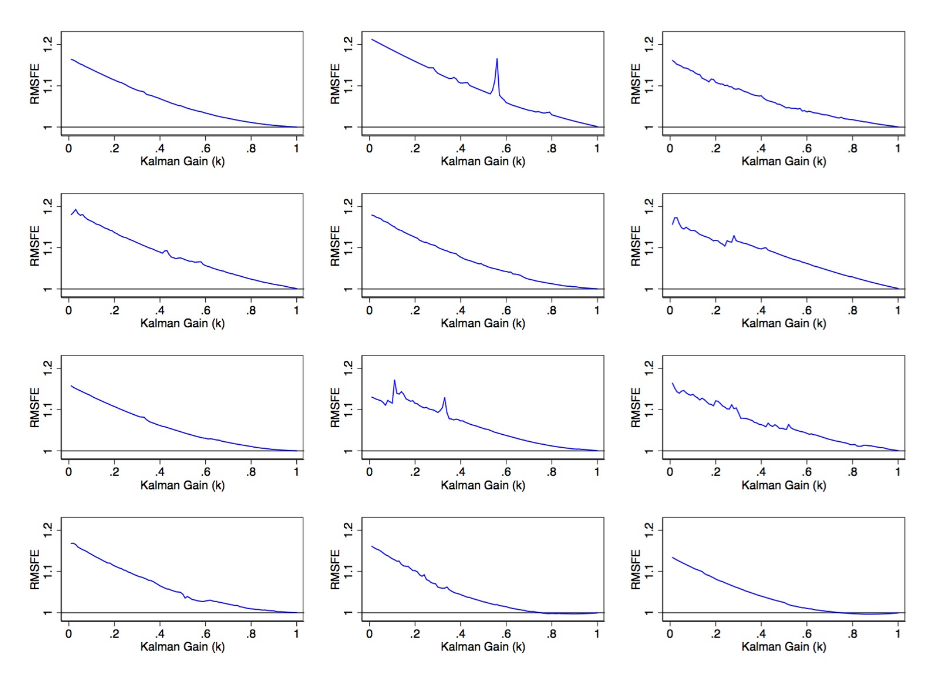
Table 3.12: Robust Check: Simulation Results $h = 3$

	RMSFE			RMAFE			RMAPFE		
		90% Interval			90% Interval			90% Interval	
Country	Median	Low	High	Median	Low	High	Median	Low	High
Canada	1.08	1.01	1.15	1.04	1.00	1.08	1.04	1.00	1.08
Egypt	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
EURO	1.08	1.01	1.15	1.04	1.00	1.08	1.04	1.00	1.08
Israel	1.09	1.01	1.17	1.04	1.00	1.09	1.05	1.00	1.09
Japan	1.06	1.00	1.11	1.03	1.00	1.06	1.03	0.99	1.07
Nigeria	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
South Africa	1.11	1.03	1.20	1.05	1.01	1.10	1.06	0.99	1.14
U.K	1.00	0.96	1.04	1.00	0.97	1.02	1.00	0.97	1.03
Denmark	4.15	2.33	7.47	2.06	1.53	2.83	2.06	1.53	2.82
Norway	1.09	1.00	1.17	1.04	1.00	1.09	1.04	1.00	1.09
Sweden	1.42	1.16	1.73	1.19	1.07	1.33	1.20	1.07	1.33
Switzerland	0.98	0.95	1.01	0.99	0.97	1.01	0.99	0.97	1.01

Notes: I simulate the model for 10000 times. For each simulation, I compute the RMSFE, RMAFE and RMAPFE. The Low and High columns correspond to the 5 and the 95 percentiles respectively.

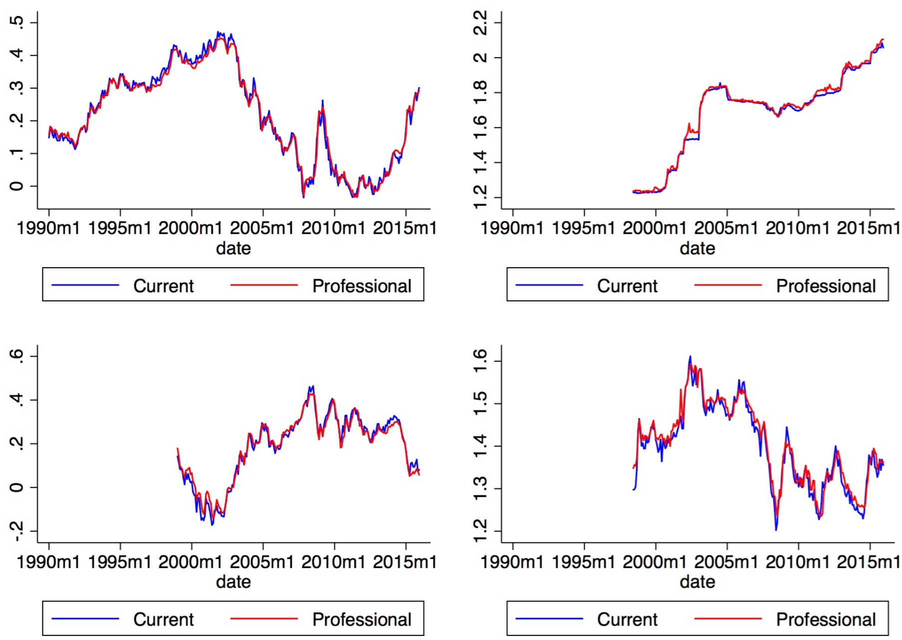
3.6.2 Figures

Figure 3.3: The RMSFE(κ) of Synthetic Forecasts for all Countries



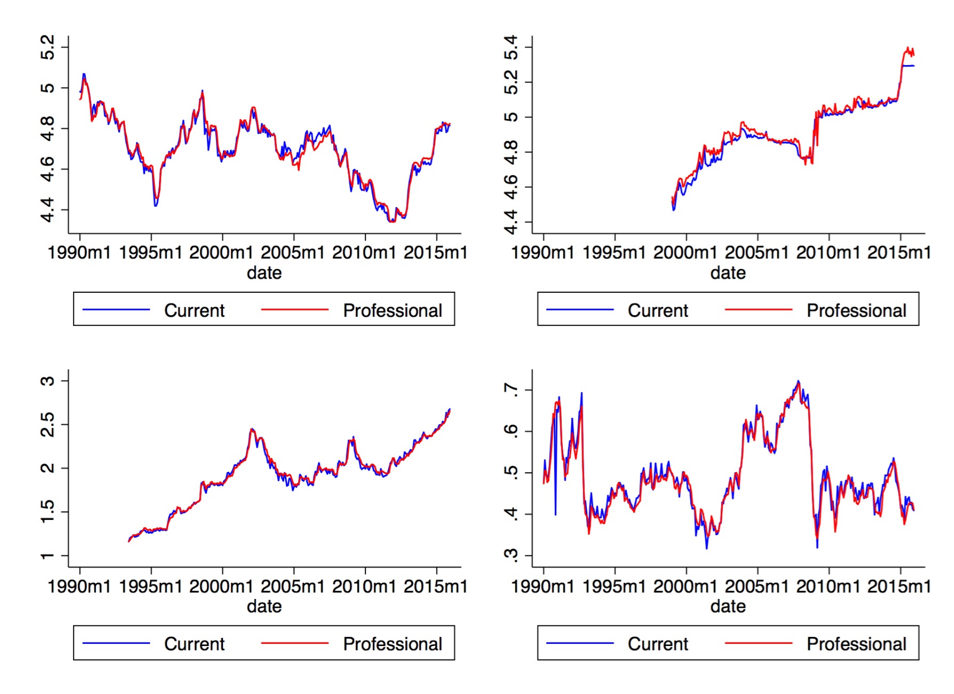
The synthetic forecast are constructed using $y^{syn}_{c,t+3|t} = (1-\kappa)y^{pro}_{c,t+2|t-1} + \kappa y_{c,t}$. From the left to the right, up to down the countries are: Canada, Egypt, Euro zone, Israel, Japan, Nigeria, South Africa, U.K, Denmark, Norway, Sweden, Switzerland.

Figure 3.4: Current Exchange rate v.s Professional Forecast: Canada, Egypt, Euro zone, Israel.



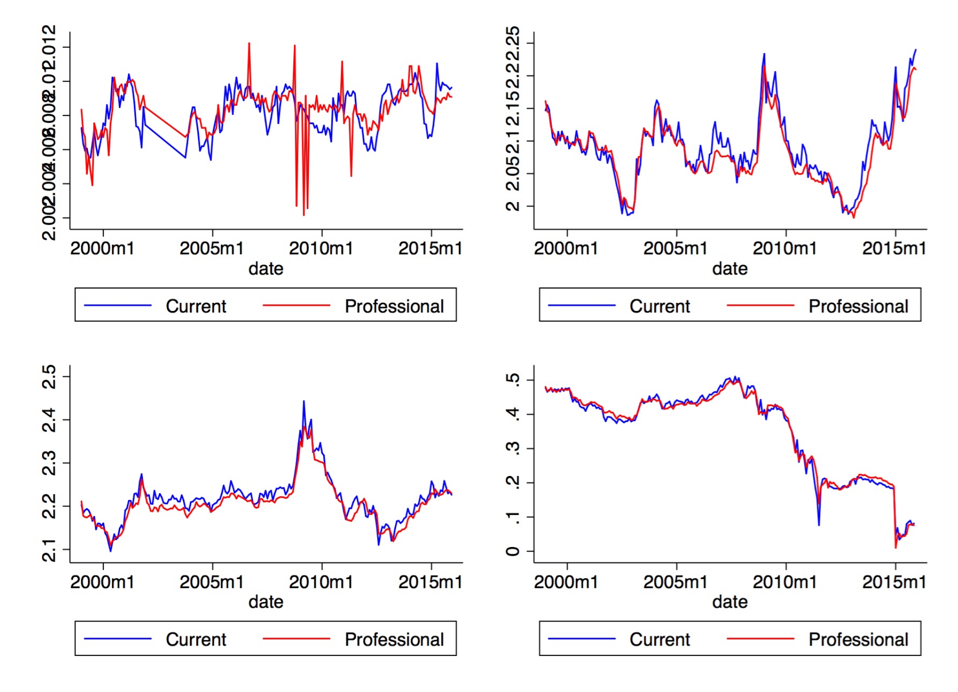
This figure plots the current exchange rate, y_t in blue, together with the current professional forecast of exchange rate at 3-month ahead, $y^{pro}_{c,t+3|t}$ in red. From the left to the right, up to down the countries are: Canada, Egypt, Euro zone, Israel.

Figure 3.5: Current Exchange rate v.s Professional Forecast: Japan, Nigeria, South Africa, U.K



This figure plots the current exchange rate, y_t in blue, together with the current professional forecast of exchange rate at 3-month ahead, $y^{pro}_{c,t+3|t}$ in red. From the left to the right, up to down the countries are: Japan, Nigeria, South Africa, U.K.

Figure 3.6: Current Exchange rate v.s Professional Forecast: Denmark, Norway, Sweden, Switzerland



This figure plots the current exchange rate, y_t in blue, together with the current professional forecast of exchange rate at 3-month ahead, $y^{pro}_{c,t+3|t}$ in red. From the left to the right, up to down the countries are: Denmark, Norway, Sweden, Switzerland.

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