ESSAYS IN MACROECONOMICS

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My doctoral research focuses, first, on the effect of central bank transparency on people's expectation formation and, second, on the relationship between financial frictions and the macroeconomy. In Chapter 1, I study how the central bank transparency affects disagreement in inflation expectations. In Chapter 2, I investigate the optimal degree of transparency about inflation target for a central bank. In Chapter 3, I examine the impact of financial factors on the growth of total factor productivity.

Chapter 1. In this analysis I measures the transparency of the Federal Reserve Board (FRB) regarding its target inflation rate before its adoption of inflation targeting using data on the disagreement in inflation expectations among U.S. consumers. We construct a model of inflation forecasters employing the frameworks of both an unobserved components model and a noisy information model. We estimate the model and extract the transparency of the FRB regarding the target as the standard deviation of the heterogeneous noise in the inflation trend signal, where the trend proxies the FRB's inflation target. The results show a great improvement in transparency after the mid-1990s as well as its significant contribution to the decline in the disagreement in long-horizon inflation expectations.

Chapter 2. We examined the optimal degree of transparency for a central bank about its inflation target. We construct a new Keynesian model with dispersed information in which policy rate signals information about underlying shocks. We have shown that a transparent inflation target is not always optimal in the presence of the signaling effects of the policy rate. In addition, it is shown that the optimal degree of transparency depends on the relative size and the persistence of the underlying shocks.

Chapter 3. After the global financial crisis, slowdowns of total factor productivity (TFP), often measured as the Solow residual, have been observed across major countries.

This study offers an explanation for this by focusing on Japan's financial crises during the 1990s. We first incorporate credit constraints, for financial intermediaries (FIs) and firms, and input–output structure into the standard New Keynesian model, and show that the model delivers multiple channels through which damaged balance sheets reduce measured TFP. We then estimate the model using Japanese data, and show that adverse shocks to FIs' balance sheets played a substantial role in lowering measured TFP.

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CHAPTER 1

Central Bank Transparency and Disagreement in Inflation Expectations

1.1 Introduction

One consensus view in recent central banking is that central banks around the world have become more transparent over the past few decades. In fact, the FRB has allowed the disclosure of information related to its monetary policy-making, such as moves in the target federal funds rate, past transcripts of policy meetings, longer economic forecasts, and inflation targets since the 1990s. A number of central banks in other economies have also increased the disclosure of their internal information related to monetary policy, such as economic projections and policy goals. How these initiatives have influenced the transparency of central banks and hence affected the expectation formation of private agents are interesting questions.

Nonetheless, studies that measure the degree of transparency are scarce. An independent central bank needs to be accountable and accountability requires the bank to be transparent. Therefore, the degree of transparency of a central bank is itself an important topic. Several studies have tried to measure the degree of transparency and they evaluate central bank transparency using discrete values, such as whether a bank has a numerical inflation target or not. Assessing a central bank's actions or communication mechanically in this manner is one natural way to measure transparency. However, even among central banks that have an explicit numerical target there are differences in the institutional setup or the wording of the target. Moreover, even for central banks that do not declare an explicit target there exist numerous ways to deliver information about the target, such as economic projections, speeches, transcripts, and monetary policymaking itself.[1] In this study we focus on transparency regarding the inflation target,[2] but we measure central bank transparency from the information that economic agents finally have rather than following each action of the central bank.

We focus on the relationship between the transparency of a central bank regarding the target and the disagreement in inflation expectations, which is defined as the standard deviation of inflation expectations across forecasters. Figure 1 shows the disagreement in inflation expectations from the Michigan Survey of Consumers. It shows that, while the disagreement in longer-run (LR) inflation expectations 5 to 10 years ahead was larger than that in shorter-run (SR) inflation expectations 1 year ahead in the 1990s, the reverse was true in the 2000s. Our conjecture is that this change in the relationship, where the disagreement in LR expectations has become smaller than the disagreement in SR expectations, can be attributed to the change in the FRB's transparency regarding the target. In fact, existing studies show empirically such a relationship between transparency and disagreement.

To measure the degree of transparency, this study employs a model-based approach using data on disagreement in inflation expectations. Since the amount of disagreement would have been affected not only by the FRB's transparency but also by other factors related to inflation dynamics, including the level of inflation, we construct a model of inflation forecasters that captures these factors by combining two methodologies in the literature. One is a traditional method that decomposes inflation into a temporary gap component and a permanent component, where we assume the trend component proxies the FRB's inflation target. The second method uses dispersed information, where each forecaster knows the

[1]While the Fed did not announce a numerical target for the inflation rate in the past, we find that they began to discuss a specific number in the transcripts of FOMC meetings in the mid-1990s.

[2]Geraats (2002) notes that there are several aspects of central bank transparency, such as transparency regarding economic information or that regarding operational procedure. Our focus, i.e., transparency regarding the inflation target, corresponds to "political transparency" in her terminology.

model structure and the parameters but does not know current economic variables correctly. Instead, each forecaster observes a heterogeneous noisy signal of current inflation and the inflation trend. We interpret the standard deviation of the distribution of the noise (hereafter, the size of the noise) in the inflation trend signal as the degree of the FRB's transparency regarding its inflation target. In addition, we generalize the model and consider the case where the actual size of the noise and the size of the noise as perceived by forecasters can be different. We estimate all the parameters employing both maximum likelihood and the method of moments, matching the theoretical moments from the model to the data. The data are the actual inflation rate in the U.S. and the inflation expectations of consumers from the Michigan Survey of Consumers. We split the sample into two parts, before and after 1993 (up until 2008), and compare the change in the parameters. In doing so, we quantify the change in the degree of the FRB's transparency regarding the target. Moreover, we decompose the change in the disagreement into the differences in the underlying parameters, including transparency.

Our findings are three-fold. First, we find a great improvement in our transparency measure after the mid-1990s. The actual size of the noise in the inflation trend, our index of central bank transparency, declines by more than half. This finding will be attributed to the increased disclosure by the FRB of information related to its inflation target. We also find a great decline in both the persistence of the inflation gap and the size of shocks to the inflation trend, where the latter will reflect the decline in the level of the inflation rate. Second, we find that the increase in the FRB's transparency played an important role in the change in the relationship between LR and SR disagreements. Our decomposition analysis shows that the decline in the LR disagreement relative to the SR disagreement can be attributed to several factors, including the decline in the size of trend shocks, but the increase in the FRB's transparency has contributed the most to the change in the relationship between the two disagreements. Third, we find a decline in the actual size of the noise in the inflation trend after the mid-1990s for almost all subgroups of consumers. However, there is heterogeneity and the decline was especially pronounced for the young, the educated, and those with high incomes. This suggests that whether information on the improvement in the FRB's transparency regarding the target is finally conveyed to an economic agent depends on the agent's characteristics.

Literature Review

This paper combines three strands of literature: inflation dynamics, imperfect information, and central bank transparency. The first strand of literature studies the change in inflation dynamics after the great inflation period. As is done in this study, these studies decompose inflation into a temporary component and a trend component and discuss the change in the dynamics of these components. Two stylized facts are related to this study. One is that the volatility of shocks to the permanent component declined from the great inflation period to the great moderation period (Stock and Watson (2007)).[3] The other is that the persistence of the inflation gap, which is defined as the deviation of inflation from its permanent component, declined during the same sample period (Cogley *et al.* (2010)). The decline in the fluctuation of trend inflation is consistent with Figure 1. Supposing forecasters have information with heterogeneous noise, the smaller is the trend fluctuation, the smaller will be the LR disagreement. This result comes from the decline in the signal-to-noise ratio of the trend, which means that the same noisy information becomes less informative for forecasters. Also, the decline in inflation gap persistence will also affect disagreements, though the direction of the effect is not obvious. Our contribution to this literature is that we extend this basic framework to incorporate dispersed information and provide novel empirical facts about informational frictions after the great inflation period while retaining the stylized facts about inflation dynamics.

The second strand of related literature studies imperfect information. The basic idea is that there exist informational frictions and economic agents cannot have full information

[3] Other papers that have emphasized the important role of time-varying inflation trends to explain inflation and other variables are Kozicki and Tinsley (2001, 2005, 2012), Gürkaynak *et al.* (2005), Cogley and Sbordone (2008), and Coibion and Gorodnichenko (2011).

about economic variables. One method to model imperfect information, proposed by Woodford (2001), is to assume that each agent observes heterogeneous noisy signals, or that agents have heterogeneous beliefs, about the current economic states. One of the reasons, then, behind the changing relationship between disagreements in our figure can be the change in the noisiness of the signals. Suppose that there exist informational frictions not only regarding current inflation, as is usually assumed in the noisy information literature, but also regarding its trend. Then, it is straightforward to conjecture that the noisiness of the trend signals or the heterogeneity in beliefs about the trend diminished over the sample. There are a few studies which use a dispersed information model with trend inflation. Patton and Timmermann (2010) employ a univariate model of inflation and assume that people have different priors about the long-run end point of the economy to study the source of aggregate disagreement in the Survey of Professional Forecasters. Their idea of heterogeneity in the long-run end point of the economy is similar to our heterogeneous noisy signal of the trend, but we are in particular interested in the time variation of the end point. Andrade *et al.* (2016) use an unobserved components VAR model with dispersed information, together with that with sticky information, to investigate the term structure of disagreements in the Blue Chip survey. They contribute to the literature by incorporating time-varying trends in the imperfect information framework and we extend their model by incorporating heterogeneous signals of the trend, similar to the idea of Patton and Timmermann (2010), in particular focusing on the inflation rate. Our contribution to the literature is that we discuss how people form their LR inflation expectations by explicitly incorporating the heterogeneous noisy information about the time-varying trend component, which is often associated with the FRB's policy goal.[4]

The third strand of literature studies central bank transparency. One group of papers, in-

[4]Mertens and Nason (2020) is also close to our paper. They employ an unobserved components model of inflation with sticky information and time-varying parameters and estimate the model focusing on the change in the informational stickiness parameter, which is a parameter of informational rigidity similar to the size of the noise parameter in our model. Our paper is different from theirs in that we employ data about disagreements and focus on informational rigidity related to the inflation trend.

cluding Eijffinger and Geraats (2006), Crowe and Meade (2008), and Dincer and Eichengreen (2010), measures the degree of transparency. They evaluate transparency by observing the communication or actions of central banks, but we take a different approach for the reasons mentioned above. A second group of papers about central bank transparency evaluates the effect of central bank communication on economic variables. They discuss how differences in communication strategies, either over time or across central banks, influence economic outcomes. Among them, Capistrán and Ramos-Francia (2010), Ehrmann *et al.* (2012), and Siklos (2013) use regression analysis to argue that the transparency of central banks significantly affects the disagreement in inflation expectations. However, their goal is different from ours since they take transparency indices obtained from the first group of papers for instance, as given while we extract the transparency index from inflation expectations.

This paper is organized as follows. Section 1.2 presents our model. Section 1.3 describes our estimation strategies. Section 1.4 shows our results and analysis. Finally, Section 1.5 concludes.

1.2 Model

In this paper we employ two types of similar models of inflation forecasters: a standard model and a generalized model. We first propose the standard model, and then present the generalized model to better capture the actual data.

1.2.1 Standard Model

Our model of inflation is a standard univariate unobserved components model, and we employ the method of noisy information to describe inflation forecasters. Inflation x_t is composed of an unobserved trend component x_t^*, which is associated with the inflation target, and a gap component γ_t. The trend follows a random walk while the gap between inflation and the trend component follows an AR(1) process:

$$
\begin{aligned}
x_t &\equiv \gamma_t + x_t^*, &(1.1)\\
x_t^* &= x_{t-1}^* + \varepsilon_t^*, &(1.2)\\
\gamma_t &= \phi\gamma_{t-1} + \varepsilon_t, &(1.3)
\end{aligned}
$$

where exogenous shocks ε^* and ε are i.i.d. $N(0, \sigma_{\varepsilon *}^2)$ and i.i.d. $N(0, \sigma_{\varepsilon}^2)$ respectively, and ϕ shows the persistence of the gap. Each forecaster i can observe neither inflation x_t nor the trend x_t^* directly, but instead observes two heterogeneous noisy signals, s_{it} and s_{it}^*, of them:

$$
\begin{aligned}
s_{it} &= x_t + w_{it}, &(1.4)\\
s_{it}^* &= x_t^* + w_{it}^*, &(1.5)
\end{aligned}
$$

where the heterogeneous noise components w_{it} and w_{it}^* are i.i.d. $N\left(0, \sigma_w^2\right)$ and i.i.d. $N\left(0, \sigma_{w*}^2\right)$ respectively. Here, we interpret the size of the noise in the signal of the inflation trend σ_{w*} as the index of the FRB's transparency regarding its target inflation rate. The specification is compactly described by

$$
\begin{aligned}
\xi_t &= F\xi_{t-1} + \mathbf{e}_t, &(1.6)\\
\mathbf{s}_{it} &= \xi_t + \mathbf{w}_{it}, &(1.7)
\end{aligned}
$$

where $\mathbf{e}_t$ is distributed $N\left(0, Q\right)$ and $\mathbf{w}_{it}$ is distributed $N\left(0, R\right)$. Furthermore,

$$
\begin{aligned}
\xi_t &= \begin{bmatrix} x_t \\ x_t^* \end{bmatrix}, F = \begin{bmatrix} \phi & 1-\phi \\ 0 & 1 \end{bmatrix}, \mathbf{e}_t = \begin{bmatrix} \varepsilon_t + \varepsilon_t^* \\ \varepsilon_t^* \end{bmatrix}, Q = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \sigma_\varepsilon^2 & 0 \\ 0 & \sigma_{\varepsilon *}^2 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}', \\
\mathbf{s}_{it} &= \begin{bmatrix} s_{it} \\ s_{it}^* \end{bmatrix}, \mathbf{w}_{it} = \begin{bmatrix} w_{it} \\ w_{it}^* \end{bmatrix}, R = \begin{bmatrix} \sigma_w^2 & 0 \\ 0 & \sigma_{w*}^2 \end{bmatrix}.
\end{aligned}
$$

As is common in the noisy information literature, we suppose that each agent i uses Kalman filtering to infer the unobserved processes ξ_t from his noisy signals $\mathbf{s}_{it}$. The updating equation for agent i is

$$\xi_{t|it} \equiv E_{it}\left[\xi_t\right] = \xi_{t|it-1} + G\left(\mathbf{s}_{it} - \xi_{t|it-1}\right) = \left(I - G\right)\xi_{t|it-1} + G\mathbf{s}_{it}. \tag{1.8}$$

where we denote the Kalman gain matrix as G. Agent i uses this equation to "nowcast" the current state of the economy. G is defined as $G \equiv P_1\left(P_1 + R\right)^{-1}$, and P_1 is the steady state mean squared error (hereafter, MSE) matrix of the 1-step ahead forecast. We assume that the MSE is at the steady state as is often assumed in this literature. P_1 is obtained from the Riccati equation:

$$P_1 = F\left[P_1 - P_1\left(P_1 + R\right)^{-1}P_1\right]F' + Q. \tag{1.9}$$

Aggregating the nowcasting equation for each agent to obtain the mean nowcast across forecasters leads to the following equation:

$$\bar{\xi}_{t|it} \equiv \bar{E}\left[\xi_{t|it}\right] = \bar{E}\left[\left(I - G\right)\xi_{t|it-1} + G\mathbf{s}_{it}\right] = \left(I - G\right)F\bar{\xi}_{t-1|it-1} + G\xi_t, \tag{1.10}$$

where $\bar{E}$ denotes the mean across forecasters. As we can derive the h-step ahead forecast of forecaster i as $\xi_{t+h|it} = F^h\xi_{t|it}$, the h-step ahead mean forecast is

$$\bar{\xi}_{t+h|it} = \bar{E}\left[\xi_{t+h|it}\right] = \bar{E}\left[F^h\xi_{t|it}\right] = F^h\bar{\xi}_{t|it}. \tag{1.11}$$

Therefore, the h-step ahead mean forecast of the inflation rate is given by

$$\bar{x}_{t+h|it} = S_x\bar{\xi}_{t+h|it} = S_xF^h\bar{\xi}_{t|it}, \tag{1.12}$$

where $S_x \equiv [1, 0]$ is a selector matrix used to obtain inflation x_t from vector ξ_t.

Next, we derive the theoretical disagreements, which we define as the standard deviation of forecasts across forecasters, $\sqrt{\bar{V}}$. The variance of nowcasts for the vector ξ_t is

$$\begin{aligned}
\bar{V}\left[\xi_{t|it}\right] &\equiv \bar{E}\left[\left(\xi_{t|it}-\bar{\xi}_{t|it}\right)\left(\xi_{t|it}-\bar{\xi}_{t|it}\right)'\right] \\
&= \bar{E}\left[\left(\left\{(I-G)\,\xi_{t|it-1}+G\mathbf{s}_{it}\right\}-\left\{(I-G)\,\bar{\xi}_{t|it-1}+G\xi_t\right\}\right)(...)'\right] \\
&= \bar{E}\left[\left((I-G)\,F\left(\xi_{t-1|it-1}-\bar{\xi}_{t-1|it-1}\right)+G\mathbf{w}_{it}\right)(...)'\right] \\
&= (I-G)\,F\bar{V}\left[\xi_{t-1|it-1}\right]F'\,(I-G)'+GRG'. \qquad (1.13)
\end{aligned}$$

Even though it looks like an AR(1) process, GRG' is not a stochastic shock, but rather a constant term. Hence, the variance does not fluctuate with exogenous shocks, but simply converges to its steady state. Solving equation (1.13) backwards, we can derive the steady state variance of nowcasts for the vector as follows:

$$\begin{aligned}
\bar{V}\left[\xi_0\right] &= \sum_{T=0}^{\infty}\left[(I-G)\,F\right]^T GRG'\left[F'\,(I-G)'\right]^T \\
&\quad +\lim_{T\to\infty}\left\{\left[(I-G)\,F\right]^T\bar{V}\left[\xi_{t-T|it-T}\right]\left[F'\,(I-G)'\right]^T\right\}. \qquad (1.14)
\end{aligned}$$

If all the eigenvalues $(I-G)\,F$ are inside the unit circle, the second term disappears and the variance converges to a constant. Then, we can express the variance of the h-step ahead forecasts as a function of the variance of the nowcasts:

$$\begin{aligned}
\bar{V}\left[\xi_{t+h|it}\right] &= \bar{E}\left[\left(F^h\left(\xi_{t|it}-\bar{\xi}_{t|it}\right)\right)(...)'\right]=F^h\bar{E}\left[\left(\xi_{t|it}-\bar{\xi}_{t|it}\right)(...)'\right]\left[F'\right]^h \\
&= F^h\bar{V}\left[\xi_{t|it}\right]\left[F'\right]^h. \qquad (1.15)
\end{aligned}$$

The variance of the h-step ahead inflation expectations is

$$\bar{V}\left[x_{t+h|it}\right]=S_x\bar{V}\left[\xi_{t+h|it}\right]S_x'. \qquad (1.16)$$

and the h-step ahead variance of inflation expectations at the steady state is

$$\bar{V}[x_h] = S_x F^h \bar{V}[\xi_0] \left[F^h\right]' S_x'. \tag{1.17}$$

Finally, the steady state "disagreement" about inflation expectations is given by

$$\sqrt{\bar{V}[x_h]} = \sqrt{S_x F^h \bar{V}[\xi_0] [F^h]' S_x'}. \tag{1.18}$$

1.2.2 Generalized Model

This subsection proposes a generalized model of inflation forecasters. In the standard model we assumed that forecasters know the size of noise components, σ_w and σ_{w*}, precisely, while in this generalized model we assume that forecasters do not know the true size of the noise components. This means that the size of the noise that forecasters perceive and the true size of the noise can be different.[5] For instance, forecasters might believe that their signals are precise even though the actual signal is very noisy. We describe the size of the noise components which forecasters perceive as the "subjective" size of the noise components, σ_w^{sbj} and σ_{w*}^{sbj}, and the true size of the noise components as the "objective" size of the noise components, σ_w^{obj} and σ_{w*}^{obj}. In addition, we describe the corresponding matrices of the size of the noise components R as R^{sbj} and R^{obj} respectively. We assume that all the forecasters have the same bias regarding the subjective size of the noise components.

Next, we show that we can express the generalized model by slightly modifying the standard model in Section 1.2.1. The inflation dynamics are the same as those in the standard model. In addition, forecasters can observe neither inflation x_t nor the trend x_t^* directly, but instead observe two heterogeneous signals, s_{it} and s_{it}^*, as in the standard model. Moreover,

[5] Geraats (2007) theoretically investigates the communication strategy of the central bank under a similar setup. Moreover, this type of informational friction is seen in other fields, such as psychology, microeconomics, and finance. This type of friction is called overprecision (or underprecision). It assumes that people are overconfident about the precision of their knowledge and make forecasts based on their incorrect information about that precision.

each agent i uses Kalman filtering again to infer the unobserved processes ξ_t $(= [x_t; x_t^*])$ from his noisy signals $\mathbf{s}_{it}$ $(= [s_{it}; s_{it}^*])$. Since each forecaster uses the noisy signals in his forecast, taking into account his perceived noisiness, the updating equation for forecaster i changes to

$$\xi_{t|it} = \left(I - G^{sbj}\right)\xi_{t|it-1} + G^{sbj}\mathbf{s}_{it}, \tag{1.19}$$

where the Kalman gain is $G^{sbj} \equiv P_1\left(P_1 + R^{sbj}\right)^{-1}$, and the variance-covariance matrix for the one-period-ahead forecast error P_1 is similarly obtained from the Riccati equation:

$$P_1 = F\left[P_1 - P_1\left(P_1 + R^{sbj}\right)^{-1}P_1\right]F' + Q. \tag{1.20}$$

Aggregating the nowcasting equation for each agent to obtain the mean nowcast equation results in:

$$\bar{\xi}_{t|it} \equiv \bar{E}\left[\xi_{t|it}\right] = \bar{E}\left[\left(I - G^{sbj}\right)\xi_{t|it-1} + G^{sbj}\mathbf{s}_{it}\right] = \left(I - G^{sbj}\right)F\bar{\xi}_{t-1|it-1} + G^{sbj}\xi_t. \tag{1.21}$$

The actual noise in signals $\mathbf{s}_{it}$ disappear in the mean equation while the subjective parameters for the size of noise components R^{sbj} remain in G^{sbj}. The h-step ahead mean forecast is

$$\bar{\xi}_{t+h|it} = F^h\bar{\xi}_{t|it}. \tag{1.22}$$

and the variance of nowcasts across forecasters for the vector ξ_t is

$$\begin{aligned}
\bar{V}\left[\xi_{t|it}\right] &\equiv \bar{E}\left[\left(\xi_{t|it} - \bar{\xi}_{t|it}\right)\left(\xi_{t|it} - \bar{\xi}_{t|it}\right)'\right] \\
&= \bar{E}\left[\left(\left(I - G^{sbj}\right)F\left(\xi_{t-1|it-1} - \bar{\xi}_{t-1|it-1}\right) + G^{sbj}\mathbf{w}_{it}\right)(\ldots)'\right] \\
&= \left(I - G^{sbj}\right)F\bar{V}\left[\xi_{t-1|it-1}\right]F'\left(I - G^{sbj}\right)' + G^{sbj}R^{obj}G^{sbj\prime}.
\end{aligned} \tag{1.23}$$

The objective size of noise components R^{obj} shows up in this equation. This is because the people who calculate the variance of the noise components are not the biased forecasters but rather us, econometricians who know the true size of the noise components. Finally, the steady state "disagreement" about inflation expectations is given by

$$\sqrt{\bar{V}\left[x_h\right]} = \sqrt{S_x F^h \bar{V}\left[\xi_0\right]\left[F^h\right]' S_x'}, \tag{1.24}$$

where

$$\bar{V}\left[\xi_0\right] = \sum_{T=0}^{\infty} \left[\left(I - G^{sbj}\right) F\right]^T G^{sbj} R^{obj} G^{sbj\prime} \left[F' \left(I - G^{sbj}\right)'\right]^T.$$

In Section 1.2 we noted that we interpret σ_{w*} as the transparency of the FRB regarding the target, but with this generalized model we have two sizes of noise regarding the trend: the subjective size σ_{w*}^{sbj} and the objective size σ_{w*}^{obj}. σ_{w*}^{sbj} shows the perceived size of noise in the information regarding the trend while σ_{w*}^{obj} shows the actual size of the noise. Since the objective size of the noise indicates the true accuracy of the information about the FRB's target which private agents actually have, we interpret this index as the FRB's transparency regarding the target. We will discuss how to identify these two indices in Section 1.3.2. It is important to note that, according to our model, the change in each index affects disagreement differently and this point will be further discussed in Section 1.4.

1.3 Estimation

This section explains our estimation procedure. First, we discuss the data, focusing on the MSC. Next, we explain our estimation strategy. Finally, we present our two methods of estimation: maximum likelihood estimation (hereafter, MLE) and the method of moments (hereafter, MoM).

1.3.1 Data

We estimate the model parameters using quarterly CPI inflation data from the U.S. Bureau of Labor Statistics and four time series from the MSC.[6] The four time series are the mean and standard deviation of consumers' short-run (SR) and long-run (LR) inflation expectations. To be precise, the SR measures correspond to Question 32 of the survey, which asks "By about what percent do you expect prices to go (up/down), on the average, during the next 12 months?" The LR measures correspond to Question 33, which asks "By about what percent per year do you expect prices to go (up/down) on the average, during the next 5 to 10 years?"

We use the two forecast mean series, depicted in Figure 2 along with the CPI inflation rate, for the maximum likelihood estimation below. Both the SR and LR mean expectations were very high around 1980, but they declined quickly and have been relatively stable since that period. The notable difference with the disagreements is the drastic decline during the Volcker disinflation period. In contrast, the decline of disagreements in Figure 1 was sluggish and they remained relatively high even after the disinflation period.

There are advantages and disadvantages to using the MSC. One big advantage is that it has a very long sample for LR inflation forecasts,[7] available from 1979Q1. This is crucial for our analysis because this includes the last part of the great inflation period. Another advantage is that consumers' inflation expectations are a good proxy for firms' inflation expectations. Although the price setters in the economy are not consumers but firms, the survey of firms' inflation expectations in the U.S. is limited. Coibion and Gorodnichenko

[6]The MSC is a monthly survey of consumers and the most famous series is the index of consumer sentiment. The MSC surveys more than 500 consumers via telephone interview.

[7]Almost all other surveys have shorter samples for LR inflation forecasts. The Survey of Professional Forecasters is a quarterly survey which started LR forecasts of the consumer price index in 1991Q4. The Livingston Survey is a semi-annual survey, asking about 30 individuals in a variety of institutions, which started the 10-year ahead CPI inflation forecasts in 1990. Consensus Economics is a monthly survey of market economists and it provides not only forecasts of the U.S. but also those of several major countries. This survey started in 1989. Finally, some other papers, such as Andrade *et al.* (2016) and Erceg and Levin (2003), employ the LR forecasts from Blue Chip Economic Indicators, which is also a monthly survey of professional forecasters. The length of the LR forecasts of this survey, starting in 1979Q4, is comparable to the MSC.

(2015) discuss this point and argue that inflation expectations of consumers proxy firms' expectations better than those of professional forecasters. On the other hand, one of the disadvantages of the MSC is that the survey does not specify the inflation index. Thus, some consumers may answer based on the CPI or PCE deflator while others may answer based on their own consumption baskets. Another disadvantage of the MSC is the measurement error. There is potential misreporting because consumers answer the survey on the phone. Since these disadvantages can generate additional heterogeneity, the estimated size of the noise could be biased upward.

We split the sample into the periods: 1978Q1-1992Q4 and 1993Q1-2008Q3, estimate the model for both samples, and then compare the parameters. We exclude the sample after the Lehman shock period since the inclusion of the period greatly changes the statistical properties of the inflation process. As the motivation of this research is the comparison between the relatively high disagreement period and the relatively stable moderation period after that, the effect of the financial crisis on inflation disagreements is not our focus.

1.3.2 Estimation Strategy

In our estimation, we first estimate the standard model and the first stage of the generalized model using MLE and then conduct the second stage estimation of the generalized model using the MoM. The background of this strategy is as follows. The observable variables are the five time series explained in Section 1.3.1. One might think of simply putting all these time series into observation equations, setting the dynamics equations in Section 1.2 as state equations, and estimating all the parameters using MLE. However, we will not use the disagreements data for the MLE. The disagreement is theoretically not affected by idiosyncratic shocks, as shown in equation 1.13, and it does not fluctuate but rather simply converges to the steady state from the initial value.[8] Therefore, even if we put the disagreements into a state space model, it follows a deterministic path to the steady state

[8]Coibion and Gorodonichenko (2012) empirically shows that disagreement is not affected by exogenous shocks.

perfectly depending on the initial value, which will not yield stable estimation results. For this reason we use the sample mean of the disagreement data and match it to the theoretical steady state values using the MoM so that the initial value does not affect the result.

Next, we specifically lay out how we estimate each parameters. We employ only MLE in estimating the standard model because all the parameters are included in the equations of actual inflation (1.6) and mean inflation expectations (1.10). Meanwhile, in the generalized model, the equation of mean inflation expectations (1.21) includes the subjective size of the noise components $\{\sigma_w^{sbj}, \sigma_{w*}^{sbj}\}$ but does not include the objective size of the noise components $\{\sigma_w^{obj}, \sigma_{w*}^{obj}\}$. These are included only in the equation of disagreement (1.23). Therefore, we first estimate all parameters other than the objective size of noise components in the MLE using the data on mean inflation expectations and, given the estimated parameters, estimate the remaining parameters for the objective size of noise components using the MoM. It can be argued that this two stage estimation procedure allows us to identify the objective size of noise components separately from the subjective ones.

1.3.3 Maximum Likelihood Estimation

We estimate the parameters of inflation dynamics and mean forecast models using three time series: the quarterly inflation rate x_t^{obs}, the 1-year ahead mean forecast $\bar{x}_{t+1y|it}^{obs}$, and the 5-to-10-years ahead mean forecast $\bar{x}_{t+5y|it}^{obs}$. The theoretical 1-year ahead and 5-to-10 years ahead mean forecasts are

$$\bar{x}_{t+1y|it} = \frac{1}{4}\sum_{h=1}^{4}\bar{x}_{t+h|it} = S_x\frac{1}{4}\sum_{h=1}^{4}F^h\bar{\xi}_{t|it} = S_xF_{1y}(F)\bar{\xi}_{t|it}, \tag{1.25}$$

$$\bar{x}_{t+5y|it} = \frac{1}{6}\sum_{j=5}^{10}\frac{1}{4}\sum_{h=4*(j-1)+1}^{4*(j-1)+4}\bar{x}_{t+h|it} = S_x\frac{1}{24}\sum_{h=17}^{40}F^h\bar{\xi}_{t|it} = S_xF_{5y}(F)\bar{\xi}_{t|it}, \tag{1.26}$$

where

$$F_{1y}(F) \equiv \frac{1}{4}\sum_{h=1}^{4}F^h \text{ and } F_{5y}(F) \equiv \frac{1}{24}\sum_{h=17}^{40}F^h.$$

The above equations suggest that both mean forecasts are perfectly correlated because both of them include the mean nowcast, $\bar{\xi}_{t|it}$, which is obviously not the case in the data. We therefore assume that the observable mean forecasts include white noise measurement errors. Thus, we have

$$\bar{x}^{obs}_{t+1y|it} = S_x F_{1y}(F)\bar{\xi}_{t|it} + v_{1y,t}, \tag{1.27}$$

$$\bar{x}^{obs}_{t+5y|it} = S_x F_{5y}(F)\bar{\xi}_{t|it} + v_{5y,t}, \tag{1.28}$$

where the measurement errors $v_{1y,t}$ and $v_{5y,t}$ are i.i.d. $N\left(0, \sigma^2_{v1y}\right)$ and i.i.d. $N\left(0, \sigma^2_{v5y}\right)$, respectively. We can construct a state space model with these equations. To fit them to a state space model, the mean nowcasts equation (1.10) is rewritten as

$$\bar{\xi}_{t|it} = (I - G)\, F\bar{\xi}_{t-1|it-1} + GF\xi_{t-1} + G\mathbf{e}_t, \tag{1.29}$$

where we assume the standard model. Then, the state equations are,

$$\begin{bmatrix} \xi_t \\ \bar{\xi}_{t|it} \end{bmatrix} = \begin{bmatrix} F & 0 \\ GF & (I-G)\, F \end{bmatrix} \begin{bmatrix} \xi_{t-1} \\ \bar{\xi}_{t-1|it-1} \end{bmatrix} + \begin{bmatrix} I \\ G \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ \varepsilon^*_t \end{bmatrix}. \tag{1.30}$$

The innovation process is distributed $N\left(0, \Sigma^{\epsilon}\right)$, where

$$\Sigma^{\epsilon} = \begin{bmatrix} I \\ G \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \sigma^2_{\varepsilon} & 0 \\ 0 & \sigma^2_{\varepsilon*} \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}' \begin{bmatrix} I \\ G \end{bmatrix}'. \tag{1.31}$$

The observation equations are

$$\begin{bmatrix} x^{obs}_t \\ \bar{x}^{obs}_{t+1y|it} \\ \bar{x}^{obs}_{t+5y|it} \end{bmatrix} = \begin{bmatrix} S_x & 0 \\ 0 & S_x F_{1y}(F) \\ 0 & S_x F_{5y}(F) \end{bmatrix} \begin{bmatrix} \xi_t \\ \bar{\xi}_{t|it} \end{bmatrix} + \begin{bmatrix} 0 \\ v_{1y,t} \\ v_{5y,t} \end{bmatrix}. \tag{1.32}$$

The innovation process is distributed $N\left(0, \Sigma^{\upsilon}\right)$, where

$$\Sigma^{\upsilon} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \sigma_{v1y}^2 & 0 \\ 0 & 0 & \sigma_{v5y}^2 \end{bmatrix}. \tag{1.33}$$

The state space equations and the observation equations can be simplified as,

$$\mathbf{\Xi}_t = D\mathbf{\Xi}_{t-1} + \epsilon_t, \tag{1.34}$$

$$\mathbf{X}_t = H'\mathbf{\Xi}_t + \upsilon_t, \tag{1.35}$$

where $\epsilon_t \sim N\left(0, \Sigma^{\epsilon}\right)$ and $\upsilon_t \sim N\left(0, \Sigma^{\upsilon}\right)$. As can be observed in Figure 2, some of the mean forecasts of the 5-to-10-years ahead inflation expectations are missing. To deal with this problem, we employ the method of Harvey (1990), which is described in detail in Appendix 1.A. For the estimation of the standard model, the parameters to be estimated are those for the actual process of inflation, $\{\phi, \sigma_{\varepsilon}, \sigma_{\varepsilon*}\}$, those for the informational frictions, $\{\sigma_w, \sigma_{w*}\}$, and the measurement error parameters $\{\sigma_{v1y}, \sigma_{v5y}\}$. We do not distinguish between the subjective and objective size of noise components in this model. On the other hand, in the first stage estimation of the generalized model, the parameters to be estimated are the same as those in the case of the standard model, but we replace the parameters of the size of the noise components $\{\sigma_w, \sigma_{w*}\}$ with those of the subjective size of the noise components $\{\sigma_w^{sbj}, \sigma_{w*}^{sbj}\}$.

1.3.4 Method of Moments Estimation

Next, we estimate the objective size of the noise components $\{\sigma_w^{obj}, \sigma_{w*}^{obj}\}$, our measures of transparency in the generalized model, by matching the theoretical steady state disagreements to the data given the estimated parameters in the MLE. We employ the method of moments estimation and use data on the average (across time) of the variance (across forecasters) of the 1-year ahead inflation expectations, $\bar{V}_{1y}^{obs}$, which is the square of the SR disagreement, and that of the 5-to-10-years ahead inflation expectations, $\bar{V}_{5y}^{obs}$, which is the square of the LR disagreement,

$$\bar{V}_{1y}^{obs} = \frac{1}{n_{1y}} \sum_{t=1}^{n_{1y}} \bar{V}_{t+1y|t}^{obs} \tag{1.36}$$

$$\bar{V}_{5y}^{obs} = \frac{1}{n_{5y}} \sum_{t=1}^{n_{5y}} \bar{V}_{t+5y|t}^{obs}, \tag{1.37}$$

where n_{1y} and n_{5y} are the number of observations for each moment. We match theoretical variances at the steady state to average variances in the sample. The theoretical variance of the 1-year ahead inflation expectations at the steady state is

$$\bar{V}\left[x_{1y}\right] = S_x F_{1y}(F) \bar{V}\left[\xi_0\right] F_{1y}(F)' S_x'. \tag{1.38}$$

Similarly, the theoretical variance for the 5 to 10 years ahead expectations at the steady state is

$$\bar{V}\left[x_{5y}\right] = S_x F_{5y}(F) \bar{V}\left[\xi_0\right] F_{5y}(F)' S_x'. \tag{1.39}$$

We choose parameters $\hat{\theta}$ which satisfy the following equation:

$$\mathbf{m}^{\mathbf{obs}} - \mathbf{m}\left(\hat{\theta}\right) = 0, \tag{1.40}$$

where

$$\hat{\theta} = \begin{bmatrix} \hat{\sigma}_w^{obj} \\ \hat{\sigma}_{w*}^{obj} \end{bmatrix}, \ \mathbf{m}^{\mathbf{obs}} = \begin{bmatrix} \bar{V}_{1y}^{obs} \\ \bar{V}_{5y}^{obs} \end{bmatrix}, \ \mathbf{m}\left(\theta\right) = \begin{bmatrix} \bar{V}\left[x_{1y}\right] \\ \bar{V}\left[x_{5y}\right] \end{bmatrix}.$$

In this way we estimate the objective size of the noise components in the generalized model.

Table 1.1: MLE for the Standard Model

	ϕ	σ_{ε}	$\sigma_{\varepsilon *}$	σ_{w}	σ_{w*}	σ_{v1y}	σ_{v5y}
1978Q1 to 1992Q4	0.825	1.943	0.635	2.862	1.967	0.525	0.342
	(0.025)	(0.181)	(0.142)	(0.549)	(0.896)	(0.052)	(0.058)
1993Q1 to 2008Q3	0.564	1.482	0.174	1.143	0.301	0.516	0.245
	(0.074)	(0.133)	(0.049)	(0.570)	(0.147)	(0.050)	(0.026)

Note: Standard errors are in parentheses.

Table 1.2: Fitted Disagreements for the Standard Model

	Data			Estimated		
	S.run	L.run	Diff.	S.run	L.run	Diff.
1978Q1 to 1992Q4	7.305	7.678	-0.373	1.038	0.749	0.288
	(1.435)	(1.205)	(2.292)	(0.154)	(0.222)	(0.175)
1993Q1 to 2008Q3	4.330	3.714	0.616	0.259	0.157	0.102
	(1.137)	(1.327)	(0.605)	(0.091)	(0.059)	(0.091)

Note: "Diff." shows disagreement in SR inflation expectations minus disagreement in LR inflation expectations. Standard errors are in parentheses.

1.4 Results

1.4.1 Estimation Results for the Standard Model

We begin with the standard model. Table 1.1 shows the estimation results of the MLE for the standard model, but we will point out crucial problems with the model. With the estimated parameters in Table 1.1, we can calculate theoretical disagreements at the steady state, as in equations (1.38) and (1.39).

Table 1.2 shows the theoretical disagreements together with actual disagreements.[9] Two problems can be observed. First, the estimated disagreements are far smaller than the actual disagreements for both SR and LR disagreements. All the estimated disagreements are almost one-tenth of actual disagreements. Second, the estimated disagreements do not

[9]The standard errors for estimated disagreements are obtained using the Delta method.

Table 1.3: MLE for the Generalized Model

	ϕ	σ_ε	$\sigma_{\varepsilon*}$	σ_w^{sbj}	σ_{w*}^{sbj}	σ_{v1y}	σ_{v5y}
1978Q1 to 1992Q4	0.825	1.943	0.635	2.862	1.967	0.525	0.342
	(0.025)	(0.181)	(0.142)	(0.549)	(0.896)	(0.052)	(0.058)
1993Q1 to 2008Q3	0.564	1.482	0.174	1.143	0.301	0.516	0.245
	(0.074)	(0.133)	(0.049)	(0.570)	(0.147)	(0.050)	(0.026)

Note: Standard errors are in parentheses.

show the crossing of disagreements, which is a notable characteristic of the data. In the first row, which covers the period before the crossing, the LR disagreement in the data is larger than the SR disagreement while in the second row, the LR disagreement in the data is lower than the SR disagreement. However, the estimated LR disagreement is always lower than the estimated SR disagreement and the model fails to describe the dynamics of disagreements in the data. We will discuss the limitations of this model in the Appendix.

1.4.2 Estimation Results for the Generalized Model

This section shows our estimation results for the generalized model. The first stage estimation to derive the dynamics of inflation $\{\phi, \sigma_\varepsilon, \sigma_{\varepsilon*}\}$ and the subjective size of the noise components $\{\sigma_w^{sbj}, \sigma_{w*}^{sbj}\}$ are exactly the same as those for the standard model in Section 1.4.1. We present the results again in Table 1.3 for reference. We find that the inflation gap is less persistent in the latter sample compared to that in the earlier sample. This implies that the FRB has become more aggressive in preventing inflation from deviating from the target (Cogley *et al.* (2010)). In addition, comparing the first and the second rows again, the size of the gap shocks σ_ε is 24% smaller in the latter sample while the size of trend shocks $\sigma_{\varepsilon*}$ is 73% smaller in the latter period. The results basically reflect the level effect: as the level of inflation has declined, the volatility of the shocks has also declined. Moreover, these results are consistent with the literature: the decline in the volatility of trend inflation contributed much to the stabilization of the inflation rate (Stock and Watson (2007)). Finally, the two

Table 1.4: Fitted Disagreements for the Generalized Model

	Data			Estimated		
	S.run	L.run	Diff.	S.run	L.run	Diff.
1978Q1 to 1992Q4	7.305	7.678	-0.373	7.305	7.678	-0.373
	(1.435)	(1.205)	(2.292)	(0.477)	(1.385)	(1.132)
1993Q1 to 2008Q3	4.330	3.714	0.616	4.330	3.714	0.616
	(1.137)	(1.327)	(0.605)	(0.474)	(0.525)	(0.471)

Note: "Diff." shows disagreement in SR inflation expectations minus disagreement in LR inflation expectations. Standard errors are in parentheses.

Table 1.5: Estimated Objective Size of Noise Components for the Generalized Model

	σ_w^{obj}	σ_{w*}^{obj}
1978Q1 to 1992Q4	18.057	20.382
	(0.515)	(0.560)
1993Q1 to 2008Q3	16.148	7.117
	(0.512)	(0.318)

Note: Standard errors are in parentheses.

subjective sizes of the noise components σ_w^{sbj} and σ_{w*}^{sbj} are smaller in the latter sample than in the earlier sample. In particular, the subjective size of the noise component in the inflation trend is 85% smaller. This implies that people have come to believe that the size of noise is smaller and put a lot more weight, or trust, on the signal of the inflation trend in making their forecast.

Table 1.4 shows the fitted disagreements for the generalized model using the estimated objective size of the noise components $\{\sigma_w^{obj}, \sigma_{w*}^{obj}\}$ from method of moments estimation.[10] In contrast to Table 1.2, the model tracks the disagreements in the MSC. In particular, the estimated model can produce the crossing of the SR and LR disagreements. Table 1.5 shows the estimated objective size of the noise components in the second stage estimation. The table shows that the objective size of the noise components is smaller in the latter sample than in the earlier sample. Specifically, the objective size of inflation noise is 12% lower

[10]The standard errors for estimated disagreements are obtained using the Delta method by assuming there's no correlation between the parameters estimated in the MLE and those in the method of moments.

while that of trend noise is 63% lower. The decline in the latter parameter, our measure of the transparency, is one of the key findings of this paper. This implies that people received more precise information about the inflation trend in the latter sample and it suggests an improvement in the FRB's transparency. This finding can be attributed to the increased disclosure by the FRB regarding information related to its inflation target. In addition, the estimated objective size of the noise components is larger than the subjective size of the noise components, implying that the consumers answering the survey are overconfident about the precision of their knowledge. The results are consistent with the literature, which shows that people tend to be overconfident about their information.[11]

Finally, Table 1.6 shows the decomposition of the crossing of disagreements into the effects of parameter changes. As shown in the table, both the SR and LR disagreements are smaller in the latter sample, but the decline is relatively larger in the LR disagreement, by 0.989, which results in the crossing of the two disagreement as in Figure 1. To calculate the contribution of each parameter to the crossing, we conduct counterfactual simulations. Specifically, we calculate a hypothetical disagreement using parameter A from the first sample and the remaining parameters from the second sample. We then take the difference between the disagreement in the second sample and the hypothetical disagreement to be the contribution of the change in parameter A. We calculated the hypothetical disagreements for both the SR and the LR disagreements for each parameter.

Our results show that the decline in the objective size of noise components σ_{w*}^{obj}, the FRB's

[11]We briefly discuss the plausibility of the degree of overconfidence estimated in our study. We define the measure of overprecision as $\delta_w = \sigma_w^{sbj}/\sigma_w^{obj}$ and $\delta_{w*} = \sigma_{w*}^{sbj}/\sigma_{w*}^{obj}$ following Grubb and Osborne (2015). The overconfidence of each signal is 0.155 and 0.095 respectively in the earlier sample, and 0.070 and 0.040 respectively in the latter sample. Grubb and Osborne (2015) measure the overconfidence of U.S. consumers regarding the accuracy of their own forecasts by how much calling they do per month when choosing cell phone plans. Their estimate is 0.383, which is relatively higher than our estimates. This means that the consumers in their survey have more accurate understanding of the precision of their knowledge. One possible reason why their parameter is higher is that consumers may think more seriously in selecting cell phone plans since it affects their expenditure directly. Thus, the gap between their perceived precision and their actual precision could be smaller. On the other hand, consumers may have less incentive to be careful when they answer questions about the future inflation rate on a phone interview with the MSC because the answer will not affect their future expenditures. This could be the reason why our estimates of the parameter are smaller.

Table 1.6: Decomposition of the Difference in Disagreements

	S.run	L.run	Diff.
1978Q1 to 1992Q4	7.305	7.678	-0.373
1993Q1 to 2008Q3	4.330	3.714	0.616
Change in disagreements	-2.975	-3.964	0.989
Contribution of the change in			
ϕ	-2.992	0.235	-3.228
σ_{ε}	-0.137	0.215	-0.352
$\sigma_{\varepsilon*}$	-1.353	-2.026	0.673
σ_{w}^{sbj}	0.881	0.211	0.671
σ_{w*}^{sbj}	0.594	2.356	-1.762
σ_{w}^{obj}	-0.149	0.226	-0.374
σ_{w*}^{obj}	-4.374	-6.691	2.317
Cross terms	4.555	1.511	3.044

Note: "Diff." shows disagreement in SR inflation expectations minus disagreement in LR inflation expectations.

transparency, has contributed the most to the crossing of disagreements. The mechanism works as follows. As we can expect from equation 1.22, the longer the horizon of the inflation expectation is, the smaller the effect of the inflation gap becomes. Thus, when a consumer makes a forecast on LR inflation, he relies far more on the trend signal. As a result, the effect of the change in the size of the noise for the trend signal is larger for the LR disagreement than that for SR disagreement. In addition, the decline in the size of trend shocks $\sigma_{\varepsilon*}$ and that of the subjective size of inflation noise σ_{w}^{sbj} have also contributed to the crossing. The former suggests that the key parameter in the literature for the stabilization of the great inflation has also played a role in the crossing of the two disagreements. Finally, the decline in the persistence parameter ϕ and the subjective size of noise components σ_{w*}^{sbj} have affected the relationship between the two disagreements in opposite directions.

In conclusion, we find a large improvement in the FRB's transparency regarding its policy objective, which is extracted from the consumer survey data using a generalized noisy information framework. Moreover, this factor has contributed the most to the decline in the LR disagreement in inflation expectations relative to that in the SR disagreement.

Table 1.7: Estimated Objective Size of Noise Components of Trend Signal, Age Subgroups

	age 18-34	age 35-44	age 45-54	age 55-64	age 65-97
1978Q1 to 1992Q4	18.699	16.715	7.754	6.813	7.679
	(0.489)	(0.655)	(0.341)	(0.366)	(0.368)
1993Q1 to 2008Q3	7.604	7.062	6.106	6.309	5.753
	(0.372)	(0.328)	(0.302)	(0.299)	(0.234)

Note: Standard errors are in parentheses.

Table 1.8: Estimated Objective Size of Noise Components of Trend Signal, Income Subgroups

	Bottom 25%	Second 25%	Third 25%	Top 25%
1978Q1 to 1992Q4	9.761	17.352	22.510	12.613
	(0.274)	(0.545)	(0.949)	(0.631)
1993Q1 to 2008Q3	10.985	6.802	6.392	4.840
	(0.555)	(0.401)	(0.263)	(0.216)

Note: Standard errors are in parentheses.

1.4.3 Estimation Using Subgroup Data

This section shows the estimation results of our generalized model using subgroup data from the MSC. The MSC collects data on several characteristics of the forecasters, and we estimate the model using data for age, income, and education subgroups. The estimation procedure is the same as that for the full sample of the MSC in Section 1.4.2. We estimate all parameters other than the objective size of the noise components using MLE and then estimate the objective size of the noise components using the method of moments given the estimated parameters from the MLE.

Tables 1.7 through 1.9 show the estimated objective size of the noise component in the signal of inflation trend, which is our measure of the FRB's transparency.[12] Overall, it declined after the mid-1990s for all the subgroups except for the bottom 25% income subgroup. The results are consistent with our main results in Section 1.4.2. There is also some heterogeneity. Regarding age subgroups, we found a large decline in the size of noise for young

[12] We also estimate the parameters for gender and regional subgroups, but the results are similar to our main results in Section 1.4.2.

Table 1.9: Estimated Objective Size of Noise Components of Trend Signal, Education Subgroups

	Less than HS	HS deg.	Some Cllg	Cllg deg.	Grad
1978Q1 to 1992Q4	22.398	17.423	21.524	17.156	12.927
	(0.682)	(0.529)	(0.691)	(0.734)	(0.860)
1993Q1 to 2008Q3	10.318	7.767	7.768	5.109	4.784
	(0.542)	(0.440)	(0.344)	(0.241)	(0.216)

Note: Less than HS: Less than High School, HS deg.: High School degree, Some Cllg: Some college, Cllg deg.: College degree, Grad: Graduate studies. Standard errors are in parentheses.

people, those aged 18 to 44, while the change is relatively modest for older people, those 45 and older. This suggests that the improvement in the FRB's transparency was most effective for young people. Regarding income subgroups the size of noise for the bottom 25% did not changed much, while for the education subgroups the decline in the size of noise for those with less than a high school education subgroup is smaller than that for the other education subgroups. This suggests that the improvement in the FRB's transparency was relatively ineffective for the people in these subgroups. In summary, we found a decline in the actual size of noise in the inflation trend after the mid-1990s for almost all subgroups. However, there exists heterogeneity and the decline was especially great for the young, educated, and those in high income groups. This suggests that whether or not the improvement in the FRB's transparency regarding the target is conveyed to an economic agent depends on his/her characteristics to some extent.

1.5 Conclusion

This study measures the FRB's transparency regarding its target inflation rate using survey data of the disagreement in inflation expectations among U.S. consumers from the late 1970s to the early 2000s. We construct a model of inflation forecasters employing the frameworks of both an unobserved components model and a noisy information model. In particular, we explicitly model how people make use of heterogeneous noisy signals about the inflation trend, which proxies the FRB's inflation target. With this model in hand, we estimate the parameters including the size of noise in the trend signal, which we interpret as the degree of the FRB's transparency regarding the target inflation rate. We estimate all the parameters including the transparency employing both maximum likelihood and the methods of moments, matching the theoretical moments from the model to the data. The results show that the index of transparency largely improved after the mid-1990s. In addition, we show that the change in transparency regarding the target had a large impact on the term structure of disagreements in inflation expectations. Finally, we run the same estimation using subgroup data and show that the improvement in the FRB's transparency was more effective on the young, educated, and those in high income groups.

While we have focused on U.S. consumers, this approach can be applied to other economic agents. One of the reasons for using the MSC is its long sample for long horizon forecasts since our focus is on the great inflation period, a relatively old episode. However, if one focuses, for example, on the introduction of an inflation target in the U.S. or the global financial crisis, other rich survey data are also available. In addition, our model can be extended to focus on specific events. Since we simply split the sample into two parts and estimate the parameters for each sample, we do not argue what specific actions by the FRB have improved the transparency measure. One possible extension is to incorporate stochastic volatility in the size of the noise and evaluate the effect of specific actions by central banks on the estimated size of noise.

Appendix 1.A Maximum Likelihood Estimation with Missing Observations

The state space equation and the observation equation are described in Section 1.3.3:

$$\mathbf{\Xi}_t = D\mathbf{\Xi}_{t-1} + \epsilon_t, \quad (1.A.1)$$

$$\mathbf{X}_t = H'\mathbf{\Xi}_t + \upsilon_t, \quad (1.A.2)$$

where $\epsilon_t \sim N(0, \Sigma^{\epsilon})$, $\upsilon_t \sim N(0, \Sigma^{\upsilon})$, and $\mathbf{X}_t \equiv \left[x_t^{obs}; \bar{x}_{t+1y|it}^{obs}; \bar{x}_{t+5y|it}^{obs}\right]$. Unfortunately, some of the mean forecast of 5 to 10 years ahead inflation expectations $\bar{x}_{t+5y|it}^{obs}$ are missing as in Figure 2. To deal with this problem, this section applies the method proposed in Harvey (1990) to our estimation. The idea is simple: we update state variables without making use of unavailable observations. The parameters to be estimated are summarized as $\theta = \{\phi, \sigma_{\varepsilon}, \sigma_{\varepsilon *}, \sigma_w, \sigma_{w*}, \sigma_{v1y}, \sigma_{v5y}\}$.

Given the initial values $\mathbf{\Xi}_{0|0}$ and $P_{1|0}$, we begin with a period when all three observations are available. The updating equation is

$$\mathbf{\Xi}_{t|t} = D\mathbf{\Xi}_{t-1|t-1} + K_t\left(\mathbf{X}_t - H'D\mathbf{\Xi}_{t-1|t-1}\right), \quad (1.A.3)$$

where the Kalman gain, a 3×3 matrix, is given by

$$K_t = P_{t|t-1}H'\left(HP_{t|t-1}H' + \Sigma^{\upsilon}\right)^{-1}. \quad (1.A.4)$$

The MSE of the forecast of $\mathbf{\Xi}_t$ with information up until $t-1$, denoted by $P_{t|t-1}$, evolves according to

$$P_{t+1|t} = D\left[P_{t|t-1} - P_{t|t-1}H\left(H'P_{t|t-1}H + \Sigma^{\upsilon}\right)^{-1}H'P_{t|t-1}\right]D' + \Sigma^{\epsilon}. \quad (1.A.5)$$

Then, denoting the error by $\mathbf{u}_t = \mathbf{X}_t - \mathbf{X}_{t|t-1} = \mathbf{X}_t - H' D \boldsymbol{\Xi}_{t-1|t-1}$, the MSE of the forecast of $\mathbf{X}_t$ is given by

$$\Omega_t \equiv E\left[\mathbf{u}_t \mathbf{u}_t'\right] = H' P_{t|t-1} H + \Sigma^{v}. \tag{1.A.6}$$

Finally, the log likelihood function for these observations is

$$\ln f\left(\mathbf{X}_t | \theta, \mathbf{X}_{t-1}, ..., \mathbf{X}_0\right) = -\frac{3}{2} \ln 2\pi - \frac{1}{2} \ln |\Omega_t| - \frac{1}{2} \mathbf{u}_t' \Omega_t^{-1} \mathbf{u}_t. \tag{1.A.7}$$

Next, we will describe the likelihood function in periods when we do not have the LR mean inflation expectations, specifically $\mathbf{X}_t = \left[x_t^{obs}; \bar{x}_{t+1y|it}^{obs}; N/A\right]$. We introduce a selector matrix to obtain available observations as below,

$$S = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}. \tag{1.A.8}$$

The updating equation is

$$\boldsymbol{\Xi}_{t|t} = D \boldsymbol{\Xi}_{t-1|t-1} + K_t \left(S \mathbf{X}_t - S H' D \boldsymbol{\Xi}_{t-1|t-1} \right), \tag{1.A.9}$$

where the Kalman gain, a 3×2 matrix, is given by

$$K_t = P_{t|t-1} \left(SH\right)' \left(\left(SH\right) P_{t|t-1}' \left(SH\right)' + S \Sigma^{v} S' \right)^{-1}. \tag{1.A.10}$$

Thus, we simply skip the unavailable LR mean forecast. The MSE of the forecast of $\boldsymbol{\Xi}_t$ with information up until $t-1$, denoted by $P_{t|t-1}$, evolves according to

$$P_{t+1|t} = D \left[P_{t|t-1} - P_{t|t-1} \left(SH\right) \left(\left(SH\right)' P_{t|t-1} \left(SH\right) + S \Sigma^{v} S' \right)^{-1} \left(SH\right)' P_{t|t-1} \right] D' + \Sigma^{\epsilon}. \tag{1.A.11}$$

Then, the MSE of the forecast of $\mathbf{X}_t$, denoted by $\mathbf{u}_t = S\mathbf{X}_t - S\mathbf{X}_{t|t-1} = S\mathbf{X}_t - SH' D \boldsymbol{\Xi}_{t-1|t-1}$, is given by

$$\Omega_t \equiv E\left[\mathbf{u}_t \mathbf{u}_t'\right] = (SH)' P_{t|t-1} SH + S\Sigma^v S'. \tag{1.A.12}$$

Finally, the log likelihood function for these observations is

$$\ln f\left(\mathbf{X}_t | \theta, \mathbf{X}_{t-1}, ..., \mathbf{X}_0\right) = -\ln 2\pi - \frac{1}{2}\ln|\Omega_t| - \frac{1}{2}\mathbf{u}_t'\Omega_t^{-1}\mathbf{u}_t. \tag{1.A.13}$$

Appendix 1.B Properties of the Standard and the Generalized Model

In this section, we discuss why the standard model cannot describe disagreements in the survey data while the generalized model can.

We address two properties of the standard model, which is a basic noisy information model. First, both noise components need to be very large so that the model has a high level of disagreement according to our numerical exercise. Figure A-1 shows the level of theoretical disagreement for SR and LR inflation forecasts, respectively. We use the parameters of the inflation process $\{\phi, \sigma_\varepsilon, \sigma_{\varepsilon *}\}$ for the sample from 1978Q1 to 2008Q3. The horizontal axis shows the size of noise in the signal of the inflation rate while the vertical axis shows the size of noise in the signal of the inflation trend. The contours show the level of theoretical disagreement. Since both disagreements in the survey data are higher than 3.5, as in Table 2, we need a value of more than 60 for both noise components. This means that that an average forecaster gets a signal about the quarterly percentage growth of the inflation rate, that is different from the actual inflation rate by 60 percentage points. This is not realistic.

The mechanism explaining this point is the two opposing effects of noise on disagreement, which is also discussed in Andrade and Le Bihan (2013). The first effect is the positive "direct effect." If the size of the noise is larger, the information is more dispersed, which raises the disagreement in the variable. The other effect is the negative "weight effect." If the size of noise is larger, the forecaster puts less weight on the signal because the information is not reliable, which decreases the disagreement. The latter effect arises due to the optimal filtering assumption, that is, the Kalman filtering, where a forecaster puts optimal weights on her current noisy signals considering the usefulness of the signal. Since the forecaster optimally reduces the weight on the signal as the size of the noise increases, the pace of increase in the level of disagreement is slow.

Second, SR disagreement in the model is always larger than LR disagreement when we have large noise components in both signals. As a result, we cannot generate the crossing of the SR and LR disagreements, which is crucial for this study. Figure A-2 shows the difference in the level of theoretical disagreements, that is, SR disagreements minus LR disagreements. As the figure shows, almost the entire area is positive, which means that SR disagreements are higher than LR disagreements. In particular, the difference is always positive in the upper right region where both sizes of the noise components are large and the level of disagreement is high.

The mechanism explaining this point is again the weight effect. Given the size of noise, the weight on the signal increases as the MSE of the 1-period-ahead forecast of the variable increases. This is because the signal-to-noise ratio increases - in other words, the signal becomes relatively reliable. The MSE of the inflation rate is higher than that of the trend component because the inflation rate is the sum of the gap and the trend. As a result, suppose that a forecaster uses the same noisy signal to infer each variable and the level of disagreement in inflation tends to be higher than that of the trend because the weight becomes larger. Then, since the SR disagreement is the weighted average of the nowcast disagreement in inflation and the trend while the LR disagreement is almost entirely the nowcast disagreement in the trend, the SR disagreement tends to be higher than the LR disagreement, as shown in Figure A-2.

As seen above, the standard model, which is the basic noisy information model, is unable to capture the observed patterns of the term structure of disagreement in the survey data. This problem is related to the negative weight effect that comes from the optimal forecast. Thus, we use the generalized model explained in Section 1.2.2 and slightly relax the theoretical restriction on the weights. We continue to use Kalman filtering, but the generalized model has weights on signals which are different from the optimal weights and result from assuming that people have imperfect information about the distribution of the noise components: $R^{sbj} \neq R^{obj}$.[13]

[13] As noted in the footnote in Section 1.2.2, we use this setting following the literature. In addition, there can be other reasons why the weighting matrix can deviate from the optimal weighting matrix, the

Next, we discuss the properties of the generalized model and show why the model can produce the dynamics of the disagreements in the survey data. Figure A-3 describes numerical examples of SR and LR disagreements from the model when we change the objective/true the size of noise components. We employ the parameters of the true inflation process $\{\phi, \sigma_\varepsilon, \sigma_{\varepsilon*}\}$ and the subjective size of the noise components $\{\sigma_w^{sbj}, \sigma_{w*}^{sbj}\}$ from the estimation results of the sample from 1978Q1 to 2008Q3. We can observe two properties from the figures. First, the level of disagreement is much higher than that in the standard model, which is presented in Figure A-1. Since this model does not impose an optimal weight restriction, which gives rise to the negative weight effect seen in the standard model, but rather employs estimated fixed subjective sizes of the noise components, the negative weight effect disappears. As the figure shows, given the estimated weights, the model can express a high level of disagreement with smaller noise components. Second, the elasticity of SR disagreement with respect to the size of inflation noise is comparable to that with respect to the size of trend noise. Also, the elasticity of LR disagreement with respect to inflation noise is almost zero while that with respect to trend noise is very large. The different elasticities of the disagreements reflect different informativeness of signals in forecasting each variable. In fact, the weights on the signals, which depend on the estimated subjective size of the noise components, suggest that forecasters rely far more on the inflation signal to nowcast inflation while they rely far more on the trend signal to nowcast the trend.

Finally, Figure A-4 describes the theoretical difference between the SR and the LR disagreements: SR minus LR. The important properties of the model are that the difference between disagreements can be large, and, more importantly, that the model can describe not only the case where SR disagreement is greater than LR disagreement but also the opposite case. The mechanism is the same as discussed above in relation to the previous figures: the disappearance of the negative weight effect. Thus, when the size of trend noise increases,

Kalman gain, which is used in pure noisy information models. One reason is that there may exist strategic interaction across forecasters, as discussed in Morris and Shin (2002) and Coibion and Gorodnichenko (2012). Alternatively, there may exist naive forecasters, who do not use optimal filtering to extract information from signals. In either case, the weighting matrix is different from the optimal weighting matrix.

the LR disagreement increases relative to the SR disagreement. Meanwhile, when the size of inflation noise increases, the SR disagreement increases relative to the LR disagreement. Overall, we can describe the dynamics of the term structures of disagreement in the data.

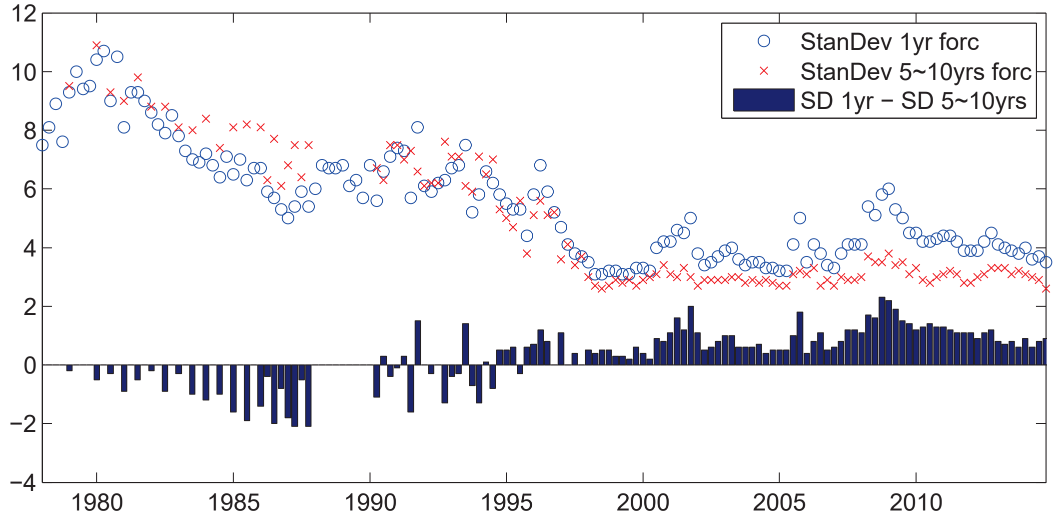


Figure 1.1: Disagreement in Inflation Forecasts

Source: Survey of Consumers, University of Michigan

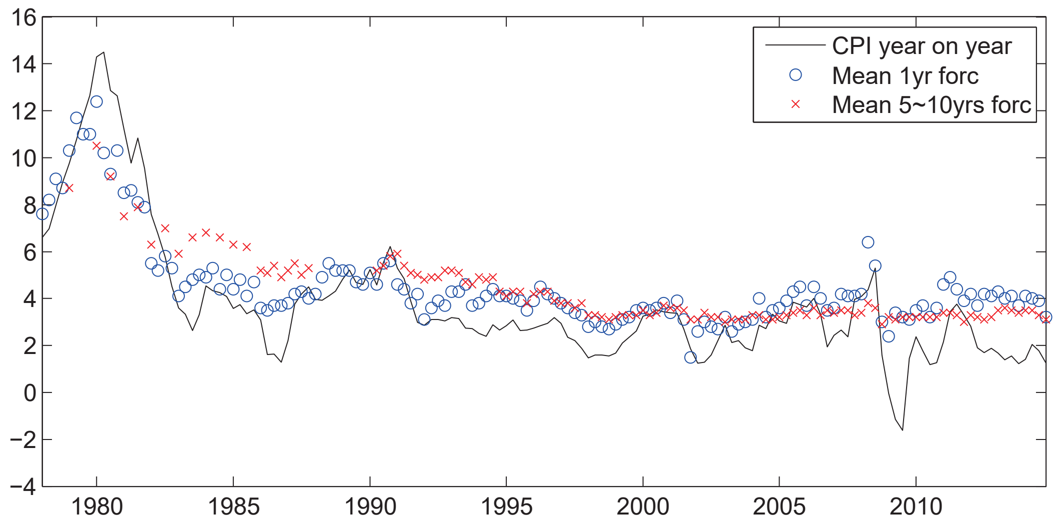


Figure 1.2: Mean Inflation Forecasts

Source: Survey of Consumers, University of Michigan

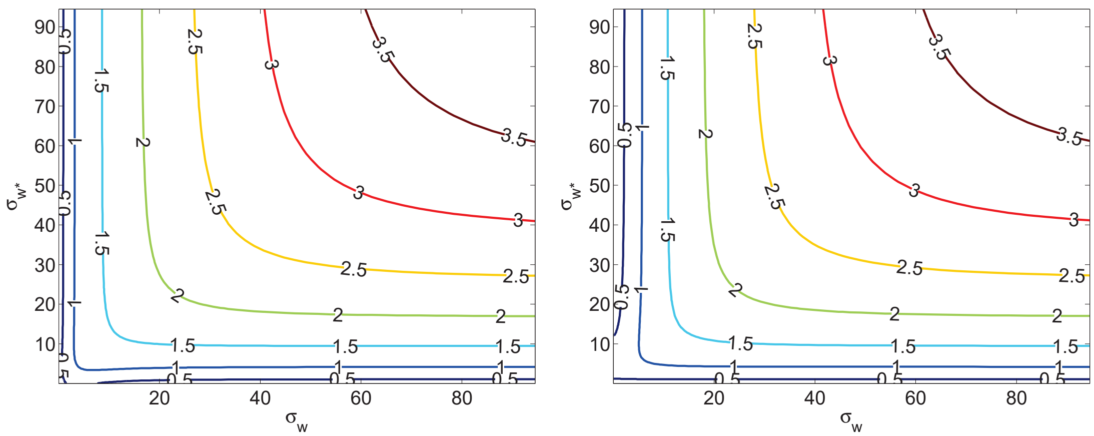


Figure 1.3: Theoretical Disagreement in Short-run (top) and Long-run (bottom) Inflation Forecasts: the Standard Model

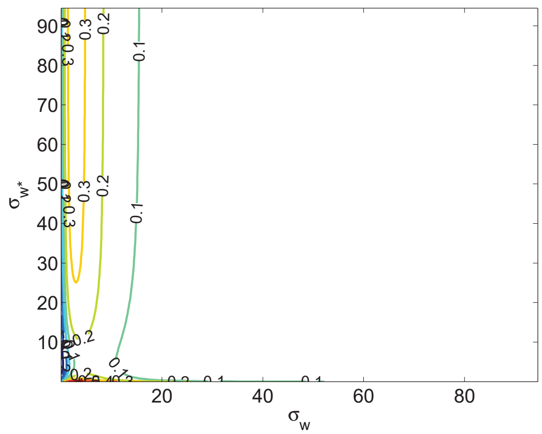


Figure 1.4: Difference between Theoretical Disagreements: the Standard Model

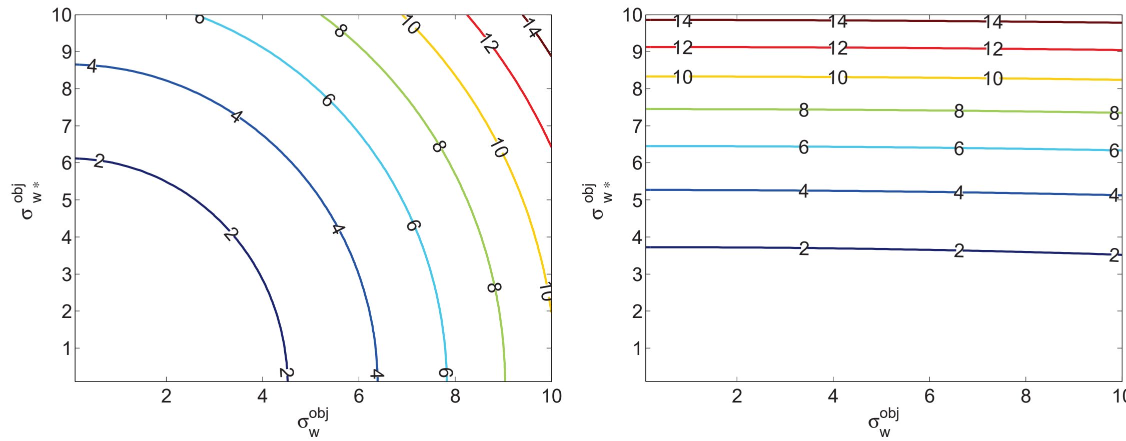


Figure 1.5: Theoretical Disagreement in Short-run (left) and Long-run (right) Inflation Forecasts: the Generalized Model

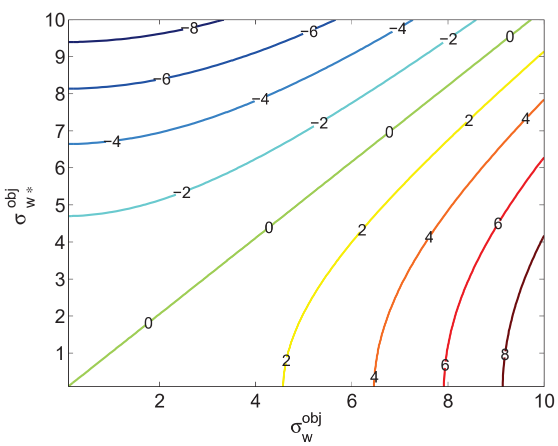


Figure 1.6: Difference between Theoretical Disagreements: the Generalized Model

CHAPTER 2

Imperfect Information, Signaling Effect, and Transparency about the Inflation Target

2.1 Introduction

In the last several decades central banks around the world had gravitated towards choosing a transparent two percent inflation target. A transparent communication about the target helps align the long-run inflation expectations of the public. A common view is that the introduction of transparent target and the subsequent stable inflation are the success of modern central banking. However, inflation rate has run above target after the pandemic in most of those same countries. Moreover, recent heightened geopolitical risks and the movement toward decarbonization have brought about a surge in commodity prices, which will result in higher inflation rate around the globe. In the end, many economists have come to associate recent situation with that in the 1970s when many economies were suffering high inflation without transparent inflation target. The situation motivates us to reassess the well-established monetary policy framework, in particular, the authenticity of transparent communication about inflation target.

This paper asks whether a strategy communicating inflation target transparently is desirable to achieve policy objectives for central banks. We investigate the optimal degree of transparency about the inflation target. We employ an imperfect information model, *a la* Woodford (2001), where both markup shocks and inflation target shocks hit the economy.[1]

[1] Inflation target shocks in our model can be interpreted broadly as shifts in the central bank's preference.

In the model all agents understand the structure of the economy including the structural parameters, but all agents except for central bankers have imperfect information about economic variables: aggregate output, inflation rate, policy target, and so on. Thus, there exists an informational asymmetry between central bankers and private agents. Then, if the central bank announce more (less) about their own information, we call it more transparent (opaque). We assume that the central bank can change the size of noise included in private agents' signal about inflation target, making the target transparent or opaque. Moreover, we assume a rule based nominal interest rate, which is assumed to be perfectly observed by private agents. Thus, private agents try to disentangle information about shocks from this policy instrument and their own noisy private information about shocks. This is called the signaling effect of the policy rate in the literature.

The findings of the paper are mainly two folds. The first finding is that transparent inflation target is not always optimal. The model presents a tug-of-war between three benefits over the optimal degree of transparency. The first, as noted earlier, is the benefit of transparency. Transparency helps the central bank align inflation expectations since when the target is transparent, firms' inflation expectations are highly responsive to changes in inflation targets. The second is the benefit of opacity. If private agents are unaware of shocks that reduce the efficiency of the economy, such as markup shocks, this is beneficial for the economy. When the inflation target is transparent, people can perfectly back out information about detrimental shocks by subtracting shifts in central bank preferences from those in policy rates due to signaling effect, creating extra amplitude in the economy. From this perspective, less transparent inflation target is desirable. The third is another advantage of opacity. In a new Keynesian model, if the inflation target is highly persistent, inflation rate will change more than the change in the inflation target, causing additional amplitude in the economy.[2] However, if the information on the inflation target is not perfect, our model

Thus, they can be the shifts in the long-run inflation target or, simply, monetary policy shocks.

[2]This mechanism is not a special case only in my model. It is also seen in Ireland (2007) and Cogley *et al.* (2010). Moreover, as I noted above, inflation target shocks in our model can also be interpreted as standard monetary policy shocks. The overshooting of inflation in response to an inflation target shock corresponds to

shows that this overshooting can be reduced by misleading people into believing that some of the change in the policy rate is due to a negative shock to the inflation rate.

The second finding is that the optimal degree of transparency depends on the relative size and the persistence of shocks in the economy. The relative power of the benefits described above depends on the relative size of shocks. It is shown that while a transparent target is optimal in our baseline case, an opaque target is optimal when the standard deviation of inflation target shocks is relatively small. This is because the benefit of transparency to inflation target shocks is smaller in that case. For example, when commodity prices are highly volatile due to geopolitical risks, the proportion of markup shocks among the sources of economic fluctuations will be larger. According to our results, the cost of revealing the target of the central bank is also higher in this case as it conveys the information about detrimental shocks to private agents. The relative power of the benefits also depends on the persistence of shocks. In the baseline case, the overshooting of the inflation rate in response to a inflation target shock does not arise. However, when the inflation target is persistent, the inflation overshooting occurs, and a fully transparent target increases loss in the economy. In this case, it is optimal to limit the strong reaction of the inflation rate by setting a moderately transparent target.

Literature Review

This paper builds on the literature on central bank transparency. Existing studies discuss whether more information is desirable to help stabilization policy in the setting where there is information asymmetry between authorities and private agents. For example, Geraats (2002) classifies central bank transparency into five categories, and this paper deals with two of them simultaneously: transparency of policy objectives and transparency of the economic states. Other recent papers closely related to ours is Angeletos and Pavan (2007) and Angeletos

the case when nominal interest rate declines in response to a positive and persistent monetary policy shock, which is often seen in new Keynesian models (for example, in Galí (2008)). Here, we suppose a Taylor rule that central bank responds only to inflation rate and monetary policy shocks. If we interpret the positive monetary policy shock as a decline in the target inflation rate, the decline in the nominal interest rate means that the decline in actual inflation rate is larger than that in the hypothetical target inflation rate.

et al. (2016). They classify whether more information is desirable or not according to the type of shocks that drive the business cycle, and the mechanism in this paper relies on this property. Another literature related to this paper is that on the signaling effects of monetary policy. It deals with the effect that not only the information that the central bank explicitly releases but also the policy change itself reveals the information that the central bank has. Indeed, some studies, such as Romer and Romer (2000), Melosi (2017), and Nakamura and Steinsson (2018), have quantitatively shown the signaling effects in the United States. This field overlaps with the aforementioned field of central bank transparency, and existing studies have pointed to the need to take signaling effects into account when considering optimal monetary policy and communication strategies. The contribution of our paper to the literature is to study how the consensus among central banks that transparent inflation targeting is desirable changes when signaling effect and distortional shocks to the economy are considered in a standard New Keynesian framework.

There are studies that discuss the transparency of central bank targets under the presence of signaling effect. Walsh (2007) discusses the optimal transparency of the central bank target but differs from ours in that he focuses on noise in central bank information and assumes optimal monetary policy. He shows as a benefit of transparency that publication allows the central bank to offset demand shocks through optimal monetary policy, which differs from the mechanism we consider. Frankel and Kartik (2018) also analyzes the optimal transparency regarding the central bank's target while considering the signaling of the policy instrument. He discusses transparency under optimal discretionary monetary policy by a central bank with an inflation bias. They present a different benefit than we do, that the target opacity will reduce the excess inflation that results from the bias.[3] One study that does not discuss target transparency but is close to ours is Kohlhas (2022). He considers a two-sided flow of information between private agents and central bank and shows that it is better for central banks to disclose their internal information. His model is close to ours as it assumes a Taylor

[3] Tang (2015) also discusses the signaling effect and transparency of central bank's target under optimal discretionary monetary policy.

rule in some cases, as well as inefficient markup shocks and the signaling effect. However, his focus is on economic transparency, not target transparency, and the signaling effect plays quantitatively a minor role in his model.[4] In summary, although existing studies have analyzed interactions through target transparency and signaling effect, there are differences from ours in the setting of monetary policy, central bank incentives, information structure, and so forth. Thus, the mechanism of our focus, the tug-of-war between the three benefits has not been discussed.

2.2 Model

The present model is based on Lorenzoni (2009). The model is a standard new Keynesian model with dispersed information. The economy is hit by markup shocks and inflation target shocks. There exists an informational asymmetry between the central bank and the private agents. The central bank has perfect information about aggregate economy and set nominal interest rate according to a simple Taylor rule reacting only to the difference between inflation rate and the target rate (inflation gap). The private agents cannot observe aggregate variables directly except for the current nominal interest rate and live in informationally isolated islands. They observe heterogeneous noisy signals about markup and inflation target, in addition to interest rate. Each period consumers in island l visit islands $\mathcal{B}_{l,t} \subset [0,1]$ to buy the composite of goods while firms in island l is visited by consumers from islands $\mathcal{C}_{l,t} \subset [0,1]$. Both $\mathcal{B}_{l,t}$ and $\mathcal{C}_{l,t}$ are randomly selected.[5]

[4]Another study that is close to ours is Baeriswyl and Cornand (2010). They have similarities with our study, such as signaling effects of policy instruments and the detrimental effect of markup shocks. They differ from ours in that they focus on economic transparency rather than target transparency and that they also discuss optimal monetary policy. In a related study, Tamura (2016) explores the optimal instrument policy and the optimal communication policy at the same time.

[5]These island specifications are to avoid agents in an island to learn aggregate price and output perfectly through the goods price they buy and the demand function of their produced goods.

2.2.1 Households

The preference of the representative consumer in island l is given by

$$E_{l,t}\sum_{t=0}^{\infty}\beta^{t}U\left(C_{l,t},N_{l,t}\right), \tag{2.2.1}$$

where

$$U\left(C_{l,t},N_{l,t}\right)=\ln C_{l,t}-\frac{N_{l,t}^{1+\zeta}}{1+\zeta}.$$

The composite consumption good for the consumer from island l includes only the goods in the consumption basket $\mathcal{B}_{l,t}$ that is

$$C_{l.t}=\left(\int_{\mathcal{B}_{l,t}}\int_{0}^{1}C_{j,m,l,t}^{(\gamma_t-1)/\gamma_t}dj\,dm\right)^{\gamma_t/(\gamma_t-1)}, \tag{2.2.2}$$

where $C_{j,m,l,t}$ is the consumption of variety j produced in island m, by the consumer from island l at time t. The intertemporal budget constraint for a consumer is

$$B_{l,t}+\int_{\mathcal{B}_{l,t}}\int_{0}^{1}P_{j,m,t}C_{j,m,l,t}dj\,dm=\left(1+i_{t-1}\right)B_{l,t-1}+W_{l,t}N_{l,t}+\int_{0}^{1}D_{j,l,t}dj. \tag{2.2.3}$$

In equilibrium, consumers choose consumption, hours worked, and bond holdings, so as to maximize their expected utility.

There are two price indexes in each island: the local producer price index $P_{l,t}$ and the consumer price index $\bar{P}_{l,t}$, given by

$$P_{l,t} = \left(\int_{0}^{1}P_{j,l,t}^{1-\gamma_t}dj\right)^{1/(1-\gamma_t)}, \tag{2.2.4}$$

$$\bar{P}_{l,t} = \left(\int_{\mathcal{B}_{l,t}}P_{m,t}^{1-\gamma_t}dm\right)^{1/(1-\gamma_t)}. \tag{2.2.5}$$

The demand for good j in island $m \in \mathcal{B}_{l,t}$ by consumers from island l is

$$C_{j,m,l,t} = \left(\frac{P_{j,m,t}}{\bar{P}_{l,t}}\right)^{-\gamma_t} C_{l,t}. \tag{2.2.6}$$

Aggregating the demand of all consumers in $\mathcal{C}_{l,t}$ gives the demand for the good produced by firm j, l

$$Y_{j,l,t} = \int_{\mathcal{C}_{l,t}} \left(\frac{P_{j,l,t}}{\bar{P}_{m,t}}\right)^{-\gamma_t} C_{m,t} dm. \tag{2.2.7}$$

The economy wide price index is defined

$$P_t = \left(\int_0^1 P_{l,t}^{1-\gamma_t} dl\right)^{1/(1-\gamma_t)}. \tag{2.2.8}$$

2.2.2 Firms

Firms set price *a la* Calvo (1983). Each period, on each island, a fraction $1-\theta$ of firms are allowed to reset their price. $E_{l,t}$ denotes the expectation of the agents located in island l. $P^*_{l,t}$ denotes the optimal price for a firm j who can adjust its price in island l at time t. The problem of this firm is to maximize

$$\sum_{k=0}^{\infty} (\theta\beta)^k E_{l,t}\left[\frac{\lambda_{l,t+k}}{\lambda_{l,t}}\left(PY_{j,l,t+k} - W_{l,t+k}N_{j,l,t+k}\right)\right], \tag{2.2.9}$$

subject to

$$Y_{j,l,t} = \int_{\mathcal{C}_{l,t}} \left(\frac{P_{j,l,t}}{\bar{P}_{m,t}}\right)^{-\gamma_t} C_{m,t} dm \tag{2.2.10}$$

and the production function is

$$Y_{j,l,t} = N_{j,l,t}. \tag{2.2.11}$$

It is assumed that there is no technological fluctuations are for simplicity.

2.2.3 Monetary Policy

We assume a simple instrument rule reacting only to the gap between the inflation and the time-varying inflation target:

$$i_t = \delta_\pi \left(\pi_t - \pi_t^*\right). \tag{2.2.12}$$

It is assumed that firms have perfect information about i_t, and they try to disentangle shocks to the economy from the changes in the policy rate.

2.2.4 Signals and Shock Processes

Endogeneous signals

The log linearization of the demand equation with time varying elasticity of substitution is

$$y_{j,l,t} = \int_{\mathcal{C}_{l,t}} \left(c_{m,t} + \gamma \bar{p}_{m,t}\right) dm - \gamma p_{j,l,t}, \tag{2.2.13}$$

where γ is the steady state elasticity of substitution. We avoid the perfect identification of aggregate prices and output by agents through the consumption price index and the demand function of their goods by introducing heterogeneity in random selection $\mathcal{B}_{l,t}$ and $\mathcal{C}_{l,t}$. As in Nimark (2014), we assume that the random selection of islands are, in log-linear approximation,[6]

$$\bar{p}_{l,t} = p_t + \xi_{l,t}^p, \tag{2.2.14}$$

$$y_{j,l,t} = y_t - \gamma \left(p_{j,l,t} - p_t\right) + \xi_{l,t}^y, \tag{2.2.15}$$

[6] We employ these specifications following Nimark (2014) so that we have stationary signals.

where $\xi_{l,t}^{p}$ follows $N\left(p_{l,t-1}-p_{t-1},\sigma_{\xi p}^{2}\right)$ and $\xi_{l,t}^{y}$ follows $N\left(\gamma\left(p_{j,l,t-1}-p_{t-1}\right),\sigma_{\xi y}^{2}\right)$. Thus,

$$\begin{aligned}
\bar{p}_{l,t} &= p_{l,t-1}+\pi_{t}+\xi_{l,t}^{1}, && (2.2.16)\\
E_{l,t}\bar{\pi}_{l,t+1} &= E_{l,t}\pi_{t+1}+\pi_{l,t}-\pi_{t}-\xi_{l,t}^{1}, && (2.2.17)\\
y_{l,t} &= y_{t}-\gamma\left(\pi_{l,t}-\pi_{t}\right)+\xi_{l,t}^{2}, && (2.2.18)
\end{aligned}$$

where $\xi_{l,t}^{1}$ follows $N\left(0,\sigma_{\xi p}^{2}\right)$ and $\xi_{l,t}^{2}$ follows $N\left(0,\sigma_{\xi y}^{2}\right)$. We make use of the fact that all firms in island l face the same demand function to have $y_{l,t}$.

Exogenous signals

People in island l receive two exogenous signals about markup and inflation target:

$$\begin{aligned}
s_{l,t}^{\mu} &= \mu_{t}+w_{l,t}^{\mu}, && (2.2.19)\\
s_{l,t}^{\pi*} &= \pi_{t}^{*}+w_{l,t}^{\pi*}, && (2.2.20)
\end{aligned}$$

where $w_{l,t}^{\mu}$ follows $N\left(0,\sigma_{w,\mu}^{2}\right)$ and ε_{t}^{μ} follows $N\left(0,\sigma_{\varepsilon,\mu}^{2}\right)$.

Shock Processes

We assume that

$$\begin{aligned}
\pi_{t}^{*} &= \rho_{\pi*}\pi_{t-1}^{*}+\varepsilon_{t}^{\pi*}, && (2.2.21)\\
\mu_{t} &= \rho_{\mu}\mu_{t-1}+\varepsilon_{t}^{\mu}, && (2.2.22)
\end{aligned}$$

where ε_{t}^{μ} follows $N\left(0,\sigma_{\varepsilon,\mu}^{2}\right)$ and $\varepsilon_{t}^{\pi*}$ follows $N\left(0,\sigma_{\varepsilon,\pi*}^{2}\right)$.

2.2.5 Equilibrium

The model will be solved numerically. We study a log-linear approximation to a rational expectations equilibrium.

Individual Optimality Conditions

The Euler equation and labor supply condition is given by

$$\frac{1}{C_{l,t}\bar{P}_{l,t}} = \beta\left(1+i_t\right)E_{l,t}\left[\frac{1}{C_{l,t+1}\bar{P}_{l,t+1}}\right], \tag{2.2.23}$$

$$\frac{N_{l,t}^{\zeta}}{C_{l,t}^{-1}} = \frac{W_{l,t}}{\bar{P}_{l,t}}. \tag{2.2.24}$$

We log linearize the conditions around non-stochastic steady state. We have

$$c_{l,t} = E_{l,t}\left[c_{l,t+1}\right] - i_t + E_{l,t}\left[\bar{\pi}_{l,t+1}\right], \tag{2.2.25}$$

$$c_{l,t} = -\zeta n_{l,t} + w_{l,t} - \bar{p}_{l,t}. \tag{2.2.26}$$

The first order condition for the firms is

$$\sum_{k=0}^{\infty}\left(\theta\beta\right)^k E_{l,t}\left[\frac{\lambda_{l,t+k}}{\lambda_{l,t}}Y_{j,l,t+k}\left(P_{j.l.t}^{*} - M_{t+k}W_{l,t+k}\right)\right] = 0,$$

where we define markup rate as $M_{t+k} = \gamma_{t+k}/\left(\gamma_{t+k}-1\right)$. In a symmetric equilibrium, all firms in island l make identical decisions. So, the firm's optimality condition is

$$\sum_{k=0}^{\infty}\left(\theta\beta\right)^k E_{l,t}\left[\frac{\lambda_{l,t+k}}{\lambda_{l,t}}Y_{l,t+k}\left(P_{l,t}^{*} - M_{t+k}W_{l,t+k}\right)\right] = 0.$$

We log linearize the conditions around non-stochastic steady state

$$p_{l,t}^{*} = \left(1-\beta\theta\right)\sum_{k=0}^{\infty}\left(\beta\theta\right)^k E_{l,t}\left[\mu_{t+k} + w_{l,t+k}\right].$$

It becomes a recursive form:

$$p_{l,t}^{*}=(1-\beta\theta)\left(E_{l,t}\left[\mu_{t}\right]+w_{l,t}\right)+\beta\theta E_{l,t}\left[p_{l,t+1}^{*}\right].$$

The law of motion for the local price index is given by

$$p_{l,t}=\theta p_{l,t-1}+(1-\theta)\,p_{l,t}^{*}.$$

With this law of motion, labor supply condition, labor market clearing condition $n_{l,t}=y_{l,t}$, and the demand relationship, we have

$$\pi_{l,t}=\lambda E_{l,t}\left[\mu_{t}\right]+\lambda c_{l,t}+\lambda\zeta y_{t}-\lambda\left(1+\zeta\gamma\right)\left(\pi_{l,t}-\pi_{t}\right)+\beta E_{l,t}\left[\pi_{l,t+1}\right]+\lambda\xi_{l,t}^{1}+\lambda\zeta\xi_{l,t}^{2},$$

where $\lambda=(1-\theta)(1-\beta\theta)/\theta$. Then, setting $\Lambda^{-1}=1+\lambda\left(1+\zeta\gamma\right)$, we have

$$\pi_{l,t}=\Lambda\lambda E_{l,t}\left[\mu_{t}\right]+\Lambda\lambda c_{l,t}+\Lambda\lambda\zeta y_{t}+\Lambda\lambda\left(1+\zeta\gamma\right)\pi_{t}+\Lambda\beta E_{l,t}\left[\pi_{l,t+1}\right]+\Lambda\lambda\xi_{l,t}^{1}+\Lambda\lambda\zeta\xi_{l,t}^{2}. \quad (2.2.27)$$

Learning and Aggregation

The economy's aggregate dynamics will be described in terms of the variables $z_t\equiv(\mu_t,\pi_t^*,\pi_t,i)$.[7] The state of the economy is captured by the infinite dimensional vector $\mathbf{z}_t=(z_t,z_{t-1},\ldots)$. We look for a linear equilibrium where the law of motion for $\mathbf{z}_t$ takes the form

$$\mathbf{z}_{t}=\mathbf{A}\mathbf{z}_{t-1}+\mathbf{B}\mathbf{u}_{t}^{1}, \quad (2.2.28)$$

with

$$\mathbf{u}_{t}^{1}\equiv\left(\varepsilon_{t}^{\mu},\varepsilon_{t}^{\pi*}\right), \quad (2.2.29)$$

[7] We follow Lorenzoni (2009) to solve the model.

and the appropriate rows of $\mathbf{A}$ and $\mathbf{B}$ conform with the law of motion of shock processes and with the monetary policy rule.

We can conjecture $\mathbf{A}$ and $\mathbf{B}$ as follows

$$\mathbf{A}=\begin{bmatrix}\mathbf{A}_1,\mathbf{0}\\ \mathbf{A}_p\\ \delta_\pi\left(\mathbf{A}_p-(0,\rho_{\pi*},\mathbf{0})\right)\\ I,\mathbf{0}\end{bmatrix},\mathbf{B}=\begin{bmatrix}I_{2x2}\\ \mathbf{B}_p\\ \delta_\pi\left(\mathbf{B}_p-(0,1,\mathbf{0})\right)\\ \mathbf{0}\end{bmatrix},\mathbf{A}_1\equiv\begin{bmatrix}\rho_\mu & 0\\ 0 & \rho_{\pi*}\end{bmatrix}.$$

Recall the Euler equation and the Philips curve

$$\begin{aligned}\pi_{l,t} &= \Lambda\lambda E_{l,t}\left[\mu_t\right]+\Lambda\lambda c_{l,t}+\Lambda\lambda\zeta y_t+\Lambda\lambda\left(1+\zeta\gamma\right)\pi_t+\Lambda\beta E_{l,t}\left[\pi_{l,t+1}\right]+\Lambda\lambda\xi^1_{l,t}+\Lambda\lambda\zeta\xi^2_{l,t},\\ c_{l,t} &= E_{l,t}\left[c_{l,t+1}\right]-i_t+E_{l,t}\left[\bar{\pi}_{l,t+1}\right].\end{aligned}$$

To solve for a rational expectations equilibrium, we conjecture that π_t and x_t follow the rules

$$\pi_{l,t} = q_y y_t+q_{cpi}\bar{\pi}_{l,t}+q_{pi}\pi_t+q_{ps}\pi^*_t+q_z E_{l,t}\mathbf{z}_t+u^\pi_{l,t}, \tag{2.2.30}$$

$$c_{l,t} = b_y y_t+b_{cpi}\bar{\pi}_{l,t}+b_{pi}\pi_t+b_{ps}\pi^*_t+b_z E_{l,t}\mathbf{z}_t+u^c_{l,t}. \tag{2.2.31}$$

Here, averaging both $u_{l,t}$ makes it disappear. The expressions represent the optimal pricing policy of the firms in island l (aggregated across firms) and the optimal consumption policy of the representative consumer in island l, respectively.

Plugging conjecture equations into the Philips curve, we have

$$\begin{aligned}\pi_{l,t} &= \Lambda\lambda E_{l,t}\left[\mu_t\right]+\Lambda\lambda\left(b_y y_t+b_{cpi}\bar{\pi}_{l,t}+b_{pi}\pi_t+b_{ps}\pi^*_t+b_z E_{l,t}\mathbf{z}_t\right)+\Lambda\lambda\zeta y_t+\Lambda\lambda\left(1+\zeta\gamma\right)\pi_t\\ &\quad+\Lambda\beta E_{l,t}\left[q_y y_{t+1}+q_{cpi}\bar{\pi}_{l,t+1}+q_{pi}\pi_{t+1}+q_{ps}\pi^*_{t+1}+q_z E_{l,t+1}\mathbf{z}_{t+1}\right]+u^\pi_{l,t}.\end{aligned}$$

We assumed

$$y_t = \mathbf{\Psi} \mathbf{z}_t, \tag{2.2.32}$$

and use $E_{l,t}\bar{\pi}_{l,t+1} = E_{l,t}\pi_{t+1} + \pi_{l,t} - \pi_t - \xi^1_{l,t}$ repeatedly. Thus,

$$\begin{aligned} \pi_{l,t} &= \Lambda\lambda\left(b_y+\zeta\right)y_t + \Lambda\lambda b_{cpi}\bar{\pi}_{l,t} + \left\{\Lambda\lambda\left(b_{pi}+1+\zeta\gamma\right) - \Lambda\beta q_{cpi}\right\}\pi_t + \Lambda\lambda b_{ps}\pi^*_t + \Lambda\beta q_{cpi}\pi_{l,t} \\ &\quad + \left\{\Lambda\lambda\mathbf{e}_\mu + \Lambda\lambda b_z + \Lambda\beta\left(q_y\mathbf{\Psi} + \left(q_{cpi}+q_{pi}\right)\mathbf{e}_{pi} + q_{ps}\mathbf{e}_{ps} + q_z\right)\mathbf{A}\right\}E_{l,t}\mathbf{z}_t + u^\pi_{l,t}. \end{aligned}$$

where $\mathbf{e}_e$ is the unitary vector that selects e_t from $\mathbf{z}_t$. Thus,

$$\begin{aligned} \pi_{l,t} &= \Lambda_2\Lambda\lambda\left(b_y+\zeta\right)y_t + \Lambda_2\Lambda\lambda b_{cpi}\bar{\pi}_{l,t} + \Lambda_2\left\{\Lambda\lambda\left(b_{pi}+1+\zeta\gamma\right) - \Lambda\beta q_{cpi}\right\}\pi_t + \Lambda_2\Lambda\lambda b_{ps}\pi^*_t \\ &\quad + \Lambda_2\left\{\Lambda\lambda\mathbf{e}_\mu + \Lambda\lambda b_z + \Lambda\beta\left(q_y\mathbf{\Psi} + \left(q_{cpi}+q_{pi}\right)\mathbf{e}_{pi} + q_{ps}\mathbf{e}_{ps} + q_z\right)\mathbf{A}\right\}E_{l,t}\mathbf{z}_t + u^\pi_{l,t}. \end{aligned}$$

where $\Lambda_2^{-1} = 1 - \Lambda\beta q_{cpi}$. Similarly, plugging the conjecture equations into the Euler equation, we have

$$\begin{aligned} c_{l,t} &= \left\{\left(b_y\mathbf{\Psi} + \left(b_{pi}+b_{cpi}+1\right)\mathbf{e}_{pi} + b_{ps}\mathbf{e}_{ps} + b_z\right)\mathbf{A} + \left(b_{cpi}+1\right)q_z\right\}E_{l,t}\mathbf{z}_t + \left(b_{cpi}+1\right)q_y y_t \\ &\quad - \left(\delta_\pi + \left(b_{cpi}+1\right)\left(1-q_{pi}\right)\right)\pi_t + \left(b_{cpi}+1\right)q_{cpi}\bar{\pi}_{l,t} + \left(\delta_\pi + \left(b_{cpi}+1\right)q_{ps}\right)\pi^*_t \end{aligned}$$

We can find restrictions on coefficients of the conjecture equations:

$$q_y = \Lambda_2\Lambda\lambda\left(b_y+\zeta\right), \tag{2.2.33}$$

$$q_{cpi} = \Lambda_2\Lambda\lambda b_{cpi}, \tag{2.2.34}$$

$$q_{pi} = \Lambda_2\left\{\Lambda\lambda\left(b_{pi}+1+\zeta\gamma\right) - \Lambda\beta q_{cpi}\right\}, \tag{2.2.35}$$

$$q_{ps} = \Lambda_2\Lambda\lambda b_{ps}, \tag{2.2.36}$$

$$q_z = \Lambda_2\left\{\Lambda\lambda\left(\mathbf{e}_\mu + b_z\right) + \Lambda\beta\left(q_y\mathbf{\Psi} + \left(q_{cpi}+q_{pi}\right)\mathbf{e}_{pi} + q_{ps}\mathbf{e}_{ps} + q_z\right)\mathbf{A}\right\}, \tag{2.2.37}$$

and

$$\begin{aligned}
b_y &= (b_{cpi}+1)\, q_y, && (2.2.38)\\
b_{cpi} &= (b_{cpi}+1)\, q_{cpi}, && (2.2.39)\\
b_{pi} &= -\left(\delta_\pi + (b_{cpi}+1)(1-q_{pi})\right), && (2.2.40)\\
b_{ps} &= \delta_\pi + (b_{cpi}+1)\, q_{ps}, && (2.2.41)\\
b_z &= \left(b_y\boldsymbol{\Psi} + (b_{pi}+b_{cpi}+1)\,\mathbf{e}_{pi} + b_{ps}\mathbf{e}_{ps} + b_z\right)\mathbf{A} + (b_{cpi}+1)\, q_z. && (2.2.42)
\end{aligned}$$

People understand the structure of the economy $\mathbf{z}_t = \mathbf{A}\mathbf{z}_{t-1} + \mathbf{B}\mathbf{u}_t$ and $\mathbf{u}_t$, which follows $N(0, \boldsymbol{\Sigma})$. However, they cannot observe the variables directly, except for nominal interest rate. So, they use Kalman filtering to infer the aggregate states of the economy:

$$E_{l,t}\mathbf{z}_t = \mathbf{A}\mathbf{E}_{l,t-1}\mathbf{z}_{t-1} + \mathbf{C}\left(\mathbf{s}_{l,t} - E_{l,t-1}\mathbf{s}_{l,t}\right), \tag{2.2.43}$$

where $\mathbf{s}_{l,t}$ is the vector of signals observed by the agents in island l,

$$\mathbf{s}_{l,t} = \left(s^u_{l,t}, s^{\pi*}_{l,t}, i_t, \bar{p}_{l,t}, y_{l,t}\right)', \tag{2.2.44}$$

and C is a matrix of Kalman gains.

The signals can be rewritten as

$$\begin{aligned}
\mathbf{s}_{l,t} &= \begin{bmatrix} s^u_{l,t} \\ s^{\pi*}_{l,t} \\ i_t \\ \bar{p}_{l,t} \\ y_{l,t} \end{bmatrix} = \begin{bmatrix} u_t + w^u_{l,t} \\ \pi^*_t + w^{\pi*}_{l,t} \\ i_t \\ p_{l,t-1} + \pi_t + \xi^1_{l,t} \\ y_t - \gamma\left(\pi_{l,t} - \pi_t\right) + \xi^2_{l,t} \end{bmatrix} = \begin{bmatrix} \mathbf{e}_\mu \\ \mathbf{e}_{ps} \\ \mathbf{e}_i \\ \mathbf{e}_{pi} \\ \boldsymbol{\Psi}+\gamma\mathbf{e}_{pi} \end{bmatrix}\mathbf{z}_t + \begin{bmatrix} 0 \\ 0 \\ 0 \\ p_{l,t-1} \\ -\gamma\pi_{l,t} \end{bmatrix} + \mathbf{G}\begin{bmatrix} w^u_{l,t} \\ w^{\pi*}_{l,t} \\ \xi^i_{l,t} \\ \xi^1_{l,t} \\ \xi^2_{l,t} \end{bmatrix} \\
&= \mathbf{F}\mathbf{z}_t + \mathbf{G}\mathbf{u}^2_{l,t},
\end{aligned}$$

where

$$\mathbf{u}_{l,t}^2 = \begin{bmatrix} w_{l,t}^u \\ w_{l,t}^{\pi*} \\ \xi_{l,t}^i \\ \xi_{l,t}^1 \\ \xi_{l,t}^2 \end{bmatrix}, \quad \mathbf{F} = \begin{bmatrix} e_\mu \\ e_{ps} \\ e_i \\ e_{pi} \\ \Psi + \gamma e_{pi} \end{bmatrix}, \quad \mathbf{G} = \mathbf{I}, \quad \mathbf{\Sigma} = \begin{bmatrix} \sigma_{\varepsilon,u}^2 & 0 \\ 0 & \sigma_{\varepsilon,\pi*}^2 \end{bmatrix},$$

$$\mathbf{V} = \begin{bmatrix} \sigma_{w,u}^2 & 0 & 0 & 0 & 0 \\ 0 & \sigma_{w,\pi*}^2 & 0 & 0 & 0 \\ 0 & 0 & \sigma_{\xi,i}^2 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{\xi,1}^2 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{\xi,2}^2 \end{bmatrix},$$

and let $\mathbf{\Omega}$ be defined as the squared forecast error matrix. Then the Kalman gain $\mathbf{C}$ is given by

$$\mathbf{C} = \mathbf{\Omega F}' \left(\mathbf{F \Omega F}' + \mathbf{GVG}' \right)^{-1}, \tag{2.2.45}$$

and $\mathbf{\Omega}$ must satisfy the Riccati equation

$$\mathbf{\Omega} = \mathbf{A} \left(\mathbf{\Omega} - \mathbf{CF\Omega} \right) \mathbf{A}' + \mathbf{B \Sigma B}'. \tag{2.2.46}$$

Let $\mathbf{z}_{t|t}$ denote the average expectation regarding the aggregate state $\mathbf{z}_t$ defined as

$$\mathbf{z}_{t|t} = \int_0^1 E_{l,t} \mathbf{z}_t dl. \tag{2.2.47}$$

The island specific updating rules can then be aggregated to find a matrix Ξ such that

$$\mathbf{z}_{t|t} = \Xi \mathbf{z}_t. \tag{2.2.48}$$

In equilibrium, aggregate output y_t is given by

$$y_t = \mathbf{\Psi z}_t.$$

where $\mathbf{\Psi}$ is a vector of constant coefficients.

Aggregating the updating equation gives

$$\begin{aligned}
\mathbf{z}_{t|t} &= \mathbf{A z}_{t-1|t-1} + \mathbf{C}\left(\mathbf{F z}_t - \mathbf{s}_{t|t-1}\right) = \mathbf{A z}_{t-1|t-1} + \mathbf{C}\left(\mathbf{F z}_t - \mathbf{F A z}_{t-1|t-1}\right) \\
&= \left(\mathbf{I} - \mathbf{CF}\right)\mathbf{A z}_{t-1|t-1} + \mathbf{CF z}_t.
\end{aligned}$$

Therefore, Ξ must satisfy the condition below

$$\Xi \mathbf{z}_t = \left(I - \mathbf{CF}\right)\mathbf{A}\boldsymbol{\Xi}\mathbf{z}_{t-1} + \mathbf{CF z}_t. \tag{2.2.49}$$

Aggregating the individual decision rules to find

$$\begin{aligned}
\pi_t &= q_y y_t + q_{cpi}\pi_t + q_{pi}\pi_t + q_{ps}\pi_t^* + q_z \mathbf{z}_{t|t} = \left(q_y \mathbf{\Psi} + \left(q_{cpi} + q_{pi}\right)\mathbf{e}_\pi + q_{ps}\mathbf{e}_{ps} + q_z \Xi\right)\mathbf{z}_t, \\
c_t &= b_y y_t + b_{cpi}\pi_t + b_{pi}\pi_t + b_{ps}\pi_t^* + b_z \mathbf{z}_{t|t} = \left(b_y \mathbf{\Psi} + \left(b_{cpi} + b_{pi}\right)\mathbf{e}_\pi + b_{ps}\mathbf{e}_{ps} + b_z \Xi\right)\mathbf{z}_t.
\end{aligned}$$

Thus, we have

$$\begin{aligned}
\mathbf{e}_\pi &= q_y \mathbf{\Psi} + \left(q_{cpi} + q_{pi}\right)\mathbf{e}_\pi + q_{ps}\mathbf{e}_{ps} + q_z \Xi, \\
\mathbf{\Psi} &= b_y \mathbf{\Psi} + \left(b_{cpi} + b_{pi}\right)\mathbf{e}_\pi + b_{ps}\mathbf{e}_{ps} + b_z \Xi.
\end{aligned}$$

The solution of the model requires finding matrices $\mathbf{A}, \mathbf{B}, \mathbf{C}, \Xi$, and vectors $\mathbf{\Psi}$, $\{q_y, q_{pi}, q_{ps}, q_z\}$ and $\{b_y, b_{pi}, b_{ps}, b_z\}$ that are consistent with agents' optimality, with Bayesian updating, and with market clearing in the goods and labor markets. Computing an equilibrium requires dealing with the infinite histories $\mathbf{z}_t$. We replace $\mathbf{z}_t$ with a truncated vector of state

$\mathbf{z}_t^{[T]} = \{z_t, ..., z_{t-T}\}'$. Numerical results show that when T is sufficiently large the choice of T does not affect the equilibrium dynamics. For the simulations presented below, we use $T = 15$.

To compute an equilibrium, we apply the following algorithm. We start with some initial value for $\{\mathbf{A}_p, \mathbf{B}_p, \mathbf{\Psi}\}$. We derive the values of $\{q_y, q_{pi}, q_{ps}, q_z\}$ and $\{b_y, b_{pi}, b_{ps}, b_z\}$, which satisfy individual optimality, by substituting the conjectured prices and quantities rules into the Philips curve and the Euler equation. Next, we solve for $\mathbf{C}$ and $\mathbf{\Omega}$ in the individual inference problem. Since the vector $\mathbf{z}_t^{[T]}$ is truncated, we set to zero the value of z_{t-T-1} in $\mathbf{z}_{t-1}^{[T]}$ and replace

$$\Xi \mathbf{z}_t = (I - \mathbf{CF})\, \mathbf{A} \Xi \mathbf{z}_{t-1} + \mathbf{CF} \mathbf{z}_t,$$

with

$$\Xi \mathbf{z}_t^{[T]} = (I - \mathbf{CF})\, \mathbf{A} \Xi \mathbf{M} \mathbf{z}_t^{[T]} + \mathbf{CF} \mathbf{z}_t^{[T]},$$

where

$$\mathbf{M} \equiv \begin{bmatrix} \mathbf{0} & \mathbf{I} \\ \mathbf{0} & \mathbf{0} \end{bmatrix}.$$

This gives the following relation, which is used iteratively to compute Ξ:

$$\Xi = (I - \mathbf{CF})\, \mathbf{A} \Xi \mathbf{M} + \mathbf{CF}. \tag{2.2.50}$$

We then apply the updating rule

$$\mathbf{A}_p = (q_y \mathbf{\Psi} + (q_{cpi} + q_{pi})\, \mathbf{e}_\pi + q_{ps} \mathbf{e}_{ps} + q_z \Xi)\, \mathbf{A}, \tag{2.2.51}$$

$$\mathbf{B}_p = (q_y \mathbf{\Psi} + (q_{cpi} + q_{pi})\, \mathbf{e}_\pi + q_{ps} \mathbf{e}_{ps} + q_z \Xi)\, \mathbf{B}, \tag{2.2.52}$$

$$\mathbf{\Psi} = b_y \mathbf{\Psi} + (b_{cpi} + b_{pi})\, \mathbf{e}_\pi + b_{ps} \mathbf{e}_{ps} + b_z \Xi. \tag{2.2.53}$$

and repeat until convergence is achieved. The convergence criterion is given by the quadratic distance of the each coefficients values for the old and updated values.

β	θ	ζ	γ	ϕ_π	ρ_μ	$\rho_{\pi*}$	$\sigma^2_{\varepsilon,u}$	$\sigma^2_{\varepsilon,\pi*}$	$\sigma^2_{w,u}$	$\sigma^2_{w,\pi*}$	$\sigma^2_{\xi,i}$	$\sigma^2_{\xi,1}$	$\sigma^2_{\xi,2}$
0.99	2/3	1	7.5	1.5	0.5	0.5	2	0.2	1	See the text	0	400	400

Table 2.1: Baseline calibration

2.3 Results

2.3.1 Calibration

Discount factor β, price stickiness θ, inverse Frisch elasticity of labor supply ζ, steady state elasticity of substitution γ, and reaction coefficient to inflation gap ϕ_π are all standard. We assume the size of markup shocks is larger than that of inflation target shocks. We interpret the size of noise on inflation target signal $\sigma^2_{w,\pi*}$ as the transparency of the central bank about inflation target. The size of noises on endogenous signals, $\sigma^2_{\xi,1}$ and $\sigma^2_{\xi,2}$, are set so that agents in each island cannot know the aggregate variables from island specific variables.

2.3.2 Impulse Response Functions

In this section, we see the impulse response functions (hereafter, IRFs), first, with standard calibration and, then, with calibration where the size of inflation target shock is smaller.

Figure 2.1 shows the IRFs under baseline calibration and perfect transparency about inflation target, muting the noise on inflation target signal, $\sigma^2_{w,\pi*} = 0$. The left panels show the IRFs to one unit of a markup shock and the right panels show the IRFs to one unit of an inflation target shock. There are two variables in each panel, noted on the left of each panel. The solid lines show the left variables, for instance y_t (output gap)[8], and the dotted lines show the right variables, for instance $y_{t|t}$ (expected output gap).

Figure 2.1 shows that firms can perfectly identify economic variables. They have clear information about nominal interest rate and inflation target, and they have noisy information

[8] Since there are only markup shocks and target inflation shocks, output is equal to output gap in this economy.

about markup shocks. Even though the nominal interest rate contains information about both markup shocks and inflation target shocks, they can make use of clear information about inflation target to identify each shocks. Therefore, the equilibrium is identical to the one under full information, where actual variables, z_ts, are equal to their expectations, $z_{t|t}$s. As a result, when a markup shock hits the economy, inflation π_t rises, nominal and real interest rates, i_t and r_t, rise, and output y_t goes down. The situation is not comfortable for the central bank in terms of both output y_t and inflation gap $\pi_t - \pi_t^*$. Then, we turn to the inflation target shock. If the shock hit the target, the target π_t^* rises, and the inflation and the expectation, π_t and $\pi_{t|t}$, rises following the inflation target. The shift of inflation is comfortable for the central bank.

Figure 2.2 shows the IRFs under opaque inflation target. First, we focus on the case of a markup shock in the left panels. We assume that firms can observe nominal interest rate perfectly, which can contain the information about both markup shocks and target shocks. However, since firms don't know that the inflation target is fixed, they cannot identify markup shocks from the shift in nominal interest rate. Even though they have noisy signal about markup shock, it's not enough. They attribute some shift in nominal interest rate to target shocks. Thus, inflation target π_t^* doesn't change while the expectation $\pi_{t|t}^*$ declines. Then, the reaction of inflation π_t and the inflation expectation $\pi_{t|t}$ are lower than that in the case under perfect transparency. However, this is beneficial for the central bank who cares about output and inflation gap. Next, we turn to the case of a target shock in the right panels. Firms use noisy heterogeneous signals and nominal interest rate to identify inflation target. However, they cannot perfectly identify the target shock and attribute some shift in nominal interest rate to a markup shock. Thus, markup μ_t doesn't change while the expectation $\mu_{t|t}$ declines. As a result, the expectation of inflation target $\pi_{t|t}^*$ is lower than the actual target π_t^*, and inflation expectation $\pi_{t|t}$ is lower. Therefore, inflation π_t deviates from the target π_t^*. Contrary to the case of the markup shock, it's the cost of opaque inflation target.

Figure 2.3 shows the case under perfectly transparent inflation target with smaller size of target shocks. Thus, private agents understand that the target inflation does not fluctuate a lot. Note that even though we change the assumption about distribution of shocks, we give a unit of each shock in this exercise. Therefore, the IRFs are the same as Figure 2.1.

Figure 2.4 shows the case under perfectly opaque inflation target with smaller distribution of inflation target shock, changing $\sigma^2_{\varepsilon,\pi*}$ from 0.2 to 0.05. First, we focus on a markup shock in the left panels. Since private agents understand that markup shocks μ_t are dominant in the economy, price setting firms attribute a lot of movement in nominal interest rate i_t to markup shocks. Thus, the rise of expectation of markup $\mu_{t|t}$ and inflation $\pi_{t|t}$ are larger than those in baseline case (Figure 2.2). As a result, inflation π_t is higher. Thus, the benefit of opacity about inflation target is smaller in this environment. Next, we turn to a target shock. Since the markup shocks are now dominant in the economy, nominal interest rate becomes noisier signal about inflation target for firms. Thus, they attribute the shift in nominal interest rate more to markup shocks. The figure shows the decline in $\mu_{t|t}$ is larger and the rise in $\pi^*_{t|t}$ is smaller compared to those in figure 2.2. Thus, inflation expectation $\pi_{t|t}$ reacts less, and inflation π_t deviates more from the target. The cost of inflation target opacity is larger in this environment.

In this analysis we discuss the reaction of the economy to each of shocks to understand the mechanism well. However, this exercise does not consider more realistic environment where both shocks are present. Thus, we consider the case in next section.

2.3.3 Optimal Degree of Transparency

This section investigates optimal transparency about inflation target in terms of a central bank's loss function. We assume that the central bank's objective is to minimize a standard quadratic loss that depends on the variability of inflation gap $\pi_t - \pi^*_t$ and that of output gap

y_t. Specifically, let loss be given by

$$L = \alpha_\pi \sigma_\pi^2 + (1 - \alpha_\pi)\, \sigma_y^2, \tag{2.3.1}$$

where σ_z denotes the variance of z. We assume $\alpha_\pi = 0.5$, where the central bank cares about inflation gap and output gap equally. We compute implied standard deviation for both gaps and the loss from the above equation.

Case 1: Baseline calibration

Figure 2.5 shows the relationship between the degree of transparency about inflation target (horizontal axis), i.e., the size of noise on the inflation target signal $\sigma_{w,\pi*}$, and the loss function defined above (vertical axis). It shows that the loss is smallest when the target is transparent and that transparent inflation target is optimal for a central bank with the loss function.

Figure 2.6 decomposes the loss into the contribution of each of the shocks. Technically, the loss is computed for each of the shocks, assuming that only one of them exists in the economy. It says that in the economy where the only shocks are markup shocks the loss decreases as the inflation target becomes more opaque and that opaque inflation target is the optimal. It shows the benefit of opacity, which we discussed in Section 2.3.2. As the inflation target becomes more opaque, the loss from both gaps decreases because private agents have difficulty to identify detrimental markup shocks, mitigating the bad effect. On the other hand, it says that in the economy where the only shocks are inflation target shocks the loss decreases as the inflation target becomes more transparent, and transparent inflation target is the optimal. It shows the benefit of transparency, which induces the reaction of inflation expectations following the change in the target inflation rate. Thus, there are two opposing effects behind the Figure 5: the benefit of opacity for markup shocks and the benefit of transparency for inflation target shocks, and the figure shows that the latter effect wins as a result of the tug-of-war between the two benefits.

Case 2: Smaller inflation target shocks

Next, we consider the case when the size of inflation target shock is relatively small as in the IRF analysis in Section 2.3.2, changing $\sigma^2_{\varepsilon,\pi*}$ from 0.2 to 0.05. Figure 2.7 shows again the relationship between the degree of transparency of inflation target and the loss. In this case opaque inflation target (right edge) is optimal.

Figure 2.8 shows the same decomposition of loss for each shock as in Figure 2.6. The figure looks the same as Figure 2.6, but the difference is that the loss for inflation target shocks alone is about one-third smaller. Thus, the benefit of transparency on target shocks has a smaller impact on overall loss. Therefore, in Figure 2.7, where inflation target shocks are smaller than in Figure 2.5, in the tug-of-war between the benefit of opacity for markup shocks and the benefit of transparency for target shocks, the former wins.

The result shows that relative size of different shocks is also important to consider the optimal transparency. For example, when the commodity prices are very volatile due to heightened geopolitical risks, the proportion of markup shocks among the sources of economic fluctuations will be higher. According to our results, the cost of revealing the target or preference of central bankers is also higher in this case as it conveys the information of detrimental markup shock to the private agents. Thus, there's a benefit for the central bank to lower the transparency of their target in such an environment.

Case 3: Persistent inflation target shocks

Finally, we consider the case when the target shock is more persistent, changing $\rho_{\pi*}$ from 0.5 to 0.6. Figure 2.9 shows again the relationship between the degree of transparency of inflation target and the loss. It shows that the optimal transparency lies in the mid-point between perfect transparency and perfect opacity. It suggests that the central bank should not go extreme, neither transparent nor opaque, but choose appropriate degree of transparency about inflation target and communicate with private agents.

There are three effects behind this result. The first two, as we have explained, are the benefit of opacity for markup shocks and the benefit of transparency for inflation target shocks. The effects and relative importance of the two are similar to the baseline case. The shape of Figure 2.10, which decomposes the loss into each shock, is similar to Figure 2.6 except for around the midpoint.

Comparing the endpoints in Figure 2.9, the losses are smaller in the transparent case, which indicates that the benefit of transparency for target shocks is stronger. However, the optimal transparency lies in the middle between transparency and opacity, which is due to another benefit of opacity. In a typical New-Keynesian model with perfect information, the inflation gap overshoots in response to an inflation target shock when the shocks are persistent. This is because private agents believe that monetary environment will continue to be accommodative for a long time when the target shocks are persistent, and inflation expectations respond too strongly. This is also seen in Ireland (2007) and Cogley *et al.* (2010). On the other hand, under incomplete information, a part of the interest rate decline is interpreted as a negative markup shock through signaling effect, which suppresses the response of inflation expectations. Figure 2.11 shows the responses of inflation gap to an inflation target shock in the three cases: transparent target, optimal transparency, and opaque target. It shows that the overshooting is exactly canceled out in the optimal transparency case. This reduces the loss due to the inflation gap. In addition, this effect also affects the loss from output gap: the central bank's reaction to overshooting adds additional amplitude to economic activities. Thus, the loss from output gap is also reduced when moderate transparency offsets the overshooting. As a result, the tug-of-war between three effects: this benefit of opacity for target shocks (canceling effect), the benefit of transparency for target shocks, and the benefit of opacity for markup shocks results in the optimal transparency being the middle point. This shows that the persistence of shocks also plays a role for the optimal degree of transparency about inflation target.

2.4 Conclusion

The study examined the optimal degree of transparency for central bank about its inflation target. We employ an imperfect information model, in the spirit of Woodford (2001), where both markup shocks and inflation target shocks hit the economy. In this economy, the central bank has perfect information while private agents do not. Private agents obtain the information about underlying shocks not only through the heterogeneous noisy signals but also through the movements in the policy rate. We assume that the central bank can change the size of noise included in private agents' signal about inflation target, making the target transparent or opaque and partially controlling the information set of private agents. The findings of the paper are mainly two folds. The first finding is that transparent inflation target is not always optimal. Our model shows that the optimal degree of transparency is the result of a tug-of-war between three effects: transparency helps align inflation expectations, transparency reveals inefficient shocks to the economy through the signaling effect of the policy rate, and transparency can trigger an excess response of inflation expectation to the policy target changes. Consequently, it is shown that a transparent target is not necessarily optimal. The second finding is that the optimal degree of transparency depends on the relative size and the persistence of the underlying shocks. In particular, our model shows that when inefficient shocks to the economy are dominant, for example, higher inflation associated with heightened geopolitical risk, the cost of transparency is relatively large, making a transparent target not optimal. These results suggest that central banks need to consider the appropriate amount of communication of their policy objectives, taking into account the various effects it may have.

Finally, we discuss the limitations of our analysis. As noted earlier, there are many previous studies on optimal transparency, and there are other settings and mechanisms. For example, imperfect information for central bank side or the existence of other shocks in the economy are not considered in this study. These settings could add new channels to the effects of inflation target transparency. Another issue is that, although this model basically follows general parameter settings in new Keynesian models, parameters for underlying shocks and noises, for instance, the persistence of shocks, relative size of shocks, and the size of noise, have room for further investigation based on empirical evidence. This study shows that there are several optimal degrees of transparency depending on the parameter values, but by refining or limiting the range of the parameters, it could be possible to conclude that the optimal transparency is uniquely determined. These are issues to be addressed in the future.

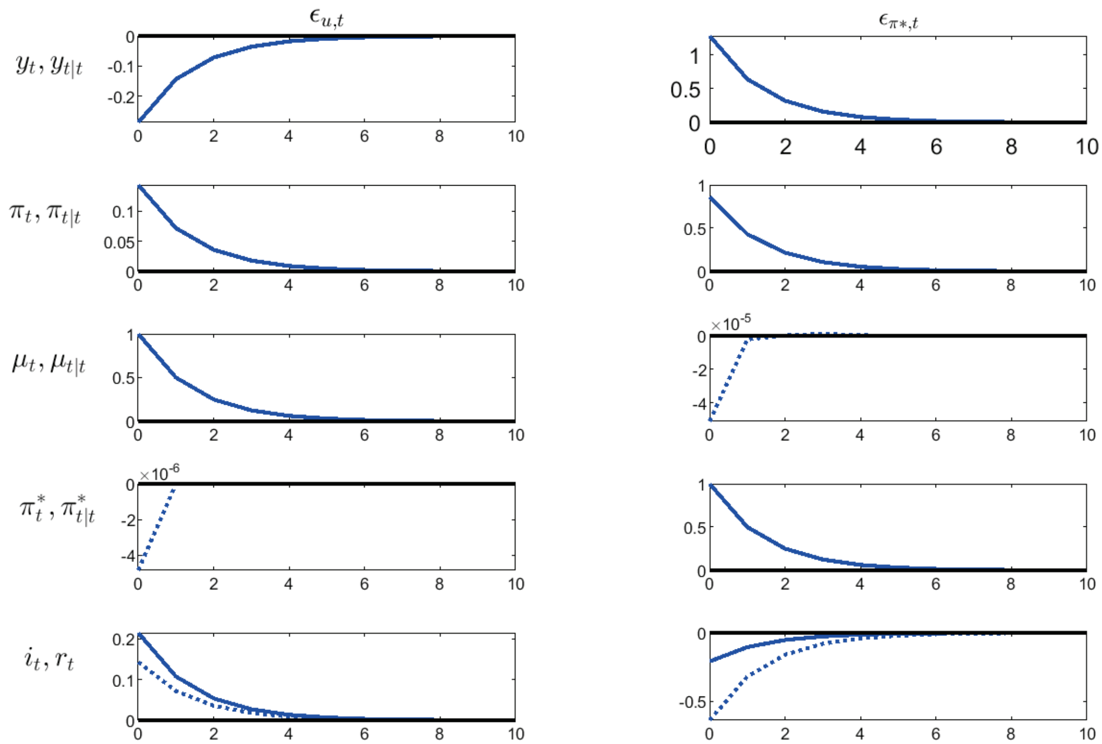


Figure 2.1: Impulse response functions (transparent target, baseline calibration)

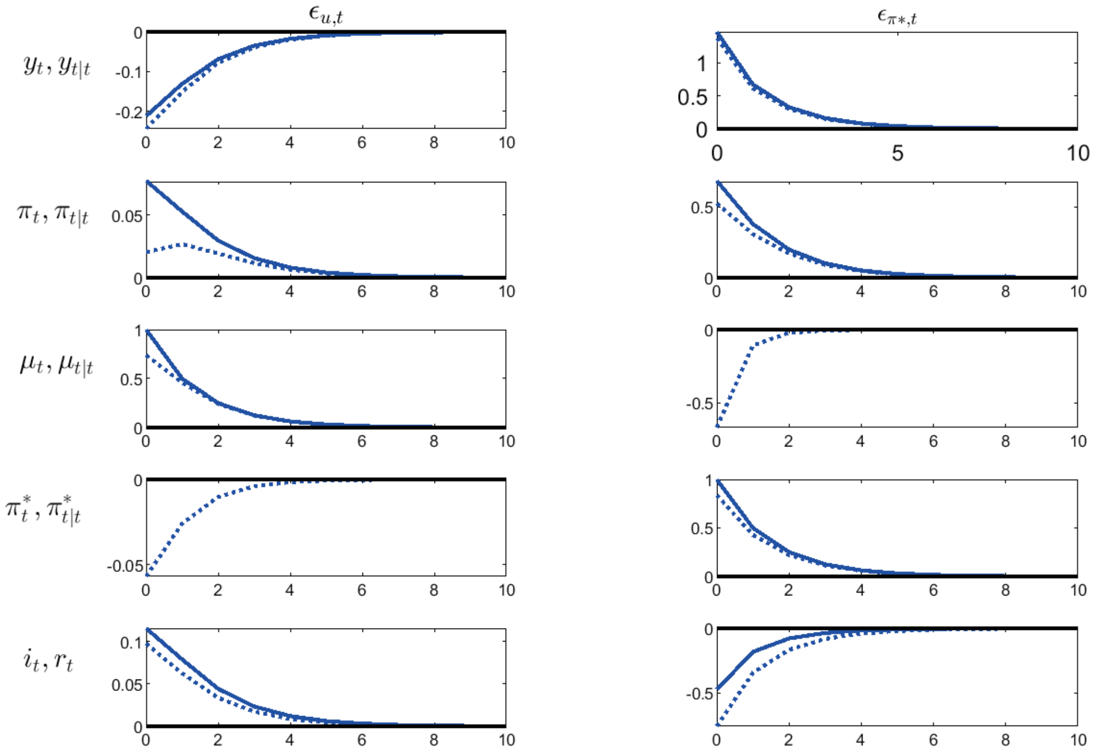


Figure 2.2: Impulse response functions (opaque target, baseline calibration)

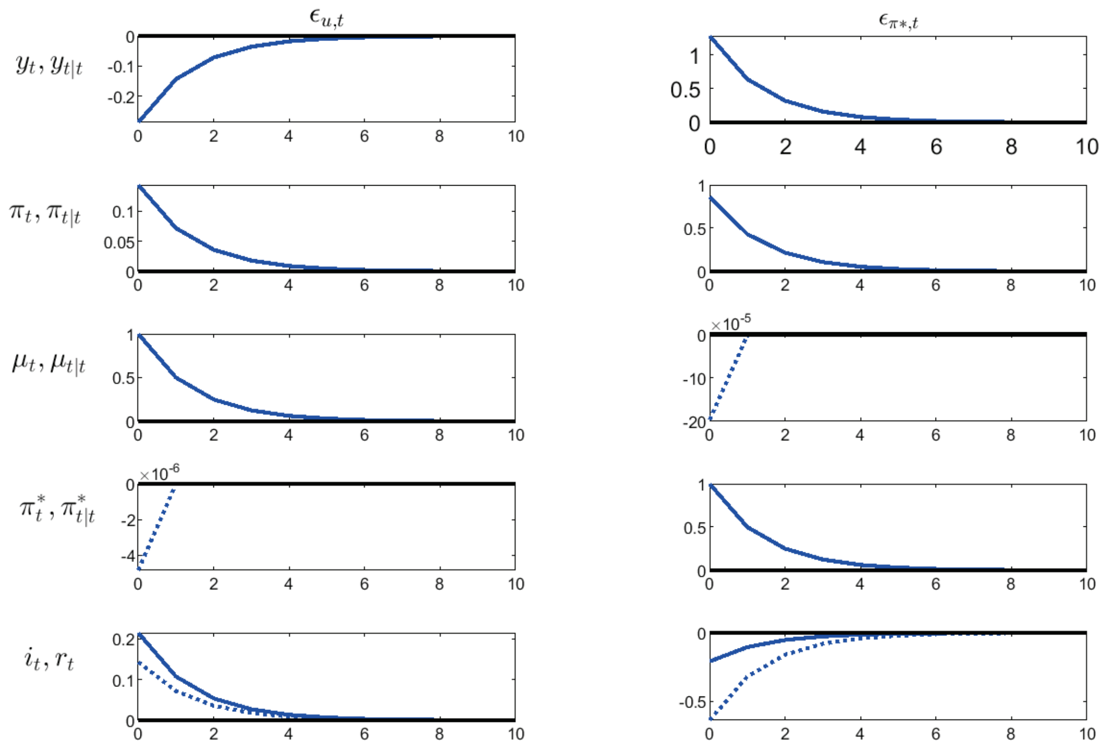


Figure 2.3: Impulse response functions (transparent target, small target shock)

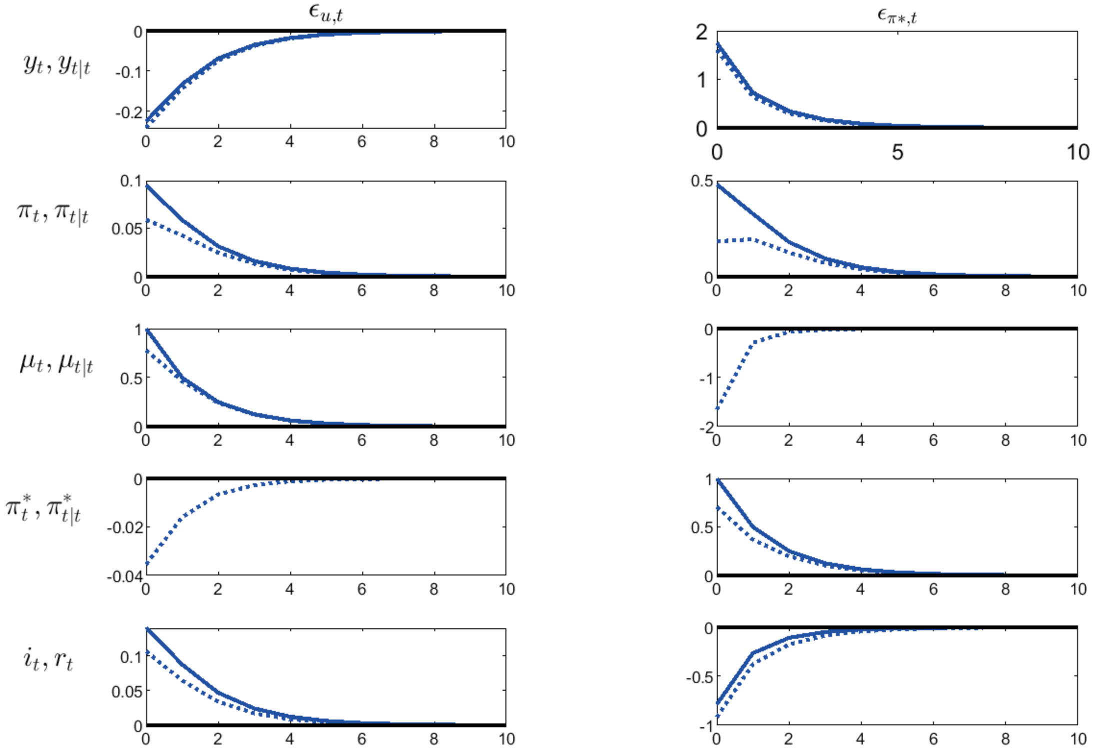


Figure 2.4: Impulse response functions (opaque target, small target shocks)

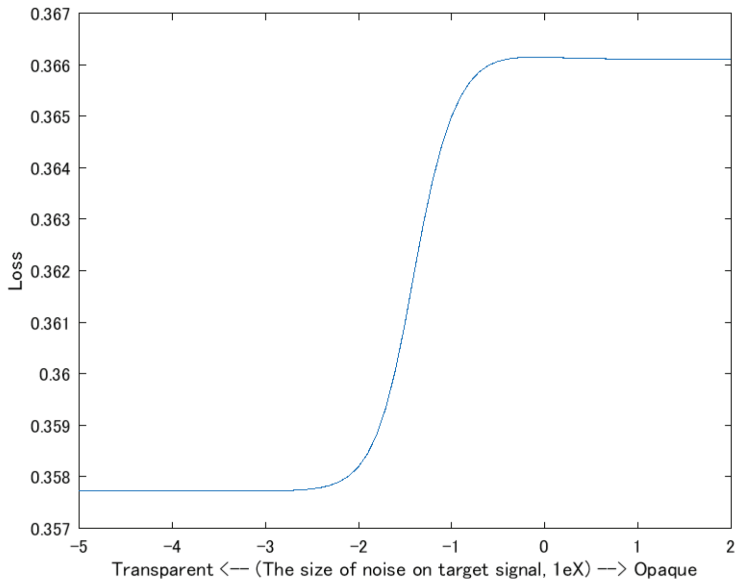


Figure 2.5: Loss function (baseline calibration)

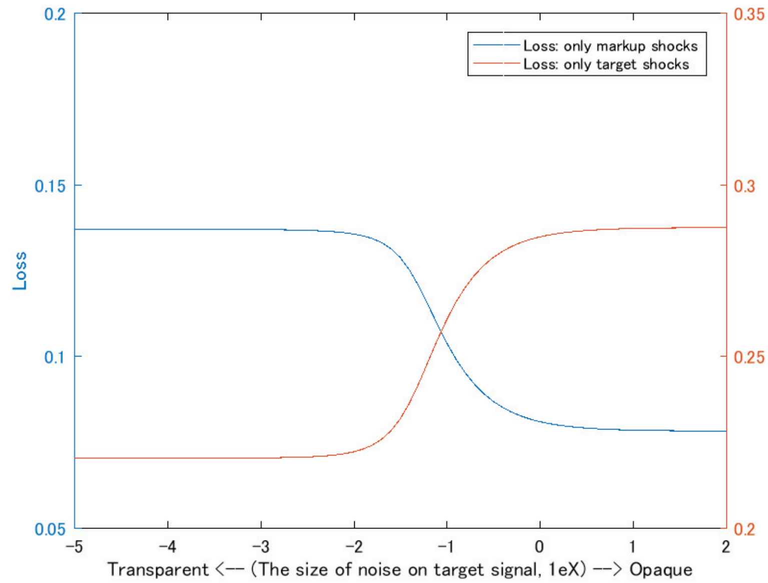


Figure 2.6: Decomposition of loss function (baseline calibration)

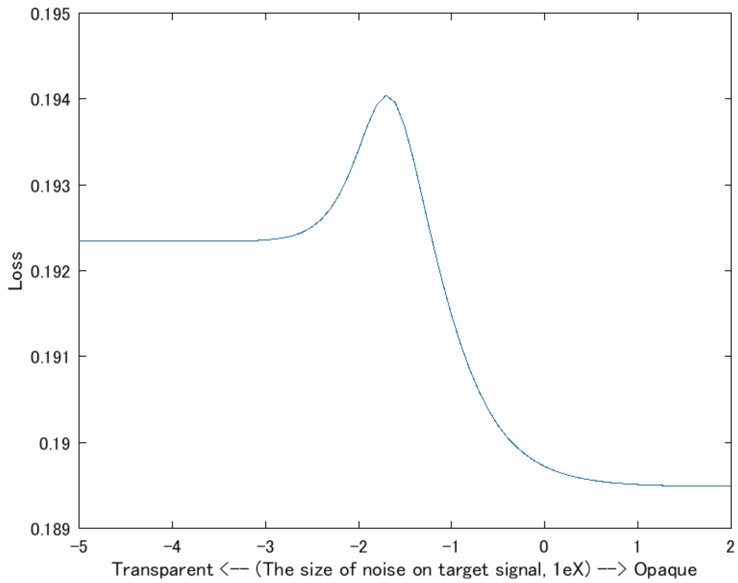


Figure 2.7: Loss function (smaller preference shocks)

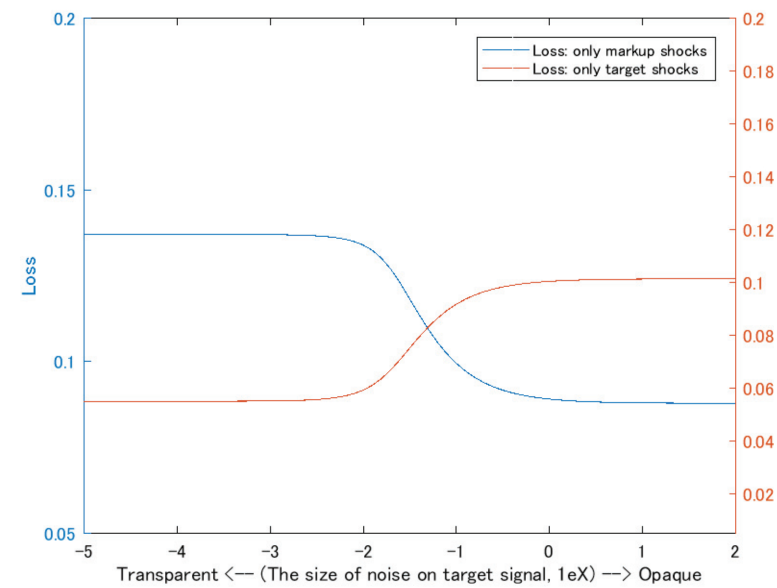


Figure 2.8: Decomposition of loss function (smaller preference shocks)

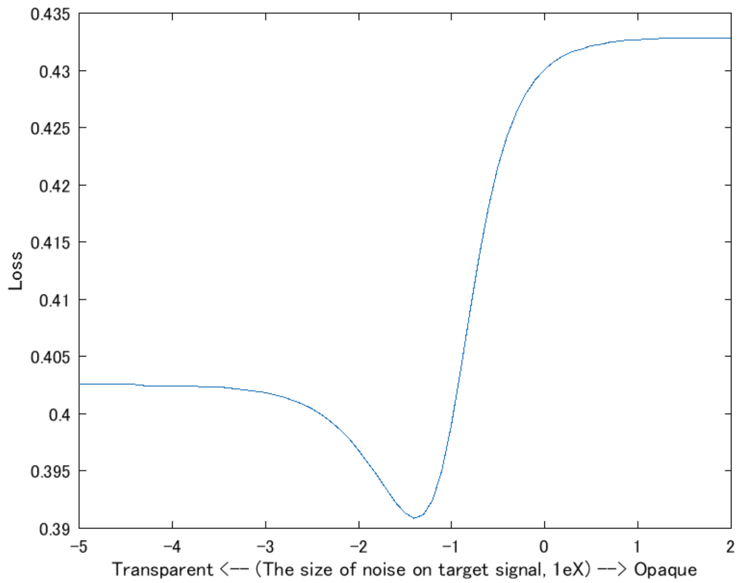


Figure 2.9: Loss function (persistent inflation target shocks)

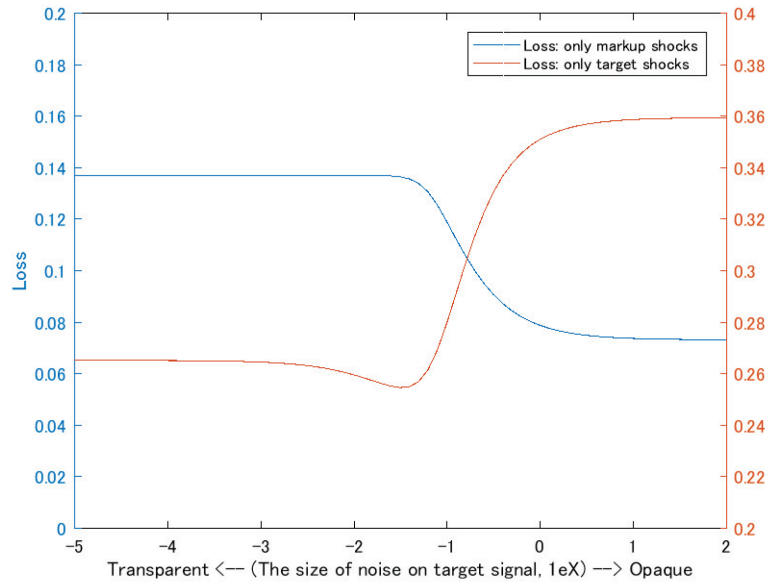


Figure 2.10: Decomposition of loss function (persistent preference shocks)

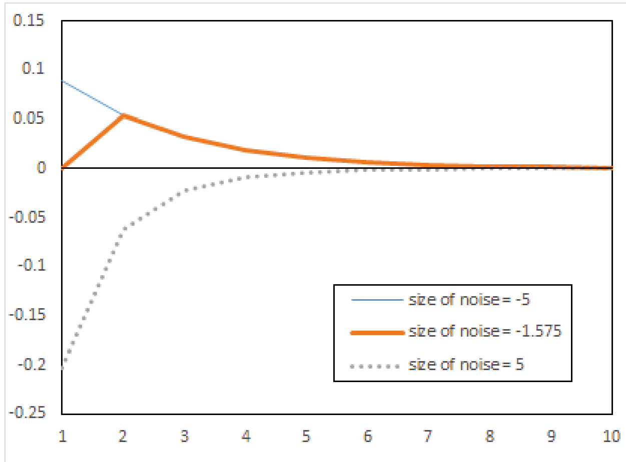


Figure 2.11: Responses of Inflation gap to an inflation target shock

CHAPTER 3

Productivity Slowdown in Japan's Lost Decades: How Much of It Can Be Attributed to Damaged Balance Sheets

3.1 Introduction

Following the global financial crisis, slowdowns of total factor productivity (TFP) growth have been observed in many countries. Eichengreen *et al.* (2017), for example, point out the fact that the world-wide TFP growth rate has declined from 1% in 1996-2006 to 0-0.5% afterwards. They call this recent slowdown in measured TFP growth as the "Global Productivity Slump," and state that "this is one of the most disturbing and, no doubt, important phenomena affecting the world economy." Their cross-country regression analysis suggests that the global financial crisis marked by higher TED spreads negatively affected measured TFP growth across countries. Redmond *et al.* (2016) also investigate the observational relationship between credit conditions and TFP growth particularly in the United States, and obtain some empirical support for the possibility that adverse credit conditions during the global financial crisis dampened TFP growth.

Despite these empirical findings, studies on the structural relationship between financial crises and measured TFP growth rates have been still scarce. To fill this gap, this study examines a cause of this empirical regularity within a dynamic stochastic general equilibrium (DSGE) framework in which financial shocks affect measured TFP growth. Specifically, we focus on the case of Japan during the 1990s and beyond, when the long-lasting slowdown of TFP growth was witnessed following financial crises. There were financial crises during the 1990s in Japan, which lasted from 1992 to 2001 when following the dating adopted by Reinhart and Rogoff (2011). It was triggered by two crises: the bubble burst in February 1991, and the banking crisis that began in November 1997.[1,2] In both episodes, balance sheets, in particular those of the FI sector, were damaged, leading to disruptions in financial intermediation. Figure 3.1 displays the time path of two diffusion indices released from the Bank of Japan. One index shows the financial position of non-financial firms, which is calculated by subtracting "tight" from "easy," and the other index shows the lending attitude of FIs, calculated by subtracting "severe" from "accommodative." Both series agree that credit was severely tightened at the time of the crises.[3] The real economy has been burdened with a persistent economic stagnation during the period. The output growth rate slowed during the early 1990s, and the economy never recovered the growth rate of the 1980s. Hayashi and Prescott (2002), in their pioneering work, therefore coined the period after the early 1990s the "lost decade." Measured TFP also started to fall around the early 1990s. As shown in Figure 3.2, measured TFP grew steadily during the bubble boom period in the late 1980s, but then decelerated dramatically in the early 1990s, and continued growing at a low rate in subsequent years.[4]

Though the financial crisis and a decline in measured TFP coexisted in the same period of time, they are often analyzed separately in the literature on the causes of the lost decades.

[1]The first crisis was initiated by a large decline in land and stock prices. As documented by Bayoumi (2001), it immediately affected the real economy. Financial intermediaries (FIs) held most of their assets in stocks and non-financial firms held most of their assets in land assets at that time. Consequently, the collapse in asset prices eroded their balance sheets. The second crisis was triggered by the abrupt failure of a securities house, Sanyo Securities, the first default in the history of the interbank market in Japan. A large number of financial institutions defaulted due to solvency problems, and the Japan premium, a premium paid for interbank borrowing by Japanese banks relative to their major competitors in the United States and Europe (Peek and Rosengren, 2001), went up. See Nakaso (2001) and Hoshi and Kashyap (2010) for details of how the second crisis occurred.

[2]Throughout this paper, we refer to February 1991 as the period when the bubble economy burst. This is because it is the peak of the business cycle boom that started in the late 1980s. There is, however, no consensus regarding when the bubble economy ended. For instance, Okina *et al.* (2001) consider the period from 1987 to 1990 as the "emergence and expansion of the bubble period," because the simultaneous rise in stock and land prices, economic activity, and money supply was observed during the period.

[3]See the discussion in Peek and Rosengren (1997) regarding how the damaged balance sheets of Japanese banks resulted in a reduction in lending to borrowers overseas.

[4]The average measured TFP growth rate during the 1980s was 1.78% per year. By contrast, the growth rates during the following two decades were 0.77% and 0.31% per year, respectively.

Hayashi and Prescott (2002) use the observed measured TFP series and feed the series into the standard growth model in which TFP moves only in response to exogenous technology movements, and show that the model with the TFP alone accurately replicates the output slump during the early 1990s and beyond.[5] By contrast, Bayoumi (2001) discusses that a disruption in financial intermediation was the key driver of the stagnation after the bubble burst, based on the time-series analysis. Hoshi and Kashyap (2010) also document how a failure of financial institutions has occurred during the banking crisis due to their deteriorated balance sheets, dampening banks' lending and output. These studies, however, do not explore the linkage between financial crises and measured TFP.[6]

In this study, to explain why financial crisis tends to be followed by the stagnant growth of measured TFP, we develop a DSGE model that includes some mechanisms through which financial shocks affect measured TFP growth. Our model is an extended version of (Hirakata *et al.*, 2011, 2013, 2017) (hereafter HSU).[7] The model of HSU is built upon the financial accelerator model of Bernanke *et al.* (1999) (hereafter BGG), where the net worth of (non-financial) entrepreneurs plays an important role in amplifying and propagating exogenous shocks. A series of studies of HSU augment the model of BGG to incorporate credit-constrained (monopolistic) financial intermediaries (hereafter FIs) as well as credit-constrained entrepreneurs, both of which raise external funds by making credit contracts.

[5] As in Hayashi and Prescott (2002), our TFP series is computed from the logarithm of output growth less the weighted average of the logarithm of labor input and capital input growth. There are, however, three differences between our TFP and theirs: (i) the output series that is used for constructing our TFP series is GDP series, while the output series used for constructing their TFP is GNP less government capital consumption; (ii) the capital stock series used for constructing our TFP is adjusted for capacity utilization of the capital stock, while the capital stock series used for constructing their TFP is not adjusted for capacity utilization; and (iii) households' residential and foreign assets are not included in our capital stock series, while these two components are included by Hayashi and Prescott (2002).

[6] The only exception is the empirical work by Caballero *et al.* (2008). They show that due to impairments of balance sheet stemming from the bubble burst and tightened capital requirements, Japanese banks during the 1990s continued misdirected lending to insolvent borrowers (zombies), hampering entries of healthy firms and leading to lower productivity in the economy. The key difference of our paper from Caballero *et al.* (2008) is that it estimates effects of impairments of the balance sheets on productivity using a DSGE framework, explicitly incorporating the general equilibrium effect through prices and wages.

[7] In terms of model structure, our model is close to Gertler and Kiyotaki (2010) and Gertler and Karadi (2011) as well as to HSU (2011, 2013, and 2017). The difference between these two models and our own is that our model provides channels through which FIs' balance sheet conditions affect not only GDP but also measured TFP.

This means that there are two types of credit contracts: contracts between FIs and entrepreneurs, and those between FIs and households.[8] Because of the information asymmetry that is present between borrowers and lenders, both credit contracts involve costly state verifications. That is, whenever the borrowers default, lenders must pay additional costs to assess defaulting borrowers' assets.[9] As a consequence, unexpected shocks to the net worth of FIs as well as to those of entrepreneurs affect aggregate investment by changing funding expenses.

In our extended model, there are multiple channels through which financial shocks affect measured TFP growth. The first channel is *the monitoring cost channel*, which is the direct consequence of disruptions to financial intermediation. A large number of firms and FIs faced repayment problems and defaulted as a result of damaged balance sheets. Other things being equal, an increase in borrower defaults or default probability affects the value-added of FIs not only by reducing the net interest flows from their assets, directly reducing the value-added of FIs, but also by making financial intermediation less efficient ex-post, as it forces lenders to pay additional costs. This is because lenders need to intensify their monitoring of borrowers' activities or liquidate defaulting entities.[10,11] The efficiency of the FIs, therefore, declines, as more resources are spent on these activities. The second channel is *the factor market distortion channel*, which is the indirect effect originating from factor price distortion caused by a deflationary pressure due to disruptions in financial intermediation. As shown by Basu (1995), theoretically, deflation can lead to a decline in measured TFP growth rate, when intermediate goods markets are monopolistically competitive and speeds of price

[8]As we explain below, we make a technical assumption that households make credit contracts with the FI only indirectly through risk-neutral agents called investors. Investors collect households' deposits, lend them to FIs.

[9]Following BGG (1999), we call them monitoring costs. BGG (1999) discuss that this monitoring cost includes the cost of auditing, accounting, and legal costs, as well as losses associated with asset liquidation and interruption of business. These monitoring costs are paid in terms of goods, and not counted as a part of the GDP.

[10]See, for example, Berger and DeYoung (1997). They use the data of commercial banks in the US to show that high levels of non-performing loans Granger-cause reductions in measured cost efficiency, arguing that this observation is consistent with the extra costs of administering these loans.

[11]It is typically the case that the liquidation value is quite low. See, for example, Ramey and Shapiro (2001) for the case of an aerospace plant.

adjustments are different across production inputs such as labor inputs and intermediate goods inputs.[12] In such an economic environment, deflation distorts allocation of production inputs by reducing intermediate inputs, which leads to a fall in measured TFP. The third channel is *increasing returns to scale*, which is pointed out by (Hall, 1988, 1990). If there exist fixed costs in the production function, the output declines due to negative demand shocks more than proportionally to the decline of primary inputs. This means that increasing returns to scale yields pro-cyclical movements of measured TFP growth.[13]

We use Japanese data including measured TFP from 1980:2Q to 2011:4Q to estimate our model parameters, including the size of monitoring costs, and time series of structural shocks, including shocks to the balance sheets of FIs and the goods-producing sector.[14] We show that the model with the estimated parameters delivers a substantial decline in measured TFP in response to a negative shock to the balance sheets of both FIs and the goods-producing sector, through multiple mechanisms mentioned above. We find that if the contribution of shocks to balance sheets had been absent, measured TFP growth rates during the 1990s would have been on average 0.78 percentage point higher than the actual growth rate. In particular, without the contribution of shocks to the balance sheets of FIs, measured TFP growth rates would have been on average 0.84 percentage point higher than the actual growth rate. Given that the actual measured TFP growth rate during the 1990s was on average 0.77%, this means that measured TFP growth rates would have been more than twice as high as it actually was.

Our study is built upon three strands of literature. The first strand of literature including Guerrón-Quintana and Jinnai (2014), Anzoategui *et al.* (2019) and Garcia-Macia (2017) studies how a financial crisis lowers the productivity of the economy. These studies typically

[12]Whether or not intermediate goods prices fall at a slower pace depends on the degree of nominal rigidity of intermediate inputs and other production inputs. We document in the estimation analysis below that in Japan the nominal rigidity is indeed higher and therefore price adjustments are slower for intermediate inputs.

[13]We thank the referee for pointing out this channel.

[14]In this study, we use the term "shocks to the balance sheets" and "shocks to the net worth" interchangeably.

stress a channel through which a financial crisis hampers development and/or adoption of new technologies. By contrast, our study stresses the channel where a financial crisis worsens inefficiency arising from imperfect competition and lowers productivity, based on theoretical results found in Basu (1995) or Basu and Fernald (2002). The second strand of literature includes studies such as Nolan and Thoenissen (2009), Hirakata *et al.* (2011), and Christiano *et al.* (2014) (hereafter CMR).[15] They estimate a DSGE model with a financial friction to quantitatively assess contributions of net worth shocks to firms or banks' balance sheets to output variations in the U.S., in particular those during the global financial crisis. Our study differs from them in terms of its focus on measured TFP rather than output. The third strand of literature includes studies on the cause of Japan's lost decades. While there are several candidate explanations, existing studies, including Hayashi and Prescott (2002), Bayoumi (2001), Nakakuki *et al.* (2004), Kawamoto and others (2005), and Kwon *et al.* (2015), agree that the slowdown of measured TFP growth or financial crisis is the most important element. Our study offers a novel insight to this literature by showing that both a decline in measured TFP and that in output are the consequence of impairments of assets in balance sheets of FIs and firms that were triggered by the financial crisis during the lost decades.

This study is divided into five sections, the first being this introduction. Section 2 describes our model. Section 3 estimates our model using Japanese data and shows how measured TFP in our model responds to shocks to balance sheets of the FI and the goods-producing sectors. Section 4 assesses the quantitative contribution of shocks to balance sheets on the TFP slowdown in Japan during the early 1990s and beyond. Section 5 draws some conclusions.

[15] Chugh (2013) and Mumtaz and Zanetti (2016) enrich the financial accelerator model of BGG (1999) to introduce search and matching frictions in the labor market.

3.2 The economy

The outline of the model is shown in Figure 3.3. The economy consists of four sectors: the household sector, the financial intermediary (FI) sector, the goods-producing sector, and the government sector. The settings of FI sector are based on the studies of HSU (2011, 2013, and 2017). The key difference of HSU (2011, 2013, and 2017) from the standard financial accelerator model, such as BGG (1999), is that there are two types of credit-constrained borrowers, FIs and entrepreneurs, that both rely on external finance. Because the FIs are monopolistic, they earn positive profits from the credit contracts. This contrasts with BGG (1999) where FIs receive an expected return equal to the opportunity cost and make zero profit.[16] The credit-constrained FIs make credit contracts with delegates of households, called investors, raising the external funds and lend to entrepreneurs what they raise from the deposit contract and their own net worth.[17] As in BGG (1999), credit-constrained entrepreneurs also make credit contracts with the FIs and invest what they borrow from the FIs and their own net worth for their projects. Information friction is present in both types of credit contracts, and the borrowing rates in the contracts are contingent on the sizes of borrowers' net worth. As a result, unexpected shocks to the net worth of FIs as well as to those of entrepreneurs affect aggregate output by changing funding expenses. We further extend the model of HSU by explicitly incorporating intermediate input usage in goods production function. Following Basu (1995), our model incorporates the input-output production structure and the monopolistic competition in the intermediate inputs market. By doing so, we can introduce a mechanism through which allocations of different production inputs, such as labor inputs and intermediate goods inputs, affect measured TFP growth. Other settings, such as the household and the government sector, are standard that are

[16]The setting of HSU is in line with the existing studies such as Klein (1971), Monti (1972), and Freixas and Rochet (2008).

[17]The FIs in the settings of HSU are broadly defined as agents that intermediate funds from ultimate lenders, the households, to ultimate borrowers, the entrepreneurs. They include financial institutions other than banks, including security, insurance, pension, and a shadow banking system.

similar to those used in existing DSGE models including CMR (2014).

3.2.1 Credit contracts

The participants of credit markets are investors, FIs and entrepreneurs. There are two types of credit contracts, FE and IF contracts. In the FE contracts, the lender is an FI and the borrower is a large number of entrepreneurs. In the IF contracts, the lenders are investors and the borrower is a large number of FIs. The lending rates associated with the two credit contracts are determined as the solution of an FI's profit maximization problem. In this section, we explain the outline of credit contracts. The settings for credit contracts are the same as those used in HSU (2011, 2013, and 2017).[18]

Outline of credit contracts

Flow of funds in the model

In each period, investors collect deposits D_t with the risk-free rate R_t from households, and invest all of what they collect as loans to a large number of FIs through the IF contracts with the lending rate $r_{F,t+1}$. FIs lend what they borrow from investors and their net worth $N_{F,t}$, $D_t + N_{F,t}$, to a large number of entrepreneurs through the FE contracts with the lending rate $r_{E,t+1}$. Entrepreneurs hold net worth $N_{E,t}$ and conduct projects of the size $Q_t K_t$, where Q_t is the price of capital and K_t is capital. The balance sheet of the FIs and entrepreneurs is described by the following two equations.

$$
\begin{aligned}
\overbrace{Q_t K_t - N_{E,t}}^{\text{Lending to entrepreneurs}} &= \overbrace{D_t}^{\text{Borrowings from investors}} + \overbrace{N_{F,t}}^{\text{FI's net worth}}, \\
\overbrace{Q_t K_t}^{\text{Investment on project}} &= \overbrace{Q_t K_t - N_{E,t}}^{\text{Borrowings from a FI}} + \overbrace{N_{E,t}}^{\text{Entrepreneurial net worth}},
\end{aligned}
$$

where the left and right hand side of each equation stands for the asset and liability side of

[18] Online appendix of HSU (2017) provides full descriptions of the model.

each entity, respectively.

Credit contracts

The return to each entrepreneur's project is given by the ex post aggregate return to capital, which we denote by $R_{E,t+1}$, as well as an idiosyncratic productivity shock $\omega_{E,t+1} > 0$. The latter shocks are independently drawn by each entrepreneur. Their mean is one and the standard deviation is σ_E. An entrepreneur defaults whenever it draws $\omega_{E,t+1}$ that is so low so that the entrepreneur cannot repay its debt to the lending FI with the borrowing rate $r_{E,t+1}$. We denote the cut-off value of this idiosyncratic productivity shock by $\overline{\omega}_{E,t+1}$. Note that the borrowing rate $r_{E,t+1}$ is related to the cut-off value $\overline{\omega}_{E,t+1}$ as follows.

$$r_{E,t+1} \equiv \frac{\overline{\omega}_{E,t+1} R_{E,t+1} Q_t K_t}{Q_t K_t - N_{E,t}}$$

Because of informational friction, the lending FI can observe the realization of idiosyncratic shocks only by paying the monitoring cost. A FI does not monitor the size of an idiosyncratic productivity shock $\omega_{E,t+1}$ for borrowers who repay their debt (i.e., those whose idiosyncratic shock is above the cut-off value $\overline{\omega}_{E,t+1}$). When a borrower declares the default (i.e., when an idiosyncratic shock is below the cut-off value $\overline{\omega}_{E,t+1}$ for the borrower), the FI pays the monitoring costs to monitor the size of its idiosyncratic productivity shock $\omega_{E,t+1}$ and takes all of what the borrower has $\omega_{E,t+1} R_{E,t+1} Q_t K_t$. Similar to BGG (1999), the expected return to an entrepreneur's project is divided to the borrower and lender in the FE contract by this cut-off value $\overline{\omega}_{E,t+1}$ as follows.

$$\overbrace{R_{E,t+1} Q_t K_t}^{\text{Expected return to an entrepreneur's project}} = R_{E,t+1} Q_t K_t \times \left[\overbrace{1 - \Gamma_{E,t+1}}^{\text{Expected share of profits going to the entrepreneur if it does not default}} + \overbrace{\Gamma_{E,t+1}}^{\text{Expected gross share of profits going to the FI}} \right]$$

$$
= R_{E,t+1} Q_t K_t \times \begin{bmatrix} 1 - \Gamma_{E,t+1} \\ + \overbrace{\Phi_{E,t+1}}^{\text{Expected net share of profits going to the FI}} \\ + \overbrace{\mu_E G_{E,t+1}}^{\text{Expected monitoring cost paid by the FI}} \end{bmatrix},
$$

where

$$
\Gamma_{E,t+1} \equiv \overline{\omega}_{E,t+1} \int_{\overline{\omega}_{E,t+1}}^{\infty} dF_E(\omega_E) + \int_0^{\overline{\omega}_{E,t+1}} \omega_E dF_E(\omega_E), \tag{3.2.1}
$$

$$
\Phi_{E,t+1} \equiv \overline{\omega}_{E,t+1} \int_{\overline{\omega}_{E,t+1}}^{\infty} dF_E(\omega_E) + (1 - \mu_E) \int_0^{\overline{\omega}_{E,t+1}} \omega_E dF_E(\omega_E), \tag{3.2.2}
$$

$$
G_{E,t+1} \equiv \int_0^{\overline{\omega}_{E,t+1}} \omega_E dF_E(\omega_E). \tag{3.2.3}
$$

Here, $F_E(\bullet)$ is the cumulative distribution function of idiosyncratic productivity shocks ω_E, and $\mu_E > 0$ is the parameter that governs the size of monitoring costs.

Similarly, an FI's net profit is affected by an idiosyncratic shock $\omega_{F,t+1} > 0$. This shock represents the technological differences across the FIs, for example, those associated with risk management, the maturity mismatch control, loan securitization, and cyber risks facing a specific FI.[19] The shock is independently drawn by each FI. Their mean is one and the standard deviation is σ_F. Again, there is the cut-off value, which we denote by $\overline{\omega}_{F,t+1}$, and the borrowing rate $r_{F,t+1}$ is related to this value by the following equation.

$$
r_{F,t+1} \equiv \frac{\overline{\omega}_{F,t+1} \Phi_{E,t+1} R_{E,t+1} Q_t K_t}{Q_t K_t - N_{E,t} - N_{F,t}}.
$$

The expected earnings that an FI receives from entrepreneurs is divided to the FI and

[19]This idiosyncratic shock can be alternatively interpreted as common shocks specific to a group of firms, such as those in the same industry or region. Suppose that there is an infinite number of industries (regions) that consist of an infinite number of firms and that each FI chooses either one of the industries (regions). Industry-specific (region-specific) shocks affect the individual FI's earning as if the FI is hit by the idiosyncratic productivity.

the lenders (investors) in the IF contract by the cut-off value $\overline{\omega}_{F,t+1}$ as shown below.

$$
\begin{aligned}
\overbrace{\Phi_{E,t+1}R_{E,t+1}Q_tK_t}^{\text{Expected earnings of an FI}} &= \Phi_{E,t+1}R_{E,t+1}Q_tK_t \\
&\times \left[\begin{array}{l} \overbrace{1-\Gamma_{F,t+1}}^{\text{Expected share of profits going to the FI if it does not default}} \\ + \overbrace{\Gamma_{F,t+1}}^{\text{Expected gross share of profits going to investors}} \end{array}\right]
\end{aligned}
$$

$$
= \Phi_{E,t+1}R_{E,t+1}Q_tK_t \times \left[\begin{array}{l} 1-\Gamma_{F,t+1} \\ + \overbrace{\Phi_{F,t+1}}^{\text{Expected net share of profits going to investors}} \\ + \overbrace{\mu_F G_{F,t+1}}^{\text{Expected monitoring cost paid by investors}} \end{array}\right],
$$

where $\Gamma_{F,t+1}$, $\Phi_{F,t+1}$, and $G_{F,t+1}$ are defined in the similar way to those defined in the equations (3.2.1), (3.2.2), and (3.2.3), with $F_E(\bullet)$ in these equations replaced with $F_F(\bullet)$, where $F_F(\bullet)$ is the cumulative distribution function of idiosyncratic shocks ω_F. Note that $\mu_F > 0$ is the parameter that governs the size of monitoring costs.

FIs' optimization problem

The two cut-off values $\overline{\omega}_{E,t+1}$ and $\overline{\omega}_{F,t+1}$ (or equivalently lending rates $r_{E,t+1}$ and $r_{F,t+1}$) and the total amount of lending $Q_tK_t - N_{F,t} - N_{E,t}$ are chosen by FIs so as to maximize their expected profits, given that the participation constraints of investors and entrepreneurs are satisfied. Formally, FIs' optimization problem is described as follows.

$$
\max_{\overline{\omega}_{E,t+1}, \overline{\omega}_{F,t+1}, \text{ and } Q_tK_t - N_{F,t} - N_{E,t},} \left(1-\Gamma_{F,t+1}\right)\Phi_{E,t+1}R_{E,t+1}Q_tK_t \tag{3.2.4}
$$

s.t.

$$
\begin{aligned}
\Phi_{F,t+1}\Phi_{E,t+1}R_{E,t+1}Q_tK_t &\geq R_t\left(Q_tK_t - N_{F,t} - N_{E,t}\right), && (3.2.5)\\
\left(1-\Gamma_{E,t+1}\right)R_{E,t+1}Q_tK_t &\geq R_{E,t+1}N_{E,t}. && (3.2.6)
\end{aligned}
$$

The inequality (5) is the participation constraint of investors and the inequality (6) is the participation constraint of entrepreneurs. We assume that investors can alternatively invest in the risk-free asset if they do not participate in the IF contracts and that entrepreneurs can alternatively conduct the investment project by using only their net worth $N_{E,t}$ without borrowing funds from an FI. The two participation constraints (3.2.5) and (3.2.6) above say that cut-off values and the size of an FI's lending are set by the FI so that investors and entrepreneurs are better off participating in the IF and FE contracts compared to cases under their alternative investment decisions.[20,21]

The optimization problem for FIs in our model is similar to, but different from that used in Bernanke and Gertler (1989) (hereafter BG) and BGG (1999). In their models, the only borrower of a credit contract is an entrepreneur that maximizes its expected profit, subject to the lender's participation constraint where the lender's revenue from the credit contract must be higher than its opportunity cost. In our model, FIs maximize the expected profits so that the participation constraint of the investors (5) and the participation constraint of entrepreneurs (6) are satisfied. In the FE contract, lenders, namely the FIs, make the take-it-or-leave-it offer to entrepreneurs, but their ability to lend is limited because of the following two reasons. First, FIs are not able to purchase capital goods from the capital goods producers nor lend capital goods to goods producers, unlike entrepreneurs. Therefore, FIs need to be generous to entrepreneurs, so that the entrepreneurs are willing to participate in the credit contract. In the FE contracts, entrepreneurs' expected payoff from the credit contract is set higher or at least equal to what they would receive if they do not participate in the credit contract. Second, since FIs are borrowers in the contracts with investors, they

[20] In the FE contract, the default probability of FIs does not affect the expected income earned by the entrepreneurs, as is shown in the participation constraint of entrepreneurs (6). This is because FIs' idiosyncratic productivity shocks $\omega_{F,t+1}$ arrive only after entrepreneurs repay the debt to the FIs.

[21] In our model, entrepreneurs are not able to choose FIs and borrow only from a specific FI, and the FI has a monopolistic power over its borrowers, setting lending rate so as to maximize its expected profit. Our preferred interpretation of this relationship between the entrepreneurs and each FI in our model is that it reflects a form of relationship banking that is seen in the actual economy. Existing studies, including for example, Berger and Udell (1995), agree that the relationship tends to be long-lived, since the borrower's information collected over a long period benefits both parties.

face the problem similar to what entrepreneurs face in BG (1989) and BGG (1999). Because FIs do have insufficient net worth, it is necessary for FIs to get investors to participate in credit contracts as well. In IF contracts, investors' expected payoff from the credit contract is set higher or at least equal to what they would receive if they do not participate in the credit contract. Under this setting, FIs cannot raise unlimited amounts of money from investors. Because of the capital market frictions similar to BG (1989) and BGG (1999), in the IF contracts, the external finance premium depends inversely on the share of the capital investment that is financed by the net worth of borrowers, namely $Q_t K_t / (N_{E,t} + N_{F,t})$. Other things being equal, as the capital investment $Q_t K_t$ becomes larger, FIs need to promise in advance to pay higher interest rates so that investors will be willing to participate in funding contracts. FIs cannot pass on this high interest rate burden to entrepreneurs because FIs also need the entrepreneurs to participate in the FE contract. If they were to pass it on, the condition of participation of the entrepreneur would not be met. Therefore, as FIs increase their borrowing $Q_t K_t - N_{E,t} - N_{F,t}$, FIs need to bear a higher borrowing rate and will not invest indefinitely. As a result, as discussed below, the net worth of the FIs as well as that of the entrepreneur affects the lending rate in our model, as opposed to that only the net worth of the entrepreneur matters in BG (1989) and BGG (1999)'s model.

Effects of net worth on size of investment and monitoring costs

Similar to BGG (1999), the net worth in the two sectors $N_{F,t}$ and $N_{E,t}$ inversely affects lending rates $r_{F,t+1}$ and $r_{E,t+1}$ in the credit contracts, influencing the size of capital purchases $Q_t K_t$ and monitoring costs $R_{E,t+1} Q_t K_t \mu_E G_{E,t+1}$ and $\Phi_{E,t+1} R_{E,t+1} Q_t K_t \mu_F G_{F,t+1}$.[22] To see this, following BGG (1999), we conduct a numerical exercise to illustrate the relationship

[22] The mechanism that a scarce net worth of borrowers of credit contract relative to the size of capital purchases is also seen in the model of BG (1989) and BGG (1999). Due to financial friction that arises from information asymmetry between lenders and borrowers, lenders require a higher lending rate when borrowers' net worth is small and therefore default probability of the borrowers is higher. Because there are two types of borrowers in our model, borrowers of the IF contracts, i.e., FIs and borrowers of the EF contracts, i.e., entrepreneurs and the two types of credit contracts are chained, lending rates facing the ultimate borrowers, i.e., entrepreneurs are affected by net worth of both FIs and entrepreneurs.

among these variables. The top left panel of Figure 3.4 displays the supply curve for capital stock $Q_t K_t$ derived from the first order conditions of an FI's optimization problem (3.2.4), (3.2.5), and (3.2.6), as well as the demand curve for the capital stock. To do the simulation, we calibrate the model using the parameter values in Section 3, and set the values of net worth of the two sectors at the steady state value. The y-axis indicates the ratio of the cost of the external finance to the risk-free rate, which is interpreted as the external finance premium, $R_{E,t+1} R_t^{-1}$, and the x-axis indicates the quantity of capital purchased relative to our baseline steady state. The demand curve is given by the horizontal line, since the return to capital relative to the risk-free rate, which is determined in the goods market, is equated to the external finance premium at the equilibrium. The supply curve is upward sloping, reflecting the funding cost whose size is determined by the size of the net worth. For capital purchases that can be financed by the sum of FIs' and entrepreneurs' net worth $N_{F,t} + N_{E,t}$, which in our baseline model is $Q_t K_t < 0.7$, the cost of funds is close to the risk-free rate. The cost of funds starts to rise as the capital purchases exceed 0.7.

The reason why the cost of funds increases with the size of capital purchases is because expected default probabilities of borrowers increase, as shown in the bottom two panels, and monitoring costs that lenders need to pay increase, as shown in the upper right panel. In the FE contracts, when net worth of an entrepreneur is small relative to the capital purchases, an FI sets a higher lending rate $r_{E,t+1}$, or equivalently a higher cut-off value $\overline{\omega}_{E,t+1}$, since the expected default probability of the borrower is high and therefore monitoring costs are expected to be high. Similarly, when net worth of an FI is small, the FI sets a higher cut-off value $\overline{\omega}_{F,t+1}$ and compensates for the higher monitoring costs that investors' need to pay if the borrowing FI defaults so that investors' participation constraint is satisfied.

The thick solid lines and dotted lines depict the external finance premium, the expected default probabilities, and the monitoring costs, when the net worth of FIs or that of both the FIs and entrepreneurs drops by 10%. A decline in net worth brings about an upward shift of the supply curve, leading to a rise in the monitoring costs and a decline in the quantity of capital purchased. As we discuss below, both an increase in monitoring costs and a decline in capital purchases lower measured TFP through the monitoring costs channel and factor markets distortion channel, respectively.

Dynamic behavior of net worth

The main source of net worth accumulation is the earnings from the credit contracts discussed above. In addition, there are two other sources of earnings. First, and more importantly, the net worth accumulation is affected by exogenous disturbances $\varepsilon_{N_{F,t+1}}$ and $\varepsilon_{N_{E,t+1}}$. These shocks are i.i.d. and orthogonal to the earnings from the credit contracts. Existing studies, such as Gilchrist and Leahy (2002) and Nolan and Thoenissen (2009), have already incorporated the same class of shocks to their DSGE model and assessed implications of these shocks. In particular, Nolan and Thoenissen (2009) find that these shocks account for a large part of the variations in GDP in the U.S. These studies interpret net worth shocks to include "asset bubble and burst of asset bubble," "irrational exuberance," or an "innovation in the efficiency of credit contracts," and we follow the interpretations. Our preferred interpretation is that these shocks capture impairments of assets in balance sheets of FIs and the goods-producing sector that occurred during the crisis period in Japan.

Second and less importantly, the FIs and entrepreneurs inelastically supply a unit of labor to the goods producers and receive in return labor income that is depicted by $W_{F,t}$ and $W_{E,t}$, respectively.[23]

The aggregate net worth of the FIs and the entrepreneurs then evolve according to equations below:

$$N_{F,t+1} = \gamma_F V_{F,t+1} + \frac{W_{F,t}}{P_t} + \varepsilon_{N_{F,t+1}}, \text{ and} \tag{3.2.7}$$

$$N_{E,t+1} = \gamma_E V_{E,t+1} + \frac{W_{E,t}}{P_t} + \varepsilon_{N_E,t+1}, \tag{3.2.8}$$

[23] See BGG (1999) for the reason for introducing an inelastic labor supply from the FIs and the entrepreneurs.

with

$$
\begin{aligned}
V_{F,t+1} &\equiv (1-\Gamma_{F,t+1})\,\Phi_{E,t+1}R_{E,t+1}Q_tK_t, \text{ and} \\
V_{E,t+1} &\equiv (1-\Gamma_{E,t+1})\,R_{E,t+1}Q_tK_t.
\end{aligned}
$$

Here, P_t denotes the nominal price of consumption goods. The first, second, and third terms in these equations above stand for changes in net worth associated with credit contracts, inelastic labor supply, and net worth shocks. Following BGG (1999), we assume that FIs and entrepreneurs survive into the next period with a probability γ_F and γ_E, and those who are in business in period t and fail to survive into period $t+1$ consume $(1-\gamma_E)\,V_{E,t+1}$ and $(1-\gamma_F)\,V_{F,t+1}$ and exit from the economy.

3.2.2 Households

Settings

There is a continuum of households indexed by $h \in [0,1]$. A household h is an infinitely-lived representative agent with preferences over consumption $C_t(h)$ and labor input $L_t(h)$ as described in the expected utility function:

$$
U_t \equiv \mathrm{E}_t\left[\sum_{s=0}^{\infty}\beta^q\left[\ln\left(C_{t+q}(h)-\rho_h C_{t+q-1}(h)\right)-\varphi\frac{L_{t+q}(h)^{1+v}}{1+v}\right]\right], \tag{3.2.9}
$$

where $\beta \in (0,1)$ is the discount factor, $\rho_h \in (0,1)$ is the degree of internal habit persistence in consumption preferences, $v > 0$ is the inverse of the Frisch labor-supply elasticity, and φ is the weighting assigned to leisure. The budget constraint for household h is given by

$$
C_t(h)+S_t(h) \leq \left[\begin{array}{c} \frac{W_t(h)L_t(h)}{P_t}-\frac{\kappa_w}{2}\left(\frac{W_t(h)}{W_{t-1}(h)}-1\right)^2\frac{W_tL_t}{P_t} \\ +R_{t-1}S_{t-1}(h)+\frac{\Omega_t(h)-\tau_t(h)}{P_t} \end{array}\right], \tag{3.2.10}
$$

where $S_{t-1}(h)$ is the real saving, R_t is the real interest rate on deposit, $\Omega_t(h)$ is the nominal profit returned to the household, and τ_t is the lump-sum nominal tax taken by the government. $W_t(h)$ is the nominal wage set by a household h and W_t is the aggregate index of the nominal wage. The second term in the right hand side of the equation stands for the nominal cost associated with adjusting nominal wage $W_t(h)$, and κ_w is the parameter that governs the size of the adjustment cost.

Labor supply decision

A household h has monopolistic power in its differentiated labor input $L_t(h)$. The demand of the differentiated labor is given by

$$L_t(h) = \left(\frac{W_t(h)}{W_t}\right)^{-\theta_{W,t}} L_t, \tag{3.2.11}$$

where L_t is the aggregate index of labor inputs that is defined as

$$L_t = \left[\int_0^1 L_t(h)^{(\theta_{W,t}-1)/\theta_{W,t}}\, dh\right]^{\theta_{W,t}/(\theta_{W,t}-1)},$$

where $\theta_{W,t} \in (1, \infty)$ is the time-varying elasticity of labor demand for differentiated labor input with respect to wages.

3.2.3 Goods producers

Settings

The goods producers are standard except that the goods they produce serve not only as final goods but also as intermediate goods, as in Basu (1995), and goods used for financial intermediation activity, as in CMR (2014). We assume that the goods-producing sector comprises a continuum of firms, each producing differentiated products, as indexed by $l \in [0, 1]$. We use $Y_{g,t}$ to denote the gross output of the composite that is produced from the differentiated products $\{Y_{g,t}(l)\}_{\ l\in[0,1]}$. The production function of the composite is

$$Y_{g,t} = \left[\int_0^1 Y_{g,t}(l)^{(\theta_{P_Y,t}-1)/\theta_{P_Y,t}}\ dl\right]^{\theta_{P_Y,t}/(\theta_{P_Y,t}-1)},$$

where $\theta_{P_Y,t} \in (1,\infty)$ denotes the time-varying elasticity of substitution between differentiated products. The composite is produced by an aggregator that faces perfect competition. The demand function for the differentiated product produced by firm l is derived from the optimization behavior of the aggregator and is represented by

$$Y_{g,t}(l) = \left[\frac{P_t(l)}{P_t}\right]^{-\theta_{P_Y,t}} Y_{g,t}, \tag{3.2.12}$$

where $\{P_t(l)\}_{\ l\in[0,1]}$ is the nominal price of the differentiated products. These prices are related to the nominal price of the final goods by

$$P_t = \left[\int_0^1 P_t(l)^{1-\theta_{P_Y,t}}\, dl\right]^{\frac{1}{1-\theta_{P_Y,t}}}.$$

The composite serves either as final goods, such as consumption goods and investment goods, as intermediate production inputs, or as goods that are used for monitoring costs. The allocation of the gross output is given by

$$\begin{aligned} Y_{g,t} \;=\; & C_t + \frac{I_t}{A_{I,t}} + G_t + \int_0^1 \Psi_t(l)\, dl + \frac{\kappa_w}{2}\left(\frac{W_t}{W_{t-1}} - 1\right)^2 \frac{W_t L_t}{P_t} \\ & + Q_t \frac{\kappa_I}{2}\left(\frac{I_t Z_{I,t}}{I_{t-1}} - 1\right)^2 I_t + \frac{\kappa_p}{2}\left(\frac{P_t}{P_{t-1}} - 1\right)^2 Y_{g,t} + \frac{\kappa_U\left((A_{U,t}U_t)^{\gamma_U+1} - 1\right)}{\Upsilon_U + 1} K_{t-1} \\ & + \overbrace{\mu_E G_{E,t} R_{E,t} Q_{t-1} K_{t-1} + \mu_F G_{F,t} \Phi_{E,t} R_{E,t} Q_{t-1} K_{t-1}}^{\text{Total amount of monitoring costs}} \\ & + (1-\gamma_F) V_{F,t} + (1-\gamma_E) V_{E,t}. \end{aligned} \tag{3.2.13}$$

where I_t is aggregate investment, $A_{I,t}$ is investment specific technology, and G_t is government expenditure. The fourth term represents intermediate production inputs, and the fifth, sixth, seventh, and eighth terms are the adjustment costs associated with wage, investment, price, and the capacity utilization rate of capital inputs, respectively. The monitoring costs are shown in the ninth and tenth terms, which means that, as in CMR (2014), the monitoring costs are spent in the form of the composite. The last two terms are resources consumed by the exiting FIs and entrepreneurs.

Production function

The inputs used by a differentiated firm are labor, capital, and intermediate inputs. The production function of a firm l is given by

$$Y_{g,t}(l) = Z_t A_t \Psi_t(l)^{\gamma} \left[L_t(l)^{\alpha} 1^{\alpha_E} 1^{\alpha_{FI}}\right]^{1-\gamma} \left[\left(K_{t-1}(l)\, U_t(l)\right)^{1-\alpha-\alpha_E-\alpha_{FI}}\right]^{1-\gamma} - F_t \qquad (3.2.14)$$

Here, Z_t is a non-stationary component of technology, and A_t is a stationary component of technology. $L_t(l)$, $K_{t-1}(l)$, and $U_t(l)$ are labor inputs, capital stock, and capacity utilization rate of the capital stock in firm l. Parameters γ and α are the cost share of intermediate inputs and labor inputs, respectively, and F_t is a fixed cost which is exogenous to firms.[24]

Firms in the goods-producing sector are price-takers in the input markets. The cost-minimization problem of firm l therefore yields the following marginal cost function $MC_t(l)$:

$$MC_t(l) = \frac{\bar{\phi} P_t^{\gamma}}{A_t Z_t} \left[W_t^{\alpha} W_{E,t}^{\alpha_E} W_{F,t}^{\alpha_{FI}} \tilde{R}_{E,t}^{1-\alpha-\alpha_E-\alpha_{FI}}\right]^{1-\gamma}, \qquad (3.2.15)$$

where $\bar{\phi}$ is a constant and $\tilde{R}_{E,t}$ is the nominal gross return to capital inputs, $K_{t-1}(l)\, U_t(l)$.

The total capacity utilization rate of capital stock is determined by entrepreneurs. We

[24] The size of the fixed cost F_t is set so that the profits from operating in the goods-producing sector are zero at the steady state. Following CMR (2010, 2014), we further assume that the fixed cost F_t exogenously grows at the same growth rate as does the non-stationary component of $Y_{g,t}(l)$, that is $Z_t^{\frac{1}{\alpha(1-\gamma)}}$, and that firms stop producing goods if the fixed cost exceeds the first term of the equation (3.2.14).

assume that entrepreneurs need to pay the real cost of

$$\frac{\kappa_U \left((A_{U,t} U_t)^{\Upsilon_U + 1} - 1 \right)}{\Upsilon_U + 1},$$

in choosing the capacity utilization rate of capital U_t. Here κ_U, Υ_U are parameters and $A_{U,t}$ represents the technology for adjusting the capacity utilization rate.[25] The real net return on capital K_{t-1} received by the entrepreneurs can then be expressed by the following equation.

$$R_{E,t} = \frac{\frac{U_t \tilde{R}_{E,t}}{P_t} - \frac{\kappa_U \left((A_{U,t} U_t)^{\Upsilon_U + 1} - 1 \right)}{\Upsilon_U + 1} + (1 - \delta) Q_t}{Q_{t-1}}.$$

Price setting

Differentiated firms in the goods-producing sector are monopolistic competitors in the products market. A firm l sets the price for its products $P_t(l)$ in reference to the demand given by (3.2.12) . It can reset the prices solving the following problem:

$$\max_{P_t(l)} \mathrm{E}_t \left[\sum_{q=0}^{\infty} \beta^{t+q} \frac{\Lambda_{t+q}}{\Lambda_t} \frac{\Pi_{t+q}(l)}{P_{t+q}} \right] \tag{3.2.16}$$

$$s.t.\ \Pi_{t+q}(l) = P_{t+q}(l) Y_{g,t+q}(l) - MC_{t+q}(l) \left(Y_{g,t+q}(l) + F_t \right) - \frac{\kappa_p}{2} \left(\frac{P_{t+q}(l)}{P_{t+q-1}(l)} - 1 \right)^2 P_{t+q} Y_{g,t+q} \tag{3.2.17}$$

where Λ_{t+q} is the Lagrange multiplier associated with budget constraint (3.2.10) in period $t+q$, and κ_p is the parameter associated with price adjustment.

[25] Sugo and Ueda (2008) showed the importance of capital utilization for a DSGE model to describe realistic fluctuations of economic variables using Japanese data. Capital utilization is also important for our study to measure TFP as the Solow residual. Thus, to reproduce the observed utilization data, we follow Sugo and Ueda (2008) and introduce a structural shock, which can be interpreted as the shift in the parameter of adjustment cost of capital utilization.

3.2.4 Capital goods producer

Capital goods producers purchase final goods $I_t/A_{I,t}$ from goods producers, convert them to capital goods K_t, using technology $F_{I,t}$, and sell them to the entrepreneurs at price Q_t. The capital goods producers' problem is to maximize the profit function as shown below:

$$\max_{I_t} \mathrm{E}_t \left[\sum_{q=0}^{\infty} \beta^{t+q} \frac{\Lambda_{t+q}}{\Lambda_t} \left[Q_{t+q} \left(K_{t+q} - (1-\delta) K_{t+q-1} \right) - \frac{I_{t+q}}{A_{I,t+q}} \right] \right].$$

Capital depreciates in each period and the total capital evolves as follows:

$$K_t = \left(1 - F_I \left(I_t, I_{t-1}\right)\right) I_t + (1-\delta) K_{t-1}, \tag{3.2.18}$$

where F_I is defined as follows:

$$F_I \left(I_{t+q}, I_{t+q-1}, Z_{I,t+q}\right) \equiv \frac{\kappa_I}{2} \left(\frac{I_{t+q} Z_{I,t+q}}{I_{t+q-1}} - 1 \right)^2.$$

Here, $\delta \in (0,1)$ is the depreciation rate of the capital stock, and κ_I and $Z_{I,t+q}$ are the constant and the time-varying components of investment adjustment cost, respectively.[26]

3.2.5 Entrepreneurs

In the goods-producing activities, entrepreneurs appear as suppliers of capital goods K_{t-1} to goods producers. In each period, entrepreneurs have the option of participating in the FE contract or not; if they do not enter into the FE contract, they purchase the capital goods K_{t-1} from the capital goods producers at price Q_{t-1}, using only their own net worth $N_{E,t-1}$, determine the optimal capacity utilization rate U_t, lend them to the goods producers, and receive the proceeds in return. The revenue in this case is given as $R_{E,t} N_{E,t-1}$. If

[26]Note that the functional form of our capital producing technology is different from BGG (1999), and the zero-profit condition is not necessarily satisfied in the equilibrium. However, since we assume that households own the firms and receive the profits/losses, these profits/losses do not affect other financial contracts. The setting is conceptually consistent with the one in CMR (2014).

they enter the credit contract, entrepreneurs purchase the capital goods K_{t-1} from capital goods producers at price Q_{t-1}, using their own net worth $N_{E,t-1}$ and the external finance $Q_{t-1}K_{t-1} - N_{E,t-1}$ borrowed from FIs through the FE contracts. Indeed, as described above, because of the participation constraint (3.2.6), entrepreneurs choose to participate in the FE contract. Entrepreneurs then determine the capacity utilization rate of the capital goods U_t and lend the capital goods K_{t-1} to goods producers. After receiving proceeds from goods producers, entrepreneurs sell the used capital goods to capital goods producers at the end of the period.[27] At this stage, what entrepreneurs have in their hand is given by $R_{E,t}Q_{t-1}K_{t-1}$.

Each of entrepreneurs then draws an idiosyncratic productivity shock $\omega_{E,t}$. An entrepreneur who draws a shock below the cut-off value $\overline{\omega}_{E,t}$ defaults and earns zero, while an entrepreneur that draws a shock above the cut-off value $\overline{\omega}_{E,t}$ repays the debt to the FIs, which is expressed as follows.[28]

$$r_{E,t}\left(Q_{t-1}K_{t-1} - N_{E,t-1}\right) = \overline{\omega}_{E,t}R_{E,t}Q_{t-1}K_{t-1}.$$

3.2.6 Defining aggregate variables

As with CMR (2010), the real GDP Y_t in the model is given as follows:

$$Y_t = C_t + \frac{I_t}{A_{I,t}} + G_t, \tag{3.2.19}$$

The CPI π_t is defined by

$$\pi_t = \frac{P_t}{P_{t-1}}. \tag{3.2.20}$$

[27] This assumption that entrepreneurs sell back capital goods to capital goods producers is borrowed from BGG (1999). Similar to BGG (1999), we assume this setting so that adjustment cost of capital goods Q_t becomes external to entrepreneurs.

[28] After receiving repayments from non-defaulting entrepreneurs and paying the costs of monitoring earnings of defaulting entrepreneurs, a FI draws its own idiosyncratic productivity shock $\omega_{F,t}$, and defaults when the realization of the idiosyncratic productivity shock falls below the cut-off value $\overline{\omega}_{F,t}$. When a FI defaults, all of the entrepreneurs that have received credits from the FI exit the market, regardless of the realization of its own entrepreneurial idiosyncratic shock $\omega_{E,t}$. That is, defaulting entrepreneurs, i.e., entrepreneurs those draw low entrepreneurial idiosyncratic productivity shock, exit the market with no income, while non-defaulting entrepreneurs exit the economy with the income they receive from the credit contract, $\left(\omega_{E,t} - \overline{\omega}_{E,t}\right) R_{E,t}Q_{t-1}K_{t-1}$.

The real interest rate R_t is given by the Fisher equation that connects the nominal interest rate $R_{n,t}$ and the expected inflation $\mathrm{E}_t[\pi_{t+1}]$:

$$R_t = \frac{R_{n,t}}{\mathrm{E}_t[\pi_{t+1}]}.$$

The aggregate TFP λ_t in the model is measured as below following a conventional treatment:

$$\lambda_t = \frac{Y_t}{(L_t)^{\psi_L}(K_{t-1}U_t)^{1-\psi_L}}, \tag{3.2.21}$$

where ψ_L is the steady state labor share of income[29].

3.2.7 Government sector

The government collects a lump-sum tax τ_t from households to finance government purchase P_tG_t whose amount is exogenously given. We assume that a balanced budget is maintained in each period t as follows:

$$P_tG_t = \tau_t$$

The central bank adjusts the policy rate according to the following Taylor rule:

$$R_{n,t} = R_{n,t-1}^{\rho}\pi_t^{(1-\rho)\varphi_\pi}\exp(\epsilon_{R_n,t}). \tag{3.2.22}$$

Here, $\rho \in (0,1)$ is the persistency parameter of the monetary policy rule, $\varphi > 1$ is the policy weight attached to the inflation rate and $\epsilon_{R_n,t}$ is an i.i.d. shock to the rule.

3.2.8 Fundamental shocks

In addition to the key structural shocks, $\varepsilon_{N_F,t}$ and $\varepsilon_{N_E,t}$, there are nine fundamental shocks. Those are shocks to the stationary and non-stationary components of technology in the

[29]The numerator of labor share ψ_L includes only households' labor income. It does not count the income of entrepreneurs and FIs.

goods producers' production function Z_t and A_t, shocks to investment-specific technology $A_{I,t}$, technology for capacity utilization of capital inputs $A_{U,t}$, government spending G_t, the investment adjustment cost $Z_{I,t}$, the price markup $\theta_{P_Y,t}$, and the wage markup $\theta_{W,t}$ as well as i.i.d. monetary policy shocks $\epsilon_{R_n,t}$. The laws of motion for structural shocks are given by the equations below:

$$
\begin{aligned}
\ln Z_t &= \ln Z_{t-1} + u_{Z,t},\ u_{Z,t} = \rho_Z u_{Z,t-1} + \epsilon_{Z,t}, \\
\ln A_t &= (1-\rho_A)\ln A + \rho_A \ln A_{t-1} + \epsilon_{A,t}, \\
\varepsilon_{N_\zeta,t} &= \rho_{N_\zeta}\varepsilon_{N_\zeta,t-1} + \epsilon_{N_\zeta,t},\ \text{for } \zeta = F \text{ and } E, \\
\ln A_{I,t} &= (1-\rho_{A_I})\ln A_I + \rho_{A_I}\ln A_{I,t-1} + \epsilon_{A_I,t}, \\
\ln A_{U,t} &= (1-\rho_{A_U})\ln A_U + \rho_{A_U}\ln A_{U,t-1} + \epsilon_{A_U,t}, \\
\ln G_t &= (1-\rho_G)\ln G + \rho_G \ln G_{t-1} + \epsilon_{G,t}, \\
\ln Z_{I,t} &= (1-\rho_I)\ln Z_I + \rho_{Z_I}\ln Z_{I,t-1} + \epsilon_{Z_I,t}, \\
\ln \theta_{P_Y,t} &= (1-\rho_{P_Y})\ln \theta_{P_Y} + \rho_{P_Y}\ln \theta_{P_Y,t-1} + \epsilon_{P_Y,t}, \\
\ln \theta_{W,t} &= (1-\rho_W)\ln \theta_W + \rho_W \ln \theta_{W,t-1} + \epsilon_{W,t},
\end{aligned}
$$

where ρ_Z, ρ_A, ρ_{N_F}, ρ_{N_E}, ρ_{A_I}, ρ_{A_U}, ρ_G, ρ_{κ_I}, ρ_{P_Y} and $\rho_W \in (0,1)$ are the autoregressive root of the corresponding shocks, and $\epsilon_{Z,t}$, $\epsilon_{A,t}$, $\epsilon_{N_{F,t}}$, $\epsilon_{N_E,t}$, $\epsilon_{A_I,t}$, $\epsilon_{AU,t}$, $\epsilon_{G,t}$, $\epsilon_{Z_I,t}$, $\epsilon_{P_Y,t}$, and $\epsilon_{W,t}$ are the exogenous i.i.d. shocks that are normally distributed with mean zero.

3.2.9 Equilibrium

An equilibrium consists of a set of prices, $\{W_t(h)$ for all $h \in [0,1]$, $P_t(l)$ for all $l \in [0,1]$, P_t, W_t, $W_{E,t}$, $W_{F,t}$, $R_{E,t}$, $\tilde{R}_t$, R_t, Q_t, $r_{E,t}$, $r_{F,t}\}_{t=0}^{\infty}$, and the allocations $\{C_t(h)$, $L_t(h)$, $S_t(h)$ for all $h \in [0,1]$, $Y_{g,t}(l)$, $\Psi_t(l)$, $L_t(l)$, $K_t(l)$, $U_t(l)$ for all $l \in [0,1]$, $\overline{\omega}_{E,t}$, $\overline{\omega}_{F,t}$, $N_{E,t}$, $N_{F,t}$, $Y_{g,t}$, C_t, D_t, I_t, $K_t, U_t\}_{t=0}^{\infty}$ for given government policy $\{G_t,\ \tau_t,\ R_{n,t}\}_{t=0}^{\infty}$, realization of exogenous variables $\{\epsilon_{Z,t}$, $\epsilon_{A,t}$, $\epsilon_{A_I,t}$, $\epsilon_{AU,t}$, $\epsilon_{N_F,t}$, $\epsilon_{N_E,t}$, $\epsilon_{G,t}$, $\epsilon_{\kappa_I,t}$, $\epsilon_{P_Y,t}$, $\epsilon_{W,t}$, $\epsilon_{R_n,t}\}_{t=0}^{\infty}$, and initial conditions $\{N_{F,-1}, N_{E,-1}, K_{-1}\}$ such that for all t, the following conditions are satisfied.

(i) each household h maximizes its utility given prices;

(ii) each FI maximizes its profits given prices and its net worth;

(iii) each entrepreneur in the goods-producing sector maximizes its profits given prices and its net worth;

(iv) each goods producer l in the goods-producing sector maximizes its profits given prices;

(v) each capital goods producer in the goods-producing sector maximizes its profits given prices;

(vi) the government budget constraint holds;

(vii) the central bank sets the policy rate following the Taylor rule; and

($viii$) markets clear.

The market clearing conditions are given as follows:

(a) labour market clears, which means that labour supply from household h equals to the aggregate demand for the differentiated labour h from all the goods producers $l \in [0, 1]$ in each of differentiated labor h market;

(b) capital goods market clears, which means that capital goods supply from capital producers equals to the demand from entrepreneurs; and

(c) goods market clears, which means that goods supply from goods producer l equals to the demand for the differentiated goods l from aggregator in each of differentiated goods l market, and equation (3.2.13) holds for the composite.

3.3 Quantitative analysis

In this section, we firstly explain the data and method used for estimating the model presented in the previous section. We then show the estimated shocks to the balance sheets of the FIs and goods-producing sectors.

3.3.1 Estimation strategy

We first detrend the model variables by dividing them by the I(1) stochastic trend term. We then log-linearize the detrended model around the deterministic steady state. All of the equilibrium conditions are shown in the appendix. We then conduct a Bayesian estimation following existing studies, including CMR (2014). To do this, we first write the equilibrium conditions of the model in a state-space representation and derive the likelihood function of the system of equilibrium conditions using the Kalman filter. Next, we combine the likelihood function with the priors for the parameters to obtain the posterior density function numerically. In this process, we use the random walk Metropolis-Hastings algorithm.

3.3.2 Data

We use time series of 11 variables from 1980:2Q to 2011:4Q. We display the data series used for estimation in Figure 3.5.[30] The data includes 9 aggregate variables and two variables that are balance sheet data of the FIs and goods-producing sectors: (1) real GDP Y_t, (2) real investment I_t, (3) GDP deflator P_t, (4) deflator of investment $P_t/A_{I,t}$, (5) nominal wage per unit of labor W_t, (6) working hours L_t, (7) capacity utilization rate of capital stock U_t, (8) the policy rate $R_{n,t}$, (9) measured TFP as the Solow residual that is not adjusted for the capacity utilization of the capital stock $Y_t\left((L_t)^{\psi_L}(K_{t-1})^{1-\psi_L}\right)^{-1}$, (10) real net worth of the FI sector $N_{F,t}P_t^{-1}$, and (11) real net worth of the entrepreneurs in the goods-producing sector $N_{E,t}P_t^{-1}$.

The data source of these series, unless otherwise noted, is the System of National Accounts (hereafter SNA) released by the Cabinet Office of Japan. Series (5) is constructed from the compensation of employees based on the SNA, divided by series (6). Series (6) is obtained from the number of employees based on the Labour Force Survey, multiplied by hours worked

[30] All of the series other than series (8) is displayed on a year-on-year basis. Note, however, that we use a quarter-on-quarter change rather than a year-on-year change of a variable in our estimation. We use the level series for series (8) in our estimation.

per employee based on the Monthly Labour Survey. Series (7) is obtained from the utilization rate of capital stock in the manufacturing sector, based on the Index of Industrial Production multiplied by 0.6. This construction methodology is the same as that used in Sugo and Ueda (2008).[31] Series (8) is the shadow rate of the short-term nominal interest rate in Japan. We employ the shadow short rate series[32] to avoid biased estimation as explained in the following paragraph. We augment the series, which is available from 1995:1Q and beyond, with overnight call rate in Japan, the main policy tool for the Bank of Japan, following Wu and Zhang (2019), where they augment their shadow short rate series for the U.S. with the fed funds rate during non-zero lower bound period for their analysis on the shadow rate dynamics.[33]

In our model, there are two measures of TFP, the utilization-unadjusted TFP $Y_t\left((L_t)^{\psi_L}(K_{t-1})^{1-\psi_L}\right)^{-1}$ and utilization-adjusted TFP λ_t, defined as $Y_t\left((L_t)^{\psi_L}(K_{t-1}U_t)^{1-\psi_L}\right)^{-1}$. The former series is presented in panel (9), and the latter is presented in panel (12) of Figure 3.5. Although the difference between these two series is not negligible, we would like to stress that either series can be used for the estimation, as long as the data is consistent with the variable defined in the model. We choose to use the former series as an observable variable in our estimation. We also use the series of capacity utilization, which is presented in panel (7) of Figure 3.5, as another observable. Consequently, TFP series generated from the model coincides with the data for the two measures of TFP.

Series (10) and (11), the two net worth series, are constructed from the outstanding of shares issued by depository corporations and non-financial corporations in Japan. They are taken from the Flow of Funds Accounts. In the Flow of Funds Accounts, the reported series of outstanding of shares are those evaluated not at market value, but at book value before

[31] Because the data series for the capacity utilization rate of capital stock is only available for manufacturing firms in Japan, we follow Sugo and Ueda (2008) and assume that non-manufacturing firms adjust the rate to a lesser extent than non-manufacturing firms.

[32] We use shadow rate series for Japan estimated by Krippner (2016). Krippner (2015) discusses the methodological background.

[33] Ikeda *et al.* (2021) also formalizes the equivalence of the shadow rate to the standard short-time interest rate, based on their empirical findings in Japan and the US.

1995:4Q for depository corporations and before 1994:4Q for non-financial corporations. We therefore extend each series evaluated at market value backward using the quarterly growth rate of the market capitalization of banks and of non-financial firms.

A major concern to estimate parameters related to monetary policy using Japanese data is that the fact that the policy rate in Japan was set and maintained close to zero in February 1999 and beyond. If we disregard the zero lower bound of policy rate and simply use the full sample data for the estimation, then the estimated parameters in the Taylor rule will be biased. We therefore employ the shadow rate of the short-term nominal interest rate in Japan estimated by Krippner (2016). The shadow rate is essentially equivalent to the prevailing short-term interest rate when it is positive, and is equivalent to what the short-term interest rate would be without the zero lower bound when it is negative. Shadow rates are increasingly used in studies of monetary policy implementation under the zero lower bound. For instance, Wu and Xia (2016) construct the shadow federal funds rate and estimate the impulse response of macroeconomic variables to a shock to the shadow rate. Similarly to a negative shock to the federal funds rate, they find that a negative shock to the shadow federal funds rate leads to an increase in production activity and a fall in the unemployment rate. Following Wu and Zhang (2019), we assume that the central bank adjusts the shadow rate of the short-term interest rate as the policy rate $R_{n,t}$ and use the rate in our estimation.[34,35]

In estimating the model, we take the first difference for all of the series except for series (8). To convert the nominal series into the quantity series, we employ the GDP deflator. We also divide all of the quantity series by the number of the population over 15 reported in

[34]In the working paper version of this paper, we estimate the posterior distribution of policy weight φ_π and smoothing parameter ρ in the Taylor rule using the subsample that covers the period from 1980:2Q to 1998:4Q. We estimate the posterior distributions of the other parameters using the full sample, from 1980:2Q to 2011:4Q, with a policy weight and a smoothing parameter in the Taylor rule fixed to the mean of the distribution obtained from the subsample estimation. The estimated impulse response functions and the decomposition of measured TFP are little changed from what are obtained from the estimation using the shadow rate.

[35]See also Hirose and Inoue (2016) for the related issue. They analyze to what extent parameter estimates can be biased in a model that omits the zero lower bound constraint on the nominal interest rate, by estimating a New Keynesian sticky price model. They find that such biases are not quantitatively significant.

the Labor Force Survey to obtain the series on a per-capita basis. We demean all the series other than (8) to remove the deterministic trend so as to prevent low frequency trends in the data from distorting implications in higher business cycle frequencies, following previous studies such as CMR (2014).

3.3.3 Calibration, Prior Distribution, and Posterior Distribution

Some parameter values are calibrated following existing studies. These include the discount factor β, the elasticity of substitution between differentiated products θ_{P_Y}, the elasticity of substitution between differentiated labor inputs θ_W, the depreciation rate of the capital stock δ, the share of the intermediate input, labor input, entrepreneurial labor input and the FI labor input in goods production γ, α, α_E and α_F, and the utility weight on leisure φ.[36] Values for γ and α are constructed using the historical average of intermediate goods usage divided by gross output, both of which are reported in an input-output table, and the compensation of employees divided by GDP in SNA, respectively. In addition, we set κ_U so that the utilization rate of capital stock is unity at the steady state. See the lower part of Table 1 for the values of these parameters.

Since the parameters related to financial contracts are crucial for our quantitative results, we employ an approach to make them being consistent with Japanese financial data. The parameters related to the IF and FE contracts include two parameters that govern monitoring costs μ_F and μ_E, variance of idiosyncratic shocks to borrowers σ_F and σ_E, and survival rates γ_F and γ_E. As for the six parameters, we use tight prior in order to match the observation of Japanese financial data as is summarized in Table 1. We set the prior mean of these parameters so that they satisfy the six equilibrium conditions stated below at the steady state: (1) the annualized spread between the FIs' borrowing rate and the risk-free rate $r_F - R$ is 56 bps; (2) the ratio of net worth held by FIs to aggregate capital stock $N_F/\left(QK\right)$

[36]We follow CMR (2014) for the calibration of the elasticity of substitution between differentiated products, BGG (1999) for the calibration of the share of entrepreneurial labor input and the FI labor input in goods productions, and HSU (2011, 2013, and 2017) for the calibration of the utility weight on leisure.

is 0.1; (3) the ratio of net worth held by the entrepreneurs in the goods-producing sector to aggregate capital stock $N_E/(QK)$ is 0.6; (4) the annualized failure rate of the FIs is 1%; (5) the annualized failure rate of the entrepreneurs in the goods-producing sector is 1%; and (6) the annualized spread between the FI loan rate and the FI borrowing rate $r_E - r_F$, equals 441 bps. Except for conditions (4) and (5), the conditions above are chosen so that they are consistent with the historical average of Japanese data.[37] We borrow condition (5) from BGG (1999) and assume that the same condition holds in the FI sector as well. This can be seen in condition (4).

We estimate the remaining parameters as in the upper part of Table 1. The type, mean, and standard deviation of the prior distribution are mostly taken from existing studies such as Edge *et al.* (2010). They are given in the first to the third columns. To calculate the posterior distribution and to evaluate the marginal likelihood of the model, we employ the Metropolis-Hastings algorithm. To do this, we create a sample of 400,000 draws, disregarding the initial 200,000 draws. Estimated posterior distributions of parameters are shown in the upper section of Table 1. The last three columns of the table display the posterior mean and the confidence intervals for the estimated parameters.

3.3.4 Estimated shocks to balance sheets

In Figure 3.6, we show the time path of shocks to the balance sheets of the FIs and goods-producing sectors. In the figure, we also show the time path of the Financial Position Index of firms based on the Short-Term Economic Survey of Enterprises, shown in Figure 3.1, and indicate the timings of the outbreak of the two financial crises by bars.

The net worth shocks to FIs took large positive values continuously from the late 1980s to the early 1990s. From the early 1990s, they started to take negative values, indicating that the balance sheets of FIs had been damaged. The size of the negative shocks gradually

[37] We take the numbers for conditions (2) and (3) from the Flow of Funds Accounts. We use the long-term prime lending rate and the deposit rate adopted by the Bank of Japan to obtain conditions (1) and (6), respectively.

increased, reaching a peak during the late 1990s. The shocks remained negative until the mid-2000s, becoming positive in the mid-2000s. These realizations of the shocks are in line with the observations made by Hoshi and Kashyap (2010). They point out that the acute phase of the Japanese banking crisis was from 1997:4Q to 1999:1Q, and that the phase when the crisis bottomed out was from 1999:1Q to early 2003. It is also important to note that time paths of the estimated net worth shocks to the FI and Financial Position Index roughly coincide over the estimation period. During and after each of the two financial crises, the index decreased, indicating that financial positions became tightened, and large negative shocks occurred to the net worth of the FI sector. In contrast to shocks to the balance sheets of the FI sector, shocks to the balance sheets of the goods-producing sector took large negative values during the early 1990s, and relatively small negative values during the late 1990s.

3.3.5 Impulse response functions

Using the estimated parameters, we next show how the key macroeconomic variables, including measured TFP, respond to unanticipated shocks to net worth.

We begin with an analysis of the consequences of a net worth shock to the FIs $\epsilon_{N_F,t}$. This shock arises from the FI sector and is described as an innovation to equation (3.2.7). Figure 3.7 shows the impulse response function of macroeconomic variables to a negative shock to the FIs' net worth. As the FIs' net worth becomes significantly reduced because of the shock, the FIs are more likely to default on their loans. The investors then require a higher external finance premium in the IF contracts, which results in a higher borrowing rate $r_{F,t}$. Since the higher borrowing rate in the IF contracts is translated to the higher borrowing rate in the FE contracts $r_{E,t}$, the entrepreneurs reduce their external funding and purchase less capital goods Q_tK_t. Consequently, capital goods supply to the goods-producers decreases. With a lower capital input, investment and GDP are dampened. Inflation also falls, reflecting the weak aggregate demand. A decline in GDP causes the second round effect to emerge.

The economic downturn due to the shock hampers the net worth accumulation in the two sectors since the retained earnings in these sectors diminish as equations (3.2.7) and (3.2.8) indicate. The deteriorated net worth results in a further rise in the external finance premium and in the two borrowing rates $r_{F,t}$ and $r_{E,t}$, further dampening GDP. The shock also lowers measured TFP through multiple channels, which will be discussed in the next section.

We next discuss the model's response to an unexpected net worth disruption in the goods-producing sector $\epsilon_{N_E,t}$. Figure 3.8 shows the impulse response function of the variables to the shock. Similar to an adverse net worth shock to the FIs, the shock delivers a decline in measured TFP. The working mechanism is also similar. Entrepreneurs in the goods-producing sector with damaged balance sheets face a higher external finance premium in the FE contracts and borrow less, which results in smaller capital goods supply to the economy. Consequently, investment and GDP fall. As GDP falls, the second round effect discussed above emerges and the net worth of the FIs and the entrepreneurs both endogenously deteriorates. As in the case of the FIs' net worth shock, the negative shock to the entrepreneurial net worth reduces measured TFP.

3.4 Productivity slowdown due to damaged balance sheets

In this section, we firstly explain the channels through which the shocks to net worth in the FI and the good-producing sectors affect measured TFP growth. We then show the quantitative contributions of these shocks to the slowdown of measured TFP during the lost decades by using the distilled time series of shocks to net worth in the FI and the good-producing sectors. Finally, we examine the quantitative importance of each channel through which the net worth shocks have influence on the decline in measured TFP.

3.4.1 Endogenous variations in measured TFP

In a standard growth model, measured TFP movements are fully attributed to exogenously driven technology shocks. By contrast, measured TFP in our model varies with non-technology shocks, in particular shocks to the net worth of FIs and entrepreneurs, through the multiple channels discussed below. To see the effect of financial shocks on TFP variations, we incorporate several channels discussed in the literature into the model.

The first channel is the monitoring cost channel, which is the direct consequence of disruptions to financial intermediation.[38] Figure 3.4 shows that whenever a borrower's net worth falls, monitoring costs spent by the lender increase, since the borrower is more likely to default. The size of monitoring costs affects measured TFP, since, as the sum of the sixth and the seventh term in equation (3.2.13) shows, monitoring costs are spent in the form of the gross output that would otherwise serve as value-added or as intermediate inputs. Since TFP is measured by the value-added divided by the primary inputs, other things being equal, TFP falls when monitoring costs increase.

The second channel is the factor market distortion channel, which is proposed by Basu (1995). It is important to recall that, similar to the model of Basu (1995), our model incorporates the input-output production structure and the monopolistic competition in the intermediate inputs market. Our economy is therefore not efficient even at the steady state, because goods producers set their prices as a markup on marginal cost and too few intermediate goods are used in goods production. In dynamics, the economy experiences further inefficiency. Suppose that a contractionary monetary policy shock occurs. If goods prices are adjusted at a slower rate than the marginal cost, which as shown in equation (3.2.15) is a function of prices of production inputs, the markup of intermediate goods increases in the short-run. Because intermediate goods becomes more expensive, goods producers use fewer intermediate goods and more primary inputs. This moves the economy

[38]This channel is also present in models that employ the costly state verification framework. See for instance CMR (2010, 2014).

further away from the efficient allocation of production inputs, thereby reducing TFP.

The third channel is the increasing returns to scale, which is pointed out in various existing studies, for example, by Hall (1988, 1990). Because we assume that there are fixed costs in goods production, following the setting employed by CMR (2014), when a contractionary non-technological shock, including a demand shock, takes place, the output declines greater than do the primary inputs. In other words, increasing returns to scale yields pro-cyclical movements of measured TFP growth. To illustrate this, abstract from intermediate inputs, capacity utilization, and technology shocks, and consider the production function $Y_t = L_t^{\alpha} K_t^{1-\alpha} - F$. If all the inputs, L_t and K_t, increase by 1%, the output increases more than 1% due to F term, which results in an increase in measured TFP, $\lambda_t \equiv Y_t / \left(L_t^{\alpha} K_t^{1-\alpha}\right)$.

To show how these channels affect measured TFP analytically, we consider, for a moment, a simple model in which gross output $Y_{g,t}$ is produced from intermediate inputs and labor input.[39] We further assume other specifications are unchanged from the baseline model. From the resource constraint (3.2.13) and the production function (3.2.14), we can derive the expression that relates measured TFP λ_t with the channels described above:

$$\lambda_t = \frac{Y_{g,t}}{\Psi_t^{\gamma} L_t^{1-\gamma}} \frac{\Psi_t^{\gamma} L_t^{1-\gamma}}{L_t} - \frac{\Omega_t}{L_t} - \frac{\Xi_t}{L_t}. \tag{3.4.1}$$

where, Ψ_t, Ω_t and Ξ_t are the amount of the gross output that serves for intermediate goods, monitoring cost, and other terms included in the resource constraint, respectively in this simple model. The expression $Y_{g,t} / \left(\Psi_t^{\gamma} L_t^{1-\gamma}\right)$ that appears in the first term represents the ratio of the gross output to all of the inputs, intending to capture changes in measured TFP λ_t through increasing returns to scale due to the presence of the fixed costs F_t. The other expression $\left(\Psi_t^{\gamma} L_t^{1-\gamma}\right) / L_t$ represents the ratio of all of the inputs to the primary inputs, intending to capture changes in measured TFP λ_t due to changes in the factor market

[39] By assuming that intermediate inputs and labor input are the only production input, we implicitly assume that the parameter α takes unity, and parameters α_E, and α_F as well as the last four terms in equation (3.2.13) are zero.

distortions. The terms Ω_t/L_t and Ξ_t/L_t intend to capture changes in measured TFP λ_t due to changes in the use of goods as monitoring cost and other costs including the liquidation costs of FIs and entrepreneurs.

Next, by taking the first derivative of both sides of the equations with respect to a non-technology shock, ϵ_t, at the steady state, we obtain the following expression:

$$\frac{\partial \lambda_t}{\partial \epsilon_t} = \left(\frac{\Psi^\gamma L^{1-\gamma}}{L}\right)\frac{\partial}{\partial \epsilon_t}\left(\frac{Y_{g,t}}{\Psi_t^\gamma L_t^{1-\gamma}}\right) + \left(\frac{Y_g}{\Psi^\gamma L^{1-\gamma}}\right)\frac{\partial}{\partial \epsilon_t}\left(\frac{\Psi_t^\gamma L_t^{1-\gamma}}{L_t}\right) - \frac{\partial}{\partial \epsilon_t}\left(\frac{\Omega_t}{L_t}\right) - \frac{\partial}{\partial \epsilon_t}\left(\frac{\Xi_t}{L_t}\right), \tag{3.4.2}$$

where $\partial x_t/\partial \epsilon_t$ and x denote the first derivative of a variable x_t with respect to the shock ϵ_t and the steady state of x_t, respectively. The equation thus indicates that even when technology is unchanged, measured TFP can change through multiple channels.

Figure 3.7 and 3.8, the impulse responses to a negative shock to net worth, show that these channels are actually working in our estimated model. To illustrate the presence of the monitoring costs, we define a measure of monitoring costs as follows, and show the impulse response function in the panel (10)

$$\left(\mu_E G_{E,t} R_{E,t} Q_{t-1} K_{t-1} + \mu_F G_{F,t} \Phi_{E,t} R_{E,t} Q_{t-1} K_{t-1}\right) / \left(\left(L_t\right)^{\psi_L}\left(K_{t-1} U_t\right)^{1-\psi_L}\right).$$

It is the proportion of monitoring cost over the weighted average of primary inputs, corresponding to Ω_t/L_t of the simplified model. In response to the shock, the monitoring cost rises. If the net worth in the FIs deteriorates, the investors require a higher cut-off value $\overline{\omega}_{F,t}$ in the IF contracts, leading to a higher value for the FI borrowing rate $r_{F,t}$. As discussed above, a higher cut-off value for $\overline{\omega}_{F,t}$ implies that a greater amount of resources is spent as monitoring costs in the IF contracts. Consequently, measured TFP falls. In addition, since the net worth shock to FIs also leads to an endogenous deterioration of net worth in the goods-producing sector, the cut-off value in the FE contracts $\overline{\omega}_{E,t}$ increases, which results in a further decline in measured TFP.

The presence of the factor market distortion channel is seen in the increase in the markup of the goods-producing sector in the panel (4). Note that a positive response of the markup, defined as P_t/MC_t, indicates that the intermediate goods price rises relative to the prices of primary inputs. Though both goods price and nominal wage are adjusted in a sluggish manner, the estimated response of the markup indicates that a nominal marginal cost adjusts more rapidly than goods prices.[40] To illustrate its effect on firms' input choice, we define inputs of intermediate goods over primary inputs as follows, and show the impulse response function in the panel (11).

$$\Psi_t / \left((L_t)^{\psi_L} (K_{t-1} U_t)^{1-\psi_L} \right).$$

The panel shows that an increased markup of goods makes goods producers hire more primary inputs and less intermediate inputs than otherwise, exacerbating the inefficiency of production inputs. Consequently, measured TFP falls.

To see the presence of the increasing returns to scale channel, we define gross output over all of the inputs as follows, and show the impulse response function in the panel (12).

$$Y_{g,t} / \left(\Psi_t^{\gamma} \left[L_t^{\psi_L} \right]^{1-\gamma} \left[(K_t U_t)^{1-\psi_L} \right]^{1-\gamma} \right).$$

As is consistent with our example above using a model only with labour and capital inputs, the panel shows that the decline in gross output is greater than that of all of the inputs due to the fixed costs. When positive net worth shocks occur and the first term in the RHS of equation (14) increases due to a lower funding costs facing entrepreneurs and a larger demand for capital goods, the second term of the equation, i.e., fixed costs, does not increase, giving a disproportionately large increase in gross output $Y_{g,t}$. In other words, a change in gross output $Y_{g,t}$ relative to a change in production inputs increases after net worth shocks, leading to variations in measured TFP. This is another factor which contributes to the fall in measured TFP.

[40] This can also be seen in the estimation results for the adjustment cost of price and nominal wage κ_p and κ_w. As shown in Table 1, the estimated adjustment cost of price is greater than that of wages.

3.4.2 Decomposition of measured TFP

In order to assess the contributions of net worth shocks, we compute three measures for measured TFP, which we call TFP I, TFP II, and TFP III, respectively.[41] These TFP series are defined as follows:

- TFP I: the actual measured TFP series λ_t for the period before the bubble burst, namely t =1980:2Q, ... , 1991:1Q, and the actual measured TFP series λ_t less the portion of measured TFP variations attributed to shocks to FIs' net worth $\epsilon_{N_{F,t}}$ for the period after the bubble burst, which spans from 1991:2Q and beyond. Note that because the model is log-linearized around the steady state in our estimation, variations in the growth rate of measured TFP λ_t over the sample period can be expressed as a linear combination of the contribution of each of the estimated 11 fundamental shocks described in Section 2.7. In computing the TFP I series, we first calculate the entire contribution of all of the fundamental shocks to variations in the TFP growth rate for t =1980:2Q, ... , 2011:4Q and then set the contribution of shocks $\epsilon_{N_{F,t}}$ to zero only for t = 1991:2Q, ... , 2011:4Q.

- TFP II: the actual measured TFP series λ_t for t =1980:2Q, ... , 1991:1Q, and the actual series λ_t less the portion of measured TFP variations attributed to shocks to entrepreneurial net worth $\epsilon_{N_{E,t}}$ from 1991:2Q and beyond.

- TFP III: the actual TFP series λ_t for t =1980:2Q, ... , 1991:1Q, and the actual series λ_t less portion of measured TFP variations attributed to shocks to the FIs' net worth $\epsilon_{N_{F,t}}$ and the entrepreneurial net worth $\epsilon_{N_{E,t}}$ from 1991:2Q and beyond.

In Figure 3.9, we show TFP I, II, and III as well as the actual measured TFP series in levels. Note that the actual series coincides with measured TFP series in an economy where the entire contribution of all the fundamental shocks is present during the full sample

[41]These three measures of TFP are adjusted for capital utilization as with λ_t defined in equation (21).

period. The discrepancy between the actual series and TFP III captures the contribution of two types of net worth shocks to variations in the actual measured TFP during the 1990s and beyond. Similarly, the discrepancy between the actual series and TFP I, and that between the actual series and TFP II captures the contribution of net worth shocks to the FI sector and the goods-producing sector respectively to variations in the actual series during the 1990s and beyond. Quantitatively, the discrepancy between the actual series and TFP I is substantial, while the discrepancy between the actual series and TFP II is minor. This observation suggests that net worth shocks to the FI sector played a more important role in measured TFP decline. It can also be seen that the gap between the actual series and TFP I was small in the early 1990s, but started to widen from the latter half of the 1990s. This observation accords well with the assessment by Hoshi and Kashyap (2010) that the latter half of the 1990s was the "acute phase" of the banking crisis in Japan.[42]

The table in Figure 3.9 shows the average annual growth rate of the actual measured TFP and the three TFP measures, TFP I, TFP II, and TFP III, in the 1980s, 1990s, and 2000s and beyond. The table also shows, for each of the four TFP measures, the difference in the average annual growth rates between the 1980s and the 1990s, and that between the 1980s and the 2000s and beyond. Among the three TFP measures, the growth rate decline during the lost decades is largest in TFP II, while the growth rate decline in the other two measures is moderate. Quantitatively, if the effect of the net worth shocks to the FI had been absent, the slowdown in measured TFP growth rate from the 1980s to the 1990s would have been more moderate by an average of 0.84 percentage points. Meanwhile, even if the effect of the net worth shocks to the goods-producing sector had been absent, TFP slowdown

[42]Actual measured TFP series increased following the last global financial crisis even though our model estimates large negative net worth shocks to the FI sector over this period as in Figure 3.6. Based on our model, this is because there were not only the negative net worth shocks but also large favorable non-net worth shocks around that time, and the effect of the latter shocks on TFP dominates that of the former shocks.

These observations are consistent with existing works, such as Nakaso (2017), that document a quick recovery of Japan's economy after the current global financial crisis, comparing it with the prolonged stagnation after the banking crisis in the late 1990s. Measured TFP series released from the Bank of Japan also exhibit a quick recovery after the period of the global financial crisis.

during the same period would have been present.

Shocks to FI balance sheets also had an important effect on the slowdown of GDP Y_t. To illustrate this, we construct three GDP measures, GDP I, GDP II, and GDP III, that correspond respectively to each of the three TFP measures above.[43] Figure 3.10 shows the actual GDP together with the three GDP measures. As with the comparison of TFP measures demonstrated in Figure 3.9, it is clear that shocks to FI net worth played an important role in lowering the GDP growth rate, particularly during the 1990s. Without the contribution of net worth shocks to FIs, the decline in GDP growth rate from the 1980s to the 1990s would have been mitigated by 2.09 percentage points on average. By contrast, without the contribution of net worth shocks to the goods-producing sector, the decline in GDP growth rate from the 1980s to the 1990s would not have been mitigated.[44,45]

Figure 3.9 and 3.10 suggest that the two likely explanations of the cause of Japan's lost decades, the TFP growth rate slowdown and the malfunction of financial intermediation, are not mutually exclusive. On the one hand, as pointed out by Hayashi and Prescott (2002), the decline in measured TFP growth rate went hand in hand with the decline in GDP rate, because both variables were affected by net worth shocks. On the other hand, as pointed by

[43]We do this by first decomposing the actual GDP growth rates into the contribution of the 11 fundamental shocks, and set the contribution of the relevant shocks to zero from 1991:2Q and beyond. That is, GDP I is the GDP series in which the contribution of shocks to FI net worth $\epsilon_{N_{F,t}}$ is absent from 1991:2Q and beyond, GDP II is the series in which the contribution of shocks to entrepreneurial net worth $\epsilon_{N_{E,t}}$ is absent from 1991:2Q and beyond, and GDP III is the series in which the contribution of both of the two types of net worth shocks $\epsilon_{N_{F,t}}$ and $\epsilon_{N_{E,t}}$ is absent from 1991:2Q and beyond.

[44]Kaihatsu and Kurozumi (2014) estimate a financial accelerator model similar to Bernanke *et al.* (1999) using Japanese data, where only non-financial firms are credit constrained. They show that damaged balance sheets of non-financial firms played a minor role in the decline in output during the early 1990s. Our result on the quantitative contribution of net worth shocks to the entrepreneurs is therefore in line with their finding.

[45]The contribution of net worth shocks to FIs is greater than that to entrepreneurs though the estimated variance of net worth shocks to FIs is smaller than that to entrepreneurs. This is because, as shown in HSU (2017), parameters related to financial contracts affect the impact of net worth shocks. For instance, the greater the monitoring cost is, the higher the external finance premium becomes. Table 1 shows that the estimated monitoring cost of the IF contracts ($\mu_F = 0.53$) is far greater than that to the FE contracts ($\mu_E = 0.005$). That is why shocks to the FI's net worth play more important roles than those to the entrepreneur's net worth.

In addition, the difference in the way that net worth shocks occurred during the 1990s affected the contribution of two shocks to missing TFP. Figure 3.6 shows that the FI's net worth shocks persistently turned for the worse from positive values to negative ones through the 1990s, worsening the performance of measured TFP. Meanwhile, the entrepreneurial net worth shocks went back and forth taking both positive and negative values, offsetting the effect of each other on measured TFP.

Bayoumi (2001) and others, the malfunction of financial intermediation played an important role in lowering measured TFP. The crucial driving force behind the malfunction was an adverse shock to FI balance sheets. As shown in Figure 3.6, a realization of this type of shock took a high positive value during the 1980s, started to take a much smaller value in the early 1990s, and took a negative value persistently from the latter half of the 1990s to the early half of the 2000s. Since these shocks impaired FIs' balance sheet, measured TFP declined due to the multiple channels, as suggested by Figure 3.7.

It is also important to give the explanation for why FI net worth shocks had a persistent effect on measured TFP and GDP as shown in Figure 3.9 and 3.10, even though net worth shocks themselves are transitory shocks as shown in Figure 3.7 and 3.8. The key explanation is the way that FI net worth shocks occurred during the sample period. As Figure 3.6 shows, FI net worth shocks continuously took large positive values up to the bubble burst in 1991. During the early 1990s, FI net worth shocks on average took slightly positive values, which implies that the increase in measured TFP growth rate due to shocks that occurred during this period did not offset measured TFP growth rate declines due to the large positive FI net worth shocks that occurred before the bubble burst.[46] During the late 1990s and early 2000s, FI net worth shocks continuously took large negative values which contributed to a further decline in measured TFP growth rate.

3.4.3 Role of channels in the decline in measured TFP

We have shown above that the net worth shocks to FIs played an important role in the decline of measured TFP. We now show quantitatively the channels through which the net worth shocks brought down measured TFP. To do this, we construct an additional TFP measures, which we call TFP I-I, I-II, and I-III, which decompose the effect of the net worth shocks into multiple channels[47]. TFP I-I is the TFP I series that would have been generated if the

[46] Note that as shown in Figure 3.7 a positive FI net worth shock leads to a positive measured TFP growth over a few quarters after the shock, and leads to a negative measured TFP growth beyond that quarter.

[47] The detailed construction of each series is in Appendix.

value added that is actually used for monitoring costs had been recorded as value added. TFP I-II is the TFP I-I series plus the impact of value-added losses due to factor market distortions, if such losses are not lost, and TFP I-III is TFP I-II series plus the impact of value-added losses due to the increasing returns to scale, if such losses are not lost.

Figure 3.11 shows five TFP series, the actual measured TFP series, TFP I, TFP I-I, TFP I-II and TFP I-III. First, the discrepancy between the actual series and TFP I-I stands for the contribution of the decline in measured TFP due to shocks to FI net worth that is explained by the monitoring costs channel. Second, the discrepancy between TFP I-I and TFP I-II stands for the contribution of the factor market distortion channel to the total size of a measured TFP decline that is brought about by shocks to FI net worth. Third, the discrepancy between TFP I-II and TFP I-III stands for the contribution of the increasing returns to scale channel to the total size of a measured TFP decline that is brought about by shocks to FI net worth.

As is shown in the figure, each of these channels played an important role in the decline in measured TFP due to net worth shocks to the FIs. As the bottom row of the table shows, while the absence of contribution of net worth shocks to the FI sector increases measured TFP growth rate by 0.84 percentage points from the 1980s to the 1990s on average, the absence of each of the monitoring costs channel, factor market distortion channel, increasing returns to scale channel increases measured TFP growth rate by 0.23, 0.25, and 0.45 percentage points, respectively.[48,49] Thus, to put it the other way around, without either of these channels we will underestimate the effect of the FIs net worth shocks on measured TFP.

[48]The sum of the contribution of three channels exceeds the difference between the actual TFP and TFP I. This is because there are other channels in the resource constraint, such as the cost of intermediate goods usage and liquidation cost, which affect TFP in the opposite direction, though the total effect is quantitatively minor.

[49]The impact of the increasing returns to scale channel reflects the size of the fixed cost. Although the exact reason for this is beyond our scope, an intuitive explanation could be that Japanese firms were unable to scale down their once-expanded production capacity smoothly in the early 1990s due to economic or institutional costs even after it became clear that the TFP indeed started to slowdown. Our preferred interpretation is that the large contribution of IRS reflects these costs of adjusting production capacity facing firms. For example, Kuroda *et al.* (2007) provide some institutional characteristics of Japan's labor market, such as strict employment protection legislation. This kind of institutional background could be a possible reason why labor input has quasi-fixed nature, especially in Japan.

3.5 Concluding remarks

In this study, we have examined the structural relationship between financial crises and slowing measured TFP growth by focusing on the experience of Japan during the 1990s and beyond, typically referred to as the lost decades, when the long-lasting measured TFP slowdown was witnessed following the financial crises, the bubble burst in the early 1990s and the banking crisis in the late 1990s. We have constructed and estimated a New Keynesian model that incorporates multiple channels through which balance sheet conditions of non-financial firms and financial intermediaries (FIs) affect measured TFP. We have found that adverse shocks to balance sheets, in particular those to FIs' balance sheets, played a quantitatively significant role in lowering measured TFP during the lost decades. Based on our estimates, the average annual measured TFP growth rate during the 1990s would have been more than twice as high as its actual growth rate if these shocks had not occurred. Our study therefore has shown that the slowdown of measured TFP growth was the outcome of the financial crisis. This provides new insights into discussions on the cause of Japan's lost decades.[50] Although it only presents the empirical results in the case of Japan, it could be the case that our findings have more general implications for the discussions on the causes of slowdowns of measured TFP growth observed in many countries after the global financial crisis. This possibility should be explored in future research.

[50]It is important, however, to point out that the current paper studies on measured TFP, which means that it does not take account of the impact of financial crisis on purely technological factors. For instance, Ogawa (2007), using a panel data of manufacturing firms, argues that there are statistical linkages between the outstanding debt of these firms, their R&D investment, and their firm-level TFP. Extending our framework by incorporating these channels is left as our future research agenda.

Table 3.1: Estimated Parameters

(1) Values of Estimated Parameters (Prior and Posterior Distributions)

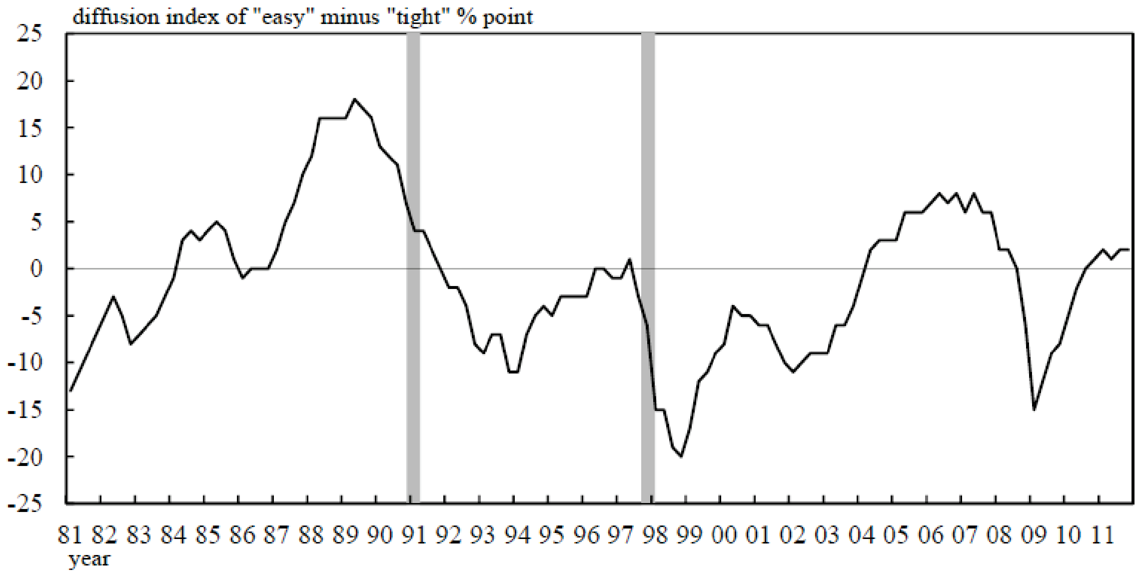
		Prior Distribution			Posterior Distribution		
		Distribution	Mean	S.D.	Mean	5th perc.	95th perc.
ν	Elasticity of Labor Supply	gamma	1	0.1	0.94	0.81	1.07
κ_I	Capital Stock Adjustment Cost	gamma	1	0.1	1.39	1.21	1.56
κ_p	Price Adjustment Cost	gamma	20	10	9.49	6.43	12.45
κ_w	Nominal Wage Adjustment Cost	gamma	20	10	5.24	1.09	9.35
ψ_π	Policy Weight on Inflation in Taylor Rule	gamma	2	0.05	2.05	1.97	2.13
ρ	Monetary Policy Smoothing	gamma	0.9	0.1	0.83	0.81	0.86
Υ_U	Inverse Elasticity of Capital Utilization Rate	gamma	5	1	4.57	3.03	6.12
ρ_h	Degree of Internal Habit Persistence	beta	0.5	0.15	0.70	0.55	0.84
σ_F	Riskiness of Idiosyncratic Productivities (FI)	gamma	0.104	0.002	0.10	0.10	0.10
σ_E	Riskiness of Idiosyncratic Productivities (Entrepreneurs)	gamma	0.309	0.002	0.31	0.31	0.31
μ_F	Monitoring Cost (IF Contract)	gamma	0.539	0.01	0.53	0.52	0.55
μ_E	Monitoring Cost (FE Contract)	gamma	0.02	0.01	0.00	0.00	0.01
γ_F	Survival Rates (FI)	beta	0.923	0.001	0.93	0.92	0.93
γ_E	Survival Rates (Entrepreneurs)	beta	0.974	0.001	0.97	0.97	0.97
ρ_Z	Permanent Technology Shock AR	beta	0.5	0.15	0.13	0.05	0.20
ρ_A	Temporary Technology Shock (Common) AR	beta	0.5	0.15	0.86	0.82	0.91
ρ_{A_I}	Temporary Technology Shock (Investment Specific) AR	beta	0.5	0.15	0.97	0.96	0.99
ρ_{N_F}	Net Worth Shock (FI) AR	beta	0.5	0.15	0.62	0.43	0.81
ρ_{N_E}	Net Worth Shock (Entrepreneur) AR	beta	0.5	0.15	0.13	0.06	0.19
ρ_G	Demand Shock AR	beta	0.5	0.15	0.81	0.72	0.91
ρ_{Z_I}	Investment Adjustment Shock AR	beta	0.5	0.15	0.87	0.83	0.91
ρ_{P_Y}	Price Markup Shock AR	beta	0.5	0.15	0.87	0.83	0.92
ρ_W	Nominal Wage Markup Shock AR	beta	0.5	0.15	0.40	0.11	0.72
ρ_{A_U}	Utilization Adjustment Cost Shock AR	beta	0.5	0.15	0.84	0.78	0.91
σ_Z	Permanent Technology Shock SD	invg	0.05	5	0.007	0.006	0.007
σ_A	Temporary Technology Shock (Common) SD	invg	0.05	5	0.006	0.006	0.007
σ_{A_I}	Temporary Technology Shock (Investment Specific) SD	invg	0.05	5	0.006	0.006	0.007
σ_{R_n}	Monetary Policy Shock SD	invg	0.01	5	0.002	0.002	0.002
σ_{N_F}	Net Worth Shock (FIs) SD	invg	0.02	5	0.008	0.005	0.011
σ_{N_E}	Net Worth Shock (Entrepreneurs) SD	invg	0.05	5	0.03	0.03	0.04
σ_G	Demand Shock SD	invg	0.3	5	0.05	0.04	0.05
σ_{A_I}	Investment Adjustment Shock SD	invg	0.5	5	0.22	0.17	0.28
σ_{P_Y}	Price Markup Shock SD	invg	0.1	5	0.04	0.03	0.04
σ_W	Nominal Wage Markup Shock SD	invg	0.1	5	0.11	0.06	0.16
σ_{A_U}	Utilization Adjustment Cost Shock SD	invg	0.1	5	0.02	0.02	0.02

(2) Values of Calibrated Parameters

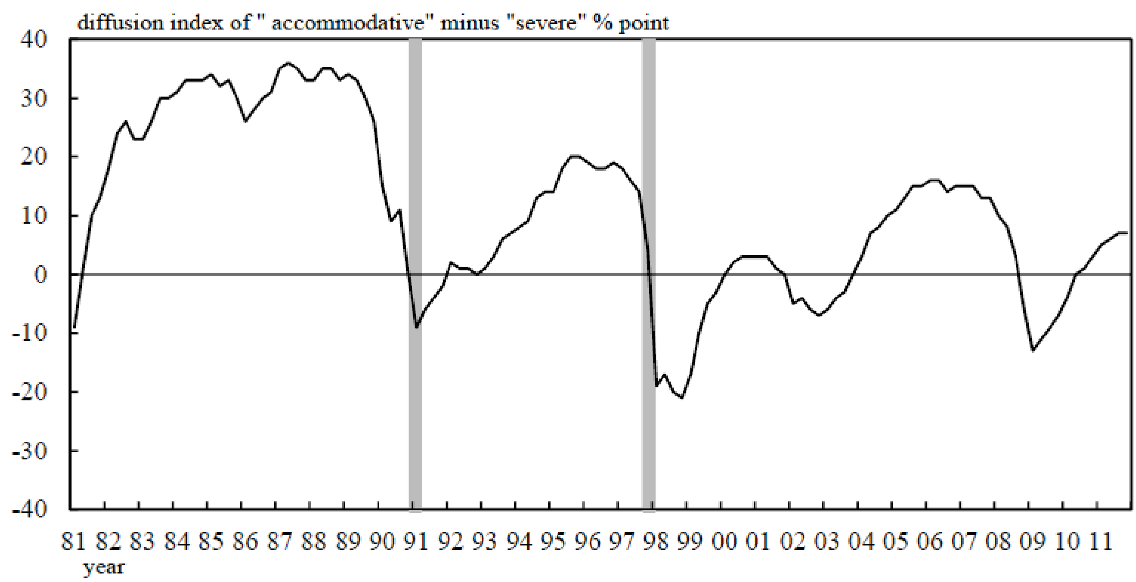
α	Labor Share (Household)	0.6
α_E	Labor Share (Entrepreneur)	0.02
α_{FI}	Labor Share (FI)	0.02
γ	Share of Intermediate Goods	0.583
κ_U	Scaling of Capital Utilization Adjustment Cost	0.05
ψ	Disutility weight on Labor	0.2
β	Households' Discount Factor	0.99
δ	Capital Depreciation Rate	0.028
θ_{P_Y}	Elasticity of Substitution between Differentiated Products at Steady State	6
θ_W	Elasticity of Substitution between Differentiated Labor Inputs at Steady State	6

Figure 3.1: Financial Situation of Non-financial Firms

(1) Financial Position (All Firms)



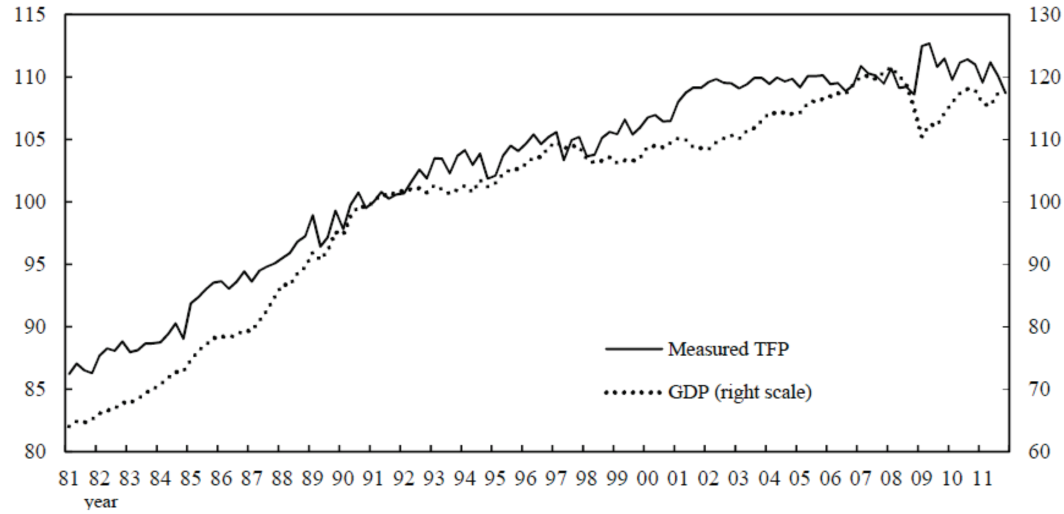
(2) Lending Attitude of Financial Institutions (All Firms)



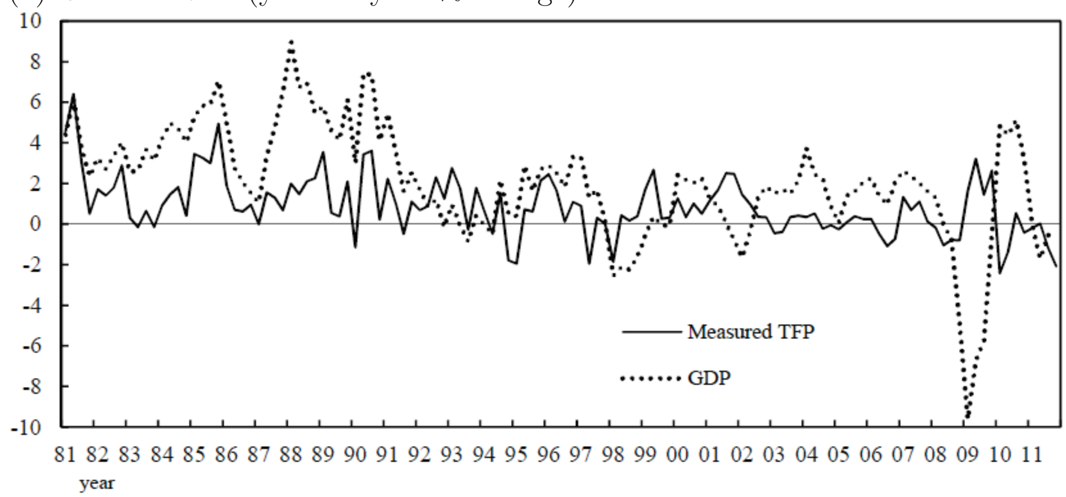
Notes: 1. The two diffusion indices are based on the Short-Term Economic Survey of Enterprises in Japan, which is also known as Tankan, conducted by the Bank of Japan. Regarding financial position, responding enterprises are asked to choose one alternative among three, 1) Easy, 2) Not so tight, and 3) Tight, as the best descriptor of prevailing conditions, excluding seasonal factors at the time of the survey and three months hence. Financial position stands for the general cash position of the responding enterprise, on account of the level of cash and cash equivalent, lending attitude of financial institutions, and payment and repayment terms. Regarding lending attitude of financial institutions, responding enterprises are asked to choose one alternative among three, 1) Accommodative, 2) Not so severe, and 3) Severe. The responses are aggregated into diffusion indices as the percentage share of enterprises responding choice one minus percentage share of enterprises responding choice three.
2. Gray bars in the panels (1991:1Q and 1997:4Q) show a period when financial crisis started.
Source: Bank of Japan, "Tankan, Short-term Economic Survey of Enterprises in Japan."

Figure 3.2: Measured TFP and GDP

(1) Level (1991:1Q=100)



(2) Growth Rate (year on year % change)



(3) Growth Rate (average of 10 years)

	1980s	1990s	2000s and Beyond
Measured TFP	1.78	0.77	0.31
		-1.01	-1.47
GDP	4.44	1.42	0.73
		-3.02	-3.71

Note: year on year % change. Numbers reported below growth rates are differences in growth rate from that in 1980s.

Sources: Cabinet Office, "National Accounts," Ministry of Health, Labour and Welfare, "Monthly Labour Survey," Ministry of Internal Affairs and Communications, "Labour Force Survey," Ministry of Economy, Trade and Industry, "Indices of Industrial Production."

Figure 3.3: The Outline of the Model

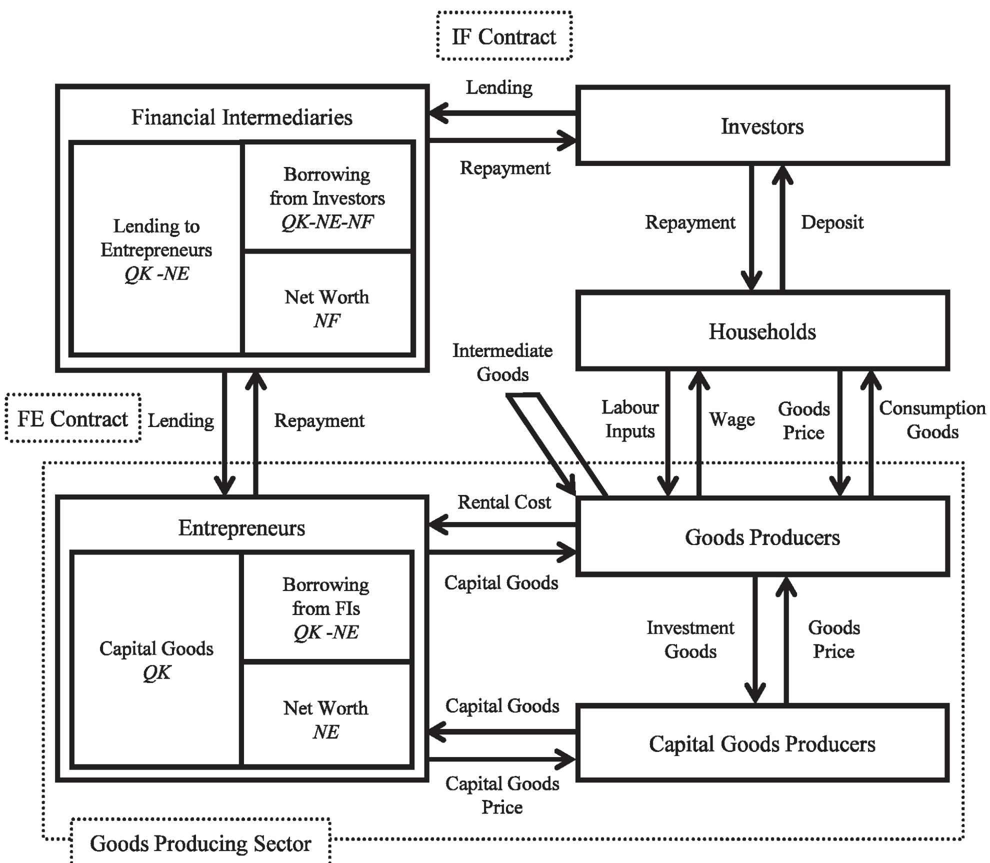
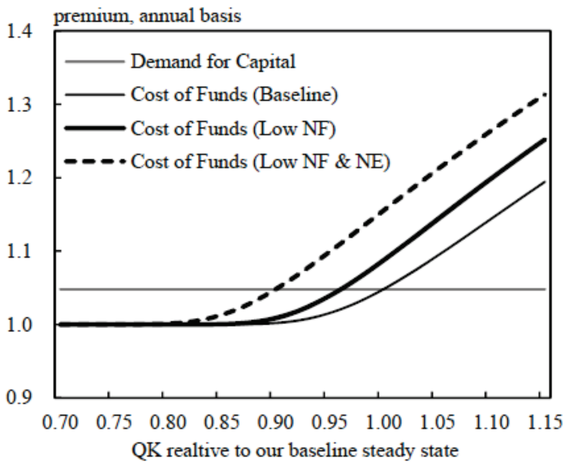
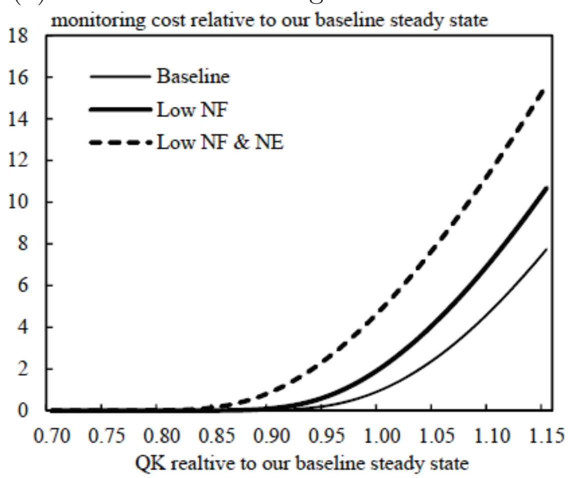


Figure 3.4: The Effects of Net Worth

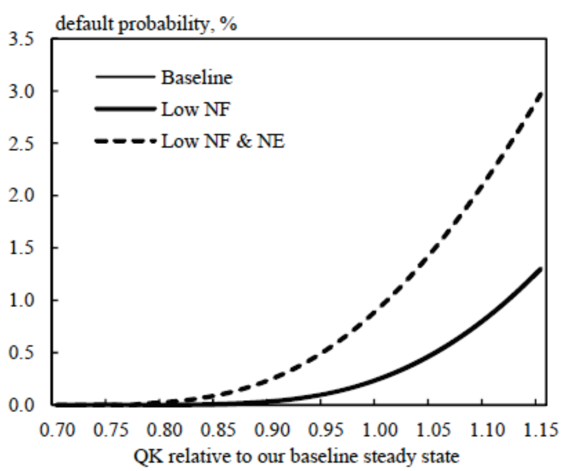
(1) Effect on the External Finance Premium



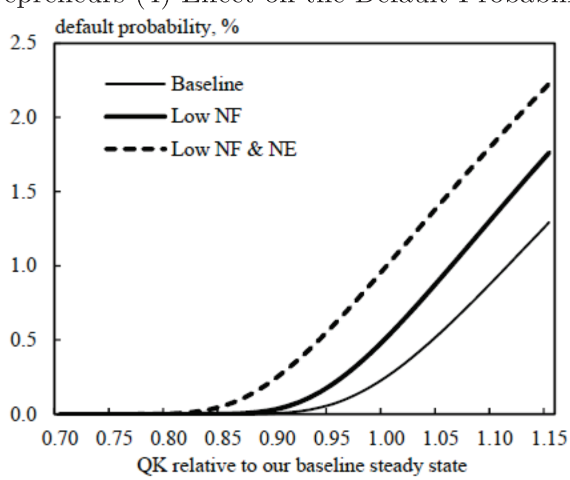
(2) Effect on Monitoring Cost



(3) Effect on the Default Probability of Entrepreneurs



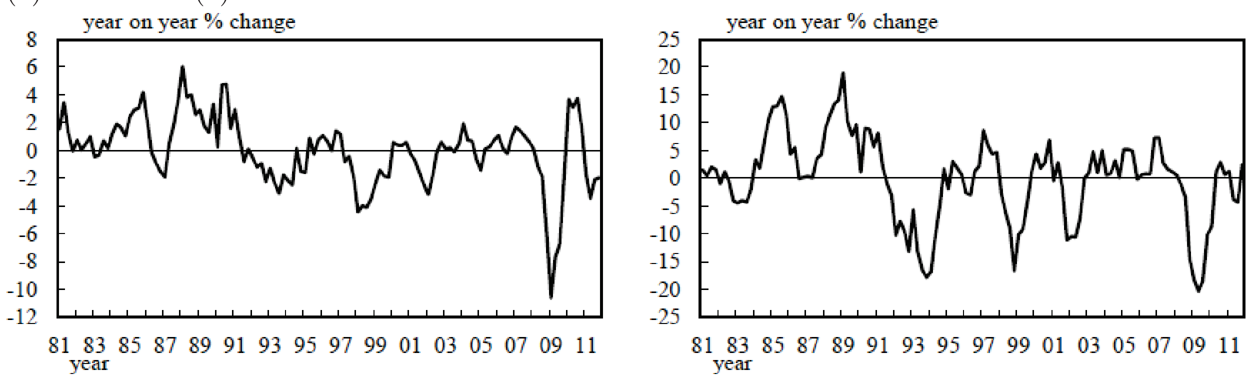
(4) Effect on the Default Probability of FIs



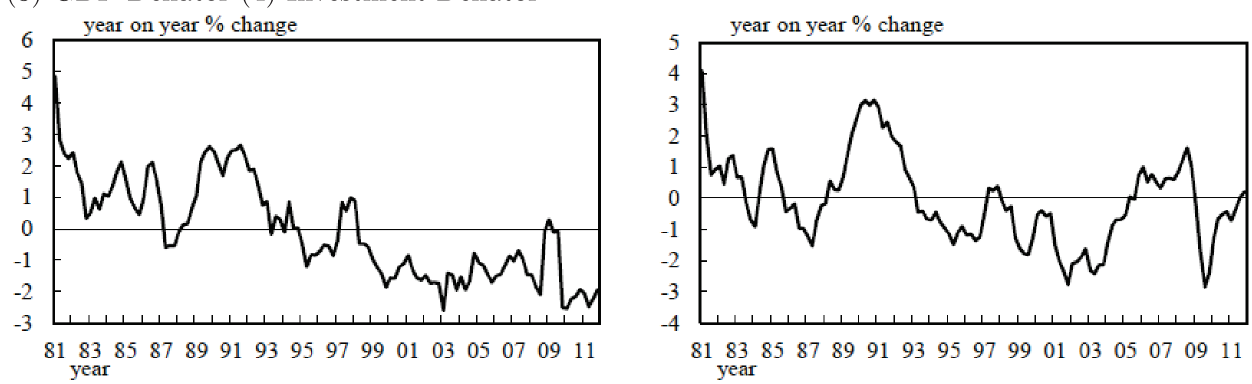
Notes: The panels show the premium of funds, monitoring costs, and default probabilities of borrowers implied by the optimal IF and FE contracts where FIs choose investment of different amount of capital stock, QK, for different amount of net worth, NF and NE. Low NF shows the case where the amount of net worth for FIs is 10% lower than that in our baseline case. Low NF & NE shows the case where the amount of net worth for both FIs and entrepreneurs is 10% lower than that in our baseline case.

Figure 3.5: Data

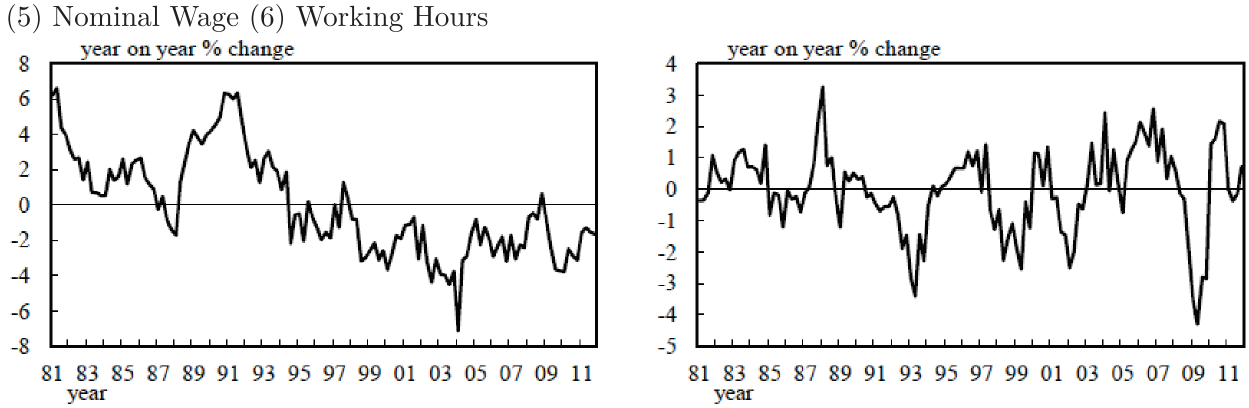
(1) Real GDP (2) Real Investment



(3) GDP Deflator (4) Investment Deflator

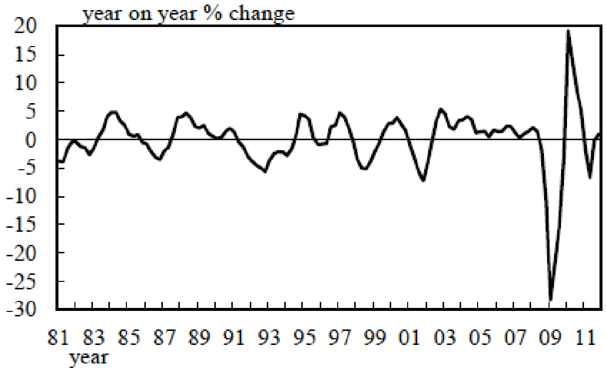


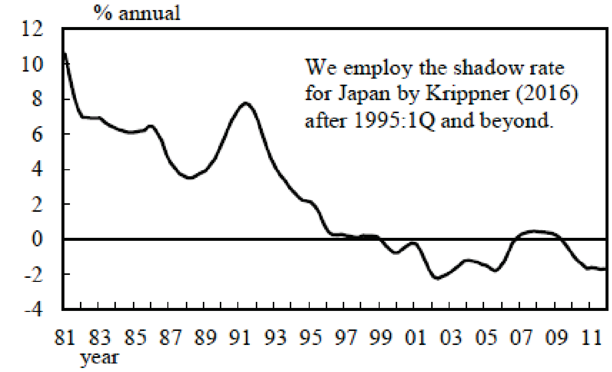
(5) Nominal Wage (6) Working Hours



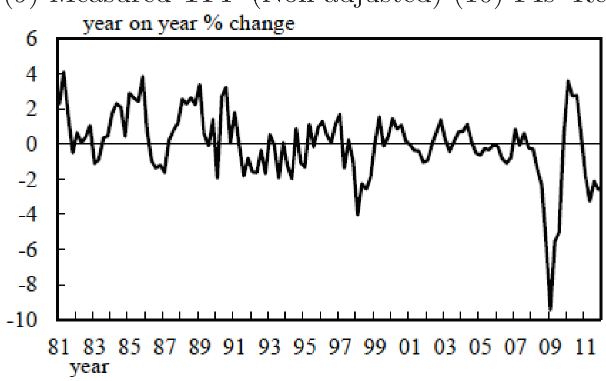
Notes: Series (1), (2), and (6) are on a per capita basis using population aged 15 and over. All series are demeaned.
Sources: Cabinet Office, "National Accounts," Ministry of Health, Labour and Welfare, "Monthly Labour Survey,"Ministry of Internal Affairs and Communications, "Labour Force Survey," Ministry of Economy, Trade and Industry, "Indices of Industrial Production," Japan Exchange Group, Inc., "Market Capitalization"; Bank of Japan, "Flow of Funds Accounts," "Call Rates, Uncollateralized Overnight," "Call Rates, Collateralized Overnight, Average."

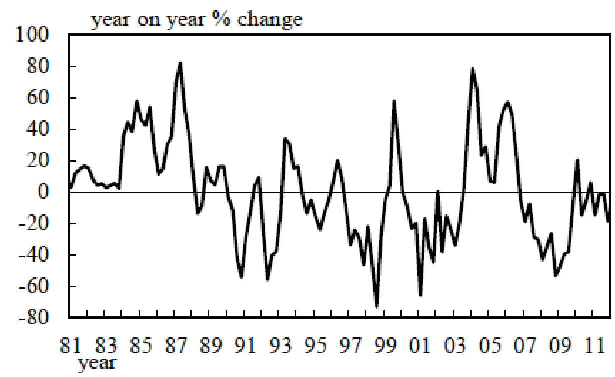
(7) Capacity Utilization Rate of Capital (8) Policy Rate (Shadow Rate)



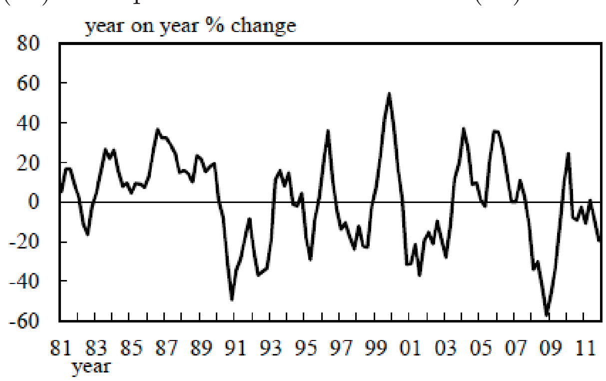


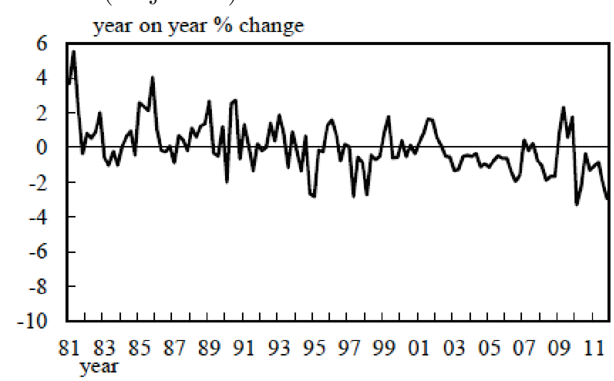
(9) Measured TFP (Non-adjusted) (10) FIs' Real Net Worth





(11) Entrepreneurs' Real Net Worth (12) Measured TFP (Adjusted)

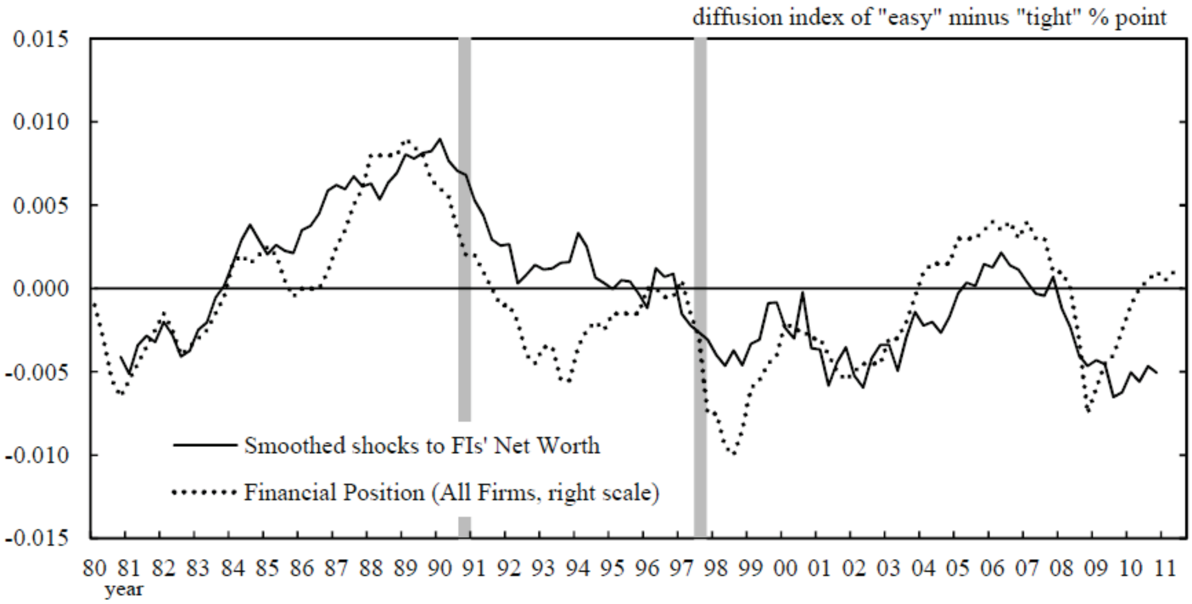




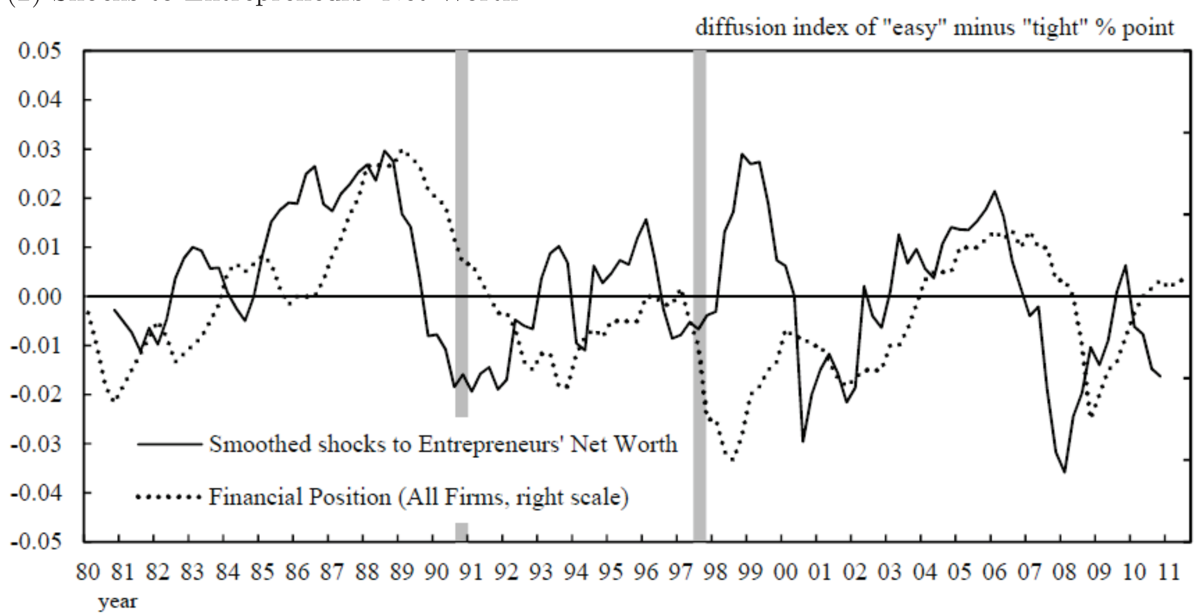
Notes: Series (9) is measured TFP not adjusted for capital utilization rate while series (12) is measured TFP adjusted for capital utilization rate. The latter series are not used for estimation. Series (10) and (11) are on a per capita basis using population aged 15 and over. All series other than the series (8) are demeaned.
Sources: Cabinet Office, "National Accounts," Ministry of Health, Labour and Welfare, "Monthly Labour Survey," Ministry of Internal Affairs and Communications, "Labour Force Survey," Ministry of Economy, Trade and Industry, "Indices of Industrial Production," Japan Exchange Group, Inc., "Market Capitalization"; Bank of Japan, "Flow of Funds Accounts," "Call Rates, Uncollateralized Overnight," "Call Rates, Collateralized Overnight, Average."

Figure 3.6: Estimated Shocks to Net Worth

(1) Shocks to FIs' Net Worth



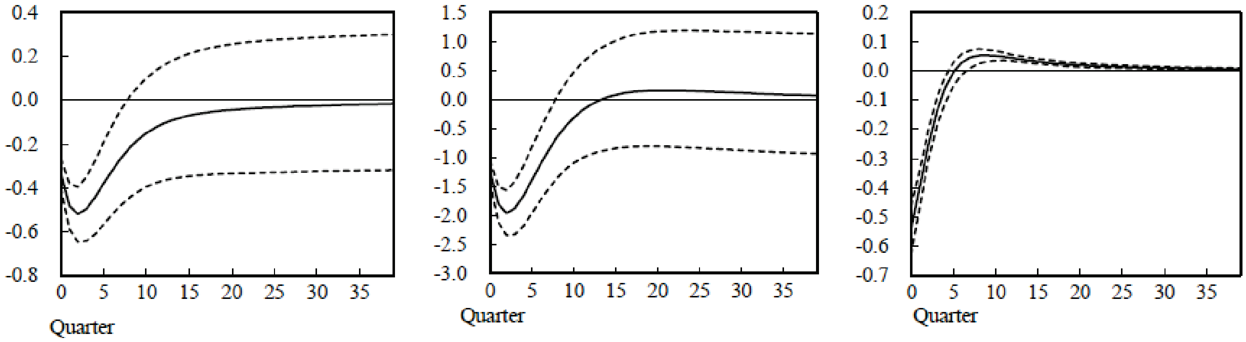
(2) Shocks to Entrepreneurs' Net Worth



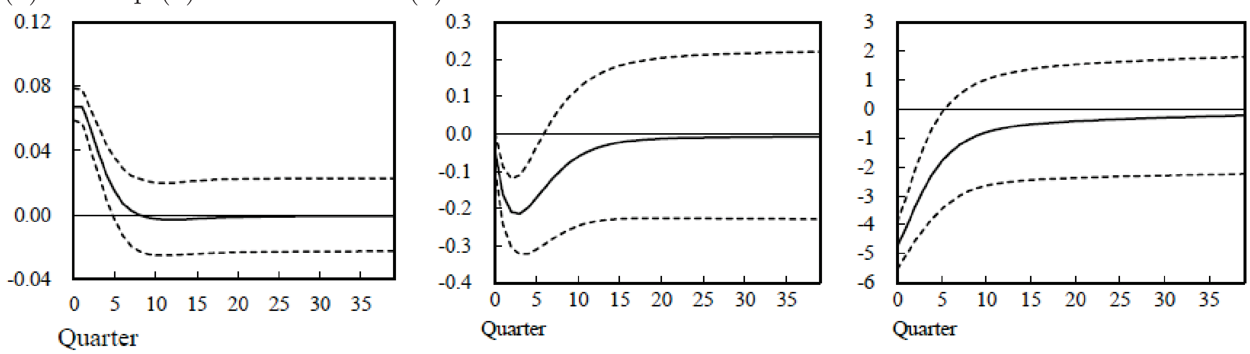
Notes: 1. Gray bars in the panels (1991:1Q and 1997:4Q) show a period when financial crisis started. 2. We smoothed shocks by taking the moving averages of both forward and backward 3 quarters. 3. See footnote of Figure 1 for the index of Financial Position.
Source: Bank of Japan, "Tankan, Short-term Economic Survey of Enterprises in Japan."

Figure 3.7: Response to a Negative Shock to FIs' Net Worth

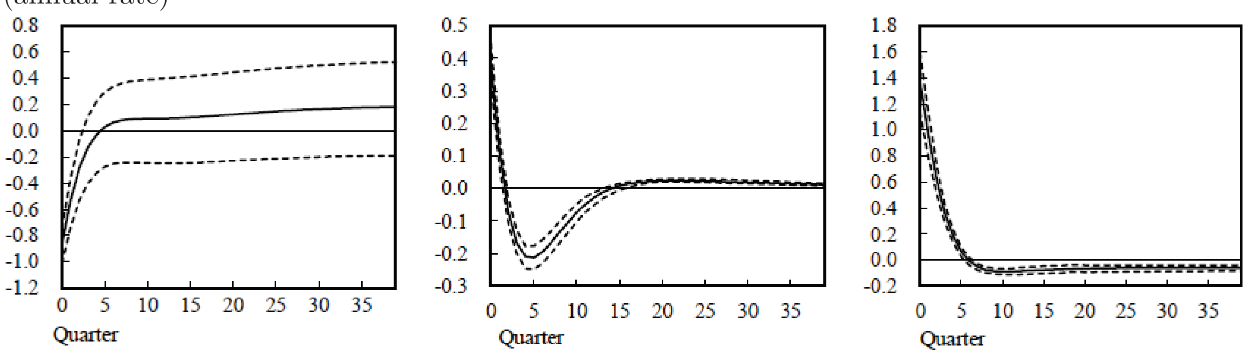
(1) GDP (2) Investment (3) Inflation (annual rate)



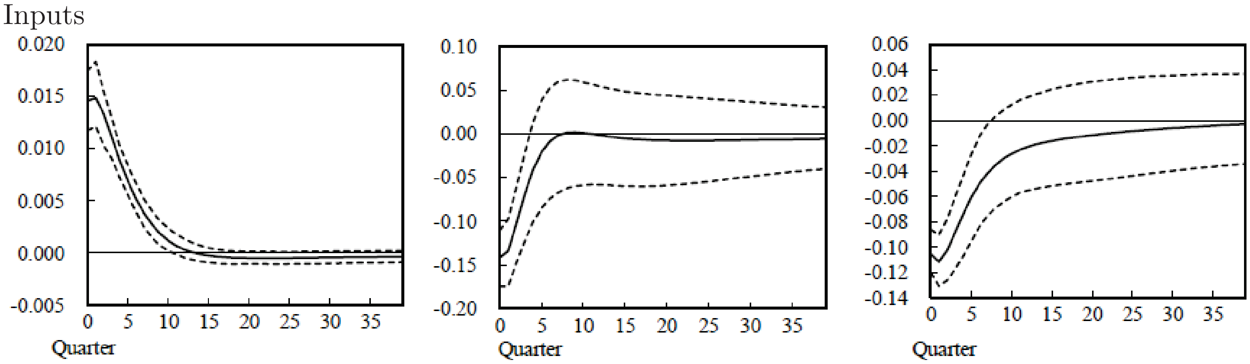
(4) Markup (5) Measured TFP (6) FIs' Net Worth



(7) Entrepreneurs' Net Worth (8) FIs' Borrowing Rate (annual rate) (9) FIs' Lending Rate (annual rate)



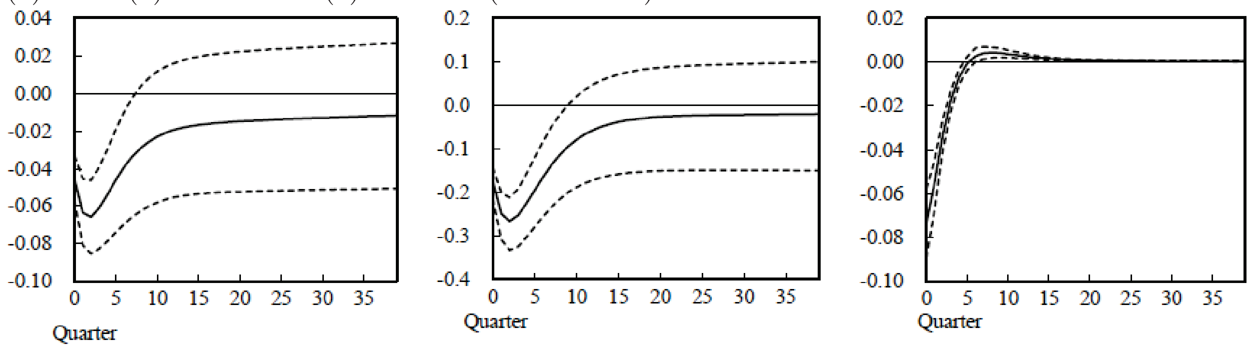
(10) Monitoring Cost (11) Int. Inputs over Primary Inputs (12) Gross Output over All of the Inputs



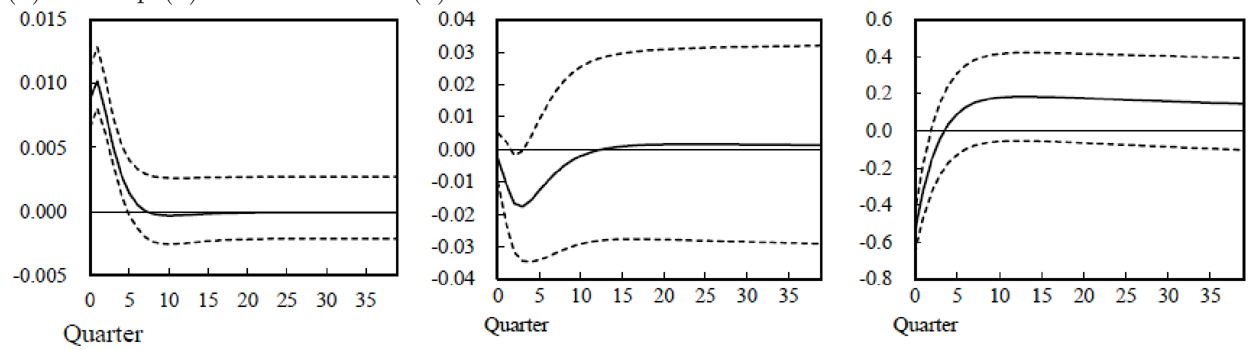
Notes: Interest rates, inflation and markup are deviation from the non-stochastic steady state. Others are percentage deviation from the non-stochastic steady state. Inflation and FI's borrowing & lending rates are on an annual basis. The dotted lines show 90 percent credible intervals.

Figure 3.8: Response to a Negative Shock to Entrepreneurs' Net Worth

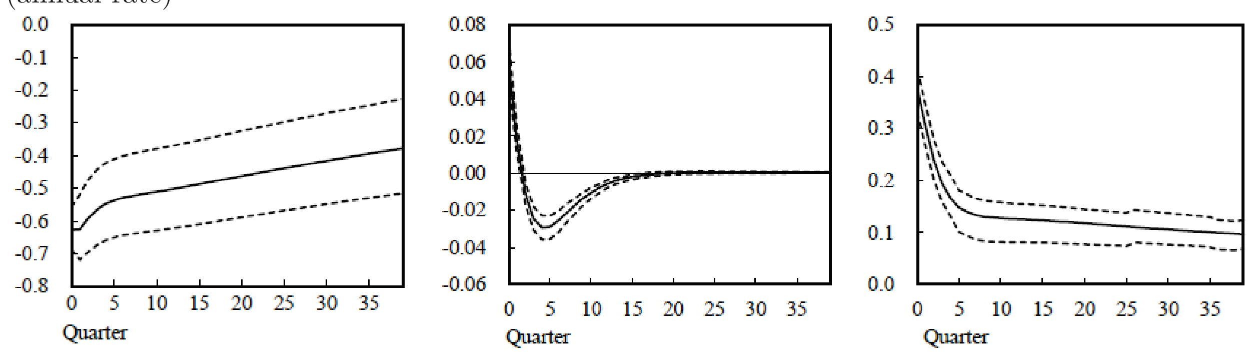
(1) GDP (2) Investment (3) Inflation (annual rate)



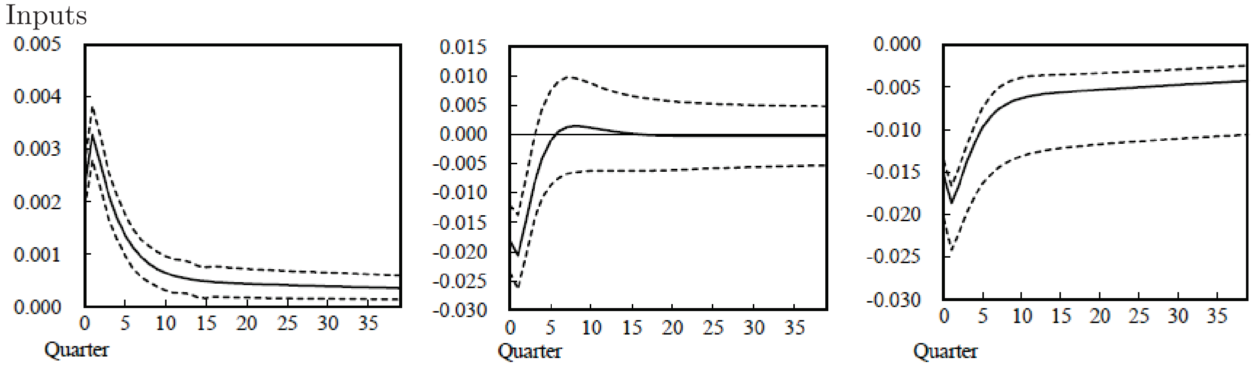
(4) Markup (5) Measured TFP (6) FIs' Net Worth



(7) Entrepreneurs' Net Worth (8) FIs' Borrowing Rate (annual rate) (9) FIs' Lending Rate (annual rate)

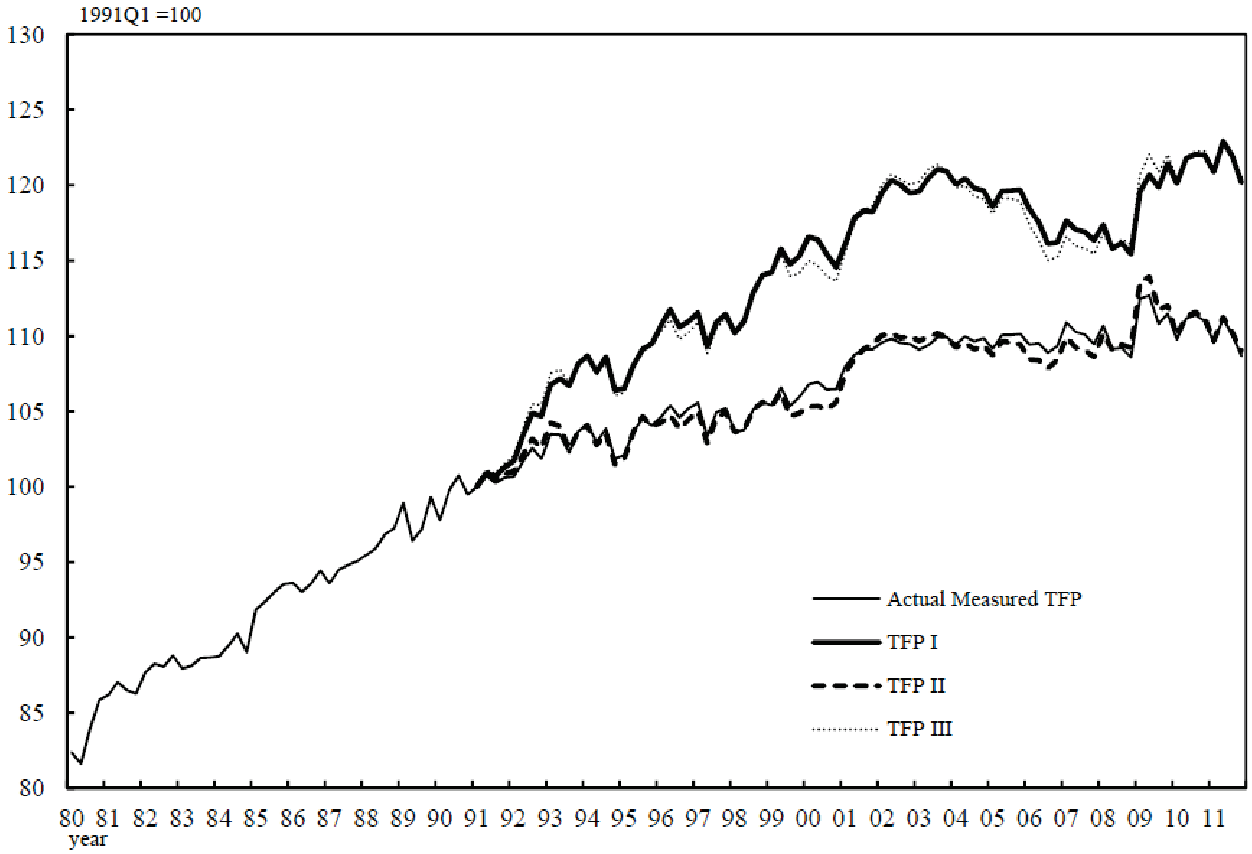


(10) Monitoring Cost (11) Int. Inputs over Primary Inputs (12) Gross Output over All of the Inputs



Notes: Interest rates, inflation and markup are deviation from the non-stochastic steady state. Others are percentage deviation from the non-stochastic steady state. Inflation and FI's borrowing & lending rates are on an annual basis. The dotted lines show 90 percent credible intervals.

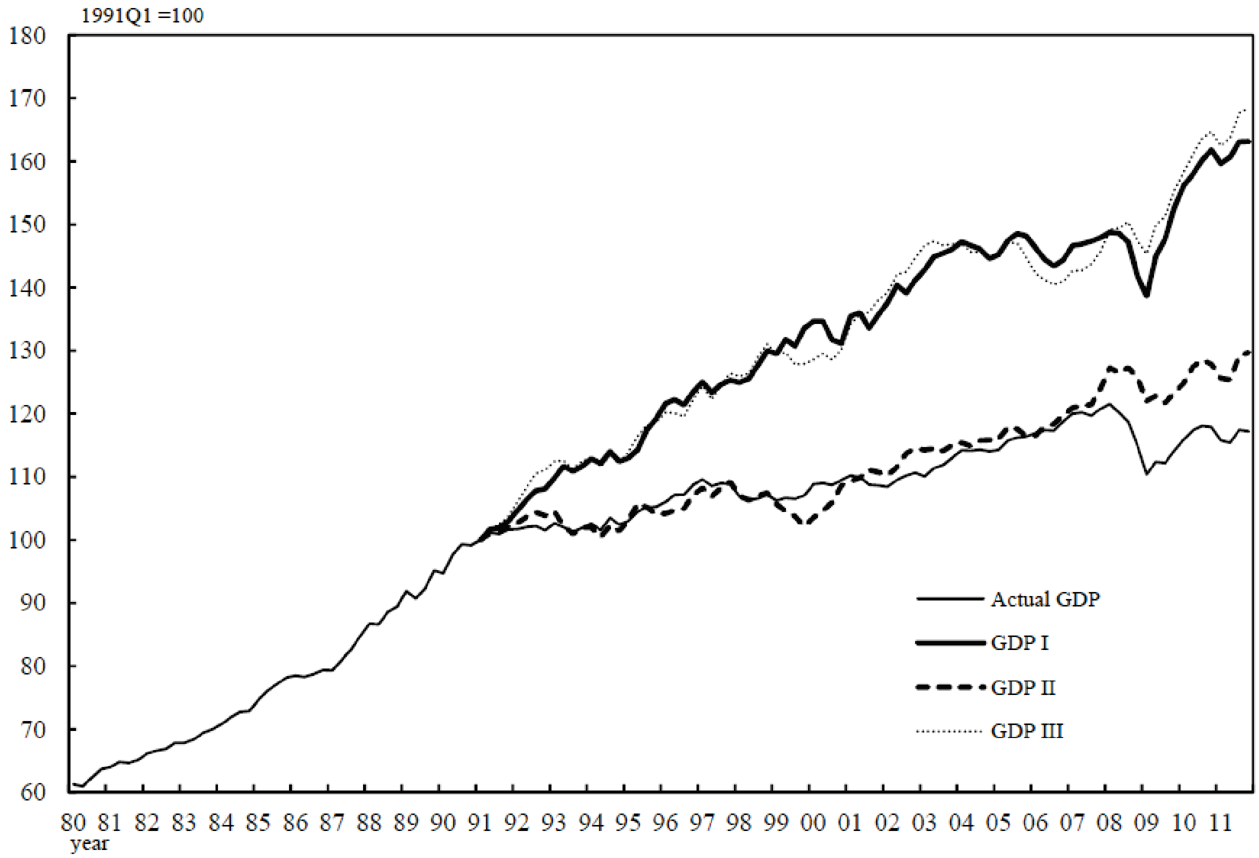
Figure 3.9: Counterfactual Simulations for Measured TFP: Contribution of Each Net Worth Shock



	1980s	1990s			2000s and Beyond
			1st Half	2nd Half	
Actual Measured TFP	1.78	0.77	1.04	0.50	0.31
		-1.01			-1.47
TFP I	1.78	1.61	1.92	1.29	0.46
		-0.17			-1.32
TFP II	1.78	0.72	1.00	0.45	0.37
		-1.06			-1.41
TFP III	1.78	1.55	1.88	1.23	0.51
		-0.23			-1.27

Notes: Year on year % change. Numbers reported below growth rates are differences in growth rate from that in 1980s. TFP I: the actual measured TFP series less portion of TFP variations attributed to shocks to the FIs' net worth from 1991:2Q and beyond. TFP II: the actual measured TFP series less portion of TFP variations attributed to shocks to the entrepreneurial net worth from 1991:2Q and beyond. TFP III: the actual measured TFP series less portion of TFP variations attributed to shocks to the FIs' net worth and the entrepreneurial net worth from 1991:2Q and beyond.

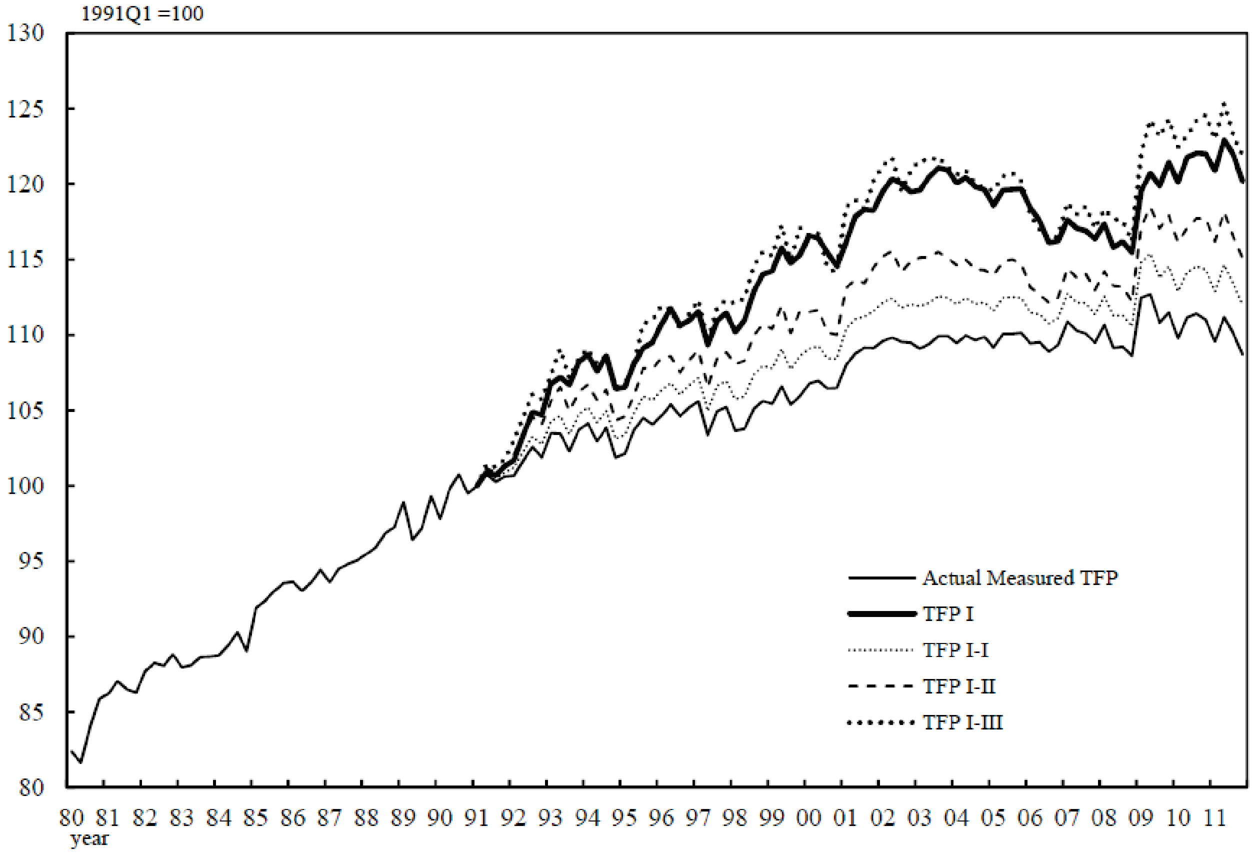
Figure 3.10: Counterfactual Simulations for GDP Contribution of Each Net Worth Shock



	1980s	1990s	2000s and Beyond
Actual GDP	4.44	1.42	0.73
		-3.02	-3.71
GDP I	4.44	3.51	1.73
		-0.93	-2.71
GDP II	4.44	1.17	1.69
		-3.27	-2.75
GDP III	4.44	3.30	2.10
		-1.14	-2.34

Notes: Year on year % change. Numbers reported below growth rates are differences in growth rate from that in 1980s. GDP I: GDP series in which contribution of shocks to the FIs' net worth is absent from 1991:2Q and beyond. GDP II: GDP series in which contribution of shocks to the entrepreneurial net worth is absent from 1991:2Q and beyond. GDP III: GDP series in which contribution of both of two types of net worth shocks is absent from 1991:2Q and beyond.

Figure 3.11: Counterfactual Simulations for Measured TFP: Relative Contribution of Each Channel



	1980s	1990s	2000s and Beyond
Actual Measured TFP	1.78	0.77	0.31
		-1.01	-1.47
TFP I	1.78	1.61	0.46
		-0.17	-1.32
TFP I-I	1.78	1.00	0.37
		-0.78	-1.41
TFP I-II	1.78	1.25	0.40
		-0.53	-1.38
TFP I-III	1.78	1.70	0.50
		-0.08	-1.28

Notes: Year on year % change. Numbers reported below growth rates are differences in growth rate from that in 1980s. TFP I: the actual measured TFP series less portion of TFP variations attributed to shocks to the FIs' net worth from 1991:2Q and beyond. TFP I-I: the actual measured TFP series less portion of TFP variations due to shocks to the FIs' net worth attributed to the change in monitoring cost from 1991:2Q and beyond. TFP I-II: TFP I-I less portion of TFP variations due to shocks to the FIs' net worth attributed to the change in the proportion between intermediate goods and primary inputs from 1991:2Q and beyond. TFP I-III: TFP I-II less portion of TFP variations due to shocks to the FIs' net worth attributed to the effect of increasing return to scale from 1991:2Q and beyond.

Bibliography

Philippe Andrade and Hervé Le Bihan. Inattentive professional forecasters. *Journal of Monetary Economics*, 60(8):967–982, 2013.

Philippe Andrade, Richard K Crump, Stefano Eusepi, and Emanuel Moench. Fundamental disagreement. *Journal of Monetary Economics*, 83:106–128, 2016.

George-Marios Angeletos and Alessandro Pavan. Efficient use of information and social value of information. *Econometrica*, 75(4):1103–1142, 2007.

George-Marios Angeletos, Luigi Iovino, and Jennifer La'o. Real rigidity, nominal rigidity, and the social value of information. *American Economic Review*, 106(1):200–227, 2016.

Diego Anzoategui, Diego Comin, Mark Gertler, and Joseba Martinez. Endogenous technology adoption and r&d as sources of business cycle persistence. *American Economic Journal: Macroeconomics*, 11(3):67–110, 2019.

Romain Baeriswyl and Camille Cornand. The signaling role of policy actions. *Journal of Monetary Economics*, 57(6):682–695, 2010.

Susanto Basu and John G Fernald. Aggregate productivity and aggregate technology. *European Economic Review*, 46(6):963–991, 2002.

Susanto Basu. Intermediate goods and business cycles: Implications for productivity and welfare. *The American Economic Review*, 85(3):512, 1995.

Tamim Bayoumi. The morning after: explaining the slowdown in japanese growth in the 1990s. *Journal of international Economics*, 53(2):241–259, 2001.

Allen N Berger and Robert DeYoung. Problem loans and cost efficiency in commercial banks. *Journal of Banking & Finance*, 21(6):849–870, 1997.

Allen N Berger and Gregory F Udell. Relationship lending and lines of credit in small firm finance. *Journal of business*, pages 351–381, 1995.

Ben Bernanke and Mark Gertler. Agency costs, collateral, and business cycle fluctuations. *American Economic Review*, 79:14–31, 1989.

Ben S Bernanke, Mark Gertler, and Simon Gilchrist. The financial accelerator in a quantitative business cycle framework. *Handbook of macroeconomics*, 1:1341–1393, 1999.

Ricardo J Caballero, Takeo Hoshi, and Anil K Kashyap. Zombie lending and depressed restructuring in japan. *American economic review*, 98(5):1943–77, 2008.

Carlos Capistrán and Manuel Ramos-Francia. Does inflation targeting affect the dispersion of inflation expectations? *Journal of Money, Credit and Banking*, 42(1):113–134, 2010.

Lawrence J Christiano, Roberto Motto, and Massimo Rostagno. Risk shocks. *American Economic Review*, 104(1):27–65, 2014.

Sanjay K Chugh. Costly external finance and labor market dynamics. *Journal of Economic Dynamics and Control*, 37(12):2882–2912, 2013.

Timothy Cogley and Argia M Sbordone. Trend inflation, indexation, and inflation persistence in the new keynesian phillips curve. *American Economic Review*, 98(5):2101–2126, 2008.

Timothy Cogley, Giorgio E Primiceri, and Thomas J Sargent. Inflation-gap persistence in the us. *American Economic Journal: Macroeconomics*, pages 43–69, 2010.

Olivier Coibion and Yuriy Gorodnichenko. Monetary policy, trend inflation, and the great moderation: An alternative interpretation. *American Economic Review*, pages 341–370, 2011.

Olivier Coibion and Yuriy Gorodnichenko. What can survey forecasts tell us about information rigidities? *Journal of Political Economy*, 120(1):116–159, 2012.

Olivier Coibion and Yuriy Gorodnichenko. Is the phillips curve alive and well after all? inflation expectations and the missing disinflation. *American Economic Journal: Macroeconomics*, 7(1):197–232, 2015.

Christopher Crowe and Ellen E Meade. Central bank independence and transparency: Evolution and effectiveness. *European Journal of Political Economy*, 24(4):763–777, 2008.

Nergiz Dincer and Barry Eichengreen. Central bank transparency: Causes, consequences and updates. *Theoretical Inquiries in Law*, 11(1):75–123, 2010.

Rochelle M Edge, Michael T Kiley, and Jean-Philippe Laforte. A comparison of forecast performance between federal reserve staff forecasts, simple reduced-form models, and a dsge model. *Journal of Applied Econometrics*, 25(4):720–754, 2010.

Michael Ehrmann, Sylvester Eijffinger, and Marcel Fratzscher. The role of central bank transparency for guiding private sector forecasts. *The Scandinavian Journal of Economics*, 114(3):1018–1052, 2012.

Barry Eichengreen, Donghyun Park, and Kwanho Shin. The global productivity slump: common and country-specific factors. *Asian Economic Papers*, 16(3):1–41, 2017.

Sylvester CW Eijffinger and Petra M Geraats. How transparent are central banks? *European Journal of Political Economy*, 22(1):1–21, 2006.

Christopher J Erceg and Andrew T Levin. Imperfect credibility and inflation persistence. *Journal of monetary economics*, 50(4):915–944, 2003.

Alex Frankel and Navin Kartik. What kind of central bank competence? *Theoretical Economics*, 13(2):697–727, 2018.

Xavier Freixas and Jean-Charles Rochet. *Microeconomics of banking*. MIT press, 2008.

Jordi Galí. Introduction to monetary policy, inflation, and the business cycle: An introduction to the new keynesian framework. Technical report, Princeton University Press, 2008.

Daniel Garcia-Macia. *The financing of ideas and the great deviation*. International Monetary Fund, 2017.

Petra M Geraats. Central bank transparency. *The economic journal*, 112(483):F532–F565, 2002.

Petra M Geraats. The mystique of central bank speak. *International Journal of Central Banking*, 2007.

Mark Gertler and Peter Karadi. A model of unconventional monetary policy. *Journal of monetary Economics*, 58(1):17–34, 2011.

Mark Gertler and Nobuhiro Kiyotaki. Financial intermediation and credit policy in business cycle analysis. In *Handbook of monetary economics*, volume 3, pages 547–599. Elsevier, 2010.

Simon Gilchrist and John V Leahy. Monetary policy and asset prices. *Journal of monetary Economics*, 49(1):75–97, 2002.

Michael D Grubb and Matthew Osborne. Cellular service demand: Biased beliefs, learning, and bill shock. *American Economic Review*, 105(1):234–71, 2015.

Pablo Guerrón-Quintana and Ryo Jinnai. Lliquidity, trends, and the great recession. Technical report, Federal Reserve Bank of Philadelphia, 2014.

Refet S Gürkaynak, Brian Sack, and Eric Swanson. The sensitivity of long-term interest rates to economic news: Evidence and implications for macroeconomic models. *American economic review*, pages 425–436, 2005.

Robert E Hall. The relation between price and marginal cost in us industry. *Journal of political Economy*, 96(5):921–947, 1988.

Robert E Hall. 5 invariance properties of. *Growth, Productivity, Unemployment: Essays to Celebrate Bob Solow's Birthday*, page 71, 1990.

Andrew C Harvey. *Forecasting, structural time series models and the Kalman filter*. Cambridge university press, 1990.

Fumio Hayashi and Edward C Prescott. The 1990s in japan: A lost decade. *Review of Economic Dynamics*, 5(1):206–235, 2002.

Naohisa Hirakata, Nao Sudo, and Kozo Ueda. Do banking shocks matter for the us economy? *Journal of Economic Dynamics and Control*, 35(12):2042–2063, 2011.

Naohisa Hirakata, Nao Sudo, and Kozo Ueda. Capital injection, monetary policy, and financial accelerators. *International Journal of Central Banking*, 9(2):101–145, 2013.

Naohisa Hirakata, Nao Sudo, and Kozo Ueda. Chained credit contracts and financial accelerators. *Economic Inquiry*, 55(1):565–579, 2017.

Yasuo Hirose and Atsushi Inoue. The zero lower bound and parameter bias in an estimated dsge model. *Journal of Applied Econometrics*, 31(4):630–651, 2016.

Takeo Hoshi and Anil K Kashyap. Will the us bank recapitalization succeed? eight lessons from japan. *Journal of Financial Economics*, 97(3):398–417, 2010.

Daisuke Ikeda, Shangshang Li, Sophocles Mavroeidis, and Francesco Zanetti. Testing the effectiveness of unconventional monetary policy in japan and the united states. 2021.

Peter N Ireland. Changes in the federal reserve's inflation target: Causes and consequences. *Journal of Money, credit and Banking*, 39(8):1851–1882, 2007.

Sohei Kaihatsu and Takushi Kurozumi. What caused japan's great stagnation in the 1990s? evidence from an estimated dsge model. *Journal of the Japanese and International Economies*, 34:217–235, 2014.

Takuji Kawamoto et al. What do the purified solow residuals tell us about japan's lost decade? *Monetary and Economic Studies*, 23(1):113–148, 2005.

Michael A Klein. A theory of the banking firm. *Journal of money, credit and banking*, 3(2):205–218, 1971.

Alexandre N Kohlhas. Learning by sharing: monetary policy and common knowledge. *American Economic Journal: Macroeconomics*, 14(3):324–64, 2022.

Sharon Kozicki and Peter A Tinsley. Shifting endpoints in the term structure of interest rates. *Journal of monetary Economics*, 47(3):613–652, 2001.

Sharon Kozicki and Peter A Tinsley. Permanent and transitory policy shocks in an empirical macro model with asymmetric information. *Journal of economic dynamics and control*, 29(11):1985–2015, 2005.

Sharon Kozicki and Peter A Tinsley. Effective use of survey information in estimating the evolution of expected inflation. *Journal of Money, Credit and Banking*, 44(1):145–169, 2012.

Leo Krippner. *Zero lower bound term structure modeling: A practitioner's guide*. Springer, 2015.

Leo Krippner. Comparison of international monetary policy measures. *RBNZ Additional Research, available at: http://www. rbnz. govt. nz/research-andpublications/research-*

programme/additional-research/measures-of-the-stance-of-unitedstates-monetary-policy/comparison-of-international-monetary-policy-measures, 2016.

Sachiko Kuroda, Isamu Yamamoto, et al. Why are nominal wages downwardly rigid, but less so in japan? an explanation based on behavioral economics and labor market/macroeconomic differences. *Monetary and Economic Studies*, 25(2):45–88, 2007.

Hyeog Ug Kwon, Futoshi Narita, and Machiko Narita. Resource reallocation and zombie lending in japan in the 1990s. *Review of Economic Dynamics*, 18(4):709–732, 2015.

Guido Lorenzoni. A theory of demand shocks. *American Economic Review*, 99(5):2050–84, 2009.

Leonardo Melosi. Signalling effects of monetary policy. *The Review of Economic Studies*, 84(2):853–884, 2017.

Elmar Mertens and James M Nason. Inflation and professional forecast dynamics: An evaluation of stickiness, persistence, and volatility. *Quantitative Economics*, 11(4):1485–1520, 2020.

Mario Monti. *Deposit, credit and interest rate determination under alternative bank objective function.* North-Holland/American Elsevier, 1972.

Stephen Morris and Hyun Song Shin. Social value of public information. *American Economic Review*, 92(5):1521–1534, 2002.

Haroon Mumtaz and Francesco Zanetti. The effect of labor and financial frictions on aggregate fluctuations. *Macroeconomic Dynamics*, 20(1):313–341, 2016.

Masayuki Nakakuki, Akira Otani, Shigenori Shiratsuka, et al. Distortions in factor markets and structural adjustments in the economy. *Monetary and Economic Studies*, 22(2):71–99, 2004.

Emi Nakamura and Jón Steinsson. High-frequency identification of monetary non-neutrality: the information effect. *The Quarterly Journal of Economics*, 133(3):1283–1330, 2018.

Hiroshi Nakaso. The financial crisis in japan during the 1990s: how the bank of japan responded and the lessons learnt. 2001.

Hiroshi Nakaso. New frontier of macroprudential policy: addressing financial institutions' low profitability and intensified competition. In *Speech at the Kin'yu Konwa Kai (Financial Discussion Meeting) Hosted by the Jiji Press. Bank of Japan*, 2017.

Kristoffer Nimark. Man-bites-dog business cycles. *The American Economic Review*, 104(8):2320–2367, 2014.

Charles Nolan and Christoph Thoenissen. Financial shocks and the us business cycle. *Journal of Monetary Economics*, 56(4):596–604, 2009.

Kazuo Ogawa. Debt, r&d investment and technological progress: A panel study of japanese manufacturing firms' behavior during the 1990s. *Journal of the Japanese and International Economies*, 21(4):403–423, 2007.

Kunio Okina, Masaaki Shirakawa, and Shigenori Shiratsuka. The asset price bubble and monetary policy: Japan's experience in the late 1980s and the lessons. *Monetary and Economic Studies (special edition)*, 19(2):395–450, 2001.

Andrew J Patton and Allan Timmermann. Why do forecasters disagree? lessons from the term structure of cross-sectional dispersion. *Journal of Monetary Economics*, 57(7):803–820, 2010.

Joe Peek and Eric S Rosengren. The international transmission of financial shocks: The case of japan. *The American Economic Review*, pages 495–505, 1997.

Joe Peek and Eric S Rosengren. Determinants of the japan premium: actions speak louder than words. *Journal of international Economics*, 53(2):283–305, 2001.

Valerie A Ramey and Matthew D Shapiro. Displaced capital: A study of aerospace plant closings. *Journal of political Economy*, 109(5):958–992, 2001.

Michael Redmond, Willem Van Zandweghe, et al. The lasting damage from the financial crisis to us productivity. *Economic Review*, 1612387(101):39–64, 2016.

Carmen M Reinhart and Kenneth S Rogoff. From financial crash to debt crisis. *American economic review*, 101(5):1676–1706, 2011.

Christina D Romer and David H Romer. Federal reserve information and the behavior of interest rates. *American economic review*, 90(3):429–457, 2000.

Pierre L Siklos. Sources of disagreement in inflation forecasts: An international empirical investigation. *Journal of International Economics*, 90(1):218–231, 2013.

James H Stock and Mark W Watson. Why has us inflation become harder to forecast? *Journal of Money, Credit and Banking*, 39(s1):3–33, 2007.

Tomohiro Sugo and Kozo Ueda. Estimating a dynamic stochastic general equilibrium model for japan. *Journal of the Japanese and International Economies*, 22(4):476–502, 2008.

Wataru Tamura. Optimal monetary policy and transparency under informational frictions. *Journal of Money, Credit and Banking*, 48(6):1293–1314, 2016.

Jenny Tang. Uncertainty and the signaling channel of monetary policy. Technical report, Federal Reserve Bank of Boston, 2015.

Carl E Walsh. Optimal economic transparency. *International Journal of Central Banking*, 3(1):5–36, 2007.

Michael Woodford. Imperfect common knowledge and the effects of monetary policy. Technical report, National Bureau of Economic Research, 2001.

Jing Cynthia Wu and Fan Dora Xia. Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking*, 48(2-3):253–291, 2016.

Jing Cynthia Wu and Ji Zhang. A shadow rate new keynesian model. *Journal of Economic Dynamics and Control*, 107:103728, 2019.