

Central Bank Credibility, Perceived Economic Risk, and Simulated Moments

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List of Acronyms

AR	Autoregressive (Process)
BR	Bounded Rationality
CEV	Consumption Equivalent Variation
COVID-19	Coronavirus Disease discovered in 2019
DSGE	Dynamic Stochastic General Equilibrium (model)
ECB	European Central Bank
EFFR	Effective Federal Funds Rate
Fed	Federal Reserve
FF	Financial Frictions
GDP	Gross Domestic Product
GDPPD	Gross Domestic Product Price Deflator
GFC	Global Financial Crisis
GLA	Genetic Learning Algorithm
GPDI	Gross Private Domestic Investment
HP	Hodrick-Prescott
HSM	Heuristic Switching Model
IRF	Impulse Response Function
JB	Jarque-Bera
LtFE	Learning to Forecast Experiment
LtOE	Learning to Optimize Experiment
MEI	Marginal Efficiency of Investment
MSFE	Mean Squared Forecast Error

NK	New Keynesian
OSR	Optimized Simple Rule
PCE(eFE)	Personal Consumption Expenditure (excluding Food and Energy)
pGDP	Potential Gross Domestic Product
QE	Quantitative Easing
RANK	Representative Agent New Keynesian (model)
RE	Rational Expectations
SMM	Simulated Method of Moments
SW	Smets and Wouters (2007) New Keynesian Framework
TR	Taylor Rule
ZLB	Zero Lower Bound

1 Introduction

In June 2022, the United States experienced an increase in annual inflation, reaching a peak of slightly above 9% after being nearly on target in March 2021 with 2.6%. This abrupt increase was primarily attributable to an excess of demand resulting partly from the implementation of extensive fiscal stimulus packages following the global outbreak of the coronavirus disease (COVID-19) in early 2020. Additionally, inflationary pressure was prevalent in the eurozone due to Russia's unjustified and unprovoked war against Ukraine beginning in February 2022. The subsequent disruptions to the supply chain and energy markets on a global scale resulted in elevated production costs across nearly all sectors.

The credibility of central banks' reactions to combat high inflation was subjected to rigorous scrutiny. The public discourse was centered on the question of whether the European Central Bank (ECB) and the Federal Reserve (Fed) could effectively address inflationary pressures in a reasonable timeframe. Furthermore, concerns about the potential for high interest rates to impede investment opportunities have given rise to more pessimistic forecasts regarding the possibility of stagflation. Consequently, the economic risk perceived by households and firms was rising, given the uncertainty surrounding the persistence of inflationary pressures and the resulting high interest rates. Furthermore, when the credibility of the monetary authority is undermined in the public domain, the risk of deanchored inflation expectations makes it challenging to pursue effective monetary policy, which can result in additional inflationary pressures, as evidenced by the studies of Reis (2022) and Hilscher et al. (2022).

In light of these considerations, I propose the following research question to guide this thesis: How does perceived economic risk and its interaction with the central bank’s credibility affect monetary policy?

This question will be addressed through the lens of a medium-scale New Keynesian (NK) dynamic stochastic general equilibrium (DSGE) framework, as outlined in the seminal work of Smets and Wouters (2007) (SW), with a particular focus on boundedly rational expectations, as elucidated by De Grauwe (2011). This thesis introduces measures for perceived economic risk and central bank credibility, as well as a more complex approach to model expectation heuristics, with the aim of enhancing the explanatory power of the framework. I contribute to the field by estimating these novel approaches to perceived risk and expectation modeling. With the resulting estimates, I contribute to the ongoing discussion on how the monetary policy stance should change when agents form boundedly rational expectations. The optimized monetary policy responses to varying central bank credibility environments are of particular interest. The estimated model is also used for welfare experiments with the risk and expectation channel components.

In order to formulate expectations within the macroeconomic framework, I utilize the heuristic switching model (HSM) approach as proposed by Brock and Hommes (1997). This approach was subsequently employed by De Grauwe (2011) in a small-scale NK DSGE model for the purpose of conducting monetary policy experiments. However, this literature strain has since evolved with the latest contributions implementing endogenous central bank credibility into the baseline NK model by Hommes and Lustenhouwer (2019), which I will also employ. The latest class of bounded ra-

tionality (BR) lends itself to analyzing credibility problems because in the model, the fraction of agents that believe in the target set by the central bank yields a self-evident measure of central bank credibility. The fraction believing in the central bank target changes depending on the bank's past track record in achieving its goal. Furthermore, the HSM-NK framework is capable of reproducing non-Gaussian business cycles in accordance with the argumentation presented by Jordà et al. (2020), who assert that US business cycles since the late 19th century are not normally distributed. The framework developed by De Grauwe (2011) with the switching model by Brock and Hommes (1997) is well-suited to matching moments resulting from non-normal distributions, specifically skewness and excess kurtosis. By incorporating a newly formalized risk and expectation channel, my proposed framework can more effectively match these higher moments than a BR-HSM-NK with financial frictions.

The framework I propose employs the endogenous central bank credibility measure developed by Hommes and Lustenhouwer (2019). The framework is extended by introducing a perceived risk equation that captures economic conditions, central bank trust, and pessimistic sentiments. This approach combines the risk formulations of Proaño and Lojak (2020) and Brenneisen (2022). The risk measure was first introduced by Adrian et al. (2010) and subsequently employed in the NK framework to establish a risk premium in addition to the risk-free rate, with the intention of encompassing the risk perceptions of households and financial intermediaries. Furthermore, I employ this measure as an additional component in the interest rate channel, as well as in the investment expectation channel, in accordance with Brenn-

eisen (2022). In addition to anticipating the central bank's targets for inflation and output, I permit agents to apply an underutilized, modular expectation heuristic, which enhances the model's explanatory power concerning the alignment of higher empirical data moments. Depending on the parameter selection, the heuristic developed by Hommes et al. (2017) can result in static, trend extrapolation or anchoring expectations of agents.

The extent to which credibility, perceived risk, and expectations influence the framework remains uncertain within the existing literature. A thorough examination of these magnitudes is a pivotal aspect of my thesis. The resulting parameter estimates will provide a well-informed intuition regarding the functioning of these channels. Another goal of my thesis will be to ascertain whether my model framework performs similarly or more effectively than a model containing financial frictions in matching empirical data. To gain a comprehensive understanding of the risk and expectation channel, I pose four secondary research questions:

- 1) How do central bank credibility, perceived economic risk, and expectations interact and affect model stability?
- 2) Is there empirical evidence for the risk channel, and what is its underlying magnitude?
- 3) Does the risk channel compensate for the lack of financial frictions in an NK framework?
- 4) What are the implications of the risk channel for optimal monetary policy and welfare in the economy?

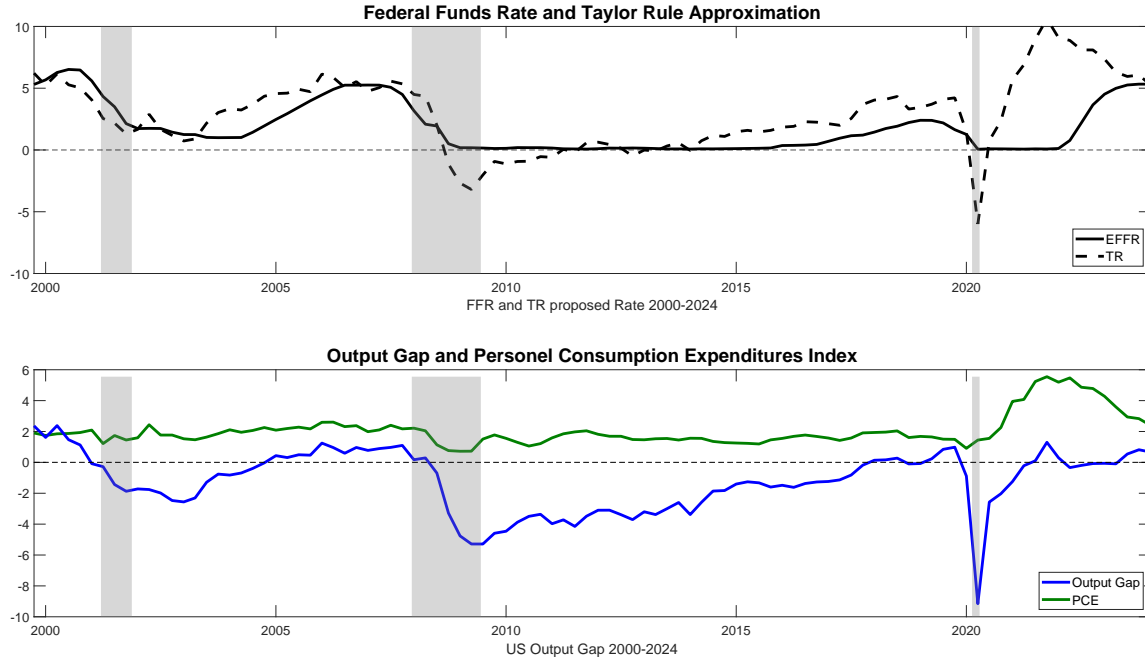


Figure 1: EFFR (black line), TR proposed rate (black dashed line), personal consumption expenditure index inflation (green line), output gap (blue line) 2000–2024. Grey areas depict recessions in the US. Data source: Fed (2024).

To further illustrate the significance of central bank credibility, perceived risk, and expectations, I present a graphical representation of the effective federal funds rate (EFFR), US inflation, and the output gap in Figure 1, which I then contrast with a proposed Taylor rule (TR) rate, as outlined in Taylor (1993).¹ In the aftermath of the global financial crisis (GFC) and the subsequent COVID-19 pandemic, the zero lower bound (ZLB) of the conventional monetary policy instrument became binding in the United States. At the beginning of 2022, the year-on-year quarterly inflation in the private consumption expenditure index (excl. food and energy, PCEeFE, solid

¹ Simplified TR used: $i^{TR} = \pi_t + 0.5(\pi_t - 2) + x_t + 2$. π_t : private consumption expenditure excluding food and energy (PCEeFE); x_t : $(rGDP - rpGDP)/rpGDP$; real (potential) gross domestic product (r(p)GDP).

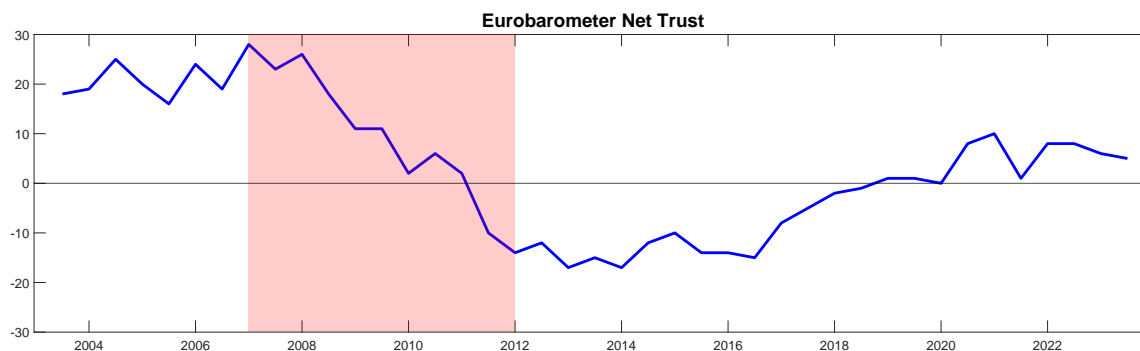


Figure 2: Eurobarometer Net ECB Trust: % of people that answered ‘tend to trust’ the ECB minus % of people that answered they ‘tend not to trust.’ Data source: Standard Eurobarometer from fall 2003 to spring 2023. The red area depicts the beginning of the Global Financial Crisis till the peak of the European debt crisis.

green line) reached 5.8%, a level that should have been accompanied by rising interest rates (see black dashed line). The Federal Reserve did not promptly increase the EFFR, citing that long-term inflation expectations remain at 2%. (Board of Governors of the Federal Reserve System (2022)). However, the Fed commenced raising the EFFR until it reached 5.33% in July 2023, suggesting that inflation expectations may undergo a deanchoring process due to mounting inflationary pressure.

While direct access to data regarding the credibility or trust placed in the US central bank is not available, the Eurobarometer survey provides insight into the level of trust placed in the ECB by households. This is illustrated in Figure 2. A mere few years ago, the credibility of the European monetary authority was already facing significant challenges. A structural break in the series can be observed during the GFC. Net trust exhibited a downward trajectory during the Great Recession and reached net negative levels during the European debt crisis. After approaching zero-net trust levels from 2016 to 2020, it reached a net 10% during the COVID-19 pandemic, while

the measure appears to fluctuate in the recent high inflation environment at the end of the survey horizon.

The impact of central bank credibility (or trust) and inflation deanchoring cannot be easily explained by the baseline NK framework; however, it can be explained by the extended BR-HSM framework developed in this thesis. Before introducing the framework developed in this thesis, I will briefly recapitulate the main takeaways of the heuristic switching literature in Section 2 to emphasize the extension this thesis will provide. Subsequently, Section 3 presents the core model and the respective variants used for comparison and subsequent analysis. The well-known SW-NK framework is augmented with the heuristic switching procedure, which is used to model formation agents' expectations about the future realization of key economic variables. Furthermore, the model incorporates the endogenous formation of central bank credibility, whereby agents perceive general economic conditions as risk, and this perception is passed through the model to affect the credibility measure. However, certain modifications have been made to ensure the model remains tractable with respect to the risk and expectation channel. Nevertheless, financial frictions, as a driver of business cycles, as formulated by Becard and Gauthier (2022) following Brenneisen (2022), are added into the framework to compare it with the model containing the risk channel. Adjacent to the introduction of the DSGE framework, a brief discussion regarding the specific banking mechanism used in the model comparison section is incorporated into the framework for comparison with the model containing the risk channel. In addition, a brief discussion regarding the specific banking mechanism used in the model comparison section is presented.

Section 4 presents a verification of the importance of the risk channel and subsequent interaction with central bank credibility through an empirical analysis. This analysis involves a comparison between the simulated moments of the model and the empirical moments of US output gap, inflation, and interest rate data, among other variables. This section addresses questions 3) and 4). It adheres to the empirical thread of the heuristic switching DSGE framework, particularly as elucidated in De Grauwe and Macchiarelli (2015) and Jang and Sacht (2022).

The central part of the thesis concludes with Section 5, in which I analyze the requisite monetary policy response to the additional business cycle amplifications resulting from the incorporation of the risk and expectation channels. In this section, simple instrument rules are optimized under two central bank policy mandates: flexible inflation targeting and flexible heuristic targeting. Whereas the latter describes the objective of the central bank to lower the share of agents that do not follow the targets set by the central bank. This thesis concludes with a summary of the findings and remarks on further research.

2 Bounded Rationality

In the baseline rational agent NK literature developed by Clarida et al. (1999), Woodford (2003) and Galí (2015), among others, the *homo economicus* fills the role of a member of a household that consumes goods. These goods are produced by firms to which the household supplies its labor service. In light of a budget constraint,

the household strives to maximize lifetime utility through the application of rational expectations (RE) concerning prospective economic conditions. Additionally, the individual considers allocating a portion of their income from wages and income from holding bonds to smooth out the consumption stream. He understands and knows the model framework at hand, uses all available information, and optimizes lifetime consumption and labor supply. From his behavior, the equilibrium conditions in the economic sectors can be formulated. In aggregate, he and his neighboring households in the model economy reach a steady state in the absence of exogenous shocks. Every period is predictable except for ongoing exogenous shocks. Nevertheless, the convergence path for his consumption and labor choices is clear, and he makes no systematic errors.

The assumption of rational, model-consistent expectation formation according to Lucas (1972) inherent to the members of NK model households renders the model tractable, mathematically solvable, and therefore well suited for policy discussion and response evaluation. This type of model is capable of replicating a number of stylized facts pertaining to business cycles. Nevertheless, at least since Tversky and Kahneman (1974) and Kahneman (2003) presented a psychology-based counterargument to the rational agent, economists know quite well that people systematically make mistakes under uncertainty at the microeconomic level. The assumption of rational decision-making is occasionally superseded by more straightforward decision rules or a broader concept of BR in humans.

Just before and especially after the financial crisis of 2007 and 2008, there was considerable debate surrounding the assumption of rational agents in macroeconomic

models. Subsequent literature, including pre-crisis literature and new research, has led to a revised approach to formulating agents' expectations in NK models.²

Brock and Hommes (1997) were at the forefront of the field, introducing specific heuristics to agents with whom they could form expectations. In a cobweb-type demand-supply model, agents endogenously choose the expectation strategy that delivers the best track record of expected variable realization compared to the variable's actual value. In this model, a subset of agents may modify their respective expectation heuristics for each period, contingent on the updated error function and the specific strategy generated. The *intensity of choice* parameter calibrates the switching probability concerning the error function via a discrete choice model by Manski et al. (1981). This discrete choice heuristic switching approach has been implemented in numerous financial market models, including those presented in Westerhoff (2004) and Hommes, Huang and Wang (2005), and has been instrumental in elucidating the formation of asset bubbles in financial markets.

The proposed HSM mechanism lies in a logit transformation that returns the fraction of agents $\omega_t^{v,h}$ that use a given heuristic h for some model inherent variable v_t to form their aggregate expectations $\tilde{E}_t v_{t+1}$, where \tilde{E}_t is the BR expectation operator.³ This is the sum of heuristics weighted at the respective share of agents believing in said

² This thesis focuses on a specific type of expectation formation. Expectations formed under conditions of incomplete or noisy information are not considered here. For a detailed comparison of these alternatives to the full-information RE operator in the standard DSGE literature, see Coibion et al. (2018).

³ As I will present later in this section, there is not yet a consensus on the heuristics best used in a DSGE framework.

heuristic:

$$\tilde{E}_t v_{t+1} = \sum_h \omega_t^{v,h} \tilde{E}_t^{v,h} v_{t+1} \quad (2.1)$$

and

$$\omega_t^{v,h} = \frac{\exp\{\mu A_t^{v,h}\}}{\sum_h \exp\{\mu A_t^{v,h}\}}, \quad (2.2)$$

where μ is the *intensity of choice* parameter and $A_t^{v,h}$ is the attractiveness of the heuristic h . Agents use a goodness-of-fit function to decide which heuristic h works best in the given environment, e.g., via an aggregated mean squared forecast error (MSFE):

$$A_t^{v,h} = -(v_{t-1} - \tilde{E}_{t-2}^h v_{t-1})^2 \quad (2.3)$$

I will revisit these equations and expand upon them at the conclusion of Section 3, where I will present my BR-HSM-NK framework. Prior to that, I will provide further justification for the incorporation of heterogeneity in expectation formation within macroeconomic models. There are multiple methodologies for demonstrating BR in humans confronted with macroeconomic decision-making. One strand of literature focuses on the dissection of inflation and output survey data in order to verify the switching approach proposed by Brock and Hommes (1997). Among the earliest contributions to this field was that of Branch (2004), who found that this type of model can predict the inflation rate survey data with a high degree of accuracy.

However, agents within the framework have been observed to display a tendency or bias towards adhering to the heuristic they initially select, even when the MSFE recommends a change in strategy.

Furthermore, evidence for this modeling framework has been identified in laboratory experiments. The subsequent section will provide a detailed account of these experiments, along with an explanation of the rationale behind the selection of expectation heuristic for the forthcoming model discussion. Additionally, I try to match some experimental findings regarding monetary policy with the BR model analyzed in this thesis.

2.1 Macroeconomic Laboratory Experiments

Two principal experimental design features have emerged in the recent macroeconomic experimental literature: learning to forecast experiments (LtFE) and learning to optimize experiments (LtOE). In a learning-to-forecast-experiment (LtFE), subjects are asked to provide a price that is then realized via the average of their submitted forecasts. The price setting in this framework is self-referencing, with contemporaneous prices depending on pricing expectations. Subjects can then adapt their forecast and find a Nash equilibrium with their peers in subsequent periods. Thereby, “individual forecasts affect and co-create aggregate behavior” (Assenza et al. 2014, p. 20). In LtOE, subjects make economic decisions regarding quantities, e.g., a consumption bundle. After each subject submits their decision, the aggregate over all subjects is formed, and the equilibrium price is determined. Both types of

experimental designs play a role in the BR literature. They are sometimes interlinked when experimenters inquire about stated prices, e.g., inflation and bundles of goods that subjects intend to consume. Subjects receive monetary compensation for the accuracy of their decisions.

The first charge of experimental evidence for BR did not stem from inflation forecasting exercises but from asset pricing experiments, which were much more prevalent at the inception of the field in the 90s and early 2000s, see, e.g., Marimon et al. (1993) and Hommes et al. (2005), among others. Assenza et al. (2014) and Bao et al. (2021) go to great length in recapitulating the progress in the field with their reviews of recent experimental literature.

However, for the approach of this thesis, I select a few LtFE concerning monetary policy that are relevant for Sections 3 and 4.⁴ I will briefly discuss the findings from the laboratory by Pfajfar and Žakelj (2018), Assenza et al. (2021), Mauersberger (2021) and Hommes et al. (2019), who bring their experimental designs into the realm of the NK framework and shed light on some forecasting strategies.

In Pfajfar and Žakelj (2018), subjects are asked to forecast one period ahead of inflation. In contrast, past realizations of output, interest rate, and inflation are known to them and part of their information set. They face an IS curve that is backward-looking in output but consists of a standard real interest rate channel. A TR with either a reaction to expected or contemporaneous inflation and different magnitudes of the respective coefficient closes the model. The subjects' individual forecasting

⁴ There is also experimental literature concerning Forward Guidance where central bank communication has a stabilizing effect on individual and aggregate outcomes, e.g., Kryvtsov and Petersen (2021). However, Forward Guidance is not part of my modeling approach. Therefore, I leave these papers out of this short review.

strategy can be deduced from their submitted inflation predictions via previously codified heuristics.⁵

The authors' primary findings are as follows: 1) Instrument rules that respond to actual inflation rather than forecasted inflation result in a reduction in inflation variance. 2) Mechanisms for forecasting that are destabilizing, particularly those based on extrapolating trends, are more frequently selected when the stabilization of inflation in the instrument rule is weaker, resulting in a higher inflation variance. 3) Adaptive expectations strategies contribute to stabilizing inflation, in contrast to trend extrapolation strategies that amplify cycles. 4) In environments with high inflation variance, there is an increased proportion of trend extrapolation rules, which further destabilize inflation.

Following the previous experimental design, Assenza et al. (2021) also let the subjects forecast the output gap. Their treatments alter the inflation reaction coefficient, but in closer proximity to unity and even below that, so that the Taylor principle is violated.⁶ They find that 5) the Taylor principle is a necessary but insufficient condition for stability. Especially as the inflation reaction coefficient δ_π is nearing unity from above (i.e., $\delta_\pi = 1.015$), the adjustment path to the inflation target is not ensured anymore. At the same time, the Blanchard-Kahn conditions hold for the RE-NK model. Only strong negative feedback to inflation leads to stability in their experimental framework. As the LtFE of Pfajfar and Žakelj (2018), subjects'

⁵ The subjects' individual forecasts are estimated with the ordinary least-squares estimator. The expectation heuristic that produces the lowest root-mean-squared error is then said to be used by the subject.

⁶ This is comparable to the result of Bullard and Mitra (2002) who used the adaptive learning framework by Evans and Honkapohja (2001) to study monetary policy.

forecasts are codified into different strategies. They use a linear prediction equation to estimate their subjects' respective forecasting heuristic with the coefficients α^e , α^π , and α^y and the following rule composed of chained past inflation estimates π_{t-i}^e , past realized inflation π_{t-i} and output y_{t-i} :

$$\pi_{t+1}^e = \text{const.} + \sum_{i=0}^2 \alpha^e \pi_{t-i}^e + \sum_{i=0}^3 \alpha^\pi \pi_{t-i} + \sum_{i=0}^3 \alpha^y \pi_{t-i}^e + \varepsilon_t \quad (2.4)$$

They verify the results already stated in 3) and 4).

In the LtFE by Mauersberger (2021), subjects do not form forecasts on the aggregate IS and Phillips curve level but on the individual household and firm level, which then get aggregated. The author finds an even higher inflation response from the central bank is necessary to tame the subjects' expectations. Convergence to the RE steady state is achieved with $\delta_\pi = 3$, therefore underpinning finding 5).

Finding 6) is deduced from the laboratory experiment by Hommes et al. (2019). A comparison is made between a rational agent New Keynesian model (RANK) and a BR-NK model comprising the same channels, with the exception of the formation of expectations. In their framework, central banks are confronted with a trade-off: reacting to the output gap increases inflation volatility, whereas under BR expectations, it can reduce both inflation and output gap volatility to a certain extent. These stylized facts are then tested in a laboratory setting to ascertain whether the central bank in the experimental economy faces the same trade-off as in the RE model. The central bank's instrument rule differentiates the underlying treatments, either targeting inflation or both inflation and the output gap. The laboratory results support the BR model as a superior fit in two ways: lower inflation volatility

and the behavioral model's U-shaped relationship between inflation volatility and the output gap reaction coefficient, which was confirmed experimentally. Hommes et al. (2019) also use the individual forecast data to motivate the subjects' strategies by employing an HSM.⁷ The data showed that 6) adaptive and anchoring rules were more frequently used while trend-following rules were less common over time.

In conclusion, experimental studies emphasize the significance of formulating resilient monetary policies that consider the manner in which economic agents shape expectations. In environments with high inflation, self-fulfilling prophecies emerge as a result of an increase in the use of extrapolation expectation strategies. From a formal perspective, an inflation reaction coefficient approaching unity may contribute to instability in a BR framework when an RE model is technically stable. However, subjects tend to employ adaptive or anchoring heuristics when inflation volatility is low. This can be inferred by codifying the individual subjects' forecast submissions ad-hoc and categorizing them according to a specified strategy. In a computational study by Hommes et al. (2017), however, available experimental data is used to train a genetic learning algorithm (GLA) model with the objective of gaining a deeper understanding of the subjects' strategies. I will elaborate on GLAs and their respective results in Section 3. After presenting some experimental evidence in support of BR and HSM, I want to give insight into the literature on which I build my research. I will then discuss which of those 'model ingredients' I choose for the framework of this thesis.

⁷ They compute the prediction error separately for each individual and assign the heuristic with the best fitting heuristic.

2.2 Heuristic Switching in New Keynesian Models

Incorporating BR agents into NK models has taken many forms over the years. E.g., Evans and Honkapohja (2009) let agents learn and update their statistically informed expectations. In contrast, Gasteiger (2014) conducts monetary policy with RE as well as BR heuristics that a calibrated share of agents use without being able to switch between them. Gabaix (2020) also combines RE and BR expectations into the NK framework with the help of *cognitive discounting*.⁸ In all of these models, agents are not assumed to be irrational but just unable to understand every economic implication of the world they live in.

This thesis follows the approach by Branch and McGough (2009), De Grauwe (2011, 2012, 2015), and Lengnick and Wohltmann (2016). Recent additions to this specific approach in HSM are De Grauwe and Foresti (2023) and Seemann (2024), among others. The main modeling contributions of Hommes and Lustenhouwer (2019), Proaño and Lojak (2020), and Brenneisen (2022) are at the core of the framework I propose. I will briefly depict their findings in the coming passages, which I will then integrate into my formalized framework in Section 3.

Hommes and Lustenhouwer (2019) introduce endogenous central bank credibility to the NK-HSM approach. Like them, e.g., De Grauwe (2011) or Lengnick and Wohltmann (2016), they give agents two heuristics to choose from: either believing in the ability of the central bank to achieve its targets (*tar*) and therefore expecting it for the next period, $\tilde{E}_t^{tar} v_{t+1} = v_t^T$ or naive expectations (*nai*), $\tilde{E}_t^{nai} v_{t+1} = v_{t-1}$, so

⁸ *Cognitive discounting* assumes that the agent is able to predict the nearest future evolution of model variables quite well. Still, the further his predictions go, the more dim these predictions become.

$h \in \{tar, nai\}$. Agents need to form expectations for both inflation and the output gap, so $v_t \in \{x_t, \pi_t\}$. Their performance measure equation also contains a memory parameter that adds past performances to the recent ones. This build-up of past performances leads to the aforementioned switching retention found in survey data by Branch (2004). However, the difference lies in interpreting and reformulating the fractions of agents. Those who follow the heuristic *tar* find the central bank's policy credible, and the opposite is true for followers of naive expectation heuristic *nai*. ω^{tar} or $1 - \omega^{nai}$ is then the endogenous measure for the central bank's credibility. With this measure, they conduct stability analysis in a standard BR-NK model. They find that the central bank's credibility plays a crucial role in stabilizing the economy, especially at the ZLB: 1) If the central bank has high credibility, it needs to do less regarding current interest rate policy to stabilize expectations. Conversely, with low credibility, deflationary spirals are more likely; and 2) In the face of liquidity traps, where the economy is stuck with low inflation and output, they suggest that increasing the inflation target and implementing aggressive monetary easing can help the economy recover.

Keynes' (1936) *animal spirits* are a recurring term in the BR literature. First introduced by De Grauwe (2011) into the HSM-NK modeling space, these capture optimistic or pessimistic expectations in his framework, e.g., via tracking the sign of the *naive* or backward-looking heuristic $\tilde{E}_t^{nai} v_{t+1} = v_{t-1}$. If agents expect a positive future value because the past realization was positive, they are optimistic, and vice versa. Proaño and Lojak (2020) use another behaviorally informed measure for *animal spirits*. They propose that these are the difference between *naive* (in their paper

pessimistic) and *target* (*optimistic*) heuristics, so $S_t = \omega_t^{tar} - \omega_t^{nai}$. The measure is situated between minus unity and unity, $S_t \in [-1, 1]$. It is fed into an equation that measures economic risk according to the expected deviation from the inflation target, the past realization of output, and the government budget. In their NK framework, they add this measure to the nominal interest rate and thereby affect the household's intertemporal decision process with respect to consumption smoothing. However, S_t is set to zero when the ZLB is not binding. They find that in a binding ZLB environment, the economic downturn is exacerbated by increased risk premia and, therefore, pessimistic *animal spirits*.

Brenneisen (2022) combines the endogenous central bank credibility approach by Hommes and Lustenhouwer (2019) with a risk measure by Proaño and Lojak (2020) but does not consider an *animal spirits* component. This risk measure originates from Adrian et al. (2010) who used it to link the yield spread of financial assets to GDP growth and risk appetite of financial intermediaries.⁹ In the BR-HSM framework, the risk measure can be given additional context with central bank credibility measures or *animal spirits*. The latter has been employed by Proaño and Lojak (2020) while the central bank credibility measure m_t^{CB} was introduced by Brenneisen (2022) to the risk measure:

$$\zeta_t = -\xi_m (m_t^{CB} - \bar{m}^{CB}) + \xi_\pi (|E_t \pi_{t+1} - \pi^T|) - \xi_y y_{t-1} + \xi_b b_{t-1}^g \quad (2.5)$$

⁹ Here, risk appetite is interpreted as the balance sheet tightness of financial intermediaries. The risk appetite is considered high when a financial intermediary's balance sheet constraints are tight.

ξ_m , ξ_π , ξ_y , and ξ_b are the respective risk parameters for central bank credibility, deviation of inflation from its target π^T , output, and government debt. Deviations below the steady-state central bank credibility \bar{m}^{CB} let perceived risk rise. So does a negative output gap and absolute, expected deviations from the inflation target and government debt b_{t-1}^g . Positive past realizations of output lower the perceived risk. A government surplus also leads to lower risk. His reformulated measure is then added to the economic decision rules of financial intermediaries in his NK framework, and he conducts monetary policy simulations. He concludes that – along the line of Hommes and Lustenhouwer (2019): The effectiveness of monetary policy instruments strongly depends on the credibility environment. I.e., unconventional, active credit policy is especially effective when the central bank faces low credibility.

I contribute to the presented literature by extending the risk measure and by finding empirical validation for this approach, as explained in the next section. As these papers show, the BR-NK modeling toolbox lends itself to exploring perceived risk measures and central bank credibility problems. However, the validated magnitude of the channel is still not apparent. Proaño and Lojak (2020) and Brenneisen (2022) choose relatively small values for parameters inherent to the risk measurement. However, I will contribute to the discussion of this measure and show that these are much larger under the empirical method used in this thesis.

In the next section, I will present the BR-HSM-NK framework. Additionally, financial frictions will be introduced. This model extension is later used to answer question 3), namely whether the risk channel is a suitable substitute for financial frictions. Subsequently, empirical evidence for the risk channel will be presented.

Finally, the expectation and risk channels will be explored in order to ascertain their impact on monetary policy.

3 A New Keynesian Model

The modeling approach I choose for the NK core is closely related to Christiano et al. (2005) and Smets and Wouters (2007) but with less emphasis on real frictions since the agents' BR expectations also account for persistent adjustment paths. This means I omit real frictions in the form of partial price indexation in the labor and goods market. Additionally, to maintain comparability with Brenneisen (2022) as well as De Grauwe (2011) and Proaño and Lojak (2020), I set up the household side of the model in the same manner, i.e., without habits in the utility function.

After presenting the altered microfoundation of the DSGE framework, the implementation of financial frictions by Brenneisen (2022) who followed Becard and Gauthier (2022), is discussed. The linearized model is then augmented with the HSM extension.

3.1 A Brief Overview of Microfoundations

The private sector population of the underlying economy consists of households, intermediate goods firms, and final goods firms. Households also function as capital investors. The policymaker follows a standard TR. Capital letters depict gross values and letters with an overbar are steady-state expressions.¹⁰

¹⁰ Previous mentions and definitions of functions, variables, and parameters from the literature review are overwritten to keep things readable, and the number of unique characters needed

Households

Households in the economy maximize a separable utility function depending on consumption C_t and disutility from hours worked L_t with relative risk aversion parameter for consumption σ_c , the inverse Frisch labor supply elasticity σ_l and the discounting parameter β . Habits in consumption behavior are not accounted for. The expected lifetime utility reads:

$$E_t \sum_{i=0}^{\infty} \beta^i \left[\frac{C_{t+i}^{1-\sigma_c}}{1-\sigma_c} - \frac{L_{t+i}^{1+\sigma_l}}{1+\sigma_l} \right] \quad (3.1)$$

Besides real consumption C_t , the household expenditure comprises real investment I_t and savings in bonds $\frac{B_t}{\varepsilon_t^b R_t P_t}$, with the bond premium AR(1) shock ε_t^b and the risk-free rate R_t at goods prices P_t . The income side is composed of its labor income $\frac{W_t L_t}{P_t}$, last period bond holding $\frac{B_{t-1}}{P_t}$, returns $R_t^h Z_t K_{t-1}$ from renting capital K_{t-1} at the utilization rate Z_t and household lending rate R_t^h to intermediate goods firms as well as net lump-sum taxes and transfers T_t it has to pay. The budget constraint is then:

$$C_t + I_t + \frac{B_t}{\varepsilon_t^b R_t P_t} = \frac{W_t}{P_t} L_t + \frac{B_{t-1}}{P_t} + \frac{R_t^h Z_t K_{t-1}}{P_t} - a(Z_t) K_{t-1} - T_t \quad (3.2)$$

Here, $a(Z_t)$ is the capital utilization adjustment function with the corresponding utilization rate Z_t . It satisfies $a(1) = 0$, $a'(1) = \bar{R}^h$ and $a''(1) = \psi$, whereas ψ is the capital utilization adjustment cost. Capital stock K_t depreciates with δ and is

manageable.

replenished by new investment:

$$K_t = (1 - \delta)K_{t-1} + \varepsilon_t^i \left[1 - F\left(\frac{I_t}{I_{t-1}}\right) \right] I_t \quad (3.3)$$

Following Christiano et al. (2005), capital producing households face adjustment cost for investment captured in $F(\cdot)$ which satisfies $F(1) = F'(1) = 0$ and $F''(1) = \phi > 0$. ε_t^i captures a shock to the marginal efficiency of investment and follows an AR(1) process. δ is the depreciation rate of capital.

The amount of capital households rent to intermediate goods firms, i.e., capital services K_t^s , reads

$$K_t^s = Z_t K_{t-1} \quad (3.4)$$

The capital adjustment costs are $P_t a(Z_t) K_{t-1}$. At the steady state, the adjustment function $a(\cdot)$ is $a(\bar{Z}) = 0$.

After solving the households' optimization problem with the Lagrangian, the Euler equation is given by the stochastic discount factor $\Lambda_{t,t+1} = \frac{\lambda_{t+1}^b}{\lambda_t^b}$, the shadow price of the budget constraint lagrangian λ_t^b , with the first order condition $\lambda_t^b \stackrel{!}{=} U_{C_t}$:

$$\beta \cdot R_t E_t \Lambda_{t,t+1} = 1 \quad (3.5)$$

Capital Producers

Tobin's Q relation (1975) is also derived by the households' Lagrangian. Q_t is the ratio of the shadow prices of the households' optimization problem with λ_t^k from the

investment decision, $Q_t = \frac{\lambda_t^b}{\lambda_t^k}$. In the core model without financial frictions, households fill the role of capital investors. They purchase an investment and depreciated capital to transform it into new capital sold to firms and used for production in the next period.

The optimality condition for their profits connects the marginal adjustment cost of investment to the price of capital:

$$1 = Q_t \varepsilon_t^i \left[1 - F\left(\frac{I_t}{I_{t-1}}\right) - F'\left(\frac{I_t}{I_{t-1}}\right) \left(\frac{I_t}{I_{t-1}}\right) \right] + \beta E_t \left[\Lambda_{t,t+1} Q_{t+1} \varepsilon_{t+1}^i F'\left(\frac{I_{t+1}}{I_t}\right) \left(\frac{I_{t+1}}{I_t}\right)^2 \right] \quad (3.6)$$

Intermediate Goods Firms

Intermediate goods firms indexed by $f \in (0, 1)$ are set in a market with monopolistic competition and produce the intermediate goods $Y_t(f)$. The allocation of household labor units $L_t(f)$ and acquired capital from capital services $K_t^s(f)$ in the production function

$$Y_t(f) = A_t (K_t^s(f))^\alpha L_t(f)^{1-\alpha} \quad (3.7)$$

is chosen via cost minimization.¹¹ α is the capital share of production. The AR(1) process A_t captures technological progress. The first-order conditions of the opti-

¹¹ Aggregate labor and capital service are $L_t = \int_0^1 L_t(f) df$ and $K_t^s = \int_0^1 K_t^s(f) df$.

mization problem are used to formulate R_t^k , i.e., the real gross return on assets:

$$E_t R_{t+1}^k = E_t \left[\frac{R_{t+1}^h + (1 - \delta)Q_{t+1}}{Q_t} \right] \quad (3.8)$$

and a marginal cost MC_t , which is common to all intermediate goods firms:

$$MC_t = \left(\frac{W_t}{1 - \alpha} \right)^{1-\alpha} \left(\frac{R_t^k}{\alpha} \right)^\alpha (A_t)^{-1} \quad (3.9)$$

Final Goods Firm

The final goods producers operate in a perfectly competitive market and buy the intermediate goods and repack them to assemble the final goods Y_t . Different from SW, I follow Galí (2015) and do not account for price indexing via a specific price indexation trajectory in the final goods production function. The technology used to repack the intermediate goods $f \in (0, 1)$ reads:

$$Y_t = \left(\int_0^1 Y_t(f)^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}}, \quad (3.10)$$

where $\epsilon > 1$ is the demand elasticity. Demand for the intermediate goods depends on their price $P_t(f)$ and is :

$$Y_t(f) = \left(\frac{P_t(f)}{P_t} \right)^{-\epsilon} Y_t \quad (3.11)$$

Price Setting

Intermediate goods prices are set with the Calvo (1983) pricing mechanism. The Calvo parameter χ_p depicts the probability at which an intermediate goods firm sets a new price according to aggregate inflation. In contrast, with probability $1 - \chi_p$, the firm must adapt its price based on the marginal cost in each period. Intermediate goods firms resetting their price in period t maximize the following flow of discounted profits to the optimal price P_t^* for the intermediate goods f , i.e.,

$$E_t \sum_{s=0}^{\infty} (\chi_p)^s \Lambda_{t,t+s} Y_{t+s}(f) \left[\frac{P_t^*(f)}{P_{t+s}} - \frac{\epsilon}{\epsilon - 1} MC_{t+s} \right] \quad (3.12)$$

The law of motion for the aggregate price level is then

$$P_t = \left[(1 - \chi_p) (P_t^*)^{1-\epsilon} + \chi_p (P_{t-1})^{1-\epsilon} \right]^{\frac{1}{1-\epsilon}} \quad (3.13)$$

Market Clearing

The goods market is cleared with the resource constraint

$$Y_t = C_t + I_t + G_t + a(Z_t)K_{t-1} \quad (3.14)$$

Here, G_t is an AR(1) process that captures fiscal policy measures.

Monetary Policy Maker

To close the model, the central bank follows a TR with interest rate smoothing:

$$R_t^n = (R_{t-1}^n)^{\rho^r} \cdot \left(\left(\frac{\Pi_t}{\Pi^T} \right)^{\delta_\pi} \cdot \left(\frac{Y_t}{Y_t^P} \right)^{\delta_y} \right)^{(1-\rho^r)} \cdot \varepsilon_t^r \quad (3.15)$$

Following this rule, the interest rate R_t^n reacts positively to inflation Π_t deviations from the inflation target Π^T and output Y_t relative to its potential Y_t^P with reaction parameters δ_π and δ_y , respectively. The smoothing parameter ρ^r indexes the contemporaneous interest rate to its past realization, smoothing the model economy's adjustment path. The AR(1) process ε_t^r depicts shocks to the policy rate. For the linearized model, I assume the inflation target π^T and the potential output y_t^P to be zero.

However, Section 5 extends the policy rule by one additional observable instrument at a time: either by a short-term output growth component, q -targeting following Heer et al. (2017), and by targeting via the risk measure ζ_t , respectively. These additional instruments may facilitate the central bank's stabilization effort. Before I augment the model with the HSM approach, a short discussion about the financial intermediaries extension following Brenneisen (2022) is conducted. I use this extension to compare it to the model with behaviorally formulated risk measure.

3.2 Financial Intermediaries

Incorporating financial frictions in NK-DSGE frameworks has greatly expanded following the GFC. Especially after the Fed began its quantitative easing (QE) policy,

transmission channels needed to be explored to measure its effectiveness and possible risks. The well-received contributions of Bernanke et al. (1999), Gertler and Karadi (2011), Chen et al. (2012), and Becard and Gauthier (2022) have substantially impacted the field, among others. In this section, I will shortly restate their findings and recent empirical track record and extend the linearized framework from the last section with Becard and Gauthier (2022) approach, as incorporated into the BR framework by Brenneisen (2022).

In the financial accelerator model by Bernanke et al. (1999), the information set contains frictions. Here, market participants have asymmetric information, and capital lenders incur auditing costs to verify borrowing firms' returns. The cost of capital is then financed partly by the firm's net worth and the remainder by auditing-cost-adjusted borrowing. The resulting external financing premium depends inversely on the firm's leverage ratio. Contrary to that, financial intermediaries in Gertler and Karadi (2011) face balance sheet constraints due to agency problems with their household depositors and not with the goods-producing firms. Households deal with moral hazard issues as bankers might divert a fraction of funds and leave the banking space. To solve this, an incentive compatibility constraint ensures households are willing to deposit money with banks. That means the asset acquisitions of banks depend on their net worth.

These financial intermediaries approaches have been empirically tested in an otherwise SW framework by Villa (2016) with data up until Q3 2008 for the US and euro area. The author shows that – under a conventional monetary policy stance – the

moral hazard approach by Gertler and Karadi (2011) has a better fit to the data.¹² This is reinforced by Boehl and Strobel (2022), who argue that during the ZLB period and QE measures, the financial accelerator in the SW framework is not able to fit the opposite evolution of the credit spread and the leverage ratio, see Del Negro and Schorfheide (2013) and Del Negro et al. (2015) for the framework used in their analysis.

Chen et al. (2012) incorporate financial frictions by segmenting the household into patient and impatient households. The former saves in government bonds and lends capital to firms, while the latter borrows long-term loans to smooth out consumption. In their framework, QE has a direct expansionary effect on impatient households' consumption. This approach is fused with the moral hazard agency problem from Gertler and Karadi (2011) in the large-scale NK framework by Boehl et al. (2022) and shows a good fit to the data moments.

Household saving segmentation is also a key feature of the financial intermediary foundation proposed by Becard and Gauthier (2022). Again, similar to Chen et al. (2012), households are either borrowers or lenders. However, borrowers, i.e., impatient households, may default due to a stochastic shock – the bank hedges against this risk by requiring collateral assets from borrowers. If the impatient household goes bankrupt, the bank resells the collateralized assets. This is costly for the bank and is, therefore, inherent to the revenue maximization problem. Additionally, the model distinguishes between housing, capital, and overall financial market shocks.

¹² Brzoza-Brezeczina and Kolasa (2013) also conclude that the financial accelerator is not well suited to explain rising spreads in the data – indeed predicting falling spreads for the period after the GFC.

I borrow from the aforementioned default risk and collateral approach to compare the ad-hoc behaviorally motivated risk channel proposed by Proaño and Lojak (2020). This has been simplified and adjusted to the BR-HSM framework by Brenneisen (2022), which I will use as the basis for my goodness-of-fit analysis.

3.3 The Linearized DSGE Framework

After the core model presented in Section 3.1 is log-linearization around the steady state and some reformulations are undertaken, I arrive at the following model equations.¹³ Here, the RE operator E_t is substituted by the BR expectation formation operator \tilde{E}_t . Composite parameters carry a numerical index, e.g., k_1 or q_1 . Small letters depict steady-state deviations from the respective capital letter counterparts. The demand side of the economy is mainly derived from the household optimization problem. Following Proaño and Lojak (2020), I add the risk measurement ζ_t (Eq. 3.43) onto the risk-free rate to induce an endogenous risk premium with the coefficient ξ_r . The additive to the risk-free rate is typically chosen for confidence shocks in the banking system (see SW and Boehl and Strobel (2022), among others). The AR(1) shock term ε_t^c captures a preference shock. The linearized consumption Euler equation reads:

$$c_t = \tilde{E}_t c_{t+1} - \sigma_c^{-1}(r_t + \varepsilon_t^b + \xi_r \zeta_t) + \varepsilon_t^c \quad (3.16)$$

¹³ These can also be found in an overview in Appendix A.

Included here is the inter-temporal saving decision over the risk-free real interest rate, i.e., the Fischer equation $r_t = r_t^n - \tilde{E}_t \pi_{t+1}$ with the nominal interest rate r_t^n and inflation expectations $\tilde{E}_t \pi_{t+1}$. The labor supply equation is

$$w_t = \sigma_c c_t + \sigma_l l_t \quad (3.17)$$

Changes in investment i_t are costly, as captured by the elasticity of the capital adjustment cost function ϕ , and are mainly driven by households' investment decisions captured in the arbitrage equation q_t :

$$i_t = \frac{1}{1+\beta} i_{t-1} + \frac{\beta}{1+\beta} \tilde{E}_t i_{t+1} + \frac{1}{(1+\beta)\phi} q_t + \varepsilon_t^i \quad (3.18)$$

The AR(1) shock process ε_t^i captures the effect of changing the marginal efficiency of investment, following Justiniano et al. (2011).

The wedge between investing capital at r_t^k or saving at the risk-induced rate $(r_t + \zeta_t)$ is expressed by the capital arbitrage or price of capital equation, i.e., Tobin's Q :

$$q_t = \beta(1-\delta)\tilde{E}_t q_{t+1} + (1-\beta(1-\delta))r_t^k - (r_t + \xi_r \zeta_t) \quad (3.19)$$

At the steady-state, capital depreciates at rate δ and the parameter ϕ also penalizes newly installed capital in the composite parameter $k_1 = (1 - (1-\delta))\phi$, so the law of motion for capital reads:

$$k_t = (1-\delta)k_{t-1} + (1-k_1)i_t + k_1\varepsilon_t^i \quad (3.20)$$

On the supply side, intermediate goods firms utilize capital and labor for production:

$$y_t = \alpha k_t^s + (1 - \alpha)l_t + a_t \quad (3.21)$$

whereas the disturbance a_t captures the AR(1) technology shock and capital services k_t^s , i.e., capital rent to firms by capital producers,

$$k_t^s = k_{t-1} + z_t \quad (3.22)$$

also face adjustment cost ψ via the degree of capital utilization z_t :

$$z_t = \frac{(1 - \psi)}{\psi} r_t^k \quad (3.23)$$

From the first-order condition of the cost minimization optimization of the intermediate goods firm, the rental rate of capital is computed:

$$r_t^k = -(k_t - l_t) + w_t \quad (3.24)$$

Marginal costs from the intermediate goods sector of the economy mainly drive inflation:

$$mc_t = w_t - \alpha(k_t^s - l_t) - a_t \quad (3.25)$$

The Phillips curve, therefore, reads

$$\pi_t = \beta \tilde{E}_t \pi_{t+1} + \pi_1 m c_t + \varepsilon_t^p \quad (3.26)$$

with $\pi_1 = \frac{(1-\beta\chi_p)(1-\chi_p)}{\chi_p}$ and the AR(1) cost-push shock ε_t^p . The resource constraint with the following steady-state ratios: consumption-to-output $c_y = 1 - g_y - i_y$, investment-to-output $i_y = \delta k_y$ and utilization-to-output $z_y = (\beta^{-1} - (1 - \delta)) k_y$ in

$$y_t = c_y c_t + i_y i_t + z_y z_t + g_y g_t \quad (3.27)$$

clears the goods market. g_y is the steady-state government-spending-to-GDP ratio.

The composite parameter k_y contains the steady-state values of R_t^k and W_t and is

$$k_y = \left(\frac{1-\alpha}{\alpha} \frac{\bar{R}^k}{\bar{W}} \right)^{\alpha-1}.$$

The Taylor rule

$$r_t^n = \rho^r r_{t-1}^n + (1 - \rho^r) [\delta_\pi \pi_t + \delta_y y_t] + \varepsilon_t^r \quad (3.28)$$

closes the core model.

For the goodness-of-fit comparison in Section 4, I choose the modeling approach of financial intermediaries as presented by Brenneisen (2022). Here, entrepreneurs enter the market and are endowed with start-up equity from the respective households they originate from. To fund new capital for firms' production functions, they take on loans collateralized by the banks they borrow from. When the collateral shock forces the entrepreneur to default by diminishing the value of assets he holds, banks seize

the remaining assets and resell them to other entrepreneurs.

The aggregate entrepreneurial net worth \hat{n}_t is affected by real capital stock and its returns in a positive way. The credit rate to entrepreneurs \hat{r}_t^e , entrepreneurs default risk \hat{p}_t^d and the loan-to-value ratio $\hat{\varphi}_t$ lower agents net worth.¹⁴ The two latter variables are AR(1) processes in this framework. The linearized function reads

$$\hat{n}_t = (1 - n_1)\hat{n}_{t-1} + n_1(\hat{q}_{t-1} + k_{t-1}) + n_2\hat{R}_t^k - n_3\hat{r}_t^e - n_4\hat{p}_{t-1}^d - n_5\hat{\varphi}_{t-1} \quad (3.29)$$

The capital arbitrage equation of the core model (3.19) needs to be replaced by default risk and loan-to-value ratio induced capital arbitrage equation:

$$\hat{q}_t = q_1\hat{q}_{t-1} + (1 - q_1)r_{t-1}^k - (\hat{r}_t^e - \tilde{E}_t\pi_{t+1}) + q_2\hat{p}_t^d - q_3\hat{\varphi}_t \quad (3.30)$$

The return on capital \hat{R}_t^k is given by the price of capital \hat{q}_t and the rental rate of capital r_t^k :

$$\hat{R}_t^k = q_1\hat{q}_t + (1 - q_1)r_t^k - \hat{q}_{t-1} \quad (3.31)$$

Since the collateral and LTV shocks are non-observables, banks hand out loan contracts in a uniform way with the spread

$$\hat{r}_t^e - r_t^n = b_1\widehat{lev}_t + b_2\hat{p}_t^d - b_3\hat{\varphi}_t, \quad (3.32)$$

¹⁴ I denote the newly arising financial friction extension variables with hats to distinguish them from the core model better. The composite parameters are given in Appendix A.2.

where \widehat{lev}_t is the leverage ratio of entrepreneurs

$$\widehat{lev}_t = \hat{q}_t + k_t - \hat{n}_t \quad (3.33)$$

With this extension, I can answer whether the risk channel is a fitting substitute for financial frictions by comparing the explanatory power of the two model variants in matching empirical moments. The following section elaborates on the BR-HSM augmentation to the linearized model and its financial friction variant I just presented.

3.4 Risk Channel & Heuristics

The underlying HSM in my thesis builds upon the results of macroeconomic experiments in the lab and modeling advances discussed in the last section. Since I am using the Smets and Wouters (2007) framework as a basis, agents need to formulate expectations concerning steady-state deviations of consumption c_t , inflation π_t , capital price q_t and investment i_t .¹⁵

The general aggregation of expectations remains the same:

$$\tilde{E}_t v_{t+1} = \sum_h \omega_t^{v,h} \tilde{E}_t^{v,h} v_{t+1} \quad (3.34)$$

The *target* heuristic *tar*

$$\tilde{E}_t^{tar} v_{t+1} = v_t^T \quad (3.35)$$

¹⁵ I do not want to overload the expectation channel and to uphold comparability with the other BR-HSM studies, the expectations for capital arbitrage are assumed to be *naïve*, i.e., $\tilde{E}_t q_{t+1} = q_{t-1}$.

enables endogenous central bank credibility as proposed by Hommes and Lustenhouwer (2019). I use a second heuristic that is computationally motivated by Hommes et al. (2017), coined *deanchoring* heuristic *dac*, so $h \in tar, dac$. They use the LtFE data from Assenza et al. (2013) to train a GLA model proposed by Anufriev et al. (2018). In the experiment that provides data to the GLA, subjects forecast either inflation or additionally the output gap in a baseline NK model with different monetary policy regimes. The GLA then uses the individual's forecast data and optimizes several forecasting heuristics. The algorithm can combine heuristics to form new ones in every iteration.¹⁶ The result is the following three component heuristic used in this thesis for $v_t \in (y_t, \pi_t)$, which has not been employed in a SW framework before:

$$\begin{aligned}
\tilde{E}_t^{dac} v_{t+1} = & \underbrace{\varpi \sum_{s=1}^N v_{t-s} N^{-1}}_{\text{New Anchor}} \\
& + \underbrace{(1 - \varpi)(\Upsilon v_{t-1} + (1 - \Upsilon)\tilde{E}_{t-1}^{dac} v_t)}_{\text{Adaptive Term}} \\
& + \underbrace{\Omega(v_{t-1} - v_{t-2})}_{\text{Extrapolative Term}}
\end{aligned} \tag{3.36}$$

The new anchor consists of a moving average weighed by ϖ , where N represents the number of periods the agent forms a new expectation anchor from.¹⁷ The adaptive term is connected with the counterweight $(1 - \varpi)$. Υ gives the rate at which agents

¹⁶ The GLA goes through four stages of optimization in which it changes parameters, uses other or additional variables, combines forecast equations, and then selects the best fitting heuristic, i.e., reproduction, mutation, crossover, and election of the genome.

¹⁷ Since the agent can memorize only a finite horizon of past variable realizations, I set this parameter $N = 4$, which leads to a moving average spanning four quarters or one year.

adapt to the actual past realization of the variable. Lastly, a trend extrapolating term is added with Ω , which allows for trend-following behavior. The GLA proposes the following calibration: $\varpi, \Upsilon \in [0, 1]$ and $\Omega \in [0, 3]$. This heuristic allows the model to explain experimental findings discussed in Section 2.2. With the calibration of $\varpi = \Omega = 0$ and $\Upsilon = 1$ it collapses to the backward-looking or *naive* expectation heuristic $\tilde{E}_t^{dac} v_{t+1} = \tilde{E}_t^{nai} v_{t+1} = v_{t-1}$. While $\varpi = \Upsilon = 0$ leads to purely extrapolative expectations *extr*: $\tilde{E}_t^{dac} v_{t+1} = \tilde{E}_t^{extr} v_{t+1} = \Omega(v_{t-1} - v_{t-2})$. The resulting heuristics from these corner case calibrations are frequently utilized in other studies, e.g., Lengnick and Wohltmann (2016) and Brenneisen (2022). Consequently, the functional form of the *deanchoring* heuristic is highly modular and can reproduce numerous findings from the LtFE literature, as well as other BR-HSM studies contingent on its calibration.

I follow Hommes and Lustenhouwer (2019) as well as Brenneisen (2022) in measuring credibility with the help of multinomial logit probabilities. To capture the stickiness to switch found in Branch (2004), I connect the past realized fraction central bank followers ω_t^{CB} to the next iteration with a switching retention parameter $\xi_\omega \in (0, 1)$ in addition to the memory coefficient:

$$\omega_t^{CB} = \xi_\omega \omega_{t-1}^{CB} + (1 - \xi_\omega) \frac{\exp\{\mu(A_t^{y, tar} + A_t^{\pi, tar}) + \bar{c}\}}{1 + \exp\{\mu(A_t^{y, tar} + A_t^{\pi, tar}) + \bar{c}\}} \quad (3.37)$$

Proposed by Brenneisen (2022), \bar{c} calibrates the steady-state credibility \bar{m}^{CB} . It lies between $-\infty$ and $+\infty$, resulting in either $\omega_t^{CB} = \bar{m}^{CB} = 0$ or $\omega_t^{CB} = \bar{m}^{CB} = 1$, respectively. Both extreme cases do not lead to switching behavior among agents. They either stay with the *deanchoring* heuristic in case of $\bar{c} = -\infty$ or the *target*

heuristic for $\bar{c} = +\infty$.

The fraction of agents that follow the *deanchoring* heuristic is implied by ω_t^{CB} , so $\omega_t^{dac} = 1 - \omega_t^{CB}$. The central bank's credibility measure is then

$$m_t^{CB} = \omega_t^{CB} - \omega_t^{dac} = 2\omega_t^{CB} - 1 \quad (3.38)$$

The attractivity of the *target* heuristic is measured with

$$A_t^{y, tar} = \xi_A A_{t-1}^{y, tar} - (1 - \xi_A)(y_{t-1} - y^T)^2 \quad \text{and} \quad (3.39)$$

$$A_t^{\pi, tar} = \xi_A A_{t-1}^{\pi, tar} - (1 - \xi_A)(\pi_{t-1} - \pi^T)^2 \quad (3.40)$$

for output and inflation, whereas y^T and π^T represent the targets of the central bank, which are assumed to be zero. $\xi_A \in (0, 1)$ is the *memory parameter* which lets agents remember past divergences from the central bank's targets, i.e., $y_{t-1} - y^T$. When ξ_A approaches zero, agents consider only the recent forecasting error. I assume the central bank targets y^T and π^T to be zero.

Lastly, the expectation formation needs to be fully formulated. Following Proaño and Lojak (2020), agents build their expectations for c_t and i_t upon developing output y_t since there is a high correlation between these variables and aggregate output. This also aligns with the assumption that agents do not have unlimited cognitive skills to compute forecasts for every variable but use simple yet informed procedures, see De Grauwe (2012). Therefore, the expectations for consumption and investment

with the adaption coefficients ϵ_c and ϵ_i read:

$$\tilde{E}_t c_{t+1} = \epsilon_c \tilde{E}_t y_{t+1} \quad (3.41)$$

$$\tilde{E}_t i_{t+1} = \epsilon_i \tilde{E}_t y_{t+1} + \xi_i \zeta_t \quad (3.42)$$

Unforeseeable risk accompanies investment decisions. Therefore, $\tilde{E}_t i_{t+1}$ inherits the aforementioned risk measure ζ_t . Its impact is controlled via the investment risk channel parameter ξ_i that is later estimated.

$$\zeta_t = \xi_m (\bar{m}^{CB} - m_t^{CB}) + \xi_\pi (|\tilde{E}_t \pi_{t+1} - \pi^T|) - \xi_y y_{t-1} + \xi_s S_t, \quad (3.43)$$

ζ_t now combines the divergence from steady-state credibility and *animal spirits* after De Grauwe (2011) in S_t ; thus merging the approaches by Proaño and Lojak (2020) and Brenneisen (2022). As mentioned earlier, the risk measure was originally used to explain the yield spread of financial assets with the help of banks' balance sheets. This framework, however, gives a behaviorally motivated measure of perceived risk via steady-state deviations of credibility, output, and inflation. Additionally, variable S_t captures optimism and pessimism in the output expectation channel with the coefficient ξ_s :

$$S_t = \begin{cases} \omega_t^{dac} & \text{if } \tilde{E}_t^{dac} y_{t+1} < 0 \\ 0 & \text{if } \tilde{E}_t^{dac} y_{t+1} \geq 0 \end{cases} \quad (3.44)$$

The perceived risk measure in the economy is raised when the share of agents following the *deanchoring* heuristic ω_t^{dac} expect a negative development in output and vice versa.

3.5 Model Solution

The model arising from (3.16) to (3.28), or to (3.33) – in its extended version with financial friction – together with the BR-HSM augmentation from (3.34) to (3.44), can be solved via forward iteration since all variables depend on past realizations. Formally, the BR-HSM augmented system is non-linear, and its state-space representation reads

$$\mathbf{A}\mathbf{V}_t = \mathbf{B}\mathbf{V}_{t-1} + \mathbf{C}\tilde{\mathbf{E}}_t\mathbf{V}_{t+1} + \mathbf{D}\mathbf{e}_t \quad (3.45)$$

with $\mathbf{V}_t = (y_t, c_t, i_t, k_t, l_t, q_t, \pi_t, r_t^k, w_t, r_t^n)^T$

and $\mathbf{e}_t = (\varepsilon_t^c, \varepsilon_t^b, \varepsilon_t^i, a_t, \varepsilon_t^p, \varepsilon_t^r)^T$

The model equations can be reduced to form a 10×10 linear system with the respective system matrices \mathbf{A} , \mathbf{B} and \mathbf{C} . The matrix \mathbf{D} captures the connections of i.i.d. AR(1) processes of the shock terms \mathbf{e}_t to the model equations.

Externally, the fractions of agents that believe in the *target* or *deanchoring* heuristic (3.35) and (3.36) are computed via the multinomial logit transformation (3.37). The MSFE equations for output y_t (3.39) and inflation π_t (3.40) close the HSM block. The risk measure ζ_t (3.43) can be computed with the credibility measure of the cen-

tral bank (3.38).

I follow the heterogeneous expectation axioms stated by Branch and McGough (2009) regarding model consistent expectations. Here, agents understand some of the economic structure of the underlying model and incorporate this knowledge to form expectations. While agents are not rational in the sense that they know each friction and model moment exactly, they are also not irrational in their forecasts. They adapt to their previous forecast errors and learn from their prediction mistakes, similar to the statistical learning literature around Sargent (1993) and Honkapohja et al. (2013).

4 Minimizing Distance of Moments

This section presents one of my two contributions to the field of the BR-HSM framework. I conduct minimal distance-of-moment experiments with the formulated BR-HSM-NK framework from Section 3 and investigate its stability constraints with respect to central bank credibility, expectations, and the risk channel. I then compare the results with different estimation procedures, namely an identity weighting matrix in the moment distance function and a weighting matrix constructed from the inverse of the variance-covariance matrix of moment distances.

The estimation of the risk and expectation channel parameters contributes to the BR-HSM research discussion and adds greater relevance to the monetary policy experiments conducted in Section 5.

The procedure in this section has been employed by other studies relevant to the

BR-HSM-NK framework literature, e.g., Franke et al. (2015), Jang and Sacht (2012, 2016, 2021), De Grauwe and Macchiarelli (2015) and De Grauwe and Gerba (2018).¹⁸

There is still no consensus on the magnitude of the *intensity of choice* or *memory* parameter. My estimate of this parameter together with an estimate of the steady-state credibility parameter \bar{c} might complement the recent discussion. However, the estimation of the parameters inherent to the logit transformation of the HSM may produce or capture dynamics of the model that make it hard to interpret.

After describing the data and moments to be matched, I will present the moment distance minimization (or Simulated Method of Moments) procedure following the standard approach by Ruge-Murcia (2012) and Evans (2023). The estimation results for the different weighting matrix approaches follow. The goal of this thesis is not to absolutely match the empirical data moments but to get an informed, if flawed, estimate of the risk and expectation parameters. Since others have not yet explored the impact of the risk measure in the BR-HSM framework, I provide a first range of their parameter values. Additionally, to further the substance of my estimation procedure, I conduct robustness checks of the risk channel parameter estimates by calibrating some BR-HSM risk parameters to zero to infer if they provide more explanatory power to the model concerning the distance of simulated moments.

4.1 Data Description

The baseline model used in this dissertation contains six main observables: output, consumption, investment, capital, inflation, and the nominal interest rate. The US

¹⁸ For reference: Bayesian estimation techniques are used by these authors: Fischer (2022), Grazzini et al. (2017), Kukacka and Sacht (2023), and Ozden (2021).

Variable	US Data Series	Frequency	Data Code	Period
Y_t	Real Gross Domestic Product (GDP)	quarterly	[GDPC1]	1953:I–2024:I
C_t	Real Personal Consumption Expenditures (PCE)	quarterly	[PCECC96]	1953:I–2024:I
I_t	Real Gross Private Domestic Investment (GPDI)	quarterly	[GPDIC1]	1953:I–2024:I
K_t	Capital Stock at Constant National Prices	annually	[RKNANPUSA666NRUG]	1953–2019
R_t^n	Effective Federal Funds Rate	quarterly	[BOGZ1FL072052006Q]	1953:I–2024:I
Π_t	Gross Domestic Product Price Deflator (GDPPD)	quarterly	[GDPDEF]	1953:I–2024:I

Table 1: All variables were downloaded on April 20th, 2024. GDP deflator quarterly change. Sources: Federal Reserve Bank of St. Louis (2024a,b,c,d,e,f); Feenstra et al. (2015).

time series for these variables are widely used and are available for large sample sizes. Table 1 gives an overview of the time series used for the estimation. To maintain comparability with other studies, I choose the data sample time frame from Q1 1953 to Q1 2024, including ten business cycles, recent periods with binding ZLB, and strong inflation dynamics.¹⁹ The cyclical components for real GDP, real PCE, real GPDI, and capital stock are obtained by taking logs and applying the Hodrick-Prescott (HP) filter method.²⁰ These are interpreted as deviations from the respective trend of the variable. I then compute the following data moments as in De Grauwe and Gerba (2018) from the cyclical components and the EFFR as well as the GDPPD: autocorrelation $\rho(v_{t-j})$ up to lag $j = 3$, standard deviation $\sigma(v_t)$, cross-correlation of y_t with c_t , i_t , π_t and r_t^n , skewness, and kurtosis of all observable data series. Inflation and interest rate data are handled in decimals and not percentage points. The data moments of skewness and kurtosis for real variables are especially relevant to match.

¹⁹ This starting period is typically used because periods before that likely include inconvenient noise and data recording issues (see Stock and Watson (1999)).

²⁰ The penalty parameter λ^{HP} is set equal to 1600 for monthly and 100 for annual data series, see Hodrick and Prescott (1997). The cyclical components' first and last four periods are cut off to avoid end-point problems.

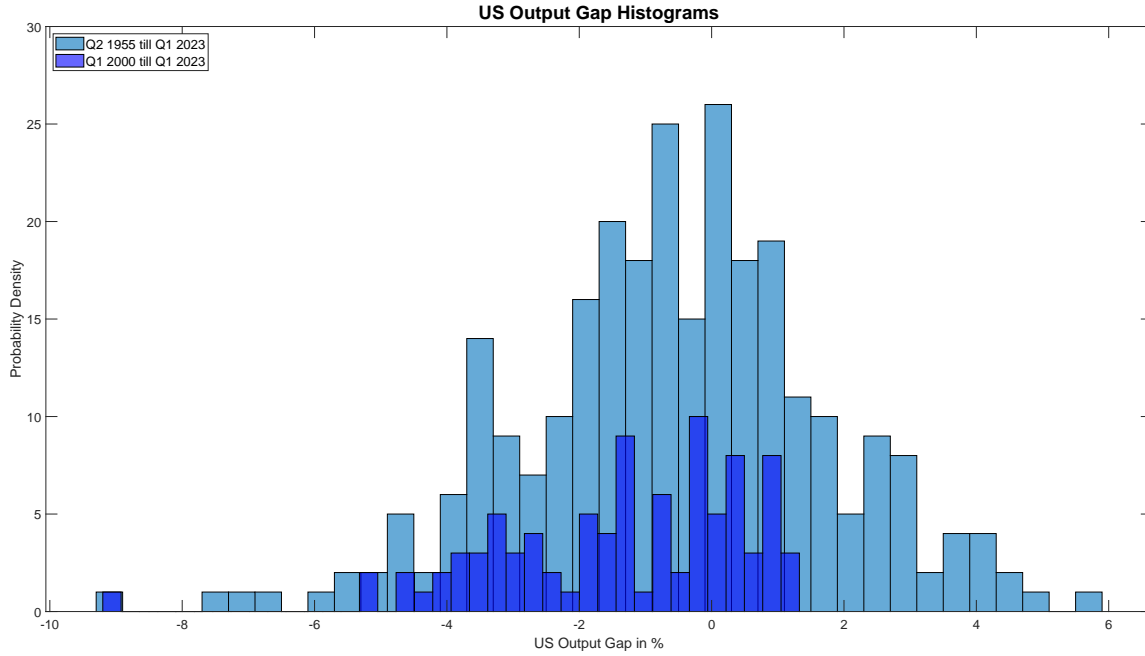


Figure 3: Histogram of the US output gap, HP filtered cyclical component of logged real GDP for Q1 1954–Q1 2023 (light blue) and Q1 2000–Q1 2023 (dark blue). Third and fourth moment Q1 1954–Q1 2023: $Skew = -0.2248$, $Kur = 3.5888$, $JB_{test} = 5.7897$, H_0 rejected at 5% level, $p = 0.0493$; Q1 2000–Q1 2024: $Skew = -1.0173$, $Kur = 4.2119$, $JB_{test} = 18.9295$, H_0 rejected at 1% level, $p = 0.0040$. Data source: Federal Reserve Bank of St. Louis (2024a).

Jordà et al. (2020), using a data sample beginning in 1870, argue that business cycles are not symmetric and deviate significantly from the Gaussian norm. Additionally, all variables are highly autocorrelated.

Besides skewness and kurtosis, I additionally check for non-normality in the data series, i.e., I conduct the Jarque-Bera test (JB, Jarque and Bera (1980)) under the null hypotheses H_0 the data series is normally distributed and the alternative hypothesis

H_1 that it is not.²¹ For the computed output gap the test statistic $JB_{test} = 5.7897$ lies over the critical value of $JB_{crit} = 5.7512$ at the 5% level ($p = 0.0493$) and therefore H_0 can be rejected. The corresponding histogram of the output gap depicted in Figure 3 shows this graphically, i.e., negative skewness, excess kurtosis, and a non-normally distributed frequency of data observations. Additionally, periodic outliers during extreme recessions can be observed. Appendix B reports the empirical data moments $M(x)$ and the simulated data moments. The model presented in Section 3 and the respective parameters which are going to be estimated in this section are presented in Appendix A.1 in a textless overview.

The more recent data sample from Q1 2000 to Q1 2024 shows much higher skewness and kurtosis in its histogram plot. There are three recessions within this time frame: the dot-com bubble crash, the GFC, and the COVID-19 pandemic. Returning to Figure 1 in the introduction, especially after the GFC, the return to potential GDP lasted nearly ten years after the trough in 2009, therefore suggesting non-Gaussian cycles following Jordà et al. (2020). Compared to the full sample, the recent 24 years can be tested at the 1%-level and return a H_0 rejection against the critical value $JB_{crit} = 12.5835$ with $JB_{test} = 18.9295$. From this, I motivate a second estimation of the model against the shorter data sample to see if the BR-HSM-Risk model has a better fit for the sample moments.

²¹ The test statistic is $JB = \frac{n}{6} \left(Skew^2 + \frac{(Kur-3)^2}{4} \right)$. The test statistic is always non-negative and follows the χ^2 distribution.

4.2 Estimation Procedure

The underlying procedure to gather simulated moments is as follows: I construct a grid with G different parameter combinations θ_g and simulate the model \tilde{x} for $T = 260$ periods over $J = 1000$ normally distributed random i.i.d. number drawings for the AR(1) white noise shocks. The vector of moments M_r of the J simulation runs is computed for every θ_r , where R is the total number of target moments computed per simulation run j . Furthermore, I calculate the average of each moment in M_r across all J to arrive at a combination of parameters θ_g from the grid and corresponding averaged moments M_r :

$$\widehat{M}_r(\tilde{x} \mid \theta) = \frac{1}{J} \sum_{j=1}^J m_{j,g}(\tilde{x}_j \mid \theta) \quad (4.1)$$

Then, the simulated moments are compared to the empirical ones. The smallest distance gives the best fit to the target moments and, thereby, the simulated method of moments (SMM) estimates:

$$\hat{\theta}_g^{SMM} : \arg \min_{\theta} \| e_g(\tilde{x}, x \mid \theta)^T \mathbf{W} e_g(\tilde{x}, x \mid \theta) \|, \quad (4.2)$$

where $e_g(\tilde{x}, x \mid \theta)$ is the vector of distances between the simulated moments M_g and the true empirical moments $M(x)$. So, an identity weighting matrix $\mathbf{W} = \mathbf{I}$ gives a scalar containing the sum of the squared distances. The weights in \mathbf{W} can be arbitrarily chosen. However, I want to be agnostic in the formulation of the weighting matrix. Therefore, I use the identity matrix \mathbf{I} and, after that, the often employed variance-covariance matrix of the distances across moments M_j . The latter is used

to account for the variances in moments resulting from the J simulation runs of the model.

To obtain the variance-covariance matrix, I estimate the model using the identity matrix \mathbf{I} as weight and compute the resulting distances from $\hat{\theta}_{SMM}$ for each simulation run J and their corresponding simulated moment \widehat{M}_r and collect them in the matrix Δ :

$$\Delta_g(\tilde{x}, x \mid \theta_g) = \begin{pmatrix} m_1(\tilde{x}_1 \mid \theta) - m_1(x) & m_1(\tilde{x}_2 \mid \theta) - m_1(x) & \cdots & m_1(\tilde{x}_J \mid \theta) - m_1(x) \\ m_2(\tilde{x}_1 \mid \theta) - m_2(x) & m_2(\tilde{x}_2 \mid \theta) - m_2(x) & \cdots & m_2(\tilde{x}_J \mid \theta) - m_2(x) \\ \vdots & \vdots & \ddots & \vdots \\ m_R(\tilde{x}_1 \mid \theta) - m_R(x) & m_R(\tilde{x}_2 \mid \theta) - m_R(x) & \cdots & m_R(\tilde{x}_J \mid \theta) - m_R(x) \end{pmatrix} \quad (4.3)$$

The matrix Δ can then be used to construct an estimate of the variance-covariance matrix of moment distances of the J simulation runs:

$$\hat{\Gamma} = \frac{1}{J} \sum_{j=1}^J \Delta(\tilde{x}, x \mid \theta) \Delta(\tilde{x}, x \mid \theta)^T \quad (4.4)$$

The new weighting matrix is then inverse of $\hat{\Gamma}$:

$$\widehat{\mathbf{W}} = \hat{\Gamma}^{-1} \quad (4.5)$$

and the estimator reads:

$$\hat{\theta}_{2,SMM} : \arg \min_{\theta} \| e_r(\tilde{x}, x \mid \theta)^T \widehat{\mathbf{W}} e_r(\tilde{x}, x \mid \theta) \| \quad (4.6)$$

Discount Factor	$\beta = 0.99$	Depreciation Rate	$\delta = 0.025$
Capital Share in Production	$\alpha = 0.33$	Gov.-Spending-to-Output	$g_y = 0.12$

Table 2: Calibrated parameters used in SMM Estimation following Villa (2016).

Using $\widehat{\mathbf{W}}$ instead of an identity matrix reduces the impact of significant differences in moments. E.g., if under the identity matrix, the distance of kurtosis measures of output is equal to two for one simulation and four in another, the distance measure goes up by four and 16 points, respectively, because it is squared (see Equation (4.2)). The matrix $\widehat{\mathbf{W}}$ should combat this by scaling the distances according to their variance. For computational reasons, I do not construct a grid of infinitesimally small increments over the upper and lower bounds of all estimation parameters. I choose a more granular approach that hands a section of starting points to a solving algorithm. The grid I construct stretches over some parameters, e.g., the intensity of choice, risk channel parameters, central bank inflation reaction coefficient, and capital adjustment cost, resulting in about half a million parameter combinations. The first 100 smallest distances \hat{m}_g with respective θ_g are then handed over to the MATLAB *MultiStart* optimization solver with Equation (4.2) as the objective function and θ_g as inputs. This method suffices for the goal of this thesis since it gives an informed estimate of the existence and magnitude of the risk channel in the empirical data. However, the solver may run into local minima but miss the global ones. I account for this problem by spanning a large grid of starting points for the solver. Unfortunately, this may not rule out spikes in the value function that are somewhat distant from the grid starting values.

Expectations	HSM	Risk Channel	NK Core	AR(1)
$\varpi \in [0, 1]$	$\mu \in [0, 10]$	$\xi_m \in [0, \infty)$	$\chi_p \in (0, 1)$	$\rho_{\varepsilon^c} \in (0, 1)$
$\mathcal{Y} \in [0, 1]$	$\xi_A \in [0, 1]$	$\xi_y \in [0, \infty)$	$\sigma_c \in (0, \infty)$	$\rho_{\varepsilon^b} \in (0, 1)$
$\Omega \in [0, 3]$	$\xi_\omega \in [0, 1]$	$\xi_\pi \in [0, \infty)$	$\sigma_l \in (0, \infty)$	$\rho_{\varepsilon^i} \in (0, 1)$
	$\bar{c} \in [-1, 1]$	$\xi_s \in [0, \infty)$	$\phi \in (0, \infty)$	$\rho_{\varepsilon^a} \in (0, 1)$
		$\xi_i \in [0, \infty)$	$\delta_\pi \in [0, \infty)$	$\rho_{\varepsilon^p} \in (0, 1)$
		$\xi_r \in [0, \infty)$	$\delta_y \in [0, \infty)$	$\rho_{\varepsilon^r} \in (0, 1)$
			$\psi \in (0, \infty)$	
			$\rho^r \in (0, 1)$	

Table 3: Upper and lower bounds for the MATLAB solver in the SMM estimation.

Following Villa (2016), I calibrate some established parameters presented in Table 2: the discount rate β is set to 0.99 and the quarterly depreciation rate δ to 0.025, resulting in an annualized depreciation rate of capital of approximately 10%. Lastly, the share of capital used in production α is set to 0.33, and the government-spending-to-GDP ratio g_y is 0.12. The remaining parameters of the BR-HSM, the NK core, the AR(1) processes, and their respective standard errors of the i.i.d. shock terms are estimated via SMM. Their theoretical parameter domains present the upper and lower limits for the solving algorithm presented in Table 3. If a parameter does not have a domain, the solver is given an arbitrarily large number as a proxy for being virtually unbound. This results in 37 estimation parameters with 40 model moments as empirical observations.

BR-HSM	Estimate	NK Core	Estimate	AR(1)	Estimate
θ	4.7642	σ_c	1.2468	σ_{ε^c}	0.3918
ξ_A	0.0707	σ_l	1.2915	σ_{ε^i}	0.4234
ξ_ω	0.0118	ϕ	5.9901	σ_{ε^b}	0.0576
\bar{c}	0.9649	χ_p	0.7631	σ_a	0.1143
ξ_m	0.1113	ψ	0.2550	σ_{ε^p}	0.4062
ξ_y	0.0032	δ_π	1.5634	σ_{ε^r}	0.0463
ξ_π	0.1342	δ_y	0.2396	ρ_{ε^c}	0.5451
ξ_s	0.0924	ρ^r	0.7667	ρ_{ε^i}	0.9512
ξ_i	1.5893			ρ_{ε^b}	0.8867
ξ_r	0.1351			ρ_a	0.8967
ϖ	0.1928			ρ_{ε^p}	0.9599
Υ	0.6599			ρ_{ε^r}	0.0868
Ω	0.5156				
ϵ_i	0.2066				
ϵ_c	0.3737				

Table 4: SMM estimation results for BR-HSM-NK-Risk model variant with identity weighting matrix \mathbf{W} for US data Q2 1955–Q1 2023. Distance Score: 96.8776.

4.3 Empirical Importance of HSM

In this section, I will present the estimation results of the BR-HSM-NK model framework. Furthermore, I will examine whether the risk channel parameters or individual elements of the risk measure contribute to the discrepancy between the model moments and the empirical ones. The overall distance measure for the vector of estimated parameters and shock standard deviations is 96.8776. This score is the sum of the squared distances under the identity weight. For example, distances in the kurtosis measure may be larger than in the autocorrelation measure because these

are decimal point differences, whereas the latter are full integers. This gives kurtosis a greater absolute weight, which is a desirable effect in this thesis. Their values are presented in Table 4. In this section, I will restate some relevant equations from the BR-HSM-NK framework for improved readability.

Beginning with the *deanchoring* heuristic,

$$\begin{aligned}
\tilde{E}_t^{dac} v_{t+1} = & \underbrace{\varpi \sum_{s=1}^N v_{t-s} N^{-1}}_{\text{New Anchor}} \\
& + \underbrace{(1 - \varpi)(\Upsilon v_{t-1} + (1 - \Upsilon)\tilde{E}_{t-1}^{dac} v_t)}_{\text{Adaptive Term}} \\
& + \underbrace{\Omega(v_{t-1} - v_{t-2})}_{\text{Extrapolative Term}}
\end{aligned} \tag{4.7}$$

I can report that the data best fits with a mixture of adaptiveness and extrapolation. The new anchor itself, parameterized with ϖ , is about 0.2, which, in turn, means that the expectations are mainly driven by the adaptive term with the counterweight $(1 - \varpi)$ and 0.65 for past realizations Υ to 0.35 past expectation $(1 - \Upsilon)$. Trend extrapolation also plays a role with the coefficient Ω at about 0.5.

In my estimation, the *intensity of choice* parameter in the equation for the share of agents that follow the *target* heuristic

$$\omega_t^{CB} = \xi_\omega \omega_{t-1}^{CB} + (1 - \xi_\omega) \frac{\exp\{\mu(A_t^{y, tar} + A_t^{\pi, tar}) + \bar{c}\}}{1 + \exp\{\mu(A_t^{y, tar} + A_t^{\pi, tar}) + \bar{c}\}} \tag{4.8}$$

is about $\mu \approx 4.8$. The study by Fischer (2022) finds an estimate at approximately $\mu = 1.8$ for this parameter. However, here, the assumed heuristics agents can choose

from are not directly comparable. The parameter deviates from the calibration of $\mu = 1$ used in other studies. In a regular BR-HSM framework used in Jang and Sacht (2021, 2016), agents' switching behavior would be amplified by my parameter estimate of μ . However, the steady-state central bank credibility \bar{m}^{CB} leads to an advance in trust (Eq. (3.38)), and the higher *intensity of choice* is offset by this. With the credibility shift parameter \bar{c} at about 0.96, the steady-state credibility is \bar{m}^{CB} at approximately 40%. The resulting leap of faith toward the central banks leads to less switching away from the *target* heuristic.

The *memory* ξ_A and switching retention parameter ξ_ω are relatively small with 0.07 and 0.01, respectively, therefore confirming Jang and Sacht (2016), and Kukacka and Sacht (2023) in their calibration of zero for these parameters.

The estimates of ξ_y and ξ_π in the risk measure

$$\zeta_t = \xi_m (\bar{m}^{CB} - m_t^{CB}) + \xi_\pi | \tilde{E}_t \pi_{t+1} - \pi^T | + \xi_y y_{t-1} + \xi_s S_t, \quad (4.9)$$

differ from the calibrations of Proaño and Lojak (2020). They chose $\xi_y = 0.05$ and $\xi_\pi = 0.2$, whereas the solver estimates 0.003 and 0.13, respectively. However, the risk channel in their framework was not as pronounced as in this thesis. The small estimate for ξ_y may stem from the large percentage changes of output around the steady state, which I will pick up again in the section. Compared to the calibration of ξ_m from Brenneisen (2022), the estimates seem to confirm his assumption in parameter choice. The animal spirits pass-through ξ_s is about 0.1 and nearly matches the calibration used in Proaño and Lojak (2020). This leads to strong oscillatory adjustment paths, as shown in the robustness check in Section 4.4.

The impact of the risk measure on investment expectations ξ_i in

$$\tilde{E}_t i_{t+1} = \epsilon_i \tilde{E}_t y_{t+1} + \xi_i \zeta_t \quad (4.10)$$

is relatively large, with approximately 1.6 compared to the risk measure in the interest rate channel $\xi_r \approx 0.14$. However, the pass-through of risk through the interest rate channel ($r_t + \xi_r \zeta_t$) affects households' decisions on bond buying in addition to their expectations of capital arbitrage possibilities with capital services at the same time, doubling its contact points.

The remaining parameters of the BR-HSM model block are the adaption coefficients of output forecasts in consumption and investment expectations, i.e., ϵ_i and ϵ_c . These differ from a direct, unitary pass-through because the output comprises consumption and investment. The coefficients ϵ_i and ϵ_c roughly mirror the relative composition of the resource constraint for c_t and i_t .

Regarding the estimates of the NK core model, which leans heavily on the SW framework, I can report that these are roughly in line with the estimation of Boehl et al. (2022) of the SW framework with an updated data set stretching to 2020. The investment adjustment cost and capital utilization cost parameters are $\phi = 5.99$ and $\psi = 0.26$ compared to the modes of 5.28 and 0.71 of the posterior distribution in Boehl et al. (2022), respectively. Of course, the underlying models and estimation procedures are different. Still, the BR-HSM extension could have led to unexpected estimation results, which might be hard to explain in the context of other empirical studies. However, the parameter estimates stayed in the well-established realm of SW estimations.

Variable	BR-HSM-Risk			US Data Q2 1955–Q1 2023		
	Skewness	Kurtosis	JB_{test}	Skewness	Kurtosis	JB_{test}
Output y_t	−0.3651	3.5305	8.9987	−0.2248	3.5588	5.7897
Consumption c_t	−0.9712	6.6713	190.4979	−1.0065	6.6564	195.9929
Investment i_t	−0.2907	9.8165	516.7877	−1.9328	16.5174	$2.22 \cdot 10^3$
Capital k_t	−0.2267	6.6119	36.4402	0.1809	2.1268	2.2703
EFFR r_t^n	0.9761	4.5047	67.0881	1.0750	4.6884	86.8837
Inflation π_t	0.7358	4.9734	66.9157	1.3040	4.5951	108.6591
Distance Score	96.8776					

Table 5: Simulated moments from the SMM estimator with identity weighting matrix \mathbf{W} and empirical moments from US data Q2 1955–Q1 2023. Jarque-Bera test at 5% level with $JB_{crit} = 5.7512$.

The autocorrelation parameters also fit the original SW posterior modes in that all shocks show high autocorrelation values at about near or above 0.5. However, the autocorrelation parameter of the monetary policy shock ρ_{ϵ^r} is relatively small with about 0.09, which is in line with Boehl et al. (2022).

The parameter estimates resulted in the following kurtosis and skewness measures of the six variables I am interested in matching reported in Table 5. The remaining moments are Tables B.12, B.10, and B.13 in Appendix B. Nevertheless, I will present them here and contextualize the results.

The skewness observed in the simulated data exhibits a similar sign and magnitude as that observed in the empirical data for the output gap, consumption, and nominal interest rate (or EFFR), respectively. Furthermore, the signs of the mean steady-state deviations of investment and inflation are also accurate. Nevertheless,

the discrepancy in skewness magnitude between the simulated and empirical data is considerable, with approximately 85% divergence observed in the simulated investment time series and 43% in the inflation series, respectively. The attempt to align the skewness with capital proved unsuccessful. As the empirical data indicate, the simulated data exhibit a distribution that is oriented towards the west rather than the east. As previously discussed, capital utilization and investment adjustment costs exert an indirect influence on this variable. However, the estimation results for these factors are adequate.

Capital also exhibits an anomalous kurtosis measure. The Fed time series of capital exhibits a platykurtic distribution, whereas the simulated data displays a leptokurtic distribution. Furthermore, the null hypothesis of normality should not be rejected. However, the other variables align with their empirical counterparts in kurtosis and non-normality, as measured by the Jarque-Bera test. Notably, only investment does not align with the magnitude, exhibiting a percentage deviation of approximately 40% from the empirical data.

The autocorrelation results for the second and especially the third lag of output do not match the US data in magnitude with 35% and 72% less history dependence (see Table B.2 in Appendix B. For $\rho(k, k_{t-3})$ the simulated time series gives a far larger autocorrelation value than is present in the data, 0.59 vs. 0.07.

The interaction of output and inflation representing the Phillips curve relationship is far larger in the simulated time series than in the actual US data by about fivefold in the cross-correlation measure as presented in Table B.1. Additionally, the signs of $\rho(y_t, r_t^n)$ and $\rho(y_t, i_t)$ are not correctly matched. This is problematic since investment

Variable	BR-HSM-Risk			US Data Q1 2000–Q1 2023		
	Skewness	Kurtosis	JB_{test}	Skewness	Kurtosis	JB_{test}
Output y_t	0.0403	2.9946	0.0721	−1.0173	4.2119	18.9295
Consumption c_t	2.0155	15.8330	1997.8	−2.6115	16.1271	673.6648
Investment i_t	2.0958	16.8990	2370.0	−3.9609	27.6436	2260.0
Capital k_t	1.8758	14.7961	2.6344	0.5626	2.2821	1.5589
EFFR r_t^n	0.3320	3.1655	5.1717	1.0156	2.5637	14.5692
Inflation π_t	−0.0608	3.1856	0.5438	1.2589	6.1994	55.9456
Distance Score	350.4868					

Table 6: Simulated moments from the SMM estimator with identity weighting matrix \mathbf{W} and empirical moments from US data Q1 2000–Q1 2023. Jarque-Bera Test at 5% level with $JB_{crit} = 5.7512$.

is part of the resource constraint and, therefore, should positively affect contemporaneous output. However, the cross-correlation of output and consumption are within a 5% margin and thereby sufficiently identified for the purpose of this thesis.

The standard deviations show the correct signs and mostly correct magnitude, except $\sigma(k_t)$ and $\sigma(r_t^n)$ whose simulated data moments are three and five times higher than the data moments.

The estimation is repeated for a shorter time series with very high third and fourth moments for consumption and investment. The results for skewness, kurtosis, and JB_{test} at 5% level are presented in Table 6. The remaining simulation and empirical moments are in Tables B.4, B.5, and B.6 in Appendix B.

Highly relevant from these are the following two cross-correlations. The Phillips curve relationship from the empirical data could again not be matched correctly.

The estimation results in a negative, contemporaneous relation of output and inflation with $\rho(y_t, \pi_t) \approx -0.6$. While the empirical cross-correlation of output and investment, is now much small with 0.02, the estimation still has a negative relation for $\rho(y_t, i_t)$ with -0.16 .

The estimation procedure used in this thesis leads to mismatched variable skewness and some remote kurtosis measures when faced with a crisis-driven data sample. Instead of being platykurtic, the EFR data sample is leptokurtic during the prolonged low interest rate period, which the estimated model could not match. While trying to match the high excess kurtosis of consumption and investment, the Jarque-Bera test for output and inflation does not reject the H_0 , which is one of the main goals of this framework. Also, the skewness direction is opposite for output, consumption, and investment, which was not true for the full sample estimate.

However, the results are not surprising considering the use of the unity weighting matrix. Since this weight leads to the sum of squares of individual moment distances, the estimator tries to match large deviations first above all others.

The next section presents the moment matching results from the variance-covariance matrix \widehat{W} . After that, I contextualize the parameter estimates by presenting different BR-HSM parameter calibrations in an impulse response function (IRF) exercise while holding the other parameters at their estimates from Table 4.

4.4 Results from \widehat{W}

Instead of an identity weight, I compute the variance-covariance matrix across S simulation runs of one given parameter set θ_r . The results for the third and fourth

Variable	$\widehat{W} = \Omega^{-1}$		$W = I$		US Data Q2 1955–Q1 2023	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
Output y_t	0.1554	3.1729	−0.3651	3.5305	−0.2248	3.5588
Consumption c_t	0.2468	3.0633	−0.9712	6.6713	−1.0065	6.6564
Investment i_t	0.0575	2.7725	−0.2907	9.8165	−1.9328	16.5174
Capital k_t	0.0578	2.7640	−0.2267	6.6119	0.1809	2.1268
EFFR r_t^n	0.0968	2.9263	0.9761	4.5047	1.0750	4.6884
Inflation π_t	0.0461	3.0574	0.7358	4.9734	1.3040	4.5951
Distance Score	8.74 (222.67)		96.8776		—	

Table 7: Simulated skewness and kurtosis from the SMM estimator with variance-covariance weighting matrix \widehat{W} (left) and W (middle) and empirical skewness and kurtosis from US data Q2 1955–Q1 2023.

moments are reported in Table 7. The other resulting moments are reported in Tables B.7, B.8, and B.9 in Appendix B.

Regarding skewness, the variance-covariance weighting approach does not seem to produce negative values that would fit the empirical data. Additionally, simulated data kurtosis for all variables is rarely in desirable proximity to the data. The values are very near the mesokurtic bounds, i.e., showing little to no excess kurtosis. Higher degrees of this moment are important features of the consumption and investment data series.

Similar mismatches can also be found in the autocorrelation moments. The second and third lag of output and inflation and the third lag of the nominal interest rate show negative autocorrelations, which do not coincide with known facts about these variables. Additionally, the values for $\rho(c_t, c_{t-2})$ and $\rho(c_t, c_{t-3})$ are approximately 0.4 and 0.2 off from the data, which the unity-weighted estimation matched in a 7% and

5% margin of error.

Since the alternative weighting procedure dampens the distance measure for larger moment distances such as kurtosis produces, the parameters in the risk measure equation are nearly all some magnitudes smaller than in the identity weighting approach, except for ξ_y which is the other way around. Comparing $\xi_m \approx 0.0286$ from the alternative weight to 0.1113 from the previous estimates is a nearly four-fold difference that compounds together with the other risk parameters that are eight times and fifty times larger for ξ_s and ξ_π , respectively. This leads to higher kurtosis and skewness in the simulated data.

I showed that the alternative estimation results are not particularly enticing. Still, I will also report the variance-covariance-weighting results from the financial friction model in Appendix B without going into further detail.

I conclude this section with a comparison between the moment matching results presented before with the BR-HSM-Risk and BR-HSM-Riskless variants and the financial friction extension building on Becard and Gauthier (2022) collateral shock approach introduced in Section 3.3, collated in Appendix A.1 and A.2.

4.5 Robustness Checks

In this section, I use IRFs for the range of shocks the model can explain to visually inspect the effects of different calibrations on the BR-HSM parameters. Additionally, I re-estimate the model while calibrating one or more BR-HSM parameters to zero to show their impact on the simulated moments and distance to the empirical ones. Knowing which parameters change drastically or if the standard deviation of shocks

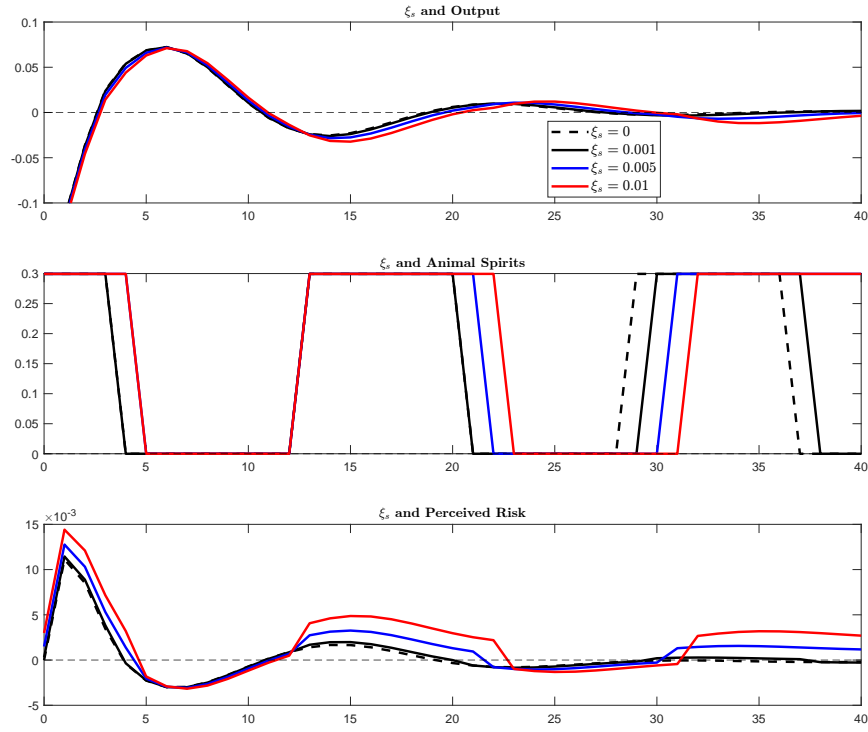


Figure 4: Impulse responses to a negative preference shock $\varepsilon_t^c < 0$ with different calibrations of animal spirits risk coefficient: $\xi_s = 0$ (black dashed line), $\xi_s = 0.001$ (black line), $\xi_s = 0.005$ (blue line), $\xi_s = 0.01$ (red line). All other parameters are at their estimated values from Table 4.

picks up the leftover effects will be of particular interest.

Risk Channel

First, I want to give some intuition on how the animal spirits S_t (cf. Eq. (3.44)) in the risk measure ζ_t (cf. Eq. (3.43)) change the adjustment path, recalling that it measures the fraction of pessimistic agents, i.e., forecast negative development of output. Figure 4 depicts a negative preference shock ε_t^c that leads to a contraction of consumption at first. Agents demand fewer goods on the goods market due to

a preference shift. After falling sharply, output overshoots and oscillates to the old steady state. During the first periods, the share of agents that switch from the *target* heuristic to the dynamic *deanchoring* heuristic grows; thereby, the fraction of agents that are pessimistic about the output development is rising. Due to their negative forecast, they raise the perceived risk level and dampen the overshooting of output, which one may call a self-fulfilling prophecy. Additionally, the deterioration of central bank trust and missing the inflation target lead to higher levels of perceived risk. Just before period five, agents acknowledge the overshooting of output and become optimistic again, leading to lower levels of risk. During the 40 periods depicted here, animal spirits change their pessimistic outlook to an optimistic view three times. Looking at the different calibrations, the larger the parameter ξ_s , the stronger the subsequent rises of the risk measure and, thereby the dampening effect of output becomes. It also leads to a prolonging of the business cycle fluctuation. The estimate is close to $\xi_s \approx 0.01$ and therefore follows the red line in Figure 4.

The other parameters inherent to the perceived risk measure are ξ_m , ξ_y , and ξ_π . I computed the IRFs of a negative monetary policy shock ε_t^r for output and risk under different calibrations for these parameters to show their respective impact on output development as shown in Figure 5. Graphically, the effects of ξ_m and ξ_π are minor compared to the effect that output generates on the risk measure. The calibrations of $\xi_m = 0.1$ (blue line), $\xi_\pi = 0.1$ (black line), and $\xi_y = 0.05$ (black line) mostly match the parameter estimates and, in the aggregate, moderately affect the output movement.

To quantify the effects of these parameters on output skewness and kurtosis, I re-

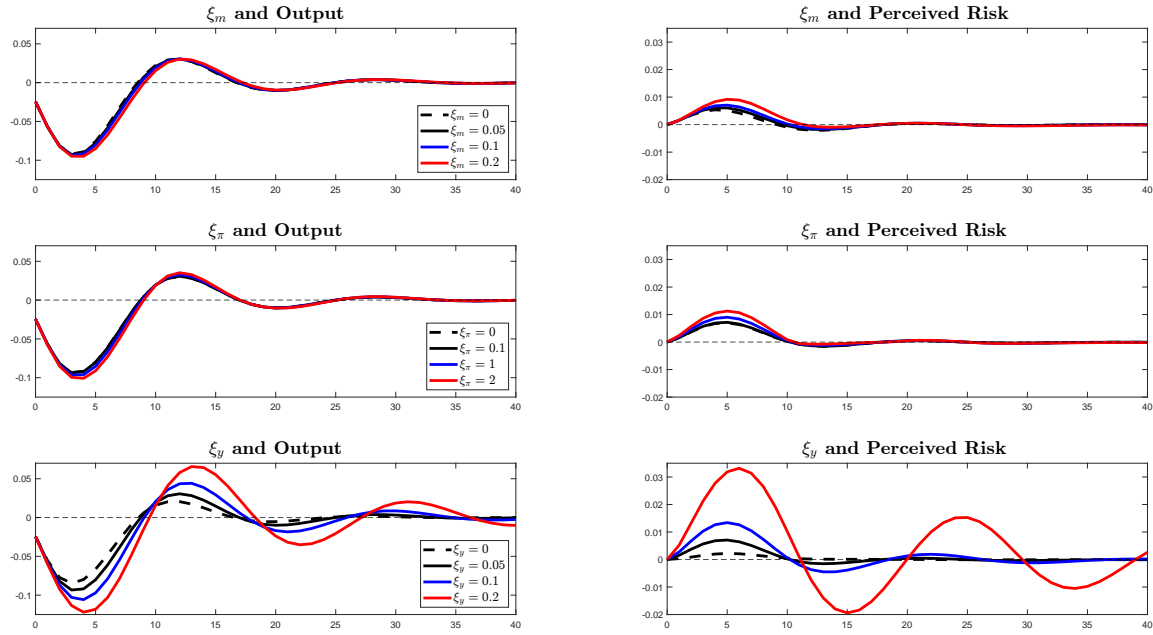


Figure 5: Impulse responses to a positive monetary policy shock $\varepsilon_t^r > 0$ with different calibrations of the credibility, inflation and output risk coefficients ξ_m , ξ_π , and ξ_y . For illustration purposes $\xi_s = 0$. All other parameters are at their estimated values from Table 4.

estimated the model while holding their respective parameter values fixed. The results are shown in Table 8 together with the Jarque-Bera test value and the resulting distance score of the SMM estimation. The parameter estimates can be found in Table B.11 and the simulated moments in Tables B.12, B.10, and B.13 in Appendix B.

Compared with the fully estimated model (BR-HSM-Risk), all re-estimated model variants with less pronounced or no risk measure (BR-HSM-Riskless) equation produce a higher distance score. This is mainly due to mismatching output kurtosis entirely as with $\xi_\pi = 0$, $\xi_s = 0$, and the riskless variant. When omitting the *animal spirits* parameter ξ_s , the increase in distance score compared to the full model's

Risk Parameter	Output Moments			Dist. Score	Rel. Dist.
	Skewness	Kurtosis	JB_{test}		
$\xi_m = 0$	-0.1842	3.7856	8.3124	106.0935	9.5%
$\xi_\pi = 0$	-1.0329	4.6201	19.4916	110.8853	14.4%
$\xi_y = 0$	-0.0255	3.9296	9.5697	103.0007	6.3%
$\xi_s = 0$	0.1199	2.9580	0.6549	146.5917	51.3%
BR-HSM-Riskless	0.1149	5.2135	5.2135	134.0575	38.4%
BR-HSM-Risk	-0.3651	3.5305	8.9987	96.8776	—
US Data	-0.2248	3.5588	5.7897	—	—

Table 8: Simulated skewness and kurtosis from the SMM estimator with identity weighting matrix \mathbf{W} and zero-setting for risk channel parameters ξ_m , ξ_π , ξ_y , and ξ_s and empirical skewness and kurtosis from US data Q2 1955–Q1 2023. Jarque-Bera test at 5% level with $JB_{crit} = 5.7512$.

96.8776 is the highest at +49.7141 (+51%), implying that this risk component is the most relevant. The fact that the riskless variant produces a lower score than the variant with $\xi_s = 0$ is curious. I suspect this is mainly driven by the mismatch of output and consumption kurtosis, resulting in a less favorable estimation for other parameters.

The US data distribution for output also shows skewness to the west, whereas the output distributions of the variant with $\xi_s = 0$ and riskless variant lean to the east. The resulting Jarque-Bera test values reject the H_0 for normal distributions in all but one case, $\xi_s = 0$. Additionally, in case of no *animal spirits* impact on risk $\xi_s = 0$, the distribution is leptokurtic instead of platykurtic. All of the re-estimated variants show positive skewness values for investment and capital. Additionally, the riskless

variant also produces positive skewness for output and consumption.

The full estimates, however, show that the solver algorithm is prone to error under certain circumstances. E.g., the $\xi_s = 0$ -Variant gives very high shock standard errors for output, nominal interest rate, and inflation with values well above $\sigma(\cdot) > 2.5$, which means there is a high degree of disagreement between the simulation runs. Some zero-calibrations lead to high standard error of white noise shock terms, such as the $\xi_m = 0$ - and $\xi_y = 0$ -variants. This is offset by low expectation adaptation parameters ϵ_i and ϵ_c , and near zero AR(1) shock autocorrelation. Especially the uncommon results for the standard errors and corresponding AR(1) are not verified by other studies; see, e.g., Boehl et al. (2022) who estimate them below 1.5.

None of the model variants produces a positive value for $\rho(y_t, \pi_t)$, except for the BR-HSM-Riskless-variant. However, in contrast to the full model, the cross-correlation of $\rho(y_t, i_t)$ is positive. In summary, the fully equipped risk measure leads to a more accurate description of the data moments compared to the more intuitive parameter and shock standard deviation estimates that are verifiable within the literature.

I progress to the interest rate channel affected by the risk measure via the parameter ξ_r . Figure 6 depicts the IRFs of a positive marginal efficiency of investment shock with different parameter calibrations. The shock leads to an immediate jump in investment and, thereby, output and inflation. However, a sharp decline in the rental rate due to the abundance of investable capital subsequently leads to the substitution of labor and capital in the production function. In turn, this lowers hours worked and consumption. Output contracts while inflation deviates negatively from the target. Since inflation is not on its target for the first five periods, the central bank loses

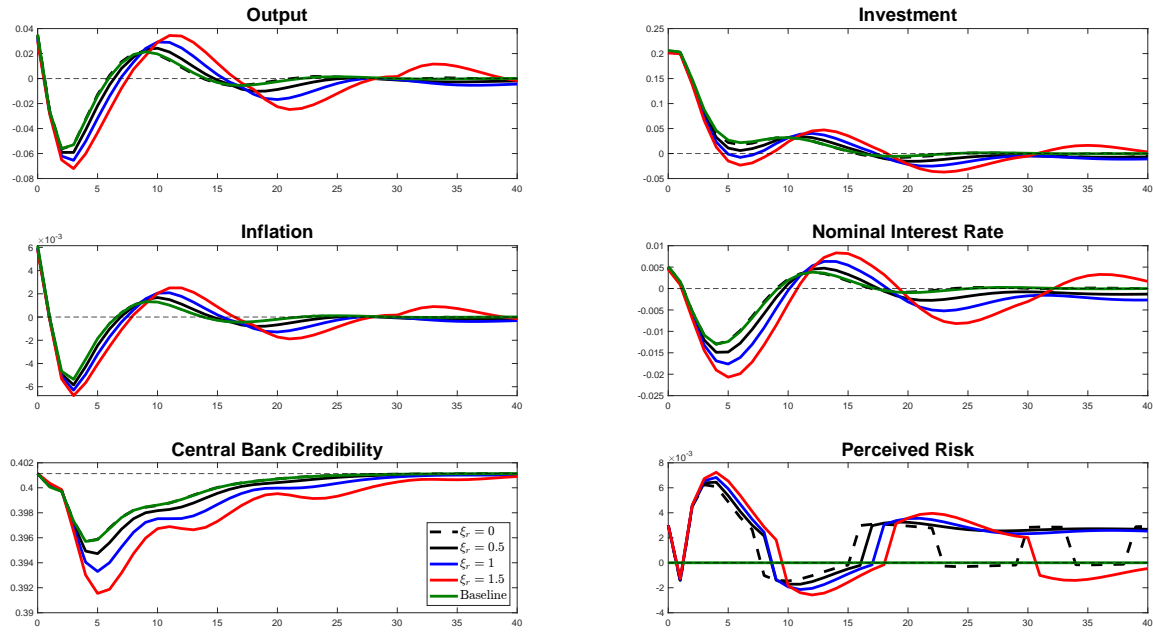


Figure 6: Impulse responses to a positive marginal efficiency of investment shock $\varepsilon_t^i > 0$ with different calibrations of the interest rate channel risk pass-through coefficient ξ_r . All other parameters are at their estimated values from Table 4.

trust among agents, i.e., the attractiveness measure for the *target* heuristic becomes less viable compared to the *deanchoring* heuristic. The credibility loss, negative output adjustment, deviation from the inflation target, and pessimistic animal spirits drive up the perceived risk measure that deepens the ongoing recession through the interest rate channel and investment expectations. The larger the parameter ξ_r , the deeper the contraction in investment and output. The parameter estimate is about $\xi_r \approx 0.14$ and thus lies between the dashed black and the solid black line.

Besides the calibrations of ξ_r , I plot the IRF to the same shock but with the risk channel switched off completely, i.e., the risk measurement is zero throughout the simulation. The movement of the green line shows a faster convergence to the steady

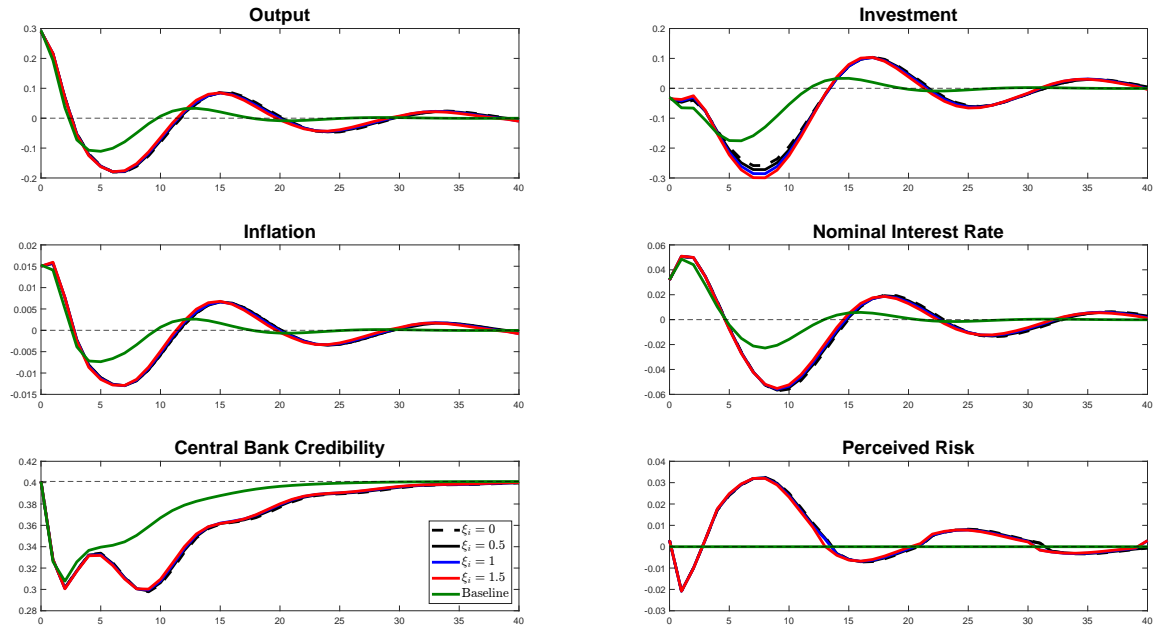


Figure 7: Impulse responses to a positive preference shock $\varepsilon_t^c > 0$ with different calibrations of the investment expectation risk pass-through coefficient ξ_i . For illustration purposes $\xi_s = 0$. All other parameters are at their estimated values from Table 4.

state and lower amplitudes while doing so. This is also reported in Table 5.

Perceived risk via an estimated parameter, ξ_i , also affects investment expectations. Compared to the aforementioned interest rate channel risk coefficient, its estimate is relatively large with $\xi_i \approx 1.6$. However, formed expectations get dampened again by the output expectation adaptation parameter ϵ_i . Figure 7 depicts the IRFs of a positive preference shock with varying calibrations of ξ_i , which show a small impact of the risk measure in the investment expectation channel. Additionally, the *animal spirits* risk coefficient ξ_s is set to 0, making the adjustment changes visible. Intuitively, investment is mainly affected, but all other variables are not. Again, compared to the baseline model without risk channels, the hump-shaped developments are more

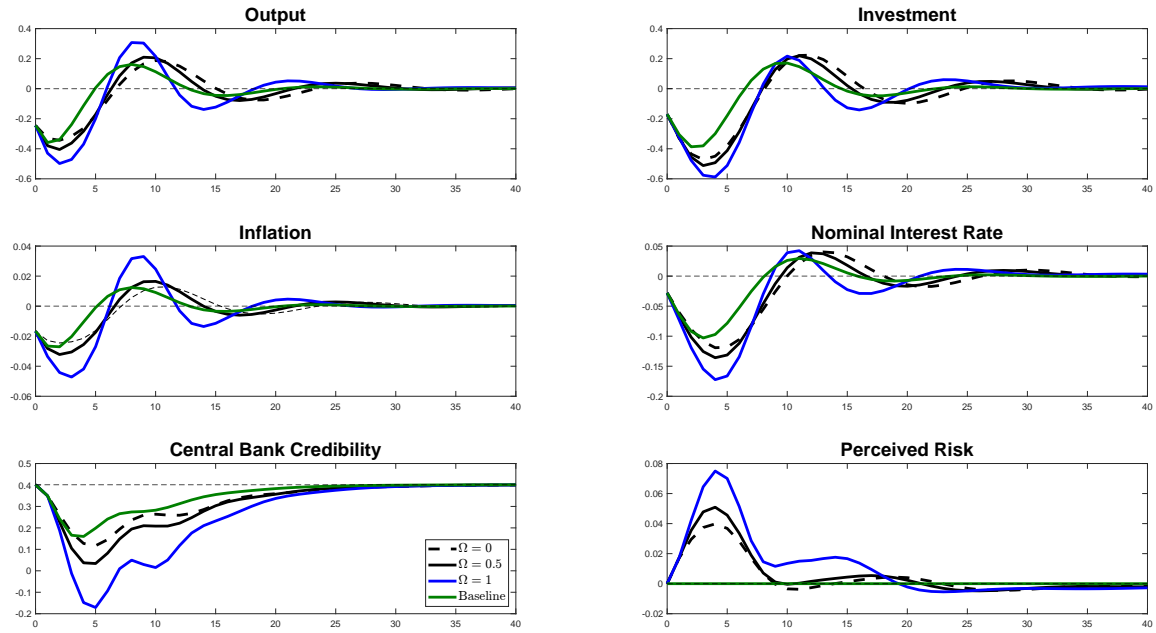


Figure 8: Impulse responses to a positive bond premium shock $\varepsilon_t^b > 0$ with different calibrations of the trend extrapolation parameter Ω . For illustration purposes $\xi_s = 0$. All other parameters are at their estimated values from Table 4.

significant in amplitude, and the adjustment process is prolonged.

Expectation Channel

The parameters inherent to the *deanchoring* heuristic affect the expectations at large. Each of the three parameters controls a different aspect of expectation formation: anchoring with ϖ , adaptation by Υ , and extrapolation with Ω . The most interesting might be the extrapolation parameter because it can lead to volatile adjustment paths and explosive behavior. I look at these parameters in more detail in the following paragraphs.

Figure 8 shows a contractionary premium shock ε_t^b . Depending on the calibration

of Ω , the negative downturn of output and inflation is strongly deepened and perceived risk amplified. Again, this suggests self-fulfilling prophecies of pessimism in the downturn and waves of optimism in the overshooting phase of the shock adjustment path.

The IRFs are simulated with the estimated steady-state credibility shift of $\bar{c} \approx 0.96$, resulting in the steady-state value of $\bar{m}^{CB} \approx 0.4$. In these simulations, the central bank has a relatively large base level of trust among agents. When the share of extrapolative expectations grows more extensive, the model becomes explosive, as shown in the left panel of Figure 9.

Here, I simulated the model for each parameter combination in 0.001 steps for the extrapolation parameter $\Omega \in [0, 3]$ and the steady-state credibility shift $\bar{c} \in [-1, 1]$. The latter represents a range of -45% to $+45\%$ of steady-state central bank credibility, i.e., of mistrust or trust in the central bank. This means a fraction of agents are biased towards sticking to *target* heuristic regardless of the attractivity. I then plotted a dot for each successful, i.e., non-explosive simulation run. An analytical stability analysis is infeasible due to the periodically changing weights on agents' expectations ω_t^{CB} and ω_t^{dac} . The calibration of the other expectation parameters was fixed at $\varpi = \Upsilon = 0.5$; therefore, giving a balanced calibration between anchoring via the average and adaptive expectations. The extrapolation term gets added on top of these two measures and thereby drives the expectation up or down, depending on the trend of past realizations.

The left figure shows a strong dependency on stability and credibility regarding the extrapolation term. If the central bank faces mistrust, i.e., non-positive values for \bar{c} ,

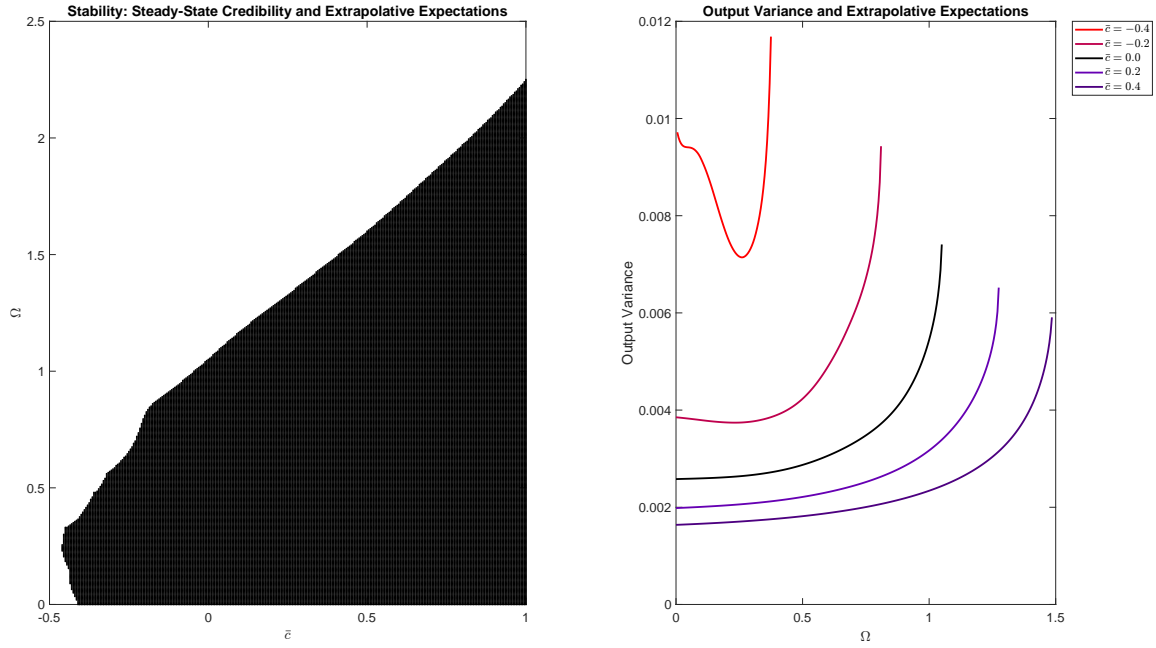


Figure 9: Stability and output variance for steady-state credibility \bar{c} and extrapolative expectations weight Ω under $\varpi = 0.5$ and $\Upsilon = 0.5$. The white area depicts indeterminacy/explosiveness; the black area depicts stable simulation runs. All other parameters are at their estimated values from Table 4.

the extrapolative feature of the *deanchoring* heuristic leads to unstable adjustment paths for Ω values nearing unity. The stability-frontier is nearly linear from $\bar{c} \approx -0.2$ and $\Omega \approx 0.9$ till $\bar{c} = 1$ and $\Omega \approx 2.3$. Under the calibration of $\varpi = \Upsilon = 0.5$ and $\bar{c} \approx -0.45$, a rising parameter value for Ω even contributes to more stability in the model.

This can also be observed in the left panel of Figure 9, which depicts output variance under different calibrations for Ω and \bar{c} in stable model simulations. When steady-state credibility is very low, e.g., at a \bar{c} value of -0.4 , extrapolative expectations may lower output variance until $\Omega \approx 0.3$ (red line), which can be used as another

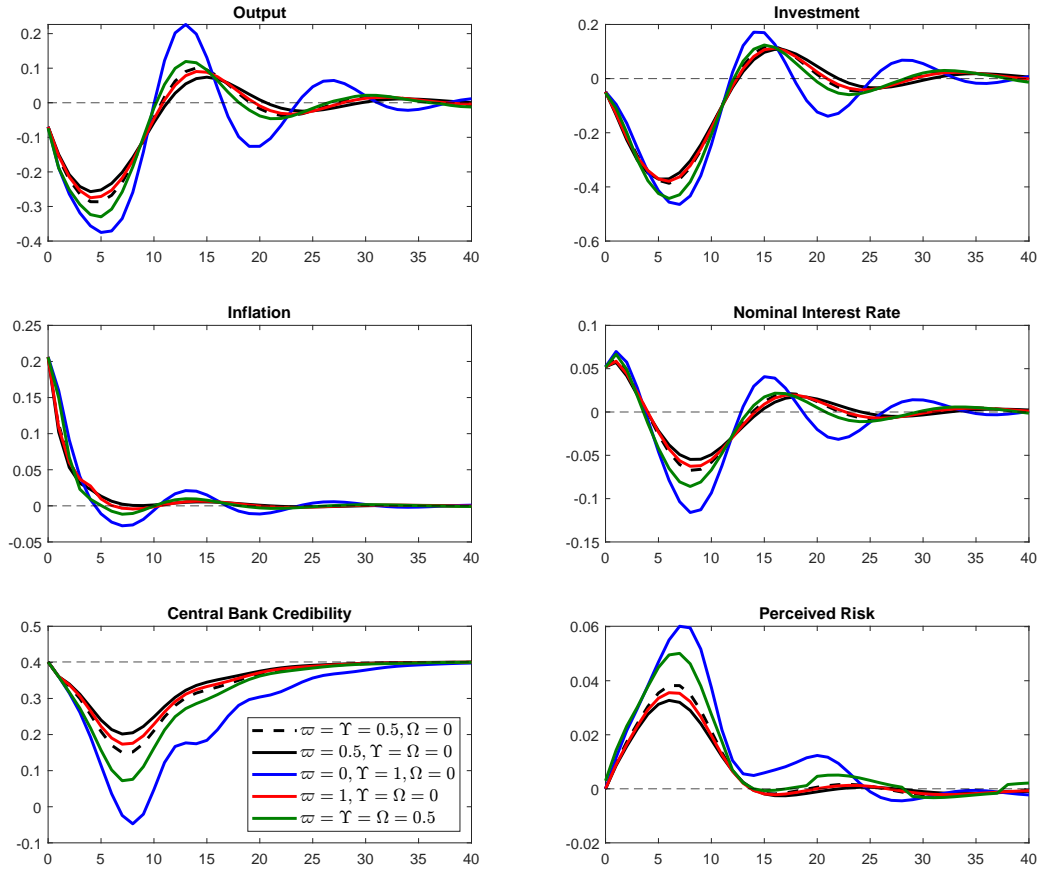


Figure 10: Impulse responses to a positive cost-push shock $\varepsilon_t^p > 0$ with different calibrations of the *deanchoring* heuristic parameters ϖ , Υ , and Ω . For illustration purposes $\xi_s = 0$. All other parameters are at their estimated values from Table 4.

measure for stability in a given simulation run. However, higher values of Ω lead to a sharp rise in variance. Regarding \bar{c} itself, one can observe that it dampens output variance.

The two remaining parameters of the *deanchoring* heuristic are also explored in combination with Ω . Figure 10 depicts a contractionary cost-push shock ε_t^p that leads to an increase in inflation and, therefore, a rising nominal interest rate via the TR. This then leads to contractions in investment, consumption, and, subsequently,

output. Since inflation deviates from its target, the central bank loses credibility among agents, and they begin to switch to the *deanchoring* heuristic, which gives better (or more attractive) forecasts in turbulent times. The different calibrations of the *deanchoring* heuristic that now meaningfully influences the adjustment path of model variables are the following: purely anchoring at a new value (red line, $\varpi = 1$, $\Upsilon = \Omega = 0$), purely naive (blue line, $\Upsilon = 1$, $\varpi = \Omega = 0$), a mixture of these two (solid black line, $\Omega = 0.5$, $\Upsilon = \Omega = 0$), anchoring combined with adaptation (dashed black line, $\Omega = \Upsilon = 0.5$, $\Omega = 0$) and the latter combined with some amount of trend extrapolation (green line, $\varpi = \Upsilon = \Omega = 0.5$).

The mixed *deanchoring* and *naive* calibration of the *deanchoring* heuristic create the lowest deviations from the steady state, thereby letting the risk measure rise moderately. In contrast, the purely naive expectation heuristic raises the adjustment amplitudes for all variables, leading to a longer adjustment path until the steady state is reached. It also affects the credibility of the central bank the most, whereas all other calibrations do not lead to that level of distrust in the model institution. The risk measure is also exceptionally high, with naive expectations in the first ten periods because of the strong history-dependence of the adjustment path. Additionally, its plot shows a kink after starkly falling in period eleven, where it begins to rise again. This can be explained by the closed output gap and met inflation target at period ten. The risk measure considers these variables with a one-period lag. After that, output and inflation overshoot the steady state, and the perceived risk rises again. Second in line for amplification of the business cycle is the balanced calibration with $\varpi = \Upsilon = \Omega = 0.5$ (green line). It also shows a kink in its adjustment path,

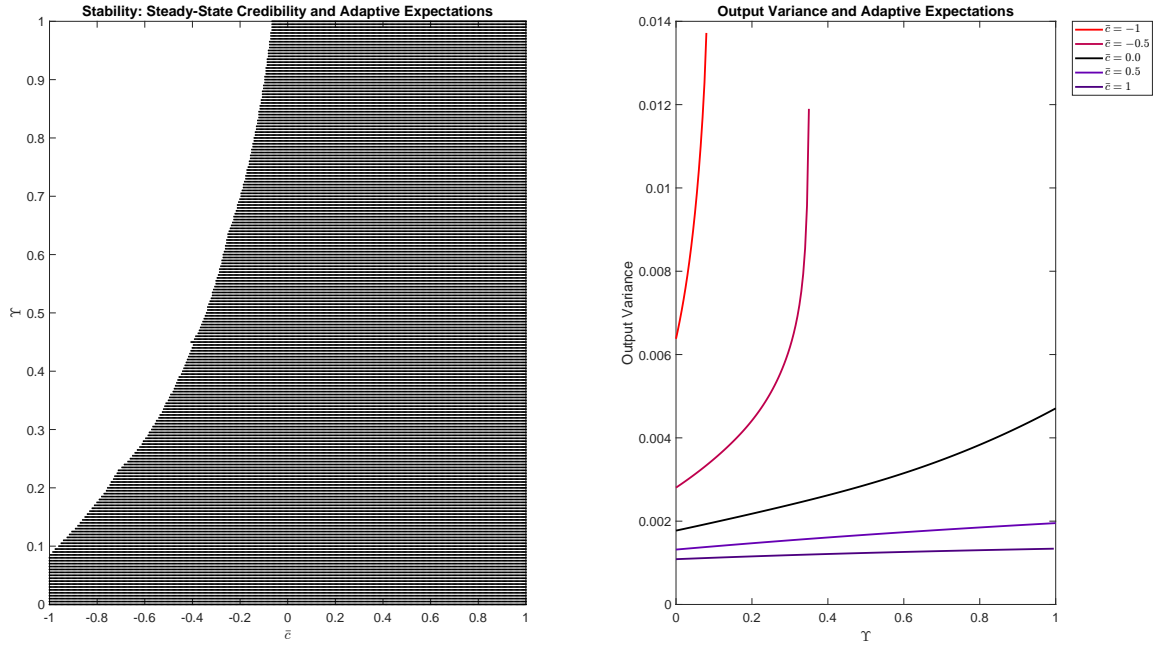


Figure 11: Stability and output variance for steady-state credibility \bar{c} and adaptive expectation parameter Υ under $\Omega = 0.5$ and $\varpi = 0.5$. The white area depicts indeterminacy/explosiveness; the black area depicts stable simulation runs. All other parameters are at their estimated values from Table 4.

however not as pronounced as in the purely naive expectation case.

Regarding the stability of model simulations and output variance, the adaptive expectation term shows different results than those from the extrapolation term. In Figure 11, I conducted the same numerical analysis as with the extrapolation parameter Ω for the adaptive expectation term under balanced calibration of the three parameters ($\varpi = \Upsilon = \Omega = 0.5$).

The plot shows that under comparably small adaptive behavior of agents, the model is always stable within the set parameter bound of $\bar{c} \in [-1, 1]$. Recalling that the adaptive expectation term is $(1 - \varpi)(\Upsilon v_{t-1} + (1 - \Upsilon)\tilde{E}_{t-1}^{dac} v_t)$, setting Υ to 0.1, while

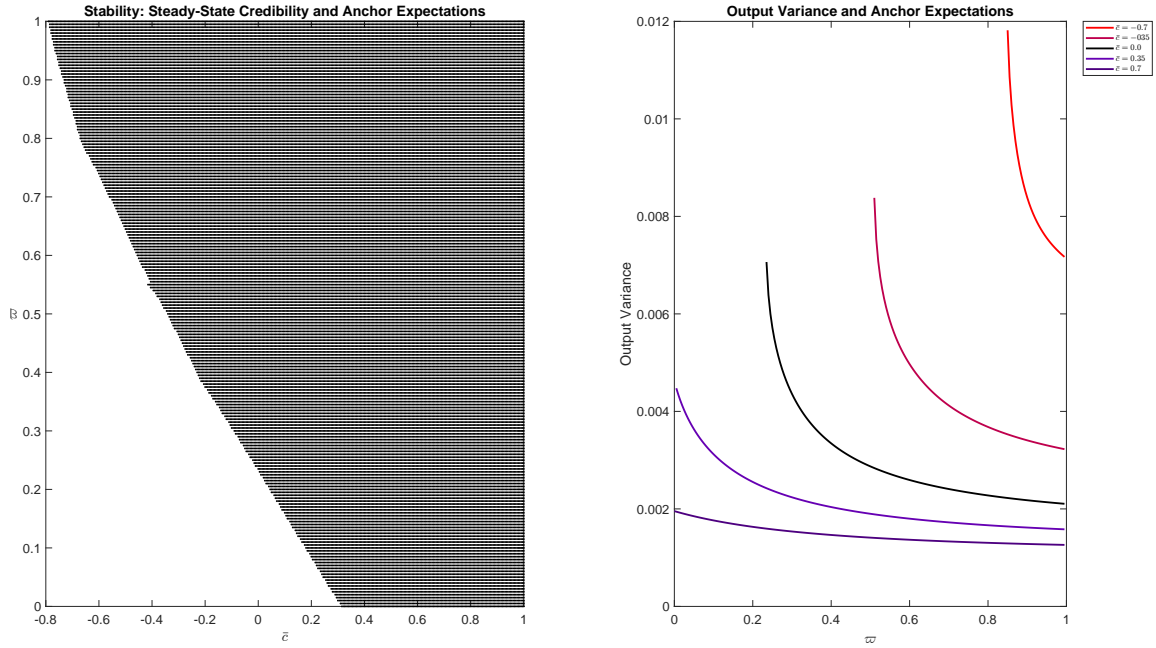


Figure 12: Stability and output variance for steady-state credibility \bar{c} and anchoring expectation parameter ϖ under $\Omega = 0.5$ and $\Upsilon = 0.5$. The white area depicts indeterminacy/explosiveness; the black area depicts stable simulation runs. All other parameters are at their estimated values from Table 4.

the parameter ϖ is 0.5, means that there is a considerable amount of past forecast realization in the expectation present. This leads to moderate adjustments around the anchoring and trend extrapolation component. The more naive the adaption term becomes with rising parameter values Υ , the less stable the model gets while the calibration is in the realm of negative \bar{c} .

The adaptation parameter considerably contributes to an output variance for negative and small positive values of \bar{c} . This effect declines sharply for positive values of the steady-state credibility shift parameter \bar{c} . The reverse is true for the anchoring parameter ϖ , as shown in Figure 12.

Intuitively, a more significant amount of anchoring in the expectation channel leads to less variability and, therefore, variance since expectations react sluggishly to exogenous shocks. Additionally, the absence of the anchoring term gives rise to stability issues. When $\Upsilon = \Omega = 0.5$ and the credibility is below $\bar{c} \approx 0.3$, simulations are unsuccessful, and the model is unstable. Going from $\varpi = 0$ to $\varpi = 1$ in the left subplot means the adaptive term gets smaller and drops when ϖ reaches unity. Here, every simulation is stable.

4.6 Model Comparison

Table 9 presents the parameter estimation results of the BR-HSM financial friction (FF) model variant. The six parameters from the risk channel are not the model's content and, thereby, dropped from the estimation. Additionally, the risk premium shock ε_t^b from the SW framework is not necessary anymore because the financial friction model endogenizes turbulences in the financial sector. The extension brings four new parameters and two additional AR(1) white noise standard deviation and autocorrelation parameters, respectively. These parameters include the steady-state entrepreneur default risk p^d , the income transfer share to new entrepreneurs κ , the entrepreneurial capital w^d , the steady-state LTV ratio ν , the AR(1) autocorrelation parameters $\rho_{\varepsilon^{LTV}}$ and $\rho_{\varepsilon^{p^d}}$ with the white noise shock standard deviations $\sigma_{\varepsilon^{LTV}}$ and $\sigma_{\varepsilon^{p^d}}$.

This thesis' steady-state entrepreneurial default risk estimate at $p^d \approx 0.0094$ differs widely from the reported posterior distribution of Becard and Gauthier (2022). Their estimate is more than twice that size with approximately 0.027. However, since the

BR-HSM	Estimate	NK & Extension	Estimate	AR(1)	Estimate
θ	8.5089	σ_c	2.0221	σ_{ε^c}	0.2813
ξ_A	0.0660	σ_l	1.2025	σ_{ε^i}	0.1871
ξ_ω	0.0510	ϕ	5.8305	$\sigma_{\varepsilon^{p^d}}$	0.3749
\bar{c}	0.8742	ψ	0.6894	σ_{ε^a}	0.3747
ϵ_i	0.5389	χ_p	0.6632	σ_{ε^p}	0.3758
ϵ_c	0.6701	ρ^r	0.7722	σ_{ε^r}	0.6748
ϖ	0.0166	δ_π	3.8620	$\sigma_{\varepsilon^{LTV}}$	0.5559
Υ	0.6372	δ_y	1.1585		
Ω	0.0191			$\rho_{\varepsilon^{LTV}}$	0.8869
				ρ_{ε^c}	0.2877
				ρ_{ε^i}	0.5602
		w^d	0.0483	$\rho_{\varepsilon^{p^d}}$	0.4949
		κ	0.0467	ρ_{ε^a}	0.8285
		ν	0.5185	ρ_{ε^p}	0.8285
		p^d	0.0094	ρ_{ε^r}	0.8412

Table 9: SMM estimation results for BR-HSM-NK-FF model variant with identity weighting matrix \mathbf{W} for US data Q2 1955–Q1 2023. Distance Score: 120.2934.

structure of their approach has been changed considerably, the comparison is difficult to accentuate. The other two estimates that can be directly linked to Becard and Gauthier (2022) are the standard deviation of the collateral shock $\sigma_{\varepsilon^{p^d}}$ and the respective autocorrelation parameter from the AR(1) shock process $\rho_{\varepsilon^{p^d}}$. For these, I can report $\sigma_{\varepsilon^{p^d}} = 0.37$ and $\rho_{\varepsilon^{p^d}} = 0.49$, compared to their estimated posterior modes of 0.031 and 0.96 respectively.

Other parameters have no counterpart to their paper and stem instead from Brenneisen (2022). They align well with his calibration, except for entrepreneurial capital w^d , which is small in my estimate by a magnitude of ten compared to his calibration.

Variable	BR-HSM-Risk		BR-HSM-FF		BR-HSM-Riskless		US Data	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
Output gap y_t	-0.3651	3.5305	-0.8160	4.4977	0.1149	5.2134	-0.2248	3.5588
Consumption c_t	-0.9712	6.6713	-0.7197	4.2818	0.1403	5.2239	-1.0065	6.6564
Investment i_t	-0.2907	9.8165	-1.5213	8.5565	0.5142	8.8115	-1.9328	16.5174
Capital k_t	-0.2990	8.9360	-1.4533	8.3510	0.5097	8.7159	0.1809	2.1268
EFFR r_t^n	0.9761	4.5047	-0.3143	4.1765	0.4590	5.2336	1.0750	4.6884
Inflation π_t	0.7358	4.9734	-0.3902	3.4211	0.4130	5.3207	1.3040	4.5951
Distance Score	96.8776		120.2934		134.0753		–	

Table 10: Comparison between the model variants BR-HSM-Risk (left), BR-HSM-FF (middle) and BR-HSM-Riskless (right) with simulated skewness and kurtosis from the SMM estimator with identity weighting matrix \mathbf{W} and empirical skewness and kurtosis from US data Q2 1955–Q1 2023.

The parameter sets the endowment of the financial intermediaries, broadening the scope of their financial services. It amplifies the revenue stream from lending and thus positively affects their net worth.

The lack of anchoring and extrapolation in the expectation channel via ϖ and Ω are noteworthy on the BR-HSM parameter side. Agents form their expectations by adapting to their previous forecast with Υ . The steady-state credibility shift \bar{c} is again relatively high, accompanied by minimal switching retention ξ_ω and memory about past heuristic attractivity ξ_A .

Regarding the NK core parameters, the estimation returns a high value for the inflation reaction coefficient of the TR $\delta_\pi \approx 3.86$, which can be explained by the accompanying estimate for the relative risk aversion parameter $\sigma_c \approx 2$ that inversely sets the interest rate reactivity of consumption.

The financial friction extension does produce a lower distance measure than the risk-

less model variant, mainly due to a better match of output and consumption kurtosis, as reported in Table 10. While the BR-HSM-Risk variant produces a better overall distance score, the financial friction extension can better match investment skewness. Concerning the other third and fourth moments, the BR-HSM-Risk variant has the edge. The second moment of the nominal interest rate and inflation is incorrect in sign and thereby diminishes the explanatory power of the extension.

Tables B.1 and B.2 in Appendix B report the remaining moments. Compared with the model variant containing the risk measure, the financial friction extension gives similar moments for autocorrelation, except for $\rho(r_t^n, r_{t-3}^n)$, which the simulation gives as -0.012 . In contrast, the empirical data are strongly positive at 0.8790 . The extension provides a better match of cross correlation between output and investment than the variant with the risk measure. Here, $\rho(y_t, i_t) \approx 0.6517$ is close to the empirical moment of 0.6939 and much better than the negative cross-correlation of the other variant returns.

Summing up, the estimation procedure used in this section generates model estimates that can replicate most of the third and fourth empirical moments for the full sample from Q2 1953 till Q1 2023. The smaller sample size and the accompanying crisis-driven moments could not be convincingly matched. The robustness check shows that the risk channel contributes to matching skewness and kurtosis. Especially the *animal spirits* measure in the risk channel with its coefficient ξ_s accounts for a better fit to the empirical moments. However, the baseline facts about the co-movement of output, inflation, and investment could mostly not be correctly matched.

I have also shown that the expectation channel affects model stability under varying

central bank credibility environments. When agents do not trust the central bank in the model, the extrapolation and adaptation components of the *deanchoring* heuristic may lead to unstable and undesirable model adjustment paths. Consequently, I will further explore the expectation channel and its components with respect to monetary policy. The risk channel will also be examined through the lens of the central bank, and additional components for the Taylor instrument rule will be analyzed.

5 Monetary Policy

The second contribution of this thesis is formulating an optimal monetary policy response to business cycle disturbances caused by the risk and expectation channels. Furthermore, this section addresses the welfare optimization and general stabilization problem faced by the central bank in varying levels of credibility environments. In order to analyze the optimal monetary policy responses for central bank trust levels, it is necessary to optimize simple monetary policy rules that use observable contemporaneous variable realizations to inform the decision on the new periodic monetary policy rate. However, in this behaviorally informed framework, it is not sensible to equip the central bank with perfect knowledge of the model economy and agents' expectations. Therefore, I follow the argumentation of Schmitt-Grohé and Uribe (2005, 2007) and formulate simple policy reaction functions that use information all agents can access, including the central bank.

This form of policy optimization is widely used in the BR-HSM framework to contrast or verify standard monetary policy facts of RANK models, see Lengnick and

Wohltmann (2016), Seemann (2024) and Brenneisen (2022). De Grauwe (2011) and De Grauwe and Macchiarelli (2015) conduct monetary policy experiments and find that a larger amount of output stabilization is needed for the volatile effects of pessimistic or optimistic *animal spirits*. The need for higher degrees of output stabilization diminishes when goods market frictions are smaller, for example, through structural reforms as De Grauwe and Ji (2020b) show. The estimated BR-HSM-NK framework by Fischer (2022) shows that deanchored expectations lead to higher inflation variance and deflationary spirals at the ZLB.

In BR models without HSM, optimal monetary policy under commitment and discretion rules can be computed again; see Gasteiger (2014, 2021). In a recent literature entry by Gáti (2023), who is using the adaptive learning approach by Evans and Honkapohja (2001) in her framework, the unanchoring of expectation leads to hawkish monetary policy stances to guide expectations back to the desired target.

Furthermore, Proaño and Lojak (2020) showed that implementing an endogenously formed inflation target at the ZLB stabilizes output but consequently leads to higher inflation. Brenneisen (2022) conducts unconventional monetary policy via credit lending and stock purchases at the ZLB. Here, the effects are twofold: model stability is lowered, but welfare in low central bank credibility environments is increased. The collective findings of numerous studies indicate that output stabilization assumes heightened significance within the BR-HSM framework. This is due to the fact that the central bank is compelled to maintain stability within the expectation channel, which, if left unchecked, could potentially give rise to self-fulfilling prophecies of optimism or pessimism, as evidenced by the *animal spirits* measure. This results in an

additional loss of welfare, particularly if trend extrapolation expectations are among the heuristics that agents can choose. Furthermore, since the BR-HSM framework is strongly history-dependent, backward-looking policy rules lead to higher welfare losses and instability.²² However, instrument rules that use the market expectations from the HSM may also generate a higher loss than contemporaneous rules as De Grauwe and Ji (2020a) show.

Following Lengnick and Wohltmann (2016), I use ad-hoc formulated welfare loss functions to quantify the performance of monetary policy. Different optimized simple rules (*OSR*) are computed and compared by their relative welfare losses expressed as consumption equivalent variations (CEV). The optimized interest rate rule with smoothing *OSR*^s (Eq. (3.28)) acts as a baseline comparison. The CEV measure can be interpreted as the forgoing of consumption units when moving from one simple rule regime to another evaluated at the efficient steady-state.

5.1 Welfare Loss Criteria

The first ad-hoc loss function stems from the approach by Söderlind (1999). The loss function is equipped with an additional instrument stabilization term, compared to the microfounded loss function developed by Rotemberg and Woodford (1999):

$$\mathbb{L}^{instr} = \sum_{t=0}^{\infty} \beta^t \left[l_1 \pi_t^2 + l_2 y_t^2 + l_3 (r_t^n)^2 \right] \quad (5.1)$$

²² This has also been formulated in the RANK literature, see Leitmo (2008) and Svensson and Woodford (2004).

The corresponding weights l_1 , l_2 , and l_3 are set such that the primary target for the central bank is price stability. The less important target is output stability, followed by instrument stability, implying flexible inflation targeting ($l_1 > l_2 > l_3$). I follow Lengnick and Wohltmann (2016) and calibrate the loss weights with $l_1 = 1$, $l_2 = 0.5$, and $l_3 = 0.1$ for this and the following loss function.

In the second loss function, the central bank explicitly considers targeting the share of agents that follow the *deanchoring* heuristic instead of instrument stabilization.

$$\mathbb{L}^{dac} = \sum_{t=0}^{\infty} \beta^t \left[l_1 \pi_t^2 + l_2 y_t^2 + l_3 (w_t^{dac})^2 \right] \quad (5.2)$$

The intuition behind this heuristic stabilization mandate is comparable with Lengnick and Wohltmann (2016) and Seemann (2024), which allow the central bank to consider either the stock price of assets or the exchange rate in its loss measure. Since the *deanchoring* heuristic causes additional units of welfare loss by amplifying the variance of output, consumption, investment, and inflation by fueling self-fulfilling prophecies of pessimistic or optimistic expectations, it might be favorable for the central bank to keep the respective share of agents, that follow this heuristic, small. Since the loss values of Equations (5.1) and (5.2) are not directly comparable, I also compute the variances of output, investment, and inflation as well as the mean and variance of the share of agents that follow the *target* heuristic.

Within the different central bank mandates of either instrument or heuristic stabilization, comparing optimized simple rules is conducted via CEV. The baseline loss \mathbb{L}^s for comparison is given by the optimized TR with smoothing OSR^s and no additional instruments (Eq. (3.28)) for the respective credibility environment. To put

the difference between the baseline loss value and the loss value of the comparison rule into relation to the household inherent to the model, they are expressed in terms of CEV:

$$CEV = \frac{\mathbb{L}^i - \mathbb{L}^s}{\frac{\partial U_t}{\partial C_t} |_{C_t=\bar{C}} \bar{C}} = \frac{\mathbb{L}^i - \mathbb{L}^s}{\bar{C}^{1-\sigma_c} \frac{1}{1+\sigma_l} \bar{L}^{1+\sigma_l}} \quad (5.3)$$

Equation (5.3) can be interpreted as the (steady state) gain or loss of consumption units when moving from rule OSR^i ($i \in (\Delta y, q, \zeta)$) to OSR^s , thereby achieving higher or lower overall welfare in the economy.

The instrument rules I am interested in contain one additional instrument each: a short-term output growth component with reaction coefficient $\delta_{\Delta y}$, a capital price term with δ_q and a term containing the risk measure with δ_ζ . Interest rate smoothing is assumed for all instrument rules; however, the optimization results show that the smoothing parameter ρ^r is often best set to minimal values or zero.

For the short-term growth component addition, I follow the baseline SW model that uses periodic changes in output Δy_t over time:

$$OSR^{\Delta y} : \quad r_t^n = \rho^r r_{t-1}^n + (1 - \rho^r) [\delta_\pi \pi_t + \delta_y y_t + \delta_{\Delta y} (y_t - y_{t-1})] \quad (5.4)$$

Since investment is greatly impacted by the risk measure ζ and the corresponding risk channel coefficients ξ_i and ξ_r , I use the price of capital q_t as an additional instrument for the interest rule, following Heer et al. (2017):

$$OSR^q : \quad r_t^n = \rho^r r_{t-1}^n + (1 - \rho^r) [\delta_\pi \pi_t + \delta_y y_t + \delta_q q_t] \quad (5.5)$$

They analyze this rule in a SW framework and instead find small gains in households' welfare because the friction in the capital market is not as welfare-impeding as frictions in the goods market. However, in the underlying BR-HSM framework, greater welfare can occur. The risk and expectation channel leads to prolonged adjustment paths and welfare losses, which has been shown in Section 4.3.

The last rule I want to optimize and compare with the others directly uses the risk measure ζ_t as an input argument:

$$OSR^\zeta : \quad r_t^n = \rho^r r_{t-1}^n + (1 - \rho^r)[\delta_\pi \pi_t + \delta_y y_t + \delta_\zeta \zeta_t] \quad (5.6)$$

Given that the risk measure incorporates both past variable realizations and heuristic expectations, it is not implausible that a central bank could pursue an active policy based on this measurement. Modern central banks frequently utilize opinion polls and surveys concerning future realizations of macroeconomic variables. Consequently, the model central bank must also possess the capacity to do so and make informed decisions that align with the agents' prevailing economic perspectives. Brenneisen (2022) also used the additional ζ_t instrument, but the risk equation did not contain the agents' waves of optimism and pessimism defined as *animal spirits* with the coefficient ξ_s . Therefore, I find it necessary to incorporate this instrument in my analysis.

Before conducting the interest rule optimization, I want to visualize the possible welfare gains when moving from the estimated instrument rule parameters to the optimized ones. Additionally, the welfare effects of the expectation channel (ϖ , Υ , and Ω) and risk channel parameters (ξ_r and ξ_i) are computed with respect to welfare.

To illustrate this, I plotted average loss values from Equation (5.1) as contours for the instrument rule parameters and different steady-state credibility values \bar{c} .

The calibration is taken from the estimation results from Table 4. However, the model's welfare reacts adversely to higher magnitudes of interest rate smoothing via ρ^r . Therefore, this parameter is set to zero in all computations for Figures 14 and 15. In Figure 13, ρ^r is calibrated at the estimated value of 0.73 to contrast its impact on the welfare measure. The white areas do not automatically depict unstable calibrations but far diverging welfare losses compared to the black outlines. However, infinitely high welfare losses implicate model divergence.

Beginning with the left panel of Figure 13, one can see that low central bank credibility environments lead to higher losses in welfare. This can be upset by higher values of the inflation reaction parameter δ_π until a ceiling is reached from where the loss rises again. From the corner case of $\bar{c} = 1$ and $\delta_\pi = 0$ it can be deduced that the credibility parameter itself also plays a crucial role in welfare and stability.²³ At this vertical axis, the loss is always small in magnitude compared to higher degrees of δ_π . This reinforces the finding of Hommes and Lustenhouwer (2019) in that the central bank relaxes the monetary policy conditions when trust levels are high. In their framework, this is even true at the ZLB.

The right panel contrasts the finding for δ_π . More output stabilization in the interest rate rule always seems to improve the welfare, especially above unity in the depicted parameter window. The additional welfare effects decline at about $\delta_y \approx 15$, which is very high compared to the value Taylor (1993) proposed. This is due to the am-

²³ When δ_π is 0 in the graph, there is still some interest reaction to output variations present in the instrument rule with δ_y as per its estimate of 0.23 that also influences welfare and stability.

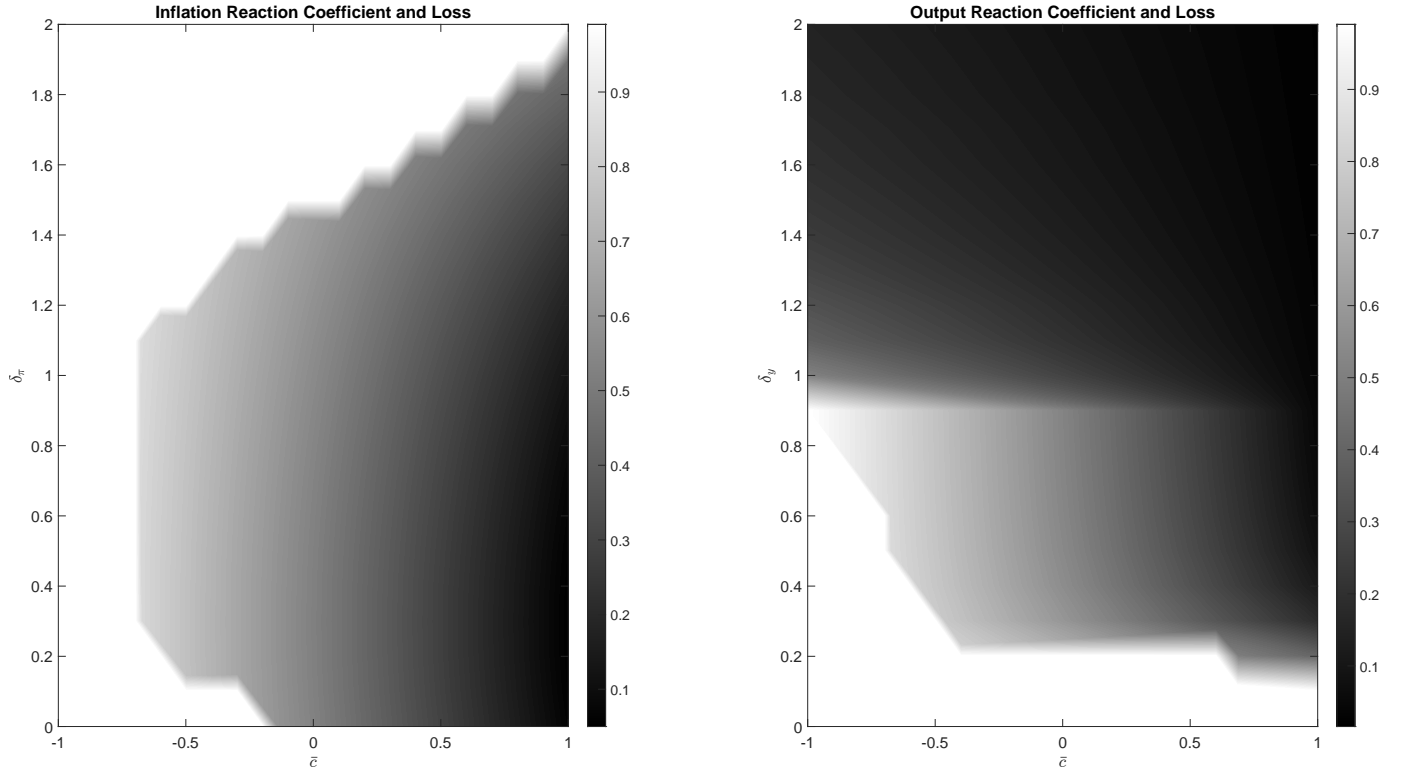


Figure 13: Average welfare loss for different calibrations of output and inflation reaction coefficients δ_y and δ_π , respectively, for different credibility environments controlled by steady-state credibility shift \bar{c} . Loss is computed for 100 periods of 1000 Monte Carlo runs via the instrument stabilization rule. Smoothing parameter $\rho^r = 0.7$. All other parameters are at their estimated values from Table 4.

plification effect of the risk channel against which the central bank has to conduct monetary policy. My study is not the only one that finds relatively high optimal values for the policy rule.²⁴

The parameter estimates at $\delta_\pi = 1.56$, $\delta_y = 0.23$, and $\rho^r = 0.76$ at $\bar{c} = 0.96$ leave

²⁴ Edge et al. (2010) find inflation and output reaction coefficients of $\delta_\pi = 5.57$ and $\delta_y = 23.14$ in their framework under parameter uncertainty, while Debortoli et al. (2015) compute optimal values for inflation and output reaction of $\delta_\pi = 29.28$ and $\delta_y = 54.81$ in a SW framework with additional price and wage mark-up shocks.

much room for the optimization of welfare as I will show in the next subsection. Especially the smoothing parameter needs to be tuned down so that the instrument rule becomes less history-dependent to counteract the turbulence from the risk and expectation channel. Therefore, I have simulated the contour plots without any interest rate smoothing ($\rho^r = 0$) in Figure 14 to show what the optimization will later arrive at. Additionally, the new instruments from Equations (5.4), (5.5), and (5.6) are also shown with their respective effect on welfare loss. The corresponding parameter variation is continuously computed with the estimated parameter values from Table 4, except $\rho^r = 0$. Compared to Figure 13, one can see the immediate welfare gain in the absence of interest rate smoothing. Also clearly visible is the importance of the output instrument relative to other instruments in all credibility environments. However, the effect strongly diminishes above $\delta_y = 0.5$ and gives only small decimal gains in welfare, as I will show in Table 12.

The panels depicting the newly added instruments δ_q and δ_ζ show that the credibility environment limits the effectiveness of these instruments. When credibility is low, their capacity to expand the economy welfare is relatively small, and for higher values, even counterproductive in expanding welfare. This mirrors the finding of Brenneisen (2022), who conducted a similar analysis at the ZLB. Here, δ_ζ is also limited by the credibility environment. Similarly, the limitation of \bar{c} can also be observed for variations of $\delta_{\Delta y}$ except that it does not have an adverse effect on the given parameter bound of the panel.

Lastly, in the bottom right panel, it is evident that elevated smoothing values have a detrimental impact on welfare. As previously stated in this section's introduction,

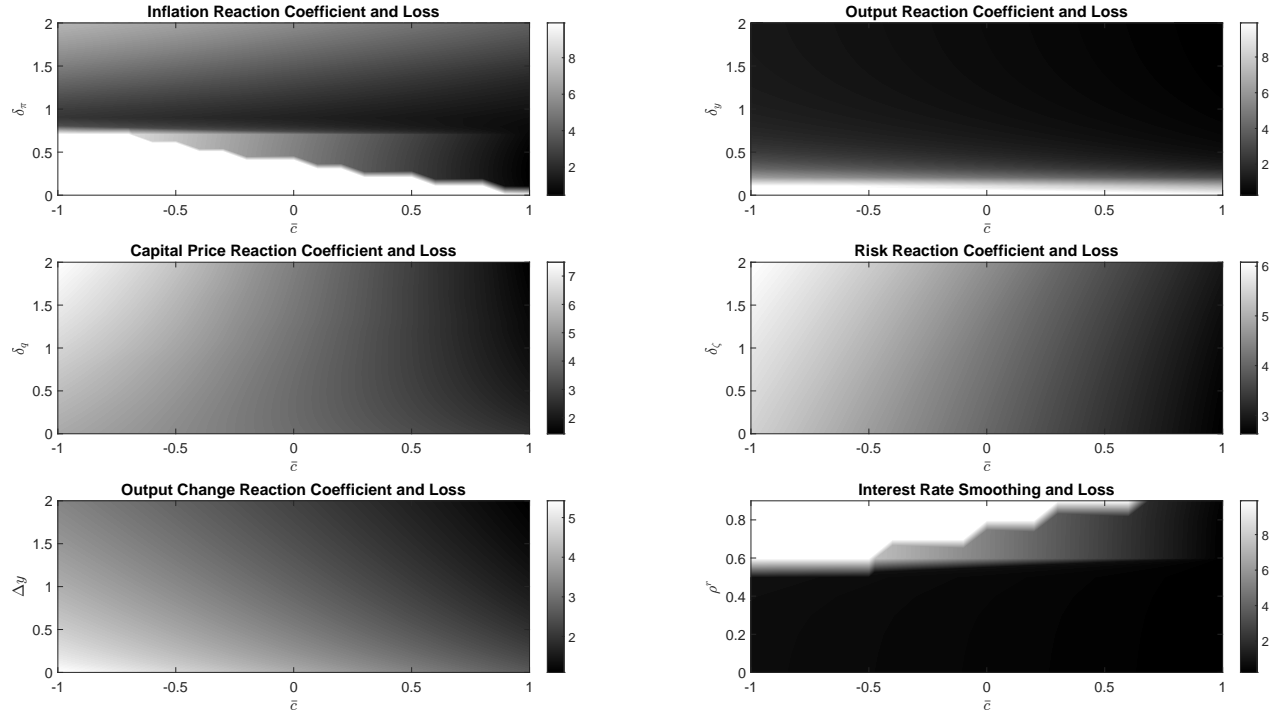


Figure 14: Average welfare loss for different calibrations of output, inflation, output growth, capital price, risk reaction coefficients δ_y , δ_π , $\delta_{\Delta y}$, δ_q , δ_ζ , ρ^r , and \bar{c} , respectively for different credibility environments controlled by steady-state credibility shift \bar{c} . Loss is computed for 100 periods of 1000 Monte Carlo runs via the instrument stabilization rule. Smoothing parameter $\rho^r = 0$, except in the bottom right panel.

history-dependent models necessitate contemporaneous or better forward-looking instruments to maintain stability in welfare. A delayed policy response increases the propensity to employ a non-*target* heuristic, leading to further destabilization of output and inflation. This, in turn, creates a self-fulfilling prophecy of the central bank's inability to control inflation effectively.

Before I move on to the *OSR* discussion, I want to illustrate the effects of the expectation and risk channel on overall welfare. Figure 15 shows loss contour plots for the *deanchoring* heuristic (3.36) and the risk channel parameters ξ_r and ξ_i in vary-

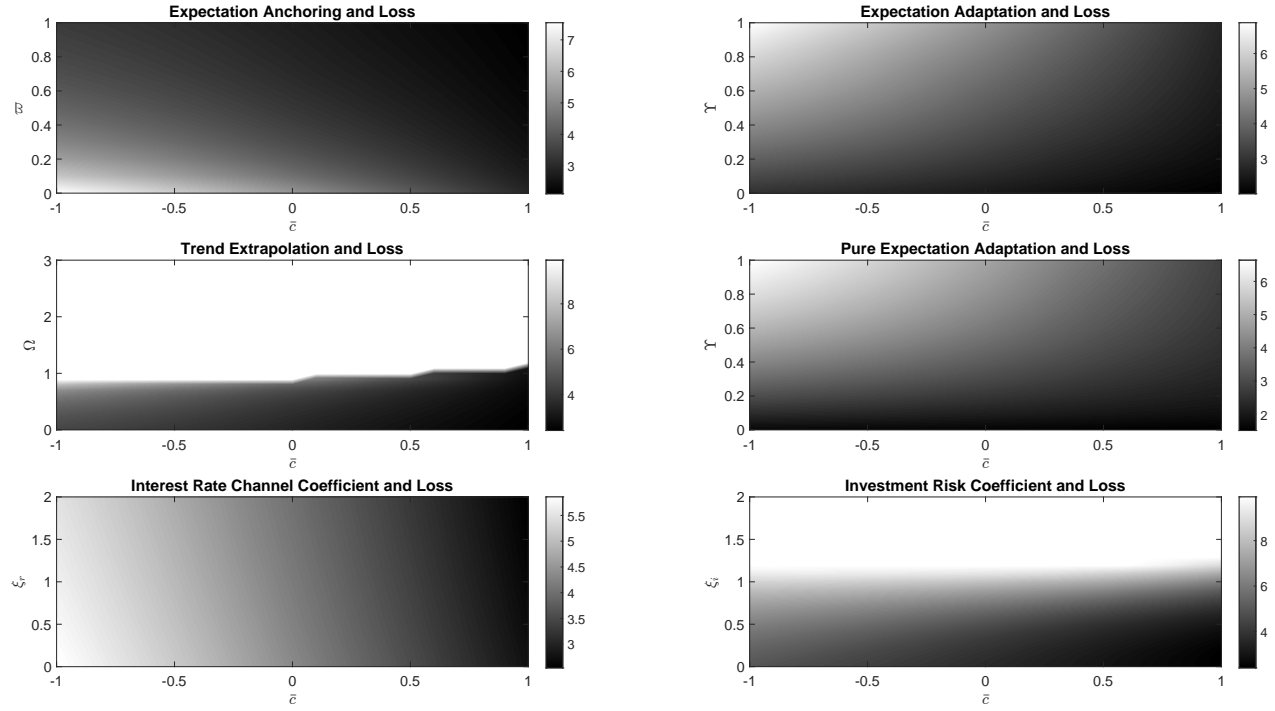


Figure 15: Average welfare loss for different calibrations of anchoring, adaptation, trend extrapolation, interest rate risk pass-through, and investment risk pass-through parameters ϖ , Υ , Ω , ξ_r , and ξ_i , respectively, for different credibility environments controlled by steady-state credibility shift \bar{c} . Loss is computed for 100 periods of 1000 Monte Carlo runs via the instrument stabilization rule. Smoothing parameter $\rho^r = 0$.

ing ranges of central bank credibility. Beginning with the upper left panel, it can be stated that higher degrees of expectation anchoring via ϖ lead to fewer welfare losses. This is also congruent with the finding from Figure 12 in that the anchoring parameter reduces output variance. The reverse is true for the adaptation parameter Υ and even more so for the trend extrapolation parameters Ω depicted in the upper right and middle left panels. In contrast to the aforementioned findings, low values of Υ contribute to an increase in welfare across all credibility calibrations. Conversely,

as the heuristic becomes more backward-looking, the welfare loss in low credibility environments also increases. The loss-generating feature of trend extrapolation is less pronounced when higher degrees of credibility are present. However, when the parameter surpasses unity, the loss rises significantly outside of the defined contour limits.

The middle right panel depicts the pure adaptation calibration, where $\varpi = \Omega = 0$. When Υ is moving from zero to unity, the heuristic becomes more backward-looking, while the corner cases $\Upsilon = 0$ and $\Upsilon = 1$ result in the *target* and *naïve* heuristic, respectively. Omitting Ω and ϖ in this panel does not substantially change the finding from the panel directly above: the more backward-looking the expectations are, the worse off is the economy's welfare.

Curiously, the magnitude of the risk pass-through parameter in the interest rate channel does not drastically lower loss compared to the investment expectation risk pass-through parameter in Eq. (3.42). The parameter estimates are at $\xi_i = 1.5$ and $\xi_r = 0.3$.

The presented figures show that the economy's welfare can be uplifted under the parameter estimates with the optimized parameter choices for the instrument rules. In the next section, parameters will be optimized under the aforementioned welfare criteria with instrument stabilization (see Eq. (5.1)) and heuristic stabilization, respectively (see Eq. (5.2)). To compare the two welfare mandates, I will also use the variances of output, inflation, and investment and the variance of the targeting heuristic.

5.2 Optimized Taylor Rules

The optimization procedure used in this section is comparable to the estimation procedure in Section 4, with the exception that the grid is much smaller since the number of parameters is limited to three in case of OSR^s (3.28) and four for the rules with short-term growth, capital price, or risk component, $OSR^{\Delta y}$ (Eq. (5.4)), OSR^q (Eq. (5.5)), and OSR^ζ (Eq. (5.6)), respectively. The constructed grid contains circa 100 combinations, and with these average losses over $K = 1000$ i.i.d., white noise shock drawings are simulated for $T = 1000$ periods. Then, the five parameter combinations that result in the lowest losses of Eq. (5.1) and Eq. (5.2), respectively, are handed over to the MATLAB *Multistart* solver to find the local minima of the parameter combination from the grid. I do not expect singular spikes outside the grid; therefore, I consider this approach robust.

Instrument Stabilization

First, I assume the following welfare criterion \mathbb{L}^{instr} (see Eq. (5.1)) which acts as the objective function that needs to be optimized via the instrument parameters $z \in \{\rho^r, \delta_\pi, \delta_y, \delta_{\Delta y}, \delta_q, \delta_\zeta\}$ by the central bank:

$$z^* = \arg \min_z \mathbb{L}^{instr} \quad (5.7)$$

whereas z^* are the optimized instrument rule parameters $z^* \in \{\rho^{r,*}, \delta_\pi^*, \delta_y^*, \delta_{\Delta y}^*, \delta_q^*, \delta_\zeta^*\}$.

Under the single mandate to minimize inflation, I assume flexible inflation targeting and instrument stabilization. The optimization procedure is conducted for different

central bank credibility environments, controlled by the steady-state credibility shift parameter \bar{c} . The optimized instrument rule parameters are shown in Table 11. For a better visualization, I plot the different parameter calibrations in Figure 16 in relation to \bar{c} . The respective descriptive statistics can be found in Table 12.

I begin with a comparison of the optimized instrument rule with smoothing OSR^s and the rule with the short-term output growth component $OSR^{\Delta y}$. They both produce nearly the same optimized parameter values in δ_π , δ_y , and ρ^r but the fourth instrument in $OSR^{\Delta y}$ enables a lower loss across all credibility environments. From the top panels of Figure 16 and the top two rows of Table 11, one can see that δ_π stays between four and six, whereas the output reaction coefficient δ_y rises while moving into higher degrees of central bank credibility. This is because agents give the central bank an advance in trust and do not switch immediately to the *deanchoring* heuristic when the economy diverges from the target inflation rate. This allows the monetary authority to increase the policy pressure and persuade some of the agents that find the central bank not credible to switch.

The growth component coefficient $\delta_{\Delta y}$ also sharply rises after \bar{c} surpasses $\bar{c} = 0.1$. However, this does lead to minimal welfare gains. The smoothing coefficient ρ^r is near zero for all credibility environments and is not surpassing $\rho^r = 0.14$ in $OSR^{\Delta y}$. Capital price q_t and perceived risk ζ_t as instruments provide additional but minimal welfare gains under instrument targeting. The respective instrument coefficients δ_q and δ_ζ can be negative in sign. This mimics the result from Heer et al. (2017) for the capital price coefficient. Their intuition is as follows: when inflation declines due to a productivity shock and the central bank lowers the interest rate accordingly, the

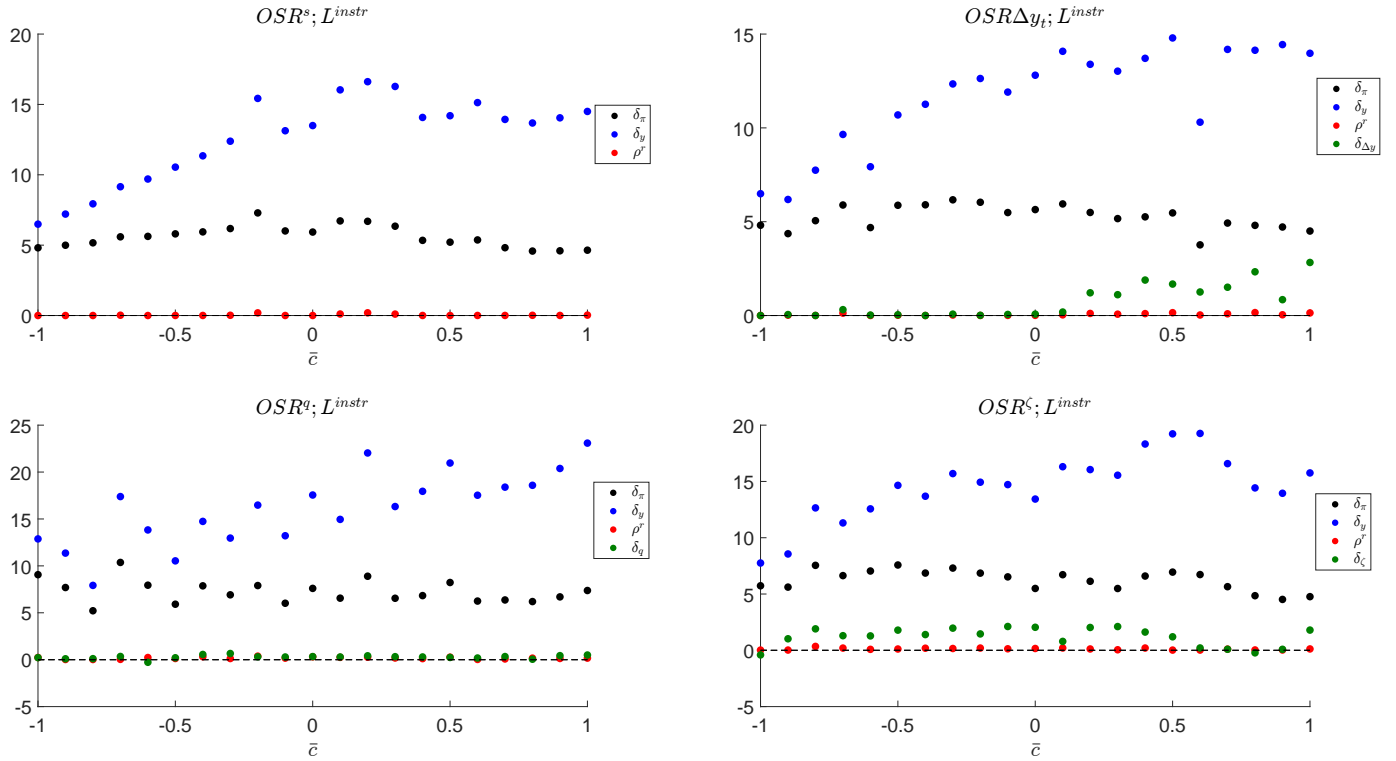


Figure 16: Distribution of OSR parameters for different credibility environments controlled by steady-state credibility shift \bar{c} from Table 11.

arbitrage condition via Tobin's Q leads to an upswing in investment and households smooth out consumption. Both effects result in an increase in inflation, which overshoots its target. If the central bank considers the price of capital, it can reduce the extent of the overshooting of inflation and thereby minimize the welfare loss that would otherwise occur by setting a slightly lower nominal interest rate in the first place. However, the framework presented in this thesis is based on perceived risk that directly affects investment and consumption. The intuition for positive values of δ_q in this framework is entailed with the expectation channel. The central bank is keen on further controlling the investment variance since investment is driven by the

capital price q_t and the share of agents that follow the *deanchoring* heuristic. When q_t rises, leading to higher investment and output, the nominal interest rate r_t^n rises as well, toning down output expectations that might otherwise lead to self-fulfilling prophecies of output expansion.

Regarding the risk reaction coefficient δ_ζ , the optimization results are also ambiva-

		\bar{c}				
		-1	-0.5	0	0.5	-1
OSR^s	δ_π	4.8111	5.8019	5.9169	5.2124	4.6422
	δ_y	6.4916	10.5440	13.4642	14.1976	14.5014
	ρ^r	0.0000	0.0031	0.0000	0.0000	0.0276
$OSR^{\Delta y}$	δ_π	4.8110	5.8755	5.6454	5.4681	4.5020
	δ_y	6.4915	10.6904	12.8064	14.7930	13.9752
	$\delta_{\Delta y}$	0.0000	0.0395	0.0732	1.6760	2.8273
	ρ^r	0.0000	0.0136	0.0091	0.1516	0.1380
OSR^q	δ_π	9.0605	6.0284	7.6002	8.2278	7.5400
	δ_y	12.8749	10.7334	17.5527	20.9617	23.5764
	δ_q	0.2178	0.4739	0.3313	0.0240	0.5616
	ρ^r	0.2327	0.2549	0.3026	0.2699	0.1948
OSR^ζ	δ_π	5.7317	7.5774	5.4946	6.9464	4.7653
	δ_y	7.7534	14.6540	13.4351	19.2267	15.7560
	δ_ζ	-0.4082	1.7924	2.0454	1.1993	1.7966
	ρ^r	0.0193	0.1154	0.1617	0.0196	0.1220

Table 11: Results for OSR parameters with instrument stabilization objective for different credibility environments controlled by steady-state credibility shift \bar{c} .

lent in sign. According to the estimates of $\xi_m \approx 0.1$, $\xi_s \approx 0.1$, and $\xi_\pi \approx 1.3$, risk mainly reacts to deviation from steady-state credibility, pessimistic *animal spirits*,

and absolute deviation of inflation expectation from the target and to a lesser extent on past output realization with $\xi_y \approx 0.003$. While higher deviations of m_t^{CB} and $\tilde{E}_t \pi_{t+1}$ from their targets ask for higher interest rates, it is countermanded by the possibility of a recession and, therefore, rising pessimistic expectations, which would lead to more risk in the coming period.

Therefore, the central bank has to balance credibility and inflation expectations with the possibility of pessimistic *animal spirits* that feed recessionary downward spirals. The sign of δ_ζ can either favor ‘taming’ *animal spirits* or stabilize credibility, depending on the steady-state credibility shift \bar{c} and the other instrument rule parameters. The optimal output reaction coefficients from all *OSRs* increase in unison with the credibility environment. This may indicate that as the central bank’s credibility grows, the more stringent it can pursue its goals with a diminishing risk of doing too much for pessimistic animal spirits and their tendency to destabilize the economy. A pattern for the inflation or third instruments reaction coefficient is not directly deductible.

The resulting losses \mathbb{L} from Eq. (5.1) can be found in Table 12. Additionally, I computed the resulting variances for output, inflation, investment, and the share of agents that follow the target heuristic to portray a broader picture of the conducted optimized monetary policy.

As the left panel of Figure 17 shows, the welfare states under different instrument rules are more dependent on the credibility shift \bar{c} and differ minimally over the

		-1	-0.5	\bar{c} 0	0.5	-1
\mathbb{L}	OSR^s	0.0377	0.0250	0.0170	0.0123	0.0095
	$OSR^{\Delta y}$	0.0373	0.0248	0.0168	0.0121	0.0094
	OSR^q	0.0367	0.0243	0.0165	0.0119	0.0092
	OSR^ζ	0.0365	0.0242	0.0164	0.0118	0.0092
CEV	$OSR^{\Delta y}$	-0.0140	-0.0094	-0.0065	-0.0052	-0.0042
	OSR^q	-0.0419	-0.0288	-0.0200	-0.0151	-0.0114
	OSR^ζ	-0.0444	-0.0321	-0.0202	-0.0150	-0.0112
$var(y_t) (10^{-4})$	OSR^s	2.1396	0.8875	0.4061	0.2101	0.1274
	$OSR^{\Delta y}$	2.1198	0.8785	0.4026	0.2092	0.1241
	OSR^q	2.1747	0.9382	0.4068	0.2462	0.1288
	OSR^ζ	2.1753	0.8813	0.3943	0.2089	0.1247
$var(\pi_t) (10^{-3})$	OSR^s	0.4898	0.3412	0.2349	0.1696	0.1314
	$OSR^{\Delta y}$	0.4852	0.3379	0.2327	0.1680	0.1303
	OSR^q	0.4926	0.3417	0.2368	0.1692	0.1323
	OSR^ζ	0.4925	0.3435	0.2370	0.1710	0.1325
$var(i_t) (10^{-3})$	OSR^s	2.2079	1.5386	0.9750	0.5387	0.2648
	$OSR^{\Delta y}$	2.2075	1.5414	0.9750	0.5475	0.2744
	OSR^q	2.2686	1.5221	0.9574	0.5376	0.2632
	OSR^ζ	2.2482	1.5767	0.9697	0.5370	0.2666
$var(\omega^{CB}) (10^{-5})$	OSR^s	0.1096	0.0582	0.0268	0.0113	0.0045
	$OSR^{\Delta y}$	0.1075	0.0571	0.0263	0.0110	0.0044
	OSR^q	0.0992	0.0530	0.0243	0.0105	0.0041
	OSR^ζ	0.0991	0.0521	0.0241	0.0103	0.0041

Table 12: Resulting loss, CEV, and unconditional variances of output, inflation, investment and share ω_t^{CB} from $OSRs$ with instrument stabilization objective for different credibility environments controlled by steady-state credibility shift \bar{c} . Loss is computed for 100 periods of 1000 Monte Carlo runs.

actual $OSRs$. They all nearly coincide at $\bar{c} = 1$. The right panel shows an enhanced view of the welfare losses in the credibility domain of $\bar{c} = [-0.6, -0.4]$. Here, one can see the near-perfect alignment of OSR^q and OSR^ζ , while OSR^s and $OSR^{\Delta y}$ lie

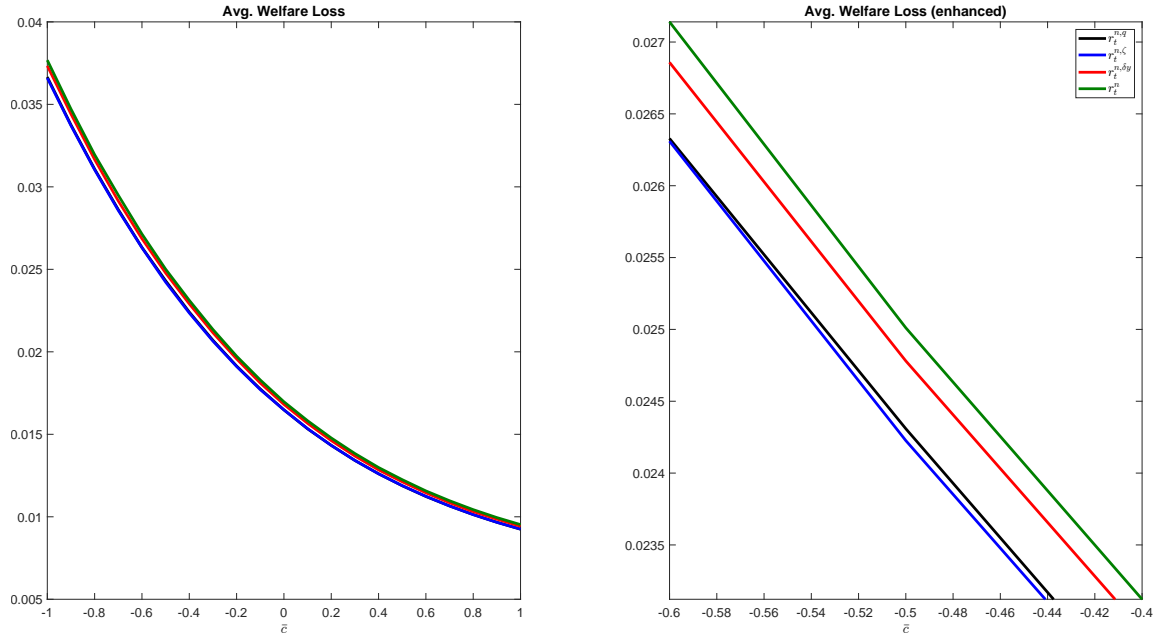


Figure 17: Average loss from *OSRs* in different credibility environments with instrument stabilization objective (left) and enhanced at $\bar{c} = [-0.6, -0.4]$ (right). Results from Table 12.

further to the north. The later simple rules also differ to some degree from one another. From the households' perspective, moving from the best performing rule OSR^ζ to the worst performing, OSR^s , would lead to ≈ 0.04 less consumption units in a low credibility environment ($\bar{c} = -1$) and ≈ 0.01 less consumption units in a high credibility environment ($\bar{c} = 1$), see Table 12 in the second row. The plots for output, inflation, and investment variances draw a similar picture to the average losses. They do not significantly diverge from each other. Not surprisingly, OSR^{4y} is the front runner for output stabilization for many credibility environments since the rule is more or less fine-tuned to tone down the adjustment path of output. Interestingly, OSR^ζ overtakes the growth component rule for some positive steady-state credibility

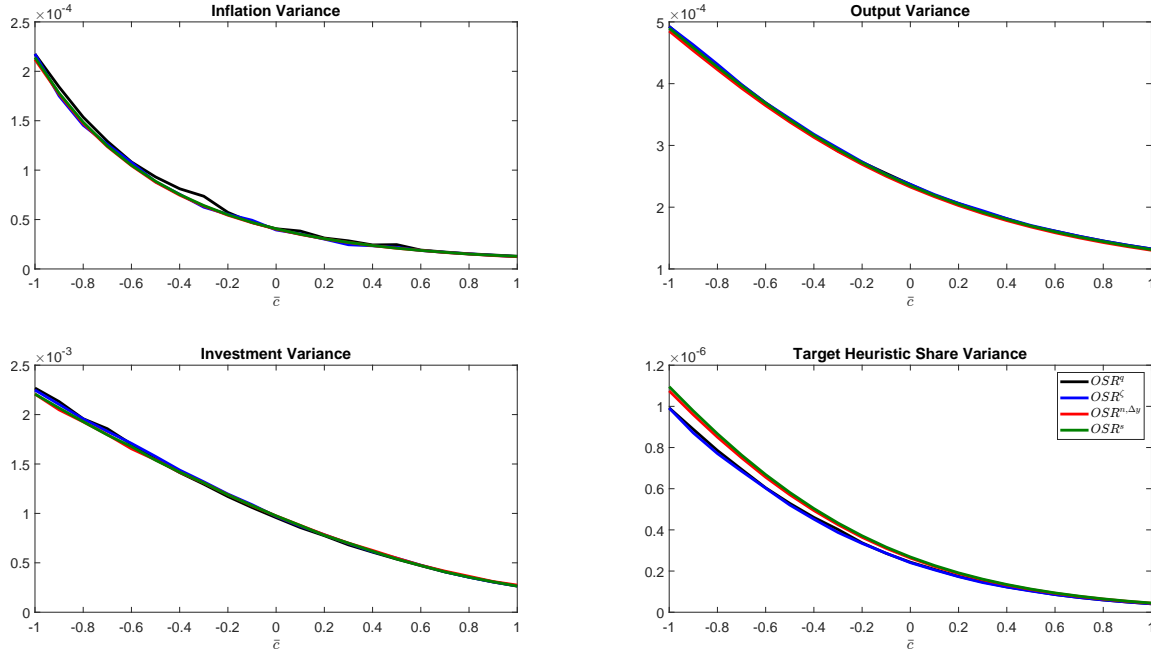


Figure 18: Output, inflation, investment, and share of ω_t^{CB} variances from $OSRs$ in different credibility environments with instrument stabilization objective. Results from Table 12.

values, e.g., between $\bar{c} = [0, 0.5]$. The same is true for the variance of inflation and investment, where $OSR^{\Delta y}$ and OSR^s seem to perform comparably well in producing lower variances. However, they still generate higher losses.

The bottom right panel depicts the variance of the share of agents that follow the *target* heuristic. Here, $OSR^{\Delta y}$ and OSR^s produce lower variances, implying that agents do not switch as frequently from and to the target heuristic as they do with the other two rules. In fact, the respective mean of ω_t^{CB} for the simulations under $OSR^{\Delta y}$ and OSR^s is some minimal degrees (10^{-5}) lower for these rules, which explains the higher outcome for the welfare loss.

Consequently, I consider the central bank to acknowledge that the *deanchoring*

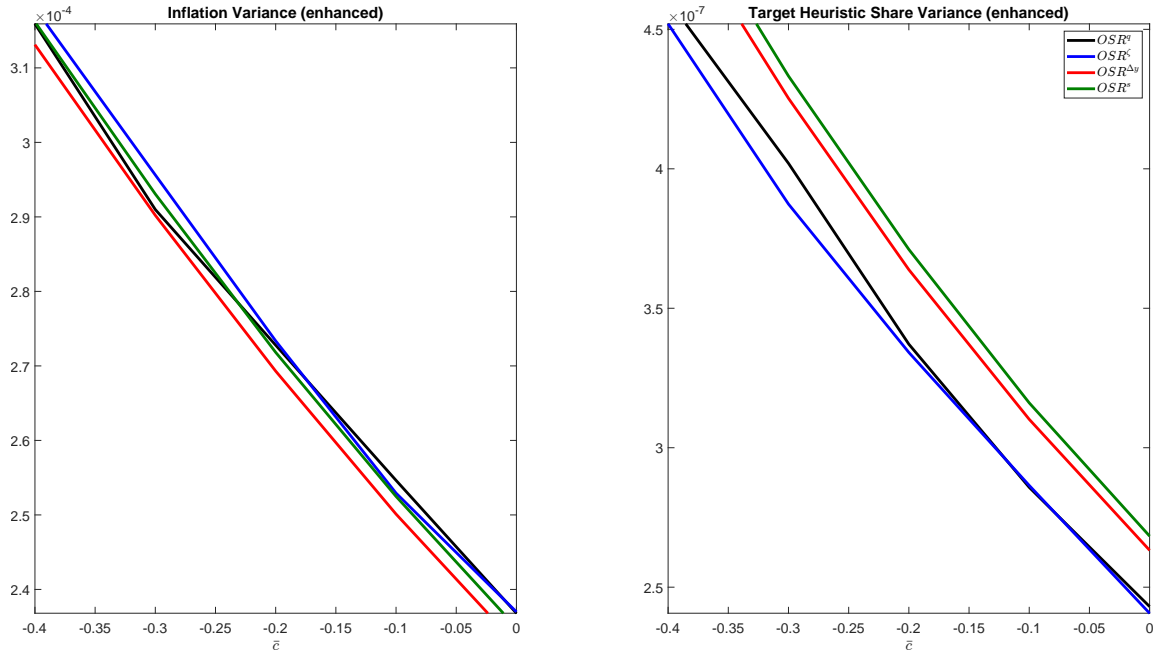


Figure 19: Enhanced inflation and share of ω_t^{CB} at $\bar{c} = [-0.4, 0]$. Results from Table 12.

heuristic diminishes the economy's welfare, thus including it in the objective function instead of instrument stabilization.

Heuristic Stabilization

Recalling the heuristic stabilization welfare criterion

$$\mathbb{L}^{dac} = \sum_{t=0}^{\infty} \beta^t \left[l_1 \pi_t^2 + l_2 y_t^2 + l_3 (w_t^{dac})^2 \right], \quad (5.8)$$

the central bank now stabilizes the share of agents that follow the *deanchoring* heuristic. The objective function then reads

$$z^* = \arg \min_z \mathbb{L}^{dac} \quad (5.9)$$

with instrument parameters $z \in \{\rho^r, \delta_\pi, \delta_y, \delta_{\Delta y}, \delta_q, \delta_\zeta\}$ and z^* comprising the optimized instrument rule parameters $z^* \in \{\rho^{r,*}, \delta_\pi^*, \delta_y^*, \delta_{\Delta y}^*, \delta_q^*, \delta_\zeta^*\}$.

The resulting optimized *OSR* parameters differ widely in magnitude from their counterparts from the instrument stabilization welfare criterion as reported in Figure 20 and Table 13. Output reaction via δ_y is much stronger, e.g., $\delta_y \approx 25$ at range of $\bar{c} = [-0.3, 0.3]$ on $OSR^{\Delta y}$ and OSR^s . The inflation reaction coefficient also produces higher optimal values for these rules and partly for OSR^ζ and OSR^q .

The sign of δ_q is now mainly negative. Thereby, the policy intuition by Heer et al. (2017) is more applicable. Interest rate smoothing via ρ^r is still not important.

The greater magnitude in policy response is because ω_t^{dac} generates a considerable amount of loss when not adequately targeted since it is the fraction of agents and not a percentage deviation of steady-state values like π_t and y_t . This is a desirable outcome with the calibration of $l_3 = 0.1$ in mind. Simulations of loss optimization, including steady-state deviations of the credibility measure, did not result in a notable alteration in the variance and mean of the proportion of agents that adhere to the target heuristic. Given that the heuristic stabilization component's absolute contribution is considerable in comparison to that of inflation, it is more appropriate to refer to this weighting scheme as flexible heuristic targeting.

Comparable to instrument stabilization, the *OSRs* that include the price of capital q_t

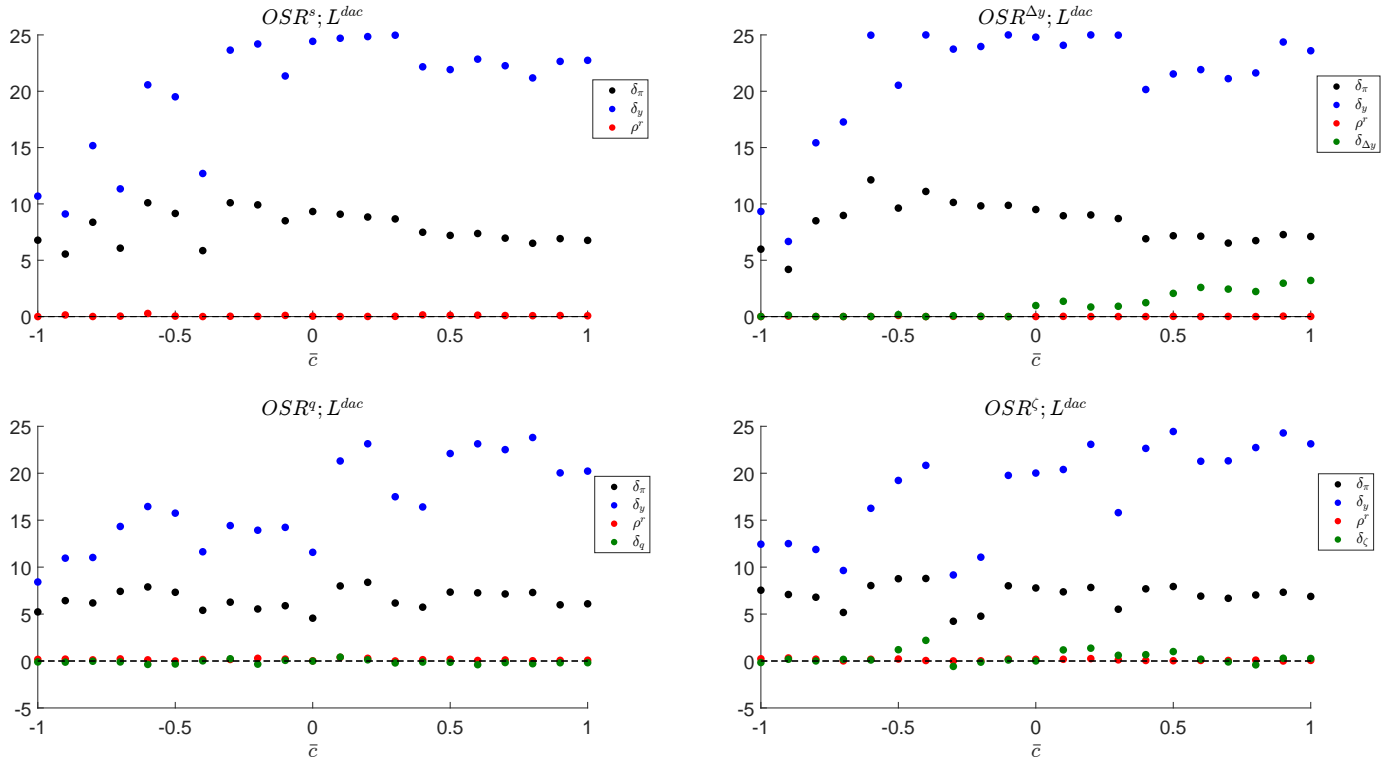


Figure 20: Distribution of OSR parameters for different credibility environments controlled by steady-state credibility shift \bar{c} from Table 13.

and the risk measure ζ perform best in minimizing welfare loss. When moving from OSR^ζ to OSR^s the household would lose 0.05 consumption units in a low credibility environment and 0.01 in a high credibility environment with $\bar{c} = -1$ and $\bar{c} = 1$, respectively. Additionally, this optimized rule produces the most minor variance in ω_t^{CB} . However, the highest mean values are obtained by OSR^s and $OSR^{\Delta y}$, therefore conflicting the result of the instrument stabilization objective where OSR^q and OSR^ζ produces the highest mean of the agents that follow the targeting heuristic.

OSR^q and OSR^ζ under the heuristic stabilization objective achieve the lowest welfare losses and lead to 0.05 to 0.01 more consumption units within the credibility

		\bar{c}				
		-1	-0.5	0	0.5	-1
OSR^s	δ_π	6.7820	9.1530	9.3257	7.2049	6.7653
	δ_y	10.6877	19.5068	24.4302	21.9217	22.7453
	ρ^r	0.0000	0.0427	0.0362	0.1120	0.0717
$OSR^{\Delta y}$	δ_π	5.9836	9.6287	9.3348	7.1734	7.1056
	δ_y	9.3306	20.5322	24.4566	21.5343	23.5946
	$\delta_{\Delta y}$	0.0066	0.1702	0.1317	2.0609	3.2066
	ρ^r	0.0031	0.0940	0.0155	0.0220	0.0142
OSR^q	δ_π	5.2296	7.3200	4.5618	7.3373	6.0928
	δ_y	8.4174	15.7483	11.5777	22.0990	20.2251
	δ_q	-0.0983	-0.3182	-0.0102	-0.1334	-0.1796
	ρ^r	0.1735	0.0007	0.0215	0.1798	0.0826
OSR^ζ	δ_π	7.5409	4.7457	9.4086	7.9332	6.8785
	δ_y	12.4423	9.5202	24.1745	24.4439	23.1300
	δ_ζ	-0.1653	-0.3955	0.0738	1.0061	0.2701
	ρ^r	0.2367	0.0137	0.2665	0.0286	0.0665

Table 13: Results for OSR parameters with heuristic stabilization objective for different credibility environments controlled by steady-state credibility shift \bar{c} .

environments presented here when compared with OSR^s and $OSR^{\Delta y}$ under the same objective. Since the resulting losses from the different objectives are not directly comparable to each other, I plot the variances of the best performing $OSRs$ in Figure 21.

Again, the variances of output, inflation, investment, and the share ω_t^{CB} are comparably near one another for the different objective functions. Whereas output variance is lower in the heuristic stabilization approach, inflation variance is higher than in

		\bar{c}				
		-1	-0.5	0	0.5	-1
\mathbb{L}	OSR^s	5.1243	3.7122	2.3957	1.3681	0.6974
	$OSR^{\Delta y}$	5.1239	3.7120	2.3955	1.3680	0.6972
	OSR^q	5.1230	3.7113	2.3950	1.3677	0.6970
	OSR^ζ	5.1230	3.7113	2.3951	1.3677	0.6970
CEV	$OSR^{\Delta y}$	-0.0171	-0.0111	-0.0068	-0.0053	-0.0037
	OSR^q	-0.0517	-0.0358	-0.0237	-0.0151	-0.0113
	OSR^ζ	-0.0529	-0.0352	-0.0226	-0.0152	-0.0111
$var(y_t) (10^{-4})$	OSR^s	1.7314	0.6973	0.3232	0.1748	0.1117
	$OSR^{\Delta y}$	1.6988	0.6840	0.3170	0.1714	0.1096
	OSR^q	1.6254	0.6791	0.3258	0.1802	0.1165
	OSR^ζ	1.6459	0.7117	0.3406	0.1775	0.1141
$var(\pi_t) (10^{-3})$	OSR^s	0.5063	0.3479	0.2469	0.1697	0.1308
	$OSR^{\Delta y}$	0.4967	0.3412	0.2324	0.1665	0.1283
	OSR^q	0.5225	0.3550	0.2410	0.1725	0.1329
	OSR^ζ	0.5217	0.3542	0.2405	0.1726	0.1330
$var(i_t) (10^{-3})$	OSR^s	2.1919	1.563	0.9916	0.5569	0.2801
	$OSR^{\Delta y}$	2.1885	1.5608	0.9902	0.5569	0.2800
	OSR^q	2.1808	1.5605	0.9500	0.5384	0.2687
	OSR^ζ	2.2176	1.5629	0.9689	0.5454	0.2692
$var(\omega_t^{CB}) (10^{-5})$	OSR^s	0.0987	0.0529	0.0247	0.0104	0.0042
	$OSR^{\Delta y}$	0.0987	0.0529	0.0257	0.0105	0.0042
	OSR^q	0.0922	0.0501	0.0236	0.0101	0.0040
	OSR^ζ	0.0927	0.0548	0.0237	0.0101	0.0040

Table 14: Resulting loss, CEV, and unconditional variances of output, inflation, investment and share ω_t^{CB} from $OSRs$ with heuristic stabilization objective for different credibility environments controlled by steady-state credibility shift \bar{c} . Loss is computed for 100 periods of 1000 Monte Carlo runs. All other parameters are at their estimated values from Table 4.

the instrument stabilization objective. The difference in output variance closes at approximately $\bar{c} \approx 0.6$, while the distance is nearly closed at $\bar{c} \approx 0.0$ for inflation.

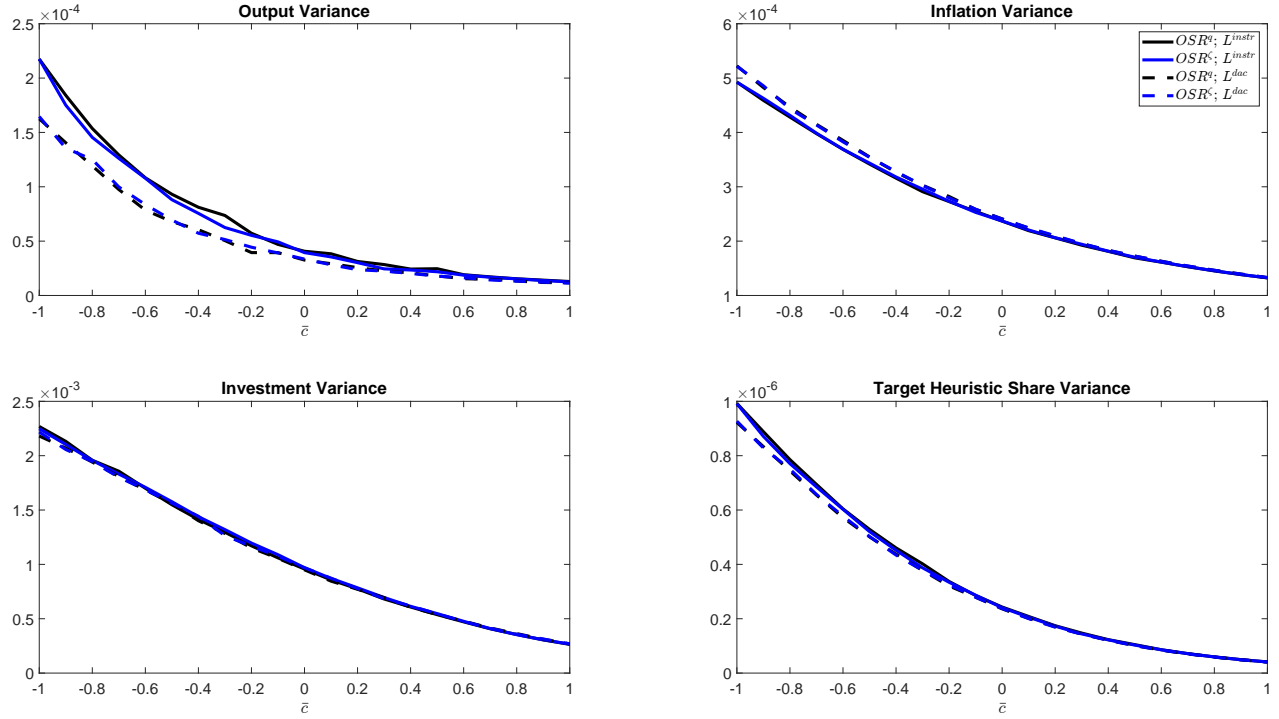


Figure 21: Variance comparison between the lowest loss generating *OSRs* from the heuristic and instrument stabilization objective optimizations.

The investment variances graphically are at different scales than output and inflation (10^{-3} to 10^{-4}) and do not lie directly on top of each other. The dashed lines of the heuristic stabilizing approach produce lower investment variances. The difference in the target heuristic share variance is also minimal.

Additionally, I compute the differences in means of the target heuristic shares for the two pairs of *OSRs* and find a reduction for all credibility environments in favor of the heuristic stabilization approach, as depicted in Figure 22. However, the stabilization advantage diminishes in higher credibility environments. This indicates that the policy response from the heuristic stabilizing approach effectively steers agents

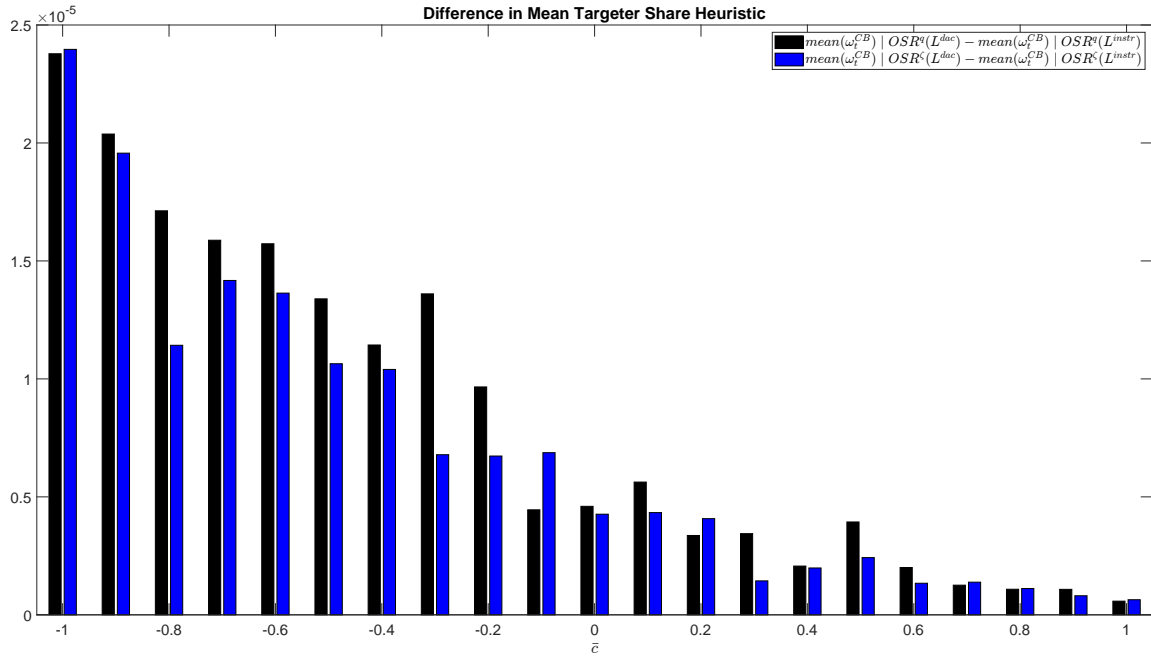


Figure 22: Difference in mean share of target heuristic Comparison for OSR^q and OSR^zeta from heuristic and instrument stabilization objectives. Black bars depict the difference of $mean(\omega_t^{CB}) | OSR^q(\mathbb{L}^{dac}) - (\omega_t^{CB}) | OSR^q(\mathbb{L}^{instr})$ while blue bars depict the difference for OSR^zeta for the respective credibility environment \bar{c} .

to the target heuristic compared with the other central bank objective.

The results of the monetary policy analysis conducted in this section are connected to the studies mentioned before and especially extend on the findings of Hommes and Lustenhouwer (2019) and Brenneisen (2022) at the ZLB for normal times. In my framework, I find that output stabilization has far greater relevance than in a BR-HSM model without the risk measure and *deanchoring* heuristic. The welfare loss is also strongly dependent on the credibility environment. The contribution to welfare loss for the risk pass-through in the investment expectation channel is greater than the pass-through in the interest rate channel. Intuitively, while extrapolative

expectations lead to higher welfare loss, expectation anchoring leads to lower loss. The *OSRs* with instruments targeting the price of capital or the risk measure itself performs better than the others. But the advantage is minimal. The parameter for interest rate smoothing is small for all *OSRs*.

A comparison of the two proposed central bank objectives, flexible inflation targeting with instrument stabilization and flexible heuristic targeting, reveals that under the latter, the proportion of agents that adhere to the deanchoring heuristic and output variance can be substantially diminished. However, under flexible heuristic targeting, inflation variance is higher in low credibility environments, thereby creating a trade-off for the central bank in either reducing the inflation variance or the volatility stemming from the expectation channel.

6 Conclusion

This dissertation has investigated the interplay between boundedly rational agents, central bank credibility, and perceived economic risk within a New Keynesian framework. The primary objective was to explore whether there is empirical evidence for the risk channel and how the risk and expectation channel influence monetary policy and overall economic stability.

I contribute to the field by incorporating a more realistic and modular expectation formation process, deviating from the traditional full information rational expectations assumption. This approach allowed me to formulate an endogenous central bank credibility measure and to capture the heterogeneity in agents' expectations

better. I merged the credibility and *animal spirits* measures to formalize economic risk as perceived by agents, influencing their investment and consumption decisions. I provide empirical evidence for the risk channel's existence and significance by matching empirical moments with simulated ones generated by the framework built in this thesis. A robustness check resulted in additional evidence for the significance of the risk channel because the riskless model variant produces a higher distance score to the empirical moments. Additionally, I find that the framework including the risk channel is better suited to matching higher moments than the extended riskless, financial frictions framework.

In Section 4.5, I conduct stability analysis with the modular *denanchoring* heuristic and find that in high credibility environments, the model economy is more stable when agents choose trend extrapolation or adaptive expectation heuristics. When agents are strongly anchored, output variability declines and the model is stable even in low credibility environments.

The contributions to the discussion on optimal monetary policy and the risk channel highlight the significant role of central bank credibility in stabilizing the economy. One finding is that the monetary policy stance can be more hawkish in high-credibility environments. Conversely, low-credibility environments exacerbate economic volatility, making it challenging for central banks to manage both inflation and output effectively. Adding the price of capital and the risk measure as instruments to the monetary policy rule improves welfare in all credibility environments, but the effect is minimal. Lastly, the central bank faces a trade-off within the mandate to target the share of agents following the *deanchoring* heuristic. The flexible

heuristic targeting objective produces lower output variance but, in turn, higher inflation volatility in low-credibility environments.

These findings have important implications for conducting monetary policy. Central banks must prioritize the maintenance of their credibility in order to foster economic stability. Furthermore, an understanding of the behavioral foundations of risk perception and expectation formation among economic agents can enhance the efficacy of monetary policy.

Further research could utilize the credibility and risk modeling approach of this thesis to examine the interactions between monetary policy and macroprudential policies in maintaining financial stability. Specifically, if these measures influence the effectiveness of tools such as capital requirements, leverage ratios, and stress testing in different economic environments. From a modeling perspective, one could change the underlying structure of the credibility measure in the logit transformation function. While the credibility measure is endogenous, the steady-state shifting parameter is estimated in my framework. Accordingly, an updated framework with an equally endogenously formulated credibility shift parameter could yield intriguing implications for monetary policy and, ultimately, facilitate more fluid anchoring and deanchoring of agents' expectations.

Future research that is not related to monetary policy might also implement the BR-HSM framework and conduct a more detailed examination of endogenously formulated credibility measures in New Keynesian DSGE models, e.g., the framework could be used to model government-set greenhouse gas emissions targets following Annicchiarico et al. (2024) but using the divergence from the target heuristics to

model the credibility of government climate policies.

In conclusion, this dissertation contributes to the ongoing discourse on monetary policy by integrating endogenous credibility and perceived risk into the New Keynesian framework. The insights gained underscore the importance of central bank credibility and the potential of behavioral models in macroeconomic analysis.

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A Model Overview

A.1 BR-HSM-NK-Risk Model

$$\text{Cons. Euler Eq.} \quad c_t = \tilde{E}_t c_{t+1} - \sigma_c^{-1}(r_t + \xi_r \zeta_t) + \varepsilon_t^c \quad (\text{A.1})$$

$$\text{Labor Supply} \quad w_t = \sigma_c c_t + \sigma_l l_t \quad (\text{A.2})$$

$$\begin{aligned} \text{Inv. Euler Eq.} \quad i_t &= \frac{1}{1 + \beta} i_{t-1} + \frac{\beta}{1 + \beta} \tilde{E}_t i_{t+1} \\ &+ \frac{1}{(1 + \beta)\phi} q_t + \varepsilon_t^i \end{aligned} \quad (\text{A.3})$$

$$\begin{aligned} \text{Capital Arbitrage} \quad q_t &= \beta(1 - \delta) \tilde{E}_t q_{t+1} + (1 - \beta(1 - \delta)) r_t^k \\ &- (r_t + \xi_r \zeta_t) \end{aligned} \quad (\text{A.4})$$

$$\text{Installed Capital} \quad k_t = (1 - \delta) k_{t-1} + (1 - (1 - (1 - \delta)) \phi) i_t + k_1 \varepsilon_t^i \quad (\text{A.5})$$

$$\text{Production Function} \quad y_t = \alpha k_t^s + (1 - \alpha) l_t + a_t \quad (\text{A.6})$$

$$\text{Cap. Services} \quad k_t^s = k_{t-1} + z_t \quad (\text{A.7})$$

$$\text{Degr. of Cap. Util.} \quad z_t = \frac{(1 - \psi)}{\psi} r_t^k \quad (\text{A.8})$$

$$\text{Rental Rate of Cap.} \quad r_t^k = -(k_t - l_t) + w_t \quad (\text{A.9})$$

$$\text{Marginal Cost} \quad mc_t = w_t - \alpha(k_t^s - l_t) - a_t \quad (\text{A.10})$$

$$\text{Phillips Curve} \quad \pi_t = +\beta \tilde{E}_t \pi_{t+1} + \frac{(1 - \beta \chi_p)(1 - \chi_p)}{\chi_p} mc_t + \varepsilon_t^p \quad (\text{A.11})$$

$$\begin{aligned} \text{Resource Constraint} \quad y_t &= (1 - g_y - (\delta k_y)) c_t + (\delta k_y) i_t \\ &+ z_y z_t + g_y g_t \text{ with } c_y = (1 - g_y - i_y, \end{aligned} \quad (\text{A.12})$$

$$i_y = \delta k_y, \quad z_y = \left(\beta^{-1} - (1 - \delta) \right) k_y, \quad k_y = \left(\frac{(1 - \alpha) \bar{R}^k}{\alpha \bar{W}} \right)^{(\alpha-1)}$$

$$\text{Mon. Pol. Rule} \quad r_t^n = \rho^r r_{t-1}^n + (1 - \rho^r) [\delta_\pi (\pi_t - \pi^T) + \delta_y y_t] + \varepsilon_t^r \quad (\text{A.13})$$

$$\text{Aggregate Exp. } \tilde{E}_t v_{t+1} = \sum_h \omega_t^{v,h} \tilde{E}_t^{v,h} v_{t+1} \quad (\text{A.14})$$

with $v_t \in (y_t, \pi_t)$ and $h \in (tar, dac)$

$$\text{Target Heuristic } \tilde{E}_t^{tar} v_{t+1} = v_t^T \quad (\text{A.15})$$

$$\begin{aligned} \text{Deanchored Heuristic } \tilde{E}_t^{dac} v_{t+1} &= \underbrace{\varpi \sum_{s=1}^N v_{t-s} N^{-1}}_{\text{New Anchor}} \\ &+ \underbrace{(1 - \varpi)(\mathcal{Y} v_{t-1} + (1 - \mathcal{Y}) \tilde{E}_{t-1}^{dac} v_t)}_{\text{Adaptive Term}} \\ &+ \underbrace{\Omega(v_{t-1} - v_{t-2})}_{\text{Extrapolative Term}} \end{aligned} \quad (\text{A.16})$$

$$\begin{aligned} \text{Share of target Agents } \omega_t^{CB} &= \xi_\omega \omega_{t-1}^{CB} \\ &+ (1 - \xi_\omega) \frac{\exp\{\mu(A_t^{y, tar} + A_t^{\pi, tar}) + \bar{c}\}}{1 + \exp\{\mu(A_t^{y, tar} + A_t^{\pi, tar}) + \bar{c}\}} \end{aligned} \quad (\text{A.17})$$

$$\text{Central Bank Cred. } m_t^{CB} = \omega_t^{CB} - \omega_t^{dac} = 2\omega_t^{CB} - 1 \quad (\text{A.18})$$

$$\text{Attractivity Output } A_t^{y, tar} = \xi_A A_{t-1}^{y, tar} - (1 - \xi_A)(y_{t-1} - y^T)^2 \quad (\text{A.19})$$

$$\text{Attractivity Inflation } A_t^{\pi, tar} = \xi_A A_{t-1}^{\pi, tar} - (1 - \xi_A)(\pi_{t-1} - \pi^T)^2 \quad (\text{A.20})$$

$$\text{Capital Price Exp. } \tilde{E}_t q_{t+1} = q_{t-1} \quad (\text{A.21})$$

$$\text{Cons. Exp. } \tilde{E}_t c_{t+1} = \tilde{E}_t y_{t+1} \quad (\text{A.22})$$

$$\text{Inv. Exp. } \tilde{E}_t i_{t+1} = \tilde{E}_t y_{t+1} + \xi_i \zeta_t \quad (\text{A.23})$$

$$\begin{aligned} \text{Perc. Risk } \zeta_t &= \xi_m (\bar{m}^{CB} - m_t^{CB}) + \xi_\pi (|\tilde{E}_t \pi_{t+1} - \pi^T|) \\ &+ \xi_y y_{t-1} + \xi_s S_t \end{aligned} \quad (\text{A.24})$$

$$\text{Animal Spirits } S_t = \begin{cases} \omega_t^{dac} & \text{if } \tilde{E}_t^{dac} y_{t+1} < 0 \\ 0 & \text{if } \tilde{E}_t^{dac} y_{t+1} \geq 0 \end{cases} \quad (\text{A.25})$$

A.2 BR-HSM-NK-FF Model Extension

Substitute (A.4) for (A.28). The microfoundation can be found in Brenneisen (2022).

$$\begin{aligned} \text{Net Worth} \quad \hat{n}_t &= (1 - n_1)\hat{n}_{t-1} + n_1(\hat{q}_{t-1} + k_{t-1}) + n_2\hat{R}_t^k \\ &\quad - n_3\hat{r}_t^e - n_4\hat{p}_{t-1}^d - n_5\hat{\varphi}_t \end{aligned} \quad (\text{A.26})$$

$$\begin{aligned} \text{with} \quad n_1 &= 1 - (1 - p^d)\bar{R}^e, \quad n_2 = n_1 + (1 - p^d), \\ n_3 &= (1 - n_1)(L\bar{T}V - 1), \quad n_4 = p^d \left[(\bar{R}^k - \bar{R}^e)L\bar{T}V + \bar{R}^e \right], \\ n_5 &= \kappa w^d \nu \bar{R}^k L\bar{T}V \end{aligned}$$

$$\text{Rental Rate} \quad \hat{R}_t^k = q_1\hat{q}_t + (1 - q_1)\hat{r}_t^k - \hat{q}_{t-1} \quad (\text{A.27})$$

$$\text{with} \quad q_1 = \frac{1 - \delta}{\bar{R}_k}$$

$$\begin{aligned} \text{Capital Price} \quad \hat{q}_t &= q_1\hat{q}_{t-1} + (1 - q_1)\hat{r}_{t-1}^k - (\hat{r}_t^e - \tilde{E}_t\pi_{t+1}) + q_2\hat{p}_t^d - q_3\hat{\varphi}_t \end{aligned} \quad (\text{A.28})$$

$$\text{with} \quad q_2 = \frac{\bar{R}^e - \bar{R}^k}{(1 - p^d)\bar{R}^e}, \quad q_3 = \frac{p^d w^d \phi \bar{R}^k}{(1 - p^d)\bar{R}^e}$$

$$\text{Leverage Ratio} \quad \widehat{ltv}_t = \hat{q}_t + k_t - \hat{n}_t \quad (\text{A.29})$$

$$\text{Spread} \quad \hat{r}_t^e - r_t^n = b_1\widehat{ltv}_t + b_2\hat{p}_t^d - b_3\hat{\varphi}_t \quad (\text{A.30})$$

$$\begin{aligned} \text{with} \quad b_1 &= \left[\frac{1 - (1 - p^d)\beta\bar{R}^e}{L\bar{T}V - 1} \right], \\ b_2 &= \frac{p^d}{1 - p^d}\beta\bar{R}^e - \left[1 - (1 - p^d)\beta\bar{R}^e \right] (1 - q_2), \\ b_3 &= \left[1 - (1 - p^d)\beta\bar{R}^e \right] (1 + q_3) \end{aligned}$$

$$\text{Entr. Risk} \quad \hat{p}_t^d = \varepsilon_t^d \quad (\text{A.31})$$

$$\text{LTV Constr.} \quad \hat{\varphi}_t = \varepsilon_t^\varphi \quad (\text{A.32})$$

B Estimation

B.1 Identity Weight

Variable	BR-HSM-Risk	BR-HSM-FF	BR-HSM-Riskless	US Data
$\rho(y_t, \pi_t)$	0.4663	0.4687	0.5138	0.0875
$\rho(y_t, r_t^n)$	-0.1640	0.0301	0.1034	0.1190
$\rho(y_t, c_t)$	0.8269	0.9882	0.9403	0.7827
$\rho(y_t, i_t)$	-0.0973	0.6517	-0.5948	0.6939
$\sigma(y_t)$	0.0496	0.0185	0.2077	0.0233
$\sigma(c_t)$	0.0134	0.0153	0.0119	0.0154
$\sigma(i_t)$	0.0255	0.0050	0.0045	0.0135
$\sigma(k_t)$	0.0267	0.0052	0.0044	0.0061
$\sigma(r_t^n)$	0.0073	0.0197	0.0151	0.0358
$\sigma(\pi_t)$	0.0082	0.0160	0.0146	0.0057
Distance Score	96.8776	120.2934	134.0753	—

Table B.1: Simulated moments from the SMM estimator for BR-HSM-Risk, BR-HSM-FF and BR-HSM-Riskless variants with identity weighting matrix \mathbf{W} and empirical moments from US data Q2 1955–Q1 2023.

Variable	BR-HSM-Risk	BR-HSM-FF	BR-HSM-Riskless	US Data
$\rho(y_t, y_{t-1})$	0.8309	0.8672	0.2742	0.8939
$\rho(y_t, y_{t-2})$	0.5030	0.6039	-0.5968	0.7819
$\rho(y_t, y_{t-3})$	0.1863	0.3184	-0.5257	0.6635
$\rho(c_t, c_{t-1})$	0.8612	0.8761	0.3594	0.7692
$\rho(c_t, c_{t-2})$	0.5937	0.6188	-0.4642	0.5510
$\rho(c_t, c_{t-3})$	0.3161	0.3328	-0.4384	0.3320
$\rho(i_t, i_{t-1})$	0.8993	0.8843	0.3885	0.7367
$\rho(i_t, i_{t-2})$	0.7354	0.6815	-0.4335	0.5352
$\rho(i_t, i_{t-3})$	0.5668	0.4611	-0.4037	0.3417
$\rho(k_t, k_{t-1})$	0.9047	0.8766	0.3922	0.8258
$\rho(k_t, k_{t-2})$	0.7508	0.6739	-0.4255	0.4505
$\rho(k_t, k_{t-3})$	0.5909	0.4562	-0.3985	0.0702
$\rho(r_t^n, r_{t-1}^n)$	0.9046	0.8087	0.4986	0.9496
$\rho(r_t^n, r_{t-2}^n)$	0.7308	0.3970	-0.2619	0.9073
$\rho(r_t^n, r_{t-3}^n)$	0.5308	-0.0120	-0.4146	0.8790
$\rho(\pi_t, \pi_{t-1})$	0.7654	0.8701	0.3469	0.8518
$\rho(\pi_t, \pi_{t-2})$	0.5708	0.6083	-0.4820	0.8147
$\rho(\pi_t, \pi_{t-3})$	0.4320	0.3138	-0.5139	0.7643
Distance Score	96.8776	120.2934	134.0753	—

Table B.2: Simulated moments from the SMM estimator for BR-HSM-Risk, BR-HSM-FF, and BR-HSM-Riskless variants with identity weighting matrix \mathbf{W} and empirical moments from US data Q2 1955–Q1 2023.

Variable	BR-HSM-Risk		BR-HSM- FF		BR-HSM-Riskless		US Data Q2 1955–Q1 2023	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
Output y_t	-0.3651	3.5305	-0.8160	4.4977	0.1149	5.2134	-0.2248	3.5588
Consumption c_t	-0.9712	6.6713	-0.7197	4.2818	0.1403	5.2239	-1.0065	6.6564
Investment i_t	-0.2907	9.8165	-1.5213	8.5565	0.5142	8.8115	-1.9328	16.5174
Capital k_t	-0.2990	8.9360	-1.4533	8.3510	0.5097	8.7159	0.1809	2.1268
EFFR r_t^n	0.9761	4.5047	-0.3143	4.1765	0.4590	5.2336	1.0750	4.6884
Inflation π_t	0.7358	4.9734	-0.3902	3.4211	0.4130	5.3207	1.3040	4.5951
Distance Score	96.8776		120.2934		134.0753		–	

Table B.3: Simulated moments from the SMM estimator for BR-HSM-Risk, BR-HSM-FF, and BR-HSM-Riskless variants with identity weighting matrix \mathbf{W} and empirical moments from US data Q2 1955–Q1 2023.

Variable	BR-HSM-Risk	US Data Q1 2000–Q1 2023
$\rho(y_t, \pi_t)$	-0.6247	0.4842
$\rho(y_t, r_t^n)$	0.2959	0.6775
$\rho(y_t, c_t)$	0.2304	0.0093
$\rho(y_t, i_t)$	-0.1638	0.0222
$\sigma(y_t)$	0.0086	0.0201
$\sigma(c_t)$	0.0040	0.0148
$\sigma(i_t)$	0.0108	0.0157
$\sigma(k_t)$	0.0116	0.0073
$\sigma(r_t^n)$	0.0047	0.0183
$\sigma(\pi_t)$	0.0087	0.0043
Distance Score	350.4868	–

Table B.4: Simulated moments from the SMM estimator for BR-HSM-Risk, BR-HSM-FF, and BR-HSM-Riskless variants with identity weighting matrix \mathbf{W} and empirical moments from US data Q1 2000–Q1 2023.

Variable	BR-HSM-Risk	US Data Q1 2000–Q1 2023
$\rho(y_t, y_{t-1})$	0.2682	0.7786
$\rho(y_t, y_{t-2})$	-0.1656	0.6396
$\rho(y_t, y_{t-3})$	-0.1930	0.5319
$\rho(c_t, c_{t-1})$	0.6736	0.5592
$\rho(c_t, c_{t-2})$	0.3489	0.3138
$\rho(c_t, c_{t-3})$	0.1800	0.1437
$\rho(i_t, i_{t-1})$	0.5123	0.5495
$\rho(i_t, i_{t-2})$	0.2638	0.3071
$\rho(i_t, i_{t-3})$	0.0872	0.1176
$\rho(k_t, k_{t-1})$	0.4871	0.8498
$\rho(k_t, k_{t-2})$	0.2550	0.5295
$\rho(k_t, k_{t-3})$	0.0833	0.1787
$\rho(r_t^n, r_{t-1}^n)$	0.5855	0.9427
$\rho(r_t^n, r_{t-2}^n)$	0.4283	0.8450
$\rho(r_t^n, r_{t-3}^n)$	0.2897	0.7191
$\rho(\pi_t, \pi_{t-1})$	0.1762	0.6939
$\rho(\pi_t, \pi_{t-2})$	0.1278	0.6171
$\rho(\pi_t, \pi_{t-3})$	0.0992	0.4929
Distance Score	350.4868	—

Table B.5: Simulated moments from the SMM estimator for BR-HSM-Risk, BR-HSM-FF, BR-HSM-Riskless variants with identity weighting matrix \mathbf{W} and empirical moments from US data Q1 2000–Q1 2023.

BR-HSM Parameter	Estimate	NK Parameter	Estimate	NK Parameter	Estimate
θ	4.5207	σ_c	1.1024	σ_{ε^c}	0.0444
ξ_A	0.0392	σ_l	1.0882	σ_{ε^i}	0.7316
ξ_ω	0.0245	ϕ	5.9978	σ_{ε^b}	0.2833
\bar{c}	0.0043	ψ	0.2008	σ_a	0.1071
ξ_m	0.4934	χ_p	0.7428	σ_{ε^p}	0.7085
ξ_y	0.0038	ρ^r	0.5030	σ_{ε^r}	0.0052
ξ_π	0.1457	δ_π	1.0048		
ξ_s	0.1122	δ_y	0.9963		
ξ_i	1.9376				
ξ_r	0.2087	ρ_{ε^c}	0.8511		
ϖ	0.9239	ρ_{ε^i}	0.0009		
\mathcal{I}	0.5203	ρ_{ε^b}	0.5197		
Ω	0.0107	ρ_a	0.6690		
ϵ_i	0.0201	ρ_{ε^p}	0.0422		
ϵ_c	0.0510	ρ_{ε^r}	0.3774		

Table B.6: SMM estimation results for different model variants with identity weighting matrix \mathbf{W} for US data Q1 2000–Q1 2023.

B.2 Variance-Covariance Weight

BR-HSM Parameter	Estimate	NK Parameter	Estimate	NK Parameter	Estimate
θ	2.4634	σ_c	2.2308	σ_{ε^c}	0.6534
ξ_A	0.7364	σ_l	2.1287	σ_{ε^i}	0.0500
ξ_ω	0.1208	ϕ	4.2830	σ_{ε^b}	0.6065
\bar{c}	0.1084	ψ	0.6906	σ_a	0.3870
ξ_m	0.0286	χ_p	0.9890	σ_{ε^p}	0.4086
ξ_y	0.0406	ρ^r	0.6586	σ_{ε^r}	0.5410
ξ_π	0.0039	δ_π	1.7820		
ξ_s	0.0183	δ_y	1.8997		
ξ_i	1.5208				
ξ_r	0.7860	ρ_{ε^c}	0.7671		
ϖ	0.9503	ρ_{ε^i}	0.7604		
γ	0.8960	ρ_{ε^b}	0.0948		
Ω	0.8182	ρ_a	0.9495		
ϵ_i	0.9431	ρ_{ε^p}	0.2233		
ϵ_c	0.2535	ρ_{ε^r}	0.4229		

Table B.7: SMM estimation results for different model variants with identity weighting matrix $\widehat{\mathbf{W}}$ for US data Q2 1955–Q1 2023.

Variable	$\mathbf{W} = \Omega^{-1}$	$\mathbf{W} = \mathbf{I}$	US Data Q2 1955–Q1 2023
$\rho(y_t, y_{t-1})$	0.5395	0.8309	0.8939
$\rho(y_t, y_{t-2})$	-0.1029	0.5030	0.7819
$\rho(y_t, y_{t-3})$	-0.1630	0.1863	0.6635
$\rho(c_t, c_{t-1})$	0.6520	0.8612	0.7692
$\rho(c_t, c_{t-2})$	0.1607	0.5937	0.5510
$\rho(c_t, c_{t-3})$	0.1015	0.3161	0.3320
$\rho(i_t, i_{t-1})$	0.9389	0.8993	0.7367
$\rho(i_t, i_{t-2})$	0.8117	0.7354	0.5352
$\rho(i_t, i_{t-3})$	0.6796	0.5668	0.3417
$\rho(k_t, k_{t-1})$	0.9394	0.9047	0.8258
$\rho(k_t, k_{t-2})$	0.8130	0.7508	0.4505
$\rho(k_t, k_{t-3})$	0.6808	0.5909	0.0702
$\rho(r_t^n, r_{t-1}^n)$	0.6343	0.9046	0.9496
$\rho(r_t^n, r_{t-2}^n)$	0.0970	0.7308	0.9073
$\rho(r_t^n, r_{t-3}^n)$	-0.1484	0.5308	0.8790
$\rho(\pi_t, \pi_{t-1})$	0.4846	0.7654	0.8518
$\rho(\pi_t, \pi_{t-2})$	-0.0611	0.5708	0.8147
$\rho(\pi_t, \pi_{t-3})$	-0.1519	0.4320	0.7643
Distance Score	8.7497	96.8776	—

Table B.8: Simulated moments from the SMM estimator for BR-HSM-Risk with identity weighting matrix $\widehat{\mathbf{W}}$ and empirical moments from US data Q2 1955–Q1 2023.

Variable	$\mathbf{W} = \Omega^{-1}$	$\mathbf{W} = \mathbf{I}$	US Data Q2 1955–Q1 2023
$\rho(y_t, \pi_t)$	-0.1249	0.4663	0.0875
$\rho(y_t, r_t^n)$	0.5603	-0.1640	0.1190
$\rho(y_t, c_t)$	0.7570	0.8269	0.7827
$\rho(y_t, i_t)$	0.1899	-0.0973	0.6939
$\sigma(y_t)$	0.0161	0.0496	0.0233
$\sigma(c_t)$	0.0130	0.0134	0.0154
$\sigma(i_t)$	0.0060	0.0255	0.0135
$\sigma(k_t)$	0.0060	0.0267	0.0061
$\sigma(r_t^n)$	0.0131	0.0073	0.0358
$\sigma(\pi_t)$	0.0058	0.0082	0.0057
Distance Score	8.7497	96.8776	—

Table B.9: Simulated moments from the SMM estimator for BR-HSM-Risk with identity weighting matrix $\widehat{\mathbf{W}}$ and empirical moments from US Data Q2 1955–Q1 2023.

B.3 Robustness Checks

Variable	$\xi_m = 0$	$\xi_y = 0$	$\xi_\pi = 0$	$\xi_s = 0$	BR-HSM-Riskless	BR-HSM-Risk
$\rho(y_t, \pi_t)$	-0.3661	-0.5336	-0.9073	-0.9854	0.5138	0.4663
$\rho(y_t, r_t^n)$	0.6835	0.2372	-0.7325	-0.9526	0.1034	-0.1640
$\rho(y_t, c_t)$	0.7207	0.6672	0.9968	0.9628	0.9403	0.8269
$\rho(y_t, i_t)$	0.4667	0.3555	0.0660	0.3946	-0.5948	-0.0973
$\sigma(y_t)$	0.0317	-0.0255	0.0511	2.8517	0.2077	0.0496
$\sigma(c_t)$	0.0225	0.0341	0.0498	0.6211	0.0119	0.0134
$\sigma(i_t)$	0.0249	0.0207	0.0181	0.6880	0.0045	0.0255
$\sigma(k_t)$	0.0265	0.0021	0.0192	0.6891	0.0044	0.0267
$\sigma(r_t^n)$	0.0262	0.0292	0.0705	2.5391	0.0151	0.0073
$\sigma(\pi_t)$	0.0118	0.0301	0.0758	2.9643	0.0146	0.0082
Distance Score	106.0935	103.0006	110.8853	146.5917	134.0753	96.8776

Table B.10: Simulated moments from the SMM estimator for different model variants with identity weighting matrix \mathbf{W} and empirical moments from US data Q2 1955–Q1 2023.

Parameter	$\xi_m = 0$	$\xi_y = 0$	$\xi_\pi = 0$	$\xi_s = 0$	BR-HSM-Riskless	BR-HSM-Risk
θ	3.8086	2.6901	6.5295	1.2861	6.7381	4.7642
ξ_A	0.1355	0.3962	0.2788	0.8234	0.4528	0.0707
ξ_ω	0.0876	0.0506	0.2721	0.2732	0.0894	0.0118
\bar{c}	0.3062	0.1198	0.4401	0.2967	0.5000	0.9649
ξ_m	0	0.1327	0.1586	0.1311	0	0.1113
ξ_y	0.0173	0	0.0047	0.1120	0	0.0032
ξ_π	0.1653	0.0075	0	0.0833	0	0.1342
ξ_s	0.1948	0.1929	0.1887	0	0	0.0924
ξ_i	1.4249	0.7195	0.5893	0.6204	0	1.5893
ξ_r	1.9479	1.5589	0.5128	0.2322	0	0.1351
ϖ	0.0700	0.1131	0.1357	0.4352	0.4530	0.1928
Υ	0.5362	0.6029	0.8363	0.0829	0.4837	0.6599
Ω	0.0481	0.2914	0.5490	0.0088	0.6323	0.5156
ϵ_i	0.0168	0.0015	0.0026	0.0031	0.6232	0.2066
ϵ_c	0.0295	0.0049	0.0043	0.5835	0.3801	0.3737
σ_c	1.2792	1.0055	1.0088	2.1223	1.1341	1.2468
σ_l	1.2762	1.0666	1.0279	2.4387	2.2543	1.2915
ϕ	5.9673	5.9959	5.9928	4.4591	4.3559	5.9909
ψ	0.6392	0.3026	0.6982	0.2558	0.4389	0.2550
χ_p	0.9497	0.8933	0.9692	0.8606	0.5564	0.7631
ρ	0.5215	0.5275	0.5034	0.8606	0.6903	0.7667
δ_π	1.7615	1.3402	2.0540	1.1662	2.5749	1.5634
δ_y	1.0523	0.9218	1.9027	0.5802	0.3255	0.2396
ρ_{ϵ^c}	0.8645	0.7685	0.5829	0.3891	0.2099	0.5451
ρ_{ϵ^i}	0.0000	0.0013	0.0033	0.4480	0.0631	0.9512
ρ_{ϵ^b}	0.7412	0.7025	0.0436	0.4639	0.3046	0.9512
ρ_{ϵ^a}	0.1980	0.0144	0.1830	0.4740	0.0973	0.8867
ρ_{ϵ^p}	0.8455	0.8873	0.6884	0.2656	0.2816	0.9599
ρ_{ϵ^r}	0.4651	0.4092	0.0557	0.6422	0.1203	0.0868
σ_{ϵ^c}	1.0139	1.1550	1.7329	0.5996	0.4758	0.3918
σ_{ϵ^i}	1.6328	1.4632	1.1613	0.3193	0.0312	0.4234
σ_{ϵ^b}	0.7412	0.6622	3.1671	0.4519	0.7386	0.0576
σ_{ϵ^a}	3.5823	7.9087	0.8329	0.7674	0.4281	0.1143
σ_{ϵ^p}	0.2625	0.3707	0.8379	0.2340	0.2816	0.4062
σ_{ϵ^r}	0.3003	0.3352	0.7594	0.0822	0.1203	0.0463
Distance Score	106.0935	103.0006	110.8853	146.5917	134.0753	96.8776

Table B.11: SMM estimation results for different model variants with identity weighting matrix \mathbf{W} for US data Q2 1955–Q1 2023.

Variable	$\xi_{\pi} = 0$			$\xi_{\pi} = 0$			$\xi_{\pi} = 0$			$\xi_{\pi} = 0$			BR-HSM-Riskless			BR-HSM-Risk		
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
Output y_t	-0.1842	3.7856	-0.0255	3.9296	-1.0329	4.6201	-0.0767	1.6802	0.1149	5.2134	-0.3651	3.5308	0.1149	5.2134	-0.3651	3.5308		
Consumption c_t	-0.6089	6.4944	-0.3177	6.4091	-0.9942	4.6021	-0.2557	1.7794	0.1403	5.2239	-0.9712	6.6713	0.1403	5.2239	-0.9712	6.6713		
Investment i_t	1.3665	9.8992	1.4181	10.1442	1.5172	9.8036	1.7507	8.5966	0.5142	8.8115	-0.2907	9.8165	0.5142	8.8115	-0.2907	9.8165		
Capital k_t	1.2480	8.9176	1.2565	8.9058	1.3501	8.7189	1.7497	8.5955	0.5097	8.7159	-0.2267	6.6119	0.5097	8.7159	-0.2267	6.6119		
EFFR r_t^e	0.7162	4.7359	0.6841	4.8210	0.8306	4.0821	-0.0062	1.5430	0.4590	5.2336	0.9761	4.5047	0.4590	5.2336	0.9761	4.5047		
Inflation π_t	0.2948	3.3647	0.5788	3.4875	1.1009	4.6670	-0.0006	1.5682	0.4130	5.3207	0.7358	4.9734	0.4130	5.3207	0.7358	4.9734		
Distance Score	106.0935		103.0006		110.8853		146.5917		134.0753		96.8776							

Table B.12: Simulated moments from the SMM estimator for different Model Variants with identity weighting matrix \mathbf{W} and empirical moments from US data Q2 1955–Q1 2023. Jarque–Bera Test at 5% level with $JB_{crit} = 5.7512$.

Variable	$\xi_m = 0$	$\xi_y = 0$	$\xi_\pi = 0$	$\xi_s = 0$	BR-HSM-Riskless	BR-HSM-Risk
$\rho(y_t, y_{t-1})$	0.6243	0.4991	0.8658	0.9894	0.2742	0.8309
$\rho(y_t, y_{t-2})$	0.5139	0.3917	0.7921	0.9786	-0.5968	0.5030
$\rho(y_t, y_{t-3})$	0.3995	0.0422	0.7535	0.9786	-0.5257	0.1863
$\rho(c_t, c_{t-1})$	0.8110	0.5787	0.8718	0.9898	0.3594	0.8612
$\rho(c_t, c_{t-2})$	0.6311	0.3552	0.7958	0.9786	-0.4642	0.5937
$\rho(c_t, c_{t-3})$	0.4960	0.1832	0.7580	0.9688	-0.4384	0.3161
$\rho(i_t, i_{t-1})$	0.6204	0.5421	0.6245	0.9510	0.3885	0.8993
$\rho(i_t, i_{t-2})$	0.4037	0.3340	0.4103	0.8968	-0.4335	0.7354
$\rho(i_t, i_{t-3})$	0.2404	0.1665	0.2415	0.8452	-0.4037	0.5668
$\rho(k_t, k_{t-1})$	0.5851	0.7821	0.5892	0.9508	0.3922	0.9047
$\rho(k_t, k_{t-2})$	0.3814	0.6259	0.3868	0.8963	-0.4255	0.7508
$\rho(k_t, k_{t-3})$	0.2220	0.4667	0.2219	0.8445	-0.3985	0.5909
$\rho(r_t^n, r_{t-1}^n)$	0.8137	0.7821	0.9348	0.9930	0.4986	0.9046
$\rho(r_t^n, r_{t-2}^n)$	0.6360	0.6259	0.8623	0.9856	-0.2619	0.7308
$\rho(r_t^n, r_{t-3}^n)$	0.4607	0.4667	0.8042	0.9778	-0.4146	0.5308
$\rho(\pi_t, \pi_{t-1})$	0.9590	0.9758	0.9855	0.9967	0.3469	0.7654
$\rho(\pi_t, \pi_{t-2})$	0.9105	0.9457	0.9535	0.9923	-0.4820	0.5708
$\rho(\pi_t, \pi_{t-3})$	0.8598	0.9108	0.9147	0.9868	-0.5139	0.4320
Distance Score	106.0935	103.0006	110.8853	146.5917	134.0753	96.8776

Table B.13: Simulated moments from the SMM estimator for different Model Variants with identity weighting matrix \mathbf{W} and empirical moments from US data Q2 1955–Q1 2023.

Affirmation – Erklärung zum selbständigen Verfassen der Arbeit

Ich erkläre hiermit, dass ich meine Doktorarbeit „*Central Bank Credibility, Perceived Economic Risk, and Simulated Moments*“ selbstständig und ohne fremde Hilfe angefertigt habe und dass ich alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehrenden Ausführungen meiner Arbeit, besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert habe.

(Datum, Unterschrift)