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Leaning Against Credit? Evidence that the Fed Incorporates Financial Stability Considerations into Monetary Policy

a thesis presented

by

Ramiz Aziz Razzak

to

The Department of Applied Mathematics

in partial fulfillment of the honors requirements

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Leaning Against Credit? Evidence that the Fed Incorporates Financial Stability Considerations into Monetary Policy

Abstract

There is a lively debate among academics and central bankers about whether monetary policy should "lean against the wind" by responding to asset-market booms with higher interest rates in order to promote financial stability. By constructing measures of sentiment in credit and equity markets, I find novel evidence that the Federal Reserve's interest rate policy has been responsive to financial stability considerations in addition to the dual mandate. Rather than leaning against the wind in general, the Federal Reserve appears to *lean against credit*, consistent with the documented impact of credit on financial stability. These findings show that actual Federal Reserve practice runs counter to the mainstream view that central bankers should steer clear of addressing financial stability concerns using monetary policy. Finally, I study the optimal conduct of monetary policy in a model where agents deviate from rational expectations. This exercise generates two salient conclusions: central banks should tighten monetary policy as they become increasingly uncertain about households' behavioral biases, and they can increase expected utility by leaning against the wind to quell overoptimism. Considered as whole, this paper highlights that there exists not only historical precedent, but also sound theoretical justification, for central bankers to lean against the wind.

An important principle is that economic policies should only have goals that they can achieve. . . . Monetary policy can achieve price stability, but it cannot achieve financial stability.

Lars E.O. Svensson

[W]hile monetary policy may not be quite the right tool for the job, it has one important advantage relative to supervision and regulation—namely that it gets in all of the cracks.

Jeremy C. Stein

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Introduction

Is monetary policy an appropriate tool to stabilize exuberant financial markets? While financial crises often generate significant economic costs (Reinhart and Rogoff, 2014) and asset prices are inextricably tied to real economic variables like inflation and unemployment that are of interest to central banks, economists and central bankers disagree about whether monetary policy ought to be used to mitigate financial excesses.

Caballero and Simsek (2019) refer to two prominent positions in this debate as the *fully-separable* and *non-separable* views. Proponents of the fully-separable position contend that the Federal Reserve (the "Fed") should focus exclusively on its dual mandate of ensuring price stability and full employment when determining at what level to set the policy rate. As such, while developments in financial markets will influence monetary policy insofar as they affect near-term expectations of inflation and unemployment, partisans of the fully-separable view believe that broader financial stability concerns should be delegated to authorities equipped with more targeted tools.

This position, which is epitomized by Bernanke and Gertler (1999) (see also Posen (2006) and Bean (2003)), rests upon a few key arguments. First, while defenders of the fully-separable view concede that financial market variables such as asset prices and leverage are informative about risks to financial stability, they contend that monetary policy is too blunt an instrument to meaningfully address these risks. Second, they argue that central bankers likely cannot distinguish

whether changes in asset prices are driven by fundamental or behavioral factors: as such, far from managing exuberance in financial markets, using monetary policy to respond to financial stability concerns could inadvertently be destabilizing. It is from this perspective that former Federal Reserve Chairman Alan Greenspan argued that "The notion that a well-timed incremental tightening could have been calibrated to prevent the late 1990's bubble is almost surely an illusion." (Greenspan, 2002).

Supporters of the non-separable view instead argue that macroprudential policy is necessary but plainly insufficient to address financial stability concerns in practice. Regulation is enacted slowly and is often difficult to adjust rapidly enough to address real-time changes in credit-market conditions (Dudley, 2015). Furthermore, the thriftiness of financial intermediaries implies that such policies are often easily circumvented (Stein, 2021). In a second-best world, interest rate policy can therefore serve as a useful—albeit imperfect—time-varying tool to tame financial cycles. Importantly, in the context of the Federal Reserve, proponents of the non-separable view in the United States need not argue for a third mandate for monetary policy, as do Peek et al. (2016). Many instead contend that central bankers should consider financial stability insofar as it affects their ability to meet their dual mandate targets in the longer run (Cecchetti et al., 2002), for instance because of how developments in financial markets today may cause reversal effects that affect the mean or the variance of longer-run inflation and unemployment. It is from the vantage point of this intertemporal tradeoff that Stein (2014, 2) notes that "all else being equal, monetary policy should be less accommodative—by which I mean that it should be willing to tolerate a larger forecast shortfall of the path of the unemployment rate from its full-employment level—when estimates of risk premiums in the bond market are abnormally low."

This thesis contributes to the debate on the interplay between monetary policy and financial stability through two independent parts. The first and primary com-

ponent, which is the focus of Chapters 1 and 2, takes a positive stance and focuses on four key empirical questions, each geared at shedding light on whether the historical rate-setting behavior of the Federal Open Markets Committee ("FOMC") has been most compatible with the fully-separable or the non-separable view. After all, if the federal funds rate has already been responsive to financial stability considerations beyond the effects of developments in asset markets on near-term inflation and unemployment, then we can usefully reparametrize the debate on the interplay between monetary policy and financial stability by moving from the extensive to the intensive margin — from whether the Fed should use interest rate policy as a means of achieving financial stability to *how elastically* they should respond to data that is informative of financial stability concerns when setting the federal funds rate[1].

To begin, I construct credit and equity-related proxies for financial stability to examine whether the Federal Open Markets Committee has historically been responsive to these proxies, above and beyond its response to its staff's near-term staff forecasts of inflation and unemployment. Since credit-related variables are well documented in the literature as being informative about the risks of future economic crises while equity-related variables are not, I contend that we should expect the Fed to exhibit a responsiveness to credit market sentiment but not to equity market sentiment *if* they are responding to financial stability concerns rather than to broader changes in asset prices. Second, I analyze the time-varying sensitivity of the Federal Reserve's reaction function to credit market sentiment. Researchers have posited that the Fed's increased emphasis on output stabilization in recent decades may reflect a heightened appreciation for the importance of financial market disruptions, and I verify whether there is evidence to support this view in the

[1]Importantly, I am not claiming that evidence of the Fed's responsiveness to financial stability would imply that such behavior is normatively desirable. Instead, I am suggesting that evidence of this kind would shift the debate from a theoretical discussion about the merits of using monetary policy to address financial stability concerns to a practical discussion about the optimal weight that policymakers ought to ascribe to data on financial stability when setting the Federal Funds Rate.

data by examining whether American monetary policy has become more sensitive to credit market sentiment over time. Third, I analyze the drivers of changes in the federal funds rate to examine whether the Fed conveys a path of policy to fixed income markets that goes above and beyond what is implied by the meeting-over-meeting changes in its staff's forecasts of inflation and unemployment. Fourth, and finally, I delve deeper into the dynamics of the relationship between proxies for financial stability and the federal funds rate to study whether American monetary policy has exhibited a *prudential* dimension—that is, whether central bankers have responded to periods of rising financial stability concerns by incrementally raising interests beyond what would be warranted by changes in expected inflation and unemployment—and whether the policy rate has responded asymmetrically to periods of rising and falling sentiment.

I find that measures of credit market sentiment are statistically significant predictors of the federal funds rate, even after accounting for the Federal Reserve Board's staff forecasts of inflation and unemployment. However, this effect does not extend to measures of equity market sentiment. I estimate that a one-standard-deviation increase in a simple composite measure of credit sentiment is associated with an 18-basis-point increase in the federal funds rate—which corresponds to nearly one standard rate hike—holding all else constant. This finding is compatible with the approach to monetary policy endorsed by proponents of the non-separable view, as it shows that the FOMC has not been indiscriminately influenced by developments in financial markets; rather, they appear to be paying attention primarily to developments in credit markets, which, unlike their counterparts in the stock market, have been robustly identified in the literature as being informative about reversal risks and financial crises. This result withstands various robustness checks, including the use of augmented inflation and unemployment forecasts, which I construct to directly incorporate information on financial stability concerns, and the exclusion of outliers such as the Great Financial Crisis from the sample. I

also find that the sensitivity of the federal funds rate to a one-standard-deviation increase in credit market sentiment has increased progressively from around 18-basis-points for a 10-year rolling window beginning in 1987 to nearly 30-basis-points for a window beginning in 2002. Furthermore, I document that changes in credit market sentiment statistically significantly forecast changes in market expectations of the path of monetary policy, which suggests that policymakers may be factoring financial stability considerations into the path of policy that they convey to financial markets. Finally, I find that Fed policy does exhibit a prudential dimension, as periods of rising credit market sentiment are associated with a rising federal funds rate, even after controlling for changes in the Tealbook forecasts for inflation and unemployment. As such, the response of monetary policy to financial stability considerations is not simply one-sided, as we might have expected if central bankers predominantly responded to tumultuous economic episodes by swiftly cutting interest rates. Jointly, my findings suggest that the Federal Reserve's reaction function exhibits a robust, statistically significant, and increasing sensitivity to proxies for financial stability concerns between 1987 and 2008. These findings show that actual Federal Reserve practice runs counter to the mainstream, fully-separable view that monetary policy should not be used to promote financial stability.

The second section of this thesis, which features in Chapter 3, fits within the broader theoretical literature on prudential monetary policy. Unlike the empirical section, which was a positive exercise geared at uncovering patterns in the FOMC's behavior based on their historical decision making, this chapter explores whether there are normative reasons for central banks to use interest-rate policy to respond to financial stability concerns in a model where agents exhibit behavioral biases. In particular, I explore how the optimal policy rate set by the central bank changes as they become more uncertain about the behavioral biases of households. Furthermore, I examine whether there are conditions under which central banks

can increase expected utility by increasing interest rates to curb overoptimism. Questions of a similar flavor have recently been examined within elaborate macroeconomic frameworks which combine both frictions (such as nominal rigidities or financial frictions) and behavioral deviations from rationality. My contribution is to assess how the theoretical case for using monetary policy to quell exuberance in financial markets changes in a framework which only make assumptions about behavioral biases, so as to provide more color on which modelling assumptions appear necessary to warrant prudential central bank intervention.

In a setting of the model that uses logarithmic utility, and for reasonable parameter values, I demonstrate two key propositions. First, I show that the central bank has greater incentives to raise the policy rate as they become increasingly uncertain about the return of the economy's risky asset. This counter-intuitive result, which stems from a precautionary savings motive, aligns with the findings of Fontanier (2021) but does not rely on the presence of financial frictions within the economy. Second, I demonstrate that the optimal policy rate set by the central bank is rising in the central bank's relative pessimism about the return of the economy's risky asset. By raising interest rates as they become more pessimistic than households about the prospects of the economy's risky asset, the central bank seeks to dissuade households, which they believe to be overly optimistic, from over-investing in the risky asset and inadvertently ending up in a state of the world with low consumption and high marginal utility. Finally, I extend my analysis beyond the special case of logarithmic utility to describe how the model's predictions vary as a function of the the coefficient of relative risk aversion.

The upcoming sections of this paper will be organized as follows. The next section discusses related literature and contributions. In Chapter 1, Section 1.1 motivates the analysis by providing a brief history of the Federal Reserve and exploring the underpinnings of monetary policy rules. Section 1.2 outlines the data collected to perform the empirical analysis. Section 1.3 lays out the regression

specifications that undergird the analysis. Chapter 2 provides the results of the analysis. Chapter 3 presents the economic model as well as its predictions. The final section concludes.

Related Literature and Contributions

This paper contributes to the growing literature on monetary policy and financial stability, and in particular to research on the incorporation of asset-market variables in monetary policy rules and on the use of monetary policy as a prudential tool.

On the empirical front, authors have studied many different dimensions of the Federal Reserve's historical rate-setting behavior. Much of the research in this vein has centered on the interplay between monetary policy and equity markets. Bernanke and Gertler (1999) estimate forward-looking Taylor rules which include past stock returns alongside forecasts for inflation and unemployment. For a sample period running from 1979 to 1997, they find that the Fed has responded strongly to changes in forecasted output and inflation but minimally to changes in equity prices (beyond the effects of stock prices on inflation and output): that is, their estimated coefficient for the response of the federal funds rate to the stock market is small, statistically insignificant, and negative. They argue that this behavior is consistent with their normative view that monetary policy ought to only respond to asset prices insofar as they affect near-term expected inflation. In a similar vein, by comparing the ability of stock prices to predict the federal funds rate relative to a broad range of alternative macroeconomic indicators and by conducting textual analysis on FOMC transcripts, Cieslak and Vissing-Jorgensen (2020) find evidence of a Fed put—namely, both negative stock returns and a large number of mentions of negative stock market events in FOMC transcripts predict cuts in the Funds Rate. However, consistent with Bernanke and Gertler,

they find that the stock market is a statistically insignificant predictor of changes in the federal funds rate, after controlling for inflation and unemployment. To measure the magnitude of the Fed's response to changes in stock prices, Rigobon and Sack (2001) use a novel identification strategy that leverages heteroskedasticity. They find that that a 5 percent increase in the S&P 500 raises the probability of a rate hike by one half. Switching gears, Malmendier et al. (2017) examine whether the personal experiences that FOMC members have had of inflation over their lifetimes influence their policymaking stance. They find that an averaged measure of inflation experiences across the twelve members of the FOMC serves as a statistically significant predictor of the federal funds rate, above and beyond the dual mandate variables.

The work most closely related to this paper is authored by Peek et al. (2016), who study the interplay between financial stability and monetary policy by parsing FOMC transcripts to count words associated with financial instability. After categorizing these words as suggestive of either overvaluation or a cleaning-up event following a crisis, the co-authors regress the federal funds rate on a reaction function that incorporates their measure of word counts as a proxy for financial stability. They show that an increase in negative words in FOMC transcripts (that is, words which imply a concern for the stability of the financial system) is a statistically significant predictor of a rate cut while an increase in positive words (that is, words which imply over-optimism in financial markets) predicts a statistically insignificant rise in the federal funds rate.

This paper builds on that effort in a few ways. First, using word counts as a proxy for financial stability faces various challenges. Classifying words is a subjective process[2], and word counts are sensitive to the composition of the FOMC, since more frequent mentions of financial stability may simply align with periods where a larger-than-usual share of FOMC members are attuned to financial stability

[2]For instance, words such as "stock prices" and "house prices" are classified as positive, while words such as "loan officer" and "lending standards" are classified as negative.

concerns. Using market-based indicators of financial conditions that policy makers likely encounter when debating the path of policy circumvents these issues. Second, establishing a relationship between word counts and policy-setting decisions does not provide color on the factors underlying the FOMC's more frequent discussions about financial stability. Using a heterogeneous set of market indicators as proxies for financial stability can therefore provide a more granular account of which metrics, if any, are influencing the conduct of monetary policy. Finally, I conduct various additional tests in this paper, including an analysis of the asymmetries in the Fed's response to credit market sentiment and an exploration of the drivers of the path of monetary policy conveyed to financial market intermediaries, provide additional insights into the relationship between financial market variables and Fed policy.

On the theoretical front, which is the emphasis of the second portion of this paper, a wide range of recent work analyzes the role of monetary policy in leaning against financial excesses, as summarized by Adrian and Liang (2014). Caballero and Simsek (2019) construct a model in which monetary policy can provide stabilization benefits akin to an increase in leverage limits through its effect on asset prices. Under this framework, prudential monetary policy can enhance welfare in the presence of aggregate demand externalities. Farhi and Werning (2019) propose a cohesive framework for analyzing the appropriate role of monetary policy and macroprudential policy—which, in their model, are represented by two policy instruments, short-term interest rates and a leverage tax, respectively. Their key finding is that the optimal mapping from monetary policy tools (macroprudential policy and interest rate policy) to targets (financial stability and macroeconomic stability) depends on whether investors are behaviorally biased. In a world with financial frictions and rational expectations, they find that macroprudential policy is sufficient to optimally promote financial stability; monetary policy should simply focus on stabilizing prices and other broad macroeconomic variables, unless macro-

prudential policy is unavailable or constrained. However, if, in addition to financial frictions, investors also have extrapolative expectations, then central banks must use both macroprudential policy and monetary policy to achieve optimal financial stability. In such a world, macroprudential policy should focus on restricting leverage, while monetary policy should play on asset prices and agents' beliefs. In line with this finding, the work of Fontanier (2021) finds that prudentially raising interest rates can be welfare-enhancing in a world with behavioral agents and a particular kind of financial friction: a collateral externality. More surprisingly, he also finds that uncertainty surrounding the behavioral biases of agents actually *strengthens* the case for preemptive monetary policy action.

The second part of this thesis contributes to this literature by exploring whether some of the important results surrounding the optimal conduct of monetary policy in the existing literature remain in a model which includes behavioral biases but rids itself of financial frictions. In particular, I examine whether a simple two-period macroeconomic model with behavioral deviations can capture (a) the benefits of using monetary policy (in particular, rate hikes) as a means of quelling exuberance in financial markets and (b) Fontanier (2021)'s important policy uncertainty result. For realistic parameter values, and for a logarithmic utility function, I show that the optimal policy rate set by the central bank is both rising in the central bank's pessimism about the prospects of the economy's risky asset and in the central bank's greater uncertainty about households' behavioral biases. Furthermore, I show that these results depend importantly on the coefficient of relative risk aversion in a more general framework.

Chapter 1

Empirical Background

1.1 Background

In this section, I present a brief history of the Federal Reserve and the explore origins of the dual mandate. Furthermore, I provide more color on monetary policy rules such as the Taylor Rule.

1.1.1 A Brief History of the Federal Reserve

The Federal Reserve System was founded when Woodrow Wilson signed the Federal Reserve Act in 1913. The formation of the United States' central bank was prompted by a series of financial panics and bank runs which culminated in the Panic of 1907. One of the central goals of the Fed at its inception was to furnish an "elastic" currency (Wheelock, 2021): policymakers believed that providing a central bank with the authority to control the money supply would attenuate systemic financial stability issues that arose in a banking system where most currency had until then consisted primarily of private bank notes.

One of the primary tools of the Federal Reserve in its early years was the discount window, which effectively allowed the Fed to serve as a lender-of-last-resort to the American banking sector. The Federal Reserve act stipulated that member banks

had to hold reserves at their regional Federal Reserve Bank, and these banks could obtain additional currency or reserves during periods of stress and illiquidity by borrowing from the Fed's discount window. This measure was designed to address liquidity crises, as it allowed solvent banks that were liquidity constrained during periods of financial panic to borrow from the Fed against good collateral (for example, commercial or agricultural loans).

Since the Federal Reserve's formation, the central bank has adapted rapidly in the face of evolving economic conditions. The Banking Act of 1935, which was established after the Great Depression, created the Federal Open Markets Committee and furnished this body with the authority to set monetary policy; in the Federal Reserve Reform Act of 1977 and the Full Employment and Balanced Growth Act of 1978, Congress legally enshrined the Fed's dual mandate of price stability and full employment; in 2010, Congress passed the Dodd-Frank Act, which bolstered the Fed's regulatory and supervisory authority over the banking sector (Federal Reserve Bank of San Francisco, 2012a).

The Fed's modern-day toolkit consists of two key prongs: monetary policy, and regulation and supervision. Monetary policy involves setting short-term interest rates, and its effects are summarized succinctly by former Federal Reserve chair Yellen (2017): "When the economy is weak and unemployment is on the rise, we encourage spending and investing by pushing short-term interest rates lower. [...] Lowering short-term rates in turn puts downward pressure on longer-term interest rates, making credit more affordable—for families, for instance, to buy a house or for businesses to expand. Similarly, when the economy is threatening to push inflation too high down the road, we increase interest rates to keep the economy on a sustainable path and lean against its tendency to boom and then bust."

On the regulatory and supervisory front, the Fed looks over various financial institutions, such as banks that are members of the Federal Reserve system, financial holding companies, and systemically important financial institutions (Federal

Reserve Bank of San Francisco, 2012b). Discussions on regulatory policy often draw a distinction between microprudential and macroprudential policies. Typically, microprudential policy refers to regulation geared at bolstering the resilience of individual financial institutions, while macroprudential policy refers to regulatory and supervisory efforts aimed at stabilizing the broader financial system. Examples of microprudential policy include the enforcement of capital and leverage requirements for individual banks. Examples of systemic risks that are within the purview of macroprudential policy include excessive private sector leverage and an over-reliance on short-term and unsecured funding. To address these sorts of risks, the 2010 Dodd-Frank Act established a Financial Stability Oversight Council, whose role is to monitor systemic risks to the American financial sector.

As highlighted in the introduction, the mainstream perspective today, championed by prominent Fed officials such as former chair Ben Bernanke, is that the Fed ought to abstain from using monetary policy to promote financial stability and delegate this objective to regulation and supervision. Under this conception, monetary policy should be adjusted only in relation to the dual mandate of price stability and full employment. The next two chapters of this thesis are geared at examining whether this is in fact how monetary policy has been conducted in the United States in recent decades.

1.1.2 The Taylor Rule

Although the Federal Reserve's monetary policy is set discretionarily—that is, members of the Federal Open Markets committee exercise their judgement to set the federal funds rate rather than following a predetermined rule—many researchers have documented that Fed decisions can be well explained by interest rate rules which take a few key macroeconomic variables as arguments.

As highlighted by Fair (2004) and Lo (2010), one of the first monetary policy rules of this kind was formulated by Dewald and Johnson, who posited that the

Treasury Bill Rate could be well predicted by a function of its first-order lag, the unemployment rate, real GNP, the balance-of-payments deficit, and the Consumer Price Index. After estimating this relationship with data, the co-authors found that most of the predictors in this specification were statistically significant and that the rule explained a large portion of the variance in the setting of the federal funds rate.

Despite this early contribution to the literature on policy rules, interest rate rules nowadays commonly bear the name of Taylor Rules, after the economist John Taylor. In 1993, Taylor suggested that the Fed's historical rate-setting behavior could be described by an equation of the following form:

$$FFR_t = \pi_{t-1,t} + 2 + 0.5(\pi_{t-1,t} - 2) + 0.5(y_{t-1,t} - \bar{y})$$

where, as noted by Lo (2010), $\pi_{t-1,t}$ is the inflation rate over the past four quarters, $y_{t-1,t}$ is the logarithm of real GDP over the same period, and $\bar{y}$ is the logarithm of a historical estimate of potential output.

At its essence, Taylor's rule expresses the Fed's reaction function as linear in the deviations from its inflation and output targets. This linear functional form can arise from minimizing a quadratic loss function over the Fed's dual mandate objectives, where the convexity of the loss function encapsulates the increasingly staunch penalty incurred by the Fed as inflation and unemployment deviate further from the central bank's target [1]. Using Okun's Law, the output gap can also be expressed as the deviation of unemployment from NAIRU[2].

In the years since Taylor published his seminal paper, researchers have proposed various modifications to his rule. Below, I explore some of these adjustments, which

[1] The quadratic loss function can be viewed as a second-order Taylor approximation of any higher-order convex function, and is therefore general.

[2] In its original form, Okun's Law estimates that a one-percentage-point reduction in unemployment would induce an approximately three percentage point rise in output. Since Okun's work was published, the magnitude of this relationship has been revisited.

I will use when estimating Taylor-style regressions in Chapter 2.

Adjustments to the Taylor Rule

The literature on Taylor Rules distinguishes between two different kinds of rules: those which are forward-looking, and thereby rely on expectations of parameter values such as inflation and unemployment, and those which instead use realized values of these quantities. Orphanides (2001, 2003) documents that forward-looking rules, such as those estimated by Clarida et al. (1998), more robustly explain the rate-setting behavior of the Federal Open Markets Committee than rules that use realized data.

Researchers have also documented that the Fed gradually adjusts its policy rule, in a process known as interest rate smoothing (English et al., 2002; Campbell et al., 2013). Many explanations have been proposed for this behavior, including a fear of spooking financial markets (Stein and Sunderam, 2018), a desire to maintain credibility, and a gradual incorporation of information (Castelnuovo, 2003).

Clarida et al. (1998, 8) model this smoothing according to the following model for the federal funds rate:

$$r_t = (1-\rho)r_t^* + \rho r_{t-1} + \nu_t$$

where the current period federal funds rate, r_t, is a weighted average of the Fed's target rate, r^*, and the previous period's policy rate, r_{t-1}, and $\rho \in [0,1)$ captures how gradually the Fed adjusts policy.

Given the robust literature on these adjustments to the Taylor rule, I will be using forward-looking Taylor rules which account for interest rate smoothing throughout this paper.

1.2 Data

For this project, I construct a consolidated dataset containing two distinct flavors of data: policy-related variables, including historical values of the federal funds rate and the Tealbook forecasts of inflation and unemployment, and financial data, including credit and equity market indicators. All variables are ultimately resampled at a common frequency, namely the calendar dates of FOMC meetings from February 1987 to December 2008. I provide a short description of key variables below.

1.2.1 Policy-Related Variables

The Tealbook—which was formerly published as two separate notebooks, the Greenbook and the Bluebook—is a handbook produced by staff at the Board of Governors of the Federal Reserve. It is provided to members of the FOMC before each of their eight annual meetings, and it is released to the public with a five-year lag. The Tealbook contains simulations and forecasts of key economic variables including real GDP, the civilian unemployment rate, and inflation for periods ranging from one to eight quarters ahead. For this paper, I use the forecasts of Core PCE inflation[3] over the next year as well as the four-quarter-ahead forecasts of the U3 unemployment rate contained in the Tealbook Greensheets[4]. In addition to these forecasts, I consider the average value of the federal funds rate for a week following each FOMC meeting. These data were kindly provided to me by Joe Peek, Eric Rosengren and Jeffrey Tootell at the Federal Reserve Bank of Boston for the period between February 2, 1982 and December 15, 2008. Following Peek et al. (2016), I begin my analysis in 1987, which corresponds to the start of the Greenspan

[3] I account for the fact that the Fed transitioned from considering core CPI to considering core PCE inflation between the October 2005 and December 2005 FOMC meetings.

[4] In particular, I calculate the staff's annualized inflation forecast over the next year by computing the geometric average of the Greensheet inflation forecasts for each of the four quarters following an FOMC meeting.

era. This is both to avoid skewing my analysis with the unusually high settings of the federal funds rate prior to this period and because my data on credit spreads, which I will discuss below, only begins in 1986. I end my analysis in 2008 because the dependent variable in my analysis, the federal funds rate, ceases to vary as it hits the zero lower bound during this period in response to the Great Financial Crisis.

Table 1.1 provides key summary statistics for these policy data during the sample. Since the Tealbook forecasts are produced by Fed staff based on all the information available to them prior to an FOMC meeting, they are designed to incorporate the relevant effects of realized or potential financial stability concerns on near-term inflation and unemployment insofar as they are informationally efficient forecasts.

Table 1.1: Summary Statistics of Policy-Related Variables

	$FFR_{t,t+1}$	$\pi^{\text{teal}}_{t,t+1}$	$UE^{\text{teal}}_{t,t+1}$	$\pi^{\text{realized}}_{t,t+1}$	$UE^{\text{realized}}_{t,t+1}$
Observations	176.00	175.00	176.00	176.00	176.00
Mean	4.77	2.93	5.62	2.79	5.63
SD	2.18	1.04	0.82	1.09	1.21
Min	0.15	1.05	3.90	0.70	3.90
25%	3.09	2.17	5.00	2.10	4.78
50%	5.22	2.66	5.60	2.53	5.47
75%	5.95	3.32	6.10	3.29	6.03
Max	9.88	5.41	8.30	5.49	9.93

Notes: This table provides summary statistics (number of observations, mean, median, standard deviation, extreme values, and quartiles) for the policy-related variables used throughout the analysis in this paper. $FFR_{t,t+1}$ represents the average value of the federal funds rate for a week following each FOMC meeting in the sample. $\pi^{\text{teal}}_{t,t+1}$ is the Tealbook forecast for inflation over the next year. $UE^{\text{teal}}_{t,t+1}$ is the four-quarter ahead Tealbook forecast for the U3 unemployment. $\pi^{\text{realized}}_{t,t+1}$ is the realized value of inflation over the forecast window. $UE^{\text{realized}}_{t,t+1}$ is the realized value of unemployment over the forecast window. Source: Board of Governors, FRED and Bureau of Labor Statistics

1.2.2 Credit Variables

To assess sentiment in credit markets using market-based indicators, I consider two key variables. In upcoming sections, I provide more color on the economic justification for using these variables as empirical proxies for financial stability.

1. **High-Yield Share:** The high-yield share measures the fraction of quarterly debt issuance by non-financial corporations attributable to companies clas-

sified as non-investment-grade by Moody's[5]. In particular, Greenwood and Hanson (2013, 42) define the high-yield share as "the log fraction of non-financial corporate bond issuance with a high-yield rating from Moody's." They propose the high-yield share as a measure of credit market sentiment and find that periods of high credit growth among low-quality issuers are correlated with low future returns on debt. A large high-yield share is indicative of high credit market sentiment, as it signals easy financing conditions for riskier firms. These data are available at a quarterly frequency beginning in 1983.

2. **Credit Spreads:** I construct credit spreads using Moody's Seasoned Baa Corporate Bond Yield, which reflects the yield on a basket of mid-tier investment grade bonds with maturities 20 years and above, as in Lopez-Salido et al. (2015). In particular, I construct credit spreads using the difference between this bond yield index and the constant-maturity 10-year Treasury rate. Low credit spreads on high-yield bonds are indicative of high credit market sentiment, as they reflect the low compensation for default risk required by investors purchasing corporate debt. Credit spreads are also useful predictors for economic crises, because they blend information on liquidity premia, risk premia, and default risk, each of which rises in periods of declining economic activity (Gilchrist and Zakrajsek, 2012). These data are available at a daily frequency beginning in 1986.[6]

[5] High-yield bonds hold a Moody's rating of Ba1 or lower, which corresponds to an S&P rating of BB+ or lower.

[6] An alternative source of data for credit spreads I considered was Bank of America's US High Yield Index Option-Adjusted spread, which measures the daily difference between the yield on an index of high-yield bonds (adjusted for the option-value embedded in certain securities like callable bonds) and a spot Treasury curve. However, these data only become available in 1997, which significantly reduces the size of the analyzable sample.

1.2.3 Equity Variables

To assess equity sentiment using market-based indicators, I considered two time-series.

1. **Equity Market Sentiment:** Baker and Wurgler (2007) construct a composite measure of sentiment in equity markets by taking the first principal component of six distinct variables correlated with investor enthusiasm: trading volume as measured by NYSE turnover, the dividend premium, the closed-end fund discount, the number of IPOs and their corresponding first-day returns, and the equity share in new issues. Time-series data for this sentiment measure is provided at a monthly frequency beginning in 1958.

2. **Cyclically-Adjusted Price-to-Earnings Ratio (CAPE):** The CAPE ratio, also commonly referred to as the Shiller P/E Ratio, is the inflation-adjusted ratio of the market capitalization of the S&P 500 to the 10-year trailing mean of earnings. The price-to-earnings ratio provides a crude proxy for relative valuations in the stock market, and the CAPE smooths the volatility in yearly earnings to provide a more stable time-series. These data are provided by Robert J. Shiller at a monthly frequency beginning in 1871.

1.3 Empirical Strategy

In this section, I describe some foundations for the regression specifications that I estimate in Chapter 2.

1.3.1 Inertial Taylor Rule

As discussed in Section 1.1.2, a common assumption in the literature on monetary policy rules is to model the Fed's reaction function as linear in the deviations from its inflation and unemployment targets. As Clarida et al. (1998) highlight,

this formulation is attractive from both a theoretical and an empirical perspective: authors like Michael Woodford have demonstrated that this approach can be micro-founded under certain conditions, while others have documented that American monetary policy is well described by Taylor-like rules. In this paper, I am using the Taylor Rule as an atheoretic descriptor of Fed behavior, as it encapsulates the dual mandate variables which should be considered by members of the Federal Open Markets Committee according to the Fed's mandate from Congress.

Specifications of the Taylor rule often include deviations from output, but I follow Peek et al. (2016) in using the unemployment rate for data availability purposes and noting that it is relatable to the output gap via Okun's law. Hence, the inertial Taylor Rule is:

$$\begin{aligned} FFR_{t,t+1} &= r^*_{t,t+1} + \pi^*_{t,t+1} + \Phi_\pi(\pi_{t,t+1} - \pi^*_{t,t+1}) + \Phi_{UE}(UE_{t,t+1} - UE^*_{t,t+1}) \\ &= \left(r^*_{t,t+1} + \pi^*_{t,t+1} - \Phi_\pi \pi^*_{t,t+1} - \Phi_{UE} UE^*_{t,t+1}\right) + \Phi_\pi \pi_{t,t+1} + \Phi_{UE} UE_{t,t+1} \end{aligned} \tag{1.1}$$

where Equation 1.1 represents a standard Taylor Rule and its re-arranged form. $r^*_{t,t+1}$ represents the one-period real interest rate consistent with stable prices and full employment. $\pi_{t,t+1}$ and and $UE_{t,t+1}$ represent the rate of inflation and the unemployment rate, respectively, while $\pi^*_{t,t+1}$ and and $UE^*_{t,t+1}$ represent the Fed's target level of inflation and the natural rate of unemployment, respectively.

This Taylor rule can be estimated via the regression equation specified by Equation 1.2 using the Tealbook forecasts for inflation and unemployment and the lagged federal funds rate, which I include to allow for gradual changes in the policy rate, as discussed in Section 1.1.2.

$$FFR_{t,t+1} = \beta_0 + \beta_1 FFR_{t-1,t} + \beta_2 \pi_{t,t+1} + \beta_3 UE_{t,t+1} + \epsilon_t \tag{1.2}$$

1.3.2 Augmenting the Taylor Rule with Proxies for Financial Stability

In this section, I add measures of credit and equity market sentiment to the baseline inertial Taylor Rule outlined in Equation 1.2. As Bernanke and Gertler (1999, 38) highlight when studying the effects of the stock market on monetary policy, there are two ways in which we can think about the results stemming from such an exercise:

> There are two ways to think about the addition of stock market returns to the reaction function. The first is to interpret it literally as saying that monetary policy is reacting directly to stock prices, as well as to the output gap and expected inflation. The second is to treat the addition of stock returns as a general specification test that reveals whether monetary policy is pursuing other objectives besides stabilization of output and expected inflation. To the extent that policy has other objectives, and there is information about these objectives in the stock market, then we would expect to see stock returns enter the central bank's reaction function with a statistically significant coefficient.

That is, the Fed's dual mandate legally enshrines the null hypothesis that monetary policy ought to react solely to expected inflation and unemployment. Finding that credit or equity market sentiment provide additional and statistically significant explanatory power in a Taylor-like regression would therefore serve as convincing evidence against this null hypothesis, even if such a finding does not rule out the possibility that policymakers are ultimately looking at another underlying factor that is correlated with credit or equity market sentiment.

One may rightfully note that credit or equity market sentiment could also appear to be statistically significant in the reaction function if the Tealbook forecasts for inflation and unemployment are only partial indicators of the information that

members of the Federal Open Markets Committee are using to form views about the near-term path of the dual mandate variables. If this is the case, then the Committee could effectively be using information on credit or equity markets to enhance their near-term inflation and unemployment forecasts, and *this* could explain why credit or equity market sentiment appear to be statistically significant drivers of the Fed's monetary policy. While there are good reasons to believe that the Tealbook forecasts are efficient, as I will discuss shortly, I address this possibility in Section 2.7.2 by constructing *augmented* inflation and unemployment forecasts which I allow to directly incorporate information on credit market sentiment. I then verify whether relevant proxies for financial stability remain independently significant predictors of the federal funds rate after conditioning on these adjusted near-term forecasts.

Monetary Policy and Credit Markets

To examine whether the Fed incorporates financial stability considerations into monetary policy above and beyond their effects on near-term inflation and unemployment as forecasted by Fed staff, I estimate the following *credit-augmented* Taylor rule:

$$FFR_{t,t+1} = \beta_0 + \beta_1 FFR_{t-1,t} + \beta_2 \pi_{t,t+1} + \beta_3 UE_{t,t+1} + \beta_4 CS_t + \epsilon_t \tag{1.3}$$

where CS_t is a composite credit sentiment measure that I construct by combining the standardized values of Greenwood and Hanson's high-yield share measure, HYS_t, and the standardized values of the average Baa credit spread six weeks before an FOMC meeting, $spread_t$:

$$CS_t = \frac{1}{2}\left(\frac{\left(HYS_t - \overline{HYS}\right)}{\sigma_{HYS}} - \frac{\left(spread_t - \overline{spread}\right)}{\sigma_{spread}} \right) \tag{1.4}$$

The construction of this composite credit sentiment measure as a proxy for

financial stability is motivated by a rich literature on credit cycles that documents that both the *quantity* and the *price* of credit contain pertinent information for long-run economic risks. As noted in Section 1.2, Greenwood and Hanson (2013) show that narrow credit spreads and a high share of debt issuance going towards risky firms meaningfully forecast low subsequent returns to credit, and hence serve as useful proxies for the risk appetite of credit investors. Jorda et al. (2011) study private credit overhang between 1870 and 2008 in 14 countries, including Canada, the United States, the United Kingdom, and Japan. They find that credit-fueled economic expansions are followed by particularly damaging recessions. Furthermore, they document that this relationship between the quantity of credit and the intensity of ensuing recessions is not merely observed during large, systemic financial crises. Their research therefore documents the phenomenon of a *reversal effect* with credit, which they pithily refer to as "credit biting back": economic expansions fueled by rapid credit creation are more likely associated with deeper subsequent recessions and slower ensuing recoveries.

Shifting gears to the pricing of credit and behavioral theories of credit cycles à la Minsky (1986) and Bordalo et al. (2016), Lopez-Salido et al. (2015) find that high investor sentiment in credit markets—proxied for by aggressively priced debt instruments, a large share of corporate bond issuance going to junk-rated firms, and a tight term spread— is associated with reversal effects. Namely, from 1929 to 2015, the co-authors document that periods of high sentiment in credit markets are correlated with declining economic activity two to three years out. To explain this finding, they posit a supply-side theory: exuberance in credit markets today leads to reversal effects which reduce the supply of credit in the future, thereby adversely affecting economic conditions.

Finally, Kirti (2018) argues that the high-yield share incorporates information on lending standards which can be used to distinguish healthy from damaging periods of credit growth: namely, he finds that a combination of booming credit

(measured using credit-to-GDP ratios) and a rising high-yield share forecasts lower subsequent output growth better than booming credit-market conditions alone.

Jointly, these papers provide an economic grounding for the formulation of my composite credit sentiment measure as a proxy variable for financial stability concerns. Beyond its economic foundations, this blended measure, displayed alongside its constituent components in Figure 1.1, has two key advantages. First, since the purpose of this section is to construct a proxy for credit sentiment using variables that FOMC members are likely to observe when setting policy, augmenting the high-yield share with readily available data on spreads seems natural. Second, since high-yield share data is sampled quarterly, combining it with higher frequency data on spreads allows the resulting measure to incorporate recent changes in credit conditions that might not be captured by the high-yield share. Figure 1.1 shows the evolution of CS_t, as well as its constituent components, over time.

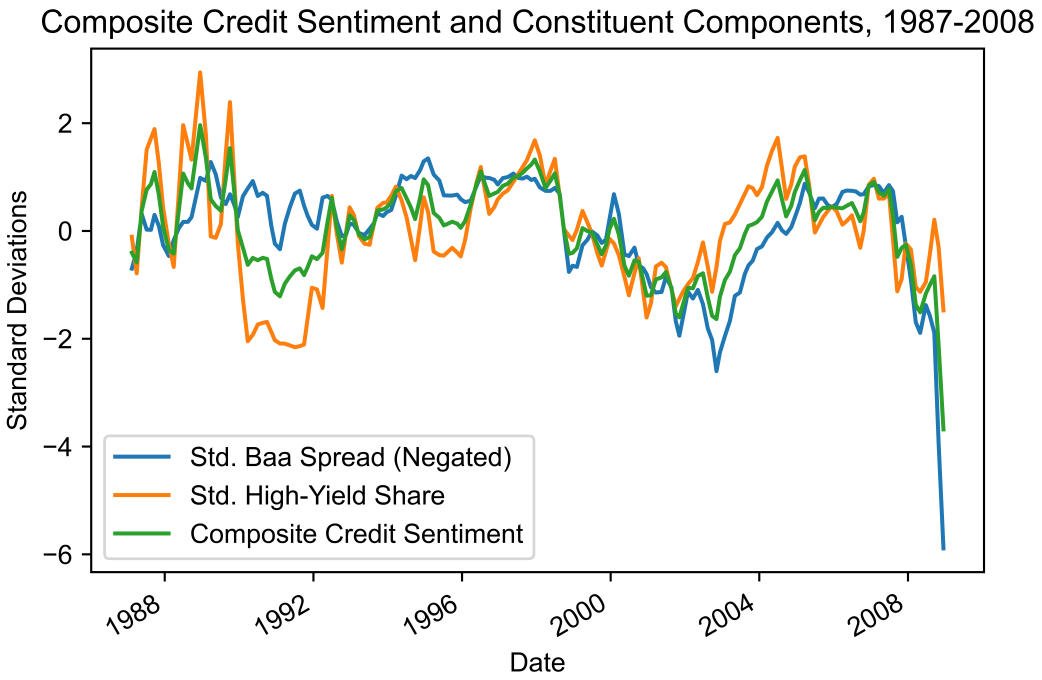


Figure 1.1: Composite Credit Sentiment and Constituent Components, 1987-2008. The blue line represents the standardized spread between the yield of Moody's Baa corporate bond index and the 10-year constant maturity Treasury yield, negated to reflect that narrow credit spreads reflect higher credit market sentiment. The orange line depicts the evolution of the standardized high-yield share. The green line reflects the composite credit sentiment index, $CS_t = \frac{1}{2}\left(\frac{(HYS_t - \overline{HYS})}{\sigma_{HYS}} - \frac{(spread_t - \overline{spread})}{\sigma_{spread}}\right)$.

Monetary Policy and Equity Markets

Using equity market indicators as proxies for financial stability, I estimate the following *equity-augmented* Taylor rule, which closely resembles its credit-based counterpart defined above:

$$FFR_{t,t+1} = \beta_0 + \beta_1 FFR_{t-1,t} + \beta_2 \pi_{t,t+1} + \beta_3 UE_{t,t+1} + \beta_4 ES_t + \epsilon_t \tag{1.5}$$

where ES_t is a composite equity sentiment measure that I construct by taking the average of standardized versions of Baker and Wurgler's sentiment measure and

the Cyclically-Adjusted Price-to-Earnings ratio:

$$ES_t = \frac{1}{2}\left(\frac{\left(BW_t - \overline{BW}\right)}{\sigma_{BW}} - \frac{\left(CAPE_t - \overline{CAPE}\right)}{\sigma_{CAPE}}\right) \tag{1.6}$$

Both the Baker and Wurgler sentiment index and the CAPE ratio feature commonly in the literature on forecasting aggregate stock market returns. By combining a measure of sentiment with a proxy for valuation, ES_t is constructed to serve as a comparable counterpart to the composite credit series CS_t. Figure 1.2 charts the evolution of ES_t, as well as its constituent components, over time.

As noted previously, unlike with credit market sentiment, the literature does not robustly document that the stock market is an indicator of reversal risk or a strong predictor of future financial crises. Indeed, Lopez-Salido et al. (2015) find that the Cyclically-Adjusted Price-to-Earnings ratio is a poor predictor of future real economic activity. As such, if the FOMC is paying attention to financial stability, as opposed to asset prices *simpliciter*, we should expect their behavior to exhibit less sensitivity to equity market sentiment than to credit market sentiment.

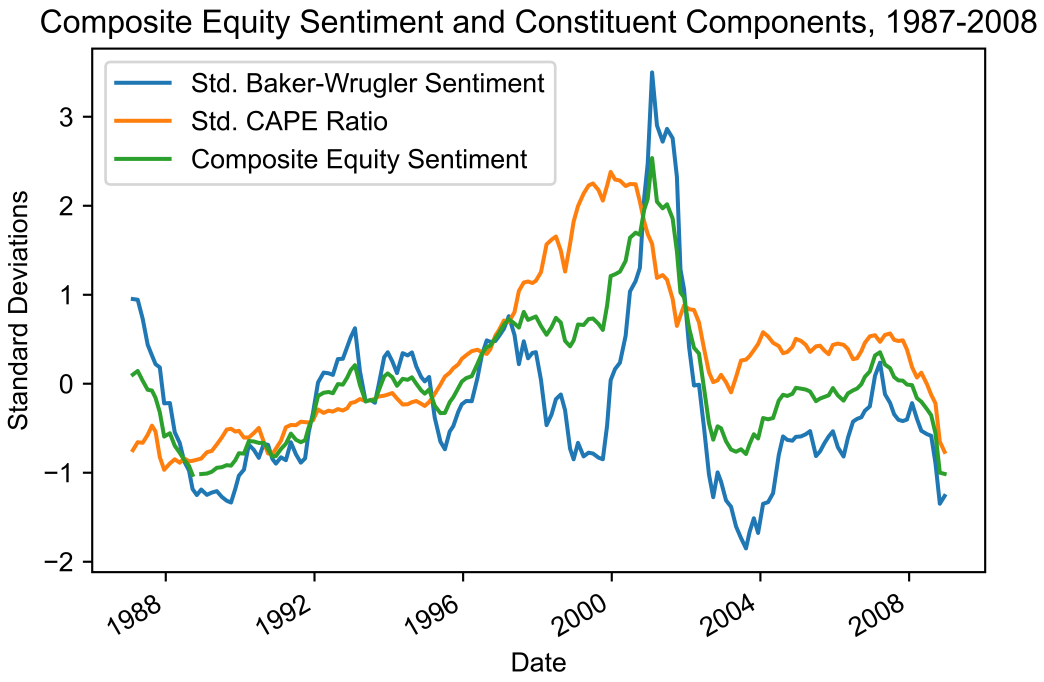


Figure 1.2: Composite Equity Sentiment and Constituent Components, 1987-2008. The blue line represents the standardized Baker and Wurgler equity sentiment index. The orange line depicts the evolution of the standardized Cyclically-Adjusted Price-to-Earnings ratio. The green line reflects the composite equity sentiment index, $ES_t = \frac{1}{2}\left(\frac{(BW_t - \overline{BW})}{\sigma_{BW}} - \frac{(CAPE_t - \overline{CAPE})}{\sigma_{CAPE}}\right)$.

Chapter 2

Empirical Results

2.1 Estimating the Inertial Taylor Rule

Table 2.1 shows the results of estimating Equation 1.2. The signs of the coefficients associated with inflation and unemployment align with notion that the FOMC raises rates to tame inflation and cuts rates in response to rising unemployment. In terms of magnitudes, a one-percentage-point increase in expected inflation is associated with a 32-basis-point hike in the policy rate, holding the lagged federal funds rate and the Tealbook forecast for unemployment constant, while a one-percentage-point increase in unemployment is associated with an 28-basis-point decrease in the policy rate, holding the lagged federal funds rate and the Tealbook forecast for inflation constant. All coefficients are statistically significant at the 1% level, which is consistent with the Fed targeting its dual mandate objective, and the combination of inflation, unemployment and the lagged federal funds rate explains 98% of the variation in the federal funds rate over the sample period from 1987 to 2008.

As a sanity check, I verify whether these findings respect the Taylor Principle, according to which the estimated coefficient on inflation, $\pi_{t,t+1}$, should be greater than one. This is because the Federal Open Markets Committee should respond to

a one-percent increase in expected inflation by a greater-than-one-percent increase in the federal funds rate, so that it is effectively raising the real federal funds rate, all else held constant. Although Mehra (2002) has documented that the Taylor principle was violated during early periods ranging from the first quarter of 1968 to the second quarter of 1979—meaning that the Fed effectively acted too slowly to changes in macroeconomic conditions during this period, thereby inadvertently reducing the real federal funds rate in response to rising expected inflation—the Federal Open Markets Committee seems to have corrected this error in later sample periods.

The addition of the lagged federal funds rate as a prediction in the inertial Taylor rule slightly complicates our verification of the Taylor principle. Indeed, the lagged dependent variable is included to indicate the gradual adjustment in the path of policy, so the relevant question is whether the coefficient on expected inflation exceeds unity once the inertia in the system has been resolved. Then, $FFR_{t,t+1} = FFR_{t,t-1}$, and Equation 1.2 becomes:

$$FFR_{t,t+1} = \frac{1}{1-\beta_1}(\beta_0 + \beta_2 \pi_{t,t+1} + \beta_3 UE_{t,t+1} + \epsilon_t) \tag{2.1}$$

where $\frac{\beta_2}{1-\beta_1}$ reflects the response of the federal funds rate to a one-percent increase in the Tealbook forecast for inflation once the inertia in the system is resolved. According to the Taylor principle, we should observe that $\frac{\beta_2}{1-\beta_1} > 1$. Using the coefficients reported in Table 2.1, we see that $\frac{\beta_2}{1-\beta_1} = \frac{0.32}{1-0.86} = 2.29$. Hence, the Taylor principle is satisfied, in line with research conducted over the same period.

Table 2.1: Estimation of the Inertial Taylor Rule, 1987-2008

	Federal Funds Rate $FFR_{t,t+1}$
Covariates	(1)
Constant	1.25^{***}
	(0.18)
Tealbook Inflation Forecast ($\pi_{t,t+1}$)	0.32^{***}
	(0.051)
Tealbook Unemployment Forecast ($UE_{t,t+1}$)	-0.28^{***}
	(0.039)
Lagged federal funds rate ($FFR_{t-1,t}$)	0.86^{***}
	(0.020)
Obs	175
R^2	0.982

***/**/* denote significance at the 1%, 5%, and 10% level, respectively

Notes: The dependent variable is $FFR_{t,t+1}$, the average value of the federal funds rate for a week following each FOMC meeting in the sample. $\pi^{\text{teal}}_{t,t+1}$ is the Tealbook forecast for inflation over the next year. $UE^{\text{teal}}_{t,t+1}$ is the four-quarter ahead Tealbook forecast for the U3 unemployment rate. $FFR_{t-1,t}$ is the lagged dependent variable.

2.2 Estimating the Credit-Augmented Taylor Rule

Column (1) of Table 2.2 estimates Equation 1.3 using the composite credit sentiment measure CS_t defined in Equation 1.4. The coefficients associated with inflation and unemployment retain the sign, overall magnitude and statistical significance of the inertial specification. In addition, holding all else constant, a one-standard-deviation increase in composite credit sentiment is associated with a 18-basis-point increase in the federal funds rate. This corresponds to almost one standard Fed rate hike. This relationship is positive and statistically significant at the 1% level.

For additional color, columns (2) to (5) estimate equation 1.3 by replacing CS_t by the standardized high-yield share or by combinations of the standardized level and change in corporate credit spreads in the six weeks preceding an FOMC meeting. The six-week lookback window used to calculate the average spread represents the approximate length of time between FOMC meetings. Column (2) highlights that a one-standard-deviation increase in the high-yield share forecasts a nine-basis-point increase in the federal funds rate . This result is significant at the 1% level. Columns (3) and (4) show that a one-standard-deviation increase in the average level and the change in credit spreads is associated with a 17-basis-point and 7-basis-point reduction in the federal funds rate, respectively. These results are intuitive, as rising spreads signal negative credit market sentiment and are therefore associated with an easier stance of monetary policy. Finally, column (5) considers both the average level and the change in high-yield credit spreads jointly. While the coefficient associated with the level of spreads remains negative and statistically significant at the 1% level, the change in spreads is negative but no longer statistically significant.

To provide visually compelling evidence that the statistical significance of the relationship between the federal funds rate and credit sentiment is not predominantly driven by a few notable events in the sample, I plot the standardized residuals of the Inertial Taylor Rule estimated in 2.1 against the Composite Credit Sentiment measure CS_t described by Equation 1.4.

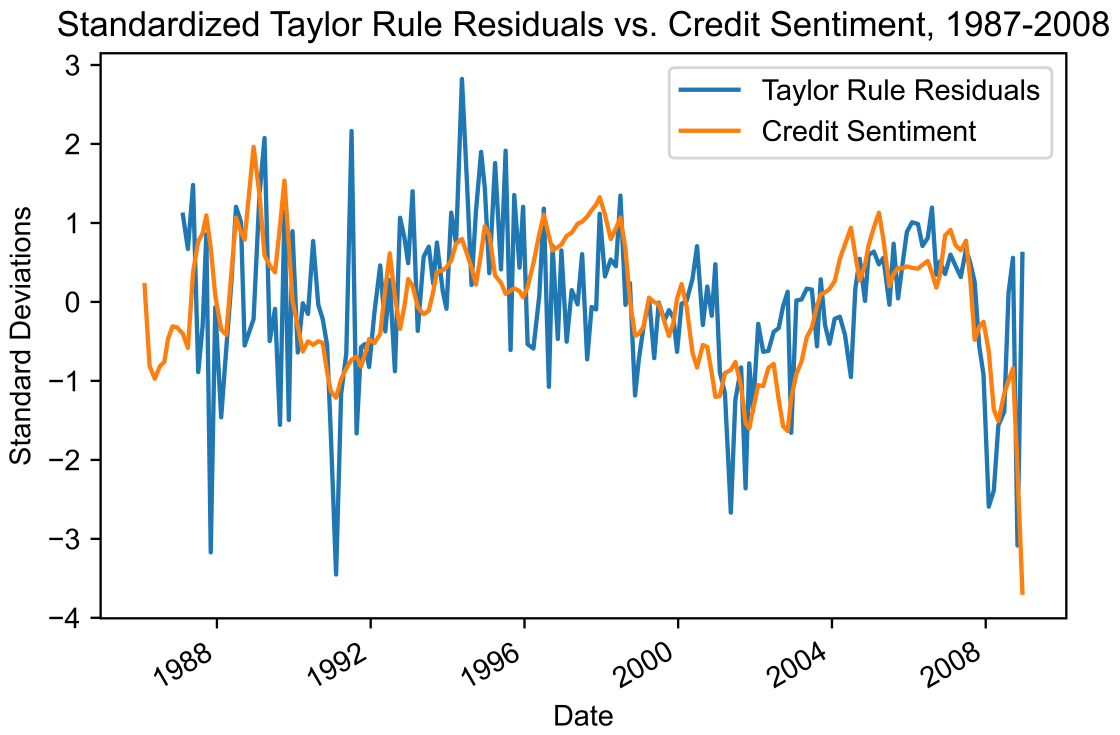


Figure 2.1: Standardized Taylor Residuals and Credit Market Sentiment: The blue line depicts the residuals from the Inertial Taylor Rule in 1.2, $\epsilon_t = FFR_{t,t+1} - (\beta_0 + \beta_1 FFR_{t-1,t} + \beta_2 \pi_{t,t+1} + \beta_3 UE_{t,t+1})$, after being standardized. The orange line represents the composite credit sentiment index, $CS_t = \frac{1}{2}\left(\frac{(HYS_t - \overline{HYS})}{\sigma_{HYS}} - \frac{(spread_t - \overline{spread})}{\sigma_{spread}}\right)$.

Figure 2.1 shows that Composite Credit Sentiment is remarkably highly correlated with the standardized residual portion of the federal funds rate that is not explained by inflation or unemployment. This provides an additional, visually compelling representation of the regression results in Column (1) of Table 2.2, which highlights the high statistical significance of credit market sentiment as a predictor of the federal funds rate.

Taken together, these findings provide compelling evidence that the federal funds rate has historically exhibited a responsiveness to financial stability—as proxied for by various credit-related variables—above and beyond its responsiveness to the Tealbook forecasts for inflation and unemployment, which are designed to capture the effects of asset-market variables on near-term output. As will be

discussed in Section 2.7, this key result is robust to various stress tests, including the use of inflation and unemployment forecasts that are augmented to directly incorporate information on financial stability.

Table 2.2: Estimation of Credit-Augmented Taylor Rule

	Federal Funds Rate $FFR_{t,t+1}$				
Covariates	(1)	(2)	(3)	(4)	(5)
Tealbook Inflation Forecast ($\pi_{t,t+1}$)	0.268***	0.289***	0.285***	0.280***	0.269***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
Tealbook Unemployment Forecast ($UE_{t,t+1}$)	-0.206***	-0.236***	-0.228***	-0.249***	-0.217***
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
Lagged federal funds rate ($FFR_{t-1,t}$)	0.872***	0.882***	0.843***	0.882***	0.852***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Composite Credit Index (CS_t)	0.178***				
	(0.03)				
High-yield Share (HYS_t)		0.0871***			
		(0.02)			
Credit Spread, Level ($spread_t$)			-0.166***		-0.156***
			(0.04)		(0.04)
Credit Spread, Change ($\triangle spread_t$)				-0.0715**	-0.0312
				(0.03)	(0.03)
Constant	0.949***	1.006***	1.154***	1.110***	1.099***
	(0.18)	(0.20)	(0.21)	(0.16)	(0.21)
Obs.	175	175	175	175	175
R^2	0.986	0.983	0.986	0.983	0.986
Adj. R^2	0.985	0.983	0.986	0.982	0.986

Standard errors in parentheses
***/**/* denote significance at the 1%, 5%, and 10% level, respectively
All credit-related variables are standardized

Notes: The dependent variable is $FFR_{t,t+1}$, the average value of the federal funds rate for a week following each FOMC meeting in the sample. $\pi^{\text{teal}}_{t,t+1}$ is the Tealbook forecast for inflation over the next year. $UE^{\text{teal}}_{t,t+1}$ is the four-quarter ahead Tealbook forecast for the U3 unemployment rate. $FFR_{t-1,t}$ is the lagged dependent variable. The composite credit sentiment index, CS_t, is an equally weighted average of the standardized high-yield share, HYS, and the standardized average level of Baa credit spreads six weeks before each FOMC meeting, $spread_t$: $CS_t = \frac{1}{2}\left(\frac{(HYS_t - \overline{HYS})}{\sigma_{HYS}} - \frac{(spread_t - \overline{spread})}{\sigma_{spread}}\right)$. $\triangle spread_t$ is the standardized change in Baa credit spreads in the six weeks leading up to each FOMC meeting.

2.3 Estimating the Equity-Augmented Taylor Rule

Column (1) of Table 2.3 estimates equation 1.5 using the composite equity sentiment series ES_t. The coefficient associated with equity market sentiment is negative, which is inconsistent with the Fed leaning against rising exuberance in the stock market, and the result is statistically insignificant. Columns (2) and (3) estimate the same specification using the Baker and Wurgler's equity market sentiment measure and the Cyclically-Adjusted P/E ratio. Both yield negative and statistically insignificant regression coefficients.

Overall, unlike when dealing with financial stability proxies in credit, where our results were statistically significant and robust, equity market indicators do not appear to bear on the federal funds rate in a systematic way after controlling for the Tealbook forecasts for inflation and unemployment. This finding is consistent with the work of Bernanke and Gertler (1999) and Cieslak and Vissing-Jorgensen (2020).

As discussed in Section 1.3.2, this asymmetry between the responsiveness of monetary policy to credit and equity market sentiment is compatible with the literature studying the differential informational content of these two variables as proxies for financial stability. Namely, while equity market sentiment forecasts aggregate stock market returns, a high level of the stock market itself is generally a weak predictor of recessions. In contrast, a rich body of research documents the robust predictive power of credit market variables for future real economic activity, as highlighted previously[1]. As such, while both higher stock prices and lower credit spreads may have stimulating effects for near-term output, which would already be captured by the conventional Taylor Rule terms, lower credit spreads are *additionally* associated with a reversal effect, wherein they meaningfully forecast lower output at a longer horizon.

Importantly, the finding that the Fed appears to have reacted primarily to devel-

[1] A variety of factors may explain this difference, including the fact that credit consistently drives investment, while equity issuance rarely serves as an incremental source of financing after a public offering.

opments in credit markets—which I refer to in this paper as *leaning against credit*, rather than indiscriminately responding to developments in asset markets—is consistent with the approach to conducting monetary policy endorsed by proponents of the non-separable view, according to which "preventing asset price misalignments will allow policy-makers to more successfully stabilize output and inflation (the policy-makers' objectives) by avoiding the large disruptions to the economy that might occur when those misalignments unwind" (Rigobon and Sack, 2001, 641). Indeed, those in the non-separable camp would agree that the influence of equity markets on monetary policy should be captured by the Tealbook forecasts for inflation and unemployment, insofar as changing conditions in the stock market predominantly contain information about near-term output and inflation. However, since changes in credit conditions portend both effects on near-term output *and* longer-term reversal effects which can influence the Fed's ability to meet their dual mandate at longer horizons, defenders of the non-separable position would argue that monetary policy should pay attention to developments in credit markets above and beyond their effects on near-term expected inflation and unemployment, as I find in Table 2.2.

Table 2.3: Estimation of Equity-Augmented Taylor Rule

	Federal Funds Rate $FFR_{t,t+1}$		
Covariates	(1)	(2)	(3)
Tealbook Inflation Forecast ($\pi_{t,t+1}$)	0.302***	0.313***	0.290***
	(0.06)	(0.05)	(0.06)
Tealbook Unemployment Forecast ($UE_{t,t+1}$)	-0.291***	-0.277***	-0.321***
	(0.04)	(0.04)	(0.05)
Lagged federal funds rate ($FFR_{t-1,t}$)	0.870***	0.868***	0.869***
	(0.02)	(0.02)	(0.02)
Composite Equity Index (ES_t)	-0.0479		
	(0.04)		
Baker-Wurgler Sentiment (BW_t)		-0.0251	
		(0.03)	
Cyclically-Adjusted P/E Ratio ($CAPE_t$)			-0.0694
			(0.05)
Constant	1.337***	1.228***	1.564***
	(0.19)	(0.19)	(0.28)
Obs.	175	175	175
R^2	0.982	0.982	0.982
Adj.	0.982	0.982	0.982

Standard errors in parentheses
***/**/* denote significance at the 1%, 5%, and 10% level, respectively
All equity-related variables are standardized

Notes: The dependent variable is $FFR_{t,t+1}$, the average value of the federal funds rate for a week following each FOMC meeting in the sample. $\pi^{\text{teal}}_{t,t+1}$ is the Tealbook forecast for inflation over the next year. $UE^{\text{teal}}_{t,t+1}$ is the four-quarter ahead Tealbook forecast for the U3 unemployment rate. $FFR_{t-1,t}$ is the lagged dependent variable. The composite equity sentiment index, ES_t, is an equally weighted average of the the standardized average level of the Baker-Wrugler sentiment index six weeks before each FOMC meeting, BW_t, and the standardized average level of the Cyclically-Adjusted Price-to-Earnings Ratio six weeks before each FOMC meeting, $CAPE_t$: $ES_t = \frac{1}{2}\left(\frac{(BW_t - \overline{BW})}{\sigma_{BW}} - \frac{(CAPE_t - \overline{CAPE})}{\sigma_{CAPE}}\right)$.

2.4 Time Variation in the Fed's Responsiveness to Credit Market Sentiment

Having established that credit market sentiment is a statistically significant predictor of the federal funds rate after accounting for expected inflation and unemployment, I examine whether the magnitude of the federal funds rate's sensitivity to credit markets varies over time.

Campbell et al. (2013) have argued that the Taylor Rule became more inertial after 2000, as the Fed transitioned from aiming for inflation stabilization in the Volcker era to emphasizing output stabilization. As a candidate explanation for this finding, Stein and Sunderam (2018) have argued that this increased inertia in the Fed's adjustment of monetary policy may reflect the Fed's greater concern for developments in financial markets: insofar as monetary policy makers are averse to excess market volatility, they may seek to adjust policy more gradually to avoid spooking out investors. This explanation is consistent with their empirical finding that the frequency of words related to financial stability[2] has risen substantially in a sample of FOMC transcripts from 1985 to 2011.

Since changes in investment account for a notable share of the volatility in output[3], and since investment is sensitive to credit market conditions, I hypothesize that a corollary of Campbell, Pflueger and Viceira's finding is that a Fed that is increasingly concerned with stabilizing output should also be increasingly attuned to developments in credit markets. To test this hypothesis, I estimate the credit-augmented Taylor rule for various sub-sample start dates between 1987 and 2002. In particular, I run a series of rolling regressions where the window size is set to the minimum of 10 years of data or the remaining data in the sample, so as to

[2]These words are "financial market", "equity market", "bond market", "credit market", "fixed income", and "volatility" (Stein and Sunderam, 2018, 100)

[3]While Gross Private Domestic Investment makes up approximately 18% of US GDP, it accounts for a significant portion of the percent change in GDP and therefore plays an important role in business cycle fluctuations.

accommodate sub-sample start dates in the early 2000s, where slightly less than 10 years of data are available. I opt for rolling rather than expanding windows for each regression in order to avoid an increased emphasis on particular events in the sample, even if this leads to larger average standard errors given the limited sample size used to estimate each rolling regression. To ensure that results are not driven by large and anomalous observations in the data (e.g., the Great Financial Crisis), I also remove outliers where credit sentiment exceeds two standard deviations from the mean from the sample. Finally, I plot each point estimate with its corresponding standard errors to indicate whether the effect that is being captured is statistically significant.

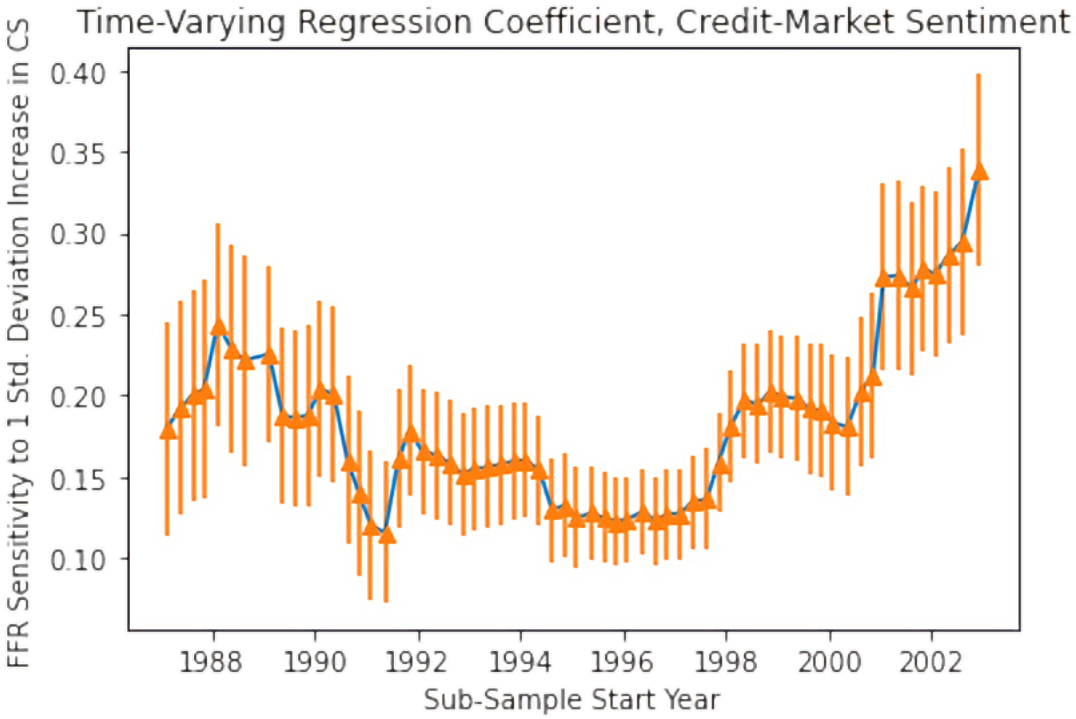


Figure 2.2: Time-Varying Sensitivity of the Federal Funds Rate to Credit Market Sentiment. This figure plots the point estimates, as well as the associated standard errors, for the regression coefficient associated with CS_t (the standardized credit index) in a series of rolling regressions of the form $FFR_{t,t+1} = \beta_0 + \beta_1 FFR_{t-1,t} + \beta_2 \pi_{t,t+1} + \beta_3 UE_{t,t+1} + \beta_4 CS_t + \epsilon_t$. Each rolling regression comprises the minimum of 10 years of data, or the remaining data in the sample. The x-axis notes the start of the sample used to generate the coefficient estimate for each rolling regression. The y-axis notes the magnitude of the regression coefficient, β_4, which reflects the response of the federal funds rate to a one-standard-deviation increase in CS_t, holding all else constant.

Figure 2.2 summarizes my findings. A few points are noteworthy. As with the initial estimation of the credit-augmented Taylor Rule, credit market sentiment is positively correlated with the federal funds rate, as we would expect. This effect is also statistically significant for all of the sub-samples in this analysis. Although the coefficient estimates are somewhat noisy for earlier sub-samples, we notice a general trend wherein the federal funds rate exhibits a positive and increasing sensitivity to credit market sentiment. In particular, the sensitivity of the federal funds rate to a one-standard-deviation increase in credit market sentiment nearly

doubles from an average of 15 basis-points for a sample beginning in 1992 and ending in 2002 to an average of almost 30-basis-points for a sample beginning in 2002. This sharp increase in the provides support for the hypothesis that the Fed has placed a greater emphasis on developments in credit markets in the latter half of the 1990's.

2.5 Analyzing the Drivers of Changes in the Conveyed Path of Monetary Policy

Thus far, we have documented that credit market sentiment contains incremental and statistically significant information on the level of the federal funds rate, after controlling for the Tealbook forecasts for inflation and unemployment. Thus, American monetary policy appears to have responded to financial stability concerns during the period studied in this paper. Another dimension through which we can analyze the interplay between monetary policy and financial stability is in differences rather than in levels.

Following a policy meeting, the FOMC shares their projected path of monetary policy with market participants. In essence, what policymakers are conveying to the market is their projected *forward curve* for the policy rate. To a first-order approximation, changes in short-term Treasury Bill rates reflect the market's expectation of the path of short-term interest rates. Hence, we can take changes in the 1-year Treasury Bill rate as reflecting changes in the expected path of monetary policy, as inferred by the market. The advantage of using short-term Treasury rates to proxy for changes in the path of policy is that these rates are traded actively, and therefore exhibit real-time variation. In contrast, the federal funds rate exhibits a high degree of inertia, which makes it less useful as an outcome variable if our purpose is to analyze the drivers of *changes* in the path of monetary policy. Indeed, within the sample, which runs from 1987-2008, the correlation between the federal funds rate

and the 1-Year Constant Maturity US Treasury Yield for observations sampled at every FOMC meeting is 97%. However, in the same sample, the correlation between changes in these two rates between FOMC meetings is of merely 56%. This behavior is consistent with the fact that (a) both interest rates closely track each other in levels throughout the sample, since short-term Treasury rates primarily reflect the expected path of monetary policy and (b) the federal funds rate exhibits less time variation than the 1-Year Treasury yield, since the former is a variable targeted by policymakers while the latter is an interest rate determined in equilibrium in an actively traded market.

Given this background, I estimate the regression defined by Equation 2.2:

$$\Delta r^{1-\text{year}}_{t-1,t} = \rho_0 + \rho_1 \Delta \pi^{\text{teal}}_{t-1,t} + \rho_2 \Delta UE^{\text{teal}}_{t-1,t} + \rho_3 \Delta CS^{*}_{t-1,t} + \gamma_t \tag{2.2}$$

Note that $t-1$ represents the date of the previous FOMC meeting and t represents the date of the current FOMC meeting: hence, we are estimating whether changes in the Tealbook forecasts for inflation and unemployment as well as changes in credit spreads between FOMC meetings serve as meaningful predictors of changes in the expected path of monetary policy over the same period. Importantly, I opt to use negated standardized credit spreads rather than my composite measure of credit market sentiment (which includes both standardized credit spreads and the standardized high-yield share) for this regression in first differences. That is, I define a new variable to capture credit sentiment:

$$CS^{*}_{t} = -\frac{\left(spread_t - \overline{spread}\right)}{\sigma_{spread}}$$

Much like the original measure that I use to proxy for credit market sentiment, this measure reflects how lower credit spreads are indicative of higher credit market sentiment. I use this updated measure of sentiment for all specifications in changes in this paper, because the high-yield share already captures the change in corporate

bond issuance to high-yield issuers over time; hence, including changes in high-yield share into the regression can lead to undesired second-order effects, as we would then capture the change-in-changes in high-yield bond issuance.

This specification allows us to shed light on two key questions:

1. Do changes in market expectations of the path of monetary policy following an FOMC meeting go above and beyond what would be implied by changes in the FOMC's projections for inflation and unemployment? For instance, are Fed Governors conveying a path of policy to the market that is more hawkish or more dovish than would be implied by changes in the Tealbook forecasts for inflation and unemployment alone? If the latter case holds, then we have another indication that policy makers may be factoring financial stability concerns into their communication of their expected path of policy to market participants, above and beyond how these financial stability concerns contribute to changes in the dual mandate variables.

2. As an additional robustness check, do changes in credit market sentiment remain a statistically significant predictor of changes in the expected path of policy, even after excluding outlier events from the sample? A benefit of specifying this regression in changes rather than in levels is that we can define an intuitive criterion for filtering large and potentially abnormal changes in credit sentiment from the sample in lieu of discretionarily removing these observations from the sample. In this paper, I define outlier events as any observation for which the meeting-over-meeting change in CS_t^* exceeds two standard deviations above or below the mean. This filtering rule removes eight observations from the sample, including—as desired—observations from periods of great financial turmoil during the Great Financial Crisis.

The results of this analysis are reported in Table 2.4. Columns (1) and (2) report the estimated regression coefficients over the whole sample and the filtered

sample, respectively. In both specifications, increases in the Tealbook inflation forecasts predict a rise in the expected path of policy, whilst the opposite holds true for increases in the Tealbook forecasts for unemployment. Furthermore, rising credit sentiment in the lead-up to an FOMC meeting is associated with an increase in the expected path of policy, above and beyond changes in the staff forecasts for the dual mandate variables. Coefficients from both specifications share the same sign and roughly the same magnitude, and the coefficients for the change in credit sentiment are both statistically significant at the 1% level. These findings suggest that the Fed may be communicating a path of policy to Treasury market participants that is influenced by financial stability considerations in addition to the evolving dynamics of its staff inflation and unemployment forecasts, and that the consistent predictive power of credit spreads (and, more broadly, of credit market sentiment) documented throughout this paper is not merely attributable to large and anomalous events in the sample.

Table 2.4: Estimation of the Drivers of Changes in the Conveyed Path of Monetary Policy, proxied by changes in the 1-Year T-Bill Rate, with Full Sample Results in Column (1) and Filtered Sample Results in Column (2)

	$\Delta r^{1-\text{year}}_{t-1,t}$	
	(1)	(2)
Change in Inflation Forecast ($\Delta\pi_{t,t+1}$)	0.218	0.278**
	(0.14)	(0.12)
Change in Unemployment Forecast ($\Delta UE_{t,t+1}$)	-0.338**	-0.430***
	(0.16)	(0.15)
Change in Composite Credit Index* ($\Delta CS^*_{t,t+1}$)	0.505***	0.795***
	(0.14)	(0.10)
Constant	-0.0103	-0.0297
	(0.02)	(0.02)
Obs.	175.000	167.000
R^2	0.36	0.42
Adj. R^2	0.35	0.41

Standard errors in parentheses

***/**/* denote significance at the 1%, 5%, and 10% level, respectively

Notes: The dependent variable is $\Delta r^{1-\text{year}}_{t-1,t}$, the change in the 1-year Treasury Bill Rate between FOMC meetings. $\Delta\pi_{t,t+1}$ is the between-meeting-change in the Tealbook forecast for inflation over the next year. $\Delta UE_{t,t+1}$ is the change in the four-quarter ahead Tealbook forecast for the U3 unemployment rate between FOMC meetings. $FFR_{t-1,t}$ is the lagged dependent variable. $CS^*_t = -\frac{(spread_t - \overline{spread})}{\sigma_{spread}}$ is the change in an adjusted credit sentiment index, which reflects information on credit spreads, between FOMC meetings. Column (1) contains the results of the regression estimated over the full sample, while Column (2) contains the results estimated over a sample which excludes observations for which $\Delta CS^*_{t,t+1}$ exceed two standard deviations from the mean.

2.6 Assessing Dynamics: Responses to Rising and Falling Sentiment

Thus far, the analysis in this paper has documented a strong historical relationship, both in levels and in changes, between credit market sentiment and monetary policy in the United States. However, we may wonder whether the Federal Open Markets Committee has responded both to periods where credit market sentiment was falling and to periods where it was rising. In particular, I am interested in examining whether monetary policy has exhibited a prudential dimension, in the sense that central bankers have responded to increases in financial stability concerns by tightening monetary policy beyond what was warranted by the evolution of inflation and unemployment. In this section, I outline two approaches that could be used to shed light on this question.

The first approach is to split the data on US monetary policy into two distinct samples, depending on whether credit market sentiment increased or decreased between the FOMC meeting at time $t-1$ to the current meeting at time t. Discerning differences in the Fed's response to rising and falling credit market sentiment would then merely involve re-estimating regressions from previous sections, separately for each sub-sample, and interpreting the coefficient associated with credit market sentiment in each regression accordingly.

However, we may wish to estimate a single set of regression coefficients for the effects of changes in inflation and unemployment on the T-Bill rate across the entire sample, rather than allowing these coefficients to vary by sub-sample. To achieve this, we can leverage an alternative regression specification which includes interaction effects between an indicator random variable for rising credit market sentiment and the absolute value of the change in credit market sentiment, as specified in Equation 2.3:

$$\Delta r_{t-1,t}^{1-\text{year}} = \kappa_0 + \kappa_1 \Delta \pi_{t-1,t}^{\text{teal}} + \kappa_2 \Delta UE_{t-1,t}^{\text{teal}} + \kappa_3 \mathbb{1}(\Delta CS_{t-1,t}^{*} > 0) \cdot |\Delta CS_{t-1,t}^{*}| + \kappa_4 (1 - \mathbb{1}(\Delta CS_{t-1,t}^{*} > 0)) \cdot |\Delta CS_{t-1,t}^{*}| + \Gamma_t \tag{2.3}$$

Note that if Equation 2.3 also included interaction terms between changes in inflation and unemployment and our indicator variable for rising credit market sentiment, then the results of this approach would coincide with those of the sub-sample approach detailed above.

The regression results for this specification are summarized in Table 2.5. Column (1) reports the results over the whole sample, while column (2) filters out observations where the change in sentiment exceeds two standard deviations above or below the mean. Across both samples, changes in the Tealbook forecasts for inflation are associated with an increase in the path of policy as captured by the 1-year Treasury Bill rate, while the opposite holds true for changes in the Tealbook forecast for unemployment. These coefficients are statistically significant across samples, and their signs concord with economic intuition, as discussed in Section 2.5. We also observe that rising credit sentiment is associated with a rising path of monetary policy, holding fixed the effects of changing inflation and unemployment forecasts. This effect is statistically significant at the 1% level. Similarly, periods of falling credit market sentiment are associated with a falling path of monetary policy, although this effect is only statistically significant in the sample which omits outliers[4].

Jointly, these results convey that the sensitivity of monetary policy to credit market sentiment is not merely one-sided, as we might have expected if policymakers had only been responding to periods of significant economic turmoil via a series of

[4]Rate hikes often occur gradually, while rate cuts can occur switfly during periods of economic distress. The policy rate may therefore exhibit higher variance during periods where credit market sentiment is falling, which may in turn explain why the standard errors associated with the regression coefficients for falling credit market sentiment are larger than those associated with rising credit market sentiment.

swift interest rate cuts. While this regression does demonstrate that the policy rate tends to fall as credit sentiment weakens, the data is also conveying that the Fed appears to have leaned against the wind, given that periods of rising sentiment have independent explanatory power for explaining increases in the 1-year Treasury Bill rate, even after controlling for changes in the Fed's dual mandate variables.

Table 2.5: Estimation of the Dynamics of the Fed's Response to Rising and Falling Credit Market Sentiment

	$\Delta r_{t-1,t}^{1-\text{year}}$	
	(1)	(2)
Change in Inflation Forecast ($\Delta\pi_{t,t+1}$)	0.230*	0.272**
	(0.13)	(0.12)
Change in Unemployment Forecast ($\Delta UE_{t,t+1}$)	-0.465***	-0.401**
	(0.15)	(0.16)
$\mathbb{1}(\Delta CS^*_{t-1,t} > 0) \cdot \lvert\Delta CS^*_{t-1,t}\rvert$	1.049***	0.650***
	(0.16)	(0.16)
$(1 - \mathbb{1}(\Delta CS^*_{t-1,t} > 0)) \cdot \lvert\Delta CS^*_{t-1,t}\rvert$	-0.210	-0.946***
	(0.18)	(0.20)
Constant	-0.098***	-0.003
	(0.04)	(0.03)
Obs.	175.000	167.000
R^2	0.41	0.42
Adj. R^2	0.40	0.41

Standard Errors in parentheses

***/**/* denote significance at the 1%, 5%, and 10% level, respectively

Notes: The dependent variable is $\Delta r_{t-1,t}^{1-\text{year}}$, the change in the 1-year Treasury Bill Rate between FOMC meetings. $\Delta\pi_{t,t+1}$ is the between-meeting change in the Tealbook forecast for inflation over the next year. $\Delta UE_{t,t+1}$ is the change in the four-quarter ahead Tealbook forecast for the U3 unemployment rate between FOMC meetings. $CS^*_t = -\frac{(spread_t - \overline{spread})}{\sigma_{spread}}$ is the change in an adjusted credit sentiment index, which reflects information on credit spreads, between FOMC meetings. $\mathbb{1}(\Delta CS^*_{t-1,t} > 0) \cdot |\Delta CS^*_{t-1,t}|$ and $(1 - \mathbb{1}(\Delta CS^*_{t-1,t} > 0)) \cdot |\Delta CS^*_{t-1,t}|$ are two interaction terms between an indicator random variable, which equals 1 if sentiment increased between FOMC meetings and 0 otherwise, and the magnitude of the change in the adjusted credit sentiment over the same period.

2.7 Robustness Tests

In this section, I briefly document some robustness tests performed on the results established in Section 2.

2.7.1 Excluding Outliers

As outlined in Section 2.5, I analyze whether changes in credit market sentiment remain statistically significant predictors of changes in the expected path of policy, as inferred by changes in the 1-Year Treasury Bill Rate between FOMC meetings, if we exclude observations which exhibit large variations in credit market sentiment from the sample. Column (2) of Table 2.4 relates these results. Eight observations in the sample contain changes in credit market sentiment which exceed two standard deviations from the mean, and these include notable periods of financial distress such as the Great Financial Crisis. After excluding these observations, changes in credit market sentiment are still positive and statistically significant predictors of changes in the 1-Year Treasury Bill Rate. This provides strong evidence that the relationship between monetary policy and credit market sentiment uncovered in this paper is not merely attributable to a few outlier observations. In 2.6, I repeat this exercise by estimating the regression in Equation 2.3 both over the full sample and for a sub-sample that excludes observations where credit market sentiment exceeds two standard deviations from the mean. Columns (2) of Table 2.5 reports these results for the sub-sample which excludes outliers, and indicates that the prudential pattern to policy uncovered in this paper—wherein rising credit market sentiment predicts a rising path of monetary policy, controlling for changing inflation and unemployment forecasts—remains even after omitting periods of significant credit market volatility from the sample.

2.7.2 Augmented Inflation and Unemployment Forecasts

When estimating the Taylor rule augmented with credit market sentiment in Table 2.2, an important assumption is that the Tealbook forecasts for inflation and unemployment are informationally efficient. In other words, FOMC members must believe that these forecasts adequately account, to the degree that is possible ex-ante, for the effects that financial stability could exert on near-term inflation and unemployment. There are various reasons to believe that this assumption is reasonable. From a positive standpoint, the Tealbook forecasts are produced by economists at the Board of Governors of the Fed, and they serve as the main point of reference for Fed Governors as they decide the path of policy; as such, it is plausible to assume that FOMC members simply rely on the information of their professional staff of forecasters without discretionarily overriding or adjusting their forecasts. From a normative standpoint, Svensson (1998) argues that the role of FOMC members is to select the socially optimal path of monetary policy within a menu of options, *taking staff forecasts of various macroeconomic outcomes as given*. Romer and Romer (2008) lend credence to this position by finding that the forecasts of key macroeconomic variables produced by members of the FOMC between 1979 and 2001 (and released in the Fed's Monetary Policy Report) did not contain useful information in excess of the Board's staff forecasts. Policymakers may therefore believe that it is not part of their responsibility to serve in the business of forecasting.

Nevertheless, it is possible that FOMC members treat the Tealbook forecasts as incomplete estimates of inflation and unemployment. If this is the case, then the significance of the coefficients associated with credit market sentiment may merely reflect the fact that FOMC members are using information on financial stability to improve the Tealbook forecasts for inflation and unemployment, rather than to tend to potential financial stability concerns.

To examine this possibility, I construct adjusted inflation and unemployment forecasts, which I allow to directly incorporate information credit market senti-

ment. Then, I estimate the Credit-Augmented Taylor rule anew, this time using the augmented forecasts for inflation and unemployment, to determine whether the statistically significant and positive relationship between credit market sentiment and the federal funds rate is preserved even after allowing credit market sentiment to directly bolster forecasted inflation and unemployment.

To construct these adjusted forecasts, I regress realized inflation and unemployment on a constant, their Tealbook counterparts, and credit market sentiment. Specifically, I run a series of rolling regressions of the following form:

$$\pi_j^{\text{realized}} = \alpha_0 + \alpha_1 \pi_j^{\text{teal}} + \alpha_2 CS_j + \eta_j, \forall j < t \tag{2.4}$$

$$UE_j^{\text{realized}} = \gamma_0 + \gamma_1 UE_j^{\text{teal}} + \gamma_2 CS_j + \psi_j, \forall j < t \tag{2.5}$$

Then, using these regressions, I produce fitted values for augmented inflation and unemployment forecasts for each FOMC meeting in the sample. Intuitively, my procedure replicates the approach an FOMC member can take if they wish to augment the Tealbook forecasts for a given meeting. Namely, they can observe all the instantiations of credit market sentiment and the realizations and forecasts for inflation and unemployment that fall before the FOMC meeting they are attending, run the regressions in Equation 2.4 and Equation 2.5, and then produce fitted inflation and unemployment forecasts, $\hat{\pi}_t$ and $\hat{UE}_t$, using the time t values of π_t^{teal},$UE_{t,t+1}^{\text{teal}}$ and CS_t provided by their staff.

I use a series of rolling regressions, rather than two whole-sample auxiliary regressions for fitted inflation and unemployment, to avoid issues with forward-looking bias that would arise if I allowed information from future monetary policy meetings to affect the regression coefficients used to generate fitted forecast values for earlier policy meetings. Furthermore, as with the Tealbook forecasts themselves, I move from collecting realizations of Core CPI to realizations of Core PCE as of the December 2005 FOMC meeting. The first fitted value is constructed using the first

40 observations in the sample, and subsequent fitted values are estimated using an expanding window of data. For comparability, I also present the results of this exercise alongside the baseline Credit-Augmented Taylor Rule estimated over the same interval.

Table 2.6 summarizes the results of this exercise, where Column (1) relates the results using the Tealbook forecasts and Column (2) relates the results using the augmented forecasts for inflation and unemployment. In both regressions, inflation, unemployment, and the lagged federal funds rate are statistically significant at the 1% level and preserve the same signs and relative magnitudes. Crucially, even after allowing inflation and unemployment forecasts to directly incorporate information on credit market sentiment, higher credit market sentiment is still associated with an independently positive and statistically significant effect on the federal funds rate. However, the magnitude of the effect is reduced, since we are allowing the forecasts to soak up some of the explanatory power of credit market sentiment as a stand-alone variable: a one-standard-deviation increase in credit market sentiment is now associated with a 6-basis-point increase in the federal funds rate, ceteris paribus. This result therefore provides compelling evidence that the relationship uncovered in this paper between credit market sentiment and the federal funds rate is robust, and that it is not merely due to FOMC members using information on financial stability to enhance their forecasts for inflation and unemployment.

Table 2.6: Estimation of the Credit-Augmented Taylor Rule, with Tealbook Forecasts in Column (1) and Augmented Forecasts in column (2), 1992-2008

	Federal Funds Rate $FFR_{t,t+1}$	
Covariates	(1)	(2)
Constant	0.74***	0.94***
	(0.18)	(0.28)
Inflation Forecast ($\pi_{t,t+1}$)	0.33***	0.24***
	(0.062)	(0.083)
Unemployment Forecast ($UE_{t,t+1}$)	-0.20***	-0.21***
	(0.035)	(0.068)
Lagged federal funds rate ($FFR_{t-1,t}$)	0.88***	0.90***
	(0.019)	(0.023)
Composite Credit Index (CS_t)	0.17 ***	0.06**
	(0.027)	(0.030)
Obs	134	135
R^2	0.983	0.982

***/**/* denote significance at the 1%, 5%, and 10% level, respectively

Column (1) uses Tealbook forecasts; Column (2) uses augmented forecasts

Notes: The dependent variable is $FFR_{t,t+1}$, the average value of the federal funds rate for a week following each FOMC meeting in the sample. $\pi_{t,t+1}$ is a forecast for inflation over the next year. $UE_{t,t+1}$ is a four-quarter ahead forecast for the U3 unemployment rate. $FFR_{t-1,t}$ is the lagged dependent variable. The composite credit sentiment index, CS_t, is an equally weighted average of the standardized high-yield share, HYS, and the standardized average level of Baa credit spreads six weeks before each FOMC meeting, $spread_t$: $CS_t = \frac{1}{2}\left(\frac{(HYS_t - \overline{HYS})}{\sigma_{HYS}} - \frac{(spread_t - \overline{spread})}{\sigma_{spread}}\right)$. In Column (1), $\pi_{t,t+1}$ and $UE_{t,t+1}$ correspond to the Tealbook forecasts for inflation and unemployment, respectively. In Column (2), $\pi_{t,t+1}$ and $UE_{t,t+1}$ correspond to augmented inflation and unemployment forecasts, which blend information from the Tealbook forecasts with realizations of CS_t according to a series of rolling regressions.

2.8 Discussion

In summary, this chapter has documented, through various angles, the sensitivity of the Federal Reserve's monetary policy to financial stability considerations, above and beyond the Federal Open Market Committee's responsiveness to their dual mandate variables of inflation and unemployment.

Importantly, these findings are robust to a variety of potential objections. First, the fact that both declining *and* rising credit market sentiment foreshadow corresponding decreases and increases in the path of policy suggests that the sensitivity of the federal funds rate to credit market sentiment is not merely one-sided, as one might have expected if they believed that policymakers only used monetary policy to respond to adverse developments in financial markets. Second, the fact that monetary policy remains sensitive to credit market sentiment even after large outliers are removed from the analysis indicates that the effects captured in this paper are not merely attributable to a few anomalous occurrences like the Great Financial Crisis. Finally, the findings in this paper withstand the potential objection that credit market sentiment may only be statistically significant in a Taylor-like rule because policymakers are using credit-related information to improve their near-term forecasts of inflation and unemployment. Even if we control for augmented inflation and unemployment forecasts which I bolster with real-time information on credit market sentiment, our credit-related proxy for financial stability considerations still remains an independent, statistically significant predictor of the level of the federal funds rate.

These descriptive findings indicate that the behavior of the Federal Open Markets Committee from 1987 to 2008 is at odds with the mainstream narrative upheld by proponents of the fully-separable view, according to which monetary policy should not respond to financial stability concerns beyond their effects on near-term output and inflation. Surprisingly, the behavior exhibited by central bankers at the Fed instead aligns with the approach to conducting monetary policy advocated for

by proponents of the non-separable view. In particular, the Federal Open Markets Committee does not appear to indiscriminately respond to developments in asset markets: instead, they only appear to *lean against credit*, as they are responsive to credit market sentiment but not to equity market sentiment. This is consistent with the fact that only the former proxy for financial stability is robustly identified in the literature as being informative of reversal risk and future crises.

Chapter 3

Theory and Model

In this final chapter, as outlined in the introduction, I move to a distinct theoretical exercise and delineate a stylized model geared at answering the following questions about the optimal conduct of monetary policy in an environment where agents deviate from rational expectations:

1. How does the optimal interest rate set by the central bank change as they become increasingly uncertain the behavioral biases of households and, by extension, about whether current asset prices reflect exuberance or a rational pricing of strong fundamentals?

2. Can central banks increase expected utility by increasing interest rates to quell exuberance in financial markets?

3.1 Model Setup

The model has two periods, $t \in \{0, 1\}$, and a single type of agent, households, present in measure 1. There are two types of assets that households can purchase at $t = 0$: a safe asset, and a risky asset which pays a stochastic dividend at $t = 1$. The central bank sets the safe interest rate from period 0 to period 1 as a policy variable. For

the purposes of interpreting this environment, the risky asset can be thought of as a debt instrument, for instance corporate bonds or mortgage-backed securities.

Preferences

Households have CRRA utility over consumption in both periods $t = 0$ and $t = 1$. Denoting time t consumption by c_t and the time discount factor by β, we have the following utility function:

$$U(c_0, c_1) = \mathbb{E}_0[U(c_0) + \beta U(c_1)] \tag{3.1}$$

$$U(C) = \begin{cases} \frac{C^{1-\rho}}{1-\rho} & \text{if } \rho > 1, \\ \log C & \text{if } \rho = 1. \end{cases} \tag{3.2}$$

Where the parameter ρ captures both risk aversion and the intertemporal elasticity of substitution. In the first section of this chapter, I solve the model for the special case of log utility ($\rho = 1$), similarly to Fontanier (2021). This specification is more tractable, and lends itself more readily to analysis. For completeness[1], I subsequently solve the model for the more general case where $\rho \neq 1$.

The particular way in which households form their beliefs when taking expectations is described in more detail in upcoming sections.

Financial Assets

This economy has two financial assets. First, there is a safe asset, which provides a known gross rate of return $R^s = e^{r^s}$ to agents from $t = 0$ to $t = 1$. The central bank sets this interest rate as a policy variable. Second, there is a risky asset, which provides a stochastic return which crystallizes at $t = 1$. This asset has log-normally distributed gross returns[2], $R^r > R^s$, such that $\log(R^r) \equiv r^r \sim \mathcal{N}(\overline{r^r} - \frac{\sigma_r^2}{2}, \sigma_r^2)$, where

[1] As Campbell (2018, 11) notes, log utility has many convenient properties, but relative risk aversion of 1 is hard to square with historical risk premia in the United States.

[2] One benefit of using a log-normal distribution is that its support is defined only over non-negative real values. This ensures that gross returns are non-negative, which must hold in practice

the mean and variance parameters are exogenous constants. The risky asset can be thought of as a storage technology in the economy which agents can invest in at will. Shares of this asset are available in perfectly elastic supply—for example, we can imagine they are supplied by entrepreneurs with a linear production technology—such that price and expected return are fixed while the quantity supplied adjust as a function of demand from households.

Importantly, the mean of the normally-distributed net returns of the risky asset r^r is chosen so that changing the variance of the asset, σ_r^2, does not change its expected return, which is $\mathbb{E}[R^r] = e^{\overline{r^r}}$[3].

As noted by Carroll (2021), we can define the the risk-premium in this two-asset economy (in logs) as:

$$\begin{aligned}\eta = \log(R^r - R^s) &= r^r - r^s + \frac{\text{Var}(r^r)}{2} \\ &= r^r - r^s + \frac{\sigma_r^2}{2}\end{aligned}$$

where the term $\frac{\sigma_r^2}{2}$ accounts for the fact that, via Jensen's inequality, the logarithm of the risk premium exceeds the difference between the logarithms of the safe and risky rates.

Constraints

Households faces two flow budget constraints. In the first period, they are endowed wealth y_0. The central bank implements a proportional income tax in Period 0, which leaves the household with a wealth of $y_0(1-\tau)$ which they can allocate to three different purposes: consumption at $t = 0$, saving via the safe asset, and saving via the risky asset. The motivation for the assumption of a tax imposed by the central bank is discussed in more detail in subsequent sections detailing the planner's

given the existence of the principle of limited liability.

[3]Recall that if $X \sim \mathcal{N}(\mu, \sigma^2)$, then e^X is log-normally distributed, and $\mathbb{E}[e^X] = e^{\mu + \frac{\sigma^2}{2}}$.

problem. In the second period, household consumption is simply the value of their savings multiplied by their portfolio's gross return, $(R^s + (R^r - R^s)\gamma) = R^P$:

$$y_0(1-\tau) = c_0 + a_0, \tag{3.3}$$

$$\begin{aligned} c_1 &= a_0(R^s + (R^r - R^r)\gamma) \\ &= a_0 R^P. \end{aligned} \tag{3.4}$$

Beliefs

In this model, households and the central bank have different beliefs about the distribution of the log risky asset return, $r^r = \log(R^r)$. In line with Fontanier (2021), I model this divergence in beliefs by allowing a wedge term, Ω, to enter their respective distributions of beliefs about the return of the risky asset in the economy—and, in turn, their beliefs about the risk-premium afforded by this asset over the safe asset. In particular, I model the household and the central bank's perceptions about the risky asset's log return as a simple linear combination of the true risky asset return and their respective wedge terms.

In the case of the household, Ω_{HH} captures the behavioral biases of households: that is, the degree to which they overstate the return of the risky asset. I denote this quantity the *behavioral wedge*. For example, if $\Omega_{\text{HH}} > 0$, then households are over-optimistic about the prospects of the economy's risky asset. This parameter is designed to capture a whole class of possible behavioral deviations from rationality. For instance, if households form extrapolative beliefs about the risky asset's future returns, as in Farhi and Werning (2019), then the behavioral wedge could be modelled in closed-form as $\Omega_{\text{HH}} = \alpha(R^r_t - R^r_{t-1})$, as discussed by Fontanier (2021), where α is a parameter guiding the degree of extrapolation. In such a case, households would deviate from rational expectations when pricing the risky asset at t (by overstating the likelihood of an increase in the asset return from t to $t+1$) if the return of the risky asset increased from $t-1$ to t. For the configuration of

the model that I examine in this paper, I model Ω_{HH} as a positive constant: the household overestimates the return of the risky asset, as they believe with complete confidence that $\Omega_{HH} = \kappa > 0$. We have:

$$r^r_{HH} = r^r + \Omega_{HH}, \tag{3.5}$$

$$r^r_{HH} \sim \mathcal{N}(\overline{r^r} + \kappa - \frac{\sigma_r^2}{2}, \sigma_r^2). \tag{3.6}$$

In the case of the central bank, Ω_{CB} is a random variable that captures the central bank's overall degree of optimism as well as their uncertainty about households' behavioral biases, and by extension their uncertainty about the return of the risky asset. Indeed, while the central bank can observe the demand of households for the risky asset, they are uncertain about whether this demand reflects over-optimism from households or the truth about the generating process of the risky asset return. As such, as they become more uncertain about how behaviorally biased households are, they also become increasingly uncertain about the return profile afforded by the risky asset. In particular, I define Ω_{CB} as being normally distributed with the following mean and variance parameters: $\Omega_{CB} \sim \mathcal{N}(\mu_\Omega - \frac{\sigma_\Omega^2}{2}, \sigma_\Omega^2)$. Similarly to the definition of r^r, the $-\frac{\sigma_\Omega^2}{2}$ term in the mean of Ω_{CB} is included to ensure that the central bank's expectation of the risky asset return, $\mathbb{E}[e^{r^r_{CB}}] = e^{\bar{r}_r + \mu_\Omega}$, does not vary as a function of σ_r or σ_Ω. This will be especially important when analyzing comparative statics with respect to σ_Ω.

Given this convenient choice of distributions, r^r_{CB} is a convolution of normal random variables, and is hence itself normally distributed. For instance, if $\mu_\Omega = 0$ and $\sigma_\Omega \neq 0$, then the central bank is correct about the risky asset's mean return on average (they are neither optimistic nor pessimistic), as $\mathbb{E}[r^r_{CB}] = \mathbb{E}[r^r]$. However, given their uncertainty surrounding Ω_{CB}, their perceived distribution of the risky asset return will have a higher variance than that of the true generating process.

We have:

$$r^r_{\text{CB}} = r^r + \Omega_{\text{CB}}, \tag{3.7}$$

$$r^r_{\text{CB}} \sim \mathcal{N}(\overline{r^r} + \mu_\Omega - \frac{\sigma_r^2 + \sigma_\Omega^2}{2}, \sigma_r^2 + \sigma_\Omega^2). \tag{3.8}$$

Figure 3.1 displays the distribution of beliefs of the household and the central bank for one particular configuration of the model, where $0 < \mu_\Omega < \kappa$. The black distribution represents the true underlying distribution of the risky asset, as determined by the exogenous parameters $\bar{r^r}$ and σ_r. The blue and red distributions reflect the risky asset's distribution of returns, as perceived by the central bank and the household, respectively. In this example, since both households and the central bank are over-optimistic about the return on the risky asset, their mean belief about the risky asset return exceeds the mean of the true return distribution. Furthermore, since $\kappa > \mu_\Omega$, the central bank has a more pessimistic view of the mean risky asset return than households. Finally, since Ω_{HH} is modelled as a constant, the household's distribution of beliefs about the risky asset has the same variance as the distribution of the true risky return; since the central bank faces added uncertainty about the risky asset return via Ω_{CB}, its overall distribution of beliefs exhibits a higher variance.

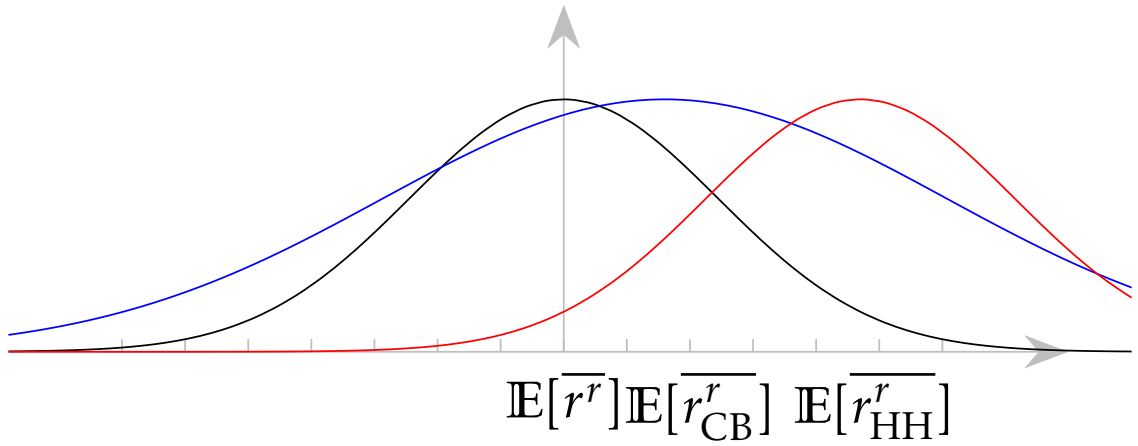


Figure 3.1: Risky Asset Return Distributions: This figure plots various distributions associated with the return of the economy's risky asset for a particular configuration of beliefs. In this example, the central bank and the household are both overoptimistic about the mean risky asset return, with the household's mean belief exceeding the central bank's mean belief. The black curve plots the distribution of r^r, the true distribution of the log risky asset return, as determined by the production technology in the economy. The blue curve plots the distribution of r^r_{CB}, the risky asset return as perceived by the central bank. The red curve plots the distribution of r^r_{HH}, the risky asset return as perceived by the household.

Having defined the differing beliefs of the household and the central bank vis-à-vis the risky asset, we can finally express their respective beliefs about the log risk premium afforded by the risky asset, which is ultimately the quantity that will drive their expectations of second-period utility from consumption. Namely, since the log risk premium is simply a linear combination of the log risky asset return

and constants, it will also be normally distributed:

$$\begin{aligned}
\tilde{\eta}_{\text{HH}} &\sim \mathcal{N}\left(\mathbb{E}[r^r_{\text{HH}}] - r^s + \frac{\text{Var}(r^r_{\text{HH}})}{2}, \text{Var}(r^r_{\text{HH}})\right) \\
&\sim \mathcal{N}\left(r^r + \kappa - r^s, \sigma_r^2\right) \\
&\sim \mathcal{N}\left(\eta^{\text{HH}} - \frac{\sigma_r^2}{2}, \sigma_r^2\right)
\end{aligned} \tag{3.9}$$

$$\begin{aligned}
\tilde{\eta}_{\text{CB}} &\sim \mathcal{N}\left(\mathbb{E}[r^r_{\text{CB}}] - r^s + \frac{\text{Var}(r^r_{\text{CB}})}{2}, \text{Var}(r^r_{\text{CB}})\right) \\
, \qquad &\sim \mathcal{N}\left(r^r + \mu_\Omega - r^s, \sigma_r^2 + \sigma_\Omega^2\right) \qquad , \\
&\sim \mathcal{N}\left(\eta^{\text{CB}} - \frac{\sigma_r^2 + \sigma_\Omega^2}{2}, \sigma_r^2 + \sigma_\Omega^2\right)
\end{aligned} \tag{3.10}$$

where I introduce the following constant quantities, η^{HH} and η^{CB}, in the expressions for the distributions of $\tilde{\eta}_{\text{HH}}$ and $\tilde{\eta}_{\text{CB}}$ for notational simplicity:

$$\eta^{\text{HH}} = \log \mathbb{E}^{\text{HH}}(e^{\eta}) = \mathbb{E}^{\text{HH}}[\eta] + \frac{\sigma_r^2}{2} = \bar{r^r} + \kappa - r^s + \frac{\sigma_r^2}{2}, \tag{3.11}$$

$$\eta^{\text{CB}} = \log \mathbb{E}^{\text{CB}}(e^{\eta}) = \mathbb{E}^{\text{CB}}[\eta] + \frac{\sigma_r^2 + \sigma_\Omega^2}{2} = \bar{r^r} + \mu_\Omega - r^s + \frac{\sigma_r^2 + \sigma_\Omega^2}{2} \tag{3.12}$$

These terms will figure regularly in subsequent sections of this chapter.

3.2 The Special Case of Logarithmic Utility

3.2.1 Household Maximization Problem

Households seek to maximize their expected utility from consumption over two periods by jointly selecting a_0, the amount of their endowed wealth they choose to save at $t = 0$, and γ, the share of their savings which they allocate to the economy's risky asset. These two choices in turn determine c_0 and c_1, the consumption bundles over the two periods of the model. I find these quantities by solving the following constrained maximization problem. The household's problem is inspired by Merton

and Samuelson's portfolio choice problem with CRRA utility, where households select the optimal share of their endowed wealth to invest in an economy with two assets (Campbell, 2018; Carroll, 2021). However, in my model, rather than solving a static portfolio-choice problem, the household additionally selects its level of savings in the first period of the model endogenously. The maximization problem therefore takes the following form:

$$\begin{aligned} \underset{a_0,\gamma}{\text{maximize}} \quad & U(C_0) + \beta \mathbb{E}[U(C_1)] \\ \text{subject to} \quad & y_0(1-\tau) = c_0 + a_0, \\ & c_1 = a_0(R^s + (R^r - R^s)\gamma). \end{aligned}$$

Substituting for the log utility function and the flow budget constraints, the problem becomes:

$$\underset{a_0,\gamma}{\text{maximize}} \quad \log(y_0(1-\tau) - a_0) + \beta \mathbb{E}^{\text{HH}}[\log(a_0 R^P)]$$

Since the portfolio return R^P is a linear combination of a log-normally-distributed risky return and the risk-free rate of interest, and convolutions of log-normal random variables are not log-normally distributed, R^P does not have a simple, known distribution. Hence, the expectation term $\mathbb{E}^{\text{HH}}[\log(a_0 R^P)]$ may at first appear analytically intractable. However, Campbell and Viceira (2002) highlight that we can make substantial progress on simplifying expectations of this kind by noting that for many distributions, the log of the portfolio return, $r^P = \log(R^P)$, can be well approximated by the following relationship[4]:

[4]The derivation for this expression is in Section 2.1 of Campbell and Viceira (2002). Intuitively, it is a second-order Taylor approximation, and it expresses that the "log excess portfolio return takes the same form as the simple excess portfolio return, with an adjustment factor in the variance of the risky asset return" (Campbell and Viceira, 2002, 2).

$$r^P \approx r^s + \gamma\eta + \gamma\frac{\text{Var}(r^r)}{2} - \gamma^2\frac{\text{Var}(r^r)}{2} \tag{3.13}$$

$$= r^s + \gamma\eta + \gamma\frac{\sigma_r^2}{2} - \gamma^2\frac{\sigma_r^2}{2} \tag{3.14}$$

Using this approximation for the log portfolio returns generates a tractable expectation in the household's maximization problem:

$$\begin{aligned}
\mathbb{E}^{\text{HH}}[\log(a_0 R^P)] &\approx \mathbb{E}^{\text{HH}}[\log(a_0 e^{r^P_{\text{HH}}})] \\
&= \mathbb{E}^{\text{HH}}[\log(a_0) + r^P_{\text{HH}}] \\
&= \log(a_0) + \mathbb{E}^{\text{HH}}[r^s + \gamma\tilde{\eta}_{\text{HH}} + \gamma\frac{\sigma_r^2}{2} - \gamma^2\frac{\sigma_r^2}{2}] \\
&= \log(a_0) + \mathbb{E}^{\text{HH}}[r^s + \gamma\tilde{\eta}_{\text{HH}} + \gamma(1-\gamma)\frac{\sigma_r^2}{2}] \\
&= \log(a_0) + r^s + \gamma(1-\gamma)\frac{\sigma_r^2}{2} + \gamma\mathbb{E}^{\text{HH}}[\tilde{\eta}_{\text{HH}}] \\
&= \log(a_0) + r^s + \gamma(1-\gamma)\frac{\sigma_r^2}{2} + \gamma\left(\eta^{\text{HH}} - \frac{\sigma_r^2}{2}\right),
\end{aligned}$$

where, in the final step, we note from Equation 3.9 that the risk premium as perceived by the household is normally distributed with mean $\eta^{\text{HH}} - \frac{\sigma_r^2}{2}$.

The approximated formulation of the household's problem therefore simplifies to:

$$\underset{a_0,\gamma}{\text{maximize}} \quad \log(y_0(1-\tau) - a_0) + \beta\left(\log(a_0) + r^s + \gamma(1-\gamma)\frac{\sigma_r^2}{2}\right) + \beta\gamma\left(\eta^{\text{HH}} - \frac{\sigma_r^2}{2}\right) \tag{3.15}$$

Equilibrium Endogenous Quantities

Taking first-order conditions generates the following equilibrium quantities for the representative household, as a function of the model's exogenous parameters:

$$\gamma^* = \frac{\eta^{\text{HH}}}{\sigma_r^2} = \frac{\bar{r^r} + \kappa - r^s + \frac{\sigma_r^2}{2}}{\sigma_r^2}, \tag{3.16}$$

$$a_0^* = \frac{\beta(1-\tau)y}{\beta+1}, \tag{3.17}$$

$$c_0^* = y_0(1-\tau) - a_0^*, \tag{3.18}$$

$$c_1^* = a_0^*(R^s + (R^r - R^r)\gamma^*). \tag{3.19}$$

Second-order conditions were verified. The optimal portfolio share takes the canonical form of a CRRA–Log-Normal portfolio allocation problem. It is rising in the log of the expected risk premium and declining in the variance of the risky asset. Second, because of the assumption that the risky asset return is provided in perfectly elastic supply and is a random variable with a fixed mean and variance, changing the safe rate of interest affects the risk premium, and $\frac{\partial \gamma^*}{\partial R^s} = -\frac{1}{R\sigma_r^2}$, reflecting that an increase in the safe rate of return reduces the share of savings that the household allocates to the risky asset.

Moreover, if we set the rate of time preference $\beta = 1$, then the household saves exactly half of their after-tax income. Finally, $\frac{\partial a^*}{\partial R^s} = 0$: since income and substitution effects are perfectly offset in the case of logarithmic utility, changing the safe rate of interest offered by the central bank does not influence the household's optimal savings allocation. Eventually, when we move to analyzing the problem when $\rho \neq 1$, changes in the policy rate will also affect $a0^*$, leading to more subtle dynamics.

3.2.2 The Central Bank's Problem

The central bank in this model sets the policy tool, the safe interest rate R^s, in order to maximize the expected utility of households, taking the household's maximization problem, which depends on this safe rate of interest, as given. In this paper, I focus on the case where $\kappa > \mu_\Omega$, which I denote the *exuberant case*. In this starting configuration of the model, households are more optimistic about the risky asset than the central bank, and this disagreement sets the stage for investigating the potency of prudential monetary policy.

Importantly, and as discussed in the section on beliefs, the central bank can observe household behavior, but they are uncertain about whether households are acting rationally or behaviorally deciding how much of the risky asset to hold. By extension, this makes the central bank more uncertain about the risky asset's return profile. This uncertainty is captured by the parameter σ_{CB}.

Furthermore, while the household takes the tax rate τ as given, the central bank selects a tax rate $\tilde{\tau}$, which is defined implicitly according to the following balanced-budget constraint:

$$a_0^*(\tilde{\tau})(1-\gamma^*)(R^s-1) = \tilde{\tau} y_0$$

Namely, the central bank must ensure that the amount they will disburse in interest payments at $t = 1$ on the share of savings that household invest in the safe asset, $a_0^*(\tilde{\tau})(1-\gamma^*)(R^s-1)$, matches the amount which that they collect by taxing the household's endowment in Period 0, $\tilde{\tau} y_0$. Importantly, this tax is used as a modelling tool, and is not a literal representation of central-bank practice. Indeed, raising interest rates is costly in practice because it is contractionary for output. Since I abstract away from production and a firm sector in this model to focus more clearly on the linkages between monetary policy and behavioral biases, the assumption of a tax is simply meant to reflect that raising rates has both benefits

and costs[5]. Absent this modelling device, the central bank would be unconstrained in their ability to increase the safe rate and, by proxy, the household's last-period consumption[6]. Hence, in solving their problem, the planner internalizes the fact that the tax rate must be set at the following level, which stems from solving for $\tilde{\tau}$ in Equation 3.2.2:

$$\tilde{\tau} = \frac{\beta(R^s - 1)\left(\eta^{\text{HH}} - \sigma_r^2\right)}{\beta(R^s - 1)\eta^{\text{HH}} - \sigma_r^2(\beta R^s + 1)}. \tag{3.20}$$

The central bank therefore sets the policy rate, R^s, in order to maximize the expected utility of households, taking as given their optimal savings decision, $a_0^*(\cdot)$, their optimal share of savings in the risky asset, $\gamma^*(\cdot)$, and the tax rate implied by the balanced-budget constraint, $\tilde{\tau}(\cdot)$, all of which are functions of R^s. Furthermore, in solving this problem, they compute expected utility with respect to their perceived distribution of beliefs about the risky asset's return, which is expressed in Equation 3.10. The central bank's value function can therefore be expressed as:

$$\begin{aligned}
\mathbb{V} &= U\left(c_0^*\left(a_0^*(\cdot), \tilde{\tau}(\cdot)\right)\right) + \beta \mathbb{E}^{\text{CB}}\left[U\left(c_1^*\left(R^s, a_0^*(\cdot), \gamma^*(\cdot)\right)\right)\right] \\
&= \log\left(y_0(1-\tilde{\tau}) - a_0^*\right) + \beta \mathbb{E}^{\text{CB}}[\log(a_0^* R^P)]
\end{aligned}$$

where I drop the arguments of functions in the second line for notational simplicity. The central bank's uncertainty over outcomes at $t = 1$ pertains to both the realizations of the risky asset return and their distribution over possible values of the behavioral wedge Ω. Similarly to the household problem, we can use the return approximation in Equation 3.13, substituting for the variance of the risky

[5]Note that if we interpret the environment as consisting of a central bank and financial intermediaries that are depository institutions at the central bank, then the central bank can be thought of as changing the rate of interest on excess reserves, and the tax in such an environment could plausibly be conceptualized as an inflation tax stemming from their creation of additional reserves.

[6]In simple two-period New Keynesian models, where the central bank also sets the nominal interest rate as a policy variable, this is sometimes addressed by pinning down certain variables, such as output in certain periods. In this model, since I abstract away from the production side of the economy, I constrain the central bank's ability to influence consumption at $t = 1$ via a balanced-budget assumption.

asset as perceived by the central bank. This allows us to simplify the planner's expectation of second-period utility in a similar fashion to the household's problem, this time by taking the expectation over utility from second-period consumption over the random variable $\tilde{\eta}_{\text{CB}}$ rather than $\tilde{\eta}_{\text{HH}}$:

$$\begin{aligned}
\mathbb{E}^{\text{CB}}[\log(a_0^* R^P)] &\approx \mathbb{E}^{\text{CB}}[\log(a_0^* e^{r^P_{\text{CB}}})] \\
&= \mathbb{E}^{\text{CB}}[\log(a_0^* e^{r^s+\gamma^*\tilde{\eta}_{\text{CB}}+\gamma^*\frac{\sigma_r^2+\sigma_\Omega^2}{2}-\gamma^{*2}\frac{\sigma_r^2+\sigma_\Omega^2}{2}})] \\
&= \mathbb{E}^{\text{CB}}[\log(a_0^*) + r^s + \gamma^*\tilde{\eta}_{\text{CB}} + \gamma^*(1-\gamma^*)\frac{\sigma_r^2+\sigma_\Omega^2}{2}] \\
&= \log(a_0^* + r^s + \gamma^*(1-\gamma^*)\frac{\sigma_r^2+\sigma_\Omega^2}{2}] + \mathbb{E}^{\text{CB}}\left[\gamma^*\tilde{\eta}_{\text{CB}}\right] \\
&= \log(a_0^*) + r^s + \gamma^*(1-\gamma^*)\frac{\sigma_r^2+\sigma_\Omega^2}{2} + \gamma^*\left(\eta^{\text{CB}} - \frac{\sigma_r^2+\sigma_\Omega^2}{2}\right)
\end{aligned}$$

And the planner's problem simplifies to:

$$\mathbb{V} = \underbrace{\log(y_0(1-\tilde{\tau}) - a_0^*)}_{\mathbb{V}_0} + \underbrace{\beta\left(\log(a_0^*) + r^s + \gamma^*(1-\gamma^*)\frac{\sigma_r^2+\sigma_\Omega^2}{2}\right) + \beta\gamma^*\left(\eta^{\text{CB}} - \frac{\sigma_r^2+\sigma_\Omega^2}{2}\right)}_{\mathbb{V}_1} \tag{3.21}$$

where $\mathbb{V}_0$ and $\mathbb{V}_1$ are placeholder variables for each term in $\mathbb{V}$. This compares to the central bank's value function if they shared the same beliefs as the household, which I denote as $\mathbb{U}$:

$$\mathbb{U} = \underbrace{\log(y_0(1-\tilde{\tau}) - a_0^*)}_{\mathbb{U}_0} + \underbrace{\beta\left(\log(a_0^*) + r^s + \gamma^*(1-\gamma^*)\frac{\sigma_r^2}{2}\right) + \beta\gamma^*\left(\eta^{\text{HH}} - \frac{\sigma_r^2}{2}\right)}_{\mathbb{U}_1} \tag{3.22}$$

where $\mathbb{U}_0$ and $\mathbb{U}_1$ are placeholder variables for each term in $\mathbb{V}$. $\mathbb{V}_0 = \mathbb{U}_0$, and if we set $\mu_\Omega = \kappa$ and let $\sigma_\Omega \to 0$—that is, if we make the household and the central

bank share the same beliefs about the risky asset—then $\mathbb{V}_1 = \mathbb{U}_1$, and $\mathbb{V} = \mathbb{U}$.

A Useful Reparameterization of the Planner's Problem

As noted above, in general $\mathbb{V}_0 = \mathbb{U}_0$ but $\mathbb{V}_1 \neq \mathbb{U}_1$: that is, the planner's problem differs depending on whether they share the same beliefs as the household about the prospects of the economy's risky asset. Since the two value functions differ only by a multiplicative factor over utility over consumption at time $t = 1$, we can we can usefully re-write the planner's problem under differing beliefs, $\mathbb{V}$, as the planner's problem under shared beliefs, $\mathbb{U}$, adjusted for a multiplicative factor $\mathbb{H}$:

$$\mathbb{V} = \mathbb{U}_0 + \mathbb{U}_1 \mathbb{H}$$

Intuitively, $\mathbb{H}$ is a multiplier which, when multiplied by second-period utility in the planner's problem under the beliefs of the household, generates second-period utility in the planner's value function under the planner's beliefs. The benefit of this re-expression of the problem is the following: since the parameters associated with the central bank's beliefs do not appear in $\mathbb{U}$, we have effectively isolated all instances of the policy-variables $(\sigma_\Omega, \mu_\Omega)$ into one term, $\mathbb{H}$, which generates more-interpretable results for the comparative statics of interest for this analysis. Nothing that $\mathbb{U}_1 \mathbb{H} = \mathbb{V}_1$, we have:

$$\mathbb{H} = \frac{\mathbb{V}_1}{\mathbb{U}_1} = \frac{\eta^{\text{HH}}\left(2\sigma_r^2\left(\eta^{\text{HH}} - \eta^{\text{HH}}\right) - \eta^{\text{HH}}{\sigma_\Omega}^2\right)}{{\eta^{\text{HH}}}^2\sigma_r^2 + 2\sigma_r^4\left(\log\left(\frac{\beta\gamma\sigma_r^2}{\eta^{\text{HH}}(\beta - \beta R^s) + \sigma_r^2(\beta R + 1)}\right) + r^s\right)} + 1 \tag{3.23}$$

3.3 Model Predictions

In this section, I use the model to analyze how the optimal conduct of monetary policy changes as a function of exogenous parameters that reflect the beliefs of the central bank.

Proposition 1 (Optimal Monetary Policy and Policy Uncertainty)**.** *In the case of logarithmic utility, and for historically reasonable parameter values, the optimal safe rate of interest set by the central bank, R^{s*}, is rising in the central bank's uncertainty about households' behavioral biases, σ_Ω.*

Proof. We are looking to sign the comparative static $\frac{\partial R^{s*}}{\partial \sigma_\Omega}$. Using the implicit function theorem to express this derivative as a function of derivatives of $\mathbb{V}$, and then leveraging the chain rule as applied to Equation 3.2.2, our desired comparative static can be expressed as a function of simpler building blocks:

$$\begin{aligned} \frac{\partial R^{s*}}{\partial \sigma_\Omega} = \frac{\mathbb{V}_{R^s,\sigma_\Omega}}{-\mathbb{V}_{R^s,R^s}} &\propto \mathbb{V}_{R^s,\sigma_\Omega} \\ &= \frac{\partial \mathbb{U}_1}{\partial R^s}\frac{\partial \mathbb{H}(\cdot)}{\partial \sigma_\Omega} + \mathbb{U}_1 \frac{\partial^2 \mathbb{H}(\cdot)}{\partial \sigma_\Omega \partial R^s}. \end{aligned} \tag{3.24}$$

The proportionality is established because the term $\mathbb{V}_{R^s,R^s}$ reflects second-order conditions and is negative. Finding out how the optimal policy rate set by the central bank varies as a function of policy uncertainty therefore relies on signing each of the constituent terms in Equation 3.24.

The first term, which reflects the derivative of second-period utility from consumption under the household's beliefs for a change in the safe rate of interest, takes the following form:

$$\frac{\partial \mathbb{U}_1}{\partial R^s} = \frac{1}{2}\beta\left(-\frac{2\eta^{\text{HH}}}{R^s\sigma_r^2} - \frac{2\beta\left(\sigma_r^2 - \frac{2}{R^s} + 2\log(R^s) - 2(\kappa + \bar{r}^r - 1)\right)}{\sigma_r^2(\beta + \beta R^s + 2) - 2\beta(R^s - 1)\eta^{\text{HH}}} + \frac{1}{R^s}\right) \tag{3.25}$$

While this expression can be difficult to interpret by inspection, Figure 3.2 shows the value of this derivative for various pairings of the risky asset's standard deviation and expected log return. This figure conveys that, for economically reasonable pairings of the risky asset variance and expected log return, $\frac{\partial \mathbb{U}_1}{\partial R^s} < 0$. Indeed, this holds true for all cases where $\sigma_r^2 \leq 0.3$ and $\bar{r}^r \geq 0.03$, which reasonably encompasses the characteristics of risky assets such as equities in the United States

during the last few decades. The exceptional cases where $\frac{\partial \mathbb{U}_1}{\partial R^s}$ is positive lie in the bottom-left quadrant of the heatmap: namely, cases where the risky asset is both highly volatile and provides a low expected rate of return relative to the safe asset. Economically, utility from consumption in the model's second period under the household's beliefs about the risky asset is typically declining as the safe rate of interest increases—while each dollar saved in the safe asset garners a higher rate of return, raising the safe rate also generates a higher tax at $t = 0$, which implies that less after-tax endowed income is left to allocate between consumption and savings, and the latter effect typically dominates the former. The exception is if the economy's risky asset exhibits a particularly low Sharpe ratio, in which case the alternative to holding the safe asset is sufficiently unattractive to justify the costs of raising the safe rate.

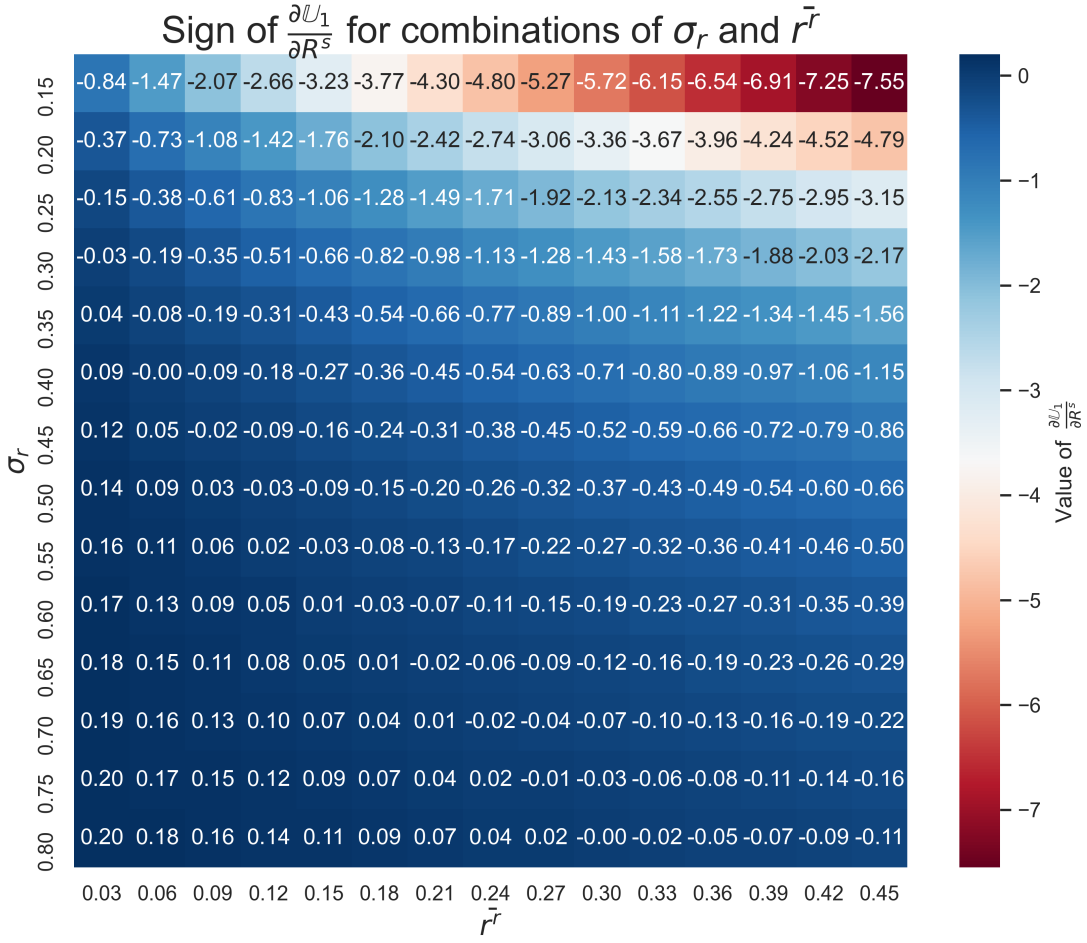


Figure 3.2: Notes: This figures plots the sign of the derivative, $\frac{\partial \mathbb{U}_1}{\partial R^s}$, for various combinations of the risky asset's variance (σ_r^2) and expected log rate of return ($\bar{r}^r$), holding all other parameters constant. In particular, $\beta = 1$, $y_0 = 1000$, $R = 1.02$, and $\kappa = 0.02$.

The second term $\frac{\partial \mathbb{H}(\cdot)}{\partial \sigma_\Omega}$, can be expressed as follows:

$$\frac{\partial \mathbb{H}(\cdot)}{\partial \sigma_\Omega} = \frac{2\eta^{\text{HH}}\sigma_\Omega\left(\sigma_r^2 - \eta^{\text{HH}}\right)}{\eta^{\text{HH}^2}\sigma_r^2 + 2\sigma_r^4\left(\log\left(\frac{\beta y_0 \sigma_r^2}{\eta^{\text{HH}}(\beta - \beta R) + \sigma_r^2(\beta R + 1)}\right) + r^s\right)}. \tag{3.26}$$

Since the denominator is always positive, the sign of this expression depends entirely on the term $\left(\sigma_r^2 - \eta^{\text{HH}}\right)$: that is, the difference between the variance of the

risky asset and the log expected risk premium, as perceived by the household. For risky assets such as the US equity market, for example, Carroll (2021) remarks that the annualized standard deviation of the S&P 500 has sat around 0.2 during the last few decades (such that $\sigma_r^2 = 0.04$), while the historical equity premium has been around eight percent ($\eta^{\text{HH}} = 0.08$, insofar as we set the household's exuberance parameter $\kappa = 0$). As the household's behavioral bias term κ rises, their perceived log risk premium only further rises. As such, for historically motivated choices of σ_r and η^{HH}, and even for significantly lower average estimates of the risk premium in the United States, we expect that $\left(\sigma_r^2 - \eta^{\text{HH}}\right) < 0$, and therefore that $\frac{\partial \mathbb{H}(\cdot)}{\partial \sigma_\Omega} < 0$. This is intuitive: as the central bank becomes more uncertain about households' behavioral biases, and by extension about the return profile of the risky asset, the multiplier term $\mathbb{H}$ should fall. In periods of high volatility and low expected returns on the risky asset, however, this derivative would take the opposite sign.

The third term, $\mathbb{U}_1$, represents the utility from consumption in the second period of the model, assuming the household and the central bank share the same beliefs about the risky asset return. This quantity is non-negative.

Finally, let us examine the fourth term, $\frac{\partial^2 \mathbb{H}(\cdot)}{\partial \sigma_\Omega \partial R^s}$:

$$\begin{aligned}\frac{\partial^2 \mathbb{H}(\cdot)}{\partial \sigma_\Omega \partial R^s} = \chi\Bigg(&\frac{\left(2\eta^{\text{HH}} - \sigma_r^2\right)\left(4{\eta^{\text{HH}}}^2\sigma_r^2 + 4\sigma_r^4\left(2\log\left(\frac{2\beta y \sigma_r^2}{\sigma_r^2(\beta+\beta R^s+2)-2\beta(R^s-1)\eta^{\text{HH}}}\right) + \kappa + r^s + r^r\right) + \sigma_r^6\right)}{R^s} \\ &+ \frac{\left(2\eta^{\text{HH}} + \sigma_r^2\right)\left(4{\eta^{\text{HH}}}^2\sigma_r^2 + 4\sigma_r^4\left(2\log\left(\frac{2\beta y_0 \sigma_r^2}{\sigma_r^2(\beta+\beta R^s+2)-2\beta(R^s-1)\eta^{\text{HH}}}\right) + \kappa + r^s + r^r\right) + \sigma_r^6\right)}{R^s} \\ &- \frac{8\left(4{\eta^{\text{HH}}}^2 - \sigma_r^4\right)\left(-4\sigma_r^4\left(\eta^{\text{HH}} + \beta(R^s-1)\right) + 4\beta(R^s-1){\eta^{\text{HH}}}^2\sigma_r^2 + \sigma_r^6(\beta + \beta(-R^s) + 2)\right)}{8\beta(R^s-1)R^s\eta^{\text{HH}} - 4R^s\sigma_r^2(\beta + \beta R^s + 2)}\Bigg)\end{aligned} \tag{3.27}$$

where $\chi = \left(\frac{4\left(\sigma_r^2\left(\eta^{\text{HH}} + \frac{\sigma_r^2}{2}\right)^2 + 2\sigma_r^4\left(\log\left(\frac{2\beta y_0 \sigma_r^2}{\sigma_r^2(\beta+\beta R^s+2)-2\beta(R^s-1)\eta^{\text{HH}}}\right) + r^s\right)\right)^2}{\sigma_\Omega}\right)^{-1}$. $\chi > 0$, and the first two sums in the sum consist of strictly positive quantities. Since the sign of the

third term appears to depend on the prevailing parameter values, it is difficult to intuitively sign this derivative as-is. However, if we set $\beta = 1$ and $R^s = 1$ for ease of interpretation, this expression simplifies to:

$$\frac{\partial^2 \mathbb{H}(\cdot)}{\partial \sigma_\Omega \partial R^s}\Big|_{\beta=1, R^s=1} = \frac{4\sigma_\Omega\left(8\eta^{\text{HH}3} + 6\eta^{\text{HH}}\sigma_r^4 + 4\eta^{\text{HH}}\sigma_r^2\left(\eta^{\text{HH}} + 4\left(\kappa + r^r + 2\log\left(\frac{y_0}{2}\right)\right)\right) - \sigma_r^6\right)}{\left(4\eta^{\text{HH}2}\sigma_r + 4\sigma_r^3\left(\eta^{\text{HH}} + 2\log\left(\frac{y_0}{2}\right)\right) + \sigma_r^5\right)^2}$$

In this simplified form, it becomes apparent that this derivative is positive, as the denominator of the expression is positive, and the numerator consists of a sum of positive terms which strictly dominate $-\sigma_r^6$. To reinforce this intuition, I plot a heatmap of the value of this derivative for various combinations of the risky asset standard deviation and risky asset return in Figure 3.3, holding all other parameters constant ($\beta = 1$, $y_0 = 1000$, $R = 1.02$, and $\kappa = 0.02$).

Two important features emerge from this figure. First, $\frac{\partial^2 \mathbb{H}(\cdot)}{\partial \sigma_\Omega \partial R^s} > 0$ for all pairings examined in this figure, including cases where the risky asset has a very poor risk-return profile (for instance, a standard deviation of 0.8 and a mean log return of 0.03). Second, this derivative becomes more positive as the risky asset becomes more attractive: that is, combinations of low risky asset variance and high risky asset return generate strongly positive values of this derivative, while combinations of high risky asset variance and low risky asset return lead this derivative to approach zero.

Hence, putting all of these results together, we have shown that for reasonable parameter values, and certainly if we conceptualize the risky asset as risky US credit instruments during the last few decades, the optimal safe rate of interest set by the central bank, R^{s*}, is rising in policy uncertainty about the risky asset's return:

$$\frac{\partial R^{s*}}{\partial \sigma_\Omega} \propto \underbrace{\frac{\partial \mathbb{U}_1}{\partial R^s}}_{<0} \underbrace{\frac{\partial \mathbb{H}(\cdot)}{\partial \sigma_\Omega}}_{<0} + \underbrace{\mathbb{U}_1}_{>0} \underbrace{\frac{\partial^2 \mathbb{H}(\cdot)}{\partial \sigma_\Omega \partial R^s}}_{>0} > 0$$

□

My findings therefore align qualitatively with the findings of Fontanier (2021, 1), who is the first to my knowledge to document that, in a macroeconomic model with behavioral deviations and financial frictions, "uncertainty about the precise extent of behavioral biases in financial markets increases the incentives for the planner to act early." Interestingly, however, in my model, this result is achieved using only the assumption that agents are behaviorally biased, which suggests that findings of this sort do not necessarily hinge on modelling assumption relating to financial frictions. The economic intuition for this finding is similar to the intuition for a precautionary savings motive in the traditional macroeconomics literature (Lugilde et al., 2017). As the central bank becomes more uncertain about the behavioral biases of households and the return profile of the risky asset—and given that we are dealing with a utility function where marginal utility is convex—they seek to incentivize the household to save more, which they achieve by raising the safe rate of interest.

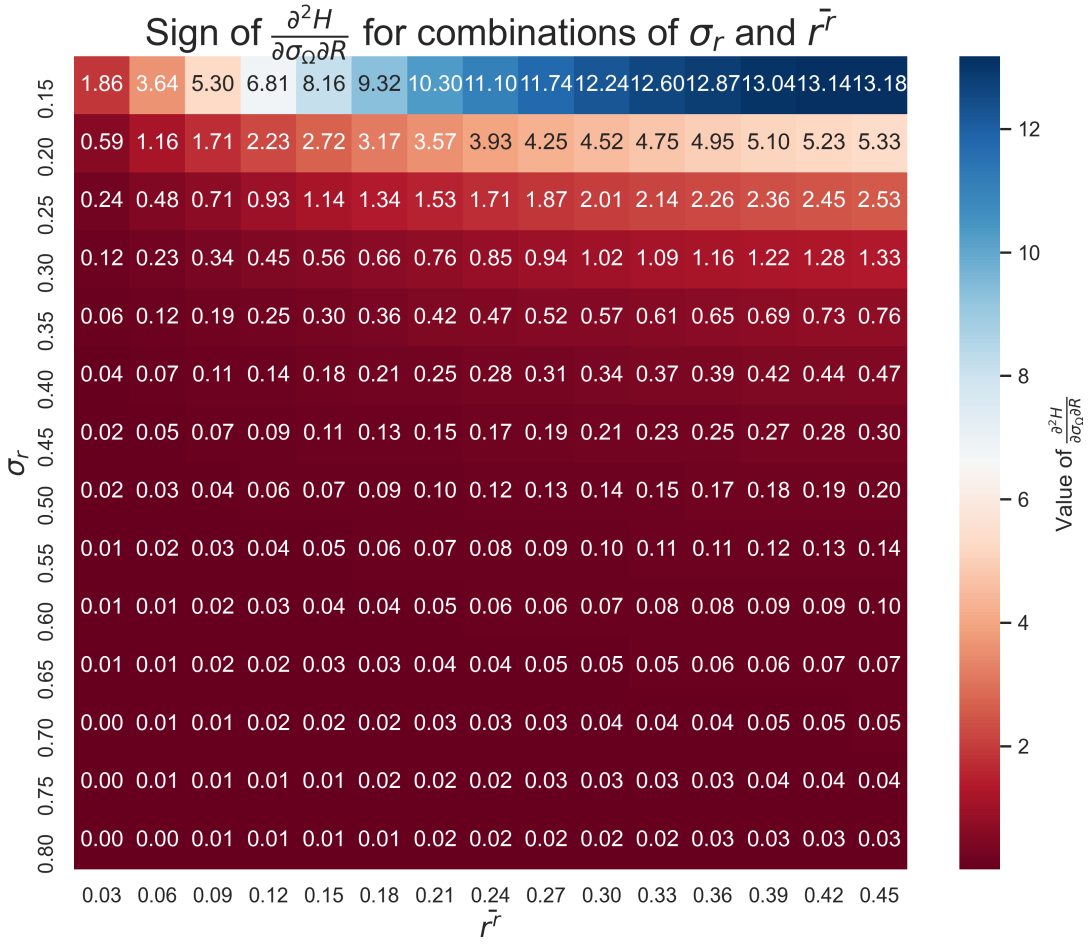


Figure 3.3: Notes: This figures plots the sign of the derivative, $\frac{\partial^2 \mathbb{H}}{\partial \sigma_\Omega \partial R^s}$, for various combinations of the risky asset's variance (σ_r^2) and expected log rate of return ($\bar{r}^r$), holding all other parameters constant. In particular, $\beta = 1$, $y_0 = 1000$, $R = 1.02$, and $\kappa = 0.02$.

Proposition 2 (Optimal Monetary Policy and Central Bank Optimism)**.** *In the case of logarithmic utility, and for reasonable parameter values, the optimal safe rate of interest set by the central bank, R^s, increases as the central bank becomes more pessimistic about the risky asset's return (that is, μ_Ω falls)*

Proof. We are looking to sign $\frac{\partial R^{s*}}{\partial \mu_\Omega}$ to ascertain how the optimal safe rate set by the central bank varies as a function of their optimism or pessimism about the risky

asset's return profile. Similarly to the approach used in the proof of Proposition 1, we can begin by leveraging the implicit function theorem and the chain rule to express this comparative static as follows:

$$\begin{aligned}\frac{\partial R^{s*}}{\partial \mu_\Omega} = \frac{\mathbb{V}_{R^s,\kappa}}{-\mathbb{V}_{R^s,R^s}} &\propto \mathbb{V}_{R^s,\kappa} \\ &= \frac{\partial \mathbb{U}_1}{\partial R^s}\frac{\partial \mathbb{H}(\cdot)}{\partial \mu_\Omega} + \mathbb{U}_1 \frac{\partial^2 \mathbb{H}(\cdot)}{\partial \mu_\Omega \partial R^s}\end{aligned} \tag{3.28}$$

Signing this comparative static requires signing each of these four components. We have already analyzed the first term, $\frac{\partial \mathbb{U}_1}{\partial R^s}$, as summarized by Equation 3.25: this term is generally negative, unless the economy's risky asset is particularly unattractive.

The second term, $\frac{\partial \mathbb{H}(\cdot)}{\partial \mu_\Omega}$, has the following form:

$$\frac{\partial \mathbb{H}}{\partial \mu_\Omega} = \frac{2\eta^{\text{HH}}}{\eta^{\text{HH}2} + 2\sigma_r^2\left(\log\left(\frac{\beta y \sigma_r^2}{\eta^{\text{HH}}(\beta - \beta R) + \sigma_r^2(\beta R + 1)}\right) + r^s\right)} \tag{3.29}$$

This term consists of strictly positive terms in both the denominator and the numerator, and is therefore strictly positive. Economically, this result is intuitive. $\mathbb{H}$ is a multiplicative term that reflects how much greater expected second-period utility is under the planner's beliefs about the risky asset return relative to the household's beliefs about the risky asset return. As the central bank's optimism about the mean return on the risky asset, μ_Ω, rises, this multiplier should rise as well.

The third term, $\mathbb{U}_1$, represents the utility from consumption in the second period of the model, assuming the household and the central bank share the same beliefs about the risky asset return. This quantity is non-negative.

Finally, we can sign $\frac{\partial^2 \mathbb{H}}{\partial \mu_\Omega \partial R^s}$. After ignoring a positive denominator, this quantity

is proportional to:

$$\frac{\partial^2 \mathbb{H}}{\partial \mu_\Omega \partial R^s} \propto \frac{\left(2\eta^{\text{HH}} + \sigma_r^2\right)\left(-4\sigma_r^2\left(\eta^{\text{HH}} + \beta(R^s - 1)\right) + 4\beta(R^s - 1){\eta^{\text{HH}}}^2 + \sigma_r^4(\beta + \beta(-R^s) + 2)\right)}{4\beta(R^s - 1)R\eta^{\text{HH}} - 2R^s\sigma_r^2(\beta + \beta R^s + 2)} - \frac{\left(\eta^{\text{HH}} + \frac{\sigma_r^2}{2}\right)^2 + 2\sigma_r^2\left(\log\left(\frac{2\beta y_0 \sigma_r^2}{\sigma_r^2(\beta + \beta R^s + 2) - 2\beta(R^s - 1)\eta^{\text{HH}}}\right) + \log(R^s)\right)}{R^s}. \tag{3.30}$$

While the sign of this expression is difficult to intuit in this form, setting $\beta = 1$ and $R^s = 1$ provides some more color on the behavior of this expression:

$$\begin{aligned}\frac{\partial^2 \mathbb{H}}{\partial \mu_\Omega \partial R^s}\Big|_{\beta=1, R^s=1} &= \frac{2\left(-\left(\eta^{\text{HH}} + \frac{\sigma_r^2}{2}\right)^2 - \frac{\left(2\eta^{\text{HH}} + \sigma_r^2\right)\left(2\sigma_r^4 - 4\eta^{\text{HH}}\sigma_r^2\right)}{8\sigma_r^2} - 2\sigma_r^2 \log\left(\frac{y_0}{2}\right)\right)}{\left(\left(\eta^{\text{HH}} + \frac{\sigma_r^2}{2}\right)^2 + 2\sigma_r^2 \log\left(\frac{y_0}{2}\right)\right)^2} \\ &\propto -\left(\eta^{\text{HH}} + \frac{\sigma_r^2}{2}\right)^2 - \frac{\left(2\eta^{\text{HH}} + \sigma_r^2\right)\left(2\sigma_r^4 - 4\eta^{\text{HH}}\sigma_r^2\right)}{8\sigma_r^2} - 2\sigma_r^2 \log\left(\frac{y_0}{2}\right).\end{aligned}$$

Each of the three terms in this simplified expression is negative, and hence their sum is negative. To solidify this intuition and to provide more intuition on how the sign of $\frac{\partial^2 \mathbb{H}}{\partial \mu_\Omega \partial R^s}$ varies according to different parameter choices, I plot a heatmap of the value of this derivative for pairings of σ_r^2 and $\bar{r^r}$. The results of this exercise are reported in Figure 3.4. For all pairings exhibited, the sign of $\frac{\partial^2 \mathbb{H}}{\partial \mu_\Omega \partial R^s}$ is positive. Furthermore, there is a general trend wherein the sign of this derivative is most negative in the top left quadrant of the figure, for pairings of low volatility and low expected returns, and least negative on the bottom right quadrant, for pairings of high volatility and high expected return. As such, it appears that $\frac{\partial^2 \mathbb{H}}{\partial \mu_\Omega \partial R^s}$ is monotonically increasing (that is, this quantity becomes less negative) in the risky asset's standard deviation and log expected return.

Putting all of these results together, we have shown that for reasonable parameter values, the optimal safe rate of interest set by the central bank, R^{s*}, rises as the central bank becomes more pessimistic about the risky asset's return profile (which

means μ_Ω falls):

$$\frac{\partial R^{s*}}{\partial \mu_\Omega} \propto \underbrace{\frac{\partial \mathbb{U}_1}{\partial R^s}}_{<0} \underbrace{\frac{\partial \mathbb{H}(\cdot)}{\partial \mu_\Omega}}_{>0} + \underbrace{\mathbb{U}_1}_{>0} \underbrace{\frac{\partial^2 \mathbb{H}(\cdot)}{\partial \mu_\Omega \partial R^s}}_{<0} < 0.$$

□

Economically, this result appears to provide support for an *insurance-based motive* for prudential monetary policy. Namely, as the central bank becomes more pessimistic about the risky asset relative to the household, they raise interest rates to encourage the household to reduce γ^*, their share of savings in the risky asset. This is effective because, in this model, $\frac{\partial \gamma}{\partial R^s} = \frac{-1}{R^s \sigma_r^2}$. While this increase in the safe rate has costs—as encapsulated by $\frac{\partial \mathbb{U}_1}{\partial R^s}$—it increases total expected utility from the planner's perspective, as it discourages households from over-investing in the risky asset due to their positive behavioral bias Ω_{HH}. As I will discuss in the next section, changes in R^s will additionally lead to changes in a_0^* when $\rho \neq 1$.

Importantly, while the central bank may increase expected utility, as computed under their distribution of beliefs, by raising the safe rate of interest in the face of rising pessimism about the risky asset relative to households, this does not mean that such behavior is necessarily desirable. Instead, this depends on whether the central bank's beliefs are closer to the truth about the true generating process of the risky asset than the beliefs of the households. Whether we have reason to believe that central banks in the real world have more accurate and less behaviorally-biased beliefs about the prospects of the economy's financial sector than those of certain behaviorally-biased players in financial markets is a separate but important question that bears on the practical relevance of this result. While some contend that it is unreasonable to expect that central banks can meaningfully identify when to lean against exuberance in financial markets if sophisticated investors often cannot, others respond, in-line with the literature on limits to arbitrage, that sophisticated investors may fail to capitalize on exuberance in markets not because

of a lack of information but instead because of institutional constraints (Stein, 2021). From this vantage point, central banks that are free from such institutional constraints may therefore be well positioned to meaningfully act on their informed beliefs about over-heating in financial markets.

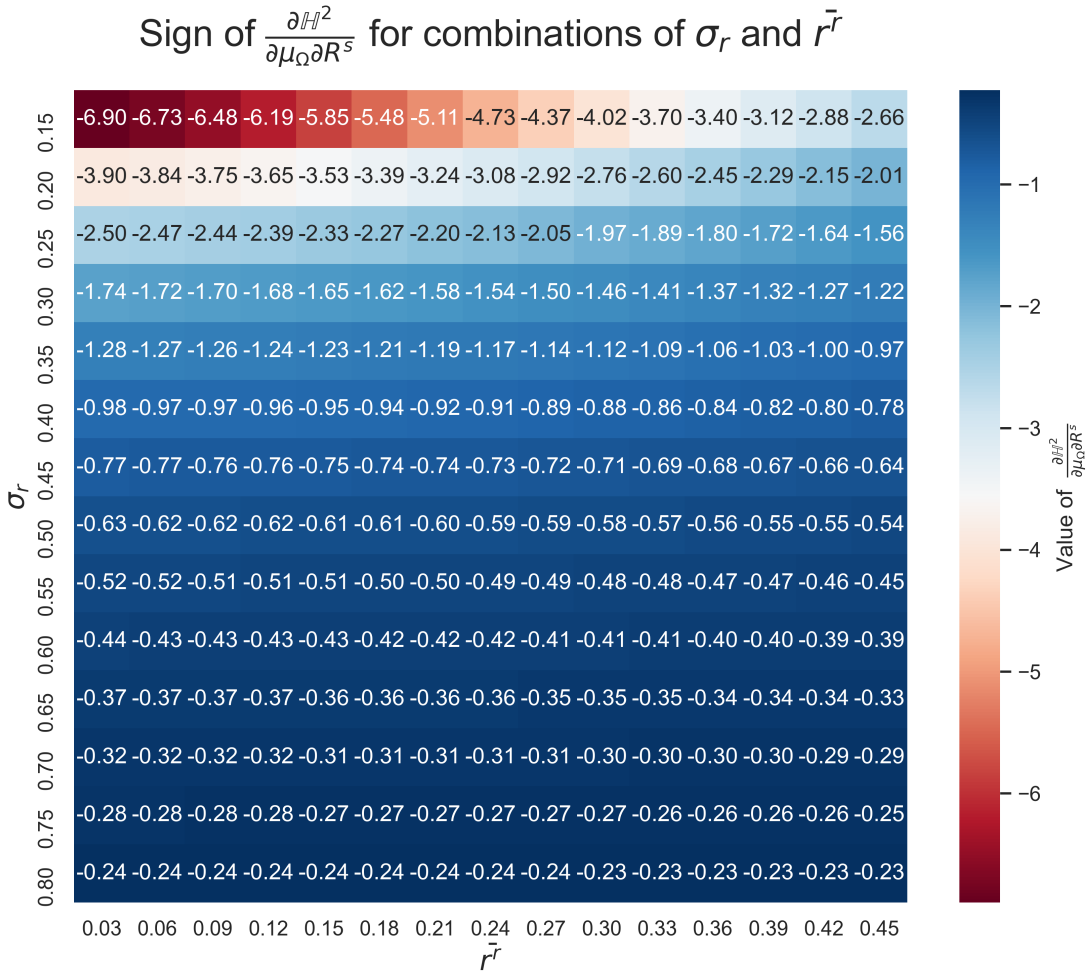


Figure 3.4: Notes: This figures plots the sign of the derivative, $\frac{\partial^2 \mathbb{H}}{\partial \mu_\Omega \partial R^s}$, for various combinations of the risky asset's variance (σ_r^2) and expected log rate of return ($\bar{r}^r$), holding all other parameters constant. In particular, $\beta = 1$, $y_0 = 1000$, $R = 1.02$, and $\kappa = 0.02$.

3.4 Moving Beyond Logarithmic Utility

Thus far, we have solved the model using logarithmic utility. In this section, I solve the problem for values of $\rho \neq 1$, and I provide some intuition for how the propositions detailed in the previous section vary as a function of ρ, the coefficient of relative risk aversion. Since much of the derivations proceed similarly to the case with log utility case, I will go over them summarily.

3.4.1 Household Maximization Problem, Revisited

For a general CRRA utility function, the household's problem becomes:

$$\underset{a_0,\gamma}{\text{maximize}} \quad (1-\rho)^{-1}\left(y_0(1-\tau)-a_0\right)^{1-\rho} + \beta(1-\rho)^{-1}\mathbb{E}[(a_0R^P)^{1-\rho}].$$

As before, we can use the approximation for the portfolio's log rate of return expressed in Equation 3.13 to simplify the household's expected utility from consumption in the second period:

$$\begin{aligned}
\mathbb{E}[(a_0R^P)^{1-\rho}] &\approx \mathbb{E}[(a_0e^{r^P_{\text{HH}}})^{1-\rho}] \\
&= \mathbb{E}[(a_0e^{r^s+\gamma\tilde{\eta}_{\text{HH}}+\gamma\frac{\sigma_r^2}{2}-\gamma^2\frac{\sigma_r^2}{2}})^{1-\rho}] \\
&= \mathbb{E}[(a_0e^{r^s}e^{\gamma\tilde{\eta}_{\text{HH}}+\gamma(1-\gamma)\frac{\sigma_r^2}{2}})^{1-\rho}] \\
&= (a_0R^s)^{1-\rho}e^{\gamma(1-\gamma)(1-\rho)\frac{\sigma_r^2}{2}}\mathbb{E}[e^{\gamma\tilde{\eta}_{\text{HH}}(1-\rho)}]
\end{aligned}$$

As expressed in Equation 3.9, the risk premium as perceived by the household is normally distributed. Hence, the random variable $\gamma\tilde{\boldsymbol{\eta}}_{HH}(1-\rho) \sim \mathcal{N}(\gamma(1-\rho)(\eta^{HH} - \frac{\sigma_r^2}{2}), (\gamma(1-\rho))^2\sigma_r^2)$, which implies $e^{\gamma\tilde{\eta}_{HH}(1-\rho)}$ is log-normally distributed, and we

have:

$$\begin{aligned}\mathbb{E}[e^{\gamma\tilde{\eta}_{HH}(1-\rho)}] &= e^{\gamma(1-\rho)\eta^{HH}-\gamma(1-\rho)\frac{\sigma_r^2}{2}+(1-\rho)^2\gamma^2\frac{\sigma_r^2}{2}} \\ &= e^{\gamma(1-\rho)\eta^{HH}-\gamma(1-\rho)\frac{\sigma_r^2}{2}[1-\gamma(1-\rho)]} \\ &= e^{\gamma(1-\rho)\eta^{HH}-\gamma(1-\rho)\frac{\sigma_r^2}{2}[(1-\gamma)+\gamma\rho]} \\ &= e^{\gamma(1-\rho)\eta^{HH}-\gamma(1-\gamma)(1-\rho)\frac{\sigma_r^2}{2}-\rho(1-\rho)\gamma^2\frac{\sigma_r^2}{2}}\end{aligned}$$

The approximated formulation of the household's problem therefore simplifies to:

$$\underset{a_0,\gamma}{\text{maximize}} \quad (1-\rho)^{-1}\left(y_0(1-\tau)-a_0\right)^{1-\rho}+\beta(1-\rho)^{-1}(a_0R^s)^{1-\rho}e^{\gamma(1-\rho)\eta^{HH}-\rho(1-\rho)\gamma^2\frac{\sigma_r^2}{2}} \tag{3.31}$$

Equilibrium Endogenous Quantities

Taking first-order conditions and solving yields the following optimal endogenous quantities for households, as a function of the model's exogenous parameters:

$$\gamma^* = \frac{\eta^{\text{HH}}}{\rho\sigma_r^2} = \frac{\bar{r^r}+\kappa-r^s+\frac{\sigma_r^2}{2}}{\rho\sigma_r^2} \tag{3.32}$$

$$a_0^* = (1-\tau)y_0\left(1-\frac{R^s}{\beta^{1/\rho}R^{s\,1/\rho}e^{\frac{\gamma(\rho-1)\left(\gamma\rho\sigma_r^2-2\eta^{\text{HH}}\right)}{2\rho}}+R^s}\right) \tag{3.33}$$

$$c_0^* = y_0(1-\tau)-a_0^* \tag{3.34}$$

$$c_1^* = a_0^*(R^s+(R^r-R^s)\gamma^*) \tag{3.35}$$

Second-order conditions were verified. Importantly, and unlike with logarithmic utility, the household's optimal choice of savings, a_0^*, is now a function of the safe rate of interest set by the central bank, R^s. As such, changes in the safe rate R^s will now operate along *two* margins: they will affect both the household's allocation towards the risky asset and their first-period savings.

3.4.2 The Central Bank's Problem, Revisited

The central bank's problem remains to set the safe rate, R^s, in order to maximize expected household welfare, taking as given the household's optimal inter-temporal consumption plans. Furthermore, in accordance with the balanced budget constraint in Equation 3.20, they set the tax at the following level:

$$\tilde{\tau} = \frac{(R-1)\beta^{1/\rho}R^{1/\rho}\left(\eta^{\text{HH}} - \rho\sigma_r^2\right)}{\beta^{1/\rho}R^{1/\rho}\left(\eta^{\text{HH}}(R-1) - \rho R\sigma_r^2\right) - \rho R\sigma_r^2 e^{\frac{{\eta^{\text{HH}}}^2(\rho-1)}{2\rho^2\sigma_r^2}}} \tag{3.36}$$

The planner's problem can therefore be expressed as:

$$\begin{aligned}
\mathbb{V} &= U\left(c_0^*\left(a_0^*(\cdot), \tilde{\tau}(\cdot)\right)\right) + \beta\mathbb{E}^{\text{CB}}\left[U\left(c_1^*\left(R^s, a_0^*(\cdot), \gamma^*(\cdot)\right)\right)\right] \\
&= (1-\rho)^{-1}\left(y_0(1-\tilde{\tau}) - a_0^*\right)^{1-\rho} + \beta(1-\rho)^{-1}\mathbb{E}^{\text{CB}}[(a_0^* R^P)^{1-\rho}]
\end{aligned}$$

where:

$$\begin{aligned}
\mathbb{E}^{CB}[(a_0^* R_{CB}^P)^{1-\rho}] &\approx \mathbb{E}^{CB}[(a_0^* e^{r_{CB}^P})^{1-\rho}] \\
&= \mathbb{E}^{CB}[(a_0^* e^{r^s + \gamma^*\tilde{\eta}_{CB} + \gamma^*\frac{\sigma_r^2+\sigma_\Omega^2}{2} - \gamma^{*2}\frac{\sigma_r^2+\sigma_\Omega^2}{2}})^{1-\rho}] \\
&= \mathbb{E}^{CB}[(a_0^* e^{r^s} e^{\gamma^*\tilde{\eta}_{CB} + \gamma^*(1-\gamma^*)\frac{\sigma_r^2+\sigma_\Omega^2}{2}})^{1-\rho}] \\
&= (a_0^* R^s)^{1-\rho} e^{\gamma^*(1-\gamma^*)(1-\rho)\frac{\sigma_r^2+\sigma_\Omega^2}{2}} \mathbb{E}^{CB}[e^{\gamma^*\tilde{\eta}_{CB}(1-\rho)}].
\end{aligned}$$

The expectation that remains is now with respect to the random variable $\tilde{\eta}_{CB}$

rather than $\tilde{\eta}_{HH}$. Hence, the random variable $\gamma^*\tilde{\eta}_{CB}(1-\rho) \sim \mathcal{N}(\gamma^*(1-\rho)(\eta^{CB} - \frac{\sigma_r^2+\sigma_\Omega^2}{2}), (\gamma^*(1-\rho))^2(\sigma_r^2+\sigma_\Omega^2))$. As with the household problem, $e^{\gamma^*\tilde{\eta}_{CB}(1-\rho)}$ is therefore log-normally distributed, and the expectation simplifies to:

$$\begin{aligned}
\mathbb{E}[e^{\gamma^*\tilde{\eta}_{CB}(1-\rho)}] &= e^{\gamma^*(1-\rho)\eta^{CB} - \gamma^*(1-\rho)\frac{\sigma_r^2+\sigma_\Omega^2}{2} + (1-\rho)^2\gamma^{*2}\frac{\sigma_r^2+\sigma_\Omega^2}{2}} \\
&= e^{\gamma^*(1-\rho)\eta^{CB} - \gamma^*(1-\rho)\frac{\sigma_r^2+\sigma_\Omega^2}{2}[1-\gamma^*(1-\rho)]} \\
&= e^{\gamma^*(1-\rho)\eta^{CB} - \gamma^*(1-\rho)\frac{\sigma_r^2+\sigma_\Omega^2}{2}[(1-\gamma^*)+\gamma^*\rho]} \\
&= e^{\gamma^*(1-\rho)\eta^{CB} - \gamma^*(1-\gamma^*)(1-\rho)\frac{\sigma_r^2+\sigma_\Omega^2}{2} - \rho(1-\rho)\gamma^{*2}\frac{\sigma_r^2+\sigma_\Omega^2}{2}}.
\end{aligned}$$

Thus, we can express $\mathbb{V}$ and $\mathbb{U}$, the central bank's value functions under differing and shared beliefs with the households, respectively, as:

$$\mathbb{V} = \underbrace{(1-\rho)^{-1}\left(y_0(1-\tilde{\tau}) - a_0^*\right)^{1-\rho}}_{\mathbb{V}_0} + \underbrace{\beta(1-\rho)^{-1}(a_0^* R^s)^{1-\rho} e^{\gamma^*(1-\rho)\eta^{CB} - \rho(1-\rho)\gamma^{*2}\frac{\sigma_r^2+\sigma_\Omega^2}{2}}}_{\mathbb{V}_1} \tag{3.37}$$

$$\mathbb{U} = \underbrace{(1-\rho)^{-1}\left(y_0(1-\tilde{\tau}) - a_0^*\right)^{1-\rho}}_{\mathbb{U}_0} + \underbrace{\beta(1-\rho)^{-1}(a_0^* R^s)^{1-\rho} e^{\gamma^*(1-\rho)\eta^{HH} - \rho(1-\rho)\gamma^{*2}\frac{\sigma_r^2}{2}}}_{\mathbb{U}_1} \tag{3.38}$$

Noting that $\mathbb{H} = \frac{\mathbb{V}_1}{\mathbb{U}_1}$, we finally have:

$$\mathbb{H} = e^{\frac{1}{2}\gamma^*(\rho-1)\left(\gamma^*\rho\sigma_\Omega^2 + 2\eta^{HH} - 2\eta^{CB}\right)} \tag{3.39}$$

3.4.3 Model Predictions, Revisited

In this section, I aim to provide some intuition for how the key results on policy uncertainty and central bank optimism unfold if $\rho \neq 1$—that is, if we do not constrain ourselves to the special and most tractable case of logarithmic utility. In

particular, I will discuss, in broad strokes, how the prescriptions for the optimal conduct of monetary policy in this model evolve as a function of the coefficient of relative risk aversion ρ.

Since some derivatives and expressions become especially unwieldy in this general formulation of the model, given that a_0^* is now a function of R^s, I will regularly switch between presenting between general mathematical representations (where intuitively interpretable) and particular solutions for selected parameter values.

Optimal Monetary Policy and Policy Uncertainty, Revisited

Recall that, from Equation 3.24,

$$\frac{\partial R^{s*}}{\partial \sigma_\Omega} \propto \frac{\partial \mathbb{U}_1}{\partial R^s} \frac{\partial \mathbb{H}(\cdot)}{\partial \sigma_\Omega} + \mathbb{U}_1 \frac{\partial^2 \mathbb{H}(\cdot)}{\partial \sigma_\Omega \partial R^s}.$$

In the case of logarithmic utility, the first term in this expression, $\frac{\partial \mathbb{U}_1}{\partial R^s}$, was generally negative. To show how the sign of this term changes as ρ changes, Figure 3.5 describes the magnitude and the sign of this derivative for various pairings of the risky asset's standard deviation and expected log return and for four different choices of the parameter ρ. The general trend conveyed by this figure is that $\frac{\partial \mathbb{U}_1}{\partial R^s} < 0$ in most cases where $\rho < 1$ (namely, for the illustrative examples where $\rho = 0.5$ and $\rho = 0.8$). Furthermore, when $\rho > 1$, the sign of $\frac{\partial \mathbb{U}_1}{\partial R^s} > 0$ is less clear: for low σ_r, this derivative is negative, while the reverse holds true for high σ_r.

A few other trends are noteworthy. First, unlike in the initial setup with logarithmic utility, the value of this derivative exhibits non-linear behavior for extreme values of σ_r and $\bar{r}^r$. As I will discuss in later section, this is likely due to the fact that raising interest rates in this setting of the model has a variety of competing effects which can at times play in opposite directions: not only does changing the safe rate influence the tax rate set by the central bank as well as the household's portfolio

allocation decision, as in the log utility case, but it also affects the household's optimal savings decision. Second, the magnitude of this derivative is generally decreasing in ρ.

The second term, $\frac{\partial \mathbb{H}(\cdot)}{\partial \sigma_\Omega}$, has a neat closed-form expression:

$$\frac{\partial \mathbb{H}(\cdot)}{\partial \sigma_\Omega} = \frac{(1-\rho)\sigma_\Omega\left(\sigma_r^4 - 4\eta^{HH\,2}\right)e^{\left(\frac{(\rho-1)\left(2\eta^{HH}+\sigma_r^2\right)\left(2\eta^{HH}{\sigma_\Omega}^2-\sigma_r^2\left(-4\kappa+4\mu+{\sigma_\Omega}^2\right)\right)}{8\rho\sigma_r^4}\right)}}{4\rho\sigma_r^4}. \tag{3.40}$$

As argued in more detail while signing this expression under logarithmic utility in Equation 3.26, for realistic parameter values, $\eta^{HH} > \sigma_r^2$, which implies that $\sigma_r^4 - 4\eta^{HH\,2} < 0$. The sign of this derivative therefore hinges on the sign of $(1-\rho)$: if $\rho < 1$, then $\frac{\partial \mathbb{H}(\cdot)}{\partial \sigma_\Omega} < 0$, and if $\rho > 1$, then $\frac{\partial \mathbb{H}(\cdot)}{\partial \sigma_\Omega} > 0$.

The third term, $\mathbb{U}_1$, is non-negative, so we are left with the fourth and final term, $\frac{\partial^2 \mathbb{H}(\cdot)}{\partial \sigma_\Omega \partial R^s}$. Recall that with logarithmic utility, this term was positive for all permutations of σ_r and $\bar{r}^r$ examined in Figure 3.3. In the more general case where $\rho \neq 1$, it appears from Figure 3.6 that $\frac{\partial^2 \mathbb{H}(\cdot)}{\partial \sigma_\Omega \partial R^s} > 0$ if $\rho < 1$ and $\frac{\partial^2 \mathbb{H}(\cdot)}{\partial \sigma_\Omega \partial R^s} < 0$ if $\rho > 1$. Indeed, this is true for all permutations of σ_r and $\bar{r}^r$ considered for $\rho = 0.8$, $\rho = 2$, and $\rho = 4$, and for almost all permutations when $\rho = 0.5$.

While informal and predicated on a range of particular parameter values, this analysis provides valuable insight into the sign of our comparative static of interest, $\frac{\partial R^{s*}}{\partial \sigma_\Omega}$, evolves as a function of the coefficient of relative risk aversion. If $\rho < 1$, then, we have shown that for certain realistic parameter values, the result on optimal monetary policy and policy uncertainty still holds:

$$\frac{\partial R^{s*}}{\partial \sigma_\Omega} \propto \underbrace{\frac{\partial \mathbb{U}_1}{\partial R^s}}_{<0}\underbrace{\frac{\partial \mathbb{H}(\cdot)}{\partial \sigma_\Omega}}_{<0} + \underbrace{\mathbb{U}_1}_{>0}\underbrace{\frac{\partial^2 \mathbb{H}(\cdot)}{\partial \sigma_\Omega \partial R^s}}_{>0} > 0.$$

If $\rho > 1$, and if we are in a case where $\frac{\partial \mathbb{U}_1}{\partial R^s} > 0$, then the sign of our desired comparative static is muddled, as it depends on relative magnitude of the two terms

in the following sum:

$$\frac{\partial R^{s*}}{\partial \sigma_\Omega} \propto \underbrace{\frac{\partial \mathbb{U}_1}{\partial R^s}}_{>0} \underbrace{\frac{\partial \mathbb{H}(\cdot)}{\partial \sigma_\Omega}}_{>0} + \underbrace{\mathbb{U}_1}_{>0} \underbrace{\frac{\partial^2 \mathbb{H}(\cdot)}{\partial \sigma_\Omega \partial R^s}}_{<0} < 0.$$

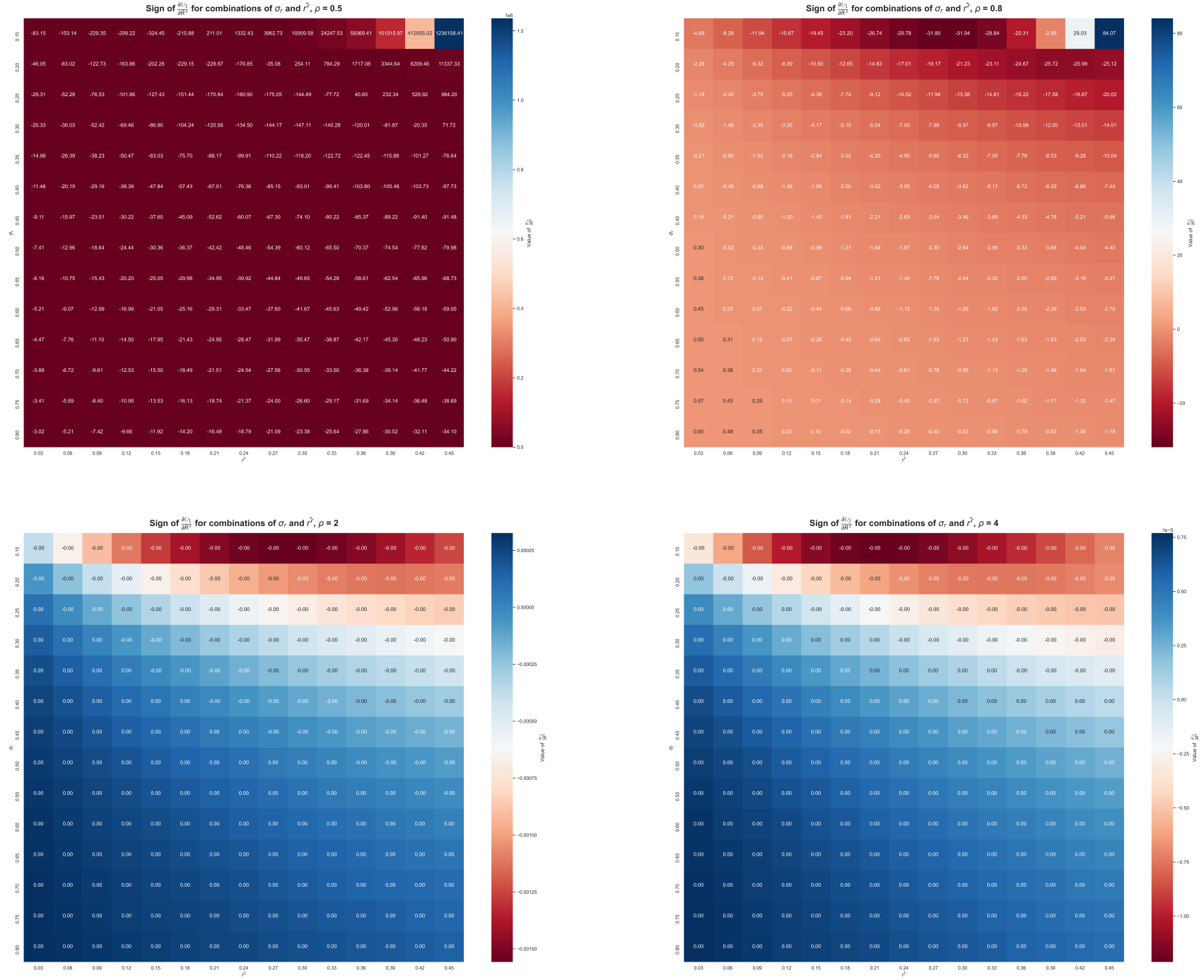


Figure 3.5: Notes: This figures plots the sign of the derivative, $\frac{\partial \mathbb{U}_1}{\partial R^s}$, for four values of ρ: $\rho = 0.5$ (top left), $\rho = 0.8$ (top right), $\rho = 2$ (bottom left) and $\rho = 4$ (bottom right). For each of these figures, the value of $\frac{\partial \mathbb{U}_1}{\partial R^s}$ is provided for various combinations of the risky asset's variance (σ_r^2) and expected log rate of return ($\bar{r}^r$), holding all other parameters constant. In particular, $\beta = 1$, $y_0 = 1000$, $R = 1.02$, and $\kappa = 0.02$.

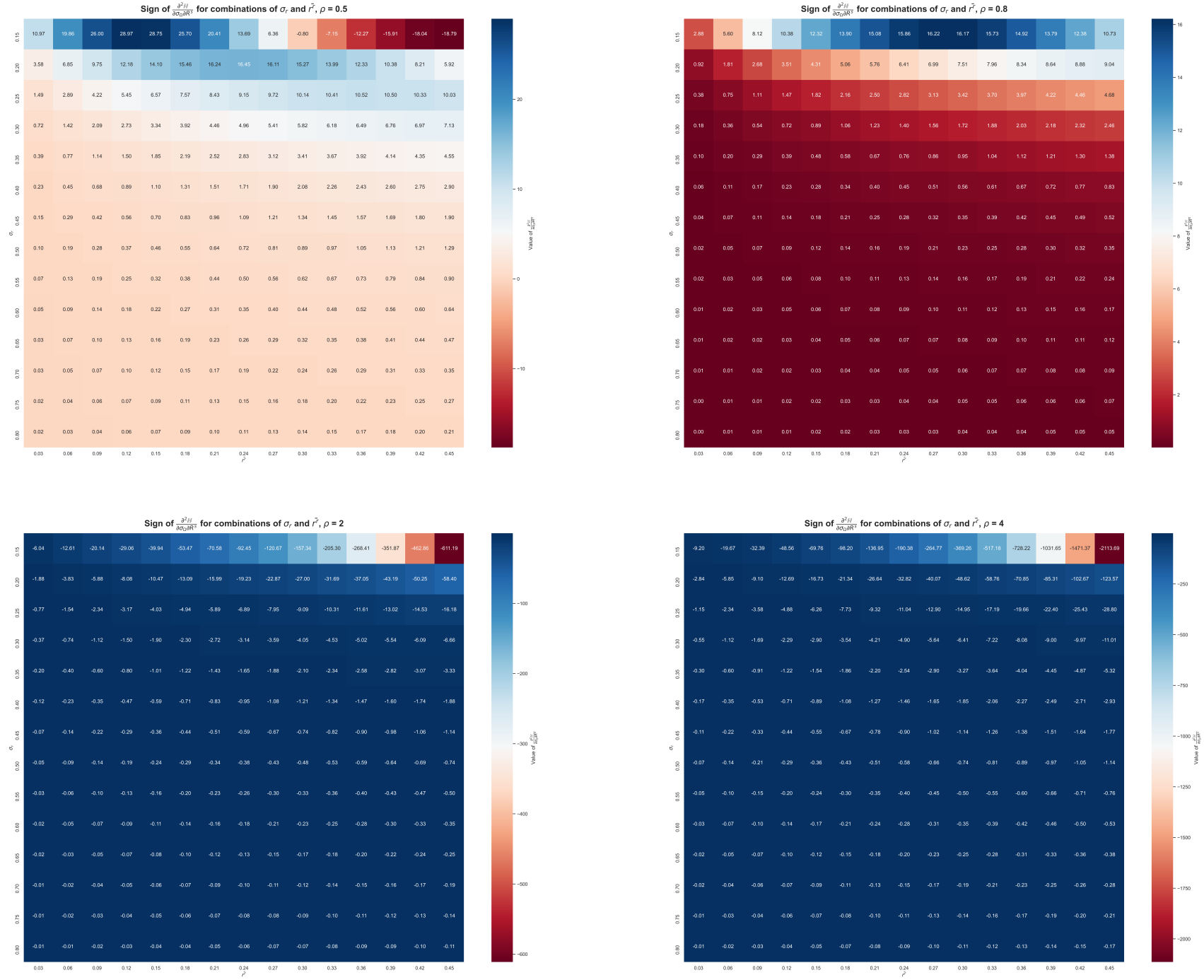


Figure 3.6: Notes: This figures plots the sign of the derivative, $\frac{\partial^2 \mathbb{H}}{\partial \sigma_\Omega \partial R^s}$, for four values of ρ: $\rho = 0.5$ (top left), $\rho = 0.8$ (top right), $\rho = 2$ (bottom left) and $\rho = 4$ (bottom right). For each of these figures, the value of $\frac{\partial^2 \mathbb{H}}{\partial \sigma_\Omega \partial R^s}$ is provided for various combinations of the risky asset's variance (σ_r^2) and expected log rate of return ($\bar{r}^r$), holding all other parameters constant. In particular, $\beta = 1$, $y_0 = 1000$, $R = 1.02$, $\kappa = 0.02$, $\mu_\Omega = 0$, and $\sigma_\Omega = 0.1$.

Optimal Monetary Policy and Central Bank Optimism, Revisited

Recall, from Equation 3.28, that our desired comparative static with respect to central bank optimism can be expressed as:

$$\frac{\partial R^{s*}}{\partial \mu_\Omega} \propto \frac{\partial \mathbb{U}_1}{\partial R^s}\frac{\partial \mathbb{H}(\cdot)}{\partial \mu_\Omega} + \mathbb{U}_1 \frac{\partial^2 \mathbb{H}(\cdot)}{\partial \mu_\Omega \partial R^s}$$

The case for both $\frac{\partial \mathbb{U}_1}{\partial R^s}$ and $\mathbb{U}_1$ has already been discussed. The expression for $\frac{\partial \mathbb{H}(\cdot)}{\partial \mu_\Omega}$ is:

$$\frac{\partial \mathbb{H}(\cdot)}{\partial \mu_\Omega} = \frac{(1-\rho)\left(2\eta^{HH}+\sigma_r^2\right)e^{\left(\frac{(\rho-1)\left(2\eta^{HH}+\sigma_r^2\right)\left(2\eta^{HH}{\sigma_\Omega}^2-\sigma_r^2\left(-4\kappa+4\mu+{\sigma_\Omega}^2\right)\right)}{8\rho\sigma_r^4}\right)}}{2\rho\sigma_r^2} \tag{3.41}$$

The sign of this derivative hinges on ρ: $\frac{\partial \mathbb{H}(\cdot)}{\partial \mu_\Omega} > 0$ if $\rho < 1$, and $\frac{\partial \mathbb{H}(\cdot)}{\partial \mu_\Omega} < 0$ if $\rho > 1$.

Finally, Figure 3.6 plots a heatmap of the value of the fourth term, $\frac{\partial^2 \mathbb{H}(\cdot)}{\partial \mu_\Omega \partial R^s}$, for various parameter choices. In almost all cases, $\frac{\partial^2 \mathbb{H}(\cdot)}{\partial \mu_\Omega \partial R^s} < 0$ if $\rho < 1$ while $\frac{\partial^2 \mathbb{H}(\cdot)}{\partial \mu_\Omega \partial R^s} > 0$ if $\rho > 1$.

Putting all these results together, the sign of our desired comparative static if $\rho < 1$ is:

$$\frac{\partial R^{s*}}{\partial \mu_\Omega} \propto \underbrace{\frac{\partial \mathbb{U}_1}{\partial R^s}}_{<0}\underbrace{\frac{\partial \mathbb{H}(\cdot)}{\partial \mu_\Omega}}_{>0} + \underbrace{\mathbb{U}_1}_{>0}\underbrace{\frac{\partial^2 \mathbb{H}(\cdot)}{\partial \mu_\Omega \partial R^s}}_{<0} < 0$$

which matches the result under logarithmic utility. For $\rho > 1$, and assuming $\frac{\partial \mathbb{U}_1}{\partial R^s} > 0$, we instead have that the net sign depends on which of the two terms in the following sum dominates:

$$\frac{\partial R^{s*}}{\partial \mu_\Omega} \propto \underbrace{\frac{\partial \mathbb{U}_1}{\partial R^s}}_{>0}\underbrace{\frac{\partial \mathbb{H}(\cdot)}{\partial \mu_\Omega}}_{<0} + \underbrace{\mathbb{U}_1}_{>0}\underbrace{\frac{\partial^2 \mathbb{H}(\cdot)}{\partial \mu_\Omega \partial R^s}}_{>0}$$

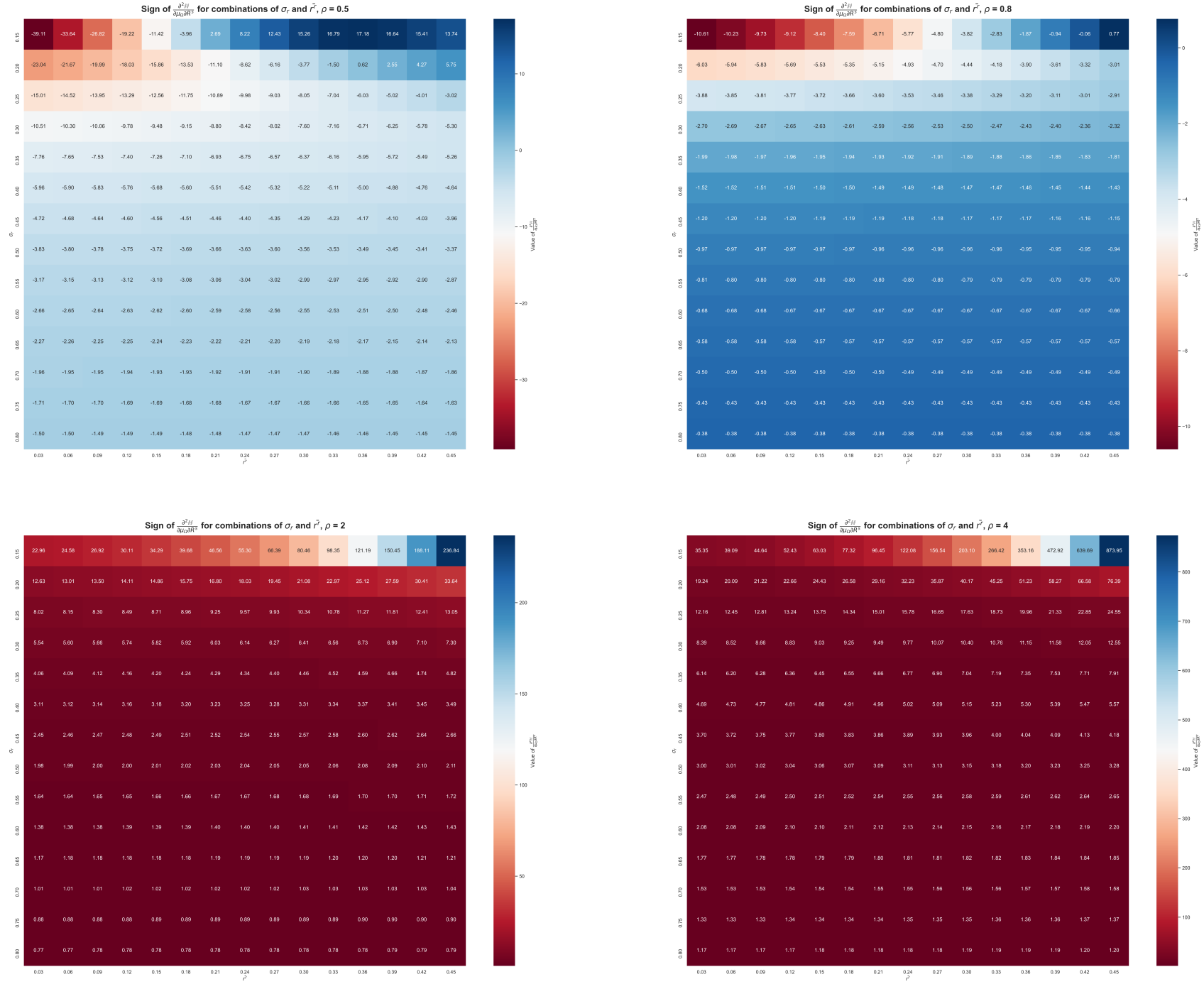


Figure 3.7: Notes: This figures plots the sign of the derivative, $\frac{\partial^2 \mathbb{H}}{\partial \mu_\Omega \partial R^s}$, for four values of ρ: $\rho = 0.5$ (top left), $\rho = 0.8$ (top right), $\rho = 2$ (bottom left) and $\rho = 4$ (bottom right). For each of these figures, the value of $\frac{\partial^2 \mathbb{H}}{\partial \mu_\Omega \partial R^s}$ is provided for various combinations of the risky asset's variance (σ_r^2) and expected log rate of return ($\bar{r}^r$), holding all other parameters constant. In particular, $\beta = 1$, $y_0 = 1000$, $R = 1.02$, $\kappa = 0.02$, $\mu_\Omega = 0$, and $\sigma_\Omega = 0.1$.

3.4.4 Unpacking the Influence of the Coefficient of Relative Risk Aversion, ρ

The analysis thus far has indicated that the case for raising interest rates in the face of rising uncertainty and rising pessimism from the central bank depends importantly on ρ. Namely, the results established in Propositions 1 and 2 under logarithmic utility generally persist if $\rho < 1$, while their interpretation becomes more muddled if $\rho > 1$. Why is this? Below, I provide some intuitions for some of the dynamics at play:

1. We are considering settings of the model where the behavioral biases of households make them overoptimistic about the risky asset's return profile relative to the central bank: that is, $\kappa > \mu_\Omega$. This has two implications: in the eyes of the central bank, the household both over-saves in the risky asset and exuberantly over-invests in the risky asset as a share of their endowed income. In other words, the central bank believes that households select sub-optimally high values of γ^* and $a_0^*\gamma^*$.

2. While the central bank would like to address the household's behavior along both of these margins, they only have one tool to do so: their ability to raise the safe rate of interest. However, not only is using this tool costly, as it implies that the central bank must set a higher effective tax rate, but it may also be insufficient to jointly affect both the household's portfolio allocation decision and their savings decision in the desired direction. Namely, as the central bank raises R^s:

    - The household's optimal portfolio share in the risky asset, $\gamma^*(R^s)$, is always declining.
    - The effect on the household's optimal savings, $a_0^*(R^s, \gamma^*(R^s))$, depends on various parameters of the model, including ρ. In particular, it is the case,

for reasonable risky asset return profiles, that $\frac{\partial a_0^*(\cdot)}{\partial R^s} < 0$ if $\rho < 1$, while the opposite holds true if $\rho > 1$.

3. As such, if $\rho < 1$, the central bank can effectively reduce both γ^* and a^*—and, therefore, the household's savings in the risky asset, $a_0^*\gamma^*$—by raising the safe rate of interest. However, if $\rho > 1$, then raising R^s exerts two opposing pressures on the agent's risky asset savings: while γ^* is reduced, a_0^* rises.

Conclusion

In the first two chapters of this paper, I examine the Federal Open Market Committee's historical rate-setting behavior to assess the sensitivity of American monetary policy to financial stability concerns. By estimating various monetary policy reaction functions, I find that proxies for credit market sentiment are strong predictors of the federal funds rate, even after controlling for the Board of Governors' staff forecasts for inflation and unemployment. This relationship is statistically significant for a variety of credit market indicators, including the high-yield share, both the level and the change in Baa credit spreads, and a simple composite measure of credit sentiment. Holding all else constant, a one-standard-deviation increase in a composite measure of credit sentiment predicts an 18-basis-points increase in the federal funds rate, which is in the ballpark of a standard 25-basis-point rate hike. Importantly, this effect is localized to credit, and it is robust to a variety of robustness checks, including the exclusion of outliers such as the Great Financial Crisis from the sample and the use of augmented inflation and unemployment forecasts that directly incorporate information on credit market sentiment.

Beyond documenting novel evidence that developments in credit markets have historically served as independent and statistically significant predictors of the path of American monetary policy, this paper also finds that this relationship has become stronger over time. For rolling windows beginning annually from 1987 to 2002, I document that the response of the policy rate to a one-standard-deviation increase in credit market sentiment nearly doubles from the beginning to the end

of my sample.

Finally, I show that the Federal Open Markets Committee has responded both to periods where credit market sentiment was falling and to periods where it was rising. This finding therefore indicates that American monetary policy has *leaned against credit*, as central bankers have responded to rising financial stability concerns by tightening monetary policy beyond what was warranted by the evolution of inflation and unemployment.

In the last chapter, I switch gears to a separate theoretical exercise aimed at exploring whether there are normative reasons to use interest-rate policy to quell over-optimism in financial markets in a simple macroeconomic model where agents deviate from rational expectations. In a setting of the model with logarithmic utility, and for reasonable parameter values, I demonstrate that central banks should raise interest rates both as they become more uncertain about households' behavioral biases and as they become more pessimistic about the risky asset's return relative to households. The former result stems from a precautionary savings motive under greater uncertainty, while the later result flows from the central bank's desire to curb the household's exuberant allocation towards the risky asset. Furthermore, I show how the results of my analysis of the optimal conduct of monetary policy in this model evolve as a function of the coefficient of relative risk aversion when we move beyond a logarithmic utility function. In particular, the propositions I present in the case of logarithmic utility generally continue to hold if $\rho < 1$ but become more difficult to interpret if $\rho > 1$.

Considered as a whole, this paper not only suggests that the fully-separable view does not reflect the conduct of American monetary policy between 1987 and 2008, but that there may also be sound theoretical justifications for the behavior exhibited by members of the Federal Open Markets Committee during this period. In light of these findings, we may wonder whether "the core challenge for monetary policymaking [rests] not ... so much in recognizing when markets are overheating,

but rather in deciding how much weight to put on this data" (Stein, 2021).

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