Monetary Policy and the Equity Term Structure

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Abstract

We use a high-frequency event study approach to analyze the impact of monetary policy surprises on the term structure of equity prices. We document that short-term and long-term equity prices respond in opposite ways to changes in monetary policy. Following an unanticipated cut to the target rate, short-term equity prices fall while long-term equity prices rise on average. We develop a model which shows this pattern arises when policy decisions signal information about economic conditions. Consistent with model predictions, the short-term asset price response significantly predicts short-term macroeconomic growth and is positively related to central bank soft information.

JEL Classification: E50, G10

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1 Introduction

Asset prices provide an important way to study the impact of monetary policy. Unlike economic outcomes, which are often realized far into the future, the market prices of claims to real assets quickly adjust to incorporate the expected impact of monetary policy news on the future path of the economy. Prior research has documented that unexpected cuts to the target federal funds rate are associated with increases in stock market prices (Bernanke and Kuttner, 2005), a finding consistent with the conventional interpretation of monetary policy in which lower rates reduce the cost of capital and increase spending and investment. In this paper, we estimate the term structure of equity prices in order to measure the differential effects of central bank policy announcements across the short- and long-term horizons. The empirical facts we document provide new evidence in the debate in the recent literature about whether Fed policy announcements reveal information about the current economic conditions.[1]

We estimate the term structure of market prices using information embedded in the price of European options on the S&P 500 index. Intuitively, an investor who holds a replicating portfolio of the S&P 500 index will receive dividend payments from its constituent firms while an investor who uses options to create synthetic exposure to the S&P 500 index will not be entitled to dividends. This allows us to estimate the implied prices of short-term dividend strips from the difference between option-implied prices and the value of the underlying index. We innovate on the methodology used in Van Binsbergen et al. (2012) and Golez and Jackwerth (2022) and employ the linear regression approach to simultaneously estimate intra-daily dividend prices and risk-free rates from the put-call parity restriction. We implement this procedure using options of different maturities to obtain the implied prices of short-term assets which pay the dividends of the S&P 500 over near-term horizons ranging from 180 days to 540 days.

We study the price response of these short-horizon assets to each FOMC announcement. We follow the high-frequency approach used in Gürkaynak et al.

[1] Work in this area includes Romer and Romer (2000); Faust et al. (2004); Campbell et al. (2012); Nakamura and Steinsson (2018); Lunsford (2020); Bundick and Smith (2020); Bauer and Swanson (2020).

(2004) and Nakamura and Steinsson (2018), by measuring unexpected changes in interest rates around the 30-minute window surrounding scheduled Federal Reserve announcements using tick-by-tick data on the 30 Day Federal Funds Futures. We similarly estimate the change in price of the equity dividend strips over the same 30-minute window: from 10 minutes before the FOMC decision is released to 20 minutes after. Unlike the market, the short-maturity assets only provide claims to cash flows over the immediate horizon and not over longer horizons. This allows us to isolate investor beliefs about the short-horizon impacts of Fed announcements.[2] We also estimate the response of the long-term equity asset, the S&P 500 index return, over this same interval for comparison.

We find that the prices of the short-term equity assets and the price of the long-term equity asset (the market) respond to changes in monetary policy in the exact opposite way. First, we replicate the findings in the prior literature by regressing the market return over the 30-minute window around the FOMC announcement on the monetary policy surprise. Consistent with the findings in Bernanke and Kuttner (2005), we estimate a negative and significant coefficient on the monetary policy shock in the market regression. We then run separate regressions of the 30-minute FOMC announcement window returns for dividend strips at maturities ranging from 180-days to 540-days on the monetary policy surprise. The coefficient estimates on the monetary policy shock are positive at all maturities and significant at the 5 percent level at the 180 day horizon. A one standard deviation increase (decrease) in the monetary policy shock corresponds to a 0.75 percent increase (decrease) in the price of the short-term asset and a 0.18 percent decrease (increase) in the market price.

In a simple non-parametric test, we categorize each FOMC announcement as positive, negative or zero based on the sign of the monetary policy shock at each meeting date and then estimate the average response of each dividend strip and the market within each category. The results presented in Figure 1 are consistent with our baseline findings: following positive (negative) monetary policy shocks, the price of the 180-day dividend strip increases (decreases) while the price of the

[2] Our identification comes from the fact that all public information at start of the 30-minute announcement window is already embedded into the initial Fed Funds futures and options prices.

long-term asset falls (increases) on average. The average response of dividend strip prices to monetary shocks attenuates as the maturity of dividend strips increases.

The opposite response of the short-term assets and the long-term asset to monetary policy news cannot be explained by the change in the risk-free rates since short-term risk-free rates move in the same direction as the short-term asset prices. One channel that could generate our empirical findings is the idea that central bank policy announcements reveal information about the current state of the economy (referred to as "Fed Information effects" in the literature). For example, while the aggregate stock market may respond favorably to an unexpected cut to the target Federal Funds rate given the impact of lower rates on spending and investment in the long run (Bernanke and Kuttner (2005)), this decision may signal to investors that economic conditions are worse than previously assumed, causing investors to revise down forecasts for near-term future cash flows and lowering the short-term asset price.

To substantiate the precise relationship between the short-term asset response and information effects, we write a model of Fed information effects and the term structure of equity prices. The model shows how information effects produce the documented opposite response of long- and short-term assets and develops additional implications which motivate our subsequent empirical tests. We specify a persistent central bank policy rule which incorporates central bank economic growth forecasts and also includes an exogenous shock, μ. Economic growth is a persistent process and is affected by central bank policy. We model information effects as a private signal, ε, received by the central bank about next period GDP growth. Investors know the central bank policy rule and observe realized GDP growth and the central bank policy decision but do not observe μ or ε. Based on the realized policy decision, investors infer a posterior distribution of ε and μ which they use to update forecasts for the future path of interest rates and economic growth. Following an unexpected cut to the target rate, investors infer a negative realization of the central bank private signal, ε, with beliefs about the magnitude of the shock determined by the relative variance of μ and ε. Investors revise downward next period economic growth forecasts and the price of the short-term asset falls. The long-term asset price is negatively impacted by the shock to near-term economic growth expectations but positively affected by the higher expected long-term economic growth generated by the conventional effects of monetary policy. When monetary policy is persistent, the conventional effects outweigh the more transitory information effects and the market return is positive.

The model makes several additional predictions which we test empirically. First, the short-term asset return around each FOMC announcement should forecast measures of near-term economic conditions with a positive coefficient. We run predictive regressions of $k-quarter$ ahead real dividend (real GDP) growth on price changes in the 180-day dividend strip in the 30-minute window around each FOMC announcement and document evidence of significant, positive predictability.[3] The short-term asset announcement return predicts dividend growth with positive and significant coefficients[4] with the coefficients increasing from 1 to 4 quarters and then decreasing thereafter. The results are economically significant, a one standard deviation decrease in short-term asset price corresponds to a 0.45 percent decline in real dividend growth over the next four quarters. The coefficients for 1 to 5 quarter ahead forecasts remain significant after controlling for the surprise change in the federal funds target rate. The $k-quarter$ ahead quarterly real GDP growth predictive regression results are similar. Notably, this pattern of predictability occurs only on FOMC announcement days: we run the same specification on non-FOMC days and find no evidence of dividend growth or GDP predictability.

Finally, the model implies that soft information about economic conditions released by the central bank drives important variation in the short-term asset return. To test this prediction, we construct two measures of soft information based on discussion about economic growth in the FOMC minutes: a measure constructed using an unsupervised machine learning technique, latent Dirichlet allocation (LDA), to identify discussion about favorable economic growth prospects; and a measure constructed using the sentiment classification dictionary developed in Loughran and

[3] $k \in \{1,2,...,8\}$. In the model, dividends are proportional to GDP growth. To account for seasonality, we calculate quarterly dividend growth as the difference in log dividends in quarter k and log dividends in the same quarter in the previous year, $\Delta d_{t+k} = log\left(\frac{D_{t+k}}{D_{t+k-4}}\right)$. Similarly, we calculate quarterly GDP growth as $\Delta gdp_{t+k} = log\left(\frac{GDP_{t+k}}{GDP_{t+k-4}}\right)$.

[4] Coefficients are significant at the 5 percent level using Newey-West adjusted standard errors with two lags.

McDonald (2011). We document a positive and significant association between both measures and the short-term asset returns around the FOMC announcements.

Our work relates to a large body of literature which studies the impact of monetary surprises on asset prices and macroeconomy (Kuttner (2001); Gilchrist and Leahy (2002); Gürkaynak et al. (2004); Bernanke and Kuttner (2005); Campbell et al. (2012); Gorodnichenko and Weber (2016); Ozdagli and Weber (2017); Nakamura and Steinsson (2018); Drechsler et al. (2018); Cieslak and Schrimpf (2019); Neuhierl and Weber (2019); Jarocinski and Karadi (2020); Swanson (2021)). Our study contributes to the debate in the literature on the existence of Fed information effects (Romer and Romer (2000); Faust et al. (2004); Campbell et al. (2012); Nakamura and Steinsson (2018); Lunsford (2020); Bundick and Smith (2020); Bauer and Swanson (2020)).[5] Some of the strongest evidence of a Fed Information effect is provided by Nakamura and Steinsson (2018), who document that unexpected changes to interest rates over the 30-minute window surrounding Federal Reserve announcements predict private sector forecast revisions for output growth with a positive sign (the opposite sign expected under the conventional interpretation of monetary policy shocks). However, a number of studies have questioned the existence of information effects (Faust et al. (2004); Bundick and Smith (2020); Bauer and Swanson (2020)). Bauer and Swanson (2020) argue that the results in Nakamura and Steinsson (2018) could be driven by macroeconomic news released between the time the private sector forecasts are measured and the FOMC meeting date. Our measure of short-term asset price response in the tight window around the FOMC announcements addresses the critique raised by Bauer and Swanson (2020) and others about the low-frequency nature of forecast-based evidence by providing a high-frequency, direct measure of investor beliefs about the short-horizon impact of each policy announcement.

We also contribute to a fast-growing body of work analyzing the term structure of equity returns (Van Binsbergen et al. (2012); Van Binsbergen and Koijen (2017); Weber (2018); Li and Wang (2018); Gormsen (2018); Bansal et al. (2019); Golez

[5] Our paper also contributes to theory work on monetary policy and information effects (Cukierman and Meltzer (1986); Ellingsen and Soderstrom (2001); Melosi (2017); Nakamura and Steinsson (2018); Miranda-Agrippino and Ricco (2021)).

and Jackwerth (2022)). While this literature focuses on the level and the time-series variation in the term structure of equity returns at monthly or lower frequencies, we analyze the high frequency response of the term structure to key macroeconomic shocks to understand precisely how this news transmits into the market and the economy.

The rest of the paper is organized as follows. In Section 2, we describe the construction of the monetary policy shock and the estimation of the short-term equity prices. Section 3 presents our main empirical results. Section 4 presents the theoretical framework of the Fed Information channel. Section 5 documents results from empirical tests of the additional predictions of the model. Section 6 concludes.

2 Measure Construction

In this section, we discuss the construction of the monetary policy shock and the estimation of the high-frequency changes in short- and long-horizon equity prices around each FOMC announcement.

2.1 Monetary Policy Shock

We obtain FOMC meeting dates and the timestamp when the meeting decision was made public from January 2004 to December 2019.[6] This is the period over which we have high-frequency option pricing data used to construct the implied dividend strip prices. We use tick-by-tick data on the 30 Day Federal Funds Futures contract from the CME group to measure changes in expectations of the current month Federal Funds rate around each FOMC announcement. We follow the high-frequency approach used in Gürkaynak et al. (2004) and Nakamura and Steinsson (2018),

[6]The dates and times of FOMC meetings until June 2013 are provided in the Appendix of Lucca and Moench (2015) and from Bernile et al. (2016). We extend the data to December 2019 by obtaining FOMC meeting dates from the Federal Reserve website. We obtain the time of each announcement following a similar procedure from Fleming and Piazzesi (2005). Specifically, we record the timestamp of the earliest Dow Jones newswires on the day of each announcement with "Federal Reserve", or "Fed", or "Federal Open Market Committee", or "FOMC" in the headline. We verify that this procedure generates the same times as in Bernile, Hu, and Tang (2016) in the latter portion of their sample and then populate the meetings from June 2013 to December 2019.

by measuring unexpected changes in interest rates around the 30-minute window surrounding scheduled Federal Reserve announcements,[7] which provides stronger identification than monetary policy shocks constructed using daily futures data.

A federal funds futures contract pays off $100 - \bar{r}$ where $\bar{r}$ is the average effective federal funds rate over the month. For an FOMC announcement occurring on date t, we define f_{t-} as the implied rate from the current month federal funds futures contract immediately before the FOMC announcement time and f_{t+} as the implied rate from this contract immediately following the announcement. Specifically, f_{t-} is based on the price of the last trade which occurred at least 10 minutes before the FOMC announcement and f_{t+} is based on the price of the first trade that occurred at least 20 minutes after the FOMC announcement. We construct the FOMC shock variable, $\Delta\iota_t^s$ as:

$$\Delta\iota_t^s = E_{t+}r - E_{t-}r = \frac{m}{m-d}\left(f_{t+} - f_{t-}\right) \tag{1}$$

where d be the day in the month of the FOMC announcement, m is the number of days in the month, and r is the average federal funds rate for the remainder of the month.[8] Panel A of Table 1 presents summary statistics of our monetary policy shock. The monetary policy shock runs from January 2004 to December 2019 and covers 128 scheduled FOMC meetings.

2.2 Term Structure of Equity Prices

We estimate the term structure of market prices from the put-call parity relationship spanning prices of European put and call options on the S&P 500 index.[9] Assuming an exogenous risk-free rate, we can invert the put-call parity relationship and

[7] We measure the surprise to the current federal funds rate similar to Kuttner (2001); Gürkaynak et al. (2004); Bernanke and Kuttner (2005).

[8] We scale the price change by $\frac{m}{m-d}$ to account for the fact that the contract's settlement is based on the average federal funds rate over the entire month. We use the current month futures except when the FOMC meeting occurs in the last 7 days in the month, in which case we use the change in price of the next month's contract. Increases (decreases) in Δi_t^u correspond to increases (decreases) in expected Federal Funds rates.

[9] The put-call parity restriction dictates that at any given moment s:

$$c_s^h(X) - p_s^h(X) = \left(S_s - P_s^h\right) - Xe^{-rf_s^h \times h}$$

estimate prices of short-term dividend P directly from the observed options prices (Van Binsbergen et al. (2012)).[10] In this paper, we build on the approach used in Golez and Jackwerth (2022) to simultaneously estimate dividend prices and risk-free rates from the put-call parity restriction using ordinary least squares.

We obtain minute-by-minute data for S&P 500 options (henceforth SPX options) from 2004 to 2019 from the Chicago Board of Options Exchange (CBOE).[11] We estimate prices of dividend strips and risk-free rates from these option prices immediately before each FOMC announcement and immediately after. For each FOMC announcement day, we define two 30 minute periods: the pre-announcement window and the post-announcement window. The pre-announcement window runs from 40 minutes before to 10 minutes before the FOMC announcement time. The post-announcement window runs from 20 minutes after to 50 minutes after the announcement time. For each estimation window, we run the following regression based on all put-call pairs within that interval:

$$S_s - c_s^h(X) + p_s^h(X) = \alpha + \beta X + \varepsilon \tag{2}$$

where c is the price of a European call option, p is the price of a European put option with the same strike price X and maturity h, S is the value of the underlying index. All prices are measured at the same minute s. Identification comes from variation in the strike price X across put-call pairs with the same time-to-expiration h. The implied price of dividends over horizon h is $P_s^h = \hat{\alpha}$. The implied risk-free rate

where h is the time-to-expiration (horizon) of the options, c is the price of a European call option, p is the price of a European put option, S is the value of the underlying index, P is the price of dividends on the underlying index during the life of the options, X is the strike price and rf^h is the annualized required risk-free rate of return over the corresponding period of options maturity.

[10] Recent work has argued that even small deviations in interest rates can have an important impact on estimated dividend prices (Boguth et al. (2019)). This is particularly important in our setting as FOMC announcements have a direct effect on interest rates. Golez and Jackwerth (2022) advocate an interest rate invariant approach by first using a regression-based approach to estimate risk-free rates implied in the option prices (similar to Van Binsbergen et al. (2019)), and then using these implied interest rates in the put-call parity relation to estimate dividend prices. This procedure ensures that dividend prices are internally consistent with the estimated risk-free rates.

[11] The data includes quotes on all the SPX options along with implied volatilities. We only keep standard monthly options that expire on the third Friday each month and have more than 90 days until the expiration. We use the bid-ask midpoint and we eliminate all options with bid or ask prices lower than 3 dollars. We also eliminate options with moneyness levels below 0.5 or above 1.5.

is $rf^h = -\frac{1}{h} log\left(\hat{\beta}\right)$. We estimate the implied dividend prices and risk-free rates for 180 day to 540 day maturities in the 30 minute windows around each FOMC announcement.[12] We construct asset returns as the change in log prices around the FOMC announcement.[13]

3 Term Structure Response to Monetary Policy

In this section, we study the impact of monetary policy shocks on the term structure of equity prices.

3.1 Baseline Results

We estimate the response of short-term dividend strip prices and the long-term asset to unexpected changes in the Federal Funds rate. We estimate the model:

$$\Delta x_t^h = \alpha + \beta \Delta \iota_t^s + \varepsilon \tag{3}$$

where $\Delta \iota_t^s$ is the monetary policy surprise estimated in the 30-minute window around the FOMC announcement at date t and Δx_t^h is the change in the asset price of interest estimated over the same window. We report the results for all FOMC days in Panel A of Table 2. We run separate regressions for dividend strips of each maturity with maturities ranging from 180 days to 540 days and report the results of each specification in separate columns. The last column with the heading "∞" reports the results using the S&P 500 index return as the dependent variable. OLS standard errors are in parentheses below each coefficient estimate.

For the aggregate market, we find a negative and significant coefficient on the monetary policy shock, consistent with prior literature. The response of the short-term dividend strips is opposite of the response of the market: the β estimates are positive. The estimate is 0.249 and significant at the 5 percent level in the 180-day

[12] At the beginning of our sample period (first FOMC meeting is on January 28, 2004), we have at least 500 observations for each maturity for which we estimate dividend strip prices and interest rates. This number increases to close to 2,000 by the end of our sample period (last FOMC announcement is on December 11, 2019).

[13] See Section 8.1 in the Appendix for details.

strip specification. The coefficient estimates decrease and become insignificant using dividend strips with longer maturities. The coefficient on the market return is –0.059 and significant at the 1 percent level. The standard deviation of the monetary policy shock is 0.030 so a one standard deviation increase in the shock corresponds to a 0.75 percent increase in the return of the short-term asset and a 0.178 percent decrease in the market return. In Panel B of Table 2, we restrict the sample to only those FOMC days with non-zero monetary policy shock. The results are qualitatively similar and the coefficient on the short-term dividend strip is significant at the 1 percent level. We also verify that our results are not driven by outliers by winsorizing the dividend returns at the 5 percent level. Table A.1 in the Appendix presents the results. The coefficient estimates are positive at all horizons and significant at the 1 percent level for the 180-day strip.

These results document the consistent opposite response of the 180-day dividend asset and the aggregate stock market to monetary policy shocks. Following an unexpected decrease (increase) in the federal funds rate, the market price increases (decreases) while the short-term asset price decreases (increases) on average. We explore this result further in a simple non-parametric test based on the monetary policy shock sign in the next section.

3.2 Average Response by Announcement Type

We categorize each FOMC announcement as positive, negative or zero based on the sign of the monetary policy shock at each meeting date: Positive: $\{\Delta\iota_t^s > 0\}$, Negative: $\{\Delta\iota_t^s < 0\}$, Zero: $\{\Delta\iota_t^s = 0\}$. We then estimate the average response of dividend strip and market prices within each monetary policy shock group.

Figure 1 presents the average return of the short-term dividend assets with maturities from 180 days to 540 days for positive (plotted in blue squares) and negative (plotted in red dots) monetary policy shocks. The corresponding values are reported in the summary statistics in Panel B of Table 1. The x-axis denotes the horizon of each dividend strip and the y-axis is the average log return. We plot the average return of the long-term asset (the S&P 500 index return) following positive and negative monetary policy shocks on the right-hand side denoted by $'\infty'$. Following a positive (negative) monetary policy shock, the price of the 180-day strip increases (decreases) while the price of the long-term asset falls (increases) on average. The average returns of the longer horizon dividend strips (360 days and beyond) tend towards 0 in response to both positive and negative monetary policy shocks.

These results indicate that the opposite response of the short-term asset and long-term asset to monetary policy shocks occurs following both positive and negative monetary policy shocks. In the next section, we explore potential mechanisms behind the pattern of opposite responses of the short-term and long-term assets to monetary policy shocks. We focus on the 180-day dividend strip (which we denote the "short-term asset" in the following sections) given that we find the strongest response at this horizon.

3.3 Fed Information Channel

Our results show that the short-term assets and the long-term asset respond in opposite ways to monetary policy news. This pattern is not driven by fluctuations in risk-free rates. We obtain direct estimates of the risk-free rates at each horizon through our estimation based on the put-call parity restriction. Figure A.1 in the Appendix plots the average response of implied risk-free rates at different horizons following positive and negative monetary policy shocks. Following an unexpected increase (decrease) in the federal funds rate, implied risk-free rates increase (decrease) across all horizons. All else equal, this would decrease (increase) the short-term asset price and generate the opposite pattern that we observe empirically.

One channel that could generate our empirical findings is the idea that central bank policy announcements reveal information about the state of the economy to market participants.[14] For example, an unexpected cut to the target federal funds rate during an economic downturn is favorable news for the aggregate stock market given the positive impact of lower rates on spending and investment in the long run. However, the central bank decision may also signal to investors that economic con-

[14] This idea has been termed the "Fed Information channel." The existence of Fed Information effects is debated in the literature Romer and Romer (2000); Faust et al. (2004); Campbell et al. (2012); Nakamura and Steinsson (2018); Lunsford (2020); Bundick and Smith (2020); Bauer and Swanson (2020).

ditions are worse than previously assumed causing investors to revise down forecasts of near-term future cash flows which pushes down the price of the short-term asset. In the next section we write a model to formalize this intuition and to provide a precise characterization of the relationship between our empirical evidence and the existence of information effects.

4 Model

We present a stylized model of Fed Information effects and the term structure. We show how information effects will generate the documented opposite response of long- and short-term assets and derive new testable implications of the existence of this channel.

4.1 Setup

There are two agents in our model, a central bank and an investor. There are two assets, a long-term asset which is a claim to all future dividends of the market and a short-term asset which is a claim to the next period dividend. Time is indexed by t with each period t divided into two subperiods $\underline{t}$ and $\bar{t}$. The GDP growth process is given by:

$$\Delta\widehat{GDP}_{t+1} = \rho_g \Delta\widehat{GDP}_t + \varepsilon_{\bar{t}} + b\iota_t + w_{t+1} \tag{4}$$

Where $\Delta\widehat{GDP}_t$ denotes the deviation, in percent, of GDP growth from steady state, $0 < \rho_g < 1$ is the persistence of the process, w_{t+1} is an exogenous shock with $w_{t+1} \sim i.i.d.\ N\left(0, \sigma_w^2\right)$, and $b < 0$ is the effect of monetary policy, ι_t. We model Fed information effects through $\varepsilon_{\bar{t}}$, an exogenous shock with $\varepsilon_{\bar{t}} \sim i.i.d.N\left(0, \sigma_\varepsilon^2\right)$ that is observed by the central bank but not by the investor in period $\bar{t}$. $\Delta\widehat{GDP}_t$ is realized in subperiod $\underline{t}$ and is observed by both agents. The investor sets the price of the long-term and short-term assets. In subperiod $\bar{t}$, the central bank receives the private signal, $\varepsilon_{\bar{t}}$, updates forecasts for next period GDP growth and sets the target Federal funds rate, ι_t, following the policy rule:

$$\widehat{\iota}_t = \rho_\iota \widehat{\iota}_{t-1} + \alpha \mathbb{E}^{cb}_{\bar{t}}\left(\Delta \widehat{GDP}_{t+1}\right) + \mu_{\bar{t}} \tag{5}$$

Where $\widehat{\iota}_t$ denotes the deviation in percent of the target Federal funds rate from steady state, $0 < \rho_\iota < 1$ is the process persistence, and $\alpha > 0$ is the response of central bank policy to forecasted deviations of GDP growth from steady state. $\mathbb{E}^{cb}_{\bar{t}}\left(\Delta \widehat{GDP}_{t+1}\right)$ denotes the forecast of the central bank, *cb*, based on its time $\bar{t}$ information set.[15] $\mu_{\bar{t}} \sim i.i.d.N\left(0, \sigma^2_\mu\right)$ is an exogenous shock to the target rate independent from the private signal about economic conditions, ε.

The investor infers the posterior distribution of $\varepsilon_{\bar{t}}$ based on the monetary policy decision the unconditional distributions of ε and μ.[16] Additionally, we model soft information released by the central bank by assuming the central bank releases a noisy signal about ε to investors. This assumption is necessary to decouple the dividend strip return from the monetary policy surprise, but it is not necessary to generate the opposite response of the long-term and short-term asset to monetary policy surprises.

Following the monetary policy decision, the investor updates beliefs about the future path of interest rates and GDP growth and sets the new prices of long- and short-term assets. We assume a simple relationship between dividend growth and GDP growth:

$$\Delta d_t = \alpha_d + \beta_d \Delta \widehat{GDP}_t + \omega_t \tag{6}$$

where $\beta_d > 0$ and $\omega_t \sim N\left(0, \sigma^2_\omega\right)$.

Next, we derive how changes in economic growth and target rate forecasts propagate across the term structure. Then we derive expressions for the change in investor expectations of next period growth following a monetary policy surprise. From these we obtain closed form expressions for the long- and short-term asset price responses to monetary policy news and show conditions under which the assets will respond in opposite ways. Finally, we discuss a simple extension of the

[15] The target rate $\widehat{\iota}_t$ is chosen at time $\bar{t}$ and affects economic growth realized at time $\underline{t+1}$. Figure A.6 in the Appendix summarizes the timeline of our stylized framework.

[16] In the model, the investor knows the variance of the shocks, the policy rule, and the economic growth process.

baseline framework that incorporates soft information released by the central bank and discuss additional testable predictions of information effects.

4.2 Propagation Across the Term Structure

We determine how changes in expectations about the target federal funds rate and GDP growth propagate across the horizon. Applying the expectations operator to Equations 4 and 5 we have:

$$\mathbb{E}_t\left(\Delta GDP_{t+k+1}\right) = \rho_g \mathbb{E}_t\left(\Delta \widehat{GDP}_{t+k}\right) + b\mathbb{E}_t\left(\widehat{\iota}_{t+k}\right) \tag{7}$$

$$\mathbb{E}_t\left(\widehat{\iota}_{t+k}\right) = \rho_\iota \mathbb{E}_t\left(\widehat{\iota}_{t+k-1}\right) + \alpha\mathbb{E}_t\left(\Delta \widehat{GDP}_{t+k+1}\right) \tag{8}$$

Expectations about next period GDP growth and next period interest rates are jointly determined. We obtain an expression for $\mathbb{E}_t\left(\Delta GDP_{t+k+1}\right)$ by substituting Equation 8 into Equation 7 to obtain:

$$\mathbb{E}_t\left(\Delta GDP_{t+k+1}\right) = \frac{1}{1-\alpha b}\left(\rho_g \mathbb{E}_t\left(\Delta \widehat{GDP}_{t+k}\right) + b\rho_\iota \mathbb{E}_t\left(\widehat{\iota}_{t+k-1}\right)\right)$$

Similarly we have:

$$\mathbb{E}_t\left(\widehat{\iota}_{t+k}\right) = \frac{1}{1-\alpha b}\left(\alpha\rho_g \mathbb{E}_t\left(\Delta \widehat{GDP}_{t+k}\right) + \rho_\iota \mathbb{E}_t\left(\widehat{\iota}_{t+k-1}\right)\right)$$

We can express this recurrence relation in matrix form as:

$$\begin{pmatrix} \mathbb{E}_t\left(\Delta GDP_{t+k+1}\right) \\ \mathbb{E}_t\left(\widehat{\iota}_{t+k}\right) \end{pmatrix} = \frac{1}{(1-\alpha b)^k}\begin{pmatrix} \rho_g & b\rho_\iota \\ \alpha\rho_g & \rho_\iota \end{pmatrix}^k \begin{pmatrix} \mathbb{E}_t\left(\Delta GDP_{t+1}\right) \\ \mathbb{E}_t\left(\widehat{\iota}_t\right) \end{pmatrix} \tag{9}$$

In order to obtain a closed-form expression for the long-term asset return in the next section, we express matrix $A = \begin{pmatrix} \rho_g & b\rho_\iota \\ \alpha\rho_g & \rho_\iota \end{pmatrix}$ in the form $A = PDP^{-1}$, the product of diagonal matrix D and change of basis matrices P and P^{-1}. Expressions for P, D, and P^{-1} are obtained in the standard procedure: we compute the eigenvalues of matrix A, denoted by λ_1 and λ_2 respectively, as the roots of the characteristic polynomial[17]; we obtain eigenvectors associated with each eigenvalue, λ_i, as any vector that spans the kernel $A-\lambda_i I$ where I is the 2×2 identity matrix. Expressions for P and D in terms of model primitives are provided in Section 8.2.1 in the Appendix.

The expression PDP^{-1} is a linear transformation of input vector $\begin{pmatrix}\mathbb{E}_t\left(\Delta GDP_{t+1}\right)\\ \mathbb{E}_t\left(\widehat{\iota}_t\right)\end{pmatrix}$ so we can express changes in forecasts from $\underline{t}$ to $\bar{t}$ as:

$$\begin{pmatrix}\Delta\mathbb{E}_{\bar{t}}\left(\Delta GDP_{t+k+1}\right)\\ \Delta\mathbb{E}_{\bar{t}}\left(\widehat{\iota}_{t+k}\right)\end{pmatrix}=\frac{1}{(1-\alpha b)^k}PD^kP^{-1}\begin{pmatrix}\Delta\mathbb{E}_{\bar{t}}\left(\Delta GDP_{t+1}\right)\\ \Delta\mathbb{E}_{\bar{t}}\left(\widehat{\iota}_t\right)\end{pmatrix} \tag{10}$$

where $\Delta\mathbb{E}_{\bar{t}}\left(\Delta GDP_{t+1}\right)=\mathbb{E}_{\bar{t}}\left(\Delta GDP_{t+1}\right)-\mathbb{E}_{\underline{t}}\left(\Delta GDP_{t+1}\right)$ and $\Delta\mathbb{E}_{\bar{t}}\left(\widehat{\iota}_t\right)=\mathbb{E}_{\bar{t}}\left(\widehat{\iota}_t\right)-\mathbb{E}_{\underline{t}}\left(\widehat{\iota}_t\right)$. This expression determines how changes to expectations propagate across the horizon in our model.[18]

4.3 Expectation Revisions

We obtain expressions for the change in investor expectations, $\Delta\mathbb{E}_{\bar{t}}\left(\Delta GDP_{t+1}\right)$ and $\Delta\mathbb{E}_{\bar{t}}\left(\widehat{\iota}_t\right)$ from Equation 10, after shocks are realized in time $\bar{t}$. First, we examine the central bank policy rule and show how the shocks ε and μ determine the target rate surprise. Then we discuss the revision in investor expectations for next period economic growth from $\underline{t}$ to $\bar{t}$ after observing the monetary policy decision.

[17] $\lambda_1 = \frac{1}{2}\left(\rho_g+\rho_\iota+\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota\left(4\alpha b-2\right)\right)^{\frac{1}{2}}\right)$ and $\lambda_2 = \frac{1}{2}\left(\rho_g+\rho_\iota-\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota\left(4\alpha b-2\right)\right)^{\frac{1}{2}}\right)$

[18] We require $\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota\left(4\alpha b-2\right)>0$ to ensure real roots.

4.3.1 Central Bank

We determine central bank expectations and the policy decision after observing shocks ε and μ. At time $\bar{t}$ after observing $\varepsilon_{\bar{t}}$, the central bank forms its expectation of future growth, $\Delta\widehat{GDP}_{t+1}$, as:

$$\mathbb{E}_{\bar{t}}\left(\Delta\widehat{GDP}_{t+1}\right) = \frac{1}{1-\alpha b}\left(b\rho_\iota\widehat{\iota}_{t-1} + \rho_g\Delta\widehat{GDP}_t + \varepsilon_{\bar{t}} + b\mu_{\bar{t}}\right)$$

Based on this forecast, the central bank sets the target rate (expressed in terms of percent deviations from steady state) following the policy rule in Equation 5. Substituting in the central bank's forecast we have:

$$\widehat{\iota}_t = \frac{1}{1-\alpha b}\left(\rho_\iota\widehat{\iota}_{t-1} + \alpha\rho_g\Delta\widehat{GDP}_t + \alpha\varepsilon_{\bar{t}} + \mu_{\bar{t}}\right)$$

The central bank sets the target rate based on the prior target rate $\widehat{\iota}_{t-1}$, the policy rule, α, applied to current economic growth after adjusting for the mean reversion ρ_g, the private signal about next period growth, ε, and the monetary policy shock, μ.

4.3.2 Investor

At time $\bar{t}$, after observing the central bank target rate, $\widehat{\iota}_t$, the investor infers the distribution of $\mu_{\bar{t}}$ and $\varepsilon_{\bar{t}}$ based on the monetary policy surprise, $\widehat{\iota}_t - \mathbb{E}^i_{\underline{t}}(\widehat{\iota}_t)$:

$$\begin{aligned}\widehat{\iota}_{\bar{t}} - \mathbb{E}^i_{\underline{t}}(\widehat{\iota}_t) &= \widehat{\iota}_t - \frac{1}{1-\alpha b}\left(\rho_\iota\widehat{\iota}_{t-1} + \alpha\rho_g\Delta\widehat{GDP}_t\right) \\ &= \frac{1}{1-\alpha b}\left(\alpha\varepsilon_{\bar{t}} + \mu_{\bar{t}}\right)\end{aligned} \tag{11}$$

Equation 11 maps the unobserved shocks, μ and ε, to the observed target rate surprise, $\widehat{\iota}_{\bar{t}} - F^i_{\underline{t}}(\widehat{\iota}_t)$. We define $\Delta\iota^s_{\bar{t}} = \widehat{\iota}_{\bar{t}} - F^i_{\underline{t}}(\widehat{\iota}_{\bar{t}})$, the monetary policy surprise from our empirical tests in the previous section. We express Equation 11 as:

$$\mu_{\bar{t}} + \alpha\varepsilon_{\bar{t}} = \Delta\iota^s_{\bar{t}}\left(1-\alpha b\right) \tag{12}$$

We denote investor beliefs about the realized values of $\varepsilon_{\bar{t}}$ and $\mu_{\bar{t}}$ by $\varepsilon^{i,*}_{\bar{t}}$ and $\mu^{i,*}_{\bar{t}}$ respectively. Equation 12 specifies a curve on the surface of the bivariate normal distribution of μ and ε of pairs $(\mu_{\bar{t}}, \varepsilon_{\bar{t}})$ that would generate the observed target rate surprise, $\Delta\iota^s_{\bar{t}}$. This normalized probability density of this curve forms the posterior distribution of ε and μ: conditional on $\Delta\iota^s_{\bar{t}}$, $\varepsilon^{i,*}_{\bar{t}}$ is normally distributed with:

$$\varepsilon^{i,*}_{\bar{t}} | \Delta\iota^s_{\bar{t}} \sim N\left(\frac{(1-\alpha b)}{\alpha}\frac{\sigma^2_{\alpha\varepsilon}}{\sigma^2_{\alpha\varepsilon}+\sigma^2_{\mu}}\Delta\iota^s_{\bar{t}}, \frac{1}{\alpha^2}\frac{\sigma^2_{\alpha\varepsilon}\sigma^2_{\mu}}{\sigma^2_{\alpha\varepsilon}+\sigma^2_{\mu}}\right) \tag{13}$$

where $\sigma^2_{\alpha\varepsilon} = \alpha^2\sigma^2_{\varepsilon}$ and σ^2_{μ} are the variances of $\alpha\varepsilon$ and μ respectively, $\alpha > 0$ is the response of central bank policy to forecasted deviations of GDP growth from steady state, $b < 0$ is the effect of the target rate on economic growth. The relation from Equation 12 pins down $\mu^{i,*}_{\bar{t}}$ as a function of $\varepsilon^*_{\bar{t}}$ and the target rate surprise $\Delta\iota^s_{\bar{t}}$.

Beliefs About Future Economic Growth Given the belief distributions $\varepsilon^{i,*}_{\bar{t}}$ and $\mu^{i,*}_{\bar{t}}$, the change in expected economic growth from $\underline{t}$ to $\bar{t}$ can be expressed as:

$$\mathbb{E}^i_{\bar{t}}\left(\Delta\widehat{GDP}_{t+1}\right) - \mathbb{E}^i_{\underline{t}}\left(\Delta\widehat{GDP}_{t+1}\right) = b\Delta\iota^s_{\bar{t}} + \mathbb{E}^i_{\bar{t}}\left(\varepsilon^{i,*}_{\bar{t}}\right) \tag{14}$$

Combining with Equation 10 we have:

$$\begin{pmatrix} \Delta\mathbb{E}_{\bar{t}}\left(\Delta GDP_{t+k+1}\right) \\ \Delta\mathbb{E}_{\bar{t}}\left(\widehat{\iota}_{t+k}\right) \end{pmatrix} = \frac{1}{(1-\alpha b)^k} PD^kP^{-1}\begin{pmatrix} b\Delta\iota^s_{\bar{t}} + \mathbb{E}^i_{\bar{t}}\left(\varepsilon^{i,*}_{\bar{t}}\right) \\ \Delta\iota^s_{\bar{t}} \end{pmatrix} \tag{15}$$

Changes in investor beliefs about future GDP growth and target rates across the term structure are linear transformations of the target rate surprise and normally distributed beliefs, $\varepsilon^{i,*}_{\bar{t}}$, and so are normally distributed. The monetary policy surprise, $\Delta\iota^s_{\bar{t}}$, pins down the distribution of $\varepsilon^{i,*}_{\bar{t}}$ so we can use Equation 13 to substitute out $\mathbb{E}^i_{\bar{t}}\left(\varepsilon^{i,*}_{\bar{t}}\right)$ to obtain:

$$b\Delta\iota_{\bar{t}}^{s}+\mathbb{E}_{\bar{t}}^{i}\left(\varepsilon_{\bar{t}}^{i,*}\right)=\left(\frac{b\alpha\sigma_{\mu}^{2}+\sigma_{\alpha\varepsilon}^{2}}{\alpha\left(\sigma_{\alpha\varepsilon}^{2}+\sigma_{\mu}^{2}\right)}\right)\Delta\iota_{\bar{t}}^{s}$$

So we have:

$$\begin{pmatrix}\Delta\mathbb{E}_{\bar{t}}\left(\Delta GDP_{t+k+1}\right)\\ \Delta\mathbb{E}_{\bar{t}}\left(\widehat{\iota}_{t+k}\right)\end{pmatrix}=\frac{1}{\left(1-\alpha b\right)^{k}}PD^{k}P^{-1}\begin{pmatrix}\left(\frac{b\alpha\sigma_{\mu}^{2}+\sigma_{\alpha\varepsilon}^{2}}{\alpha\left(\sigma_{\alpha\varepsilon}^{2}+\sigma_{\mu}^{2}\right)}\right)\\ 1\end{pmatrix}\Delta\iota_{\bar{t}}^{s} \qquad (16)$$

Investors cannot condition on the realized values of ε and μ so the monetary policy surprise completely determines investor forecast revisions across the term structure.

4.4 Asset Prices

We express the price of the long-term asset following the Campbell and Shiller (1988) decomposition as:

$$p_t-d_t=\sum_{j=0}^{\infty}\rho^{j}\mathbb{E}_t\left(\Delta d_{t+j+1}\right)-\sum_{j=0}^{\infty}\rho^{j}\mathbb{E}_t\left(r_{t+j+1}\right)+\frac{\kappa}{1-\rho} \qquad (17)$$

where t indexes quarters, p_t is the log price, d_t is log dividend, $\rho=\frac{1}{1+\frac{D}{P}}\approx 0.99$, $\kappa=-log\left(\rho\right)-\left(1-\rho\right)log\left(\frac{1}{\rho}-1\right)$, Δd_{t+j+1} is the dividend growth rate from $t+j$ to $t+j+1$, r_{t+j+1} is the return from $t+j$ to $t+j+1$. Assuming d_t is fixed in the 30-minute window around the FOMC announcement and constant risk premia we have:

$$r_{\bar{t}}^{\infty}=\sum_{j=0}^{\infty}\rho^{j}\beta_{d}\left(\mathbb{E}_{\bar{t}}-\mathbb{E}_{\underline{t}}\right)\left(\Delta\widehat{GDP}_{t+j+1}\right) \qquad (18)$$

where $\mathbb{E}_{\bar{t}}-\mathbb{E}_{\underline{t}}$ denotes the change in expectations from pre- to post-announcement. The return on the short-term dividend strip is similarly given by:

$$r_{\bar{t}}^{1} = \rho \beta_d \left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}} \right) \left(\Delta \widehat{GDP}_{t+1} \right) \tag{19}$$

Assumption of Constant Risk Premia We model information effects through the cash flow channel in-line with the idea that central bank announcements contain information about near-term economic conditions. It is plausible that information effects also operate through the discount rate channel whereby announcements signal information about aggregate conditions leading to changes in risk premia: unexpected easing (tightening) signals weak (strong) conditions and increase (decrease) short-horizon discount rates. Incorporating a mean-reverting discount rate process in the model that loads negatively on the monetary policy surprise would still generate the opposite response of the short-term and long-term asset. While this is an interesting extension, we lack empirical support for this channel.[19] Accordingly, we elect not to model the discount rate process for parsimony and to demonstrate that information effects can generate the opposite response of the short- and long-term asset within our simple framework.

Long-term Asset Response We derive an expression of the long-term asset return in terms of model parameters to determine the parametrizations which will generate an opposite response to monetary policy surprises. We substitute Equation 10 into the long-term asset return given in Equation 18 and reorder the terms to substitute in the closed form of the infinite geometric series and obtain a simple expression for the long-term asset response:[20]

[19] If monetary easing signals increased uncertainty over short-horizon, we would expect the short-term implied volatility (IV) on the S&P 500 index to increase relative to long-termer implied volatility following a surprise cut in the target federal funds rate. Figure A.2 in the Appendix plots the change in the implied volatility for S&P 500 options for maturities of 180, 360, and 540 days, separately for positive and negative monetary policy shocks. We note that implied volatility decreases around both negative and positive shocks which is consistent with the fact that FOMC announcements reduce uncertainty. However, the opposite response of the short-term and long-term asset to positive and negative shocks cannot be explained solely by this reduction in uncertainty. In particular, we note that negative monetary policy shocks induce a greater reduction in short-term implied volatility compared with long-term implied volatility which is opposite pattern we would expect under the uncertainty channel.

[20] Derivation in Section 8.2.2 in the Appendix.

$$r_t^{\infty} = \frac{\beta_d}{(\rho\rho_g - 1)(\rho\rho_\iota - 1) - \alpha b}\left((1 - \alpha b - \rho_\iota \rho)\left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)(\Delta GDP_{t+1}) + b\rho\rho_\iota\left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)(\widehat{\iota}_t)\right) \tag{20}$$

The term $(\rho\rho_g - 1)(\rho\rho_\iota - 1) - \alpha b > 0$ for the range of our parametrizations, $0 < \rho, \rho_\iota, \rho_g < 1$ and $b < 0$ and $0 < \alpha < 1$. Similarly, the coefficient on the change in GDP forecasts, $(1 - \alpha b - \rho_\iota \rho)$ is positive and the coefficient on the change in target rate, $b\rho\rho_\iota$, is negative. The long-term asset returns load positively on shocks to growth expectations and negatively on monetary policy shocks.

4.5 Opposite Response to Monetary Policy

First, we show that without information effects, it is not possible to generate an opposite response of the short-term and long-term asset to monetary policy shocks. We shut down the private information channel, ε, so the change in investor beliefs about next period economic growth and interest rates following target rate surprise, $\Delta\iota_{\bar{t}}^s$, are given by:

$$\begin{pmatrix} \Delta\mathbb{E}_t\left(\Delta GDP_{t+k+1}\right) \\ \Delta\mathbb{E}_t\left(\widehat{\iota}_{t+k}\right) \end{pmatrix} = \frac{1}{(1 - \alpha b)^k} P D^k P^{-1} \begin{pmatrix} b \\ 1 \end{pmatrix} \Delta\iota_{\bar{t}}^s \tag{21}$$

The long-term asset return is:

$$\begin{aligned} r_t^{market} &= \frac{\beta_d}{(\rho\rho_g - 1)(\rho\rho_\iota - 1) - \alpha b}\left((1 - \alpha b - \rho_\iota \rho)\left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)(\Delta GDP_{t+1}) + b\rho\rho_\iota\left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)(\widehat{\iota}_t)\right) \\ &= \frac{b(1 - \alpha b)\beta_d}{(\rho\rho_g - 1)(\rho\rho_\iota - 1) - \alpha b}\Delta\iota_{\bar{t}}^s \end{aligned}$$

As discussed above, for our range of our parametrizations the denominator will always be non-negative and the numerator will always be negative. The market will respond to unexpected cuts (increases) in the target rate with a positive (negative) return consistent with Bernanke and Kuttner (2005). The return of the short-term asset is:

$$r_{\bar{t}}^{1} = \rho\beta_d\left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)\left(\Delta\widehat{GDP}_{t+1}\right) = \rho b\beta_d\Delta\iota_{\bar{t}}^{s} \tag{22}$$

So the return on the short-term asset will always be the same sign as the return of the long-term asset.

With information effects, the long-term and short-term asset may respond in opposite directions to monetary policy surprises. We identify the range of parameter values under which the two assets will respond in opposite directions using the intuition that the long-term asset return is the short-term asset return plus the sum of $j \geq 1$ terms. This yields the boundary condition across which the sign of the asset responses will differ: $r_{\bar{t}}^{market} = 0$. Substituting in from Equation 16, we have:

$$\begin{aligned}
r_{t}^{market} &= \frac{\beta_d}{(\rho\rho_g - 1)(\rho\rho_\iota - 1) - \alpha b}\left((1 - \alpha b - \rho_\iota\rho)\left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)(\Delta GDP_{t+1}) + b\rho\rho_\iota\left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)(\widehat{\iota}_t)\right)\\
&= \frac{\beta_d}{(\rho\rho_g - 1)(\rho\rho_\iota - 1) - \alpha b}\left(\left(\frac{(1 - \alpha b - \rho_\iota\rho)\left(b\alpha\sigma_\mu^2 + \sigma_{\alpha\varepsilon}^2\right)}{\alpha\left(\sigma_{\alpha\varepsilon}^2 + \sigma_\mu^2\right)}\right) + b\rho\rho_\iota\right)\Delta\iota_{\bar{t}}^{s}\\
&= \frac{\beta_d(\alpha b - 1)}{((\rho\rho_g - 1)(\rho\rho_\iota - 1) - \alpha b)\,\alpha\left(\sigma_{\alpha\varepsilon}^2 + \sigma_\mu^2\right)}\left(-\alpha b\sigma_\mu^2 + \rho_\iota\rho\sigma_{\alpha\varepsilon}^2 - \sigma_{\alpha\varepsilon}^2\right)\Delta\iota_{\bar{t}}^{s}
\end{aligned}$$

Under our range of parametrizations this expression has a root at $\frac{\sigma_\mu^2}{\sigma_{\alpha\varepsilon}^2} = \frac{(\rho_\iota\rho - 1)}{\alpha b}$.[21] When the central bank cuts the target rate, investors infer poor near-term economic growth and the price of the short-term asset falls. The price of the long-term asset is also exposed to the impact of the policy surprise on short-horizon economic growth expectations. However, monetary policy transmits persistently across the term structure compared to the more transitory growth shock (in our calibration we estimate $\rho_\iota > \rho_g$). This slow adjustment of policy can generate sustained periods of economic growth above steady state in the medium-term before the target rate and economic growth converge to steady state in the long-run. The price response

[21] The other roots are not in the span of our parametrizations: $b = \frac{1}{\alpha}$; $\alpha = 0, \rho_\iota \neq 0$, and $\rho = \frac{1}{\rho_\iota}$; $\alpha = 0$, $\rho_\iota\rho - 1 \neq 0$, and $\sigma_{\alpha\varepsilon}^2 = 0$; $b = 0$, $\rho_\iota \neq 0$, $\alpha \neq 0$, and $\rho = \frac{1}{\rho_\iota}$.

of the long-term asset depends on the relative contribution of these two effects. If the short-horizon information effect of monetary policy dominates, the long-term asset return will be negative like the short-term asset. If the long-horizon effects of policy easing dominate, the long-term asset return will be positive with the opposite sign of the short-term asset.

4.6 Model Extension: Soft Information

In the baseline model, the target rate surprise uniquely determines revisions in investor expectations across the term structure and pins down both the short- and long-term asset return. Empirically, the short-term asset return does not move in lockstep with the target rate surprise. This additional variation is important because it reflects conditioning information that may not be captured in the target rate surprise (which is fixed at the time of the announcement). The short-term asset price adjusts after the announcement so that the measured price response will reflect information such as: soft information and forward guidance from the central bank; and variation in economic and financial conditions at different announcement dates which leads investors to interpret identical policy surprises (sign and magnitude) differently in different contexts.[22] For example, if there is no monetary policy surprise but the central bank discusses concern about economic conditions, the short-term asset price may fall.

We model soft information released by the central bank by supposing that the central bank provides a noisy signal, $\eta_{\bar{t}} \sim N\left(\varepsilon_{\bar{t}}, \sigma_\eta^2\right)$, to investors about its private information about GDP growth, ε. The distribution of $\eta_{\bar{t}}$ is centered at the realized value of $\varepsilon_{\bar{t}}$ with variance σ_η^2. The central bank cannot inform investors the precise private signal.[23] Investor's conjugate prior is given by Equation 13, and the posterior distribution of beliefs, $\varepsilon^{i,*}_{\bar{t},soft}$, after observing the signal $\eta_{\bar{t}}$ is:

[22]Another way to capture the idea of variation in announcement contexts is to introduce stochastic volatility in the μ and ε distributions. In this case, identical target rate surprises will generate different posterior beliefs about ε and μ depending on the volatilities at the time of each announcement.

[23]This could arise for several reasons including central bank credibility but we do not take a stance in our model.

$$\varepsilon_{\bar{t},soft}^{i,*} \sim N\left(\varepsilon_p \frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2} + \varepsilon_{\bar{t}} \frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2}, \left(\frac{1}{\sigma_\eta^2}+\frac{1}{\sigma_p^2}\right)^{-1}\right) \tag{23}$$

where $\varepsilon_{\bar{t}}$ is the realization of ε, $\varepsilon_p = \frac{(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2}\Delta\iota_{\bar{t}}^s$ is the investor's expected value of $\varepsilon_{\bar{t}}$ (from Equation 13) based on the observed target rate surprise, $\sigma_p^2 = \frac{1}{\alpha^2}\frac{\sigma_{\alpha\varepsilon}^2\sigma_\mu^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2}$, and $\Delta\iota_{\bar{t}}^s$ is the target rate surprise. Changes in investor beliefs about future economic growth are still governed by Equation 15 but with $\mathbb{E}_{\bar{t}}^i\left(\varepsilon_{\bar{t},soft}^{i,*}\right) = \frac{(1-\alpha b)\sigma_{\alpha\varepsilon}^2\sigma_\eta^2}{\alpha\left(\sigma_\eta^2+\sigma_p^2\right)\left(\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2\right)}\Delta\iota_{\bar{t}}^s + \varepsilon_{\bar{t}}\frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2}$ so that this term does not depend solely on the target rate surprise, $\Delta\iota_{\bar{t}}^s$.

On average, soft information shifts investor beliefs towards the true realization of ε. The weight placed on the soft information provided by the central bank depends on the variance of the noisy signal compared with the variance of the prior beliefs about ε. Without soft information, an unexpected cut in the target rate causes investors to infer a negative realization of ε. With soft information, if the unexpected cut in target rate is driven by a large negative shock, μ, but the realization of ε is positive, investors may infer a positive ε after incorporating the soft information released by the central bank. This decouples the one-to-one mapping from the target rate surprise to investor beliefs about $\varepsilon_{\bar{t}}$ and expected growth rates that is present in the baseline model.

4.7 Model Predictions

The model makes strong predictions about the relationship between the short-term asset response and near-term economic growth. We outline these predictions for the baseline model and contrast them with the additional predictions steming from the extended version of the model incorporating soft information released by the central bank. We start by discussing the relationship between the target rate surprise and future economic growth, followed by the relationship between the short-term asset return and future economic growth.

Target Rate Surprise We examine the regression of next period GDP growth on the target rate surprise:

$$\Delta\widehat{GDP}_{t+1} = \alpha^c + \beta^c \Delta\iota^s_{\bar{t}} + \delta^c_{t+1} \tag{24}$$

where $\Delta\iota^s_{\bar{t}}$ is the target rate surprise. With information effects but no soft information, the coefficient on the target rate surprise, β^c, is given by:

$$\frac{Cov\left(\Delta\iota^s_{\bar{t}}, \Delta\widehat{GDP}_{t+1}\right)}{Var\left(\Delta\iota^s_{\bar{t}}\right)} = \frac{bVar\left(\mu_{\bar{t}}\right) + \alpha Var\left(\varepsilon_{\bar{t}}\right)}{Var\left(\mu_{\bar{t}}\right) + \alpha^2 Var\left(\varepsilon_{\bar{t}}\right)}$$

$b < 0$ and $\alpha > 0$ so the relative variance of shocks determines the sign of the coefficient. Intuitively, an unexpected cut to the target rate can arise from an negative shock to monetary policy, μ, or due to bad news about economic conditions, ε. In the former case, the cut in target rate will be associated with higher future economic growth through the impact of the lower rate on growth (the magnitude of the effect is governed by b). In the latter case, the unexpected cut in the target rate is associated with lower next period GDP growth as the cut is driven by information received by the central bank about poor economic growth, $\varepsilon < 0$. The relative variances of the shocks ε and μ determine which the average contribution to observed target rate surprises: when $Var(\mu)$ ($Var(\varepsilon)$) is relatively high, the inferred contribution of μ (ε) to an observed target rate surprise is higher.

Without information effects, the regression coefficient will be $b < 0$ and cuts (increases) to the target rate will predict higher (lower) next period economic growth. The model implications are related to the result in Nakamura and Steinsson (2018) who find evidence of information effects by documenting a positive coefficient on the target rate surprise in a regression of economic growth forecast revisions on the target rate surprise. In our model, without information effects the estimated coefficient, β^c, will be negative, while with information effects β^c may be positive depending on the relative variances of μ and ε.

Short-term Asset Return Next, we consider the relationship between near-term economic growth and the short-term asset return with information effects but without soft information:

$$\Delta\widehat{GDP}_{t+1} = \alpha^1 + \beta^1 r^1_{\bar{t}} + \delta^1_{t+1} \tag{25}$$

The coefficient estimate, β^1, is given by:[24]

$$\beta^1 = \frac{1}{\rho\beta_d} \tag{26}$$

The coefficient β^1 will be positive under the full range of parametrizations we assume. The positive coefficient arises because of the assumption in Equation 19 that fluctuations in the short-term asset price around central bank announcements are driven by changing cash flow expectations. Equation 26 suggests a way to examine this assumption is to test whether the short-term asset return positively predicts next period economic growth.

Notably, the model-implied coefficient estimate on β^1 after shutting down the information effect channel remains the same, $\frac{1}{\rho\beta_d}$. This follows naturally from the fact that variation in the short-term asset price is driven by changes in rational expectations of next period economic growth, $\left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)\left(\Delta\widehat{GDP}_{t+1}\right)$, which implies the same beta regardless of whether variation in expected growth is driven by μ or ε. Furthermore, in the baseline model without soft information, the predictive power of the short-term asset return for next period GDP is subsumed by the the target rate surprise as the short-term asset return and the target rate surprise are collinear in the predictability regression:

$$\Delta GDP_{t+1} = \alpha + \beta^1 r^{st}_t + \beta^c \Delta\iota^s_{\bar{t}} + \delta_{t+1} \tag{27}$$

This result follows from the result above that without soft information, the target rate surprise uniquely determines the short-term asset return: the short-term asset

[24]See Section 8.2.3 in the Appendix.

return is given by $r_t^1 = \rho\beta_d \frac{b\alpha\sigma_\mu^2+\sigma_{\alpha\varepsilon}^2}{\alpha\left(\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2\right)}\Delta\iota_{\tilde{t}}^s$ which falls in the span of the target rate surprise.

In the model with soft information, the short-term asset return is not collinear with the target rate surprise. In Section 8.2.5 in the Appendix we derive the expression for the coefficient, β^1 on the short-term asset return in the multivariate specification given in Equation 27. Intuitively, with soft information the short-term asset return is given by $r_t^1 = \rho\beta_d\left(\frac{(1-\alpha b)\sigma_{\alpha\varepsilon}^2\sigma_\eta^2}{\alpha\left(\sigma_\eta^2+\sigma_p^2\right)\left(\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2\right)}\Delta\iota_{\tilde{t}}^s + \varepsilon_{\tilde{t}}\frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2}\right)$ and the short-term asset return is no longer spanned by the target rate surprise. For each realization of target rate surprise, $\Delta\iota_{\tilde{t}}^s$, there are is a distribution of short-term asset returns with infinite support corresponding to the realized soft information, η, drawn from the normal distribution centered at the realized value of ε. The excess variation of the short-term asset return outside the span of the target rate surprise is positively correlated with the realized ε and therefore has positive predictive power for next period GDP. This presents an additional test of the existence of information effects: a positive coefficient on the short-term asset return in the specification from Equation 27 which includes the monetary policy surprise as an additional predictor.

A final implication is that measures of soft information from the central bank, η, should positively predict near-term economic growth and should be positively related to the short-term asset return, r_t^1. We highlight features of the model using a simple calibration in the next subsection. Then in the next section, we test the additional predictions of the model related to economic growth predictability and soft information.

4.8 Calibration and Model Predictions

We present a simple calibration of the model to illustrate how information effects generate the documented opposite response of short-term and long-term assets to monetary policy news. We use parametrizations that approximate real-world properties where possible.[25]

[25] We discuss the calibration parameters in Section 8.3 in the Appendix.

4.8.1 Propagation of Monetary Policy

We show the model-implied change in expected quarterly growth rates and change in expected target rates following negative and positive monetary policy surprises. In each scenario below, we assume the target rate and economic growth start at steady state prior to the monetary policy surprise.

Figure 2 presents the model-implied change in expectations following a monetary policy surprise of -1% (unexpected easing).[26] Panel A shows the change in expected quarterly economic growth across the term structure - the x-axis indicates the quarters ahead from the monetary policy shock which occurs at quarter 0. Panel B shows the change in expected target rate. The dashed green "Mu" (blue "Epsilon") line shows the change in expectations if the investor observes the shocks, ε and μ, and the entire monetary policy surprise is driven by the exogenous shock μ (ε). The black line labeled "Baseline" shows the change in investor expectations following the monetary policy surprise.

We consider the case where investors observe the shocks and the monetary policy surprise is driven by the central bank information about economic conditions, ε. In this case, the central bank information is incorporated into next period investor economic growth expectations which are revised downwards sharply. Two-period ahead economic growth expectations are also revised downwards but the magnitude of revisions is smaller because of the low persistence of the economic growth process, ρ_g, and the impact of the lower target rate on economic growth. The monetary policy surprise is persistent and generates a downward revision of expected target rates across the horizon. The expected target rate eventually converges to steady state but generates modest upward revisions in economic growth forecasts at medium- and long-term horizons. When the monetary policy surprise is driven completely by an observed shock ε, the downward revision of near-term economic growth expectations dominates the upward revisions to longer-term economic growth forecasts and both the long-term and short-term asset returns are

[26] Figure A.7 in the Appendix shows the model-implied change in expectations across the term structure following a monetary policy surprise of 1% (unexpected tightening). The results are similar conceptually to those following an unexpected easing but with opposite signs following the positive monetary policy surprise.

negative (-3.15 percent and -3.96 percent respectively).

Next, we consider the case where the investor observes the shocks and the monetary policy surprise is driven by μ. In this scenario there are no central bank information effects. Next period economic growth forecasts are revised upwards based on the effect of lower target rates on growth. Economic growth expectations are revised upward (target rate expectations are revised downwards) across the term structure and converge towards their steady state values. The long-term and short-term asset returns are positive in this case.

In the baseline case where investors do not observe the shocks and must infer the distribution of ε and μ from the observed target rate surprise, investor beliefs lie between the prior two cases. Based on the negative monetary policy surprise, investors infer a negative realization of ε and revise their expectations of next period economic growth downwards. Similar to the pure ε case discussed above, investor expectations about medium- and long-term economic growth are revised upwards because of the persistent effect of the monetary policy shock on economic growth. The higher expected medium- and long-horizon economic growth expectations outweigh the lower near-term expected economic growth and the market return is positive. The short-term asset return is negative which generates the opposite response of the short-term and long-term asset to the monetary policy surprise.

4.8.2 Soft Information

We introduce soft information and discuss how this changes the model implications. Figure A.8 in the Appendix plots the model-implied change in expectations following a monetary policy surprise of -1% (unexpected easing). Panel A shows the change in expected quarterly economic growth where the x-axis indicates the quarters ahead (the monetary policy shock occurs at quarter 0). Panel B shows the change in expected target rate. The solid green line "Soft (u)" shows the change in investor expectations with soft information from the central bank in the scenario where the entire monetary policy surprise is driven by the exogenous shock μ. The solid blue line "Soft (e)" shows the change in investor expectations with soft information if the entire surprise is driven by ε.[27]

With soft information, investor beliefs shift away from the baseline towards the full information beliefs (the dashed lines). In the baseline case (black line) when the monetary policy surprise is driven by ε, investors can only make inference based on the target rate surprise and the unconditional variances of the shocks μ and ε. The higher the relative variance of ε compared to the variance of μ, the more negative investor beliefs about the realization of ε following a negative monetary policy surprise. The investor cannot distinguish between a -1% monetary policy surprise driven completely by μ and one driven completely by ε. Soft information provides valuable conditioning information that allows investors to distinguish between these scenarios and investor beliefs shift towards the complete information beliefs.

5 Tests of Fed Information Effects

In this section we test several predictions of the model. First, the short-term asset return should positively predict near-term economic growth (dividends and GDP in the model) controlling for the monetary policy surprise. Second, the short-term asset return should be positively associated with soft information released by the central bank about favorable economic conditions. Finally, we revisit the short-term asset return on monetary policy surprise regression in the context of the model.

5.1 Macroeconomic Predictability

We test the predictive power of short-term asset announcement returns for real dividend growth and real GDP growth over different horizons. We estimate the model:

$$\Delta x_{t+k} = \alpha_k + \beta_k \Delta P_t^{180} + \delta_k \Delta i_t^u + \varepsilon_{t+k}, k \in \{1, 2, ..., 8\} \tag{28}$$

where Δx_{t+k} is the $k-$quarter ahead real economic growth (real dividend or real GDP growth), ΔP_t^{180} is the return on the 180-day dividend strip in the 30-minute

[27] For reference, we plot the change in investor expectations with no soft information (black line) and the change in investor expectations in the scenarios where the investor directly observes the shocks and the entire monetary policy surprise is driven by the exogenous shock μ (dashed green line) or by ε (dashed blue line).

window around the FOMC announcements in quarter t, and Δi_t^u is the monetary policy shock. Dividend growth corresponds to dividends accrued by the S&P 500 index.[28] To account for seasonality, we calculate quarterly dividend growth as the difference in log dividends in quarter k and log dividends in the same quarter in the previous year, $\Delta d_{t+k} = log\left(\frac{D_{t+k}}{D_{t+k-4}}\right)$. Similarly, we calculate quarterly GDP growth as $\Delta gdp_{t+k} = log\left(\frac{GDP_{t+k}}{GDP_{t+k-4}}\right)$ using seasonally unadjusted real quarterly GDP growth from the St. Louis Federal Reserve. To account for possible autocorrelation in error terms arising from the data structure, we use Newey-West standard errors with two lags.[29] We run our baseline predictability tests on the sample of FOMC announcements with non-zero monetary policy shocks.[30]

Panel A of Table 3 presents the results of the predictive regressions for real dividend growth. In the univariate regression, the estimated coefficient β_k on the short-term asset return is positive and significant at every quarterly horizon up to eight quarters ahead. The coefficient on one-quarter ahead dividend growth is 0.67. The coefficient estimates increase until reaching a maximum of 1.15 for four-quarter ahead dividend growth and then decrease to 0.46 for eight-quarter ahead dividend growth. These magnitudes are economically significant - based on the standard deviation of quarterly dividend growth of 0.10, a one standard deviation decrease in the short-term asset price corresponds to a 0.34 standard deviation decline in real dividend growth over the next four quarters. Additionally, we present results from specifications which include the monetary policy surprise as a control variable. The coefficient estimates on the short-term asset return, β_k, follow a similar pattern to the univariate specification. The coefficients are significant at the 5 percent level

[28] We construct dividends following the approach in Golez (2014). We first estimate daily dividends from the S&P 500 price index and total return index from Datastream. We then aggregate daily dividends to the monthly level, at which point we adjust dividends for inflation using the monthly CPI time series from Robert Shiller's webpage. We aggregate real monthly dividends across each quarter.

[29] We are forecasting quarterly macroeconomic growth rates using two FOMC announcements per quarter.

[30] A monetary shock equal of 0 occurs in the model if (i) the FOMC announcement contains no news about policy preferences or economic conditions not already anticipated by investors or (ii) the policy preference shock exactly offsets the information effect. The latter is a knife-edge case in the model, and in practice, meetings with no monetary policy surprise conceivably carry less information than meetings with non-zero surprises.

for the one-quarter to six-quarter ahead forecasts. The coefficients on the monetary policy surprise are positive but insignificant.

Panel B in Table 3 presents the results of the predictive regressions for real GDP growth. The overall pattern of results is similar to the real dividend growth forecasting regressions: the coefficient on the short-term asset return is 0.13 for one-quarter ahead GDP growth and increases to 0.19 for three-quarter ahead GDP growth before decreasing to 0.06 for eight-quarter ahead GDP growth. A one standard deviation decrease in short-term asset price corresponds to a 0.23 standard deviation decline in real dividend growth over the next three quarters. The estimated coefficients on the short-term asset return remains significant for up to four-quarter ahead GDP growth when controlling for monetary policy shock. Both the dividend growth and GDP growth predictability results are robust to a variety of alternative specifications which we report in the Appendix.[31]

5.1.1 Macroeconomic Predictability: Non-FOMC Days

Information effects should be concentrated on days when the central bank releases new information (i.e. FOMC announcements with non-zero monetary policy shocks) and absent from days without new information from the central bank (i.e. many non-FOMC meeting days). As a placebo test of our predictability results, we estimate the change in the short-term asset price seven days before and seven days after each FOMC announcement date using a 30 minute window around the same time of day of the actual FOMC announcement.[32] We note that the 180-day strip return and the market return are uncorrelated on non-FOMC days. While the correlation is -0.17 with a p-value of 0.05 on FOMC days (-0.31 with a p-value of 0.00 on FOMC days with non-zero monetary shocks), it is -0.02 and insigificant (p-value of 0.72)

[31] Table A.2 reports results from the predictive regressions including additional control variables: the market return and change in the SPX implied volatility with maturity of 180 days. Tables A.3 and A.4 report results for three additional specifications (for dividend growth and GDP growth respectively): Newey West standard errors with 8 lags; using only the latest FOMC meeting each quarter; using all FOMC meeting dates including days with zero monetary policy shock. The predictability results are: not sensitive to the number of lags in the calculation of standard errors; stronger using the latest announcement from each quarter; weaker using all FOMC dates.

[32] For example, if FOMC announcement takes place on Thursday at 2pm, we estimate short-term asset return on the previous and next Thursday over the 30 minute window around the 2pm.

on non-FOMC days.

We run the same predictive regressions using the return of the short-term asset on these non-FOMC meeting days and report the results in Table A.5 in the Appendix.[33] The short-term asset return on non-FOMC days has no predictive power for future dividend growth or GDP growth at any horizon - most coefficient estimates are negative and all are insignificant.

We implement a joint specification which combines FOMC meetings with the non-FOMC days and run the following predictive regression:

$$\Delta x_{t+k} = \alpha_k + \beta_k \Delta P_t^{180} + \delta_k FOMC_t^{NZ} + \theta_k \Delta P_t^{180} \times FOMC_t^{NZ} + \varepsilon_{t+k}, k \in \{1, 2, ..., 8\}$$

where Δx_{t+k} is the $k-$quarter ahead real economic growth (real dividend or real GDP growth) and $FOMC^{NZ}$ a dummy variable equal to 1 on non-zero monetary policy shock meeting days and 0 otherwise.[34] Panel A in Table A.6 in the Appendix reports the results for the dividend growth specifications. We focus on the interaction term, θ_k, which estimates the differential relationship between the short-term asset return and future economic conditions on FOMC announcement days versus on non-announcement days. The coefficient estimate on the interaction term is positive and significant at all horizons. The results for the real GDP growth regressions are reported in Panel B in Table A.6 and show a similar pattern. The predictive power of the short-term asset return is specific to information about economic conditions contained in central bank announcements and does not occur outside of these FOMC meeting days.

5.1.2 Additional Results

We supplement our predictability results using private sector forecast data from the Survey of Professional Forecasters (SPF). We find that the short-term asset response to FOMC announcements positively and significantly predicts SPF forecast errors for annual real GDP growth. Section 8.4.1 in the Appendix discusses the data con-

[33] We use Newey West adjusted standard errors with 4 lags.
[34] We use Newey-West adjusted standard errors with 6 lags.

struction, empirical design, and results. Lastly, we extract FOMC participant forecasts for real GDP growth from the advance release of the Summary of Economic Projections. We construct a measure of the gap between central bank and private sector forecasts for real GDP growth as the central bank forecast minus the SPF forecast. We regress the short-term asset response to each FOMC announcement on the forecast gap and estimate a positive coefficient on the forecast gap that is significant at the 1 percent level: the higher short-term asset returns are associated with higher central bank economic growth forecasts compared to SPF forecasts. Section 8.4.2 in the Appendix discusses the measure construction and results.

5.2 Announcement Return and Soft Information

The model implies that the short-term asset return should be positively associated with soft information (η in the model) released by the central bank about favorable economic conditions. To test this prediction, we construct two measures of central bank soft information about economic conditions based on discussion about economic growth in the FOMC minutes. For the first measure, we use an unsupervised machine learning technique, latent Dirichlet allocation (LDA), to factor the high-dimension text data into a small set of topics based on words which commonly occur together.[35] We identify discussion by the central bank about favorable economic growth prospects and construct the time-series of the prevalence of this topic in central bank discussion at each meeting. We construct our second measure following a traditional dictionary-based approach: we assign a numerical score to the discussion about economic growth prospects at each meeting using the sentiment text classification dictionary developed in Loughran and McDonald (2011). We test the relationship between these text-based measures and the short-term asset return.

5.2.1 Measure Construction

We obtain the full text minutes from each FOMC meeting from January 2004 to December 2019 from the Federal Reserve Board website. The meeting minutes

[35] This approach has been used in a number of settings in the economics and finance literature including early work on FOMC transcripts by Hansen et al. (2018).

contain several distinct sections based on the topic of discussion.[36] We parse each section and focus on the Staff Economic Outlook section (SEO) which comprises staff discussion about expected economic growth, inflation, and unemployment. We apply a regular expression to each sentence in the SEO to identify sentences containing any of the following words or phrases: "gdp", "output", "the economy", "economic growth", "spending", "investment." This restricts our focus to discussion about economic growth and avoids semantic issues which could affect our text-based measures.[37] We preprocess the raw text following standard practice by removing punctuation, common English stopwords, stemming words, and applying a term document-inverse document frequency filter which we discuss in more detail in Section 8.5.1 in the Appendix.

Our first measure of central bank discussion about economic growth prospects is based on a machine learning technique known as latent Dirichlet allocation (LDA) developed in Blei et al. (2003). LDA is a statistical model used to identify the topics that occur in a set of text documents and to estimate the prevalence of these topics in each document. In this framework, a topic is a probability distribution over a fixed set of words where the most relevant words to the topic are assigned higher probabilities. Similarly, a document is represented as a probability distribution over the set of topics.[38] The LDA model assumes the observed set of documents arose from a generative process based on each document's latent topic distribution and each topic's latent word distribution. This generative process specifies the joint

[36]Developments in Financial Markets (DFM); Staff Review of the Economic Situation (SRES); Staff Review of the Financial Situation (SRFS); Economic Outlook (EO); Participants' Views on Current Conditions (PVCC); and Committee Policy Action (CPA).

[37]For example, "high", "increasing", "significant" are positive in the context of economic growth but not for inflation or unemployment.

[38]To present a stylized example, assume there are two topics: stock market and politics. The stock market topic is a probability distribution over the 5,000 unique words and bigrams contained in the corpus. Words and phrases with higher probability in the stock market topic may be "stock market", "nyse", "tech sector", "realized gain", and "trading profits". Words and phrases with higher probability in the "politics" topic distribution may be "democrat", "republican", "congress", "sec", and "president". These topics are identified by the machine learning algorithm based on clusters of words which co-occur in the same documents without input from the researcher. An article which discusses the high return of the stock market on that day is represented as a probability distribution over topics and would place a high probability of the "stock market" topic and a low probability on the "politics" topic.

distribution over the observed documents and the latent random variables in the model. Using Gibbs sampling, a Markov chain Monte Carlo algorithm, we can infer the posterior distribution of these latent variables and extract the set of topics and the topic proportions within each document.[39] We apply the LDA model to our text data and identify a topic with a strong connection with positive central bank views about economic growth prospects: the top terms in the topic distribution include "gdp_expand", "faster_pace", and "real_gdp_expand".[40] We construct our time-series measure which we denote η_t^{lda} as the average probability weight of the topic across all documents[41] in the FOMC meeting at date t.

We construct a second measure based on the sentiment text classification dictionary developed in Loughran and McDonald (2011). We apply this dictionary to the SEO discussion about economic growth and obtain a count of the number of positive and negative words at each FOMC meeting.[42] We subtract the number of negative words and phrases from the number of positive words and phrases which occur in a given meeting and normalize by their sum to obtain η_t^{lm}. We describe the measure construction in more detail in Section 8.5.3 in the Appendix.

5.2.2 Results

We study the relationship between the short-term asset announcement return and our text-based measures of soft information, η. We run the following specification for each measure of soft information:

$$\Delta P_t = \alpha + \beta \eta_t + \nu_t \tag{29}$$

where $\Delta P_t \in \left\{\Delta P_t^{180}, \Delta P_t^{\infty}\right\}$ is the short-term asset return or the long-term asset return around the FOMC announcement at date t and $\eta_t \in \left\{\eta_t^{lda}, \eta_t^{lm}\right\}$ is our

[39] We describe the procedure in detail in Section 8.5.2 in the Appendix.

[40] The top terms for each of the five topics are presented in Table A.10 in the Appendix.

[41] Each sentence is a separate "document" in our estimation (similar to the method implemented by Hansen et al. (2018)).

[42] We account for phrases which may change the meaning of constitutent words (i.e. "reduce" and "uncertainty" become "reduce uncertainty") by constructing a list of all bigrams and trigrams (two or three word phrases) that occur more than five times in the text and manually categorizing these phrases as positive, neutral, or negative.

measure of soft information based on LDA or the Loughran-McDonald sentiment dictionary. Table 4 presents the results of this regression. The first four columns present the results using the short-term asset return, ΔP_t^{180}, as the dependent variable. Coefficient estimates are presented with standard errors in parentheses and t-statistics in brackets. The coefficient on η_t^{lda} in the univariate specification in Column 1 is positive and significant at the 5 percent level. Positive soft information about economic growth prospects extracted from the text using the LDA procedure are associated with higher short-term asset returns. The second column includes the monetary policy shock, $\Delta \iota_t^s$, as an additional explanatory variable. The coefficients on η_t^{lda} and $\Delta \iota_t^s$ are both positive and significant at the 5 percent level. The third and fourth columns present results from similar specifications using the Loughran-McDonald-based measure of soft information, η_t^{lm}. The coefficient on η_t^{lm} is positive and significant at the 5 percent level in the univariate model and in the specification which includes the monetary policy surprise as an additional explanatory variable. The last four columns present regressions of the long-term asset return, ΔP_t^{∞}, on our text-based measures of soft information. The coefficients on η_t^{lda} are not significant in the univariate specification or when included alongside the monetary policy shock. The coefficient on η_t^{lm} is negative and significant at the 10 percent level in both specifications.

These results are consistent with the existence of soft information about economic growth prospects which drive variation in the short-term asset return around the FOMC announcement. While the minutes are released weeks after the FOMC announcement, these results suggest that the tone and topics of central bank discussion are related to the short-term asset return and may be transmitted at the time of announcement.

5.3 Short-term Asset Response to Monetary Policy Shocks Revisited

We examine our baseline regression of the short-term asset response, ΔP_t^{180}, to monetary policy surprises, $\Delta \iota_t^s$, from Equation 3:

$$\Delta P_t^{180} = \alpha + \beta \Delta \iota_t^s + \varepsilon \tag{30}$$

Our estimate for β is positive and significant at the 5 percent level in our baseline specification and significant at the 1 percent level in the non-zero monetary policy shock specification. Our model of information effects and the equity term structure allows for a tighter characterization of these tests. With no information effects, the short-term asset response is given by Equation 22: since $b < 0$, the short-term asset return will always be the opposite sign of the monetary policy surprise. The negative sign arises from the conventional effects of monetary policy shocks on interest rates and means the coefficient, β, in the regression from Equation 30 will be negative under the null hypothesis of no information effects. Accordingly, we estimate Equation 30 under the null hypothesis of $\beta < 0$. In our baseline specification using all FOMC announcements, the coefficient β on the monetary policy surprise is positive and significant with a $p-value$ of 0.01025 from the one-tailed t-test. In the specification restricted to non-zero monetary policy surprise days, the coefficient on the monetary policy surprise is positive and highly significant with a $p-value$ of 0.00444.

6 Conclusion

In this paper, we study the short-horizon impact of monetary policy using the price of a short-term equity strip. We find that the prices of short-term and long-term equity respond to monetary policy news in opposite ways. Following an unexpected decrease (increase) in the Federal Funds rate, market prices rise (fall) while short-term dividend prices fall (rise) on average. We write a stylized model about information effects and the term structure of equity prices and show that information effects can generate the opposite response of the short- and long-term asset to monetary policy surprises. The model makes additional predictions which we test empirically. Consistent with this channel, we find that the price response of the short-term dividend asset in the 30-minute window around FOMC announcements predicts short-term dividend growth and macroeconomic growth. We also find that short-term dividend announcement return is positively related to measures of central bank soft information about favorable economic conditions. Our results support the existence of Fed information effects which represents an important transmission channel for monetary policy.

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7 Tables & Figures

Table 1: **Monetary Policy Shock Summary Statistics**

Panel A: Monetary Policy Shock

	All	*Positive*	*Negative*
N	128	31	53
Mean	-0.0033	0.0196	-0.0195
Std. Dev.	0.0301	0.0244	0.0358

Panel B: Asset Return Around Monetary Policy Shock

	ΔP^{180}	ΔP^{360}	ΔP^{540}	ΔP^{∞}
All Shocks				
Mean	0.0027	0.0005	-0.0004	0.0009
Std. Dev.	0.0366	0.0138	0.0106	0.0056
$corr(\cdot, \Delta P^{\infty})$	-0.1720	-0.2412	-0.1331	1
Positive Shocks				
Mean	0.0116	0.0021	0.0015	-0.0010
Std. Dev.	0.0270	0.0132	0.0113	0.0055
$corr(\cdot, \Delta P^{\infty})$	-0.1518	-0.0697	0.0119	1
Negative Shocks				
Mean	-0.0066	-0.0013	-0.0019	0.0018
Std. Dev.	0.0322	0.0123	0.0079	0.0064
$corr(\cdot, \Delta P^{\infty})$	-0.3161	-0.2695	-0.2052	1

Panel A presents the summary statistics for the monetary policy shocks. Panel B presents the summary statistics for log asset returns around each FOMC announcement. Statistics are calculated separately for announcement returns of assets with different maturities, ΔP^h, where $h \in \{180, 360, 540, \infty\}$ days. ΔP^{∞} is the market return. The last row in each panel, $corr(\cdot, \Delta P^{\infty})$, reports the correlation of the FOMC announcement window return of each asset with the market return. Statistics are reported for all monetary shocks and separately for positive and negative shocks. The period is from January 2004 until December 2019.

Table 2: **Asset Return on Monetary Policy Shock**

	ΔP^{180}	ΔP^{360}	ΔP^{540}	ΔP^{∞}
Panel A: All Monetary Policy Shocks				
Δi_t^u	0.249	0.040	0.021	-0.059
	(0.106)	(0.041)	(0.031)	(0.016)
Adj. R^2	0.034	0.000	-0.004	0.095
Obs.	128	128	128	128
Panel B: Non-Zero Monetary Policy Shocks				
Δi_t^u	0.241	0.038	0.021	-0.060
	(0.090)	(0.038)	(0.028)	(0.017)
Adj. R^2	0.069	0.000	-0.005	0.121
Obs.	84	84	84	84

This table presents results from the regression of asset return on the monetary policy shock:

$$\Delta P_t^h = \alpha + \beta \Delta i_t^u + \varepsilon$$

where ΔP_t^h is the logarithmic return on the asset with maturity $h \in \{180, 360, 540, \infty\}$ days and Δi_t^u is the unexpected change in target federal funds rate around the FOMC announcement at date t. ΔP^{∞} stands for the market return. OLS standard errors are reported in parentheses below the coefficient estimate. Top panel presents results for all monetary policy shocks in the period from January 2004 until December 2019. Panel B presents results for non-zero monetary policy shocks. The intercept, α, is not reported.

Table 3: **Real Dividend and GDP Forecasting**

Horizon	1Q	2Q	3Q	4Q	5Q	6Q	7Q	8Q
Panel A: Real Dividend Growth								
ΔP^{180}	0.669	0.874	0.965	1.147	1.063	0.947	0.542	0.462
	(0.242)	(0.236)	(0.306)	(0.363)	(0.362)	(0.340)	(0.219)	(0.193)
Adj. R^2	0.046	0.079	0.076	0.106	0.092	0.075	0.017	0.012
ΔP^{180}	0.604	0.792	0.899	1.099	1.057	0.875	0.397	0.322
	(0.233)	(0.227)	(0.346)	(0.410)	(0.428)	(0.417)	(0.322)	(0.247)
Δi_t^u	0.194	0.247	0.196	0.143	0.017	0.226	0.441	0.429
	(0.245)	(0.318)	(0.356)	(0.371)	(0.376)	(0.394)	(0.465)	(0.439)
Adj. R^2	0.040	0.077	0.070	0.098	0.081	0.069	0.029	0.025
Obs.	84	84	84	84	83	81	79	79
Panel B: Real GDP Growth								
ΔP^{180}	0.127	0.173	0.192	0.149	0.111	0.039	0.094	0.057
	(0.060)	(0.072)	(0.102)	(0.079)	(0.054)	(0.037)	(0.122)	(0.089)
Adj. R^2	0.034	0.044	0.041	0.019	0.018	-0.011	0.002	-0.008
ΔP^{180}	0.110	0.174	0.216	0.174	0.102	0.029	0.090	0.044
	(0.058)	(0.081)	(0.097)	(0.087)	(0.068)	(0.049)	(0.142)	(0.097)
Δi_t^u	0.052	-0.003	-0.072	-0.076	0.029	0.032	0.013	0.039
	(0.081)	(0.081)	(0.096)	(0.103)	(0.083)	(0.125)	(0.111)	(0.066)
Adj. R^2	0.033	0.032	0.039	0.018	0.008	-0.022	-0.011	-0.018
Obs.	84	84	84	83	81	79	79	77

Panel A presents the results from the predictive regression of k-quarter ahead real dividend growth on the 180-day dividend strip return ΔP_t^{180} in the 30 minute window around the FOMC announcements with non-zero monetary policy surprises:

$$log\left(\frac{D_{t+k}}{D_{t+k-4}}\right) = \alpha_k + \beta_k \Delta P_t^{180} + \delta_k \Delta i_t^u + \varepsilon_{t+k}, k \in \{1,2,...,8\}$$

The control variable Δi_t^u is the monetary policy shock. Panel B presents the same results for predicting real GDP growth. We report Newey-West adjusted standard errors with 2 lags in parentheses below the coefficient estimates. The period is from January 2004 until December 2019.

Table 4: **Text-based Measures and Short-term Asset Return**

	Short-term asset return $\left(\Delta P^{180}\right)$				Market return $\left(\Delta P^{\infty}\right)$			
η_t^{lda}	0.243	0.240			0.003	0.005		
	(0.103)	(0.101)			(0.016)	(0.015)		
η_t^{sent}			0.015	0.015			-0.002	-0.002
			(0.007)	(0.007)			(0.001)	(0.001)
$\Delta\iota_t^s$		0.242		0.245		-0.060		-0.059
		(0.104)		(0.105)		(0.016)		(0.016)
Adj. R^2	0.036	0.068	0.027	0.059	0.008	0.089	0.018	0.111
Obs.	128	128	128	128	128	128	128	128

This table presents the results from the regression of the short-term and long-term asset response on our two measures of soft information:

$$\Delta P_t = \alpha + \beta \eta_t + \nu_t$$

where $\Delta P_t \in \left\{\Delta P_t^{180}, \Delta P_t^{\infty}\right\}$ is the short-term asset return or the long-term asset return in the 30-minute window around the FOMC announcement at date t, and $\eta_t \in \left\{\eta_t^{lda}, \eta_t^{lm}\right\}$ is our measure of soft information based on LDA or the Loughran-McDonald sentiment dictionary. Standard errors are presented in parentheses below the coefficient estimates.

Figure 1: **Average Dividend Strip Return by Monetary Policy Shock**

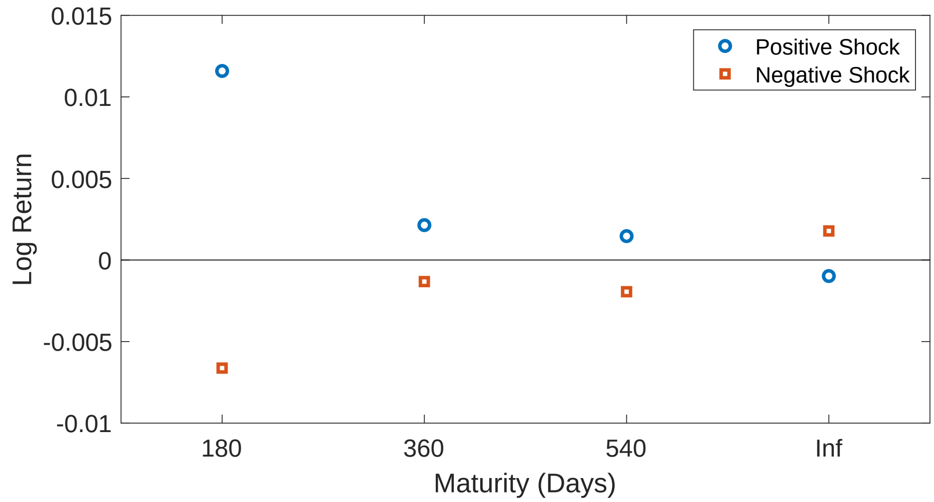
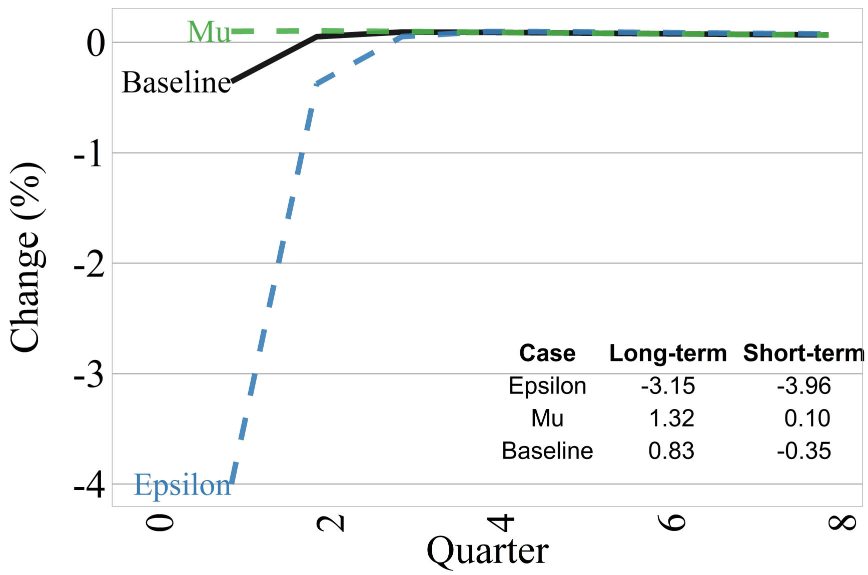


Figure 1 plots the average return of dividend strips by maturity grouped by the sign of the monetary policy shock. The return of the long-term asset (S&P 500 index) is plotted on the right-hand side and denoted by infinite maturity "Inf".

Figure 2: **Propagation of Monetary Policy Surprise: Easing**

(a) Change in Expected GDP Growth



(b) Change in Expected Target Rate

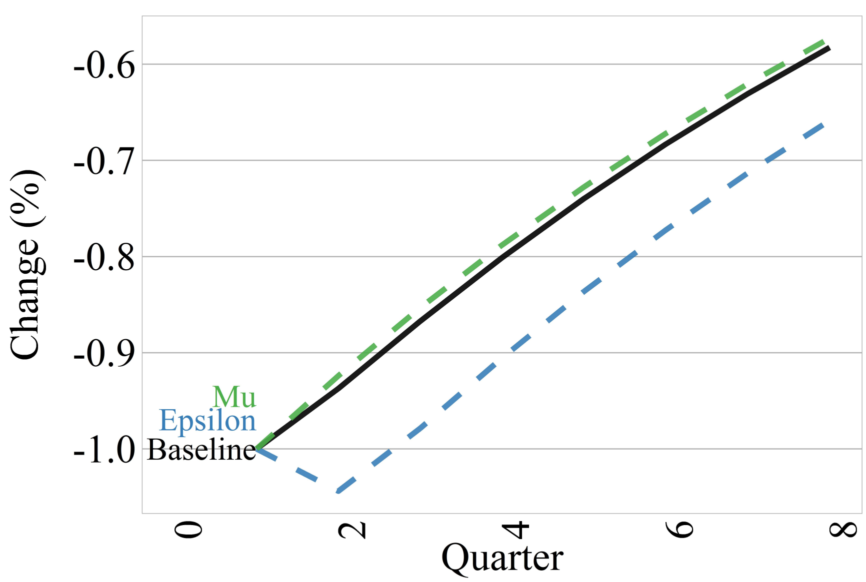


Figure 2 plots the model-implied change in expectations across the term structure following a monetary policy surprise of -1% (unexpected easing). Panel A shows the change in expected quarterly economic growth where the x-axis indicates the quarters ahead (the monetary policy shock occurs at quarter 0). Panel B shows the change in expected target rate across the term structure. The dashed green “Mu” (blue “Epsilon”) line shows the change in expectations if the investor observes the shocks, ε and μ, and the entire monetary policy surprise is driven by the shock μ (ε). The black line labeled “Baseline” shows the change in investor expectations following the monetary policy surprise when the investor does not observe the shocks directly.

8 Appendix: For Online Publication

8.1 Option-Implied Variable Construction

We denote by P^h_{t-} the price of the S&P 500 dividend strip with maturity h estimated in the 30 minute window before the FOMC announcement on date t. P^h_{t+} denotes the price of the S&P 500 dividend strip with maturity h estimated in the 30 minute window after the FOMC announcement on date t. The rf^h_{t-} and the rf^h_{t+} mark the pre-announcement and the post-announcement risk-free rates. We denote by P^∞_{t-} and P^∞_{t+} the average value of the S&P 500 index over the same 30-minute intervals used for calculating dividend price before and after the FOMC announcement time on date t. The IV^h_{t-} and IV^h_{t+} denote the average volatility implied by SPX options for a given options maturity h over the same 30-minute intervals before and after each FOMC announcement.

The horizons h depend on the maturities of the option contracts used in the estimation and the date t of the given FOMC announcement. We estimate the dividend strip prices at a set of standardized maturities, $h \in \{180, 360, 540\}$ (in days), by linearly interpolating between the option-implied prices for horizons slightly above and below each standardized maturity. We follow a similar procedure to obtain option-implied risk-free rates and the options implied volatilities at the same standardized horizons.[43]

We measure the response of asset prices, risk-free rates, and implied volatility at each horizon to monetary policy shocks by computing the change in each variable from immediately before to immediately after each FOMC announcement. For asset prices, we use the change in log prices, $\Delta P^h_t = log\left(\frac{P^h_{t+}}{P^h_{t-}}\right)$ and $\Delta P^\infty_t = log\left(\frac{P^\infty_{t+}}{P^\infty_{t-}}\right)$, where t is the FOMC announcement date and $h \in \{180, 360, 540\}$ is the horizon in days. We use simple differences to measure the FOMC response of the risk-free rate and the implied volatility over the same 30-minute intervals before and after the FOMC announcements, $\Delta rf^h_t = rf^h_{t+} - rf^h_{t-}$, and $\Delta IV^h_t = IV^h_{t+} - IV^h_{t-}$.

[43] On FOMC dates where the standardized shorter horizon maturities do not fall between the option-maturities, we linearly extrapolate dividend prices based on the price of the shortest interior maturity and using the fact that dividend price ultimately converges to zero at the options maturity. For the risk-free rate and the implied volatility, we extrapolate by setting the values equal to the interest-rate and the implied volatility of the closest interior maturity.

8.2 Derivations

This section supplements the model developed in Section 4.

8.2.1 Propagation of Forecasts

We diagonalize the matrix, $A = \begin{pmatrix} \rho_g & b\rho_\iota \\ \alpha\rho_g & \rho_\iota \end{pmatrix}$, which determines the recurrence relation between forecasts for economic growth and the target rate:

$$\begin{pmatrix} \mathbb{E}_t\left(\Delta GDP_{t+k+1}\right) \\ \mathbb{E}_t\left(\widehat{\iota}_{t+k}\right) \end{pmatrix} = \frac{1}{(1-\alpha b)^k} \begin{pmatrix} \rho_g & b\rho_\iota \\ \alpha\rho_g & \rho_\iota \end{pmatrix}^k \begin{pmatrix} \mathbb{E}_t\left(\Delta GDP_t\right) \\ \mathbb{E}_t\left(\widehat{\iota}_{t-1}\right) \end{pmatrix}$$

We compute the eigenvalues of matrix $A = \begin{pmatrix} \rho_g & b\rho_\iota \\ \alpha\rho_g & \rho_\iota \end{pmatrix}$ from the characteristic polynomial: $C_A(\lambda) = det\left(A - \lambda I\right)$, where I is the identity matrix:

$$C_A(\lambda) = \left(\rho_g - \lambda\right)\left(\rho_\iota - \lambda\right) - \alpha b \rho_g \rho_\iota = \lambda^2 - \left(\rho_g + \rho_\iota\right)\lambda + \rho_g\rho_\iota\left(1 - \alpha b\right)$$

The roots of the characteristic polynomial are: $\frac{\rho_g+\rho_\iota\pm\left(\left(\rho_g+\rho_\iota\right)^2-4\rho_g\rho_\iota(1-\alpha b)\right)^{\frac{1}{2}}}{2} = \frac{\rho_g+\rho_\iota\pm\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota(4\alpha b-2)\right)^{\frac{1}{2}}}{2}$. The eigenvalues, λ_1 and λ_2 are:

$$\lambda_1 = \frac{1}{2}\left(\rho_g + \rho_\iota + \left(\rho_g^2 + \rho_\iota^2 + \rho_g\rho_\iota\left(4\alpha b - 2\right)\right)^{\frac{1}{2}}\right)$$

and

$$\lambda_2 = \frac{1}{2}\left(\rho_g + \rho_\iota - \left(\rho_g^2 + \rho_\iota^2 + \rho_g\rho_\iota\left(4\alpha b - 2\right)\right)^{\frac{1}{2}}\right)$$

We find eigenvectors associated with each eigenvalue. An eigenvector, $v^{\lambda_1} = \begin{pmatrix} v_1^{\lambda_1} \\ v_2^{\lambda_1} \end{pmatrix}$, corresponding to eigenvalue, λ_1, is any vector which spans the kernel $A - \lambda_1 I$. We have:

$$A-\lambda_1 I=\begin{pmatrix}\rho_g-\frac{1}{2}\left(\rho_g+\rho_\iota+\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota\left(4\alpha b-2\right)\right)^{\frac{1}{2}}\right) & b\rho_\iota \\ \alpha\rho_g & \rho_\iota-\frac{1}{2}\left(\rho_g+\rho_\iota+\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota\left(4\alpha b-2\right)\right)^{\frac{1}{2}}\right)\end{pmatrix}$$

So an eigenvector must satisfy: $v_1^{\lambda_1}\left(\rho_g-\frac{1}{2}\left(\rho_g+\rho_\iota+\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota\left(4\alpha b-2\right)\right)^{\frac{1}{2}}\right)\right)+v_2^{\lambda_1}b\rho_\iota=0$ and $v_1^{\lambda_1}\alpha\rho_g+v_2^{\lambda_1}\left(\rho_\iota-\frac{1}{2}\left(\rho_g+\rho_\iota+\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota\left(4\alpha b-2\right)\right)^{\frac{1}{2}}\right)\right)=0$. From the first equation we have:

$$v_1^{\lambda_1}=-v_2^{\lambda_1}\frac{b\rho_\iota}{\left(\rho_g-\frac{1}{2}\left(\rho_g+\rho_\iota+\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota\left(4\alpha b-2\right)\right)^{\frac{1}{2}}\right)\right)}$$

[44]

We obtain the eigenvector corresponding to eigenvalue, λ_2, following a similar procedure:

$$v_1^{\lambda_2}=-v_2^{\lambda_2}\frac{b\rho_\iota}{\rho_g-\frac{1}{2}\left(\rho_g+\rho_\iota-\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota\left(4\alpha b-2\right)\right)^{\frac{1}{2}}\right)}$$

The eigenvectors, v^{λ_1} and v^{λ_2}, produce the change of basis matrices, P and P^{-1}:

[44] We verify that the second equation also equals 0:

$$\begin{aligned}
&v_1\alpha\rho_g+v_2\left(\rho_\iota-\frac{1}{2}\left(\rho_g+\rho_\iota+\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota\left(4\alpha b-2\right)\right)^{\frac{1}{2}}\right)\right)\\
&=-v_2\frac{b\rho_\iota}{\left(\rho_g-\frac{1}{2}\left(\rho_g+\rho_\iota+\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota\left(4\alpha b-2\right)\right)^{\frac{1}{2}}\right)\right)}\alpha\rho_g+v_2\left(\rho_\iota-\frac{1}{2}\left(\rho_g+\rho_\iota+\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota\left(4\alpha b-2\right)\right)^{\frac{1}{2}}\right)\right)\\
&=v_2\left(\frac{\left(\rho_\iota-\frac{1}{2}\left(\rho_g+\rho_\iota+\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota\left(4\alpha b-2\right)\right)^{\frac{1}{2}}\right)\right)\times\left(\rho_g-\frac{1}{2}\left(\rho_g+\rho_\iota+\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota\left(4\alpha b-2\right)\right)^{\frac{1}{2}}\right)\right)-\alpha b\rho_\iota\rho_g}{\left(\rho_g-\frac{1}{2}\left(\rho_g+\rho_\iota+\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota\left(4\alpha b-2\right)\right)^{\frac{1}{2}}\right)\right)}\right)\\
&=v_2\left(\frac{2\rho_\iota\rho_g+4\alpha b\rho_g\rho_\iota-2\rho_g\rho_\iota-4\alpha b\rho_\iota\rho_g}{4\left(\rho_g-\frac{1}{2}\left(\rho_g+\rho_\iota+\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota\left(4\alpha b-2\right)\right)^{\frac{1}{2}}\right)\right)}\right)\\
&=0
\end{aligned}$$

$$P=\begin{pmatrix} -\frac{b\rho_\iota}{\left(\rho_g-\frac{1}{2}\left(\rho_g+\rho_\iota+\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota(4\alpha b-2)\right)^{\frac{1}{2}}\right)\right)} & -\frac{b\rho_\iota}{\rho_g-\frac{1}{2}\left(\rho_g+\rho_\iota-\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota(4\alpha b-2)\right)^{\frac{1}{2}}\right)} \\ 1 & 1 \end{pmatrix}$$

and P^{-1}:

$$P^{-1}=p_{scalar}\begin{pmatrix} 1 & \frac{b\rho_\iota}{\rho_g-\frac{1}{2}\left(\rho_g+\rho_\iota-\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota(4\alpha b-2)\right)^{\frac{1}{2}}\right)} \\ -1 & -\frac{b\rho_\iota}{\rho_g-\frac{1}{2}\left(\rho_g+\rho_\iota+\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota(4\alpha b-2)\right)^{\frac{1}{2}}\right)} \end{pmatrix}$$

where $p_{scalar}=\frac{\left(\rho_g-\frac{1}{2}\rho_g-\frac{1}{2}\rho_\iota+\frac{1}{2}\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota(4\alpha b-2)\right)^{\frac{1}{2}}\right)\left(\rho_g-\frac{1}{2}\rho_g-\frac{1}{2}\rho_\iota-\frac{1}{2}\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota(4\alpha b-2)\right)^{\frac{1}{2}}\right)}{-b\rho_\iota\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota(4\alpha b-2)\right)^{\frac{1}{2}}}$.

Finally, the diagonalized matrix, D, is given by:

$$D=\begin{pmatrix} \frac{1}{2}\left(\rho_g+\rho_\iota+\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota\left(4\alpha b-2\right)\right)^{\frac{1}{2}}\right) & 0 \\ 0 & \frac{1}{2}\left(\rho_g+\rho_\iota-\left(\rho_g^2+\rho_\iota^2+\rho_g\rho_\iota\left(4\alpha b-2\right)\right)^{\frac{1}{2}}\right) \end{pmatrix} \tag{31}$$

So we can express $A=\begin{pmatrix}\rho_g & b\rho_\iota \\ \alpha\rho_g & \rho_\iota\end{pmatrix}=PDP^{-1}$. Since $A^k=\left(PDP^{-1}\right)^k=PDP^{-1}PDP^{-1}...PDP^{-1}=PD^kP^{-1}$ we can express forecasts for economic growth and the target rate at any horizon, k, by:

$$\begin{pmatrix}\mathbb{E}_t\left(\Delta GDP_{t+k+1}\right) \\ \mathbb{E}_t\left(\widehat{\iota}_{t+k}\right)\end{pmatrix}=\frac{1}{\left(1-\alpha b\right)^k}\begin{pmatrix}\rho_g & b\rho_\iota \\ \alpha\rho_g & \rho_\iota\end{pmatrix}^k\begin{pmatrix}\mathbb{E}_t\left(\Delta GDP_{t+1}\right) \\ \mathbb{E}_t\left(\widehat{\iota}_t\right)\end{pmatrix}$$
$$\frac{1}{\left(1-\alpha b\right)^k}PD^kP^{-1}\begin{pmatrix}\mathbb{E}_t\left(\Delta GDP_{t+1}\right) \\ \mathbb{E}_t\left(\widehat{\iota}_t\right)\end{pmatrix}$$

8.2.2 Long-term Asset Response

The long-term asset response to monetary policy is given by:

$$r_{\bar{t}}^{\infty} = \sum_{j=0}^{\infty} \rho^j \beta_d \left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right) \left(\Delta\widehat{GDP}_{t+j+1}\right)$$

$$= \sum_{j=0}^{\infty} \rho^j \beta_d \frac{1}{(1-\alpha b)^j} \begin{pmatrix} 1 & 0 \end{pmatrix} PD^j P^{-1} \begin{pmatrix} \left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)(\Delta GDP_{t+1}) \\ \left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)(\widehat{\iota}_t) \end{pmatrix}$$

We can rewrite the infinite sum as:

$$r_{\bar{t}}^{\infty} = \beta_d \begin{pmatrix} 1 & 0 \end{pmatrix} P \left(\sum_{j=0}^{\infty} \frac{\rho^j}{(1-\alpha b)^j} D^j\right) P^{-1} \begin{pmatrix} \left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)(\Delta GDP_{t+1}) \\ \left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)(\widehat{\iota}_t) \end{pmatrix}$$

$$= \beta_d \begin{pmatrix} 1 & 0 \end{pmatrix} PD^* P^{-1} \begin{pmatrix} \left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)(\Delta GDP_{t+1}) \\ \left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)(\widehat{\iota}_t) \end{pmatrix}$$

Where D^* is a diagonal matrix with entries, $d_{11}^* = \frac{1}{1-\frac{\rho}{(1-\alpha b)}d_{11}}$ and $d_{22}^* = \frac{1}{1-\frac{\rho}{(1-\alpha b)}d_{22}}$.[45] For convenience denote the entries in the change of basis matrices, P and P^{-1} as: $P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix}$, $P^{-1} = \frac{1}{p_{11}p_{22}-p_{12}p_{21}} \begin{pmatrix} p_{22} & -p_{12} \\ -p_{21} & p_{11} \end{pmatrix}$, and $D^* = \begin{pmatrix} d_{11}^* & 0 \\ 0 & d_{22}^* \end{pmatrix}$. Then we have:

$$PD^*P^{-1}$$

$$= \frac{1}{p_{11}p_{22}-p_{12}p_{21}} \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix} \begin{pmatrix} d_{11}^* & 0 \\ 0 & d_{22}^* \end{pmatrix} \begin{pmatrix} p_{22} & -p_{12} \\ -p_{21} & p_{11} \end{pmatrix}$$

$$= \frac{1}{p_{11}p_{22}-p_{12}p_{21}} \begin{pmatrix} p_{11}p_{22}d_{11}^* - p_{21}p_{12}d_{22}^* & p_{12}p_{11}d_{22}^* - p_{11}p_{12}d_{11}^* \\ p_{21}p_{22}d_{11}^* - p_{22}p_{21}d_{22}^* & p_{22}p_{11}d_{22}^* - p_{21}p_{12}d_{11}^* \end{pmatrix}$$

[45] Where $d_{11} = \frac{1}{2}\left(\rho_g + \rho_\iota + \left(\rho_g^2 + \rho_\iota^2 + \rho_g\rho_\iota(4\alpha b - 2)\right)^{\frac{1}{2}}\right)$ and $d_{22} = \frac{1}{2}\left(\rho_g + \rho_\iota - \left(\rho_g^2 + \rho_\iota^2 + \rho_g\rho_\iota(4\alpha b - 2)\right)^{\frac{1}{2}}\right)$ are the entries in the diagonal matrix D from Equation 31.

So we have:

$$
\begin{aligned}
r_{\bar{t}}^{\infty} &= \begin{pmatrix} 1 & 0 \end{pmatrix} \beta_d P D^* P^{-1} \overrightarrow{v}_{input} \\
&= \begin{pmatrix} 1 & 0 \end{pmatrix} \frac{\beta_d}{p_{11}p_{22} - p_{12}p_{21}} \begin{pmatrix} p_{11}p_{22}d_{11}^* - p_{21}p_{12}d_{22}^* & p_{12}p_{11}d_{22}^* - p_{11}p_{12}d_{11}^* \\ p_{21}p_{22}d_{11}^* - p_{22}p_{21}d_{22}^* & p_{22}p_{11}d_{22}^* - p_{21}p_{12}d_{11}^* \end{pmatrix} \overrightarrow{v}_{input} \\
&= \frac{\beta_d}{p_{11}p_{22} - p_{12}p_{21}} \left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)\left(\Delta GDP_{t+1}\right)\left(p_{11}p_{22}d_{11}^* - p_{21}p_{12}d_{22}^*\right) \\
&\quad + \frac{\beta_d}{p_{11}p_{22} - p_{12}p_{21}} \left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)\left(\widehat{\iota}_t\right)\left(p_{12}p_{11}d_{22}^* - p_{11}p_{12}d_{11}^*\right)
\end{aligned}
$$

where $\overrightarrow{v}_{input} = \begin{pmatrix} \left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)\left(\Delta GDP_{t+1}\right) \\ \left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)\left(\widehat{\iota}_t\right) \end{pmatrix}$.

We substitute in the expressions for p_{11}, p_{22}, p_{12}, p_{21}, d_{11}^*, and d_{22}^* in terms of model parameters from the equations for P and D. We will calculate the coefficient, $\frac{\beta_d}{p_{11}p_{22}-p_{12}p_{21}}$, the coefficent on economic growth, $p_{11}p_{22}d_{11}^* - p_{21}p_{12}d_{22}^*$, and the coefficient on the target rate, $p_{12}p_{11}d_{22}^* - p_{11}p_{12}d_{11}^*$.

We start with the coefficient $\frac{\beta_d}{p_{11}p_{22}-p_{12}p_{21}}$. For tractability we define: $X \equiv \left(\rho_g^2 + \rho_\iota^2 + \rho_g\rho_\iota\left(4\alpha b - 2\right)\right)^{\frac{1}{2}}$, $A \equiv \frac{1}{2}\rho_g - \frac{1}{2}\rho_\iota$ and $B \equiv \rho_g + \rho_\iota$. Then we have:

$$
\begin{aligned}
& p_{11}p_{22} - p_{21}p_{12} \\
&= -\frac{b\rho_\iota}{\rho_g - \frac{1}{2}\left(\rho_g + \rho_\iota + \left(\rho_g^2 + \rho_\iota^2 + \rho_g\rho_\iota\left(4\alpha b - 2\right)\right)^{\frac{1}{2}}\right)} + \frac{b\rho_\iota}{\rho_g - \frac{1}{2}\left(\rho_g + \rho_\iota - \left(\rho_g^2 + \rho_\iota^2 + \rho_g\rho_\iota\left(4\alpha b - 2\right)\right)^{\frac{1}{2}}\right)} \\
&= 2\frac{b\rho_\iota}{\rho_g - \rho_\iota + X} - \frac{b\rho_\iota}{\rho_g - \rho_\iota - X} \\
&= \frac{-4Xb\rho_\iota}{(2A - X)(2A + X)} \\
&= \frac{-4Xb\rho_\iota}{\rho_g^2 + \rho_\iota^2 - 2\rho_\iota\rho_g - \rho_g^2 - \rho_\iota^2 - \rho_g\rho_\iota 4\alpha b + \rho_g\rho_\iota 2} \\
&= \frac{X}{\rho_g\alpha}
\end{aligned}
$$

Next, we calculate the coefficient on economic growth, $p_{11}p_{22}d_{11}^* - p_{21}p_{12}d_{22}^*$:

$$p_{11}p_{22}d_{11}^{*} - p_{21}p_{12}d_{22}^{*}$$

$$= -\frac{b\rho_\iota}{\rho_g - \frac{1}{2}\left(\rho_g + \rho_\iota + X\right)} \times \frac{1}{1 - \frac{\rho}{(1-\alpha b)}\frac{1}{2}\left(\rho_g + \rho_\iota + X\right)} + \frac{b\rho_\iota}{\rho_g - \frac{1}{2}\left(\rho_g + \rho_\iota - X\right)} \times \frac{1}{1 - \frac{\rho}{(1-\alpha b)}\frac{1}{2}\left(\rho_g + \rho_\iota - X\right)}$$

$$= \frac{b\rho_\iota\left[\left(\left(A - \frac{1}{2}X\right) - \left(A - \frac{1}{2}X\right)\frac{\rho}{(1-\alpha b)}\frac{1}{2}\left(B + X\right)\right) - \left(\left(A + \frac{1}{2}X\right) - \left(A + \frac{1}{2}X\right)\frac{\rho}{(1-\alpha b)}\frac{1}{2}\left(B - X\right)\right)\right]}{\left(\left(A - \frac{1}{2}X\right) - \left(A - \frac{1}{2}X\right)\frac{\rho}{(1-\alpha b)}\frac{1}{2}\left(B + X\right)\right)\left(\left(A + \frac{1}{2}X\right) - \left(A + \frac{1}{2}X\right)\frac{\rho}{(1-\alpha b)}\frac{1}{2}\left(B - X\right)\right)}$$

$$= \frac{\frac{b\rho_\iota}{2(1-\alpha b)}\left[\rho\left(B - 2A\right) - 2\left(1 - \alpha b\right)\right]X}{A^2 - \frac{1}{4}X^2 - B\left[A^2 - \frac{1}{4}X^2\right]\frac{\rho}{(1-\alpha b)} + \left(\frac{\rho}{(1-\alpha b)}\frac{1}{2}\right)^2\left(A^2 - \frac{1}{4}X^2\right)\left(B^2 - X^2\right)}$$

$$= \frac{\left[\rho_\iota\rho - 1 + \alpha b\right]X}{\rho_g\alpha\left(\rho\rho_g + \rho\rho_\iota + \frac{\rho^2}{(1-\alpha b)}\left(\rho_g\rho_\iota\alpha b - \rho_g\rho_\iota\right) - 1 + \alpha b\right)}$$

$$= \frac{-X\left(\rho_\iota\rho - 1 + \alpha b\right)}{\rho\alpha\rho_g\left(\frac{(1-\alpha b)}{\rho} + \rho\rho_g\rho_\iota - \rho_g - \rho_\iota\right)}$$

Finally, we calculate the coefficient on the target rate, $p_{12}p_{11}d_{22}^{*} - p_{11}p_{12}d_{11}^{*}$:

$$p_{12}p_{11}d_{22}^{*} - p_{11}p_{12}d_{11}^{*}$$

$$= p_{12}p_{11}\left(d_{22}^{*} - d_{11}^{*}\right)$$

$$= \left(1 - \alpha b\right)\frac{b\rho_\iota}{\frac{1}{2}\rho_g - \frac{1}{2}\rho_\iota + \frac{1}{2}X} \times \frac{b\rho_\iota}{\frac{1}{2}\rho_g - \frac{1}{2}\rho_\iota - \frac{1}{2}X} \times \left(\frac{1}{(1-\alpha b) - \rho\frac{1}{2}\left(B - X\right)} - \frac{1}{(1-\alpha b) - \rho\frac{1}{2}\left(B + X\right)}\right)$$

$$= \left(1 - \alpha b\right)\frac{b^2\rho_\iota^2}{A^2 - \frac{1}{4}X^2} \times \left(\frac{-\rho X}{\left((1-\alpha b) - \rho\frac{1}{2}\left(B - X\right)\right)\left((1-\alpha b) - \rho\frac{1}{2}\left(B + X\right)\right)}\right)$$

$$= \left(1 - \alpha b\right)\frac{b\rho_\iota}{-\rho_g\alpha} \times \left(\frac{-\rho X}{\left(\left(1 - \alpha b\right)^2 - \rho\left(1 - \alpha b\right)\left(\rho_g + \rho_\iota\right) + \rho^2\left(-\rho_g\rho_\iota\alpha b + \rho_g\rho_\iota\right)\right)}\right)$$

$$= \frac{b\rho_\iota X}{\alpha\rho_g\left(\frac{(1-\alpha b)}{\rho} + \rho\rho_g\rho_\iota - \rho_g - \rho_\iota\right)}$$

We input these expressions into the long-term asset response equation to obtain:

$$r_t^{\infty} = \frac{\beta_d}{\left(\rho\rho_g - 1\right)\left(\rho\rho_\iota - 1\right) - \alpha b}\left(\left(1 - \alpha b - \rho_\iota\rho\right)\left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)\left(\Delta GDP_{t+1}\right) + b\rho\rho_\iota\left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)\left(\widehat{\iota}_t\right)\right)$$

8.2.3 Economic Predictability: Short-term Asset with Soft Information

We derive the expression for the coefficient on the short-term asset return in the economic growth predictability regressions from from Section 5. The predictive regression is given by:

$$\Delta\widehat{GDP}_{t+1} = \alpha^1 + \beta^1 r^1_{\bar{t}} + \varepsilon^1_{t+1}$$

where $r^1_{\bar{t}}$ is the short-term asset return in the 30-minute window around FOMC announcement in time t. We compute the coefficient, β^1, assuming no soft information:

$$
\begin{aligned}
\beta^1 &= \frac{Cov\left(r^1_{\bar{t}}, \Delta\widehat{GDP}_{t+1}\right)}{Var\left(r^1_{\bar{t}}\right)} \\
&= \frac{Cov\left(\rho\beta_d\left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)\left(\Delta\widehat{GDP}_{t+1}\right), \rho_g\Delta\widehat{GDP}_t + \varepsilon_{\bar{t}} + b\iota_t + w_{t+1}\right)}{Var\left(r^1_{\bar{t}}\right)} \\
&= \frac{\rho\beta_d Cov\left(\frac{b\alpha\sigma^2_\mu + \sigma^2_{\alpha\varepsilon}}{\alpha\left(\sigma^2_{\alpha\varepsilon}+\sigma^2_\mu\right)}\frac{\mu+\alpha\varepsilon}{(1-\alpha b)}, \varepsilon_{\bar{t}} + b\frac{\mu+\alpha\varepsilon}{(1-\alpha b)}\right)}{\rho^2\beta_d^2 Var\left(\frac{b\alpha\sigma^2_\mu + \sigma^2_{\alpha\varepsilon}}{\alpha\left(\sigma^2_{\alpha\varepsilon}+\sigma^2_\mu\right)}\frac{\mu+\alpha\varepsilon}{(1-\alpha b)}\right)} \\
&= \frac{\rho\beta_d Cov\left(\mu+\alpha\varepsilon, \varepsilon_{\bar{t}} + b\mu\right)}{\rho^2\beta_d^2\frac{b\alpha\sigma^2_\mu + \sigma^2_{\alpha\varepsilon}}{\alpha\left(\sigma^2_{\alpha\varepsilon}+\sigma^2_\mu\right)}Var\left(\left(\mu+\alpha\varepsilon\right)\right)} \\
&= \frac{bVar\left(\mu\right) + \alpha Var\left(\varepsilon\right)}{\rho\beta_d\frac{b\alpha\sigma^2_\mu + \sigma^2_{\alpha\varepsilon}}{\alpha\left(\sigma^2_{\alpha\varepsilon}+\sigma^2_\mu\right)}Var\left(\left(\mu+\alpha\varepsilon\right)\right)} \\
&= \frac{\frac{\alpha\left(\sigma^2_{\alpha\varepsilon}+\sigma^2_\mu\right)\left(b\sigma^2_\mu+\alpha\sigma^2_\varepsilon\right)}{\rho\beta_d b\alpha\sigma^2_\mu + \rho\beta_d\sigma^2_{\alpha\varepsilon}}}{Var\left(\left(\mu+\alpha\varepsilon\right)\right)} \\
&= \frac{\left(\alpha^2\sigma^2_\varepsilon + \sigma^2_\mu\right)}{\rho\beta_d\left(\sigma^2_\mu + \alpha^2\sigma^2_\varepsilon\right)} \\
&= \frac{1}{\rho\beta_d}
\end{aligned}
$$

8.2.4 Economic Predictability: Multiple Variables

We consider the predictive regression:

$$\Delta GDP_{t+1} = \alpha + \beta^1 r^1_t + \beta^c \Delta\iota^s_{\bar{t}} + \varepsilon_{t+1}$$

where r^1_t is the short-term asset return and $\Delta\iota^s_{\bar{t}}$ is the target rate surprise. We want expressions for β_1 and β_2. We obtain expressions from:

$$Cov(Y,X_1) = Cov(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon, X_2) = \beta_1 Var(X_1) + \beta_2 Cov(X_2, X_1)$$
$$Cov(Y,X_2) = Cov(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon, X_2) = \beta_1 Cov(X_1, X_2) + \beta_2 Var(X_2)$$

Which gives expressions for β_1 and β_2:

$$\begin{aligned}
\beta_2 = \frac{Cov(Y,X_2) - \beta_1 Cov(X_1,X_2)}{Var(X_2)} \\
\rightarrow Cov(Y,X_1) = \beta_1 Var(X_1) \\
+\frac{Cov(Y,X_2) - \beta_1 Cov(X_1,X_2)}{Var(X_2)} Cov(X_2,X_1) \\
\rightarrow Cov(Y,X_1) Var(X_2) = \beta_1 Var(X_1) Var(X_2) \\
+Cov(Y,X_2) Cov(X_2,X_1) - \beta_1 Cov(X_1,X_2) Cov(X_2,X_1) \\
\rightarrow \beta_1 = \frac{Cov(Y,X_1) Var(X_2) - Cov(Y,X_2) Cov(X_2,X_1)}{(Var(X_1) Var(X_2) - Cov(X_1,X_2) Cov(X_2,X_1))}
\end{aligned}$$

So we need to calculate $Cov\left(\Delta\widehat{GDP}_{t+1}, r_t^1\right)$, $Cov\left(\Delta\widehat{GDP}_{t+1}, \Delta\iota_{\tilde{t}}^s\right)$, $Var\left(r_t^1\right)$, and $Var\left(\Delta\iota_{\tilde{t}}^s\right)$. Then $\beta^1 = \frac{Cov\left(\Delta\widehat{GDP}_{t+1}, r_t^1\right) Var\left(\Delta\iota_{\tilde{t}}^s\right) - Cov\left(\Delta\widehat{GDP}_{t+1}, \Delta\iota_{\tilde{t}}^s\right) Cov\left(r_t^1, \Delta\iota_{\tilde{t}}^s\right)}{\left(Var\left(r_t^1\right) Var\left(\Delta\iota_{\tilde{t}}^s\right) - Cov\left(r_t^1, \Delta\iota_{\tilde{t}}^s\right) Cov\left(r_t^1, \Delta\iota_{\tilde{t}}^s\right)\right)}$

Assuming information effects but no soft information, we calculate these expressions below:

$$Cov\left(r_{\bar{t}}^1, \Delta\widehat{GDP}_{t+1}\right) = Cov\left(\rho\beta_d\left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)\left(\Delta\widehat{GDP}_{t+1}\right), \rho_g\Delta\widehat{GDP}_t + \varepsilon_{\bar{t}} + b\iota_t + w_{t+1}\right)$$

$$= \rho\beta_d Cov\left(\frac{b\alpha\sigma_\mu^2 + \sigma_{\alpha\varepsilon}^2}{\alpha\left(\sigma_{\alpha\varepsilon}^2 + \sigma_\mu^2\right)}\frac{\mu + \alpha\varepsilon}{(1-\alpha b)}, \varepsilon_{\bar{t}} + b\frac{\mu + \alpha\varepsilon}{(1-\alpha b)}\right)$$

$$Cov\left(C_t, \Delta\widehat{GDP}_{t+1}\right) = Cov\left(\Delta\iota_{\bar{t}}^s, \rho_g\Delta\widehat{GDP}_t + \varepsilon_{\bar{t}} + b\iota_t + w_{t+1}\right)$$

$$= Cov\left(\frac{\mu + \alpha\varepsilon}{(1-\alpha b)}, \varepsilon_{\bar{t}} + b\frac{\mu + \alpha\varepsilon}{(1-\alpha b)}\right)$$

$$Var\left(\Delta\iota_{\bar{t}}^s\right) = Var\left(\frac{\mu + \alpha\varepsilon}{(1-\alpha b)}\right)$$

$$Var\left(r_t^1\right) = (\rho\beta_d)^2 Var\left(\frac{b\alpha\sigma_\mu^2 + \sigma_{\alpha\varepsilon}^2}{\alpha\left(\sigma_{\alpha\varepsilon}^2 + \sigma_\mu^2\right)}\frac{\mu + \alpha\varepsilon}{(1-\alpha b)}\right)$$

$$Cov\left(r_t^1, C_t\right) = Cov\left(\frac{b\alpha\sigma_\mu^2 + \sigma_{\alpha\varepsilon}^2}{\alpha\left(\sigma_{\alpha\varepsilon}^2 + \sigma_\mu^2\right)}\frac{\mu + \alpha\varepsilon}{(1-\alpha b)}, \frac{\mu + \alpha\varepsilon}{(1-\alpha b)}\right)$$

We calculate the denominator of the expression:

$$Var\left(r_t^1\right) Var\left(\Delta\iota_{\bar{t}}^s\right) - Cov\left(r_t^1, \Delta\iota_{\bar{t}}^s\right) Cov\left(r_t^1, \Delta\iota_{\bar{t}}^s\right)$$

$$= (\rho\beta_d)^2 Var\left(\frac{b\alpha\sigma_\mu^2 + \sigma_{\alpha\varepsilon}^2}{\alpha\left(\sigma_{\alpha\varepsilon}^2 + \sigma_\mu^2\right)}\frac{\mu + \alpha\varepsilon}{(1-\alpha b)}\right) Var\left(\frac{\mu + \alpha\varepsilon}{(1-\alpha b)}\right)$$

$$-Cov\left(\rho\beta_d\frac{b\alpha\sigma_\mu^2 + \sigma_{\alpha\varepsilon}^2}{\alpha\left(\sigma_{\alpha\varepsilon}^2 + \sigma_\mu^2\right)}\frac{\mu + \alpha\varepsilon}{(1-\alpha b)}, \frac{\mu + \alpha\varepsilon}{(1-\alpha b)}\right) Cov\left(\rho\beta_d\frac{b\alpha\sigma_\mu^2 + \sigma_{\alpha\varepsilon}^2}{\alpha\left(\sigma_{\alpha\varepsilon}^2 + \sigma_\mu^2\right)}\frac{\mu + \alpha\varepsilon}{(1-\alpha b)}, \frac{\mu + \alpha\varepsilon}{(1-\alpha b)}\right)$$

$$= \left(\rho\beta_d\frac{b\alpha\sigma_\mu^2 + \sigma_{\alpha\varepsilon}^2}{\alpha(1-\alpha b)^2\left(\sigma_{\alpha\varepsilon}^2 + \sigma_\mu^2\right)}\right)^2 \left(Var(\mu + \alpha\varepsilon)^2 - Var(\mu + \alpha\varepsilon)^2\right)$$

$$= 0$$

The coefficient is undefined since without soft information the target rate surprise determines the short-term asset return and the two variables are collinear.

8.2.5 Economic Predictability: Multiple Variables & Soft Information

We derive the coefficient estimate on the short-term asset return from the predictability regression with soft information:

$$\Delta GDP_{t+1} = \alpha + \beta^1 r_t^1 + \beta^c \Delta \iota_t^s + \varepsilon_{t+1}$$

where r_t^1 is the short-term asset return and $\Delta \iota_t^s$ is the target rate surprise. Our goal is to obtain an expression for β^1. In general, in a regression, $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon$, we can solve for the coefficient on X_1 using $Cov(Y, X_1)$ and $Cov(Y, X_2)$:

$$\begin{aligned}
Cov(Y, X_1) &= Cov(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon, X_2) = \beta_1 Var(X_1) + \beta_2 Cov(X_2, X_1) \\
Cov(Y, X_2) &= Cov(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon, X_2) = \beta_1 Cov(X_1, X_2) + \beta_2 Var(X_2)
\end{aligned}$$

We solve for β_1 and β_2:

$$\begin{aligned}
\beta_2 &= \frac{Cov(Y, X_2) - \beta_1 Cov(X_1, X_2)}{Var(X_2)} \\
&\rightarrow Cov(Y, X_1) = \beta_1 Var(X_1) \\
&+ \frac{Cov(Y, X_2) - \beta_1 Cov(X_1, X_2)}{Var(X_2)} Cov(X_2, X_1) \\
&\rightarrow Cov(Y, X_1) Var(X_2) = \beta_1 Var(X_1) Var(X_2) \\
&+ Cov(Y, X_2) Cov(X_2, X_1) - \beta_1 Cov(X_1, X_2) Cov(X_2, X_1) \\
\rightarrow \beta_1 &= \frac{Cov(Y, X_1) Var(X_2) - Cov(Y, X_2) Cov(X_2, X_1)}{(Var(X_1) Var(X_2) - Cov(X_1, X_2) Cov(X_2, X_1))}
\end{aligned}$$

So in our setting to obtain the coefficient on r_t^1 is given by:

$$\beta^1 = \frac{Cov\left(\Delta\widehat{GDP}_{t+1}, r_t^1\right) Var\left(\Delta\iota_{\bar{t}}^s\right) - Cov\left(\Delta\widehat{GDP}_{t+1}, \Delta\iota_{\bar{t}}^s\right) Cov\left(r_t^1, \Delta\iota_{\bar{t}}^s\right)}{\left(Var\left(r_t^1\right) Var\left(\Delta\iota_{\bar{t}}^s\right) - Cov\left(r_t^1, \Delta\iota_{\bar{t}}^s\right) Cov\left(r_t^1, \Delta\iota_{\bar{t}}^s\right)\right)}$$

We determine the expressions for: $Cov\left(\Delta\widehat{GDP}_{t+1}, r_t^1\right)$, $Cov\left(\Delta\widehat{GDP}_{t+1}, \Delta\iota_{\bar{t}}^s\right)$, $Var\left(r_t^1\right)$, and $Var\left(\Delta\iota_{\bar{t}}^s\right)$. Expressions for each of these quantities are provided below:

$$\begin{aligned}
Cov\left(r_{\bar{t}}^1, \Delta\widehat{GDP}_{t+1}\right) &= Cov\left(\rho\beta_d\left(\mathbb{E}_{\bar{t}} - \mathbb{E}_{\underline{t}}\right)\left(\Delta\widehat{GDP}_{t+1}\right), \rho_g\Delta\widehat{GDP}_t + \varepsilon_{\bar{t}} + b\iota_t + w_{t+1}\right) \\
&= \rho\beta_d Cov\left(\frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_p^2}\frac{(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2 + \sigma_\mu^2}\Delta\iota_{\bar{t}}^s + \varepsilon_{\bar{t}}\frac{\sigma_p^2}{\sigma_\eta^2 + \sigma_p^2}, \varepsilon_{\bar{t}} + b\Delta\iota_{\bar{t}}^s\right) \\
&= \rho\beta_d\frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_p^2}\frac{b(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2 + \sigma_\mu^2}Var\left(\Delta\iota_{\bar{t}}^s\right) \\
&\quad + \rho\beta_d\frac{\sigma_p^2}{\sigma_\eta^2 + \sigma_p^2}Var\left(\varepsilon_{\bar{t}}\right) \\
&\quad + \rho\beta_d\left(\frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_p^2}\frac{(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2 + \sigma_\mu^2} + \frac{b\sigma_p^2}{\sigma_\eta^2 + \sigma_p^2}\right)Cov\left(\Delta\iota_{\bar{t}}^s, \varepsilon_{\bar{t}}\right)
\end{aligned}$$

$$
\begin{aligned}
Cov\left(\Delta\iota_{\bar{t}}^{s},\Delta\widehat{GDP}_{t+1}\right) &= Cov\left(\Delta\iota_{\bar{t}}^{s},\rho_g\Delta\widehat{GDP}_{t}+\varepsilon_{\bar{t}}+b\iota_t+w_{t+1}\right)\\
&= Cov\left(\Delta\iota_{\bar{t}}^{s},\varepsilon_{\bar{t}}+b\Delta\iota_{\bar{t}}^{s}\right)\\
&= bVar\left(\Delta\iota_{\bar{t}}^{s}\right)+Cov\left(\Delta\iota_{\bar{t}}^{s},\varepsilon_{\bar{t}}\right)
\end{aligned}
$$

$$
\begin{aligned}
Var\left(C_t\right) &= Var\left(\frac{\mu+\alpha\varepsilon}{(1-\alpha b)}\right)\\
Var\left(r_t^1\right) &= Var\left(\frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2}\frac{(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2}C_t+\varepsilon_{\bar{t}}\frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2}\right)\\
Cov\left(r_t^1,\Delta\iota_{\bar{t}}^{s}\right) &= Cov\left(\frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2}\frac{(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2}\Delta\iota_{\bar{t}}^{s}+\varepsilon_{\bar{t}}\frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2},\frac{\mu+\alpha\varepsilon}{(1-\alpha b)}\right)\\
&= \left(\frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2}\frac{(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2}\right)Var\left(\Delta\iota_{\bar{t}}^{s}\right)+\frac{\alpha}{1-\alpha b}\left(\frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2}\right)Var\left(\varepsilon_{\bar{t}}\right)
\end{aligned}
$$

We evaluate the numerator on the β^1 coefficient:

$$
\begin{aligned}
&Cov\left(\Delta\widehat{GDP}_{t+1}, r_t^1\right) Var\left(\Delta\iota_{\bar{t}}^s\right) - Cov\left(\Delta\widehat{GDP}_{t+1}, \Delta\iota_{\bar{t}}^s\right) Cov\left(r_t^1, \Delta\iota_{\bar{t}}^s\right) \\
&\rho\beta_d \frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2}\frac{b(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2} Var\left(\Delta\iota_{\bar{t}}^s\right) Var\left(\Delta\iota_{\bar{t}}^s\right) + \rho\beta_d \frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2} Var\left(\varepsilon_{\bar{t}}\right) Var\left(\Delta\iota_{\bar{t}}^s\right) \\
&+\rho\beta_d \left(\frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2}\frac{(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2} + \frac{b\sigma_p^2}{\sigma_\eta^2+\sigma_p^2}\right) Cov\left(\Delta\iota_{\bar{t}}^s, \varepsilon_{\bar{t}}\right) Var\left(\Delta\iota_{\bar{t}}^s\right) \\
&-\left(\frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2}\frac{b(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2}\right) Var\left(\Delta\iota_{\bar{t}}^s\right) Var\left(\Delta\iota_{\bar{t}}^s\right) - \frac{\alpha b}{1-\alpha b}\left(\frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2}\right) Var\left(\Delta\iota_{\bar{t}}^s\right) Var\left(\varepsilon_{\bar{t}}\right) \\
&-\left(\frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2}\frac{(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2}\right) Cov\left(\Delta\iota_{\bar{t}}^s, \varepsilon_{\bar{t}}\right) Var\left(\Delta\iota_{\bar{t}}^s\right) - \frac{\alpha}{1-\alpha b}\left(\frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2}\right) Cov\left(\Delta\iota_{\bar{t}}^s, \varepsilon_{\bar{t}}\right) Var\left(\varepsilon_{\bar{t}}\right) \\
&= \frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2}\frac{b(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2}(\rho\beta_d - 1) Var\left(\Delta\iota_{\bar{t}}^s\right) Var\left(\Delta\iota_{\bar{t}}^s\right) \\
&+\left(\rho\beta_d \frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2} - \frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2}\frac{\alpha b}{1-\alpha b}\right) Var\left(\varepsilon_{\bar{t}}\right) Var\left(\Delta\iota_{\bar{t}}^s\right) \\
&+\left(\rho\beta_d \frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2}\frac{(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2} + \rho\beta_d \frac{b\sigma_p^2}{\sigma_\eta^2+\sigma_p^2} - \frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2}\frac{(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2}\right) Cov\left(\Delta\iota_{\bar{t}}^s, \varepsilon_{\bar{t}}\right) Var\left(\Delta\iota_{\bar{t}}^s\right) \\
&-\frac{\alpha}{1-\alpha b}\left(\frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2}\right) Cov\left(\Delta\iota_{\bar{t}}^s, \varepsilon_{\bar{t}}\right) Var\left(\varepsilon_{\bar{t}}\right) \\
&= \frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2}\frac{b(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2}(\rho\beta_d - 1) Var\left(\Delta\iota_{\bar{t}}^s\right) Var\left(\Delta\iota_{\bar{t}}^s\right) \\
&+\frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2}\left(\frac{\rho\beta_d(1-\alpha b) - \alpha b}{1-\alpha b}\right) Var\left(\varepsilon_{\bar{t}}\right) Var\left(\Delta\iota_{\bar{t}}^s\right) \\
&+\left(\frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2}(\rho\beta_d - 1) + \rho\beta_d \frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2}\frac{\alpha b}{1-\alpha b}\right) Var\left(\varepsilon_{\bar{t}}\right) Var\left(\Delta\iota_{\bar{t}}^s\right) \\
&-\left(\frac{\alpha}{1-\alpha b}\right)^2 \left(\frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2}\right) Var\left(\varepsilon_{\bar{t}}\right) Var\left(\varepsilon_{\bar{t}}\right)
\end{aligned}
$$

The denominator is given by:

$$
\begin{aligned}
&Var\left(r_t^1\right)Var\left(\Delta\iota_{\bar{t}}^s\right)-Cov\left(r_t^1,\Delta\iota_{\bar{t}}^s\right)Cov\left(r_t^1,\Delta\iota_{\bar{t}}^s\right)\\
&=\beta_d^2\rho^2 Var\left(\frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2}\frac{(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2}\Delta\iota_{\bar{t}}^s+\varepsilon_{\bar{t}}\frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2}\right)Var\left(\Delta\iota_{\bar{t}}^s\right)\\
&-Cov\left(\beta_d\rho\frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2}\frac{(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2}\Delta\iota_{\bar{t}}^s+\varepsilon_{\bar{t}}\frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2},\Delta\iota_{\bar{t}}^s\right)^2\\
&=\beta_d^2\rho^2\left(\frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2}\frac{(1-\alpha b)}{\alpha}\right)^2 Var\left(\Delta\iota_{\bar{t}}^s\right)^2\\
&-\left(\beta_d\rho\frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2}\frac{(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2}\right)^2 Var\left(\Delta\iota_{\bar{t}}^s\right)^2\\
&+\beta_d^2\rho^2\left(\frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2}\right)^2 Var\left(\varepsilon_{\bar{t}}\right)Var\left(\Delta\iota_{\bar{t}}^s\right)\\
&+2\beta_d^2\rho^2\frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2}\frac{(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2}\frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2}Cov\left(\Delta\iota_{\bar{t}}^s,\varepsilon_{\bar{t}}\right)Var\left(\Delta\iota_{\bar{t}}^s\right)\\
&-\left(\frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2}\right)^2 Cov\left(\Delta\iota_{\bar{t}}^s,\varepsilon_{\bar{t}}\right)^2\\
&-2\left(\frac{\sigma_p^2}{\sigma_\eta^2+\sigma_p^2}\right)\beta_d\rho\frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_p^2}\frac{(1-\alpha b)}{\alpha}\frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2+\sigma_\mu^2}Cov\left(\Delta\iota_{\bar{t}}^s,\varepsilon_{\bar{t}}\right)Var\left(\Delta\iota_{\bar{t}}^s\right)
\end{aligned}
$$

$$
\begin{aligned}
&= \beta_d^2 \rho^2 \left(\frac{\sigma_p^2}{\sigma_\eta^2 + \sigma_p^2} \right)^2 Var\left(\varepsilon_{\bar{t}}\right) Var\left(\Delta \iota_{\bar{t}}^s\right) \\
&+ \frac{\alpha}{1-\alpha b} 2\beta_d^2 \rho^2 \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_p^2} \frac{(1-\alpha b)}{\alpha} \frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2 + \sigma_\mu^2} \frac{\sigma_p^2}{\sigma_\eta^2 + \sigma_p^2} Var\left(\varepsilon_{\bar{t}}\right) Var\left(\Delta \iota_{\bar{t}}^s\right) \\
&- 2\frac{\alpha}{1-\alpha b} \left(\frac{\sigma_p^2}{\sigma_\eta^2 + \sigma_p^2} \right) \beta_d \rho \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_p^2} \frac{(1-\alpha b)}{\alpha} \frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2 + \sigma_\mu^2} Var\left(\varepsilon_{\bar{t}}\right) Var\left(\Delta \iota_{\bar{t}}^s\right) \\
&- \left(\frac{\sigma_p^2}{\sigma_\eta^2 + \sigma_p^2} \right)^2 Cov\left(\Delta \iota_{\bar{t}}^s, \varepsilon_{\bar{t}}\right)^2 \\
&= \beta_d^2 \rho^2 \left(\frac{\sigma_p^2}{\sigma_\eta^2 + \sigma_p^2} \right)^2 Var\left(\varepsilon_{\bar{t}}\right) Var\left(\Delta \iota_{\bar{t}}^s\right) \\
&+ \left(\frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_p^2} \frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2 + \sigma_\mu^2} 2\beta_d \rho \frac{\sigma_p^2}{\sigma_\eta^2 + \sigma_p^2} \right) (\beta_d \rho - 1) Var\left(\varepsilon_{\bar{t}}\right) Var\left(\Delta \iota_{\bar{t}}^s\right) \\
&- \left(\frac{\sigma_p^2}{\sigma_\eta^2 + \sigma_p^2} \right)^2 \left(\frac{\alpha}{1-\alpha b} \right)^2 Var\left(\varepsilon_{\bar{t}}\right)^2 \\
&= Var\left(\varepsilon_{\bar{t}}\right) Var\left(\Delta \iota_{\bar{t}}^s\right) \left(\frac{\sigma_p^2}{\sigma_\eta^2 + \sigma_p^2} \right)^2 \left(\beta_d^2 \rho^2 + \left(\frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_p^2} \frac{\sigma_{\alpha\varepsilon}^2}{\sigma_{\alpha\varepsilon}^2 + \sigma_\mu^2} 2\beta_d \rho \right) (\beta_d \rho - 1) \right) \\
&- Var\left(\varepsilon_{\bar{t}}\right) \left(\frac{\sigma_p^2}{\sigma_\eta^2 + \sigma_p^2} \right)^2 \left(\frac{\alpha}{1-\alpha b} \right)^2 Var\left(\varepsilon_{\bar{t}}\right)
\end{aligned}
$$

8.3 Model Calibration

We estimate the persistence of quarterly real GDP growth using data from the third quarter of 1947 to the fourth quarter of 2021. We estimate the persistence of the target federal funds rate using the effective federal funds rate each quarter. Based on these estimates, our baseline quarterly calibration uses $\rho_g = 0.12$ and $\rho_\iota = 0.95$. We use a quarterly time discount rate, ρ, of 0.99 corresponding to an annual rate of 0.96. We set $b = -0.1$, a 1 percentage point decrease in the target federal funds rate corresponds with a 0.1 percentage point increase in economic growth. We set

$\alpha = 0.25$, the central bank lowers (raises) rates given lower (higher) expectations about next period economic growth. The variances of the shocks, σ_μ^2, σ_ε^2 determines how investors infer the contribution of the shocks μ and ε to an observed target rate surprise. The ratio of the variance parameters is important for model-implied expected values. Similarly, for the variance of soft information, σ_η^2, determines the relative weight on the soft information released by the central bank compared with the investor's prior from the observed target federal funds rate. We choose $\sigma_\varepsilon^2 = 4$ (quantities in the model are in percent), $\sigma_\mu^2 = 2$ and $\sigma_\eta^2 = 3$. The higher variance of ε versus μ will cause investors to attribute more of the target rate surprise to private information of the central bank. Finally, we set β_d, the parameter governing the relationship between dividend growth and GDP growth from Equation 6, equal to 1. This parameter scales the model-implied returns of the short-term and long-term assets.

8.4 Additional Macroeconomic Predictability Results

8.4.1 Professional Forecasts

We construct a set of tests which incorporate measures of private sector beliefs using macroeconomic forecast data from the Survey of Professional Forecasters (SPF), a survey of professional forecasters trained in economics and statistics conducted by the Federal Reserve Bank of Philadelphia.[46] We consider professional forecasts for annual real GDP growth made before each FOMC meeting and test whether the short-term dividend return predicts errors in these forecasts with a positive sign. If the short-term dividend price response to the monetary policy news released at the corresponding FOMC meeting does not contain new information

[46]The SPF is a quarterly survey in which participants are asked to provide forecasts for a number of U.S. macroeconomic variables at quarterly horizons from the current quarter to four quarters out. The survey timing is based on the Bureau of Economic Analysis' (BEA)' advance report of the national income and product accounts which is released at the end of the first month of each quarter and contains the initial estimates of GDP and its components for the previous quarter. The survey is sent after this report is released to the public and includes the recent historical values of variables from the BEA's advance report and the most recent reports of other government statistical agencies. The response deadlines are set at late in the second to third week of the middle month of each quarter.

about macroeconomic conditions, then forecast errors should not correlated with these price movements. On the other hand, predictability in forecast errors suggests that Fed announcements embed relevant information about macroeconomic conditions.

For each quarter, we obtain the average quarterly growth forecasts across all analysts in the SPF survey for real GDP growth (Δgdp). We obtain realizations of real GDP growth from the Philadelphia Federal Reserve's Real-Time Data Set for Macroeconomists which records historical vintages of the data from the National Income and Product Accounts (NIPA). We obtain the SPF forecast deadline from the Federal Reserve Bank of Philadelphia website. We match each forecast deadline with the nearest FOMC meeting which occurs after the deadline. We denote actual real GDP growth over the next year by $\Delta x_{t+1\to t+4}$ and the average SPF growth rate forecast for annual real GDP growth made in quarter t by $F_{t-}\left(\Delta x_{t+1\to t+4}\right)$. We calculate the forecast error as the difference between realized real GDP growth and the average forecast, $\Delta x_{t+1\to t+4} - F_{t-}\left(\Delta x_{t+1\to t+4}\right)$. We calculate the 180-day dividend return in the 30-minute window around the FOMC announcement for the nearest FOMC meeting at date $t+$ after the SPF forecast deadline. This meeting falls within the same quarter as the SPF deadline or in the first 30 days of the next quarter in all cases. We also include the change in nonfarm payroll employment, ΔNFP_t, released in the monthly Bureau of Labor Statistics' employment report between the SPF forecast date, $t-$, and the subsequent FOMC meeting date, $t+$. Bauer and Swanson (2020) use this variable as a measure of economic news that may be relevant for macroeconomic forecasts. We include this variable as a robustness test of our baseline result. We use $t-$, t, and $t+$ subscripts with the SPF forecasts, change in nonfarm payroll employment, and short-term dividend return respectively to indicate the timing of each variable within the same quarter. Figure A.9 in the Appendix documents the timing of each variable.

We regress forecast errors for annual macroeconomic growth on the price response of the short-term dividend strip around the nearest FOMC meeting after the SPF forecasts are made and the change in nonfarm payroll employment. Equation 32 presents the regression specification:

$$\Delta gdp_{t+1\to t+4} - F_{t-}\left(\Delta x_{t+1\to t+4}\right) = \alpha + \beta \Delta P^{180}_{t+} + \delta \Delta NFP_t + \varepsilon_{t+1\to t+4} \tag{32}$$

where, as described above, $\Delta gdp_{t+1\to t+4}$ is the actual annual growth rate of real GDP, $F_{t-}\left(\Delta gdp_{t+1\to t+4}\right)$ is the average forecast from the Survey of Professional Forecasters made in quarter t, ΔP^{180}_{t+} is the return of the 180-day dividend strip in the 30-minute window around the FOMC announcement at date $t+$, and ΔNFP_t is the monthly change in non-farm payroll employment based on the Bureau of Labor Statistics' employment report released between the SPF forecast deadline and the FOMC meeting.

Table A.7 in the Appendix presents the results of this regression. Column 1 presents our baseline specification. The coefficient β on the short-term dividend return is positive and significant at the 5 percent level using Newey-West adjusted standard errors. The positive sign is consistent with the Fed information channel: positive (negative) news from the FOMC announcement about economic conditions is incorporated into the short-term asset price generating a positive (negative) announcement return; this positive (negative) short-term asset announcement return positively predicts forecast errors. The adjusted R-squared of the regression is 6 percent. Column 2 presents a specification run using the short-term dividend return, the change in non-farm payrolls, and the monetary policy shock. The coefficient on the short-term dividend return remains positive and is significant at the 10 percent level. The coefficient on the monetary policy shock is negative but not significant.

8.4.2 Summary of Economic Projections

We measure the difference between the economic growth forecasts from the central bank released following an FOMC meeting and existing private sector forecasts. We study the relationship between the short-term asset price response to the FOMC announcement and this forecast gap. Our measure of central bank economic growth forecasts comes from the advance release of the Summary of Economic Projections (SEP) and our measure of private sector growth forecasts comes from the latest Survey of Professional Forecasters report released prior to each FOMC meeting.

Meeting participants, the 7 members of the Board of Governors and the 12 presidents of the Federal Reserve Banks submit individual projections for key economic variables including: annual change in real GDP from the fourth quarter of the previous year to the fourth quarter of the year indicated; the average civilian Unemployment rate in the fourth quarter of each year; the change in personal consumption expenditures (PCE) price index from the fourth quarter of the previous year to the fourth quarter of the year indicated; and projections for the appropriate level of the target federal funds rate.[47] For the FOMC meeting on date t, each individual i, makes forecasts $F_t^i\left(x_{year(k)}\right)$, for variable x at horizon $k \in \{0, 1, 2, 3, LongRun\}$. For example, if we take x to be real GDP growth and $k = 0$, then $\left\{F_t^i\left(\Delta rgdp_{year(0)}\right)\right\}_{i,t}$ is the set of forecasts for current year real GDP growth. On meeting date t^* there are 19 forecasts, $F_{t^*}^i\left(\Delta rgdp_{year(0)}\right)$, corresponding to each individual i for the annual real GDP growth in the year of the meeting.

The Federal Reserve began to provide an advance version of these economic projections in conjunction with the Chairman's the post-meeting press conference beginning in 2011. While the advance version of the SEP does not provide individual level forecasts, the report provides the ranges and central tendencies of the participants' projections. Specifically, for a given economic variable x and horizon k, the advance version of the SEP provides: the highest forecast among the i participants at meeting t, which we denote "range upper" $F_t^{ru}(x_k)$; the lowest forecast among the i participants at meeting t, which we denote "range lower" $F_t^{rl}(x_k)$; the highest forecast among the i participants at meeting t after removing the three highest forecasts, which we denote "central tendency upper" $F_t^{cu}(x_k)$; and the lowest forecast among the i participants at meeting t after removing the lowest three forecasts, which we denote "central tendency lower" $F_t^{cl}(x_k)$. We parse the advance version of the economic projections for the 36 meetings where the data was released between April 2011 to December 2019 to obtain measures of the central tendency and range for annual real GDP growth, annual percent change in PCE in-

[47]These projections are collected four times year, typically in the March, June, September, and December meetings. The horizon of the March and June meeting annual projections are for the current year, the subsequent two years, and the longer run. The projections made in the September and December meetings are for the current year, the subsequent three years, and the longer run. The longer run projections reflect the rates to which the forecaster expects the economy to converge to over time in the absence of further shocks.

flation, fourth quarter Unemployment rate, and projections of the appropriate level of the Federal Funds rate at each horizon at each meeting.[48]

We focus on advance projections for current year real GDP growth. For each FOMC meeting where advance projections are available, we take the midpoint of the lower and upper values of the central tendency and denote this forecast as $F_t^{FED}\left(\Delta rgdp_{year(0)}\right)$, the Fed forecast for current year real GDP growth made at meeting date t. Private sector forecasts for annual real GDP growth are constructed using data from the Survey of Professional Forecasters. For each quarter, SPF quarterly growth forecasts for the remaining quarters in the year are combined with the actual quarterly real GDP growth in the prior quarters of the calendar year from the National Income and Product Accounts (NIPA) using the latest vintage available at the time the SPF forecasts were made. We denote these forecasts $F_{t-}^{SPF}\left(\Delta rgdp_{year(0)}\right)$, the latest SPF forecast for the current year real GDP growth made prior to the FOMC meeting at date t. We calculate the difference between the Fed forecasts and the SPF forecasts as: $ForecastGapUnadj_t = F_t^{FED}\left(\Delta rgdp_{year(0)}\right) - F_{t-}^{SPF}\left(\Delta rgdp_{year(0)}\right)$. The date of the FOMC meeting determines how many quarters of the current year GDP are known at the time of each forecast. When the meeting falls in the first quarter of the year, the forecast gap reflects differences in forecasts real GDP growth over the next four quarters. When the meeting falls in the fourth quarter, the forecast gap reflects differences in forecasts of current quarter only. We standardize the different horizons by scaling the forecast gap based on the number of quarters remaining in the year at the time of the forecasts: $ForecastGap_t = (1 + ForecastGapUnadj_t)^{\frac{4}{k}} - 1$. Where k denotes the number of quarters remaining in the year. We run the following regression:

[48]Table A.8 in the Appendix presents the summary statistics of the central tendency measures for each variable. We calculate the average, standard deviation, minimum and maximum for each measure separately (central tendency: upper and lower). For instance, for current year real GDP growth ($x = \Delta rgdp$ and $k = 0$), we have $F_t^{cl}\left(\Delta rgdp_{year(0)}\right)$ and $F_t^{cu}\left(\Delta rgdp_{year(0)}\right)$ the 36 central lower and 36 central upper forecasts for this variable at the 36 meetings in our sample. We calculate the average of each measure across the 36 meetings as: $F_{avg}^{cl}(x_k) = \frac{1}{T}\sum_t F_t^{cl}(x_k)$ and $F_{avg}^{cu}(x_k) = \frac{1}{T}\sum_t F_t^{cu}(x_k)$. The table contains statistics for the central tendency measures presented in the format F^{cl}, F^{cu}, the lower central tendency statistic followed by the upper central tendency statistic separated by a comma. For example, the top left entry: Change in real GDP, Current Year, Average provides the average of the lower central tendency and upper central tendency for current year real GDP growth forecasts, $F_{avg}^{cl}\left(\Delta rgdp_{year(0)}\right)$ and $F_{avg}^{cl}\left(\Delta rgdp_{year(0)}\right)$ as 2.197 and 2.428 respectively.

$$\Delta P_t^{180} = \alpha + \beta ForecastGap_t + \varepsilon_t$$

where ΔP_t^{180} is the return of the 180-day dividend strip in the 30-minute window around the FOMC meeting announcement at date t and $ForecastGap_t$ is the standardized difference in central bank SEP and private sector real GDP forecasts defined above.

Table A.9 in the Appendix presents the results from this regression. Newey-West adjusted standard errors are presented in parentheses below the coefficient estimates. The coefficient on the $ForecastGap$ is positive and significant at the 1 percent level. Based on the coefficient estimate of 5.820, a 1 percent increase in the gap between the central bank and private sector annual real GDP forecasts corresponds to an increase in the price of the short-term asset of about 6 percent in the 30-minute window around the FOMC announcement. The forecast gap explains 8 percent of the variation in the 180-day dividend strip announcement returns.

8.5 Soft Information Measures

8.5.1 Preprocessing Text Data

We represent our text data as a document-term matrix f, a $D \times V$ matrix whose rows correspond to the set of D documents in our corpus and the columns correspond to the V unique terms which occur in the text. Each document is a separate sentence from the Staff Economic Outlook section pertaining to economic growth. The entries in f which we denote by $f_{d,v}$ correspond to the number of times that the vth term occurs in document d.[49] To preprocess the text data we first remove punctuation, numbers, and symbols and convert to lower case. Then we remove a standardized set of english stopwords as well as a set of words "first", "second", "third", "fourth", "quarter", "year" which often occur in template form in the statements. We stem all words and then construct a set of all uni-, bi-, and trigrams

[49] For example, if our corpus consists of two documents and three terms, "gdp expand", "gdp contract", and "fiscal policy", then document-term matrix is a 2×3 matrix with each row corresponding to a document and each column corresponding to the three terms. If the first document contains the phrase "gdp expand" twice, "gdp contract" zero times, and "fiscal policy" once, this corresponds to the vector $f_{1,v} = \begin{pmatrix} 2 & 0 & 1 \end{pmatrix}$.

within the text. We compute the term frequency-inverse document frequency, tf-idf, for each word and phrase in the corpus as $tfidf\left(v,d,D\right)=\left(1+log\left(f_{d,v}\right)\right)\times log\left(\frac{N}{\{d\in D:v\in d\}}\right)$ where $f_{d,v}$ is the count of the number of occurrences of term v in document d, N is the total number of documents, and $\{d\in D:v\in d\}$ is the number of documents containing the term v. The term frequency-inverse document frequency measures how important a word or phrase is to a document within a corpus - high values of tf-idf occur when term v has a high prevalence in a given document d relative to its occurrence in other documents. We filter out observations with tf-idf less than 6. Finally, we require a word to occur a minimum of five times throughout the entire corpus.

8.5.2 LDA Measure

Our first measure of central bank discussion about economic growth prospects is based on a machine learning technique known as latent Dirichlet allocation (LDA) developed in Blei et al. (2003). LDA is a statistical model used to identify the topics that occur in a set of text documents and to estimate the prevalence of these topics in each document. A topic, β_k, is defined as a distribution over a fixed vocabulary where the number of topics, K, is a hyperparameter of the model. A document defined as a distribution over the set of topics, $\theta_d=(\theta_{d1},\theta_{d2},...,\theta_{dK})$, where θ_{dk} denotes the topic proportion of topic k in document d. The actual topic assignments for document d are $z_d=(z_{d1},z_{d2},...,z_{dN})$ where z_{dn} is the topic assignment of the nth word of document d and N is the total number of words in the document. The observed words which comprise document d are given by $w_d=(w_{d1},w_{d2},...,w_{dN})$ where w_{dn} is the nth word in document d.

Given this structure, the joint probability distribution of the latent variables and observed text data is given by:

$$p\left(\beta_{1:K},\theta_{1:D},z_{1:D},w_{1:D}\right)=\prod_{i=1}^{K}p\left(\beta_i\right)\prod_{d=1}^{D}p\left(\theta_d\right)\left(\prod_{n=1}^{N}p\left(z_{d,n}|\theta_d\right)p\left(w_{d,n}|\beta_{1:K},z_{d,n}\right)\right)$$

where $\beta_{1:K}$ is the set of topics, $\theta_{1:D}$ is the set of document-topic distributions,

$z_{1:D}$ is the topic assignment of each word in each document, and $w_{1:D}$ is the observed words in each document.

Our goal is to infer the conditional distribution of the latent factors, in particular $\beta_{1:K}$ and $\theta_{1:D}$, given the observed text data $w_{1:D}$. The posterior is given by:

$$p\left(\beta_{1:K}, \theta_{1:D}, z_{1:D} | w_{1:D}\right) = \frac{p\left(\beta_{1:K}, \theta_{1:D}, z_{1:D}, w_{1:D}\right)}{p\left(w_{1:D}\right)}$$

While the numerator is straightforward to compute as the joint distribution of the random variables, the denominator is the marginal probability of observing the given text across all possible topic models and is generally untractable to compute. Researchers typically rely on Gibbs sampling, a Markov chain Monte Carlo algorithm, to estimate the posterior distribution of the latent variables, β and θ.[50]

We apply the LDA model to our text data with $K = 5$ topics and obtain estimates for $\beta_{1:5}$ and $\theta_{1:128}$. Table A.10 in the Appendix presents the top ten words in each the word distribution for each of the five topics. The words which comprise β_1 have a strong connection with positive central bank views about economic growth prospects: top words include "gdp_expand", "faster_pace", and "real_gdp_expand". We label this topic $EconomicGrowth$.[51]

We focus on the economic growth topic and construct a time-series measure of this topic's prevalence in FOMC meetings. We aggregate topic allocation across all documents in each meeting to obtain a measure of topic prevalence at the FOMC meeting level:

$$\eta_t^{lda} = \frac{\sum_d \theta_{dk} \mathbb{I}\left(d \in t\right)}{\sum_d \mathbb{I}\left(d \in t\right)}$$

where θ_{dk} is the prevalence of topic k in document d and $\mathbb{I}\left(d \in t\right)$ is an indicator variable equal to 1 if document d occurred during FOMC meeting at date t and 0 otherwise. η_t^{lda} denotes our LDA based measure of soft information, η, at each meeting date t.

[50] Steyvers and Griffiths (2007) discuss this approach in detail.

[51] The other topics are interesting but do not have a clear semantic connection with economic growth. For instance, β_5, includes terms "dollar", "project_path", and "medium term" which may be related to interest and exchange rates.

8.5.3 Sentiment Dictionary Measure

We construct a second measure based on the sentiment text classification dictionary developed in Loughran and McDonald (2011). This dictionary classifies sets of words as "positive" or "negative" in tone based on their use in financial contexts and provides an improvement over standard sentiment dictionaries which are not constructed based on financial or economic discussion. We apply this dictionary to the SEO discussion about economic growth and obtain a count of the number of positive and negative words at each FOMC meeting. We account for phrases which may change the meaning of constitutent words (i.e. "reduce" and "uncertainty" become "reduce uncertainty") by constructing a list of all bigrams and trigrams (two or three word phrases) that occur more than five times in the text and manually categorizing these phrases as positive, neutral, or negative. We supplement the unigram sentiment measure with our bigram and trigram sentiment measures to construct our measure, η_t^{lm}, at each FOMC meeting date t as:

$$\eta_t^{lm} = \frac{Pos_t^1 + Pos_t^2 + Pos_t^3 - Neg_t^1 - Neg_t^2 - Neg_t^3}{1 + Pos_t^1 + Pos_t^2 + Pos_t^3 + Neg_t^1 + Neg_t^2 + Neg_t^3}$$

where Pos_t^1 (Neg_t^1) is the total number of positive (negative) sentiment unigrams from the Loughran-McDonald dictionary, Pos_t^2 (Neg_t^2) is the total number of positive (negative) bigrams, and Pos_t^3 (Neg_t^3) is the total number of positive (negative) trigrams.

We plot the time-series of both measures, η_t^{lda} and η_t^{lm}, in Figure A.10 in the Appendix. Both measures increase in the years following the 2008 recession and then decline in 2019. The measures are positively correlated with a correlation of 0.385 over our sample.

8.6 Tables & Figures

Table A.1: **Asset Return on Monetary Policy Shock: Winsorized**

	ΔP^{180}	ΔP^{360}	ΔP^{540}
Panel A: All Monetary Policy Shocks			
Δi_t^u	0.205	0.038	0.021
	(0.067)	(0.032)	(0.025)
Adj. R^2	0.063	0.004	-0.002
Obs.	128	128	128
Panel B: Non-Zero Monetary Policy Shocks			
Δi_t^u	0.206	0.034	0.017
	(0.068)	(0.031)	(0.022)
Adj. R^2	0.090	0.002	-0.005
Obs.	84	84	84

This table presents results from the regression of asset return on the monetary policy shock:

$$\Delta P_t^h = \alpha + \beta \Delta i_t^u + \varepsilon$$

where ΔP_t^h is the log return on the asset with maturity $h \in \{180, 360, 540\}$ days and Δi_t^u is the unexpected change in target federal funds rate around the FOMC announcement. Asset returns are winsorized at the 5 percent level. OLS standard errors are reported in parentheses below the coefficient estimate. Top panel presents results for all monetary policy shocks in the period from January 2004 until December 2019. Panel B presents results for non-zero monetary policy shocks. The intercept, α, is not reported.

Table A.2: **Real Dividend and GDP Forecasting: Additional Controls**

Horizon	1Q	2Q	3Q	4Q	5Q	6Q	7Q	8Q
Panel A: Real Dividend Growth								
ΔP^{180}	0.512	0.723	0.836	1.061	1.058	0.929	0.440	0.404
	(0.227)	(0.223)	(0.359)	(0.422)	(0.407)	(0.373)	(0.284)	(0.263)
Δi_t^u	0.077	0.162	0.120	0.103	0.028	0.308	0.518	0.546
	(0.286)	(0.340)	(0.373)	(0.395)	(0.437)	(0.479)	(0.539)	(0.505)
ΔP^{∞}	-5.050	-3.338	-2.471	-0.394	2.184	4.921	4.910	4.683
	(3.674)	(3.654)	(3.788)	(3.519)	(4.235)	(4.380)	(4.448)	(3.904)
ΔIV_t^{180}	-6.705	-4.037	-2.351	1.006	4.850	8.317	8.736	6.179
	(4.557)	(4.293)	(4.814)	(5.628)	(7.069)	(7.415)	(7.703)	(6.078)
Adj. R^2	0.067	0.075	0.056	0.077	0.066	0.083	0.044	0.038
Obs.	84	84	84	84	83	81	79	79
Panel B: Real GDP Growth								
ΔP^{180}	0.094	0.167	0.229	0.183	0.129	0.063	0.113	0.050
	(0.056)	(0.080)	(0.096)	(0.082)	(0.057)	(0.051)	(0.151)	(0.107)
Δi_t^u	0.035	-0.010	-0.056	-0.065	0.062	0.077	0.041	0.043
	(0.087)	(0.086)	(0.096)	(0.115)	(0.102)	(0.136)	(0.110)	(0.063)
ΔP^{∞}	-0.437	-0.044	0.420	0.543	1.213	1.260	0.445	-0.237
	(0.663)	(0.589)	(0.486)	(0.774)	(0.865)	(0.771)	(0.512)	(0.404)
ΔIV_t^{180}	-0.194	0.255	0.267	0.786	1.349	1.032	-0.237	-0.799
	(0.755)	(0.933)	(1.134)	(1.475)	(1.545)	(1.441)	(0.892)	(0.831)
Adj. R^2	0.021	0.009	0.020	-0.001	0.041	-0.002	-0.021	-0.042
Obs.	84	84	84	83	81	79	79	77

Panel A presents the results from the predictive regression of k quarter ahead real dividend growth on the short-term dividend strip return ΔP^{180} in the 30 minute window around the FOMC announcements with non-zero monetary policy surprises:

$$log\left(\frac{D_{t+k}}{D_{t+k-4}}\right) = \alpha_k + \beta_k \Delta P_t^{180} + \delta_k Controls_t + \varepsilon_{t+k}, k \in \{1,2,...,8\}$$

Control variables include monetary policy shock Δi_t^u, market return in the 30 minute window around the FOMC announcement ΔP^{∞}, and change in the implied volatility with maturity of 180 days ΔIV_t^{180}. Panel B presents the real GDP growth predictability specifications. We report Newey-West adjusted standard errors with two lags in parentheses below the coefficient estimates. The period is from January 2004 until December 2019.

Table A.3: **Real Dividend Forecasting: Robustness**

Horizon	1Q	2Q	3Q	4Q	5Q	6Q	7Q	8Q
Newy-West 8 lags								
ΔP^{180}	0.669	0.874	0.965	1.147	1.063	0.947	0.542	0.462
	(0.234)	(0.251)	(0.397)	(0.460)	(0.424)	(0.356)	(0.228)	(0.194)
Adj. R^2	0.046	0.079	0.076	0.106	0.092	0.075	0.017	0.012
Obs.	84	84	84	84	83	81	79	79
Non-Zero Shocks, Latest								
ΔP^{180}	0.763	0.946	1.074	1.167	1.002	0.922	0.500	0.311
	(0.338)	(0.359)	(0.376)	(0.396)	(0.349)	(0.334)	(0.199)	(0.192)
Adj. R^2	0.080	0.141	0.159	0.177	0.127	0.109	0.014	-0.010
Obs.	40	40	40	40	40	39	38	38
All FOMC Shocks								
ΔP^{180}	0.363	0.400	0.453	0.605	0.641	0.486	0.305	0.197
	(0.158)	(0.191)	(0.254)	(0.312)	(0.282)	(0.274)	(0.171)	(0.129)
Adj. R^2	0.014	0.019	0.026	0.051	0.059	0.030	0.007	-0.002
Obs.	128	128	128	128	126	124	122	120

This table presents the results from four robustness specifications for the predictive regression of k quarter ahead real dividend growth on the short-term dividend strip return ΔP^{180} in the 30 minute window around the FOMC announcement with non-zero monetary policy shocks:

$$log\left(\frac{D_{t+k}}{D_{t+k-4}}\right) = \alpha_k + \beta_k \Delta P_t^{180} + \varepsilon_{t+k}, k \in \{1,2,...,8\}$$

Each column reports results from specifications run separately for each quarterly horizon k. The first panel reports results using Newey-West adjusted standard errors with eight lags (rather than two). The second panel, “Non-zero Dates, Latest”, reports the results for the specification using the short-term asset return from the latest FOMC meeting each quarter. The final panel, “All FOMC Dates”, reports the results using all FOMC meeting dates including days where the monetary policy shock is zero. The period is from January 2004 until December 2019.

Table A.4: **Real GDP Forecasting: Robustness**

Horizon	1Q	2Q	3Q	4Q	5Q	6Q	7Q	8Q
Newy-West 8 lags								
ΔP^{180}	0.127	0.173	0.192	0.149	0.111	0.039	0.094	0.057
	(0.070)	(0.086)	(0.116)	(0.083)	(0.053)	(0.034)	(0.132)	(0.103)
Adj. R^2	0.034	0.044	0.041	0.019	0.018	-0.011	0.002	-0.008
Obs.	84	84	84	83	81	79	79	77
Non-Zero Shocks, Latest								
ΔP^{180}	0.169	0.177	0.180	0.147	0.108	0.011	0.071	0.033
	(0.083)	(0.081)	(0.121)	(0.071)	(0.054)	(0.051)	(0.117)	(0.094)
Adj. R^2	0.105	0.112	0.051	0.024	0.020	-0.027	-0.014	-0.026
Obs.	40	40	40	40	39	38	38	37
All FOMC Shocks								
ΔP^{180}	0.054	0.091	0.101	0.092	0.087	0.041	0.055	0.029
	(0.046)	(0.057)	(0.072)	(0.056)	(0.039)	(0.032)	(0.063)	(0.047)
Adj. R^2	0.005	0.014	0.018	0.014	0.011	-0.004	0.000	-0.006
Obs.	128	128	128	126	124	122	120	118

This table presents the results from four robustness specifications for the predictive regression of k quarter ahead real GDP growth on the 180-day dividend strip return ΔP^{180} in the 30 minute window around the FOMC announcement with non-zero monetary policy shocks:

$$log\left(\frac{GDP_{t+k}}{GDP_{t+k-4}}\right) = \alpha_k + \beta_k \Delta P_t^h + \varepsilon_{t+k}, k \in \{1, 2, ..., 8\}$$

Each column reports results from specifications run separately for each quarterly horizon k. The first panel reports results using Newey-West adjusted standard errors with eight lags (rather than two). The second panel, “Non-zero Dates, Latest”, reports the results for the specification using the short-term asset return from the latest FOMC meeting each quarter. The final panel, “All FOMC Dates”, reports the results using all FOMC meeting dates including days where the monetary policy shock is zero. The period is from January 2004 until December 2019.

Table A.5: **Real Dividend and GDP Forecasting: Non-FOMC Days**

Horizon	1Q	2Q	3Q	4Q	5Q	6Q	7Q	8Q
Panel A: Real Dividend Growth								
ΔP^{180}	-0.045	-0.045	0.030	-0.075	-0.012	0.033	-0.051	0.089
	(0.081)	(0.110)	(0.086)	(0.136)	(0.159)	(0.155)	(0.150)	(0.140)
Adj. R^2	-0.004	-0.004	-0.004	-0.003	-0.004	-0.004	-0.004	-0.003
Obs.	256	256	256	256	252	248	244	240
Panel B: Real GDP Growth								
ΔP^{180}	-0.035	-0.020	-0.024	-0.030	-0.021	-0.019	0.021	0.016
	(0.023)	(0.030)	(0.030)	(0.032)	(0.032)	(0.036)	(0.036)	(0.042)
Adj. R^2	0.000	-0.003	-0.003	-0.002	-0.003	-0.004	-0.003	-0.004
Obs.	256	256	256	252	248	244	240	235

Panel A presents the results from the predictive regression of k quarter ahead real dividend growth on the 180-day dividend strip return in the 30 minute window seven days before and seven days after the FOMC announcement:

$$log\left(\frac{D_{t+k}}{D_{t+k-4}}\right) = \alpha_k + \beta_k \Delta P_t^h + \varepsilon_{t+k}, k \in \{1,2,...,8\}$$

Panel B presents the same results for predicting real GDP growth. Newey-West adjusted t-statistics with four lags are in parentheses below the coefficient estimates. The period is from January 2004 until December 2019.

Table A.6: **Real Dividend and GDP Forecasting: Comparison to Non-FOMC Days**

Horizon	1Q	2Q	3Q	4Q	5Q	6Q	7Q	8Q
Panel A: Real Dividend Growth								
ΔP^{180}	-0.012	-0.048	0.011	-0.034	0.053	0.035	-0.017	0.048
	(0.088)	(0.091)	(0.074)	(0.099)	(0.124)	(0.103)	(0.103)	(0.091)
$FOMC^{NZ}$	-0.005	-0.012	-0.014	-0.021	-0.021	-0.015	-0.011	-0.006
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
$\Delta P^{180} \times FOMC^{NZ}$	0.681	0.923	0.954	1.180	1.010	0.912	0.559	0.414
	(0.264)	(0.260)	(0.310)	(0.369)	(0.373)	(0.348)	(0.246)	(0.206)
Adj. R^2	0.005	0.016	0.020	0.035	0.031	0.021	0.002	-0.002
Obs.	384	384	384	384	378	372	366	360
Panel B: Real GDP Growth								
ΔP^{180}	-0.030	-0.012	-0.015	-0.013	0.002	-0.003	0.020	0.012
	(0.019)	(0.027)	(0.028)	(0.027)	(0.028)	(0.032)	(0.026)	(0.031)
$FOMC^{NZ}$	-0.002	-0.003	-0.005	-0.006	-0.001	-0.002	-0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
$\Delta P^{180} \times FOMC^{NZ}$	0.157	0.185	0.207	0.161	0.109	0.042	0.074	0.044
	(0.064)	(0.074)	(0.106)	(0.081)	(0.060)	(0.050)	(0.112)	(0.085)
Adj. R^2	0.009	0.009	0.017	0.013	-0.002	-0.007	-0.002	-0.007
Obs.	384	384	384	378	372	366	360	353

Panel A presents the results from the predictive regression of k quarter ahead real dividend growth on the 180-day dividend strip return ΔP_t^{180} in the 30 minute window on FOMC announcement days and non-FOMC announcement days (seven days before and seven days after the FOMC announcement):

$$log\left(\frac{D_{t+k}}{D_{t+k-4}}\right) = \alpha_k + \beta_k \Delta P_t^{180} + \delta_k FOMC_t^{NZ} + \theta_k \Delta P_t^{180} \times FOMC_t^{NZ} + \varepsilon_{t+k}, k \in \{1,2,...,8\}$$

where $FOMC^{NZ}$ is a dummy variable equal to 1 on FOMC announcement dates with a non-zero monetary policy shock and 0 otherwise. Panel B presents results from the GDP growth predictability specifications. We report Newey-West adjusted standard errors with 6 lags in parentheses below the coefficient estimates. The period is from January 2004 until December 2019.

Table A.7: **Predicting SPF Forecast Errors**

	RGDP	
	(1)	(2)
ΔP^{180}	0.081	0.095
	(0.041)	(0.056)
nfp	0.000	0.000
	(0.000)	(0.000)
$\Delta \iota^s_{t+}$		-0.096
		(0.061)
Adj. R^2	0.06	0.11
Obs	60	60

Table A.7 presents the results from the regression specification of forecast errors on the short-term asset return and the change in nonfarm payroll employment. For each quarter, t, we obtain the average SPF growth rate forecast for annual real GDP growth, $F_{t-}(\Delta gdp_{t+1\to t+4})$, and calculate the forecast error as the difference between realized real GDP growth and the average forecast, $\Delta gdp_{t+1\to t+4} - F_{t-}(\Delta gdp_{t+1\to t+4})$. We calculate the 180-day dividend return in the 30-minute window around the FOMC announcement for the nearest FOMC meeting at date $t+$ after the SPF forecast deadline. We also include the change in nonfarm payroll employment, ΔNFP_t, released in the monthly Bureau of Labor Statistics' employment report between the SPF forecast date, $t-$, and the subsequent FOMC meeting date, $t+$. We use $t-$, t, and $t+$ subscripts with the SPF forecasts, change in nonfarm payroll employment, and short-term dividend return respectively to indicate the timing of each variable within the same quarter. We also include the monetary policy shock from the meeting at date $t+$, $\Delta \iota^s_{t+}$, in some specifications. The full regression specification is:

$$\Delta gdp_{t+1\to t+4} - F_{t-}(\Delta gdp_{t+1\to t+4}) = \alpha + \beta \Delta P^{180}_{t+} + \delta \Delta NFP_t + \eta \Delta \iota^s_{t+} + \varepsilon_{t+1\to t+4}$$

Newey-West adjusted standard errors are in parentheses below the coefficient estimates.

Table A.8: **Macroeconomic Forecast Summary Statistics**

	Central Tendency				
	Current Year	One year out	Two years out	Three years out	Longer run
$\Delta RGDP$					
Mean	2.197, 2.428	2.383, 2.758	2.336, 2.756	2.094, 2.488	2.014, 2.253
SD	0.385, 0.418	0.459, 0.503	0.604, 0.764	0.532, 0.661	0.25, 0.267
Min	1.6, 1.7	1.8, 2	1.7, 2	1.5, 2	1.7, 1.9
Max	3.1, 3.3	3.5, 4.2	3.5, 4.3	3, 3.9	2.5, 2.8
$\Delta PCEI$					
Mean	1.442, 1.639	1.611, 1.961	1.794, 2.033	1.876, 2.059	1.975, 2
SD	0.516, 0.534	0.248, 0.132	0.21, 0.063	0.152, 0.08	0.084, 0
Min	0.3, 0.4	1, 1.6	1.4, 2	1.5, 2	1.7, 2
Max	2.7, 2.9	2, 2.2	2.1, 2.2	2, 2.2	2, 2
Q4 U					
Mean	5.636, 5.772	5.267, 5.539	5.003, 5.403	4.659, 5.153	4.803, 5.242
SD	1.776, 1.818	1.58, 1.641	1.286, 1.367	0.992, 1.104	0.438, 0.574
Min	3.5, 3.6	3.4, 3.5	3.4, 3.7	3.5, 3.9	3.9, 4.3
Max	9, 9.1	8.5, 8.7	7.8, 8.2	6.8, 7.7	5.2, 6
FFR					
Mean	0.951	1.529	2.249	2.695	3.384
SD	0.79	0.85	0.799	0.639	0.554
Min	0.125	0.303	0.605	1.355	2.539
Max	2.493	3.016	3.325	3.544	4.206

Table A.8 presents the summary statistics of the central tendency measures of the advance Summary of Economic Projections released by the Fed for: $\Delta RGDP$ the change in real GDP, $\Delta PCEI$ the change in PCE Inflation, $Q4\ U$ Q4 Unemployment rate, and FFR the target federal funds rate. We parse the advance version of the economic projections for the 36 meetings where the data was released from April 2011 to December 2019 to obtain measures of central tendency for each meeting for each of these four measures at different horizons. The central tendency measures are aggregated from individual forecasts. For the FOMC meeting on date t, each individual i, makes forecasts $F_t^i\left(x_{year(k)}\right)$, for variable x at horizon $k \in \{0,1,2,3,LongRun\}$. We calculate the average, standard deviation, minimum and maximum for each measure separately (central tendency: upper and lower).We calculate the average of each measure across the 36 meetings as: $F_{avg}^{cl}(x_k) = \frac{1}{T}\sum_t F_t^{cl}(x_k)$ and $F_{avg}^{cu}(x_k) = \frac{1}{T}\sum_t F_t^{cu}(x_k)$. The table contain statistics for the central tendency measures presented in the format F^{cl}, F^{cu}, the lower central tendency statistic followed by the upper central tendency statistic separated by a comma. For example, the top left entry: $\Delta RGDP$, Current Year, Average provides the average of the lower central tendency and upper central tendency for current year real GDP growth forecasts, $F_{avg}^{cl}\left(\Delta rgdp_{year(0)}\right)$ and $F_{avg}^{cl}\left(\Delta rgdp_{year(0)}\right)$ as 2.197 and 2.428 respectively.

Table A.9: **Dividend Strip Return and Forecast Gap**

	ΔP^{180}
ForecastGap	5.820
	(2.864)
Intercept	0.010
	(0.008)
Adjusted R^2	0.08
Obs	36

Table A.9 presents the results from the regression of the 180-day dividend strip return around the FOMC announcement occurring on date t and the forecast gap between the Fed Guidance and the latest SPF forecasts for the balance of year real GDP Growth. The regression specification is:

$$\Delta P_t^{180} = \alpha + \beta ForecastGap_t + \varepsilon_t$$

where ΔP_t^{180} is the return of the 180-day dividend strip in the 30-minute window around the FOMC meeting announcement at date t, and the forecast gap, $ForecastGap_t = \left(F_t^{FED}\left(\Delta rgdp_{year(0)}\right) - F_{t-}^{SPF}\left(\Delta rgdp_{year(0)}\right)\right)^{\frac{k}{4}}$, is the standardized difference in Fed and SPF real GDP growth forecasts where k denotes the number of quarters remaining in the year. To obtain $F_t^{FED}\left(\Delta rgdp_{year(0)}\right)$, we take the midpoint of the lower and upper values of the central tendency for the Fed forecast for current year real GDP growth made at meeting date t. $F_{t-}^{SPF}\left(\Delta rgdp_{year(0)}\right)$ is the latest SPF forecast for the current year real GDP growth made prior to the FOMC meeting at date t combined with the actual quarterly real GDP growth in the prior quarters of the year from the National Income and Product Accounts (NIPA) using the latest vintage available at the time the SPF forecasts were made. Newey-West adjusted standard errors are presented in parentheses below the coefficient estimates.

Table A.10: LDA Topic Terms

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
gdp_expand	posit	declin	growth_half	also
faster_pace	around_project	period	increas_real	medium-term
real_gdp_expand	uncertainti_around_project	forecast_prepar_meet	econom_forecast	dollar
accommod	around_project_real	end	econom_forecast_prepar	medium
credit	tilt	potenti_output_growth	meet_staff	medium_term
avail	well	remain	gdp_growth_half	project_path
continu_project	advers	hous	usa_econom	valu
consum_busi	shock	level	near	howev
pace_potenti	substanti	prepar_meet	net	part
pace_potenti_output	assess	labor_market	slower	offset

This table presents the top 10 terms in each of the topic word distributions estimated from the LDA model.

Figure A.1: **Response of Implied Risk-free Rates**

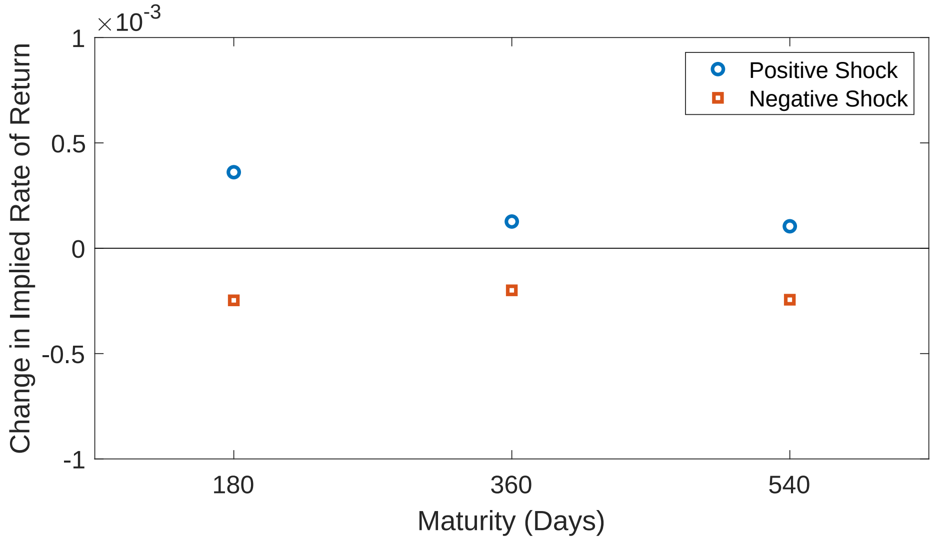


Figure A.1 plots the average implied risk-free rate of return by maturity grouped by the sign of the monetary policy shock.

Figure A.2: **Response of Implied Volatility**

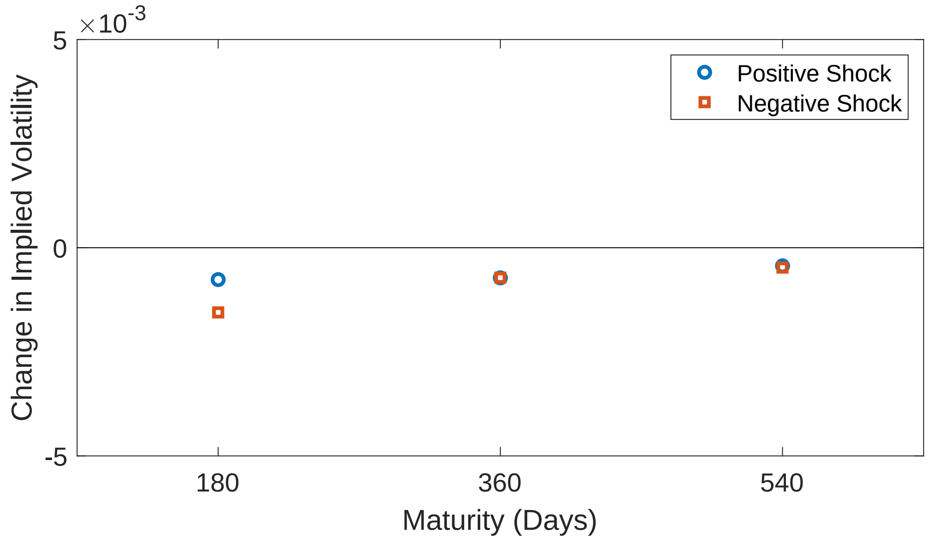


Figure A.2 plots the average change in implied volatility by maturity grouped by the sign of the monetary policy shock.

Figure A.3: **Monetary Policy Shock**

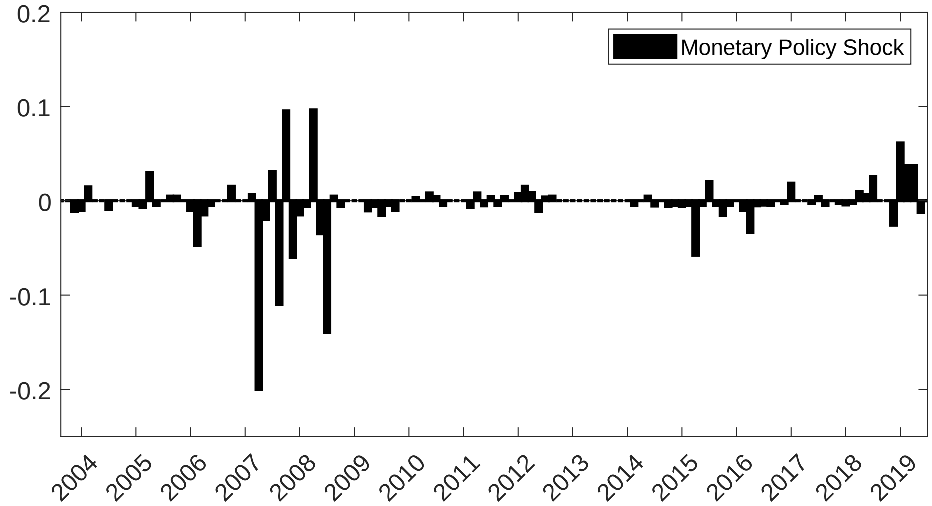
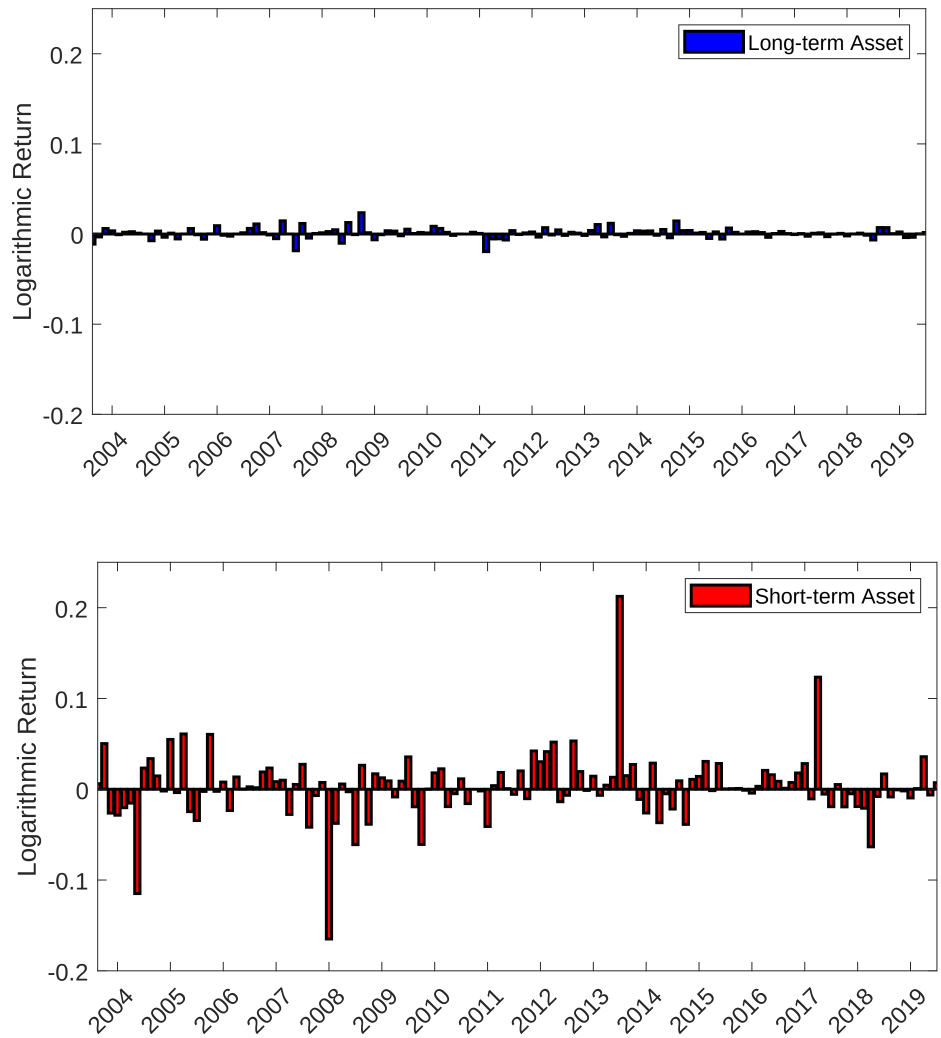


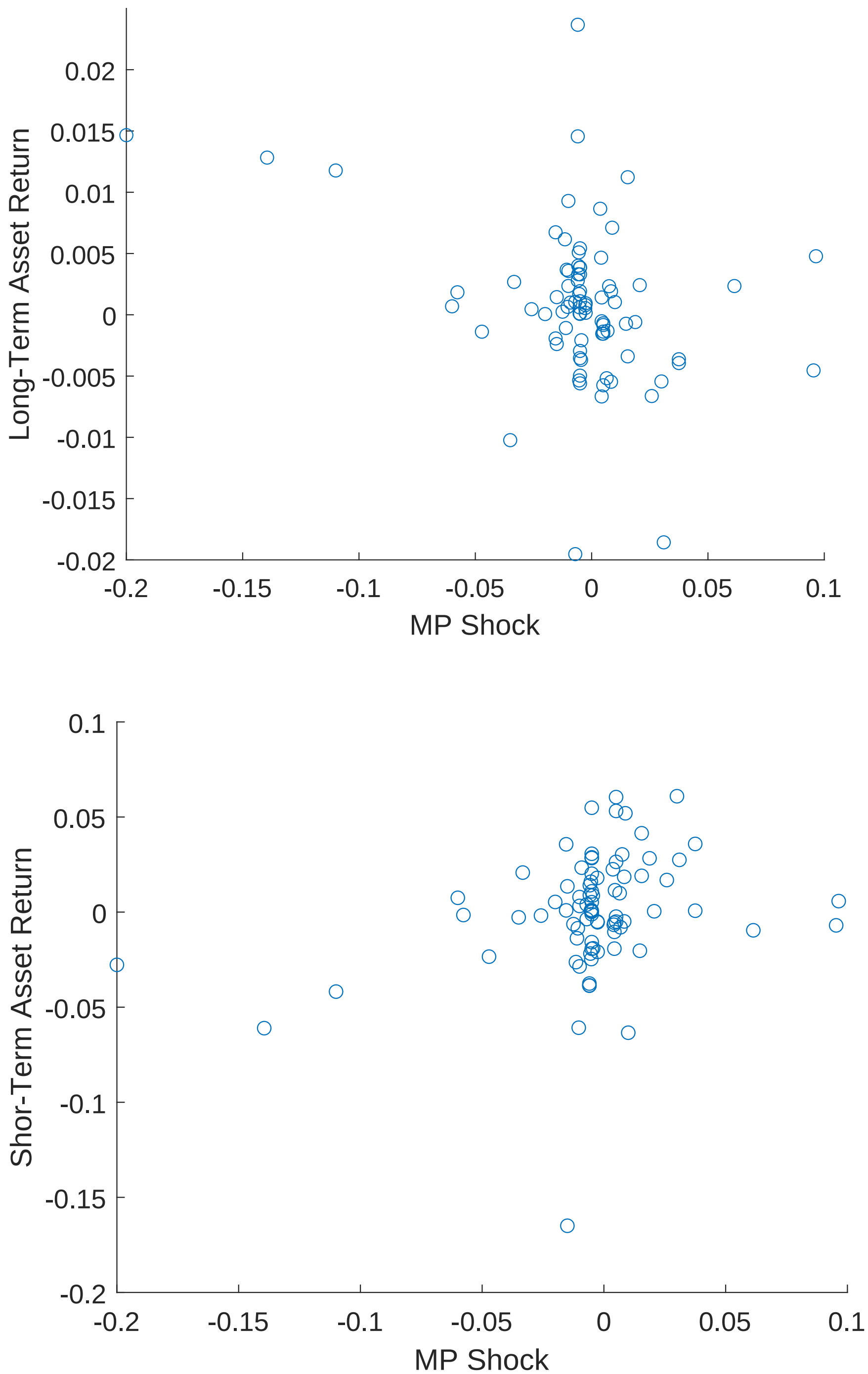
Figure A.3 plots the time-series of monetary policy shocks. The time period is January 2004 to December 2019.

Figure A.4: **Asset Return**



The top figure plots the time-series of market returns over the 30-minute window around each FOMC announcement. The lower figure plots the corresponding short-term asset return. The time period is January 2004 to December 2019.

Figure A.5: **Asset Return with Monetary Policy Shocks**



The top figure presents a scatter plot of market return against the monetary policy shock. The bottom figure presents a scatter plot of the short-term asset return against the monetary policy shock. The time period is from January 2004 to December 2019.

Figure A.6: **Stylized Framework Timing**

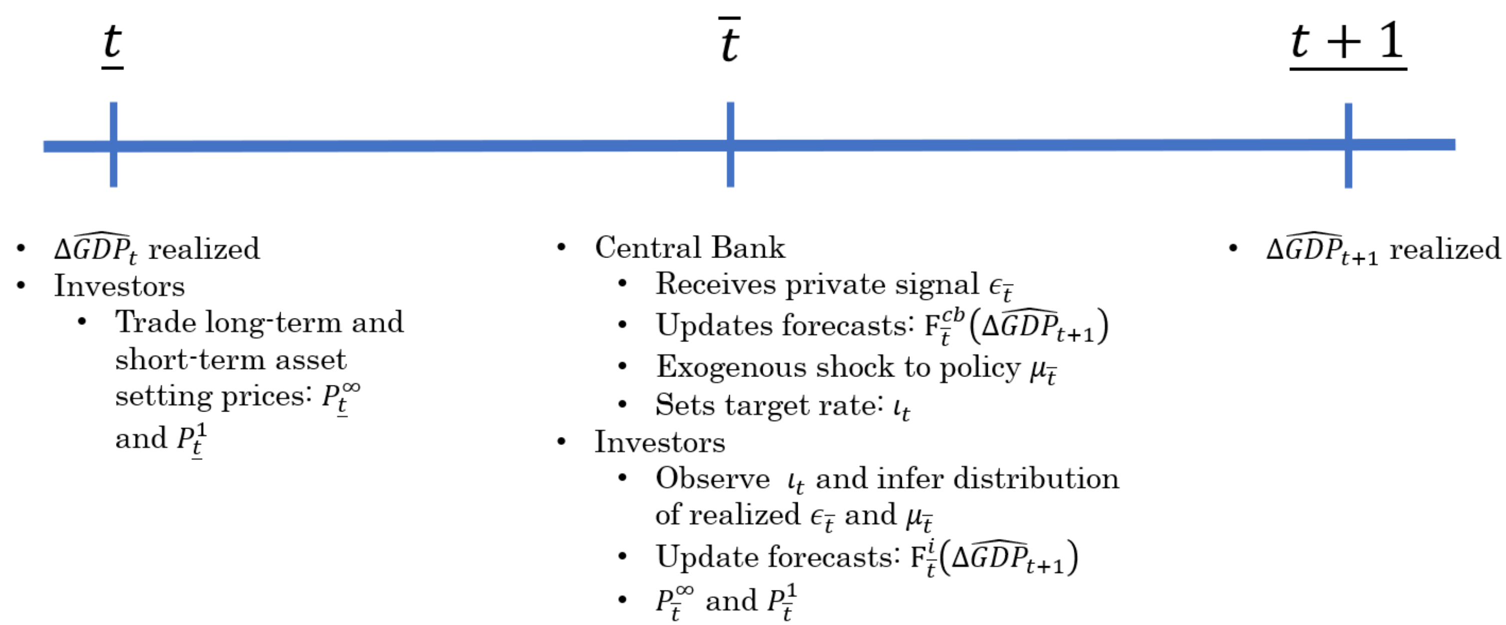
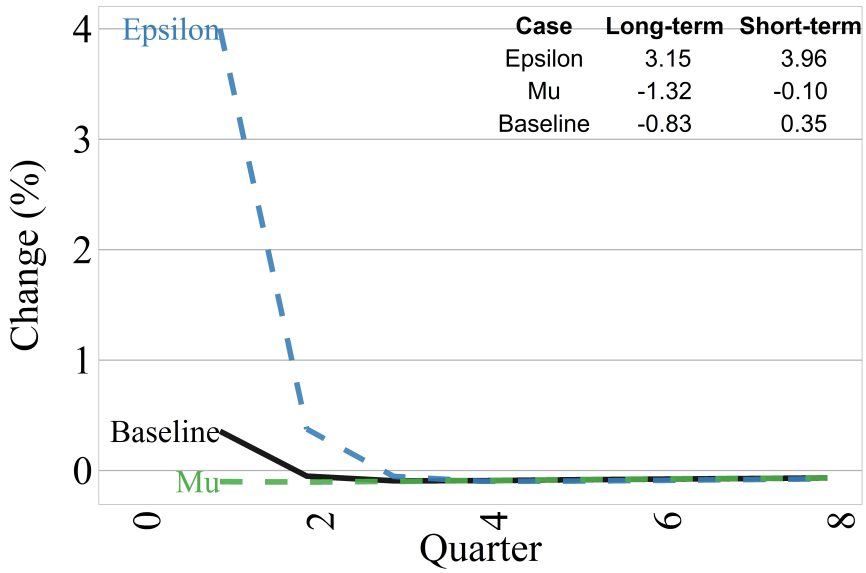


Figure A.6 shows the timing of the stylized framework from Section A.6.

Figure A.7: **Propagation of Monetary Policy Surprise: Tightening**

(a) Change in Expected GDP Growth



(b) Change in Expected Target Rate

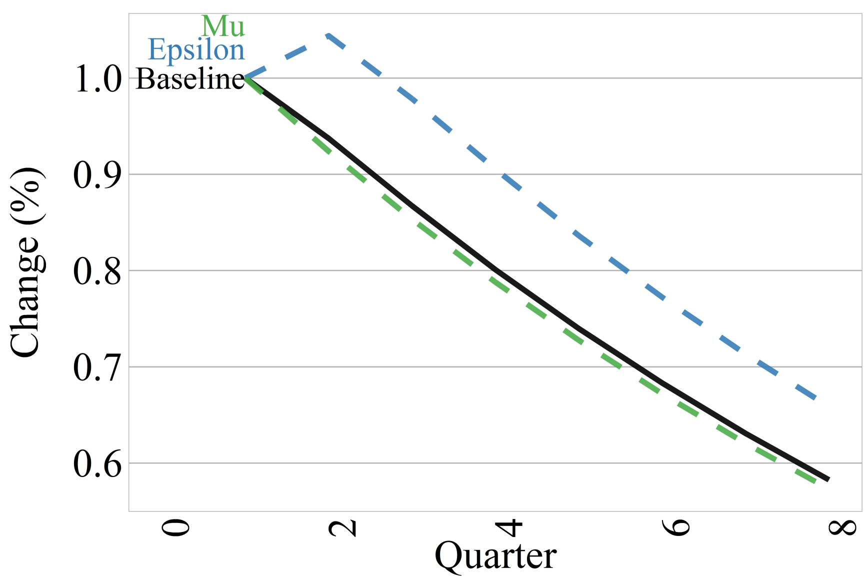
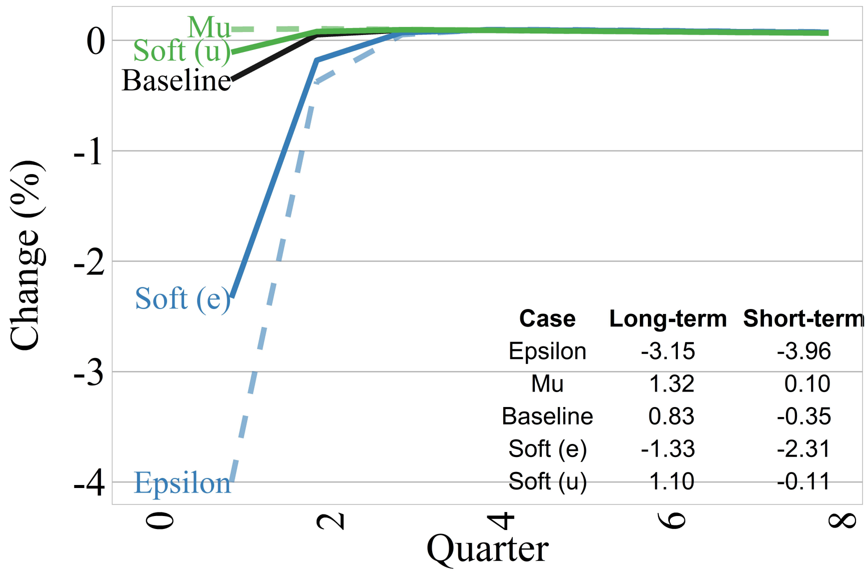


Figure A.7 plots the model-implied change in expectations across the term structure following a monetary policy surprise of 1% (unexpected tightening). Panel A shows the change in expected quarterly economic growth where the x-axis indicates the quarters ahead (the monetary policy shock occurs at quarter 0). The long-term and short-term asset return (in percent) are presented in the table in the top right corner. Panel B shows the change in expected target rate across the term structure. The dashed green "Mu" (blue "Epsilon") line shows the change in expectations if the investor observes the shocks, ε and μ, and the entire monetary policy surprise is driven by the shock μ (ε). The black line labeled "Baseline" shows the change in investor expectations following the monetary policy surprise when the investor does not observe the shocks directly.

Figure A.8: **Propagation of Monetary Policy Surprise: Soft Information**

(a) Change in Expected GDP Growth



(b) Change in Expected Target Rate

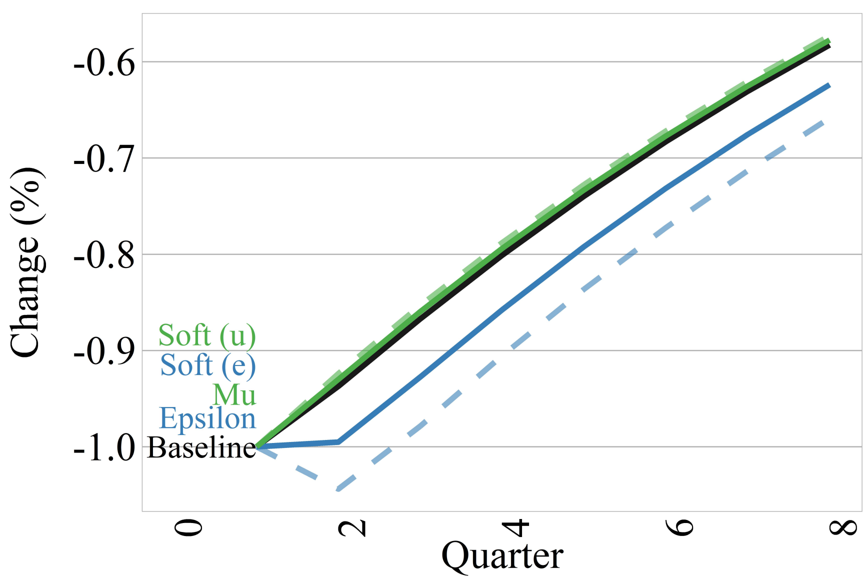


Figure A.8 plots the model-implied change in expectations across the term structure following a monetary policy surprise of -1% (unexpected easing). Panel A shows the change in expected quarterly economic growth where the x-axis indicates the quarters ahead (the monetary policy shock occurs at quarter 0). Panel B shows the change in expected target rate across the term structure. The solid green line "Soft (u)" shows the change in investor expectations with soft information from the central bank if the entire monetary policy surprise is driven by the exogenous shock μ. The solid blue line "Soft (e)" shows the change in investor expectations with soft information if the entire surprise is driven by ε. For reference, we plot the change in investor expectations with no soft information (black line) and the change in investor expectations if the investor directly observes the shocks and the entire monetary policy surprise is driven by the shock μ (dashed green line) or by ε (dashed blue line).

Figure A.9: **Timing of SPF Forecasts and FOMC announcements**

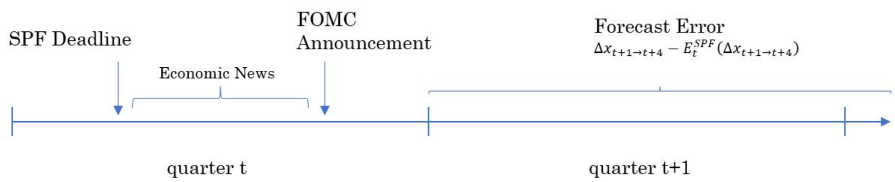


Figure A.9 shows the timing of the Survey of Professional Forecasts, economic news, and the subsequent FOMC announcement. The Survey of Professional Forecasters response deadlines are set at late in the second to third week of the middle month of each quarter. We obtain the date of the next FOMC meeting following the SPF deadline. This meeting falls within the same quarter as the SPF deadline in all cases. We calculate the SPF forecast errors for subsequent annual growth rates (growth over quarters $t+1$ to $t+4$).

Figure A.10: **Soft Information Time-series**

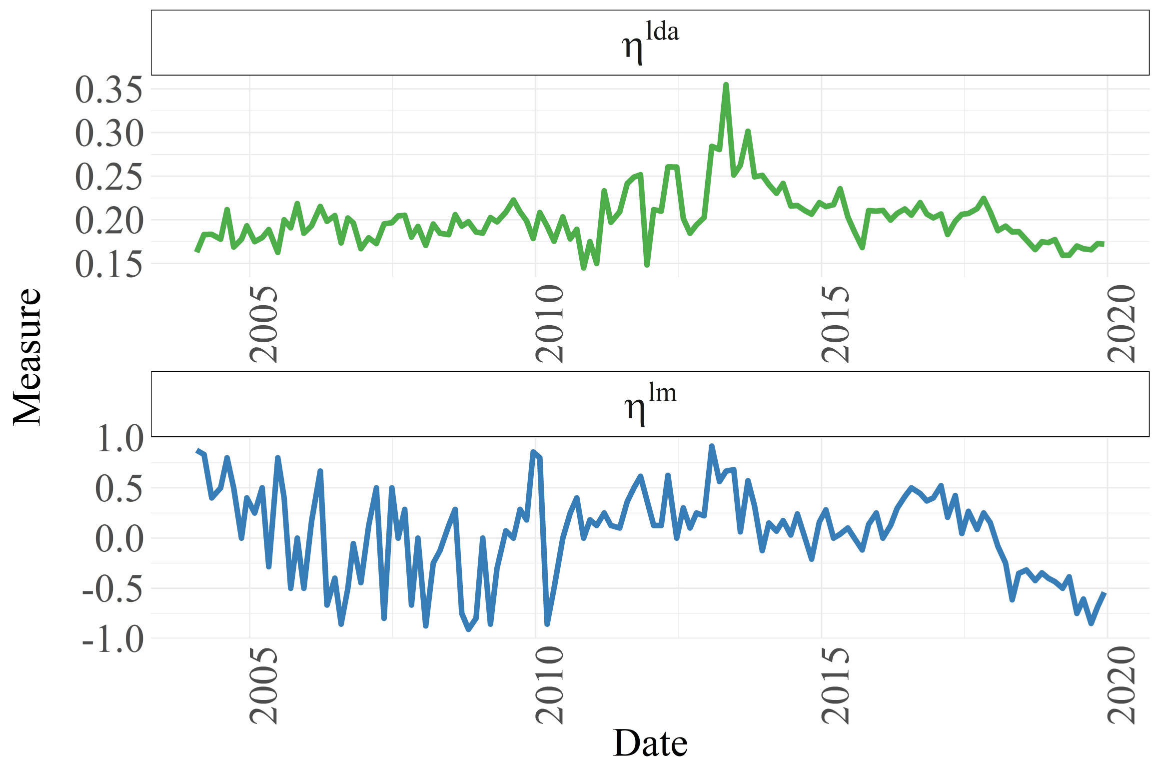


Figure A.10 plots the times-series of the two measures of central bank soft information about economic conditions. The top panel, η^{lda}, presents the measure based on central bank discussion about favorable economic conditions from the LDA model. The bottom panel, η^{lm}, presents the measure based on the text sentiment classification dictionary from Loughran and McDonald (2011).