Always Silent? Endogenous Central Bank Communication During the Quiet Period

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Abstract

This paper analyzes the imperative of central banks consistently adhering to the quiet period policy. The financial market model describes a multifaceted trade–off, wherein the central bank not only gauges the instantaneous market reactions to a quiet period communication but also assesses both the effects of an upcoming Board meeting and changes in market volatility. Consequently, we explore scenarios where proactive communication during the quiet period is deemed necessary. Key determinants for such communication include the willingness to look beyond the immediate consequences of the intervention and the allocation of uncertainty between the central bank's reaction function and the uncertainty associated with the Board meeting dissent. Adopting a collegial approach during the quiet period, effective communication may display distinctive features, such as response asymmetry. The central bank is more reluctant to convey negative news about its economic assessments to the markets. The resolution of uncertainty stemming from such communications can influence the current state of the quiet period with emerging leaks, individual breaches, and unattributed informal communications.

JEL codes: D81, D83, E52, E58, G19

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1 Introduction

Many central banks adhere to some form of quiet period[2] policy in the days leading up to their Board of Governors[3] meetings, during which no market–sensitive statements are allowed. With eight meetings annually, the quiet period amounts to 15% of all days in a year for the ECB and 28% for the Fed, as illustrated below.

Figure 1 — ECB quiet periods in 2023

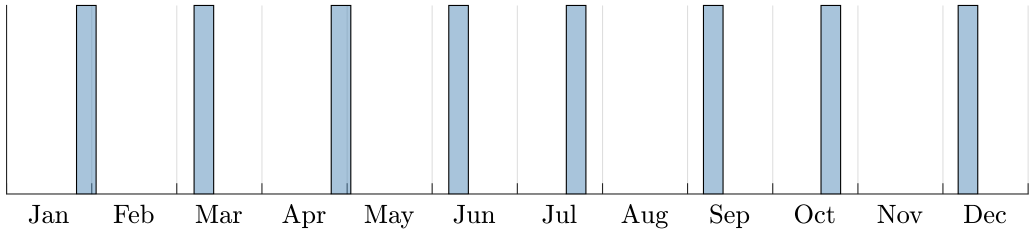
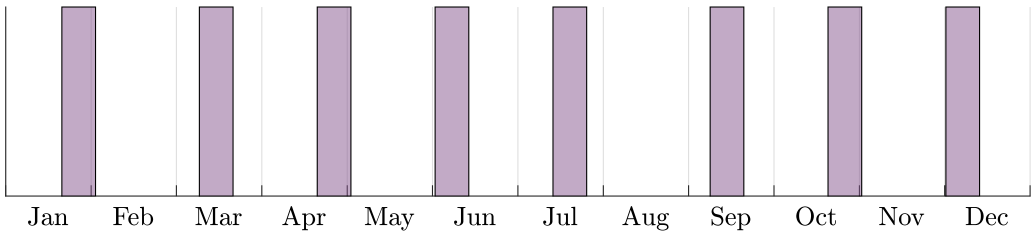


Figure 2 — Fed quiet periods in 2023



Many central banks, similar to the ECB and the Fed, adopt a quiet period policy with a comparably extensive duration. In light of central banks' increased communication activities in recent decades, these extended periods without official communications lead to an uneven distribution of information releases throughout the year. During these quiet periods, however, some communications still seep into the market. These often include unattributed "sources stories" type communications and individual breaches when Board of Governors members discuss sensitive topics despite the restrictions.

The studies by Gnan, Rieder (2023) and Ehrmann, Gnan, Rieder (2023) indicate that such

[2]This period can be called and defined in different ways. For instance, the European Central Bank calls it the quiet period and defines it as the period beginning one week before and ending with the meeting. The Federal Reserve calls it the blackout period. It starts on the second Saturday before the meeting. It ends on the Thursday after the meeting, meaning that the blackout period starts ten days before and ends the day after for a normal Tuesday through Wednesday meeting. In this paper, we use "quiet period" and "blackout period" interchangeably, without implying a specific duration.

[3]We refer to a meeting at which the key rate decision is made as the Board of Governors meeting, although governing bodies and their meetings are called differently for different central banks.

communications not only significantly move markets but also tend to broadcast dissenting views, which can introduce more noise rather than clarity regarding the policymaker's policies. This leads to our research question: Is an unconditional quiet period policy optimal for central bank communication? Or might a more flexible communication policy yield better overall results?

To answer this question, our paper explores the three–dimensional trade–off faced by the central bank when deciding on communication policies. This analysis combines aspects currently considered by policymakers with new ones. We start by examining the rationale behind the existing quiet period regime. The primary reason, as echoed from Ehrmann, Fratzscher (2009) seminal paper and reflected in the ECB's official explanation, is "to help prevent excessive market volatility or unnecessary speculation." Another factor influencing the quiet period is the discussion of the upcoming decision, which can also affect its duration. For example, the Federal Reserve extended its blackout period from seven to ten days before meetings in 2017. This change, documented in the Federal Open Market Committee (FOMC) Transcripts, was guided largely by the fact that Committee participants receive draft monetary policy alternatives ten days prior to the meeting, and communications after this point could inadvertently reveal sensitive information.

In our model, the central bank's rationale is structured as follows: First, it focuses on the immediate market shock that occurs following a possible quiet period breach. Second, the central bank aims to mitigate major market shocks on the press release day. This is precisely one of the key mechanisms of our model — the central bank is faced with choosing between strong market impacts at different points in time. Third, the central bank is concerned about the level of market uncertainty regarding the Board of Governors meeting. Excessive uncertainty can increase market volatility, while too little uncertainty leads market participants to expect no surprises from the policymaker, thereby perceiving the communications as binding commitments.

This paper models the actions of the central bank, which is focused on preventing major market shocks during both the quiet period and after the press release. Simultaneously, the policymaker seeks to maintain flexibility without constraining market expectations to a single option on the meeting day. To balance these objectives, the central bank differentiates between two types of uncertainty: the uncertainty about the central bank's reaction function to macroeconomic shocks and the uncertainty stemming from potential disagreements within the Board, which could lead to varied rate decisions. For instance, the central bank might remove uncertainty about its reaction function by partially releasing information contained in the draft of alternatives. However, while the central bank can clarify its stance on economic conditions before the Board of Governors' discussions begin, it cannot directly communicate the extent of the Board's dissent. This dissent is nonetheless considered in deciding whether to intervene in the market. Therefore, the central bank's decisions are influenced both by its utility function and by how it anticipates the market will react to these decisions.

Our formulated model lacks a closed-form solution, necessitating a two-step computational approach for its resolution. In the first step, using a machine learning algorithm for a particular set of parameters, we determine the scenarios in which the central bank is required to communicate. Following this, the second step involves employing a Monte Carlo simulation to analyze how the solution varies with changes in the model parameters. This dual-step process allows us to comprehensively understand the model's behavior under various conditions.

As a result, sometimes, the central bank finds it optimal to communicate during the quiet period, even though such communication does shake the markets considerably. In these instances, the subsequent market reaction to the press release is often less intense. Moreover, through these communications, markets gain a clearer understanding of the central bank's reaction function. They also obtain a more accurate insight into the level of dissent within the Board, free from distortions that might arise from leaks, individual breaches, or unattributed informal communications.

As an additional exercise, we compare the current "never intervene" regime with its direct counterpart, the "always intervene" regime. This comparison considers the challenges of implementing a mechanism where the central bank occasionally makes verbal interventions during the quiet period. Under the "always intervene" regime, the central bank loses the ability to indirectly inform markets about the uncertainty level of key rate decisions. However, even with this limitation, the ability to provide insights about the central bank's reaction function makes the "always intervene" regime yield better results. This conclusion remains robust unless the central bank's utility function heavily penalizes price shocks during the quiet period while being much more tolerant of shocks following the press release.

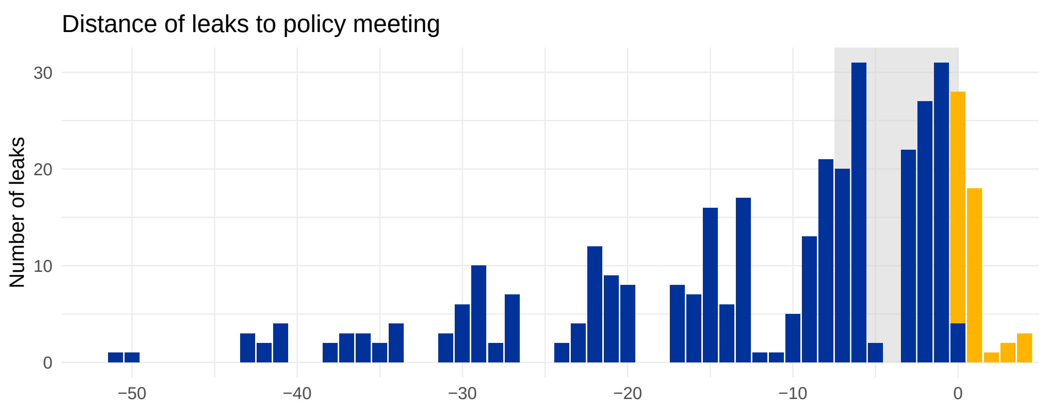
The paper is structured as follows: In Section 2, we delve into the paper's contributions to the existing literature on central bank communication, the quiet period, and pre–announcement drift. Section 3 is dedicated to formulating the model assumptions, exploring the central bank's strategies for managing the quiet period, and outlining our modeling approach. We then present our model results in Section 4, focusing on how a multifaceted trade–off between market shocks and uncertainty management affects central bank behavior. Finally, Section 5 explores potential methods for applying the model's recommendations in practical scenarios.

2 Literature, discussion and contribution

Our paper contributes to several literatures. First, we study the quiet period. Current research, such as Istrefi, Odendahl, and Sestieri (2022), suggests the importance of communications outside of regular monetary policy meeting days. Moreover, Bianchi, Ludvigson, and Ma (2022) showed that most of the variation in beliefs about future Fed policy doesn't occur around FOMC announcement dates. Meanwhile, the possible desire of policymakers to prepare markets for the coming decision leads to more frequent communications before the meetings rather than after, especially before rate changes, as found in Ehrmann, Fratzscher (2007), highlighting the importance of the quiet period. According to van Dijk, Lumsdaine, and van der Wel (2016), the central bank may be quite successful in this policy, and the markets may set up well in advance of known announcement days. Such informal communications also have limitations, Galloppo et al. (2021) inquired that the effect becomes weaker if messages start to be repeated. However, Ehrmann, Fratzscher (2009) found that the reaction of markets to news within a quiet period is strong enough to talk about an excessive shock to the markets. In addition, such news increases volatility. Despite the general idea of welfare–reducing communication, the authors in their discussion leave the possibility of not only withholding information but also mention that it can be "channeled in a specific manner". Hereinafter, we model this idea of specific collegial communication, which aims to reveal the central bank's reaction function but leave the uncertainty associated with Board members' deliberations. At present, the quiet period policy implies that central banks refrain from making official statements on topics deemed sensitive, thereby avoiding potential market disturbances. However, there are still violations of the quiet period policy by individual Board members. Gnan, Rieder (2023) subsequently analyzed the database for all quiet period breaches. They not only confirmed and extended Ehrmann, Fratzscher (2009) findings of severe market shocks caused by quiet period violations but also found that inflation deviations and interest rate spreads of policymakers' constituencies were the main determinants of Governing Council members' violations. The influence of regional variables on the communication of policymakers is not unique to Europe; for the US, this issue has been studied by Hayo, Neuenkirch (2012).

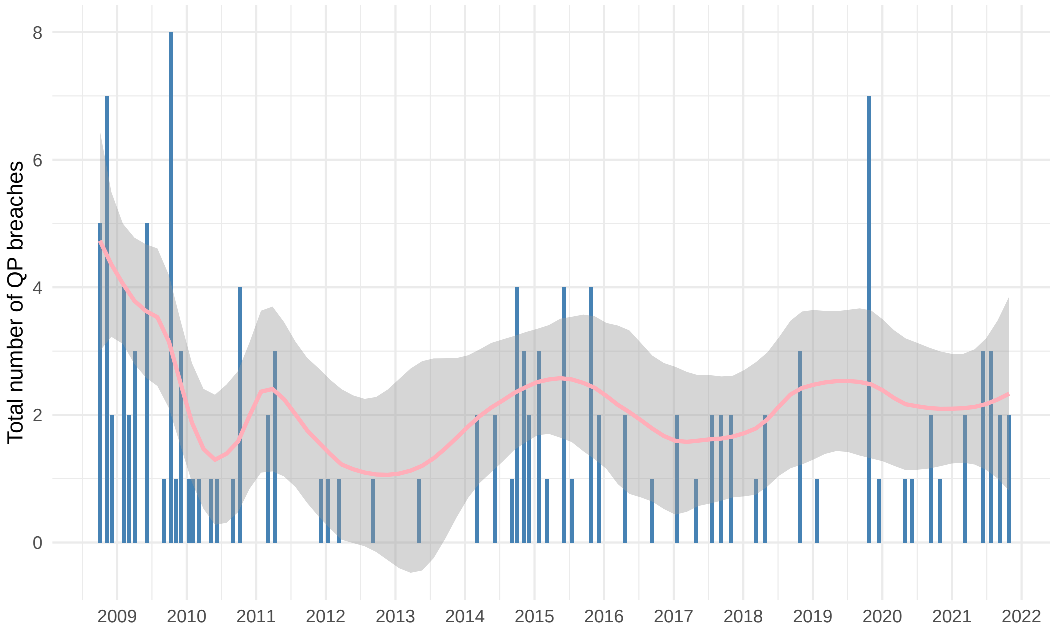
Quiet period breaches can also be carried out as anonymous unattributed communications, and Ehrmann, Gnan, and Rieder (2023) found that such communications are probably not plants, so they express dissent views. Despite this, the markets likely perceive the situation differently, as evidenced by the significant reaction to such unattributed communications and the attention paid to so–called Fed whisperers — journalists rumored to be a regular source for Fed leaks. A recent example involves Nick Timiraos from the Wall Street Journal, whose article The Wall Street Journal (2022) made a prediction against the consensus forecast of investors. Despite this fact, being released during a quiet period two days before the press release, the article was taken seriously. It influenced market expectations, seen as a prominent example of leakage. In the figure below from Ehrmann, Gnan, and Rieder (2023), we can see that the number of unattributed publications rises strongly shortly before the meetings (in blue) and drops immediately after the press release is published (in yellow):

Figure 3 — Time distribution of leakages



Additionally, Figure 4 from Gnan, Rieder (2023) illustrates that non–anonymous quiet period breaches occur regularly, as indicated by the number of breaches prior to separate meetings. Also, Ehrmann, Gnan, and Rieder (2023) found that attributed communication can effectively mitigate the effects of leaks, whether they are plants or an expression of dissenting views (and our paper will be agnostic as to which explanation is closer to reality). A similar idea is also explored in Vissing–Jorgensen (2020), suggesting a consensus–building approach akin to that of the ECB to address the barrage of unattributed informal communications. Hence, the issue of having official communications during the blackout period considered in our model is also a matter of counteracting the actions of certain Governors trying to pursue their agenda by adding noise to market assessments of the situation. Cacophonic communications, which can

Figure 4 — Breaches of quiet period rules



also increase due to the lack of centralized communications, can be detrimental to the welfare. Lustenberger, Rossi (2018) found that such communications result in larger macroeconomic forecast errors, Ehrmann, Fratzscher (2013) showed that insufficiently unified communication accounts for one-third to one-half of the market's prediction errors of FOMC policy decisions. And Vissing–Jorgensen (2019) concluded that the so–called "communication arms race" might damage both the central bank's reputation and decision–making process. A common line of thought proposed by Vissing–Jorgensen (2019) was to reduce the "lack of understanding of the Fed's decision rule." In our model, we precisely describe the communications that convey the Fed's reaction function to the markets while intentionally leaving some uncertainty. However, specific suggestions of Vissing–Jorgensen (2019) were to "reduce the number of Federal Reserve districts and avoid FOMC rotation," and our model considers only the short quiet period and parses possible official collegial communications during this period.

In addition, Tillmann, Walter (2019) found that divergence between monetary authorities (the ECB and the Bundesbank, in that case) leads to higher policy uncertainty, market volatility, and higher risk premium. This result has a twofold impact on our problem. On the one hand, it confirms the intuition behind our model and the suggestion of introducing centralized communication during a quiet period. But on the other hand, this result makes a potential empirical analysis of the problem very difficult. The available quiet period communications may be perceived by markets quite differently from the counterfactuals under consideration — potential "one voice" communications aiming to reveal the central bank's assessment of the current situation.

Second, we contribute to the more general literature on central bank communication effects. The study of central bank communication problems has its origins in the rise of openness of central bank communications in the 90s and 00s, but more general Sender–Receiver communication models trace their roots back to earlier work such as Crawford, Sobel (1982). Subsequently, Morris, Shin (2002) opened up a new debate on the possible negative effects of excessive provision of public information on public welfare. After that, for the case of central bank communications, in Morris, Shin (2005), greater transparency might reduce the signal value of private sector actions. To date, the problem of central bank transparency and commitment has become an integral aspect of the broader issue of optimal central bank design, as discussed in the review by Reis (2013). Also, in the modern context, according to Hahn, (2012), it is becoming easier for economic agents to obtain information independently from the central bank, which increases the importance of more open communication about the central bank's assessment of the economy. Empirically, Van der Cruijsen, Eijffinger, and Hoogduin (2010) confirmed the optimality of some intermediate level of monetary policy transparency, particularly in the case of inflation persistence as a dependent variable. However, an alternative view is presented in Svensson (2005), which shows that for realistic assumptions about the parameters of the model, the result of Morris, Shin (2002) "is actually pro–transparency, not con." Another contribution to this discussion came from Roca (2010), where a comparison of the beneficial effects of reduced imperfect common knowledge resulting from greater transparency with the negative effects of a potential rise in aggregate volatility concluded in favor of the steady dominance of the former. While our paper advocates for increased transparency, it acknowledges existing constraints — the central bank cannot provide precise information about the level of dissent within the Board and cannot disclose details of internal deliberations to the public.

The benefits of transparency also depend on the balance between the precision of private and public information. For example, in the setup of Amato, Morris, and Shin (2005), when private information is very precise, high precision of public information can lead to market overreaction and drift away from fundamentals. On the contrary, the current paper investigates a period of high uncertainty and lack of precise private information, which supports the case for greater transparency. Another consequence of high uncertainty, as demonstrated by Born, Dovern, and Enders (2020), is an increase in the market's reaction to the news. This effect has been particularly detailed in Kurov, Stan (2018), which emphasizes the amplified response to monetary policy in Treasuries, interest rates, and foreign exchange markets. The key point of our model is that the central bank aims to manage uncertainty, which in turn affects the risk premium demanded by investors. This strong interdependence of uncertainty associated with macro announcements and the risk premium has been demonstrated in Londono, Samadi (2023). Additionally, Pflueger, Rinaldi (2022) found that the risk premium accounts for a significant portion of the shock resulting from monetary policy actions. Thus, in our model, there exists a simple trade–off: the introduction of an additional communication shock during the quiet period serves to reduce uncertainty, consequently altering market shocks within the quiet period and at the press release date.

Why do the fluctuations in financial markets matter to the central bank, underlying the logic of the quiet period? The problem of the two–way influence of monetary policy and the financial market is extensively researched. In particular, examining notes from the Fed's internal deliberations, Cieslak, Vissing–Jorgensen (2021) found that "Fed views the stock market as informative for policy–making," assigning more weight to its influence on the economy rather than to its role as a predictor of future direction of the economy. Theoretically, monetary authorities' attention to financial markets serves the purpose of dampening waves of optimism and pessimism if these fluctuations are disconnected from underlying economic fundamentals, as demonstrated by Ifrim (2021). Similarly, in Caballero, Simsek (2022), the central bank mitigates shocks originating in the financial market itself but is willing, on the contrary, to increase the volatility of asset prices and the aggregate risk premium in case of imbalances in the real economy, using the financial market as the fastest transmission mechanism that can counter such shocks. However, while the central bank's focus on financial markets is crucial, it must operate within certain limitations. One possible negative effect of the so–called Fed put may be the potential moral hazard effects resulting from loose policy (although Cieslak, Vissing–Jorgensen (2021) found that this effect is a concern for a relatively small fraction of policymakers). Additionally, Morris, Shin (2018) deconstructed the central bank's dilemma when determining weights assigned to market signals versus other information. They revealed a crucial trade–off — the more weight a market signal carries, the less informative it becomes due to its own endogeneity. Thus, the central bank, if able to commit to its guidance, may significantly underweight market signals.

Another area that has garnered significant attention in current research on communication effects is the realm of Bayesian persuasion models exploring the problem of optimal communication with commitment. Kamenica, Gentzkow (2011) studied a model of a Sender sending signals to a Receiver to influence his actions — an idea close to our model. This paper even discusses that special case "where ω (state of the world) is a real–valued random variable, Receiver's action depends only on the expectation $E[\omega]$," which makes the models even more similar. In addition, this approach is also applicable in the more special case of central bank communication. Herbert (2021) parsed a setup with heterogeneous Receivers in which the central bank sends signals about the state of the world to influence investment decisions. And the optimal strategy is to send moderating signals, calming investors in overly good/bad times, where the bias itself negatively depends on the dispersion of investor beliefs. Also, Cieslak, Malamud, and Schrimpf (2019) demonstrated that in scenarios involving a discrete and multidimensional space of potential communications, the optimal strategy for policymakers is to partition the state space. This partition allows the policymaker to inform the public about the specific "cluster" to which the current state belongs, aiding in more effective communication. Furthermore, this paper presents a distinct approach from the traditional Bayesian persuasion model. It establishes that under certain conditions, employing randomization in central bank communications is never optimal.

Additionally, Gati (2022) investigated that when endogenous financial market's prior beliefs are included in the model, they can dampen the persuasiveness of the central bank's signal so that the central bank has to send signals that are not very precise, so that not very tight priors leave some room for communication efficiency. However, despite these parallels, three significant differences exist between the Bayesian persuasion setup and our model. First, in our model, the Sender—represented by the analytical department of the central bank—cannot strategically design or select signals to influence expectations; it is limited to disclosing information provided to the Board of Governors. Furthermore, investors in our model receive several signals about the state of the world, including an initial shock unrelated to the monetary authority, the central bank's reaction to this shock, and the discussion outcomes during the Board meeting. Finally, given our model's shorter time horizon and focus on the financial market, uncertainty aversion leads to a distinct risk premium. In the following work, Gentzkow, Kamenica (2017) compared mandatory and optional disclosure in a model where Experts send signals to Receivers about the results of experiments (whose informativeness is not costless) about the state of the world. Their findings suggest that endogenous information will always be disclosed, and disclosure requirements have no impact on outcomes. However, a crucial distinction from our model lies in the central bank's inability to disclose all available information, particularly about the level of disagreement within the Board. From the perspective of Gati (2022), this addition of uncertainty also prevents the formation of too–tight prior beliefs and does not stifle the effectiveness of communications.

In our model, we allow the central bank's analytical department to publish its results, roughly speaking Tealbook, assuming that it describes the expected value of the decision without considering the uncertainty associated with Board members' disagreement. This premise is a simplification of the discussion started by Romer, Romer (2008), who argued that policymakers, such as the FOMC, do not really add value, in terms of having useful information, to the forecasts of the Fed's stuff. This result was further extended by Binder, Wetzel (2018), suggesting that policymakers may not add value during normal times, although their forecasts could still be informative in more challenging conditions. Alternatively, Ellison, Sargent (2009) posited that forecasts might add value as worst–case scenarios, guiding decisions that are robust to model misspecifications. But then we would, for simplicity, assume that markets can account for that and incorporate such caution into their perception of the emerging communication.

Third, we contribute to the large literature on the pre–announcement premium and, more general, studies of financial markets around major events. Starting from the seminal paper of Lucca, Moench (2015), which first identified the puzzle of large average excess returns in anticipation of monetary policy decisions, a significant body of work has explored this phenomenon. The pre–announcement drift pattern found in Lucca, Moench (2015) may undergo slight changes over time. Alam (2022) found that pre–FOMC drift is characteristic of only the meetings, which followed large key macro data releases published a few days before the meeting. Lucca, Moench (2018) revisited more recent data (up to 2018) and found that drift remains, but only for meetings followed by a press conference by the Chair. In addition, sometimes, the pre–announcement premium can shift a bit within the FOMC cycle. Gu, Kurov, and Wolfe (2017) showed that if after the meeting there will be a publication of Summary of Economic Projections and a press conference, a part of the premium can be realized after the publication of the press release, due to the same mechanism of resolution of uncertainty.

This phenomenon is not specific to U.S. securities. Pre–announcement drift was recorded in the EU in the paper of Ulrich et al. (2017). Similarly, in China Guo, Jia, and Sun (2022) observed a pre–announcement drift for uncertainly defined dates of announcements. Moreover, Hillenbrand (2021) explored this drift in the context of long–term interest rates, with the secular decline in U.S. Treasury yields almost entirely concentrated inside the short windows around Fed meetings. Corporate bonds exhibited a similar phenomenon, as detailed by Abdi, Wu (2018), and notably, this effect preceded movements in the stock market. Nor is this phenomenon exclusive to announcements by the monetary authorities. Fed news has a more significant effect compared to the rest of the macro–announcements. Still, the latter can also be characterized by positive average returns realized before the announcement (Hu et al. (2022)).

There are several possible explanations for the observed drift. In our model, we build upon the fundamental concept of uncertainty resolution. This idea is substantiated by the empirical findings of Gao, Hu, and Zhang (2020), who observed higher pre–announcement returns for firms with elevated uncertainty and under conditions of higher aggregate market uncertainty. Additionally, Bauer, Lakdawala, and Mueller (2019) detailed the dynamics of uncertainty within the FOMC cycle with the resolution of uncertainty around announcements, emphasizing the positive relationship between uncertainty levels and the magnitude of financial market reactions to announcements. The pattern of decreasing uncertainty in FOMC meetings, as described by Krieger, Mauck, and Chen (2010) for the VIX — Chicago Board Options Exchange Volatility Index as an uncertainty metric. VIX also serves as one of the most appropriate interpretations of the variance of future returns in our model. Moreover, Beckmeyer, Branger, and Grünthaler (2019) showed that the left–tail uncertainty is the main contributor to uncertainty, leading to more expensive insurance for adverse economic states due to supply shocks in the market for crash insurance. The endogenous central bank communication considered in our model may, in particular, reduce this additional premium by disclosing information and minimizing the probability of significant shocks on the day of the Board meeting.

But then, it is possible to explore various explanations for the intuition behind the resolution of uncertainty. A significant body of research has focused on explaining the puzzle through information leaks. Initially, short–term evidence of informed trading in the 30–minute news lock–up period before the FOMC announcement (when government agencies provide accredited news outlets with pre–release access to information under embargo agreements) was observed in Bernile, Hu, and Tang (2015) and Kurov et al (2016). Similarly, as demonstrated in Kurov, Sancetta, and Wolfe (2019), the drift weakened after the discontinuation of early access in the UK. However, the time period can be extended to several days before the meeting, as explored in Mano (2021). Moreover, evidence of markets receiving information from the Fed during the blackout period exists right up to the start of the quiet period, as highlighted in Bradley et al. (2020). In our paper, we consider time periods of a few days, aiming to respond to macroeconomic shocks at the beginning of the quiet period, smooth out the long lack of communication within the quiet period, and mitigate the sharp reaction to the press release publication. Ying (2020) provides an explanatory theoretical mechanism that includes risk compensation for the market makers updating their beliefs by observing informed trading in the period leading up to the meeting.

How informed traders gain knowledge about upcoming decisions remains an open question. Mano (2021) showed that "the Fed's informal communication with the financial sector seems to be driven by the non–voting members of the FOMC." Another perspective, presented by Morse, Vissing–Jorgensen (2020) emphasizes the role of communication between Federal Reserve governors and Federal Reserve Bank presidents. Cieslak, Morse, and Vissing–Jorgensen (2019) discussed that systematic informal communication could be in the form of both outright leaks and systematic preferential access to the Fed for select private financial institutions. The authors also delved into the motivations for such communications throughout the entire FOMC cycle, with their main finding indicating that equity premium is earned entirely in weeks zero, two, four, and six in the FOMC cycle. For example, systematic informal communications offer flexibility in implementing more continuous policy, making a case for some form of communication during the quiet period. Additionally, such communications provide "a channel for learning how the Fed's assessment of the economy compares to that of the financial sector and how markets are likely to react to a particular policy decision." Public central bank communications then address the information asymmetry, reducing the advantage of individual financial institutions. Additionally, communications are a way for individual Board members to drive the market perceptions toward their optimal policies, which also raises concerns about cacophony communications, suggesting that centralized communication might be an improvement.

Another possible explanation for the pre–announcement drift is information acquisition by some market participants, as discussed in Ai, Bansal, and Han (2021). These models attempt to accommodate the main empirical fact that information leaks are not readily consistent with reduced realized volatility during the drift period. Another inconsistency of the information leakage hypothesis is the inconsistency between positive drift and the results of Bradley et al. (2020). This study revealed that informal communications in the run–up to Fed meetings may involve information gathering through face–to–face interactions when the Fed possesses negative private information about the economy, a scenario that contradicts a positive drift. The result of Bradley et al. (2020) also brings about additional considerations regarding the rationale for disclosing information during the quiet period. Suppose some of the information about the state of the economy was obtained through informal communications with market participants in a two–way information exchange. In that case, greater openness in the public disclosure of this information removes the asymmetry of information created by the Fed itself. In the information acquisition hypothesis, investor heterogeneity appears in the model. However, the empirical evidence can be explained by different variations of investor disagreement. Ai, Bansal, and Han (2021) employed a setup in which the uninformed are incentivized to bear the costs of obtaining the information and liquidate their lack of information over the informed just before the release of an important macro–announcement. In another perspective, Cocoma (2017) categorized investors into those who completely trust the Fed's communication and those who completely disbelieve it.

Supporting the idea of a practical information acquisition mechanism, Ehrmann, Hubert (2023) presented evidence that the intensity of monetary policy discussion on Twitter during the quiet period is associated with smaller surprises on the day of the meeting. In a related study, Gu, Kurov (2017) demonstrated that pre–announcement premia in gas futures trading could be partially explained by the superior information held by certain market participants with a history of high forecasting accuracy. Additionally, Zhu (2021) contributes to this narrative by revealing that the presence of private information, stemming from both potential leakage and heterogeneity in traders' abilities to process public information, leads to declining volume dynamics before announcements. These emerging liquidity shocks can explain one–third of the pre–FOMC drift. An idea related to the current study — central bank communication as a cause of information acquisition before announcements — was explored in Tsukioka, Yamasaki (2020), who highlighted the role of positive news in Beige book as a potential explanation for the drift. This positive news might act as information that was always public but not universally processed by all investors. However, the Beige book is published before the quiet period, two weeks before the meeting. Thus, similarly, the disclosure of Tealbook information within the quiet period might respond to more recent news, potentially serving as a smoothing factor for more continuous central bank communication. It's noteworthy that our paper adopts a more general modeling approach, refraining from delving into investor heterogeneity or aligning with specific explanations for market drift. However, even the simplified version of the model we use (Hu et al. (2022)) effectively explains a wide range of empirical facts about the drift.

What is the difference between the problem at hand and the pre–announcement puzzle? We do not directly model the pattern "large pre–announcement returns with small variances, followed by small post–announcement returns with large variances" from Hu et al. (2022) in our paper. Instead, our paper employs an alternative framework that effectively captures the pre–announcement puzzle dynamics while introducing an endogenous role for the central bank communication, which generates excess returns and affects both returns and stock price volatility. In contrast to the pre–announcement puzzle literature focusing on average returns, our primary concern lies in the central bank's endeavor to prevent significant market shocks. Accordingly, the model may also be left to answer how uncertainty is resolved. Possible explanations include the information leakage hypothesis of Cieslak, Morse, and Vissing–Jorgensen (2018) and the active endogenous information acquisition hypothesis, which partially resolves the uncertainty for uninformed traders from the work of Ai, Bansal, Han (2021). Our model uniquely empowers the central bank to actively manage the reduction of uncertainty through official communications. This leaves only a fraction of the uncertainty to be shared by possible explanations for the currently observed pre–announcement puzzle.

The pre–announcement premium, as observed in both the original work by Lucca, Moench (2015) and subsequent research Lucca, Moench (2018), exhibits a concentrated surge in a narrow window approximately one day before the press release. If the central bank permits interventions during the quiet period, these are likely to occur earlier, perhaps closer to the middle of the quiet period. This approach aligns with the idea of reacting to unexpected news within the quiet period and ensures a more even distribution of central bank communications. In contrast to a simplistic mechanism of "uncertainty generation and uncertainty resolution on the last day before the meeting," the mechanism of our model allows the central bank to precede the second step with its interventions by resolving uncertainty earlier. While this generates excess returns, it simultaneously diminishes market volatility and reduces the anticipated magnitude of the shock at the time of the key rate decision release. Moreover, the central bank distinguishes between two types of uncertainty: uncertainty regarding the central bank's reaction function and uncertainty about the Board's disagreement, translated into different monetary policy decisions on the day of the meeting. In the model, the central bank faces decisions on the extent to which it wants to eliminate uncertainty. While it considers fully resolving the uncertainty linked to the markets' misunderstanding of its reaction function, it adopts a more cautious approach to uncertainty about the Board of Governors' decision. Even though the central bank refrains from providing precise details on this latter uncertainty, it still manages to partially reduce it. From a normative standpoint, this paper does not directly confront individual central bankers' existing prohibition on sensitive communications. However, it advocates the introduction of "one voice" communications during the quiet period. Such communications can effectively alleviate some of the uncertainty that emerges before the Board of Governors meeting. Simultaneously, this approach ensures that the central bank retains flexibility in its monetary policy decisions and is not unduly confined to a single option, aligned with investors' expectations.

3 Model

The model description comprises several key elements: the depiction of shocks and financial markets, underlying assumptions discussions, the timing of events, and, finally, the financial market model featuring the central bank's endogenous communication.

3.1 Securities market

The model represents a financial market economy unfolding across four dates, $t = 0, 1, 2, 3$. Similar to Hu et al. (2022), the financial market features two primitive assets: a bond and a share. Each unit of the bond yields a terminal payoff of one at $t = 3$. Each share of the stock pays a terminal risky payoff D at the same date. However, unlike Hu et al. (2022), our model incorporates a more intricate timeline and structure of shocks, some of which are endogenous. D is given by

$$D = \bar{D} + \sigma\varepsilon = \bar{D} + \sigma(\varepsilon_1 + \varepsilon_2 + \varepsilon_3), \tag{1}$$

where $\varepsilon_1 \in S_1$, $\varepsilon_2 \in S_2$, $\varepsilon_3 \in S_3$ represent market–moving news, with detailed descriptions of their properties provided below, and σ^2 denotes the magnitude of news impact on asset payoffs. The simplicity of the financial market within the model is partially justified by the overarching focus on the primary mechanism: the buildup and resolution of uncertainty, which might lead to the pre–announcement drift. Our primary consideration revolves around the stock market, however, since drift is also observed in bonds (Abdi, Wu (2018)), and for interest rates (Hillenbrand (2021)), our securities market can be interpreted in slightly different ways.

3.2 Investors

Following Hu et al. (2022) there is a unit mass of identical, infinitesimal, and competitive investors, endowed with zero units of the bond and one share of the stock. Furthermore, we assume that all investors have Constant Absolute Risk Aversion (CARA) utility over their terminal wealth:

$$\mathrm{U} = -exp\{-\alpha W_3\}, \tag{2}$$

where $\alpha > 0$ represents the risk aversion coefficient and W_3 denotes the wealth at $t = 3$.

3.3 Central bank

In the model, the central bank is solving the following problem: firstly, it must decide whether to breach the blackout period regime and, secondly, it needs to decide on the fundamental, such as the press release containing the key rate and forward guidance, on the day of the Board of Governors meeting.

What underlying communication design and central bank decision–making mechanism do we have in mind? At date 1, the market receives a news shock $\varepsilon_1 \sim \mathrm{N}(0, \delta_1)$. This could represent various events, such as the release of macroeconomic statistics or any unexpected occurrence. Notably, this event occurs at the onset of the quiet period, during the central bank's preparations for the upcoming Board of Governors meeting. At this juncture, certain members of the Board of Governors are restricted from public communication. Simultaneously, the analytical department of the bank (this entity may be called differently, depending on the policymaker, but we will refer to it as the analytical department hereafter) has to recalculate model outcomes using the new data and craft an analytical note detailing the current state of the economy. This note will be placed on the Board of Governors' table on the day of the meeting or during the decision process if it takes an extended period of time. The results presented in this report can be considered a starting point for discussing the meeting's decision. The insights presented by the analytical department of the central bank constitute our potential communication within the quiet period, denoted as a possible shock ε_2 that the central bank may choose to communicate to the market or, alternatively, remain silent about. The mode of communication can vary; for instance, it could involve publishing the complete analytical report, such as the entire Tealbook. Alternatively, the central bank might publish only partial information or a concise message assessing how the news shock influenced the policymaker's economic stance, without monetary policy alternatives included. However, the precise nature and structure of communication fall partially outside the scope of this paper. The shock ε_2 is contingent on the shock ε_1. We assume they form a bivariate normal distribution, denoting their correlation coefficient by

ρ. The unconditional distribution of ε_2 is given by $\varepsilon_2 \sim \mathrm{N}(0, \delta_2)$ — meaning both the markets and the central bank have already factored in all prior shocks. However, ε_1 and the reaction to it may influence ε_2. We remain agnostic about the magnitude of ρ but not its sign. $\rho < 0$ represents the degree of countercyclicality in central bank policy. In cases of modulus large values of ρ, we observe a strongly countercyclical central bank — more inclined to respond to an unexpected positive shock ε_1 with a more restrictive policy ($\varepsilon_2 < 0$) and vice versa. This leads to a conditional distribution

$$\varepsilon_2 \sim \mathrm{N}\left(\rho\sqrt{\frac{\delta_2}{\delta_1}}\varepsilon_1,\ \delta_2(1-\rho^2)\right). \tag{3}$$

The intuitive rationale for such communication is grounded not only in the policymaker's previously discussed desire for more continuous communication but also in the recognition that effective communication policy should address the information deficit in markets. As emphasized in Byrne et al. (2023), it is crucial to convey how central banks are evaluating incoming data and how this evaluation shapes their perspectives on both the current state (evaluation) and the future state (projection) of the economy. Additionally, Laarits (2019) underscored the significance of news preceding FOMC meetings. Investors may interpret the announcements differently, perceiving them as signals about economic conditions after positive news and as indicators of the Fed's own policy stance after negative news. Therefore, by communicating its accurate assessment of the economic conditions, the Fed can bridge the gap between its own more informed evaluation and the uncertain assessment of investors.

At the same time, the resulting decision of the meeting may diverge from the presented results of the note. The Board members utilize it merely as a starting point for discussions, and the deliberations on the optimal monetary policy during the meeting may lead to a decision that deviates from the perceived signal of the analytical note. This means there is also a third shock, denoted as ε_3 in the model, occurring at date 3, reflecting the discussions among the Board members. However, we assume that the estimation of the analytical department is unbiased, implying $E[\varepsilon_3] = 0$. The intuition behind this premise can be divided into two parts. The analytical department avoids adding known bias themselves for reputation–building reasons, since for investors to perceive the communication as an unbiased forecast, as demonstrated in McMahon, Rholes (2023), previous forecast performance is crucial. Alternatively, if bias arises due to differing views within the Board, we assume that investors can well account for that. They are aware of the average preferences of policymakers, incorporating this bias into their estimate of ε_3, and this addition is considered common knowledge. Another perspective on $E[\varepsilon_3]$ is conceivable, where the shock at date 3 has an expected value different from zero due to a shift in the composition of the Board of Directors towards hawks or doves. In such a case, an additional measure of uncertainty is introduced to the model, which has not been investigated to date. Cieslak, McMahon (2023) demonstrated that the internal policy stance, potentially revealed through internal FOMC deliberations, possesses predictive power for the risk premium. However, the predictability of this internal stance increases smoothly in the weeks following the meeting, and we currently lack a clear theoretical model describing how markets form expectations of this variable before the meeting. For simplicity, we assume the expectation of the hawks–and–doves imbalance to be negligible. Additionally, the results are not expected to change significantly even if markets have relatively accurate information about such an imbalance and can at least estimate the value of $\mathrm{E}[\varepsilon_3]$ correctly.

Without loss of generality, we assume the third shock to be independent of ε_1 and ε_2, with a variance of $\beta\delta_3$. This variance comprises two components. δ_3 is known to both investors and the central bank from date 0, representing the ex–ante expected uncertainty about the Board's deliberations on the optimal decision on the meeting day. On the other hand, $\beta \in B$ is the second component of information asymmetry in our model. It becomes known to the central bank's analytical department at date 2 but remains undisclosed to investors. β reflects the degree of confidence that the decision on the day of the meeting will not deviate from the results of the analytical work presented to the members of the Board of Governors. In essence, when preparing the results of analytical models, the representatives of the analytical department both see the persuasiveness of these models in favor of a decision aligned with the optimal policy results in these models and gain insights into the ongoing internal discussions. These discussions do not only occur on the day of the meeting but, instead, start from the beginning of the circulation of monetary policy alternatives. However, officials cannot communicate this level of confidence to investors. Two primary reasons motivate this premise. Firstly, such communication would closely resemble a commitment to a particular decision on the meeting day, essentially binding policymakers and compromising their flexibility. Secondly, when β approaches zero, such communication becomes closer to normative rather than positive statement, a territory typically outside the purview of individuals not directly involved in decision–making within the central bank. Therefore, at date 1, both for the central bank and investors, $\mathrm{Var}_1[\varepsilon_3] = \mathrm{E}_1[\beta]\delta_3$. It's essential to note that, at this point, we are referring solely to the expected variance at date 1. As we progress to date 2, investors observe either the adherence to the quiet period regime or its violation, prompting an update to their opinions regarding the variance of ε_3. That is, for the central bank, $\mathrm{Var}_2[\varepsilon_3] = \beta\delta_3$. However, the perspective differs for the markets. Let's re–define the perceived ε_2 as ε_2^p. If the blackout period is violated, $\varepsilon_2^p = \varepsilon_2$, and without intervention, $\varepsilon_2^p = 0$. Then, in the case of intervention for investors

$$\mathrm{Var}_2[\varepsilon_3] = \mathrm{E}_2[\beta^+]\delta_3 = \mathrm{E}_2[\beta|\varepsilon_2^p \neq 0]\delta_3, \tag{4}$$

and in the case of silence

$$\mathrm{Var}_2[\varepsilon_3] = \mathrm{E}_2[\beta^-]\delta_3 = \mathrm{E}_2[\beta|\varepsilon_2^p = 0]\delta_3. \tag{5}$$

We observe a similar distinction in the expected values of shocks at dates 2 and 3. Investors build their expectations based on higher–order beliefs, emphasizing the importance of knowing whether the central bank adheres to or violates the quiet period regime, echoing the sentiment found in Maor, Gilad, and Bloom (2013) that "words are actions, and, occasionally, so is regulatory silence." For the sake of modeling convenience, we establish a relationship $\delta_1 + \delta_2 + \delta_3 = 1$, ensuring our focus is on the ratio of variances, such as $\frac{\delta_3}{\delta_1}$, indicating the relative magnitude of uncertainty between shocks. It is essential to note that for the ε_2 shock we employ the conditional variance $\sigma_{\varepsilon_2}^2 = \delta_2(1-\rho^2)$, since it is known to both investors and the central bank in advance. Normalization will not impact the modeling results, since all δ values are known at date 0. All three shocks follow a normal distribution, i.e.

$$\varepsilon_1 \sim \mathrm{N}(0, \delta_1), \quad \varepsilon_2 \sim \mathrm{N}\left(\rho\sqrt{\frac{\delta_2}{\delta_1}}\varepsilon_1,\ \delta_2(1-\rho^2)\right), \quad \varepsilon_3 \sim \mathrm{N}(0, \delta_3). \tag{6}$$

How does the central bank arrive at decisions within our model? By observing all market expectations, the central bank employs a quadratic utility function to guide its actions:

$$U = -\Big(o_1\big(\widehat{\mathrm{Var}_2}[R_3] - \mathrm{Var}_2[R_3]\big)^2 + o_2\big(\mathrm{E}_2[R_2]\big)^2 + \big(\mathrm{E}_2[R_3]\big)^2\Big), \tag{7}$$

where R_2 and R_3 are conditioned on the central bank's chosen policy, whether adhering to or violating the quiet period. The weights o_1 and o_2 represent relative weights of $(\widehat{\mathrm{Var}_2}[R_3] -$

$\text{Var}_2[R_3])^2$ and $(\text{E}_2[R_2])^2 + (\text{E}_2[R_3])^2$ respectively, and $\widehat{\text{Var}_2}[R_3]$ denotes the variance of R_3 as observed by the central bank (or what would the markets observe if they had complete information about β). That is

$$\text{U}^w = -\Big(o_1\big(\widehat{\text{Var}_2^w}[R_3] - \text{Var}_2^w[R_3]\big)^2 + o_2\big(\text{E}_2^w[R_2]\big)^2 + \big(\text{E}_2^w[R_3]\big)^2\Big), \tag{8}$$

$$\text{U}^{w/o} = -\Big(o_1\big(\widehat{\text{Var}_2^{w/o}}[R_3] + \text{Var}_2^{w/o}[R_3]\big)^2 + o_2\big(\text{E}_2^{w/o}[R_2]\big)^2 - \big(\text{E}_2^{w/o}[R_3]\big)^2\Big). \tag{9}$$

The central bank maintains the blackout period policy if $\text{U}^{w/o} \geq \text{U}^w$ and violates it if $\text{U}^{w/o} \leq \text{U}^w$.

Considering the utility function employed, what exactly does the central bank look at? First of all, it focuses on R_2 and R_3, the changes in the stock price at dates 2 and 3 — the very price spikes that the central bank aims to avoid. Importantly, in our model, the central bank attends not only to the immediate aftermath of the broken quiet period, R_2, but also to the anticipated impact on the markets following the Board of Governors meeting itself, R_3. The parameter o_2 determines the relative weight of the shock to investors at date 2 compared to the shock at date 3. The term responsible for the variation in our model, $\widehat{\text{Var}_2}[R_3] - \text{Var}_2[R_3]$, essentially represents the deviation of expected variance of R_3 from the level that would be observed if markets had complete information (disclosing accurate information about β, which the policy-maker can't do in our model). We discuss the intuition and potential observed variables behind this parameter later in the text.

3.4 Timeline

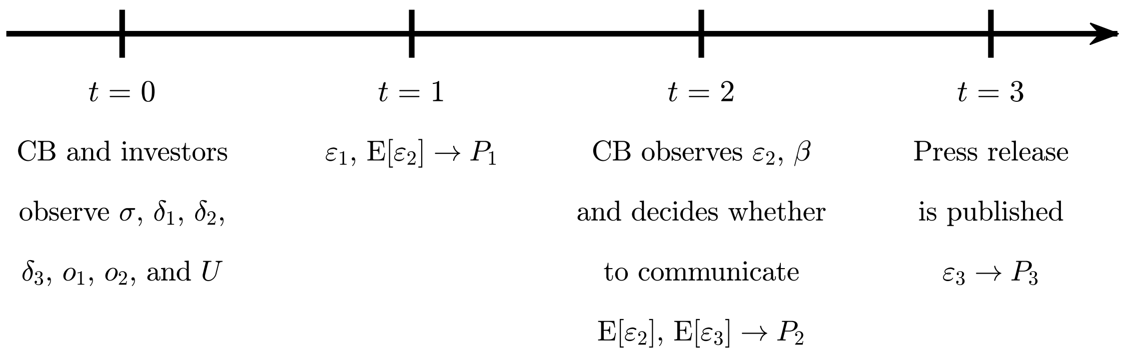
At $t = 0$, both investors and the central bank know underlying model parameters σ, δ_1, δ_2, δ_3, o_1, o_2, and the utility function. However, they have yet to observe shocks ε_1, ε_2, ε_3, and β. Based on the probability distributions, investors trade the stock against the bond by submitting competitive demand functions, and the market clears at the equilibrium price P_0.

At $t = 1$, investors and the central bank find out ε_1. Investors trade in the market again, yielding the equilibrium stock price P_1 given both ε_1 and their expectation of ε_2.

At $t = 2$, the central bank gains knowledge of ε_2 and β. The central bank decides whether to disclose ε_2 to the market. If the central bank chooses to communicate, investors become aware of ε_2 but remain uninformed about β, only possessing the expectation $\text{E}_2[\beta^+]$. Conversely, if the central bank refrains from breaching the blackout period, investors do not receive information about both ε_2 and β, building their expectations $E_2[\varepsilon_2^-]$, and $E_2[\beta^-]$. Investors trade in the market again, yielding the equilibrium stock price P_2.

At $t = 3$, investors learn ε_3 (and ε_2 if not communicated at date 2) from the central bank meeting. The dividend D is paid on the stock, and investors consume their terminal wealth. Figure 5 illustrates this timing of events.

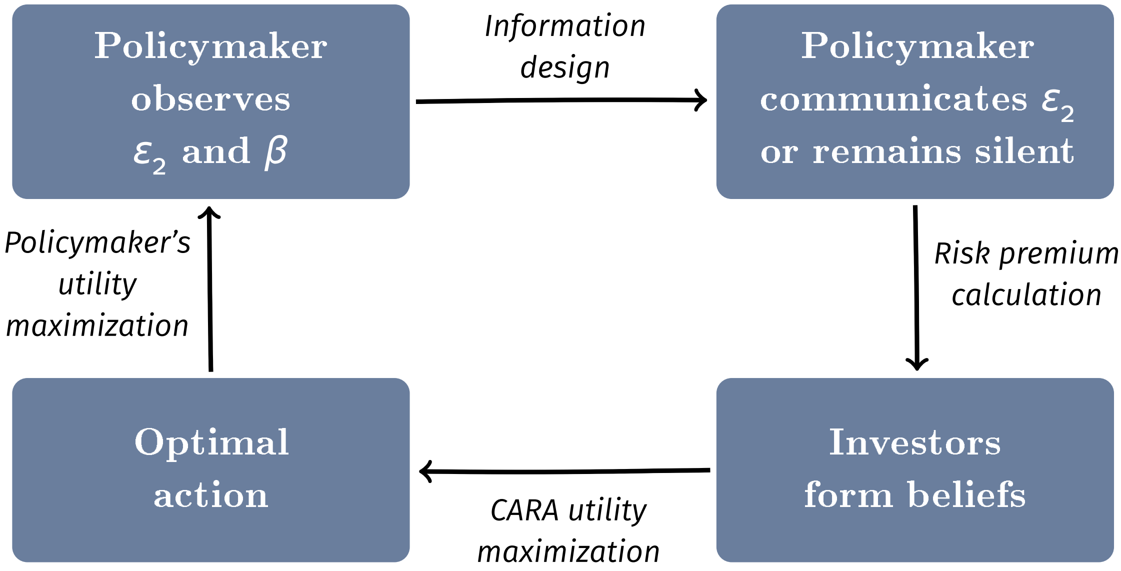
Figure 5 — Timeline



3.5 Discussion

Thus, the model contains 5 sources of risk that resolve over time: σ, ε_1, ε_2, ε_3, and β. At date 0, investors and the central bank learn a measure of uncertainty σ, or the impact risk. At date 1, investors acquire information about the initial shock to the economy ε_1 and build their expectations regarding the central bank's potential reaction to this shock. At date 2, the central bank decides whether to adhere to the quiet period policy or mitigate additional uncertainty associated with its reaction function by disclosing ε_2 to investors. In both scenarios, β remains unknown to investors. However, they learn some information about β since β^+ and β^- represent truncated distributions of β. And for the central bank, this source of uncertainty is already resolved at date 2. Finally, at date 3, ε_3 — the last source of risk in the model — is revealed to investors. The intuitive idea is that within the quiet period, the central bank endogenously manages the information provided so that the resolution of uncertainty and information on the central bank's assessment of the economic situation does not cause major market shocks, and investors have as accurate picture of the upcoming decision uncertainty as possible. Figure 6 illustrates the key mechanism of our model.

Figure 6 — Mechanism illustration



The importance of uncertainty is emphasized in $(\widehat{\text{Var}_2}[R_3] - \text{Var}_2[R_3])^2$ in the central bank's utility function. $\text{Var}_2[R_3]$ is the uncertainty metric in our model. As demonstrated by Hu et al. (2022), the most appropriate observables to describe the dynamics of $\text{Var}_2[R_3]$ include implied volatility and VIX (the risk–neutral expectation of equity index volatility over the next 30 days). Although VIX is a valuable predictor of future realized volatility, we refrain from categorizing our model as a model describing the realized volatility of R_3, since in addition to changes in expected volatility, VIX can also change due to shifts in preferences towards volatility that generate the variance risk premium (for an overview of the informational content of various uncertainty and volatility metrics, see Cascaldi–Garcia et al (2023)). Another reason is that spikes in realized volatility are tied to the publication of news; a significant cause of spikes in realized volatility is the sharp resolution of uncertainty associated with news releases, as demonstrated in Ai, Bansal, and Han (2021) for the FOMC press release and potential information leaks during the blackout period. In this sense, our model shares some similarities with the intertemporal mechanism proposed by Ai, Han, and Xu (2021), where variations in stock market volatility are driven by information, and high realized variances of past returns predict lower future variances. In our model, the market will learn the value of ε_2 sooner or later anyway, and the central question becomes when the sharp resolution of uncertainty leading to a spike in volatility occurs — whether at date 2 or date 3.

Why is the utility function symmetric for both upward and downward deviations in volatility?

Firstly, excessive uncertainty serves as an additional incentive for investors to mine information prior to the announcement, provoking the emergence of leaks, breaches, and unattributed communications. Secondly, if uncertainty is not partially resolved beforehand, a sharp increase in uncertainty at the time of the press release causes a more substantial spike in volatility at date 3. On the contrary, overly low uncertainty, which underestimates the level of disagreement within the Board, causes investors' expectations to anchor on a single expected option. This, in turn, may lock in Board members, limiting their flexibility in making decisions.

3.6 Distribution of model parameters

We have discussed how the shocks ε_1, ε_2 and ε_3 are distributed. As for the remaining variables, it is essential to note that the distribution function itself does not influence the model solution's trajectory. Therefore, we aim to maintain agnosticism regarding the distribution parameters. We consider ρ to be uniformly distributed on $(-1, 0)$. This choice doesn't impact the model solution, as the value of ρ becomes known to all economic agents already at date 0. However, this approach enables us to uniformly cover all possible cases during Monte Carlo simulations.

σ^2 follows an exponential distribution with location parameter λ_0 and scale parameter λ, where λ_0 and λ are known at date 0. Consequently, the support of σ^2 is $[\lambda_0, \infty)$, and the difference $\sigma^2 - \lambda_0$ follows an exponential distribution with variance λ^2. To encompass a broader range of possibilities for comparing uncertainties, we employ uniform distributions for both parameters, with $\lambda_0 \sim \mathrm{U}(0, 1)$ and $\lambda \sim \mathrm{U}(0, 10)$.

We adopt two distinct approaches for modeling β, generating Monte Carlo observations for two scenarios: $\beta \in (0, 1)$ and $\beta \in (0, 2)$. In the first case, δ_3 serves as an upper bound on the possible uncertainty about the Board meeting, while in the second case, it represents the expected value of this uncertainty. For both scenarios, we use a uniform distribution. It's essential to note that this choice doesn't alter the model's solution, as we solely utilize the first two moments of the distribution. The results from both approaches are qualitatively similar; therefore, we focus on reporting the findings from the model where β ranges between zero and two in the subsequent sections.

Empirical estimates of absolute risk aversion coefficients exhibit substantial variability, as documented by Conniffe, O'Neill (2012). We opt for a specific value, setting $\alpha = 0.005$, to tractabilize the results due to the numerous degrees of freedom associated with other variables. This choice is grounded in its realism, supported by a review of the estimation results from

Babcock, Choi, and Feinerman (1993). By adopting this fixed value, we aim to shift the focus to variations in other model variables.

Lastly, to ensure maximum flexibility, we maintain agnosticism about the weights o_1 and o_2 in the central bank's utility function. Unable to use random weights with any continuous distribution, as this would interfere with the comparability of the results, we use discrete distributions to facilitate a meaningful comparison across different scenarios — when the central bank pays strongly less, slightly less, slightly more, and strongly more attention to a certain factor in the utility function. Specifically, we assign the following weights for o_1: 0.01, 0.1, 1, 10, 100. Conversely, for o_2, we consider the weights: 0, 0.01, 0.1, 0.5, 1, 2, 10, 100. The rationale behind the choice of different distributions is that the values of R_2 and R_3 themselves are easily comparable to each other, so we can aim to capture subtle nuances when the weights are in close proximity. In contrast, deviations in the variance of $\mathrm{Var}_2[R_3]$ from $\widehat{\mathrm{Var}_2}[R_3]$ are not directly comparable to the returns; hence we use a more sparse scale.

3.7 Equilibrium

In this section, we solve the model backward. Specifically, at date 3, the optimization problem for a generic investor looks as follows:

$$
\begin{aligned}
J_2 &= \max_{\theta_2} \mathrm{E}_2 \big\{ -\exp\{-\alpha[W_2 + \theta_2(D - P_2)]\}\big\} = \\
&= \max_{\theta_2} \mathrm{E}_2 \big\{ -\exp\{-\alpha[W_2 + \theta_2(\bar{D} + \sigma\varepsilon_1 + \sigma\varepsilon_2 - P_2) - \frac{1}{2}\alpha\theta_2^2 \,\mathrm{Var}_2[D]]\}\big\} = \\
&= \max_{\theta_2} \mathrm{E}_2 \big\{ -\exp\{-\alpha[W_2 + \theta_2(\bar{D} + \sigma\varepsilon_1 + \sigma\varepsilon_2 - P_2) - \frac{1}{2}\alpha\theta_2^2\sigma^2 \,\mathrm{Var}_2[\varepsilon_2 + \varepsilon_3]]\}\big\},
\end{aligned}
\tag{10}
$$

where θ_2 denotes the investor's demand of the risky asset at date 2.

At this stage, investors already know whether the central bank has conducted a verbal intervention, and in case of its presence, $\mathrm{Var}[\varepsilon_2] = 0$. Therefore, we consider two cases based on the presence or absence of intervention. Hereafter, we denote the presence of intervention by J_2^w and the absence by $J_2^{w/o}$. In the case of communication:

$$
J_2^w = \max_{\theta_2} \mathrm{E}_2 \big\{ -\exp\{-\alpha[W_2 + \theta_2(\bar{D} + \sigma\varepsilon_1 + \sigma\varepsilon_2 - P_2) - \frac{1}{2}\alpha\theta_2^2\sigma^2 \,\mathrm{E}_2[\beta^+]\delta_3]\}\big\}. \tag{11}
$$

And without communication:

$$J_2^{w/o} = \max_{\theta_2} \mathrm{E}_2 \Big\{ -\exp\{-\alpha[W_2 + \theta_2(\bar{D} + \sigma\varepsilon_1 + \sigma\varepsilon_2 - P_2) - \frac{1}{2}\alpha\theta_2^2\sigma^2 \operatorname{Var}_2[\varepsilon_2^- + \varepsilon_3]]\}\Big\} =$$
$$= \max_{\theta_2} \mathrm{E}_2 \Big\{ -\exp\{-\alpha[W_2 + \theta_2(\bar{D} + \sigma\varepsilon_1 + \sigma\varepsilon_2 - P_2) - \frac{1}{2}\alpha\theta_2^2\sigma^2 (\operatorname{Var}_2[\varepsilon_2^-] + \mathrm{E}_2[\beta^-]\delta_3)]\}\Big\}. \quad (12)$$

We can now find the equilibrium P_2 in both scenarios.

$$\frac{\partial J_2^w}{\partial\theta_2} = \bar{D} + \sigma\varepsilon_1 + \sigma\varepsilon_2 - P_2 - \alpha\theta_2\sigma^2 \mathrm{E}_2[\beta^+]\delta_3. \quad (13)$$

Then

$$\theta_2 = \frac{\bar{D} + \sigma\varepsilon_1 + \sigma\varepsilon_2 - P_2}{\alpha\sigma^2 \mathrm{E}_2[\beta^+]\delta_3}, \quad (14)$$

and with the given $\theta_2 = 1$ equilibrium

$$P_2 = \bar{D} + \sigma\varepsilon_1 + \sigma\varepsilon_2 - \alpha\sigma^2 \mathrm{E}_2[\beta^+]\delta_3. \quad (15)$$

Where S.O.C.:

$$\frac{\partial^2 J_2^w}{\partial^2\theta_2} = -\alpha\sigma^2 \mathrm{E}_2[\beta^+]\delta_3 < 0. \quad (16)$$

In turn, for the absence of communication:

$$\frac{\partial J_2^{w/o}}{\partial\theta_2} = \bar{D} + \sigma\varepsilon_1 + \sigma \mathrm{E}_2[\varepsilon_2^-] - P_2 - \alpha\theta_2\sigma^2(\operatorname{Var}_2[\varepsilon_2^-] + \mathrm{E}_2[\beta^-]\delta_3), \quad (17)$$

$$\theta_2 = \frac{\bar{D} + \sigma\varepsilon_1 + \sigma \mathrm{E}_2[\varepsilon_2^-] - P_2}{\alpha\theta_2\sigma^2(\operatorname{Var}_2[\varepsilon_2^-] + \mathrm{E}_2[\beta^-]\delta_3)}. \quad (18)$$

And with the given $\theta_2 = 1$ equilibrium price

$$P_2 = \bar{D} + \sigma\varepsilon_1 + \sigma \mathrm{E}_2[\varepsilon_2^-] - \alpha\sigma^2(\operatorname{Var}_2[\varepsilon_2^-] + \mathrm{E}_2[\beta^-]\delta_3). \quad (19)$$

Where S.O.C.:

$$\frac{\partial^2 J_2^{w/o}}{\partial^2\theta_2} = \alpha\sigma^2(\operatorname{Var}_2[\varepsilon_2^-] + \mathrm{E}_2[\beta^-]\delta_3) < 0. \quad (20)$$

For the sake of clarity, we collectively describe both scenarios, utilizing the notation

$$\widetilde{\varepsilon_2} = \begin{cases} \varepsilon_2, & \text{with intervention} \\ \mathrm{E}_2[\varepsilon_2^-], & \text{without} \end{cases} \quad \text{and} \quad \widetilde{\delta_3} = \begin{cases} \mathrm{E}_2[\beta^+]\delta_3, & \text{with intervention} \\ \mathrm{Var}_2[\varepsilon_2^-] + \mathrm{E}_2[\beta^-]\delta_3, & \text{without.} \end{cases} \tag{21}$$

To understand the dynamics at date 1, it is essential to examine the evolution of the information set. Regarding $\mathrm{Var}_2[\varepsilon_2^-]$ and $\mathrm{E}_2[\beta^-]$ at date 2, no new information occurs; the information sets at dates 1 and 2 remain identical. Consequently, $\mathrm{Var}_1[\varepsilon_2^-] = \mathrm{Var}_2[\varepsilon_2^-]$, $\mathrm{E}_1[\beta^-] = \mathrm{E}_2[\beta^-]$. For convenience, we will consistently use the notation $t = 2$ for these variables, even when discussing the equilibrium at date 1. However, if the central bank communicates at date 2, markets gain access to the value of ε_2 and then $\mathrm{E}_2[\beta^+] = \mathrm{E}_1[\beta^+|\varepsilon_2] \neq \mathrm{E}_1[\beta^+]$.

Now redefined $P_2 = \bar{D} + \sigma\varepsilon_1 + \sigma\widetilde{\varepsilon_2} - \alpha\sigma^2\widetilde{\delta_3}$ and at date 1 investor's optimization problem looks as follows:

$$\begin{aligned} J_2 &= -\exp\{-\alpha[W_1 + \theta_1(P_2 - P_1) + \theta_2(D - P_2) - \frac{1}{2}\alpha\sigma^2\widetilde{\delta_3}]\} = \\ &= -\exp\{-\alpha[W_1 + \theta_1(\bar{D} + \sigma\varepsilon_1 + \sigma\widetilde{\varepsilon_2} - \alpha\sigma^2\widetilde{\delta_3} - P_1) + \\ &+ \theta_2(\bar{D} + \sigma\varepsilon_1 + \sigma\widetilde{\varepsilon_2} - \bar{D} - \sigma\varepsilon_1 - \sigma\widetilde{\varepsilon_2} + \alpha\sigma^2\widetilde{\delta_3}) - \frac{1}{2}\alpha\sigma^2\widetilde{\delta_3}]\} = \\ &= -\exp\{-\alpha[W_1 + \theta_1(\bar{D} + \sigma\varepsilon_1 + \sigma\widetilde{\varepsilon_2} - \alpha\sigma^2\widetilde{\delta_3} - P_1) + \frac{1}{2}\alpha\sigma^2\widetilde{\delta_3}]\}, \end{aligned} \tag{22}$$

$$\begin{aligned} \mathrm{E}_1(J_2) = -\exp\{-\alpha[W_1 + \theta_1(\bar{D} + \sigma\varepsilon_1 + \sigma\,\mathrm{E}_1[\widetilde{\varepsilon_2}] - \alpha\sigma^2\,\mathrm{E}_1[\widetilde{\delta_3}] - P_1) + \\ + \frac{1}{2}\alpha\sigma^2\,\mathrm{E}_1[\widetilde{\delta_3}] - \frac{1}{2}\alpha\,\mathrm{Var}[\theta_1\sigma\widetilde{\varepsilon_2} - \alpha\sigma^2\widetilde{\delta_3}(\theta_1 - \frac{1}{2})]]\}. \end{aligned} \tag{23}$$

Let's redefine

$$\mathrm{V}_1 = \mathrm{Var}[\theta_1\sigma\widetilde{\varepsilon_2} - \alpha\sigma^2\widetilde{\delta_3}(\theta_1 - \frac{1}{2})]. \tag{24}$$

Now F.O.C.

$$\frac{\partial\,\mathrm{E}_1[J_2]}{\partial\theta_1} = \bar{D} + \sigma\varepsilon_1 + \sigma\,\mathrm{E}_1[\widetilde{\varepsilon_2}] - \alpha\sigma^2\,\mathrm{E}_1[\widetilde{\delta_3}] - P_1 - \frac{1}{2}\alpha\,\mathrm{V}_1'\,. \tag{25}$$

And given $\theta_1 = 1$ equilibrium

$$P_1 = \bar{D} + \sigma\varepsilon_1 + \sigma\,\mathrm{E}_1[\widetilde{\varepsilon_2}] - \alpha\sigma^2\,\mathrm{E}_1[\widetilde{\delta_3}] - \frac{1}{2}\alpha\,\mathrm{V}_1'\,. \tag{26}$$

The task at hand is to express $\mathrm{E}_2[R_2]$, $\mathrm{E}_2[R_3]$, $\mathrm{Var}_2[R_3]$, $\widehat{\mathrm{Var}_2}[R_3]$ in terms of the moments of ε_2^+, ε_2^-, β^+, β^-, which we can subsequently estimate in a Monte Carlo simulation. To facilitate this, let Pr^+ denote the probability of intervention, which is identically estimated by both market participants and the central bank at date 1, given the absence of information asymmetry at this stage. Then (see Appendix 2 for a detailed derivation):

$$\mathrm{E}_1[\widetilde{\varepsilon_2}] = Pr^+\,\mathrm{E}_1[\varepsilon_2^+] + (1-Pr^+)\,\mathrm{E}_2[\varepsilon_2^-], \tag{27}$$

$$\mathrm{E}_1[\widetilde{\delta_3}] = Pr^+\,\mathrm{E}_1[\beta^+]\delta_3 + (1-Pr^+)(\mathrm{Var}_2[\varepsilon_2^-] + \mathrm{E}_2[\beta^-]\delta_3), \tag{28}$$

$$\begin{gathered}\mathrm{Var}_1[\theta_1\sigma\widetilde{\varepsilon_2} - \alpha\sigma^2\widetilde{\delta_3}(\theta_1 - \frac{1}{2})] = \theta_1^2\sigma^2\,\mathrm{Var}_1[\widetilde{\varepsilon_2}] + \\ +\alpha^2\sigma^4(\theta_1-\frac{1}{2})^2\,\mathrm{Var}_1[\widetilde{\delta_3}] - 2\theta_1(\theta_1-\frac{1}{2})\alpha\sigma^3\,\mathrm{E}_1[\widetilde{\varepsilon_2}\widetilde{\delta_3}] + 2\theta_1(\theta_1-\frac{1}{2})\alpha\sigma^3\,\mathrm{E}_1[\widetilde{\varepsilon_2}]\,\mathrm{E}_1[\widetilde{\delta_3}],\end{gathered} \tag{29}$$

$$\begin{gathered}\frac{\partial\,\mathrm{V}_1}{\partial\theta_1} = 2\theta_1\sigma^2\,\mathrm{Var}_1[\widetilde{\varepsilon_2}] + (2\theta_1-1)\alpha^2\sigma^4\,\mathrm{Var}_1[\widetilde{\delta_3}] - \\ -2(2\theta_1-\frac{1}{2})\alpha\sigma^3\,\mathrm{E}_1[\widetilde{\varepsilon_2}\widetilde{\delta_3}] + 2(2\theta_1-\frac{1}{2})\alpha\sigma^3\,\mathrm{E}_1[\widetilde{\varepsilon_2}]\,\mathrm{E}_1[\widetilde{\delta_3}],\end{gathered} \tag{30}$$

$$V_1'(\theta_1=1) = 2\sigma^2\,\mathrm{Var}_1[\widetilde{\varepsilon_2}] + \alpha^2\sigma^4\,\mathrm{Var}_1[\widetilde{\delta_3}] - 3\alpha\sigma^3\,\mathrm{E}_1[\widetilde{\varepsilon_2}\widetilde{\delta_3}] + 3\alpha\sigma^3\,\mathrm{E}_1[\widetilde{\varepsilon_2}]\,\mathrm{E}_1[\widetilde{\delta_3}]. \tag{31}$$

Now, express the individual summands V_1':

$$\mathrm{Var}[\widetilde{\delta_3}] = Pr^+(1-Pr^+)(\mathrm{E}_1[\beta^+]\delta_3 - \mathrm{Var}_2[\varepsilon_2^-] - \mathrm{E}_2[\beta^-]\delta_3)^2, \tag{32}$$

$$\mathrm{Var}_1[\widetilde{\varepsilon_2}] = Pr^+(1-Pr^+)(\mathrm{E}_1[\varepsilon_2^+] - \mathrm{E}_2[\varepsilon_2^-])^2, \tag{33}$$

$$\mathrm{E}_1[\widetilde{\varepsilon_2}\widetilde{\delta_3}] = Pr^+\delta_3\,\mathrm{E}_1[\varepsilon_2^+]\,\mathrm{E}_1[\beta^+] + (1-Pr^+)\,\mathrm{E}_2[\varepsilon_2^-]\,\mathrm{Var}_2[\varepsilon_2^-] + (1-Pr^+)\delta_3\,\mathrm{E}_2[\varepsilon_2^-]\,\mathrm{E}_2[\beta^-]. \tag{34}$$

Hence

$$\begin{gathered}V_1'(\theta_1=1) = 2\sigma^2 Pr^+(1-Pr^+)(\mathrm{E}_1[\varepsilon_2^+] - \mathrm{E}_2[\varepsilon_2^-])^2 + \alpha^2\sigma^4 Pr^+(1-Pr^+)(\mathrm{E}_1[\beta^+]\delta_3 - \\ -\mathrm{Var}_2[\varepsilon_2^-] - \mathrm{E}_2[\beta^-]\delta_3)^2 - 3\alpha\sigma^3\big(Pr^+\delta_3\,\mathrm{E}_1[\varepsilon_2^+]\,\mathrm{E}_1[\beta^+] + (1-Pr^+)\,\mathrm{E}_2[\varepsilon_2^-]\,\mathrm{Var}_2[\varepsilon_2^-] + \\ +(1-Pr^+)\delta_3\,\mathrm{E}_2[\varepsilon_2^-]\,\mathrm{E}_2[\beta^-]\big) + 3\alpha\sigma^3\big(Pr^+\,\mathrm{E}_1[\varepsilon_2^+] + \\ +(1-Pr^+)\,\mathrm{E}_2[\varepsilon_2^-]\big)\big(Pr^+\,\mathrm{E}_1[\beta^+]\delta_3 + (1-Pr^+)(\mathrm{Var}_2[\varepsilon_2^-] + \mathrm{E}_2[\beta^-]\delta_3)\big).\end{gathered} \tag{35}$$

See Appendix 3 for the second–order condition. And then

$$
\begin{aligned}
P_1 = \bar{D} + \sigma\varepsilon_1 + \sigma Pr^+ \operatorname{E}_1[\varepsilon_2^+] + \sigma(1 - Pr^+) \operatorname{E}_2[\varepsilon_2^-] - \alpha\sigma^2\big(Pr^+ \operatorname{E}_1[\beta^+]\delta_3 + \\
+(1 - Pr^+)(\operatorname{Var}_2[\varepsilon_2^-] + \operatorname{E}_2[\beta^-]\delta_3)\big) - \alpha\sigma^2 Pr^+(1 - Pr^+)(\operatorname{E}_1[\varepsilon_2^+] - \operatorname{E}_2[\varepsilon_2^-])^2 - \\
-\frac{1}{2}\alpha^3\sigma^4 Pr^+(1 - Pr^+)(\operatorname{E}_1[\beta^+]\delta_3 - \operatorname{Var}_2[\varepsilon_2^-] - \operatorname{E}_2[\beta^-]\delta_3)^2 + \frac{3}{2}\alpha^2\sigma^3\big(Pr^+\delta_3 \operatorname{E}_1[\varepsilon_2^+] \operatorname{E}_1[\beta^+] + \\
+(1 - Pr^+) \operatorname{E}_2[\varepsilon_2^-] \operatorname{Var}_2[\varepsilon_2^-] + (1 - Pr^+)\delta_3 \operatorname{E}_2[\varepsilon_2^-] \operatorname{E}_2[\beta^-]\big) - \frac{3}{2}\alpha^2\sigma^3\big(Pr^+ \operatorname{E}_1[\varepsilon_2^+] + \\
+(1 - Pr^+) \operatorname{E}_2[\varepsilon_2^-]\big)\big(Pr^+ \operatorname{E}_1[\beta^+]\delta_3 + (1 - Pr^+)(\operatorname{Var}_2[\varepsilon_2^-] + \operatorname{E}_2[\beta^-]\delta_3)\big).
\end{aligned} \tag{36}
$$

Thus, we estimate

$$
P_1 = \bar{D} + \sigma\varepsilon_1 + \sigma Pr^+ \operatorname{E}_1[\varepsilon_2^+] + \sigma(1 - Pr^+) \operatorname{E}_2[\varepsilon_2^-] - rp_1, \tag{37}
$$

where the risk premium at date 1:

$$
\begin{aligned}
rp_1 = \alpha\sigma^2\big(Pr^+ \operatorname{E}_1[\beta^+]\delta_3 + (1 - Pr^+)(\operatorname{Var}_2[\varepsilon_2^-] + \operatorname{E}_2[\beta^-]\delta_3)\big) + \\
+\alpha\sigma^2 Pr^+(1 - Pr^+)(\operatorname{E}_1[\varepsilon_2^+] - \operatorname{E}_2[\varepsilon_2^-])^2 + \frac{1}{2}\alpha^3\sigma^4 Pr^+(1 - Pr^+)(\operatorname{E}_1[\beta^+]\delta_3 - \operatorname{Var}_2[\varepsilon_2^-] - \\
- \operatorname{E}_2[\beta^-]\delta_3)^2 - \frac{3}{2}\alpha^2\sigma^3\big(Pr^+\delta_3 \operatorname{E}_1[\varepsilon_2^+] \operatorname{E}_1[\beta^+] + (1 - Pr^+) \operatorname{E}_2[\varepsilon_2^-] \operatorname{Var}_2[\varepsilon_2^-] + \\
+(1 - Pr^+)\delta_3 \operatorname{E}_2[\varepsilon_2^-] \operatorname{E}_2[\beta^-]\big) + \frac{3}{2}\alpha^2\sigma^3\big(Pr^+ \operatorname{E}_1[\varepsilon_2^+] + (1 - Pr^+) \operatorname{E}_2[\varepsilon_2^-]\big)\big(Pr^+ \operatorname{E}_1[\beta^+]\delta_3 + \\
+(1 - Pr^+)(\operatorname{Var}_2[\varepsilon_2^-] + \operatorname{E}_2[\beta^-]\delta_3)\big).
\end{aligned} \tag{38}
$$

Given that the central bank is the decision–maker regarding intervention, we are primarily interested in its assessment of the potential outcomes in the stock market. We can calculate the components of the utility function in the absence of intervention:

$$
\begin{aligned}
\operatorname{E}_2^{w/o}[R_3] = \operatorname{E}_2^{w/o}[P_3 - P_2] = \operatorname{E}_2^{w/o}[\bar{D} + \sigma\varepsilon_1 + \sigma\varepsilon_2 + \sigma\varepsilon_3 - \bar{D} - \sigma\varepsilon_1 - \sigma\widetilde{\varepsilon_2} + \alpha\sigma^2\widetilde{\delta_3}] = \\
= \operatorname{E}_2^{w/o}[\sigma\varepsilon_2 + \sigma\varepsilon_3 - \sigma\widetilde{\varepsilon_2} + \alpha\sigma^2\widetilde{\delta_3}] = \operatorname{E}_2^{w/o}[\sigma\varepsilon_2 + \sigma\varepsilon_3 - \sigma \operatorname{E}_2[\varepsilon_2^-] + \\
+\alpha\sigma^2(\operatorname{Var}_2[\varepsilon_2^-] + \operatorname{E}_2[\beta^-]\delta_3)] = \sigma\varepsilon_2 - \sigma \operatorname{E}_2[\varepsilon_2^-] + \alpha\sigma^2(\operatorname{Var}_2[\varepsilon_2^-] + \operatorname{E}_2[\beta^-]\delta_3),
\end{aligned} \tag{39}
$$

$$
\begin{aligned}
\operatorname{E}_2^{w/o}[R_2] = \operatorname{E}_2^{w/o}[P_2 - P_1] = \\
= -\alpha\sigma^2(\operatorname{Var}_2[\varepsilon_2^-] + \operatorname{E}_2[\beta^-]\delta_3) - \sigma Pr^+ \operatorname{E}_1[\varepsilon_2^+] + \sigma Pr^+ \operatorname{E}_2[\varepsilon_2^-] + rp_1,
\end{aligned} \tag{40}
$$

$$
\operatorname{Var}_2^{w/o}[R_3] = \operatorname{Var}_2^{w/o}[P_3 - P_2] = \sigma^2 \operatorname{Var}_2[\varepsilon_2^-] + \sigma^2 \operatorname{E}_2[\beta^-]\delta_3. \tag{41}
$$

And

$$\widehat{\mathrm{Var}}_2^{w/o}[R_3] = \widehat{\mathrm{Var}}_2^{w/o}[P_3 - P_2] = \widehat{\mathrm{Var}}_2^{w/o}[\sigma\varepsilon_3] = \sigma^2\beta\delta_3. \tag{42}$$

And in the case of an intervention:

$$\begin{aligned}\mathrm{E}_2^w[R_3] = \mathrm{E}_2^w[P_3 - P_2] = \mathrm{E}_2^w[\bar{D} + \sigma\varepsilon_1 + \sigma\varepsilon_2 + \sigma\varepsilon_3 - \bar{D} - \sigma\varepsilon_1 - \sigma\widetilde{\varepsilon_2} + \alpha\sigma^2\widetilde{\delta_3}] = \\ = \mathrm{E}_2^w[\sigma\varepsilon_2 + \sigma\varepsilon_3 - \sigma\widetilde{\varepsilon_2} + \alpha\sigma^2\widetilde{\delta_3}] = \\ = \mathrm{E}_2^w[\sigma\varepsilon_2 + \sigma\varepsilon_3 - \sigma\varepsilon_2 + \alpha\sigma^2\,\mathrm{E}_2[\beta^+]\delta_3] = \alpha\sigma^2\,\mathrm{E}_2[\beta^+]\delta_3,\end{aligned} \tag{43}$$

$$\mathrm{E}_2^w[R_2] = \mathrm{E}_2^w[P_2 - P_1] = \sigma\varepsilon_2 - \alpha\sigma^2\,\mathrm{E}_2[\beta^+]\delta_3 - \sigma Pr^+\,\mathrm{E}_1[\varepsilon_2^+] - \sigma(1 - Pr^+)\,\mathrm{E}_2[\varepsilon_2^-] + rp_1, \tag{44}$$

$$\begin{aligned}\mathrm{Var}_2^w[R_3] = \mathrm{Var}_2^w[P_3 - P_2] = \mathrm{Var}_2^w[\bar{D} + \sigma\varepsilon_1 + \sigma\varepsilon_2 + \sigma\varepsilon_3 - \bar{D} - \sigma\varepsilon_1 - \sigma\widetilde{\varepsilon_2} + \alpha\sigma^2\widetilde{\delta_3}] = \\ = \mathrm{Var}_2^w[\sigma\varepsilon_2 + \sigma\varepsilon_3 - \sigma\widetilde{\varepsilon_2} + \alpha\sigma^2\widetilde{\delta_3}] = \\ = \mathrm{Var}_2^w[\sigma\varepsilon_2 + \sigma\varepsilon_3 - \sigma\varepsilon_2 + \alpha\sigma^2\,\mathrm{E}_2[\beta^+]\delta_3] = \mathrm{Var}_2^w[\sigma\varepsilon_3] = \sigma^2\,\mathrm{E}_2[\beta^+]\delta_3.\end{aligned} \tag{45}$$

And $\widehat{\mathrm{Var}}_2^w[R_3]$ remains exactly the same, since

$$\widehat{\mathrm{Var}}_2^w[R_3] = \widehat{\mathrm{Var}}_2^w[P_3 - P_2] = \widehat{\mathrm{Var}}_2^w[\sigma\varepsilon_3] = \sigma^2\beta\delta_3. \tag{46}$$

Finally, we put this together into the difference of utility function

$$\begin{aligned}\mathrm{U}^w - \mathrm{U}^{w/o} = o_1\big(\widehat{\mathrm{Var}}_2^w[R_3] - \mathrm{Var}_2^w[R_3]\big)^2 + o_2\big(\mathrm{E}_2^w[R_2]\big)^2 + \big(\mathrm{E}_2^w[R_3]\big)^2 - \\ -o_1\big(\widehat{\mathrm{Var}}_2^{w/o}[R_3] - \mathrm{Var}_2^{w/o}[R_3]\big)^2 - o_2\big(\mathrm{E}_2^{w/o}[R_2]\big)^2 - \big(\mathrm{E}_2^{w/o}[R_3]\big)^2,\end{aligned} \tag{47}$$

$$\begin{aligned}\mathrm{U}^w - \mathrm{U}^{w/o} = o_1\big(\sigma^2\beta\delta_3 - \sigma^2\,\mathrm{E}_2[\beta^+]\delta_3\big)^2 + o_2\big(\sigma\varepsilon_2 - \alpha\sigma^2\,\mathrm{E}_2[\beta^+]\delta_3 - \sigma Pr^+\,\mathrm{E}_1[\varepsilon_2^+] - \\ -\sigma(1 - Pr^+)\,\mathrm{E}_2[\varepsilon_2^-] + rp_1\big)^2 + \big(\alpha\sigma^2\,\mathrm{E}_2[\beta^+]\delta_3\big)^2 - \\ -o_1\big(\sigma^2\beta\delta_3 - \sigma^2\,\mathrm{Var}_2[\varepsilon_2^-] - \sigma^2\,\mathrm{E}_2[\beta^-]\delta_3\big)^2 - o_2\big(-\alpha\sigma^2(\mathrm{Var}_2[\varepsilon_2^-] + \mathrm{E}_2[\beta^-]\delta_3) - \\ -\sigma Pr^+\,\mathrm{E}_1[\varepsilon_2^+] + \sigma Pr^+\,\mathrm{E}_2[\varepsilon_2^-] + rp_1\big)^2 - \big(\sigma\varepsilon_2 - \sigma\,\mathrm{E}_2[\varepsilon_2^-] + \alpha\sigma^2(\mathrm{Var}_2[\varepsilon_2^-] + \mathrm{E}_2[\beta^-]\delta_3)\big)^2.\end{aligned} \tag{48}$$

The problem is now reduced to finding the mapping by which the central bank decides when to communicate and when not to communicate during the quiet period. This is done in such a way that $\mathrm{U}^{w/o} \geq \mathrm{U}^w$ holds for those values of ε_2 and β at which it decides to follow the policy of the blackout period, and $\mathrm{U}^{w/o} \leq \mathrm{U}^w$ holds for those ε_2 and β at which the central bank decides to communicate.

3.8 Monte Carlo simulation

To find the solution, we employ the following algorithm. Our goal is to construct a surjective mapping $f : (S_1, S_2, \alpha, B, \theta, \sigma, \delta_1, \delta_2, \delta_3) \rightarrow \{1, 2\}$, from the parameter space to a set containing two classes: Class 1, representing the decision not to communicate, and Class 2, representing the decision to communicate. This mapping is established for any parameter values α, $\beta \in B$, θ, σ, δ_1, δ_2, δ_3 and realizations of $\varepsilon_1 \in S_1$, $\varepsilon_2 \in S_2$ from the corresponding distributions.

We divide the solution into three steps:

1) Utilizing Monte Carlo simulation (see Casarin (2023) for an overview of Monte Carlo methods), we randomly generate 10 000 pairs of ε_2 and β for a specific set of parameters: $\{\varepsilon_1, \alpha, \theta, \sigma, \delta_1, \delta_2, \delta_3\}$. Here, $\varepsilon_2 \sim \mathrm{N}\left(\rho\sqrt{\frac{\delta_2}{\delta_1}}\varepsilon_1,\ \delta_2(1-\rho^2)\right)$ and $\beta \sim \mathrm{U}(0, 2)$. This process allows us to establish a mapping $(S_2, B) \rightarrow \{1, 2\}$, yielding values for the required parameters such as $\mathrm{E}_2[\beta^-]$, $\mathrm{E}_2[\beta^+]$, $\mathrm{E}_1[\varepsilon_2^+]$, $\mathrm{E}_2[\varepsilon_2^-]$, $\mathrm{Var}_2[\varepsilon_2^-]$, and Pr^+. The use of Monte Carlo is imperative as a closed–form solution is unavailable for comparing $\mathrm{U}^w - \mathrm{U}^{w/o}$ to zero. Details of the machine learning algorithm employed for this mapping can be found in Appendix 1.

2) With the obtained parameters $\mathrm{E}_2[\beta^-]$, $\mathrm{E}_2[\beta^+]$, $\mathrm{E}_1[\varepsilon_2^+]$, $\mathrm{E}_1[\varepsilon_2^-]$, $\mathrm{Var}_2[\varepsilon_2^-]$, Pr^+, we directly estimate the utility function values by substituting parameter values into $\mathrm{U}^w - \mathrm{U}^{w/o}$. This step enables us to determine the classification of each point in our parameter space (ε_2, β) into either Class 1 or Class 2.

3) We iterate over Steps 1 and 2, generating new sets of parameters $\{\varepsilon_1, \alpha, \theta, \sigma, \delta_1, \delta_2, \delta_3\}$ from the corresponding distributions. Each iteration contributes one observation to the final dataset under study. Then, the entire dataset will allow us to determine which parameters influence the central bank's decision to adhere or to deviate from the quiet period regime. Further details of the Monte Carlo algorithm can be found in Appendix 1, while Appendix 4 discusses several robustness checks confirming the stability of the algorithm's results.

4 Results

Now, we delve into the analysis of the obtained results by addressing the following questions:

1) How frequently is it optimal to break the silence?

2) Which scenario is more favorable: "never intervene" or "endogenously intervene"? What about "never intervene" versus "always intervene"?

3) Under what conditions regarding ε_2 and *beta* do we choose to break or adhere to the quiet

period regime?

4) How do the model parameters influence the answers to these questions?

5) Is there symmetry in responses to positive and negative shocks?

4.1 Communication likelihood

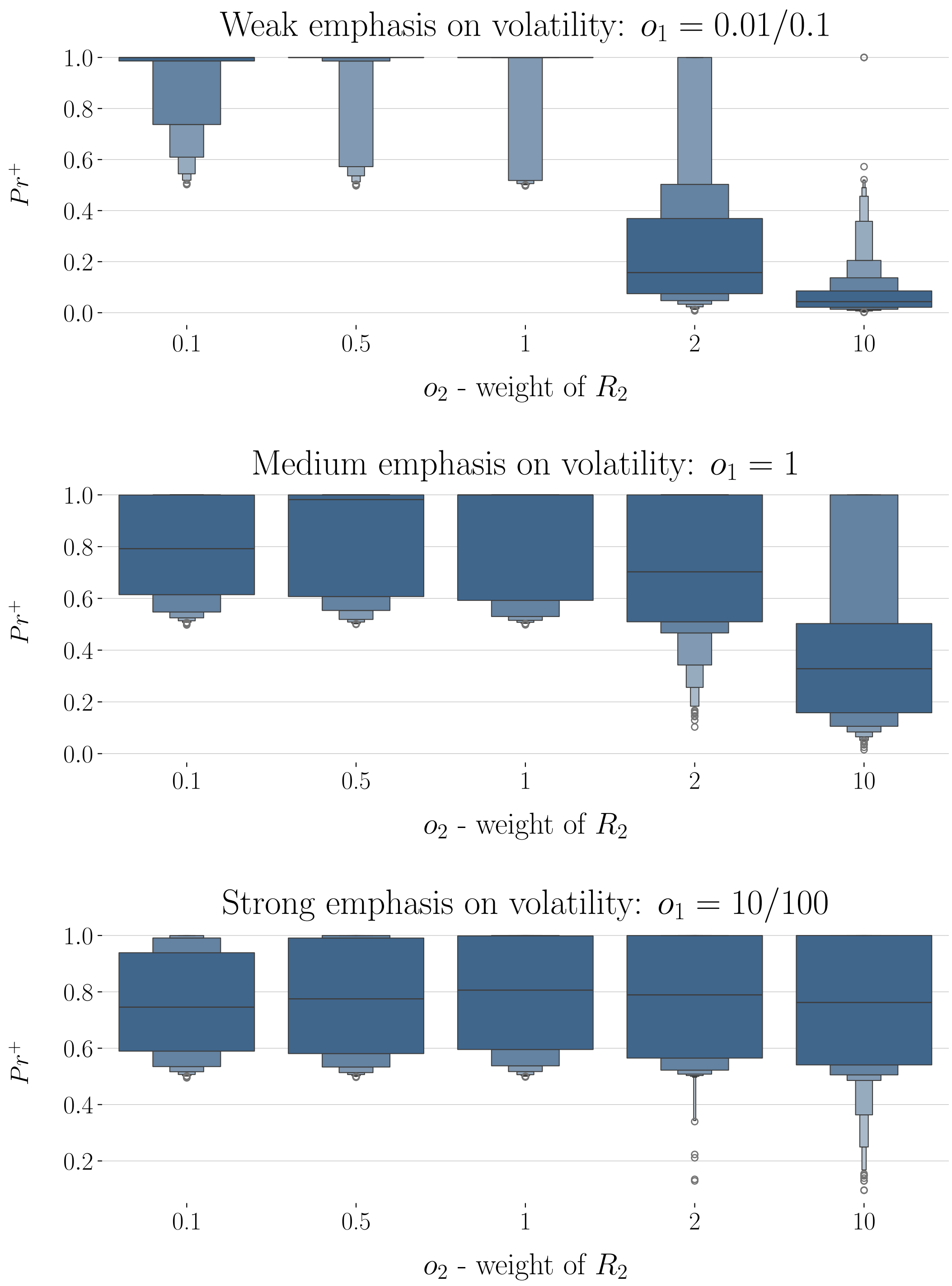
Figure 7 illustrates the likelihood of central bank intervention at various values of the weights for the second–period return R_2 and volatility of R_3. To provide a clearer visualization of our data, we utilize letter-value plots (Hofmann, Wickham, and Kafadar (2017)), which is an extended form of box plots. It includes boxes on either side of the median representing various distribution quantiles, such as the fourth, eighth, sixteenth, and so on. In Figure 7, we specifically focus on the distributions for o_2 values of 0.1, 0.5, 1, 2, and 10. These values correspond to scenarios where the weight of R_2 is lower than, slightly lower than, equal to, slightly higher than, and higher than R_3, respectively. Additionally, we have categorized variable o_1 into three groups: 0.01/0.1, 1, and 10/100. Detailed results are available in Appendix 6 for a comprehensive examination of all o_1 and o_2 values.

Without focusing on specific values of o_1 and o_2, the key observation from these graphs is the considerable heterogeneity in results. Instances exist where the central bank should refrain from intervention almost entirely, while in other scenarios, intervention is warranted at any values of shock ε_2 and confidence levels in the future decision β. To ensure robustness in our analysis, we also examine the more trivial volatility weight cases with $o_1 = 0.001$ and $o_1 = 0.0001$. The detailed findings from these scenarios are documented in Appendix 7. Based on the outcomes of this robustness check, we have decided not to include these scenarios in our future analyses.

The distribution of communication likelihood Pr^+ for the entire sample is illustrated in Figure 8. We observe considerable heterogeneity in the results, particularly noted by a majority of Pr^+ values being greater than 0.5. However, it's important to mention that our model parameters were set with relatively loose constraints, as we did not calibrate them against actual central bank communications data. Moving forward, a key focus will be to meticulously examine how varying these model parameters influences the frequency of central bank communications.

Another critical question is analyzing ε_2 and β parameters for a fixed value of Pr^+, under which the central bank should choose to communicate more frequently or, conversely, remain silent. Typical mappings, indicating the values of ε_2 and β at which the central bank should communicate, are depicted in Figures 9 and 10. For convenience, we have categorized the cases

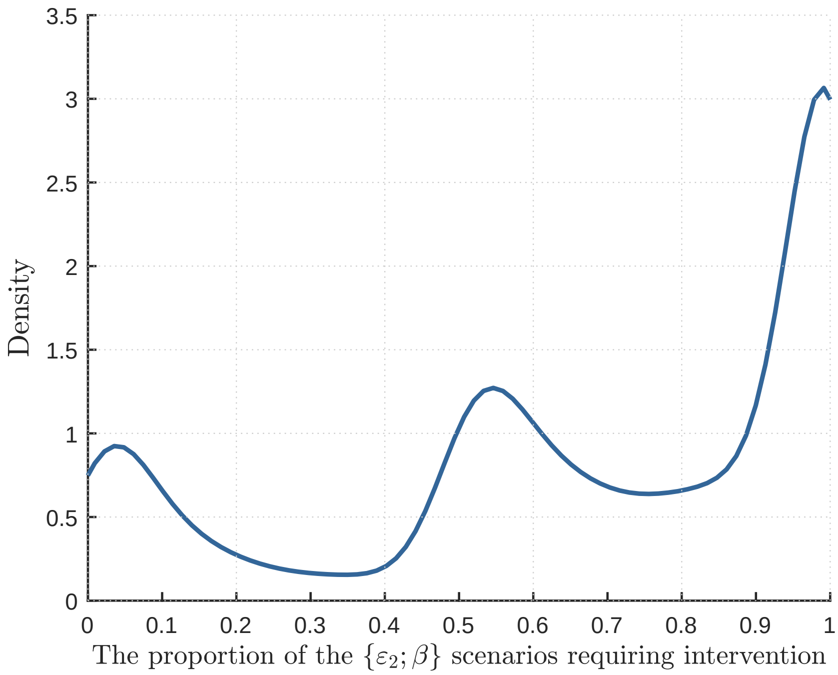
Figure 7 — Communication likelihood letter-value plots for different values of o_1 and o_2



into $Pr^+ \leq 0.5$ and $Pr^+ \geq 0.5$. A key observation from our analysis is the tendency of the central bank to communicate more frequently when the uncertainty regarding the upcoming decision is low. Conversely, when the level of dissent within the Board is high, the central bank communicates less often.

To identify the factors influencing central bank decisions, we initially examine the most ap-

Figure 8 — Density of the communication likelihood



parent candidates — weights o_1 and o_2. The impact of o_2, representing the weight of R_2 in the utility function, is straightforward: the more concerned the policymaker is about potential market spikes when breaking the silence, the less inclined it is to intervene by disclosing ε_2. The influence of this factor varies for different values of o_1. In a regression model of the form $Pr^+ = a_1 + a_2 \log_{10} o_2 + +a_3 \log_{10}^2 o_2 + const$, the logarithm of o_2 explains from 2.5% of the variance of Pr^+ at $o_1 = 100$ up to 74% of the variance of Pr^+ at $o_1 = 0.01$.

The weight of volatility, denoted as o_1 in the policymaker's utility function, has a distinct impact on Pr^+. For $o_2 \leq 1$, there is a negative influence — indicating that the policymaker intervenes less frequently as it places greater importance on volatility. However, in this scenario, o_1 explains only a modest portion of Pr^+ variance, approximately $10 - 15\%$ (other factors will be discussed later). Conversely, when $o_2 > 1$, the policymaker's increased concern about volatility leads to more frequent interventions. In this case, o_1 alone accounts for a substantial $50 - 70\%$ of Pr^+ variance.

Let us focus on specific $\{o_1, o_2\}$ pairs and the determinants of Pr^+ within each of these pairings. As observed earlier, substantial heterogeneity exists in Pr^+ for nearly every combination of o_1 and o_2 values. What might explain this variation? Intuitively, the magnitude of shocks does not affect Pr^+ in our model, as investors are capable of factoring it into their expectations.

The primary factors explaining the central bank's willingness to break the silence are δ_2 and

Figure 9 — Communication decision under different ε_2 and β for $Pr^+ < 0.5$

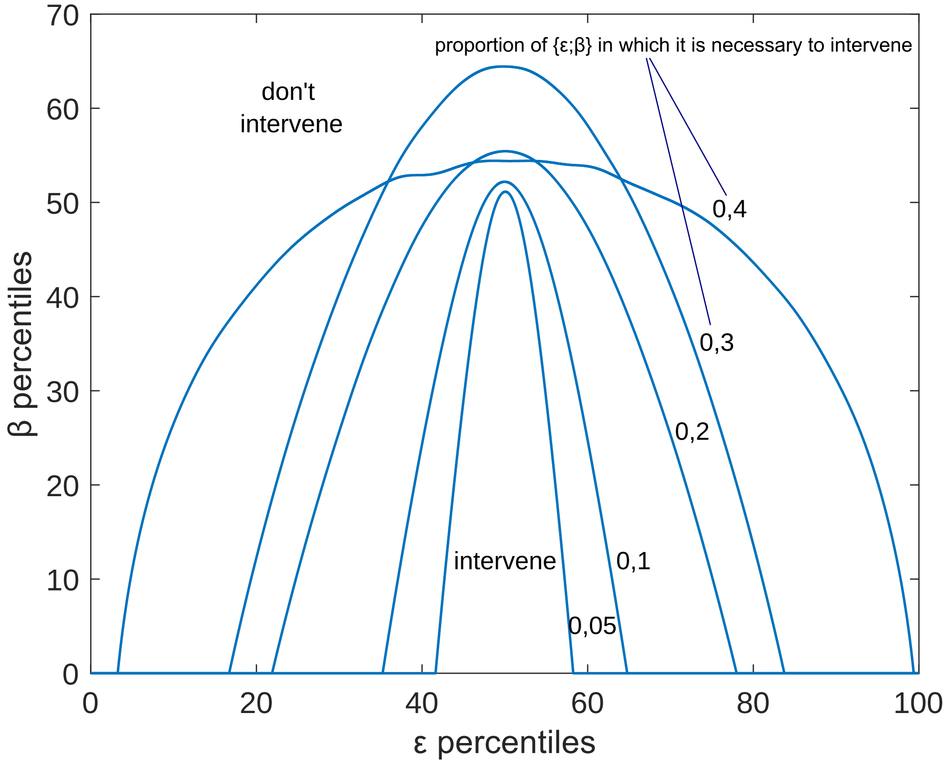
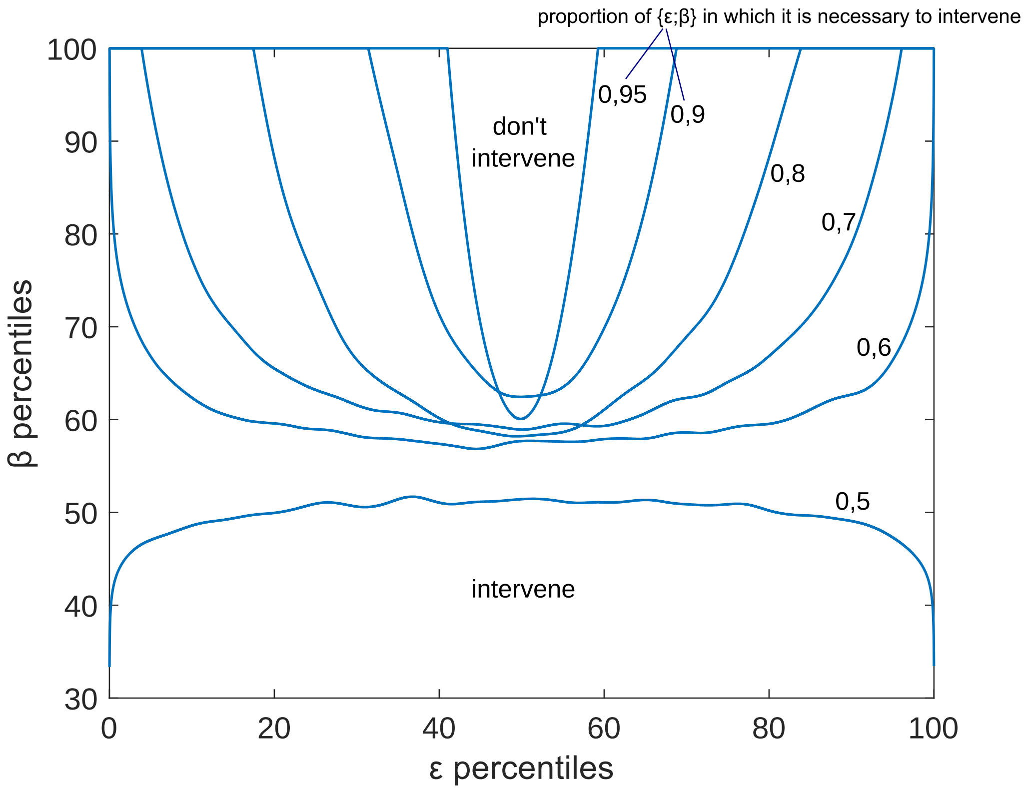


Figure 10 — Communication decision under different ε_2 and β for $Pr^+ \geq 0.5$



δ_3, representing the remaining uncertainty regarding shocks (the central bank's reaction to the ε_1 shock and discussion shock on the day of the meeting) after period 1. It's worth noting that the uncertainty regarding the initial shock ε_1 is already resolved by the time the central bank makes its decision at date 2, and thus, it does not directly impact the central bank's actions. To facilitate result comparison, we normalize the sum of δ_1, δ_2 and δ_3 to one, allowing us to examine the proportional magnitudes of uncertainties associated with different shocks.

To understand how the probability Pr^+ of communication within the quiet period changes with the increasing ratio of uncertainties associated with the second and third shocks $\sigma_{\varepsilon_2}/\sigma_{\varepsilon_3}$, we examine different combinations of o_1 and o_2. Figures 11 and 12 illustrate this relationship. Our analysis primarily focuses on scenario $o_2 = 1$ for the relative weight of R_3, as it evenly addresses policymaker's attention to market shocks at various points in time. Results for other values of o_2 are presented in Appendix 8. Additionally, in the second chart, we group the outcomes based on different o_1 values, specifically considering values 0.1, 1, and 10. Results for other values of o_1 are also presented in Appendix 8.

It can be observed that as the uncertainty regarding the central bank's reaction function becomes more pronounced, the willingness to communicate during the quiet period increases.

4.2 Scenario comparison

To assess the necessity of central bank intervention during the quiet period, we compare three distinct regimes: "never intervene," "always intervene," and "endogenously intervene." In the first two scenarios, we assume investors anticipate either no intervention or consistent intervention by the central bank. Consequently, at date 2 investors remain uninformed about β, and the distinction between $\mathrm{E}[\varepsilon_2^-]$ and $\mathrm{E}[\varepsilon_2^+]$ is irrelevant for them. The third scenario, as detailed in the previous section, involves the central bank's decision to intervene based on parameters such as ε_1, ε_2, α, θ, σ, δ_1, δ_2, δ_3, o_1 and o_2.

To initiate our comparison, we begin by evaluating the utility function values for the "never intervene," "always intervene," and "endogenously intervene" scenarios in Figure 13. As evident, opting for a regime of endogenous collegial communications during the quiet period appears reasonable for the central bank. The situation is almost a coin flip only for β values close to 1, but it still leans in favor of occasional communications.

In this case, the main driver of the outcome is the relative weight assigned to the yield R_2 — denoted as o_2. If the central bank places significant emphasis on mitigating a price jump at date

Figure 11 — Communication likelihood under different uncertainty sources for $o_2 = 1$

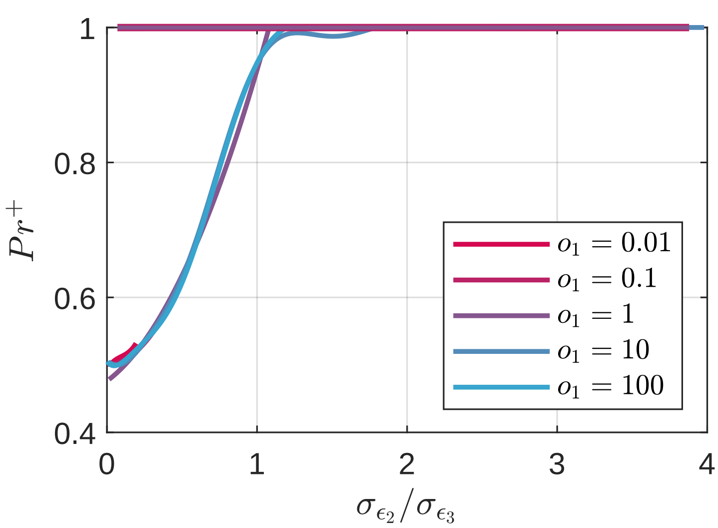
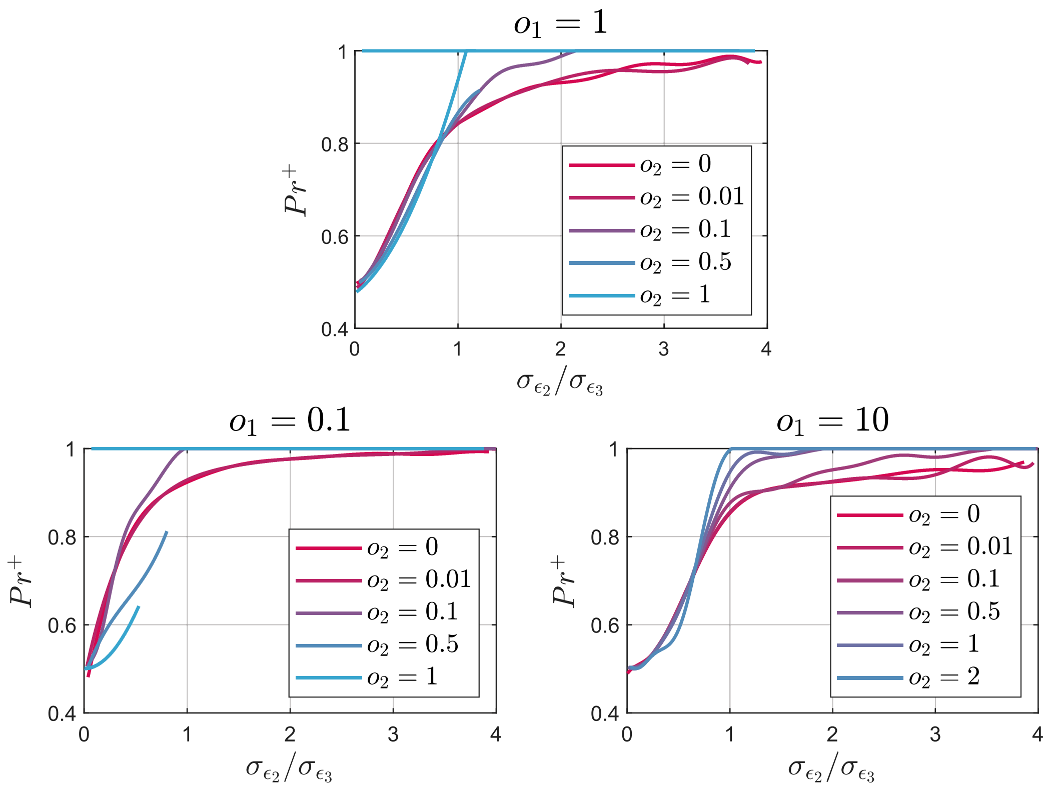
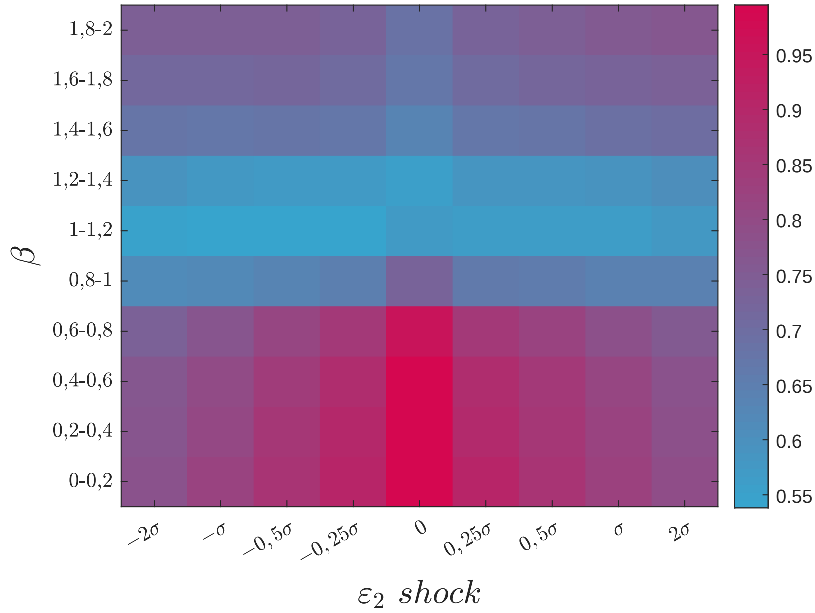


Figure 12 — Communication likelihood under different uncertainty sources



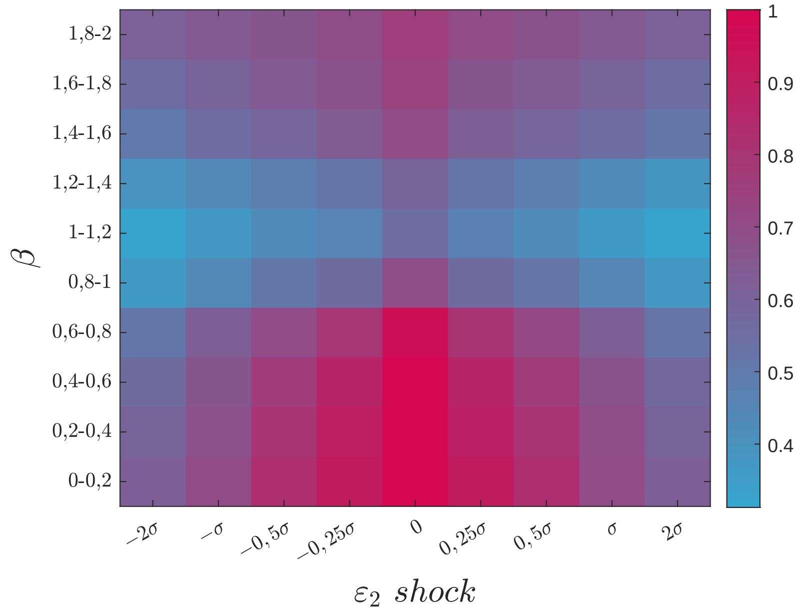
2 ($o_2 > 1$), it tends to intervene less frequently on average. This is because more substantial price jumps, resulting from the communication of ε_2, become less desirable. For cases where $o_2 = 0.5$ and $o_2 = 1$, the results are relatively trivial — the central bank should switch to the "endogenously intervene" regime; this can be observed in Appendix 9. A more meaningful

Figure 13 — Comparison of the "never intervene" and "endogenously intervene" regimes for the whole sample



Note: The graph indicates the probability that the value of the central bank's utility function in the "never intervene" regime is lower than in the "endogenously intervene" regime, given the distributions of ε_1, ε_3, α, β, θ, σ, δ_1, δ_2, δ_3; and o_1, o_2 are distributed equally among all the values used. For ε_2, discrete shocks of $-2\sigma_{\varepsilon_2}$, $-\sigma_{\varepsilon_2}$, $-0.5\sigma_{\varepsilon_2}$, $-0.25\sigma_{\varepsilon_2}$, 0, $0.25\sigma_{\varepsilon_2}$, $0.5\sigma_{\varepsilon_2}$, σ_{ε_2}, $2\sigma_{\varepsilon_2}$ are used, while for β all values from zero to two in steps of 0.002 are used, which are then grouped into 10 clusters in steps of 0.2.

Figure 14 — Comparison of the "never intervene" and "endogenously intervene" regimes for $o_2 = 2$



Note: The graph indicates the probability that the value of the central bank's utility function in the "never intervene" regime is lower than in the "endogenously intervene" regime, given the distributions of ε_1, ε_3, α, β, θ, σ, δ_1, δ_2, δ_3, and o_1 is distributed equally among all the values used. For ε_2, discrete shocks of $-2\sigma_{\varepsilon_2}$, $-\sigma_{\varepsilon_2}$, $-0.5\sigma_{\varepsilon_2}$, $-0.25\sigma_{\varepsilon_2}$, 0, $0.25\sigma_{\varepsilon_2}$, $0.5\sigma_{\varepsilon_2}$, σ_{ε_2}, $2\sigma_{\varepsilon_2}$ are used, while for β all values from zero to two in steps of 0.002 are used, which are then grouped into 10 clusters in steps of 0.2.

scenario, where the "endogenously intervene" regime does not consistently offer an advantage, is when $o_2 = 2$. The results of the comparison of regimes in this case can be seen in Figure 14.

In other words, even if the central bank expresses twice the concern about a price hike at date 2, on average, it remains sensible for the central bank to adhere to a regime of endogenous collegial communications during the quiet period. However, this result does not hold for β values close to 1 and large ε_2 shocks.

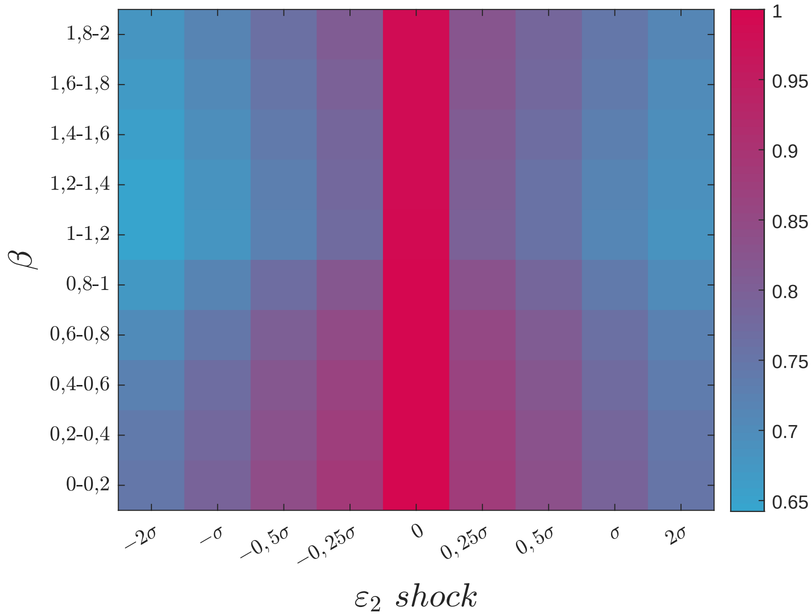
As illustrated in Figures 15 and 16, the results are similar for scenarios "never intervene" and "always intervene" for the entire sample. Nevertheless, in the borderline case $o_2 = 2$, the "always intervene" regime performs worse than "endogenously intervene," although it still exhibits reasonable performance compared to the "never intervene" option.

Results comparing communication regimes in the more trivial cases $o_2 = 0.5$ and $o_2 = 1$ can be seen in Appendix 10. As evidenced in our analysis, it is advantageous for the central bank to maintain a transparent communication policy during the quiet period, even in the face of large shocks (indicated by high modulo ε_2 values). In this context, we specifically explore market reactions at dates 2 and 3 in scenarios where the central bank intervenes, as detailed in Appendix 5. This comparison reveals that the size of the market reaction R_2 at date 2 is comparable to R_3, even when the central bank is optimally communicating. Therefore, the occurrence of sharp market reactions alone should not deter policymakers from breaking the quiet period regime when it is strategically beneficial.

4.3 Asymmetry

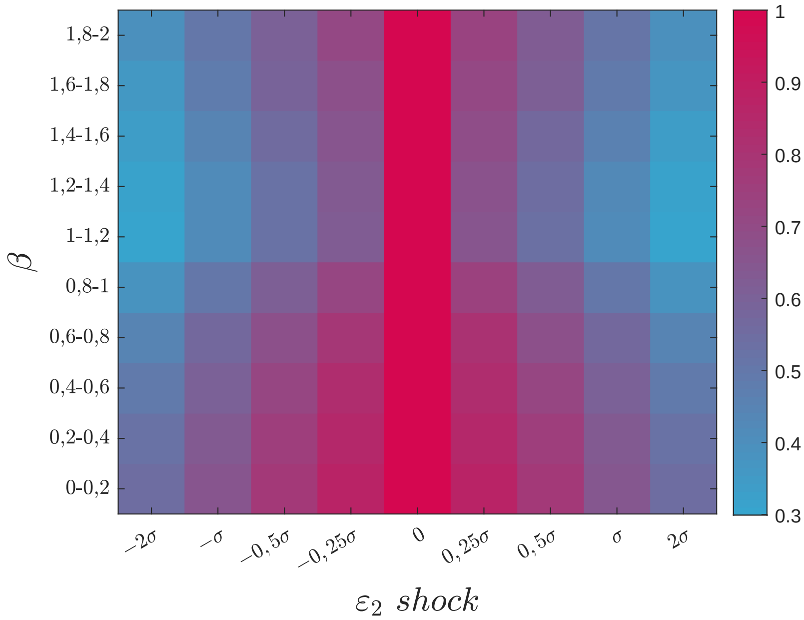
For the most part, the central bank's interventions in our model exhibit symmetry; that is, the policymaker reacts similarly to negative and positive shocks regarding whether or not to communicate. However, a notable exception introduces a novel mechanism. When the likelihood of communication, denoted as Pr^+, is close to one (indicating frequent interventions), the central bank becomes less inclined to communicate in the face of negative news. This asymmetry stems from the presence of the pre–announcement drift. Throughout the considered period, the stock price gradually increases due to the uncertainty risk premium demanded by investors in the absence of additional shocks. In scenarios where the central bank's estimate of ε_2 is negative, the mechanism unfolds as follows: if investors are aware that the central bank almost always intervenes collegially during the quiet period, the absence of intervention signals a significant β. Consequently, the lack of intervention not only fails to maintain the existing uncertainty but

Figure 15 — Comparison of "never intervene" and "always intervene" regimes for the whole sample



Note: The graph indicates the probability that the value of the central bank's utility function in the "never intervene" regime is lower than in the "always intervene" regime, given the distributions of ε_1, ε_3, α, β, θ, σ, δ_1, δ_2, δ_3; and o_1, o_2 are distributed equally among all the values used. For ε_2, discrete shocks of $-2\sigma_{\varepsilon_2}$, $-\sigma_{\varepsilon_2}$, $-0.5\sigma_{\varepsilon_2}$, $-0.25\sigma_{\varepsilon_2}$, 0, $0.25\sigma_{\varepsilon_2}$, $0.5\sigma_{\varepsilon_2}$, σ_{ε_2}, $2\sigma_{\varepsilon_2}$ are used, while for β all values from zero to two in steps of 0.002 are used, which are then grouped into 10 clusters in steps of 0.2.

Figure 16 — Comparison of "never intervene" and "always intervene" regimes for $o_2 = 2$

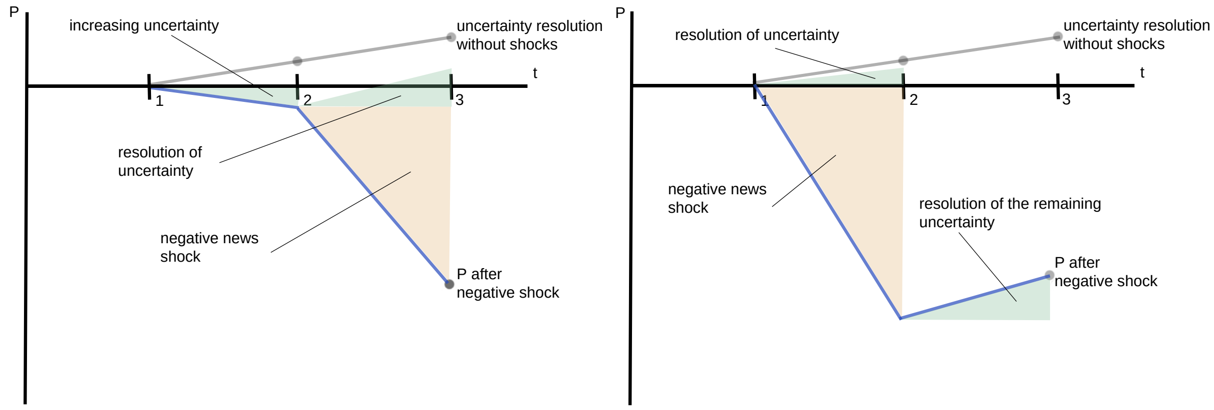


Note: The graph indicates the probability that the value of the central bank's utility function in the "never intervene" regime is lower than in the "always intervene" regime, given the distributions of ε_1, ε_3, α, β, θ, σ, δ_1, δ_2, δ_3, and o_1 is distributed equally among all the values used. For ε_2, discrete shocks of $-2\sigma_{\varepsilon_2}$, $-\sigma_{\varepsilon_2}$, $-0.5\sigma_{\varepsilon_2}$, $-0.25\sigma_{\varepsilon_2}$, 0, $0.25\sigma_{\varepsilon_2}$, $0.5\sigma_{\varepsilon_2}$, σ_{ε_2}, $2\sigma_{\varepsilon_2}$ are used, while for β all values from zero to two in steps of 0.002 are used, which are then grouped into 10 clusters in steps of 0.2.

actually increases it. Thus, at date 2, we witness a continued process of uncertainty buildup. Investors demand a higher risk premium at date 2, leading to a decline in the price P_2 (see Figure 17 below). Subsequently, at date 3, with the revelation of negative ε_2, the price P_3 experiences a further decrease. So, in the scenario of a negative realization of ε_2 and the absence of central bank communication at date 2, this mechanism essentially mimics the central bank's role in smoothing out financial market fluctuations. However, when the central bank communicates at date 2, revealing ε_2, the price falls sharply and even overshoots the final price. This happens because, at high Pr^+, investors do not significantly lower their estimate of β, as it remains close to the unconditional mean. Consequently, they continue to demand a substantial risk premium or, in other words, a positive pre–announcement drift still lies ahead. This dynamic results in more pronounced market swings, as illustrated in Figure 17.

Empirically, analogous mechanism have been identified by Kawamura et al. (2019) for the

Figure 17 — Central bank uncertainty management mechanism



1: Quiet period   2: Communication

Bank of Japan, where the central bank deliberately obfuscates reports to avoid disclosing unfavorable private information. While this behavior aligns with our model's findings, alternative explanations may exist. One possibility is that the central bank aims to manipulate the economy, reminiscent of dynamic inconsistency models. However, our model presents a shorter–term story: when faced with a negative shock ε_2, the central bank might strategically choose not to communicate information to the market. This decision is driven by investors' realization that the central bank does not communicate only when uncertainty about the upcoming meeting is very high. This, in turn, leads to higher uncertainty and lower stock price, forcing investors to do some of the central bank's work themselves, moving the stock price toward fundamentals, even without explicit communication in that direction.

5 Discussion of Potential Policy Implications

While operating mechanisms may vary across central banks, the collegiality of the decision–making process on the meeting day is less significant for our results. However, the collegiality of the communication policy, which also differs among central banks, is more important. As described in Ehrmann, Fratzscher (2005), the Fed adopts an individualistic communication strategy, whereas the ECB and the Bank of England employ a more collegial approach to communication. Our research underscores the potential advantages of centralized communication during the quiet period, which involves varying degrees of change in current practices across central banks. We suggest that these changes, albeit varying degrees, may apply to a wide range of monetary authorities. In particular, moving to more centralized communications may mitigate the effects of cacophonic communications, as was suggested in Vissing–Jorgensen (2019), who argued that the Fed should consider transitioning to a more centralized communication approach.

6 Concluding remarks

When evaluating whether the central bank should always adhere to a quiet period policy, it becomes imperative for the policymaker to extend its focus beyond the immediate consequences of such communications. Our financial market model captures a multivariate trade–off. It requires the central bank to weigh the instantaneous market reactions to quiet period breaches against potential impacts on the forthcoming Board meeting and changes in market volatility. In this context, a more dynamic approach involving either endogenous or regular communication during the quiet period could yield better results. This approach should be collegial and convey the central bank's reaction function. Despite potential asymmetry where the central bank refrains from communicating negative news at times, such a communication policy can effectively dampen financial market fluctuations and give investors more precise information about the central bank's assessment of the economy.

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Appendix

Appendix 1 — Detailed algorithm for generating observations using the Monte Carlo method

Back to the text

To find the mapping $f : (S_1,\ S_2,\ \alpha,\ B,\ \theta,\ \sigma,\ \delta_1,\ \delta_2,\ \delta_3) \to \{1, 2\}$, the algorithm focuses on classifying each pair $\{\varepsilon_2, \beta\}$ into one of two categories: Class 1 (no communication) or Class 2 (presence of communication), for a given set $\{\varepsilon_1,\ \alpha,\ \theta,\ \sigma,\ \delta_1,\ \delta_2,\ \delta_3\}$. This task closely resembles a clustering problem in machine learning since, in the context of unsupervised learning, the classification problem is a clustering problem. However, unlike traditional clustering methods that rely on a metric measuring the distance of a point from its class, our approach focuses on the characteristics of the classes themselves and the coordinates of the points. Consider this scenario: if we take a finite set of points and assign a class to each, we determine the function $\mathrm{U}^w - \mathrm{U}^{w/o}$ for each point. Notably, for a particular point this value depends on collective characteristics of all points assigned to each class ($\mathrm{E}_2[\beta^-]$, $\mathrm{E}_2[\beta^+]$, $\mathrm{E}_1[\varepsilon_2^+]$, $\mathrm{E}_2[\varepsilon_2^-]$, $\mathrm{Var}_2[\varepsilon_2^-]$, and Pr^+) and on the coordinates of the point (ε_2 and β), but not on the class of this particular point.

To optimize our classification process, we draw inspiration from k–medoid and k–means algorithms in machine learning. These algorithms are particularly useful as they allow for iterative refinement of class assignments, gradually improving our classification accuracy. We tested two algorithms: one akin to Partitioning Around Medoids for the k–medoids problem, and another similar to the Hartigan–Wong algorithm for the k–means problem. Our findings revealed that the first algorithm, the analog of Partitioning Around Medoids, offers more stable convergence. Consequently, we have chosen it as our primary method.

In more detail, our iterative algorithm is as follows:

1a) Generate a random set of parameters $\{\varepsilon_1,\ \alpha,\ \theta,\ \sigma,\ \delta_1,\ \delta_2,\ \delta_3\}$ from their respective distributions.

1b) Generate 400 points $\{\varepsilon_2, \beta\}$ on an even grid, derived from the percentiles of the distributions of ε_2 and β. We denote this as the small model.

1c) Begin with a random allocation of points into classes $\{1, 2\}$ and iteratively reassign them in the following manner. For the current classes, calculate $\mathrm{E}_2[\beta^-]$, $\mathrm{E}_2[\beta^+]$, $\mathrm{E}_1[\varepsilon_2^+]$, $\mathrm{E}_2[\varepsilon_2^-]$, $\mathrm{Var}_2[\varepsilon_2^-]$, Pr^+ and the value of the function $\mathrm{U}^w - \mathrm{U}^{w/o}$ for each point. Recall that a point must belong to Class 1 (indicating no communication scenario) if $\mathrm{U}^w - \mathrm{U}^{w/o} < 0$. Accordingly, we identify some incorrectly classified points. We introduce the error metric in this case

$$Err = \begin{cases} 0, & \text{if } \mathrm{U}^w - \mathrm{U}^{w/o} < 0 \text{ and } class = 1 \\ 0, & \text{if } \mathrm{U}^w - \mathrm{U}^{w/o} > 0 \text{ and } class = 2 \\ |\,\mathrm{U}^w - \mathrm{U}^{w/o}\,|, & else. \end{cases} \tag{49}$$

Now, we determine the point with the highest error value by finding $\operatorname{argmax}_{\varepsilon_2,\beta} Err$ and then reassign this point to a different class. This step specifically targets the point with the most significant miscalculation in the $\mathrm{U}^w - \mathrm{U}^{w/o}$ function. Although this reassignment corrects the class for that point, it necessitates a recalculation of the values $\mathrm{E}_2[\beta^-]$, $\mathrm{E}_2[\beta^+]$, $\mathrm{E}_1[\varepsilon_2^+]$, $\mathrm{E}_2[\varepsilon_2^-]$, $\mathrm{Var}_2[\varepsilon_2^-]$, Pr^+. Thus, there is no guarantee that classes initially assigned correctly will remain so, or that those initially determined incorrectly will not be accidentally corrected.

1d) We repeat the process from the previous step, addressing the next point with the largest error, and continue this until all points are correctly classified, i.e., when $\sum_{i=1}^{10\ 000} Err_i = 0$. Instances where the algorithm does not converge to zero will be discussed later.

1e) We store the final class assignments from the small model to facilitate the initial class assignment in the large model.

1f) We generate 10 000 points $\{\varepsilon_2, \beta\}$ based on the distributions of ε_2 and β. We denote this as the large model.

1g) Initial classes are assigned to these points based on the closest corresponding point in the small model's solution.

1h) The steps 1c) to 1e) are repeated for this larger set of points. This process involves reclassifying any incorrectly assigned classes and, finally, storing all calculated values of expectations and variances: $\mathrm{E}_2[\beta^-]$, $\mathrm{E}_2[\beta^+]$, $\mathrm{E}_1[\varepsilon_2^+]$, $\mathrm{E}_2[\varepsilon_2^-]$, $\mathrm{Var}_2[\varepsilon_2^-]$, and Pr^+.

2) The second step of our algorithm, which is not computationally complex, involves simply calculating the values of the utility function $\mathrm{U}^w - \mathrm{U}^{w/o}$ and comparing them to zero. Given its computational efficiency, we can afford to use a denser grid for this analysis. We partition our space $(\varepsilon_2, \beta) : (-\infty, \infty) * [0, 2]$ using a $10\ 000 * 10\ 000$ grid. Each node on this grid is assigned uniformly across β and at every 10 000th percentile for ε_2. Using the values of $\mathrm{E}_2[\beta^-]$, $\mathrm{E}_2[\beta^+]$, $\mathrm{E}_1[\varepsilon_2^+]$, $\mathrm{E}_2[\varepsilon_2^-]$, $\mathrm{Var}_2[\varepsilon_2^-]$, Pr^+ obtained from the first step, we then estimate $\mathrm{U}^w - \mathrm{U}^{w/o}$ for each point on the grid. Based on these estimations, each point is assigned to the appropriate class,

ending the algorithm.

Empirically, our algorithm tends to converge quickly, typically within $\leq 6\ 000$ iterations, resulting in a stable separation of all points into two classes and eliminating erroneously assigned classes $\sum_{i=1}^{10\ 000} Err_i = 0$. However, in some rare cases, convergence is not as swift. This slower convergence is often attributed to the algorithm finding local extrema instead of global ones, akin to the behavior seen in k–means–like algorithms. In such scenarios, the algorithm might enter a loop, repeatedly changing the class of one or more points without achieving $\sum_{i=1}^{10\ 000} Err_i = 0$.

To address these cases, we've implemented several constraints in the first step of the algorithm. Firstly, if the loop results in exactly one erroneously defined point, and this recurs over ten iterations, we halt the algorithm. Secondly, we set a maximum of 10 000 iterations, after which we stop the algorithm upon reaching a local minimum within the loop and proceed with the results to the second step. Thirdly, if the loop consistently shows the same number or more than 30 erroneously defined point classes (i.e., more than 0.3% of all points), the algorithm is stopped after 11 000 iterations, and we move to the second step.

These conditions do introduce a potential vulnerability to the algorithm's accuracy. However, the second step acts as a safeguard, checking the correctness of the algorithm's outcomes. In our observations, loops leading to more than 10 000 iterations occur in less than 4% of cases. In two–thirds of these instances, the number of incorrectly defined classes is 10 or fewer ($\leq 0.1\%$ of points). In 1.08% of cases, errors range between 10 and 30 (0.1% to 0.3% of points), and in 0.25% of cases, errors exceed 30 ($> 0.3\%$ of points).

In this case, the second step of the algorithm serves as a method to verify its accuracy. Specifically, it checks whether the class partitioning generated matches that of the first step. We directly assign points to classes using the parameters obtained in the first step — $\mathrm{E}_2[\beta^-]$, $\mathrm{E}_2[\beta^+]$, $\mathrm{E}_1[\varepsilon_2^+]$, $\mathrm{E}_2[\varepsilon_2^-]$, $\mathrm{Var}_2[\varepsilon_2^-]$, Pr^+ — by comparing $\mathrm{U}^w - \mathrm{U}^{w/o}$ with zero. Subsequently, we assess how closely these parameter values, estimated during the first step, align with those derived from the second step.

Appendix 2 — Detailed calculations from the *Equilibrium* section

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Equation (29):

$$
\begin{aligned}
&\mathrm{Var}_1[\theta_1\sigma\widetilde{\varepsilon}_2 - \alpha\sigma^2\widetilde{\delta}_3(\theta_1 - \frac{1}{2})] = \mathrm{Var}_1[\theta_1\sigma\widetilde{\varepsilon}_2] + \mathrm{Var}_1[\alpha\sigma^2\widetilde{\delta}_3(\theta_1 - \frac{1}{2})] - \\
&-2\,\mathrm{cov}[\theta_1\sigma\widetilde{\varepsilon}_2,\ \alpha\sigma^2\widetilde{\delta}_3(\theta_1 - \frac{1}{2})] = \theta_1^2\sigma^2\,\mathrm{Var}_1[\widetilde{\varepsilon}_2] + \alpha^2\sigma^4(\theta_1 - \frac{1}{2})^2\,\mathrm{Var}_1[\widetilde{\delta}_3] - \\
&-2\,\mathrm{E}_1[\theta_1(\theta_1 - \frac{1}{2})\alpha\sigma^3\widetilde{\varepsilon}_2\widetilde{\delta}_3] + 2\,\mathrm{E}_1[\theta_1\sigma\widetilde{\varepsilon}_2]\,\mathrm{E}_1[\alpha\sigma^2\widetilde{\delta}_3(\theta_1 - \frac{1}{2})] = \theta_1^2\sigma^2\,\mathrm{Var}_1[\widetilde{\varepsilon}_2] + \\
&+\alpha^2\sigma^4(\theta_1 - \frac{1}{2})^2\,\mathrm{Var}_1[\widetilde{\delta}_3] - 2\theta_1(\theta_1 - \frac{1}{2})\alpha\sigma^3\,\mathrm{E}_1[\widetilde{\varepsilon}_2\widetilde{\delta}_3] + 2\theta_1(\theta_1 - \frac{1}{2})\alpha\sigma^3\,\mathrm{E}_1[\widetilde{\varepsilon}_2]\,\mathrm{E}_1[\widetilde{\delta}_3].
\end{aligned}
\tag{50}
$$

Equation (32):

$$
\begin{aligned}
&\mathrm{Var}[\widetilde{\delta}_3] = \mathrm{E}_1[\widetilde{\delta}_3]^2 - \mathrm{E}_1^2[\widetilde{\delta}_3] = Pr^+\,\mathrm{E}_1[\beta^+]^2\delta_3^2 + (1 - Pr^+)(\mathrm{Var}_2[\varepsilon_2^-] + \mathrm{E}_2[\beta^-]\delta_3)^2 - \\
&-(Pr^+\,\mathrm{E}_1[\beta^+]\delta_3 + (1 - Pr^+)(\mathrm{Var}_2[\varepsilon_2^-] + \mathrm{E}_2[\beta^-]\delta_3))^2 = \\
&= Pr^+(1 - Pr^+)(\mathrm{E}_1[\beta^+]\delta_3 - \mathrm{Var}_2[\varepsilon_2^-] - \mathrm{E}_2[\beta^-]\delta_3)^2.
\end{aligned}
\tag{51}
$$

Equation (33):

$$
\begin{aligned}
&\mathrm{Var}_1[\widetilde{\varepsilon}_2] = \mathrm{E}_1[\widetilde{\varepsilon}_2]^2 - \mathrm{E}_1^2[\widetilde{\varepsilon}_2] = Pr^+\,\mathrm{E}_1[\varepsilon_2^+]^2 + (1 - Pr^+)\,\mathrm{E}_2[\varepsilon_2^-]^2 - (Pr^+\,\mathrm{E}_1[\varepsilon_2^+] + \\
&+(1 - Pr^+)\,\mathrm{E}_2[\varepsilon_2^-])^2 = Pr^+(1 - Pr^+)(\mathrm{E}_1[\varepsilon_2^+] - \mathrm{E}_2[\varepsilon_2^-])^2.
\end{aligned}
\tag{52}
$$

Equation (34):

$$
\begin{aligned}
&\mathrm{E}_1[\widetilde{\varepsilon}_2\widetilde{\delta}_3] = Pr^+\,\mathrm{E}_1[\varepsilon_2^+\beta^+\delta_3] + (1 - Pr^+)\,\mathrm{E}_2[\varepsilon_2^-(\mathrm{Var}_2[\varepsilon_2^-] + \beta^-\delta_3)] = Pr^+\delta_3\,\mathrm{E}_1[\varepsilon_2^+\beta^+] + \\
&+(1 - Pr^+)\,\mathrm{E}_2[\varepsilon_2^-]\,\mathrm{Var}_2[\varepsilon_2^-] + (1 - Pr^+)\delta_3\,\mathrm{E}_2[\varepsilon_2^-\beta^-] = \\
&= Pr^+\delta_3\,\mathrm{E}_1[\varepsilon_2^+\,\mathrm{E}_2[\beta^+]] + (1 - Pr^+)\,\mathrm{E}_2[\varepsilon_2^-]\,\mathrm{Var}_2[\varepsilon_2^-] + (1 - Pr^+)\delta_3\,\mathrm{E}_1[\mathrm{E}_2[\varepsilon_2^-]\,\mathrm{E}_2[\beta^-]] = \\
&= Pr^+\delta_3\,\mathrm{E}_1[\varepsilon_2^+]\,\mathrm{E}_1[\beta^+] + (1 - Pr^+)\,\mathrm{E}_2[\varepsilon_2^-]\,\mathrm{Var}_2[\varepsilon_2^-] + (1 - Pr^+)\delta_3\,\mathrm{E}_2[\varepsilon_2^-]\,\mathrm{E}_2[\beta^-].
\end{aligned}
\tag{53}
$$

Equation (40):

$$\begin{aligned}\mathrm{E}_2^{w/o}[R_2] = \mathrm{E}_2^{w/o}[P_2 - P_1] = \mathrm{E}_2^{w/o}[\bar{D} + \sigma\varepsilon_1 + \sigma\widetilde{\varepsilon_2} - \alpha\sigma^2\widetilde{\delta_3} - \bar{D} - \\ -\sigma\varepsilon_1 - \sigma Pr^+ \mathrm{E}_1[\varepsilon_2^+] - \sigma(1 - Pr^+)\,\mathrm{E}_2[\varepsilon_2^-] + rp_1] = \mathrm{E}_2^{w/o}[\sigma\widetilde{\varepsilon_2} - \alpha\sigma^2\widetilde{\delta_3} - \sigma Pr^+ \mathrm{E}_1[\varepsilon_2^+] - \\ -\sigma(1 - Pr^+)\,\mathrm{E}_2[\varepsilon_2^-] + rp_1] = \mathrm{E}_2^{w/o}[\sigma\,\mathrm{E}_2[\varepsilon_2^-] - \alpha\sigma^2(\mathrm{Var}_2[\varepsilon_2^-] + \mathrm{E}_2[\beta^-]\delta_3) - \\ -\sigma Pr^+ \mathrm{E}_1[\varepsilon_2^+] - \sigma(1 - Pr^+)\,\mathrm{E}_2[\varepsilon_2^-] + rp_1] = -\alpha\sigma^2(\mathrm{Var}_2[\varepsilon_2^-] + \mathrm{E}_2[\beta^-]\delta_3) - \\ -\sigma Pr^+ \mathrm{E}_1[\varepsilon_2^+] + \sigma Pr^+ \mathrm{E}_2[\varepsilon_2^-] + rp_1.\end{aligned} \tag{54}$$

Equation (41):

$$\begin{aligned}\mathrm{Var}_2^{w/o}[R_3] = \mathrm{Var}_2^{w/o}[P_3 - P_2] = \mathrm{Var}_2^{w/o}[\bar{D} + \sigma\varepsilon_1 + \sigma\varepsilon_2 + \sigma\varepsilon_3 - \bar{D} - \sigma\varepsilon_1 - \sigma\widetilde{\varepsilon_2} + \\ +\alpha\sigma^2\widetilde{\delta_3}] = \mathrm{Var}_2^{w/o}[\sigma\varepsilon_2 + \sigma\varepsilon_3 - \sigma\widetilde{\varepsilon_2} + \alpha\sigma^2\widetilde{\delta_3}] = \mathrm{Var}_2^{w/o}[\sigma\varepsilon_2^- + \sigma\varepsilon_3 - \sigma\,\mathrm{E}_2[\varepsilon_2^-] + \\ +\alpha\sigma^2(\mathrm{Var}_2[\varepsilon_2^-] + \mathrm{E}_2[\beta^-]\delta_3)] = \mathrm{Var}_2^{w/o}[\sigma\varepsilon_2^- + \sigma\varepsilon_3] = \sigma^2\,\mathrm{Var}_2[\varepsilon_2^-] + \sigma^2\,\mathrm{E}_2[\beta^-]\delta_3.\end{aligned} \tag{55}$$

Equation (44):

$$\begin{aligned}\mathrm{E}_2^{w}[R_2] = \mathrm{E}_2^{w}[P_2 - P_1] = \mathrm{E}_2^{w}[\bar{D} + \sigma\varepsilon_1 + \sigma\widetilde{\varepsilon_2} - \alpha\sigma^2\widetilde{\delta_3} - \bar{D} - \sigma\varepsilon_1 - \sigma Pr^+ \mathrm{E}_1[\varepsilon_2^+] - \\ -\sigma(1 - Pr^+)\,\mathrm{E}_2[\varepsilon_2^-] + rp_1] = \mathrm{E}_2^{w}[\sigma\widetilde{\varepsilon_2} - \alpha\sigma^2\widetilde{\delta_3} - \sigma Pr^+ \mathrm{E}_1[\varepsilon_2^+] - \\ -\sigma(1 - Pr^+)\,\mathrm{E}_2[\varepsilon_2^-] + rp_1] = \mathrm{E}_2^{w}[\sigma\varepsilon_2 - \alpha\sigma^2\,\mathrm{E}_2[\beta^+]\delta_3 - \sigma Pr^+ \mathrm{E}_1[\varepsilon_2^+] - \\ -\sigma(1 - Pr^+)\,\mathrm{E}_2[\varepsilon_2^-] + rp_1] = \sigma\varepsilon_2 - \alpha\sigma^2\,\mathrm{E}_2[\beta^+]\delta_3 - \\ -\sigma Pr^+ \mathrm{E}_1[\varepsilon_2^+] - \sigma(1 - Pr^+)\,\mathrm{E}_2[\varepsilon_2^-] + rp_1.\end{aligned} \tag{56}$$

Appendix 3 — Second–order condition for V_1'

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$$
\begin{aligned}
\frac{\partial^2 \mathrm{E}_1[J_2]}{\partial^2\theta_1} = -\frac{1}{2}\alpha\frac{\partial^2 V_1}{\partial^2\theta_1} = -\frac{1}{2}\alpha\Big[2\sigma^2 Pr^+(1-Pr^+)(\mathrm{E}_1[\varepsilon_2^+]-\mathrm{E}_2[\varepsilon_2^-])^2+\\
+2\alpha^2\sigma^4 Pr^+(1-Pr^+)(\mathrm{E}_1[\beta^+]\delta_3-\mathrm{Var}_2[\varepsilon_2^-]-\mathrm{E}_2[\beta^-]\delta_3)^2-4\alpha\sigma^3\big(Pr^+\delta_3\,\mathrm{E}_1[\varepsilon_2^+\beta^+]+\\
+(1-Pr^+)\,\mathrm{E}_2[\varepsilon_2^-]\,\mathrm{Var}_2[\varepsilon_2^-]+(1-Pr^+)\delta_3\,\mathrm{E}_2[\varepsilon_2^-\beta^-]\big)+4\alpha\sigma^3\big(Pr^+\,\mathrm{E}_1[\varepsilon_2^+]+\\
+(1-Pr^+)\,\mathrm{E}_2[\varepsilon_2^-]\big)\big(Pr^+\,\mathrm{E}_1[\beta^+]\delta_3+(1-Pr^+)(\mathrm{Var}_2[\varepsilon_2^-]+\mathrm{E}_2[\beta^-]\delta_3)\big)\Big]=\\
=-\frac{1}{2}\alpha\Big[2\sigma^2 Pr^+(1-Pr^+)(\mathrm{E}_1[\varepsilon_2^+]-\mathrm{E}_2[\varepsilon_2^-])^2+2\alpha^2\sigma^4 Pr^+(1-Pr^+)(\mathrm{E}_1[\beta^+]\delta_3-\\
-\mathrm{Var}_2[\varepsilon_2^-]-\mathrm{E}_2[\beta^-]\delta_3)^2-4\alpha\sigma^3\big(Pr^+\delta_3\,\mathrm{E}_1[\varepsilon_2^+\,\mathrm{E}_2[\beta^+]]+(1-Pr^+)\,\mathrm{E}_2[\varepsilon_2^-]\,\mathrm{Var}_2[\varepsilon_2^-]+\\
+(1-Pr^+)\delta_3\,\mathrm{E}_1[\mathrm{E}_2[\varepsilon_2^-]\,\mathrm{E}_2[\beta^-]]\big)+4\alpha\sigma^3\big(Pr^+\,\mathrm{E}_1[\varepsilon_2^+]+\\
+(1-Pr^+)\,\mathrm{E}_2[\varepsilon_2^-]\big)\big(Pr^+\,\mathrm{E}_1[\beta^+]\delta_3+(1-Pr^+)(\mathrm{Var}_2[\varepsilon_2^-]+\mathrm{E}_2[\beta^-]\delta_3)\big)\Big]=\\
=-\frac{1}{2}\alpha\Big[2\sigma^2 Pr^+(1-Pr^+)(\mathrm{E}_1[\varepsilon_2^+]-\mathrm{E}_2[\varepsilon_2^-])^2+2\alpha^2\sigma^4 Pr^+(1-Pr^+)(\mathrm{E}_1[\beta^+]\delta_3-\\
-\mathrm{Var}_2[\varepsilon_2^-]-\mathrm{E}_2[\beta^-]\delta_3)^2-4\alpha\sigma^3\big(Pr^+\delta_3\,\mathrm{E}_1[\varepsilon_2^+]\,\mathrm{E}_1[\beta^+]+(1-Pr^+)\,\mathrm{E}_2[\varepsilon_2^-]\,\mathrm{Var}_2[\varepsilon_2^-]+\\
+(1-Pr^+)\delta_3\,\mathrm{E}_1[\varepsilon_2^-]\,\mathrm{E}_1[\beta^-]\big)+4\alpha\sigma^3\big(Pr^+\,\mathrm{E}_1[\varepsilon_2^+]+\\
+(1-Pr^+)\,\mathrm{E}_2[\varepsilon_2^-]\big)\big(Pr^+\,\mathrm{E}_1[\beta^+]\delta_3+(1-Pr^+)(\mathrm{Var}_2[\varepsilon_2^-]+\mathrm{E}_2[\beta^-]\delta_3)\big)\Big]=\\
=-\frac{1}{2}\alpha\Big[2\sigma^2 Pr^+(1-Pr^+)(\mathrm{E}_1[\varepsilon_2^+]-\mathrm{E}_2[\varepsilon_2^-])^2+2\alpha^2\sigma^4 Pr^+(1-Pr^+)(\mathrm{E}_1[\beta^+]\delta_3-\\
-\mathrm{Var}_2[\varepsilon_2^-]-\mathrm{E}_2[\beta^-]\delta_3)^2+4\alpha\sigma^3\Big(-Pr^+\delta_3\,\mathrm{E}_1[\varepsilon_2^+]\,\mathrm{E}_1[\beta^+]-(1-Pr^+)\,\mathrm{E}_2[\varepsilon_2^-]\,\mathrm{Var}_2[\varepsilon_2^-]-\\
-(1-Pr^+)\delta_3\,\mathrm{E}_2[\varepsilon_2^-]\,\mathrm{E}_2[\beta^-]+(Pr^+)^2\,\mathrm{E}_1[\varepsilon_2^+]\,\mathrm{E}_1[\beta^+]\delta_3+\\
+Pr^+(1-Pr^+)\,\mathrm{E}_1[\varepsilon_2^+](\mathrm{Var}_2[\varepsilon_2^-]+\mathrm{E}_2[\beta^-]\delta_3)+\\
+Pr^+(1-Pr^+)\,\mathrm{E}_2[\varepsilon_2^-]\,\mathrm{E}_1[\beta^+]\delta_3+(1-Pr^+)^2\,\mathrm{E}_2[\varepsilon_2^-](\mathrm{Var}_2[\varepsilon_2^-]+\mathrm{E}_2[\beta^-]\delta_3)\Big)\Big]=\\
=-\frac{1}{2}\alpha\Big[2\sigma^2 Pr^+(1-Pr^+)(\mathrm{E}_1[\varepsilon_2^+]-\mathrm{E}_2[\varepsilon_2^-])^2+2\alpha^2\sigma^4 Pr^+(1-Pr^+)(\mathrm{E}_1[\beta^+]\delta_3-\\
-\mathrm{Var}_2[\varepsilon_2^-]-\mathrm{E}_2[\beta^-]\delta_3)^2+4\alpha\sigma^3\Big(-\delta_3\,\mathrm{E}_1[\varepsilon_2^+]\,\mathrm{E}_1[\beta^+]Pr^+(1-Pr^+)-\\
-\mathrm{E}_2[\varepsilon_2^-](\mathrm{Var}_2[\varepsilon_2^-]+\mathrm{E}_2[\beta^-]\delta_3)Pr^+(1-Pr^+)+Pr^+(1-Pr^+)\,\mathrm{E}_1[\varepsilon_2^+](\mathrm{Var}_2[\varepsilon_2^-]+\\
+\mathrm{E}_2[\beta^-]\delta_3)+Pr^+(1-Pr^+)\,\mathrm{E}_2[\varepsilon_2^-]\,\mathrm{E}_1[\beta^+]\delta_3\Big)\Big]=\\
=-\frac{1}{2}\alpha\Big[2\sigma^2 Pr^+(1-Pr^+)(\mathrm{E}_1[\varepsilon_2^+]-\mathrm{E}_2[\varepsilon_2^-])^2+2\alpha^2\sigma^4 Pr^+(1-Pr^+)(\mathrm{E}_1[\beta^+]\delta_3-
\end{aligned}
\tag{57}
$$

$$- \mathrm{Var}_2[\varepsilon_2^-] - \mathrm{E}_2[\beta^-]\delta_3)^2 + 4\alpha\sigma^3 Pr^+(1-Pr^+)\Big(\mathrm{E}_1[\varepsilon_2^+](-\delta_3\,\mathrm{E}_1[\beta^+] + \mathrm{Var}_2[\varepsilon_2^-] +$$

$$+ \mathrm{E}_2[\beta^-]\delta_3) - \mathrm{E}_2[\varepsilon_2^-](\mathrm{Var}_2[\varepsilon_2^-] + \mathrm{E}_2[\beta^-]\delta_3 - \mathrm{E}_1[\beta^+]\delta_3)\Big)\Big] =$$

$$= -\frac{1}{2}\alpha\Big[2\sigma^2 Pr^+(1-Pr^+)(\mathrm{E}_1[\varepsilon_2^+] - \mathrm{E}_2[\varepsilon_2^-])^2 + 2\alpha^2\sigma^4 Pr^+(1-Pr^+)(\mathrm{E}_1[\beta^+]\delta_3 -$$
$$- \mathrm{Var}_2[\varepsilon_2^-] - \mathrm{E}_2[\beta^-]\delta_3)^2 + 4\alpha\sigma^3 Pr^+(1-Pr^+)(\mathrm{E}_1[\varepsilon_2^+] - \mathrm{E}_2[\varepsilon_2^-])(-\delta_3\,\mathrm{E}_1[\beta^+] + \tag{57}$$
$$+ \mathrm{Var}_2[\varepsilon_2^-] + \mathrm{E}_2[\beta^-]\delta_3)\Big] = -\alpha Pr^+(1-Pr^+)\Big[\sigma(\mathrm{E}_1[\varepsilon_2^+] - \mathrm{E}_2[\varepsilon_2^-]) -$$
$$- \alpha\sigma^2(\mathrm{E}_1[\beta^+]\delta_3 - \mathrm{Var}_2[\varepsilon_2^-] - \mathrm{E}_2[\beta^-]\delta_3)\Big]^2 < 0.$$

Appendix 4 — Robustness checks

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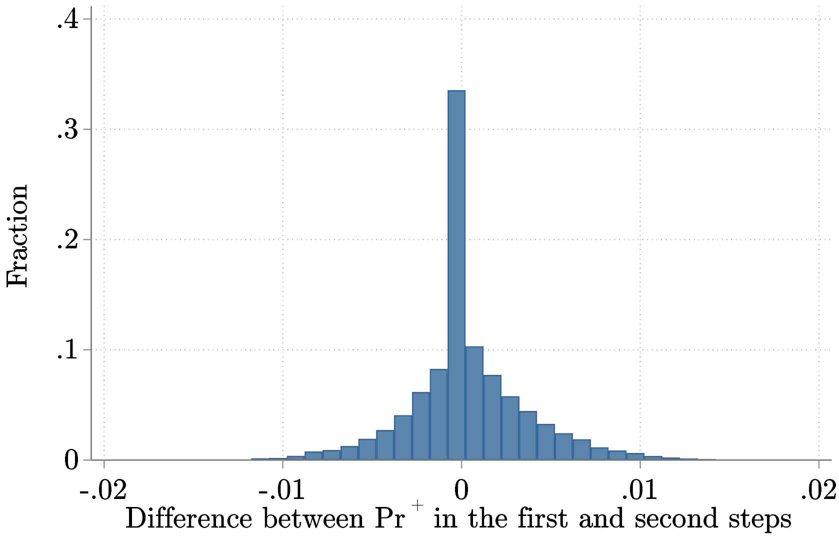
To verify the robustness of our results, we employ several methods. Firstly, we compare the outcomes of our algorithm's first and second steps as a metric of its quality. This involves assessing how accurately the moments of ε_2^+, ε_2^-, β^+, β^- are estimated in the first step. Specifically, we examine whether the iterative algorithm can accurately match the mapping from (S_2, B) to $\{1, 2\}$ of the second step, where we substitute the moments of distribution into the utility function. We do not compare individual points and intervention decisions between the first step (which involves 10 000 randomly distributed points due to computational constraints) and the second step (where we construct a fixed grid of 100 million points). Instead, we focus on comparing two key aspects: the Pr^+ values and the moments $\mathrm{E}_2[\varepsilon_2^+]$, $\mathrm{E}_2[\varepsilon_2^-]$, $\mathrm{E}_2[\beta_2^+]$, $\mathrm{E}_2[\beta_2^-]$. The table below details the absolute differences in these indicators. For Pr^+ and β, we use the values directly, while for ε_2, we employ distribution percentiles to ensure comparability between observations. In addition, we observed that for cases where $Pr^+ > 0.99$ — indicating only isolated instances requiring central bank intervention — the algorithm accurately predicts the deviations of Pr^+ and $\mathrm{E}_2[\varepsilon_2]$ between the first and second steps. However, it is less precise in predicting $\mathrm{E}_2[\beta_2]$ deviations. This discrepancy arises because, in the first step, the algorithm operates on sparser subsets of the (ε_2, β) space. Consequently, when only a few points out of 10 000 are considered in the first step, the second step translates this into a narrowly defined region for a small ε_2 interval, it might have a slightly different shape. This limited number of points does not sufficiently define the region in terms of the expected value $E[\beta^-]$, leading to notable variations in $E[\beta^-]$. Therefore, we report the deviation values separately for all observations and specifically for those where $Pr^+ < 0.99$.

Moments	Mean	Std. deviation
Pr^+	0.0022	0.0028
$\mathrm{E}_2[\varepsilon_2^+]$	0.33	0.30
$\mathrm{E}_2[\varepsilon_2^-]$	0.74	3.09
$\mathrm{E}_2[\beta_2^+]$	0.0085	0.0157
$\mathrm{E}_2[\beta_2^-]$	0.0048	0.0063
$\mathrm{E}_2[\beta_2^+]all$	0.0072	0.0133
$\mathrm{E}_2[\beta_2^-]all$	0.0643	0.1709

In addition, we analyze the distribution of the difference in Pr^+ values between the first and second steps of the algorithm ($Pr_1^+ - Pr_2^+$). Figure 18 illustrates this comparison with an error histogram. The histogram indicates that the difference is generally close to zero, with no significant outliers.

Figure 18 — Error histogram of the iterative algorithm



For further robustness checks, we increase the number of generated $\{\varepsilon_2, \beta\}$ pairs per observation. To enhance accuracy when advancing to the second step of the algorithm, we repeat the class assignment procedure for 10 000 generated points five times. Consequently, we estimate $\mathrm{E}_2[\beta^-]$, $\mathrm{E}_2[\beta^+]$, $\mathrm{E}_1[\varepsilon_2^+]$, $\mathrm{E}_2[\varepsilon_2^-]$, $\mathrm{Var}_2[\varepsilon_2^-]$, and Pr^+ across all 50 000 points. Rather than directly using 50 000 points for the iterative class assignment, we use this approach due to computational constraints. The computational complexity of the procedure increases non-linearly with the number of points, making a direct estimation for 50 000 points prohibitively resource-intensive.

Appendix 5 — Comparison of returns

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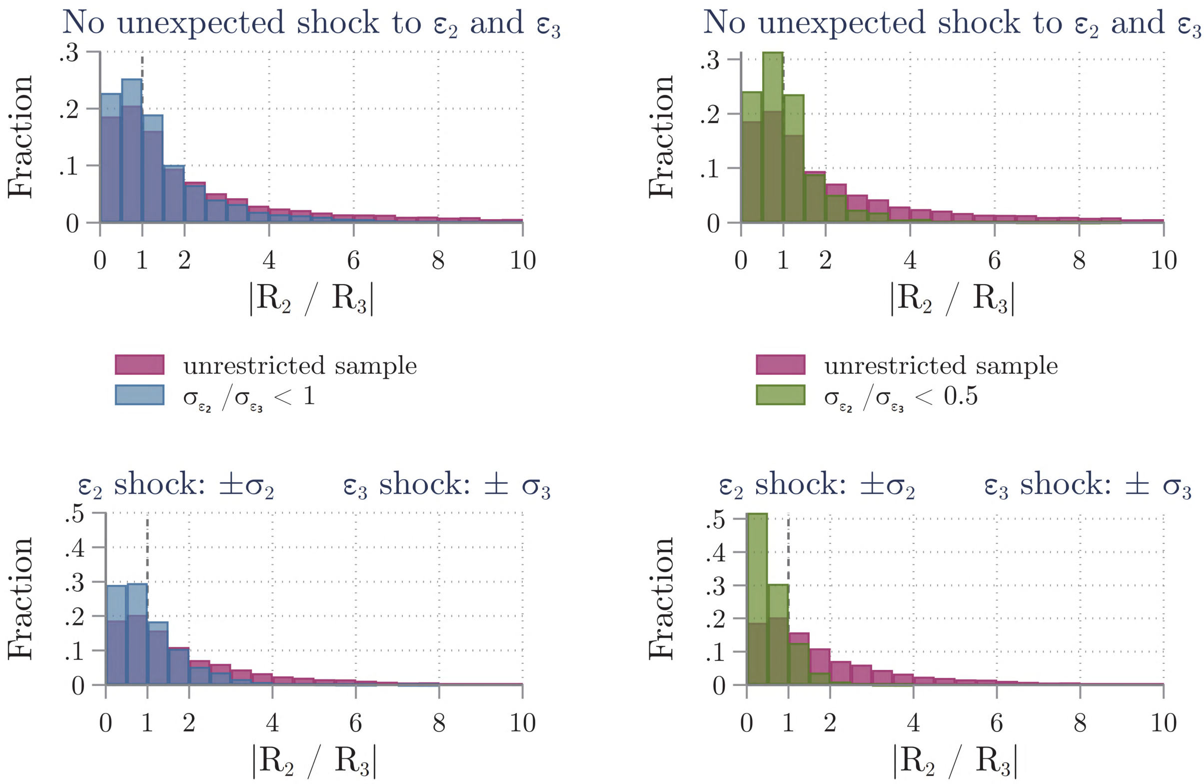
Our model investigates the central bank's perception of immediate market consequences following a breach of the quiet period. One key aspect we examine is the significant market reaction that occurs right after such a breach, a factor that crucially influences real-world central bank decisions. To analyze this, we compare the yields R_2 and R_3 using the ratio $|R_2/R_3|$. This ratio helps us understand the relative magnitude of a market shock at the time of a quiet period breach compared to the expected market response on the announcement day. Our focus is on scenarios where the central bank chooses to intervene. For convenience, we set β to 1, its mean value, and consider various shock scenarios for ε_2, including values of 0, $-\sigma_{\varepsilon_2}$, and σ_{ε_2}.

In scenarios without an unexpected shock, we use $\varepsilon_2 = \mathrm{E}_1[\varepsilon_2] = \rho\sqrt{\frac{\delta_2}{\delta_1}}\varepsilon_1$ and $\varepsilon_3 = \mathrm{E}_1[\varepsilon_3] = 0$. However, when ε_2 experiences a shock of $\pm\sigma_{\varepsilon_2}$ and $\varepsilon_2 = \mathrm{E}_1[\varepsilon_2] \pm \sigma_{\varepsilon_2} = \rho\sqrt{\frac{\delta_2}{\delta_1}}\varepsilon_1 \pm \sqrt{\delta_2(1-\rho^2)}$, we employ a comparable shock to ε_3, calculated as $\varepsilon_3 = \mathrm{E}_1[\varepsilon_3] \pm \sigma_{\varepsilon_3} = 0 \pm \sqrt{\delta_3}$. In our analysis, we aim to avoid biasing the results in favor of R_2. To achieve this, we ensure that the shocks applied to both R_2 and R_3 are of equal relative magnitude. For instance, if we apply one standard deviation shock for R_2, we then apply a shock of the same relative size to R_3. This approach allows us to compare "shocks of equal surprise." Doing so prevents the scenario where a zero shock to R_3 would make the ratio $|R_2/R_3|$ almost always greater than one. It's important to note that in our analysis, the comparison of returns is also influenced by the ratio of variables δ_2 and δ_3. These variables are vital in determining the degree of surprise in shocks ε_2 and ε_3. In the context of our problem condition, δ_3 is expected to be larger in absolute value compared to δ_2, due to the correlation of shock ε_2 with ε_1. For the entire sample we analyzed, this relationship results in $\mathrm{E}\left[\left|\varepsilon_2 - \mathrm{E}[\varepsilon_2]\right|\right] / \mathrm{E}\left[\left|\varepsilon_3\right|\right] = 0.77$. Additionally, we found that the signs of the shocks do not significantly influence the results. Therefore, we use a common sample for shocks of size $\pm\sigma$ for both dates.

In cases without unexpected shocks to ε_2 and ε_3, we observe that the median value of $|R_2/R_3|$ is 1.55. Furthermore, for only 35% of observations $|R_2|$ is less than $|R_3|$. This indicates that in 65% of observations, market movements are more pronounced after a breach of the blackout period than after the press release following the Board meeting. Additionally, our analysis extends to restricted samples with $o_2 > 1$ and different o_1 values. However, these variations do not significantly alter the results, suggesting that the central bank's target function has a minimal impact on these findings. Instead, the ratio $|R_2/R_3|$ is influenced by the ratio $\sigma_{\varepsilon_2}/\sigma_{\varepsilon_3}$, which represents the uncertainty of the central bank's reaction function relative to the uncertainty stemming from dissent at the Board meeting.

To further clarify these insights, we analyze the density distribution of $|R_2/R_3|$ in three scenarios: across the entire sample; where the ratio of the standard deviations $\sigma_{\varepsilon_2}/\sigma_{\varepsilon_3}$ is less than one, implying that investors perceive the uncertainty surrounding the Board of Governors meeting to be greater than that of the central bank's reaction function; and where this ratio is less than 0.5, indicating a significantly higher perceived uncertainty regarding the Board meeting.

Figure 19 — Comparison of returns: $|R_2/R_3|$ density plots



Note: For clarity in our density plots, we plot $|R_2/R_3|$ range from zero to ten. In scenarios with no unexpected shock, a value of ten corresponds to the 88th percentile of observations in the unrestricted sample. For the restricted samples where $\sigma_{\varepsilon_2}/\sigma_{\varepsilon_3} < 1$ and $\sigma_{\varepsilon_2}/\sigma_{\varepsilon_3} < 0.5$, it aligns with the 99th percentile. For shocks of $\pm\sigma$, the value of ten matches the 96th percentile in the unrestricted sample. In the cases where $\sigma_{\varepsilon_2}/\sigma_{\varepsilon_3} < 1$ and $\sigma_{\varepsilon_2}/\sigma_{\varepsilon_3} < 0.5$, the maximum observed value in the sample does not exceed ten.

In the case without unexpected shocks, we observe a notable decrease in the median value of $|R_2/R_3|$, from 1.55 to 1.04 when $\sigma_{\varepsilon_2}/\sigma_{\varepsilon_3} < 1$, and further down to 0.93 for $\sigma_{\varepsilon_2}/\sigma_{\varepsilon_3} < 0.5$. Similarly, for shocks of $\pm\sigma$, the median value of $|R_2/R_3|$ reduces from 1.41 in the entire sample to 0.84 at $\sigma_{\varepsilon_2}/\sigma_{\varepsilon_3} < 1$ and to 0.49 at $\sigma_{\varepsilon_2}/\sigma_{\varepsilon_3} < 0.5$.

In the context of these findings, it is interesting to compare our results with those from Gnan, Rieder (2023), who, when examining the impact of quiet period breaches versus market reaction to the ECB's press release statements from Altavilla et al. (2019), found that the effect of breaches ranged between 50 and 80 percent of press release impacts. While Board leaks are not precisely the same as the interventions considered in our study, they are the closest such events. Our findings suggest that even with a higher uncertainty of the Board meeting relative to the central bank's reaction function, the market reactions at date 2 are still significant, aligning with these empirical observations.

Furthermore, our model shows that the weight placed on R_2 in the central bank's target function does not significantly influence the ratio $|R_2/R_3|$. This implies that even if the central bank is highly concerned about the magnitude of market shock at date 2, it may still find it optimal to occasionally break the silence, despite the potential for a substantial jump in stock prices at that time. Additionally, the model generates a R_2 return larger in absolute value compared to the return R_3, indicating a pronounced market reaction at date 2.

Appendix 6 — Communication likelihood letter-value plots

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Figure 26 — Communication likelihood letter-value plots for different o_2 values

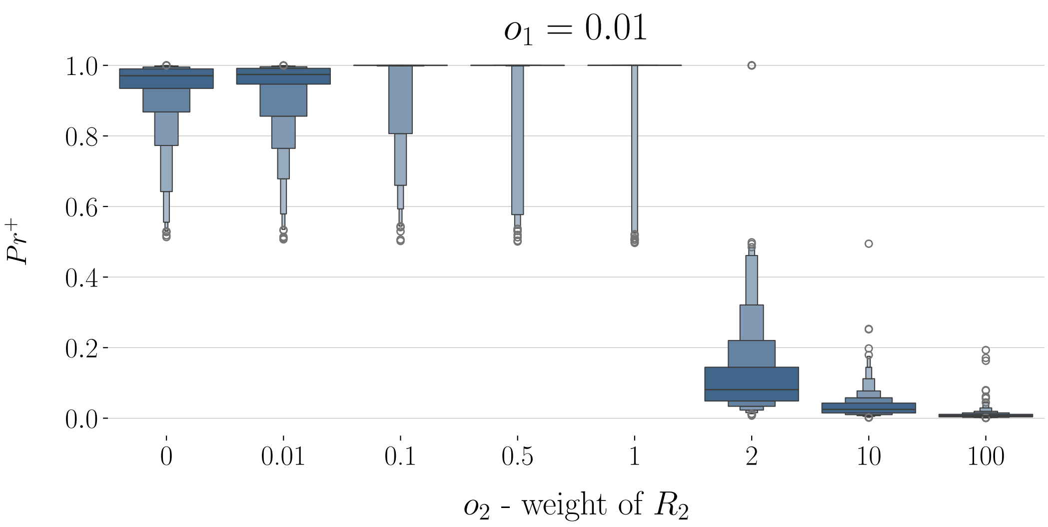


Figure 27 — Communication likelihood letter-value plots for different o_2 values

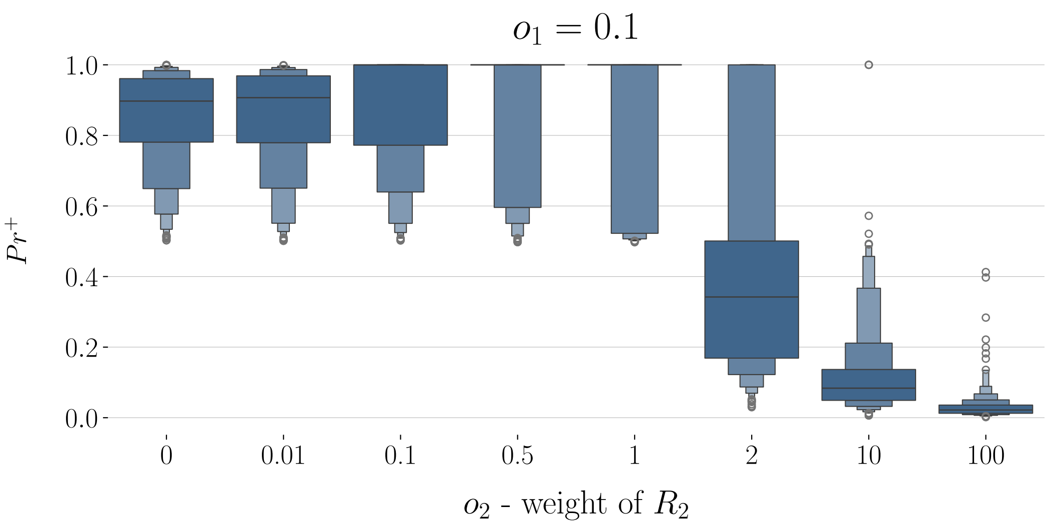


Figure 28 — Communication likelihood letter-value plots for different o_2 values

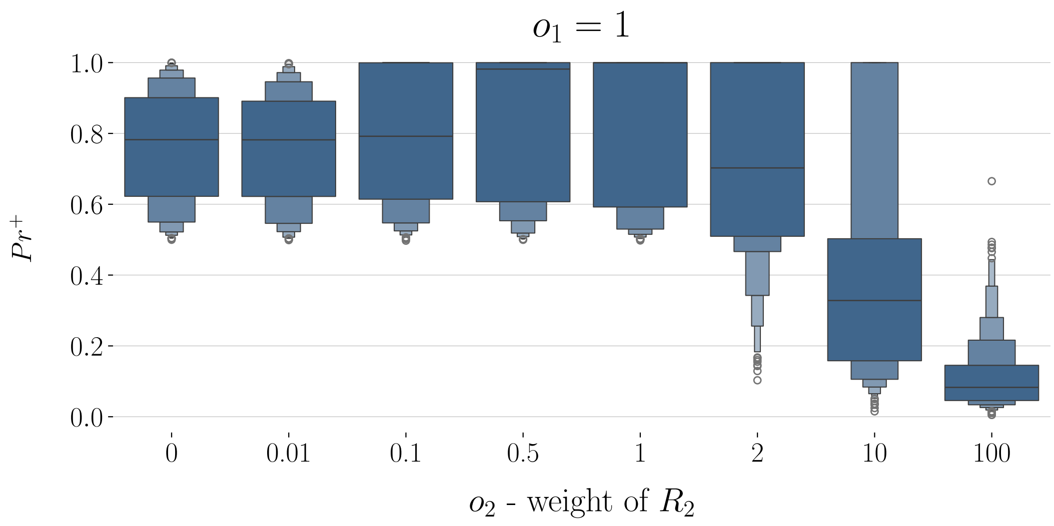


Figure 29 — Communication likelihood letter-value plots for different o_2 values

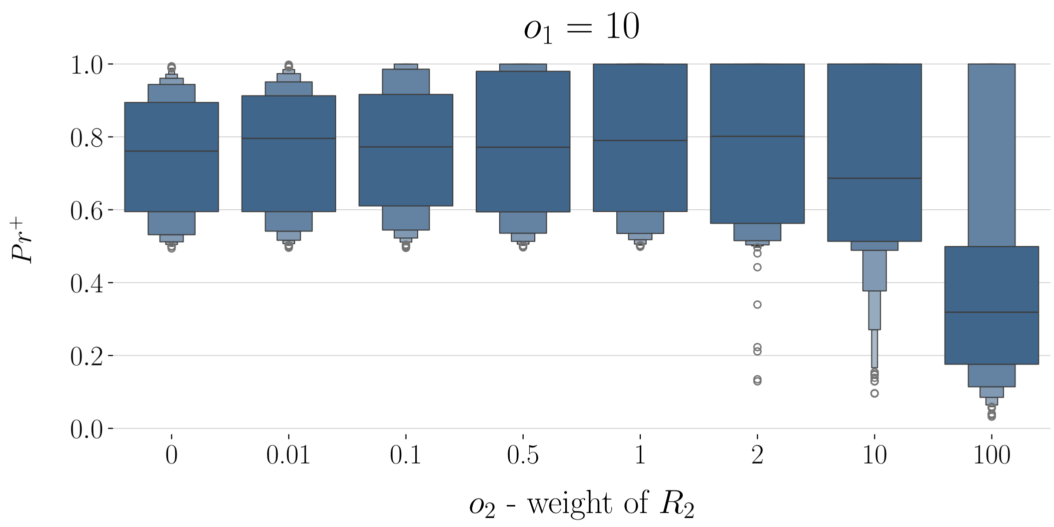
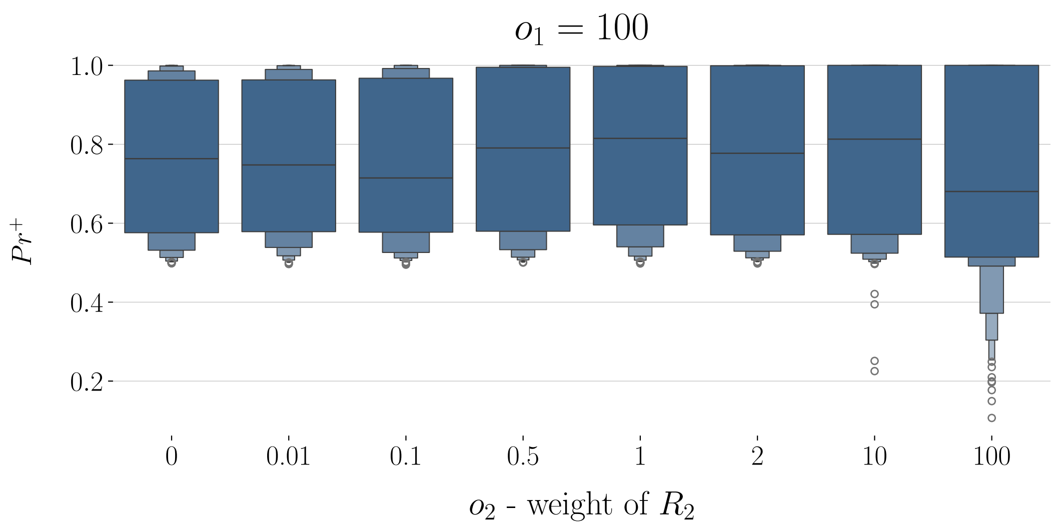


Figure 30 — Communication likelihood letter-value plots for different o_2 values



Appendix 7 — Case of insignificant volatility

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What is the effect of further reducing the weight of variation $\sigma^2 \beta \delta_3 - \sigma^2 \mathrm{E}_2[\beta^+]\delta_3$ in the central bank's target function? For instance, what if we use $o_1 = 0.001$ or $o_1 = 0.0001$? Under these conditions, our model degenerates significantly to a trivial one. When o_1 is set to such low values, it results in $Pr^+ \approx 0$ for $o_2 > 1$ and $Pr^+ \approx 1$ for $o_2 \leq 1$. This indicates that if the central bank places almost no importance on the variation due to the Board meeting, it essentially has to choose between always informing the market at date 2 or never doing so, based solely on comparing the weights of R_2 and R_3. This outcome is expected, as earlier findings indicate a significant jump in the stock price R_2 when the quiet period is breached, even exceeding the meeting's effect. Conversely, preserving the blackout period regime typically results in a smaller absolute value of R_2. Notably, the currently adopted quiet period policy seems to align with a scenario where $o_1 \approx 0$ and $o_2 > 1$. However, public discussions about the blackout period regime often overlook these considerations.

Appendix 8 — Communication likelihood under different uncertainty sources

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Figure 24 — Communication likelihood under different uncertainty sources, sorted by o_2

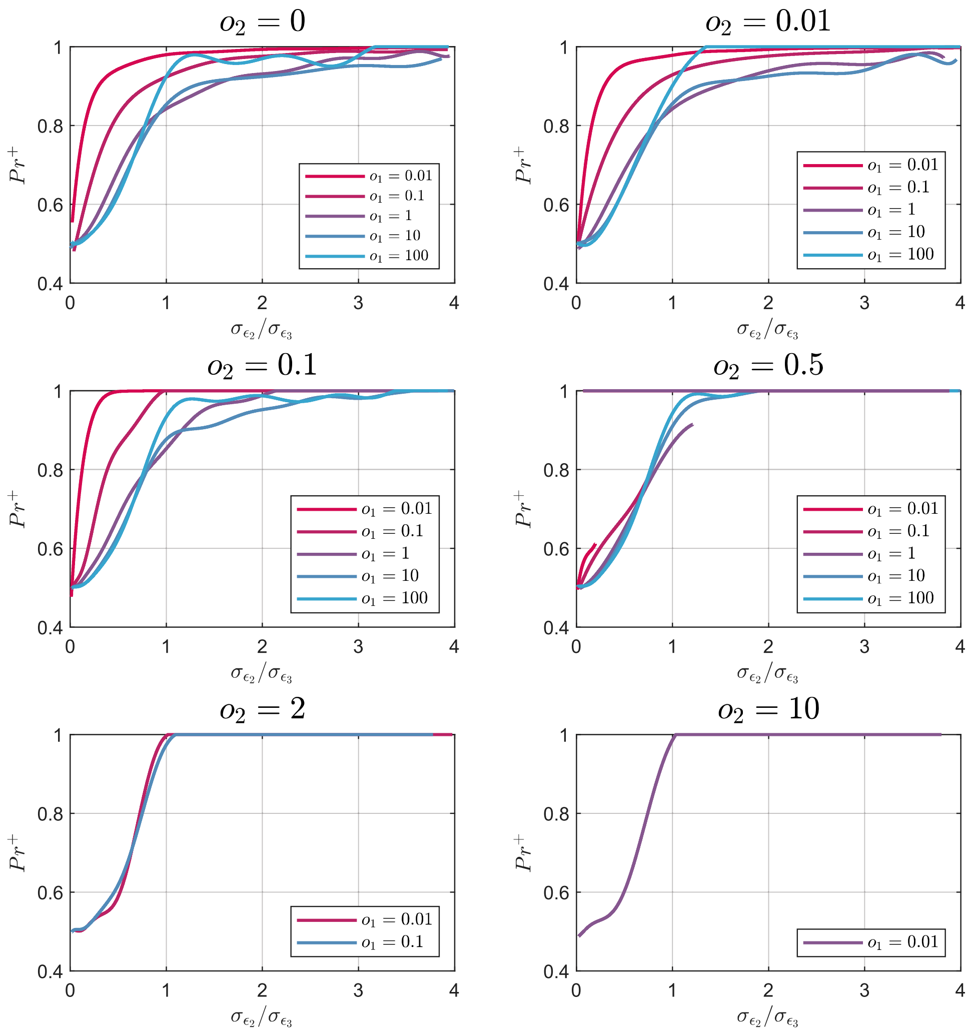
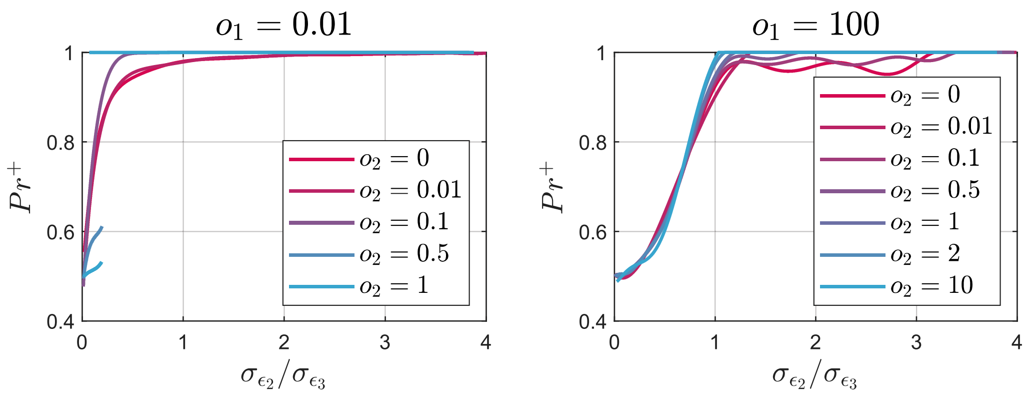


Figure 25 — Communication likelihood under different uncertainty sources, sorted by o_1



Appendix 9 — Comparison of the "never intervene" and "always intervene" regimes for $o_2 = 0.5$ and $o_2 = 1$

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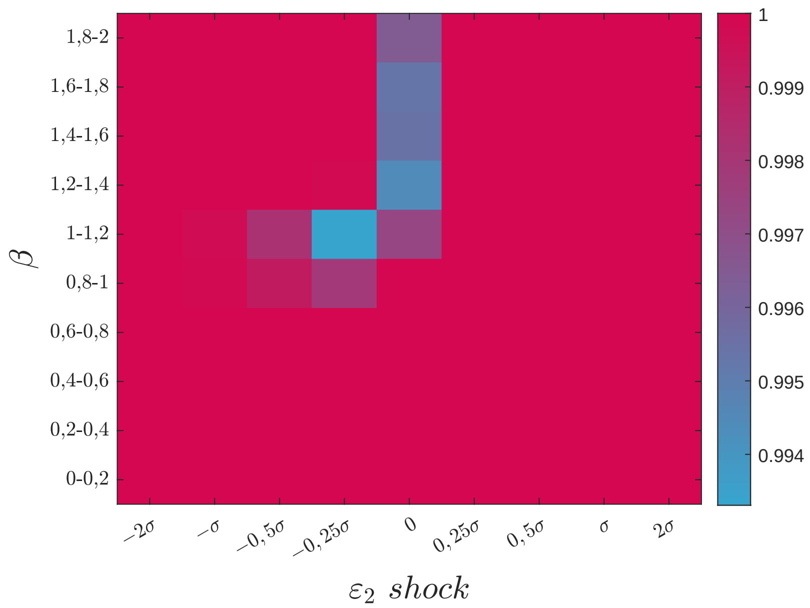
Focusing on the $o_2 = 1$ case, where the central bank is equally averse to large stock market jumps at dates 2 and 3, our findings clearly favor the "always intervene" policy. Figure 20 illustrates that the central bank typically increases its utility function value by adopting an intervention approach. This holds even when considering specific betas and large negative shocks, where the benefits of intervention outweigh the costs in at least 66% of the cases. A notable asymmetry arises due to the risk premium required by investors: a large negative shock, if not communicated to the market at date 2, will be partially offset by the required risk premium, resulting in a relatively smaller price fall at date 3. Hence, P_2 — the stock price at date 2 in the absence of intervention — will be lower, accounting for the risk premium that encompasses all risks associated with ε_2, ε_3 and β. In cases where ε_2 has a negative realization, P_2 may end up being quite close to P_3.

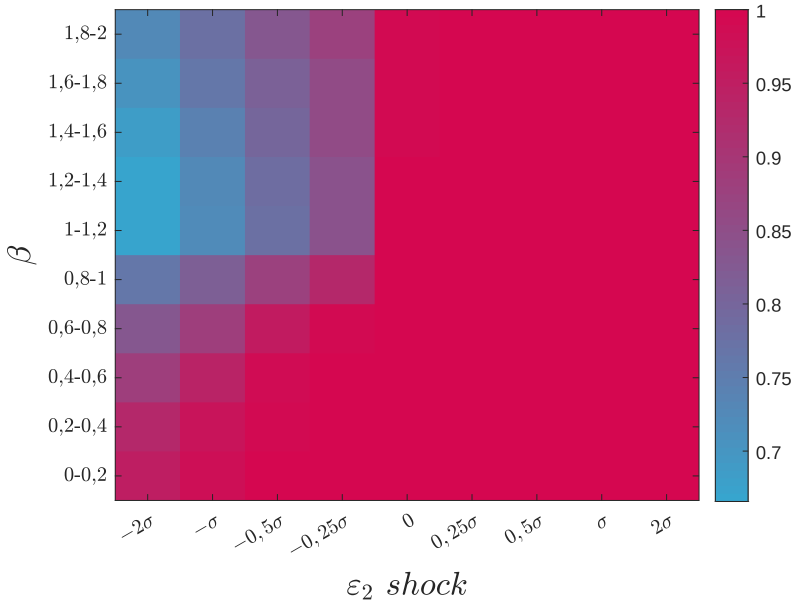
Figure 20 — Comparison of "never intervene" and "always intervene" regimes for $o_2 = 1$



Note: The graph indicates the probability that the value of the central bank's utility function in the "never intervene" regime is lower than in the "always intervene" regime, given the distributions of ε_1, ε_3, α, β, θ, σ, δ_1, δ_2, δ_3, and o_1 is distributed equally among all the values used. For ε_2, discrete shocks of $-2\sigma_{\varepsilon_2}$, $-\sigma_{\varepsilon_2}$, $-0.5\sigma_{\varepsilon_2}$, $-0.25\sigma_{\varepsilon_2}$, 0, $0.25\sigma_{\varepsilon_2}$, $0.5\sigma_{\varepsilon_2}$, σ_{ε_2}, $2\sigma_{\varepsilon_2}$ are used, while for β all values from zero to two in steps of 0.002 are used, which are then grouped into 10 clusters in steps of 0.2.

In the scenario where $o_2 = 0.5$, indicating that the central bank places slightly more emphasis on price fluctuations on the day of the Board meeting, the outcome becomes quite trivial, as depicted in Figure 21. In this case, our model suggests that the central bank benefits from intervening in most situations rather than adhering to a non-intervention approach.

Figure 21 — Comparison of "never intervene" and "always intervene" regimes for $o_2 = 0.5$



Note: The graph indicates the probability that the value of the central bank's utility function in the "never intervene" regime is lower than in the "always intervene" regime, given the distributions of ε_1, ε_3, α, β, θ, σ, δ_1, δ_2, δ_3, *and* o_1 *is distributed equally among all the values used. For* ε_2, *discrete shocks of* $-2\sigma_{\varepsilon_2}$, $-\sigma_{\varepsilon_2}$, $-0.5\sigma_{\varepsilon_2}$, $-0.25\sigma_{\varepsilon_2}$, 0, $0.25\sigma_{\varepsilon_2}$, $0.5\sigma_{\varepsilon_2}$, σ_{ε_2}, $2\sigma_{\varepsilon_2}$ *are used, while for* β *all values from zero to two in steps of 0.002 are used, which are then grouped into 10 clusters in steps of 0.2.*

Appendix 10 — Comparison of ”never intervene” and ”endogenously intervene” cases for $o_2 = 0.5$ and $o_2 = 1$

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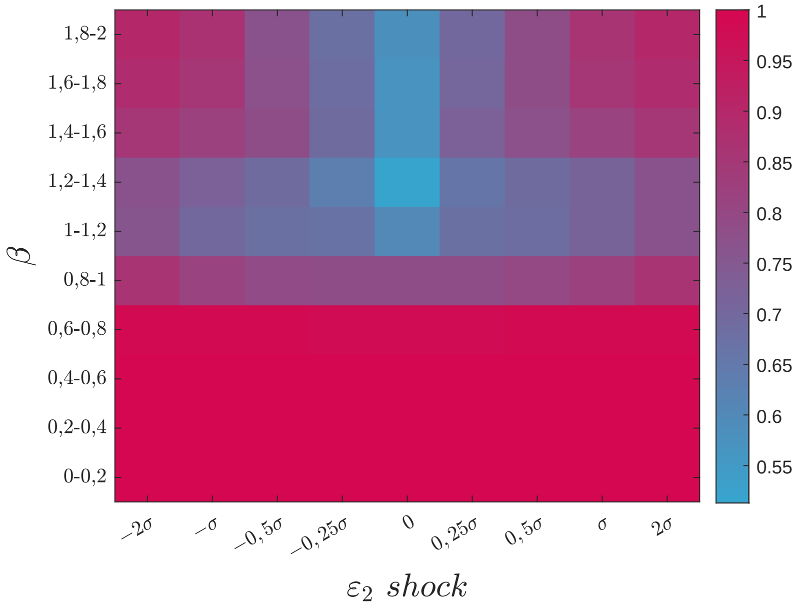
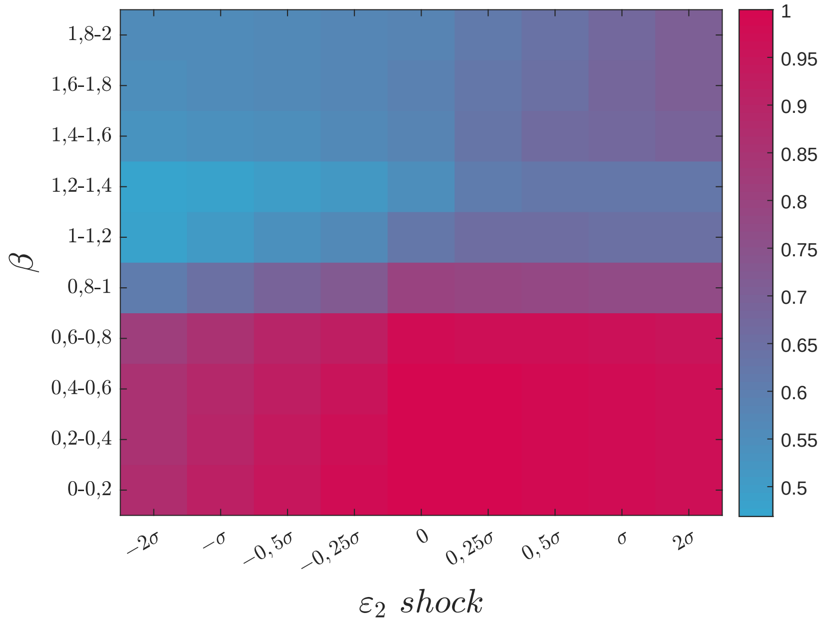
Figure 22 — Comparison of ”never intervene” and ”endogenously intervene” regimes for $o_2 = 0.5$



Note: The graph indicates the probability that the value of the central bank's utility function in the ”never intervene” regime is lower than in the ”endogenously intervene” regime, given the distributions of ε_1, ε_3, α, β, θ, σ, δ_1, δ_2, δ_3, and o_1 is distributed equally among all the values used. For ε_2, discrete shocks of $-2\sigma_{\varepsilon_2}$, $-\sigma_{\varepsilon_2}$, $-0.5\sigma_{\varepsilon_2}$, $-0.25\sigma_{\varepsilon_2}$, 0, $0.25\sigma_{\varepsilon_2}$, $0.5\sigma_{\varepsilon_2}$, σ_{ε_2}, $2\sigma_{\varepsilon_2}$ are used, while for β all values from zero to two in steps of 0.002 are used, which are then grouped into 10 clusters in steps of 0.2.

Figure 23 — Comparison of "never intervene" and "endogenously intervene" regimes for $o_2 = 1$



Note: The graph indicates the probability that the value of the central bank's utility function in the "never intervene" regime is lower than in the "endogenously intervene" regime, given the distributions of ε_1, ε_3, α, β, θ, σ, δ_1, δ_2, δ_3, and o_1 is distributed equally among all the values used. For ε_2, discrete shocks of $-2\sigma_{\varepsilon_2}$, $-\sigma_{\varepsilon_2}$, $-0.5\sigma_{\varepsilon_2}$, $-0.25\sigma_{\varepsilon_2}$, 0, $0.25\sigma_{\varepsilon_2}$, $0.5\sigma_{\varepsilon_2}$, σ_{ε_2}, $2\sigma_{\varepsilon_2}$ are used, while for β all values from zero to two in steps of 0.002 are used, which are then grouped into 10 clusters in steps of 0.2.