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B. C.

Abstract

This thesis uses machine learning techniques and text data to investigate the relationships that arise between the Fed and financial markets, and their consequences for asset prices.

The first chapter, entitled *Market Expectations and the Impact of Unconventional Monetary Policy: An Application to Twitter Data*, is an answer to (Greenlaw et al., 2018), who show, by looking at a large set of monetary policy announcements made between November 2008 and December 2017 - FOMC meetings, release of minutes and speeches of the Fed Chair - that long term yields tended to increase following these events. By doing so, the authors challenge common wisdom according to which the central bank intervention in the aftermath of the financial crisis lowered long term rates (Gagnon, 2016). Using machine learning and twitter data, this chapter develops a novel measure of market expectations of monetary policy, and shows that the increase in yields was simply due to a marginal adjustment of market expectations following announcements being less dovish than expected.

The second chapter, entitled *Informational Feedback Loop, Monetary Policy Decisions and Asset Prices Dynamics*, investigates the consequences of a Fed that uses (1) its own private signal and (2) fed funds futures to take its monetary policy decision. Fed funds futures aggregate private information received by financial markets participants - *traders* - but they also depend on traders' expectations about the Fed's behavior, which makes futures endogenous in the central bank decision. The theoretical model shows that the surprise generated by monetary policy announcements and the subsequent adjustment in short term U.S. treasury yields depend on the precision of the signals received by each agent. When the signal received by traders is more precise than the central bank's, the latter relies more on fed funds futures to take its decision, and the surprise and adjustment of short term yields are smaller. By contrast, long term yields adjust only because the announcement provides traders with new information about the state of the economy, by revealing the central bank's private signal. Finally, when the Fed is averse to financial markets volatility, it tends to put some weight on fed funds futures even if they are not informative about the state of the economy. The empirical part of the paper provides some evidence supporting these channels, by using a *topic and tone* approach (Hansen and McMahon, 2016) to extract the precision of the signals received by the central bank and traders from FOMC minutes and tweets respectively.

Keywords: monetary policy, rational expectations equilibrium, financial instability, BERT, LDA.

Résumé

Cette thèse utilise des techniques d'apprentissage automatique et des données textuelles pour étudier les mécanismes qui régissent les relations entre la Fed et les marchés financiers, et leurs conséquences sur le prix des actifs.

Le premier chapitre, intitulé *"Market Expectations and the Impact of Unconventional Monetary Policy : An Application to Twitter Data,"* est une réponse à Greenlaw et al. (2018), qui montrent, en examinant un large ensemble d'annonces de politique monétaire faites entre novembre 2008 et décembre 2017 - annonces réalisées à l'issue des réunions du FOMC, publication des minutes de ces réunions, et discours des présidents de la Fed - que les taux d'intérêt à long terme ont eu tendance à augmenter suite à ces événements. Ainsi, ces auteurs remettent en cause le quasi consensus selon lequel l'intervention de la banque centrale après la crise financière aurait fait baisser les taux d'intérêt à long terme (Gagnon, 2016). En utilisant des techniques d'apprentissage automatique et des données extraites de la plateforme de microblogging Twitter, ce chapitre développe une nouvelle mesure des attentes du marché en matière de politique monétaire, et montre que la hausse des taux d'intérêt à long terme peut être expliquée par un ajustement marginal des attentes du marché suite à des annonces moins accommodante qu'anticipé.

Le deuxième chapitre, intitulé *Informational Feedback Loop, Monetary Policy Decisions and Asset Prices Dynamics*, étudie les conséquences d'une Fed qui utilise (1) son propre signal privé et (2) les contrats à terme sur le taux directeur de la Fed pour prendre sa décision de politique monétaire. Les contrats à terme agrègent l'information privée reçue par les participants aux marchés financiers - les *traders* - mais ils dépendent aussi des anticipations de ces derniers concernant le comportement de la Fed, ce qui rend ces contrats endogènes vis à vis de la décision de la banque centrale. Le modèle théorique montre que la surprise générée par les annonces de politique monétaire et l'ajustement des rendements des bons du Trésor américain à court terme dépendent de la précision des signaux reçus par chaque agent. Lorsque le signal reçu par les traders est plus précis que celui de la banque centrale, cette dernière s'appuie davantage sur les contrats à terme pour prendre sa décision, et la surprise et l'ajustement des rendements à court terme sont plus faibles. En revanche, les rendements à long terme s'ajustent uniquement parce que l'annonce fournit aux traders de nouvelles informations sur l'état de l'économie, en révélant le signal privé de la banque centrale. Enfin, lorsque la Fed est averse à la volatilité des marchés financiers, elle continue de mettre du poids sur les contrats à terme dans sa prise de décision, même s'ils ne contiennent aucune information sur l'état de l'économie. La partie empirique du papier fournit quelques éléments qui appuient ces hypothèses, en utilisant une approche *thème et ton* (Hansen et McMahon, 2016), qui permet d'extraire la précision des signaux reçus par la banque centrale et les traders à partir des minutes des réunions du FOMC et des tweets respectivement.

Mots Clés : politique monétaire, équilibre avec anticipations rationnelles, instabilité financière, BERT, LDA.

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1 Introduction

The 2007-2008 financial crisis provided two important insights with respect to the financial sector and to monetary policy. First, it showed that the real economy could be subject to severe negative shocks originating from financial markets; second, it put monetary policy at the forefront of public intervention as an answer to financial and economic crises, with the implementation of measures - e.g. forward guidance and quantitative easing - that were unprecedented by their size and scope. For example, data from the Federal Reserve Economic Database (FRED) show that the effective federal funds rate remained around zero for about seven years, between December 2008 and December 2015; moreover, during the same time period, the central bank's balance sheet was multiplied by five, from $900 billion to $4.5 trillion. Interestingly, the recent covid-crisis features a similar pattern. In a recent report summarizing the Fed's response to the pandemic, Cheng et al. (2021) indicate that the fed funds rate has been around zero since March 2020, and that the Fed reused several of the tools it used during the 2007-2008 financial crisis, to support the financial sector. Those include the Primary Dealer Credit Facility, the Money Market Mutual Fund Liquidity Facility and quantitative easing, with the purchase of treasuries and government-guaranteed mortgage backed securities. Once again, the size of the Fed's intervention was huge: the authors indicate that due to the latter program, the portfolio of securities held by the central bank increased from $3.9 trillion to $6.6 trillion between mid-March 2020 and December 2020.

This increased importance of monetary policy and how it relates to financial markets triggered numerous contributions from the academic literature, trying (1) to assess the impact of the Fed's intervention, i.e. whether or not forward guidance and quantitative easing were successful in reaching their goal; and more generally, (2) to better understand the channels through which monetary policy impacts financial markets. The two chapters of this thesis contribute respectively to these two streams of literature.

The first chapter (chapter 2) deals with the Fed's response to the 2007-2008 financial crisis. In particular, it is an answer to Greenlaw et al.'s (2018) paper, which puts into question the efficiency of the quantitative easing programs implemented by the Fed. Indeed, by looking at a large set of monetary policy announcements made between November 2008 and December

2017 - FOMC meetings, release of minutes and speeches of the Fed Chair - the authors show that yields tended to increase on these dates. These results are puzzling, since during most of that period, monetary policy was very expansionary - including notably three quantitative easing programs. A significant part of the literature has shown that the Fed unconventional policies - quantitative easing and forward guidance - were successful in lowering long term rates (Gagnon et al. (2011); Krishnamurthy and Vissing-Jorgensen (2011); Gagnon (2016); Borio and Zabai (2018); Kuttner (2018)). Therefore, Greenlaw et al. (2018) argue that a potential explanation that could reconcile their results with most of the literature is that this increase in yields following the release of new information about monetary policy could come from the central bank disappointing market expectations by not being as expansionary as what was expected and priced by markets. Unfortunately, they add that this hypothesis cannot be tested, as there is no time series that could account for expectations related to unconventional monetary policy.

The main contribution of the first chapter is therefore to provide a new measure of market expectations of conventional and unconventional monetary policy, to be able to test the hypothesis put forward by Greenlaw et al. In particular, market expectations are measured using a machine learning algorithm that classifies tweets published around monetary policy events as *hawkish*, *dovish*, *neutral* or *non-relevant*. The surprise is then measured in two steps: first, market expectations are obtained by aggregating the tweets before and after the event; and second, the surprise is computed as the change in market expectations following the event. Results presented in the empirical analysis suggest that a negative surprise - e.g. due to the release of new information being less dovish than expected - results in an increase in the 10-year nominal treasury yield.

The second chapter (chapter 3) investigates, in a more general context, how the Fed and financial markets interact together. More specifically, it looks at the effect on monetary policy and asset prices dynamics, of an informational feedback loop that arises when the Fed benefits from a private signal about the state of the economy, and also considers information produced by financial markets when taking its federal funds rate decision, but that information is endogenous in market expectations about that same decision - e.g. when it looks at the information conveyed by federal funds futures. This phenomenon has already been investigated by Morris and Shin (2018) and Bond and Goldstein (2015), who show that the informational feedback loop gives rise to a *reflection* problem that reduces the information content of asset prices. This chapter contributes to this literature by looking at another of its effects, namely, the underlying mechanism through which it influences the monetary policy decision, and its impact on the dynamics of bond prices.

Using a rational expectations model with a central bank and strategic traders *à la* Lee and Kyle (2018), the theoretical part of this chapter predicts that the surprise generated by monetary policy announcements and the subsequent adjustment in short term yields depend on three things: the precision of the private signals received respectively by (1) the central bank and (2) traders, as well as (3) the central bank's aversion to financial markets volatility. By contrast, long term yield adjustments do not depend on the precision of the signal received by traders or the central bank aversion to financial market volatility. These results are due to the fact that the central bank puts a larger weight on fed funds futures compared to its own signal if traders' signal is more informative or if it is more averse to financial market volatility. This has a significant impact on the surprise and on short term yields adjustments, while long term yields react only to the amount of new information revealed to traders by the announcement - i.e. the private signal of the central bank.

The major challenge in testing these hypotheses is to create proxies for the precision of the signals received by the central bank and traders respectively. This paper uses a *topic and tone* approach (Hansen and McMahon, 2016) which enables to extract those from FOMC minutes (precision of the Fed's signal) and tweets (precision of traders' signal). More precisely, the *topic and tone* approach consists in (1) identifying the topics - *signals* - embedded in a corpus of texts by using a topic identification algorithm - in this case Latent Dirichlet Allocation (Blei et al., 2003) - and (2) using a dictionary method to count, for each topic, the number of words representative of the *sentiment* the researcher seeks to measure - in this case, the inverse of the *precision* of the signal, i.e. *uncertain* words (Loughran and Mcdonald, 2011). This methodology is able to provide some (weak) empirical evidence supporting the hypotheses identified by the theoretical part.

2 Market Expectations and the Impact of Unconventional Monetary Policy: An Application to Twitter Data

2.1 Introduction

The Great Recession put monetary policy in the spotlight, triggering unprecedented reactions from central banks all over the world, first and foremost from the Fed. In September 2007, it started a series of rate cuts which brought the fed funds rate to virtually zero in December 2008. With its traditional monetary policy tool stuck at the zero lower bound, the Federal Reserve had to turn to unconventional monetary policies to provide further loosening: At the end of 2008, it engaged in quantitative easing (QE), implementing three large scale asset purchase programs (LSAPs) in six years.[1] Data from the Federal Reserve of St. Louis (FRED) show that total reserve balances maintained with Federal Reserve Banks increased from around $900 billion at the beginning of 2008 to $4.5 trillion at the end of 2014; On August 9th 2011, the Fed also started "forward guidance," providing in its Federal Open Market Committee (FOMC) statement explicit information about the likely path of the federal funds interest rate:

> "The Committee currently anticipates that economic conditions - including low rates of resource utilization and a subdued outlook for inflation over the medium run - are likely to warrant exceptionally low levels for the federal funds rate at least through mid-2013."

[1] Quantitative easing was actually implemented in two phases. A first phase, at the onset of the crisis, which consisted in several programs aiming at providing emergency loans to troubled financial institutions (Term Auction Credit, Commercial Paper Funding Facility and currency swaps). The second phase, much more important in terms of scale, consisted in a large expansion of the Fed's balance sheet, with the purchase of Treasury bonds and mortgage backed securities. The three LSAP correspond to the second phase of this policy. Exhibit 2.1 of Greenlaw et al. (2018) provides the following information about each of these programs: QE1 was implemented on the period 11/2008-08/2009, and consisted in the purchase by the Fed of $200 billion of agency debt, $1,250 billion of agency MBS and $300 billion of Treasuries; for QE2, it purchased $600 billion of Treasuries between 11/2010 and 06/2011; finally, QE3 spanned the period 09/2012-12/2014, and the central bank purchased between $40 billion and $85 billion of MBS and Treasuries each month.

The rationale behind the Fed's intervention was to help stabilize and stimulate the economy by lowering long term bond rates. In particular, Gagnon (2016, p.1) identifies three objectives: reducing risk spreads associated with market panics; reducing expectations of the future short-term policy interest rate; reducing the term premium in bond yields by reducing the premium of long-term bonds.

Therefore, an important question that arises is whether the Fed's unconventional policies (QE and forward guidance) implemented after the financial crisis had the intended stabilization and expansionary effects. There has been an extensive literature trying to answer this question. The reviews by Kuttner (2018) and Borio and Zabai (2018) suggest that unconventional monetary policies were successful in lowering long term interest rates. According to Borio and Zabai (2018, p.430) the cumulative impact of the Fed's measures reduced 10-year government bond yields by 100 basis points (bp). However, these results are highly contested. For example, Cochrane (2017) argues that even though the first QE episode may have indeed lowered 10-year yields by 100 bp, they quickly bounced back - price movements due to large trading volumes being usually only temporary - and yields actually increased during the second and third QE programs. Similarly, Greenlaw et al. (2018) look at days during which there was news about monetary policy between November 2008 and December 2017 - due to the release of FOMC meeting minutes, FOMC statements and speeches of the Fed Chair - and show that on most of these days, yields tended to increase. The authors therefore, advocate for adopting a skeptical view when it comes to assessing the impact of the expansion of the Fed's balance sheet. Interestingly, a potential explanation they suggest, which could explain their puzzling result and reconcile the two views, is that the accommodative stance of monetary policy was already priced by the market, and the increase in yields would come from the Fed disappointing market expectations by not being as expansionary as what was expected. Unfortunately, they argue that such an hypothesis is difficult to test, as there is no time series of market expectations of unconventional monetary policies that covers the full period of implementation of these programs.[2]

The goal of this paper is therefore to test empirically the hypothesis put forward by Greenlaw et al. (2018). In particular, it aims at showing that the increase in yields during the implementation of QE and forward guidance reflects an adjustment of market expectations of monetary policy following disappointing announcements.

The key novelty of the paper is to develop an objective measure of market participants' expectations of both conventional and unconventional monetary policies,[3] and of the surprise generated by the communication of the central bank. Market expectations are identified using

[2] For example, the New York survey of primary dealers, which could be used to measure expectations about the size of the Fed's QE programs, starts only in January 2011 (Greenlaw et al., 2018).

[3] The measure of market expectations presented in this paper does not discriminate between expectations of conventional and unconventional monetary policies. However, during most of the period considered (November 2008-December 2017), the fed funds rate was at the zero lower bond, and monetary policy consisted mainly in using unconventional tools (forward guidance and QE). As a result, expectations measured in this paper are mostly about unconventional monetary policies.

tweets published around the release of new information about monetary policy - following the release of FOMC statements and FOMC meeting minutes - between November 2008 and December 2017. More specifically, building on the latest developments in natural language processing, I use Devlin et al. (2019) pre-trained BERT (Bidirectional Encoder Representations from Transformers) model augmented with a linear classifier layer to sort tweets depending on their tone: *dovish* (+1), *hawkish* (-1), *neutral* (0) or *non relevant*. Then, by averaging out these tweets before or after an announcement, I am able to give market expectations of monetary policy a score on a *hawkish-dovish* scale. Finally, by taking the difference of this score before and after the announcement, I can measure the surprise generated by the communication of the central bank. This measure of the surprise is then used in the empirical analysis as the main variable explaining the evolution of the yield of the US 10-year Treasury note.

While the use of natural language processing (NLP) and machine learning for text classification is not new,[4] the approach proposed in this paper is different because it does not seek to measure *positive* or *negative* sentiment, but instead, the *hawkish vs dovish* tone of people's talks about conventional and unconventional monetary policies. Indeed, market participants may have different preferences towards monetary policy, and a tweet about a loosening of monetary policy may translate into a positive or a negative sentiment depending on those preferences.[5]

The empirical analysis provides evidence of the existence of a strong relationship between monetary policy surprises as measured by the variable presented in this paper and long term yields. In other words, a negative surprise - an announcement being perceived by the market as more hawkish, or, equivalently, less dovish than expected - results in an increase in long term yields: a one standard deviation negative shock to the measure of the surprise increases the nominal 10-year treasury yield by 2.66 basis points. Breaking down the nominal yield into its real and inflation compensation components (Gürkaynak et al., 2010), it is interesting to see that the impact [standard error] is mostly on real rates (2.59 bp [0.73]) rather than on inflation expectations (0.08bp [0.42]). Additionally, consistent with the *long term safety channel* (Krishnamurthy and Vissing-Jorgensen, 2011) and the *reaching for yield channel* (Hanson and Stein, 2015), the impact on the term premium of the 10-year nominal treasury yield is statistically significant (1.26bp [0.35]) and large. While properly testing for the actual channel would be beyond the scope of this paper,[6] I interpret this result by the fact that the increases in

[4]For applications in economics and finance, see for example Tetlock (2007),Tetlock et al. (2008), Azar and Lo (2016), Hansen and McMahon (2016), Hansen et al. (2018), Hubert and Burda (2018), Lee et al. (2019), or Shapiro et al. (2019). For an extensive review of the literature, see Loughran and Mcdonald (2016).

[5]In other words, the goal here is to create a measure of market expectations about the *stance* - i.e. *dovish* vs *hawkish* - of monetary policy, and not of the *sentiment* conveyed by talks about the stance of monetary policy. For example, consider a situation in which the Fed is expected to announce a new quantitative easing program. An *hawkish* analyst may write *negative* tweets about such a move, by saying that it might not be necessary given the current state of the economy, while a *dovish* analyst would welcome such a news by employing *positive* words in his tweets. As a result, under a traditional *sentiment* analysis - i.e. measuring the tone of a piece of text based on the use of *positive* and *negative* words - tweets emphasizing these two views would likely contain a more *negative* tone in tweets written by the *hawkish* analyst, and a more *positive* tone in tweets written by the *dovish* analyst; by contrast, the algorithm used in this paper would classify both of these tweets as *dovish*.

[6]The primary goal of this paper is to demonstrate that the increase in yields spotted by Greenlaw et al. (2018)

yields following monetary policy announcements were the result of the central bank sending signals about the future state of the economy that conflicted with market participants forecasts, thereby increasing market uncertainty and anxiety towards a potential economic recovery. As a result, investors became reluctant to take on duration risk, which increased the term premium.

That mechanism is perfectly illustrated by the 2013 tapering episode: while QE3 started in September 2012, talks about the end of the program already appeared at the December 2012 meeting, when some participants expressed their wish to stop it before the end of 2013. Strikingly, while the Fed started to taper - i.e. to reduce the pace of its asset purchases - only in December 2013, they had discussed about it during most of the meetings organized through 2013. Excerpts of central bank communication and the associated market commentary provided in tables A.1- A.4 clearly show that during that time, the *positive* news that tapering did not occur was overshadowed by the *negative* perception that it would occur very soon, which resulted in yield increases.

The rest of this paper is organized as follows. Section 2.2 reviews the different strands of literature related to this research question. Section 2.3 describes the methodology used in this study and section 2.4 presents the results of the empirical analysis. Finally, section 2.5 concludes.

2.2 Related literature

This paper is related to two streams of literature. First, it relates to the literature assessing the impact of unconventional monetary policies as an answer to the 2008 financial crisis. Second, it also contributes to the literature on central bank communication, which has gone through a period of tremendous growth in the last two decades, thanks to the development of computing power, and the increasing use of natural language processing and machine learning techniques in the fields of economics and finance.

2.2.1 The impact of unconventional monetary policies in the aftermath of the financial crisis

Following the implementation of unconventional monetary policies (QE and forward guidance), numerous event studies have been conducted to try to assess their impact. The basic principle underlying those studies is to look at the evolution of a variable during a short time-period surrounding an announcement. That interval must be large enough to capture the full impact of the shock, but small enough to ensure that the measured effect is not due to factors

during the three quantitative easing programs could be explained by the central bank surprising markets negatively. This implies that a change in yields would simply reflect marginal adjustments in market expectations, rather than a lack of efficiency of the policy. Testing for the nature of those adjustments is beyond the scope of this paper, nonetheless, I discuss possible explanations in subsection 2.4.2.2.

other than the one considered. Under the efficient market hypothesis, asset prices reflect all information available to market participants. Therefore, any price movement following the release of new information should be due to that event and to the resulting adjustment of market expectations. However, by focusing on a small time-interval, those studies may fail at taking reversals into account.[7] That dilemma is at the roots of the debate on the actual impact of the Fed's balance sheet presented hereafter.

Reviewing the literature about the impact of quantitative easing, Gagnon (2016, p.4) suggests that the impact of LSAPs in the U.S. amounted to about 1.2 percentage points. One of the most prominent paper in this literature has been written by Gagnon et al. (2011). The authors aim at assessing the impact of the first quantitative easing program implemented by the Fed, by investigating the changes in interest rates around eight official central bank communication events. They estimate that the first LSAP had a significant negative impact, with the ten-year Treasury yield declining by 91 basis points. Adding QE2 dates, Krishnamurthy and Vissing-Jorgensen (2011) find evidence consistent with Gagnon et al. (2011), and identified several transmission channels. Both QE1 and QE2 featured a *signaling channel* driving down the yield on all bonds through market expectations of the future path of the short rate;[8] a *long term safety channel* through which yields on medium- and long-maturity safe bonds fell because of portfolio balance effect - the reduction in supply triggered by the Fed purchase increased the premium on those assets that are not easily substitutable due to the safety benefits they provide; and an *inflation channel*, where increased inflation expectations implied larger reductions in real than in nominal rates.

Other studies have shown that forward guidance too was successful in lowering yields. Using the two-year nominal treasury yield as a proxy for market expectations of the future path of the federal funds rate, Hanson and Stein (2015) show that a 100 basis point increase in that variable on a FOMC announcement day was associated with a 42bp increase in the ten-year forward overnight real rate. The authors illustrate their findings with the FOMC announcement of January 25, 2012, when it was declared that the federal funds rate would remain near zero through late 2014, instead of mid-2013 as was previously stated. In response to this forward guidance shock, the expected path of short term nominal rates fell significantly, the two year nominal yield dropping by 5bp and the five year yield by 14bp. Interestingly, long term rates also appeared to react to forward guidance as the 10- and 20-year real forward rates declined by 5bp and 9bp respectively. The authors explain this phenomenon by *demand-supply* effects, with yield-oriented investors increasing their demand for long term treasuries following a decrease in short term rates, thereby inducing pressure on the price of those assets and lowering the term premium. By contrast, Campbell et al. (2012) and Nakamura and Steinsson

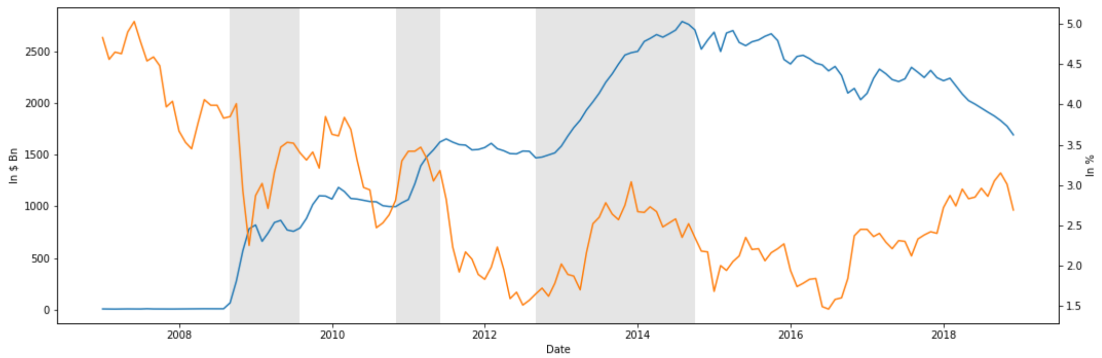
[7] Greenlaw et al. (2018, p.38) provide three potential explanations for these reversals: (1) markets overreacting to an unusual event and readjusting their expectations over time; (2) markets readjusting expectations after having wrongly assumed that more announcements similar to the adjustment that was just made would follow. When those do not arrive, then rates readjust; (3) QE requiring more frequent interventions by the central bank to have a sustained effect.

[8] In other words, QE announcements provided markets with a *signal* that allowed them to infer future federal funds rates (Krishnamurthy and Vissing-Jorgensen, 2011).

(2018) suggest that at that time, forward guidance mainly operated through a *Delphic* channel, where the Fed communication was perceived as a signal of its superior information about weak fundamentals: a surprise expansion of monetary policy would therefore be associated to lower expectations about growth and inflation.

In spite of such discussions about the actual transmission channel(s) through which monetary policy operates, there appears to be a consensus in the literature about the direction and significance of its impact. Both reviews conducted by Borio and Zabai (2018) and Kuttner (2018) suggest that unconventional monetary policies were successful in easing financial conditions by lowering long term interest rates. Borio and Zabai (2018, p.410) estimate that the "cumulative impact of the Fed programs on ten-year government bond yields may have been of the order of over -100 basis points."

Figure 2.1: **Total balances maintained with Federal Reserve banks (left axis, blue) and 10-year Treasuries constant maturity rate (right axis, orange):** Shaded areas represent respectively QE1 (11/2008-08/2009), QE2 (11/2010-06/2011) and QE3 (09/2012-10/2014). Reserve balance data come from FRED and yield data from Gürkaynak et al. (2007b).



However, skeptics about the impact of the Fed's balance sheet point out that event studies overestimate the impact of unconventional monetary policies, by focusing only on the most significant events and the ones more likely to confirm their hypotheses (Greenlaw et al., 2018). Inspecting Figure 2.1, it is interesting to see that indeed, while there may be a significant decrease in yields after the announcement of QE1 in September 2008, yields bounce right back a few months later - price movements due to large transactions being usually temporary - and increase during the implementation of QE2 and QE3 (Cochrane, 2017).

Greenlaw et al. (2018) therefore investigate the impact of unconventional monetary policies by constructing a broader set of monetary policy announcements. More specifically, they identify all days during which there were monetary policy news between November 2008 and December 2017 - i.e. due to the issuance of FOMC statements, the release of FOMC meeting minutes or speeches by the Fed Chair - and look at the movements of the 10-year treasury yield during those days, i.e. the *close to close* change in yield. Out of the the 2'374 days in their sample, they find 255 such days which they label "Fed Days." Then, they compute the cumulative change on those 255 days and find that the 10-year treasury yield tends to increase on Fed days during that period. Figure 2.2 replicates this experiment, with the exception that it excludes speeches of the Fed Chair, as it was not possible to exactly recover the dates considered by the authors. It confirms the authors' results, namely that QE does not appear to have had a major cumulative effect on interest rates. Admittedly, the 10-year bond yield fell at the start of QE1, but the cumulative impact of the moves during days that featured the release of FOMC meeting minutes - "release of minutes" days - and days that featured the release of a statement after a FOMC meeting - "FOMC meeting" days - trends higher through both QE2 and QE3.

Figure 2.2: **Cumulative Change in the 10-year Treasury yield on "FOMC meeting" and "release of minutes days":** This figure represents the cumulative *close to close* change in the ten-year U.S. treasury yield during two types of days: the release of statements following FOMC meetings ("FOMC meeting" days, which amount to 73 in the sample); and the release of FOMC meeting minutes ("release of minutes" days, which also amount to 73 in the sample). Shaded areas correspond to the three QE episodes. Yields come from Gürkaynak et al. (2007b); event Dates are identified looking at the *Historical Material by Year* section of the Fed's website. The figure replicates Greenlaw et al.'s (2018) experiment whose results are presented in exhibit 4.2 of their paper, with the exception that it excludes speeches of the Fed Chair, as it was not possible to exactly recover the dates considered by the authors.

Greenlaw et al.'s approach is very interesting as it provides evidence that challenge common wisdom about the impact of the Fed's balance sheet. While they do not attempt to test any hypothesis that could explain their results, they suggest that yields may increase during "Fed Days" because the Fed disappoints markets by not being sufficiently expansionary. One of the reasons why they did not test this hypothesis is that "it is impossible to construct a complete time series on unconventional policies expectations" (p.25), due to the lack of quantitative data on market participants' expectations.[9] The key novelty of this paper is therefore to provide an objective measure of market expectations of conventional and unconventional monetary policies and of the surprise generated by central bank announcements, by using NLP and machine learning techniques to extract that information from tweets.

[9]The only data available regarding market expectations of unconventional monetary policies are surveys of market participants' balance-sheet expectations conducted by the Business Press in the run-up of QE1, and the New-York Fed's survey of primary dealers that started in January 2011. Those data however, when accessible, do not cover the whole duration of the three LSAPs and therefore do not allow to build a reliable and comprehensive time-series.

2.2.2 NLP and Central Bank communication

As the previous subsection explained, event studies' identification strategy is based on the efficient market hypothesis, according to which all public information is embedded into prices. As new information becomes public, prices adjust automatically based on the new information set. Following this reasoning, any news about monetary policy and the future path of interest rates should have an impact on market expectations, and therefore translate into movements of financial market variables. Reviewing the literature on central bank communication, Blinder et al. (2008) stress how managing expectations has become a cornerstone of monetary policy, either by *creating news* - which has a direct impact on market expectations - or by *reducing noise* - through the increase in the predictability of central bank actions. However, one of the main challenges in analysing the impact of central bank communication is that its content is largely qualitative. More and more, academics have used automated content analysis techniques to help them measure and quantify such data. This section reviews some of this literature, classifying the techniques used in two categories: topic identification and polarity classification.

2.2.2.1 Topic identification

It is possible to provide rich representations of documents using NLP techniques that identify their underlying subjects or topics. There are two popular approaches used by the literature: Latent Semantic Analysis (LSA) and Latent Dirichlet Analysis (LDA).

LSA is a dimensionality reduction technique that consists in applying singular value decomposition to the term-document matrix - the matrix counting, for each word (rows) the number of times they appear in a document (columns). The approach is similar in spirit to PCA, as it provides the most important factors - which can be interpreted as topics - of variation accross documents. The decomposition allows to see how important a word is to a given topic, and how important that topic is to a given document. Boukus and Rosenberg (2006) are among the first to apply LSA to central bank communication, investigating the information content of FOMC minutes released between 1987 and 2005. They find that yield changes depend on the topics embedded in the central bank's communication documents - e.g. output growth, labor market conditions, prices and inflation. More specifically, they find that terms such as *growth, price, market, econom, business* or *inflat* used in FOMC minutes are correlated with current and future macroeconomic and financial indicators. As a result, market participants use FOMC minutes to extract signals about future economic outlook, which has in turn an impact on financial markets and especially on long term rates. Hendry and Madeley (2010) apply the same technique to the central bank of Canada's communication during the period 2002-2008. They find that the information contained in those documents has a significant impact on market returns and volatility, which goes above and beyond the policy rate surprise. Hendry (2012) uses LSA to identify which themes from the central bank of Canada communication and the subsequent market commentary have an impact on the volatility and the level of short term interest rates.

Blei et al. (2003) develop another kind of method, an unsupervised machine learning algorithm - Latent Dirichlet Allocation or LDA - which is used to identify the topics of a corpus of documents based on the words they use. More precisely, it is a generative probabilistic model of a corpus of documents, in which each document is represented as a random mixture over latent topics and each topic is distributed over words. In other words, their model gives the probability that a given topic belongs to each document and the probability that each word belongs to each topic. Hansen and McMahon (2016); Hansen et al. (2018) are two interesting applications of LDA. Hansen et al. (2018) aim at measuring the impact of transparency on FOMC deliberations. Looking at the transcripts since 1970, they use LDA to identify the topics informative of FOMC members' policy preferences in those meetings, and build communication measures at the meeting-speeker level. Then, using the release in 1993 of all FOMC transcripts since 1970, they conduct a natural experiment to measure the impact of transparency on deliberations. They find large changes in communication patterns after transparency, due to both discipline and conformity effects. Hansen and McMahon (2016) use both LDA- and dictionary-based methods to identify the topics and tone of 142 FOMC statements between 1998 and 2015. The authors aim at measuring the impact of communication from FOMC statements about the state of the economy and forward guidance on financial and real variables. Interestingly, they find that shocks to forward guidance are more important than FOMC communication about the current state of the economy.

These techniques open exciting new paths for research in economics and finance. First, by providing quantitative representations of qualitative data, they enable to tackle subjects which were up to now difficult to study - e.g. central bank communication. Second, by providing access to new sources of data, they allow researchers to adopt new perspectives and test new hypotheses. This is what this paper attempts to do. I aim at creating a measure of market surprises related to conventional and unconventional monetary policies, by extracting data from tweets published around monetary policy announcements. However, I use a different approach than topic identification, because even if LSA or LDA are good at summarizing the key component of a document or a piece of text, they are unable to tell *how* authors *talk* about those topics - e.g. positive *vs* negative, increase *vs* decrease, hawkish *vs* dovish, etc. This can be done using polarity classification algorithms.

2.2.2.2 Polarity classification

Compared to topic identification, polarity classification consists in providing a much simpler representation of a piece of text - e.g. a document, a sentence or a tweet - by reducing it to its semantic orientation - e.g. positive *vs* negative sentiment. Polarity classification has evolved over time, from manual classification, to automated algorithms using dictionaries or machine learning techniques.

Early studies classified documents manually. For example, Romer and Romer (2003) read the content of Record of Policy Actions, Minutes and Transcripts of the FOMC to identify the intended committee actions towards the fed funds rate decision - increase, decrease, no move. Then, they use this measure of intended change to control for the anticipated change of monetary policy and develop a new measure of monetary policy shocks; Ehrmann and Fratzscher (2007) manually classify the news reports written about forward-looking policy statements made by the members of the committees of the European Central Bank (ECB), the Bank of England (BoE) and the Fed between 1999 and 2004, on whether they gave an inclination of tighter versus no change versus lower interest rates (+1, 0,-1 respectively), or stronger versus unchanged versus weaker economic outlook (+1, 0, -1 respectively). They use these indicators to measure the impact of central banks' communication strategies on financial markets.

While these studies allow the analysis of qualitative textual data, they lack the objectivity, scale and level of details that automatic content analysis techniques offer. Therefore, in the past ten years, academics in economics and finance have increasingly resorted to automated techniques to analyze central bank communication. A popular methodology is to build dictionaries with words having a clear tone or semantic orientation, and to count the number of such words in pieces of texts. Popular dictionaries include: the Harvard IV-4 dictionary, which provides a list of generic positive and negative words; the Loughran and Mcdonald (2011) dictionary, specifically adapted to financial contexts - for example, terms such as tax, cost or capital are considered as negative in the Harvard IV-4 dictionary, while they are not in financial contexts; the Apel and Blix-Grimaldi (2012) and Picault and Renault (2017) dictionaries, which can be used to analyze the content of monetary policy announcements; finally, the NRC-Canada system (Mohammad et al., 2013) is very successful in identifying tweet sentiment.

Numerous papers use dictionaries to analyze monetary policy communication. To cite a few, Shapiro and Wilson (2019) use Loughran and Mcdonald's dictionary to estimate the central bank short-run loss function and the implied inflation target. They construct, for each speaker at each FOMC meeting, a measure of the net negativity of their remarks based on their differential use of negative and positive words. Interestingly, they find that the FOMC had an implicit inflation target of approximately 1.5% - lower than the official 2% - and that its loss function is monotically decreasing in real economic activity - implying that the FOMC would concede higher inflation to increase real activity. Hubert and Burda (2018) use both the Loughran and Mcdonald (2011) and Apel and Blix-Grimaldi (2012) dictionaries to investigate whether sentiment conveyed by policymakers in FOMC statements affects the term structure of private agents' short term interest rate expectations. They notably find that optimistic sentiment increases the term structure of interest rates primarily at the 1-year maturity.

Other studies use self-created dictionaries. In order to measure the impact of shocks in beliefs about QE3 tapering by the Fed, Meinusch and Tillmann (2015) use a list of predetermined keywords to separate tweets on whether they expect tapering to occur soon *vs* later. They use these tweets to build a measure of market beliefs about tapering, and find that a shock to these beliefs has significant effects on exchange rates and asset prices; Lucca and Trebbi (2009) develop a dictionary - two sets of hawkish and dovish words - to extract the content of central bank communication about future interest rate decisions from news sources. They start by computing the co-occurence between monetary policy words - e.g. "rates," "Fed" - and hawkish *vs* dovish words. This indicator tells, for example, how often the term "Fed" and those belonging to the "hawkish" dictionary are associated in a given document.[10] From this, they are able to compute the *semantic orientation score* of a text on a hawkish-dovish scale. Then, by aggregating those scores, they obtain the semantic orientation of monetary policy communication. Finally, they compute this monetary policy semantic orientation score before and after an announcement, to precisely estimate the surprise generated by monetary policy communication. Using intraday data, they find that short term rates react to changes in the policy rate, while longer-term treasury rates respond mainly to unexpected changes in central bank communication. In this paper I use a similar approach to compute a measure of the surprise generated by monetary policy announcements, but I let a machine learning algorithm recover the underlying association between words instead of simply estimating their joint distribution by counting the number of times they appear together. Therefore, even though I use these dictionaries to label the tweets used in the training sample, my algorithm is able to provide a much richer representation of the latent structure that shapes relationships between words than Lucca and Trebbi's approach.

The use of machine learning techniques for polarity classification applied to finance has known a period of tremendous growth in the past few years. For example, Azar and Lo (2016) use the python package “Pattern,” a machine learning based algorithm developed by De Smedt and Daelemans (2012), to give tweets published prior to the release of FOMC statements a polarity score between -1 and +1 (purely negative to purely positive). Then, they build a measure of market sentiment, and are able to show that tweets contain information useful to predict how asset prices evolve following FOMC announcements. Closer to this paper, Lee et al. (2019) investigate the impact of monetary policy surprises generated by announcements made by the Bank of Korea between 2005 and 2017. The surprise is proxied by the shift in the tone of the news articles published before and after the announcements. The tone is identified using a machine learning algorithm that classifies sequences of five words - also called 5-gram - as hawkish or dovish, and aggregating over the relevant time period. They do find that monetary policy surprises - i.e. shift in the tone of the news articles talking about monetary policy - has an impact on yields of various maturities, especially on long term maturities. This work is very close in spirit to the work conducted in the current paper and presented below. However, the results provided by the authors are limited to South Korea. This makes them unable to answer Greenlaw et al.'s critique, as they merely provide anecdotal evidence which may not apply to the American market, or to the policy implemented by the Fed as a response to the 2008 financial crisis. This paper aims at filling this gap.

[10] Their approach is similar to the pointwise mutual information score (PMI), which is a common indicator used in NLP to identify the degree of association between two words or pieces of text.

2.3 Methodology

I use a machine learning algorithm to classify tweets as *dovish*, *hawkish*, *neutral* or *non relevant*. This section describes the data employed and the classification methodology.

2.3.1 Data

Three types of data were used in this analysis: "Event days," financial data and tweets. Those are presented hereafter.

2.3.1.1 Event Days

Following Greenlaw et al. (2018), I focus on the period November 2008-December 2017. It features 73 "FOMC meeting" days and 73 "releases of minutes" days, which amounts to 146 "Event Days," i.e. days during which new information about monetary policy was released. The dates were identified from the *Historical Material by Year* section of the Federal Reserve Board website.

Note that I choose not to include the speeches of the Chair of the Fed, as it is difficult to distinguish which ones had been subject to the release of new information. Moreover, including speeches of the Chair would require to consider also speeches of other members of the board, who often intervened to comment on monetary policy and the economic situation. Designing an approach to select those would be heuristic and risks to increase noise in the dataset. Speeches are therefore left out of the analysis.

Furthermore, in order to control for the importance of the event, I consulted daily *Market wrap-up* from the Thomson Reuters database. These reports indicate which factors moved markets on each day, through a range of interviews conducted with market participants. Since the data I use is at a daily frequency, this step allows me to identify the days during which market movements are really a result of the Fed announcements. If the hypothesis tested in this paper holds, the effect should be stronger on those days. As a result, this translates into the creation of a dummy variable, D_t, distinguishing monetary policy *events* (1) from *non events* (0). In the empirical analysis, those days are called *Reuters FOMC days.*

Finally, almost all of the announcements during the period occur between 2pm and 2:30pm Eastern Time (ET).[11] I am able to recover the exact time at which they were made each day, by looking at the time at which the first tweet announcing the publication of new information about monetary policy had been published.

[11] Eastern Time (ET) is the time zone in which Washington DC is located. It is five hours behind the Coordinated Universal Time in autumn/winter (UTC-05:00) when observing standard time (Eastern Standard Time or EST), and four hours behind UTC in spring/summer (UTC-04:00) when observing daylight saving time (Eastern Daylight Time or EDT).

2.3.1.2 Financial Data

There are three types of financial data: (1) yields & forward rates; (2) the term premium of nominal yields and forwards; and (3) the effective fed funds rate and the daily return of the S&P 500.

Nominal, on the one hand, and, on the other hand, real and breakeven yields & forwards data, come from Gürkaynak et al. (2007b) and Gürkaynak et al. (2010)[12] respectively. The data is easily accessible through the Fed website or the FRED database. Quotes are taken between 3pm and 3:30pm each day. In this paper, those are qualified as *close price* and are used to compute the *close to close* change in yields and forwards rate. They serve as dependent variables in the several regressions run in the empirical analysis.

The term premium of nominal yields comes also from the FRED database. It was computed according to Kim and Wright' (2005) methodology, by fitting a simple three-factor arbitrage-free term structure model to U.S. treasury yields, in order to estimate a decomposition of the term structure of nominal interest rates into (1) expected future short rates and (2) term premiums.

The daily return of the value weighted S&P 500 including dividends and the daily change in the effective fed funds rate are used as control variables. The former was extracted from CRSP while the latter comes from the FRED database.

2.3.1.3 Tweets

Tweets are used to build the main explanatory variable, i.e. monetary policy surprises. They are downloaded using the GetOldTweet3 python package, which scraps from the web publicly available tweets using the Advanced Research tool embedded on the Twitter website. For three-day periods centered around each of the 146 "Event Days," I collect all the tweets that contain at least one of the following keywords: *"federal reserve," "the fed," "quantitative easing," "FOMC," "#QE,"*[13] *"#QE2," "#QE3," "Bernanke"* and *"Yellen."* Table 2.1 provides summary statistics about those tweets. The raw dataset contains 2'066'114 tweets. After removing duplicates and similar tweets[14] posted by bots, the dataset shrinks to 1'264'409. In order to build the measure of the surprise, the window size was reduced to eight hours centered around the announcement. This limits the noise generated by people not tweeting about the recent announcement.

[12] In the former paper, Gürkaynak et al. provide estimates for the nominal yield and forward curves. In the later paper, they build on that work to provide estimates of the treasury inflation protected security (TIPS) and inflation compensation yield and forward curves.

[13] The "#" character was necessary to avoid collecting irrelevant tweets with words containing "qe."

[14] Tweets were considered as similar if their first 30 characters were identical.

Table 2.1: Summary statistics: Tweets per window centered around each event date

Variable	Mean	SD	Min	Max	Median	Total
# tweets per three-day window	8'658	6'610	281	3'4975	6'678	1'264'073
# tweets per eight-hour window	2'855	2'698	77	14'292	1'996	416'782

Upon collection, tweets are automatically cleaned in order to be fed to the algorithm. The steps performed involved: removing all HTML tags and replacing them with their ASCII decoded version; removing URLs; transforming contractions into their original forms (e.g. "U" into "you"); correcting the most common misspells; replacing hashtags by actual in-vocabulary forms (e.g. "#ratehike" is replaced by "# rate hike"); replacing usernames by actual in-vocabulary forms when those are likely to have an impact on the results (e.g. "@federalreserve" is replaced by "@ federal reserve"); introducing a space between punctuation and characters; and converting posting time from UTC to ET. Those transformations enable BERT embeddings to cover most of the words used in the tweets.

2.3.2 Classification Methodology

Classification is done in three steps: creating a training set; designing the algorithm; and measuring its performance.

First, I build on Apel and Blix-Grimaldi's (2012) dictionary to manually classify 7'550 tweets posted around each monetary policy announcement on their *dovish*, *hawkish*, *neutral* or *non relevant* tone. In order to be considered as hawkish, dovish, or neutral, tweets needed to fit two criteria: (1) talking about monetary policy (e.g. "rate," "balance sheet") or macroeconomic conditions (e.g. "inflation", "unemployment"); and (2) giving information about the direction of the move (e.g. "increase," "keep at 0," "taper", "unchanged"). Table 2.2 provides an example of tweets belonging to each category. I also created and added 50 tweets to the sample, in order to give a higher weight to important patterns (e.g. "The Federal Reserve started to reduce its balance sheet").[15]

In total, I labelled 1'220 tweets as dovish, 887 as hawkish and 461 as neutral - including the synthetic tweets. The remaining 5'032 tweets were classified as non relevant. Finally, 10% of this dataset is set aside to create a validation set dedicated to measuring the performance of the model. The algorithm is therefore actually trained on 6'840 tweets.

Second, for the classification algorithm, I use the BERT base uncased model (Devlin et al., 2019) with an additional linear layer for sentence classification. BERT is a general-purpose "language

[15] The creation of synthetic tweets is useful because it enables to increase the size of the sample, and put a larger weight on interesting patterns that the algorithm should learn. Indeed, while at first glance the size of the sample of labelled tweets appears to be quite significant (7'550), only 2'518 are actually relevant for the analysis, i.e. labeled as either *hawkish, dovish* or *neutral*.

Table 2.2: Examples of dovish, hawkish neutral and non relevant tweets

Examples of dovish tweets
"DTN Financial News: Fed ponders more easing as economy stumbles (Reuters): Reuters - The Federal Reserve meet..." "I am just writing the Fed's statement for tomorrow.. cut rates by 0.25%. global conditions deteriorating. inflation expectations weakening. Need to protect USA economic expansion. Why do they need to have a meeting?"
Examples of hawkish tweets
"The fed raised rates today, so now we have a 0.50%-0.75% guided base rate on the USD. No matter what anyone says, this is impressive for now" "Breaking: FED Raises Rates and removes reference to "Accommodate" policy FED FOMC"
Examples of neutral tweets
"The fed kept rates unchanged" "In a few minutes we will have a white smoke (quantitative easing) or black smoke (not quantitative easing), as in a Papal Conclave #FOMC #Bernanke #quantitative easing "
Examples of non relevant tweets
"Understanding Fed policy: Some mysteries cleared, plot thickens on others: The Fed chairman announced that he will soon start giving press conferences every — rather than every other — policy meeting Powered by WPeMatico" "video How the Fed built a $ 3 trillion balance sheet: The Federal Reserve's amazing asset accumulation was... news"

understanding" model, pre-trained on a large corpora of text (Wikipedia and BookCorpus, 2.5 billion and 800 million words respectively), which provides context specific word embeddings - i.e. vectors summarizing the meaning of a word depending on its context. Those can then be used for a wide range of downstream NLP tasks such as sentence classification, translation, etc.

BERT's advantages are two-fold. First, compared to previous word embeddings models such as Word2Vec (Mikolov et al., 2013) or GLoVe (Pennington et al., 2014), it provides truly contextual word embeddings, meaning that the word "bank" would have two different representations if it is a "bank account" or a "river bank." Second, contextual representations are bidirectional, meaning that they take both left and right contexts into account. This is allowed by their novel approach, consisting in two things. First, they mask 15% of the words in the input, run the entire sequence through a deep bidirectional transformer encoder (Vaswani et al., 2017), and predict only the masked word. Second, in order to learn the relationship between sentences, they also train the model to recognize whether a sentence B comes after sentence A or whether it is just a random sentence from the corpus.

The BERT base model features 12 transformer encoder layers with 768 hidden dimensions and 12 multi-head attention pre-trained on two large corpora representing 3.3 billion words, with a batch size of 128'000 words and around 1 million steps. Pre-training took four days on 4x4 TPU slices according to the authors' github repository.

Pre-training is a one-time procedure done at Google. The outcome - context-dependent word embeddings - is made freely available by the authors and can be used for a wide range of downstream tasks. It only requires to add one or several layers on top of BERT consistent with the task at hands, and to *fine tune* the model's parameters with the investigated dataset.

For this paper, I used the model *BertForSequenceClassification* from the Python library *Transformers* to classify tweets as *hawkish, dovish, neutral* and *non relevant*.[16] Fine tuning of the model takes about 15 minutes, and after 4 epochs, the algorithm produces an accuracy (% of good classification) on the validation set of 88%. This performance could be improved, notably by increasing the size of the training set, but after a manual inspection of randomly selected classification errors, it appears to be sufficient to conduct the rest of the analysis.

2.4 Empirical Analysis

The trained model is used to assign labels on the entire corpus of tweets. These are then used to build the variable measuring the surprise, which construction is described in the first subsection. In the second subsection, I investigate to which extent that measure of the surprise explains the change in yields during monetary policy announcements.

2.4.1 Measure of the surprise

Building on the *semantic orientation score* developed by Lucca and Trebbi (2009), I create a measure of the surprise generated by monetary policy announcements in two steps: (1) estimation of *market expectations*; and (2) computation of the *surprise* as the difference between market expectations before and after an announcement.

Market expectations of monetary policy for period t, ME_t, are computed in the following way: each dovish tweet is given a score of +1; each hawkish tweet a score of -1; each neutral tweet a score of 0; and non relevant tweets are left out of the analysis. Then, market expectations are simply the average of those tweets. Equation (2.1) summarizes those computations:

$$ME_t = \frac{\text{\# dovish tweets - \# hawkish tweets}}{\text{\# dovish tweets + \# hawkish tweets + \# neutral tweets}}, \in [-1, 1]. \tag{2.1}$$

The ME_t score can be interpreted as the aggregate perception of monetary policy by market participants, or in other words, market expectations of monetary policy. $ME_t > 0$ would mean that people tend to perceive or expect monetary policy to be rather dovish.

[16] *BertForSequenceClassification* contains two modules: BERT and a linear classifier layer.

This measure of market expectations of monetary policy is then used to compute the surprise, i.e. the unexpected change in the stance of monetary policy expressed by the announcement occurring at time t. It is done by finding the difference between the market expectations score (ME_t) before and after the announcement. More specifically, given all the tweets published during day t, T_t, consider $T_{t^-} \subset T_t$ the set of tweets published before the announcement and $T_{t^+} \subset T_t$ the set of tweets published after the announcement. ME_{t^-} and ME_{t^+} may thus be interpreted as the market view of monetary policy or the market expectations of monetary policy before and after the announcement respectively. Equation (2.2) computes the difference between those two measures:

$$\Delta ME_t = ME_{t^+} - ME_{t^-}, \tag{2.2}$$

with ΔME_t taking values in the interval $[-2,2]$. ΔME_t measures the surprise associated with the monetary policy announcement and the resulting adjustment of expectations. For example, assume that in the announcement to come, the market expects officials to announce that monetary policy will be very expansionary. Then, ME_{t^-} would be positive and large. Now, assume that the announcement does provide information about an increase in quantitative easing, but to a lesser extent than what markets anticipated. Then, it is likely that ME_{t^+}, even if positive, would be inferior to ME_{t^-}. In that case, $\Delta ME_t = ME_{t^+} - ME_{t^-} < 0$ and we have a negative surprise, even though the announcement had emphasized an expansion of the balance sheet. In such a case, yields should increase. This is the main hypothesis tested in this paper, which, if confirmed, would provide an explanation for the puzzling increase in long term yields that occurred during the several episodes of quantitative easing as emphasized by Greenlaw et al. (2018).

2.4.2 Estimating the impact of the surprise on long term rates

Estimations are obtained using ordinary least squares (OLS) and heteroskedasticity & autocorrelation robust standard errors with small sample correction[17] using one lag to take care of the overlapping nature of FOMC announcements and release of minutes. I start by presenting results from the baseline regression and alternative specifications that test for the robustness of the results. Then, I break down the 10-year nominal yield into its real, breakeven and term premium components, to attempt to pin down the channel through which monetary policy has an impact on nominal yields.

2.4.2.1 Baseline regression & alternative specifications

As a start, measuring the impact of the surprise on long term yields may simply be done by regressing the close to close change in the 10-year nominal Treasury yield,[18] $\Delta_{t-1,t}\, y_t$, on the

[17] Following Andrews (1991), this consists in applying a small sample correction factor to the estimated covariance matrix. This factor is equal to $\frac{T}{T-r}$, where T is size of the sample, and r is the size of the vector of parameters to be estimated.

[18] The close to close change is computed as the close yield the day of the announcement, y_t minus the close yield the day prior to the announcement, y_{t-1}. In mathematical terms: $\Delta_{t-1,t}\, y_t = y_t - y_{t-1}$.

Table 2.3: BERT - Baseline OLS Regression & Alternative Specifications

	(1) $\Delta_{t-1,t}$ *10-year yield*	(2) $\Delta_{t-1,t}$ *10-year yield*	(3) $\Delta_{t-1,t}$ *10-year yield*	(4) $\Delta_{t-1,t}$ *10-year yield*	(5) $\Delta_{t-1,t+1}$ *10-year yield*	(6) $\Delta_{t-1,t}$ *10-year forward*	(7) $\Delta_{t-1,t}$ *10-year forward*	(8) $\Delta_{t-1,t}$ *10-year forward*	(9) $\Delta_{t-1,t}$ *10-year forward*	(10) $\Delta_{t-1,t+1}$ *10-year forward*
α_t	-0.0010	-0.0020	-0.0002	0.0013	-0.0090	0.0068	0.0028	0.0103	0.0112	-0.0093
	(0.0064)	(0.0060)	(0.0100)	(0.0094)	(0.0096)	(0.0067)	(0.0062)	(0.0098)	(0.0096)	(0.0118)
ΔME_t	-0.0263***	-0.0266***	-0.0266***	-0.0073	-0.0313***	-0.0155**	-0.0157**	-0.0156**	-0.0042	-0.0256*
	(0.0081)	(0.0080)	(0.0079)	(0.0077)	(0.0120)	(0.0073)	(0.0069)	(0.0069)	(0.0075)	(0.0135)
R_t^{SP}		0.0026	0.0026	0.0024	0.0114		0.0161**	0.0162**	0.0161**	0.0259
		(0.0079)	(0.0079)	(0.0077)	(0.0136)		(0.0080)	(0.0079)	(0.0079)	(0.0187)
ΔFFR_t		0.8514	0.8364	0.7114	1.3397*		0.6666	0.6039	0.5299	1.4604
		(0.5376)	(0.5353)	(0.5185)	(0.7470)		(0.5141)	(0.5136)	(0.5028)	(0.8976)
D_t			-0.0025	-0.0038				-0.0104	-0.0112	
			(0.0121)	(0.0120)				(0.0124)	(0.0123)	
$D_t \times ME_t$				-0.0283***					-0.0168	
				(0.0100)					(0.0109)	
N	146	146	146	146	146	146	146	146	146	146
R2	0.11	0.13	0.13	0.16	0.11	0.04	0.11	0.11	0.12	0.10

The estimated baseline regression & alternative specifications are variants of $\Delta_{t-1,j} X_t = \alpha + \beta_{ME}\Delta ME_t + \beta_{SP} R_t^{SP} + \beta_{FFR}\Delta FFR_t + \beta_D D_t + \beta_{D\times ME}(D_t \times \Delta ME_t) + \varepsilon_t$, where $j = \{t, t+1\}$ to allow for different window sizes, $X_t = \{y_t, f_t\}$, the 10-year yield and the instantaneous forward rate 10 years from now respectively, both expressed in nominal terms. The estimated coefficient associated to ΔME_t indicates the percentage point response of the endogenous variable per standard deviation of the surprise indicator. The estimated coefficients associated to $R_t^{S\&P500}$ and ΔFFR_t indicate the percentage point response of the endogenous variable per 1 percentage point increase in the daily return of the $S\&P500$ and the daily change of the effective fed funds rate respectively. The coefficient associated to D_t measures the average change, in percentage point, of the endogenous variable during Reuters FOMC days and the coefficient associated to $D_t \times \Delta ME_t$ measures the percentage point change of the endogenous variable per standard deviation shock of the surprise indicator during Reuters FOMC days. Standard errors in parenthesis are heteroscedasticity and autocorrelation robust (HAC) using 1 lags and with small sample correction. * indicates significance at the 10-percent level, ** indicates significance at the 5-percent level, and *** indicates significance at the 1-percent level.

measure of the surprise, ΔME_t. The equation to be estimated is given by Equation (2.3):

$$\Delta_{t-1,t}\ y_t = \alpha + \beta\ \Delta ME_t + \varepsilon_t, \tag{2.3}$$

with α and β the parameters to estimate and ε_t the error term. Note that in order to make the estimated β coefficient more interpretable, I divide the measure of the surprise (ΔME_t) by its standard deviation.[19] As a result, β can be interpreted as the response in percentage point to a one standard deviation increase in the measure of the surprise.

Results are presented in Column (1) of table A.13. The coefficient associated to the measure of the surprise is negative and statistically significant at the one percent level, meaning that a one standard deviation negative shock to the measure of the surprise increases 10-year nominal yields by 2.63 basis points. The order of magnitudes are consistent with Gürkaynak et al. (2005) who investigate the sensitivity of long-term interest rates to economic news (capacity utilization, unemployment rates, etc.). This result provides evidence for the hypothesis tested in this paper, i.e. that the increase in yields following the release of new monetary policy information during the implementation of QE2 and QE3 does not reflect a lack of efficiency of the policy, but rather the Fed disappointing market expectations. For example, it is interesting to see that the surprise during these two quantitative programs[20] was on average negative, amounting to -0.14 and -0.31 respectively.

In order to test the robustness of that result, I run several regressions with alternative specifications. They are all variants of Equation (2.4):

$$\Delta_{t-1,j} X_t = \alpha + \beta_{ME}\Delta ME_t + \beta_{SP} R_t^{SP} + \beta_{FFR}\Delta FFR_t + \beta_D D_t + \beta_{D\times ME}\left(D_t \times \Delta ME_t\right) + \varepsilon_t, \tag{2.4}$$

First, in order to deal with a potential omitted variable bias, I add two control variables, R_t^{SP}, the daily return of the S&P500, and ΔFFR_t, the daily change in the effective fed funds rate. Adding the former is necessary as numerous papers have shown that (1) stock and bond markets are correlated, even though the correlation may vary over time (Andersson et al., 2008), and (2) the relationship between FOMC announcements and the stock market is non neutral (Bernanke and Kuttner, 2005; Lucca and Moench, 2015). The daily change of the effective fed funds rate should also be added as a control variable, since monetary policy surprises may materialize by an increase in the target policy rate, which has an impact on long term rates (Kuttner, 2001; Gürkaynak et al., 2005). Results are shown in Column (2) of table 2.3. Interestingly, the two coefficients associated to those variables are not statistically significant,

[19] In the remainder of this paper, the measure of the surprise should be understood as the measure of the surprise ΔME_t given by equation (2.2), divided by its standard deviation. For simplicity, the notation ΔME_t is kept to designate the normalized variable.

[20] The average surprises for QE2 and QE3 were computed by taking the mean of the ΔME_t variables on the periods 11/2008-08/2009 and 09/2012-12/2014 respectively.

and adding them barely changes the results.

Second, I investigate whether the negative impact of the surprise on long term rates is indeed due to monetary policy announcements, or rather to other factors happening on those days. To do so, I consulted the *Reuters market wrap-ups*, which identify from interviews with market participants, which factors moved markets during the current trading day. Then, I used this information to create a *Reuters FOMC days* dummy variable, D_t, which is equal to one if market participants identified monetary policy as an important factor in moving markets on that day, and zero otherwise. This allows to distinguish monetary policy events from non-events, even if admittedly, this approach is limited by the subjective nature of market participants' opinions. The coefficient associated with D_t measures whether there is significant changes in the endogenous variable during *Reuters FOMC days* compared to other days. I also add an interaction term between the measure of the surprise (ΔME_t) and the *Reuters FOMC days* dummy variable (D_t), to measure to what extent the impact the surprise on the 10-year nominal rate during *Reuters FOMC days* differs from other days. As expected, results in Column (3) of table A.13 show that *FOMC Reuters days* are no different than other days apart from monetary policy surprises. Additionally, the estimates shown in Column (4) of Table A.13 suggest that the impact of the surprise on the ten-year nominal rate is -0.73bp (not statistically significant) on *non FOMC Reuters days*, compared to $-0.73-2.83 = -3.56$bp on *FOMC Reuters days*. Those results support the idea that the main factor moving yields during the days considered in this sample is monetary policy surprises.

Third, following Hanson and Stein (2015), I allow for different window sizes for the endogenous variable. Based on treasury market microstructure evidence,[21] the authors argue that bond markets may take time to incorporate new information into prices, and quotes taken between 3pm and 3.30pm for an announcement made between 2pm and 2.30pm may not capture the full market response to monetary policy announcements. Therefore, they compute the change in yield for an announcement made at date t, by taking the difference between the close yield the day prior to the event, y_{t-1}, and the close yield the day following the event, y_{t+1}. As a result, I denote the endogenous variable for an announcement made at time t by $\Delta_{t-1,t+1} y_t$. Results shown in Column (5) indicate that the impact of the surprise is significant and stronger for the $t-1, t+1$ window than for the smaller window: a one standard deviation negative shock to the surprise indicator increases 10-year nominal yields by 3.13bp - vs 2.66bp for the $t-1, t$ window, as shown by column (2).

Finally, Columns (6)-(10) of table A.13 run the same regressions as those displayed in Columns (1)-(5), but the endogenous variable considered is $X_t = f_t$, where f_t is the treasury instantaneous forward rate 10 years from now, instead of $X_t = y_t$, where y_t is the 10-year nominal treasury yield. Forward rates are interesting because they may notably be interpreted as reflecting market expectations of future short-term interest rates (Svensson, 1994). Interestingly, the coefficient associated with the daily return of the S&P500 is positive and statistically

[21] For example, Fleming and Remolona (1999) estimate that following major announcements, price formation in the treasury market is gradual, with heightened levels of volume and volatility lasting 90 or more minutes.

significant, which may be explained by the fact that an increase in stock indices may reflect more optimistic beliefs about the future of the economy, which has an impact on market participants' expectations about the future path of short term interest rates. Regarding monetary policy surprises, statistical significance of the surprise indicator appears to be less strong than for nominal yield. Nevertheless, monetary policy surprises are negatively associated with long term instantaneous forward rates, which supports the hypothesis tested in this paper.[22]

2.4.2.2 The transmission channel of monetary policy surprises to long term nominal yields

In this section, I take a first stab at investigating the channel through which monetary policy impacts long term nominal yields. I conduct this analysis in two steps: First, I look at the impact on real and breakeven inflation rates, and second, on the term premium.

First, I start by splitting the nominal yield into its nominal and real components. Following Hanson and Stein (2015),[23] I estimate the three following regressions, for maturity n ranging from 2 to 10 years, as well as 15 and 20 years:

$$\Delta y_t^{\$(n)} = \alpha^{\$(n)} + \beta_{ME}^{\$(n)} + \Delta ME_t \beta_{SP}^{\$(n)} R_t^{SP} + \beta_{FFR}^{\$(n)} \Delta FFR_t + \varepsilon_t^{\$(n)} \quad (2.5)$$

$$\Delta y_t^{TIPS(n)} = \alpha^{TIPS(n)} + \beta_{ME}^{TIPS(n)} + \Delta ME_t \beta_{SP}^{TIPS(n)} R_t^{SP} + \beta_{FFR}^{TIPS(n)} \Delta FFR_t + \varepsilon_t^{TIPS(n)} \quad (2.6)$$

$$\Delta y_t^{\pi(n)} = \alpha^{\pi(n)} + \beta_{ME}^{\pi(n)} + \Delta ME_t \beta_{SP}^{\pi(n)} R_t^{SP} + \beta_{FFR}^{\pi(n)} \Delta FFR_t + \varepsilon_t^{\pi(n)}, \quad (2.7)$$

where the superscripts $\$(n)$, $TIPS(n)$ and $\pi(n)$ denote respectively regressions on the changes of the nominal yield of maturity n, and its real and breakeven inflation components.

Table 2.4 summarizes the estimates of the coefficients associated with the measure of the surprise for nominal, real and breakeven yields for all maturities.[24] The impact of the surprise

[22] One remaining concern regarding the validity of the results presented in this paper is that market expectations after the announcement $\left(ME_{t^+}\right)$ could be endogenous in the reaction of the 10-year treasury yield, thereby generating reverse causality: by seeing yields increasing following an announcement, market participants could interpret the decision of the central bank as being hawkish and tweet about it; In such a case, ME_{t^+} would be more negative, and so would the measure of the surprise ΔME_t. An important counterargument to the hypothesis of reverse causality is due to the way the measure of the surprise is built. Indeed, in order to be considered in the analysis, tweets needed to fit two criteria that are - a priori - independent from the evolution of bond prices: mentioning a monetary policy tool or macroeconomic conditions - e.g. rate, balance sheet, economic growth, inflation; and indicating a direction - e.g. increase, decrease, stay at 0. By design, such a methodology should rule out reverse causality. Nevertheless, this is an important issue and Appendix A.3 provides (mixed) statistical evidence supporting the absence of reverse causality.

[23] Hanson and Stein (2015) regress the 10-year instantaneous forward nominal, real and breakeven rates respectively on the 2-year nominal treasury rate, the later being used as a proxy for the expected path of the short-term interest rate. My approach differs in four ways: (1) the use of yields instead of forward rates, since the focus of my analysis is on identifying the factors that moved that variable; (2) the use of daily data *vs* intraday in their paper; (3) the inclusion of a different measure of the shock to monetary policy expectations; and (4) the inclusion of several control variables.

[24] Tables A.5, A.6 and A.7 in the appendix provide the full results of the regressions on nominal, real and breakeven yields respectively.

on nominal and real Treasury yields is statistically significant and negative, consistent with the hypothesis tested in this paper. Interestingly, the impact is stronger for medium-term Treasuries: a one standard negative shock to the surprise indicator increases 6-year nominal and 5-year real yields by 2.93bp and 3.19bp respectively. By contrast, the impact on breakeven rates is small, and only significant for the short end of the yield curve. The positivity of the estimated coefficient suggests that a surprise tightening of monetary policy lowers short term inflation expectations. This result rules out the *Delphic* channel of forward guidance emphasized by Campbell et al. (2012) and Nakamura and Steinsson (2018), according to which a surprise tightening (e.g. a surprise increase in the fed funds rate) reveals the central bank's optimistic information about the state of the economy, which raises inflation expectations and lowers unemployment expectations. The discrepancy between those results may be explained by the use of an indicator of the surprise in this paper that covers both conventional and unconventional monetary policies, thereby providing a more faithful picture of the actual surprise generated by the announcement.

Second, since those results suggest that monetary policy has an impact on long term nominal and real rates, the question that arises is the same as in Hanson and Stein (2015), i.e., whether they reflect a change in the expected path of the short-term interest rate or of the term premium. Therefore, I estimate the impact of monetary policy surprises on the term premium component of nominal yields. The regression is given by equation (2.8):

$$\Delta_{t-1,t} tp_t^{y(n)} = \alpha^{y(n)} + \beta_{ME}^{y(n)} \Delta ME_t + \beta_{SP}^{y(n)} R_t^{SP} + \beta_{FFR}^{y(n)} \Delta FFR_t + \varepsilon_t^{y(n)}, \tag{2.8}$$

where $n \in \{1,2,3,4,5,6,7,8,9,10\}$ is the maturity of the bond, $tp_t^{y(n)}$ is the term premium on the n-year treasury yield, and $\Delta_{t-1,t} tp_t^{y(n)}$ is the close $(t-1)$ to close (t) change in term premium for an announcement made during day t.

Table 2.5 shows that monetary policy surprises are negatively correlated with the term premium, meaning that a negative (positive) surprise - a monetary policy announcement being perceived as hawkish (dovish) - increases (decreases) the term premium. There may be several non exclusive explanations for this result, revolving around supply and demand effects or signals sent to market participants.[25] For example, the *reaching for yield channel* emphasized by Hanson and Stein (2015) suggests that monetary policy may have an impact on the real term premium because markets are segmented, and when short term rates are low, yield-oriented investors start searching for yield, which increases the demand for long-term assets. In turn, this pushes down long-term real yields and lowers the term premium. Another channel could be the *long-term safety channel* of Krishnamurthy and Vissing-Jorgensen (2011), through which yields on medium and long maturity safe bonds fall because of portfolio balance effects: the reduction in supply triggered by the Fed purchase increases the premium on those assets that are not easily substitutable due to the safety benefits they provide. Finally, a third explanation consistent with the hypothesis tested in this paper, could be that Fed negative surprises

[25] Formally testing for the three channels proposed hereafter is out of the scope of this paper. However, an example providing anecdotal evidence supporting the third channel is discussed below.

Table 2.4: Multivariate OLS regression on nominal, real and breakeven yields of maturity n

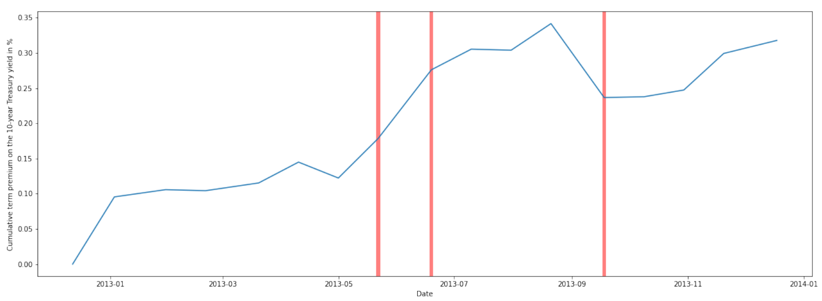
	Nominal Yield			Real Yield			Break-Even rate		
n	$\beta_{ME}^{\$(n)}$	standard error	R2	$\beta_{ME}^{TIPS(n)}$	standard error	R2	$\beta_{ME}^{\pi(n)}$	standard error	R2
2	-0.0173***	(0.0044)	0.15	-0.0269***	(0.0063)	0.23	0.0095**	(0.0043)	0.26
3	-0.0231***	(0.0057)	0.16	-0.0306***	(0.0067)	0.24	0.0075**	(0.0032)	0.31
4	-0.0267***	(0.0067)	0.16	-0.0318***	(0.0071)	0.24	0.0051*	(0.0027)	0.35
5	-0.0286***	(0.0074)	0.15	-0.0319***	(0.0073)	0.24	0.0034	(0.0027)	0.36
6	-0.0293***	(0.0078)	0.15	-0.0313***	(0.0073)	0.23	0.0021	(0.0029)	0.36
7	-0.0291***	(0.0081)	0.15	-0.0303***	(0.0073)	0.22	0.0011	(0.0033)	0.35
8	-0.0285***	(0.0082)	0.14	-0.0289***	(0.0073)	0.21	0.0003	(0.0037)	0.34
9	-0.0277***	(0.0081)	0.14	-0.0274***	(0.0073)	0.19	-0.0003	(0.0040)	0.34
10	-0.0266***	(0.0080)	0.13	-0.0259***	(0.0073)	0.18	-0.0008	(0.0042)	0.34
15	-0.0213***	(0.0067)	0.12	-0.0202***	(0.0063)	0.14	-0.0010	(0.0037)	0.38
20	-0.0175***	(0.0057)	0.13	-0.0171***	(0.0055)	0.13	-0.0004	(0.0037)	0.40

The estimated regressions are all variants of $\Delta_{t-1,t} y_t^{k(n)} = \alpha^{k(n)} + \beta_{ME}^{k(n)} \Delta ME_t + \beta_{SP}^{k(n)} R_t^{SP} + \beta_{FFR}^{k(n)} \Delta FFR_t + \varepsilon_t^{k(n)}$, where $k = \{\$, TIPS, \pi\}$ denotes nominal, real and breakeven yields respectively of maturity $n \in \{2,3,4,5,6,7,8,9,10,15,20\}$. The estimated coefficient associated to ΔME_t indicates the percentage point response of the endogenous variable per standard deviation of the surprise indicator. The estimated coefficients associated to $R_t^{S\&P500}$ and ΔFFR_t indicate the percentage point response of the endogenous variable per 1 percentage point increase in the daily return of the $S\&P500$ and the daily change of the effective fed funds rate respectively. Standard errors in parenthesis are heteroscedasticity and autocorrelation robust (HAC) using 1 lags and with small sample correction. * indicates significance at the 10-percent level, ** indicates significance at the 5-percent level, and *** indicates significance at the 1-percent level.

increase the term premium because they contradict market expectations of the future state of the economy, which increases uncertainty when it comes to the actual recovery of the economy. Investors are therefore reluctant to take on duration risk and the term premium increases.

A perfect example of the latter channel is the *tapering* episode - i.e. the reduction in the central bank's pace of purchases - that occurred during the implementation of QE3. QE3 started in September 2012, and while the Fed started to *taper* only in December 2013, FOMC members had debated about it as soon as December 2012, and then on most of the meetings organized through 2013. For example, as shown by the data provided in table A.1 and A.2 in appendix A.1, 10-year yields increased by 10bp and 17bp in May 22nd and June 16th 2013 respectively. Looking at the FOMC communication thanks to the excerpts provided in these tables, it is interesting to see that the central bank sent clear signals about the fact that tapering would come sooner rather than later, should economic conditions continue to improve. Interestingly, market commentaries surrounding those events showed that this communication was interpreted as hawkish by financial markets, thereby increasing yields. Moreover, this increase in yields appears to be correlated with an increase in the term premium: Figure 2.3 shows the cumulative increase in the term premium of the 10-year treasury yield, following the release of new information about monetary policy between December 2012 and December 2013. It clearly shows that the term premium increased during the May and June events. The only significant decrease in the term premium occurred during the September 18th FOMC meeting, when the FOMC statement indicated that tapering would be delayed, in an attempt to reassure markets as they started to panic with the prospect that QE might end in spite of grim economic data. As indicated previously, tapering eventually occurred in December 2013, seven full months after the May comments. In the meantime, yields and especially the term premium increased, as the positive news that tapering did not occur was overshadowed by the negative perception that it would occur very soon, and harm the economic recovery.

Figure 2.3: **Cumulative Change in term premium of the 10-year Treasury yield during the tapering debate episode.** The red lines indicate respectively the May 22nd 2013 release of minutes, the June 19th 2013 FOMC meeting and the September 18th 2013 FOMC meeting.



That explanation is interesting because it can contribute to reconciling skeptics about the

Table 2.5: Multivariate regression on the term premium of the *n*-year nominal yield

	1	2	3	4	5	6	7	8	9	10
α_t	-0.0009	-0.0014	-0.0018	-0.0020	-0.0022	-0.0023	-0.0023	-0.0024	-0.0024	-0.0024
	(0.0008)	(0.0014)	(0.0017)	(0.0020)	(0.0022)	(0.0024)	(0.0025)	(0.0026)	(0.0027)	(0.0028)
ΔME_t	-0.0040***	-0.0067***	-0.0085***	-0.0097***	-0.0106***	-0.0112***	-0.0117***	-0.0120***	-0.0124***	-0.0126***
	(0.0011)	(0.0018)	(0.0023)	(0.0026)	(0.0029)	(0.0031)	(0.0032)	(0.0033)	(0.0035)	(0.0035)
$R^{SP}_{t-1,t}$	-0.0003	-0.0005	-0.0006	-0.0005	-0.0005	-0.0004	-0.0003	-0.0002	-0.0001	-0.0001
	(0.0010)	(0.0017)	(0.0022)	(0.0026)	(0.0029)	(0.0031)	(0.0033)	(0.0035)	(0.0036)	(0.0037)
ΔFFR_t	0.1086*	0.1811*	0.2294	0.2626	0.2861	0.3031	0.3178	0.3286	0.3377	0.3459
	(0.0655)	(0.1098)	(0.1416)	(0.1654)	(0.1838)	(0.1988)	(0.2109)	(0.2212)	(0.2298)	(0.2371)
N	146	146	146	146	146	146	146	146	146	146
R2	0.15	0.15	0.15	0.15	0.15	0.15	0.14	0.14	0.14	0.14

The estimated regressions are all variants of $\Delta_{t-1,t} tp_t^{y(n)} = \alpha^{y(n)} + \beta_{ME}^{y(n)} \Delta ME_t + \beta_{SP}^{y(n)} R_t^{SP} + \beta_{FFR}^{y(n)} \Delta FFR_t + \epsilon_t^{y(n)}$, with $n \in \{1,2,3,4,5,6,7,8,9,10\}$. The estimated coefficient associated to ΔME_t indicates the percentage point response of the endogenous variable per standard deviation of the surprise indicator. The estimated coefficients associated to $R_t^{S\&P500}$ and ΔFFR_t indicate the percentage point response of the endogenous variable per 1 percentage point increase in the daily return of the $S\&P500$ and the daily change of the effective fed funds rate respectively. Standard errors in parenthesis are heteroscedasticity and autocorrelation robust (HAC) using 1 lags and with small sample correction. * indicates significance at the 10-percent level, ** indicates significance at the 5-percent level, and *** indicates significance at the 1-percent level.

impact of the Fed balance sheet with the rest of the literature. It suggests that the increase in yields emphasized by Greenlaw et al. (2018) was not due to the quantitative easing programs' lack of efficiency, but rather to a noisy central bank communication. By sending mixed signals about the state of the economy and the future course of its policy, the central bank increased market anxiety which resulted in an increase in the term premium.

2.5 Conclusion

The goal of this paper was to investigate the puzzling increase in long term yields following monetary policy announcements spotted by Greenlaw et al. (2018), which according to them, put into question the efficiency of the quantitative easing programs implemented by the Fed in the aftermath of the 2008 financial crisis.

Building on recent developments in natural language processing, I develop a novel measure of monetary policy expectations of conventional and unconventional monetary policies, which I use to create a measure of the surprise generated by the release of new information by the Fed.

Then, I estimate the impact of that measure of the surprise on long-term yields. My results suggest that there is a negative correlation between monetary policy surprises and long term yields. In other words, a negative surprise generated by an announcement reflecting a monetary policy less expansionary than expected results in an increase in long term nominal and real yields. Those results are consistent with Hanson and Stein (2015) or Krishnamurthy and Vissing-Jorgensen (2011), which show that the impact of monetary policy at that time went mainly through the term premium. I complement these analyses by making the hypothesis that the increase in the term premium was due to the central bank sending mixed signals about the future state of the economy and the course of its policy. Properly testing that hypothesis is beyond the scope of this paper, but this may be an interesting area for future research.

3 Informational Feedback Loop, Monetary Policy Decisions and Asset Prices Dynamics

3.1 Introduction

The first half of the year 2021 was special: for the first time in more than a decade, inflation seemed to be back. As an example, the June inflation report for the U.S.[1] indicated that the Consumer Price Index for All Urban Consumers (CPI-U) increased by 0.9 percent that month (seasonally adjusted), the largest month to month price increase since June 2008. But this increase was just the most recent of a series of strong inflation numbers that had started several months ago. Indeed, the report indicated that the CPI-U had already increased by 0.6% in May, 0.8% in April, and 0.6% in March 2021. Taken together, between July 2020 and June 2021, prices increased by 5.4% (not seasonally adjusted), the largest 12-month increase since August 2008.

Even more interesting than the return of inflation was the bond market reaction to it and the resulting discussions: while the 2-year treasury yield increased by 2.2 basis points (bp), which represented a 9.7% increase, the 10-year treasury yield increased by only 1.3 bp, i.e. a mere 1% increase.[2] This reaction was puzzling: if inflation was coming back, what could explain such a tame adjustment from long-term bonds? In an column published in the Financial Times in July 2021, Robert Armstrong perfectly accounts for the discussions happening at the time. In particular, the journalist reports two comments made by Thomas Tzitzouris of Strategas Research Partners, an advisory company based in New York:

[1] Inflation reports are published monthly by the U.S. Bureau of Labor Statistics. The June report is available here: https://www.bls.gov/news.release/archives/cpi_07132021.htm.

[2] The June inflation report was published the 13$^{\text{th}}$ of July 2021 at 8:30 am Eastern Time (E.T.), and the yield reactions were computed using a 30-minute window around the event. Yields time series are the U.S. benchmark 10-year and the U.S. benchmark 2-year treasury yields, taken at a 5-minute frequency, and coming form the Refinitiv Eikon database. Yields adjustments in basis points were computed by taking the difference between the yields at 8:45 am and the yields at 8:15 am. Yields increases in percent are the growth rate of the yields between the two times.

> "Like a surgeon that always wants to cut, the Fed, over the last 40+ years, has consistently chosen to tighten more than the bond market said was warranted. So betting odds would suggest that once inflation enters an uncomfortable zone, the Fed is going to respond by raising short rates more than they should, and thus forcing long rates lower, all the while scratching their head and uttering gibberish about why the move in long rates doesn't make sense."

When Armstrong pressed him to explain why it was so obvious to anticipate a mistake by the Fed, and why the recent surge in inflation would not, instead, justify a little short-end tightening in order for the central bank to control inflation and reach a "modest new normal of long-term growth" - which would explain the flattening of the yield curve - Tzitzouris replied:

> "Historically, the Fed has regularly ignored the fact that they've proven impatient and artificially moved rates well above healthy levels on the front end and forced the back end lower, and then continued to raise rates into inversion [of the yield curve]... [Ben] Bernanke began to accept that the market had a better grasp on where neutral [interest rates were],[3] and [Jay] Powell appears to fully embrace the notion that no amount of PhDs can match the wisdom of the cowboys in the trading pits (or over the phones in the case of bonds). Still, the market thinks the Powell Fed is no different from prior Feds, and the market is saying Powell will eventually tighten until something breaks."

This discussion raises interesting questions: What could explain this puzzling discrepancy in yields reactions following the publication of the inflation report? Does the weak reaction of long term bond rates reflect expectations of a policy that successfully tackles inflation generated by an overheating economy, or does it result from expectations of a Fed killing growth in the midst of a post-covid recovery, overreacting to its imprecise signal about the state of the economy, and unwilling to listen to financial markets? Is Powell's Fed really no different from prior Feds in that regard?

A piece of explanation may come from three important insights suggested by Tzitzouris' comments, and describing the back and forth informational game between the central bank and the private sector. The first one is that financial markets produce valuable information about the state of the economy. This is consistent with a basic tenet of financial economics,

[3] Indeed, in a speech held before the Investment Analysts Society of Chicago, Bernanke (2004), then a member of the Federal Reserve board of governors, said the following:

> "Central bankers naturally pay close attention to interest rates and asset prices, in large part because these variables are the principal conduits through which monetary policy affects real activity and inflation. But policymakers watch financial markets carefully for another reason, which is that asset prices and yields are potentially valuable sources of timely information about economic and financial conditions. Because the future returns on most financial assets depend sensitively on economic conditions, asset prices - if determined in sufficiently liquid markets - should embody a great deal of investors' collective information and beliefs about the future course of the economy."

The speech can be found here: https://www.federalreserve.gov/boarddocs/speeches/2004/20040415/default.htm.

according to which prices aggregate information dispersed among many different sources, and help coordinate economic agents (Hayek, 1945). The second one is that the market scrutinizes the Fed's every moves, trying to anticipate monetary policy decisions, and these expectations are eventually incorporated into asset prices. This is especially the case for federal funds futures, which are derivative contracts allowing the buyer to lock-in the federal funds rate at a given level for a pre-determined maturity date: a large empirical literature has shown that fed funds futures are good predictors of monetary policy (Krueger and Kuttner, 1996; Kuttner, 2001; Gürkaynak et al., 2007a; Piazzesi and Swanson, 2008).[4] The third one is that since financial markets produce information about the state of the economy, the central bank should use that information in its decision making process. Bernanke's April 2004 speech perfectly describes how the information contained in asset prices help monetary policymakers assess the state of the economy, and take a decision in line with the Fed's *dual mandate* - i.e. maximum employment and stable prices.[5] But the central bank may also look at financial markets for another reason: the 2008 financial crisis has shown how extreme financial volatility can affect the real economy, and impair its ability to fulfill its dual mandate. As a result, several authors have argued that the Fed actually follows a ternary mandate (Peek et al., 2015; Stein and Sunderam, 2018), i.e. that the Fed has a third (implicit) objective in addition to maximum employment and stable prices: financial stability.

According to Tzitzouris, the lack of reaction at the end of the yield curve following the publication of the June inflation report comes from the Fed not taking into account signals produced by financial markets. But if it did, how would markets have reacted? Indeed, if the Fed looks at financial markets to take its decisions, while at the same time, financial markets try to anticipate the central bank's next move, what would be the impact of that informational feedback loop on the monetary policy decision process - i.e. the surprise generated by monetary policy announcements, or, in other words, the extent to which the Fed follows the market signal to take its decision compared to its own; and on asset prices dynamics - i.e. bond yields adjustments - following monetary policy announcements?[6] This paper aims at answering this question.

The informational feedback loop between the Fed and financial markets has already been studied in the macroeconomics and finance literatures. In particular, Woodford (1994), Bernanke

[4] Gürkaynak et al. (2007a) in particular conduct a review of different financial instruments that can be used to measure monetary policy expectations.

[5] The *Statement on Longer-Run Goals and Monetary Policy Strategy*, reaffirms the commitment of the Federal Open Market Committee (FOMC) "to fulfilling its statutory mandate from the Congress of promoting maximum employment, stable prices, and moderate long-term interest rates." Note that the *dual mandate* as stated here actually contains three objectives. However, the Fed considers that when prices are stable, longer-term interest rates remain at moderate levels. The second and third objectives are therefore grouped together in a *stable prices* objective. The most recent *Statement on Longer-Run Goals and Monetary Policy Strategy* at the time of writing this paper (January 26th, 2021) can be found here: https://www.federalreserve.gov/monetarypolicy/files/FOMC_LongerRunGoals.pdf.

[6] An important disclaimer at this point is that this paper focuses on monetary policy announcements following FOMC meetings, which are admittedly different from the publication of inflation reports. That example was nevertheless relevant because the resulting discussion perfectly describes the informational feedback loop arising from the interactions between the Fed and financial markets.

and Woodford (1997), and Morris and Shin (2018) show that when such a situation arises, it might lead to the emergence of a *reflection* problem (Samuelson, 1994),[7] which reduces the informational content of the signal produced by the market - i.e. asset prices tend to reflect more market expectations of the central bank's decision rather than the underlying fundamentals of the economy - which puts into question the adequacy of a decision based on that signal. Bond and Goldstein (2015) show in a more general framework that a similar phenomenon may arise when a government grounds a public policy decision - e.g. bailing out a troubled financial institution - in its stock price, the stock price being endogenous in the policy decision. The key contribution that the current paper provides compared to this literature is to look above and beyond the potential *reflection* problem, to investigate the impact of that informational feedback loop on the surprise generated by policy announcements and asset prices reactions.

To do so, the approach adopted in this paper consist of two steps. First it builds on the intuition behind Bond and Goldstein (2015), and on Lee and Kyle's (2018) market microstructure model with strategic traders, to model the informational feedback loop arising between a central bank and N strategic traders. The model provides interesting insights regarding the dynamics of fed funds futures contracts, short term, and long term bonds following monetary policy announcements. In particular, it enables to formulate four empirically testable hypotheses:[8]

Hypothesis 1. *When the central bank looks at financial markets, either to learn from the market signal or because it is averse to financial market volatility, if the precision of the central bank's signal is low compared to that of traders', it puts a lower weight on its own private signal, and a higher weight on the market signal. In such a case, the surprise is low, as well as short and long term rates adjustments; in particular, the lower the precision of the central bank signal, the lower the surprise and the adjustments.*

Hypothesis 2. *When the central bank looks at financial markets, either to learn from the market signal or because it is averse to financial market volatility, if the precision of traders' signal is low compared to that of the signal received by the central bank, it puts a lower weight on the market signal than on its own, meaning that it relies less on the information produced by financial markets to recover the state of the economy. In that case, the surprise and adjustments of the short term bond yield are high. By contrast, adjustments of the long term bond yield are insensitive to the precision of the signal received by traders, as it only adjusts to the arrival of information that are new to traders following monetary policy announcements.*

[7] Samuelson compares the *reflection* problem arising from the Fed looking at asset prices to a monkey that would see a mirror for the first time: by looking at its reflection in the mirror, including the surprises, he thinks that it is learning new information, while it actually only sees its own reactions.

[8] Again, note that this paper is agnostic about the reflection problem. Indeed, the goal here is to investigate the impact of the informational feedback loop on monetary policy surprises and on asset prices dynamics. These dynamics, may lead to a reflection problem as suggested by Bond and Goldstein (2015) or Morris and Shin (2018), but investigating this issue is out of the scope of this paper.

Hypothesis 3. *The central bank aversion to bond market volatility reduces the magnitude of the surprise and of adjustments of the short term bond yield. However, it does not have an impact on the adjustment of the long term bond yield, as the central bank aversion to financial markets volatility does not have an impact on the amount of news contained in its signal, which is revealed to traders by the announcement.*

Hypothesis 4. *When the central bank does not learn from the market signal and is not averse to financial markets volatility, if it has a very noisy signal, then, adjustments of the long term bond yield are low, while the surprise is high and adjustments of the short term bond yield are high. This is because the central bank relies on a weak signal, which is not known by financial markets ex-ante. Therefore, the decision is far from market expectations, forcing the short term rate to adjust; however, it contains very few new information about the state of the economy, so the long term rate adjusts only slightly.*

Second, it conducts an empirical analysis which takes a first stab at testing empirically these hypotheses. The key challenge is to create proxies, not for the signals received by the central bank and the private sector[9] respectively, but for the *precision* - or equivalently the *uncertainty* - of these signals. To do so, this paper builds on recent developments in natural language processing (NLP) and uses the *topic and tone* approach developed by Hansen and McMahon (2016) and Jegadeesh and Wu (2015). The idea is simple: economic agents may react differently to different topics, and especially to the *tone* employed to talk about these topics.[10] As a result, adopting an approach that can capture such a level of granularity is important. The *topic and tone* approach consists in (1) using a topic identification algorithm - e.g. Latent Dirichlet Allocation (LDA, Blei et al. 2003) - to extract the *topics* underlying a corpus of documents, and then identifying the (2) *tone* - i.e. sentiment - conveyed by discussions about the previously identified topics, by using dictionaries that contain words representative of the sentiment one wants to measure. For example, Loughran and Mcdonald (2011) have created dictionaries of *positive*, *negative*, *litigious* and *uncertain* adapted to a financial context. This paper creates proxies for the precision of the signals received by the central bank and the private sector respectively, by applying the *topic and tone* approach to FOMC minutes and to tweets published 4 hours prior to FOMC announcements. The Fed's signal is proxied by a topic dealing with *Economic Outlook*, while the private sector's signal is proxied, by a topic related to the Fed's *Dual Mandate*. Then, *tone* is assessed by counting the number of *uncertain* words (Loughran and Mcdonald, 2011) in the discussions related to the selected topics. This *topic and tone* approach allows therefore to measure the *uncertainty*, a.k.a. *precision* of the signals received by the central bank and the private sector respectively. Then, the precision of each

[9] In the remaining of this paper, the terms *private sector*, *traders* and *financial markets* are used interchangeably.

[10] For example, Jegadeesh and Wu (2015) showed that following the release of FOMC minutes, the S&P500 reacted strongly to negative news about inflation, while it did not react to positive ones.

signal is used in a regression to measure their impact on the surprise generated by monetary policy announcements - computed using fed funds futures and Kuttner's (2001) method - and on the subsequent adjustments of the U.S. 3-month, U.S. 2-year and U.S. 10-year treasury yields. This is done by conducting an event study using monetary policy announcements following FOMC meetings made during the period December 2008 to June 2021.

In spite of mixed statistical evidence, the empirical analysis provides some support to hypothesis 1, namely that a decrease in the precision of the signal received by the central bank decreases the surprise and adjustments of short and long term yields. The mechanism suggested in this paper differs depending on the maturity of the bond: the lower magnitude for the surprise and the lower adjustment of the short term bond are due to the central bank putting a lower weight on its private information, and a larger weight on the information produced by financial markets; by contrast, the lower adjustment of the long term bond yield is due to fewer information about the fundamentals of the economy being released by the announcement. However, there is no statistical evidence to support the fact that the surprise and yields adjustments are sensitive to the precision of the signal received by financial markets (hypothesis 2). This lack of evidence may however be explained by the data used to estimate the precision of the signal received by financial markets (tweets), which limits considerably the size of the sample. The paper offers some suggestions to improve the measurement of this variable in future work. There is nevertheless stronger support for hypotheses 3 and 4. Indeed, results suggest that the central bank cares about financial markets volatility (hypothesis 3 and Peek et al. 2015), as the magnitude of the surprise and adjustments of the short term bond yield tend to decrease when the *Financial Markets* topic represents a larger share of FOMC minutes in a given meeting compared to the previous one. This is particularly interesting, as it seems the Fed's behavior has evolved with that respect: before the financial crisis, the magnitude of the surprise tended to increase when the signal received by the central bank was uncertain, while it decreased after the financial crisis. According to hypothesis 4, this suggests that prior to the financial crisis, the Fed did not care so much about what happened on financial markets when taking its decision, not even to learn economic fundamentals from market prices - unlike Bernanke's (2004) assertion - but that it started doing so after the financial crisis.[11]

The rest of this paper is organized as follows: Section 3.2 provides a succinct review of the literature related to the current research question, and section 3.3 makes a short description of fed funds futures contracts, which are a key component of the theoretical model presented in section 3.4. Then, section 3.5 derives the theoretical predictions that are tested empirically in section 3.6. Finally, section 3.7 concludes. Appendix B contains all proofs.

[11] As a side note, this result is also interesting as it provides anecdotal evidence that can be used to answer Tzitzouris' comments: it does seem that Powell's Fed is different from prior Feds, and that it actually listens to financial markets. Apparently, this has been the case even before him.

3.2 Literature Review

This paper aims at investigating the impact of the informational feedback loop between financial markets and the Fed on the monetary policy decision process and asset prices dynamics. As a result, it contributes to three streams of literature.

First, it builds on the literature that models strategic interactions between private agents and a government - or, in this case, a central bank. Early contributions in this area come from the *rule vs discretion* literature. In particular, seminal work by Kydland and Prescott (1977) and Barro and Gordon (1983) show that without a commitment mechanism, the central bank, which communicates on its inflation target in order to set inflation expectations, has an incentive to systematically deviate from its announcement, in order to lower unemployment. However, the private sector being rational anticipates such a behavior, and adjusts upward its inflation expectations. As a result, the economy ends up in a state where the level of unemployment remains the same, but inflation is larger. The authors show that this issue could be solved by the implementation of a rule that would prevent the central bank from deviating from a predetermined monetary policy path. Rogoff (1985) argues that such a solution could be to appoint a central banker that features a larger aversion for inflation than society does. Those papers, are interesting in the context of the current research question because they offer a simple framework to think about the interactions that arise between a central bank and a private sector. An important limitation, however, lies in the fact that inflation expectations are completely determined by the central bank announcement and its subsequent behavior.

By contrast, Woodford (1994) and Bernanke and Woodford (1997) develop models to analyze *inflation targeting* policy - i.e. the adoption and communication to the public of an explicit inflation target - and in which the central bank decision depends on signals coming from the private sector. Indeed, an important issue that arises with inflation targeting is to determine which indicator(s) to monitor. For example, Bernanke and Woodford (1997) argue that current inflation responds with a one- to two-year lag to monetary policy, which is problematic. As a result, one of the solutions that has emerged has been to use *nonstandard indicators*, i.e. indicators that can be used to predict inflation or which may provide information about the future path of inflation (Woodford, 1994).[12] Here, the goal for the central bank is to use information produced by the private sector to get a signal about the state of the economy and the future path of inflation. However, Woodford (1994) shows in a rational expectation setting that if the central bank places a too large weight on indicators representing inflation expectations, this would trigger a feedback loop between the private sector and the central bank - or, in other words, between inflation forecasts and the monetary policy decision - resulting in policy and inflation instability, and a breakdown of the rational expectations equilibrium. As a result, the author argues that the central bank should monitor indicators related to the *causes of inflation* (e.g. output gap) rather than to *inflation expectations*. Similarly, Bernanke and Woodford (1997) show that a strict targeting of private sector inflation forecasts is inconsistent with a

[12] Woodford (1994, p. 95) provides of list of those *nonstandard indicators*: commodity price indexes, nominal exchange rates, and spreads between the interest yields on longer- and shorter-maturity Treasury securities.

rational expectations equilibrium, and advocate for complementing that signal with information produced internally, e.g. through the use of structural models of the economy. Therefore, these two papers provide interesting insights on the value for policymakers to using signals from different sources - i.e. their own signal but also the one(s) coming from the private sector. But they also shed light on the negative consequences associated to an excessive reliance on the private sector's signal and the resulting feedback loop between the two types of agents.[13]

More recently, Morris and Shin (2018) investigate that phenomenon in the context of forward guidance. In their model, the reaction function of the central bank depends on a market signal and on its own private information. They show that when market participants want to match the central bank's response - e.g. when financial markets try to guess the central bank's decision prior to an announcement - a *reflection* problem may arise if the central bank puts too much weight on the market signal. Following Samuelson (1994), they define the *reflection* problem as a situation in which the market signal ends up reflecting the decision of the central bank, rather than being informative about the state of the economy. They explain the rationale as the following: "if market participants place a large weight on correctly guessing the actions of the central bank, they may underplay their own judgment and overweight their assessment of what the central bank is likely to do" (Morris and Shin, 2018, p. 573). Interestingly, they show that if the central bank can clearly commit to its *Odyssean* forward guidance, then, it would place a lower weight on the market signal, and the latter would then become more informative.[14] Bond and Goldstein (2015) build on the market microstructure literature to show that the *reflection* problem can also arise in other contexts, e.g. when a government has to make a decision on whether or not to bail a financial institution, and uses its stock price to take the decision. The issue is that the government's intervention is anticipated by rational markets, and is already embedded into prices. The authors therefore argue that in some cases, it would be optimal for the government to limit its reliance on the market signal, in order to improve information aggregation by asset prices. The reflection problem can therefore be an important issue triggered by the feedback loop between the private sector and a central bank - or a government. However, above and beyond the issue of price informativeness, neither of these two papers investigate the impact of the feedback loop between the private sector and the central bank on asset prices dynamics. The present paper aims at bridging this gap.

The literature presented so far investigated the strategic interactions between a private sec-

[13] Morris and Shin (2005, p. 3) perfectly characterize the problem for the central bank: "The central bank cannot manipulate prices, and at the same time, hope that prices yield informative signals. [...] This tension between managing expectations and learning from them reflects the dual role of a central bank in the conduct of monetary policy."

[14] *Odyssean vs Delphic* forward guidance refer to a terminology developed by Campbell et al. (2012), following the increased reliance by the Fed on unconventional monetary policy tools in the aftermath of the 2007-2008 financial crisis. *Delphic* forward guidance refers to a central bank communication that would provide forecasts of future macroeconomic performance and the likely resulting monetary policy actions; by contrast *Odyssean* forward guidance would publicly commit the central bank to a given course of action, i.e. that the central bank would maintain the announced policy path even as new information about the economy is released. Morris and Shin (2018) argument is therefore that by design, *Odyssean* forward guidance puts a lesser weight on incoming information - i.e. market signals - thereby reducing the reflection problem.

tor and a central bank, where the latter used the signal produced by the former - such as movements in asset prices (Woodford, 1994) - to assess the state of the economy and the appropriate monetary policy response. This is in line with Bernanke and Gertler (2001, p. 253), who argue that "changes in asset prices should affect monetary policy *only* to the extent that they affect the central bank's forecast of inflation." However, an alternative view embodied by a second stream of literature suggests that financial instability can build up in low inflation environments, which if not taken into account by the central bank, could generate disruptive boom and bust cycles, later diminishing its ability to act (Bordo and Jeanne, 2002; Bean, 2004; Borio and Lowe, 2005).[15] The 2007-2008 Great Recession, which was characterized by a financial crisis followed by a credit crunch and a central bank limited in its ability to fulfill its dual mandate due to the fed funds rate being stuck at zero, perfectly illustrates this point. As a result, several papers have argued that the central bank actually also has a financial stability objective. For example, Peek et al. (2015) provide empirical evidence that the central bank has an (implicit) ternary mandate, by estimating a Taylor rule augmented with a financial stability objective; Stein and Sunderam (2018) develop a theoretical model which explains gradualism of monetary policy - the fact that decisions are characterized by successive steps of 0.25 bp increments - by the central bank's aversion to volatility in the bond market. They also show that rational markets anticipate gradualism, and volatility in the bond market after the announcement is greater than anticipated by the central bank, due to the feedback loop between the two types of agents. Similar to Stein and Sunderam (2018), the current paper analyzes asset prices dynamics due to the informational feedback loop between the Fed and financial markets. However, it provides a different perspective for three reasons: (1) private agents are allowed to receive a private signal about the state of the economy; (2) the signal received by the central bank contains some noise; (3) similar to Stein and Sunderam (2018), the central bank is averse to financial markets volatility, but it also takes into account the signal produced by the private sector - embedded in asset prices - in its decision making process.

These two streams of literature shed light on the importance of signals - signals produced by market participants and the signal received by the central bank - for the monetary policy decision and asset prices dynamics. As a result, because the current paper is also an empirical paper, one of the key issues is to create proxies for these signals. To do so, it builds on a third stream of literature, which uses NLP techniques to identify the content of the signals received by the central bank and the private sector.[16]

First of all, an extensive literature has used NLP techniques to study central bank communication. For example Boukus and Rosenberg (2006) use an algorithm - singular value decomposi-

[15] Bean (2004) provides an enlightening description of the mechanism: in good times, positive supply shocks may result in excessive optimism about future returns, which drives asset prices up, and increase borrowing to finance further capital accumulation. Additionally, the increase in asset prices increases the value of collateral, which fuels even further the accumulation of debt. However, when the bubble bursts, the net worth of the borrowers deteriorates sharply - e.g. due to the financial accelerator (Bernanke et al., 1999) - and the subsequent tightening of credit by financial institutions may result in a credit crunch with significant macroeconomic impact.

[16] See Loughran and Mcdonald (2016) for an extensive review of the literature on the use of NLP techniques in accounting and finance.

tion (SVD) - to identify the topics embedded in FOMC minutes, and measure which ones have an impact on current and future economic conditions. They show that changes in treasury yields around the release of minutes are correlated with the importance in FOMC minutes of themes such as *monetary policy uncertainty* and *economic outlook*. Similarly, Hendry (2012) apply SVD to both (1) Bank of Canada minutes and (2) Reuters news to identify which information have a significant impact on the level and volatility of short term rates. Hansen and McMahon (2016) and Jegadeesh and Wu (2015) adopt a more sophisticated approach, by identifying both the *topics* of central bank communication, and their *tone*.[17] *Topics* are identified using an algorithm developed by Blei et al. (2003) called Latent Dirichlet Allocation (LDA);[18] Once topics are identified, at the level of a paragraph (Jegadeesh and Wu, 2015) or a sentence (Hansen and McMahon, 2016), *tone* is measured using dictionaries listing *positive* or *negative* words.[19] Jegadeesh and Wu (2015) measure the tone of their topics by counting the number of positive and negative words using a dictionary that features words from the Harvard IV psychological as well as Loughran and Mcdonald (2011) dictionaries.[20] Hansen and McMahon (2016) use instead the Apel and Blix-Grimaldi (2012) dictionary. Then, Jegadeesh and Wu (2015) conduct an event study analyzing market volatility in a 15-minute window around the release of FOMC minutes published between 2000 and 2015. They find that the S&P500 reacts strongly to minutes containing negative content about inflation, policy and unemployment, while it does not react to positive discussions related to these topics; Hansen and McMahon (2016) use their *topic and tone* score in a FAVAR model estimated using monthly data from January 1998 to December 2014, to measure the impact of central bank communication about growth and forward guidance on financial and real variables. They find that forward guidance generally has a larger impact on financial variables than communication on growth, but that neither variable has a significant impact on real variables.

Finally, while most of the papers presented above focus on textual data coming from central bank communication, the literature has also used microblogging data to investigate the relationships between the central bank and financial markets. In particular, Azar and Lo (2016) show that the sentiment conveyed by tweets containing the words *Federal Reserve* is a good predictor of stock returns following FOMC announcements; Similarly, Cornet (2020) uses tweets published around two types of events - FOMC announcements and the release of

[17]Hansen and McMahon (2016) look at FOMC statements while Jegadeesh and Wu (2015) consider FOMC minutes.

[18]Thanks to the significant improvements in computing power in the past decade, this algorithm has been extensively used in economics and finance. See for example Tobback et al. (2017), Hansen et al. (2018) and Bybee et al. (2020).

[19]There exists numerous dictionaries to compute the *tone* or *sentiment* of a text depending on the purpose of the analysis. The most commonly used is the Harvard IV dictionary, which provides lists of generic positive and negative words. However, these lists may not necessarily be adapted to a financial context, as some words with a negative connotation in that dictionary - e.g. cost - may not be considered as such in finance. As a result Loughran and Mcdonald (2011) have developed lists of *negative*, *positive*, *uncertain*, and *litigious* words adapted to financial contexts. Other dictionaries have been developed to analyze central bank communication and measure the stance of monetary policy (Apel and Blix-Grimaldi, 2012; Picault and Renault, 2017).

[20]Note that they also claim to count the number of uncertain words using Loughran and Mcdonald's *uncertain* words dictionary, but do not do anything with that measure in the paper, leaving it for future research.

minutes - to identify market expectations of monetary policy, and to explain the surprising increase in bond yields during the implementation of unconventional monetary policies (quantitative easing and forward guidance).

The *topic and tone* approach is therefore applied to measure the precision of the signals received by the central bank and the private sector respectively. The main difference between the current paper and the approach adopted in Hansen and McMahon (2016) and Jegadeesh and Wu (2015) is that the *tone* considered here is the *uncertainty* (Loughran and Mcdonald, 2011) of the *topics*, in order to proxy for the *precision* of the *signals* received by each agent.

3.3 A Brief Overview of the Federal Funds Futures Market

Federal funds futures are derivative contracts traded on the Chicago Mercantile Exchange (CME), which allow financial institutions, portfolio managers or traders to hedge against - or speculate on - changes in the federal funds rate, by locking in a rate up to the maturity of the contract.

These contracts are listed monthly, for the current month and up to 60 month out on the yield curve, and are quoted in International Monetary Market terms (IMM). This means that their price is indicated as 100 minus the average expected fed funds rate for the month considered.

Trading of a given contract ends the last business day of the contract month and is cash settled. Settlement occurs on the first business day following the last trading day, and is based on the difference between the average federal funds rate for the delivery month - as reported by the Federal Reserve Bank of New York (FRBNY) - and the rate implied by the price of the contract. That difference determines the amount of interest to pay for the borrowing of a principal amount of $4'167 for 30 days.[21]

As an example, consider a buyer in August 2021 of a 30-day fed funds futures contract for the month of September 2021. If the fed funds futures contract for the month of September is quoted at 98.5, it means that the average fed funds rate for that month is expected to be 1.5% in annualized terms. If the actual average fed funds rate for the month of September as reported by the FRBNY rate was 1%, then the settlement price is $100 - 1 = 99$, and the buyer of the contract will have to pay an interest of $(99 - 98.5)/30 \times 4,167 = \$69.45$ on the first business day of October.

An interesting feature of federal funds futures contracts is that their pricing information is widely available and numerous studies have shown that they are very good at predicting monetary policy decisions (Krueger and Kuttner, 1996; Kuttner, 2001; Gürkaynak et al., 2007a; Piazzesi and Swanson, 2008). As a result, they represent an interesting market-wide measure

[21] In other words, each contract is valued $4'167 times the contract grade index, which is equal to 100 minus the average rate of the month in annualized terms. See the Fed Funds Settlement Methodology for more information https://www.cmegroup.com/content/dam/cmegroup/rulebook/CBOT/III/22.pdf.

of monetary policy expectations, and it is as such that they are used in this paper.

3.4 The Model

This section presents a model that captures the informational feedback loop that arises between the central bank - the Fed - and financial market participants - also called *traders* - during the monetary policy decision process. While this is a static model, there is an implicit four-step timing happening as follows: first, at the beginning of period t, the economy is subject to a macroeconomic shock, and each agent - the Fed and individual traders - receives a noisy private signal about the new state of the economy; second, the traders trade fed funds futures contracts[22] based on their private information, the current futures rate, and their beliefs about the Fed's reaction function; third, the Fed looks at its private signal and the futures rate determined by the market to take a monetary policy decision, characterized in this model by a decision about the federal funds rate; fourth, cash flows are realized and traders are paid.

Subsection 3.4.1 provides an general overview of the setup of the model along the lines presented above. Then, subsections 3.4.2 and 3.4.3 describe in more details the equilibrium outcome arising from the maximization problems of the traders and of the Fed respectively. Finally, subsection 3.4.4 puts those results together to characterize the global equilibrium of the model. Appendix B.1 provides proofs of all the results stated in this section.

3.4.1 Setup

The Fed's dual mandate - i.e. promoting maximum employment and stable prices - implies that the central bank closely monitors the state of the economy, in order to adopt the appropriate response by adjusting the federal funds rate.[23] As a result, the approach adopted here, similar in spirit to Stein and Sunderam (2018), models the state of the economy by a target rate i_t^* of the form

$$i_t^* = i_{t-1}^* + \varepsilon_t^i, \tag{3.1}$$

[22]For simplicity, federal funds futures contracts are also just called futures.

[23]This is clearly emphasized in the *Statement on Longer-Run Goals and Monetary Policy Strategy* effective in January 26$^{\text{th}}$, 2020, in which the Federal Open Market Committee (FOMC) states: "Employment, inflation, and long-term interest rates fluctuate over time in response to economic and financial disturbances. Monetary policy plays an important role in stabilizing the economy in response to these disturbances. The Committee's primary means of adjusting the stance of monetary policy is through changes in the target range for the federal funds rate." See: https://www.federalreserve.gov/monetarypolicy/guide-to-changes-in-statement-on-longer-run-goals-monetary-policy-strategy.htm.

where i^*_{t-1} is the target rate at the previous period,[24] and $\varepsilon^i_t \sim N\left(0, \sigma^2_i \equiv \frac{1}{\tau_i}\right)$ is a normally distributed random shock to the target rate, with mean zero, variance σ^2_i, and precision τ_i. ε^i_t can be interpreted as a macroeconomic shock hitting the economy - e.g. inflationary shock, growth shock - which brings the Fed to modify the level of the fed funds rate to accommodate the new macroeconomic conditions in accordance with its dual mandate.

An important assumption of the model is that neither traders, nor the central bank directly observe the target rate i^*_t, but instead, receive a noisy private signal about it. Therefore, the central bank attempts to retrieve the state of the economy thanks to two pieces of information: its private signal, s^B_t, given by

$$s^B_t = i^*_t + \varepsilon^B_t = i_{t-1} + \varepsilon^i_t + \varepsilon^B_t, \tag{3.2}$$

where the noise in the central bank signal, $\varepsilon^B_t \sim N\left(0, \sigma^2_B \equiv \frac{1}{\tau_B}\right)$, is independent from the macroeconomic shock ε^i_t; and the federal funds futures rate f_t, which is endogenously determined by financial markets and aggregates traders' private information (Bernanke, 2004).

A second important assumption of the model is that aside from the information content embedded in the fed funds futures market rate, the central bank may take it into consideration because it cares about financial markets volatility. Indeed, the 2008 financial crisis has shown that financial instability may have severe consequences in terms of inflation and unemployment, which may threaten the central bank's ability to fulfill its dual mandate (Peek et al., 2015).

Therefore, the central bank's optimization problem is formulated to accommodate these two issues. In particular, the federal funds rate i_t is chosen by the Fed to minimize an expected loss function L_t of the form:

$$\min_{i_t} \mathbb{E}\left[L_t | s^B_t, f_t\right] = \mathbb{E}\left[\left(i^*_t - i_t\right)^2 + \theta\left(f_t - i_t\right)^2 | s^B_t, f_t\right] = \mathbb{E}\left[\left(i^*_t - i_t\right)^2 | s^B_t, f_t\right] + \theta\left(f_t - i_t\right)^2. \tag{3.3}$$

The first quadratic term in equation (3.3) represents the traditional *dual mandate* of the central bank, which aims at minimizing the distance between the fed funds rate i_t, and the state of the economy i^*_t. i^*_t is estimated by the central bank using its information set $\mathscr{F}^B_t = \{s^B_t, f_t\}$. The second quadratic term, measurable with respect to $\mathscr{F}^B_t$, aims at capturing the *financial instability* objective, i.e. how far the federal funds rate i_t is from market expectations of the central bank's policy. θ measures the relative importance of this *financial stability* objective compared to the *dual mandate* objective. Finally, the Fed's optimization problem is

[24] Two clarifications need to be made at this point about the static property of the model and the choice of notation: first, time subscripts are kept because they are used to distinguish the target rate i^* (resp. the fed funds rate i) before (time index $t-1$) and after (time index t) the shock to the economy is realized (resp. the Fed takes its decision); second, it is assumed that the economy is at the steady state when it enters period t, and before the macroeconomic shock ε^i_t occurs. This implies that $i^*_{t-1} = i_{t-1}$, and in order to ease the notations, only i_{t-1} will be used in the remainder of this paper.

conjectured to yield a *reaction function* of the following form:

$$i_t = I i_{t-1} + S s_t^B + F f_t, \tag{3.4}$$

where I, S and F are respectively the weights put by the central bank on the previous period interest rate i_{t-1}, its private signal s_t^B, and the futures rate f_t when setting the federal funds rate i_t.

The futures rate f_t is endogenously determined by trading futures contracts on financial markets. The market for futures contracts is modeled following Lee and Kyle (2018): There are N strategic traders with homogeneous preferences and prior beliefs indexed $n = 1, ..., N$.[25] At the beginning of period t, just after the realization of the shock ε_t^i determining the state variable i_t^* and before trading, each trader n receives - costlessly - two private signals: private information about i_t^* of the form

$$s_t^n = i_t^* + \varepsilon_t^n = i_{t-1} + \varepsilon_t^i + \varepsilon_t^n, \text{ with } \varepsilon_t^n \sim N\left(0, \sigma_T^2 \equiv \frac{1}{\tau_T}\right); \tag{3.5}$$

and a random *endowment* shock $e_t^n \sim N\left(0, \sigma_e^2 \equiv \frac{1}{\tau_e}\right)$. This endowment shock can be thought of as representing futures contracts in which traders entered to hedge against potential risks associated for example to their business activity or their investment strategies; The heterogeneity in the private signals s_t^n received by traders can be interpreted as different traders having access to different datasets, or being more or less skilled in estimating the state of the economy. The macroeconomic shock ε_t^i, the noise in the central bank signal ε_t^B, the noise in the signal of each trader n, ε_t^n,[26] and their endowment, e_t^n are all assumed to be independent, and jointly normal.[27]

Upon reception of their private signals, traders have therefore two motives for trading and adjusting their position in futures contracts: speculating on their private information s_t^n - *trading motive* - or hedging - *hedging motive*. They do so by exchanging the quantity X_t^n. Remember that futures contracts are cash settled, therefore, they do not require any investment at inception, and the security simply pays at maturity a cash flow v_t of the form:

$$v_t = i_t - f_t. \tag{3.6}$$

Equation (3.6) embodies the main difference there is between Lee and Kyle's model and the current setup: while in the former, the cash flow v_t is modeled as a normally distributed random variable, here, it directly depends on the central bank's choice of i_t.[28] Therefore, a

[25] The hypothesis of *strategic* traders is made to increase the realism of the model, as it has been shown that futures markets (Kyle, 1984) and cash-settled derivative contracts (Zhang, 2020) could be subject to strategic trading and manipulation.

[26] It is important to note here that only the noise embedded in the signals received by the traders and the central bank - i.e. ε_t^n for $n = 1, ..., N$ and ε_t^B - are independent. By contrast, the signals themselves - i.e. s_t^n for $n = 1, ..., N$ and s_t^B - are correlated, since they all provide information about the state of the economy i_t^*.

[27] Lemma B.1 in Appendix B.1.1 characterizes the joint distribution of these random variables.

[28] This is similar in spirit to Bond and Goldstein (2015), where the government looks at a firm's share price to

key implication is that traders' expectations about the central bank behavior matter for their optimization problem. To see that, assume traders are rational and conjecture a central bank reaction function of the following form:

$$i_t = \bar{I} i_{t-1} + \bar{S} s_t^B + \bar{F} f_t, \tag{3.7}$$

where $\bar{I}, \bar{S}$ and $\bar{F}$ are traders' conjecture about the weights I, S and F introduced in equation (3.4). It is shown in subsection 3.4.2 that these weights appear in trader n's optimal demand schedule.

For $n = 1, ..., N$, trader n has constant absolute risk aversion (CARA) utility, and trades the asset based on the information available to him at time t $\left(\mathscr{F}_t^n = \left\{s_t^n, e_t^n, f_t\right\}\right)$, and his beliefs about the central bank's reaction function (equation 3.7). Then, he submits a demand schedule $X_t^n(f_t, i_t^n, e_t^n)$,[29] which depends on the current futures rate f_t, as well as its two private signals s_t^n and e_t^n. Trader n's optimal demand schedule is the one that maximizes his expected utility J_t^n given by:

$$\max_{X_t^n} \mathbb{E}\left[J_t^n | s_t^n, e_t^n, f_t\right] = \mathbb{E}\left[-e^{-Av_t(X_t^n + e_t^n)} | s_t^n, e_t^n, f_t\right], \tag{3.8}$$

where $A > 0$ is the risk aversion coefficient, and the futures rate f_t is determined by the market clearing condition:

$$\sum_{n=1}^{N} X_t^n = 0. \tag{3.9}$$

Finally, the equilibrium studied in this paper can be defined as follows:

Definition 1. *A rational expectations equilibrium is defined by two elements:*

(a) a set of demand schedules X_t^n for $n = 1, ..., N$, such that each trader chooses his strategy to maximize his expected utility given his information set $\mathscr{F}_t^n$, correctly conjectures the strategies of the $N-1$ other traders as well as the central bank's reaction function, and the market for futures contracts clears. This is called the "financial market side" of the equilibrium;

(b) a reaction function i_t for the central bank that minimizes its expected loss given its information set $\mathscr{F}_t^B$, and coincides with the traders' conjecture, i.e. $I = \bar{I}, S = \bar{S}$ and $F = \bar{F}$. This is called the "central bank side" of the equilibrium.

The following two subsections explain how each side of the equilibrium is obtained, by

determine whether it should intervene to save it or not, but the share price directly depends on the government intervention. They identify conditions under which this feedback loop brings the government to follow too much (resp. too little) financial markets. Morris and Shin (2018) call this issue the *reflection problem* and discuss its potentially negative implications for central bank forward guidance. The focus of the current study is different: the goal is not to put those results into questions, but to investigate the implications of this informational feedback loop between policymakers and financial markets in terms of monetary policy decision and asset prices dynamics.

[29] In order to ease the notation, $X_t^n(f_t, i_t^n, e_t^n)$ is denoted X_t^n.

describing the optimization problem of the traders and of the central bank respectively. The final subsection gathers those result to describe the global equilibrium and to present the dynamics of the model.

3.4.2 The Federal Funds Futures Market

The financial market side of the equilibrium is found following Lee and Kyle (2018), by conjecturing a *symmetric linear demand schedule*, i.e. a demand schedule which is identical for all traders and is of the form:

$$X_t^n = \pi_i i_{t-1} - \pi_f f_t + \pi_s s_t^n - \pi_e e_t^n, \tag{3.10}$$

where π_i, π_f, π_s and π_e are respectively the weights put by trader n on the previous period fed funds rate, the current futures rate, his private signal about the state economy, and his private endowment, when taking a decision about the amount of futures contracts to trade. Trader n's demand schedule X_t^n is found in two steps: (1) learning from the futures market rate f_t as well as his private signals s_t^n and e_t^n; and (2) choosing the optimal quantity to trade.

First, to understand learning from the market rate, consider trader n, who takes as given the other traders' strategies. Then, market clearing (equation 3.9) implies that the trader faces the following residual supply schedule:

$$f_t = f_t^n + \lambda X_t^n = \frac{\pi_i}{\pi_f} i_{t-1} + \frac{\pi_s}{\pi_f}\frac{\sum_{k\neq n} s_t^n}{N-1} - \frac{\pi_e}{\pi_f}\frac{\sum_{k\neq n} e_t^n}{N-1} + \lambda X_t^n, \tag{3.11}$$

where $f_t^n := \frac{\pi_i}{\pi_f} i_{t-1} + \frac{\pi_s}{\pi_f} s_t^{-n} - \frac{\pi_e}{\pi_f} e_t^{-n}$, for $j \in \{s_t^n, e_t^n\}$, $j_t^{-n} := \frac{1}{N-1}\sum_{k\neq n} j_t^k$, and $\lambda := \frac{1}{(N-1)\pi_f}$. Similar to Lee and Kyle (2018), in the strategic setting, the futures rate is characterized by an intercept and a slope: the intercept f_t^n is the rate that would prevail absent any trade by trader n; the slope λ is the *Kyle (1985) price impact*, which measures the marginal effect on the futures rate of trading one additional contract. Then, learning from the market rate is obtained by rewriting equation (3.11) as follows:

$$\tilde{f}_t^n = \frac{\pi_f}{\pi_s}\left[f_t - \frac{\pi_i}{\pi_f} i_{t-1} - \lambda X_t^n\right] = i_t^* + \varepsilon_t^{-n} - \frac{\pi_e}{\pi_s} e_t^{-n} = i_t^* + \nu_t^n, \tag{3.12}$$

with

$$\nu_t^n := \varepsilon_t^{-n} - \frac{\pi_e}{\pi_s} e_t^{-n}. \tag{3.13}$$

Observing f_t is informationally equivalent to observing $\tilde{f}_t^n$, which provides trader n with a signal - hereafter called the *market signal* - about the state of the economy i_t^* with noise ν_t^n. Interestingly, the precision of the market signal, $\tau_\nu \equiv \mathbb{V}\left[\nu_t^n\right]^{-1} = \left[\frac{1}{(N-1)\tau_T} + \left(\frac{\pi_e}{\pi_s}\right)^2 \frac{1}{(N-1)\tau_e}\right]^{-1}$, depends on two things: the amount of noise in the economy which is due to the noise traders' private information $\left(\tau_T^{-1}\right)$ and the volatility of their private endowment $\left(\tau_e^{-1}\right)$; and the intensity with which traders *speculate* on their private information (given by π_s) compared to *hedge* their endowment (given by π_e). The more traders speculate on their private information compared to hedging ($\downarrow \frac{\pi_e}{\pi_s}$), the more of traders' private information is embedded into the futures rate, and the more precise is the market signal ($\uparrow \tau_v$).

As can be seen in equation (3.8), traders use the information provided by the market signal $\tilde{f}_t^n$, their private signal s_t^n, their endowment e_t^n, as well as their beliefs about the central bank's reaction function (equation 3.7), to learn about the payoff of the federal funds rate $v_t = i_t - f_t$. Since f_t is measurable with respect to $\mathscr{F}_t^n = \{\tilde{f}_t^n, s_t^n, e_t^n\}$, learning about the payoff v_t amounts to learning about the fed funds rate i_t, which yields:

$$\mathbb{E}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right] = \bar{I} i_{t-1} + \bar{S}\left(\frac{\tau_i}{\tau_i + \tau_T + \tau_v} i_{t-1} + \frac{\tau_T}{\tau_i + \tau_T + \tau_v} s_t^n + \frac{\tau_v}{\tau_i + \tau_T + \tau_v} \tilde{f}_t^n\right) + \bar{F} f_t, \quad (3.14)$$

$$\mathbb{V}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right] = \bar{S}^2\left(\frac{1}{\tau_i + \tau_T + \tau_v} + \frac{1}{\tau_B}\right). \quad (3.15)$$

Equation (3.14) provides three intuitive insights about how trader n estimates the fed funds rate decision. First, he relies more on his private information s_t^n when it is more precise (τ_T high), and less when the market signal is informative (τ_v high). Second, his conjecture about the Fed's reaction function plays an important role: the more weight the central bank is expected to put on its private information ($\bar{S}$ high), the more he relies on his different signals to try to recover the central bank's private information. Third, the conditional expectation of the federal funds rate depends on the futures rate f_t, which according to equation (3.11), depends on X_t^n. This implies that strategic trader n also takes into account the impact of its demand - its price impact - on the expected fed funds rate: $\frac{\partial \mathbb{E}[i_t|f_t, s_t^n, e_t^n]}{\partial X_t^n} = \frac{\partial f_t}{\partial X_t^n}\frac{\partial \mathbb{E}[i_t|f_t, s_t^n, e_t^n]}{\partial f_t} = \lambda \bar{F}$. In other words, if trader n increases its demand by one unit, then the market rate f_t increases by λ, and the expected fed funds rate by $\lambda\bar{F}$. Eventually, the expected payoff is only reduced by $\left(1-\bar{F}\right)\lambda$.

After learning from prices and their private signals, traders find their best response by choosing the trading quantity that maximizes equation (3.8). The first order condition for trader n is found using well-known arguments for a CARA utility agent subject to normally distributed shocks, and solving for X_t^n:

$$\begin{aligned} X_t^n &= \frac{\mathbb{E}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right] - f_t^n - e_t^n\left(\lambda\left(1-\bar{F}\right) + A\mathbb{V}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right]\right)}{2\lambda\left(1-\bar{F}\right) + A\mathbb{V}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right]} \\ &= \frac{\bar{I} i_{t-1} + \bar{S}\left(\frac{\tau_i i_{t-1} + \tau_T s_t^n + \tau_v \tilde{f}_t^n}{\tau_i + \tau_T + \tau_v}\right) + \bar{F} f_t^n - f_t^n - e_t^n\left(\lambda\left(1-\bar{F}\right) + A\mathbb{V}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right]\right)}{2\lambda\left(1-\bar{F}\right) + A\mathbb{V}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right]}. \end{aligned} \quad (3.16)$$

And the second order condition is given by:

$$2\lambda\left(1-\bar{F}\right) + A\mathbb{V}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right] > 0. \quad (3.17)$$

Finally, trader n's best response X_t^n is found by substituting the expressions for f_t^n (equation 3.11) and $\tilde{f}_t^n$ (equation 3.12) into the first order condition (equation 3.16), solving for X_t^n, and matching the coefficients with the conjectured demand schedule (equation 3.10). This gives the financial market side of the equilibrium, which is stated in Lemma 1.

Lemma 1. *The financial market side of the equilibrium, excluding no trade equilibrium, exists if and only if:*

$$\tau_v < \frac{1}{2}(N-2)\tau_T, \tag{3.18}$$

with τ_v *being a solution to the following equation:*

$$\tau_v = \left[\frac{1}{(N-1)\tau_T} + \frac{A^2(N-1)\bar{S}^2\left(1-\frac{\tau_v}{(N-1)\tau_T}\right)^2(\tau_B+\tau_i+\tau_v+\tau_T)^2}{\tau_B^2\tau_e\left((N-2)\tau_T-2\tau_v\right)^2}\right]^{-1}. \tag{3.19}$$

While τ_v *may have several real solutions, only one satisfies the equilibrium condition given by equation* (3.18).

The set of demand schedules is given by:

$$\begin{aligned} X_t^n = \frac{1}{A}\left[\frac{N-2}{N-1} - 2\frac{\tau_v}{(N-1)\tau_T}\right]\frac{\tau_B}{\tau_B+\tau_i+\tau_T+\tau_v}\Bigg(&\frac{\bar{I}(\tau_i+\tau_T+\tau_v)+\bar{S}\tau_i}{\bar{S}^2}\frac{\tau_T}{\tau_T+\tau_v}i_{t-1} \\ &- \frac{1-\bar{F}}{\bar{S}^2}\frac{\tau_T}{\tau_T+\tau_v}(\tau_i+\tau_T+\tau_v)f_t \\ &+ \frac{\bar{S}}{\bar{S}^2}\tau_T s_t^n\Bigg) - \left(1-\frac{\tau_v}{(N-1)\tau_T}\right)e_t^n, \end{aligned} \tag{3.20}$$

with

$$\pi_i = \frac{1}{A}\left[\frac{N-2}{N-1} - 2\frac{\tau_v}{(N-1)\tau_T}\right]\frac{\tau_B}{\tau_B+\tau_i+\tau_T+\tau_v}\left(\frac{\bar{I}(\tau_i+\tau_T+\tau_v)+\bar{S}\tau_i}{\bar{S}^2}\frac{\tau_T}{\tau_T+\tau_v}\right)i_{t-1} \tag{3.21}$$

$$\pi_f = \frac{1}{A}\left[\frac{N-2}{N-1} - 2\frac{\tau_v}{(N-1)\tau_T}\right]\frac{\tau_B}{\tau_B+\tau_i+\tau_T+\tau_v}\left(\frac{1-\bar{F}}{\bar{S}^2}\frac{\tau_T}{\tau_T+\tau_v}(\tau_i+\tau_T+\tau_v)\right)f_t \tag{3.22}$$

$$\pi_s = \frac{1}{A}\left[\frac{N-2}{N-1} - 2\frac{\tau_v}{(N-1)\tau_T}\right]\frac{\tau_B}{\tau_B+\tau_i+\tau_T+\tau_v}\frac{\bar{S}}{\bar{S}^2}\tau_T s_t^n \tag{3.23}$$

$$\pi_e = 1 - \frac{\tau_v}{(N-1)\tau_T}. \tag{3.24}$$

Then, the market clearing rate is given by

$$\begin{aligned} f_t = &\frac{\bar{I}(\tau_i+\tau_T+\tau_v)+\bar{S}\tau_i}{\left(1-\bar{F}\right)(\tau_i+\tau_T+\tau_v)}i_{t-1} + \frac{\bar{S}(\tau_T+\tau_v)}{\left(1-\bar{F}\right)(\tau_i+\tau_T+\tau_v)}\frac{\sum_{n=1}^N s_t^n}{N} \\ &- \frac{A(\tau_B+\tau_i+\tau_T+\tau_v)(\tau_T+\tau_v)\bar{S}^2\left(1-\frac{\tau_v}{(N-1)\tau_T}\right)}{\left[\frac{N-2}{N-1}-2\frac{\tau_v}{(N-1)\tau_T}\right]\tau_B(\tau_i+\tau_T+\tau_v)\left(1-\bar{F}\right)}\frac{\sum_{n=1}^N e_t^n}{N}, \end{aligned} \tag{3.25}$$

and the price impact λ is given by:

$$\lambda = \frac{1}{(N-1)\,\pi_f} = \frac{A\,(\tau_B+\tau_i+\tau_T+\tau_v)\,(\tau_T+\tau_v)\,\bar{S}^2}{[(N-2)\,\tau_T-2\tau_v]\,\tau_B\,(\tau_i+\tau_T+\tau_v)\left(1-\bar{F}\right)}. \tag{3.26}$$

Lemma 1 provides two interesting insights about the financial market side of the equilibrium. First, for an equilibrium to exist, the price must not reveal too much of the traders' private information. If that would be the case - i.e. when equation (3.18) is violated - the price impact would become negative, meaning that a positive demand by trader n would decrease the market rate, and by equation (3.6), increase the payoff of the security. The security would then become even more attractive, and the trader would like to increase his demand further, which would again increase the payoff. Eventually, the trader would end up having an infinite demand for futures, thereby generating infinite profits.

Second, expectations about the central bank behavior have a direct impact on traders' decision and on the market rate. Indeed, equations (3.20) and (3.25) clearly show that the conjectured weights $\bar{I}, \bar{S}, \bar{F}$ appear in trader n's demand schedule and in the market rate.

3.4.3 The Central Bank

This section characterizes the central bank side of the equilibrium. The central bank chooses the fed funds rate i_t so as to minimize its expected loss function given by equation (3.3). The problem is solved in the same two steps as for the traders: first, it learns from its information set $\mathscr{F}_t^B = \{s_t^B, f_t\}$; second, it solves its optimization problem by taking as given the traders' conjecture about its own behavior - i.e. $\bar{I}$, $\bar{S}$ and $\bar{F}$. The solution of the optimization problem gives the central bank's *best response function*, also called *reaction function*, i.e. the weights I, S and F as a function of traders' conjectures.

First, to describe learning from the market rate, equation (3.25) is rewritten

$$f_t = \frac{\pi_i}{\pi_f} i_{t-1} + \frac{\pi_s}{\pi_f}\frac{\sum_{n=1}^N s_t^n}{N} - \frac{\pi_e}{\pi_f}\frac{\sum_{n=1}^N e_t^n}{N}, \tag{3.27}$$

where π_i, π_s, π_f and π_e are given by equations (3.21), (3.23), (3.22) and (3.24). Those expressions depend on $\bar{I}$, $\bar{S}$, and $\bar{F}$, which as mentioned before, are taken by the central bank as parameters. Then, learning from the market rate (equation 3.27) for the central bank is informationally equivalent to learning from the following linear transformation:

$$\tilde{f}_t^B = \frac{\pi_f}{\pi_s}\left[f_t - \frac{\pi_i}{\pi_f} i_{t-1}\right] = i_t^* + \eta_t, \tag{3.28}$$

where $\eta := \frac{\sum_{n=1}^{N}\varepsilon_t^n}{N} - \frac{\pi_e}{\pi_s}\frac{\sum_{n=1}^{N}e_t^n}{N}$. $\tilde{f}_t^B$ can be interpreted as the *market signal* received by the central bank, and η_t is the noise of that signal.[30] The precision of the central bank's market signal is given by $\tau_\eta := \mathbb{V}\left[\eta_t\right]^{-1} = \left[\frac{1}{N\tau_T} + \left(\frac{\pi_e}{\pi_s}\right)^2\frac{1}{N\tau_e}\right]^{-1}$.

As can be seen in equation (3.3), the Fed uses the market rate and its private signal s_t^B to learn about the state of the economy i_t^*. As a result, the the central bank's expectation and variance of i_t^* conditional on its information set are given by:

$$\mathbb{E}\left[i_t^*|s_t^B,\tilde{f}_t^B\right] = \frac{\tau_i}{\tau_i+\tau_B+\tau_\eta}i_{t-1} + \frac{\tau_B}{\tau_i+\tau_B+\tau_\eta}s_t^B + \frac{\tau_\eta}{\tau_i+\tau_B+\tau_\eta}\tilde{f}_t^B, \tag{3.29}$$

$$\mathbb{V}\left[i_t^*|s_t^B,\tilde{f}_t^B\right] = \frac{1}{\tau_i+\tau_B+\tau_\eta}. \tag{3.30}$$

Second, the Fed's optimization problem consists in choosing the optimal federal funds rate i_t to minimize the conditional expectation of its loss function (equation 3.3). Using the *market signal* $\tilde{f}_t^B$ in the information set instead of the futures rate f_t, the problem becomes:

$$\min_{i_t}\ \mathbb{E}\left[L_t|s_t^B,\tilde{f}_t^B\right] = \mathbb{E}\left[\left(i_t^*-i_t\right)^2|s_t^B,\tilde{f}_t^B\right] + \theta\left(f_t-i_t\right)^2.$$

The central bank's optimal decision - or *reaction function* - is obtained by taking the first order condition and solving for the federal funds rate i_t:

$$i_t = \frac{1}{1+\theta}\left(\mathbb{E}\left[i_t^*|\tilde{f}_t^B,s_t^B\right]+\theta f_t\right). \tag{3.31}$$

The reaction function perfectly reflects the two objectives of the central bank: First, the fed funds rate depends on the central bank's expectation of the state variable i_t^*, consistent with its *dual mandate* objective; second, it also depends on market expectations through f_t. These two characteristics have respectively a weight of $\frac{1}{1+\theta}$ and $\frac{\theta}{1+\theta}$, which sum up to one, and are consistent with their relative weight in the central bank's objective function. Note also that the second order condition requires that $2+2\theta>0$, which is always satisfied since $\theta>0$.

Therefore, plugging equation (3.29) into equation (3.31) and replacing τ_η and $\tilde{f}_t^B$ by their expressions gives the reaction function of the central bank, which is linear in its signals s_t^B and

[30] As a side note, it is interesting at this point to discuss what traders and the Fed try respectively to learn form the *market signal* they receive - i.e. $\tilde{f}_t^B$ for the Fed and $\tilde{f}_t^n$ for trader n. For both types of agent, the market rate is used to recover the actual state of the economy i_t^*. However, the reason for what they do so is quite different: from equation (3.3), it is possible to see that the Fed tries to recover the state of the economy, because this is the state variable on which its utility - and therefore its intervention - directly depends on. However, for trader n, the variable of interest is the actual payoff $v_t = i_t - f_t$, not the state variable i_t^*. The traders nevertheless attempt to learn i_t^* in order to infer the central bank's signal s_t^B, and ultimately the fed funds rate i_t.

f_t, as well as in i_{t-1}:

$$i_t = \frac{1}{1+\theta}\left[\frac{\left(\frac{\pi_s}{\pi_f}\right)^2 \tau_e\tau_i + \left(\frac{\pi_e}{\pi_f}\right)^2 \tau_i\tau_T - \left(\frac{\pi_i}{\pi_f}\right)\left(\frac{\pi_s}{\pi_f}\right) N\tau_e\tau_T}{\left(\frac{\pi_s}{\pi_f}\right)^2 \tau_e\left(\tau_B+\tau_i+N\tau_T\right) + \left(\frac{\pi_e}{\pi_f}\right)^2 \tau_T\left(\tau_B+\tau_i\right)} i_{t-1} \right.$$
$$+ \frac{\tau_B\left(\left(\frac{\pi_s}{\pi_f}\right)^2 \tau_e + \left(\frac{\pi_e}{\pi_f}\right)^2 \tau_T\right)}{\left(\frac{\pi_s}{\pi_f}\right)^2 \tau_e\left(\tau_B+\tau_i+N\tau_T\right) + \left(\frac{\pi_e}{\pi_f}\right)^2 \tau_T\left(\tau_B+\tau_i\right)} s_t^B$$
$$\left. + \left(\frac{\left(\frac{\pi_s}{\pi_f}\right) N\tau_e\tau_T}{\left(\frac{\pi_s}{\pi_f}\right)^2 \tau_e\left(\tau_B+\tau_i+N\tau_T\right) + \left(\frac{\pi_e}{\pi_f}\right)^2 \tau_T\left(\tau_B+\tau_i\right)} + \theta\right) f_t\right]. \tag{3.32}$$

Replacing π_i, π_f, π_s and π_e by their expressions (equations 3.21, 3.22, 3.23 and 3.24) and matching the coefficients in equation (3.32) with the initial guess given by equation (3.4) yields the central bank's best response function with weights I, S and F, given traders' conjectures $\bar{I}, \bar{S}$ and $\bar{F}$. This concludes the central bank side of the equilibrium, which is summarized by Lemma 2.

Lemma 2. *The central bank side of the equilibrium, exists if and only if:*

$$2 + 2\theta > 0,$$

which is always satisfied since $\theta > 0$.

And the central bank's best response function, also called reaction function, is given by:

$$i_t = I i_{t-1} + S s_t^B + F f_t,$$

where the weights $I = I\left(\bar{I}, \bar{S}, \bar{F}\right)$, $S = S\left(\bar{I}, \bar{S}, \bar{F}\right)$ *and* $F = F\left(\bar{I}, \bar{S}, \bar{F}\right)$ *are functions of traders' conjectures* $\bar{I}, \bar{S}, \bar{F}$ *about the Fed's reaction function.*

3.4.4 Equilibrium

This subsection starts with a description of the equilibrium, before conducting a calibration exercise to discuss the dynamics of the model.

First, provided that the results stated in Lemmas 1 and 2 hold, the equilibrium of the model is obtained when the traders' conjecture about the central bank's reaction function turns out to be true, i.e. when $\bar{I} = I\left(\bar{I}, \bar{S}, \bar{F}\right)$, $\bar{S} = S\left(\bar{I}, \bar{S}, \bar{F}\right)$ and $\bar{F} = F\left(\bar{I}, \bar{S}, \bar{F}\right)$. It is shown in Appendix B.1.4 that these three equations can be expressed as a function of a single variable, $\bar{S}$. As a result, the solution of the model is obtained by solving a fixed point of the form $\bar{S} = S\left(\bar{S}\right)$. It is also shown that one solution always satisfies the condition that the weights I, S and F sum up to one. The analysis focuses on the equilibrium satisfying this condition.[31] These results, which characterize what is hereafter referred to as the *Benchmark* model, are summarized in Lemma 3.

Lemma 3. *If the results stated in Lemmas 1 and 2 hold, the rational expectations equilibrium of the model is reached when the traders' conjecture about the central bank's reaction function is correct, i.e. when*

$$\bar{I} = I,\ \bar{S} = S \ \text{ and } \ \bar{F} = F.$$

In such a case, the solution of the model is found by solving the following fixed point:

$$\bar{S} = S\left(\bar{S}\right) = \frac{\frac{A^2\bar{S}^2(\tau_v-(N-1)\tau_T)^2(\tau_B+\tau_i+\tau_v+\tau_T)^2}{\tau_T((N-2)\tau_T-2\tau_v)^2} + \tau_e\tau_B^2}{(1+\theta)\tau_B\left(\frac{A^2\bar{S}^2(\tau_i+\tau_B)(\tau_v-(N-1)\tau_T)^2(\tau_B+\tau_i+\tau_v+\tau_T)^2}{\tau_B^2\tau_T((N-2)\tau_T-2\tau_v)^2} + \tau_e\tau_B + \tau_e\tau_i + N\tau_e\tau_T\right)}. \tag{3.33}$$

One equilibrium satisfies the condition $I + S + F = 1$.

Second, the fixed point defined in Lemma 3 is solved numerically using as a baseline calibration the following set of parameters: $\{\tau_B \to 25, \tau_T \to 5, A \to 5, \tau_e \to 5, \tau_i \to 5, N \to 25, \theta \to 0.2\}$. Since the model is very stylized, its goal is to offer a qualitative representation of the informational feedback loop arising between the Fed and financial markets, and in no way to produce quantitatively realistic predictions. As a result, the parameters have been chosen with this limitation in mind. The number of traders, N, is set to 25 in order to take into account the fact that fed funds futures tend to be a rather *small* market;[32] The precision of the central bank, τ_B (25), is set larger than the precision of individual traders, τ_T (5), but lower than the aggregate information produced by financial markets $\tau_T \times N$ (125). Indeed, while it may be argued that the Fed has more information than individual traders - because it has for example access to data not available to the public - it is hard to imagine that it has a better signal than the market as a whole.[33] Then, τ_i, τ_e and A are chosen to generate enough noise in the economy to allow

[31] It is a possibility - especially in a setup involving a feedback loop - that other equilibria not satisfying $I+S+F=1$ exist. However, the numerical simulations systematically generated solutions in which that equation was satisfied - without imposing it ex-ante - for different parameter values and different starting values for S - the fixed point is solved using the function *FindRoot* in Mathematica. As a result, only the equilibrium satisfying this condition is analyzed here. However, it could be interesting, in future iterations of this work, to (1) prove whether the equilibrium is indeed unique or not, and if not, (2) analyze these other equilibria.

[32] A report published by the World Federation of Exchanges in 2021 shows that the number of fed funds futures contracts traded in 2020 amounted to about 52 million. By contrast, more than 500 million Eurodollar Futures - the most traded short term interest rate derivative contract in the CME Group exchange - were traded in 2020. Moreover, to put these figures into prospective, the study indicated that in total, 3.98 billion interest rate derivative contracts were traded in 2020 in the exchanges taking part to the study. Regarding the volumes of other derivative classes, equity derivative contracts amounted to 25.98 billion, commodity derivatives to 9.30 billion, currency derivatives to 3.82 billion, and ETF derivatives to 3.07 billion.

[33] This assumption reflects the discussions emphasized in the introduction and the literature review: following Bernanke and Woodford (1997), sophisticated structural models of the economy are likely to provide the central bank with a better signal than individual traders; however, as emphasized by Tzitzouris, this signal is unlikely

for an equilibrium, while at the same time having traders risk tolerant enough to trade on their private information. Finally, θ is set to 0.2, to keep the dual mandate as the main objective of the Fed's policy.

Figures 3.1, 3.2 and 3.3 present respectively the comparative statics of the *Benchmark* model with respect to τ_B, τ_T and θ. In each of these figures, Panel (a) presents the dynamics of the variables related to the central bank's behavior, i.e. the weights I (left), S (center), and F (right); Panel (b) presents traders' trading motives, i.e. π_i (left), π_s (center), and π_e (right), as well as their relative weight with respect to π_f; finally, Panel (c) presents some variables which are relevant for the equilibrium dynamics, namely τ_v, the precision of the *market signal* received by traders (left), the price impact λ (center), and the second order condition which must be superior to zero (right).[34]

To summarize those results, it appears that F, i.e. the weight the central bank attaches to the market rate f_t, depends on how informative it is compared to its private signal s_t^B. For example, the right plot of panel (a) in figure 3.1 shows that F decreases with τ_B. This is because the informativeness of the central bank's signal increases significantly compared to the informativeness of the market signal τ_v (figure 3.1 panel (c) left plot).[35] By contrast, the right plot of panel (a) in figure 3.2 shows that F increases with the precision of traders' information. This is because the market signal becomes very informative, as shown by the left plot of panel (c) in figure 3.2: The central bank decides to put more weight on the futures rate when setting the fed funds rate because it contains more information than its own private signal. For similar reasons, plots B.2-B.5 in Appendix B.2.1 show that F is decreasing in risk aversion (A), in the volatility of the endowment shock ($1/\tau_e$), and in macroeconomic volatility ($1/\tau_i$). However, it is increasing in N. These results are similar to Bond and Goldstein (2015), except that in the current model, the weight the central bank puts on the market signal is monotonically decreasing in the central bank signal's precision (right plot of panel (a) in figure 3.1), while it is ambiguous in their model.

Finally, the comparative statics with respect to θ are fairly intuitive: figure 3.3 panel (a) shows that the more averse to financial market volatility the central bank is ($\uparrow \theta$), the more weight it puts on the market rate ($\uparrow F$, right plot) and the less weight it puts on its private signal ($\downarrow S$, center plot).

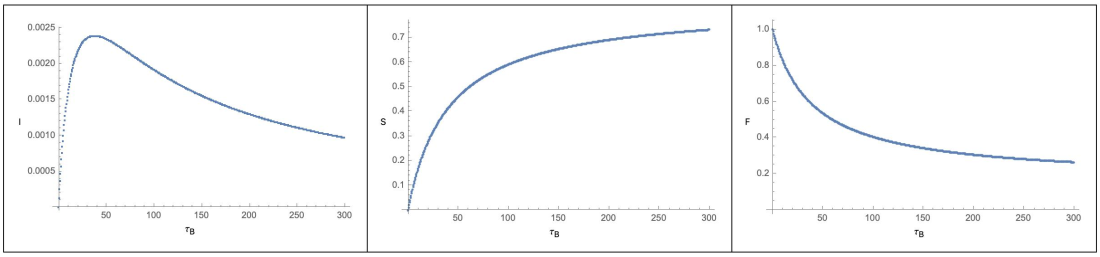
to be as good as the signal embedded in market prices, which aggregate information possessed by all market participants.

[34]Comparative statics with respect to the other parameters (A, τ_e, τ_i and N) can be found in Appendix B.2.1.

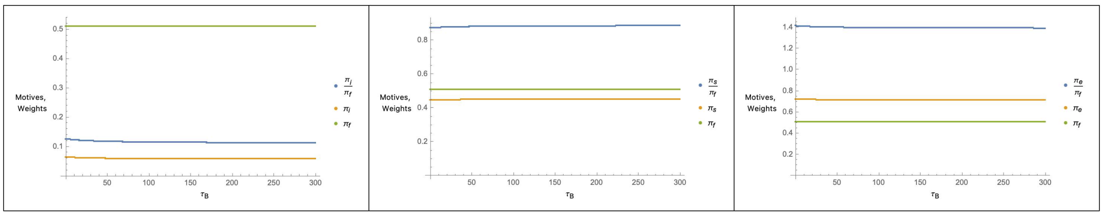
[35]Admittedly, the precision of the market signal plotted here is $\tau_v = \left[\frac{1}{(N-1)\tau_T} + \left(\frac{\pi_e}{\pi_s}\right)^2 \frac{1}{(N-1)\tau_e}\right]^{-1}$, i.e. that of the signal observed by traders, and not by the central bank. The precision of the market signal observed by the central bank is actually $\tau_\eta = \left[\frac{1}{N\tau_T} + \left(\frac{\pi_e}{\pi_s}\right)^2 \frac{1}{N\tau_e}\right]^{-1} = \frac{N}{N-1}\tau_v$. Since the only difference in these two variables is the factor $\frac{N}{N-1}$ their dynamics are qualitatively similar, and in order to limit the number of plots, τ_v is used as a proxy for τ_η to account for the informativeness of the market signal for the central bank.

Figure 3.1: **Comparative statics for the Benchmark Model with respect to τ_B.**
The baseline parameters used for the analysis are $\{\tau_B \to x, \tau_T \to 5, A \to 5, \tau_e \to 5, \tau_i \to 5, N \to 25, \theta \to 0.2\}$; Panel (a) presents the dynamics of the variables related to the central bank's behavior, i.e. the weights I (left), S (center), and F (right); Panel (b) presents traders' trading motives, i.e. π_i (left), π_s (center), and π_e (right), as well as their relative weight with respect to π_f; finally, Panel (c) presents some variables which are relevant for the equilibrium dynamics, namely τ_v, the precision of the *market signal* received by traders (left), the price impact λ (center), and the second order condition which must be superior to zero (right).

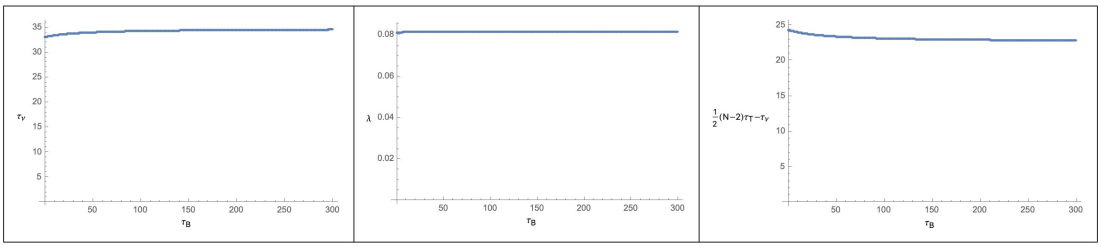
(a) Weights of the Central Bank's Reaction Function



(b) Traders' Trading Motives



(c) Equilibrium Variables

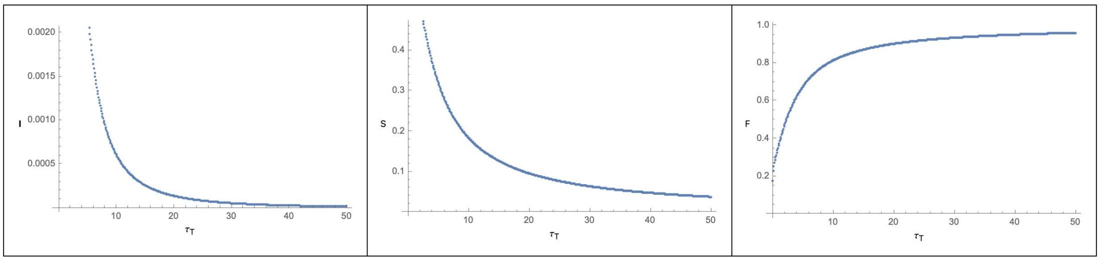


3.5 Theoretical Predictions

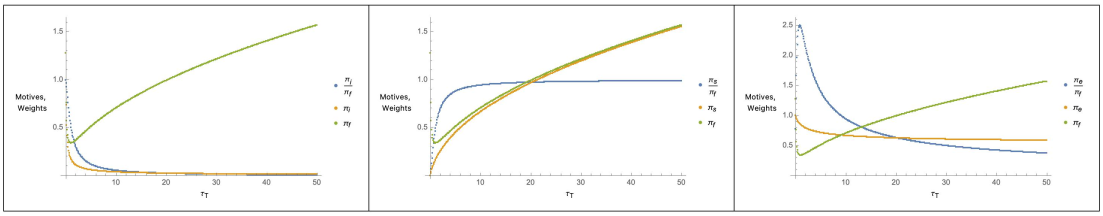
This section investigates the impact of the informational feedback loop between the Fed and financial markets on two critical issues - the monetary policy decision (subsection 3.5.1) and asset pricing dynamics (subsection 3.5.2) - in order to identify empirically testable hypotheses.

Figure 3.2: **Comparative statics for the Benchmark Model with respect to τ_T.**
The baseline parameters used for the analysis are $\{\tau_B \to 25, \tau_T \to x, A \to 5, \tau_e \to 5, \tau_i \to 5, N \to 25, \theta \to 0.2\}$; Panel (a) presents the dynamics of the variables related to the central bank's behavior, i.e. the weights I (left), S (center), and F (right); Panel (b) presents traders' trading motives, i.e. π_i (left), π_s (center), and π_e (right), as well as their relative weight with respect to π_f; finally, Panel (c) presents some variables which are relevant for the equilibrium dynamics, namely τ_v, the precision of the *market signal* received by traders (left), the price impact λ (center), and the second order condition which must be superior to zero (right).

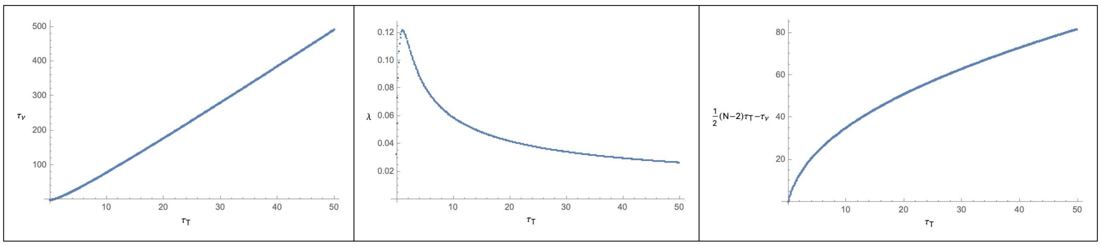
(a) Weights of the Central Bank's Reaction Function



(b) Traders' Trading Motives



(c) Equilibrium Variables

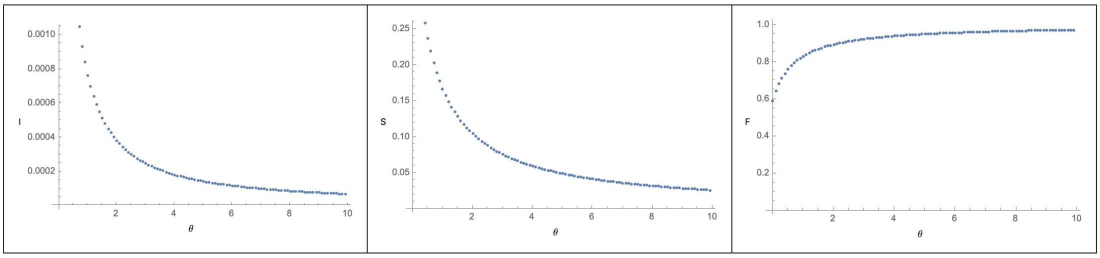


3.5.1 Monetary Policy Implications

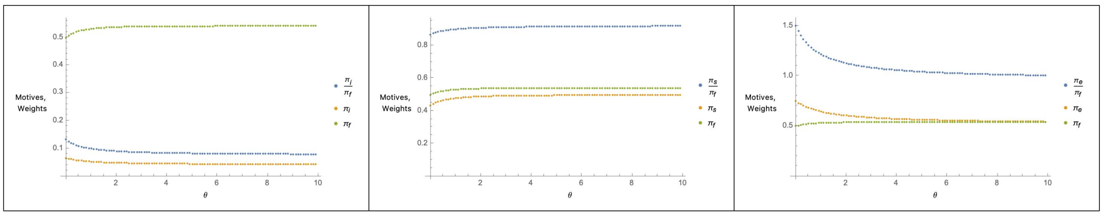
In order to understand the impact of the informational feedback loop between the Fed and financial markets on monetary policy decisions, two modified versions of the *Benchmark* model are introduced. In the first one - referred to as *Alternative 1* in the rest of this paper - the Fed does not learn from the market rate and is not averse to financial markets volatility. This has two consequences compared to the benchmark model: (1) In the initial conjecture about the central bank's reaction function (equation 3.4), the assumption that the Fed does not learn from the market rate is equivalent to set $F = 0$, i.e. $\mathscr{F}_t^B = \{s_t^B\}$. Therefore, the conjectured

Figure 3.3: **Comparative statics for the Benchmark Model with respect to θ.**
The baseline parameters used for the analysis are $\{\tau_B \to 25, \tau_T \to 5, A \to 5, \tau_e \to 5, \tau_i \to 5, N \to 25, \theta \to x\}$; Panel (a) presents the dynamics of the variables related to the central bank's behavior, i.e. the weights I (left), S (center), and F (right); Panel (b) presents traders' trading motives, i.e. π_i (left), π_s (center), and π_e (right), as well as their relative weight with respect to π_f; finally, Panel (c) presents some variables which are relevant for the equilibrium dynamics, namely τ_v, the precision of the *market signal* received by traders (left), the price impact λ (center), and the second order condition which must be superior to zero (right).

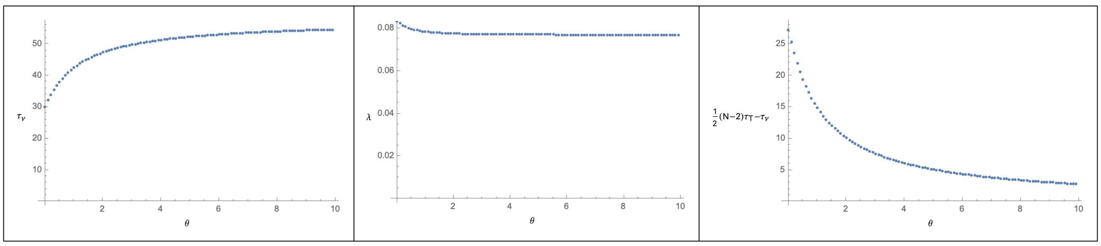
(a) Weights of the Central Bank's Reaction Function



(b) Traders' Trading Motives



(c) Equilibrium Variables



reaction function is of the form:

$$i_t = I i_{t-1} + S s_t^B, \tag{3.34}$$

and the traders' conjecture is given by:

$$i_t = \bar{I} i_{t-1} + \bar{S} s_t^B; \tag{3.35}$$

(2) Assuming that the Fed does not have a *financial stability* objective is equivalent to set $\theta = 0$ in the Fed's optimization problem (equation 3.3). Taking these two assumptions into account,

the Fed's optimization problem reduces to:

$$\min_{i_t} \mathbb{E}\left[L_t | s_t^B\right] = E\left[\left(i_t^* - i_t\right)^2 | s_t^B\right], \tag{3.36}$$

and the first order condition becomes:[36]

$$i_t = \mathbb{E}\left[i_t^* | s_t^B\right]. \tag{3.37}$$

In this alternative model, the Fed only cares about its dual mandate, so the central bank's first order condition reflects this new preference, and the federal funds rate decision is now the central bank's expected state of the economy, filtered with respect to its information set. Remember that in the reaction function of the *Benchmark* model, $\mathbb{E}\left[i_t^* | s_t^B, \tilde{f}_t^B\right]$ had a weight of $\frac{1}{1+\theta}$ (equation 3.31), which was consistent with its relative weight in the central bank's objective function (equation 3.3).

Apart from these two changes, the model is solved in the same way as the benchmark model, and the rational expectations equilibrium is given by Lemma 4.

Lemma 4. *There exists a rational expectations equilibrium in which the central bank does not take financial markets into consideration, if and only if the (i) financial market and (ii) central bank sides of the equilibrium are satisfied, and if (iii) the traders' conjecture about the Fed's reaction function turns out to be true.*

(i) On the financial side of the equilibrium, this implies:

$$\tau_v < \frac{1}{2}(N-2)\tau_T, \tag{3.38}$$

with τ_v being a solution to the following equation:

$$\tau_v = \left[\frac{1}{(N-1)\tau_T} + \frac{A^2(N-1)\bar{S}^2\left(1 - \frac{\tau_v}{(N-1)\tau_T}\right)^2(\tau_B + \tau_i + \tau_v + \tau_T)^2}{\tau_B^2\tau_e\left((N-2)\tau_T - 2\tau_v\right)^2}\right]^{-1}. \tag{3.39}$$

While τ_v may have several solutions, only one satisfies the equilibrium condition given by equation (3.38).

[36] The second order condition is obviously always satisfied.

The set of demand schedules is given by:

$$X_t^n = \frac{1}{A}\left[\frac{N-2}{N-1} - 2\frac{\tau_v}{(N-1)\tau_T}\right]\frac{\tau_B}{\tau_B+\tau_i+\tau_T+\tau_v}\left(\frac{\bar{I}(\tau_i+\tau_T+\tau_v)+\bar{S}\tau_i}{\bar{S}^2}\frac{\tau_T}{\tau_T+\tau_v}i_{t-1}\right.$$
$$-\frac{1}{\bar{S}^2}\frac{\tau_T}{\tau_T+\tau_v}(\tau_i+\tau_T+\tau_v)f_t$$
$$\left.+\frac{\bar{S}}{\bar{S}^2}\tau_T s_t^n\right) - \left(1-\frac{\tau_v}{(N-1)\tau_T}\right)e_t^n, \tag{3.40}$$

with

$$\pi_i = \frac{1}{A}\left[\frac{N-2}{N-1} - 2\frac{\tau_v}{(N-1)\tau_T}\right]\frac{\tau_B}{\tau_B+\tau_i+\tau_T+\tau_v}\left(\frac{\bar{I}(\tau_i+\tau_T+\tau_v)+\bar{S}\tau_i}{\bar{S}^2}\frac{\tau_T}{\tau_T+\tau_v}\right)i_{t-1} \tag{3.41}$$

$$\pi_f = \frac{1}{A}\left[\frac{N-2}{N-1} - 2\frac{\tau_v}{(N-1)\tau_T}\right]\frac{\tau_B}{\tau_B+\tau_i+\tau_T+\tau_v}\left(\frac{1}{\bar{S}^2}\frac{\tau_T}{\tau_T+\tau_v}(\tau_i+\tau_T+\tau_v)\right)f_t \tag{3.42}$$

$$\pi_s = \frac{1}{A}\left[\frac{N-2}{N-1} - 2\frac{\tau_v}{(N-1)\tau_T}\right]\frac{\tau_B}{\tau_B+\tau_i+\tau_T+\tau_v}\frac{\bar{S}}{\bar{S}^2}\tau_T s_t^n \tag{3.43}$$

$$\pi_e = 1 - \frac{\tau_v}{(N-1)\tau_T}. \tag{3.44}$$

Then, the market clearing rate is given by

$$f_t = \frac{\bar{I}(\tau_i+\tau_T+\tau_v)+\bar{S}\tau_i}{(\tau_i+\tau_T+\tau_v)}i_{t-1} + \frac{\bar{S}(\tau_T+\tau_v)}{(\tau_i+\tau_T+\tau_v)}\frac{\sum_{n=1}^N s_t^n}{N}$$
$$-\frac{A(\tau_B+\tau_i+\tau_T+\tau_v)(\tau_T+\tau_v)\bar{S}^2\left(1-\frac{\tau_v}{(N-1)\tau_T}\right)}{\left[\frac{N-2}{N-1}-2\frac{\tau_v}{(N-1)\tau_T}\right]\tau_B(\tau_i+\tau_T+\tau_v)}\frac{\sum_{n=1}^N e_t^n}{N}, \tag{3.45}$$

and the price impact λ is given by:

$$\lambda = \frac{1}{(N-1)\pi_f}$$
$$= \frac{A(\tau_B+\tau_i+\tau_T+\tau_v)(\tau_T+\tau_v)\bar{S}^2}{[(N-2)\tau_T-2\tau_v]\tau_B(\tau_i+\tau_T+\tau_v)}. \tag{3.46}$$

(ii) The central bank side of the equilibrium, always exists, and the central bank's best response function is given by:

$$i_t = \mathbb{E}\left[i_t^*|s_t^B\right] = \frac{\tau_i}{\tau_i+\tau_B}i_{t-1} + \frac{\tau_B}{\tau_i+\tau_B}s_t^B, \tag{3.47}$$

where the weights $I = \frac{\tau_i}{\tau_i+\tau_B}$ and $S = \frac{\tau_B}{\tau_i+\tau_B}$: (1) do not depend on traders' conjectures $\bar{I}$ and $\bar{S}$, and (2) sum up to one.

(iii) The rational expectations equilibrium of the model is reached when the traders' conjecture

about the central bank's reaction function is satisfied, i.e. when:

$$\bar{I} = I = \frac{\tau_i}{\tau_i + \tau_B}, \;\; and \;\; \bar{S} = S = \frac{\tau_B}{\tau_i + \tau_B}. \tag{3.48}$$

In this model, the weights of the reaction function only depend on two things: the precision of the central bank's signal, τ_B, and macroeconomic volatility, $1/\tau_i$. Market expectations are not taken into account by the central bank. As a result, in this model, the *two-way* feedback loop is replaced by a *one-way* two-step process: (1) the Fed sets the fed funds rate to comply with its dual mandate, relying solely on its private information to recover the state of the economy i_t^*; (2) Financial markets use their private information as well as the market signal to try to infer the central bank's signal s_t^B, and ultimately the fed funds rate i_t.

In the second alternative model - referred to as *Alternative 2* in the rest of this paper - the Fed is allowed to learn from the market rate ($F > 0$, i.e. $\mathscr{F}_t^B = \{s_t^B, \tilde{f}_t^B\}$), but it only cares about the dual mandate ($\theta = 0$). Therefore, the conjecture about the central bank reaction function is given by equation (3.4), and traders' conjecture is given by equation (3.7). Because the reaction function conjectures are the same in this model compared to the benchmark model, nothing changes on the financial side of the equilibrium, and the solution is identical to that of the benchmark model stated in Lemma 1.

On the central bank side of the equilibrium, the only difference lies in the central bank's optimization problem, which now features only the dual mandate objective. It is given by:

$$\min_{i_t} \mathbb{E}\left[L_t | s_t^B, f_t\right] = E\left[\left(i_t^* - i_t\right)^2 | s_t^B, f_t\right]. \tag{3.49}$$

And the first order condition is given by:

$$i_t = \mathbb{E}\left[i_t^* | s_t^B, f_t\right]. \tag{3.50}$$

Similar to the benchmark case, the Fed learns from its private signal and from the fed funds futures f_t - or equivalently the *market signal* $\tilde{f}_t^B$ (equation 3.28). Therefore, the central bank's conditional expectation of the state of the economy i_t^* is given by equation (3.29), and the rest of the model is solved in the same way as for the benchmark case. The result is stated in Lemma 5.

Lemma 5. *There exists a rational expectations equilibrium in which the central bank learns from the market rate but does not care about financial market volatility if and only if:*

(i) The conditions stated in Lemma 1 hold. In this case, the financial side of the equilibrium is identical to the results stated in that Lemma.

(ii) The central bank's best response function is given by:

$$i_t = \mathbb{E}\left[i_t^* | s_t^B, f_t\right] = I i_{t-1} + S s_t^B + F f_t, \tag{3.51}$$

where $I = I\left(\bar{I}, \bar{S}, \bar{F}\right), S = S\left(\bar{I}, \bar{S}, \bar{F}\right)$ and $F = F\left(\bar{I}, \bar{S}, \bar{F}\right)$ are the weights of central bank's best response function, and these weights depend on the traders' conjecture. They are given in Appendix B.1.5 by equations (B.39), (B.40) *and* (B.41)

(iii) The equilibrium is found by solving the fixed point $\bar{S} = S\left(\bar{S}\right)$ for $\bar{S}$.

The equilibrium considered in the analysis satisfies the condition $I + S + F = 1$.

Because the central bank learns from the futures market rate, the informational feedback loop is also present in this alternative model: traders' trading motives and the central bank's best response function depend on traders' conjecture about the central bank behavior - i.e. $\bar{I}, \bar{S}$ and $\bar{F}$.

Figure 3.4 presents comparative statics for the three models with respect to three parameters: τ_B (Panel a), τ_T (Panel b), and θ (Panel c). The inclusion of a financial stability objective mechanically shifts F upwards compared to a world in which the Fed would only learn from financial markets (the blue line is above the yellow line in the right plot of panels a, b, and c). This means that the *financial stability* objective brings the Fed to set a larger weight on the market rate than what it would do if it was only learning from it. Moreover, when traders have a very precise signal ($\tau_T \to \infty$), the right plot in panel (b) shows that the monetary policy decision becomes entirely determined by financial markets - provided that the central bank learns from the market rate.

However, the right plots in panels (a) and (b) also show that when the central bank cares about financial market volatility, even if the central bank is much more informed than financial markets ($\tau_B \to \infty$ or $\tau_T \to 0$), it keeps some weight on f_t ($F > 0$) to fulfill that objective.

3.5.2 Asset Pricing Implications

This section focuses on the impact of the informational feedback loop between the central bank and financial markets on asset prices dynamics. To do so, two securities are introduced: a short term bond and a long term bond.

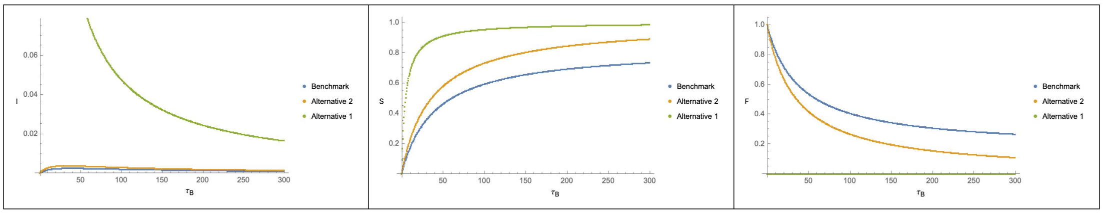
The yield of the short term bond, i_t^{ST}, is modeled as the average market expectation of the fed funds rate i_t at time t before the monetary policy announcement.[37] It is formally given by the

[37] Admittedly, this is a strong assumption, compared to the fact that the futures rate is determined endogenously by risk averse agents. Nevertheless, this hypothesis is made to simplify the analysis and the introduction of the two new securities.

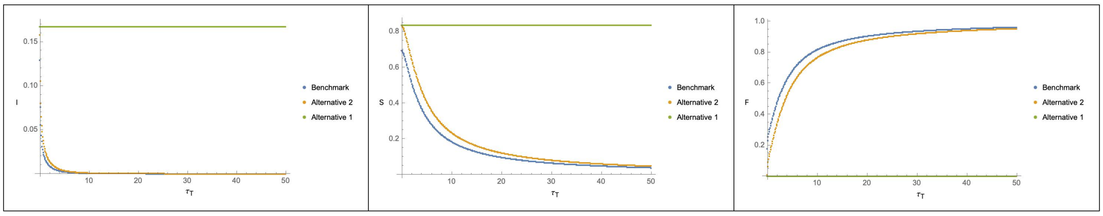
Figure 3.4: **Comparison of the three models to analyze the impact of the informational feedback loop between the central bank and financial markets on the monetary policy decision.**

Panels (a), (b) and (c) present respectively the results for the parameters τ_B, τ_T, and θ; the blue line represents the *Benchmark* model $\left(\theta = 0.2 \text{ and } f_t \in \mathscr{F}_t^B\right)$, the yellow line represent the *Alternative 2* model $\left(\theta = 0 \text{ and } f_t \in \mathscr{F}_t^B\right)$, and the green line represents the *Alternative 1* model $\left(\theta = 0 \text{ and } f_t \notin \mathscr{F}_t^B\right)$. Within each panel, the plots represent the weight of the central bank's best response function: I (left plot), S (center plot) and F (right plot).

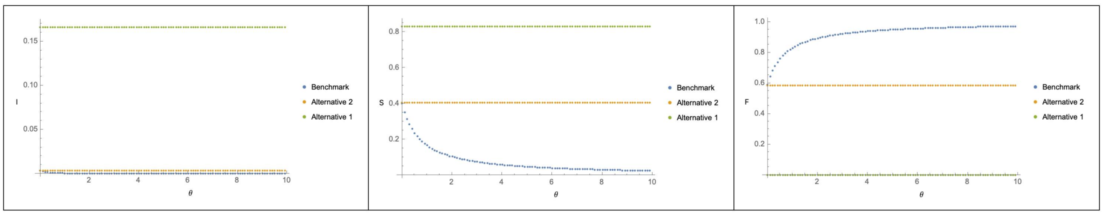
(a) τ_B: $\{\tau_B \to x, \tau_T \to 5, A \to 5, \tau_e \to 5, \tau_i \to 5, N \to 25, \theta \to 0.2\}$



(b) τ_T: $\{\tau_B \to 25, \tau_T \to x, A \to 5, \tau_e \to 5, \tau_i \to 5, N \to 25, \theta \to 0.2\}$



(c) θ: $\{\tau_B \to 25, \tau_T \to 5, A \to 5, \tau_e \to 5, \tau_i \to 5, N \to 25, \theta \to x\}$



following equation:

$$i_t^{ST} = \frac{1}{N} \sum_{n=1}^{N} \mathbb{E}\left[i_t | s_t^n, e_t^n, f_t \right]. \tag{3.52}$$

The yield of the long term bond is modeled as the market expectation of the state of the economy at time t. The underlying hypothesis is that in the long run, rates adjust towards the rate implied by the state of the economy. The long term bond yield, denoted i_t^{LT}, is therefore given by the following equation:

$$i_t^{LT} = \frac{1}{N} \sum_{n=1}^{N} \mathbb{E}\left[i_t^* | s_t^n, e_t^n, f_t \right]. \tag{3.53}$$

As mentioned, the goal here is to investigate the impact of the informational feedback loop on asset prices dynamics, and in particular, to understand how prices adjust following monetary policy announcements. As a result, the variables considered in this section are the variance of bond yields adjustments following monetary policy announcements, as well as the variance of the surprise. Those are given by $\mathbb{V}\left[i_t - i_t^{ST} \right]$ for the short term bond - i.e. the difference between the rate actually set by the central bank and the short term bond rate prior to the announcement; by $\mathbb{V}\left[i_{post}^{LT} - i_t^{LT} \right]$ for the long term bond, where i_{post}^{LT} denotes the long term yield after the announcement, i.e. taking into account the monetary policy decision i_t:

$$i_{post}^{LT} = \frac{1}{N} \sum_{n=1}^{N} \mathbb{E}\left[i_t^* | s_t^n, e_t^n, f_t, i_t \right]; \tag{3.54}$$

and finally by $\mathbb{V}\left[i_t - f_t \right]$ for the surprise, i.e. the difference between the fed funds rate and the futures rate. Expressions for these variables are given in Lemma 6.

Lemma 6. *Provided that the results stated in Lemmas 3, 4 and 5 hold, the variance of the adjustments of the short term bond yield and of the long term bond yield due to monetary policy announcements are respectively given by equations* (3.55) *and* (3.56)*:*

$$\mathbb{V}\left[i_t - i_t^{ST} \right] = \bar{S}^2 \left[\frac{\tau_i}{(\tau_i + \tau_T + \tau_v)^2} + \frac{1}{\tau_B} + \frac{1}{N} \left(\frac{(\tau_T + \tau_v)^2}{(\tau_i + \tau_T + \tau_v)^2 \tau_T} + \left(\frac{\pi_e}{\pi_s} \right)^2 \frac{\tau_v^2}{(\tau_i + \tau_T + \tau_v)^2 \tau_e} \right) \right]; \tag{3.55}$$

$$\begin{aligned} \mathbb{V}\left[i_{post}^{LT} - i_t^{LT} \right] = & \left(\frac{\tau_B + \tau_T + \tau_v}{\tau_B + \tau_i + \tau_T + \tau_v} \right)^2 \frac{1}{\tau_i} + \frac{\tau_B}{(\tau_B + \tau_i + \tau_T + \tau_v)^2} \\ & + \frac{1}{N} \left(\frac{\tau_B}{(\tau_i + \tau_T + \tau_v)(\tau_B + \tau_i + \tau_T + \tau_v)} \right)^2 \left[\frac{(\tau_T + \tau_v)^2}{\tau_T} + \left(\frac{\pi_e}{\pi_s} \right)^2 \frac{\tau_v^2}{\tau_e} \right], \end{aligned} \tag{3.56}$$

which are identical for the three models;

And the surprise following monetary policy announcements is given by

$$\mathbb{V}\left[i_t - f_t\right] = \left[\bar{S} - \left(1-\bar{F}\right)\frac{\pi_s}{\pi_f}\right]^2 \frac{1}{\tau_i} + \frac{\bar{S}^2}{\tau_B} + \left[\left(1-\bar{F}\right)\frac{\pi_s}{\pi_f}\right]^2 \frac{1}{N\tau_T} + \left[\left(1-\bar{F}\right)\frac{\pi_e}{\pi_f}\right]^2 \frac{1}{N\tau_e} \tag{3.57}$$

for the Benchmark and Alternative 2 models, and by

$$\mathbb{V}\left[i_t - f_t\right] = \left(\bar{S} - \frac{\pi_s}{\pi_f}\right)^2 \frac{1}{\tau_i} + \frac{\bar{S}^2}{\tau_B} + \left(\frac{\pi_s}{\pi_f}\right)^2 \frac{1}{N\tau_T} + \left(\frac{\pi_e}{\pi_f}\right)^2 \frac{1}{N\tau_e} \tag{3.58}$$

for the Alternative 1 model.

Figure 3.5 shows the comparative statics of the variance of the surprise (equations 3.57 and 3.58, left plot), of the short term yield adjustments (equation 3.55, center plot), and of the long term yield adjustments (equation 3.56, right plot) following monetary policy announcements, with respect to τ_B (Panel a), τ_T (Panel b) and θ (Panel c).

The results are quite intuitive: panels (a), (b) and (c) show that when the central bank learns from financial markets (yellow, blue lines) and when it cares about financial market volatility (blue line), the variance of the surprise (left plot) and of the adjustments of the short term bond yield (center plot) are lower compared to a world in which it would neither learn from financial markets nor care about their volatility (green line). This is because in such cases, the central bank puts a larger weight on the futures rate (higher F),[38] so the fed funds rate is closer to the futures rate.

Then, focusing on panel (a), which presents the comparative statics with respect to the precision of the central bank's signal τ_B, it appears that when the central bank learns from the market signal (yellow line) and is also averse to financial market volatility (blue line), the surprise (left plot) and the adjustment of the short term bond yield (center plot) are decreasing when the signal contains more noise. This is because in such cases, the central bank relies less on its private signal ($\downarrow S$) and more on the market signal ($\uparrow F$) to recover the actual state of the economy. However, those two plots also show that when the central bank neither learns from financial markets nor cares about financial market volatility (green line), the surprise generated by the announcement and the adjustment of the short term bond yield increase. This is due to the central bank relying only on its private information to decide over the fed funds rate, but since its signal is very imprecise, the decision ends up far from market expectations.

Comparative statics with respect to the precision of traders' signal τ_T presented in panel (b) feature the same kind of dynamics than those identified for the precision of the central bank signal: The more noise the market signal contains, the less the central bank relies on this information to take its decision ($\downarrow F$), and the more weight it puts on its own private information ($\uparrow S$). As a result, the surprise and the adjustment of the short term bond yield

[38] Which implies a lower S.

following monetary policy announcements increase.

By contrast, the right plot in panels (a), (b) and (c) show that the variance of adjustments of the long term bond yield is quite insensitive to τ_T (right plot in panel b), θ (right plot in panel c), as well as any assumption related to the central bank behavior: whether or not it learns from the market signal and cares about financial stability, the three lines consistently stay close together. This is explained by the fact that the long term bond yield represents average expectations of the fundamentals of the economy - i.e. average expectations about i_t^* - and traders use the monetary policy announcement to get additional information about i_t^* by inferring the central bank's private signal s_t^B from the decision.[39] Therefore, if the central bank sets i_t closer to f_t because it is averse to financial markets volatility or because traders's signal is much more precise than the central bank's, this would not change how the long term yield adjusts because such a move by the central bank provides no additional information about the state of the economy other than that contained in its private signal and perfectly recovered by traders, whatever the decision is.[40] Consistent with this explanation, the long term bond yield reacts however to the precision of the central bank's signal. Indeed, the right plot of panel (b) shows that when the central bank's private signal contains a lot of noise, the long term bond yield adjusts less. This is because the central bank follows more the information contained in financial markets' signal ($\uparrow F$), so the weight associated to the central bank's signal is low ($\downarrow S$), and the announcement contains very little new information about the underlying fundamentals of the economy.

Those results are summarized by the following set of hypotheses:

Hypothesis 1. *When the central bank looks at financial markets, either to learn from the market signal or because it is averse to financial market volatility, if the precision of the central bank's signal is low compared to that of traders', it puts a lower weight on its own private signal, and a higher weight on the market signal. In such a case, the surprise is low, as well as short and long term rates adjustments; in particular, the lower the precision of the central bank signal, the lower the surprise and the adjustments.*

Hypothesis 2. *When the central bank looks at financial markets, either to learn from the market signal or because it is averse to financial market volatility, if the precision of traders' signal is low compared to that of the signal received by the central bank, it puts a lower weight on the market signal than on its own, meaning that it relies less on the information produced by financial markets to recover the state of the economy. In that case, the surprise and adjustments of the short term bond yield are high. By contrast, adjustments of the long term bond yield are*

[39] Equation (B.45) in the Appendix shows that traders are able to perfectly recover the central bank's signal from the monetary policy decision.

[40] This outcome may be debatable, as one could argue, for example, that setting the fed funds rate at a level that is higher than what would be required by the dual mandate could slow down the economy and depress long term real rates. Subsection 3.6.3.2 elaborates on this. Note that this idea is also in line with Tzitzouris' comment, according to which the central bank is going to depress the economy by tightening too strongly too early.

insensitive to the precision of the signal received by traders, as it only adjusts to the arrival of information that are new to traders following monetary policy announcements.

Hypothesis 3. *The central bank aversion to bond market volatility reduces the magnitude of the surprise and of adjustments of the short term bond yield. However, it does not have an impact on the adjustment of the long term bond yield, as the central bank aversion to financial markets volatility does not have an impact on the amount of news contained in its signal, which is revealed to traders by the announcement.*

Hypothesis 4. *When the central bank does not learn from the market signal and is not averse to financial markets volatility, if it has a very noisy signal, then, adjustments of the long term bond yield are low, while the surprise is high and adjustments of the short term bond yield are high. This is because the central bank relies on a weak signal, which is not known by financial markets ex-ante. Therefore, the decision is far from market expectations, forcing the short term rate to adjust; however, it contains very few new information about the state of the economy, so the long term rate adjusts only slightly.*

3.6 Empirical Analysis

This section presents an empirical analysis that aims at providing some empirical support to the hypotheses formulated in the theoretical part of this paper. More precisely, it consists in an event study - using FOMC meetings - which goal is to identify the impact of the informational feedback loop arising between the central bank and the financial sector on the monetary policy decision process and on asset prices dynamics. Concretely, this is done by estimating the impact of the precision of the signals received by each agent on the surprise generated by monetary policy announcements and the subsequent adjustment of short and long term treasury yields.

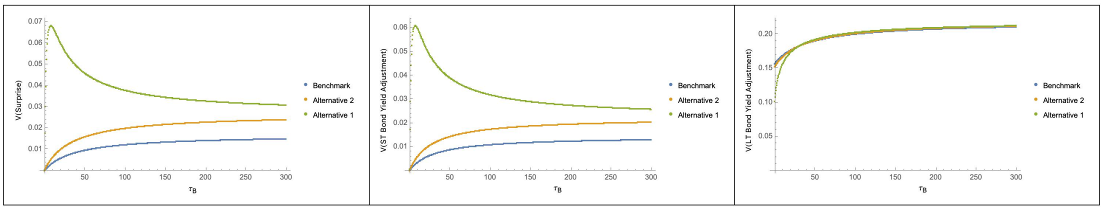
This section describes the empirical analysis in three steps: it starts by introducing the dataset, before explaining how the time series are built; finally, results are presented and discussed.

3.6.1 The Dataset

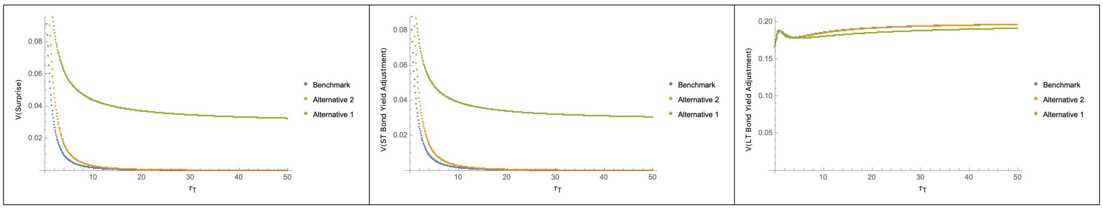
Two types of data are considered in this analysis. First, financial data are used to measure the surprise and the variance of the adjustments of the short and long term treasury yields following monetary policy announcements. Second, the signals received by the the Fed and by the private sector are extracted from textual data. The signal of the former is extracted from

Figure 3.5: **Comparative statics of the adjustment in yields following monetary policy announcements (parameters: τ_B, τ_T, θ):** Panels (a), (b) and (c) presents respectively the results for the parameters τ_B, τ_T, and θ; the blue line represents the *Benchmark* model $\left(\theta = 0.2 \text{ and } f_t \in \mathscr{F}_t^B\right)$, the yellow line represent the *Alternative 2* model $\left(\theta = 0 \text{ and } f_t \in \mathscr{F}_t^B\right)$, and the green line represents the *Alternative 1* model $\left(\theta = 0 \text{ and } f_t \notin \mathscr{F}_t^B\right)$. Within each panel, the plots represent the variance of the surprise (left plot), the variance of the short term bond yield (center plot), and the variance of the long term bond yield (right plot), following monetary policy announcements .

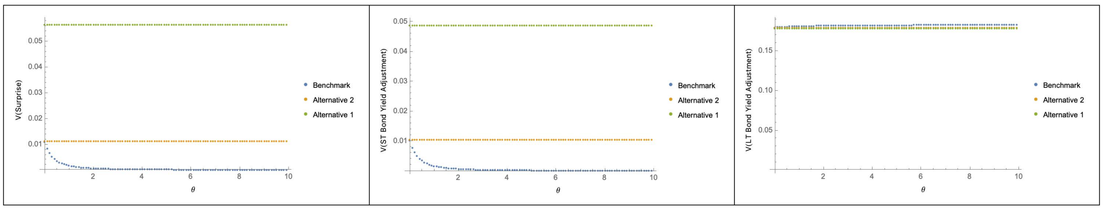
(a) τ_B: $\{\tau_B \to x, \tau_T \to 5, A \to 5, \tau_e \to 5, \tau_i \to 5, N \to 25, \theta \to 0.2\}$



(b) τ_T: $\{\tau_B \to 25, \tau_T \to x, A \to 5, \tau_e \to 5, \tau_i \to 5, N \to 25, \theta \to 0.2\}$



(c) θ: $\{\tau_B \to 25, \tau_T \to 5, A \to 5, \tau_e \to 5, \tau_i \to 5, N \to 25, \theta \to x\}$



FOMC minutes,[41] and the signal of the latter is extracted from tweets published four hours prior to the announcement. These three subsets of the dataset are presented hereafter.

3.6.1.1 Financial data

The financial data used in this paper are taken at a daily frequency and are of two types: the Federal funds futures rate and nominal treasury yields.

Daily Fed funds futures quotes are used to compute the surprise generated by monetary policy announcements. Two series are considered: the 30-day federal funds futures for the current month, and one month ahead. The data, available from February 2002 to June 2021, come from the Datastream database.

Second, this analysis looks at the adjustment of treasury yields of three different maturities: three months, two years and ten years. More precisely, the series, directly downloaded from the FRED Website, are identified as DGS3M, DGS2 and DGS10, and represent respectively the 3-month, 2-year and 10-year constant maturity treasury yield. Quotes are taken between 3 pm and 3:30 pm E.T. each day, and are qualified as *close* yields in this paper. They are used to compute the absolute value of the *close to close* change in nominal yields.

3.6.1.2 FOMC minutes

FOMC minutes are used to build a proxy for the precision of the signal received by the central bank, τ_B. They are usually published three weeks after each FOMC meeting, and can be downloaded directly from the *Transcripts and other historical material* section of the Fed website. The time period considered in this paper covers all FOMC minutes from January 1994 to June 2021.[42] The sample starts in January 1994 because this is the time at which the Fed started disclosing its decision with the publication of a statement at the end of each meeting. This is important for the identification of the surprise and of the yield adjustments, because it means that the news should be incorporated into prices once the announcement is made, and therefore be embedded into quotes taken at the end of the trading day. Prior to 1994, economic agents had to wait a few days to observe the actual implementation of the Fed's policy and be able to infer its decision.[43] The sample ends in June 2021 because it was the latest date

[41] The FOMC meets eight times per year to discuss current economic and financial conditions, and determine the appropriate monetary policy response. At the end of those meetings, a statement is released - usually between 2 pm and 2:30 pm Eastern Time (E.T.) - providing a short summary of the meeting and of the decision(s) taken by the committee. Then, three weeks after the meeting, minutes providing a more detailed summary of those discussions are published. Minutes are the data used in this analysis, similar to Jegadeesh and Wu (2015). By contrast, Hansen and McMahon (2016) used FOMC statements.

[42] Note that the base regression is estimated on the December 2008-June 2021 period, due to the lack of data availability for the private sector. Nevertheless it is useful to gather as many FOMC minutes as possible, in order to facilitate the identification of the topics by the algorithm.

[43] This argument is made here in case the futures sample - currently starting in 2002 - could be increased up to 1994. But even if that was not the case, it would make sense to use this date as the starting date for the sample, since it characterizes the beginning of a new period regarding monetary policy communication by the Fed.

available at the time of writing this paper. The FOMC minutes data sample therefore contains 220 documents. This subsection starts by motivating the choice of FOMC minutes, before explaining how the data was preprocessed in order to be exploited in this empirical analysis.

FOMC meeting minutes are an ideal source of data for the current analysis for two reasons. First, they provide an extensive summary of the discussions held between FOMC members about the latest macroeconomic data releases, presentations of staff forecasts, the elements motivating the monetary policy decision, etc., which can be used to estimate the signal received by the Fed.[44] Second, the structure of FOMC minutes has been highly consistent across the years, which enables to create a time series that spans the whole sample. They usually contain five sections: the first section is dedicated to the administrative details of the meeting - e.g. members present; the second section is dedicated to financial markets;[45] the third section is dedicated to the staff, which provides its assessment of the state of the economy, the financial situation, and the economic outlook; the fourth section is dedicated to discussions between FOMC members about their own assessment of the fundamentals of the economy. The fifth section is dedicated to discussing the appropriate course of monetary policy. Finally, the minutes end with a conclusion restating the policy actions, their rationale with respect to the state of the economy, and members' votes.

In order to be used in the empirical analysis, the FOMC minutes have been retreated in the following way: First, only useful sections are kept. As a result, following Jegadeesh and Wu (2015), the introductory section is removed because it contains only administrative details; in addition, in the current analysis, the concluding section is also removed, as it simply summarizes information already expressed in the previous sections. Finally, the tables presenting the votes and the names of FOMC members voting for a policy action have also been removed, as they contain no information relevant for the current analysis.

Each document is then split into sentences, and the text is preprocessed using the library developed by Hansen et al. (2018) to analyze central banks' communication documents.[46] Pre-processing contains two steps: First, sentences are cleaned by converting contractions into their underlying words (e.g. "it's" into "it is"), by transforming all words into lowercase, and by breaking the text in tokens corresponding to their underlying linguistic components (words, numbers, punctuation, etc.). In total, the clean corpus contains 220 meetings, 38'741 sentences, and 637'307 tokens representing 7'580 unique tokens. Unique tokens form the *vocabulary* of the dataset. Second, the size of the vocabulary is reduced so as to contain only

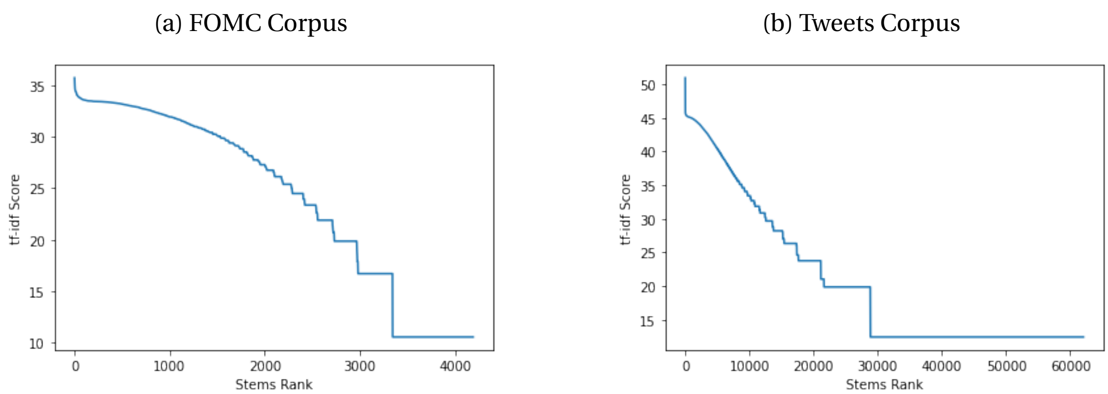
[44] Admittedly, transcripts would have been an even better source of information, as they transcribe, almost word by word, the debates occurring during meetings; by contrast, minutes are just a summary. However, transcripts are only available 5 years after the realization of a meeting, while minutes are published within three weeks. As a result, FOMC minutes appear to be a good tradeoff between content and sample size.

[45] This section is the section that has evolved the most between 1994 and 2021: prior to the financial crisis, it was fairly short, and consisted mainly in reviewing previous open market operations; following the financial crisis however, FOMC members increased significantly their attention to financial markets. This materialized by an increase in the size of this section in FOMC minutes, to account for developments in financial markets and the evolution of the central bank balance sheet.

[46] The code can be accessed via Stephen Hansen's github repository: https://github.com/sekhansen.

the terms that are representative of the underlying content of the documents, and facilitate the identification of semantically meaningful topics. This is done by: removing *stopwords*, i.e. words such as "a" or "the", which are very common in the English language, but are not representative of the content of a text;[47] removing non alphabetical characters; removing any remaining word of only one character; and reducing words to their *root*, a process called *stemming*, which aims at gathering together words that have a similar meaning but are grammatically different - e.g. the words "reduce" and "reducing" are stemmed to "reduc".[48] The resulting tokens, also named *stems*, amount to 4'193 unique terms. Finally, similar to Hansen et al. (2018), the size of the vocabulary is reduced one last time by removing words which have a low *term frequency-inverse document frequency* (*tf-idf*) score.[49] This score penalizes words that appear either very rarely in the corpus - i.e. term frequency is low - or very often - i.e. that appear in a lot of documents. Indeed, words that are either too rare or too frequent do not contain information that would make them useful to create semantically meaningful topics. Figure 3.6a ranks the unique stems of the FOMC minutes sample in a decreasing order according to their *tf-idf* score. All the stems that belong to the last two "stairs" - *tf-idf* < 17 - have been removed from the analysis. After all these steps, the FOMC minutes corpus contains 2'982 unique stems.

Figure 3.6: **Ranking of unique stem tokens according to their *tf-idf* rank:** Panel (a) represents the 4'193 unique stems of the FOMC minutes corpus ranked according to their *tf-idf* score. Panel (b) represents the 62'052 unique stems of the Tweets corpus ranked according to their *tf-idf* score.



[47]Note that there is no list of stopwords that would be used universally. The one used in the current analysis is the *long stopword list* suggested by the authors.

[48]This is achieved using the Porter Stemmer, which is the one suggested by the authors and which is widely used in the literature.

[49]As described in Hansen et al. (2018, p. 819), the *tf-idf* score is computed in the following way: First, let n_v be the count of term v in the corpus. Then the *term frequency* of word v is equal to : $tf_v = 1 + \log(n_v)$; second, let D be the number of documents - here FOMC minutes - in the corpus and D_v be the number of documents in which the term v appears. Then the *inverse document frequency* of word v is equal to $idf_v = \log\left(\frac{D}{D_v}\right)$. Finally, the *tf-idf* score is equal to: *tf-idf*$= tf_v \times idf_v$.

3.6.1.3 Tweets

Tweets are used to create a proxy for the precision of the signal received by traders, τ_T. Tweets have been chosen as the sole source of data to extract the private sector's signal for two reasons: first, because this is a source of data that is free and accessible by any researcher. Indeed, in February 2021, Twitter launched an API that allows academic researchers to search the entire Twitter database since the first tweet published in March 2006; second, because previous research has shown that tweets could be used to investigate monetary policy related research questions (Azar and Lo, 2016; Cornet, 2020).

Twitter's API for academic researchers has therefore been used to collect all the tweets dealing with monetary policy, inflation and economic growth. More precisely, tweets needed to contain at least one of the following keywords: "monetary policy," "quantitative easing," "federal reserve," "the fed," "bernanke," "yellen," "economic growth," "inflation," "deflation," or "FOMC". Moreover, the query to download tweets contained three additional criteria: (1) be written in English, (2) not be a retweet and (3) be published less than four hours before a FOMC announcement. This last criterion has been set to reduce the number of potentially non relevant tweets. In total, the raw sample contains 307'419 tweets.

Then, two additional cleaning steps are performed before preprocessing the Tweets sample using Hansen et al.'s (2018) procedure: first, duplicates are removed which makes the total number of tweets fall to 248'394. Table 3.1 provides summary statistics related to the number of tweets per day. It is striking to see that the dispersion across days, especially at the beginning of the sample, is large. For example, the minimum number of tweets for a given day in the sample is one. This corresponds to March 21$^{\text{st}}$ 2007, which is the very first time at which a tweet corresponding to the criteria mentioned above had been published. The topic identification step uses the whole Tweets sample, i.e. the sample starting in March 21$^{\text{st}}$ 2007, to provide the topic identification algorithm with as much data as possible; however, in order to constitute a relevant observation, days needed to contain enough tweets. As a result, event observations are considered in the event study if they contain a minimum of 150 tweets. This is the case for all observations from the 16$^{\text{th}}$ of December 2008 onward. This is the date at which the private sector's signal time series starts. The second cleaning step follows Cornet (2020),

Table 3.1: Tweets sample summary statistics after removing duplicates

Variable	**Mean**	**SD**	**Min**	**Max**	**Median**	**Total**
# tweets/day published 4h prior to announcement	2'160	1'362	1	7'598	2'265	248'394

This table reoprts summary statistics about the Tweets sample after removing duplicates. In order to compute those statistics, only the days that feature at least one tweet have been counted. Those correspond to all the FOMC meetings from the 21$^{\text{st}}$ of March 2007 onward.

and consists in removing urls, transforming abbreviations commonly used in tweets to their original form (e.g. "U" into "you"), correcting the most common misspells, replacing hashtags by their actual in-vocabulary form (e.g. "#ratehike" is replaced by "# rate hike"), and replacing usernames by actual in-vocabulary forms when those are likely to have a meaningful content (e.g. "@federal-reserve" is replaced by "@ federal reserve").

Finally, similar to FOMC minutes, tweets are preprocessed following Hansen et al. (2018). In this case, dimensionality reduction is even more important than for FOMC minutes, in light of the large amount of data considered. Table 3.2 provides some figures comparing the two datasets. The Tweets dataset is enormous, but the data cleaning and preprocessing steps enable to reduce dimensionality significantly. After removing unique stems with a *tf-idf* score inferior to 21 - to remove the last two "stairs" of unique stems in the Tweets dataset ranked according to their *tf-idf* score as shown in figure 3.6b - the final sample contains 21'608 unique stems.

Table 3.2: FOMC Minutes and Tweets dataset pre-processing steps and figures

	FOMC Minutes	**Tweets**
Total sample dates (number)	January 1994 - June 2021 (220)	March 2007 - June 2021 (115)
Max possible sample for empirical analysis (number)	February 2002 - June 2021 (154)	December 2008 - June 2021 (100)
Number of sentences/Tweets	38'741	248'394
Number of words, *raw dataset*	637'307	2'762'279
Number of unique words, *raw dataset*	7'580	80'699
Number of unique stems, *clean dataset*	4'193	62'052
Number of unique stems (*tf-idf* > *threshold*)	2'982	21'608

This table reports summary statistics associated to the preprocessing of the two text datasets: FOMC Minutes and Tweets. Raw datasets contain textual data after the cleaning step, but before the vocabulary reduction step. Clean datasets involve all the cleaning and pre-processing steps, conducted prior to computing the *tf-idf* score. The threshold variable corresponds to a *tf-idf* value of 17 for FOMC minutes and 21 for tweets. The reported number of unique stems is the number of unique stems having a *tf-idf* score larger than the threshold.

3.6.2 Building Time Series

Financial data, FOMC minutes and Tweets are used to build the time series used in the regressions conducted in this empirical analysis. In particular, financial data are used to compute the surprise and yields adjustments, and FOMC Minutes and Tweets are used to create proxies for the precision of the signals received by the Fed and the private sector respectively.

3.6.2.1 Surprise and yields adjustments

This subsection presents the computation of the surprise and of the yields adjustments.

The surprise is computed following the methodology described in Kuttner (2001). As a start, consider the following notations: let s be the current month, m be the total number of days in month s, and t be a day within that month. Then, $f^0_{s,t}$ denotes the futures rate for the current month at time t, i.e. the spot-month futures rate, and $f^1_{s,t}$ denotes the one-month ahead futures rate at time t. The surprise is given by the one-day change in the spot-month futures rate:

$$Surprise_t = \frac{m}{m-t}\left(f^0_{s,t} - f^0_{s,t-1}\right), \tag{3.59}$$

where the coefficient $\frac{m}{m-t}$ is used to account for the number of days impacted by the change.[50]

The key insight behind Kuttner's methodology is the following: consider an announcement scheduled at 2 pm at time t. Then, expected changes of monetary policy are already priced in the day $t-1$ spot-month futures rate. If the policy decision is identical to expectations, then the date t spot-month futures rate - the quote is taken at the end of the day, so the announcement has already been made at that time - remains unchanged. However, if the announcement is different from market expectations, the spot-month futures rate at time t should reflect the new information provided by the announcement, adjusting by an amount proportional to the number of days affected by the change.

Two additional precisions need to be made regarding the computation of the surprise. If the announcement occurs the first day of the month, then the surprise is computed as the difference between the spot-month rate ($f^0_{s,1}$) and the 1-month ahead futures rate taken during the last day of the previous month ($f^1_{s-1,m}$). Additionally, the 1-month ahead future rate ($f^1_{s,t}$) is used instead of the spot-month future rate ($f^0_{s,t}$) when the announcement is made within 3 days of the end of the month, in order not to bias the results by granting too much weight to targeting errors.[51]

Yields adjustment are computed by taking the difference between the *close* yield before and after an announcement. For example, for an announcement happening during day t, then, adjustments of a treasury bond yield with maturity $x \in \{\textit{3-month (3M), 2-year (2Y), 10-year (10Y)}\}$, Δy^x_t, is computed as follows:

$$\Delta y^x_t = y^x_t - y^x_{t-1}, \tag{3.60}$$

where $t-1$ is the day prior to the announcement.

Finally, this empirical analysis is interested in the magnitude of the surprise and of the yields adjustments. As a result, the time series considered are the absolute value of the surprise given by equation (3.59), $|Surprise_t|$, and of the yields adjustments given by equation (3.60), $|\Delta y^x_t|$, for $x \in \{3M, 2Y, 10Y\}$.

3.6.2.2 Identifying the precision of the signals: A *topic and tone* approach

The core of this empirical analysis is to identify the precision of the signals received by each type of agents: the Fed and financial markets. This is done by applying a *topic and tone* approach (Hansen and McMahon, 2016; Jegadeesh and Wu, 2015) to the two textual datasets

[50] Futures contracts' settlement price (or equivalently rate) is based on the average of the relevant month's effective overnight federal funds rate, rather than the rate on any specific day. This factor enables to *undo* the time-averaging to get a correct measure of the surprise.

[51] Kuttner (2001, p. 528) defines targeting errors as "unanticipated movements in reserves supply or demand." These errors arise because futures contracts are based on the target rate instead of the effective fed funds rate. In monthly averages, the errors average out and can be ignored, but this is not the case at a daily frequency. As a result, at the end of the month, the coefficient $\frac{m}{m-t}$ is large, which amplifies targeting errors and generate a bias in the computation of the surprise.

(FOMC minutes and Tweets respectively). The *topic* step enables to identify the signals received by the agents, and the *tone* step their precision. This subsection presents respectively these two steps, before explaining how their results are used to create the time series used in the regressions.

Topic (signal): First, *topics* are identified using Latent Dirichlet Allocation (LDA), a topic-identification algorithm developed by Blei et al. (2003). LDA is a clustering algorithm that groups words together in *topics* based on the frequency at which they occur together in a corpus of documents. In particular, it produces two outputs: The first one is a distribution of words for each topic $k \in K$, where K is the number of topics to be estimated by the algorithm. More precisely, each topic k is a distribution $\phi_k \in \Delta^V$ over the V unique tokens in the corpus vocabulary. In other words, for each word v in vocabulary V, the algorithm gives the weight of word v in topic k compared to the other $V-1$ words. The second output is the distribution of topics $\theta_d \in \Delta^K$ within each document $d \in D$, where Δ^K is the K-simplex and D the total number of documents.

The model is estimated at the sentence (resp. tweet) level - i.e. sentences (tweets) are considered as documents - using Hansen et al.'s (2018) library. This library estimates topics from a corpus of text using a collapsed Gibbs sampling algorithm, which uses a Markov Chain Monte Carlo method. The algorithm provides measures of the distributions at every iteration of the chain, and those used for this analysis are an average of 20 samples taken at different points of that chain. In particular, there is a *burning* phase of 2'000 iteration, and *thinning* intervals of 50 iterations. As a result, the two distributions used in this analysis are an average of iterations 2'050, 2'100, ..., 3'000.[52]

LDA is applied separately to FOMC minutes and to Tweets. To do so, three parameters have to be chosen by the researcher: the first two are the Dirichlet priors, α and β, associated respectively to the topic-document distribution (θ_d) and to the word-topic distribution (ϕ_k). For each of these parameters, a low value indicates that the distribution should be sparse, i.e. with most of the probability mass concentrated on a a few elements. For example, a low α would favor a topic distribution according to which sentences would feature a limited number of topics. The third parameter to be chosen is the number of topics to be identified by the algorithm, K. Ideally, the three parameters would be chosen based on the optimization of a quantitative metrics. One possibility is to use *perplexity*, which is a measure used in information theory to predict how well a probability distribution predicts a sample. However, Chang et al. (2009) showed that models obtained by optimizing measures such as perplexity might generate less semantically meaningful topics compared to human judgement. Similarly, talking about measures of model fit such as perplexity, Blei (2012, p.83) indicate that "there is no technical reason to suppose that held-out accuracy corresponds to better organization or easier interpretation." In other words, interpretability can also be a legitimate reason

[52] For a precise description of the statistical foundations of LDA and of the collapsed Gibbs sampler, the interested reader can refer to Hansen and McMahon (2016) and its online appendix.

to decide over the hyperparameters of a topic model (Hansen et al., 2018). As a result, it is based on exploration, on the application of this *interpretability* criteria, and following Hansen et al. (2018) that the hyperparameters of the model presented in table 3.3 have been chosen. In particular, the choice of α should be low because it is unlikely that all K topics are represented in each sentences (tweets); the choice of β follows Hansen et al.'s code, i.e. for corpus $c \in \{FOMC\ minutes,\ Tweets\}$, $\beta^c = \frac{200}{V^c}$, with V^c the size of the vocabulary of corpus c.

Table 3.3: Value of the hyperparameters of the LDA algorithm

Hyperparameters	**FOMC Minutes**	**Tweets**
α	0.1	0.5
β	$\frac{200}{V^{FOMC}} = 0,067$	$\frac{200}{V^{Tweets}} = 0.01$
K (# topics)	8	15

The results of the *topic* step are therefore given by two distributions for each sample. The first set of distributions, the word-topic distributions, is given by tables 3.4 and 3.5. These two tables show the Top 20 and Top 15 words for each topic identified by the algorithm in the FOMC minutes and Tweets samples respectively. From table 3.4, it is interesting to see that the topics are quite well identified.[53] Those are: *Financial markets* (Topic 0), *Inflation* (Topic 1), *International* (Topic 2), *Supply* (Topic 3), *Demand* (Topic 4), *Unemployment* (Topic 5), *Economic Outlook* (Topic 6) and *Policy* (Topic 7). Among these topics, the most interesting for the current analysis is Topic 6, which deals with discussions by FOMC members about the economic outlook. This is the topic that is used as a proxy for the signal about the state of the economy received by the central bank.

Table 3.5 provides an overview of the topics identified in the tweets dataset. Topic 0 and 12 are not very interpretable,[54] but apart from them, the remaining topics are quite meaningful. They deal with: *Tax policy* (Topic 1), *Fed rate policy* (Topic 2), *Inflation* (Topic 3), *Global economic growth* (Topic 4), *Domestic economic growth* (Topic 5), *Currency markets* (Topic 6), *Upcoming announcement* (Topic 7 and 10), *Fed Quantitative Easing policy* (Topic 8), *Names* (Topic 9), *Politics* (Topic 11), and *Financial markets* (Topics 13 and 14).[55] The topics of interest for the current analysis are topics which deal with the dual mandate of the central bank, i.e. inflation (topic 3), global growth (topic 4) and and U.S. domestic growth (topic 5). Those topics are grouped together in a *Dual mandate* topic, which is used as a proxy for the signal about fundamentals of the economy received by the private sector.

[53] The topics are also quite similar to those presented in Table 1 of Jegadeesh and Wu (2015). The eight topics they identify are: Policy, Inflation, Market, Employment, Growth, Trade, Consumption and Investment.

[54] Those topics also appear with both a bigger and a lower number of topics, except when the number of topics is very low (e.g. 5), but then, topics are too general to be used.

[55] Looking at a larger number of words, Topic 13 is more tilted towards financial indexes and tickers, while topic 14 is more about financial markets with respect to the upcoming announcement.

Table 3.4: Distribution of the Top 20 words for each topic identified in the FOMC minutes corpus

Topic 0		Topic 1		Topic 2		Topic 3	
Weight	Word	Weight	Word	Weight	Word	Weight	Word
0.0240	credit	0.0700	price	0.0400	market	0.0320	quarter
0.0230	market	0.0690	inflat	0.0340	unit	0.0190	increas
0.0220	loan	0.0240	expect	0.0340	state	0.0180	sale
0.0200	rate	0.0230	measur	0.0260	foreign	0.0160	declin
0.0190	remain	0.0230	energi	0.0250	period	0.0160	product
0.0170	yield	0.0220	consum	0.0190	financi	0.0130	good
0.0160	bank	0.0220	year	0.0180	dollar	0.0120	industri
0.0150	treasuri	0.0210	month	0.0140	trade	0.0120	manufactur
0.0140	spread	0.0190	increas	0.0140	econom	0.0120	month
0.0140	condit	0.0170	core	0.0140	economi	0.0120	inventori
0.0130	mortgag	0.0160	remain	0.0130	intermeet	0.0110	spend
0.0130	secur	0.0150	percent	0.0120	system	0.0110	vehicl
0.0130	period	0.0130	longer	0.0120	develop	0.0110	sector
0.0130	bond	0.0130	recent	0.0110	currenc	0.0100	motor
0.0120	term	0.0130	declin	0.0100	price	0.0100	real
0.0120	continu	0.0120	run	0.0090	open	0.0100	level
0.0110	commerci	0.0120	compens	0.0090	domest	0.0090	pace
0.0110	corpor	0.0110	term	0.0090	report	0.0090	busi
0.0100	issuanc	0.0110	survey	0.0090	declin	0.0090	home
0.0100	intermeet	0.0110	index	0.0080	exchang	0.0090	equip
Topic 4		Topic 5		Topic 6		Topic 7	
Weight	Word	Weight	Word	Weight	Word	Weight	Word
0.0240	busi	0.0380	rate	0.0310	polici	0.0420	feder
0.0200	spend	0.0350	growth	0.0270	inflat	0.0400	rate
0.0150	growth	0.0280	econom	0.0270	econom	0.0270	fund
0.0140	consum	0.0230	unemploy	0.0230	particip	0.0240	reserv
0.0120	continu	0.0230	quarter	0.0230	committe	0.0220	committe
0.0120	household	0.0210	labor	0.0210	risk	0.0190	market
0.0120	hous	0.0190	year	0.0200	member	0.0160	particip
0.0110	demand	0.0170	pace	0.0150	outlook	0.0150	polici
0.0110	particip	0.0160	real	0.0150	monetari	0.0140	meet
0.0110	recent	0.0150	activ	0.0110	financi	0.0130	target
0.0110	activ	0.0150	gdp	0.0100	expect	0.0120	purchas
0.0100	invest	0.0140	particip	0.0090	economi	0.0110	rang
0.0100	increas	0.0140	meet	0.0080	view	0.0100	secur
0.0090	sector	0.0140	staff	0.0080	time	0.0090	oper
0.0090	price	0.0140	continu	0.0080	note	0.0080	term
0.0090	report	0.0130	project	0.0080	continu	0.0080	discuss
0.0080	market	0.0130	indic	0.0080	develop	0.0080	bank
0.0080	incom	0.0130	market	0.0080	market	0.0070	period
0.0070	effect	0.0130	moder	0.0080	condit	0.0070	increas
0.0070	remain	0.0120	suggest	0.0070	agre	0.0060	maintain

This table reports the top 20 words for each of the 8 topics identified in the FOMC minutes from January 1994 to June 2021 along with their weight, i.e. the probability that word $v \in V^{FOMCminutes}$ belongs to topic k.

Table 3.5: Distribution of the Top 15 words for each topic identified in the Tweets corpus

Topic 0		Topic 1		Topic 2		Topic 3	
Weight	Word	Weight	Word	Weight	Word	Weight	Word
0.0200	know	0.0290	tax	0.2140	rate	0.0760	price
0.0140	think	0.0220	wage	0.0900	interest	0.0360	year
0.0130	good	0.0210	increas	0.0670	will	0.0290	rise
0.0110	can	0.0180	pay	0.0450	hike	0.0210	month
0.0090	realli	0.0140	year	0.0400	rais	0.0160	low
0.0090	thing	0.0130	debt	0.0350	expect	0.0160	food
0.0090	time	0.0120	cost	0.0280	today	0.0150	consum
0.0080	got	0.0110	govern	0.0220	cut	0.0130	may
0.0080	talk	0.0110	billion	0.0140	decis	0.0120	last
0.0080	want	0.0100	incom	0.0130	market	0.0120	hit
0.0080	need	0.0100	adjust	0.0130	time	0.0120	fall
0.0070	let	0.0090	spend	0.0120	erest	0.0110	oil
0.0070	right	0.0090	peopl	0.0110	low	0.0110	increas
0.0070	look	0.0090	will	0.0100	keep	0.0100	cpi
0.0070	lol	0.0080	real	0.0100	mortgag	0.0090	hous
Topic 4		**Topic 5**		**Topic 6**		**Topic 7**	
Weight	Word	Weight	Word	Weight	Word	Weight	Word
0.0850	econom	0.0870	econom	0.0620	usd	0.0630	today
0.0840	growth	0.0810	growth	0.0610	forex	0.0430	will
0.0440	economi	0.0170	job	0.0470	dollar	0.0340	decis
0.0300	usa	0.0100	busi	0.0450	ahead	0.0330	live
0.0180	gdp	0.0090	develop	0.0400	trade	0.0290	statement
0.0170	slow	0.0090	invest	0.0180	fx	0.0270	meet
0.0160	forecast	0.0080	support	0.0180	eur	0.0270	yellen
0.0150	global	0.0070	drive	0.0140	usa	0.0260	watch
0.0150	china	0.0070	can	0.0140	eurusd	0.0250	press
0.0130	uk	0.0070	sustain	0.0130	via	0.0230	confer
0.0120	world	0.0060	help	0.0120	decis	0.0200	announc
0.0100	show	0.0060	chang	0.0120	euro	0.0200	minut
0.0100	via	0.0060	need	0.0100	level	0.0160	releas
0.0090	quarter	0.0060	creat	0.0100	risk	0.0140	et
0.0090	year	0.0050	citi	0.0090	eye	0.0140	powel

Topic 8		Topic 9		Topic 10		Topic 11	
Weight	Word	Weight	Word	Weight	Word	Weight	Word
0.0760	polici	0.0930	bernank	0.1810	feder	0.0200	govern
0.0510	eas	0.0460	yellen	0.1760	reserv	0.0170	trump
0.0470	monetari	0.0300	time	0.0390	usa	0.0140	state
0.0420	quantit	0.0280	rt	0.0320	bank	0.0140	peopl
0.0350	bank	0.0270	ben	0.0220	meet	0.0080	want
0.0230	will	0.0170	year	0.0210	expect	0.0080	will
0.0150	market	0.0150	via	0.0210	news	0.0070	can
0.0150	central	0.0150	janet	0.0140	reuter	0.0070	right
0.0140	end	0.0120	person	0.0140	busi	0.0070	control
0.0110	target	0.0110	chairman	0.0140	via	0.0070	gov
0.0110	balanc	0.0090	paul	0.0120	set	0.0060	presid
0.0090	financi	0.0090	obama	0.0110	announc	0.0060	need
0.0080	bond	0.0080	name	0.0100	wednesday	0.0060	elect
0.0080	fiscal	0.0080	audit	0.0090	washington	0.0060	countri
0.0070	ecb	0.0070	chair	0.0090	economi	0.0050	american

Topic 12		Topic 13		Topic 14	
Weight	Word	Weight	Word	Weight	Word
0.0410	money	0.0240	market	0.0760	stock
0.0290	will	0.0230	day	0.0690	market
0.0200	can	0.0210	will	0.0520	ahead
0.0140	print	0.0210	spi	0.0480	gold
0.0130	think	0.0210	today	0.0250	investor
0.0130	bitcoin	0.0190	futur	0.0230	usa
0.0110	deflat	0.0160	trade	0.0190	higher
0.0090	much	0.0150	gt	0.0180	await
0.0090	real	0.0150	move	0.0160	decis
0.0080	peopl	0.0150	look	0.0150	wait
0.0080	buy	0.0150	wait	0.0150	bond
0.0080	valu	0.0150	short	0.0140	wallstreet
0.0070	caus	0.0130	spx	0.0140	day
0.0070	currenc	0.0100	sell	0.0130	meet
0.0070	supeopley	0.0090	come	0.0130	lower

This table reports the top 15 words for each of the 15 topics identified in the Tweets sample from September 2008 to June 2021 along with their weight, i.e. the probability that word $v \in V^{Tweets}$ belongs to topic k.

The second set of distributions provided by the LDA algorithm are the topic-document distributions.[56] These distribution are used to label each sentence according to their main topic,

[56]Two important precisions: first, remember that in this analysis, documents are sentences and tweets; second, since the approach detailed here is identical for the two datasets, only sentences are mentioned, but it is also applied to tweets.

simply by finding which topic has the larger probability mass for each sentence. More precisely, sentence d is labeled as being about topic k if topic k is the topic with the largest weight in the distribution. For example, if a sentence is estimated to be 20% about topic 0, 55% about topic 1, 5% about topic 2, etc., then the sentence is labeled as being about topic 1.

In summary, the LDA approach enables to identify the topics embedded in the two datasets. In particular, it allows to identify excerpts of text that can be used to estimate the signals related to the state of the economy received by the central bank and the private sector. The signal of the central bank is proxied by the *Economic Outlook* topic, and the signal of the private sector by three topics grouped together to form a *Dual Mandate* topic. Now that the signals are identified, the second step consists in measuring their precision.

Tone: *Tone* is used to estimate the precision of the signals. More precisely, what is actually measured by the tone approach in this analysis is the inverse of the precision of the signals, i.e., their uncertainty. This is done by using a *dictionary* method. It consists in counting the number of words belonging to a predetermined list of words, representative of the *tone* the researcher is looking to measure. In particular, the current analysis is interested in *uncertain* words. As a result, it uses the dictionary of *uncertain* words adapted to a financial context developed by Loughran and Mcdonald (2011). Sentences and tweets are labelled as *uncertain* if they contain at least one word belonging to that list.[57]

In order to be consistent with this methodology and to simplify the interpretation of the results presented in the next subsection, the term *precision* of the signal is replaced by *uncertainty* of the signal. These two terms are the two opposite sides of the same coin, so a decrease in the precision of the signal should be understood as an increase in the uncertainty of the signal.

The *topic and tone* approach therefore provides each document (i.e. each sentence and each tweet) with two labels: a *topic* label and an *uncertainty* label. Tables 3.6 and 3.7 provide respectively examples of certain and uncertain sentences and tweets belonging to the topics considered in the empirical analysis.

Building the time series: The empirical analysis is an event study conducted at the FOMC meeting level. As a result, it is necessary to aggregate the *topic and tone* labels of sentences and tweets at the event level. The following explains how this is done, and leads to the creation of two time series measuring the uncertainty of the signals received by the central bank and the private sector respectively. The last paragraph explains how the topic labels are also used to create a proxy for the Fed's aversion to financial markets volatility.

Uncertainty of the signal of the central bank (τ_B^{-1}) is measured in three steps. The first step consists in identifying the strength of the signal received by the central bank. This is done by aggregating the sentences at the FOMC minutes level, and computing the share of each topic

[57] Sentences and tweets that are not labelled as *uncertain* are labelled as *certain*.

Table 3.6: Example of sentences belonging to the*Economic Outlook* topic of the FOMC minutes sample

Meeting (YYY-MM-DD)	*Uncertain (Yes/No)*	*Sentence*
2008-12-16	Yes	The Committee's statement noted that economic activity appeared to have slowed markedly, due importantly to a decline in consumer expenditures
2008-12-16	No	In their discussion of the economic situation and outlook, all meeting participants agreed that the economic downturn had intensified over the fall
2013-05-01	Yes	Most observed that the outlook for the labor market had shown progress since the program was started in September, but many of these participants indicated that continued progress, more confidence in the outlook, or diminished downside risks would be required before slowing the pace of purchases would become appropriate
2013-05-01	No	Regarding the composition of purchases, one participant expressed the view that, in light of the substantial improvement in the housing market and to avoid further credit allocation across sectors of the economy, the Committee should start to shift any asset purchases away from MBS and toward Treasury securities
20020-06-10	Yes	Participants commented that there remained an extraordinary amount of uncertainty and considerable risks to the economic outlook
20020-06-10	No	Participants stressed that measures taken in the areas of health-care policy and fiscal policy, together with actions by households and businesses, would shape the prospects for a prompt and timely return of the United States economy to more normal conditions

in each minutes. Formally, consider FOMC minutes $d \in D$; then, the share of topic $k \in K^{FOMC}$

Table 3.7: Example of tweets belonging to the*Dual Mandate* topic of the Tweets sample

Meeting (YYY-MM-DD)	*Labels*	*Tweet*
2013-05-01	Uncertain Inflation	@geffbeck unemployment is the highest right now...deflation measures were predictable. Consumption surprisingly low too!
2013-05-01	Certain Inflation	Very low inflation and jobs slowdown. #Fed must include in policy statement. Make clear no shift in reserve-adding & bond-buying.
2013-05-01	Uncertain Global growth	Quick USD/JPY Sell Ahead of the Fed: The recent poor economic data suggests the Fed may be more dovish than us...
2013-05-01	Certain Global growth	Euro area unemployment at record high, inflation retreats to raise interest-rate cut forecasts: European unemp...
2013-05-01	Uncertain Domestic growth	'Bernanke's Magic Recovery Plan' | Internet Marketing & SEO Forum: "There may be a “recovery” going on. But it...
2013-05-01	Certain Domestic growth	Economic Report: Private-sector jobs growth slows in April: ADP

in FOMC minutes d is computed as follows:

$$TopicShare_{k,d} = \frac{\textit{Number of sentences about topic k in minutes d}}{\textit{Total number of sentences in minutes d}}. \tag{3.61}$$

The second step consists in measuring the uncertainty of signal k received by FOMC members during meeting d. Similar to the strength of the signal, this is done by computing the share of uncertain sentences about topic k among the sentences dealing with topic k. Formally *uncertainty* of signal k during meeting d is given by:

$$UncertaintyShare_{k,d} = \frac{\textit{Number of uncertain sentences about topic k in minutes d}}{\textit{Total number of sentences about topic k in minutes d}}. \tag{3.62}$$

The third and final step consists in computing the uncertainty *Score* of signal k in minutes d. This is done as follows:

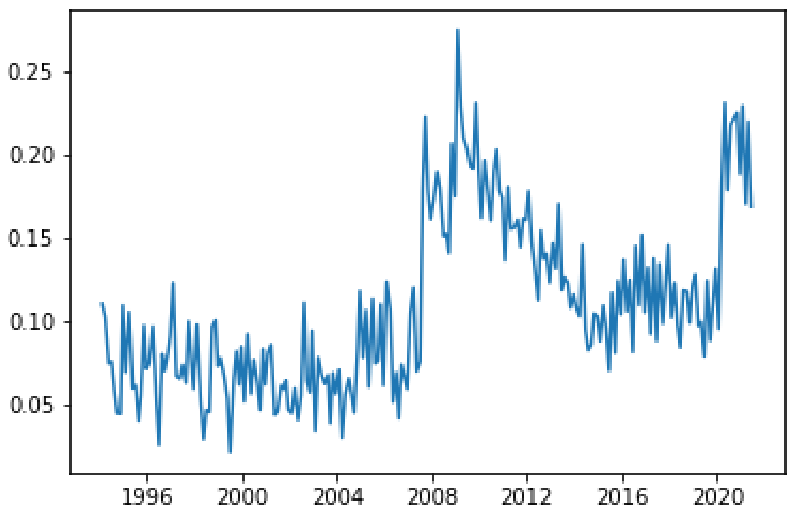
$$Score_{k,d} = TopicShare_{k,d} \times UncertaintyShare_{k,d}. \tag{3.63}$$

The rationale behind the variable *Score* is that if the signal received by the central bank is uncertain, then the score should be high. However, uncertainty is scaled by the topic share to take into account the strength of the signal. Indeed, a weak signal, even if uncertain, is unlikely to be considered in the monetary policy decision process. Finally, as mentioned earlier, the topic used as a proxy for the central bank's signal is the *Economic Outlook* topic.

Uncertainty of the signal of the private sector (τ_T^{-1}) is measured by simply computing, for each event, the uncertainty share of tweets labelled as being about the *Dual Mandate*. This is done in the same way as for sentences, using equation (3.62). Note that the score is not computed for tweets, because the dataset is much less well structured than FOMC minutes.[58]

Finally, the share of the *Financial Markets* topic in FOMC minutes - given by equation (3.61), with k = *Financial Markets* - could be used as a proxy for the Fed's aversion to financial markets volatility (θ). Indeed, another way to interpret this variable is the *attention* (Bybee et al., 2020) allocated by committee members to this topic. However, as figure 3.7 shows, the time series does not appear to be stationary. This is confirmed by a Dickey Fuller test, which cannot reject the null hypothesis that the series is not stationary (p-value of 0.32). One solution is to use

Figure 3.7: **Evolution of the share of the *Financial Markets* topic in FOMC minutes:** The share of the *Financial Markets* topic in FOMC minutes is given by the computation of the variable $TopicShare_{\textit{Financial markets},d}$, for every meeting conducted between January 1994 and June 2021.



innovations in the *Financial Markets* topic attention ($TopicShare_{\textit{Financial markets},d}$), instead of

[58] Two examples may illustrate this point: first, there is a small number of tweets at the beginning of the sample, which makes the computation of topics' share not very reliable; second, in spite of the efforts made in the downloading query to limit the search only to tweets relevant for the current analysis, there is a significant amount of them that are not useful, and that introduce some noise in the sample. Selecting only the tweets belonging to the *Dual Mandate* helps filtering out these useless tweets, but some remain.

the series in level.[59] Those are obtained by taking the residuals of a fitted AR(1) model of the $TopicShare_{Financial\ markets,d}$ time series. As a result, central bank aversion to financial market volatility is not measured by how much FOMC members talk about financial markets, but how much *more* - or *less* - they discuss that topic compared to the previous meeting.

3.6.3 Results & Discussion

The impact of the informational feedback loop between the Fed and financial markets on the monetary policy decision and asset prices dynamics is estimated by measuring how the uncertainty of the signals received by the central bank and the private sector respectively, relates to the surprise generated by the announcement and the subsequent yields adjustments.

This subsection starts by presenting the results, before discussing their limitations and providing suggestions for future work.

3.6.3.1 Results

The baseline equation to be estimated is the following:[60]

$$|Y_t| = \alpha + \beta_B(\tau_{B,t})^{-1} + \beta_T(\tau_{T,t})^{-1} + \beta_\theta \Delta\theta_{Financial\ Markets,t} + \gamma X_t + \varepsilon_t, \tag{3.64}$$

where $Y_t \in \left\{Surprise_t, \Delta y_t^{3M}, \Delta y_t^{2Y}, \Delta y_t^{10Y}\right\}$ is the endogenous variable,[61] $(\tau_{B,t})^{-1}$ is the $Score_{Economic\ Outlook,t}$ of the *Economic Outlook* topic, $(\tau_{T,t})^{-1}$ is the $UncertaintyShare_{Dual\ Mandate,t}$ of the *Dual Mandate* topic, $\Delta\theta_{Financial\ Markets,t}$ is the innovation in central bank attention towards financial markets in FOMC minutes, and X_t is a control variable that is equal to zero in the surprise regression, and to the absolute value of the surprise ($|Surprise_t|$) in the yields regressions. Finally, $\alpha, \beta_B, \beta_T, \beta_\theta$ and γ are the parameters to estimate, and ε_t is the error term. α is the constant of the model; β_B and β_T measure respectively by how much the magnitude of the surprise and of the yields adjustments change with a change in the uncertainty of the signals received by the Fed and the private sector respectively. More precisely, a negative β_B indicates that the bigger the uncertainty of the private signal received by the central bank is, the lower the surprise and the yields adjustments are; β_θ measures by how much the surprise and yields adjustments change with innovations in the central bank attention to financial markets. A negative β_θ would mean that the surprise and the yields adjustments decrease

[59] The author is grateful to Alexis Marchal for pointing out this suggestion.

[60] Two important remarks should be made about the notations: first, in the previous subsection, t designated days and d the events considered in the event study. In particular, $t-1$ and t referred to two successive days, while $d-1$ and d referred to two successive FOMC meetings. Since here it is obvious that observations refer to event days, the time subscript used in the equations is t instead of d. As a result, from now on, $t-1$ and t refer to two successive meetings; Second, the α and β used here are different from the Dirichlet priors presented in the previous subsection. The Dirichlet priors were not renamed in order to remain consistent with the notations used in the literature.

[61] The 3-month and 2-year maturities are considered to be *short term* maturities, while the 10-year maturity is considered *long term*.

when the central bank allocates a larger share of meeting t to financial markets, compared to meeting $t-1$. γ measures the impact of the magnitude of the surprise on yields adjustments.

Equation (3.64) is estimated on the December 2008-June 2021 sample (100 observations) using ordinary least squares (OLS). Results are presented in table 3.8. Columns (1)-(4) respectively show the results when the endogenous variable is the absolute value of the surprise, and the absolute value of the adjustment of the 3-month, 2-year and 10-year treasury yields.

Table 3.8: Baseline OLS Regression including the topics *Economic Outlook* (Fed) and *Dual Mandate* (private sector)

	(1) |*Surprise*|	(2) |Δ *3-M yield*|	(3) |Δ *2-Y yield*|	(4) |Δ *10-Y yield*|
α	0.0290*	0.0141**	0.0387***	0.0971***
	(0.0147)	(0.0056)	(0.0120)	(0.0223)
β_B $(\tau_{B,t}^{-1})$	-0.3306	-0.0120	-0.2579	-0.8295**
	(0.2269)	(0.0862)	(0.1841)	(0.3417)
β_T $(\tau_{T,t}^{-1})$	0.0576	-0.0371	0.0708	-0.0132
	(0.0928)	(0.0350)	(0.0747)	(0.1386)
β_θ $(\Delta\theta_{Financial\ Markets,t})$	-0.2230	-0.0094	-0.2822**	-0.1909
	(0.1347)	(0.0513)	(0.1097)	(0.2035)
γ $(\|Surprise_t\|)$		0.1001**	0.1913**	0.1269
		(0.0384)	(0.0819)	(0.1520)
N	100	100	100	100
R2	0.04	0.08	0.15	0.07

The estimated models are variants of $|Y_t| = \alpha + \beta_B(\tau_{B,t})^{-1} + \beta_T(\tau_{T,t})^{-1} + \beta_\theta\theta_{Financial\ Markets,t} + X_t + \varepsilon_t$, where $Y_t \in \{Surprise_t, \Delta y_t^{3M}, \Delta y_t^{2Y}, \Delta y_t^{10Y}\}$. α is the constant of the model; the coefficients associated to $\tau_{B,t}^{-1}$ and $\tau_{T,t}^{-1}$ measure how the endogenous variable moves with the uncertainty of the signal received by the central bank and the private sector respectively; the coefficient associated to $\Delta\theta_{Financial\ Markets,t}$ measures how the endogenous variables moves with innovations in the attention allocated to the *Financial Market* topic in FOMC minutes; the coefficient associated to $|Surprise_t|$ measures how the endogenous variable moves with the absolute value of the surprise. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

The first observation is that unfortunately, few estimates are statistically significant. The only variable on which the uncertainty of the central bank's signal appears to have a statistically significant negative impact is on the adjustment of the 10-year treasury yield (model 4). This means that the larger the uncertainty of the signal received by the central bank is, the smaller the adjustment of the 10-year treasury yield is. This is consistent with hypothesis 1 and the right panel of figure 3.5a. Moreover, it is important to note that the signs of the estimates of the impact of the uncertainty of the central bank signal on the magnitude of the surprise (model 1) and on the absolute value of the adjustment of the 2-year treasury yield (model 3) are also negative and not far from being statistically significant at the 10% level (p-values of 0.15 and 0.16 respectively). This provides additional (weak) support for hypothesis 1, and the middle and left panels of figure 3.5a (blue line, since β_θ appears to be also statistically significant).

Additionally, consistent with hypothesis 3, innovations in the central bank aversion to financial markets volatility appear to reduce volatility in the short end of the yield curve, but not in the long end. Indeed, the coefficient is statistically significant at the 5% level for the two-year treasury yield (model 3), and very close to be statistically significant for the magnitude of the surprise (model 1, p-value of 0.101). However, as predicted by the right plot in figure 3.5c, innovations in the Fed aversion to financial markets volatility do not have an impact on the 10-year treasury yield (model 4, the standard error of the coefficient estimate is large).

The methodology, however, fails to provide empirical evidence supporting hypothesis 2. Indeed, while the sign of all the estimates is consistent with the hypothesis by being positive - meaning that an increase in the uncertainty of the signal received by the private sector increases the magnitude of the surprise and yields adjustments - none of them are statistically significant. Two remarks can nevertheless be done to put this lack of statistical significance into prospective. The first one is that the sample size is very small, and tweets tend to be a rather noisy dataset.[62] As a result, it is encouraging to have the right sign, in spite of the lack of statistical significance. The second remark is that compared to models (1) and (3), the standard error of the estimate of model (4) is one order of magnitude larger than the estimated coefficient. Therefore, setting aside the noise contained in the dataset, this could mean that the uncertainty of the signal received by the private sector is really not correlated to adjustments in the 10-year yield (consistent with the right plot in figure 3.5b), but that it might be positively correlated to the magnitude of the surprise and of adjustments of the 2-year treasury yield (consistent with the left and center plots in figure 3.5b).

Finally, model (2) shows that among the variables considered in the regression, only the magnitude of the surprise has a statistically significant impact on adjustments of the 3-month treasury yield.

To complement those results and provide further statistical evidence supporting the hypotheses tested in this empirical analysis, a second equation is estimated. It is given by:

$$|Y_t| = \alpha + \beta_B(\tau_{B,t})^{-1} + \beta_D D_t + \beta_{B\times D}(\tau_{B,t})^{-1} \times D_t + +\gamma X_t + \varepsilon_t. \tag{3.65}$$

Equation (3.65) differs from equation (3.64) in two important ways. The first one is that the uncertainty of the signal received by the private sector is not taken into account, so as to be able to increase the size of the sample. Doing so enables to start the sample in February 2002, the time at which the futures time series used in this analysis starts. The number of observations is 154. The second difference is the presence of the dummy variable D_t - equal to 1 from September 2007 onward, which is considered to be the start of the financial crisis in this analysis,[63] and to 0 before - and of the interaction term $(\tau_{B,t})^{-1} \times D_t$. The coefficient

[62] The days at the beginning of the sample feature a small amount of tweets; and in spite of the contingencies implemented to filter out semantically meaningless tweets - download query, topics, etc. - some of them are still featured in the *Dual Mandate* topic. The next subsection provides some suggestions to solve these issues.

[63] Indeed, early signs of the financial crisis appeared in August 2007, and the September 2007 meeting was the first scheduled FOMC meeting during which members talked about the subject.

β_D associated to the dummy variable measures how different on average the surprise was after the start of the financial crisis, compared to before; the coefficient $\beta_{B\times D}$ associated to the interaction term measures how the Fed reacted to an increase in the uncertainty score of its signal after the start of the financial crisis.

The estimates are presented in table 3.9. One result is particularly interesting: model (1) shows that the coefficient associated to the uncertainty of the signal received by the central bank is positive and statistically significant, while the coefficient associated to the interaction term is negative and also statistically significant at the 1% level. This difference emphasizes a shift in the behavior of the central bank, triggered by the financial crisis. Indeed, these results suggest that before the financial crisis, the central bank was not averse to financial market volatility - and according to the theory, this implies that it was not either taking financial markets information into account, contrary to Bernanke's (2004) assertion. As a result, an increase in the uncertainty of the signal of the central bank before the financial crisis resulted in an increase in the surprise, consistent with hypothesis 4 and the green line featured in the left plot of figure 3.5a). However, after the financial crisis, the relationship changed, and the magnitude of the surprise decreased when the uncertainty of the signal of the central bank increased. This is consistent with Peek et al. (2015) and the adoption of a *ternary mandate* for Fed, which aims at limiting financial instability.

Results for adjustments of the 2-year yield (model 3) are similar but less statistically significant. In particular, the coefficient associated to the uncertainty of the signal received by the central bank is not statistically significant. Moreover, while not statistically significant, this coefficient is also positive for the adjustment in the 10-year treasury yield (model 4). The theory predicts that this coefficient should be equal to zero.

3.6.3.2 Discussion of the results & limitations

In spite of the lack of statistical significance, the results presented in the empirical analysis are interesting. Indeed, they provide some (weak) evidence consistent with three out of the four hypotheses emphasized in the theoretical part, as well as the literature, such as Peek et al. (2015). The lack of evidence for hypothesis 2 could be explained by two reasons: either the mechanism emphasized in the theoretical part does not hold; or the dataset used to estimate the signal received by the private sector is too noisy to be able to extract the uncertainty of the signal received by the private sector. This subsection therefore provides two suggestions that could be implemented, at the theoretical and empirical levels respectively, to solve these issues.

At the theoretical level, if the mechanism emphasized in the model is indeed not rich enough to account for the impact of the informational feedback loop arising between the Fed and the financial sector, an interesting extension could be to introduce a real sector. Indeed, the model predicts for example that the central bank's aversion to financial markets volatility mainly has an impact on the short end of the yield curve, but not on the long end. However, as suggested

Table 3.9: Alternative OLS Regression including the topics *Economic Outlook* (Fed)

	(1) |*Surprise*|	(2) |Δ *3-M yield*|	(3) |Δ *2-Y yield*|	(4) |Δ *10-Y yield*|
α	-0.0844*	0.0057	0.0265	0.0174
	(0.0440)	(0.0140)	(0.0205)	(0.0270)
β_B $(\tau_{B,t}^{-1})$	2.2974***	0.1281	0.4684	0.3525
	(0.7328)	(0.2379)	(0.3493)	(0.4587)
β_D (D_t)	0.1330**	0.0150	0.0228	0.0768**
	(0.0510)	(0.0164)	(0.0241)	(0.0316)
$\beta_{B\times D}$ $(\tau_{B,t}^{-1} \times D_t)$	-2.7291***	-0.2535	-0.7298*	-1.1106**
	(0.8670)	(0.2815)	(0.4134)	(0.5429)
γ $(\lvert Surprise_t \rvert)$		0.1974***	0.1635***	0.0433
		(0.0257)	(0.0377)	(0.0495)
N	154	154	154	154
R2	0.08	0.31	0.19	0.08

The estimated models are variants of $|Y_t| = \alpha + \beta_B(\tau_{B,t})^{-1} + \beta_D D_t + \beta_{B\times D}(\tau_{B,t})^{-1} \times D_t + X_t + \varepsilon_t$, where $Y_t \in \{Surprise_t, \Delta y_t^{3M}, \Delta y_t^{2Y}, \Delta y_t^{10Y}\}$. α is the constant of the model; the coefficient associated to $\tau_{B,t}^{-1}$ measures how the endogenous variable moves with the uncertainty of the signal received by the central bank; the coefficient associated to D_t measures on average how different were the surprise and the yields adjustments after September 2007 - which is considered as the start of the 2007-2008 financial crisis in this analysis; the coefficient associated to $\tau_{B,t}^{-1} \times D_t$ measures how different were the surprise and yields adjustments reactions to uncertainty of the signal received by the central bank after the start of the financial crisis compared to before; the coefficient associated to $|Surprise_t|$ measures how the endogenous variable moves with the absolute value of the surprise. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

by Tzitzouris and more formally by Woodford (1994) and Bernanke and Woodford (1997), the central bank's decision (such as excessive tightening) has an impact on the real economy (depresses growth), and thereby on long term rates (lower long term rates). Integrating this into the model would have two consequences. First, it could change the way the central bank relies on private information to take its decision, and this would generate different hypotheses related to the private sector's signal that could then be tested empirically; second and more importantly, it would make adjustments of the long term yield endogenous in the central bank decision, while now, adjustments are simply due to the market learning new information related to the fundamentals of the economy, by inferring the central bank's signal from its decision.

At the empirical level, the main limitation lies in the lack of data availability to estimate the uncertainty of the signals received by the private sector, which limits considerably the size of the sample. One way to solve this issue would be to use articles from the business press or from Newsrooms - e.g. Reuters - in order to benefit from a dataset (1) of better quality and (2) with a larger number of observations. Additionally, if the size of the sample increases at the beginning of the sample, it could be possible to improve the measurement of the uncertainty of the signal received by the central bank by using FOMC meeting transcripts instead of minutes.

3.7 Conclusion

The goal of this paper was to investigate the impact of the informational feedback loop arising between the Fed and financial markets on the monetary policy decision and asset prices dynamics.

To do so, a theoretical model has been developed, which sheds light on the role played by the precision of the signal received by the central bank and by the private sector respectively. In particular, it showed that when the precision of the signal received by the central bank (resp. private sector) increases, the central bank puts a larger weight on its own information (resp. the information produced by financial markets), which increases (resp. decreases) the magnitude of the surprise generated by the announcement and the subsequent adjustment of the short term bond yield. Moreover, an increase in the precision of the central bank's signal also increases adjustments of the long term yield, but the latter is insensitive to changes in the precision of the private sector's signal. Finally, the model is able to make two predictions related to the central bank aversion to financial markets volatility, emphasized in Peek et al. (2015) and Stein and Sunderam (2018). First, it predicts that if the central bank is not averse to financial markets volatility and if it does not learn about economic fundamentals from market prices, then, its reliance on an imprecise signal increases the magnitude of the surprise and of the adjustment of the short term bond yield. Second, if the central bank does care about financial markets volatility, then, an increase in the central bank aversion to financial markets volatility decreases the magnitude of the surprise, as well as adjustments of the short term bond yield. However, in those two cases, adjustments of the long term bond yield are not impacted by the central bank's aversion to financial markets volatility. This is because the long term bond yield is determined only by economic fundamentals, and in the model, the central bank decision does not have an impact on those fundamentals. This is the main limitation of the theoretical model.

The empirical analysis aims at providing empirical support to the hypotheses identified by the theory, by building on recent developments in natural language processing. In particular, it adopts a *topic and tone* approach (Hansen and McMahon, 2016; Jegadeesh and Wu, 2015), which consists in using LDA, a topic-identification algorithm (Blei et al., 2003), and a dictionary method to: (1) identify the signals received by the Fed (extracted from FOMC minutes) and the private sector (extracted from Tweets); and (2) measure their uncertainty using the Loughran and Mcdonald (2011) dictionary of *uncertainty* words adapted to a financial context. Results, while not strongly statistically significant, do provide evidence supporting most of the hypotheses identified by the theoretical model. The main limitation lies in the lack of empirical support for the impact of the uncertainty of the signal received by the private sector, which most likely comes from the noise embedded in the Tweets dataset. This analysis could therefore be improved by using other text datasets to better estimate that variable.

4 Conclusion

The two chapters presented in this thesis use natural language processing and machine learning techniques to contribute to the literature investigating the links between the Fed and financial markets.

The first chapter uses a BERT model augmented with a linear classifier layer to classify tweets dealing with monetary policy and published around monetary policy events as *hawkish, dovish, neutral* or *non relevant*. Aggregating these tweets before and after a given event enables to measure market expectations of monetary policy, as well as the surprise generated by the event - given by the change in market expectations. Results suggest that this measure of the surprise is negatively associated with changes in the 10-year treasury yield, i.e. that a negative surprise - e.g. due to the release of new information indicating a monetary policy less dovish than expected by markets - generates an increase in the 10-year treasury yield. These results are interesting as they help explaining the puzzling increase in yields following the release of new monetary policy information in the aftermath of the financial crisis, when the stance of monetary policy was clearly accommodative (Greenlaw et al., 2018).

The second chapter looks at the impact of the informational feedback loop arising between the Fed and financial markets on the monetary policy decision process and asset prices dynamics. The theoretical model predicts that the central bank puts a larger weight on the signal that provides it with the best information about economic fundamentals, which has a significant impact on the surprise generated by monetary policy announcements and on adjustments at the short end of the yield curve. Similarly, the central bank's aversion to financial markets volatility decreases monetary policy surprises and short term yields adjustments are smaller, because the central bank decision tends to be closer to fed funds futures; by contrast, adjustments at the long end of the yield curve respond only to the precision of the signal of the central bank. Finally, the model also predicts that when the central bank does not take financial markets into account, monetary policy decisions may generate excess volatility through larger surprises and larger adjustments at the short end of the yield curve. The empirical section tests these hypotheses by creating proxies for the signals received by the Fed and the private sector. To do so, it uses a *topic and tone approach*, which uses both an unsupervised machine learning algorithm to identify the topics of two texts corpora, and a dictionary method to measure the uncertainty of these topics. While not strongly statistically significant, the analysis does provide some evidence that the central bank tends to put a larger weight on its own signal when it is more precise, and that since the 2007-2008 financial crisis, it has taken financial markets into account when setting the federal funds rate.

4.1 Policy implications

Taken together, those results have interesting policy implications. First, hypothesis four in the second chapter showed that learning from asset prices could be useful for a central bank, as not doing so could create excess financial volatility. Second, they also shed light on the role played by uncertainty at two levels: (1) the macroeconomic context - i.e., the precision of the signals received by the central bank and the private sector; and (2) the communication of the central bank. To illustrate, consider the tapering event that occurred during the third quantitative episode in 2013. At the time, conflicting estimates of future macroeconomic prospects between the central bank and the private sector, along with a central bank sending mixed signal in its communication regarding the end of QE3, are likely to have created an increase in long term yields through an increase in the term premium which offset the accommodating stance of monetary policy.

As a result, when the central bank uses information produced by the private sector to take its monetary policy decision, it may want to consider the relative precision of that signal with respect to its own. To do so, the learning policy of the central bank could consist in two steps: (1) inferring the private sector's signal about the state of the economy by relying on a wide range of indicators - e.g. tweets sentiment, analysts, stock prices and interest rates, its own surveys of private economic agents estimates of the state of the economy; (2) looking at the dispersion of those estimates, *within* and *across* indicators.[1] If dispersion is small, the central bank may want to rely more on the information produced by the private sector; If it is large, it may prefer putting the emphasis on its own signal. Finally, similar to forward guidance which provides a clear vision of the likely path of future interest rate, the central bank could provide, in its communication about quantitative easing, a clear vision of the future path of the program.

[1] Dispersion *within* indicators would consist in looking at the standard deviation of indicators such as the private sector's estimate of the economy; Dispersion *across* indicators would consist in looking at whether several indicators yield the same outcome. For example, if growth is expected to be strong and tweets sentiment is positive, then those indicators can be considered as going in the same direction, i.e. as being *close*. In such a case, the signal received by the private sector is likely to be *precise*.

4.2 Future work

The work presented in this thesis offers opportunities for future work along three dimensions, consistent with the suggestions made at the end of each chapter.

To start with, it is shown in the first chapter that the increase in yields following the release of new information about monetary policy is associated with an increase in the term premium. The explanation provided in the chapter was that the Fed disappointed market expectations by sending mixed signals about its policy and the economic outlook, thereby casting doubt on the strength of the recovery, which made financial markets reluctant to take on duration risk. However, the evidence provided in the chapter is quite anecdotal, and there may be other channels explaining the impact of monetary policy on the term premium, such as the *reaching for yield* channel of Hanson and Stein (2015) or the *long term safety* channel of Krishnamurthy and Vissing-Jorgensen (2011). As a result, a potential area for future research could be to try to measure the respective share of these channels in yields adjustments following monetary policy events during the period that followed the 2007-2008 financial crisis. Additionally, it could be interesting to look at how these results compare to the central bank intervention associated to the covid crisis, in order to see whether the channels underlying the impact of monetary policy on financial markets were the same during that crisis compared to the previous one, in spite of the initial shocks being of very different nature.

The second area for future work could be to introduce a real sector in the theoretical model presented in the second chapter, so as to make the state of the economy i_t^* endogenous in the central bank's decision i_t. This would be interesting as it would enrich the model with more realistic dynamics.

The third suggestion would be to conduct an empirical study similar to the one presented in the second chapter, but using a different set of data to estimate the precision of the signal received by the private sector - for example by using articles from the business press. This would enable to significantly reduce noise in the dataset, while at the same time expanding the number of observations.

A Appendix to Chapter 2

A.1 Text Data Excerpts

Table A.1: Excerpts of text surrounding tapering of QE3 - Part 1

Date *(type of event)*	**FOMC Excerpts** *(type of document)*	**Market Commentary** *(type of source)*
03/01/2013 (*Minutes release*) Surprise (ΔME_t): -0.53 $\Delta y_t^{\$(10)} = 0.076$	"In considering the outlook for the labor market and the broader economy, a few members expressed the view that ongoing asset purchases would likely be warranted until about the end of 2013, while a few others emphasized the need for considerable policy accommodation but did not state a specific time frame or total for purchases. Several others thought that it would probably be appropriate to slow or to stop purchases well before the end of 2013, citing concerns about financial stability or the size of the balance sheet. One member viewed any additional purchases as unwarranted." *(Minutes of the 12/12/2012 FOMC meeting)*	"NEW YORK, Jan 7 (Reuters) - Yields [U.S. Treasuries] moved to eight-month highs last week [Jan 3] after minutes from the Fed's December policy meeting caused investors to wonder whether the central bank might end its bond purchases - an unconventional monetary easing strategy - earlier than many had thought." *(Reuters market wrap-up)* "US FOMC Meeting minutes from quantitative easing 4 meeting in 5 minutes - markets could rock" *(dovish tweet published before the event)* "BREAKING: Fed says few on FOMC wanted quantitative easing until about the end of 2013"*(hawkish tweet published after the event)*
22/05/2013 (*Minutes release*) Surprise (ΔME_t): -0.09 $\Delta y_t^{\$(10)} = 0.01$	"A number of participants expressed willingness to adjust the flow of purchases downward as early as the June meeting if the economic information received by that time showed evidence of sufficiently strong and sustained growth; however, views differed about what evidence would be necessary and the likelihood of that outcome. One participant preferred to begin decreasing the rate of purchases immediately, while another participant preferred to add more monetary accommodation at the current meeting and mentioned that the Committee had several other tools it could potentially use to do so. Most participants emphasized that it was important for the Committee to be prepared to adjust the pace of its purchases up or down as needed to align the degree of policy accommodation with changes in the outlook for the labor market and inflation as well as the extent of progress toward the Committee's economic objectives." *(Minutes of the 12/12/2012 FOMC meeting)*	"NEW YORK, May 22 (Reuters) - U.S. Treasury yields on the benchmark 10-year note rose above the key 2 percent level on Wednesday, the highest level in two months, as Federal Reserve Chairman Ben Bernanke added to bond investor fears that the U.S. central bank might slow its bond purchases later this year if the economy improves further." *(Reuters market wrap-up)* "@steveliesman reevaluating his communication strategy on how markets misunderstood #Bernanke meant #quantitativeeasing for ever." *(dovish tweets published before the event)* "The one thing i did see in the fed statement is that most governors want to end or taper quantitative easing sooner rather than later." *(hawkish tweets published after the event)*

This table presents, on the 'Date' column, some key information about the event considered. Those are: (1) the date and the type of event it is (*FOMC Meeting* or *Release of minutes*; (2) the surprise as measured by equation (2.2); and (3) the change in the 10-year nominal treasury yield. The column 'FOMC Excerpts' provides some excerpts of central bank communication. During *FOMC Meetings* days, those may come either from press conferences conducted by the Chair or from FOMC statements. During *Release of minutes* days, those come from FOMC minutes. The 'Market Commentary' column provides text excerpts coming from two source: *Reuters market wrap-up*, and *tweets* labelled by the algorithm.

Table A.2: Excerpts of text surrounding tapering of QE3 - Part 2

Date *(type of event)*	**FOMC Excerpts** *(type of document)*	**Market Commentary** *(type of source)*
19/06/2013 (*FOMC Meeting*) Surprise (ΔME_t): 0.02* $\Delta y_t^{\$(10)} = 0.17$	"If the incoming data are broadly consistent with this forecast, the Committee currently anticipates that it would be appropriate to moderate the monthly pace of purchases later this year. And if the subsequent data remain broadly aligned with our current expectations for the economy, we would continue to reduce the pace of purchases in measured steps through the first half of next year, ending purchases around midyear." *(Press conference following the 19/06/2013 FOMC meeting)*	"NEW YORK, June 19 (Reuters) - U.S. Treasuries prices slid on Wednesday as the Federal Reserve chairman suggested the U.S. central bank was prepared to reduce its bond purchases if its economic outlook proves correct, even though the U.S. economy remained stuck at a sluggish pace." *(Reuters market wrap-up)* "We expect quantitative easing to continue through at least 2014Q1. Expect #Bernanke to express concerns about failure to meet inflation targets. #econstats" *(dovish tweet published before the event)* "What if it is a tiny taper ? Say $ 5B/mth. Then what? #Bernanke's Fed" *(hawkish tweet published before the event)* "No change to the Fed's $85 billion per month quantitative easing purchases. Full release here:" *(dovish tweet published after the event)* "Overall $FED #FOMC statement and projections are relatively hawkish - keeps the #taper on track for later this year IMO" *(hawkish tweet published after the event)*
31/07/2013 (*FOMC Meeting*) Surprise (ΔME_t): 0.31 $\Delta y_t^{\$(10)} = -0.018$	"The Committee will closely monitor incoming information on economic and financial developments in coming months. The Committee will continue its purchases of Treasury and agency mortgage-backed securities, and employ its other policy tools as appropriate, until the outlook for the labor market has improved substantially in a context of price stability." *(Statement following the 31/07/2013 FOMC meeting)*	NEW YORK, July 31 (Reuters) - Prices for U.S. Treasuries rose on Wednesday, reversing early losses after the Federal Reserve gave no hint of a pullback in bond buying at the end of a two-day policy meeting. *(Reuters market wrap-up)* "do not think this meeting will reveal much difference from last... Bernanke has made his points about tapering and such with his testimony" *(hawkish tweet published before the event)* "BREAKING: NO TAPER. The Fed decides to maintain the same pace of bond buying ($85 billion/month)" *(dovish tweet published after the event)*

This table presents, on the 'Date' column, some key information about the event considered. Those are: (1) the date and the type of event it is (*FOMC Meeting* or *Release of minutes*; (2) the surprise as measured by equation (2.2); and (3) the change in the 10-year nominal treasury yield. The column 'FOMC Excerpts' provides some excerpts of central bank communication. During *FOMC Meetings* days, those may come either from press conferences conducted by the Chair or from FOMC statements. During *Release of minutes* days, those come from FOMC minutes. The 'Market Commentary' column provides text excerpts coming from two source: *Reuters market wrap-up*, and *tweets* labelled by the algorithm.

*The measure of the surprise fails at pinning down the negative surprise here. There are two reasons for that: first, the general expected stance was already *hawkish*, due the the market wondering whether the FOMC would decide to taper or not, as the idea had already emerged in December 2012, and resurfaced more significantly in the minutes published in May 2013; second, even though the FOMC statement sent mixed signals, the current pace of purchases was maintained, which is considered as dovish by the algorithm. As a result, even if after the event the measure $ME_{t^+} < 0$, it is superior to ME_{t^-}, and $\Delta ME_t > 0$. Such measurement errors are rare, as the other 6 examples provided in tables A.1-A.4 show.

Table A.3: Excerpts of text surrounding tapering of QE3 - Part 3

Date *(type of event)*	**FOMC Excerpts** *(type of document)*	**Market Commentary** *(type of source)*
21/08/2013 (*Minutes Meeting*) Surprise (ΔME_t): -0.29 $\Delta y_t^{\$(10)} = 0.07$	"In looking ahead, meeting participants commented on several considerations pertaining to the course of monetary policy. First, almost all participants confirmed that they were broadly comfortable with the characterization of the contingent outlook for asset purchases that was presented in the June postmeeting press conference and in the July monetary policy testimony. Under that outlook, if economic conditions improved broadly as expected, the Committee would moderate the pace of its securities purchases later this year. And if economic conditions continued to develop broadly as anticipated, the Committee would reduce the pace of purchases in measured steps and conclude the purchase program around the middle of 2014." *(Minutes of the 31/07/2013 FOMC meeting)*	"NEW YORK, Aug 21 (Reuters) - U.S. Treasuries yields rose on Wednesday after the Federal Reserve released minutes of its July meeting, which offered few new clues on when the central bank is likely to pare back its bond purchase program but maintained expectations it is likely to occur soon." *(Reuters market wrap-up)* "In the next hours the Federal Reserve will present a report about continue with the economic stimulus of Quantitative Easing..." *(dovish tweet published before the event)* "FOMC minutes show broad support for tapering" *(hawkish tweet published after the event)*
18/09/2013 (*FOMC Meeting*) Surprise (ΔME_t): 0.68 $\Delta y_t^{\$(10)} = -0.16$	"However, the Committee decided to await more evidence that progress will be sustained before adjusting the pace of its purchases. Accordingly, the Committee decided to continue purchasing additional agency mortgage-backed securities at a pace of $40 billion per month and longer-term Treasury securities at a pace of $45 billion per month. The Committee is maintaining its existing policy of reinvesting principal payments from its holdings of agency debt and agency mortgage-backed securities in agency mortgage-backed securities and of rolling over maturing Treasury securities at auction." *(Statement following the 18/09/2013 FOMC meeting)*	"NEW YORK, Sept 18 (Reuters) - U.S. Treasuries yields dropped on Wednesday to their lowest in over a month after the Federal Reserve said it would maintain its bond purchases at $85 billion a month, surprising investors who had expected it would reduce the size of its buying program." *(Reuters market wrap-up)* "I am hoping the FOMC starts the taper – that way we can get that monkey off of the markets back." *(hawkish tweet published before the event)* "The Fed announces it will not taper its quantitative easing 3 program." *(dovish tweet published after the event)*

This table presents, on the 'Date' column, some key information about the event considered. Those are: (1) the date and the type of event it is (*FOMC Meeting* or *Release of minutes*; (2) the surprise as measured by equation (2.2); and (3) the change in the 10-year nominal treasury yield. The column 'FOMC Excerpts' provides some excerpts of central bank communication. During *FOMC Meetings* days, those may come either from press conferences conducted by the Chair or from FOMC statements. During *Release of minutes* days, those come from FOMC minutes. The 'Market Commentary' column provides text excerpts coming from two source: *Reuters market wrap-up*, and *tweets* labelled by the algorithm.

Table A.4: Excerpts of text surrounding tapering of QE3 - Part 4

Date *(type of event)*	**FOMC Excerpts** *(type of document)*	**Market Commentary** *(type of source)*
09/10/2013 (*Minutes release*) Surprise (ΔME_t): -0.31 $\Delta y_t^{\$(10)} = 0.02$	"During the exchange of views on whether to trim the flow of asset purchases at this meeting, a number of members emphasized the contingent and data-dependent nature of the Committee's purchase program. In light of the mixed data recently, including inflation readings that remained below the Committee's longer-run objective, and the concerns over near-term fiscal uncertainties, some members indicated that they preferred to await more evidence that their expectation of continuing improvement would be realized. But with financial markets appearing to expect a reduction in purchases at this meeting, concerns were raised about the effectiveness of FOMC communications if the Committee did not take that step. For several members, the various considerations made the decision to maintain an unchanged pace of asset purchases at this meeting a relatively close call." *(Minutes of the 18/09/2013 FOMC meeting)*	NEW YORK, Oct 9 (Reuters) - The Federal Reserve's minutes from its September meeting showed that most members of the central bank's policy committee thought they needed more evidence of sustainable economic progress, though the Fed said it was a "relatively close call" for several voters. "It's interesting that there would be such a heated debate, since it is painfully clear that the economy is still in such a fragile state that the Fed can't start the tapering process," said Todd Schoenberger, managing partner at LandColt Capital in New York. "Some were looking for improvements in data, but clearly the economy can't stand on its own without intervention. Between slow growth and the shutdown, it's clear we're in troubled times. I wouldn't expect any tapering for quarters from now." *(Reuters market wrap-up)* "#ABQ Fed now unlikely to slow bond buying before 2014 - WASHINGTON - The Federal Reserve's decision last month to..." *(dovish tweet published before the event)* "The Fed: Minutes show Fed still sees taper this year: Most members of the Federal Reserve still thought that it would be... #pennystocks" *(hawkish tweet published after the event)*

This table presents, on the 'Date' column, some key information about the event considered. Those are: (1) the date and the type of event it is (*FOMC Meeting* or *Release of minutes*; (2) the surprise as measured by equation (2.2); and (3) the change in the 10-year nominal treasury yield. The column 'FOMC Excerpts' provides some excerpts of central bank communication. During *FOMC Meetings* days, those may come either from press conferences conducted by the Chair or from FOMC statements. During *Release of minutes* days, those come from FOMC minutes. The 'Market Commentary' column provides text excerpts coming from two source: *Reuters market wrap-up*, and *tweets* labelled by the algorithm.

A.2 Additional Regression Tables

Table A.5: Multivariate regression on n-year nominal yield

	2	3	4	5	6	7	8	9	10	15	20
α_t	-0.0023	-0.0023	-0.0024	-0.0026	-0.0028	-0.0028	-0.0027	-0.0024	-0.0020	0.0009	0.0026
	(0.0036)	(0.0047)	(0.0054)	(0.0059)	(0.0061)	(0.0062)	(0.0062)	(0.0061)	(0.0060)	(0.0055)	(0.0053)
ΔME_t	-0.0173***	-0.0231***	-0.0267***	-0.0286***	-0.0293***	-0.0291***	-0.0285***	-0.0277***	-0.0266***	-0.0213***	-0.0175***
	(0.0044)	(0.0057)	(0.0067)	(0.0074)	(0.0078)	(0.0081)	(0.0082)	(0.0081)	(0.0080)	(0.0067)	(0.0057)
$R^{SP}_{t-1,t}$	-0.0017	-0.0028	-0.0032	-0.0030	-0.0023	-0.0013	-0.0001	0.0012	0.0026	0.0087	0.0127*
	(0.0039)	(0.0051)	(0.0061)	(0.0068)	(0.0074)	(0.0077)	(0.0079)	(0.0079)	(0.0079)	(0.0072)	(0.0067)
ΔFFR_t	0.3410*	0.4997*	0.6220*	0.7169*	0.7865	0.8333	0.8578	0.8621	0.8514	0.6642	0.4785
	(0.1909)	(0.2775)	(0.3603)	(0.4283)	(0.4785)	(0.5121)	(0.5315)	(0.5390)	(0.5376)	(0.4629)	(0.3866)
N	146	146	146	146	146	146	146	146	146	146	146
R2	0.15	0.16	0.16	0.15	0.15	0.15	0.14	0.14	0.13	0.12	0.13

The estimated regressions are all variants of $\Delta_{t-1,t} y_t^{\$(n)} = \alpha^{\$(n)} + \beta_{ME}^{\$(n)} \Delta ME_t + \beta_{SP}^{\$(n)} R_t^{SP} + \beta_{FFR}^{\$(n)} \Delta FFR_t + \varepsilon_t^{\$(n)}$, with maturity $n \in \{2,3,4,5,6,7,8,9,10,15,20\}$. The estimated coefficient associated to ΔME_t indicates the percentage point response of the endogenous variable per standard deviation of the surprise indicator. The estimated coefficients associated to $R_t^{S\&P500}$ and ΔFFR_t indicate the percentage point response of the endogenous variable per 1 percentage point increase in the daily return of the $S\&P500$ and the daily change of the effective fed funds rate respectively. Standard errors in parenthesis are heteroscedasticity and autocorrelation robust (HAC) using 1 lags and with small sample correction. * indicates significance at the 10-percent level, ** indicates significance at the 5-percent level, and *** indicates significance at the 1-percent level.

Table A.6: Multivariate regression on n-year real yield

	2	3	4	5	6	7	8	9	10	15	20
α_t	-0.0072	-0.0074	-0.0067	-0.0058	-0.0051	-0.0044	-0.0037	-0.0032	-0.0027	-0.0007	0.0007
	(0.0058)	(0.0059)	(0.0060)	(0.0060)	(0.0060)	(0.0059)	(0.0058)	(0.0057)	(0.0056)	(0.0051)	(0.0050)
ΔME_t	-0.0269***	-0.0306***	-0.0318***	-0.0319***	-0.0313***	-0.0303***	-0.0289***	-0.0274***	-0.0259***	-0.0202***	-0.0171***
	(0.0063)	(0.0067)	(0.0071)	(0.0073)	(0.0073)	(0.0073)	(0.0073)	(0.0073)	(0.0073)	(0.0063)	(0.0055)
$R^{SP}_{t-1,t}$	-0.0259***	-0.0248***	-0.0243***	-0.0233***	-0.0218***	-0.0202***	-0.0187***	-0.0173***	-0.0160**	-0.0124*	-0.0121
	(0.0066)	(0.0066)	(0.0067)	(0.0066)	(0.0066)	(0.0066)	(0.0066)	(0.0066)	(0.0066)	(0.0069)	(0.0082)
ΔFFR_t	0.5359	0.6123	0.6795	0.7273	0.7546	0.7666	0.7689	0.7661	0.7591	0.7151	0.6236
	(0.4853)	(0.4793)	(0.4886)	(0.5005)	(0.5099)	(0.5158)	(0.5186)	(0.5187)	(0.5164)	(0.4805)	(0.4155)
N	146	146	146	146	146	146	146	146	146	146	146
R2	0.23	0.24	0.24	0.24	0.23	0.22	0.21	0.19	0.18	0.14	0.13

The estimated regressions are all variants of $\Delta_{t-1,t} y_t^{TIPS(n)} = \alpha^{TIPS(n)} + \beta_{ME}^{TIPS(n)} \Delta ME_t + \beta_{SP}^{TIPS(n)} R_t^{SP} + \beta_{FFR}^{TIPS(n)} \Delta FFR_t + \varepsilon_t^{TIPS(n)}$, with maturity $n \in \{2,3,4,5,6,7,8,9,10,15,20\}$. The estimated coefficient associated to ΔME_t indicates the percentage point response of the endogenous variable per standard deviation of the surprise indicator. The estimated coefficients associated to $R_t^{S\&P500}$ and ΔFFR_t indicate the percentage point response of the endogenous variable per 1 percentage point increase in the daily return of the $S\&P500$ and the daily change of the effective fed funds rate respectively. Standard errors in parenthesis are heteroscedasticity and autocorrelation robust (HAC) using 1 lags and with small sample correction. * indicates significance at the 10-percent level, ** indicates significance at the 5-percent level, and *** indicates significance at the 1-percent level.

Table A.7: Multivariate regression on n-year breakeven yield

	2	3	4	5	6	7	8	9	10	15	20
α_t	0.0049	0.0051	0.0042	0.0032	0.0023	0.0015	0.0011	0.0008	0.0007	0.0016	0.0018
	(0.0041)	(0.0033)	(0.0028)	(0.0026)	(0.0025)	(0.0024)	(0.0024)	(0.0023)	(0.0023)	(0.0028)	(0.0038)
ΔME_t	0.0095**	0.0075**	0.0051*	0.0034	0.0021	0.0011	0.0003	-0.0003	-0.0008	-0.0010	-0.0004
	(0.0043)	(0.0032)	(0.0027)	(0.0027)	(0.0029)	(0.0033)	(0.0037)	(0.0040)	(0.0042)	(0.0037)	(0.0037)
$R^{SP}_{t-1,t}$	0.0241***	0.0220***	0.0211***	0.0203***	0.0196***	0.0190***	0.0186***	0.0185***	0.0186***	0.0211***	0.0248***
	(0.0046)	(0.0038)	(0.0035)	(0.0033)	(0.0032)	(0.0032)	(0.0033)	(0.0034)	(0.0035)	(0.0044)	(0.0064)
ΔFFR_t	-0.1945	-0.1119	-0.0574	-0.0106	0.0317	0.0666	0.0886	0.0968	0.0917	-0.0510	-0.1450
	(0.3642)	(0.2772)	(0.2209)	(0.1884)	(0.1724)	(0.1663)	(0.1642)	(0.1625)	(0.1588)	(0.1365)	(0.1465)
N	146	146	146	146	146	146	146	146	146	146	146
R2	0.26	0.31	0.35	0.36	0.36	0.35	0.34	0.34	0.34	0.38	0.40

The estimated regressions are all variants of $\Delta_{t-1,t} y_t^{\pi(n)} = \alpha^{\pi(n)} + \beta_{ME}^{\pi(n)} \Delta ME_t + \beta_{SP}^{\pi(n)} R_t^{SP} + \beta_{FFR}^{\pi(n)} \Delta FFR_t + \varepsilon_t^{\pi(n)}$, with maturity $n \in \{2,3,4,5,6,7,8,9,10,15,20\}$. The estimated coefficient associated to ΔME_t indicates the percentage point response of the endogenous variable per standard deviation of the surprise indicator. The estimated coefficients associated to $R_t^{S\&P500}$ and ΔFFR_t indicate the percentage point response of the endogenous variable per 1 percentage point increase in the daily return of the $S\&P500$ and the daily change of the effective fed funds rate respectively. Standard errors in parenthesis are heteroscedasticity and autocorrelation robust (HAC) using 1 lags and with small sample correction. * indicates significance at the 10-percent level, ** indicates significance at the 5-percent level, and *** indicates significance at the 1-percent level.

Table A.8: Multivariate OLS regression on nominal, on n-year instantaneous forward nominal, real and breakeven rates.

	Nominal instantaneous forward rate			Real instantaneous forward rate			Break-Even instantaneous forward rate		
n	$\beta_{ME}^{\$(n)}$	standard error	R2	$\beta_{ME}^{TIPS(n)}$	standard error	R2	$\beta_{ME}^{\pi(n)}$	standard error	R2
2	-0.0313***	(0.0077)	0.15	-0.0393***	(0.0089)	0.20	0.0080**	(0.0033)	0.17
3	-0.0370***	(0.0095)	0.15	-0.0369***	(0.0093)	0.22	-0.0001	(0.0033)	0.22
4	-0.0372***	(0.0106)	0.14	-0.0341***	(0.0087)	0.21	-0.0032	(0.0039)	0.19
5	-0.0346***	(0.0109)	0.13	-0.0304***	(0.0082)	0.18	-0.0041	(0.0048)	0.17
6	-0.0306***	(0.0106)	0.11	-0.0261***	(0.0086)	0.14	-0.0045	(0.0060)	0.16
7	-0.0264***	(0.0099)	0.10	-0.0215**	(0.0092)	0.10	-0.0049	(0.0070)	0.16
8	-0.0224**	(0.0089)	0.10	-0.0172*	(0.0095)	0.07	-0.0052	(0.0074)	0.18
9	-0.0188**	(0.0079)	0.10	-0.0135	(0.0092)	0.05	-0.0052	(0.0072)	0.20
10	-0.0157**	(0.0069)	0.11	-0.0109	(0.0083)	0.04	-0.0049	(0.0064)	0.23
15	-0.0072	(0.0046)	0.16	-0.0096	(0.0081)	0.04	0.0024	(0.0080)	0.24
20	-0.0064	(0.0044)	0.18	-0.0011	(0.0060)	0.10	-0.0053	(0.0067)	0.39

The estimated regressions are all variants of $\Delta_{t-1,t} f_t^{k(n)} = \alpha^{k(n)} + \beta_{ME}^{k(n)} \Delta ME_t + \beta_{SP}^{k(n)} R_t^{SP} + \beta_{FFR}^{k(n)} \Delta FFR_t + \varepsilon_t^{k(n)}$, where $k = \{\$, TIPS, \pi\}$ denotes nominal, real and breakeven instantaneous rates n years from now, with $n \in \{2,3,4,5,6,7,8,9,10,15,20\}$. The estimated coefficient associated to ΔME_t indicates the percentage point response of the endogenous variable per standard deviation of the surprise indicator. The estimated coefficients associated to $R_t^{S\&P500}$ and ΔFFR_t indicate the percentage point response of the endogenous variable per 1 percentage point increase in the daily return of the $S\&P500$ and the daily change of the effective fed funds rate respectively. Standard errors in parenthesis are heteroscedasticity and autocorrelation robust (HAC) using 1 lags and with small sample correction. * indicates significance at the 10-percent level, ** indicates significance at the 5-percent level, and *** indicates significance at the 1-percent level.

Table A.9: Multivariate regression on n-year instantaneous forward nominal rate

	2	3	4	5	6	7	8	9	10	15	20
α_t	-0.0019	-0.0026	-0.0033	-0.0036	-0.0034	-0.0024	-0.0009	0.0009	0.0028	0.0086	0.0053
	(0.0066)	(0.0078)	(0.0082)	(0.0082)	(0.0078)	(0.0074)	(0.0069)	(0.0065)	(0.0062)	(0.0059)	(0.0060)
ΔME_t	-0.0313***	-0.0370***	-0.0372***	-0.0346***	-0.0306***	-0.0264***	-0.0224**	-0.0188**	-0.0157**	-0.0072	-0.0064
	(0.0077)	(0.0095)	(0.0106)	(0.0109)	(0.0106)	(0.0099)	(0.0089)	(0.0079)	(0.0069)	(0.0046)	(0.0044)
$R^{SP}_{t-1,t}$	-0.0041	-0.0050	-0.0035	-0.0006	0.0029	0.0066	0.0101	0.0133	0.0161**	0.0242***	0.0246***
	(0.0068)	(0.0087)	(0.0099)	(0.0104)	(0.0104)	(0.0100)	(0.0093)	(0.0086)	(0.0080)	(0.0067)	(0.0070)
ΔFFR_t	0.7089*	0.9137	1.0523	1.1269	1.1350	1.0788	0.9714	0.8286	0.6666	-0.0050	-0.0438
	(0.3839)	(0.5681)	(0.6906)	(0.7483)	(0.7541)	(0.7221)	(0.6648)	(0.5923)	(0.5141)	(0.2853)	(0.3243)
N	146	146	146	146	146	146	146	146	146	146	146
R2	0.15	0.15	0.14	0.13	0.11	0.10	0.10	0.10	0.11	0.16	0.18

The estimated regressions are all variants of $\Delta_{t-1,t} f_t^{\$(n)} = \alpha^{\$(n)} + \beta_{ME}^{\$(n)} \Delta ME_t + \beta_{SP}^{\$(n)} R_t^{SP} + \beta_{FFR}^{\$(n)} \Delta FFR_t + \varepsilon_t^{\$(n)}$, with $n \in \{2,3,4,5,6,7,8,9,10,15,20\}$. The estimated coefficient associated to ΔME_t indicates the percentage point response of the endogenous variable per standard deviation of the surprise indicator. The estimated coefficients associated to $R_t^{S\&P500}$ and ΔFFR_t indicate the percentage point response of the endogenous variable per 1 percentage point increase in the daily return of the $S\&P500$ and the daily change of the effective fed funds rate respectively. Standard errors in parenthesis are heteroscedasticity and autocorrelation robust (HAC) using 1 lags and with small sample correction. * indicates significance at the 10-percent level, ** indicates significance at the 5-percent level, and *** indicates significance at the 1-percent level.

Table A.10: Multivariate regression on n-year instantaneous forward real rate

	2	3	4	5	6	7	8	9	10	15	20
α_t	-0.0105	-0.0058	-0.0033	-0.0018	-0.0007	0.0003	0.0011	0.0017	0.0022	0.0039	0.0065
	(0.0074)	(0.0073)	(0.0070)	(0.0066)	(0.0064)	(0.0063)	(0.0061)	(0.0059)	(0.0057)	(0.0070)	(0.0075)
ΔME_t	-0.0393***	-0.0369***	-0.0341***	-0.0304***	-0.0261***	-0.0215**	-0.0172*	-0.0135	-0.0109	-0.0096	-0.0011
	(0.0089)	(0.0093)	(0.0087)	(0.0082)	(0.0086)	(0.0092)	(0.0095)	(0.0092)	(0.0083)	(0.0081)	(0.0060)
$R^{SP}_{t-1,t}$	-0.0217***	-0.0234***	-0.0214***	-0.0170**	-0.0125*	-0.0089	-0.0066	-0.0054	-0.0049	-0.0064	-0.0191
	(0.0084)	(0.0077)	(0.0074)	(0.0071)	(0.0073)	(0.0076)	(0.0077)	(0.0076)	(0.0077)	(0.0146)	(0.0154)
ΔFFR_t	0.7202	0.8312	0.9133	0.9117	0.8684	0.8129	0.7602	0.7175	0.6857	0.5552	0.0245
	(0.5147)	(0.5325)	(0.5652)	(0.5768)	(0.5762)	(0.5682)	(0.5539)	(0.5349)	(0.5127)	(0.4062)	(0.2637)
N	146	146	146	146	146	146	146	146	146	146	146
R2	0.20	0.22	0.21	0.18	0.14	0.10	0.07	0.05	0.04	0.04	0.10

The estimated regressions are all variants of $\Delta_{t-1,t} f_t^{\pi(n)} = \alpha^{\pi(n)} + \beta^{\pi(n)}_{ME} \Delta ME_t + \beta^{\pi(n)}_{SP} R^{SP}_t + \beta^{\pi(n)}_{FFR} \Delta FFR_t + \varepsilon^{\pi(n)}_t$, with $n \in \{2,3,4,5,6,7,8,9,10,15,20\}$. The estimated coefficient associated to ΔME_t indicates the percentage point response of the endogenous variable per standard deviation of the surprise indicator. The estimated coefficients associated to $R_t^{S\&P500}$ and ΔFFR_t indicate the percentage point response of the endogenous variable per 1 percentage point increase in the daily return of the $S\&P500$ and the daily change of the effective fed funds rate respectively. Standard errors in parenthesis are heteroscedasticity and autocorrelation robust (HAC) using 1 lags and with small sample correction. * indicates significance at the 10-percent level, ** indicates significance at the 5-percent level, and *** indicates significance at the 1-percent level.

Table A.11: Multivariate regression on n-year instantaneous forward breakeven rate

	2	3	4	5	6	7	8	9	10	15	20
α_t	0.0086**	0.0032	0.0000	-0.0018	-0.0027	-0.0027	-0.0020	-0.0008	0.0006	0.0047	-0.0012
	(0.0037)	(0.0035)	(0.0037)	(0.0034)	(0.0033)	(0.0033)	(0.0034)	(0.0036)	(0.0039)	(0.0070)	(0.0077)
ΔME_t	0.0080**	-0.0001	-0.0032	-0.0041	-0.0045	-0.0049	-0.0052	-0.0052	-0.0049	0.0024	-0.0053
	(0.0033)	(0.0033)	(0.0039)	(0.0048)	(0.0060)	(0.0070)	(0.0074)	(0.0072)	(0.0064)	(0.0080)	(0.0067)
$R^{SP}_{t-1,t}$	0.0176***	0.0184***	0.0179***	0.0164***	0.0154***	0.0155***	0.0167***	0.0187***	0.0210***	0.0306**	0.0437***
	(0.0039)	(0.0044)	(0.0049)	(0.0050)	(0.0053)	(0.0056)	(0.0057)	(0.0055)	(0.0054)	(0.0124)	(0.0143)
ΔFFR_t	-0.0113	0.0824	0.1390	0.2153	0.2667	0.2659	0.2112	0.1111	-0.0191	-0.5602	-0.0683
	(0.2135)	(0.1674)	(0.2195)	(0.2534)	(0.2717)	(0.2707)	(0.2519)	(0.2250)	(0.2072)	(0.3517)	(0.2125)
N	146	146	146	146	146	146	146	146	146	146	146
R2	0.17	0.22	0.19	0.17	0.16	0.16	0.18	0.20	0.23	0.24	0.39

The estimated regressions are all variants of $\Delta_{t-1,t} f_t^{\pi(n)} = \alpha^{\pi(n)} + \beta_{ME}^{\pi(n)} \Delta ME_t + \beta_{SP}^{\pi(n)} R_t^{SP} + \beta_{FFR}^{\pi(n)} \Delta FFR_t + \varepsilon_t^{\pi(n)}$, with $n \in \{2,3,4,5,6,7,8,9,10,15,20\}$. The estimated coefficient associated to ΔME_t indicates the percentage point response of the endogenous variable per standard deviation of the surprise indicator. The estimated coefficients associated to $R_t^{S\&P500}$ and ΔFFR_t indicate the percentage point response of the endogenous variable per 1 percentage point increase in the daily return of the $S\&P$500 and the daily change of the effective fed funds rate respectively. Standard errors in parenthesis are heteroscedasticity and autocorrelation robust (HAC) using 1 lags and with small sample correction. * indicates significance at the 10-percent level, ** indicates significance at the 5-percent level, and *** indicates significance at the 1-percent level.

Table A.12: Multivariate regression on the term premium of the n-year instantaneous forward nominal rate

	1	2	3	4	5	6	7	8	9	10
α_t	-0.0016	-0.0023	-0.0026	-0.0027	-0.0027	-0.0027	-0.0027	-0.0027	-0.0027	-0.0027
	(0.0015)	(0.0023)	(0.0027)	(0.0030)	(0.0031)	(0.0033)	(0.0034)	(0.0035)	(0.0035)	(0.0036)
ΔME_t	-0.0073***	-0.0111***	-0.0129***	-0.0137***	-0.0141***	-0.0144***	-0.0146***	-0.0148***	-0.0149***	-0.0150***
	(0.0020)	(0.0030)	(0.0035)	(0.0038)	(0.0040)	(0.0041)	(0.0042)	(0.0043)	(0.0043)	(0.0044)
$R^{SP}_{t-1,t}$	-0.0005	-0.0007	-0.0006	-0.0004	-0.0001	0.0001	0.0003	0.0005	0.0006	0.0006
	(0.0019)	(0.0029)	(0.0035)	(0.0039)	(0.0042)	(0.0044)	(0.0046)	(0.0047)	(0.0048)	(0.0049)
ΔFFR_t	0.1973*	0.2976	0.3466	0.3722	0.3872	0.3969	0.4042	0.4101	0.4148	0.4185
	(0.1186)	(0.1839)	(0.2233)	(0.2491)	(0.2670)	(0.2801)	(0.2896)	(0.2969)	(0.3018)	(0.3052)
N	146	146	146	146	146	146	146	146	146	146
R2	0.15	0.15	0.15	0.14	0.14	0.13	0.13	0.13	0.13	0.13

The estimated regressions are all variants of $\Delta_{t-1,t}\, tp_t^{f(n)} = \alpha^{f(n)} + \beta_{ME}^{f(n)} \Delta ME_t + \beta_{SP}^{f(n)} R_t^{SP} + \beta_{FFR}^{f(n)} \Delta FFR_t + \varepsilon_t^{f(n)}$, with $n \in \{1,2,3,4,5,6,7,8,9,10\}$. The estimated coefficient associated to ΔME_t indicates the percentage point response of the endogenous variable per standard deviation of the surprise indicator. The estimated coefficients associated to $R_t^{S\&P500}$ and ΔFFR_t indicate the percentage point response of the endogenous variable per 1 percentage point increase in the daily return of the $S\&P500$ and the daily change of the effective fed funds rate respectively. Standard errors in parenthesis are heteroscedasticity and autocorrelation robust (HAC) using 1 lags and with small sample correction. * indicates significance at the 10-percent level, ** indicates significance at the 5-percent level, and *** indicates significance at the 1-percent level.

A.3 Reverse Causality

In order to test for the hypothesis of reverse causality,[1] I run several regressions which differ from equation (2.4) in two ways: First, for sake of brevity, only the change in the 10-year nominal treasury yield is used as endogenous variable;[2] Second, the variable ΔME_t is replaced by ME_{t^-}, i.e. market expectations of monetary policy prior to the announcement. The intuition behind this change is that if the central bank does indeed disappoint market expectations, then, when market expectations prior to the announcement tend to be more dovish, one should expect an increase in long term yields following monetary policy announcements.

Table A.13 presents the results of the regressions. Interestingly, the estimated coefficient associated to ME_{t^-} is positive in models (1)-(3) and (5), as expected in the absence of reverse causality. However, they are not statistically significant; Additionally, the coefficient associated to $D_t \times ME_{t^-}$ in model (4) is negative and statistically significant. These results are surprising, but they could be explained by two things: First, the sample contains only 146 observations, which may limit the power of the test; Second, the choice of using market expectations prior to the announcement may be debatable, as what matters for the analysis at hand is not variations of that variable, but rather how it compares to market expectations after the announcement.

As a result, while the estimates presented in Table A.13 do not invalidate the main result of the current paper, they do not either provide clear evidence that would help definitively ruling out the existence of reverse causality.

[1] According to which market expectations after the announcement and consequently the measure of the surprise would be endogenous in changes in the 10-year treasury yield.

[2] Results are quantitatively similar when the instantaneous forward rate 10 years from now is used as endogenous variable instead.

Table A.13: BERT - Reverse causality regressions on the 10-year treasury yield, $\Delta_{t-1,t+1} y_t^{\$10}$

	(1)	(2)	(3)	(4)	(5)
	$\Delta_{t-1,t} y_t^{\$10}$	$\Delta_{t-1,t} y_t^{\$10}$	$\Delta_{t-1,t} y_t^{\$10}$	$\Delta_{t-1,t} y_t^{\$10}$	$\Delta_{t-1,t+1} y_t^{\$10}$
α_t	-0.0034	-0.0050	-0.0031	-0.0261*	-0.0110
	(0.0064)	(0.0068)	(0.0115)	(0.0148)	(0.0094)
ME_{t^-}	0.0036	0.0047	0.0045	0.0285**	0.0031
	(0.0069)	(0.0064)	(0.0068)	(0.0118)	(0.0105)
R_t^{SP}		0.0022	0.0022	0.0008	0.0111
		(0.0090)	(0.0090)	(0.0089)	(0.0150)
ΔFFR_t		0.8454	0.8288	1.0290*	1.3113*
		(0.5667)	(0.5525)	(0.5611)	(0.7877)
D_t			-0.0025	0.0260	
			(0.0134)	(0.0159)	
$D_t \times ME_{t^-}$				-0.0325**	
				(0.0165)	
N	146	146	146	146	146
R2	0.00	0.02	0.02	0.06	0.04

The estimated regressions are all variants of $\Delta_{t-1,j} y_t^{\$10} = \alpha + \beta_{ME} ME_{t^-} + \beta_{SP} R_t^{SP} + \beta_{FFR} \Delta FFR_t + \beta_D D_t + \beta_{D\times ME} (D_t \times ME_{t^-}) + \varepsilon_t$, where $j = \{t, t+1\}$ to allow for different window sizes, and $y_t^{\$10}$ is the 10-year nominal yield. The estimated coefficient associated to ME_{t^-} indicates the percentage point response of the endogenous variable per standard deviation of the measure of market expectations before the announcement. The estimated coefficients associated to $R_t^{S\&P500}$ and ΔFFR_t indicate the percentage point response of the endogenous variable per 1 percentage point increase in the daily return of the $S\&P500$ and the daily change of the effective fed funds rate respectively. The coefficient associated to D_t measures the average change, in percentage point, of the endogenous variable during Reuters FOMC days, and the coefficient associated to $D_t \times ME_{t^-}$ measures the percentage point change of the endogenous variable per standard deviation shock of market expectations before the announcement during Reuters FOMC days. Standard errors in parenthesis are heteroscedasticity and autocorrelation robust (HAC) using 1 lags and with small sample correction. * indicates significance at the 10-percent level, ** indicates significance at the 5-percent level, and *** indicates significance at the 1-percent level.

B Appendix to Chapter 3

This appendix contains all the results stated in Chapter 3. Those include proofs of the results used to solve the theoretical model (Section B.1), and comparative statics associated to the calibration exercise (Section B.2)

B.1 Model Proofs

This section gathers all the proofs of the results used to solve the theoretical model. The model is solved using Mathematica. Subsection B.1.1 introduces lemmas extensively used during the resolution of the model; Subsections B.1.2, B.1.3 and B.1.4 present respectively the proofs related to the federal funds futures side of the equilibrium, the central bank side of the equilibrium, and the general equilibrium of the model. Finally, Subsections B.1.5 and B.1.6 present the proofs related to the *Monetary Policy* and *Asset pricing implications* sections.

B.1.1 Useful Lemmas

Several results are based on the following lemmas.[1]

Lemma B.1. *For* $n = 1, \ldots, N$*, let* i_t^* *be given by equation* (3.1)*,* s_t^B *by equation* (3.2)*,* s_t^n *by equation* (3.5) *and* $\tilde{f}_t^n$ *by equation* (3.12)*.*

Then, for $n = 1, \ldots, N$ *and* $\forall k \in [1, N] \neq n$*,* $i_t^*, s_t^B, s_t^n, s_t^k, e_t^n, e_t^k, \tilde{f}_t^n$ *are jointly normal and their*

[1] In terms of notations, given two random variables X and Y, $\sigma_{X,Y} = Cov(X, Y)$ and $\sigma_X^2 = \mathbb{V}[X]$ denote respectively the unconditional covariance and variance of the considered random variable(s).

distribution is given by:

$$\begin{pmatrix} i_t^* \\ s_t^B \\ s_t^n \\ s_t^k \\ e_t^n \\ e_t^k \\ \tilde{f}_t^n \end{pmatrix} \sim N\left(\mu^T, \Omega^T\right), \tag{B.1}$$

where

$$\mu^T = \begin{pmatrix} i_{t-1} \\ i_{t-1} \\ i_{t-1} \\ i_{t-1} \\ 0 \\ 0 \\ i_{t-1} \end{pmatrix}, \tag{B.2}$$

and

$$\Omega^T = \begin{pmatrix} \sigma_{i^*}^2 & \sigma_{i^*,s^B} & \sigma_{i^*,s^n} & \sigma_{i^*,s^k} & \sigma_{i^*,e^n} & \sigma_{i^*,e^k} & \sigma_{i^*,\tilde{f}^n} \\ \sigma_{s^B,i^*} & \sigma_{s^B}^2 & \sigma_{s^B,s^n} & \sigma_{s^B,s^k} & \sigma_{s^B,e^n} & \sigma_{s^B,e^k} & \sigma_{s^B,\tilde{f}^n} \\ \sigma_{s^n,i^*} & \sigma_{s^n,s^B} & \sigma_{s^n}^2 & \sigma_{s^n,s^k} & \sigma_{s^n,e^n} & \sigma_{s^n,e^k} & \sigma_{s^n,\tilde{f}^n} \\ \sigma_{s^k,i^*} & \sigma_{s^k,s^B} & \sigma_{s^k,s^n} & \sigma_{s^k}^2 & \sigma_{s^k,e^n} & \sigma_{s^k,e^k} & \sigma_{s^k,\tilde{f}^n} \\ \sigma_{e^n,i^*} & \sigma_{e^n,s^B} & \sigma_{e^n,s^n} & \sigma_{e^n,s^k} & \sigma_{e^n}^2 & \sigma_{e^n,e^k} & \sigma_{e^n,\tilde{f}^n} \\ \sigma_{e^k,i^*} & \sigma_{e^k,s^B} & \sigma_{e^k,s^n} & \sigma_{e^k,s^k} & \sigma_{e^k,e^n} & \sigma_{e^k}^2 & \sigma_{e^k,\tilde{f}^n} \\ \sigma_{\tilde{f}^n,i^*} & \sigma_{\tilde{f}^n,s^B} & \sigma_{\tilde{f}^n,s^n} & \sigma_{\tilde{f}^n}^2 & \sigma_{\tilde{f}^n,e^n} & \sigma_{\tilde{f}^n,e^k} & \sigma_{\tilde{f}^n}^2 \end{pmatrix}$$

$$= \begin{pmatrix} \sigma_i^2 & \sigma_i^2 & \sigma_i^2 & \sigma_i^2 & 0 & 0 & \sigma_i^2 \\ \sigma_i^2 & \sigma_i^2+\sigma_B^2 & \sigma_i^2 & \sigma_i^2 & 0 & 0 & \sigma_i^2 \\ \sigma_i^2 & \sigma_i^2 & \sigma_i^2+\sigma_T^2 & \sigma_i^2 & 0 & 0 & \sigma_i^2 \\ \sigma_i^2 & \sigma_i^2 & \sigma_i^2 & \sigma_i^2+\sigma_T^2 & 0 & 0 & \sigma_i^2+\frac{1}{N-1}\sigma_T^2 \\ 0 & 0 & 0 & 0 & \sigma_e^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_e^2 & -\frac{1}{N-1}\left(\frac{\pi_e}{\pi_s}\right)\sigma_e^2 \\ \sigma_i^2 & \sigma_i^2 & \sigma_i^2 & \sigma_i^2+\frac{1}{N-1}\sigma_T^2 & 0 & -\frac{1}{N-1}\left(\frac{\pi_e}{\pi_s}\right)\sigma_e^2 & \sigma_i^2+\sigma_\nu^2 \end{pmatrix}. \tag{B.3}$$

Proof of Lemma B.1. The result comes from: independence of the random variables $\varepsilon_t^i, \varepsilon_t^B, \varepsilon_t^n$ and e_t^n, for $n = 1, \ldots, N$; normality of any linear transformation of a normal random variable; and normality of the sum of two independent and normally distributed random variables. □

Lemma B.2. *For $n = 1, \ldots, N$, let i_t^* be given by equation* (3.1)*, s_t^B by equation* (3.2)*, s_t^n by equation* (3.5) *and $\tilde{f}_t^B$ by equation* (3.28).

Then, for $n = 1, ..., N$, $i_t^*, s_t^B, s_t^n, \tilde{f}_t^B$ are jointly normal and their distribution is given by:

$$\begin{pmatrix} i_t^* \\ s_t^B \\ s_t^n \\ e_t^n \\ \tilde{f}_t^B \end{pmatrix} \sim N\left(\mu^B, \Omega^B\right), \tag{B.4}$$

where

$$\mu^B = \begin{pmatrix} i_{t-1} \\ i_{t-1} \\ i_{t-1} \\ 0 \\ i_{t-1} \end{pmatrix}, \tag{B.5}$$

and

$$\begin{aligned} \Omega^B &= \begin{pmatrix} \sigma_{i^*}^2 & \sigma_{i^*,s^B} & \sigma_{i^*,s^n} & \sigma_{i^*,e^n} & \sigma_{i^*,\tilde{f}^B} \\ \sigma_{s^B,i^*} & \sigma_{s^B}^2 & \sigma_{s^B,s^n} & \sigma_{s^B,e^n} & \sigma_{s^B,\tilde{f}^B} \\ \sigma_{s^n,i^*} & \sigma_{s^n,s^B} & \sigma_{s^n}^2 & \sigma_{s^n,e^n} & \sigma_{s^n,\tilde{f}^B} \\ \sigma_{e^n,i^*} & \sigma_{e^n,s^B} & \sigma_{e^n,s^n} & \sigma_{e^n}^2 & \sigma_{e^n,\tilde{f}^B} \\ \sigma_{\tilde{f}^B,i^*} & \sigma_{\tilde{f}^B,s^B}^2 & \sigma_{\tilde{f}^B,s^n} & \sigma_{\tilde{f}^B,e^n} & \sigma_{\tilde{f}^B}^2 \end{pmatrix} \\ &= \begin{pmatrix} \sigma_i^2 & \sigma_i^2 & \sigma_i^2 & 0 & \sigma_i^2 \\ \sigma_i^2 & \sigma_i^2 + \sigma_B^2 & \sigma_i^2 & 0 & \sigma_i^2 \\ \sigma_i^2 & \sigma_i^2 & \sigma_i^2 + \sigma_T^2 & 0 & \sigma_i^2 + \frac{1}{N}\sigma_T^2 \\ 0 & 0 & 0 & \sigma_e^2 & -\frac{\tilde{E}}{\tilde{S}}\frac{1}{N}\sigma_e^2 \\ \sigma_i^2 & \sigma_i^2 & \sigma_i^2 + \frac{1}{N}\sigma_T^2 & -\frac{\tilde{E}}{\tilde{S}}\frac{1}{N}\sigma_e^2 & \sigma_i^2 + \sigma_\eta^2 \end{pmatrix}. \end{aligned} \tag{B.6}$$

Proof of Lemma B.2. The proof is similar to the proof of Lemma B.1. □

Lemma B.3. *Let (X, Y, Z) be jointly normal. Then,*

$$\mathbb{E}[X|Y,Z] = \mathbb{E}[X] + \begin{pmatrix} \sigma_{X,Y} & \sigma_{X,Z} \end{pmatrix} \begin{pmatrix} \sigma_Y^2 & \sigma_{Y,Z} \\ \sigma_{Y,Z} & \sigma_Z^2 \end{pmatrix}^{-1} \begin{pmatrix} Y - \mathbb{E}[Y] \\ Z - \mathbb{E}[Z] \end{pmatrix}, \tag{B.7}$$

and,

$$\mathbb{V}[X|Y,Z] = \mathbb{V}[X] - \begin{pmatrix} \sigma_{X,Y} & \sigma_{X,Z} \end{pmatrix} \begin{pmatrix} \sigma_Y^2 & \sigma_{Y,Z} \\ \sigma_{Y,Z} & \sigma_Z^2 \end{pmatrix}^{-1} \begin{pmatrix} \sigma_{X,Y} \\ \sigma_{Y,Z} \end{pmatrix}. \tag{B.8}$$

Proof. The result follows from normality of the joint distribution of (X, Y, Z), and the use the Gaussian projection theorem. □

B.1.2 Federal Funds Futures Market Proofs

Proof of equation 3.11. First, starting from the Market clearing equation (3.9) and plugging in the individual traders' demand schedule X_t^n (equation 3.10) gives:

$$\begin{aligned}
&\sum_{n=1}^{N} X_t^n = 0\\
&\sum_{n=1}^{N} \left(\pi_i i_{t-1} - \pi_f f_t + \pi_s s_t^k - \pi_e e_t^k\right) = 0\\
&\sum_{k\neq n} \left(\pi_i i_{t-1} - \pi_f f_t + \pi_s s_t^k - \pi_e e_t^k\right) + \pi_i i_{t-1} - \pi_f f_t + \pi_s s_t^n - \pi_e e_t^n = 0\\
&\sum_{k\neq n} \left(\pi_i i_{t-1} - \pi_f f_t + \pi_s s_t^k - \pi_e e_t^k\right) + X_t^n = 0\\
&(N-1)\left(\pi_i i_{t-1} - \pi_f f_t\right) + \sum_{k\neq n} \left(\pi_s s_t^k - \pi_e e_t^k\right) + X_t^n = 0.
\end{aligned}$$

Then, solving for f_t yields:

$$\begin{aligned}
f_t &= \frac{\pi_i}{\pi_f} i_{t-1} + \frac{\pi_s}{\pi_f}\left(\frac{1}{N-1}\sum_{k\neq n} s_t^k\right) - \frac{\pi_e}{\pi_f}\left(\frac{1}{N-1}\sum_{k\neq n} e_t^k\right) + \frac{1}{(N-1)\pi_f} X_t^n\\
f_t &= \frac{\pi_i}{\pi_f} i_{t-1} + \frac{\pi_s}{\pi_f} s_t^{-n} - \frac{\pi_e}{\pi_f} e_t^{-n} + \frac{1}{(N-1)\pi_f} X_t^n\\
f_t &= f_t^n + \lambda X_t^n.
\end{aligned} \tag{B.9}$$

□

Proof of equations (3.14) *and* (3.15). First, using the payoff equation (3.6), and noting that f_t is measurable with respect to $\mathscr{F}_t^n$, rewrite:

$$\begin{aligned}
&\mathbb{E}\left[v_t|\tilde{f}_t^n, s_t^n, e_t^n\right] = \mathbb{E}\left[i_t - f_t|\tilde{f}_t^n, s_t^n, e_t^n\right] = \mathbb{E}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right] - f_t\\
&\qquad\qquad and\\
&\mathbb{V}\left[v_t|\tilde{f}_t^n, s_t^n, e_t^n\right] = \mathbb{V}\left[i_t - f_t|\tilde{f}_t^n, s_t^n, e_t^n\right] = \mathbb{V}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right].
\end{aligned}$$

This shows that in order to learn about the payoff v_t, trader n has to learn about the Fed's decision regarding the federal funds rate i_t. As a result, using the traders' conjecture about the central bank's reaction function (equation 3.7), the fact that the random variables are all jointly normal (Lemma B.1), Bayesian updating (Lemma B.3), and the fact that ε_t^B is not measurable with respect to $\mathscr{F}_t^n$ yields:

$$\begin{aligned}
\mathbb{E}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right] &= \mathbb{E}\left[\bar{I}i_{t-1} + \bar{S}s_t^B + \bar{F}f_t|\tilde{f}_t^n, s_t^n, e_t^n\right] \\
&= \bar{I}i_{t-1} + \bar{S}\mathbb{E}\left[s_t^B|\tilde{f}_t^n, s_t^n, e_t^n\right] + \bar{F}f_t \\
&= \bar{I}i_{t-1} + \bar{S}\left(\frac{\sigma_T^2\left(\sigma_i^2\tilde{f}_t^n + i_{t-1}\sigma_v^2\right) + \sigma_i^2\sigma_v^2 s_t^n}{\sigma_i^2\left(\sigma_v^2 + \sigma_T^2\right) + \sigma_v^2\sigma_T^2}\right) + \bar{F}f_t \\
&= \bar{I}i_{t-1} + \bar{S}\left(\frac{\tau_i}{\tau_i + \tau_T + \tau_v}i_{t-1} + \frac{\tau_T}{\tau_i + \tau_T + \tau_v}s_t^n + \frac{\tau_v}{\tau_i + \tau_T + \tau_v}\tilde{f}_t^n\right) + \bar{F}f_t, \quad \text{(B.10)}
\end{aligned}$$

and

$$\begin{aligned}
\mathbb{V}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right] &= \mathbb{V}\left[\bar{I}i_{t-1} + \bar{S}s_t^B + \bar{F}f_t|\tilde{f}_t^n, s_t^n, e_t^n\right] \\
&= \bar{S}^2\mathbb{V}\left[s_t^B|\tilde{f}_t^n, s_t^n, e_t^n\right] \\
&= \bar{S}^2\left(\mathbb{V}\left[\varepsilon_t^i|\tilde{f}_t^n, s_t^n, e_t^n\right] + \mathbb{V}\left[\varepsilon_t^B\right]\right) \\
&= \bar{S}^2\left(\frac{\sigma_i^2\sigma_v^2\sigma_T^2}{\sigma_i^2\left(\sigma_v^2 + \sigma_T^2\right) + \sigma_v^2\sigma_T^2} + \sigma_B^2\right) \\
&= \bar{S}^2\left(\frac{1}{\tau_i + \tau_T + \tau_v} + \frac{1}{\tau_B}\right). \quad \text{(B.11)}
\end{aligned}$$

□

Proof of equations (3.16) *and* (3.17). First, using the traders' objective function (equation 3.8) and the payoff equation (3.6), rewrite:

$$\max_{X_t^n} \mathbb{E}\left[J_t^n|f_t, s_t^n, e_t^n\right] = \mathbb{E}\left[-e^{-Av_t(X_t^n+e_t^n)}|f_t, s_t^n, e_t^n\right] = \mathbb{E}\left[-e^{-A(i_t-f_t)(X_t^n+e_t^n)}|\tilde{f}_t^n, s_t^n, e_t^n\right]. \quad \text{(B.12)}$$

Then, since the random variables are jointly normal (Lemma B.1), the conditional distribution $\mathbb{E}\left[s_t^B|\tilde{f}_t^n, s_t^n, e_t^n\right]$ is also normal. As a result, noting that X_t^n and e_t^n are measurable with respect to $\mathscr{F}_t^n$ and using the moment generating function of a normally distributed random variable, equation (B.12) can be rewritten as follows:

$$\mathbb{E}\left[-e^{-A(i_t-f_t)(X_t^n+e_t^n)}|\tilde{f}_t^n, s_t^n, e_t^n\right] = -e^{-A(\mathbb{E}[i_t|\tilde{f}_t^n,s_t^n,e_t^n]-f_t)(X_t^n+e_t^n)+\frac{1}{2}A^2(X_t^n+e_t^n)^2\mathbb{V}[i_t|\tilde{f}_t^n,s_t^n,e_t^n]}.$$

And so maximizing equation (3.8) is equivalent to maximizing:

$$\max_{X_t^n} \mathbb{E}\left[J'^n_t|\tilde{f}_t^n, s_t^n, e_t^n\right] = A\left(\mathbb{E}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right] - f_t\right)\left(X_t^n + e_t^n\right) - \frac{1}{2}A^2\left(X_t^n + e_t^n\right)^2\mathbb{V}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right].$$

Then, because $f_t = f_t^n + \lambda X_t^n$ (equation 3.11) depends on X_t^n, $\mathbb{E}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right]$ (equation 3.14) also depends on X_t^n through the term $\bar{F}f_t$. As a result, the first order condition is given by:

$$\mathbb{E}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right] - f_t^n - \lambda X_t^n + \left(X_t^n + e_t^n\right)\left[\frac{\partial\mathbb{E}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right]}{\partial X_t^n} - \lambda\right] - A\left(X_t^n + e_t^n\right)\mathbb{V}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right] = 0,$$

with $\frac{\partial\mathbb{E}[i_t|\tilde{f}_t^n,s_t^n,e_t^n]}{\partial X_t^n} = \frac{\partial f_t}{\partial X_t^n}\frac{\partial\mathbb{E}[i_t|\tilde{f}_t^n,s_t^n,e_t^n]}{\partial f_t} = \lambda\bar{F}$. As a result, the first order condition can be rewritten:

$$X_t^n = \frac{\bar{I} i_{t-1} + \bar{S}\left(\frac{\tau_i i_{t-1} + \tau_T s_t^n + \tau_v \tilde{f}_t^n}{\tau_i + \tau_T + \tau_v}\right) + \bar{F} f_t^n - f_t^n - e_t^n \left(\lambda\left(1-\bar{F}\right) + A\mathbb{V}\left[i_t | \tilde{f}_t^n, s_t^n, e_t^n\right]\right)}{2\lambda\left(1-\bar{F}\right) + A\mathbb{V}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right]}$$

Finally, because this is a maximization problem, the second order condition must be negative to make sure the function is concave in X_t^n, which by simplifying gives:

$$2\lambda\left(1-\bar{F}\right) + A\mathbb{V}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right] > 0. \tag{B.13}$$

□

Proof of Lemma 1. The proof consists in two steps: (1) finding the optimal demand schedule X_t^n, as well as f_t and λ; and (2) stating the equilibrium condition(s).

First, substituting the expressions for f_t^n (equation 3.11) and $\tilde{f}_t^n$ (equation 3.12) into the first order condition (equation 3.16) yields:

$$\begin{aligned} X_t^n = \frac{1}{A}\left[\frac{N-2}{N-1} - 2\frac{\tau_v}{(N-1)\,\tau_T}\right]\frac{\tau_B}{\tau_B+\tau_i+\tau_T+\tau_v}\Bigg(&\frac{\bar{I}\left(\tau_i+\tau_T+\tau_v\right)+\bar{S}\tau_i}{\bar{S}^2}\frac{\tau_T}{\tau_T+\tau_v} i_{t-1} \\ &-\frac{1-\bar{F}}{\bar{S}^2}\frac{\tau_T}{\tau_T+\tau_v}\left(\tau_i+\tau_T+\tau_v\right) f_t \\ &+\frac{\bar{S}}{\bar{S}^2}\tau_T s_t^n\Bigg) - \left(1-\frac{\tau_v}{(N-1)\,\tau_T}\right) e_t^n. \end{aligned} \tag{B.14}$$

And the coefficients of the linear demand schedule (equation 3.10) are found by matching them with the coefficients of equation (B.14), which gives:

$$\pi_i = \frac{1}{A}\left[\frac{N-2}{N-1} - 2\frac{\tau_v}{(N-1)\,\tau_T}\right]\frac{\tau_B}{\tau_B+\tau_i+\tau_T+\tau_v}\left(\frac{\bar{I}\left(\tau_i+\tau_T+\tau_v\right)+\bar{S}\tau_i}{\bar{S}^2}\frac{\tau_T}{\tau_T+\tau_v}\right) \tag{B.15}$$

$$\pi_f = \frac{1}{A}\left[\frac{N-2}{N-1} - 2\frac{\tau_v}{(N-1)\,\tau_T}\right]\frac{\tau_B}{\tau_B+\tau_i+\tau_T+\tau_v}\left(\frac{1-\bar{F}}{\bar{S}^2}\frac{\tau_T}{\tau_T+\tau_v}\left(\tau_i+\tau_T+\tau_v\right)\right) \tag{B.16}$$

$$\pi_s = \frac{1}{A}\left[\frac{N-2}{N-1} - 2\frac{\tau_v}{(N-1)\,\tau_T}\right]\frac{\tau_B}{\tau_B+\tau_i+\tau_T+\tau_v}\frac{\bar{S}}{\bar{S}^2}\tau_T \tag{B.17}$$

$$\pi_e = 1 - \frac{\tau_v}{(N-1)\,\tau_T}. \tag{B.18}$$

Now, equation (B.14) can be used along with the market clearing condition (equation 3.9) to solve for the equilibrium rate f_t:

$$\begin{aligned}
f_t =& \frac{\pi_i}{\pi_f} i_{t-1} + \frac{\pi_s}{\pi_f} \frac{\sum_{n=1}^N s_t^n}{N} - \frac{\pi_e}{\pi_f} \frac{\sum_{n=1}^N e_t^n}{N} \\
=& \frac{\bar{I}\left(\tau_i + \tau_T + \tau_v\right) + \bar{S}\tau_i}{\left(1-\bar{F}\right)\left(\tau_i + \tau_T + \tau_v\right)} i_{t-1} + \frac{\bar{S}\left(\tau_T + \tau_v\right)}{\left(1-\bar{F}\right)\left(\tau_i + \tau_T + \tau_v\right)} \frac{\sum_{n=1}^N s_t^n}{N} \\
&- \frac{A\left(\tau_B + \tau_i + \tau_T + \tau_v\right)\left(\tau_T + \tau_v\right)\bar{S}^2\left(1 - \frac{\tau_v}{(N-1)\tau_T}\right)}{\left[\frac{N-2}{N-1} - 2\frac{\tau_v}{(N-1)\tau_T}\right]\tau_B\left(\tau_i + \tau_T + \tau_v\right)\left(1-\bar{F}\right)} \frac{\sum_{n=1}^N e_t^n}{N}.
\end{aligned} \tag{B.19}$$

And using equation (B.16), λ is given by:

$$\begin{aligned}
\lambda =& \frac{1}{(N-1)\pi_f} \\
=& \frac{A\left(\tau_B + \tau_i + \tau_T + \tau_v\right)\left(\tau_T + \tau_v\right)\bar{S}^2}{\left[(N-2)\tau_T - 2\tau_v\right]\tau_B\left(\tau_i + \tau_T + \tau_v\right)\left(1-\bar{F}\right)},
\end{aligned} \tag{B.20}$$

with τ_v being a solution of the following equation:

$$\begin{aligned}
\tau_v =& \left[\frac{1}{(N-1)\tau_T} + \left(\frac{\pi_e}{\pi_s}\right)^2 \frac{1}{(N-1)\tau_e}\right]^{-1} \\
\tau_v =& \left[\frac{1}{(N-1)\tau_T} + \left(\frac{A(N-1)\bar{S}\left(1 - \frac{\tau_v}{(N-1)\tau_T}\right)\left(\tau_B + \tau_i + \tau_v + \tau_T\right)}{\tau_B\left((N-2)\tau_T - 2\tau_v\right)}\right)^2 \frac{1}{(N-1)\tau_e}\right]^{-1} \\
\tau_v =& \frac{1}{\frac{A^2(N-1)\bar{S}^2\left(1 - \frac{\tau_v}{(N-1)\tau_T}\right)^2\left(\tau_B + \tau_i + \tau_v + \tau_T\right)^2}{\tau_B^2\tau_e\left((N-2)\tau_T - 2\tau_v\right)^2} + \frac{1}{(N-1)\tau_T}}
\end{aligned} \tag{B.21}$$

Solving equation (B.21) for τ_v using Mathematica yields several solutions including several real solutions. Note that since only $\bar{S}$ appears in equation (B.21), each solution can be expressed solely as a function of $\bar{S}$ - i.e. those solutions would not include $\bar{I}$ and $\bar{F}$.

Second, plugging equation (B.20) and equation (B.11) into the second order equation (B.13) yields:

$$\begin{aligned}
& 2\lambda\left(1-\bar{F}\right) + A\mathbb{V}\left[i_t | \tilde{f}_t^n, s_t^n, e_t^n\right] > 0 \\
\Leftrightarrow\ & 2\left(1-\bar{F}\right)\frac{A\left(\tau_B + \tau_i + \tau_T + \tau_v\right)\left(\tau_T + \tau_v\right)\bar{S}^2}{\left[(N-2)\tau_T - 2\tau_v\right]\tau_B\left(\tau_i + \tau_T + \tau_v\right)\left(1-\bar{F}\right)} + A\bar{S}^2\left(\frac{1}{\tau_i + \tau_T + \tau_v} + \frac{1}{\tau_B}\right) > 0 \\
\Leftrightarrow\ & \frac{A\left(\tau_B + \tau_i + \tau_T + \tau_v\right)\tau_T N\bar{S}^2}{\left[(N-2)\tau_T - 2\tau_v\right]\tau_B\left(\tau_i + \tau_T + \tau_v\right)} > 0.
\end{aligned} \tag{B.22}$$

Since all the parameters of the model as well as τ_v are positive, the sign of equation (B.22) depends on the sign of $(N-2)\,\tau_T - 2\tau_v$:

$$
\begin{aligned}
&(N-2)\,\tau_T - 2\tau_v > 0 \\
\Leftrightarrow\ &\tau_v < \frac{1}{2}\,(N-2)\,\tau_T,
\end{aligned}
\tag{B.23}
$$

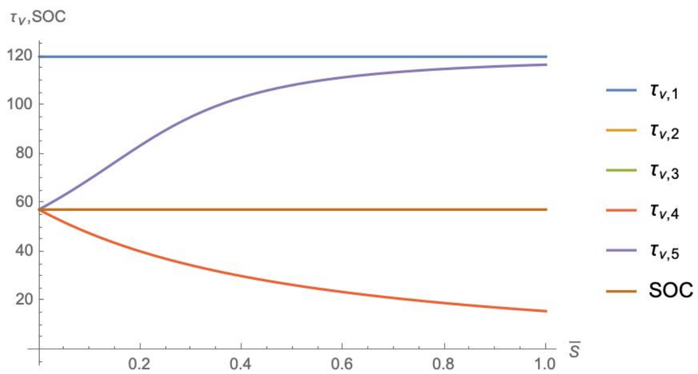
This gives the second order condition. Moreover, when the second order condition is satisfied, then $1-\frac{\tau_v}{(N-1)\tau_T} > 0$:

$$
1-\frac{\tau_v}{(N-1)\,\tau_T} > 0 \Leftrightarrow \tau_v < (N-1)\,\tau_T,
$$

which is clearly satisfied since $(N-1)\,\tau_T > \frac{1}{2}\,(N-2)\,\tau_T$, and therefore, π_i, π_f, π_s and $\pi_e > 0$.

Finally, it is possible to show - unfortunately not analytically - using a numerical example that only one solution τ_v satisfies the second order condition. Consider a model calibrated with the following baseline parameters $\{\tau_B \to 25, \tau_T \to 5, A \to 5, \tau_e \to 5, \tau_i \to 5, N \to 25, \theta \to 0.2\}$. Figure B.1 plots each solution - labelled $\tau_{v,1}, \tau_{v,2}, \tau_{v,3}\tau_{v,4}\tau_{v,5}$ as well as the expression $SOC = \frac{1}{2}\,(N-2)\,\tau_T$ as a function of $\bar{S}$.

Figure B.1: **Comparative analysis of different solutions for τ_v.**
The baseline parameters used for the analysis are: $\{\tau_B \to 25, \tau_T \to 5, A \to 5, \tau_e \to 5, \tau_i \to 5, N \to 25, \theta \to 0.2\}$. Each line represent a solution for τ_v given by Mathematica. The brown line represent the second order condition (SOC) $\frac{1}{2}\,(N-2)\,\tau_T$. A solution $\tau_{v,k}$ must satisfy two conditions to satisfy the second order condition: (1) being real, i.e. appearing in the plot, and (2) being below SOC.



In order to satisfy the second order condition, a solution for τ_v must be (1) real and (2) inferior to SOC. Figure B.1 shows that only one solution fits these two criteria, $\tau_{v,4}$. Indeed, $\tau_{v,2}$ and $\tau_{v,3}$ are not real solutions, and therefore do not appear on the graph; solution $\tau_{v,5}$ is always above SOC, which violates equation (B.23). Only $\tau_{v,4}$ is both real and below SOC, and this remains the case with different parameter values. As a result, $\tau_{v,4}$ is used as the solution of equation (B.21) for the remaining of this analysis.[2]

[2] In order to check for the robustness of this result, two tests are realized. In the first test, the plot presented in figure B.1 is realized for different parameter values. They systematically show that $\tau_{v,4}$ is the only solution satisfying the second order condition; In the second test, the model is solved twice: once as a fixed point involving a single equation, $\bar{S} = S(\bar{S})$, plugging $\tau_{v,4}$ into the equation for S; and a second time as a fixed point of two

□

B.1.3 Central Bank Proofs

Proof of Lemma 2. From equation (3.32), plugging in the expressions π_i, π_f, π_s and π_e given by equations (3.21), (3.22), (3.23) and (3.24), and matching the coefficients with equation (3.4) yields:

$$i_t = I i_{t-1} + S s_t^B + F f_t, \tag{B.24}$$

with

$$I = \frac{\frac{A^2 \bar{S}^3 \tau_i (\tau_v + \tau_T)(\tau_v - (N-1)\tau_T)^2 (\tau_B + \tau_i + \tau_v + \tau_T)^2}{\tau_B^2 \tau_T ((N-2)\tau_T - 2\tau_v)^2} - N\tau_e \tau_T \left(\left(\bar{S} + \bar{I}\right)\tau_i + \bar{I}(\tau_v + \tau_T)\right) + \tau_e \bar{S} \tau_i (\tau_v + \tau_T)}{(1+\theta)\bar{S}(\tau_v + \tau_T)\left(\frac{A^2 \bar{S}^2 (\tau_B + \tau_i)(\tau_v - (N-1)\tau_T)^2 (\tau_B + \tau_i + \tau_v + \tau_T)^2}{\tau_B^2 \tau_T ((N-2)\tau_T - 2\tau_v)^2} + \tau_e (\tau_B + \tau_i + N\tau_T)\right)} \tag{B.25}$$

$$S = \frac{\frac{A^2 \bar{S}^2 (\tau_v - (N-1)\tau_T)^2 (\tau_B + \tau_i + \tau_v + \tau_T)^2}{\tau_T ((N-2)\tau_T - 2\tau_v)^2} + \tau_e \tau_B^2}{(1+\theta)\tau_B \left(\frac{A^2 \bar{S}^2 \tau_i (\tau_v - (N-1)\tau_T)^2 (\tau_B + \tau_i + \tau_v + \tau_T)^2}{\tau_B^2 \tau_T ((N-2)\tau_T - 2\tau_v)^2} + \frac{A^2 \bar{S}^2 (\tau_v - (N-1)\tau_T)^2 (\tau_B + \tau_i + \tau_v + \tau_T)^2}{\tau_B \tau_T ((N-2)\tau_T - 2\tau_v)^2} + \tau_e \tau_B + \tau_e \tau_i + N\tau_e \tau_T\right)} \tag{B.26}$$

$$F = \frac{\theta + \frac{N\tau_e \left(1 - \bar{F}\right)\tau_T (\tau_i + \tau_v + \tau_T)}{\bar{S}(\tau_v + \tau_T)\left(\frac{A^2 \bar{S}^2 (\tau_B + \tau_i)(\tau_v - (N-1)\tau_T)^2 (\tau_B + \tau_i + \tau_v + \tau_T)^2}{\tau_B^2 \tau_T ((N-2)\tau_T - 2\tau_v)^2} + \tau_e (\tau_B + \tau_i + N\tau_T)\right)}}{1+\theta}. \tag{B.27}$$

So the central bank's reaction function is indeed a linear function of i_{t-1}, s_t^B and f_t, and the weights I, S, F depend on the traders' conjectures $\bar{I}, \bar{S}$, and $\bar{F}$, that are taken as parameters. They can be rewritten $I\left(\bar{I}, \bar{S}, \bar{F}\right), S\left(\bar{I}, \bar{S}, \bar{F}\right)$, and $F\left(\bar{I}, \bar{S}, \bar{F}\right)$. □

B.1.4 Equilibrium Proofs

Proof of Lemma 3. This proof consists in two parts. First, showing that solving the equilibrium can be reduced to solving the fixed point given by $\bar{S} = S\left(\bar{S}\right)$; second, showing that one equilibrium satisfies the condition $I + S + F = 1$.

First, from equations (B.25) and (B.27), it appears that I and F are linear in $\bar{I}$ and $\bar{F}$ respectively. Moreover, noting from equation (B.21) that τ_v depends only on $\bar{S}$, it is easy to see that I does not depend on $\bar{F}$ and F does not depend on $\bar{I}$, and that S depends only on $\bar{S}$. As a result,

equations, $\bar{S} = S(\bar{S}, \tau_v)$ and equation (B.21). The solutions given by the two models are most of the time identical: the cases when they are not are when in the two-equation fixed point, the starting value for τ_v is set too close from $\tau_{v,1} = (N-1)\tau_T$. Such high starting values are avoided since they violate in any case the second order condition.

equations (B.25) and (B.27) can be expressed in terms of $\bar{S}$:

$$\bar{I} = \frac{\tau_i\left(\tau_e\left(1-\frac{N\tau_T}{\tau_v+\tau_T}\right)+\frac{A^2\bar{S}^2(\tau_v-(N-1)\tau_T)^2(\tau_B+\tau_i+\tau_v+\tau_T)^2}{\tau_B^2\tau_T((N-2)\tau_T-2\tau_v)^2}\right)}{\Psi}$$
$$\bar{F} = \frac{\frac{A^2\theta\bar{S}^2(\tau_B+\tau_i)(\tau_v-(N-1)\tau_T)^2(\tau_B+\tau_i+\tau_v+\tau_T)^2}{\tau_B^2\tau_T((N-2)\tau_T-2\tau_v)^2}+\theta\tau_e(\tau_B+\tau_i+N\tau_T)+\frac{N\tau_e\tau_T(\tau_i+\tau_v+\tau_T)}{\bar{S}(\tau_v+\tau_T)}}{\Psi},$$

where

$$\Psi := (1+\theta)\left(\frac{A^2\bar{S}^2(\tau_B+\tau_i)(\tau_v-(N-1)\tau_T)^2(\tau_B+\tau_i+\tau_v+\tau_T)^2}{\tau_B^2\tau_T((N-2)\tau_T-2\tau_v)^2}+\tau_e(\tau_B+\tau_i+N\tau_T)\right)$$
$$\times\left(1+\frac{N\tau_e\tau_T(\tau_i+\tau_v+\tau_T)}{(1+\theta)\bar{S}(\tau_v+\tau_T)\left(\frac{A^2\bar{S}^2(\tau_B+\tau_i)(\tau_v-(N-1)\tau_T)^2(\tau_B+\tau_i+\tau_v+\tau_T)^2}{\tau_B^2\tau_T((N-2)\tau_T-2\tau_v)^2}+\tau_e(\tau_B+\tau_i+N\tau_T)\right)}\right).$$

And the equilibrium is found by plugging in $\tau_{v,4}$ into equation (B.26), and solving the fixed point $\bar{S} = S(\bar{S})$ for $\bar{S}$.

Second, in order to show that one equilibrium satisfies the condition $I+S+F=1$, the following definition are made to simplify the notations:

$$\tilde{I} := \frac{\pi_i}{\pi_f} = \frac{\bar{S}\tau_i+\bar{I}(\tau_i+\tau_v+\tau_T)}{(1-\bar{F})(\tau_i+\tau_v+\tau_T)} \tag{B.28}$$
$$\tilde{S} := \frac{\pi_s}{\pi_f} = \frac{\bar{S}(\tau_v+\tau_T)}{(1-\bar{F})(\tau_i+\tau_v+\tau_T)} \tag{B.29}$$
$$\tilde{E} := \frac{\pi_e}{\pi_f} = \frac{A(N-1)\bar{S}^2(\tau_v+\tau_T)\left(\frac{\tau_v}{\tau_T-N\tau_T}+1\right)(\tau_B+\tau_i+\tau_v+\tau_T)}{(1-\bar{F})\tau_B(\tau_i+\tau_v+\tau_T)((N-2)\tau_T-2\tau_v)} \tag{B.30}$$

Now, assuming that $\bar{I}+\bar{S}+\bar{F}=1$, it is possible to rewrite equation (B.28) as:

$$\begin{aligned}\tilde{I} = \frac{\pi_i}{\pi_f} &= \frac{\bar{S}\tau_i+(1-\bar{S}-\bar{F})(\tau_i+\tau_v+\tau_T)}{(1-\bar{F})(\tau_i+\tau_v+\tau_T)}\\ &= 1-\frac{\bar{S}(\tau_v+\tau_T)}{(1-\bar{F})(\tau_i+\tau_v+\tau_T)}\\ &= 1-\tilde{S}\end{aligned} \tag{B.31}$$

Then, the goal is to show that the weights I, S and F, associated to i_{t-1}, s_t^B and f_t respectively in equation (3.32), also sum up to one. Using those weights as well as the new notations (equations B.28, B.29 and B.30) yields:

$$
\begin{aligned}
I+S+F=&\frac{\tilde{S}^2\tau_e\left[(1+\theta)\left(\tau_B+\tau_i\right)+\theta N\tau_T\right]+\left(1-\tilde{I}\right)\tilde{S}N\tau_e\tau_T+(1+\theta)\tilde{E}^2\tau_T\left(\tau_B+\tau_i\right)}{(1+\theta)\left(\tilde{S}^2\tau_e\left(\tau_B+\tau_i+N\tau_T\right)+\tilde{E}^2\tau_T\left(\tau_B+\tau_i\right)\right)},\\
=&1, \qquad\qquad \text{(B.32)}
\end{aligned}
$$

noting from equation (B.31) that $\tilde{S}=1-\tilde{I}$. Since the weights do sum up to one, it must be the case that the initial assumption is correct, which means that there is one equilibrium that satisfies the condition $I+S+F=1$. □

B.1.5 Monetary Policy Implications Proofs

Proof of Lemma 4. In this version of the model, the central bank does not learn from the market rate ($\bar{F}=0$), and does not take financial market volatility into account when taking its monetary policy decision ($\theta=0$). The model is solved in the exact same three steps than for the benchmark model.

First, on the financial market side of the equilibrium, everything is similar except for traders' conjecture about the central bank's reaction function.[3] The new conjecture is given by equation (3.35) and this has a direct impact market expectations of monetary policy.[4] Using Lemmas B.1 and B.3, trader n's expectation of the federal funds rate is equal to:

$$
\begin{aligned}
\mathbb{E}\left[i_t|s_t^n,e_t^n,\tilde{f}_t^n\right]=&\bar{I}i_{t-1}+\bar{S}_t\mathbb{E}\left[s_t^B|s_t^n,e_t^n,\tilde{f}_t^n\right]\\
=&\bar{I}i_{t-1}+\bar{S}\left(\frac{\tau_i}{\tau_i+\tau_T+\tau_v}i_{t-1}+\frac{\tau_T}{\tau_i+\tau_T+\tau_v}s_t^n+\frac{\tau_v}{\tau_i+\tau_T+\tau_v}\tilde{f}_t^n\right)\\
&and\\
\mathbb{V}\left[i_t|s_t^n,e_t^n,\tilde{f}_t^n\right]=&\mathbb{V}\left[\bar{I}i_{t-1}+\bar{S}_ts_t^B|s_t^n,e_t^n,\tilde{f}_t^n\right]\\
=&\bar{S}_t^2\mathbb{V}\left[s_t^B|s_t^n,e_t^n,\tilde{f}_t^n\right].
\end{aligned}
$$

The conditional expectation of the fed funds rate does not depend on the market rate f_t anymore.[5] Importantly, trader n cannot influence market expectations of the federal funds rate with his demand schedule, i.e. $\frac{\partial\mathbb{E}[i_t|f_t,s_t^n,e_t^n]}{\partial X_t^n}=0$, and the first order condition of trader n's optimization problem becomes:

$$
\mathbb{E}\left[i_t|f_t,s_t^n,e_t^n\right]-f_t^n-2\lambda X_t^n-\lambda e_t^n-A\left(X_t^n+e_t^n\right)\mathbb{V}\left[i_t|f_t,s_t^n,e_t^n\right]=0.
$$

[3]Because the maximization problem of the traders in this version of the model is very similar to that of the benchmark model, only the steps that are different are mentioned here. For the full proof of the financial market side of the equilibrium, the interested reader is invited to refer to Appendix B.1.2.

[4]Note that traders' information set remains the same, with $\mathscr{F}_t^n=\{s_t^n,e_t^n,\tilde{f}_t^n\}$.

[5]The conditional variance remains, however, identical to that of the benchmark model (equation B.11).

Solving for X_t^n, the first order condition can be rewritten as:

$$X_t^n = \frac{\bar{I} i_{t-1} + \bar{S}\left(\frac{\tau_i i_{t-1} + \tau_T s_t^n + \tau_v \tilde{f}_t^n}{\tau_i + \tau_T + \tau_v}\right) - f_t^n - e_t^n \left(\lambda + A\mathbb{V}\left[i_t | \tilde{f}_t^n, s_t^n, e_t^n\right]\right)}{2\lambda + A\mathbb{V}\left[i_t | \tilde{f}_t^n, s_t^n, e_t^n\right]} \tag{B.33}$$

Finally, because this is a maximization problem, the second order condition must be negative to make sure the function is concave in X_t^n, which after simplifying gives:

$$2\lambda + A\mathbb{V}\left[i_t | \tilde{f}_t^n, s_t^n, e_t^n\right] > 0; \tag{B.34}$$

Replacing f_t^n, $\tilde{f}_t^n$ by their expressions (equations 3.11 and 3.12) in the first order condition (equation B.33) and solving for X_t^n gives:

$$\begin{aligned} X_t^n = \frac{1}{A}\left[\frac{N-2}{N-1} - 2\frac{\tau_v}{(N-1)\tau_T}\right] \frac{\tau_B}{\tau_B + \tau_i + \tau_T + \tau_v} & \left(\frac{\bar{I}(\tau_i + \tau_T + \tau_v) + \bar{S}\tau_i}{\bar{S}^2} \frac{\tau_T}{\tau_T + \tau_v} i_{t-1}\right. \\ & - \frac{1}{\bar{S}^2}\frac{\tau_T}{\tau_T + \tau_v}(\tau_i + \tau_T + \tau_v) f_t \\ & \left. + \frac{\bar{S}}{\bar{S}^2}\tau_T s_t^n\right) - \left(1 - \frac{\tau_v}{(N-1)\tau_T}\right) e_t^n. \end{aligned} \tag{B.35}$$

The only difference between equation (B.35) and equation (B.14) lies in π_f, where $\bar{F} = 0$, which results from the initial conjecture that the central bank does not look at the futures rate f_t when deciding on the level of the federal funds rate to set.

Then, equation (B.35) can be used along with the market clearing condition (3.9) to solve for the equilibrium rate f_t:

$$\begin{aligned} f_t = & \frac{\bar{I}(\tau_i + \tau_T + \tau_v) + \bar{S}\tau_i}{(\tau_i + \tau_T + \tau_v)} i_{t-1} + \frac{\bar{S}(\tau_T + \tau_v)}{(\tau_i + \tau_T + \tau_v)} \frac{\sum_{n=1}^N s_t^n}{N} \\ & - \frac{A(\tau_B + \tau_i + \tau_T + \tau_v)(\tau_T + \tau_v)\bar{S}^2\left(1 - \frac{\tau_v}{(N-1)\tau_T}\right)}{\left[\frac{N-2}{N-1} - 2\frac{\tau_v}{(N-1)\tau_T}\right]\tau_B(\tau_i + \tau_T + \tau_v)} \frac{\sum_{n=1}^N e_t^n}{N}. \end{aligned} \tag{B.36}$$

And λ is given by:

$$\begin{aligned} \lambda = & \frac{1}{(N-1)\pi_f} \\ = & \frac{A(\tau_B + \tau_i + \tau_T + \tau_v)(\tau_T + \tau_v)\bar{S}^2}{[(N-2)\tau_T - 2\tau_v]\tau_B(\tau_i + \tau_T + \tau_v)}. \end{aligned} \tag{B.37}$$

Since π_s and π_e are identical compared to the benchmark case (equations B.17 and B.18), τ_v does not change and is still given equation (B.21).

Finally, the second order condition given by equation (B.34) must satisfy:

$$\begin{aligned}&2\lambda + A\mathbb{V}\left[i_t|\tilde{f}_t^n, s_t^n, e_t^n\right] > 0\\ \Leftrightarrow &\frac{A\left(\tau_B + \tau_i + \tau_T + \tau_v\right)\tau_T N\bar{S}^2}{\left[(N-2)\,\tau_T - 2\tau_v\right]\tau_B\left(\tau_i + \tau_T + \tau_v\right)} > 0,\end{aligned}$$

which is identical to the condition given by equation (B.22). Therefore, the second order condition must also satisfy:

$$\tau_v < \frac{1}{2}\,(N-2)\,\tau_T.$$

Similar to the benchmark case, only one solution for τ_v satisfies the equilibrium condition.

Second, the central bank side of the equilibrium is significantly modified, due to the two new assumptions that $F = 0$ and $\theta = 0$. The problem of the central bank is now given by equation (3.36), and the first order condition is given by equation (3.37). The second order condition implies that $1 > 0$, which is always satisfied.

By assumption, the Fed does not learn from the market rate ($\mathscr{F}_t^B = \{s_t^B\}$), so central bank's Bayesian inference of the state of the economy is given by:

$$\mathbb{E}\left[i_t^*|s_t^B\right] = \frac{\tau_i}{\tau_i + \tau_B}\,i_{t-1} + \frac{\tau_B}{\tau_i + \tau_B}\,s_t^B. \tag{B.38}$$

Third, using the initial conjecture about the central bank reaction function (equation 3.34), the first order condition (equation 3.37) and the central bank's estimate of the state of the economy (equation B.38), the central bank side of the equilibrium is reached when $I = \frac{\tau_i}{\tau_i+\tau_B}$ and $S = \frac{\tau_B}{\tau_i+\tau_B}$, and the global equilibrium of the model when $\bar{I} = I = \frac{\tau_i}{\tau_i+\tau_B}$ and $\bar{S} = S = \frac{\tau_B}{\tau_i+\tau_B}$.

□

Proof of Lemma 5. Since the conjecture about the central bank behavior is identical in this model compared to that of the benchmark model, the financial side of the equilibrium remains the same. The central bank side of the equilibrium is however different: the optimization problem is given by equation (3.49) and the first order condition by equation (3.50). Then, from equation (3.50), the system of equations below is obtained in four steps: (1) plugging in equation (3.29) and the expression for τ_η; (2) plugging in the expressions for π_i, π_f, π_s and π_e given by equations (B.15), (B.16), (B.17) and (B.18); (3) plugging in the solution $\tau_{v,4}$ of equation (B.21), i.e. the solution that satisfies the equilibrium condition given by equation (B.23); and (4) matching the coefficients with equation (3.4). This yields:

$$i_t = I i_{t-1} + S s_t^B + F f_t,$$

with

$$I = \frac{\frac{A^2\bar{S}^3\tau_i(\tau_v+\tau_T)(\tau_v-(N-1)\tau_T)^2(\tau_B+\tau_i+\tau_v+\tau_T)^2}{\tau_B^2\tau_T((N-2)\tau_T-2\tau_v)^2} - N\tau_e\tau_T\left(\left(\bar{S}+\bar{I}\right)\tau_i + \bar{I}\left(\tau_v+\tau_T\right)\right) + \tau_e\bar{S}\tau_i\left(\tau_v+\tau_T\right)}{\bar{S}\left(\tau_v+\tau_T\right)\left(\frac{A^2\bar{S}^2(\tau_B+\tau_i)(\tau_v-(N-1)\tau_T)^2(\tau_B+\tau_i+\tau_v+\tau_T)^2}{\tau_B^2\tau_T((N-2)\tau_T-2\tau_v)^2} + \tau_e\left(\tau_B+\tau_i+N\tau_T\right)\right)} \tag{B.39}$$

$$S = \frac{\frac{A^2\bar{S}^2(\tau_v-(N-1)\tau_T)^2(\tau_B+\tau_i+\tau_v+\tau_T)^2}{\tau_T((N-2)\tau_T-2\tau_v)^2} + \tau_e\tau_B^2}{\tau_B\left(\frac{A^2\bar{S}^2\tau_i(\tau_v-(N-1)\tau_T)^2(\tau_B+\tau_i+\tau_v+\tau_T)^2}{\tau_B^2\tau_T((N-2)\tau_T-2\tau_v)^2} + \frac{A^2\bar{S}^2(\tau_v-(N-1)\tau_T)^2(\tau_B+\tau_i+\tau_v+\tau_T)^2}{\tau_B\tau_T((N-2)\tau_T-2\tau_v)^2} + \tau_e\tau_B + \tau_e\tau_i + N\tau_e\tau_T\right)} \tag{B.40}$$

$$F = \frac{N\tau_e\left(1-\bar{F}\right)\tau_T\left(\tau_i+\tau_v+\tau_T\right)}{\bar{S}\left(\tau_v+\tau_T\right)\left(\frac{A^2\bar{S}^2(\tau_B+\tau_i)(\tau_v-(N-1)\tau_T)^2(\tau_B+\tau_i+\tau_v+\tau_T)^2}{\tau_B^2\tau_T((N-2)\tau_T-2\tau_v)^2} + \tau_e\left(\tau_B+\tau_i+N\tau_T\right)\right)} \tag{B.41}$$

So the central bank's reaction function is indeed a linear function of i_{t-1}, s_t^B and f_t, and the weights I, S, F depend on the traders' conjectures $\bar{I}$, $\bar{S}$, and $\bar{F}$, which it takes as parameters. They can be rewritten $I\left(\bar{I},\bar{S},\bar{F}\right)$, $S\left(\bar{I},\bar{S},\bar{F}\right)$, and $F\left(\bar{I},\bar{S},\bar{F}\right)$.

Then, the proof showing how to find $\bar{I},\bar{S}$ and $\bar{F}$ is identical to that of Lemma 3, except that $\theta = 0$: The solution of the model is found by solving the fixed point equilibrium given by $\bar{I} = I\left(\bar{I},\bar{S},\bar{F}\right)$, $\bar{S} = S\left(\bar{I},\bar{S},\bar{F}\right)$ and $\bar{F} = F\left(\bar{I},\bar{S},\bar{F}\right)$ (equations B.39, B.40 and B.41) for $\bar{I}$,$\bar{S}$ and $\bar{F}$ respectively. But since equation (B.39) and (B.41) are linear in $\bar{I}$ and $\bar{F}$ respectively, and do not depend on $\bar{F}$ and $\bar{I}$ respectively, they can be solved for $\bar{I}$ and $\bar{F}$ in order to only depend on $\bar{S}$. The solutions are given by:

$$\begin{aligned}
\bar{I} &= -\frac{\tau_i(-N\tau_T+\tau_v+\tau_T)\left(-\frac{A^2\bar{S}^2(-N\tau_T+\tau_v+\tau_T)(\tau_B+\tau_i+\tau_v+\tau_T)^2}{\tau_T((N-2)\tau_B\tau_T-2\tau_B\tau_v)^2} - \frac{\tau_e}{\tau_v+\tau_T}\right)}{\Psi'} \\
\bar{F} &= \frac{N\tau_e\tau_T(\tau_i+\tau_v+\tau_T)}{\bar{S}(\tau_v+\tau_T)\Psi'},
\end{aligned}$$

where

$$\begin{aligned}
\Psi' := &\left(\frac{A^2\bar{S}^2(\tau_B+\tau_i)(-N\tau_T+\tau_v+\tau_T)^2(\tau_B+\tau_i+\tau_v+\tau_T)^2}{\tau_T((N-2)\tau_B\tau_T-2\tau_B\tau_v)^2} + \tau_e(N\tau_T+\tau_B+\tau_i)\right) \\
&\times\left(1 + \frac{N\tau_e\tau_T(\tau_i+\tau_v+\tau_T)}{\bar{S}(\tau_v+\tau_T)\left(\frac{A^2\bar{S}^2(\tau_B+\tau_i)(-N\tau_T+\tau_v+\tau_T)^2(\tau_B+\tau_i+\tau_v+\tau_T)^2}{\tau_T((N-2)\tau_B\tau_T-2\tau_B\tau_v)^2} + \tau_e(N\tau_T+\tau_B+\tau_i)\right)}\right).
\end{aligned}$$

Finally, the solution of the model is found by solving the fixed point $\bar{S} = S\left(\bar{S}\right)$ for $\bar{S}$, with S given by equation (B.40). Moreover, similar to Lemma 3, there exists one equilibrium satisfying $I + S + F = 1$ - the proof is similar to that given in Lemma 3. □

B.1.6 Asset Pricing Implications Proofs

Proof of Lemma 6. This proof describes the derivation of the variance of the change in yields following monetary policy announcements. The computations are first made for the long term yield, then for the short term yield, and finally for the surprise.

Using Lemmas B.1 and B.3 and knowing that s_t^n and $\tilde{f}_t^n$ are given by equations (3.5) and (3.12), the long term yield is given by:

$$
\begin{aligned}
i_t^{LT} =& \frac{1}{N}\sum_{n=1}^{N}\mathbb{E}\left[i_t^*|s_t^n, e_t^n, \tilde{f}_t^n\right] \\
=& \frac{1}{N}\sum_{n=1}^{N}\left[\frac{\tau_i}{\tau_i+\tau_T+\tau_v}i_{t-1} + \frac{\tau_T}{\tau_i+\tau_T+\tau_v}s_t^n + \frac{\tau_v}{\tau_i+\tau_T+\tau_v}\tilde{f}_t^n\right] \\
=& \frac{\tau_i}{\tau_i+\tau_T+\tau_v}i_{t-1} + \frac{\tau_T+\tau_v}{\tau_i+\tau_T+\tau_v}i_t^* + \frac{1}{N}\sum_{n=1}^{N}\left[\frac{\tau_T}{\tau_i+\tau_T+\tau_v}\varepsilon_t^n + \frac{\tau_v}{\tau_i+\tau_T+\tau_v}v_t^n\right].
\end{aligned}
\tag{B.42}
$$

Then, from equation (3.13), v_t^n is equal to:

$$
\begin{aligned}
v_t^n =& \frac{1}{N-1}\sum_{k\neq n}\varepsilon_t^k - \frac{\pi_e}{\pi_s}\frac{1}{N-1}\sum_{k\neq n}e_t^k \\
=& \frac{1}{N-1}\left(\sum_{k\neq n}\varepsilon_t^k - \frac{\pi_e}{\pi_s}\sum_{k\neq n}e_t^k\right).
\end{aligned}
$$

As a result, the part associated to v_t^n in equation (B.42) can be rewritten:

$$
\begin{aligned}
\frac{1}{N}\sum_{n=1}^{N}\frac{\tau_v}{\tau_i+\tau_T+\tau_v}v_t^n =& \frac{1}{N}\left(\frac{\tau_v}{\tau_i+\tau_T+\tau_v}\right)\left[v_t^1+v_t^2+v_t^3+\ldots+v_t^{N-1}+v_t^N\right] \\
=& \frac{1}{N}\left(\frac{\tau_v}{\tau_i+\tau_T+\tau_v}\right)\Bigg[\frac{1}{N-1}\Bigg(\sum_{j=2}^{N}\left(\varepsilon_t^j-\frac{\pi_e}{\pi_s}e_t^j\right) \\
& + \varepsilon_t^1 + \sum_{j=3}^{N}\left(\varepsilon_t^j-\frac{\pi_e}{\pi_s}e_t^j\right) \\
& + \varepsilon_t^1 + \varepsilon_t^2 + \sum_{j=4}^{N}\left(\varepsilon_t^j-\frac{\pi_e}{\pi_s}e_t^j\right) \\
& + \ldots \\
& + \sum_{j=1}^{N-2}\left(\varepsilon_t^j-\frac{\pi_e}{\pi_s}e_t^j\right) + \varepsilon_t^N \\
& + \sum_{j=1}^{N-1}\left(\varepsilon_t^j-\frac{\pi_e}{\pi_s}e_t^j\right)\Bigg)\Bigg] \\
=& \frac{1}{N}\left(\frac{\tau_v}{\tau_i+\tau_T+\tau_v}\right)\sum_{j=1}^{N}\left(\varepsilon_t^j-\frac{\pi_e}{\pi_s}e_t^j\right),
\end{aligned}
\tag{B.43}
$$

noting that there are $(N-1)$ times the sum $\sum_{j=1}^{N}\left(\varepsilon_t^j - \frac{\pi_e}{\pi_s} e_t^j\right)$.

Then, using the result in equation (B.43), equation (B.42) becomes:

$$\begin{aligned} i_t^{LT} =& \frac{\tau_i}{\tau_i+\tau_T+\tau_v} i_{t-1} + \frac{\tau_T+\tau_v}{\tau_i+\tau_T+\tau_v} i_t^* + \frac{1}{N}\sum_{n=1}^{N}\left[\frac{\tau_T}{\tau_i+\tau_T+\tau_v}\varepsilon_t^n + \frac{\tau_v}{\tau_i+\tau_T+\tau_v}\left(\varepsilon_t^n - \frac{\pi_e}{\pi_s}e_t^n\right)\right] \\ =& \frac{\tau_i}{\tau_i+\tau_T+\tau_v} i_{t-1} + \frac{\tau_T+\tau_v}{\tau_i+\tau_T+\tau_v} i_t^* + \frac{1}{N}\left(\frac{\tau_T+\tau_v}{\tau_i+\tau_T+\tau_v}\right)\sum_{n=1}^{N}\varepsilon_t^n - \frac{1}{N}\left(\frac{\tau_v}{\tau_i+\tau_T+\tau_v}\right)\frac{\pi_e}{\pi_s}\sum_{n=1}^{N} e_t^n. \end{aligned} \tag{B.44}$$

The long term yield in the *Alternative 1* and *Alternative 2* models is also given by equation (B.44), since the traders have the same information set in the three models. Note however that the value of τ_v, which depends on $\bar{S}$, is different between the three models, thereby generating different dynamics.

In order to compute the long term yield adjustment following monetary policy announcements, it is necessary to compute i_{post}^{LT}, which is given by equation (3.54). In this case, since the announcement has already been made, traders are able to observe i_t, so learning from the interest rate for trader n is equivalent to learning from the following linear transformation of i_t:

$$\hat{i}_t = \frac{1}{\bar{S}}\left[i_t - \bar{I} i_{t-1} - \bar{F} f_t\right] = s_t^B, \tag{B.45}$$

which is identical for all traders. It is interesting to see that here, the announcement perfectly reveals the central bank's signal, since the traders also observes f_t. This additional piece of information is used by traders to estimate more precisely the state of the economy, which determines the new level of the long term yield.

Note also that for simplicity, the *market signal* received by trader n is expressed as follows:

$$\hat{f}_t^n = \left(\frac{N}{N-1}\right)\frac{\pi_f}{\pi_s}\left[f_t - \frac{\pi_i}{\pi_f} i_{t-1} - \frac{\pi_s}{\pi_f}\frac{s_t^n}{N} + \frac{\pi_e}{\pi_f}\frac{e_t^n}{N}\right] = i_t^* + v_t^n, \tag{B.46}$$

where all the variables on the LHS are observed by trader n at time t and those on the RHS are not. As a result, using Lemmas B.1 and B.3, Bayesian learning about i_t^* is equal to:

$$\mathbb{E}\left[i_t^* | s_t^n, e_t^n, \hat{f}_t^n, \hat{i}_t\right] = \frac{1}{\tau_B+\tau_i+\tau_T+\tau_v}\left[\tau_B \hat{i}_t + \tau_i i_{t-1} + \tau_T s_t^n + \tau_v \hat{f}_t\right].$$

Then, replacing $\hat{i}_t$ (equation B.45), $\hat{f}_t$ (equation B.46), s_t^B (equation 3.2) and s_t^n (equation 3.5) by their expressions gives:

$$\mathbb{E}\left[i_t^* | s_t^n, e_t^n, \hat{f}_t^n, \hat{i}_t\right] = \frac{1}{\tau_B+\tau_i+\tau_T+\tau_v}\left[\tau_i i_{t-1} + (\tau_B+\tau_T+\tau_v)\, i_t^* + \tau_B \varepsilon_t^B + \tau_T \varepsilon_t^n + \tau_v v_t^n\right]. \tag{B.47}$$

And using equation (B.47), it is easy to compute i_{post}^{LT}:

$$
\begin{aligned}
i_{post}^{LT} =& \frac{1}{N}\sum_{n=1}^{N}\mathbb{E}\left[i_t^*|s_t^n, e_t^n, \hat{f}_t^n, \hat{i}_t\right] \\
=& \frac{1}{\tau_B+\tau_i+\tau_T+\tau_v}\left[\tau_i i_{t-1} + (\tau_B+\tau_T+\tau_v)\, i_t^* + \tau_B\varepsilon_t^B + \frac{1}{N}\sum_{n=1}^{N}\left(\tau_T\varepsilon_t^n + \tau_v v_t^n\right)\right] \\
=& \frac{1}{\tau_B+\tau_i+\tau_T+\tau_v}\left[\tau_i i_{t-1} + (\tau_B+\tau_T+\tau_v)\, i_t^* + \tau_B\varepsilon_t^B + \frac{1}{N}(\tau_T+\tau_v)\sum_{n=1}^{N}\varepsilon_t^n - \frac{1}{N}\tau_v\frac{\pi_e}{\pi_s}\sum_{n=1}^{N}e_t^n\right].
\end{aligned}
\tag{B.48}
$$

In spite of a different conjecture about the reaction function in the *Alternative 1* model compared to the other 2, the expression for the long term yield post announcement is identical in the three models. This is because learning from the interest rate is identical: In all cases, the unknown part of $\hat{i}_t$, the *monetary policy signal*, is s_t^B. And since traders' information set is identical in all three models, learning is identical. Again, the dynamics produced in each of these model should however be different because of different equilibrium values for $\bar{S}$.

From equations (B.44) and (B.48), it is possible to get the adjustment of the long term yield following monetary policy announcements:

$$
\begin{aligned}
i_{post}^{LT} - i_t^{LT} =& \frac{\tau_B+\tau_T+\tau_v}{\tau_B+\tau_i+\tau_T+\tau_v}i_t^* + \frac{\tau_B}{\tau_B+\tau_i+\tau_T+\tau_v}\varepsilon_t^B \\
&- \frac{\tau_B}{(\tau_i+\tau_T+\tau_v)(\tau_B\tau_i+\tau_T+\tau_v)}\left[\tau_i i_{t-1} + (\tau_T+\tau_v)\frac{\sum_{n=1}^{N}\varepsilon_t^n}{N} - \tau_v\frac{\pi_e}{\pi_s}\frac{\sum_{n=1}^{N}e_t^n}{N}\right].
\end{aligned}
\tag{B.49}
$$

Finally, the variance of the adjustment of the long term yield following monetary policy announcements is given by:

$$
\begin{aligned}
\mathbb{V}\left[i_{post}^{LT} - i_t^{LT}\right] =& \left(\frac{\tau_B+\tau_T+\tau_v}{\tau_B+\tau_i+\tau_T+\tau_v}\right)^2\frac{1}{\tau_i} + \frac{\tau_B}{(\tau_B+\tau_i+\tau_T+\tau_v)^2} \\
&+ \frac{1}{N}\left(\frac{\tau_B}{(\tau_i+\tau_T+\tau_v)(\tau_B+\tau_i+\tau_T+\tau_v)}\right)^2\left[\frac{(\tau_T+\tau_v)^2}{\tau_T} + \left(\frac{\pi_e}{\pi_s}\right)^2\frac{\tau_v^2}{\tau_e}\right].
\end{aligned}
\tag{B.50}
$$

The variance of the adjustment of the short term bond yield following monetary policy announcement is found in the same way as for the long term bond. Using equation (B.10), this gives:

$$
\begin{aligned}
i_t^{ST} =& \frac{1}{N}\sum_{n=1}^{N}\mathbb{E}\left[i_t | s_t^n, e_t^n, \hat{f}_t^n\right] \\
=& \frac{1}{N}\sum_{n=1}^{N}\left[\bar{I} i_{t-1} + \bar{S}\left(\frac{\tau_i}{\tau_i+\tau_T+\tau_v} i_{t-1} + \frac{\tau_T}{\tau_i+\tau_T+\tau_v} s_t^n + \frac{\tau_v}{\tau_i+\tau_T+\tau_v}\hat{f}_t^n\right) + \bar{F} f_t\right] \\
=& \bar{I} i_{t-1} + \bar{F} f_t + \frac{\bar{S}}{N}\sum_{n=1}^{N}\left(\frac{\tau_i}{\tau_i+\tau_T+\tau_v} i_{t-1} + \frac{\tau_T}{\tau_i+\tau_T+\tau_v} s_t^n + \frac{\tau_v}{\tau_i+\tau_T+\tau_v}\hat{f}_t^n\right) \\
=& \bar{I} i_{t-1} + \bar{F} f_t \\
&+ \bar{S}\left[\frac{\tau_i}{\tau_i+\tau_T+\tau_v} i_{t-1} + \frac{\tau_T+\tau_v}{\tau_i+\tau_T+\tau_v} i_t^* + \frac{1}{N}\left(\frac{\tau_T+\tau_v}{\tau_i+\tau_T+\tau_v}\right)\sum_{n=1}^{N}\varepsilon_t^n - \frac{1}{N}\left(\frac{\tau_v}{\tau_i+\tau_T+\tau_v}\right)\frac{\pi_e}{\pi_s}\sum_{n=1}^{N} e_t^n\right].
\end{aligned}
\tag{B.51}
$$

And so the adjustment in expectations following the central bank announcement is given by:

$$
\begin{aligned}
i_t - i_t^{ST} =& \bar{I} i_{t-1} + \bar{S} s_t^B + \bar{F} f_t - \Bigg\{\bar{I} i_{t-1} + \bar{F} f_t \\
&+ \bar{S}\left[\frac{\tau_i}{\tau_i+\tau_T+\tau_v} i_{t-1} + \frac{\tau_T+\tau_v}{\tau_i+\tau_T+\tau_v} i_t^* + \frac{1}{N}\left(\frac{\tau_T+\tau_v}{\tau_i+\tau_T+\tau_v}\right)\sum_{n=1}^{N}\varepsilon_t^n - \frac{1}{N}\left(\frac{\tau_v}{\tau_i+\tau_T+\tau_v}\right)\frac{\pi_e}{\pi_s}\sum_{n=1}^{N} e_t^n\right]\Bigg\} \\
=& \bar{S}\left[\frac{\tau_i}{\tau_i+\tau_T+\tau_v} i_t^* - \frac{\tau_i}{\tau_i+\tau_T+\tau_v} i_{t-1} + \varepsilon_t^B - \frac{1}{N}\left(\frac{\tau_T+\tau_v}{\tau_i+\tau_T+\tau_v}\right)\sum_{n=1}^{N}\varepsilon_t^n + \frac{1}{N}\left(\frac{\tau_v}{\tau_i+\tau_T+\tau_v}\right)\frac{\pi_e}{\pi_s}\sum_{n=1}^{N} e_t^n\right].
\end{aligned}
\tag{B.52}
$$

Finally, the variance of the adjustment of the short term yield is given by:

$$
\mathbb{V}\left[i_t - i_t^{ST}\right] = \bar{S}^2\left[\frac{\tau_i}{(\tau_i+\tau_T+\tau_v)^2} + \frac{1}{\tau_B} + \frac{1}{N}\left(\frac{(\tau_T+\tau_v)^2}{(\tau_i+\tau_T+\tau_v)^2\tau_T} + \left(\frac{\pi_e}{\pi_s}\right)^2\frac{\tau_v^2}{(\tau_i+\tau_T+\tau_v)^2\tau_e}\right)\right].
\tag{B.53}
$$

Regarding the other two models, the variance of the adjustment of the short term yield in the *Alternative 2* model is also given by equation (B.53), since the reaction function conjecture and the optimization problem of the traders are identical to those of the *Benchmark* model. This will also be the case for the *Alternative 1* model, in spite of a different reaction function conjecture. To see that, let $i_t^{ST,Alt1}$ denote the short term yield before the announcement of the *Alternative 1* model. It is given by:

$$
\begin{aligned}
i_t^{ST,Alt1} =& \frac{1}{N}\sum_{n=1}^{N}\mathbb{E}\left[i_t|s_t^n, e_t^n, \hat{f}_t^n\right] \\
=& \frac{1}{N}\sum_{n=1}^{N}\left[\bar{I}i_{t-1} + \bar{S}\left(\frac{\tau_i}{\tau_i+\tau_T+\tau_v}i_{t-1} + \frac{\tau_T}{\tau_i+\tau_T+\tau_v}s_t^n + \frac{\tau_v}{\tau_i+\tau_T+\tau_v}\hat{f}_t^n\right)\right] \\
=& \bar{I}i_{t-1} \\
&+ \bar{S}\left[\frac{\tau_i}{\tau_i+\tau_T+\tau_v}i_{t-1} + \frac{\tau_T+\tau_v}{\tau_i+\tau_T+\tau_v}i_t^* + \frac{1}{N}\left(\frac{\tau_T+\tau_v}{\tau_i+\tau_T+\tau_v}\right)\sum_{n=1}^{N}\varepsilon_t^n - \frac{1}{N}\left(\frac{\tau_v}{\tau_i+\tau_T+\tau_v}\right)\frac{\pi_e}{\pi_s}\sum_{n=1}^{N}e_t^n\right].
\end{aligned}
$$

So the yield adjustment following the monetary policy announcement is given by:

$$
\begin{aligned}
i_t - i_t^{ST,Alt1} = \bar{S}\Bigg[&\frac{\tau_i}{\tau_i+\tau_T+\tau_v}i_t^* - \frac{\tau_i}{\tau_i+\tau_T+\tau_v}i_{t-1} + \varepsilon_t^B - \frac{1}{N}\left(\frac{\tau_T+\tau_v}{\tau_i+\tau_T+\tau_v}\right)\sum_{n=1}^{N}\varepsilon_t^n \\
&+ \frac{1}{N}\left(\frac{\tau_v}{\tau_i+\tau_T+\tau_v}\right)\frac{\pi_e}{\pi_s}\sum_{n=1}^{N}e_t^n\Bigg],
\end{aligned}
$$

which is identical to equation (B.52).

Finally, the surprise is given by the difference between the federal funds rate i_t and market expectations given by f_t:

$$
\begin{aligned}
i_t - f_t =& \bar{I}i_{t-1} + \bar{S}s_t^B + \bar{F}f_t - f_t \\
=& \bar{I}i_{t-1} + \bar{S}s_t^B - \left(1-\bar{F}\right)\left[\frac{\pi_i}{\pi_f}i_{t-1} + \frac{\pi_s}{\pi_f}\frac{\sum_{n=1}^{N}s_t^n}{N} - \frac{\pi_e}{\pi_f}\frac{\sum_{n=1}^{N}e_t^n}{N}\right].
\end{aligned}
\tag{B.54}
$$

And so the variance is given by:

$$
\mathbb{V}\left[i_t - f_t\right] = \left[\bar{S} - \left(1-\bar{F}\right)\frac{\pi_s}{\pi_f}\right]^2\frac{1}{\tau_i} + \frac{\bar{S}^2}{\tau_B} + \left[\left(1-\bar{F}\right)\frac{\pi_s}{\pi_f}\right]^2\frac{1}{N\tau_T} + \left[\left(1-\bar{F}\right)\frac{\pi_e}{\pi_f}\right]^2\frac{1}{N\tau_e}. \tag{B.55}
$$

Since the conjecture about the central bank reaction function is identical in the *Alternative 2* and in the *Benchmark* model, the surprise in the former model will also be given by equation (B.55). In the *Alternative 1* model, however, the conjecture is different ($F = 0$), and it is easy to show that the surprise is given by:

$$
\mathbb{V}\left[i_t - f_t\right] = \left(\bar{S} - \frac{\pi_s}{\pi_f}\right)^2\frac{1}{\tau_i} + \frac{\bar{S}^2}{\tau_B} + \left(\frac{\pi_s}{\pi_f}\right)^2\frac{1}{N\tau_T} + \left(\frac{\pi_e}{\pi_f}\right)^2\frac{1}{N\tau_e}. \tag{B.56}
$$

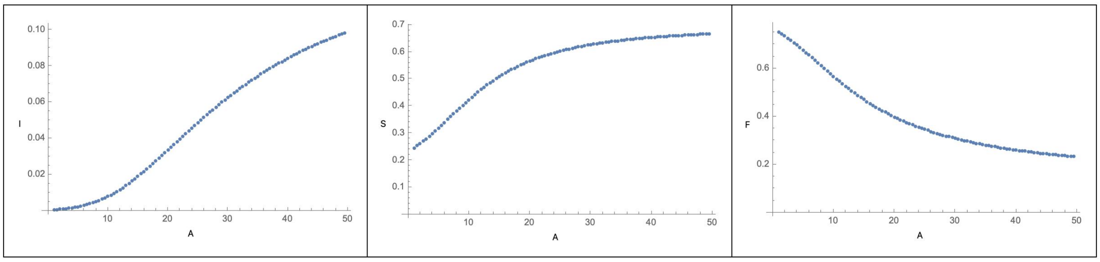
□

B.2 Comparative Statics Plots

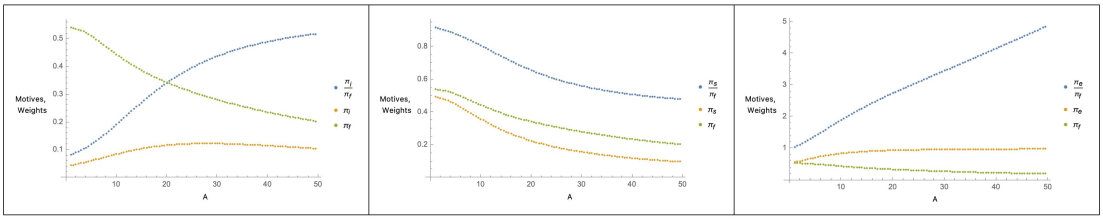
B.2.1 Comparative Statics - Benchmark Model

Figure B.2: **Comparative statics for the Benchmark Model with respect to** A**.**
The baseline parameters used for the analysis are $\{\tau_B \to 25, \tau_T \to 5, A \to x, \tau_e \to 5, \tau_i \to 5, N \to 25, \theta \to 0.2\}$; Panel (a) presents the dynamics of the variables related to the central bank's behavior, i.e. the weights I (left), S (center), and F (right); Panel (b) presents traders' trading motives, i.e. π_i (left), π_s (center), and π_e (right), as well as their relative weight with respect to π_f; finally, Panel (c) presents some variables which are relevant for the equilibrium dynamics, namely τ_v, the precision of the *market signal* received by traders (left), the price impact λ (center), and the second order condition which must be superior to zero (right).

(a) Weights of the Central Bank's Reaction Function



(b) Traders' Trading Motives



(c) Equilibrium Variables

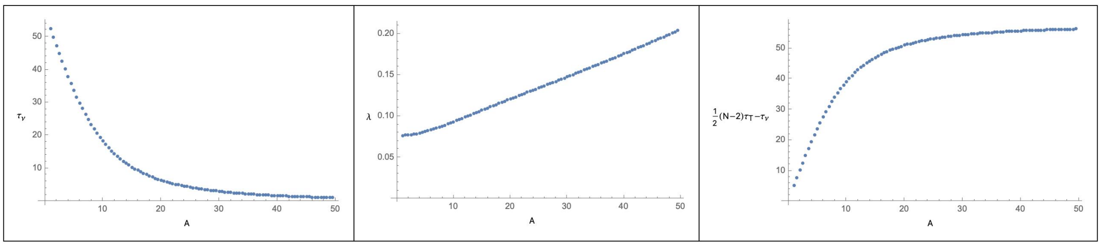
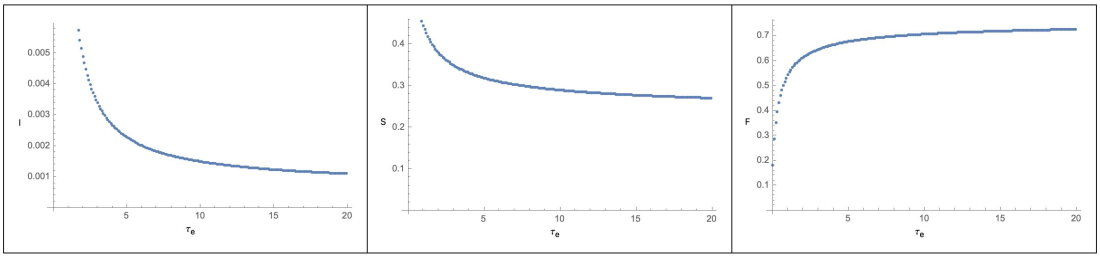
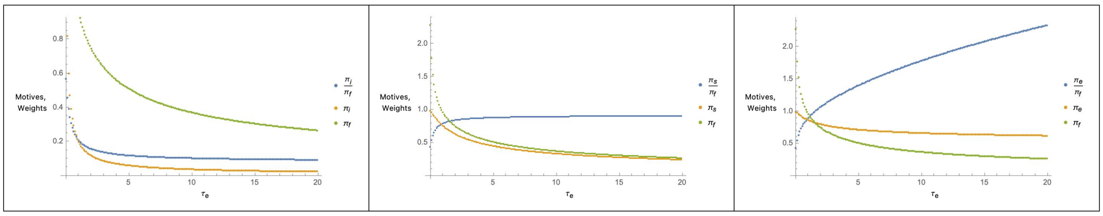


Figure B.3: **Comparative statics for the Benchmark Model with respect to τ_e**
The baseline parameters used for the analysis are $\{\tau_B \to 25, \tau_T \to 5, A \to 5, \tau_e \to x, \tau_i \to 5, N \to 25, \theta \to 0.2\}$; Panel (a) presents the dynamics of the variables related to the central bank's behavior, i.e. the weights I (left), S (center), and F (right); Panel (b) presents traders' trading motives, i.e. π_i (left), π_s (center), and π_e (right), as well as their relative weight with respect to π_f; finally, Panel (c) presents some variables which are relevant for the equilibrium dynamics, namely τ_v, the precision of the *market signal* received by traders (left), the price impact λ (center), and the second order condition which must be superior to zero (right).

(a) Weights of the Central Bank's Reaction Function



(b) Traders' Trading Motives



(c) Equilibrium Variables

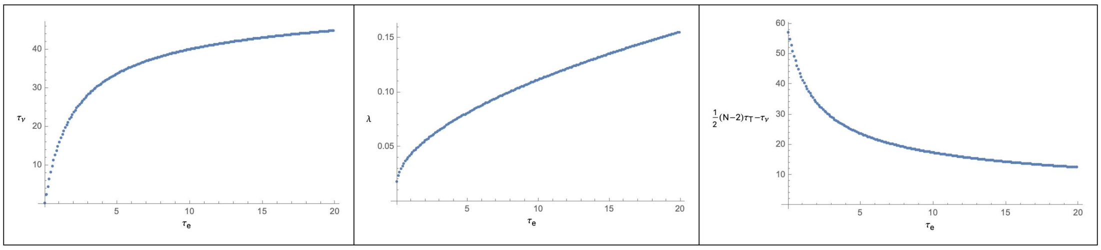
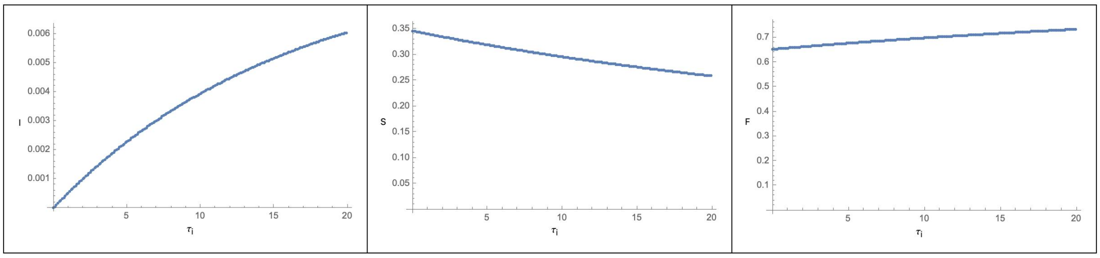
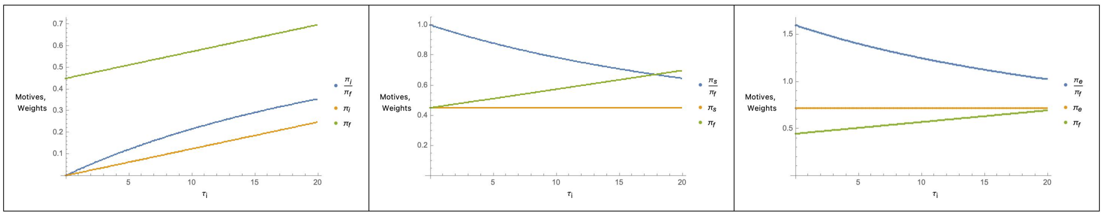


Figure B.4: **Comparative statics for the Benchmark Model with respect to τ_i.**
The baseline parameters used for the analysis are $\{\tau_B \to 25, \tau_T \to 5, A \to 5, \tau_e \to 5, \tau_i \to x, N \to 25, \theta \to 0.2\}$; Panel (a) presents the dynamics of the variables related to the central bank's behavior, i.e. the weights I (left), S (center), and F (right); Panel (b) presents traders' trading motives, i.e. π_i (left), π_s (center), and π_e (right), as well as their relative weight with respect to π_f; finally, Panel (c) presents some variables which are relevant for the equilibrium dynamics, namely τ_V, the precision of the *market signal* received by traders (left), the price impact λ (center), and the second order condition which must be superior to zero (right).

(a) Weights of the Central Bank's Reaction Function



(b) Traders' Trading Motives



(c) Equilibrium Variables

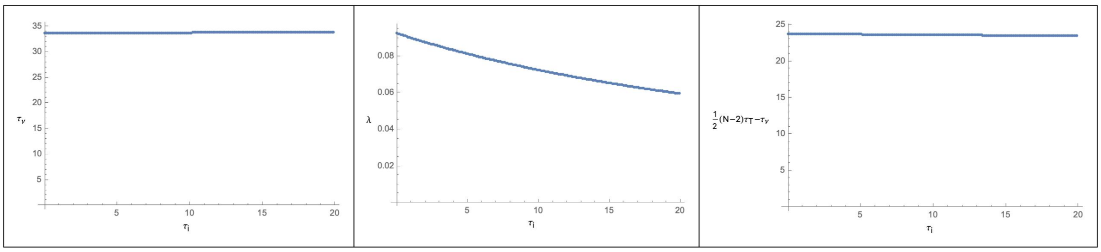
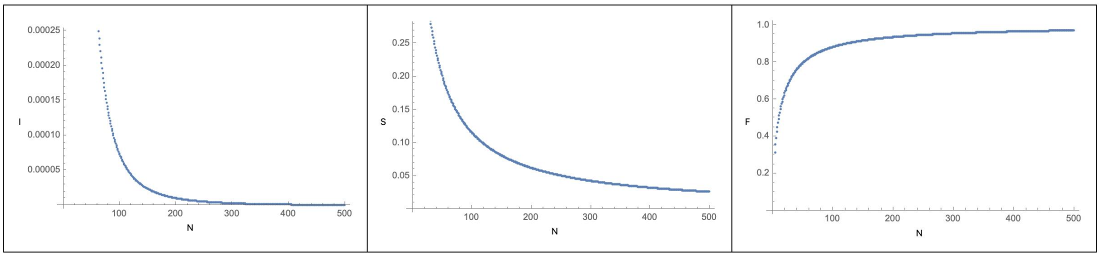
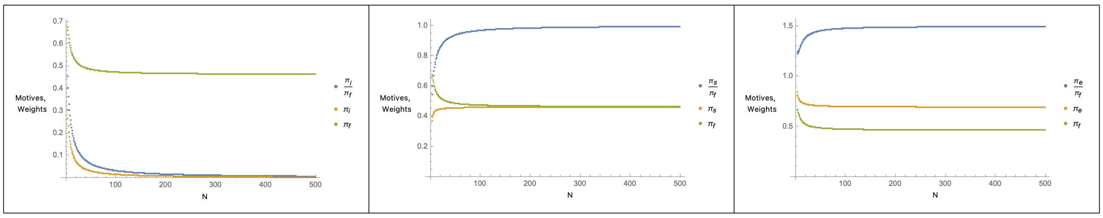


Figure B.5: **Comparative statics for the Benchmark Model with respect to N.**
The baseline parameters used for the analysis are $\{\tau_B \to 25, \tau_T \to 5, A \to 5, \tau_e \to 5, \tau_i \to 5, N \to x, \theta \to 0.2\}$; Panel (a) presents the dynamics of the variables related to the central bank's behavior, i.e. the weights I (left), S (center), and F (right); Panel (b) presents traders' trading motives, i.e. π_i (left), π_s (center), and π_e (right), as well as their relative weight with respect to π_f; finally, Panel (c) presents some variables which are relevant for the equilibrium dynamics, namely τ_v, the precision of the *market signal* received by traders (left), the price impact λ (center), and the second order condition which must be superior to zero (right).

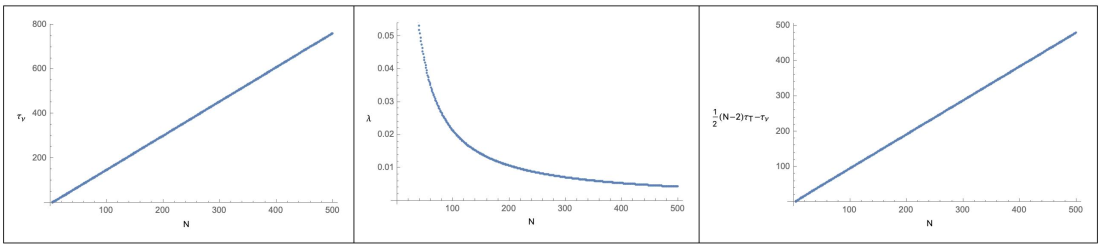
(a) Weights of the Central Bank's Reaction Function



(b) Traders' Trading Motives



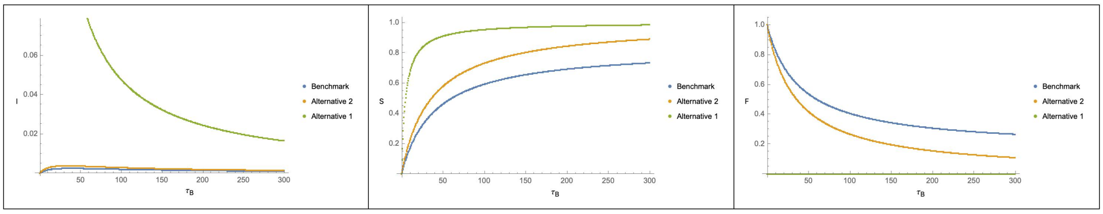
(c) Equilibrium Variables



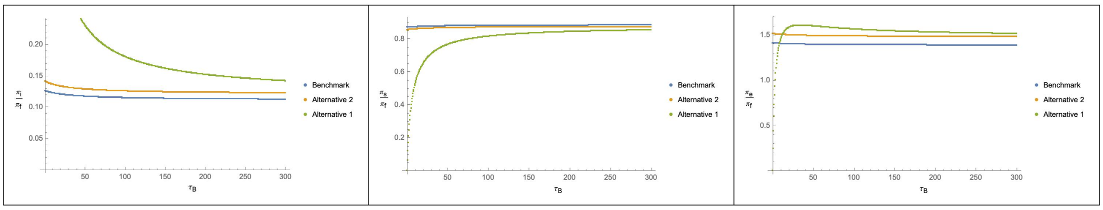
B.2.2 Comparative Statics - 3 Models

Figure B.6: **Comparative statics for the three models with respect to τ_B.**
The baseline parameters used for the analysis are $\{\tau_B \to x, \tau_T \to 1, A \to 5, \tau_e \to 5, \tau_i \to 5, N \to 25, \theta \to 0.2\}$. The blue line represents the *Benchmark* model, i.e. a model where $\theta > 0$ and $f_t \in \mathscr{F}_t^B$; The yellow line represents the *Alternative 2* model, where $\theta = 0$ and $f_t \in \mathscr{F}_t^B$; The green line represents the *Alternative 1* model, where $\theta = 0$ and $f_t \notin \mathscr{F}_t^B$. Panel (a) presents the dynamics of the variables related to the central bank's behavior, i.e. the weights I (left), S (center), and F (right); Panel (b) presents traders' trading motives with respect to π_f i.e. $\frac{\pi_i}{\pi_f}$ (left), $\frac{\pi_s}{\pi_f}$ (center), and $\frac{\pi_e}{\pi_f}$ (right); Panel (c) presents some variables which are relevant for the equilibrium dynamics, namely τ_v, the precision of the *market signal* received by traders (left), the price impact λ (center), and the second order condition which must be superior to zero (right); Finally, Panel (d) presents the variance of the surprise ($\mathbb{V}[i_t - f_t]$, left plot), of the short term bond yield ($\mathbb{V}[i_t - i_t^{ST}]$, center plot), and of the long term bond yield ($\mathbb{V}[i_{post}^{LT} - i_t^{LT}]$, right plot), following monetary policy announcements.

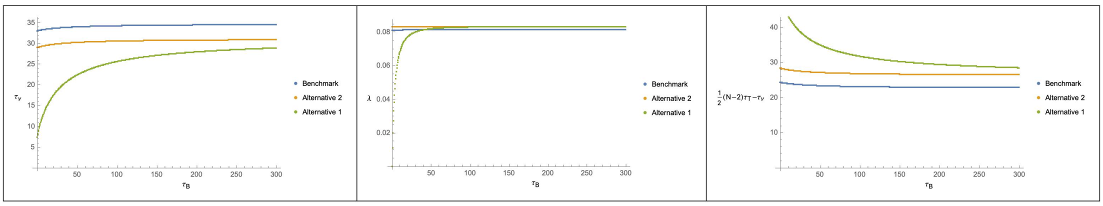
(a) Weights of the Central Bank's Reaction Function



(b) Traders' Trading Motives



(c) Equilibrium Variables



(d) Asset Prices Adjustment

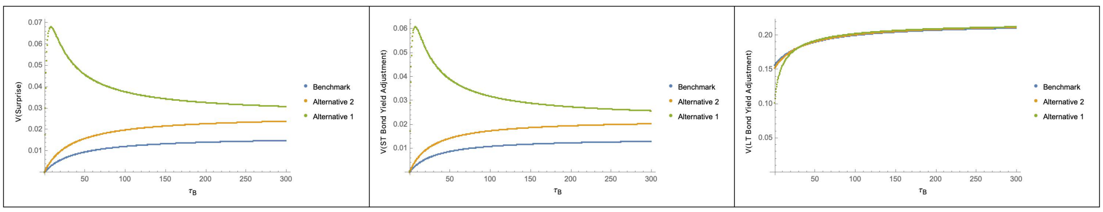
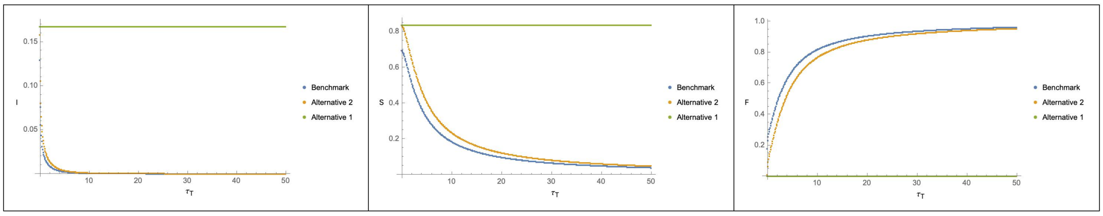
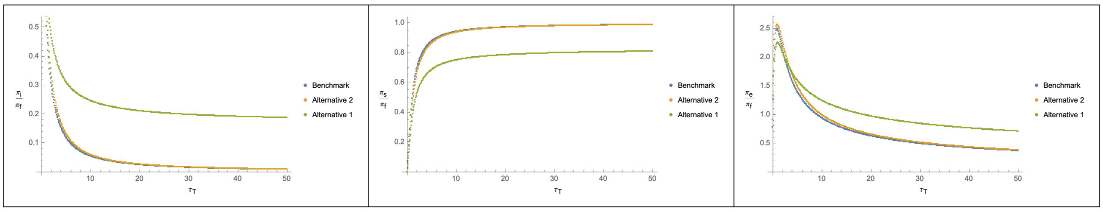


Figure B.7: **Comparative statics for the three models with respect to τ_T.**
The baseline parameters used for the analysis are $\{\tau_B \to 25, \tau_T \to x, A \to 5, \tau_e \to 5, \tau_i \to 5, N \to 25, \theta \to 0.2\}$. The blue line represents the *Benchmark* model, i.e. a model where $\theta > 0$ and $f_t \in \mathscr{F}_t^B$; The yellow line represents the *Alternative 2* model, where $\theta = 0$ and $f_t \in \mathscr{F}_t^B$; The green line represents the *Alternative 1* model, where $\theta = 0$ and $f_t \notin \mathscr{F}_t^B$. Panel (a) presents the dynamics of the variables related to the central bank's behavior, i.e. the weights I (left), S (center), and F (right); Panel (b) presents traders' trading motives with respect to π_f i.e. $\frac{\pi_i}{\pi_f}$ (left), $\frac{\pi_s}{\pi_f}$ (center), and $\frac{\pi_e}{\pi_f}$ (right); Panel (c) presents some variables which are relevant for the equilibrium dynamics, namely τ_v, the precision of the *market signal* received by traders (left), the price impact λ (center), and the second order condition which must be superior to zero (right); Finally, Panel (d) presents the variance of the surprise ($\mathbb{V}[i_t - f_t]$, left plot), of the short term bond yield ($\mathbb{V}[i_t - i_t^{ST}]$, center plot), and of the long term bond yield ($\mathbb{V}[i_{post}^{LT} - i_t^{LT}]$, right plot), following monetary policy announcements.

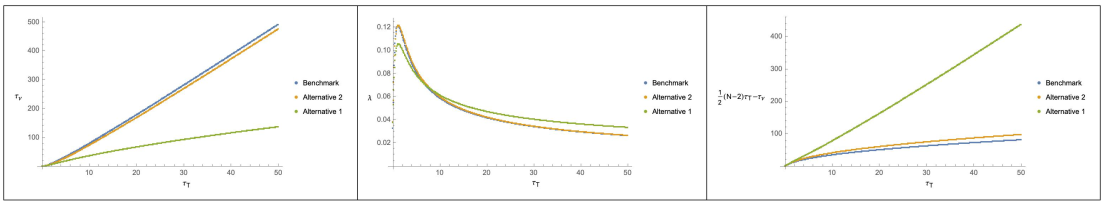
(a) Weights of the Central Bank's Reaction Function



(b) Traders' Trading Motives



(c) Equilibrium Variables



(d) Asset Prices Adjustment

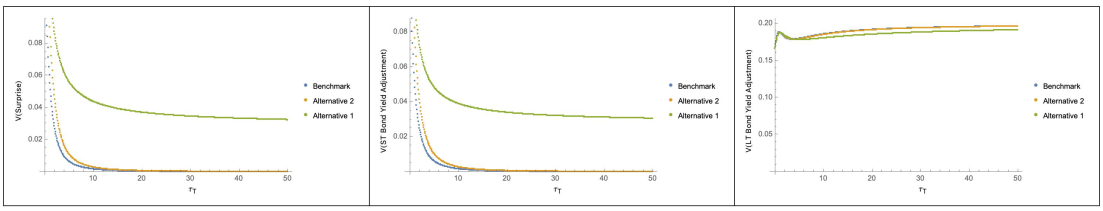
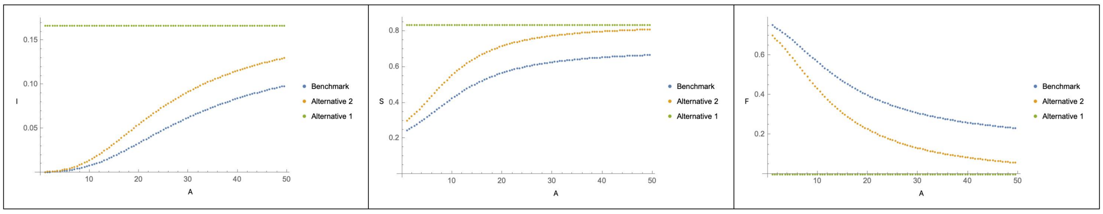
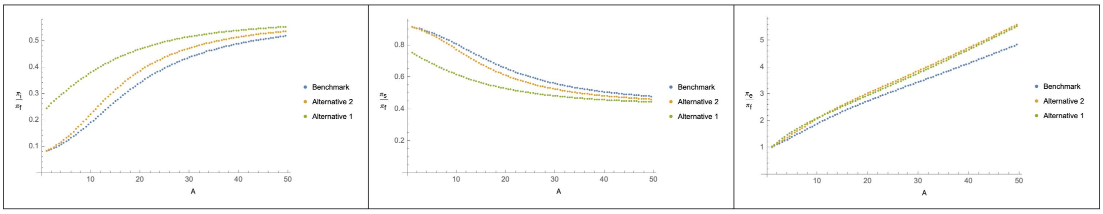


Figure B.8: **Comparative statics for the three models with respect to A.**
The baseline parameters used for the analysis are $\{\tau_B \to 25, \tau_T \to 5, A \to x, \tau_e \to 5, \tau_i \to 5, N \to 25, \theta \to 0.2\}$. The blue line represents the *Benchmark* model, i.e. a model where $\theta > 0$ and $f_t \in \mathscr{F}_t^B$; The yellow line represents the *Alternative 2* model, where $\theta = 0$ and $f_t \in \mathscr{F}_t^B$; The green line represents the *Alternative 1* model, where $\theta = 0$ and $f_t \notin \mathscr{F}_t^B$. Panel (a) presents the dynamics of the variables related to the central bank's behavior, i.e. the weights I (left), S (center), and F (right); Panel (b) presents traders' trading motives with respect to π_f i.e. $\frac{\pi_i}{\pi_f}$ (left), $\frac{\pi_s}{\pi_f}$ (center), and $\frac{\pi_e}{\pi_f}$ (right); Panel (c) presents some variables which are relevant for the equilibrium dynamics, namely τ_v, the precision of the *market signal* received by traders (left), the price impact λ (center), and the second order condition which must be superior to zero (right); Finally, Panel (d) presents the variance of the surprise ($\mathbb{V}[i_t - f_t]$, left plot), of the short term bond yield ($\mathbb{V}[i_t - i_t^{ST}]$, center plot), and of the long term bond yield ($\mathbb{V}[i_{post}^{LT} - i_t^{LT}]$, right plot), following monetary policy announcements.

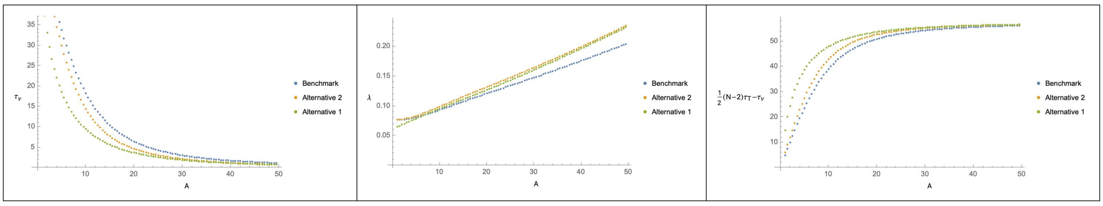
(a) Weights of the Central Bank's Reaction Function



(b) Traders' Trading Motives



(c) Equilibrium Variables



(d) Asset Prices Adjustment

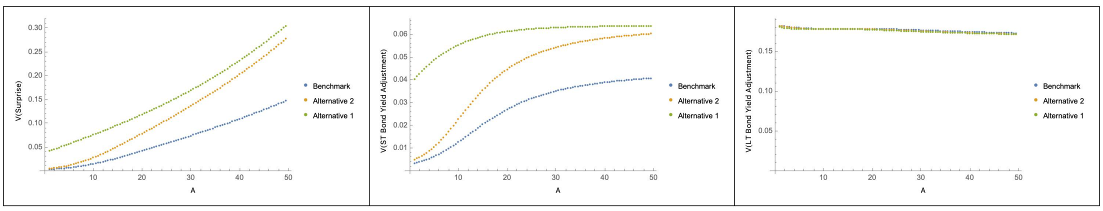
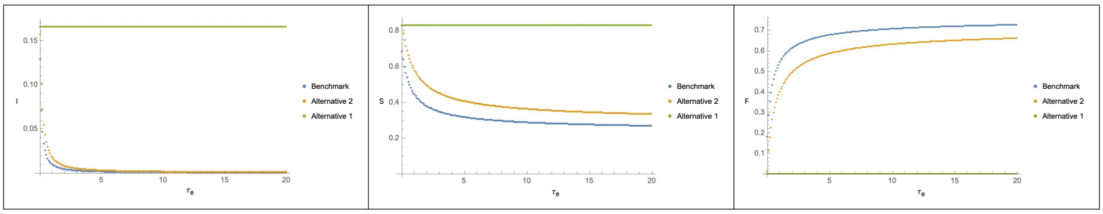
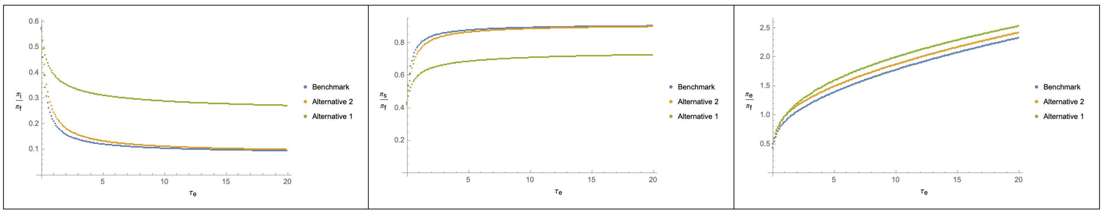


Figure B.9: **Comparative statics for the three models with respect to τ_e.**
The baseline parameters used for the analysis are $\{\tau_B \to 25, \tau_T \to 5, A \to 5, \tau_e \to x, \tau_i \to 5, N \to 25, \theta \to 0.2\}$. The blue line represents the *Benchmark* model, i.e. a model where $\theta > 0$ and $f_t \in \mathscr{F}_t^B$; The yellow line represents the *Alternative 2* model, where $\theta = 0$ and $f_t \in \mathscr{F}_t^B$; The green line represents the *Alternative 1* model, where $\theta = 0$ and $f_t \notin \mathscr{F}_t^B$. Panel (a) presents the dynamics of the variables related to the central bank's behavior, i.e. the weights I (left), S (center), and F (right); Panel (b) presents traders' trading motives with respect to π_f i.e. $\frac{\pi_i}{\pi_f}$ (left), $\frac{\pi_s}{\pi_f}$ (center), and $\frac{\pi_e}{\pi_f}$ (right); Panel (c) presents some variables which are relevant for the equilibrium dynamics, namely τ_v, the precision of the *market signal* received by traders (left), the price impact λ (center), and the second order condition which must be superior to zero (right); Finally, Panel (d) presents the variance of the surprise ($\mathbb{V}[i_t - f_t]$, left plot), of the short term bond yield ($\mathbb{V}[i_t - i_t^{ST}]$, center plot), and of the long term bond yield ($\mathbb{V}[i_{post}^{LT} - i_t^{LT}]$, right plot), following monetary policy announcements.

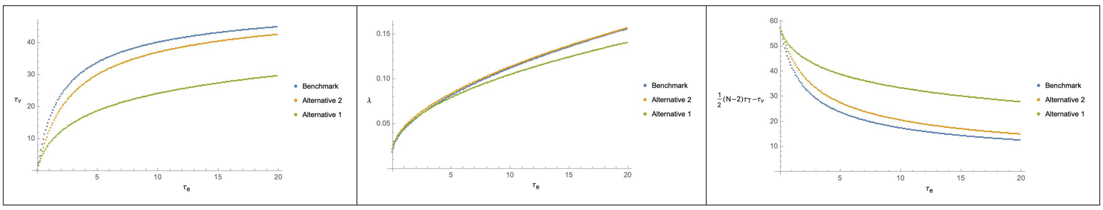
(a) Weights of the Central Bank's Reaction Function



(b) Traders' Trading Motives



(c) Equilibrium Variables



(d) Asset Prices Adjustment

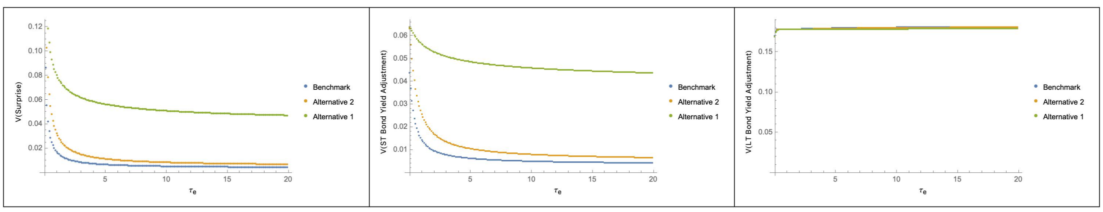
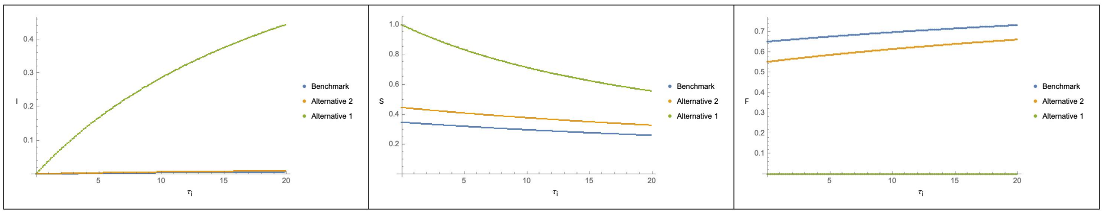
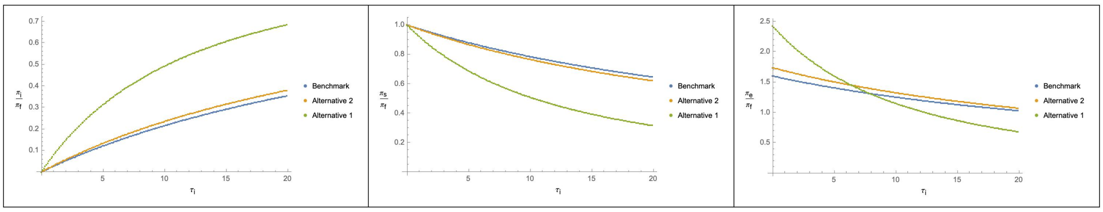


Figure B.10: **Comparative statics for the three models with respect to τ_i.**
The baseline parameters used for the analysis are $\{\tau_B \to 25, \tau_T \to 5, A \to 5, \tau_e \to 5, \tau_i \to x, N \to 25, \theta \to 0.2\}$. The blue line represents the *Benchmark* model, i.e. a model where $\theta > 0$ and $f_t \in \mathscr{F}_t^B$; The yellow line represents the *Alternative 2* model, where $\theta = 0$ and $f_t \in \mathscr{F}_t^B$; The green line represents the *Alternative 1* model, where $\theta = 0$ and $f_t \notin \mathscr{F}_t^B$. Panel (a) presents the dynamics of the variables related to the central bank's behavior, i.e. the weights I (left), S (center), and F (right); Panel (b) presents traders' trading motives with respect to π_f i.e. $\frac{\pi_i}{\pi_f}$ (left), $\frac{\pi_s}{\pi_f}$ (center), and $\frac{\pi_e}{\pi_f}$ (right); Panel (c) presents some variables which are relevant for the equilibrium dynamics, namely τ_v, the precision of the *market signal* received by traders (left), the price impact λ (center), and the second order condition which must be superior to zero (right); Finally, Panel (d) presents the variance of the surprise ($\mathbb{V}[i_t - f_t]$, left plot), of the short term bond yield ($\mathbb{V}[i_t - i_t^{ST}]$, center plot), and of the long term bond yield ($\mathbb{V}[i_{post}^{LT} - i_t^{LT}]$, right plot), following monetary policy announcements.

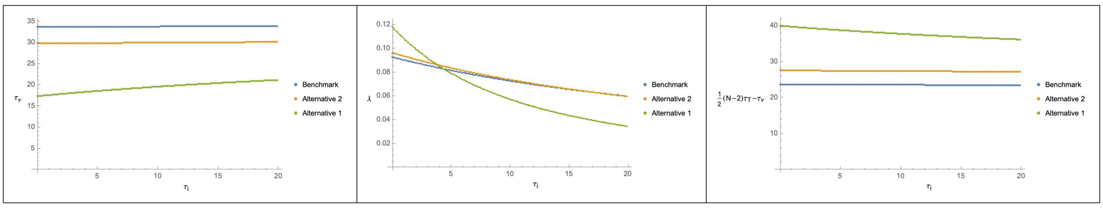
(a) Weights of the Central Bank's Reaction Function



(b) Traders' Trading Motives



(c) Equilibrium Variables



(d) Asset Prices Adjustment

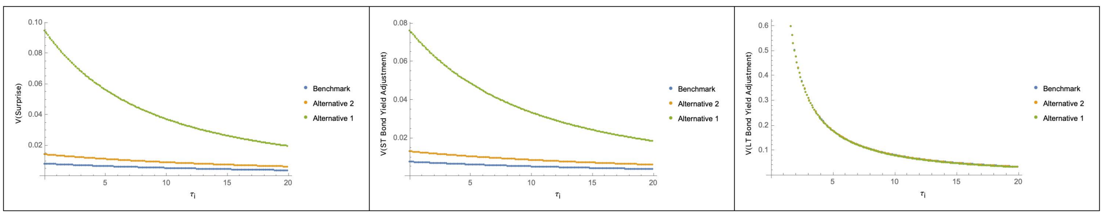
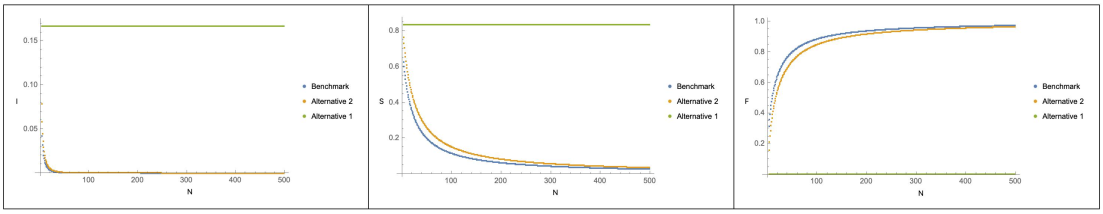
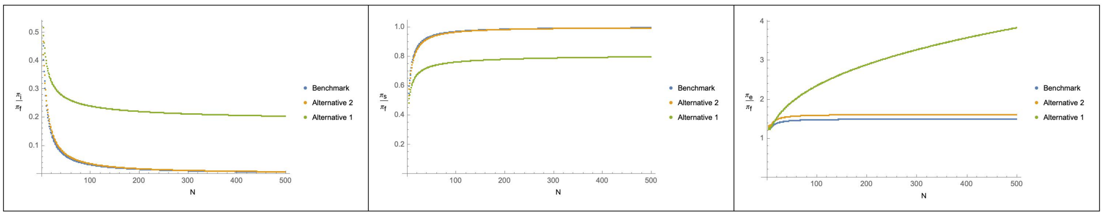


Figure B.11: **Comparative statics for the three models with respect to N.**
The baseline parameters used for the analysis are $\{\tau_B \to 25, \tau_T \to 5, A \to 5, \tau_e \to 5, \tau_i \to 5, N \to x, \theta \to 0.2\}$. The blue line represents the *Benchmark* model, i.e. a model where $\theta > 0$ and $f_t \in \mathscr{F}_t^B$; The yellow line represents the *Alternative 2* model, where $\theta = 0$ and $f_t \in \mathscr{F}_t^B$; The green line represents the *Alternative 1* model, where $\theta = 0$ and $f_t \notin \mathscr{F}_t^B$. Panel (a) presents the dynamics of the variables related to the central bank's behavior, i.e. the weights I (left), S (center), and F (right); Panel (b) presents traders' trading motives with respect to π_f i.e. $\frac{\pi_i}{\pi_f}$ (left), $\frac{\pi_s}{\pi_f}$ (center), and $\frac{\pi_e}{\pi_f}$ (right); Panel (c) presents some variables which are relevant for the equilibrium dynamics, namely τ_v, the precision of the *market signal* received by traders (left), the price impact λ (center), and the second order condition which must be superior to zero (right); Finally, Panel (d) presents the variance of the surprise ($\mathbb{V}[i_t - f_t]$, left plot), of the short term bond yield ($\mathbb{V}[i_t - i_t^{ST}]$, center plot), and of the long term bond yield ($\mathbb{V}[i_{post}^{LT} - i_t^{LT}]$, right plot), following monetary policy announcements.

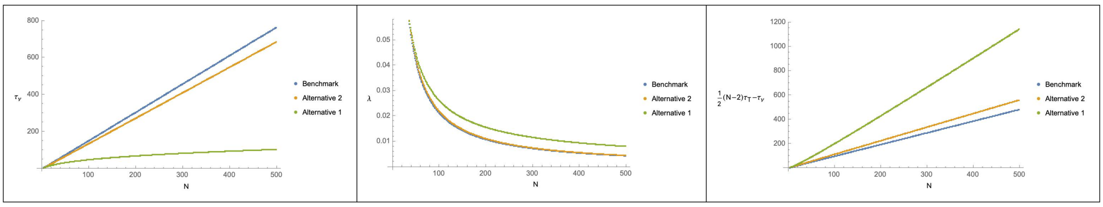
(a) Weights of the Central Bank's Reaction Function



(b) Traders' Trading Motives



(c) Equilibrium Variables



(d) Asset Prices Adjustment

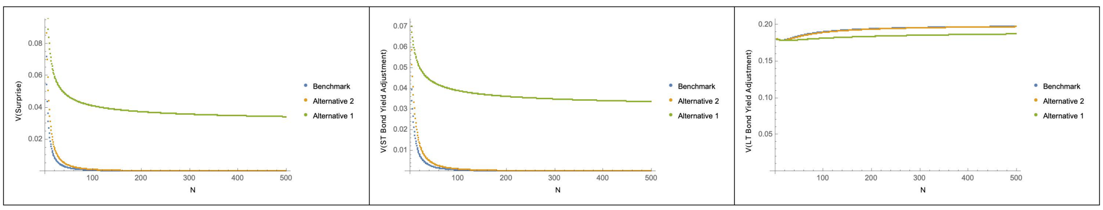
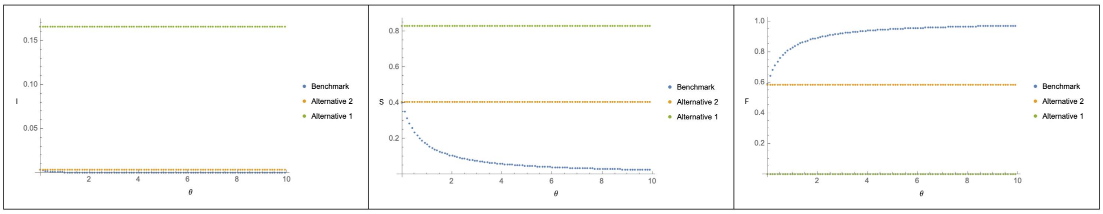
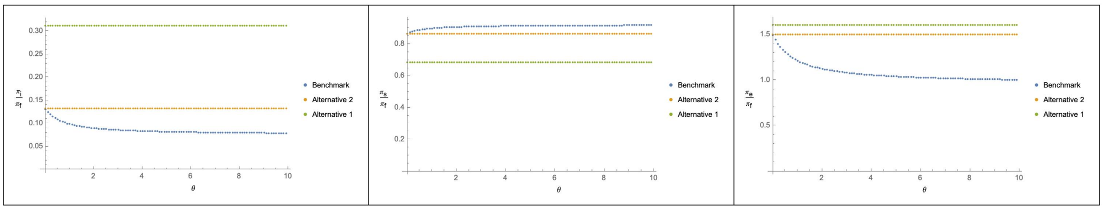


Figure B.12: **Comparative statics for the three models with respect to θ.**
The baseline parameters used for the analysis are $\{\tau_B \to 25, \tau_T \to 5, A \to 5, \tau_e \to 5, \tau_i \to 5, N \to 25, \theta \to x\}$. The blue line represents the *Benchmark* model, i.e. a model where $\theta > 0$ and $f_t \in \mathscr{F}_t^B$; The yellow line represents the *Alternative 2* model, where $\theta = 0$ and $f_t \in \mathscr{F}_t^B$; The green line represents the *Alternative 1* model, where $\theta = 0$ and $f_t \notin \mathscr{F}_t^B$. Panel (a) presents the dynamics of the variables related to the central bank's behavior, i.e. the weights I (left), S (center), and F (right); Panel (b) presents traders' trading motives with respect to π_f i.e. $\frac{\pi_i}{\pi_f}$ (left), $\frac{\pi_s}{\pi_f}$ (center), and $\frac{\pi_e}{\pi_f}$ (right); Panel (c) presents some variables which are relevant for the equilibrium dynamics, namely τ_v, the precision of the *market signal* received by traders (left), the price impact λ (center), and the second order condition which must be superior to zero (right); Finally, Panel (d) presents the variance of the surprise ($\mathbb{V}[i_t - f_t]$, left plot), of the short term bond yield ($\mathbb{V}[i_t - i_t^{ST}]$, center plot), and of the long term bond yield ($\mathbb{V}[i_{post}^{LT} - i_t^{LT}]$, right plot), following monetary policy announcements.

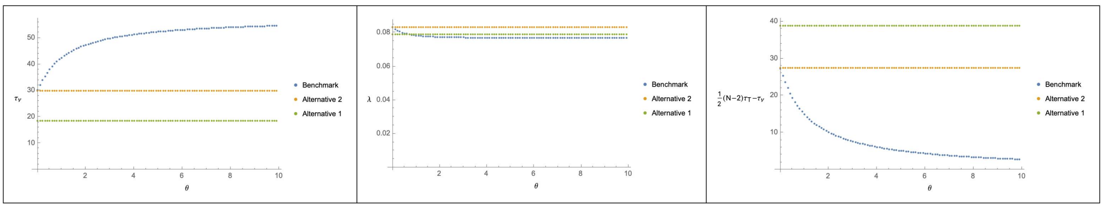
(a) Weights of the Central Bank's Reaction Function



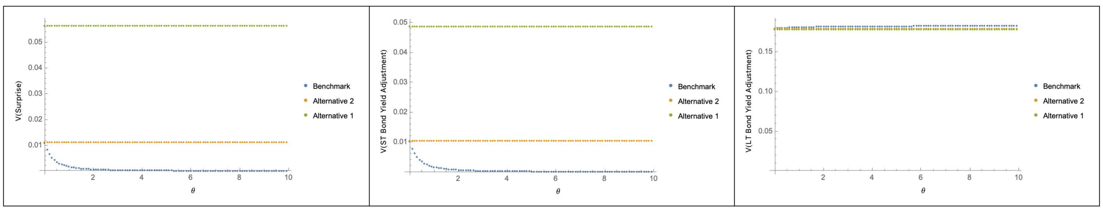
(b) Traders' Trading Motives



(c) Equilibrium Variables



(d) Asset Prices Adjustment



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