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Essays in central bank communication and bank lending conditions for firms

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Declaration

I declare that this thesis, submitted to Trinity College Dublin for the degree of Doctor in Philosophy (Ph.D.) has not been submitted as an exercise for a degree at this or any other university. All research contained herein is entirely my and my co-authors' work and all errors are our own. I also declare that I was the lead author for each of the co-authored chapters in the thesis. Views expressed in this dissertation are my own and my co-authors' and do not necessarily reflect those of the European Central Bank, the Central Bank of Ireland or the ESCB.

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Abstract

This dissertation is composed of three independent essays in the broad fields of central bank communication and the transmission of changes in bank lending conditions to firms. The first two essays examine the transmission of monetary policy through words, as central banks communicate with the public, while the third focuses on the more conventional channel of how changes in bank side credit conditions pass through to firms.

The first essay (published in the *European Journal of Political Economy*) examines the financial market impact of ECB monetary policy press conferences. Using natural language processing methods, in this paper I create two measures of the monetary policy tilt of the ECB for each press conference, indicating how hawkish or dovish the communication is. These two measures closely track interest rate expectations over the tightening and loosening cycle, and provide a particularly useful measure of monetary policy tilt at the zero lower bound. Using intraday data I investigate the impact of changes in the hawkishness or dovishness of the press conference that is free of the impact of the monetary policy decision itself. I show a non-negligible positive (negative) effect on stock prices of a more hawkish (dovish) tone. This indicates that the ECB releases some degree of private information during this press conference, with market participants internalising this communication as being indicative of good (bad) news regarding the future state of the economy rather than indication of future potential increases (decreases) in interest rates. The effect is stronger prior to the introduction of formal forward guidance in July 2013, suggesting that since this period ECB communication has been less surprising to markets, perhaps indicating evidence of more certainty in the future path of rates and perspectives on monetary policy between that date and the end point of the study in 2020.

The second essay builds on themes in the first essay by also examining topics from central bank communication, but this time turning to the temporal aspects of communication rather than the tone. It presents an additional explanation for why central bank communication moves markets beyond the simple release of private central bank communication. This paper posits that markets move due to an “information deficit” that is held by the public that the central bank helps to “fill in” using its communication. We posit that there are three channels through which this

information deficit can be filled in, namely through the central bank providing (i) an updated evaluation regarding the state of the economy (ii) a different projection from the current state to the likely future evolution of the economy and (iii) differences in how the policymaker responds to the assessed economic outlook. Using NLP methods we produce measures of the temporality of central bank communication and illustrate that both communication about the past and future significantly improve the ability to explain the news in yields around both the Federal Reserve and ECB policy statements compared to pure topic based measures. We surmise this is evidence of both the projection and evaluation channels at play. Moreover, to further illustrate the importance of the information deficit, we show that speeches generate greater news effects through moving yields when the information deficit is greater following the press conference, as measured using the similarity of speeches and responses to questions. From a policy perspective we suggest that these results make the communication of a single fixed reaction function very difficult even if it is highly desirable due to changes in the assessment of what is driving underlying changes.

The third essay examines a more conventional approach to assessing the impact of retail bank behaviour on the broader real economy by examining how changes in credit standards by individual banks feed through to firm outcomes. Using a novel dataset linking firm level data from the Survey on Access to Finance for Enterprises (SAFE) and bank level data from the Bank Lending Survey (BLS) we find that tighter credit standards decrease loan availability as reported by firms, increase the likelihood they report access to finance as the worst problem they are facing and decreases their investment activity. This effect fades when adding country-sector-time fixed effects, suggesting that this aggregate effect is more indicative of cyclical conditions, however the results become significant once interacting with firm-level demand as proxied by their reported change in need for bank loans. We find that results are asymmetric, with stronger effects for a tightening than an easing, while a more diversified array of funding sources insulates firms from changes in credit standards. This illustrates the importance of investigating both demand and supply side behaviour when investigating changes in credit standards and has implications for understanding the bank lending channel of monetary policy. We use these micro results to propose a new measure of demand adjusted credit standards that can be used to analyse broader credit dynamics.

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Chapter 1

Overview and Summary

This dissertation provides insights into some key questions that will help the reader to understand more the transmission of monetary policy through conventional and less conventional channels through three independent but broadly linked essays. The first essay explores how precisely ECB monetary policy communication during their press conferences moves financial markets, and we ask how precisely markets react to more hawkish or dovish communication. The second essay further builds on this topic of examining this “less conventional” channel of monetary policy by exploring why communication moves markets and explores the role of the temporality of news releases. The third essay explores a more conventional question and asks how precisely changes in bank credit standards transmits to firms and explores the role of interactions between demand and supply. This has implications for the understanding of the bank lending channel of monetary policy. Between the three essays the reader gains insight into core topics of interest over the last number of years in both the sphere of central banking and firm financing conditions. As such, there is a clear strand of both understanding what I denote as the “less conventional” channels of monetary policy in the first two essays and the “more conventional” channels of monetary policy that are evident in the third essay. All papers have a broad trend of attempting to understand either the movements in markets or changes in firm behaviour as a result of actions that fundamentally can be seen as having their roots in the implementation of monetary policy.

In more detail, the first essay (chapter 2 of this dissertation) which has been published as an independent single authored paper in the *European Journal of Political economy* as Parle (2022) is fundamentally aimed at examining the financial market

impact of the European Central Bank's monetary policy press conferences. This essay aims to examine the impact that changes in the monetary policy tilt, i.e. how hawkish or dovish the communicated stance of the ECB is in the press conference, has on financial markets. This in itself is a non-trivial question, as in one sense a more hawkish perspective may be indicative of higher interest rates in the future and thus should be deflating for stock markets if we view this from a conventional perspective. On the other hand, if the hawkish stance is indirectly indicative of a more bullish economic perspective, and news that the central banks' perspective on economic conditions is quite positive, then this would have a positive impact on financial markets. Exploring this question is of a high degree of interest from an economic perspective.

In exploring this question, this essay has two core contributions. The first contribution is on the measurement side. The essay introduces two measures of the monetary policy tilt of the ECB using text based approaches that can be viewed as complementary to each other. The first measure is purely dictionary based while the second measure combines a dynamic topic model with an adjustable dictionary of sentiment words to reflect the tone of the extracted topics. These measures closely track derived expectations of future monetary policy as measured through interest rate expectations. This is of particular interest during effective lower bound episodes, when interest rate based measures lose their power to measure the monetary policy tilt.

Alongside the measurement contribution, this essay provides insight into how the changes in the communicated monetary policy tilt move markets. Using an event study approach, I show that there is a positive (negative) relationship between stock market movements during the press conference and the hawkishness (dovishness) of the press conference. This is indicative of evidence that markets interpret such communication as indicative of a better (worse) economic sentiment rather than tighter (looser) monetary policy. It should be noted, however, that this effect disappears post the introduction of formal forward guidance in 2013, suggesting there is more certainty and consistent communication since then. The results of this paper have implications for the understanding of how central bank communication can move markets and thus can inform policymakers in drafting such communications.

The second essay, joint with David Byrne and Robert Goodhead (both Central Bank of Ireland) alongside Michael McMahon (University of Oxford) can be seen as being strongly related to the first and builds on the understanding of how

central bank communication moves markets. This paper is primarily concerned with understanding channels through which central bank communication can move markets over and beyond the standard understanding of the revelation of private central bank information and explores the role of the temporality of communication in moving markets. This paper also has a twofold contribution by introducing NLP driven measures of the temporality of monetary policy communication but also simultaneously linking this to a model of the transmission of information from central bank communication to the public.

This essay firstly asks exactly why central bank communication can move markets. In many models with asymmetric information, there is an assumption of superior central bank information being implicitly (or explicitly) revealed to markets during communication events. In this essay, we highlight the role of conjunctural economic assessment in how communication affects asset prices. This assessment role does not arise in standard models and captures the mapping from observed macroeconomic and financial data to the underlying state of the economy such as shocks that have hit the economy, their persistence and latent measures such as the output gap. We argue that there is a role for this conjunctural assessment in the provision of market news by central banks. We surmise that this can in part fill the “information deficit” between market participants and central banks. We propose a model that shows that market surprises can be broadly decomposed into four components: updated preferences of the central bank, reassessment in a forward looking sense (projection), reassessment in the form of a changed assessment of the current state of the economy (evaluation) and outright new information.

To shed light on this, we contribute to the measurement literature by proposing text based measures of the temporality of communication, i.e. how future or past oriented communication events are. By positing that the projection component of communication mainly relates to communication about the future and evaluation mainly relates to communication about the current state of the economy we show that both kinds of communication can move markets in a way beyond solely topic based measures for both the ECB and Federal Reserve. We complement these findings by developing a measure of the information deficit using the questions asked by journalists following monetary policy press conferences of the ECB, with this deficit containing a significant conjunctural assessment dimension. We show that questions following the monetary policy press conference play an important role in identifying information gaps, and this

is confirmed by the fact that speeches in the weeks following each press conference that are more closely related to the questions asked during the press conference move markets more. Moreover, these questions are not solely related to forward guidance and relate also to conjunctural assessment providing additional evidence for our results regarding the role of evaluation of economic conditions in moving markets.

The third essay (chapter 4), written jointly with Annalisa Ferrando and Sarah Holton (both ECB) explores the key question of how precisely changes in bank credit standards impact on firms. This has key implications for understanding the more conventional bank lending channel of monetary policy and how it precisely passes through to firm behaviour and their individual financing conditions. We particularly explore the role of interactions between demand and supply, while also exploring the role of having a more diversified funding base in insulating banks from supply side shocks.

This essay uses a unique dataset combining two of the ECB and European Commission's flagship survey, namely the Bank Lending Survey (BLS) and Survey on Access to Finance for Enterprises (SAFE). The first survey asks banks about changes in their lending behaviour over each quarter, while the second survey is more concerned with changes in firms financing conditions alongside their real outcomes. Using anonymised firm level data extracted from their returns and collected by Orbis, we manually match firms to BLS banks from free text entries about their banking relationships. This allows us to explore the implications of changes in supply side changes in credit standards implemented by each individual firms' banks on both their investment behaviour and financing conditions, which are both crucial items to understand the bank based transmission of monetary policy and implications of credit supply shocks. The linking of these surveys is in itself a contribution and allows for richer micro level analysis of firm outcomes at a more regular frequency than was previously possible if using annual accounts.

We find that relatively tighter credit standards decrease firms' perceived bank loan availability, lead firms to be more likely to report access to finance as the worst problem facing the firm and leads to lower investment. These effects are absorbed when adding country-sector-time fixed effects perhaps suggesting that the aggregate results are somewhat cyclical. This changes, however, when adding controls for demand as measured by changes in firms' need for bank loans. An interaction between this measure and bank credit standards is significant and of expected sign,

even in the most saturated specification, suggesting that it is essential to account for demand when analysing the pass through of supply side shocks. Moreover, we find that effects are asymmetric, with stronger responses to a tightening of credit standards than an easing, while firms with a more diversified array of financing sources are more insulated from any tightening effects impacting on loan availability, though there is little insulation for the impact on investment decisions. Beyond the micro results, this paper also has a measurement component, proposing a measure of “demand adjusted credit standards” that can illustrate how biting changes in credit standards are by adjusting for firm level demand.

On the whole, the three essays explore topics that are of interest in the fields of monetary policy and firm level credit conditions, with all essays having both an econometric contribution through either event studies or analysis of survey data but also adding to the measurement literature by creating measures of monetary policy tilt, the temporality of monetary policy communication and demand adjusted credit standards respectively. These essays contribute to both the “less conventional” and “more conventional” literature on monetary policy and invite the reader to consider some topics that have been central to banking discourse in recent years. Chapter 5 thus marries these concepts for a broad conclusion on their implications for the understanding of their central themes.

Chapter 2

The financial market impact of ECB monetary policy press conferences - a text based approach ¹

Abstract

Using natural language processing techniques I create two measures of the monetary policy tilt of the ECB, that outline the beliefs of the ECB on the current state of the economy and the outlook for growth and inflation. These measures closely track interest rate expectations over the tightening and loosening cycle, and can provide a useful measure of monetary policy tilt at the zero lower bound and contains information about the state of the economy. I exploit the time lag between the announcement of the monetary policy decision, and the ECB's monetary policy press conference to assess the immediate financial market impact of changes in communication within the press conference, free from the effects of the shock from the monetary policy decision. Consistent with the literature on the information channel of monetary policy, I find a non-negligible positive (negative) effect on stock prices of a more hawkish (dovish) tone in the press conference. This indicates that the ECB reveals "private information" during these press conferences, and that market participants internalise this as good (bad) news regarding the future state of the economy, rather than internalising a future potential increase (decrease) in interest rates. This effect is stronger prior to the introduction of formal forward guidance in July 2013, suggesting that since then ECB communication has been less surprising to markets in recent times.

¹This paper is single authored and has been published in this form in the European Journal of Political Economy as Parle (2022). I also thank participants at the TCD PhD Seminar Series, the Banca D'Italia Workshop on Big Data and Machine Learning Applications for Central Banks, the U Essex, UCD and Central Bank of Ireland workshop on central bank communication and the Central Bank of Ireland Seminar Series for useful comments

2.1 Introduction and Background

One of the key challenges in the study of central bank communication is the quantification of the textual content of information releases in such a way that they can be used to examine key economic questions regarding their impact. Understanding the informational content of monetary policy communication can help shed light on the idea of the “information channel” of monetary policy, that is that while communicating, central bankers can release “private information” regarding their assessment of current economic conditions to financial market participants, causing them to update their beliefs about the state of the economy, as well as regarding the future path of monetary policy.

This concept has become more important in a euro area context, as the European Central Bank (ECB) has increased its emphasis on using communication as a policy tool to convey information about the macroeconomy, future economic policy intentions or to better clarify the rationale behind policy decisions. An important method of communication is the ECB’s Governing Council press conference, held forty-five minutes after the announcement of its monetary policy decision in the form of a press release.² This press conference is followed closely by market participants and can influence greatly their overall economic assessment. Understanding the impact that the press conference can have on markets is therefore of high importance to both policymakers and analysts.

In this paper I present two methods of measuring the economic sentiment contained within the ECB monetary policy press conferences, which I denote as *Hawk-Dove Indices*. These measures proxy the “monetary policy tilt” of the ECB at a given time point. Positive (negative) expectations regarding economic conditions or higher (lower) inflation are associated with a more *hawkish* (*dovish*) sentiment, and hence a tendency towards a monetary policy tightening (loosening). The first measure relies on a dictionary approach, in line with a methodology first developed by Tadle (2019), while the second method takes a topic modelling approach, using the dynamic topic model algorithm of Blei and Lafferty (2006) to classify paragraphs with economic information, and a list of modifiers to assess whether they convey a hawkish or dovish

²Between 1999 and 2014, the ECB took monetary policy decisions every month. Since 2015 decisions are taken every six weeks.

tone. Both measures strongly track market implied measures of future interest rate changes and a survey based measure of economic conditions.

Next I contextualise how sentiment conveyed in press conferences can have an impact on stock markets through private market participants updating their beliefs regarding a central bank's views on the state of the economy. Within this context, I provide a mathematical decomposition of the ideas of conventional and information based monetary policy shocks in line with Jarocinski and Karadi (2018).

In this setup a more “hawkish” tone is associated with a belief that economic growth and inflation will be more pronounced in the future, and increases the likelihood of a monetary policy tightening, while a more “dovish” tone is associated with a more subdued belief about the future of the economy, and a higher likelihood of accommodative monetary policy. The impact of such communication on stock markets is ambiguous. In one sense, a more hawkish (dovish) tone should indicate a higher probability of a tightening (loosening) of monetary policy, suggesting that a more hawkish (dovish) tone should lead to a fall (increase) in stock prices owing to an increase (decrease) in the expected discount rate. On the other hand, if participants internalise this information as being indicative of better (worse) than expected economic conditions, the impact on stock markets of a more hawkish (dovish) tone may actually be positive (negative), owing to improvements in expected future dividends. This paper aims to shed light on which of these effects dominates.

Understanding the impact that monetary policy communication can have on stock markets is of a high degree of importance to policymakers, given that movements in stock markets can have a knock on effect on investment decisions and capital flows. Moreover, it is important to understand how monetary policy communication is in itself perceived, to help tailor future policy announcements to best steer the path of expectations.

To evaluate the immediate market impact, I explore patterns in intradaily data before and after the ECB press conference in the period spanning from 1999 to 2020. ECB press conferences are held forty-five minutes after the announcement of the monetary policy decision. Any asset price movements during the “press conference window” should therefore be free of most of the direct effect of explicit changes in headline interest rates. Using the novel dataset of Altavilla et al. (2019a), I measure market impact in an event study approach by exploring the relationship between these asset price changes and the sentiment as measured by the “Hawk-Dove Indices”.

The stock market reaction measured in this study is the immediate market response rather than longer term perseverance, and as such the impact of communication is only measured at this short-term margin. This is a trade off arising from the narrow nature of the event study window. While the results are likely free from the influence of external factors, I note that the long run impact of communication may be more ambiguous. Nonetheless, there is potential for short run fluctuations to pass through to longer term patterns and as such there are still policy implications for the manner in which communication can move markets.

I find that communication of a more hawkish (dovish) stance tends to increase (decrease) stock prices, suggesting the impact of communication on economic expectations dominates the impact of expected changes in interest rates. Specifically, a one standard deviation increase in hawkishness (dovishness) in each of the two Hawk-Dove Indices are associated with an increase of 0.155 and 0.140 percentage points in the Eurostoxx Index, and increases of 0.282 and 0.226 percentage points in the SX7E Index of bank stocks. This is suggestive of an economically significant short-run impact.

Moreover, the observed effect on stock markets was stronger prior to the introduction of formal forward guidance in 2013 by the ECB, suggesting market impacts have been more subdued since the ECB has implemented a more forward looking strategy to communicate information about the present state of the economy and likely future course of monetary policy. This suggests that since this more explicit steering of expectations, central bank private information revealed in the monetary policy press conference is less of a surprise to financial market participants. This is of interest in that it highlights how exactly the tone of each ECB press conference is interpreted by markets, and provides evidence that markets extract information regarding the ECB's private beliefs in relation to current macroeconomic conditions from the press conference itself, beyond information that is already available.

These results are robust to the use of alternative monetary policy sentiment dictionaries, and no direct effect of sentiment on expected interest rates is found, providing further proof that information effects mainly manifest themselves through updated economic expectations, rather than revised assessments of future monetary policy. The findings of this paper outline the transmission channels of monetary policy communication as a policy tool, and evidence for both the existence of an

“information channel” for monetary policy, and the direction in which it impacts markets.

This paper is structured as follows. Section 2.2 outlines the current state of the literature. Section 2.3 links this paper to the literature on the information channel of monetary policy and provides a mathematical decomposition of conventional and information based monetary policy shocks. Section 2.4 summarises the methodology used to measure informational content while Section 2.5 summarises the results obtained using these measures. Section 2.6 presents the event study approach and empirical findings of the paper and Section 2.7 concludes.

2.2 Motivation and Literature Review

The idea of central bank communication as a policy tool has recently come to the forefront of monetary policy literature. Interest in this topic has grown rapidly since the early 2000s (Hansen and McMahon 2016b). Central banks can use communication to steer market expectations of their future actions, and as such the content of speeches and policy releases is analysed with much interest. This paper explores not just the impact of ECB communication on markets, but elucidates the *mechanisms* through which communication can impact markets. The impact of differing informational content *within* the ECB monetary policy press conference on markets is shown, rather than the net effect of such communication.

The literature on communication and information effects to date can be broadly split into two main categories. The first involves indirect measures of the overall effect of central bank communication using high frequency data to explore information effects and the transmission of private central bank information. The second involves the direct measurement of the textual content of central bank policy releases using either manual classification or techniques from computational linguistics. By presenting novel measures of the informational content of ECB communication and examining the impact on financial markets in an event study approach motivated by a model of noisy information transmission, I contribute to both strands of literature.

The first strand of literature mainly focuses on examining fluctuations in high frequency data in and around monetary policy decisions to indirectly measure the impact of central bank communication on markets. Gürkaynak et al. (2005) show

that on Federal Reserve Board (Fed) monetary policy decision days, policy statements move markets in a manner which is beyond the amount expected by changes in the Fed policy rate. In particular, the authors show that Fed statements have an important impact on longer term treasury yields, highlighting the role played by clear communication in steering market expectations. This stylised fact is reflected in a number of other papers. Ehrmann and Fratzscher (2009) show that ECB press conferences have a larger impact on financial markets than corresponding policy decisions, while the “question and answer” component of the ECB press conference fulfils a clarification role during periods of high economic uncertainty, while the work of Goodhead and Kolb (2018) uses federal funds futures data to show the importance of “surprise communication” as a component of U.S. monetary policy.

The net effect of communication has also been studied for the euro area in the work of Whelan et al. (2017), Altavilla et al. (2019a) and Kersefischer (2019), by Nakamura and Steinsson (2018), Jarocinski and Karadi (2018) for the Fed and in a more general setting for 37 different central banks in the work of Born et al. (2014). Studies are unanimous in showing that communication shocks have an impact beyond that of standard monetary policy.

While it is clear that communication itself has an impact on markets, it is important to explore both the mechanisms through which communication can have an impact, and the impact of differing information within releases. Nakamura and Steinsson (2018) and Miranda-Agrippino and Ricco (2021) build a framework to study the “information channel” of monetary policy. Under such models, private market participants update their prior on the state of the economy as a result of the communication of private central bank information. Jarociński and Karadi (2020) expand on this concept by disentangling two channels through which an announcement can have an impact: through information on monetary policy, and the central bank’s assessment of the economic outlook. This idea has its roots in the early work of Ehrmann and Fratzscher (2007), in which the authors distinguish between statements that are about direct monetary policy actions and the economic outlook of the policymakers. Disentangling these effects can shed light on the different manners in which statements can move financial markets.

Beyond the examination of the net effect of communication, it is also possible to quantify the information contained within the text of a policy release. This may be identified using manual coding of statements, or automated approaches from the

field of computational linguistics. An example of the former approach can be seen in Ehrmann and Fratzscher (2009), where the authors manually classify real time newswire reports into categories to measure the relative importance of topics in each news release. The authors find the main topics that move markets are statements relating to inflation or interest rates. Similarly, Rosa and Verga (2007) measure the sentiment of ECB statements by hand coding each ECB Governing Council monetary policy statement. The authors show that their measure has predictive power for future ECB policy decisions. A similar manual approach is taken by Picault and Renault (2017).

In addition, the identification of the tone of central bank releases can be undertaken using pre-set dictionaries, or by developing unique word sets for central banking, rather than ex-post subjective measurement. Schmeling and Wagner (2019) use the Loughran-McDonald financial dictionary to measure the relative *negativity* of ECB press conferences. The authors find some evidence that a shift in tone to a more positive outlook increases stock prices. In the case of the Fed, Gorodnichenko et al. (2021) highlight a positive relationship between the tone of speakers and stock prices while Cannon (2015) finds a relationship between the tone of the Fed's minutes and contemporary measures of economic activity, evidence of some degree of an information effect. A number of other studies concentrate on the tone of economic and monetary policy releases such as Shapiro et al. (2017), Hubert and Labondance (2021) and Jegadeesh and Wu (2013).

Other papers have created specific measures tailored towards monetary policy. In a methodology followed by this paper, Tadle (2019) creates a word list of hawkish and dovish terms, and contextualises them using positive and negative modifiers to create a measure of the monetary policy tilt of a document, and whether it has a more hawkish or dovish tone to create a continuous index. The author exploits the difference between the sentiment of policy statements and the full minutes released two weeks later to measure "surprise" shifts in sentiment and the interpretation of these by markets. A similar method is used by Apel et al. (2022), where words related to the Fed's monetary policy stance are contextualised using positive and negative word lists that occur within a seven word window to create a measure of the Fed's communicated stance, while Bennani and Neuenkirch (2017) construct a measure for Eurosystem central banks using a list of hawkish and dovish terms. Another method adjacent to this is the KOF MPC indicator (Conrad and Lamla 2010), which

specifically focuses on statements made by the ECB regarding price stability. Non dictionary based measures of hawkishness and dovishness are developed by Tobback et al. (2017) using newspaper reports on ECB monetary policy and Lucca and Trebbi (2009) using “Google semantic scores” for Fed statements.

Alongside tone, an important factor to measure is the topical content of monetary policy releases. Topic models such as Latent Dirichlet Allocation (Blei et al. 2003) have begun to be increasingly used in the study of monetary policy communication. These models both identify latent topics that commonly occur within policy releases, but also classify bodies of text into these different topics in a probabilistic manner. This method has been used to show the importance of the topical content contained in the Bank of England Inflation Report (Hansen et al. 2019) and changes in informational content in Fed releases (Hansen and McMahon 2016a). Other studies apply these methods to Turkish (Iglesias et al. 2017) and Japanese (Oshima and Matsubayashi 2018) monetary policy statements.

This paper contributes to the literature along two key dimensions. First, I create two measures of the ECB’s monetary policy tilt, which I denote the *Hawk-Dove Indices*. The first follows the dictionary based approach of Tadde (2019). The second uses the Dynamic Topic Model algorithm of Blei and Lafferty (2006) to extract latent topics from the ECB press conferences. I identify a number of topics that reveal information related to the monetary policy tilt of the ECB, and using the classification of each paragraph into each of these categories I create a measure of the direction of the tilt using positive and negative “shift words”. These measures can be directly compared in terms of aim with the indices proposed by Apel et al. (2022) and Bennani and Neuenkirch (2017), who take slightly different approaches to a similar problem. In addition, contrasting results obtained using these measures and the measure of Conrad and Lamla (2010), who have an index more explicitly related to price stability can allow for a further exploration into the differences between broader economic commentary and price stability specific commentary.

Second, I use these measures in an event study setting to build on the existing models of Nakamura and Steinsson (2018), Miranda-Agrippino and Ricco (2021) and Jarocinski and Karadi (2018) and explore further the information channel of monetary policy. By using an event study approach and analysing how changes in stock market prices react to the relative “hawkishness” or “dovishness” of the press conference, I can discern whether (a) there is evidence of a communication effect and (b) if such

an effect exists, whether the impact of updated beliefs regarding the state of the economy or the internalisation of changes in the expected path of monetary policy dominates.

2.3 Central bank private information and stock prices

The concept of how central bank communication can move markets has been discussed in great detail from both a theoretical and empirical perspective. On one hand communication as the idea of a central bank revealing direct private information regarding the state of the economy, and financial market participants can update their own noisy beliefs in light of this information. On the other hand, this can also be interpreted as the central bank revealing its own assessment of data which have been already released. In this case, financial market participants are reacting in response to the central bank's interpretation of the already public data and thus updating their own noisy beliefs in light of this perspective.

Models such as that of Miranda-Agrippino and Ricco (2021) and Nakamura and Steinsson (2018) outline the idea of a central bank information channel whereby market participants update their beliefs about the state of the economy based on of central bank communication through either policy releases or direct communication events. As the market participants update their beliefs, asset prices can move in response to this. This can be further seen in the findings of Ehrmann and Fratzscher (2007) and Cieslak and Schrimpf (2019), who show evidence of the existence of such an information channel through financial market reactions. On the other hand, recent papers such as that of Hoesch et al. (2020) find that this information channel (hence, information advantage) has disappeared over the past number of years.

These private information releases by central banks can be interpreted in two ways. It can be the concept of the central bank revealing direct information regarding the state of the economy, and financial market participants can update their beliefs in light of this information. On the other hand, this can also be interpreted as the central bank revealing its beliefs and interpretation of data which have been already released. In this case, financial market participants update their beliefs in response to the central bank's interpretation of the already public data, by updating their interpretation to account for the interpretation of the central bank.

While there is evidence that private information releases can influence asset prices, it is important to discern the theoretical direction in which information can impact stock markets. I outline this by presenting a simple mathematical framework to highlight the ambiguous impact of information shocks on stock markets in line with Jarocinski and Karadi (2018). This setup can be seen as a formal extension to the distinction between communication on monetary policy and the economic outlook outlined by Ehrmann and Fratzscher (2007), and shows how both forms of communication can have an opposing effect on stock prices.³

Consider two kinds of monetary policy shocks, a conventional shock ϵ_t and an information shock σ_t . The conventional shock ϵ_t is a typical monetary policy shock, that agents assess as a sudden deviation away from the Taylor rule of a central bank. The information shock σ_t relates to the reaction of agents with constrained information to an implicit or explicit communication regarding the state of the economy. In the following example I consider the impact of a contractionary shock (e.g. a sudden increase in the policy rate), but the logic generalises to that of an expansionary one.

Let S_t be the price of a stock. This depends on both ϵ_t and σ_t through effects on the discount rate r_t and effects on future dividends X_t :

$$S_t(r_t(\epsilon_t, \sigma_t), X_t(\epsilon_t, \sigma_t)) \quad (2.1)$$

The effect of a conventional shock is unambiguous:

$$\frac{dS_t}{d\epsilon_t} = \frac{\partial S_t}{\partial r_t} \frac{dr_t}{d\epsilon_t} + \frac{\partial S_t}{\partial X_t} \frac{dX_t}{d\epsilon_t} \quad (2.2)$$

In this case, we know the following:

- $\frac{\partial S_t}{\partial r_t} < 0$, as stocks depend negatively on the discount rate.
- $\frac{dr_t}{d\epsilon_t} > 0$, as the conventional shock is an increase in headline interest rates, it also increases the discount rate.
- $\frac{\partial S_t}{\partial X_t} > 0$, as stock prices are positively related to expected dividend flows.

³This concept was particularly highlighted in the discussion of this paper by Lakdawala (2018).

- $\frac{dX_t}{d\epsilon_t} < 0$, as a conventional tightening increases interest rates, and hence depresses expected future dividend flows.

As such, the net impact of a conventional contractionary shock is unambiguously negative on stock prices. On the other hand, consider the impact of the equivalent information shock σ_t (Equation 2.3).

$$\frac{dS_t}{d\sigma_t} = \frac{\partial S_t}{\partial r_t} \frac{dr_t}{d\sigma_t} + \frac{\partial S_t}{\partial X_t} \frac{dX_t}{d\sigma_t} \quad (2.3)$$

The sign of $\frac{dr_t}{d\sigma_t}$ is negative. This is due to the fact that a contractionary information shock reveals an increased probability of a rate increase, hence discount rates rise. On the other hand, the sign of $\frac{dX_t}{d\sigma_t}$ is positive, as a contractionary monetary policy shock can be internalised as the central bank having positive information regarding the state of the economy, and as such there is a perception of improved flows of dividends. Thus, the sign of the net effect of a contractionary information shock on stock prices, $\frac{dS_t}{d\sigma_t}$ is ambiguous.

A challenge in monetary policy literature to date has been the isolation of pure information effects. Information effects generally are discussed in the context of revealed implicit information arising from interest rate decisions, and as such the net impact on financial markets is hard to discern as there is noise arising from the contemporaneous conventional shock. Through the introduction of ways to measure the information content of the ECB monetary policy press release, and exploiting the fact that the ECB's press conference takes place forty five minutes after the monetary policy decision announcement, I examine the changes in asset prices in the window before and after the press conference, to discern a "pure information effect". Through this, I aim to shed light on the sign of such information shocks. This is discussed in more detail in Section 2.6.

2.4 Methodology and Data

2.4.1 The ECB Press Conference

This paper examines the information conveyed during the press conference following the ECB Governing Council's monetary policy decisions. This is usually conducted by the President of the ECB, assisted by the Vice-President.

The ECB's monetary policy decisions are published online and in a press release at 13:45 CET on the second day of the Governing Council meeting. This states concisely the policy change (or lack thereof).

The press conference begins at 14:30 CET and consists of two parts. First, there is the *Introductory Statement* which explains the rationale behind the ECB's decision. This is followed by the *question and answers* component with members of the media.

The Introductory Statement contains information on a number of elements, and follows a set structure. First, the text contains information regarding the monetary policy decision announced at 13:45 CET. Prior to the period of unconventional monetary policy, this mainly related to information on interest rates. Since then there has been information on the operational aspects of unconventional measures such as the Extended Asset Purchase Programme (APP) or Targeted Long Term Refinancing Operations (TLTROs). From July 2013 onwards, this also contained explicit forward guidance to steer expectations of future policy decisions.

The next sections contain information on *economic* and *monetary analysis*, the two pillars on which the ECB bases its monetary policy decision. The economic analysis component of the Introductory Statement contains information regarding general macroeconomic conditions. Alongside this, there is an assessment of the *balance of risks* to the euro area economy and whether risks are "broadly balanced", "tilted to the downside" or "balanced to the upside". This section is indicative of the ECB's beliefs about the current state of the economy.

Following this, there is a *monetary analysis* section containing information on the broader monetary developments in the euro area, such as changes in credit or other monetary aggregates. This section is usually followed by a *cross check* of the monetary and economic analysis, linking the two strands.

In addition, from September 2004, four times per year in line with the release of the ECB's macroeconomic projections, the Introductory Statement contained the ECB's current year and one year ahead inflation and GDP projections. This is quantitative information which provides a clear signal of the ECB's views on future economic conditions. There is also a brief comment on *structural reforms* and *fiscal policies*, contextualised within the wider fiscal and economic governance framework of the EU. This is immediately followed by the *question and answers* segment.

The sample covered in this paper consists of 225 Governing Council meetings, from 7th January 1999 to 4th June 2020. This period spans the leadership of four

Presidents: Wim Duisenberg (June 1998 to October 2003), Jean-Claude Trichet (November 2003 to October 2011), Mario Draghi (November 2011 to October 2019) and Christine Lagarde (November 2019 to June 2020). The press conference texts were sourced from the ECB website, and the question and answers section was cleaned of any media questions, to only have direct ECB communication in the sample.

The ECB press conference has a unique structure in that the policy decision is announced forty five minutes before the press conference outlining the decision. In the context of discerning the differing effects of conventional monetary policy shocks (ϵ_t) and information shocks (σ_t), this feature is crucial. Since the monetary policy decision is pre-announced, any information revealed during the press conference should be a pure information shock. I exploit the staggered nature of the ECB's decision and press conference in the event study approach outlined in Section 2.6.

2.4.2 Conventional Sentiment Measures

Measuring the tone of a body of text is a rather typical problem in the natural language processing literature. There are a number of conventional methods that use pre-chosen dictionaries of positive and negative terms, and calculate the sentiment as being the difference between the number of positive and negative terms in a piece. Two such methods are the approaches of Nielsen (2011) (AFinn) and Loughran and McDonald (2014) (Loughran-McDonald). These are described in Appendix 2.8.1.

While these measures serve as a useful benchmark, both the AFinn and Loughran-McDonald measures are limited in their use for analysing monetary policy statements. Negative or positive terms of interest to markets or related to monetary policy information are given the same weighting as superfluous polarised phrases that are uninformative to markets. These measures are highly likely to be volatile and are very sensitive to the structure of the given document. For example, if there is a lot of discussion of operational concepts in a given press conference, this may be accompanied by polarised terms, but would not be informative from a monetary policy perspective. In addition, both methods are not robust to negation.

This motivates the development of targeted monetary policy approaches. I calculate two such measures. The first follows a dictionary approach, while the second follows a topic modelling approach.

2.4.3 Dictionary Based Hawk-Dove Index

To address the weaknesses of conventional sentiment measures I first propose the use of a monetary policy dictionary as outlined in the work of Tadle (2019). I use this dictionary to create a measure of the monetary policy tilt of the ECB for each press conference, which I denote as the “Dictionary Hawk-Dove Index”.

The words in this dictionary are divided into four categories. First, a list of economic terms are classified as (i) “neutral economic” or (ii) “pessimistic economic” in order to highlight the information contained within the text. Second, descriptive words are classified as (i) positive tone or (ii) negative tone. This method both controls for the polarity of the sentence, but also concentrates on information that is likely to be informative in a monetary policy setting.

The lists of economic and tone words are shown in are Tables [B1](#) and [B2](#) in Appendix [2.8.2](#) respectively.

Each document is analysed at the *sentence level*. First, the number of neutral and pessimistic economic terms in the sentence are counted. If there are more neutral than pessimistic terms, the sentence is classified as having a neutral base tone, while it is classified as being pessimistically tilted otherwise. Sentences containing none of these words are removed from examination as they are deemed to have low relevant informational content. This removes noise generated by sentences that relate to non-economic concepts.

Next, the polarity of the sentence is assessed by counting the number of terms of positive and negative tone. For sentences that are classified as having a neutral base tone measured by the economic terms, if it is accompanied by a majority of positive tone words it is classified as hawkish, otherwise it is classified as dovish. Similarly, if a sentence is classified as having a pessimistic base score, it is dovish if accompanied by a majority of positive terms, and hawkish otherwise. This controls for the fact that negation of the pessimistic economic terms is indicative of upward economic pressures.

The purpose of this is to separate sentences that are generally indicative of upward pressures on economic growth and inflation, and therefore indicative of increased likelihood of an interest rate rise (a more hawkish perspective), from those which are more indicative of downward pressure on growth and inflation and indicative of an increased likelihood of an interest rate cut (a more dovish perspective). It should be

noted that this definition of hawkishness and dovishness is in line with the concept put forward in papers such as Bennani and Neuenkirch (2017) and Tadle (2019), rather than the alternative interpretation of a more hawkish (dovish) sentiment being indicative of a preference for an interest rate higher (lower) than an implied neutral rate). As such, this measure should be interpreted as indicative of a level of monetary policy tilt, rather than relative to a neutral interest rate.

To illustrate, consider the following three sentences, with neutral economic terms underlined, pessimistic economic terms in *italics*, positive tone words in **bold** and negative tone words denoted with an *asterisk*:

1. On another occasion, I remarked on the very **high** level of youth *unemployment* that we are seeing today - and, by the way, *unemployment* is a tragedy and youth *unemployment* is an even bigger tragedy.
2. We have to distinguish, here, the outlook for the short term, which shows *weak* consumption, *weak* investment overall, *weak* domestic demand and **high** *unemployment*.
3. We still see the risk of a *recession* as being pretty *low*, all in all.

The first two sentences are classified as dovish, and can be indicative of increased likelihood of a monetary policy loosening (or lower likelihood of a tightening). The first contains unemployment repeated three times, and as there are no neutral terms, it has a base pessimistic score. Given it is accompanied by a positive tone word (high), the overall sentence is classified as dovish. On the other hand, the second sentence contains three neutral terms (consumption, investment and demand) and one pessimistic term (unemployment). Given the majority of terms are neutral, this sentence receives a base neutral score. In addition there are three negative terms (weak repeated three times) and one positive word (high). As the number of negative terms exceeds the number of positive terms, and the sentence has a base neutral score, this sentence is classified as dovish.

The third sentence is classed as hawkish and is indicative of a tendency towards a tightening (or alternatively a lower probability of a policy loosening), as it has one pessimistic term (recession) accompanied by a negative tone word (low).

More formally let $sent_{i,t}$ be the “Dictionary Hawk-Dove Index” score of sentence i in the press conference at time t . Let $pos_{i,t}$ be the number of positive words in the

sentence, $neg_{i,t}$ the number of negative, $neut_{i,t}$ the number of neutral economic terms and $pess_{i,t}$ the number of pessimistic economic terms.

We define the score of this sentence to be:

$$sent_{i,t} = \begin{cases} 1 & \text{if } neut_{i,t} > pess_{i,t} \text{ and } pos_{i,t} > neg_{i,t} \\ -1 & \text{if } neut_{i,t} > pess_{i,t} \text{ and } pos_{i,t} < neg_{i,t} \\ 1 & \text{if } neut_{i,t} < pess_{i,t} \text{ and } pos_{i,t} < neg_{i,t} \\ -1 & \text{if } neut_{i,t} < pess_{i,t} \text{ and } pos_{i,t} > neg_{i,t} \\ 0 & \text{otherwise} \end{cases} \quad (2.4)$$

The total score for the press conference at time t is defined as:

$$DictionaryHawkDoveIndex_t = 100 \times \frac{\sum_{i=1}^J (sent_{i,t})}{J} \quad (2.5)$$

Where J is the number of sentences containing at least one economic term from Table B2, and sentences are indexed $i = 1, \dots, J$. Dividing by the total number of sentences creates a bounded index between 100 and -100, and allows for a normalised comparison between press conferences with a differing number of sentences with at least one of the economic terms outlined in Table B1.

The more positive the value of this index, the more hawkish the sentiment, and the more negative the value of this index, the more dovish. This proxies the relative monetary policy tilt of the ECB at each point in time, and is both robust to negation and considers the context of each sentence.

2.4.4 Topic Model Based Hawk-Dove Index

While the above index is based on words that are directly related to monetary policy, it is still dependent on a pre-chosen list. This motivates the construction of a complementary measure that is based on a topic modelling approach, which involves the extraction of non-preselected topics. A topic model extracts latent groups of words that occur regularly together to create K topics, where K is chosen prior to fitting the algorithm. Each document is then classified into each of the topics with a given probability. For the purposes of fitting the model, I split the press conference

outputs into paragraphs, with each individual paragraph making up a “document” D for these purposes. This is an approach common to a number of papers examining the content of central bank releases (for example Hansen et al. (2019) or Jegadeesh and Wu (2017)).

The most commonly used approach in economic literature to date is Latent Dirichlet Allocation (Blei et al. 2003), and has been widely applied since. It is performed on a “corpus” of documents D . There are $N = 9,840$ documents (paragraphs) in the sample across all press conferences. Rather than proceeding with an LDA approach, I instead implement the Dynamic Topic Model approach to topic modelling (Blei and Lafferty 2006) of the Latent Dirichlet Allocation algorithm. This methodology considers the sequential nature of the documents that are being analysed, which contrasts with the basic LDA approach that is agnostic to the ordering of documents. The topics generated are allowed to evolve over time, and this can allow for structural breaks in the manner in which topics are discussed, but can also account in the case of the ECB for differences in speakers. A description of the algorithm is outlined in Appendix [2.8.3](#).

A strength of this approach is that it allows for the recognition of changes in the manner in which topics are discussed - it addresses the fact that monetary policy language is adaptive. For example, it can address the fact that “PEPP” will often be used during the leadership of President Lagarde in a way in which “APP” was used during the leadership of President Draghi. In a non-time sensitive model, the use of the term PEPP would be overlooked, due to its low use relative to the overall sample, but the Dynamic Topic Model approach can recognise the emergence of new language during a particular time period.

Implementation

Before estimating the Dynamic Topic Model (DTM), a number of *pre-processing steps* are taken. These are described in Appendix [2.8.4](#).

The DTM algorithm is implemented using the *gensim* package in Python (Rehurek and Sojka 2011). Prior hyperparameters are chosen as $K = 16$ and $\alpha = 0.5$, with η informed by initial runs of the model. The choice of $K = 16$ is partly informed ex-post

by interpretability of the topics.⁴ A relatively low value of α is chosen, as ECB press conference paragraphs are relatively short, and rarely about multiple topics.

Next, I denote each paragraph with subscript d , and each press conference with subscript t . The DTM algorithm returns $\hat{\beta}_{s,k}$, a set of vectors of probabilities of each word belonging to each topic $k = 1, \dots, 16$ in time slice $s = 1, \dots, 4$ and $\hat{\theta}_{k,d,t}$ the associated probability of each topic k generating paragraph d in press conference t .

To allow for the fact that there are likely to be some paragraphs that do not fit into any of the topics, I make a slight adjustment to $\hat{\theta}_{k,d,t}$. If the fitted probability of paragraph d being in topic k is less than 0.2, I adjust this down to zero. This removes any noise from ambiguous paragraphs. Any remaining probabilities are normalised such that their total adds to one. This means that paragraphs are likely to be a mix of fewer topics, in line with the short nature of the paragraphs. It is a middle ground between “winner takes all classification”, where paragraphs are assigned to the topic with highest probability that allows for some degree of a mixture of topics to be discussed in a given paragraph. This also adjusts for the fact that some sentences may be classified with low probability into certain topics due to co-occurrence of words - for example if President Duisenberg used some words associated with asset purchases, a spurious classification may occur. The threshold of 0.2 will filter out a large number of these spurious classifications, but allows for paragraphs to still be classified as mixtures of topics.⁵ In addition, if no topic has a probability of greater than 0.2, this allows for a “null” classification of a paragraph. I denote this adjusted version of $\hat{\theta}_{k,d,t}$ as $\tilde{\theta}_{k,d,t}$.

Thus the formula in Equation 2.6 is used to calculate the proportion of press conference t dedicated to topic k .

$$TopicProportion_{k,t} = \sum_{d=1}^D \tilde{\theta}_{k,d,t} \times \frac{WC_{d,t}}{WC_t} \quad (2.6)$$

In Equation 2.6, D is the number of paragraphs in press conference t , WC_t is the total wordcount of press conference t , and $WC_{d,t}$ is the total wordcount of paragraph d in press conference t . Multiplying by $\frac{WC_{d,t}}{WC_t}$ controls for the relative importance of

⁴The results of the empirical analysis in Section 2.6 are similar for other choices of K , and this low value of K is similar in size to the number of topics chosen by similar studies (for example Istrefi et al. (2020) use 12 topics when examining the financial stability component of Fed speeches.)

⁵All results are robust to alternative thresholds of 0.05 and 0.35.

each paragraph in the overall scope of the press conference in that larger paragraphs are given higher weight.

The fitted topics

The topics extracted from the fitting of the topic model are for each of the four time points in Tables B5 to B8, in Appendix 2.8.5.

Using these topics I propose the creation of the *DTM Hawk-Dove Index*. A number of fitted topics are likely to be about economic information that communicate the monetary policy tilt of the ECB. I label these topics as the “information topics”. The “information” topics will have a function analogous to the “topical words” listed in the hawkish and dovish terms for the dictionary based approach (Table B1). I identify six topics that seem to contain some direct informational content regarding the state of the economy, that I label *risk*, *projections*, *credit*, *long term inflation*, *price developments* and *inflation expectations*. While the topic I label “data analysis” may seem to have some degree of information, a list of polarised words to gauge the tilt of this topic is hard to define, as the list is predominantly agnostic “analysis terms” rather than about specific economic concepts.⁶ These relate to both the primary mandate of the ECB (price stability), but also broader conditions that make up the broader components of the ECB’s assessment of economic conditions. For each of these topics, I create a list of positive and negative shifters to create an index in line with the Dictionary Hawk-Dove Index. The positive and negative shifters are identical to those in Table B2 for all topics bar the risk topic. This is because terms such as “increased” or “elevated” are likely to have a negative tone when referring to the risk environment. The list of positive and negative shifters for the risk topic are shown in Table B3, Appendix 2.8.2.

The index is constructed as follows. Let I be the set of information topics. Let $i \in I$ be an individual topic denoted as an information topic. For a given paragraph d let $\tilde{\theta}_{i,d,t}$ be the adjusted probability that this paragraph belongs to a given information topic. If $\sum_{i \in I} \tilde{\theta}_{i,d,t} = 0$, define that paragraph as being non informative and drop it from the sample. Then for a given paragraph, we calculate $\tilde{\Omega}_{i,d,t}$ as the “adjusted” contribution of each of the topics for a given paragraph to the overall index:

⁶I note that all main results of this paper are robust to the inclusion of the data analysis topic in the construction of the DTM Hawk-Dove Index.

$$\tilde{\Omega}_{i,d,t} = \begin{cases} \tilde{\theta}_{i,d,t} & \text{if } pos_{i,d,t} > neg_{i,d,t} \\ -1 \times \tilde{\theta}_{i,d,t} & \text{if } neg_{i,d,t} > pos_{i,d,t} \\ 0 & \text{otherwise} \end{cases} \quad (2.7)$$

where $pos_{i,d,t}$ and $neg_{i,d,t}$ are the number of positive and negative shift words from the lists associated with information topic i in paragraph d .

The final step is to aggregate these to the document level, and this is shown in Equation 2.8. In this equation, i refers to the information topic, I the set of information topics, d the paragraph and t the press conference. $WC_{d,t}$ is the word count of paragraph d and WC_t is the word count of all paragraphs with some “information” content in press conference t .⁷

$$DTMHawkDoveIndex_t = 100 \times \sum_{\forall d \in t} \left(\left(\frac{WC_{d,t}}{WC_t} \right) \times \sum_{\forall i \in I} \tilde{\Omega}_{i,d,t} \right) \quad (2.8)$$

This produces an index with upper bound of 100 and lower bound of -100, which is analogous in interpretation to the Dictionary Hawk-Dove Index in Equation 2.5. Positive values outline a more hawkish tilt, negative values a more dovish tilt.

This measure should be seen as complementary to the dictionary based method rather than a preferred option. It has a core strength of being agnostic to the prior fitting of topics and can perhaps pick up on some latent use of economic terms that may be missed by using a fixed pre-set word list. On the other hand, the topics are a mixture of words, and as such some paragraphs may have some spurious use of related words that causes them to be classified into an information topic. This is less of an issue for the dictionary approach, where the words are fixed. This motivates the use of both measures.

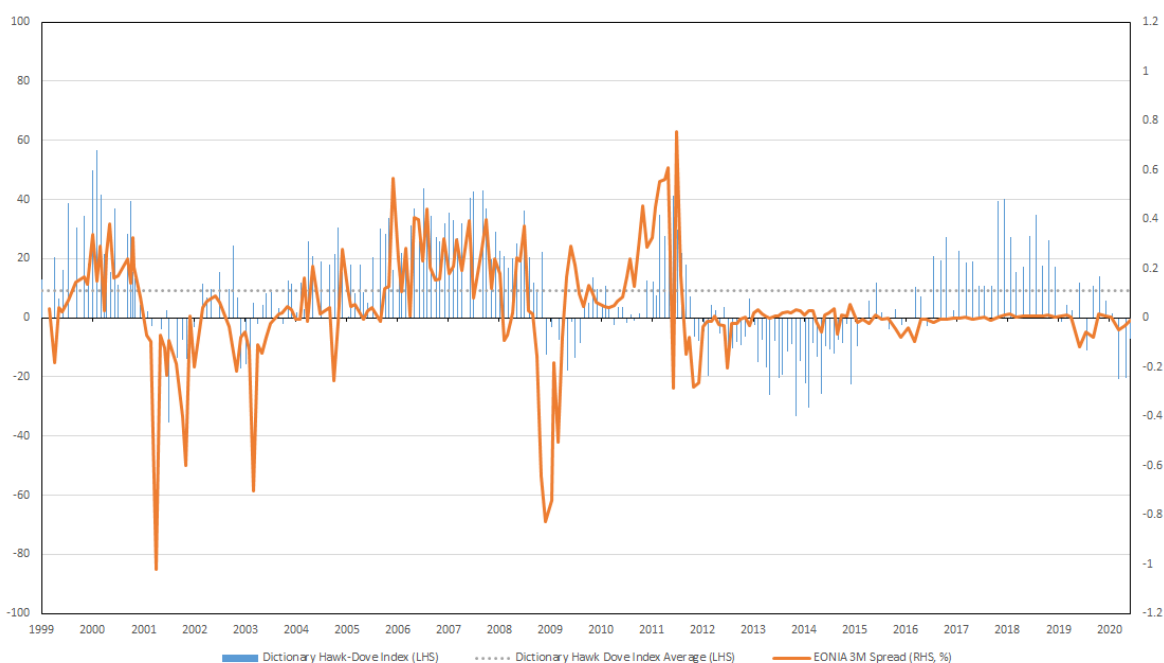
2.5 Baseline Results - Goodness of Fit

While conventional measures of sentiment are interesting from a baseline perspective, they lack consistency between meetings and when plotted are quite noisy (time series for these measures are shown in Appendix 2.8.1, Figures B1 and B2). This

⁷I note that in part, the selection of a threshold of 0.2 also allows for the removal of paragraphs with low levels of content that can be deemed as related to economic information.

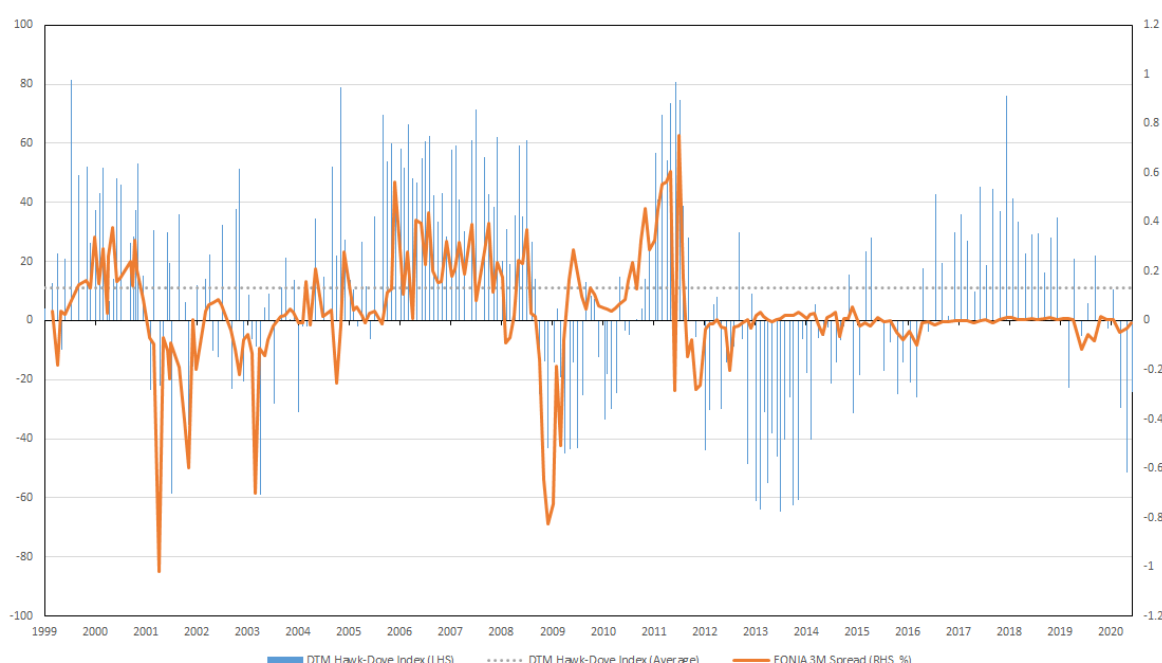
motivates further the development of the Hawk-Dove Indices, as removing polarised but non informative terms can create a more consistent time series. Figures 2.1 and 2.2 plot the time series of the dictionary based and DTM based hawk dove indices respectively. Alongside these the difference between the EONIA 3-month swap rate and the EONIA spot rate is shown. These are measured at market close the evening after the press conference. The EONIA rate is the overnight interest rate used as a benchmark for the euro area, while the three month swap rate is the average rate for a swap contract to be settled in three months. This acts as a measure of market expectations of future euro area monetary policy. If this is positive (negative), it is indicative of expected *interest rate increases (decreases)*, hence markets view policy as quite *hawkish (dovish)*. Moreover, this can be used as a tool for measuring the release of central bank private information regarding both the state of the economy and the future likely monetary policy stance, and hence it will highlight the potential role the information channel can play in monetary policy transmission.

Figure 2.1. Dictionary Hawk-Dove Index contrasted with euro area market interest rate expectations



Notes: This figure shows the estimated Dictionary Hawk-Dove Index scores, outlined in Equation 2.5 for each ECB press conference over time, with this scale being shown on the left hand Y-axis. On the right hand Y-axis the difference between 3-month OIS and Eonia rates are shown in percentage terms, as a form of measuring market expectations of upcoming changes in policy rates.

Figure 2.2. DTM Hawk-Dove Index contrasted with euro area market interest rate expectations



Notes: This figure shows the estimated DTM Hawk-Dove Index scores, outlined in Equation 2.8 for each ECB press conference over time, with this scale being shown on the left hand Y-axis. On the right hand Y-axis the difference between 3-month OIS and Eonia rates are shown in percentage terms, as a form of measuring market expectations of upcoming changes in policy rates.

Figures 2.1 and 2.2 show that the Hawk-Dove Indices appear to track the market expectations of euro area monetary policy as measured through expected interest rate changes quite well up until 2013. At this point, policy rates hit an effective lower bound, and there was an increasing reliance on unconventional monetary policies (such as asset purchase programmes or targeted long term refinancing operations). This in a sense marks a strength of the Hawk-Dove Indices as an alternative measure of ECB monetary policy tilt to measures that use market implied future interest rates, which do not pick up on such unconventional measures.

Further to this, the Hawk-Dove Indices clearly pick up on a number of key events in ECB monetary policy. In 2011, the ECB raised rates post crisis against the backdrop of an uptick in some inflation measures, and both indices clearly show a shift to a more “hawkish” tone at that time point. This is reversed in 2012, post the “whatever it takes” speech by President Draghi, as the more dovish tone that underlay the era of unconventional monetary policy is evident. Finally, in 2020, there is a clear, sudden, dovish shift, in line with the Covid-19 crisis.

To further compare the appropriateness of the Hawk-Dove Indices for measuring the stance of monetary policy communication, Table 2.1 presents the results of a descriptive regression of all four measures of sentiment on two indicators of interest.⁸ The first is the difference between the 3-month EONIA swap rate and the EONIA spot rate as outlined above. The second is the ZEW measure of the current euro area economic situation. This is published monthly by the German ZEW economic research institute. This is a survey measure of market participants' assessment of current economic conditions. Both of these measures should be related directly to any measure of the tone of ECB press conferences, either through market expectations of future rates, or through the current positive or negative economic outlook.

As expected all measures have a positive and significant relationship with these two economic indicators. Of note is the higher R^2 recorded by the regressions involving the Hawk-Dove Indices relative to the other non-specific tone measures, suggesting that these measures may exhibit a stronger degree of fit to monetary policy expectations and current economic assessment.

Table 2.1. Descriptive Correlations Between Sentiment Measures and ZEW Indicator/OIS Spread

	Dict Hawk-Dove	Dict Hawk-Dove	DTM Hawk-Dove	DTM Hawk-Dove	Loughran	Loughran	AFinn	AFinn
EONIA 3M Spread	31.87*** (5.124)		65.10*** (7.902)		0.00905*** (0.00132)		0.0103*** (0.00235)	
ZEW Current Index		0.260*** (0.0162)		0.482*** (0.0331)		0.0000338*** (0.00000713)		0.0000637*** (0.0000151)
Constant	7.971*** (1.105)	14.82*** (0.931)	8.699*** (2.080)	21.54*** (1.717)	-0.00352*** (0.000335)	-0.00245*** (0.000377)	0.0354*** (0.000733)	0.0370*** (0.000703)
Observations	224	225	224	225	224	225	224	225
R^2	0.154	0.444	0.177	0.417	0.132	0.080	0.040	0.064

Dependent variables are the Hawk-Dove index scores, Loughran-McDonald measure of net sentiment and AFinn sentiment measures outlined in Section 2.4 for each Governing Council press conference. The independent variables are the ZEW measure of current economic sentiment, measured the same calendar month as the Governing Council meeting, and the difference between the 3 month EONIA OIS rate and EONIA spot rate the evening after the press conference. These proxy macroeconomic conditions and market interest rate expectations respectively. Results are intended to be descriptive not causal. Standard errors in parentheses. *** denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level.

These descriptive results motivate the use of the Hawk-Dove Indices as appropriate measures of both the ECB's monetary policy tilt and overall viewpoint on the broader macroeconomy.

⁸Such regressions are not causal - simple correlations are examined to motivate the relationship of our measures to other summary measures.

2.6 Econometric Specification and Empirical Results

While the results in Section 2.5 hold rich descriptive properties, of interest is the differential effect of topic and tone on financial markets. To examine this, I adopt an event study approach, concentrating on the variation in asset prices around the ECB press conference. As discussed in Section 2.4, the ECB press conference occurs at a time separate from the announcement of monetary policy decisions. Any movement in asset prices before and after the press conference can be interpreted as mostly a communication effect. This allows us to extract a net information effect free from the impact of a conventional monetary policy shock. This will allow the estimation of the impact of an information effect on stock prices, in line with the concepts outlined in Equation 2.3. Stock prices are chosen to be able to assess which effect (the negative impact of a changed discount rate or positive effect of expected future dividends) dominates.

This issue is examined using high frequency data from the “Euro area monetary policy database” (EA-MPD) dataset of Altavilla et al. (2019a), which contains *the change in price* of a number of key assets from before to after the ECB press conference.⁹ Since the time window of interest is quite tight, it is unlikely that the analysis is influenced by confounding factors, while also being mostly free of any direct effect arising from the monetary policy decision.

The following regression is estimated in an event study setting:

$$\Delta AssetPrice_t = \beta_0 + \beta_1 HawkDoveIndex_t + \Phi X_t + \epsilon_t \quad (2.9)$$

where $\Delta AssetPrice_t$ is the change in the median price of a stock index before and after the press conference at time t . The two stock indices of interest are the Eurostoxx 50 index, which is a stock index of the fifty largest euro area stocks designed by the Deutsche Borse Group, and the SX7E index, an index of the banking component of the Eurostoxx 50 index. Both of these are measured in terms of their change in percentage points from before to after the press conference. $HawkDoveIndex_t$ is the value of either the dictionary or DTM based Hawk-Dove Index at time t , while X_t is a vector of controls. From an interpretation perspective, a

⁹This is defined as the change in median quote from the window 14:15-14:25 before the press conference to the median quote in the window 15:40-15:50 after it. The press conference takes place between 14:30 and 15:30.

value of $\beta > 0$ would imply that for a more hawkish tone, the impact of higher expected future dividends owing to the positive news dominates the impact of a higher discount rate on stock prices, while $\beta < 0$ implies the opposite. This regression should shed light on the net impact of the information channel of monetary policy as it transmits through communication releases.

All dependent variables are composed of changes in the short run window around the press conference. As such, any significant values for β in Equation 2.9 should be interpreted as such, rather than longer term persistent effects. The interpretation should highlight the information effect of the policy releases, rather than the longer term path determination of these financial series. I also note that the transmission of communication through this path can be both directly through the following of the press conference by financial market participants, and indirectly through interpretations by newswire services who are assumed to pass on the sentiment of the press conference to more passive followers (Hayo and Neuenkirch (2015) show that many financial market participants follow this kind of communication through newswire reports, particularly when it is related to non-domestic decisions.)

A weakness of this specification is the fact that the press conference is treated as one event, rather than being able to separately consider the Introductory Statement and Questions and Answers components as separate concepts. This is primarily due to data availability issues, with the dataset of Altavilla et al. (2019a) only containing the changes in stock prices either side of the press conference, rather than either side of the component parts. It should therefore be noted that any results should be interpreted as the net effects of the overall communication event, rather than the impact of either specific part of the press conference. Further analysis of the role of the separate parts of the press conference may be an avenue for future research, and the work of Hayo et al. (2020) has shown that the Question and Answers segment of the press conference can play a role in enhancing participants' information processing.

2.6.1 Baseline Results

Table 2.2 shows the results from a baseline regression without controls. The independent variables are the Hawk-Dove Indices for the press conference on each given date. Results show a positive and significant relationship between immediate movements in the Eurostoxx and SX7E stock indices and the Hawk-Dove Indices for

both the dictionary and DTM based methods. All relationships are significant at the one percent level. This relationship also appears economically significant. For the dictionary based index, a one standard deviation increase in the dictionary Hawk-Dove Index is associated with a 0.13 percentage point increase in the Eurostoxx index, and a 0.22 percentage point increase in the SX7E index. Similarly, for the DTM method, the figures are 0.13 percentage points and 0.21 percentage points respectively.¹⁰

Table 2.2. Baseline Regression of stock market indices on Hawk-Dove Index Scores

	Eurostoxx	Sx7e	Eurostoxx	Sx7e
Dictionary Hawk-Dove Index	0.00751*** (0.00237)	0.0128*** (0.00447)		
DTM Hawk-Dove Index			0.00392*** (0.00119)	0.00619*** (0.00209)
Constant	-0.154*** (0.0536)	-0.305*** (0.0997)	-0.129*** (0.0470)	-0.256*** (0.0829)
Observations	225	225	225	225
R^2	0.048	0.048	0.047	0.041

The dependent variables are the change in the Eurostoxx and SX7E indices before and after the ECB press conference. Eurostoxx measures the change in percentage points of the Eurostoxx 50 stock index of prominent euro area companies. SX7E measures the change in percentage points of the SX7E stock index of prominent euro area bank stocks. The independent variable is the value of the Dictionary and DTM Hawk-Dove Indices, derived in Equations 2.5 and 2.8. Robust standard errors in parentheses. *** denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level.

This reaction is consistent with the idea that markets do not react to a more hawkish (dovish) tone by internalising the idea that there will be a monetary tightening (loosening). Instead they react by interpreting the hawkish (dovish) tone as being indicative of the fact that central banks have positive (negative) news about future market prospects.

While the baseline results are indicative of some underlying relationships, to comment on a causal relationship in any direction I must control for potential omitted variables which can bias the above relationships.

¹⁰Average changes over the sample are 0.08 and 0.18 percentage points for each of the series respectively, suggesting a one standard deviation change in these indices is associated with an economically significant change in these indices.

First, it is natural to assume that the interest rate decision taken on the day of the press conference can have some impact on markets. Even though the event study is only conducted using changes around the press conference, there may be differing reactions as a result of delayed market reaction to the decision release. As such it is natural to control for changes in interest rates on the day of the press conference. This is controlled for using *change in the deposit facility rate* at the Governing Council meeting.

Second, from September 2004, the ECB began to release headline results of its macroeconomic projections exercise for the given quarter during four press conferences a year (March, June, September, December). Inflation and GDP projections for the current and next calendar years began to be announced at the press conference. This quantitative information can have market impacts, and as such must be controlled for. Due to confounding information from realised values that can impact current year forecasts, I choose to control for revisions to the forecasts of inflation and GDP for the next calendar year outlined during the press conference. In addition, a dummy variable is added to control for meetings when projections are announced.

Third, following principal component approaches of Whelan et al. (2017) and Altavilla et al. (2019a), I control for the presence of a monetary policy shock during the period of interest. These authors use intradaily data to develop a monetary policy shock that is composed of the first principal component of changes in EONIA Overnight Interest Rate Swap prices over the monetary policy decision window for maturities of one, three and six months, and one and two years. This common factor can be interpreted as the unanticipated movement in the yield curve as a result of the monetary policy decision.

Of further interest are differing reactions of markets to changes in the Hawk-Dove Indices as the level of the monetary policy shock varies. For example, does a more hawkish sentiment following a hawkish (positive) monetary policy shock reinforce this effect, or are effects greater if hawkish sentiment follows a dovish (negative) monetary policy shock? To measure this, an interaction term is included between the Hawk-Dove Index and the monetary policy shock.¹¹

¹¹Due to missing data towards the start of the sample in the dataset of Altavilla et al. (2019a), when including the monetary policy shock, there is a slightly smaller sample size

A full list of control variables and sources is shown in Table B9. I note that the headline results omit speaker fixed effects. There are two core reasons for this. First, it is hard to establish a theoretical directional relationship between speaker effects and market movements, and the content should matter more than the speaker given the fact I examine directional movements of assets rather than absolute values. In addition, in the case of the DTM Hawk-Dove Index, the speaker based patterns are already controlled for ex-ante, by creating the time slices such that the topic model accounts for the changes in speaker. I note, however, that headline results are unchanged with the inclusion of such effects for both the dictionary and DTM based method, and this is shown in Table B10 in the appendix.

Table 2.3 shows results for specifications including controls. Across all specifications, the coefficient on the Hawk-Dove Index variable remains positive and highly significant. This is evidence in favour of the hypothesis that markets react to a more hawkish (dovish) tone as being indicative of positive (negative) economic news, and hence improved future dividends.

Moreover, a one standard deviation increase (decrease) in the Dictionary Hawk-Dove Index is associated with a 0.156 and 0.287 percentage point increase (decrease) in the Eurostoxx and SX7E series respectively, while a similar increase (decrease) for the DTM Hawk-Dove Index is associated with a 0.139 and 0.226 percentage point increase (decrease) in these series.¹² This is suggestive of a short-run impact of economic significance.

In line with the results of Altavilla et al. (2019a), the coefficient on the monetary policy shock is insignificant in all regressions. This highlights the additional information that is gained by extracting the narrative information conveyed during the press conference. Moreover, perhaps more surprisingly, the coefficients on interaction between monetary policy shocks and the Hawk-Dove Indices are not significantly different from zero. It would have been expected that markets may be more reactive to the information conveyed by tone in a “surprise” decision environment.

¹²These figures are equivalent to a 0.259 and 0.278 standard deviation change in the Eurostoxx and SX7E series for the Dictionary measure, and a change of 0.233 and 0.223 for the DTM measure. Further observing the distributional properties of the overall changes in the indices during press conferences also shows that a one standard deviation change in each index is associated with a greater change than was seen overall in the entire interval for between 29% and 42% of press conferences depending on the metric used.

Table 2.3. Regression of changes in the Stock Indices on the Hawk-Dove Indices

	Eurostoxx	Sx7e	Eurostoxx	Sx7e
Dictionary Hawk-Dove Index	0.00893*** (0.00286)	0.0162*** (0.00553)		
DTM Hawk-Dove Index			0.00419*** (0.00143)	0.00680*** (0.00258)
Change Deposit Facility Rate	-0.0774 (0.334)	-0.0737 (0.605)	-0.0695 (0.349)	-0.00978 (0.635)
Projections Released	0.0437 (0.0876)	0.00528 (0.147)	0.0160 (0.0894)	-0.0457 (0.154)
Medium Term Inflation Forecast Revision	-0.207 (0.300)	-0.104 (0.483)	-0.235 (0.291)	-0.120 (0.487)
Medium Term GDP Revision	-0.105 (0.139)	-0.255 (0.238)	-0.0721 (0.148)	-0.197 (0.247)
Monetary Policy Shock	-0.0119 (0.0144)	-0.0234 (0.0341)	-0.00336 (0.0154)	-0.00805 (0.0277)
Monetary Policy Shock × Dictionary Hawk-Dove Index	0.00122 (0.000819)	0.00259 (0.00224)		
Monetary Policy Shock × DTM Hawk-Dove Index			0.000387 (0.00070)	0.000691 (0.00184)
Constant	-0.205*** (0.0669)	-0.369*** (0.123)	-0.127** (0.0515)	-0.276*** (0.102)
Observations	192	192	192	192
R ²	0.074	0.086	0.054	0.050

The dependent variables measure the change in percentage points of the Eurostoxx 50 stock index of prominent euro area companies and SX7E stock index of prominent euro area bank stocks from before to after the ECB press conference. The independent variables are, in order of appearance in table, as follows. The value of the dictionary Hawk-Dove Index, derived in Equation 2.5. The value of the DTM Hawk-Dove index, derived in Equation 2.8. The change in the ECB deposit facility rate, if any, at the monetary policy meeting. A dummy variable taking a value of one if macroeconomic projections were released, zero otherwise. The revision to inflation forecasts for the next calendar year in percentage points. The revision to GDP forecasts in the next calendar year in percentage points. A measure of monetary policy shocks, in line with Altavilla et al. (2019a). An interaction between the Hawk-Dove index score and the monetary policy shock series. Robust standard errors in parentheses. *** denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level.

2.6.2 Forward Guidance

From July 2013, the ECB began to introduce explicit monetary policy communication in the form of forward guidance. With this policy, the ECB aims to give an indication of the future path of interest rates, as well as other operations such as future purchases under the APP. In general, this should be associated with increased market certainty. From the perspective of the noisy model of central bank private information presented in Section 2.3, the central bank has already revealed more of a signal regarding its perspective on the future path of monetary policy, implying there is less new information to be revealed during the press conference for the financial market participants to update their noisy beliefs regarding the state of the world. In doing so, central banks are also revealing further information regarding their beliefs on the state of the economy, and hence their interpretation of incoming data. This would imply that any communications should be less surprising to markets, due to higher certainty regarding the central bank's outlook. As such, it would be expected for there to be a

stronger effect on asset prices in the period of time before formal forward guidance was introduced.

I therefore split the sample in two, with press conferences before July 2013 being defined as being in the “pre-forward guidance” sample, and all others as being in the “post forward guidance”. Results are re-estimated and shown in Tables 2.4 and 2.5.

Table 2.4. Regression results prior to formal forward guidance

	Eurostoxx	Sx7e	Eurostoxx	Sx7e
Dictionary Hawk-Dove Index	0.0118*** (0.00332)	0.0174*** (0.00599)		
DTM Hawk-Dove Index			0.00506*** (0.00136)	0.00677*** (0.00203)
Change Deposit Facility Rate	-0.177 (0.301)	-0.139 (0.493)	-0.125 (0.340)	-0.00395 (0.580)
Projections Released	0.210** (0.0815)	0.205 (0.140)	0.218*** (0.0803)	0.233* (0.139)
Medium Term Inflation Forecast Revision	-0.802*** (0.253)	-0.589 (0.565)	-0.899*** (0.230)	-0.657 (0.507)
Medium Term GDP Revision	0.0465 (0.159)	-0.0666 (0.327)	0.177 (0.146)	0.103 (0.304)
Monetary Policy Shock	0.0106 (0.0115)	0.0249 (0.0261)	0.0152 (0.0103)	0.0162 (0.0199)
Monetary Policy Shock × Dictionary Hawk-Dove Index	0.000469 (0.000749)	-0.000610 (0.00164)		
Monetary Policy Shock × DTM Hawk-Dove Index			-0.000445 (0.000463)	-0.00177** (0.000834)
Constant	-0.304*** (0.0739)	-0.470*** (0.141)	-0.242*** (0.0581)	-0.393*** (0.104)
Observations	130	130	130	130
R ²	0.183	0.121	0.184	0.126

The dependent variables are the change in a number of variables before and after the ECB press conference. Eurostoxx measures the change in percentage points of the Eurostoxx 50 stock index of prominent euro area companies. SX7E measures the change in percentage points of the SX7E stock index of prominent euro area bank stocks. The values of the dictionary and DTM Hawk-Dove Indices, derived in Equations 2.5 and 2.8. The change in the ECB deposit facility rate, if any, at the monetary policy meeting. A dummy variable taking a value of one if macroeconomic projections were released, zero otherwise. The revision to inflation forecasts for the next calendar year in percentage points. The revision to GDP forecasts in the next calendar year in percentage points. A measure of monetary policy shocks, in line with Altavilla et al. (2019a). An interaction between the Hawk-Dove index score and the monetary policy shock series. Robust standard errors in parentheses. *** denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level.

Table 2.5. Regression results during forward guidance

	Eurostoxx	Sx7e	Eurostoxx	Sx7e
Dictionary Hawk-Dove Index	0.00211 (0.00422)	0.00988 (0.00860)		
DTM Hawk-Dove Index			0.00218 (0.00299)	0.00708 (0.00604)
Change Deposit Facility Rate	4.049 (3.366)	5.282 (5.916)	4.411 (3.397)	4.844 (6.062)
Projections Released	-0.149 (0.166)	-0.336 (0.309)	-0.193 (0.163)	-0.317 (0.317)
Medium Term Inflation Forecast Revision	0.683 (0.452)	1.048 (0.769)	0.776* (0.435)	0.894 (0.712)
Medium Term GDP Revision	0.0558 (0.266)	0.0625 (0.318)	0.0882 (0.239)	-0.0316 (0.301)
Monetary Policy Shock	-0.149*** (0.0340)	-0.107** (0.0495)	-0.132*** (0.0469)	-0.108 (0.0808)
Monetary Policy Shock × Dictionary Hawk-Dove Index	-0.00328** (0.00156)	0.00500 (0.00317)		
Monetary Policy Shock × DTM Hawk-Dove Index			-0.00132 (0.00152)	0.00305 (0.00341)
Constant	0.0308 (0.139)	0.00966 (0.249)	0.0626 (0.135)	0.00508 (0.234)
Observations	62	62	62	62
R ²	0.347	0.299	0.333	0.295

The dependent variables are the change in a number of variables before and after the ECB press conference. Eurostoxx measures the change in percentage points of the Eurostoxx 50 stock index of prominent euro area companies. SX7E measures the change in percentage points of the SX7E stock index of prominent euro area bank stocks. The independent variables are, in order of appearance in table, as follows. The values of the dictionary and DTM Hawk-Dove Indices, derived in Equations 2.5 and 2.8. The change in the ECB deposit facility rate, if any, at the monetary policy meeting. A dummy variable taking a value of one if macroeconomic projections were released, zero otherwise. The revision to inflation forecasts for the next calendar year in percentage points. The revision to GDP forecasts in the next calendar year in percentage points. A measure of monetary policy shocks, in line with Altavilla et al. (2019a). An interaction between the Hawk-Dove index score and the monetary policy shock series. Robust standard errors in parentheses. *** denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level.

As can be seen, the coefficients on the Hawk-Dove Indices are significant prior to forward guidance, but lose significance in the later sample. This supports the hypothesis that more certain information about the future path of monetary policy dulls the effect of hawkish or dovish communication on asset prices. This can provide evidence that communication regarding the ECB's assessment of the state of the economy or implied future policy rates has become less surprising in the later sample.^{13 14}

¹³Such results are backed up by a simple rolling regression analysis, where I re-estimate the regressions from Table 2.3. Figure B3 shows the evolution of the regression coefficient from the regression of Eurostoxx on the dictionary based measure, and it can be seen that this has a clear turn point between the pre and post forward guidance period. A similar turn point can be seen for all other measures (Figure B4). It should be noted that a slight upward drift is seen towards the end of the sample, although results remain insignificant. This may suggest show evidence of a fading effect of forward guidance on predictability, should such a trend continue.

¹⁴A nested regression approach with interaction terms backs up the finding that results are insignificant in the post forward guidance period.

Such a finding backs up the results of Hoesch et al. (2020), who find that over the last decade, the Fed has lost its information advantage. This can potentially be linked to an improvement in communications and overall transparency, which is consistent with the theorised effects of a shift towards forward guidance. Use of forward guidance adds another aspect to communication, and a greater degree transparency regarding the rationale behind future monetary policy decisions. Further to this effects may have been further dampened by additional communication events such as the publication of accounts of Governing Council meetings.

It is also important to connect these results to the work of Hayo and Neuenkirch (2018). Within this work, these authors find that a perception of good communication skills and an ability to convey objectives by central banks are strongly associated with financial market participants' assessment of the predictability of central banks. On the other hand, more specific instruments aimed at enhancing transparency such as transcripts and minutes and availability of voting records are seen to have lower importance. Read alongside these results, the findings of this paper may suggest that the impact of forward guidance may be through a clearer conveying of information surrounding objectives.¹⁵

An alternative explanation for this fading effect may be a learning effect by central banks. If markets were experiencing short-run volatility in the time period around the press conference in the pre-forward guidance period, and such volatility were deemed undesirable, this may have motivated a move towards more careful use of language. This could be seen as complementary to the impact of forward guidance through improved transparency and clarity of communication, and lessened the likelihood of communication surprises.

2.6.3 Robustness - OIS 1Y

In Section 2.3, the information shock σ_t was decomposed into two potential effects on stock prices - the impact on the discount rate $\frac{dr_t}{d\sigma_t}$ and the impact on the future flow of dividends $\frac{dX_t}{d\sigma_t}$. I have argued that from the initial shock that the future dividend

¹⁵For example, statements such as “In support of its symmetric 2% inflation target and in line with its monetary policy strategy, the Governing Council expects the key ECB interest rates to remain at their present or lower levels until it sees inflation reaching 2% well ahead of the end of its projection horizon...” (ECB 2021) provide both policy information and a re-statement of objectives.

effect dominates, but it is also possible to extract direct information as to whether communication has a direct effect on interest rates. Using the dataset of Altavilla et al. (2019a), I estimate an additional specification in which the dependent variable in Equation 2.9 is the change in the 1 year overnight interest rate swap rate (OIS 1Y) before and after the press conference. This should proxy the impact of a change in communication on the discount rate r_t .¹⁶ Results are shown in Table 2.6.

As can be seen, there is no clear impact of a more hawkish or dovish tone on the OIS 1Y rate. This, combined with the robust evidence of a the impact of a change in the monetary policy tilt on both the Eurostoxx and SX7E indices is evidence in favour of the hypothesis that information effects mainly manifest themselves through changes in perceptions regarding the state of the economy, rather than changes in expected future interest rates. No effect is also evident in the pre and post-forward guidance subsamples. To check the robustness of these findings to longer maturities I re-estimate a similar model for German, French and Italian 5 and 10 year bonds. Similar to for the OIS1Y regression no statistically significant effect is discovered. These results are also in line with the results of Gorodnichenko et al. (2021), who find that the tone of Fed chairs rarely moves bond markets.

Table 2.6. Regression of the OIS1Y rate on the Hawk-Dove Indices

	Full Sample	Full Sample	Pre-FG	Pre-FG	Post-FG	Post-FG
Dictionary Hawk-Dove Index	0.00230 (0.0165)		0.00839 (0.0233)		-0.00653 (0.0104)	
DTM Hawk-Dove Index		-0.00317 (0.00858)		-0.00345 (0.0110)		-0.00332 (0.00659)
Change Deposit Facility Rate	-2.756 (2.005)	-2.524 (1.972)	-3.070 (2.151)	-2.636 (2.071)	7.644 (7.183)	7.661 (7.333)
Projections Released	1.042* (0.559)	1.055* (0.559)	0.943 (0.834)	0.979 (0.844)	0.648* (0.352)	0.656* (0.350)
Medium Term Inflation Forecast Revision	1.281 (1.852)	1.460 (1.884)	2.719 (2.993)	2.943 (3.102)	-1.088* (0.650)	-1.123* (0.587)
Medium Term GDP Revision	-0.295 (0.891)	-0.310 (0.900)	-0.806 (1.606)	-0.784 (1.666)	-0.155 (0.254)	-0.145 (0.239)
Constant	-0.242 (0.283)	-0.186 (0.281)	-0.330 (0.386)	-0.183 (0.358)	-0.0263 (0.265)	-0.0418 (0.248)
Observations	225	225	163	163	62	62
R ²	0.032	0.032	0.036	0.035	0.121	0.119

The dependent variable is the change in the OIS 1Y rate before and after the ECB press conference. Full sample regressions are calculated on the full sample, while Pre-FG regressions are calculated on the sample prior to July 2013 (the pre-forward guidance period), and Post-FG regressions are calculated on the sample after July 2013 (the post forward guidance period). The independent variables are, in order of appearance in table, as follows. The values of the dictionary and DTM Hawk-Dove Indices, derived in Equations 2.5 and 2.8. The change in the ECB deposit facility rate, if any, at the monetary policy meeting. A dummy variable taking a value of one if macroeconomic projections were released, zero otherwise. The revision to inflation forecasts for the next calendar year in percentage points. The revision to GDP forecasts in the next calendar year in percentage points. Robust standard errors in parentheses. *** denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level.

¹⁶I note that due to the fact the OIS1Y rate is used to calculate the monetary policy shock variable, it is not possible to include this in the set of control variables

2.6.4 Robustness - Alternative Dictionaries

As a robustness check, I propose the use of alternative measures of the monetary policy tilt of a central bank, in line with Apel et al. (2022), Bennani and Neuenkirch (2017) and Conrad and Lamla (2010). The method of Apel et al. (2022) is similar in ways to the dictionary based Hawk-Dove Index, but relies on much fewer keywords. Its interpretation is similar to both Hawk-Dove Indices, in that a more positive value denotes a more hawkish/positive tone, and a negative value denotes a more dovish/negative tone.¹⁷ Added to this, Bennani and Neuenkirch (2017) measure the monetary policy tilt using a list of purely hawkish and dovish terms without modifiers, while Conrad and Lamla (2010) create a measure that concentrates purely on price stability. Both have signs interpretable in a similar way to the Hawk-Dove Indices. Results for the specification in Equation 2.9 for each of these measures can be seen in Appendix 2.8.6, Tables B11, B12 and B13.

It should be noted that in the case of Apel et al. (2022) and Bennani and Neuenkirch (2017) both measures are positive and significant at the 5% level. This gives a degree of external validity to the initial results using the derived Hawk-Dove indices, and provides further evidence in favour of the communication of a more hawkish (dovish) tone being interpreted by private sector agents as a signal of improved economic conditions, rather than being internalised as a higher probability of a future interest rate hike. In addition, similar results to the Hawk Dove-Indices emerge for the pre and post forward guidance timeline using this measure. On the other hand no clear effect is present for the series constructed by Conrad and Lamla (2010). As this measure concentrates on communications relating to price stability, this may provide evidence that it is information about the broader economy that drives changes in asset prices.

¹⁷For the purposes of fitting this dictionary to ECB communication I make one small edit to the keywords. Instead of “consumer price inflation”, I use the terms HICP and prices, and in addition to “economic growth” I use “GDP growth” as a keyword. This is to adjust for the language used by the ECB, as the original measure is designed for the Fed. In addition, I merge the polarity words for “inflationary pressures” and “inflation”. Results are similar in both cases

2.7 Conclusion

Communication has become, and remains a highly important tool as part of a modern suite of non-standard monetary policy measures. Many central banks have explored how to use communication to both explicitly guide markets and convey private information surrounding the central bank's beliefs regarding future economic conditions. Based on my results, it is clear that central bank communication can have market impacts beyond that of merely guiding future interest rate expectations. This provides evidence of the existence of the "information channel" of monetary policy, and helps to reconcile the manner in which communication of a more "hawkish" or "dovish" perspective regarding the state of the economy can pass through to financial markets. It is clear that in certain scenarios, the language in ECB press conferences or communication documents can have an economically significant impact on financial markets.

Moreover, rather than just showing that language can have an impact the results indicate additional information on how communication has an impact. In the context of a simple economic model, results indicate that the effect of a more hawkish (dovish) tone has a positive (negative) impact on markets, suggesting that the impact on expected future dividends or the broader economic outlook dominates the impact on expected changes in future discount rates. This suggests that markets put heavier weight on broader information about how central banks perceive the current economic situation, rather than the implications for any expected changes in future policy. Such an observation sheds light on the political economy of interactions between market participants and central bank communication, and highlights the importance of selecting the right language to use in given scenarios, given that informational content contained in the ECB press conference has an economically significant impact on markets in the short-run.

Of note, however, is that that most effects arising from the sentiment of the press conference have faded after the ECB introduced a policy of explicit forward guidance, and continued to move towards a more transparent and consistent communication strategy. This can highlight the market assuring role that such consistent communications can have. This is especially important in situations such as when policymakers may indicate a dovish stance when attempting to stimulate the economy. If markets react negatively to such a statement, this language may have had

unintended consequences. Clear, transparent communication may be able to mitigate these concerns and manage market volatility.

While this paper examines measures of the current policy stance communicated by the ECB in a systematic method, it only examines immediate market impacts. As such there is potential for further work along a number of dimensions. Further understanding can be gained through an analysis of the persistence of these market effects and to what extent they spill over to the wider economy.

2.8 Appendices

2.8.1 Sentiment

The AFinn method assigns values of between -5 and +5 to a list of words depending on how positive or negative they are perceived to be. A rolling sum is calculated and this, divided by the total number of words in the body of text is defined to be its sentiment score. Explicitly, let $Polarity_{i,t}$ be the polarity of word i in document t from -5 to +5 and $Wordcount_t$ be the total number of words in document t . The AFinn sentiment score is:

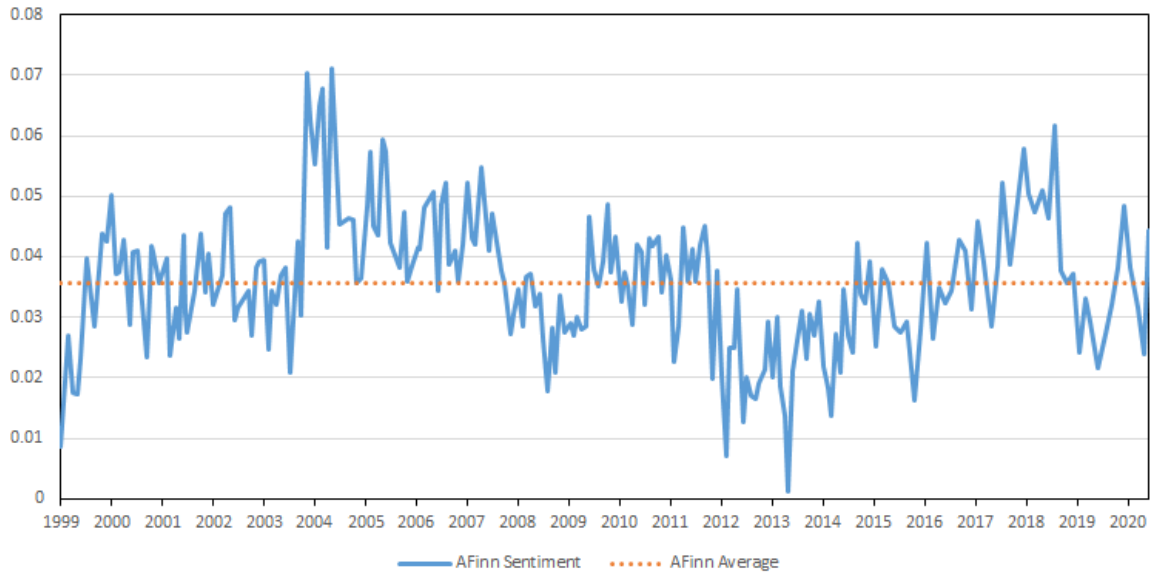
$$AFinn_t = \frac{\sum_{\forall i} Polarity_{i,t}}{Wordcount_t} \quad (2.10)$$

A weakness of AFinn is that it was designed for the analysis of microblogs (such as Twitter), as such it may not be appropriate in an economic context. This weakness motivated the development of the Loughran-McDonald approach, which uses a list of sentiment words developed for the analysis of U.S. 10K filings to create a dictionary that is more focused on financial reporting. The Loughran-McDonald measure takes a simpler counting approach, where the difference between the raw number of positive and negative terms, divided by the total wordcount is the overall sentiment score. Explicitly, let $NumPos_t$ and $NumNeg_t$ be the count of the positive and negative terms in document t and $Wordcount_t$ be the total number of words in such a document. The Loughran-McDonald sentiment score is defined as:

$$LoughranMcDonald_t = \frac{NumPos_t - NumNeg_t}{Wordcount_t} \quad (2.11)$$

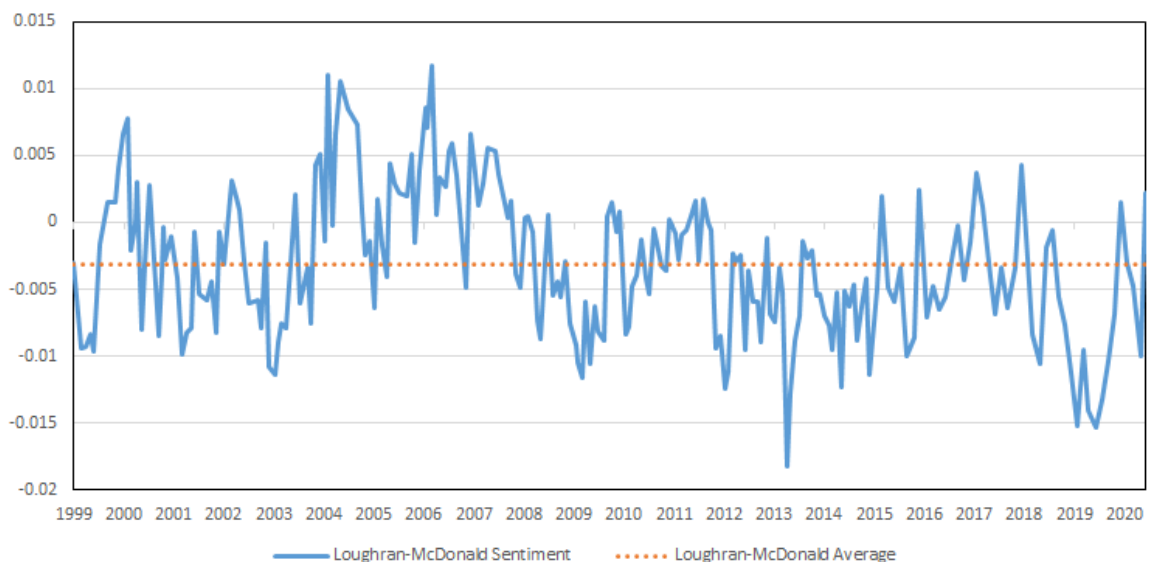
The time series for the AFinn and Loughran-McDonald are shown in Figures [B1](#) and [B2](#). In each case the series average is shown using an orange dotted line, to allow a clear indication of when sentiment was elevated relative to the long run average.

Figure B1. AFinn Sentiment Time Series



Notes: This figure shows the evolution of the AFinn method of sentiment applied to ECB Governing Council press conferences. The Y-axis shows the relative sentiment score, divided by the total word count of the document, with larger (smaller) numbers indicating a more positive (negative) sentiment.

Figure B2. Loughran Sentiment Time Series



Notes: This figure shows the evolution of the Loughran-McDonald method of sentiment applied to ECB Governing Council press conferences. The Y-axis shows the relative sentiment score, defined as the total number of positive terms less the number of negative terms, divided by the total words in the document. Larger (smaller) numbers indicate a more positive (negative) sentiment.

From the above, a number of observations are clear. First, the data are quite volatile. At times there are sustained trends in sentiment, but the meeting to meeting change is often quite large. Since monetary policy communication is quite consistent over time, it is unlikely that such movements should be so volatile. Between meeting changes may be driven by spurious changes in sentiment owing to language not related to monetary policy. This volatility motivates the development of a monetary policy specific measure of sentiment.

Second, it is that a number of key events can be accounted for in these measures. All measures are quite positive from 2005 to 2008, before turning negative during the Great Financial Crisis. Positive outlook also increases during the period between the Great Financial Crisis and the euro area Sovereign Debt Crisis, before turning rather negative again for this period. Finally, recent dynamics are clear. Sentiment began to become more elevated between 2016 and the first half of 2018 in light of positive economic data, but eventually turns more negative in 2019, and severely negative in early 2020 as the Covid-19 crisis took hold. Despite the volatility of these measures, they convey some descriptive information.

2.8.2 Hawk Dove Indices - Word Lists

Table B1. Economic Terms

Neutral Economic		
business	businesses	demand
economic	economy	employment
energy	equities	equity
expansion	financial	growth
housing	income	indicators
inflation	inflationary	investment
investments	labour	manufacturing
outlook	output	price
prices	production	recovery
resource	securities	slack
spending	target	toll
wage	wages	
Pessimistic Economic		
accommodation	devastation	downturn
recession	unemployment	

Table B2. Tone Terms

Positive Tone				
abating	accelerated	add	advance	advanced
augmented	balanced	better	bolsters	boom
booming	boost	boosted	eased	elevated
elevating	expand	expanding	expansionary	extend
extended	fast	faster	firmer	gains
growing	heightened	high	higher	improved
improvement	improving	increase	increased	increases
increasing	more	raise	rapid	rebounded
recovering	rise	risen	rising	robust
rose	significant	solid	sooner	spike
spikes	spiking	stable	strength	strengthen
strengthened	strengthens	strong	stronger	supportive
up	upside	upswing	uptick	
Negative Tone				
adverse	back	below	constrained	contract
contracting	contraction	cooling	correction	dampen
dampening	decelerated	decline	declined	declines
declining	decrease	decreases	decreasing	deepening
depressed	deteriorated	deterioration	diminished	disappointing
dislocation	disruptions	down	downbeat	downside
drop	dropping	ebbed	erosion	fade
faded	fading	fall	fallen	falling
fell	insufficient	less	limit	low
lower	moderated	moderating	moderation	reduce
reduced	reduction	reluctant	removed	restrain
restrained	restraining	restraint	resumption	reversed
slack	slow	slowed	slower	slowing
slowly	sluggish	sluggishness	slumped	soft
softened	softening	stimulate	strained	strains
stress	subdued	tragic	turmoil	underutilization
volatile	vulnerable	wary	weak	weakened
weaker	weakness			

Table B3. Positive and Negative Terms - Risk Topic

Positive Terms				
abating	balanced	better	bolsters	boom
booming	boost	boosted	improved	improving
robust	recovering	less	reduce	reduced
reduction	upside	improvement	strength	strengthen
strengthened	strengthening	strong	stronger	supportive
up	upswing	uptick	decline	decreased
decrease	decreasing	low	lower	
Negative Terms				
accelerated	elevated	heightened	high	higher
increase	increased	increases	increasing	raise
rapid	risen	cooling	correction	dampen
down	downbeat	downside	drop	dropping
ebbed	erosion	restrain	spike	adverse
back	below	constrained	contract	contracting
contraction	restrained	soft	rising	sluggish
stress	turmoil	tragic	underutilisation	volatile
weak	weaker	weakness	sluggishness	subdued

2.8.3 The Topic Modelling Process

Let V be the total number of unique words across all documents. These words form a total of K topics, where each topic $k \in 1, \dots, K$ has an associated probability vector $\beta_k \in \Delta^V$, which is a distribution over these V words. The v th element of the probability vector associated with topic k , β_k^v is the probability that a given word appears in topic k .

Each document is modelled as a distribution over topics. $\theta_d \in \Delta^K$ is defined as being the distribution of topics in document d , where θ_d^k represents the share of topic k in document d . θ_d can be considered a choice variable of the policymaker that generates document d .

Omitting the d subscript out of convenience, the word generation process for each document proceeds as follows. Each document has N words that fill N slots. In the first step, each slot $n \in 1, \dots, N$ is independently allocated a topic assignment $z_n \in 1, \dots, K$ according to the probability vector θ corresponding to the distribution

over topics in the document. These topic assignments are unobserved, and are therefore latent variables in this model.

In the second step, a word is drawn for the n th slot in this document from the probability vector β_{z_n} corresponding to the assignment z_n . Given θ , the distribution of topics, and probability vectors β_k for topics $k = 1, \dots, K$ are now observed, the overall probability of observing the list of words corresponding to the document d is:

$$\prod_{n=1}^N \sum_{z_n} Pr(z_n|\theta) Pr(w_n|\beta_{z_n}) \quad (2.12)$$

where the summation is over all possible topic assignments for individual word w_n .

Hansen et al. (2017) note that computations on Equation 2.12 are generally intractable. Direct maximum likelihood is therefore infeasible. Instead, the LDA approach assumes θ_d is drawn from the symmetric Dirichlet(α) prior over K dimensions. Each β_k is drawn from a Dirichlet(η) prior with V dimensions. Realisations of Dirichlet distributions with M dimensions lie within the M -simplex, and the hyperparameters α and η determine the concentration of these realisations. The higher they are, the more even the probability mass spread across the dimensions. A low value of α for example will lead to the spread of the probabilities across topics to be more concentrated in a few topics, while a larger α will lead to a more even spread. Given these priors, the probability of observing the words in document d is shown in Equation 2.13. This can be estimated using Bayesian methods.

$$\int \dots \int \prod_{k=1}^K Pr(\beta_k|\eta) Pr(\theta|\alpha) \left(\prod_{n=1}^N \sum_{z_n} Pr(z_n|\theta) Pr(w_n|\beta_{z_n}) \right) d\theta d\beta_1 \dots d\beta_K \quad (2.13)$$

There are some key items of note when using this methodology. Firstly, this is known as a *bag of words* approach. This means that each “document” (paragraph) is treated as a collection of words, rather than an ordered set. Since paragraphs are examined rather than modelling the text as a whole, some degree of ordering is defined, limiting information loss.

One of the issues with the LDA approach is that the set of probability vectors β_k associated with each topic k are not allowed to evolve over time. The text of each press conference is treated as independent, and topics are assumed to be static over the entire corpus. I address this by using the *dynamic topic models (DTM)* approach

of Blei and Lafferty (2006). This extension of the LDA algorithm allows each topic's probability vector β_k to evolve over time, by dividing the sample into time slices. For the purposes of this study the time slices are the four time periods associated with the leadership each of the four ECB presidents (at the time of writing).

Each topic's probability vector is thus expressed as $\beta_{t,k}$, where t refers to the relevant time slice, and k refers to the topic. The probability vectors underlying the topics evolve according to a form of Brownian motion (Equation 2.14), and topics evolve smoothly from slice to slice with Gaussian noise.

$$\beta_{t,k}|\beta_{t-1,k} \sim N(\beta_{t-1}, \sigma^2 I) \quad (2.14)$$

2.8.4 Pre-processing steps

These steps are consistent with the literature.¹⁸

Pre-processing steps are taken using the *quanteda* package for *R* (Benoit et al. 2018), and are as follows:

1. Each press conference is split into paragraphs.
2. A list of common stopwords are dropped from the text - these are very common words that add no informational content such as “the”, “and”, “or” etc.
3. A list of words common to ECB text that convey no major new information are dropped. These were selected after looking at a list of commonly occurring words after the removal of stopwords. This minimises ambiguity caused by the cross occurrence of common non-informative words across paragraphs.¹⁹
4. All numeric characters and punctuation are removed.

¹⁸I note that the topic model is fit on a slightly extended sample that includes data as far as October 2020. Results used in regressions only extend as far as June 2020, due to this being the end point of the latest version of the EA-MPD dataset of Altavilla et al. (2019a) at the time of writing

¹⁹These words are: Duisenberg, Noyer, Draghi, Trichet, said, see, regard, fact, mention, particular, time, know, look, also, number, since, m, month, January, February, March, think, one, discuss, April, May, June, July, August, September, October, November, December, way, now, want, first, Ladies, Gentlemen, today, here, ladies, gentlemen, question, disposal, questions, answer, answers, let, welcome, statement, press, second, report, take, say, clear, go, can, point, just, discussion.

5. All characters are coerced to lowercase ensuring results are invariant to capitalisation.

6. Each press conference is split into paragraphs using the *corpus_reshape* function in *quanteda*. These were inspected for consistency.

It should also be noted that in the DTM algorithm, it is explicitly *tokens* not words which are examined. Each slot is filled by a token, which is a string of characters. These are not necessarily only words but can be combinations of words. As such, in an additional step, I identify a list of words that commonly occur together and can unambiguously be read as a single string (for example “deposit facility rate”), and treat these as single tokens. Strings of n words combined in such a way are referred to as *n-grams*. For example, “European Central Bank” is defined as a 3-gram. This improves the fit of the model by enhancing the predictive power, addressing the limitation of the methodology being invariant to ordering. All *n-grams* are shown in Table B4. Words are combined using the *tokens_compound* function in *quanteda*. An underscore () character links words of interest.

Finally, the document is *stemmed* using the standard Porter stemming function in *quanteda*. This function converts the words to their English language root word. For example, inflation and inflationary would both be read as “inflat”, while observe, observed and observing would be read as “observ”. This improves fit by informing the algorithm of relationships between words that convey the same general meaning.

Table B4. Common n-grams

euro area	interest rate	fiscal policy	business cycle
Governing Council	GDP growth	banking system	firm anchoring
price stability	outlook price	yield curve	futures prices
monetary policy	real economy	disposable income	global imbalances
interest rates	nonfinancial corporations	monetary developments	financial system
medium term	financing conditions	monetary accommodation	economic expansion
inflation expectations	fiscal policies	asset purchases	financial environment
structural reforms	labour market	low inflation	Executive Board
inflation rates	balance sheet	purchasing power	strong growth
exchange rate	commodity prices	full allotment	potential growth
monetary analysis	downside risks	accommodative monetary	labour costs
HICP inflation	money market	world economy	price inflation
economic growth	firmly anchored	Central Bank	sustained adjustment
price developments	macroeconomic projections	social partners	monetary growth
private sector	inflationary pressures	economic developments	productivity growth
central banks	inflation rate	gradual recovery	consumer prices
economic analysis	economic recovery	European Council	global demand
oil prices	oil price	Monetary Union	inflationary pressure
annual growth	credit growth	monetary credit	credit risk
real GDP	financial stability	asset purchase	nonstandard monetary
United States	nonstandard measures	developments remain	financial conditions
policy measures	sustainable growth	wage developments	wage growth
press conference	inflationary expectations	Federal Reserve	Euro area
central bank	European Union	Inflation expectations	employment growth
annual HICP	European Commission	European Parliament	monetary union
job creation	labour markets	structural reform	risk premia
financial markets	headline inflation	excess liquidity	capital markets
upside risks	public finances	single currency	consumer confidence
fiscal consolidation	global economy	monetary aggregate	longerterm inflation
financial market	bank lending	private consumption	structural unemployment
automatic stabilisers	monetary policy strategy	longerterm expectations	oil price developments
ECB interest rates	annual inflation rates	oil price increases	higher oil prices
annual HICP inflation	asset purchase programme	credit private sector	HICP inflation rate
monetary policy measures	bank lending survey	fixed rate tender	exchange rate policy
real GDP growth	nonstandard monetary policy	labour market reforms	Federal Reserve System
staff macroeconomic projections	HICP inflation rates	sustainable economic growth	remain broadly balanced
interest rates unchanged	adjustment path inflation	potential output growth	anchor inflation expectations
growth rate loans	Eurosystem staff projections	balance sheet adjustment	support economic recovery
remain firmly anchored	longerterm refinancing operations	marginal lending facility	upside risks price stability
national central banks	annual growth rates	domestic price pressures	ECB staff macroeconomic projections
economic data	longterm interest	banking union	core inflation
wage moderation	labour product	fiscal imbalances	fiscal framework
excessive deficit	upward risks	foreign demand	emerging markets
labour productivity	liquidity conditions	price rises	Eurosystem staff macroeconomic projections
current account	credit standards	European economy	deposit facility rate
market expectations	growth prospects	appreciation euro	
economic conditions	stress tests	inflationary risks	
monetary aggregates	lending rates	Annual growth	
negative rates	liquidity situation	money markets	

2.8.5 The Fitted Topics

The following tables outline the topics extracted from the Dynamic Topic Model process within each time slice.

Table B5. Dynamic Topic Model - Extracted Topics, Time Slice 1 (Wim Duisenberg)

Topic Name	Structural Reforms	Institutions	Discursive	Fiscal Policy	Governing Council Meetings	Risk	Liquidity and Operations	Projections
Term 1	euro_area	euro_area	differ	countri	will	risk	relat	project
Term 2	economi	countri	bank	govern	govern_council	economi	rate	ecb
Term 3	structur_reform	will	certain	stabil	decis	develop	oper	staff
Term 4	competit	full	countri	fiscal	meet	concern	risk	eurosystem
Term 5	growth	implement	actual	growth	confer	world	main	forecast
Term 6	product	euro	mani	pact	presid	factor	liquid	reflect
Term 7	invest	european	go	fiscal_polici	vice-presid	unit_state	balanc	publish
Term 8	improv	area	effect	euro_area	outcom	well	refinanc	assess
Term 9	increas	order	thing	posit	ecb	us	financi_market	rang
Term 10	reform	econom	much	commit	discuss	market	possibl	revis
Term 11	market	singl	well	need	inform	uncertainiti	interest_rate	euro_area
Term 12	employ	framework	now	confid	taken	global	will	broad
Term 13	wage	decis	quit	deficit	mr	far	money_market	intern
Term 14	unemploy	nation	two	plan	like	europ	may	compar
Term 15	support	step	part	consolid	member	futur	outlook	macroeconom_project
Topic Name	Decisions	Credit	Long Term Inflation	Data Analysis	Price Developments	Asset Purchases	Monetary Policy Mandate	Inflation Expectations
Term 1	central_bank	rate	price_stabil	year	price	measur	monetari_polici	price_stabil
Term 2	respons	loan	euro	will	euro_area	will	programm	remain
Term 3	institut	credit	exchang_rate	last	expect	end	polici	medium_term
Term 4	import	growth	will	figur	increas	use	ecb	close
Term 5	comment	continu	rate	observ	remain	inflat	object	continu
Term 6	will	annual_growth	market	regard	quarter	billion	condit	euro_area
Term 7	possibl	bank	deliv	chang	continu	instrument	mandat	monetari
Term 8	work	privat_sector	us	growth	year	interest_rate	act	monitor
Term 9	regard	corpor	interest_rate	level	growth	monetari_polici	word	confirm
Term 10	govern	household	credibl	cours	oil_price	purchas	greec	will
Term 11	alreadi	non-financi	appropri	mention	recent	period	place	inflat_expect
Term 12	european	money	exchang	ago	econom	necessari	say	assess
Term 13	author	remain	import	inflat	activ	forward	govern	monetari_polici
Term 14	done	increas	currenc	next	effect	continu	will	econom
Term 15	level	month	anchor	month	energi	non-standard	well	level

Notes: This table shows the 16 extracted topics, with the component words listed in descending order of size of $P(word|topic)$. This table is for the first time slice corresponding with the presidency of Wim Duisenberg.

Table B6. Dynamic Topic Model - Extracted Topics, Time Slice 1 (Jean Claude Trichet)

Topic Name	Structural Reforms	Institutions	Discursive	Fiscal Policy	Governing Council Meetings	Risk	Liquidity and Operations	Projections
Term 1	economi	euro_area	differ	countri	will	risk	risk	project
Term 2	structur_reform	countri	bank	govern	govern_council	economi	oper	staff
Term 3	euro_area	implement	certain	fiscal	decis	develop	relat	ecb
Term 4	competit	full	actual	stabil	meet	concern	rate	eurosystem
Term 5	growth	will	countri	growth	confer	world	liquid	reflect
Term 6	invest	order	mani	fiscal_polici	presid	factor	main	forecast
Term 7	improv	area	go	pact	vice-presid	global	balanc	assess
Term 8	product	european	effect	euro_area	outcom	unit_state	financi_market	revis
Term 9	increas	euro	thing	need	discuss	market	refinanc	rang
Term 10	reform	econom	much	commit	taken	well	possibl	publish
Term 11	market	singl	now	confid	ecb	us	outlook	euro_area
Term 12	employ	framework	well	deficit	inform	uncertainiti	money_market	broad
Term 13	wage	decis	quit	posit	mr	major	will	macroeconom_project
Term 14	support	nation	two	debt	unanim	europ	interest_rate	collater
Term 15	unemploy	step	part	plan	like	far	may	compar
Topic Name	Decisions	Credit	Long Term Inflation	Data Analysis	Price Developments	Asset Purchases	Monetary Policy Mandate	Inflation Expectations
Term 1	central_bank	loan	price_stabil	year	price	measur	monetari_polici	price_stabil
Term 2	respons	credit	euro	will	euro_area	will	programm	remain
Term 3	import	rate	rate	last	expect	end	polici	medium_term
Term 4	institut	growth	will	observ	quarter	inflat	object	close
Term 5	comment	continu	deliv	figur	increas	use	ecb	continu
Term 6	will	annual_growth	market	regard	remain	instrument	condit	euro_area
Term 7	work	bank	us	chang	continu	purchas	mandat	monetari
Term 8	possibl	corpor	exchang_rate	level	year	billion	act	monitor
Term 9	regard	household	credibl	growth	growth	monetari_polici	say	confirm
Term 10	govern	non-financi	interest_rate	mention	activ	interest_rate	place	inflat_expect
Term 11	alreadi	privat_sector	appropri	cours	oil_price	forward	greec	will
Term 12	level	remain	import	ago	econom	necessari	govern	econom
Term 13	done	increas	anchor	inflat	recent	non-standard	will	level
Term 14	author	money	currenc	present	effect	continu	word	monetari_polici
Term 15	decis	month	definit	situat	energi	period	realli	assess

Notes: This table shows the 16 extracted topics, with the component words listed in descending order of size of $P(word|topic)$. This table is for the first time slice corresponding with the presidency of Jean Claude Trichet.

Table B7. Dynamic Topic Model - Extracted Topics, Time Slice 1 (Mario Draghi)

Topic Name	Structural Reforms	Institutions	Discursive	Fiscal Policy	Governing Council Meetings	Risk	Liquidity and Operations	Projections
Term 1	economi	euro_area	differ	countri	will	risk	oper	project
Term 2	structur_reform	countri	bank	govern	govern_council	economi	risk	staff
Term 3	euro_area	implement	actual	fiscal	decis	develop	relat	ecb
Term 4	invest	full	certain	fiscal_polici	meet	factor	rate	eurosystem
Term 5	competit	will	countri	stabil	confer	concern	liquid	reflect
Term 6	growth	order	mani	growth	presid	world	main	assess
Term 7	improv	area	go	euro_area	outcom	uncertain	balanc	revis
Term 8	product	european	effect	pact	vice-presid	market	refinanc	macroeconom_project
Term 9	increas	euro	thing	need	discuss	well	financi_market	forecast
Term 10	reform	econom	much	debt	taken	us	outlook	collater
Term 11	recoveri	decis	now	commit	unanim	unit_state	possibl	euro_area
Term 12	support	singl	quit	confid	ecb	global	will	broad
Term 13	unemploy	step	well	fiscal_consolid	member	confid	downsid_risk	rang
Term 14	market	framework	two	plan	communic	major	money_market	compar
Term 15	employ	nation	part	posit	mr	far	interest_rate	publish
Topic Name	Decisions	Credit	Long Term Inflation	Data Analysis	Price Developments	Asset Purchases	Monetary Policy Mandate	Inflation Expectations
Term 1	central_bank	credit	price_stabil	year	price	will	monetari_polici	medium_term
Term 2	respons	loan	euro	last	euro_area	measur	programm	remain
Term 3	institut	rate	rate	will	expect	inflat	object	close
Term 4	import	continu	will	observ	quarter	end	condit	price_stabil
Term 5	work	growth	deliv	figur	increas	purchas	ecb	continu
Term 6	comment	bank	exchang_rate	chang	continu	instrument	polici	monetari
Term 7	will	annual_growth	market	regard	remain	use	mandat	level
Term 8	possibl	household	us	ago	growth	forward	act	euro_area
Term 9	govern	corpor	credibl	inflat	year	monetari_polici	place	confirm
Term 10	regard	non-financi	interest_rate	mention	econom	billion	realli	inflat_expect
Term 11	done	money	exchang	level	activ	interest_rate	say	monitor
Term 12	alreadi	increas	appropri	growth	oil_price	continu	govern	econom
Term 13	european	remain	import	cours	energi	necessari	will	inflat_rate
Term 14	author	privat_sector	currenc	next	support	period	thing	monetari_polici
Term 15	level	broad	anchor	two	inflat	guidanc	greec	line

Notes: This table shows the 16 extracted topics, with the component words listed in descending order of size of $P(word|topic)$. This table is for the first time slice corresponding with the presidency of Mario Draghi.

Table B8. Dynamic Topic Model - Extracted Topics, Time Slice 4 (Christine Lagarde)

Topic Name	Structural Reforms	Institutions	Discursive	Fiscal Policy	Governing Council Meetings	Risk	Liquidity and Operations	Projections
Term 1	economi	euro_area	differ	fiscal	will	risk	oper	project
Term 2	structur_reform	countri	actual	countri	govern_council	economi	relat	staff
Term 3	euro_area	implement	bank	govern	decis	factor	risk	ecb
Term 4	invest	full	certain	fiscal_polici	meet	develop	rate	eurosystem
Term 5	improv	will	countri	stabil	confer	concern	liquid	reflect
Term 6	growth	order	go	euro_area	presid	world	refinanc	assess
Term 7	competit	area	mani	growth	outcom	uncertain	main	macroeconom_project
Term 8	recoveri	european	effect	pact	vice-presid	well	balanc	revis
Term 9	product	econom	much	debt	discuss	us	outlook	forecast
Term 10	support	euro	thing	need	taken	market	financi_market	collater
Term 11	increas	decis	now	commit	unanim	unit_state	possibl	euro_area
Term 12	reform	singl	well	confid	communic	global	will	broad
Term 13	unemploy	step	quit	plan	member	major	downsid_risk	compar
Term 14	employ	framework	two	fiscal_consolid	ecb	confid	interest_rate	rang
Term 15	market	nation	part	posit	mr	certain	money_market	publish
Topic Name	Decisions	Credit	Long Term Inflation	Data Analysis	Price Developments	Asset Purchases	Monetary Policy Mandate	Inflation Expectations
Term 1	central_bank	credit	price_stabil	year	euro_area	will	monetari_polici	medium_term
Term 2	respons	loan	euro	last	price	measur	programm	close
Term 3	work	continu	rate	will	expect	inflat	object	remain
Term 4	institut	rate	exchang_rate	observ	quarter	end	condit	price_stabil
Term 5	import	growth	will	figur	increas	purchas	ecb	continu
Term 6	will	household	deliv	chang	continu	use	mandat	level
Term 7	comment	bank	us	inflat	remain	instrument	polici	monetari
Term 8	possibl	corpor	market	ago	growth	monetari_polici	place	inflat_expect
Term 9	govern	annual_growth	credibl	regard	year	billion	act	monitor
Term 10	done	non-financi	interest_rate	mention	activ	continu	realli	confirm
Term 11	european	money	exchang	level	econom	interest_rate	say	euro_area
Term 12	regard	increas	appropri	cours	energi	forward	will	inflat_rate
Term 13	alreadi	remain	import	growth	inflat	necessari	govern	econom
Term 14	author	privat_sector	currenc	next	oil_price	period	thing	monetari_polici
Term 15	level	broad	mandat	two	demand	long	greec	line

Notes: This table shows the 16 extracted topics, with the component words listed in descending order of size of $P(word|topic)$. This table is for the first time slice corresponding with the presidency of Christine Lagarde.

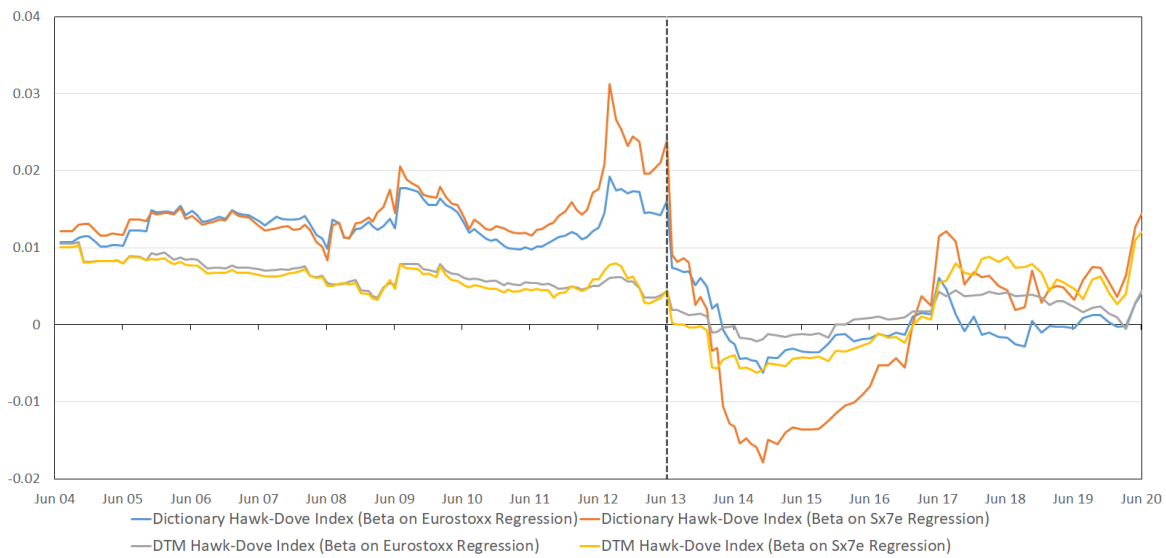
2.8.6 Control variables, rolling regressions, speaker fixed effects and alternative measures

Figure B3. Coefficients on Rolling Regressions, Backward Looking Window - 60 observations, Dictionary Hawk Dove Index (Eurostoxx Regression)



Notes: This figure shows the regression coefficient on the Dictionary Hawk-Dove Index from the regression of Eurostoxx on this variable, with a backward rolling window of 60 observations. The dashed line splits the sample after June 2013, creating a pre and post-forward guidance phase. Other lines show upper and lower bounds on 90 and 95% confidence intervals.

Figure B4. Coefficients on Rolling Regressions, Backward Looking Window - 60 observations



Notes: This figure shows the regression coefficient on the relevant Hawk-Dove Indices for regressions equivalent to those shown in Table 2.3, but estimated with a backward looking rolling window of 60 observations. The dashed line splits the sample after June 2013, creating a pre and post-forward guidance phase.

Table B9. Control Variables

Code	Description	Unit of measure	Source
Change Deposit Facility Rate	The change in the ECB deposit facility rate at the meeting in question.	Change in percentage points	ECB SDW
Projections Released	A dummy variable if macroeconomic projections were released during the press conference.	Dummy variable	ECB Calendar
Medium Term Inflation Forecast Revision	The change in the inflation projection for the next calendar year in the macroeconomic projections if applicable.	Change in percentage points	ECB Documentation
Medium Term GDP Forecast Revision	The change in the real GDP projection for the next calendar year in the macroeconomic projections if applicable.	Change in percentage points	ECB Documentation
Monetary Policy Shock	Monetary policy shock series calculated using the dataset of Altavilla et al. (2019a).	Percentage points	Own Calculations

Table B10. Headline regressions with speaker fixed effects

	Eurostoxx	Sx7e	Eurostoxx	Sx7e
Dictionary Hawk-Dove Index	0.00818*** (0.00295)	0.0131*** (0.00500)		
DTM Hawk-Dove Index			0.00366** (0.00149)	0.00492** (0.00244)
Change Deposit Facility Rate	-0.0888 (0.347)	0.000994 (0.615)	-0.0876 (0.376)	0.0606 (0.659)
Projections Released	0.0383 (0.0930)	0.0558 (0.159)	0.0182 (0.0948)	0.0284 (0.164)
Medium Term Inflation Forecast Revision	-0.216 (0.300)	-0.161 (0.506)	-0.256 (0.303)	-0.188 (0.509)
Medium Term GDP Revision	-0.0578 (0.154)	-0.0804 (0.288)	-0.00330 (0.156)	0.0213 (0.290)
Monetary Policy Shock	-0.0101 (0.0150)	-0.0183 (0.0319)	-0.00150 (0.0151)	-0.00653 (0.0261)
Monetary Policy Shock × Dictionary Hawk-Dove Index	0.00109 (0.000827)	0.00206 (0.00199)		
Monetary Policy Shock × DTM Hawk-Dove Index			0.000396 (0.000607)	0.000421 (0.00147)
Constant	-0.287** (0.126)	-0.299** (0.134)	-0.275** (0.121)	-0.266** (0.134)
Observations	192	192	192	192
R^2	0.079	0.102	0.067	0.082

The dependent variable measures the change in percentage points of the Eurostoxx 50 and SX7E stock indices from before to after the ECB press conference. The independent variables are, in order of appearance in table, as follows. The value of the dictionary and DTMHawk-Dove indices, derived in Equation 2.5. The change in the ECB deposit facility rate, if any, at the monetary policy meeting. A dummy variable taking a value of one if macroeconomic projections were released, zero otherwise. The revision to inflation forecasts for the next calendar year in percentage points. The revision to GDP forecasts in the next calendar year in percentage points. A measure of monetary policy shocks, in line with Altavilla et al. (2019a). An interaction between the Hawk-Dove index score and the monetary policy shock series. All regressions contain speaker fixed effects. Robust standard errors in parentheses. *** denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level.

Table B11. Regression using the measure derived by Apel et al. (2022)

	Eurostoxx	Sx7e	Eurostoxx - Pre FG	Sx7e - Pre FG	Eurostoxx - FG	Sx7e - FG
Apel Index	0.253** (0.102)	0.399** (0.182)	0.277*** (0.101)	0.336** (0.145)	0.140 (0.160)	0.293 (0.303)
Change Deposit Facility Rate	-0.0344 (0.358)	0.0577 (0.651)	-0.0144 (0.341)	0.209 (0.603)	4.120 (3.485)	5.166 (6.206)
Projections Released	0.0437 (0.0862)	-0.00112 (0.148)	0.209** (0.0823)	0.206 (0.140)	-0.178 (0.167)	-0.305 (0.315)
Medium Term Inflation Forecast Revision	-0.229 (0.311)	-0.100 (0.512)	-0.835*** (0.254)	-0.563 (0.549)	0.755* (0.442)	1.059 (0.788)
Medium Term GDP Revision	-0.0716 (0.144)	-0.196 (0.238)	0.0889 (0.151)	-0.0244 (0.304)	0.110 (0.246)	0.0819 (0.343)
Monetary Policy Shock	-0.0411 (0.0393)	-0.0693 (0.0992)	0.0217 (0.0282)	0.0859 (0.0535)	-0.0656* (0.0382)	-0.229** (0.0938)
Monetary Policy Shock × Apel Index	0.0450 (0.0433)	0.0721 (0.101)	-0.00838 (0.0321)	-0.0764 (0.0559)	-0.0946 (0.0911)	0.147 (0.237)
Constant	-0.400*** (0.133)	-0.657*** (0.235)	-0.495*** (0.134)	-0.671*** (0.200)	-0.0787 (0.200)	-0.226 (0.374)
Observations	192	192	130	130	62	62
R ²	0.051	0.046	0.134	0.089	0.335	0.280

The dependent variables are the change in a number of variables before and after the ECB press conference. Eurostoxx measures the change in percentage points of the Eurostoxx 50 stock index of prominent euro area companies. SX7E measures the change in percentage points of the SX7E stock index of prominent euro area bank stocks. Full sample regressions (the first two columns) are calculated on the full sample, while Pre-FG regressions are calculated on the sample prior to July 2013 (the pre-forward guidance period), and Post-FG regressions are calculated on the sample after July 2013 (the post forward guidance period). The independent variables are, in order of appearance in table, as follows. The value of the monetary policy tilt measure of Apel et al. (2022). The change in the ECB deposit facility rate, if any, at the monetary policy meeting. A dummy variable taking a value of one if macroeconomic projections were released, zero otherwise. The revision to inflation forecasts for the next calendar year in percentage points. The revision to GDP forecasts in the next calendar year in percentage points. A measure of monetary policy shocks, in line with Altavilla et al. (2019a). An interaction between the measure of Apel et al. (2022) and the monetary policy shock series. Robust standard errors in parentheses. *** denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level.

Table B12. Regression using the measure derived by Conrad and Lamla (2010) (KOF MPC Index)

	Eurostoxx	Sx7e	Eurostoxx - Pre FG	Sx7e - Pre FG	Eurostoxx - FG	Sx7e - FG
KOF MPC Index	-0.0634 (0.154)	-0.262 (0.270)	0.0698 (0.209)	0.0256 (0.313)	-0.0926 (0.232)	-0.363 (0.438)
Change Deposit Facility Rate	0.0480 (0.342)	0.189 (0.603)	0.0899 (0.348)	0.245 (0.623)	4.057 (3.399)	3.677 (5.866)
Projections Released	0.0858 (0.0829)	0.0795 (0.144)	0.230*** (0.0827)	0.252* (0.145)	-0.110 (0.172)	-0.166 (0.335)
Medium Term Inflation Forecast Revision	0.00458 (0.273)	0.340 (0.448)	-0.647*** (0.243)	-0.345 (0.528)	0.957** (0.474)	1.233 (0.840)
Medium Term GDP Revision	-0.0190 (0.129)	-0.106 (0.216)	0.126 (0.144)	0.0250 (0.296)	0.0907 (0.265)	0.0146 (0.398)
Monetary Policy Shock	-0.0379*** (0.0141)	-0.0729** (0.0302)	-0.00829 (0.0170)	-0.0220 (0.0414)	-0.0975*** (0.0264)	-0.160*** (0.0438)
Monetary Policy Shock × KOF MPC Index	-0.241*** (0.0636)	-0.462*** (0.138)	-0.143** (0.0672)	-0.280** (0.139)	-0.103 (0.0683)	-0.301 (0.184)
Constant	-0.140*** (0.0532)	-0.249*** (0.0894)	-0.179*** (0.0556)	-0.298*** (0.0960)	0.0515 (0.142)	-0.0156 (0.244)
Observations	192	192	130	130	62	62
R ²	0.108	0.132	0.111	0.073	0.332	0.310

The dependent variables are the change in a number of variables before and after the ECB press conference. Eurostoxx measures the change in percentage points of the Eurostoxx 50 stock index of prominent euro area companies. SX7E measures the change in percentage points of the SX7E stock index of prominent euro area bank stocks. Full sample regressions (the first two columns) are calculated on the full sample, while Pre-FG regressions are calculated on the sample prior to July 2013 (the pre-forward guidance period), and Post-FG regressions are calculated on the sample after July 2013 (the post forward guidance period). The independent variables are, in order of appearance in table, as follows. The value of the monetary policy tilt measure of Conrad and Lamla (2010). The change in the ECB deposit facility rate, if any, at the monetary policy meeting. A dummy variable taking a value of one if macroeconomic projections were released, zero otherwise. The revision to inflation forecasts for the next calendar year in percentage points. The revision to GDP forecasts in the next calendar year in percentage points. A measure of monetary policy shocks, in line with Altavilla et al. (2019a). An interaction between the measure of Conrad and Lamla (2010) and the monetary policy shock series. Robust standard errors in parentheses. *** denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level.

Table B13. Regression using the measure derived by Bennani and Neuenkirch (2017)
(BN Index)

	Eurostoxx	Sx7e	Eurostoxx - Pre FG	Sx7e - Pre FG	Eurostoxx - FG	Sx7e - FG
BN Index	0.521*** (0.190)	0.948*** (0.326)	0.856*** (0.188)	1.336*** (0.297)	0.138 (0.336)	0.622 (0.558)
Change Deposit Facility Rate	-0.120 (0.360)	-0.190 (0.648)	-0.376 (0.330)	-0.550 (0.562)	3.947 (3.391)	4.531 (6.020)
Projections Released	0.0580 (0.0901)	0.0108 (0.152)	0.218** (0.0843)	0.198 (0.141)	-0.159 (0.160)	-0.301 (0.311)
Medium Term Inflation Forecast Revision	-0.325 (0.296)	-0.290 (0.489)	-0.987*** (0.229)	-0.823 (0.521)	0.798* (0.453)	0.787 (0.741)
Medium Term GDP Revision	-0.110 (0.140)	-0.241 (0.241)	0.0353 (0.161)	-0.0572 (0.326)	0.0751 (0.262)	-0.0205 (0.340)
Monetary Policy Shock	-0.0176 (0.0201)	-0.0255 (0.0527)	0.0113 (0.0125)	0.0402 (0.0256)	-0.106*** (0.0188)	-0.175*** (0.0410)
Monetary Policy Shock × BN Index	0.0584 (0.0667)	0.0494 (0.161)	0.0137 (0.0457)	-0.106 (0.0908)	-0.163 (0.217)	0.245 (0.276)
Constant	-0.287*** (0.0957)	-0.516*** (0.164)	-0.498*** (0.0996)	-0.783*** (0.171)	0.0264 (0.160)	-0.0627 (0.270)
Observations	192	192	130	130	62	62
R ²	0.060	0.062	0.203	0.157	0.328	0.283

The dependent variables are the change in a number of variables before and after the ECB press conference. Eurostoxx measures the change in percentage points of the Eurostoxx 50 stock index of prominent euro area companies. SX7E measures the change in percentage points of the SX7E stock index of prominent euro area bank stocks. Full sample regressions (the first two columns) are calculated on the full sample, while Pre-FG regressions are calculated on the sample prior to July 2013 (the pre-forward guidance period), and Post-FG regressions are calculated on the sample after July 2013 (the post forward guidance period). The independent variables are, in order of appearance in table, as follows. The value of the monetary policy tilt measure of Bennani and Neuenkirch (2017). The change in the ECB deposit facility rate, if any, at the monetary policy meeting. A dummy variable taking a value of one if macroeconomic projections were released, zero otherwise. The revision to inflation forecasts for the next calendar year in percentage points. The revision to GDP forecasts in the next calendar year in percentage points. A measure of monetary policy shocks, in line with Altavilla et al. (2019a). An interaction between the measure of Bennani and Neuenkirch (2017) and the monetary policy shock series. Robust standard errors in parentheses. *** denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level.

Chapter 3

The central bank crystal ball: temporal information in monetary policy communication ¹

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Abstract

Effective central bank communication provides information that the public does not have but wants. Rather than arising from private information per se, we argue that the public's information deficit reflects three main channels: (i) an updated *evaluation* of the state of the economy based on past data, (ii) a different *projection* from the state to the likely future evolution of the economy, and (iii) differences in how the policymaker responds to the assessed economic outlook. This paper provides a methodology to quantify the temporal information in the text of central bank communication. Both the *evaluation* and *projection* channels significantly improve the ability to explain the news in yields around Federal Reserve and ECB policy announcements compared with topic-based text analysis. We also show that speeches generate greater news in yields the larger the information deficit remaining after the previous ECB Governing Council press conference. The implication of this is that the communication of a single, fixed reaction function, even if highly desirable, is likely impossible even if preferences remain fixed over time. Communication of how the central bank is assessing the economy should be emphasised in addition to any explicit forward guidance.

3.1 Introduction

Does the fact that asset prices move in response to central bank statements mean markets are learning from a central bank crystal ball? A burgeoning literature uses high-frequency asset price movements around communication events to provide evidence that monetary policymakers influence market expectations when they communicate (for instance, studies such as Kuttner (2001). Gürkaynak et al. (2005) and Gertler and Karadi 2015). Such studies provide strong evidence of market participants having an “*information deficit*” relative to policymakers, in the sense that market participants are unable to fully anticipate what a central banker will say, prior to their statements. This information deficit is, at least partly, filled by central bank statements that transmit useful information for the formation of expectations. But what is the source of the information about the future that the central bank provides such that markets can be influenced by its pronouncements? Understanding the answer is vital in order to be able to think about what and how a central bank should optimally communicate.

In many models used for the analysis of monetary policy, the assumptions of full information and rational expectations (FIRE), such as in Eggertsson and Woodford (2003) or Galí (2008), mean that the central bank only usefully communicates two things. First, it communicates its reaction function, although when the central bank is assumed to commit, they only have to do this once. Second, it can communicate forward guidance in the form of planned deviations from the reaction function. In models of asymmetric information, it can also communicate its superior economic information.

In this paper, we highlight the role of conjunctural economic assessment in how communication affects asset prices. This assessment role does not arise in standard models, though it is a core idea in the work on real-time monetary policymaking (Orphanides 2001). It captures the mapping from observed macroeconomic and financial data to the underlying (latent) state of the economy such as the shocks that have hit the economy, their persistence and the state of the output gap. This mapping is a key source of uncertainty facing the central bank, markets and other economic agents, even where they are only concerned with the forward-looking nature of monetary policy.

The potentially important role of private knowledge about the economy for yield curve movements is evident in many papers considering the information effect as in, for example, Romer and Romer (2000), Ellingsen and Söderström (2001), and Nakamura and Steinsson (2018). Other papers show that the information could be related to communication of uncertainty or risk-premia (Hansen et al. 2019, Cieslak and Schrimpf 2019). Our focus on conjunctural assessment is consistent with these approaches though, importantly, we argue that communicating a different assessment does not necessarily reflect *superior* information. Instead, it constitutes an important element of communicating the reaction function. And overlooking its role, as the literature has typically done, risks unduly focusing on the role of forward guidance.

Our main contribution is empirical. We study new measures of both the communication transmission mechanism, and the information deficit. It is part of a complementary empirical approach that begins with the content of statements and relates these to the asset price movements. By directly quantifying the extent of any information deficit between market participants and policymakers, this approach can foster a greater understanding of the communication transmission mechanism.

Specifically, in this paper we contribute to the literature in four main ways. First, we present a framework to describe monetary policy decision making, and the market anticipation of the decisions, that is more general than the one that arises from standard monetary DSGE models. *A priori*, information regarding the future might be expected to be especially important for financial markets, relative to information about the past. This is especially true if we believe that policymakers and markets have similar access to the necessary information on the state of the economy. However, our description of the monetary policy decision-making process shows that, even with the same basic information, central banks' *assessments* of economic conditions and their likely evolution are potentially important sources of the information deficit. This conjunctural assessment relies on both an *evaluation* of the current state of the economy based on past data, and a *projection* from the current state to the future.

Second, we develop an algorithm to quantify the temporal dimensions of central bank communication. Our methodology adapts new tools from the Natural Language Processing (NLP) literature in order to suit our particular context. We validate our approach using labelled Federal Reserve text from separate parts of the Tealbook briefings; our methodology maps well to the framework we outline. This algorithm

allows us to understand the role and importance of temporal information in the communication transmission mechanism. While there has been a growing emphasis on the importance of communicating the future intentions of monetary policy makers as part of the management of expectations, studies into the explicit importance of temporal information in textual data are surprisingly rare to date. This algorithm, potentially following topic-specific adjustments, is likely to be useful in other applications. In a companion paper (Byrne et al. 2023) we explore the details of the algorithm in a broader setting and clarify where other researchers may wish to adapt, extend, or revise our approach to fit different contexts.

Having successfully tagged cases of temporal information in our corpora, our third contribution is to show the importance of this information for both the Federal Reserve and the ECB. We find that information regarding the future is important for explaining asset price movements. We interpret this as evidence in support of the idea that markets react to information in central bank forecasts and their forward guidance. More surprisingly, we show that even backward-looking data is extremely informative. This, we argue, captures important contextualisation of the data contained in the central bank's economic assessment, to which markets react.

Our fourth contribution is to develop a novel measure of the information deficit itself using the questions raised by journalists after monetary policy announcements. This complements the NLP approach with more direct evidence showing that the information deficit includes a significant conjunctural assessment dimension. For this analysis, we focus on the ECB which has the advantage of having a longer, and more consistent, approach to post-meeting press conferences than the Fed. The idea is that, having heard the opening statement, financial journalists query policymakers to fill in gaps that their readers will have. These are, to the best of our knowledge, the first direct measures of the information deficit.

To validate this interpretation, we show that the more closely subsequent speeches are related to the questions that were asked in the most recent press conference, the stronger is the market reaction, indicating greater news and belief updating. This suggests that questions contain important signals of the information that markets wish to hear about; that is, they reflect the information deficit between the ECB and financial markets. We then show that these questions are not just about the ECB's forward guidance, but, as suggested by our framework and NLP analysis, also concern the conjunctural assessment.

Why does the finding that markets garner important information from the central bank's assessment of recently released (mostly common) information matter? This result is important because it identifies one of the key sources of uncertainty that central banks face. Orphanides (2001) highlighted the difficult task that central banks face when making policy in real time by showing that policy reaction functions estimated using real-time data differ considerably from those estimated with ex-post, revised data. But our paper also goes further in showing that the parsing of real-time data into signals about the state of the economy seems to be as much, or more, of a problem for markets, and that markets react to how the central bank views the world.

Our findings also matter for discussions of rules versus discretion, and the role of communication. Kocherlakota (2016) shows that discretion can be optimal in environments where there is a very large set of economic variables that matter for assessing the state of the economy and optimal policy, making it impossible to contract on the full set of possible variables. In FIRE models, where there is knowledge of the full structure of the economy, central bank credibility is assured by a commitment to a sufficiently aggressive linear inflation rule. By contrast, Orphanides and Williams (2005) showed that the job of anchoring inflation expectations is more difficult when agents do not understand the structure of the economy and/or the central bank's rule, or if the central bank has some superior information. This is because the link between economic outcomes and expectations is broken. In such an environment, agents may react to the assessments of the state of the economy, or their outlook for the future, and the central bank may have to regularly renew its vow to aim to achieve its objective of price stability. Communication takes on a much broader role.

The rest of the paper is structured as follows. In Section 3.2, we present our framework for how monetary policy is set and then we relate this framework to the temporal dimension of the policy decision. We then outline our NLP methodology to measure the temporal dimension of policy communications (Section 3.3). Our NLP analysis in Section 3.4 focuses on both the Federal Reserve and the ECB. In the penultimate section of the paper (Section 3.5), we develop our novel measure of the information deficit using journalists' questions at the ECB's post-meeting press conferences. Section 3.6 concludes.

3.2 Monetary Policy Surprises and Information Deficits

In this section we show that the complexity of the monetary policymaking process can be grouped into three broad aspects. Each is a potential source of news for market participants. Although monetary policy is inherently forward-looking, we show that the source of news that generates market surprises could as reasonably come as much from backward-looking assessments of the current data context as from the forward-looking forecast.

3.2.1 Monetary Policymaking Process

Consider a monetary policymaker in month m who has to decide the interest rate, i_m . They have access to a large amount of data capturing macroeconomic trends, surveys, market prices, and other relevant information. We represent this as a high dimensional vector X_m^{CB} . Their decision-making process can be summarised in two broad steps:

1. The policymaker maps the data into a vector of beliefs about the current state of the economy: $\Omega_m^{CB} = g_m(X_m^{CB})$ where $g_m(\cdot)$ captures the analysis of the data available at meeting m , as well as the forecast (including the judgement applied);
2. The policymaker selects the appropriate interest rate as a function of this state to reflect their preferences: $i_m = f_m(g_m(X_m^{CB}))$.

The reaction function maps the objective economic data to the desired interest rate. In our case it is given by the nested function: $f_m(g_m(X_m^{CB}))$. In many standard reaction functions, the states to which monetary policy reacts consist of inflation deviations from target and the output gap ($X_m^{CB} = [\hat{\pi}_m, \hat{y}_m]$). This is because in FIRE models these contemporaneous state variables are assumed to be perfectly observable and, since the structural parameters of the economy are known with certainty, the mapping from the current state of the economy to the optimal forecast is straightforward. The current state variables are sufficient statistics for the optimal h -period ahead forecasts ($\hat{\pi}_{m,m+h}^e, \hat{y}_{m,m+h}^e$), leaving no role for assessment of the state through $g_m(\cdot)$.

In FIRE models, $f_m(\cdot)$ is typically linear, reflecting the linearity of the underlying model, and does not vary with time, reflecting the assumption of central bank commitment. Moreover, an exogenous monetary policy shock is often added linearly to the endogenous reaction terms; in our framework, $f_m(g_m(X_m^{CB})) - f_{m-}(g_m(X_m^{CB}))$

would capture the same kind of shift in policy for a given state of the economy. The difference is that, in our case, the cause of the shift may be endogenous to economic conditions, as in McMahon and Munday (2022a).

In our generic description, we have allowed both elements of the reaction function to vary at each meeting. Carney (2017) argues that time-varying reaction functions are completely natural in the practice of monetary policy, even if they are not standard in our models.² Clarida et al. (1999) and Sims and Zha (2006), among many others, find evidence for low-frequency changes in the reaction function in the US. McMahon and Munday (2022b) present some updated evidence for time-varying reaction functions in the US, while the role played by reaction function variation for market surprises is emphasised by McMahon and Munday (2022a). While we acknowledge that possibility in this paper, and we may capture some of this variation with our textual measures, reaction function variation is not the main focus of this paper.

We focus on the aspect of the policy process that has received less attention in macro models: $g_m(\cdot)$. As should be clear to central bankers, this function captures the very heart of the interest rate process, and the work of economists in central banks. And it is not just of practical relevance. Even if the central bank, as is desirable in many models of optimal policy, could commit to its preferences ($f_m(\cdot) = f_{m-1}(\cdot) \forall m$), and communicate those perfectly, the presence of a time-varying $g_m(\cdot)$ assessment function means that it would be impossible to have a time-invariant mapping between macro data X_m and interest rate choices. This means that identified time-variation in estimated reaction functions *could* reflect evolving assessments of the economy, rather than changing preferences.³

The assessment function captures a different type of uncertainty than the linearly separable shocks that we typically include in macroeconomic models. Those shocks represent *aleatoric* uncertainty, that relates to the outcomes of random processes. Consistent with the growing literature on narrative models (Shiller 2017, Larsen et al. 2021, Goetzmann et al. 2022, Andre et al. 2022, Flynn and Sastry 2022), we

²The cause of such changing reaction functions includes changing membership of the monetary policy committee, central bank uncertainty about the structure of the economy which changes over time, and time variation in the persistence of shocks.

³ $g_m(\cdot)$ is more than just a mapping from contemporaneous data to the forecasts for those data. The mapping between, for example, forecasts for inflation and other macro variables may vary depending on assessments about the type and persistence of the shocks that have hit the economy.

can think of the assessment function as reflecting *ontological* uncertainty.⁴ That is, without perfect knowledge of the true data-generating model, different agents process the same generated data through the models in their own heads, and can reach different conceptualizations of the current state of the economy and its likely evolution. Macaulay and Song (2022) find that multiple distinct economic narratives often circulate about the same economic events. Such ontological uncertainty is exacerbated by *epistemic* uncertainty: the occurrence of events or shocks that have not been seen before enough, or ever, to understand their effects properly.

In summary, the assessment function $g_m(\cdot)$ acknowledges and represents the more general forms of uncertainty faced by policymakers, and those who try to interpret policymakers' communications, than can be represented in models that exclude it.

3.2.2 Information Deficits and Market Surprises

As it is an important novelty in this paper, we will return to discuss the assessment function in more detail below. But first we show how understanding the policy process can help us to understand the sources of market surprises.

We assume that market participants are interested in what policies the central bank will adopt in the future, as in Ellingsen and Söderström (2001). That is, they form expectations of the central bank policy choice and these are reflected in market prices of various securities. We denote the average expectation just before the announcement of the monetary policy decision at time m as $\mathbb{E}[i_t | \mathcal{I}_{m-}^{mkt}] = \tilde{f}_{m-}(\tilde{g}_{m-}(X_{m-}^{mkt}))$ where $m-$ indicates the moment just before the month m decision, $\mathcal{I}_{m-}^{mkt}$ is the information set at that moment, X_{m-}^{mkt} is the economic data that the market have, and $\tilde{f}_m(\cdot)$ and $\tilde{g}_m(\cdot)$ are the market beliefs about the central bank equivalent functions described earlier.

A monetary event, such as an announcement of policy and the associated communications, provides information from the central bank. The new, updated information is $\mathcal{I}_m^{mkt}$ and the expectation is $\tilde{f}_m(\tilde{g}_m(X_m^{mkt}))$. The market surprise, as measured in the empirical literature is, therefore, $\varepsilon_m = \mathbb{E}[i_m | \mathcal{I}_m^{mkt}] - \mathbb{E}[i_{m-} | \mathcal{I}_{m-}^{mkt}]$. This surprise could be generated by changes in any of the three broad factors in the central bank decision.

⁴A familiar form of ontological uncertainty for economists is identification uncertainty. Multiple model specifications can be put forward to capture an economic quantity of interest given the true data-generating process is unknown.

1. X_m^{CB} could be revealed to include new information not in X_m^{mkt} .
2. The central bank could provide an updated assessment/forecast of the economy. This would reveal if it has re-evaluated how it is assessing the state of economy and forecasting its evolution as captured by $g_m(\cdot) \neq \tilde{g}_{m-}(\cdot)$.
3. The central bank may choose to react to a given state of the economy more or less aggressively than previously; $f_m(\cdot) \neq \tilde{f}_{m-}(\cdot)$.

The market surprise is therefore given by: $\varepsilon_m \equiv \tilde{f}_m(\Omega_m^{mkt}) - \tilde{f}_{m-}(\Omega_{m-}^{mkt})$. To understand its drivers, we can approximately decompose it using a first-order Taylor series expansion of $\tilde{f}_m(\Omega_m^{mkt})$ around the pre-announcement view of the economic state Ω_{m-}^{mkt} .⁵

$$\varepsilon_m \approx \underbrace{\tilde{f}_m(\Omega_{m-}^{mkt}) - \tilde{f}_{m-}(\Omega_{m-}^{mkt})}_{\text{Updated Preferences}} + \underbrace{(\Omega_m^{mkt} - \Omega_{m-}^{mkt}) \tilde{f}'_m(\Omega_{m-}^{mkt})}_{\text{Reassessment of State}} \quad (3.1)$$

To see this decomposition visually, consider Figure 3.1. Point A is the pre-announcement expectation for the interest rate ($i_{m-} = \tilde{f}_{m-}(\Omega_{m-}^{mkt})$); Point C captures the expectations post-announcement ($i_m = \tilde{f}_m(\Omega_m^{mkt})$).⁶ The effect of the updated preferences is captured by the move from A to B, while B to C reflects the impact of the reassessment of the state of the economy through the updated preferences.⁷

3.2.3 The Temporal Dimension of Economic Assessment

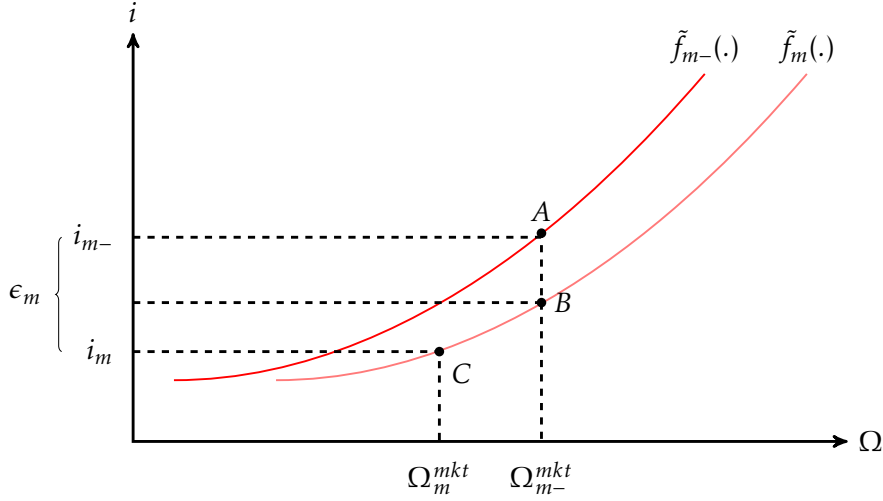
The economic assessment function $g_m(\cdot)$ is not widely studied in the context of empirical and theoretical studies of monetary policy. When one considers the degree of uncertainty about the structure of the economy, which is constantly evolving, the crucial importance of assessing the state of the economy is clear. Even the data on the state of the economy are noisy and released with substantial lags. As such, central banks are constantly monitoring data, adjusting their views of what shocks have hit

⁵ $\tilde{f}_m(\Omega_m^{mkt}) \approx \tilde{f}_m(\Omega_{m-}^{mkt}) + (\Omega_m^{mkt} - \Omega_{m-}^{mkt}) \tilde{f}'_m(\Omega_{m-}^{mkt})$. Subtracting this from $\tilde{f}_m(\Omega_{m-}^{mkt})$ yields the expression in the text.

⁶ Following the interest rate announcement, there is knowledge of the revealed policy interest rate but markets still have to form expectations for longer maturity rates.

⁷ Of course, where the preferences are non-linear, as depicted, other decompositions between A and C are possible and each will give slightly different weight to each component.

Figure 3.1. Market Surprise Decomposition



the economy and modifying their forecast judgements as part of the policy process. This is why central banks invest heavily in the process of nowcasting and in attempts to uncover the state of latent variables like the output gap.

As discussed above, a FIRE environment admits little role for communication other than of a commitment to deviate policy from one's reaction function and forward guidance of deviations from this rule. Though the central bank looks into its crystal ball to forecast, central banks and markets in such environments form the same expectations. In reality, there are more dimensions than this through which a central bank can influence markets with its communication, and the assessment function is at the core of several of these.

We argue that assessment communications are inherently temporal in nature: including both forward-looking dimensions, such as projections, and backward-looking dimensions, such as interpretations of the data. To see this, we further split the assessment function, $g_m(X_m^{CB})$ into two distinct steps:

Evaluation: This involves following developments across a range of domestic and international markets using macroeconomic, financial and other data. Recent data are analysed and put in context in order to interpret its movements (e.g., is a recent increase in inflation likely to be transitory?). This analysis is backward-looking in the sense that it uses the latest available past data pertaining to recent developments, and also more historical data for context and within statistical analyses.

Specifically, let the conjunctural economic analysis function map observed (past) data into a view of the current economic state (and the shocks that have hit it):

$$\Sigma_m^{CB} = s_m(X_m^{CB}). \quad (3.2)$$

Projection: One reason for the existing focus on the forward guidance dimension of central bank communication is that monetary policy is inherently forward-looking. It is made on the basis of forecasts of key variables, and the risks around them. Forecasts typically use a suite of models, and judgement informed by the economic analysis, to map the current conjunctural assessment to the relevant future horizons:

$$\Omega_m^{CB} = p_m(\Sigma_m^{CB}). \quad (3.3)$$

Our description allows both analysis and forecasting functions to vary each meeting. $s_m(\cdot)$ might vary because unfolding data, including past data revisions, might change our view of what types of shocks have hit or how persistent they are likely to be. $p_m(\cdot)$ updates may reflect new forecast judgements about the likely future evolution of the economy. We will utilise Natural Language Processing techniques that measure temporality inherent in the evaluation and projection steps.

Since $g_m(\cdot) = p_m(s_m(\cdot))$, we can further decompose the market surprise:⁸

$$\begin{aligned} \varepsilon_m \approx & \underbrace{\tilde{f}_m(\Omega_{m-}^{mkt}) - \tilde{f}_{m-}(\Omega_{m-}^{mkt})}_{\text{Updated Preferences}} \\ & + \underbrace{\left[\tilde{p}_m(s_{m-}(X_{m-}^{mkt})) - \tilde{p}_{m-}(s_{m-}(X_{m-}^{mkt})) \right] \tilde{f}_m'(\Omega_{m-}^{mkt})}_{\text{Reassessment: Projection}} \\ & + \underbrace{\left[\tilde{s}_m(X_{m-}^{mkt}) - \tilde{s}_{m-}(X_{m-}^{mkt}) \right] \tilde{p}_m'(s_{m-}(X_{m-}^{mkt})) \tilde{f}_m'(\Omega_{m-}^{mkt})}_{\text{Reassessment: Evaluation}} \\ & + \underbrace{(X_m^{mkt} - X_{m-}^{mkt}) \tilde{s}_m'(X_{m-}^{mkt}) \tilde{p}_m'(s_{m-}(X_{m-}^{mkt})) \tilde{f}_m'(\Omega_{m-}^{mkt})}_{\text{Reassessment: New Information}} \end{aligned} \quad (3.4)$$

As noted in the Introduction, an earlier literature discussed whether there is an important role for private information in monetary policy. It is true that central banks

⁸We sequentially applying a first-order Taylor series expansion on $\tilde{p}_m(\cdot)$ and $\tilde{s}_m(\cdot)$ around $s_{m-}(X_{m-}^{mkt})$ and X_{m-}^{mkt} respectively.

have *some* information that is not publicly available, such as regulatory data from financial firms, and sometimes have early access to data. Nonetheless, markets have access to almost all of the underlying data, and it would be rare for the central bank announcement to formally reveal whatever private information there is. If $X_m^{CB} \simeq X_m^{mkt}$, genuinely new, private information (the third reassessment channel in Equation 3.4) would not be an important driver of the surprises (as argued by Bauer and Swanson 2020).

What is revealed, and what could be the source of perceived informational advantage, is a differential assessment of economic conditions. The central bank often has greater analytical resources in the form of large teams of economists and multiple models, which is captured by $s_m(\cdot)$. Reassessments of the economic state are often communicated. For example, this could be putting more or less weight on different sources of data at different times to better explain the observed developments. This is the backward-looking *evaluation* of the data. The central bank may also communicate its updated views and assumptions on the outlook for the economy over the forecast horizon. This is captured by $p_m(\cdot)$. For instance, an updated forecast might follow from having reassessed the nature and pattern of recent forecast errors. This is the future-focused *projection* dimension.

A typical example of the importance of assessment in communication comes from the monetary policy statement of the ECB in September 2019 (Draghi 2019). The text comprises 23 paragraphs, of which 17 relate to assessment ($g_m(\cdot)$) and the remainder to the mapping into the policy decision ($f_m(\cdot)$). Within the assessment portion of the text, all but two paragraphs relate to the ECB's re-assessed evaluation of the state ($s_m(\cdot)$). Those remaining two paragraphs cover the ECB's latest projections ($p_m(\cdot)$). Similarly for the Federal Reserve, a typical FOMC statement begins with an evaluation of the recent data, followed by the policy decision, projections, and an expressed intention to base decisions at future meetings on re-evaluations of the state at those times.⁹

These examples highlight the importance of the assessment function in central bank communication. More pertinently however, they emphasize the temporality embedded in the communication, and the particular weight given to backward-looking evaluation.

⁹See [June 2019 Federal Reserve Statement](#).

3.3 Measuring Temporal Communication

The previous section has established that market surprises may come from both the projection and the evaluation aspects of central bank decision making. We do not, at present, have a method to precisely identify communication corresponding to each stage of the assessment and policy preference functions outlined above; the high-dimensional nature of communication and the over-lapping nature of the language make this a difficult task. In order to examine the extent to which these channels matter in practice, we will conduct an empirical test of the importance of future and past temporal information.

Before we can examine the role of temporal information empirically, we have to measure it. While existing studies of central bank communication have emphasised two Ts, Topic and Tone, attention on the “third T”, Time (temporality), is limited. One reason for this is that extracting temporal information from text can be a demanding task. In this section, we present an algorithm that we have developed specifically for measuring the temporal dimension of central bank textual data. Before describing our algorithm, we will summarise briefly the existing economic literature focused on the quantification of textual data.¹⁰

3.3.1 The Three Ts of Text Analysis

The NLP literature quantifying the tone of text has been widely adapted for economics. Early studies used manual coding of texts to measure tone (Ehrmann and Fratzscher 2009, Rosa and Verga 2007, Hayo and Neuenkirch 2010, Picault and Renault 2017), while others studies have used standard dictionaries (Schmeling and Wagner 2019, Cannon 2015). Some approaches have devised dictionaries specific to the language of central banking and monetary policy (Bennani and Neuenkirch 2017, Apel et al. 2022, Hubert and Labondance 2021, Hansen and McMahon 2016a, Shapiro et al. 2017, Parle 2022) while others used non-dictionary methods (Lucca and Trebbi 2009, Tobback et al. 2017, Arismendi-Zambrano et al. 2021). In more recent times, papers have turned towards deep learning to address this problem, such as Gorodnichenko et al. (2021). Others have quantified the extent to which uncertainty

¹⁰A more detailed literature summary can be found in the companion paper, Byrne et al. (2023).

is emphasised in text by both dictionary and non-dictionary approaches (Baker et al. 2016, Hassan et al. 2019, Caldara and Iacoviello 2022).

On the topic side, many studies have used approaches adapted from the Latent Dirichlet Allocation methods of Blei et al. (2003). Parle (2022) uses a dynamic adaptation of this algorithm to measure tone for each ECB president, while Cross and Greene (2020) use a non-negative matrix factorization approach. Other papers that examine topic include Hansen et al. (2019) for the Bank of England, Istrefi et al. (2021) for the Fed and Aguilar and Pérez-Cervantes (2022) for the Banco de México. Other studies using such methods for central banking analysis include Hendry and Madeley (2010) and Boukus and Rosenberg (2006), while Bybee et al. (2020) study business news.

The time dimension is the least explored thus far in central bank literature. Thus far we are aware of a small number of papers that examine this dimension, including the work of Galardo and Guerrieri (2017), whereby the number of uses of “may” or “might” in a text are counted, on the premise that these seem to have an unambiguous forward looking component. Coenen et al. (2017) apply the algorithm of Galardo and Guerrieri (2017) and find evidence for an increasingly forward-looking orientation in Federal Reserve and ECB communication. Relative to these early treatments, the algorithms deployed in this paper represent a significant extension in our ability to quantify multiple forms of temporality in central bank communication. Rather than word counts, we use algorithms designed to take into account the structure of English grammar, and we are able to extract numerical and categorical references to time, as will be described.

3.3.2 Our ECB and Fed Textual Data

In this study we examine textual data from two central banks, the US Federal Reserve (Fed) and the European Central Bank (ECB). For both, we use textual data from different forms of communication at different points in our study. Complete summary statistics for the textual data used are presented in Table 3.1.

For the Fed, we focus on three types of textual data: (1) announcements during policy event days; (2) the minutes of policy events, released after a policy event with a short lag; (3) textual data from the Greenbook accompanying files, released after a policy event with a significant time lag of 5 years.

The textual data relating to the policy event days can be sub-divided further. The Fed releases a short statement summarising the decision at the beginning of given policy release events. We have data relating to 207 statements in our dataset. Of these, 197 were scheduled meetings with 10 being unscheduled. Beginning in April 2011, the Fed introduced press conferences following policy meetings (at first for alternate meetings, and since 2019 for every meeting). We have 57 press conferences in our dataset. From these conferences, we have the transcripts of the President's introductory statement. We will always refer to this corpus as that of the "introductory statement", to distinguish it from the non-verbal "statement" that is released on the website. We also have transcripts of the questions and answers during the press conference.

We also have access to Greenbook textual data, which are derived from the supporting materials presented to the members of the FOMC prior to each meeting, and include not only charts and tables, but extensive verbal discussions.

For the ECB, we use the ECB press conferences (including the introductory statement, and the associated Q&A session with journalists) and the text of speeches delivered by members of the ECB executive board (discussed in Section 3.5). We analyse the press conferences starting with the first conference of 9th June 1998 and ending with the conference of 10th September 2020. We have a corpus of 240 introductory statements by the ECB President, and we also have 237 Q&A sessions.¹¹ We also source data from speeches by ECB Executive Board members, which we extract from the ECB Speeches dataset, that can be found on the website of the ECB.

When conducting event studies of policy meeting days, we will consider all textual data released within the window of the event as one combined corpus. This means, for the case of the Fed, we amalgamate textual data from the statement, the introductory statement to the press conference, and the answers to questions during the press conference, as well as any textual data relating to unscheduled conference calls. For the case of the ECB, we combine textual data from the introductory statement to the press conference, as well as the answers to journalists' questions. We refer to the combined corpora as the policy event corpora. Note that we do not include the

¹¹The data from the ECB press conferences were manually taken from the website of the ECB: <https://www.ecb.europa.eu/press/pressconf/html/index.en.html>. The number of Q&A sessions is lower than the number of statements because questions were not taken during the first three press conferences.

questions of the journalists themselves in our event corpora, though these questions do occur during the event windows.

In our investigations, we map textual data from the policy event corpora to high-frequency asset price movements in response to the announcements. For the case of the ECB, we have textual data from the introductory statements and the press conference answers at a regular frequency throughout the sample, since the ECB conducted press conferences from its inception. For the Fed, however, there is greater sparsity of textual data across the sample period. Firstly, for the period in the 1990s, there are decision days for which the FOMC made no statement, meaning there are no textual data. Secondly, the press conferences began in 2011, meaning that we have greater volumes of textual data for policy events after this date.

Though the sources of data present the text in a relatively regular manner, in order to use these data we apply some standard cleaning procedures. One important difference is that we need to preserve numerical information associated with dates, whereas numerical information is often jettisoned in other applied computational linguistics studies. A full discussion of cleaning procedures is detailed in Byrne et al. (2023).

Table 3.1. Corpora Characteristics

	Documents	Start	End	Median	Std	Min	Max
Fed Statements	207	1994/02/04	2021/12/15	15	6.09	4	33
Fed PC: Introductory Statement	57	2011/04/27	2021/12/15	61	14.00	23	113
Fed PC: Answers	57	2011/04/27	2021/12/15	226	86.33	75	539
Fed PC: Questions	57	2011/04/27	2021/12/15	110	34.26	48	266
Fed Minutes	413	1976/01/20	2021/12/15	196	150.37	3	834
Fed Greenbook: Part 1	145	1990/02/07	2010/04/28	997	138.24	551	1830
Fed Greenbook: Part 2	149	1990/02/07	2010/04/28	1777	387.95	34	2739
Fed Speeches	4568	1993/04/02	2022/05/11	118	70.51	2	1276
ECB Statements	240	1998/06/09	2020/09/10	60	15.09	16	133
ECB Answers	237	1998/10/13	2020/09/10	153	47.12	34	238
ECB Questions	237	1998/10/13	2020/09/10	63	16.08	23	116
ECB Speeches	2203	1997/02/07	2020/09/15	112	69.38	4	793

Notes: This table shows key summary statistics regarding the number of documents in each corpora and sub-corpora used in this study. The table also displays information on the number of sentences per document.

3.3.3 Algorithm: Temporal Tagging

The approach to temporal tagging used in this study categorizes textual data according to three dimensions:

1. *categorical* references to time: these refer to time only in a general sense, and include references such as “the future”, “in the long-run”, “currently”;
2. *numerical* references to time: references that can be placed on a calendar such as “next year”, “in the last few months”, as well as more direct numerical references such as “1st January 2020” and “2020”;
3. *grammatical* tense: our tagging algorithm also recognises whether sentences include the use of the present, past, and future tenses.

We shall now explain the tools we used to tag categorical, numerical, and grammatical references in sequence. There is an accompanying technical guide to the algorithms which will provide the interested reader with even more information (Byrne et al. 2023).

To extract numerical and categorical temporal references, we use the SUTime temporal tagger created by Chang and Manning (2012). SUTime is a rules-based temporal tagger built on regular expression patterns rather than on statistical relationships. SUTime is able to extract not only explicit references to dates (“January 2020”), but also relative date formats such as “two months from now”, conditional on a reference date for a given document.

We make a number of adjustments to the SUTime algorithm, to take into account the particularities of central bank communication. For example, central bank policymakers will often use phrases such as “short-term”, or “long-run” in their discussions, referring to periods in the future. We add such phrases to the SUTime library, since these were not previously included. We also created a list of commonly understood historical events, that often feature in our textual data. The speaker may refer to the “Great Depression”, “Bretton Woods era” or “Global Financial Crisis” for example, and we tag such references by their underlying dates. These adjustments are described in Byrne et al. (2023).

To tag usage of the past, present, and future tenses, we use the Tense-Mood-Voice (TMV) tool of Ramm et al. (2017). The TMV algorithm uses a list of rules to classify verbal complexes (sequences of verbal tokens within a given verbal phrase) into their

tense. The system takes as its argument textual data to which Part of Speech (POS) tags have already been assigned (e.g. verbs, nouns, determiners are identified).¹² The TMV algorithm is designed to isolate verbal complexes from the parsed sentences, before applying a rich sequence of rules to identify their tense¹³. For example, TMV will assign the verbal complex “I will go” to the simple future tense, since it recognises that the modal auxiliary “will” precedes the infinitive form of the verb (“go”). TMV recognises four forms of each of the past, present, future tense and two each of the conditional past and future tenses. We consolidate the TMV output into three general tenses: past, present and future, incorporating the conditional forms.

Table 3.2. Example of Our Temporal Parsing Approach

Past Tag	Textual Data	Future Tag
	“In the absence of improvement, such that the sustained return of inflation to our aim is threatened, additional stimulus will be required. In our recent deliberations, the members of the Governing Council expressed their conviction in pursuing our aim of inflation close to 2% in a symmetric fashion. ECB President Draghi, Speech at Sintra, 18th June 2019.	Tense
Tense		
	“Over the medium term underlying inflation is expected to increase, supported by our monetary policy measures, the ongoing economic expansion and robust wage growth. ... This assessment is also broadly reflected in the September 2019 ECB staff macroeconomic projections for the euro area, which foresee annual HICP inflation at 1.2% in 2019, 1.0% in 2020 and 1.5% in 2021.” ECB President Draghi, Press Conference, 12th September 2019.	Categorical Tense* Tense* Numerical Numerical
Numerical		
Numerical		

Notes: Phrases marked Numerical are tagged as future/past using the SUTime tool. Phrases marked Categorical are tagged using the SUTime tool, with an additional bespoke dictionary of central-banking-specific future words (for example, “medium-run”). Phrases marked with Tense are tagged as future/past tense using the TMV tool. Phrases marked with Tense* are tagged as present tense using the TMV tool, but coded as future using a bespoke dictionary of present tense phrases that evoke future considerations, designed for use with central bank communications (for example, “expect”, “foresee”).

¹²Ramm et al. (2017) first parse textual data using the MATE parser (Björkelund et al. 2010), and we use the same algorithm.

¹³Note that although English does not have an inflectional future tense, as is found in some other languages, the “future tense” is an output of the TMV rules-based approach. We follow Ramm et al. (2017) in referring to the “future tense” throughout.

Having assigned verbal complexes to their tense, we applied an additional adjustment. In the language of central bank communication, we frequently observe statements such as “we expect”, “we forecast”, or “we predict”. While these verbal complexes are in the present tense, and will be identified as such by TMV, they typically express views about the future. We therefore re-assigned such verbal complexes from the present to the future tense. The full list of verb forms that we re-assign are reported in Byrne et al. (2023), along with more detail on the TMV algorithm.

To recap, by applying the SUTime and TMV approaches, we identify numerical and categorical time-references (SUTime), as well as past, present, and future verbal complexes (TMV). Table 3.2 shows two example sentences from our corpora. The blue highlighted text captures future tagged content while the orange highlights capture the past references. Phrases marked `Numerical` or `Categorical` are tagged using the SUTime tool (or our additional central bank time references), while phrases marked with `Tense` are tagged using the TMV tool. Phrases marked with `Tense*` are tagged as present tense using the TMV tool, but coded as future using our bespoke dictionary of present tense phrases that evoke future considerations.

The first sentence from the speech of ECB President Draghi at Sintra is clearly about the future, and the second is clearly referring to the past but providing context to their recent decision making. Our argument is that such context, especially the symmetric nature of their objective function, is useful and important information for markets trying to predict future interest rates.

The sentences from the press conference highlight another important aspect of the measures. The first of these sentences shows that we capture important forward-looking information with the adjusted tense reference as well as the categorical SUTime measure; standard tense analysis would either miss this reference, or even classify it as past tense. The second of these sentences highlights that the numerical references may sometimes blur the measure of temporal orientation coming from the other measures. Our baseline measures described below classify future and past according to sentences tagged by *any* of the measures. We also conduct our analysis using topics constructed according to each temporal tagger separately; this

more disaggregated approach will generally generate even stronger results though the qualitative nature of the baseline results is the same.¹⁴

3.3.4 Measures of Document Temporal Orientation

Once sentences are tagged appropriately, we are in a position to create measures of temporal orientation from our textual data. Our aim here is to develop document-level measures of past and future orientation. Here, future (past) orientation is understood as cases in which a given document contains a large or small amount of future (past) information. While we focus on overall temporal measures initially, in the following section we will construct similar measures that are disaggregated by topic. To do this we first identify all sentences in our corpora that contain *at least one* reference to the future, be it a numerical future reference, a categorical future reference, or the use of the future tense. We then identify all sentences in our corpora that contain at least one reference to the past (according to any form of tag).

Formally, consider a sentence $s \in \{1, 2, \dots, N^d\}$ found in document d . Let T_{ds}^{fut} denote a dummy variable taking value 1 if and only if sentence s contains at least one temporal expression relating to the future (be it numerical, categorical, or the use of the future tense). Define T_{ds}^{pst} analogously as an indicator variable that equals 1, if and only if sentence s contains at least one reference to the past. Note that a sentence can be tagged as *both* about the future, and about the past, according to this scheme.

The document level overall temporal orientation measures, p_d^{fut} for future and p_d^{pst} for past, are defined as:

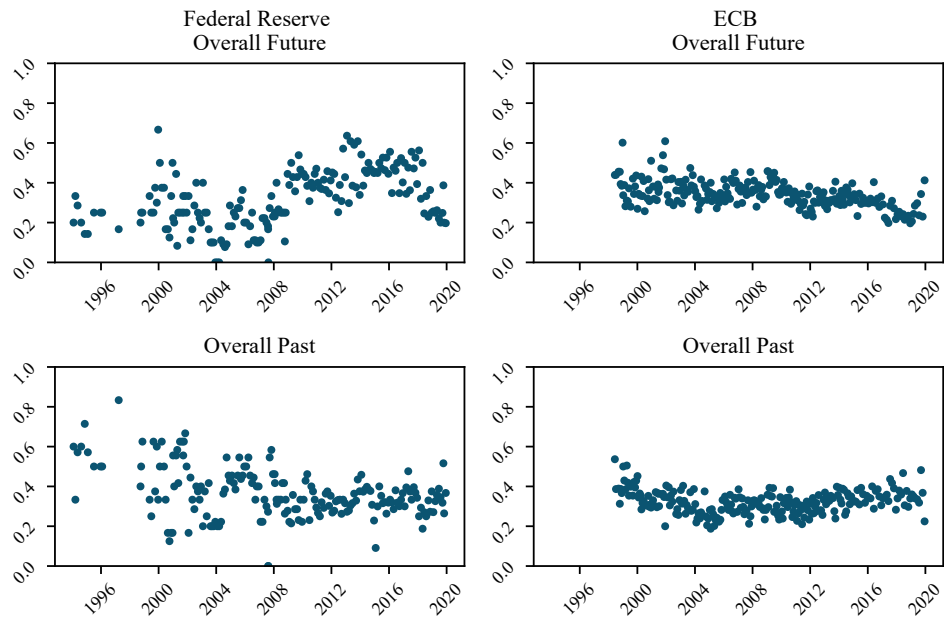
$$p_d^{fut} = \frac{1}{N^d} \sum_{s=1}^{s=N^d} T_{ds}^{fut}, \quad \text{and} \quad p_d^{pst} = \frac{1}{N^d} \sum_{s=1}^{s=N^d} T_{ds}^{pst}.$$

These measures can be interpreted simply as the fraction of sentences in a given document with at least one future or past tag, respectively.

Figure 3.2 shows the time-series of the future and past overall orientation measures, for both the Fed and ECB. Note that the share of sentences marked as future and past fluctuates around 40% for each of the corpora. The future and past shares do appear to be inversely correlated for particular periods, which makes sense, given their construction. The negative correlation is not a strong one, however, taking

¹⁴Results available on request.

Figure 3.2. The Time-Series of Overall Temporal Orientation of Policy Events



Notes: Figure shows the overall fraction of sentences marked with at least one temporal tag (be it future or past, respectively). The textual data are derived from the policy event corpora. The textual data from the Federal Reserve include statements (scheduled and unscheduled), introductory statements to press conferences, and answers. The ECB textual data contain information from introductory statements to press conferences, and answers. Textual data from event days are collated together when constructing these measures.

values of -0.11 for the Fed, and -0.06 for the ECB. We have constructed our temporal taggers to allocate phrases or words to the mutually exclusive categories of past, present, and future. *Ceteris paribus*, an increased number of sentences tagged only as future will lead to a reduced past share. However, it is still possible that the future and past shares can co-move positively if the share of sentences marked only as present falls.

From Figure 3.2, several stylised facts emerge about temporal information in central bank communication. For the case of the Fed, we observe an increase in the future orientation of policy event communication from 2009 period to around 2014. Interestingly, this broadly overlaps with the forward guidance period. This evidence is also consistent with the evidence for the Fed statements presented in Coenen et al. (2017). We do observe, however, a fall in future orientation after around 2018. For the ECB, we observe a gradual secular decline in the overall future orientation, despite

the fact our sample includes a period of forward guidance (from July 2013 onwards).¹⁵ Our estimates therefore lend limited support for the general finding of Coenen et al. (2017) that “central bank statements have on average become more forward looking”.

3.3.5 A Validation Exercise for Document Temporal Orientation

At this stage we will establish a relationship between the temporal indicators (“futureness” and “pastness”) and the distinction between an evaluation step and a projection step, as detailed in Section 3.2. We find it reasonable to believe that communications regarding evaluation will include more frequent references to past data, while communications regarding projection will include more future references. Of course, however, given the complexity of language, any given statement regarding evaluation or projection is likely to include both references to past and future. In this study we posit that evaluation and projection can still be distinguished by their average levels of past and future references. It is on this basis that we interpret later results indicating the importance of future and past temporal references at explaining high-frequency news.

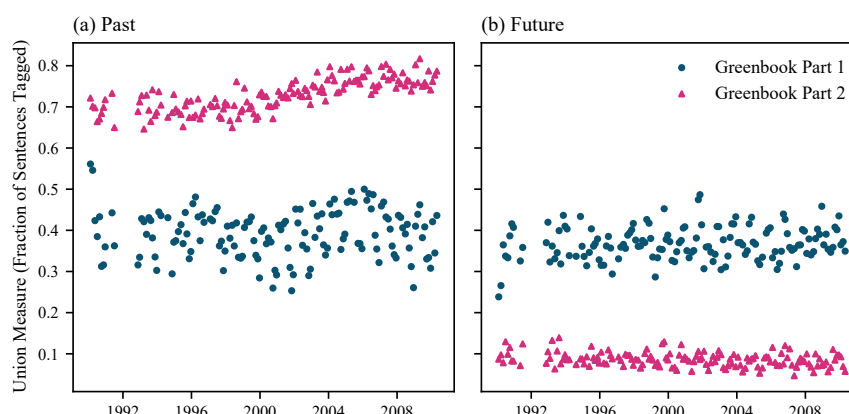
In this sub-section we perform an empirical validation exercise for our proposed relationship between the temporal tags generated by our algorithm, and the evaluation and projection steps. To do this we use data from the Fed. Specifically, we use the Greenbook data, which are a collection of discussions regarding the economic situation as well as forecasting exercises, and are produced to accompany each policy meeting of the FOMC. For a portion of our sample, the Greenbook textual data are actually divided into two distinct parts by Fed economists. The first part (“Summary and Outlook”) relates specifically to the forecasting exercises. The second part (“Recent Developments”) represents a series of evaluations regarding the present state of important economic variables, as well as recent trends. Importantly, the division of the corpora into two was performed by Fed staff, and is not a subjective division by the authors of the present study. Moreover, the fact that the Fed divided their analyses into separate evaluation and projection portions lends weight

¹⁵Coenen et al. (2017) were not in a position to observe the falls in future orientation for the Fed post 2018, since their sample ended in March 2017. The behaviour we observe for the ECB is not evident in the estimates of Coenen et al. (2017) based on introductory statements. Note that these authors use the algorithm of Galardo and Guerrieri (2017), that does not identify numerical or categorical references, and uses a simplified approach to grammatical tense.

to our assertion that the distinction between the two steps is of important practical relevance for the conduct of central banking.

The two parts of the Greenbook data represent ideal corpora for evaluation, since we would expect our document level measures of futureness to be higher when applied to part one, relative to part two. Conversely, we would expect our document level measures of pastness to be higher when applied to part two, relative to part one. This is exactly the relationship that we find, as demonstrated in Figure 3.3. The measures generated by our algorithm are entirely successful at distinguishing between the evaluation portion of the Greenbook corpus, and the projection portion. For no meeting does part two of the corpus have a lower measure of pastness than part one, and the converse is true for the measure of futureness. This exercise therefore provides important direct evidence that our interpretation of futureness and pastness as summary measures of evaluation and projection is a reasonable one to make.

Figure 3.3. Validation of Our Temporal Indicators



Notes: Figure shows temporal measures constructed based on parts one and two of the Greenbook materials. Part one is “Summary and Outlook”. Part two is “Recent Developments”. Panel (a) displays the fraction of sentences tagged with at least one past tag. Panel (b) displays the fraction of sentences tagged with at least one future tag.

3.3.6 Construction of Temporal Topics

While document-level future and past orientation measures may provide reasonable measures of the overall temporal orientation of a speech, or press conference, one concern is that such an approach would amalgamate information from a fairly diverse range of subjects. It is also of interest to study whether the temporal orientation of

given topics within a speech changes the way market participants respond to given speeches. For example, a discussion of the future path of interest rates in a given speech may be more relevant for market participants than a discussion of past interest rate choices (even though the context of how the past is shaping current decisions may also be informative).

We shall assume that sentences are generated according to the following process. Each word is a random draw from the overall vocabulary, and the probability of drawing a given word from the vocabulary is determined by its topic. The topic of the word is itself randomly drawn from a sentence-level distribution over topics. A topic is thus synonymous with a probability distribution over words, and each sentence is associated with a probability distribution over topics. Let $\theta_{k,ds}$ denote the probability associated with topic k , $k \in (1, \dots, K)$ in sentence s and document d .

Expressed in words, the future (past) temporal topic for a given document represents the average topic share for that topic, when we restrict the corpus to only those sentences that contain a future (past) reference. Formally, for a given document d with N_d sentences, and a given topic k , $k \in (1, \dots, K)$ with $K = 15$, we denote the statement (or speech) future oriented topic measure ($\theta_d^{fut}(k)$) and the past orientation measure ($\theta_d^{pst}(k)$) respectively according to:

$$\theta_d^{fut}(k) = \frac{1}{N_d^{fut}} \sum_{s=1}^{s=N_d} T_{ds}^{fut} \theta_{k,ds}, \quad \text{where } N_d^{fut} \equiv \sum_{i=1}^{i=N_d} T_{di}^{fut},$$

$$\theta_d^{pst}(k) = \frac{1}{N_d^{pst}} \sum_{s=1}^{s=N_d} T_{ds}^{pst} \theta_{k,ds}, \quad \text{where } N_d^{pst} \equiv \sum_{i=1}^{i=N_d} T_{di}^{pst}.$$

Of course, the parameters $\theta_{k,ds}$ are not observable, and must be estimated. To measure topics, we use Latent Dirichlet Allocation (LDA) following Blei et al. (2003) and applied to central bank communication in Hansen et al. (2017). We apply LDA at the sentence level (rather than at the document level). We chose to estimate distinct topic models for the ECB based on its policy event corpus. For the Fed, we estimate the topic model based on the policy event corpus in combination with the minutes. The reason is that the sparsity of statement data limits our ability to estimate an interpretable topic model for the Fed, so we bolster the textual data from the policy events with related information from the minutes, when estimating the topic model. This is the only point at which the minutes data are analysed in our study, and they are

not used in event studies, since they are not released during the events.¹⁶ The topic model for the Fed is estimated on textual data from the decision of 4 February 1994 to that of 11 December 2019. The topic model for the ECB is estimated on textual data from 9 June 1998 to 10 September 2020.

We set the number of topics to 15, which led to a distinct and interpretable series of topics. In order to interpret the topics, we examine those words that are associated with the topics with highest probability. We display the ten most probable words, conditional on topic, in Tables B5 and B4. The fifteen generated topics each have meanings that are broadly interpretable in line with certain aspects of central bank communication. A number of topics are directly related to inflation (Topics 2 and 3 for the Fed, and Topics 3, 6, and 7 for the ECB), while other groups are more directly related to monetary policy actions (Topics 4 and 11 for the Fed, and Topics 14 and 15 for the ECB). Certain topics are closely associated with discussion of underlying data (Topics 1, 10, and 5 for the Fed, and Topics 5 and 10 for the ECB).

Having successfully estimated topic models at the sentence level, we are able to construct the temporal topic measures. To demonstrate some of the properties of our new measures of temporal orientation, Panel (a) of Figure 3.4 displays the evolution of measures relating to Topic 3 for the Fed and Topic 7 for the ECB over time. Both of these topics relate to inflation, as can be seen from the word clouds presented in Panels (b) and (c). These measures are constructed for the policy event corpora, and therefore vary at the frequency of the policy meetings.

Part of the contribution of this study is to separately estimate temporal topic shares, and their evolution is also plotted in Figure 3.4. We can observe several features of the shares immediately. The first is that they are correlated with the overall topic share. This is unsurprising, given that they are calculated essentially as “sub-corpora” of the overall corpus.¹⁷ The measures also appear more volatile than

¹⁶A number of pre-processing steps are taken prior to the fitting of the topic model. Note that these pre-processing steps are applied to the corpus prior to the application of the LDA model, but not prior to the application of the SUTime and TMV tools. These steps are largely standard, and include the removal of numbers and punctuation, the removal of standard English stopwords (e.g. “the”), the conversion of words to lower case and the use of a stemmer to reduce words to their root form (so “developing” and “developed” are both stemmed to the same root, “develop”). The model was estimated using a Gibbs sampling approach, with a burn in of 1,000 iterations and a total of 2,000 iterations for the fitting process.

¹⁷For Fed Topic 3, the correlation of the future temporal topic with the overall topic is 0.56, and the correlation of the past temporal topic with the overall topic is 0.58. For ECB Topic 7, the correlation between the future topic share and the overall share is 0.9, while the

the overall measure. Again, this was perhaps to be anticipated, given that they are averages applied to a smaller number of sentences (i.e., those only those sentences that are tagged as future or past, respectively). This makes it likely that the new measures exhibit a somewhat greater degree of noise. However, what is also clear from Figure 3.4 is that the new temporal topics are not reducible to the overall topic measure, and that they can display interesting dynamics that are less pronounced in the overall measure. For example, for the case of Fed Topic 3, we observe large measures of the past-topic in the post-2012 period. In the case of Topic 7 for the ECB, we note that there is a clear increase in the future topic share during the 2008 crisis period. There is also a larger increase during the period of 2015 to 2019, during which the ECB was conducting purchases as part of its QE programme. This was also the period during which the ECB President linked net asset purchases to a “sustained adjustment in the path of inflation”, meaning the future evolution of inflation received a great deal of emphasis in discussion.

3.4 Analysis of the Yield Curve News

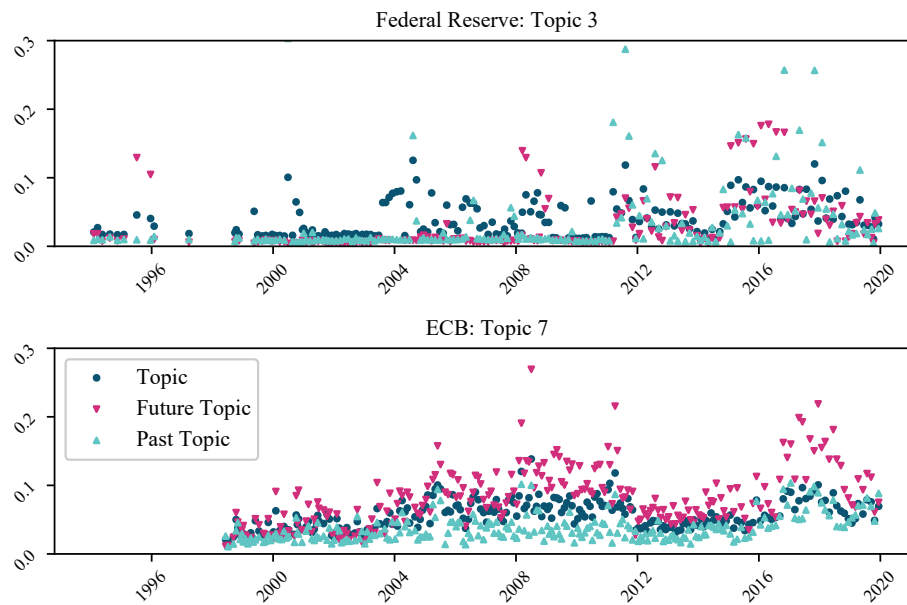
The framework presented in Section 3.2 suggests that central bank communication can cause market news when market participants, in aggregate, update their beliefs because the communication addresses an information deficit that they had. While some of the information deficit may relate to the central bank’s outlook for the economy (the projection dimension), and how they might react to future states, it may also relate to assessments of the state of the economy and the need for contextualisation of current data.

Armed with our measures of the temporal dimension of communication, we can provide an empirical assessment of the temporal drivers of market surprises. If the information deficit only derives from the projection dimension of policy making, the inclusion or exclusion of past information should have no bearing on the extent to which we can systematically explain the asset price news. On the other hand, if conjunctural assessment matters, it should, at least on average, result in past temporal topics being able to explain some of the asset price news.

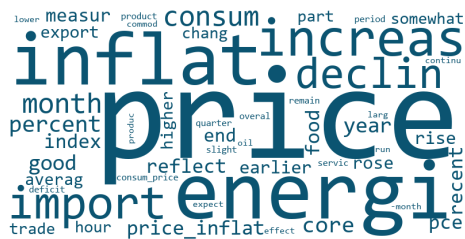
correlation between the past share and the overall share is 0.71. The correlation between the past and future of Fed Topic 7 is positive, at 0.37. The correlation between the future and past share of ECB Topic 8 is also positive, at 0.69.

Figure 3.4. Topics and Temporal Topics, Two Examples from the Statements Corpus

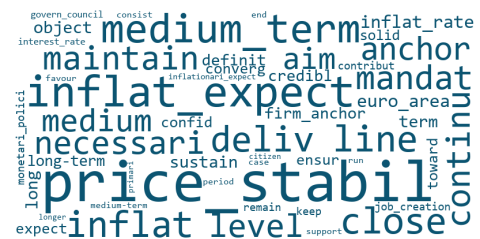
(a) Evolution Over Time, Federal Reserve Topic 3 and ECB Topic 7



(b) Federal Reserve: Topic 3



(c) ECB: Topic 7



Notes: Panel (a) of the Figure displays the evolution over time of the document-level topic share, the future topic share, and the past topic share, for two example topics, Topics 7 and 12. Note that these measures are derived from the statements corpus (including the introductory statement and the answers during the press conference). In the case that there is more than one statement per month, the values are averaged. Panels (b) and (c) of the Figure display, for reference, the estimated “word clouds” of Topic 7 and 12 respectively, i.e. a representation of the highest probability words associated with the topic, where the size of the word indicates its weight.

3.4.1 Empirical Framework

In theory, with a large enough data set, we could explore the empirical relationship between the market news and the temporal dimension of communication using a simple OLS regression of our market news variable on all the temporal dimensions of communication controlling for other released information such as numerical forecast information. In practice, we have a large number of independent variables of interest (our baseline specification has 14 topic main effects, 14 future topics, and 14 past topics, as well as other control variables) and relatively few observations.¹⁸ Therefore, we follow Hansen et al. (2019) and adopt the “elastic net” LASSO specification of Zou and Hastie (2005).

Take a sample of N observations of a given response variable $\{y_i\}_{i=1}^N$ and a corresponding observations of a vector of p potential predictor variables $\{\mathbf{x}_i\}_{i=1}^N$, where $\mathbf{x}_i$ is of dimension $(p \times 1)$. The minimisation problem is:

$$\min_{\beta \in \mathbb{R}^p} \left\{ \frac{1}{2} \sum_{i=1}^N (y_i - \mathbf{x}_i \beta)^2 + \lambda \left[\frac{1}{2} (1 - \alpha) \|\beta\|_2^2 + \alpha \|\beta\|_1 \right] \right\},$$

for some $\lambda \geq 0$ and $\alpha \in [0, 1]$, where $\|u\|_p \equiv \sum_{j=1}^N (|u_j|^p)^{1/p}$ is the l_1 -norm. Here $y = (y_1, \dots, y_N)$ denotes an N -vector of responses of interest, and $\mathbf{X}$ is a $N \times p$ matrix of independent variables. Note that when $\alpha = 1$ this specification is standard LASSO.

We define the parameter α to be equal to 0.99 and estimate the parameter λ by 10-fold cross-validation. We measure market news as the absolute value of the change in yields; this gives a measure of the update in beliefs without direction mattering.

One complicating factor when using LASSO estimation is that, in the case of highly correlated independent variables, parameters can be selected by the routine as non-zero in a somewhat arbitrary manner.¹⁹ To account for this, we summarise the results from our LASSO estimation routine using a non-parametric bootstrap. We draw with replacement from our dataset M observations, and do this 500 times, storing the distribution of estimated parameters. Note that for each bootstrapped dataset, we

¹⁸The topic model contains 15 topics, but we drop one topic measure in regressions to avoid multicollinearity.

¹⁹This issue is widely known in the LASSO literature. Taddy (2017) cautions that (for the case of LASSO) cross-validation “can lead to over-fit for unstable algorithms whose results change dramatically in response to data jitter”. See also Gentzkow et al. (2019) for discussion of this issue.

estimate a different value of λ via 10-fold CV. To compute the distribution of adjusted R^2 we adopt the following procedure. For a given bootstrapped dataset, having estimated a LASSO specification, we then re-estimate our prediction equation via OLS, conditional on the subset of variables that were assigned non-zero coefficients by the LASSO algorithm. Our measure of adjusted R^2 for this draw is taken from this OLS regression.

3.4.2 Asset Market Data and Control Variables

A growing literature in the empirical macro-economics literature focuses on the extraction of monetary policy surprises from policy announcements, by isolating changes in asset prices in narrow windows around the announcement. Early papers studied uni-dimensional monetary policy surprises (Kuttner 2001), and thus to study the impact of our textual measures of Fed and ECB communication on market yields, we use intra-daily data from Bauer and Swanson (2022) for the Fed, and the Euro Area Monetary Policy Event Database (EA-MPD) of Altavilla et al. (2019a) for the ECB. These data are the change in asset prices in response to the Fed and ECB statements and press conferences, recorded as the difference in the price of assets before and after a narrow window (around 30-45 minutes) of each press conference or announcement. The assumption is that monetary policy news should be the most important source of variation for these asset prices, given the tightness of the time-span of the window. In this case, our measures of the signal financial markets receive (in response to information from the press conference) should not be systematically related to other signals (for example signals about aggregate demand that do not come from discussions within the press conference). For the ECB, we exploit the fact that the press conferences follows the release with a lag, and use the press conference window only from the EA-MPD. All textual data for the ECB used in the event study comes from the press conference.

In the case of the Fed, the contracts of interest are the first and fourth Eurodollar contracts (ED1 and ED4), alongside Treasury yields with maturities of two, five and ten years (US 2Y, US 5Y and US 10Y). For the ECB, the contracts examined are OIS EONIA swaps with one month, one year and two year maturities (OIS 1M, OIS 1Y and OIS 2Y), while for the longer end of the yield curve German Bunds with yields of five and ten years are used (DE 5Y, DE 10Y).

Recent contributions in the monetary event study literature have followed Gürkaynak et al. (2005) and sought to decompose asset price movements into multiple forms of surprise, according to structural criteria. This study employs a number of monetary policy surprise series from leading recent papers in the literature, and this is discussed in more detail alongside results in Section 3.4.6.

Each LASSO specification contains a baseline set of controls. For the US, we use the 6 control variables used in the study of Bauer and Swanson (2022). These authors argue that the fact that market participants do not know the reaction function of the policymaker can lead to ex post predictability of surprises, given past financial data. For this reason these authors argue one should control for these financial data. For the ECB cases, we merely control for releases relating to the macroeconomic projections, which is numerical information released during the event window and could thus be correlated with both the dependent variable and our textual measures. For each of these sets of control variables, we force LASSO to include all such variables across all bootstrap draws via penalisation.

Finally, we should be clear on our sample selection. Since the Fed only began releasing statements in 1994, our event study for the US begins with the decision of 4 February 1994. Since Altavilla et al. (2019a) state that the OIS data are too illiquid to analyse prior to 2002, we commence our event study for the ECB from the conference of 3 January 2002. We also exclude the pandemic period from our sample period, ending our event study with the Fed and ECB meetings of 11 and 12 December 2019 respectively. Analysis of the pandemic period is left for future work, in particular since the manner of communication shifted from in-person press conferences, to online video conferences. This could have introduced an important structural break in our textual data.

3.4.3 Effects of Temporal Communication on Market Yield News

Table 3.3 presents the bootstrapped mean Adjusted R^2 values from post-LASSO OLS regressions of the absolute value of changes in yields on sets of variables selected by the LASSO estimation. Results are shown for both the Federal Reserve (panel a) and the ECB (panel b). The main message is that the temporal dimension is highly relevant for explaining the news and both future and past temporal topics matter.

This suggests that communication of both evaluation and projection are important for addressing the market's information deficit.

The most basic measures of communication content, the topics θ_k , capture some of the news systematically. Including the topics improves the Adjusted R^2 for the Fed sample by between 0.14 and 0.22 and for the ECB sample by between 0.15 and 0.25 compared with just the baseline controls for each case. This suggests that simply knowing what the press conference discussion is about is useful for picking up systematic variation in the market reaction.

Separately adding past and future topics to the independent variable set also increases explanatory power (rows 3 and 4). For the 2 year Treasury bond yields, the explanatory power increases from 0.21 on Adjusted R^2 to 0.3 (past added) and 0.29 (future added). For the ECB sample explanatory power goes from 0.28 on Adjusted R^2 to 0.36 (past added) or 0.37 (future added) for the 2 year OIS. In both cases, nearer the short end, the past topics actually capture more of the variation whereas further out the yield curve, the future topics typically explain more.

For both samples and across all asset classes, the strongest explanatory power comes from specifications that allow the LASSO to select over topics from both past and future dimensions. These additional increases in Adjusted R^2 suggest that the past and future topics are not measuring the same source of additional information, since using the measures in combination explains more news than specifications using only one set of measures.

Table 3.4 repeats the analysis but instead reports the Pseudo Out-of-Sample (OOS) Mean Squared Error (MSE). This is constructed as the average MSE across the "left-out" folds of data, which were utilised in the CV approach we took to generate our estimates of λ . In this case, results are always compared to the MSE from a specification only with topics data. This MSE is then indexed to 100. A lower MSE arising from adding temporal indicators indicates that the addition of these variables improves the fit. The conclusions reached with the analysis of the Adjusted R^2 are endorsed with the MSE analysis in that our temporal measures explain news beyond what has been achieved in the previous literature.

3.4.4 Robustness of the Main Results

We perform two forms of robustness check on our baseline results for the yield curve. Firstly, we implement a placebo test to assess the reliability of our approach to mapping news signals to asset price responses. Secondly, we incorporate additional plausible control variables, based on the existing literature.

Placebo Tests

One immediate concern may be that, despite using the elastic net procedure to select only covariates that systematically help to explain the market news, we may nonetheless be achieving greater explanatory power simply by adding more disaggregate variables that the elastic net is able to choose from. To allay these concerns, we conduct a placebo test by randomly shuffling (with replacement) the generated topic and temporal measures across meetings, without permuting the controls and dependent variables. We then repeat the exercise of the previous subsection on the newly created placebo dataset.

Table 3.5 is the equivalent of Table 3.3 but reports the results of this exercise. What is clear from these results, and was found in Hansen et al. (2019), is that the elastic net procedure does not naturally generate the explanatory power. The bootstrapped mean Adjusted R^2 values from the placebo test indicate essentially no improvement of fit from adding the placebo data. This is what one should expect from randomised data. We find similar effects looking at MSE but do not report the results here in the interests of space.

Additional Controls

In our study, we began from the observation that asset price reactions to central bank statements imply the existence of an information deficit between market participants and monetary policymakers. We have found that temporal information accounts for an important portion of this deficit. One general concern is that our measures of temporality may correlate with other features of the textual data that could drive the results. In this subsection we investigate the roles of measures of uncertainty and of document tone, the second “T” of text. We first describe the additional controls we use, before discussing the results for each investigation.

Table 3.3. Adjusted R^2 , Yield Curve News, Intraday Dependent Variables

(a) Federal Reserve					
Specification	ED1	ED4	US 2Y	US 5Y	US 10Y
Controls Only	0.182	0.102	0.067	0.026	0.039
Topics	0.344	0.324	0.213	0.166	0.191
Topics, Past Topics	0.392	0.394	0.298	0.232	0.254
Topics, Future Topics	0.386	0.391	0.288	0.259	0.272
Topics, Future and Past Topics	0.432	0.462	0.379	0.318	0.327
(b) ECB					
Specification	OIS 1M	OIS 1Y	OIS 2Y	DE 5Y	DE 10Y
Controls Only	0.030	0.072	0.072	0.008	0.014
Topics	0.256	0.288	0.282	0.187	0.150
Topics, Past Topics	0.356	0.368	0.357	0.220	0.194
Topics, Future Topics	0.322	0.362	0.368	0.251	0.195
Topics, Future and Past Topics	0.409	0.430	0.427	0.274	0.236

Notes: This table shows the adjusted R^2 for specifications predicting the responses of the absolute value of intraday changes in yields at different maturities for the Federal Reserve (top panel, a) and the ECB (lower panel, b). The “Controls Only” specification contains only the controls of Bauer and Swanson (2022) as independent variables, and is estimated by OLS. The remaining four specifications are estimated using an Elastic Net specification, which selects over different bundles of potential predictors. The “Topics Only” bundle contains controls, plus 14 topic main effects. The “Topics and Past” and “Topics and Future” specifications contain the same bundle as that for “Topics Only”, and additionally allow for the inclusion of 14 temporal topics, respectively relating to past and future. The “Topics, Future and Past” uses the super-set of the previous bundles as the set of potential predictors. For the Elastic Net specifications we display the median estimated adjusted R^2 across 500 draws from a non-parametric bootstrap algorithm. For each bootstrap draw, the Elastic Net is estimated by 20-fold cross-validation. The adjusted R^2 is computed on the basis of OLS estimates of the prediction equation, using only those explanatory variables selected by the Elastic Net. For each Elastic Net specification, we force estimates to include the baseline control variables via penalisation. Intraday asset price movements for the Federal Reserve are taken from the dataset of Bauer and Swanson (2022). Intraday asset price movements for the ECB are taken from the dataset of Altavilla et al. (2019a).

Table 3.4. Pseudo-OOS MSE, Yield Curve News, Intraday Dependent Variables

(a) Federal Reserve					
Specification	ED1	ED4	US 2Y	US 5Y	US 10Y
Topics	100.00	100.00	100.00	100.00	100.00
Topics, Past Topics	96.78	97.75	96.58	98.40	98.70
Topics, Future Topics	100.44	98.07	98.17	97.02	97.17
Topics, Future and Past Topics	96.01	95.54	94.02	95.48	96.32
(b) ECB					
Specification	OIS 1M	OIS 1Y	OIS 2Y	DE 5Y	DE 10Y
Topics	100.00	100.00	100.00	100.00	100.00
Topics, Past Topics	93.01	94.95	95.88	99.76	99.19
Topics, Future Topics	97.16	95.53	93.99	97.03	98.39
Topics, Future and Past Topics	90.68	90.74	91.06	97.50	97.55

Notes: This table shows the pseudo out-of-sample (OOS) mean squared error (MSE) for specifications predicting the responses of the absolute value of intraday changes in yields at different maturities, respectively for the Federal Reserve (top panel) and the ECB (lower panel). We express the OOS MSE relative to that of the “Topics Only” specification, which is normalised to equal 100. For each bootstrap draw, the pseudo OOS MSE is computed as the average MSE associated with the left-out fold of the 20-fold cross-validation procedure, under the optimal estimate of λ , across each of the 20 folds. We take the median OOS MSE across the 500 non-parametric bootstrap draws. Intraday asset price movements for the Federal Reserve are taken from the dataset of Bauer and Swanson (2022). Intraday asset price movements for the ECB are taken from the dataset of Altavilla et al. (2019a). See Notes to Table 3.3 for further details regarding the Elastic Net specifications.

Table 3.5. Placebo Test: Adjusted R^2 , Yield Curve News, Intraday Dependent Variables

(a) Federal Reserve					
Specification	ED1	ED4	US 2Y	US 5Y	US 10Y
Controls Only	0.182	0.102	0.067	0.026	0.039
Topics	0.192	0.115	0.078	0.040	0.053
Topics, Past Topics	0.197	0.120	0.082	0.045	0.059
Topics, Future Topics	0.196	0.120	0.081	0.043	0.057
Topics, Future and Past Topics	0.199	0.124	0.084	0.047	0.061

(b) ECB					
Specification	OIS 1M	OIS 1Y	OIS 2Y	DE 5Y	DE 10Y
Controls Only	0.030	0.072	0.072	0.008	0.014
Topics	0.046	0.086	0.087	0.024	0.030
Topics, Past Topics	0.058	0.092	0.093	0.029	0.038
Topics, Future Topics	0.058	0.092	0.092	0.028	0.037
Topics, Future and Past Topics	0.068	0.095	0.096	0.032	0.042

Notes: This table shows the adjusted R^2 for specifications predicting the responses of the absolute value of intraday changes in yields at different maturities, respectively for the Federal Reserve (top panel) and the ECB (lower panel). Independent variables (excluding controls) were reshuffled randomly across meetings, in order to construct a placebo test, as described in the text. Intraday asset price movements for the Federal Reserve are taken from the dataset of Bauer and Swanson (2022). Intraday asset price movements for the ECB are taken from the dataset of Altavilla et al. (2019a). See Notes to Table 3.3 for further details regarding the Elastic Net specifications.

Many of the early applications of NLP methodologies to finance found that the tone of information releases can influence asset prices (e.g., Das and Chen 2007, Tetlock 2007). To assess whether the tone of the documents within the event corpora could account for our findings, we construct a measure of the tone of given communication events (at the policy day frequency). We measure the tone of each document using the expansionary (i.e., positive terms) and contractionary economic terms (i.e., negative terms) from Hansen and McMahon (2016a). The tone of each document is defined by:

$$tone_d = \frac{N_{pos,d} - N_{neg,d}}{N_{pos,d} + N_{neg,d}},$$

where $N_{pos,d}$ is the count of the number of positive terms and $N_{neg,d}$ is the number of negative terms within each document d . We enter this textual measure of tone as an additional control.

Another robustness check is to assess whether our measures are somehow proxying for uncertainty. For example, if policymakers were to release more temporal information at times of high uncertainty, this would bias our estimates. We have good reason to be interested in the relation between our results and uncertainty, since recent papers have shown non-linearities in the effects of surprises and the uncertainty prior to monetary policy meetings (Bundick et al. 2021, Bauer et al. 2021, De Pooter et al. 2021). In addition our high-frequency news measures are defined in terms of absolute values which means that we would naturally expect larger realisations of the dependent variable during periods of high uncertainty.

To control for this kind of uncertainty, we add a control for the lagged value of market-based uncertainty prior to the monetary policy announcement, using the VIX derived respectively from US and German equity markets. We can think of such market uncertainty regarding the state of the economy as being a mixture of aleatoric, ontological and epistemic uncertainty; there is an element of randomness of outcomes to the current economic process (aleatoric), it is difficult to know the precise levels of concepts such as potential GDP due to the requirement of model assumptions (ontological) and data limitations mean we cannot fully assess how new information will play out (epistemic).

In addition, we note that information from policy statements can in itself signal the central banks' beliefs about broader policy uncertainty, as is found in Hansen et al. (2019). As such, independent of the level of market uncertainty prior to the

meeting, communication of uncertainty can have an impact and textual controls can have an additional contribution. We control for this using the count of words from uncertainty subset of the dictionary of Loughran and McDonald (2011) within each document normalised by the length of the text.

Finally, in this sub-section we will examine whether the structural features of the Fed policy releases affect results. As previously mentioned, prior to the introduction of press conferences in 2011, the Fed released relatively short statements. For this reason, our measures of temporality could be relatively noisy for those events without press conferences. Therefore we perform an investigation with press conferences removed. We also perform an investigation where we remove the unscheduled meetings from our sample for the Fed.

When repeating the exercises with additional controls, the additional variable, like all control variables throughout, is constrained to be included in all specifications (it is not subject to deselection by the LASSO algorithm).

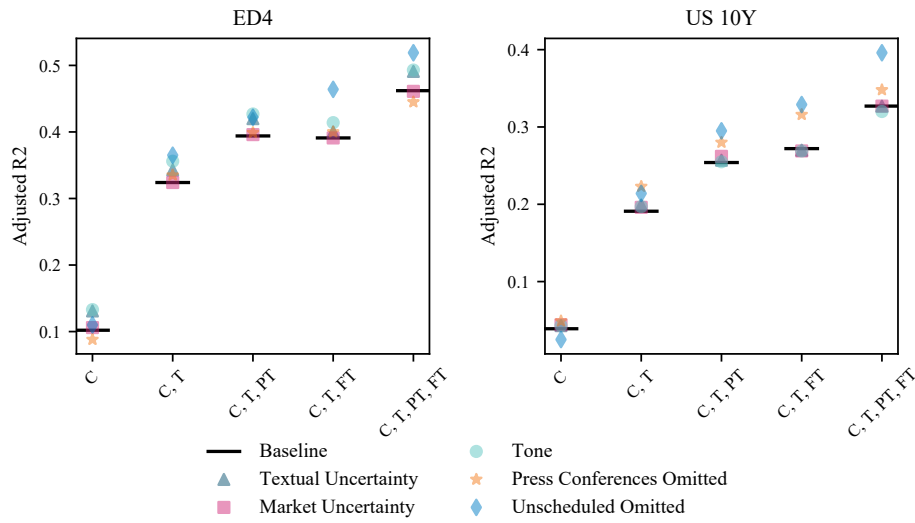
We display a summary of our estimates for two contracts, for each of the two central banks, in Figure 3.5. We choose to display results for ED4 and the Treasury 10-year rate for the Fed, and the one-year OIS and 10-year German yield for the ECB.²⁰ We have generally found that adding additional controls for the influence of the potential omitted variables we have discussed makes little difference to our findings. Adding a measure of tone appears to raise the explanatory power of all specifications by a small amount, without affecting the ordering over specifications. Similar findings are in evidence for specifications with the two uncertainty controls. We conclude that our measures of temporality are not reducible to tone, or to uncertainty measures.

We do see some evidence that the unscheduled meetings weaken the relation between our temporal topics and the measures of market news. This can be seen for both ED4 and the 10-year yield in Figure 3.5a, and is particularly true for the future temporal topics. One explanation is that important information regarding future outcomes is more typically conveyed in the scheduled meeting statements, while the unscheduled meetings focus on extraneous contemporary shocks. Further, removing the press conferences has little effect on the qualitative findings. We conclude that our baseline results are highly robust.

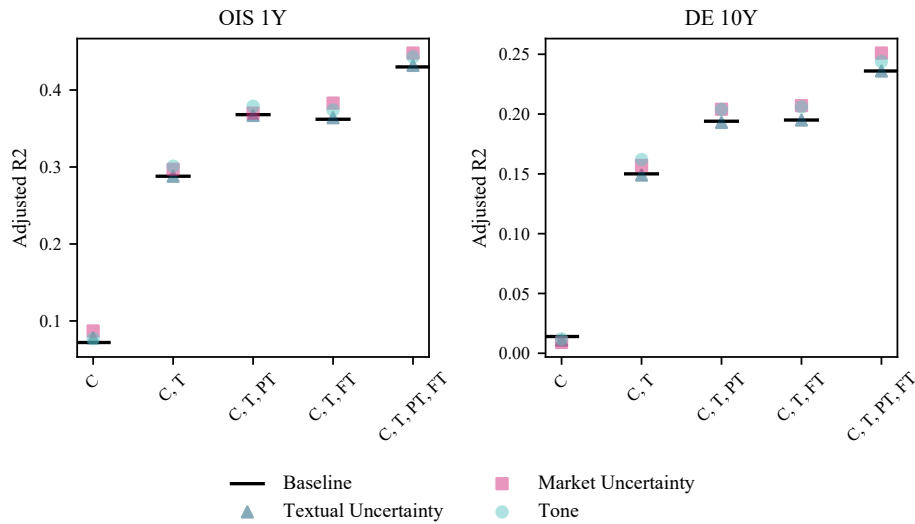
²⁰Results for the other contracts are available on request, though conclusions are unchanged.

Figure 3.5. Summary of Robustness Exercises

(a) Federal Reserve



(b) ECB

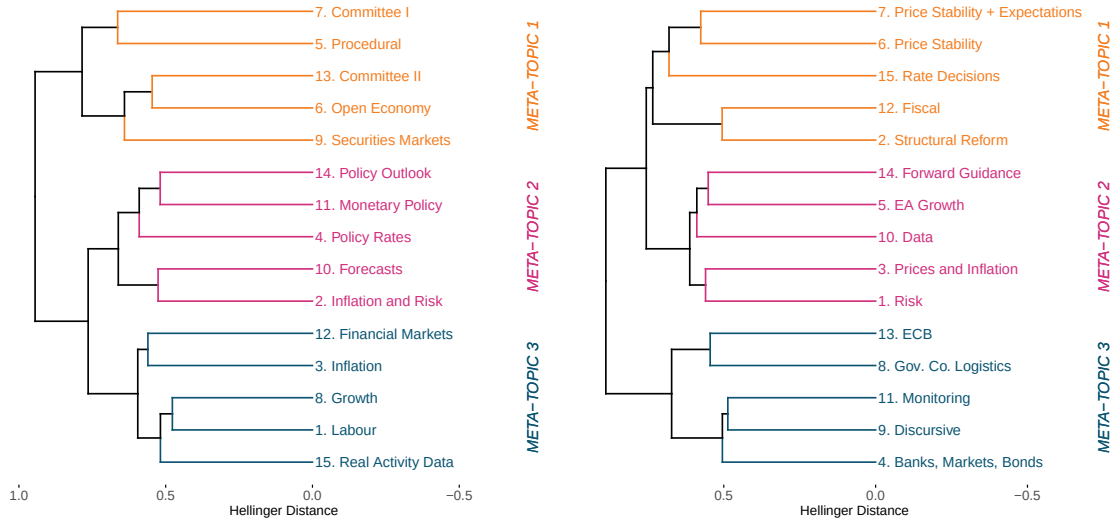


Notes: This figure shows the adjusted R^2 for specifications predicting the responses of the absolute value of intraday changes in yields at different maturities, respectively for the Federal Reserve (top panel) and the ECB (lower panel). C: controls only; C,T: controls and topics; C,T,PT: controls, topics, past topics; C,T,FT: controls, topics, future topics; C,T,PT,FT: controls, topics, future topics, past topics. In addition to the baseline controls, each specification contained additional different control variables: (1) a measure of textual uncertainty; (2) a measure of market uncertainty (lagged VIX); (3) a measure of the tone of the textual data. For the case of the Fed, we additionally estimate a specification with the press conferences omitted from the sample, and another with the unscheduled meetings removed from the sample. Intraday asset price movements for the Fed and ECB taken from the datasets of Bauer and Swanson (2022) and Altavilla et al. (2019a) respectively. See Notes to Table 3.3 for further details regarding the Elastic Net specifications.

3.4.5 The Relation Between Explanatory Power, Temporality, and Topic

While our previous specifications shed light on the information gained by adding temporal and topical information, it is difficult to assess which kinds of information are driving these gains. This is partly due to a dimensionality issue - with a large number of topics, identification of precise marginal effects is difficult. In order to try to overcome this challenge, we construct “meta topics”, combining fourteen of the topics²¹ based on their similarity according to the distance between the topic-word distribution of each topic, as measured using the Hellinger distance.²² These are clustered using a dendrogram as shown in Figures 3.6.

Figure 3.6. Dendrogram clustering



Notes: This figure shows the dendrogram constructed using Hellinger distance for the Fed topic model (LHS) and the ECB topic model (RHS). Each node shows the level of dissimilarity between each branch.

We repeat the Adjusted R^2 analysis for the Fed and ECB using the fourth eurodollar futures contract (ED4) and one year OIS rates (OIS 1Y) respectively. In each case, we omit one meta topic each time, inferring that any reduction in the explanatory power

²¹One of the fifteen generated topics is omitted in each case, in line with the main specification.

²²The Hellinger distance between topics A and B, where a_i and b_i is the weight on token i in each topic, is:

$$dist_{AB} = \frac{1}{\sqrt{2}} \left(\sum_{i=1}^k (\sqrt{a_i} - \sqrt{b_i})^2 \right)$$

can be attributed to removing this meta topic. The results are shown in Tables 3.6a and 3.6b.

Table 3.6. Hellinger metatopics analysis

(a) Federal Reserve				
Specification	Full	Cut MT 1	Cut MT 2	Cut MT 3
Controls Only	0.102			
Topics	0.324	0.278	0.261	0.305
Topics, Past Topics	0.394	0.366	0.304	0.370
Topics, Future Topics	0.391	0.341	0.290	0.337
Topics, Future and Past Topics	0.462	0.420	0.332	0.395

(b) ECB				
Specification	Full	Cut MT 1	Cut MT 2	Cut MT 3
Controls Only	0.072			
Topics	0.288	0.232	0.234	0.256
Topics, Past Topics	0.368	0.278	0.300	0.332
Topics, Future Topics	0.362	0.279	0.285	0.335
Topics, Future and Past Topics	0.430	0.310	0.353	0.408

Notes: This table shows the adjusted R^2 for specifications predicting the responses of the absolute value of intraday changes in yields at different maturities, respectively for the Federal Reserve (top panel) and the ECB (lower panel). Specifications are identical to Table 3.3, with the exception that in each case one Hellinger distance generated meta topic is dropped (excluding the first baseline specification). Intraday asset price movements for the Federal Reserve are taken from the dataset of Bauer and Swanson (2022). Intraday asset price movements for the ECB are taken from the dataset of Altavilla et al. (2019a). See Notes to Table 3.3 for further details regarding the Elastic Net specifications.

For the Fed, the largest drop in Adjusted R^2 is seen when dropping Meta Topic 2, which is the topic most broadly related to monetary policy. This provides some evidence that topics more related to the monetary policy mandate more strongly drive the increase in explanatory power, both when included alone but also when interacted with the temporal aspects. In the case of the third meta topic, which relates to data analysis, there is not a large reduction in explanatory power in a topic specification. However the reduction is larger in the interaction with future temporal information, suggesting this meta topic may capture forecasting/projection information.

In the case of the ECB, a broadly similar narrative emerges. There is limited evidence that Meta Topic 1, relating to monetary policy, expectations and fiscal policy, has more explanatory power than the other meta topics, particularly when interacted

with the temporal information. It should be noted however, that the explanatory power relating to broader economic discussions (Meta Topic 2) is also reasonably large.

On the whole, this evidence suggests that it is primarily monetary policy discussion, relating both to mandate and policy decisions, that may be driving effects, although there is also a role for broader economic analysis.

3.4.6 Monetary Policy Surprise Analysis

In our previous investigations, we examined only the response of asset prices across the yield curve to textual measures. In an influential contribution, Gürkaynak et al. (2005) argued that such asset price movements can be interpreted as reduced form responses to more than one monetary policy shock with a structural interpretation. These authors found that two such shocks were sufficient to explain observed variation. Therefore, an interesting question is whether our textual signals have differing capacity to explain the structural components of asset price responses.

Therefore we repeat our previous analysis, with structurally decomposed shocks as dependent variables. Specifically, we use the Swanson (2021) structural surprises for the Federal Reserve, which are measures of target, forward guidance, and large-scale asset purchase (LSAP) surprises. The study of Altavilla et al. (2019a) applied a very similar decomposition to euro area data, generating target, forward guidance and quantitative easing (QE) surprises. These authors also extract an additional form of forward guidance surprise, which they term the timing surprise, since it relates to the timing of decisions, that are in some sense already “priced in” by market participants.

Neither of these two surprise series separates monetary policy surprises from so-called “information surprises”. It is of particular interest to our study as to whether our textual data signals are related systematically to monetary policy or information effects. Many of the signals we have generated are direct measures of topics that are focussed on discussions of data, or forecasts. We have also motivated why discussions by policymakers of recent data may themselves be a source of news to market participants, to the extent they inform markets of central bank evaluation functions. For this reason we examine also the responses of information

and monetary policy surprises based on the decomposition of Jarociński and Karadi (2020), in addition to the two decompositions already discussed.²³

We display our results in Table 3.7. The basic result of the earlier analysis remains - both forward and backward looking temporal topics play an important role in explaining news variation. For both the Fed and for the ECB, future temporal topics explain more variation in target surprise news relative to past temporal topics, though the difference in Adjusted R^2 is greater for the ECB. For the two forward guidance surprises, we also find that future topics have larger explanatory power than past topics, and again the difference is greater for the ECB. One explanation for the greater difference for the ECB would be that the decomposition of Altavilla et al. (2019a) separately extracts timing surprises, for which past information has greater explanatory power than future. To the extent that this result is general, and the Swanson (2021) subsumes timing and forward guidance together, this may explain the stronger relation between future topics and forward guidance in the ECB cases. For the case of the Fed LSAP and ECB QE surprises, we only observe a difference between past and future topics for the case of the Fed, where past topics have greater explanatory power. This suggests that guidance regarding LSAPs was quite closely related to the evaluation step of the Fed.

Table 3.7 also shows the responses of the Jarociński and Karadi (2020) surprises by specification. As before, both temporal topics systematically contain information to explain each shock, and the joint inclusion captures the most variation. Here we observe some interesting differences between the Fed and ECB results. For the case of the Fed, our measures have consistently greater ability to explain the monetary policy surprise, and less so the information surprise. For the ECB, we observe a broadly comparable ability to explain the two surprises when we use the specification with both future and past topics. One explanation for this finding could be that the structure of Fed and ECB communication favours the mapping between textual data and information surprises for the ECB. The reason is that the volume of textual data revealed to market participants during the event window was far smaller, for the Fed, prior to the press conferences, as previously mentioned. Statements that were released before the period of press conferences were typically terse, and related only

²³We constructed updated versions of Jarociński and Karadi (2020) based on a sign-restrictions algorithm applied only to intraday data, using identical restrictions to those used in the original study.

Table 3.7. Adjusted R^2 , Decomposed Surprises**(a) Federal Reserve**

Specification	Target	FG	LSAP	INFO	MPOL
Controls Only	0.175	0.020	0.054	0.115	0.259
Topics	0.317	0.233	0.166	0.234	0.390
Topics, Past Topics	0.373	0.308	0.208	0.275	0.441
Topics, Future Topics	0.380	0.313	0.187	0.273	0.493
Topics, Future and Past Topics	0.431	0.373	0.228	0.309	0.526

(b) ECB

Specification	Target	Timing	FG	QE	INFO	MPOL
Controls Only	0.020	0.020	0.033	0.096	0.007	-0.023
Topics	0.217	0.280	0.289	0.208	0.165	0.167
Topics, Past Topics	0.275	0.360	0.329	0.262	0.262	0.238
Topics, Future Topics	0.330	0.352	0.342	0.263	0.271	0.251
Topics, Future and Past Topics	0.373	0.415	0.372	0.312	0.339	0.325

Notes: The top panel of this table shows the adjusted R^2 for specifications predicting the responses of the absolute value of intraday changes in (i) Swanson (2021) surprises at different maturities, (ii) Bauer and Swanson (2022) surprise (the first principal component, not orthogonalised). The bottom panel of this table shows the adjusted R^2 for specifications predicting the responses of the absolute value of intraday changes in the Altavilla et al. (2019a) surprises. See Notes to Table 3.3 for further details regarding the Elastic Net specifications.

to monetary policy. On the contrary, the ECB conducted press conferences, during which macroeconomic data was discussed, throughout our sample period.

Another feature of our results is that we do not find strong evidence that the information effect is more related to the evaluation step (proxied by backward-looking information), relative to the projection step (proxied by forward-looking information), since both future and past topics relate to information shock news in a similar way across cases. We conclude that information effects are likely to reflect both projection and evaluation to a comparable degree. In Appendix Section 3.7.1 we show that temporal information can be helpful to differentiate the separate information conveyed as part of information and monetary policy surprises.

3.5 Press questions as an information deficit measure

The analysis so far provides evidence that the central bank's conjunctural assessment is an important source of information for markets. However, it is difficult to specifically identify what the market does not know in order to assess the information deficit. To proceed, we develop an alternative, novel measure of the information deficit. This approach provides direct evidence of the time-varying nature of the deficit.

To do this, we exploit the Q&A part of the ECB press conferences and we focus on the questions asked by financial journalists as a measure of the information deficit. Between October 1998 and September 2022, there have been 6,175 questions asked by journalists when called upon by the ECB's Director General of Communications. Journalists typically ask two questions when they are called upon in the press conference. Our measure is based on the assumption that the questions highlight the issues that journalists, after hearing the opening statement, require clarification on, and that these reflect the information gaps that their financial market readers would also have.

3.5.1 Validating the use of journalists' questions

While we argue that journalists' questions should be a signal of the information deficit at the time of the press conference, we wish to formally show this. For this, we extend our analysis to ECB Executive Board member speeches but combine the analysis with the questions from the preceding Q&A.

Our idea is as follows. Given that the impact of any communication is related to its newsworthiness, a speech which addresses market participants' information deficit is more likely to generate news and lead beliefs to update. The speech may clarify areas about which the market is unclear, or it may inform on the latest thinking of the central bank on the state of the economy or the reaction of monetary policy. In order to show that the questions reasonably reflect the information deficit, we shall show that speeches delivered in the inter-meeting period that address issues raised in the questions generate more market news than speeches that do not.

The speeches we use come from the ECB Speeches Dataset. This is an archive of all speeches by ECB Executive Board members, dating back to February 1997.²⁴ These data are continually updated by the ECB, we use the version of the dataset that ends with a speech on the 15th September 2020. Our sample includes 2,203 English speeches.²⁵ As more than one speech is often given on a particular day, the total number of days on which one or more speech occurs is 1,713. We treat speeches given on the same day essentially as one document because we will use a one-day asset price window. We otherwise process the speeches in the same way as the statements, though some more cleaning was required in the case of the speeches, as discussed in Byrne et al. (2023).²⁶

The temporal dimension of speeches generates similar, albeit less systematic, market news on the yield curve as the main announcements; Table B3 in the Appendix presents the baseline yield curve analysis but applied to the speeches for both the

²⁴The dataset includes speeches delivered by senior officials prior to the formal creation of the ECB in June 1998. It is available here: <https://www.ecb.europa.eu/press/key/html/downloads.en.html>

²⁵We exclude 159 non-English speeches. There are 16 speeches for which no text is available, which are discarded. There are 34 speeches that merely summarise the title and topic of the speech, and provide a hyperlink to lecture slides – these are also discarded.

²⁶Note that our topic models were estimated on the policy event corpora, and therefore did not include data from the speeches. Given the event corpora topic models, we extrapolate our topic model to the textual data from the speeches (*querying* in the language of information retrieval). We prefer to use topic models that were estimated on textual data purely focused on monetary policy and its interpretation, rather than models that would incorporate information from the speeches that is frequently quite varied (including discussions of politics or law, for instance). This decision ensures consistency of topics across our investigations. The baseline fitted 15-topic LDA model was extrapolated out of sample to the relevant speeches dataset. A potential concern is the existence of words that may be in the speeches data but not the press conferences. Reassuringly, in total these account for only 4.3% of the total count of words in the ECB speeches that occur in the speeches dataset, and as such their exclusion from the training data is unlikely to have a fundamental impact on our goodness of fit.

ECB and Fed. This likely reflects that speeches are, on average, less central to market monetary policy belief formation. This may be because the speeches are not always about monetary policy. Or, even when they are about monetary policy, they are less likely to introduce new information and may often just restate the opening statement that has already been communicated (i.e., stale information may not get the same amount of attention, as in Ehrmann and Sondermann 2012). Nonetheless, we know that some speeches, such as ECB President Mario Draghi’s “whatever it takes” speech have had large scale market impacts. Further to this, speeches can play a role in clarifying comments made in the previous press conference, or indeed can be used to steer the conversation ahead of upcoming monetary policy decisions.

In order to show that journalists’ questions are an indicator of the information deficit, we now identify the similarity of speech content and the questions (representing the information deficit). We compute our similarity measure using the document term matrix in which terms are weighted by the term frequency-inverse document frequency (TF-IDF) score.²⁷ Using this weighted document-term matrix, and letting dtm_i be a vector corresponding to the row of the weighted document term matrix associated with document i , we calculate the similarity between two documents i and j as:

$$Sim_{i,j} \equiv \frac{\sum_{k=1}^n (dtm_{ik} \times dtm_{jk})}{\sqrt{\sum_{k=1}^n dtm_{ik}^2} \times \sqrt{\sum_{k=1}^n dtm_{jk}^2}} \quad (3.5)$$

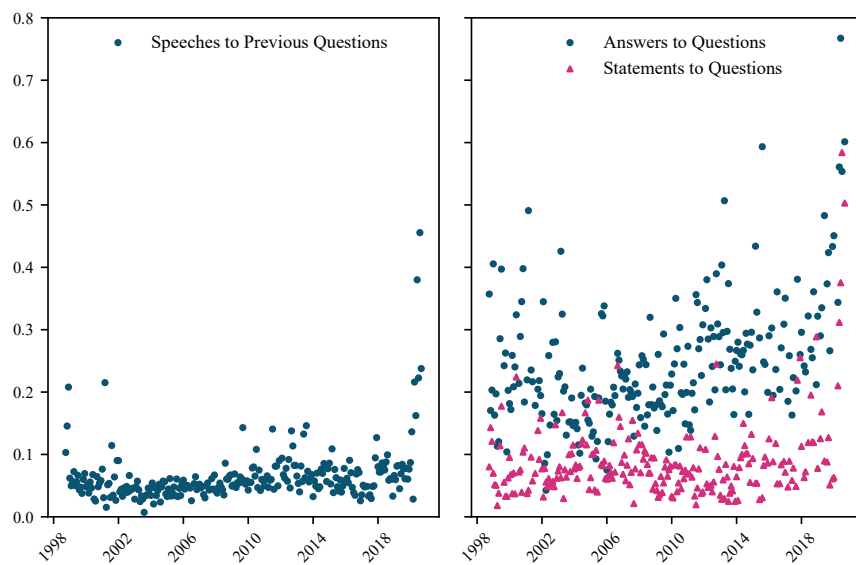
where n is the total number of terms in the document term matrix, and dtm_{ik} refers to the k th term in the vector corresponding to document i .

Figure 3.7, left panel, plots the similarity for speeches compared to the questions from the previous press conference ($Sim_{Sp,Q}$). Each speech day is an individual observation, but they are stacked on the date of the Governing Council meeting from which the questions are derived. There is a sharp increase in similarity towards the end of the sample. This is primarily driven by the onset of the Covid-19 crisis in 2020,

²⁷Prior to calculation, cleaning steps are taken in line with the steps for the topic model, excluding the creation of the set of n-grams. In addition, due to the large sparse nature of the weighted document term matrix, an additional step is taken to remove the most rare and most frequent terms (those that occur in less than 1% of the documents and greater than 50% of the documents respectively). All speeches that occur on the same day as a Governing Council press conference are dropped from the sample for the calculation of similarity indices.

where the topics of all discussions became polarised towards one specific topic. Other clusters of increased similarity are seen across the sample. A notable example is in late 2009, when a large number of speeches were made discussing the path forward for ECB monetary policy in the context of the crisis measures implemented during the financial crisis. In addition, it is noteworthy that speeches that contain references to “hearing” and “European Parliament” in their titles have, on average, a much larger recorded similarity score (0.102 compared to 0.062). This highlights the extent to which such meetings can be used to fill any information deficit.

Figure 3.7. Similarity Measures



Notes: This Figure shows similarity measures constructed according to (3.5). Panel (a) displays the similarity between each speech and the questions in the press conference that preceded it. Panel (b) shows the similarity between the questions and (i) the answers given and (ii) the opening statement of the same press conference. For these time-series plots, we display similarity measures averaged across months.

Our argument is that Governing Council members’ speeches that address the information deficit should contain more newsworthy information. Of course, ECB officials can address journalists’ questions in the press conference through their direct answers at that point, so we will also assess the extent to which they do this. The fact that they had answered a question on a prevalent topic would not necessarily mean an exhaustion of all interest in that issue, particularly if it were complicated or multi-faceted, however. The right panel of Figure 3.7 shows the similarity scores for statements ($Sim_{S,Q}$) and answers ($Sim_{A,Q}$) when both are compared to the questions in the associated press conference. Three key findings emerge. First, questions

are, in general, not that similar to the statement which fits with our assumption that journalists seek missing information with their questions. Second, questions are consistently more similar to answers than to other measures. This is reassuring since the answers should, in theory, directly address the topics in the questions. Finally, a pandemic effect is present in the data from 2020.

Table 3.8 presents the results of a regression to test whether asset price news, associated with a speech, depends on whether the speech addresses the information deficit measured using our press-questions' similarity. We include the similarity of the press conference answers to the press conference questions to capture the already-provided information, as well as its interaction with $Sim_{Sp,Q}$. The results support our hypothesis at the 6-month to 2-year maturity range; speeches addressing the information deficit give rise to more market news. However, the extent of this news may be reduced when speeches are similar to the answers given in the press conference.²⁸ At the 1 year maturity, a speech with similarity to the questions at the 75th percentile ($Sim_{Sp,Q} = 0.08$) generates 0.26 basis points of market reaction at an average value of answer-question similarity ($Sim_{A,Q} = 0.24$). If the speech were to follow a press conference in which the answers had not addressed the questions at all ($Sim_{A,Q} = 0$), so the information deficit was larger, the market reaction would rise to approximately 1 basis point. Given that the average value of market news on ECB speech days in our sample is 2.11bp, the potential contribution of targeting communication to filling information deficits is reasonably large.

3.5.2 The temporal nature of journalists' questions

Having shown that the questions are reflective of the state of the information deficit at the time, we now look at the temporal nature of this novel measure of the information deficit. Alongside our algorithm measure for topic and temporality, these questions have also been hand-coded both in terms of topic and temporal orientation.

The key summary statistics are provided below in Table 3.9. Over the sample, we have 6,175 total questions, of which approximately a third contain information about the past and just under two-thirds contain future information. These shares are similar for the first three sets of questions posed to the President.

²⁸Table B1 shows that these results are robust to also controlling for statement-to-questions similarity.

Table 3.8. Speech-Question similarity and Information Deficit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OIS 1M	OIS 6M	OIS 1Y	OIS 2Y	OIS 3Y	DE 5Y	DE 10Y
Sim. Sp. to Q.	-0.75 (5.00)	9.15** (3.90)	12.30** (5.16)	11.93* (7.01)	12.48 (7.77)	7.81 (9.11)	5.90 (8.84)
Sim. A. to Q.	-0.17 (1.49)	1.86 (1.16)	1.57 (1.54)	2.40 (2.09)	0.69 (2.38)	2.21 (2.72)	2.42 (2.64)
Sim. Sp. to Q. × Sim. A. to Q.	-8.04 (17.25)	-32.19** (13.45)	-37.69** (17.79)	-37.90 (24.21)	-36.42 (26.60)	-28.51 (31.46)	-20.79 (30.49)
Constant	1.97 (4.12)	5.33* (3.21)	9.72** (4.25)	8.92 (5.78)	6.62 (6.49)	7.38 (7.49)	0.25 (7.26)
Speaker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Topics, Future and Past	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1,120	1,120	1,120	1,120	1,007	1,122	1,122
<i>R</i> ²	0.258	0.373	0.409	0.390	0.342	0.222	0.148
Adj. <i>R</i> ²	0.185	0.310	0.351	0.330	0.274	0.145	0.064

Notes: This table shows OLS estimates from regressions of the absolute value of the two day change in yields around a speech on measures of the speech similarity with the press conference questions and the Information Deficit. “ $Sim_{Sp,Q}$ ” and “ $Sim_{A,Q}$ ” denote the similarity of a speech and of the press conference answers to the questions, respectively. Fixed effects are included for the Executive Board member, for the year and for the day of the week in which the speech was given. Six macroeconomic surprises are included, five for the euro area and one for the US. Parentheses below point estimates indicate standard errors. The statistical significance level is displayed as * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 3.9. ECB Press Conference: Journalists' Questions

	Total	Past	Mixture	Future
Number	6,175	1,684	626	3,865
Percentage		27%	10%	63%
Percentage 1st 3 Q's		28%	10%	61%

Notes: This table shows summary statistics about the temporal nature of journalists' questions during the ECB press conference.

Journalists frequently ask questions on past data to enquire about (re)assessment of the state and how reassessments affect the ECB's preferences. A common example of a question about how recent data affect preferences relates observations of exchange rate movements to a possible monetary policy response. For instance, in October 1998, a journalist noted that President Duisenberg had previously said that "a fall in the dollar could be seen to have an impact [on competitiveness]" and asked "[n]ow the dollar has fallen even further and there are forecasts this will continue. What does that mean [...] for the monetary strategy of the ECB?".

Journalists frequently ask about the assessment of the state to reduce uncertainty and better communicate the ECB's view to the public. For example, in October 2007, a journalist noted to President Trichet that the recent level of inflation expectations were "higher than they been [since] the time of the euro changeover". He was then asked to clarify how these data affect his assessment and outlook. Another example comes from President Draghi's tenure, in April 2014, in which one of the first questions at the press conference sought to clarify the assessment of the state of the inflation process. The journalist noted that if one looked at producer prices rather than consumer prices, "[they were] already in a deflationary scenario", and asked how these data sources were weighed in Draghi's assessment.

A more recent example comes from October 2021, in which President Lagarde was asked whether there had been "at least a slightly different assessment to the nature of inflation given that inflation is at a 30-year high now for the [euro area]". In this instance, the journalist asked whether the policymaker might have taken a new view on how the already-observed past data might have been generated. We display the full text of these examples in Table B2, along with three examples of reassessment questions from Federal Reserve press conferences.

3.6 Conclusion

Over recent decades, central banks have increased the depth, range and frequency of their communication with the public. Central bankers give speeches to the public, respond to queries from the media, interpret recent economic developments, project their intended policy path, and provide forecasts of key economic variables. A number of studies have shown that central bank communication can measurably surprise, or

generate news. For communication to be effective in this way, it must, at least in part, fill some information deficit on the part of the public. The exact nature of the information deficit has proved difficult to quantify.

Some earlier studies supposed that the information deficit was related to private information on the part of the central bank. However, at least in the narrow interpretation of private information, markets have broadly the same access to data that the central bank has, reducing the scope for substantively new information of this type to be released by the central bank. We argue instead that the source of the information advantage that generates the news in central bank communication comes from the central bank updating either its evaluation of the current state of the economy, or its mapping of the state into the appropriate monetary policy stance going forward.

Our analysis of the temporal dimension of communication, facilitated by our new measurement methodology, suggests that the information communicated by central banks that is relevant for forward-looking expectations is multi-faceted and is not reducible to the numerical forecast data that they also publish, or to explicit policy forward guidance. While central banks may have no advantage purely in terms of methodology or training than markets, they often have an advantage in terms of resources: the number of staff and models available to generate the assessment of the state. Hence the central bank can devote resources to *evaluation* of economic data - choosing the weights to put on different data sources at each point in time and how to place developments in the data into context. This process is inherently backward-looking.

An implication of having an important role for an evolving (time-varying) assessment is that the market could always be in deficit. This means that the communication of a fixed reaction function, which is highly desirable in many FIRE models, is likely impossible in practice. This is because of time-variation in the way that the macroeconomic data maps to the likely state of the world to which policy has to respond. This is true even if preferences remain fixed over time, but preferences may also evolve. As emphasised by Williams (2019) when thinking about the data-dependence of monetary policy: “I wish I could now tell you with certainty what will happen to the economy, but anyone who promises they can see into the future is a charlatan. However, what I can do is provide you with some insight into how I assess

the health of the economy and what that means for my view on the monetary policy decisions before us.”

While this means that central banks *could* always provide useful information, it does not follow that the central bank *should* provide constant updates to the markets. It is likely that the central bank is also learning and exploring possible narratives that explain the observed data. In this environment, and given this process is subject to noise, it might be optimal only to incrementally update the market with their views. We leave this question of how often to communicate updated views to future research.

Our work does indicate what it is that is important to communicate. Even though markets may be solely interested in the outlook for future monetary policy, their interest will be in more than just forward guidance. Policymakers should try to communicate how they are assessing incoming data, and how this affects their thinking about both the current (evaluation) and future (projection) state of the economy. This goes beyond the recommendations from standard models used in the analysis of monetary policy.

3.7 Appendix

Table B1. Speech-Question similarity and Information Deficit - Robustness to Statements

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OIS 1M	OIS 6M	OIS 1Y	OIS 2Y	OIS 3Y	DE 5Y	DE 10Y
Sim. Sp. to Q.	-1.56 (5.11)	8.58** (3.98)	11.64** (5.26)	11.34 (7.15)	11.74 (7.91)	7.48 (9.28)	7.16 (9.00)
Sim. A. to Q.	0.21 (1.55)	2.29* (1.21)	2.04 (1.60)	3.05 (2.17)	1.33 (2.47)	3.13 (2.82)	2.72 (2.73)
Sim. S. to Q.	-2.14 (2.40)	-3.30* (1.87)	-3.53 (2.48)	-5.61* (3.37)	-4.80 (3.67)	-9.17** (4.37)	-6.42 (4.23)
Sim. Sp. to Q. $\times$ Sim. A. to Q.	-12.75 (18.26)	-35.45** (14.22)	-41.52** (18.82)	-41.34 (25.59)	-41.04 (28.07)	-30.46 (33.20)	-13.55 (32.18)
Sim. Sp. to Q. $\times$ Sim. S. to Q.	20.91 (25.07)	16.80 (19.52)	19.28 (25.84)	20.41 (35.13)	23.40 (37.31)	19.14 (45.58)	-19.84 (44.17)
Constant	2.24 (4.13)	5.57* (3.22)	9.99** (4.26)	9.24 (5.79)	7.24 (6.52)	7.70 (7.49)	0.11 (7.26)
Speaker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Topics, Future and Past	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1,120	1,120	1,120	1,120	1,007	1,122	1,122
<i>R</i> ²	0.259	0.375	0.411	0.392	0.344	0.227	0.154
Adj. <i>R</i> ²	0.184	0.311	0.351	0.331	0.274	0.149	0.068

Notes: This table shows OLS estimates from regressions of the absolute value of the two day change in yields around a speech on measures of the speech similarity with the press conference questions and the Information Deficit. " $Sim_{Sp,Q}$ ", " $Sim_{A,Q}$ " and " $Sim_{S,Q}$ " denote the similarity of a speech, of the press conference answers and of the Introductory Statement to the questions, respectively. Fixed effects are included for the Executive Board member, for the year and for the day of the week in which the speech was given. Six macroeconomic surprises are included, five for the euro area and one for the US. Parentheses below point estimates indicate standard errors. The statistical significance level is displayed as * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table B2. Examples of Journalist Questions Regarding Central Bank Evaluation

Central Bank	Date	Question
ECB	04/10/2007	You mentioned inflation expectations as something very important to the Governing Council. If I have got this right, inflation expectations in a number of countries are actually quite high, higher than they have been or at levels around at the time of the euro changeover. Can you talk a little bit about how that is figuring into your expectations and into your calculations?
ECB	03/04/2014	A first question relating to the inflation rate and referring not so much to consumer prices but to producer prices, where we have seen two consecutive months of a decline – so, if you take producer prices, you could actually argue that we are already in a deflationary scenario. To what extent would you consider producer prices and how important are they for your assessment?
ECB	28/10/2021	I was wondering, because the markets were – well, everybody was anticipating that this meeting was all about inflation, so what have you been discussing, and what was on top of your agenda? Was there at least a slightly different assessment to the nature of inflation, given that inflation is at a 30-year high now for the eurozone.
Federal Reserve	25/01/2012	Mr. Chairman, we've had several months of economic data that's been stronger than most forecasters expected—employment was over 200,000, the unemployment rate's come down to 8.5 percent—but there seems to be very little mention of this recent strength in the statement. Do you and the Committee, Mr. Chairman, harbor doubts about the recent strength in the economy?
Federal Reserve	19/03/2014	You mentioned in your testimony on Capitol Hill recently that the Fed was trying to assess the balance of weather effects versus more fundamental weakness in the economy as the reason for the slowdown in growth in the first quarter, and you guys mentioned in the statement weather specifically. Does that mean that the Fed's analysis has come down on the side of weather, or are you still concerned that there could be something else going on that could be contributing to slower growth?
Federal Reserve	30/01/2019	I am struggling a little bit to understand what has changed since we sat here with you six weeks ago. You've said today that you think that inflation would be the reason that the Fed would need to continue raising rates. Has the inflation outlook shifted that dramatically in the last six weeks?

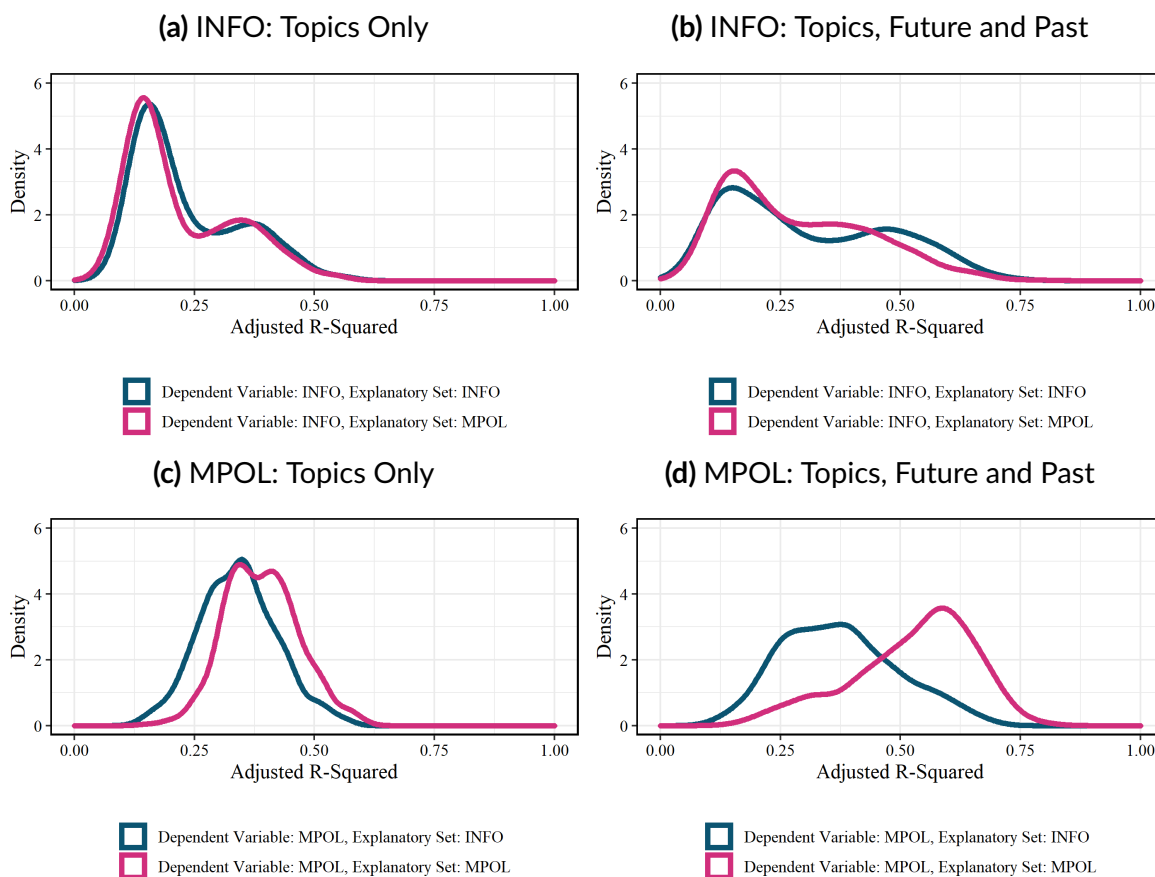
3.7.1 The Relation Between Monetary and Information Surprises and Temporal Information

Figure B2 plots for the ECB data the full distributions of Adjusted R-Squared values from Post-LASSO Ordinary Least Squares regressions that underpin the results for the Jarociński and Karadi (2020) surprises in Table 3.7. The left column shows the regressions for the exercise in which only topics without any temporal dimension are included in the topic set (“Topics Only” row of the table), while the right column show the most disaggregate results with both future and past temporal topics (“Topics, Future and Past*” row).²⁹ The top row, Figures B2a and B2b, show the results for the information surprise, “INFO”, and each figure includes the findings from regressing on the set of variables selected by LASSO for the information surprise itself and the set selected for the monetary policy surprise (“MPOL”) for the same bootstrap draw. Figures B2c and B2d repeat these results but where the monetary policy surprise (“MPOL”) is the dependent variable.

Two main results stand out. The first is that the topics, while capturing broad themes, are too broad to capture a lot of the market news. This is reflected in both the fact the Adjusted R^2 is relatively low at around 0.2 (as in the Table). The second is that there is little extra explanatory power from using the topics selected by LASSO for one surprise in explaining the other surprise – the distributions are very similar. When we instead use the disaggregated temporal shocks, the Adjusted R^2 jumps up to around 0.6-0.7 for the own shocks, and the specificity of the selected is much greater – using the topics selected for the other shock, almost halves the explanatory power. This shows that the communication that moves markets is best captured in high-dimensional measures of the messaging rather than simply broad themes.

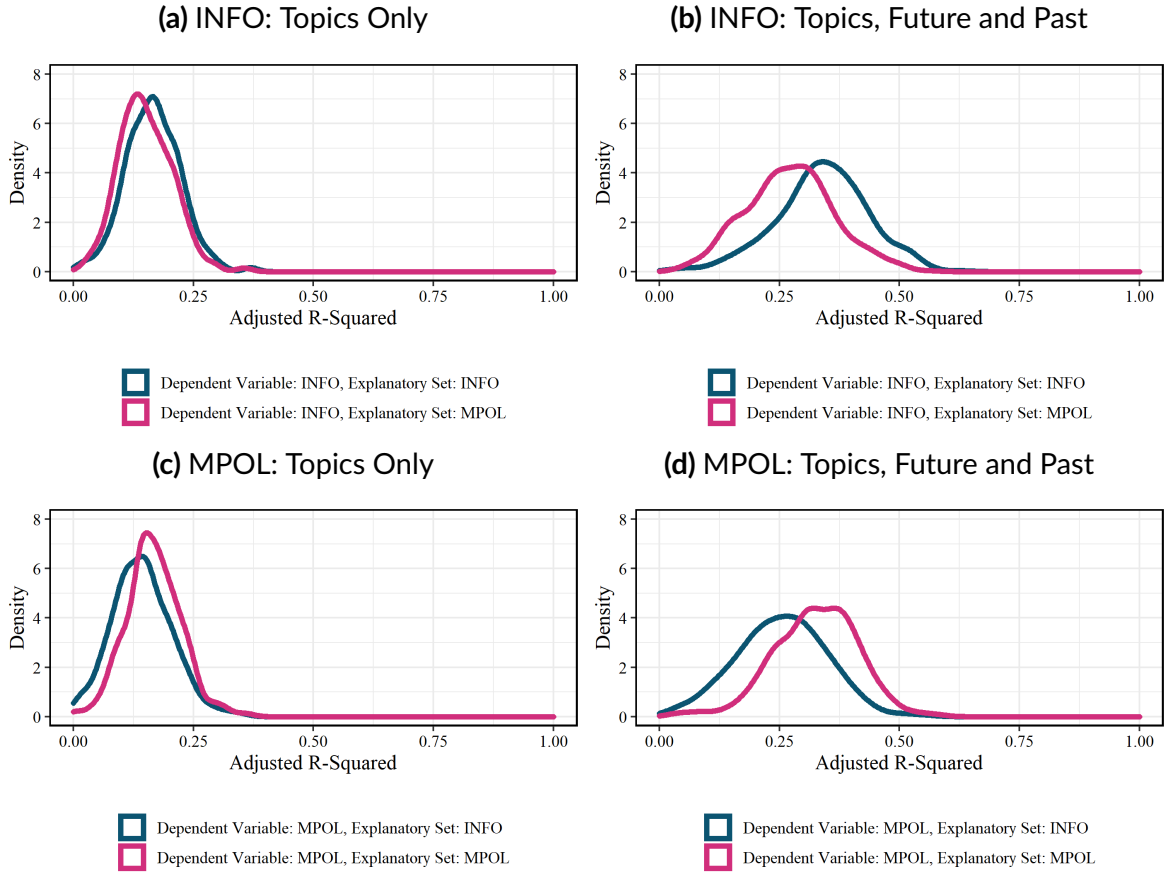
²⁹Forecast control variables are constrained to be always included in the set of selected variables.

Figure B1. Identifying Distinct Information Sets Using Topics and Temporal Topics
Federal Reserve



Notes: The top row shows the distributions of Adjusted R-Squared values from Post-LASSO Ordinary Least Squares regressions of the information surprise ("INFO") on the set of variables selected by LASSO for the information surprise itself and the set selected for the monetary policy surprise ("MPOL") for the same bootstrap draw. The set of variables available to be selected includes the Topics only (θ_k). The bottom row shows the distributions of Adjusted R-Squared across the bootstrap draws when the set of variables available to be selected has Topics (θ_k), Future (θ_k^{FUT}) and Past (θ_k^{PAST}). Each specification includes forecasts of current year and one year ahead annual GDP growth and inflation, and revisions to these forecasts where applicable. The forecast variables are constrained to be always included in the set of selected variables.

Figure B2. Identifying Distinct Information Sets Using Topics and Temporal Topics ECB



Notes: The top row shows the distributions of Adjusted R-Squared values from Post-LASSO Ordinary Least Squares regressions of the information surprise ("INFO") on the set of variables selected by LASSO for the information surprise itself and the set selected for the monetary policy surprise ("MPOL") for the same bootstrap draw. The set of variables available to be selected includes the Topics only (θ_k). The bottom row shows the distributions of Adjusted R-Squared across the bootstrap draws when the set of variables available to be selected has Topics (θ_k), Future (θ_k^{FUT}) and Past (θ_k^{PAST}). Each specification includes forecasts of current year and one year ahead annual GDP growth and inflation, and revisions to these forecasts where applicable. The forecast variables are constrained to be always included in the set of selected variables.

3.7.2 ECB Speeches: Baseline Analysis

As described in the main text, we repeat the baseline analysis for the speeches. When studying the effect of the speeches on financial market variables, we use daily (end-of-day) series, downloaded from Bloomberg. There are several reasons for this. The first is that many of the speeches are given outside market trading hours, meaning the construction of an intra-daily movement is impossible. The second is that we do not know exactly when the information contained within the speeches became generally available to markets, since this information is not recorded in the dataset.³⁰ For our empirical specifications, we drop 90 speech-day observations that fall on Saturdays or Sundays, and we also drop 150 speech-day observations that fall on Governing Council meeting days, the day before, or the day after. This means the total number of speech-day observations available for analysis is 1,473.

Table B3b presents the main analysis; it repeats the baseline analysis of Table 3.3 but applied to the speeches. The temporal dimension of speeches generates similar, albeit less systematic, market news.

³⁰Note that for a speech delivered on a Friday, we employ a window from market-close on Thursday to market-close on Monday. We account for potential heterogeneity in the treatment of speeches across days using day-of-the-week fixed effects in our empirical specifications.

Table B3. Policymaker Speeches**(a) Federal Reserve**

Specification	ED1	ED4	US 2Y	US 5Y	US 10Y
Controls Only	0.245	0.237	0.176	0.209	0.173
Topics	0.261	0.255	0.199	0.228	0.194
Topics, Future Topics	0.265	0.259	0.203	0.232	0.198
Topics, Past Topics	0.264	0.256	0.201	0.229	0.195
Topics, Future and Past Topics	0.268	0.260	0.205	0.233	0.200
Topics, Future and Past Topics*	0.321	0.314	0.262	0.278	0.249

(b) ECB

Specification	OIS 1M	OIS 1Y	OIS 2Y	DE 5Y	DE 10Y
Controls Only	0.198	0.329	0.322	0.255	0.146
Topics	0.243	0.367	0.360	0.292	0.186
Topics, Future Topics	0.251	0.370	0.363	0.297	0.197
Topics, Past Topics	0.254	0.371	0.365	0.298	0.195
Topics, Future and Past Topics	0.262	0.375	0.369	0.304	0.205
Topics, Future and Past Topics*	0.289	0.411	0.411	0.347	0.252

Notes: This table shows the adjusted R^2 for specifications predicting the responses of the absolute value of two-day changes in yields at different maturities, respectively for the Federal Reserve (top panel) and the ECB (lower panel). The events studied in this exercise relate to policymaker speech days. Specifications are identical to Table 3.3, excepting the changes in events, the dependent variables, and differing control variables. Daily financial data was sourced from Bloomberg. See Notes to Table 3.3 for further details regarding the Elastic Net specifications. The additional specification, “Topics, Future and Past Topics*” refers to a case where we include controls, topics, and temporal topics. In this case the temporal topics are disaggregated, meaning we have temporal topics based separately on tags from categorical, numerical, and grammatical tags, respectively for past and future.

Table B4. Topic Model: Federal Reserve

1	2	3	4	5
Labour	Inflation Risk	and Inflation	Policy Rates	Procedural
labor	measur	price	rate	bank
market	inflat	energi	feder	feder_reserv
rate	project	inflat	fund	messr
remain	risk	increas	committe	action
inflat	particip	import	percent	presid
unemploy	rang	declin	target	economist
particip	uncertainti	consum	rang	vote
pressur	year	month	level	respect
recent	inflat_expect	percent	inflat	general
increas	forecast	core	market	counsel
6	7	8	9	10
Open Economy	Committee I	Growth	Securities Markets	Forecasts
market	board	growth	secur	rate
foreign	governor	economi	agenc	project
oper	divis	busi	loan	year
system	director	econom	credit	unemploy
open	monetari	particip	treasuri	percent
currenc	affair	activ	hold	particip
account	secretari	spend	purchas	staff
bank	assist	continu	mortgage-back	forecast
manag	research	effect	continu	estim
committe	offic	member	bank	longer-run
11	12	13	14	15
Monetary Policy	Financial Markets	Committee II	Policy Outlook	Real Data
polici	period	committe	committe	quarter
particip	market	market	econom	busi
well	intermeet	meet	inflat	spend
economi	yield	open	polici	sale
monetari_polici	dollar	feder	outlook	increas
that	declin	vote	member	pace
use	spread	direct	continu	continu
provid	price	unanim	inform	product
effect	equiti	releas	market	month
chang	treasuri	held	monetari_polici	declin

Table B5. Topic Model: ECB

1	2	3	4	5
Risk	Structural Reform	Prices Inflation	and Banks, Bonds	Markets, EA Growth
risk	euro_area	price	bank	euro_area
uncertainty	structur_reform	increas	measur	continu
econom	market	inflat	market	support
euro_area	competit	effect	bond	growth
outlook	economi	expect	monetari_polic	expect
relat	increas	year	programm	demand
financi_market	countri	month	certain	loan
develop	need	oil_price	differ	remain
high	growth	inflat_rate	liquid	recoveri
growth	product	energi	effect	credit
6	7	8	9	10
Price Stability	Price and Expectations	Gov. Logistics	Co. Discursive	Data
price_stabil	price_stabil	meet	well	year
monetari_polic	inflat_expect	govern_council	go	quarter
govern_council	medium_term	ecb	chang	growth
risk	close	confer	comment	euro_area
monitor	line	presid	thing	data
develop	inflat	outcom	last	indic
decis	deliv	introductori	certain	last
close	mandat	decis	ask	confirm
stanc	maintain	staff	actual	assess
assess	continu	project	discuss	inform
11	12	13	14	15
Monitoring	Fiscal	ECB	Forward Guidance	Rate Decisions
import	countri	ecb	rate	rate
situat	govern	central_bank	continu	interest_rate
observ	fiscal	govern_council	remain	decid
market	growth	european	monetari_analysi	key
regard	stabil	euro	growth	basi
cours	euro_area	member	under	ecb_interest_rate
economi	fiscal_polic	institut	low	oper
europ	implement	presid	monetari	point
level	pact	decis	money	loan
present	need	govern	confirm	accord

Chapter 4

The transmission of bank credit conditions to firms - evidence from linked surveys¹

Abstract

Using a novel dataset linking firm level data from the Survey on Access to Finance for Enterprises (SAFE) and bank level data from the Bank Lending Survey (BLS), we explore how changes in credit standards pass through to firms at a granular level. We find that tighter credit standards decrease loan availability reported by firms, increase the likelihood they report access to finance as the worst problem and decrease their investment. After controlling for country-sector-time fixed effects that capture cyclical macroeconomic conditions, effects only remain for firms that need finance. Moreover, we find that a more diversified funding base insulates firms from the negative impacts of tighter credit standards on availability of bank loans and access to finance, although there is little evidence of such an effect for investment. Effects are asymmetric, with stronger impacts recorded for a tightening than an easing. Our results underscore the importance of demand conditions when interpreting any changes in credit conditions and we thus propose a new indicator of demand adjusted credit standards at a euro area level, which can be used to analyse broader credit dynamics.

¹This chapter is coauthored with Annalisa Ferrando and Sarah Holton (both ECB). We thank participants at the ECB MPC task force for bank lending, the ECB internal seminar series, the Bank Lending Survey annual meeting and participants at a seminar at De Nederlandsche Bank for helpful comments.

4.1 Introduction

The pass through of changes in credit conditions to firms is of great interest to policymakers studying the transmission of monetary policy through the banking system. Using a unique dataset linking the ECB's Survey on Access to Finance for Enterprises (SAFE) and Bank Lending Survey (BLS), this paper aims to quantify the impact of changes in credit standards as measured by bank responses to the BLS on the availability of loans to firms, the likelihood of firms in reporting access to finance as the worst problem facing their business and the pass through to their investment decisions. By linking the surveys at a granular level, we explore not just the direct impact of changes in contemporaneous credit standards, but the accumulation of changes over multiple periods. This combines the strengths of the two surveys well. While the SAFE is useful for exploring contemporaneous changes, it is not a balanced panel. Firms may appear multiple times in the survey but they do not necessarily take part in consecutive surveys. This makes it difficult to assess the cumulative impact of credit constraints, and indeed any longer term effects. However, the use of BLS credit supply variables helps us to deduce a raw bank loan supply effect. Second, SAFE contains useful data on firm specific outcomes such as their investment decisions or individual level firm demand that can be explored at a micro level. Using the individual BLS (iBLS) alone to make judgements on firm level demand (or indeed demand for loans for investment) would not allow to exploit the rich heterogeneity that can be found by using firm level data. As such, this approach can amplify the benefits of using these rich micro level survey data together.

We find that when using firm level fixed effects, as expected, tighter (looser) credit standards (a) lead to a decrease (increase) in firm level reported loan availability, (b) lead to an increased (decreased) likelihood of reporting access to finance as the worst problem facing their firm and (c) leads to lower (higher) investment. This effect disappears however once country-sector-time fixed effects are introduced, suggesting that any initial effects may simply be as a result of an element of cyclical tightening.

Crucially, using demand as measured by whether firms in the SAFE had reported an increased need for bank loans we see that there is evidence of a strong interaction effect with the expected sign across all three variables. This implies that the pass through of tighter credit standards to firms is dependent on the firms' individual

level of loan demand. This has implications for the interpretation of macro measures of credit standards, suggesting they cannot be read independent of firms' demand conditions.

Moreover, using further information from the SAFE we provide evidence of the role of having access to a diversified funding base in mitigating against the impact of a credit tightening. We find, using a triple interaction specification that having a more diversified funding base can counteract the effect of a tightening for those firms who had increased need for bank loans, providing evidence of the role of access to finance in the smooth functioning of firm dynamics.

In addition, by exploring some asymmetries, we find that our results are mainly driven by periods of tightening, with very little effects present for periods of easing. This suggests that either the pass through of credit standards is stronger in periods of tightening, or the surveys themselves have an element of a tightening bias, with firms being either more aware of tightening episodes in the case of the SAFE, or banks being more pronounced in reporting tightening episodes in the case of the BLS.

Exploring asymmetries on the other side, we see that tighter (looser) credit standards mainly pass through to investment through a lower (higher) probability of increasing investment, rather than a higher (lower) probability of decreasing investment, with a one unit increase in the relative tightness of credit standards decreasing the probability of increasing investment by 0.08 points after one period, rising to 0.13 after 3 periods of tightening, illustrating the combination of both a lagging and cumulative effect.² For availability, effects of a tightening (easing) of credit standards are stronger for increasing (decreasing) the probability of reporting declining loan availability (0.03 points after one period, rising to 0.10 after three periods), but it should be noted that some effect is still present on the other side. Both of these effects are strong relative to the overall proportion of firms that report increases or decreases each period.

Finally, leaning on the micro level information, we propose a new measure of demand adjusted credit standards that can provide a deeper understanding of the dynamics of credit conditions in the euro area. We note that by looking at a raw credit standards series alone, the effects would likely be overestimated in times of low demand, and underestimated in times of high demand. When comparing

²Periods in this case refer to the six-monthly periods making up each wave of the SAFE

our series to an unadjusted series, we find that during the sovereign debt crisis, examining unadjusted credit standards would have shown a relatively more benign picture compared to the adjusted series. On the other hand, during the tightening period in 2022, the adjusted series is lower than the unadjusted series, albeit at one of its highest levels in the series history. We posit that this new indicator can enhance our understanding of the pass through of credit standards to the real economy, and leaves the door open for further research.

The rest of the paper proceeds as follows. Section 4.2 provides a brief overview of the literature, section 4.3 introduces our data sources, section 4.4 shows our empirical results, section 4.5 introduces demand adjusted credit standards and section 4.6 concludes.

4.2 Literature Review

The study of firm financing conditions has long been of great interest in the literature, with the role of banks within this of particular importance. This paper adds in particular to the growing literature on the importance of banks for individual firm financing, while also adding to the literature on measurement of aggregate credit shocks by providing an aggregate measure of how binding changes in credit conditions are at a macro level, motivated by micro level findings.

One of the main ways that monetary policy affects the economy is by impacting credit conditions. Understanding how changes in credit conditions transmit through the economy is a key question in macroeconomic policy. The credit channel of the monetary policy transmission is primarily concerned with how monetary policy changes affect the real economy, and how "frictions in credit markets" affect the external finance premia and the private sector's ability to access finance (Bernanke and Gertler 1995). Within this, there is a bank lending channel - asserting that bank-specific characteristics can have a large impact on the provision of credit (see for example Jiménez et al. (2012) and Altavilla et al. (2021)) - and a borrower balance sheet channel - concerned with how the characteristics of borrowers affect their ability to access finance (Ciccarelli et al. 2015). While there is ample literature on these channels, there is limited research on the interactions between them. For instance, for a given change in monetary policy, heterogeneity in borrower outcomes

could potentially stem from various sources. On the one hand, differences across banks may lead to variation in how the shock propagates. On the other hand, firm characteristics may alter how the credit supply shock ultimately impacts on their outcomes. Combining these channels is important in understanding the transmission and distributional impact of monetary policy.

One strand of literature that we particularly extend on in the literature that use survey information to explore the factors that impact firms' access to finance. This is particularly possible using the wide array of firm specific information available within the SAFE. Our results particularly speak to the findings of Ongena et al. (2012) find that firms with alternative sources of finance are less likely to need bank credit. In this paper, we show that firms with a more diversified funding base are less affected by a bank based tightening of credit standards in cases where firms have higher demand. Additionally, our findings regarding the importance of adding fixed effect controls at a country-sector-time and firm level speak to the work of Beck et al. (2005) who show that firm and country-level characteristics are relevant determinants for access to finance. Other work such as Beck et al. (2006) find that older, larger and foreign owned firms are less likely to experience financial constraints, while Ferrando and Grieshaber (2011) find that firm age and size are significant determinants of financing obstacles.

In addition, we contribute to the literature that assesses the information content of lending surveys to examine both credit conditions and their impact on the economy (Lown and Morgan (2006), de Bondt et al. (2010), Del Giovane et al. (2011) and Altavilla et al. (2019b)). This literature typically uses loan flows to analyse banks' survey responses but using survey data allows us to directly assess the impact of changes in credit supply on firms financing situation, as they report directly on their credit demand, their perceived supply conditions and their economic outcomes. Moreover, the consistent nature of the SAFE survey allows us to build a large sample of responses over time in a clean fashion, building on previous work to assess qualitatively measured outcomes and responses of firms.

To the best of our knowledge, this is the first paper to formally link the granular level SAFE and BLS data for broader analysis. This has the advantage of matching data that corresponds to the exact periods of both surveys, and allows for a detailed analysis of firm-bank level outcomes at a half-yearly basis. Moreover, at a micro level we can control for both bank supply and firm-level demand to explore the interaction

between the two factors, and this spurs on our contribution to the measurement literature at an aggregate level. Our measure of demand adjusted credit standards can be viewed as adjacent to other projects that have measured raw supply shocks such as the work of Altavilla et al. (2019b) or have used the SAFE survey to construct measures of the "Financing Gap" for firms (Ferrando et al. 2013).

4.3 Data

Our empirical methodology relies on several data sources, the key two being the individual level Survey on Access to Finance for Enterprises (SAFE) and Bank Lending Survey (BLS) datasets. A crucial innovation of this study is that these two datasets are then matched using a dataset of the banks used by individual firms obtained from BvD Orbis. We briefly describe the attributes of each dataset.

4.3.1 SAFE

The SAFE has been conducted by the ECB/EC since 2009 and asks euro area firms for details on their financing conditions, concentrating in particular on the need for and availability of financing. The survey is conducted at half yearly intervals with questions examining the previous and next six months. The first two surveys were conducted with the periods of interest being January-June and July-December, but since the first survey in 2010, the survey concentrates on the periods April-September and October-March. Most firms within the survey are SMEs and are thus more reliant on financing from banks relative to large enterprises. Thus, the survey is highly appropriate for analysing the pass through of monetary policy to firms, as well as the impact of changes in bank side credit standards or terms and conditions.

4.3.2 BLS

The BLS has been conducted by the ECB since 2003 and asks a panel of euro area banks about changes in their lending conditions. The survey is conducted quarterly with key questions focusing on changes in credit standards, terms and conditions, rejection rates and the demand for loans set by or faced by each bank. Questions are

either backward looking over the previous three months or forward looking over the next three months.

4.3.3 The matching process - Bvd Orbis-Amadeus

The core component of this paper involves matching the BLS and SAFE individual level results, and this is done by using an ECB proprietary data set that has been developed together with Bureau Van Dijk (BvD) using its Orbis and Amadeus databases. Each SAFE firm is given an anonymised firm ID, and these are matched confidentially to a firm's company ID within Orbis and Amadeus, with the data provider outputting an anonymised dataset providing the firm ID and information from this database.

These data contain a list of each firm's banks. These are compiled by BvD using a combination of firm registries and direct interviews with firm representatives. It should be noted that it is not a necessity that all firms only report one bank, with many having a wide array of reported banks. We exploit this full universe of banks within our matching process, in order to match all possible banks to each individual firm. This contrasts with prior approaches that made an assumption that banks were ordered in terms of their importance to each individual firm (see for example Corbisiero and Faccia (2020), Ferrando et al. (2019) and Kalemli-Özcan et al. (2022)). We also assume that bank relationships are unchanged throughout our sample, as in general bank-firm relationships tend to be sticky over time. This is backed by evidence seen in Kalemli-Özcan et al. (2022) and Giannetti and Ongena (2012), who find that by comparing multiple vintages of the Orbis-Amadeus bank-firm matches, that there are very limited changes over time. Moreover, this is even less likely to be an issue in our case in that we do not restrict ourselves to only focusing on a single bank of a given firm, and instead use all for whom they have a working relationship.

It should be noted that the data provided come in uncleaned format, with only the raw text names of banks. As such, the matching process between SAFE and BLS necessarily contains both an automated and manual component. As a first step, firms for whom their banks' names match precisely the legal name of a BLS bank are automatically mapped to that bank. Regarding the remainder, manual matching is undertaken, with each unique entry assessed and matched to a BLS bank if a match exists. Such an approach is preferable to a fuzzy matching approach, in that human judgement is required for matches in many cases when either colloquial names are

used for banks, or individual banks have similar names. This both maximises the size of our matched set and minimises our risks of false positives.

4.3.4 Dataset characteristics

Of 29,768 firms in our dataset 22,799 are matched to at least one bank. Of these, 13,703 (60.1%) are matched to one single bank, while the rest are matched to more than one bank from the BLS sample, varying from a total of 2 matches to 19 for three cases. The distribution of these is shown in Table 4.1.

Regarding the panel structure of the dataset, the total number of firms broken down by their number of occurrences is shown in Table 4.2 while the total number of observations per wave is shown in Table 4.3. As can be seen the majority of firms appears more than once in the survey, allowing us to use fixed effects. Regarding the time distribution, survey rounds prior to the eleventh wave (September 2014) are relatively underrepresented, with the first three waves having particularly low numbers. This is as a result of the greater coverage in the anonymised Orbis-Amadeus dataset from this point onwards for firms, we thus note that any results may be slightly more representative of the later portion of the dataset.

Table 4.1. Distribution of total number of banks for each firm

Number of BLS Matches	Total Matches	Percentage
1	13703	60.10
2	3700	16.23
3	1736	7.61
4	1024	4.49
5	579	2.54
6	551	2.42
7	407	1.79
8	286	1.25
9	229	1.00
10-14	501	2.21
15-19	83	0.36
Total	22799	100

Table 4.2. Distribution of the number of waves each firm appears in the survey

Appearances in dataset	Number of firms	Percentage of dataset
1	7854	34.45
2	4578	20.08
3	3019	13.24
4	1990	8.73
5	1809	7.93
6	970	4.25
7	1231	5.40
8	534	2.34
9	302	1.32
10-14	472	2.07
15-22	40	0.18
Total	22799	100

Table 4.3. Total observations by wave

Wave number	Total observations	Wave number	Total observations
1	39	15	3621
2	145	16	3901
3	182	17	3637
4	602	18	3713
5	749	19	3579
6	987	20	3686
7	1411	21	3536
8	1706	22	3456
9	2226	23	3552
10	2023	24	3403
11	3603	25	3424
12	3922	26	3526
13	3628	27	2520
14	3658		

On the country level, we have observations from 11 euro area countries, limited on one side by non-full country level coverage in the iBLS dataset, and on the other side by limitations in which countries have firm-bank data in Orbis-Amadeus. The distribution of the number of firms by country is shown in Table 4.4, alongside their

relative matching rates. In general, the larger countries have a higher number of observations, with Germany, Spain and France making up the largest proportion of our sample. Regarding matching, we see that in Austria and Germany the relative matching rate is lower, partly reflecting the high number of banks within those countries, while countries with a more concentrated banking system have a higher matching rate.

Table 4.4. Distribution of sample by country

<i>Country</i>	<i>Total Firms</i>	<i>Un-matched</i>	<i>Matched unique firms in final dataset</i>	<i>Matching Success Rate</i>	<i>Total observations in sample</i>	<i>Average observations per firm</i>
<i>Austria</i>	3382	1796	1586	46.90%	4793	3.02
<i>Germany</i>	7354	3365	3989	54.24%	12117	3.04
<i>Estonia</i>	325	1	324	99.69%	607	1.87
<i>Spain</i>	5276	127	5149	97.59%	17418	3.38
<i>France</i>	4272	813	3459	80.97%	10912	3.15
<i>Ireland</i>	2023	100	1923	95.06%	6206	3.23
<i>Lithuania</i>	647	104	543	83.93%	1154	2.13
<i>Luxembourg</i>	259	11	248	95.75%	511	2.06
<i>Latvia</i>	544	255	289	53.13%	557	1.93
<i>Netherlands</i>	3166	217	2949	93.15%	8967	3.04
<i>Portugal</i>	2520	180	2340	92.86%	7193	3.07
TOTAL:	29768	6969	22799	76.59%	70435	3.09

4.3.5 Key Variables

Within our analytical results, we use measures of credit supply from the BLS and assess their impact on firm level results from the SAFE. This exploits a key advantage of our matched dataset in that, since the SAFE is not a balanced panel, we cannot delve into the longer run effects of changes in loan supply - we only have contemporaneous measures. As such, by measuring credit supply using the BLS we can use longer run information, and do so by constructing a backward looking average,

with a horizon of one and a half years as the longest period we examine, alongside more contemporaneous metrics.

To measure credit supply, we use banks responses to a question on credit standards from the BLS. Banks are asked each quarter about changes in their credit standards applied to loans to firms over the previous three months. Banks can respond with five possible answers, each reflecting the direction and level of intensity of changes. The question is framed in terms of a tightening or an easing, with banks stating whether: (with the standard numerical values assigned to each response in brackets afterwards) "tightened considerably" (1), "tightened somewhat" (2), "unchanged" (3), "eased somewhat" (4) and "eased considerably" (5).

As the BLS is quarterly, and the SAFE is biannual, we average banks responses to the credit standards question over the two BLS rounds that correspond to each SAFE wave. As SAFE questions refer to changes over the six months encompassing each wave, this averaging ensures that BLS responses also map to the same time period.

As firms are often matched to multiple banks, we construct a firm level measure of credit standards by averaging the responses of each bank matched to the firm. This gives us a continuous scale measuring the full universe of credit standards faced by each firm in a wave. We transform the responses to be on a scale between -2 and +2, with +2 being the strongest tightening and -2 the strongest easing.³

We are interested in both the impact of short-run changes in credit standards but also the longer run changes - taking individual wave responses alone will not account for the impact of continuous changes in credit standards across multiple periods. Letting $oneperiodcs_{f,t}$ denote the individual period credit standards facing firm f at time t . We construct the following measure:

$$CS_{f,t} = \frac{\sum_{k=0}^{K-1} oneperiodcs_{f,t-k}}{K} \quad (4.1)$$

We construct this measure for $K = 1, 2, 3$. This provides 3 measures of credit standards - $K = 1$ is simply equivalent to $oneperiodcs_{t,f}$ and is the single period change in contemporaneous credit standards. For $K = 2$ and $K = 3$ we measure the longer run credit standards facing a firm, for periods of a year and a year and a half respectively. A one unit increase for $K = 1$ is equivalent to a single unit of increased tightening,

³This is done in order to maintain an easy to interpret base group in any regressions with interaction terms, with zero values mapping to firms who experienced no change in credit standards.

while for $K = 2$ and $K = 3$, a one unit increase can be interpreted as a more long run continuous tightening.

From the SAFE, we are interested in measuring potential responses of firms to changes in credit standards. We do so by extracting three variables measuring (a) changes in the availability of bank loans (b) whether access to finance was the worst problem facing a firm and (c) changes in investment by firms, with each variable being measured over the previous six months corresponding to the SAFE wave.

Changes in the availability of bank loans is measured using a trinomial scale, whereby firms are asked if the availability of bank loans (with assigned numeric values in brackets) improved (1) remained unchanged (2) or deteriorated (3) over the last six months. We exclude all don't know and not applicable responses, and for the purposes of our regressions all values are multiplied by -1 such that larger figures correspond to an increase and smaller to a decrease.⁴

By measuring the response of bank loan availability we achieve two main goals. First, to some extent this acts as a sense check on our matching - we should hope to see a structural relationship between credit standards and availability. In addition to this, by examining interactions and the variation of responses according to how long the trailing average of credit standards used is we can comment on precisely which firms are impacted by changing credit standards, but also over which time horizon impacts are most strongly felt.

Second, we construct a measure of whether access to finance was the worst problem facing a firm over a given time period. Prior to the second wave in 2012, firms were asked directly what the most pressing problem facing their firm was from a list (including access to finance). In all rounds after, firms were asked on a scale of one to ten, how pressing was a list of the same problems. We use the information from this question to construct a simple binary variable taking on a value of 1 if access to finance was the worst problem facing a firm and 0 otherwise.

This variable functions as a measure of perceived financial constraint. Rather than the pure bank loan availability measure that is specialised to bank lending, this variable allows us to assess the pass through of credit standards changes to a broader concept of being financially constrained.

⁴We additionally run specifications in which response variables are indicator variables rather than assuming continuity across the scale.

Table 4.5. SAFE Response Variables

	Yes	No	
<i>Finance Worst Problem</i>	6.49%	93.51%	
	<i>Increase/Im-</i>	<i>No Change</i>	<i>Decrease/De-</i>
	<i>provement</i>		<i>terioration</i>
<i>Investment</i>	29.58%	57.20%	13.22%
<i>Availability</i>	23.35%	64.35%	12.29%

Finally, we wish to study the transmission of credit standards changes to the real economy, and do so by measuring investment. Similarly to the question about bank loan availability, responses are trinomial, taking on values of 1 for an increase, 2 for unchanged and 3 for a decrease in fixed investment by a firm over the previous six months. We invert the sign on the variable to keep it consistent with higher values indicating an increase.

Descriptive statistics for our three key response variables are shown in Table 4.5. As can be seen access to finance as the worst problem facing the firm is a relatively rare event, with only a small number of firms noting this as a factor. This motivates our use of a linear probability model approach, in that a LPM outperforms models such as logistic regression for rare events data with fixed effects (Timoneda 2021). Regarding the other variables both cases show a slight bias towards reporting an increase/improvement relative to a decrease/deterioration while no change is the largest set of responses although there is a reasonable degree of variability overall.

4.4 Empirical approach and results

Within this study, we take use high dimensional fixed effects in an OLS regression with robust standard errors to assess the impact of changing standards on the real decisions and outcomes of firms within our sample. In each case we estimate the regression shown in Equation 4.2.⁵

$$SAFEVariable_{f,c,s,t} = \alpha_f + \delta_{c,s,t} + \gamma_1 CS_{f,c,t} + \epsilon_{f,c,s,t} \quad (4.2)$$

⁵All estimations are carried out using the **reghdfe** package in STATA (Correia 2016).

In each case, $SAFEVariable_{f,c,s,t}$ refers to our SAFE variable of interest for firm f in country c , in sector s at time t . $CS_{f,t}$ refers to a firms' credit standards at that time point (with this variable being either a vector of individual lags or a backward looking average). In all specifications, we add firm fixed effects α_f to account for time invariant firm specific factors, exploiting the fact that most firms in the SAFE have multiple observations. To control for time varying macroeconomic factors that may also impact on these results, we add country-sector-time fixed effects, to control for variability at this level, with the time unit in question being the six month periods of the SAFE survey. This controls for any broader macroeconomic factors that may be driving our results, and saturates the regression specification significantly.

We estimate this regression for our key variables of interest, namely access to finance being the worst problem facing a firm, availability of bank loans and investment.

4.4.1 Baseline results

Baseline results for estimating Equation 4.2 for each of our three key dependent variables are shown in Tables 4.6 to 4.8, with and without the addition of country-sector-time fixed effects.

Table 4.6. Regression of bank loan availability on BLS credit standards

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Standards - 1 Period	-0.106*** (0.000)			-0.00961 (0.613)		
Credit Standards - 2 Periods		-0.183*** (0.000)			-0.00182 (0.944)	
Credit Standards - 3 Periods			-0.229*** (0.000)			0.0310 (0.329)
Constant	-1.876*** (0.000)	-1.875*** (0.000)	-1.874*** (0.000)	-1.879*** (0.000)	-1.879*** (0.000)	-1.880*** (0.000)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country Sector Wave FE	No	No	No	Yes	Yes	Yes
Observations	35883	35920	35965	35784	35821	35866
R^2	0.406	0.407	0.407	0.463	0.463	0.463

Notes: Table shows the results of a regression in which the dependent variable is a trinomial variable taking on a value of -1 if firms in SAFE reported increase in bank loan availability, -2 if they reported no change and -3 for a decrease in bank loan availability. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. Higher values indicate tighter credit standards. Parentheses show p-values, with the following convention: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.7. Regression of finance being the worst problem facing a firm on BLS credit standards

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Standards - 1 Period	-0.00383 (0.355)			-0.00449 (0.443)		
Credit Standards - 2 Periods		0.00608 (0.253)			-0.00150 (0.851)	
Credit Standards - 3 Periods			0.0166*** (0.008)			-0.00319 (0.744)
Constant	0.0639*** (0.000)	0.0636*** (0.000)	0.0633*** (0.000)	0.0640*** (0.000)	0.0638*** (0.000)	0.0638*** (0.000)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country Sector Wave FE	No	No	No	Yes	Yes	Yes
Observations	54526	54593	54668	54469	54536	54611
R^2	0.419	0.419	0.419	0.452	0.452	0.452

Notes: Table shows the results of a regression in which the dependent variable is a binary variable taking on a value of 1 if access to finance was reported as the most pressing problem facing a firm during the SAFE survey period and 0 otherwise. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. Higher values indicate tighter credit standards. Parentheses show p-values, with the following convention: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.8. Regression of investment on BLS credit standards

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Standards - 1 Period	-0.0931*** (0.000)			-0.0245 (0.137)		
Credit Standards - 2 Periods		-0.175*** (0.000)			-0.0360 (0.118)	
Credit Standards - 3 Periods			-0.209*** (0.000)			-0.0271 (0.341)
Constant	-1.831*** (0.000)	-1.830*** (0.000)	-1.831*** (0.000)	-1.833*** (0.000)	-1.833*** (0.000)	-1.833*** (0.000)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country Sector Wave FE	No	No	No	Yes	Yes	Yes
Observations	49320	49386	49462	49312	49378	49454
R^2	0.385	0.385	0.385	0.415	0.415	0.415

Notes: Table shows the results of a regression in which the dependent variable is a trinomial variable taking on a value of -1 if firms in SAFE reported increase in investment, -2 if they reported no change and -3 for a decrease in investment. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. Higher values indicate tighter credit standards. Parentheses show p-values, with the following convention: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In the specification without country-sector-time fixed effects, for loan availability and investment, we note that the variables enter with expected sign immediately and are strongly significant, with a negative relationship in both cases. For finance being the worst problem, the effect is as expected and enters with the correct sign, but is only significant in the three period case (i.e. the averaging of credit standards over three SAFE waves). Taken together, these results can be read as indicating a successful matching process - i.e. for a given firm, controlling for their innate characteristics, if credit standards have tightened the response variables behave as expected.

Of more fundamental interest however, is that once country-sector-time fixed effects are added, these effects are absorbed throughout. This suggests that there are broader factors driving this effect, and we cannot rule out that the baseline effect from the specification with firm specific fixed effects is not indicative of an underlying macro pattern specific to given sectors within countries at each time point. This would highlight that the base effects for changes in credit standards may be cyclical - credit standards tighten in a downturn, but investment also falls, financial constraints are

more likely to bite and loan availability is likely to decrease - as such this is what our base effect may pick up on.

4.4.2 Introducing Demand

One aspect of the SAFE survey is that we can directly control for the demand for firms. This is a key innovation beyond what can be measured at firm level by BLS demand metrics, where it is a macro level judgement by individual banks - for regressions involving findings from the individual banks in the BLS regarding demand, we cannot identify which precise firms have increased or decreased demand, or indeed any heterogeneity within those banks customers. The SAFE, however, has a direct question on whether firms had increased, decreased or unchanged need for bank loans over the previous six months. This measure allows us to introduce a direct microeconomic measure of loan demand into our main regression specification.⁶

We add a baseline demand effect to Equation 4.2 alongside an interaction between demand and credit standards, in the form of a binary variable taking on a value of one if a firms loan demand increased and zero otherwise. This allows us to directly build on the results from the previous subsection and allows us to ask the following: while the effects for credit standards are insignificant on the whole, is there a differing effect depending on individual firms loan demand over a given SAFE wave? Results are shown in Tables 4.9 and 4.11, with all specifications having both firm and country-sector-time fixed effects, allowing for maximum saturation. The introduction of demand shows a strong interaction effect with the expected sign throughout for all three variables of interest.

⁶We also note that this particular question focuses on the need for bank loans rather than a broader demand concept. This thus is a more supply free measure of loan demand in that other measures such as whether a firm applied for a loan may be impacted on by changes credit standards themselves. The pure need for bank loans is itself likely to be more reflective of individual firms financing needs at each point in time.

Table 4.9. Regression of bank loan availability on BLS credit standards

	(1)	(2)	(3)
Credit Standards - 1 Period	-0.00251 (0.905)		
Increased Need For Bank Loans=1	0.0561*** (0.000)	0.0583*** (0.000)	0.0585*** (0.000)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period	-0.0386 (0.232)		
Credit Standards - 2 Periods		0.0308 (0.279)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods		-0.126*** (0.002)	
Credit Standards - 3 Periods			0.0649* (0.058)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods			-0.135*** (0.002)
Constant	-1.888*** (0.000)	-1.889*** (0.000)	-1.890*** (0.000)
Firm FE	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes
Observations	34069	34103	34148
R^2	0.465	0.466	0.465

Notes: Table shows the results of a regression in which the dependent variable is a value of -1 if firms in SAFE reported increase in bank loan availability, -2 if they reported no change and -3 for a decrease in bank loan availability. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. Higher values indicate tighter credit standards. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

Table 4.10. Regression of finance being the worst problem facing a firm on BLS credit standards

	(1)	(2)	(3)
Credit Standards - 1 Period	-0.00968 (0.341)		
Increased Need For Bank Loans=1	0.0441*** (0.000)	0.0430*** (0.000)	0.0423*** (0.000)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period	0.0257 (0.109)		
Credit Standards - 2 Periods		-0.0110 (0.423)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods		0.0618*** (0.001)	
Credit Standards - 3 Periods			-0.0177 (0.282)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods			0.0811*** (0.000)
Constant	0.0752*** (0.000)	0.0751*** (0.000)	0.0752*** (0.000)
Firm FE	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes
Observations	31590	31623	31666
R^2	0.487	0.487	0.488

Notes: Table shows the results of a regression in which the dependent variable is a binary variable taking on a value of 1 if access to finance was reported as the most pressing problem facing a firm during the SAFE survey period and 0 otherwise. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over, looking backwards from the current period. Higher values indicate tighter credit standards. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

Table 4.11. Regression of investment on BLS credit standards

	(1)	(2)	(3)
Credit Standards - 1 Period	0.00336 (0.898)		
Increased Need For Bank Loans=1	0.183** (0.000)	0.184*** (0.000)	0.184*** (0.000)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period	-0.0892** (0.040)		
Credit Standards - 2 Periods		0.00763 (0.834)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods		-0.147** (0.013)	
Credit Standards - 3 Periods			0.0139 (0.756)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods			-0.152** (0.031)
Constant	-1.849*** (0.000)	-1.849*** (0.000)	-1.850*** (0.000)
Firm FE	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes
Observations	28229	28263	28310
R^2	0.450	0.450	0.450

Notes: Table shows the results of a regression in which the dependent variable is a trinomial variable taking on a value of -1 if firms in SAFE reported increase in investment, -2 if they reported no change and -3 for a decrease in investment. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over, looking backwards from the current period. Higher values indicate tighter credit standards. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

For loan availability, there is a strong and significant negative relationship with changing credit standards, conditional on the firm having an increased need for bank loans, with the effect becoming significant after two periods. This suggests that if a firm has increased need for loans and faces a tightening (easing) of credit standards, their loan availability declines (improves), providing evidence that it is not only important to control for demand at a micro level, it is important to assess exactly which firms feel the bite of credit standards changes.

This interaction effect moves against the base effect for an increased need for bank loans, which is positive as anticipated as those firms that are more likely to need bank loans are also more likely to apply for bank loans and thus an improvement in perceived availability is more likely to be noted. As such, taking these results together it may highlight that if firms had no tightening (or easing) of credit standards, and they had increased need for bank loans, they are more likely to report improved loan availability, which in the absence of credit standards changes is to be expected. This base effect is overruled by the interaction with credit standards after two periods, shedding light on how changing credit standards pass through to firms.

In addition, the base effect for the impact of changing credit standards on loan availability insignificant as in our baseline results in all but the three period case, where it enters with an unexpected positive sign. When we consider the base group, for which this effect is attributed to firms with decreasing or unchanged loan demand, it may be indicative of a selection effect by banks, whereby in periods of consecutive tightening credit standards are passed through less substantially to those firms who are less financially constrained, and such firms may even be "preferred" in such cases. Moreover, against the backdrop of noticeably tighter credit standards, such firms may perceive that their loan availability is better in relative terms compared to others. We note, however, the effect is relatively small and only enters in this specification.

To further shed light on this, we re-estimate this regression, only making the need for bank loans variable a three way categorical variable, with no change in need as the base effect, and decreasing and increasing need as separate categorical variables. Results for this specification are shown in the Appendix in Table C1. Once again, we see a relatively strong interaction effect between increased need for bank loans and credit standards, backing up our initial results, while the unexpected positive coefficient on credit standards enters as a base effect for the no change group, albeit weaker than before, but the interaction is insignificant for the decreasing need group. This may suggest weak evidence of a selection effect for those firms with unchanged loan demand during continuous tightening (or easing) cycles. Interestingly, the base effect for bank loan need is positive for both the increasing and decreasing loan need case. This may indicate two contradictory factors - those with decreasing need for bank loans may be financially healthier and as such are preferred by the banks relative to those with no change, while those with increasing need may be reporting increasing availability, purely by the nature of engaging with banks in looking for loans.

For finance being the worst problem facing a firm, there is a positive and significant interaction effect from the two period average onwards, with the effect after one period being only marginally insignificant at the 10% level (and indeed this becomes significant in the specification with the broader split of the need for bank loans variable in Table C2). Once again, combined with the baseline results showing no effect, and the insignificant base effects for credit standards it suggests that the impact of changing credit standards is felt by those firms with increased need for bank loans.

Finally, on the investment side, we see an immediate negative interaction effect, significant throughout at the 5% level. This highlights that it is not only on the supply side that the interaction effect feeds through, but it also impacts on the investment decisions of banks. Firms with increased need for bank loans are more likely to increase investment as expected, but if they are faced with tighter (looser) credit standards, this effect is dampened (amplified). In the case of a tightening cycle, this indicates that tightening credit standards can clearly dampen demand in the case of an environment of high demand - suggesting lessons for monetary policy from this. These effects hold in the broader split of the need for bank loans variable as shown in Table C3.

Taken together, these results provide a strong message for the pass through of credit conditions to firms: changes in credit standards are mostly felt by those firms who are actively needing loans, and as such effects are likely to be stronger during cycles in which there is increasing demand. Thus it is necessary for policymakers to examine these concepts simultaneously, rather than relying on separate individual indicators.

4.4.3 The impact of diverse financing sources

While we have established that credit standards pass through to firms that have an increased need for bank loans, it is worth considering what other interaction effects may exist. One potential source of this variability is the diversity of funding sources available to each individual bank. To shed light on this, we turn to more data from the

SAFE survey, examining a question in which firms are asked whether different sources of finance are relevant for their firm, with firms providing a simple yes or no answer.⁷

We use this question to construct a measure of the level of concentration of the funding base of each individual firm. We construct a variable $FinanceSource_{f,c,s,t}$ for each firm f , defined as the count of the number of financing sources a firm deemed as relevant in that survey round, divided by the total number of financing sources listed in that survey round (excluding do-not knows). As such, higher values denote a more diversified portfolio of financing sources and a lower value indicates a more concentrated funding base. We augment the specification in 4.2 by adding a triple interaction between this measure and the need for bank loans and credit standards. This allows us to delve into (a) the base effect of having a diversified financing source, but also how it interacts with both need for bank loans and credit standards individually and as a triple interaction (i.e. for firms that had an increasing need and changing credit standards simultaneously). The triple interaction is crucial for augmenting the results shown in the previous subsection, as theoretically a diversified funding base should mitigate to some extent the impact of the tightening for firms with increased need for bank loans, through a more diversified funding base. Results can be seen in Tables 4.12 to 4.14. We note that in these regressions, the base effects for credit standards and need for bank loans (and their interaction) becomes difficult to interpret, as they condition on the financing source variable taking on a value of zero (i.e. no financing sources are relevant to the firm). For this reason, we do not examine these coefficients in detail in the below, and thus concentrate on interactions involving the financing source variable as the average effects for these initial coefficients can be seen in the analysis in Section 4.4.2.

⁷The sources of finance that firms are asked about are: bank loans, credit lines, grants or subsidised bank loans, trade credit, other loans, leasing or hire purchase, debt securities, equity capital, factoring, sale of assets or retained earnings, other sources of financing (such as subordinated debt, participating loans, peer to peer lending or crowdfunding) and mezzanine financing

Table 4.12. Regression of bank loan availability on BLS credit standards

	(1)	(2)	(3)
Credit Standards - 1 Period	-0.0753 (0.145)		
Increased Need For Bank Loans=1	-0.000746 (0.976)	0.00496 (0.840)	0.00739 (0.764)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period	-0.241** (0.012)		
Fin Source Concentration	0.0490* (0.064)	0.0503* (0.058)	0.0541** (0.042)
Credit Standards - 1 Period X Fin Source Concentration	0.124 (0.131)		
Increased Need For Bank Loans=1 X Fin Source Concentration	0.109** (0.011)	0.102** (0.018)	0.0977** (0.024)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period X Fin Source Concentration	0.397** (0.020)		
Credit Standards - 2 Periods		-0.0336 (0.593)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods		-0.402*** (0.000)	
Credit Standards - 2 Periods X Fin Source Concentration		0.108 (0.279)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods X Fin Source Concentration		0.541*** (0.007)	
Credit Standards - 3 Periods			0.0215 (0.763)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods			-0.420*** (0.001)
Credit Standards - 3 Periods X Fin Source Concentration			0.0705 (0.525)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods X Fin Source Concentration			0.565*** (0.009)
Constant	-1.915*** (0.000)	-1.917*** (0.000)	-1.920*** (0.000)
Firm FE	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes
Observations	34069	34103	34148
R ²	0.466	0.466	0.466

Notes: Table shows the results of a regression in which the dependent variable is a value of -1 if firms in SAFE reported increase in bank loan availability, -2 if they reported no change and -3 for a decrease in bank loan availability. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. Higher values indicate tighter credit standards. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. Fin source concentration is an index between 0 and 1, whereby higher values indicate a wider diversification of funding sources. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

Table 4.13. Regression of finance being the worst problem facing a firm on BLS credit standards

	(1)	(2)	(3)
Credit Standards - 1 Period	-0.0439* (0.072)		
Increased Need For Bank Loans=1	0.0736*** (0.000)	0.0721*** (0.000)	0.0717*** (0.000)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period	0.117** (0.015)		
Fin Source Concentration	-0.0262** (0.039)	-0.0268** (0.035)	-0.0264** (0.038)
Credit Standards - 1 Period X Fin Source Concentration	0.0600 (0.119)		
Increased Need For Bank Loans=1 X Fin Source Concentration	-0.0558*** (0.009)	-0.0549** (0.011)	-0.0555** (0.011)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period X Fin Source Concentration	-0.170** (0.044)		
Credit Standards - 2 Periods		-0.0514* (0.080)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods		0.161*** (0.003)	
Credit Standards - 2 Periods X Fin Source Concentration		0.0727 (0.112)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods X Fin Source Concentration		-0.186* (0.054)	
Credit Standards - 3 Periods			-0.0442 (0.179)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods			0.140** (0.016)
Credit Standards - 3 Periods X Fin Source Concentration			0.0482 (0.339)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods X Fin Source Concentration			-0.113 (0.273)
Constant	0.0899*** (0.000)	0.0901*** (0.000)	0.0900*** (0.000)
Firm FE	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes
Observations	31590	31623	31666
R ²	0.488	0.488	0.488

Notes: Table shows the results of a regression in which the dependent variable is a binary variable taking on a value of 1 if access to finance was reported as the most pressing problem facing a firm during the SAFE survey period and 0 otherwise. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. Higher values indicate tighter credit standards. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. Fin source concentration is an index between 0 and 1, whereby higher values indicate a wider diversification of funding sources. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

Table 4.14. Regression of investment on BLS credit standards

	(1)	(2)	(3)
Credit Standards - 1 Period	0.0520 (0.476)		
Increased Need For Bank Loans=1	0.126*** (0.000)	0.121*** (0.000)	0.114*** (0.001)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period	-0.263* (0.062)		
Fin Source Concentration	0.00836 (0.813)	0.0106 (0.763)	0.0103 (0.770)
Credit Standards - 1 Period X Fin Source Concentration	-0.0829 (0.469)		
Increased Need For Bank Loans=1 X Fin Source Concentration	0.104* (0.073)	0.114** (0.050)	0.125** (0.031)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period X Fin Source Concentration	0.315 (0.191)		
Credit Standards - 2 Periods		0.110 (0.265)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods		-0.234 (0.218)	
Credit Standards - 2 Periods X Fin Source Concentration		-0.173 (0.263)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods X Fin Source Concentration		0.150 (0.644)	
Credit Standards - 3 Periods			0.129 (0.264)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods			-0.00992 (0.964)
Credit Standards - 3 Periods X Fin Source Concentration			-0.195 (0.282)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods X Fin Source Concentration			-0.270 (0.475)
Constant	-1.854*** (0.000)	-1.855*** (0.000)	-1.855*** (0.000)
Firm FE	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes
Observations	28229	28263	28310
R ²	0.450	0.450	0.450

Notes: Table shows the results of a regression in which the dependent variable is a trinomial variable taking on a value of -1 if firms in SAFE reported increase in investment, -2 if they reported no change and -3 for a decrease in investment. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. Higher values indicate tighter credit standards. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. Fin source concentration is an index between 0 and 1, whereby higher values indicate a wider diversification of funding sources. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

For both availability and the likelihood of reporting access to finance being the worst problem, the base effect for financing source (interpretable as the effect for firms with no change in credit standards and no change in need for bank loans) is positive and negative respectively. This is as expected - a diversified funding base means that firms are more likely to report improved loan availability, but also are less

likely to report that they are financially constrained. Interestingly there is no clear base effect for investment, suggesting that in this case, a diversified funding source does not materially impact on firms' investment decisions.

Turning to the interaction effects, we see a positive and negative interaction respectively throughout for changes in financing sources and loan availability and financing being the worst problem facing a firm. In both cases this indicative of an improvement - for those who needed bank loans they are more likely to report improved availability, and less likely to be financially constrained if they have a more diversified array of financing options. Interestingly, in the case of investment, there is a positive interaction throughout - suggesting that for those firms who needed bank loans and faced no change in credit standards, a diversified funding base increases the likelihood of increasing investment.

On the other hand, there is no clear effect in either case of the interaction between a more diversified financing source and changes in credit standards in any case for the interaction of these variables. This is perhaps to be expected, as this pertains to the base group (i.e. firms that had no increase in need for bank loans). It re-enforces our findings from Section 4.4.2 - firms who do not have increased need for bank loans do not feel the impact of changes in credit standards, and furthermore, there is no additional impact of having access to more diversified financing sources in such cases.

Finally, turning to the triple interaction some strong results become evident. For loan availability in particular, the triple interaction gives large and as expected negative coefficients - for those firms experiencing a tightening in credit standards that had an increase in loan demand, having access to a diversified funding base insulates against the negative impact of a tightening (with the opposite for the case of an easing). For finance being the worst problem facing a firm results are similar for the one and two period case, but less clear for the three period case, with an expected negative coefficient for the first two, and no significance in the final case. This is some evidence of this "insulation effect" - with a diversified funding base lowering the likelihood of being financially constrained if a firm with increased need faced a tightening. Interestingly, there is no clear impact of this triple interaction for investment, suggesting that diversified funding sources has no impact here, unlike the supply side variables. Indeed most credit standards variables become insignificant for investment, suggesting some evidence that diversified funding sources may have significant influence on the transmission of credit standards shocks, although

interactions still enter with the expected sign, and the one period figure remains significant when interacted with need for bank loans.

4.4.4 Asymmetric effects of tightening and easing

Thus far, results have assumed a symmetric reaction to changes in credit standards across firms - with both an easing and a tightening assumed to have the same effect in a symmetric fashion. To examine if this is actually the case, we split our credit standards variables in two, to create two separate variables. Considering our credit standards variable $CS_{f,t}$ is an interval between -2 and +2, with -2 being the strongest easing and +2 the strongest tightening, with 0 signifying unchanged, we define $Ease_{f,t}$ and $Tight_{f,t}$ as:

$$Ease_{f,t} = \begin{cases} -1 \times CS_{f,t} & \text{if } CS_{f,t} < 0 \\ 0 & \text{if } CS_{f,t} \geq 0 \end{cases}$$

$$Tight_{f,t} = \begin{cases} CS_{f,t} & \text{if } CS_{f,t} > 0 \\ 0 & \text{if } CS_{f,t} \leq 0 \end{cases}$$

This thus defines these variables as taking a continuous value on a scale of 0 to 2 depending on the intensity of the easing in the case of $Ease_{f,t}$ and the intensity of the tightening in the case of $Tight_{f,t}$. We repeat our specification with demand interactions, and show the results in Tables 4.15 to 4.17.

Table 4.15. Regression of bank loan availability on BLS credit standards

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Standards - 1 Period Tightening Only	0.00823 (0.771)					
Increased Need For Bank Loans=1	0.0593*** (0.000)	0.0663*** (0.000)	0.0672*** (0.000)	0.0557*** (0.000)	0.0553*** (0.000)	0.0566*** (0.000)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period Tightening Only	-0.0713* (0.076)					
Credit Standards - 2 Period Tightening Only		0.0611 (0.117)				
Increased Need For Bank Loans=1 X Credit Standards - 2 Period Tightening Only		-0.198*** (0.000)				
Credit Standards - 3 Period Tightening Only			0.124*** (0.009)			
Increased Need For Bank Loans=1 X Credit Standards - 3 Period Tightening Only			-0.224*** (0.000)			
Credit Standards - 1 Period Easing Only				0.0242 (0.490)		
Increased Need For Bank Loans=1 X Credit Standards - 1 Period Easing Only				-0.0252 (0.683)		
Credit Standards - 2 Period Easing Only					0.0154 (0.738)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Period Easing Only					-0.0181 (0.823)	
Credit Standards - 3 Period Easing Only						0.0128 (0.810)
Increased Need For Bank Loans=1 X Credit Standards - 3 Period Easing Only						-0.0618 (0.510)
Constant	-1.889*** (0.000)	-1.891*** (0.000)	-1.895*** (0.000)	-1.889*** (0.000)	-1.889*** (0.000)	-1.889*** (0.000)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34069	34103	34148	34069	34103	34148
R ²	0.465	0.466	0.465	0.465	0.465	0.465

Notes: Table shows the results of a regression in which the dependent variable is a value of -1 if firms in SAFE reported increase in bank loan availability, -2 if they reported no change and -3 for a decrease in bank loan availability. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. The credit standards variable is split into two separate variables, taking on an index value equalling the magnitude of the tightening or easing respectively (between 0 and 2), and is coerced to equal zero otherwise. Higher values for the tightening variable indicate a larger degree of tightening, while higher values for the easing variable indicate a larger degree of easing. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

Table 4.16. Regression of finance being the worst problem facing a firm on BLS credit standards

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Standards - 1 Period Tightening Only	-0.0179 (0.188)					
Increased Need For Bank Loans=1	0.0421*** (0.000)	0.0394*** (0.000)	0.0386*** (0.000)	0.0445*** (0.000)	0.0448*** (0.000)	0.0456*** (0.000)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period Tightening Only	0.0435** (0.029)					
Credit Standards - 2 Period Tightening Only		-0.0193 (0.303)				
Increased Need For Bank Loans=1 X Credit Standards - 2 Period Tightening Only		0.0912*** (0.000)				
Credit Standards - 3 Period Tightening Only			-0.0375* (0.099)			
Increased Need For Bank Loans=1 X Credit Standards - 3 Period Tightening Only			0.106*** (0.000)			
Credit Standards - 1 Period Easing Only				-0.00313 (0.853)		
Increased Need For Bank Loans=1 X Credit Standards - 1 Period Easing Only				0.00841 (0.783)		
Credit Standards - 2 Period Easing Only					-0.00292 (0.895)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Period Easing Only					-0.00372 (0.925)	
Credit Standards - 3 Period Easing Only						-0.00731 (0.776)
Increased Need For Bank Loans=1 X Credit Standards - 3 Period Easing Only						-0.0392 (0.398)
Constant	0.0760*** (0.000)	0.0759*** (0.000)	0.0768*** (0.000)	0.0751*** (0.000)	0.0750*** (0.000)	0.0751*** (0.000)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31590	31623	31666	31590	31623	31666
R ²	0.487	0.487	0.488	0.487	0.487	0.487

Notes: Table shows the results of a regression in which the dependent variable is a binary variable taking on a value of 1 if access to finance was reported as the most pressing problem facing a firm during the SAFE survey period and 0 otherwise. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. The credit standards variable is split into two separate variables, taking on an index value equalling the magnitude of the tightening or easing respectively (between 0 and 2), and is coerced to equal zero otherwise. Higher values for the tightening variable indicate a larger degree of tightening, while higher values for the easing variable indicate a larger degree of easing. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

Table 4.17. Regression of investment on BLS credit standards

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Standards - 1 Period Tightening Only	0.0363 (0.315)					
Increased Need For Bank Loans=1	0.192*** (0.000)	0.195*** (0.000)	0.196*** (0.000)	0.182*** (0.000)	0.181*** (0.000)	0.182*** (0.000)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period Tightening Only	-0.182*** (0.001)					
Credit Standards - 2 Period Tightening Only		0.0319 (0.544)				
Increased Need For Bank Loans=1 X Credit Standards - 2 Period Tightening Only		-0.271*** (0.001)				
Credit Standards - 3 Period Tightening Only			0.0783 (0.247)			
Increased Need For Bank Loans=1 X Credit Standards - 3 Period Tightening Only			-0.328*** (0.001)			
Credit Standards - 1 Period Easing Only				0.0493 (0.243)		
Increased Need For Bank Loans=1 X Credit Standards - 1 Period Easing Only				-0.0640 (0.414)		
Credit Standards - 2 Period Easing Only					0.0232 (0.675)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Period Easing Only					-0.0147 (0.887)	
Credit Standards - 3 Period Easing Only						0.0420 (0.507)
Increased Need For Bank Loans=1 X Credit Standards - 3 Period Easing Only						-0.0373 (0.752)
Constant	-1.851*** (0.000)	-1.851*** (0.000)	-1.853*** (0.000)	-1.851*** (0.000)	-1.850*** (0.000)	-1.851*** (0.000)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28229	28263	28310	28229	28263	28310
R ²	0.450	0.450	0.450	0.450	0.449	0.449

Notes: Table shows the results of a regression in which the dependent variable is a trinomial variable taking on a value of -1 if firms in SAFE reported increase in investment, -2 if they reported no change and -3 for a decrease in investment. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. The credit standards variable is split into two separate variables, taking on an index value equalling the magnitude of the tightening or easing respectively (between 0 and 2), and is coerced to equal zero otherwise. Higher values for the tightening variable indicate a larger degree of tightening, while higher values for the easing variable indicate a larger degree of easing. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

In all cases, results show that there is a highly asymmetric response of the dependent variables to a tightening and an easing of credit standards, with most effects concentrated on the tightening side. In each case, the interaction term and base effect are both insignificant for the easing variable, indicative of a much weaker pass through of an easing of credit standards to firm's perceived loan availability, probability of reporting access to finance as their worst problem and changes in investment. On the other hand, results for a tightening are stronger than seen in

Section 4.4.2, suggesting that the effects estimated by the aggregate variables are underestimating the impact of a tightening, and overstating the impact of an easing when viewed alongside each other with the assumption of symmetry. Compared to the baseline specifications, our interaction effects are significant instantaneously, rather than with a slight lag and all have the expected sign (for banks with increased need for bank loans, a tightening lowers loan availability, increases the likelihood of access to finance being the worst problem facing a firm, and decreases investment).

Interestingly, the puzzling positive coefficient after 3 periods for the credit standards base effect persists for loan availability, and indeed a significant negative coefficient is also present in the 3 period case for the base effect for finance being the worst problem facing a firm. The fact this is not present short-run but is long-run may indicate a paradoxical effect as mentioned before - in periods of longer term tightening, firms with no increased need are potentially experiencing positive "selection effects" relative to those firms who have increased financing needs, and are thus perceiving loan availability as being relatively more available when compared to the broader tightening environment.

4.4.5 Asymmetric responses increases and decreases in availability and investment

While the previous section deals with asymmetry of the independent variable, we have not commented on potential asymmetries in the dependent variable. For availability and investment, each variable is takes a value on a scale from -1 to -3, depending on if the firm saw an increase (-1), no change (-2) and a decrease (-3). Previous regressions have also been hard to interpret quantitatively in essence, the interpretation can be seen as the change in the average rank of the variable for a given change in credit standards (or loan need), but it is difficult to put into meaningful numeric terms (as is the case for interpreting the change in probability of reporting access to finance as the worst problem facing a firm).

Thus, to explore asymmetry and produce more meaningful numeric results, we run two separate specifications in each case, with binary dependent variables taking on a value of 1 in the case of an increase and 0 otherwise, with a complementary specification for the case of a decrease. Results are shown in Tables 4.18 to 4.21. This allows for the interpretation of coefficients as the impact on the likelihood of

reporting an increase/decrease relative to not doing so, for given changes in credit standards.

Table 4.18. Regression of increased bank loan availability on BLS credit standards

	(1)	(2)	(3)
Credit Standards - 1 Period	-0.0113 (0.472)		
Increased Need For Bank Loans=1	0.0970*** (0.000)	0.0980*** (0.000)	0.0978*** (0.000)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period	-0.00993 (0.679)		
Credit Standards - 2 Periods		0.00132 (0.950)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods		-0.0499* (0.092)	
Credit Standards - 3 Periods			0.0115 (0.652)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods			-0.0392 (0.235)
Constant	0.223*** (0.000)	0.223*** (0.000)	0.222*** (0.000)
Firm FE	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes
Observations	34069	34103	34148
R^2	0.439	0.439	0.439

Notes: Table shows the results of a regression of a binary variable taking on a value of one if firms in SAFE reported increased availability of bank loans and zero otherwise. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. Higher values indicate tighter credit standards. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

Table 4.19. Regression of decreased bank loan availability on BLS credit standards

	(1)	(2)	(3)
Credit Standards - 1 Period	-0.00877 (0.445)		
Increased Need For Bank Loans=1	0.0410*** (0.000)	0.0396*** (0.000)	0.0393*** (0.000)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period	0.0287 (0.103)		
Credit Standards - 2 Periods		-0.0295* (0.057)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods		0.0762*** (0.000)	
Credit Standards - 3 Periods			-0.0534*** (0.004)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods			0.0963*** (0.000)
Constant	0.111*** (0.000)	0.111*** (0.000)	0.112*** (0.000)
Firm FE	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes
Observations	34069	34103	34148
R^2	0.476	0.476	0.476

Notes: Table shows the results of a regression of a binary variable taking on a value of one if firms in SAFE reported decreased availability of bank loans and zero otherwise. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. Higher values indicate tighter credit standards. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.20. Regression of increased investment on BLS credit standards

	(1)	(2)	(3)
Credit Standards - 1 Period	0.000767 (0.967)		
Increased Need For Bank Loans=1	0.157*** (0.000)	0.157*** (0.000)	0.157*** (0.000)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period	-0.0813*** (0.008)		
Credit Standards - 2 Periods		0.0225 (0.380)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods		-0.113*** (0.007)	
Credit Standards - 3 Periods			0.0417 (0.186)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods			-0.130*** (0.009)
Constant	0.298*** (0.000)	0.297*** (0.000)	0.297*** (0.000)
Firm FE	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes
Observations	28229	28263	28310
R^2	0.461	0.461	0.461

Notes: Table shows the results of a regression of a binary variable taking on a value of one if firms in SAFE reported increased investment and zero otherwise. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. Higher values indicate tighter credit standards. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

Table 4.21. Regression of decreased investment on BLS credit standards

	(1)	(2)	(3)
Credit Standards - 1 Period	-0.00259 (0.854)		
Increased Need For Bank Loans=1	-0.0259*** (0.000)	-0.0267*** (0.000)	-0.0263*** (0.000)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period	0.00796 (0.734)		
Credit Standards - 2 Periods		0.0149 (0.448)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods		0.0334 (0.295)	
Credit Standards - 3 Periods			0.0278 (0.249)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods			0.0226 (0.552)
Constant	0.147*** (0.000)	0.147*** (0.000)	0.147*** (0.000)
Firm FE	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes
Observations	28229	28263	28310
R ²	0.420	0.420	0.420

Notes: Table shows the results of a regression of a binary variable taking on a value of one if firms in SAFE reported decreased investment and zero otherwise. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. Higher values indicate tighter credit standards. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

In both cases, result reveal a relatively asymmetric reaction of the response variables, with this being particularly stark in the case of investment.

Concentrating on the key interaction effects, we see a instantaneous increase (decrease) in the likelihood of reporting a decrease in availability for a tightening (easing) of credit standards, given a firm had an increased need for bank loans. This is only marginally insignificant after one period and becomes strongly significant after two periods, with a 1 unit change in credit standards over two periods increasing the probability of reporting lower loan availability by 0.08 points, with the effect

remaining significant over 3 periods. On the other hand, the likelihood of reporting an increase in availability is very weak after one period, but mildly significant and negative after two periods, although insignificant again after three periods. The effect is as expected, with a tightening (easing) of credit standards lowering (increasing) the likelihood of reporting improved loan availability. Taken together, it suggests that credit standards changes primarily impact on loan availability through changing the relative likelihood of firms seeing a decrease in availability, although some effect is present on the other side.

For investment the results are much more stark. Conditional on needing a bank loan, the effect of a change in credit standards is primarily felt through changing the likelihood of increasing investment, with no such effects present for decreasing investment. Considering a tightening, after one period a one unit relative tightening of credit standards reduces the likelihood of reporting an increase in investment for firms with higher need for bank loans by 0.08, while this rises to 0.13 after 3 periods of consistent tightening. We thus posit that the core effect is a disinvestment one, rather than an active decrease in investment, and as such, a tightening of credit standards may to some extent cool investment when rising sharply, while not necessarily leading to a decrease at an individual firm level.

Additionally, for loan availability, intriguingly the base effect of need for bank loans is positive for both an increase and a decrease. Considering that this is the estimated effect for firms facing no change in credit standards, this may indicate two competing effects at play - on one side, firms are more likely to engage with a bank if they have increased need for bank loans, and thus have a higher likelihood of reporting improved loan availability through such engagement. On the other side, firms may also be more likely to report a decrease in loan availability if they are financially in a weaker position and need bank loans. While seemingly paradoxical at first, taken together this may simply indicate that firms in this category are less likely to have reported no change on aggregate, and are more likely to have formed an impression of perceived availability given their search for finance. This may to some extent explain the result seen in Table C1, whereby firms with decreasing loan demand were reporting improved loan availability - as this may be purely reflecting the relative financial health of such firms, while firms with increased need have competing factors - namely increased awareness of loan availability making them more likely to report improvements, while

their innate need for more loans may indicate weaker balance sheets, and thus lowers the likelihood of reporting greater loan availability.

Results for interactions with financing sources can be seen in the Appendix, in Figures C7 to C10. For availability, the results for the triple interaction reflect the baseline case, with most of the impact being seen on the decrease side, with a strong mitigation effect of having a diversified funding source on the likelihood of reporting a decrease in loan availability, conditional on having an increased need for bank loans and facing a tightening of credit standards. Results are much more muted for an increase, with the triple interaction having expected sign, albeit statistically insignificant with p-values of between 0.141 and 0.175. For investment, along with the baseline results we see no effect for the triple interaction term, in line with previous results.

4.5 Demand adjusted credit standards - a new macroeconomic variable

The key finding in this paper is that changes in credit standards alone do not impact on firms both (a) in their likelihood of having financial constraints and (b) in their investment decisions, it only does so conditional on the firm having increased need for bank loans. This has implications for the interpretation of surveys at an aggregate level, in that by examining credit standards alone, one is likely to underestimate the impact of a tightening in times of levels of high demand, and overestimate the impact of a tightening in periods of low demand. We thus propose a new macroeconomic indicator that accounts for this at an aggregate level that we denote as *demand adjusted credit standards*. This builds on previous work in the development of a financing gap indicator for the SAFE seen in Ferrando et al. (2013), and can be seen as a complement to measures such as the Loan Supply Indicator constructed in Altavilla et al. (2019b). While the Loan Supply Indicator focuses on a pure supply effect, this measure can be seen as measuring the interacting effects of supply and demand.

To construct this, we calculate a simple net percentage. Let $CS_{f,t}$ be the universe of credit standards facing a firm f during SAFE wave t , defined on the -2 to +2 scale as before. Consider the following trinomial variable for a firm f :

$$DemAdjCS_{f,t} = \begin{cases} -1 & \text{if } CS_{f,t} < 0 \text{ and } NeedBankLoan = 1 \\ 1 & \text{if } CS_{f,t} > 0 \text{ and } NeedBankLoan = 1 \\ 0 & \text{Otherwise} \end{cases}$$

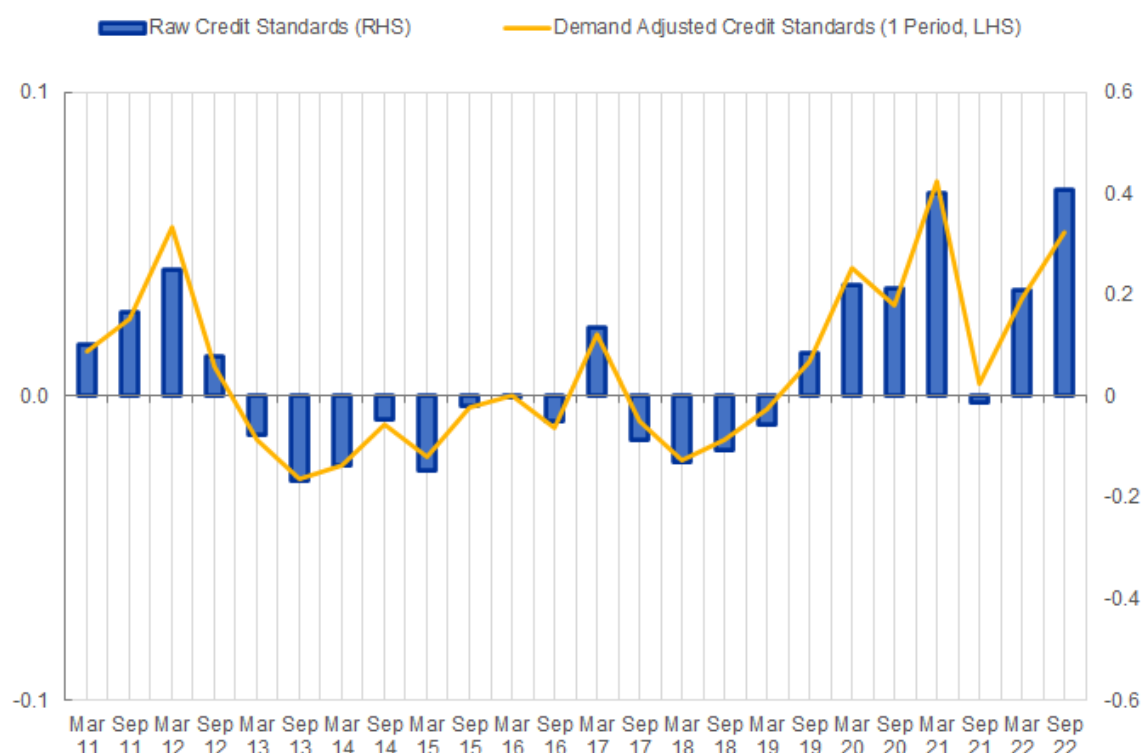
In other words, taking a value of -1 for an easing, 1 for a tightening, conditional on having an increased need for bank loans and 0 otherwise. To aggregate this to a macro level, we sum this value across all firms, and divide by the total number of firms (excluding those with no response to either the need bank loans question or with no recorded credit standards in that period). Thus we define demand adjusted credit standards for the euro area at each time point (with F firms, labelled $1, \dots, F$) as:

$$DemAdjCS_t = \frac{\sum_{f=1}^F DemAdjCS_{f,t}}{F} \quad (4.3)$$

In essence, this is the total number of firms reporting a tightening, less the total number of firms reporting an easing of credit standards conditional on having increased need for bank loans. This series is shown in Figure 4.1.⁸ As a comparison we also plot a raw net percentage of unadjusted credit standards (i.e. we construct the equivalent to Equation 4.3 only without conditioning on needing bank loans. This is preferable to comparing to the standard BLS credit standards series as it keeps (A) our sample constant and (B) aligns with our aggregated measure of credit standards across all banks at the firm level. This is particularly important as our sample only contains a subset of euro area countries, while the headline BLS series contains data for all 19 that were in the euro area during our sample.

⁸We note that the first three SAFE waves are omitted owing to a relatively low number of matched firms.

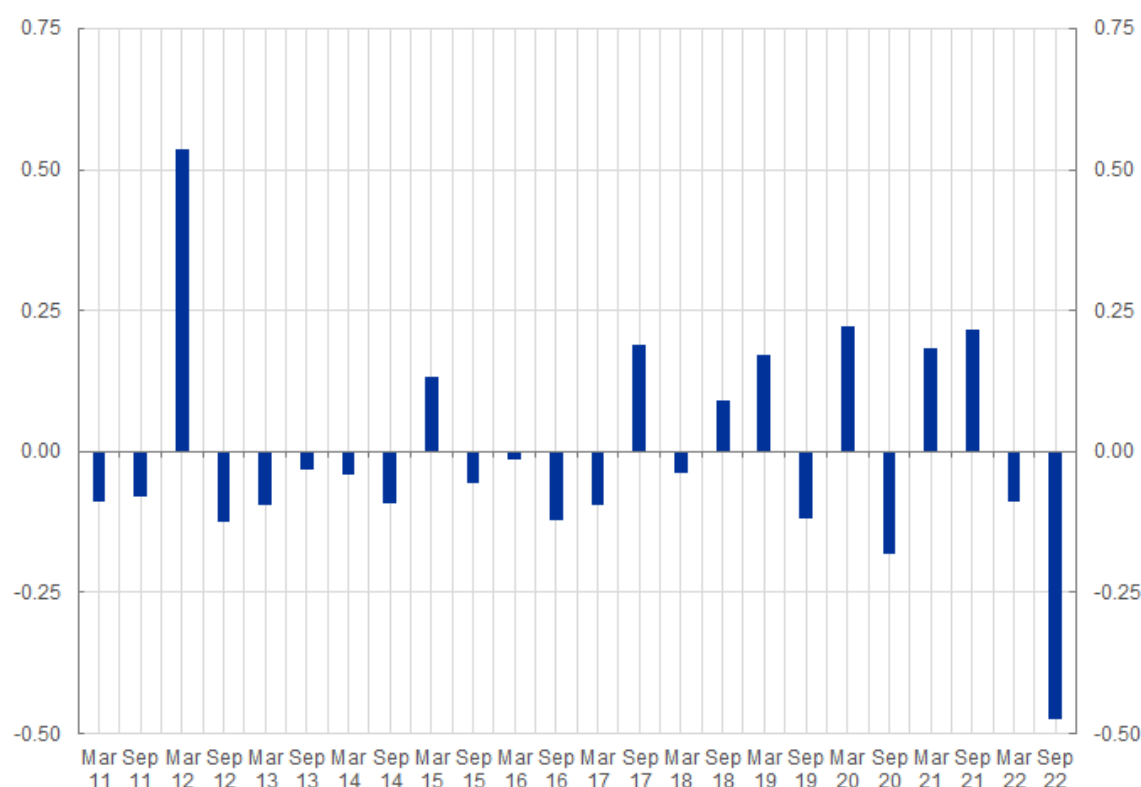
Figure 4.1. Comparison of demand adjusted credit standards with unadjusted credit standards



As can be seen, by construction the net percentages for the adjusted series are much lower, given the more restricted sample at each time point. While the two measures track each other quite closely in terms of overall patterns, if we concentrate on mapping the levels on to each other it becomes clear that there are a number of time points in which the adjusted series gives a relatively more (or less) pronounced reading for similar levels of the unadjusted series.

To show this more clearly, Figure 4.2 shows the difference between unadjusted and demand adjusted credit standards, with both series standardised to have a mean of zero and standard deviation of one. Positive values indicate that unadjusted credit standards had a higher relative value, while negative values indicate that adjusted credit standards had a higher relative value.

Figure 4.2. Difference between normalised unadjusted credit standards and demand adjusted credit standards



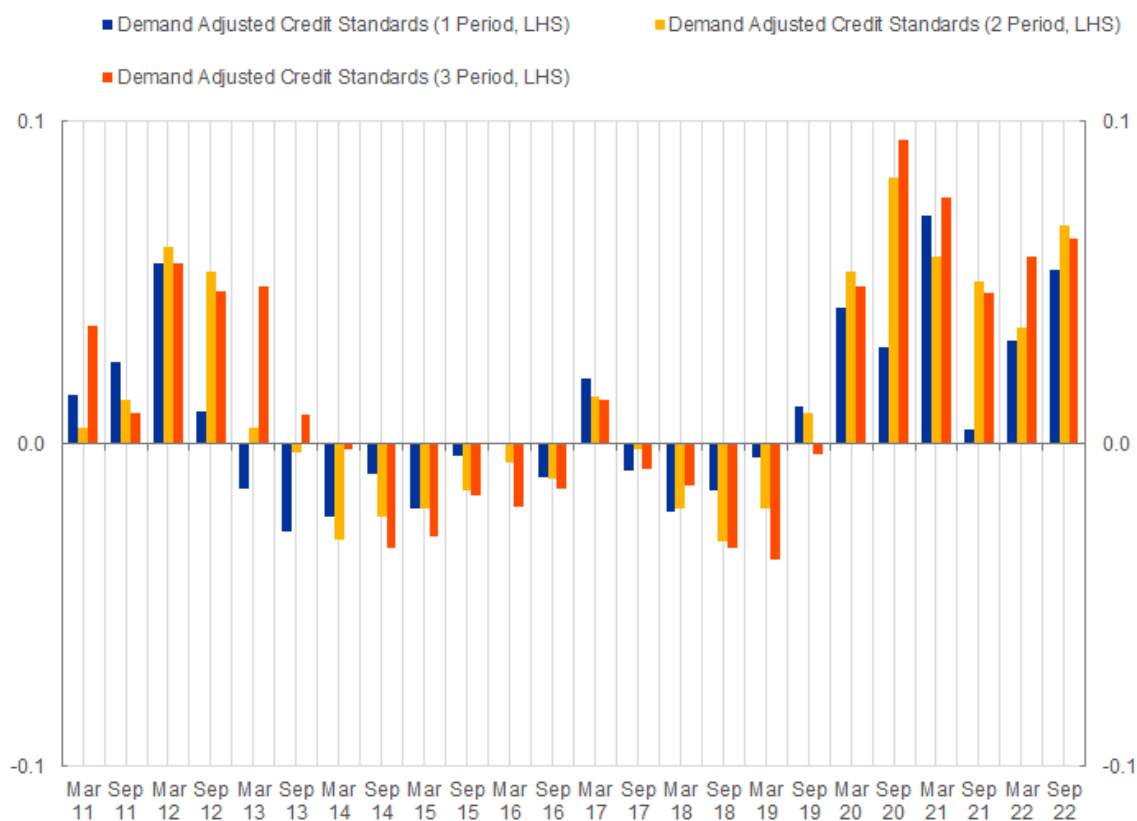
Two figures immediately stick out, and that is that during the sovereign debt crisis (towards the end of 2011 and start of 2012), demand adjusted credit standards reported a much higher relative figure than unadjusted credit standards. If we compare this to Figure 4.1, we see that while the unadjusted credit standards figure is low relative to the Covid-19 period, or the tightening of credit standards seen in 2022, the adjusted figure lies somewhere between the two. This is indicative that examining unadjusted credit standards alone during this time period would likely have underestimated the macroeconomic impact of the tightening.

On the other hand, it is notable that for the final wave in our sample, during the credit standards tightening period seen between March and September 2022, the adjusted figure is much lower than the unadjusted figure in relative terms. It should be noted that the adjusted figure is still high in relative terms compared to the rest of the sample, standing at its second highest reading in our sample period, but it is lower than would be implied when reading the raw figures. This can be clearly seen in that the unadjusted figure is comparable to levels seen during the Covid-19 pandemic, but the adjusted figure is much more benign. This indicates that the tightening in

that period may be slightly less biting than would be anticipated by the raw figures, although it is still relatively large and close to a series maxima.

Next, it is important to consider the other dimension that we have explored in this paper - that is the fact that the effects of credit standards tend to cumulate, and impact on firms with a mild lag. To adjust for the interdependence of time periods, we emulate the construction of demand adjusted credit standards in Equation 4.3, but in this case rather than single period credit standards, we also use the rolling average of firm level credit standards over two and three periods, in line with our main regression specifications. These indicators are shown in Figure 4.3.

Figure 4.3. Comparison of demand adjusted credit standards with varying backward looking windows



When examining these, two items stick out by construction. Firstly, the longer period measures are more persistent, and the variance tends to increase across the measures. This is as expected, with more firms experiencing a tightening the wider the window, but also the interdependence between periods makes the measures more sticky.

Once again, a couple of periods stick out as interesting when comparing across measures. First, we see that the moderation of the tightening of credit standards seen at the end of 2021 is picked up on by the one period measure, but is not seen in the longer term measures. This highlights to some extent the relative suitability of the longer term metrics, in that it is likely, based on the leading indicator properties of the BLS (as seen in Köhler-Ulbrich and Hünnekes (2023)), that the effects of the vast tightening seen in late 2020 and early 2021 would still be felt. The longer term measures also allow for the compounding of the two tightening periods either side of September 2021, with a movement from the Covid-19 period tightening to the tightening seen during the monetary policy normalisation period in 2022.

Secondly, the March 2013 period is of interest in that it highlights a more lagged movement of the three period metric once the relative easing began. This shows that the three period measure is likely to pick up to a reasonable degree on residual pass through of lagged changes in credit standards, while also incorporating information from the latest time periods. The longer term measures indicate cumulative effects, while shorter term measures are more instantaneous snapshots. Given previous results at a micro level, it is important to analyse the longer term measures to fully examine the potential pass through to outcomes such as firms being financially constrained and their investment decisions.

4.6 Conclusion

Firm-bank relationships are a highly important aspect of the functioning of the broader macroeconomy, and thus understanding the transmission of changes in credit standards to firms can help us understand the dynamics of the broader financial system. Using linked surveys we have shown that while on the baseline there is a strong pass through of changes in credit standards to perceived bank loan availability, the likelihood of access to finance being the worst problem facing a firm and investment, but this relationship becomes insignificant when country-sector-time controls are added suggesting that the baseline relationship is mainly driven by broader macroeconomic conditions. Instead, we show that when controlling for such factors, the relationship is concentrated solely in those firms that had an increased need for bank loans, indicating the importance of controlling for demand

when assessing the pass through of credit conditions to the macroeconomy and firms overall access to finance and bank loans.

Furthermore, we highlight the importance of having a diversified array of financing sources for mitigating against supply side shocks, highlighting that those firms with a more diversified set of financing sources are less likely to face constraints relating to the availability of bank loans or overall access to finance as a result of changing credit standards. This emphasises the important role that a healthy array of sources of finance can play in broader financial intermediation, and highlights the importance for policymakers to foster such relationships.

We also show a degree of asymmetry in the reaction of variables to changes in credit standards, with tightening of credit standards appearing to have more bite than easing, suggesting a stronger impact of constraining credit conditions rather than accommodative ones, or a greater recognition of the role of these in times of tightening.

Given the importance of controlling for demand, we posit that it is necessary to adjust macroeconomic indicators to account for firm level demand. We propose a new euro area measure of demand adjusted credit standards that we propose can be used as a real time indicator of the level of binding credit standards facing firms. This can provide real time information on the likely pass through of constraints to firms, and can be useful for policymakers going forward. This is illustrated by unadjusted credit standards figures likely underestimating the impact of a tightening during the sovereign debt crisis, when loan demand was high, while in 2022 as credit standards were at elevated levels, demand dynamics are likely indicative of a slightly softer pass through, although still at historic highs.

4.7 Appendix

Table C1. Regression of bank loan availability on BLS credit standards

	(1)	(2)	(3)
Credit Standards - 1 Period	0.00229 (0.921)		
Need For Bank Loans=1	0.0630*** (0.000)	0.0628*** (0.000)	0.0628*** (0.000)
Need For Bank Loans=3	0.0725*** (0.000)	0.0746*** (0.000)	0.0748*** (0.000)
Need For Bank Loans=1 X Credit Standards - 1 Period	-0.0136 (0.710)		
Need For Bank Loans=3 X Credit Standards - 1 Period	-0.0436 (0.193)		
Credit Standards - 2 Periods		0.0286 (0.352)	
Need For Bank Loans=1 X Credit Standards - 2 Periods		0.0150 (0.744)	
Need For Bank Loans=3 X Credit Standards - 2 Periods		-0.125*** (0.002)	
Credit Standards - 3 Periods			0.0642* (0.080)
Need For Bank Loans=1 X Credit Standards - 3 Periods			0.00703 (0.892)
Need For Bank Loans=3 X Credit Standards - 3 Periods			-0.137*** (0.003)
Constant	-1.905*** (0.000)	-1.905*** (0.000)	-1.906*** (0.000)
Firm FE	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes
Observations	34069	34103	34148
R ²	0.466	0.467	0.466

Notes: Table shows the results of a regression in which the dependent variable is a value of -1 if firms in SAFE reported increase in bank loan availability, -2 if they reported no change and -3 for a decrease in bank loan availability. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. Higher values indicate tighter credit standards. Need for bank loans is a categorical value with 1 indicating a decreased need, 3 an increased need, and 2 acting as a base category (no change in need). All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

Table C2. Regression of finance being the worst problem for firms on BLS credit standards

	(1)	(2)	(3)
Credit Standards - 1 Period	-0.0123 (0.265)		
Need For Bank Loans=1	-0.00721 (0.114)	-0.00718 (0.115)	-0.00731 (0.108)
Need For Bank Loans=3	0.0421*** (0.000)	0.0411*** (0.000)	0.0403*** (0.000)
Need For Bank Loans=1 X Credit Standards - 1 Period	0.00959 (0.576)		
Need For Bank Loans=3 X Credit Standards - 1 Period	0.0283* (0.087)		
Credit Standards - 2 Periods		-0.0131 (0.377)	
Need For Bank Loans=1 X Credit Standards - 2 Periods		0.00709 (0.737)	
Need For Bank Loans=3 X Credit Standards - 2 Periods		0.0639*** (0.001)	
Credit Standards - 3 Periods			-0.0216 (0.222)
Need For Bank Loans=1 X Credit Standards - 3 Periods			0.0135 (0.570)
Need For Bank Loans=3 X Credit Standards - 3 Periods			0.0848*** (0.000)
Constant	0.0772*** (0.000)	0.0770*** (0.000)	0.0772*** (0.000)
Firm FE	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes
Observations	31590	31623	31666
R ²	0.487	0.487	0.488

Notes: Table shows the results of a regression in which the dependent variable is a binary variable taking on a value of 1 if access to finance was reported as the most pressing problem facing a firm during the SAFE survey period and 0 otherwise. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over, looking backwards from the current period. Higher values indicate tighter credit standards. Need for bank loans is a categorical value with 1 indicating a decreased need, 3 an increased need, and 2 acting as a base category (no change in need). All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

Table C3. Regression of investment on BLS credit standards

	(1)	(2)	(3)
Credit Standards - 1 Period	-0.00557 (0.847)		
Need For Bank Loans=1	-0.0663*** (0.000)	-0.0666*** (0.000)	-0.0667*** (0.000)
Need For Bank Loans=3	0.166*** (0.000)	0.167*** (0.000)	0.166*** (0.000)
Need For Bank Loans=1 X Credit Standards - 1 Period	0.0291 (0.539)		
Need For Bank Loans=3 X Credit Standards - 1 Period	-0.0799* (0.076)		
Credit Standards - 2 Periods		-0.0188 (0.639)	
Need For Bank Loans=1 X Credit Standards - 2 Periods		0.0927 (0.148)	
Need For Bank Loans=3 X Credit Standards - 2 Periods		-0.120** (0.049)	
Credit Standards - 3 Periods			-0.0104 (0.832)
Need For Bank Loans=1 X Credit Standards - 3 Periods			0.0823 (0.273)
Need For Bank Loans=3 X Credit Standards - 3 Periods			-0.127* (0.082)
Constant	-1.832*** (0.000)	-1.832*** (0.000)	-1.832*** (0.000)
Firm FE	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes
Observations	28229	28263	28310
R^2	0.450	0.450	0.450

Notes: Table shows the results of a regression in which the dependent variable is a trinomial variable taking on a value of -1 if firms in SAFE reported increase in investment, -2 if they reported no change and -3 for a decrease in investment. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over, looking backwards from the current period. Higher values indicate tighter credit standards. Need for bank loans is a categorical value with 1 indicating a decreased need, 3 an increased need, and 2 acting as a base category (no change in need). All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

Table C4. Regression of bank loan availability on BLS credit standards

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Standards - 1 Period Tightening Only	-0.0532 (0.408)					
Increased Need For Bank Loans=1	0.0112 (0.660)	0.0233 (0.363)	0.0272 (0.293)	-0.0117 (0.639)	-0.0131 (0.603)	-0.0110 (0.665)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period Tightening Only	-0.324*** (0.005)					
Fin Source Concentration	0.0462* (0.090)	0.0461* (0.093)	0.0539* (0.052)	0.0615** (0.022)	0.0591** (0.029)	0.0630** (0.020)
Credit Standards - 1 Period Tightening Only X Fin Source Concentration	0.109 (0.286)					
Increased Need For Bank Loans=1 X Fin Source Concentration	0.0915** (0.040)	0.0810* (0.072)	0.0755* (0.097)	0.129*** (0.003)	0.131*** (0.003)	0.129*** (0.004)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period Tightening Only X Fin Source Concentration	0.498** (0.016)					
Credit Standards - 2 Period Tightening Only		-0.0101 (0.896)				
Increased Need For Bank Loans=1 X Credit Standards - 2 Period Tightening Only		-0.527*** (0.000)				
Credit Standards - 2 Period Tightening Only X Fin Source Concentration		0.125 (0.305)				
Increased Need For Bank Loans=1 X Credit Standards - 2 Period Tightening Only X Fin Source Concentration		0.649*** (0.007)				
Credit Standards - 3 Period Tightening Only			0.0964 (0.275)			
Increased Need For Bank Loans=1 X Credit Standards - 3 Period Tightening Only			-0.566*** (0.000)			
Credit Standards - 3 Period Tightening Only X Fin Source Concentration			0.0471 (0.730)			
Increased Need For Bank Loans=1 X Credit Standards - 3 Period Tightening Only X Fin Source Concentration			0.684*** (0.007)			
Credit Standards - 1 Period Easing Only				0.138 (0.149)		
Increased Need For Bank Loans=1 X Credit Standards - 1 Period Easing Only				0.0839 (0.666)		
Credit Standards - 1 Period Easing Only X Fin Source Concentration				-0.195 (0.208)		
Increased Need For Bank Loans=1 X Credit Standards - 1 Period Easing Only X Fin Source Concentration				-0.216 (0.525)		
Credit Standards - 2 Period Easing Only					0.0914 (0.460)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Period Easing Only					0.136 (0.587)	
Credit Standards - 2 Period Easing Only X Fin Source Concentration					-0.127 (0.525)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Period Easing Only X Fin Source Concentration					-0.301 (0.495)	
Credit Standards - 3 Period Easing Only						0.141 (0.314)
Increased Need For Bank Loans=1 X Credit Standards - 3 Period Easing Only						0.0697 (0.809)
Credit Standards - 3 Period Easing Only X Fin Source Concentration						-0.217 (0.335)
Increased Need For Bank Loans=1 X Credit Standards - 3 Period Easing Only X Fin Source Concentration						-0.266 (0.603)
Constant	-1.914*** (0.000)	-1.917*** (0.000)	-1.925*** (0.000)	-1.923*** (0.000)	-1.922*** (0.000)	-1.924*** (0.000)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34069	34103	34148	34069	34103	34148
R ²	0.466	0.467	0.466	0.466	0.466	0.466

Notes: Table shows the results of a regression in which the dependent variable is a value of -1 if firms in SAFE reported increase in bank loan availability, -2 if they reported no change and -3 for a decrease in bank loan availability. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. The credit standards variable is split into two separate variables, taking on an index value equalling the magnitude of the tightening or easing respectively (between 0 and 2), and is coerced to equal zero otherwise. Higher values for the tightening variable indicate a larger degree of tightening, while higher values for the easing variable indicate a larger degree of easing. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. Fin source concentration is an index between 0 and 1, whereby higher values indicate a wider diversification of funding sources. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

Table C5. Regression of finance being the worst problem facing a firm on BLS credit standards

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Standards - 1 Period Tightening Only	-0.0514* (0.085)					
Increased Need For Bank Loans=1	0.0675*** (0.000)	0.0665*** (0.000)	0.0676*** (0.000)	0.0782*** (0.000)	0.0819*** (0.000)	0.0819*** (0.000)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period Tightening Only	0.161*** (0.006)					
Fin Source Concentration	-0.0281** (0.031)	-0.0277** (0.035)	-0.0259* (0.051)	-0.0218* (0.090)	-0.0194 (0.136)	-0.0200 (0.125)
Credit Standards - 1 Period Tightening Only X Fin Source Concentration	0.0592 (0.209)					
Increased Need For Bank Loans=1 X Fin Source Concentration	-0.0479** (0.031)	-0.0509** (0.024)	-0.0545** (0.016)	-0.0634*** (0.004)	-0.0696*** (0.002)	-0.0681*** (0.002)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period Tightening Only X Fin Source Concentration	-0.219** (0.031)					
Credit Standards - 2 Period Tightening Only		-0.0467 (0.187)				
Increased Need For Bank Loans=1 X Credit Standards - 2 Period Tightening Only		0.178*** (0.006)				
Credit Standards - 2 Period Tightening Only X Fin Source Concentration		0.0503 (0.357)				
Increased Need For Bank Loans=1 X Credit Standards - 2 Period Tightening Only X Fin Source Concentration		-0.166 (0.147)				
Credit Standards - 3 Period Tightening Only			-0.0479 (0.231)			
Increased Need For Bank Loans=1 X Credit Standards - 3 Period Tightening Only			0.146** (0.030)			
Credit Standards - 3 Period Tightening Only X Fin Source Concentration			0.0193 (0.749)			
Increased Need For Bank Loans=1 X Credit Standards - 3 Period Tightening Only X Fin Source Concentration			-0.0795 (0.506)			
Credit Standards - 1 Period Easing Only				0.0389 (0.409)		
Increased Need For Bank Loans=1 X Credit Standards - 1 Period Easing Only				-0.0254 (0.793)		
Credit Standards - 1 Period Easing Only X Fin Source Concentration				-0.0724 (0.338)		
Increased Need For Bank Loans=1 X Credit Standards - 1 Period Easing Only X Fin Source Concentration				0.0605 (0.720)		
Credit Standards - 2 Period Easing Only					0.0858 (0.158)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Period Easing Only					-0.156 (0.204)	
Credit Standards - 2 Period Easing Only X Fin Source Concentration					-0.155 (0.113)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Period Easing Only X Fin Source Concentration					0.278 (0.197)	
Credit Standards - 3 Period Easing Only						0.0753 (0.279)
Increased Need For Bank Loans=1 X Credit Standards - 3 Period Easing Only						-0.173 (0.225)
Credit Standards - 3 Period Easing Only X Fin Source Concentration						-0.144 (0.194)
Increased Need For Bank Loans=1 X Credit Standards - 3 Period Easing Only X Fin Source Concentration						0.246 (0.331)
Constant	0.0918*** (0.000)	0.0914*** (0.000)	0.0914*** (0.000)	0.0873*** (0.000)	0.0858*** (0.000)	0.0863*** (0.000)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31590	31623	31666	31590	31623	31666
R ²	0.488	0.488	0.488	0.488	0.488	0.488

Notes: Table shows the results of a regression in which the dependent variable is a binary variable taking on a value of 1 if access to finance was reported as the most pressing problem facing a firm during the SAFE survey period and 0 otherwise. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. The credit standards variable is split into two separate variables, taking on an index value equaling the magnitude of the tightening or easing respectively (between 0 and 2), and is coerced to equal zero otherwise. Higher values for the tightening variable indicate a larger degree of tightening, while higher values for the easing variable indicate a larger degree of easing. Increased need for bank loans is a binary variable, taking on a value of 1 if a firm's need for bank loans increased, and 0 otherwise. Fin source concentration is an index between 0 and 1, whereby higher values indicate a wider diversification of funding sources. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

Table C6. Regression of investment on BLS credit standards

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Standards - 1 Period Tightening Only	0.0510 (0.601)					
Increased Need For Bank Loans=1	0.148*** (0.000)	0.147*** (0.000)	0.141*** (0.000)	0.120*** (0.001)	0.124*** (0.000)	0.136*** (0.000)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period Tightening Only	-0.480*** (0.007)					
Fin Source Concentration	0.00711 (0.845)	0.0157 (0.673)	0.0213 (0.571)	0.000408 (0.991)	-0.0000211 (1.000)	0.00170 (0.963)
Credit Standards - 1 Period Tightening Only X Fin Source Concentration	-0.0261 (0.865)					
Increased Need For Bank Loans=1 X Fin Source Concentration	0.0780 (0.200)	0.0863 (0.164)	0.100 (0.110)	0.112* (0.059)	0.102* (0.088)	0.0825 (0.172)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period Tightening Only X Fin Source Concentration	0.552* (0.073)					
Credit Standards - 2 Period Tightening Only		0.131 (0.344)				
Increased Need For Bank Loans=1 X Credit Standards - 2 Period Tightening Only		-0.576** (0.022)				
Credit Standards - 2 Period Tightening Only X Fin Source Concentration		-0.170 (0.433)				
Increased Need For Bank Loans=1 X Credit Standards - 2 Period Tightening Only X Fin Source Concentration		0.551 (0.202)				
Credit Standards - 3 Period Tightening Only			0.251 (0.147)			
Increased Need For Bank Loans=1 X Credit Standards - 3 Period Tightening Only			-0.516* (0.093)			
Credit Standards - 3 Period Tightening Only X Fin Source Concentration			-0.294 (0.278)			
Increased Need For Bank Loans=1 X Credit Standards - 3 Period Tightening Only X Fin Source Concentration			0.328 (0.530)			
Credit Standards - 1 Period Easing Only				-0.0749 (0.533)		
Increased Need For Bank Loans=1 X Credit Standards - 1 Period Easing Only				-0.173 (0.500)		
Credit Standards - 1 Period Easing Only X Fin Source Concentration				0.209 (0.274)		
Increased Need For Bank Loans=1 X Credit Standards - 1 Period Easing Only X Fin Source Concentration				0.204 (0.641)		
Credit Standards - 2 Period Easing Only					-0.121 (0.437)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Period Easing Only					-0.346 (0.303)	
Credit Standards - 2 Period Easing Only X Fin Source Concentration					0.242 (0.329)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Period Easing Only X Fin Source Concentration					0.610 (0.290)	
Credit Standards - 3 Period Easing Only						-0.0618 (0.722)
Increased Need For Bank Loans=1 X Credit Standards - 3 Period Easing Only						-0.765** (0.042)
Credit Standards - 3 Period Easing Only X Fin Source Concentration						0.171 (0.537)
Increased Need For Bank Loans=1 X Credit Standards - 3 Period Easing Only X Fin Source Concentration						1.343** (0.039)
Constant	-1.855*** (0.000)	-1.860*** (0.000)	-1.865*** (0.000)	-1.851*** (0.000)	-1.850*** (0.000)	-1.851*** (0.000)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28229	28263	28310	28229	28263	28310
R ²	0.450	0.450	0.450	0.450	0.450	0.450

Notes: Table shows the results of a regression in which the dependent variable is a trinomial variable taking on a value of -1 if firms in SAFE reported increase in investment, -2 if they reported no change and -3 for a decrease in investment. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. The credit standards variable is split into two separate variables, taking on an index value equalling the magnitude of the tightening or easing respectively (between 0 and 2), and is coerced to equal zero otherwise. Higher values for the tightening variable indicate a larger degree of tightening, while higher values for the easing variable indicate a larger degree of easing. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. Fin source concentration is an index between 0 and 1, whereby higher values indicate a wider diversification of funding sources. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

Interactions with financing sources

Table C7. Regression of increased bank loan availability on BLS credit standards

	(1)	(2)	(3)
Credit Standards - 1 Period	-0.0547 (0.154)		
Increased Need For Bank Loans=1	0.0618*** (0.001)	0.0636*** (0.000)	0.0644*** (0.000)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period	-0.100 (0.163)		
Fin Source Concentration	0.0177 (0.370)	0.0185 (0.349)	0.0197 (0.320)
Credit Standards - 1 Period X Fin Source Concentration	0.0746 (0.223)		
Increased Need For Bank Loans=1 X Fin Source Concentration	0.0671** (0.035)	0.0653** (0.042)	0.0633** (0.049)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period X Fin Source Concentration	0.179 (0.159)		
Credit Standards - 2 Periods		-0.0354 (0.450)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods		-0.153* (0.070)	
Credit Standards - 2 Periods X Fin Source Concentration		0.0625 (0.399)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods X Fin Source Concentration		0.203 (0.175)	
Credit Standards - 3 Periods			-0.0231 (0.663)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods			-0.157* (0.081)
Credit Standards - 3 Periods X Fin Source Concentration			0.0583 (0.481)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods X Fin Source Concentration			0.236 (0.141)
Constant	0.213*** (0.000)	0.212*** (0.000)	0.211*** (0.000)
Firm FE	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes
Observations	34069	34103	34148
R ²	0.440	0.440	0.439

Notes: Table shows the results of a regression of a binary variable taking on a value of one if firms in SAFE reported increased availability of bank loans and zero otherwise. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. The credit standards variable is split into two separate variables, taking on an index value equalling the magnitude of the tightening or easing respectively (between 0 and 2), and is coerced to equal zero otherwise. Higher values for the tightening variable indicate a larger degree of tightening, while higher values for the easing variable indicate a larger degree of easing. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. Fin source concentration is an index between 0 and 1, whereby higher values indicate a wider diversification of funding sources. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

Table C8. Regression of decreased bank loan availability on BLS credit standards

	(1)	(2)	(3)
Credit Standards - 1 Period	0.0206 (0.464)		
Increased Need For Bank Loans=1	0.0626*** (0.000)	0.0586*** (0.000)	0.0571*** (0.000)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period	0.141*** (0.007)		
Fin Source Concentration	-0.0313** (0.030)	-0.0319** (0.027)	-0.0344** (0.017)
Credit Standards - 1 Period X Fin Source Concentration	-0.0499 (0.266)		
Increased Need For Bank Loans=1 X Fin Source Concentration	-0.0418* (0.073)	-0.0366 (0.118)	-0.0344 (0.143)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period X Fin Source Concentration	-0.219** (0.018)		
Credit Standards - 2 Periods		-0.00180 (0.958)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods		0.250*** (0.000)	
Credit Standards - 2 Periods X Fin Source Concentration		-0.0453 (0.403)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods X Fin Source Concentration		-0.338*** (0.002)	
Credit Standards - 3 Periods			-0.0445 (0.250)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods			0.263*** (0.000)
Credit Standards - 3 Periods X Fin Source Concentration			-0.0122 (0.840)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods X Fin Source Concentration			-0.329*** (0.005)
Constant	0.128*** (0.000)	0.129*** (0.000)	0.131*** (0.000)
Firm FE	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes
Observations	34069	34103	34148
R ²	0.476	0.477	0.477

Notes: Table shows the results of a regression of a binary variable taking on a value of one if firms in SAFE reported decreased availability of bank loans and zero otherwise. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. The credit standards variable is split into two separate variables, taking on an index value equalling the magnitude of the tightening or easing respectively (between 0 and 2), and is coerced to equal zero otherwise. Higher values for the tightening variable indicate a larger degree of tightening, while higher values for the easing variable indicate a larger degree of easing. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. Fin source concentration is an index between 0 and 1, whereby higher values indicate a wider diversification of funding sources. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

Table C9. Regression of increased investment on BLS credit standards - asymmetric responses

	(1)	(2)	(3)
Credit Standards - 1 Period	0.0227 (0.659)		
Increased Need For Bank Loans=1	0.0973*** (0.000)	0.0923*** (0.000)	0.0879*** (0.000)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period	-0.175* (0.078)		
Fin Source Concentration	-0.0461* (0.065)	-0.0457* (0.067)	-0.0463* (0.063)
Credit Standards - 1 Period X Fin Source Concentration	-0.0374 (0.643)		
Increased Need For Bank Loans=1 X Fin Source Concentration	0.107*** (0.009)	0.116*** (0.005)	0.124*** (0.002)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period X Fin Source Concentration	0.171 (0.314)		
Credit Standards - 2 Periods		0.0509 (0.463)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods		-0.115 (0.391)	
Credit Standards - 2 Periods X Fin Source Concentration		-0.0480 (0.660)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods X Fin Source Concentration		0.000780 (0.997)	
Credit Standards - 3 Periods			0.0460 (0.572)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods			0.0633 (0.685)
Credit Standards - 3 Periods X Fin Source Concentration			-0.00572 (0.964)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods X Fin Source Concentration			-0.354 (0.185)
Constant	0.325*** (0.000)	0.324*** (0.000)	0.324*** (0.000)
Firm FE	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes
Observations	28229	28263	28310
R ²	0.461	0.461	0.461

Notes: Table shows the results of a regression of a binary variable taking on a value of one if firms in SAFE reported decreased investment and zero otherwise. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. The credit standards variable is split into two separate variables, taking on an index value equalling the magnitude of the tightening or easing respectively (between 0 and 2), and is coerced to equal zero otherwise. Higher values for the tightening variable indicate a larger degree of tightening, while higher values for the easing variable indicate a larger degree of easing. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. Fin source concentration is an index between 0 and 1, whereby higher values indicate a wider diversification of funding sources. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

Table C10. Regression of decreased investment on BLS credit standards

	(1)	(2)	(3)
Credit Standards - 1 Period	-0.0293 (0.456)		
Increased Need For Bank Loans=1	-0.0282 (0.128)	-0.0285 (0.123)	-0.0262 (0.155)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period	0.0878 (0.248)		
Fin Source Concentration	-0.0544*** (0.004)	-0.0563*** (0.003)	-0.0566*** (0.003)
Credit Standards - 1 Period X Fin Source Concentration	0.0455 (0.461)		
Increased Need For Bank Loans=1 X Fin Source Concentration	0.00269 (0.931)	0.00188 (0.952)	-0.00133 (0.966)
Increased Need For Bank Loans=1 X Credit Standards - 1 Period X Fin Source Concentration	-0.144 (0.268)		
Credit Standards - 2 Periods		-0.0587 (0.269)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods		0.119 (0.247)	
Credit Standards - 2 Periods X Fin Source Concentration		0.125 (0.134)	
Increased Need For Bank Loans=1 X Credit Standards - 2 Periods X Fin Source Concentration		-0.150 (0.394)	
Credit Standards - 3 Periods			-0.0830 (0.183)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods			0.0732 (0.539)
Credit Standards - 3 Periods X Fin Source Concentration			0.189* (0.053)
Increased Need For Bank Loans=1 X Credit Standards - 3 Periods X Fin Source Concentration			-0.0837 (0.682)
Constant	0.179*** (0.000)	0.180*** (0.000)	0.180*** (0.000)
Firm FE	Yes	Yes	Yes
Country Sector Wave FE	Yes	Yes	Yes
Observations	28229	28263	28310
R ²	0.421	0.421	0.421

Notes: Table shows the results of a regression of a binary variable taking on a value of one if firms in SAFE reported increased investment and zero otherwise. Credit standards are measured using the responses of the firms' matched BLS banks, and are averaged over time, with the number of periods referring to the number of SAFE waves they have been averaged over looking backwards from the current period. The credit standards variable is split into two separate variables, taking on an index value equalling the magnitude of the tightening or easing respectively (between 0 and 2), and is coerced to equal zero otherwise. Higher values for the tightening variable indicate a larger degree of tightening, while higher values for the easing variable indicate a larger degree of easing. Increased need for bank loans is a binary variable, taking on a value of 1 if a firms need for bank loans increased, and 0 otherwise. Fin source concentration is an index between 0 and 1, whereby higher values indicate a wider diversification of funding sources. All regressions have firm and country-sector-wave fixed effects. Parentheses show p-values, with the following convention: * p<0.1, ** p<0.05, *** p<0.01.

Chapter 5

Conclusion

This dissertation explored broad topics in what could be deemed “less conventional” and “more conventional” monetary policy, by exploring key questions in these fields. Broadly, the first essay explored how ECB monetary policy communication during their press conferences moves financial markets, the second essay asks how understanding the temporality of central bank communication can help answer why communication moves markets while the third essay helps to understand the role of changing bank credit standards in understanding firm financing conditions and their investment behaviour. Moreover, all three papers contribute to the measurement literature by providing either text based measures of communication concepts or by using linked surveys to create a new aggregate measure of demand adjusted credit standards.

The first essay has key implications for the literature on monetary policy communication and helps to understand the ways in which monetary policy communication can influence financial markets. The first key contribution of this paper is to measure the monetary policy tilt of each ECB press conference and shows how hawkish or dovish the communication is at each individual press conference. From a policy perspective this measure can complement interest rate expectations based measures of policy tilt, and has particular use during zero lower bound episodes. This measure is then used to explore a key question of how financial markets interpret more hawkish or dovish language and finds that an information effect dominates a traditional monetary policy effect, but this effect fades in the post forward guidance period. This in a sense can help policymakers to understand how their language can

shape markets and illustrates perhaps the key role for more certain information in insulating from market volatility in and around communication announcements.

The second essay in a similar vein to the first one has both a measurement contribution alongside an empirical and theoretical one. The measurement of the temporality of monetary policy communication provides future guidance for those wishing to explore this topic, while a model of how market surprises can stem from factors beyond “superior central bank information” adds to the information surprise literature. Our simple model and empirical results provide evidence for both the existence of an information deficit, and shows that conjunctural assessments of current and past data can have an impact alongside communication of projected future paths of monetary policy or forecasts of variables. This is of importance for understanding the interactions between policymakers and markets and from a policymaker perspective shows the importance of this assessment function when communicating to the public. Our results show the joint importance of these factors and goes beyond the recommendations from standard models of monetary policy.

The third essay enhances our understanding of how changes in bank level credit standards are transmitted to firms and thus allows us to understand in more detail the functioning of the bank lending channel of monetary policy, and implications of supply side shocks for firms investment decisions and their financing conditions. Crucially we illustrate that accounting for demand and firms need for loans is essential in such analysis, and this motivates a new measure of demand adjusted credit standards. The policy implications of this paper are not only restricted to the findings of the microeconomic regressions, but also extend to our understanding of aggregate measures. Analysing credit standards changes alone would miss out on a core additional dimension, whereby if firms are not needing loans, a tightening will be less biting and thus this motivates the joint analysis of key measures.

Together the essays in this dissertation enhance our understanding of key issues in central bank communication and the understanding of firm financing conditions and contribute from both a measurement and policy perspective.

Bibliography

- Aguilar, A. and Pérez-Cervantes, F. (2022). Communication, monetary policy, and financial markets in Mexico. BIS Working Papers 1025, Bank for International Settlements.
- Altavilla, C., Boucinha, M., Holton, S., and Ongena, S. (2021). Credit supply and demand in unconventional times. *Journey of Money, Credit and Banking*, 53(8):2071–98.
- Altavilla, C., Brugnolini, L., Gürkaynak, R. S., Motto, R., and Ragusa, G. (2019a). Measuring euro area monetary policy. *Journal of Monetary Economics*, 108:162–179.
- Altavilla, C., Darracq Paries, M., and Nicoletti, G. (2019b). Loan supply, credit markets and the euro area financial crisis. *Journal of Banking Finance*, 109(C).
- Andre, P., Pizzinelli, C., Roth, C., and Wohlfart, J. (2022). Subjective Models of the Macroeconomy: Evidence From Experts and Representative Samples. *The Review of Economic Studies*, 89(6):2958–2991.
- Apel, M., Grimaldi, M. B., and Hull, I. (2022). How Much Information Do Monetary Policy Committees Disclose? Evidence from the FOMC’s Minutes and Transcripts. *Journal of Money, Credit and Banking*, 54(5):1459–1490.
- Arismendi-Zambrano, J., Kypraios, E., and Paccagnini, A. (2021). Federal Reserve Chair Communication Sentiments’ Heterogeneity, Personal Characteristics, and their Impact on Uncertainty and Target Rate Discovery. Technical Report ICM-2021-01, Henley Business School, ICMA Centre.
- Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4):1593–1636.
- Bauer, M. D., Lakdawala, A. K., and Mueller, P. (2021). Market-Based Monetary Policy Uncertainty. *The Economic Journal*.

- Bauer, M. D. and Swanson, E. T. (2020). An alternative explanation for the “fed information effect”. Working Paper 27013, National Bureau of Economic Research.
- Bauer, M. D. and Swanson, E. T. (2022). A reassessment of monetary policy surprises and high-frequency identification. Technical report, mimeo.
- Beck, T., Demirgüç-Kunt, A., Laeven, L., and Maksimovic, V. (2006). The determinants of financing obstacles. *Journal of International Money and Finance*, 25(6):932–952.
- Beck, T., Demirgüç-Kunt, A., and Maksimovic, V. (2005). Financial and Legal Constraints to Growth: Does Firm Size Matter? *Journal of Finance*, 60(1):137–177.
- Bennani, H. and Neuenkirch, M. (2017). The (home) bias of European central bankers: new evidence based on speeches. *Applied Economics*, 49(11):1114–1131.
- Benoit, K., Watanabe, K., Wang, H., Nulty, P., Obeng, A., Müller, S., and Matsuo, A. (2018). quanteda: An R package for the quantitative analysis of textual data. *Journal of Open Source Software*, 3(30):774.
- Bernanke, B. S. and Gertler, M. (1995). Inside the Black Box: The Credit Channel of Monetary Policy Transmission. *Journal of Economic Perspectives*, 9(4):27–48.
- Björkelund, A., Bohnet, B., Hafdell, L., and Nugues, P. (2010). A High-Performance Syntactic and Semantic Dependency Parser. Technical report, Coling 2010: Demonstrations.
- Blei, D. M. and Lafferty, J. D. (2006). Dynamic topic models. In *Proceedings of the 23rd International Conference on Machine Learning*, ICML '06, page 113–120, New York, NY, USA. Association for Computing Machinery.
- Blei, D. M., Ng, A. Y., and Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of Machine Learning Research*, 3:993–1022.
- Born, B., Ehrmann, M., and Fratzscher, M. (2014). Central bank communication on financial stability. *Economic Journal*, 124(577):701–734.
- Boukus, E. and Rosenberg, J. V. (2006). The information content of fomc minutes. Technical report, Federal Reserve Bank of New York.
- Bundick, B., Herriford, T., and Smith, A. L. (2021). Forward Guidance, Monetary Policy Uncertainty, and the Term Premium. Research Working Paper 17-07, Federal Reserve Bank of Kansas City.

- Bybee, L., Kelly, B., Manela, A., and Xiu, D. (2020). The structure of economic news. *mimeo*.
- Byrne, D., Goodhead, R., McMahon, M., and Parle, C. (2023). Measuring the Temporal Dimension of Text: An Application to Policymaker Speeches. Research Technical Paper 2023/02, Central Bank of Ireland.
- Caldara, D. and Iacoviello, M. (2022). Measuring geopolitical risk. *American Economic Review*, 112(4):1194–1225.
- Cannon, S. (2015). Sentiment of the FOMC: Unscripted. *Economic Review*, (Q IV):5–31.
- Carney, M. (2017). Lambda. Speech given by Mark Carney, Governor of the Bank of England.
- Chang, A. X. and Manning, C. (2012). SUTime: A library for recognizing and normalizing time expressions. In *Proceedings of the Eighth International Conference on Language Resources and Evaluation (LREC'12)*, pages 3735–3740, Istanbul, Turkey. European Language Resources Association (ELRA).
- Ciccarelli, M., Maddaloni, A., and Peydró, J.-L. (2015). Trusting the bankers: A new look at the credit channel of monetary policy. *Review of Economic Dynamics*, 18(4):979–1002.
- Cieslak, A. and Schrimpf, A. (2019). Non-monetary news in central bank communication. *Journal of International Economics*, 118:293–315.
- Clarida, R., Galí, J., and Gertler, M. (1999). The science of monetary policy: A new keynesian perspective. *Journal of Economic Literature*, 37(4):1661–1707.
- Coenen, G., Ehrmann, M., Gaballo, G., Hoffmann, P., Nakov, A., Nardelli, S., Persson, E., and Strasser, G. (2017). Communication of monetary policy in unconventional times. Working Paper Series 2080, European Central Bank.
- Conrad, C. and Lamla, M. (2010). The high-frequency response of the EUR-US Dollar exchange rate to ECB monetary policy announcements. *Journal of Money, Credit and Banking*, 72(7):1391–1417.
- Corbisiero, G. and Faccia, D. (2020). Firm or bank weakness? access to finance since the european sovereign debt crisis. Working Paper Series 2361, European Central Bank.

- Correia, S. (2016). Linear models with high-dimensional fixed effects: An efficient and feasible estimator. Technical report. Working Paper.
- Cross, J. P. and Greene, D. (2020). Talk is not cheap: Policy agendas, information processing, and the unusually proportional nature of european central bank communications policy responses. *Governance*, 33:425–444.
- Das, S. R. and Chen, M. Y. (2007). Yahoo! for amazon: Sentiment extraction from small talk on the web. *Management Science*, 53(9):1375–1388.
- de Bondt, G., Maddaloni, A., Peydró, J.-L., and Scopel, S. (2010). The euro area Bank Lending Survey matters: empirical evidence for credit and output growth. Working Paper Series 1160, European Central Bank.
- De Pooter, M., Favara, G., Modugno, M., and Wu, J. (2021). Monetary policy uncertainty and monetary policy surprises. *Journal of International Money and Finance*, 114(102401).
- Del Giovane, P., Eramo, G., and Nobili, A. (2011). Disentangling demand and supply in credit developments: A survey-based analysis for italy. *Journal of Banking Finance*, 35(10):2719–2732.
- Draghi, M. (2019). Introductory statement, press conference, 12 September 2019.
- ECB (2021). Monetary policy decisions - December 2021. Technical Report 2021.
- Eggertsson, G. B. and Woodford, M. (2003). The zero bound on interest rates and optimal monetary policy. *Brookings Papers on Economic Activity*, 2003(1):139–211.
- Ehrmann, M. and Fratzscher, M. (2007). Communication by central bank committee members: Different strategies, same effectiveness? *Journal of Money, Credit and Banking*, 39(2/3):pp. 509–541.
- Ehrmann, M. and Fratzscher, M. (2009). Explaining Monetary Policy in Press Conferences. *International Journal of Central Banking*, 5(2):42–84.
- Ehrmann, M. and Sondermann, D. (2012). The News Content of Macroeconomic Announcements: What if Central Bank Communication Becomes Stale? *International Journal of Central Banking*, 8(3):1–53.
- Ellingsen, T. and Söderström, U. (2001). Monetary policy and market interest rates. *American Economic Review*, 91(5):1594–1607.

- Ferrando, A. and Griesshaber, N. (2011). Financing obstacles among euro area firms: Who suffers the most? Working Paper Series 1293, European Central Bank.
- Ferrando, A., Griesshaber, N., Köhler-Ulbrich, P., Pérez-Duarte, S., and Schmitt, N. (2013). Measuring the opinion of firms on the supply and demand of external financing in the euro area. In for International Settlements, B., editor, *Proceedings of the Sixth IFC Conference on "Statistical issues and activities in a changing environment", Basel, 28-29 August 2012.*, volume 36 of *IFC Bulletins chapters*, pages 283–303. Bank for International Settlements.
- Ferrando, A., Popov, A., and Udell, G. F. (2019). Do SMEs Benefit from Unconventional Monetary Policy and How? Microevidence from the Eurozone. *Journal of Money, Credit and Banking*, 51(4):895–928.
- Flynn, J. P. and Sastry, K. (2022). The macroeconomics of narratives. Available at SSRN 4140751.
- Galardo, M. and Guerrieri, C. (2017). The effects of central bank’s verbal guidance: evidence from the ECB. Temi di discussione (Economic working papers) 1129, Bank of Italy, Economic Research and International Relations Area.
- Galí, J. (2008). *Monetary Policy, Inflation, and the Business Cycle: An Introduction to the New Keynesian Framework*. Princeton University Press, Princeton, USA and Oxford, UK.
- Gentzkow, M., Kelly, B., and Taddy, M. (2019). Text as Data. *Journal of Economic Literature*, 57(3):535–574.
- Gertler, M. and Karadi, P. (2015). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics*, 7(1):44–76.
- Giannetti, M. and Ongena, S. (2012). “lending by example”: Direct and indirect effects of foreign banks in emerging markets. *Journal of International Economics*, 86(1):167–180.
- Goetzmann, W. N., Kim, D., and Shiller, R. J. (2022). Crash narratives. Working Paper 30195, National Bureau of Economic Research.
- Goodhead, R. and Kolb, B. (2018). Monetary Policy Communication Shocks and the Macroeconomy. Research Technical Papers 15/RT/18, Central Bank of Ireland.

- Gorodnichenko, Y., Pham, T., and Talavera, O. (2021). The Voice of Monetary Policy. NBER Working Papers 28592, National Bureau of Economic Research, Inc.
- Gürkaynak, R. S., Sack, B., and Swanson, E. (2005). Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements. *International Journal of Central Banking*, 1(1).
- Hansen, S. and McMahon, M. (2016a). Shocking language: Understanding the macroeconomic effects of central bank communication. *Journal of International Economics*, 99(S1):S114–S133.
- Hansen, S. and McMahon, M. (2016b). The nature and effectiveness of central bank communication. *VoxEU*.
- Hansen, S., McMahon, M., and Prat, A. (2017). Transparency and Deliberation within the FOMC: A Computational Linguistics Approach. *The Quarterly Journal of Economics*. Forthcoming.
- Hansen, S., McMahon, M., and Tong, M. (2019). The long-run information effect of central bank communication. *Journal of Monetary Economics*, 108:185–202.
- Hassan, T. A., Hollander, S., van Lent, L., and Tahoun, A. (2019). Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics*, 134(4):2135–2202.
- Hayo, B., Henseler, K., Rapp, M. S., and Zahner, J. (2020). Complexity of ecb communication and financial market trading. Magks papers on economics, Philipps-Universität Marburg, Faculty of Business Administration and Economics, Department of Economics (Volkswirtschaftliche Abteilung).
- Hayo, B. and Neuenkirch, M. (2010). Do federal reserve communications help predict federal funds target rate decisions? *Journal of Macroeconomics*, 32:1014–1024.
- Hayo, B. and Neuenkirch, M. (2015). Self-monitoring or reliance on media reporting: How do financial market participants process central bank news? *Journal of Banking and Finance*, 59(C):27–37.
- Hayo, B. and Neuenkirch, M. (2018). Central Banks' Predictability: An Assessment by Financial Market Participants. *International Journal of Central Banking*, 14(4):163–185.
- Hendry, S. and Madeley, A. (2010). Text mining and the information content of bank of canada communications. Technical Report 31, Bank of Canada.

- Hoesch, L., Rossi, B., and Sekhposyan, T. (2020). Has the Information Channel of Monetary Policy Disappeared? Revisiting the Empirical Evidence. Working paper series, Federal Reserve Bank of San Francisco.
- Hubert, P. and Labondance, F. (2021). The signaling effects of central bank tone. *European Economic Review*, 133(C).
- Iglesias, J., Ortiz, A., and Rodrigo, T. (2017). How do the EM Central Bank talk? A Big Data approach to the Central Bank of Turkey. Working Papers 17/24, BBVA Bank, Economic Research Department.
- Istrefi, K., Odendahl, F., and Sesteri, G. (2020). Fed Communication on Financial Stability Concerns and Monetary Policy Decisions: Revelations from Speeches. Working papers 779, Banque de France.
- Istrefi, K., Odendahl, F., and Sestieri, G. (2021). Fed communication on financial stability concerns and monetary policy decisions: revelations from speeches. Working Papers 2110, Banco de España.
- Jarocinski, M. and Karadi, P. (2018). Deconstructing monetary policy surprises: the role of information shocks. Working Paper Series 2133, European Central Bank.
- Jarociński, M. and Karadi, P. (2020). Deconstructing monetary policy surprises? the role of information shocks. *American Economic Journal: Macroeconomics*, 12(2):1–43.
- Jegadeesh, N. and Wu, A. (2017). Deciphering Fedspeak: The information content of FOMC meetings. *Available at SSRN*.
- Jegadeesh, N. and Wu, D. (2013). Word power: A new approach for content analysis. *Journal of Financial Economics*, 110(3):712–729.
- Jiménez, G., Ongena, S., Peydró, J.-L., and Saurina, J. (2012). Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications. *American Economic Review*, 102(5):2301–26.
- Kalemli-Özcan, , Laeven, L., and Moreno, D. (2022). Debt Overhang, Rollover Risk, and Corporate Investment: Evidence from the European Crisis. *Journal of the European Economic Association*, 20(6):2353–2395.
- Kerssenfischer, M. (2019). Information effects of euro area monetary policy: New evidence from high-frequency futures data. Discussion Papers 07/2019, Deutsche

Bundesbank.

- Kocherlakota, N. (2016). Rules versus discretion: A reconsideration. *Brookings Papers on Economic Activity*, pages 1–36.
- Kuttner, K. N. (2001). Monetary policy surprises and interest rates: Evidence from the fed funds futures market. *Journal of Monetary Economics*, 47(3):523–544.
- Köhler-Ulbrich, P. and Hünnekes, F. (2023). What information does the euro area bank lending survey provide on future loan developments? *Economic Bulletin Boxes*, 8.
- Lakdawala, A. (2018). Discussion of jarocinski and karadi: Deconstructing monetary policy surprises: the role of information shocks. *Bank of Canada Conference on Central Bank Communication*.
- Larsen, V. H., Thorsrud, L. A., and Zhulanova, J. (2021). News-driven inflation expectations and information rigidities. *Journal of Monetary Economics*, 117:507–520.
- Loughran, T. and McDonald, B. (2011). When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10Ks. *Journal of Finance*, 66(1):35–65.
- Loughran, T. and McDonald, B. (2014). Measuring Readability in Financial Disclosures. *Journal of Finance*, 69:1643–1671.
- Lown, C. and Morgan, D. P. (2006). The credit cycle and the business cycle: New findings using the loan officer opinion survey. *Journal of Money, Credit and Banking*, 38(6):1575–1597.
- Lucca, D. O. and Trebbi, F. (2009). Measuring Central Bank Communication: An Automated Approach with Application to FOMC Statements. NBER Working Papers 15367, National Bureau of Economic Research, Inc.
- Macaulay, A. and Song, W. (2022). Narrative-driven fluctuations in sentiment: Evidence linking traditional and social media. *Available at SSRN 4150087*.
- McMahon, M. and Munday, T. (2022a). The element(s) of surprise. Working paper, Mimeograph.
- McMahon, M. and Munday, T. (2022b). Uncertainty and time-varying monetary policy. Working paper, Mimeograph.
- Miranda-Agrippino, S. and Ricco, G. (2021). The transmission of monetary policy shocks. *American Economic Journal: Macroeconomics*, 13(3):74–107.

- Nakamura, E. and Steinsson, J. (2018). High-Frequency Identification of Monetary Non-Neutrality: The Information Effect. *The Quarterly Journal of Economics*, 133(3):1283–1330.
- Nielsen, F. A. (2011). A new ANEW: Evaluation of a word list for sentiment analysis in microblogs. *CoRR*.
- Ongena, S., Popov, A., Brown, M., and Yesin, P. (2012). Who needs credit and who gets credit in Eastern Europe? Working Paper Series 1421, European Central Bank.
- Orphanides, A. (2001). Monetary policy rules based on real-time data. *The American Economic Review*, 91(4):964–985.
- Orphanides, A. and Williams, J. C. (2005). Inflation scares and forecast-based monetary policy. *Review of Economic Dynamics*, 8(2):498–527.
- Oshima, Y. and Matsubayashi, Y. (2018). Monetary Policy Communication of the Bank of Japan: Computational Text Analysis. Discussion Papers 1816, Graduate School of Economics, Kobe University.
- Parle, C. (2022). The financial market impact of ecb monetary policy press conferences – a text based approach. *European Journal of Political Economy*, 74:102230.
- Picault, M. and Renault, T. (2017). Words are not all created equal: A new measure of ecb communication. *Journal of International Money and Finance*, 79:136–156.
- Ramm, A., Loáiciga, S., Friedrich, A., and Fraser, A. (2017). Annotating tense, mood and voice for English, French and German. In *Proceedings of ACL 2017, System Demonstrations*, pages 1–6, Vancouver, Canada. Association for Computational Linguistics.
- Rehurek, R. and Sojka, P. (2011). Gensim–python framework for vector space modelling. *NLP Centre, Faculty of Informatics, Masaryk University, Brno, Czech Republic*, 3(2).
- Romer, C. D. and Romer, D. H. (2000). Federal reserve information and the behavior of interest rates. *American Economic Review*, 90(3):429–457.
- Rosa, C. and Verga, G. (2007). On the consistency and effectiveness of central bank communication: Evidence from the ECB. *European Journal of Political Economy*, 23(1):146–175.

- Schmeling, M. and Wagner, C. (2019). Does Central Bank Tone Move Asset Prices? CEPR Discussion Papers 13490, C.E.P.R. Discussion Papers.
- Shapiro, A. H., Sudhof, M., and Wilson, D. J. (2017). Measuring News Sentiment. Working Paper Series 2017-1, Federal Reserve Bank of San Francisco.
- Shiller, R. J. (2017). Narrative Economics. *American Economic Review*, 107(4):967–1004.
- Sims, C. A. and Zha, T. (2006). Were There Regime Switches in U.S. Monetary Policy? *American Economic Review*, 96(1):54–81.
- Swanson, E. T. (2021). Measuring the Effects of Federal Reserve Forward Guidance and Asset Purchases on Financial Markets. *Journal of Monetary Economics*, (118):32–53.
- Taddy, M. (2017). One-Step Estimator Paths for Concave Regularization. *Journal of Computational and Graphical Statistics*, 26(3):525–536.
- Tadle, R. C. (2019). FOMC Minutes Sentiment Surprises and their Impact on Financial Markets. *Job Market Paper*.
- Tetlock, P. (2007). Giving Content to Investor Sentiment: The Role of Media in the Stock Market. *Journal of Finance*, 62:1139–1168.
- Timoneda, J. C. (2021). Estimating group fixed effects in panel data with a binary dependent variable: How the lpm outperforms logistic regression in rare events data. *Social Science Research*, 93:102486.
- Tobback, E., Nardelli, S., and Martens, D. (2017). Between hawks and doves: measuring central bank communication. Working Paper Series 2085, European Central Bank.
- Whelan, P., Venter, G., Vedolin, A., and Leombroni, M. (2017). Central Bank Communication and the Yield Curve. 2017 Meeting Papers 844, Society for Economic Dynamics.
- Williams, J. (2019). Monetary policy—a “data dependent” approach. At the New Jersey Bankers Association’s Economic Leadership Forum, Somerset, New Jersey, 18 January 2019.
- Zou, H. and Hastie, T. (2005). Regularization and Variable Selection via the Elastic Net. *Journal of the Royal Statistical Society*, 67:301–320. Part 2.