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Abstract

Using the variation in national television news of four major member states in the Eurozone, we find causal effects of coverage of high-frequency identified monetary policy announcements on households' inflation expectations in an event study and a generalized Difference-in-Differences approach with stacked data. If a monetary policy decision receives news coverage, the adaptation of inflation expectations is stronger than without coverage. Second, we find that coverage of 'delphic' monetary policy announcements, which are primarily informational in nature, leads to an inverse adjustment, i.e., expansionary shocks lead to households lowering their inflation expectations, as opposed to coverage of a textbook, 'odyssean', monetary policy shock.

JEL-Codes: E310, E520, E580, C830, D840.

Keywords: inflation expectations, media coverage, transmission of monetary policy, quasi-experimental evidence.

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1 Introduction

Forming and updating inflation expectations through communication has become an important objective for central banks in their monetary policy announcements (see, e.g., Woodford, 2001; Gürkaynak et al., 2005; Blinder et al., 2008; King et al., 2008; Coibion et al., 2020).[1] While the initial focus was on anchoring inflation expectations, their contemporary management has become more important over time as policymakers, first, had to cope with various crises and interest rates at the zero lower bound (Blinder et al., 2017; Coenen et al., 2017) and, second, more recently, facing high inflation rates. The relationship between central bank communication and the inflation expectations that emerge in markets is well-researched. Surprisingly little is known, however, about the influence on households' expectation formation.[2] To this date, there is a widespread view that central bank communication has limited influence on the formation of the public's inflation expectations (see, e.g., Binder, 2017a,b; De Fiore et al., 2022), thus, central bankers still "face a difficult communication and education challenge when advocating inflationary policies" (Bachmann et al., 2015, p. 3).

The biggest obstacle to central banks' communication with the public has come to be known as 'rational inattention' of households. As a result, inflation expectations tend to be rigid and, assuming complete information about economic developments, not fully rational (see Maćkowiak et al., 2021, for a review). It is possible that rational inattention is a direct consequence of central banks' success in stabilizing inflation and interest rates (Coibion et al., 2020). Initially, however, Mankiw and Reis (2002) and Sims (2003) attribute this behavior to the fact that households are subject to constraints, i.e., rational expectations cannot be formed because it is costly to obtain information about the latest monetary policy decision and to process it correctly.[3]

Subsequently, the seminal study by Carroll (2003) formally emphasized the crucial role of mass media in the formation of the public's macroeconomic expecta-

[1] For a critical discussion of the importance of inflation expectations as a determinant of actual inflation, see Rudd (2021). In particular, the author questions whether central banks should rely on them for policy-making given what he sees as a weak theoretical foundation and an alleged lack of empirical context. The conventional view is that the public's inflation expectations are of interest to central banks, because they can feed back to actual inflation through household behavior, e.g., their saving and consumption decisions or their wage demands. Indeed, Reis (2022) blames the burst of high inflation in 2021/22 in part on a neglect of expectations data that was driven by the belief that inflation expectations were firmly anchored.

[2] Besides stressing the need for better granular data in that respect, in a December 2019 speech, ECB chief economist Lane (2019) thus expressed that for the transmission of monetary policy an "important element is to better understand how consumers form expectations".

[3] Because of the public's rational inattention, a research agenda has emerged to address, for example, the optimal quantity of central bank communication (e.g., Chahrour, 2014), or the relevance of accuracy of forward guidance (e.g., Gaballo, 2016), both of which can have unintended consequences for transmission.

tions. In a microfounded epidemiological model and in line with empirical findings, Carroll (2003) assumes that households occasionally follow economic news and infrequently update their information sets and expectations. The analysis concludes that the intensity of newspaper coverage is related to the frequency of updating in the population. Thus, it is argued that the media provide a shortcut to information and less costly access to, for example, central bank announcements and the views of professional forecasters, thereby promoting the general dissemination of information.

Media and knowledge about monetary policy also represent two of four decisive determinants of households' inflation expectations, according to Coibion et al. (2020). In addition, the survey identifies priors and perceptions as well as shopping experiences, while the present study is limited to analyzing the combination of the former two determinants and focuses on television news in particular. This is in contrast to the trend of increasingly focusing on the role of the fifth estate, i.e., social media (see, e.g., Haldane et al., 2020; Conrad et al., 2021; Ehrmann and Wabitsch, 2022), while, in our view, there remain open questions about the role of the fourth estate, including newspapers and television.[4]

Accordingly, this study analyzes the role of news following monetary policy announcements for household inflation expectations, exploiting the mass media's straightforward and most prominent role: the coverage of the day's main events in the television evening news. More precisely, we analyze how households in the four larger European Monetary Union (EMU) countries – France, Germany, Italy and Spain – adjust their inflation expectations in response to media coverage of Governing Council decisions.[5] Identification of the media effect is based on quasi-experimental variation in coverage across countries and time, i.e., whether an event is reported at all and how intensively the decision is discussed on the news. The structure of the EMU provides a unique opportunity for this purpose. The European Central Bank (ECB) currently conducts monetary policy for 19 countries that have adopted the Euro. Different languages and the absence of major Union-wide television channels allow us to measure the effect of media coverage of monetary policy decisions focusing on national television markets.

We use an event study and a generalized Difference-in-Differences (DiD) approach to estimate the causal effect of coverage of ECB monetary policy deci-

[4]Bracke (2020) looks at the development and progress of (direct) central bank communication in the first two decades of the ECB. The paper shows how communication evolved, first through the establishment of press conferences and eventually through the use of social media. In addition, the content itself had become less technical, presented in simpler language, and thus accessible to a wider audience of citizens.

[5]Our decision to focus exclusively on households is based on the assumption that evening television news coverage is less important to professional forecasters (e.g., the ECB survey of professional forecasters) or financial markets.

sions on household inflation expectations.[6] Our dataset covers 124 ECB Governing Council announcements from 2006 to 2016, categorized and quantified using high-frequency identification based on data from Altavilla et al. (2019). Utilizing immediate changes in interest rates and the stock market in response to the announcements allows us to distinguish between pure monetary policy (*odyssean*) and information shocks (*delphic*) based on Campbell et al. (2012). News coverage variables are derived from a large and detailed hand-coded observational dataset comprising the leading newscasts of the four largest EMU countries. Quantitative inflation expectations are obtained from qualitative survey data provided by the European Commission.

The main finding is evidence of a causal relationship between television coverage of ECB announcements and the response of households in updating their inflation expectations. First, however, our results confirm that television news about rising inflation is associated with an upward revision of households' inflation expectations (and vice versa), which is consistent with previous findings in the literature using newspaper articles. Second, not only do households tend to adjust their inflation expectations in response to news that clearly indicates changes in the inflation rate, but they also respond to news coverage of monetary policy announcements. Third, and most importantly, our identification method allows us to show that evening television coverage is indeed a relevant channel and that the media serve as a mediator for prompt and stronger responses of inflation expectations to monetary policy announcements.

Fourth, our results highlight the importance of distinguishing between delphic and odyssean shocks, as the adjustment responses are inversely related. Coverage of odyssean announcements evokes the textbook effect: expansionary shocks raise expected inflation, while contractionary shocks reduce it. In the case of delphic announcements, an expectation-lowering effect for expansionary measures is observed. This seems counterintuitive at first, but it is consistent with the rationale for distinguishing between the two types in the first place. Information effects are those in which central banks additionally signal or disclose their assessment of the economic outlook, for example. The sizes of the estimated coverage effects is economically relevant. Mean coverage of a monetary policy shock of average size affects inflation expectations by about 0.1 percentage points, all other things being equal.

The remainder of the paper is structured as follows. In Section 2, we review the findings of the related literature and discuss identification via television news.

[6]The strength of this approach is the reliance on natural behavior of people with actual policy and media treatments. We are well aware of the weaknesses of the approach and the assumptions we impose (discussed in Section 4.3).

We describe our dataset in Section 3 with a focus on the compilation of media variables and the high-frequency identified monetary policy announcements. Section 4 outlines the empirical framework and provides information on identifying assumptions. In Section 5 we present our results and test robustness to alternative models and data specifications. Section 6 concludes.

2 Identification and Relation to Literature

The power and influence of the media, especially television news, can be attributed to their easy accessibility and availability (Iyengar, 1990). People's judgments and decisions, including their expectations, are influenced by the availability of information on a topic, its accessibility and its ease of retrieval from memory. Hence, the more frequently and timely information is broadcast, the more likely it is to capture people's attention and influence their opinions including macroeconomic expectations (Carroll, 2003). This makes television news a suitable medium for investigating our research question, which, however, is based on three assumptions that are important for the approach of the paper and will therefore be discussed below on the basis of existing literature: (1) the importance of television news as a source of (economic) information has remained central during the period under study; (2) major media, especially television, assume the role of agenda setter in their respective national media markets; and (3) national media markets are highly exclusive in Europe.

In the early 2000s, i.e., at the beginning of our sample period, traditional mass media were the population's most important source of information on politics and the economy, with television dominating by far, according to a survey by Blinder and Krueger (2004). Around 47% of respondents named television as the most important source of information when it came to news about monetary policy or price developments; newspapers and, at the time, the internet were well behind. However, the last two decades have been marked by the emergence of new, disruptive technologies that have also had a major impact on the media. Online platforms and social media in particular have gained attention, especially as providers of news.

More recent figures show that television remains the most important source of news for the general public (e.g., Newman and Levy, 2014; Kennedy and Prat, 2019). Data from the trans-European Eurobarometer surveys show that citizens in all Member States continue to regard television as their preferred source of news, both for national and European politics, with 77% and 72% respectively (Eurobarometer 86, fall 2016). Television also remains an important source of economic news, including information on price developments, monetary policy (e.g., Jansen and Neuenkirch, 2018; D'Acunto et al., 2019) and information on the ECB (e.g., Hayo and Neuenkirch, 2018; Conrad et al., 2021). At the same time, trust in the medium remains high, which, in addition to easy access to information and the (pre)selection of the most important news, is likely to play a decisive role in the continuing importance of television.

This is supported by a recent large field experiment with randomized treatments that, contrary to the claim that the "time when the nightly TV news set a common agenda for the vast majority of citizens" is over (Gentzkow, 2017, p. 726), found a causal relationship between news coverage by small local stations and subsequent societal discussion of the news in question (King et al., 2017). The second assumption ties directly back to this. Leading television news programs and their editors are considered to take the role of national agenda setters through their news selections (McCombs and Shaw, 1972). In addition to directly influencing public debate, it can be assumed that these broadcasters additionally assume the role of decisive intermediaries through cross-media agenda setting, with other media reproducing and disseminating the news.[7] Moreover, many formerly television-only news outlets have additionally established online formats spreading the content and increasing their reach (Newman and Levy, 2014). Overall, this leads to a high concentration of power, measured by the visibility of the selected news, among a relatively small number of providers, i.e., the agenda setters.

The above assumption is of importance because we observe only one news outlet in each country, albeit the market leader. The key to causal identification is thus the news exposure of households due to spatial availability (as in DellaVigna and Kaplan, 2007; Moskowitz, 2021) in combination with the assumption that television in the respective spoken language is preferred (as in Oberholzer-Gee and Waldfogel, 2009). The country-specific and exclusive television markets in Europe thus provide a quasi-experimental panel structure, with news coverage varying across countries.[8]

Content-wise, this study is most closely related to three studies, all of which provide empirical evidence on the importance of media coverage of Federal Open Market Committee (FOMC) decisions for U.S. household inflation expectations.

[7]For instance, Larsen et al. (2021, p. 509) argue along the same lines when claiming that the Dow Jones company "has a large footprint in the U.S. media landscape, and it is likely that its news coverage spills over to news sources that households follow more directly."

[8]The coverage selection and prominence of topics and events in television news is usually event-driven and thus subject to editorial discretion. Research on the factors that determine coverage shows that among other things, the media tend to filter based on audience prior beliefs and consumer preferences (e.g., Gentzkow and Shapiro, 2006, 2010). However, high competition in the individual markets, public broadcasters and reputation concerns disciplines outlets and reduces media bias and slant. Still, selection of news is conditional on the national news pressure (see, e.g., Eisensee and Strömberg, 2007), that is likely to vary across countries, and may crowd out coverage of other issues, such as ECB announcements.

First, Hünnekes (2020) uses micro data from the Michigan Survey of Consumers, similarly relies on high-frequency identified monetary policy surprises, and finds that the information effect dominates the response of inflation expectations. That is, households adjust their inflation expectations based on implicit information on the inflation outlook rather than on the change in the stance of monetary policy. The estimated media effects are on the one hand based on a textual analysis focusing on the direction of inflation in newspaper articles following FOMC meetings, and on the other hand rely on respondent-reported news exposure about inflation and interest rates. Second, Mazumder (2021) finds that references in newspapers to the Federal Reserve (Fed) increase the accuracy of inflation expectations.[9] The author argues that central banks should therefore take into account newspaper coverage of them in order to manage inflation expectations. This seems all the more justified since the central bank's direct communication with the public has no measurable impact on households' inflation expectations, as the third, closely related paper by Lamla and Vinogradov (2019) shows. Their estimation results, based on a survey conducted immediately before and after FOMC meetings, suggest that the communication effect, if any, is due to increased media attention, such that announcements increase the likelihood that people will receive news about central bank policy.

Beyond this, there is indirect evidence on the importance of the news media in communicating monetary policy to laypersons with respect to inflation expectations. This literature consistently finds that the proportion of those who rely more heavily on newspapers and other traditional media sources for economic information form lower and more accurate inflation expectations (e.g., Conrad et al., 2021), and generally have better anchored inflation expectations (e.g., Binder, 2017a). This is most likely due to a better understanding of economic concepts that improve the efficiency of monetary policy transmission (Dräger et al., 2016), as well as a better awareness of the ECB's monetary policy and the dissemination of monetary policy objectives (van der Cruijsen et al., 2015).

This literature is supplemented by studies that examine the relationship between household inflation expectation formation and the media independent of monetary policy and central bank communication. The main finding from this literature is that increased media coverage of inflation-related issues tends to increase the accuracy of inflation expectations and leads to more frequent updating, and that some of the remaining disagreement depends on the heterogeneity of news

[9]The accuracy of inflation expectations is a frequently used variable in empirical work on this topic. It is usually defined as the difference between household inflation expectations and the expectations of professional forecasters. It is also referred to as disagreement in inflation expectations, expectations gap or bias (see, e.g., Capistrán and Timmermann, 2009; Pfajfar and Santoro, 2013; Lamla and Lein, 2014; Lamla and Vinogradov, 2019).

content and tone of the news (e.g., Lamla and Maag, 2012; Menz and Poppitz, 2013; Pfajfar and Santoro, 2013; Lamla and Lein, 2014; Dräger and Lamla, 2017; D'Acunto et al., 2019; Larsen et al., 2021).

Our work also relates to the growing literature that uses high-frequency empirically quantified and decomposed monetary policy announcements to examine their real economic, fiscal, and financial implications (e.g., Altavilla et al., 2019; Cieslak and Schrimpf, 2019; Jarociński and Karadi, 2020; Andrade and Ferroni, 2021; Breitenlechner et al., 2021). Some articles already incorporate high-frequency identified policy variables into research on inflation expectations. For example, Nakamura and Steinsson (2018) focus on the response of inflation expectations by professional forecasters and find little impact. Kerssenfischer (2019), on the other hand, finds that information effects a la Campbell et al. (2012) are decisive for the effects of ECB announcements on market-based measures of inflation expectations as well as on survey expectations of analysts and professional forecasters.

Finally, with its focus on television news, this study contributes to the vast literature on the importance of (mass) media in shaping a variety of economic outcomes and human behavior in general, as well as in politics. For an overview, see DellaVigna and La Ferrara (2015) or Strömberg (2015). Television news inclusion has proven to be a particularly fruitful area of research in analyzing the impact on voters' political preferences or election outcomes in general (e.g., Sanders and Gavin, 2004; Gentzkow, 2006; DellaVigna and Kaplan, 2007; Durante and Knight, 2012).

3 Data

Our analysis of the role of prime-time television news coverage in the formation of household inflation expectations following ECB announcements is based on a sample covering the four largest economies of the Eurozone, namely France, Germany, Italy and Spain, from 2006 to the end of 2016. This selection is based on the availability of television news data. In this section, we present our data, focusing in particular on variables derived from the monetary policy event study database by Altavilla et al. (2019), the television news coverage data provided by Mediatenor and households' inflation expectations derived from EC survey data.[10]

[10]For further information on data description, sources and summary statistics of all variables see Appendix A.

3.1 Monetary Policy Data

In the sample period, the Governing Council met 124 times; we refer to each of these meetings as a monetary policy event. Thus, in all but eight months, the ECB announced at least one monetary policy decision. Not every one of these meetings, however, involved a change in one of the central bank's key interest rates, but each was accompanied by a press release and a subsequent press conference, potentially attracting media attention on the one hand and enabling new approaches to quantifying monetary policy decisions on the other. This has become necessary because for some time now, changes in central bank policy rates, such as the ECB's main refinancing rate, have not been able to exclusively and adequately represent the monetary policy stance (Gürkaynak et al., 2005). The approach to the zero lower bound and unconventional monetary policy measures such as quantitative easing and forward guidance have exacerbated this need. Among other things, high-frequency identification has therefore proved to be a valuable alternative for operationalizing central bank announcements and measuring the impact of monetary policy shocks on the macroeconomy and financial markets (see, e.g., Brand et al., 2010; Altavilla et al., 2019; Kerssenfischer, 2019; Jarociński and Karadi, 2020; Andrade and Ferroni, 2021).[11] In this context, it was pointed out that the announcements often not only convey information on monetary policy itself, but also provide information on the central bank's assessment of the economic environment and outlook. Forward guidance has reinforced this tendency to reveal non-monetary policy information. Therefore, to estimate the impact of the ECB announcements on household expectations, we quantify the policies and categorize each of these using high-frequency observations.

We use data from the Euro Area Monetary Policy Event-Study Database (EA-MPD) provided by Altavilla et al. (2019). It provides open access to event-related market reactions to Governing Council monetary policy decisions as changes in an event window around the announcement for a wide range of financial variables. To capture monetary policy decisions, we consider changes in the 3-month interest rates of the overnight index swaps, OIS_3M, based on the EONIA and the change in the stock market index of the (EURO-)$STOXX50$.[12]

[11] Such market-based approaches, which use financial market data to infer the nature of the shock from its changes in a sufficiently small window of time around the policy announcement, have simplified the assessment of the stance of monetary policy, especially for unconventional measures (Breitenlechner et al., 2021), and have made it possible to overcome subjective interpretations of announcements or approaches relying on inaccurate word-counting techniques. Previous attempts to construct monetary policy surprise measures also include comparing surveyed ex ante expectations with actual interest rate changes (e.g., Conrad and Lamla, 2010) or using day-to-day changes in federal funds futures contracts (Bernanke and Kuttner, 2005).

[12] We use changes due to the entire monetary policy event, reflecting all released information. The effect is thus measured as the difference in the variables before the press release and after the press conference. The well-known and fixed timing of the ECB's monetary policy announce-

Monetary policy announcements are categorized along two dimensions, distinguishing between two categories in each case, resulting in four different types of measures. First, the change in the market interest rate OIS_3M indicates the fundamental nature of the decision, which we refer to as the direction of the monetary policy shock. Hence, *contractionary* (*expansionary*) monetary policy announcements are reflected in immediate positive (negative) changes in OIS_3M. Second, additional information on stock market movements – we use the change in $STOXX50$ – allows us to further distinguish between two *types*.

Using the following two sign restrictions, we separate purely monetary policy shocks from informational shocks: (1) If the signs of the change in OIS_3M and $STOXX50$ are the same, we refer to a *delphic* policy. The term, borrowed from Greek mythology and referring to the Oracle of Delphi, was first introduced into the monetary policy context by Campbell et al. (2012) and has subsequently been used to describe an announcement that is primarily informative in nature regarding the state of the economy, macroeconomic performance, and the likely future stance of monetary policy (Altavilla et al., 2019; Andrade and Ferroni, 2021).[13] For example, if the Governing Council announces a contractionary measure that increases market interest rates, and at the same time the stock market rises, this must be related to positive information about the economic outlook.

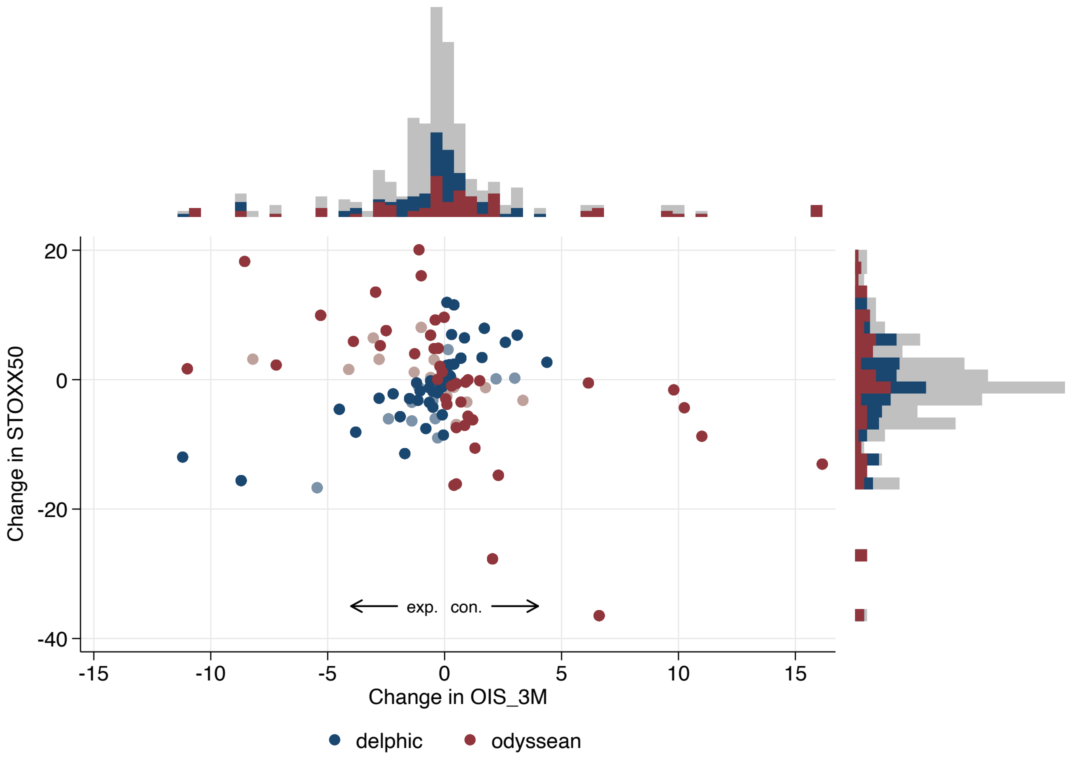
(2) In contrast, unequal signs are referred to as *odyssean* measures, where the central bank, like Odysseus, in order to resist the call of the sirens, ties its hand and commits to follow a certain (pure) monetary policy. The identifying assumption is textbook economics, according to which a change in the interest rate affects asset prices, i.e., the stock market reacts in the opposite direction.[14] The scatter plot depicted in Figure 1 illustrates the categorization of each of the 124 monetary policy events. Along the x-axis showing the change of OIS_3M, we can distinguish

ments would even allow for a more precise identification, distinguishing between the effect of the monetary policy announcement and the effect of the press conference (Altavilla et al., 2019). It should also be noted that high-frequency identification is generally based on the assumption that no other shocks affect the variables of interest within the event window. Although it is acknowledged that such external shocks occur during the event windows under consideration, such biases, however, are generally considered to be small (Kerssenfischer, 2019; Jarociński and Karadi, 2020).

[13]This, in turn, builds on the work of Romer and Romer (2000), who were among the first to highlight the role of information in central bank announcements. Because central banks have more and better information than the public, they can use disclosure of their views on macroeconomic fundamentals and the economic outlook as a policy tool.

[14]Due to its simplicity, Jarociński and Karadi (2020, p. 15) refer to the implementation as "Poor man's sign restrictions". However, the authors show that this approach leads to results that are largely comparable to an alternative identification with VARs. Altavilla et al. (2019) differ in their identification in two respects. First, they look at 2-year OIS rates, and second, they include inflation-linked swaps as a third series in the identification via co-movements. However, stock prices and swaps almost always move in the same direction, which minimizes the additional benefit and accuracy.

FIGURE 1: HIGH-FREQUENCY IDENTIFICATION OF THE MONETARY POLICY TYPE AND MEDIA COVERAGE



NOTES: Each dot in the scatter plot represents one of the 124 monetary policy events during the sample period. The graph is adapted from a representation in Jarociński and Karadi (2020) and allows to distinguish between *delphic* and *odyssean* shocks. To illustrate, in the upper right quadrant, both the change in the three-month interest rate OIS_3M (in basis points) and the change in the stock market index $STOXX50$ (in percentage points) have the same sign (+) and are thus defined *delphic* and *contractionary*. The histograms show the overall distribution as well as the shares of monetary policy events that were covered on the evening news in the four countries. Light dots and grey bars represent events without coverage on the evening news.

between the direction of the shock, i.e., *contractionary* and *expansionary*. The two types, *delphic* and *odyssean*, are shown in two different colors. Finally, we are able to distinguish between *delphic contractionary*, *delphic expansionary*, *odyssean contractionary*, and *odyssean expansionary* measures, denoted in the following by the index k.

We create two sets of variables for the monetary policy announcements. The $policy_{ikt}$ variables indicate the magnitude of a k-type shock in month t, quantified by the change in OIS_3M in the event window, expressed in basis points:

$$policy_{ikt} = \begin{cases} |OIS\_3M|, & \text{for policy of type } k, \\ 0, & \text{otherwise.} \end{cases}$$

Countries i in the monetary union are assumed to be equally affected by each monetary policy announcement. For most of the analysis, the shocks in the regressions are used in absolute values to facilitate the interpretation of the coefficients, as indicated by the magnitude sign. In line with common practice in event studies and DiD approaches, we additionally use dummy variables in our regressions instead of accounting for the magnitudes of the shocks:

$$policy\ dummy_{ikt} = \begin{cases} 1, & \text{if } policy_{ikt} \neq 0, \\ 0, & \text{if } policy_{ikt} = 0. \end{cases}$$

Table A.1 in the Appendix provides summary statistics differentiated by type of monetary policy event. The number of individual event types ranges from 66 to 119, with *delphic con.* being the least and *delphic exp.* the most frequent. Moreover, *odyssean* shocks are slightly larger than *delphic* shocks in terms of mean and standard deviation. No such difference in magnitude is apparent between *expansionary* and *contractionary* shocks.

3.2 Media Data

News data is provided and compiled by Mediatenor, a private research institute that provides information based on media content analysis.[15] News items are categorized by human analysts using standardized characteristics defined in a binding codebook that ensures objectivity and comparability across markets and time. Newscasts are analyzed in their entirety and coded news item by news item.[16] This means each new piece of information segment triggers an additional news item to be coded. Items are coded and categorized by topic group (e.g., ECB, currency/Euro/monetary policy, economy), topic (e.g., interest rate, money supply, monetary policy, increasing inflation or high level, decreasing inflation or low level), which depict subgroups of the former, and many others, such as protagonists, region or time of reference and tonality of the report.

Table 1 provides a descriptive overview of our sample, including information on newscasts and news items. The newscasts studied are the leading, most-watched and best-known in each of the four media markets (e.g., Newman and Levy, 2014; Kennedy and Prat, 2019). Surveys show that the weekly reach of these prime-time programs is about half the population.[17] The total number of news items collected

[15] See www.mediatenor.com. Related studies also using Mediatenor data include Lamla and Maag (2012); Lamla and Lein (2014, 2015); Dräger (2015); Dräger and Lamla (2017), which, however, focus on newspaper coverage.

[16] Other related analyses often rely on keyword-identified articles and items. Our approach, in contrast, is based on analysts actually watching and categorizing the news reports. Supervision and standardized controls result in high accuracy of coded news.

[17] A large majority of respondents indicate that their usage of the respective programs is more than three times a week. Trust in these brands increases the credibility and reach of the selected television news programs. This also applies to their well-established online presences, which are also among the most popular Internet and social media sources (Newman and Levy, 2014).

Table 1: Media Data Overview

Country	TV Newscast	Reach	Sample Period	No. of News Items: Total	Euro/ ECB	Mon. Policy	Prices incr.	Prices decr.
France	TF1 Le Journal	47%	04/07 –11/16	98,586	27 (631)	17 (392)	3 (69)	0 (29)
Germany	ARD Tagesschau	57%	01/06 –11/16	80,833	102 (626)	71 (171)	0 (44)	0 (8)
Italy	RAI1 TeleGiornale	65%	01/06 –11/16	140,222	119 (857)	54 (316)	4 (133)	5 (55)
Spain	TVE1 Telediario	44%	06/07 –11/16	177,859	147 (1,333)	94 (722)	9 (120)	6 (107)
Total				497,500	395 (3,447)	236 (1,601)	16 (366)	11 (199)

Notes: The table provides an overview of the newscasts and the news items. The reported reach of the respective newscasts illustrates weekly usage in 2014, i.e., toward the end of the sample period, according to a representative survey (Newman and Levy, 2014). While the leading French newscast 'TF1 Le Journal de 20h' is private, all other newscasts included are broadcast on public channels. The number of news items related to a specific topic differs between the news items broadcast on the days of the Governing Council monetary policy meetings, $coverage^{MP}$, and the total monthly *coverage* (in parentheses).

on all topics during the sample period is almost 500,000, of which we use about 5,000 to create the variables employed in the analysis. Topics of interest for this study are news about the 'Euro/ECB' in general, the ECB's 'monetary policy' in particular, and news related to 'increasing' or 'decreasing' prices or inflation rates, and are considered relevant if the content of the news relates to the domestic economy or the Eurozone as a whole. An additional feature of the media data we use is the coding of the tonality of the news.[18]

For the analyses, we convert news items at daily frequency into monthly variables denoted by the time index t. These $coverage_{it}$ variables are calculated as a share of total monthly news, which is intended to reflect both the relevance and prominence of the topic in the media market of country i:

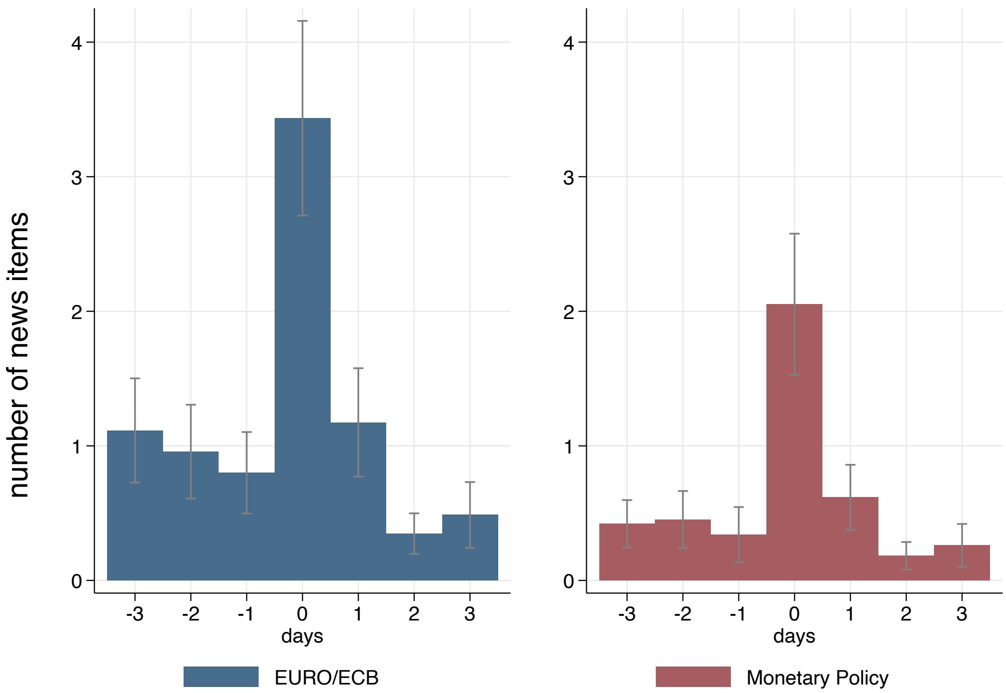
$$coverage_{it} = \frac{\text{No. of topic-specific news per month}_{it}}{\text{No. of total news per month}_{it}} \times 100$$

Shares are expressed as percentages and can be regarded as the intensity of reporting.[19] As noted above, we create topic-specific variables indicating *increasing* and

[18]This line of research is pursued because there is evidence that tonality can influence expectation formation (e.g., Lamla and Lein, 2014).

[19]Among others, Carroll (2003), Lamla and Lein (2014), and Dräger et al. (2016) point out the importance of considering the intensity of coverage when analyzing the impact on expectation

Figure 2: Daily reporting on and around the meetings of the Governing Council



Notes: The bars show the average number of news items in the four newscasts around the Governing Council meeting days. The grey lines indicate 95% confidence intervals.

decreasing inflation, a reference to *Euro/ECB*, and *monetary policy*. In addition, $increasing^{MP}$, $decreasing^{MP}$, $Euro/ECB^{MP}$, and $monetary\ policy^{MP}$ represent variables generated from the subsamples where we consider only news broadcast on days of ECB Governing Council monetary policy announcements, as indicated by the superscript MP:

$$coverage_{it}^{MP} = \frac{\text{No. of topic-specific news on MP day}_{it}}{\text{No. of total news per month}_{it}} \times 100$$

Restricting our analysis to news directly related to monetary policy events allows to shed light on the role of the media in the transmission of announcements. In the main part of the analysis, we focus on $Euro/ECB^{MP}$ coverage and assume that all evening news related to these topic groups on an event day are related to the announcement.[20] Indeed, coverage is significantly higher on days of ECB

formation. However, standardization by the total number of monthly news items is important for another reason. Newscasts differ in length of the program, e.g., 15 min 'Tagesschau' vs. 45 min 'Le Journal', and the number of reports covered.

[20]We focus on $Euro/ECB^{MP}$ as our main explanatory variable rather than $monetary\ policy^{MP}$ because coverage of the Euro and the ECB on a day of a monetary policy event is very likely to include all related information, taking into account imperfectly coded information that may not be captured by the more narrowly defined variable.

Governing Council meetings than on days before and after (see Figure 2). 12% of all news about the Euro or the ECB is broadcast on these days. Considering that monetary policy decisions are made every four to six weeks, this suggests that monetary policy decisions is breaking news.

For the event study and the generalized DiD, we further differentiate $Euro/ECB_{it}^{MP}$ by policy type as described in Section 3.1. Thus, $Euro/ECB_{ikt}^{MP}$ indicates the intensity of news coverage on a ECB Governing Council decision of type k in country i in month t:

$$Euro/ECB_{ikt}^{MP} = \begin{cases} Euro/ECB_{it}^{MP}, & \text{for coverage of policy of type } k \\ 0, & \text{otherwise.} \end{cases}$$

Consistent with the formalization of the monetary policy shocks, we also use dummies for the media variables, as is common in a DiD framework. These represent our form of a treatment variable and indicate whether or not a k-type monetary policy event was reported on the evening news, regardless of the number of news items, i.e., the intensity of coverage devoted to the event. The *coverage dummy* is defined as:

$$Euro/ECB_{ikt}^{MP} \; cov.\; dummy = \begin{cases} 1, & \text{if } \; Euro/ECB_{ikt}^{MP} > 0, \\ 0, & \text{otherwise.} \end{cases}$$

Additional descriptive statistics and figures on the coverage variables are provided in Appendix A. Figure A.1 shows the intensity of reporting on *increasing* and *decreasing* inflation over time and for the four sample countries. Most of the coverage of inflation relates to the first half of our sample period and focuses on rising prices, while it is rarely on the evening news in the second half. Indeed, the latter period coincides with a period of relatively stable and lower inflation rates and inflation expectations closer to the ECB target (see Figure B.1). Interestingly, on days of Governing Council meetings, the news very rarely reports on either increasing or decreasing inflation (see also Table 1). As for the main variable of interest *Euro/ECB*, coverage reached a peak of media attention twice: during the financial crisis in 2008 and at the height of the Euro crisis in 2012 (see Figure A.2). With respect to the intensity of coverage, the mean values of $Euro/ECB_{ikt}^{MP}$ do not differ significantly across the different types of measures (see Table A.1). Moreover, no type stands out as attracting more media attention. Finally, note that the assembled panel is slightly unbalanced due to missing data in the provided media dataset by Mediatenor and thus missing observations for the coverage variables, as we exclude all observations from the affected months in the regressions and statistics presented.[21]

3.3 Inflation Expectations Data

Household *inflation expectations* denote our main dependent variable. We use data from the business and consumer tendency survey of the European Commission.[22] The published qualitative data series provide harmonized and representative information on inflation expectations in the EU countries at monthly frequency. In particular, the series reflect responses to the question: "By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months? They will...". Respondents expectations are stated in one of six categories, ranging from "fall" to "increase more rapidly". We follow the often employed probability method first proposed by Carlson and Parkin (1975) to quantify the series.[23] For a detailed description of the quantification exercise and for further references see Appendix B. Figure B.1 displays *HICP inflation, inflation perceptions* and *inflation expectations*. By construction, the computed series track *HICP inflation* relatively closely, while larger deviations can only be observed at the time of the 2008 financial crisis, when additionally food and energy prices soared and *inflation perceptions* spiked. However, the descriptive cross-country comparison suggests some heterogeneity among European households, and households tend to systematically overestimate current and future inflation rates, which is a recurring result (e.g., Dräger and Nghiem, 2018).

Timing is critical for an analysis that aims to determine the impact of monetary policy announcements and related media coverage. Therefore, all variables employed are adjusted to take into account the fieldwork period of the survey on the dependent variable, inflation expectations. According to the European Commission, fieldwork is typically conducted during the first two to three weeks of each month, pending the release of preliminary "flash" results, and full survey results are released at the end of each month. Thus, for example, we aggregate daily media data from the end of fieldwork in month $t-1$ to the end of fieldwork in month t to match inflation expectations in month t (see the Section 4.3 for a detailed discussion of this and other assumptions).

In one series of regressions, we deviate and use the *inflation expectations gap* as the dependent variable, defined as the absolute distance of expectations from

[21]For the two markets France and Spain, news observations are missing at the beginning of the sample period and for a limited period in 2013/14 and 2011/12, respectively.

[22]Inflation expectations are either derived from financial market data, e.g., inflation swaps, or calculated from survey data. Surveys are classified depending on the targeted respondents, e.g., professional forecasters, firms or consumers.

[23]See Berk (1999) for a detailed and critical analysis of the use of tendency survey and properties of quantified figures. See Menz and Poppitz (2013); Lamla and Lein (2014); Dräger (2015) for examples of related applied research using such series.

the ECB's target rate of 2% (which was actually defined as below, but close to, this value until 2021). As mentioned above, it is quite common to measure the impact of media coverage on the discrepancy between consumer expectations and those of professional forecasters in order to determine the accuracy of expectations (see, e.g., Carroll, 2003; Pfajfar and Santoro, 2013; Lamla and Lein, 2014; Lamla and Vinogradov, 2019). Thus, the measure used here relates more directly to anchoring.

3.4 Controls

In all regressions, we use a fixed set of control variables.[24] Even though inflation data are published after survey expectations have already been indicated, we take current *HICP inflation* into account because observable price changes, such as for fuel at the gas station or food at the supermarket, are likely to affect consumers' inflation expectations (Binder, 2018; D'Acunto et al., 2019; Coibion et al., 2020). In comparison, Lamla and Lein (2014) use the lagged inflation rate to control for the information set available for respondents in the survey period. Dräger (2015) uses inflation perceptions instead claiming that household expectations are related to individual beliefs rather than actual inflation. We do not follow this approach and retain *HICP inflation* for two reasons. First, the previously cited finding is at odds with the results of Menz and Poppitz (2013), showing that perceptions play a minor role. Second, using actual inflation provides rates better protection against spurious correlations as a result of the stepwise quantification of the series. Further controls include two standard macroeconomic variables, the *production gap* and the *unemployment rate*. Both variables are indicators of economic performance, which we also use t to t.

4 Empirical Framework

The compiled dataset described in section 3 can be analyzed using conventional panel methods. Therefore, in section 4.1 we present the empirical framework we use to analyze this time-series cross-sectional (TSCS) dataset. Besides determining the relation between selected media variables and inflation expectations formation, the models allow us to conduct our main analysis focusing on the effect of media coverage following monetary policy decisions in an event study design. To improve on identification, in Section 4.2 we describe how we transform our data to a stacked event panel allowing us to employ a generalized Difference-in-Differences (DiD)

[24] Only the selection of controls is discussed in this section. For data sources and further information, see Appendix A.

design. Both approaches are subject to assumptions that we outline in Section 4.3.

4.1 The TSCS and the Event Study Model

Due to the high persistence of the main dependent variable *inflation expectations* and for efficiency reasons, the analysis is conducted in first differences and with the inclusion of a lagged dependent variable.[25] Thus, the baseline regression model is as follows, where t denotes the monthly time dimension and i denotes the cross-section:

$$\Delta y_{it} = \rho\, \Delta y_{it-1} + \delta\, X_{it} + \gamma\, coverage_{it} + \beta\, coverage_{it}^{MP} + \alpha_i + \lambda_t^{ym} + \epsilon_{it} \tag{1}$$

where Δy_{it} is the first-differenced dependent variable, for the most part *inflation expectations*, unless otherwise noted. The set of controls, $\Delta HICP\ inflation$, *production gap* and *unemployment rate*, are included in the vector X_{it}. Both γ and β are the coefficients of interest, with $coverage_{it}$ referring to the media variables that reflect the intensity of coverage of a particular topic. The variable $coverage_{it}^{MP}$ is restricted to the corresponding news on the days of the Governing Council's monetary policy meetings. Country fixed effects are denoted by α_i and map distinct linear trends in the dependent variable. However, the use of conventional time fixed effects is too restrictive for a model with four cross sections. Instead, we include year fixed effects to capture dynamic changes in inflation expectations over time and to control for specific periods such as the financial crisis, and for month fixed effects to account for seasonal patterns in the data. Both are represented by the variable λ_t^{ym}. Moreover, compared to monthly fixed effects, they are less prone to overfitting the model, i.e., constraining the variance. Since initial tests indicate the presence of serial correlation and cross-sectional dependence, in addition to a lagged dependent variable, we adopt an error structure ϵ_{it} with panel-specific first-order autoregressive disturbances (AR1) to account for remaining serial correlation:

$$\epsilon_{it} = \rho_i \epsilon_{it-1} + \nu_{it} \tag{2}$$

where the residual error ν_{it} is assumed to be normally distributed with a mean of zero. The distinct ρ_i denote the panel-specific autoregressive parameters of an AR(1) error process for each country, which gives the model greater flexibility, jus-

[25] Initial tests reject the stationarity of the variables on the levels. However, stationarity is confirmed for first differences, while serial correlation persists, justifying the use of a dynamic panel specification. This specification is thus also consistent with epidemiological adjustment of inflation expectations (Carroll, 2003). In contrast, for instance Dräger (2015) uses an approach that models a cointegration relationship between actual inflation and inflation expectations.

tified by the time dimension T being significantly larger than the cross-sectional dimension N. Indeed, the estimates show that the autocorrelation parameters in the error term differ significantly between panels, justifying this modeling. The models denoted in equation 1 above and equation 3 below are estimated using the generalized least squares estimator of the Prais-Winston method with panel-corrected standard errors (PCSE), accounting for heteroskedasticity and correlation across cross sections, as proposed by Beck and Katz (1995).[26]

To study the coverage effects of distinct monetary policy announcements we use an event study design as our baseline model. More specifically, in the first-difference framework, we examine how *inflation expectations* change immediately after monetary policy announcements. Remember, the four EMU countries are repeatedly exposed to common surprise monetary policy shocks, while only some of the events are covered on the evening news. This allows us to distinguish between the sender channel, the sole ECB announcement, and the transmission channel via the media (Dräger et al., 2016).

As described in Section 3.1, we use the dataset provided by Altavilla et al. (2019) to quantify the size of the shock and distinguish between different types of monetary policy announcements. Using information from our media dataset, we can determine whether a country is treated, i.e., whether the public is informed about ECB policies through coverage of Euro/ECB content on the evening news of the leading television networks. This quasi-experimental framework allows the estimation of the following panel regression model for the analysis as an event study:

$$\begin{aligned}\Delta y_{it} = \rho\, \Delta y_{it-1} + \delta\, X_{it} + \sum_k (\phi_k\, policy_{ikt} + \beta_k\, policy_{ikt} \times Euro/ECB^{MP}_{ikt}) \\ + \alpha_i + \lambda^{ym}_t + \epsilon_{it}\end{aligned} \tag{3}$$

where the main variables remain the same as in equation 1. The variable $policy_{ikt}$ refers to the repeatedly occurring monetary policy shocks of type k. As described in Section 3.1 we distinguish between *expansionary* and *contractionary*, *delphic* and *odyssean* as well as between the combinations thereof (*delphic exp.*, *delphic con.*,

[26]In this paper we only present results using the PCSE estimator (Stata module `xtpcse`), although we also tested pooled OLS with clustered standard errors and pooled FGLS (`xtgls`) to check the robustness of our results. Our main results remain unchanged; the additional estimates are available upon request. However, PCSE outperforms clustered standard errors in heterogeneous panels that are prone to common contemporaneous shocks, and the model does not report overly optimistic standard error estimates, unlike other FGLS estimators (Beck and Katz, 1995; Hoechle, 2007; Reed and Ye, 2011). Studies considering a single country have been employing the Newey–West estimator to report robust standard errors (e.g., Lamla and Maag, 2012; Dräger, 2015). Further, since T is much larger than N, our TSCS panel satisfies the critical properties of a finite sample, so dynamic panel biases as described by Nickell (1981) is not an issue.

odyssean exp. and *odyssean con.*). The variable $Euro/ECB^{MP}_{ikt}$ denotes coverage of the event on the evening news of the day of the monetary policy announcement. The coefficients ϕ_k on the $policy_{ikt}$ variables cover the overall effects of the shocks, while the coefficient on the interaction term β_k denote the coverage effect. Note that throughout the analysis of the announcements we use representations of the variables that account for the size of the shock and the intensity of coverage, namely $policy_{ikt}$ and $Euro/ECB^{MP}_{ikt}$, as well as dummies for both.

4.2 The Stacked Difference-in-Differences Model

To complement and test the results of the event study, we compile what has recently become known as a stacked panel to examine effects in a generalized DiD design (see, e.g., Cengiz et al., 2019; Deshpande and Li, 2019; Clemens and Strain, 2021). This approach has gained prominence because of biases associated with weighting issues and time-varying treatment effects for DiDs with staggered treatments. This fits well with our data, as monetary policy events and associated news coverage are also sequential. The stacked panel model uses the non-treated, i.e., the monetary policy events that received no news coverage, and the preceding observations as counterfactual control groups.

We stack the data as follows: For each monetary policy announcement and country, we create a cross-sectional event j that occurs at time $t = 0$, the last period. This results in a number of 376 cross sections. In the time dimension, we consider seven months, i.e., we use data on the dependent and control variables for the six months preceding each event, and the calendar months are now referred to as event time.[27] This means that the event panel is different from our baseline setup in terms of dimensions, being wide with large N and small T. Note that the dataset is constructed so that treatments, both the monetary policy shock and media coverage in country i, occur only in the last period t of the respective panel j. Technically, the stacked DiD panel yields a mixed within and between design.

The analysis of the stacked panel is based on the empirical DiD framework as outlined in Angrist and Pischke (2008). We estimate a dynamic model in levels, i.e., including a lagged dependent variable, as well as using two-way fixed effects.[28]

[27] The decision to consider six periods in advance is a compromise between the number of observations of pretreatment data for each event needed to test assumptions, control for confounding factors, and avoid bias in estimation, and the desire not to inflate the sample too much. In any case, overlaps of events are inevitable since the interval between Governing Council meetings, as described, is usually four to six weeks.

[28] Conventional DiD models are usually modeled in levels and include time and group fixed effects. While high persistence and serial correlation are less of an issue in a short panel estimation, we mainly include a lagged dependent variable, which essentially yields a change estimator, since past expectations are an important time-varying confounder that is poorly captured by time-invariant fixed effects (Angrist and Pischke, 2008). Moreover, the inclusion of a lagged

In detail, the estimated specification of the generalized DiD regression model is:

$$y_{jt} = \rho\, y_{jt-1} + \delta\, X_{jt} + \sum_{k} (\phi_k\, policy_{jkt} + \beta_k\, policy_{jkt} \times Euro/ECB^{MP}_{jk}) \\ + \alpha_j + \lambda_t + \epsilon_{jt} \tag{4}$$

where y_{jt} refers to the dependent variable, *inflation expectations*. As indicated, the index j denotes the panel variable, where each $j = 1, ..., 376$ represents pairs of a monetary policy event and country. With respect to the variables of interest, the coefficient ϕ_k denotes the effect of the k-type monetary policy announcement itself, while β_k depicts the causal effect of the additional evening news coverage. The coefficients α_j and λ_t denote event and time fixed effects, respectively. Although we are aware of the more demanding conditions associated with the additional use of conventional cross-sectional fixed effects in a dynamic panel, we employ this estimator after conducting an initial Hausman test.[29] As noted by Angrist and Pischke (2008), the two model features have a useful bracket relationship, but only parallel use results in a model that nests both fixed effects and a lagged dependent variable. Nevertheless, when estimating equation 4, we must be particularly aware of the induced bias due to a possible correlation between the lagged outcome variable and the error term (Nickell, 1981). For our analysis, this means that after the benchmark OLS estimation with two-way fixed effects, we use a GMM estimator in a second step to account for potential bias.[30]

Both estimators are linear in the explanatory variables, allowing their use in a generalized DiD. However, compiling the stacked panel increases the number of observations from 433 to 2,595, as a significant number of months and their associated observations fall within the time frame of more than one monetary policy event. Accordingly, the asymptotic standard errors and confidence intervals calculated in the conventional way are incorrect. To enable valid statistical inference, we use clustered standard errors that are considered sufficient in the literature (compare

dependent variable mitigates the requirement of parallel trends as an assumption (see Section 4.3 for a discussion).

[29]The use of fixed effects also means that time-invariant DiD group fixed effects, which would indicate for the entire panel whether an event is treated in terms of coverage, are omitted.

[30]The standard GMM estimator proposed by Arellano and Bond (1991) is known to be substantially downward biased when the autoregressive coefficient is close to unity. Thus we rely on the estimates of the System-GMM estimator proposed by Blundell and Bond (1998) to appropriately estimate the dynamic linear panel model using the stata module `xtabond2`. Estimating a system of equations including an equation in first-differences and the equation in levels, with differences used as instruments for the variables in levels, results in a lower bias and higher efficiency for dynamic models that is increasing in N. While accounting for potential endogeneity between current realizations of inflation expectations and the HICP inflation, unemployment, the production gap as well as their past values, respectively, we treat the monetary policy and coverage variables as exogenous. The estimator refers to a two-step System-GMM with lags 1 through 3 as instruments and bootstrapped (cluster-)robust standard errors.

e.g., Cengiz et al., 2019; Clemens and Strain, 2021), and supplement them with standard errors computed using panel bootstrapping methods that resample entire cross-sections to account for the inflated sample.[31] Bootstrap standard errors, moreover, not only account for the problem of an inflated sample, but also correct for potentially biased estimates of standard errors in DiDs due to serial correlation in the individual events (Bertrand et al., 2004).

4.3 Hypothesis and Identifying Assumptions

As described, using available television news on inflation, we first attempt to replicate the results of previous research on the role of the media in shaping households' inflation expectations. The main focus of this paper, however, is on the effects of evening coverage of specific monetary policy announcements. Therefore, we formulate the following main hypothesis:

> **Hypothesis 1:** The coverage of the ECB's monetary policy announcements on the evening television news affects the formation of households' inflation expectations.

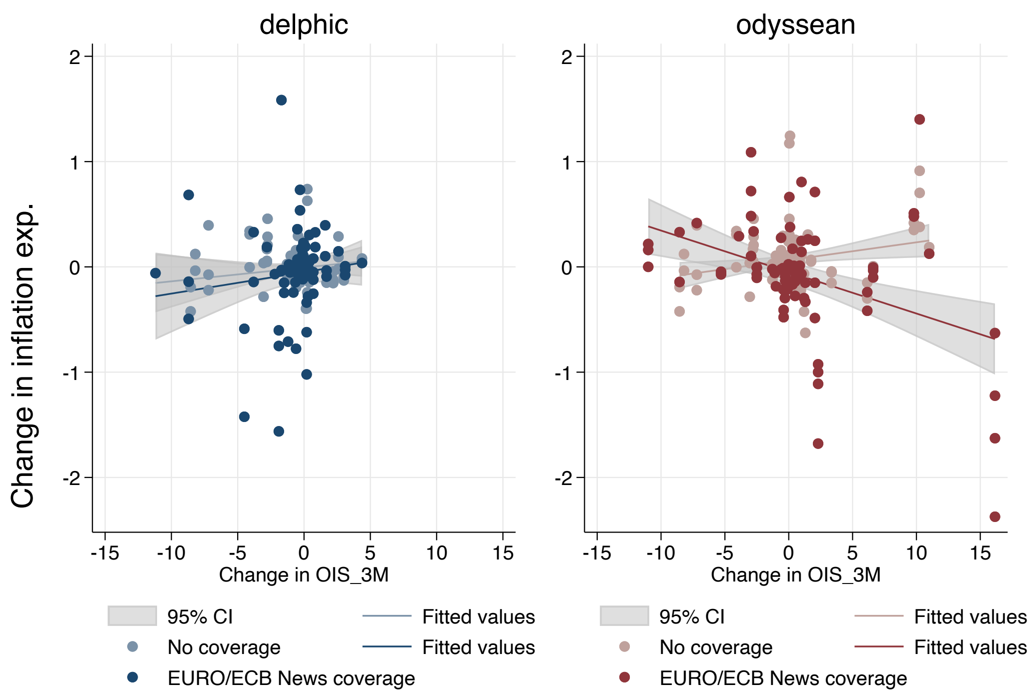
To disentangle the media effect from the direct announcement effect, we use additional information on the type and size of the monetary policy surprise. Figure 3 shows the correlations between *inflation expectations* and OIS_3M shocks for both policy types and whether or not each event receives news coverage. Preliminary descriptive evidence regarding the hypothesis suggests that news coverage is relevant for *odyssean* ECB policies, while no such effect is observed for *delphic* policies.

Both the event study and the DiD model allow us to provide empirical evidence for our hypothesis in a quasi-experimental setting. DiD designs in particular have become a standard method for conducting causal inference in this context, but have high assumption requirements. Therefore, we propose multiple models, use of different variables, perform multiple robustness tests, and place particular emphasis on the assumption of parallel trends. An overview of the assumptions on which the identification of the media effect in the above hypothesis is based is presented below:

(1) Since we cannot determine the full content of individual news items from our dataset, we assume that *Euro/ECB*'s coverage on the days of monetary policy decisions is directly related to the announced measures (see also Section 3.2).

[31] These have also become known as block or cluster bootstrapping methods. The algorithm creates i.i.d. distributed sub-samples by drawing entire events from the stacked sample with replacement. The number of replications to calculate bootstrap standard errors is 2,000.

Figure 3: Monetary Policy Surprises and Inflation Expectations



Notes: Each dot in the scatterplots depicts a monetary policy surprise in the sample period including information on the size of the shock OIS_3M and the respective change in *inflation expectations* in the four countries respectively. Light-coloured dots depict events without coverage.

(2) Considering only one news program for each media market, albeit arguably the most important one, another identifying assumption is that they play the role of agenda setter within a country. The Tucker coefficients presented in Table 2 allow us to draw conclusions about the similarity of news coverage across countries. The level of agreement on whether the Governing Council's monetary policy meetings are covered varies considerably between each two media markets respectively, ranging from 0.32 to 0.58. For comparison, we consider the coverage of the two major German news programs 'Tagesschau' and 'ZDF heute journal,' which is the only addition also available to us. Here, the decision of the two newsrooms whether to cover the events or not shows a Tucker coefficient of 0.65, which is higher than for all other pairwise combinations. This is in favor of the agenda-setting theory discussed in Section 2.

(3) As indicated in the model equations 1–4, we assume an immediate t on t response of inflation expectations to a monetary policy announcement. That is, for *inflation expectations* data released at the end of month t, we consider news coverage and monetary policy events in the period beginning in month $t-1$ after the end of fieldwork until the end of fieldwork in month t (see also the discussion in Section 3.3). We are aware of the imprecision that people who participate in

Table 2: Cross-Coverage Matrix of Euro/ECB-Coverage

	France	Germany	Italy	Spain
France	1			
Germany	0.40	1		
Italy	0.32	0.55	1	
Spain	0.32	0.46	0.58	1

Notes: The table shows the cross-market Tucker coefficients for the congruence of media coverage of all monetary policy surprises, i.e., the degree to which newscasts in two markets match in their decision to report or not report on them. The higher the coefficient, the more congruent the coverage of the events. For comparison, the coefficient between the two most important German newscasts across channels, 'ARD Tagesschau' and 'ZDF heute journal', is 0.65.
Tucker coefficients are calculated as $\varphi_{ij} = \frac{\sum cov.\ dummy_{it} \times cov.\ dummy_{jt}}{\sqrt{\sum cov.\ dummy_{it} \times \sum cov.\ dummy_{jt}}}$.

the survey at an early time may not be able to respond to news days later. We have tried other cutoff dates, but this setup has proven most convincing to us, both theoretically and empirically. Further, media reports from $t-1$ have been found to be incorporated into the lagged dependent variable by Lamla and Maag (2012), so other related studies have also regressed on t only (e.g. Lamla and Lein, 2014; Dräger et al., 2016). Other reasons are, first, that the data are time series with repeated treatment, as the Governing Council meets every four to six weeks. In the 131 months of our sample period, a total of 124 meetings take place, which means that a monetary policy announcement is made in almost every month. Hence, lagged variables are not as easily attributable and thus induce a bias in the effects. Second, the high persistence of the dependent variable leads us to use first differences and a lagged dependent variable model respectively, which inevitably leads to contemporaneous effects.

(4) We rely on exogenous variation in whether countries and events are treated, i.e., whether they receive coverage in the respective newscast or not. In this context, a direct relationship with the dependent variable can be ruled out with certainty, i.e., the decision to cover an event does not depend on its impact on inflation expectations. The timing in our model prevents such endogeneity, as the surveyed expectations are published long after the reference period. However, we must acknowledge that coverage of certain topics, such as inflation or Governing Council announcements, is not necessarily random. For example, unobserved features of the economic situation, special incidents at the event, or other events with greater news pressure may lead editors to decide whether or not to include the specific announcement in the time-limited newscast. One problem is that the coverage decision is likely to depend on the importance of the monetary policy decision, which also affects inflation expectations. However, as long as the coverage deci-

sion is not directly related to the expected change in inflation expectations, the information on inclusion or non-inclusion is sufficient to determine the impact of media coverage. Further, a comparison of coverage decisions across markets shows that there are large differences in coverage across and within countries. Table 2 illustrates the very small overlap in coverage across markets for the full sample, while the histograms in Figure 1 show no skewed distribution in favor of coverage of large events. Instead, coverage is fairly evenly distributed, with rarely complete coverage of an event across all countries. We conclude that the treated, i.e., covered monetary policy decisions do not differ fundamentally in size or scope. Nonetheless, we account for the size of each shock in the regressions and compare these results with those from dummy estimates. Finally, as a robustness check, we introduce a restricted panel in which we exclude all events that do not exhibit differences in coverage across markets.

(5) We assume that *inflation expectations* are not prone to anticipation effects with respect to the treatment. That is, in the month before a potential monetary policy announcement, household survey respondents cannot anticipate whether it will be reported on the television news. In a robustness check, we therefore also include leads of the variables of interest.

(6) As mentioned above, the key assumption for causal inference in a conventional DiD is common pre-dynamics or parallel trends. This implies that the dynamics in inflation expectations are the same prior to the monetary policy events and whether or not the measure is on the news. Such comparability can be considered in levels, both unconditional and conditional on covariates. In our setup, assuming common trends, we would expect similar effects of the announced ECB measures in the absence of television coverage. Section 5.3 provides some empirical estimates on pre-treatment dynamics.[32] However, the assumption we use in our stacked-DiD setup is the following. Conditional on two-way fixed effects, the lagged dependent variable as well as the vector of controls, we assume that the same types of monetary events covered on the evening news are independent of those not covered:

$$E[y_{jt}|\alpha_j, y_{jt-1}, X_{jt}, policy_{jt}, Euro/ECB^{MP}_{jt}] = E[y_{jt}|\alpha_j, y_{jt-1}, X_{jt}, policy_{jt}] \quad (5)$$

Angrist and Pischke (2008) argue that the coverage effect estimates denoted by β_k from equation 4 are causal if conditional independence holds, that is, if the

[32]One approach sometimes used to control for common trends is to include time trends in the DiD model. However, we only do so as a robustness check, as this could lead to an overfitted specification and potentially hurt the relationship between monetary policy and coverage and inflation expectations. For example, Wolfers (2006) has shown that controlling for pre-existing trends could cancel out the effect of policy or treatment.

expected outcomes for the treatment and control groups are the same (see equation 5). Moreover, the inclusion of a lagged dependent variable is considered the best proxy for the effects of omitted unobservable confounders. And when the assumption of common trends does not hold, adjusting for the lagged dependent variable has been shown to be the best approach (less biased, most efficient) when conducting causal inference in a generalized DiD design (O'Neill et al., 2016).

5 Results

5.1 TSCS Results

Table 3 shows regression results for equation 1 focusing on media coverage of inflation. News indicating an *increasing* inflation rate is positively correlated with an upward adjustment in *inflation expectations*. The opposite is true for news about *decreasing* inflation, which shows a negative correlation. Both coefficients are highly statistically significant and the magnitudes of the two effects are quite similar. A one percentage point increase in monthly news correlates with an adjustment of inflation expectations by more than 0.5 percentage point in the corresponding direction. Differentiating by tone shows that the correlation for news indicating *increasing* inflation is driven by those with negative tone. In contrast, for decreasing reports, we find that positively toned news shows the strongest significant correlation. With respect to the time reference of news, it is not surprising that a reference to the past is not significant, and both present and future news indicating rising prices have positive significant coefficients. In contrast, news indicating falling prices is consistently non-significant. Thus, in general, we can replicate the results of, e.g., Lamla and Lein (2014) or Dräger and Lamla (2017) with our TSCS dataset for four EMU countries and television news.

As in this first estimation, the controls remain statistically significant for the most part in the further specifications and consistently show the expected signs. In particular, the coefficients for the lagged dependent variable are highly significant, although the persistence in first differences is not very high. The change in the actual inflation rate is also highly relevant and positively associated. With restrictions, the output gap can also be considered relevant, while for the unemployment rate we can demonstrate statistical significance only in estimations of the stacked model below.

Focusing only on inflation-related news broadcast on days of monetary policy decisions, e.g., $increase^{MP}$, we find stronger effects, but the estimates tend not to be significant. This is not surprising, since messages indicating the direction of inflation are very rare on days of Government Council meetings (see Figure A.1).

Table 3: News about the Direction of Inflation and Inflation Expectations

	(1)		(2)			(3)	
ΔInflation Expectations$_{t-1}$	0.385***		0.385***			0.397***	
	(0.0507)		(0.0501)			(0.0489)	
ΔHICP Inflation	0.213***		0.200***			0.218***	
	(0.0454)		(0.0452)			(0.0444)	
Production Gap	0.00999		0.00979			0.0110*	
	(0.00688)		(0.00683)			(0.00662)	
Unemployment Rate	0.00257		0.00347			0.00297	
	(0.00409)		(0.00403)			(0.00394)	
Tone/Time Ref.		*pos.*	*neut.*	*neg.*	*past*	*pres.*	*fut.*
Increasing cov.	0.508***	-0.126	-0.00783	0.708***	-0.176	0.843***	1.328***
	(0.0843)	(0.807)	(0.183)	(0.103)	(0.270)	(0.203)	(0.400)
Decreasing cov.	-0.523***	-0.996***	-0.366*	-0.616	-0.556	-0.615	1.230
	(0.170)	(0.364)	(0.213)	(0.614)	(0.462)	(0.406)	(0.887)
Increasing^{MP} cov.	1.080		1.217			0.785	
	(0.773)		(0.774)			(0.750)	
Decreasing^{MP} cov.	-0.807		-0.467			-1.108	
	(0.765)		(0.778)			(0.762)	
Country FE	Yes		Yes			Yes	
Year FE	Yes		Yes			Yes	
Month FE	Yes		Yes			Yes	
No. of Observations	433		433			433	
R^2	0.550		0.568			0.568	

Notes: The dependent variable is $\Delta Inflation\ Expectations$. The table reports coefficients estimated using the PCSE estimator. Coefficients on dummies and panel-specific effects ρ_i are not reported. Panel corrected standard errors in parentheses. Standard errors account for cross-sectional dependence, heteroscedasticity and panel-specific autocorrelation of the error term.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

One could argue that this is incompatible with the ECB's primary objective. In particular, news about future price developments should be discussed more frequently. The magnitude of the impact suggests the potential importance that such reports and the coverage of central bank announcements can have. Assuming that a large share of households have very limited knowledge about central banks and monetary policy – let alone how to properly process announcements – additional information (about increasing or decreasing inflation) on days of Governing council meetings could improve understanding.

Table 4 shows estimates based on a slightly adjusted setup compared to equation 1. We are interested in the effects of monetary policy announcements and assume that the ECB's objective function is of Taylor rule type and that an inflation target of 2% applies. Therefore, we focus on the *inflation exp. gap* in-

Table 4: Monetary Policy News and the Inflation Expectations Gap

	(1)		(2)		(3)		(4)		(5)		(6)	
ΔInflation	0.397***		0.374***		0.395***		0.405***		0.385***		0.407***	
Exp. Gap_{t-1}	(0.0555)		(0.0548)		(0.0556)		(0.0562)		(0.0554)		(0.0561)	
ΔHICP Inflation	0.165***		0.161***		0.165***		0.165***		0.161***		0.168***	
	(0.0511)		(0.0497)		(0.0512)		(0.0519)		(0.0511)		(0.0520)	
Production Gap	0.0154*		0.0105		0.0159*		0.0171**		0.0147*		0.0170**	
	(0.00813)		(0.00809)		(0.00815)		(0.00825)		(0.00809)		(0.00827)	
Unemployment	-0.000102		0.00478		-0.0000869		0.00133		0.00490		0.00114	
Rate	(0.00486)		(0.00493)		(0.00486)		(0.00488)		(0.00498)		(0.00490)	
		pos.	*neut.*	*neg.*								
Euro/ECB cov.	0.0909***	0.0365	-0.00903	0.286***	0.0897***							
	(0.0234)	(0.109)	(0.0325)	(0.0518)	(0.0233)							
Euro/ECB^{MP} cov.	-0.250**	0.201	-0.0777	-0.775***	-0.284**	-0.189						
	(0.100)	(0.450)	(0.117)	(0.217)	(0.120)	(0.144)						
					delphic	*odyssean*						
								pos.	*neut.*	*neg.*		
Monetary Policy cov.							0.124***	-0.0671	-0.0383	0.378***	0.118***	
							(0.0458)	(0.167)	(0.0711)	(0.0847)	(0.0453)	
Monetary Policy^{MP} cov.							-0.337***	-0.215	-0.0769	-0.861***	-0.304*	-0.329*
							(0.127)	(0.664)	(0.155)	(0.241)	(0.166)	(0.169)
											delphic	*odyssean*
Country FE	Yes		Yes		Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes		Yes		Yes	
Month FE	Yes		Yes		Yes		Yes		Yes		Yes	
No. of Observations	433		433		433		433		433		433	
R^2	0.348		0.388		0.348		0.341		0.368		0.341	

Notes: The dependent variable is the *ΔInflation Expectations Gap*, i.e., it measures whether the distance of households expectations increase or decrease with respect to the ECB's target of 2%. The table reports coefficients estimated using the PCSE estimator. Panel corrected standard errors in parentheses. Standard errors account for cross-sectional dependence, heteroscedasticity and panel-specific autocorrelation of the error term.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

stead of considering *inflation expectations* as the dependent variable. The main explanatory variables are *Euro/ECB* and the more narrowly defined *monetary policy*. Overall, these two coverage variables show a positive correlation with the expectations gap, i.e., a deviation of expectations from the inflation target with increased coverage (see coefficients in columns 1 and 4). In contrast, $Euro/ECB^{MP}$ and *monetary policy*^{MP} are also significantly correlated but tend to close the gap. Thus, we find that central bank announcements via the media contribute to the anchoring of inflation expectations. Our estimation results further suggest a stronger and highly significant effect of negative news (columns 2 and 5).

Possible explanations for the relevance of negative news are discussed by Soroka (2006), among others, and can be twofold. First, negative news tends to be more prominent in the mass media, especially in time-limited television news programs, because of their selection. In other words, negative or controversial economic developments are more likely to make it into the news than positive ones. For example, in our sample, 67.2% of news stories pointing to *increasing* prices and 56.5% with reference to *Euro/ECB* are negatively toned. Second, it is well known that the public tends to react asymmetrically to news, with a stronger reaction to negative news, consistent with prospect theory (Kahneman and Tversky, 1980). Accordingly, Pfajfar and Santoro (2013) suggest that consumers perceive unfavorable inflation-related news more strongly. This is consistent with evidence showing that negatively toned news about inflation worsens the accuracy of inflation expectations, while positive news narrows the gap (Lamla and Lein, 2014) and affects the consistency of expectations (Dräger et al., 2016). In contrast, however, our results show that $Euro/ECB^{MP}$ closes the gap mainly when coverage of the policy takes on a negative tone. We suspect that the generally quite skeptical coverage of the ECB in the sample explains this.

Columns 3 and 6 of Table 4 show coefficients on the $Euro/ECB^{MP}$ and *monetary policy*^{MP} variables, differentiated by the type of monetary policy shock. We find that both news related to *delphic* and *odyssean* announcements tend to close the *inflation expectations gap*. However, in the case of the more broadly defined $Euro/ECB^{MP}$ news, the effect is not significant for *odyssean* measures. Overall, these results are consistent with recent research by Mazumder (2021), who finds that Fed coverage in newspapers closes the gap between consumer and professional forecasters' inflation expectations. While we find evidence of a narrowing effect of MP announcements in the media on inflation targeting, anchoring inflation expectations may not be the ultimate and only goal of monetary policy. Therefore, we proceed with the effect on *inflation expectations* itself to determine the relevance of coverage for different types of policy surprises.

Next, we present our main findings, focusing on the impact of various mone-

Table 5: Coverage of Monetary Policy by Direction and Type and Inflation Expectations

	Direction						*Type*		
	(1) pol. dummy	(2) policy	(3) pol. dummy × cov. dummy	(4) pol. dummy × coverage	(5) policy × cov. dummy	(6) policy × coverage	(7) policy	(8) policy × cov. dummy	(9) policy × coverage
exp. policy	0.0135	0.00208	-0.00971	0.0249	-0.00744	0.00271			
	(0.0622)	(0.00863)	(0.0621)	(0.0626)	(0.00899)	(0.00952)			
exp. policy × Euro/ECB^{MP} cov.			0.0539	-0.126	0.0202*	-0.00313			
			(0.0458)	(0.119)	(0.0107)	(0.0210)			
con. policy	0.0129	-0.0194**	0.0560	0.0294	0.0156*	-0.00749			
	(0.0610)	(0.00829)	(0.0609)	(0.0617)	(0.00926)	(0.00873)			
con. policy × Euro/ECB^{MP} cov.			-0.0984**	-0.180	-0.0526***	-0.0612***			
			(0.0465)	(0.116)	(0.0109)	(0.0187)			
delphic policy							0.00548	0.00967	-0.00417
							(0.0115)	(0.0122)	(0.0130)
delphic policy × Euro/ECB^{MP} cov.								-0.00785	0.0565*
								(0.0158)	(0.0289)
odyssean policy							-0.0163***	0.0122*	-0.00370
							(0.00600)	(0.00691)	(0.00656)
odyssean policy × Euro/ECB^{MP} cov.								-0.0452***	-0.0648***
								(0.00859)	(0.0175)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	433	433	433	433	433	433	433	433	433
R^2	0.509	0.511	0.519	0.512	0.545	0.519	0.510	0.544	0.527

Notes: The dependent variable is $\Delta Inflation$ *Expectations*. The table reports coefficients estimated using the PCSE estimator. *Policy* shocks differentiation by *direction* use the absolute values. Differentiation by type of policy use negative and positive values. Panel corrected standard errors in parentheses. Standard errors account for cross-sectional dependence, heteroscedasticity and panel-specific autocorrelation of the error term.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

tary policy shocks and their media coverage in an event study. Compared to other studies, we decouple the coverage effects from the overall reaction to the monetary policy shock. The estimates are obtained by including an interaction between the two variables as described in equation 2. We use both dummy variables and variables that capture the size of the shock and the intensity of coverage, respectively. The tables are organized to move from a general shock categorization to a more detailed categorization. In Table 5, we present coefficients that differentiate first by the *direction* and second by the *type* of shocks. The estimates in columns 1, 2, and 7 include only the monetary policy shocks and omit the interaction with the coverage variables.[33] While *expansionary* and *contractionary policy dummies* show no significant correlation with inflation expectations, *contractionary policy* that takes into account the size of the shock is negatively correlated. Coverage variables interacted with shocks show significant effects, especially for *contractionary* measures. Note that for a linear model and nonzero $coverage^{MP}$, only when a corresponding shock is observed, the interaction terms can be interpreted directly. The coefficients of the interaction term $policy \times Euro/ECB^{MP}\ cov.$ thus denote the marginal effects of coverage, so that the effect is measured against the overall effect of *policy*. The negative coefficients for *odyssean policy* in column 7 and for interactions with $Euro/ECB^{MP}\ cov.$ in column 8 and indicate the textbook adjustment of inflation expectations, i.e., an expansionary (negative) shock leads to an upward adjustment of these. In contrast, the coefficient on $delphic\ policy \times Euro/ECB^{MP}\ cov.$ in column 9 specification shows a positive coefficient and indicates an opposite adjustment of inflation expectations.

Table 6 presents event study estimates differentiating by all four policy types. We find significant coefficients on the interactions between policy and coverage for *delphic exp.*, *odyssean exp.*, and *odyssean con.* policies. By contrast, neglecting news coverage, we find only a significant coefficient for an *odyssean con.* policy shock. This clearly speaks for the media effect, while the specific adjustment of inflation expectations are subject to different patterns. On the one hand, following the announcement of an *odyssean* policy, the adjustment due to coverage is in the expected (textbook) direction for both expansionary and contractionary shocks. On the other hand, the coefficient on $delphic\ exp. \times Euro/ECB^{MP}\ cov.$ is of negative sign. This suggests that the coverage of additional information revealed by the central bank, e.g., on the state of the economy, leads to a downward revision of inflation expectations, even if the policy is of expansionary nature. Interestingly,

[33]Remember, to facilitate the interpretation of the coefficients, we use the absolute values of *policy* shocks wherever appropriate, e.g., when differentiating by *direction*. When differentiating by the *type* of measure, we use negative and positive values for *policy* shocks, since both include *contractionary* and *expansionary* policies. Accordingly, a dummy representation is not meaningful.

Table 6: Coverage of Monetary Policy Events and Inflation Expectations

	(1) pol. dummy	(2) policy	(3) pol. dummy × cov. dummy	(4) pol. dummy × coverage	(5) policy × cov. dummy	(6) policy × coverage
ΔInflation Expectations$_{t-1}$	0.495***	0.487***	0.486***	0.472***	0.473***	0.480***
	(0.0535)	(0.0528)	(0.0522)	(0.0527)	(0.0486)	(0.0508)
ΔHICP Inflation	0.216***	0.207***	0.218***	0.211***	0.192***	0.201***
	(0.0490)	(0.0476)	(0.0478)	(0.0479)	(0.0436)	(0.0457)
Production Gap	0.0165**	0.0137*	0.0156**	0.0147**	0.0116*	0.0130*
	(0.00726)	(0.00729)	(0.00724)	(0.00724)	(0.00694)	(0.00719)
Unemployment Rate	0.00104	0.00120	0.00117	0.00131	0.000994	0.00192
	(0.00456)	(0.00437)	(0.00464)	(0.00459)	(0.00430)	(0.00441)
delphic exp.	0.0268	-0.00997	-0.00370	0.0448	-0.00986	0.00371
	(0.0625)	(0.0132)	(0.0634)	(0.0627)	(0.0141)	(0.0153)
delphic exp. × Euro/ECB^{MP} cov.			0.0593	-0.286*	0.00306	-0.0668**
			(0.0593)	(0.156)	(0.0172)	(0.0314)
delphic con.	0.0438	-0.00977	0.0751	0.0408	0.0121	-0.00480
	(0.0688)	(0.0297)	(0.0739)	(0.0705)	(0.0278)	(0.0291)
delphic con. × Euro/ECB^{MP} cov.			-0.0680	-0.0160	-0.0444	-0.0546
			(0.0730)	(0.150)	(0.0435)	(0.0879)
odyssean exp.	0.0500	0.0107	0.0212	0.0488	-0.00593	-0.00242
	(0.0659)	(0.0109)	(0.0658)	(0.0663)	(0.0117)	(0.0122)
odyssean exp. × Euro/ECB^{MP} cov.			0.0650	0.0396	0.0322**	0.0755*
			(0.0664)	(0.178)	(0.0149)	(0.0408)
odyssean con.	0.0226	-0.0199**	0.0700	0.0617	0.0163*	-0.00687
	(0.0648)	(0.00854)	(0.0647)	(0.0650)	(0.00957)	(0.00897)
odyssean con. × Euro/ECB^{MP} cov.			-0.126**	-0.409**	-0.0530***	-0.0617***
			(0.0598)	(0.178)	(0.0113)	(0.0191)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	433	433	433	433	433	433
R^2	0.505	0.512	0.514	0.507	0.549	0.529

Notes: The dependent variable is the Δ*Inflation Expectations*. The table reports coefficients estimated using the PCSE estimator. Panel corrected standard errors in parentheses. Standard errors account for cross-sectional dependence, heteroscedasticity and panel-specific autocorrelation of the error term.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

then, households react in line with financial markets – measured by the nature of the shock – contrary to the theory that households often have heterogeneous views and understand the same announcement differently (Andrade et al., 2019). The direct involvement of experts in the news, who help prepare the reports and offer interpretations, can be seen as an explanation.

In terms of interpretation and magnitude of the effects, interactions with dummy variables are the easiest to read. For example, column 3 shows that inflation expectations are about 0.13 percentage points lower for an *odyssean con.* policy that receives news coverage compared with a policy of the same type that is not. Again, it is important to note that we find no significant effect of the *policy* itself, either in this regression or without considering the coverage at all (see column 1). Therefore, we are confident to say that the effects are also economically significant. The interpretation is different for interactions that consider the size of the shock, the intensity of coverage, or both at the same time. For example, the results in column 6 indicate the impact of a 1.0 percentage point coverage of a 1.0 basis point policy shock, ceteris paribus.[34] With a positive coefficient, this means that the linear marginal effect increases in both the size of the shock and the intensity of the coverage. That is, the larger the shock or the more intense the reporting, the stronger the effect of the central bank's announcements. Assuming, for example, that two *odyssean exp.* monetary shocks, small and large, experience the same intensity of coverage, the model suggests a stronger upward adjustment in inflation expectations for the larger shock. Similarly, for two monetary shocks of equal size with lower and greater coverage, greater coverage leads to a stronger adjustment in expectations. From Table A.1 we know that a mean shock is 2.5 basis points and mean coverage is 0.28 for *odyssean exp.* policies.[35] This corresponds to an average treatment effect of 0.05 percentage points upward adjustment in household inflation expectations relative to an uncovered shock.

5.2 Stacked DiD Results

In this section, we briefly report estimation results using the stacked data set, which allows us to use a generalized Difference-in-Differences design in levels with a lagged dependent variable to determine causality. In Table 7 we present regression results from the model depicted in equation 4 estimated using two-way fixed effects (POLS) and System-GMM.[36] As described in the methodological Section 4.2, we specify two types of standard errors to check the robustness of out findings, namely clustered and block bootstrapped standard errors. Note that we estimate the models in levels, but differences in inflation expectations between events are captured by event fixed effects as well as the lagged dependent variable.[37] Moreover, the regression results presented include all events from all four policy types in a single regression, which has the advantage that we have more observations and thus controls. Since the stacked dataset allows for individual estimation, see Section 5.3 and Table C.3 in the Appendix for policy-type specific estimates.

A comparison between the two-way fixed effects estimates and the GMM esti-

[34]We do not standardize the coefficients to either mean or standard deviation, because we comprehend these as less comparable across shock types.

[35]The mean sizes of the shocks differ significantly, while coverage intensity is fairly equal across the four policy types.

[36]For the stacked DiD equivalent of Table 5, i.e., regressions only differentiating between *direction* and *type*, please see Table C.2 in the Appendix.

[37]In DiD POLS regressions using the stacked panel, two-way fixed effects are included to account for unobserved heterogeneity across countries and time. In addition, it is standard to include time fixed effects as exogenous variables in a System-GMM, while fixed effects are assumed to be intrinsic to the estimator.

Table 7: Stacked DiD Estimates

	Fixed Effects				*GMM*			
	(1) pol. dum. × cov. dum.	(2) pol. dum. × cov. share	(3) policy × cov. dum.	(4) policy × cov. share	(5) pol. dum. × cov. dum.	(6) pol. dum. × cov. share	(7) policy × cov. dum.	(8) policy × cov. share
Inflation Expectations$_{t-1}$	0.701***	0.701***	0.704***	0.704***	1.180***	1.155***	1.152***	1.152***
	(0.0189)	(0.0192)	(0.0181)	(0.0186)	(0.107)	(0.106)	(0.111)	(0.109)
	(0.0185)	(0.0187)	(0.0177)	(0.0181)	(0.0932)	(0.0932)	(0.0950)	(0.0948)
Inflation Expectations$_{t-2}$					-0.386***	-0.362***	-0.358***	-0.359***
					(0.0935)	(0.0928)	(0.0973)	(0.0953)
					(0.0807)	(0.0811)	(0.0827)	(0.0824)
HICP Inflation	0.360***	0.356***	0.350***	0.353***	0.301***	0.304***	0.307***	0.310***
	(0.0309)	(0.0309)	(0.0302)	(0.0303)	(0.0354)	(0.0343)	(0.0360)	(0.0357)
	(0.0308)	(0.0307)	(0.0302)	(0.0301)	(0.0362)	(0.0357)	(0.0361)	(0.0363)
Production Gap	0.00832*	0.00810*	0.00791*	0.00770*	-0.00543	-0.00388	-0.00437	-0.00465
	(0.00457)	(0.00453)	(0.00460)	(0.00460)	(0.00749)	(0.00743)	(0.00765)	(0.00746)
	(0.00464)	(0.00462)	(0.00464)	(0.00465)	(0.00652)	(0.00657)	(0.00664)	(0.00660)
Unemployment Rate	-0.0624	-0.0613	-0.0611	-0.0647	-0.00959***	-0.00987***	-0.0100***	-0.0104***
	(0.0426)	(0.0429)	(0.0426)	(0.0427)	(0.00303)	(0.00299)	(0.00300)	(0.00298)
	(0.0443)	(0.0446)	(0.0442)	(0.0443)	(0.00325)	(0.00325)	(0.00317)	(0.00319)
delphic exp.	0.0130	0.0499	0.00661	0.0168	-0.0163	0.000739	-0.00181	0.00652
	(0.0331)	(0.0351)	(0.0114)	(0.0137)	(0.0275)	(0.0260)	(0.0125)	(0.0150)
	(0.0332)	(0.0355)	(0.0136)	(0.0151)	(0.0302)	(0.0277)	(0.0119)	(0.0149)
delphic exp. × Euro/ECB^{MP} cov.	0.0357	-0.289*	-0.0122	-0.0800**	0.00906	-0.222**	-0.00424	-0.0580*
	(0.0707)	(0.169)	(0.0218)	(0.0387)	(0.0655)	(0.0886)	(0.0246)	(0.0310)
	(0.0703)	(0.176)	(0.0255)	(0.0562)	(0.0644)	(0.106)	(0.0265)	(0.0412)
delphic con.	0.0772*	0.0364	0.0259	0.0108	0.0302	0.0218	0.0162	0.0212
	(0.0444)	(0.0336)	(0.0217)	(0.0183)	(0.0362)	(0.0296)	(0.0141)	(0.0142)
	(0.0449)	(0.0347)	(0.0223)	(0.0191)	(0.0375)	(0.0307)	(0.0148)	(0.0138)
delphic con. × Euro/ECB^{MP} cov.	-0.0858	-0.0182	-0.0408	0.00563	-0.0198	-0.0666	0.00478	-0.0345
	(0.0538)	(0.109)	(0.0277)	(0.0458)	(0.0517)	(0.0788)	(0.0272)	(0.0272)
	(0.0544)	(0.147)	(0.0295)	(0.127)	(0.0501)	(0.129)	(0.0251)	(0.0723)
odyssean exp.	-0.0649**	-0.0177	-0.0213**	-0.0104	-0.0459	-0.0174	-0.0202	-0.0125
	(0.0311)	(0.0294)	(0.00990)	(0.0102)	(0.0298)	(0.0309)	(0.0124)	(0.0118)
	(0.0316)	(0.0298)	(0.0107)	(0.0107)	(0.0258)	(0.0284)	(0.0103)	(0.0104)
odyssean exp. × Euro/ECB^{MP} cov.	0.183***	0.269*	0.0418***	0.0800*	0.154**	0.282*	0.0429**	0.112***
	(0.0534)	(0.151)	(0.0144)	(0.0439)	(0.0655)	(0.161)	(0.0200)	(0.0421)
	(0.0538)	(0.161)	(0.0162)	(0.0561)	(0.0622)	(0.184)	(0.0195)	(0.0554)
odyssean con.	0.0409	0.0243	0.0220**	0.000440	0.0216	0.0325	0.00908	0.00184
	(0.0373)	(0.0428)	(0.00935)	(0.0162)	(0.0392)	(0.0396)	(0.0104)	(0.0101)
	(0.0371)	(0.0432)	(0.00992)	(0.0170)	(0.0358)	(0.0383)	(0.0120)	(0.0146)
odyssean con. × Euro/ECB^{MP} cov.	-0.123	-0.329	-0.0528***	-0.0683*	-0.0823	-0.474*	-0.0359**	-0.0738***
	(0.0803)	(0.313)	(0.0191)	(0.0376)	(0.0559)	(0.251)	(0.0145)	(0.0235)
	(0.0794)	(0.311)	(0.0207)	(0.0592)	(0.0641)	(0.243)	(0.0205)	(0.0425)
Event FE	Yes	Yes	Yes	Yes	No	No	No	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	2,595	2,595	2,595	2,595	2,583	2,583	2,583	2,583
No. of Events	376	376	376	376	374	374	374	374
No. of instruments					97	97	97	97
AR1 (p-value)					[0.000]	[0.000]	[0.000]	[0.000]
AR2 (p-value)					[0.419]	[0.348]	[0.385]	[0.354]
Hansen-J (p-value)					[0.778]	[0.754]	[0.810]	[0.778]
R^2	0.833	0.833	0.834	0.833				

Notes: The dependent variable is *Inflation Expectations* in levels. The table reports coefficients estimated using two-way fixed effects and two-step System-GMM (GMM-Style: control variables considering up to three lags; IV-Style: policy and coverage variables as well as time dummies considered exogenous in the level equation). In addition to clustered standard errors at the individual event level (upper parentheses) we report panel (block-)bootstrapped standard errors estimated using 2000 replications (lower parentheses).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using clustered standard errors.

mates confirms the consistency of the models used.[38] However, the coefficients of interest in the GMM regression are found to be slightly less statistically significant. But overall, the generalized DiDs confirm the results from the TSCS event study. Again, we find significant effects for all interaction terms except for the coverage of *delphic con.*, and we find no evidence that adjustment is driven solely by the policy shocks themselves. In most cases, the coefficients for the policy variables are not significant, and sometimes they even have opposite signs. This means we are able to confirm the textbook effect for coverage of *odyssean* shocks and the counterintuitive effect for coverage of *delphic exp.* policies. However, the results remain inconclusive with respect to *delphic con.* policies, as the coefficients in all specifications show different signs and magnitudes.

5.3 Evaluating the Common Trend Assumption and Model Robustness

The availability of multiple pre-treatment periods for each event allows us to empirically test the assumption of a common trend. Table 8 shows the results of our tests. We compute the mean values of $\Delta inflation\ expectations$ for the six months preceding the monetary policy decisions from the stacked dataset. We distinguish between the different types of policies and according to whether an event is on the news or not. The calculated mean differences can be used to assess the equivalence of trends, and a standard t test determines statistical significance. We find evidence of common trends for all types of measures except *delphic exp.*, where the null is rejected at 10%. However, for the conditional means, computed as the residuals of a regression of our dependent variable on the full set of controls in the periods preceding each event, the estimated differences decrease. In terms of statistical significance, we can no longer reject the assumption of common pre-dynamics for all four types of measures. As an additional test, we use the statistical package of Mora and Reggio (2015), which includes a quantitative test for the assumption of common pre-dynamics. For all four specifications, the test fails

[38] As noted above, we use the System-GMM estimator to adequately account for potential endogeneity problems arising from the parallel use of fixed effects and the lagged dependent variable (Blundell and Bond, 1998). The significant coefficient on lagged inflation expectations in the level model indicates high persistence of the dependent variable, justifying dynamic modeling and the use of the System-GMM estimator. The Arellano-Bond test for AR(2) rejects the null hypothesis of no second-order serial correlation of the first-differenced errors. Thus, for the GMM specification, both the AR(2) and Hansen overidentification tests support the specification. The number of instruments is significantly lower than the total number of observations, with $T < N$, we do not interpret the relatively high value in the Hansen statistic as a concern and suspect that the instrument proliferation as described by Roodman (2009) is not a problem. The compound coefficient on the two lags of the dependent variable confirms the high persistence, but solves the problem of higher order serial correlation. Further, we assume that the variables of interest *policy* and $policy \times Euro/ECB^{MP}cov.$ are strictly exogenous.

to reject the hypothesis of common pre-dynamics at conventional levels under the assumption of the so-called fully flexible model. In addition to these tests, Figure C.1 in the Appendix shows the trends in levels. However, visual inspection is not entirely conclusive in this regard. Moreover, the effects of the policy shock and its range tend not to be large in the unconditional data series presented.

Given the limited evidence of common trends in a few cases, we would like to remind that rejecting the assumption of common trends does not automatically invalidate the results. In particular, the inclusion of a lagged dependent variable in the stacked DiD model and the use of a GMM estimator allow us to consider the evidence as causal (Angrist and Pischke, 2008; O'Neill et al., 2016). Nevertheless, it is important to check the robustness of the results in additional series of robustness tests with alternative estimations, which we discuss below.

First, we are confident that the model specifications we used and the composition of the variables confirm the internal validity of the results. Comparing the estimated coefficients from the event study in Table 6 and the DiD estimates in Table 7, we find that the effects of coverage do not depend on functional form. In addition to using two different datasets and applying complementary estimators, we use both dummy variables and intensity variables as our main explanatory variables. Although we believe it is important to control for the magnitude of shocks and coverage covering the significance of the monetary surprise and intensity of reporting, we also find effects with the dummy variables representing a conventional DiD approach.

Second, Figure C.2 in the Appendix shows a standard event study plot from TSCS panel estimates, that is, the evolution of the coefficients over time in our case with a lead effect (to capture potential anticipatory effects) and a lag effect (effects with a time lag or explained by imprecise isolation of the measures and the survey period) of the interactions between policy and coverage. The figure shows a clear spike in effects at the time of the event, significant except for *delphic con.* at the 10% level, which is also an additional indicator of the credibility of the assumption of parallel trends. Only the lead coefficient for *odyssean exp.* events is also slightly statistically significant. Anticipation, however, is almost impossible because the relevant treatment is not the shock but the coverage. This is only plausible for a large announcement that is highly likely to occur due to a worsening economic situation and is therefore likely to be captured. This seems to be the case for *odyssean exp.* announcements, as indeed in a number of additional regressions we can trace the effect to announcements at the height of the financial crisis in 2008. Moreover, by comparison, we find no such effect when using leads in DiD specifications.[39]

[39]Tables for these results are available upon request.

TABLE 8: TESTING FOR COMMON PRE-DYNAMICS

	unconditional means					*conditional means*					MR(2015)
	no cov.	Euro/ECB cov.	diff.	No of Observations		no cov.	Euro/ECB cov.	diff.	No of Observations		H0: Common Pre-Dynamics
ΔInflation Expectations											
delphic exp.	0.00721	-0.0767	0.0839	233	169	0.00120	0.00396	-0.00276	217	147	8.388
	(0.0258)	(0.0365)	[0.0539]			(0.0225)	(0.0335)	[0.943]			[0.136]
delphic con.	-0.0828	-0.0898	0.00706	168	166	0.0151	-0.0229	-0.0379	146	145	4.849
	(0.0311)	(0.0321)	[0.875]			(0.0235)	(0.0277)	[0.296]			[0.435]
odyssean exp.	0.00815	0.0406	-0.0325	206	184	-0.0164	0.0157	-0.0320	182	161	5.452
	(0.0160)	(0.0211)	[0.215]			(0.0161)	(0.0222)	[0.237]			[0.363]
odyssean con.	0.0120	-0.0253	-0.0373	232	183	-0.00228	-0.00992	-0.00764	207	161	9.070
	(0.0202)	(0.0365)	[0.347]			(0.0190)	(0.0331)	[0.833]			[0.106]

NOTES: This table reports the mean values of $\Delta Inflation\ Expectations$ related to the indicated monetary policy events. The statistics are computed using pooled observations (from the stacked dataset and adjusted for duplicates) for the six months ahead of the event; for each, the treatment period, where the ECB's policy takes place and receives coverage or not is dropped. We distinguish between the means of the treated group and the control group. A non-significant t-test on the difference indicates common trends. P-values are denoted in brackets. Conditional means are computed using the residuals from the baseline model denoted in equation 4 including the full set of controls and time dummies. Additionally, we make use of the Stata programme `didq` by Mora and Reggio (2015). The fully flexible model either assume parallel paths (Parallel-1) or parallel growth rates (Parallel-2) of the dependent variable. Standard errors are adjusted for clusters in the individual events. The test for common pre-dynamics tests for the joint equivalence of all parallel-q assumptions (up to the number of included pre-treatment periods).

Third, Table C.1 in the Appendix provides estimates for a number of robustness checks using the event study framework with the TSCS panel. These include various model specifications, falsification tests using an unrelated dependent variable, and the use of alternative or restricted samples. The main results appear to be quite robust, although we note some limitations, which we attribute mainly to the relatively small sample. While the other coefficients remain robust, we find that the coefficient on *odyssean exp.* $\times$ $Euro/ECB^{MP}$ is no longer significant for a model without controls, a model without lagged dependent variable, a model without the monetary policy variables, and a model with 90% winsorized variables.[40] Since the direction and magnitude of the effect are fairly stable, these results suggest only weak statistical identification. Column 4 shows the results of a falsification test using *inflation perceptions* as a placebo outcome variable. In theory, the 12-month perceptions reported in the survey should not be affected by monetary policy interventions and their reporting within the last month. The estimated coefficients provide a strong empirical case for this and hence in favor of our main results; the coefficients are very small and not statistically different from zero. The (insignificant) estimates from the post-GFC sample in column 5 are likely due to the smaller sample size, but may also indicate a lack of effectiveness of *odyssean* policies during this period. In addition, *contractionary* policies have become less important during this period, which may also contribute to the low coefficients on these policies.

Another important problem, which we also discuss in Section 4.3, is the possible endogeneity of coverage. The problem is that the effect actually caused by the policy surprise may be reflected in the coefficients of the media variables. To control for the possibility that only larger and more important ECB decisions receive coverage on the evening news, we run an additional regression with a restricted data set denoted in column 7. We restrict the TSCS panel in two ways: (1) We exclude all shocks and coverage of events that are not covered by any country and would otherwise serve as a control group, and (2) those where all countries cover the event simultaneously. In this way, we exclude all minor and major policy announcements. Overall, the results show the robustness of the *expansionary* policy results. However, the coefficient for *odyssean con.* $\times$ $Euro/ECB^{MP}cov.$ becomes irrelevant both from an economic point of view and in terms of statistical significance, while the coefficient on *odyssean con.* policy is even implausible. We again attribute this result to the lower statistical significance of the restricted data set.

Fourth, Table C.3 in the Appendix provides estimates for the following two

[40] We winsorize inflation expectations, the size of the monetary policy shock, and the intensity of coverage.

model-specific robustness checks using the DiD framework with the stacked panel: (1) As discussed in Section 5.3, some DiD specifications promote the addition of policy-specific linear trends. We find that the DiD results are robust to the inclusion of trends, especially in the most precise specifications of $policy \times coverage$ (see the left-hand side of Table C.3). (2) The results are slightly less significant if we estimate the coefficients for each panel containing only observations for policy k individually, rather than estimating the coefficients in the pooled stacked panel (see the right-hand side of Table C.3). Again, the specifications including an interaction between *policy* $\times$ *coverage* are the most robust, while estimates with *dummy* variables are less robust.

6 Conclusion

This paper argues that evening news is a shortcut to central bank announcements for the general public. The main results suggest that there is a causal relationship between the coverage of Governing Council decisions and households' 12-month inflation expectations. That is, when a monetary policy measure receives news coverage, the adjustment in inflation expectations is stronger than when it is not covered.

We first use the evening television news to confirm previous findings that there is a transmission mechanism between news coverage and household inflation expectations when changes in the inflation rate are clearly indicated. We now add to this that households also respond to news coverage of monetary policy announcements. Our identification method shows that evening news coverage is indeed a relevant channel, and we expect the news to serve as a mediator for the prompt and stronger response of inflation expectations to monetary policy announcements because of (1) the higher visibility of the decision, i.e., more people take notice of it, and (2) the greater importance attached to the monetary policy announcements through news coverage. This applies both to individuals in their expectation formation and to other news outlets in their role as agenda setters. First, we find a causal relationship between the optimal announced signals and inflation expectations conditional on communication and coverage, i.e., noise. Second, we inform the model by empirical evidence to differentiate between delphic monetary policy announcements, which are primarily informational in nature, and lead to a reverse adjustment, i.e., expansionary surprises cause households to lower their inflation expectations, as opposed to a textbook odyssean shock, is consistent with the findings of the related literature for financial markets (e.g., Kerssenfischer, 2019).

The following recommendations for central banks can be derived from the findings. Apart from pushing into new formats such as social media, policymakers should continue to view television news as a form of traditional mass media that also provides a window with direct access to households. This follows from two observations. First, the evening news still draws the public's attention to new information – in our case, the summary of the monetary policy decision in a condensed and widely accessible overview – that they might otherwise overlook or obtain only at greater cost. Second, usage of original material, such as the President's statements at the press conference, allows policymakers to provide an unfiltered view. However, since (evening) news is time-limited, newsrooms will only cover monetary policy events if they are considered relevant enough and news pressure allows for it, as they compete with other newsworthy events, a restriction we implicitly use for identification. Further research could therefore discuss and analyze the factors that determine the likelihood of coverage in a manner similar to the analysis of the favorability of coverage by Berger et al. (2011) and Ehrmann and Wabitsch (2022). It is reasonable to assume, however, that direct, unfiltered access to people's living rooms through television is only possible if the messages are short enough to be captured and if they are written in language that can be understood by a wide audience. Our results therefore point in the direction of the finding in the literature that simple messages are better (e.g., Coibion et al., 2020; Kryvtsov and Petersen, 2021).

Further research should also expand the sample of countries and extend the time period to improve statistical inference in the effect of coverage treatments. This would then even allow for the use of a conventional DiD to determine the causal effects even more explicitly. Other lines of research could also focus on and analyze heterogeneities in the transmission of monetary policy announcements through the media, especially television, across time, countries, and sociodemographic factors.

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A Further Information on the Dataset

The monthly data series cover the period from January 2006 to November 2016. This results in a theoretical maximum number of 131 observations each. However, due to missing data for each of the four country cross sections France, Germany, Italy and Spain, this number is lower in each case and ranges between 94 and 129. Summary statistics for the main variables are presented in Table A.1.

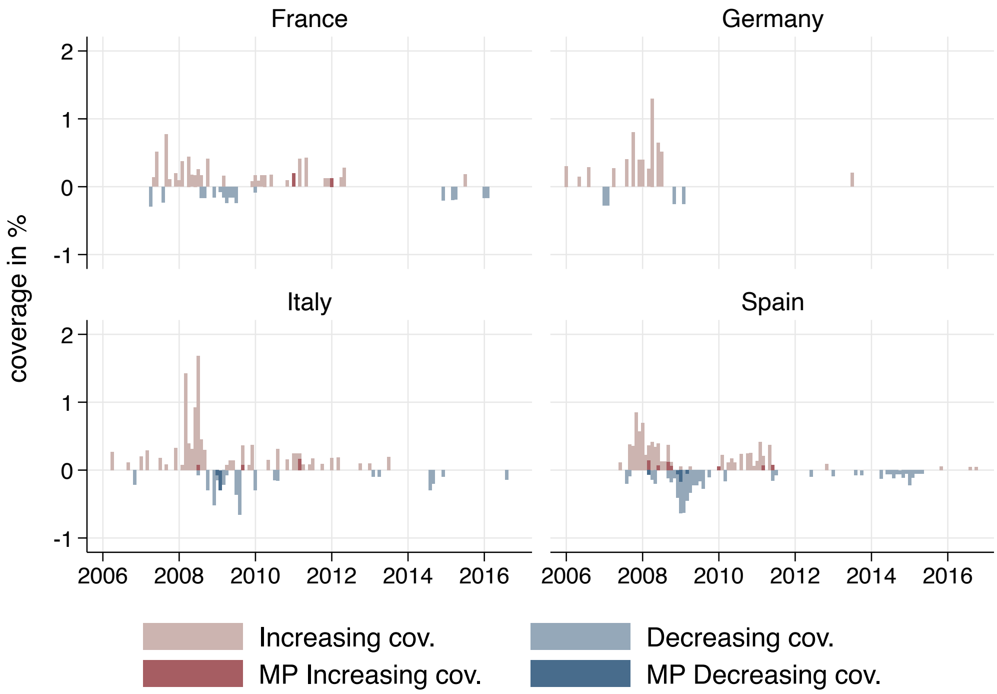
HICP Inflation: Monthly annual growth rate of the country-specific Harmonized Index of Consumer Prices (HICP) in percent. Source: Eurostat.
Inflation Expectations: Quantitative data from the qualitative question Q6 in the harmonized business and consumer surveys. See Appendix B for information on quantification. In addition, we use question Q5 in the quantification exercise, which yields the variable *inflation perceptions*. Accurate information on the survey period and release dates of the surveys is used to adjust the daily series on monetary policy events and media coverage. *Inflation expectations* and *Inflation perceptions* are expressed as annual percentage changes. Source: European Commission.
Media Data: All news items are available at daily frequency. The *coverage* variables used in the regressions are the monthly shares of specific news items of total news items in percent. Source: Mediatenor.
Monetary Policy Data: Shocks are quantified by the change in the three-month index swap rate (*OIS_3M*) in basis points in the event window. Daily data are transformed into monthly data. In all but one month, there is at most one monetary policy surprise. The two shocks in October 2008 are of different types and are therefore included individually. Identifying *odyssean* (purely monetary) and *delphic* (primarily informational) shocks follows high-frequency identification using sign restrictions for OIS_3M and (EURO-)$STOXX\_50$ (Jarociński and Karadi, 2020). Source: Altavilla et al. (2019).
Production Gap: Volume index of production including construction. Seasonally and calendar adjusted. Cylical component of the HP-filtered series (λ = 14,400) in percentage points. Source: Eurostat.
Unemployment Rate: Harmonized unemployment rates (ILO) in percent. Seasonally adjusted. Source: Eurostat.

Table A.1: Summary Statistics

	No. of Obs.	mean	sd	min	max
Inflation Exp.	433	1.595	1.750	-0.368	8.844
ΔInflation Exp.	433	-0.011	0.365	-2.373	1.584
ΔInflation Exp. Gap	433	0.087	3.513	-13.583	10.404
ΔInflation Perc.	433	-0.019	0.522	-3.430	2.598
ΔHICP Inflation	433	-0.012	0.380	-1.200	2.300
Production Gap	433	0.060	3.552	-13.583	10.404
Unemployment Rate	433	10.751	5.681	3.900	26.300
Increasing cov.	433	0.070	0.182	0	1.682
Increasing^{MP}*cov.*	433	0.003	0.191	0	0.196
Decreasing cov.	433	0.033	0.091	0	0.660
Decreasing ^{MP}*cov.*	433	0.017	0.018	0	0.295
Euro/ECB cov.	433	0.746	0.853	0	5.534
Euro/ECB^{MP}*cov.*	433	0.095	0.175	0	1.410
delphic exp.					
ΔInflation Exp.	119	-0.040	0.411	-1.562	1.584
policy	119	1.718	2.234	0.050	11.200
coverage	41	0.255	0.224	0.056	0.984
delphic con.					
ΔInflation Exp.	66	-0.025	0.240	-1.021	0.739
policy	66	1.120	1.275	0.075	4.375
coverage	33	0.240	0.265	0.051	1.410
odyssean exp.					
ΔInflation Exp.	90	0.043	0.228	-0.478	1.088
policy	90	2.458	2.934	0.015	11.000
coverage	38	0.275	0.178	0.053	0.830
odyssean con.					
ΔInflation Exp.	99	-0.030	0.533	-2.373	1.401
policy	99	2.923	4.145	0.050	16.150
coverage	43	0.259	0.154	0.056	0.766
Monetary Policy cov.	433	0.320	0.435	0	3.111
Monetary Policy^{MP}*cov.*	433	0.058	0.134	0	0.940

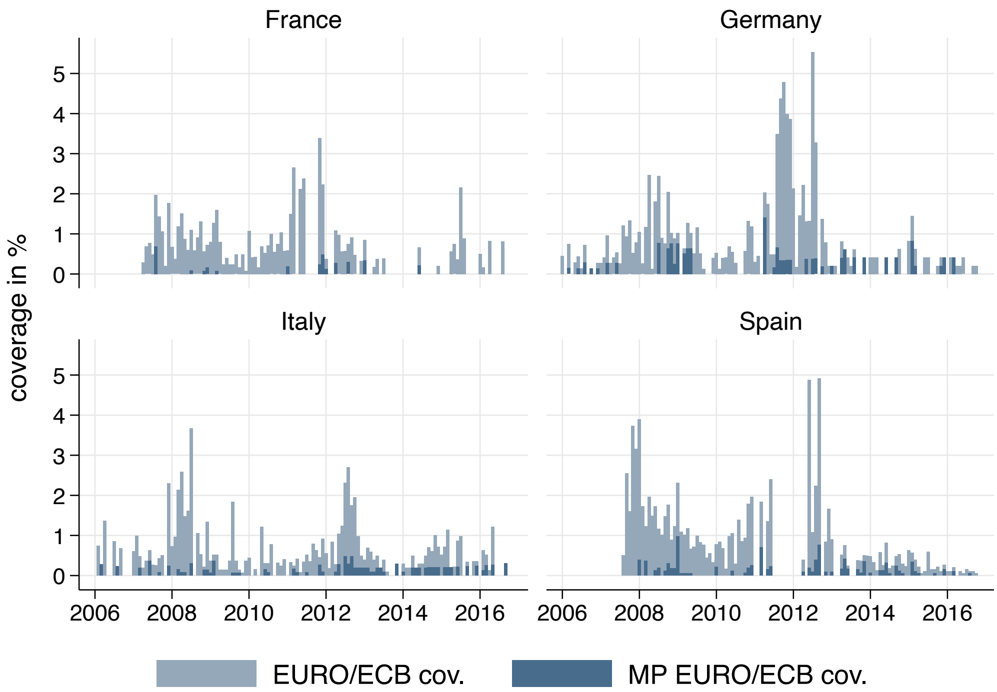
Notes: *Inflation exp.*, the *unemployment rate* and the individual *coverage* shares are expressed in percent. Changes (Δ) and the *production gap* are measured in percentage points. Monetary *policy* shocks (event window OIS_3M changes) are denoted in basis points. The statistics presented under each of the four policy *types* refer to these events and for meaningful information include only data where the variable is different from zero. *Coverage* refers to *Euro/ECB* news and is denoted in percent. Dummy variables are omitted as they can be inferred from the number of observations.

Figure A.1: News indicating the Direction of Inflation



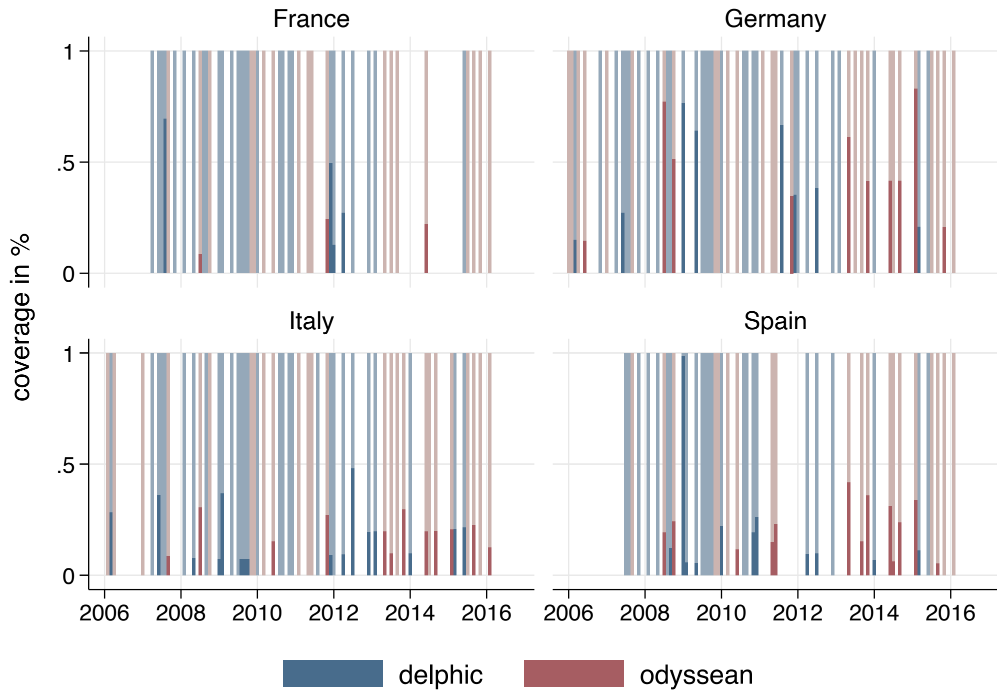
Notes: The variables *increasing*^{MP} and *decreasing*^{MP}, respectively, refer to news on days of a Governing Council monetary policy meeting and are therefore subsamples of the overall monthly reporting of *increasing* and *decreasing* inflation. The coverage shares are calculated as the number of news with the respective content divided by all monthly news.

Figure A.2: Euro/ECB on the News



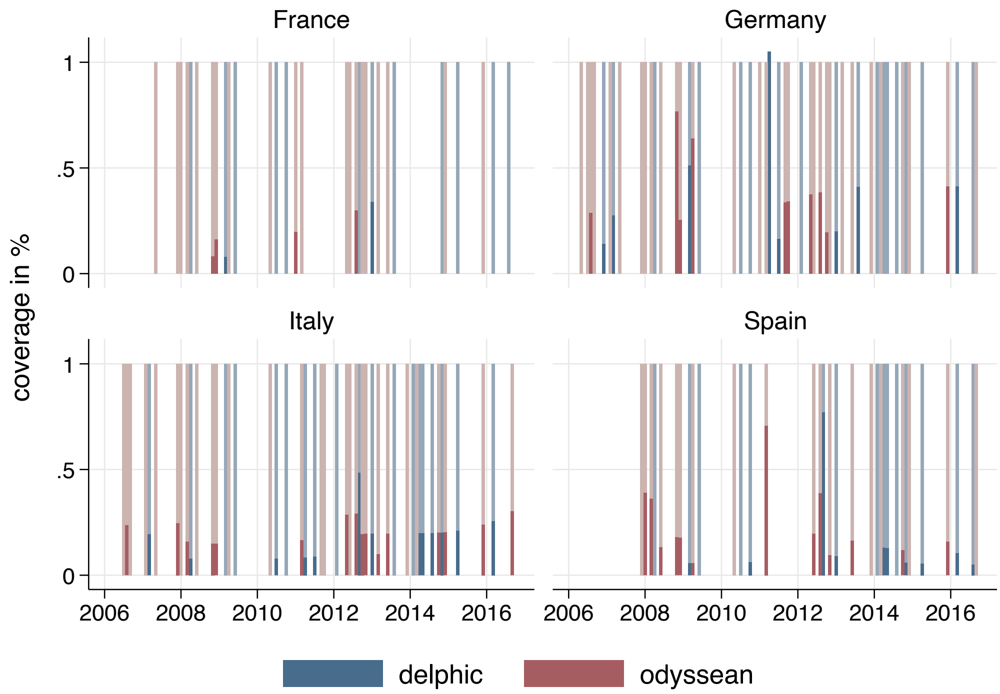
Notes: The variable $Euro/ECB^{MP}$ refers to news on days of a Governing Council monetary policy meeting and is therefore a subsample of the overall monthly coverage of the $Euro/ECB$. The coverage shares are calculated as the number of news with the respective content divided by all monthly news.

FIGURE A.3: EXPANSIONARY MONETARY POLICY AND COVERAGE



NOTES: Light-colored bars indicate the type of the monetary policy decision. The dark bars indicate whether an event received coverage on the evening news on the day of the event while the shares documents the intensity of reporting. Months with missing media data are omitted.

FIGURE A.4: CONTRACTIONARY MONETARY POLICY AND COVERAGE



NOTES: Light-colored bars indicate the type of the monetary policy decision. The dark bars indicate whether an event received coverage on the evening news on the day of the event while the shares documents the intensity of reporting. Months with missing media data are omitted.

B Quantification of Inflation Expectations

We quantify consumers' *inflation expectations* using data series from the European Commission's (EC) polychotomous tendency survey.[41] The calculation follows the probabilistic approach first proposed by Carlson and Parkin (1975). Modified forms of this approach have been widely used for EC business and consumer survey data (e.g., Forsells and Kenny, 2004; Arnold and Lemmen, 2008; Lamla and Lein, 2014; Dräger, 2015; Lamla and Lein, 2015). The assumptions, caveats, and strengths of such approaches have been critically discussed in many of these studies.

As can be seen in equation 6 below, the approach first requires a scaling factor, since respondents are likely to base their expectations on perceptions of current inflation (Forsells and Kenny, 2004). Assuming that consumers' perceived inflation rate is unlikely to be adequately and fully represented by the current official rate, as suggested by Berk (1999), we use the quantified subjective *inflation perception* π^p derived from the preceding survey question and relates to the twelve months before.[42] The quantification of the *inflation perception* series is similar to the calculation of the *inflation expectations* π^e. Here, we use the three-month moving average of the *HICP inflation rate* π as the corresponding scaling factor.

The original survey questions are:

Question 5: How do you think that consumer prices have developed over the last 12 months? They have...

...risen a lot (PP)

...risen moderately (P)

...risen slightly (E)

...stayed about the same (M)

...fallen (MM)

...don't know (N)

[41] We use only the "total" series, which are intended to reflect representative expectations of households. The database also offers the possibility to differentiate by sociodemographic categories such as income, age, occupation, or education.

[42] Berk (1999) point out that making use of further survey information requires an adaption in the calculation due to different wording of the answers. Assuming ordinal order we basically shift each answer (except MM) upwards as indicated.

Question 6: By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months? They will...

...increase more rapidly (PP)

...increase at the same rate (P)

...increase at a slower rate (E)

...stay about the same (M)

...fall (MM)

...don't know (N)

The calculation of the twelve months ahead quantitative *inflation expectations* series follows Forsells and Kenny (2004):

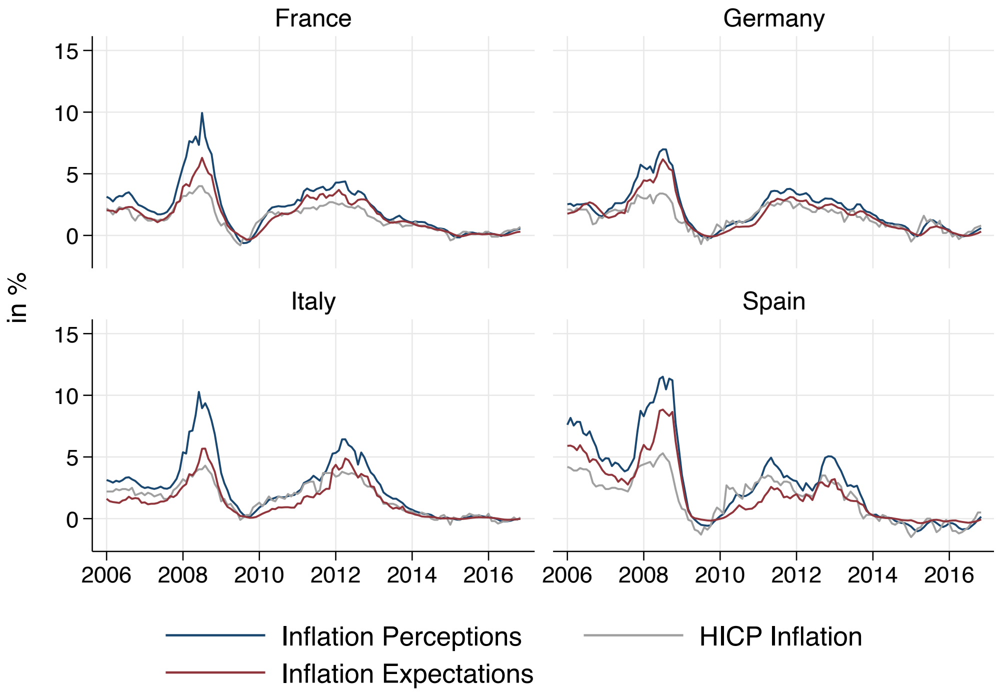
$$\pi_t^e = -\pi_t^p \left(\frac{Z_t^3 + Z_t^4}{Z_t^1 + Z_t^2 f Z_t^3 - Z_t^4} \right) \tag{6}$$

with

$$\begin{aligned}
Z_t^1 &= N^{-1}(1 - S_t^{PP}) \\
Z_t^2 &= N^{-1}(1 - S_t^{PP} - S_t^P) \\
Z_t^3 &= N^{-1}(1 - S_t^{PP} - S_t^P - S_t^E) \\
Z_t^4 &= N^{-1}(S_t^{MM})
\end{aligned}$$

where, e.g., S_t^{PP} is the share of respondents expecting a rapid increase (see abbreviations above) in the inflation rate and N^{-1} describes the inverse of the assumed cumulative probability function of inflation expectations in the population. The distribution function is assumed to be normal because Berk (1999) has shown that a normal distribution is as accurate as non-normal peaked or asymmetric distributions.

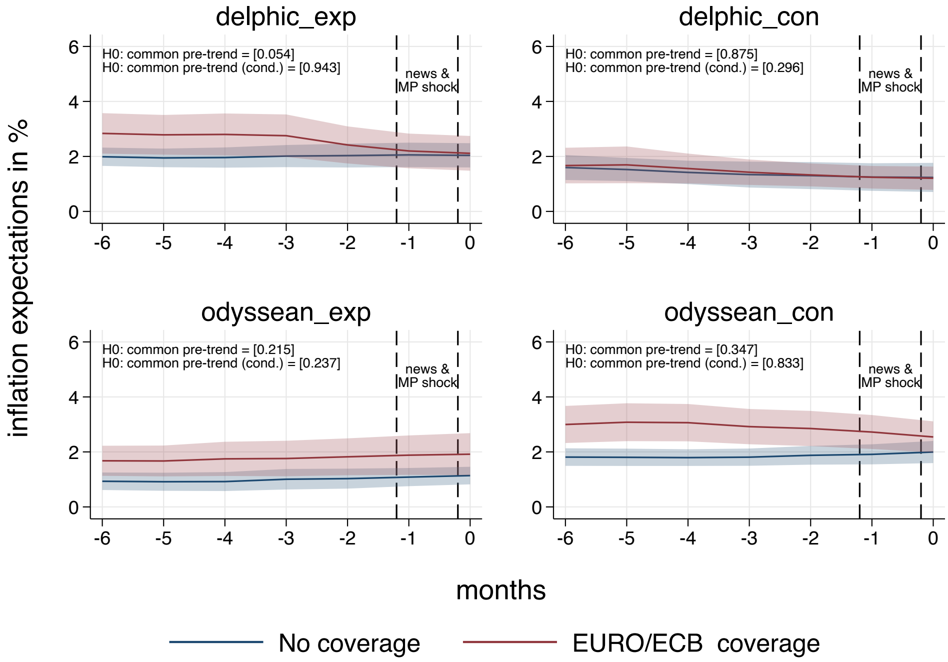
Figure B.1: Inflation, Inflation Perceptions and Inflation Expectations across Countries



Notes: Household *inflation expectations* and *inflation perceptions* are derived from qualitative data series of the European Commission (EC) tendency survey, following the approach by Forsells and Kenny (2004). *HICP inflation* is based on Eurostat data.

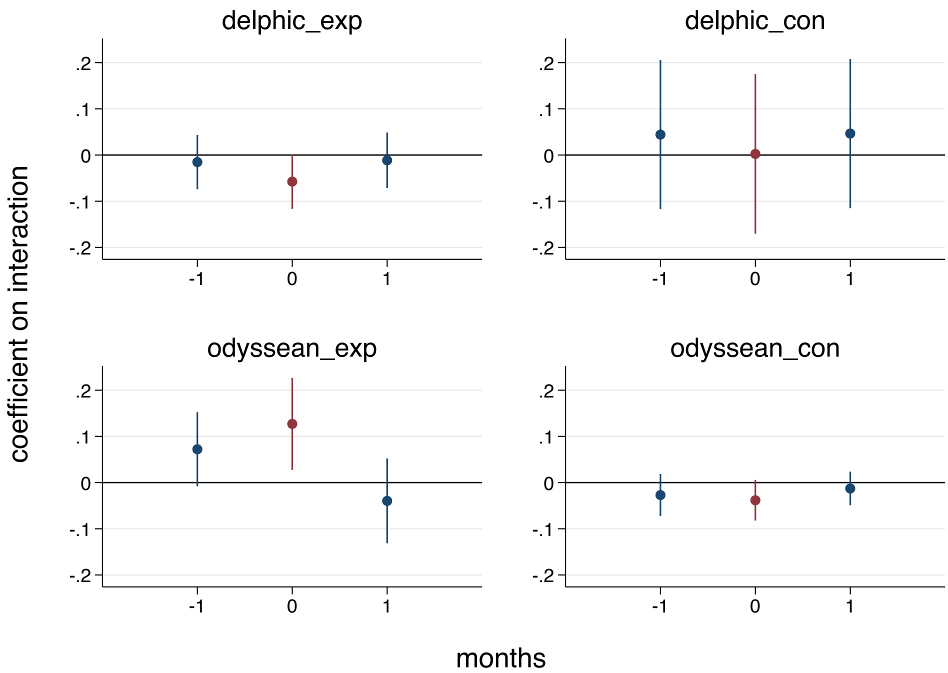
C Further Figures and Tables

Figure C.1: Pre-dynamics of Inflation Expectations by Event



Notes: The charts show the unweighted average pre-announcement dynamics of *inflation expectations* by type of monetary policy decision. Shaded bands reflect 95% confidence intervals. The monetary policy announcement and coverage thereof take place at time = 0. For each type we distinguish between the countries treated, i.e., the policies receiving coverage, and the untreated.

Figure C.2: Event Study with Leads and Lags



Notes: The plots show the values of the estimated coefficients on the interaction term between the variables denoting the size of the monetary *policy* shock and the *coverage* intensity with 95% confidence intervals from our TSCS model. Leads and lags refer to one month before and one month after the actual event.

Table C.1: Event Study Model Robustness

	(1) without controls	(2) without lagged dependent	(3) without MP surprises	(4) Dep. Inflation Perceptions	(5) Post GFC	(6) Winsorized Variables	(7) Restricted Dataset
ΔInflation Expectations$_{t-1}$	0.537***		0.472***		0.203***	0.401***	0.476***
	(0.0538)		(0.0526)		(0.0577)	(0.0480)	(0.0523)
ΔInflation Perceptions$_{t-1}$				0.446***			
				(0.0448)			
ΔHICP Inflation		0.164***	0.212***	0.524***	0.0298	0.130***	0.207***
		(0.0475)	(0.0480)	(0.0561)	(0.0321)	(0.0320)	(0.0466)
Production Gap		0.0235***	0.0150**	0.0209**	0.00989	0.0150***	0.0191***
		(0.00850)	(0.00726)	(0.00937)	(0.00686)	(0.00526)	(0.00705)
Unemployment Rate		0.00214	0.00258	-0.00254	0.0118***	0.000676	0.00200
		(0.00613)	(0.00440)	(0.00554)	(0.00441)	(0.00363)	(0.00439)
delphic exp.	0.00395	0.00140		0.00349	0.00728	-0.00509	0.0122
	(0.0168)	(0.0163)		(0.0195)	(0.0111)	(0.0162)	(0.0163)
delphic exp. × Euro/ECB^{MP} cov.	-0.0651**	-0.0586*		-0.0569	-0.0642***	-0.106**	-0.0746**
	(0.0325)	(0.0324)		(0.0438)	(0.0208)	(0.0468)	(0.0341)
Euro/ECB cov. (delphic exp.)			-0.278*				
			(0.148)				
delphic con.	-0.00609	0.000704		-0.0112	-0.00968	0.00491	-0.00862
	(0.0320)	(0.0304)		(0.0353)	(0.0155)	(0.0240)	(0.0380)
delphic con. × Euro/ECB^{MP} cov.	-0.0370	-0.0344		-0.00653	-0.00326	-0.0323	-0.0686
	(0.0907)	(0.0934)		(0.117)	(0.0483)	(0.132)	(0.185)
Euro/ECB cov. (delphic con.)			-0.0179				
			(0.140)				
odyssean exp.	-0.000167	0.00534		-0.00484	-0.00872	0.00291	0.00574
	(0.0135)	(0.0133)		(0.0155)	(0.0135)	(0.00985)	(0.0172)
odyssean exp. × Euro/ECB^{MP} cov.	0.0609	0.0531		0.0376	0.0601	0.0564	0.114*
	(0.0438)	(0.0446)		(0.0519)	(0.0474)	(0.0367)	(0.0623)
Euro/ECB cov. (odyssean exp.)			0.0563				
			(0.170)				
odyssean con.	-0.0114	-0.00268		-0.0152	-0.00312	0.0113	0.0285***
	(0.00990)	(0.00978)		(0.0109)	(0.00927)	(0.00835)	(0.0108)
odyssean con. × Euro/ECB^{MP} cov.	-0.0762***	-0.0611***		-0.00211	0.0289	-0.0663**	-0.00984
	(0.0193)	(0.0192)		(0.0249)	(0.0261)	(0.0333)	(0.0359)
Euro/ECB cov. (odyssean con.)			-0.365**				
			(0.171)				
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	433	435	433	433	286	433	433
R^2	0.456	0.248	0.509	0.594	0.319	0.475	0.519

Notes: Except for the model depicted in column 4 the dependent variable is Δ*Inflation Expectations*. The table reports coefficients estimated using the PCSE estimator. Panel corrected standard errors in parentheses. Standard errors account for cross-sectional dependence, heteroscedasticity and panel-specific autocorrelation of the error term. We use continuous measures for both the monetary policy shock and news coverage. Robustness tests in columns 1, 2 and 3 are self-explanatory. Further tests include a placebo with Δ*Inflation Perceptions* as the dependent variable (4), the sample restricted to the post GFC period (5), a model with 90% winsorized dependent and main explanatory variables (6) and the use of a restricted dataset with neither all countries nor none country 'treated' with coverage of a policy event (7).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.2: Complementing Eventpanel DiD Estimates

	(1) policy dummy	(2) policy	(3) policy dummy × cov. dummy	(4) policy dummy × cov. share	(5) policy × cov. dummy	(6) policy × cov. share	(7) policy	(8) policy × cov. dummy	(9) policy × cov. share
exp. policy	0.0199	0.000296	-0.0181	0.0223	-0.0113*	-0.000101			
	(0.0216)	(0.00676)	(0.0236)	(0.0249)	(0.00677)	(0.00819)			
exp. policy × Euro/ECB^{MP} cov.			0.100**	-0.0231	0.0230**	0.00422			
			(0.0452)	(0.127)	(0.0107)	(0.0201)			
con. policy	0.00613	-0.0132	0.0542*	0.0240	0.0219**	0.000385			
	(0.0259)	(0.0142)	(0.0293)	(0.0289)	(0.00880)	(0.0153)			
con. policy × Euro/ECB^{MP} cov.			-0.105**	-0.155	-0.0524***	-0.0669*			
			(0.0514)	(0.172)	(0.0181)	(0.0360)			
delphic policy							0.000792	-0.000158	-0.0109
							(0.00945)	(0.0102)	(0.0111)
delphic policy × Euro/ECB^{MP} cov.								0.00296	0.0671**
								(0.0194)	(0.0329)
odyssean policy							-0.00998	0.0217***	0.00382
							(0.00975)	(0.00648)	(0.0108)
odyssean policy × Euro/ECB^{MP} cov.								-0.0494***	-0.0718**
								(0.0141)	(0.0313)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Event FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	2,595	2,595	2,595	2,595	2,595	2,595	2,595	2,595	2,595
R^2	0.832	0.832	0.833	0.832	0.834	0.833	0.832	0.834	0.833

Notes: The dependent variable is *Inflation Expectations* in levels. The table reports coefficients estimated using two-way fixed effects (POLS). Clustered standard errors at the individual event level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE C.3: STACKED DID ROBUSTNESS

	Linear Trends by Type of Monetary Policy				*Monetary Policy Type-specific DiD*			
	(1) pol. dummy × cov. dummy	(2) pol. dummy × cov. share	(3) policy × cov. dummy	(4) policy × cov. share	(5) pol. dummy × cov. dummy	(6) pol. dummy × cov. share	(7) policy × cov. dummy	(8) policy × cov. share
delphic exp.	0.00598	0.0440	-0.00179	0.00895	0.00545	0.0405	0.00512	0.0151
	(0.0408)	(0.0423)	(0.0121)	(0.0141)	(0.0337)	(0.0374)	(0.0137)	(0.0160)
delphic exp. ×	0.0375	-0.286*	-0.00940	-0.0737*	0.0176	-0.335*	-0.0150	-0.0788*
Euro/ECB^{MP} cov.	(0.0708)	(0.168)	(0.0222)	(0.0396)	(0.0670)	(0.190)	(0.0211)	(0.0438)
delphic con.	0.126**	0.0853**	0.0281	0.0132	0.0853*	0.0443	0.0216	0.00830
	(0.0501)	(0.0406)	(0.0211)	(0.0180)	(0.0480)	(0.0373)	(0.0222)	(0.0200)
delphic con. ×	-0.0858	-0.0185	-0.0406	0.00710	-0.0764	0.0219	-0.0382	0.0145
Euro/ECB^{MP} cov.	(0.0539)	(0.109)	(0.0285)	(0.0470)	(0.0536)	(0.102)	(0.0272)	(0.0517)
odyssean exp.	-0.0323	0.0140	-0.0217**	-0.0106	-0.0293	-0.00128	-0.0175	-0.00823
	(0.0376)	(0.0365)	(0.0100)	(0.0104)	(0.0248)	(0.0273)	(0.0124)	(0.0126)
odyssean exp. ×	0.184***	0.269*	0.0420***	0.0803*	0.0688	0.0121	0.0279*	0.0423
Euro/ECB^{MP} cov.	(0.0535)	(0.151)	(0.0144)	(0.0439)	(0.0545)	(0.149)	(0.0153)	(0.0476)
odyssean con.	0.122**	0.106*	0.0270***	0.00441	0.0322	0.0310	0.0221*	0.00742
	(0.0535)	(0.0550)	(0.00996)	(0.0168)	(0.0408)	(0.0420)	(0.0114)	(0.0146)
odyssean con. ×	-0.122	-0.326	-0.0543***	-0.0700*	-0.0462	-0.167	-0.0382**	-0.0565*
Euro/ECB^{MP} cov.	(0.0803)	(0.314)	(0.0194)	(0.0383)	(0.0678)	(0.260)	(0.0175)	(0.0314)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Event FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear Trends	Yes	Yes	Yes	Yes	No	No	No	No
No. of Observations	2,595	2,595	2,595	2,595	462-823	462-823	462-823	462-823
No. of Events	376	376	376	376	66-119	66-119	66-119	66-119
R^2	0.834	0.833	0.835	0.834				

NOTES: The dependent variable is *Inflation Expectations* in levels. The table presents the coefficients estimated using two-way fixed effects (POLS) and including linear trends by type of monetary policy k (left panel) and estimation of subsamples differentiated by k (right panel). For the latter, each combination of *policy* and *policy × coverage* refers to an individual estimation, hence a range of the number of observations is shown and no R^2 is reported. Clustered standard errors at the individual event level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$