PLACEHOLDER Title

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Abstract

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1. Introduction

Central bank communication has become a vital instrument in modern monetary policy (Blinder et al., 2017). Central banks use communication as a tool for guiding inflation expectations and ensuring trust in their monetary policy. Historically, much of this communication has been directed towards financial experts. However, in recent years, central banks have increasingly been reaching out to the general public (Blinder et al., 2022). The media plays a critical role in this process by disseminating central bank communication to a broader audience. Therefore, it is essential to understand how the media reports on central bank communication to analyze the impact of central bank communication on the general public.

Since Carroll (2003) created a model for inflation expectations that considers the amount of media coverage several studies have analyzed the role of media coverage for the inflation expectation forming process. Van der Cruijsen et al. (2015) find a small effect of media on inflation expectations and perception for Sweden. Similar, Lamla & Lein (2014) find that media reporting report the accuracy of German household inflation expectations. (Larsen et al., 2021) show that the news topics also have predictive power inflation expectation. Ehrmann et al. (2017) show that increased media coverage leads to the strongest improvements in inflation expectations accuracy during recessions and for individuals with pessimistic views or financial difficulties.

Another recent branch of the literature investigates the impact of central bank communication on household inflation expectations. Coibion et al. (2022) show that the Fed's communication can have a significant effect on the households inflation expectations when the communication is directly presented to the households. However, the effect of the communication is significantly damped when the same information is presented in the form of newspaper articles. This view is in line with Gardt et al. (2022) who demonstrate that households mostly hear about the ECB's monetary policy through television and newspapers (online and printed) and rarely by using direct sources like the ECB website. Similar, Lamla & Vinogradov (2019) find that FOMC announcements have no impact on consumers' inflation perception and expectation, but that FOMC announcements increase the probability of consumers to receive news about the FOMC announcements.

Several studies investigate how central bank communication is perceived by the media Berger et al. (2011) and Picault et al. (2022) show that the medias assessment of ECB policy decision is highly responsive to the content of ECB press conferences.

Similar to Picault et al. (2022), I adopt a framework proposed by Hayo & Neuenkirch (2015) where the media acts as a channel between central bank communication and the perception of monetary policy by financial markets. Following Nimark & Pitschner (2019) who formalize that agents delegate their information choice to the media rather than monitor all relevant events themselves. Hence, news act as a channel between through which households receive information about the central bank communication. Building on these two frameworks, I assume that the media coverage of central bank communication acts as a channel between the central bank and households. I assume that households consume the news from the media about the central bank communication rather than directly from the central bank communication itself.

I am examining the impact of media coverage in newspapers on households' inflation expectation accuracy, specifically focusing on reporting of ECB press conferences and news about inflation. Firstly, I explore whether the inflation information presented in newspapers deviates from the inflation information in the press conferences by the ECB. Secondly, I investigate the extent to which the deviation of inflation information in media coverage and ECB press conferences contributes to explaining the errors in households' inflation expectations. This paper is, to my knowledge, the first to explicitly investigate the link between central bank communication and news coverage concerning household inflation expectations. Furthermore, it contributes to the literature by demonstrating how news about inflation deviates from the corresponding ECB communication, allowing for a better understanding of how central bank communication is conveyed to the general public and explaining the channel through which the general public reacts to central bank communication.

I built on the Bayesian learning model (Lamla & Lein, 2014) to examine the impact of the difference between inflation related information in media reporting and ECB press conferences on households inflation expectations accuracy. To quantify the inflation related information in the ECB press conferences and news, I apply the lexicon driven procedure by Picault & Renault (2017) to create lexicons for inflation related information for the news and for the ECB press conferences. To measure how closely the media follows ECB press conferences in their news I apply a similar procedure likePicault et al. (2022) and use dependency parsing to identify the grammatical structure of a text and filter out the share of news that reproduce ECB press conferences from general news about inflation. This allow me to measure how closely the media reporting follows the ECB' press conferences.

I find that inflation information in the news and ECB press conferences is strongly correlated with the current inflation in Germany. Furthermore, the the difference inflation reporting in news and ECB press conferences is strongly correlated with the inflation expectation gap between German households and professional inflation forecasts.

2. Model

I augment the Bayesian learning model for inflation expectation by Lamla & Lein (2014) by explicitly adding a channel for central banks communication. I assume that the central bank sends a noisy signal for the future inflation π_{t+1} based on the observation to the media. Let c_t denote the signal that captures inflation-related information about the central bank's inflation forecast Θ_t that the central bank communicates to the media, i.e., inflation-related information in press conferences. I further assume that the signal is normally distributed $c_t \sim N(\Theta_t, \sigma_t^c)$ with variance σ_t^c. This assumption also implies that the central bank only sends one unambiguous signal at each period t rather than multiple conflicting signal at the same period. Without the central bank's communication, the media sends a noisy "baseline" signal about the rational forecast of inflation Ψ_t to the households based on a number of media reports V with $s^b_{\nu,t} \sim N(\Psi_t + \alpha_t, \sigma^{sb}_t)$ where α_t captures the media bias. The media can decide how closely to follow the central bank's communication. Hence, the media's inflation signal can be defined as

$$s_{\nu,t} = (1 - \lambda_{\nu,t})s^b_{\nu,t} + \lambda_{\nu,t}c_t \quad 0 \leq \lambda_{\nu,t} \leq 1 \tag{1}$$

where $\lambda_{\nu,t}$ denotes the weight that the media report places on the central bank's signal c_t relative to the "baseline" media signal $s^b_{\nu,t}$. $\lambda_{\nu,t} = 0$ would indicate that the media report ignores the central bank's communication completely while $\lambda_{\nu,t} = 1$ would describe a situation in which the media only reproduces the information from the central bank's communication.

Given that $s_{\nu,t}$ is a linear combination of normal random variables and assuming that σ^c_t and $\sigma^{sb}_{\nu,t}$ are independent, the media sends a normally distributed signal about π_{t+1} with $s_{\nu,t} \sim N(\mu_s, \sigma^s_{\nu,t})$ where

$$\mu^s_{\nu,t} = (1 - \lambda_{\nu,t})(\alpha_t + \Psi_t) + \lambda_{\nu,t}\Theta_t \tag{2}$$

$$\sigma^s_{\nu,t} = \lambda^2_{\nu,t}\sigma^{s^b}_{\nu,t} + (1 - \lambda_{\nu,t})^2\sigma^c_{\nu,t} \tag{3}$$

The households hold a prior belief $\gamma_t \sim N(\pi_t, \sigma^h_t)$ about the future inflation π_{t+1}. Hence, the representative household forms its inflation expectations according to

$$f(\pi_{t+1}|s_{\nu,t}) \propto \Pi^V_{\nu=1} h(s_{\nu,t}|\alpha_t, \pi_t, \lambda_{\nu,t}, c_t)k(\pi_t) \tag{4}$$

where $f(.)$ is the posterior belief of a representative household on inflation π_{t+1} after receiving the inflation related news signal. Assuming normality the posterior distribution is a normal distribution with mean μ_t

$$\mu_t = \rho_t\pi_t + (1 - \rho_t)\bar{\mu}^s_t \tag{5}$$

where

$$\bar{\mu_t^s} = V^{-1}\sum_{\nu=1}^{V}\mu_{\nu,t}^s = V^{-1}\sum_{\nu=1}^{V}(1-\lambda_{\nu,t})(\alpha_t+\Psi_t) + V^{-1}\sum_{\nu=1}^{V}\lambda_{\nu,t}\Theta_t \tag{6}$$

$$= \Psi_t + \alpha_t - \bar{\lambda_t}\alpha_t - \bar{\lambda_t}\Psi_t + \bar{\lambda_t}\Theta_t \tag{7}$$

$$= \bar{\lambda_t}(\Theta_t - \Psi_t) + \Psi_t + \alpha_t(1-\bar{\lambda_t}) \tag{8}$$

and

$$\rho_t = \frac{\frac{1}{V}\sigma_t^s}{\sigma_t^h + \frac{1}{V}\sigma_t^s} \tag{9}$$

For $\bar{\lambda_t} = 0$ the mean would be $\mu_t = \rho_t\pi_t + (1-\rho)(\Psi_t + \alpha_t)$. Hence, if the media completely ignores the central bank communication, the mean of the posterior is the weighted average of the prior and the biased media signal[1]. If the media perfectly reproduce the central bank communication, i.e, $\bar{\lambda_t} = 1$ the mean would be $\mu_t = \rho_t\pi_t + (1-\rho_t)\Theta_t$.

I follow Ehrmann et al. (2017) and define two different types of inflation expectation biases; $\mathbf{B}_t = \{B_t^r, B_t^e\}$ where B_t^r is the difference between the HCPI and the household inflation expectation at the forecast horizon, and B_t^e is the difference between the professional inflation forecast and the household inflation expectations. I assume that the rational inflation signal of the ECB and of the media are similar, i.e, $\Theta_t \approx \Psi_t$.

$$B_t^e = |\bar{\mu_t^s} - \Psi_t| = |\rho_t(\pi_t - \Psi_t) + (1-\rho_t)(\alpha_t - \bar{\lambda_t}\alpha_t)| \tag{10}$$

I would actually need to assume $(\pi_t - \Psi_t) \geq 0$ to get a simple solution for the derivative. Is there a way circumvent this?

$$\frac{\partial \mathbf{B}_t}{\partial \bar{\lambda_t}} = -(1-\rho_t)\alpha_t < 0 \quad \alpha_t > 0 \tag{11}$$

[1]This case is equivalent to the model from Lamla & Lein (2014) with media bias.

$$\frac{\partial \mathbf{B}_t}{\partial \bar{\lambda_t}} = (1-\rho_t)\alpha_t < 0 \quad \alpha_t < 0 \tag{12}$$

Thus, the partial effect of the weight given to the central bank increases the inflation forecast accuracy. The effect is stronger, the larger the media bias is. The weight determines how closely the media follows their "baseline" signal. The "baseline" signal biases the overall media signal by the media bias. Hence, the closer the media follows their "baseline" the stronger the media bias in the overall media signal. From this follows my first hypothesis

Hypothesis 1: *If the medias signal is affected by a media bias, an increase of the weight given to the central bank communication by the media has a positive effect on the household inflation forecasting accuracy.*

Regarding the partial effect of the media bias

$$\frac{\partial \mathbf{B}_t}{\partial \alpha_t} = (1-\rho_t)(1-\bar{\lambda_t}) > 0 \quad \lambda_t \neq 0 \tag{13}$$

The partial effect of the media bias is always positive and its size depends on the average weight given to the "baseline" signal of the media $1-\bar{\lambda_t}$. A high weight of the media's "baseline" signal increases the effect the media bias has on the overall media signal. Hence, my second hypothesis is

Hypothesis 2: *A increase of the media bias, leads to a decrease of the forecast inflation accuracy.*

3. Data

My dataset consists of two different parts. The textual data from the ECB and the Media and the quantitative data regarding inflation and inflation expectations. In section 3.1 I describe the textual data. In section 4 I describe how I transformed the textual data into quantitative data and in section 3.2 I describe the remaining quantitative data.

3.1. Textual Data

I collected two separate datasets for the textual analysis, one for the ECB communication and one for the media news. The ECB's main channel for communication to the media are their press conferences. The press conferences are in English and take place after the ECB's Governing Council took their monetary policy decision every six weeks. I collected ECB press conference from 2000 until 2022 with a webscrapper from the official ECB website. I discarded the Q&A section and all sections which carry no significance, like greetings and acknowledgments, leaving only the introductory statements.
The media news data was provided by the largest German news agency Dpa. The data consists of over 7 million newspaper articles published from 1991 until 2018. I filtered out all articles which are unrelated to the economy as well as all articles which are purely financial news, like reporting of stock movement or business news. For all detailed description see Cite Mariia, Philip, Kai and me
To filter out any data that is not relevant for inflation, I only included sentences which contain the word "Inflation" (inflation) and synonyms of inflation like "Preisteigerung" (price increase).
To reduce the dimensionality of the data I apply several pre-processing steps to the two datasets which are commonly used in the literature: Lowercasing, removing punctuation, removing stopwords (e.g., and, but, or) which carry no information and removing numbers.

3.2. Quantitative Data

The ECB surveys each quarter professional forecasters regarding their annual HICP expectations and provides the results to the general public. The survey ranges from the first quarter of 1999 up until the last quarter of 2022. I use the one-year-ahead annual HCPI point forecast averaged over all responds as my professional inflation forecast.
The consumer inflation expectation is based on the results from the monthly European Commission's Business and Consumer Survey. The survey collects

information about households inflation expectations by asking them if they expect that the prices increase more rapidly, increase at the same rate, remain unchanged or decrease in the next 12 months. To transform the qualitative survey answers into quantitative inflation expectations, I use the rolling-window regression based approach by Lahiri & Zhao (2015). See Appendix A for an explanation.

4. Text Classification

In the following section I will lay out how I quantified the ECB communication and news. I do this by separating my dataset into individual sentences and then classify each sentence according to predefined categories. The ECB press conferences are classified into three categories where each category consists of three classes. The first two categories are taken from Picault et. al (2017). The first category describes the monetary stance expressed as monetary hawkish, monetary neutral or monetary dovish. The second category describes the economic outlook either as positive, neutral, or negative. I add a third class which describes the inflation outlook either as increasing, steady or decreasing. This third class allows for a direct comparison of the inflation expectations communicated in the ECB press conference to the inflation expectations expressed by the news media. The News articles are classified into two categories where each category consists of three classes. The first category describes the economic effect of the inflation expressed in the news which can be either positive, neutral, or negative. The second category describes the inflation direction which can be either increasing, neutral or decreasing.

4.1. Method for Quantifying the Central Bank Communication and News Coverage

Two main approaches are mostly used for text classification, the lexicon-based approach, and the machine learning approach. For the lexicon approach a text is classified by taking a list of words, the lexicon, where each word belongs to one of the desired categories, such as “good” for positive sentiment or “bad” for negative sentiment. The text is classified by counting the occurrence of each of these word in the text. The lexicon approach can be modified by adding linguistic rules like negations CITE?.

The machine learning text classification approach classifies a text based on supervised or semi-supervised models to a given category. In recent years, deep-learning models have been widely used for text classification. Continue this part with some examples

4.2. Training Dataset

In the next section I will use supervised models to classify my data into several categories. I trained the models with two trainings dataset which I created, one for the news and one for the ECB press conference. I manually classified 3000 randomly drawn sentences from the ECB press conferences according to the three categories where each sentence was labeled with one of the three classes for each category. Similarly, 3000 sentence were randomly drawn from the news corpus and labeled based on the two categories. The sentences were then used to classify the remaining sentences from my dataset with the method described in the next two sections.

Note 1: Is it obvious enough why I used two different training datasets?

I should further describe my annotation scheme in the appendix and give some examples.

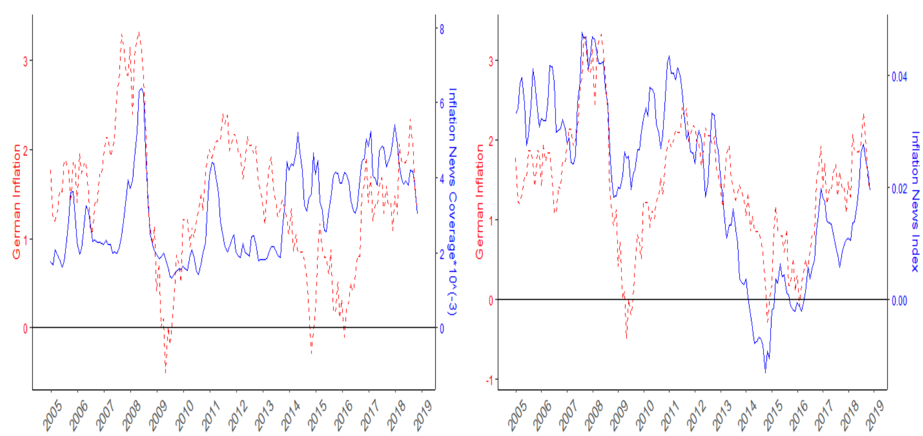
4.3. Lexicon Based Text Classification

The simple implementation and transparency of Lexicon-based sentiment classification has made it widely used in the literature Shapiro (2020), (CITE), (CITE), (CITE), (CITE). Several lexicons exist for sentiment classification (CITE), (CITE), (CITE). However, these lexicons are not optimized for ECB communication or economic news. (FIND EXAMPLE). Picault et. al (2017) solve this problem by manually classifying each sentence in the ECB press conference based on their monetary stance and economic outlook. The classified sentences are then used to build a lexicon from the word used in the press conferences to classify the monetary stance and economic outlook of a press conference. I implement their approach with my own training dataset. The resulting lexicon is then used to classify each sentence in the ECB press conference for each of the three categories with the formula: Insert Formula, same as in Picault et. al (2017) or any other similar papers. It's just positive words – negative words divided by all words,) with the class score s, the press conference i, the category c, the class j and the number of word occurrences n. A final score for each category in each press conference is calculated by taking the averaging the category score over all sentences from the corresponding press conference. I slightly deviate from Picault et. al (2017) by first calculating the category score for each sentence instead of directly calculating score for the full press conference. My approach however is in line with most of the literature (Example from book or paper?). Similiar to the press conferences, I calculate the category score for the news. First I create a lexicon for each of the two categories with the method from Picault et. al (2017). The category score for each news sentence in my dataset is calculated with (EQ). A monthly category score is calculated by averaging the sentence score for each month.

I further deviate from Picault et. al (2017) or similar papers like Marozzi (2021) (Still WP, and he at least uses valence shifters) by applying several linguistic rules to take grammatical(?) relations into account. (I added negation handling and I will add some more rules. Not sure if I should describe that in the main text or in the appendix. The rules are using POS tags to identify negative and positive phrases, e.g., a negative adjective in front of a positive noun results in a negative phrase instead of a neutral phrase.

5. Descriptive Analysis

I relate my news index and the amount of media coverage with the inflation. In general, inflation related news is strongly correlated with inflation itself. As figure 1(a) shows the high inflation phases in 2008 and 2011/2012 are both accompanied by a short peak in inflation related news while phases of lower inflation in between are accompanied by less media coverage. However, after 2013 media coverage peaked during the low inflation phase of 2014 to 2017 and remained elevated afterwards. Figure 1(b) shows that the news index correlates with the inflation with the noticeable exception of the inflation decrease during the Great Recession which was acompanied by a only moderate decrease of the INI. The low inflation phase from 2014 to 2016 was however accompanied by a dip of the INI which was lower than during the Great Recession.

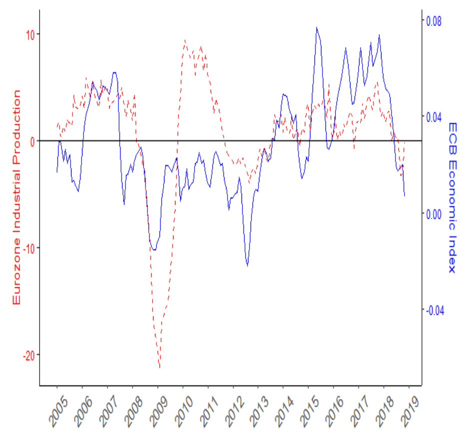


(a) Media Coverage and Inflation

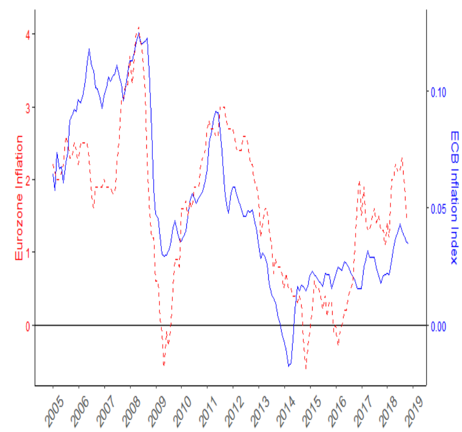
(b) News Inflation Index and Inflation

Figure 1: Media Reporting and Inflation. Figure (a) depicts the monthly HICP growth for Germany and the media coverage. Media Coverage is defined as inflation related sentence divided by the total number of sentences to account for the varying number of articles in each year. Figure (b) depics the monthly HICP growth for Germany and the INI.

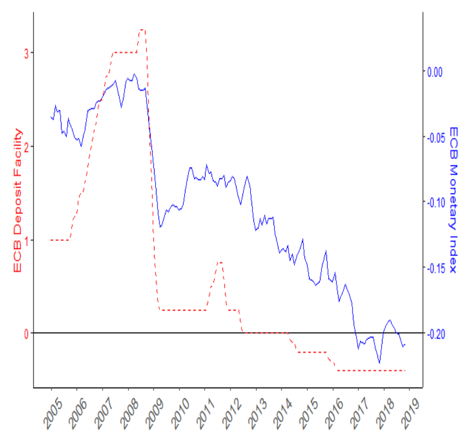
Figure 2 depicts the three ECB indezes and corresponding macroeconomic variables.



(a) ECB Economic Outlook



(b) ECB Inflation



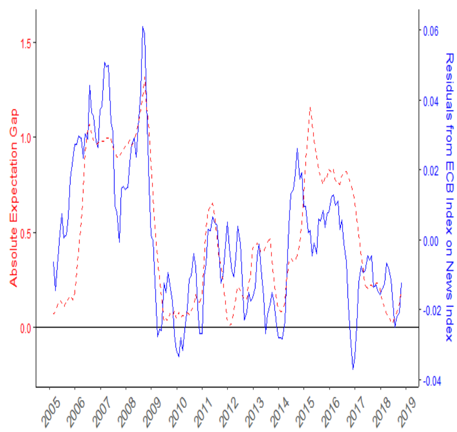
(c) ECB Monetary

Figure 2: ECB Indices. Figure (a) depicts the monthly growth of the industrial production in the Eurzone together with the Ecoonomic Outlook index. Figure (b) depicts the monthly HICP growth for the Eurzone together with the ECB inflation outlook index. Figure (c) depicts the deposit facilitie rates together with the monetary outlook index.

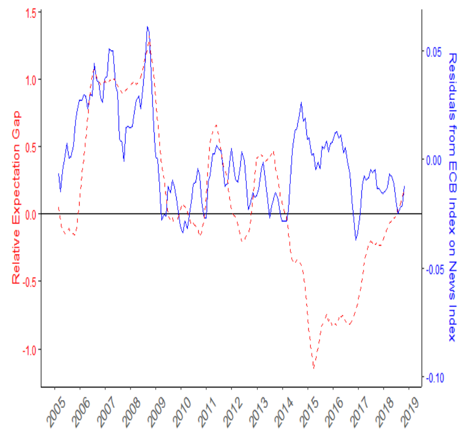
NOTE 1: Professional Forecaster Inflation Expectations are stronger correlated with ECB Inflation Index than with Inflation Expectations. Could be because of the European prof. Inf. Exp.

NOTE 2: The results are quite similar to Picault et. al (2017) and Marozzi (2021), which is reassuring, but I only add 4 more years to the dataset. Therefore, my approach adds little new information regarding the ECB indices.

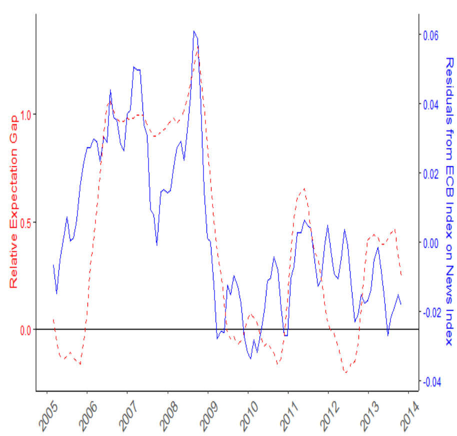
Both the relative and absolute residuals show a strong correlation until 2014. However,



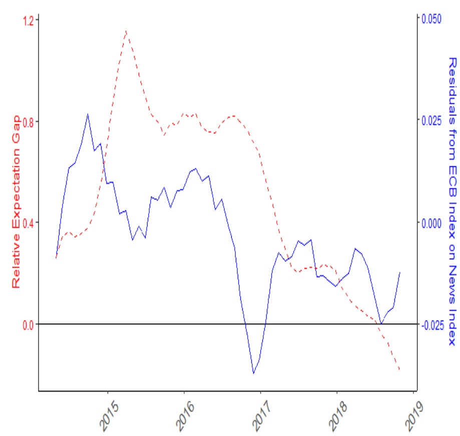
(a) Absolute Expt. Gap



(b) Relative Expt. Gap



(c) Relative Expt. Gap - Before 2014



(d) Negative Relative Expt. Gap - After 2014

Figure 3: Figure (a) shows the absolute expectation gap and regression residuals between the ECB inflation outlook and News inflation indices. Figure (b) presents the relative expectation gap and corresponding residuals. Figures (c) and (d) display the relative expectation gap for 2005-2014 and 2014-2018, respectively.

6. Econometric Framework

To test my hypthesis to close to Erhmann et al. 2017?

$\mathbf{B}_t = \alpha + \beta_1 Media_t^{count} + \beta_2 Media_t^{i} + \beta_3 Media_t^{cb} + \beta_3 \pi_{t-1} + \epsilon_t$

where α is a constant,

The equation is estimated via OLS using Newey-West standard errors.
To avoid simultaneity issues I follow Lamla & Lein (2014) In order to obtain media data for a given month, I aggregate the media reports for each month, excluding any articles which are potentially related to the consumer survey results in the month. Specifically, I sum up the media articles until the day before the consumer survey is released. The sentences from the summed up articles are then used to derive the news index and news count for the given month.
Andere finden die das ähnlich gemacht haben.

Table 1: Inflation Expectation Gap

	B_t^r	B_t^e	π_{t+1}
B_{t-1}^r			
B_{t-1}^e			
$NewsInflation_t$			
$ECBInflation_t$			
$ECBMonetary_t$			
$ECBOutlook_t$			
$NewsECBDifference_t$			
π_t			
$Constant$			
R^2			

7. Results

8. Conclusions

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Appendix A. Quantification of Inflation Expectations

The European Commission's Business and Consumer Survey consumers are asked if they expect prices to fall, stay the same, increase slower than before, increase at the same rate or increase at a higher rate in the coming 12 months and in the last 12 months.

I use the rolling-window-regression approach by Lahiri & Zhao (2015) which is based on an extended version of the Carlson-Parkin method (Carlson & Parkin, 1975) by Berk (1999). The extended version of Berk (1999) does not impose unbiasedness of inflation expectations. Instead the current perceived inflation rate is directly linked to the expected inflation rate.

By assumption each responded i forms a subjective probability distribution for individuals percentage price changes y_{it} over the next twelve months. Let $f_i(y_i t)$ be the subjective probability distribution with mean μ_{it} and variance σ_{it}. Following Batchelor & Orr (1988) method assumes for a survey with five possible answers that the respondent answers prices in the future increase, increase at the same rate, increase at a slower rate, stay the same or fall according as $y_{it} < -\delta_{it}^L, -\delta_{it}^L < y_{it} < \delta_{it}^U, \delta_{it}^L < y_{it} < \delta_{it}^U, \delta_{it}^U < y_{it} < \lambda_{it}, \lambda_{it} < y_{it}$ Nochmal überprüfen, Ist Notation von Batchelor & Orr (1988) besser?. Based on the survey responses the corresponding aggregate probabilities can be formulated as $P(y < -\delta_{it}^L) = A_t, P(y < \delta_{it}^U) - P(y > -\delta_{it}^L) = B_t, P(y < \delta_{it}^U) - P(y > \delta_{it}^L) = C_t, P(y < \lambda_{it}) - P(y > \delta_{it}^U) = D_t$. I denote a_t, b_t, c_t and d_t the abscissae of the standard logistical distribution function corresponding to the cumulative probabilities $A_t,\ A_t + B_t,\ A_t + B_t + C_t$ and $A_t + B_t + C_t + D_t$. The mean expected inflation rate $\mu_t = E_t \pi_{t+12}$ can then be formulated as

$$\mu_t = \lambda_t \frac{(a_t + b_t)}{(a_t + b_t - c_t - d_t)}$$

Similarly, I denote a_t', b_t', c_t' and d_t' as the abscissae of the standard logistical distribution function for the perceived inflation. Assuming that the response threshold λ_{it} Nochmal überprüfen is the same for expected and perceived inflation, the perceived inflation can be formulated as

$$\mu_t' = \lambda_t \frac{(a_t' + b_t')}{(a_t' + b_t' - c_t' - d_t')}$$

For the choice of the scaling parameter λ_t I use the rolling window based regression by Lahiri & Zhao (2015). Following Rosenblatt-Wisch & Scheufele (2015) running the regression

$$\pi_t = \lambda \frac{(a_t' + b_t')}{(a_t' + b_t' - c_t' - d_t')} + u_t$$

using a sample window of $t - w + 1tot$ implies

$$\hat{\lambda}_t = \frac{\sum_{k=t-w+1}^{t} (a_t' + b_t')/(a_t' + b_t' - c_t' - d_t')\pi_t}{\sum_{k=t-w+1}^{t} (a_t' + b_t')/((a_t' + b_t' - c_t' - d_t'))^2}$$

where w is the size of the rolling window. Lahiri & Zhao (2015) choose w as nine years for the inflation expectations of the Michigan Consumer Survey. I follow Lahiri & Zhao (2015) and also choose nine years for w. The resulting household inflation expectations and the professional inflation expectations are shown in figure Appendix A.

Robustness Check for different windows?

TO CLOSE TO Rosenblatt-Wisch and Scheufele 2014??

Appendix B. Additional Rules for Lexicon Text Classification

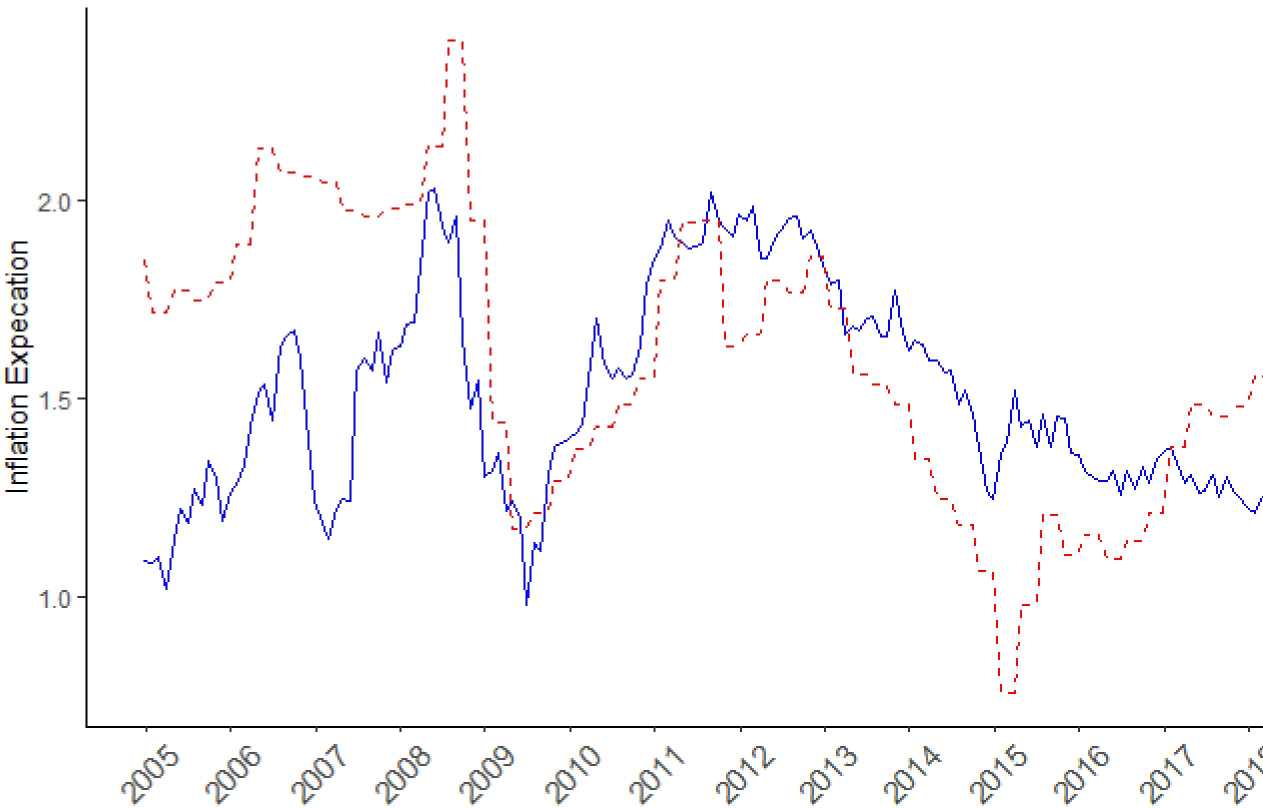

Figure A.4: Inflation Expectations: Household inflation expectations are in blue, Professional forecaster inflation expectations are in red