Beyond the Fed's Reach: Media Narratives and Consumer Inflation Perceptions

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Abstract

Using data from late 2009 to the present, I find no statistically significant evidence that media sentiment impacts a consumer's inflation expectations, potentially due to a reduced reliance on the media as a source of economic information. In order to investigate the relationship between the two, I use an instrumental variable regression where my instrument is the sentiment of the Federal Reserve Beige Books, a publication produced by the bank two weeks before their FOMC meeting. Besides media sentiment, I confirm that consumers rely on changes in food prices and their inflation expectations in the previous period to update their future inflation expectations.

Contents

1 Introduction

In this paper, I am interested in the impact of the media sentiment on consumer inflation expectations. For example, if the media reports negatively about the state of the economy and signals an incoming recession, to what extent do consumers read this media and update their inflation expectations? The question of how a consumer forms their inflation expectations is paramount to the Federal Reserve as the impact of monetary policy on the economy as well as how households decide to spend and save depends on people's expectations. According to Coibion, Gorodnichenko **and** Weber (2022), the Federal Reserve relies on media outlets to diffuse macroeconomic news, trends, and information to the general public rather than rely on their own direct communications. Thus, understanding how effective media diffusion, or how news outlets communicate economic information and trends to consumers, is at affecting consumer expectations is at the heart of answering how Federal Reserve communications and intentions are received by the public.

Many papers, such as Armantier, Nelson, Topa, Van der Klaauw **and** Zafar (2016) and Coibion, Gorodnichenko **and** Weber (2022), explore how consumers, when exposed to new economic information in a randomized controlled trial (RCT) setting, update their expectations on inflation and the economy. For example, in the second paper, the authors show participants summary statistics on inflation, FOMC press releases, and USA Today's coverage of the corresponding press release. In this paper, they find that all three have an effect on a consumer's inflation expectations, with the USA Today media coverage having slightly less of an impact than the other two forms of information. As a result, it is clear that media sentiment and economic information have an effect on the way a consumer forms their expectations. That being said, because this was a controlled experiment where participants were instructed to read and believe economic information relayed through the news, this does not measure the true impact of media sentiment on consumers. I am interested in how the media affects consumer expectations in practice, or how effective media diffusion is in getting across economic information to consumers. If consumers do not read the news to inform their expectations, then media diffusion is low. As a result, no matter how negative or positive media sentiment is, it will have no effect on consumer expectations in this scenario.

In this paper, I employ a two-stage least squares regression, which I will refer to as "IV regression" as short, to investigate the relationship between media sentiment and consumer expectations. Given that consumer expectations are potentially affected by countless different factors other than media sentiment, it becomes difficult to estimate this effect with OLS regression, necessitating an instrument. The instrument that I employ is Federal Reserve Beige Book sentiment. The Beige Book, also referred to as the Summary of Commentary on Current Economic Conditions, is a report jointly written by the twelve Federal Reserve regions on current economic conditions and trends, and is published two weeks prior to the FOMC meeting. The FOMC reads this document in preparation to the meeting to decide what monetary policy action to take. Essentially, I argue in this paper that changes in Beige Book sentiment cause changes in news sentiment because the media bases their articles on future economic trends off the Beige Book. I hypothesize that, in turn, consumers read news articles about the state of the economy and thereby update their inflation expectations based on the sentiment of these articles, and I will refer to these updates as "media based inflation expectations". I can therefore use IV regression to isolate the impact of the media on consumer sentiment.

The Literature Review section will delve into similar studies in the field of inflation expectations and elucidate the contribution of this paper. Additionally, I will discuss the efficacy of my IV regression instrument in achieving exclusion. Following this, I introduce a theoretical framework to elucidate how consumers form their inflation expectations, alongside a detailed discussion of the data and econometric specifications used to investigate the structural components of the theoretical model. Finally, I conclude this paper with the potential policy implications of my research.

2 Literature review

2.1 Media & Updating Economic Beliefs

There are numerous papers that discuss the impact of the media on consumer inflation expectations. For instance, the papers mentioned previously such as Armantier, Nelson, Topa, Van der Klaauw **and** Zafar (2016) and Coibion, Gorodnichenko **and** Weber (2022) show participants economic information in an RCT setting and observe how participants update their inflation expectations. Another paper, Lamla **and** Lein (2014), using media data from Germany showed that the volume of news affects consumer inflation expectations and builds a theoretical model for expected inflation from which I draw elements from for my theoretical model. That being said, I make some deviations from the papers mentioned. In this paper, I am interested in how consumers react to imperfect information similar to the sticky information model introduced by Mankiw **and** Reis (2002). In a sticky information model, people update their information and beliefs about the economy periodically, as frequently consuming information and updating their beliefs is too costly. While in this model, the authors assume that people possess full information after acquiring the information and updating their beliefs, I take a different approach with my model. In my model, I introduce a parameter ϕ that symbolizes how much consumers rely on the media for information (which is entirely based on how frequently people read news articles) rather than use a Bayesian framework to represent how people update their beliefs. As a result, my paper provides a new approach to analyzing how media consumption in a non-experimental setting influences consumer expectations.

2.2 Fed Communications As An Instrument

There are many confounding variables that could potentially affect a consumer's inflation expectations; in order to isolate the effect of of media sentiment on inflation expectations, I use Federal Reserve Beige Book sentiment as an instrument. The media heavily relies on the Beige Book released two weeks before the FOMC meeting to get an idea of where the Federal Reserve is planning on taking interest rates. As a result, I argue that any indications about the health of the economy in the Beige Book will be picked up by the media, which in turn will shape consumer expectations.

There are some anticipated challenges with using this instrument. For instance, it could be argued that Beige Book sentiment affects consumers directly rather than through the media. However, I believe that consumers generally have a lack of awareness about the Federal Reserve and its policy intent. According to Jackson (2022), an Ipsos poll in 2022, only 8% of survey respondents could correctly identify the purpose of the Federal Reserve. Moreover, Motel (2014), a poll conducted by the Pew Research Center in 2014, found that only 24% of respondents could identify that Janet Yellen was the current Fed chairwoman at the time. In addition to both polls, Coibion, Gorodnichenko **and** Weber (2022) found that 40% of Americans believe that the Federal Reserve's target inflation rate was more than 10% which is way off from the actual goal of 2%. All in all, it is clear that Americans have little awareness about the Federal Reserve and its communications, possibly because it is difficult to read and interpret such communications. Referring back elements of the sticky information model, people might think that it is too costly — in other words, not worth their time — to go to the Federal Reserve's website and read through these released Beige Books. Beyond this, it is clear that people form their inflation expectations heavily off of the price increases they see when they shop for goods and services. Businesses who price goods higher or lower might do so because they read the Beige Book and change their prices to reflect their own inflation expectations, thus harming my exclusion claim. However, Candia, Coibion **and** Gorodnichenko (2021) showed using survey data that businesses are mostly unaware of current inflation levels and the Fed's inflation goals, and their inflation expectations differ significantly from households and professional forecasters. Therefore, my instrument does not invoke a change in business pricing. In addition to these two factors potentially harming exclusion, another element is the FOMC press conference that happens two weeks after the Beige Book release. In Lamla **and** Vinogradov (2019), the authors show that while central bank press conferences to the public do not directly affect inflation expectations, they cause consumers read the news more. This is essentially a change in the media diffusion parameter that is caused by an external factor — if consumers decide to read the news and this impacts their expectations, it will be unclear whether it is because of the news that they read or because the FOMC press conference led them to read more articles which then impacted their expectations. To account for this in my model, I only look at news sentiment data between the release of the Beige Book for a current period and the 14 days after it, right up until the FOMC meeting. Thus, my instrument still maintains its exclusion because the aggregated news sentiment value for that period is unaffected by the FOMC meeting and/or press conference that will happen in the future.

3 Theoretical Framework

Essentially, there are three components that affect expected future inflation: current realized changes in the price level, past experiences (price changes in previous years), and media sentiment. I estimate this relationship with Equations (1-3).

$$\pi^e_{k,t+1} = \bar{\pi}_t + (1 - \phi_{k,t})(\tau_k \Delta p_t + \sum_{i=1}^{j} \alpha_{i,k} \Delta p_{t-8i}) + \phi_{k,t} \overline{\psi}_{k,t} + \epsilon_{k,t} \tag{1}$$

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \sigma_{\lambda,t} \lambda_t \tag{2}$$

$$\overline{\psi}_{k,t} = \psi_{k,t}(\Delta p^e_{t+1} | \bar{\theta}_t) \tag{3}$$

I represent expected inflation in time period $t + 1$ for individual k with $\pi^e_{k,t+1}$. The value $\bar{\pi}_t$ is long-run inflation and forms the base of future expectations. The long-run inflation is an AR(1) model comprised of the long-run inflation rate in the previous period and $\sigma_{\lambda,t}\lambda_t$, where $\lambda_t \sim N(0, V)$ represents a macroeconomic shock or change, V is an arbitrary variance value, and $\sigma_{\lambda,t}$ is it's parameter. Furthermore, Δp_t represents the realized change in price levels for food between period $t-1$ and t. The parameters τ_k and $\alpha_{i,k}$ represent the weights placed on the current price level change and previous price level changes, respectively. It is important to note that $\alpha_{i,k} > 0$ and has no specific upper bound. In cases where $\tau_k > \alpha_{i,k}$, it shows that more recent price level changes play a larger role in forming individual k's inflation expectations than in that previous period. In addition, j is a parameter I use to represent the number of years a person has "noticed" inflation. Drawing from an example used in Malmendier **and** Nagel (2011), assume that I have an individual of age s and another of age $s+j$. The second individual will use those extra j years that they have been alive to help form their inflation expectations for the future. The expression Δp_{t-8i} represents food price level changes in previous years — given that there are eight FOMC meetings every year, Δp_{t-8i} represents the change in food CPI levels from period t and i years before that. Together, $(\tau_k \Delta p_t + \sum_{i=1}^{j} \alpha_k^i \Delta p_{t-8i})$ represents two of the components of how individuals use current and previous price changes to influence their expectations.

The third component is news based inflation expectations, or $\overline{\psi}_{k,t}$. This value is the price level change that consumers expect to happen from period t to $t+1$. This expected price level change is based off of $\bar{\theta}_t$, which is the average sentiment of the news during that time period. Thus, $\psi_{k,t}(\cdot)$ is a function that represents how individual k reads the news and makes a prediction about the change in price levels.

The parameter $\phi_{k,t} \in [0,1]$ represents media diffusion. As stated earlier, the Federal Reserve relies on news outlets to diffuse information to the general public, meaning that the reliance on media to inform inflation expectations is represented by this parameter. For instance, in Coibion, Gorodnichenko **and** Weber (2022), where the authors instruct readers to read articles that cover an FOMC meeting, $\phi_{k,t} \approx 1$ because readers are instructed to read and believe this information in an RCT setting. On the other hand, if individual k does not rely on the news to inform their expectations, then $\phi_{k,t} \approx 0$. This is similar to the sticky information model, where the $\phi_{k,t}$ parameter in my model represents the degree to which individuals benefit from reading the news up until the point where they believe it is too costly to keep consuming it. As a result, I weight $\overline{\psi}_{k,t}$ by $\phi_{k,t}$ and consequently the reliance on realized current and previous price changes by $1 - \phi_{k,t}$.

I first take the partial derivative of $\pi^e_{k,t+1}$ with respect to media diffusion.

$$\frac{\partial \pi^e_{k,t+1}}{\partial \phi_{k,t}} = -\tau_k \Delta p_t - \sum_{i=1}^{j} \alpha_{i,k} \Delta p_{t-8i} + \overline{\psi}_{k,t}$$

The equation above represents the rate of change for expected inflation for a per unit change in $\phi_{k,t}$. If $\frac{\partial \pi^e_{k,t+1}}{\partial \phi_{k,t}} > 0$, that means that $\tau_k \Delta p_t + \sum_{i=1}^{j} \alpha_{i,k} \Delta p_{t-12i} < \overline{\psi}_{k,t}$. This result intuitively makes sense — when individual k's reliance on the media increases, their inflation expectations also increase when news based inflation expectation changes are higher than past experience based inflation expectation changes. Next, taking the derivative with respect to $\bar{\theta}_t$ gives us:

$$\frac{\partial^2 \pi^e_{k,t+1}}{\partial \phi_{k,t} \partial \bar{\theta}_t} = \frac{\partial \overline{\psi}_{k,t}}{\partial \bar{\theta}_t}$$

The left-hand side of the equation above is what I will try to estimate in my econometric specifications. I hypothesize that this expression has a negative value, meaning that as news sentiment rises, I expect to see a reduction in news based inflation expectations. This, of course, depends on the media diffusion parameter. If $\phi_{k,t} \approx 0$, meaning the media has little to no impact on individual k's inflation expectations, this expression will be equal to 0. Thus, I have the following hypotheses below:

$$H_0 : \frac{\partial^2 \pi^e_{k,t+1}}{\partial \phi_{k,t} \partial \bar{\theta}_t} = 0 \tag{4}$$

$$H_1 : \frac{\partial^2 \pi^e_{k,t+1}}{\partial \phi_{k,t} \partial \bar{\theta}_t} < 0 \tag{5}$$

4 Data

In this paper, I only consider data between late 2009 up to the present. Due to the financial crisis of 2007 and 2008, there were many financial anomalies and shocks leading up to 2009 that would be too difficult to account for in my model. Thus, I restrict my analysis to this period to better isolate the causal effect of media sentiment on consumer inflation expectations. My final dataset is 108 rows, where each row corresponds to a Beige Book release and other variables corresponding to the release such as the sentiment of the Beige Book, its date, and more. Every year, the Federal Reserve publishes eight Beige Books, one before every FOMC meeting. The summary statistics are shown below in Table 1.

Variable Name	Count	Mean	Std Dev.	Min	Median	Max	ADF Test Results	
							p-value	Stationary?
$News\_Sent\_Agg$	108	0.959	0.172	0.385	0.980	1.321	0.000	Yes
$LMpolarity$	108	-0.090	0.162	-0.617	-0.061	0.253	0.010	Yes
$Food\_Inf$	108	0.235	0.277	-0.152	0.156	1.394	0.043	Yes
Inf_Exp_Agg	108	3.208	0.796	2.1	3	5.4	0.010	Yes
$Days\_After\_Abs$	108	9.129	5.285	1	8.5	17	NA	NA

Table 1: Summary Statistics

4.1 Text Data

In order to gather sentiment data on the Beige Book, I applied the Loughran-McDonald sentiment dictionary algorithm from Loughran **and** McDonald (2011) to every Beige Book published between late 2009 to October 2023. For reference, I downloaded the books from the Federal Reserve Board of Governor's historical archives directly. Essentially, the Loughran-McDonald dictionary classifies words into two categories: positive and negative. There are approximately 2,300 positive words and 350 negative words. This dictionary is best suited for economic and financial textual data contexts as it does not unnecessarily penalize words such as "tax" or "depreciation" — other dictionaries, such as NLTK, will categorize these words as negative even though, in a financial context, these words might be used in a neutral or positive context. The formula, given below, calculates document sentiment as follows:

$$Polarity = \frac{N_{pos} - N_{neg}}{N_{pos} + N_{neg}} \tag{6}$$

where $Polarity$ is the sentiment I am interested in and N_{pos} and N_{neg} represent the number of positive and negative words in a document, respectively. The variable I use to represent this in my dataset is $LMpolarity$.

In order to get media sentiment data, I used the San Francisco Federal Reserve Bank's Daily News Sentiment Index, which calculates an aggregated economic news sentiment value every day from the 1980s to the present based on articles published by 24 major news outlets such as the Wall Street Journal, New York Times, and more — I utilized this data from Shapiro, Sudhof **and** Wilson (2022). The articles are compiled by Factiva, a news aggregator service, where the topic is ensured to be "economics" while the country subject is "United States". Because each row of my dataset corresponds to a Beige Book release, I average the news sentiment index values for the day of the Beige Book release up until 14 days after when the FOMC meeting happens — this aggregate value is then the average media sentiment response that is assigned to a Beige Book. I only aggregate the news sentiment index values from between the Beige Book release and FOMC press conference to ensure that the average media response sentiment value is unaffected by the press conference. The variable that I use to represent media sentiment is $News\_Sent\_Agg$.

4.2 Non-Text Data

Other than media sentiment, I hypothesize others factors that affect inflation expectations are current and previously realized price changes. Specifically, I use realized price changes in food — DâAcunto, Malmendier, Ospina **and** Weber (2019) shows that one of the main factors that contributes to a consumer's inflation expectations is the price change in grocery bundles they realize when they go shopping. As a result, I focus specifically on food CPI level changes data, gathered from the FRED St. Louis database. This data is collected on a monthly basis with every value recorded on the first day of the month, and this variable is denoted as $\Delta FoodInf$ in my dataset. As we can see from Figure 1 and Figure 2, I believe that using lags of 1, 2, and 8 are appropriate for my econometric model specifications.

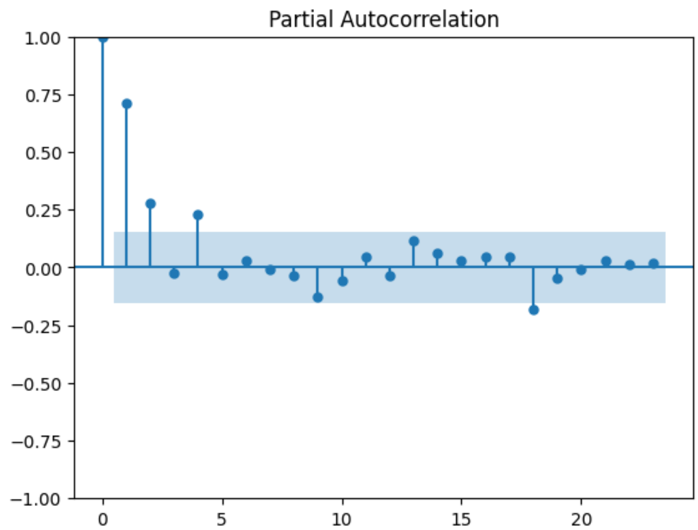

Figure 1: Food CPI Change PACF Plot

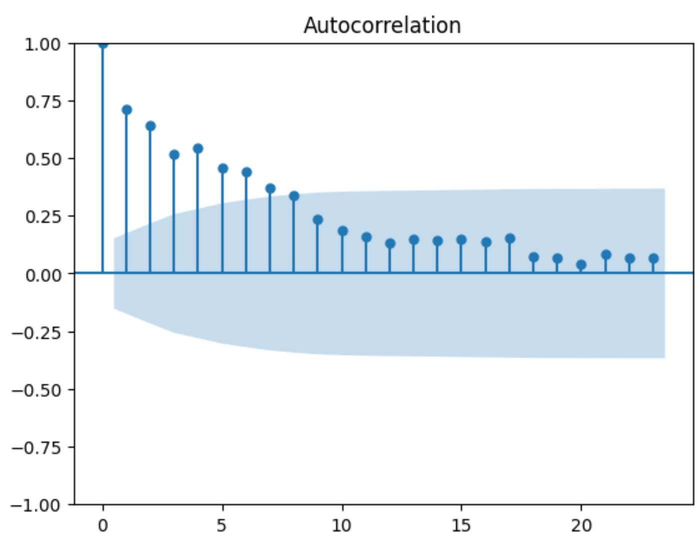

Figure 2: Food CPI Change ACF Plot

Furthermore, I used the University of Michigan's Surveys of Consumers data to get monthly inflation expectations, where all of the values are also recorded on the first day of the month. This variable is denoted as Inf_Exp in my dataset. There is significant autocorrelation with lag 1, so I include this as a regressor in my econometric models as well.

Again, given that each row of my data corresponds to a Beige Book release, I must assign the most recent values of Inf_Exp and $\Delta Food\_Inf$ happening after the release to each record. For instance, if there was a Beige Book release on July 12, 2017, then I would assign the inflation expectation and change in food CPI value recorded on August 1, 2017 even though the average media sentiment value assigned to this row is only comprised of sentiment index values from July 12, 2017 to July 26, 2017, or the 14-day news cycle following the release. Unless a row is assigned a inflation expectations value that was recorded on the day the 14-day news cycle ends, this will not account for the time in between the end of a cycle and the day the expectations value is published. Running an IV regression on this data without accounting for the number of days in between a release and the day an expectations value is published will weight all average media sentiment values equally, even though this variable is more likely to have a potential impact the closer it is to the end of a 14-day news cycle.

To account for this, I create another non-text variable denoted as $Days\_After$, which is used to show the number of days after the inflation expectation and food CPI change values were recorded after the date of the Beige Book release. In Figure 3, I present a CDF plot for the $Days\_After$ variable. In this plot, approximately 46.3% of inflation expectations values are recorded between 10 and 20 days of the Beige Book release, which is the ideal range of days I am looking for. Although it would be much better for this study to have an even higher percentage of values recorded close to the end of the 14-day news cycle, I unfortunately cannot conduct an analysis based on such data given the frequency of the consumer inflation expectations survey. That being said, both the mean and median values for $Days\_After$ are approximately 17, which is reasonably close to 14.

Using this, I created transformed version of $Days\_After$ designated as $Days\_After\_Abs$,

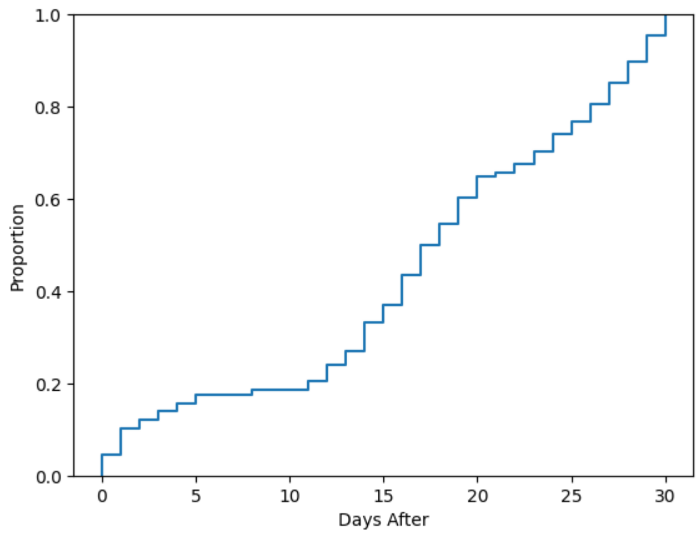

Figure 3: CDF Plot of Days After

with the formula given below:

$$Days\_After\_Abs = 17 - |Days\_After - 14| \tag{7}$$

In my econometric specification, I weight the instrumented average media sentiment variable with $Days\_After\_Abs$. Given that I only look at average media sentiment between the day of a Beige Book release and 14 days after, I use this transformed variable because I want to place more emphasis on inflation expectation values that were published closer to end of the 14-day news cycle following a release. The maximum of $|Days\_After - 14|$ is 16, so by subtracting $|Days\_After - 14|$ from 17, I create a new variable that is within the range $[1, 17]$. Essentially, the higher $Days\_After\_Abs$ is, or the closer $Days\_After$ is to 14, the more likely it is to have been impacted by the 14-day news cycle. For example, inflation expectations values published exactly 14 days after a Beige Book release will have had the full news cycle to become potentially impacted by media sentiment during this period, which is why their weight is the highest. However, values recorded 1 day after or 30 days after the release will potentially be much less impacted by the media.

4.3 Model

Before delving into the econometric specifications, I present the following causal diagram in Figure 4 to illustrate the underlying economic relationship between the variables in my dataset from which the specifications are derived from.

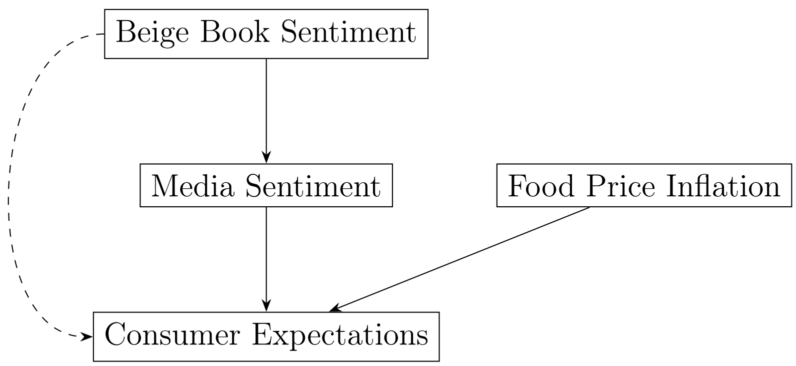

Figure 4: Causal Diagram

Essentially, I use the following main econometric models to estimate the impact of the media on consumer expectations:

$$\begin{aligned} Inf\_Exp\_Agg_t &= \alpha + \beta_0 Food\_Inf_t + \beta_1 Food\_Inf_{t-1} + \beta_2 Food\_Inf_{t-2} \\ &+ \beta_3 Food\_Inf_{t-8} + \beta_4 News\_\widehat{Sent}\_Agg_t \times Days\_After\_Abs_t + \\ &\beta_5 Inf\_Exp\_Agg_{t-1} + \epsilon_t \end{aligned} \tag{8}$$

$$\begin{aligned} News\_\widehat{Sent}\_Agg_t &= \hat{\delta}_0 + \hat{\delta}_1 Food\_Inf_t + \hat{\delta}_2 Food\_Inf_{t-1} \\ &+ \hat{\delta}_3 Food\_Inf_{t-2} + \hat{\delta}_4 Food\_Inf_{t-8} + \hat{\delta}_5 LMpolarity_t \end{aligned} \tag{9}$$

To reiterate, $Inf\_Exp\_Agg_t$ represents inflation expectations at time t, α is an intercept coefficient, $\Delta Food\_Inf_t$ represents the change in food CPI levels from period $t-1$ to t (where I use lags of 0, 1, 2, and 8), $News\_\widehat{Sent}\_Agg_t$ represents the aggregate news sentiment estimate, $Days\_After\_Abs_t$ accounts for the closeness of the date the inflation expectation value was recorded to the end of the 14-day news cycle after a release, and ϵ_t is an error term. Specifically, I construct the estimate for aggregate news sentiment using $\Delta Food\_Inf_t$ as an exogenous variable, and the Beige Book sentiment given by $LMpolarity_t$, where LM stands for Loughran-McDonald.

To further illustrate these relationships within the data and why these specifications are appropriate, I include Figure 5 and Figure 6. I use standardized values to allow for better visual comparison, as some variables are on vastly different scales than others. In Figure 5, we can see that Beige Book and media sentiment closely follow each other, further solidifying the relevance of using Beige Book sentiment as an instrument. As a result, it is clear that when Beige Book sentiment trends upward, media sentiment also trends upward, meaning the two have a strong, positive relationship. In Figure 6, we can see that every time media sentiment (unweighted from $Days\_After\_Abs$) starts trending upward, inflation expectations start trending downwards and vice versa. While this relationship is not as strong as the one between Beige Book and media sentiment, this graph could still indicate a potential inverse relationship between the two.

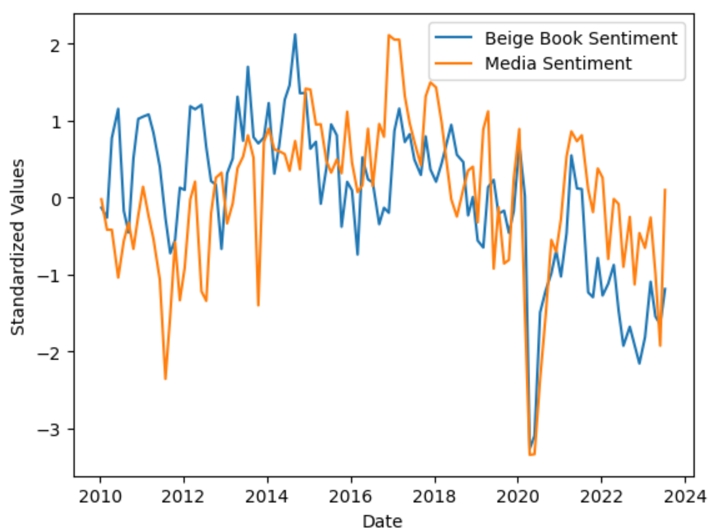

Figure 5: Standardized Comparison of Beige Book Sentiment and Media Sentiment

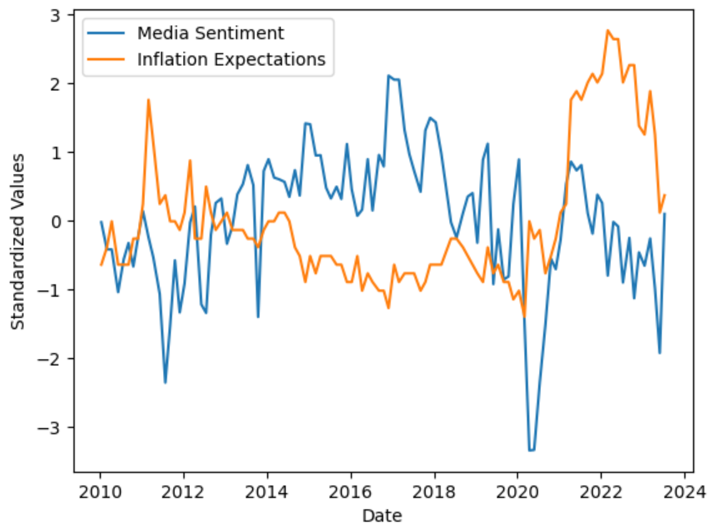

Figure 6: Standardized Comparison of Media Sentiment and Inflation Expectations

5 Results

5.1 Main Results

In order to quantify the relevance condition for Beige Book sentiment on aggregate new sentiment, I run a first stage regression between $News\_Sent\_Agg \times Days\_After\_Abs$, $LMpolarity$, and the exogenous food CPI change variables shown in Table 2. In this analysis, it is clear that this variable is a statistically significant and relevant instrument for aggregate news sentiment.

Next, I use these results to estimate the impact of media sentiment on consumer inflation expectations shown in Table 3. I estimate four models, where the first is the model with all of my variables of interest. As we go down the number of models, I increasingly restrict the specifications. Constructed with heteroskedasticity- and autocorrelation-consistent standard errors (Newey-West estimators), the regression results show that the effects of news sentiment are not statistically significant in any model. These results are opposite of what I expected, as I hypothesized that an upward trend in media sentiment would cause a very clear and prominent decrease in consumer inflation expectations. These results also indicate that people do indeed

	$News\_Sent\_Agg \times Days\_After\_Abs$
R-squared	0.0437
Partial R-squared	0.0200
Partial F-statistic	3.4015
P-value (Partial F-stat)	0.0651
Intercept	11.542***
	(6.6166)
Inf_Exp_Agg_Lag1	-0.9244
	(-1.2554)
Food_Inf	-1.2459
	(-0.4822)
Food_Inf_Lag1	-0.5856
	(-0.1303)
Food_Inf_Lag2	4.2386*
	(1.4191)
Food_Inf_Lag8	0.8512
	(0.3838)
LMpolarity	6.3292**
	(1.8443)

Note: T-stats reported in parentheses. The parameter for LMpolarity is statistically significant at the 5% level using right-tailed threshold with 103 degrees of freedom. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 2: First Stage Estimation Results

rely on food price changes to inform their inflation expectations, with there being strong evidence for a reliance on the period before and a year before. The statistically significant intercept in Model 4 and the lagged aggregated inflation expectations values demonstrates that people have a baseline long-run inflation in mind of approximately 3% and that current expectations rely significantly on expectations in the previous period.

5.2 Robustness Checks

I run the Wooldridge's regression test of exogeneity on my first model, where the null hypothesis stipulated that the endogenous variables are exogenous. Running this test output a p-value of 0.287, meaning that I can reject the null in favor of the alternative hypothesis. Thus, using

$LMpolarity$ as an instrument for $News\_Sent\_Agg \times Days\_After\_Abs$ gave me a robust model.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Dep. Variable	Inf_Exp_Agg	Inf_Exp_Agg	Inf_Exp_Agg	Inf_Exp_Agg
Estimator	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS
No. Observations	100	100	107	107
Cov. Est.	kernel	kernel	kernel	kernel
R-squared	0.7389	0.5271	0.8297	0.4405
Adj. R-squared	0.7220	0.5072	0.8248	0.4297
F-statistic	695.99	336.79	733.48	19.873
P-value (F-stat)	0.0000	0.0000	0.0000	4.837e-05
Intercept	-0.0277	-0.3612	0.2552	3.0117*
	(-0.0485)	(-0.3307)	(0.4393)	(1.7205)
Inf_Exp_Agg_Lag1	0.7597***	0.7699***	0.8051***	
	(9.2304)	(9.9667)	(16.927)	
Food_Inf	0.3968*			
	(1.4475)			
Food_Inf_Lag1	0.5756**	0.7068**	0.5375***	1.9359***
	(2.0222)	(2.0370)	(3.2460)	(4.3631)
Food_Inf_Lag2	-0.2881			
	(-1.0250)			
Food_Inf_Lag8	0.3284**	0.3198*		
	(2.1676)	(1.5181)		
$News\_Sent\_Agg \times Days\_After\_Abs$	0.0647	0.0987	0.0288	-0.0291
	(1.1410)	(0.8546)	(0.4891)	(-0.1515)
Instruments	LMpolarity	LMpolarity	LMpolarity	LMpolarity

Note: T-stats reported in parentheses. Statistical significance levels for $News\_Sent\_Agg \times Days\_After\_Abs$ were assigned using right-tailed thresholds. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: Regression Results

Furthermore, I plotted the fitted values from Model 3 to its residuals and found no visual pattern in the graph (in Figure 7). As a result, I reasoned that this was a good model to use.

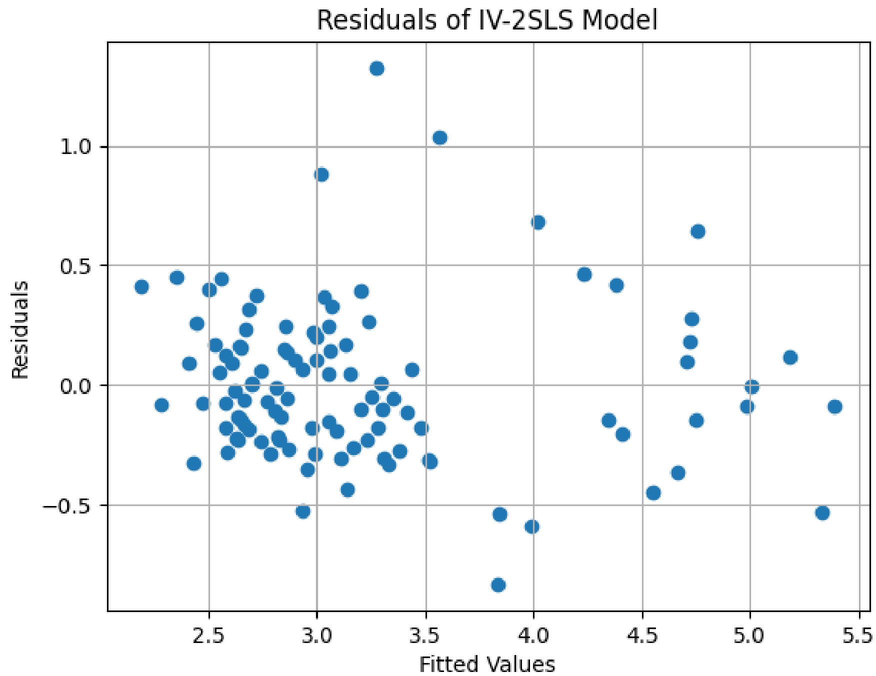

Figure 7: Model 3 Fitted Valus vs. Residuals

6 Conclusion

In this project, I set out to investigate the impact of the media on consumer inflation expectations. Using an IV regression model with Beige Book sentiment as an instrument, I find no statistically significant evidence that media sentiment has an impact on consumer inflation expectations. It is clear from Coibion, Gorodnichenko **and** Weber (2022) that when people are presented with news articles in front of them, they update their inflation expectations accordingly. As a result, media reporting does indeed have an impact in an RCT setting when consumers are directly faced with economic information; however, the results in my paper indicate that, in practice, people might not heavily rely on the news of economic information. In this sense, the results could show that $\bar{\phi} \approx 0$. Putting it in terms of the sticky information model, the data potentially demonstrates that, at least in the post-Great Recession era, people increasingly believe reading economic news is very costly and not worth their time. All in all, the reason that there is no evidence to show that the media impacts consumer sentiment is not because journalists fail to convey information about the economy to readers, but rather that people do not read the news as much as we might believe.

That being said, there were many limitations to this study. The data that I used was restricted in size — given the Great Recession, I limited my time period from late 2009 to the present, which prevented me from conducting any seasonal time series analysis beyond a seasonal lag of 1. Another issue I faced regarding the data was the frequency of the University of Michigan survey data. Given that it was monthly, I had to weight media sentiment by the timings of the survey data and Beige Book releases. If it was weekly, I could have used a stronger link between the news sentiment in the 14 day cycle prior to the Beige Book release and the consumer inflation expectation value for the week after the release, and there would be no need to weight this variable by time. Nonetheless, most monthly inflation values were published 1.5 or 2.5 weeks after the Beige Book release, meaning this specific data frequency limitation was not too significant when working with the data. Beyond data limitations, I did not include other factors such as news volume in my analysis. News volume could be a significant factor in media based inflation expectations if some periods have more published news articles than others, leading to consumers reading the news more during these periods. Hypothetically, during these specific periods, media sentiment could have had more impact on inflation expectations, meaning $\phi_{k,t}$ is closer to 1 than 0. In essence, there are many avenues to improve upon this paper.

This research has significant policy applications. Specifically, it shows that the media diffusion effect in recent times that the Federal Reserve relies on to disseminate economic information is not as strong as they might believe it to be. As such, there should be an increased effort to promote the institution's public engagement and marketing to get important information out to the public so that they may effectively shape consumers' inflation expectations. The Federal Reserve's influence on inflation expectations matters significantly for the effectiveness of monetary policy and controlling recessions — consumer spending is heavily affected by the view that consumers have on the economy and their belief of the current state of inflation. All things considered, in the post-Great Recession era, media is not as influential on consumer expectations as one might have imagined.

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