Inflation Attention Cycles: A Costly Information Model of Inflation Expectations

(Job Market Paper Draft)*

Jonathan Tregde†

Abstract

This paper contributes to the discussion and understanding of how households update their inflation expectations. I develop a model where it is costly for individuals to gather information about the state of the economy, but beneficial for them to do so. Using a new dataset of the number of daily U.S. newspaper articles related to inflation combined with CPI announcement dates, I estimate the effect of information availability and inflation announcements on household inflation forecast error. I find little evidence that forecast error decreases after inflation data is released. I do note some demographic differences in inflation forecast error that are consistent with the literature.

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†The University of South Carolina, Department of Economics, 1014 Greene Street, Columbia, SC 29208; Email: jonathan.tregde@grad.moore.sc.edu, http://jtregde.github.io

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1 Introduction

To quote Federal Reserve Board Chairman Jerome Powell, "... Inflation has just about everyone's attention right now..." (Powell, 2022) Inflation expectations have long been discussed as an important determinant of economic outcomes. Their importance can be traced all the way back to Irving Fisher who claimed that nominal interest rates are determined by real interest rates and expected inflation. However, they remain relevant in the recent literature since the New Keynesian Phillips Curve uses inflation expectations as a determinant of inflation. Even more recently, in his speech at the annual Kansas City Fed's annual Jackson Hole Economic Symposium, Chair Powell noted that "the public's expectations about future inflation can play an important role in setting the path of inflation over time." Powell (2022) went on to explain how during periods of high inflation, "the anticipation of high inflation became entrenched in the economic decisionmaking of households and businesses." But how do agents form their expectations? Answers to this question originally hinged on backward-looking agents adapting to recent developments in inflation (adaptive expectations: expand). More recent developments assume a rational, forward-looking agent who utilizes all the information available to them in order to form accurate predictions about future inflation.

But are consumers fully rational when it comes to forming their inflation expectations? Much recent literature, such as Coibion and Gorodnichenko (2015), Coibion et al. (2018), and Coibion et al. (2020), has focused on relaxing the strict assumption of full information in the full information rational expectations (FIRE) models. This paper contributes to this literature by using a new data set of newspaper articles as a measure of the relative cost of information gathering. As the relative number of articles about inflation/prices increases, the time cost of gathering information should decrease. I use this to estimate an equation of inflation expectations for consumer forecasts from the New York Fed's Survey of Consumer Expectations (SCE). I look for evidence that consumers are rationally inattentive/ choose to be uninformed when the cost of information is high/benefit is low, but begin gathering information when the cost of information is low/the benefit is high. That is, I predict that agents' expectations about inflation will be more informed when inflation is higher (more salient) and less informed when inflation is lower (less salient).

I also develop a simple costly information model of consumer inflation expectations similar to Reis (2006). The consumers face a time cost of observing a signal which provides information aboout the state of the economy. Observing the signal reduces their forecast error, but at the cost of signal acquisition. This cost of signal acquisition is state-dependent, therefore I predict that it is only optimal to observe the signal in some states and not in others. That is, agents will rationally choose to not gain information before forming their expectations in some states of the economy, but will choose to bear the cost in other states.

Expectations have long been considered important in economic decision-making. Irving Fisher introduced the idea of adaptive expectations and noted how realized inflation could affect expectations about future inflation. Work by Phelps (1967) and Friedman (1968) found that in fact, expected inflation could also affect realized inflation. A main point under this framework was that *unanticipated* inflation caused the trade-off between unemployment and inflation. This implied that expectations were made in a backward-looking manner. However, as Binder and Kamdar (2022) note, "if inflation expectations are formed in a backward-looking manner, then expected inflation for the next period will rise. In order to maintain the low unemployment rate, inflation must once again surpass the newly-revised expectations, and so on."

After Muth (1961) introduced the idea of rational expectations, Lucas (1972) developed a model of inflation expectations in which agents use all the information that is useful in predicting future inflation, not just lagged inflation data. The rational expectations approach is used in the New Keynesian framework which is a popular approach currently. This approach utilizes profit maximizing firms that face pricing frictions. But could economic agents perhaps face some information frictions when forming their beliefs about the future?

Some questions still remain about what affects the way agents form their expectations. Fisher (1911) recognized that agents may be inattentive to information or unable to process information accurately in a manner that would allow them to form good expectations. For instance, it is well-documented that changes in gas prices have a strong impact on consumer inflation expectations (Binder, 2018). Similarly, D'Acunto et al. (2019) find evidnce that households' inflation expectations are shaped by the prices they see when shopping for non-durable goods. They use the Nielsen Homescan Panel to create household-level inflation perceptions which they use to analyze the relationship between perceived inflation and expectations. Gas and grocery prices can be thought of as being quite salient, and thus are perhaps a low-cost indicator for agents to use in forming their expectations. If agents make their information acquisition decisions in this manner, that is, only choosing to acquire information from relatively low-cost indicators, or only choosing to view the indicators when the cost is low, then it would follow that agents would acquire more information about the economy when the cost to viewing this information is quite low. The cost to acquiring this information should be directly related to the amount of information that is available, and one should expect information to be more plentiful in times of higher uncertainty or when inflation is reaching unexpected levels.

Reis (2006) proposes a model where consumers face costs associated with acquiring and processing information. His model implies that agents sporadically update their consumption plans, and do so only when the marginal benefit of updating equals the marginal cost of updating. His model focuses on consumer behavior as it applies to aggregate consumption. Using aggregate consumption data, he finds that for some consumers, consumption responds sluggishly to an income shock, while for others their consumption plan is never updated.

Others have examined how consumer expectations are impacted by central bank announcements and other news. Lamla and Vinogradov (2019) find that there is little to no effect of Fed announcements on expectations. However, numerate individuals' inflation expectations were affected by the June 2021 CPI release (Binder, 2021). In that work, Binder also found a fairly large increase in the number of respondents who had heard news about inflation. While the survey used only focused on a single month's announcement, it does seem likely that announcements where the statistic being released is quite shocking would tend to increase awareness of that statistic. Carroll (2003) finds evidence that households only occasionally update their expectations which leads to "'stickyness' in aggregate expectations." Carroll's work also uses news reports, but focuses on how households update their expectations to the reported expectations of professionals as found in the news. I instead use numbers of news articles in given time periods to proxy for the time cost of gathering information about inflation as well as the published year-over-year inflation rate.

Expectations are important to the extent that they affect economic agents' decisions. Coibion et al. (2019) find that Italian firms do make pricing and employment decisions based on their inflation expectations. Crump et al. (2021) find that consumers do change their planned consumption growth in response to changes in the expected rate of return. Further, Coibion et al. (2020) show that consumers do indeed pay closer attention to inflation when it is running high, which is consistent with rational inattention.

The remainder of the paper is organized as follows. Section 2 develops a costly information model of inflation expectations. Section 3 describes the data used and the surveys from which the data was gathered. Section 4 explains the empirical methodology used. Section 5 explains the empirical results and checks for robustness of the results. Section 6 concludes.

2 Model

I consider a model of inflation expectations similar to that of Frankel and Kamenica (2019) where it is costly for agents to observe a signal which provides information about the true state of the economy. The model is also a simplified, discrete time version of the continuous time model of Reis (2006). Observing the signal reduces their forecast error, but at the cost of signal acquisition. The cost of the signal is state-dependent, so choices regarding signal observation may vary by state. Each period, agents must decide whether to observe the signal or not, then they make their forecast. Agents know the cost of observation, and can only know the true state of the economy by observing the signal. I first illustrate a simple version of this model.

There is an objective state space, $\Omega = \{\omega_H, \omega_L\}$, with ω_H and ω_L denoting a state of high inflation and low inflation, respectively. The economy in this model follows a Markov process. Agents have a prior belief, μ, which is a distribution on Ω that puts weight μ^ω on state ω. Information is generated by signals $\gamma \subset S$, and an element $s \in S$ is a signal realization. Let α denote the S-valued random variable induced by signal γ_α. Given a prior μ, we denote posterior induced by signal realization s by $\mu(s)$. For every signal γ_α, we have $E[\mu(\alpha)] = \mu$.

A decision problem $D = (A, B, u)$ specifies an action set A, an information choice B, and a quadratic utility function $u : A \times \Omega \to \mathbb{R}$. Assume that there exists some action a such that $u(a, \omega)$ is finite for every ω. The information choice, B, is the agent's decision regarding whether or not to incur the cost, C, of observing the signal, γ.

The value of information for D, denoted v_D, is given by

$$v_D(p,q) = E_q[u(a^*(q),\omega)] - E_q[u(a^*(p),\omega)] \tag{1}$$

where, for belief q, $a^*(q) \in \arg\max_{a\in A} E_q[u(a,\omega)]$. I denote the prior belief as p and the posterior as q where these are the believed probability that $\omega = 1$. An agent with posterior q views the pay off to $a^*(p)$ as $E_q[u(a^*(p),\omega)]$, while the payoff of taking the "correct" action under this belief is $E_q[u(a^*(q),\omega)]$. So $v_D(p,q)$ denotes the ex post value of information that updates beliefs from p to q.

I assume a quadratic utility function as this yields the benefit of allowing the use of mean-variance analysis. Agents are risk averse, and thus their expected utility increases in the expected value of their action's expected outcome but decreases in the variance of the their action's expected outcome. That is, higher volatility has a negative impact on expected utility. The utility function is

$$E[u(a,\omega)] = E(a,\omega) - \{Var(a,\omega) + [E(a,\omega)]^2\} \tag{2}$$

Agents can choose one of two forecast actions $a \in \{0,1\}$, which correspond to expecting either low or high inflation, respectively. I now denote the states of the world as $\omega \in \{0,1\}$ so the actions match their appropriate states. I normalize the payoff of $a = 0$ to zero in both states. The action $a = 1$ is optimal if $\mu u(1,1) + (1-\mu)u(1,0) \geq 0$, where μ is the probability of $\omega = 1$. The resulting payoffs can be summarized as follows: if an agent expects low inflation, and inflation is in fact low, their payoff is 0. If an agent expects low inflation, and inflation turns out to be high, they again receive 0. This is because the payoff of $a = 0$ is normalized to 0, and because if we assume our agent, who should be thought of as a consumer, is a net borrower, then unanticipated high inflation does not make them worse off. If the agent expects high inflation, but inflation turns out to be high, then the payoff is -1, because if our agent is a net borrower, then unanticipated lower inflation makes them worse off. Finally, if the agent expects high inflation, and inflation is indeed high then the aggent receives a payoff of 1.

The cost of information, $C(\omega)$, is only dependent on the state ω since it is independent of the amount of information acquired and only determined by a "time cost" spent observing the signal. The time cost is lower in the high inflation state since information is assumed to be more easily accessible, thus $C(\omega)$ is decreasing in ω. I assume that when the cost is revealed to the agent, this does not explicitly or implicitly reveal the state to the agent. I can relax this assumption and still achieve a similar result.

2.1 Agent's Optimization Problem

The decision-maker's optimization problem is

$$\begin{aligned} &\max_{a,b}\, (1-b)\Big(E_p[u(a,\omega)]\Big) + b\Big(E_q[u(a,\omega)] - C(\omega)\Big) \\ &\text{s.t. } v_D(p,q) \geq C(\omega) \\ &\qquad E[u(a,\omega)] = E(a,\omega) - \{Var(a,\omega) + [E(a,\omega)]^2\} \end{aligned} \tag{3}$$

where $b \in [0,1]$ and $b = 1$ when the agent chooses to observe the signal, thus incurring the cost of signal acquisition. Thus, since the agent knows the cost, they will choose to observe the signal when the net expected utility of updating their belief is greater than the expected utility of their prior.

This problem yields the result that the value of information $v_D(p,q)$ must be greater than or equal to the difference in expected utilities between the posterior q and the prior p. That is, agents should only choose to observe the signal if the cost of signal acquisition is less than or equal to the value of the information. Since the value of information increases in ω and the cost decreases in ω,

$$b^* = \begin{cases} 1 & if\, \omega = 1 \\ 0 & if\, \omega = 0 \end{cases}$$

If the cost of information itself reveals the state, relaxing the earlier assumption, then agents do not need to make an information acquisition decision. Agents will implicitly know the state just from observing the cost, and can therefore infer their best-response forecast based only only on the cost. One could imagine a scenario where the cost approaches zero with the presence of social media and cell phone news notifications, so the choice to observe the signal is no longer in the hands of the agent, rather they're faced with realizing that they have to spend no time searching for information about the economy, and that itself tells them something about the state of the economy. In this case, again, the agent's best response is to not incur the cost when it is not low, but to take on the costless information granted by seeing the influx of news. This again leads to the result that information should be updated in the high inflation environment.

3 Data

I use Inflation expectations data from the New York Federal Reserve's Survey of Consumer Expectations (SCE) * which gives 127,905 observations over the sample period June 2013- July 2021. This is a monthly survey of a rotating panel of around 1,300 consumers. Respondents participate for up to 12 months before being cycled out of the panel, with individuals being cycled out in equal numbers each month. The responses to the survey occur throughout the month, with the date of the response being recorded. This allows me to identify individuals who respond to the survey before the most recent inflation statistics are released and those who respond after the release.

I also gather data on news articles about inflation from major US newspapers using the Newspaper Source Plus database. This database contains full text for close to 500 U.S. newspapers. I retrieve 24,075 articles from a search of this database for articles containing certain key phrases related to inflation over the sample period, then calculate the number of news articles related to inflation on different days as a proxy for the salience of inflation information. Periods where there are more articles about inflation are periods where it is easier to access information on inflation

* "Source: Survey of Consumer Expectations, © 2013- 2020 Federal Reserve Bank of New York (FRBNY). The SCE data are available without charge at http://www.newyorkfed.org/microeconomics/sce and may be used subject to license terms posted there. FRBNY disclaims any responsibility for this analysis and interpretation of Survey of Consumer Expectations data."

since the news media are discussing it more.

Table 1: Summary Statistics

	Pre	Post
Female	0.228	0.254
Full time	0.258	0.291
Part time	0.062	0.070
Student	0.014	0.015
Retired	0.114	0.121
Hispanic	0.037	0.044
Black	0.043	0.047
Asian	0.019	0.020
Other race	0.002	0.002
Inc under 50k	0.171	0.183
Inc between 50k and 100k	0.167	0.188
Inc over 100K	0.131	0.150
High School	0.054	0.060
Some College	0.156	0.174
College	0.262	0.292

I match the SCE and newspaper data to the Bureau of Labor Statistics' (BLS) closest CPI release date and calculate how many days before or after the announcement the survey response was recorded or the article was printed. Figure 1 shows the average number of news articles by days since the last inflation announcement. There appears to be a cyclical nature to these articles in that there are spikes roughly every seven days. By far the largest spike occurs right after an announcement, suggesting that news outlets do tend to produce more articles about inflation right after the monthly announcement.

Figure 2 appears to show a local decrease in the forecast error at the announcement date. Forecast error then returns to pre-announcement levels for a couple days before decreasing again about a week after the announcement. This lines up fairly well with the spikes in news articles about inflation after the announcement date which provides suggestive evidence that forecast error decreases as the number of relevant articles increases.

Figure 3 shows the difference in consumer forecasts from the inflation level at the time they took the survey, what I call "current error" here. This should show how close forecasts of future inflation match curent inflation. Some consumers may just see current inflation numbers and make that their prediction if they expect inflation to just continue at the same rate. We do see a pretty drastic dip in this difference on the day of the announcement, but it quickly returns to pre-announcement level in a couple of days. There is another dip around 10 days after the announcement, which again mirrors the spike in number of inflation articles on the same relative day.

Figure 1: Average Number of News Articles

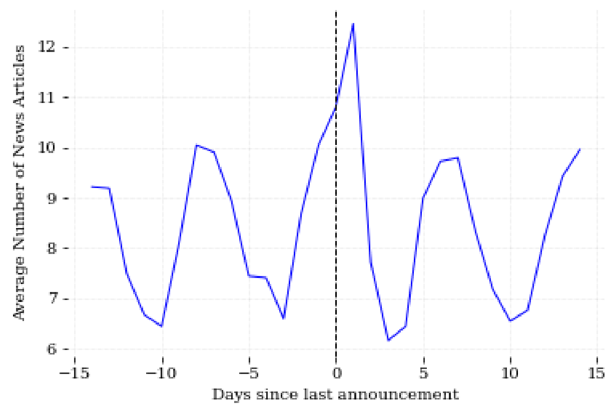
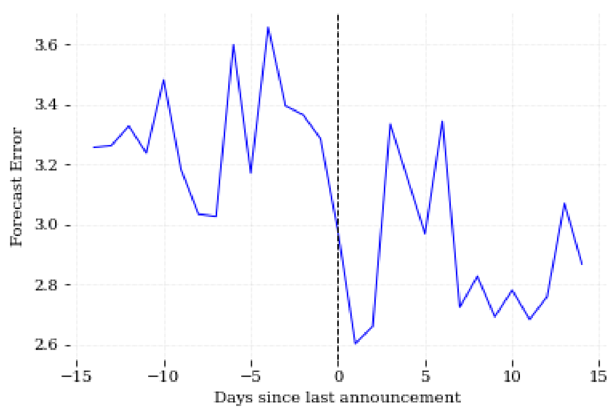
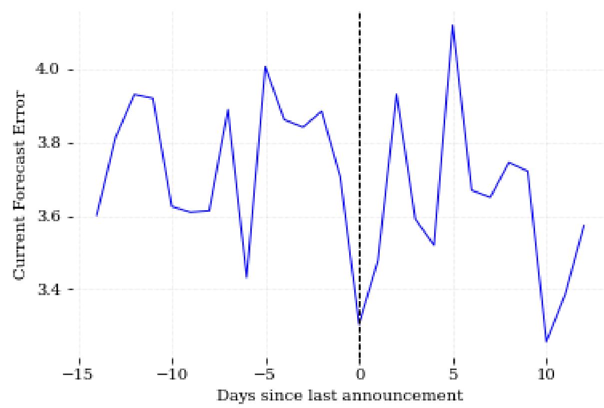


Figure 2: Forecast Error Averages



Note: Forecast error is calculated as the difference between consumers' forecast of inflation in 12 months and what realized inflation was at that time.

Figure 3: Current Error Averages



Note: Current error is calculated as the difference between consumers' forecast of inflation in 12 months and what inflation was in the period in which the survey was taken.

4 Empirical Methodology

I will use the SCE data to estimate individuals' responses to information shocks. I use the monthly CPI announcement dates from the Bureau of Labor Statistics (BLS) as an exogenous information shock since these are predetermined dates that are not affected by the level of the CPI. The SCE data gives the exact date that the respondent completed the survey, so I can use variations in individuals' forecast errors around announcement dates to determine if agent forecast error is lower after an announcement. I estimate a fixed effects model to identify the effect of the same individual responding to the survey prior to an announcement date versus just after the data release.

I first estimate the following

$$FE_{t+1|t,i} = \alpha + \gamma_1 Post_{i,t} + \gamma_2 Infl_t + \gamma_3 Post_{i,t} \times Infl_t + \nu_i + \varepsilon_{i,t} \tag{4}$$

Where $Post$ indicates if the observation was during the seven days after the most recent CPI announcement and gives the difference in the mean forecast error between forecasts made before and after a CPI announcement. $Infl_t$ is the current period inflation level that would have been reported in the recent announcement. The coefficient (γ_3) in $Post \times Infl$ shows the relationship between inflation and forecast error for forecasts made after an announcement. The model would sugest that γ_3 should be negative since individuals should be choosing to acquire information about inflation when inflation is higher, thus reducing their forecast error. Variable α is the intercept, and ν_i is the individual fixed effect. I use panel clustered standard errors clustered at the individual level. Stock and Watson (2008) show that these errors are robust to heteroskedasticity and provide consistent variance estimates.

Next, I use the news data as proxy for the availibility of information about inflation on the day the individual completed the survey. Recall, that the higher the number of articles, the lower the cost of acquiring information should be, so the lower the forecast error should be.

$$FE_{t+1|t,i} = \alpha + \gamma_1 Post_{i,t} + \gamma_2 News\_count_t + \gamma_3 Post_{i,t} \times News\_count_t + \nu_i + \varepsilon_{i,t} \tag{5}$$

$Post$ has the same definition as above, but I now use $News_count$ to denote the number of news articles about inflation at time t. Again I would expect that responding in the post period at a given number of news articles would result in a lower forecast error, meaning γ_3 should be negative.

5 Results

I report the results from estimating Equations 4 and 5 in Table 2. Focusing first on Column (1), Inflation has a significant positive association with forecast error. However, the interaction term, while not significant, does indicate a negative relationship between forecast error and inflation when responding in the post period. Specifically, when inflation is at 2%, responding to the survey after an announcement compared to answering before is associated with a 0.14 percentage point lower forecast error.

Now focusing on Column (2) of Table 2, being in the post period is still associated with a decrease in forecast error, but it is still not significant. When holding the number of articles about inflation constant, forecast errors during the week following an announcement were on average 0.21 percentage points lower than forecast errors before an announcement. The news count measure has a positive, though statisticly insignificant relationship with forecast error. The interaction term again is not significant, and is actually positive. Inerpreting this at the mean number of articles, 8.6, responding to the survey after an announcement, as compared to before, is associated with a 0.12 percentage point decrease in forecast error.

Table 2: Main Results

	(1) FE	(2) FE	(3) FE
Post	-0.004	-0.208	-0.066
	(0.141)	(0.138)	(0.213)
Inflation Rate	0.340^{***}		0.336^{***}
	(0.067)		(0.068)
Post x Infl	-0.066		-0.059
	(0.073)		(0.076)
News Count		0.002	0.003
		(0.008)	(0.008)
post x News Count		0.010	0.005
		(0.012)	(0.013)
Constant	2.561^{***}	3.114^{***}	2.543^{***}
	(0.115)	(0.070)	(0.139)
R-squared	0.000	0.000	0.000
N	116860	116860	116860

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The last column of Table 2 shows results from a full specification of the model which includes both inflation and the count of news articles. The inflation rate remains significant and positive, and all other variables retain their signs. The coefficient on the inflation rate implies that a one percentage point increase in the inflation rate is associated with a 0.34 percentage point increase in forecast error.

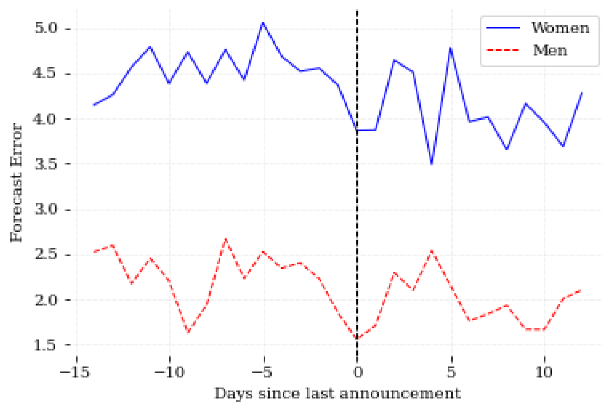
While the estimates are generally statisically insignificant, they do imply movement of forecast error in the predicted direction. That is, there is suggestive evidence that individuals have a lower forecast error when responding to the survey after an inflation data release.

5.1 Heterogeneity

I look for heterogeneity in the results by splitting the sample on several different demographic variables including gender, numeracy, education, and income. I also split the sample by Fed chair (Bernanke (-2014), Yellen (2014-2018), and Powell (2018-current)).

I first show the two-day average forecast errors for males and females. Figure 4 show these. The average female forecast error is always higher than that of males, but both males and females see a decrease in forecast error on the day of announcemnt. However, there does not appear to be a general decrease in forecast error for either gender in the post-period.

FIGURE 4: AVERAGE FORECAST ERROR BY GENDER (2-DAY AVERAGES)

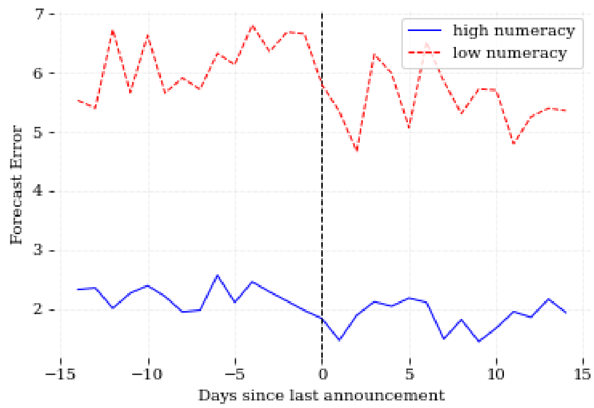


The results from estimating Equations 4 and 5, shown in Tables 3 and 4, show that men who answer the survey in the week following an announcement do not have a significantly lower forecast error than those who answer before. The coefficients on inflation do differ between men and women. A one percentage point increase in the inflation rate is associated with a 0.38 percentage point increase in forecast error for men, while the same increase in inflation is associated with a 0.29 percentage point increase in forecast error for women. The magnitudes for the coefficients on *Post* are generally larger for women and of opposite sign than those for men, but they are never significant.

Next I turned focus to the forecast errors of highly numerate individuals compared to forecast errors of less numerate individuals. Survey participants were asked several mathematical questions and classified as either “high” or “low” numeracy based on the accuracy of their answers. As shown in Figure 5, the average forecast error for more numerate individuals was much lower than that of less numerate individuals. There appears to be a slight decrease in forecast error for highly numerate individuals after an announcement. Less numerate individuals have a local decrease in the two days after an announcement.

Tables 5 and 6 show the results from estimating the fixed effects model for high and low numeracy individuals, respectively. Again, the inflation rate is the only variable with a signficant coefficient. A one percentage point increase in the inflation rate is associated with a much higher increase in the forecast error for less numerate individuals than it is for more numerate individuals. Despite this, there appears to be very little evidence that less numerate individuals are paying attention to new inflation news around the time it is released aside from the visual evidence in Figure 5.

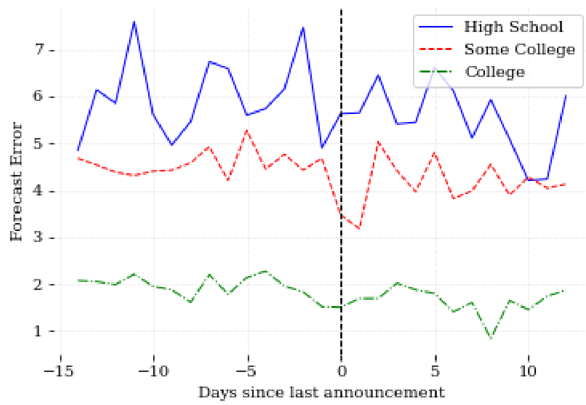
FIGURE 5: AVERAGE FORECAST ERROR BY NUMERACY (2-DAY AVERAGES)



Now focusing on differences in education, we see that more people with more eductation tend to have lower forecast errors. Figure 6 ndividuals with a college degreee have much lower forecast errors than individuals with only a high school degree or only some time spent in college. Interestingly, though, there is only a noticable dip in forecast error right after an announcement day for individuals who haven't completed college. There is hardly any noticable change in forecast error for college graduates or high school graduates. The results from estimating the fixed effects model for individuals with college degrees yields outcomes in line with what I would expect. When the inflation rate is at a level of 2%, responding to the survey within a week after the announcement is associated with a 0.06 percentage point decrease in forecast error. The coefficient on *Post* in column (1) is positive which is unexpected, but the interaction term with inflation is negative, which implies that forecast error does decrase as inflation increases as an individual goes from answering before the announcement to answering after the announcement. The interaction remains significant and of similar magnitude in column (3) when including the news count measure as well.

Figure 7 shows forecast error by income. It is clear that low-income individuals have a generally higher forecast error than either middle- or high-income individuals. This may in part be due to correlation of income with education, but could also be driven by "paycheck to paycheck" living which would render consideration for future prices unimportant. Interestingly, despite this, the point estimates from the fixed effects model for low-income individuals imply a larger decrease

Figure 6: Average Forecast Error by Education (2-day averages)



in forecast error in the post period as compared to the decrease in forecast error for high-income earners. Visually, it seems that there is a decrease in forecast error for high-income individuals leading up to BLS announcement days, which could mean that these people are able to learn about upcoming inflation data before it is officially released.

Figure 7: Average Forecast Error by Income (2-day averages)

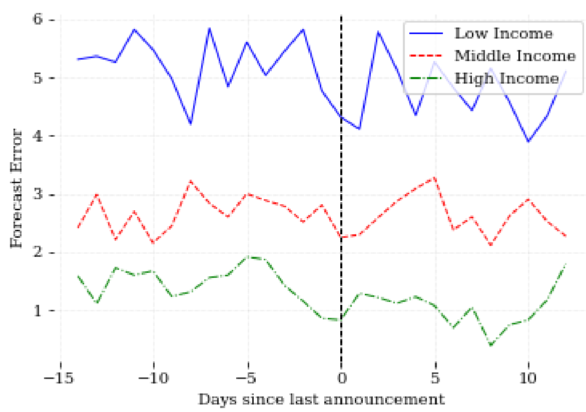
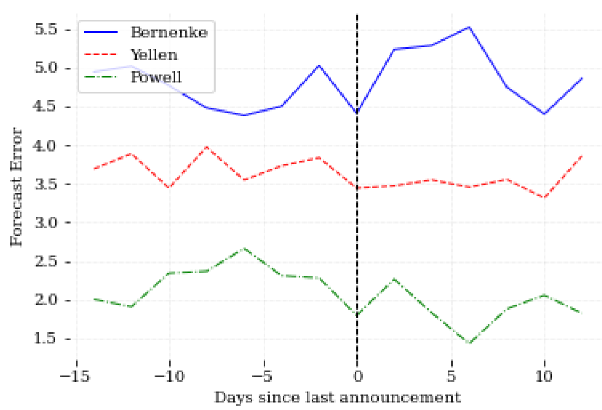


Figure 8 shows average forecast error relative to announcement dates split by Fed Chair. For the period for which I have data, inflation was relatively stable during the period of chair Bernanke's tenure as well as the entirety of chair Yellen's tenure, so it is not too surprising that we see little evidence that consumers are paying attention to announcements of inflation during these periods.

Chair Powell has had the unfortunate task of being at the helm during the pandemic and the aftermath, however, there is not much evidence that forecast error decreases around inflation announcement days. The clear differences in level of forecast error between each of the chairs is rather interesting. The high forecast error observed during Chair Bernanke's tenure may be attributable to general uncertainty post-fiancial crisis. The relatively lower forecast error during Chair Yellen's tenure is probably due to the low, stable inflaiton that persisted while she was in office. The much lower forecast error during Chair Powell's time could be in part due to the low and stable inflation he inherited at the beginning of his time, but could also be due to an increase in the general level of attention paid to economic news because of the Covid-19 pandemic and the government's response to it. However, there is not much evidence in the figure that forecast error changed much after inflation announcements.

Tables 13, 14, and 15 show the results from estimating the fixed effects model by Fed Chair. Interestingly, none of the coefficients are significant during Chair Bernanke's tenure, and the coefficient on inflation is actually negative. Inflation does have a significant positive relationship with forecast error during Chair Yellen's tenure, and the same holds true for Chair Powell. The coefficient on the news count measure is positive and significant during Chair Powell's tenure. The interaction of news count with being in the post period implies that at the average number of news articles, 8.6, responding to the survey in the week following an announcement, as compared to before, is associated with a 0.029 percentage point increase in forecast error. This is in fact the opposite of what I had expected, but could be because of

Figure 8: Average Forecast Error During Recent Fed Chairs



I use FOMC announcement dates rather than BLS announcements to check if agents pay more attention to Fed announcements rather than CPI releases.

6 Conclusion

Inflation expectations remain an important factor for central banks to consider when making policy. Chairman Powell has noted recently the importance of the public's inflation expectations in affecting the future path of inflation, as well as how important it is to manage expectations of high inflation. I develop a model of costly information where agents must decide whether or not to acquire information about current inflation. The model provides insight into how rational consumers might engage in information acquisation when it comes to forming their inflation expectations. The model implies that agents should acquire more information when the economy is in a state of higher inflation, and thus have a more accurate inflation forecast. I then investigate if the release of inflation data induces consumers to pay attention and have more accurate forecasts of future inflation. I find suggestive evidence that forecast error decreases after an announcement about current inflation is made. I also find heterogeneity in forecast error. Consistent with the literature, I find that women have a generally higher forecast error than men. I also see forecast error decrease for higher levels of education or income. These latter findings are consistent with the model predicitons of Reis (2006), in that he also finds that agents with a high cost of consumption planning will choose to never update their consumption plan. These people face high costs of planning due to things such as lack of education, less ability to afford financial planning services, etc.

One extension of this paper could be to follow individuals within the panel and examine *changes* in their expectations rather than forecast error. This could provide insight into what induces individuals to change their expecations. For instance, this would yield the benefit of seeing when an individual's short-run expectations become unanchored. More importantly, perhaps, would be to look at longer time horizon expectations from recent surveys to see if long-run individual expectations become unanchored in the face of eleveated inflation.

My analysis does face the limitation that the sample period I consider does not contain many incidences of elevated inflation, so it may be difficult to extrapolate from these results whether historically high CPI or inflation shocks would show a larger effect or not. As SCE data from more recent surveys is released, it would be easy to extend this work to include the current period where inflation has been very high.

Understanding who is (and who isn't) paying attention to inflation information could be beneficial to officials who might need to engage these agents in efforts to reign in their inflation expectations. For instance, if their is fear that inflation expectations will become unanchored due to persistant high or volatile inflation, then targetted news articles or announcements could be used to calm consumer nerves. In the era of targetted ads

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7 Appendix

Table 3: Men

	(1) FE	(2) FE	(3) FE
Post	-0.048	0.036	0.104
	(0.136)	(0.134)	(0.198)
infl_t	0.376***		0.382***
	(0.053)		(0.053)
post7_x_infl	-0.000		-0.019
	(0.071)		(0.073)
count		0.007	0.007
		(0.008)	(0.008)
post7_x_count		-0.011	-0.014
		(0.013)	(0.013)
Constant	1.498***	2.069***	1.426***
	(0.096)	(0.077)	(0.121)
R-squared	-0.171	-0.172	-0.171
N	64645	64645	64645

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Women

	(1) FE	(2) FE	(3) FE
Post	0.054	-0.518*	-0.284
	(0.244)	(0.238)	(0.355)
infl_t	0.290**		0.274**
	(0.098)		(0.099)
post7_x_infl	-0.148		-0.109
	(0.127)		(0.131)
count		-0.005	-0.003
		(0.014)	(0.014)
post7_x_count		0.036	0.030
		(0.022)	(0.023)
Constant	3.885***	4.407***	3.938***
	(0.176)	(0.136)	(0.219)
R-squared	-0.181	-0.181	-0.181
N	52215	52215	52215

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: High Numeracy

	(1) FE	(2) FE	(3) FE
Post	0.093	-0.127	0.078
	(0.112)	(0.110)	(0.164)
infl_t	0.290***		0.289***
	(0.044)		(0.045)
post7_x_infl	-0.093		-0.092
	(0.059)		(0.060)
count		0.006	0.007
		(0.007)	(0.007)
post7_x_count		0.006	0.001
		(0.010)	(0.011)
Constant	1.562***	1.999***	1.503***
	(0.080)	(0.063)	(0.100)
R-squared	-0.169	-0.170	-0.169
N	84335	84335	84335

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Low Numeracy

	(1) FE	(2) FE	(3) FE
Post	-0.246	-0.418	-0.430
	(0.374)	(0.368)	(0.545)
infl_t	0.471**		0.463**
	(0.149)		(0.151)
post7_x_infl	-0.001		0.022
	(0.194)		(0.200)
count		-0.009	-0.010
		(0.022)	(0.023)
post7_x_count		0.018	0.017
		(0.035)	(0.036)
Constant	5.154***	6.017***	5.251***
	(0.270)	(0.214)	(0.338)
R-squared	-0.191	-0.192	-0.191
N	32469	32469	32469

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Education: High School

	(1) FE	(2) FE	(3) FE
Post	0.093	-0.450	-0.424
	(0.588)	(0.575)	(0.858)
infl_t	0.623**		0.604*
	(0.236)		(0.237)
post7_x_infl	-0.067		-0.000
	(0.306)		(0.315)
count		-0.047	-0.048
		(0.034)	(0.035)
post7_x_count		0.050	0.048
		(0.053)	(0.055)
Constant	4.701***	6.153***	5.138***
	(0.425)	(0.329)	(0.530)
R-squared	-0.190	-0.190	-0.190
N	13313	13313	13313

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Education: Some College

	(1) FE	(2) FE	(3) FE
Post	-0.469	-0.303	-0.424
	(0.271)	(0.265)	(0.394)
infl_t	0.180		0.181
	(0.108)		(0.109)
post7_x_infl	0.080		0.071
	(0.144)		(0.148)
count		0.020	0.019
		(0.016)	(0.016)
post7_x_count		-0.007	-0.005
		(0.025)	(0.025)
Constant	4.164***	4.294***	4.005***
	(0.191)	(0.151)	(0.240)
R-squared	-0.185	-0.185	-0.185
N	38517	38517	38517

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Education: College

	(1) FE	(2) FE	(3) FE
Post	0.257*	-0.118	0.212
	(0.130)	(0.128)	(0.190)
infl_t	0.370***		0.368***
	(0.051)		(0.051)
post7_x_infl	-0.156*		-0.151*
	(0.067)		(0.069)
count		0.001	0.004
		(0.008)	(0.008)
post7_x_count		0.012	0.004
		(0.012)	(0.013)
Constant	1.170***	1.784***	1.145***
	(0.093)	(0.074)	(0.117)
R-squared	-0.167	-0.168	-0.167
N	64830	64830	64830

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Low Income

	(1)	(2)	(3)
	FE	FE	FE
Post	-0.194	-0.384	-0.249
	(0.286)	(0.283)	(0.419)
infl_t	0.434***		0.431***
	(0.114)		(0.115)
post7_x_infl	-0.066		-0.060
	(0.151)		(0.155)
count		0.001	0.001
		(0.017)	(0.017)
post7_x_count		0.008	0.005
		(0.026)	(0.027)
Constant	4.377***	5.088***	4.371***
	(0.203)	(0.161)	(0.255)
R-squared	-0.176	-0.176	-0.176
N	41237	41237	41237

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Middle Income

	(1)	(2)	(3)
	FE	FE	FE
Post	0.237	-0.234	-0.123
	(0.199)	(0.196)	(0.290)
infl_t	0.191*		0.174*
	(0.078)		(0.079)
post7_x_infl	-0.090		-0.047
	(0.104)		(0.107)
count		-0.010	-0.009
		(0.012)	(0.012)
post7_x_count		0.036	0.032
		(0.018)	(0.019)
Constant	2.316***	2.719***	2.420***
	(0.142)	(0.113)	(0.178)
R-squared	-0.174	-0.174	-0.174
N	41543	41543	41543

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: High Income

	(1)	(2)	(3)
	FE	FE	FE
Post	-0.041	0.035	0.266
	(0.163)	(0.157)	(0.234)
infl_t	0.432***		0.445***
	(0.063)		(0.064)
post7_x_infl	-0.061		-0.099
	(0.083)		(0.085)
count		0.019	0.020*
		(0.010)	(0.010)
post7_x_count		-0.022	-0.029
		(0.015)	(0.015)
Constant	0.552***	1.134***	0.367*
	(0.116)	(0.091)	(0.145)
R-squared	-0.177	-0.179	-0.177
N	32827	32827	32827

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Chair Bernanke

	(1) FE	(2) FE	(3) FE
Post	-0.351	0.253	-0.356
	(1.019)	(0.558)	(1.142)
infl_t	-0.303		-0.294
	(0.486)		(0.487)
post7_x_infl	0.447		0.451
	(0.739)		(0.740)
count		-0.012	-0.012
		(0.025)	(0.025)
post7_x_count		0.001	0.001
		(0.045)	(0.045)
Constant	5.213***	4.924***	5.330***
	(0.682)	(0.288)	(0.727)
R-squared	-0.411	-0.411	-0.412
N	10414	10414	10414

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Chair Yellen

	(1) FE	(2) FE	(3) FE
Post	0.120	0.139	0.324
	(0.172)	(0.202)	(0.271)
infl_t	0.387***		0.383***
	(0.090)		(0.090)
post7_x_infl	-0.109		-0.128
	(0.113)		(0.115)
count		-0.009	-0.005
		(0.010)	(0.010)
post7_x_count		-0.011	-0.015
		(0.016)	(0.016)
Constant	3.134***	3.730***	3.188***
	(0.125)	(0.107)	(0.167)
R-squared	-0.180	-0.181	-0.180
N	58347	58347	58347

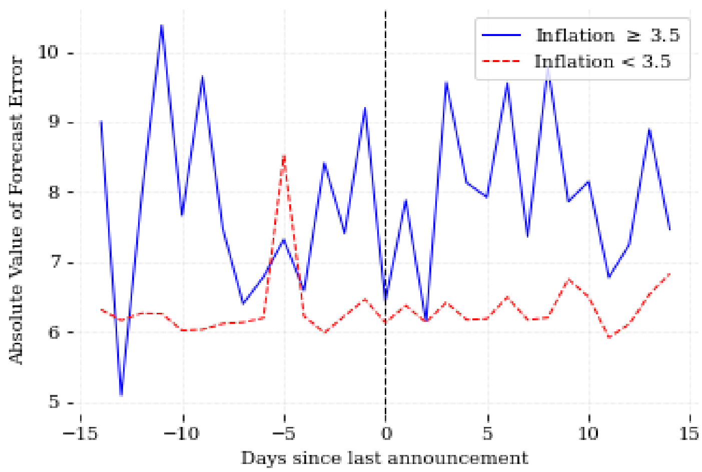
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Chair Powell

	(1) FE	(2) FE	(3) FE
Post	-0.451	-0.317	-0.408
	(0.246)	(0.202)	(0.293)
infl_t	0.308***		0.282***
	(0.070)		(0.071)
post7_x_infl	0.076		0.065
	(0.104)		(0.104)
count		0.063***	0.056**
		(0.017)	(0.017)
post7_x_count		-0.004	-0.008
		(0.027)	(0.027)
Constant	1.474***	1.784***	1.209***
	(0.164)	(0.115)	(0.186)
R-squared	-0.195	-0.195	-0.194
N	48099	48099	48099

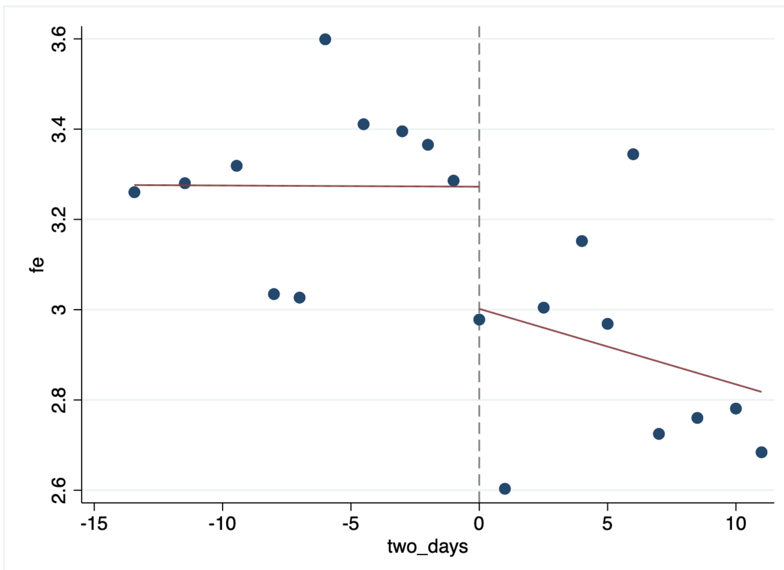
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 9: FE by Inflation Levels



Note: Forecast error is calculated as the difference between consumers' forecast of inflation in 12 months and what realized inflation was at that time.

Figure 10: Two-day Binned Average Forecast Error



Note: Forecast error is calculated as the difference between consumers' forecast of inflation in 12 months and what realized inflation was at that time.