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**Google inflation? The Formation of Households' Inflation Expectations since 2013**

Prüfer: Prof. Dr. Lena Dräger  
Betreuer: Dr. Giang Nghiem

vorgelegt von:

Name:	Veronika Schick	Luca Daniel Strickrodt
Anschrift:	Königsworther Platz 1	Stolzestraße 39
	30167 Hannover	30171 Hannover
Studiengang:	Wirtschaftswissenschaft	Wirtschaftswissenschaft
Fachsemester:	1	2
Matrikelnummer:	1234567	2891740

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# 1 Introduction

Since the last two years inflation has been risen to levels even professional forecasters have never expected (Powell (2022)). This development bears high risks as stable and low inflation rates are a necessity for a healthy economy (Brainard (2022)). Inflation rates play a significant part in determining the economic conditions as Bernanke (2007) explains in his speech “Inflation Expectations and Inflation Forecasting”. Low inflation coincides with “growth, efficiency, and stability” (Bernanke (2007), S.2), as high inflation can lead to uncertainty and losses in public confidence (Bernanke (2007)). Another important aspect of inflation are inflation expectations for their influence on economic policy (Dräger & Lamla (2017)) and the spending behavior of consumers (Dräger & Nghiem (2021)). For example, in the last two years, particular with the beginning of the Russian assault on Ukraine, inflation expectations of German households increased and have become more uncertain (Afunts, Cato, Helmschrott, & Schmidt (2022)).

This thesis wants to analyze the formation and updating behavior of inflation expectations of US households with the help of survey data. By combining data from the Survey of Consumers Expectations and Google search terms it will be possible to determine under what circumstances do households update their knowledge and therefore their short-term expectations. After a presentation of the literature the hypotheses for the further analysis are formulated. In Chapter 3 a short descriptive analysis of the one-year expectations from the last ten years is conducted which also focuses on differences between demographic characteristics like age, education and income. The time series for Google Trends is presented in a similar way. Following the descriptive analysis computations on the updating behavior with the available micro data are executed. At last regressions show the relationship between expectations and uncertainty, actual inflation, searching behavior and updating behavior.

## 2 Theoretical Background

### 2.1 Why are Expectations relevant?

Bernanke (2007) stresses the importance of expectations on actual inflation. This influence works mostly through two channels, the real rate and consumption. As

described in the Fisher equation, the real interest rate depends positively on the nominal interest rate and negatively on the expected inflation (Blanchard, Amighini, & Giavazzi (2010)). The second channel is explained by the Euler Equation. This relationship is explained by Dräger & Nghiem (2021) as the spending possibilities of a consumer as a relationship between real consumption and expected future consumption, nominal interest rates and expected inflation (Dräger & Nghiem (2021)). By using survey data of German households Dräger & Nghiem (2021) find that higher inflation expectations lead to an increase in the likelihood of higher consumption today. Weber, D’Acunto, Gorodnichenko, & Coibion (2021) conclude that expectations about future prices matter today through the influence on current decisions.

## 2.2 Measurements Demographic Differences

Expectations can be measured by surveys and the results can be used to monitor public expectations about inflation (Bernanke (2007)). Surveys, especially for the US, exist for different target groups like households or professional financial forecasters (Coibion, Gorodnichenko, Kumar, & Pedemonte (2020)). In Chapter 3 surveys in general and particular the survey used for the later analysis will be explained in more detail.

Inflation expectations differ across different groups, for example households and professionals (Coibion et al. (2020)). Professionals and households can best be separated by their grade of anchoring of inflation expectations (Coibion et al. (2020)). Bernanke (2007) describes anchoring as achieved, if price shocks impact only short-term expectations, while long-term expectations remain stable. Carvalho, Eusepi, Moench, & Preston (2021) define long-term expectations as endogenous and heavily influenced by short-term expectations. This aspect of expectations is crucial for Central Banks, as stable long-term expectations impact long-term decisions (Powell (2022)). In contrast to professionals, Coibion et al. (2020) state that households are much less anchored. Another distinction between professionals and households is the spread between expected and actual inflation. While professionals have expectations close to the actual inflation households often report upward biased expectations (D’Acunto, Malmendier, & Weber (2022)).

D’Acunto et al. (2022) also mention substantial dispersion between households’

beliefs, for example across countries. Ha, Kose, Matsuoka, Panizza, & Vorisek (2022) find that expectations in emerging market and developing economies (EMDE) have a higher sensitivity towards shocks and are overall less anchored as in developed countries. Indeed households in developed countries are “remarkably inattentive to inflation dynamics” (Coibion et al. (2020), P.2). The main reason for this dynamic lies in the stable inflation rates for most developed countries during the last decades (D’Acunto et al. (2022)). Coibion et al. (2020) credit this rational inattention to the successful monetary policy of central banks.

Chapter 3 shows more demographic differences between inflation expectations that will be presented in more detail in combination of the data presentation. In short, inflation expectations also differ for age, education, income and cognitive capabilities (Brainard (2022), Coibion et al. (2020) and Weber et al. (2021)).

### **2.3 The Importance of Price Signals**

Due to the rational inattention (D’Acunto, Malmendier, Ospina, & Weber (2019)) regarding actual inflation households build their expectations through other channels. One important channel to gather informations lies in daily shopping and the then perceived prices (Cavallo, Cruces, & Perez-Truglia (2017)). Weber et al. (2021) name food and gasoline prices as one of the major channels in the US. Goods, that are purchased more frequently are weighted higher and introduce further bias into the formation of expectations (Weber et al. (2021)). D’Acunto et al. (2019) also show that the overall frequency of purchases of non-durable goods positively correlates with inflation expectations. The relative higher volatility of gasoline and food prices could therefore be one reason for the upward biased expectations and the spread between households and professionals (Corsello, Neri, & Tagliabracci (2021)). Coibion et al. (2020) conclude that price signals in form of good purchases are therefore one important channel in the formation of expectations.

### **2.4 The Importance of Information Signals**

As previous mentioned, households in developed economies payed little to none attention to actual inflation rates and updated their expectations only slowly at the beginning of the Covid-19 pandemic (Armantier et al. (2020)). But as Afunts et al. (2022) present, a widened news coverage of inflation increases in combination with

the shocks at the energy market has lead to in increase in households expectations. With the help of a survey consisting of 145 tenured economics professors in Germany Dräger, Gründler, & Potrafke (2022) find evidence for an increase in expectations for professionals. Both observations are in line with the findings of Dräger & Lamla (2017) that volatility in inflation leads to the updating of expectations.

Weber et al. (2021) state news coverage as one possible factor for the formation of expectations. Information treatments lead to strong responses and therefore adjustments towards actual inflation (Coibion et al. (2020)). But the role and influence of media coverage for the formation of expectations is seen as relative small. Coibion et al. (2020) see media coverage as only a “relatively force” (P.6) and for D’Acunto et al. (2022) available information did not play a significant role for formation in the past. News about inflation, monetary policy ore statements by a Central Bank effect only informend specialists (Coibion et al. (2020)). Weber et al. (2021) acknowledge these findings for low inflation environments. Nonetheless in their paper “Imperfect Information and Consumer Inflation Expectations: Evidence from Microdata” Dräger & Lamla (2017) state that receiving news on inflation increases the probability of updating expectations. In this model with imperfect information, participants in the Michigan Survey of Consumers update their expectations if professional forecasts become more volatile (Dräger & Lamla (2017)).

In conclusion, Coibion et al. write that “economic agents update their beliefs depending on the strengths of their priors and signals” (Coibion et al. (2020), P.5), which can heavily differentiate in different economic environments. With worsening of economic conditions individuals update their expectations towards the real value and towards professional forecasts (Coibion et al. (2020)). Under favorable conditions households act under rational inattention, which leads to the observed upward bias of households’ expectations (Cavallo et al. (2017)).

## 2.5 Our Hypotheses

With the theoretical background layed out, the following two hypotheses are formulated:

- $H_1$  : There is a positive correlation between aggregated inflation expectations and uncertainty, Google searches and the actual inflation.

- $H_2$  : There is a positive correlation between Google searches and updating behavior of individual consumers.

The first hypothesis wants to answer if the relationship between rational inattention and economic conditions can be observed by analyzing survey data from the SCE. If shocks trigger updating behavior it must be possible to track this effect in the data. By looking at Google searches for inflation this thesis provides a proxy for searching behavior. The theoretical background for the analysis of Google search terms will be described in more detail in the next chapter. The second hypothesis tries to understand the relationship of searching- and updating behavior, which will be conducted with the help of available microdata. Combining the results of Dräger & Lamla (2017) with the time series of Google searches it may be possible to see how individuals update their expectations.

## 3 Data

### 3.1 The Dataset

The high quality of public accessible surveys for households in the US allows to use them as a tool in analyzing the formation and evolution of inflation expectations (Coibion et al. (2020)). This thesis uses the Survey of Consumer Expectations (SCE) founded in June 2013 by the New York FED. The survey consists as a rotating panel in which around 1,300 participants are asked about their views towards inflation, income or employment. The data used for this thesis are extracted with the questions Q8v2part2 and Q9. Here participants are first asked about their perception of short-term inflation. The answer is used to aggregate a point estimate for inflation expectations. After that participants have to give their subjective probabilities that inflation will be in different provided non-overlapping bins, for example the probability that inflation will be between 2% and 4%, to compute individual probability distributions. Further characteristics such as age or education are asked at the end of the survey. Each household is encouraged to participate at up to 12 follow-up surveys to analyse the evolution of individual expectations. D’Acunto et al. (2022) list the SCE as one of the most common surveys due to the high number of participants, but see disadvantages resulting from the relative short time span. For more information Weber et al. (2021) gives a more detailed



introduction of the survey.

### 3.2 Descriptive Statistics

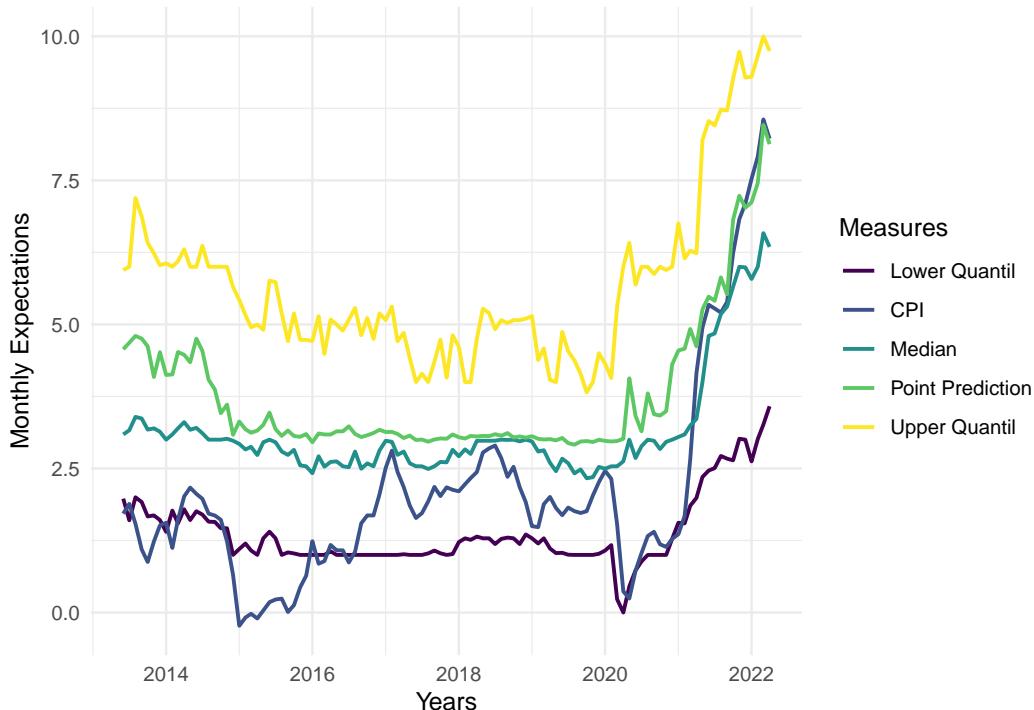


Figure 1: Short-term Expectations from 2013-present

Figure 1 shows the one-year expectations since the introduction of the SCE. As measures, the point prediction extracted from the quantitative question and median, upper and lower quantile from the probability distribution are plotted. These aggregated expectations are combined with the actual inflation measured by the CPI. Upward bias as explained by D’Acunto et al. (2022) can be detected as actual inflation remains significantly below the median and point prediction. Second, with the beginning of the COVID-19 pandemic, expectations and actual inflation are less biased and move now much more closely which confirm previously presented theories about rational inattention, for example in Cavallo et al. (2017).

To highlight the shifting in expectations over the last two years even more, the data are split into two intervals. Table 1 and 2 present different measures for both time intervals. It is possible to distinguish between a relatively stable phase until 2020 and an increase of the median, point prediction, CPI and uncertainty, defined as the spread between upper and lower quantile of expectations (Center for Microeconomic

Table 1: Summary for Expectations from 2013-2020

Measure	Mean	Volatility
Median	2.8139	0.2571
Point Prediction	3.3510	0.5623
Uncertainty	2.4658	0.2735
CPI	1.5714	0.7864

Table 2: Summary for Expectations from 2020-present

Measure	Mean	Volatility
Median	4.1441	1.4169
Point Prediction	5.1335	1.6749
Uncertainty	3.6013	0.5268
CPI	3.7927	2.8292

Data, New York Fed (2022)). Volatility has also risen significantly with values of 0.2571 to 1.4169 for the median. D’Acunto et al. (2022) describe this disagreement in their analysis with the roots lying in large economic shocks resulting from the ongoing pandemic. For the last several months it is possible to detect further increases in uncertainty and short-term expectations. This could be due to the start of the Russian invasion of Ukraine, as Afunts et al. (2022) and Dräger et al. (2022) presents updating behavior of German households and professionals.

### 3.3 Some Demographic Differences

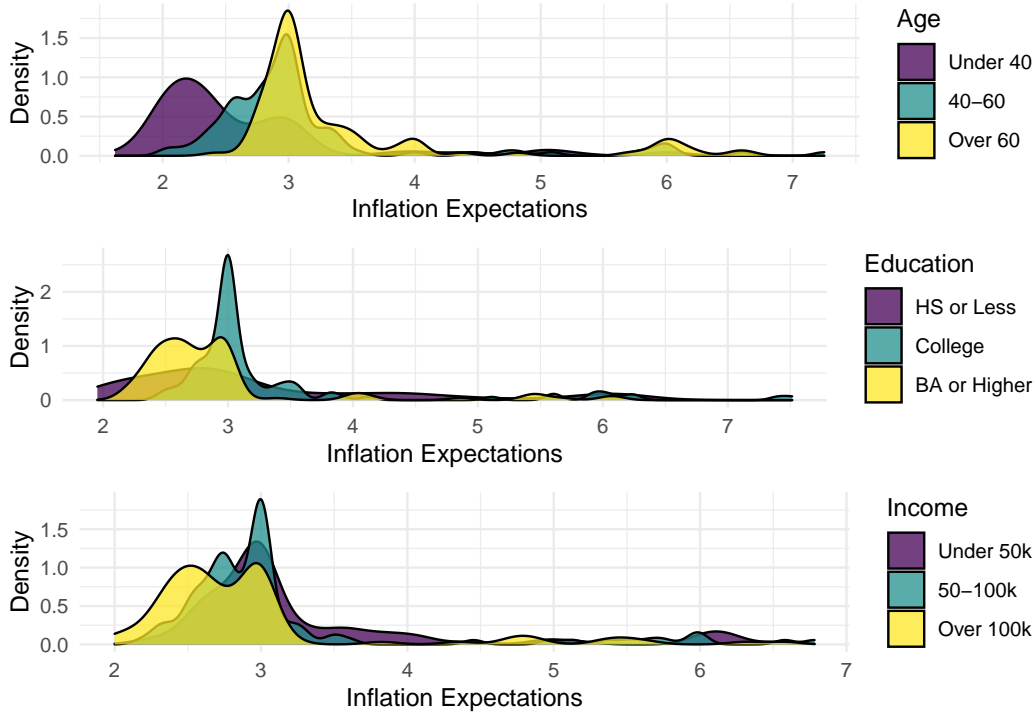


Figure 2: Density Functions for Age, Education and Income

Figure 2 shows the density of short-term inflation expectations of three different demographic characteristics, namely Age, Education and Income. The first plot presents the density for age groups. As often published age and expectations are positively correlated (see D’Acunto et al. (2022)). Due to higher inflation rates during the 70s and 80s older people are influenced by these experiences and report higher inflation rates as younger generations (Malmendier & Nagel (2015)). Additionally, Dräger & Lamla (2018) show with the help of the MSC dataset that older participants change their perceptions about inflation more often and are generally less anchored.

The second plot presents the density of inflation expectations for three education levels, namely High School or less, College and BA or Higher as defined by the SCE. As clearly seen there are remarkable differences in inflation expectations. Participants with within the lowest education level are defined by a much higher volatility of 1.1499 as compared to 0.7939 for BA or Higher. Expectations for College and BA or Higher are more concentrated around the actual inflation target of western central banks. For college levels the figure shows a concentration around 3%, for BA or Higher two peaks at around 3% and the true inflation target of 2%. This shows the

underlying relationship between education and knowledge about actual inflation as analyzed by Weber et al. (2021).

The last sub figure plots the density for the three income levels. BA or Higher and an income level of over 100k show very similar densities, which could link to a high correlation between income, education and generally cognitive abilities (Coibion et al. (2020)). Participants with lower income show more volatile expectations, which confirms the findings presented by Weber et al. (2021) that the bias in expectations and income of households are negatively correlated.

### 3.4 GoogleTrends Searches

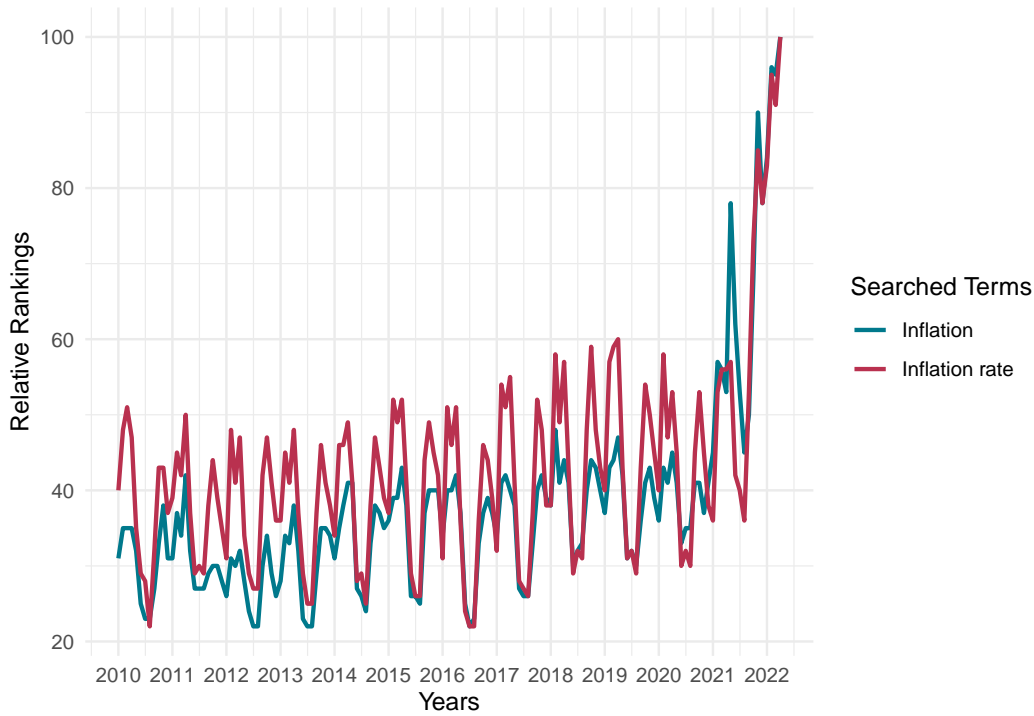


Figure 3: US Google Trends Results for Inflation and Inflation rate from 2010-present

Figure 3 presents the Google Trends results for the two searching terms “inflation” and “inflation rate” from 2010-present. The idea as presented by Seabold & Coppola (2015) is to use Google Searches as a proxy for updating behavior. Seabold & Coppola (2015) argue that in the absence of high quality data it is possible to “nowcasting” prices with the help of Google Trends. By looking at certain key words, in the case of this thesis inflation, the searching behavior can be compared with households’ short-term inflation expectations. As we can see, there is a striking similarity in

the evolution of Google Searches and short-term expectations. Like in Figure 1 we see stable behavior until 2022, after that spikes in the searching behavior. Searches for both key words move rather identical with only one exception around April 2021. Until 2021 both search terms move cyclical over the years with low searches in the summer and spikes around black friday and the holiday season. In conclusion, searches show a similar pattern like the expectations of households.

By combining the results of the descriptive analysis it is possible to interpret higher volatility and uncertainty in inflation expectations in the last two years as a sign of an underlying relationship between uncertainty and expectations. The time series for expectations and Google searches show a similar behavior. This hints to a link between searching behavior and expectations development. In the next chapter this thesis will first introduce the microdata for the SCE survey, compute aspects of updating behavior and then proof both hypothesis with several regressions.

Table 3: Summary for Updating Frequency

Measure	Mean	Volatility
Updating Frequency	0.4998	0.235

## 4 Results

### 4.1 Updating Behavior

To analyze individual behavior, for example in updating their expectations, and the relationship with Google searches this thesis uses a similar approach as in the paper “Updating inflation expectations: Evidence from micro-data” by Dräger & Lamla (2017). Dräger et al. use microdata from the Survey of Consumers conducted by the University of Michigan (MSC) from 78-2011. In this survey some participants are questioned a second time, which allows Dräger & Lamla (2017) to show individual updating behavior by computing updating shares and updating frequency. For the updating frequency Dräger & Lamla (2017) receive 8 or 16 months for the quantitative and qualitative questions targeting at inflation expectations in the short run. Dräger & Lamla (2017) demonstrate 74.1 in updating share for the quantitative and 38.2 for the qualitative answer, with higher spreads for the qualitative answer. The crises of 2001 and 2008 also increased shares significantly. Dräger & Lamla (2017) conclude that updating behavior depends on the business cycle fluctuations, with higher shares and frequency around crises and lower adjustments for stable conditions and long-term expectations.

This thesis investigates these finding by analyzing the updating behavior of individuals within the SCE. For this, the focus is layed on the quantitative answers that are aggregated to the already established point prediction. As in Dräger & Lamla (2017), the upper and lower 2.5% of the distribution are detected as outliers and therefore are rejected from the analysis. After combining all available microdata published by the SCE the updating frequency of all participants is presented in Table 3. The average updating frequency is determined as 0.4998. With an average tenure of 9 months, participants update their expectations around five times within the survey.

Figure 4 shows the density function for the whole sample distinguished for the three age categories. Other demographic differences like education and income result in similar distributions. As clearly seen all age groups follow a general pattern with

only minor differences. There is a significant part of participants that do not upgrade their expectations at all. This behavior is shown by around 7.5% of participants in the whole sample and coincides with a smaller tenure of 5 months. Due to the limitations of the available microdata it is not possible to distinguish between the same two time intervals as for the aggregated data.

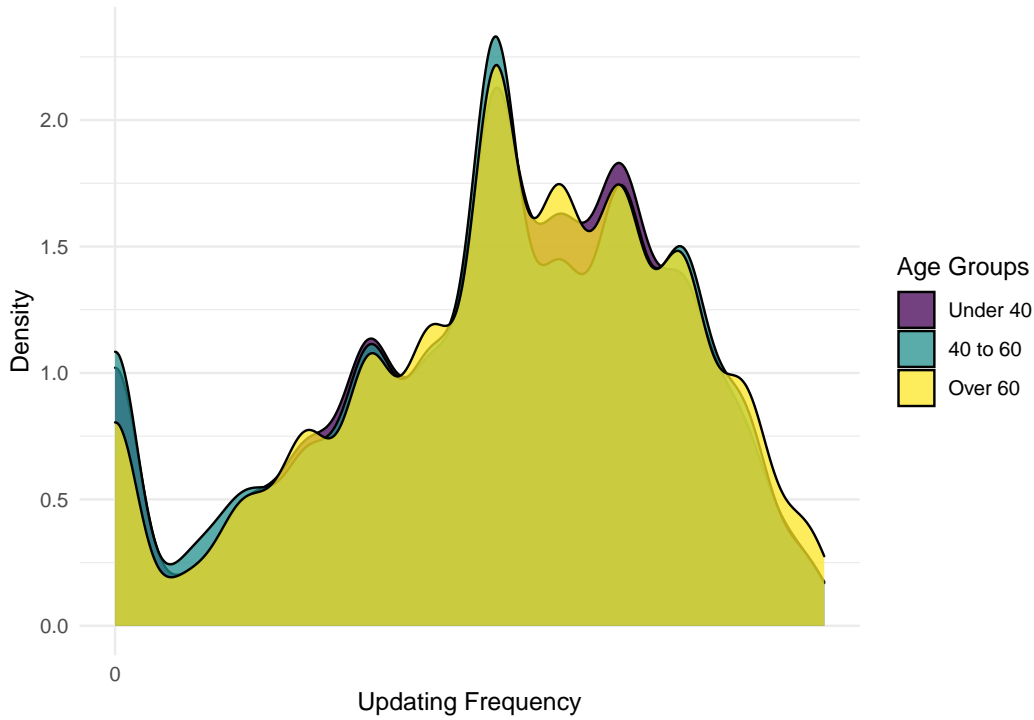


Figure 4: Density Functions of the Updating Frequency

Figure 5 plots the updating share over the whole sample again for Age, Education and Income. Over the full sample the average updating share lies at 55.63%. All three age groups show similar behavior with old participants expressing slightly higher updating shares. For Education higher educated participants show lower updating shares which could hint at already existing knowledge about actual inflation. For Income it is possible to detect a negative relationship between Income and updating, as poorer participants have slightly higher values for the updating share. The microdata reveal for all three demographics an updating spike at the beginning of the Covid19-Crises but can not show a possible manifestation of this trend due to the lack of data after July 2021.

Comparing the results with the findings of Dräger & Lamla (2017), fewer participants in the SCE update their expectations every month, but with a higher frequency. The

spike in updating share at the beginning of the Covid19-Crises can be interpreted as a reaction to the business cycle as shown by Dräger & Lamla (2017).

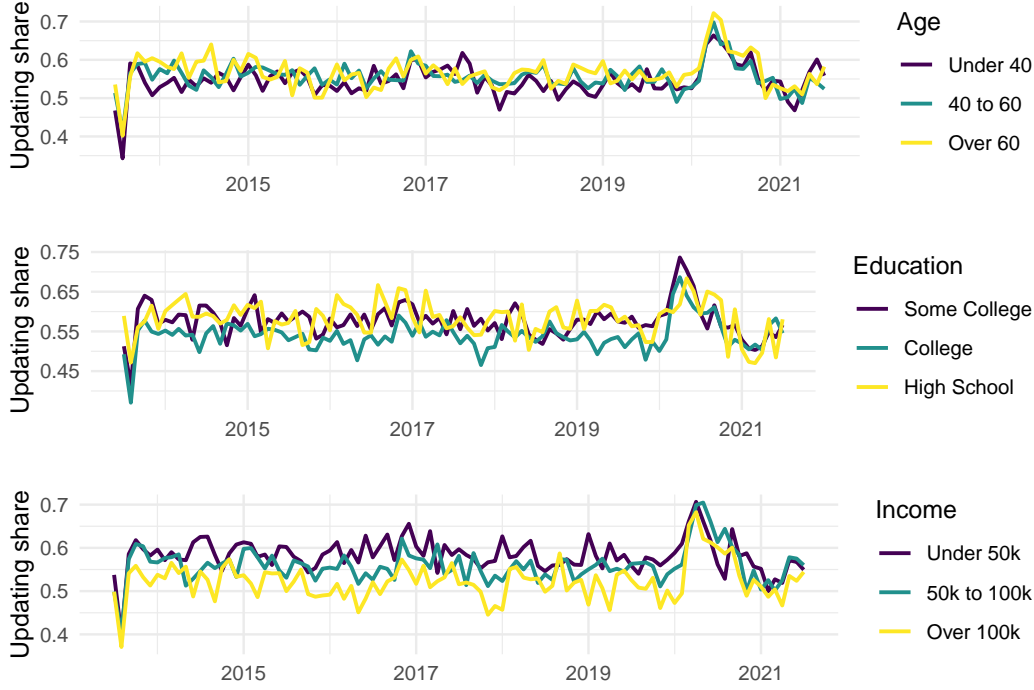


Figure 5: Updating Shares for Age, Education and Income

## 4.2 Regressions

After the descriptive analyses of the provided aggregated data, the presentation of demographic differences in inflation expectations and the use of microdata to display individual updating behavior this sub chapter puts a light on the relationships that influence inflation expectations. Due to the shorter time series for the micro data two different regression tables are build to perform the regressions. To avoid heteroscedasticity only the search term inflation is used in assumption that there is a significant overlap between both search terms.

### 4.2.1 Regressions with aggregated data

To test the first hypothesis the aggregated data are used for two regression models:

- $H_1 : \text{Uncertainty } GS_{infl} + CPI$
- $H_2 : \text{Pointprediction } GS_{infl} + \text{Uncertainty} + CPI$



As previously done in Chapter 3 all regressions are conducted for the two sub time-series to analyze differences in the correlations.

Table 4: Regressions for Aggregated Data, 2013-present

	<i>Dependent variable:</i>	
	Uncertainty	‘Point Prediction’
GS_infl	0.016*** (0.005)	0.002 (0.005)
Uncertainty		1.253*** (0.106)
CPI	0.116*** (0.040)	0.248*** (0.045)
Constant	1.844*** (0.140)	−0.265 (0.247)
Observations	107	107
Adjusted R <sup>2</sup>	0.504	0.860
Residual Std. Error	0.423 (df = 104)	0.458 (df = 103)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01		

The results for the whole sample are presented in Table 4. As seen in the first model searching behavior and actual inflation both play a significant role for Uncertainty. Searching for inflation increases uncertainty, but with a weaker effect as actual inflation. In the second model, significant values for Uncertainty and CPI demonstrate the influence of actual inflation for the point estimation.

Table 5 shows the results for the first time interval. CPI and searching behavior have a negative effect on uncertainty, which hints at a stabilization effect for the distribution of expectations. Uncertainty has now the highest value of 1.447. A weaker Adj. R<sup>2</sup>. could be due to overall stable expectations and low inflation in the first time interval.

The regressions for the second interval are presented in Table 6. In the first model only CPI has a significant value. Searches for inflation now positively correlate with the Point Prediction in the second model. In both models actual inflation has the biggest influence of all three intervals, which shows the importance of the increase in

Table 5: Regressions for Aggregated Data, sample from 2013-2020

	<i>Dependent variable:</i>	
	Uncertainty	‘Point Prediction‘
GS_infl	−0.016*** (0.004)	−0.011 (0.007)
Uncertainty		1.447*** (0.182)
CPI	−0.082** (0.035)	0.127** (0.058)
Constant	3.166*** (0.153)	−0.027 (0.627)
Observations	81	81
Adjusted R <sup>2</sup>	0.212	0.518
Residual Std. Error	0.243 (df = 78)	0.390 (df = 77)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01		

Table 6: Regressions for Aggregated Data, sample 2020-present

	<i>Dependent variable:</i>	
	Uncertainty	‘Point Prediction‘
GS_infl	0.002 (0.005)	0.023** (0.009)
Uncertainty		0.931** (0.367)
CPI	0.154*** (0.037)	0.254*** (0.086)
Constant	2.892*** (0.176)	−0.503 (1.105)
Observations	26	26
Adjusted R <sup>2</sup>	0.804	0.940
Residual Std. Error	0.233 (df = 23)	0.411 (df = 22)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01		

inflation for inflation expectations. Both models also show higher values for Adj.  $R^2$  in all three models than in first intervals. In conclusion, all three regression tables show the importance of actual inflation, but also searching behavior for distribution and point estimation of inflation expectations.

#### 4.2.2 Regressions with microdata

In the next regressions, the influence of the already presented demographic aspects Age, Education and Income are analyzed. Table 7 presents the results, which confirm the previous findings but with very weak values for the Adj.  $R^2$ .

Table 7: Regressions for Age, Education and Income

	<i>Dependent variable:</i>			
	Expectation			
Age40_60	0.810*** (0.047)			0.591*** (0.046)
AgeO60	0.922*** (0.048)			0.354*** (0.048)
Edu_SC		-1.222*** (0.065)		-1.033*** (0.065)
Edu_C		-3.320*** (0.061)		-2.542*** (0.064)
Inc50_100			-1.744*** (0.044)	-1.324*** (0.045)
IncO100			-2.943*** (0.047)	-2.165*** (0.050)
Constant	4.381*** (0.036)	7.283*** (0.056)	6.495*** (0.032)	7.547*** (0.068)
Observations	121,575	121,458	120,322	120,128
Adjusted $R^2$	0.004	0.036	0.033	0.053
Residual Std. Error	6.552 (df = 121572)	6.439 (df = 121455)	6.455 (df = 120319)	6.384 (df = 120121)

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

After the regressions for properties the microdata are used for the second hypothesis with the following regression models:

- *Updatingshare GS\_infl*
- *Updatingshare Uncertainty*
- *GS\_infl Updatingshare*
- *Uncertainty Updatingshare*

Table 8: Regressions for Microdata

	<i>Dependent variable:</i>			
	‘Updating share’	GS_infl	Uncertainty	
GS_infl	0.0001 (0.0004)			
Uncertainty	0.013 (0.008)			
‘Updating share’		9.060 (25.457)	1.949 (1.234)	
Constant	0.551*** (0.016)	0.523*** (0.022)	32.696** (14.206)	1.525** (0.689)
Observations	97	97	97	97
Adjusted R <sup>2</sup>	−0.009	0.015	−0.009	0.015
Residual Std. Error (df = 95)	0.035	0.034	8.660	0.420

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 8 presents the four models for the microdata. For all models no significant values for Uncertainty, updating behavior or searching behavior can be found. This is combined with values for the Adj.  $R^2$  at zero or below. This makes a proper interpretation almost impossible. Maybe the regressions show that in the first (stable) period updating behavior does not depend on searching behavior because consumers have no incentive to inform themselves as previous presented by Coibion et al. (2020).

## 5 Limitations

### 5.1 Panel Conditioning

Weber et al. (2021) state in their paper that due to panel conditioning, which describes the learning effect occurring by enrolling multiple times in a survey, the

results of the survey can be biased. This learning behavior would differentiate the participants from the underlying population, which would mean that the sample can not longer be representative for the population (Kim & Binder (2020)).

## **5.2 The Time Interval**

The analysis of the updating behavior faces huge limitations. Due to contract dependent limitations the SCE publishes the microdata with a one year delay. As seen in the previous chapters, the biggest increases in expectations and searching behavior lay in the last six months. This missing of the most crucial time interval for changes in inflation expectations is responsible for the missing interpretation of changes in updating behavior in the last months and maybe weak regression results.

## **6 Conclusion**

This thesis tries to answer the question under which circumstances and how often households update their inflation expectations. As shown with the help of aggregated and micro data from the SCE expectations have changed significantly over the last two years. Microdata show a spike in updating share and updating behavior at the beginning of 2020. By combining survey data with data from GoogleTrends it is possible to highlight the role of searching behavior as a channel for updating expectations. Due to the lack of available microdata all analyses for microdata provide only limited explanations for the changes in the last twelve months. All analyses are influenced by limitations through panel conditioning who are unable to match with the limited extent of this thesis. With access to more recent microdata and more sound analyses regarding the underlying limitations of survey data future research can fill this void and provide a more satisfying answer to these important questions.

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## Ehrenwörtliche Erklärung

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Ort, Datum

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Veronika Schick

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Ort, Datum

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Luca Daniel Strickrodt