Essays on Expectation Formation, Inflation Dynamics, and Monetary Policy

Dissertation zur Erlangung des akademischen Grades

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Contents

Chapter 1

Introduction

In macroeconomics, it is common to use models that assume fully informed agents who have all available information at every point in time. Recently, these models have been challenged by models which are based on the idea that new information is not always available to every agent (e.g. Mankiw and Reis 2002, Sims 2003, Reis 2006a, 2006b, Mackowiak and Wiederholt 2009, Mankiw and Reis 2011). This type of models includes sticky-information models and models of rational inattention. The basic idea distinguishing these new models from mainstream models is the consideration of information costs which can be real resource costs, utility losses, or limited capacities (Sims 2005, Mankiw and Reis 2011).

The two types of models differ in the way how agents form expectations. In mainstream models, agents use all currently available information and form rational expectations (full-information rationality) which imply that agents' expectations are the same as the prediction of the respective model. In models with information costs by contrast, agents rationally economize on these costs and frequently form expectations based on outdated information (delayed-information rationality). Depending on the underlying assumptions about information, the models predict different inflation dynamics (e.g. Mankiw and Reis 2002) and have other implications for monetary policy (e.g. Ball et al. 2005, Mankiw and Reis 2011).

In this thesis, I compare the notions of information underlying these two branches of macroeconomic research empirically. The thesis presents five empirical contributions on the comparison of the competing concepts using different types of data. Chapters 2 and 3 use survey data on expectations and analyzes their formation. Chapter 4 compares two models with different assumptions about information using macro data and thereby tests which expectations are relevant for macroeconomic dynamics. Chapters 5 and 6 provide experimental evidence on the existence and handling of information costs in expectation formation.

Chapter 2 presents an empirical test of the two different concepts of rationality underlying the competing types of models: full-information vs. delayed-information rationality. Survey data on inflation expectations of German consumers are considered. I test different implications of the two forms of expectation formation taking both an aggregate and disaggregated view on the data.

The contribution of the essay presented in Chapter 2 is twofold. First, it directly compares the two different concepts of rationality, full-information and delayed-information rationality while most previous studies (e.g. Roberts 1997, Thomas 1999, Andolfatto et al. 2008) have considered only one of these concepts. Second, by considering also disaggregated data the essay seeks to discover possible rationality biases suspected by the literature (e.g. Bonham and Cohen 2001, Demery and Duck 2007).

Full-information rationality implies unbiasedness of expectations, the absence of serial correlation in forecast errors, the efficiency of expectations, and their orthogonality to any available information. Tests of these hypotheses indicate that inflation expectations of German consumers cannot be described as full-information rational and provide hints for adaptive patterns. This result holds for the total sample as well as within population subgroups.

The analysis with respect to delayed-information rationality relies on a model proposed by Carroll (2003). The results support delayed-information rationality based on both aggregate and disaggregated data. Delayed-information rationality is supported based on results from a baseline OLS model and an error-correction model.

The essay presented in Chapter 3 investigates implications about expectation formation that are derived from rational-inattentiveness models and sticky-information models. Agents in these models do not collect perfect information in every period because information is costly. One consequence is that the lower the cost of information, the more often rational agents will update their information set. The essay makes use of news coverage as an inverse proxy for information costs. A testable implication of rational inattentiveness then is that news coverage and forecast deviation are negatively correlated.

The chapter tests this hypothesis with respect to inflation forecasts and unemployment forecasts. It uses data on the amount of news about the respective topic (inflation or unemployment) in U.S. newspapers and analyzes its influences on the differences between expectations of consumers and professional forecasters. The essay contributes to previous studies on the relation between news and forecast accuracy (e.g. Carroll 2003, Badarinza and Buchmann 2009) which solely focus on inflation by extending the analysis also to unemployment. Furthermore, I use a more purposive measure of news coverage and the analysis is done for the representative U.S. consumer and also for different subgroups. In addition, I control for other variables that could influence forecast accuracy like macroeconomic variables, major events, and elections.

The results show that consumers' inflation forecast of the representative U.S. consumer is closer to professionals' forecast when more news about inflation is printed in newspapers. This confirms the theoretical prediction of a negative correlation between news coverage and forecast deviation. But the effect vanishes partly in a subgroup analysis. Quantitatively, the gap between consumers' and professionals' inflation forecasts is reduced by approximately one average absolute forecast error if one more article about inflation is published in a newspaper per day.

However, the correlation between news about unemployment and unemployment forecast deviation has the opposite sign as predicted by the theory. The results concerning unemployment indicate a positive effect of news about unemployment on unemployment forecast deviation. Thus, the theoretical prediction of a negative correlation between the amount of news and forecast deviation occurs empirically for inflation but the opposite correlation emerges in the case of unemployment. Both findings are robust to the inclusion of macroeconomic variables, major events, and elections.

While Chapters 2 and 3 have considered survey data on expectation formation, Bredemeier and Goecke take in Chapter 4 a more indirect view on the role of expectations. The chapter presents an empirical comparison between the sticky-information and the sticky-price Phillips curves. Both Phillips curves differ in the expectation terms they include. In the sticky-price Phillips curve, inflation depends on current expectations of future inflation while the sticky-information Phillips curve contains all past expectations of current inflation. The chapter analyzes which concept is more successful in explaining empirical inflation dynamics.

The chapter adds to the literature in various respects. First, it examines whether the finding that a simple sticky-information model matches selected second moments of US inflation reasonably well (Reis 2006b) can also be achieved using a sticky-price model. Other than previous comparisons of the two concepts (e.g. Korenok and Swanson 2007, Korenok 2008, Abbott 2010), we take a broad look on inflation dynamics and consider inflation variance and persistence as well as its relation to dynamics in demand and supply. Furthermore, our cross-country perspective allows to analyze whether relative model performances are country-specific.

Our results indicate that the overall empirical performance allows no clear distinction between the two concepts. However, if one is predominantly interested in matching unconditional moments of inflation dynamics, sticky prices should be used. Researchers who focus on co-movements of inflation with demand will obtain better results applying sticky information. These results rely on our cross-country perspective since, in the US, model performances are almost identical.

While Chapters 2 to 4 have used field data, Goecke, Luhan, and Roos employ data from experiments in Chapters 5 and 6. These chapters provide experimental evidence on the existence and handling of information costs in expectation formation. Information costs in the experiment presented in Chapter 5 are monetarized and exogenously given as assumed in rational-inattentiveness models. Chapter 6 tests the existence of information costs.

Chapter 5 presents the first experimental test of rational-inattentiveness models in the spirit of Reis (2006a, 2006b). In a laboratory experiment we test the central feature of rational-inattentiveness models: subjects weigh the costs against the benefits of information acquisition and rationally ignore available information if the costs exceed the benefits. In an individual choice experiment, subjects have to predict the realization of a simple stochastic process in several periods. In each period, subjects can choose between forecasting without new information (guessing) and buying perfect information. The lab experiment allows us to control the costs and benefits of information perfectly and enables us to conduct tests against a clear theoretical benchmark.

Our results show clear evidence in favor of sticky-information and rational-inattentiveness models. Agents behave as if they are able to calculate the optimal length of inattention. They do not update information in some periods and therefore they partly stick to old information. In most treatments we cannot reject the null hypothesis that subjects update their information as predicted by the rational-inattentiveness models. Simple myopic behavior is rarely a good description of subjects' behavior. Furthermore, the results indicate that the length of inattention increases with rising information costs as predicted by the theory. These results hold in the aggregate, i.e. they describe average behavior of all subjects pooled together. Pairwise comparisons between two treatments to test rational behavior and myopic behavior show mixed evidence but favors also the rationality approach in comparison to the myopic approach. Individual behavior is less rational, but deviations from rationality are not systematic.

Chapter 6 also uses data generated in an experiment. These data are used to test different assumptions about information costs derived from rational-expectations and rational-inattentiveness models. The essay contributes to the literature by giving participants the possibility to choose the amount of information in our experiment without paying a monetary cost rather than imposing information costs directly as for example done by Gabaix et al. (2006), Kraemer et al. (2006), Huber et al. (2011), and as done in Chapter 5 of this thesis.

Information acquisition is assumed to be costless in rational-expectations models but it is considered as costly in rational-inattentiveness models. This essay provides an empirical test of these two assumptions about information costs by using data generated in a real-effort experiment. The lab experiment enables us to control the benefit of information which allows us to analyze directly the existence of information costs. In an individual choice experiment, subjects have to perform a forecast. Subjects can gain information in this real-effort experiment about the variable to be forecasted via a task. For each correct solution of the task, the range of possible numbers, of the variable that has to be forecasted, shrinks by a certain amount.

The task in the real-effort experiment consists of simple mathematical problems which captures the processing of information. We test whether the effort of solving the mathematical problems is perceived as costs by the participants. Given the existence of costs, participants should economize on solving mathematical problems.

We analyze whether subjects acquire all information given different tasks and different benefits of information. If subjects economize on solving the simple addition problems, we conclude that they view this task as a cost. In addition, we test how the time spent to solve the tasks, as a measure of individual information costs, influences the number of calculations.

Our results show clear evidence for the existence of information costs and therefore support rational-inattentiveness models. Processing of information seems to induce costs for the participants and therefore they do not collect all available information. When considering all treatments, in half of all calculations subjects do not collect all available information. Furthermore, information processing diminishes with rising information costs. A participant, who needs 10 seconds more for one block of calculations, tends to do 0.6 rounds less of calculation.

Chapter 7 concludes the thesis.

Chapter 2

Testing Rationality of Inflation Expectations using Aggregate and Disaggregated Data

2.1 Introduction

Recently, monetary macroeconomic models that build on the assumption of fully informed agents have been challenged by models which are based on the idea that new information is not available to every agent at every point of time (e.g. Mankiw and Reis 2002). These two ideas imply two different types of rationality: full-information and delayed-information rationality. This essay provides an empirical analysis of these two kinds of rationality using data on expectations.[1]

The first rationality approach considered in this essay is the rational-expectations hypothesis of Muth (1961) that assumes full information of all agents at any point in time. The assumption of full information implies that the expectations are the same as the prediction of the model. In this essay, I will refer to this idea of rationality as "full-information rationality".

The second approach of rationality assumes that expectations are based on incomplete or delayed information. To describe this idea of rationality, different terminologies are used in the literature like "economically rational" (Feige and Pearce 1976), "bounded rationality" (Conlisk 1996), "partial-information

[1]This essay is based on Goecke (2011b).

rational expectation" (Demery and Duck 2007), or models of the "sticky information" type (Mankiw and Reis 2002). The theory of "inattentiveness" (Reis 2006a, 2006b) and the theory of "rational inattention" (Sims 2003 and Mackowiak and Wiederholt 2009) justify delayed and incomplete information, respectively. In this essay, I will refer to this approach of rationality as "delayed-information rationality".

Many papers analyze whether inflation expectations can be described as being rational (e.g. Roberts 1997, Thomas 1999, and Andolfatto et al. 2008). This is mainly done using aggregate data. But, among others, Figlewski and Wachtel (1981), Keane and Runkle (1990), Bonham and Cohen (2001), and Demery and Duck (2007) show that using an average forecast, in contrast to individual data, can lead to inconsistent estimators in rationality tests. Keane and Runkle (1990) assert that

> "...There are two problems with using consensus forecasts to test rationality... If forecasters are rational, their forecasts will differ only because of differences in their information sets. The mean of many individual rational forecasts, each conditional on a private information set, is not itself a rational forecast conditional on any particular information set... This seemingly minor issue can produce severe bias[2]... A second problem with using consensus forecasts is that this approach can mask individual deviations from rationality. Hirsch and Lovell (1969) ...found (p.71) that some firms are consistently optimistic about future sales while others are consistently pessimistic. Averaging expectations, however, can cancel these biases across firms so that industry mean expectations show no bias..." (p.717).

Furthermore, Demery and Duck (2007) show that

> "...if expectations are formed on a limited information set, the coefficients estimated from aggregate data may give quite misleading estimates of the true individual response..." (p.13)

[2]Keane and Runkle (1990) show that the estimators of parameters from rationality tests by using aggregated data are biased upwards in comparison to an estimator of parameters based on disaggregated data.

because idiosyncratic and common shocks are possibly not separately observed and the effects of the two shocks conflate. In this case, individuals could react incorrectly to a common shock in the belief that it was an idiosyncratic shock. The effects of the idiosyncratic shocks do not average out at the aggregate level which causes biased estimators.

This essay analyzes whether inflation expectations of German consumers can be described as rational and if so, by which kind of rationality. The contribution of this essay to the literature is to test the two different concepts of rationality, full-information and delayed-information rationality. This is done by using not only aggregate but also disaggregated data to discover possible rationality biases.

A further advantage of using disaggregated data, in contrast to merely using aggregate data, is the possibility to discover how demographic characteristics influence the inflation expectations process and inflation forecast accuracy. Gramlich (1983) and Blanchflower and MacCoille (2009) find demographic effects on inflation expectations and inflation forecast accuracy for the US and the UK.

A measure of inflation expectations is derived from the Business and Consumer Survey of the European Commission.[3] The analysis is done for a representative consumer and separately for different demographic groups. Consumers are asked in the survey about their expected direction of change in the price level. Therefore, the survey provides qualitative data. Since an economic interpretation of the raw qualitative data, without conversion, as expected inflation rates is not possible, the data are converted based on the method proposed by Batchelor and Orr (1988) and Berk (1999) to perform rationality tests. These methods use the answer probabilities about expected and perceived inflation of the respondents and weight these probabilities with a scaling parameter to calculate quantitative inflation forecasts. I choose the scaling factor such that expectations are on average not biased.

This essay is the first one that deals with rationality of inflation expectations with aggregate and disaggregated data for Germany. The data set used in this essay has not been applied in the literature on inflation expectations before and it is the only data set concerning inflation expectations on a

[3] Cf. European Commission (2008).

disaggregated level besides British and American data.

I test full-information rationality by testing the hypothesis of serial correlation, efficiency, and orthogonality. Results of full-information rationality tests indicate that inflation expectations of German consumers cannot be described as full-information rational and give hints to adaptive patterns. This result holds for aggregate as well as for disaggregated data. The adaptive pattern may be due to delayed-information rationality. Therefore, I check this kind of rationality using the microfoundation of the sticky-information model by Carroll (2003). I test whether Carroll's model is supported by the data. The analysis supports delayed-information rationality based on both types of data. Delayed-information rationality is supported based on results from a baseline OLS model and an error-correction model.

The closest papers to this essay are the following ones. Keane and Runkle (1990) test full information rationality using disaggregated data for the U.S. but there is no paper testing rationality using disaggregated German consumer data. A couple of papers use the idea of rational inattentiveness or sticky information but it exists no usage of theses ideas to test a special type of rationality. The closest paper in this direction is Döpke et al. (2008a). These authors test the model derived by Carroll (2003) for four major European countries but they do not interpret the results as delayed-information rationality. Furthermore no paper analyzes Carroll's model on a disaggregated level. Finally there are papers discussing rationality effects for different demographic groups but there is no study using German data. The closest paper in this direction is the one by Blanchflower and MacCoille (2009).

The remainder of this essay is organized as follows. Section 2.2 describes the data of the Business and Consumer survey and presents descriptive statistics. Section 2.3 presents rationality tests. Section 2.3.1 deals with unbiasedness of expectations which is an issue for both types of rationality considered. Section 2.3.2 illustrates the results for full-information rationality tests. Evidence for rationality based on delayed information is presented in Section 2.3.3. Section 2.4 provides the conclusion.

2.2 Data

This empirical analysis is based on data from the Joint Harmonized EU Program of Business and Consumer Surveys conducted by the European Commission (hereafter EC). In the case of Germany, the Gesellschaft für Konsumforschung (hereafter GfK) performs the survey on behalf of the EC. For Germany, approximately 2,500 consumers are interviewed every month since 1985. From January 1985 to the end of 1996, only residents of West Germany completed the survey while since January 1997 the GfK has also queried 500 respondents from East Germany.[4] The German data set has the important but rare characteristic that it contains aggregate as well as disaggregated data. It is thus possible to analyze the total sample and subgroups separately. To the best of my knowledge, disaggregated German data has not been used in the literature on inflation expectations so far and there exists no data set in the literature on a disaggregated level for other countries except British and American data.

The composition of respondents is chosen in a way that the aggregate answers of the total sample can be interpreted as answers of a representative German consumer. Response data is available for the total sample and on a disaggregated level. The sample is differentiated in the following categories: gender, education (primary; secondary; further), age (16-29; 30-49; 50-64; 65+), income (which I group by quartiles), and occupation (ten classifications).[5]

2.2.1 Descriptive Statistics: EC Index Value

Questions number five and six of the survey are of interest for the analysis of this essay.[6] These questions deal with perceived and expected inflation. The respondents are asked for their tendency. Therefore, the resulting survey data is qualitative. Table 2.1 shows the exact wording of both questions and the possible answers for the respondents.

For each question, the EC calculates an index value B based on the first five possible answers in the following way. The total percentage value of the first (risen a lot/increase more rapidly), second (risen moderately/increase at the same rate), third (risen slightly/increase at a slower rate), fourth (stayed

[4]Cf. Deutsche Bundesbank (2001), page 38.

[5]The different occupations are: self employed and professional, self employed farmers, clerical and office employees, skilled manual workers, other manual workers, total workers, work full-time, work part-time, other occupations, and unemployed. The group of unemployed individuals includes students, jobless, and retired persons.

[6]For the relevant part of the survey cf. European Commission (2008), page 34 and 35.

Question five	Question six
"How do you think that consumer prices have developed over the last 12 months? They have..."	"By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months? They will..."
risen a lot	increase more rapidly
risen moderately	increase at the same rate
risen slightly	increase at a slower rate
stayed about the same	stay about the same
fallen	fall
don't know	don't know

Table 2.1: Questions five and six of the consumer survey

about the same/ stay about the same), and fifth (fallen/fall) answer categories are denoted PP, P, E, M, and MM, respectively. The EC calculates the balance index B by:[7]

$$B = (PP + 0.5 \cdot P) - (MM + 0.5 \cdot M)$$

The index that results from this calculation is published monthly by the EC and is the starting point of my analysis. To provide an overview over the data, Figure 2.1 depicts the aggregate answer percentages given by all respondents concerning perceived past annual inflation between January 1985 and June 2008. The horizontal axes show the time horizon and the vertical axes show the percentages of respondents for each possible answer. Figure 2.2 presents the results of all respondents in the same way as Figure 2.1, but with respect to expectations of future inflation (question 6).

Graphs in both figures show the effects of the second Gulf War at the beginning of the 1990's, the Euro cash introduction in January 2002, and the three percentage point VAT increase in Germany in January 2007 for expected inflation and perceived inflation. The events Gulf War and tax increase cause the answer probabilities "risen a lot/increase more rapidly" to rise. The Euro

[7] Under additional consideration of a seasonal adjustment. Cf. European Commission (2008) page 24.

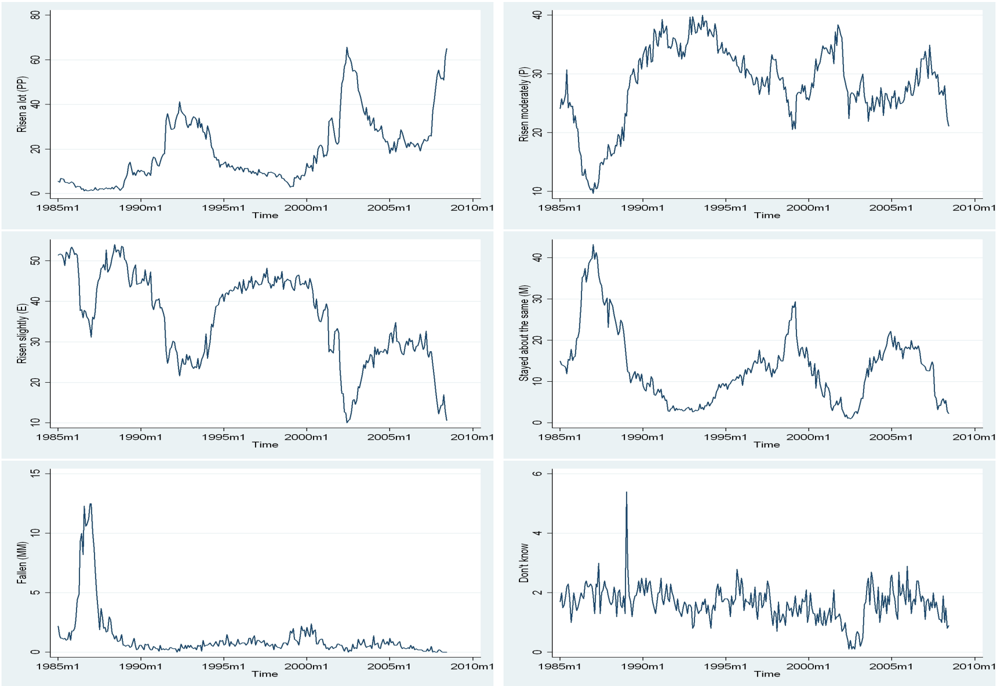

Figure 2.1: Aggregate answer percentages to question five

cash introduction in 2002 induces the answer probabilities for a higher perceived inflation ("risen a lot") to rise. The increase in perceived inflation rate throughout the course of the Euro cash introduction in Germany is a known phenomenon.[8] Concerning inflation expectations (Figure 2.2), the Euro cash introduction induces the answer probabilities for a rising and stable inflation expectation to fall and for a lower inflation, no inflation, and deflation in expectations to rise.

Following the graphical overview for the total sample, Table 2.2 presents descriptive statistics of the EC index value for inflation expectations and perceived inflation of German consumers on aggregate and disaggregated levels. It shows the outcome for the EC balance index for expected inflation and perceived inflation for the total sample and different groups from the first quarter of 1990 to the second quarter of 2008.[9] The analysis does not start before 1990 because disaggregated data is only available since January 1990. For reasons of clarity, only two out of ten different occupations are used throughout the

[8] Cf. Brachinger (2006) and Hoffmann et al. (2006).

[9] In the following analysis, data is used that is only available on a quarterly basis. For uniformity and comparability of the results, the whole analysis is done on a quarterly basis.

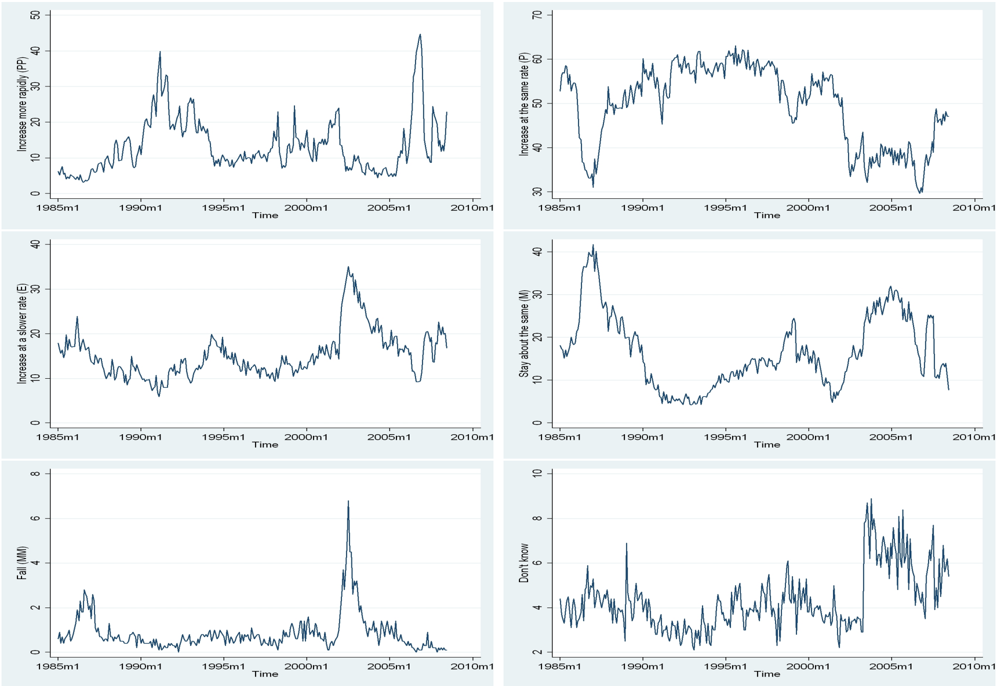

Figure 2.2: Aggregate answer percentages to question six

whole essay. These are "work full-time" and "unemployed". The results of the rationality tests in the following sections for "work full-time" individuals are similar for all excluded occupations.[10] Means, standard deviations (SD), and p-values are presented in Table 2.2. The p-value corresponds to the test of the hypothesis that inflation expectations are equal. For every profile (gender, education, age, income, occupation), I compare the inflation expectation of each group with the highest inflation expectation in the same profile.[11] The same is also done for perceived inflation.

The results for male and female indicate that their mean and standard deviation are close to one another. The p-values show that no statistically significant difference exists concerning inflation expectations and perceived inflation among men and women.

Results for the educational group show that individuals with secondary education have the lowest expected inflation. Furthermore, perceived inflation falls with higher education. For expected inflation, the p-values indicate no

[10]The results of the excluded groups can be found in Appendix 2.A.

[11]For example 3rd quartile income vs. 1st quartile income because 1st quartile income is the group with the highest mean inflation expectation in the income profile.

	Inflation expectation			Perceived inflation		
Group	Mean	SD	p-value	Mean	SD	p-value
Full sample	32.0	12.9		32.9	17.4	
Male	32.2	12.8		32.2	17.2	0.66
Female	31.8	13.0	0.86	33.5	17.5	
Primary education	32.4	12.8	0.53	35.4	17.2	
Secondary education	31.3	13.1	0.26	30.6	17.6	0.10
Further education	33.8	14.2		27.9	18.7	0.01
16-29 years old	29.4	13.1	0.08	29.5	16.8	0.10
30-49 years old	32.4	13.8	0.74	33.6	17.4	0.83
50-64 years old	33.1	12.6		34.0	17.8	0.95
above 65 years	32.9	12.9	0.90	34.2	18.2	
1st quartile income	33.7	12.1		35.2	17.2	
2nd quartile income	32.9	13.5	0.72	33.6	18.3	0.59
3rd quartile income	32.6	12.5	0.60	32.2	17.6	0.29
4th quartile income	31.1	13.6	0.22	29.5	17.9	0.05
Work full-time	31.8	13.3	0.05	32.1	17.4	0.01
Unemployed	35.9	12.0		39.3	17.0	

Balance index about inflation expectations and perceived inflation in Germany. The data covers the time period from the first quarter 1990 to the second quarter 2008.

Table 2.2: Index values of expected and perceived inflation on a quarterly basis

statistically significant difference between the groups. However, perceived inflation of primary educated individuals is significantly higher than perceived inflation of secondary and further educated individuals using a significance level of ten percent.

With respect to different age categories, inflation expectations of the youngest individuals are different from the group of the 50-64 years old. The youngest individuals have lower inflation expectations. Perceived inflation of the youngest is different from the oldest group. The perceived inflation is lower for the 16-29 years old individuals. The difference for all other groups to the group with the highest value is not significant concerning inflation expectations and perceived inflation.

Inflation expectations and perceived inflation seem to fall with rising income. But only perceived inflation of the 4th income quartile agents is statistically significantly different from perceived inflation from agents of the first income quartile. Otherwise, no statistically significant difference between the groups is present.

In addition to this, the expected and perceived inflation of the unemployed are higher compared to all other groups. Inflation expectation and perceived inflation are statistically different from the "work full-time" individuals. To summarize, the descriptive statistics indicate some heterogeneity between different groups concerning their inflation expectations and their perceived inflation. The analysis in Section 2.3 will check whether differences are also present in rationality tests.

2.2.2 Descriptive Statistics: Converted Data

So far, qualitative data and the EC index have been used. In order to be able to interpret the qualitative data and the EC index value as values of expected inflation rates, the data have to be converted. The conversion methods of Batchelor and Orr (1988) and Berk (1999) are used in this analysis to calculate quantitative inflation expectations from the survey. Both methods end up with the same equation for calculating expected inflation π_t^e:

$$\pi_t^e = \mu_t' \cdot \frac{(a_t + b_t)}{(a_t + b_t - c_t - d_t)} \tag{2.1}$$

where the parameter a_t is the value of the inverse cumulative standard normal distribution of the percentage value of the answer category "fall", the parameter b_t of the answer category "fall" plus "stay the same", c_t of the answer category "fall" plus "stay about the same" plus "increase at a slower rate", and so forth. μ_t' is a scaling factor. The parameters a_t, b_t, c_t, and d_t can be calculated with the percentage values of the different answer categories and an assumption about the subjective distribution function of the future price level. Both conversion methods only differ in the determination of the scaling factor.

The answer proportions to question five of the survey which asks about perceived inflation, combined as given by the fraction in equation (2.1), and actual inflation over the last year are used as the scaling factor in the method of Batchelor and Orr (1988). The method of Berk (1999) works as follows: the answer categories of question five are aggregated into three categories. These three categories and the assumption that perceived inflation is on average equal to the true past inflation is used to calculate the scaling factor μ'_t. The scaling factor is used to weight the fraction of answer probabilities shown in equation (2.1).[12] For both methods, I assume a normal distribution for the probability distribution function of the subjective expected inflation rate which is the common approach in literature (Batchelor and Orr 1988, Berk 1999, Deutsche Bundesbank 2001, Berk 2002, Lyziak 2003, Mankiw et al. 2004, Henzel and Wollmershäuser 2005, Berk and Hebbink 2006, Döpke et al. 2008a, Lein and Maag 2011). Applying these methods leads to expectations which, on average, underestimate actual inflation.[13] However, this does not falsify rationality since it could also be the conversion method which causes this bias. In order to ensure that results are not driven by the conversion method applied, I choose the scaling factor μ'_t such that expectations are on average correct. Otherwise the conversion of the data used in the analysis of this essay is performed as in Berk (1999).[14] As a graphical example for the results after adjusted conversion, Figure 2.3 shows calculated inflation expectation for the total sample in comparison to actual inflation. As a consequence of the conversion method chosen, both time series have the same mean.

Figure 2.3 indicates that the calculated inflation expectations for the total sample is often close to inflation. Only after the Euro cash introduction in 2002, individuals' expectations overpredict inflation substantially.

2.3 Analysis

Following the descriptive statistics of the disaggregated inflation expectations, this section performs rationality tests to answer the question if German inflation expectations can be described as being rational.[15] I distinguish between two kinds of rationality: full-information rationality and delayed-information

[12] The methods are explained in more detail in Appendix 2.B.

[13] Graphically results are shown in Appendix 2.C. Inflation is measured as monthly CPI inflation and calculated as yearly changes. For data details see Appendix 2.D.

[14] All results are qualitatively the same for the method from Batchelor and Orr (1988). All omitted results are shown in Appendix 2.E.

[15] Ideally, an analysis of the expectation formation process of the different demographic groups would require the usage of group-specific inflation rates but unfortunately this kind of data is not provided by the German statistical office. Therefore, the general inflation rate has to be used for the total sample and all demographic groups.

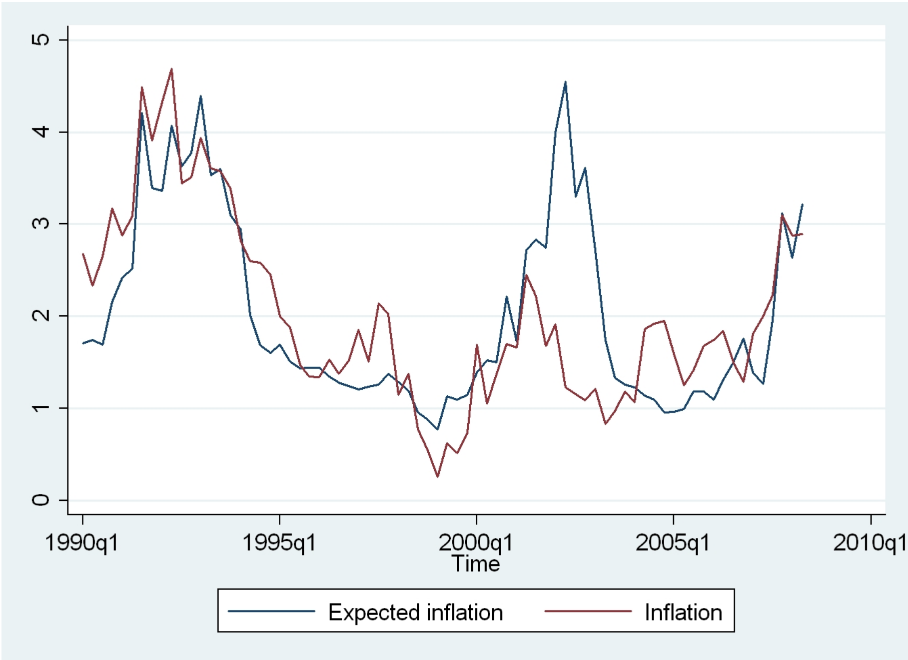

Figure 2.3: Actual and expected inflation

rationality. The definition of full-information rational expectations follows the one of Muth in the interpretation of Evans and Gulamani (1984) “Expectations of agents are said to be rational if they are equal to the true mathematical expectation conditioned on all relevant information known at the time forecasts were made...”(page 3). The tests for full-information rationality are based on Begg (1982).

Delayed-information rationality follows the idea of Feige and Pearce (1976) “This (...) concept simply emphasizes that an economic agent should consider the trade-off between the benefits and costs of added information when forecasting...”(page 500) and therefore possibly not to update expectations with new information in each period. I define expectations which are built partly on new information and partly on outdated information as rational in the delayed-information sense. It is analyzed whether inflation expectations can be described by one of these rationality definitions. For both rationality concepts, different properties have to be fulfilled by the data. The analysis is done with aggregate data and at the disaggregated level because of possibly biased results.

Both types of rationality have to fulfill unbiasedness. Full-information rationality and delayed-information rationality predict that forecasts are on average correct. In the model of delayed-information rationality agents build their forecast partly based on outdated information but nevertheless these forecasts must not be biased on average. Furthermore, for full-information rationality, expectation errors have to be serially uncorrelated, forecasts have to be efficient, and have to fulfill orthogonality with respect to any other available information. Under delayed-information rationality, expectations do not have to fulfill these properties because delayed-information rationality is based on the idea that not all currently available information is taken into account. But the concepts of serially uncorrelated errors, efficiency, and orthogonality are based on the assumption that all available information is used and therefore these concepts do not have to be fulfilled by the delayed-information rationality approach. In the following sections, I will test these different properties of rationality.

2.3.1 Unbiasedness

In a first step, I check unbiasedness of inflation expectations which has to hold for both concepts of rationality. Unbiasedness requires that expectations are on average correct (e.g. Theil 1966). As explained in the previous section, the data is converted in a way that expectations are on average correct to make sure that the results concerning rationality are not biased by the conversion method. Thus unbiasedness cannot be rejected with the so converted data. By using this converted data in the following analysis we know that all later results that possibly indicate irrationality are not due to level biases in the conversion method. Tests for full and delayed-information rationality are presented separately in the next two sections.

2.3.2 Full-information Rationality Tests

This section deals with additional properties that have to be fulfilled under full-information rationality but not necessarily under delayed-information rationality. The next property that is tested is the one of serially uncorrelated inflation forecasts following Anderson and Goldsmith (1994). If all available information is used, as proposed by full-information rationality, no systematic relationship between current and lagged forecast errors should exist because lagged forecast errors are known and should be thus included in a rational forecast. To check serially uncorrelated errors, I estimate the following equation

$$\pi_t - \pi_t^e = \gamma_1 + \gamma_2(\pi_{t-1} - \pi_{t-1}^e) + \psi_t \tag{2.2}$$

with OLS. In equation (2.2), and all following equations, π_t is the actual inflation rate in period t and π_t^e is the expected inflation rate for time t. Furthermore γ_1 is a constant and ψ_t is an error term. I test the null hypothesis $\gamma_2 = 0$. If the forecast error of the previous period has explanatory power for the current forecast error, the parameter γ_2 would be significantly different from zero. Thus, the hypothesis of full-information rationality has to be rejected in this case. The estimated values and standard errors for both coefficients are presented in Table 2.3.

The results show that the estimated values for the constant are essentially zero but the estimators for γ_2 are significantly different from zero for the total sample and for all subgroups. These results yield first evidence against full-information rationality that does not depend on the conversion method.

Furthermore these results indicate some adaptive or delayed pattern in inflation expectations because γ_2 is positive and significantly different from zero. This is consistent with delayed information processing by individuals. Under delayed-information rationality the following happens: if an inflation shock hits the economy, inflation increases unexpectedly i.e. inflation forecast errors become positive. In the next period, only a fraction of agents in the economy update and realize the shock in the previous period and their forecast error and adjust their inflation forecasts. The remaining fraction of agents does not update. They do not take into account their previous forecast error. Thus, the forecast error is still positive but is lower than in the first period. Therefore delayed-information rationality generates positive serial correlation in forecast errors that is also present in the data. If forecast errors are positive serial correlated, agents adjust their forecasts insufficiently. Note that the finding of serial correlation is not evidence for the delayed-information concept but a hint toward this direction. More formal tests of delayed-information rationality are performed in the next section. But before doing so, it is checked for completeness whether the data fulfill the last two properties of full-information rationality: efficiency and orthogonality.

The next property which is tested is efficiency following Thomas (1999). Efficiency implies that all available information about the variable of interest

$\pi_t - \pi^e_{i,t} = \gamma_1 + \gamma_2(\pi_{t-1} - \pi^e_{i,t-1}) + \psi_t$				
	$\widehat{\gamma_1}$	SE	$\widehat{\gamma_2}$	SE
Full sample	0.00	0.08	0.80	0.07***
Male	0.00	0.09	0.79	0.08***
Female	0.00	0.09	0.81	0.07***
Primary education	0.00	0.09	0.78	0.08***
Secondary education	0.00	0.09	0.80	0.07***
Further education	0.01	0.09	0.77	0.08***
16-29 years old	0.00	0.10	0.72	0.09***
30-49 years old	0.00	0.09	0.82	0.07***
50-64 years old	0.00	0.09	0.76	0.08***
above 65 years	0.00	0.09	0.70	0.09***
1st quartile income	0.00	0.09	0.79	0.08***
2nd quartile income	0.00	0.10	0.73	0.08***
3rd quartile income	0.00	0.09	0.79	0.08***
4th quartile income	0.00	0.09	0.76	0.08***
Work full-time	0.00	0.09	0.78	0.08***
Unemployed	0.00	0.16	0.58	0.10***

*** indicate statistical significance at 1 percent level. All data concern Germany. Converted inflation expectation data are used. Data for the inflation rate (CPI) are taken from the Bundesbank. The data cover the time period from the first quarter 1990 to the second quarter 2008.

Table 2.3: Full information rationality test: serial correlation

is used in the forecast. The past realizations of the variable of interest are available at the moment of forecasting. Thus the information which is present in lagged values should be included in the forecast. To test efficiency, I run a regression of the forecast error on inflation up to the third lag of inflation and test for $\rho_j = 0$ for $1 \leq j \leq 4$.[16]

$$\pi_t - \pi^e_t = \rho_1 + \sum_{j=2}^{4} \rho_j \pi_{t-j+1} + \xi_t \tag{2.3}$$

[16]The test for efficiency starts initially with six lags of inflation. To simplify the exposition of the results, I drop insignificant last lags until I arrive at a process with a significant last lag. This procedure results for all groups, with the exception of the unemployed, in an equation with three lags of inflation.

$$\pi_t - \pi^e_{i,t} = \rho_1 + \sum_{j=2}^{4} \rho_j \pi_{i,t-j+1} + \xi_t$$

	$\widehat{\rho_1}$	SE	$\widehat{\rho_2}$	SE	$\widehat{\rho_3}$	SE	$\widehat{\rho_4}$	SE
Full sample	0.33	0.29	0.31	0.31	0.21	0.39	-0.72	0.31**
Male	0.34	0.29	0.30	0.31	0.18	0.38	-0.68	0.31**
Female	0.31	0.31	0.34	0.32	0.25	0.41	-0.78	0.33**
Primary education	0.38	0.29	0.31	0.31	0.15	0.38	-0.69	0.31**
Secondary education	0.12	0.31	0.33	0.33	0.30	0.41	-0.72	0.33**
Further education	0.22	0.31	0.41	0.33	0.12	0.41	-0.67	0.33**
16-29 years old	0.27	0.31	0.26	0.33	0.36	0.41	-0.78	0.33**
30-49 years old	0.40	0.32	0.32	0.34	0.10	0.42	-0.66	0.34*
50-64 years old	0.38	0.30	0.33	0.31	0.18	0.39	-0.73	0.31**
above 65 years	0.33	0.27	0.43	0.29	-0.23	0.36	-0.41	0.29
1st quartile income	0.45	0.29	0.28	0.31	0.06	0.39	-0.60	0.31*
2nd quartile income	0.38	0.29	0.32	0.31	0.15	0.39	-0.70	0.31**
3rd quartile income	0.36	0.29	0.40	0.31	0.11	0.38	-0.72	0.31**
4th quartile income	0.36	0.28	0.29	0.30	0.22	0.37	-0.73	0.30**
Work full-time	0.31	0.29	0.24	0.31	0.29	0.38	-0.72	0.31**
Unemployed	0.87	0.40**	0.95	0.43**	-1.13	0.53**	-0.30	0.43

*, **, *** indicate statistical significance at the 10, 5, and 1 percent level, respectively. All data concern Germany. Converted inflation expectation data are used. Data for the inflation rate (CPI) are taken from the Bundesbank. The data cover the time period from the first quarter 1990 to the second quarter 2008.

Table 2.4: Full information rationality test: efficiency

Here ρ_1 is a constant and ξ_t is an error term. Results are presented in Table 2.4.

Using a significance level of ten percent, the results show that at least one of the three lags of inflation contains information for the forecast error for the total sample and all subgroups (with the exception of the above 65 years old). Thus, the data do not show efficiency and therefore the concept of full-information rationality is rejected.

The last property of full-information rationality, orthogonality with respect to any other available information, requires that all other available information is used for the forecast in each period. To test for orthogonality I follow Mankiw et al. (2004). I extend equation (2.3) by also taking into account the lagged value of the unemployment rate and the lagged value of the three month interest rate. It is checked whether these additional variables contain information that can be used to improve the forecast. To test orthogonality, a regression is run on the equation

$$\pi_t - \pi^e_{i,t} = \delta_1 + \delta_2 \pi_{i,t-1} + \delta_3 \pi_{i,t-2} + \delta_4 \pi_{i,t-3} + \delta_5 u_{t-1} + \delta_6 i_{t-1} + \eta_t, \tag{2.4}$$

where δ_1 is a constant, u_t is the unemployment rate in period t, i_t is the three month interest rate in period t, and η_t is the error term. If expectations of respondents can be described as full-information rational, all estimated coefficients would not be significantly different from zero. Once again, an OLS regression on equation (2.4) is run for the total sample and all subgroups separately. The results of the estimated coefficients and the respective standard errors of this estimation are presented in Table 2.5.

Similar results in comparison to the results of the efficiency test occur. The estimated parameters for δ_4 is significantly different from zero for aggregate and most of the disaggregated data (with the exception of the above 65 years old and the unemployed). The unemployment rate does not contain any information that can be used to improve the forecast error. The estimators for the interest rate are only in three cases different from zero by applying a significance level of 10%. Therefore the null hypothesis of full-information rationality for German consumers has to be rejected once again for both types of data.

The analysis up to here shows that German data cannot be described as full-information rational. Three tests for full-information rationality of inflation expectations based on both types of data show that the hypothesis of full-information rationality has to be rejected. The tests also indicate patterns of delayed information. Whether the expectation data can be described by the concept of delayed-information rationality is checked in the next section.

$\pi_t - \pi^e_{i,t} = \delta_1 + \delta_2\pi_{i,t-1} + \delta_3\pi_{i,t-2} + \delta_4\pi_{i,t-3} + \delta_5 u_{t-1} + \delta_6 i_{t-1} + \eta_t$												
	$\widehat{\delta_1}$	SE	$\widehat{\delta_2}$	SE	$\widehat{\delta_3}$	SE	$\widehat{\delta_4}$	SE	$\widehat{\delta_5}$	SE	$\widehat{\delta_6}$	SE
Full sample	-1.04	2.27	0.07	0.34	0.08	0.39	-0.81	0.32**	0.10	0.17	0.28	0.18
Male	-0.93	2.24	0.08	0.33	0.06	0.39	-0.76	0.31**	0.09	0.17	0.26	0.18
Female	-1.30	2.36	0.07	0.35	0.11	0.41	-0.88	0.33***	0.11	0.17	0.31	0.19
Primary education	-0.65	2.26	0.10	0.34	0.05	0.39	-0.77	0.31**	0.07	0.17	0.23	0.18
Secondary education	-1.60	2.40	0.02	0.36	0.15	0.41	-0.84	0.33**	0.12	0.18	0.34	0.19*
Further education	-2.43	2.39	0.13	0.36	-0.05	0.41	-0.79	0.33**	0.19	0.18	0.38	0.19*
16-29 years old	-0.88	2.38	-0.02	0.36	0.22	0.41	-0.88	0.33**	0.08	0.18	0.29	0.19
30-49 years old	-1.18	2.47	0.09	0.37	-0.02	0.43	-0.75	0.34**	0.11	0.18	0.28	0.20
50-64 years old	-1.39	2.29	0.11	0.34	0.05	0.40	-0.83	0.32**	0.13	0.17	0.28	0.18
above 65 years	-0.18	2.11	0.17	0.32	-0.34	0.36	-0.48	0.29	0.03	0.16	0.24	0.17
1st quartile income	-1.52	2.25	0.01	0.34	-0.09	0.39	-0.72	0.31**	0.14	0.17	0.33	0.18*
2nd quartile income	-1.20	2.25	0.07	0.34	0.02	0.39	-0.80	0.31**	0.11	0.17	0.29	0.18
3rd quartile income	-0.93	2.25	0.16	0.34	-0.01	0.39	-0.81	0.31**	0.09	0.17	0.26	0.18
4th quartile income	-0.41	2.18	0.08	0.33	0.12	0.38	-0.80	0.30**	0.05	0.16	0.22	0.18
Work full-time	-0.77	2.25	0.03	0.34	0.19	0.39	-0.80	0.31**	0.07	0.17	0.23	0.18
Unemployed	-0.88	3.18	0.83	0.48*	-1.21	0.55**	-0.37	0.44	0.13	0.24	0.20	0.26

*, **, *** indicate statistical significance at the 10, 5, and 1 percent level respectively. All data concern Germany. Converted inflation expectation data are used. Data for the inflation rate (CPI) and the three month interest rate are taken from the Bundesbank. Data for the unemployment rate are taken from the German Federal Employment Agency (Bundesagentur für Arbeit). The data cover the time period from the first quarter 1990 to the second quarter 2008.

Table 2.5: Full information rationality tests: orthogonality

2.3.3 Delayed-information Rationality Tests

The previous section has shown that inflation expectations cannot be described by full-information rationality. Furthermore, the test for the hypothesis of serial correlation indicates some pattern of delay in inflation expectations. In this section, I conduct tests if the expectations can be described by delayed-information rationality. I do this once again for aggregate and disaggregated data to control for a possible bias. Delayed-information rationality is the key concept in the monetary sticky-information model by Mankiw and Reis (2002). To check this kind of rationality, I follow Carroll (2003) and his derivation of a micro foundation for sticky-information models. I reject the hypothesis of delayed-information rationality if the model of Carroll is rejected by the data.

The basic idea of Carroll's model is that consumers form their inflation expectations by adapting expectations published in the media. But not all consumers have full and current information about the published inflation forecast as it would be the case under the full-information rationality assumption. In Carroll's model, just a fraction λ of the population have current information in any period and build rational inflation forecasts based on this information set. But the remainder of the population forms their inflation forecasts based on outdated information. On an aggregate level, this implies that inflation forecasts depend on forecasts in newspapers in the current period (actual information) and on the own previous inflation forecasts.[17] If this pattern is present in the data, the inflation forecasts can be described as delayed-information rational.

Carroll assumes that the inflation forecasts printed in newspapers are made by professional forecasters. Following Carroll, the variables of interest are the inflation forecasts of professional forecasters and past consumer inflation forecasts. Professional expectations are given by data from *Consensus Economics*. *Consensus Economics* interviews about 30 banks and research institutions in Germany, among other things, about their quantitative inflation forecasts.[18]

[17] For a derivation see Carroll (2003).

[18] The survey data are available from the second quarter of 1994 to the second quarter of 2008. Therefore the analysis refers to this time horizon. Based on the survey data, professional forecasts for the next year on a quarterly basis are calculated. For Germany the following institutes and firms are interviewed by *Consensus Economics*: IW-Cologne Institute, Bayerische LBank, Delbruck & Co, DIW- Berlin, Commerzbank, DekaBank, Dresdner

The mean of all answers is used as professional inflation expectations. Consumer inflation forecasts are again taken from the Business and Consumer Survey.

Baseline Model

Consumers should assume that forecasts from professional forecasters are better than their own ones because professionals have experience, are trained to do forecasts, and spend a lot of time making forecasts whereas standard laymen do not. If the predominance of professional forecasts concerning accuracy holds, consumers should not build forecasts on their own but just adopt the forecasts of professionals. Predominance of professional forecasts exists in the case of Germany. Their mean squared forecast error is lower in comparison to the total sample and all subgroups, based on the adjusted conversion method. The mean squared forecast error for the different demographic groups and the professionals are shown in Table 2.6.

The results show that the forecast errors of all demographic groups exceed the professional forecast error. Consumers' errors are more than twice the size of the professionals' forecasts. Therefore the assumption that consumers should adopt the professional forecasts is a good description of German reality.

Carroll (2003) shows that inflation forecasts of U.S. consumers are influenced by their own inflation forecast of the previous quarter and the professional forecast of the current quarter and does not find any other significant determinant. Based on the findings of Carroll, this section presents results of the analysis if this result also holds for German consumers or whether delayed-information rationality has to be rejected. This is done by the following baseline model:

$$\pi_t^e = \alpha_1 \pi_t^{Pro} + \alpha_2 \pi_{t-1}^e + \tau_t \tag{2.5}$$

Where π_t^e are the consumer's inflation expectations, π_t^{Pro} are the professional forecasts for period t, and τ_t is an error term. The results of an OLS regression are presented in Table 2.7.

Bank, DZ Bank, FAZ Institute, Helaba Frankfurt, Lehman Brothers, UBS Warburg, West LB, WGZ Bank, Bank Julius Baer, Bankgesellschaft Berlin, BHF Bank, Deutsche Bank, HSBC Trinkaus, HWWA, HypoVereinsbank, Invesco Bank, JP Morgan, MM Warburg, Morgan Stanley, RWI Essen, Sal Oppenheim and SEB.

	$MSFE$
Professionals	0.49
Full sample	1.17
Male	1.10
Female	1.32
Primary education	1.09
Secondary education	1.39
Further education	1.32
16-29 years old	1.31
30-49 years old	1.39
50-64 years old	1.16
above 65 years	0.95
1st quartile income	1.09
2nd quartile income	1.11
3rd quartile income	1.17
4th quartile income	1.05
Work full-time	1.11
Unemployed	1.75

All data concern Germany. Converted inflation expectation data are used. Data for the inflation rate (CPI) are taken from the Bundesbank. Data for professional forecasters are taken from *Consensus Economics*. The data cover the time period from the first quarter 1990 to the second quarter 2008.

Table 2.6: Mean squared forecast errors

The results show that the adjusted R^2 is very high for the total sample and all different demographic groups. $\widehat{\alpha_1}$ and $\widehat{\alpha_2}$ are significantly different from zero for all groups (with the exception of $\widehat{\alpha_1}$ for the third quartile income group). The findings for the different groups indicate only quantitative differences. The estimated coefficient $\widehat{\alpha_1}$ is located between 0.16 and 0.39. A value of 0.25 would indicate that one-fourth of all agents have an up-to-date forecast. For a specific agent this means that he updates his information set on average once a year ($1/0.25 = 4$ quarters). Following this interpretation, this implies that consumers update their inflation expectations from professional expectations between every half ($1/0.39 = 2.56$ quarters) and every one and a half year ($1/0.16 = 6.25$ quarters). These results are in line with the results of Döpke

$\pi^e_{i,t} = \alpha_1 \pi^{Pro}_t + \alpha_2 \pi^e_{i,t-1} + \tau_t$						
	$\widehat{\alpha_1}$	SE	$\widehat{\alpha_2}$	SE	Adj. R^2	p-value
Full sample	0.18	0.08**	0.84	0.09***	0.95	0.60
Male	0.18	0.07**	0.84	0.09***	0.96	0.66
Female	0.20	0.08**	0.83	0.09***	0.94	0.58
Primary education	0.17	0.07**	0.85	0.08***	0.96	0.66
Secondary education	0.21	0.09**	0.82	0.10***	0.94	0.51
Further education	0.23	0.08***	0.78	0.09***	0.92	0.82
16-29 years old	0.29	0.10***	0.73	0.11***	0.91	0.74
30-49 years old	0.17	0.07**	0.85	0.09***	0.95	0.76
50-64 years old	0.18	0.08**	0.83	0.10***	0.95	0.71
above 65 years	0.33	0.10***	0.70	0.10***	0.91	0.68
1st quartile income	0.16	0.07**	0.85	0.09***	0.96	0.80
2nd quartile income	0.39	0.12***	0.63	0.09***	0.87	0.79
3rd quartile income	0.17	0.10	0.84	0.07***	0.94	0.73
4th quartile income	0.24	0.08***	0.76	0.09***	0.93	0.87
Work full-time	0.16	0.08**	0.86	0.09***	0.96	0.75
Unemployed	0.25	0.09**	0.76	0.11***	0.87	0.91

All standard errors are corrected for heteroscedasticity and serial correlation using a Newey-West procedure with four lags. *, **, *** indicate statistical significance at the 10, 5, and 1 percent level respectively. All data concern Germany. Converted inflation expectation data are used. Data for the inflation rate (CPI) are taken from the Bundesbank. Data for professional forecasters are taken from *Consensus Economics.* The data cover the time period from the first quarter 1990 to the second quarter 2008.

Table 2.7: Delayed-information rationality test: baseline model

et al. (2008a). They show that a representative German consumer updates his expectations between every three quarters and every one and a half year depending on specification.

The theory assumes that individuals obtain their macroeconomic view from the media with a given probability. Furthermore, the media are assumed to represent professional forecasters' view. The theory predicts that consumers build their forecasts based on only two sources: professionals' forecast (periods with an information update) and their own lagged forecast (periods without an information update). Because the expectation process only depends on two sources, the influence of these two sources can be interpreted as weights. Because weights add up to one, the theory predicts that both coefficients add to one if the influence of both sources is estimated. The p-value in Table 2.7 corresponds to the test of the hypothesis that the sum of $\widehat{\alpha_1}$ and $\widehat{\alpha_2}$ is equal to one. The p-values show that no statistically significant difference exists between the sum of the estimated coefficients and one for all groups.

P-values from a test of a pooled regression against varying slopes for the different categories are as follows: gender 0.10; education 0.02; age 0.11; income 0.02; occupation 0.00. The hypothesis of poolability of the data has to be rejected, at least at a significance level of 10%, for almost all categories. Only for the age category, poolability cannot be rejected. The rejections of poolability represent a further argument in favor of using disaggregated data.

In summary, the results show that the inflation expectations of consumers are influenced by professional expectations and their own past inflation expectations. Therefore the results support delayed-information rationality based on aggregate and disaggregated data.

Error-correction Model

The previous section has shown that, by using an OLS regression, consumer inflation expectations are influenced by professionals' inflation expectations and lagged values of consumers' inflation expectations and therefore consumers' inflation forecasts support the idea of delayed-information rationality. It is also possible that a stable long-run relationship between the consumers' and professionals' expectations exists. If a long-run relationship exists, an error-correction model is the appropriate econometric model to distinguish between the long run and the short run influence of professionals' forecasts on consumers' inflation expectation. This is done by the following error-correction model:

$$\triangle\pi_t^e = \beta_1\pi_{t-1}^e + \beta_2 \triangle \pi_t^{Pro} + \beta_3\pi_{t-1}^{Pro} + \phi_t \tag{2.6}$$

The long-run relationship between the consumer forecast π_t^e and the professional forecast π_t^{Pro} is given by $-\beta_3/\beta_1$ and the short-run relationship by β_2. Carroll's model assumes that consumers update their inflation expectations from professionals' forecasts. Therefore the model predicts a long-run relationship of one. An estimation of the error-correction model delivers the results presented in Table 2.8.

$\triangle\pi_{i,t}^e = \beta_1\pi_{t-1}^e + \beta_2 \triangle \pi_t^{Pro} + \beta_3\pi_{t-1}^{Pro} + \phi_t$								
	$\widehat{\beta_1}$	SE	$\widehat{\beta_2}$	SE	$\widehat{\beta_3}$	SE	Long	p-value
Full sample	-0.12	0.06*	0.60	0.19***	0.13	0.07**	1.17	0.50
Male	-0.11	0.06*	0.59	0.17***	0.13	0.06**	1.14	0.55
Female	-0.13	0.07*	0.63	0.23***	0.16	0.07**	1.17	0.49
Primary education	-0.10	0.06*	0.55	0.17***	0.12	0.06**	1.14	0.55
Secondary education	-0.14	0.07*	0.68	0.24***	0.16	0.08**	1.20	0.44
Further education	-0.22	0.08***	0.21	0.27	0.23	0.09***	1.04	0.82
16-29 years old	-0.22	0.08**	0.78	0.28***	0.23	0.09**	1.07	0.74
30-49 years old	-0.12	0.06*	0.51	0.21**	0.13	0.06**	1.11	0.68
50-64 years old	-0.13	0.06**	0.49	0.20**	0.15	0.07**	1.10	0.66
above 65 years	-0.28	0.10***	0.55	0.28*	0.30	0.11***	1.08	0.62
1st quartile income	-0.13	0.06**	0.35	0.19*	0.14	0.07**	1.07	0.75
2nd quartile income	-0.36	0.10***	0.52	0.35	0.37	0.12***	1.04	0.80
3rd quartile income	-0.14	0.07**	0.35	0.22	0.16	0.07**	1.09	0.69
4th quartile income	-0.17	0.08**	0.76	0.22***	0.18	0.08**	1.03	0.88
Work full-time	-0.10	0.05*	0.52	0.16***	0.11	0.06*	1.10	0.69
Unemployed	-0.18	0.08**	0.95	0.32***	0.19	0.08**	1.05	0.86

*, **, *** indicate statistical significance to the 10, 5, and 1 percent level respectively. All data concern Germany. Converted inflation expectation data are used. Data for the inflation rate (CPI) are taken from the Bundesbank. Data for professional forecasters are taken from *Consensus Economics*. The data cover the time period from the first quarter 1990 to the second quarter 2008.

Table 2.8: Delayed-information rationality test: error-correction model

The results show that a long-run relationship between consumers' forecasts and professionals' forecasts exists and therefore provides further evidence in favor of delayed-information rationality. The column titled "Long" presents evidence for the long-run relationship. The last column presents the p-value for the test of the null hypothesis that the long-run relationship is one. It can be seen that this proposition of the theory cannot be rejected at any

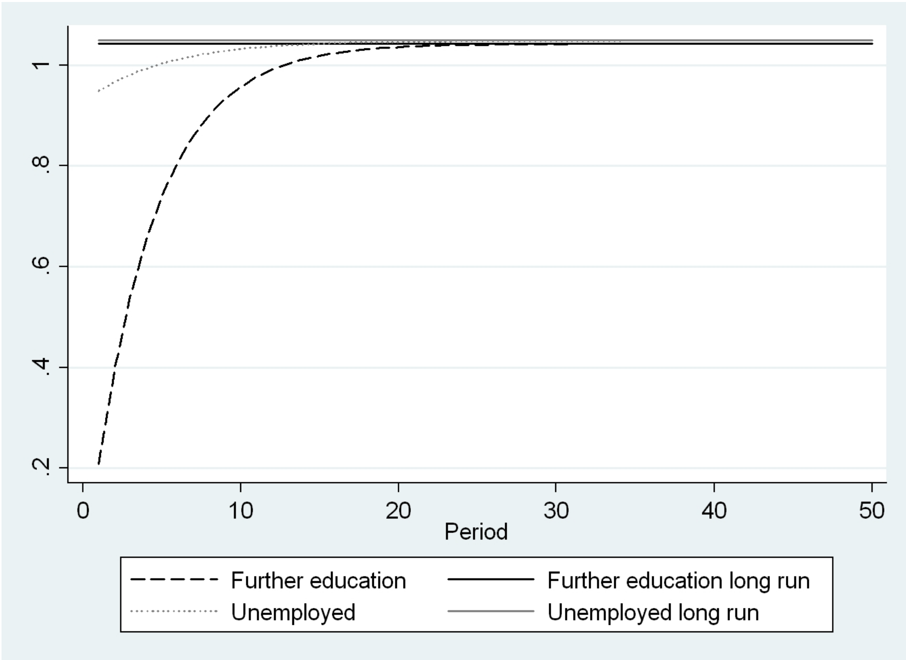

Figure 2.4: Impulse response of the unemployed and further educated individuals on a permanent shock of one on professionals' inflation forecast

usual significance level. The error-correction model also indicates a significant short-run relationship between consumers' and professionals' forecasts (with the exception of three groups). Thus beside the short-run dependence of professional and consumers forecasts, there also exists a long-run relationship. Furthermore, the results about the short-run effect show differences between the subgroups. The differences, the values are between 0.21 and 0.95, indicate the importance of taking into account the analysis not only based on aggregate data but also based on disaggregated data. Figure 2.4 illustrates the importance graphically by presenting the impulse responses to a permanent shock on professionals' inflation forecasts of one percentage point. The figure shows the impulse responses for two population subgroups. The black dashed line represents the response of further educated individuals (short run effect of 0.21 percentage points) while the grey dotted line belongs to the unemployed (short run effect of 0.95 percentage points). The figure indicates that unemployed individuals' expectations reach their long run reaction after about 10 periods whereas, for further educated individuals, it takes about 20 periods.

It can be summarized that a short-run and long-run relationship between consumers' inflation expectations and professionals' inflation expectations exists for each group. This result further supports delayed-information rationality once again based on aggregate and disaggregated data.

2.4 Conclusion

This essay tested empirically for two different kinds of rationality that are used in monetary models, full-information rationality (Muth 1961) and delayed-information rationality (Mankiw and Reis 2002). The analysis was done with a unique German data set. To take into account the possibility of biases of the results, aggregate and disaggregated data were used in the analysis. Rationality tests indicated that the inflation expectations of German consumers could not be described as full-information rationality based on aggregate as well as based on disaggregated data. The analysis indicated delayed-information rationality based on both types of data. Delayed-information rationality was supported in a baseline model and an error-correction model.

In summary, the results of this empirical investigation showed that the assumption of full-information rational inflation expectations in economic models cannot be supported by aggregate as well as disaggregated German data. The approach of delayed-information rationality on the other hand is supported by both types of data in the German case.

Appendix

2.A Further Results: Omitted Groups

	Inflation expectation			Perceived Inflation		
Group	Mean	SD	p-value	Mean	SD	p-value
Full sample	32.0	12.9		32.9	17.4	
Work full-time	31.8	13.3	0.05	32.1	17.4	0.01
Unemployed	35.9	12.0		39.3	17.0	
Self employed	31.2	14.1	0.03	31.5	17.5	0.01
Farmers	29.6	17.5	0.01	28.9	22.6	0.00
Office employees	31.3	13.6	0.03	30.7	17.7	0.00
Skilled manual workers	33.0	12.7	0.16	35.2	17.3	0.15
Other manual workers	32.5	13.4	0.11	36.0	17.5	0.25
Total worker	32.9	12.7	0.14	35.3	17.0	0.15
Other occupations	31.5	13.0	0.03	32.4	17.8	0.02
Work part-time	32.3	14.1	0.10	33.5	18.0	0.05

Table 2.9: Index values of expected and perceived inflation on a quarterly basis, all occupations[19]

$\pi_t - \pi^e_{i,t} = \gamma_1 + \gamma_2(\pi_{t-1} - \pi^e_{i,t-1}) + \psi_t$				
	$\widehat{\gamma_1}$	SE	$\widehat{\gamma_2}$	SE
Full sample	0.00	0.08	0.80	0.07***
Work full-time	0.00	0.09	0.78	0.08***
Unemployed	0.00	0.16	0.58	0.10***
Self employed	-0.01	0.15	0.53	0.10***
Farmers	-0.05	2.47	-0.02	0.12
Office employees	0.00	0.09	0.80	0.07***
Skilled manual workers	0.00	0.10	0.73	0.09***
Other manual workers	-0.01	0.11	0.69	0.09***
Total worker	0.00	0.09	0.74	0.08***
Other occupations	0.00	0.09	0.79	0.08***
Work part-time	0.00	0.13	0.64	0.10***

*** indicate statistical significance at 1 percent level. All data concern Germany. Converted inflation expectation data are used. Data for the inflation rate (CPI) are taken from the Bundesbank. The data cover the time period from the first quarter 1990 to the second quarter 2008.

Table 2.10: Full information rationality test: serial correlation, all occupations

[19]Total worker is an occupation category chosen by the European Commission and not the sum of all occupations. The raw data for the farmers contain many observations that have to be adjusted. Therefore the results for this group should not be taken too seriously.

$\pi_t - \pi_{i,t}^e = \rho_1 + \sum_{j=2}^{4} \rho_j \pi_{i,t-j+1} + \xi_t$								
	$\widehat{\rho}_1$	SE	$\widehat{\rho}_2$	SE	$\widehat{\rho}_3$	SE	$\widehat{\rho}_4$	SE
Full sample	0.33	0.29	0.31	0.31	0.21	0.39	-0.72	0.31**
Work full-time	0.31	0.29	0.24	0.31	0.29	0.38	-0.72	0.31**
Unemployed	0.87	0.40**	0.95	0.43**	-1.13	0.53**	-0.30	0.43
Self employed	-0.07	0.39	0.27	0.41	0.59	0.51	-0.86	0.41**
Farmers	7.19	5.69	-7.44	6.00	3.41	7.51	0.26	6.04
Office employees	0.25	0.31	0.38	0.32	0.27	0.41	-0.80	0.33**
Skilled manual workers	0.48	0.29	0.06	0.30	0.38	0.38	-0.71	0.30**
Other manual workers	0.53	0.31*	0.32	0.33	0.14	0.41	-0.76	0.33**
Total worker	0.49	0.28*	0.12	0.30	0.31	0.38	-0.71	0.30**
Other occupations	0.38	0.29	0.35	0.31	0.08	0.39	-0.66	0.31**
Work part-time	0.59	0.36	0.44	0.38	0.22	0.47	-0.99	0.38**

*, **, *** indicate statistical significance at the 10, 5, and 1 percent level, respectively. All data concern Germany. Converted inflation expectation data are used. Data for the inflation rate (CPI) are taken from the Bundesbank. The data cover the time period from the first quarter 1990 to the second quarter 2008.

Table 2.11: Full information rationality test: efficiency, all occupations

$\pi_t - \pi^e_{i,t} = \delta_1 + \delta_2\pi_{i,t-1} + \delta_3\pi_{i,t-2} + \delta_4\pi_{i,t-3} + \delta_5 u_{t-1} + \delta_6 i_{t-1} + \eta_t$												
	$\widehat{\delta_1}$	SE	$\widehat{\delta_2}$	SE	$\widehat{\delta_3}$	SE	$\widehat{\delta_4}$	SE	$\widehat{\delta_5}$	SE	$\widehat{\delta_6}$	SE
Full sample	-1.04	2.27	0.07	0.34	0.08	0.39	-0.81	0.32**	0.10	0.17	0.28	0.18
Work full-time	-0.77	2.25	0.03	0.34	0.19	0.39	-0.80	0.31**	0.07	0.17	0.23	0.18
Unemployed	-0.88	3.18	0.83	0.48*	-1.21	0.55**	-0.37	0.44	0.13	0.24	0.20	0.26
Self employed	-1.35	3.04	0.09	0.45	0.49	0.53	-0.93	0.42**	0.09	0.22	0.22	0.25
Farmers	77.24	44.12*	-7.60	6.59	4.77	7.62	1.75	6.14	-5.24	3.26	-4.13	3.56
Office employees	-1.46	2.36	0.09	0.35	0.12	0.41	-0.91	0.33***	0.12	0.17	0.33	0.19*
Skilled manual workers	-0.08	2.23	-0.12	0.33	0.29	0.38	-0.77	0.31**	0.04	0.16	0.17	0.18
Other manual workers	1.14	2.47	0.19	0.37	0.10	0.43	-0.78	0.34**	-0.05	0.18	0.07	0.20
Total worker	0.32	2.22	-0.05	0.33	0.24	0.38	-0.76	0.31**	0.01	0.16	0.15	0.18
Other occupations	-1.11	2.26	0.09	0.34	-0.06	0.39	-0.76	0.31**	0.10	0.17	0.30	0.18
Work part-time	-1.69	2.73	0.06	0.41	0.02	0.47	-1.14	0.38***	0.16	0.20	0.44	0.22**

*, **, *** indicate statistical significance at the 10, 5, and 1 percent level respectively. All data concern Germany. Converted inflation expectation data are used. Data for the inflation rate (CPI) and the three month interest rate are taken from the Bundesbank. Data for the unemployment rate are taken from the Bundesagentur für Arbeit. The data cover the time period from the first quarter 1990 to the second quarter 2008.

Table 2.12: Full information rationality tests: orthogonality, all occupations

	$MSFE$
Professionals	0.49
Full sample	1.17
Work full-time	1.11
Unemployed	1.75
Self employed	2.15
Farmers	3.94
Office employees	1.31
Skilled manual workers	1.01
Other manual workers	1.09
Total worker	0.97
Other occupations	1.17
Work part-time	1.50

All data concern Germany. Converted inflation expectation data are used. Data for the inflation rate (CPI) are taken from the Bundesbank. Data for professional forecasters are taken from *Consensus Economics*. The data cover the time period from the first quarter 1990 to the second quarter 2008.

Table 2.13: Mean squared forecast errors, all occupations

$\pi^e_{i,t} = \alpha_1 \pi^{Pro}_t + \alpha_2 \pi^e_{i,t-1} + \tau_t$						
	$\widehat{\alpha_1}$	SE	$\widehat{\alpha_2}$	SE	Adj. R^2	p-value
Full sample	0.18	0.08**	0.84	0.09***	0.95	0.60
Work full-time	0.16	0.08**	0.86	0.09***	0.96	0.75
Unemployed	0.25	0.09**	0.76	0.11***	0.87	0.91
Self employed	0.57	0.14***	0.43	0.10***	0.72	0.94
Farmers	-0.08	0.01***	0.59	0.06***	0.94	0.00
Office employees	0.18	0.09**	0.84	0.10***	0.95	0.65
Skilled manual workers	0.26	0.08***	0.74	0.09***	0.92	0.89
Other manual workers	0.28	0.07***	0.71	0.07***	0.92	0.81
Total worker	0.24	0.07***	0.75	0.08***	0.93	0.87
Other occupations	0.20	0.08**	0.83	0.09***	0.94	0.49
Work part-time	0.31	0.09***	0.68	0.11***	0.86	0.83

All standard errors are corrected for heteroscedasticity and serial correlation using a Newey-West procedure with four lags. *, **, *** indicate statistical significance at the 10, 5, and 1 percent level respectively. All data concern Germany. Converted inflation expectation data are used. Data for the inflation rate (CPI) are taken from the Bundesbank. Data for professional forecasters are taken from *Consensus Economics*. The data cover the time period from the first quarter 1990 to the second quarter 2008.

Table 2.14: Delayed-information rationality: baseline model, all occupations

$\triangle\pi^e_{i,t} = \beta_1\pi^e_{t-1} + \beta_2 \triangle \pi^{Pro}_t + \beta_3\pi^{Pro}_{t-1} + \phi_t$								
	$\widehat{\beta_1}$	SE	$\widehat{\beta_2}$	SE	$\widehat{\beta_3}$	SE	Long	p-value
Full sample	-0.12	0.06*	0.60	0.19***	0.13	0.07**	1.17	0.87
Work full-time	-0.10	0.05*	0.52	0.16***	0.11	0.06*	1.10	0.67
Unemployed	-0.18	0.08**	0.95	0.32***	0.19	0.08**	1.05	0.97
Self employed	-0.56	0.12***	0.63	0.56	0.57	0.15***	1.01	0.22
Farmers	-0.38	0.10***	-0.11	0.05**	-0.08	0.02***	-0.21	0.00
Office employees	-0.12	0.06*	0.56	0.21***	0.14	0.07**	1.14	0.73
Skilled manual workers	-0.24	0.09***	0.50	0.24**	0.23	0.09**	0.97	0.28
Other manual workers	-0.25	0.09***	0.54	0.25**	0.24	0.09***	0.96	0.32
Total worker	-0.22	0.08***	0.48	0.22**	0.21	0.08**	0.97	0.29
Other occupations	-0.12	0.07*	0.68	0.21***	0.15	0.07**	1.25	0.95
Work part-time	-0.31	0.10***	0.48	0.35	0.29	0.11***	0.95	0.29

*, **, *** indicate statistical significance to the 10, 5, and 1 percent level respectively. All data concern Germany. Converted inflation expectation data are used. Data for the inflation rate (CPI) are taken from the Bundesbank. Data for professional forecasters are taken from *Consensus Economics*. The data cover the time period from the first quarter 1990 to the second quarter 2008.

Table 2.15: Delayed-information rationality: error-correction model, all occupations

2.B Data Conversion and Correction

Quantitative data is needed to do rationality tests. Therefore the qualitative data from the EC must be converted into quantitative data. For the computation, the probability approach of Batchelor and Orr (1988) and Berk (1999) is used. The basis for both approaches is the work of Carlson and Parkin (1975). Carlson and Parkin designed a probability method to convert qualitative into quantitative data for survey questions with three response categories. Batchelor and Orr (1988) extend the probability method for survey questions with four and five response categories. Berk (1999) combines both approaches. These conversion methods have been applied by many researchers (including among others Berk 1999, Mankiw et al. 2004, Berk and Hebbink 2006, Döpke et al. 2008a, Lein and Maag 2011) and a lot of institutions (European Central Bank, Bundesbank, Centre of European Economic Research).

In the EC survey, consumers have to choose between six answers categories. The fractions of the answer "don't know" are divided into the other response categories in equal parts to get data from only five answer categories. This procedure does not change the results and is the common approach in the literature.[20] Thus the Business and Consumer Survey can be interpreted as a survey with five response possibilities and the probability methods of Batchelor and Orr and Berk can be applied.

The basic idea of these conversion methods is that the inflation expectation of an individual is based on a subjective distribution function of the future price level. The mean of the distribution function is the inflation expectation of each individual. The subjective distribution functions can be aggregated to the expectations distribution function $f(x_{t+1})$ that is presented as normally distributed in Figure 2.5. Where $\pm\delta$ is the just noticeable difference of the inflation around zero and $\pm\epsilon$ is the just noticeable difference of the inflation around the perceived inflation μ'_t.

The mean of the distribution function μ_t can be interpreted as expected future inflation π^e_t. Based on a distribution assumption, the expected inflation can be calculated by:

$$\pi^e_t = \mu'_t \cdot \frac{(a_t + b_t)}{(a_t + b_t - c_t - d_t)} \tag{2.7}$$

[20] Cf. Berk (1999), Berk (2002), Nardo (2003), and Nielsen (2003). For a discussion cf. Visco (1984).

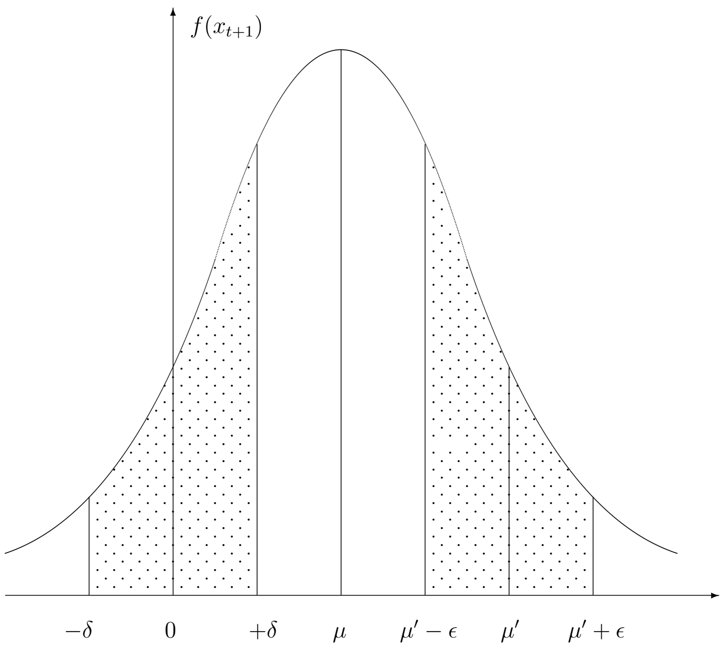

Figure 2.5: Quantification for surveys with five answer possibilities: expectation distribution

The parameter a_t is the standardized value of the percentage answer category "fall", the parameter b_t of the answer category "fall" plus "stay the same", c_t of the answer category "fall" plus "stay about the same" plus "increase at a slower rate", and so forth. The parameters a_t, b_t, c_t, and d_t can be calculated with the percentage values of the different answers categories and an assumption about the distribution function. Equation (2.7) is the same as equation (2.1).

The difference between both conversion methods mentioned above is the calculation of perceived past inflation μ_t'. For the method from Batchelor and Orr the answer proportions out of question five, that asks about the perceived inflation, and the inflation over the last year are used as a measurement of the perceived past inflation. The answer proportions out of question five are combined as given by the fraction in equation (2.7).[21]. For the method from Berk the answer categories of question five are aggregate into three categories. These three categories and the assumption that the perceived inflation of the consumers is on average equal to the true past inflation is used to produce a

[21]For more details cf. Batchelor and Orr (1988).

measurement for the perceived past inflation.[22]. In order to ensure that results are not driven by the conversion method applied, I adjust the scaling factor such that expectations are on average correct.

A problem with the conversion method occurs because it is not always possible to calculate a value for the parameters a_t, b_t, c_t, and d_t because of undefined values of the distribution function. There are three cases in which equation (2.7) cannot be calculated and therefore the data has to be corrected:[23]

- The value of the aggregate distribution function is zero.
- The value of the aggregate distribution function is one.
- The denominator is zero.

If the value of the aggregate distribution function is zero, the value of the inverse of the normal distribution approaches minus infinity. In this case I added $1/(2n+1)$ to the response category that is equal to zero. Whereas n is the number of respondents in the corresponding category. This procedure can be justified by the fact that the survey only approximates the representative consumer or consumer group. In addition to this, the change of the correction is negligible. The lowest number of respondents is in the category "further education" in which 159 individuals are interviewed. If the aggregate distribution function in this group is zero, the data are corrected by adding $1/(2n+1) = 0.003$ to this category. This value is very close to the value of zero.

If the value of the aggregate distribution function is one, the value of the inverse of the normal distribution approaches plus infinity. If this occurs $1/(2n+1)$ is subtracted from the aggregate distribution function. The third case is only a theoretical one. It does not appear in the data used in this essay.

[22] For more details cf. Berk (1999).

[23] For the correction of the data I am following mainly Henzel and Wollmershäuser (2005).

2.C Further Results: Graphs

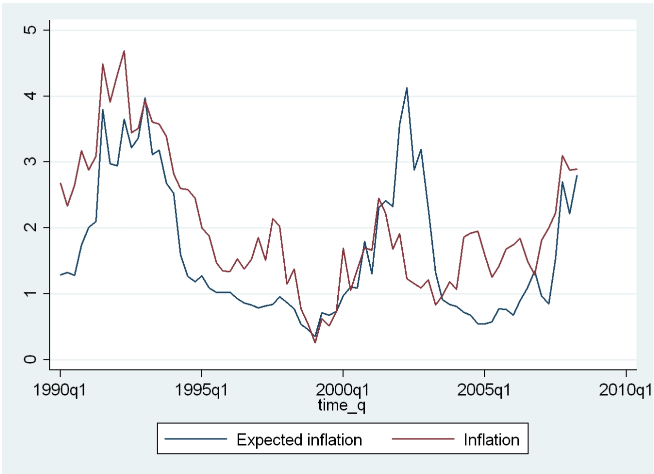

Figure 2.6: Actual and expected inflation: Berk's conversion method not adjusted

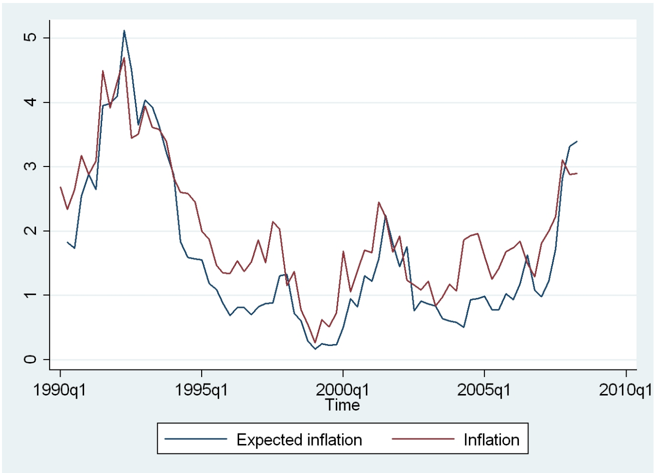

Figure 2.7: Actual and expected inflation: Bachelor and Orr's conversion method not adjusted

2.D Inflation Data

Monthly CPI data are taken from the Bundesbank. The series is seasonally adjusted and named USFB99. Based on this series, inflation is calculated as twelve month percentage growth changes.

2.E Further Results: Bachelor and Orr Conversion Method

$\pi_t - \pi^e_{i,t} = \gamma_1 + \gamma_2(\pi_{t-1} - \pi^e_{i,t-1}) + \psi_t$				
	$\widehat{\gamma_1}$	SE	$\widehat{\gamma_2}$	SE
Full sample	0.00	0.08	0.74	0.08***
Male	0.00	0.08	0.74	0.08***
Female	0.00	0.08	0.74	0.08***
Primary education	0.00	0.08	0.74	0.08***
Secondary education	0.00	0.08	0.73	0.09***
Further education	0.01	0.08	0.70	0.09***
16-29 years old	0.00	0.08	0.73	0.09***
30-49 years old	0.00	0.08	0.75	0.08***
50-64 years old	0.00	0.08	0.73	0.08***
above 65 years	0.00	0.08	0.75	0.08***
1st quartile income	0.00	0.08	0.73	0.08***
2nd quartile income	0.00	0.08	0.74	0.08***
3rd quartile income	0.00	0.08	0.73	0.09***
4th quartile income	0.00	0.08	0.73	0.09***
Work full-time	0.00	0.08	0.74	0.08***
Unemployed	0.00	0.08	0.77	0.08***
Self employed	0.00	0.08	0.71	0.09***
Farmers	0.00	0.08	0.74	0.08***
Office employees	0.00	0.08	0.74	0.08***
Skilled manual workers	0.00	0.08	0.74	0.08***
Other manual workers	0.00	0.08	0.77	0.08***
Total worker	0.00	0.08	0.75	0.08***
Other occupations	0.00	0.08	0.73	0.08***
Work part-time	0.00	0.08	0.74	0.08***

*** indicate statistical significance at 1 percent level. All data concern Germany. Converted inflation expectation data are used. Data for the inflation rate (CPI) are taken from the Bundesbank. The data cover the time period from the second quarter 1990 to the second quarter 2008.

Table 2.16: Bachelor and Orr's conversion method: full information rationality test: serial correlation

$\pi_t - \pi^e_{i,t} = \rho_1 + \sum_{j=2}^{4} \rho_j \pi_{i,t-j+1} + \xi_t$								
	$\widehat{\rho_1}$	SE	$\widehat{\rho_2}$	SE	$\widehat{\rho_3}$	SE	$\widehat{\rho_4}$	SE
Full sample	1.11	0.19***	-0.34	0.20	0.18	0.26	-0.42	0.21**
Male	1.10	0.19***	-0.34	0.20	0.17	0.26	-0.41	0.21**
Female	1.13	0.19***	-0.34	0.20	0.18	0.26	-0.43	0.21**
Primary education	1.16	0.20***	-0.37	0.21*	0.18	0.26	-0.43	0.21**
Secondary education	0.99	0.19***	-0.29	0.20	0.17	0.26	-0.40	0.21*
Further education	1.08	0.19***	-0.31	0.20	0.20	0.25	-0.45	0.20**
16-29 years old	1.00	0.19***	-0.28	0.20	0.18	0.25	-0.43	0.20**
30-49 years old	1.18	0.20***	-0.38	0.21*	0.18	0.26	-0.43	0.21**
50-64 years old	1.14	0.19***	-0.34	0.20*	0.16	0.25	-0.41	0.20**
above 65 years	1.19	0.19***	-0.36	0.20*	0.16	0.24	-0.43	0.20**
1st quartile income	1.26	0.20***	-0.38	0.21*	0.17	0.27	-0.46	0.21**
2nd quartile income	1.17	0.19***	-0.37	0.20*	0.18	0.25	-0.42	0.20**
3rd quartile income	1.11	0.19***	-0.35	0.20*	0.19	0.25	-0.43	0.20**
4th quartile income	1.06	0.19***	-0.32	0.20	0.16	0.25	-0.40	0.20**
Work full-time	1.10	0.19***	-0.34	0.20*	0.18	0.26	-0.42	0.21**
Unemployed	1.39	0.21***	-0.36	0.22	0.00	0.28	-0.37	0.22
Self employed	0.97	0.19***	-0.34	0.21	0.20	0.26	-0.37	0.21*
Farmers	1.16	0.19***	-0.34	0.20	0.04	0.26	-0.31	0.21
Office employees	1.07	0.19***	-0.31	0.20	0.17	0.25	-0.42	0.20**
Skilled manual workers	1.17	0.20***	-0.40	0.21*	0.21	0.26	-0.43	0.21**
Other manual workers	1.38	0.21***	-0.39	0.22*	0.19	0.28	-0.52	0.22**
Total worker	1.20	0.20***	-0.39	0.21*	0.20	0.26	-0.44	0.21**
Other occupations	1.11	0.19***	-0.33	0.20	0.17	0.25	-0.43	0.20**
Work part-time	1.19	0.20***	-0.32	0.21	0.21	0.27	-0.52	0.21**

*, **, *** indicate statistical significance at the 10, 5, and 1 percent level, respectively. All data concern Germany. Converted inflation expectation data are used. Data for the inflation rate (CPI) are taken from the Bundesbank. The data cover the time period from the second quarter 1990 to the second quarter 2008.

Table 2.17: Full information rationality test: efficiency

$\pi_t - \pi^e_{i,t} = \delta_1 + \delta_2\pi_{i,t-1} + \delta_3\pi_{i,t-2} + \delta_4\pi_{i,t-3} + \delta_5 u_{t-1} + \delta_6 i_{t-1} + \eta_t$												
	$\widehat{\delta_1}$	SE	$\widehat{\delta_2}$	SE	$\widehat{\delta_3}$	SE	$\widehat{\delta_4}$	SE	$\widehat{\delta_5}$	SE	$\widehat{\delta_6}$	SE
Full sample	3.28	1.42**	-0.57	0.21**	0.13	0.25	-0.43	0.20**	-0.17	0.11	0.05	0.12
Male	3.22	1.43**	-0.56	0.21**	0.13	0.25	-0.42	0.20**	-0.16	0.11	0.05	0.12
Female	3.33	1.42**	-0.57	0.21***	0.14	0.25	-0.45	0.20**	-0.17	0.11	0.05	0.11
Primary education	3.36	1.44**	-0.59	0.21***	0.14	0.25	-0.44	0.20**	-0.17	0.11	0.04	0.12
Secondary education	3.10	1.42**	-0.53	0.21**	0.12	0.25	-0.42	0.20**	-0.16	0.11	0.06	0.11
Further education	3.26	1.39**	-0.53	0.21**	0.15	0.24	-0.46	0.19**	-0.17	0.10	0.04	0.11
16-29 years old	3.16	1.41**	-0.52	0.21**	0.13	0.24	-0.44	0.20**	-0.17	0.10	0.06	0.11
30-49 years old	3.44	1.46**	-0.59	0.22***	0.15	0.25	-0.43	0.20**	-0.17	0.11	0.03	0.12
50-64 years old	3.24	1.42**	-0.57	0.21**	0.11	0.24	-0.42	0.20**	-0.16	0.10	0.05	0.11
above 65 years	3.23	1.37**	-0.57	0.20***	0.12	0.24	-0.44	0.19**	-0.16	0.10	0.04	0.11
1st quartile income	3.41	1.48**	-0.64	0.22***	0.11	0.26	-0.48	0.21**	-0.17	0.11	0.07	0.12
2nd quartile income	3.42	1.39**	-0.60	0.21***	0.13	0.24	-0.43	0.19**	-0.17	0.10*	0.05	0.11
3rd quartile income	3.20	1.39**	-0.58	0.21***	0.15	0.24	-0.44	0.19**	-0.16	0.10	0.05	0.11
4th quartile income	3.19	1.38**	-0.52	0.21**	0.13	0.24	-0.41	0.19**	-0.16	0.10	0.03	0.11
Work full-time	3.31	1.43**	-0.56	0.21***	0.14	0.25	-0.42	0.20**	-0.17	0.11	0.04	0.12
Unemployed	3.48	1.56**	-0.58	0.23**	-0.04	0.27	-0.38	0.22*	-0.16	0.12	0.05	0.13
Self employed	3.10	1.44**	-0.55	0.22**	0.15	0.25	-0.38	0.20*	-0.17	0.11	0.04	0.12
Farmers	4.05	1.44***	-0.52	0.21**	0.03	0.25	-0.30	0.20	-0.22	0.11**	-0.04	0.12
Office employees	3.26	1.41**	-0.54	0.21**	0.13	0.24	-0.42	0.20**	-0.17	0.10	0.04	0.11
Skilled manual workers	3.42	1.45**	-0.62	0.22***	0.17	0.25	-0.44	0.20**	-0.17	0.11	0.04	0.12
Other manual workers	4.12	1.58**	-0.58	0.24**	0.17	0.27	-0.51	0.22**	-0.21	0.12*	-0.02	0.13
Total worker	3.56	1.48**	-0.61	0.22***	0.16	0.25	-0.45	0.21**	-0.18	0.11	0.03	0.12
Other occupations	3.14	1.39**	-0.55	0.21***	0.13	0.24	-0.45	0.19**	-0.16	0.10	0.05	0.11
Work part-time	3.79	1.49**	-0.55	0.22**	0.17	0.26	-0.52	0.21**	-0.20	0.11*	0.02	0.12

*, **, *** indicate statistical significance at the 10, 5, and 1 percent level respectively. All data concern Germany. Converted inflation expectation data are used. Data for the inflation rate (CPI) and the three month interest rate are taken from the Bundesbank. Data for the unemployment rate are taken from the Bundesagentur für Arbeit. The data cover the time period from the second quarter 1990 to the second quarter 2008.

Table 2.18: Bachelor and Orr's conversion method: full information rationality tests: orthogonality

	$MSFE$
Professionals	0.49
Full sample	0.59
Male	0.59
Female	0.60
Primary education	0.61
Secondary education	0.56
Further education	0.57
16-29 years old	0.56
30-49 years old	0.63
50-64 years old	0.59
above 65 years	0.57
1st quartile income	0.65
2nd quartile income	0.59
3rd quartile income	0.58
4th quartile income	0.54
Work full-time	0.59
Unemployed	0.75
Self employed	0.57
Farmers	0.65
Office employees	0.58
Skilled manual workers	0.63
Other manual workers	0.66
Total worker	0.63
Other occupations	0.56
Work part-time	0.62

All data concern Germany. Converted inflation expectation data are used. Data for the inflation rate (CPI) are taken from the Bundesbank. Data for professional forecasters are taken from *Consensus Economics*. The data cover the time period from the first quarter 1990 to the second quarter 2008.

Table 2.19: Bachelor and Orr's conversion method: mean squared forecast errors

$\pi^e_{i,t} = \alpha_1 \pi^{Pro}_t + \alpha_2 \pi^e_{i,t-1} + \tau_t$						
	$\widehat{\alpha_1}$	SE	$\widehat{\alpha_2}$	SE	Adj. R^2	p-value
Full sample	0.29	0.10***	0.69	0.14***	0.96	0.71
Male	0.30	0.09***	0.67	0.14***	0.96	0.66
Female	0.28	0.10***	0.70	0.14***	0.96	0.76
Primary education	0.29	0.10***	0.69	0.14***	0.96	0.70
Secondary education	0.29	0.09***	0.70	0.13***	0.96	0.78
Further education	0.31	0.10***	0.67	0.15***	0.96	0.67
16-29 years old	0.33	0.08***	0.64	0.12***	0.97	0.54
30-49 years old	0.32	0.08***	0.65	0.12***	0.96	0.56
50-64 years old	0.27	0.10***	0.71	0.15***	0.96	0.78
above 65 years	0.23	0.11**	0.76	0.15***	0.96	0.89
1st quartile income	0.30	0.11***	0.68	0.16***	0.95	0.70
2nd quartile income	0.28	0.10***	0.70	0.14***	0.96	0.74
3rd quartile income	0.31	0.11***	0.67	0.15***	0.96	0.65
4th quartile income	0.29	0.09***	0.69	0.13***	0.97	0.69
Work full-time	0.31	0.09***	0.67	0.13***	0.96	0.62
Unemployed	0.30	0.09***	0.68	0.14***	0.94	0.70
Self employed	0.30	0.08***	0.69	0.12***	0.96	0.72
Farmers	0.38	0.09***	0.57	0.14***	0.95	0.40
Office employees	0.30	0.09***	0.68	0.13***	0.96	0.68
Skilled manual workers	0.33	0.10***	0.64	0.14***	0.96	0.60
Other manual workers	0.34	0.07***	0.62	0.11***	0.95	0.37
Total worker	0.33	0.09***	0.63	0.13***	0.96	0.53
Other occupations	0.27	0.10***	0.72	0.15***	0.96	0.77
Work part-time	0.31	0.09***	0.67	0.13***	0.96	0.63

All standard errors are corrected for heteroscedasticity and serial correlation using a Newey-West procedure with four lags. *, **, *** indicate statistical significance at the 10, 5, and 1 percent level respectively. All data concern Germany. Converted inflation expectation data are used. Data for the inflation rate (CPI) are taken from the Bundesbank. Data for professional forecasters are taken from *Consensus Economics*. The data cover the time period from the first quarter 1990 to the second quarter 2008.

Table 2.20: Bachelor and Orr's conversion method: delayed-information rationality test: baseline model

$\triangle\pi^e_{i,t} = \beta_1\pi^e_{t-1} + \beta_2 \triangle \pi^{Pro}_t + \beta_3\pi^{Pro}_{t-1} + \phi_t$								
	$\widehat{\beta_1}$	SE	$\widehat{\beta_2}$	SE	$\widehat{\beta_3}$	SE	Long	p-value
Full sample	-0.19	0.10*	0.42	0.15***	0.20	0.09**	1.02	0.56
Male	-0.21	0.10**	0.40	0.15***	0.21	0.09**	1.01	0.66
Female	-0.18	0.10*	0.43	0.15***	0.19	0.09**	1.04	0.44
Primary education	-0.19	0.10*	0.40	0.16**	0.20	0.09**	1.02	0.57
Secondary education	-0.19	0.10*	0.43	0.15***	0.20	0.09**	1.04	0.57
Further education	-0.23	0.10**	0.42	0.15***	0.23	0.09**	1.00	0.39
16-29 years old	-0.26	0.10**	0.36	0.14**	0.26	0.09***	0.97	0.15
30-49 years old	-0.23	0.10**	0.44	0.15***	0.23	0.09**	0.98	0.30
50-64 years old	-0.17	0.10*	0.40	0.16**	0.18	0.09**	1.05	0.71
above 65 years	-0.14	0.10	0.40	0.16**	0.15	0.09*	1.10	0.95
1st quartile income	-0.18	0.10*	0.42	0.17**	0.19	0.09**	1.04	0.69
2nd quartile income	-0.21	0.10**	0.36	0.16**	0.21	0.09**	1.02	0.49
3rd quartile income	-0.18	0.10*	0.44	0.15***	0.19	0.09**	1.02	0.58
4th quartile income	-0.17	0.10*	0.46	0.14***	0.18	0.09*	1.02	0.62
Work full-time	-0.21	0.10**	0.43	0.15***	0.21	0.09**	1.00	0.37
Unemployed	-0.20	0.10**	0.46	0.18**	0.21	0.09**	1.03	0.79
Self employed	-0.22	0.10**	0.43	0.15***	0.22	0.09**	1.01	0.32
Farmers	-0.35	0.11***	0.30	0.17*	0.32	0.10***	0.93	0.04
Office employees	-0.19	0.10*	0.45	0.14***	0.19	0.09**	1.02	0.57
Skilled manual workers	-0.25	0.10**	0.39	0.16**	0.24	0.09**	0.98	0.30
Other manual workers	-0.31	0.10***	0.44	0.16**	0.28	0.09***	0.91	0.07
Total worker	-0.26	0.10**	0.40	0.16**	0.25	0.09***	0.96	0.20
Other occupations	-0.16	0.10*	0.39	0.15**	0.17	0.09*	1.06	0.76
Work part-time	-0.23	0.10**	0.41	0.16**	0.23	0.09**	0.98	0.32

*, **, *** indicate statistical significance to the 10, 5, and 1 percent level respectively. All data concern Germany. Converted inflation expectation data are used. Data for the inflation rate (CPI) are taken from the Bundesbank. Data for professional forecasters are taken from *Consensus Economics*. The data cover the time period from the first quarter 1990 to the second quarter 2008.

Table 2.21: Bachelor and Orr's conversion method: delayed-information rationality test: error-correction model

Chapter 3

Information Stickiness and the Influence of News on Expectation Accuracy

3.1 Introduction

Two kinds of models that include agents with staggered information updating are used for monetary economic analysis. These models are rational-inattention and sticky-information models (e.g. Mankiw and Reis 2002, Sims 2003, Moscarini 2004, Reis 2006a, Reis 2006b, and Mackowiak and Wiederholt 2009). Agents in these models do not collect perfect information in every period. One reason for this staggered updating behavior is that information gathering, filtering, and processing is costly. The higher the cost of information, the less often will agents update their information set. A hypothesis that can be derived from these models is that news coverage and forecast accuracy are positive correlated. The idea is as follows: the more news, the less time have to be spend to find the information, therefore the lower information cost, the more often agents update, the better the forecast. The aim of this essay is to test the hypothesis of a negative correlation between news coverage and forecast deviation, as an inverse measure of forecast accuracy.[1] This is done with respect to inflation forecasts and unemployment forecasts.

This essay analyzes the influence of the amount of news in U.S. newspa-

[1]This essay is based on Goecke (2011a).

pers on the differences between expectations of consumers and professional forecasters. Consumers' forecast deviation is measured as the absolute deviation of professionals' and consumers' forecasts. High forecast accuracy is given by a low forecast deviation. The effect of the amount of news about inflation in a given year on quarterly inflation forecast accuracy has been tested by Carroll (2003) using his microfoundation of sticky-information models.[2] This essay contributes to the literature by extending the existing analysis in several respects.[3] First, I examine whether the correlation between news and consumers' inflation forecast accuracy is unique to inflation or whether it exists also a correlation between news about unemployment and consumers' unemployment accuracy. Second, my approach does not have a timing problem with respect to data measurement as in the analysis by Carroll (2003). The timing problem occurs by the fact that Carroll explains, at least partly, current forecast differences by the amount of news articles in the future. I get rid of the problem by measuring the amount of news as rolling windows. To check the robustness of the results, the analysis is done for the representative U.S. consumer on a yearly, quarterly, and monthly basis and also for different subgroups. In addition to that I also check for other variables that could influence forecast accuracy like macroeconomic variables, major events, and elections.

A further contribution to the existing literature is that inflation news is represented in this essay not only by an index news variable that measures the relative amount of news but also by the absolute amount of news. By measuring news as absolute data, it is possible to give economic interpretation about by how much the average forecast accuracy tends to improve if one more article about the associated macroeconomic variable is published.

[2]For another approach of a microfoundation of sticky-information models see Reis (2006b).

[3]Previous studies in this area that differ from Carroll's and my analysis are as follows: Doms and Morin (2004) measure news coverage by the amount of U.S. newspaper articles that deal with recessions and find that consumers update their expectations more frequently during times of high news coverage. Badarinza and Buchmann (2009) use European data and show that consumers' forecast improve during times of high news coverage. Maag and Lamla (2009) use German data in a Bayesian learning model and they find no influence of news coverage on German consumer forecast accuracy. Roos (2007) finds a positive correlation between news coverage and forecast accuracy based on a survey among German students. Abel et al. (2007) show that information costs lead to inattention in a stock market context.

The results show that consumers' inflation forecast of the representative U.S. consumer is closer to professionals' forecast if more news about inflation is printed in newspapers. This result does not change in almost all robustness checks. But the effect vanishes partly in a micro analysis. The gap between consumers' and professionals' inflation forecasts is reduced by approximately one average absolute forecast error if one more newspaper article is published each day. The correlation between news about unemployment and unemployment forecast deviation has the opposite sign as predicted by the theory. The results concerning unemployment indicate a positive effect of news about unemployment on unemployment forecast deviation. Thus, the theoretical prediction of a negative correlation between the amount of news and forecast deviation occurs for inflation but the opposite correlation emerges in the case of unemployment.

The remainder of the essay is organized as follows. Section 3.2 deals with the impact of news on forecast accuracy that would be expected theoretically. Section 3.3 describes the data used in the analysis. Section 3.4 presents empirical results. Finally Section 3.5 concludes.

3.2 Model of News Coverage and Forecast Accuracy

Rational-inattention models predict a positive correlation between news coverage and forecast accuracy. In these models agents do not update their expectations correctly because of noisy information. They choose the precision of information but filtering the noise is costly. Concerning the influence of news coverage on forecast accuracy, Sims (2005) mentioned:

> "If there are enough other semi-public filterers of monetary news (TV, newspapers, investment clubs, lunchtable conversation), the signal processing noise in them may partially cancel out at the aggregate level..." (p. 21)

meaning that more filterers lead to less signal noise and therefore in an improved forecast accuracy. Therefore, I conclude that the concept of rational inattention predicts a positive correlation between news coverage and forecast accuracy.

Another model that predicts a positive correlation between news coverage and forecast accuracy that this essay follows mainly is the one of sticky information in the seminal paper of Mankiw and Reis (2002). In the sticky-information literature agents do not have correct forecasts in every period because they do not update their information set in each period. They update only sporadically because of costly information. Recently, a growing literature emerges using the idea of sticky information (e.g. Mankiw and Reis 2007, Döpke et al. 2008a, Coibion 2010, Dixon and Kara 2010, Dupor et al. 2010, Korenok et al. 2010). The probability of updating is given exogenously in the simplest version of these sticky-information models. In more sophisticated models, the probability of updating depends negatively on the cost of planning. Part of these cost occurs due to acquiring, absorbing, and processing information (see Reis 2006b). Agents have to spend time finding information, for example. If more news is available, information cost decreases because of falling search cost. Agents have to spend less time on getting information about inflation if the information is in a leading article on the front page of a newspaper in comparison to a small article in the business section. Agents update more often with falling information cost, therefore forecast accuracy improves with more information. Thus, sticky-information models also predict a positive correlation between news coverage and forecast accuracy.

The aim of this essay is to test the hypothesis of a positive correlation between news coverage and forecast accuracy as predicted by the theory.

Carroll (2003) tests the hypothesis that more news coverage and better forecasts should be correlated with the following equation:[4]

$$\pi_t^{dev} = \alpha_1 + \alpha_2 \pi_t^{News} + \varepsilon_t, \tag{3.1}$$

where π_t^{News} represents the amount of articles concerning inflation and π_t^{dev} denotes the inflation forecast deviation between professionals π_t^{Pro} and consumers π_t^{Con}. The forecast deviation, as an inverse measure of forecast accuracy, is calculated in this essay by:

$$\pi_t^{dev} = |\pi_t^{Pro} - \pi_t^{Con}|$$

3.2.1 Carroll's Timing Problem

Carroll (2003) analyzes equation (3.1) and finds the estimator of the constant $\widehat{\alpha_1}$ to be significantly positive and that the amount of news concerning inflation

[4]For a justification of this specification see Appendix 3.A.

has a significantly negative influence on the level of inflation forecast deviation for the representative U.S. consumer. One innovation in this analysis is a robustness check of Carroll's results that has to be made because of a timing problem in Carroll's analysis. The timing problem occurs as follows: he uses the amount of inflation news in a total year to explain the inflation expectations of consumers in each quarter of the same year. This implicitly assumes that the amount of news at the end of the year also influences consumer's expectations built in the first quarter. To me, this seems to be unreasonable.[5] I measure the amount of news as rolling windows. The rolling windows are constructed in a way that the news variable measures the number of articles that are available at the time the forecast is made. Furthermore, I check the robustness of the results by measuring news more precisely on a yearly, quarterly, and monthly basis. So that for example, measuring news on a quarterly basis means that the news variable contains information about the current month, in that the forecast deviation π_t^{dev} is measured, and the two previous months. These three months do not have to be equal to the quarters of a year as shown graphically in Figure 3.1.

With this approach I check whether Carroll's results can be confirmed or not. Therefore I change equation (3.1) by explicitly using different frequencies. I measure the amount of news in the last year by counting the number of articles about news in the last twelve month ($\pi_t^{News,12m}$), in the last quarter by using the last three month ($\pi_t^{News,3m}$), and monthly ($\pi_t^{News,1m}$). The forecast deviation is measured on a quarterly ($\pi_t^{dev,q}$) or monthly ($\pi_t^{dev,m}$) basis. I analyze the following equations,

$$\pi_t^{dev,q} = \alpha_1 + \alpha_2 \pi_t^{News,12m} + \varepsilon_t, \tag{3.2}$$

$$\pi_t^{dev,q} = \alpha_1 + \alpha_2 \pi_t^{News,3m} + \varepsilon_t, \tag{3.3}$$

$$\pi_t^{dev,m} = \alpha_1 + \alpha_2 \pi_t^{News,1m} + \varepsilon_t, \tag{3.4}$$

3.2.2 News Coverage and Unemployment Forecasts

The basic idea of the theory is that in times of higher news coverage the cost of producing good forecasts is lower for consumers. This should hold in general

[5] Carroll (2001) discusses the timing problem of his model with respect to the influence of professionals' inflation forecasts on consumers' inflation forecast but not with respect to the influence of news coverage on forecast accuracy.

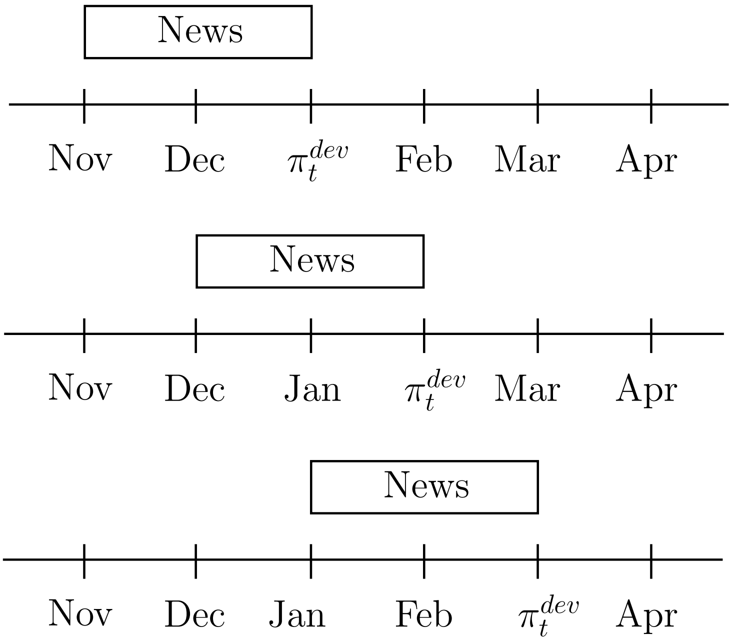

Figure 3.1: Quarterly rolling windows

and not only for inflation forecasts. Thus, I apply this idea to unemployment. I test the impact of unemployment news coverage on unemployment forecast accuracy. To test this, a similar analysis as explained in the previous section is done for news coverage and expectations about unemployment, using the following equation to take into account once again the timing issue:

$$u_t^{dev,q} = \beta_1 + \beta_2 u_t^{News,12m} + \tau_t, \tag{3.5}$$

$$u_t^{dev,q} = \beta_1 + \beta_2 u_t^{News,3m} + \tau_t, \tag{3.6}$$

$$u_t^{dev,m} = \beta_1 + \beta_2 u_t^{News,1m} + \tau_t, \tag{3.7}$$

where u_t^{dev} is the deviation between consumers' and professionals' forecast about the future unemployment rate and u_t^{News} represents the amount of articles concerning unemployment.

3.2.3 Evidence at the Micro Level

A further robustness check of Carroll's results is done by taking into account the correlation between news coverage and forecast accuracy on a disaggregated level. The importance of an analysis about the effect of news on consumers' inflation forecasts on a micro level is presented by Carrillo and Emran (2011). They show that news about inflation influences consumers' price expectations but the effect is stronger for specific demographic groups than for others. Therefore, I split up the data into different demographic groups. These groups are constructed using gender, education (low; middle; high), age (under 34 years; 35-53 years; above 53 years), and income (first; second; third; fourth quartile).[6]

3.2.4 Influence of Macroeconomic Data, Major Events, and Elections

The next innovation is to extend the analysis by taking into account other variables that could influence forecast accuracy, beside the effect of news coverage: macroeconomic data, major events, and elections.

If agents forecast a macroeconomic variable, past and current values of this variable itself and other variables that influence the variable of interest could have an effect on the variable and therefore on the forecast and possibly on forecast accuracy. In the case of inflation I check for lagged inflation, the unemployment growth rate, and the current and lagged growth rate of a monetary aggregate. I do not take into account the current inflation rate because of possible multicollinearity that may occur based on the high correlation between current and lagged inflation.

Concerning the effect of major events on forecast accuracy, Eisensee and Strömberg (2007) show that major events, like Olympic Games and Football World Cups, crowd out other news. This suggests that forecast accuracy could be worse in times of major events because news coverage concerning other topics should be lower and the attention of agents is pointed to the major events. The equations that are estimated will also incorporate an interaction term of major events and news to take into account interaction effects.

Considering national elections, Berlemann and Elzemann (2006) show that a link between inflation forecasts and election outcome expectations exists. Furthermore, Roos (2005) shows that before national elections the influence

[6] Individuals with no high school diploma belong to the least educated group, individuals with high school diploma but without a college degree belong to the education group of the middle category, and individuals with a college degree belong to the most educated group.

of professionals on consumers' expectations is higher than during other times. The idea is that consumers pay more attention to professional forecasts before elections.

Furthermore I also take into account the lagged forecast deviation. Therefore the equation that will be used to test the effect of inflation news by including all the above-mentioned variables changes to:

$$\begin{aligned}\pi_t^{dev} =& \alpha_1 + \alpha_2 \pi_t^{News} + \alpha_3 ME_t + \alpha_4 \left(\pi_t^{News} * ME_t\right) + \alpha_5 \pi_{t-1} + \alpha_6 \Delta u_t \\ &+ \alpha_7 Election_{t+1} + \alpha_8 \Delta M1_t + \alpha_9 \Delta M1_{t-1} + \alpha_{10} \pi_{t-1}^{dev} + \varepsilon_t,\end{aligned} \tag{3.8}$$

where ME is a dummy for major events (the dummy is one if there is a Football World Cup tournament or Olympic Games, otherwise zero), π_{t-1} is the lagged annual inflation rate (based on the comparison between the consumer price level in a specific month and the consumer price level in the same month in the previous year), Δu_t is the unemployment growth rate, *Election* is a dummy for a presidential election (one if there is an election, otherwise zero), and $\Delta M1$ represents the growth rate of the monetary aggregate $M1$.

To test for variables that could influence the forecast accuracy of unemployment I include a variable for major events and the corresponding interaction term, an election variable, the change in the unemployment rate, and a measure based on the OECD leading indicator. I include the change in the unemployment rate because a more volatile unemployment rate may induce higher forecast deviation. The OECD variable is included to check for economic activity. Thus the following equation will be used for the unemployment case:

$$\begin{aligned}u_t^{dev} =& \beta_1 u_t^{News} + \beta_2 ME_t + \beta_3 \left(u_t^{News} * ME_t\right) + \beta_4 Election_{t+1} \\ &+ \beta_5 \Delta u_t + \beta_6 \Delta u_{t-1} + \beta_7 OECD_t + \beta_8 OECD_{t-1} + \tau_t,\end{aligned} \tag{3.9}$$

where all variables are defined as above and $OECD$ measures the economic activity. This equation is estimated by an ordered logistic regression because the depending variable is a discrete variable with three outcomes that have a natural order.[7]

[7] u_t^{dev} is measured as the difference between professionals' and consumers' unemployment forecast. Professionals' unemployment forecast is available as quantitative data but consumers' unemployment forecast is only available as qualitative data. Therefore it is not

3.3 Data

To answer the question whether and in what direction the amount of news influences the deviation between consumers' and professionals' forecasts concerning inflation and unemployment, three variables are needed: a measure for the amount of news, consumers' forecasts, and professionals' forecast. All variables are needed with respect to inflation and unemployment.

3.3.1 Inflation Data

A news index is calculated as a measure for the amount of news about inflation following Carroll (2003). The news index is based on the amount of inflation news on the front page of the *New York Times* and the *Washington Post*. All articles from these two newspapers are available via the database *LexisNexis* from January 1980 onwards on a daily basis. All other newspapers would lead to shorter samples. To calculate the news coverage variable I search for articles that are printed on the front page and that include the word root "inflation". Thus it is searched for "inflation" and for example "inflationary" as well. Carroll counts the number of inflation news articles in each newspaper for each year. He calculates a news index by dividing the amount of inflation news articles in each year by the maximum number of news articles in any year. This index is calculated for both newspapers. Finally, both individual indices are aggregated into one news index by calculating the mean of both indices. This index is used for his analysis.

I calculate the news variable as rolling windows. The amount of news measured on a yearly basis is not as in Carroll's case the amount of news in the current year but the amount of news in the previous twelve months. I also calculate the news variable more precisely on a quarterly and monthly basis. Otherwise, the news index variables are calculated using the method described above.

Professional forecasts for inflation over the next 12 month are taken from the Survey of Professional Forecasters (hereafter SPF). The SPF has been conducted by the Federal Reserve Bank of Philadelphia on a quarterly basis

possible to calculate an unemployment deviation without any rescaling. Details about the calculation of the unemployment deviation as discrete variable with three outcomes are presented in Section 3.3.2.

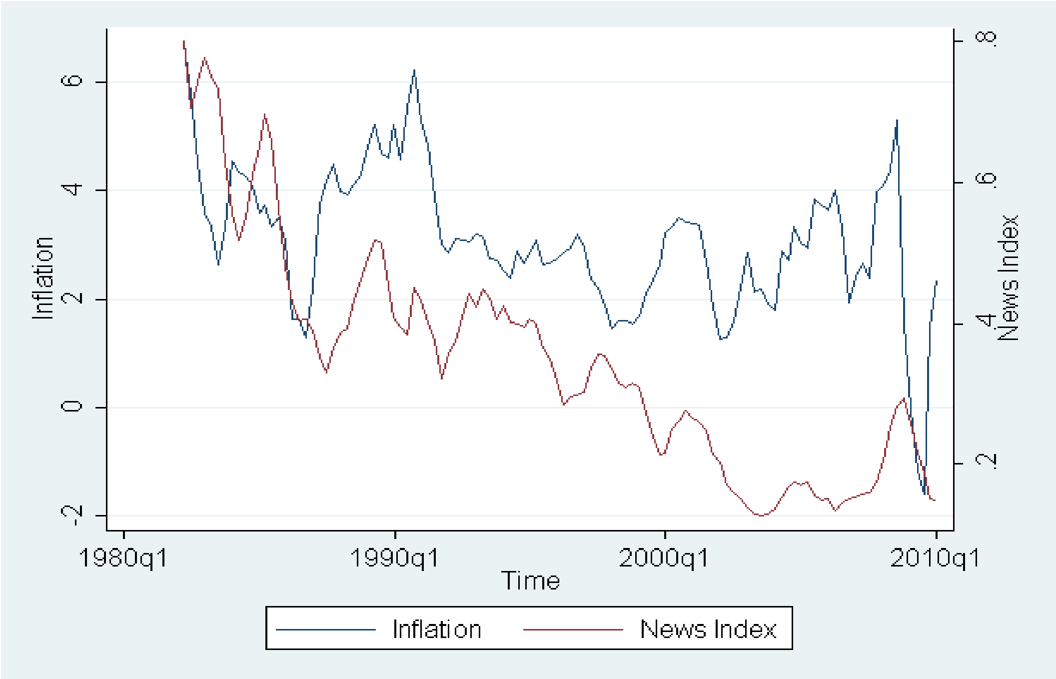

Figure 3.2: Inflation and news index

since the third quarter of 1981. The questionnaire is distributed just after the middle of the second month of each quarter and has to be answered in the following couple of weeks. The mean of the one-year-ahead forecasts for consumer prices is used as professionals' inflation expectation.

The last variable that is needed for the inflation analysis is consumers' inflation expectations for the next 12 months. To calculate consumers' expectations, micro data from the Michigan Survey of Consumers is used. The University of Michigan has conducted the consumer survey on a monthly basis since January 1978. One question in the survey asks how much inflation the respondent expects over the next year.[8] After data correction, the means of the answers from the total sample, which is weighted in a way that is equal to the representative U.S. consumer, is used as inflation expectation of consumers.[9]

For illustrative purposes, Figure 3.2 presents the inflation rate and the news

[8] The exact wording of the question is: "During the next 12 month, do you think that prices in general will go up, or go down, or stay where they are now?" The majority of the respondents answer "go up". If the respondents expect the prices to go up/down, they are asked: "By about what percent do you expect prices to go (up/down) on the average, during the next 12 month?"

[9] Details of the data correction are presented in Appendix 3.B.

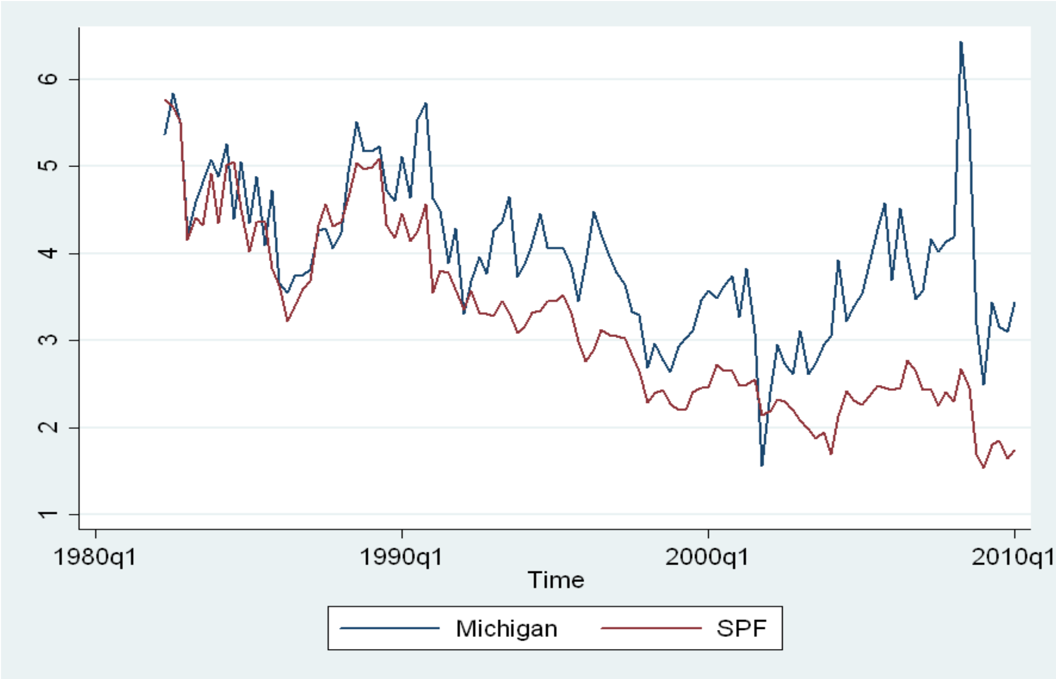

Figure 3.3: Consumers' and professionals' inflation forecasts

index on a quarterly basis over time. The graph indicates that the amount of news decreases over time. The inflation rate varies strongly due to the recession at the end of the sample period. Figure 3.3 illustrates quarterly consumers' and professionals' forecasts over time. The graph shows that consumers' forecasts are most of the time higher than professionals' forecasts. Both forecasts move closely together until the end of the 1980's. After 1990 the gap between both time series gets bigger. In 2009 the biggest deviation occurs during the recession.

3.3.2 Unemployment Data

The variable that accounts for the amount of news that deals with unemployment is calculated similarly to the one of inflation news coverage. An index variable is calculated based on the amount of articles that are printed on the front page that include the word "unemployment" in the *New York Times* and the *Washington Post* during the same time horizon. The index is once again calculated on a yearly, quarterly, and monthly basis by using the method of rolling windows. The quarterly news index concerning unemployment and the U.S. unemployment rate over time are shown in Figure 3.4. The figure

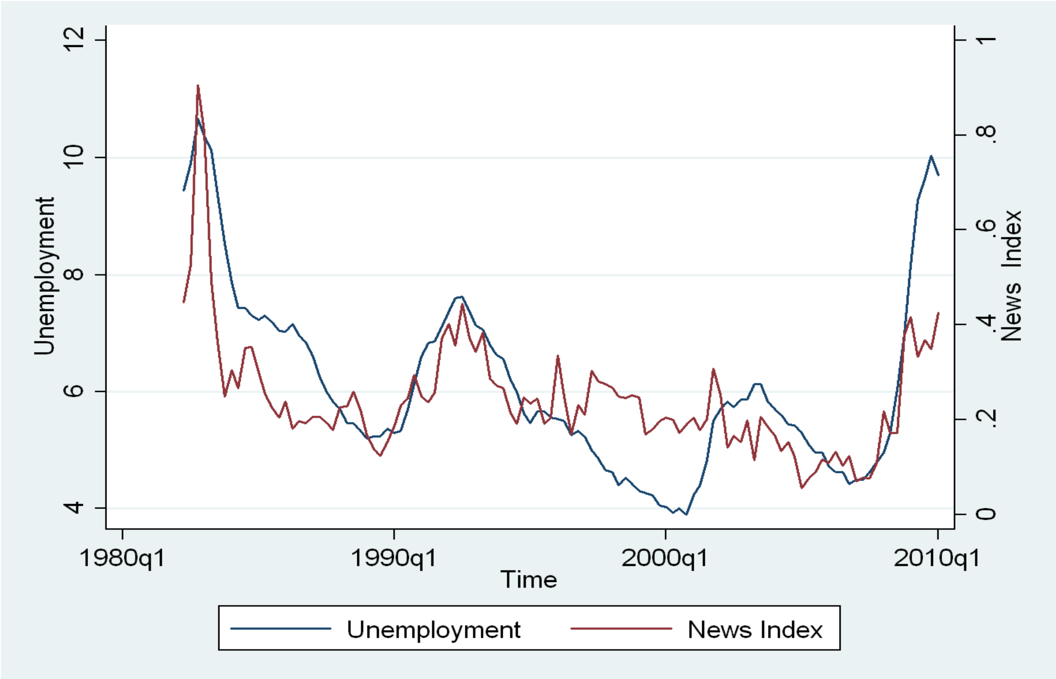

Figure 3.4: U.S. unemployment and news index

indicates a high correlation between these two variables.

Professional forecasts for the unemployment rate over the next 12 month are again taken from the SPF. Consumers' forecasts are taken from the Michigan Survey of Consumers. Unfortunately, consumers are only asked about their expected direction of the evolution of the unemployment rate and they are not asked for a quantitative forecast.[10] To analyze the effect of news coverage on the unemployment forecast accuracy, I take the consumer forecasts from the survey so that the variable consists of values "more", "about the same", and "less". To compare both variables, I rescale the professionals' forecast by comparing their current forecast with the current value of unemployment. If their current forecast of the unemployment rate in 12 months u_t^e is more than one fourth of the standard deviation of unemployment σ^u above the current value u_t, the forecast is scaled as "more".[11] If their forecast is more than one

[10]The exact wording of the question is: "How about people out of work during the coming 12 months–do you think that there will be more unemployment than now, about the same, or less?"

[11]The quantitative professional forecast deviation from the current unemployment rate is low therefore the threshold is chosen in the way described above to receive variation in the resulting variable.

fourth of the standard deviation of unemployment below the current value, the forecast is scaled as "less". In all other cases forecasts are rescaled as "about the same":[12]

$$\text{"more", if } u_t^e - u_t > 0.25 \cdot \sigma^u$$
$$\text{"about the same"} \quad \text{if } -0.25 \cdot \sigma^u < u_t^e - u_t < 0.25 \cdot \sigma^u$$
$$\text{"less" , if } u_t^e - u_t > -0.25 \cdot \sigma^u$$

Afterwards a dummy u_t^{dev} is calculated that indicates whether consumer and professionals expect the same evolution of unemployment. If they forecast the same, the dummy is zero. If they forecast the opposite ("more" vs. "less"), the dummy is two and otherwise one. The dummy variable u_t^{dev} is the dependent variable.

3.4 Estimation Results

The time horizon of the analysis ranges from the second quarter of 1982 to the first quarter of 2010. Following the argumentation in Section 3.2, a negative relationship between the amount of news and the deviation between consumers' and professionals' forecasts would be expected. The results of inflation forecast deviation with different timing and based on the calculation of the independent variables as rolling windows are presented in Table 3.1.

The results show indeed a clear finding in favor of the hypothesis that inflation news influences inflation forecast deviation negatively. All estimated coefficients of the influence of news are statistically significantly different from zero and negative. This result is independent of the time choice of the news variable and in this specification the timing problem does not occur because the variable in this essay is measured as rolling windows.

Because of the index structure of the news variable, it is not possible to get a proper economic interpretation of the estimated coefficients. To have the possibility of an economic interpretation, I also use the total number of news articles in this context in addition to the index value. The results are presented in Table 3.2. The results show that all estimated coefficients of the influence of news are once again statistically significantly different from zero and negative.

[12]The results of the analysis do not change at any significant amount if the threshold is set to 0.1, 0.15, or 0.2. Values higher than 0.25 produce almost no variation in the consumers' forecast variable.

	π_t^{dev}	π_t^{dev}	π_t^{dev}
News_Year	-1.97***		
	(0.39)		
News_Quarter		-2.19***	
		(0.43)	
News_Month			-1.88***
			(0.33)
Constant	1.50***	1.41***	1.23***
	(0.20)	(0.18)	(0.11)
R^2	0.28	0.23	0.11

Newey-West standard errors in parentheses. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1: Effect of news coverage: news index measured as rolling windows and different timing

	π_t^{dev}	π_t^{dev}	π_t^{dev}
News_Year_Abs	-0.0027***		
	(0.0005)		
News_Quarter_Abs		-0.0089***	
		(0.0017)	
News_Month_Abs			-0.0185***
			(0.0032)
Constant	1.4787***	1.3649***	1.2253***
	(0.1851)	(0.1722)	(0.1085)
R^2	0.26	0.21	0.11

Newey-West standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2: Effect of news coverage: news measured in absolute terms as rolling windows and different timing

The estimators seem to be quite small in magnitude. But the estimated effect of news on a quarterly basis (-0.0089) indicates that one additional article in three months, in one of the two newspapers, narrows the forecast gap by 0.0089. Thus one additional article a day, in one of the newspapers, narrows the gap by 0.89 if it is assumed that a quarter consists of 100 days for simplicity. This is remarkable because the average forecast deviation is only 0.81. Similar results occur by using the other two measurements. Thus one additional article a day reduces the difference between professionals' and consumers' inflation forecasts by about the size of one average absolute forecast error.

As a robustness check I test whether the results also hold on the micro level. A micro analysis delivers a deeper understanding of the influence of news with respect to different demographic groups. This approach discovers whether all demographic groups are affected by news in the same way. The analysis is done for demographic groups separated by gender, education, age, and income. Standard errors are presented in parentheses under the estimated values and the column "Obs." in Table 3.3 presents the number of observations in the respective group over the whole sample period. The results in Table 3.3 indicate that the negative influence of news coverage on forecast deviation does not hold for all demographic groups. The effect of the amount of news is not statistically significantly different from zero for men and the rich. A further result is that the amount of news has a stronger effect on older people (35 years and above) in comparison to younger people. This result is also found by Carrillo and Emran (2011).

Another robustness check is to take into account macroeconomic variables, major events, and elections which could influence forecast accuracy in addition to the effect of news coverage. The theoretical predictions of the different influences are explained in Section 3.2.4. The results of an OLS regression are presented in Table 3.4.

Columns (1), (2), and (3) of Table 3.4 display the estimation results of equation (3.8) without the interaction term between major events and news by using news measured on a yearly basis (Column (1)), on a quarterly basis (Column (2)), and on a monthly basis (Column (3)). The estimators show, that the negative influence of news on forecast deviation for all specifications is still highly statistically significant and negative. Beside the news variable and the constant, no other variable has explanatory power for the forecast

$\pi_{i,t}^{dev} =$	$\alpha_1 + \alpha_2\pi_t^{News} + \varepsilon_t$		Obs.
	$\widehat{\alpha_1}$	$\widehat{\alpha_2}$	
Full sample	1.41***	-2.19***	152,056
	(0.18)	(0.43)	
Male	0.76***	-0.47	70,167
	(0.20)	(0.56)	
Female	1.67***	-1.45***	81,889
	(0.18)	(0.43)	
Low education	2.21***	-1.76**	13,822
	(0.26)	(0.70)	
Middle education	1.74***	-2.88***	79,244
	(0.20)	(0.48)	
High education	0.88***	-1.19**	57,879
	(0.17)	(0.45)	
under 34 years	1.20***	-0.97**	36,074
	(0.16)	(0.39)	
35-53 years old	1.30***	-1.69***	67,796
	(0.17)	(0.42)	
above 54 years	1.29***	-1.54*	50,797
	(0.25)	(0.81)	
1st Quartile Income	2.03***	-1.79***	38,107
	(0.21)	(0.49)	
2nd Quartile Income	1.46***	-2.19***	36,997
	(0.21)	(0.53)	
3rd Quartile Income	0.92***	-1.11**	34,994
	(0.17)	(0.43)	
4th Quartile Income	0.49***	0.28	32,938
	(0.14)	(0.42)	

Newey-West standard errors in parentheses. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3: Effect of news coverage: micro level, news measured quarterly as rolling windows

Estimated equation: $\pi_t^{dev} = \alpha_1 + \alpha_2\pi_t^{News} + \alpha_3 ME_t + \alpha_4\left(\pi_t^{News} * ME_t\right) + \alpha_5\pi_{t-1} + \alpha_6\Delta u_t + \alpha_7 Election_{t+1} + \alpha_8\Delta M1_t + \alpha_9\Delta M1_{t-1} + \alpha_{10}\pi_{t-1}^{dev} + \varepsilon_t$

Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	π_t^{dev}	π_t^{dev}	π_t^{dev}	π_t^{dev}	π_t^{dev}	π_t^{dev}	π_t^{dev}	π_t^{dev}	π_t^{dev}
News_Year	-2.10***			-1.95***			-0.65**		
	(0.55)			(0.53)			(0.27)		
News_Quarter		-2.17***			-2.00***			-0.82***	
		(0.58)			(0.56)			(0.29)	
News_Month			-2.11***			-2.05***			-0.58**
			(0.42)			(0.42)			(0.23)
ME	-0.01	0.08	-0.06	0.26	0.35	0.09	-0.00	0.08	-0.25*
	(0.08)	(0.08)	(0.08)	(0.22)	(0.25)	(0.20)	(0.19)	(0.19)	(0.13)
News_Year*ME				-0.83			0.18		
				(0.64)			(0.52)		
News_Quarter*ME					-0.92			0.12	
					(0.83)			(0.61)	
News_Month*ME						-0.68			0.76
						(0.78)			(0.51)
π_{t-1}	0.07	0.05	0.07	0.07	0.05	0.07	-0.01	-0.00	0.01
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.03)	(0.02)	(0.02)
Δu_t	0.30	0.41	0.44	0.32	0.42	0.45	0.07	0.01	0.08
	(0.26)	(0.25)	(0.31)	(0.27)	(0.26)	(0.32)	(0.11)	(0.09)	(0.14)
Election$_{t+1}$	0.28	0.20	0.15	0.29	0.18	0.14	-0.04	-0.07	-0.07
	(0.21)	(0.21)	(0.16)	(0.21)	(0.20)	(0.16)	(0.18)	(0.18)	(0.08)
$\Delta M1_t$	-0.01	-0.03	0.00	-0.01	-0.03	0.00	-0.03		-0.00
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)		(0.03)
$\Delta M1_{t-1}$	0.00	0.02	-0.02	0.01	0.02	-0.01	0.02		-0.00
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)		(0.02)
π_{t-1}^{dev}							0.65***	0.67***	0.74***
							(0.09)	(0.10)	(0.07)
Constant	1.34***	1.28***	1.12***	1.28***	1.23***	1.11***	0.56***	0.49***	0.36***
	(0.18)	(0.19)	(0.15)	(0.19)	(0.19)	(0.15)	(0.14)	(0.14)	(0.09)
R^2	0.35	0.31	0.17	0.35	0.32	0.17	0.59	0.58	0.61

Newey-West standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4: Effect of news, macroeconomic variables, major events, and elections

	u_t^{dev}	u_t^{dev}	u_t^{dev}
News_Year_Unemployment	4.25***		
	(1.36)		
News_Quarter_Unemployment		6.75***	
		(1.97)	
News_Month_Unemployment			5.69***
			(1.05)
Pseudo R^2	0.08	0.12	0.07

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5: Effect of unemployment news coverage on unemployment forecast accuracy

deviation.

Columns (4), (5) and (6) present results for the same analysis but with an interaction term between major events and news coverage. The basic results do not change: news coverage still has a negative influence on inflation forecast deviation.

Columns (7), (8), and (9) consider the results for regressions of news coverage, all other variables used before, and last period's forecast deviation on the current deviation by using yearly, quarterly, and monthly measurement of news coverage. The results show that the previous forecast deviation has a positive influence on the forecast deviation in the current period for all types of news measurement. The higher the forecast deviation in the previous period is, the higher the forecast deviation in the current period. Concerning the effect of news coverage, the effect on forecast accuracy is still significantly negative. Also the constants are still statistically significant. Almost all other variables are statistically insignificant. All in all, the result of a negative influence of news coverage on forecast deviation appears robust.

The same analysis is done with respect to unemployment. All results are calculated by using an ordered logistic regression. The ordered logistic regression is used because the dependent variable is a discrete variable with three outcomes. Furthermore, the dependent variable has a specific order - the higher the dependent variable the higher the forecast disagreement. The results from the estimations of equation (3.5) to equation (3.7) are presented in Table 3.5.

The results show a positive effect of news coverage about unemployment on unemployment forecast disagreement. The positive effect occurs independently of whether news is measured on a yearly, quarterly, or monthly basis. The correlation between news about unemployment and forecast deviation has the opposite sign in comparison to the correlation between news coverage about inflation and inflation forecast deviation. In the unemployment case, more news tends to increase consumers' forecast deviation. Consumers' unemployment expectations deviate more from professionals' unemployment expectation if more articles about unemployment are printed.

I check the robustness of this result by also taking into account the variables "major events" and "elections". The results, presented in columns (1), (2), and (3) in Table 3.6, show that the positive effect of news coverage on forecast deviation remains when taking into account major events and elections.

An explanation for the phenomenon of a positive correlation between news coverage and forecast deviation could be that articles about unemployment are printed more often in periods of higher unemployment variance. Forecasts are more difficult in periods of higher unemployment change and therefore a higher forecast deviation occurs. To control for this, the current and lagged change of the unemployment rate are included in the regression. To control also for economic activity I include the OECD composite leading indicator. The results, presented in columns (4), (5), and (6) in Table 3.6, show that the positive effect of news coverage on forecast disagreement survives if unemployment change and the OECD indicator are also considered.

There are a couple of possible explanations why more news about unemployment and unemployment forecast deviations are not negatively correlated as in the inflation case. Forecast deviation is defined as the difference between consumers' and professionals' forecasts. Maybe, in the case of unemployment, the articles about unemployment do not mention professionals' forecasts and therefore a negative correlation cannot occur. A second explanation could be that consumers feel more familiar with unemployment than inflation. Maybe consumers read professionals' forecast but they think they can do a better unemployment forecast on their own, based on their private information. But these two explanations only give a hint why there is no negative correlation between news coverage about unemployment and forecast deviation. Why the data indicates a positive correlation remains a task for further research.

Estimated equation: $u_t^{dev} =$
$\beta_1 u_t^{News} + \beta_2 ME_t + \beta_3 \left(u_t^{News} * ME_t\right) + \beta_4 Election_{t+1} + \beta_5 \Delta u_t + \beta_6 \Delta u_{t-1} + \beta_7 OECD_t + \beta_8 OECD_{t-1} + \tau_t,$

Column	(1)	(2)	(3)	(4)	(5)	(6)
	u_t^{dev}	u_t^{dev}	u_t^{dev}	u_t^{dev}	u_t^{dev}	u_t^{dev}
News_Year_Unemployment	3.93***			6.86***		
	(1.49)			(2.16)		
News_Quarter_Unemployment		5.23***			5.55**	
		(2.03)			(2.51)	
News_Month_Unemployment			5.19***			3.65***
			(1.10)			(1.31)
ME	-2.18	-3.62*	-1.24	-0.59	-4.23	-0.94
	(1.92)	(2.01)	(1.07)	(2.35)	(2.64)	(1.09)
News_Year_Unemp*ME	8.09*			3.68		
	(4.54)			(6.03)		
News_Quarter_Unemp*ME		15.03**			16.73**	
		(6.21)			(8.44)	
News_Month_Unemp*ME			8.67**			8.41**
			(3.94)			(4.08)
Election$_{t+1}$	0.70	1.14	-0.09	-0.77	0.71	-0.64
	(1.01)	(1.18)	(0.54)	(1.50)	(1.55)	(0.67)
Δu_t				4.29**	3.65**	3.29***
				(1.76)	(1.75)	(1.04)
Δu_{t-1}				-1.20	-1.61	2.42**
				(1.65)	(1.65)	(1.01)
OECD$_t$				-0.23	0.19	-0.11
				(0.68)	(0.64)	(0.78)
OECD$_{t-1}$				0.68	0.14	-0.13
				(0.64)	(0.57)	(0.74)
Pseudo R^2	0.21	0.22	0.10	0.22	0.22	0.20

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6: Effect of unemployment news, major events, elections, unemployment variance, and economic activity on unemployment forecast accuracy

All in all, the investigation shows that news coverage concerning inflation improves forecast accuracy independently of the measurement of the news variable and independently of the model that is used. The effect vanishes partly in a micro analysis. Concerning unemployment, the results show that more news coverage worsens forecast accuracy.

3.5 Conclusion

This essay analyzed the influence of the amount of news in U.S. newspapers on the differences between expectations of consumers and professionals with respect to two main macroeconomic variables: inflation and unemployment. Rational-inattention and sticky-information models predict that news coverage and forecast deviations are negatively correlated.

In a first step, this analysis is a robustness check of Carroll's analysis by using more specific measurement of the variables (rolling windows and different timing), by checking the results on a micro level, and by incorporating macroeconomic variables and the own lagged forecast error. The results show evidence in favor of Carroll's finding of a negative correlation between news coverage and forecast disagreement in the context of inflation. The negative effect survives in almost all specifications and models. The effect only vanishes for men and the rich in a micro analysis. One additional article about inflation a day reduces the difference between professionals' and consumers' inflation forecasts by approximately one average absolute forecast error.

In a second step, the analysis is extended by applying this approach to data concerning unemployment. The results are different to the one found with respect to inflation. A rise in the number of articles on unemployment worsens consumers' unemployment forecasts. This result holds independently of the measurement of the news variable. The positive correlation between news coverage and forecast deviation also remains by controlling for major events, elections, the variance of unemployment, and economic activity.

Appendix

3.A Carroll's Model

Carroll (2003) develops a theoretical model that is based on the idea that acquiring, absorbing, collecting, and processing information, which is needed for a rational forecast, is costly for economic agents. But utility gains from improved forecasts are not infinite.

A good knowledge about the future leads to better choices. With better knowledge, an individual makes more adequate choices and therefore higher utility is gained. Thus, an individual should collect and process information until their marginal cost is equal to their marginal benefits. Inflation expectations will be formed on a limited but optimally chosen information set. Buiter (1980) refers to this point by stating:

> "In accordance with normal usage in economics, the term rational (or optimal) expectations ought to be reserved for forecasts generated by a rational, expected utility maximizing decision process in which the costs of acquiring, processing and evaluating additional information are balanced against the anticipated benefits from further refinement of the forecast..." (p. 35).

Such economizing on information may lead agents not to process all available information to make their forecast. With costly information acquisition and processing however, a level of inattention and therefore a deviation of the realized inflation forecasts from the realized inflation in the future is rational.

Thus there are two different kinds of rational forecasts. The first one is the *mathematically rational forecast* that is based on all available information. The second one is the *realized rational forecast* that is the forecast that is made by individuals on the basis of, rationally chosen, imperfect information.

In Carroll's model, agents receive their information from newspaper articles. The variables of interest in this essay are the deviation of consumers' inflation forecasts and forecasts written in newspapers with respect to inflation and unemployment.[13] Articles in newspapers that contain forecasts are assumed to depict professionals' forecasts. Therefore a pool of professionals'

[13] Both of these forecasts will not be equal to the future value because of shocks.

forecast is used as proxy for forecasts printed in newspapers. The absolute deviation between consumers' and professionals' forecasts is called forecast accuracy.

Consumers should assume that forecasts from professional forecasters are better than their own ones because professionals have experience, are trained to do forecasts, and spend a lot of time making forecasts whereas standard laymen do not. If the predominance of professional forecasts concerning accuracy holds, consumers should not build forecasts on their own but just adopt the forecasts of professional forecasters. But there are still costs for the consumer to get this information. Presumably, consumers therefore do not read and remember the forecasts of professionals every period. Some consumers know the current professional forecast, others not. Consumers that do not adopt current professionals' forecast stick to their own past forecast. Thus, the average consumer forecast looks as if it follows an autoregressive process.

Empirically, it can be verified that consumers should adopt professionals' forecast. Forecast errors are calculated by the squared differences between consumer price inflation and the inflation forecasts of professionals and consumers. The mean of the squared forecast error of U.S. consumers is 2.9 compared with 1.5 for professionals. Consumers' squared forecast error is almost twice as high as professionals' squared error.[14] Thus consumers should adopt professionals' inflation forecasts. Empirically, the influence of professional forecasts and the autoregressive behavior of consumer forecasts is well documented. Several researchers (among others Carroll 2003, Döpke et al. 2008a, and Döpke et al. 2008b) have shown empirically that the inflation expectations of consumers are influenced by professionals' forecasts and their own past inflation forecast.

Concerning the effect of news on forecast accuracy, Carroll's approach can be summarized as follows: The difference between consumers' forecasts and professionals' forecasts is the variable of interest. Consumers receive information about the view of professional via the mass media. But there are still costs for the consumer to get this information by spending time reading the newspaper, finding the article about inflation and keeping the inflation forecast of professionals in mind. With more news articles, the costs of getting the information are lower and therefore more individuals adopt professionals'

[14] It is not possible to compare consumers' and professionals' forecast error about unemployment because consumers' forecasts are qualitative.

forecasts. The hypothesis from this theory is that the deviation between professionals' and consumers' forecasts should narrow with a rising amount of articles. Carroll (2003) writes: "...we should expect that when there are more news stories people should be better informed..." (p. 287).

This essay tests empirically if the hypothesis of a positive correlation between news coverage and forecasts accuracy holds for inflation and unemployment. High forecast accuracy is given by a low forecast deviation. Thus, news coverage and forecast deviation are predicted to be negatively correlated. I calculate the inflation forecast deviation between professionals π_t^{Pro} and consumers π_t^{Con} by:

$$\pi_t^{dev} = |\pi_t^{Pro} - \pi_t^{Con}|$$

The hypothesis whether the level of deviation falls if more inflation news is available is checked by the following baseline equation:

$$\pi_t^{dev} = \alpha_1 + \alpha_2 \pi_t^{News} + \varepsilon_t$$

Where the variable π_t^{News} represents the amount of articles concerning inflation.

3.B Data Correction

Consumer data is corrected in the following way. Respondents, whose inflation expectations are smaller than -10 percent or bigger than 50 percent, are excluded to correct the data for participants that possibly do not understand the question. This procedure follows the method applied by the University of Michigan for calculating mean values of the inflation expectations (Curtin 1996). The respondents also have the possibility to answer that they expect the prices to be unchanged over the next 12 months. If this answer is given, it is imaginable that respondents are confused between unchanged prices and unchanged inflation. To take into account this potential misinterpretation, the people are asked since March 1982 whether their answer "stay the same" corresponds to the price level or the growth rate of the price level. Asking this question reveals that one third to one half of the respondents in each month that answer "stay the same", mean the inflation rate and not the price level. Without this check the calculated means of the inflation expectation would be biased. To avoid this problem my analysis starts in March 1982. Finally the data is weighted to be representative for the U.S. citizens following again the methods used by the Michigan University (Curtin 1996).

Chapter 4

Sticky Prices vs. Sticky Information - a Cross-Country Study of Inflation Dynamics

4.1 Introduction

Mankiw and Reis (2002) proposed sticky information as an alternative to the workhorse of monetary analysis, the sticky-price approach. The basic idea of sticky information is that information spreads slowly through the economy. Mankiw and Reis argue that this approach is favorable to the sticky-price approach because it is able to predict certain empirical observations that cannot be generated by sticky prices: hump-shaped responses of inflation to monetary impulses, contractionary disinflations, and the acceleration phenomenon.

Reis (2006b) examines the second-moment performance of the sticky-information Phillips curve in the otherwise simple Mankiw and Reis (2002) model. In this model, the sticky-information Phillips curve represents the monetary side of the economy, while the model is closed by exogenous stochastic processes on the real side. Reis finds that even such a simple sticky-information model matches selected second moments of US inflation reasonably well.

In this essay, we examine whether the finding of Reis is unique to a sticky-information model or whether it can also be achieved using a sticky-price model.[1] We contribute to the literature on the horse race between sticky in-

[1]This essay is based on Bredemeier and Goecke (2011).

formation and sticky prices methodologically in several respects. While certain previous studies have focussed on selected properties (e.g. Korenok and Swanson 2007, Korenok 2008, Abbott 2010), we take a broader look on inflation dynamics and consider inflation variance and persistence as well as its relation to dynamics in demand and supply. Considering only some properties of the inflation process may be misleading as we find that improving a model's fit to e.g. inflation persistence worsens its ability to predict e.g. responses to demand shocks.

Furthermore we do not only consider US inflation dynamics, but also those in five more countries, the UK, Germany, France, Canada, and Japan. Our motivation to take this cross-country perspective is to test whether relative model performances are country-specific. We find that some moments which are important for the identification of our two models (predominantly inflation persistence and its reaction to demand innovations) differ substantially across countries. It is therefore interesting to evaluate how the models cope with these differences. The unique cross-country perspective further distinguishes our study from the existing literature on the horse race between sticky information and sticky prices.

Finally, we compare the model performances both in moment-based and likelihood evaluations. Considering the models from both points of view reveals the interesting fact that, in many cases, one model is supported in the moment-based evaluation and the other in the likelihood-based comparison. Relying on only one perspective may therefore be misleading.

We compare the two Phillips curves in the framework of the Mankiw-Reis model which allows a comparison on a leveled playing field. For a fair comparison, the two Phillips curves should be applied in models which are otherwise identical. Furthermore, the estimation of the rest of the model should be separable from the estimation of the Phillips curve. Otherwise, parameter estimates for the other equations would be influenced by the specific Phillips curve chosen. The Mankiw-Reis model fulfills these criteria. When we estimate the models, we make use of the separability of the model and first estimate the real side of the economy and then the Phillips curves. This ensures that, when comparing models, both have not only the same equations but also the same parameter estimates on the real side of the economy and are exposed to the same sequence of shocks.[2]

Although the Mankiw-Reis model is very stylized in the way the model is closed, it seems sophisticated enough to capture inflation dynamics well. In our empirical analysis, we can reject equality between moments generated by the estimated models and empirical moments at 99% significance in only 2% of the cases.

Our empirical procedure is a simulation-based moment evaluation. We estimate stochastic processes governing the dynamics of the output gap and solve for inflation as a rational-expectations equilibrium response to innovations in these variables. For a set of selected second moments of inflation, we generate distributions of model moments by repeated simulations of the models.

We compare the empirical performance of the two models on the ground of the absolute difference between model moments and empirical moments, the number of moments for which equality of empirical and model moment can be rejected, and the likelihoods of the two models given the empirical moments. We perform two comparisons of sticky prices and sticky information. In the first comparison, we regard calibrated versions of the two models, whereas we consider estimated models in the second comparison.

Our results do not clearly support one of the two competing models. In the baseline calibration, the models perform similarly in the US, Germany, France, Canada, and Japan. Only in the UK, sticky information is clearly supported by the data. Under the estimated parametrization, sticky prices perform slightly better in the UK and Germany, while sticky information is supported by French data, and both models perform similarly in the US, Canada, and Japan.

The unique cross-country perspective of our study furthermore reveals that both models systematically generate very smooth inflation and have difficulties in countries where inflation persistence is relatively low compared to the US. A similar result is found with respect to cross-correlations which empirically differ from the US observations. The finding of a country-dependent model performance is a new insight as no previous study in the literature has compared sticky information and sticky prices in a cross-country perspective.

Our broad view on the inflation process reveals that sticky prices perform

[2]These features distinguish our work from most previous studies comparing Phillips curves empirically. For more details on previous comparisons of sticky prices and sticky information, see the literature overview at the end of this section.

rather well in matching unconditional moments of the inflation process, while being less successful with inflation reactions to changes in demand. For sticky information, we observe a trade-off in the empirical fit. Calibrations which are successful in generating empirical cross-correlations of inflation with supply and demand have a worse fit in unconditional moments and vice versa.

To sum up our results, the overall empirical performance allows no clear distinction between the two concepts. However, if one is predominantly interested in matching unconditional moments of inflation dynamics, sticky prices should be used. Researchers who focus on co-movements of inflation with demand may obtain better results applying sticky information. These results rely on our cross-country perspective since, in the US, model performances are almost identical.

A number of previous papers have compared sticky prices and sticky information empirically for one specific economy. In line with our results, evidence from the literature is also mixed and does not clearly favor one of the models.

In this literature, Mankiw and Reis (2002), Kiley (2007), and Korenok (2008) work with similar model approaches than we do, but these studies are different from ours in other respects. Mankiw and Reis (2002) consider impulse responses of inflation qualitatively. They conclude that sticky information matches the shape of observed impulse responses better than sticky prices. Our study evaluates the empirical performance quantitatively and also targets unconditional moments of inflation dynamics.

Similarly to the Mankiw-Reis model, Kiley (2007) works in models which consist of a Phillips curve and reduced-form equations for the rest of the economy. His evaluations are based on the predictive power of the different Phillips curves for inflation where expectations that enter the Phillips curves are obtained from a reduced-form system for marginal cost. By contrast, we approach the inflation process in a broader way also considering higher moments of inflation and use model-consistent rational expectations. In the results of Kiley (2007), the sticky-price model fits better than the sticky-information model.

A modeling strategy similar to ours is used by Korenok (2008) who determines the rational-expectations solution in a model which consists of a Phillips curve and an exogenous stochastic process for unit labor costs. His analysis differs from ours in the estimation method and the focus of the model evaluation. Korenok (2008) uses a Bayesian full information likelihood approach and estimates both sides of the model jointly whereas we apply a two-step procedure. The model evaluation of Korenok (2008) is based on a likelihood evaluation in a bivariate model with inflation and unit labor costs, while we also distinguish between the relations to demand and supply, respectively. The results of Korenok (2008) favor the sticky-price model.

Opposed to our closed-form expectations approach, Coibion (2010), Ciobîcă (2010), and Dupor, Kitamura, and Tsuruga (2010) perform single equation evaluations of the competing Phillips curves determining the expectation terms outside the model. Coibion (2010) estimates different Phillips curves with US data using instruments for the output gap and expectations determined from VARs or survey data, respectively. He performs two regression-based tests to compare the competing Phillips curves. In his results, the sticky-information Phillips curve is statistically dominated by the new Keynesian Phillips curve. Ciobîcă (2010) basically repeats the analysis of Coibion (2010) with Romanian data and comes to the same conclusion. Dupor et al. (2010) compare sticky prices and sticky information in a nested model and obtain predicted series of a real marginal cost measure and inflation from a VAR. They, too, find that sticky prices dominate sticky information empirically.

A third group of papers compare the different Phillips curves within complete DSGE models. Therein, expectations are rational but the choice of the Phillips curve affects the estimates for the other parts of the model. Andrés, López-Salido, and Nelson (2005) use a model without capital accumulation which, next to the Phillips curve, encompasses an IS relation and equations for money demand and money growth. They estimate the model using Maximum Likelihood for US data. In their estimation results, sticky information has the higher likelihood.

Korenok and Swanson (2007) use a calibrated DSGE model with different Phillips curves. They base their model evaluation on impulse response analyses and on evaluating the joint distribution of inflation and the output gap. They find that, for a standard level of stickiness, the sticky-information model performs better than the standard sticky-price model.

Abbott (2010) uses the same model as Korenok and Swanson (2007) and focuses on the reaction of inflation to monetary innovations. The results confirm the results of Korenok and Swanson (2007) and also support sticky information relative to the standard sticky-price model.

Paustian and Pytlarczyk (2006) consider sticky-price and sticky-information variants of the Smets and Wouters (2003) DSGE model which they estimate with Bayesian techniques for the Euro Area. Based on the posterior odds ratio, they conclude that the sticky-price model dominates the sticky-information model.

Laforte (2007) considers sticky-price and sticky-information pricing in a smaller DSGE model which he estimates with Bayesian techniques for US data. In his results, sticky information has the higher posterior odds than sticky prices.

Some studies also allow for lags of inflation in the Phillips curves. It can be summarized as a general result, that, when allowing for lags, a sticky-price Phillips curve with sufficiently many lags of inflation fits best (see e.g. Kiley 2007, Korenok and Swanson 2007, and Abbott 2010) although there is often no sticky-information Phillips curve with backward-looking parts included in the comparisons. Kiley (2007) and Dupor et al. (2010) also allow for combinations of sticky prices and sticky information which dominate the pure versions further confirming the impression that both concepts have empirical support.

The remainder of the essay is organized as follows. Section 4.2 presents models and our empirical strategy. The results of the analysis can be found in Section 4.3. Finally, Section 4.4 concludes.

4.2 Models and Empirical Strategy

4.2.1 Models

Phillips curves. We compare the concepts of sticky information and sticky prices which result in different Phillips curves. For the following empirical analysis, we use only the two Phillips curves and close the models identically in the simple way proposed by Mankiw and Reis (2002).

The sticky-price Phillips curve takes the form

$$\pi_t = \left[\frac{\alpha\lambda^2}{1-\lambda}\right] y_t + E_t\pi_{t+1}, \tag{4.1}$$

where π_t denotes inflation, y_t is the log output gap and E_t is the expectations operator based on the information set of period t.[3] The parameter α is a measure of real rigidities that measures the dependency of an individual firm's

[3]This particular form of the Phillips curve results from the sticky-price model used in

optimal price on the output gap. The parameter λ denotes the fraction of prices changed in every period and is a measure of nominal rigidity.

The sticky-information Phillips curve takes the form

$$\pi_t = \left[\frac{\alpha\lambda}{1-\lambda}\right] y_t + \lambda \sum_{j=0}^{\infty} (1-\lambda)^j E_{t-1-j} (\pi_t + \alpha \Delta y_t), \tag{4.2}$$

where Δ is the difference operator, i.e. $\Delta y_t = y_t - y_{t-1}$. Here, λ is a measure of price rigidity which measures the fraction of firms receiving new information in each period.

The main difference between the two Phillips curves (4.1) and (4.2) is the presence of different expectation terms. As equation (4.1) states, in the sticky-price model, inflation depends on current expectations of future inflation because this is the information used by firms that currently change prices. The sticky-information Phillips curve (4.2) contains all past expectations of current inflation reflecting that a fraction of firms change prices based on obsolete information of different age.

Closing the Models. A Phillips curve represents a relationship between two endogenous variables, inflation π_t and the log output gap y_t. In order to close the model, a second relationship between these two variables is needed. Assuming that natural output is equal to labor productivity, the log output gap y_t can be written as

$$y_t = m_t - p_t - a_t,$$

where m_t is log nominal income, p_t is the log price level, and a_t is the log labor productivity. We follow the empirical analysis of Mankiw and Reis (2002), Reis (2006b), and Mankiw and Reis (2011) and use their assumptions regarding m_t and a_t: we assume that these variables are exogenous to inflation and that they follow independent stochastic processes.

While Reis (2006b) finds that first-order auto-regressive processes are sufficient for quarterly US data, processes of higher order describe the growth rates of nominal income and productivity in other countries more adequately. We therefore allow the growth rates Δa_t and Δm_t to follow auto-regressive processes of up to order eight. Given such processes, we write Δm_t and Δa_t

Mankiw and Reis (2002). Similarly, the following sticky-information Phillips curve stems from the same paper.

as a moving average of past shocks,

$$\Delta a_t = \sum_{i=0}^{\infty} \omega_i \varepsilon_{t-i}^a \tag{4.3}$$

and

$$\Delta m_t = \sum_{i=0}^{\infty} \chi_i \varepsilon_{t-i}^m. \tag{4.4}$$

While assuming that productivity follows an exogenous stochastic process as in (4.3) is standard in the literature, assuming this also for nominal income is rather unusual. Mankiw and Reis (2011) justify this assumption by describing how monetary policy can ensure that nominal income follows such a process. Throughout the model, we will refer to Δm and Δa as changes in demand and supply, respectively.

Modeling the dynamics of nominal income and productivity in this way implies ignoring any structural relationships governing these dynamics. However, estimating (4.4) captures any structure in the data which does not include feedback from inflation to nominal income. Structural relations that are missed by the assumptions (4.3) and (4.4) are missed in both models equally. Furthermore, our modeling strategy ensures that the model can be estimated recursively and hence the choice of the Phillips curve does not influence estimates for other equations of the model. The Mankiw-Reis model seems sophisticated enough to capture inflation dynamics well. In our empirical analysis, we can reject equality between moments generated by the estimated models and empirical moments at 99% significance in only 2% of the cases.

Solving the Models. Both, the sticky-information model (SI) and the sticky-price model (SP), consist of a Phillips curve and the exogenous stochastic processes for nominal income and productivity growth described above. Shocks to Δm_t and Δa_t are thus the only driving forces for dynamics in the models. The solution for inflation is a moving average of past shocks to nominal income and productivity,

$$\pi_t = \sum_{i=0}^{\infty} \gamma_i^z \varepsilon_{t-i}^m + \sum_{i=0}^{\infty} \xi_i^z \varepsilon_{t-i}^a, \tag{4.5}$$

where $z = SI, SP$. We solve for the coefficients γ_i^{SI} and ξ_i^{SI}, or γ_i^{SP} and ξ_i^{SP} respectively, using the method of undetermined coefficients, see Appendix 4.A.

4.2.2 Empirical Strategy

Our first empirical analysis starts from the empirical exercise reported in Reis (2006b). He considers the Mankiw and Reis (2002) model with sticky information for the U.S., i.e. the model consists of equations (4.2), (4.3), and (4.4) where the parameters in (4.3) are such that the process is white noise and (4.4) is AR(1). He determines a sequence of model-predicted inflation rates by combining the estimated empirical innovations to nominal income and productivity with the MA coefficients of inflation (4.5) for a chosen parametrization $\alpha = 0.11$ and $\lambda = 0.25$. He calculates the second moments of this sequence and compares them to the empirically observed counterparts. His informal judgement about the accuracy of the model is based on the absolute differences between empirical and model moments.

The quantitative analysis of Reis is augmented in several respects in this essay. First, we consider five more countries, the UK, Germany, France, Canada, and Japan. Second, we also consider a sticky-price Phillips curve and compare the two concepts. We third extend the analysis methodologically by comparing not only absolute deviations between model moments and empirical observations but also evaluating the statistical properties of these differences. We generate a distribution of model moments by repeated simulation. Using this distribution, we perform a t-test of significant difference to the empirical moments for each model moment. Furthermore, we evaluate the likelihoods of the two models as the joint density of the empirical moments in the joint distribution of model moments. We determine the probability distribution of the empirical moments by a bootstrapping method.

In the empirical analysis, we simulate the model on a quarterly basis as described in the previous section but evaluate the dynamics of annual changes, i.e. we target the dynamics of $\Delta_4 p_t = p_t - p_{t-4}$.[4] The reason to use annual changes lies in potential measurement errors in quarterly seasonally adjusted data which are extenuated by considering annual changes. Using quarterly changes, second moments of inflation dynamics in some countries differ substantially from what is observed in the US. For annual changes, moments are much more similar across countries. For example, the autocorrelation of quarterly inflation in Japan is only one third of the US value, while the auto-

[4]Throughout the essay, we use Δ_4 as $1 - L^4$ where L is the lag operator.

correlation of annual inflation rates is almost the same in the two countries. Inflation persistence is an important moment for the identification of the models which systematically predict very smooth inflation. We therefore want to avoid measurement error in this important moment and use annual changes.

As Reis (2006b), we take a broad perspective on the inflation process. Our set of considered moments therefore includes unconditional moments of inflation dynamics (standard deviation and autocorrelation) as well as measures of the co-movements with supply and demand (cross-correlation with leads and lags of nominal income and labor productivity).

In order to relate our results to those of Reis (2006b), we use the same data and sample period in the case of the US. For comparability to Reis (2006b), we also start with a given benchmark parametrization, $\alpha = 0.11$ and $\lambda = 0.25$. Later on, we also estimate α and λ for each model and country using the method of simulated moments (Davidson and MacKinnon 2004, Chapter 7). We then repeat the comparison of the two models under the estimated parametrization. A detailed description of our empirical strategy can be found in Appendix 4.B. The appendix also contains the results of a Monte Carlo study in which we check the reliability of the estimation procedure.

In our analysis, we use quarterly data on nominal income, labor productivity, and consumer price indices. Most of our data stems from the OECD and the respective national statistical offices. Data sources and details are described in Appendix 4.C.

4.3 Results

Our empirical analysis starts with an estimation of the auto-regressive processes for nominal income and productivity growth for the six countries in our sample. In 7 of the 12 cases, higher-order processes are needed to describe the dynamics in productivity and nominal income growth in the various countries. The estimated auto-regressive processes are reported in Appendix 4.D.

4.3.1 Results under Baseline Calibration

Table 4.1 presents the results of the model comparison under the baseline parametrization. For each country and moment, the following information is reported in the table: the first line in each cell presents the two moments predicted by the sticky-information model (S.I.) and the sticky-price model

(S.P.) as well as the observed value from the data. The numbers reported in round brackets are the standard deviations of the respective model moments. The numbers in square brackets represent the p-values of a test of equality between the respective model moment and the empirical counterpart.

We evaluate the empirical performance of the models by different measures which can be found at the bottom of the table. The first measure is the number of moments which are closer to the empirical moment in absolute terms than the moment of the competing model. We then count the moments for which we can reject that they are equal to the empirical moment at the 5% level. The third measure of performance is the model's likelihood given the empirical moments, $\Pi_{x \in X} f(x)$. Since this joint density is in general a very small number, the table reports the common logarithm.

First, the results confirm our view that the Mankiw-Reis model is sufficiently sophisticated for our analysis. The models match most considered moments well with not more than two (out of 16) rejected moments per country in the US, Germany, France, and Japan. From the six rejected moments in Canada, only two are also rejected at the 1% significance level. Although the models are less successful in matching UK inflation dynamics, we regard the overall performances as sufficiently good to draw conclusions from these results. We now compare the two models' performances country by country.

For the US, absolute deviations between model and empirical moments are small. A similar results is also observed by Reis (2006b) who considers quarterly inflation and finds that, with the exception of the autocorrelation, predictions of the sticky-information model do not differ from the empirical counterpart by much. Focussing on annual inflation, we find that this result also holds for the autocorrelation of inflation. However, this finding is not unique to the sticky-information model, the sticky-price model performs similarly.

Considering only absolute differences does not exploit the statistical properties of the moments. For this reason, we also present standard deviations as well as p-values of a t-test of significant difference between the respective model moment and the empirical counterpart. The results confirm Reis' judgement that the sticky-information model fits the data remarkably well. No model moment is significantly different from the data moments at the 5% level. But models perform similarly again with no rejected moment also for sticky prices.

	United States			United Kingdom			Germany		
	S.I.	S.P.	data	S.I.	S.P.	data	S.I.	S.P.	data
S.D.$(\Delta_4 p_t)$	0.0228	0.0213	0.0235	0.0104	0.0080	0.0500	0.0316	0.0242	0.0158
	(0.0028)	(0.0023)	(0.0023)	(0.0025)	(0.0021)	(0.0063)	(0.0084)	(0.0069)	(0.0016)
	[0.8382]	[0.4880]		[0.0000]	[0.0000]		[0.0640]	[0.2345]	
Corr$(\Delta_4 p_t, \Delta_4 p_{t-1})$	0.9968	0.9959	0.9864	0.9838	0.9818	0.9738	0.9951	0.9943	0.9503
	(0.0042)	(0.0123)	(0.0436)	(0.0049)	(0.0101)	(0.0435)	(0.0057)	(0.0102)	(0.0507)
	[0.8122]	[0.8326]		[0.8199]	[0.8578]		[0.3792]	[0.3949]	
Corr$(\Delta_4 p_t, \Delta_4 m_t)$	0.5258	0.5647	0.5883	-0.1048	0.1420	-0.4391	0.6150	0.7249	0.4460
	(0.1454)	(0.1096)	(0.0719)	(0.1471)	(0.1167)	(0.1047)	(0.1948)	(0.1017)	(0.0867)
	[0.6999]	[0.8570]		[0.0641]	[0.0002]		[0.4281]	[0.0369]	
Corr$(\Delta_4 p_t, \Delta_4 m_{t-1})$	0.5633	0.6250	0.6167	0.0082	0.2761	-0.4012	0.6521	0.7406	0.5254
	(0.1324)	(0.0938)	(0.0673)	(0.1366)	(0.1000)	(0.0928)	(0.1730)	(0.0756)	(0.0807)
	[0.7191]	[0.9424]		[0.0132]	[0.0000]		[0.5070]	[0.0519]	
Corr$(\Delta_4 p_t, \Delta_4 m_{t+1})$	0.4960	0.5151	0.5523	-0.1993	-0.0036	-0.4416	0.5856	0.6939	0.3775
	(0.1557)	(0.1281)	(0.0721)	(0.1536)	(0.1337)	(0.0871)	(0.2095)	(0.1321)	(0.0800)
	[0.7428]	[0.8005]		[0.1699]	[0.0061]		[0.3532]	[0.0404]	
Corr$(\Delta_4 p_t, \Delta_4 a_t)$	-0.4026	-0.4721	-0.4310	-0.4784	-0.4379	-0.2325	-0.1777	-0.1840	-0.0059
	(0.1444)	(0.1339)	(0.1001)	(0.1387)	(0.1234)	(0.1302)	(0.1796)	(0.1777)	(0.1348)
	[0.8716]	[0.8059]		[0.1961]	[0.2523]		[0.4444]	[0.4248]	
Corr$(\Delta_4 p_t, \Delta_4 a_{t-1})$	-0.4162	-0.4675	-0.4312	-0.4981	-0.4075	-0.2462	-0.2376	-0.2237	-0.0060
	(0.1407)	(0.1261)	(0.0867)	(0.1325)	(0.1122)	(0.1026)	(0.1801)	(0.1771)	(0.1098)
	[0.9273]	[0.8126]		[0.1329]	[0.2888]		[0.2722]	[0.2959]	
Corr$(\Delta_4 p_t, \Delta_4 a_{t+1})$	-0.3890	-0.4627	-0.4176	-0.4427	-0.4644	-0.1851	-0.1492	-0.1723	-0.0549
	(0.1471)	(0.1414)	(0.0878)	(0.1434)	(0.1336)	(0.1035)	(0.1806)	(0.1796)	(0.1070)
	[0.8675]	[0.7863]		[0.1452]	[0.0984]		[0.6532]	[0.5742]	
moments closer to data	4	4		5	3		5	3	
moments rejected at 5%	0	0		2	4		0	2	
$\log_{10} \Pi_{x \in X} f(x)$	5.31	6.43		-52.80	-96.95		-9.86	-3.44	

Table 4.1: Second moments of inflation as predicted by models and in data

	France			Canada			Japan		
	S.I.	S.P.	data	S.I.	S.P.	data	S.I.	S.P.	data
S.D.($\Delta_4 p_t$)	0.1726	0.0344	0.0109	0.0139	0.0141	0.0138	0.0967	0.0233	0.0221
	(0.0104)	(0.0081)	(0.0056)	(0.0028)	(0.0031)	(0.0039)	(0.0239)	(0.0161)	(0.0088)
	[0.0000]	[0.0165]		[0.9945]	[0.9626]		[0.0034]	[0.9450]	
Corr($\Delta_4 p_t, \Delta_4 p_{t-1}$)	0.9999	0.9964	0.9253	0.9920	0.9942	0.8686	0.9983	0.9826	0.9592
	(0.0002)	(0.0062)	(0.0568)	(0.0123)	(0.0107)	(0.0657)	(0.0028)	(0.0090)	(0.0510)
	[0.1887]	[0.2130]		[0.0647]	[0.0590]		[0.4435]	[0.6506]	
Corr($\Delta_4 p_t, \Delta_4 m_t$)	0.6480	0.7904	0.4693	0.2403	0.1838	-0.4161	0.6556	0.6298	0.7598
	(0.3696)	(0.2608)	(0.0469)	(0.1785)	(0.1915)	(0.2329)	(0.3176)	(0.1791)	(0.0326)
	[0.6314]	[0.2257]		[0.0253]	[0.0467]		[0.7442]	[0.4754]	
Corr($\Delta_4 p_t, \Delta_4 m_{t-1}$)	0.6602	0.7975	0.4743	0.3392	0.2426	-0.3099	0.6640	0.6395	0.7806
	(0.3709)	(0.2405)	(0.0671)	(0.1776)	(0.1812)	(0.1725)	(0.3094)	(0.1454)	(0.0629)
	[0.6220]	[0.1957]		[0.0088]	[0.0272]		[0.7119]	[0.3731]	
Corr($\Delta_4 p_t, \Delta_4 m_{t+1}$)	0.6585	0.7669	0.4500	0.0962	0.0388	-0.5437	0.6375	0.5867	0.7382
	(0.3723)	(0.2766)	(0.0678)	(0.1784)	(0.1998)	(0.1707)	(0.3218)	(0.1986)	(0.0560)
	[0.5816]	[0.2657]		[0.0096]	[0.0267]		[0.7580]	[0.4631]	
Corr($\Delta_4 p_t, \Delta_4 a_t$)	0.3777	0.4747	0.2626	-0.1079	-0.1307	-0.3398	0.1321	0.0175	0.0903
	(0.2465)	(0.2294)	(0.1427)	(0.1929)	(0.1980)	(0.1686)	(0.1789)	(0.1595)	(0.2201)
	[0.6861]	[0.4323]		[0.3655]	[0.4215]		[0.8827]	[0.7888]	
Corr($\Delta_4 p_t, \Delta_4 a_{t-1}$)	0.3803	0.4812	0.2499	-0.0733	-0.1199	-0.3384	0.0976	0.0209	0.1708
	(0.2476)	(0.2329)	(0.1212)	(0.1924)	(0.1923)	(0.1281)	(0.1793)	(0.1683)	(0.1589)
	[0.6360]	[0.3783]		[0.2515]	[0.3443]		[0.7599]	[0.5173]	
Corr($\Delta_4 p_t, \Delta_4 a_{t+1}$)	0.4047	0.4530	0.2753	-0.1300	-0.1489	-0.3264	0.1341	0.0186	-0.0221
	(0.2475)	(0.2305)	(0.1179)	(0.1957)	(0.2050)	(0.1421)	(0.1786)	(0.1521)	(0.1695)
	[0.6371]	[0.4926]		[0.4167]	[0.4765]		[0.5257]	[0.8579]	
moments closer to data	6	2		2	6		5	3	
moments rejected at 5%	1	1		3	3		1	0	
$\log_{10} \Pi_{x \in X} f(x)$	-323.00	-27.43		-25.69	-31.28		-41.08	3.16	

Table 4.1 continued

Comparing the two competing models for the US, sticky prices perform slightly better than sticky information. The number of moments closer to the data is equal for both models and, in both models, no moment is rejected. Considering the models' likelihoods, sticky prices perform slightly better than sticky information.

For the UK, the sticky-information model performs better than the sticky-price model. The sticky-information model produces moments that are closer to the data in five out of eight cases. For sticky information, two moments are rejected at the 5% level and, for sticky prices, four moments are rejected. As a result of this disability to generate certain data moments, both joint densities are low with sticky information performing better.

For Germany, the results do not allow a clear discrimination between the models. A moments-based evaluation supports sticky information, while sticky prices dominate in a likelihood comparison. The sticky-information model produces five moments that are closer to the data. This finding is confirmed when considering the statistical properties of the moments. For sticky prices, two moments are significantly different from the data moments, while no moment is rejected for sticky information. However, the likelihood is higher for sticky prices than for sticky information in the case of Germany.

A similar picture arises for France. In a moments-based evaluation, sticky information is more successful than sticky prices. The absolute distance to the empirical moments is lower for sticky information in six out of eight cases. For both models, only one moment is rejected. A likelihood comparison, by contrast, supports sticky prices as the likelihood of the sticky-information model is effectively zero. This is driven by the standard deviation of inflation which is strongly rejected for the sticky-information model.

Also for Canada, moments-based evaluation and likelihood comparison show different results. Sticky prices match more moments closer in absolute terms but the number of rejected moments is equal. However, the likelihood is higher for sticky information.

Sticky prices are slightly better in the case of Japan. Sticky information matches more moments closer to the data but has one more rejected moment. Considering the likelihood of the models, sticky prices are supported by Japanese data.

Leaving the country-by-country comparisons of overall model performances, it is also interesting to elicit how the two models perform in situations where moments empirically differ substantially from the US benchmark. One of such moments is the Canadian autocorrelation which is considerably lower than in the other countries. Both models overpredict this moment substantially though equality to the empirical moment can only just not be rejected at 5% significance. Another interesting constellation is given by the negative cross-correlations of inflation to changes in demand in the UK and Canada. In the UK, sticky information can generate two out of three negative signs, while sticky prices are successful in one case. Neither model can generate a negative sign for Canada. Finally, models are more successful with respect to the unusual positive cross-correlations of inflation with changes in supply which are observed in France and Japan. Here, both models predict the signs correctly, while they are also successful in matching the negative relations to supply in the other countries.

All in all, our results do not allow a clear discrimination between the two models. In only one country, we find clear evidence in favor of one model. In the UK, sticky information dominates both in moment and likelihood-based comparisons. Considering the other five countries, evidence is mixed. In moments-based evaluations, sticky information performs better in Germany and France but worse in Canada. For the US and Japan, model performance is similar. In likelihood comparisons, sticky prices perform better in four countries (US, Germany, France, and Japan). The results also show that it is valuable to consider the inflation process broadly. While sticky information is less successful in matching unconditional moments of inflation dynamics (3 vs. 2 rejected moments), it performs better with respect to the inflation reactions to changes in demand (4 vs. 8 rejected moments). The latter finding is in line with Mankiw and Reis (2002) who demonstrated qualitatively that sticky information generates empirically superior inflation responses to demand shocks compared to the sticky-price alternative.

4.3.2 Estimation Results

This section presents the results from our estimation procedure of the Phillips curve parameters. We estimate the parameters α and λ by matching our two models to the observed second moments of inflation using the method of simulated moments. The results are summarized in Table 4.2. The table reports the point estimates for the parameters α and λ as well as their standard deviations (in brackets) for each country and model.

	SI		SP	
	α	λ	α	λ
US	0.2480	0.2604	0.2455	0.2558
	(0.0097)	(0.0070)	(1.8260)	(0.8151)
UK	0.1066	0.0890	0.0019	0.2526
	(0.0966)	(0.0714)	(0.0113)	(0.6056)
Germany	0.2785	0.0105	0.0305	0.2446
	(0.0831)	(0.0022)	(0.0907)	(0.3189)
France	18.2122	0.0325	0.2406	0.2377
	(19.9889)	(0.0355)	(0.9102)	(0.4041)
Canada	3.1487	0.0353	0.0689	0.2377
	(1.3804)	(0.0161)	(0.0447)	(0.0676)
Japan	6.5188	0.0261	0.0394	0.2251
	(1.9556)	(0.0083)	(0.1325)	(0.3388)

Table 4.2: Estimated values for α and λ from the method of simulated moments estimation

For the sticky-price model, our estimates for the parameter λ, measuring nominal rigidity, are close to those used in common calibrations ($\lambda \approx 0.25$, e.g. Mankiw and Reis 2002). Concerning real rigidities, measured by α, the estimated values differ substantially across countries. For sticky prices, our estimates lie somewhat above the values discussed in the literature, which range from 0.11 (Reis 2006b) to 0.17 (Chari et al. 2000), in two countries, the US and France.[5] The estimates for the other countries are lower.

For the sticky-information model, our results are different. Except for the US, informational rigidities, λ, are lower than those found in the literature (Khan and Zhu 2002, Carroll 2003, Döpke et al. 2008b). The estimated

[5]In the Mankiw and Reis (2002) version of the two Phillips curves we use, α is a combination of the mark-up power of monopolistic firms θ, the labor-supply elasticity of real wages ψ, and the income elasticity of real wages σ, $\alpha = \frac{\sigma+\psi}{1+\theta\psi}$. Chari, Kehoe, and McGrattan (2000) offer a quantification of these structural parameters which results in the stated value $\alpha = 0.17$.

real-rigidity parameter α lies very close to the baseline in the UK whereas our estimates are higher for the other five countries. For France, we find a very high point estimate for α which is associated with a very high standard deviation. The problem of an imprecisely estimated degree of real rigidity when both Phillips-curve parameters are estimated jointly is a known phenomenon in the literature (see Khan and Zhu 2002, Döpke et al. 2008b).

4.3.3 Results under Estimated Parametrization

We repeat the model comparison using the estimated parametrization. The results are presented in Table 4.3. The table is the counterpart to Table 4.1 and is arranged conformably. Note that the estimation is based on a moment distance such that the moment-based performance tends to improve as compared to the baseline parametrization (at 1% significance, only 2 of the 96 model moments can be rejected). However, we also observe trade-offs in the empirical performances of the models. In particular, sticky information becomes more successful in matching unconditional moments of inflation dynamics when using the estimated parametrization but at the costs of the fit to the empirical cross-correlations. In contrast to the moment-based evaluations, the models' likelihoods are non-targeted measures in the estimation.

The model predicted moments are very similar to those from the baseline parametrization in case of the US. As a consequence, all model evaluations show similar results as under the baseline parametrization. The two competing models perform almost identically.

For the UK, model moments change substantially when using the estimated parameters. Sticky information predicts the standard deviation of inflation substantially better than under the baseline. This however forces the model to perform worse with respect to other moments (the cross-correlation with changes in supply and demand) which results in six rejected moments at the 5% level. This is put into perspective when recognizing that only one of those moments is also rejected at the 1% level (see the reported p-values in the table). The sticky-price model gains with respect to the cross-correlations of inflation with demand and loses concerning other moments. All in all, sticky prices perform slightly better under the estimated parametrization.

	United States			United Kingdom			Germany		
	S.I.	S.P.	data	S.I.	S.P.	data	S.I.	S.P.	data
S.D.($\Delta_4 p_t$)	0.0240	0.0233	0.0235	0.0477	0.0106	0.0500	0.0188	0.0297	0.0158
	(0.0028)	(0.0025)	(0.0023)	(0.0029)	(0.0019)	(0.0063)	(0.0011)	(0.0075)	(0.0016)
	[0.8926]	[0.9480]		[0.7369]	[0.0000]		[0.1126]	[0.0703]	
Corr($\Delta_4 p_t, \Delta_4 p_{t-1}$)	0.9942	0.9937	0.9864	0.9997	0.9998	0.9738	0.9992	0.9986	0.9503
	(0.0070)	(0.0125)	(0.0436)	(0.0001)	(0.0003)	(0.0435)	(0.0002)	(0.0067)	(0.0507)
	[0.8587]	[0.8711]		[0.5514]	[0.5503]		[0.3349]	[0.3450]	
Corr($\Delta_4 p_t, \Delta_4 m_t$)	0.5566	0.6026	0.5883	0.0348	-0.0328	-0.4391	0.2826	0.6212	0.4460
	(0.1265)	(0.1038)	(0.0719)	(0.1638)	(0.1660)	(0.1047)	(0.2806)	(0.1829)	(0.0867)
	[0.8274]	[0.9099]		[0.0148]	[0.0384]		[0.5781]	[0.3869]	
Corr($\Delta_4 p_t, \Delta_4 m_{t-1}$)	0.6178	0.6726	0.6167	0.0309	-0.0355	-0.4012	0.2709	0.6307	0.5254
	(0.1051)	(0.0848)	(0.0673)	(0.1638)	(0.1649)	(0.0928)	(0.2826)	(0.1642)	(0.0807)
	[0.9929]	[0.6059]		[0.0217]	[0.0532]		[0.3863]	[0.5651]	
Corr($\Delta_4 p_t, \Delta_4 m_{t+1}$)	0.5100	0.5434	0.5523	0.0398	-0.0457	-0.4416	0.2693	0.5967	0.3775
	(0.1451)	(0.1255)	(0.0721)	(0.1646)	(0.1679)	(0.0871)	(0.2811)	(0.2005)	(0.0800)
	[0.7939]	[0.9507]		[0.0097]	[0.0363]		[0.7113]	[0.3098]	
Corr($\Delta_4 p_t, \Delta_4 a_t$)	-0.4752	-0.4973	-0.4310	0.2187	0.1578	-0.2325	0.2523	-0.1147	-0.0059
	(0.1391)	(0.1313)	(0.1001)	(0.1523)	(0.1512)	(0.1302)	(0.1829)	(0.1764)	(0.1348)
	[0.7967]	[0.6880]		[0.0243]	[0.0505]		[0.2558]	[0.6243]	
Corr($\Delta_4 p_t, \Delta_4 a_{t-1}$)	-0.4877	-0.4901	-0.4312	0.2138	0.1457	-0.2462	0.1599	-0.1611	-0.0060
	(0.1320)	(0.1222)	(0.0867)	(0.1525)	(0.1503)	(0.1026)	(0.1835)	(0.1774)	(0.1098)
	[0.7208]	[0.6943]		[0.0123]	[0.0313]		[0.4379]	[0.4571]	
Corr($\Delta_4 p_t, \Delta_4 a_{t+1}$)	-0.4525	-0.4886	-0.4176	0.2430	0.1687	-0.1851	0.2675	-0.1223	-0.0549
	(0.1445)	(0.1397)	(0.0878)	(0.1522)	(0.1521)	(0.1035)	(0.1840)	(0.1781)	(0.1070)
	[0.8365]	[0.6668]		[0.0200]	[0.0544]		[0.1298]	[0.7457]	
moments closer to data	4	4		2	6		3	5	
moments rejected at 5%	0	0		6	4		0	0	
$\log_{10} \Pi_{x \in X} f(x)$	6.42	6.59		-323.00	-323.00		-323.00	-7.27	

Table 4.3: Model comparison under estimated parametrization

	France			Canada			Japan		
	S.I.	S.P.	data	S.I.	S.P.	data	S.I.	S.P.	data
S.D.$(\Delta_4 p_t)$	0.0273	0.0288	0.0109	0.0215	0.0215	0.0138	0.0380	0.0337	0.0221
	(0.0075)	(0.0076)	(0.0056)	(0.0034)	(0.0034)	(0.0039)	(0.0170)	(0.0169)	(0.0088)
	[0.0773]	[0.0569]		[0.1397]	[0.1354]		[0.4072]	[0.5416]	
Corr$(\Delta_4 p_t, \Delta_4 p_{t-1})$	0.9941	0.9939	0.9253	0.9970	0.9986	0.8686	0.9689	0.9970	0.9592
	(0.0104)	(0.0083)	(0.0568)	(0.0040)	(0.0020)	(0.0657)	(0.0093)	(0.0071)	(0.0510)
	[0.2333]	[0.2319]		[0.0510]	[0.0477]		[0.8510]	[0.4625]	
Corr$(\Delta_4 p_t, \Delta_4 m_t)$	0.7924	0.8164	0.4693	0.0626	0.0036	-0.4161	0.5793	0.7704	0.7598
	(0.1965)	(0.2095)	(0.0469)	(0.2237)	(0.2187)	(0.2329)	(0.2246)	(0.2445)	(0.0326)
	[0.1096]	[0.1058]		[0.1383]	[0.1890]		[0.4266]	[0.9657]	
Corr$(\Delta_4 p_t, \Delta_4 m_{t-1})$	0.8366	0.8236	0.4743	0.0956	0.0218	-0.3099	0.6043	0.7773	0.7806
	(0.1714)	(0.1856)	(0.0671)	(0.2191)	(0.2149)	(0.1725)	(0.2042)	(0.2163)	(0.0629)
	[0.0491]	[0.0768]		[0.1460]	[0.2287]		[0.4093]	[0.9885]	
Corr$(\Delta_4 p_t, \Delta_4 m_{t+1})$	0.7506	0.7864	0.4500	-0.0620	-0.1118	-0.5437	0.5488	0.7435	0.7382
	(0.2183)	(0.2296)	(0.0678)	(0.2249)	(0.2215)	(0.1707)	(0.2346)	(0.2593)	(0.0560)
	[0.1884]	[0.1598]		[0.0880]	[0.1225]		[0.4323]	[0.9840]	
Corr$(\Delta_4 p_t, \Delta_4 a_t)$	0.3721	0.4658	0.2626	-0.0974	-0.1490	-0.3398	-0.2018	0.1982	0.0903
	(0.2272)	(0.2231)	(0.1427)	(0.2136)	(0.2145)	(0.1686)	(0.1654)	(0.1796)	(0.2201)
	[0.6830]	[0.4430]		[0.3731]	[0.4844]		[0.2888]	[0.7040]	
Corr$(\Delta_4 p_t, \Delta_4 a_{t-1})$	0.4192	0.4735	0.2499	-0.0932	-0.1564	-0.3384	-0.2415	0.1987	0.1708
	(0.2362)	(0.2284)	(0.1212)	(0.2117)	(0.2144)	(0.1281)	(0.1766)	(0.1863)	(0.1589)
	[0.5238]	[0.3870]		[0.3218]	[0.4661]		[0.0827]	[0.9090]	
Corr$(\Delta_4 p_t, \Delta_4 a_{t+1})$	0.3430	0.4329	0.2753	-0.1095	-0.1549	-0.3264	-0.1294	0.1762	-0.0221
	(0.2237)	(0.2231)	(0.1179)	(0.2164)	(0.2163)	(0.1421)	(0.1581)	(0.1733)	(0.1695)
	[0.7890]	[0.5323]		[0.4020]	[0.5074]		[0.6435]	[0.4133]	
moments closer to data	6	2		2	6		2	6	
moments rejected at 5%	1	0		0	1		0	0	
$\log_{10} \Pi_{x \in X} f(x)$	-7.66	-13.24		-219.82	-323.00		2.08	-1.76	

Table 4.3 continued

For Germany, no moment is rejected under the estimated parametrization. Sticky prices match more moments closer and the model has the higher likelihood.

Considering France, sticky information wins the horse race under the estimated parametrization. The sticky-information model performs considerably better than under the baseline calibration whereas the performance of sticky prices does not change much. Sticky information has the higher density and matches more moments more closely.

Concerning Canada, sticky information is not better than sticky prices. Using the estimated parameters, both models improve as less moments are rejected, but at the cost of lower overall likelihoods. Comparing the model performances, no clear evidence occurs.

Also, the results for Japan allow no clear discrimination between models. For both models, no moment is rejected but sticky price match six moments closer. By contrast, sticky information has the higher likelihood.

Also, under the estimated parametrization we want to draw special attention to the unusual moments which the models failed to generate under the baseline calibration (see Section 4.3.1). Also here, both models substantially overpredict the relatively low Canadian inflation persistence. This indicates that the two models systematically generate too much inflation smoothness. This result is in line with those of previous studies. In Coibion (2010), the poor performance of the sticky-information approach is partly driven by the fact that predicted inflation is excessively smooth. Also in the study of Paustian and Pytlarczyk (2006), the origin of the poor fit of sticky information is the inability of the model to match the autocorrelation of inflation. With respect to the negative correlations of inflation with movements in demand (UK and Canada), the sticky-price model is rather successful under the estimated parametrization. The model now predicts four of the six negative signs correctly while still generating all the positive signs in the other countries. In this respect, the sticky-information model performs even worse than under the baseline calibration, a consequence of the improved fit in the unconditional moments of inflation dynamics (see above).

All in all, the comparison of the estimated models shows weak support for one of the competing models in three countries. Sticky prices perform slightly better in the UK and Germany, while sticky information is supported by French data. Performances of the two models are very similar in the other three countries.

4.4 Conclusion

This essay has provided an empirical cross-country comparison of the sticky-price and sticky-information Phillips curves on the basis of second moments of inflation. The analysis contributed to the literature on the horse race between the two concepts methodologically in several respects. We compared the model performances both in moment-based and likelihood evaluations. In addition, we took a broad look on inflation dynamics considering inflation variance and persistence as well as its relation to dynamics in demand and supply. Finally, our cross-country perspective allowed to test whether model performances are country-specific.

We performed two comparisons of sticky prices and sticky information. In the first we compared calibrated versions of the two models, whereas we considered estimated models in the second comparison. Our results do not clearly support one of the two competing models. Relative model performances depend on the calibration, the country, and on which moments of the inflation process one focuses.

In the baseline calibration, the two models perform similarly in most countries. Only in the UK, sticky information is clearly supported. When comparing the estimated models, our results indicate that sticky information performs better in France, while sticky prices dominate in the UK and Germany and both models perform similarly in the US, Canada, and Japan.

The cross-country perspective of our essay revealed that both models' performances worsen where inflation dynamics deviate from US observations. Our broad view on the inflation process allowed disentangling the model performances. We find that sticky prices match unconditional moments of inflation dynamics better while sticky information is more successful in matching co-movements of inflation with demand.

Appendix

4.A Model Solution

We determine the model solution by a guess-and-verify approach. We guess that inflation is a moving average of past shocks, see equation (4.5).

4.A.1 Sticky Information

We start from the Sticky-information Phillips curve (4.2). In this appendix, we solve for the coefficients on Δm_t, the solution for the coefficients on Δa_t is equivalent except for the opposite sign. We solve for coefficients on Δm_t using the method of undetermined coefficients. First, we consider $\Delta a_{t+i} = 0 \; \forall i$. Our guessed solution for inflation (4.5) then simplifies to

$$\pi_t = \sum_{i=0}^{\infty} \gamma_i^{SI} \varepsilon_{t-i}^m. \tag{4.6}$$

Plugging the solution for inflation into (4.2) yields:

$$\sum_{i=0}^{\infty} \gamma_i^{SI} \varepsilon_{t-i}^m = \left[\frac{\alpha\lambda}{1-\lambda}\right] y_t + \lambda \sum_{j=0}^{\infty} (1-\lambda)^j \, E_{t-1-j} \left(\sum_{i=0}^{\infty} \gamma_i^{SI} \varepsilon_{t-i}^m + \alpha \Delta y_t \right)$$

Thus expressions for the log output gap and the log output gap growth are needed. Using the definition of the output gap, the MA representation of nominal income growth (4.4),

$$\Delta m_t = \sum_{i=0}^{\infty} \chi_i \varepsilon_{t-i}^m,$$

and the assumption of $\Delta a_{t+i} = a_{t+i} = 0 \; \forall i$ gives an expression for the log output gap growth:

$$\begin{aligned} \Delta y_t &= \Delta m_t - \Delta p_t \\ &= \sum_{i=0}^{\infty} \chi_i \varepsilon_{t-i}^m - \sum_{i=0}^{\infty} \gamma_i^{SI} \varepsilon_{t-i}^m \end{aligned} \tag{4.7}$$

The log output y_t can be described by using equation (4.7) as:

$$\begin{aligned} y_t &= \sum_{i=0}^{\infty} \chi_i \varepsilon_{t-i}^m - \sum_{i=0}^{\infty} \gamma_i^{SI} \varepsilon_{t-i}^m + y_{t-1} \\ &= \sum_{i=0}^{\infty} \chi_i \left[\sum_{k=0}^{\infty} \varepsilon_{t-k-i}^m \right] - \sum_{i=0}^{\infty} \gamma_i^{SI} \left[\sum_{k=0}^{\infty} \varepsilon_{t-k-i}^m \right] \end{aligned} \tag{4.8}$$

Substituting (4.7) and (4.8) into the Phillips curve (4.2):

$$
\begin{aligned}
\sum_{i=0}^{\infty} \gamma_i^{SI} \varepsilon_{t-i}^m = & \left[\frac{\alpha\lambda}{1-\lambda}\right] \left\{ \sum_{i=0}^{\infty} \chi_i \left[\sum_{k=0}^{\infty} \varepsilon_{t-k-i}^m\right] - \sum_{i=0}^{\infty} \gamma_i^{SI} \left[\sum_{k=0}^{\infty} \varepsilon_{t-k-i}^m\right]\right\} \\
& + \lambda \sum_{j=0}^{\infty} (1-\lambda)^j E_{t-1-j} \left\{ \sum_{i=0}^{\infty} \gamma_i^{SI} \varepsilon_{t-i}^m \right. \\
& \left. +\alpha \left[\sum_{i=0}^{\infty} \chi_i \varepsilon_{t-i}^m - \sum_{i=0}^{\infty} \gamma_i^{SI} \varepsilon_{t-i}^m\right]\right\} \qquad (4.9) \\
= & \left[\frac{\alpha\lambda}{1-\lambda}\right] \left\{ \sum_{i=0}^{\infty} \chi_i \left[\sum_{k=0}^{\infty} \varepsilon_{t-k-i}^m\right] - \sum_{i=0}^{\infty} \gamma_i^{SI} \left[\sum_{k=0}^{\infty} \varepsilon_{t-k-i}^m\right]\right\} \\
& + \lambda \sum_{j=0}^{\infty} (1-\lambda)^j \left\{ (1-\alpha) \sum_{i=j+1}^{\infty} \gamma_i^{SI} \varepsilon_{t-i}^m + \alpha \sum_{i=j+1}^{\infty} \chi_i \varepsilon_{t-i}^m \right\}
\end{aligned}
$$

Because (4.9) must hold for all possible realizations of ε_{t-j-k}^m, we can use $\varepsilon_t^m = 1$, $\varepsilon_{t-u}^m = 0 \ \forall u > 0$ to determine the coefficient γ_0^{SI}. Under this realization, equation (4.9) simplifies to:

$$
\begin{aligned}
\gamma_0^{SI} &= \left[\frac{\alpha\lambda}{1-\lambda}\right] \left\{ \chi_0 - \gamma_0^{SI} \right\} \\
&= \left[\frac{\alpha\lambda}{1-\lambda}\right] \left\{ 1 - \gamma_0^{SI} \right\} \\
\Leftrightarrow \gamma_0^{SI} &= \left[\frac{\alpha\lambda}{1-\lambda+\alpha\lambda}\right]
\end{aligned}
$$

For a general k, we use the realization $\varepsilon_{t-k}^m = 1$, $\varepsilon_{t-u}^m = 0 \ \forall u \neq k$ for which (4.9) becomes:

$$
\begin{aligned}
\gamma_k^{SI} &= \left[\frac{\alpha\lambda}{1-\lambda}\right] \left\{ \sum_{i=0}^{k} \chi_i - \sum_{i=0}^{k} \gamma_i^{SI} \right\} + \lambda \sum_{i=0}^{k-1} (1-\lambda)^j \left\{ (1-\alpha)\gamma_k^{SI} + \alpha\chi_k \right\} \\
&= \left[\frac{\alpha\lambda}{1-\lambda}\right] \left\{ \sum_{i=0}^{k} \chi_i - \sum_{i=0}^{k} \gamma_i^{SI} \right\} + \lambda \left\{ (1-\alpha)\gamma_k^{SI} + \alpha\chi_k \right\} \cdot \sum_{i=0}^{k-1} (1-\lambda)^i \\
\gamma_k^{SI} &= \alpha\lambda \left(1 - \lambda(1-\alpha) \sum_{i=0}^{k} (1-\lambda)^i \right)^{-1} \\
& \cdot \left[1 - \sum_{i=0}^{k-1} \gamma_i^{SI} + \sum_{i=1}^{k} \chi_i + \chi_k \sum_{i=1}^{k} (1-\lambda)^i \right]
\end{aligned}
$$

4.A.2 Sticky Prices

We start from the following representation of the Sticky-price Phillips curve (4.1),

$$p_t = \theta p_{t-1} + (1-\theta)^2 \sum_{i=0}^{\infty} \theta^i E_t \left(m_{t+i} - a_{t+i} \right), \tag{4.10}$$

which is equation (A13) from Mankiw and Reis (2002) extended with a non-constant log productivity a_t. In this appendix, we solve for the coefficients on innovations to nominal income, the solution for the coefficients on innovations to productivity is again equivalent except for the opposite sign.

We solve for coefficients on Δm_t using the method of undetermined coefficients. For convenience, we assume $\Delta a_{t+i} = 0 \ \forall i$. Our guessed solution for inflation (4.5) then simplifies to

$$\pi_t = \sum_{i=0}^{\infty} \gamma_i^{SP} \varepsilon_{t-i}^m. \tag{4.11}$$

We also use the MA representation of nominal income growth (4.4). Eliminating the difference operator by backward iteration yields

$$p_t = \sum_{j=0}^{\infty} \gamma_j^{SP} \sum_{k=0}^{\infty} \varepsilon_{t-j-k}^m \tag{4.12}$$

$$m_t = \sum_{j=0}^{\infty} \chi_j \sum_{k=0}^{\infty} \varepsilon_{t-j-k}^m \tag{4.13}$$

Plugging (4.12) and (4.13) into (4.10) gives

$$\sum_{j=0}^{\infty} \gamma_j^{SP} \sum_{k=0}^{\infty} \varepsilon_{t-j-k}^m = \theta \sum_{j=0}^{\infty} \gamma_j^{SP} \sum_{k=0}^{\infty} \varepsilon_{t-j-k-1}^m + (1-\theta)^2 \sum_{i=0}^{\infty} \theta^i E_t \sum_{j=0}^{\infty} \chi_j \sum_{k=0}^{\infty} \varepsilon_{t-j-k+i}^m$$

which can be simplified to

$$\begin{aligned} \sum_{j=0}^{\infty} \gamma_j^{SP} \sum_{k=0}^{\infty} \varepsilon_{t-j-k}^m =& \theta \sum_{j=0}^{\infty} \gamma_j^{SP} \sum_{k=0}^{\infty} \varepsilon_{t-j-k-1}^m \\ & + (1-\theta)^2 \sum_{i=0}^{\infty} \theta^i \sum_{j=0}^{\infty} \chi_j \sum_{k=\max(i-j,0)}^{\infty} \varepsilon_{t-j-k+i}^m. \end{aligned} \tag{4.14}$$

Using matching coefficients as described in the preceding section (use the realization $\varepsilon_t^m = 1$, $\varepsilon_{t-u}^m = 0\ \forall u > 0$ in (4.14)) yields for γ_0^{SP}:

$$\begin{aligned}
\gamma_0^{SP} &= 0 + (1-\theta)^2 \sum_{i=0}^{\infty} \theta^i \sum_{j=0}^{i} \chi_j = (1-\theta)^2 \sum_{i=0}^{\infty} \chi_i \sum_{j=i}^{\infty} \theta^j \\
&= (1-\theta)^2 \sum_{i=0}^{\infty} \chi_i \left\{ \sum_{j=0}^{\infty} \theta^j - \sum_{j=0}^{i-1} \theta^j \right\} = (1-\theta)^2 \sum_{i=0}^{\infty} \chi_i \left\{ \frac{1}{1-\theta} - \frac{\theta^i - 1}{\theta - 1} \right\} \\
&= (1-\theta)^2 \sum_{i=0}^{\infty} \chi_i \cdot \frac{-\theta^i}{\theta - 1} = (1-\theta) \sum_{i=0}^{\infty} \theta^i \chi_i.
\end{aligned}$$

and for γ_j^{SP} (using $\varepsilon_{t-j}^m = 1$, $\varepsilon_{t-u}^m = 0\ \forall u \neq j$ in (4.14))

$$\begin{aligned}
\sum_{j=0}^{v} \gamma_j^{SP} &= \theta \sum_{j=0}^{v-1} \gamma_j^{SP} + (1-\theta)^2 \sum_{i=0}^{\infty} \theta^i \sum_{j=0}^{v+i} \chi_j \\
\Leftrightarrow \gamma_v^{SP} + \sum_{j=0}^{v-1} \gamma_j^{SP} &= \theta \sum_{j=0}^{v-1} \gamma_j^{SP} + (1-\theta)^2 \sum_{i=0}^{\infty} \theta^i \sum_{j=0}^{v+i} \chi_j \\
\Leftrightarrow \gamma_v^{SP} &= (\theta - 1) \sum_{j=0}^{v-1} \gamma_j^{SP} + (1-\theta)^2 \sum_{i=0}^{\infty} \theta^i \sum_{j=0}^{v+i} \chi_j
\end{aligned} \tag{4.15}$$

The double sum $\sum_{i=0}^{\infty} \theta^i \sum_{j=0}^{v+i} \chi_j$ at the right hand side of (4.15) can be expressed as follows:

$$\begin{aligned}
\sum_{i=0}^{\infty} \theta^i \sum_{j=0}^{v+i} \chi_j &= \sum_{i=0}^{\infty} \chi_i \sum_{j=\max(0,i-v)}^{\infty} \theta^j \\
&= \sum_{i=0}^{\infty} \chi_i \left\{ \sum_{j=0}^{\infty} \theta^j - \sum_{j=0}^{i-v-1} \theta^j \right\} \\
&= \sum_{i=0}^{\infty} \chi_i \left\{ \frac{1}{1-\theta} - \max\left(\frac{\theta^{i-v} - 1}{\theta - 1}, 0 \right) \right\} \\
&= \frac{1}{1-\theta} \sum_{i=0}^{\infty} \chi_i - \sum_{i=v}^{\infty} \chi_i \left(\frac{\theta^{i-v} - 1}{\theta - 1} \right) \\
&= \frac{1}{1-\theta} \left[\sum_{i=0}^{\infty} \chi_i - \sum_{i=v}^{\infty} \chi_i \left(1 - \theta^{i-v}\right) \right] \\
&= \frac{1}{1-\theta} \left[\sum_{i=0}^{\infty} \chi_i - \sum_{i=v}^{\infty} \chi_i + \sum_{i=v}^{\infty} \chi_i \theta^{i-v} \right] \\
&= \frac{1}{1-\theta} \left[\sum_{i=0}^{v-1} \chi_i + \sum_{i=v}^{\infty} \chi_i \theta^{i-v} \right]
\end{aligned}$$

Using this, (4.15) becomes

$$\gamma_v^{SP} = (\theta - 1)\sum_{j=0}^{v-1}\gamma_j^{SP} - (\theta-1)\left[\sum_{i=0}^{v-1}\chi_i + \sum_{i=v}^{\infty}\chi_i\theta^{i-v}\right]$$
$$\Leftrightarrow \gamma_v^{SP} = (\theta - 1)\left\{\sum_{j=0}^{v-1}\gamma_j^{SP} - \sum_{i=0}^{v-1}\chi_i - \sum_{i=v}^{\infty}\chi_i\theta^{i-v}\right\}.$$

4.B Empirical Strategy: Formal Description

Model Comparison. In detail, our empirical procedure under a certain parametrization, α and λ, proceeds as follows: for each country c and model z, the analysis consists of a complete model parametrization and a repeated model simulation and proceeds as follows:

1. In the parametrization phase, we first estimate processes for nominal income growth and productivity growth from the data. In any country and for both time series, we start with estimating the parameters of an AR(4) process by OLS. If the coefficient on the last lag is not significantly different from zero, we drop that lag and re-estimate an auto-regressive process of order 3. We drop insignificant lags until we arrive at a process with a significant last lag (sequential t-testing).[6] Having found such an auto-regressive process, we invert it into its MA representation. We collect the values for the coefficients $\{\chi_i^c\}$ and $\{\omega_i^c\}$ and the innovation variances $\sigma_{m,c}^2$ and $\sigma_{a,c}^2$ governing the dynamics of nominal income growth and productivity growth for this country in $\Omega_c = \left\{\{\chi_i^c\}_{i=0}^{\infty}, \sigma_{m,c}^2, \{\omega_i^c\}_{i=0}^{\infty}, \sigma_{a,c}^2\right\}$. The model is now completely quantified, the parametrization is described by $\alpha_{c,z}, \lambda_{c,z}$, and Ω_c.[7]

2. Using the values for the coefficients $\{\chi_i^c\}$ and $\{\omega_i^c\}$ and the parameters α and λ_c, we calculate the coefficients $\{\gamma_i^{c,z}\}$ and $\{\xi_i^{c,z}\}$ in the MA representation of inflation (4.5).

3. Combining the sequence of residuals, derived from estimating (3) and (4) in step 1, with the MA coefficients from (4.5) derived in step 2,

[6] Concerning Canada and Japan, we use eight lags in the processes for Δa_t and Δm_t as we found that estimation precision on subsequent stages improves substantially.

[7] In the comparison of the calibrated models, $\alpha_{c,z} = 0.11$, $\lambda_{c,z} = 0.25\ \forall c, z$. In the comparison of the estimated models, $\alpha_{c,z}$ and $\lambda_{c,z}$ refer to the estimated parameters.

we calculate a sequence of quarterly inflation rates Δp_t predicted by model z for country c. We then calculate selected second moments of corresponding annual changes. Specifically, we calculate the following set of second moments X:

$$X = \left\{ \begin{array}{c} S.D.(\Delta_4 p_t), Corr(\Delta_4 p_t, \Delta_4 p_{t-1}), \\ Corr(\Delta_4 p_t, \Delta_4 m_t), Corr(\Delta_4 p_t, \Delta_4 m_{t-1}), Corr(\Delta_4 p_t, \Delta_4 m_{t+1}), \\ Corr(\Delta_4 p_t, \Delta_4 a_t), Corr(\Delta_4 p_t, \Delta_4 a_{t-1}), Corr(\Delta_4 p_t, \Delta_4 a_{t+1}) \end{array} \right\}$$

These moments can be compared to the empirical moments on the basis of absolute deviations. This, however, ignores the statistical properties of the moments and thus does not allow inference.

4. In order to evaluate the statistical properties of the model moments, we simulate the model 10,000 times. In each simulation, we draw sequences of innovations $\{\varepsilon_t^{m,c}\}$ and $\{\varepsilon_t^{a,c}\}$ from normal distributions with mean zero and variances $\sigma_{m,c}^2$ or $\sigma_{a,c}^2$ and feed them into the model. Combining the innovations $\{\varepsilon_t^{m,c}\}$ and $\{\varepsilon_t^{a,c}\}$ and the MA coefficients of inflation $\{\gamma_i^{c,z}\}$ and $\{\xi_i^{c,z}\}$, we generate a sequence of inflation rates $\{\pi_t^{c,z}\}$ as predicted by the respective model z given Ω_c.

   For each simulation, we calculate the standard deviation of inflation, its auto-correlation, and its cross-correlations to current values, leads, and lags of nominal income and productivity growth. We thus generate a distribution of model moments by simulation. The resulting distributions are well approximated by normal distributions. For each moment $x \in X$, we then estimate a density function $f_x^{c,z}(x|\alpha, \lambda_c, \Omega_c)$ from the 10,000 generated observations using Maximum Likelihood. We use the function $f_x^{c,z}(x|\alpha, \lambda_c, \Omega_c)$ to test for difference between empirical moment $x^{c,data}$ and model moment $x^{c,z}$. To determine the standard deviations of the empirical moments we use the method of moving blocks bootstrap (Efron and Tibshirani 1998, Chapter 8.6).

Estimation. For each country c and model z, we estimate the degrees of rigidity, α and λ, using the method of simulated moments described by Davidson and MacKinnon (2004, Chapter 9.6). Our vector of moments X is the same as used in the model evaluation. The function to be minimized is a weighted

	"true" value	Mean estimator	5% quantile	95% quantile
SI: α	0.1100	0.1669	0.0567	0.3317
SI: λ	0.2500	0.1756	0.0861	0.2934
SP: α	0.1100	0.0643	0.0210	0.1179
SP: λ	0.2500	0.2403	0.2157	0.2658

Table 4.4: Monte Carlo study, estimated α and λ for both models

average of the squared differences between empirical and model moments,

$$Q\left(\alpha, \lambda, X^{c,z}, X^{c}\right) = \frac{1}{n} \cdot \left[X^{c,z}\left(\alpha, \lambda, \Omega_c\right) - X^{c}\right]' \cdot W \cdot \left[X^{c,z}\left(\alpha, \lambda, \Omega_c\right) - X^{c}\right],$$

where n is the number of observations for each moment. The vector of mean model moments $X^{c,z}\left(\alpha, \lambda, \Omega_c\right)$ is determined as described in steps 2 and 3 above. X^c is the vector of empirical moments. The weighting matrix W is the covariance matrix of $X^{c,z}\left(\alpha, \lambda, \Omega_c\right) - X^c$ and is determined by bootstrapping from the innovations to nominal income and productivity using the method of moving blocks bootstrap (Efron and Tibshirani 1998, Chapter 8.6). The estimators $\alpha_{c,z}$ and $\lambda_{c,z}$ are the solution to $\min_{\alpha,\lambda} Q\left(\alpha, \lambda, X^{c,z}, X^{c}\right)$. We compare the models under the estimated parametrization repeating the described above using $\alpha_{c,z}$ and $\lambda_{c,z}$.

Monte Carlo Study. We check the reliability of the estimation procedure in a Monte Carlo study using 10,000 simulated data sets of length 80 (the length of our US data set). These data sets stem from simulations of the respective models under a pre-determined parametrization. The results (Table 4.4) of the Monte Carlo study confirm our confidence in the estimation procedure, no estimator is significantly biased.

4.C Data

For our empirical analysis, data on inflation, productivity, and nominal income is needed. We have quarterly data on these three variables for a sufficiently long period for the following six countries: the US, the UK, Germany, France, Canada, and Japan. However, the period for which we have complete data varies considerably between the different countries.

For inflation and nominal income, we use CPI inflation and nominal GDP per capita, respectively, for all countries. Concerning labor productivity which we use as a measure of natural output, our variable of choice is output per working person which we have for five countries. For reasons of data availability, we use productivity per working hour for Germany.

The longest sample is available for the US. For comparability with Reis (2006b), we use the same US sample. For Canada, the shortest sample in our data set, only data from the first quarter of 1981 is available for all three variables. All data is taken from the OECD, Datastream, and national statistical offices.[8] Table 4.5 provides sources and details on the data used.

Country	Nominal GDP	CPI	Productivity	Sample period
US	Bureau of Economic Analysis; Table 1.1.5. Gross Domestic Product [Billions of dollars]; Seasonally adjusted at annual rates	Bureau of Labor Statistics; Series Id: CUUR0000SA0; Not Seasonally Adjusted Area: U.S. city average Item: All items; Base Period: 1982-84=100	Bureau of Labor Statistics; Output per Person; Nonfarming Sector; 1992=100	1960 to 2003
UK	Office for National Statistics UK; ABMI; Gross Domestic Product; Chained volume measures; Seasonally adjusted; Constant 2003 prices	OECD; Index 2005=100	Office for National Statistics UK; A4YM; Output per Worker; Whole Economy SA; Index 2003=100; Seasonally adjusted	1959 to 2008
Germany	Bundesamt für Statistik; before 1990 West Germany; linear extrapolation of growth rate in 1990Q1	OECD; Index 2005=100	Bundesbank; Productivity per hour; Seasonally adjusted; Index 1995=100	1970 to 2008
France	INSEE National Institute of Statistics and Economic Studies	OECD; Index 2005=100	National Institute of Statistics and Economic Studies; GDP per employed person	1978 to 2008
Canada	Datastream	OECD; Index 2005=100	Cansim; Labour productivity; Total economy	1981 to 2008
Japan	DSI Data Service; Seasonally adjusted	OECD; Index 2005=100	Datastream; Labour productivity; Total economy	1970 to 2008

Table 4.5: Sample periods, data sources, and details

4.D Nominal Income and Productivity Processes

Table 4.6 reports the estimated auto-regressive processes for nominal income and productivity growth for the six countries in our sample. The order of the processes has been determined by sequential t-testing. In 5 of the 12 cases, it is sufficient to use not more than one lag to describe the dynamics in productivity

[8] In the first quarter of 1990, a linear extrapolation for nominal income growth is used for Germany in consideration of the re-unification.

and nominal income growth in the various countries. Growth in nominal income can be described as an AR(1) process for the United States. For the UK, nominal income growth seems to be i.i.d. For Germany, France, Canada and Japan, growth of nominal income is best described by auto-regressive processes of higher order. Productivity growth can be described as i.i.d. with positive mean for the US, the UK, and Germany. French, Canadian, and Japanese growth rates show some significant auto-regressive components.

nominal income growth						
	cons $\cdot\ 10^2$	$t-1$	$t-2$	$t-3$	$t-4$	$\sigma_m^2 \cdot 10^4$
US	1.0700 (0.1290)	0.3788 (0.0655)				0.8147
UK	0.6060 (0.0695)					0.9511
Germany	0.3154 (0.1573)	0.0371 (0.0775)	0.1489 (0.0760)	0.1373 (0.0759)	0.3667 (0.0747)	0.8875
France	0.1309 (0.0904)	0.4798 (0.0863)	0.3985 (0.0851)			0.2772
Canada	0.3257 (0.1112)	0.5301 (0.0966)	-0.0450 (0.1059)	0.3057 (0.1058)	-0.2561 (0.1097)	0.2933
Japan	0.0516 (0.1197)	0.1445 (0.0808)	0.2882 (0.0823)	0.2282 (0.0858)	0.1731 (0.0886)	1.0226
productivity growth						
	cons $\cdot 10^2$	$t-1$	$t-2$	$t-3$	$t-4$	$\sigma_a^2 \cdot 10^4$
US	0.5437 (0.0602)					0.7218
UK	0.4994 (0.0635)					0.7933
Germany	0.9054 (0.1017)					1.6026
France	0.2822 (0.0626)	-0.0258 (0.0913)	0.2329 (0.0885)			0.1834
Canada	0.2198 (0.0848)	0.1285 (0.0971)	-0.0762 (0.0967)	0.2828 (0.0953)	-0.0487 (0.0987)	0.2043
Japan	0.2129 (0.1580)	0.4923 (0.0955)	0.2305 (0.1061)	-0.0006 (0.1059)	-0.2848 (0.1042)	3.0287

Table 4.6: Estimated coefficients and shock variances for productivity and nominal income growth processes

Notes: For Canada and Japan, the coefficients on the lags 5 to 8 are: Canada, nominal income: 0.0196 (0.1091), 0.0144 (0.1056), 0.0626 (0.1040), -0.1057 (0.0906). Canada, productivity: 0.0191 (0.0993), 0.0851 (0.0963), -0.0284 (0.0931), -0.1208 (0.0909). Japan, nominal income: 0.0939 (0.0889), 0.0976 (0.0872), -0.0201 (0.0834), -0.1056 (0.0832). Japan, productivity: -0.2175 (0.1043), 0.2186 (0.1057), 0.1175 (0.1052), -0.3015 (0.0955).

Chapter 5

Rational Inattentiveness in the Lab: the Effect of Information Costs on Forecasting

5.1 Introduction

Mankiw and Reis (2002) proposed the sticky-information Phillips curve as an alternative to the standard sticky-price Phillips curve which has some undesirable implications (Ball 1994, Mankiw and Reis 2001). In sticky-information models subjects make choices in every period, but they do not update their information set before each choice. As a consequence subjects form their expectations partly on the basis of out-dated information. A microeconomic justification for this behavior is provided by rational-inattentiveness models (e.g. Sims 2003, Reis 2006a, Reis 2006b). This essay presents the first experimental test of rational-inattentiveness models.[1]

The basic idea in these models is that gathering and/or processing information is costly. These costs occur in reality by spending time finding information or by having mental effort doing calculations. The theory assumes that information is a normal good and that information costs can be monetized. Given information costs, it may be rational for agents not to use all available information in each period to form forecasts. Rational agents will update their information only if the benefit from an improved current and future forecast

[1] This essay is based on Goecke et al. (2011b).

exceeds the information costs.

The empirical evidence with respect to the validity of sticky-information models is mixed. Support for the sticky-information Phillips curve is reported in Mankiw and Reis (2007), Döpke et al. (2008a), and Dupor et al. (2010) while Korenok (2008), Carrillo (2010), Coibion (2010), and Korenok et al. (2010) find that the sticky-information models fit the data rather poorly. One problem that typically plagues these studies using aggregate data is that subjects' expectations are hard to measure and that their individual information sets are unobservable. Testing rational-inattentiveness models with micro data from the field is practically impossible as the costs and benefits of information cannot be measured.

We use a laboratory experiment to test the central implication of rational-inattentiveness models that subjects weigh the costs against the benefits of information acquisition and rationally ignore available information if the costs exceed the benefits. The lab experiment allows us to control the costs and benefits of information perfectly and enables us to conduct tests against a clear theoretical benchmark. In an individual choice experiment, subjects have to predict the realization of a simple stochastic process in several periods. In each period, subjects can choose between forecasting without new information (guessing) and buying information. Information that can be bought is perfect, meaning it provides the true value of the process in the current period.

We analyze whether subjects acquire information as predicted by the theoretical model. We choose the costs and benefits of new information such that expected payoffs are maximized by not buying information in every period. Our first test is to check whether subjects' average duration of inattentiveness equals the theoretically optimal one given values of information costs, benefits, process length, and the process itself. We then vary the costs of information holding the benefits constant in order to find out whether the chosen frequency of information updating depends on the cost parameter. By varying other parameters of the model, we check whether a myopic heuristic explains the information updating pattern better than the rational-inattentiveness model.

While there does not exist an experimental test of rational-inattentiveness models in the spirit of Reis (2006a, 2006b) in the literature, our essay is closely related to Rötheli (2001). Rötheli reports an experiment in which subjects can acquire costly information to uncover deterministic relationships between three variables and the outcome of two prospects. Like in our experiment, it is possible to determine the optimal amount of information to be acquired as a function of costs and benefits of information and the length of the experiment. In his experiment, the majority of subjects do not acquire information efficiently. Many subjects underestimate the value of information, especially for the revelation of the causal structures in the model. Other subjects detect the causal structure but fail to implement their insights in the cost-minimizing way. In contrast to our experiment, Rötheli (2001) does not answer the question of how subjects respond to changes in the relative costs of information.

Given the macroeconomic research question, our essay is also related to other experiments on macroeconomic topics (see Ricciuti 2008 and Duffy 2008 for surveys). Our essay is particularly related to experimental studies on the Phillips curve (Adam 2007, Pfajfar and Zakelj 2009).

Our results show clear evidence in favor of sticky-information and rational-inattentiveness models. Agents behave as if they are able to calculate the optimal length of inattention. They do not update information in every period and therefore they stick partly to old information. Thus, an adaptive forecast behavior emerges because without new information the current forecast is based on the previous one. In most treatments we cannot reject the null hypothesis that subjects update their information as predicted by the rational-inattentiveness models. Simple myopic behavior as used for example in models by Feldstein (1985) and Lovo and Polemarchakis (2010) is rarely a good description of subjects' behavior. Furthermore, the results indicate that the length of inattention increases with rising information costs as predicted by the theory. These results hold in the aggregate, i.e. they describe average behavior of all subjects pooled together. Pairwise comparisons between two treatments to test rational behavior and myopic behavior show mixed evidence but favors also the rationality approach in comparison to the myopic approach. Individual behavior is less rational, but deviations from rationality are not systematic.

The remainder of the essay is organized as follows. The theoretical background is described in Section 5.2. Section 5.3 presents the design and the hypotheses that are tested. The experimental procedure is described in Section 5.4. The results of the analysis can be found in Section 5.5. Finally, Section 5.6 concludes.

5.2 Theory

Rather than implementing a specific inattentiveness model from the theoretical literature, we designed a simple stylized model that captures the main idea of the rational-inattentiveness literature and allows us to derive the optimal information updating frequency easily. The essence of rational inattentiveness is that subjects weigh the benefits of new information against the costs of its acquisition. If the costs are higher than the expected benefits, they may rationally decide not to get the available information.

As our experiment is motivated by the macroeconomic literature about the Phillips curve, we chose a forecasting task to test inattentiveness. In the sticky-information Phillips curve models, subjects must form expectations about future prices and sometimes do so based on outdated information sets.

We model a situation where subjects forecast realizations p of a stochastic process. The stochastic process is a random walk in which the variation ε_t is drawn from a discrete uniform distribution:

$$p_t = p_{t-1} + \varepsilon_t \tag{5.1}$$

with $\varepsilon_t \in \{x_0, x_1, ..., x_n\}$ and $prob(x_i) = \frac{1}{n} \forall i$.

The initial value p_0 of the stochastic process is given. The initial value is 0 in every treatment. All possible realizations of the random walk over the whole forecast horizon were shown in a table that was part of the instructions. The corresponding probabilities q_{jt} of each realization j in each period t were also presented in the table. Therefore, forecasting the realizations of the stochastic process reduces to guessing one of the possible values. The best forecast in every period t is the realization in period t with the highest probability q_t^*. The probability of a correct forecast is one in periods in which information is bought. The more periods a participant does not update his information the more realizations of the random walk are possible and therefore all probabilities, including q_t^*, decrease. If ε_t is drawn from a set that is symmetric around zero, $\varepsilon_t = 0$ yields the highest probability at any point in time, therefore $E_{t-1}p_t = p_{t-1}$ is the best forecast in this case.

In each period t, subjects choose whether they would like to observe the current realization of the random variable p_t at fixed costs c or to guess the current realization. Observing the realization is equivalent to guessing correctly. In each period a correct guess generates a payoff of b, an incorrect guess generates a payoff of 0. Observing the realization generates a certain payoff $b - c$, while guessing results in an expected payoff $b \cdot q_t^*$. The certain payoff stays unchanged within a treatment but the expected payoffs decline in the number of periods until the next information update. This tradeoff between information costs and declining expected payoffs of guessing implies a deterministic optimal updating frequency.

Given a finite number of forecasting periods N, a risk neutral agent aiming to maximize expected payoffs will choose the updating frequency T:[2]

$$T^* = \arg\max\left(\Pi\left(T\right)\right) \tag{5.2}$$

with

$$E\left(\Pi\left(T\right)\right) = \left[\frac{N}{T}\right]\left((b-c) + b\sum_{t=1}^{T-1} q_t^*\right) + \Psi_{N \bmod T}. \tag{5.3}$$

The expected payoff contains the safe element $(b - c)$ which is earned whenever the subject buys information. The uncertain element $b\sum_{t=1}^{T-1} q_t^*$ results from guessing that value of p which has the highest probability q_t^* in period t in which no information is acquired. $T - 1$ is the length of inattentiveness between two updating periods resulting from the decision to update information every T periods. Within a finite number of N periods, not every updating frequency T is feasible without a remainder $(N \bmod T)$. In those remaining periods, $\Psi_{N \bmod T}$ delivers the maximal expected payoff.

A rational, payoff-maximizing agent will determine T^* by computing and comparing expected payoffs in equation (5.3) for different updating frequencies T. It is difficult to provide a closed-form general solution to the problem of finding the optimal T^* because of the complication that any given N is not divisible by all potential T. It is however clear that the optimal T^* exists and depends on the costs c, the length of the round N, and the number n of possible realizations of ε_t which determines q_t^*. For a given set of parameters, the expected payoff of every possible T can be computed thus revealing the optimal one.

Alternatively, agents may not behave in such a strict payoff-maximizing way, but might use some heuristics. A plausible heuristic might be myopic behavior by which agents do not take into account that updating information

[2]For details of the derivation see Appendix 5.A.

in the current period affects future expected values. Myopic subjects might perform a stepwise optimization rather than a complete one. Agents that only consider the current period make the decision whether to update in the current period or not but they do not take into account the periods after the current period. If they update, they receive the certain payoff $b - c$. If they do not update, they receive the expected payoff $q_1^* b$. Thus, agents who only consider the current period base their information updating decision on the comparison between $b - c$ and $q_1^* b$. If they consider the current and the first future period, they make the decision whether to update in the second period (the first future period) or not after no update in the first period. Once again, they do not take into account the periods after an information update in the second period. If they update in period two, they receive the certain payoff $b - c$ in the second period and the expected payoff from the first period $q_1^* b$. If they do not update in the second period, they receive the expected payoff from the first period $q_1^* b$ and the expected payoff from the second period $q_2^* b$. Doing the comparison, the expected payoffs from the first period cancel out. Thus, agents who consider the current period and the first future period base their information update decision on the comparison between $b - c$ and $q_2^* b$. Similar comparisons occur for agents who consider only the next three, four, five, and so forth periods. This leads to a simple decision rule: myopic subjects are inattentive for the next t period if the expected payoff in that period exceeds the net benefit of acquiring information:

$$q_t^* b > b - c \tag{5.4}$$

5.3 Design and Hypotheses

The main question of our experiment is whether subjects' behavior in the given forecasting task is best predicted by rational-inattentiveness behavior or by myopic behavior. We test the null hypothesis that subjects behave rationally inattentive. By varying the variables q_t^*, c, and N we generate different predictions of the updating frequency T that allow us to test our null hypothesis against the alternative.

To keep the forecasting task as simple as possible, we at first limit ε_t to two-realizations -1 and $+1$, with a commonly known initial value of $p_0 = 0$. The resulting probabilities for all possible realizations are summarized exemplarily for periods 0 to 4 in Table 5.1.[3] The probability of any given realization declines the further the respective period lies in the future.

The complexity of the random walk that has to be forecasted is our first treatment variable. To analyze how a higher number of possible realizations affects subjects' behavior, we implement a second stochastic process where $\varepsilon_t \in \{-2, -1, 0, +1, +2\}$. If subjects are rationally inattentive, they should update their information set more frequently in the treatment with the five-realizations process than in the treatment with the two-realizations random walk. This is due to the higher variance of the five-realizations process. The five-realizations process can reach more values in a given forecast horizon than the two-realizations random walk. If participants have a forecast horizon of two, meaning that they do not update for two periods in a row, the five-realizations process can have nine realizations in the second period and the two-realizations process can only have three realizations. Thus, the probabilities for a specific realization in the five-realizations random walk decrease more for a given forecast horizon in comparison to the two-realizations random walk. Participants should update more often the lower the probabilities and therefore the lower the expected payoff of guessing ceteris paribus. With this variation we determine the impact of q_t^* on the updating frequency. Table 5.2 presents the probabilities for realizations of the five-realizations random walk in the first four periods.[4]

		Values of p								
Period		**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**
0	Probability					1.000				
1					0.500	0	0.500			
2				0.250	0	0.500	0	0.250		
3			0.125	0	0.375	0	0.375	0	0.125	
4		0.063	0	0.250	0	0.375	0	0.250	0	0.063

Table 5.1: Probability distribution: two-realizations random walk

The payoff for correct predictions is fixed at $b = 30$. In order to analyze the impact of information costs, our second treatment variable is c. The costs

[3] The complete table, summarizing the probabilities for up to 20 periods, can be found in Appendix 5.B.

[4] Again, the complete table can be found in Appendix 5.B.

Period		Values of p -4	-3	-2	-1	0	1	2	3	4
0	Probability					1.000				
1				0.2	0.2	0.2	0.2	0.2		
2		0.04	0.08	0.12	0.16	0.2	0.16	0.12	0.08	0.04
3		0.048	0.08	0.12	0.14	0.152	0.14	0.12	0.08	0.048
4		0.056	0.083	0.109	0.13	0.136	0.13	0.109	0.083	0.056

Table 5.2: Probability distribution: five-realizations random walk

can be either lower than the payoff at $c = 20$ and $c = 26$, or higher than the payoff at $c = 35$. This last parameterization was chosen to analyze whether subjects comprehend the fact that buying information might create a loss in the current period but increases the expected payoffs in future periods.

Our third treatment variable is the number of forecasting periods N. We implement two process durations, $N = 12$ and $N = 20$. The calibration is such that the length of the process should hardly affect the updating frequency. These three treatment variables constitute a $2\times3\times2$ design that is summarized with the respective treatment numbers in Table 5.3.

Process=	$\mathbf{e}_t\in\{-\mathbf{1},\mathbf{1}\}$		$\boldsymbol{\eta}_t\in\{-\mathbf{2},-\mathbf{1},\mathbf{0},+\mathbf{1},+\mathbf{2}\}$	
N =	**12**	**20**	**12**	**20**
b = 30 **c = 20**	1	2	7	8
b = 30 **c = 26**	3	4	9	10
b = 30 **c = 35**	5	6	11	12

Table 5.3: Treatment numbers

Within the framework of these 12 treatments we test the hypothesis of rational-inattentiveness behavior:

Hypothesis 1: Subjects are rationally inattentive and choose the optimal length of inattentiveness.

With the parameterization in treatments 1-12, we can calculate the predicted updating frequencies and the resulting length of inattentiveness between information purchases resulting from our competing behavioral models. Equations (5.2) and (5.3) deliver the optimal updating frequencies that maximize the overall expected payoffs in each treatment. These optimal spans of inattentiveness are contained in the columns labeled "Rational" in Table 5.4 (page 117). To test hypothesis 1 we compare these theoretical predictions to the update frequencies observed in the experiment. This test includes variations in all three treatment variables.

Corollaries about the effect from variations in either q^*, c, or N on the length of inattention based on rational inattentiveness can be derived from hypothesis one. These corollaries can be interpreted as a check for internal consistency of the theory of rational inattentiveness. The theoretically predicted reactions of a rationally inattentive agent to changes in q^*, c, or N are presented in corollaries 1.a to 1.d.

With rational behavior, the length of inattention...

Corollary 1.a: ... does not decrease in c.

Corollary 1.b: ... will be lower or equal in the 5-realizations process than in the 2-realizations process.

Corollary 1.c: ... does not increase in N.

Corollary 1.d: ... is smaller than N.

We test Corollaries $1.a - 1.d$ by using pairwise comparisons between respective treatments and a regression approach.

Rejecting these hypotheses might be evidence in favor of heuristic behavior but it is not a sufficient test. Likewise to the rational behavior, the myopic heuristic delivers point predictions for our 12 treatments (equation (5.4)) as well as predicted reactions to changes in single treatment variables. The point predictions of the durations of inattentiveness for the myopic can be found in the corresponding columns of Table 5.4 (page 117). By using the point predictions of the myopic approach we test the hypothesis of myopic behavior:

Hypothesis 2: Subjects are myopic and decide to update their information according to equation (5.4).

A subject using the myopic heuristic will take into account the interval of possible realizations of p, as well as the payoff and the costs but will not alter his update frequency when the number of periods changes. Thus, corollaries about the effect from variations in either q^*, c, or N on the length of inattention in the case of myopic behavior can be derived from hypothesis two.

With myopic behavior, the length of inattention...

Corollary 2.a: ... does not decrease in c.

Corollary 2.b: ... will be lower or equal in the 5-realizations process than in the 2-realizations process.

Corollary 2.c: ... does not increase in N.

Corollary 2.d: ... is equal to N if $c > b$.

The corollaries $1.a - 1.c$ (rational inattentiveness) and $2.a - 2.c$ (myopic behavior) are identical. Only corollaries $1.d$ and $2.d$ are different.

5.4 Procedure

The experiment was computerized using z-Tree (Fischbacher 2007) and was conducted at the RUBex laboratory at the Ruhr-University Bochum in winter 2010. The 46 participants were students from economics and other fields of the Ruhr-University of Bochum.

Upon arrival in the lab, subjects were randomly seated at workstations separated by blinds. The instructions (see Appendix 5.C for details) contained complete lists of probabilities for the respective processes for up to 20 periods. Instructions were read aloud and subjects were encouraged to ask questions at any point of the experiment. A comprehension test was conducted to assure that all participants had understood how to use the probability tables and how to calculate probabilities after an information purchase (see Appendix 5.D for details). A calculator was provided via the software.

We implemented a within-subjects design with respect to changes in information costs and the number of periods. We decided to test the impact of the process between subjects. This enables us to test corollaries $1.a$, $1.c$, $1.d$, $2.a$, $2.c$, and $2.d$ within subjects but compare the impact of forecasting complexity between subjects. We decided against a test within subjects of the corollaries 1.b and 2.b as this would have increased the time in the lab to more than two hours. Furthermore, a change of processes (or several changes) could have confused participants and might have resulted in mistakes from using the wrong probability table. Each subject therefore completed either treatments 1-6 or treatments 7-12. We randomly ordered the treatments but kept the order constant in all sessions.

One of the six treatments was chosen randomly at the end of the experiment and participants were paid for the sum of their accumulated payoffs in that treatment. As the maximal payoff in a 12 period treatment is 360 and in a 20 period treatment is 600, we normalized the payoffs by dividing the payoff by the number of periods in that treatment. The conversion rate was 2.5 euros per normalized payoff point to get the profit of the participants measured in €.

As a frequency of information updates higher than predicted by theory might indicate risk aversion, a standard Holt and Laury (2002) risk aversion test was conducted at the end of the experiment and paid separately (see Appendix 5.E for details).[5]

One session lasted on average 80 minutes, the average payoff (including a 4 euros show up fee) was 24.83 euros, the maximal payoff was 47.8 euros, and the minimal payoff was 8 euros.

5.5 Results

We test the main hypotheses 1 and 2 described in Section 5.3 by comparing the theoretical predictions with the behavior observed in the experiment. Furthermore, we extend the analysis by testing the corollaries $1.a - 1.d$ and $2.a - 2.d$ by doing a pairwise comparison between specific treatments and a regression analysis. Figure 5.1 shows a participant's updating behavior in treatments seven until twelve. The x-axes show the number of periods in each treatment (12 or 20 depending on the process length). The y-axes indicate whether the participant bought information in the respective period or not. The value is one if the participant did not buy information and two if the participant up-

[5]The Holt and Laury test indicates that the majority of our participants are risk neutral or slightly risk averse. Risk neutrality has to be rejected for all subjects pooled together. We conclude that the low level of risk aversion in our sample is negligible because the results do not change significantly by taking into account the risk aversion. See Section 5.5 for details.

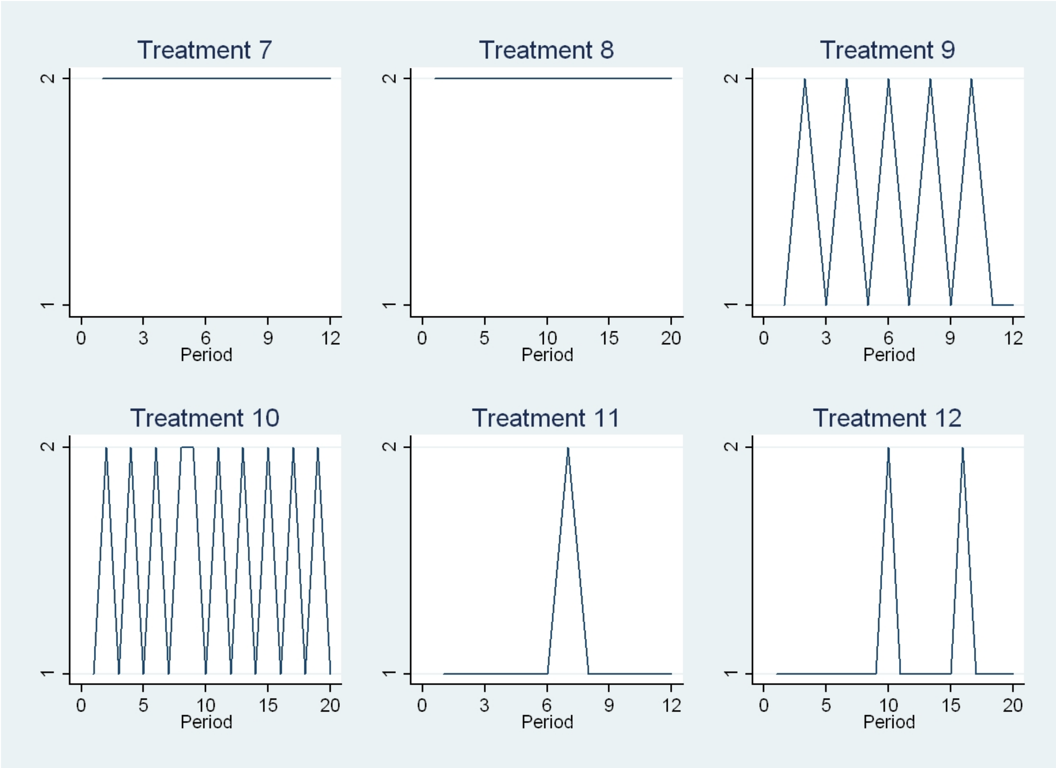

Figure 5.1: Updating behavior of an agent forecasting a five-realizations random walk

dated his information set by buying new information. Figure 5.1 demonstrates that the participant bought information in each period in treatment 7 and 8 (information costs: 20). In treatment 9 he bought five times information and he bought ten times information in treatment 10 (information costs: 26). In the treatments with the highest information costs (treatment 11 and 12) he bought twice and once information respectively (information costs: 36). We calculate the mean length of inattentiveness for each participant based on the number of periods in that the participant bought information and the length of the process. To test the hypotheses and corollaries described in Section 5.3 we aggregate the mean length of inattentiveness over all participants.

5.5.1 Point Estimator Analysis

Table 5.4 presents results for the test whether agents choose a length of inattentiveness that conforms to the rational-inattentiveness approach (test hypothesis 1) or the myopic approach (test hypothesis 2).[6] For this purpose, the differences between the length of inattentiveness predicted by the two approaches and the means of the length of inattentiveness chosen by the participants in the experiment are compared. Table 5.4 consists of two parts for the two random walks. The first rows (titled "Process") describe the possible realizations of the error of the random walk. The second rows (titled "N") present the length of the random walk. The columns "No." present the treatment numbers (as also shown in Table 5.3) and columns "Model" show the parametrization in the treatments. The value of the rational length of inattention is given in columns "Rational" and the value for myopic behavior in columns "Myopic". A 12 and 20 indicates no update at all. Columns "Results" show the aggregated mean values of the chosen length of inattentiveness in each treatment and the corresponding standard errors in parenthesis. To test hypothesis one, we compare the prediction from the rational-inattentiveness model ("Rational") with the inattention intervals observed in the lab ("Results") using t-tests. A star next to the theoretical values indicates that both numbers are statistically different from each other at a significance level of 5%. We cannot reject the null hypothesis that subjects update their information rationally in most treatments, with the exception of treatment seven, eight, and twelve.[7]

To test myopic behavior, we do the same exercise by comparing the values predicted by the myopic approach with the means from the experiment. A $\rfloor$ next to the theoretical value indicates that both numbers are statistically different at a 5% level. The results show that myopic behavior cannot be rejected only in treatment number two. Therefore, the results are only consistent with myopic behavior in one treatment. We cannot find myopic behavior as used for example in the model by Feldstein (1985) where the optimal level of social security is derived with agents that only optimize on the basis of the current period or the model used by Lovo and Polemarchakis (2010) where agents in a monetary model plan consumption only for the current period and a few periods in advance.

[6] Another alternative behavior could be that participants split the period in parts of the same length and use the resulting numbers as update frequency. We do not test this behavior because a high number of factors of the process length exists and therefore no clear results can be found.

[7] The results do not change significantly if only risk neutral agents are considered.

Process=	$e_t \in \{-1, 1\}$							
$N =$	12				20			
Model:	No.	Rational	Myopic	Results	No.	Rational	Myopic	Results
$b = 30$	1	2	$4^{\rfloor}$	2.53	2	2	4	4.26
$c = 20$				(0.32)				(1.28)
$b = 30$	3	4	$12^{\rfloor}$	2.92	4	2	$20^{\rfloor}$	4.08
$c = 26$				(0.72)				(1.24)
$b = 30$	5	6	$12^{\rfloor}$	5.85	6	6	$20^{\rfloor}$	8.09
$c = 35$				(0.97)				(1.68)
Process=	$\eta_t \in \{-2, -1, 0, +1, +2\}$							
$N =$	12				20			
Model:	No.	Rational	Myopic	Results	No.	Rational	Myopic	Results
$b = 30$	7	0^{*}	$0^{\rfloor}$	1.71	8	0^{*}	$0^{\rfloor}$	2.32
$c = 20$				(0.33)				(0.77)
$b = 30$	9	2	$4^{\rfloor}$	1.95	10	2	$4^{\rfloor}$	1.85
$c = 26$				(0.44)				(0.37)
$b = 30$	11	6	$12^{\rfloor}$	5.75	12	6^{*}	$20^{\rfloor}$	9.36
$c = 35$				(0.75)				(1.48)

A * indicates statistical difference between means and rational prediction at a significance level of 5%. A $\rfloor$ indicates statistical difference between means and myopic prediction at a significance level of 5%. Cells contain the numbering of the treatment, the predictions of the length of inattentiveness of the rational-inattentiveness and the myopic approach. Standard errors in parenthesis.

Table 5.4: Point estimator tests for rational-inattentiveness and myopic predictions

5.5.2 Pairwise Comparison Analysis

To test the corollaries $1.a - 1.d$ and $2.a - 2.$d we apply pairwise comparisons between two treatments. The results are presented in Table 5.5. The first column of Table 5.5 shows the number of the treatments that are compared to each other. The second column presents the means and the corresponding standard errors (in parenthesis) of the data observed in the experiment. The p-values of the t-tests of equal, lower, or higher means are presented in the third column. The fourth and fifth columns indicate whether rational and myopic behavior predict equal length of inattention between the two treatments (=), lower length of inattention $<$, or higher length of inattention $>$.

The results of the tests for corollaries $1.a$ and $2.a$ (different information costs) are presented in the first part of Table 5.5.[8] The corollary of the rational approach cannot be rejected by all comparisons. The comparison between treatment 3 vs. 5 and 4 vs. 6 show that the predictions of the myopic approach have to be rejected based on a significance level of 10%. Therefore we cannot reject corollary $1.a$ but we can reject corollary $2.a$.

The second part of Table 5.5 presents the results for a pairwise comparison between mean lengths of inattentiveness from treatments that differ only in the type of the process (corollaries $1.b$ and $2.b$). The results show that it is not possible to reject any prediction of both approaches using a significance level of 5%. Therefore corollaries $1.b$ and $2.b$ cannot be rejected.

The third part of Table 5.5 presents the results of a pairwise comparison between the mean lengths of inattentiveness from treatments that only differ in the process length (corollaries $1.c$ and $2.c$). With the exception of the comparison between treatment 11 and 12, no prediction of the two approaches can be rejected. The pairwise comparison indicates that a longer process does not tend to increase the time of inattentiveness. Therefore corollaries $1.c$ and $2.c$ can only be rejected based on one comparison.

The fourth part of the table presents results of a pairwise comparison between each treatment and the respective length of the process in that treatment and shows the results of the t-test whether the length of inattentiveness is smaller than the process length (corollary $1.d$). The results show that all

[8]Pairwise comparisons by considering only risk neutral agents are not possible because the samples in these case are to small.

means are smaller than the respective process length as predicted by the rational theory. Therefore corollary $1.d$ cannot be rejected.

The results of the tests for corollary $2.d$ (myopic behavior predicts that the length of inattention is equal to the length of the process if $c > b$) are presented in the last part of Table 5.5 and show that corollary $2.d$ can be rejected based on all comparisons.

All in all, the results of the pairwise comparisons favor the idea of rational-inattentiveness behavior in comparison to myopic behavior.

5.5.3 Regression Analysis

As a robustness check we test the corollaries $1.a - 1.c$ and $2.a - 2.c$ also by using a regression approach. We check the influence of information costs, the process type, and the process length on the length of inattention by running a Tobit regression. We use a Tobit regression because our depending variable, the mean length of inattention, is a censored variable. The mean length of inattention is bounded between zero and 20, meaning updating in every period and no update at all. We run the regression on the following equation:

$$I_k = \alpha_0 + \alpha_1 \Delta c_k + \alpha_X' X_k + \epsilon_k$$

The variable I_k is the mean of the length of inattention determined in the experiment. We have 276 observations (46 participants in 6 treatments) that are indicated by the index k. Δc is a dummy variable and presents information costs. The dummy is zero if the information costs are at their lowest level ($c = 20$), the dummy is one if the information costs are at their medium level ($c = 26$), and the dummy is two if the information costs are 35. All other variables are summarized in vector X_k. These variables are: the length of the process, the form of the stochastic process (five-realizations or two-realizations random walk), gender, age, duration of study, smoking behavior, and past participation in experiments. The error term is given by ϵ_k.

The results of the Tobit regression are presented in Table 5.6.[9] All estimators of the control variables that are not shown in the table are statistically not different from zero applying a significance level of 5%. The statistically

[9]The results do not change significantly if a measure derived from the Holt and Laury test is used for the level of risk aversion and integrated in the regression. The measure for risk aversion itself is statistically not different from zero.

Different information costs (1.a+2.a)				
Treatment	Means	p-value	Rational	Myopic
1 vs. 3	2.53 (0.32) vs. 2.92 (0.72)	0.6903	$<$	$<$
3 vs. 5	2.92 (0.72) vs. 5.85 (0.97)	0.9897 / 0.0206	$<$	$=$
1 vs. 5	2.53 (0.32) vs. 5.85 (0.97)	0.9982	$<$	$<$
2 vs. 4	4.26 (1.28) vs. 4.08 (1.24)	0.9213 / 0.4606	$=$	$<$
4 vs. 6	4.08 (1.24) vs. 8.09 (1.68)	0.9683 / 0.0634	$<$	$=$
2 vs. 6	4.26 (1.28) vs. 8.09 (1.68)	0.9609	$<$	$<$
7 vs. 9	1.71 (0.33) vs. 1.95 (0.44)	0.6689	$<$	$<$
9 vs. 11	1.95 (0.44) vs. 5.75 (0.75)	1.0000	$<$	$<$
7 vs. 11	1.71 (0.33) vs. 5.75 (0.75)	1.0000	$<$	$<$
8 vs. 10	2.32 (0.77) vs. 1.85 (0.37)	0.2910	$<$	$<$
10 vs. 12	1.85 (0.37) vs. 9.36 (1.48)	1.0000	$<$	$<$
8 vs. 12	2.32 (0.77) vs. 9.36 (1.48)	0.9999	$<$	$<$
Different process types (1.b+2.b)				
Treatment	Means	p-value	Rational	Myopic
1 vs. 7	2.53 (0.32) vs. 1.71 (0.33)	0.9592	$>$	$>$
2 vs. 8	4.26 (1.28) vs. 2.32 (0.77)	0.8985	$>$	$>$
3 vs. 9	2.92 (0.72) vs. 1.95 (0.44)	0.8723	$>$	$>$
4 vs. 10	4.08 (1.24) vs. 1.85 (0.37)	0.0983 / 0.9509	$=$	$>$
5 vs. 11	5.85 (0.97) vs. 5.75 (0.75)	0.9360	$=$	$=$
6 vs. 12	8.09 (1.68) vs. 9.36 (1.48)	0.5708	$=$	$=$
Different process length (1.c+2.c)				
Treatment	Means	p-value	Rational	Myopic
1 vs. 2	2.53 (0.32) vs. 4.26 (1.28)	0.2021	$=$	$=$
3 vs. 4	2.92 (0.72) vs. 4.08 (1.24)	0.2117 / 0.4235	$>$	$=$
5 vs. 6	5.85 (0.97) vs. 8.09 (1.68)	0.2577	$=$	$=$
7 vs. 8	1.71 (0.33) vs. 2.32 (0.77)	0.4688	$=$	$=$
9 vs. 10	1.95 (0.44) vs. 1.85 (0.37)	0.8590	$=$	$=$
11 vs. 12	5.75 (0.75) vs. 9.36 (1.48)	0.0358	$=$	$=$
Different to N (1.d)				
Treatment	Means and N	p-value	Rational	Myopic
1	2.53 (0.32) vs. 12	1.0000	$<$	
2	4.26 (1.28) vs. 20	1.0000	$<$	
3	2.92 (0.72) vs. 12	1.0000	$<$	
4	4.08 (1.24) vs. 20	1.0000	$<$	
5	5.85 (0.97) vs. 12	1.0000	$<$	
6	8.09 (1.68) vs. 20	1.0000	$<$	
7	1.71 (0.33) vs. 12	1.0000	$<$	
8	2.32 (0.77) vs. 20	1.0000	$<$	
9	1.95 (0.44) vs. 12	1.0000	$<$	
10	1.85 (0.37) vs. 20	1.0000	$<$	
11	5.75 (0.75) vs. 12	1.0000	$<$	
12	9.36 (1.48) vs. 20	1.0000	$<$	
Equal to N if $c > b$ (2.d)				
Treatment	Means and N	p-value	Rational	Myopic
5	5.85 (0.97) vs. 12	0.0000		$=$
6	8.09 (1.68) vs. 20	0.0000		$=$
11	5.75 (0.75) vs. 12	0.0000		$=$
12	9.36 (1.48) vs. 20	0.0000		$=$

Standard errors in parenthesis.

Table 5.5: Pairwise comparison to test corollaries

const	Δc	20 periods	5 realizations	female	smoker	Pseudo R^2	Obs.
-.16	2.64**	1.71**	-1.11	2.44**	.03	0.04	276
(0.75)	(0.37)	(0.61)	(0.62)	(0.62)	(1.25)		

** indicate statistical significance at the 1% level. Standard errors in parenthesis.

Table 5.6: Tobit regression, depending variable: mean length of inattention

positive estimated coefficient for information costs indicates that the length of inattention increases with higher information costs as predicted by the sticky-information and rational-inattentiveness theory (test corollaries 1.a and 2.a). An increase of information costs by one degree tends to increase the length of inattentiveness by 2.64 periods. Thus corollaries 1.a and 2.a cannot be rejected by the regression approach.

The Tobit regression indicates that the form of the process does not influence the length of inattentiveness. The regression analysis shows that a more complicated process, a five-realizations random walk in comparison to a two-realizations random walk, does not have a positive effect on the length of inattentiveness while controlling for other possible influences on an aggregate level. Corollaries 1.b and 2.b cannot be rejected by this approach.

The length of the process has a positive effect on the length of inattentiveness (test corollaries 1.c and 2.c). The length of inattentiveness tends to increase with a longer process. Therefore corollaries 1.c and 2.c have to be rejected based on the regression approach.

The regression approach partly rejects the corollaries of the rationality and myopic approach. No discrimination about what approach describes the behavior in a better way is possible.

5.5.4 Individual Behavior Analysis

So far the analysis has dealt with the data on an aggregated level over all treatments or between two treatments. This section presents results about rational forecast behavior on an individual level. The highest probabilities of a realization of the process, q_t^*, indicate the optimal predictions in the following periods after an information update.[10] If information was acquired in period t,

[10] The values of q_t^* and q_t can be found in the probability tables Table 5.1 and Table 5.2.

the value of p_t is known. The optimal forecast behavior for the two-realizations random walk is as follows. In the first period after an information update $t+1$ the optimal forecast is given by $p^e_{t+1} = p_t + e$ where $e \in \{-1, 1\}$. The optimal forecast for the second period after an information update is $p^e_{t+2} = p_t$. The optimal behavior is as described for all following periods until the next information update, separated into odd and even periods after an update. For the five-realization random walk, the optimal forecast for the first period after an information update is $p^e_{t+1} = p_t + \eta$ where $\eta \in \{-2, -1, 0, +1, +2\}$ if information was bought in period t. The optimal forecast is given by p_t, the know value from the last information update, in all following periods until the next information update.

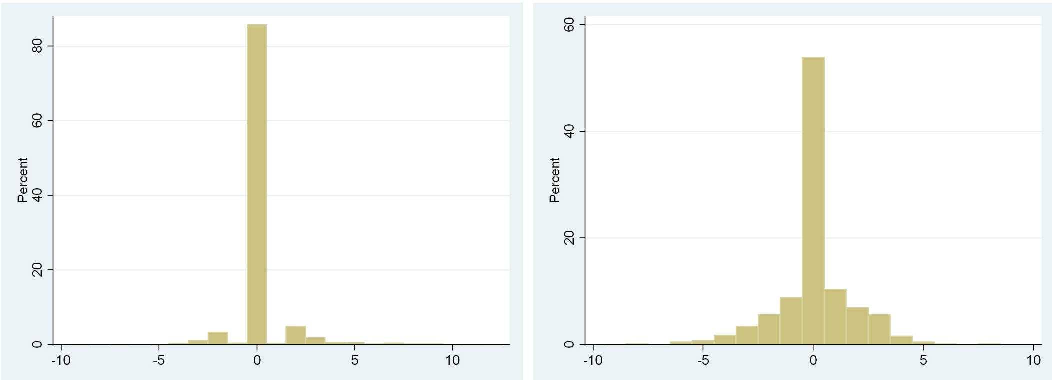

Figure 5.2: Deviation from optimal prediction: two and five-realization random walk

The left histogram in Figure 5.2 corresponds to the two-realizations random walk and the right histogram to the five-realizations random walk. The histograms present deviations from optimal prediction and indicate that the majority in both processes behaves in an optimal manner. But there are also deviations from the optimal predictions. How often the participants deviate from the optimal behavior is summarized in Table 5.7. The case that a participant bought information and made a forecast in the following period occurs in 519 cases in the two-realizations random walk. In these cases, the participants made an optimal forecast in 505 cases. All other numbers in the table has to be interpreted alike. The numbers indicate that deviation from the optimal prediction is present. Therefore, the behavior can be described on average as rational but not on an individual level.

Process:	Two realizations	Five realizations
First period: cases	519	554
First period: optimal behavior	505	545
Second period: cases	313	300
Second period: optimal behavior	157	86
Third period: cases	178	170
Third period: optimal behavior	131	45
Fourth period: cases	86	87
Fourth period: optimal behavior	42	28
Fifth period: cases	54	56
Fifth period: optimal behavior	35	10

Table 5.7: Optimal predictions after information update

5.6 Conclusion

We find clear evidence in favor of rational-inattentiveness models. By evaluating point estimators in most treatments we cannot reject the null hypothesis that subjects update their information rationally. The result of a Tobit regression also indicates that the length of inattention increases with rising information costs as predicted by the rational-inattentiveness theory. Simple myopic behavior is not a good description of subjects' behavior. These results hold in the aggregate, i.e. they describe average behavior of all subjects pooled together. Individual behavior is less rational, but deviations from rationality are not systematic.

Corollaries of the rational and myopic theory were tested with pairwise comparisons between specific treatments and a regression analysis. The results indicate mixed evidence but favor also the rationality approach in comparison to the myopic approach.

The overall results show clear evidence in favor of sticky-information and rational-inattentiveness models. On an aggregate level, agents behave rationally and seem to be able to calculate the optimal length of inattentiveness.

Appendix

Appendix 5.A presents the derivation of the maximization problem of a rationally inattentive participant. Appendix 5.B shows the probability tables, Appendix 5.C contains the instructions for the main experiment, Appendix 5.D shows the comprehension test and Appendix 5.E presents the instructions for the Holt and Laury (2002) test. All text passages shown to the participant are italicized.

5.A Derivations

This section presents the derivation of the maximization problem of the participants that is presented in equation (5.3). The participants receive a payment b if their forecast is correct, else 0. They can buy perfect information on the current value of p for a price c. The decision for the participants is to choose how long they want to stay inattentive. They decide that they want to update each T periods. If they choose $T = 1$ they buy information in every period and receive a profit of $b - c$ in each period. Each treatments contains of N periods and therefore the corresponding expected value for $T = 1$ is:

$$
\begin{aligned}
&\frac{N}{1} \cdot (b - c) \\
=&\frac{N}{T} \cdot (b - c)
\end{aligned}
$$

If participants decide to update every second period ($T = 2$). They receive $(q_1^* \cdot b)$ in expectation in periods 0, 2, 4, 6, and so forth and $b - c$ in periods 1, 3, 5, 7, and so forth. Without remaining periods ($N \bmod T = 0$), the expected value for $T = 2$ is:

$$
\begin{aligned}
&\frac{N}{2} (b - c) + \frac{N}{2} (q_1^* b) \\
=&\frac{N}{T} (b - c) + \frac{N}{T} (q_1^* b) \\
=&\frac{N}{T} ((b - c) + (q_1^* b))
\end{aligned}
$$

Without remaining periods the expected value for $T = 3$ is:

$$\begin{aligned}
&\frac{N}{3}(b-c)+\frac{N}{3}(q_1^* b)+\frac{N}{3}(q_2^* b)\\
=&\frac{N}{T}(b-c)+\frac{N}{T}(q_1^* b)+\frac{N}{T}(q_2^* b)\\
=&\frac{N}{T}((b-c)+(q_1^* b)+(q_2^* b))
\end{aligned}$$

Without remaining periods the expected value for $T = 4$ is:

$$\begin{aligned}
&\frac{N}{4}(b-c)+\frac{N}{4}(q_1^* b)+\frac{N}{4}(q_2^* b)+\frac{N}{4}(q_3^* b)\\
=&\frac{N}{T}(b-c)+\frac{N}{T}(q_1^* b)+\frac{N}{T}(q_2^* b)+\frac{N}{T}(q_3^* b)\\
=&\frac{N}{T}((b-c)+(q_1^* b)+(q_2^* b)+(q_3^* b))
\end{aligned}$$

Without remaining periods the expected value for $T = 5$ is:

$$\begin{aligned}
&\frac{N}{5}(b-c)+\frac{N}{5}(q_1^* b)+\frac{N}{5}(q_2^* b)+\frac{N}{5}(q_3^* b)+\frac{N}{5}(q_4^* b)\\
=&\frac{N}{T}(b-c)+\frac{N}{T}(q_1^* b)+\frac{N}{T}(q_2^* b)+\frac{N}{T}(q_3^* b)+\frac{N}{T}(q_4^* b)\\
=&\frac{N}{T}((b-c)+(q_1^* b)+(q_2^* b)+(q_3^* b)+(q_4^* b))
\end{aligned}$$

and similar for all other $T \leq N$. This can be summarized in the following equation:

$$E(\Pi(T)) = \left[\frac{N}{T}\right]\left((b-c)+b\sum_{t=1}^{T-1} q_t^*\right)$$

If there is a remainder ($N \bmod T \neq 0$), a profit maximizing agent chooses a combination of updating and guessing for the remaining periods that yields the maximal payoff. If there are for example four remaining periods until the end of the treatment, a profit maximizing behaving agent compares all possible combinations of guessing and updating: four periods guessing; one period guessing and three periods of information updating; two periods guessing and two periods of information updating; three periods guessing and one period of information updating; four periods of information updating. The combination with the highest expected payoff is chosen. The function $\Psi_{N \bmod T}$ delivers the highest payoff of the remaining periods. These can be summarized in the following equation that is the same as equation (5.3) presented in Section 5.2:

$$E(\Pi(T)) = \left[\frac{N}{T}\right]\left((b-c)+b\sum_{t=1}^{T-1} q_t^*\right) + \Psi_{N \bmod T}$$

5.B Probability Tables

Value Period	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	1.000															
1	0.000	0.500														
2	0.500	0.000	0.250													
3	0.000	0.375	0.000	0.125												
4	0.375	0.000	0.250	0.000	0.063											
5	0.000	0.313	0.000	0.156	0.000	0.031										
6	0.313	0.000	0.234	0.000	0.094	0.000	0.016									
7	0.000	0.273	0.000	0.164	0.000	0.055	0.000	0.008								
8	0.273	0.000	0.219	0.000	0.109	0.000	0.031	0.000	0.004							
9	0.000	0.246	0.000	0.164	0.000	0.070	0.000	0.018	0.000	0.002						
10	0.246	0.000	0.205	0.000	0.117	0.000	0.044	0.000	0.010	0.000	0.001					
11	0.000	0.226	0.000	0.161	0.000	0.081	0.000	0.027	0.000	0.005	0.000	0.000				
12	0.226	0.000	0.193	0.000	0.121	0.000	0.054	0.000	0.016	0.000	0.003	0.000	0.000			
13	0.000	0.209	0.000	0.157	0.000	0.087	0.000	0.035	0.000	0.010	0.000	0.002	0.000	0.000		
14	0.209	0.000	0.183	0.000	0.122	0.000	0.061	0.000	0.022	0.000	0.006	0.000	0.001	0.000	0.000	
15	0.000	0.196	0.000	0.153	0.000	0.092	0.000	0.042	0.000	0.014	0.000	0.003	0.000	0.000	0.000	0.000
16	0.196	0.000	0.175	0.000	0.122	0.000	0.067	0.000	0.028	0.000	0.009	0.000	0.002	0.000	0.000	0.000
17	0.000	0.185	0.000	0.148	0.000	0.094	0.000	0.047	0.000	0.018	0.000	0.005	0.000	0.001	0.000	0.000
18	0.185	0.000	0.167	0.000	0.121	0.000	0.071	0.000	0.033	0.000	0.012	0.000	0.003	0.000	0.001	0.000
19	0.000	0.176	0.000	0.144	0.000	0.096	0.000	0.052	0.000	0.022	0.000	0.007	0.000	0.002	0.000	0.000
20	0.176	0.000	0.160	0.000	0.120	0.000	0.074	0.000	0.037	0.000	0.015	0.000	0.005	0.000	0.001	0.000

Table 5.9: Probability table: two-realizations process (positive realizations)

Value	0	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10	-11	-12	-13	-14	-15
Period																
0	1.000															
1	0.000	0.500														
2	0.500	0.000	0.250													
3	0.000	0.375	0.000	0.125												
4	0.375	0.000	0.250	0.000	0.063											
5	0.000	0.313	0.000	0.156	0.000	0.031										
6	0.313	0.000	0.234	0.000	0.094	0.000	0.016									
7	0.000	0.273	0.000	0.164	0.000	0.055	0.000	0.008								
8	0.273	0.000	0.219	0.000	0.109	0.000	0.031	0.000	0.004							
9	0.000	0.246	0.000	0.164	0.000	0.070	0.000	0.018	0.000	0.002						
10	0.246	0.000	0.205	0.000	0.117	0.000	0.044	0.000	0.010	0.000	0.001					
11	0.000	0.226	0.000	0.161	0.000	0.081	0.000	0.027	0.000	0.005	0.000	0.000				
12	0.226	0.000	0.193	0.000	0.121	0.000	0.054	0.000	0.016	0.000	0.003	0.000	0.000			
13	0.000	0.209	0.000	0.157	0.000	0.087	0.000	0.035	0.000	0.010	0.000	0.002	0.000	0.000		
14	0.209	0.000	0.183	0.000	0.122	0.000	0.061	0.000	0.022	0.000	0.006	0.000	0.001	0.000	0.000	
15	0.000	0.196	0.000	0.153	0.000	0.092	0.000	0.042	0.000	0.014	0.000	0.003	0.000	0.000	0.000	0.000
16	0.196	0.000	0.175	0.000	0.122	0.000	0.067	0.000	0.028	0.000	0.009	0.000	0.002	0.000	0.000	0.000
17	0.000	0.185	0.000	0.148	0.000	0.094	0.000	0.047	0.000	0.018	0.000	0.005	0.000	0.001	0.000	0.000
18	0.185	0.000	0.167	0.000	0.121	0.000	0.071	0.000	0.033	0.000	0.012	0.000	0.003	0.000	0.001	0.000
19	0.000	0.176	0.000	0.144	0.000	0.096	0.000	0.052	0.000	0.022	0.000	0.007	0.000	0.002	0.000	0.000
20	0.176	0.000	0.160	0.000	0.120	0.000	0.074	0.000	0.037	0.000	0.015	0.000	0.005	0.000	0.001	0.000

Table 5.9: Probability table: two-realizations process (negative realizations)

Value Period	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
0	1.000															
1	0.200	0.200	0.200													
2	0.200	0.160	0.120	0.080	0.040											
3	0.152	0.144	0.120	0.080	0.048	0.024	0.008									
4	0.136	0.128	0.109	0.083	0.056	0.032	0.016	0.006	0.002							
5	0.122	0.117	0.102	0.082	0.059	0.039	0.022	0.011	0.005	0.002	0.000					
6	0.112	0.108	0.096	0.080	0.061	0.043	0.027	0.016	0.008	0.004	0.001	0.000	0.000			
7	0.104	0.101	0.091	0.078	0.061	0.045	0.031	0.019	0.011	0.006	0.003	0.001	0.000	0.000	0.000	
8	0.098	0.095	0.087	0.075	0.061	0.047	0.034	0.023	0.014	0.008	0.004	0.002	0.001	0.000	0.000	0.000
9	0.092	0.090	0.083	0.073	0.061	0.048	0.036	0.025	0.016	0.010	0.006	0.003	0.001	0.001	0.000	0.000
10	0.088	0.086	0.080	0.071	0.060	0.049	0.037	0.027	0.019	0.012	0.007	0.004	0.002	0.001	0.001	0.000
11	0.084	0.082	0.077	0.069	0.059	0.049	0.038	0.029	0.020	0.014	0.009	0.005	0.003	0.002	0.001	0.000
12	0.080	0.079	0.074	0.067	0.058	0.049	0.039	0.030	0.022	0.015	0.010	0.007	0.004	0.002	0.001	0.001
13	0.077	0.076	0.072	0.066	0.058	0.049	0.040	0.031	0.023	0.017	0.012	0.008	0.005	0.003	0.002	0.001
14	0.075	0.073	0.070	0.064	0.057	0.049	0.040	0.032	0.025	0.018	0.013	0.009	0.006	0.004	0.002	0.001
15	0.072	0.071	0.068	0.062	0.056	0.048	0.040	0.033	0.026	0.019	0.014	0.010	0.007	0.004	0.003	0.002
16	0.070	0.069	0.066	0.061	0.055	0.048	0.041	0.033	0.026	0.020	0.015	0.011	0.008	0.005	0.003	0.002
17	0.068	0.067	0.064	0.060	0.054	0.047	0.041	0.034	0.027	0.021	0.016	0.012	0.008	0.006	0.004	0.002
18	0.066	0.065	0.062	0.058	0.053	0.047	0.041	0.034	0.028	0.022	0.017	0.013	0.009	0.006	0.004	0.003
19	0.064	0.063	0.061	0.057	0.052	0.047	0.041	0.034	0.028	0.023	0.018	0.013	0.010	0.007	0.005	0.003
20	0.063	0.062	0.060	0.056	0.052	0.046	0.040	0.034	0.029	0.023	0.018	0.014	0.011	0.008	0.005	0.004

Table 5.10: Probability table: five-realizations process (positive realizations)

Value	0	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10	-11	-12	-13	-14	-15
Period																
0	1.000															
1	0.200	0.200	0.200													
2	0.200	0.160	0.120	0.080	0.040											
3	0.152	0.144	0.120	0.080	0.048	0.024	0.008									
4	0.136	0.128	0.109	0.083	0.056	0.032	0.016	0.006	0.002							
5	0.122	0.117	0.102	0.082	0.059	0.039	0.022	0.011	0.005	0.002	0.000					
6	0.112	0.108	0.096	0.080	0.061	0.043	0.027	0.016	0.008	0.004	0.001	0.000	0.000			
7	0.104	0.101	0.091	0.078	0.061	0.045	0.031	0.019	0.011	0.006	0.003	0.001	0.000	0.000	0.000	
8	0.098	0.095	0.087	0.075	0.061	0.047	0.034	0.023	0.014	0.008	0.004	0.002	0.001	0.000	0.000	0.000
9	0.092	0.090	0.083	0.073	0.061	0.048	0.036	0.025	0.016	0.010	0.006	0.003	0.001	0.001	0.000	0.000
10	0.088	0.086	0.080	0.071	0.060	0.049	0.037	0.027	0.019	0.012	0.007	0.004	0.002	0.001	0.001	0.000
11	0.084	0.082	0.077	0.069	0.059	0.049	0.038	0.029	0.020	0.014	0.009	0.005	0.003	0.002	0.001	0.000
12	0.080	0.079	0.074	0.067	0.058	0.049	0.039	0.030	0.022	0.015	0.010	0.007	0.004	0.002	0.001	0.001
13	0.077	0.076	0.072	0.066	0.058	0.049	0.040	0.031	0.023	0.017	0.012	0.008	0.005	0.003	0.002	0.001
14	0.075	0.073	0.070	0.064	0.057	0.049	0.040	0.032	0.025	0.018	0.013	0.009	0.006	0.004	0.002	0.001
15	0.072	0.071	0.068	0.062	0.056	0.048	0.040	0.033	0.026	0.019	0.014	0.010	0.007	0.004	0.003	0.002
16	0.070	0.069	0.066	0.061	0.055	0.048	0.041	0.033	0.026	0.020	0.015	0.011	0.008	0.005	0.003	0.002
17	0.068	0.067	0.064	0.060	0.054	0.047	0.041	0.034	0.027	0.021	0.016	0.012	0.008	0.006	0.004	0.002
18	0.066	0.065	0.062	0.058	0.053	0.047	0.041	0.034	0.028	0.022	0.017	0.013	0.009	0.006	0.004	0.003
19	0.064	0.063	0.061	0.057	0.052	0.047	0.041	0.034	0.028	0.023	0.018	0.013	0.010	0.007	0.005	0.003
20	0.063	0.062	0.060	0.056	0.052	0.046	0.040	0.034	0.029	0.023	0.018	0.014	0.011	0.008	0.005	0.004

Table 5.11: Probability table: five-realizations process (negative realizations)

5.C Instructions

Welcome to the experiment. Do not speak to any other participant from now onwards and use only features of the computer that are necessary for the experiment. The experiment is conducted to analyze decision behavior. You can win money in this experiment. Your profit depends only on your own decisions according to the rules described on the next pages. The data from the experiment are anonymous and cannot be connected to the participants. Neither the other participants nor the experiment conductors know your decisions or your profit during or after the experiment. This experiment consists of two independent sub experiments. At first, you receive the instruction for the first sub experiment. After the first sub experiment you will receive the instructions for the second sub experiment.

Sub Experiment 1

Task

In this experiment, you have to forecast a variable p which varies randomly. Your profit in € at the end of the experiment depends on how many correct forecasts you have done.

Procedure

This sub experiment consists of six independent treatments. Each treatment consists of a fixed number of periods. You have to forecast the value of the variable p in the current period. The number of periods can vary between the treatments and will be shown on the screen at the beginning of each treatment.

Random Process

Each treatment starts in period 0. The variable p starts with a value of 0 in period 0. The variable p follows a simple random process: the variable p can change between the previous period and the current one by:

- *rise by 1 (+1)*
- *fall by 1 (-1)*

Both events will arise with the same probability. Therefore, the potential events, +1 and -1, will arise with 50% probability. Changes of the variable are independent over periods, i.e. both changes have the same probability independent of the change in the previous period. For illustration purposes, you find a table with all possible realizations of variable p in the appendix. Please *consider the tables. Each row in a table represents a period. The columns show the value of p that can be achieved by the process during 20 periods. Each cell entry represents the probability of the respective value in the respective period.*

Example:

Please consider the following table:

Period		Values of p -4	-3	-2	-1	0	1	2	3	4
0	Probability					1.000				
1					0.500	0	0.500			
2				0.250	0	0.500	0	0.250		
3			0.125	0	0.375	0	0.375	0	0.125	
4		0.063	0	0.250	0	0.375	0	0.250	0	0.063

You can be certain that the value of the variable p in period 0 *is* 0*, i.e. the probability is* 1*. The variable will change from period 0 to period 1 by +1 or -1, both with the same probability of 50% (=0.5), likewise for the change between period 1 and period 2. The change of the variable is +1 or -1 between period 1 and period 2. Therefore, the values of p in period 2 can range between +2 and -2.*

The probability for a value +2 in period 2 is for example 25% (=0.25). This is due to the fact that a value of 2 in period 2 can only be achieved if the value of p was 1 in period 1 and rises by 1 between period 1 and period 2. Therefore the probability is $0.5 \cdot 0.5 = 0.25$*. The tables in the appendix present all probabilities for each possible value of the variable p in each period - thus you do not have to calculate the probabilities on your own.*

Forecast

You have to enter your forecast about the value of p in the current period into a box that you will see on the screen. Whether your forecasts were correct or not will be shown after all six treatments at the end of the experiment.

Information

You know that the variable p starts with a value of 0 at the beginning of each treatment. You can buy information about the current value of p in each period. This information costs you c points. The costs c can vary between the treatments but stay unchanged within a treatment. The costs of information will be shown on the screen. If you buy information, you know the current *value of p. Your forecast is automatically correct in this case and equal to the true value without the necessity to enter a value.*

Payoff

If your forecast of the value of p is correct, you will receive a payoff of b. The payoff b can vary between the treatments but stays unchanged within a treatment. The payoff will be shown on the screen. If your forecast of the value of p is wrong, you will receive a payoff of 0.

All payoffs in each period will be summed up in each treatment. The costs of buying information in all periods of a treatment will be subtracted from this sum. Please notice that you can also make losses in each treatment if the sum of costs of buying information is higher than the sum of payoffs.

Example:

Assume that a treatment consists of 10 periods, the payoff for a correct forecast in each period is $b = 5$ *and the costs of buying information is* $c = 1$. *You bought information three times and in addition to that you made three correct forecasts. Therefore you made six correct and four wrong forecasts out of 10 forecasts. Your payment in this treatment is therefore* $6 \cdot b + 4 \cdot 0 - 3 \cdot c = 6 \cdot 5 - 3 \cdot 1 = 27$.

Profit

You earn 4 euros for your participation. Your profit in € from this sub experiment depends on the payment of a randomly chosen treatment. You will be told how good your forecasts have been at the end of the first sub experiment. The payments from your forecasts in each treatment will be shown on the screen. One treatment will be chosen randomly to identify your profit. Your profit will be determined by the following equation:

$$\text{Profit} = \frac{\text{Benefit in a randomly chosen treatment}}{\text{Number of periods}} \cdot 2.5 \text{ euros}$$

Example:

Assume that the treatment from the last example is chosen to determine the profit. In this case, the payment is equal to 27 and the number of periods is 10. Your profit is therefore 6.75 euros.

Calculator

If you need a calculator, you can activate the windows calculator by using the calculator symbol in the left part of the screen.

Time

The time limit for each treatment is 5 minutes. The remaining time is shown in the upper part of the screen.

Trial

There will be a trial before the experiment starts. The trial consists of 10 periods and the time limit is 10 minutes. The trial has the same structure as the experiment, with the exception of the period length and the time limit. The results from the trial do not affect your profit at the end of the experiment.

The instructions for the participants that have to deal with the five-realizations process differ from the instructions already presented only in the section "Random process". But participants were shown the full instructions text. The altered section read as follows:

Random Process

Each treatment starts in period 0. The variable p starts with a value of 0 in period 0. The variable p follows a simple random process. The variable p can change between the previous period and the current one by:

- *rise by 2 (+2)*
- *rise by 1 (+1)*
- *stay the same (0)*
- *fall by 1 (-1)*
- *fall by 2 (-2)*

All these events will arise with the same probability. Therefore, all five possible events +2, +1, 0, -1, and -2 will arise with 20% probability. The changes of the variable are independent over periods, i.e. all changes have the same probability independent of the change in the previous period.

For illustrative purposes, you find a table with all possible realizations of variable p in the appendix. Please consider the table. Each row in the table represents a period. The columns show the value of p that can be achieved by the process during 20 periods. Each cell entry represents the probability of a specific value in the respective period.

Example

Please consider the following table:

Period		**Values of** p -4	-3	-2	-1	0	1	2	3	4
0	Probability					1.000				
1				0.2	0.2	0.2	0.2	0.2		
2		0.04	0.08	0.12	0.16	0.2	0.16	0.12	0.08	0.04
3		0.048	0.08	0.12	0.14	0.152	0.14	0.12	0.08	0.048
4		0.056	0.083	0.109	0.13	0.136	0.13	0.109	0.083	0.056

You know for sure that the value of the variable p in period 0 will be 0, i.e. the probability is 1.

The variable will change from period 0 to period 1 by +2, +1, 0, -1, or -2, all with the same probability of 20% (=0.2), likewise for the change between period 1 and period 2. The change of the variable is also +2,..., or -2 between period 1 and period 2. Therefore, the value of p in period 2 can range between +4 and -4.

The probability for a process value of +3 in period 2 is for example 8% (=0.08). This is due to the fact that a value of 3 in period 2 can only be achieved if the value of p was 1 or 2 in period 1 and rises by 2 or 1 between period 1 and period 2 respectively. Therefore the probability is $0.2 \cdot 0.2 + 0.2 \cdot 0.2 = 0.08$. *The tables in the appendix present all probabilities for each possible value of the variable p in each period - thus you do not have to calculate the probabilities on your own.*

5.D Comprehension Test

Please answer the following questions before the experiment starts. The questions will help you to understand the experiment. You are allowed to use the instructions. If you need a calculator, you can use the window calculator or your own calculator. Please raise your hand if you have any questions. The time limit is 10 minutes.

1. *What is the probability that* $p = 0$ *in period 3?*

    - *Probability:*____________________

2. *What is the probability that* $p = 4$ *in period 8?*
   - *Probability:*____________________
3. *What is the probability that* $p = -2$ *in period 10?*
   - *Probability:*____________________
4. *Assume that the length of the treatment is 16, in each period the payoff is* $b = 25$*, and the costs are* $c = 18$*. You bought information three times and you made three correct forecasts in addition. What is your payment? What is your profit?*
   - *Payment:*____________________
   - *Profit:*____________________
5. *Assume that you bought information in period 5. The current value was 2. What is the probability that the value of the process is -1 in period 7?*
   - *Probability:*____________________
6. *The payoff in each period is* $b = 30$ *and the costs* $c = 12$*. What is the expected payoff (probability* $\times$ *payoff) in period* 8 *if you never buy information and your forecast for period 8 is 0?*
   - *Expected payoff:*____________________
7. *A treatment consists of 16 periods, the payoff in each period is* $b = 30$ *and the costs are* $c = 12$*. What is the expected payoff in this treatment if you buy information in each period?*
   - *Expected profit:*____________________
8. *A treatment consists of 16 periods, the payoff in each period is* $b = 30$ *and the costs are* $c = 12$*. What is the expected payoff in this treatment if all forecasts are correct and you never bought information?*
   - *Expected profit:*____________________

5.E Holt and Laury Instructions

The first experiment is completed. The instructions for the second experiment are given below.

Sub experiment 2

Task

You have to choose ten times one lottery out of two lotteries X and Y in this second experiment. You can win two different amounts of money in each lottery.

The probabilities of each possible profit are different in every decision.

Example

Lottery X		I choose X	I choose Y	Lottery Y	
3/10, 2€	7/10, 1.6 €	□	□	3/10, 3.85 €	7/10, 0.10 €
…	…	□	□	…	…

Each lottery consists of two different events that will be realized with a given probability. A random draw determines which event is realized. Given the example above, the probability of winning 2 euros in lottery X is 3/10 and 7/10 for winning 1.6 euros. The probability of winning 3.85 euros in the lottery Y is 3/10 and 7/10 for winning 0.10 euros.

Your task is to choose one lottery in each of the ten lottery combination. When all choices are made, please confirm by clicking the "O.K." button.

All lottery combinations are shown in Table 5.12 (not presented in the instructions).

Lottery X		I choose X	I choose Y	Lottery Y	
1/10, 2€	9/10, 1.6 €	□	□	1/10, 3.85 €	9/10, 0.10 €
2/10, 2€	8/10, 1.6 €	□	□	2/10, 3.85 €	8/10, 0.10 €
3/10, 2€	7/10, 1.6 €	□	□	3/10, 3.85 €	7/10, 0.10 €
4/10, 2€	6/10, 1.6 €	□	□	4/10, 3.85 €	6/10, 0.10 €
5/10, 2€	5/10, 1.6 €	□	□	5/10, 3.85 €	5/10, 0.10 €
6/10, 2€	4/10, 1.6 €	□	□	6/10, 3.85 €	4/10, 0.10 €
7/10, 2€	3/10, 1.6 €	□	□	7/10, 3.85 €	3/10, 0.10 €
8/10, 2€	2/10, 1.6 €	□	□	8/10, 3.85 €	2/10, 0.10 €
9/10, 2€	1/10, 1.6 €	□	□	9/10, 3.85 €	1/10, 0.10 €
10/10, 2€	0/10, 1.6 €	□	□	10/10, 3.85 €	0/10, 0.10 €

Table 5.12: Holt and Laury paired lottery-choices

Benefit

One out of the ten lottery combinations will be chosen at the end of the experiment with probability 1/10. The lottery you have chosen (X oder Y) is played given the chosen lottery combination. Your profit in € is calculated by the randomly determined output of the chosen lottery.

End

Your total profit from both sub experiments will be shown on the screen. You will be asked individually to receive your profit after you have completed a short questionnaire. We ask you to bring the small card with your number and the filled receipt with you. The outpayment will be done privately and anonymously.

You get an additional profit between 0 and 1 euro to ensure that your name cannot be linked to the data from the experiment. The additional profit is determined randomly and will be added to your total profit.

Chapter 6

Endogenous Information Acquisition in a Real-Effort Experiment

6.1 Introduction

Recently, rational-expectations models that build on the assumption of fully informed agents have been challenged by models which are based on the idea that agents do not collect and/or process all available information (e.g. rational-inattentiveness models). These two types of models are based on different assumptions concerning information costs. Information acquisition is assumed to be costless in rational-expectations models but it is considered as costly in rational-inattentiveness models. This essay provides an empirical test of these two assumptions about information costs by using data generated in an experiment.[1]

The basic idea of rational-inattentiveness (e.g. Sims 2003, Reis 2006a, Reis 2006b) and sticky-information models (e.g. Mankiw and Reis 2002) is that gathering and/or processing information is costly. To motivate these costs it is argued that they occur in reality as time spent finding information or as mental effort spent on e.g. calculations. Given the existence of information costs, it may be rational for agents not to use all available information at any point in time. Agents will update their information as long as the benefit of informa-

[1]This essay is based on Goecke et al. (2011a).

tion exceeds the information costs. By contrast, rational-expectations models assume that there are no costs of collecting and/or processing information. As a consequence every individual uses all available information at every point in time in these models. The hypothesis of costless information is an important building block of rational-expectations models and distinguishes them from rational-inattentiveness models. This essay tests these two hypotheses about information costs with data that is generated in an experimental real-effort environment.

The lab experiment enables us to control the benefit of information which allows us to analyze directly the existence of information costs. In an individual choice experiment, subjects have to perform a forecast about a number fixed by the experimenter in advance. Subjects can gain information in a real-effort experiment about the number to be forecasted via a task. For each correct solution of the task, the range of possible numbers shrinks by a certain amount. This amount of reduction, together with the payoff function which decreases in the forecast error, allows to calculate the expected benefit of each piece of information. In each period, subjects decide whether to forecast the number fixed by the experimenter based on the already known information or to collect more information about the fixed number. The experiment is finished when the participant made a forecast in all treatments. So that solving the task is equivalent with forgone leisure. In contrast to the expected benefit of information, information costs are not directly observable. We test whether information costs exist or not.

The task in the real-effort experiment consists of simple mathematical problems. The solution of the mathematical problems captures the processing of information. Information is provided if the mathematical problems are solved. We test whether the effort of solving the mathematical problems describe costs to the participants. Given the existence of costs, participants should economize on solving mathematical problems.

We analyze whether subjects acquire all information given different tasks and different benefits of information. If subjects economize on solving the simple addition problems, we conclude that they view this task as a cost. In addition, we test how the time spent to solve the task influences the number of calculations. We interpret the time spent on one calculation as a proxy for the individual information cost.

Our results show clear evidence for the existence of information costs and therefore support rational-inattentiveness models. Processing of information seems to induce costs for the participants and therefore they do not collect all available information. By considering all treatments, subjects do not collect all available information in 54% of all calculations. Furthermore, information processing diminishes with rising information costs, measured as the individual time that is needed to solve an addition problem. A participant who needs 10 seconds more for one block of calculation in a treatment, tends to do 0.6 rounds less of calculation.

Our methodological approach is closest to Abeler et al. (2011). These authors use a task in a real-effort experiment to contribute to the theory of reference-dependent preferences. The participants in their experiment are faced with a table with 150 randomly ordered zeros and ones and the task is to count the number of zeros. If the number of zeros is correct, the participants receive a payoff that will be realized with 50 percent probability at the end of the experiment. The participants are free to choose how many tables they want to solve. The only limitation is a total time limit of 60 minutes. As in our experiment, the end of the experiment is determined by the decision of the participants about how long they want to work. The subjects, in their and our experiment, arrived one at a time to avoid peer effects or a desire to conformity. Another similarity between their and our experimental design is that the task is chosen to be easy enough such that everybody is in general able to solve the task. Thus, disability can plausibly be ruled out as a reason for not solving the task. Our approach and the one of Abeler et al. (2011) are very close to one another methodologically but the approaches are used to address different research questions.

A number of previous papers have analyzed information costs in an experimental environment. Huber et al. (2011) analyze the influence of endogenously chosen information in an asset market but the information costs are monetarized and do not depend on a task in a real-effort experiment. Gabaix et al. (2006) test the directed cognition model with experimental data but their information costs are either monetarized or based on time restrictions. In the experiment of Kraemer et al. (2006), participants have to forecast which state will be realized and they can buy information about the future state but the costs of information are again monetarized. Chapter 5 of this thesis analyzes the effect of information costs on forecasting behavior whereas information costs are monetarized. Thus, these studies impose information costs on subjects and study subjects' reactions given information costs. By contrast, this essay does not impose information costs directly but analyzes whether processing information is indeed perceived as a cost by subjects.

The remainder of the essay is organized as follows. The theoretical background and the hypotheses are described in Section 6.2. Section 6.3 presents the design of the experiment. The experimental procedure is described in Section 6.4. The results of the analysis can be found in Section 6.5. Finally, Section 6.6 concludes.

6.2 Theory and Hypotheses

Rational-inattentiveness models are based on the assumption that information is costly. The idea is that gathering and/or processing information produces costs. To motivate these costs it is argued that they occur in reality as time spent finding information or as mental effort spent on e.g. calculations. The essence of rational inattentiveness is that subjects weigh the expected benefit of new information against the cost of its acquisition. If the costs are higher than the expected benefits, agents decide not to use the available information and remain rationally inattentive. Thus, in these models, agents do not always collect and process all available information. The determinants of the amount of information acquisition are the marginal expected benefit b_m of information and the marginal cost of information c_m. Agents collect information as long as

$$b_m > c_m. \tag{6.1}$$

Thus, rational-inattentiveness models also predict information acquisition to fall when the marginal costs of information rise ceteris paribus. Models in spirit of the rational-expectations approach assume that there are no information costs at all. Therefore agents collect and process all available information. We derive the following three hypotheses from the different approaches:

Hypothesis 1: Subjects can be described by the rational-expectation approach and subjects collect all available information because information acquisition does not involve costs.

Hypothesis 2.a: Subjects are rationally inattentive and they do not collect all available information because information acquisition is costly.

Hypothesis 2.b: Subjects collect less information the higher the costs of information.

To test for these hypotheses, we chose a very simple forecasting test. Participants can gain information about the value that has to be forecasted by solving tasks. The amount of information is chosen by the participants.

6.3 Design

The main question that we are interested in is whether subjects' behavior in the given forecasting task is best predicted by the rational-inattentiveness approach or best predicted by the rational-expectations approach. We test the hypotheses (H1, H2.a, H2.b) described above by analyzing the information acquisition behavior of the participants.

We kept the experiment design as simple as possible. The task for the participants was to forecast a positive integer between 1 and 100 in each of five independent treatments.[2] The fixed number in each treatment was randomly determined before the experiment. The probability of any number between 1 and 100 was the same. The participants had the possibility to gain information about the fixed number by solving mathematical problems correctly. Each mathematical problem consisted of two simple additions problems in three treatments. In two treatments subjects had to solve five simple additions. We vary the amount of mathematical problems between the treatments to control for the influence of different levels of information costs. The solutions to the mathematical problems were always lower than 100. The addition problems consisted of two or three summands. See Table 6.1 for an overview. We kept the mathematical problems very simple to ensure that every participant was able to solve the mathematical problem. We interpret solving the addition problem as a process of information. Information was available to subjects but receiving it in a usable form involved some cognitive activity.

If the participants solved the mathematical problems correctly, they were informed about some numbers not being the fixed number. These numbers which were not the fixed number vanished from the screen. In the first infor-

[2]All information in this section was also known by the participants. For details of the instructions see Appendix 6.A.

Treatment number	**1 and 2**	**3**	**4**	**5**
Number of math problems	2	2	5	5
Number of summands	2	3	2	3
Examples	34+22	13+24+9	7+15	84+7+6
	65+31	40+21+18	56+33	54+33+12
			26+37	44+2+17
			88+12	3+61+28
			72+24	23+41+12

Table 6.1: Treatment numbers and corresponding mathematical problems

mation round (the first two or five mathematical problems) the quantity of all possible numbers decreased from 100 to 19. Thus the first round of solving mathematical problems eliminated 81 wrong numbers. Any following rounds of solving mathematical problems eliminated another two wrong numbers. All remaining numbers were in a consecutive row. Therefore the fixed number would have occurred after ten rounds of solving mathematical problems. The participants could collect as much information as they like. Thus the participants faced a task and they could decide how many tasks they wanted to solve and therefore how much information they wanted to acquire. The experiment was finished when the participant made a forecast in each of the five treatments.

The payoff depended on how far the forecast was away from the fixed number. The maximum value of 2.00 euros was paid for a correct forecast. The payoff diminished based on the following rule, whereas x is the fixed number and y is the participant's forecast. Loss:

0 Cent, if $\|x-y\|=0$	32 Cent, if $\|x-y\|=4$	128 Cent, if $\|x-y\|=8$
2 Cent, if $\|x-y\|=1$	50 Cent, if $\|x-y\|=5$	162 Cent, if $\|x-y\|=9$
8 Cent, if $\|x-y\|=2$	72 Cent, if $\|x-y\|=6$	198 Cent, if $\|x-y\|\geq 10$
18 Cent, if $\|x-y\|=3$	98 Cent, if $\|x-y\|=7$	

In each information stage, participants had to decide whether to acquire

Quantity of possible numbers	Round of calculation	Minimum payoff	Expected payoff of the mean	Expected benefit of information
100	0	€0.02	€0.28	
19	1	€0.02	€1.40	€1.12
17	2	€0.02	€1.52	€0.12
15	3	€0.02	€1.63	€0.11
13	4	€0.02	€1.72	€0.09
11	5	€0.02	€1.80	€0.08
9	6	€0.72	€1.87	€0.07
7	7	€1.28	€1.92	€0.05
5	8	€1.68	€1.96	€0.04
3	9	€1.92	€1.99	€0.03
1	10	€2.00	€2.00	€0.01

Table 6.2: Information in the instructions

more information given the quantity of remaining possible numbers. This decision is rationally based on their disutility of information acquisition (which can in principle be zero) and the expected benefit measured as the increase in expected payoff. Because we are not interested to test the ability of the participants to calculate expected payoffs, we showed the minimum payoffs (the payoffs in the worst case) and the expected payoffs of the means given a quantity of possible numbers to the participants as presented in Table 6.2. We showed the minimum possible payoff as a measure of the dispersion of payoffs. The difference between the expected payoffs between two possible quantities of possible numbers is the expected benefit of the next piece of information for a risk neutral subject. Within a treatment, the information costs stay constant because of the unchanged type of mathematical problems but the benefit diminishes between the rounds of calculation within a treatment. With this design we try to identify the point where the benefit of a piece of information is lower than the costs. The participants will stop collecting information at this point. The expected benefits of information and the rounds of calculations are also presented in Table 6.2 but were not shown to the participants. Except these two columns, the respective line from Table 6.2 and the corresponding means were also shown on the screen at any information stage during the experiment.

6.4 Procedure

The experiment was computerized using z-Tree (Fischbacher 2007) at the Ruhr-University Bochum and the TU Dortmund University in summer 2011. The 37 participants were students from economics and other fields of the two universities.

Subjects arrived one at a time for the experiment. We decided not to conduct the experiment in a group of subjects to avoid peer effects (Falk and Ichino 2006) or a desire for conformity (Bernheim 1994). The instructions (see Appendix 6.A for details) were read aloud and subjects were encouraged to ask questions at any point of the experiment. A comprehension test (see Appendix 6.B for details) was conducted to assure that the participants had understood how to use the information and the tables presented in the instructions.

All subjects played the same five treatments as described in Section 6.3. Before the first treatment started, a trial was played. The trial did not influence the payoff at the end of the experiment.

Each forecast in the five treatments was paid. The payoff for each forecast was determined as described in Section 6.3. In addition, the participants were paid a 2 euros show up fee.

As risk averse agents might collect more information than risk neutral agents to reduce the variance of the expected payoff, a standard Holt and Laury (2002) risk aversion test was conducted at the end of the experiment and paid separately (see Appendix 5.E, page 136, for details).

One session lasted on average 45 minutes, the average payoff (including the 2 euros show up fee and the payment for the Holt and Laury test) was 14.09 euros, the maximal payoff was 15.90 euros, and the minimal payoff was 11.60 euros.

6.5 Results

We test hypotheses 1, 2.a, and 2.b described in Section 6.2 by analyzing the information acquisition behavior of agents.

Figure 6.1 shows the information acquisition of all participants in all five treatments. The graphs indicate that, in each treatment, many participants did not calculate all ten rounds of mathematical problems and therefore did not collect all available information. Over all treatments, subjects calculated all

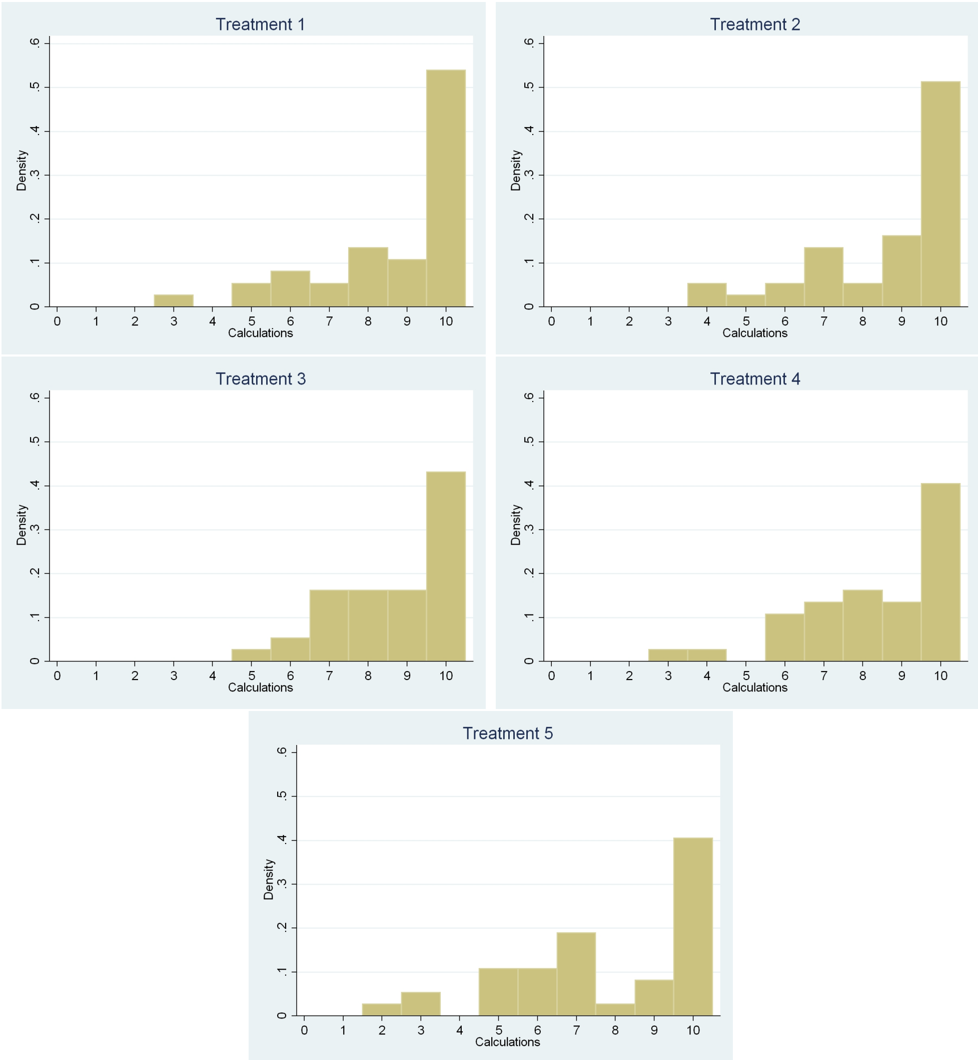

Figure 6.1: Distribution of number of calculations

ten sets of addition problems in only 46% of the cases. This means that at most 46% of observations can be explained by the approach of rational expectations. Probably, some of these 46% appear as if having rational expectations only due to their low information costs. If information costs would be increased exogenously, at least some of them are likely not to collect all information.

In 54% of the cases, subjects decided to submit their forecast without considering some information for which they would not have to pay a monetary cost. We conclude that subjects perceived the cognitive activity required to receive more information as a cost. This behavior contradicts hypothesis 1.

Treatment number	**1**	**2**	**3**	**4**	**5**
Means of calculations	8.68	8.65	8.68	8.35	7.73
Standard deviation of calculations	1.86	1.83	1.45	1.84	2.39
Means of calculation time (in seconds)	13	13	20	26	43
Standard deviation of calculation time (in seconds)	6	6	8	6	11

Table 6.3: Means of calculations and calculation time

The means of rounds of solved mathematical problems and the corresponding standard deviations are shown in Table 6.3. The prediction of the rational-expectations approach (test hypothesis 1) is that there are no information costs and therefore all available information should be used. Thus the rational-expectations approach predicts a mean of ten for the number of calculations. The data in Table 6.3 show that the means in the different treatments are lower than ten. The means are about one standard deviation lower than 10. The data cannot be higher than 10 and therefore the distribution of the data is not normally distributed. Therefore we apply a bootstrap technique and not a t-test to check whether the data is different from 10. We draw 1.000.000 random combinations with replacement of the observed data for each treatment (see Efron and Tibshirani 1998 Chapter 6). The results show that less than 1% of the randomly drawn realizations have a mean of 10. Therefore hypothesis 1 has to be rejected.

The results in Figure 6.1 show that even in treatments 1 and 2, in which the easiest calculations had to be done, almost half of the participants (49% and 46%, respectively) did not calculate until only the fixed number remained. The average time that was spend for one round of calculation in these treatments was 13 seconds what represents a comparably low effort. Mean times needed and the standard deviations for the calculations in all treatments are presented in Table 6.3. On the other hand the marginal gain of information is quite low at least after the first round of calculation. The expected marginal payoff is, for example, only 1 Euro-Cent for the last round of calculations (see Table 6.2). Thus, saving the disutility of solving the mathematical problem is worth more than 1 Euro-Cent for almost half of the participants. The results show that not all participants collect all available information and therefore hypothesis 2.a cannot be rejected.

However, hypothesis 2.a is the weaker hypothesis of the two hypotheses supporting the notion of rational inattention. If there are information costs, subjects should economize on it in a rational way. Such rational behavior would let us observe certain comparative statics. The amount of collected information should decrease with higher information costs (hypothesis 2.b). To test this hypothesis, we run a Tobit regression on the number of calculations. We use a Tobit regression because the number of calculations is restricted to integers between 0 and 10. We use two measures as proxies for information costs: the number identifying the treatment (the higher the treatment number the more difficult the mathematical problems, see Table 6.1) and the average time spent for one calculation step (total time needed in a treatment divided by the number of calculations). As a robustness check we perform the analysis with and without the first treatment to control for possible learning effects.

We check the influence of information costs by running a Tobit regression on the following equation:

$$C_k = \alpha_0 + \alpha_1 Info\_Costs_k + \alpha_2 Smoke_k + \alpha_3 Participation_k + \alpha'_X X_k + \epsilon_k$$

The variable C_k is the number of calculations chosen by the participants in the experiment. Depending on whether we also use data from treatment 1, we have 185 or 148 observations (37 participants in 4 or 5 treatments) that are indicated by the index k. The $Info\_Costs$ variable is the proxy for information costs. To proxy information costs, either the treatment number or the average time that is needed for each calculation step by the participants are used in different regressions. *Smoke* is a dummy variable that is one if the participant smokes and otherwise zero. *Participation* represents the number of previous participations in experiments. Further control variables are summarized in vector X_k. These variables are: gender, age, duration of study, field of study, and a variable that measures the degree of risk aversion based on the Holt and Laury test. α_0 is a constant and the error term is denoted by ϵ_k.

The results of the Tobit regression are presented in Table 6.4. All estimators of variables that are not shown in the table are statistically not different from zero applying a significance level of 5%. Columns (1) and (2) present the results including the first treatment and columns (3) and (4) present the results

	(1)	(2)	(3)	(4)
Time	-0.06***		-0.06***	
	(0.02)		(0.02)	
Treatment_number		-0.35**		-0.45**
		(0.15)		(0.21)
Smoker	-2.23***	-2.38***	-2.36***	-2.55***
	(0.77)	(0.80)	(0.82)	(0.86)
Participation	0.65***	0.77***	0.63***	0.75***
	(0.14)	(0.14)	(0.14)	(0.15)
Terms	0.07	0.11	0.14	0.18**
	(0.08)	(0.08)	(0.08)	(0.09)
Constant	6.97**	6.43**	8.19**	8.09**
	(3.07)	(3.21)	(3.22)	(3.45)
Pseudo R^2	0.09	0.07	0.09	0.07
noobs	185	185	148	148

*, **, *** indicate statistical significance to the 10, 5, and 1 percent level respectively. Standard errors in parenthesis.

Table 6.4: Testing the influence of information costs

excluding this treatment. The results show that higher information costs, independent of whether they are measured by the treatment number or by the time spent for one calculation, lead to less information acquisition. All estimated coefficients of higher information costs are negative and significantly different from zero at least at a significance level of 5%. Therefore hypothesis 2.b cannot be rejected, higher information costs reduce informational activity. The results let us conclude that the negative relation between information costs and information processing holds in a cross-treatment (revealed by the negative coefficient of treatment number) and a cross-subject (revealed by the negative coefficient of time) perspective. The point estimator of -0.06 for the time variable indicates that a participant who needs 10 seconds more for one calculation in a treatment, tends to do 0.6 rounds less of calculation.

In addition, more participations in previous experiments tend to increase the number of calculation rounds. This could capture the effect that people participating more often in experiments have lower acquisition costs because they could like solving mathematical problems or they like being part of an experiment. Smokers on the other side tend to calculate fewer rounds. This behavior could be explained by higher impatientness of smokers as found by Khwaja et al. (2007). The duration of study has a statistically significantly effect only if the first treatment is not taken into account.

The overall results show that the two hypotheses derived from the rational-inattentiveness models cannot be rejected but the hypothesis derived from the rational-expectations approach has to be rejected. Our results expose behavior which is well in line with the notion of rational inattentiveness. Subjects submit forecasts even though they could use more information without paying a monetary cost. Furthermore, subjects tend to economize on information cost in a rational way, i.e. they process less information when information costs increase.

6.6 Conclusion

This essay provided experimental evidence on the endogenously determined amount of information acquisition. Participants could gain information in a real-effort experiment by solving tasks. We tested assumptions about information costs underlying rational-inattentiveness models and rational-expectations models. The analysis showed that many participants did not process all information. Therefore we rejected the hypothesis of costless information as used in rational-expectations models.

The results showed clear evidence in favor of rational-inattentiveness models. Processing information induced costs for the participants and therefore they did not collect all available information. The analysis showed furthermore that higher information costs, measured as e.g. time costs, led to less information processing. Therefore we could not reject any of the two hypotheses derived from rational-inattentiveness models.

Appendix

Appendix 6.A presents the instructions of the main experiment and Appendix 6.B contains the comprehension test. All parts that were shown to the participant are italicized.

6.A Instructions

Welcome to the experiment. Please use only the computer program which is necessary for the experiment. The experiment is conducted to analyze decision behavior. You can win money in this experiment. Your benefit depends only on your own decisions accordingly to the rules described on the next pages. The data from the experiment are anonymous and cannot be connected to the participants. The experiment conductors do not know your decisions or your benefit during or after the experiment. This experiment consists of two independent sub experiments. First, you receive the instruction for the first sub experiment. After the first sub experiment you will receive the instructions for the second sub experiment.

Sub experiment 1

Task

In this experiment, you have to forecast a positive integer between 1 *and* 100 *(including these two numbers). The fixed number in the respective treatments was determined before the experiment. The fixed number in each treatment is independent of past and future fixed numbers. All realizations between* 1 *and* 100 *have the same probability at the beginning of each treatment.*

Procedure

This sub experiment consists of five independent treatments. You have to make a forecast about the fixed number in each treatment. The fixed number is always between 1 *and* 100*. You can collect information about the fixed number before you forecast. You can collect information but you do not have to. You can collect as much information as you wish. This sub experiment is finished as soon as you have submitted a forecast in each of the five treatments.*

Forecast

You can type your forecast at the bottom right corner of the screen. Your forecast can be any positive integer (between 1 *and* 100*). A button labeled "Submit forecast" is next to the forecast box. You submit your forecast by* *clicking this button. After the submission, the fixed number, your forecast error, and your payoff in this treatment are shown on the screen. Afterwards the next treatment starts. The sub experiment is finished as soon as you have submitted a forecast in each of the five treatments.*

Information

You know for sure that the value of the fixed number is between 1 *and* 100*. The probability of any number in this interval is the same at the beginning of each treatment. All* 100 *possible numbers are shown on the screen at the beginning of each treatment. Two or five addition problems, depending on the treatment, are shown in the lower part of the screen. The number of addition problems does not change within a treatment. If you want to acquire information about the fixed number, you have to solve the mathematical problems correctly. The solutions to the mathematical problems are never greater than* 100*. Push the "OK" button if you have entered the solutions in the corresponding boxes. A notice occurs if a solution is wrong. You can enter a new solution in this case. A second screen output occurs if all solutions are correct. This second screen output presents 19 numbers whereof one number is the fixed number. These 19 numbers are in a row without missing a number. Beside the 19 possible numbers, you find the same number of mathematical problems as before. Two numbers out of the 19 numbers that are not the fixed number disappear if all mathematical problems are solved correctly. These two numbers are always part of the two highest or lowest numbers out of the 19 possible numbers. But this does not imply that the fixed number is always in the middle of the row.*

Afterwards you can solve other mathematical problems to get rid of another two wrong numbers. The fixed number occurs after ten rounds of solving mathematical problems. To summarize, 81 wrong numbers are dropped after the first round of mathematical solutions. Afterwards two wrong numbers are dropped for any other round of mathematical solutions.

Payoff

You get a payoff of 2.00 euros for a correct forecast. The worse your forecast is the lower is your payoff. The decrease of the payoff is labeled loss. The loss is calculated in the following way whereas x is the fixed number and y is your forecast. The absolute difference $|x - y|$ indicates your forecast error, independent of whether your forecast is too high or too low.

Loss:

$$0 \text{ Cent, if } |x-y| = 0$$

$$2 \text{ Cent, if } |x-y| = 1$$

$$8 \text{ Cent, if } |x-y| = 2$$

$$18 \text{ Cent, if } |x-y| = 3$$

$$32 \text{ Cent, if } |x-y| = 4$$

$$50 \text{ Cent, if } |x-y| = 5$$

$$72 \text{ Cent, if } |x-y| = 6$$

$$98 \text{ Cent, if } |x-y| = 7$$

$$128 \text{ Cent, if } |x-y| = 8$$

$$162 \text{ Cent, if } |x-y| = 9$$

$$198 \text{ Cent, if } |x-y| \geq 10$$

Therefore, your payoff depends on how far your forecast is away from the fixed number. You receive the maximum value of 2.00 *euros for a correct forecast. Please note that the payoff and the loss are shown in Euro-Cent on the screen. "*200*" therefore correspond to* 2.00 *euros, "*163*" corresponds to* 1.63 *euros and so forth. The payoffs in the worst case, the minimum payoffs given a quantity of possible numbers, are shown in the following table. If you do not want to collect any more information and you want to make a guess, the mean of the remaining numbers represents the forecast with the highest expected payoff. The expected payoffs of the means are also shown in the table. The expected payoff is a statistical value, thus your payoff can be higher or lower depending of whether the mean is close to the fixed number or not. The means, the expected payoffs of the means, and the minimum payoffs are shown* *on the screen during the experiment.*

Quantity of possible numbers	Minimum payoff	Expected payoff of the mean
100	€0.02	€0.28
19	€0.02	€1.40
17	€0.02	€1.52
15	€0.02	€1.63
13	€0.02	€1.72
11	€0.02	€1.80
9	€0.72	€1.87
7	€1.28	€1.92
5	€1.68	€1.96
3	€1.92	€1.99
1	€2.00	€2.00

All payoffs from the five treatments are added and will be paid together with the payoff of the second sub experiment at the end of the experiment.

Further screen information

Three values are shown at the right part of the screen, under the table that contains all possible numbers:

- *"Mean" is the mean of all remaining numbers.*
- *"Expected payoff of mean" is the statistical expected value if the forecast is equal to the mean.*
- *"Minimum payoff" is the minimum payoff that is realized if the forecast and the fixed number have the maximum possible distance.*

Time

There is no time limit. You can spend as much time in each treatment as you like. You can collect as much or as little information as you like.

Trial

There will be a trial before the experiment starts. The trial does not affect your payoff. The trial consists of one treatment with a time limit of 10 minutes. The trial has the same structure as the experiment, with the exception of the number of mathematical problems and the time limit. The fixed number in the trial does not affect the fixed numbers in the following treatments.

Comprehension Test

Please answer the comprehension questions to make sure that you understood the instructions.

6.B Comprehension Test

Please answer the following questions before the experiment starts. The questions will help you to understand the experiment. You can use the instructions. Please raise your hand if you have any questions. The time limit is 10 minutes.

1. *What is the payoff if your forecast is two numbers above the fixed number? For example in case your forecast is* 14 *and the fixed number is* 12.
   - *Payoff:*____________________
2. *What is the payoff if your forecast is four numbers under the fixed number? For example in case your forecast is* 78 *and the fixed number is* 82.
   - *Payoff:*____________________
3. *What is the payoff if your forecast is 20 numbers above the fixed number? For example in case your forecast is* 75 *and the fixed number is* 55.
   - *Payoff:*____________________
4. *Assume that you collect information until you know that the fixed number is one of the following numbers:* $22; 23; 24; 25; 26; 27; 28; 29; 30; 31; 32$. *What is the payoff if your forecast is* 23 *and the fixed number is* 30*?*
   - *Payoff:*____________________
5. *Assume that you collect information until you know that the fixed number is one of the following numbers:* $75; 76; 77; 78; 79; 80; 81; 82; 83; 84; 85; 86; 87; 88; 89$. *What is the payoff if your forecast is* 77 *and the fixed number is* 87*?*
   - *Payoff:*____________________
6. *What is the minimum payoff if the quantity of possible numbers is reduced to 11?*
   - *Minimum payoff:*____________________

7. *What is the minimum payoff if the quantity of possible numbers is reduced to 9?*

   - *Minimum payoff:*____________________

8. *What is the expected payoff if the quantity of possible numbers is reduced to 15 and your forecast is equal to the mean?*

   - *Expected payoff:*____________________

9. *What is the expected payoff if the quantity of possible numbers is reduced to 5 and your forecast is equal to the mean?*

   - *Expected payoff:*____________________

Chapter 7

Concluding Remarks

This thesis presents five essays that compare rational-inattentiveness models and sticky-information models with rational-expectations models in several respects. Assumptions about rationality in both types of models are tested for, implications derived from rational-inattentiveness models are investigated, models' accuracies are evaluated, predicted information acquisition behavior is tested, and assumptions about information costs are inspected.

Chapter 2 presents an empirical test of the two different concepts of rationality underlying rational-expectations models and rational-inattentiveness models. The results support the concept used in rational-inattentiveness models.

Chapter 3 tests implications of rational-inattentiveness models with respect to forecasting macroeconomic variables. Rational-inattentiveness models predict a negative correlation between the amount of news and the forecast deviation. A negative correlation between news coverage and forecast deviation occurs empirically for inflation whereas a positive correlation is found in the context of unemployment.

A comparison between the sticky-information and the sticky-price Phillips curve is made in Chapter 4. The overall results of the empirical performances allow no clear distinction between the two concepts. However, if one is predominantly interested in matching unconditional moments of inflation dynamics, sticky prices should be used. Researchers who focus on co-movements of inflation with demand will obtain better results applying sticky information.

In Chapters 5 and 6, the information acquisition behavior predicted by rational-inattentiveness models and the assumptions about information costs in these models and in rational-expectations models are tested in an experimental environment. The overall results in Chapter 5 indicate that the prediction of information acquisition derived from rational-inattentiveness models cannot be rejected. The analysis in Chapter 6 shows that assumption about information costs of the rational-inattentiveness models cannot be rejected in contrast to the assumptions in rational-expectations models.

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Hiermit erkläre ich an Eides statt, dass ich die vorliegende Arbeit selbständig und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe. Die aus fremden Quellen direkt oder indirekt entnommenen Gedanken sind als solche kenntlich gemacht.
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Schwerte, September 2011