Essays on Inflation Expectation Formation

Thomas Maag

KOF Dissertation Series No 4, 2010

Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Imprint

Publisher

KOF Swiss Economic Institute, ETH Zurich

DISS. ETH NO. 18972

Essays on Inflation Expectation Formation

A dissertation submitted to

ETH Zurich

for the degree of

Doctor of Sciences

presented by

Thomas Maag

lic. oec., University of St. Gallen

born on June 8, 1979

citizen of Zürich

accepted on the recommendation of

Prof. Dr. Jan-Egbert Sturm, examiner

Prof. Dr. Gebhard Kirchgässner, co-examiner

2010

Preface

This thesis was written while I was research assistant at the chair of Prof. Jan-Egbert Sturm at the Swiss Federal Institute of Technology (ETH) Zurich. I would like to thank Prof. Jan-Egbert Sturm for providing an exceptional degree of academic freedom combined with the encouragement to shape and realize my own research agenda. Moreover, I would like to thank him for his constructive and motivating feedback through which my work has substantially benefited.

I also owe much to my second advisor, Prof. Gebhard Kirchgässner, whose lecture on time series analysis has inspired my interest in economic research. I would like to thank him especially for enabling me to participate in the PhD program at the Study Center Gerzensee and for being a member of the thesis committee.

Next, I would like to thank my colleagues at the ETH Zurich for helpful discussions, advice and collaboration, in particular Simone Elmer, Martin Gassebner, Michael J. Lamla, Sarah M. Lein, Simon Lüchinger and Christoph Moser. Moreover, I would like to thank Stephan Betschart and Marco Huwiler for sharing their knowledge about Swiss consumer price inflation. I am grateful to Marcel R. Savioz for giving me the opportunity to gain an applied perspective on monetary economics during an internship at the Swiss National Bank. Special thanks go to Katharina Bloch for assisting with various administrative issues.

This thesis was financed by a research grant from the Swiss National Science Foundation, which is highly appreciated. I would also like to thank all those who have contributed to the excellent education and research institutions that I have enjoyed at the Study Center Gerzensee and at the ETH Zurich. Furthermore, I appreciate the comments received from participants in various conferences and seminars during the past two years.

Finally, I would like to express my deepest gratitude to my parents for their constant encouragement and support, without which this thesis would never have been written. I would like to thank my sister and my friends for their support. Most of all, I am grateful to Daniela for her love, patience and faith in me, which were essential for the progress I have made over the past years.

Zürich, March 2010 *Thomas Maag*

Contents

List of Figures

List of Tables

Thesis Summary

This thesis comprises five papers that pertain to the much discussed question of how economic agents form expectations. The main objective lies in empirically investigating new approaches of expectation formation using household survey data about expected consumer price inflation. Relying on survey expectations, a large literature mainly tests the rational expectations hypothesis. However, no consensus has been reached about which model of expectation formation is empirically appropriate. While much of the existing literature examines the central tendency of survey expectations, this thesis focuses on the cross-sectional heterogeneity of expectations. The pronounced degree of cross-sectional heterogeneity is assumed to have two primary sources. On the one hand, agents may disagree because they have different information sets. On the other hand, agents may disagree because they use different models of expectation formation. Moreover, the informational requirements of the Muthian notion of rationality are mitigated. This thesis builds on the idea that agents are economically rational, optimizing how they form expectations given that acquiring and processing information is costly. The underlying theoretical frameworks are sticky information (Mankiw and Reis, 2002), rational inattention (Sims, 2003) and rationally heterogeneous expectations (Branch, 2004).

The following main results are obtained: First, it is shown that the probability method is accurate for quantifying qualitative household survey data, both for perceptions of inflation during the past 12 months and for expectations of inflation during the upcoming 12 months. This result is based on household-level data from the Swedish Consumer Tendency Survey which jointly asks for qualitative and quantitative responses. Second, a mixture model which explains survey heterogeneity by heterogeneous models of expectation formation reveals that among Swedish households, the most widely used predictor is the static expectations model. Under static expectations, expected inflation is equal to the subjective perception of current annual inflation. This finding implies an important role of inflation perceptions for expectation formation. Third, using data from the Joint Harmonized EU Consumer Survey, it is found that inflation perceptions of European households show patterns consistent with an information delay model of belief formation. However, the cross-sectional heterogeneity of inflation perceptions is too high to be accounted for by the information delay assumption alone. Fourth, it is shown that media coverage about

consumer price inflation affects the heterogeneity of household expectations. Consistent with a Bayesian learning model, household expectations become more homogeneous if inflation ranks higher on the public agenda. Fifth, it is shown that the persistence of consumer price inflation in Switzerland has declined in the early 1990s, both on the aggregate index level and on disaggregate price levels.

Zusammenfassung

Diese Arbeit umfasst fünf Artikel, die sich mit der Frage befassen, wie ökonomische Akteure ihre Erwartungen über die zukünftige Konsumentenpreisinflation bilden. Eine umfangreiche Literatur untersucht die Gültigkeit konventioneller Erwartungsbildungsmodelle anhand der mittleren Erwartung in einer Umfragestichprobe. Die vorliegende Arbeit erweitert die bestehende Literatur, indem stattdessen die Heterogenität der Erwartungen im Querschnitt der Umfragestichprobe betrachtet wird. Die Datengrundlage der empirischen Untersuchung bilden Antwortdaten aus Haushaltsumfragen über die in den kommenden 12 Monaten erwartete Inflationsrate. Die Inflationserwartungen der Haushalte weisen einen hohen Grad an Heterogenität auf, welche aus konzeptioneller Sicht zwei wesentliche Ursachen haben kann. Zum einen können die Umfrageteilnehmer unterschiedliche Informationen zur Bildung ihrer Erwartungen verwenden. Zum anderen können sich die verwendeten Erwartungsbildungsmodelle unterscheiden. Die vorliegende Arbeit geht von einem Konzept der ökonomischen Rationalität aus. Es wird angenommen, dass die Akteure den gesamten Prozess der Erwartungsbildung optimieren, also eine ökonomisch rationale Abwägung zwischen Informations- und Prognosekosten auf der einen Seite und den Vorteilen aus der erzielten Prognosegüte auf der anderen Seite vornehmen. Entsprechend werden die neuen theoretische Konzepte "sticky information" (Mankiw und Reis, 2002), "rational inattention" (Sims, 2003) und "rationally heterogeneous expectations" (Branch, 2004) aufgegriffen.

Die wichtigsten Resultate dieser Arbeit können wie folgt zusammengefasst werden: Erstens wird gezeigt, dass die Wahrscheinlichkeitsmethode zur Quantifizierung von qualitativen Antwortdaten aus der harmonisierten Verbraucherumfrage der Europäischen Union geeignet ist. Dieses Resultat basiert auf einer Auswertung von qualitativen und quantitativen Inflationserwartungen aus der Schwedischen Verbraucherumfrage. Zweitens wird unter Verwendung derselben Daten ein Modell geschätzt, welches die Heterogenität der Inflationserwartungen auf heterogene Erwartungsbildungsmodelle zurückführt. Dabei zeigt sich, dass das von Haushalten am häufigsten verwendete Erwartungsbildungsmodell ein statisches Prognosemodell ist. Bei diesem Modell entspricht die Inflationserwartung der subjektiven Wahrnehmung der momentanen Inflationsrate. Dieses Resultat deutet darauf hin, dass die subjektive Inflationswahrnehmung eine wichtige Rolle im Prozess der Erwartungsbildung spielt. Drittens wird gezeigt, dass die Dynamik der Inflationswahrnehmungen europäischer Haushalte grundsätzlich mit einem epidemiologischen Erwartungsbildungsmodell übereinstimmt. Jedoch können die Modellannahmen bezüglich des Informationsflusses nur einen Teil der beobachtbaren Heterogenität erklären. Viertens wird gezeigt, dass die Heterogenität der Inflationserwartungen von Haushalten durch die Medienberichterstattung über Inflation beeinflusst wird. In Übereinstimmung mit einem Bayesianischen Lernmodell sinkt die Heterogenität, wenn das Thema Inflation höher auf der öffentlichen Agenda steht. Fünftens zeigt sich, dass die Persistenz der Konsumentenpreisinflation in der Schweiz nach 1990 abgenommen hat. Dies kann sowohl für den Gesamtindex wie auch für disaggregierte Reihen auf Ebene der Indexpositionen nachgewiesen werden.

Chapter 1

Introduction

1.1 Empirical Evidence on Expectation Formation

This thesis comprises five papers that pertain to the question of how economic agents form expectations. The main objective lies in empirically investigating new approaches of expectation formation using household survey data about expected consumer price inflation. The concept of expectations is constitutive for contemporary economic theory that deals with decision problems under incomplete information. Various schemes of how agents form expectations have been proposed, the most influential being the rational expectations hypothesis of Muth (1961). Relying on survey expectations, a large literature mainly tests this hypothesis. However, no consensus has been reached about which model of expectation formation is empirically appropriate. While much of the existing literature examines the central tendency of survey expectations, this thesis focuses on the cross-sectional heterogeneity of expectations. The pronounced degree of heterogeneity in survey expectations is assumed to have two primary sources. On the one hand, agents may disagree because they have different information sets. On the other hand, agents may disagree because they use different models of expectation formation. Moreover, the informational requirements of the Muthian notion of rationality are mitigated. This thesis builds on the idea that agents are economically rational, optimizing how they form expectations given that acquiring and processing information is costly.

To begin with, this section briefly outlines the relevance of understanding expectation formation for macroeconomics, discusses conventional models of expectation formation and reviews empirical evidence on their validity. In line with the scope of the thesis, the discussion centers on the empirical literature about household survey expectations of inflation. Against the background of this literature, Section 1.2 discusses new approaches towards expectation formation, including rationally heterogeneous expectations (Branch, 2004), sticky information (Mankiw and Reis, 2002) and rational inattention (Sims, 2003). These new approaches constitute the main theoretical foundation of the thesis. Section 1.3 elaborates on the objectives of the thesis. Section 1.4 outlines the five papers and summarizes main findings.

The notion that individuals take economic decisions based on expectations about uncertain outcomes already underlies Daniel Bernoulli's discussion of the St. Petersburg paradox published in 1738 (reprinted in Bernoulli, 1954). It has been formalized by von Neumann and Morgenstern (1944) in their seminal expected utility theory. In macroeconomics, the assumption that agents form expectations has become increasingly popular in the 1950s and 1960s. However, the important role of expectations has been emphasized earlier, e.g., by Keynes (1936) who argues that firm decisions on production, employment and investment depend on forward looking expectations. The theoretical role of expectation formation is evident for the Phillips curve relationship. Subsequent to the empirical contributions of Phillips (1958) and Samuelson and Solow (1960), the Phillips curve has been widely understood as describing a trade-off between nominal wage and price inflation on the one side and unemployment on the other side. Phelps (1967) and Friedman (1968) argue that this tradeoff is not sustainable, as workers will ultimately expect inflation and anticipate its impact on their real wages. This idea constitutes the expectations augmented Phillips curve. Still, expectation formation was assumed to be adaptive. The expectations augmented Phillips curve thus predicts that an increase in inflation pushes unemployment below the natural rate. Only under the assumption of rational expectations advanced by Lucas (1972a) and Sargent (1973), foreseeable changes in inflation do not affect unemployment anymore. The theoretical implications of the Phillips curve thus dramatically depend on the assumed model of expectation formation.

Expectations also play a central role for central banking. As Woodford (2003) emphasizes, monetary policy affects decisions of households and firms mainly by influencing prices of financial instruments, such as long term bonds or stocks. These prices critically depend on expectations about the future path of monetary policy actions rather than just on the current interbank lending rate. A better understanding of how expectations are formed may thus enable a central bank to improve the effectiveness of monetary policy by more efficiently managing expectations.

From an empirical perspective, the analysis of survey expectations is not only relevant for inferring how economic agents form expectations, but also for improving inflation forecasts. The literature clearly shows that inflation expectations of households and professional forecasters have predictive power for actual inflation. Ang, Bekaert and Wei (2007) find that both household and professional expectations on 12 months ahead inflation outperform alternative inflation forecasts, including linear and nonlinear time-series models, Phillips curve models and models using term structure data. Ang, Bekaert and Wei (2007) further show that expectations of professional forecasters are only marginally more accurate than household expectations taken from the University of Michigan Survey of Consumers (Michigan survey). Consistent results are reported by Thomas (1999), Mehra (2002) and Croushore (2006).

Using the notation of Pesaran and Weale (2006), the expectation $\pi^e_{t,i}$ about future consumer price inflation π_{t+1} that an agent i forms in period t is given by:

$$E(\pi_{t+1}|\Omega_{t,i}) = \pi^e_{t,i} = \int \pi_{t+1} f_i(\pi_{t+1}|\Omega_{t,i})\, d\pi_{t+1} \tag{1.1}$$

where $f_i(.)$ is the subjective conditional density function of future inflation given the information set $\Omega_{t,i}$ used by individual i. Given the definition of a point expectation in Equation (1.1), a model of expectation formation is defined by a set of assumptions on $f_i(.)$ and $\Omega_{t,i}$. The concept of rational expectations as proposed by Muth (1961) and introduced to macroeconomics by Lucas (1972b, 1973) and Sargent (1973) assumes that agents have full knowledge about the structure of the economy when forming an expectation. Moreover, the model assumes that private information is irrelevant for expectation formation. The subjective probability density function is thus equal to the objective density function of future inflation:

$$f_i(\pi_{t+1}|\Omega_{t,i}) = g(\pi_{t+1}|\Omega_t)$$

where $g(.)$ is the objective density function of future inflation given the public information set $\Omega_t \subseteq \Omega_{t,i}$. Consequently, expectation errors $\pi_{t+1} - E(\pi_{t+1}|\Omega_{t,i})$ are a martingale difference sequence with respect to public information Ω_t. Hence, the model implies the testable hypotheses that expectations are unbiased and informationally efficient such that forecast errors are orthogonal to public information. Rational expectations are the standard assumption in contemporary macroeconomic models of the inflation rate, see, e.g., the literature survey of Rudd and Whelan (2007).

Two common extrapolative models of expectation formation are static expectations and adaptive expectations. Both models impose homogeneous density functions and information sets across the population, i.e. $f_i(.) = f(.)$ and $\Omega_{t,i} = \Omega_t$ for all i. The conventional static (naive) expectations model assumes that expected inflation is equal to the actual rate of inflation at the time of expectation formation:

$$\pi^e_{t,i} = \pi_t$$

Static expectations minimize the mean squared forecast error if inflation follows a random walk. This scheme of expectation formation often serves as a benchmark in empirical studies on expectation formation, see, e.g., Thomas (1999) and Mehra (2002). Static expectation formation underlies the cobweb model of Ezekiel (1938) in which producers expect current prices to last. More recently, a related scheme is employed in the hybrid New Keynesian Phillips curve proposed by Galí and Gertler (1999). Their model is based on the idea that a fraction of firms sets prices following a backward looking rule. Static behavior is also an element of the hybrid New Keynesian Phillips curve of Fuhrer and Moore (1995) who assume that workers negotiate their real wages relative to the wages payed in lagged (and expected future) wage contracts of other cohorts.

The more general model of adaptive expectations proposed by Cagan (1956) assumes that expected inflation is a weighted mean of current inflation and the past expectation:

$$\pi^e_{t,i} = \pi^e_{t-1,i} + \lambda(\pi_t - \pi^e_{t-1,i})$$

where $\lambda \in [0, 1]$. Adaptive expectations are a distributed lag of inflation rates with exponentially declining weights. Following the contributions of Phelps (1967) and Friedman

(1968), adaptive expectation schemes were employed in the literature on the expectations augmented Phillips curve and the accelerationist hypothesis.

A large literature tests the rational expectations hypothesis using household survey data, with mixed findings. Most of this literature investigates bias and information efficiency of the central tendency of expectations, commonly measured by the cross-sectional mean of survey responses. Using household response data from the Michigan survey, Thomas (1999) finds that the mean of expectations on 12 months ahead inflation is unbiased during 1960–1997. Moreover, Thomas (1999) reports that forecast errors are uncorrelated with lagged inflation, supporting weak form efficiency. However, expectations do not satisfy strong form efficiency since forecast errors are found to be correlated with other publicly available information. Thomas (1999) also shows that the median of expectations is more accurate than the mean. Consistent with his findings, Ang, Bekaert and Wei (2007) report that median expectations from the Michigan survey are essentially unbiased during 1978–2002. Ang, Bekaert and Wei (2007) find that only in some specifications, estimates indicate a nonlinear bias with households over-predicting inflation when inflation is low and accelerating. Mehra (2002) shows that mean expectations are biased during 1980–2000, whereas median expectations are not. Moreover, he finds that median expectations are strong form efficient. In contrast, Mankiw, Reis and Wolfers (2004) reject weak form and strong form efficiency of median expectations in a sample spanning 1974–2002. The earlier literature on aggregate household expectations mainly provides evidence against rationality of expectations. Amongst others, rationality is rejected by Gramlich (1983), Baghestani (1992) and Roberts (1997) for expectations from the Michigan survey and by Evans and Gulamani (1984) and Batchelor and Dua (1987) for qualitative and quantitative household survey data from the U.K. Mixed findings for countries covered by the Joint Harmonized EU Consumer Survey are reported by Papadia (1983). Results in favor of rationality of mean expectations from the Michigan survey are provided by Grant and Thomas (1999, 2001).

Tests of rationality using aggregate survey data have been questioned due to potential aggregation bias, as discussed by Bonham and Cohen (2000, 2001). First, Figlewski and Wachtel (1983) show that in a stylized framework of rational agents with heterogeneous information sets, conventional tests of unbiasedness based on the cross-sectional mean of expectations tend to incorrectly reject rationality since the mean forecast is correlated with the mean forecast error. Second, Keane and Runkle (1990) highlight that averaging expectations can cancel systematic biases in individual expectations, with the result that tests of unbiasedness incorrectly indicate rationality of the mean expectation. Only few contributions investigate rationality using microdata on household expectations. Souleles (2004) employs household-level data from the Michigan survey. Extending previous research, Souleles (2004) capitalizes on the panel structure of the survey in which households are reinterviewed once, 6 months after the first interview. Souleles (2004) assesses household inflation expectations both relative to the materialized inflation rate and, due to the availability of responses from the second interview, to the perception of current inflation elicited in the second interview. Souleles (2004) finds that relative to both benchmarks, inflation expectations are biased and inefficient. Moreover, it is shown that the accuracy of inflation expectations improves in education and income. In line with Souleles (2004), an earlier literature mainly documents that inflation expectations systematically differ across socioeconomic groups. Jonung (1981) employs cross-sectional response data from the Swedish Consumer Tendency Survey. He finds that expectations significantly decline in age. Bryan and Venkatu (2001a, 2001b) report consistent findings for U.S. survey data. Batchelor and Jonung (1989) document the significance of socioeconomic characteristics in a cross-section from a special Swedish survey conducted in 1984. Other research tests and mainly rejects rationality using microdata on expectations about individual outcome variables such as personal income (Dominitz, 1998, Das, Dominitz and van Soest, 1999) and personal financial position (Souleles, 2004).

Regarding expectations of professional forecasters, Thomas (1999) and Mehra (2002) consistently report that aggregate inflation expectations from the Livingston survey are unbiased but fail tests of strong form efficiency. Mehra (2002) further documents that expectations from the Survey of Professional Forecasters are biased and inefficient. Ang, Bekaert and Wei (2007) extend these results, showing that the mean expectation taken from the Livingston Survey exhibits a moderate degree of nonlinear bias during 1952–2002. On average, professional forecasters over-predict inflation when inflation is high but decreasing. Ang, Bekaert and Wei (2007) confirm that the Survey of Professional Forecasters is biased in the period 1981–2002. Earlier contributions of Gramlich (1983) and Batchelor and Dua (1989) more clearly reject rationality of mean expectations taken from the Livingston survey. In contrast, aggregate expectations taken from the Livingston Survey and the Survey of Professional Forecasters are found to be consistent with the rational expectations hypothesis by, e.g., Vanderhoff (1984), Grant and Thomas (1999, 2001) and Croushore (2006). The findings on disaggregate response data are also mixed. Relying on the Survey of Professional Forecasters, Keane and Runkle (1990) find that individual forecasts are both unbiased and efficient during 1968–1986. While Keane and Runkle (1990) use pooled data, Bonham and Cohen (2001) assess forecasts of individual forecasters over time. They find that between 47 and 75 percent of individual forecasters generate biased inflation forecasts. Lahiri and Sheng (2008, 2009a) propose a test of forecasting efficiency in a Bayesian learning framework. Using disaggregate inflation expectations from the Consensus Economics survey, Lahiri and Sheng (2008) show that professional forecasters in G7 countries generally make efficient use of new information during 1990–2006. Capistrán and Timmermann (2009) investigate disaggregate data from the Survey of Professional Forecasters spanning 1968–2004. They report that depending on the specification, more than half of the individual forecasters generate biased inflation forecasts. The findings of Capistrán and Timmermann (2009) suggest that measures of central tendency might still be unbiased as positively and negatively biased expectations cancel out. Consistent findings are reported by Batchelor (2007), who investigates individual forecasts from the Consensus Economics survey covering G7 countries during 1990–2005. Lovell (1986) reviews the earlier literature to conclude that the rational expectations hypothesis does not hold.

In sum, while inflation expectations assume a central role in theory, only little is known about how economic agents form expectations. The findings of the literature on survey expectations are inconclusive. Results of rationality tests critically depend on the sample horizon, the econometric specification, the set of public information considered in strong form efficiency tests and the aggregation of the response data. Studies on disaggregate data do however clearly point towards a high degree of heterogeneity in survey expectations. This heterogeneity is not accounted for by conventional models of expectation formation. Against this background, a more explorative approach seems adequate to improve our understanding of expectation formation, rather than testing conventional models of expectation formation. Moreover, new approaches should be considered that are consistent with the observed heterogeneity in survey expectations.

1.2 New Concepts of Expectation Formation

This thesis builds on the assumption that expectation formation is not costless. Consequently, economically rational agents are assumed to optimize their costs of acquiring and processing information given the resulting benefits of forecast accuracy. This notion of economic rationality is in contrast to the Muthian model of rational expectations, which assumes that expectation formation is costless. The idea that agents form economically rational forecasts is proposed by Feige and Pearce (1976). According to their notion, an agent forms economically rational expectations "only if he considers both the costs of misestimating future inflation and the costs of making his forecast of future inflation." A well known similar concept is near rationality as proposed by Akerlof, Dickens and Perry (2000). In their macroeconomic model, firms and workers do not take full account of expected inflation when setting prices and wages as long as inflation is low and not relevant in economic terms. However, near rationality as proposed by Akerlof, Dickens and Perry (2000) concerns the adjustment of prices and wages to expectations rather than the formation of expectations itself. Although the idea of economically rational expectations is not new, only recently a number of consistent approaches on expectation formation have been proposed. These include the concepts of information delay rational expectations, rational inattention and rationally heterogeneous expectations.

The concept of information delay rational expectations has been advanced by the sticky information models of Mankiw and Reis (2002, 2006). In sticky information models, agents update information sets only sporadically. Those agents who acquire new information rationally update their plans (i.e., their sequence of beliefs about future periods), whereas the rest of agents sticks to plans based on outdated information. In contrast to the standard sticky price model underlying the New Keynesian Phillips curve, the sticky information model allows agents to reset prices in every period. By incorporating sticky information, the models of Mankiw and Reis (2002, 2006) reproduce empirical patterns such as the acceleration phenomenon, smoothness of real wages and inertial responses of real variables to shocks. As argued by Mankiw and Reis (2002), a microfoundation for this behavior lies in costs associated with acquiring and processing information. Important empirical evidence in favor of sticky information is provided by Mankiw, Reis and Wolfers (2004). They find that household expectations taken from the Michigan survey show patterns consistent with sticky information. In particular, Mankiw, Reis and Wolfers (2004) show that forecast heterogeneity in an artificial population that behaves according to the sticky information assumption closely tracks heterogeneity in actual survey expectations. A related information delay approach is proposed by Carroll (2003). In his epidemiological model of expectations, only a fraction of agents encounters news about inflation in a given period. The remaining agents are assumed to stick to last period's expectation, rather than to an outdated sequence of beliefs as in the sticky information model. Relying on response data from the Michigan survey, Carroll (2003) finds that inflation expectations are consistent with the implied inertial response of aggregate expectations to new information. Carroll (2003) further highlights that the model implies a positive relation between coverage of inflation in the news media and the accuracy of inflation expectations, which is confirmed empirically.

Sims (2003) and Williams (2004) argue that information delay models are less appropriate if agents have high incentives to acquire the most recent information, which should especially apply to professional forecasters. Relying on information theory, Sims (1998, 2003) proposes the alternative concept of rational inattention. Rational inattention assumes that economic agents rationally allocate their limited capacity to acquire and process information. Sims (2003) shows that the assumption of finite information capacity induces an inertial response of beliefs to new information, similar to patterns in standard signal extraction problems. Sims (2003) further analyzes how rational agents optimally allocate capacity to monitor different information sources. His results indicate that the rational inattention framework allows to reconcile inertial responses to shocks in slow-moving variables with pronounced responses to shocks in volatile and less persistent variables. Although rational inattention bears similarity to signal extraction rational expectations as in the imperfect information model of Lucas (1973), the latter concept does not incorporate optimizing behavior but introduces exogenous assumptions on the observability of information. Sims (2003) also stresses the relevance of information coding services such as the news media. Since individuals lack the capacity to absorb all publicly available information, the coding of information, e.g., given by the visibility of an article in a newspaper, becomes relevant and may induce a common reaction in the population.

A general framework of optimizing behavior in expectation formation is the theory of rationally heterogeneous expectations proposed by Branch (2004). Building on Brock and Hommes (1997), Branch (2004) proposes a model of rational predictor selection in which agents select predictors by evaluating associated costs and benefits. The probability that an agent selects a particular model of expectation formation is governed by a discrete choice model. Branch (2004) shows that this model is consistent with household inflation expectations taken from the Michigan survey. Using the set of static expectations, adaptive expectations and vector-autoregressive forecasts, Branch (2004) finds that the probability of a particular predictor being chosen depends inversely on its mean squared error relative to realized inflation. Branch (2007) considers a different set of predictors which comprises sticky information forecasts based on alternative updating frequencies. He confirms that the rationally heterogeneous expectations model adequately reproduces the actual heterogeneity in household survey expectations. In contrast to rational inattention and sticky information, the theory of rationally heterogeneous expectations does not impose a particular scheme of expectation formation.

1.3 Objectives of the Thesis

The concepts of information delay rational expectations, rational inattention and rationally heterogeneous expectations have in common that observable expectations do not satisfy the traditional, Muthian notion of rationality. Rather, the entire process of expectation formation is subject to rational optimization. Consequently, expectation formation may vary over time. Moreover, the new approaches are consistent with heterogeneous expectations across the population. Sticky information generates heterogeneity as staggered updating leads to heterogeneous information sets. Rational inattention generates heterogeneity as capacity constraints, objective functions and information processing errors are heterogeneous. Rationally heterogeneous expectations allows for heterogeneity due to heterogeneous costs and benefits associated with predictors. That survey expectations are highly heterogeneous is documented by the literature on microdata discussed above. However, with the notable exceptions of Branch (2004, 2007), Carroll (2003) and Mankiw, Reis and Wolfers (2004), heterogeneity of household expectations is largely unexplored. Heterogeneity of inflation expectations of professional forecasters has obtained more research attention. A large literature considers the relation between survey heterogeneity and forecast uncertainty, see, e.g., Boero, Smith and Wallis (2008), Giordani and Söderlind (2003) and Lahiri and Sheng (2009b). Moreover, several contributions propose models of expert disagreement, including Bayesian learning (Lahiri and Sheng, 2008), strategic behavior (Laster, Bennett and Geoum, 1999), herding, conservatism, optimism and asymmetric loss (Batchelor, 2007, Capistrán and Timmermann, 2009).

The main objective of this thesis is to contribute to the understanding of heterogeneity of household survey expectations. Building on the notion of rationally heterogeneous expectations, Chapter 3 proposes a mixture model of survey heterogeneity. This model explains heterogeneity of inflation expectations by heterogeneity in expectation formation models. Chapter 4 investigates whether the information delay rational expectations model is consistent with the central tendency and cross-sectional heterogeneity of survey beliefs of European households.

If agents form economically rational expectations, the role of the news media becomes potentially important. Information delay rational expectations models are consistent with the notion that the absorption of new information in the population is positively correlated with the intensity of news coverage by the media. E.g., the probability that a household encounters information about inflation will increase in the salience of inflation in the news media. The theory of rational inattention suggests that media coverage has an important coding function. Given the limited capacity to acquire and process information, the attributed importance and visibility of an issue in the news media influences the absorption of information in the population. Consequently, the objective of Chapter 5 is to explore the role of media coverage for heterogeneity in inflation expectations.

Household surveys are mostly qualitative. A further objective of this thesis lies in determining how to best convert qualitative household response data into quantitative beliefs. Chapter 2 assesses common methods for quantifying both the central tendency and the cross-sectional heterogeneity of beliefs about inflation.

Finally, inflation expectation formation is directly related to the actual inflation process. On the one hand, as emphasized by Stock and Watson (2007), the time series properties of inflation have important consequences for the relative accuracy of common expectation formation models. On the other hand, in the New Keynesian model, the extent to which expectations and price setting are forward-looking is causal to the aggregate persistence of the inflation process. Chapter 6 ties in with both aspects by investigating the persistence of consumer price inflation in Switzerland. The main objectives are to estimate persistence at disaggregate price levels and to identify structural breaks in persistence.

1.4 Outline and Contribution of the Thesis

Chapter 2 assesses the validity and accuracy of the 5-category probability method for quantifying qualitative beliefs about inflation as surveyed by the Joint Harmonized EU Consumer Survey programme. The analysis capitalizes on response data from the Swedish Consumer Tendency Survey which records both qualitative and quantitative beliefs. Moreover, the Swedish survey asks households to report both the perceived inflation rate over the past 12 months (inflation perception) as well as the expected 12 months ahead inflation rate (inflation expectation). Chapter 2 extends the existing literature by joining qualitative and quantitative response data on household-level. It focuses on the 5-category probability method and discusses quantification of perceptions and expectations of inflation, whereas existing literature mostly assesses the 3-category method for quantifying inflation expectations. Moreover, methods to quantify both the central tendency and the cross-sectional heterogeneity are being discussed. Relying on monthly data spanning 1996–2008, the theoretical assumptions of the 5-category probability method are individually and jointly rejected. Maximum likelihood estimations of unrestricted response schemes indicate that the actual response scheme is neither symmetric nor homogeneous across individuals. Moreover, it is shown that qualitative inflation expectations are formed relative to inflation perceptions, which is a direct result of the survey design. Nevertheless, the accuracy of the 5-category probability method in terms of correlation with the cross-sectional mean of actual quantitative beliefs is high. For quantifying inflation expectations the accuracy of the method strongly depends on the identifying restriction imposed by the choice of reference inflation. Relying on double block bootstrap confidence intervals for Fisher's z-statistic, it is shown that setting reference inflation equal to previously quantified inflation perceptions yields significantly better results than setting reference inflation equal to actual inflation. This also suggests that the 5-category probability method with reference inflation given by quantified perceptions might gain relative accuracy once inflation perceptions substantially deviate from actual inflation. The most accurate measure of cross-sectional heterogeneity is the index of qualitative variation. This index performs significantly better than the

5-category probability method and other common approaches.

Chapter 3 infers how households form inflation expectations by estimating a model of the cross-sectional heterogeneity of survey expectations. The proposed Gaussian mixture model is a generalization of the model of rationally heterogeneous expectations, thereby extending previous literature. The mixture model constitutes a new approach towards the analysis of expectation formation: Rather than testing particular models of expectation formation, the approach allows to infer the probability that a given model is being used by survey participants. Moreover, Chapter 3 investigates the largely unexplored role of inflation perceptions for expectation formation. The Gaussian mixture model assumes that to form an inflation expectation, every household selects a predictor from a set of available predictors. However, the survey response does not need to be exactly equal to the particular predictor value. Rather, responses of households that opt for the same predictor may differ due to idiosyncrasies in rounding, differences in information sets and differences in conceptual understandings of inflation. Consequently, the model assumes that responses generated by a particular predictor are normally distributed around the predictor value. Since multiple predictors are being employed in the survey population, the probability density of survey expectations is a Gaussian mixture density. The model is estimated using quantitative household survey data from the Swedish Consumer Tendency Survey spanning 1996–2008. An explorative analysis shows that inflation expectations are highly heterogeneous and that an important relation exists between perceptions and expectations of inflation. Accordingly, the mixture model is estimated assuming that households select among conventional static expectations (equal to the official inflation figure), idiosyncratic static expectations (equal to the subjective perception of current inflation), adaptive expectations and rational expectations (equal to the mean of professional forecasts). The estimates robustly show that about 51% of households form idiosyncratic static expectations, 19% form rational expectations and 15% each form adaptive expectations and conventional static expectations. The significance and robustness of the estimates corroborate the mixture model. Overall, the results clearly show that subjective inflation perceptions are a key determinant of inflation expectations. Consequently, a better understanding of perception formation will have direct implications for our understanding of expectation formation.

Chapter 4 investigates how households form perceptions about inflation. The chapter is based on quantified inflation perceptions taken from the Joint Harmonized EU Consumer Survey. The sample covers 12 countries and spans 1993–2007. Unlike previous literature which mainly investigates the effects of the euro cash changeover and socioeconomic factors, Chapter 4 presents general evidence on the relation of actual consumer price inflation and perceived inflation. In particular, the epidemiological model of Carroll (2003) is tested using inflation perceptions rather than inflation expectations. The advantage of using inflation perceptions is that uncertainty about the rational benchmark is lower than for expectations: The rational inflation perception is given by the publicly available, official inflation figure. An explorative analysis shows that inflation perceptions are generally inaccurate and fail rationality tests. Still, perceptions are related to contemporaneous and lagged inflation. Moreover, perceptions exhibit a high degree of cross-sectional heterogeneity. These broad patterns are consistent with the epidemiological model of belief formation proposed by Carroll (2003). Consequently, it is formally tested whether the dynamics of the cross-sectional mean and standard deviation of inflation perceptions can be explained by the epidemiological model. This is, to some extent, also an assessment of the sticky information hypothesis of Mankiw and Reis (2002). In almost all countries within the sample the model is clearly rejected. In particular, it is shown that the cross-sectional heterogeneity of inflation perceptions is significantly lower in an artificial population that behaves according to the epidemiological model than in the survey data. Overall, the findings suggest that other sources of disagreement are important in addition to differences in information sets due to staggered updating.

Chapter 5 investigates the effects of media coverage on the heterogeneity of inflation expectations of German households and professional forecasters. The analysis is based on media content data that covers the most important newspapers and TV-news during 1998–2007. This chapter extends previous literature by proposing a theoretical framework that accounts for an agenda setting function of the news media. Moreover, the analysis of heterogeneity in household survey expectations adds to the literature which centers on heterogeneity of professional expectations. The effects of media coverage are embedded in a Bayesian learning model which follows Kandel and Zilberfarb (1999). The model assumes that media coverage affects forecast disagreement by influencing information sets and predictor choice of survey respondents. Forecast disagreement is governed by the dispersion of prior beliefs and by the amount, the heterogeneity and the tone of media reports about inflation. Since agents obtain signals from various sources, the empirical specifications control for a set of macroeconomic variables. The estimations show that inflation forecast disagreement of households and professional forecasters is affected by macroeconomic variables. The estimations suggest that the level of inflation is a robust driver of heterogeneity of household expectations. At low levels of inflation disagreement is declining in inflation, whereas disagreement is rising again once inflation exceeds the level consistent with price stability as defined by the European Central Bank. Conditional on the macroeconomic control variables the effects of media coverage are being investigated. The estimations confirm that media coverage plays a role for disagreement of households, but not for disagreement of professionals forecasters. This finding is in line with the conjecture that professional forecasters have incentives to acquire the most recent information and to select forecasting models irrespective of media coverage. The effects on household disagreement are limited to the tone of media reporting. The estimations robustly show that if the tone of media reporting is pessimistic, emphasizing that inflation is rising, disagreement of households declines. This is consistent with the model view that by setting the agenda, media coverage can induce a homogeneous predictor distribution among households.

Chapter 6 investigates the persistence of Swiss consumer price inflation using aggregate and disaggregate inflation data spanning 1983–2008. This chapter extends recent empirical literature on disaggregate inflation persistence which focuses on the U.S. and the euro area. Moreover, it contributes to the literature about the effects of monetary policy regimes on the inflation process by testing whether persistence has changed over time. The estimation results consistently indicate that inflation persistence has significantly declined in the early 1990s. This is suggested by median unbiased estimates of the sum of autoregressive coefficients and confidence intervals using the grid-bootstrap estimator of Hansen (1999). Formal tests of structural change signal a significant break in the sum of autoregressive coefficients in 1993. During 1993–2008, headline inflation is clearly stationary. At the disaggregate level, 87% of inflation rates at index position level are stationary. Due to the small number of observations, estimations for the new monetary policy regime introduced in December 1999 are associated with high uncertainty. The results indicate, however, that relative to the period 1993–1999, the persistence of inflation did not significantly change in the period 2000–2008. Inflation persistence significantly declined in the first half of the 1990s, several years before the announcement and implementation of the new monetary policy concept. Moreover, it is documented that inflation persistence is substantially lower at disaggregate levels than at aggregate levels, a finding which is in line with the literature. An estimated factor model provides an explanation. The factor model decomposes sectoral inflation rates into a common component and a sectoral component. The common component represents macroeconomic factors with a general impact across sectors, such as monetary policy shocks. The sectoral component captures idiosyncratic factors, such as sectoral demand and technology shocks. Depending on the sample period and aggregation level, about 70 to 90 percent of the variance in sectoral inflation rates is accounted for by sectoral factors. It is found that the common macroeconomic component is highly persistent, whereas sectoral components are not. Both the relevance and the persistence of the common component have declined over time.

Chapter 2

On the Accuracy of the Probability Method for Quantifying Beliefs About Inflation*

*This chapter is based on Maag (2009).

2.1 Introduction

Surveys of households and firms are often qualitative. Rather than giving a quantitative estimate of a particular variable, respondents are asked to indicate their beliefs on qualitative scales. In the European Union (EU), beliefs of households about inflation are surveyed as part of the Joint Harmonized EU Consumer Survey programme. Within this framework, harmonized qualitative surveys are conducted in all member states, covering a national sample size of roughly 1,500 households on a monthly basis. The EU consumer survey thus provides an extensive and consistent dataset on beliefs about inflation.[1] In particular, the EU consumer survey both asks for perceptions about current inflation and expectations about future inflation. Consequently, the response data has been investigated by a large literature. Only recently, the euro cash changeover and its effects on inflation perceptions of households has given rise to a new strand of research.[2] Since the EU consumer survey is qualitative, most empirical applications rely on a method to quantify the qualitative response data in the first place. This paper assesses the validity of one particular method, the probability method for 5-category scales, and compares its accuracy to other quantification approaches.

Possibly the most widely used quantification method is the balance statistic proposed by Anderson (1952). It is originally defined as the difference between the share of respondents that perceive or expect positive inflation rates and the share of respondents that perceive or expect negative inflation rates. Theil (1952) rationalizes the balance statistic,

[1] Currently, the Joint Harmonized EU Consumer Survey covers a monthly sample of roughly 40,000 consumers in 27 member states. The consumer survey consists of 15 qualitative questions pertaining to the household's financial situation, perceived economic conditions and planned savings and spending. The questionnaire is translated into national languages and may include additional country specific questions, see European Commission (2007).

[2] This literature centers on the rise in perceived inflation coinciding with the euro cash changeover, as documented in ECB (2005). Several explanations are being discussed, including increased information processing requirements due to conversion rates, overreaction to prices of frequently bought items and anchoring of perceptions to prior expectations. See, e.g., Ehrmann (2006), Aucremanne, Collin and Stragier (2007), Doehring and Mordonu (2007), Dziuda and Mastrobuoni (2006), Aalto-Setälä (2006) and Fluch and Stix (2007). Abstracting from the euro cash changeover, other contributions use the EU consumer survey data to investigate belief formation in general, see, e.g., Döpke, Dovern, Fritsche and Slacalek (2008a), Forsells and Kenny (2004) and Lamla and Lein (2008). Chapter 4 adds to this literature by investigating the dynamics of inflation perceptions.

demonstrating that it is an appropriate measure of the population mean if quantitative beliefs are uniformly distributed. Furthermore, Theil (1952) suggests that the distributional assumption may be relaxed by imposing a normal distribution instead. Combined with the assumption that respondents perceive or expect prices to be constant in qualitative terms if their quantitative belief is within an indifference interval around 0%, the mean and variance of the imposed distribution can be identified. The model of Theil (1952) has been rediscovered by Carlson and Parkin (1975) and is known today as the Carlson-Parkin method or the 3-category probability method.[3] Batchelor and Orr (1988) extend the probability method to response data on 5-category scales as it is available from the EU consumer survey. Taking into account the particular wording of the EU consumer survey, Berk (1999) additionally suggests an identification scheme that links inflation expectations to inflation perceptions.

The goal of this paper is to assesses the 5-category probability method and to derive lessons for applied research. The analysis relies on joining qualitative and quantitative response data on household-level, taken from the Swedish Consumer Tendency Survey. To the best of my knowledge, only two studies have investigated surveys that ask for both qualitative and quantitative responses. Defris and Williams (1979) consider a 5-year sample from an Australian consumer survey. They document that the balance statistic as well as the 3-category probability method generate series that are only weakly correlated with quantitative survey responses. Batchelor (1986) investigates micro-data from the University of Michigan Survey of Consumers. In line with Defris and Williams (1979), Batchelor (1986) finds that both the balance statistic and quantified expectations generated with the probability method are inaccurate, in particular in the short term. This result is in contrast to my findings for Sweden.

This paper extends the literature in several respects. First, it provides a detailed as-

[3] A less common quantification method is the regression approach of Pesaran (1987). The regression method extends the balance statistic, allowing for a non-linear relation between response shares and quantitative beliefs. The method is outlined in Section 2.4. Pesaran (1987) discusses the three-category probability method and the regression approach in detail. Nardo (2003) provides a recent survey of quantification methods.

sessment of the theoretical assumptions underlying the 5-category probability method. Existing research focuses on the 3-category probability method and on testing distributional assumptions. Joining quantitative and qualitative responses on household-level allows to estimate unrestricted response schemes. The restrictions imposed by the 5-category probability method can then be tested using likelihood theory. Second, the accuracy of the 5-category probability method relative to the mean and cross-sectional standard deviation of quantitative responses is assessed in a long sample of 154 monthly surveys spanning 01/1996–10/2008. The discussion centers on comparing correlation coefficients relying on the Fisher z-transformation and double block bootstrap confidence intervals. Accuracy is compared to a set of alternative quantification methods, including the 3-category probability method, the balance statistic and the regression approach. For quantifying the cross-sectional heterogeneity of beliefs, the set of alternatives includes the 3-category probability method, an index of qualitative variation, an index of ordinal variation and the disconformity index. Third, the probability method is assessed for quantifying both perceptions and expectations of inflation.

The paper is structured as follows. Section 2.2 presents the data and highlights important statistical properties. Section 2.3 assesses the assumptions of the 5-category probability method. Section 2.4 investigates the accuracy of the method and contrasts it with alternative approaches. Section 2.5 draws lessons for applied research. Section 2.6 concludes.

2.2 Data

Inflation opinions of Swedish households are being surveyed on a monthly basis since 1973. This paper uses monthly household-level response data which is available for the period 01/1996–10/2008.[4] Unlike most surveys in other countries, the Swedish Consumer Tendency Survey jointly asks for qualitative and quantitative beliefs about inflation. The questionnaire captures beliefs in two steps.[5] In a first step, households are asked to report perceived inflation on a five-category ordinal scale. This qualitative question is in line with the questionnaire of the Joint Harmonized EU Consumer Survey. The question reads:

> "Compared with 12 months ago, do you find that prices in general are. . . ?" "Lower (S_1), about the same (S_2), a little higher (S_3), somewhat higher (S_4), a lot higher (S_5), don't know".

In the following, S_1 through S_5 denote the qualitative response categories and s_1 through s_5 are the fractions of households that opt for the respective category.[6] In a second step, households are asked for a direct quantitative estimate of the current annual inflation rate. The question reads: "How much higher/lower in percent do you think prices are now? (In other words, the present rate of inflation)". As a result and in contrast to the Joint Harmonized EU Consumer Survey, households report both qualitative and quantitative beliefs about inflation. In a similar manner, expected inflation is captured in a first step by asking:

> "Compared to the situation today, do you think that in the next 12 months prices

---

[4]During this period, the survey comprises a monthly sample of roughly 1,500 households which are interviewed by telephone. The sample horizon is limited by data availability. Before 1996, qualitative responses were only recorded on a 3-option ordinal scale and quantitative beliefs were only surveyed on a quarterly basis.

[5]The exact procedure is outlined in the GfK (2002) survey manual. A schematic of the questioning can be found in Palmqvist and Strömberg (2004). Note that the English description of the response categories provided by GfK (2002) differs from the official terminology in European Commission (2007). In particular, European Commission (2007) labels the category S_4 in the question on perceived inflation "moderately higher".

[6]Response shares are computed excluding the "don't know" category, i.e. s_1 through s_5 sum up to 100%.

in general will...?" "Go down a little (S_1), stay more or less the same (S_2), go up more slowly (S_3), go up at the same rate (S_4), go up faster (S_5), don't know".

In a second step, quantitative beliefs are captured by asking: "Compared with today, how much in percent do you think prices will go up/down? (In other words, inflation/deflation 12 months from now)".

In line with the literature, the quantitative response data is adjusted for outliers. Responses outside the interval $[-30\%, 30\%]$ are omitted which reduces the sample size by 0.3%.[7] Moreover, only observations that contain non-missing responses to the qualitative and quantitative questions are considered. Regarding inflation perceptions, 13% of observations only include a qualitative but no quantitative response. Regarding inflation expectations, 15% of observations only include a qualitative but no quantitative response. As will be discussed in the next section, a theoretical assumption of quantification methods is that households form quantitative beliefs. The high shares of missing quantitative responses can therefore be considered as evidence against this assumption. However, an alternative interpretation is that qualitative responses with missing quantitative responses are uninformed and should be attributed to the "don't know" category.[8]

As Table 2.1 shows, the resulting sample includes almost 200,000 observations from 154 monthly surveys spanning 01/1996–10/2008. Throughout this paper, the discussion centers on this sample. The appendix additionally presents results for a shorter sample covering 01/2002–10/2008. I consider this subsample to account for a potential structural break due to a change in the surveying institution in 01/2002. As will be shown, results for both estimation periods are consistent, confirming the validity of the results for the full

[7] Over the entire sample period, 667 (443) observations contain quantitative inflation perceptions (expectations) that are outliers.

[8] This view is supported by the distribution of missing quantitative answers by qualitative response category. For inflation perceptions, about 70% of missing quantitative answers are accounted for by respondents that opt for the qualitative category S_3 ("a little higher"). For inflation expectations, 40% of missing quantitative answers are accounted for by respondents that opt for the qualitative category S_4 ("go up at the same rate"). Note that 1.3% (2.2%) of all observations only contain a quantitative but no qualitative perception (expectation).

TABLE 2.1: Summary statistics for quantitative responses

	Perceptions			Expectations		
	Overall	Min	Max	Overall	Min	Max
Observations	197,487	1,031	1,456	192,845	961	1,417
Number of months	154			154		
Mean	1.81	0.47	5.91	2.10	0.59	4.66
Median	0.00	0.00	5.00	1.00	0.00	4.00
Standard deviation	4.06	2.68	5.37	3.73	2.68	4.94
Share of integer answers	0.94	0.86	0.98	0.92	0.82	0.98
Share of focal point answers	0.81	0.50	0.92	0.72	0.56	0.86
Share of zero responses	0.59	0.08	0.80	0.44	0.12	0.70
Mean response, given S_1	-4.79	-20.00	-2.12	-3.89	-6.36	-2.53
Mean response, given S_2	0.03	-0.05	0.46	0.02	-0.03	0.24
Mean response, given S_3	4.72	3.98	5.95	4.06	3.04	5.55
Mean response, given S_4	7.94	5.22	10.72	4.77	3.91	6.06
Mean response, given S_5	9.58	4.25	16.00	3.98	3.12	6.14

Notes: The column *overall* presents results for the entire sample spanning 01/1996–10/2008. *Min* and *Max* are the monthly minimum and maximum of the respective statistic. All shares are relative to the overall number of observations.

sample.[9] As a measure of actual inflation I use the year-over-year percentage change in the Harmonized Index of Consumer Prices (HICP) as published by Eurostat.[10]

Figure 2.1a plots the cross-sectional mean of quantitative inflation perceptions, together with qualitative response shares and the actual inflation rate. The figure indicates that quantitative inflation perceptions closely track actual inflation. The correlation between the two series is 0.78. Moreover, the first panel of Table 2.1 shows that the overall mean of inflation perceptions is 1.81%, as opposed to an average HICP inflation rate of 1.61%. Hence, inflation perceptions of the Swedish public are roughly unbiased during 01/1996–10/2008. This finding is in line with earlier results of Jonung and Laidler (1988) for

[9]In 01/2002 the surveying institution has changed from Statistics Sweden to GfK Sweden. The change goes along with a decline in the share of missing quantitative responses. This might be partly due to differences in the questioning, as outlined by Palmqvist and Strömberg (2004). However, the share of missing observations rises again sharply in 2008 to levels before 2002. Hence, part of the initial decline in the share of missing quantitative responses appears to be coincidental.

[10]I have also considered the Consumer Price Index (CPI) and the Consumer Price Index excluding mortgage payments and indirect taxes (CPIX). Particularly at the beginning of the sample period, these indices might have obtained more attention by the Swedish public than the HICP. Employing these alternative indices does not alter the conclusions in qualitative terms.

Sweden.[11] Figure 2.1 further indicates that inflation perceptions surge in 2008, exceeding actual inflation by roughly 2%. Meanwhile, the share of qualitative responses in the lowest two categories S_1 and S_2 ("lower" and "about the same") sharply declines.

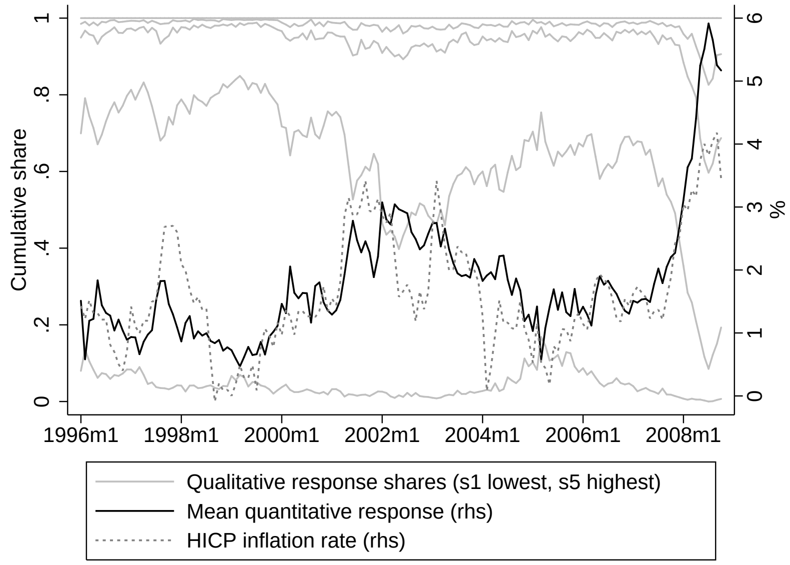
Figure 2.1b shows the cross-sectional mean of inflation expectations. Again, inflation expectations exhibit pronounced comovement with actual inflation, the correlation between the two series being 0.70. Predictive power is relatively low, as the correlation with 12 months ahead inflation is only 0.28. Table 2.1 documents that inflation expectations average somewhat higher than perceptions at 2.05%. Moreover, the figures reveal a systematic difference between qualitative perceptions and expectations of inflation. Qualitative inflation perceptions are concentrated in categories S_2 and S_3 ("about the same" and "a little higher"). During 1996–2008, 87% of respondents opt for these categories. In contrast, 70% of qualitative inflation expectations fall into categories S_2 and S_5 ("stay more or less the same" and "go up faster").

Table 2.1 highlights important properties of the quantitative response data. First, panel 1 shows that beliefs about inflation are highly heterogeneous. Despite the low cross-sectional means, inflation perceptions and expectations exhibit cross-sectional standard deviations of 4.06% and 3.73%, respectively. Second, panel 2 indicates that more than 90% of all quantitative answers are integers. Third, integer answers are concentrated at a few focal points.[12] Both for perceptions and expectations, the most frequently mentioned focal points are -5%, -2%, 0%, 2%, 5%, 10%.[13] As Table 2.1 indicates, the most important focal point is 0%, which accounts for more than half of all focal point responses. Towards the end of the sample period, the share of zero responses declines significantly. It attains a minimum of 8% for perceptions and 12% for expectations in 06/2008. The high share

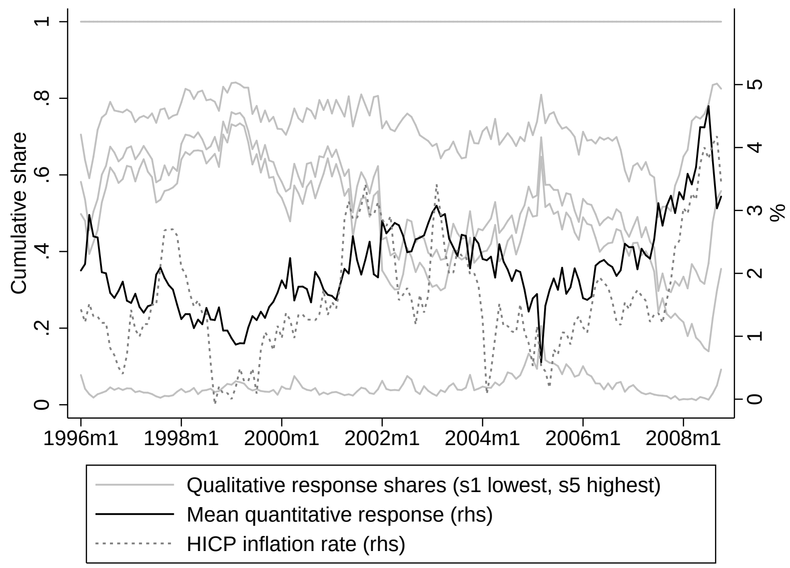
[11]Inflation perceptions in Sweden seem relatively accurate compared to other countries. Relying on a monthly household survey conducted by the Federal Reserve Bank of Cleveland, Bryan and Venkatu (2001a, 2001b) find that inflation perceptions (and expectations) exceed actual inflation by several percentage points. For the U.K., Driver and Windram (2007) report a correlation of perceived inflation with actual inflation of roughly 0.5 in a similar sample period.

[12]In line with Bryan and Palmqvist (2006), focal points are defined as integers that are mentioned more often than their neighboring integers. I have not found any evidence for important non-integer focal points.

[13]Of the remaining integers, 1, 3 and 4 obtain the highest response shares. This set accounts for 9% of quantitative inflation perceptions and for 15% of expectations.



(a) Perceptions



(b) Expectations

Figure 2.1: Qualitative response shares and mean quantitative response

Notes: The lowest grey line shows the share s_1 of qualitative answers in category S_1, the second-lowest grey line shows the cumulative share of answers in categories S_1 and S_2, etc.

of zero responses also explains the low medians of quantitative beliefs. Fourth, the cross-sectional mean of quantitative inflation perceptions is generally rising in the qualitative response category. This is shown in panel 3 which summarizes the conditional means of quantitative responses depending on the qualitative response. As opposed to inflation perceptions, qualitative inflation expectations are not ordered. For expectations, the mean response given S_4 ("go up at the same rate") is higher than the mean response given S_5 ("go up faster"). Also, in comparison to inflation perceptions, the differences between the cross-sectional means given qualitative responses S_3, S_4 and S_5 are only minor.[14] Fifth, the relation between quantitative and qualitative responses is time varying. The differences between overall, minimum and maximum conditional means are considerable for most categories. The only exception is S_2 ("about the same"): Given this qualitative response, the mean quantitative response is always close to 0%.

These initial results suggest that the relation between quantitative and qualitative beliefs about inflation is complex. The response scheme, i.e. the formal relation between quantitative and qualitative responses, appears to be time varying. Moreover, the conditional mean of quantitative expectations is not monotonously rising in the order of the qualitative response categories. While the 5-category probability method allows for a time varying response scheme, it imposes a certain symmetry on the response scheme and requires ordered qualitative data. Regarding the distributional assumptions, the mean and median values indicate that quantitative beliefs are positively skewed and therefore not normally distributed. The concentration of answers at focal points, in particular at 0%, raises additional doubt whether any of the common parametric distributions adequately describes the quantitative response data. The next section thus discusses in detail whether the assumptions of the probability method are consistent with the data.

[14] On a monthly basis, the mean of inflation perceptions is not always strictly rising too. This is indicated by the minima of monthly conditional means in panel 3 of Table 2.1. But the conditional means lack order only in 27 months, as opposed to 136 months for inflation expectations.

2.3 Validity of the Probability Method

2.3.1 Theoretical Assumptions

This section tests the main theoretical assumptions of the 5-category probability method for quantifying qualitative response data. Building on contributions of Theil (1952) and Carlson and Parkin (1975), the 5-category probability method has been proposed by Batchelor and Orr (1988). To begin with, the method is briefly outlined.

Assume that previous to answering the consumer survey, respondent i forms a quantitative belief $\pi^e_{t,i}$ about inflation over the upcoming 12 months.[15] Respondent i then answers the qualitative survey question on expected inflation according to the following response scheme:

$$\begin{aligned}
\pi^e_{t,i} < -\delta_t &\quad : \quad \textit{prices in general will} \text{ go down a little } (S_1) \\
-\delta_t \leq \pi^e_{t,i} < \delta_t &\quad : \quad \text{stay more or less the same } (S_2) \\
\delta_t \leq \pi^e_{t,i} < \pi^r_t - \eta_t &\quad : \quad \text{go up more slowly } (S_3) \\
\pi^r_t - \eta_t \leq \pi^e_{t,i} < \pi^r_t + \eta_t &\quad : \quad \text{go up at the same rate } (S_4) \\
\pi^e_{t,i} \geq \pi^r_t + \eta_t &\quad : \quad \text{go up faster } (S_5)
\end{aligned} \tag{2.1}$$

The response scheme is defined by the parameters δ_t, η_t and π^r_t. In the following, π^r_t is referred to as reference inflation. It is the inflation rate that people have in mind when opting for answer S_4 ("prices will go up at the same rate" and, for inflation perceptions, "prices are moderately higher"). The first key assumption of the probability method restricts the response scheme to be fully defined by these three parameters:

ASSUMPTION 1: The response intervals are symmetric around 0% and around π^r_t.

The corresponding intervals $[-\delta_t, \delta_t)$ and $[\pi^r_t - \eta_t, \pi^r_t + \eta_t)$ correspond to qualitative responses S_2 and S_4 respectively. A second assumption imposes structural homogeneity on the response scheme:

[15] The analogous approach for quantifying perceived inflation $\pi^p_{t,i}$ and detailed derivations can be found in Appendix A.1.

Assumption 2: Threshold parameters δ_t and η_t and the reference inflation π_t^r are identical across respondents.

Quantitative inflation expectations $\pi_{t,i}^e$ will vary across respondents due to differences in information sets and information processing. To infer the mean quantitative inflation expectation from qualitative response shares, the probability method imposes a distributional assumption on $\pi_{t,i}^e$. The standard assumption is that the cross-sectional distribution of quantitative beliefs is normal:

Assumption 3: The cross-sectional distribution of quantitative beliefs is normal, i.e. $\pi_{t,i}^e \sim N(\pi_t^e, (\sigma_t^e)^2)$.

The parameters of interest are the cross-sectional mean π_t^e and standard deviation σ_t^e of quantitative beliefs. As outlined in Appendix A.1, the above assumptions yield a system of 4 linearly independent equations with 5 unknowns (π_t^e σ_t^e, δ_t, η_t, π_t^r) which can be solved for π_t^e and σ_t^e. The solution for both parameters is equal to the product of reference inflation π_t^r and a function of the response shares $s_t^1, ..., s_t^5$.

The usual identification scheme restricts reference inflation π_t^r. For quantifying inflation expectations two choices of π_t^r are apparent. First, reference inflation can be set equal to some actual rate of inflation, assuming that the respondent knows the actual rate of inflation and answers the question relative to this value. Second, reference inflation can be set equal to previously quantified perceived inflation π_t^p as suggested by Berk (1999). This approach is supported by empirical evidence that households are not necessarily well informed about actual inflation.[16] Identifying π_t^r is less obvious for inflation perceptions. Following Carlson and Parkin (1975) it is commonly assumed that inflation perceptions are unbiased over the sample horizon. This assumption can be imposed by restricting π_t^r to a constant accordingly.[17] The last assumption thus reads:

Assumption 4: The reference rate of inflation π_t^r for quantifying inflation expectations

[16] See, e.g., Bryan and Venkatu (2001a, 2001b) who document that inflation perceptions of U.S. households are significantly biased.

[17] The solution for π_t^r is given by Equation (A.7) in the Appendix.

is equal to actual inflation or quantified perceived inflation. The reference rate of inflation for quantifying inflation perceptions is time invariant.

2.3.2 Symmetry of the Response Scheme

Assumption 1 restricts response intervals to be symmetric around 0% and around π_t^r. To test the validity of this assumption I estimate an unrestricted response scheme defined by 4 threshold parameters. Assume that respondent i answers the qualitative question according to the following scheme:[18]

$$
\begin{aligned}
\pi_{t,i}^e + \varepsilon_{t,i} < \mu_t^1 \quad &: \quad \textit{prices in general will} \text{ go down a little } (S_1) \\
\mu_t^1 \leq \pi_{t,i}^e + \varepsilon_{t,i} < \mu_t^2 \quad &: \quad \text{stay more or less the same } (S_2) \\
\mu_t^2 \leq \pi_{t,i}^e + \varepsilon_{t,i} < \mu_t^3 \quad &: \quad \text{go up more slowly } (S_3) \\
\mu_t^3 \leq \pi_{t,i}^e + \varepsilon_{t,i} < \mu_t^4 \quad &: \quad \text{go up at the same rate } (S_4) \\
\pi_{t,i}^e + \varepsilon_{t,i} \geq \mu_t^4 \quad &: \quad \text{go up faster } (S_5)
\end{aligned}
\tag{2.2}
$$

The idiosyncratic component $\varepsilon_{t,i}$ allows the response scheme to shift between individuals. Under the assumption that the idiosyncratic component represents the sum of independent idiosyncratic factors it is reasonable to assume that $\varepsilon_{t,i}$ is normally distributed. One thus obtains an ordered probit model (Zavoina and McKelvey, 1975). In contrast to the usual identification scheme, I restrict the coefficient on the quantitative belief $\pi_{t,i}^e$ to unity, whereas the variance of $\varepsilon_{t,i}$ remains unrestricted. Assuming that $\varepsilon_{t,i} \sim N(0, \sigma_t^2)$, the following probabilities are obtained:

[18]The identical scheme applies to inflation perceptions, with $\pi_{t,i}^e$ being replaced by $\pi_{t,i}^p$.

$$
\begin{aligned}
P(S_1|\pi^e_{t,i},\mu_t,\sigma_t) &= \Phi\left(\frac{-\pi^e_{t,i}+\mu^1_t}{\sigma_t}\right)\\
P(S_2|\pi^e_{t,i},\mu_t,\sigma_t) &= \Phi\left(\frac{-\pi^e_{t,i}+\mu^2_t}{\sigma_t}\right)-\Phi\left(\frac{-\pi^e_{t,i}+\mu^1_t}{\sigma_t}\right)\\
P(S_3|\pi^e_{t,i},\mu_t,\sigma_t) &= \Phi\left(\frac{-\pi^e_{t,i}+\mu^3_t}{\sigma_t}\right)-\Phi\left(\frac{-\pi^e_{t,i}+\mu^2_t}{\sigma_t}\right)\\
P(S_4|\pi^e_{t,i},\mu_t,\sigma_t) &= \Phi\left(\frac{-\pi^e_{t,i}+\mu^4_t}{\sigma_t}\right)-\Phi\left(\frac{-\pi^e_{t,i}+\mu^3_t}{\sigma_t}\right)\\
P(S_5|\pi^e_{t,i},\mu_t,\sigma_t) &= 1-\Phi\left(\frac{-\pi^e_{t,i}+\mu^4_t}{\sigma_t}\right)
\end{aligned}
$$

where $\mu_t = \{\mu^1_t, ..., \mu^4_t\}$. Deviating from the assumptions of the probability method, μ^1_t, μ^2_t and μ^3_t, μ^4_t are not required to be symmetric around 0% and the reference rate of inflation, respectively.

Table 2.2 presents the maximum likelihood estimation results of the unrestricted response scheme. By construction, the threshold parameters are rising in the qualitative response category. The model is confirmed by highly significant parameter estimates which are stable across subperiods. The width of the interval $[\mu^1_t, \mu^2_t)$ corresponding to qualitative response S_2 ("about the same") exceeds 8% both for perceptions and expectations. The estimated parameters suggest that this interval is not symmetric around 0%. Relying on maximum likelihood theory, I test the restriction that $\mu^1_t = -\mu^2_t$ with a likelihood ratio test.[19] The second panel of Table 2.2 shows that this test clearly rejects the null hypothesis of symmetry.

The estimates point to systematic differences between perceptions and expectations. While the threshold parameters for inflation perceptions are increasing from $\mu^1_t = -6.91\%$ to $\mu^4_t = 13.89\%$, the thresholds for inflation expectations range between $\mu^1_t = -7.04\%$ and $\mu^4_t = 5.61\%$. For inflation expectations, the threshold parameters that define the response intervals for S_3, S_4, S_5 are in a narrow range of 4 to 5 percent. This allows

[19] The test statistic is given by $LR = -2\,(\log L_r - \log L_i) \rightarrow \chi^2(q)$, where $\log L_r$ is the log likelihood of the restricted model and $\log L_i$ is the log likelihood of the unrestricted model. The number of restrictions is given by $q = 1$.

TABLE 2.2: Estimated response schemes for perceived and expected inflation

	1996–2008		2002–2008	
	Perceptions	Expectations	Perceptions	Expectations
μ_t^1	-6.909***	-7.404***	-7.595***	-7.883***
	(0.0300)	(0.0367)	(0.0457)	(0.0556)
μ_t^2	3.194***	1.739***	2.526***	0.617***
	(0.0138)	(0.0141)	(0.0188)	(0.0230)
μ_t^3	10.95***	2.797***	10.97***	2.005***
	(0.0267)	(0.0141)	(0.0362)	(0.0212)
μ_t^4	13.89***	5.609***	14.04***	5.682***
	(0.0388)	(0.0174)	(0.0520)	(0.0251)
σ_t	3.782***	4.427***	4.260***	5.083***
	(0.0118)	(0.0163)	(0.0181)	(0.0270)
N	197,487	192,845	110,071	109,782
Log L	-138,263	-220,521	-88,738	-136,562
Likelihood ratio tests				
H_0^1: Symmetry such that $\mu_t^2 = -\mu_t^1$ $(q = 1)$				
LR statistic	20,978.94	35,749.40	17,427.61	25,138.60
P-value	0.00	0.00	0.00	0.00

Notes: This table shows maximum likelihood estimates of the unrestricted response scheme (2.2). Monthly data, 01/1996–10/2008 and 01/2002–10/2008. N is the number of observations, log L is the log likelihood, standard errors in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

for two interpretations: Either, the response intervals are indeed narrower for inflation expectations than for inflation perceptions, or the ordered model does not adequately describe the formation of qualitative inflation expectations. The second interpretation is suggested by the lack of order in conditional means documented in Section 2.2. The unordered nature of qualitative responses seems to be caused by the relative wording of the response categories. The qualitative response S_4 ("prices will go up at the same rate") anchors the qualitative expectation to the perception of current inflation. A respondent who gives consistent answers will always opt for qualitative response S_4 if the quantitative expectation corresponds to the subjective quantitative perception of inflation, irrespective of the level of expected inflation. The second interpretation is also supported by the substantially lower log likelihood of the model for expectations, despite the lower number of observations.

I therefore estimate a scheme for positive inflation expectations $\pi^e_{t,i}$ that accounts for the role of quantitative inflation perceptions $\pi^p_{t,i}$ at the household-level:

$$\begin{aligned} \pi^e_{t,i} + \varepsilon_{t,i} < \pi^p_{t,i} + \mu^1_t &\quad : \quad \textit{prices in general will } \text{go up more slowly } (S_3) \\ \pi^p_{t,i} + \mu^1_t \leq \pi^e_{t,i} + \varepsilon_{t,i} < \pi^p_{t,i} + \mu^2_t &\quad : \quad \text{go up at the same rate } (S_4) \\ \pi^e_{t,i} + \varepsilon_{t,i} \geq \pi^p_{t,i} + \mu^2_t &\quad : \quad \text{go up faster } (S_5) \end{aligned} \tag{2.3}$$

where $\varepsilon_{t,i} \sim N(0, \sigma^2_t)$. This scheme assumes that the respondent will opt for S_4 if $\pi^e_{t,i} - \pi^p_{t,i}$ lies in the range $[\mu^1_t, \mu^2_t)$. Maximum likelihood estimation results can be found in the last column of Table 2.3. All parameters are highly significant, confirming that the qualitative response about expected inflation is linked to the quantitative inflation perception. Moreover, the response interval is highly asymmetric: Qualitative answers are more responsive to an increase of quantitative expectations over perceptions than to a decrease. The significance of the relative response scheme suggests that despite the lack of an unambiguous relation between quantitative and qualitative expectations, the 5-category survey contains more information than a 3-category survey that does not distinguish between S_3, S_4 and S_5.

In sum, the results indicate that Assumption 1 is not satisfied. Under the normality assumption, the estimated response interval is not symmetric around 0%, both for inflation perceptions and expectations.[20] Furthermore, the response interval is not symmetric around π^r_t for inflation expectations. The estimations confirm that qualitative inflation expectations are formed relative to perceived inflation. This result suggests that the link between expectations and perceptions should be exploited in quantifying qualitative responses.

[20]This finding is consistent with Henzel and Wollmershäuser (2005) who investigate data from a special edition of the ifo World Economic Survey that directly asks respondents to indicate the indifference interval. Henzel and Wollmershäuser (2005) report that the positive threshold parameter is larger in absolute terms than the negative parameter. As opposed to the Swedish survey, however, the ifo survey queries professional forecasters and answers are given on a 3-category ordinal scale.

TABLE 2.3: Estimated relative response schemes for expected inflation

Expectations	Income groups (1st quartile lowest)				
	1st quartile	2nd quartile	3rd quartile	4th quartile	Overall
μ_t^1	-7.172***	-6.014***	-5.056***	-3.928***	-5.316***
	(0.184)	(0.116)	(0.0569)	(0.0132)	(0.0500)
μ_t^2	1.322***	1.059***	0.805***	0.575***	0.814***
	(0.0839)	(0.0550)	(0.0445)	(0.0104)	(0.0242)
σ_t	6.212***	4.956***	4.056***	3.182***	4.369***
	(0.139)	(0.0826)	(0.0062)	(0.0039)	(0.0347)
N	10,046	15,133	15,584	19,618	60,381
Log L	-8,759	-12,591	-12,436	-14,921	-49,217
Likelihood ratio tests				LR statistic	P-value
H_0^1: Identical threshold parameters μ_t^1, μ_t^2 ($q = 6$)				746.60	0.00
H_0^2: Identical standard deviation σ_t ($q = 3$)				907.96	0.00
H_0^3: Identical thresholds and standard deviation ($q = 9$)				1,020.93	0.00

Notes: This table shows maximum likelihood estimates of the relative response scheme (2.3). Monthly data, 01/2002–10/2008. Standard errors in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

2.3.3 Homogeneity of the Response Scheme

Assumption 2 imposes that threshold parameters δ_t and η_t and reference inflation π_t^r are homogeneous across respondents. Since the Swedish dataset only contains one observation per individual, this assumption is tested by estimating the response scheme for different income groups.[21] Tables 2.4 and 2.5 summarize the estimation results for perceptions and expectations, respectively. The tables show that the absolute values of threshold parameters tend to decline in income. The lower panel of Tables 2.4 and 2.5 show likelihood ratio tests of three restrictions. The null hypotheses state that threshold parameters are identical across income groups (H_0^1), that standard deviations are identical across income groups (H_0^2) and that threshold parameters and standard deviations are identical across income groups (H_0^3). All three hypotheses are clearly rejected.

Table 2.3 presents estimation results for the relative response scheme (2.3) that links expected inflation to perceived inflation. Again, all three hypotheses are clearly rejected.

[21] I have also considered educational groups, with unchanged qualitative results.

TABLE 2.4: Estimated response schemes for perceived inflation by income groups

Perceptions	Income groups (1st quartile lowest)				
	1st quartile	2nd quartile	3rd quartile	4th quartile	Overall
μ_t^1	-9.074***	-8.201***	-6.657***	-5.833***	-7.308***
	(0.142)	(0.105)	(0.0821)	(0.0627)	(0.0459)
μ_t^2	2.411***	2.487***	2.405***	2.366***	2.479***
	(0.0571)	(0.0429)	(0.0352)	(0.0271)	(0.0192)
μ_t^3	11.55***	11.68***	10.63***	9.405***	10.79***
	(0.100)	(0.0824)	(0.0704)	(0.0541)	(0.0372)
μ_t^4	14.60***	15.07***	13.53***	12.16***	13.77***
	(0.136)	(0.119)	(0.104)	(0.0836)	(0.0535)
σ_t	5.232***	4.682***	3.759***	3.179***	4.120***
	(0.0583)	(0.0425)	(0.0326)	(0.0238)	(0.0183)
N	17,092	24,845	25,482	32,614	100,033
Log L	-15,584	-20,718	-19,346	-23,163	-79,851
Likelihood ratio tests				LR statistic	P-value
H_0^1: Identical threshold parameters $\mu_t^1,\ldots,\mu_t^4$ ($q = 12$)				1,868.21	0.00
H_0^2: Identical standard deviation σ_t ($q = 3$)				1,115.68	0.00
H_0^3: Identical thresholds and standard deviation ($q = 15$)				2,080.00	0.00

Notes: This table shows maximum likelihood estimates of the unrestricted response scheme (2.2). Monthly data, 01/2002–10/2008. Standard errors in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

The estimates show the same pattern as above: The absolute values of threshold parameters are declining in income. Overall, these results suggest that the response scheme systematically differs across income-groups, which implies that Assumption 2 is violated.[22]

2.3.4 Normality of Quantitative Responses

Assumption 3 requires that the cross-sectional distribution of quantitative beliefs is normal. Normality has been tested and rejected for inflation expectations of consumers (Batchelor and Dua, 1987) and professional forecasters (Carlson, 1975, Lahiri and Teigland, 1987).

[22]Note that the mean of beliefs about inflation also depends on socioeconomic characteristics. The cross-sectional means of perceptions and expectations are declining in income. This pattern is consistent with the estimated response schemes that suggest that individuals in the highest income quartile experience deviations of inflation from zero as more relevant in qualitative terms than individuals in lower income quartiles.

TABLE 2.5: Estimated response schemes for expected inflation by income groups

Expectations	Income groups (1st quartile lowest)				
	1st quartile	2nd quartile	3rd quartile	4th quartile	Overall
μ_t^1	-9.229***	-8.303***	-7.031***	-5.968***	-7.598***
	(0.165)	(0.124)	(0.102)	(0.0747)	(0.0561)
μ_t^2	0.703***	0.440***	0.591***	0.783***	0.600***
	(0.0686)	(0.0527)	(0.0429)	(0.0315)	(0.0233)
μ_t^3	2.452***	1.972***	1.816***	1.835***	1.950***
	(0.0633)	(0.0480)	(0.0394)	(0.0294)	(0.0215)
μ_t^4	7.075***	6.164***	5.136***	4.407***	5.502***
	(0.0805)	(0.0575)	(0.0452)	(0.0328)	(0.0253)
σ_t	6.089***	5.448***	4.488***	3.789***	4.905***
	(0.0827)	(0.0614)	(0.0484)	(0.0344)	(0.0271)
N	17,232	24,757	25,384	32,528	99,901
Log L	-21,816	-31,163	-31,206	-39,092	-124,179
Likelihood ratio tests				LR statistic	P-value
H_0^1: Identical threshold parameters μ_t^1,...,μ_t^4 ($q = 12$)				1,102.84	0.00
H_0^2: Identical standard deviation σ_t ($q = 3$)				1,689.36	0.00
H_0^3: Identical thresholds and standard deviation ($q = 15$)				1,804.00	0.00

Notes: This table shows maximum likelihood estimates of the unrestricted response scheme (2.2). Monthly data, 01/2002–10/2008. Standard errors in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

These studies generally find that quantitative beliefs are positively skewed and leptokurtic. Both patterns can also be found in the Swedish survey data, as panel 1 of Table 2.6 indicates. Beliefs about inflation exhibit a pronounced positive skewness and are leptokurtic. Consequently, the Jarque-Bera test rejects the null hypothesis of normality in every single survey month, as panel 2 of Table 2.6 shows.

More generally, the probability method requires that beliefs follow some identifiable parametric distribution. Lahiri and Teigland (1987) suggest a noncentral t distribution as an alternative to the normal distribution. The noncentral t distribution allows for positive skewness and fat tails. I formally test whether quantitative responses follow this distribution using the Kolmogorov-Smirnov test.[23] Results are summarized in panel 3 of

[23] The Kolmogorov-Smirnov statistic is given by $D_n(F) = \sup_x |F_n(x) - F(x)|$, where $F_n(.)$ is the empirical distribution function. Note that the noncentral t distribution is equal to the t distribution if the

Table 2.6: Tests for the distribution of quantitative responses

	Perceptions			Expectations		
	Overall	Min	Max	Overall	Min	Max
Skewness	4.04	0.05	8.50	3.64	-0.31	9.31
Kurtosis	40.51	9.96	117.20	43.96	10.85	151.95
Jarque-Bera test for normal distribution						
J-B statistic	6,099.24	771.61	22,361.00	5,837.78	543.04	27,213.38
P-value	0.00	0.00	0.00	0.00	0.00	0.00
Kolmogorov-Smirnov test for noncentral t distribution						
K-S statistic	0.31	0.12	0.41	0.24	0.14	0.37
P-value	0.00	0.00	0.00	0.00	0.00	0.00
μ	0.51	0.10	4.00	0.74	0.20	2.70
df	1.02	1	3	1.01	1	2

Notes: Monthly data, 01/1996–10/2008. *Overall* denotes the mean of monthly statistics, *Min* and *Max* are the monthly minimum and maximum of the respective statistic. The Jarque-Bera statistic is asymptotically χ^2_2 distributed. The approximate 1% critical values for the Kolmogorov-Smirnov are given by $1.52N^{-0.5}$, where N is the number of observations. The noncentral t distribution is defined by the noncentrality parameter μ and the degrees of freedom *df*. The table shows the parameters that minimize the Kolmogorov-Smirnov statistic.

Table 2.6 and show that this null hypothesis is also rejected in all months.

These formal tests do not answer the question which parametric distribution produces the best quantification results. The answer will also depend on the time period. During 1996–2007, the high share of zero responses cannot be reconciled with both the normal and noncentral t distributions. With the rise in perceptions and expectations of inflation in 2008, the shape of the empirical distribution becomes somewhat smoother and less skewed, as the share of zero responses declines. Overall, the results indicate that differences in the relative fit of common parametric distributions are predominated by the high share of zero responses. This conjecture is consistent with Berk (1999), Dasgupta and Lahiri (1992) and Smith and McAleer (1995) who find that the accuracy of the quantified series does not significantly vary between any of the common parametric distributions.

noncentrality parameter μ is zero.

2.3.5 Defined Reference Rate of Inflation

Assumption 4 requires that reference inflation π_t^r is equal to some defined value. This assumption is required to identify the system of equations that is generated by Assumptions 1 to 3. As outlined above, for identifying perceived inflation it is typically assumed that reference inflation is a constant such that perceptions are unbiased. To assess this assumption, Figure 2.2a shows the mean of quantitative inflation perceptions given by households that opt for qualitative response S_4. The conditional mean of perceptions is highly volatile with a standard deviation of 1.15%. It averages at 7.93% but shows a declining tendency over time. The assumption that the reference rate of inflation is constant over time is clearly at odds with this pattern.

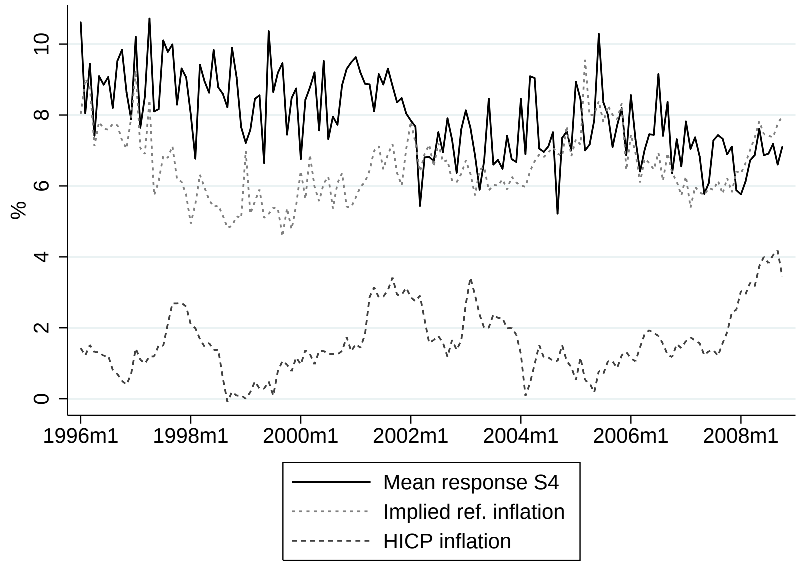
For expected inflation, reference inflation is commonly assumed to be equal to actual inflation or to (previously quantified) perceived inflation. Figure 2.2b shows that the conditional mean of inflation expectations given qualitative answer S_4 is less volatile, with a standard deviation of only 0.53%. The figure plots three alternative measures of reference inflation: The conditional mean of quantitative inflation perceptions of respondents that expect prices to "go up at the same rate" (S_4), quantified inflation perceptions and actual HICP inflation.[24] Clearly, the conditional mean of inflation perceptions closely follows the conditional mean of inflation expectations. The correlation coefficient of the two series is 0.94, the average level difference only 0.39%. The similarity of these series is in line with the finding that qualitative expectations are formed relative to quantitative perceptions. In contrast, the correlations of the conditional mean with quantified inflation perceptions and actual inflation are -0.15 and 0.06, respectively. In both cases, the level difference is substantial. Consequently, the assumption that reference inflation corresponds to quantified or actual inflation can be rejected. However, the correlations of the conditional mean with quantified inflation perceptions and actual inflation increase to 0.46 and 0.41 during 2002–2008. Notably, a comovement of these measures of moderate inflation with the conditional mean is apparent towards the end of the sample period, when actual inflation

[24]Inflation perceptions are quantified using the 5-category probability method with the unbiasedness assumption.

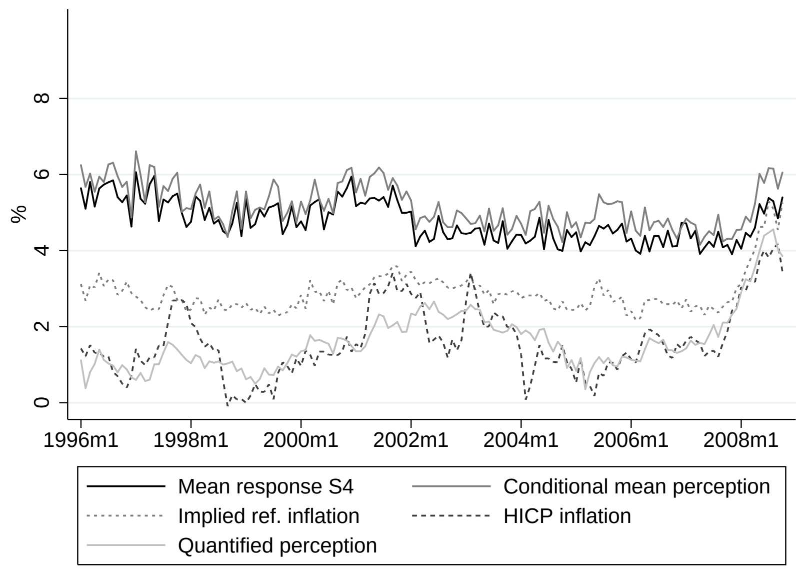
substantially increases.

Alternatively, Assumption 4 can be assessed based on the implied level of reference inflation. The implied level of reference inflation is obtained by combining the cross-sectional mean of quantitative responses with Assumptions 1 to 3.[25] Assessing this series amounts to a joint test of Assumptions 1 to 3. Figure 2.2a indicates that implied reference inflation fluctuates around a similar level as the conditional mean of inflation perceptions. However, the correlation between the two series is 0.06. For inflation expectations shown in Figure 2.2b, the implied reference inflation averages 2% below the conditional mean. The correlation of the two series is 0.31. Provided that the true reference rate of inflation is equal to the conditional mean given qualitative answer S_4, these results suggests that Assumptions 1 to 3 can be jointly rejected. In light of this finding, the next section assesses the joint validity of all 4 hypotheses in more detail.

[25] Given the cross-sectional mean π_t^e of quantitative inflation expectations, implied reference inflation can be obtained by rearranging Equation (A.3).



(A) Perceptions



(B) Expectations

Figure 2.2: Measures of reference inflation π_t^r

Notes: This figure shows alternative measures of π_t^r. *Mean response S4* is the mean quantitative belief of respondents that opt for qualitative answer S_4. *Conditional mean perception* is the mean quantitative inflation perception of respondents that opt for S_4 in the question about expected inflation. Implied reference inflation and quantified inflation perceptions are derived using the 5-category probability method. For quantifying perceptions the unbiasedness condition is imposed.

2.3.6 Joint Assessment

While all four hypotheses can be individually rejected, this section investigates the joint validity of the assumptions. The focus does not lie on rejection/non-rejection but rather on the degree of overall validity. I proceed by quantifying the qualitative survey data with the 5-category probability method.[26] This yields the threshold parameters δ_t and η_t which can be used to construct the implied response scheme on a monthly basis.

Figure 2.3 shows box plots of the distribution of monthly response shares. For each answer category, the fraction of quantitative beliefs that lie within the implied response interval ("quant.") is compared to the actual share of qualitative responses ("N").[27] For inflation perceptions, Figure 2.3a signals pronounced deviations of implied from actual response fractions in categories S_3 and S_5. The high share of quantitative responses in the implied range of S_5 is consistent with the previous finding that the distribution of responses is positively skewed and leptokurtic. Moreover, the low fraction of quantitative responses in the implied range of S_3 appears to be a direct consequence of fitting the normal distribution to the high share of zero responses.

A similar pattern is obtained for inflation expectations. Figure 2.3b illustrates that the deviation of the implied from the actual response share is highest for categories S_3, S_4 and S_5. Similar to perceptions, the fraction of quantitative responses in the implied range of S_5 exceeds the actual share of qualitative responses. This pattern also relates to the finding of the previous section, according to which the mean quantitative answer of respondents opting for qualitative answer S_4 is significantly higher than actual inflation or quantified inflation perceptions. Consequently, a large fraction of these quantitative answers fall into the interval of the qualitative answer S_5.

Further insights can be gained by looking at the fraction of quantitative responses that lie below or above the implied response interval. Figure A.1 in the Appendix shows

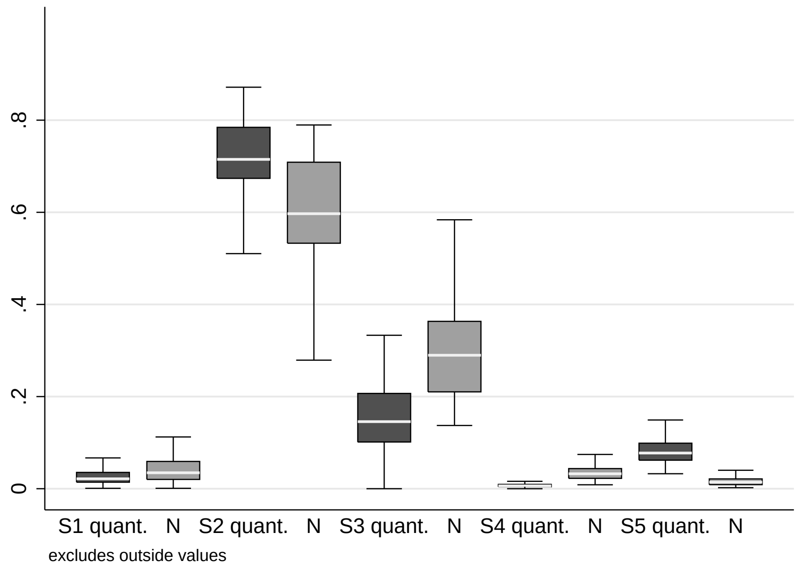
[26] Inflation perceptions are quantified by imposing the unbiasedness condition. For inflation expectations it is assumed that reference inflation is equal to quantified inflation perceptions. Detailed derivations are provided in Appendix A.1.

[27] Note that by construction, the actual share of qualitative responses corresponds to the predicted share of quantitative responses under the normality assumption.

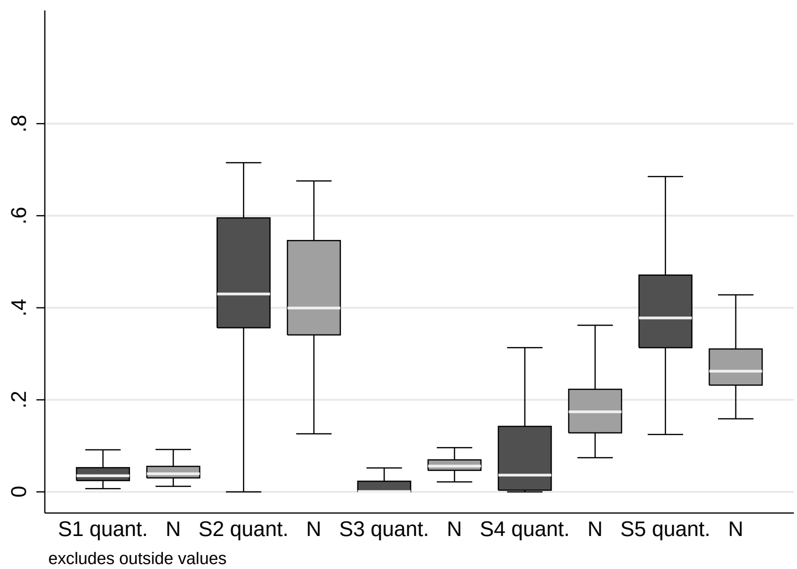
these fractions relative to the number of responses in the respective qualitative response category. Both for perceptions and expectations, the figure reveals that the 5-category probability method best accommodates qualitative answer S_2. On average, 99% of quantitative responses associated with qualitative answer S_2 lie within the implied response interval. S_2 is the most important qualitative response, accounting for roughly 59% of perceptions and 42% of expectations during 1996–2008. Regarding inflation perceptions shown in Figure A.1a, coverage for the second most important category S_3, which obtains 30% of responses, is lower. Only about 30% of quantitative responses are within the implied response interval. A relatively large share of quantitative responses lies below the implied response interval, indicating that the interval around 0% is too wide. The worst coverage results for S_4, but only 4% of respondents opt for this qualitative category.

The pattern is different for inflation expectations. Figure A.1b indicates that only about 10% of quantitative beliefs fall into the implied response intervals for S_3 and S_4. Most quantitative responses are above the implied interval. This can be explained by the high share of on average 27% of responses in category S_5. Fitting this share leads to a downward shift of the lower response intervals. Moreover, the previous section has shown that quantified perceptions are significantly lower than reference inflation π^r. Hence, the implied response intervals linked to quantified perceptions will be too low.

The above findings also hold in the 01/2002–10/2008 subperiod, as Figures A.2 and A.3 in the Appendix confirm. In sum, the results suggest that Assumptions 1 through 4 are invalid. This leads to significant distortions primarily concerning the incorporation of information from positive categories S_3, S_4, S_5, which seem more pronounced for inflation expectations than for inflation perceptions. The next section assesses the implications for the accuracy of the probability method.



(A) Perceptions



(B) Expectations

FIGURE 2.3: Actual and theoretical response fractions

Notes: These figures show the fraction of quantitative answers within the implied response interval (*quant.*) and the actual share of qualitative responses (N). *S1* through *S5* are the qualitative response categories. Sample period 01/1996–10/2008. Perceptions are quantified using the 5-category probability method unbiased with respect to HICP inflation. Expectations are quantified using the 5-category probability method with quantified perceptions as reference inflation. Each box covers the range between the 25th and 75th percentile of monthly fractions and contains a median line. Upper (lower) adjacent values are given by the highest value not greater than the 75th (25th) percentile +(-) 3/2 of the interquartile range.

2.4 Accuracy of the Probability Method

2.4.1 Level and Dynamics of Beliefs

This section assesses the accuracy of the 5-category probability method relative to the mean of actual quantitative survey responses. Perceptions and expectations of inflation are quantified by imposing the usual restrictions. Inflation perceptions are assumed to be unbiased with respect to HICP inflation. Inflation expectations are quantified by setting reference inflation equal to HICP inflation and alternatively, following Berk (1999), to quantified perceived inflation.[28] The 5-category probability method is compared to a set of alternative quantification methods. The first alternative is the 3-category probability method of Carlson and Parkin (1975).[29] The second alternative is the scaled balance statistic with mean and variance of actual inflation. In line with the literature, the 5-category balance statistic is given by $s_5+0.5s_4-0.5s_2-s_1$. The 3-category balance statistic is given by $s_5+s_4+s_3-s_1=s_t^p-s_t^n$, where s_t^p and s_t^n are the fractions of respondents that report that prices are rising and falling, respectively. The third alternative is the Pesaran (1987) regression approach for 3-category response data.[30]

The primary measure of accuracy I consider is the (Pearson) correlation coefficient between the quantified series and the cross-sectional mean of quantitative responses. As opposed to the mean absolute error (MAE) or root mean squared error (RMSE), the correlation coefficient is robust to a constant scaling of the involved series. In particular, the correlation coefficient is unaffected by the average level of reference inflation π^r. Another advantage of employing the correlation coefficient is that its distributional properties have

[28]Perceived inflation is quantified using the 5-category probability method under the assumption of unbiasedness with respect to HICP inflation.

[29]Answer categories are aggregated following Berk (1999), see Appendix A.2 for details.

[30]Unlike the early regression approaches suggested by Theil (1952) and Anderson (1952), the Pesaran (1987) approach allows for asymmetric response behavior in periods of rising and falling inflation. The Pesaran approach is based on nonlinear least squares estimation of the model $\pi_t=\frac{\beta_1 s_t^p-\beta_2 s_t^n}{1-\beta_3 s_t^p}+\varepsilon_t$, where π_t denotes actual HICP inflation. Expected inflation is generated in a second step as a prediction of this model based on answering fractions about inflation expectations (where coefficient estimates are obtained in the first step using perceptions data). A measure of perceived inflation is computed as the prediction of the model using the perceptions data it has been estimated with.

been explored. The Fisher z-transformation of the correlation coefficient results in an approximately normal random variable, provided the underlying data follows a bivariate normal distribution. Relying on the Fisher z-transformation, the null hypothesis that two correlation coefficients are equal ($\rho_1 = \rho_2$) can be tested using the following statistic:

$$z = \tanh^{-1}(\rho_1) - \tanh^{-1}(\rho_2) \tag{2.4}$$

where $\tanh^{-1}(\rho_i) = 0.5\ln\left(\frac{1+\rho_i}{1-\rho_i}\right)$. The z statistic is approximately normal with variance $\frac{1}{T_1-3} + \frac{1}{T_2-3}$, where T_1 and T_2 are the sample sizes underlying correlation coefficients ρ_1 and ρ_2, respectively. However, the normal approximation may be inaccurate in the present case because $|\rho_i|$ is high and the underlying series are serially dependent (Mudholkar, 2006). I therefore assess significance based on double block bootstrap confidence intervals for the z statistic.[31]

Table 2.7 summarizes the results. The underlying series are plotted in Figures A.4 and A.5 in the Appendix. All statistics are provided for levels and first differences. The last column in each panel shows the Fisher z statistic for testing the null hypothesis that the difference between the correlation coefficient in the first row of each panel (ρ_1) and the correlation coefficient in the respective row (ρ_2) is zero. Since the quantified series and the mean quantitative beliefs are highly persistent, the discussion focuses on results for first differences.[32] These results are not subject to spurious regression problems as the first differences are stationary. However, the results on the significance of correlation are mostly consistent for levels and first differences.

Panel 1 of Table 2.7 indicates that in terms of correlation with the mean of quantitative perceptions, all quantification methods perform well. The correlation in first differences is 0.86 for the series generated with the 5-category probability method. The 3-category probability method generates virtually identical results. Interestingly, the 5-category and 3-

[31]Matlab codes are available from the author. The double moving block bootstrap of the percentile confidence interval is based on 1,000 first level replications and 2,500 second level replications and a block size of 5. See Efron and Tibshirani (1993) for a description of the method.

[32]Employing an Augmented Dickey-Fuller test the null hypothesis of a unit root cannot be rejected on the 10% level for all actual and quantified mean series.

category balance statistics are more accurate, with correlation coefficients of 0.91 and 0.89, respectively. The z-statistic indicates that the correlation coefficient for the 5-category balance statistic is significantly higher than the correlation coefficient for the 5-category probability method.

Regarding expectations, panel 2 of Table 2.7 shows that the accuracy of the 5-category probability method depends on the imposed reference inflation. Employing quantified perceptions generates significantly better results than employing actual HICP inflation, as the z-statistic indicates. The correlation coefficients are 0.80 and 0.50, respectively. The most accurate method for quantifying inflation expectations is again a balance statistic. Moreover, the 3-category regression approach is slightly more accurate than the 5-category probability method. These differences are not statistically significant, however. Results for the sample 01/2002–10/2008 in Table A.1 confirm these findings.

In sum, all quantification methods generate series that are highly correlated with the cross-sectional mean of quantitative inflation perceptions. The 5-category balance statistic tracks actual quantitative perceptions most accurately. For expectations, none of the alternative methods performs significantly better than the 5-category probability method with reference inflation given by quantified perceptions. The reasonable performance of the probability method is in contrast to findings of Batchelor (1986) for the U.S.[33] However, the 5-category probability method may perform weakly to quantify expectations, depending on the chosen reference inflation. Moreover, the similar accuracy of the 5-category probability method and the 3-category methods signals that the 5-category probability method does not efficiently use information from positive response categories.

[33]Batchelor (1986) documents that the quantified series do not predict the direction of change in mean quantitative responses. In the present case, a comparison of signs confirms the high correlation in first differences. For inflation perceptions, the balance statistic and the probability method indicate the correct direction of change of the mean quantitative response in 131 and 129 out of 153 months, for expectations in 121 and 120 months.

Table 2.7: Accuracy of quantified inflation perceptions and expectations

Perceptions	Level					First differences				
	Bias	MAE	RMSE	ρ	z	Bias	MAE	RMSE	ρ	z
P.HICP (5 cat.)	-0.17	0.22	0.32	0.97		0.00	0.12	0.15	0.86	
P.HICP (3 cat.)	-0.17	0.19	0.24	0.98	-0.24	0.00	0.11	0.15	0.83	0.09
Balance (5 cat.)	-0.20	0.20	0.25	0.99	-0.51*	0.00	0.11	0.13	0.91	-0.22**
Balance (3 cat.)	-0.20	0.22	0.31	0.97	0.04	0.00	0.10	0.14	0.89	-0.12
Pesaran (3 cat.)	-0.21	0.25	0.47	0.94	0.44	0.00	0.12	0.16	0.85	0.02

Expectations	Level					First differences				
	Bias	MAE	RMSE	ρ	z	Bias	MAE	RMSE	ρ	z
P.Perc. (5 cat.)	-0.85	0.85	0.89	0.94		0.00	0.13	0.17	0.80	
P.HICP (5 cat.)	-0.87	0.87	0.96	0.86	0.47	0.00	0.23	0.30	0.50	0.55**
P.HICP (3 cat.)	-0.49	0.49	0.24	0.95	-0.06	0.00	0.13	0.15	0.82	-0.05
Balance (5 cat.)	-0.49	0.56	0.25	0.89	0.35	0.00	0.17	0.13	0.82	-0.06
Balance (3 cat.)	-0.49	0.51	0.31	0.96	-0.18	0.00	0.14	0.14	0.84	-0.13
Pesaran (3 cat.)	0.12	0.22	0.29	0.95	-0.08	0.00	0.13	0.18	0.81	-0.01

Notes: Accuracy is measured relative to the mean of quantitative responses, 01/1996–10/2008. For perceptions, *P.HICP (5 cat.)* and *P.HICP (3 cat.)* denote the 5-category and 3-category probability method under the assumption that perceptions are unbiased with respect to HICP inflation. For expectations, *P.Perc. (5 cat.)* and *P.HICP (5 cat.)* are the 5-category probability methods with reference inflation given by quantified perceptions and HICP inflation, respectively. *P.HICP (3 cat.)* is the 3-category probability method under the assumption that expectations are unbiased. *Bias* is defined as the difference between the mean of quantified beliefs and the mean of quantitative responses. ρ is the correlation coefficient with the mean of quantitative responses. z is the Fisher z statistic for testing the null hypothesis that the difference between the correlation coefficient in the first row of each panel and the correlation coefficient in the respective row is zero. *, ** and *** indicate statistical significance of z at the 10%, 5% and 1% level based on double block bootstrap percentile confidence intervals.

2.4.2 Heterogeneity of Beliefs

The cross-sectional heterogeneity of beliefs is subject to increasing research in macroeconomics. This section investigates how to best infer cross-sectional heterogeneity from qualitative survey data. Cross-sectional heterogeneity is measured by the standard deviation of quantitative beliefs.

The 5-category probability method not only allows to identify the mean but also the standard deviation of the fitted normal distribution given by Equation (A.4). In addition, I consider four alternative measures of heterogeneity. The first alternative is implied standard deviation from the 3-category probability method, given by Equation (A.9). The second alternative is an index of qualitative variation (IQV) based on the response shares s_1 through s_5:

$$IQV = \frac{K}{K-1}\left(1 - \sum_{i=1}^{K} s_i^2\right)$$

where $K = 5$ is the number of response categories and s_i the fraction of answers in category i. The scaling factor $\frac{K}{K-1}$ ensures that $0 \leq IQV \leq 1$. Unlike the probability method, the IQV does not account for the ordered nature of the data. The third alternative is the d^2-index of ordinal variation proposed by Lacy (2006).[34] This index is given by:

$$DSQ = \sum_{i=1}^{K-1} F_i(1 - F_i)$$

where $K = 5$ is the number of response categories and F_i the cumulative response share in category i, e.g., $F_3 = s_1 + s_2 + s_3$. As the IQV, the DSQ statistic attains its minimum of 0 if all answers lie in the same response category. But while the IQV is maximal when answers are uniformly distributed, the DSQ attains its maximum of 1 if the distribution is polarized, i.e. if $s_1 = s_5 = 0.5$. The fourth alternative is the disconformity index of Theil (1955) defined as $DIS = s_p + s_n - (s_p - s_n)^2$.[35]

[34] Lacy (2006) builds on earlier work of Blair and Lacy (1996, 2000).

[35] The disconformity index relies on the same theoretical assumptions as the 3-category balance statistic,

Table 2.8 summarizes the results. Since the time series of heterogeneity are less persistent than the series of means, the discussion centers on results in levels.[36] The alternative measures of heterogeneity are plotted in Figures A.6 and A.7. Table 2.8 shows that both the 5-category probability method and the 3-category probability method considerably underestimate actual heterogeneity of quantitative beliefs. The implied standard deviation lies 1.7% to 2.4% below the actual standard deviation of quantitative responses. This finding is consistent with earlier results of Defris and Williams (1979) and Batchelor (1986).

Regarding inflation perceptions, the first panel of Table 2.8 shows that implied standard deviation from the 5-category probability method traces actual heterogeneity only weakly. The correlation coefficient is 0.30. The 3-category probability method performs significantly better, as the z statistic indicates. Qualitative measures of variation are even more highly correlated with the standard deviation of quantitative perceptions. The correlation coefficients of the IQV and the DSQ are 0.83 and 0.87, respectively. The performance of the 3-category disconformity index is substantially lower, its correlation with actual standard deviation of quantitative responses is similar to the 5-category probability method.

The implied standard deviation from the 5-category probability method performs better for quantifying heterogeneity of inflation expectations, as the second panel of Table 2.8 indicates. Again, the correlation depends on the choice of reference inflation. Employing actual HICP inflation instead of quantified perceptions reduces the correlation coefficient significantly from 0.67 to 0.52. The implied standard deviation of the 3-category approach is about as accurate as the 5-category probability method with reference inflation given by quantified perceptions. The IQV most closely tracks actual heterogeneity of quantitative responses. Its correlation with actual standard deviation is 0.80, which is significantly higher than the correlation of the 5-category probability method. Unlike for perceptions, the DSQ statistic is only moderately correlated with actual heterogeneity. Even lower is the correlation for the disconformity index, which is in line with earlier findings of Batchelor

see Batchelor (1986).

[36]Both for perceptions and expectations, the Augmented Dickey-Fuller test rejects the null hypothesis of a unit root for the standard deviation of actual quantitative responses and for the quantified series using the 5-category probability method linked to HICP inflation.

Table 2.8: Accuracy of measures of cross-sectional heterogeneity

Perceptions	Level					First differences				
	Bias	MAE	RMSE	ρ	z	Bias	MAE	RMSE	ρ	z
Implied SD (P.HICP, 5 cat.)	-1.76	1.76	1.83	0.30		0.00	0.29	0.36	0.31	
Implied SD (P.HICP, 3 cat.)	-1.83	1.83	1.88	0.68	-0.52*	0.00	0.28	0.36	0.36	-0.06
IQV (5 cat.)				0.83	-0.90**				0.48	-0.19**
DSQ (5 cat.)				0.87	-1.01**				0.47	-0.19**
DIS (3 cat.)				0.35	-0.05				0.30	0.01

Expectations	Level					First differences				
	Bias	MAE	RMSE	ρ	z	Bias	MAE	RMSE	ρ	z
Implied SD (P.Perc., 5 cat.)	-2.42	2.42	2.45	0.67		0.00	0.27	0.33	0.40	
Implied SD (P.HICP, 5 cat.)	-2.44	2.44	2.50	0.52	0.24**	0.00	0.33	0.42	0.20	0.22**
Implied SD (P.HICP, 3 cat.)	-1.95	1.95	1.98	0.71	-0.07	0.00	0.28	0.34	0.33	0.07
IQV (5 cat.)				0.80	-0.29**				0.28	0.13
DSQ (5 cat.)				0.45	0.32				0.18	0.24**
DIS (3 cat.)				0.30	0.49**				0.14	0.27**

Notes: Accuracy is measured relative to the cross-sectional standard deviation of quantitative responses, 01/1996–10/2008. For perceptions, *Implied SD (P.HICP, 5 cat.)* is the implied standard deviation from the 5-category probability method under the HICP unbiasedness condition. For expectations, *Implied SD (P.Perc., 5 cat.)* and *Implied SD (P.HICP, 5 cat.)* are implied standard deviations from the 5-category probability method with reference inflation given by quantified perceptions and actual HICP inflation, respectively. Both for perceptions and expectations, *Implied SD (P.HICP, 3 cat.)* is the implied standard deviation from the 3-category probability method under the HICP unbiasedness condition. *IQV* is the index of qualitative variation, *DSQ* is the d^2-index of ordinal variation proposed by Lacy (2006) and *DIS* is the disconformity statistic. *Bias* is defined as the difference between the mean of quantified beliefs and the mean of quantitative responses. ρ is the correlation coefficient with the standard deviation of quantitative responses. z is the Fisher z statistic for testing the null hypothesis that the difference between the correlation coefficient in the first row of each panel and the correlation coefficient in the respective row is zero. *, ** and *** indicate statistical significance of z at the 10%, 5% and 1% level based on double block bootstrap percentile confidence intervals.

(1986). Results for first differences are broadly consistent, with the exception that for quantifying expectations the IQV does not outperform other methods anymore. Results for the shorter sample spanning 01/2002–10/2008 in Table A.2 confirm the relatively high accuracy of the IQV compared to other methods.[37]

In sum, these results suggest that while the probability method is relatively accurate in describing the central tendency, it is considerably less accurate in capturing cross-sectional heterogeneity. Moreover, the 3-category probability method performs better than the 5-category method, which is consistent with findings of the previous section.[38] The IQV generally dominates the other methods in terms of correlation with the cross-sectional standard deviation of quantitative beliefs. The DSQ is only accurate for quantifying the heterogeneity of inflation perceptions. A possible interpretation of this result is that the IQV is less distorted by the lack of order in qualitative inflation expectations than the DSQ index.

2.5 Which Quantification Method Should Be Used?

The assumptions of the 5-category probability method can be individually and jointly rejected. Moreover, the estimated response schemes indicate that qualitative inflation expectations are not strictly increasing in quantitative expectations since positive responses are given relative to perceived inflation. Both for perceptions and expectations of inflation, however, the response scheme estimates indicate that three separate positive categories S_3, S_4 and S_5 contain additional information over just one positive category.

Despite the violation of theoretical assumptions, the accuracy of the 5-category probability method for quantifying the cross-sectional mean of inflation perceptions is high. The

[37]Note that in this sample the probability method gains relative accuracy for quantifying inflation expectations. I have also assessed accuracy of the square root of the index of qualitative variation, the square root of the DSQ-statistic and the square root of the disconformity index. The correlations with actual standard deviation of survey responses do not significantly change, both in their absolute level and relative ordering.

[38]The reasonable performance of the 3-category probability method also reinforces the results of Dasgupta and Lahiri (1993) who show that implied dispersion from the 3-category method is useful for predicting business cycle turning points.

TABLE 2.9: Actual and imposed conditional means

	Perceptions			Expectations		
	Actual	Balance	P.HICP	Actual	Balance	P.Perc.
Mean response, given S_1	-4.79	-3.96	-4.94	-3.89	-2.87	-3.60
Mean response, given S_2	0.03	-0.23	0.37	0.02	-0.54	0.37
Mean response, given S_3	4.72	3.50	4.62	4.06	1.79	2.40
Mean response, given S_4	7.94	7.22	7.70	4.77	4.12	3.53
Mean response, given S_5	9.58	10.95	9.75	3.98	6.45	6.25

Notes: The column *Actual* presents results for actual quantitative survey responses, 01/1996–10/2008. *Balance* shows the mean values that the balance statistic attributes to qualitative survey categories. *P.HICP* denotes implied conditional means of the 5-category probability method unbiased with respect to HICP inflation. *P.Perc.* are the implied conditional means of the 5-category probability method with reference inflation given by quantified perceptions. Conditional means are scaled to match the mean and standard deviation of actual conditional means.

relative performance of the 3-category probability method indicates, however, that the 5-category method does not efficiently use the additional information from three positive response categories. The most accurate method is the 5-category balance statistic.

For quantifying the cross-sectional mean of inflation expectations, the accuracy of the 5-category probability method largely depends on the chosen reference inflation π_t^r. Employing quantified inflation perceptions yields significantly more accurate results than employing actual HICP inflation. At first sight this finding is inconsistent with the zero correlation of quantified perceptions and reference inflation during the full sample as documented in Section 2.3.5. But as Figure 2.2 indicates, the relation between quantified perceptions and reference inflation becomes stronger towards the end of the sample period. The correlation coefficient of reference inflation and quantified perceptions increases to 0.46 during 2002–2008. In particular, quantified perceptions surge in 2007 and 2008, while reference inflation increases to about 6%. This suggests that the 5-category probability method with quantified perceptions as reference inflation will gain relative accuracy once inflation perceptions substantially diverge from actual inflation.[39]

It remains the question why the simple balance statistic tends to trace mean beliefs even more closely than the 5-category probability method. Table 2.9 provides a possible expla-

[39]This is the case, e.g., around the euro cash changeover in 2002 (ECB, 2005).

nation. The table shows the mean of quantitative responses conditional on the qualitative response. Conditional means of actual quantitative responses are compared to the imposed conditional means of the balance statistic and of the 5-category probability method. The imposed conditional means are scaled to match the mean and variance of actual conditional means.[40] Table 2.9 reveals that both methods impose (scaled) conditional means that match actual conditional means quite well. In other words, the conditional means imposed by the balance statistic are roughly proportional to the actual conditional means in the data. Not surprisingly, the fit is better for perceptions than for expectations. This also suggests that the balance statistic, unlike the probability method, will loose relative accuracy once the ratio of conditional means changes.

The accuracy of the 5-category probability method is low for quantifying the cross-sectional standard deviation of beliefs. Here, an index of qualitative variation is preferable. The index of qualitative variation also dominates the DSQ index of ordinal variation for quantifying the heterogeneity of expectations.

In sum, these results are in favor of the 5-category probability method for quantifying the mean of beliefs. The index of qualitative variation is preferable for quantifying the cross-sectional standard deviation of beliefs. In particular, the IQV seems less distorted by a lack of order in qualitative inflation expectations than other quantification methods. The findings also indicate that the 5-category probability method with quantified perceptions as reference inflation might gain relative accuracy once inflation perceptions deviate from actual inflation. This also points to a general limitation of the results: Findings on the quantification of expectations might differ from other countries as Swedish consumers are relatively well informed about actual HICP inflation.

[40]The (unscaled) conditional means of the 5-category balance statistic are -1, 0.5, 0, 0.5, 1. The implied conditional means of the probability method are computed by numerical integration using the quantified parameters π_t^e, σ_t, δ_t, η_t, π_t^r. Perceptions are quantified employing the 5-category probability method unbiased with respect to HICP inflation. Expectations are quantified using the 5-category probability method with reference inflation given by quantified perceptions.

2.6 Conclusion

This paper assesses the validity and accuracy of the 5-category probability method for quantifying household perceptions and expectations of inflation. The analysis capitalizes on jointly available qualitative and quantitative response data from the Swedish Consumer Tendency Survey. Relying on monthly household-level data covering 01/1996–10/2008, the theoretical assumptions of the 5-category probability method are individually and jointly tested and rejected. Maximum likelihood estimations of unrestricted response schemes indicate that the actual response scheme is neither symmetric nor homogeneous across individuals. Moreover, it is found that qualitative inflation expectations are formed relative to inflation perceptions, which is a direct result of survey design. An important consequence is that the conditional mean of quantitative inflation expectations is not monotonously rising in qualitative response categories. Furthermore, quantitative beliefs are not normally distributed and cannot be reconciled with a noncentral t distribution either. The usual assumptions on the reference rate of inflation (the "moderate" rate of inflation) are shown to be at odds with the data.

Nevertheless, the accuracy of the 5-category probability method in terms of correlation with the mean of actual quantitative beliefs is high. For quantifying inflation expectations the accuracy of the method strongly depends on the identifying restriction imposed by the choice of reference inflation. Relying on double block bootstrap confidence intervals for Fisher's z statistic, it is shown that setting reference inflation equal to previously quantified inflation perceptions yields significantly better results than setting reference inflation equal to actual inflation. Nevertheless, the 5-category probability method is not more accurate than the balance statistic and the 3-category probability method. This suggests that the 5-category probability method does not efficiently use information from positive qualitative response categories. In sum, the results are still in favor of the 5-category probability method. In particular, the 5-category probability method with quantified perceptions as reference inflation might gain relative accuracy once inflation perceptions substantially deviate from actual inflation. The most accurate measure of the cross-sectional standard deviation of beliefs is the index of qualitative variation.

The findings for Sweden suggest a number of avenues for further research. To exploit the additional information from three positive response categories, research is needed on how to identify the reference rate of inflation. Moreover, a non-parametric analysis should generate further insights that will help to improve the imposed response scheme and distribution. Looking ahead, implications for survey design should also be discussed in more depth. The results for Sweden indicate that it is difficult to efficiently handle the relative nature of the positive qualitative responses about inflation expectations. Obvious alternative survey designs include to adopt the same response scheme for expectations as currently in use for perceptions or to directly ask for quantitative responses in the first place.

Chapter 3

How Do Households Form Inflation Expectations? Evidence From a Mixture Model of Survey Heterogeneity

3.1 Introduction

How do households form their expectations on inflation? In their seminal contribution on adaptive rational equilibrium dynamics, Brock and Hommes (1997) assume that agents form expectations by rationally choosing predictors from a set of available predictors. Building on the work of Brock and Hommes (1997), Branch (2004) proposes a theory of rationally heterogeneous expectations that specifically allows for heterogeneity in survey data. Using household-level data from the University of Michigan Survey of Consumers (Michigan survey), Branch (2004) empirically corroborates the model view that households rationally select predictors for forecasting consumer price inflation. His estimates show that the probability of a predictor being chosen inversely depends on its mean squared error relative to materialized inflation and its costs. Using an alternative set of predictors, Branch (2007) confirms this result. Clearly, the models of rational predictor selection as advanced by Brock and Hommes (1997) and Branch (2004) imply that observable expectations might not satisfy the traditional Muthian notion of rationality. Still, agents are rational as the entire process of expectation formation is subject to optimization. An optimizing behavior is also suggested by the concept of rational inattention advanced by Sims (2003). Sims (2003) models economic agents as having limited capacity to process information. Consequently, agents rationally allocate their attention across different sources of information when forming expectations.

Based on the notion that households dynamically select predictors, this paper aims to identify which predictors are actually being used to form inflation expectations. The analysis capitalizes on quantitative response data from the Swedish Consumer Tendency Survey, spanning 01/1996–10/2008.[1] The Swedish survey asks households to report both the perceived inflation rate over the past 12 months (inflation perception) as well as the expected

[1]The Swedish Consumer Tendency Survey data on perceived and expected inflation has only been investigated by a small number of studies. Among the topics being considered are rationality of inflation perceptions (Jonung and Laidler, 1988), near rationality and sticky information models of belief formation (Bryan and Palmqvist, 2006, and Chapter 4 of this dissertation), uncertainty about beliefs (Jonung, 1986), socioeconomic determinants of beliefs (Jonung, 1981, Palmqvist and Strömberg, 2004) and accuracy of quantification methods (Chapter 2).

12 months ahead inflation rate (inflation expectation).[2] To infer which predictors are being chosen, this paper adopts a Gaussian mixture model of heterogeneous survey expectations. The model assumes that to form an inflation expectation, every household selects a predictor from a set of available predictors. When answering the consumer survey, a household's response does not need to be exactly equal to the corresponding predictor value. Rather, responses of households that opt for the same predictor may differ due to idiosyncrasies in rounding, differences in information sets and differences in conceptual understandings of inflation. Consequently, the Gaussian mixture model assumes that responses generated by a particular predictor are normally distributed around the predictor value. Since multiple predictors are being employed in the survey population, the probability density of survey expectations is a mixture of several normal density functions, a Gaussian mixture density. Given a set of predictors, the aim is to estimate the parameters of the underlying normal densities and to compute the share of respondents that opt for a particular predictor. The Gaussian mixture model bears similarity to the model of rationally heterogeneous expectations of Branch (2004, 2007). However, as will be discussed, the Gaussian mixture model does not impose an economic model of predictor selection. While Branch (2004, 2007) demonstrates that households rationally select predictors, the Gaussian mixture model proposed in this paper aims to identify which predictors are actually being used.

The Gaussian mixture approach takes the analysis of expectation formation one step further: Rather than just testing and potentially rejecting a particular model of expectation formation (such as the rational expectations hypothesis), the Gaussian mixture approach allows to infer the probability that a particular model is actually being used by survey participants.[3] Moreover, the Gaussian mixture approach is unaffected by the aggregation bias that may emerge if expectation formation models are tested using aggregate survey

[2]In the following, beliefs about the current annual inflation rate are referred to as inflation perceptions, whereas beliefs about 12 months ahead inflation are referred to as inflation expectations. Note that to the extent that inflation perceptions are based on incomplete information, inflation perceptions can also be regarded as expectations.

[3]Rationality of inflation expectations in household survey data is tested and rejected by Evans and Gulamani (1984), Mankiw, Reis and Wolfers (2004) and Thomas (1999) using aggregate (consensus) expectations and by Souleles (2004) using household-level data.

data (Bonham and Cohen, 2000, 2001).

Furthermore, this paper puts emphasis on the largely unexplored role of perceived inflation for expectation formation. An initial explorative analysis suggests that a significant share of households give numerically identical answers to the questions on perceived and expected inflation. The Gaussian mixture model accounts for this observation by including individually perceived inflation as a predictor. Moreover, jointly considering perceptions and expectations about inflation sheds some light on the importance of idiosyncrasies in consumption baskets and in conceptual understandings of inflation for overall survey heterogeneity, as opposed to heterogeneity due to differences in predictors and information sets. As will be argued, the high degree of heterogeneity in inflation perceptions suggests that differences in predictors and information sets account for most of the heterogeneity.

Only a few contributions consider the role of perceived inflation for expectation formation. Jonung (1981) relies on cross-sectional response data from an earlier version of the Swedish Consumer Tendency Survey. He shows that a significant linear relation exists between perceived and expected inflation in 01/1978. The reported cross-sectional correlation coefficient is about 0.5. Moreover, Jonung (1981) finds that perceived and expected inflation are similarly affected by socioeconomic factors.[4] Bryan and Venkatu (2001a, 2001b) report consistent findings on the influence of socioeconomic factors for U.S. survey data. Positive correlation coefficients of perceived and expected inflation on household-level are also reported by Van der Klaauw et al. (2008) and Kemp (1987). Finally, an important case for the role of perceived inflation for expectation formation is made by Benford and Driver (2008). These authors investigate qualitative response data from a special issue of the Bank of England Inflation Attitudes Survey that directly asks households about how they form their inflation expectations. Benford and Driver (2008) find that more than 40% of households consider their perception of inflation to be a very important factor for

[4]Jonung (1981) reports that age is the only socioeconomic variable that differentially affects inflation perceptions and expectations. Conditional on the perceived rate of inflation, the expected rate of inflation declines in age. Jonung (1981) concludes that inflation expectations are influenced by the lifetime experience of respondents. He argues that older respondents tend to expect lower inflation rates than younger respondents because the experience of younger respondents is dominated by high inflation rates of the 1970s.

expectation formation. Perceived inflation rates are the most important determinant of inflation expectations, mentioned more often than the remaining factors, which include interest rates, the central bank policy target and media reports.

The findings of this paper unambiguously show that an important relation exists between inflation perceptions and inflation expectations. During 01/1996–10/2008, 49% of all respondents give identical answers to the question about perceived and expected inflation. The estimated Gaussian mixture model robustly indicates that about 51% of households form idiosyncratic static expectations that are directly based on their subjective perceptions of inflation. 19% of households form rational expectations (given by the mean of professional forecasters' expectations) and 15% each form adaptive expectations and conventional static expectations (given by the official inflation figure). On the methodical side, the significance and robustness of the estimates suggest that the Gaussian mixture model is a sound approach to understanding survey heterogeneity and expectation formation.

The paper is structured as follows. Section 3.2 presents the data. Section 3.3 provides an explorative analysis of the response data, focusing on the relation between inflation perceptions and expectations. Section 3.4 derives the Gaussian mixture model of survey heterogeneity and presents estimates of the shares of households that employ a particular predictor. Section 3.5 concludes.

3.2 Data

This paper uses monthly household-level response data from the Swedish Consumer Tendency Survey spanning 01/1996–10/2008. The questionnaire of the Swedish survey is in line with the Joint Harmonized European Union Consumer Survey. However, whereas in most European countries the questionnaire only includes qualitative questions, the Swedish survey also asks for quantitative beliefs about inflation. Quantitative inflation perceptions are captured by asking:

> "[Compared with 12 months ago,] how much higher/lower in percent do you think prices [in general] are now? (In other words, the present rate of inflation.)"

The question on quantitative inflation expectations reads:

> "[Compared with today,] how much in percent do you think prices [in general] will go up/down [in the next 12 months]? (In other words, inflation 12 months from now.)"

The actual phrasing of these questions does not mention the time horizon ("Compared with 12 months ago" and "in the next 12 months") and the scope of prices ("prices in general" rather than just "prices"). However, these aspects are specified in the qualitative questions on perceived and expected inflation that are asked directly before the quantitative questions. Consequently, the framing seems well defined.[5] Moreover, the second sentence of each question asks more precisely for inflation, whereas the first sentence asks for a change in prices. Van der Klaauw et al. (2008) show that these differences in wording affect the concept of inflation that a respondent has in mind when answering the questions. In particular, their results indicate that if households are asked for "inflation" they rather tend to think about the general consumer price inflation rate than if they are asked about

[5] The qualitative question asks households to indicate their beliefs about inflation on a 5-option scale. The full questionnaire and the questioning procedure is documented in the GfK (2002) survey manual and is further discussed by Palmqvist and Strömberg (2004). Details about the Joint Harmonized EU Consumer Survey program can be found in European Commission (2007).

the change of “prices in general”.[6] Thus, the wording of the Swedish Consumer Tendency Survey facilitates that respondents homogeneously interpret the questions as asking for the consumer price inflation rate.

In the following, $\pi^p_{t,i}$ and $\pi^e_{t,i}$ denote the responses of individual i in month t to the questions about perceived and expected inflation, respectively.[7] Household-level data is available for a sample of 154 monthly surveys spanning 01/1996–10/2008. In line with the literature, the response data is adjusted for outliers. Responses outside the interval $[-30\%, 30\%]$ are omitted which reduces the sample size by 0.3%.[8] Moreover, only observations that include non-missing responses both on perceived and expected inflation are considered. This further reduces the number of responses by 7.8% and 5.6% for inflation perceptions and expectations, respectively. The final sample includes 182,077 observations, implying an average monthly sample size of 1,182 observations. Table 3.1 provides an overview.

The discussion centers on the sample period 01/1996–10/2008. Additional results for a shorter sample covering 01/2002–10/2008 are provided to account for a potential structural break in the response data due to a change in the surveying institution. As will be shown, results for this alternative estimation period are consistent, confirming the validity of the results for the full sample.[9]

As a measure of actual inflation I use the year-over-year percentage change in the Harmonized Index of Consumer Prices (HICP) published by Statistics Sweden. The HICP time series spans 01/1995–08/2009. Inflation expectations of professional forecasters are

[6] Van der Klaauw et al. (2008) conduct qualitative interviews with consumers to find that 67% of respondents think about consumer price inflation if the question asks for “inflation”. If the question asks about the change of “prices in general”, 47% of respondents think about easily recalled items (such as gasoline), whereas only 38% think about the rate of consumer price inflation. Van der Klaauw et al. (2008) further document that this directly translates into different degrees of disagreement in inflation expectations.

[7] Note that since the Swedish Consumer Tendency Survey randomly draws a new sample from the population every month, individuals i cannot be traced over time.

[8] Over the entire sample period, 667 (443) observations contain inflation perceptions (expectations) that are outliers.

[9] In 01/2002, the surveying institution has changed from Statistics Sweden to GfK Sweden. The change coincides with a decline in the share of zero responses, as discussed by Palmqvist and Strömberg (2004).

TABLE 3.1: Summary statistics

	Perceptions			Expectations		
	Overall	Min	Max	Overall	Min	Max
Number of responses	197,487	1,031	1,456	192,845	961	1,417
Number of joint responses	182,077	878	1,380	182,077	878	1,380
Number of months	154			154		
Mean	1.83	0.47	5.89	2.11	0.60	4.63
Median	0.41	0.00	5.00	1.03	0.00	4.00
Standard deviation	4.04	2.74	5.28	3.67	2.72	4.66
Interquartile range	2.27	0.00	5.00	3.13	1.00	5.00
Quasi standard deviation	2.15	0.00	5.00	2.31	1.25	3.00
Share of integer answers	0.94	0.85	0.98	0.91	0.82	0.97
Share of focal point answers	0.75	0.38	0.83	0.72	0.56	0.86
Share of zero responses	0.57	0.07	0.78	0.41	0.11	0.67
Share of identical responses				0.49	0.26	0.69
Correlation of responses				0.52***	0.29***	0.70***

Notes: The table shows summary statistics for the sample period 01/1996–10/2008. The column *Overall* presents average statistics for the entire sample period. *Min* and *Max* are the monthly minimum and maximum of the respective statistic. *Number of responses* is the number of non-missing responses. *Number of joint responses* is the number of respondents that answer both the questions on perceived and expected inflation. The statistics in panels 2–4 are based on the sample of joint responses. *Quasi standard deviation* is defined as half the difference between the 84th and the 16th percentile. *Share of identical responses* is the share of observations for which the perception is equal to the expectation ($\pi^p_{t,i} = \pi^e_{t,i}$). *Correlation of responses* denotes the cross-sectional correlation of $\pi^p_{t,i}$ and $\pi^e_{t,i}$. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

taken from the Consensus Economics survey. Consensus Economics asks 10 to 14 Swedish institutions for forecasts of consumer price inflation over the current and the upcoming calendar year on a monthly basis. I employ the weighting approach commonly used in the literature to compute 12 months ahead inflation forecasts.[10]

[10]The 12 months ahead (fixed horizon) inflation expectation formed in month m of year y is given by $\frac{13-m}{12}\pi^{e,y}_m + \frac{m-1}{12}\pi^{e,y+1}_m$, where $\pi^{e,y}_m$ and $\pi^{e,y+1}_m$ are the (fixed event) inflation expectations for year y and $y+1$, respectively.

3.3 Explorative Analysis

3.3.1 General Response Patterns

The analysis begins by investigating main characteristics of quantitative responses. Table 3.1 presents summary statistics of the monthly survey data for the period 01/1996–10/2008. During this period, actual HICP inflation averages at 1.61%. Its volatility as measured by the standard deviation of monthly inflation rates is only 0.92%. The second panel of Table 3.1 shows that inflation perceptions average at 1.83%, close to the mean of actual HICP inflation. Inflation expectations average moderately higher at 2.11%. A somewhat more pronounced difference between perceptions and expectations emerges for the median. As the third panel of Table 3.1 suggests, this difference is caused by a relatively high share of zero responses to the question on perceived inflation.

The cross-sectional standard deviations are again similar for perceptions and expectations, averaging at 4.04% and 3.67%, respectively. As an outlier robust measure of heterogeneity I further consider the quasi-standard deviation as proposed by Giordani and Söderlind (2003).[11] The quasi standard deviations average at 2.15% and 2.31% for perceptions and expectations, respectively. The difference compared to the conventional standard deviation reflects a relatively high concentration of answers at 0%.

The degree of cross-sectional heterogeneity stands out in two respects. First, survey heterogeneity seems high given the low level and volatility of actual inflation in Sweden. Second, one would expect less heterogeneity in perceptions than in expectations because the actual rate of inflation is, with some publication lag, readily available to households. This has already been noted by Jonung (1981). The high degree of heterogeneity in inflation perceptions is not a particularity of the Swedish data, however. In their recent study, Van der Klaauw et al. (2008) provide similar evidence for the U.S. A possible explanation for heterogeneous perceptions might be that households refer to inflation in their subjective

[11]The quasi standard deviation is defined as half the difference between the 84th and 16th percentile of the quantitative responses. This measure corresponds to the usual standard deviation if point forecasts are normally distributed.

consumption baskets. But the high degree of heterogeneity in inflation perceptions can only be partially explained by differences in household specific consumption baskets. This follows from results of Kokoski (2000), who computes household specific price indices for the U.S. Kokoski (2000) shows that in the period 1988–1997, differences in annual inflation rates across household expenditure quintiles are almost negligible, ranging below 0.5% in absolute terms. Even if Kokoski (2000) notes that these estimates are only approximate due to limited data availability, it seems unlikely that actual heterogeneity is underestimated by several percentage points. This reasoning is in line with Bryan and Venkatu (2001a, 2001b) who investigate U.S. survey data on inflation perceptions. It is also supported by the wording of the Swedish survey which, as previously discussed, facilitates that the survey questions are being homogeneously interpreted. In sum, the results suggest that heterogeneity in predictors and information sets are important sources of heterogeneity in perceptions and expectations of inflation.

The third panel of Table 3.1 highlights further common response patterns. More than 90% of perceptions and expectations are integers. The concentration of answers at integers (digit preference) is in line with evidence provided by Curtin (2005) for the U.S. and by Bryan and Palmqvist (2006) for the U.S. and Sweden. Integer answers are concentrated at a few focal points which are mentioned more often than their neighboring integers.[12] Both for perceptions and expectations, the most frequently mentioned focal points are -5%, -2%, 0%, 2%, 5%, 10%. These integers account for 71% of perceptions and for 69% of expectations. About 7% of perceptions and 13% of expectations are equal to 2%, which is the inflation target of the Swedish Riksbank.[13] As the third panel of Table 3.1 further shows, the most important focal point is 0%, accounting for more than half of all focal point responses. On average, 57% of perceptions and 41% of expectations are exactly 0%.

[12] This definition of focal points follows Bryan and Palmqvist (2006). There is no evidence for important non-integer focal points in the Swedish Consumer Tendency Survey.

[13] The Swedish Riksbank has introduced inflation targeting in 1993 with an explicit target for consumer price inflation being effective from 1995 onwards. The inflation target rate is 2%, with a tolerance interval of ±1%. See Heikensten (1999) for a discussion of the Riksbank's inflation targeting policy. Of the remaining integers, 1, 3 and 4 obtain the highest response shares. This set accounts for 9% of perceptions and for 16% of expectations.

But as the monthly minima and maxima indicate, the share of zero responses fluctuates substantially.

The fourth panel of Table 3.1 presents some initial evidence on the relation of perceptions and expectations. Over the entire sample horizon, 49% of all respondents give the same quantitative answer to the questions on perceived and expected inflation. The share of identical responses, i.e. observations for which $\pi^p_{t,i} = \pi^e_{t,i}$, varies significantly over time, ranging between 26% and 69%. The cross-sectional correlation of responses is moderate in magnitude but highly significant in statistical terms. The correlation coefficient is 0.52 during 01/1996–10/2008. In a simple regression model, inflation perceptions thus explain about 27% of the variance in inflation expectations. The correlation coefficient ranges between 0.29 and 0.70 in monthly surveys and is always highly significant. Figure B.1 in the Appendix shows the variance explained over time. The finding of a significant moderate correlation of perceived and expected inflation also holds in a high inflation environment as documented by Jonung (1981). Using Swedish data from 01/1978, when mean perceived and expected inflation rates exceeded 10% and actual inflation attained 5.9%, Jonung (1981) finds a cross-sectional correlation of about 0.5.

Abstracting from the household-level, Figure 3.1 shows a high degree of comovement between cross-sectional means of perceptions and expectations. The correlation between the series is 0.89, the root mean squared error (RMSE) is 0.59%. Pronounced deviations are only apparent at the beginning and towards the end of the sample. The absolute deviation attains a maximum in 09/2008, when perceptions exceed expectations by 2.2%.[14] The figure also shows the contemporaneous and 12 months ahead HICP inflation rate. Perceptions and expectations both track contemporaneous HICP inflation quite closely, with the respective correlation coefficients being 0.76 and 0.70. The figure further indicates that expectations are only weakly correlated with 12 months ahead realized HICP inflation: The correlation coefficient is 0.25, the RMSE is 1.07%. Hence, the mean of inflation expectations is more closely related to the mean of inflation perceptions than to the

[14]Note that this rise in the mean of perceptions is atypical in the sense that the mean of expectations exceeds the mean of perceptions in 129 out of 154 months.

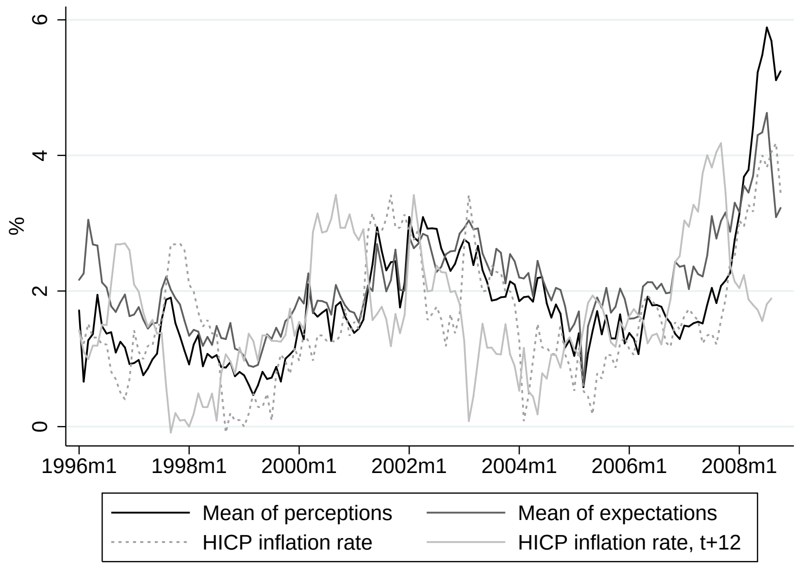


Figure 3.1: Mean of perceived and expected inflation

Notes: This figure shows the monthly means of quantitative inflation perceptions and expectations, as well as the contemporaneous and 12 months ahead HICP inflation rate.

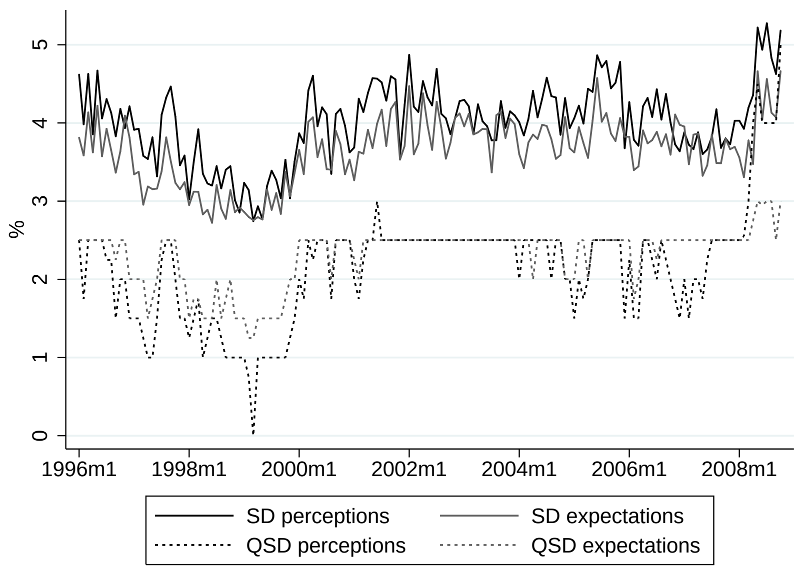


Figure 3.2: Heterogeneity of perceived and expected inflation

Notes: This figure shows measures of cross-sectional heterogeneity in monthly surveys. SD is the standard deviation. QSD is the quasi standard deviation defined as half the difference between the 84th and the 16th percentile.

contemporaneous or 12 months ahead HICP inflation rate. Figure 3.2 shows that measures of cross-sectional heterogeneity also share common dynamics. During 01/1996–10/2008, the correlation between the standard deviations of perceptions and expectations is 0.85. The correlation between the quasi standard deviations is 0.84.

Overall, the above results show that perceptions and expectations of inflation are highly heterogeneous. The magnitude of heterogeneity seems too high to be explained by idiosyncrasies in the interpretation of the questions and by differences in consumption baskets. Consequently, this paper focuses on heterogeneous predictors as an important source of overall heterogeneity. Furthermore, the observed similarities in responses suggest that inflation perceptions and expectations are closely related. In particular, a high share of respondents give identical responses to the questions on perceived and expected inflation. The cross-sectional correlation of responses is highly significant in every month. Moreover, the high degrees of comovement in central tendency and disagreement also point to an important relation between perceptions and expectations of inflation.

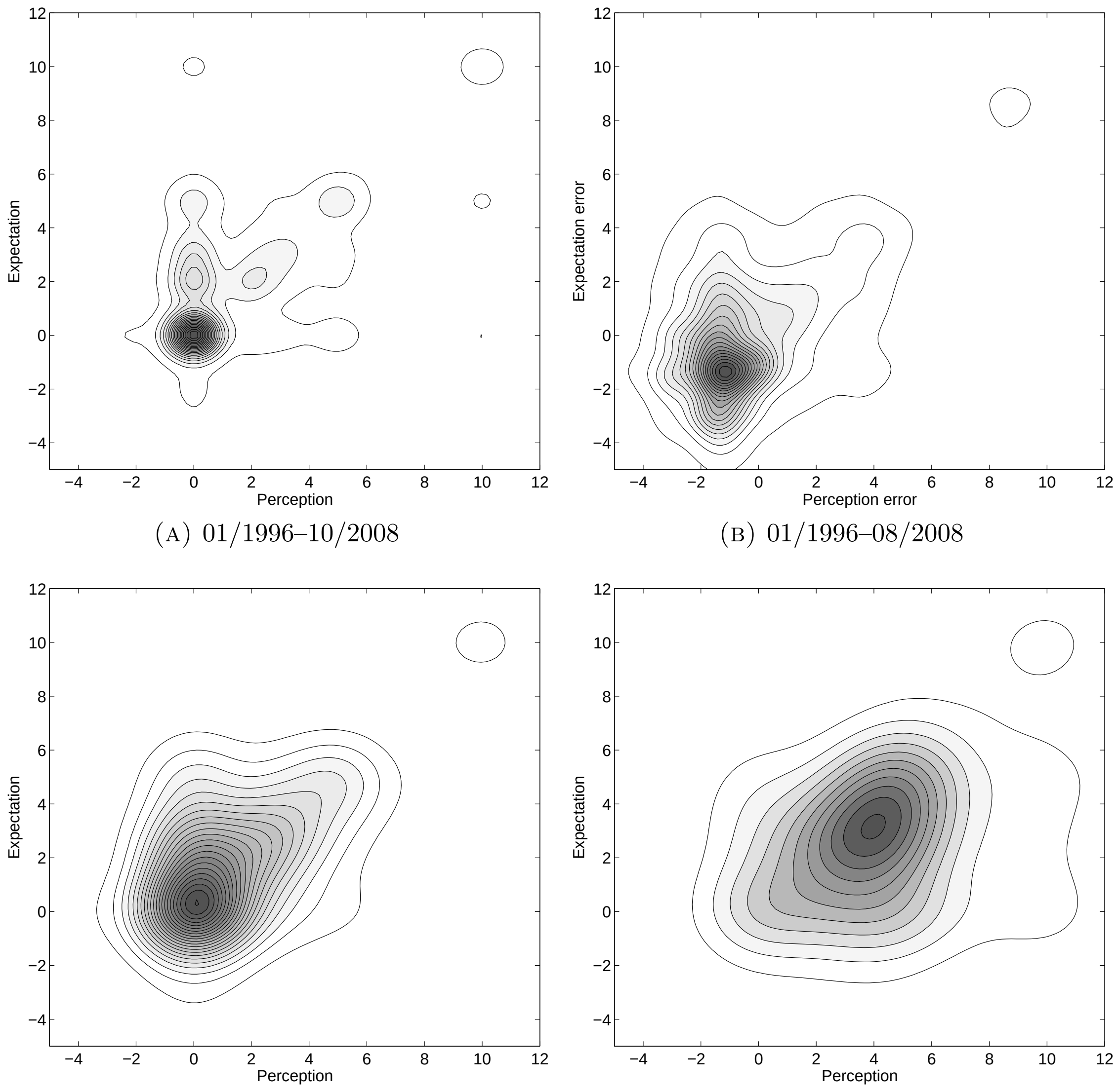
3.3.2 Joint Density Functions

Capitalizing on the household-level data, further evidence on this relation can be gained by investigating the joint density function of perceived and expected inflation. For estimating the joint density I employ the bivariate product kernel density estimator defined as:

$$\hat{f}_t(\pi^p, \pi^e) = \frac{1}{Nh_1h_2}\sum_{i=1}^{N} K\left(\frac{\pi^p - \pi_i^p}{h_1}\right) K\left(\frac{\pi^e - \pi_i^e}{h_2}\right)$$

with a normal kernel given by $K(x) = \frac{1}{\sqrt{2\pi}}e^{-0.5(x)^2}$. N denotes the number of observations and h_1 and h_2 are the window widths for perceptions and expectations, respectively. Following Scott (1992), the window width is chosen using the rule $h_k = N^{-\frac{1}{6}}\hat{\sigma}_k$, $k = \{1, 2\}$, where $\hat{\sigma}_k$ is the estimated standard deviation of the respective variable.

Figure 3.3a shows the joint density function of perceptions and expectations in the sample 01/1996–10/2008. The joint density peaks at $(\pi^p = 0\%, \pi^e = 0\%)$, which is not



(A) 01/1996–10/2008

(B) 01/1996–08/2008

(C) 01/2004

(D) 09/2008

FIGURE 3.3: Bivariate kernel density estimates

Notes: These figures show contour lines of bivariate product kernel density estimates $\hat{f}_t(\pi^p, \pi^e)$. Belief errors in Figure (B) are defined as the difference between perceived inflation and actual HICP inflation and between expected inflation and 12 months ahead HICP inflation, respectively. All variables are expressed as percentages. In Figure (A), contour lines start at 0.004 and increment by 0.01. In Figure (B), contour lines start at 0.002 and increment by 0.004. For the monthly samples in Figures (C) and (D), contour lines start at 0.002 and increment by 0.002. Estimates are based on a standard normal kernel. The window width is chosen using the rule $h_k = N^{-\frac{1}{6}}\hat{\sigma}_k$, where N is the number of observations and $\hat{\sigma}_k$, $k = \{1, 2\}$, is the standard deviation of perceptions and expectations, respectively.

surprising given the high share of zero responses. In fact, for a share of 32% of all observations, perceptions and expectations are jointly zero. The contour lines further indicate that the density is high around other integers. On the diagonal, observations are concentrated at (3%, 3%), (5%, 5%) and (10%, 10%). These pairs account for roughly 2%, 4% and 4% of all responses, respectively. Important off-diagonal response pairs include (0%, 2%), (0%, 3%), (0%, 5%), (0%, 10%) and (10%, 5%). These pairs account for 7%, 4%, 3%, 1% and 1% of all responses. The contour plot shows that while the density increases around the diagonal, it is also relatively high around the vertical at a perception of 0%. This again is in line with the finding of a moderate correlation of responses as discussed above.

Figure 3.3b tackles the intrinsic relation of perceptions and expectations that exists beyond the objective joint density of contemporaneous and 12 months ahead HICP inflation. The objective relation is accounted for by estimating the joint density of belief errors. The perception error is defined as the difference between perceived inflation and the actual HICP inflation rate. The expectation error is defined as the difference between expected inflation and the 12 months ahead realized inflation rate. The resulting contour lines are similar to Figure 3.3a. The density function peaks at (−1.61%, −1.61%), again reflecting the high share of zero responses, shifted downwards by an average HICP inflation rate of 1.61%. The figure still shows the diagonal pattern, whereas the vertical pattern at a perception of 0% is less pronounced. The correlation of perception errors and expectation errors is 0.49 during 01/1996–10/2008.

Figures 3.3c and 3.3d illustrate joint density functions of perceptions and expectations for two exemplary months. Figure 3.3c shows the joint density in 01/2004. This is an average month in the sense that perceptions and expectations average at 1.89% and 2.19%, close to their averages during 01/1996–10/2008. Figure 3.3d shows the joint density in 09/2008. As noted before, this is an unusual month in the sense that inflation perceptions average about 2.2 percentage points higher than inflation expectations. For both months, contour lines exhibit a diagonal pattern but are relatively broad along the diagonal. The density peaks at (0%, 0%) in 01/2004 and at (4%, 3%) in 09/2008.

The joint density estimates reflect that not only a high share of households opt for zero responses, but that perceptions and expectations are positively correlated at the household-level. A diagonal pattern is also apparent in the joint density of belief errors, indicating that the relation between perceptions and expectations does not simply reflect an objective joint density of contemporaneous and 12 months ahead inflation. This suggests that a share of households might form idiosyncratic static expectations: Their expectations of inflation are based on subjective perceptions of inflation.

3.3.3 Determinants of Individual Response Variation

Further evidence on expectation formation can be gained by investigating which factors affect whether a respondent gives identical answers to the questions on perceived and expected inflation. In this section it is assumed that the decision of a respondent to stick to the individually perceived inflation rate when forming an expectation can be described by a random utility model. Consequently, the probability that expected inflation differs from perceived inflation (henceforth response variation) can be evaluated in a simple probit framework:

$$P(\pi^p_{t,i} \neq \pi^e_{t,i} \mid x_{t,i}) \quad = \quad F(x_{t,i}, \beta) = \Phi\left(x'_{t,i}\beta\right)$$

where $\Phi(.)$ is the standard normal cumulative distribution function and $x_{t,i}$ a vector of explanatory variables. Clearly, this model is explorative as it only describes whether a respondent opts for identical responses or not. It does not allow inference about whether a respondent forms expectations according to a particular model. By coincidence, expected inflation might be identical to perceived inflation under alternative models of expectation formation. The Gaussian mixture model to be proposed in the next section resolves this identification problem by jointly considering multiple models of expectation formation.

The set of explanatory variables includes the HICP inflation rate in levels and first differences. To the extent that identical responses reflect idiosyncratic static expectation formation, the marginal effects of these variables should be positive. Idiosyncratic static expectation formation assumes that expected inflation is equal to the subjective perception of inflation. If inflation is high or rising, then incentives to closely track inflation should be relatively high, too. If sticking to outdated information becomes increasingly costly, households should form more elaborate forecasts that differ from their perceived inflation rates. Hence, the probability of response variation increases. This reasoning is in line with the theories of rational inattention (Sims, 2003) and rational predictor selection (Branch, 2004). Furthermore, I include the absolute mean prediction error of idiosyncratic static expectations, defined as the absolute difference between the mean of inflation perceptions in month t and in month $t-12$. The prediction error captures the average accuracy of idiosyncratic static expectations of inflation.[15] Its inclusion is motivated by results of Branch (2004) suggesting that the probability of a predictor being chosen depends inversely on its accuracy. Hence, the marginal effect of the absolute prediction error should also be positive: The less precise idiosyncratic static expectations have been in the past (the higher the prediction error), the more likely individual responses will vary in the current period. Furthermore, the absolute deviation of individually perceived inflation from actual HICP inflation is included. This variable accounts for conventional static expectation formation which assumes that expectations are equal to the official inflation figure. The larger the deviation of perceived from actual inflation, the more likely expectations differ from perceptions if some households form conventional static expectations. Finally, I consider the mean of professional inflation forecasts taken from the Consensus Economics survey. The variable is again included as an absolute difference relative to the individually perceived inflation rate. Its inclusion is motivated by recent evidence of Carroll (2003) suggesting that households absorb professional forecasts through the news media. The marginal effect should be clearly positive: The larger the absolute deviation, the more likely households will form an expectation that differs from the perceived rate of inflation.

Table 3.2 reports estimated marginal effects, evaluated at sample means. The reported robust standard errors allow for cross-sectional dependence within monthly samples. The

[15] Note that prediction errors cannot be computed at an individual level since households are interviewed only once. I have also considered the mean prediction error defined as the absolute difference between the mean perceived inflation in month t and the mean 12 months ahead inflation expectation formed in month $t-12$, with consistent results.

Table 3.2: Determinants of individual response variation

	1997–2008	2002–2008
HICP inflation rate	0.0100***	0.0072*
	(0.0035)	(0.0044)
Δ HICP inflation rate	0.0038	0.0006
	(0.0078)	(0.0100)
Abs. mean prediction error	0.0176***	0.0163***
	(0.0046)	(0.0050)
Abs. dev. HICP inflation rate	-0.0002	0.0088
	(0.0067)	(0.0069)
Abs. dev. professional forecast	0.0216***	0.0076
	(0.0067)	(0.0068)
Year $\geq$ 2002	0.1689***	
	(0.0060)	
N	167,273	103,092
Log L	-111,826	-69,409

Notes: The table shows marginal effects on the probability that a respondent's inflation expectation differs from perceived inflation. Sample periods 01/1997–10/2008 (reduced due to the inclusion of the mean prediction error) and 01/2002–10/2008, spanning 154 and 80 months, respectively. *Abs. mean prediction error* is the absolute difference between the mean of inflation perceptions in month t and in month $t-12$. *Abs. dev. HICP inflation rate* and *Abs. dev. professional forecast* are the absolute deviations of perceptions from contemporaneous actual inflation and from the mean professional forecast, respectively. N is the number of observations, *Log L* is the log-likelihood. Standard errors in parentheses allow for clustering at the level of monthly surveys. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

estimations also control for a level shift in 01/2002 to account for a potential structural break induced by the change in the surveying institution.[16] Columns 1 and 2 show estimation results for the samples 01/1997–10/2008 and 01/2002–10/2008, respectively. With one exception, all parameter estimates have the expected positive sign and are consistent across the two samples. The absolute deviation of perceived inflation from actual inflation has a negative sign during 1997–2008. However, the variable is insignificant in both samples, suggesting that conventional static expectations are not widely used. The

[16]Figure B.2 in the Appendix shows the monthly share of observations with varying responses. The monthly share increases in 01/2002, coinciding with the change in the surveying institution. Consistent with the evidence provided in Figure B.2, the indicator variable for the level shift in 2002 is highly significant. However, estimation results in column 1 are consistent for a specification that excludes the level shift dummy variable, indicating that the potential structural change is uncorrelated with the explanatory variables.

absolute deviation of perceived inflation from the mean professional forecast is highly significant during 01/1997–10/2008, indicating that households absorb professional forecasts. But the relevance of professional forecasts is limited, as the variable is insignificant during 01/2002–10/2008. In contrast, the absolute mean prediction error of idiosyncratic static expectations is highly significant in both samples. This is consistent with the notion that households who form idiosyncratic static expectations respond to their own past prediction errors. Moreover, the likelihood of response variation positively depends on the level of actual inflation. This result is consistent with the notion that the higher the actual inflation rate, the less likely households are to form idiosyncratic static expectations.[17]

The main finding of the explorative analysis is that inflation expectations are highly heterogeneous. The observed heterogeneity is too high to be accounted for by heterogeneous consumption baskets and differences in the interpretation of the survey questions. Consequently, the Gaussian mixture model proposed in the next section explains survey heterogeneity by heterogeneity in expectation formation models. The explorative analysis further suggests that subjective inflation perceptions are an important determinant of inflation expectations. During 01/1996–10/2008, 49% of respondents give identical answers to the questions on perceived and expected inflation. The estimated probit model of response variation shows that households react to the prediction error of the idiosyncratic static expectations model. Moreover, households seem to absorb expectations of professional forecasters. In addition to traditional models of expectation formation, the Gaussian mixture model thus considers predictors that build on subjective inflation perceptions and on expectations of professional forecasters.

[17] The estimation results are robust to the exclusion of explanatory variables as cross-correlations are mostly low. The only exception concerns the absolute deviation from HICP inflation and the absolute deviation from professional forecasts. These variables are highly correlated. Once the absolute deviation of HICP inflation is excluded, the absolute deviation of professional forecasts becomes highly significant during 01/2002-10/2008 as well.

3.4 Inference About Predictor Choice

3.4.1 A Gaussian Mixture Model of Survey Heterogeneity

This section proposes a model that explains heterogeneity in survey expectations by heterogeneity in expectation formation models (predictors) that households use to form inflation expectations.[18] Assume that each survey participant i uses a predictor j from a set of M available predictors. The set of predictors is given by $h_{t,i} = \{h_{t,i,1}, ..., h_{t,i,j}, ..., h_{t,i,M}\}$. Predictor values $h_{t,i,j}$ are allowed to vary across individuals i to accommodate idiosyncratic static expectations, as will be outlined below. In every month t, each survey participant selects a predictor j with corresponding predictor value $h_{t,i,j}$ and reports an inflation expectation given by:

$$\begin{aligned} \pi^e_{t,i} &= h_{t,i,j} + \varepsilon_{t,i,j} \\ \varepsilon_{t,i,j} &\sim N(0, \sigma^2_j) \end{aligned}$$

The key assumption of the model is that a household's survey response is not exactly equal to the predictor value. Rather, inflation expectations of households that opt for the same predictor j differ due to various idiosyncrasies represented by the stochastic term $\varepsilon_{t,i,j}$. These idiosyncrasies include differences in rounding, differences in information sets and differences in conceptual understandings of inflation. The standard deviation of the idiosyncratic noise term depends on the predictor. E.g., if households form idiosyncratic static expectations one would expect that expectations are approximately equal to the individually perceived inflation rate. If households stick to professional forecasts, survey responses will be distributed more loosely around the mean of professional forecasts since professional forecasts are heterogeneous and not all households will adopt the same professional forecast (which generates differences in information sets).

[18]The conceptual focus of this paper lies on heterogeneous predictors. The Gaussian mixture framework can easily be extended to the case of heterogeneous information sets, simply by adding predictors that are based on different information sets. Investigating the role of heterogeneous information sets is left to future research.

In the survey population, each predictor is chosen by a proportion $\alpha_{t,j}$, $j = 1, ..., M$, of respondents. Consequently, the probability density function of survey expectations is a mixture of M normal densities. Survey expectations follow a Gaussian mixture density defined by:

$$f_t(\pi^e_{t,i} \mid \theta_t, h_{t,i}) \;=\; \sum_{j=1}^{M} \alpha_{t,j}\varphi\left(\frac{\pi^e_{t,i} - h_{t,i,j}}{\sigma_j}\right)$$

where $\varphi(.)$ is the standard normal density function. The parameter vector is given by $\theta_t = \{\alpha_{t,1}, ..., \alpha_{t,M}, \sigma_1, ..., \sigma_M\}$. Mixing proportions $\alpha_{t,j}$ of component density j satisfy $\alpha_{t,j} \geq 0$ and $\sum_{j=1}^{M} \alpha_{t,j} = 1$ for all t and $j = 1, ..., M$. The explorative analysis has shown that response variation fluctuates over time. Consequently, the Gaussian mixture model allows for time-varying proportions $\alpha_{t,j}$.

Finite mixture models have a wide range of applications in all fields of science.[19] In economics, finite mixture models are less commonly used to directly model and classify heterogeneous data. To the best of my knowledge, only El-Gamal and Grether (1995) and Branch (2004, 2007) use mixture models in related settings. El-Gamal and Grether (1995) employ a mixture model to classify experimental data and to infer decision rules used by experimental subjects. Branch (2004, 2007) uses a similar approach to investigate survey heterogeneity in inflation expectations. But as will be discussed below, the model of rationally heterogeneous expectations of Branch (2004, 2007) differs in important aspects from the more general Gaussian mixture model used in this paper. Mixture model based approaches are commonly used to control for unobserved heterogeneity (e.g. in the Poisson regression model by Hausman et al., 1984), in latent class models (e.g. in a latent class regression of health outcomes by Morduch and Stern, 1997) and in time series models with unobserved regime changes (Hamilton, 1994).

Given the survey data on inflation expectations and a set of predictors, the aim is to identify the mixing proportions $\alpha_{t,j}$ and associated standard deviations σ_j for $j = 1, ..., M$

[19]See, e.g., Redner and Walker (1984) and Titterington, Smith and Makov (1985) for an overview of applications in non-economic settings.

and $t = 1, ..., K$. Note that, unlike in a standard Gaussian mixture model, the means $h_{t,i,j}$ of the component densities are exogenous. The log-likelihood function of the survey data is:

$$\mathscr{L}(\{\pi^e_{t,i}\}, \theta_1, ..., \theta_K, h_1, ..., h_K) = \sum_{t=1}^{K} \sum_{i=1}^{N_t} log \left[\sum_{j=1}^{M} \alpha_{t,j} \varphi \left(\frac{\pi^e_{t,i} - h_{t,i,j}}{\sigma_j} \right) \right] \tag{3.1}$$

where N_t denotes the number of observations in month t and $h_t = \{h_{t,1}, ..., h_{t,i}, ..., h_{t,N_t}\}$. Direct (Newton-type) numerical maximization of the Likelihood (3.1) proves to be difficult. The sum of M normal distributions inside the logarithm implies a complex dependence of the likelihood on the estimation parameters. In line with the literature on finite mixture models, I therefore employ the expectation maximization (EM) algorithm as formulated by Dempster, Laird and Rubin (1977).[20]

The EM algorithm is an iterative process of two alternating steps which are repeated until convergence is achieved. In the expectation step, the probability that respondent i uses predictor j is computed. Conditional on initial guesses of the estimation parameters, the posterior probability that $\pi^e_{t,i}$ is generated by $h_{t,i,j}$ is given by Bayes' rule:

$$\tau_{t,i,j} = \frac{\alpha_{t,j} \phi \left(\frac{\pi^e_{t,i} - h_{t,i,j}}{\sigma_j} \right)}{f_t(\pi^e_{t,i} \mid \theta_t, h_{t,i})}$$

[20]In economics, the EM algorithm is commonly used to estimate time-series models with unobserved regime changes. Dempster, Laird and Rubin (1977) derive general properties of the expectation maximization algorithm and outline its application to the estimation of finite mixtures. Redner and Walker (1984) specifically discuss the application of the EM algorithm and alternative methods to estimating mixture densities. A comprehensive discussion of the EM algorithm is provided by McLachlan and Krishnan (2008).

In the maximization step, the posterior probabilities are used to update the estimation parameters. The updated mixing proportions and standard deviations are given by:

$$\alpha_{t,j}^{+} = \frac{1}{N_t}\sum_{i=1}^{N_t}\tau_{t,i,j}$$
$$\sigma_j^{+} = \sqrt{\frac{1}{K}\sum_{i=1}^{K}\frac{1}{N_t}\sum_{i=1}^{N_t}\frac{\tau_{t,i,j}(\pi_{t,i}^{e}-h_{t,i,j})^2}{\alpha_{t,j}^{+}}}$$

These updated estimates maximize the likelihood given the posterior probabilities. In the subsequent iteration, the initial values are replaced by the updated mixing proportions and standard deviations. As initial values I use uniform mixture probabilities ($\alpha_{t,j}^0 = \frac{1}{M}$) and standard deviations equal to the sample standard deviation of inflation expectations. Dempster, Laird and Rubin (1977) show that the likelihood is monotonically increasing with each iteration and that the EM algorithm converges to the maximum likelihood estimator. Redner and Walker (1984) highlight a number of advantages of the EM algorithm over direct numerical maximization, the most important being more reliable convergence. However, it is well known that the Likelihood (3.1) potentially has a multitude of spurious maxima: If $\pi_{t,i}^e = h_{t,i,j}$ for an arbitrary i and j, then $\mathscr{L} \to \infty$ if $\sigma \to 0$. To prevent the estimated standard deviations from collapsing to zero I consider two alternative restrictions. The first restriction constrains standard deviations such that $\sigma_j \geq 1$. The second restriction imposes equal standard deviations for all predictors, i.e. $\sigma_j = \sigma$ for $j = 1, ..., M$.

Based on the point estimates obtained from the EM algorithm, the covariance matrix of the estimation parameters is computed using the inverse of the outer-product-of-the-gradient (OPG) estimator of the information matrix.[21]

In two seminal contributions, Branch (2004, 2007) proposes a model of rationally heterogeneous expectations. His model combines two sub-models. The first sub-model is a random utility model of individual predictor choice. Individuals are assumed to rationally

[21] Matlab source codes of the entire estimation procedure are available from the author. To compute the OPG (or BHHH) estimator as proposed by Berndt et al. (1974), numerical estimates of the gradient are employed.

select predictors based on predictor costs and benefits. Predictor costs are being estimated, whereas predictor benefits are exogenously determined by the mean squared error relative to the realized rate of inflation. The second sub-model assumes that given the individual predictor choice, the individual survey response is normally distributed around the predictor value. The model of Branch (2004, 2007) yields a likelihood similar to Equation (3.1), but with the mixing proportions $\alpha_{t,j}$ being replaced by a conditional logit function.[22] Thus, for the purpose of identifying which predictors are used by households, the Gaussian mixture model is more general than the model of rationally heterogeneous expectations. The Gaussian mixture model does not impose any structure (other than non-negativity and the sum restriction) on the monthly proportions $\alpha_{t,j}$ of respondents that use a particular predictor. Furthermore, the Gaussian mixture model as implemented in this paper allows for a predictor specific standard deviation σ_j. Allowing for predictor specific standard deviations seems important. As outlined above, theoretical arguments suggest that the degree of idiosyncrasies in information sets differs across predictors. Finally, an important difference concerns the estimation of the model. Branch (2004, 2007) uses direct maximum likelihood estimation, whereas I employ the EM algorithm.

3.4.2 Models of Expectation Formation

It remains the question among which predictors households choose to form their inflation expectations. In the following, a set of four predictors is considered.

First, households may form static (naive) expectations. The conventional static expectations model assumes that expected 12 months ahead HICP inflation is equal to the actual HICP inflation rate at the time of expectation formation:

$$h_{t,1} \quad = \quad \pi_t$$

[22]Using the above notation, the likelihood of a rational heterogeneous expectations model along the lines of Branch (2004, 2007) is given by $\mathscr{L} = \sum_{t=1}^{K} \sum_{i=1}^{N_t} log \left[\sum_{j=1}^{M} \frac{e^{\beta u_{t,j}}}{\sum_{k=1}^{M} e^{\beta u_{t,k}}} \varphi \left(\frac{\pi_{t,i}^e - h_{t,i,j}}{\sigma} \right) \right]$, where the utility of each predictor is $u_{t,j} = -MSE_{t,j} - C_j$. $MSE_{t,j}$ is the mean squared error of predictor j. The estimation parameter C_j represents costs of predictor j.

The conventional static expectations model assumes that all respondents rely on identical information to form homogeneous expectations. Conventional static expectations are optimal in the sense of minimizing the mean squared forecast error if annual HICP inflation over non-overlapping intervals follows a random walk. This is clearly not the case in the sample period 01/1996–10/2008, during which contemporaneous and 12 months ahead inflation are uncorrelated.[23] Also, the analysis of response variation has not revealed any patterns consistent with conventional static expectation formation. Conventional static expectations are thus unlikely to be widely used in the survey population.

Second, I consider the alternative model of idiosyncratic static expectations. The idiosyncratic static expectations model assumes that expected inflation is equal to the inflation rate over the past 12 months as perceived by the respondent:

$$h_{t,i,2} \quad = \quad \pi^{p}_{t,i}$$

Values of the idiosyncratic static predictor will thus vary across individuals i. The explorative analysis suggests that a significant share of respondents employ this model. Note, however, that households might as well give identical answers to the questions on perceived and expected inflation because some other predictor is equal to their perceived rate of inflation. The joint estimation with other predictors in the Gaussian mixture framework accounts for possible confounding and allows to identify the actual share of respondents using idiosyncratic static expectations.

Third, households may form adaptive expectations. The expected 12 months ahead inflation rate is a weighted mean of current inflation and the past adaptive expectation:

$$h_{t,3} \quad = \quad h_{t-12,3} + \lambda(\pi_t - h_{t-12,3}) = (1-\lambda)h_{t-12,3} + \lambda\pi_t$$

where $\lambda \in [0,1]$. Adaptive expectations are equal to conventional static expectations

[23] The regression coefficient on contemporaneous inflation from a simple linear regression of 12 months ahead inflation on contemporaneous inflation and a constant is -.0530. The parameter is not significantly different from zero.

if $\lambda = 1$. Using a grid search, I choose the λ to minimize the mean squared forecast error relative to realized HICP inflation during 01/1996–08/2008. This yields an optimal $\lambda = 0.198$, which is similar to the value of 0.216 identified by Branch (2004) for a longer sample of U.S. data. Adaptive expectations are a distributed lag of HICP inflation rates with exponentially declining weights. Hence, a low value of λ implies that expectations are relatively smooth compared to actual inflation. Figure B.3 in the Appendix shows that adaptive expectations range in a narrow interval which roughly spans 1.5% to 2.5%.

Fourth, households may form rational expectations. The concept of rational expectations as introduced by Muth (1961) assumes that agents have full knowledge about the structure of the economy when forming an expectation. In other words, households are assumed to know the objective probability density function of 12 months ahead HICP inflation. Following Evans and Honkapohja (2001), I refer to a concept of rationality that relaxes this information requirement: Rational agents are assumed to act like econometricians who re-estimate their forecasting models over time. As a proxy for rational expectations I thus employ the mean expectation of professional forecasters taken from the Consensus Economics survey. It seems plausible to assume that professional forecasters form, on average, the most well informed forecasts which are updated on a regular basis.[24] Rational households are assumed to either independently form expectations that correspond to the professional benchmark or to adopt the mean of professional expectations as transmitted through various information channels. Rational expectations are thus given by:

$$h_{t,4} \quad = \quad \bar{\pi}_t^{e,prof}$$

where $\bar{\pi}_t{}^{e,prof}$ is the mean professional forecast of 12 months ahead HICP inflation.

These four predictors rank in increasing order in terms of accuracy. During 01/1996–

[24]This view is challenged by alternative theories suggesting that professional forecasters diverge from rational expectations due to strategic behavior (Laster, Bennett and Geoum, 1999), herding, conservatism, optimism (Batchelor, 2007), or asymmetric loss functions (Capistrán and Timmermann, 2009). Nevertheless, the mean of professional forecasts is the most accurate forecast of inflation in the sample, as will be discussed below.

Table 3.3: Accuracy of predictors

	Bias	MAE	RMSE
Conventional static expectations (actual HICP inflation)	-0.10	1.04	1.28
Idiosyncratic static expectations (perceived inflation)	0.11	0.92	1.20
Adaptive expectations	0.10	0.81	1.03
Rational expectations (mean of professional forecasts)	0.01	0.75	0.93

Notes: The table shows measures of accuracy relative to 12 months ahead realized HICP inflation during 01/1996–08/2008. *Bias* is the difference between expected and realized inflation, *MAE* is the mean absolute error, *RMSE* denotes the root mean squared error.

08/2008, rational expectations is clearly the most accurate predictor with the lowest root mean squared forecast error relative to actual inflation. Table 3.3 indicates that rational expectations dominates the other predictors also regarding bias and mean absolute error. In terms of the root mean squared error, adaptive expectations are ranked second, idiosyncratic static expectations are ranked third and conventional static expectations are the least accurate predictor. Even more pronounced than the differences in accuracy are the differences in dynamics of expectations generated by these models, as illustrated in Figure B.3 in the Appendix.

The Gaussian mixture approach allows to arbitrarily extend this set of predictors. However, the four predictors considered cover the most important archetypes of expectation formation models. Extending the set of available predictors is thus left to future research.[25]

[25] Additional expectation formation models include, e.g., anchoring expectations to the central bank policy target, using a simple rule to infer financial markets expectations (Thomas, 1999) or employing a multivariate time-series model (Branch, 2004, Mankiw, Reis and Wolfers, 2004).

3.4.3 Estimation Results

The Gaussian mixture model is estimated for three sets of predictors. In a first step, the set of available predictors includes conventional static expectations, adaptive expectations and rational expectations. In a second step, conventional static expectations are replaced with idiosyncratic static expectations. In a third step, all four predictors are simultaneously included. The estimation period spans 01/1996–10/2008. To improve stability of the estimates, only responses between -10% and 10% are considered, which reduces the sample size by 6,683 observations (or 3.7%) to 175,394 observations.

Table 3.4 summarizes estimation results for the Gaussian mixture model with time-invariant mixture proportions.[26] Column 1 of Table 3.4 shows that for the set excluding idiosyncratic static expectations, predictors are virtually uniformly distributed. The estimated mixing proportions α_j are about one third each for conventional static expectations, adaptive expectations and rational expectations. Estimated standard deviations σ_j are also nearly identical across predictors, averaging at about 2.7%. The standard errors of the estimates indicate that all parameters are highly significant. Figure 3.4 shows estimation results for the model that allows for time-varying mixture proportions. The figure reveals that on a monthly basis, the proportions of respondents that form conventional static expectations and rational expectations fluctuate substantially.

Column 2 of Table 3.4 shows estimation results for the set of predictors that includes idiosyncratic static expectations rather than conventional static expectations. The estimates indicate that about 52% of respondents form idiosyncratic static expectations. The estimated proportion is in line with the share of identical responses reported in Table 3.1. The proportion of respondents forming adaptive expectations declines to 0.17, whereas the share of respondents forming rational expectations remains roughly unchanged at 0.31. The estimated standard deviations differ significantly between predictors. The standard deviation of idiosyncratic static expectations is restricted to unity. Without the restriction, the standard deviation collapses to zero during the maximization process.[27] Figure 3.5

[26] This specification imposes the restriction $\alpha_{t,j} = \alpha_j$ on the Likelihood (3.1).

[27] As outlined above, a standard deviation of zero maximizes the likelihood if a predictor value is exactly

Table 3.4: Estimated Gaussian mixture models

	(1)	(2)	(3)
Proportions α_j			
Conventional static expectations	0.3310		0.1476
	(0.0002)		(0.0000)
Idiosyncratic static expectations		0.5165	0.5095
		(0.0000)	(0.0000)
Adaptive expectations	0.3336	0.1743	0.1544
	(0.0002)	(0.0000)	(0.0000)
Rational expectations	0.3354	0.3092	0.1885
	(0.0003)	(0.0000)	(0.0000)
Standard deviations σ_j			
Conventional static expectations	2.6530		1.7167
	(0.0004)		(0.0067)
Idiosyncratic static expectations		1.0000	1.0000
Adaptive expectations	2.7237	4.1446	4.3084
	(0.0003)	(0.0009)	(0.0025)
Rational expectations	2.6532	1.6419	1.6789
	(0.0008)	(0.0002)	(0.0004)
N	175,394	175,394	175,394
Log L	-423,130	-359,390	-359,220

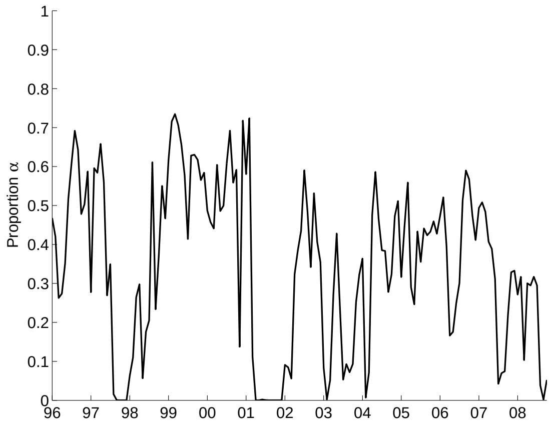
Notes: The table shows estimated proportions of respondents that use a particular predictor (mixing proportions α_j) and associated standard deviations (σ_j). All parameters are restricted to be constant across monthly surveys. In columns (2) and (3), the standard deviation of idiosyncratic static expectations is restricted to unity in order to prevent the standard deviation from collapsing to zero. N is the number of observations, *Log L* is the log-likelihood. Standard errors in parentheses are based on the OPG estimator. All estimates are significant at the 1% level.

shows monthly proportions from the model that allows for time-varying mixture proportions. The estimated proportions are less volatile than for the set with conventional static expectations. During the second half of the sample period, the proportion of agents forming rational expectations tends to increase, whereas the proportion of idiosyncratic static expectations declines.

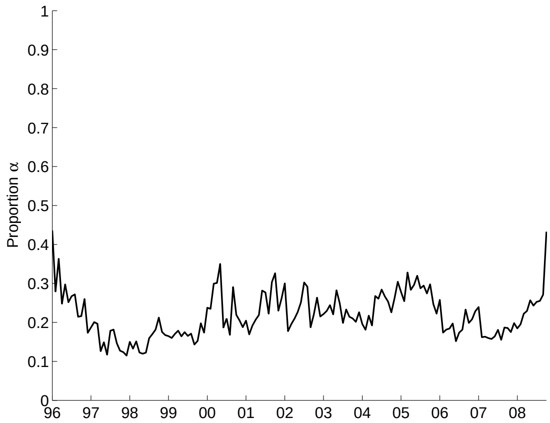
Column 3 of Table 3.4 presents the estimation results for the model that includes all four predictors. Again, the standard deviation of idiosyncratic static expectations is restricted to unity. Employing the set of all four predictors, the estimated proportion of households forming conventional static expectations declines to 0.15. Roughly half of all respondents form idiosyncratic static expectations. The share of adaptive and rational expectations decline to 0.15 and 0.19, respectively. Figure 3.6 shows monthly proportions. In comparison to Figure 3.5, the dynamics of the proportions of idiosyncratic static expectations and adaptive expectations are mainly unchanged, whereas the proportion of respondents forming rational expectations is somewhat more volatile. As above, the proportion of agents forming idiosyncratic static expectations shows a declining tendency during the second half of the sample period. Figure 3.6 confirms the main finding shown in Table 3.4: Once idiosyncratic static expectations are accounted for, the estimated proportion of households forming conventional static expectations diminishes. The estimates indicate that while all four predictors are in use, the most common predictors are idiosyncratic static expectations and rational expectations.

The robustness of these results is tested by estimating a model that restricts the standard deviations to be equal across predictors. This alternative restriction prevents the estimated standard deviations $\sigma_j = \sigma$ from collapsing to zero, since a zero variance does not maximize the likelihood anymore. The estimation results for the model with time-invariant mixing proportions are summarized in Table B.1 in the Appendix. All results are in line with the above findings. The estimated standard deviations for the predictor sets including idiosyncratic static expectations are about 2.2%. The proportion of respon-

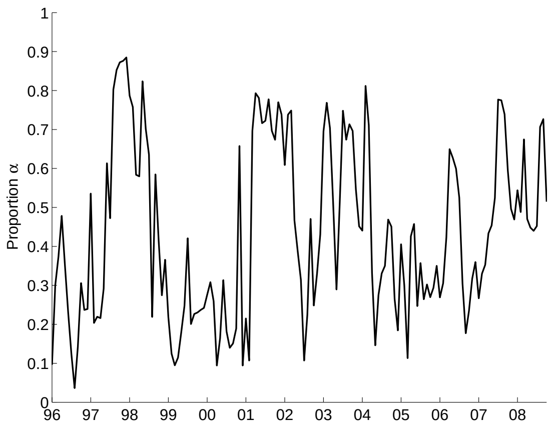
equal to a reported expectation. For idiosyncratic static expectations this condition is satisfied by 49% of observations.



(a) Conventional static expectations



(b) Adaptive expectations

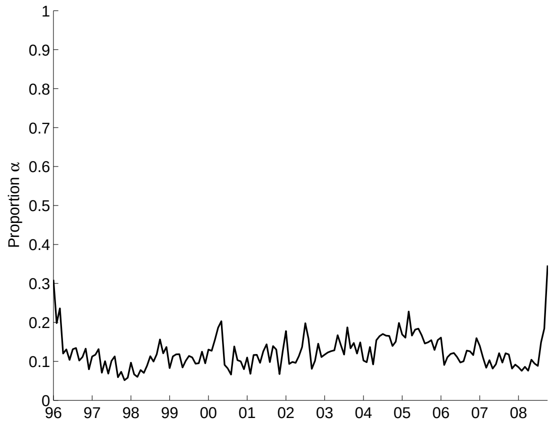


(c) Rational expectations

Figure 3.4: Monthly proportions of predictors (conventional static expectations)

Notes: These figures show monthly proportions of respondents that choose a particular predictor (mixing proportions $\alpha_{t,j}$). The set of available predictors is given by conventional static expectations (actual HICP inflation rate), adaptive expectations and rational expectations (mean of professional forecasts). The estimated time-invariant standard deviations σ_j are 1.60%, 4.70% and 1.88% for static, adaptive and rational expectations, respectively.

(A) Idiosyncratic static expectations

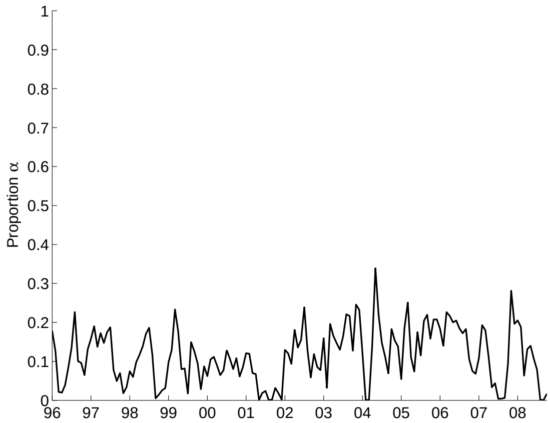


(B) Adaptive expectations

(C) Rational expectations

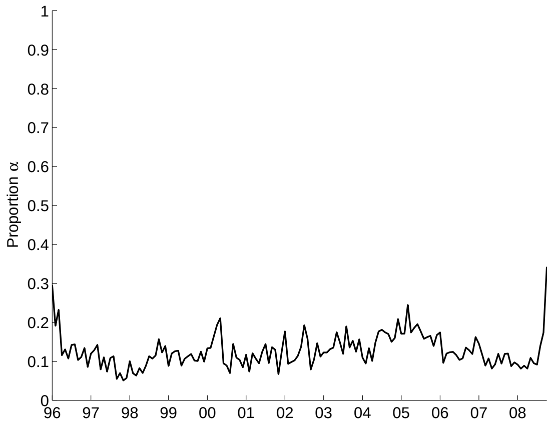
Figure 3.5: Monthly proportions of predictors (idiosyncratic static expectations)

Notes: These figures show monthly proportions of respondents that choose a particular predictor (mixing proportions $\alpha_{t,j}$). The set of available predictors is given by idiosyncratic static expectations (perceived inflation rate), adaptive expectations and rational expectations (mean of professional forecasts). The estimated time-invariant standard deviations σ_j are 1.00%, 4.70% and 1.77% for static, adaptive and rational expectations, respectively.

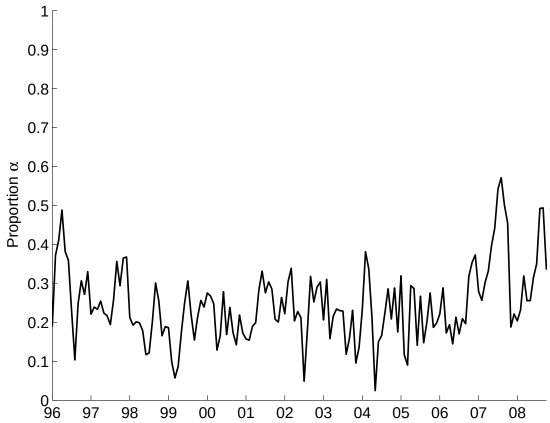


(A) Conventional static expectations

(B) Idiosyncratic static expectations



(C) Adaptive expectations



(D) Rational expectations

Figure 3.6: Monthly proportions of predictors (set of all predictors)

Notes: These figures show monthly proportions of respondents that choose a particular predictor (mixing proportions $\alpha_{t,j}$). The set of available predictors is given by conventional static expectations, idiosyncratic static expectations, adaptive expectations and rational expectations. The estimated time-invariant standard deviations σ_j are 1.50%, 1.00%, 4.49% and 1.66% for conventional static, idiosyncratic static, adaptive and rational expectations, respectively.

dents that form idiosyncratic static expectations marginally declines to about 0.47, both for the set without conventional static expectations (column 2) and for the set of all four predictors (column 3). The results for the model with time-varying mixing proportions are shown in Figures B.4, B.5 and B.6. Unlike suggested by the model with time-invariant mixing proportions, Figure B.4 reveals significant differences in the dynamics of monthly shares for the set including conventional static expectations.[28] Figures B.5 and B.6 do not show any important differences regarding the results for the predictor sets that include idiosyncratic static expectations, however.

Overall, the estimated Gaussian mixture models indicate that every second household forms idiosyncratic static expectations during 01/1996–10/2008. The estimated proportion is consistent with survey evidence provided by Benford and Driver (2008) for the U.K. These authors find that more than 40% of households consider their perception of inflation to be a very important factor for expectation formation. The high share of households forming idiosyncratic static expectations is particularly relevant, as inflation perceptions may substantially deviate from the actual rate of inflation. In the Swedish sample, the mean of inflation perceptions exceeds actual HICP inflation by 2.1 percentage points in 07/2008. For countries of the European Monetary Union, a large literature provides evidence that inflation perceptions did substantially rise above actual inflation after the euro cash changeover in 01/2002.[29] Depending on the set of available predictors, between 19 and 31 percent of households form rational expectations. The expectations of these households are based on professional forecasters' expectations. A share of 15% of households form adaptive expectations. A similar share of households form conventional static expectations that correspond to the official inflation figure. In line with findings of Ang, Bekaert

[28]This difference reflects that estimated standard deviations for the model with time-varying mixture proportions are heterogeneous. The estimated standard deviations underlying Figure 3.4 are 1.6039%, 4.6951% and 1.8829% for conventional static expectations, adaptive expectations and rational expectations, respectively.

[29]This rise in perceived inflation is documented in ECB (2005). Several explanations are being discussed in the literature, including increased information processing requirements due to conversion rates and overreaction to prices of frequently bought items. See, e.g., Ehrmann (2006), Aucremanne, Collin and Stragier (2007), Doehring and Mordonu (2007), Dziuda and Mastrobuoni (2006), Aalto-Setälä (2006) and Fluch and Stix (2007).

and Wei (2007) for the U.S., these results suggest that household expectations contain much more information than a simple random walk (conventional static) forecast. Finally, the monthly proportions of households that use a particular predictor show moderate variation. The proportions mostly fluctuate within intervals that span about 30 percentage points. The significance and robustness of the estimated proportions confirm that the Gaussian mixture model is a sound approach to disentangle survey heterogeneity.

3.5 Conclusion

Building on the idea that households dynamically select predictors to form inflation expectations, this paper proposes a Gaussian mixture model to identify which predictors are actually being used. The explorative analysis shows that inflation expectations are highly heterogeneous and that this heterogeneity cannot be explained by idiosyncrasies in concepts about inflation or consumption baskets alone. Moreover, the explorative analysis suggests that an important relation exists between inflation perceptions and inflation expectations. During 01/1996–10/2008, 49% of all respondents give identical answers to the questions about perceived and expected inflation.

Consequently, I estimate a Gaussian mixture model assuming that households dynamically select predictors from the set of conventional static expectations (given by the official inflation figure), idiosyncratic static expectations (individual perceptions of inflation), adaptive expectations and rational expectations (mean professional forecast). The proposed Gaussian mixture model takes the analysis of survey data one step further: Rather than just testing and rejecting particular models of expectation formation, the approach allows to infer the probability that a given model is actually being used by survey participants. The estimates robustly show that about 51% of households form idiosyncratic static expectations, 19% form rational expectations and 15% each form adaptive expectations and conventional static expectations. The share of households forming idiosyncratic static expectations shows a declining tendency in the second half of the sample. The significance and robustness of the estimates corroborate both the Gaussian mixture model of heterogeneity and the estimation procedure using the EM algorithm.

Overall, the results clearly show that subjective perceptions of the current annual inflation rate are a key determinant of inflation expectations. This finding is in line with qualitative survey evidence from the U.K. provided by Benford and Driver (2008). These authors find that households consider their perception of inflation to be the central factor in expectation formation. The relevance of inflation perceptions suggests that households are to a large part backward looking. The role of inflation perceptions is particularly important, as it is well documented that inflation perceptions may substantially deviate from the actual rate of inflation. A promising avenue for further research thus involves investigating how households form their perceptions about inflation. This research will have direct implications for expectation formation. Moreover, our understanding of expectation formation will substantially benefit from an integrated conceptual framework of perception and expectation formation.

Chapter 4

The Formation of Inflation Perceptions: Some Empirical Facts for European Countries*

*This chapter is based on Lein and Maag (2008).

4.1 Introduction

This paper investigates how households form inflation perceptions, defined as the beliefs at time t about the actual rate of consumer price inflation between month t-12 and t. Economic theory suggests that expectations about future inflation have predominant implications for investment, saving and consumption decisions. We argue, however, that it is just as important to investigate perceptions of current annual inflation for two main reasons. First, inflation perceptions are an important determinant of inflation expectations. This is suggested by results discussed in Chapter 3 of this dissertation and in line with survey evidence provided by Benford and Driver (2008). Benford and Driver (2008) investigate data from a special issue of the Bank of England Inflation Attitudes Survey that asks households about how they form their inflation expectations. They document that more than 40% of households consider their perception of current inflation to be a very important factor in expectation formation. Inflation perceptions are more important than the other factors mentioned, which include interest rates, the central bank policy target and media reports. Chapter 3 investigates quantitative response data from the Swedish Consumer Tendency Survey that jointly asks for perceptions and expectations of inflation. It is shown that during 1996–2008, a share of 51% of Swedish households form static expectations that are equal to the perceived rate of inflation. Second, perceptions allow for better tests of rationality and models of belief formation than expectations. Working with inflation perceptions, the benchmark for the belief that a rational household should adopt is relatively well-defined. It is the publicly available, official rate of inflation.

The empirical literature on inflation perceptions is scant, both in absolute terms and relative to the literature on inflation expectations. Only recently, the rise in inflation perceptions coinciding with the euro cash changeover in the European Monetary Union has drawn increased research attention.[1] Abstracting from the euro cash changeover, an

[1] The deviation of perceived from actual inflation rates is documented in ECB (2005). The literature investigates several explanations for this rise, including increased information processing requirements due to conversion rates, overreaction to prices of frequently bought items and anchoring of perceptions to prior beliefs. See Ehrmann (2006), Aucremanne, Collin and Stragier (2007), Doehring and Mordonu (2007), Dziuda and Mastrobuoni (2006), Aalto-Setälä (2006), Fluch and Stix (2007) and references therein.

earlier literature comprises a small number of papers that investigate household-level data. Using quantitative survey data from the U.S., Bryan and Venkatu (2001a, 2001b) find that inflation perceptions of households are significantly biased. Furthermore, they report that the accuracy of inflation perceptions correlates with demographic characteristics. Jonung (1981) and Palmqvist and Strömberg (2004) document similar patterns using survey data from Sweden.

The goal of our paper is to understand how inflation perceptions of households are related to the actual rate of inflation in a sample of 12 European countries. We aim to provide general evidence rather than focusing on specific factors associated with the euro cash changeover or with socioeconomic characteristics. Our analysis begins by presenting evidence on the dynamics and rationality of inflation perceptions. We find that inflation perceptions fail rationality tests and that perceptions exhibit a high degree of cross-sectional heterogeneity. These broad patterns are consistent with the epidemiological model of belief formation proposed by Carroll (2003). In this model, only a fraction of households update their beliefs with the latest information in each period. The rest of households is assumed to stick to outdated beliefs. This model implies an inertial response of the population mean of perceived inflation to changes in the actual rate of inflation. We formally test whether the dynamics of the survey mean and the cross-sectional heterogeneity of inflation perceptions can be explained by the epidemiological model. This is, to some extent, also an assessment of the sticky information hypothesis put forward by Mankiw and Reis (2002).[2]

We find that a share of around 11% of consumers in the euro area update their inflation perceptions within a quarter of a year. These estimates are lower than the updating frequencies reported by studies relying on survey data about inflation expectations. For European countries, Döpke, Dovern, Fritsche and Slacalek (2008a, 2008b) find that between

[2]Similar to the epidemiological model, the sticky information model of Mankiw and Reis (2002) assumes that agents that do not update their information sets stick to outdated beliefs. But unlike in the epidemiological model, agents continue to dynamically compute beliefs based on their outdated information sets. The epidemiological model assumes that agents stick to their static belief formed at the time of the last update.

20 and 30 percent of households (and firms) update their expectations within a given quarter.[3] However, we find that the epidemiological model does not adequately describe perception formation in our sample of European countries. In particular, we show that the cross-sectional heterogeneity of inflation perceptions is much higher than predicted by the model. We therefore conclude that the transmission of information to households and the formation of beliefs should be described by approaches that include alternative mechanisms which generate an extra degree of cross-sectional heterogeneity of survey responses.

The paper is structured as follows. Section 4.2 discusses models of perception formation, including the rational perceptions and the epidemiological perceptions model. Section 4.3 presents the dataset which is based on the Joint Harmonized EU Consumer Survey and the Swedish Consumer Tendency Survey. Section 4.4 investigates general properties of inflation perceptions and tests the rational perceptions hypothesis. Section 4.5 assesses the epidemiological model of perception formation. Section 4.6 concludes.

4.2 Models of Perception Formation

We initially assume that households form rational beliefs about actual consumer price inflation. Following the rational expectations literature, we define perceptions π_t^p of actual inflation π_t to be rational if:

$$\pi_t^p = E_t \pi_t$$

where E_t is the expectation of actual inflation conditional on the public information set Ω_t available at time t. The rational perceptions hypothesis assumes that agents employ all available information to form beliefs about actual inflation. This hypothesis can be tested by investigating whether inflation perceptions are unbiased and information efficient.[4]

[3] For the U.S., Carroll (2003) and Khan and Zhu (2006) estimate updating frequencies that lie in the same range.

[4] If Ω_t contains all information including π_t, perceptions are rational if the identity $\pi_t^p = \pi_t$ holds. Still, we rely on less restrictive tests of unbiasedness and information efficiency to assess the rational perceptions hypothesis since the timing of the household survey is not identical for all households. As will be discussed

As an alternative to rational perceptions, we consider the epidemiological model of belief formation proposed by Carroll (2003). The epidemiological model is based on the idea that households form inflation expectations by probabilistically acquiring new information from media reports. Carroll (2003) assumes that media reports transmit expectations of professional forecasters which are subsequently adopted by households. Every household has a constant probability λ of encountering media reports and absorbing the most recent professional forecasts in a given month t. This assumption implies that the population mean of inflation expectations can be written as a partial adjustment model:

$$\pi^e_{t,t+12} = \lambda \pi^m_{t,t+12} + (1-\lambda)\pi^e_{t-1,t+11}$$

where $\pi^e_{t,t+12}$ is the cross-sectional mean of household expectations about the one year ahead inflation rate, $\pi^m_{t,t+12}$ is the inflation forecast of professional forecasters transmitted by the media and $\pi^e_{t-1,t+11}$ is the expected one year ahead inflation rate of households in the previous month. The coefficient λ is equal to the proportion of households that update their inflation expectations with the new expectation of professional forecasters in a given month.[5] The epidemiological model is related to the concept of sticky information introduced by Mankiw and Reis (2002, 2006). The main assumption in sticky information models is that in each period, only a fraction of agents acquire new information about the state of the economy to compute a new path of optimal behavior. Those agents who update are assumed to form rational expectations based on Ω_t. Consequently, new information disperses slowly throughout the population and has a gradual and delayed effect on the aggregate behavior of agents.

The critical decision that has to be made when testing models of expectation formation concerns the identification of the new information that agents use to update their beliefs. It is inherently difficult to identify the ex-ante rational value of expectations. The literature

in Section 4.3, the household survey is conducted during the first three weeks of each month.

[5]Carroll (2003) and Döpke, Dovern, Fritsche and Slacalek (2008b) estimate this model for the U.S. and Europe respectively. They find that consumers in the U.S. update their information about once a year, in Europe about once in eighteen months.

on expectation formation mainly employs two benchmark measures: the actual rate of inflation materialized in 12 months and inflation expectations of professional forecasters, as in the model of Carroll (2003). Both benchmark measures of rational expectations can be criticized on theoretical grounds.

Using the materialized 12 months ahead inflation rate may be flawed if agents assign positive probability to an important event that does not materialize. In retrospect, one will then observe biased expectations and autocorrelated expectations errors even if expectation formation was rational.[6] Similarly, even rational agents may not identify a regime change as being permanent at first sight, in which case expectations would again fail rationality tests. Andolfatto, Hendry and Moran (2008) confirm this argument in a simulation study building on the rational expectations New Keynesian model. The model assumes that agents face a signal extraction problem as they only have incomplete information about the changing inflation target of the monetary authority. Calibrating the model to fit U.S. business cycle statistics, Andolfatto, Hendry and Moran (2008) show that conventional tests of rational expectations incorrectly reject rationality in about 30% of the simulated samples that span 80 quarters.

Using expectations of professional forecasters as the rational benchmark has some weaknesses, too. Several studies report that professional forecasts are biased, see, e.g., Ang, Bekaert and Wei (2007), Mehra (2002) and Thomas (1999). A rational household that is aware of this might thus not rely on professional forecasts when forming inflation expectations. Moreover, professional forecasters usually disagree. It is unclear which forecast households will refer to. In particular, the literature that investigates strategic forecasting commonly assumes that forecasts far off the consensus catch more media attention.[7] Therefore, the central tendency of professional forecasts might not correspond to the inflation

[6]This potential pitfall is also known as the "Peso Problem", see Jonung and Laidler (1988). For these reasons it is common practice to assess rationality of expectations only over long time periods.

[7]Making biased forecasts far from the average might in turn be rational behavior by professional economists, see e.g. Ehrbeck and Waldmann (1996) and Laster, Bennett and Geoum (1999). In the model of Laster, Bennett and Geoum (1999), forecasters are not only paid on basis of the accuracy of their forecast but also on basis of the media attention they are able to catch. The latter can be obtained by deviating significantly from the average.

forecast that households observe in the media and use to update their beliefs with.

Unlike for inflation expectations, the rational benchmark seems well-defined for inflation perceptions: It is the actual rate of consumer price inflation as published by national statistical offices. Actual consumer price inflation is, with a short publication lag, unambiguously available to all households, be it as an official news releases of the national authority, be it through media reports. Therefore, in line with the reasoning of Jonung and Laidler (1988), inflation perceptions might be better suited to asses rationality and models of belief formation than inflation expectations.

We thus rewrite the epidemiological model of Carroll (2003) to a partial adjustment model in which consumers update their inflation perceptions with the actual rate of inflation. We consider two versions of the model. The first specification assumes that households update using the contemporaneous, actual rate of inflation. Since the official inflation rate is published rather in the beginning to the middle of the following month, the model assumes that households compile new information based on price changes they observe during economic interactions in the current month. Consumers that do not update their information set stick to the same inflation perception as in the previous month. The resulting partial adjustment model (1) can be written as follows:

$$\pi_t^p = \lambda \pi_t + (1 - \lambda)\pi_{t-1}^p \tag{4.1}$$

The second specification assumes that households use the most recent available official inflation figure to update their information sets. Due to the publication lag of the official inflation figure, we therefore test whether consumers absorb the one month lagged inflation rate. The partial adjustment model (2) is given by:

$$\pi_t^p = \lambda \pi_{t-1} + (1 - \lambda)\pi_{t-1}^p \tag{4.2}$$

Similar to Carroll (2003), this model implicitly assumes that consumers update their beliefs with the latest inflation rate published in the media.

4.3 Data

In the European Union, household inflation perceptions are surveyed as part of the Joint Harmonized European Union Consumer Survey.[8] In each member state, national institutes survey about 1,500 households during the first three weeks of every month. In July 2007, the overall sample covers 39,900 consumers in 27 member states. Inflation perceptions are captured by asking households: "How do you think that consumer prices have developed over the last 12 months? They have...". Respondents are asked to indicate their beliefs on an ordinal scale with five response categories given by: "Risen a lot, risen moderately, risen slightly, stayed about the same, fallen".

In line with recent literature on expected inflation we quantify the qualitative response data using the probability method.[9] We employ the probability method for 5-category response data as proposed by Batchelor and Orr (1988). Inflation perceptions are identified by assuming that perceptions are unbiased with respect to actual consumer price inflation during the sample period. Under this identification scheme, the probability method allows to compute the mean and standard deviation of inflation perceptions among respondents in a given month. A detailed description of the approach and its identifying assumptions are provided in Appendix C.2.[10]

To assess the robustness of the quantification method, we additionally discuss estimations that are based on direct quantitative survey data obtained from the Swedish Consumer Tendency Survey. This survey has been capturing quantitative inflation perceptions

[8] The consumer survey consists of 15 qualitative questions that capture the financial situation, perceived economic conditions and planned savings and spending. This standard questionnaire is translated into national languages and may include additional country specific questions, see European Commission (2007).

[9] Recent contributions that use the probability method to quantify expected inflation are Berk (1999) and Forsells and Kenny (2004) who quantify EU consumer survey data and Mankiw, Reis and Wolfers (2004) who quantify qualitative response data from the University of Michigan Survey of Consumers.

[10] Batchelor and Orr (1988) extend the probability method developed in Theil (1952) and Carlson and Parkin (1975) to 5-category response data. Perceived inflation and implied standard deviation of perceptions are given by equations (C.1) and (C.2) in the Appendix. Chapter 2 assesses the empirical performance of the probability method using data both on qualitative and quantitative inflation perceptions taken from the Swedish Consumer Tendency Survey. It is found that in Swedish data, the method applied in this chapter generates series that have a correlation of 0.97 (0.86 in first differences) with actual quantitative inflation perceptions during 1996–2008.

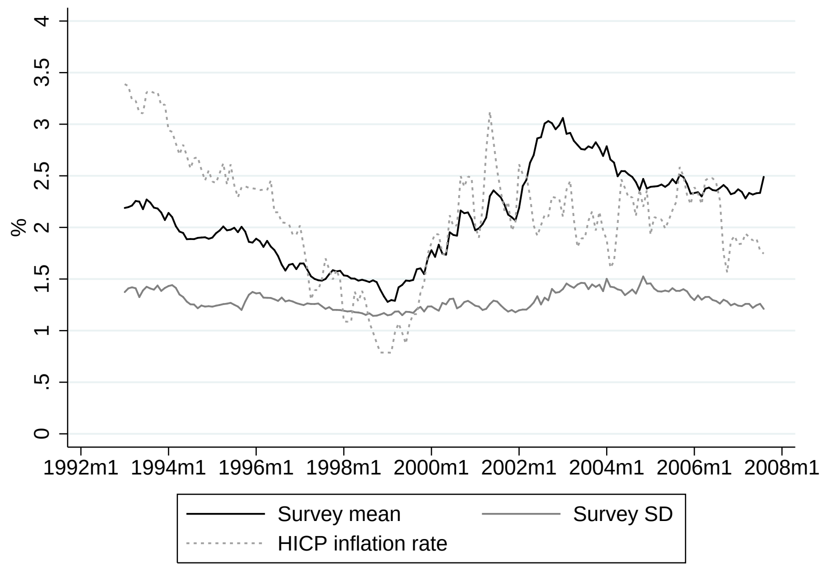


Figure 4.1: Mean and standard deviation of inflation perceptions in the euro area

Notes: The figure shows quantified mean and cross-sectional standard deviation of inflation perceptions in the euro area. Qualitative response data is quantified using the 5-category probability method under the assumption that perceptions are unbiased.

on a monthly basis since January 1996.[11]

As a measure for actual inflation we use the annual percent change in the Harmonized Index of Consumer Prices (HICP) as published by Eurostat. The actual annual inflation rate is given by $\pi_t = 100\left(\frac{P_t}{P_{t-12}} - 1\right)$, where P_t is the level of the HICP index at the end of month t. We assume that rational individuals absorb this inflation rate as their belief about actual inflation.[12] For testing the rationality of households, we also compute a price index for out-of-pocket expenditures. The out-of-pocket expenditures index covers non-durable goods and consumer services that are frequently purchased and payed in cash. It is based on disaggregate HICP data obtained from Eurostat.[13]

[11]See GfK (2002) for a description of the Swedish Consumer Tendency Survey.

[12]We have employed real time data for HICP inflation rate where available and tested the models. Differences to using ex post data were insignificant. This result is not surprising, as revisions in inflation rates are rather rare and small. Therefore, we report the ex post data results, as we have more data points available for earlier years in the time series dimension.

[13]We compute the out-of-pocket expenditures index as a consumption weighted average of price series on COICOP 2 to 4 digit level. The included items are food, beverages, tobacco, non-durable household goods, transport services, fuel, postal services, hotels, restaurants and hairdressing.

We consider a sample of 10 euro area countries, Sweden, United Kingdom and the euro area (EA) aggregate.[14] For most countries, the sample includes 176 monthly observations spanning 01/1993 to 08/2007. It may be reduced depending on the joint availability of survey data and HICP inflation rates. Table C.1 in the Appendix provides an overview. To account for potential structural breaks coinciding with the euro cash changeover, we provide additional estimation results for the subperiods 01/1993–12/2001 and 01/2003–08/2007.

Figure 4.1 shows perceived inflation in the euro area. The mean of inflation perceptions clearly exhibits the so called euro cash changeover effect. Perceived inflation rises above actual inflation in 2002 and peaks at about 3% in 01/2003. The figure indicates that the gap closes in early 2004. Perceived inflation has a low standard deviation of 0.44%, while actual HICP inflation has a standard deviation of 0.58% during 1993–2007. Relative to the variability of inflation, the quantified cross-sectional standard deviation of inflation perceptions seems high. It averages at 1.29% during 1993–2007. As will be discussed below, this quantified series even tends to underestimate the actual heterogeneity of perceptions.

For the further analysis, stationarity properties of perceived and actual inflation are critical. We discuss unit root properties and cointegration of actual and perceived inflation both on a country-by-country basis and in a panel framework. Our analysis begins by testing the null-hypothesis of a unit root using the augmented Dickey-Fuller (ADF) test. We apply the sequential model selection procedure following Perron (1988). Additionally, the null hypothesis of stationarity is tested using the Kwiatkowski, Phillips, Schmidt and Shin (1992) (KPSS) test. Tables C.2 and C.3 in the Appendix summarize the results for HICP inflation and perceived inflation, respectively. The ADF-tests indicate that actual inflation is stationary in 4 out of 12 countries, whereas perceived inflation is stationary in 2 countries. The KPSS test always rejects its null hypothesis of stationarity. Clearly, all first differences are stationary. As perceived inflation rates have substantially increased during

[14]Of the 12 countries that introduced euro banknotes and coins in 2002, Luxembourg and Portugal are not included since no survey data on inflation perceptions is available. Aggregate actual HICP inflation and perceived inflation are computed as weighted means of the euro area series. Weights are given by private domestic consumption expenditures.

the euro cash changeover in most countries of the euro area, it might well be the case that the ADF tests fail to reject the null hypothesis due to a level shift in the underlying series. We therefore additionally apply a unit root test that allows for a deterministic level shift following Saikkonen and Lütkepohl (2002) and Lanne, Lütkepohl and Saikkonen (2002). The results are reported in Table C.4 in the Appendix and the conclusions are unchanged. We cannot reject the null of a unit root in perceived and actual inflation in most countries.

While the sample includes a reasonable number of monthly observations, it covers a relatively short time span of only 14 years. As Pierse and Snell (1995) show, the power of a unit root test primarily depends on the time span rather than on the sampling frequency. To improve power, we thus additionally investigate unit root properties in a panel setting using the Im, Pesaran and Shin (2003) (IPS) and Pesaran (2007) (CIPS) panel unit root tests. These tests assesses the null hypothesis of a unit root in all countries against the alternative that inflation is stationary in a significant number of countries. Both test allow for heterogenous short run dynamics and deterministic terms. An important restriction of the IPS test is that dependence of inflation across countries is only accounted for by cross-sectional demeaning. Other forms of cross-sectional dependence that cannot be captured by a homogenous common time effect may induce a positive size bias (Breitung and Pesaran, 2005). In our panel of 12 interconnected European economies, overrejection is a relevant issue.[15] The CIPS test proposed by Pesaran (2007) is a more reliable alternative. This test allows for residual correlation that is generated by a heterogenous single-factor structure. Its limitation remains the assumption of a single common factor. Contrary to the country-by-country tests, the panel unit root tests shown in Table C.5 clearly reject the null hypothesis of a unit root in inflation. For higher lag orders, the CIPS test clearly rejects the null hypothesis of a unit root in all series, both in the period 1993–2007 period and in subperiod 1993–2001.[16] The null of a unit root is not rejected in the shorter sub-

[15]Even after controlling for common time effects, the absolute cross-sectional correlation coefficients still average at 0.32. See Wang and Wen (2007) for a discussion of potential sources of international synchronization in inflation rates.

[16]We consider the specifications that include 3 or 4 lags since under-fitting can lead to considerable size distortions as shown by Im, Pesaran and Shin (2003).

period 2003–2007. Perceived inflation appears to be more persistent than actual inflation. Both tests cannot reject the null hypothesis in the samples 1993–2007 and 1993–2001.

Due to the ambiguous findings on the stationarity properties, we additionally investigate cointegration of actual and perceived inflation. Obviously, one would expect that perceived and actual inflation move together proportionally in the long run. Hence, if the series are I(1) they should be cointegrated. Table C.6 in the Appendix reports results from Johansen trace tests on the cointegration rank. The table shows trace statistics for the null hypothesis of no cointegration ($r = 0$) and the null hypothesis of one cointegration relation ($r = 1$) between actual and perceived inflation during 1993–2007. The tests indicate that actual and perceived inflation are cointegrated only in Greece and Ireland. Consistent with the ADF test, the full rank results indicate that an estimation in levels is appropriate for Finland and Sweden. The general picture of no cointegration remains unaltered in the subperiods 1993–2001 and 2003–2007, as Tables C.7 and C.8 show.

To gain statistical power we also employ panel cointegration tests. We use the residual based tests proposed by Pedroni (1999, 2004). The null hypothesis of no cointegration in all countries is tested against the alternative hypothesis that a cointegration relation exists in a significant number of countries. Cointegration coefficients and short run dynamics are allowed to differ across countries.[17] Table C.9 in the Appendix reports the parametric (analogue to the augmented Dickey-Fuller t-statistic) and nonparametric (analogue to the Phillips and Perron t-statistic) panel and group mean t-statistics. The panel tests indicate that perceived and actual inflation are cointegrated over the full sample as well as in the two subperiods.[18] Although the panel result that actual and perceived inflation are cointegrated is intuitively appealing, the result might also mirror that actual inflation and inflation perceptions are stationary. The panel unit root tests generally reject the null hypothesis of a unit root in actual inflation and, on a country-by-country basis, a cointegration relation is detected only in a small number of countries.

[17]The limitation of this test is that it does not account for cross-sectional relations that cannot be removed by simple cross-section demeaning. Similar to the panel unit root tests, this may lead to size distortions (Banerjee, Marcellino and Osbat, 2004).

[18]This result is confirmed by the five other test statistics proposed by Pedroni (1999, 2004).

The ambiguous results are in line with the mixed findings of the empirical literature. Surveying this literature, Altissimo, Ehrmann and Smets (2006) conclude that empirical work is rather in favor of stationarity of euro area consumer price inflation.[19] Moreover, from a theoretical economic viewpoint it seems reasonable to assume that inflation and inflation perceptions are no unit root processes in the sample period considered here. We therefore estimate our baseline specifications in levels. To assess the robustness, we additionally provide estimation results in first differences.

4.4 Explorative Analysis

4.4.1 Accuracy of Inflation Perceptions

This section highlights some general statistical properties pertaining to the dynamics of inflation perceptions and empirically motivates the epidemiological model of belief formation. The analysis begins by investigating the accuracy of inflation perceptions. As Table 4.1 shows, the accuracy with respect to actual HICP inflation varies quite substantially between countries. The mean absolute error (MAE) ranges between 0.48 and 1.72 percent. It averages at 0.86% during 1993–2007. This seems relatively high, given that the quantified inflation perceptions are unbiased by assumption. Compared to the accuracy of inflation expectations as documented in the literature, inflation perceptions are only slightly more accurate.[20] This is particularly noteworthy, as inference about current and past inflation entails substantially less uncertainty compared to inference about the 12 months ahead inflation.

Table 4.1 additionally reports the correlation (ρ) of perceived with actual HICP inflation. Looking at the euro area aggregate, this correlation drops from 0.90 in the period 1993–2001 to -0.04 in the period 2003–2007. The observed decline in correlation is broadly

[19] Still, some recent studies cannot reject the null hypothesis of a unit root in inflation, see e.g. O'Reilly and Whelan (2005).

[20] E.g., Mankiw, Reis and Wolfers (2004) report that 12 months ahead inflation expectations taken from the University of Michigan Survey of Consumers have a MAE of 1.07% and a RMSE of 0.85% in the period 1982–2002.

TABLE 4.1: Accuracy of inflation perceptions by country

		1993–2007					93–01	03–07
Country		MAE	RMSE	ρ	ρ_{lag}	ρ_{OOP}	ρ	ρ
AT	Austria	0.74	0.70	0.47	0.48	0.38	0.49	0.19
BE	Belgium	0.71	0.60	0.47	0.50	0.52	0.72	0.40
DE	Germany	0.69	0.58	0.23	0.26	0.48	0.78	-0.58
EA	Euro Area	0.76	0.72	0.45	0.45	0.77	0.90	-0.04
EL	Greece	1.72	3.76	-0.17	-0.18	n.a.	0.74	-0.34
ES	Spain	0.93	1.06	0.32	0.33	0.68	0.78	0.32
FI	Finland	0.86	0.90	0.31	0.35	0.22	0.73	0.57
FR	France	0.69	0.57	0.50	0.51	0.24	0.55	0.26
IE	Ireland	0.84	0.91	0.71	0.74	0.58	0.90	0.61
IT	Italy	0.95	1.11	0.35	0.34	0.69	0.83	0.78
NL	Netherlands	0.84	1.01	0.42	0.46	0.37	0.87	0.58
SE	Sweden	0.66	0.56	0.72	0.70	0.42	0.77	0.73
SEq	Sweden quant.	0.48	0.61	0.66	0.65	0.36	0.70	0.68
UK	United Kingdom	0.63	0.51	0.35	0.35	0.29	-0.02	0.61

Notes: The table shows mean absolute error (MAE), root mean squared error (RMSE) and correlation (ρ) of perceived inflation relative to actual HICP inflation. ρ_{lag} and ρ_{OOP} denote correlation coefficients of perceived inflation with one month lagged HICP inflation and out-of-pocket expenditures inflation, respectively.

consistent across euro area countries. In Sweden and the United Kingdom, correlations are stable or even increase over time. The table also shows correlation of perceived inflation with one month lagged actual HICP inflation and with inflation in the out-of-pocket expenditures index. Correlations with one month lagged inflation are virtually identical to contemporaneous correlations. No clear pattern emerges regarding the correlation between perceived inflation and out-of-pocket inflation. For the euro area aggregate, the correlation is higher than the correlation of perceived with actual HICP inflation. At country level, however, the correlation is higher only in Belgium, Germany, Spain and Italy.

4.4.2 Rationality of Inflation Perceptions

A large literature investigates rationality of inflation expectations. We borrow rationality tests from this literature to assess inflation perceptions. Along the lines of Jonung and Laidler (1988), it may be argued that inflation perceptions are more adequate than inflation expectations for testing rationality of households, since the rational benchmark is relatively well-defined. Tests of rationality include the related aspects of unbiasedness and information efficiency. Since the quantification method imposes unbiasedness, we can only assess bias in the quantitative data for Sweden. During 01/1996–08/2007, inflation perceptions of Swedish households are unbiased with a statistically insignificant average perception error of $\pi_t - \pi_t^p = 0.01\%$. This finding is in contrast to significant biases documented by Bryan and Venkatu (2001a, 2001b) for U.S. survey data.[21]

We thus assess rationality by testing whether agents efficiently use available information to form their perceptions of inflation. As a first test of efficiency, we assess whether perception errors, defined as the difference between actual and perceived inflation, are serially correlated. Clearly, if perception formation is rational, past perception errors have no predictive content for subsequent errors. The first panel of Table 4.2 reports estimation results on the serial correlation of perception errors over non-overlapping periods. Both in the euro area and in Sweden, perception errors exhibit pronounced serial correlation.[22] The results for Sweden using quantified and quantitative (denoted by the country code *SEq*) survey data are consistent.

The second panel of Table 4.2 investigates whether perceptions efficiently incorporate publicly available information. In defining the relevant information set we follow the literature on inflation expectations and include the money market rate and the unemployment rate. In addition, we consider out-of-pocket expenditures inflation. The rationale for including the out-of-pocket expenditures inflation is that prices of out-of-pocket purchases are easily observable in daily economic interactions. In line with the availability heuristic of Tversky and Kahnemann (1973), the easily recalled out-of-pocket expenditures inflation rate may thus give direction to how households perceive actual consumer price inflation. The table shows that the unemployment rate is weakly significant in the euro area previ-

[21] Using monthly household survey data of the Federal Reserve Bank of Cleveland, Bryan and Venkatu (2001a, 2001b) show that inflation perceptions (and expectations) of U.S. households average several percentage points above actual consumer price inflation.

[22] We only report results for the EA and Sweden, the remaining country-by-country results are broadly in line with the findings for the EA aggregate.

TABLE 4.2: Information efficiency of inflation perceptions

	EA			SE	SEq
	93–07	93–01	03–07	93–07	96–07
Serial correlation					
$\pi_{t-12} - \pi^p_{t-12}$	0.3405**	0.5517***	0.0199	-0.3618***	-0.4605***
	(0.1423)	(0.1442)	(0.1687)	(0.1372)	(0.1215)
T	164	96	56	131	128
Adj. r-squared	0.47	0.45	0.47	0.13	0.23
Strong-form efficiency					
Unemployment rate (t-1)	0.0467	0.0702*	-0.3212	0.1053***	0.0976**
	(0.0294)	(0.0400)	(0.4308)	(0.0217)	(0.0376)
Money market rate (t-1)	0.0214	0.0651	-0.2048	-0.1033	-0.0069
	(0.0435)	(0.0446)	(0.3348)	(0.0648)	(0.0601)
Out-of-pocket π_{t-1}	-0.2820**	-0.0994	-0.7435***	-0.1209**	-0.0245
	(0.1094)	(0.0812)	(0.1210)	(0.0496)	(0.0703)
π_{t-1}	0.9025***	0.6380***	1.9586***	0.7214***	0.5234***
	(0.1652)	(0.1325)	(0.2600)	(0.0658)	(0.0718)
$\pi_{t-12} - \pi^{p-12}_t$	-0.1191	-0.2627***	-0.0717	-0.2032**	-0.3119***
	(0.0842)	(0.0618)	(0.1370)	(0.0813)	(0.0801)
T	127	59	56	127	127
Adj. r-squared	0.6	0.75	0.54	0.7	0.62
Anchoring to expectations					
$\pi^e_{t-12,t}$	-0.2042	0.5584	-1.2429***	-0.0765	0.0710
	(0.2682)	(0.3422)	(0.2185)	(0.3753)	(0.3478)
π^p_{t-12}	-0.0015	0.1727	-0.9928***	0.2364	0.3023
	(0.2671)	(0.6966)	(0.1349)	(0.2222)	(0.2871)
π_{t-12}	0.5083*	-0.1971	0.4401	-0.2895	-0.4550***
	(0.2756)	(0.3044)	(0.2643)	(0.2761)	(0.1206)
T	164	96	56	131	128
Adj. r-squared	0.51	0.53	0.65	0.17	0.23

Notes: This table investigates information efficiency of inflation perceptions in the euro area (EA) and Sweden (SE). Dependent variable is the perception error $\pi_t - \pi^p_t$ based on quantified inflation perceptions for the EA and based on quantified (SE) and quantitative (SEq) inflation perceptions for Sweden. Estimations covering the 1993–2007 period allow for a level shift in 2002. OLS estimation with White standard errors in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

ous to the introduction of the euro. It is highly significant for Sweden, both in quantified and quantitative survey data. While the money market rate is insignificant, out-of-pocket expenditures inflation is significant in the post-changeover period and in the quantified series for Sweden. The negative coefficient suggests that consumers over-react to out-of-pocket expenditures inflation in the sense that an increase in out-of-pocket inflation raises perceived inflation relative to actual inflation (which decreases the perception error).

Third, we investigate whether the bias in perceptions occurs because households are reluctant to revise their prior beliefs. This is the so called expectancy confirmation hypothesis investigated by Traut-Mattausch et al. (2004) in an experimental setting. As shown in the third panel of Table 4.2, past inflation expectations are significant only for the euro area and only in the post cash-changeover period.[23] The negative coefficient indicates that during this period, households' inflation perceptions overreacted to own past expectations such that perceptions exceeded actual inflation.[24]

The tests of information efficiency indicate that consumers could improve their inflation perceptions by using readily available information, such as past inflation or past perception errors. We conclude that inflation perceptions are not fully rational.

4.4.3 Relation to Actual Inflation

Given that inflation perceptions are not fully rational, it is natural to ask whether and how perceptions are temporally related to actual inflation. If households update their judgements based on official HICP releases, then the HICP inflation rate should be Granger causal to perceived inflation. We expect a lagged effect of HICP figures since inflation numbers for a given month are published rather in the beginning to the middle of the following month, while consumers are surveyed already in the first three weeks of a month.

[23] Household expectations of the inflation rate during the upcoming 12 months are also taken from the Joint Harmonized EU Consumer Survey. The qualitative response data is quantified using the probability method following Batchelor and Orr (1988). For Sweden, the mean of quantitative survey responses on expected inflation is available.

[24] This interpretation is confirmed by estimating a model that allows for different coefficients in periods of positive and negative perception errors. In both periods, the coefficient on expectations is negative.

Additionally, if consumers respond to inflation as observed in daily economic interactions, this should be reflected in an instantaneous relation between perceived and actual inflation.

We investigate Granger causality in the following bivariate vector-autoregression (VAR) with $p+1$ lags:

$$\begin{pmatrix} \pi_t^p \\ \pi_t \end{pmatrix} = y_t \quad = \quad A_0 + \Sigma_{i=1}^{p+1} A_i y_{t-i} + u_t$$

where $A_0 = \begin{pmatrix} a_0^{11} \\ a_0^{21} \end{pmatrix}$, $A_i = \begin{pmatrix} a_i^{11} & a_i^{12} \\ a_i^{21} & a_i^{22} \end{pmatrix}$ and $u_t = \begin{pmatrix} u_{1,t} \\ u_{2,t} \end{pmatrix}$. To test whether actual inflation is Granger-causal to perceived inflation we consider the Wald statistic that imposes the restriction $a_1^{12} = ... = a_p^{12} = 0$ on the first p lags in the estimated VAR($p+1$) model.[25] Instantaneous causality is assessed by testing whether contemporaneous residual correlation is zero.

The block-exogeneity tests reported in Table 4.3 suggest that actual inflation is Granger-causal to perceived inflation ($\pi \rightarrow \pi^p$) in 6 out of 12 countries. A significant instantaneous relation ($\pi \leftrightarrow \pi^p$) is detected in 8 countries. The table shows that a lagged or instantaneous relation exists in all countries except Italy and the Netherlands. For the euro area aggregate, both relations are highly significant. In sum, the results clearly indicate that households do not only react to reports on past inflation but also adjust their perceptions instantaneously to information that is available before the official HICP figures are released.

[25] It is well known that in the presence of highly persistent time series, the Wald statistic to assess Granger causality may follow a nonstandard distribution. This problem can be avoided by adding an extra lag that remains unrestricted when testing for causality, see Dolado and Lütkepohl (1996).

TABLE 4.3: Granger-causality in a bivariate VAR

Country	$\pi \leftrightarrow \pi^p$		$\pi \rightarrow \pi^p$		$\pi \leftarrow \pi^p$		Lags	T
AT	7.22	***	1.41		0.61		2	141
BE	0.27		11.53	***	1.36		2	174
DE	6.84	***	2.07		0.01		2	138
EA	11.91	***	12.97	***	0.91		2	174
EL	3.05	*	0.42		0.02		2	174
ES	3.82	**	13.95	***	0.31		2	174
FI	14.53	***	3.24		1.45		3	139
FR	1.43		15.87	***	0.00		2	173
IE	4.24	***	6.15	**	0.47		2	138
IT	16.26	***	6.15	**	5.65	**	2	174
NL	0.54		2.42		0.09		2	174
SE	14.29	***	6.12	**	0.60		2	141
SEq	10.43	***	2.31		0.01		2	138
UK	2.27		0.00		0.46		2	126

Notes: This table tests Granger-causality between perceived and actual inflation, 01/1993–07/2007. All estimations allow for a permanent level shift in 2002. To account for potential nonstationarity, the models are overfitted by including an extra lag not considered in block-exogeneity tests. *Lags* indicates the lag length as selected by Schwarz Bayesian information criterion (SBC). Instantaneous causality ($\pi \leftrightarrow \pi^p$) is tested using the statistic $T\widehat{\rho}^2$ where $\widehat{\rho}$ is the contemporaneous correlation of residuals and T is the number of observations. Under the null hypothesis that $\rho = 0$, the statistic is asymptotically $\chi^2(1)$ distributed. Granger causality ($\pi \rightarrow \pi^p$, $\pi \leftarrow \pi^p$) is assessed by testing for joint-exogeneity of lags of π and π^p in the equations for π^p and π respectively. The Wald statistic has a limiting $\chi^2(lags)$-distribution. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

4.4.4 Implications for Belief Formation

The tests for information efficiency indicate that inflation perceptions are not rational. Also, we have documented that the survey mean of inflation perceptions is relatively inaccurate. Nevertheless, inflation perceptions respond to actual inflation, as suggested by the Granger-causality tests. For most countries, these tests suggest both a contemporaneous and a lagged response of perceptions to actual inflation. These patterns are broadly consistent with the epidemiological model of Carroll (2003). In this model, only a fraction of households update their beliefs in a given period. Consequently, the cross-sectional mean of inflation perceptions will fail rationality tests but is still contemporaneously related to actual inflation.

Further insights can be gained by considering the cross-sectional heterogeneity of infla-

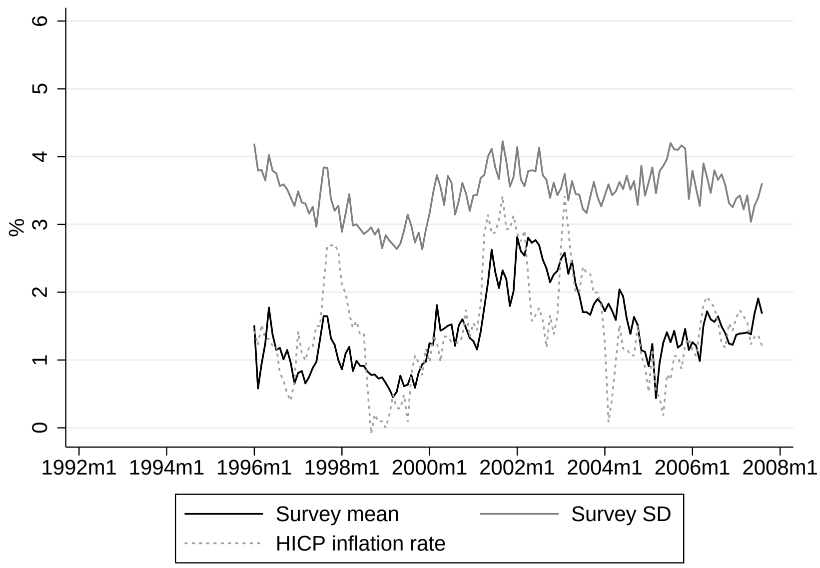


Figure 4.2: Mean and standard deviation of inflation perceptions in Sweden

Notes: This figure shows the mean and cross-sectional standard deviation of quantitative inflation perceptions from the Swedish Consumer Tendency Survey.

tion perceptions. As discussed in Section 4.3, Figure 4.1 shows the quantified cross-sectional standard deviation of perceptions in the euro area. The cross-sectional standard deviation averages at 1.29% which seems high given the moderate variability of inflation. As outlined in Appendix C.2, the quantified standard deviation is even likely to underestimate the actual degree of heterogeneity. Figure 4.2 additionally shows the cross-sectional standard deviation of quantitative inflation perceptions taken from the Swedish Consumer Tendency Survey. Quantitative survey responses exhibit an average cross-sectional standard deviation of 3.46% during 1996–2007, whereas inflation perceptions average at 1.47% during the same period.

We thus arrive at a similar conclusion as Mankiw, Reis and Wolfers (2004) who investigate inflation expectations of U.S. households. Inflation perceptions are not rational, yet related to contemporaneous and lagged actual inflation. The epidemiological model outlined in Section 4.2 is consistent with these broad patterns. Moreover, the model predicts a high degree of heterogeneity in perceptions, as the staggered updating mechanism generates heterogeneous information sets. The data confirms that inflation perceptions are highly heterogeneous. The next section thus investigates the epidemiological model in more detail.

4.5 Estimation of Epidemiological Models

4.5.1 Linear Partial Adjustment Models

This section discusses estimation results of the epidemiological models proposed in Section 4.2. Model (1) assumes that households update with contemporaneous actual inflation. The estimation equation is given by:

$$\pi_t^p = \alpha_0 + \alpha_1 \pi_t + \alpha_2 \pi_{t-1}^p + \varepsilon_t$$

Model (2) assumes that consumers who update refer to the most recent available official inflation figure, which is the one month lagged inflation rate. The regression equation reads:

$$\pi_t^p = \alpha_0 + \alpha_1 \pi_{t-1} + \alpha_2 \pi_{t-1}^p + \varepsilon_t$$

For the partial adjustment restriction to hold, we should not be able to reject the hypothesis that $\alpha_1 + \alpha_2 = 1$. We assess this restriction using a standard Wald test. To begin with, we estimate the models using ordinary least squares (OLS), employing White standard errors that allow for heteroskedasticity. The estimations for the sample period 1993–2007 control for the euro cash changeover by including an indicator variable that is unity during 2002–2007 and zero otherwise.

Tables 4.4 and 4.5 report country-by-country results for the period 1993–2007. Model (1) tends to fit marginally better than Model (2), as reflected in the R-squared and the high significance of the contemporaneous HICP inflation rate. The results for Model (2) suggest that in some countries not even a small proportion of consumers updates the perception of inflation with the lagged inflation rate. Both models are clearly rejected by the Wald test

TABLE 4.4: Model (1), 1993–2007

Country	α_1		α_2		α_0		R^2	Wald p	BG p
AT	0.0593***	(0.0217)	0.9120***	(0.0400)	0.0180	(0.0391)	0.97	0.41	0.06
BE	0.0436**	(0.0192)	0.8338***	(0.0446)	0.1923***	(0.0521)	0.92	0.00	0.00
DE	0.0312**	(0.0145)	0.9700***	(0.0295)	0.0023	(0.0379)	0.96	0.97	0.11
EA	0.0379***	(0.0121)	0.9000***	(0.0272)	0.1024***	(0.0339)	0.98	0.00	0.07
EL	0.0169**	(0.0078)	0.8435***	(0.0440)	0.5731***	(0.1688)	0.92	0.00	0.00
ES	0.0632***	(0.0144)	0.8104***	(0.0328)	0.3116***	(0.0752)	0.96	0.00	0.73
FI	0.0483***	(0.0165)	0.8811***	(0.0384)	0.0743	(0.0543)	0.96	0.06	0.05
FR	0.0406***	(0.0139)	0.8637***	(0.0398)	0.1207***	(0.0438)	0.97	0.01	0.52
IE	0.0752***	(0.0177)	0.8268***	(0.0400)	0.2528***	(0.0715)	0.94	0.00	0.00
IT	0.0405**	(0.0157)	0.8982***	(0.0317)	0.1267**	(0.0556)	0.94	0.01	0.49
NL	0.0711***	(0.0206)	0.8482***	(0.0581)	0.1218	(0.0915)	0.90	0.12	0.00
SE	0.1314***	(0.0265)	0.6903***	(0.0477)	0.2318***	(0.0539)	0.81	0.00	0.68
SEq	0.1143***	(0.0303)	0.7657***	(0.0476)	0.1987***	(0.0607)	0.81	0.00	0.54
UK	0.0277	(0.0193)	0.8760***	(0.0425)	0.1519**	(0.0610)	0.80	0.01	0.73

Notes: This table shows OLS estimates of Model (1). Sample periods are specified in Table C.1. The column *Wald p* reports the p-value of the Wald test of the restriction $\alpha_1 + \alpha_2 = 1$. *BG p* is the p-value of the Breusch-Godfrey LM test statistic for first order residual correlation. White standard errors allowing for heteroskedasticity in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

TABLE 4.5: Model (2), 1993–2007

Country	α_1		α_2		α_0		R^2	Wald p	BG p
AT	0.0356*	(0.0210)	0.9222***	(0.0419)	0.0420	(0.0387)	0.97	0.22	0.04
BE	0.0493***	(0.0171)	0.8200***	(0.0458)	0.2045***	(0.0548)	0.92	0.00	0.01
DE	0.0177	(0.0130)	0.9663***	(0.0290)	0.0225	(0.0387)	0.96	0.62	0.09
EA	0.0224*	(0.0126)	0.9217***	(0.0298)	0.0948***	(0.0358)	0.98	0.01	0.11
EL	0.0139*	(0.0082)	0.8463***	(0.0450)	0.5779***	(0.1695)	0.92	0.00	0.00
ES	0.0546***	(0.0159)	0.8181***	(0.0363)	0.3176***	(0.0774)	0.96	0.00	0.88
FI	0.0223	(0.0170)	0.9014***	(0.0403)	0.0983*	(0.0555)	0.96	0.05	0.02
FR	0.0359***	(0.0132)	0.8645***	(0.0382)	0.1268***	(0.0434)	0.97	0.00	0.32
IE	0.0752***	(0.0162)	0.8178***	(0.0383)	0.2829***	(0.0705)	0.94	0.00	0.01
IT	0.0246	(0.0161)	0.9176***	(0.0322)	0.1266**	(0.0563)	0.94	0.01	0.47
NL	0.0688***	(0.0212)	0.8475***	(0.0578)	0.1303	(0.0925)	0.90	0.11	0.00
SE	0.0823***	(0.0276)	0.7421***	(0.0546)	0.2305***	(0.0589)	0.79	0.00	0.90
SEq	0.0732**	(0.0323)	0.8029***	(0.0509)	0.2011***	(0.0623)	0.80	0.00	0.29
UK	0.0167	(0.0204)	0.8866***	(0.0453)	0.1497**	(0.0630)	0.80	0.01	0.90

Notes: This table shows OLS estimates of Model (2). The sample periods are specified in Table C.1. The column *Wald p* reports the p-value of the Wald test of the restriction $\alpha_1 + \alpha_2 = 1$. *BG p* is the p-value of the Breusch-Godfrey LM test statistic for first order residual correlation. Estimates of the indicator variable for the euro cash changeover are not reported. White standard errors allowing for heteroskedasticity in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

of the coefficient sum restriction. The respective p-values for the Wald tests of the coefficient restriction $\alpha_1 + \alpha_2 = 1$ can be found in the second last column. If one nonetheless interprets the estimated coefficient on actual inflation as an updating frequency, estimations for Model (1) imply a quarterly updating frequency of 0.11 for the euro area.[26] This is considerably lower than the frequencies reported by studies that investigate inflation expectations. Using household expectations from the University of Michigan Survey of Consumers, Carroll (2003) documents an updating frequency of 0.27. Döpke, Dovern, Fritsche and Slacalek (2008b) estimate the updating parameter for four European countries and find updating frequencies that range between 0.18 and 0.32. In contrast to our results, Carroll (2003) and Döpke, Dovern, Fritsche and Slacalek (2008b) report that the sum restriction cannot be rejected.[27] Tables C.10 through C.13 the Appendix additionally show results for the pre- and post-euro cash changeover periods. Levels as well as significances of estimated updating coefficients are mostly higher in the pre-euro cash changeover period. In all cases, the partial adjustment models are clearly rejected by the data.

Tables 4.4 and 4.5 also report the p-values of the Breusch-Godfrey LM test for first order serial correlation of residuals. For Model (1), the test signals significant residual correlation in 6 countries. For Model (2), significant residual correlation is detected in 7 countries. Due to the inclusion of a lagged dependent variable, residual correlation renders OLS inconsistent given that the lagged dependent variable is not predetermined anymore.[28] We thus additionally estimate a consistent specification that assumes an AR(1) residual process by the iterative Cochrane-Orcutt procedure. This procedure adjusts the original regression equation for first order serial correlation, such that the residuals of the resulting model are serially uncorrelated.[29] Tables C.14 and C.15 in the Appendix show

[26]Quarterly frequencies are given by $\lambda_{quarterly} = 1 - (1 - \lambda_{monthly})^3$.

[27]More precisely, Döpke, Dovern, Fritsche and Slacalek (2008b) report that the restriction is rejected for France, but holds for the other three countries as well as for the pooled sample.

[28]Given the model $y_t = \beta_0 + \beta_1 y_{t-1} + u_t$, OLS is only inconsistent if the condition $E(y_{t-1}u_t) = 0$ is violated, i.e. if regressors are not predetermined. Note that theoretically, this condition can be satisfied even if residuals $u_t = y_t - \beta_0 - \beta_1 y_{t-1}$ are serially correlated. This can be the case if u_t and y_{t-2} are correlated and $E(y_{t-1}u_t) = 0$. Then, $E(u_t u_{t-1}) = E(u_t(y_{t-1} - \beta_0 - \beta_1 y_{t-2})) = -\beta_1 E(u_t y_{t-2}) \neq 0$. In other words, consistency requires the special case that $E(u_t u_{t-1}) = -\beta_1 E(u_t y_{t-2})$.

[29]As outlined in Hamilton (1994), the Cochrane-Orcutt procedure for Model (1) converges to a (local)

the Cochrane-Orcutt estimation results for Models (1) and (2), respectively. The results are in line with the OLS estimation results. The parameter values have similar magnitudes and the Wald test generally rejects the hypothesis that $\alpha_1 + \alpha_2 = 1$.

All tables also report estimation results using the mean of quantitative survey perceptions from the Swedish Consumer Tendency Survey (denoted by the country code *SEq*). The findings are consistent with results based on the quantified inflation perceptions, which corroborates the quantification method. In Sweden, the contemporaneous HICP inflation rate is highly relevant for perceived inflation with coefficient estimates of around 0.12. Compared to euro area countries, the results are relatively stable across subperiods.

Taking into account that some of the series are highly persistent, we also estimate the models in first differences. The estimation equation for Model (1) in first differences reads:

$$\Delta\pi_t^p = \alpha_0 + \alpha_1 \Delta\pi_t + \alpha_2 \Delta\pi_{t-1}^p + \varepsilon_t$$

Tables C.16 and C.17 in the Appendix report estimation results of Models (1) and (2), respectively. Both models are rejected even more clearly. The coefficients on actual inflation are of similar magnitude or slightly higher than in the estimations in levels. The coefficients on lagged inflation perceptions are mostly negative. Again, we obtain consistent results using the quantitative and qualitative response data on inflation perceptions from the Swedish survey.

As previously mentioned, it might well be the case that households do not refer to official HICP inflation when answering the survey. Rather they might report perceptions that rely on observed price changes in frequently bought items. We have estimated the models using out-of-pocket expenditures inflation as the measure of actual inflation. Results are

---

maximum of the following conditional likelihood function:

$$\begin{aligned}\mathscr{L} = & -\frac{T-1}{2}log(2\pi) - \frac{T-1}{2}log(\sigma^2) \\ & - \frac{1}{2\sigma^2}\sum_{t=2}^{T}(\pi_t^p - \alpha_0 - \alpha_1\pi_t - \alpha_2\pi_{t-1}^p - \rho\left[\pi_{t-1}^p - \alpha_0 - \alpha_1\pi_{t-1} - \alpha_2\pi_{t-2}^p\right])^2\end{aligned}$$

The likelihood function for Model (2) is obtained by replacing π_t with π_{t-1}.

qualitatively unchanged. Again the partial adjustment model is robustly rejected.[30]

We conclude that the two epidemiological models of perception formation are not adequate in our sample of European countries. A possible reason for this negative finding might be the assumption that the fraction of updating households is time-invariant. In the next section, we assess specifications that allow for time-varying adjustment parameters.

4.5.2 Non-Linear Adjustment

If households probabilistically update their information sets, then the probability of updating will likely be time-varying. In particular, one might expect that the probability of updating is higher if the inflation rate is high and if using outdated information becomes costly. This view is supported by empirical findings of Branch (2007). Branch (2007) shows that a model in which households rationally select predictors by optimizing costs and benefits of predicting inflation is consistent with inflation expectations from the University of Michigan Survey of Consumers. The idea that economic agents only care about inflation if it becomes costly is formalized by Akerlof, Dickens and Perry (2000). These authors introduce the concept of near rationality. In their model, near rational firms only fully incorporate expected inflation in wage and price-setting if ignoring inflation is sufficiently costly.

We thus allow for nonlinear updating in models with state-dependent adjustment parameters. We consider a simple specification that allows for different updating coefficients in periods of high and low inflation. Periods of high (low) inflation are characterized by actual HICP inflation which is above (below) the sample median of HICP inflation. As the median varies between countries, the estimations take into account that consumers in some countries are accustomed to higher median inflation rates than consumers in other countries. Tables 4.6 and C.18 summarize the estimation results for Models (1) and (2). The estimates of the interaction terms show that the coefficients on contemporaneous and lagged HICP inflation are generally not higher in periods of high inflation. Also in line with

[30]Results are available upon request.

TABLE 4.6: Near-rationality in Model (1), 1993–2007

Country	α_1		α_2		$\Delta\alpha_1$		$\Delta\alpha_2$		T	Median
AT	0.0046	(0.0404)	0.8761***	(0.0334)	-0.0023	(0.0159)	0.1081	(0.0751)	142	1.76
BE	-0.0103	(0.0461)	0.7996***	(0.0451)	0.0204	(0.0179)	0.0919*	(0.0542)	175	1.88
DE	0.0261	(0.0284)	0.9613***	(0.0433)	0.0120	(0.0139)	0.0038	(0.0450)	139	1.38
EA	0.0539**	(0.0255)	0.9020***	(0.0335)	-0.0075	(0.0085)	0.0011	(0.0347)	175	2.12
EL	-0.0083	(0.0844)	0.8078***	(0.0501)	-0.0501***	(0.0155)	0.0208	(0.0840)	175	3.81
ES	0.0770**	(0.0333)	0.8056***	(0.0352)	-0.0100	(0.0071)	-0.0739	(0.0508)	175	3.31
FI	0.0905*	(0.0505)	0.8861***	(0.0308)	-0.0158	(0.0263)	-0.0529	(0.0559)	141	1.36
FR	0.0372	(0.0235)	0.8437***	(0.0520)	0.0067	(0.0134)	-0.1233**	(0.0507)	175	1.77
IE	0.0333	(0.0330)	0.8485***	(0.0351)	-0.0206	(0.0200)	0.0682*	(0.0354)	140	2.65
IT	0.0032	(0.0468)	0.8806***	(0.0345)	-0.0102	(0.0129)	0.0408	(0.0497)	175	2.41
NL	0.0260	(0.0481)	0.8108***	(0.0596)	0.0023	(0.0176)	0.0353	(0.0500)	175	1.82
SE	0.1339***	(0.0482)	0.7085***	(0.0628)	-0.0434	(0.0316)	0.0231	(0.0603)	142	1.54
SEq	0.0977**	(0.0484)	0.7863***	(0.0613)	-0.0183	(0.0306)	0.0075	(0.0667)	139	1.54
UK	-0.0331	(0.0589)	0.8462***	(0.0489)	0.0006	(0.0172)	0.1103	(0.0688)	128	1.51

Notes: Parameters $\Delta\alpha_1$ and $\Delta\alpha_2$ denote the relative change in regression parameters in periods with actual inflation above median inflation. *Median* is the sample median of HICP inflation. Estimations allow for a level shift in 2002 and include separate constants for both regimes (not reported). White standard errors allowing for heteroskedasticity in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

estimation results from the previous section, households in countries with relatively high median inflation rates (such as Ireland, Italy, Greece, Spain) do not show higher probabilities of updating. Hence, we find no evidence for non-linear adjustment or near-rationality in our sample of countries.[31]

4.5.3 Actual and Simulated Heterogeneity

The epidemiological model has direct implications for the cross-sectional heterogeneity of inflation perceptions. Hence, the model can also be tested by assessing the heterogeneity of inflation perceptions rather than the central tendency. For inflation expectations, Mankiw, Reis and Wolfers (2004) show that the sticky information model is consistent with observed heterogeneity. Building on Mankiw, Reis and Wolfers (2004), we compare the simulated cross-sectional heterogeneity of inflation perceptions in a population that is characterized by Model (1) to the actual heterogeneity of quantitative answers in the Swedish Consumer Tendency Survey. We measure heterogeneity by the cross-sectional standard deviation of quantitative survey responses. The updating parameter λ is set to 0.12, which corresponds to the coefficient estimate in the period 1996–2007. Figure 4.3 shows the simulated and survey based series. The mean perception of the simulated population is much smoother than actual mean of survey perceptions. More important, the cross-sectional standard deviation of inflation perceptions in the simulated population is considerably lower than the standard deviation of actual quantitative survey responses. Also, the actual standard deviation does not show the distinct dynamic pattern induced by the epidemiological model. According to the model, heterogeneity rises following a persistent drop or surge in actual inflation to gradually decline again, as more and more individuals adjust their beliefs to the new level of inflation. This pattern is reflected in the simulation standard deviation but it is not visible in the actual survey standard deviation.

Consistent results are obtained for the euro area. Figure 4.4 shows the quantified stan-

[31] We have also tested for more sophisticated forms of non-linearity using the smooth transition regression framework. However, using the methods proposed by Teräsvirta (2004), linearity was generally not rejected.

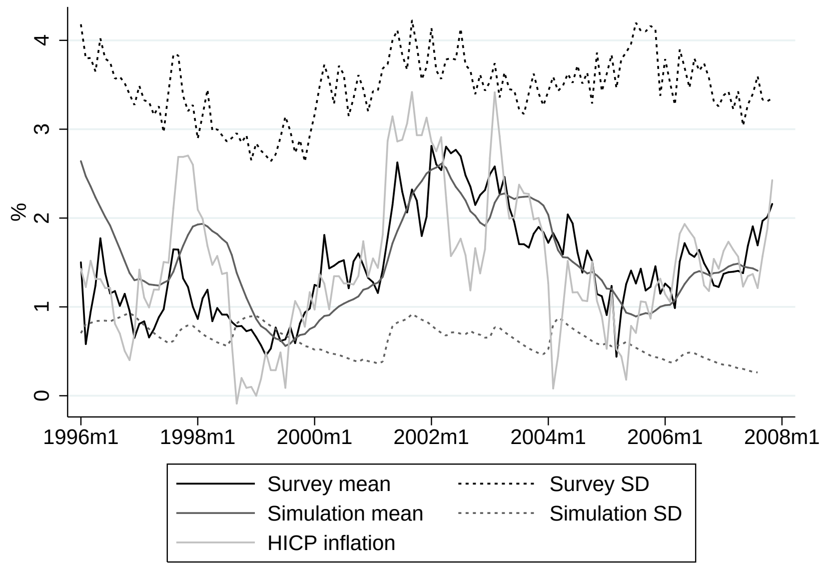


Figure 4.3: Model prediction and actual perceptions in Sweden

Notes: This figure shows actual and simulated mean and cross-sectional standard deviation (SD) of inflation perceptions from the Swedish Consumer Tendency Survey. The simulation is based on Model (1), i.e. households update with contemporaneous HICP inflation. $\lambda = 0.12$. The model is initialized in 01/1993.

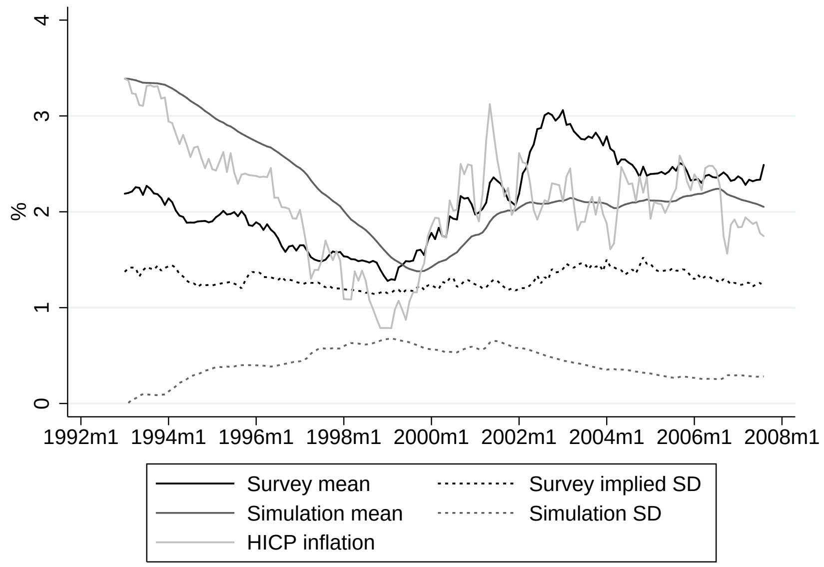


Figure 4.4: Model prediction and actual perceptions in the euro area

Notes: This figure shows the quantified and simulated mean and standard deviation (SD) of inflation perceptions in the euro area. The simulation is based on Model (1), i.e. households update with contemporaneous HICP inflation. $\lambda = 0.05$. The model is initialized in 01/1993.

dard deviation and the simulation standard deviation for the euro area aggregate. The updating parameter λ is set to 0.05. Again, the quantified standard deviation, which is likely to underestimate actual standard deviation, is much higher than the standard deviation of perceptions in the simulated population. Also, actual and simulated heterogeneity do not show common dynamics.

We conclude that the epidemiological model cannot explain the level and dynamics of cross-sectional heterogeneity. In particular, the level difference in heterogeneity suggests that other sources of heterogeneity exist than only infrequent updating. Potential sources of additional heterogeneity include that people update using different information or that people process information differently.

4.6 Conclusion

This paper investigates the dynamics of inflation perceptions in Europe. We use monthly household survey data from the Joint Harmonized EU Consumer Survey spanning 01/1993–08/2007. In an explorative investigation, we highlight three stylized facts about inflation perceptions. First, inflation perceptions do not efficiently incorporate available information and therefore fail rationality tests. Second, inflation perceptions are highly heterogeneous across the survey population. Third, inflation perceptions react both instantaneously and with a time lag to the actual rate of inflation.

These findings are broadly consistent with the epidemiological model of belief formation proposed by Carroll (2003). In this model, only a fraction of households update their information sets in a given month. The remaining households stay inattentive and stick to outdated beliefs about inflation. We estimate two epidemiological models of perception formation, assuming that households either use the contemporaneous or the lagged rate of inflation to update their beliefs with. In almost all countries within the sample, however, both epidemiological models are clearly rejected as the sum of partial adjustment coefficients is significantly different from unity. This finding is in contrast to Carroll (2003) and Döpke, Dovern, Fritsche and Slacalek (2008b). Using expectations data rather than perceptions data, the epidemiological model is not rejected by these authors.

The general picture is confirmed by quantitative response data from the Swedish Consumer Tendency Survey. Compared to euro area countries, the results are relatively stable across subperiods. Moreover, we find that estimations based on quantified qualitative survey data are consistent with estimations based on quantitative survey data. This corroborates the quantification method used for quantifying the qualitative response data from the Joint Harmonized EU Consumer Survey.

We conclude by comparing the cross-sectional heterogeneity of inflation perceptions in survey data with the heterogeneity of inflation perceptions in an artificial population that behaves according to an epidemiological model of belief formation. We find that the epidemiological model cannot explain the level and dynamics of survey heterogeneity. In particular, the model significantly underpredicts the actual level of heterogeneity. This suggests that other sources of heterogeneity exist than only infrequent updating. Potential sources of additional heterogeneity include that people update using different information or that people process information differently.

Looking ahead, further insights will be gained by investigating inflation perceptions across demographic groups. This will also contribute to the understanding of cross-sectional heterogeneity of beliefs. Moreover, for a better understanding of perception formation and to derive sensible models of aggregate dynamics, investigating household-level survey data will be essential.

Chapter 5

The Role of Media for Heterogeneity of Inflation Expectations of Households and Professional Forecasters*

*This chapter is based on Maag and Lamla (2009).

5.1 Introduction

Survey data on inflation expectations reveals that households as well as professional forecasters generally disagree about the course of inflation over the next 12 months. Relying on data from the University of Michigan Surveys of Consumers, Mankiw, Reis and Wolfers (2004) document substantial heterogeneity in households' inflation expectations.[1] Albeit on lower levels than heterogeneity of household expectations, disagreement among professional forecasters is still considerable as shown by Lahiri and Sheng (2008, 2009a) for G7 countries and by Mankiw, Reis and Wolfers (2004) for the U.S.

Recent theoretical contributions emphasize that disagreement can be persistent and may significantly affect economic allocations. Acemoglu, Chernozhukov and Yildiz (2007) show that if Bayesian agents are uncertain about the interpretation of signals, their beliefs may not converge in the limit. Omitting the typically assumed convergence significantly alters outcomes in various game theoretic and asset market settings, as Acemoglu, Chernozhukov and Yildiz (2007) further demonstrate. On entirely different theoretical grounds, the sticky information model of Mankiw and Reis (2002, 2006) establishes a relation between disagreement and macroeconomic dynamics. In the sticky information model, agents inform themselves only sporadically about the economy. As a result, information sets differ across agents, generating disagreement in expectations. Mankiw and Reis (2006) show that a model with staggered updating at the side of firms, workers and consumers reproduces empirical patterns such as the acceleration phenomenon and the smoothness of real wages. That disagreement about inflation expectations is relevant for monetary policy is highlighted by Sims (2009). Relying on a frictionless two period model, Sims (2009) demonstrates that disagreement among asset market participants may produce over-investment in real assets and may potentially delay and distort monetary policy actions.

[1] In the following, the terms heterogeneity and disagreement are used interchangeably. In the University of Michigan Survey of Consumers, disagreement in terms of the interquartile range of one year ahead expected inflation averages at about 4% after 1990. Using various surveys, other authors find that inflation expectations differ significantly across socioeconomic groups, see, e.g., Souleles (2004), Bryan and Venkatu (2001b) and Jonung (1981).

Regarding the empirical side, however, the literature on determinants of disagreement is relatively small and centers on professional disagreement.[2] Our paper contributes to the understanding of disagreement by investigating one particular source of information that is most relevant for households: the mass media. The important role of the media for belief formation is underlined by Blinder and Krueger (2004). Based on a representative survey of U.S. households, these authors find that television and newspaper news are the predominant information sources that households consult to form their expectations about economic issues.[3] That media coverage directly affects inflation expectations has, to the best of our knowledge, been shown by two papers so far. Using quarterly U.S. data spanning 1981 to 2000, Carroll (2003) investigates how the accuracy of consumers' inflation expectations is related to the number of news stories on inflation in two important newspapers. Carroll (2003) finds that the accuracy of inflation expectations is positively related to the amount of media reporting. Moreover, it is shown that in an epidemiological model households update their beliefs more frequently in periods of intense media reporting. Relying on detailed monthly media content data for Germany from 1998 to 2007, Lamla and Lein (2008) additionally consider how the tone of media coverage affects inflation expectations. In line with Carroll (2003), the authors find that the accuracy of expectations is positively related to the intensity of reporting, but that reports on rising inflation may bias households' expectations.[4]

To conceptually understand the role of media coverage for heterogeneity of inflation expectations we adopt a Bayesian learning model. In our model, agents update their prior expectations about inflation by absorbing news transmitted by television and newspapers. Each media report only contains a noisy signal about future inflation. Consequently, agents face a signal extraction problem. The basic structure of our model is borrowed

[2]See, e.g., Lahiri and Sheng (2008, 2009a), Capistrán and Timmermann (2009), Batchelor (2007), Döpke and Fritsche (2006), Giordani and Söderlind (2003) and references therein. For empirical research on household disagreement see Mankiw, Reis and Wolfers (2004) and Branch (2004, 2007).

[3]Curtin (2007) confirms this finding using data from the University of Michigan Survey of Consumers. Fullone et al. (2007) provide similar evidence for Italy based on data from the OECD.

[4]Other studies consider the relation of media activity and consumer sentiment about real economic activity rather than inflation and confirm the relevance of media reporting, see Doms and Morin (2004) and Soroka (2006).

from Kandel and Zilberfarb (1999) and Lahiri and Sheng (2008) who propose a simple approach to introduce heterogeneous forecasting models into the standard learning model. In our model, media coverage affects forecast disagreement by influencing information sets as well as by influencing how people interpret information. We empirically test for the effects of the intensity (volume) of media reporting about inflation, the heterogeneity of story content and the tone of media coverage conditional on a set of macroeconomic determinants of disagreement. As opposed to macroeconomic variables, we expect that media coverage only affects disagreement of households. Professional forecasters should generally have incentives to acquire the most recent information and select forecasting models irrespective of media activity.

This paper is structured as follows. Section 5.2 develops the theoretical framework and the hypotheses on the effects of media coverage and the macroeconomic state on inflation forecast disagreement of consumers and professional forecasters. Section 5.3 presents the data and the quantitative measures of heterogeneity and media activity. Section 5.4 discusses the empirical results. In a first step we investigate a specification that explains disagreement by macroeconomic variables only. In a second step we examine the conditional effects of media coverage. Section 5.5 concludes.

5.2 Modeling Heterogeneity of Expectations

Beliefs about future inflation may differ across respondents due to differences in information sets and forecasting models. Put more formally, survey respondent i forms a belief $z_{i,t}$ about future inflation such that:

$$z_{i,t} = f_{i,t}(I_{i,t})$$

where $I_{i,t}$ is the information set and $f_{i,t}(.)$ the forecasting model employed by respondent i at time t. A possible measure of disagreement d_t is the cross-sectional variance of beliefs:

$$d_t = \frac{1}{N-1}\sum_{i=1}^{N}(z_{i,t} - \bar{z}_t)^2$$

where N is the number of respondents and $\bar{z}_t$ the cross-sectional mean of forecasts in period t. Understanding disagreement thus requires a framework that explains the time-varying heterogeneity of information sets and forecasting models across respondents. Mankiw and Reis (2002) suggest an information delay model in which agents update their information sets only sporadically due to costs associated with acquiring and processing information. A related model is proposed by Carroll (2003). In his model only a fraction of agents encounters news about inflation at a given time, resulting in epidemiological dynamics of aggregate expectations and disagreement. But as Sims (2003) and Williams (2004) argue, information delay models seem less appropriate for explaining disagreement among (professional) forecasters who have incentives to employ the most recent information. Relying on information theory, Sims (2003) more generally models economic agents as having finite capacity to acquire and process information. Disagreement in expectations then results from idiosyncratic information processing errors and from heterogeneous objective functions and information processing constraints.[5]

[5]Alternative explanations of expert disagreement include strategic behavior (Laster, Bennett and Geoum, 1999), herding, conservatism, optimism (Batchelor, 2007) and asymmetric loss functions (Capistrán and Timmermann, 2009).

We adopt a related signal extraction model to conceptually understand the role of media coverage. In our model, agents update their prior expectations about inflation by absorbing news transmitted by television and newspapers. Each media report only contains a noisy signal about future inflation. Consequently, agents update their prior beliefs by Bayesian learning. The model's basic structure is borrowed from Kandel and Zilberfarb (1999). These authors suggest a simple approach to introduce heterogeneous forecasting models into the standard learning framework. Our model allows for two distinct mechanisms by which media coverage affects recipients' beliefs. First, the media transmits information relevant for predicting inflation, consistent with a traditional economic view of the media. Second, media coverage affects what recipients concern to be important and, consequently, how they form their forecasts. This second mechanism is motivated by agenda setting theories which play an important role in contemporary media effects research.

Assume that at the beginning of month t agent i has an initial prior belief about the future inflation rate (prior forecast). The prior belief $\Pi_{i,t}$ is normally distributed with mean $\pi_{i,t}$ and variance $a_{i,t}$:

$$\Pi_{i,t} \sim N(\pi_{i,t}, a_{i,t})$$

During each month the agent absorbs a number V of media reports. We assume that each media report only contains noisy information about future inflation. In addition, agents may disagree in their forecasts even if their information sets are identical because they employ different predictors. Conditional on a media report $\tilde{L}_{v,t}$ agent i derives the following estimate of future inflation:

$$\pi_{i,t+1} = \tilde{L}_{v,t} - \varepsilon_{v,t} - \mu_{i,t} = L_t - \mu_{i,t},\ \varepsilon_{v,t} \sim N(0, b_t)$$

This equation states that each media report contains the signal L_t (the rational forecast of inflation) and a noise term $\varepsilon_{v,t}$ which cannot be discerned by the agent. The noise term allows for heterogeneity in the content of media reports about inflation, with the degree of heterogeneity being captured by b_t. Assuming that media reports are unbiased such that $E(\varepsilon_{v,t}) = 0$ is not restrictive for the purpose of understanding disagreement, as will be shown below. Unlike in the standard learning setting, the above equation models the estimate of inflation to be individual specific by allowing agents to interpret the same media report differently. Following Kandel and Zilberfarb (1999) and Lahiri and Sheng (2008) we model this by including the individual specific term $\mu_{i,t}$. The $\mu_{i,t}$ is unknown to the agent and reflects that some agents form more optimistic or pessimistic forecasts given the same information. More generally, $\mu_{i,t}$ captures heterogeneity in forecasting models across agents.[6]

Agent i thus faces a signal extraction problem. Given the prior belief about future inflation and V units of noisy media reports the agent has to infer L_t. The agent updates his prior belief according to Bayes' rule:

$$k_i(\pi_{i,t+1}|\{\tilde{L}_{v,t}\}) \propto \prod_{v=1}^{V} f_i(\tilde{L}_{v,t}|\pi_{i,t})h(\pi_{i,t})$$

where $h(.)$ is the prior density, $f_i(.)$ the conditional density of the observed public information given the prior belief $\pi_{i,t}$ and $k_i(.)$ the resulting posterior density given media reports $\{\tilde{L}_t\} = \tilde{L}_{1,t}, ..., \tilde{L}_{V,t}$. Under the normality assumptions the posterior distribution is again normal with mean:

$$E\left(\pi_{i,t+1}|\{\tilde{L}_{v,t}\}\right) = \rho_{i,t}\pi_{i,t} + (1-\rho_{i,t})\left(\bar{L}_t - \mu_{i,t}\right)$$

where $\bar{L}_t = V^{-1}\sum_{v=1}^{V}\tilde{L}_{v,t}$. The mean of the posterior distribution (henceforth posterior forecast $\pi_{i,t+1}$) is a weighted average of the prior mean and the average noisy signal obtained from the media. The weight on the prior mean is given by:

$$\rho_{i,t} = \frac{\frac{1}{V}b_t}{a_{i,t} + \frac{1}{V}b_t} = \frac{\alpha_{i,t}}{\alpha_{i,t} + \beta_t}$$

[6] This is the so called differential interpretation hypothesis put forward by Kandel and Zilberfarb (1999).

where $\alpha_{i,t} = \frac{1}{a_{i,t}}$ and $\beta_t = \frac{1}{\frac{1}{V}b_t}$ are the precision of the prior and the precision of the public signal. Under the assumption that $\tilde{L}_{v,t}$, $\rho_{i,t}$ and $\mu_{i,t}$ are mutually independent for any t it can be shown that the cross-sectional variance of the posterior forecast is:[7]

$$
\begin{aligned}
Var(\pi_{i,t+1}) &= Var(\pi_{i,t})\left(Var(\rho_{i,t}) + E(\rho_{i,t})^2\right) \\
&+ Var(\mu_{i,t})\left(Var(\rho_{i,t}) + (1 - E(\rho_{i,t}))^2\right) \\
&+ Var(\rho_{i,t})\left(E(\bar{L}_t) - E(\mu_{i,t}) - E(\pi_{i,t})\right)^2
\end{aligned} \tag{5.1}
$$

Let us first assume that no differential interpretation of information exists, i.e. $Var(\mu_{i,t}) = 0$ and that weights on priors are identical across agents, i.e. $Var(\rho_{i,t}) = 0$. Then, Equation (5.1) reduces to:

$$Var(\pi_{i,t+1}) = Var(\pi_{i,t})\rho_t^2$$

In this simple case, a higher volume of media reporting, reflected in a higher number of media reports V, reduces disagreement. If the number of media reports V goes to infinity, the weight on prior beliefs goes to zero and all agents adopt the identical information set. If agents do not absorb any news such that $V = 0$, no updating takes place and disagreement is determined by the dispersion of prior beliefs. That the amount of media reporting about inflation is positively related to the absorption of new information by households is also suggested by empirical results of Carroll (2003) and Lamla and Lein (2008). This leads to the following hypothesis:

HYPOTHESIS 1: The higher the volume of media reporting, the lower is inflation forecast disagreement of consumers.

Not only the volume of media reporting matters, but also its content.[8] In particular, the model suggests that the more homogeneous media statements about inflation are, repre-

[7] See Kandel and Zilberfarb (1999) and Lahiri and Sheng (2008) for a derivation of this result.

[8] Previous research of Lamla and Lein (2008) shows that the content of media reporting affects accuracy of consumers' inflation expectations.

sented by a lower variance b_t of the noise term, the lower is disagreement. If all media reports contain the identical message such that the variance of the noise component collapses to 0, information sets become homogeneous. We empirically capture the heterogeneity of media reporting by computing the information entropy of media statements within a given month. This measure will be introduced in the next section. The second hypothesis reads:

HYPOTHESIS 2: The lower the heterogeneity (information entropy) of statements about inflation, the lower is inflation forecast disagreement of consumers.

Note that in the Bayesian model, heterogeneity in media coverage does not directly cause forecast disagreement. Rather, heterogeneity is averaged out in the process of Bayesian updating and exerts only an indirect effect as it determines the weight agents put on their (heterogeneous) prior beliefs. More importantly, the Bayesian model illustrates that the above relations are ambiguous once agents interpret media reports differently, i.e. if $Var(\mu_{i,t}) > 0$. In the general case, disagreement is driven by four main components: the cross-sectional variance of prior beliefs ($Var(\pi_{i,t})$), the extent of different interpretation of the public signal ($Var(\mu_{i,t})$), the average weight that agents assign to their prior forecasts ($E(\rho_{i,t})$) and the cross-sectional variance of prior weights ($Var(\rho_{i,t})$). The marginal effects of the variance terms on forecast disagreement is nonnegative, while the marginal effect of $E(\rho_{i,t})$ is ambiguous. Ignoring the indirect effect on its own variance, the marginal effect of $E(\rho_{i,t})$ depends on the dispersion of the priors and the extent of differential interpretation:

$$\frac{\partial Var(\pi_{i,t+1})}{\partial E(\rho_{i,t})} = (Var(\pi_{i,t}) + Var(\mu_{i,t}))\, 2E(\rho_{i,t}) - 2Var(\mu_{i,t}) \tag{5.2}$$

This expression tends to be positive if the cross-sectional variance of prior expectations is large relative to the extent of differential interpretation and/or if the average weight on priors is large. If information is not interpreted differentially, a lower average weight on heterogeneous prior beliefs always decreases forecast disagreement. But if new information is interpreted differentially, updating with new information may raise forecast disagreement above initial prior disagreement.[9]

[9] Moreover, if the weights on prior beliefs are heterogeneous ($Var(\rho_{i,t}) > 0$), then the level of the rational

We expect that the extent of differential interpretation $Var(\mu_{i,t})$ can be affected by media coverage. This conjecture is motivated by agenda setting theories in media effects research.[10] Agenda setting theories suggest that the primary role of media lies in influencing what people concern to be important. In traditional agenda setting models, the amount of media reporting (so called media salience) affects where an issue ranks on recipients' agendas. On empirical grounds, Sheafer (2007) extends the traditional notion, arguing that not only the volume but also the tone of media coverage is relevant for agenda setting. The findings of Sheafer (2007) suggest that in particular negative news indicating that inflation is worrisome should raise the perceived issue importance among recipients. In contrast, a neutral or positive tone of news might not affect how concerned agents are with inflation or might even decrease perceived issue importance.

We argue that, in economic terms, agenda setting affects the perceived costs and benefits agents assign to forecasting inflation. If agents are more concerned about inflation, then the cost-benefit ratio of forecasting becomes more favorable towards forming an elaborate and costly forecast. That households indeed choose predictors by rationally evaluating predictor costs and benefits is confirmed by Branch (2004, 2007).[11] If inflation moves up the public agenda, one would expect predictors to become more homogeneous. Agents that normally are not concerned with forecasting inflation begin to form more elaborate forecasts and their predictors converge towards predictors of agents that employ elaborate predictors independently of media coverage.

Apart from the effects of the volume and the heterogeneity of story content for the transmission of information, we thus expect that the extent of differential interpretation is lower in times when the amount of media reporting is high and when the tone of media

forecast may in itself play a role for disagreement. This follows from the last line of Equation (5.1): If the information transmitted by the media diverges from prior expectations, then disagreement will rise provided that updating varies across agents. It is only in this case that a systematic media bias could affect inflation forecast disagreement.

[10] See McCombs and Shaw (1972) for a seminal contribution. Recent surveys of the agenda setting literature are conducted by Dearing and Rogers (1996) and McCombs (2004).

[11] Building on the Brock and Hommes (1997) theory of rational predictor selection, Branch (2004, 2007) estimates a model in which consumers rationally choose from a set of predictors by evaluating costs and benefits of each predictor. Branch (2004, 2007) finds such a model to be consistent with response behavior in the University of Michigan Survey of Consumers.

coverage suggests that inflation is rising. Since $\frac{\partial Var(\pi_{i,t+1})}{\mu_{i,t}} > 0$ we obtain the following hypothesis:

Hypothesis 3: A high volume and, in particular, media coverage indicating rising inflation decrease inflation forecast disagreement of consumers.

As opposed to consumers, professional forecasters should generally be well informed and select predictors independently of media coverage. The last hypothesis thus reads:

Hypothesis 4: Media reporting does not affect inflation forecast disagreement of professional forecasters.

Media coverage of inflation will to some extent reflect the actual macroeconomic state. Moreover, not only professional forecasters but also households will rely on various information sources to form an inflation forecast. In particular, households obtain information from their daily economic interactions as consumers or workers. Hence, information about the macroeconomic state will directly affect expectations and thereby forecast disagreement, independently of the amount of reports, the heterogeneity of story content, or the tone of reporting. Consequently, to identify the intrinsic relevance of media coverage we need to control for confounding macroeconomic factors. Motivated by empirical findings of Mankiw, Reis and Wolfers (2004) we consider three potential macroeconomic control variables: the inflation rate, inflation volatility and relative price variability.[12]

The inclusion of these variables is also theoretically justified, although the relation with disagreement is ambiguous. Theories of rational inattention (Sims, 2003) and theories of rational predictor selection (Branch, 2004, 2007) suggest that the inflation rate is, to some extent, negatively correlated with survey disagreement. As inflation is rising, incentives to closely track inflation may rise and sticking to outdated information may become more

[12]Using U.S. data, Mankiw, Reis and Wolfers (2004) find that the inflation rate is a robust predictor of both consumer and professional disagreement, while inflation volatility and relative price variability are primarily relevant for consumers. Mankiw, Reis and Wolfers (2004) additionally consider the output gap which is significant for consumer disagreement in some specifications. All variables are found to be positively related to disagreement.

costly. If inflation exceeds some threshold, however, uncertainty about the choice of a forecasting model and disagreement about the interpretation of available information might rise as well. This effect is expected to be particularly relevant once inflation significantly deviates from the monetary policy target level or in times of a regime change (Kandel and Zilberfarb, 1999). For consumers we might thus observe a nonlinear effect of inflation on disagreement. At low levels a rise in inflation draws the attention of households who are subject to the economic incentives to track inflation more closely, lowering overall disagreement since information sets become more homogeneous. At higher levels of inflation, uncertainty about the choice of a forecasting model and differential interpretation of public information raise forecast disagreement, despite high levels of attention and homogeneous information sets. Since professional forecasters' information sets should not depend much on the level of inflation, differential interpretation should dominate for them.

The effect of inflation volatility might be similar to the effect of the inflation level. Theories of rational inattention suggest that consumers spend more time observing the inflation rate when it is volatile. But if inflation is highly volatile, uncertainty about how to predict it might also be high. Hence, differential interpretation of the same information becomes more important. That forecast disagreement is rising in inflation volatility is suggested by the sticky information model of Mankiw and Reis (2002, 2006). In this model, any change in the rate of inflation raises the heterogeneity of information sets across economic agents. Again, one would expect that the effect of attention primarily concerns consumers. The third macroeconomic variable we consider is relative price variability, i.e. the variation of inflation rates across subcomponents of the consumer price index. We expect that this variable is positively correlated with disagreement of households and professional forecasters. In particular, results of Souleles (2004) and Bryan and Venkatu (2001b) suggest that households may not necessarily have the official inflation rate in mind, but may rather refer to inflation as observed in their private consumption basket. Hence, relative price variability should directly raise forecast disagreement since it induces heterogeneity in the information sets of households. A positive correlation with professional disagreement might once more reflect uncertainty about the choice of an adequate forecasting model.

5.3 Data

Inflation expectations of households about 12 months ahead consumer price inflation are taken from the Joint Harmonized EU Consumer Survey. Within this framework a representative sample of roughly 1,500 German households is surveyed every month.[13] Inflation expectations are captured by asking households: "By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months? They will...". Respondents express their beliefs on a five-option scale: "Increase more rapidly, increase at the same rate, increase at a slower rate, stay about the same, fall".[14]

Survey results are publicly available as aggregate shares over qualitative response categories. We quantify inflation forecast disagreement of households by computing an index of qualitative variation (IQV) based on the response shares in the 5 categories:

$$Q(X) \quad = \quad \frac{K}{K-1}\left(1-\sum_{i=1}^{K} p(x_i)^2\right)$$

where $K = 5$ is the number of categories in the survey question on expected inflation and $p(x_i)$ the fraction of answers in category x_i. The scaling factor $\frac{K}{K-1}$ ensures that $0 \leq Q(X) \leq 1$. In Chapter 2 it has been shown that the IQV closely traces the actual standard deviation of quantitative responses in a survey that records both qualitative and quantitative inflation expectations. Moreover, it has been found that since the IQV does not incorporate ordinal information it outperforms other quantification approaches.[15]

Disagreement of professional forecasters is based on quantitative point forecasts taken from the Consensus Economics survey. Consensus Economics has been surveying roughly

[13] The consumer survey consists of 15 qualitative questions that pertain to the household's financial situation, perceived economic conditions and planned savings and spending, see European Commission (2007).

[14] Survey respondents may also opt for a "don't know" response.

[15] Chapter 2 documents that the correlation of the IQV with the standard deviation of actual quantitative responses is about 0.8 using monthly micro-data from the Swedish Consumer Tendency Survey, 1996–2008. The IQV performs significantly better than other quantification methods, such as the probability method and measures of ordinal variation. Due to the particular questioning of the EU survey, qualitative inflation expectations are not ordered. Consequently, measures that use ordinal information are distorted, whereas the IQV remains unaffected.

30 experts of private and public institutions in Germany on a monthly basis over the entire sample period. Unlike the consumer survey, the Consensus Economics survey asks for (fixed event) forecasts of inflation over the current and the upcoming calendar year. We adopt the weighting approach commonly used in the literature to compute 12 months ahead (fixed horizon) forecasts.[16] As a measure of disagreement we follow Giordani and Söderlind (2003) and employ the quasi-standard deviation (QSD) defined as half the difference between the 84th and 16th percentile of the point forecasts as a measure of disagreement. The quasi-standard deviation is robust to outliers and corresponds to the usual standard deviation if point forecasts are normally distributed.

Figure 5.1 shows inflation forecast disagreement of consumers and professional forecasters. The sample average of the IQV for consumers is 0.86, the average QSD for professionals 0.39%. Disagreement of consumers and professionals show considerable variation over time with standard deviations of 0.06 and 0.08% respectively. Consumer disagreement exhibits a level shift around 01/2002, coinciding with the euro cash changeover. Since our focus does not lie on understanding this particular event, we account for the shift by including an indicator variable that is equal to unity from 01/2002. Professional disagreement also rises after the euro cash changeover, but falls back to its initial level in 2004. The figure indicates that consumer and professional disagreement are only weakly correlated: The correlation coefficient is 0.39. Also, disagreement of professionals appears to be less persistent than disagreement of consumers. Overall, the figure suggests that different drivers are relevant for consumer and professional disagreement.

Our set of explanatory macroeconomic variables is based on the Harmonized Index of Consumer Prices (HICP) as published by Eurostat. The inflation rate is computed as the year-over-year percentage change of the HICP. As a measure of inflation volatility we use the squared monthly change in the inflation rate, averaged over three months (i.e. between t and $t-2$).[17] Finally, we consider relative price variability given by a weighted standard

[16] The 12 months ahead inflation expectation formed in month m of year t is given by $\frac{13-m}{12}\pi_t^c + \frac{m-1}{12}\pi_{t+1}^c$, where π_t^c is the inflation expectation for year t.

[17] We have also considered the squared monthly change and the absolute monthly change, with unchanged qualitative results.

deviation of inflation rates in HICP subcomponents (see, e.g., Jarmarillo, 1999):

$$RPV_t = \sqrt{\sum_{i}^{I} w_{i,t} \left(\pi_{i,t} - \pi_t\right)^2}$$

where $w_{i,t}$ is the weight of HICP subindex i, $\pi_{i,t}$ the inflation rate in subindex i and π_t the overall HICP inflation rate. Our measure is based on 39 monthly HICP subcomponents and annual weights obtained from Eurostat.[18]

Figure 5.2 shows the macroeconomic variables. While the HICP inflation rate exhibits only moderate variation, relative price variability is comparatively high and volatile. In the periods 2000–2001, 2004–2006 and in 2008 relative price variability attains levels of above 4%. The series is positively correlated with the inflation rate, with a correlation coefficient of 0.41. Inflation volatility is only weakly correlated with the inflation rate and relative price variability, correlation coefficients are 0.28 and 0.33 respectively. The figure also indicates that no simple linear relation exists between the macroeconomic variables and disagreement in this period of relatively low inflation.

The media content data has been provided by the media research institute Media Tenor. The dataset covers a wide range of newspapers and television news on a monthly frequency for the time span 01/1998 to 09/2007 in Germany. It covers all statements dealing with inflation which are at least five lines long in the case of printed media and last at least five seconds for television broadcasts.[19] The coding is based on the standards of media content analysis (see, e.g., Holsti, 1969). Media content analysis allows to capture the content of each statement, while being objective and reproducible. This is achieved by continuous training of the coding specialist, a solid definition of the code book and regular inter-coder

[18]The 39 subcomponents correspond to the COICOP 3-digit aggregates as provided by Eurostat. All series are available from 01/1995 onwards.

[19]The following daily newspapers are analyzed: Frankfurter Allgemeine Zeitung, Welt, Süddeutsche Zeitung, Frankfurter Rundschau, Tageszeitung, Neue Zürcher Zeitung, Berliner, Volksstimmer, Sächsische, Westdeutsche Allgemeine Zeitung, Kölner Stadt-Anzeiger, Rheinischer Merkur. The following daily TV-news are covered: ARD Tagesschau, Tagesthemen, ZDF Heute, Heute Journal, RTL Aktuell, SAT.1 18:30, ProSieben Nachrichten. Additionally, the following weekly newspapers are included: Spiegel, Focus, Die Woche, Wochenpost, Welt am Sonntag, Bild am Sonntag, Die Zeit.

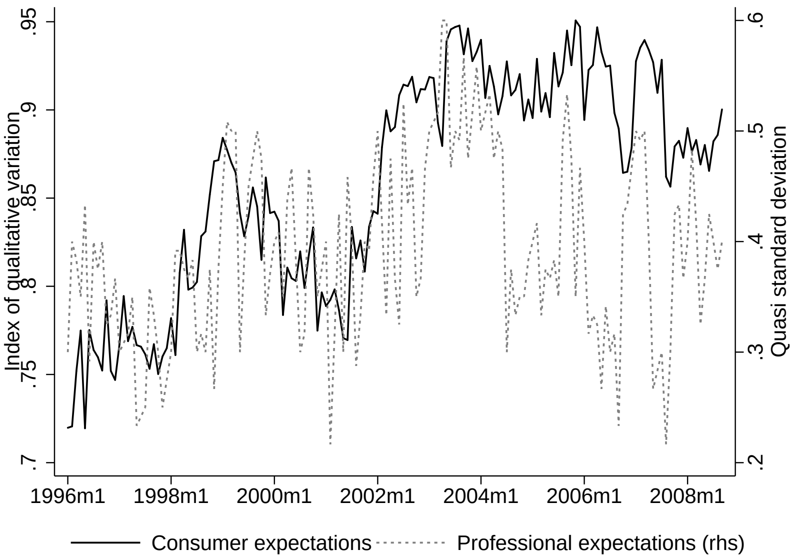


Figure 5.1: Disagreement in inflation expectations

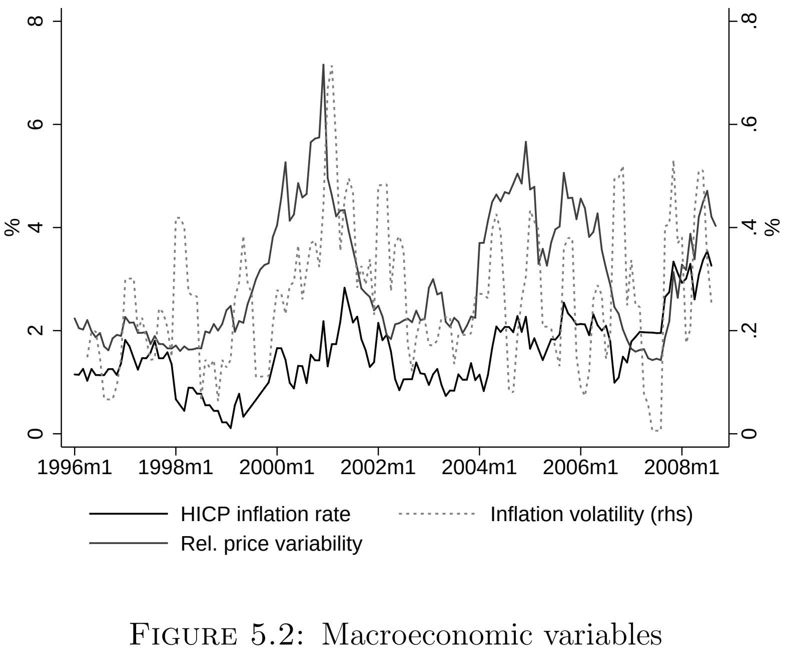


Figure 5.2: Macroeconomic variables

reliability tests. For each media report, the direction inflation is taking according to this report is encoded using the three categories "rising", "unchanged" and "falling".

Based on this data we generate a number of explanatory variables that capture media activity. The volume of media coverage (V) is simply given by the overall sum of media reports that mention inflation per month. Our measure of heterogeneity of media reports (variance b_t) is based on the information about the direction inflation is taking. Given the shares $p(x_i)$, $i = 1, 2, 3$, of reports stating that inflation is rising, unchanged and falling we compute Shannon's measure of information entropy which is given by:

$$H(X) = -\sum_{i=1}^{K} p(x_i) ln \left(p(x_i)\right)$$

where $K = 3$ is the number of values of characterizing the direction of media reports. Under the convention that $0ln(0) = 0$ this measure is bounded such that $0 \leq H(X) \leq ln(3) \approx 1.1$.

Figure 5.3 shows the volume of media coverage and the information entropy. The figure indicates that the volume is relatively high in the years 2000–2003 and in 2007, coinciding with the euro cash changeover and the rise in inflation due to energy prices at the end of the sample period. Correlation of the inflation rate with the volume of media reports is only 0.30, however. The entropy of statements about the direction inflation is taking is a highly volatile process. Only towards the end of the sample, information entropy shows a declining tendency.

The variables that capture the tone of media coverage are based on the shares of reports indicating a particular direction of inflation relative to the monthly total number of reports about inflation. We consider the tone, computed as the difference between the fraction of reports stating that inflation is rising and the fraction of reports stating that inflation is falling. A positive tone thus reflects that news indicating rising inflation predominate. Moreover, we consider the shares of reports stating that inflation takes a particular direction. Figure 5.4 shows the tone as well as the shares of reports indicating that inflation is rising and falling. The figure reveals that the share of articles with rising direction is particularly high in the years 2000–2001 and at the end of the sample period.

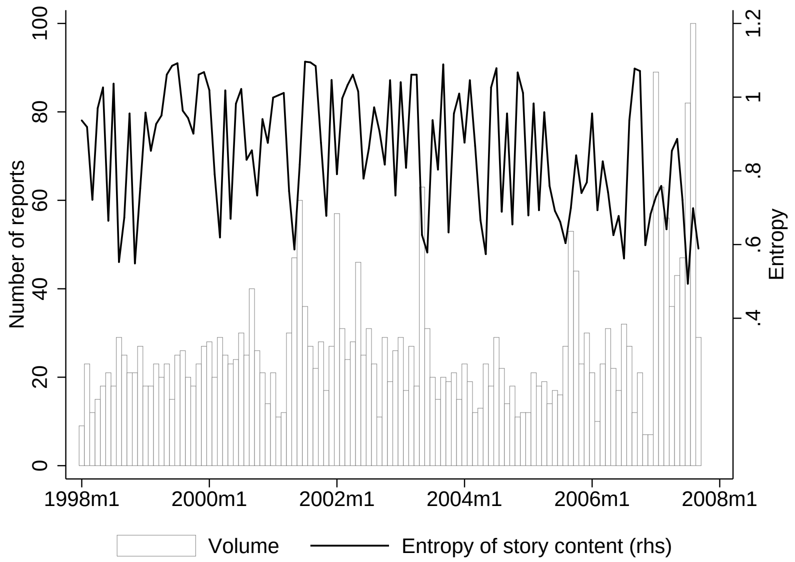


Figure 5.3: Volume and entropy of media coverage

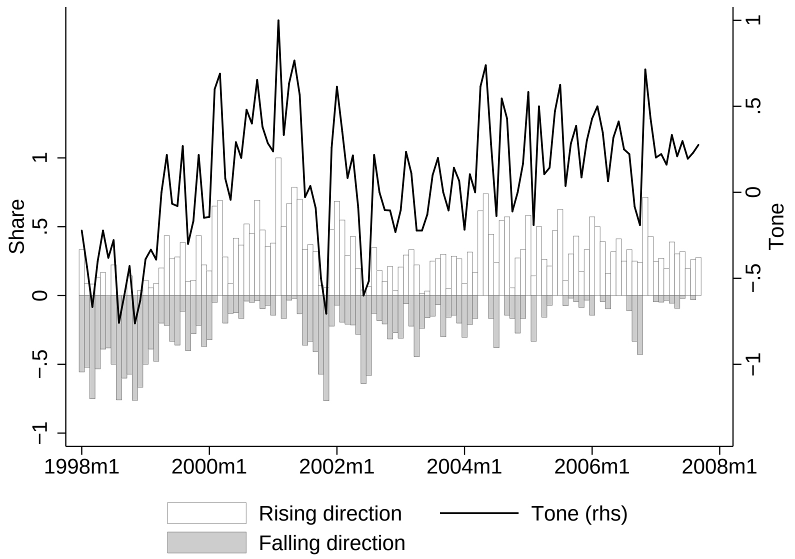


Figure 5.4: Tone of media coverage

This is also reflected in the tone of media coverage. On average, the tone is slightly positive but highly volatile with a standard deviation of about 0.3.

5.4 Estimation Results

5.4.1 Macroeconomic Determinants of Heterogeneity

Our empirical analysis of disagreement begins by looking at the macroeconomic determinants that have been motivated above. We aim at identifying a baseline specification of disagreement to which the media variables will be added in a second step. The analysis centers on linear regressions of the following form:

$$Var(\pi_{i,t}) \quad = \quad \beta_1 Var(\pi_{i,t-1}) + \beta_2 \pi_{t-1} + \beta_3 \pi_{t-1}^2 + ... + \beta_{p-1} + \beta_p d + \varepsilon_t \tag{5.3}$$

The dependent variable is the index of qualitative variation for consumers and the quasi standard deviation for professional forecasters. The specifications control for the euro cash changeover by including a step dummy d which is unity from 2002 onwards. To account for the publication lag of macroeconomic information we include the macroeconomic correlates with a one month lag. Moreover, the model contains a lagged dependent variable. This is motivated by equation (5.1) which illustrates that the heterogeneity of prior beliefs is a potentially important determinant of survey disagreement.[20] In an attempt to approach the Bayesian learning model we additionally report results for the following specification:

$$Var(\pi_{i,t}) \quad = \quad Var(\pi_{i,t-1}) \left(\beta_1 + \beta_2 \pi_{t-1} + \beta_3 \pi_{t-1}^2 + ...\right) + \beta_{p-1} + \beta_p d + \varepsilon_t \tag{5.4}$$

In this second model, the macroeconomic covariates indirectly influence forecast disagreement by affecting the weight on the proxy of prior beliefs, $Var(\pi_{i,t})$. Both models are

[20]Note that the lagged dependent variable is only an approximate measure of prior disagreement because the underlying forecasts refer to a one month lagged target horizon.

estimated using ordinary least squares.[21]

In column (1) of Table 5.1 we provide an initial specification of disagreement which is estimated over the sample period 01/1998–09/2007 for which media content data is available. This specification includes HICP inflation, inflation volatility and relative price variability. Following the theoretical line of argumentation, we allow for a nonlinear effect of the inflation rate, reflecting that inflation affects the attentiveness as well as uncertainty about the choice of a forecasting model. The estimations show that inflation and inflation squared are highly significant for consumers. For professional disagreement, only the level of inflation is significant. In contrast to our anticipation, inflation volatility and relative price variability are insignificant both for consumers and professional forecasters. The lagged dependent variable is highly significant in all specifications. The coefficient estimates suggest that disagreement of consumers is more persistent than disagreement of professionals, but that both variables are stationary. The lower persistence of professional disagreement is in line with the anticipation that professional forecasters are more responsive to new information than consumers.

Column (2) presents estimation results of the alternative model specified in Equation (5.4), including the same set of macroeconomic variables. The estimations confirm the above findings. But while inflation still exerts a significant nonlinear effect on consumer disagreement, the level of inflation is not significant for professional disagreement anymore.

Relying on these results, column (3) presents our preferred macroeconomic specification which excludes inflation volatility and relative price variability. The nonlinear effect of inflation on consumer disagreement remains highly significant. Figure 5.5 illustrates this effect. The dots represent actual observations and the dashed lines show the 95% confidence interval. The figure reveals that if inflation is below a threshold of about 1.8%, disagreement is declining in inflation. Above this threshold, however, disagreement is rising in inflation. A possible interpretation of this pattern along the lines of Kandel and Zilberfarb (1999) is

[21] All estimations allow for heteroskedasticity. Estimations of models without lagged dependent variables additionally allow for serial correlation by employing the Newey-West estimator. We have tested for residual correlation in specifications with a lagged dependent variable using the Breusch-Godfrey LM test of no serial correlation.

TABLE 5.1: Macroeconomic models of survey disagreement

	(1)		(2)		(3)		(4)	
	Cons.	*Prof.*	*Cons.*	*Prof.*	*Cons.*	*Prof.*	*Cons.*	*Prof.*
Inflation(t-1)	-0.0434***	-0.1015*	-0.0381**	-0.0848	-0.0427**	-0.0767	-0.0265***	-0.1016***
	(0.0166)	(0.0531)	(0.0181)	(0.1544)	(0.0167)	(0.0532)	(0.0089)	(0.0249)
Inflation squared(t-1)	0.0122**	0.0177	0.0104*	-0.0023	0.0120**	0.0137	0.0050**	0.0180***
	(0.0058)	(0.0199)	(0.0062)	(0.0492)	(0.0058)	(0.0199)	(0.0020)	(0.0065)
Inflation volatility(t-1)	-0.0128	0.0674	-0.0304	0.0701			0.0047	0.0747
	(0.0157)	(0.0549)	(0.0187)	(0.1676)			(0.0140)	(0.0473)
Rel. price var.(t-1)	0.0004	0.0060	0.0011	0.0095			0.0018	0.0049
	(0.0018)	(0.0055)	(0.0023)	(0.0132)			(0.0016)	(0.0044)
Lagged dependent	0.5425***	0.4574***	0.5722***	0.5826***	0.5682***	0.4868***	0.6657***	0.4283***
	(0.0853)	(0.0726)	(0.0689)	(0.1348)	(0.0812)	(0.0740)	(0.0652)	(0.0666)
Constant	0.4078***	0.2555***	0.3776***	0.1807***	0.3839***	0.2628***	0.2863***	0.2671***
	(0.0775)	(0.0442)	(0.0609)	(0.0300)	(0.0736)	(0.0447)	(0.0569)	(0.0361)
Dchangeover	0.0476***	0.0479***	0.0462***	0.0317*	0.0456***	0.0351**	0.0403***	0.0515***
	(0.0100)	(0.0157)	(0.0085)	(0.0169)	(0.0098)	(0.0155)	(0.0088)	(0.0128)
Observations	117	117	117	117	117	117	149	149
R-squared	0.87	0.42	0.87	0.38	0.87	0.40	0.89	0.45

Notes: Monthly data, 01/1998–09/2007. Columns (1) and (3)–(4) show OLS estimation results of Equation (5.3). Column (4) is based on the unrestricted sample period 04/1996–09/2008. Column (2) presents estimation results of Equation (5.4), where the coefficient in the column for the lagged dependent corresponds to β_1. Dependent variable for consumers is the index of qualitative variation, dependent variable for professional forecasters is the quasi standard deviation of quantitative survey responses. White standard errors in parentheses allowing for heteroskedasticity. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

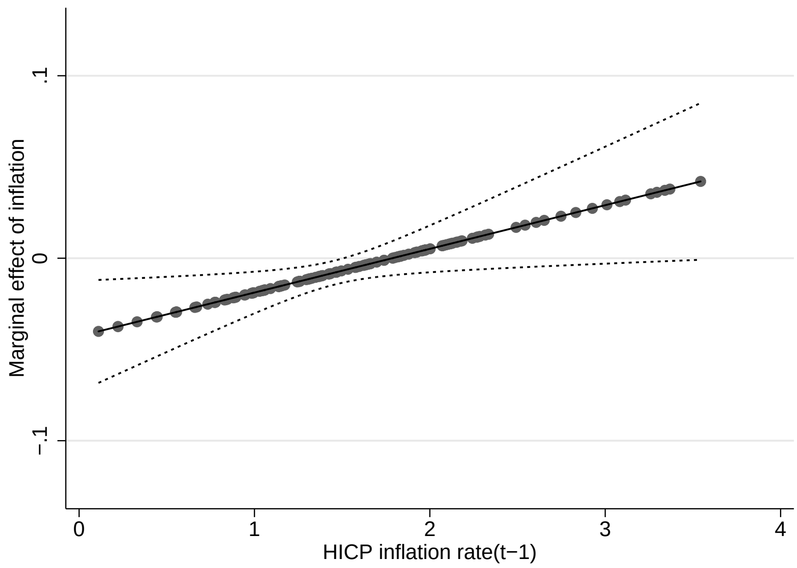


Figure 5.5: Marginal effect of inflation on consumer disagreement

Notes: The dots represent actual observations and the dashed lines show the 95% confidence interval. Then underlying regression is shown in column (3) of Table 5.1.

that agents begin to disagree about which forecasting model is adequate in an uncertain environment with inflation rates that diverge from the 2% level the ECB considers to be in line with price stability.

The findings regarding the significance of macroeconomic variables are only partially consistent with results of Mankiw, Reis and Wolfers (2004) for the U.S. These authors report that the inflation rate is a robust predictor of consumer disagreement. In contrast to our results however, Mankiw, Reis and Wolfers (2004) find that (in specifications without a lagged dependent variable) relative price variability and inflation volatility are also significant. Regarding professional disagreement, they report that the estimated effect of the inflation rate is significant and positive. These differences to our results might be explained by their sample horizon which covers 30 years and includes periods of very high inflation rates and inflation volatility. Contrary to that, our sample horizon is characterized by relatively low levels of inflation and inflation volatility, with inflation ranging between 0.1% and 2.8%. We therefore provide results for an extended sample period that includes the episode of high inflation in 2007 and 2008.[22] The estimation results are presented in column 4 of Table 5.1. While the effects of inflation on consumer disagreement are confirmed, inflation also exerts a significant nonlinear effect on professional disagreement. Professional disagreement is rising in inflation once inflation exceeds a level of about 2.7%. Thus, we presume that this non-linear effect has general validity for disagreement.

In sum the above results show that one month lagged inflation has a significant non-linear effect on consumer disagreement. Professional disagreement is less persistent than consumer disagreement. It only depends on inflation in one specification but is otherwise unrelated to the considered set of macroeconomic variables. Only in a longer sample period that includes the recent episode of high inflation we also detect a nonlinear effect of inflation on professional disagreement. We therefore include the first lags of inflation and inflation squared as control variables in evaluating the effects of media coverage.

5.4.2 Effects of Media Reporting on Heterogeneity

This section systematically adds media variables to the baseline macroeconomic specification presented in column (3) of Table 5.1. In a first step, we investigate the media variables which, according to the Bayesian learning model, are relevant for the heterogeneity of information sets. According to Hypothesis (1), an increase in the amount of media reports about inflation raises the ratio of signal to prior precision which lowers disagreement among consumers. Similarly, Hypothesis (2) states that the lower the information entropy of story content is, the less weight households will put on their (heterogeneous) prior beliefs and the lower consumer disagreement will be. In column (1) of Table 5.2 we test these hypotheses by including the monthly number of reports dealing with inflation and the information entropy of statements about the direction of inflation. In contrast to our hypotheses, both variables are insignificant.[23] From the model viewpoint this suggests that households interpret new information differentially such that the marginal effect of updating on forecast disagreement (Equation 5.2) is zero. Consistent with Hypothesis (4),

[22]This sample period covers 04/1996–09/2008 and is defined by HICP data availability.

[23]A separate inclusion of volume and entropy does not change this result.

professional disagreement is unaffected by media variables.

In a second step, we add the media variables that are expected to affect the heterogeneity of predictors. Column (2) of Table 5.2 includes the tone of media coverage, represented by the difference of the share of articles indicating that inflation is rising and the share of articles indicating that inflation is falling. The tone of media coverage is highly significant for consumers. We can also disentangle the effect of the tone into the effects of reports indicating that inflation is rising or falling. Column (3) reveals that consumer disagreement is decreasing in the share of media reports that signal rising inflation. The estimated coefficient is highly significant. The volume of media reporting, which might also be relevant for the agenda setting function, remains insignificant. Rather than the absolute volume, the relative tone of reporting is important. In line with Hypothesis (3), these results suggests that consumer disagreement is lower if media coverage emphasizes that inflation is rising. This result is consistent with the model view that by setting the agenda, media coverage influences predictor choice and thereby forecast disagreement. Column (4) of Table 5.2 presents estimation results of the alternative model specified in Equation (5.4). The estimations confirm the above findings.

Excluding the lagged dependent variable and the euro cash changeover dummy, the adjusted R-squared of a linear regression that only includes media variables is 0.33 for consumers, as compared to an R-squared of 0.05 from a regression that only includes macroeconomic variables.[24] The higher R-squared of a specification including only the media variables is in line with the notion that the media transmit macroeconomic variables and additionally interpret these variables. Therefore, the media variables contain more information than just the macroeconomic variables. Regarding the quantitative importance of the identified effects, column (3) of Table 5.1 suggests that if the share of reports pointing to rising inflation increases from 0 to the maximum of 1, forecast disagreement declines by 0.04. This may seem low given the IQV's standard deviation of 0.06, but it is economically more relevant than the effect of the inflation rate. Evaluated at the sample mean of the respective series, the marginal effect of a one standard deviation shock

[24] Detailed results are available upon request.

Table 5.2: The effect of media coverage on survey disagreement

	(1)		(2)		(3)		(4)	
	Cons.	*Prof.*	*Cons.*	*Prof.*	*Cons.*	*Prof.*	*Cons.*	*Prof.*
Volume	0.0000	0.0003	0.0000	0.0003	-0.0000	0.0003	-0.0001	0.0008
	(0.0002)	(0.0006)	(0.0002)	(0.0006)	(0.0002)	(0.0006)	(0.0003)	(0.0013)
Entropy	-0.0079	0.0318	-0.0108	0.0336	-0.0051	0.0414	-0.0060	0.0540
	(0.0114)	(0.0414)	(0.0103)	(0.0424)	(0.0105)	(0.0418)	(0.0118)	(0.1106)
Tone			-0.0152***	0.0072				
			(0.0052)	(0.0256)				
Direction rising					-0.0383***	-0.0232	-0.0480***	-0.0974
					(0.0132)	(0.0540)	(0.0151)	(0.1271)
Direction falling					-0.0109	-0.0417	-0.0086	-0.1091
					(0.0130)	(0.0541)	(0.0162)	(0.1521)
Lagged dependent	0.5692***	0.4760***	0.5801***	0.4694***	0.5345***	0.4645***	0.6105***	0.5738***
	(0.0826)	(0.0758)	(0.0766)	(0.0784)	(0.0824)	(0.0800)	(0.0709)	(0.1708)
Inflation(t-1)	-0.0425**	-0.0773	-0.0290*	-0.0836	-0.0328**	-0.0844	-0.0190	-0.0511
	(0.0171)	(0.0519)	(0.0153)	(0.0529)	(0.0156)	(0.0540)	(0.0192)	(0.1646)
Inflation squared(t-1)	0.0118*	0.0133	0.0088	0.0146	0.0102*	0.0152	0.0065	-0.0084
	(0.0060)	(0.0191)	(0.0054)	(0.0191)	(0.0054)	(0.0196)	(0.0066)	(0.0513)
Constant	0.3892***	0.2322***	0.3729***	0.2379***	0.4237***	0.2545***	0.3497***	0.1916***
	(0.0747)	(0.0614)	(0.0691)	(0.0612)	(0.0776)	(0.0648)	(0.0646)	(0.0335)
Dchangeover	0.0449***	0.0372**	0.0434***	0.0378**	0.0439***	0.0326*	0.0382***	0.0194
	(0.0100)	(0.0158)	(0.0093)	(0.0151)	(0.0092)	(0.0168)	(0.0087)	(0.0173)
Observations	117	117	117	117	117	117	117	117
R-squared	0.87	0.40	0.88	0.41	0.88	0.41	0.88	0.39

Notes: Monthly data, 01/1998–09/2007. Columns (1)–(3) show OLS estimation results of the linear model. Column (4) presents estimation results of Equation (5.4), where the coefficient in the column for the lagged dependent corresponds to β_1. Dependent variable for consumers is the index of qualitative variation, dependent variable for professional forecasters is the quasi standard deviation of survey responses. White standard errors in parentheses allowing for heteroskedasticity. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

to the share of positive reports is -0.008, while the marginal effect of a one standard deviation shock to inflation is -0.002.[25] The finding that media coverage has a stronger impact on consumer disagreement than the raw macroeconomic figure itself relates to the recent literature on macroeconomic literacy. In particular, results of Blinder and Krueger (2004) and Fullone et al. (2007) show that television and newspaper reports are the most important sources of economic information for households. In sum, these results suggest that it is primarily through the transmission and interpretation of information by the media that macroeconomic information becomes useful for consumers.

In order to account for the highly unlikely case of a possible reverse causation running from disagreement of professional forecasters forecasters and consumers to media reporting, Table D.1 in the Appendix provides estimates that include the media variables with a one month lag. In specifications excluding a lagged dependent variable, the effect of the share of reports indicating rising inflation remains highly significant. Including a lagged dependent variable, the effects of lagged media reporting are not significant anymore. This indicates that the information contained in lagged media reports has already been incorporated into prior expectations, represented by the lagged dependent variable.

Carroll (2003) and Lamla and Lein (2008) assume that the media transmit professional forecasts. Thus, the significant effect of the tone variable might be confounded by publicly available views and expectations of professional forecasts. Column (1) of Table 5.3 therefore includes the mean and the quasi standard deviation of one month lagged professional forecasts taken from the Consensus Economics survey as additional control variables. The estimations show that the coefficients on the media variables are virtually unaffected. In particular, the share of reports indicating rising inflation remains highly significant and negative.[26] Interestingly, while the mean of professional forecasts is insignificant, consumer disagreement is positively related to one month lagged professional disagreement.

Columns (2)–(4) of Table 5.3 further investigate the robustness of these results by separating the incidence of media coverage across educational groups. Our anticipation

[25]These results rely on the estimations presented in column (3) of Table 5.2.
[26]This also holds for the tone variable which is not shown in the table.

TABLE 5.3: Robustness checks and results by educational groups

	(1)	(2)–(4)			(5)-(6)	
	Cons.	*Primary*	*Secondary*	*Tertiary*	*Within*	*Between*
Volume	-0.0000	-0.0001	-0.0001	0.0002	-0.0000	0.0362
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0382)
Entropy	-0.0121	-0.0214*	-0.0071	-0.0090	-0.0044	-3.6711
	(0.0101)	(0.0116)	(0.0129)	(0.0240)	(0.0095)	(2.2238)
Direction rising	-0.0419***	-0.0366**	-0.0569***	-0.0900***	-0.0579***	-0.7549
	(0.0135)	(0.0172)	(0.0153)	(0.0289)	(0.0172)	(2.7510)
Direction falling	-0.0037	-0.0070	-0.0069	-0.0060	-0.0131	-0.5572
	(0.0127)	(0.0183)	(0.0138)	(0.0306)	(0.0172)	(3.6485)
Prof. expectation(t-1)	-0.0100	-0.0120	-0.0090	-0.0452***	-0.0231***	1.6481
	(0.0070)	(0.0086)	(0.0078)	(0.0161)	(0.0071)	(1.4053)
Prof. disagreement(t-1)	0.0570**	0.0451	0.0589**	0.0963*	0.0514**	7.6709
	(0.0252)	(0.0278)	(0.0290)	(0.0567)	(0.0250)	(6.0541)
Lagged dependent	0.4745***	0.4335***	0.3827***	0.0502		
	(0.0795)	(0.0816)	(0.0897)	(0.1092)		
Inflation(t-1)	-0.0237	-0.0309	-0.0215	-0.0835*	-0.0209	-3.0460
	(0.0154)	(0.0193)	(0.0212)	(0.0440)	(0.0234)	(3.1525)
Inflation squared(t-1)	0.0095*	0.0116*	0.0099	0.0305*	0.0084	1.0332
	(0.0053)	(0.0059)	(0.0069)	(0.0155)	(0.0078)	(1.0511)
Constant	0.4626***	0.5181***	0.5316***	0.8746***	0.6626***	0.5232
	(0.0775)	(0.0817)	(0.0864)	(0.1197)	(0.0282)	(1.1684)
Dchangeover	0.0442***	0.0490***	0.0509***	0.0672***	0.0591***	5.2248
	(0.0088)	(0.0105)	(0.0101)	(0.0130)	(0.0051)	(3.8311)
Observations	117	117	117	117	117	117
R-squared	0.89	0.85	0.85	0.60	0.79	0.11

Notes: Monthly data, 01/1998–09/2007. Dependent variable in columns (1)–(4) is the index of qualitative variation. Professional disagreement is measured by the quasi-standard deviation. White standard errors in parentheses allowing for heteroskedasticity. Within-group variation in column (5) is measured as the average index of qualitative variation over educational groups. Between-group variation in column (6) is measured as the standard deviation of group mean expectations. Mean expectations are quantified using the balance statistic. For column (5)–(6), Newey-West standard errors are reported using the bandwidth $n = 4 \approx 4(T/100)^{2/9}$ (Newey and West, 1994). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

about the relevance of the tone variables is mixed. On the one hand, higher educational groups might be more affected by the tone of media coverage as they should consume more newspaper reports and TV-news. On the other hand, higher educational groups might be less affected by media coverage as they should form more elaborate inflation expectations, similar to professional forecasters. The results in Table 5.3 indicate that the tone of media coverage affects all educational groups, but that the absolute magnitude of the effect increases in education.[27] Consistently, the mean professional expectation and lagged actual inflation are only significant for the highest educational group. Also, the coefficient on the lagged dependent variable is declining in education, suggesting that higher educational groups are more responsive to new information. This result is in line with findings in the literature that point towards a positive relation of education and the accuracy of inflation expectations (Bryan and Venkatu, 2001b, and Souleles, 2004) and financial literacy (Lusardi and Mitchell, 2007).

The estimates across educational groups are consistent with aggregate results and suggest that overall forecast disagreement is declining in the tone of media reporting because disagreement within each educational group is declining. Columns (5) and (6) of Table 5.3 confirm this finding by splitting effects on overall forecast disagreement into effects on within-group disagreement and between-group disagreement. Within-group disagreement is given by the average index of qualitative variation across the three educational groups. Between-group disagreement is measured by the standard deviation of mean expectations across educational groups.[28] The estimations show that the tone of media coverage lowers forecast disagreement by lowering disagreement within educational groups. Between-group disagreement is unaffected by media variables.

In sum, the above results confirm that media play a role for disagreement of consumers, but not for disagreement of professional forecasters. Consistent with Hypothesis (3) we

[27] The disaggregate results for educational groups do not depend on the inclusion of mean and dispersion of professional forecasts.

[28] Mean expectations are quantified employing the balance statistic defined as $p_1 + 0.5p_2 - 0.5p_4 - p_5$, where p_1 is the share of respondents opting for the qualitative answer that prices will “increase more rapidly”.

find that disagreement is declining in the share of reports that indicate rising inflation. According to the model view, this may result from a decline in predictor heterogeneity, caused by increasing importance consumers assign to predicting inflation. In contrast to our hypotheses, the volume and information entropy of media coverage do not affect disagreement of consumers. All results are conditional on a set of macroeconomic control variables and are robust to the inclusion of the mean and heterogeneity of professional forecasts.

5.5 Conclusion

While the evidence on the drivers of inflation expectations is increasing, research on disagreement in expectations remains scant at best. Meanwhile, recent theoretical contributions show that disagreement significantly affects economic allocations and may have important consequences for monetary policy. In this paper, we contribute to the understanding of disagreement by investigating the role of media coverage about inflation for inflation forecast disagreement of German households and professional forecasters. This focus is motivated by the literature on macroeconomic literacy which shows that television news and newspaper reports are the predominant sources of economic information for households. To embed the effect of media coverage, we propose a Bayesian learning model which follows Kandel and Zilberfarb (1999) in allowing for heterogeneous predictors. We assume that media coverage may affect forecast disagreement by influencing information sets and predictor choice of recipients. In our model, forecast disagreement is governed by the dispersion of prior beliefs and by the amount, the heterogeneity and the tone of media reports about consumer price inflation. Since agents obtain signals from various sources, our empirical specifications control for a set of macroeconomic variables. Motivated by findings of Mankiw, Reis and Wolfers (2004), this set includes the inflation rate, inflation volatility and relative price variability.

We show empirically that inflation forecast disagreement of consumers and professional forecasters is affected by macroeconomic variables. The estimations suggest that the level of inflation is a robust driver of consumer disagreement. Interestingly, inflation affects disagreement in a non-linear manner. At low levels of inflation, broadly in line with price stability as defined by the ECB, disagreement is declining in inflation, whereas at higher levels of inflation disagreement is rising again. A possible interpretation of this nonlinear effect is that agents begin to disagree about which forecasting model is adequate in an uncertain environment with inflation rates substantially diverging from the policy target. We detect a similar pattern for professional disagreement in an extended sample period that includes the recent episode of relatively high inflation. Inflation volatility and relative price variability are insignificant in all specifications.

Conditional on a macroeconomic specification we then test for the effects of media coverage about inflation. The inclusion of the macroeconomic control variables allows to avoid confounding effects as the media transmit relevant information about the macroeconomic state. Our results confirm that media coverage plays a role for disagreement of consumers, but not for disagreement of professional forecasters. This finding is in line with the conjecture that professional forecasters have incentives to acquire the most recent information and to select forecasting models irrespective of media coverage. The effects on consumer disagreement are limited to the tone of media reporting. Our results robustly show that if the tone of media reporting is pessimistic, emphasizing that inflation is rising, disagreement of consumers declines. This is consistent with the model view that by setting the agenda, media coverage induces a more homogeneous predictor distribution among households.

Our results suggest that examining the differential effects of media coverage on information sets and predictor choice is an important topic for future work. A possible approach is to simultaneously consider inflation perceptions, which should more closely reflect information sets. Moreover, the results on the tone variables suggest that it is the relative number of media reports with a given tone that is important. Hence, one should also investigate relative measures of volume, such as the number of news about inflation relative to the number of news about other economic issues.

Chapter 6

The Persistence of Inflation in Switzerland: Evidence From Disaggregate Data*

*This chapter is based on Elmer and Maag (2009).

6.1 Introduction

Inflation persistence is subject to a substantial debate in macroeconomics. Centering on the question whether inflation persistence is intrinsic in the sense of Lucas (1976), a large empirical literature has not reached a consensus yet.[1] Supporting intrinsic inertia, Pivetta and Reis (2007) and O'Reilly and Whelan (2005) show that inflation persistence is high and has not significantly changed over the past 30 years in the U.S. and euro area, respectively. Contrary to these studies, Cogley and Sargent (2005) find that U.S. inflation persistence has declined since the 1970s. Benati (2008) provides evidence that inflation persistence varies across monetary regimes and diminishes in inflation targeting regimes. Regarding Switzerland, Benati (2008) shows that the persistence of inflation was high during 1947–1999 and fell to roughly zero during 2000–2006. Although the reported confidence intervals still include the nonstationary case, the results of Benati (2008) suggest that inflation persistence has declined under the new monetary policy concept. Broadly in line with Benati (2008), Levin and Piger (2004) report that Swiss inflation was highly persistent in the period 1984–2003.[2]

The goal of our paper is to provide a detailed assessment of the level and change in persistence of Swiss consumer price inflation from 1983 to 2008. We investigate both headline inflation and disaggregate price data that constitutes the consumer price index (CPI). Working with disaggregate data allows to consistently estimate average persistence

[1]In the standard New Keynesian model, inflation is purely forward looking. Consequently, inflation persistence is determined by the persistence of the expected nominal marginal costs. To reconcile the model with the empirical regularity of inflation persistence, the literature has brought forward hybrid versions of the New Keynesian Phillips curve. Galí and Gertler (1999) motivate an intrinsic relevance of lagged inflation, suggesting that a fraction of firms use backward looking rule of thumb behavior to set prices. Other micro-level foundations are proposed by Christiano, Eichenbaum and Evans (2005) and Fuhrer and Moore (1995). See Rudd and Whelan (2007) and Woodford (2007) for a critical discussion of these approaches and alternative models of inflation inertia.

[2]Other research on inflation in Switzerland investigates shifts in the mean of inflation. Huwiler (2007), Rapach and Wohar (2005) and Corvoisier and Mojon (2005) document that the mean of Swiss inflation exhibits a significant break in 1993. Moreover, several authors investigate price setting behavior of firms. Using disaggregate price data underlying the Swiss consumer price index, Kaufmann (2009) finds a median price duration of 4.6 quarters in the period 1993–2005. Both the frequency of price changes and the size of price changes do not exhibit a trend over time. Goette, Minsch and Tyran (2005) use disaggregate price data to examine price setting in the restaurant sector. Lein (2007) and Zurlinden (2007) investigate price setting behavior using survey data.

of sectoral inflation rates.[3] In addition, results for disaggregate series can be used for testing robustness of the results on headline inflation. We further capitalize on the disaggregate data by estimating a factor model. This model disentangles sectoral persistence into persistence due to a common macroeconomic component and persistence due to a sectoral component of inflation. Moreover, we investigate whether inflation persistence has changed under the new monetary policy concept which has been adopted by the Swiss National Bank in December 1999. The three main elements of the new concept are: (i) a quantitative definition of price stability, (ii) a conditional inflation forecast as the main indicator for monetary policy and (iii) the announcement of a target band for the 3-month CHF Libor.[4] Introducing a quantitative definition of price stability and emphasizing the inflation forecast may have altered how economic agents form their expectations. Under the new monetary policy concept, an increasing share of agents might form forward looking expectations, such that the autoregressive component of inflation diminishes at the aggregate. In fact, this is suggested by results of Benati (2008). He finds that in an estimated hybrid New Keynesian model, the backward indexation parameter fell to nearly zero during 2000–2006.

Only few papers have investigated inflation persistence using disaggregate data. Employing price data that underlies the U.S. CPI, Bils and Klenow (2004) show that price changes are more frequent than calibrated sticky price models suggest. Moreover, they find that the frequency of price changes and inflation persistence are virtually uncorrelated. Relying on similar data, Clark (2006) finds that inflation persistence is the lower the more disaggregate the price data is. The results of Clark (2006) suggest that short-lived idiosyncratic shocks predominate at disaggregate levels, whereas at more aggregate levels, a persistent common macroeconomic component determines the dynamics of inflation. This reasoning is consistent with Boivin, Giannoni and Mihov (2009). They find that common

[3]In contrast, persistence of aggregate inflation is an inconsistent estimator of average persistence at disaggregate levels. See Pesaran and Smith (1995) on the estimation of heterogeneous dynamic panels and Zaffaroni (2004) on the aggregation of linear dynamic models.

[4]The Swiss National Bank's new monetary policy concept defines price stability as an annual CPI inflation rate of less than 2%. See Baltensperger, Hildebrand and Jordan (2007) and Jordan and Peytrignet (2001) for an overview.

macroeconomic shocks explain only about 15% of the volatility of disaggregate inflation rates in the U.S. While common macroeconomic shocks have persistent effects on inflation rates, sector specific shocks are short-lived. Boivin, Giannoni and Mihov (2009) show that in line with sticky price models, persistence due to the common factors and the volatility of sectoral inflation rates are negatively correlated. Altissimo, Mojon and Zaffaroni (2009) confirm the results of Clark (2006) for three European countries.

We find that inflation persistence has significantly declined in the early 1990s. This is suggested at all aggregation levels by median unbiased estimates of the sum of autoregressive coefficients using the grid bootstrap estimator of Hansen (1999) and the approximately median unbiased estimator of Andrews and Chen (1994). Breakpoint tests signal a significant break in the sum of autoregressive coefficients in Q3/1993. During 1993–2008, inflation is a stationary process. In line with the literature, we find that inflation persistence is lower at more disaggregate levels. An estimated factor model provides an explanation for this result. The common macroeconomic component that drives sectoral inflation rates is highly persistent, whereas sectoral components are not. Both the relevance and the persistence of the common macroeconomic component have declined. Due to the small number of observations, estimations for the new monetary policy regime are associated with high uncertainty. Our results indicate, however, that relative to the period 1993–1999, the persistence of inflation did not significantly change in the period 2000–2008.

This paper is structured as follows. Section 6.2 presents the disaggregate CPI data. Section 6.3 discusses how to define and estimate persistence and presents estimation results of aggregate and disaggregate inflation persistence. Section 6.4 investigates structural breaks in the inflation process. Section 6.5 estimates a factor model that relates aggregate and disaggregate results. Section 6.6 concludes.

6.2 Data

We use disaggregate CPI data provided by the Swiss Federal Statistical Office (FSO). Table 6.1 shows the hierarchical structure of the data. The Swiss CPI comprises 12 main groups. These can be broken down into 83 product groups and 218 index positions for which expenditure weights are available.[5] The CPI is subject to regular index revisions.[6] To obtain consistent data we restrict the sample period to 1983–2008. For this period, the FSO provides recalculated historical series in accordance with the index revision of 2005. In line with most of the literature on inflation persistence, we employ quarterly data. Using quarterly data also reduces the amount of sampling error as not all prices are collected on a monthly basis. We obtain a sample of 102 quarters spanning Q2/1983–Q3/2008. Inflation is defined as the annualized quarterly log-difference in the price index given by $\pi_{i,t} = 400ln(P_{i,t}/P_{i,t-1})$, where $P_{i,t}$ denotes the level of index series i in quarter t.

For consistency reasons we only consider series that cover the entire sample period Q1/1983–Q3/2008. Due to the index revisions in May 1993, May 2000 and December 2005, some components at product group level and index position level are not continuously available. To maximize coverage, incomplete series are replaced by their higher level aggregate. An extreme example is main group 12 ("Other goods and services") which accounts for 4.63% of consumption expenditures in 2008. Thereof, 2.65 percentage points are accounted for by product groups and index positions that are available only from Q2/2000.[7] The highest level aggregate available for the entire sample horizon is the main group 12. Therefore, the main group aggregate is included as the only product group and as the only index position. Only a small number of series for which no reasonable aggregation is possible is dropped from the sample. This results in an omission of 12 product groups

[5] To denote the hierarchical levels, we use the FSO terminology, which differs from the COICOP standard. The FSO aggregation levels "main groups", "product groups" and "index positions" roughly correspond to the COICOP levels "divisions", "groups" and "classes". We employ the structure of the 2005 index revision that has become effective in December 2005. A further break-down of the index positions includes 1046 components for which no expenditure weights exist. See FSO (2008) for more details.

[6] Since the introduction of the CPI in 1922, 8 revisions have been implemented (in 1926, 1950, 1966, 1977, 1982, 1993, 2000, 2005).

[7] The product groups and index positions of main group 12 that are not available before Q2/2000 pertain to financial services, insurance, social protection services and (residual) other personal effects.

TABLE 6.1: Structure of the Swiss CPI

Aggregation level	No. of series	Example	COICOP	Weight
Main group	12	Food and non-alcoholic beverages	01	11.091%
Product group		Food	01.1	10.119%
Product group	83	Bread, flour and food products	01.1.1	1.696%
Index position	218	Flour		0.061%
Survey position	1046	White flour		n.a.

Notes: The last column shows 2008 consumption expenditure weights.

and 21 index positions. The omitted series account for 4.16% and 5.85% of consumption expenditures at product group and index position level, respectively. The final dataset comprises 12 main groups, 64 product groups and 149 index positions.

At all aggregation levels, the index series are seasonally adjusted using the X-12-ARIMA method (see Findley et al., 1998). Due to the index revisions, some series exhibit structural breaks in their seasonal pattern. Consequently, we seasonally adjust series over subperiods with distinct seasonality.[8]

Part of our analysis relies on aggregating estimation results that are obtained at disaggregate levels. Unless otherwise indicated, all aggregates are weighted using constant consumption expenditure shares in 2008. Due to the omission of some series, we recompute the official weights to sum up to 100%. Tables E.1 through E.3 in the Appendix list the series in our dataset and the adjusted weights. We also report results for special aggregates listed in Table E.4, namely durables, semidurables, nondurables, services and the overall index excluding petroleum products.

Figure 6.1 shows the annualized quarterly CPI inflation rate and deciles of inflation rates across the 149 index positions. Annualized quarterly inflation averages at 1.89% between 1983 and 2008. Inflation peaked at 7.50% in Q3/1990, but fell back to levels below 2% after Q3/1993.[9] Since then, inflation has generally remained below 2%, with notable

[8]E.g., main group 3 ("Clothes and shoes") and corresponding product groups and index positions exhibit seasonality only after 2000 due to the inclusion of sales prices. For these series, we link the seasonally adjusted Q1/1983–Q1/2000 series to the seasonally adjusted Q2/2000–Q3/2008 series. Moreover, series that clearly do not exhibit any seasonality, e.g. "Communications" (main group 8) or "Education" (main group 10), are not seasonally adjusted.

[9]The year-over-year inflation rate attained its maximum of 6.35% in Q2/1991.

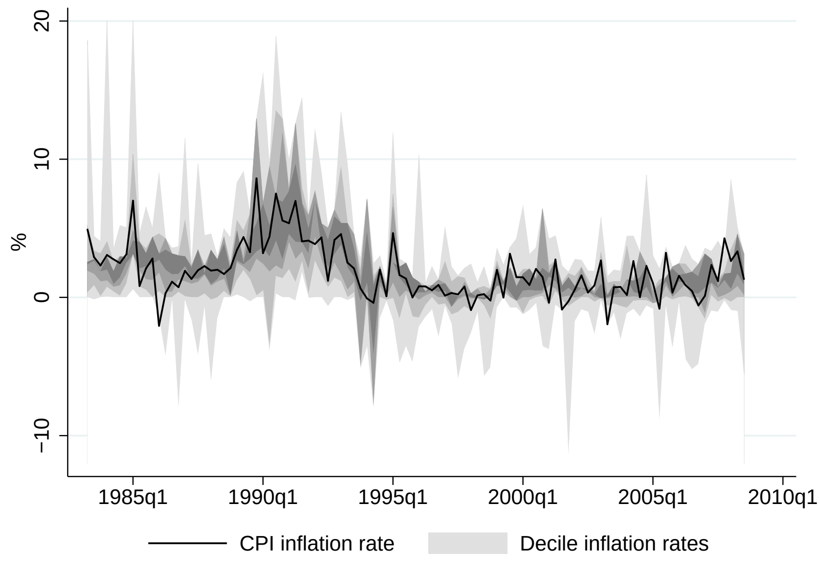


Figure 6.1: CPI inflation rate

Notes: This figure shows the annualized quarterly CPI inflation rate together with deciles of inflation rates on index position level. The lightest grey regions depict 10–20 and 80–90 percentile ranges, the darkest region shows the 40–60 percentile range. The percentiles are based on weighted inflation rates using constant 2008 consumption expenditure shares. The graphs' range of [-10, 20] does not fully cover the spike in the 90th percentile of 23.68% in Q1/1985.

exceptions in Q1/1995, caused by the introduction of the value added tax, and during Q4/2007–Q2/2008, mainly reflecting rising oil prices.[10] Quarterly inflation rates average at about 1.1% in the period 1993–2008. Not only average inflation, but also relative price variability is lower in the second half of the sample, as Figure 6.1 further indicates. The average interquartile range of inflation rates at index position level declined from 3.75% in the period 1983–1992 to 2.25% in the period 1993–2008.[11] Regarding the dynamics of inflation, Figure 6.1 suggests that persistence is low in the second half of the sample period. Moreover, the apparent declines in mean and variability of inflation indicate that when assessing persistence, potential structural breaks need to be taken into account.

[10]The VAT was raised from 6.5% to 7.5% in Q1/1999 and to 7.6% in Q1/2001.

[11]See Huwiler (2007), Appendix C, for a detailed discussion of the cross-sectional distribution of relative prices in Switzerland.

6.3 Aggregate and Disaggregate Persistence

6.3.1 Estimating Persistence

We define persistence as the cumulative long run effect of a shock to inflation. As the underlying process of the annualized quarterly inflation rate y we consider an AR(p)-model:

$$y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \epsilon_t \tag{6.1}$$

with intercept μ and AR-coefficients $(\phi_1, \phi_2, \ldots, \phi_p)$. The cumulative long-run effect of a one time shock to inflation is given by the cumulative impulse response function (CIR):

$$CIR = \sum_{h=0}^{\infty} \frac{\partial y_{t+h}}{\partial \epsilon_t} \tag{6.2}$$

From the theory of difference equations we know that this sum converges if all eigenvalues of Equation (6.1) are smaller than 1 in modulus, i.e. if y is stationary. In this case, the cumulative long-run effect can be obtained from the sum of autoregressive coefficients:[12]

$$CIR = \frac{1}{1 - \sum_{i=1}^{p} \phi_i} \tag{6.3}$$

In line with much of the literature on inflation persistence, we thus measure persistence by the sum of autoregressive coefficients (SARC).[13] It should be emphasized that the SARC is a valid measure of persistence for stationary processes only. For AR-processes with positive eigenvalues, $SARC \geq 1$ is a sufficient condition for nonstationarity. However, for AR-processes with oscillating impulse-response functions resulting from negative or complex eigenvalues, the SARC is only an ambiguous indicator of nonstationarity.[14] Extending previous literature, we thus additionally consider point estimates of the largest eigenvalue

[12] See Hamilton (1994) for a derivation of this result.

[13] Less commonly used concepts and measures of persistence are the largest autoregressive root and the half-life. See Andrews and Chen (1994) and Pivetta and Reis (2007) for critical appraisals.

[14] E.g., the AR(2)-process $y_t = -0.7y_{t-1} + 1.2y_{t-2} + \epsilon_t$ has eigenvalues -1.5 and 0.8. The SARC is 0.5 and does not reveal that the process exhibits nonstationary, explosive oscillations.

in modulus to qualitatively assess whether the SARC is valid.

We directly obtain the SARC by estimating the augmented-Dickey-Fuller representation of Equation (6.1):

$$y_t = \mu + \alpha y_{t-1} + \psi_1 \Delta y_{t-1} + \cdots \psi_{p-1} \Delta y_{t-p+1} + \epsilon_t \tag{6.4}$$

where $\alpha = \sum_{i=1}^{p} \phi_i$. We report median unbiased estimates of α computed with the grid bootstrap procedure of Hansen (1999). Employing this estimator is motivated by the negative bias of the OLS estimator of α. It is well known that this bias is particularly pronounced for persistent processes and that it may be substantial in small samples. Hansen (1999) builds on the finding that bootstrap quantile functions are not constant for α close to 1. Therefore, generating a simulation estimate of a bootstrap confidence interval using the OLS estimate $\hat{\alpha}$ as the true parameter is misleading. The Hansen (1999) bootstrap procedure considers a grid of true values instead. The resulting median unbiased estimates of the SARC have an equal probability of over- and underestimating the true persistence. We additionally report 90% grid-t bootstrap confidence intervals.[15] To select the optimal lag length p, we employ the Akaike-information criterion (AIC). In line with the literature on quarterly data, the number of lags is restricted to $p = 1, ..., 6$.

We alternatively use the approximately median unbiased estimator of Andrews and Chen (1994). Rather than considering a grid of true values, this estimator relies on an iterative procedure. In a first step, Equation (6.4) is estimated by OLS. In a second step, series for various α given $(\hat{\psi}_1, ..., \hat{\psi}_{p-1})$ are simulated and the α_{MU} is selected for which the median of OLS estimates corresponds to the initial OLS estimate. In a third step, parameters $(\psi_1, ..., \psi_{p-1})$ are re-estimated given α_{MU}. Steps 2 and 3 are repeated until convergence is achieved.[16] Unlike Hansen's (1999) grid bootstrap, the approximately median unbiased estimator does not simulate using estimated residuals but draws normally

[15] For computing grid-bootstrap confidence intervals we use Matlab codes provided by Bruce Hansen. We compute the grid-t confidence intervals based on 2,000 bootstrap replications at 200 grid-points.

[16] Matlab and R codes are available from the authors. Each simulation is based on 5,000 bootstrap replications. Convergence is achieved if the difference between the initial OLS estimate and the OLS estimate based on the simulated series is less than 0.005 in absolute terms.

distributed residuals. Under the assumption of normally distributed residuals, Hansen's (1999) grid-α bootstrap generates the same results as the estimator of Andrews and Chen (1994). As shown in the Appendix, results with the approximately median unbiased estimator of Andrews and Chen (1994) are in line with the grid-bootstrap results.

6.3.2 Persistence at the Aggregate Level

Table 6.2 shows results on the persistence of headline inflation and some key aggregates for the periods 1983–2008, 1993–2008 and 2000–2008. The table shows separate results for the sample 1993–2008, motivated by the observed decline in the level and variability of inflation in the early 1990s. The sample 2000–2008 is defined by the introduction of the new monetary policy concept. We find that the median unbiased estimate of the SARC over the entire sample period is 0.85, with the 90% grid bootstrap confidence interval including the unit root case. Persistence substantially declines to levels of 0.22 during 1993–2008 and 0.08 during 2000–2008. In the period 1993–2008, the 90% confidence interval lies far left to the unit root case. Due to a low number of observations, results for the shorter sample spanning 2000–2008 are associated with higher uncertainty, reflected in a broad confidence interval.

The finding that inflation persistence declines over the sample period is robust, as results for the other aggregates indicate. The second row in each panel of Table 6.2 presents estimates for a constant weight aggregate. The constant weight aggregate is computed from 149 seasonally adjusted index positions and constant 2008 consumption expenditures weights. Persistence estimates for the aggregate corroborate our results in two respects. First, the constant weight aggregate signals whether the decline in persistence is caused by a potential increase in the weight of index positions with low persistence. Second, the constant weight aggregate is based on index positions which have been individually seasonally adjusted. Due to the distinct seasonality of the underlying series, we expect that this is mirrored in a better seasonal adjustment than seasonally adjusting the aggregate itself. Consistent with the previous results, persistence of the constant weight aggregate declines

TABLE 6.2: Persistence of aggregate inflation

	SARC	90% CI	p	AC	R	AR(1)	Weight
			1983–2008				
Total	0.848	(0.671, 1.053)	3	0.852	0.872	0.456	100.00%
Constant weight aggregate	0.819	(0.633, 1.047)	3	0.817	0.862	0.415	100.00%
Nondurable goods	-0.064	(-0.437, 0.317)	6	-0.062	0.967	-0.051	26.37%
Semidurable goods	0.657	(0.428, 0.919)	3	0.663	0.706	0.050	7.91%
Durable goods	0.998	(0.804, 1.085)	4	0.975	0.951	0.640	9.21%
Services	0.916	(0.797, 1.041)	2	0.919	0.906	0.734	56.51%
Index ex. petroleum products	0.917	(0.803, 1.040)	2	0.922	0.910	0.764	95.31%
			1993–2008				
Total	0.222	(-0.353, 0.477)	4	0.264	0.779	0.011	100.00%
Constant weight aggregate	0.279	(-0.009, 0.578)	2	0.280	0.235	-0.011	100.00%
Nondurable goods	-0.706	(-1.294, 0.197)	6	-0.711	1.012	-0.147	26.37%
Semidurable goods	0.078	(-0.270, 0.436)	2	0.075	0.470	-0.281	7.91%
Durable goods	0.458	(0.215, 0.703)	2	0.470	0.565	0.301	9.21%
Services	0.159	(-0.110, 0.435)	3	0.166	0.622	0.271	56.51%
Index ex. petroleum products	0.178	(-0.142, 0.486)	3	0.178	0.574	0.150	95.31%
			2000–2008				
Total	0.083	(-0.712, 1.128)	4	0.020	0.741	-0.100	100.00%
Constant weight aggregate	0.269	(-0.185, 0.813)	2	0.272	0.282	-0.075	100.00%
Nondurable goods	-0.207	(-0.504, 0.092)	1	-0.203	0.224	-0.224	26.37%
Semidurable goods	-0.258	(-0.561, 0.043)	1	-0.261	0.274	-0.274	7.91%
Durable goods	0.061	(-0.246, 0.374)	1	0.060	0.028	0.028	9.21%
Services	0.458	(0.196, 0.738)	1	0.465	0.406	0.406	56.51%
Index ex. petroleum products	0.296	(-0.022, 0.630)	1	0.291	0.243	0.243	95.31%

Notes: Quarterly data, Q2/1983–Q3/2008, Q1/1993–Q3/2008 and Q1/2000–Q3/2008. *SARC* denotes the median unbiased estimate of the sum of autoregressive coefficients, estimated with Hansen's (1999) grid bootstrap. *CI* is the 90% confidence interval of the sum of autoregressive coefficients. p is the lag order of the estimated AR model. AC denotes the approximately median unbiased estimate of the sum of autoregressive coefficients following Andrews and Chen (1994). R is the largest eigenvalue in modulus. *AR(1)* is the autoregressive coefficient in an AR(1) model estimated with OLS, *Weight* denotes the 2008 consumption expenditure weight. The constant weight aggregate is computed from index positions using 2008 consumption expenditure weights.

substantially over time, indicating that the shift in persistence is not caused by changing weights. The constant weight aggregate is somewhat more persistent than aggregate CPI inflation in the samples 1993–2008 and 2000–2008. Also, the confidence interval for the constant weight aggregate is narrower due to a shorter lag structure.

The key aggregates durables, semi-durables and nondurables share the common pattern of a decline in persistence. But Table 6.2 also shows that the level of persistence substantially varies between these aggregates. In the period 1983–2008, durable goods inflation is markedly more persistent than nondurable and semi-durable goods inflation.[17] Furthermore, persistence of services inflation is higher than persistence of goods inflation. This is in line with evidence from the inflation persistence literature that price setting for labor intensive services is relatively rigid due to inflexible wages. Also, services include the highly persistent rents, which account for about 20% of consumption expenditures. Excluding petroleum products does not significantly alter the results. Only in the period 2000–2008, persistence is somewhat higher for the aggregate excluding petroleum prices. Comparing the periods 1983–2008 and 1993–2008, persistence is lower for all aggregates in the second half of the sample.

Table 6.2 further shows the largest eigenvalue in modulus and the autoregressive coefficient from an estimated AR(1) model. The largest eigenvalue is generally smaller than 1 in modulus, indicating that the SARC is a valid measure of persistence.[18] The decline in the SARC is mirrored in a decline of the autoregressive coefficients in an AR(1) model. For headline inflation, this coefficient drops from 0.456 in the full sample to around zero in the samples 1993–2008 and 2000–2008. Persistence as measured by the AR(1) coefficient is generally below persistence measured by the SARC. Moreover, the table shows that results based on the estimator of Andrews and Chen (1994) are in line with the grid bootstrap estimates.

Finally, the measured decline in persistence is not driven by a potential structural break

[17]The most important components of semi-durable goods are clothing and footwear, smaller electric household appliances, games and toys, equipment for sports and books.

[18]The only exception is nondurable goods inflation in the period 1993–2008. For this series, the largest eigenvalue is 1.012.

in the intercept of the inflation process in the early 1990s.[19] This conclusion is based on additional persistence estimates for the period 1983–1992 shown in Table E.5. We find that persistence over the full sample period lies between persistence in the subperiods 1983–1992 and 1993–2008. Also, the optimal lag length for headline inflation varies only between 3 and 4. Hence, the SARC declines due to a change in coefficients rather than due to a change in the lag structure.

In sum, our results clearly show that headline inflation is stationary during 1993–2008.[20] Persistence is substantially higher in the period 1983–1992, for which the median unbiased estimate indicates that inflation is not significantly different from a unit root process. Magnitude and change in persistence are consistent with results of Benati (2008). In line with our findings, Benati (2008) reports that persistence is lower in the period 2000–2006, compared to the period 1972–1999. However, Benati (2008) concludes that the decline in persistence is related to the introduction of the new monetary policy concept. Allowing for an additional structural break in 1993, we arrive at a different conclusion. Our results indicate that persistence of headline inflation has declined earlier in the 1990s, several years prior to the introduction of the new monetary policy concept.

6.3.3 Persistence at Disaggregate Levels

This section examines persistence at more disaggregate levels. Table 6.3 presents summary statistics for the periods 1983–2008, 1993–2008 and 2000–2008. Unless otherwise indicated, all statistics are weighted aggregates using constant 2008 consumption expenditure weights. The statistics confirm the declining tendency of persistence over time. Mean persistence at the index position level declines from 0.49 during 1983–2008 to 0.12 during 1993–2008 and to 0.10 during 2000–2008. Moreover, the table shows that the share of series for which the 90% confidence interval does not include the unit root case increases from 0.56

[19] The potential relevance of breaks in deterministic components is highlighted by Perron (1989). In particular, Perron (1989) shows that a break in the intercept of the true data-generating process leads to overestimating persistence in a model that does not account for a break.

[20] In the period 1993–2008, the 99% grid-bootstrap confidence interval for the SARC is (-0.606, 0.763), the 90% confidence interval as shown in Table 6.2 is (-0.353, 0.477).

during 1983–2008 to 0.87 during 1993–2008 and to 0.79 during 2000–2008. We further observe that the unweighted mean of persistence is generally lower than the weighted mean, indicating that more persistent series tend to have a higher weight. This is confirmed by the positive correlation coefficient between persistence and consumption expenditure weights. Finally, the share of series with eigenvalues lower than 1 in modulus lies always above 94%, indicating that the SARC is a valid measure of persistence.

Table 6.3 also indicates that the more disaggregated the underlying series are, the lower is mean persistence. Mean persistence at disaggregate levels is consistently below persistence of the constant weight aggregate shown in Table 6.2. The share of disaggregate series for which persistence is lower than aggregate persistence varies between 0.52 and 0.73, mainly depending on the sample horizon. Both patterns are in line with the aggregation result outlined by Zaffaroni (2004), according to which aggregate persistence is to some extent a statistical artefact of aggregation. Consistent with our results, Clark (2006) and Altissimo, Mojon and Zaffaroni (2009) show that similar patterns hold for U.S. and euro area inflation data.

Regarding the change in persistence over time, Table E.6 in the appendix provides further evidence that persistence has declined several years before the introduction of the new monetary policy concept. In fact, the estimates for the period 1993–1999 are very similar to the estimates for the period 2000–2008. The next section investigates the nature and date of a potential structural break in more detail.

6.4 Structural Breaks in Persistence

6.4.1 Structural Breaks at the Aggregate Level

The above results suggest that aggregate persistence has declined in the second half of the sample period. To further investigate changes in persistence over time, we start by discussing rolling estimates of the SARC over 8-year windows. Figure 6.2 presents the rolling median unbiased estimate together with a 90% grid bootstrap confidence interval for

Table 6.3: Persistence at disaggregate levels

	Main groups		Product groups		Index positions	
	SARC	90% CI	SARC	90% CI	SARC	90% CI
			1983–2008			
Mean	0.630	(0.367, 0.887)	0.518	(0.287, 0.767)	0.486	(0.265, 0.720)
Median	0.588	(0.328, 0.883)	0.656	(0.429, 0.934)	0.656	(0.416, 0.862)
75th percentile	0.844	(0.602, 1.046)	0.853	(0.710, 1.037)	0.853	(0.710, 1.037)
90th percentile	0.993	(0.684, 1.128)	0.853	(0.710, 1.088)	0.853	(0.710, 1.088)
Unweighted mean	0.587	(0.338, 0.835)	0.426	(0.163, 0.704)	0.207	(-0.063, 0.490)
SARC < a.SARC	0.726		0.717		0.713	
CI < 1	0.720		0.562		0.558	
R < 1	1.000		0.984		0.993	
r(SARC, weight)	0.209		0.099		0.175	
			1993–2008			
Mean	0.247	(-0.026, 0.477)	0.103	(-0.206, 0.421)	0.112	(-0.199, 0.436)
Median	0.184	(-0.030, 0.349)	0.182	(-0.116, 0.485)	0.182	(-0.124, 0.489)
75th percentile	0.408	(0.102, 0.722)	0.356	(0.035, 0.619)	0.309	(-0.010, 0.672)
90th percentile	1.070	(0.620, 1.245)	0.468	(0.216, 1.061)	0.468	(0.210, 1.061)
Unweighted mean	0.175	(-0.100, 0.417)	0.031	(-0.313, 0.383)	-0.111	(-0.459, 0.251)
SARC < a.SARC	0.596		0.727		0.726	
CI < 1	0.849		0.871		0.873	
R < 1	1.000		0.941		0.942	
r(SARC, weight)	0.240		0.067		0.133	
			2000–2008			
Mean	0.235	(-0.186, 0.618)	0.129	(-0.282, 0.543)	0.095	(-0.311, 0.518)
Median	0.199	(-0.103, 0.461)	0.257	(-0.190, 0.532)	0.189	(-0.226, 0.553)
75th percentile	0.352	(-0.023, 0.958)	0.355	(0.067, 0.787)	0.355	(0.067, 0.661)
90th percentile	1.168	(0.267, 1.487)	0.623	(0.183, 1.274)	0.497	(0.128, 1.235)
Unweighted mean	0.104	(-0.319, 0.514)	-0.057	(-0.541, 0.433)	-0.210	(-0.679, 0.271)
SARC < a.SARC	0.603		0.516		0.572	
CI < 1	0.849		0.756		0.786	
R < 1	1.000		0.993		0.991	
r(SARC, weight)	0.442		0.154		0.144	
No. of series	12		64		149	

Notes: Quarterly data, Q2/1983–Q3/2008, Q1/1993–Q3/2008 and Q1/2000–Q3/2008. *SARC* denotes the median unbiased estimate of the sum of autoregressive coefficients, estimated with Hansen's (1999) grid bootstrap. *CI* is the 90% confidence interval of the sum of autoregressive coefficients. All statistics are weighted using constant 2008 consumption expenditure shares unless otherwise indicated. *SARC < a.SARC* is the share of series for which the SARC is smaller than the SARC of the constant weight aggregate inflation. *CI < 1* denotes the share of series for which the 90% confidence interval for the SARC lies below unity. *R < 1* is the share of series for which the the largest eigenvalue in modulus is smaller than 1. *r(SARC, weight)* is the Pearson correlation coefficient between SARC and weight.

Figure 6.2: Rolling 8-year median unbiased estimates of persistence

Notes: This figure shows rolling median unbiased estimates of the SARC in an AR(4) model and 90% confidence bands, estimated with Hansen's (1999) grid bootstrap. The windows span 32 quarters, ranging from $t - 16$ to $t + 15$.

headline inflation. The estimated model includes 4 lags, which corresponds to the average lag structure chosen by the AIC over the subperiods discussed above. The figure indicates that persistence begins to decline in the sample 1991–1998. However, the flexibility of the rolling estimates comes at the price of wide confidence intervals which include the unit root case for most of the time. The figure also shows that persistence of headline inflation falls to -0.96 in the sample Q3/1999–Q2/2007. Although this sudden fall does not alter the general finding of a decline in persistence, it reinforces our approach to consider disaggregate data for testing robustness of the results on headline inflation.

To formally test whether inflation persistence has declined we employ the sup-Wald test with critical values given by Andrews (1993, 2003). We test for a break in the SARC, for a break in the intercept term and for a joint break in the SARC and intercept of an AR(4) model of inflation.[21] Figure 6.3 shows the Wald test statistics together with 90%

[21]Due to the relatively short sample horizon we use 25% trimming rather than the usual 15% trimming. For the AR(4) model, the period in which a structural break may occur spans Q3/1990–Q1/2002. As shown by Andrews (1993), the higher trimming results in a higher power of the sup-Wald test against

Table 6.4: Tests for structural break in aggregate inflation

	CPI inflation rate			Constant weight aggregate		
	SARC	Mean	Both	SARC	Mean	Both
Unknown break date						
supWald statistic	12.85***	3.33	23.65***	7.27*	3.43	11.25**
Break date	Q3/93	Q3/90	Q3/93	Q3/93	Q1/02	Q2/93
Break in Q1/2000						
Wald statistic, 1993–2008	0.89	0.62	0.45	0.37	1.72	0.90
Wald statistic, 1983–2008	4.56**	1.29	2.65*	3.00*	1.54	1.5

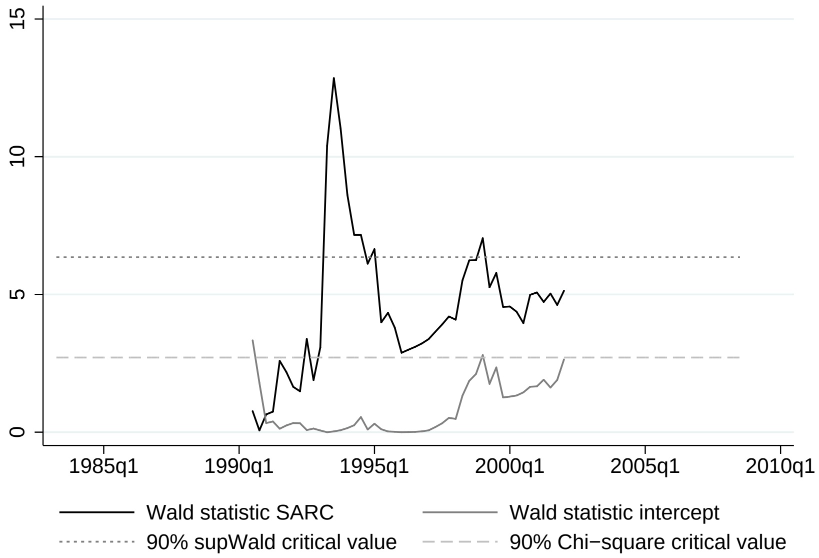
Notes: Quarterly data, Q2/1983–Q3/2008 and Q1/1993–Q3/2008. All statistics are based on an estimated AR(4) model. The constant weight aggregate is computed from index positions using 2008 consumption expenditure weights. The trimming parameter for the sup-Wald tests is set to 25%. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

critical values. The Wald statistic for a break in persistence peaks in Q3/1993 and is highly significant. The statistic exhibits a second peak in Q1/1999. Meanwhile, the Wald test statistic for a break in the intercept term is insignificant. The joint test for a break in the SARC and in the intercept mirrors the pattern of the separate test for a break in the SARC.

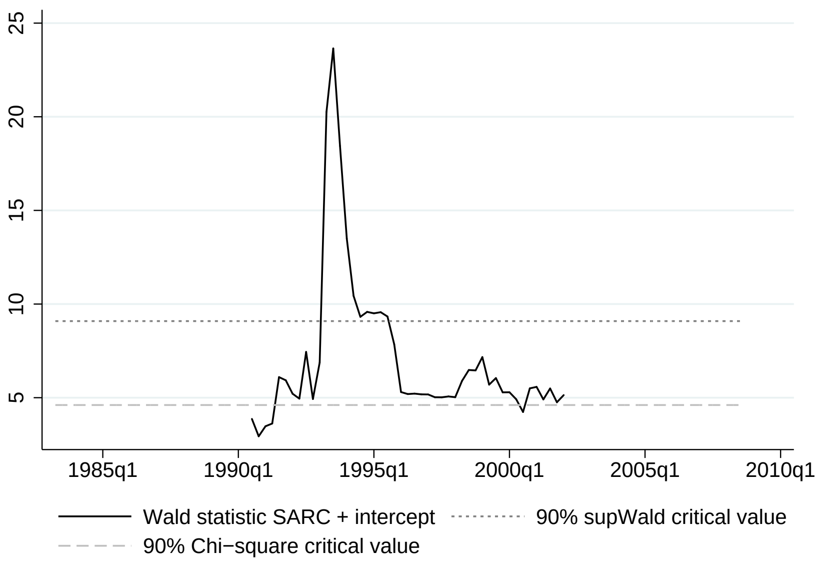
Table 6.4 summarizes results of the sup-Wald tests. The table also reports test results for the constant weight aggregate computed from 149 index positions. The sup-Wald test for a structural break at an unknown date yields consistent results for the conventional and the constant weight aggregate. For both series, the test rejects the null hypothesis of no change in the SARC and identifies Q3/1993 as the break date. Moreover, the sup-Wald tests indicate that the intercept term of the inflation process did not change between Q3/1990–Q1/2002. This further supports our results on persistence which do not seem to be affected by a structural break in the intercept.

Table 6.4 additionally presents Wald tests of the null hypothesis that inflation persistence during 2000–2008 is not different from inflation persistence in earlier periods. The results depend on the pre-break sample period. Not surprisingly, the null is rejected employing the 1983–2008 sample. Using the shorter 1993–2008 sample, however, we find no

alternative hypothesis of a structural break close to the lower or upper boundary of the sample.



(A) Separate tests



(B) Joint test

Figure 6.3: Wald test statistics for a break in the SARC and intercept

Notes: These figures show Wald test statistics for the equality of SARC and/or intercept in an AR(4) model between interval t_l to $(t-1)$ and interval t to t_h. The Wald statistics are heteroskedasticity-robust and include a degree of freedom correction. The lower and upper limits t_l and t_h are chosen to implement 25% trimming. Critical values for the sup-Wald statistic are taken from Andrews (2003).

evidence that inflation persistence declined between 1993–1999 and 2000–2008.

6.4.2 Structural Breaks at Disaggregate Levels

The above results are confirmed at disaggregate levels. Table 6.5 presents summary statistics of sup-Wald tests carried out for main groups, product groups and index positions. All statistics are weighted using constant 2008 consumption expenditures weights. The lag structures of the underlying AR models are chosen individually for each series based on the AIC. The table shows that the share of series with a significant structural break in the SARC lies between 0.47 for main groups and 0.31 for index positions. The median break date roughly corresponds to the break date of aggregate inflation. But the interquartile range of the quarter in which a break occurs indicates that the series are highly heterogeneous. The interquartile range spans about 8 years on all three aggregation levels.

Consistent with the results for headline inflation, Table 6.5 shows that the share of series with a break in the intercept term is lower than the share of series with a break in the SARC. The weighted share lies at about 0.30. Table 6.5 also presents the unweighted share and the share of series for which an AR(4) model exhibits a break. These statistics confirm the above findings. Moreover, the difference between the share of breaks in the SARC and the share of breaks in the intercept is more pronounced for the AR(4) model than for a model with an idiosyncratic lag order.

We also use disaggregate data to investigate whether a structural break coincides with the introduction of the new monetary policy concept. The summary statistics in Table 6.6 confirm the results for headline inflation, suggesting that no such break has occurred. In the sample 1993–2008, the share of series with a break in the SARC ranges between 0.07 and 0.13. This share increases to between 0.39 and 0.46 in the sample 1983–2008, again consistent with the notion that the actual break occurred earlier in the 1990s.

As previously emphasized, we thus arrive at a different conclusion than Benati (2008). Benati (2008) rejects the null hypothesis that persistence has not changed between 1972–

1999 and 2000–2008. We also reject this hypothesis, both on aggregate and disaggregate levels as Tables 6.4 and 6.6 show. Our results clearly indicate, however, that a structural break in persistence has occurred earlier in the 1990s. The sup-Wald test signals a structural break in Q3/1993. Comparing the samples 1993–1999 and 2000–2008, we find that inflation persistence did not significantly decline under the new monetary policy regime.

Moreover, we find that while the sum of autoregressive coefficients significantly declined, the intercept term remained unchanged. This is in line with Levin and Piger (2004) who detect no break in the intercept of CPI inflation but find evidence of a change in persistence during 1984–2003.[22] Using the Bai and Perron (1998) methodology, Huwiler (2007) and Rapach and Wohar (2005) find that the mean of inflation exhibits a significant break in 1993. Corvoisier and Mojon (2005) confirm this result using a different test approach. Our results suggest that the decline in the mean of inflation reflects a change in persistence rather than a change in the intercept term of the AR process.[23]

6.5 Decomposing Persistence in a Factor Model

So far we have discussed persistence of inflation in general and did not discriminate responses to specific shocks. In this section, we take the analysis one step further by estimating an approximate factor model of sectoral inflation rates. The factor model decomposes sectoral inflation rates into a common component and a sectoral component. The common component has the interpretation of reflecting factors with a general impact across sectors, such as monetary policy shocks. In contrast, the sectoral component captures idiosyncratic factors, such as sectoral demand and technology shocks. As will be shown, this model also provides an explanation for the finding that average inflation persistence is lower at disaggregate levels than at aggregate levels.

Along the lines of Stock and Watson (2002), we consider an approximate factor model

[22] See Tables 2 and 9 in Levin and Piger (2004).

[23] From Equation (6.4) we see that the unconditional mean of inflation is given by $E(y_t) = \frac{\mu}{1-\alpha}$.

Table 6.5: Breakpoint tests with an unknown date

	Main groups			Product groups			Index positions		
	SARC	Mean	Both	SARC	Mean	Both	SARC	Mean	Both
Share of breaks	0.473	0.298	0.495	0.348	0.296	0.608	0.309	0.297	0.594
Unweighted share	0.500	0.333	0.667	0.422	0.344	0.688	0.456	0.282	0.604
Share, $p = 4$	0.442	0.163	0.495	0.376	0.145	0.757	0.304	0.170	0.761
Median date	Q4/93	Q1/91	Q3/93	Q2/95	Q1/92	Q3/91	Q1/93	Q1/92	Q3/91
IQR quarter	33	10	11	37	21	18	30	21	19
No. of series	12			64			149		

Notes: Quarterly data, Q2/1983–Q3/2008. *Share of breaks* is the share of series for which the sup-Wald test rejects the null hypothesis of no structural break at the 10% level. The lag order is chosen using the AIC with p ranging from 1 to 6. *Share, p=4* is the share of series for which the null hypothesis is rejected for an AR(4) model. *Median date* denotes the median of the quarter in which the break occurs. *IQR quarter* is the interquartile range of the break dates. All statistics are weighted using constant 2008 consumption expenditure shares unless otherwise indicated.

Table 6.6: Tests for structural break in Q1/2000

	Main groups			Product groups			Index positions		
1993–2008	SARC	Mean	Both	SARC	Mean	Both	SARC	Mean	Both
Share of breaks	0.113	0.113	0.113	0.069	0.093	0.127	0.127	0.096	0.159
Unweighted share	0.083	0.083	0.083	0.141	0.109	0.219	0.174	0.107	0.215
Share of breaks, p=4	0.000	0.000	0.000	0.051	0.057	0.103	0.054	0.058	0.093
1983–2008									
Share of breaks	0.392	0.124	0.318	0.460	0.125	0.372	0.428	0.176	0.313
Unweighted share	0.417	0.167	0.417	0.391	0.172	0.531	0.362	0.128	0.416
Share of breaks, p=4	0.198	0.269	0.349	0.513	0.137	0.572	0.501	0.161	0.571
No. of series	12			64			149		

Notes: Quarterly data, Q2/1983–Q3/2008. *Share of breaks* is the share of series for which the Wald-test rejects the null hypothesis of no structural break at the 10% level. The lag order is chosen using the AIC with p ranging from 1 to 6. *Share of breaks, p=4* is the share of series for which an AR(4) model exhibits a structural break. All statistics are weighted using constant 2008 consumption expenditure shares unless otherwise indicated.

of the following form:

$$y_{it} = \lambda_i f_t + u_{it} \tag{6.5}$$

where f_t is the common component which corresponds to the first principal component of the sectoral inflation rates y_{it}. The corresponding loadings are given by λ_i. The sectoral components u_{it} are obtained as the residuals from a regression of sectoral inflation rates on the common component.

Table 6.7 shows persistence of the common and sectoral components at the three aggregation levels. As in the previous sections, persistence is estimated using the grid bootstrap estimator of Hansen (1999). The table reports median unbiased estimates and 90% confidence intervals. Additionally, Appendix E.4 provides results based on the estimator of Andrews and Chen (1994), which are in line with the grid bootstrap results. The right panel shows weighted means of the persistence of sectoral components. We find that during 1983–2008, the common component is highly persistent at all aggregation levels. The confidence intervals include the nonstationary case at all aggregation levels. Persistence of the common component declines substantially in the period 1993–2008. In the shorter sample spanning 2000–2008, persistence increases again at the level of product groups and index positions. As will be discussed below, this increase should not be over-interpreted since it is accompanied by a substantial decline in the relevance of the common component.[24] At all aggregation levels and in all sample periods, the common component absorbs the persistence of sectoral inflation rates. Consequently, the sectoral components are stationary with a persistence of close to zero.[25] Hence, the factor model provides an explanation for the lower persistence at disaggregate levels. At disaggregate levels, short-lived sectoral factors predominate. In aggregating sectoral inflation rates, the sectoral factors average out and the persistent common factor determines the dynamics of inflation. Similar conclusions

[24] Table 6.8 indicates that during 2000–2008, the R-squared drops to 0.105 and 0.087 for product groups and index positions, respectively. In this period, the common component mainly represents series from the two main groups “Food and non-alcoholic beverages” and “Restaurants and hotels”.

[25] Note that all findings are consistent with results for 1983–1992 and 1993–1999 shown in Table E.8.

Table 6.7: Persistence of common and sectoral components

	Common component		Sectoral components	
	SARC	90% CI	SARC	90% CI
		1983–2008		
Main groups	0.886	(0.752, 1.033)	0.291	(-0.046, 0.656)
Product groups	0.940	(0.832, 1.039)	0.134	(-0.079, 0.432)
Index positions	0.877	(0.761, 1.029)	0.135	(-0.136, 0.411)
		1993–2008		
Main groups	0.119	(-0.084, 0.302)	0.246	(-0.040, 0.469)
Product groups	0.340	(0.137, 0.493)	0.068	(-0.243, 0.403)
Index positions	0.249	(0.030, 0.413)	0.109	(-0.207, 0.443)
		2000–2008		
Main groups	0.143	(-0.098, 0.408)	0.110	(-0.277, 0.409)
Product groups	1.037	(0.577, 1.205)	-0.004	(-0.408, 0.429)
Index positions	0.612	(0.221, 1.124)	-0.038	(-0.454, 0.400)

Notes: Quarterly data, Q2/1983–Q3/2008, Q1/1993–Q3/2008 and Q1/2000–Q3/2008. Common and sectoral components are estimated following Stock and Watson (2002). In a first step, the common component is obtained as the first principal component of standardized inflation rates. In a second step, time series of sectoral components are obtained as the residuals from regressing the sectoral inflation rate on the common component. *SARC* denotes the median unbiased estimate of the sum of autoregressive coefficients, estimated with Hansen's (1999) grid bootstrap. *90% CI* is the 90% confidence interval of the sum of autoregressive coefficients. The statistics for the sectoral components are weighted means using constant 2008 consumption expenditure shares.

are drawn by Clark (2006) and Boivin, Giannoni and Mihov (2009) for the U.S. and by Altissimo, Mojon and Zaffaroni (2009) for the euro area.

The relevance of the common component declines over time. This is suggested by the left panel of Table 6.8 which shows the fraction of variance of sectoral inflation rates, explained by the common component. The R-squared averages between 0.25 and 0.33 in the period 1983–2008, depending on the aggregation level. In the period 2000–2008, the R-squared falls to between 0.09 and 0.14. Table E.8 in the Appendix presents estimation results for further subperiods. These indicate that the R-squared gradually declines over time, with the decline being most pronounced between 1993–1999 and 2000–2008. Hence, while the persistence in the common factor has declined after 1993, the relevance of the common factor has markedly declined after 2000.

The left panel of Table 6.8 also reports the correlation between the standard deviation and the persistence of sectoral components of inflation (u_{it}). As argued by Bils and Klenow (2004), rational expectations New Keynesian sticky price models predict a strong and negative correlation. We find a positive correlation at main group level and a negative correlation at the levels of product groups and index positions. The correlations are relatively low in absolute terms. We also consider the correlations between the standard deviation and the persistence of sectoral inflation rates (y_{it}). These correlations are negative and much more pronounced. Both findings are consistent with results of Boivin, Giannoni and Mihov (2009) for the U.S.[26] Finally, the right panel of Table 6.8 shows the standard deviation of annualized quarterly inflation rates due to the common and sectoral components. This panel mirrors the pattern in the R-squared statistics and shows that roughly 70 to 90 percent of the variance in sectoral inflation rates is accounted for by sectoral components.

As a robustness test we employ the weighted principal component analysis following Boivin and Ng (2006). We use a weighting scheme that accounts for cross-sectional correlation among sectoral components. The weighted principal component analysis confirms the above results, as can be seen from Table E.9 in the Appendix.[27] Notable difference is that the persistence of the common component at index position level remains low during 2000–2008.

In sum, the factor model reveals that inflation persistence primarily stems from a persistent macroeconomic component that is common to inflation rates across sectors. In contrast, sectoral components have low persistence. This is consistent with the finding of the previous sections according to which inflation persistence is lower at disaggregate levels. Our results further suggest that both the persistence and the relevance of the common component have declined.

[26]Note that Boivin, Giannoni and Mihov (2009) report a negative correlation of the standard deviation and the persistence of the common component of inflation, whereas we consider the total sectoral inflation rates (y_{it}).

[27]The underlying assumptions of the strict factor model can be relaxed for $N \to \infty$, see, e.g., Boivin and Ng (2006). In particular, one can allow for weak serial-correlation and cross-correlation of the idiosyncratic errors.

TABLE 6.8: Variance explained by the common component

	R-squared			Standard deviation		
	Main groups	Product groups	Index positions	Common	Sectoral	Total
			1983–2008			
Mean	0.339	0.283	0.254	1.866	5.507	5.981
Median	0.205	0.183	0.088	1.382	4.599	4.876
Unw. mean	0.320	0.211	0.140	1.508	6.636	6.931
SD	0.252	0.181	0.150	0.818	7.127	7.052
ri(SD, SARC)	0.170	-0.283	-0.273			
rt(SD, SARC)	-0.602	-0.420	-0.727			
			1993–2008			
Mean	0.204	0.124	0.111	0.959	5.148	5.374
Median	0.156	0.034	0.016	0.742	4.411	4.576
Unw. mean	0.195	0.104	0.093	1.069	6.825	7.036
SD	0.230	0.144	0.177	0.994	7.042	6.985
ri(SD, SARC)	0.030	-0.186	-0.207			
rt(SD, SARC)	-0.157	-0.299	-0.599			
			2000–2008			
Mean	0.135	0.105	0.087	1.651	7.456	5.389
Median	0.018	0.037	0.042	1.017	4.297	4.318
Unw. mean	0.171	0.112	0.098	1.621	7.456	7.722
SD	0.242	0.158	0.143	2.010	8.134	8.294
ri(SD, SARC)	0.082	-0.044	-0.084			
rt(SD, SARC)	-0.513	-0.204	-0.492			

Notes: The R-squared statistic in the left panel measures the fraction of variance explained by the common component. *SD* is the standard deviation of the sectoral R-squared, *ri(SD, SARC)* is the correlation coefficient between the standard deviation and the persistence of sectoral components (u_{it}). *rt(SD, SARC)* denotes the correlation between the standard deviation and the persistence of sectoral inflation (y_{ti}). *Unw. Mean* is the unweighed mean. The right panel shows summary statistics about the standard deviation of annualized quarterly inflation rates on index position level. We report statistics on the total sectoral standard deviation, the standard deviation attributed to the common component ($\lambda_i f_t$) and the standard deviation attributed to the sectoral component (u_{it}).

6.6 Conclusion

In this paper, we investigate the persistence of Swiss consumer price inflation using aggregate and disaggregate inflation data spanning Q2/1983–Q3/2008. Our results consistently indicate that inflation persistence significantly declined in the early 1990s. This is suggested by median unbiased estimates of the sum of autoregressive coefficients and confidence intervals using the grid-bootstrap estimator of Hansen (1999). Formal tests of structural change signal a significant break in the sum of autoregressive coefficients in Q3/1993. Point estimates of persistence and confidence intervals declined substantially at all aggregation levels. In the period 1993–2008, headline inflation is clearly stationary with a low persistence of 0.22. In this period, 87% of inflation rates at index position level are stationary. The tests further indicate that the intercept of the inflation process did not change. This suggests that the mean of headline inflation declined due to the decline in persistence only. In line with Benati (2008) and Cogley and Sargent (2005), our results confirm that inflation persistence is not time-invariant.

Due to the small number of observations, estimations for the new monetary policy regime are associated with high uncertainty. Our results indicate, however, that relative to the period 1993–1999, the persistence of inflation did not significantly change in the period 2000–2008. We conclude that inflation persistence has significantly declined in the first half of the 1990s, several years before the announcement and implementation of the new monetary policy concept. This finding is in contrast to Benati (2008). Not allowing for a structural break in the earlier 1990s, Benati (2008) concludes that the decline in persistence coincides with the introduction of the new monetary policy concept.

Moreover, we document that inflation persistence is substantially lower at disaggregate levels than at aggregate levels. Specifically, while aggregate headline inflation has a persistence of 0.97 during 1983–1993, mean persistence at index position level is only 0.43. This finding is in line with theoretical results and empirical evidence of the literature on inflation persistence. An estimated factor model provides an explanation. Depending on the sample period and aggregation level, about 70 to 90 percent of the variance in sectoral inflation rates is accounted for by sectoral factors. We find that the common macroeconomic component is highly persistent, whereas sectoral components are not. Both the relevance and the persistence of the common component have declined, consistent with the observed change in persistence of sectoral inflation rates.

Further research is needed on the determinants of the structural break in persistence of Swiss consumer price inflation in the early 1990s. Our results suggest that persistence has diminished due to a decline in the persistence of the common component. The common component reflects factors with a general impact across sectors, such as monetary policy shocks. Hence, additional insights might be gained by investigating how the responses of sectoral inflation rates to identified (monetary policy) shocks have changed over time. That these responses have actually changed during the past three decades is suggested by our results.

Appendix A

Appendix to Chapter 2

A.1 Derivation of the 5-Category Probability Method

This section derives the 5 category probability method based on the assumptions introduced in Section 2.3. The method has been originally proposed by Batchelor and Orr (1988) and relies on earlier contributions of Theil (1952) and Carlson and Parkin (1975). All derivations equally hold for quantifying inflation perceptions, in which case π_t^e is substituted with π_t^p. The response scheme for inflation perceptions is given by:

$$
\begin{aligned}
\pi_{t,i}^p < -\delta_t &: \textit{prices in general are } \text{lower } (S_1) \\
-\delta_t \leq \pi_{t,i}^p < \delta_t &: \text{about the same } (S_2) \\
\delta_t \leq \pi_{t,i}^p < \pi_t^r - \eta_t &: \text{a little higher } (S_3) \\
\pi_t^r - \eta_t \leq \pi_{t,i}^p < \pi_t^r + \eta_t &: \text{moderately higher } (S_4) \\
\pi_{t,i}^p \geq \pi_t^r + \eta_t &: \text{a lot higher } (S_5)
\end{aligned}
$$

Under the assumptions introduced in Section 2.3, the relation between aggregate response shares and expected inflation π_t^e in period t is given by:

$$
\begin{aligned}
s_t^1 &= P(\pi_{t,i}^e < -\delta_t) = \Phi\left(\frac{-\delta_t - \pi_t^e}{\sigma_t}\right) \\
s_t^2 &= P(-\delta_t \leq \pi_{t,i}^e < \delta_t) = \Phi\left(\frac{\delta_t - \pi_t^e}{\sigma_t}\right) - \Phi\left(\frac{-\delta_t - \pi_t^e}{\sigma_t}\right) \\
s_t^3 &= P(\delta_t \leq \pi_{t,i}^e < \pi_t^r - \eta_t) = \Phi\left(\frac{\pi_t^r - \eta_t - \pi_t^e}{\sigma_t}\right) - \Phi\left(\frac{\delta_t - \pi_t^e}{\sigma_t}\right) \\
s_t^4 &= P(\pi_{t,i}^r - \eta_t \leq \pi_{t,i}^e < \pi_t^r + \eta_t) = \Phi\left(\frac{\pi_t^r + \eta_t - \pi_t^e}{\sigma_t}\right) - \Phi\left(\frac{\pi_t^r - \eta_t - \pi_t^e}{\sigma_t}\right) \\
s_t^5 &= P(\pi_{t,i}^r + \eta_t \leq \pi_{t,i}^e) = 1 - \Phi\left(\frac{\pi_t^r + \eta_t - \pi_t^e}{\sigma_t}\right) \qquad \text{(A.1)}
\end{aligned}
$$

where $\Phi(.)$ is the standard normal cumulative distribution function.

The system of equations (A.1) can be rewritten to obtain a system of 4 linearly independent equations with 5 unknowns (π_t^e, σ_t, δ_t, η_t, π_t^r):

$$
\begin{aligned}
G_t^1 &= \Phi^{-1}\left(s_t^1\right) = \frac{-\delta_t - \pi_t^e}{\sigma_t} \\
G_t^2 &= \Phi^{-1}\left(1 - s_t^5 - s_t^4 - s_t^3 - s_t^2\right) = \frac{-\delta_t - \pi_t^e}{\sigma_t} \\
G_t^3 &= \Phi^{-1}\left(1 - s_t^5 - s_t^4 - s_t^3\right) = \frac{\delta_t - \pi_t^e}{\sigma_t} \\
G_t^4 &= \Phi^{-1}\left(1 - s_t^5 - s_t^4\right) = \frac{\pi_t^r - \eta_t - \pi_t^e}{\sigma_t} \\
G_t^5 &= \Phi^{-1}\left(1 - s_t^5\right) = \frac{\pi_t^r + \eta_t - \pi_t^e}{\sigma_t}
\end{aligned} \tag{A.2}
$$

System (A.2) can be solved for the mean π_t^e of expected inflation:

$$
\pi_t^e = \pi_t^r \frac{G_t^2 + G_t^3}{G_t^2 + G_t^3 - G_t^4 - G_t^5} \tag{A.3}
$$

In the following, π_t^e is referred to as "expected inflation" (rather than "mean of expected inflation"). The remaining unknowns are given by:

$$
\sigma_t = \pi_t^r \frac{-2}{G_t^2 + G_t^3 - G_t^4 - G_t^5} \tag{A.4}
$$

$$
\delta_t = \pi_t^r \frac{G_t^2 - G_t^3}{G_t^2 + G_t^3 - G_t^4 - G_t^5} \tag{A.5}
$$

$$
\eta_t = \pi_t^r \frac{G_t^4 - G_t^5}{G_t^2 + G_t^3 - G_t^4 - G_t^5} \tag{A.6}
$$

For quantifying inflation perceptions, π_t^r is commonly identified by restricting inflation perceptions to be unbiased over the sample period. Rearranging Equation (A.3) and imposing unbiasedness yields:

$$
\pi_t^r = \frac{\overline{\pi}}{\frac{1}{T}\sum_{t=1}^{T} \frac{G_t^2 + G_t^3}{G_t^2 + G_t^3 - G_t^4 - G_t^5}} \tag{A.7}
$$

where T is the number of periods and $\overline{\pi}$ the average actual rate of inflation.

A.2 Derivation of the 3-Category Probability Method

Theil (1952) and Carlson and Parkin (1975) have originally developed the probability method for three-option ordinal scales. In line with Berk (1999), the EU consumer survey responses are aggregated to three categories by defining $s_n = s_1$, $s_s = s_2$ and $s_p = s_3 + s_4 + s_5$. The relation between response shares and expected inflation is given by:

$$
\begin{aligned}
s_t^n &= P(\pi_{t,i}^e < -\delta) = \Phi\left(\frac{-\delta - \pi_t^e}{\sigma_t}\right) \\
s_t^s &= P(-\delta < \pi_{t,i}^e < \delta) = \Phi\left(\frac{\delta - \pi_t^e}{\sigma_t}\right) - \Phi\left(\frac{-\delta - \pi_t^e}{\sigma_t}\right) \\
s_t^p &= P(\delta < \pi_{t,i}^e) = 1 - \Phi\left(\frac{\delta - \pi_t^e}{\sigma_t}\right)
\end{aligned}
$$

where $\Phi(.)$ is a standard normal cumulative distribution function. At any t we have a system of 2 linearly independent equations with 3 unknowns $(\delta, \mu_t, \sigma_t)$. Solving yields:

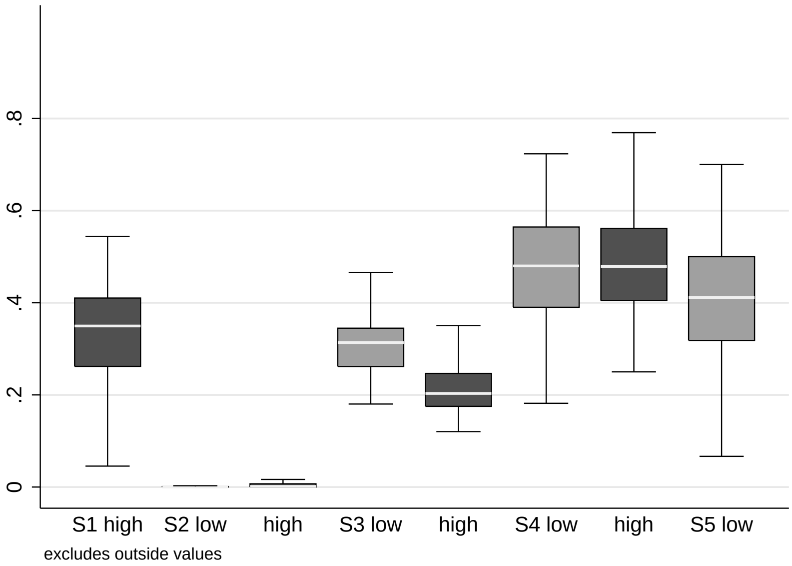
$$
\pi_t^e = \delta \frac{\Phi^{-1}(s_t^n) + \Phi^{-1}(1 - s_t^p)}{\Phi^{-1}(s_t^n) - \Phi^{-1}(1 - s_t^p)} \tag{A.8}
$$

$$
\sigma_t = \delta \frac{2}{\Phi^{-1}(1 - s_t^p) - \Phi^{-1}(s_t^n)} \tag{A.9}
$$

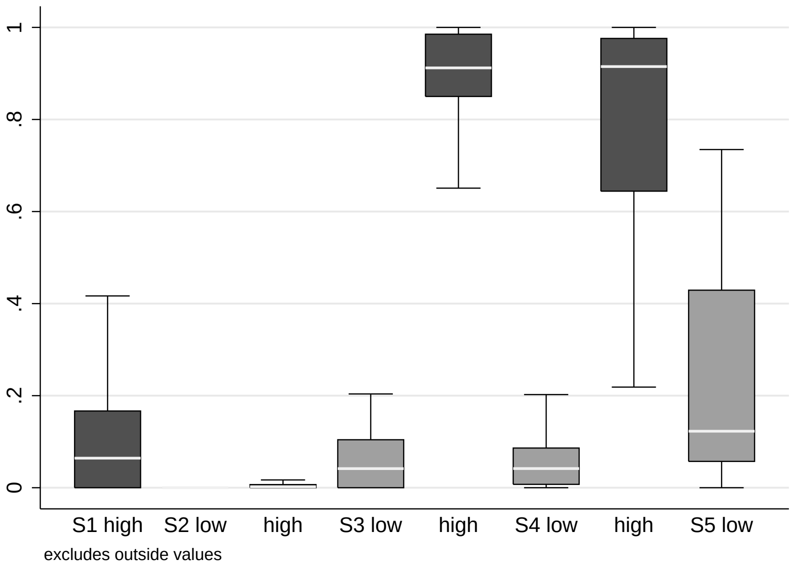
The identical equations hold for perceived inflation π_t^p. In line with the existing literature, the system is identified by imposing unbiasedness of beliefs with respect to actual inflation during the sample period. The parameter δ is restricted accordingly:

$$
\delta = \frac{\overline{\pi}}{\frac{1}{T}\sum_{t=1}^{T}\left[\frac{\Phi^{-1}(s_t^n) + \Phi^{-1}\left(1 - s_t^p\right)}{\Phi^{-1}(s_t^n) - \Phi^{-1}\left(1 - s_t^p\right)}\right]}
$$

A.3 Further Results



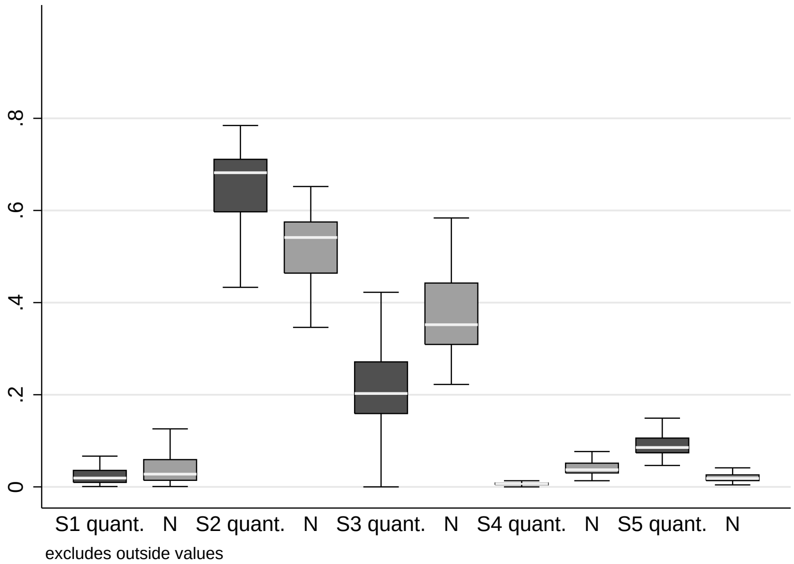
(a) Perceptions



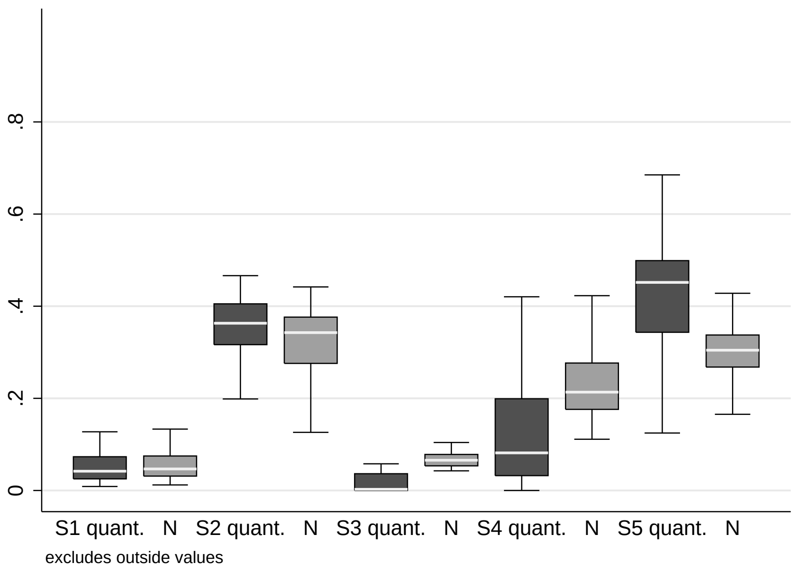
(b) Expectations

Figure A.1: Response fractions below and above the implied interval

Notes: These figures show the fractions of quantitative responses that lie below (*low*) and above (*high*) the implied response interval defined by the simultaneous qualitative response. Fractions are relative to the sum of qualitative responses in the respective category. Sample period 01/1996–10/2008. Quantified perceptions are based on the 5 category probability method unbiased with respect to HICP inflation. Expectations are quantified using the probability method with quantified perceptions as reference inflation. Each box covers the range between the 25th and 75th percentile of monthly fractions and contains a median line.



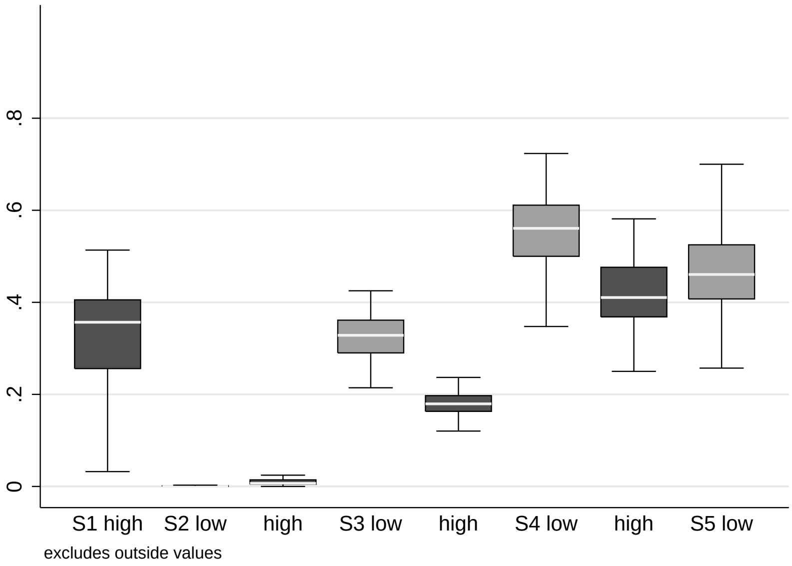
(A) Perceptions



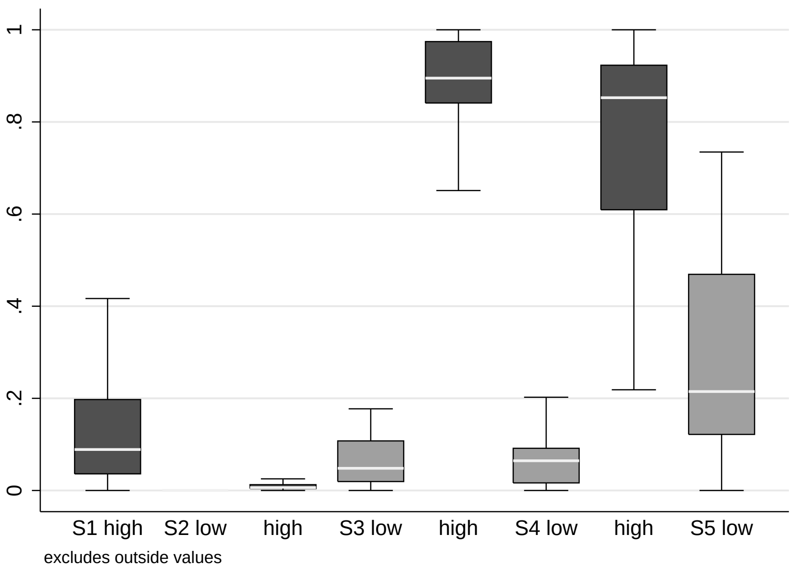
(B) Expectations

Figure A.2: Actual and theoretical response fractions, 2002–2008

Notes: Sample period 01/2002–10/2008. See footnote of Figure 2.3 for a detailed description.



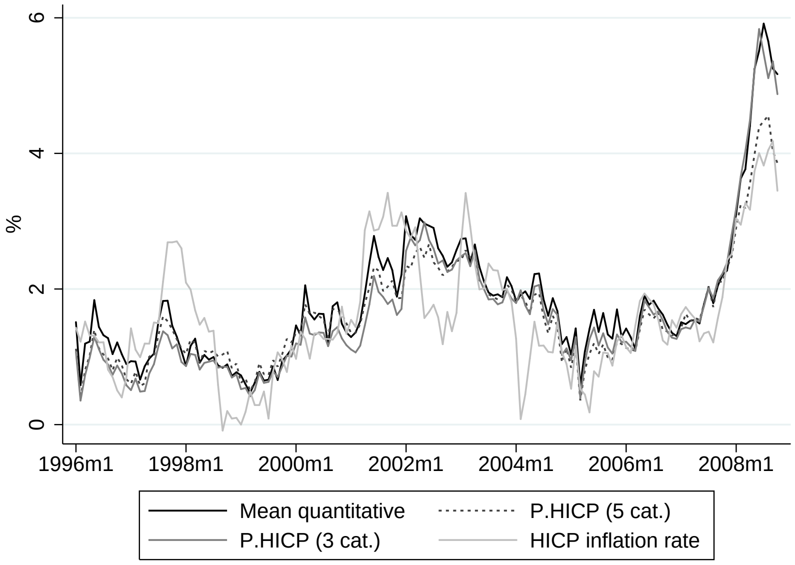
(a) Perceptions



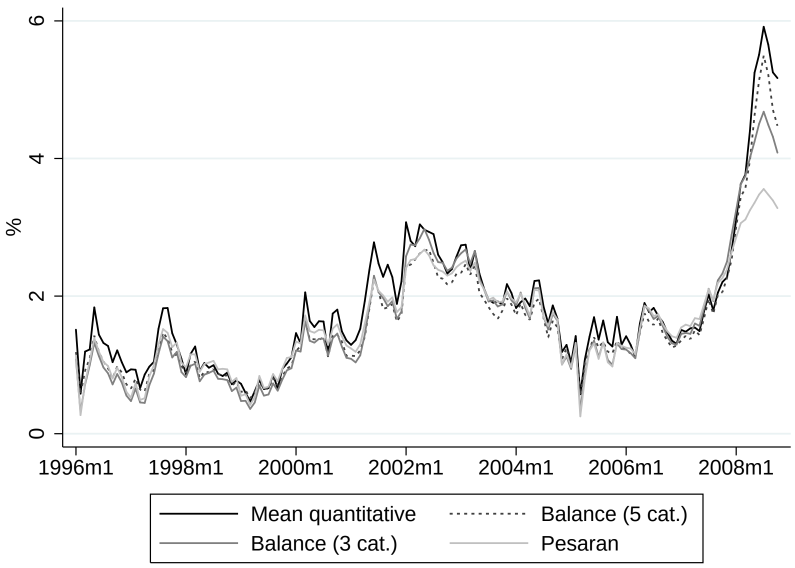
(b) Expectations

Figure A.3: Response fractions below and above the implied interval, 2002–2008

Notes: Sample period 01/2002–10/2008. See footnote of Figure A.1 for a detailed description.

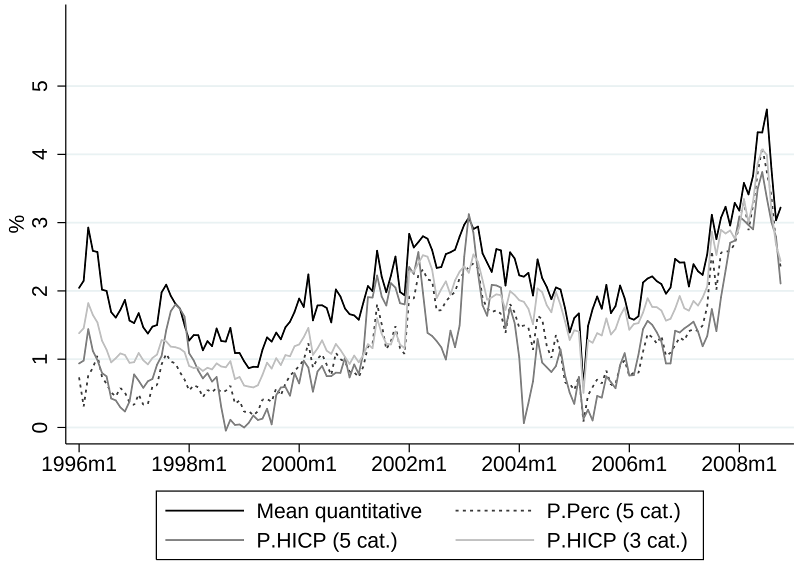


(a) Probability method

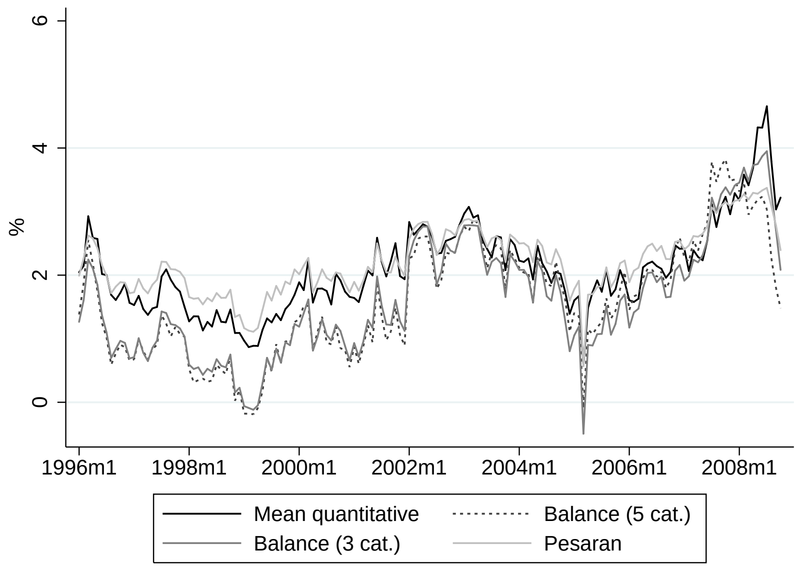


(b) Balance statistics and regression method

Figure A.4: Cross-sectional mean of inflation perceptions



(A) Probability method



(B) Balance statistics and regression method

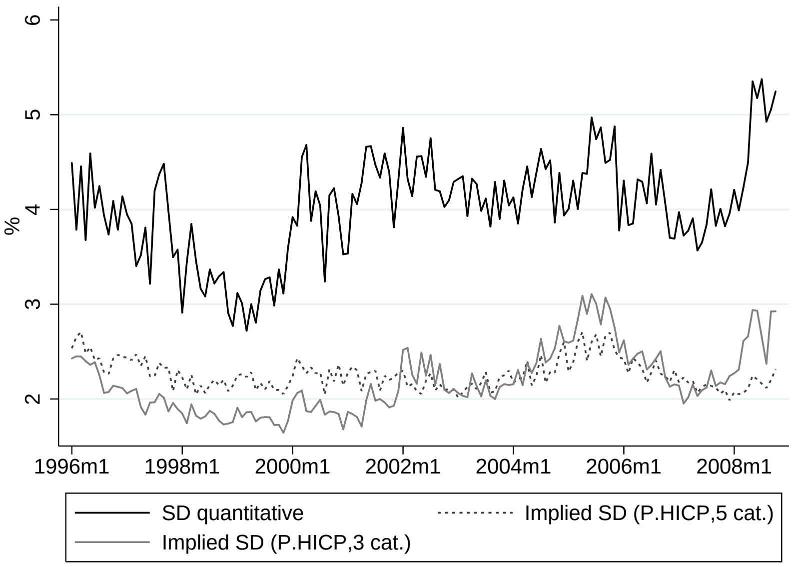
Figure A.5: Cross-sectional mean of inflation expectations

TABLE A.1: Accuracy of quantified inflation perceptions and expectations, 2002–2008

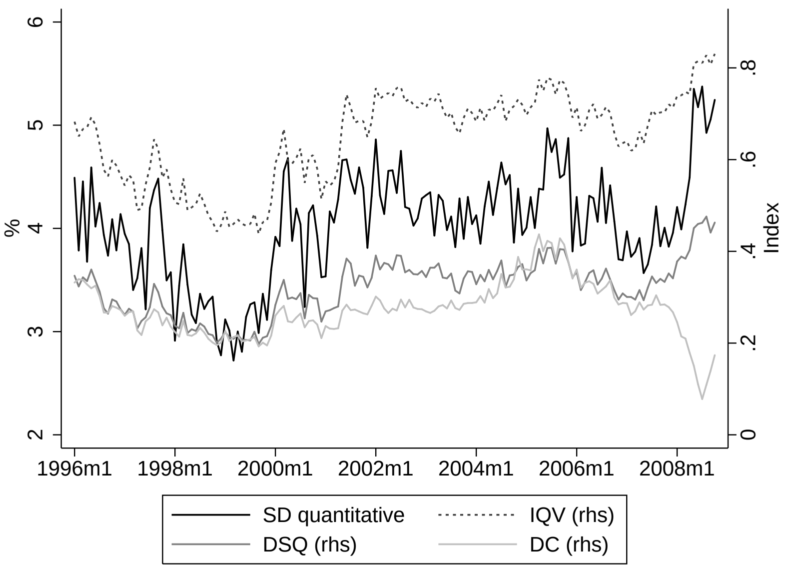
Perceptions	Level					First differences				
	Bias	MAE	RMSE	ρ	z	Bias	MAE	RMSE	ρ	z
P.HICP (5 cat.)	-0.26	0.27	0.40	0.97		0.00	0.12	0.15	0.85	
P.HICP (3 cat.)	-0.11	0.14	0.18	0.99	-0.56**	0.00	0.10	0.15	0.79	0.15
Balance (5 cat.)	-0.20	0.20	0.25	0.99	-0.79	0.00	0.10	0.12	0.89	-0.22**
Balance (3 cat.)	-0.15	0.19	0.33	0.97	0.02	0.00	0.10	0.14	0.86	-0.08
Pesaran (3 cat.)	-0.27	0.31	0.60	0.93	0.30	0.00	0.12	0.17	0.81	0.09

Expectations	Level					First differences				
	Bias	MAE	RMSE	ρ	z	Bias	MAE	RMSE	ρ	z
P.Perc. (5 cat.)	-0.76	0.76	0.80	0.97		0.00	0.15	0.20	0.79	
P.HICP (5 cat.)	-0.92	0.92	1.00	0.89	0.70**	0.00	0.26	0.35	0.51	0.50**
P.HICP (3 cat.)	-0.39	0.39	0.18	0.97	0.09	0.00	0.15	0.15	0.83	-0.08
Balance (5 cat.)	-0.22	0.35	0.25	0.82	0.99	0.00	0.17	0.12	0.84	-0.13
Balance (3 cat.)	-0.27	0.31	0.33	0.95	0.31	0.00	0.16	0.14	0.84	-0.13
Pesaran (3 cat.)	0.05	0.22	0.32	0.92	0.53	0.00	0.15	0.20	0.81	-0.03

Notes: Sample period 01/2002–10/2008. See Table 2.7 for a detailed description.



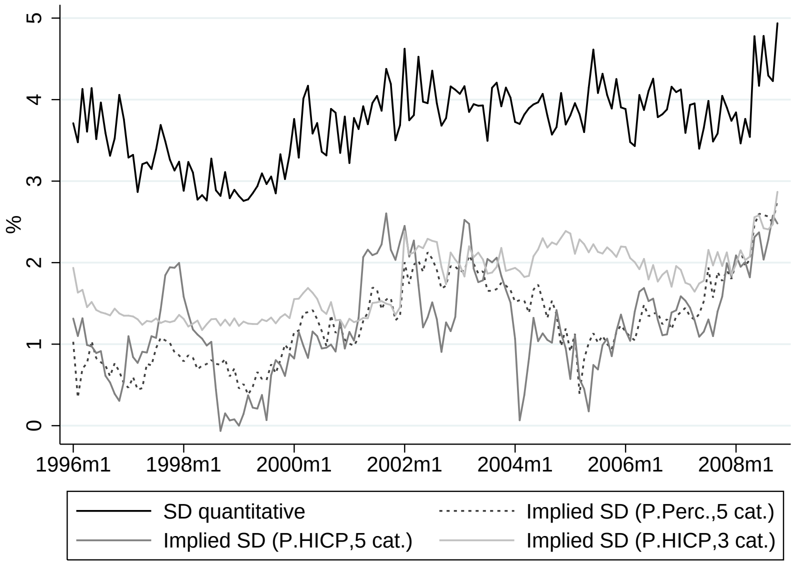
(a) Probability method



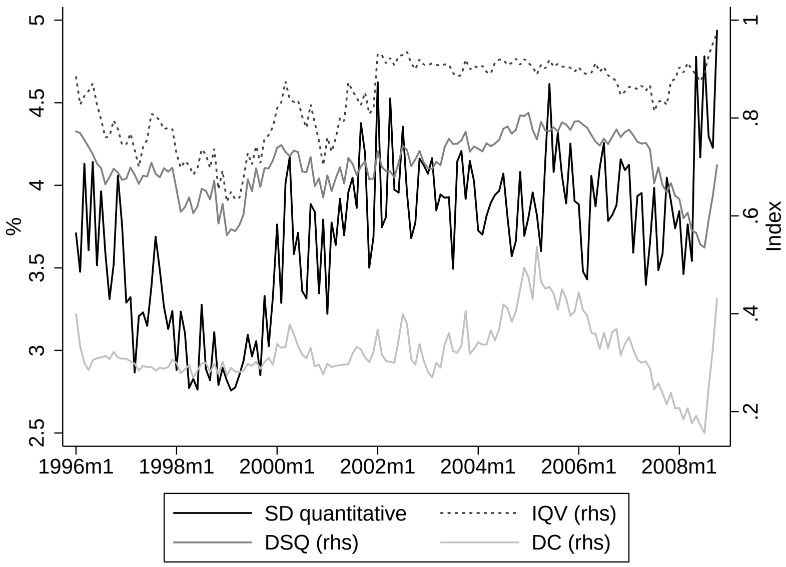
(b) Qualitative measures

Figure A.6: Heterogeneity of inflation perceptions

Notes: SD quantitative is the cross-sectional standard deviation of quantitative survey responses. *Implied SD (P.HICP, 5 cat.)* is the implied standard deviation from the 5-category probability method under the HICP unbiasedness condition. *Implied SD (P.HICP, 3 cat.)* is the implied standard deviation from the 3-category probability method under the HICP unbiasedness condition. *IQV* is the index of qualitative variation, *DSQ* is the d^2-index of ordinal variation proposed by Lacy (2006) and *DIS* is the disconformity statistic.



(a) Probability method



(b) Qualitative measures

Figure A.7: Heterogeneity of inflation expectations

Notes: SD quantitative is the cross-sectional standard deviation of quantitative survey responses. *Implied SD (P.Perc., 5 cat.)* and *Implied SD (P.HICP, 5 cat.)* are implied standard deviations from the 5-category probability method with reference inflation given by quantified perceptions and actual HICP inflation, respectively. *Implied SD (P.HICP, 3 cat.)* is the implied standard deviation from the 3-category probability method under the HICP unbiasedness condition. IQV is the index of qualitative variation, DSQ is the d^2-index of ordinal variation proposed by Lacy (2006) and DIS is the disconformity statistic.

Table A.2: Accuracy of measures of cross-sectional heterogeneity, 2002–2008

Perceptions	Level					First differences				
	Bias	MAE	RMSE	ρ	z	Bias	MAE	RMSE	ρ	z
Implied SD (P.HICP, 5 cat.)	-2.00	2.00	2.04	0.27		0.00	0.28	0.34	0.20	
Implied SD (P.HICP, 3 cat.)	-1.86	1.86	1.88	0.65	-0.51	0.00	0.24	0.31	0.45	-0.27*
IQV (5 cat.)				0.80	-0.82*				0.47	-0.26**
DSQ (5 cat.)				0.79	-0.82				0.33	-0.13
DC (3 cat.)				-0.15	0.43				0.29	-0.09

Expectations	Level					First differences				
	Bias	MAE	RMSE	ρ	z	Bias	MAE	RMSE	ρ	z
Implied SD (P.Perc, 5 cat.)	-2.35	2.35	2.40	0.30		0.00	0.28	0.36	0.27	
Implied SD (P.HICP, 5 cat.)	-2.51	2.51	2.57	0.30	0.01	0.00	0.33	0.42	0.27	-0.01
Implied SD (P.HICP, 3 cat.)	-1.88	1.88	1.90	0.42	-0.13	0.00	0.29	0.36	0.26	0.01
IQV (5 cat.)				0.33	-0.03				0.05	0.22
DSQ (5 cat.)				-0.09	0.41				0.10	0.17
DC (3 cat.)				0.09	0.23				0.13	0.14

Notes: Sample period 01/2002–10/2008. See Table 2.8 for a detailed description.

Appendix B

Appendix to Chapter 3

B.1 Further Results

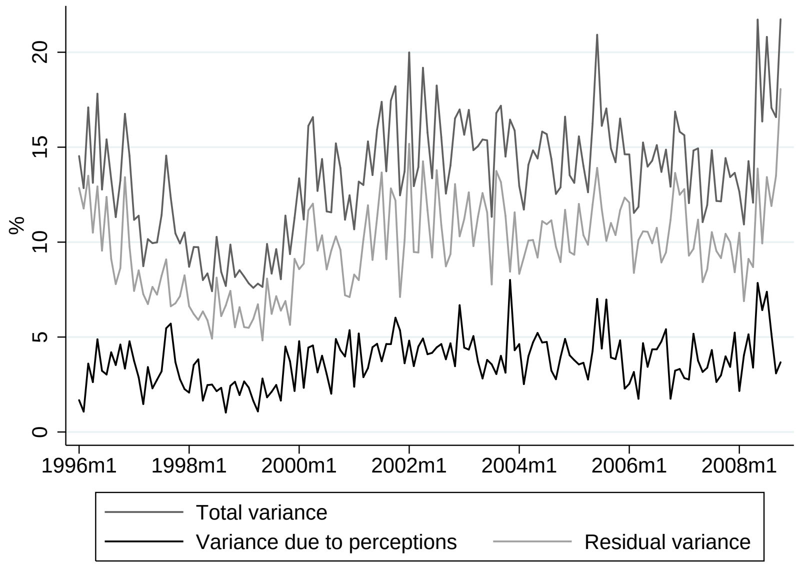


Figure B.1: Decomposing the variance of inflation expectations

Notes: This figure shows the variance of inflation expectations (total variance) as explained by inflation perceptions and residual factors in a simple regression model.

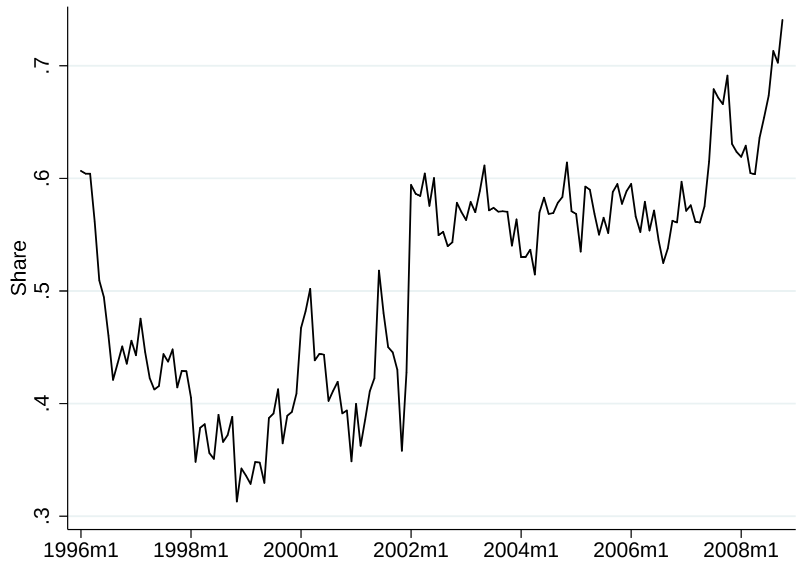


FIGURE B.2: Aggregate response variation

Notes: This figure shows aggregate response variation, defined as the monthly share of survey respondents with an unequal perception and expectation of inflation ($\pi^p_{t,i} \neq \pi^e_{t,i}$).

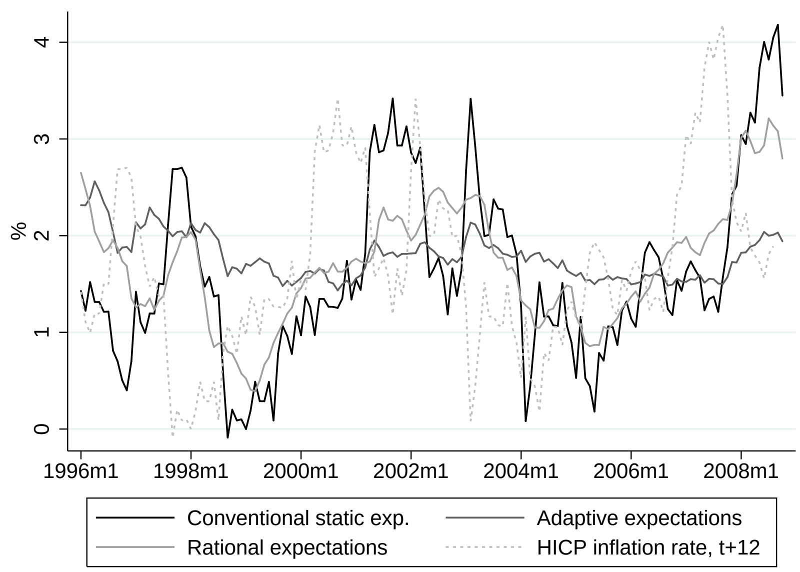


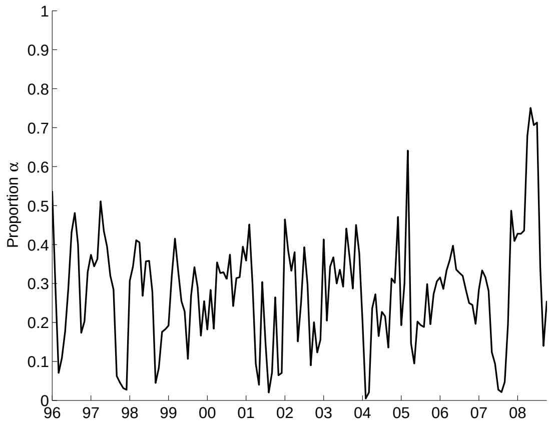
FIGURE B.3: Alternative predictors of HICP inflation

Notes: This figure shows alternative predictors of the 12 months ahead HICP inflation rate. Conventional static expectations are given by actual HICP inflation, rational expectations are equal to the mean of professional forecasts. The mean of idiosyncratic static expectations (mean of inflation perceptions) is plotted in Figure 3.1.

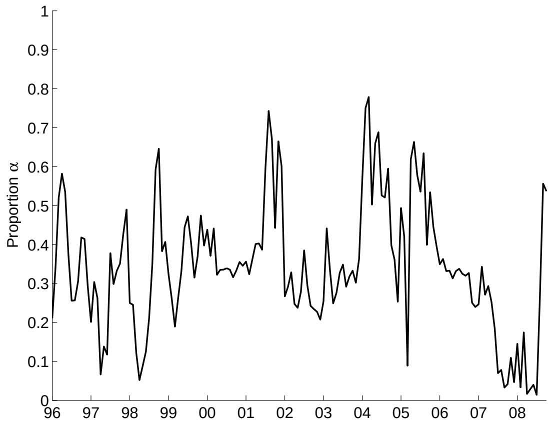
Table B.1: Estimated Gaussian mixture models, identical standard deviations

	(1)	(2)	(3)
Proportions α_j			
Conventional static expectations	0.3310		0.1529
	(0.0001)		(0.0001)
Idiosyncratic static expectations		0.4691	0.4664
		(0.0000)	(0.0000)
Adaptive expectations	0.3336	0.2495	0.1851
	(0.0001)	(0.0001)	(0.0001)
Rational expectations	0.3354	0.2814	0.1956
	(0.0002)	(0.0001)	(0.0001)
Standard deviation σ	2.6769	2.1341	2.1709
	(0.0000)	(0.0000)	(0.0000)
N	175,394	175,394	175,394
Log L	-423,220	-395,100	-395,510

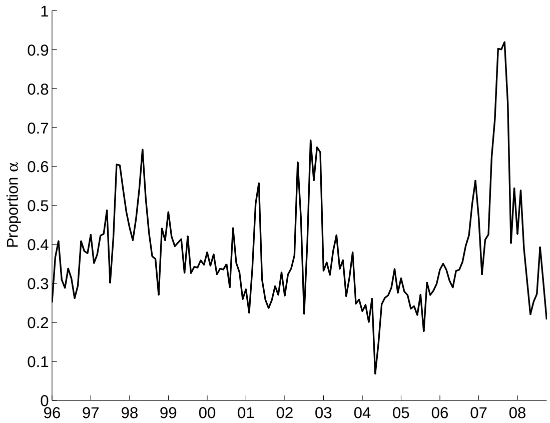
Notes: The table shows estimated proportions of respondents that use a particular predictor (mixing proportions α_j) under the restriction of a constant standard deviation across predictors ($\sigma_j = \sigma$, $j = 1, ..., m$). All parameters are restricted to be constant across monthly surveys. N is the number of observations, *Log L* is the log-likelihood. Standard errors in parentheses are based on the OPG estimator. All estimates are significant at the 1% level.



(a) Conventional static expectations



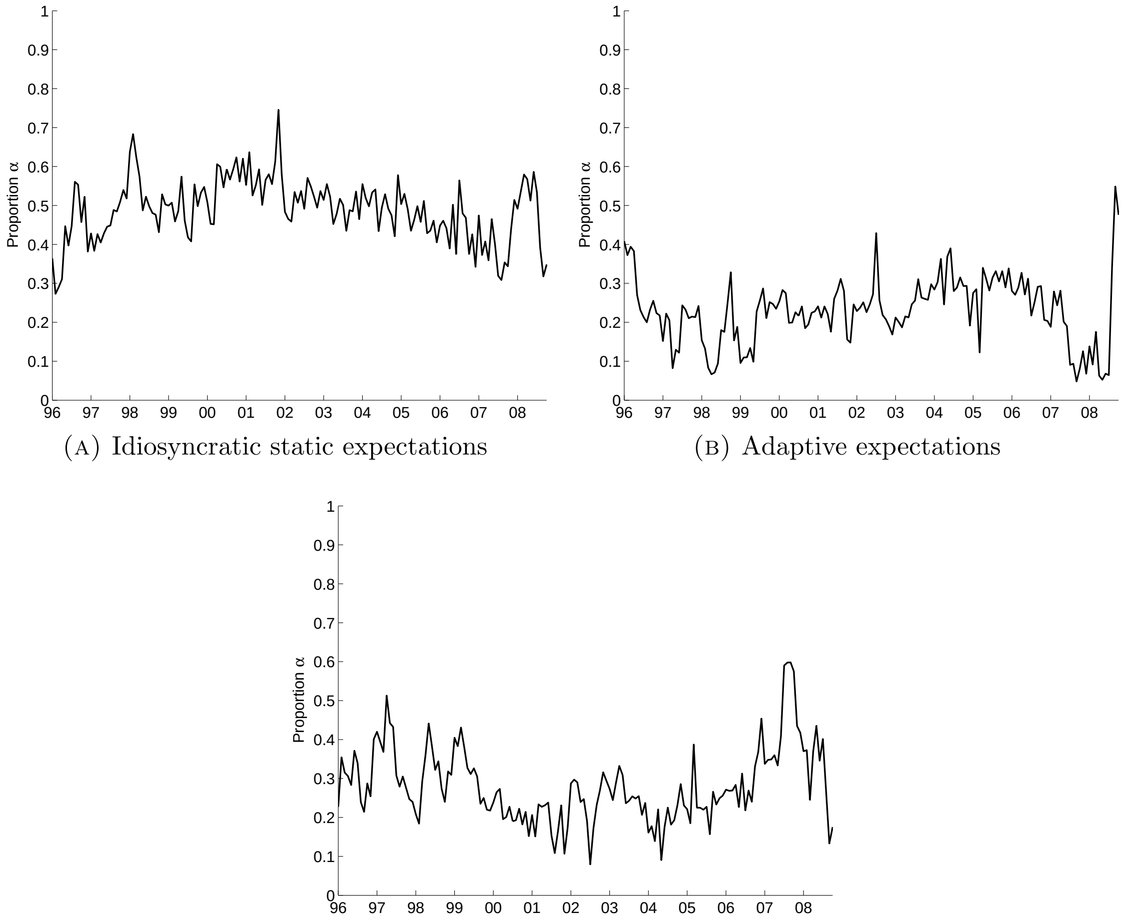
(b) Adaptive expectations



(c) Rational expectations

Figure B.4: Monthly proportions of predictors (conventional static expectations), identical standard deviations

Notes: These figures show monthly proportions of respondents that choose a particular predictor (mixing proportions $\alpha_{t,j}$). The set of available predictors is given by conventional static expectations (actual HICP inflation rate), adaptive expectations and rational expectations (mean of professional forecasts). The standard deviation is restricted to be identical across predictors, i.e. $\sigma_j = \sigma$, $j = 1, 2, 3$. The estimated time-invariant standard deviation is 2.67%.



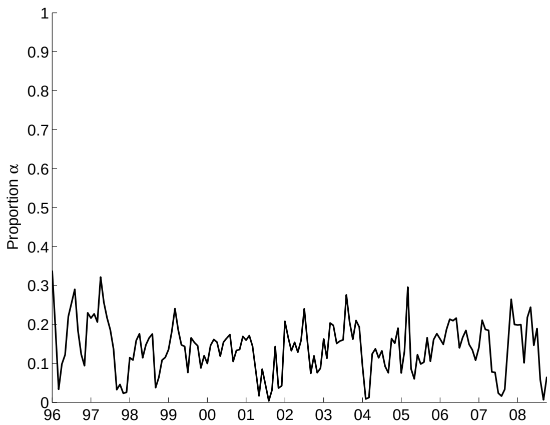
(A) Idiosyncratic static expectations

(B) Adaptive expectations

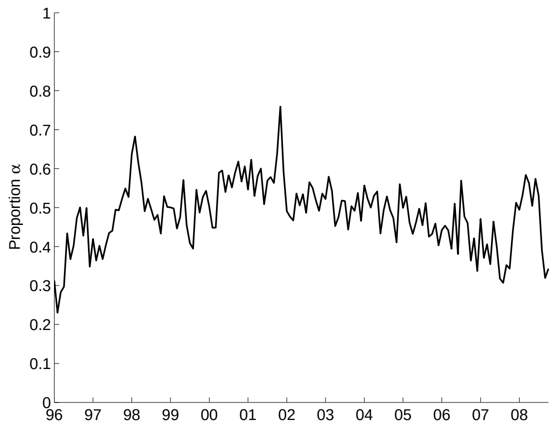
(C) Rational expectations

Figure B.5: Monthly proportions of predictors (idiosyncratic static expectations), identical standard deviations

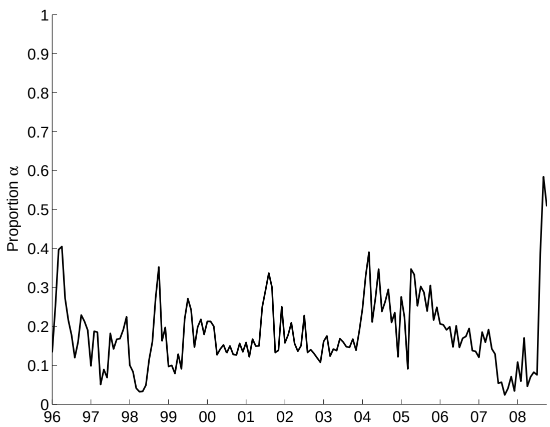
Notes: These figures show monthly proportions of respondents that choose a particular predictor (mixing proportions $\alpha_{t,j}$). The set of available predictors is given by idiosyncratic static expectations (perceived inflation rate), adaptive expectations and rational expectations (mean of professional forecasts). The standard deviation is restricted to be identical across predictors, i.e. $\sigma_j = \sigma$, $j = 1, 2, 3$. The estimated time-invariant standard deviation is 2.15%.



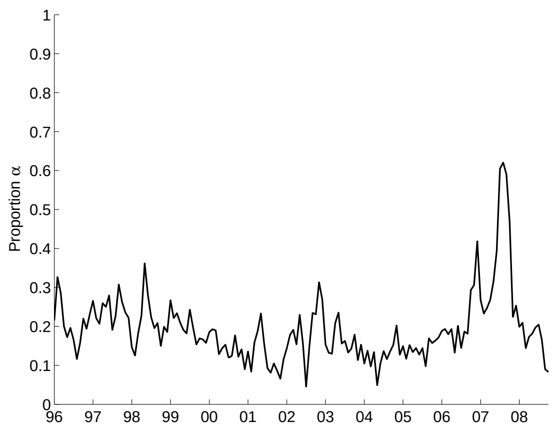
(a) Conventional static expectations



(b) Idiosyncratic static expectations



(c) Adaptive expectations



(d) Rational expectations

Figure B.6: Monthly proportions of predictors (set of all predictors), identical standard deviations

Notes: These figures show monthly proportions of respondents that choose a particular predictor (mixing proportions $\alpha_{t,j}$). The set of available predictors is given by conventional static expectations, idiosyncratic static expectations, adaptive expectations and rational expectations. The standard deviation is restricted to be identical across predictors, i.e. $\sigma_j = \sigma$, $j = 1, 2, 3, 4$. The estimated time-invariant standard deviation is 2.17%.

Appendix C

Appendix to Chapter 4

C.1 Sample Summary

Table C.1: Sample summary

Code	Country	Sample	T	Mean π	Median π	SD π
AT	Austria	10/1995 – 08/2007	143	1.58	1.68	0.60
BE	Belgium	01/1993 – 08/2007	176	1.87	1.88	0.71
DE	Germany	01/1993 – 08/2007	176	1.41	1.38	0.56
EA	Euro area	01/1993 – 08/2007	176	2.11	2.12	0.58
EL	Greece	01/1993 – 08/2007	176	5.33	3.81	3.30
ES	Spain	01/1993 – 08/2007	176	3.28	3.31	1.00
EU	Europe	01/1993 – 08/2007	176	3.21	2.95	1.37
FI	Finland	11/1995 – 08/2007	142	1.43	1.32	0.85
FR	France	01/1993 – 07/2007	175	1.71	1.77	0.59
IE	Ireland	01/1993 – 08/2007	176	3.00	2.65	1.25
IT	Italy	01/1993 – 08/2007	176	2.85	2.41	1.15
NL	Netherlands	01/1993 – 08/2007	176	2.14	1.82	1.07
SE	Sweden	10/1995 – 08/2007	143	1.48	1.37	0.79
UK	United Kingdom	01/1993 – 08/2007	176	1.57	1.51	0.54

Notes: The last three columns show mean, median and standard deviation of the HICP inflation rate in corresponding sample periods. The sample generally spans 01/1993 to 08/2007 and is defined by the joint availability of survey data and HICP inflation rates. T denotes the number of monthly observations.

C.2 Quantifying Inflation Perceptions

The Joint Harmonized EU Consumer Survey captures perceived inflation by asking: "How do you think that consumer prices have developed over the last 12 months? They have...". Answers are given on an ordinal scale: "Risen a lot (S_5), risen moderately (S_4), risen slightly (S_3), stayed about the same (S_2), fallen (s_1)". For further reference, S_1 through S_5 denote the answer categories, whereas s_1 through s_5 are the share of responses in the corresponding category excluding the additional "don't know"-category. We quantify the qualitative response data employing the 5-category probability method as outlined in Chapter 2 of this thesis. Using the notation introduced in Appendix A.1, one obtains the following expression for the mean π_t^p and cross-sectional standard deviation σ_t^p of inflation perceptions:

$$\pi_t^p = \pi_t^r \frac{G_t^2 + G_t^3}{G_t^2 + G_t^3 - G_t^4 - G_t^5} \tag{C.1}$$

$$\sigma_t^p = \pi_t^r \frac{-2}{G_t^2 + G_t^3 - G_t^4 - G_t^5} \tag{C.2}$$

Throughout this paper, π_t^p is called perceived inflation and σ_t^p is called implied (quantified) standard deviation. To identify the above system, we assume that the reference rate of inflation π_t^r (the "moderate" rate of inflation) is constant over time but may differ across countries. Hence, $\pi_t^r = \pi^r$ is a constant scaling factor to perceived inflation. To determine the moderate level of inflation, we impose unbiasedness of perceived inflation such that average perceived inflation is equal to average actual inflation over the sample period:[1]

$$\pi_t^r = \frac{\overline{\pi}}{T^{-1} \sum \frac{G_t^2 + G_t^3}{G_t^2 + G_t^3 - G_t^4 - G_t^5}} \tag{C.3}$$

where $T^{-1} \sum \pi_t^p = T^{-1} \sum \pi_t = \overline{\pi}$ and T is the number of observations.

The assumptions imposed by the probability approach have been critically discussed in Chapter 2. To assess the method, Figure C.1 shows quantified inflation perceptions as well as actual quantitative perceptions which are available from the Swedish Consumer Tendency Survey. The quantified mean closely tracks the mean of quantitative survey responses. The correlation coefficient of the two series is 0.96. The level difference averages at 0.01%. Quantitative response data is also available for Austria, where a survey was conducted in June 2004. Stix (2005) reports that inflation perceptions average at 2.7%. The probability method generates a value of 2.20%. Figure C.1 further indicates that the quantified cross-sectional standard deviation of perceptions is less accurate. The correlation of the quantified series with the standard deviation of quantitative responses is only 0.19. Moreover, the quantified standard deviation averages 1.43% below the actual standard deviation of quantitative responses. For assessing the heterogeneity generated by models

[1]The unbiasedness assumption is commonly imposed to quantify inflation expectations, see, e.g., Berk (1999) and Forsells and Kenny (2004).

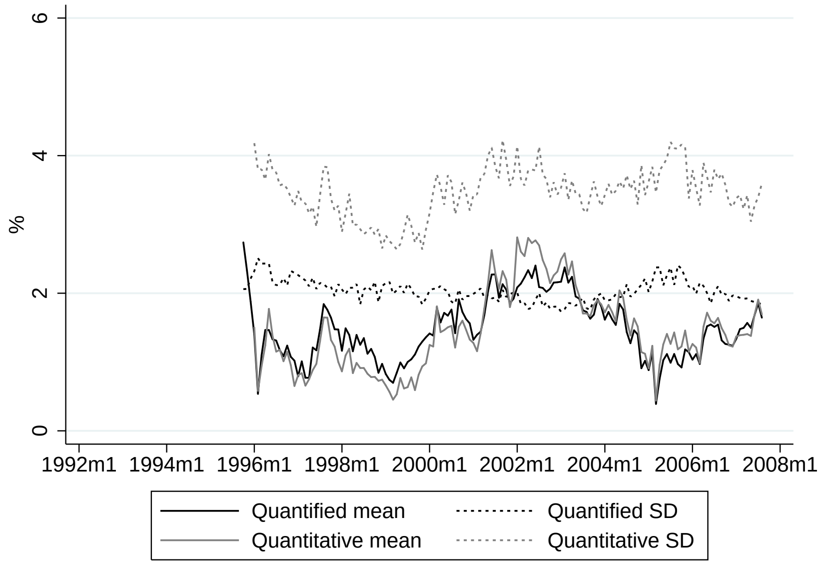


Figure C.1: Perceived inflation in Sweden

Notes: The figure shows quantified mean and cross-sectional standard deviation of inflation perceptions as well as the mean and standard deviation of quantitative inflation perceptions. Qualitative response data is quantified using the 5-category probability method under the assumption that perceptions are unbiased.

of belief formation we therefore primarily rely on the quantitative response data from Sweden.

C.3 Time Series Properties

Table C.2: Stationarity of the HICP inflation rate

Country	T	p	$\hat{\tau}_\tau$		Φ_3		$\hat{\tau}_\mu$		Φ_1		$\hat{\tau}$		Levels	1st. diff.	KPSS	
AT	142	1	-2.52		3.19		-2.07		2.20		-0.45		I(1)	I(0)	0.32	***
BE	175	1	-3.29	*	5.40		-3.26	**	5.38	**	-1.36		I(0), c	I(0)	0.42	***
DE	175	1	-2.84		4.97		-3.08	**	4.89	*	-1.74	*	I(0), c	I(0)	1.24	***
EA	175	1	-2.20		2.47		-2.17		2.46		-1.09		I(1)	I(0)	0.98	***
EL	175	1	-1.91		3.61		-2.66	*	5.57	**	-3.14	***	I(0), c	I(0)	1.81	***
ES	175	1	-2.47		3.05		-2.26		2.62		-1.00		I(1)	I(0)	1.12	***
EU	175	12	-1.94		2.57		-2.22		2.58		-1.00		I(1)	I(0)	0.26	***
FI	141	2	-1.79		1.66		-1.72		1.51		-0.61		I(1)	I(0)	0.62	***
FR	175	12	-2.24		2.52		-2.15		2.35		-0.86		I(1)	I(0)	0.16	**
IE	175	1	-2.21		2.46		-2.22		2.47		-0.79		I(1)	I(0)	0.73	***
IT	175	1	-1.85		1.76		-1.62		1.70		-1.40		I(1)	I(0)	0.99	***
NL	127	1	-1.72		1.90		-1.54		1.19		-0.68		I(1)	I(0)	0.92	***
SE	142	1	-3.50	**	6.48	***	-3.60	***	6.62	**	-2.12	***	I(0), ct	I(0)	0.34	***
UK	175	1	-2.77		3.84		-2.77	*	3.86	*	-0.69		I(1)	I(0)	0.95	***

Notes: This table shows ADF and KPSS tests on country level. The sample periods are specified in Table C.1. T is the number of observations. Following Fuller (1976) and Dickey and Fuller (1981), $\hat{\tau}_\tau$ denotes the t-statistic in the specification with constant and deterministic trend, Φ_3 is the F-statistic for the joint hypothesis that coefficient and time trend are zero. $\hat{\tau}_\mu$ denotes the t-statistic in the specification with constant only, Φ_1 is the F-statistic for the joint test that coefficient and constant are zero. $\hat{\tau}_\mu$ denotes the t-statistic in the specification without constant and trend. Columns *Levels* and *1st. diff.* show the model specification implied by the sequential procedure of Perron (1988). The number of lags p is determined using the Schwarz Bayesian information criterion (SBC). Critical values according to MacKinnon (1991) and Dickey and Fuller (1981). The KPSS test allows for deterministic trend, critical values are taken from Kwiatkowski et al. (1992). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

TABLE C.3: Stationarity of perceived inflation

Country	T	p	$\hat{\tau}_\tau$	Φ_3	$\hat{\tau}_\mu$	Φ_1	$\hat{\tau}$	Levels	1st. diff.	KPSS
AT	143	1	-2.05	2.26	-1.36	2.38	-0.95	I(1)	I(0)	0.81 ***
BE	176	1	-2.60	4.55	-1.11	0.66	-0.10	I(1)	I(0)	1.44 ***
DE	176	1	-1.93	2.59	-1.55	1.21	-0.33	I(1)	I(0)	0.77 ***
EA	176	1	-1.70	1.81	-0.91	0.46	-0.10	I(1)	I(0)	1.09 ***
EL	176	1	-2.17	3.48	-0.68	0.43	-0.44	I(1)	I(0)	1.54 ***
ES	176	1	-1.81	1.63	-1.29	0.89	-0.01	I(1)	I(0)	1.22 ***
EU	176	1	-1.84	2.14	-1.13	0.67	-0.07	I(1)	I(0)	1.17 ***
FI	142	1	-5.50 ***	19.93 ***	-5.94 ***	21.45 ***	-0.14	I(0), ct	I(0)	0.96 ***
FR	175	1	-2.17	2.36	-1.21	1.10	-0.44	I(1)	I(0)	0.97 ***
IE	176	1	-1.48	1.53	-1.73	1.57	-0.02	I(1)	I(0)	0.96 ***
IT	176	1	-2.49	3.23	-2.44 **	2.99	-0.25	I(1)	I(0)	0.83 ***
NL	176	1	-1.37	1.14	-1.51	1.14	-0.51	I(1)	I(0)	0.86 ***
SE	143	1	-3.28 **	5.72 *	-3.14 ***	4.99 **	-1.15	I(0), ct	I(0)	0.68 ***
UK	176	1	-2.49	3.23	-2.44	2.99	-0.25	I(1)	I(0)	1.03 ***

Notes: See footnote of Table C.2 for a description.

Table C.4: Unit root tests allowing for a deterministic level shift

	HICP inflation rate			Perceived inflation		
Country	Break date	Test statistic		Break date	Test statistic	
AT	04/2001	-2.89	**	06/2000	-2.43	
BE	08/2000	-2.08		06/2000	-1.71	
DE	09/2006	-1.71		01/2002	-1.90	
EA	01/2002	-1.78		02/2002	-2.16	
EL	09/1993	-3.08	**	06/2005	-1.10	
ES	07/2001	-1.68		04/2003	-0.94	
EU	01/2002	-2.16		02/2002	-2.58	*
FI	01/1994	-2.27		08/1997	-4.27	***
FR	01/2002	-2.27		09/1995	-1.00	
IE	12/2000	-1.50		12/2004	-1.87	
IT	01/2002	-1.81		11/2004	-1.63	
NL	01/2001	-0.44		10/2002	-1.18	
SE	01/1994	-2.69	**	03/2005	-2.18	
UK	10/1995	-3.02	**	03/2006	-2.45	

Notes: This table shows unit root test results for actual HICP inflation and perceived inflation. Following Saikkonen and Lütkepohl (2002) and Lanne, Lütkepohl and Saikkonen (2002) the tests allow for an exponential level shift in the data generating process. The sample periods are specified in Table C.1. T is the number of observations. The test is based on estimating the deterministic term first by generalized least squares under the null hypothesis of a unit root. Subsequently, an ADF type test is performed on the adjusted series which also includes terms to correct for estimation errors in the parameters of the deterministic part. The exponential shift begins at the break date, which is chosen to minimize the generalized sum of squared residuals. Setting the break date exogenously to 01/2002 does not change any of the results. Critical values are taken from Lanne, Lütkepohl and Saikkonen (2002). Estimation is done with the JMulti software from Lütkepohl and Krätzig (2004). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table C.5: Panel unit root tests

		p=1	p=2	p=3	p=4
		1993–2007			
π *(N=12, T=175)*	IPS	-2.520*	-2.465*	-2.758**	-2.766**
	CIPS	-2.866**	-2.780**	-3.085***	-3.141***
π^p *(N=9, T=175)*	IPS	-2.192	-2.063	-2.063	-2.048
	CIPS	-2.409	-2.246	-2.206	-2.068
		1993–2001			
π *(N=12, T=108)*	IPS	-2.222	-2.229	-2.501*	-2.567**
	CIPS	-2.473	-2.432	-2.721*	-2.978***
π^p *(N=9, T=108)*	IPS	-2.401	-2.211	-2.180	-2.211
	CIPS	-2.545	-2.364	-2.205	-2.123
		2003–2007			
π *(N=12, T=55)*	IPS	-2.528*	-2.042	-2.070	-1.944
	CIPS	-2.527	-2.178	-2.098	-1.942
π^p *(N=12, T=55)*	IPS	-2.637**	-2.464*	-2.525**	-2.302
	CIPS	-2.803**	-2.661*	-2.405	-2.512

Notes: This table shows IPS and CIPS panel unit root tests for actual HICP inflation π and perceived inflation π^p. IPS denotes the Im, Pesaran and Shin (2003) t-bar statistic and accounts for common time effects. Following Pesaran (2007), CPIS is the t-bar statistic based on cross-sectionally augmented ADF regressions. Critical values are provided in the respective papers. All statistics are based on AR(p) specifications in levels that include a deterministic trend and a constant. To obtain balanced panels for perceived inflation, AT, FI, SE are excluded in the samples 1993–2007 and 1993–2001. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table C.6: Cointegration of actual and perceived inflation, 1993–2007

Country	r=0		r=1		Implied r	β	p	T
AT	10.49		1.78		0	0.74	2	140
BE	14.36		1.57		0	0.26	2	173
DE	11.99		2.56		0	0.15	2	173
EA	6.44		0.91		0	0.19	2	173
EL	15.93	**	0.33		1	-0.06	3	172
ES	6.75		1.62		0	0.25	2	173
EU	9.89		1.40		0	0.25	2	173
FI	39.28	***	4.05	**	2	0.21	2	139
FR	14.58		1.46		0	0.52	2	173
IE	16.01	**	3.49		1	0.36	2	173
IT	5.07		2.23		0	0.23	2	173
NL	14.53		4.97	**	0	0.24	2	125
SE	26.63	***	9.60	***	2	0.37	2	140
UK	15.32		4.40	**	0	0.13	2	173

Notes: This table shows Johansen tests for the cointegration rank between actual and perceived inflation, 1993–2007. The lag order p is determined using the SBC, a minimum of one lag in first differences is included. Critical values from Johansen (1995): r=1, 15.41 (5%, **), 19.96 (1%, ***); r=2, 3.76 (5%), 9.24 (1%). β is the cointegration coefficient in the regression $y_{it} = \alpha + \beta x_{it} + \epsilon_{it}$. T denotes the number of observations.

Table C.7: Cointegration of actual and perceived inflation, 1993–2001

Country	r=0		r=1		Implied r	β	p	T
AT	6.92		1.16		0	0.55	2	73
BE	20.01	***	3.27		1	0.28	2	106
DE	9.91		3.82		0	0.26	2	106
EA	5.70		1.81		0	0.25	2	106
EL	12.56		3.33		0	0.12	2	106
ES	10.28		2.41		0	0.31	2	106
EU	8.54		2.40		0	0.32	2	106
FI	33.30	***	3.30		1	0.60	2	72
FR	8.19		2.84		0	0.27	2	106
IE	9.31		1.49		0	0.39	2	106
IT	6.94		1.83		0	0.35	2	106
NL	12.99		0.11		0	0.27	2	58
SE	22.01	***	6.30	**	2	0.33	2	73
UK	8.39		0.82		0	0.10	2	106

Notes: See footnote of Table C.6 for a description.

Table C.8: Cointegration of actual and perceived inflation, 2003–2007

Country	r=0		r=1		Implied r	β	p	T
AT	10.74		4.48	**	0	0.05	2	53
BE	10.41		3.86	**	0	0.12	2	53
DE	27.04	***	7.56	***	2	-0.24	2	53
EA	16.75	**	6.42	**	2	-0.01	2	53
EL	23.58	***	9.50	***	2	-0.55	2	53
ES	11.49		5.68	**	0	0.09	2	53
EU	26.62	**	3.07		1	-0.23	2	53
FI	12.11		2.99		0	0.14	2	53
FR	18.09	**	6.36	**	2	0.07	2	53
IE	18.65	**	4.94	**	2	0.34	2	53
IT	10.37		0.64		0	1.51	2	53
NL	22.75	***	6.18	**	2	1.12	2	53
SE	20.83	***	7.20	***	2	0.48	2	53
UK	11.44		2.02		0	0.28	2	53

Notes: See footnote of Table C.6 for a description.

Table C.9: Tests for panel cointegration

	1993–2007	1993–2001	2003–2007
Parametric t-statistic			
Panel statistic	-1.62**	-3.59***	-2.73***
Group mean statistic	-2.94***	-4.31***	-2.98***
Nonparametric t-statistic			
Panel statistic	-3.09***	-5.28***	-2.98***
Group mean statistic	-4.52***	-6.18***	-4.36***

Notes: Pedroni tests for panel cointegration of actual inflation and perceived inflation. Panel cointegration regressions include time fixed effects. All statistics are standardized and follow a $N(0, 1)$ distribution, see Pedroni (1999, 2004). Estimation has been done using the RATS procedure written by Peter Pedroni. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

C.4 Further Results

Table C.10: Model (1), 1993–2001

Country	α_1		α_2		α_0		R^2	Wald p	BG p
AT	0.0722**	(0.0273)	0.9211***	(0.0447)	-0.0090	(0.0406)	0.93	0.85	0.35
BE	0.0619**	(0.0275)	0.7957***	(0.0571)	0.2221***	(0.0576)	0.85	0.00	0.01
DE	0.0761***	(0.0258)	0.7997***	(0.0621)	0.1519***	(0.0566)	0.92	0.01	0.90
EA	0.0635***	(0.0156)	0.8301***	(0.0362)	0.1766***	(0.0426)	0.96	0.00	0.04
EL	0.0235***	(0.0082)	0.8065***	(0.0467)	0.6954***	(0.1753)	0.85	0.00	0.52
ES	0.0606***	(0.0168)	0.8186***	(0.0409)	0.2977***	(0.0887)	0.89	0.00	0.44
FI	0.0364	(0.0248)	0.9005***	(0.0399)	0.0740	(0.0615)	0.96	0.12	0.09
FR	0.0489***	(0.0179)	0.8813***	(0.0474)	0.0851*	(0.0482)	0.86	0.08	0.53
IE	0.0858***	(0.0232)	0.8050***	(0.0542)	0.2802***	(0.0895)	0.96	0.00	0.29
IT	0.0468**	(0.0208)	0.8573***	(0.0471)	0.2115***	(0.0704)	0.92	0.00	0.87
NL	0.0959***	(0.0192)	0.6509***	(0.0624)	0.4213***	(0.0832)	0.88	0.00	0.77
SE	0.1644***	(0.0320)	0.5396***	(0.0668)	0.3942***	(0.0690)	0.76	0.00	0.23
SEq	0.1091***	(0.0361)	0.7196***	(0.0719)	0.2763***	(0.0796)	0.79	0.00	0.38
UK	0.0000	(0.0306)	0.8745***	(0.0839)	0.1916	(0.1427)	0.70	0.16	0.73

Notes: See footnote of Table 4.4 for a description.

Table C.11: Model (1), 2003–2007

Country	α_1		α_2		α_0		R^2	Wald p	BG p
AT	0.0283	(0.0287)	0.5799***	(0.1111)	0.9019***	(0.2637)	0.34	0.00	0.12
BE	0.0277	(0.0248)	0.8361***	(0.0911)	0.3200*	(0.1859)	0.73	0.11	0.55
DE	-0.0011	(0.0185)	0.8478***	(0.0437)	0.2186**	(0.0885)	0.93	0.01	0.01
EA	-0.0019	(0.0317)	0.9081***	(0.0460)	0.2264	(0.1379)	0.92	0.11	0.01
EL	-0.3007*	(0.1696)	0.5523***	(0.1052)	4.1785***	(1.0516)	0.41	0.00	0.10
ES	0.0535	(0.0387)	0.7427***	(0.1123)	0.8993**	(0.4309)	0.58	0.05	0.13
FI	0.0575***	(0.0194)	0.6918***	(0.0887)	0.5023***	(0.1489)	0.65	0.00	0.43
FR	0.0199	(0.0241)	0.6074***	(0.1370)	0.8857***	(0.3169)	0.41	0.01	0.42
IE	0.0803**	(0.0354)	0.8175***	(0.0647)	0.3622*	(0.1831)	0.83	0.08	0.02
IT	0.2631**	(0.1002)	0.8462***	(0.0596)	-0.1120	(0.1620)	0.92	0.12	0.02
NL	0.2261*	(0.1256)	0.8782***	(0.0507)	-0.0960	(0.2063)	0.90	0.42	0.01
SE	0.1558**	(0.0657)	0.6863***	(0.0813)	0.2239**	(0.0873)	0.80	0.01	0.45
SEq	0.1761**	(0.0759)	0.6057***	(0.0982)	0.3561***	(0.1230)	0.70	0.00	0.49
UK	0.0492*	(0.0281)	0.8249***	(0.0564)	0.1987**	(0.0790)	0.82	0.01	0.32

Notes: See footnote of Table 4.4 for a description.

TABLE C.12: Model (2), 1993–2001

Country	α_1		α_2		α_0		R^2	Wald p	BG p
AT	0.0363	(0.0270)	0.9387***	(0.0476)	0.0249	(0.0399)	0.92	0.49	0.20
BE	0.0693***	(0.0235)	0.7766***	(0.0592)	0.2396***	(0.0653)	0.86	0.00	0.02
DE	0.0473**	(0.0218)	0.8496***	(0.0585)	0.1265**	(0.0573)	0.90	0.03	0.91
EA	0.0173	(0.0158)	0.9312***	(0.0415)	0.0880*	(0.0475)	0.95	0.07	0.27
EL	0.0189**	(0.0084)	0.8237***	(0.0487)	0.6467***	(0.1809)	0.84	0.00	0.65
ES	0.0486**	(0.0186)	0.8387***	(0.0471)	0.2807***	(0.0952)	0.88	0.00	0.40
FI	0.0073	(0.0246)	0.9238***	(0.0405)	0.0996	(0.0631)	0.96	0.10	0.05
FR	0.0321*	(0.0170)	0.8974***	(0.0452)	0.0898*	(0.0476)	0.86	0.07	0.49
IE	0.0914***	(0.0237)	0.7854***	(0.0570)	0.3224***	(0.0937)	0.96	0.00	0.86
IT	0.0256	(0.0218)	0.9010***	(0.0495)	0.1659**	(0.0732)	0.92	0.02	1.00
NL	0.0899***	(0.0219)	0.6688***	(0.0636)	0.4053***	(0.0805)	0.87	0.00	0.92
SE	0.1346***	(0.0394)	0.5760***	(0.0740)	0.3870***	(0.0722)	0.73	0.00	0.07
SEq	0.0829*	(0.0423)	0.7569***	(0.0783)	0.2579***	(0.0838)	0.78	0.01	0.46
UK	-0.0277	(0.0311)	0.8721***	(0.0855)	0.2332	(0.1412)	0.70	0.08	0.73

Notes: See footnote of Table 4.5 for a description.

Table C.13: Model (2), 2003–2007

Country	α_1		α_2		α_0		R^2	Wald p	BG p
AT	0.0305	(0.0278)	0.5725***	(0.1122)	0.9150***	(0.2555)	0.35	0.00	0.20
BE	0.0235	(0.0275)	0.8303***	(0.1001)	0.3415*	(0.1959)	0.72	0.10	0.72
DE	-0.0171	(0.0150)	0.8253***	(0.0428)	0.2790***	(0.0816)	0.93	0.00	0.01
EA	0.0118	(0.0305)	0.9084***	(0.0457)	0.1966	(0.1375)	0.92	0.17	0.01
EL	-0.2552	(0.1692)	0.5559***	(0.1136)	4.0093***	(1.1475)	0.40	0.01	0.09
ES	0.0425	(0.0441)	0.7469***	(0.1171)	0.9151**	(0.4412)	0.57	0.05	0.13
FI	0.0186	(0.0281)	0.7698***	(0.1095)	0.3994**	(0.1799)	0.61	0.03	0.14
FR	0.0407*	(0.0227)	0.5863***	(0.1361)	0.8939***	(0.3172)	0.43	0.01	0.17
IE	0.0651*	(0.0346)	0.8225***	(0.0668)	0.3854**	(0.1838)	0.82	0.05	0.01
IT	0.1738*	(0.1001)	0.8796***	(0.0552)	-0.0233	(0.1780)	0.91	0.49	0.01
NL	0.2046	(0.1491)	0.8731***	(0.0455)	-0.0547	(0.2313)	0.90	0.60	0.00
SE	0.0450	(0.0406)	0.8004***	(0.0811)	0.2159**	(0.1022)	0.77	0.02	0.11
SEq	0.0483	(0.0505)	0.7305***	(0.1061)	0.3420**	(0.1451)	0.65	0.01	0.07
UK	0.0487	(0.0297)	0.8236***	(0.0614)	0.2017**	(0.0802)	0.82	0.01	0.34

Notes: See footnote of Table 4.5 for a description.

TABLE C.14: Model (1), Cochrane-Orcutt estimates

Country	α_1		α_2		α_0		R^2	Wald p
AT	0.0525***	(0.0184)	0.9224***	(0.0355)	0.0200	(0.0339)	0.98	0.40
BE	0.0354**	(0.0153)	0.8691***	(0.0350)	0.1477***	(0.0418)	0.95	0.00
DE	0.0325*	(0.0169)	0.9550***	(0.0344)	0.0172	(0.0442)	0.94	0.74
EA	0.0475***	(0.0139)	0.8742***	(0.0300)	0.1296***	(0.0385)	0.97	0.00
EL	0.0105	(0.0065)	0.8908***	(0.0355)	0.4015***	(0.1352)	0.95	0.00
ES	0.0618***	(0.0142)	0.8161***	(0.0321)	0.3008***	(0.0737)	0.96	0.00
FI	0.0346**	(0.0135)	0.8725***	(0.0211)	0.1159***	(0.0235)	0.97	0.00
FR	0.0445***	(0.0147)	0.8478***	(0.0419)	0.1366***	(0.0460)	0.97	0.00
IE	0.0656***	(0.0134)	0.8554***	(0.0308)	0.2075***	(0.0547)	0.97	0.00
IT	0.0378**	(0.0150)	0.9064***	(0.0298)	0.1146**	(0.0522)	0.95	0.01
NL	0.0565***	(0.0168)	0.9008***	(0.0399)	0.0597	(0.0636)	0.95	0.23
SE	0.1353***	(0.0274)	0.6862***	(0.0511)	0.2340***	(0.0577)	0.79	0.00
SEq	0.1003***	(0.0285)	0.7994***	(0.0439)	0.1701***	(0.0556)	0.84	0.01
UK	0.0313	(0.0202)	0.8652***	(0.0441)	0.1653**	(0.0635)	0.79	0.01

Notes: This table shows estimates of Model (1) using the iterated Cochrane-Orcutt method, 1993–2007. The country-specific sample periods are specified in Table C.1. The column *Wald p* reports the p-value of the Wald test of the restriction $\alpha_1 + \alpha_2 = 1$. Estimates of the indicator variable for the euro cash changeover are not reported. Heteroskedasticity robust standard errors in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table C.15: Model (2), Cochrane-Orcutt estimates

Country	α_1		α_2		α_0		R^2	Wald p
AT	0.0356*	(0.0180)	0.9303***	(0.0366)	0.0365	(0.0335)	0.98	0.25
BE	0.0384***	(0.0130)	0.8599***	(0.0351)	0.1570***	(0.0441)	0.95	0.00
DE	0.0147	(0.0154)	0.9500***	(0.0343)	0.0454	(0.0454)	0.94	0.35
EA	0.0284**	(0.0142)	0.9013***	(0.0329)	0.1191***	(0.0399)	0.97	0.00
EL	0.0082	(0.0066)	0.8933***	(0.0358)	0.4041***	(0.1356)	0.95	0.00
ES	0.0546***	(0.0160)	0.8201***	(0.0361)	0.3127***	(0.0767)	0.96	0.00
FI	0.0145	(0.0143)	0.8892***	(0.0218)	0.1335***	(0.0238)	0.97	0.00
FR	0.0450***	(0.0144)	0.8318***	(0.0412)	0.1564***	(0.0473)	0.96	0.00
IE	0.0640***	(0.0131)	0.8529***	(0.0311)	0.2201***	(0.0575)	0.96	0.00
IT	0.0223	(0.0153)	0.9256***	(0.0301)	0.1138**	(0.0527)	0.95	0.02
NL	0.0548***	(0.0175)	0.9000***	(0.0397)	0.0666	(0.0643)	0.94	0.21
SE	0.0800***	(0.0277)	0.7541***	(0.0567)	0.2195***	(0.0607)	0.78	0.00
SEq	0.0603**	(0.0298)	0.8437***	(0.0450)	0.1605***	(0.0548)	0.84	0.01
UK	0.0179	(0.0209)	0.8831***	(0.0458)	0.1541**	(0.0639)	0.79	0.01

Notes: This table shows estimates of Model (2) using the iterated Cochrane-Orcutt method, 1993–2007. See footnote of Table C.14 for a description.

TABLE C.16: Model (1) in first differences

Country	α_1		α_2		α_0		R^2	Wald p	BG p
AT	0.0837*	(0.0463)	-0.1444	(0.0909)	0.0211	(0.0170)	0.06	0.00	0.02
BE	-0.0109	(0.0359)	-0.2553***	(0.0950)	-0.0049	(0.0115)	0.07	0.00	0.16
DE	0.0519*	(0.0295)	0.1549	(0.1261)	0.0027	(0.0072)	0.06	0.00	0.04
EA	0.0971**	(0.0374)	0.1000	(0.0761)	0.0001	(0.0057)	0.08	0.00	0.00
EL	0.1141***	(0.0432)	-0.2850***	(0.0914)	-0.0141	(0.0257)	0.11	0.00	0.02
ES	0.1194***	(0.0435)	-0.0664	(0.0815)	0.0017	(0.0164)	0.04	0.00	0.00
FI	0.1340***	(0.0441)	-0.1151	(0.1032)	0.0362**	(0.0169)	0.13	0.00	0.67
FR	0.0311	(0.0296)	-0.0074	(0.0777)	0.0069	(0.0107)	0.01	0.00	0.00
IE	0.0719*	(0.0381)	-0.2168***	(0.0798)	0.0143	(0.0174)	0.07	0.00	0.75
IT	0.2250***	(0.0493)	-0.1394*	(0.0823)	-0.0025	(0.0146)	0.09	0.00	0.08
NL	0.0469	(0.0584)	-0.2905**	(0.1412)	0.0066	(0.0123)	0.09	0.00	0.27
SE	0.1717***	(0.0511)	-0.1105	(0.1206)	-0.0080	(0.0270)	0.09	0.00	0.01
SEq	0.1512***	(0.0541)	-0.1594	(0.1080)	0.0016	(0.0242)	0.08	0.00	0.06
UK	0.0560	(0.0383)	-0.0465	(0.0908)	-0.0104	(0.0133)	0.03	0.00	0.56

Notes: This table shows OLS estimates of Model (1) in first differences, 1993–2007. The country-specific sample periods are specified in Table C.1. The column *Wald p* reports the p-value of the Wald test of the restriction $\alpha_1 + \alpha_2 = 1$. *BG p* is the p-value of the Breusch-Godfrey LM test statistic for first order residual correlation. Estimates of the indicator variable for the euro cash changeover are not reported. White standard errors allowing for heteroskedasticity in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table C.17: Model (2) in first differences

Country	α_1		α_2		α_0		R^2	Wald p	BG p
AT	0.0303	(0.0377)	-0.1818*	(0.0965)	0.0222	(0.0179)	0.03	0.00	0.02
BE	0.0555***	(0.0191)	-0.2491***	(0.0834)	-0.0044	(0.0112)	0.11	0.00	0.29
DE	0.0196	(0.0277)	0.1276	(0.1153)	0.0035	(0.0077)	0.03	0.00	0.04
EA	0.0994***	(0.0326)	0.0116	(0.0775)	0.0001	(0.0060)	0.08	0.00	0.52
EL	0.0492	(0.0529)	-0.2896***	(0.0900)	-0.0202	(0.0265)	0.09	0.00	0.03
ES	0.1616***	(0.0354)	-0.1175	(0.0829)	0.0032	(0.0161)	0.07	0.00	0.44
FI	0.0670	(0.0414)	-0.1797	(0.1234)	0.0408**	(0.0180)	0.05	0.00	0.02
FR	0.1090***	(0.0275)	-0.0321	(0.0760)	0.0078	(0.0103)	0.08	0.00	0.90
IE	0.0853*	(0.0476)	-0.2236***	(0.0816)	0.0132	(0.0168)	0.07	0.00	0.64
IT	0.1329**	(0.0598)	-0.1345	(0.0867)	-0.0041	(0.0149)	0.04	0.00	0.39
NL	0.0589	(0.0415)	-0.2980**	(0.1426)	0.0064	(0.0121)	0.09	0.00	0.27
SE	0.1007	(0.0671)	-0.1441	(0.1184)	-0.0076	(0.0267)	0.04	0.00	0.06
SEq	0.0604	(0.0637)	-0.1913*	(0.1102)	0.0044	(0.0239)	0.04	0.00	0.05
UK	-0.0099	(0.0445)	-0.0528	(0.0935)	-0.0112	(0.0139)	0.01	0.00	0.06

Notes: This table shows OLS estimates of Model (2) in first differences, 1993–2007. See footnote of Table C.16 for a description.

Table C.18: Near-rationality in Model (2), 1993–2007

Country	α_1		α_2		$\Delta\alpha_1$		$\Delta\alpha_2$		T	Median
AT	-0.0067	(0.0278)	0.8823***	(0.0342)	0.0258	(0.0414)	-0.0212	(0.0446)	142	1.76
BE	0.0510	(0.0426)	0.8032***	(0.0575)	0.0012	(0.0438)	-0.0014	(0.0421)	175	1.88
DE	0.0187	(0.0187)	0.9414***	(0.0333)	0.0952**	(0.0405)	-0.0761**	(0.0351)	138	1.38
EA	0.0657**	(0.0265)	0.8840***	(0.0381)	0.0514	(0.0339)	-0.0700*	(0.0400)	175	2.12
EL	0.0060	(0.0640)	0.8099***	(0.0530)	-0.0536	(0.0432)	0.0037	(0.0650)	175	3.81
ES	0.0525	(0.0371)	0.8009***	(0.0351)	0.0249	(0.0346)	-0.0443	(0.0424)	175	3.31
FI	0.0271	(0.0334)	0.8972***	(0.0304)	0.0145	(0.0391)	-0.0241	(0.0414)	141	1.36
FR	0.0325	(0.0221)	0.8289***	(0.0521)	0.0518	(0.0367)	-0.0537	(0.0338)	175	1.77
IE	0.0204	(0.0302)	0.8804***	(0.0362)	-0.0965**	(0.0425)	0.0872**	(0.0382)	139	2.65
IT	0.0339	(0.0507)	0.8815***	(0.0390)	0.0014	(0.0388)	-0.0170	(0.0539)	175	2.41
NL	0.0242	(0.0525)	0.8392***	(0.0441)	-0.0333	(0.0467)	0.0336	(0.0574)	175	1.82
SE	0.0807	(0.0550)	0.7178***	(0.0632)	0.0131	(0.0778)	-0.0477	(0.0786)	142	1.54
SEq	0.0782	(0.0546)	0.7645***	(0.0508)	0.0731	(0.0821)	-0.0937	(0.0893)	139	1.54
UK	-0.0765	(0.0512)	0.9290***	(0.0498)	-0.1412**	(0.0618)	0.1511**	(0.0586)	127	1.51

Notes: See footnote of Table 4.6 for a description.

Appendix D

Appendix to Chapter 5

D.1 Further Results

Table D.1: The effect of lagged media coverage on survey disagreement

	(1)		(2)		(3)		(4)	
	Cons.	*Prof.*	*Cons.*	*Prof.*	*Cons.*	*Prof.*	*Cons.*	*Prof.*
Volume(t-1)	-0.0001	-0.0003	-0.0001	-0.0003	-0.0000	-0.0006	-0.0000	-0.0005
	(0.0003)	(0.0008)	(0.0003)	(0.0008)	(0.0001)	(0.0004)	(0.0001)	(0.0005)
Entropy(t-1)	-0.0126	0.0034	-0.0042	0.0003	-0.0036	-0.0155	-0.0054	-0.0287
	(0.0153)	(0.0441)	(0.0147)	(0.0469)	(0.0119)	(0.0407)	(0.0124)	(0.0426)
Tone(t-1)	-0.0131	0.0320			-0.0033	0.0166		
	(0.0087)	(0.0285)			(0.0067)	(0.0229)		
Direction rising(t-1)			-0.0414**	0.0425			0.0040	0.0594
			(0.0188)	(0.0491)			(0.0149)	(0.0466)
Direction falling(t-1)			-0.0202	-0.0197			0.0113	0.0343
			(0.0207)	(0.0731)			(0.0160)	(0.0536)
Lagged dependent					0.5660***	0.4837***	0.5819***	0.4950***
					(0.0717)	(0.0808)	(0.0775)	(0.0815)
Inflation(t-1)	-0.0612***	-0.1356**	-0.0648***	-0.1343**	-0.0381**	-0.1074*	-0.0366**	-0.1011*
	(0.0223)	(0.0669)	(0.0219)	(0.0668)	(0.0160)	(0.0544)	(0.0163)	(0.0547)
Inflation squared(t-1)	0.0171**	0.0236	0.0185***	0.0231	0.0107**	0.0243	0.0102*	0.0222
	(0.0073)	(0.0235)	(0.0070)	(0.0235)	(0.0052)	(0.0176)	(0.0053)	(0.0177)
Constant	0.8750***	0.5047***	0.8901***	0.4992***	0.3866***	0.3102***	0.3691***	0.2827***
	(0.0216)	(0.0573)	(0.0217)	(0.0610)	(0.0635)	(0.0586)	(0.0711)	(0.0642)
Dchangeover	0.1020***	0.0665***	0.0974***	0.0682***	0.0454***	0.0375**	0.0450***	0.0439***
	(0.0073)	(0.0211)	(0.0080)	(0.0189)	(0.0084)	(0.0156)	(0.0084)	(0.0167)
Observations	117	117	117	117	117	117	117	117
R-squared	0.79	0.20	0.79	0.20	0.86	0.40	0.87	0.41

Notes: Monthly data, 01/1998–09/2007. Dependent variable for consumers is the index of qualitative variation, dependent variable for professional forecasters is the quasi standard deviation of survey responses. White standard errors in parentheses allowing for heteroskedasticity. For column (1)–(2) Newey-West standard errors are reported using the bandwidth $n = 4$. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Appendix E

Appendix to Chapter 6

E.1 Disaggregate Data

Table E.1: Components at aggregation level 1 (main groups)

Official ID	Component	Weight in %
1	Food and non-alcoholic beverages	11.091
2	Alcoholic beverages and tobacco	1.785
3	Clothing and Footwear	4.434
4	Housing and energy	25.212
5	Household furniture and furnishings	4.762
6	Health	14.467
7	Transport	11.285
8	Communications	2.938
9	Recreation and culture	10.607
10	Education	0.674
11	Restaurants and hotels	8.142
12	Other goods and services	4.603

Table E.2: Components at aggregation level 2 (product groups)

Official ID	Component	Weight in %
1002	Bread, flour and food products	1.790
1074	Meat, cold cuts and sausages	2.628
1179	Fish, crustaceans and seafood	0.401
1198	Milk, cheese and eggs	1.812
1284	Fats and edible oils	0.293
1306	Fruit	0.939
1359	Pulses and potatoes	1.298
1448	Sugar, jam, honey/other sugary foods	0.730
1481	Other food products	0.787
1518	Coffee, tea, cocoa and nutritional beverages	0.363
1544	Mineral waters, soft drinks and juices	0.663
2002	Spirits	0.134
2017	Wine	0.880
2064	Beer	0.134
2075	Tobacco	0.736
3002	Articles of clothing	3.537
3168	Other articles of clothing/fabrics	0.220
3189	Dry-cleaning and repair of garments	0.088
3211	Footwear	0.816
3237	Shoe repairs	0.020
4001	Rent	19.957
4010	Products for housing maintenance and repair	0.214
4020	Services for housing maintenance and repair	0.889
4050	Gas	0.656
4070	Electricity	2.116
4090	Heating oil	2.101
5002	Furniture and furnishings	1.926

Official ID	Component	Weight in %
5060	Floor coverings and carpets	0.093
5070	Household textiles	0.350
5101	Major household appliances	0.376
5120	Smaller electric household appliances	0.311
5140	Glassware, tableware and household utensils	0.359
5181	Motorized tools for DIY and garden	0.101
5200	Tools for house and garden	0.497
5221	Goods for routine household maintenance	0.587
6001	Medical products and appliances	3.181
6031	Medical services	3.626
6036	Dental services	1.594
6059	Hospital services	5.798
7002	Purchase of cars, motorcycles, bicycles	4.645
7082	Spare parts and accessories	0.397
7105	Fuels	2.844
7113	Repair services and work	1.372
7201	Public transport services by rail and road	1.545
8	Communications	3.101
9002	Television sets and audiovisual appliances	0.514
9029	Photographic equipment and optical instruments	0.156
9046	Personal computers and accessories	0.584
9085	Recording media	0.271
9120	Repair and installation	0.030
9211	Games, toys and hobbies	0.455
9230	Equipment for sport, camping and open-air recreation	0.418
9300	Plants and flowers	0.572
9320	Pets and related products	0.318
9351	Sporting and recreational services	0.771
9435	Cultural and other services	2.208
9501	Books and brochures	0.404
9525	Daily newspapers and periodicals	0.696
9555	Writing and drawing materials	0.176
9570	Package holidays	3.221
10	Education	0.711
11002	Restaurants and cafés	5.830
11170	Accommodation	0.901
12	Other goods and services	4.858

Table E.3: Components at aggregation level 3 (index positions)

Official ID	Component	Weight in %
1003	Rice	0.045
1008	Flour	0.065
1015	Bread	0.551
1027	Small baked goods	0.182
1036	Viennese pastries, pastry products	0.335
1048	Biscuit/rusk products	0.276
1058	Pasta	0.156
1065	Other cereal products	0.192

Official ID	Component	Weight in %
1076	Beef	0.430
1088	Veal	0.144
1097	Pork	0.372
1107	Lamb	0.089
1115	Poultry	0.336
1133	Other meat	0.237
1144	Processed meat and sausages	1.037
1180	Fresh fish	0.235
1187	Frozen fish	0.078
1192	Tinned fish and smoked fish	0.091
1200	Whole milk	0.181
1207	Other type of milk	0.151
1218	Hard and semi-hard cheese	0.502
1230	Fresh, soft and melted cheese	0.357
1246	Other dairy products	0.343
1265	Cream	0.134
1278	Eggs	0.156
1285	Butter	0.135
1293	Margarine, fats, edible oils	0.160
1307	Fresh fruit	0.772
1347	Dried, frozen and tinned fruit	0.173
1361	Fruiting vegetables	0.291
1369	Root vegetables	0.180
1379	Salad vegetables	0.275
1391	Brassicas	0.064
1400	Onions	0.067
1407	Other vegetables	0.065
1417	Potatoes	0.092
1423	Dried, frozen, tinned vegetables, etc.	0.142
1449	Jam and honey	0.106
1455	Chocolate	0.351
1468	Ice-cream	0.118
1475	Sugar	0.042
1482	Soups, spices, sauces	0.529
1505	Ready-made foods	0.263
1530	Coffee	0.268
1532	Tea	0.066
1539	Cocoa and nutritional beverages	0.032
1545	Natural mineral water	0.203
1552	Soft drinks	0.288
1563	Fruit or vegetable juices	0.176
2003	Spirits/brandies	0.079
2010	Liqueurs and aperitifs	0.056
2019	Swiss red wine	0.201
2031	Foreign red wine	0.404
2046	Swiss white wine	0.151
2056	Foreign white wine	0.071
2064	Beer	0.135
2076	Cigarettes	0.706
2082	Other tobaccos	0.034

Official ID	Component	Weight in %
3004	Coats, jackets	0.221
3015	Suits	0.125
3020	Trousers	0.283
3027	Shirts	0.123
3033	Sweaters	0.170
3041	Underwear	0.121
3061	Coats, jackets	0.059
3067	Costumes, trouser suits, dresses	0.070
3074	Skirts	0.198
3079	Trousers	0.407
3086	Jackets	0.336
3093	Blouses	0.136
3099	Jumpers	0.461
3106	Underwear	0.272
3126	Coats and jackets	0.042
3134	Trousers and skirts	0.093
3141	Jerseys	0.082
3150	Hosiery and underwear	0.063
3300	Sportswear	0.218
3169	Garment fabrics	0.020
3175	Haberdashery and knitting wool	0.046
3190	Garment alterations	0.023
3198	Upkeep of textiles	0.065
3212	Womens footwear	0.444
3220	Mens footwear	0.246
3228	Childrens footwear	0.131
3237	Shoe repairs	0.020
4001	Rent	20.085
4010	Products for housing maintenance and repair	0.216
4020	Services for housing maintenance and repair	0.894
4050	Gas	0.661
4070	Electricity	2.130
4090	Heating oil	2.115
5003	Living room	0.661
5020	Bedroom	0.617
5040	Kitchen and garden	0.274
5050	Furnishings	0.387
5060	Floor coverings and carpets	0.093
5071	Bed linen and household linen	0.259
5090	Curtains and curtain accessories	0.093
5101	Major household appliances	0.378
5120	Smaller electric household appliances	0.313
5141	Kitchen utensils	0.160
5150	Tableware and cutlery	0.114
5181	Motorized tools for DIY and garden	0.102
5200	Tools for house and garden	0.500
5222	Detergents and cleaning products	0.338
5250	Cleaning articles	0.019
5260	Other household articles	0.234
6001	Medical products and appliances	3.201

Official ID	Component	Weight in %
6031	Medical services	3.650
6036	Dental services	1.604
6059	Hospital services	5.836
7002	Purchase of cars, motorcycles, bicycles	4.675
7082	Spare parts and accessories	0.399
7105	Fuels	2.863
7113	Repair services and work	1.381
7210	Public transport: direct service	1.046
7220	Public transport: combined services	0.509
8	Communications	3.121
9002	Television sets and audiovisual appliances	0.517
9029	Photographic equipment and optical instruments	0.157
9046	Personal computers and accessories	0.587
9085	Recording media	0.273
9120	Repair and installation	0.030
9211	Games, toys and hobbies	0.458
9230	Equipment for sport, camping and open-air recreation	0.421
9300	Plants and flowers	0.576
9320	Pets and related products	0.320
9352	Sporting events	0.075
9400	Sports and leisure activities	0.499
9420	Mountain railways and ski lifts	0.202
9436	Cinema	0.135
9450	Theatre and concerts	0.368
9465	Radio and television licences	0.963
9475	Photographic services	0.116
9490	Leisure-time courses	0.641
9501	Books and brochures	0.407
9525	Daily newspapers and periodicals	0.700
9555	Writing and drawing materials	0.177
9570	Package holidays	3.242
10	Education	0.716
11003	Meals taken in restaurants and cafés	3.387
11052	Wine	0.699
11070	Beer	0.414
11075	Spirits, other alcoholic drinks	0.070
11091	Coffee and tea	0.679
11103	Mineral water and soft drinks	0.605
11171	Hotels	0.659
11190	Alternative accommodation facilities	0.249
12	Other goods and services	4.889

Table E.4: Special aggregates

Official ID	Component	Weight in %
50102	Nondurable goods	26.368
50103	Semidurable goods	7.914
50104	Durable goods	9.211
50105	Services	56.507
50308	Index ex. petroleum products	95.314

E.2 Results for Subsamples

Table E.5: Persistence of aggregate inflation, 1983–1992 and 1993–1999

	SARC	90% CI	p	AC	R	AR(1)	Weight
			1983–1992				
Total	0.970	(0.654, 1.234)	3	1.014	0.858	0.401	100.00%
Constant weight aggregate	0.801	(0.488, 1.126)	2	0.788	0.754	0.449	100.00%
Nondurable goods	0.750	(0.240, 1.216)	3	0.729	0.562	0.051	26.37%
Semidurable goods	0.710	(0.343, 1.117)	4	0.695	0.906	0.009	7.91%
Durable goods	0.911	(0.077, 1.364)	6	0.807	1.252	-0.004	9.21%
Services	1.034	(0.754, 1.153)	2	1.002	0.891	0.680	56.51%
Index ex. petroleum products	0.829	(0.628, 1.065)	1	0.825	0.748	0.748	95.31%
			1993–1999				
Total	0.234	(-0.051, 0.486)	1	0.245	0.192	0.192	100.00%
Constant weight aggregate	0.007	(-0.284, 0.274)	1	0.019	0.025	-0.025	100.00%
Nondurable goods	-1.303	(-2.669, 0.190)	6	-1.371	1.069	-0.067	26.37%
Semidurable goods	0.253	(-0.560, 1.247)	4	0.222	1.168	0.310	7.91%
Durable goods	0.525	(0.289, 0.751)	1	0.555	0.478	0.478	9.21%
Services	0.214	(-0.226, 0.661)	3	0.232	0.717	0.215	56.51%
Index ex. petroleum products	0.443	(-0.000, 1.036)	2	0.491	0.222	0.100	95.31%

Notes: Quarterly data, Q2/1983–Q4/1992 and Q1/1993–Q4/1999. See footnote of Table 6.2 for a detailed description.

Table E.6: Persistence at disaggregate levels, 1983–1992 and 1993–1999

	Main groups		Product groups		Index positions	
	SARC	90% CI	SARC	90% CI	SARC	90% CI
			1983–1992			
Mean	0.501	(0.140, 0.839)	0.477	(0.107, 0.806)	0.431	(0.071, 0.760)
Median	0.622	(0.250, 1.059)	0.512	(0.173, 1.121)	0.477	(0.025, 1.062)
75th percentile	0.809	(0.270, 1.246)	0.997	(0.701, 1.159)	0.997	(0.677, 1.159)
90th percentile	0.809	(0.570, 1.246)	1.035	(0.701, 1.317)	0.998	(0.701, 1.269)
Unweighted mean	0.500	(0.145, 0.848)	0.376	(-0.014, 0.763)	0.278	(-0.086, 0.641)
SARC < a.SARC	0.658		0.614		0.667	
CI < 1	0.463		0.452		0.472	
R < 1	1.000		0.971		0.966	
r(SARC, weight)	0.004		0.102		0.105	
			1993–1999			
Mean	0.323	(-0.145, 0.814)	0.110	(-0.345, 0.578)	0.127	(-0.322, 0.590)
Median	0.187	(-0.160, 0.890)	0.102	(-0.257, 0.452)	0.100	(-0.285, 0.452)
75th percentile	0.574	(0.308, 0.955)	0.349	(-0.080, 0.873)	0.419	(-0.080, 0.873)
90th percentile	1.243	(0.563, 1.611)	0.656	(0.286, 1.150)	0.656	(0.274, 1.267)
Unweighted mean	0.321	(-0.224, 0.850)	0.014	(-0.515, 0.529)	-0.066	(-0.581, 0.468)
SARC < a.SARC	0.129		0.369		0.382	
CI < 1	0.783		0.771		0.769	
R < 1	0.982		0.981		0.969	
r(SARC, weight)	0.006		0.066		0.044	
No. of series	12		64		149	

Notes: Quarterly data, Q2/1983–Q4/1992 and Q1/1993–Q4/1999. See footnote of Table 6.3 for a detailed description.

Table E.7: Persistence of common and idiosyncratic components, 1983–1992 and 1993–1999

	1983–1992			
	Common component		Sectoral components	
	SARC	90% CI	SARC	90% CI
Main groups	1.012	(0.706, 1.136)	-0.092	(-0.310, 0.661)
Product groups	0.849	(0.643, 1.072)	0.097	(-0.261, 0.573)
Index positions	0.767	(0.529, 1.066)	0.142	(-0.188, 0.586)
	1993–1999			
	Common component		Sectoral components	
	SARC	90% CI	SARC	90% CI
Main groups	0.245	(-0.058, 0.500)	0.202	(-0.225, 0.803)
Product groups	0.424	(-0.058, 0.500)	0.002	(-0.457, 0.482)
Index positions	0.259	(-0.051, 0.507)	0.040	(-0.417, 0.480)

Notes: Quarterly data, Q2/1983–Q4/1992 and Q1/1993–Q4/1999. See footnote of Table 6.7 for a detailed description.

Table E.8: Persistence of common and sectoral components, 1983–1992 and 1993–1999

	R-squared			Standard deviation		
	Main groups	Product groups	Index positions	Common	Sectoral	Total
			1983–1992			
Mean	0.310	0.285	0.234	1.537	5.302	5.696
Median	0.217	0.170	0.146	1.173	2.600	3.098
Unw. mean	0.329	0.230	0.192	1.462	5.211	5.546
SD	0.267	0.215	0.172	1.269	7.965	7.974
ri(SD, SARC)	0.211	-0.065	-0.086			
			1993–1999			
Mean	0.319	0.185	0.180	1.223	4.264	4.737
Median	0.366	0.081	0.038	0.597	2.311	2.766
Unw. mean	0.284	0.177	0.142	1.111	4.581	4.943
SD	0.217	0.198	0.243	1.396	6.186	6.163
ri(SD, SARC)	0.097	-0.055	-0.003			

Notes: See footnote of Table 6.8 for a detailed description.

E.3 Weighted Principal Component Analysis

To verify the robustness of the factor model results, we additionally estimate the common and sectoral components using weighted principal component analysis as proposed by Boivin and Ng (2006). Similar to Generalized Least Squares, the method is based on an objective function that weights the sum of squares (the variances of the idiosyncratic factors):

$$W = \frac{1}{NT}\sum_{i=1}^{N} w_{iT} \sum_{t=1}^{T} u_{it}^2$$

where w_{iT} is the weight of series i. We consider the SWb weighting scheme with weights given by:

$$w_{iT} = \left(\frac{1}{N}\sum_{j=1}^{N}\left|\hat{\Omega}_T(i,j)\right|\right)^{-1}$$

where $\hat{\Omega}_T$ is the estimated covariance matrix of idiosyncratic factors. This weighting scheme weights the sectoral series depending on their cross-correlation with other sectoral series. The higher the sum of cross-correlations in absolute terms, the lower is the weight of the respective series. In a first step, the covariance matrix $\hat{\Omega}_T$ of the residuals u_{it} is estimated. In a second step, a new common component is estimated using the weighted data. The results presented in Table E.9 are in line with the results from the conventional principal component analysis discussed in Section 6.5.

Table E.9: Results using weighted principal component analysis

	Common component		Idiosyncratic components	
	SARC	90% CI	SARC	90% CI
		1983–2008		
Main groups	0.917	(0.767, 1.059)	0.151	(-0.100, 0.417)
Product groups	0.925	(0.821, 1.037)	0.114	(-0.145, 0.379)
Index positions	0.870	(0.746, 1.030)	0.146	(-0.116, 0.413)
		1983–1992		
Main groups	0.906	(0.633, 1.139)	-0.054	(-0.352, 0.248)
Product groups	0.762	(0.644, 1.117)	0.083	(-0.316, 0.528)
Index positions	0.911	(0.611, 1.158)	0.202	(-0.153, 0.543)
		1993–2008		
Main groups	0.080	(-0.118, 0.277)	0.232	(-0.053, 0.530)
Product groups	0.452	(0.195, 0.694)	0.096	(-0.220, 0.429)
Index positions	0.190	(-0.037, 0.390)	0.126	(-0.195, 0.445)
		2000–2008		
Main groups	-0.017	(-0.322, 0.288)	-0.097	(-0.455, 0.268)
Product groups	0.744	(0.356, 1.185)	0.025	(-0.395, 0.457)
Index positions	-0.199	(-0.513, 0.095)	0.103	(-0.356, 0.555)

Notes: Quarterly data, Q2/1983–Q3/2008, Q2/1983–Q4/1992, Q1/1993–Q3/2008 and Q1/2000–Q3/2008. Common and idiosyncratic components are estimated employing weighted principal component analysis. We use the SWb weighting scheme as proposed by Boivin and Ng (2006).

E.4 Approximately Median Unbiased Estimates

Table E.10: Persistence by aggregation level, Andrews and Chen (1994)

	Main groups		Product groups		Index positions	
	SARC	90% CI	SARC	90% CI	SARC	90% CI
			1983–2008			
Mean	0.619	(0.367, 0.887)	0.518	(0.287, 0.767)	0.485	(0.265, 0.720)
Median	0.579	(0.328, 0.883)	0.654	(0.429, 0.934)	0.654	(0.416, 0.862)
75th percentile	0.838	(0.602, 1.046)	0.855	(0.710, 1.037)	0.855	(0.710, 1.037)
90th percentile	0.939	(0.685, 1.128)	0.855	(0.710, 1.088)	0.855	(0.710, 1.088)
Unweighted mean	0.628	(0.418, 0.871)	0.542	(0.283, 0.852)	0.267	(0.007, 0.577)
SARC < a.SARC	0.726		0.717		0.713	
CI < 1	0.720		0.562		0.558	
R < 1	1.000		0.984		0.993	
r(SARC, weight)	0.188		0.102		0.177	
			1993–2008			
Mean	0.236	(-0.026, 0.477)	0.112	(-0.206, 0.421)	0.121	(-0.199, 0.436)
Median	0.181	(-0.030, 0.349)	0.205	(-0.116, 0.485)	0.199	(-0.124, 0.489)
75th percentile	0.412	(0.102, 0.722)	0.357	(0.035, 0.619)	0.304	(-0.010, 0.672)
90th percentile	0.494	(0.216, 1.061)	0.030	(-0.313, 0.383)	0.987	(0.620, 1.245)
Unweighted mean	0.124	(-0.084, 0.304)	0.158	(-0.110, 0.393)	0.016	(-0.250, 0.247)
SARC < a.SARC	0.596		0.727		0.718	
CI < 1	0.849		0.871		0.873	
R < 1	1.000		0.941		0.942	
r(SARC, weight)	0.229		0.075		0.138	
			2000–2008			
Mean	0.217	(-0.186, 0.618)	0.125	(-0.282, 0.543)	0.096	(-0.311, 0.518)
Median	0.261	(-0.103, 0.461)	0.264	(-0.190, 0.532)	0.180	(-0.226, 0.553)
75th percentile	0.348	(-0.023, 0.958)	0.351	(0.067, 0.787)	0.351	(0.067, 0.661)
90th percentile	0.988	(0.267, 1.487)	0.494	(0.210, 1.061)	0.528	(0.128, 1.235)
Unweighted mean	0.042	(-0.359, 0.373)	0.045	(-0.333, 0.409)	-0.109	(-0.439, 0.241)
SARC < a.SARC	0.603		0.516		0.572	
CI < 1	0.849		0.756		0.786	
R < 1	1.000		0.993		0.991	
r(SARC, weight)	0.457		0.170		0.151	
No. of series	12		64		149	

Notes: Quarterly data, Q2/1983–Q3/2008, Q1/1993–Q3/2008 and Q1/2000–Q3/2008. *SARC* denotes the approximately median unbiased estimate of the sum of autoregressive coefficients following Andrews and Chen (1994). *CI* is the 90% confidence interval of the sum of autoregressive coefficients based on Hansen's (1999) grid bootstrap. All statistics are weighted using constant 2008 consumption expenditure shares unless otherwise indicated. *SARC < a.SARC* is the share of series for which the SARC is smaller than the SARC of the constant weight aggregate inflation. *CI < 1* denotes the share of series for which the SARC 90% confidence interval lies below unity. *R < 1* is the share of series for which the the largest eigenvalue in modulus is smaller than 1. *r(SARC, weight)* is the Pearson correlation coefficient between SARC and weight.

Table E.11: Persistence of common and sectoral components, Andrews and Chen (1994)

	Common component		Sectoral components	
	SARC	90% CI	SARC	90% CI
		1983–2008		
Main groups	0.879	(0.752, 1.033)	0.114	(-0.046, 0.656)
Product groups	0.932	(0.832, 1.039)	0.123	(-0.079, 0.432)
Index positions	0.878	(0.761, 1.029)	0.135	(-0.136, 0.411)
		1993–2008		
Main groups	0.116	(-0.084, 0.302)	0.275	(-0.040, 0.469)
Product groups	0.336	(0.137, 0.493)	0.165	(-0.243, 0.403)
Index positions	0.240	(0.030, 0.413)	0.115	(-0.207, 0.443)
		2000–2008		
Main groups	0.118	(-0.098, 0.408)	0.273	(-0.277, 0.409)
Product groups	0.914	(0.577, 1.205)	-0.032	(-0.408, 0.429)
Index positions	0.600	(0.221, 1.124)	-0.028	(-0.454, 0.400)

Notes: Quarterly data, Q2/1983–Q3/2008, Q1/1993–Q3/2008 and Q1/2000–Q3/2008. Common and sectoral components are estimated following Stock and Watson (2002). In a first step, the common component is obtained as the first principal component of standardized inflation rates. In a second step, time series of sectoral components are obtained as the residuals from regressing the sectoral inflation rate on the common component. *SARC* denotes the approximately median unbiased estimate of the sum of autoregressive coefficients following Andrews and Chen (1994). *CI* is the 90% confidence interval of the sum of autoregressive coefficients based on Hansen's (1999) grid bootstrap. The statistics for the sectoral components are weighted means using constant 2008 consumption expenditure shares.

Bibliography

Aalto-Setälä, V. (2006): "Why Do Consumers Believe That the Euro Raised Prices?," *International Journal of Consumer Studies*, 30(2), 202–206.

Acemoglu, D., V. Chernozhukov and M. Yildiz (2007): "Learning and Disagreement in an Uncertain World," NBER Working Paper 12648.

Akerlof, G. A., W. T. Dickens and G. L. Perry (2000): "Near-Rational Wage and Price Setting and the Long-Run Phillips Curve," *Brookings Papers on Economic Activity*, 31(1), 1–60.

Altissimo, F., M. Ehrmann and F. Smets (2006): "Inflation Persistence and Price-Setting Behaviour in the Euro Area," ECB Occasional Paper Series 46, European Central Bank.

Altissimo, F., B. Mojon and P. Zaffaroni (2009): "Can Aggregation Explain the Persistence of Inflation?," *Journal of Monetary Economics*, 56(2), 231–241.

Anderson, O. (1952): "The Business Test of the IFO-Institute for Economic Research Munich, and Its Theoretical Model," *Revue de l'Institut International de Statistique*, 20, 1–17.

Andolfatto, D., S. Hendry and K. Moran (2008): "Are Inflation Expectations Rational?," *Journal of Monetary Economics*, 55(2), 406–422.

Andrews, D. W. K. (1993): "Tests for Parameter Instability and Structural Change With Unknown Change Point," *Econometrica*, 61, 821–856.

——— (2003): "Tests for Parameter Instability and Structural Change With Unknown Change Point: A Corrigendum," *Econometrica*, 71(1), 395–397.

Andrews, D. W. K. and H.-Y. Chen (1994): "Approximately Median-Unbiased Estimation of Autoregressive Models," *Journal of Business & Economic Statistics*, 12(2), 187–204.

Ang, A., G. Bekaert and M. Wei (2007): "Do Macro Variables, Asset Markets, or Surveys Forecast Inflation Better?," *Journal of Monetary Economics*, 54, 1163–1212.

Aucremanne, L., M. Collin and T. Stragier (2007): "Assessing the Gap Between Observed and Perceived Inflation in the Euro Area: Is the Credibility of the HICP at Stake?," National Bank of Belgium Working Paper 112.

Baghestani, H. (1992): "Survey Evidence on the Muthian Rationality of the Inflation Forecasts of US Consumers," *Oxford Bulletin of Economics and Statistics*, 54(2), 173–186.

Bai, J. and P. Perron (1998): "Estimating and Testing Linear Models With Multiple Structural Changes," *Econometrica*, 66(1), 47–78.

Baltensperger, E., P. M. Hildebrand and T. J. Jordan (2007): "The Swiss National Bank's Monetary Policy Concept - An Example of a 'Principles-Based' Policy Framework," Swiss National Bank Economic Studies 3, Swiss National Bank.

Banerjee, A., M. Marcellino and C. Osbat (2004): "Some Cautions on the Use of Panel Methods for Integrated Series of Macroeconomic Data," *Econometrics Journal*, 7(2), 322–340.

Batchelor, R. A. (1982): "Aggregate Expectations Under the Stable Laws," *Journal of Econometrics*, 16(2), 199–210.

——— (1986): "Quantitative v. Qualitative Measures of Inflation Expectations," *Oxford Bulletin of Economics and Statistics*, 48(2), 99–120.

——— (2007): "Bias in Macroeconomic Forecasts," *International Journal of Forecasting*, 23(2), 189–203.

Batchelor, R. A. and P. Dua (1987): "The Accuracy and Rationality of UK Inflation Expectations: Some Quantitative Evidence," *Applied Economics*, 19(6), 819–828.

——— (1989): "Household Versus Economist Forecasts of Inflation: A Reassessment," *Journal of Money, Credit and Banking*, 21(2), 252–257.

Batchelor, R. A. and L. Jonung (1989): "Cross-Sectional Evidence on the Rationality of the Mean and Variance of Inflation Expectations," in *Understanding Economic Behaviour*, ed. by K. G. Grunert and F. Ölander, pp. 93–105. Kluwer Academic Publishers.

Batchelor, R. A. and A. B. Orr (1988): "Inflation Expectations Revisited," *Economica*, 55(219), 317–331.

Benati, L. (2008): "Investigating Inflation Persistence Across Monetary Regimes," *Quarterly Journal of Economics*, 123(3), 1005–1060.

Benford, J. and R. Driver (2008): "Public Attitudes to Inflation and Interest Rates," *Bank of England Quarterly Bulletin*, 48(2), 148–156.

Berk, J. M. (1999): "Measuring Inflation Expectations: A Survey Data Approach," *Applied Economics*, 31(11), 1467–1480.

Berndt, E. K., B. H. Hall, R. E. Hall and J. A. Hausman (1974): "Estimation and Inference in Nonlinear Structural Models," *Annals of Economic and Social Measurement*, 3(4), 653–665.

Bernoulli, D. (1954): "Exposition of a New Theory on the Measurement of Risk," *Econometrica*, 22(1), 23–36.

Bils, M. and P. J. Klenow (2004): "Some Evidence on the Importance of Sticky Prices," *Journal of Political Economy*, 112(5), 947–985.

Blair, J. and M. G. Lacy (1996): "Measures of Variation for Ordinal Data as Functions of the Cumulative Distribution," *Perceptual and Motor Skills*, 82(2), 411–418.

——— (2000): "Statistics of Ordinal Variation," *Sociological Methods & Research*, 28(3), 251–280.

BLINDER, A. S. AND A. B. KRUEGER (2004): "What Does the Public Know About Economic Policy, and How Does It Know It?," NBER Working Paper 10787.

BOERO, G., J. SMITH AND K. F. WALLIS (2008): "Uncertainty and Disagreement in Economic Prediction: The Bank of England Survey of External Forecasters," *Economic Journal*, 118, 1107–1127.

BOIVIN, J., M. GIANNONI AND I. MIHOV (2009): "Sticky Prices and Monetary Policy: Evidence From Disaggregated U.S. Data," *American Economic Review*, 99(1), 350–384.

BOIVIN, J. AND S. NG (2006): "Are More Data Always Better for Factor Analysis?," *Journal of Econometrics*, 132, 169–194.

BONHAM, C. S. AND R. H. COHEN (2000): "Rational Consensus Forecasts?," *Journal of Economic Perspectives*, 14(4), 228–230.

——— (2001): "To Aggregate, Pool, or Neither: Testing the Rational-Expectations Hypothesis Using Survey Data," *Journal of Business & Economic Statistics*, 19(3), 278–291.

BRANCH, W. A. (2004): "The Theory of Rationally Heterogeneous Expectations: Evidence From Survey Data on Inflation Expectations," *Economic Journal*, 114, 592–621.

——— (2007): "Sticky Information and Model Uncertainty in Survey Data on Inflation Expectations," *Journal of Economic Dynamics and Control*, 31, 245–276.

BREITUNG, J. AND M. H. PESARAN (2005): "Unit Roots and Cointegration in Panels," Deutsche Bundesbank Discussion Paper 42/2005.

BROCK, W. A. AND C. H. HOMMES (1997): "A Rational Route to Randomness," *Econometrica*, 65(5), 1059–1095.

BRYAN, M. F. AND S. PALMQVIST (2006): "Testing Near-Rationality Using Detailed Survey Data," Sveriges Riksbank Research Paper Series.

BRYAN, M. F. AND G. VENKATU (2001a): "The Curiously Different Inflation Perspectives of Men and Women," Federal Reserve Bank of Cleveland Economic Commentary Series.

——— (2001b): "The Demographics of Inflation Opinion Surveys," Federal Reserve Bank of Cleveland Economic Commentary Series.

CAGAN, P. (1956): "The Monetary Dynamics of Hyper-Inflation," in *Studies in the Quantity Theory of Money*, ed. by M. Friedman. University of Chicago Press.

CAPISTRÁN, C. AND A. TIMMERMANN (2009): "Disagreement and Biases in Inflation Expectations," *Journal of Money, Credit and Banking*, 41(2-3), 365–396.

CARLSON, J. A. (1975): "Are Price Expectations Normally Distributed?," *Journal of the American Statistical Association*, 352, 749–754.

CARLSON, J. A. AND M. PARKIN (1975): "Inflation Expectations," *Economica*, 42(166), 123–138.

CARROLL, C. D. (2003): "Macroeconomic Expectations of Households and Professional Forecasters," *Quarterly Journal of Economics*, 118(1), 269–298.

CHRISTIANO, L. J., M. EICHENBAUM AND C. L. EVANS (2005): "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," *Journal of Political Economy*, 113(1), 1–45.

CLARK, T. E. (2006): "Disaggregate Evidence on the Persistence of Consumer Price Inflation," *Journal of Applied Econometrics*, 21, 563–587.

COGLEY, T. AND T. J. SARGENT (2005): "Drifts and Volatilities: Monetary Policies and Outcomes in the Post WWII US," *Review of Economic Dynamics*, 8(2), 262–302.

Corvoisier, S. and B. Mojon (2005): “Breaks in the Mean of Inflation: How They Happen and What to Do With Them,” ECB Working Paper 451, European Central Bank.

Croushore, D. (2006): “An Evaluation of Inflation Forecasts From Surveys Using Real-Time Data,” Federal Reserve Bank of Philadelphia Workingpaper 06-19.

Curtin, R. (2005): “Inflation Expectations: Theoretical Models and Empirical Tests,” mimeo, University of Michigan.

——— (2007): “What U.S. Consumers Know About Economic Conditions,” mimeo, University of Michigan.

Das, M., J. Dominitz and A. van Soest (1999): “Comparing Predictions and Outcomes: Theory and Application to Income Changes,” *Journal of the American Statistical Association*, 94(445), 75–85.

Dasgupta, S. and K. Lahiri (1992): “A Comparative Study of Alternative Methods of Quantifying Qualitative Survey Responses Using NAPM Data,” *Journal of Business & Economic Statistics*, 10(4), 391–400.

——— (1993): “On the Use of Dispersion Measures From NAPM Surveys in Business Cycle Forecasting,” *Journal of Forecasting*, 12(3-4), 239–253.

Dearing, J. and E. Rogers (1996): *Agenda-Setting*. Sage, Thousand Oaks.

Defris, L. V. and R. A. Williams (1979): “Quantitative Versus Qualitative Measures of Price Expectations: The Evidence From Australian Consumer Surveys,” *Economics Letters*, 2(2), 169–173.

Dempster, A. P., N. M. Laird and D. B. Rubin (1977): “Maximum Likelihood From Incomplete Data via the EM Algorithm,” *Journal of the Royal Statistical Society, Series B (Methodological)*, 39(1), 1–38.

Dickey, D. A. and W. A. Fuller (1981): "Likelihood Ratio Statistics for Autoregressive Time Series With a Unit Root," *Econometrica*, 49(4), 1057–1072.

Doehring, B. and A. Mordonu (2007): "What Drives Inflation Perceptions? A Dynamic Panel Data Analysis," European Commission Economic Papers 284.

Dolado, J. and H. Lütkepohl (1996): "Making Wald Tests Work for Cointegrated VAR Systems," *Econometric Reviews*, 15, 369–386.

Dominitz, J. (1998): "Earnings Expectations, Revisions, and Realizations," *Review of Economics and Statistics*, 80(3), 374–388.

Doms, M. and N. Morin (2004): "Consumer Sentiment, the Economy, and the News Media," FRBSF Working Paper 2004-09, Federal Reserve Bank of San Francisco.

Döpke, J., J. Dovern, U. Fritsche and J. Slacalek (2008a): "The Dynamics of European Inflation Expectations," *B.E. Journal of Macroeconomics*, 8(1).

——— (2008b): "Sticky Information Phillips Curves: European Evidence," *Journal of Money, Credit and Banking*, 40(7), 1513–1520.

Döpke, J. and U. Fritsche (2006): "When Do Forecasters Disagree? An Assessment of German Growth and Inflation Forecast Dispersion," *International Journal of Forecasting*, 22(1), 125–135.

Driver, R. and R. Windram (2007): "Public Attitudes to Inflation and Interest Rates," *Bank of England Quarterly Bulletin*, 47(2), 208–223.

Dziuda, W. and G. Mastrobuoni (2006): "The Euro Changeover and Its Effects on Price Transparency and Inflation," Working Paper 26, Collegio Carlo Alberto.

ECB (2005): "Consumers' Inflation Perceptions: Still At Odds With Official Statistics?," *ECB Monthly Bulletin*, (4), 30–32.

Efron, B. and R. J. Tibshirani (1993): *An Introduction to the Bootstrap*. Chapman & Hall.

Ehrbeck, T. and R. Waldmann (1996): "Why Are Professional Forecasters Biased? Agency Versus Behavioral Explanations," *Quarterly Journal of Economics*, 111(1), 21–40.

Ehrmann, M. (2006): "Rational Inattention, Inflation Developments and Perceptions After the Euro Cash Changeover," ECB Working Paper 588, European Central Bank.

El-Gamal, M. A. and D. M. Grether (1995): "Are People Bayesian? Uncovering Behavioral Strategies," *Journal of the American Statistical Association*, 90(432), 1137–1145.

Elmer, S. and T. Maag (2009): "The Persistence of Inflation in Switzerland: Evidence From Disaggregate Data," KOF Working Papers 235, ETH Zurich.

European Commission (2007): *The Joint Harmonised EU Programme of Business and Consumer Surveys: User Guide,* European Commission, Directorate-General for Economic and Financial Affairs.

Evans, G. and R. Gulamani (1984): "Tests for Rationality of the Carlson-Parkin Inflation Expectations Data," *Oxford Bulletin of Economics and Statistics*, 46(1), 1–19.

Evans, G. W. and S. Honkapohja (2001): *Learning and Expectations in Macroeconomics*. Princeton University Press.

Ezekiel, M. (1938): "The Cobweb Theorem," *Quarterly Journal of Economics*, 52(2), 225–280.

Federal Statistical Office FSO (2008): *Consumer Price Index: Methodological Foundations.*

Feige, E. L. and D. K. Pearce (1976): "Economically Rational Expectations: Are Innovations in the Rate of Inflation Independent of Innovations in Measures of Monetary and Fiscal Policy?," *Journal of Political Economy*, 84(3), 499–522.

Figlewski, S. and P. Wachtel (1983): "Rational Expectations, Informational Efficiency, and Tests Using Survey Data: A Reply," *Review of Economics and Statistics*, 65(3), 529–531.

Findley, D. F., B. C. Monsell, W. R. Bell, M. C. Otto and B.-C. Chen (1998): "New Capabilities of the X-12-ARIMA Seasonal Adjustment Program," *Journal of Business & Economic Statistics*, 16(2), 127–177.

Fluch, M. and H. Stix (2007): "The Development of Euro Prices - Subjective Perception and Empirical Facts," *Monetary Policy and the Economy (OeNB)*, 07(1), 55–84.

Forsells, M. and G. Kenny (2004): "Survey Expectations, Rationality and the Dynamics of Euro Area Inflation," *Journal of Business Cycle Measurement and Analysis*, 1(1), 13–41.

Friedman, M. (1968): "The Role of Monetary Policy," *American Economic Review*, 58(1), 1–17.

Fuhrer, J. and G. Moore (1995): "Inflation Persistence," *Quarterly Journal of Economics*, 110(1), 127–159.

Fullone, F., M. Gamba, E. Giovannini and M. Malgarini (2007): "What Do Citizens Know About Statistics? The Results of an OECD/ISAE Survey on Italian Consumers," Report, OECD.

Galí, J. and M. Gertler (1999): "Inflation Dynamics: A Structural Econometric Analysis," *Journal of Monetary Economics*, 44(2), 195–222.

GfK (2002): *Consumer Tendency Survey,* GfK Sweden, Stockholm, Sweden.

GIORDANI, P. AND P. SÖDERLIND (2003): "Inflation Forecast Uncertainty," *European Economic Review*, 47(6), 1037–1059.

GOETTE, L., R. MINSCH AND J.-R. TYRAN (2005): "Micro Evidence on the Adjustment of Sticky-Price Goods: It's How Often, Not How Much," Department of Economics Discussion Paper 05-20, University of Copenhagen.

GRAMLICH, E. M. (1983): "Models of Inflation Expectations Formation: A Comparison of Household and Economist Forecasts," *Journal of Money, Credit and Banking*, 15(2), 155–173.

GRANT, A. P. AND L. B. THOMAS (1999): "Inflationary Expectations and Rationality Revisited," *Economics Letters*, 62(3), 331–338.

——— (2001): "Supply Shocks and the Rationality of Inflation Forecasts," *Quarterly Review of Economics and Finance*, 41(4), 515–532.

HAMILTON, J. D. (1994): *Time Series Analysis*. Princeton University Press.

HANSEN, B. E. (1999): "The Grid Bootstrap and the Autoregressive Model," *Review of Economics and Statistics*, 81(4), 594–607.

HAUSMAN, J., B. H. HALL AND Z. GRILICHES (1984): "Econometric Models for Count Data with an Application to the Patents-R&D Relationship," *Econometrica*, 52(4), 909–938.

HEIKENSTEN, L. (1999): "The Riksbank's Inflation Target — Clarification and Evaluation," *Sveriges Riksbank Economic Review*, (1), 5–17.

HENZEL, S. AND T. WOLLMERSHÄUSER (2005): "Quantifying Inflation Expectations With the Carlson-Parkin Method: A Survey-based Determination of the Just Noticeable Difference," *Journal of Business Cycle Measurement and Analysis*, 2(3).

HOLSTI, O. R. (1969): *Content Analysis for the Social Sciences and Humanities*. Addison-Wesley.

Huwiler, M. (2007): *Die Kerninflation in der Schweiz.* dissertation.de (Dissertation, University of Basel).

Im, K. S., M. H. Pesaran and Y. Shin (2003): "Testing for Unit Roots in Heterogeneous Panels," *Journal of Econometrics*, 115, 53–74.

Jaramillo, C. F. (1999): "Inflation and Relative Price Variability: Reinstating Parks' Results," *Journal of Money, Credit and Banking*, 31(3), 375–385.

Jonung, L. (1981): "Perceived and Expected Rates of Inflation in Sweden," *American Economic Review*, 71(5), 961–968.

——— (1986): "Uncertainty About Inflationary Perceptions and Expectations," *Journal of Economic Psychology*, 7(5), 315–325.

Jonung, L. and D. Laidler (1988): "Are Perceptions of Inflation Rational? Some Evidence for Sweden," *American Economic Review*, 78(5), 1080–1087.

Jordan, T. J. and M. Peytrignet (2001): "Die Inflationsprognose der Schweizerischen Nationalbank," in *Swiss National Bank Quarterly Bulletin*, no. 2, pp. 54–61.

Kandel, E. and B.-Z. Zilberfarb (1999): "Differential Interpretation of Information in Inflation Forecasts," *Review of Economics and Statistics*, 81(2), 217–226.

Kaufmann, D. (2009): "Price-Setting Behaviour in Switzerland: Evidence From CPI Micro Data," *Swiss Journal of Economics and Statistics*, 145(3), 293–349.

Keane, M. P. and D. E. Runkle (1990): "Testing the Rationality of Price Forecasts: New Evidence From Panel Data," *American Economic Review*, 80(4), 714–735.

Kemp, S. (1987): "Estimation of Past Prices," *Journal of Economic Psychology*, 8(2), 181–189.

Keynes, J. M. (1936): *The General Theory of Employment Interest and Money.* Macmillan.

Khan, H. and Z. Zhu (2006): "Estimates of the Sticky-Information Phillips Curve for the United States," *Journal of Money, Credit and Banking*, 38(1), 195–207.

Kokoski, M. (2000): "Alternative CPI Aggregations: Two Approaches," *Monthly Labor Review*, 123(11), 31–39.

Kwiatkowski, D., P. C. B. Phillips, P. Schmidt and Y. Shin (1992): "Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root: How Sure Are We That Economic Time Series Have a Unit Root?," *Journal of Econometrics*, 54(1-3), 159–178.

Lacy, M. G. (2006): "An Explained Variation Measure for Ordinal Response Models With Comparisons to Other Ordinal R^2 Measures," *Sociological Methods & Research*, 34(4), 469–520.

Lahiri, K. and X. Sheng (2008): "Evolution of Forecast Disagreement in a Bayesian Learning Model," *Journal of Econometrics*, 144(2), 325–340.

——— (2009a): "Learning and Heterogeneity in GDP and Inflation Forecasts," Discussion Paper (forthcoming, International Journal of Forecasting) 09-05, University at Albany, SUNY.

——— (2009b): "Measuring Forecast Uncertainty by Disagreement: The Missing Link," mimeo (forthcoming, Journal of Applied Econometrics), University at Albany, SUNY.

Lahiri, K. and C. Teigland (1987): "On the Normality of Probability Distributions of Inflation and GNP Forecasts," *International Journal of Forecasting*, 3(2), 269–279.

Lamla, M. J. and S. M. Lein (2008): "The Role of Media for Consumers' Inflation Expectation Formation," KOF Working Papers 201, ETH Zurich.

Lanne, M., H. Lütkepohl and P. Saikkonen (2002): "Comparison of Unit Root Tests for Time Series With Level Shifts," *Journal of Time Series Analysis*, 23(6), 667–685.

LASTER, D., P. BENNETT AND I. S. GEOUM (1999): "Rational Bias in Macroeconomic Forecasts," *Quarterly Journal of Economics*, 114(1), 293–318.

LEIN, S. M. (2007): "When Do Firms Adjust Prices? Evidence From Micro Panel Data," KOF Working Papers 160, ETH Zurich.

LEIN, S. M. AND T. MAAG (2008): "The Formation of Inflation Perceptions — Some Empirical Facts for European Countries," KOF Working Papers 204, ETH Zurich.

LEVIN, A. T. AND J. M. PIGER (2004): "Is Inflation Persistence Intrinsic in Industrial Economies?," ECB Working Paper 334, European Central Bank.

LOVELL, M. C. (1986): "Tests of the Rational Expectations Hypothesis," *American Economic Review*, 76(1), 110–124.

LUCAS, R. E. (1972a): "Econometric Testing of the Natural Rate Hypothesis," in *The Econometrics of Price Determination Conference*, ed. by O. Eckstein, pp. 50–59. Board of Governors of the Federal Reserve System (reprinted in Lucas, Robert E. (1981): *Studies in Business-Cycle Theory*, Blackwell, pp. 90-103).

——— (1972b): "Expectations and the Neutrality of Money," *Journal of Economic Theory*, 4(2), 103–124.

——— (1973): "Some International Evidence on Output-Inflation Tradeoffs," *American Economic Review*, 63(2), 326–334.

——— (1976): "Econometric Policy Evaluation: A Critique," *Carnegie-Rochester Conference Series on Public Policy*, 1, 19–46.

LUSARDI, A. AND O. S. MITCHELL (2007): "Baby Boomer Retirement Security: The Roles of Planning, Financial Literacy, and Housing Wealth," *Journal of Monetary Economics*, 54(1), 205–224.

LÜTKEPOHL, H. AND M. KRÄTZIG (eds.) (2004): *Applied Time Series Econometrics*. Cambridge University Press.

Maag, T. (2009): “On the Accuracy of the Probability Method for Quantifying Beliefs About Inflation,” KOF Working Papers 230, ETH Zurich.

Maag, T. and M. J. Lamla (2009): “The Role of Media for Inflation Forecast Disagreement of Households and Professional Forecasters,” KOF Working Papers 223, ETH Zurich.

MacKinnon, J. G. (1991): “Critical Values for Cointegration Tests,” in *Long-Run Economic Relationships: Readings in Cointegration*, ed. by R. F. Engle and C. W. J. Granger, pp. 267–276. Oxford University Press.

Mankiw, N. G. and R. Reis (2002): “Sticky Information Versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve,” *Quarterly Journal of Economics*, 117(4), 1295–1328.

——— (2006): “Pervasive Stickiness,” *American Economic Review*, 96(2), 164–169.

Mankiw, N. G., R. Reis and J. Wolfers (2004): “Disagreement About Inflation Expectations,” *NBER Macroeconomics Annual 2003*, 18, 209–248.

McCombs, E. (2004): *Setting the Agenda: The Mass Media and Public Opinion.* Polity Press Cambridge.

McCombs, E. and D. Shaw (1972): “The Agenda-Setting Function of Mass-Media,” *Public Opinion Quarterly*, 36(2), 176–187.

McLachlan, G. J. and T. Krishnan (2008): *The EM Algorithm and Extensions.* Wiley Series in Probability and Statistics, 2nd edn.

Mehra, Y. P. (2002): “Survey Measures of Expected Inflation: Revisiting the Issues of Predictive Content and Rationality,” *Economic Quarterly*, 88(3), 17–36.

Morduch, J. J. and H. S. Stern (1997): “Using Mixture Models to Detect Sex Bias in Health Outcomes in Bangladesh,” *Journal of Econometrics*, 77(1), 259–276.

MUDHOLKAR, G. S. (2006): "Fisher's z-Transformation," in *Encyclopedia of Statistical Sciences*, ed. by S. Kotz, C. B. Read, N. Balakrishnan and B. Vidakovic. Wiley.

MUTH, J. F. (1961): "Rational Expectations and the Theory of Price Movements," *Econometrica*, 29, 315–335.

NARDO, M. (2003): "The Quantification of Qualitative Survey Data: A Critical Assessment," *Journal of Economic Surveys*, 17, 645–668.

NEWEY, W. K. AND K. D. WEST (1994): "Automatic Lag Selection in Covariance Matrix Estimation," *Review of Economic Studies*, 61(3), 631–653.

O'REILLY, G. AND K. WHELAN (2005): "Has Euro-Area Inflation Persistence Changed Over Time?," *Review of Economics and Statistics*, 87(4), 709–720.

PALMQVIST, S. AND L. STRÖMBERG (2004): "Households' Inflation Opinions - A Tale of Two Surveys," *Sveriges Riksbank Economic Review*, 4, 23–42.

PAPADIA, F. (1983): "Rationality of Inflationary Expectations in the European Economic Communities Countries," *Empirical Economics*, 8(3-4), 187–202.

PEDRONI, P. (1999): "Critical Values for Cointegration Tests in Heterogeneous Panels With Multiple Regressors," *Oxford Bulletin of Economics and Statistics*, 61, 653–670.

——— (2004): "Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Tests With an Application to the PPP Hypothesis," *Econometric Theory*, 20, 597–625.

PERRON, P. (1988): "Trends and Random Walks in Macroeconomic Time Series," *Journal of Economic Dynamics and Control*, 12, 297–332.

PERRON, P. (1989): "The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis," *Econometrica*, 57(6), 1361–1401.

PESARAN, M. H. (1987): *The Limits to Rational Expectations*. Blackwell.

——— (2007): "A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence," *Journal of Applied Econometrics*, 22(2), 265–312.

PESARAN, M. H. AND R. SMITH (1995): "Estimating Long-Run Relationships From Dynamic Heterogeneous Panels," *Journal of Econometrics*, 68, 79–113.

PESARAN, M. H. AND M. WEALE (2006): "Survey Expectations," in *Handbook of Economic Forecasting*, ed. by G. Elliott, C. W. J. Granger and A. Timmermann, vol. 1, pp. 715–776. Elsevier.

PHELPS, E. S. (1967): "Phillips Curves, Expectations of Inflation and Optimal Unemployment Over Time," *Economica*, 34(135), 254–281.

PHILLIPS, A. W. (1958): "The Relation Between Unemployment and the Rate of Change of Money Wage Rates in the United Kingdom, 1861–1957," *Economica*, 25(100), 283–299.

PIERSE, R. G. AND A. J. SNELL (1995): "Temporal Aggregation and the Power of Tests for a Unit Root," *Journal of Econometrics*, 65(2), 333–429.

PIVETTA, F. AND R. REIS (2007): "The Persistence of Inflation in the United States," *Journal of Economic Dynamics and Control*, 31, 1326–1358.

RAPACH, D. E. AND M. E. WOHAR (2005): "Regime Changes in International Real Interest Rates: Are They a Monetary Phenomenon?," *Journal of Money, Credit and Banking*, 37(5), 887–906.

REDNER, R. A. AND H. F. WALKER (1984): "Mixture Densities, Maximum Likelihood and the EM Algorithm," *SIAM Review*, 26(2), 195–239.

REIS, R. (2006): "Inattentive Consumers," *Journal of Monetary Economics*, 53(8), 1761–1800.

ROBERTS, J. M. (1997): "Is Inflation Sticky?," *Journal of Monetary Economics*, 39, 173–196.

Rudd, J. and K. Whelan (2007): "Modeling Inflation Dynamics: A Critical Review of Recent Research," *Journal of Money, Credit and Banking*, 39(1), 155–170.

Saikkonen, P. and H. Lütkepohl (2002): "Testing for a Unit Root in a Time Series With a Level Shift at Unknown Time," *Econometric Theory*, 18(2), 313–348.

Samuelson, P. A. and R. M. Solow (1960): "Analytical Aspects of Anti-Inflation Policy," *American Economic Review*, 50(2), 177–194.

Sargent, T. J. (1973): "Rational Expectations, the Real Rate of Interest, and the Natural Rate of Unemployed," *Brookings Papers on Economic Activity*, (2), 429–472.

Scott, D. W. (1992): *Multivariate Density Estimation: Theory, Practice, and Visualization*. John Wiley & Sons.

Sheafer, T. (2007): "How to Evaluate It: The Role of Story-Evaluative Tone in Agenda Setting and Priming," *Journal of Communication*, 57(1), 21–39.

Sims, C. A. (1998): "Stickiness," *Carnegie-Rochester Conference Series on Public Policy*, 49, 317–356.

——— (2003): "Implications of Rational Inattention," *Journal of Monetary Economics*, 50(3), 665–690.

——— (2009): "Inflation Expectations, Uncertainty and Monetary Policy," BIS Working Papers 275, Bank for International Settlements.

Smith, J. and M. McAleer (1995): "Alternative Procedures for Converting Qualitative Response Data to Quantitative Expectations: An Application to Australian Manufacturing," *Journal of Applied Econometrics*, 10(2), 165–185.

Soroka, S. N. (2006): "Good News and Bad News: Asymmetric Responses to Economic Information," *Journal of Politics*, 68(2), 372–385.

Souleles, N. S. (2004): “Expectations, Heterogeneous Forecast Errors, and Consumption: Micro Evidence From the Michigan Consumer Sentiment Surveys,” *Journal of Money, Credit and Banking*, 36(1), 39–72.

Stix, H. (2005): “Perceived Inflation and the Euro: Why High? Why Persistent?,” in *Proceedings of OeNB Workshops: Price Setting and Inflation Persistence, December 15, 2005*, no. 8, pp. 221–249. Oesterreichische Nationalbank.

Stock, J. H. and M. W. Watson (2002): “Macroeconomic Forecasting Using Diffusion Indexes,” *Journal of Business & Economic Statistics*, 20(2), 147–162.

Stock, J. H. and M. W. Watson (2007): “Why Has U.S. Inflation Become Harder to Forecast?,” *Journal of Money, Credit and Banking*, 39(1), 3–33.

Teräsvirta, T. (2004): “Smooth Transition Regression Modelling,” in *Applied Time Series Econometrics*, ed. by H. Lütkepohl and M. Krätzig, chap. 6, pp. 222–242. Cambridge University Press.

Theil, H. (1952): “On the Shape of Microvariables and the Munich Business Test,” *Revue de l'Institut International de Statistique*, 20, 105–120.

——— (1955): “Recent Experiences With the Munich Business Test: An Expository Article,” *Econometrica*, 23(2), 184–192.

Thomas, L. B. (1999): “Survey Measures of Expected U.S. Inflation,” *Journal of Economic Perspectives*, 13(4), 125–144.

Titterington, D., A. Smith and U. Makov (1985): *Statistical Analysis of Finite Mixture Distributions.* Wiley Series in Probability and Mathematical Statistics.

Traut-Mattausch, E., S. Schulz-Hardt, T. Greitemeyer and D. Frey (2004): “Expectancy Confirmation in Spite of Disconfirming Evidence: The Case of Price Increases due to the Introduction of the Euro,” *European Journal of Social Psychology*, 34, 739–760.

TVERSKY, A. AND D. KAHNEMAN (1973): "Availability: A Heuristic for Judging Frequency and Probability," *Cognitive Psychology*, 5(2), 207–232.

VAN DER KLAAUW, W., W. B. DE BRUIN, G. TOPA, S. POTTER AND M. BRYAN (2008): "Rethinking the Measurement of Household Inflation Expectations: Preliminary Findings," Staff Report 359, Federal Reserve Bank of New York.

VANDERHOFF, J. (1984): "A 'Rational' Explanation for 'Irrational' Forecasts of Inflation," *Journal of Monetary Economics*, 13(3), 387–392.

VON NEUMANN, J. AND O. MORGENSTERN (1944): *Theory of Games and Economic Behavior*. Wiley.

WANG, P. AND Y. WEN (2007): "Inflation Dynamics: A Cross-Country Investigation," *Journal of Monetary Economics*, 54, 2004–2031.

WILLIAMS, J. C. (2004): "Comment on Disagreement About Inflation Expectations," *NBER Macroeconomics Annual 2003*, 18, 257–268.

WOODFORD, M. (2003): *Interest and Prices*. Princeton University Press.

——— (2007): "Interpreting Inflation Persistence: Comments on the Conference on 'Quantitative Evidence on Price Determination'," *Journal of Money, Credit and Banking*, 39(1), 203–210.

ZAFFARONI, P. (2004): "Contemporaneous Aggregation of Linear Dynamic Models in Large Economies," *Journal of Econometrics*, 120, 75–102.

ZAVOINA, W. AND R. D. MCKELVEY (1975): "A Statistical Model for the Analysis of Ordinal Level Dependent Variables," *Journal of Mathematical Sociology*, 4, 103–120.

ZURLINDEN, M. (2007): "Preissetzungsverhalten von Unternehmen: Auswertung einer Umfrage der Delegierten für regionale Wirtschaftskontakte," *Swiss National Bank Quarterly Bulletin*, pp. 48–55.

KOF Dissertation Series

No 1 **Causes and Consequences of Democracy and Terror**
Martin Gassebner

No 2 **The Impact of News on Expectation Formation in Monetary Policy, Business Cycles and Inflation Forecasts**
Michael J. Lamla

No 3 **Micro Price Adjustments and Macro Inflation Dynamics**
Sarah M. Lein

No 4 **Essays on Inflation Expectation Formation**
Thomas Maag

KOF

ETH Zürich
KOF Konjunkturforschungsstelle
WEH D 4
Weinbergstrasse 35
8092 Zürich

Telefon +41 44 632 42 39
Fax +41 44 632 12 18
www.kof.ethz.ch
kof@kof.ethz.ch