Individual Subjective Expectations about Macroeconomic Outcomes

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Preface

Why do we accept cash in return for goods and services? Why do people spend time and money on higher education rather than get a job and earn money right away? And why do some individuals invest their money in start-ups which are clearly not profitable, at least in the short run? Answering these questions may seem trivial, but it may be less obvious that the answers all relate to individuals' subjective expectations. We accept cash because we *expect* that cash can be exchanged for goods and services again in the future. People spend additional time obtaining a BSc or MBA because they *expect* their future earnings to compensate for forgone earnings. And individuals invest in start-ups because they *expect* them to perform well in the future and to benefit from their future profits.

Indeed, some scholars argue that this forward-looking aspect of individuals' decision-making is the key difference between the natural sciences and economics (Evans and Honkapohja, 2001). Clearly, a particle has no sense of the future, but an economic agent does. Most of the outcomes that we want to influence through our decisions only materialize in the future and are therefore subject to uncertainty. This applies to outcomes in the labor market and the financial market, as well as to educational outcomes and fertility outcomes. In brief, they include the most important aspects of human life. To incorporate this innate uncertainty, economists prefer to frame these decision-making problems of individuals in intertemporal or probabilistic contexts rather than in static or deterministic contexts. And in solving these decision problems, individuals' subjective expectations play a key role.

John Maynard Keynes is arguably one of the first scholars to emphasize the peculiar role of expectations in economics.[1] In his *General Theory of Employment, Interest and Money*, Keynes (1936) brings expectations to the center of macroeconomic analysis, determining investment as well as output and employment, but does not explicitly model how expectations are formed. The decades after Keynes' *General Theory* are marked by the introduction of expectations into most sub-fields of macroeconomics, typically in the form of *adaptive expectations* or related lag schemes (Evans and Honkapohja, 2001, p.7). The concept of *adaptive expectations* – formally introduced by Cagan (1956) – models expectations about an economic variable as a weighted average of past observations of the same variable, typically with geometrically declining weights. One of the most prominent applications is the expectations-augmented Phillips curve, which was highlighted in Milton Friedman's (1968) presidential address (Hall and Sargent, 2018).

In the 1970s, the existing macroeconomic models, and thus the *adaptive expectations* hypothesis, were challenged. The criticism focused mainly on three issues (Dovern, 2018). First, individuals are assumed to be only backward-looking. In particular, neither current conditions nor anticipated shocks are allowed to play a role in the formation of expectations. Second, individuals do not learn from their mistakes, because adjustments in expectations are purely mechanical. Expectations can therefore have systematic errors and persistent biases. Third, individuals do not react to current policy changes. This implies, for example, that the announcement of expansionary monetary policy has no effect on expectations; instead, agents will wait until they observe a potential increase in inflation and then adjust their expectations accordingly.

This criticism came from neoclassical economists, in particular Lucas (1972) and Sargent (1973), who argued that individuals are "rational" in the sense that they anticipate the effects of policy changes and adjust their expectations immediately. Building on earlier

[1] As pointed out in Evans and Honkapohja (2001, p.6), early references to economic expectations or forecasts can be found in Aristotle's *Politics* and the Bible.

work by Muth (1961), their approach of *rational expectations* imposes the strong assumption of full information and argues that economic outcomes can – under this assumption – not systematically differ from individuals' expectations. In fact, according to the *rational expectations* hypothesis individuals' subjective expectations are identical to the objective expectations of an outside observer who knows the underlying economic model (Adam et al., 2018). This does not imply that individuals do not make forecasting errors, but the errors cannot occur persistently or systematically. The underlying logic of the *rational expectations* hypothesis closely follows the oft-cited expression attributed to Abraham Lincoln:

> *"You can fool all the people some of the time, and some of the people all the time, but you cannot fool all the people all the time."*

One famous application of *rational expectations* is the efficient market hypothesis of asset prices (Fama, 1970). Assuming that asset prices fully reflect all available information, it is impossible to purchase undervalued (or sell overvalued) stocks and thus impossible to outperform the market consistently. The underlying reason is that under *rational expectations*, changes in daily stock prices follow a random walk and the best predictor of the future stock price is its current value. Another famous application is the Policy Ineffectiveness Proposition (PIP) by Sargent and Wallace (1975). Again using the concept of *rational expectations*, the PIP suggests that monetary policy cannot systematically affect output and employment in the economy. Since individuals will anticipate the effects of monetary policy, their price and wage expectations will adjust, keeping real wages and output unchanged.

Starting in the 1990s, macroeconomic models tried to relax the strong assumptions imposed by the *rational expectations* hypothesis. For example, so-called adaptive learning models assume that individuals try to estimate specific forecast rules for economic variables as new data becomes available over time. Here, individuals are only required to recognize predictable patterns in economic data, but not to know or understand the origin of these patterns, thus relaxing the assumption of omniscient individuals (cf. Evans and Honkapohja, 2001)[2]. Woodford (2013) gives a comprehensive overview of alternative and more recent approaches without the *rational expectations* hypothesis, including models with sticky, or noisy information, rational inattention, "eductive" expectations and theories of nearly correct beliefs.

Empirical research on expectations and therefore the collection of survey data on individuals' expectations significantly lagged behind, mainly for two reasons (Bachmann, 2017). The first reason is that many economists were still influenced by the behaviorist tradition. Similar to the revealed preference approach in microeconomics, they argued that only observed choices and actions matter, but not what individuals say or expect. The second reason is related to the relatively broad acceptance of *rational expectations* in economics. As stated by Adam et al. (2018), the "[...] rational expectations approach is elegant, internally consistent, and it eliminates the need to empirically study the formation of subjective expectations [...]" (p.2). Regarding the discrepancy between the number of theoretical and empirical studies on expectations, Woodford (2013) concludes:

> *"One answer would be that empirical studies should be undertaken to determine which of these possible specifications of subjective expectations best describe observed behavior. A few studies of that kind already exist, but the empirical literature remains at a fairly early stage."* (p.343)

An even earlier call for more empirical research on subjective expectations in general – not only on macroeconomic expectations – was issued by Manski (2004). He argues that – in order to understand the determinants of subjective expectations and their role in decision-making – expectations must be measured at the individual level. Probabilistic data on subjective expectations can not only help to better predict choice behavior, but also help to relax or validate assumptions about expectations in a disciplined way. Therefore, in

[2] Interestingly, learning models can often be used to provide an asymptotic justification of the *rational expectations* hypothesis (see, for example, Evans and Honkapohja, 2001; Woodford, 2013).

the 1990s and 2000s, large-scale surveys, such as the Survey of Economic Expectations, the Health and Retirement Survey, the Bank of Italy's Survey of Household Income and Wealth, and the Michigan Survey of Consumers, started to include probabilistic expectations questions in their questionnaires.[3] Examples include expectations questions about the future stock market performance, survival up to the age of 75, personal income in the coming year, the weather of tomorrow and so on.

This relatively novel survey data enables researchers to conduct a more sophisticated analysis of individuals' expectations, and also forms the basis of this dissertation. Empirical research on expectations typically identifies large, systematic differences across demographic groups (see, amongst others, Dominitz and Manski, 1997, 2011; Manski, 2004; Ranyard et al., 2008; Hurd, 2009; Hurd et al., 2011; Armantier et al., 2013). This is clearly not in line with the *rational expectations* hypothesis, which predicts no interpersonal heterogeneity given the absence of private information, as it is arguably the case for expectations about aggregate macroeconomic variables (Manski, 2018).

My dissertation contributes to the literature by empirically analyzing expectations of individuals from three different perspectives. Following the calls by Manski (2004, 2018) and Woodford (2013), I use survey data on individuals' macroeconomic expectations to better understand the sources of interpersonal heterogeneity (Chapter One), to analyze the formation process of individuals' expectations (Chapter Two) and to study how economic uncertainty is linked with response behavior in expectation data (Chapter Three). Each chapter includes its own introduction, analysis, conclusion and appendix and can be read independently. The references are presented together at the end of the dissertation.

[3] Some surveys, such as the Michigan Survey of Consumers, started to collect data on individuals' expectations even earlier. However, they asked for point expectations, rather than probabilistic expectations, which makes it impossible for the respondent to express uncertainty (Manski, 2004, 2018).

Chapter One of my dissertation is motivated by the fact that survey responses on subjective expectations are quite heterogeneous. Amongst others, income expectations, health expectations and stock market expectations are shown to systematically vary across respondents (see, for example, Dominitz and Manski, 1997; Manski, 2004, 2018; Hurd, 2009; Hurd et al., 2011). One obvious explanation for heterogeneity in expectations is private information. However, for macroeconomic expectations, i.e. individuals' expectations about macroeconomic outcomes, private information arguably should not play a role and can therefore not explain interpersonal differences.

I contribute to a recent literature arguing that individuals' expectations are influenced by their experiences during life. For example, individuals growing up in the 1970s and early 1980s, when inflation was soaring in the US, are likely to form different inflation expectations than individuals growing up in the 1990s and 2000s, when inflation rates were relatively low (Malmendier and Nagel, 2016). Building on this idea, I argue that individuals' macroeconomic expectations are systematically linked with their experiences of these macroeconomic outcomes during life. Specifically, I focus on expectations from three domains: expectations about national inflation, national unemployment and national business conditions.

My empirical approach is based on Malmendier and Nagel (2011) and summarizes individuals' experiences by a weighted average of the respective macroeconomic outcome variable over individuals' lifetime. The weights are allowed to flexibly increase, be constant or decrease over time, depending on a weighting parameter, which is estimated from the data. I extend their model by allowing for heterogeneity in both the weighting parameter and the experience effect, i.e. the effect of experience on individuals' expectations in the respective domain. Finally, I apply the model to repeated cross-sectional data between 1978 and 2017 from the Michigan Survey of Consumers.

The results suggest that respondents' experiences significantly predict their expectations. Indeed, extrapolation from past data is found in all three domains. In the inflation and unemployment domains, respondents are shown to put on average more weight on recent rather than distant years, when aggregating past information. When forming business expectations, respondents seem to use a slightly different weighting scheme. In fact, respondents' weights are in this case almost constant over time, implying that recent and distant years are equally important to respondents. I also provide evidence for gender differences in both the experience effect and the weighting pattern of past data. On average, males put more weight on distant years, when aggregating past information, and their expectations are generally less affected by past experiences, compared to females' expectations. Differences regarding other socio-economic characteristics are found to have no systematic effect, which is also supported by a Lasso analysis in the inflation domain.

Chapter Two is a joint project with Florian Heiß, Michael Hurd, Maarten van Rooij and Joachim Winter. The analysis is based on a unique data set, which covers subjective stock market expectations elicited with the same probabilistic format over a period of twelve years, including the financial market crisis. As an important innovation in the econometric methodology for the analysis of subjective expectations, we propose a panel data model with a finite mixture of expectation types who differ in how they use past stock market returns to form current stock market expectations. The model also allows for rounding in the probabilistic responses and for observed and unobserved heterogeneity at several levels.

Specifically, we follow ideas by Dominitz and Manski (2011), who suggest that the population can be described by three latent expectation types. The first type (Random Walk, RW) believes that returns are independent and identically distributed (i.i.d.) over time and – given this belief – uses the long-run historical average return to predict returns. Type two (Mean Reversion, MR) believes that recent stock market changes will be reversed in the near future and type three (Persistence, P) believes that recent stock market changes will persist into the near future.

We find that the population may indeed be described by these three distinct expectation types and estimate the distribution of (RW,MR,P) types in the population to be (0.60,0.19,0.21). In years unaffected by the 2008 financial crisis, the type distributions are very similar. However, after the onset of the crisis, we find a substantial increase in the MR type share, which is followed by a large increase in the P type share. Both effects are, however, shown to be temporary, resulting in a 2016 type distribution which is close to the pre-crisis distributions of 2004 and 2006. In addition, the analysis reveals the existence of substantial individual-specific heterogeneity in the type probabilities. For example, females are significantly more likely to be type MR or type P than males, and highly educated respondents are more likely to be type RW. We also find evidence for the importance in accounting for unobserved characteristics.

Chapter Three relates economic uncertainty and survey response behavior. In particular, it builds on work by Binder (2017) who suggests that the population can be described by a mixture of two different response types. When asked about the year-ahead inflation point expectations, type NR (non-rounder) reports her true expectation, while type RD (rounder) rounds her answer to a multiple of five percent. Binder (2017) shows that the estimated monthly share of rounders can serve as measure of economic uncertainty.

I extend her econometric model in several dimensions. First, I introduce a third response type DK for respondents, who choose a “don’t know” option, when asked about their inflation expectations. Second, I add a panel dimension to the econometric model and estimate the uncertainty index by month-year fixed effects in the model for the type probabilities, rather than by hundreds of separate estimations. Third, I allow the type probabilities to depend on both observed and unobserved heterogeneity, rather than treating them as constant scalars. I therefore contribute to the literature by providing a rich, but tractable panel data model for inflation expectations, which – in contrast to previous studies, in particular Binder (2017) – allows for an additional panel dimension, individual-specific heterogeneity and item nonresponse.

The model is applied to monthly data from the Michigan Survey of Consumers (MSC) between 1978 and 2017. Assuming type RD rounds to the next multiple of five percent, the estimated population shares of types (NR,RD,DK) are (0.65,0.28,0.07). This implies that most respondents report their true inflation expectation, while only few choose "don't know" as a response. In addition, males and respondents with at least a college degree are found to be significantly less likely to round or to choose "don't know", compared to females and respondents without a college degree. I also provide evidence for the importance in accounting for unobserved factors. Respondents who are more likely to round are shown to also be more likely to choose a "don't know" option. This also suggests that discarding non-respondents – as often done in the literature and also in Binder (2017) – is not entirely correct. In addition, my model identifies considerable heterogeneity across individuals' inflation expectations, confirming previous findings from the literature. I also find evidence for intrapersonal stability of response types. Lastly, following Binder (2017), I also construct an uncertainty index which is given by the monthly share of rounders (RD) and respondents choosing the "don't know" option (DK). The resulting uncertainty index is, however, almost identical to the uncertainty index by Binder (2017), suggesting that the advantages of the generalized model – at least in terms of measuring macroeconomic uncertainty – are small.

Chapter 1

Does experience shape subjective expectations?

Abstract

This paper documents that individuals' expectations about macroeconomic outcomes are systematically linked with their experiences of these macroeconomic outcomes during life. Focusing on expectations about national inflation, national unemployment and national business conditions, I measure individual-specific experiences as weighted averages of past inflation rates, national unemployment rates and returns of the S&P 500 index over the respondent's lifetime, respectively. I find that experience significantly predicts respondents' expectations in each of the three domains and show that individuals generally put more weight on recent rather than distant years, when aggregating past information. My empirical model also allows for heterogeneity with respect to observed socio-economic characteristics. The estimates suggest the existence of a gender effect. Compared to females, males concentrate relatively more on distant years when aggregating past information and their expectations are generally less associated with experience.

1.1 Introduction

Expectations play an important role in microeconomics and macroeconomics, and are particularly relevant when individuals face inter-temporal decision problems. However, contrary to what is predicted by many economic models, empirical evidence has pointed to substantial heterogeneity in respondents' reported expectations (cf. Manski, 2004, 2018; Hurd, 2009). Measurement error is not able to explain this heterogeneity, because expectations often vary systematically across respondents and thus not randomly. Private information is another obvious explanation for heterogeneity in expectations. However, while it may explain heterogeneity in some domains, such as expectations about survival up to age 75, it cannot explain heterogeneity in domains where private information should not matter.

In this paper, I focus on macroeconomic expectations in three different domains where private information is arguably irrelevant and thus cannot explain interpersonal heterogeneity: expectations about national inflation, national unemployment and national business conditions. I document that individuals' expectations about these macroeconomic outcomes are systematically linked with individuals' experiences of these macroeconomic outcomes during life. When asked about the future inflation rate, respondents are assumed to build their experience on past inflation rates. Similarly, in the context of unemployment expectations, I measure experience as exposure to historical, national unemployment rates. Finally, regarding business expectations, I argue that individuals concentrate on annual returns of the S&P 500 index, which they experienced during their life.

For the quantitative measurement of individuals' experiences, I rely on a methodology introduced by Malmendier and Nagel (2011) and assume that individuals summarize past information by a weighted average over their lifetime. The weights are allowed to flexibly increase, be constant or decrease over time, depending on a weighting parameter, which is estimated from the data. I extend their model by allowing for heterogeneity in both the weighting parameter and the experience effect, i.e. the effect of experience on individuals' expectations in the respective domain. Finally, I apply the model to repeated cross-sectional data between 1978 and 2017 from the Michigan Survey of Consumers.

The results suggest that respondents' experiences significantly predict their expectations in all three domains. Higher experienced inflation rates, higher experienced unemployment rates and higher experienced S&P 500 returns during a respondent's lifetime are significantly associated with higher inflation expectations, higher unemployment expectations and more optimistic expectations about future business conditions, respectively. All models control for year and age fixed effects, as well as several socio-economic variables. In the inflation and unemployment domain, respondents' weights for aggregating past information are found to increase over time, implying that respondents put on average more weight on recent years than on distant years. When forming business expectations, respondents seem to use a slightly different weighting scheme. In fact, the weights are in this case almost constant over time, implying that recent and distant years are equally important to respondents.

I find significant gender differences in both the experience effect and the weighting parameter. Regarding the experience effect, the effect of individuals' experiences on expectations is found to be significantly smaller for males than for females. Males therefore build less on their experience when forming subjective expectations, which holds in all three domains. Other socio-economic variables are found to have no systematic effect on the experience effect. This is also supported by a Lasso analysis for inflation expectations, which suggests excluding all variables other than gender from the model. Looking at the weighting parameter, males are also found to put less weight on recent information and more weight on distant information when aggregating past information, compared to females. Again, this effect is shown to hold in all three domains.

The contribution of this paper is thus threefold. First, I document that individuals' expectations about macroeconomic outcomes are systematically linked with individuals' experiences of these macroeconomic outcomes during life. Second, my analysis suggests that respondents put more weight on recent rather than distant years when aggregating past information, but to a lesser extent in the domain of future business conditions. Last, I identify a systematic gender difference in both the experience effect and the weighting parameter.

This paper relates to three different strands of the literature. First, several studies try to empirically measure the effect of personal experience on later life outcomes. The seminal paper by Malmendier and Nagel (2011) shows that respondents' investment behavior and, more generally, risk taking can be predicted by respondents' experiences of past stock market returns. In a follow-up paper, Malmendier and Nagel (2016) find that subjective inflation expectations are strongly influenced by experiences of inflation rates. Even voting decisions by the members of the Federal Open Market Committee (FOMC) and consequently also the federal funds target rate can be predicted by personal experiences of the board members (Malmendier et al., 2017). Kuchler and Zafar (2018) find that local experiences of house prices predict national house price expectations in the US and that within-individual variation in unemployment status also affect national unemployment expectations. However, personal experiences are not the only experiences shown to affect outcomes. As highlighted in Bailey et al. (2018) and Bailey et al. (2019), individuals are also influenced by their friends from social networks. They show that friends' experiences of local house prices significantly predict respondents' own house price expectations and even affect respondents' investment behavior in the housing market.

The paper also corresponds to a second and mainly theoretical literature which explicitly models adaptive and extrapolative expectations in order to match empirical findings. For example, Fuster et al. (2010) introduce a model with "natural expectations", falling between rational expectations and expectations based on naive growth regressions with a limited number of explanatory variables. Their model is thus able to predict excessively extrapolative expectations of individuals. Hirshleifer et al. (2015) introduce extrapolation bias into a standard production-based asset pricing model and show that this can help to explain volatile investment rates, volatile stock returns and smooth consumption patterns. For a detailed overview of theoretical approaches to modeling extrapolation in beliefs or expectations, see Greenwood and Shleifer (2014).

A third strand of the literature argues that experiencing dramatic events in childhood have long-lasting effects on a variety of adult outcomes. For example, exposure to war is shown to significantly predict economic and health outcomes at older ages (Kesternich et al., 2014). Akbulut-Yuksel (2014) highlights the devastating long-run consequences of war-related physical destruction in German cities on the formation of human capital. In addition, hunger in early childhood is also shown to affect health outcomes and economic preferences, such as trust (cf. Kesternich et al., 2015; van den Berg et al., 2016; Kesternich et al., 2018).

The remainder of this paper is structured as follows. After describing the data in Section 1.2, I introduce the econometric model in Section 1.3. The model estimates are presented and discussed in Section 1.4, while Section 1.5 concentrates on Lasso models. I then turn to additional robustness analyses in Section 1.6 and conclude in Section 1.7.

1.2 Data

For the outcome variables on subjective expectations, I draw on data from the Michigan Survey of Consumers (MSC).[1] This nationally representative, monthly survey started in 1978 to collect data from roughly 500 respondents for the construction of an indicator of consumer confidence.[2] Variables collected in the survey include, amongst others, confidence in government and economic policies, personal attitudes and expectations. Until today, the University of Michigan Consumer Sentiment Index is one of the leading US indicators of consumer confidence. The data set consists of repeated cross-sections, even though a small fraction of respondents is interviewed a second time, usually six months later.[3] For more details on the survey and its design, see Curtin (1982).

The analysis is based on expectation data between January 1978 and December 2017 in the following three domains: national inflation, national unemployment and national business conditions.[4] Specifically, respondents are asked the following questions:

> **Q1:** *"How about people out of work during the coming 12 months – do you think that there will be more unemployment than now, about the same, or less?"*

and

[1] After registration, the data is freely available at: https://data.sca.isr.umich.edu/ [accessed August 10, 2018].

[2] American households from Alaska and Hawaii are not included in the sample. Note also that some questionnaire items from the MSC date back to the late 1940s, when surveys were conducted on a yearly or quarterly basis. The systematic rotating panel design was incorporated in January 1978, which is also the earliest date available at the University of Michigan Survey Research Center. For more details on the survey and its design see Curtin (1982).

[3] I later utilize the panel dimension of the data for the calculation of the standard errors.

[4] In addition, the MSC collects individuals' expectations about (i) the general interest rate for borrowing and (ii) the personal financial situation. This information is not used in my analysis, because (i) it is not clear on what interest rate respondents base their experience and (ii) private information plays – in contrast to the other expectations questions – a key role. Moreover, in the late 1990s and early 2000s, several other expectations questions were added to the MSC questionnaire, such as expectations about housing prices and gasoline prices. However, these variables are only available over a much shorter time period, which does typically not allow to statistically disentangle the experience effect from the age effect.

> **Q2:** *"And how about a year from now, do you expect that in the country as a whole business conditions will be better, or worse than they are at present, or just about the same?"*

Since the answers to both questions can be ordered naturally, I generate the ordered variables **unemp** and **bexp** with three distinct values reflecting the three different response categories. Higher values indicate more expected unemployment and better expected business conditions, respectively. In addition, respondents are also presented with several questions to elicit their exact point expectation for the one-year ahead inflation rate.[5] The responses are summarized by the integer variable **px1**, with the exact question wordings being presented in Appendix A1.[6]

Table 1.1 summarizes the information from the MSC data, based on all individuals who are interviewed between January 1978 and December 2017, making a total of 271,948 observations. The number of observations varies due to item non-response. Panel A describes the three measures of respondents' expectations. On average, respondents expect an inflation rate of 4.55 percent for the year ahead, although the relatively high standard deviation of 6.30 hints at substantial disagreement among respondents. Regarding national unemployment expectations, every second respondent expects no change, while 34 percent (17 percent) of the respondents expect an increase (decrease) in unemployment. Similarly, every second respondent expects the business conditions to stay the same, while 21 percent expect them to deteriorate and 28 percent to improve over the next year.

Panel B of Table 1.1 displays summary statistics regarding several socio-demographic dummy variables. Overall, the sample contains slightly more females than males. One in five respondents is 65 or older; roughly every third respondent is younger than 40. Sixty

[5] Note that point expectations about inflation – rather than probabilistic expectations – do not allow respondents to express uncertainty. See Manski (2004, 2018), for a critical discussion.

[6] Respondents are always allowed to choose a "don't know" option. These respondents and respondents with missing information are excluded from the analysis. As shown in Table 1.1, response rates are, however, extremely high with values of 98.7% (unemp), 97.7% (bexp) and 90.7% (px1).

Table 1.1: Summary statistics for data from the Michigan Survey of Consumers

	Mean	SD	p5	p95	Min	Max	Observations
A: Expectations							
Inflation (px1) [%]	4.55	6.30	0	15	-50	50	246,683
Unemployment (unemp)							
Less [0/1]	0.17	0.38	0	1	0	1	268,362
Same [0/1]	0.48	0.50	0	1	0	1	268,362
More [0/1]	0.34	0.48	0	1	0	1	268,362
Business conditions (bexp)							
Worse [0/1]	0.21	0.40	0	1	0	1	265,617
Same [0/1]	0.51	0.50	0	1	0	1	265,617
Better [0/1]	0.28	0.45	0	1	0	1	265,617
B: Sociodemographics [0/1]							
Male	0.46	0.50	0	1	0	1	271,277
Partner	0.60	0.49	0	1	0	1	268,594
Age > 64	0.20	0.40	0	1	0	1	269,899
Age < 40	0.39	0.49	0	1	0	1	269,899
College	0.37	0.48	0	1	0	1	268,579
1st income quartile	0.21	0.41	0	1	0	1	234,095
2nd income quartile	0.21	0.41	0	1	0	1	234,095
3rd income quartile	0.28	0.45	0	1	0	1	234,095
4th income quartile	0.30	0.46	0	1	0	1	234,095
C: Regional information [0/1]							
West	0.20	0.40	0	1	0	1	271,853
Northcentral	0.27	0.44	0	1	0	1	271,853
Northeast	0.19	0.39	0	1	0	1	271,853
South	0.33	0.47	0	1	0	1	271,853

Notes: This table shows summary statistics of the MSC data, based on all respondents who are interviewed between January 1978 and December 2017, making a total of 271,948 observations. Number of observations differs due to item nonresponse. Panel A focuses on respondents' subjective expectations; panels B and C report several socio-economic dummy variables. Information on income (1st-4th quartile) not available before October 1979. For details see text.

percent of the respondents report to be living with a partner, and almost forty percent to hold at least a college degree. Starting in October 1979, respondents are also asked about their total income (all sources including job) from the previous year. In every given month-year combination, this information is used to classify respondents into income quartiles, which are also presented in Panel B. Last, Panel C reports coarse information on the region of residence at the time of the interview.[7]

Measuring respondents' experiences requires (domain-specific) data stretching back to the late nineteenth century.[8] The specific variable, on which respondents base their experience, is assumed to depend on the domain of the respective expectations question. First, for respondents' inflation expectations, it seems natural that individuals focus on realized inflation rates during their life. I therefore draw on data from Shiller (2015) who provides data on the US consumer price index (CPI), dating back to 1871.[9] Inflation rates are then calculated as yearly growth rates of the CPI. Second, for national unemployment expectations, I measure experience by individual-specific histories of national unemployment rates. Specifically, I use data on US unemployment from the Bureau of Labor Statistics at the US Department of Labor, enriched by historical estimates from Romer (1986).[10] Overall, my historical unemployment data stretches back to 1890. This implies that I have to exclude 67 respondents born before 1890 for the analysis of unemployment expectations. Third, for expectations on business conditions, it seems less clear on which variable individuals focus. Indicators trying to measure business conditions in the country as a whole are typically provided by central banks, for example the Aruoba-Diebold-Scotti (ADS) Business Conditions Index by the Federal Reserve Bank of Philadelphia, but were introduced in the late twentieth or early twenty-first century. Having the relatively strict

[7] US states are classified into the four statistical regions "West", "Northcentral", "Northeast" and "South", as defined by the United States Census Bureau.

[8] This can be illustrated by the following example. Imagine a 90-year-old respondent who was interviewed in 1980 about her inflation expectations. Examining the effect of her history of experienced inflation rates on her expectations thus requires data on the US inflation rate dating back to 1890, her year of birth.

[9] I thank Bob Shiller for providing the data on his website (http://www.econ.yale.edu/∼shiller/data.htm [accessed Jan 4, 2019]).

[10] The data on unemployment rates from the Bureau of Labor Statistics can be downloaded from the following website: https://www.bls.gov/cps/cpsaat01.htm [accessed April 18,2018].

data requirements in mind, I use the performance of the stock market as an indicator for the business condition climate. Data are again taken from Shiller (2015), who provides historical data on the S&P 500 index, dating back to 1871. Specifically, I use yearly returns of the S&P 500 index, i.e. growth rates, rather than the index itself to reflect the relative nature of question Q2.

The historical data on US inflation, unemployment and S&P 500 returns between 1880 and 2017 is depicted in Figure 1.1. Unemployment rates are usually between five and eight percent, with higher rates during the Great Depression in the 1930s. In contrast, annual stock market returns of the S&P 500 are clearly more volatile, with major dips during the 1930s, 1970s, the dotcom bubble in 2001 and the 2008 financial crisis. The figure also shows the inflation rates to be relatively volatile around 1900 and relatively stable in the 1990s and 2000s.

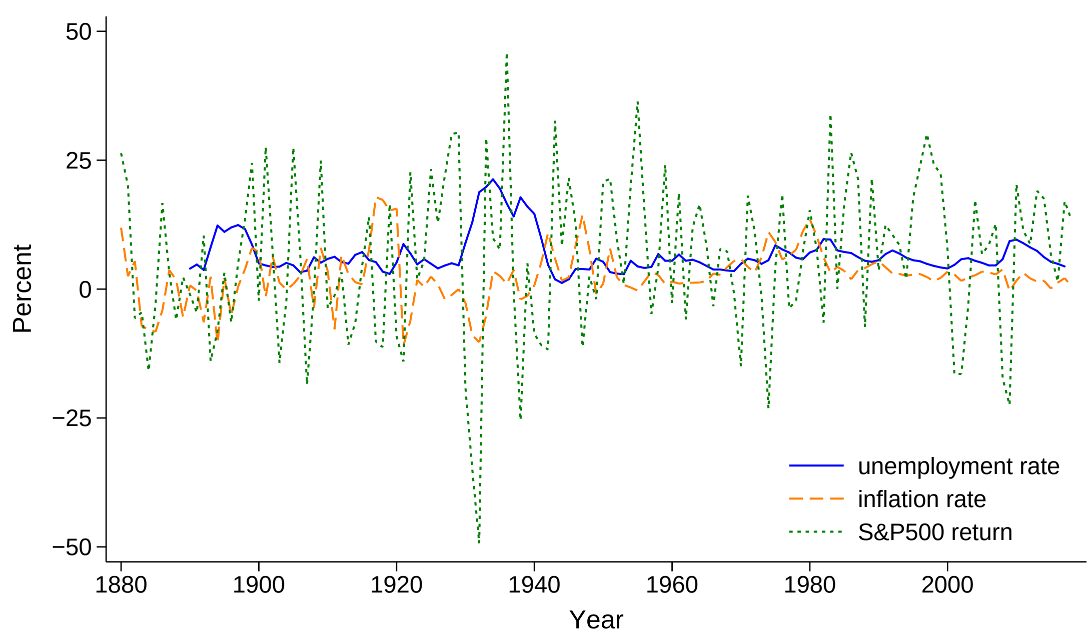


Figure 1.1: Historical data on US unemployment, inflation, and S&P 500 returns (1880-2017)

1.3 Model

1.3.1 Measuring experience

In general, this paper argues that individuals' expectations about aggregate economic outcomes are influenced by individuals' experiences of these economic outcomes during life. When asked about future inflation rates, for example, individuals may extrapolate from experienced inflation rates. Using a non-parametric approach, one could try to estimate separate coefficients for each past year of inflation back to the year of birth. However, in addition to the large number of coefficients, this approach would also imply that each respondent may have a different number of explanatory variables because respondents in a given survey year differ in age. I therefore rely on a parametric approach by Malmendier and Nagel (2011) and summarize the history of past realizations flexibly in one single variable. Specifically, the experience A_{it} of respondent i in year t is calculated as weighted average of past values of the variable of interest Z_t, e.g. the national US inflation rate:

$$A_{it}(\lambda) = \sum_{k=1}^{age_{it}-1} w_{it}(k,\lambda) Z_{t-k} \tag{1.1}$$

and

$$w_{it}(k,\lambda) = \frac{(age_{it}-k)^{\lambda}}{\sum_{k=1}^{age_{it}-1} (age_{it}-k)^{\lambda}} \tag{1.2}$$

where the weights w_{it} depend on the parameter λ. The exponential specification allows the weights to increase ($\lambda > 0$), decrease ($\lambda < 0$) or be constant ($\lambda = 0$) over time. For sake of illustration, Figure 1.2 depicts the weighting function of a 50-year-old respondent over time for different values of the weighting parameter λ.[11] As shown, $\lambda = 0$ implies that the respondent weighs every year between her birth and interview equally. Her personal experience A_{it} would then just be the simple, unweighted average of past realizations of Z_t over her lifetime. For positive values of λ, she puts more weight on recent compared

[11]Note that Figure 1.2 is inspired by Figure 2 in Malmendier and Nagel (2011, p.384).

to distant years. For example, $\lambda = 3$ implies that the most recent year before her survey interview receives a weight of almost eight percent, while the weights for years close to her birth are almost zero. $\lambda = 1$ implies that her weights increase linearly over time. In contrast, negative values of λ imply that the weights decrease over time, i.e. the respondent puts more weight on distant years compared to recent years. In summary, this methodology allows recent experiences to have different weights rather than distant experiences, with the magnitude and direction being determined by the weighting parameter λ.

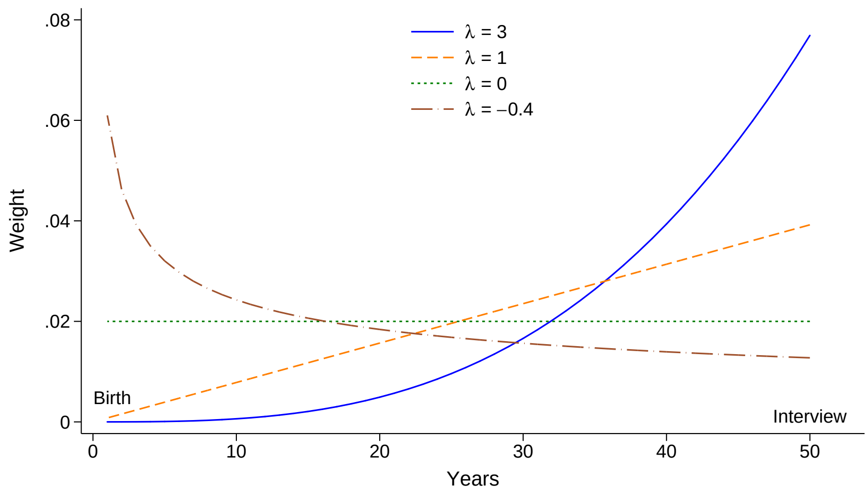


Figure 1.2: Weighting function of a 50-year-old respondent

Based on Equations 1.1 and 1.2, Table 1.2 reports summary statistics of the experience variable A_{it} for different values of the weighting parameter λ. In general, the calculations include all respondents with non-missing data on age, making a total of 269,899 observations. Panel A suggests that respondents experienced on average an inflation rate of 4.56% during their life ($\lambda = 3$). Assuming constant weights ($\lambda = 0$), their experienced inflation rate slightly decreases to 4.10%. Turning to the experienced unemployment rate (Panel B), differences between the calculated values become small. For all four values of λ, experienced (average) unemployment rates are always slightly above six percent. Differences in terms of the standard deviation are, however, larger. As already discussed in the previous section, Panel B drops respondents who are born before 1890, resulting in a small reduction in the number of observations. Last, Panel C suggests that individuals experienced an annual (average) S&P 500 return of roughly seven or eight percent, depending on the specific choice of the weighting parameter λ.

Table 1.2: Summary statistics for individuals' experiences for different values of the weighting parameter

	Mean	SD	p5	p95	Min	Max	Observations
A: Inflation rate [%]							
$\lambda = 3$	4.56	1.53	2.43	7.36	1.52	9.38	269,899
$\lambda = 1$	4.44	0.96	2.97	6.15	1.89	7.91	269,899
$\lambda = 0$	4.10	0.78	2.85	5.52	2.04	6.76	269,899
$\lambda = -.4$	3.84	0.98	2.19	5.58	0.83	7.14	269,899
B: Unemployment rate [%]							
$\lambda = 3$	6.23	0.51	5.49	7.14	4.88	7.86	269,832
$\lambda = 1$	6.14	0.35	5.50	6.69	5.13	7.33	269,832
$\lambda = 0$	6.14	0.62	5.21	7.24	4.73	7.53	269,832
$\lambda = -.4$	6.18	1.01	4.91	8.29	4.28	9.29	269,832
C: S&P500 return [%]							
$\lambda = 3$	7.84	3.12	2.72	13.48	-2.96	19.40	269,899
$\lambda = 1$	7.61	2.02	4.18	10.92	1.93	16.43	269,899
$\lambda = 0$	7.41	1.42	5.01	9.56	2.75	15.30	269,899
$\lambda = -.4$	7.29	1.77	4.22	9.94	1.69	15.91	269,899

Notes: This table reports summary statistics of the experience variable A_{it} as weighted average over respondents' lifetime for different values of the weighting parameter λ. The sample includes all MSC respondents who are interviewed between January 1978 and December 2017 and who report non-missing information on age, making a total of 269,899 observations. Number of observations in Panel B differs due to data restrictions on historical US unemployment rates. For details see text.

1.3.2 Empirical model and likelihood function

Using the definitions from the previous section, assume that the subjective expectation y_{it} of individual i in year t can be described as:

$$y_{it} = \beta A_{it}(\lambda) + \boldsymbol{x}_{it}\boldsymbol{\gamma} + \varepsilon_{it} \tag{1.3}$$

where β measures the effect of experience A_{it} on subjective expectations ("experience effect") and λ determines the shape of the weighting function ("weighting parameter"). The row vector $\boldsymbol{x}_{it}$ includes several covariates as well as time and age fixed effects, with $\boldsymbol{\gamma}$ being an appropriate coefficient column vector. ε_{it} denotes an idiosyncratic error term. Note that this specification is used by Malmendier and Nagel (2011) to estimate the effect of experienced stock market returns on risk-taking and stock market investments. In my model, however, I additionally allow for heterogeneity in both the experience effect β and the weighting parameter λ. Specifically, I parameterize both scalars as linear functions of covariates:[12]

$$\beta = \beta_{it} = \boldsymbol{w}_{it}\boldsymbol{\beta} \tag{1.4}$$

and

$$\lambda = \lambda_{it} = \boldsymbol{w}_{it}\boldsymbol{\lambda} \tag{1.5}$$

where $\boldsymbol{w}_{it}$ is a covariate row vector (including a constant) and $\boldsymbol{\beta}$ and $\boldsymbol{\lambda}$ are appropriate coefficient column vectors.

To reflect the different nature of the three outcome variables, I make different assumptions about the distribution of the error term ε_{it}. First, for the variable on inflation expectations (px1), I assume that the error term is normally distributed with mean zero and variance σ^2, i.e. $\varepsilon_{it} \sim N(0, \sigma^2)$. It is straightforward to show that the log likelihood function $\mathcal{L}(\cdot)$ of the model can then be written as:

[12] I will later also allow for more flexible specifications, such as a fully interacted model of the covariates. See Section 1.5 for more details.

$$\begin{aligned}\mathcal{L}(\boldsymbol{\beta}, \boldsymbol{\lambda}, \boldsymbol{\gamma}, \sigma) &= \sum_{i=1}^{N} \ln[\phi(y_{it}; \beta A_{it}(\lambda) + \boldsymbol{x}_{it}\boldsymbol{\gamma}; \sigma)] \\ &= \sum_{i=1}^{N} \ln[\phi(y_{it}; \boldsymbol{w}_{it}\boldsymbol{\beta} A_{it}(\boldsymbol{w}_{it}\boldsymbol{\lambda}) + \boldsymbol{x}_{it}\boldsymbol{\gamma}; \sigma)] \end{aligned} \tag{1.6}$$

where $\phi(\cdot)$ denotes the probability density function (p.d.f.) of the standard normal distribution. Recall that $\boldsymbol{\beta}$ denotes the coefficient vector determining the individual-specific effect of experience on expectations, while $\boldsymbol{\lambda}$ denotes a coefficient vector determining the shape of the weighting function w_{it} as given by Equation 1.2. $\boldsymbol{\gamma}$ denotes the direct effect of the covariates (including fixed effects) on expectations and σ denotes the standard deviation of the error term ε_{it}.

Second, for the ordinal variables on unemployment expectations (unemp) and business expectations (bexp) with $m = 3$ distinct outcome categories, I assume that the true subjective expectation y^*_{it} is in fact unobserved and given by:

$$y^*_{it} = \beta A_{it}(\lambda) + \boldsymbol{x}_{it}\boldsymbol{\gamma} + \varepsilon_{it} \tag{1.7}$$

The researcher only observes the ordered variable y_{it} with observation rule:

$$y_{it} = j \quad \text{if} \quad \kappa_{j-1} < y^*_{it} \leq \kappa_j; \quad j = 1, 2, \ldots, m \tag{1.8}$$

As in a standard ordered response model, the normalizations $\kappa_0 = -\infty$ and $\kappa_m = \infty$ apply, while the remaining cut-off parameters $\kappa_1, \ldots, \kappa_{m-1}$ are to be estimated and determine the frequencies of the ordered outcomes. In this case, the distribution of the error term is assumed to be standard normal, i.e. $\varepsilon_{it} \sim N(0, 1)$, implying that the model becomes in fact a (pooled) ordered probit model with the non-linear and non-standard experience term $A_{it}(\lambda)$. The conditional outcome probabilities and the log likelihood function can then be derived using standard calculus techniques:[13]

$$
\begin{aligned}
P(y_{it} = j|\boldsymbol{x}_{it}, \boldsymbol{w}_{it}) &= P(\kappa_{j-1} < y_{it}^{*} \leq \kappa_j) \\
&= \Phi(\kappa_j - \beta A_{it}(\lambda) - \boldsymbol{x}_{it}\boldsymbol{\gamma}) - \Phi(\kappa_{j-1} - \beta A_{it}(\lambda) - \boldsymbol{x}_{it}\boldsymbol{\gamma}) \qquad (1.9) \\
&= \Phi(\kappa_j - \boldsymbol{w}_{it}\boldsymbol{\beta} A_{it}(\boldsymbol{w}_{it}\boldsymbol{\lambda}) - \boldsymbol{x}_{it}\boldsymbol{\gamma}) - \Phi(\kappa_{j-1} - \boldsymbol{w}_{it}\boldsymbol{\beta} A_{it}(\boldsymbol{w}_{it}\boldsymbol{\lambda}) - \boldsymbol{x}_{it}\boldsymbol{\gamma})
\end{aligned}
$$

and

$$
\mathcal{L}(\boldsymbol{\beta}, \boldsymbol{\lambda}, \boldsymbol{\gamma}, \kappa_1, \kappa_2, ..., \kappa_{m-1}) = \sum_{i=1}^{N} \sum_{j=1}^{m} \mathbb{1}(y_{it} = j) \cdot \ln[P(y_{it} = j|\boldsymbol{x}_{it}, \boldsymbol{w}_{it})] \qquad (1.10)
$$

where $\Phi(\cdot)$ denotes the cumulative distribution function (c.d.f.) of the standard normal distribution and $\mathbb{1}(\cdot)$ the indicator function.

1.3.3 Estimation and identification

The model is estimated jointly by maximizing the respective log likelihood function, as given in Equations 1.6 and 1.10. I first estimate the model on a tightly spaced grid of fixed weighting parameters λ to avoid convergence to local minima.[14] The estimates with the highest log likelihood among the restricted models are then used as starting values for the numerical maximization of the unrestricted model. Alternatively, I use estimates from a model without heterogeneity as starting values for models with heterogeneity.

The identification of the experience effect closely follows Malmendier and Nagel (2011). The model includes both time and age fixed effects. The inclusion of the former allows to distinguish the experience effect from time trends and aggregate effects, such as time-varying aggregate optimism or pessimism, potentially affecting respondents' expectations. The latter removes any life cycle effects, such as age-related differences in the formation

[13] Similar to a standard ordered probit model, the constant in the coefficient vector $\boldsymbol{\beta}$ is normalized to zero to ensure identification of the model.

[14] The grid on the weighting parameter λ is based on values ranging from minus five to plus ten in intervals of one tenth. More details can also be found in Section 1.6 and Appendix D1.

process of expectations. Identification of the experience effect therefore stems from cross-sectional differences in subjective expectations and macroeconomic histories as well as from changes of those differences over time.

1.4 Results

Tables 1.3, 1.4 and 1.5 report model estimates for the dependent variable on inflation expectations, unemployment expectations and business expectations, respectively. In all three tables, the first specification (column 1) models both the experience effect β and the weighting parameter λ as constant scalars, while columns 2, 3 and 4 add heterogeneity by allowing them to depend on several socio-economic characteristics. The coefficients of the covariates can be interpreted as coefficients from interaction terms between the specific covariate and the main effect ("Constant"). The unreported model coefficients, such as the direct effects of the socio-demographic covariates on expectations ("Direct controls"), are reported and discussed in Appendix B1.

1.4.1 Inflation expectations

Table 1.3 reports model estimates for respondents' inflation expectations. Throughout all specifications, the model-implied average experience effect ($\bar{\beta}$) is significantly positive and close to 0.6. This indicates that respondents' experience of past inflation rates has indeed a significantly positive effect on respondents' expectations. More specifically, a one percentage point increase in the average experienced inflation rate is on average associated with an increase in the reported year-ahead inflation rate of more than half a percentage point. The model also identifies significant heterogeneity in the experience effect (columns 2 and 4). Importantly, females are found to have a significantly higher experience effect than males. The same also applies to college graduates and less affluent respondents (compared to non-graduates and more affluent respondents, respectively), although the differences, i.e. coefficients, are not always statistically significant.

The estimated, average weighting parameter ($\bar{\lambda}$) varies between three and four depending on the specification. This suggests that a 50-year-old respondent, for example, puts on average a weight of eight to ten percent on her most recently experienced inflation rate and a weight of almost zero percent on the inflation rate in her birth year (cf. Figures 1.2

Table 1.3: Model estimates for national inflation expectations

	Inflation expectations (px1)							
	(1)		(2)		(3)		(4)	
Experience effect (β)								
Constant	0.586***	[0.039]	0.631***	[0.048]	0.549***	[0.042]	0.519***	[0.089]
Male			-0.189***	[0.024]			-0.138***	[0.040]
Partner			0.018	[0.021]			0.058**	[0.023]
College			0.053***	[0.018]			0.029	[0.029]
1st income quartile			0.063*	[0.035]			0.256***	[0.086]
2nd income quartile			0.026	[0.026]			0.115**	[0.051]
3rd income quartile			-0.001	[0.020]			0.032	[0.031]
West			0.048*	[0.026]			0.059**	[0.029]
Northcentral			-0.080***	[0.024]			-0.047*	[0.027]
Northeast			0.035	[0.027]			0.057*	[0.033]
Weighting parameter (λ)								
Constant	3.619***	[0.383]	3.156***	[0.457]	3.512***	[0.836]	5.976***	[1.147]
Male					-1.293***	[0.237]	-0.386	[0.707]
Partner					-0.077	[0.272]	-0.784**	[0.327]
College					1.259***	[0.266]	0.561	[0.536]
1st income quartile					-0.613	[0.470]	-2.891***	[1.092]
2nd income quartile					-0.392	[0.367]	-1.844*	[0.991]
3rd income quartile					-0.169	[0.272]	-0.772	[0.743]
West					0.728**	[0.343]	-0.193	[0.477]
Northcentral					-0.683***	[0.256]	-0.541	[0.406]
Northeast					0.110	[0.301]	-0.532	[0.468]
Avg. beta ($\bar{\beta}$)	0.586		0.583		0.549		0.591	
Avg. lambda ($\bar{\lambda}$)	3.619		3.156		3.081		4.087	
Year FE	yes		yes		yes		yes	
Age FE	yes		yes		yes		yes	
Direct controls	yes		yes		yes		yes	
Log likelihood	310,807.7		310,918.8		310,890.1		310,971.5	
Observations	213,037		213,037		213,037		213,037	

Notes: This table reports maximum likelihood estimates for heterogeneity in the experience effect (β) and the weighting parameter (λ) with the dependent variable px1, i.e. respondents' point inflation expectations. Coefficients can be interpreted as interaction effects of the specific variable with the experience effect and the weighting parameter (both "Constant"), respectively. Table also reports model-implied averages for both parameters. Time and age fixed effects are included in the model. The estimated coefficients for the direct effect of the covariates on the expectations (γ) as well as the estimate for the variance of the error term σ are not reported. Standard error in brackets are clustered at the individual level. *** p <0.01, ** p <0.05, * p <0.1.

and 1.3). In addition, females, college graduates and the most affluent respondents have higher weighting parameters, i.e. they put more weight on recent rather than distant years, when aggregating information, even though significance levels vary between specifications.

A similar analysis can be found in Malmendier and Nagel (2016). They assume that individuals use an adaptive learning algorithm, i.e. they recursively estimate an AR(1) model of inflation, where the strength of updating is allowed to depend on age. Consistent with the findings in the present paper, the authors find evidence for both a positive experience effect and a similar weighting pattern in the domain of inflation expectations. However, their model does not allow for heterogeneity in both the experience effect and the weighting parameter.

1.4.2 Unemployment expectations

Table 1.4 reports model estimates for respondents' national unemployment expectations. Recall that higher values of the ordered dependent variable indicate more expected unemployment in the year ahead and that experience is measured as weighted average of national unemployment rates. Again, all four specifications identify a significantly positive experience effect ($\bar{\beta}$). Note that these coefficients have – in contrast to the previous model of inflation expectations – no quantitative interpretation due to the ordered probit nature of the model. A qualitative interpretation, however, remains suggesting that respondents who experienced higher unemployment rates during their life are more likely to expect more unemployment in the future than respondents who experienced lower unemployment rates.[15] Respondents are therefore shown to again extrapolate from their experiences. Overall, the estimates from Table 1.4 suggest that heterogeneity plays no major role for the experience effect in the unemployment domain.[16] Column 2 shows a smaller experience effect for males and a larger effect for respondents living in western US states, but the differences vanish in column 4.

More importantly, the model on unemployment expectations identifies an average weighting parameter which is remarkably close to the parameter identified by the inflation model.

[15] To be precise, the positive sign of the experience effect does – similarly to a standard ordered probit model – not generally imply a positive marginal effect of experience. Unambiguous predictions about the sign of the marginal effect can only be made for the highest and lowest category of the ordered variable, respectively. This means that a positive experience effect indicates a lower probability of expecting less unemployment (lowest category) and a higher probability of expecting more unemployment (highest category).

[16] Unfortunately, both self-reported income and education seem to cause convergence issues of the model. Potential reasons include, amongst others, a flat or even convex likelihood function as well as near-collinearities of the respective variables with the experience variable. I therefore exclude the income quartile dummies and the binary variable "College" from the model on unemployment expectations.

Table 1.4: Model estimates for national unemployment expectations

	Unemployment expectations (unemp)							
	(1)		(2)		(3)		(4)	
Experience effect (β)								
Constant	0.069***	[0.011]	0.070***	[0.013]	0.081***	[0.011]	0.073***	[0.014]
Male			-0.021**	[0.009]			0.023	[0.015]
Partner			0.011	[0.009]			0.010	[0.011]
West			0.031**	[0.012]			0.020	[0.016]
Northcentral			-0.002	[0.011]			-0.015	[0.013]
Northeast			-0.015	[0.012]			-0.011	[0.018]
Weighting parameter (λ)								
Constant	3.809***	[0.340]	4.263***	[0.539]	5.352***	[1.325]	5.439***	[1.079]
Male					-3.004***	[0.787]	-3.528***	[0.982]
Partner					0.654	[0.515]	0.450	[0.648]
West					0.815	[0.884]	0.497	[0.801]
Northcentral					0.154	[0.840]	0.799	[0.713]
Northeast					-1.043	[0.922]	-0.591	[0.906]
Avg. beta ($\bar{\beta}$)	0.069		0.069		0.081		0.088	
Avg. lambda ($\bar{\lambda}$)	3.809		4.263		4.307		4.210	
Year FE	yes		yes		yes		yes	
Age FE	yes		yes		yes		yes	
Direct controls	yes		yes		yes		yes	
Log likelihood	-226,986.1		-226,973.8		-226,964.7		-226,957.5	
Observations	228,413		228,413		228,413		228,413	

Notes: This table reports maximum likelihood estimates for heterogeneity in the experience effect (β) and the weighting parameter (λ) with the dependent variable unemp, i.e. respondents' national unemployment expectations. Coefficients can be interpreted as interaction effects of the specific variable with the experience effect and the weighting parameter (both "Constant"), respectively. Table also reports model-implied averages for both parameters. Time and age fixed effects are included in the model. The estimated coefficients for the direct effect of the covariates on the expectations (γ) as well as the estimates of the two cut-off parameters κ_1 and κ_2 are not reported. Standard error in brackets are clustered at the individual level. *** p <0.01, ** p <0.05, * p <0.1.

The predicted average weighting parameter ($\bar{\lambda}$) is always around four, implying not only that respondents put more weight on recent years (as they do in the inflation model), but also that their weighting function is similar to the one from the inflation domain. Moreover, there is strong evidence for a gender effect. In fact, both columns 3 and 4 show that males have a significantly lower weighting parameter than females. Interestingly, the coefficients of all other covariates are statistically indistinguishable from zero.

Related to this analysis, Kuchler and Zafar (2018) show that within-individual variation in unemployment status also affects expectations about national unemployment.[17] Unfortunately, the panel dimension of the MSC data is far too small to repeat their analysis and

[17] Note that the data set, on which Kuchler and Zafar (2018) base their analysis, has a panel dimension, but only covers a five-year period (December 2012–April 2017).

compare the relative importance of experiencing national versus individual unemployment. However, both effects are in fact distinct, as illustrated by the following example. Imagine two individuals who differ in age and who have never been unemployed. While in this case my model is able to explain potential differences in national unemployment expectations by experience, the approach by Kuchler and Zafar (2018) is not. In contrast, as long as one individual experiences at least some transitions from unemployment to employment or vice versa, their approach is able to explain differences in national unemployment expectations even if individuals are surveyed in the same year and are of same age, i.e. their history of experienced national unemployment is absolutely identical. Both approaches therefore use variation from different sources to identify the experience effect.

1.4.3 Business expectations

Last, I apply the model to respondents' expectations about future business conditions. Recall that higher values of the ordered dependent variable indicate more optimistic expectations and that respondents are assumed to base their experience on past returns of the S&P 500 stock market index. As shown in Table 1.5, the model-implied average experience effect is again significantly positive ($\bar{\beta}$). Therefore, respondents who experienced higher stock market returns are on average more optimistic regarding future business conditions than respondents who experienced lower returns. This implies that extrapolation is also found in the domain of business conditions. In terms of heterogeneity, both columns 2 and 4 indicate that males and college graduates have a lower experience effect, compared to females and non-graduates, respectively.[18] The coefficients of the other covariates are not statistically significant.

The average weighting parameter ($\bar{\lambda}$) is – in contrast to the previous models – a lot smaller. In fact, the estimates vary between 0.520 and 0.752, depending on the specification.

[18] I exclude income quartiles from the covariate vector for the same reasons, as in the model on unemployment expectations.

Table 1.5: Model estimates for national business expectations

	Business expectations (bexp)							
	(1)		(2)		(3)		(4)	
Experience effect (β)								
Constant	2.921***	[0.355]	4.073***	[0.476]	3.275***	[0.332]	3.949***	[0.516]
Male			-1.540***	[0.288]			-0.712*	[0.421]
Partner			0.116	[0.307]			0.090	[0.358]
College			-1.171***	[0.339]			-1.259**	[0.500]
West			-0.330	[0.410]			-0.628	[0.549]
Northcentral			-0.780**	[0.371]			-0.376	[0.463]
Northeast			-0.324	[0.416]			-0.551	[0.500]
Weighting parameter (λ)								
Constant	0.520***	[0.077]	0.752***	[0.141]	1.107***	[0.260]	0.931***	[0.261]
Male					-0.647***	[0.132]	-0.724***	[0.243]
Partner					0.074	[0.115]	0.088	[0.166]
College					-0.310	[0.192]	-0.164	[0.202]
West					0.006	[0.188]	0.257	[0.346]
Northcentral					-0.318*	[0.171]	-0.270	[0.200]
Northeast					0.009	[0.188]	0.146	[0.266]
Avg. beta ($\bar{\beta}$)	2.921		2.586		3.275		2.817	
Avg. lambda ($\bar{\lambda}$)	0.520		0.752		0.631		0.575	
Year FE	yes		yes		yes		yes	
Age FE	yes		yes		yes		yes	
Direct controls	yes		yes		yes		yes	
Log likelihood	-227,695.5		-227,671.2		-227,669.4		-227,658.4	
Observations	226,209		226,209		226,209		226,209	

Notes: This table reports maximum likelihood estimates for heterogeneity in the experience effect (β) and the weighting parameter (λ) with the dependent variable bexp, i.e. respondents' business condition expectations. Coefficients can be interpreted as interaction effects of the specific variable with the experience effect and the weighting parameter (both "Constant"), respectively. Table also reports model-implied averages for both parameters. Time and age fixed effects are included in the model. The estimated coefficients for the direct effect of the covariates on the expectations (γ) as well as the estimates of the two cut-off parameters κ_1 and κ_2 are not reported. Standard error in brackets are clustered at the individual level. *** p <0.01, ** p <0.05, * p <0.1.

Recall that a weighting parameter of zero would imply that respondents weigh past years equally (cf. Figure 1.2). The estimates therefore suggest that respondents still put more weight on recent years than on distant years when aggregating past information, but to a lesser extent than in both the unemployment and inflation domain. It seems, however, striking that despite the differences in magnitude the model again identifies a negative gender effect for males, whereas the effect of the other covariates is again negligible and statistically indistinguishable from zero.

Figure 1.3 summarizes the gender differences in the weighting parameter by plotting gender-specific and domain-specific weighting functions, implied by the estimates from Tables 1.3, 1.4 and 1.5 (column 3 each). Independent of gender, the graph illustrates the

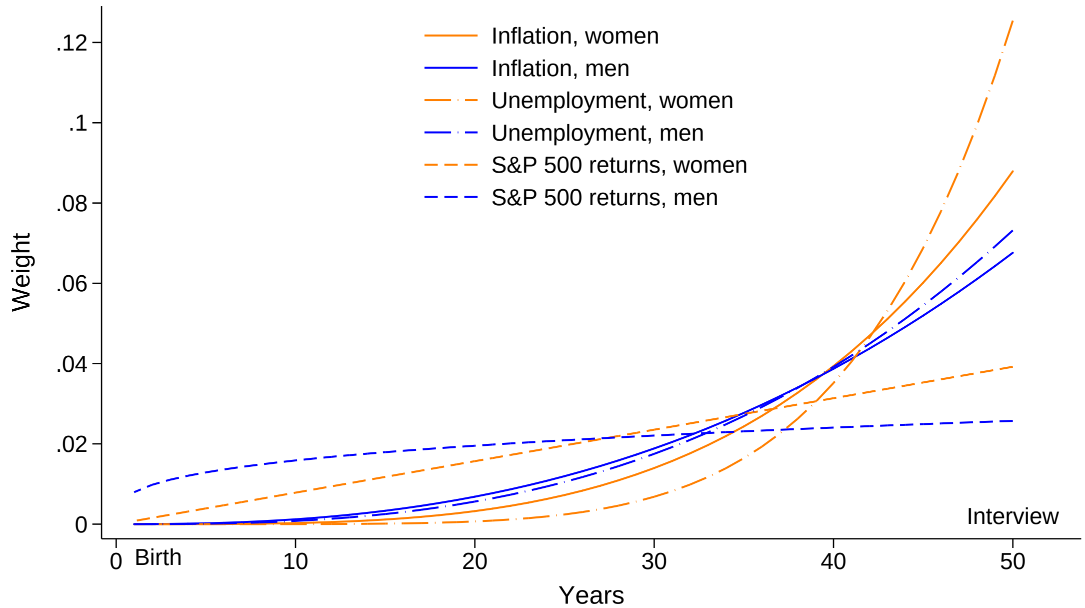


Figure 1.3: Model-implied gender differences in the weighting function of a 50-year-old respondent

similar weighting patterns in the inflation and unemployment domain and the difference to the business domain. While the weighting functions are clearly increasing in the first two domains, they are a lot flatter in the business domain. Equally important and independent of the domain, females – compared to males – always put lower weights on years close to birth and are more strongly influenced by years close to their survey interview.

1.5 Lasso estimates for experience heterogeneity

The heterogeneity analysis in both the experience effect and the weighting parameter has so far concentrated on modeling both parameters as simple linear functions of (binary) socio-economic covariates and a constant (cf. Equations 1.4 and 1.5). However, one could also imagine a more general specification allowing for arbitrary interactions between these covariates. It may, for example, be that the gender effect, which was identified in the previous section, depends on individuals' education. The most general case would include a fully interacted model of all covariates. However, as the number of coefficients in fully interacted models grows exponentially in the number of (binary) covariates, model complexity will further increase.

In order to deal with the high dimensionality of this estimation problem and to select the potentially few control variables and interactions of interest, I rely on the Lasso method (least absolute shrinkage and selection operator) as introduced by Tibshirani (1996).[19] While the literature offers multiple methods for selecting the optimal shrinkage parameter, which controls the strength of the penalization, I rely on three commonly used approaches. First, I derive the shrinkage parameter from a "rigorous", i.e. theory-driven, approach to penalization as introduced in Belloni et al. (2012) and further developed in Belloni et al. (2016). Second, I select the shrinkage parameter in a data-driven way using cross validation (CV) and minimizing the out-of-sample mean-squared prediction error (MSPE). Third, I choose the shrinkage parameter based on the Bayesian information criterion (BIC).[20]

To reduce the computational burden, I focus on the inflation model with heterogeneity in the experience effect only and fix the weighting parameter at the optimal value from the main model ($\lambda = 3.156$, Table 1.3, column 2). I estimate two different models: the

[19] For the Lasso-adjusted log likelihood function and more details, see Appendix C1.

[20] Using alternative information criteria, such as the Akaike information criterion (AIC) or the extended BIC (Chen and Chen, 2008), yields extremely similar results.

first penalized model (Table 1.6) repeats the previous analysis and includes the full vector of binary socio-economic dummy variables, but no interactions between them, while the second penalized model (Table 1.7) estimates a fully interacted model. However, for both illustrative reasons and further complexity reduction, I only consider three binary covariates and their possible interactions in the second model.

In both tables, I present five different specifications (columns). Column 1 reports estimates for an unpenalized model (with fixed weighting parameter), while columns 2, 3 and 4 report Lasso estimates using one of the three different selection criteria for the optimal shrinkage parameter, respectively. However, as any penalized regression model, the Lasso estimator is by construction biased due to its dimensionality reduction. Belloni and Chernozhukov (2013) therefore suggest to alleviate this bias by performing a post-Lasso analysis, i.e. by estimating the original, unpenalized model with these variables only, which were chosen by the Lasso in the first place. Specifically, the authors show that the post-Lasso estimator performs in the linear case at least as well as the Lasso under relatively mild additional assumptions.[21] Column 5 therefore reports post-Lasso estimates which are based on the rigorous Lasso results from column 2.[22] Note that the weighting parameter λ in the post-Lasso case is again unrestricted and should ideally be close to the estimate from the fully flexible maximum likelihood model in the previous section.

Table 1.6 reports estimates for the first model, including the full vector of binary socio-economic dummy variables, but no interactions between them.[23] Due to the (optimal) restriction of the weighting parameter, the estimates in column 1 are in fact identical to

[21] Note that fixing the weighting parameter λ makes the model on inflation expectations in fact linear in all explanatory variables (and their coefficients).

[22] Alternatively, the post-Lasso estimates could also be based on the CV Lasso or BIC Lasso results. However, since both estimators shrink only few coefficients to zero (cf. Tables 1.6 and 1.7), their post-Lasso estimates are extremely similar to the unpenalized estimates in column 1.

[23] I apply the penalization to all coefficients of the model. Alternatively, one could apply the penalization only to a subset of coefficients, for example those modeling heterogeneity. The results are almost identical.

Table 1.6: Lasso estimates for experience heterogeneity

	Inflation expectations (px1)				
	Not penalized	Lasso			Post-Lasso
	(1)	(2) Rigorous	(3) CV	(4) BIC	(5) Rigorous
Experience effect (β)					
Constant	0.631***	0.385	0.632	0.645	0.550***
	[0.032]				[0.028]
Male	-0.189***	-0.070	-0.189	-0.185	-0.187***
	[0.015]				[0.024]
Partner	0.018		0.018	0.019	
	[0.016]				
College	0.053***		0.052	0.048	
	[0.016]				
1st income quartile	0.063***	0.009	0.064	0.064	0.032
	[0.024]				[0.033]
2nd income quartile	0.026		0.026	0.026	
	[0.023]				
3rd income quartile	-0.001				
	[0.019]				
West	0.048**		0.047	0.042	
	[0.021]				
Northcentral	-0.080***		-0.079	-0.077	
	[0.019]				
Northeast	0.035		0.034	0.029	
	[0.022]				
Weighting parameter (λ)	3.156 (fixed)	3.156 (fixed)	3.156 (fixed)	3.156 (fixed)	3.165 (flexible)
Shrinkage parameter		230.599	0.448	3.015	
Year FE	yes	yes	yes	yes	yes
Age FE	yes	yes	yes	yes	yes
Direct controls	yes	yes	yes	yes	yes
Observations	213,037	213,037	213,037	213,037	213,037

Notes: This table reports estimates for heterogeneity in the experience effect (β) for the model on inflation expectations. Coefficients can be interpreted as interaction effects of the specific variable with the experience effect ("Constant"). Column 1 reports model estimates without penalization, while columns 2, 3 and 4 report Lasso estimates with different optimal shrinkage parameters. Column 5 reports post-Lasso estimates based on results from column 2. Time and age fixed effects are included in the model. The estimated coefficients for the direct effect of the covariates on the expectations (γ) are not reported. For details see text. Standard error in brackets are clustered at the individual level.
*** p <0.01, ** p <0.05, * p <0.1.

the ones from column 2 in Table 1.3. Independent of the shrinkage parameter, all three Lasso estimators identify a positive experience effect ("Constant") and confirm the gender effect from the previous analysis, i.e. the experience effect is smaller for males than for females. However, the exclusion of the other variables from the model clearly depends on the specific Lasso estimator. Using rigorous Lasso yields a relatively large shrinkage parameter of roughly 231 and therefore sets many of the other coefficients to (exactly) zero.[24] The shrinkage parameters chosen by cross-validation (column 3) and BIC (column 4) are a lot smaller; both Lasso estimators therefore shrink fewer coefficients to zero. In fact, they only set the coefficient of the third income quartile dummy to zero, while all other variables remain in the model. Not surprisingly, their Lasso estimates as well as their corresponding post-Lasso estimates (not reported) are, therefore, quantitatively very similar to the estimates from the unpenalized model in column 1. Last, column 5 reports the post-Lasso estimates based on the rigorous Lasso. Importantly, the positive experience effect and the negative gender effect are confirmed by the model. All other coefficients are either excluded in the first stage or statistically indistinguishable from zero. Most importantly, the now unrestricted weighting parameter is estimated to be 3.165, which is remarkably close to the fixed value of 3.156 from the main model (Table 1.3, column 2), providing additional support for the validity of the results.

Table 1.7 reports estimates for the fully interacted model, based on the three binary covariates “Male”, “Partner” and “College”.[25] Again, all models identify a positive experience effect (“Constant”) as well as a negative gender effect. In fact, the rigorous Lasso model sets all other coefficients except those two to zero. The CV Lasso and the BIC Lasso, in contrast, deliver lower shrinkage parameters and only exclude the interaction term between “Partner” and “College”. Again, the post-Lasso model in column 5 confirms earlier findings with an estimated weighting parameter of 3.732.

In summary, the Lasso estimates from both Tables 1.6 and 1.7 reinforce the findings from the previous section on inflation expectations. Independent of the shrinkage parameter choice, the models always identify a positive experience effect as well as a negative gender

[24] Unlike Ridge regression, which is based on an ℓ_2-penalization term, the Lasso sets the coefficients to exactly zero (see, for example, Friedman et al., 2001).

[25] As mentioned earlier, the reported coefficients of the covariates can be interpreted as interaction effects of the specific variable (or interaction term) with the experience effect (“Constant”). For example, “Male*Partner” represents the interaction effect of the interaction term of “Male” and “Partner” with “Experience”. The coefficients of *real* interaction terms (unrelated to “Experience”), such as the *real* interaction of “Male” and “Partner”, are included in the model, but not reported (cf. “Direct controls”).

Table 1.7: Lasso estimates for experience heterogeneity with three binary covariates

	Inflation expectations (px1)				
	Not penalized	Lasso			Post-Lasso
	(1)	(2) Rigorous	(3) CV	(4) BIC	(5) Rigorous
Experience effect (β)					
Constant	0.660***	0.372	0.662	0.662	0.507***
	[0.030]				[0.025]
Male	-0.274***	-0.070	-0.268	-0.269	-0.169***
	[0.029]				[0.022]
Partner	-0.033		-0.030	-0.031	
	[0.028]				
College	-0.054		-0.051	-0.051	
	[0.035]				
Male*Partner	0.039		0.034	0.034	
	[0.039]				
Male*College	0.166***		0.159	0.160	
	[0.049]				
Partner*College	-0.001				
	[0.046]				
Male*Partner*College	0.106*		0.107	0.107	
	[0.064]				
Weighting parameter ($\boldsymbol{\lambda}$)	3.156 (fixed)	3.156 (fixed)	3.156 (fixed)	3.156 (fixed)	3.732 (flexible)
Shrinkage parameter		230.627	1.189	0.899	
Year FE	yes	yes	yes	yes	yes
Age FE	yes	yes	yes	yes	yes
Direct controls	yes	yes	yes	yes	yes
Observations	213,037	213,037	213,037	213,037	213,037

Notes: This table reports estimates for heterogeneity in the experience effect (β) for the model on inflation expectations. Note that this model includes only the variables male, partner and college as well as all possible interactions to model heterogeneity. Coefficients can be interpreted as interaction effects of the specific variable or interaction term with the experience effect ("Constant"). Column 1 reports model estimates without penalization, while columns 2, 3 and 4 report Lasso estimates with different optimal shrinkage parameters. Column 5 reports post-Lasso estimates based on results from column 2. Time and age fixed effects are included in the model. The estimated coefficients for the direct effect of the covariates on the expectations (γ) as well as their interactions are not reported. For details see text. Standard error in brackets are clustered at the individual level. *** p <0.01, ** p <0.05, * p <0.1.

effect for males. Most importantly, "Male" is the only variable selected by all Lasso specifications, while the coefficients of the other variables are often shrunk to zero.

1.6 Robustness

This section provides several robustness checks to variations in methodology and data. The corresponding graphs and tables are presented in Appendix D1.

Grid estimation for fixed weighting parameters. I estimate the model on a tight grid for fixed values of the weighting parameter λ. Specifically, the values range from minus five to plus ten in intervals of one tenth. Figures D1.1, D1.2 and D1.3 plot the log likelihood for different values of λ in each of the three domains. In all three domains, the weighting parameter associated with the highest log likelihood in the restricted model is very close to the optimal weighting parameter in the fully flexible model from the main section, strengthening the validity of the results.

Starting point at age ten. In the main analysis, I assume that the starting point for accumulating lifetime experiences is at birth (cf. Malmendier and Nagel, 2011; Kuchler and Zafar, 2018). However, one might also argue that this starting point is later in life. I therefore repeat the main analysis by setting the starting point at age ten (Table D1.1). Recall that the results from the main model suggested that the first ten years have relatively little impact anyway. Consistent with that idea, the new weighting parameters slightly decrease, putting relatively more weight on, say, years between age 10 and 15; these years would otherwise have had lower weights than suggested by the original model. Most importantly, the model estimates remain qualitatively the same. The average experience effect is significantly positive in all three domains. Similarly, for both the inflation and the unemployment domain, the average weighting parameter is significantly positive and of similar magnitude as in the main section. Merely in the domain of business expectations, the average weighting parameter becomes statistically indistinguishable from zero and slightly negative. In all three domains, the gender effect for both the experience effect and the weighting parameter is found to be negative for males with identical variations in significance levels, as found in the main section.

Alternative outcome measures. I leverage the existence of alternative expectations questions from the MSC on future inflation and business conditions. First, respondents are additionally asked about their average inflation point expectations over the next five years (px5).[26] Second, the MSC also includes one question about future business expectations in absolute terms, such as "good" or "bad", rather than relative terms, such as "better" or "worse". The responses are summarized in the ordered variable bus12.[27] Table D1.2 repeats the main analysis for the two alternative outcome measures on medium-run inflation expectations (px5) and absolute business expectations (bus12) and reports estimates without heterogeneity and with full heterogeneity.[28] The model on medium inflation expectations (px5) identifies both the positive experience effect and the positive weighting parameter. The magnitudes of the estimates are close to the results from the main section, despite the considerable reduction in number of observations. The gender effect of being male is again negative for the experience effect, but slightly positive for the weighting parameter. However, the coefficient is only marginally significant ($p = 0.074$). The model on absolute business expectations (bus12) confirms both the positive experience effect and the positive weighting parameter. Moreover, the significantly negative gender effect for males is found for both parameters.

Excluding most recent experiences. The main analysis finds that the most recent experiences get on average the largest weights, when individuals aggregate past information. I therefore repeat the analysis on inflation expectations, excluding these years from the formation process of individuals' experience. If the true weighting function was, for ex-

[26]The elicitation method of the variable px5 is completely analogous to px1, the only difference being the new time horizon of five years. However, there are several years in which respondents are not asked about their medium-run inflation expectations, leading to a substantial reduction in the number of observations.

[27]The exact question wording is: "Now turning to business conditions in the country as a whole – do you think that during the next 12 months we'll have good times financially, or bad times, or what?". The five answer categories are: Bad times, Bad times with qualifications, Pro-con, Good times with qualifications and Good times.

[28]I adjust the empirical model to reflect the five answer categories in "bus12", compared to the three categories in "bexp", the main difference being the estimation of two additional cut-off parameters κ_3 and κ_4.

ample, bimodal (with sensitive periods before the survey and during early childhood), excluding the most recent years would result in a negative weighting parameter, representing the relative importance of inflation exposure in early childhood. Table D1.3 shows model estimates for excluding the last 3, 5 and 10 years of inflation rates, when aggregating experience. Most importantly, all three specifications identify a positive average weighting parameter, which is also quantitatively close to the main results. This shows again that the weighting function is increasing over time, implying that more recent years (before the excluded years) get higher weights than years close to birth. However, this is already predicted by the unrestricted estimates from the main model, strengthening the assumption on the specific form of the weighting function.

1.7 Conclusion

This paper showed that individuals' expectations about aggregate macroeconomic outcomes in at least three different domains are significantly associated with individuals' experiences of these outcomes. More specifically, higher experienced inflation rates, higher experienced unemployment rates and higher experienced S&P 500 returns during a respondent's lifetime significantly predict higher inflation expectations, higher unemployment expectations and more optimistic expectations about future business conditions, respectively. Extrapolation from past experience is thus found in all three domains, raising the question of broader applicability and the question whether or not inexplicable heterogeneity in expectations in other domains may be at least partly explained by differences in individuals' experiences.

Furthermore, the weighting parameter λ is constantly found to be positive, implying that respondents seem to generally put higher weights on recent years and lower weights on distant years, when aggregating past information. This is found in all three domains, although the magnitude differences imply that the up-weighting and down-weighting of recent and distant years, respectively, is more pronounced in the inflation and unemployment domain than in the domain of business expectations (cf. Figure 1.3).

Regarding heterogeneity in both the experience effect and the weighting parameter, there is strong evidence for the existence of a gender difference. In all three domains both parameters are usually significantly smaller (but still positive) for males than for females. Additionally, when analyzing heterogeneity in the experience effect of the inflation model, Lasso models select gender to be the only variable which is never excluded from the model. Taken together, the gender differences imply that males put on average more weight on distant years when aggregating past information and generally focus less on experiences than females.

This paper can, however, not say anything about the underlying reasons for the gender differences. In fact, the findings are consistent with multiple explanations. Psychological studies suggest, for example, that females perform slightly better at memory tasks, compared to males (Baer et al., 2006; Herlitz and Rehnman, 2008). The gender difference in the experience effect might therefore be connected to the fact that females are on average better at recalling past information than males. A related line of argument follows Jonung (1981) suggesting that females are traditionally responsible for the major share of food purchases; they are then more likely to be exposed to price changes and thus more familiar with current and past inflation rates than males.[29] Both arguments imply that males are simply less aware of past inflation rates and thus cannot base their expectations on experiences as much as females, explaining the gender difference in the experience effect. However, one could also argue for the opposite, namely that males – who are traditionally more responsible for household finances – are on average better informed about stock prices, inflation and business conditions than females. Completely unrelated to memory, an alternative explanation would be that males just form their expectations differently and, in particular, unrelated to past information. When asked about their expectations, they could, for example, rely on heuristics or intuition rather than on experience, again explaining a smaller experience effect for males. Clearly, further research is required to better understand these gender differences and their origins.

Last, other socio-economic covariates, such as education, income, having a partner or regional information, do not have a systematic impact on the experience effect and the weighting parameter. Even though their coefficients are occasionally significant, no clear pattern emerges. This finding is also supported by the Lasso analysis in this paper.

The results from this paper have two major implications for macroeconomists. First, the results should encourage researchers to incorporate extrapolative motives into economic

[29]For a critical discussion on this topic, see Bryan and Venkatu (2001a,b).

models of individual expectation formation. In particular, many dynamic stochastic general equilibrium (DSGE) models heavily rely on the assumption of rational expectations (RE). However, adaptive learning models, which relax the assumption of RE, are more in line with the results in this paper. Second, even if macroeconomic models include adaptive or extrapolative elements, they typically ignore heterogeneity. However, as shown in this paper, extrapolation depends on both age and gender and potentially even domain-specifically on other variables. Future research will therefore have to provide models, which are able to motivate and theoretically underpin this heterogeneity and thereby better match the empirical evidence.

Broadly speaking, the findings can also contribute to a better understanding of intergenerational conflicts. Different generations are – by definition – influenced by different histories of macroeconomic experiences. If experiences shape individuals' expectations, outcomes or even preferences, this could help to explain voting decisions not only of board members of the Federal Open Market Committee (FOMC) as in Malmendier et al. (2017), but also voting decisions of the entire population, as in presidential or parliamentary elections. For example, personal experiences may help to explain the generation gap in the 2016 United Kingdom EU referendum, i.e. the fact that most young people wanted to stay in the European Union, while most old people supported "Brexit" (Hobolt, 2016). Last, the potential interaction of the experience effect with socio-economic variables, such as gender, may also contribute to explaining the distinct voting patterns in the 2016 US presidential election.

Appendix

A1 Questionnaire for price expectations

Figure A1.1 describes the exact procedure for the elicitation of inflation point expectations in the short-run (px1), as asked in the Michigan Survey of Consumers (MSC). The entire questionnaire and interviewer instructions are available at the University of Michigan Survey Research Center and are described in Curtin (1996).

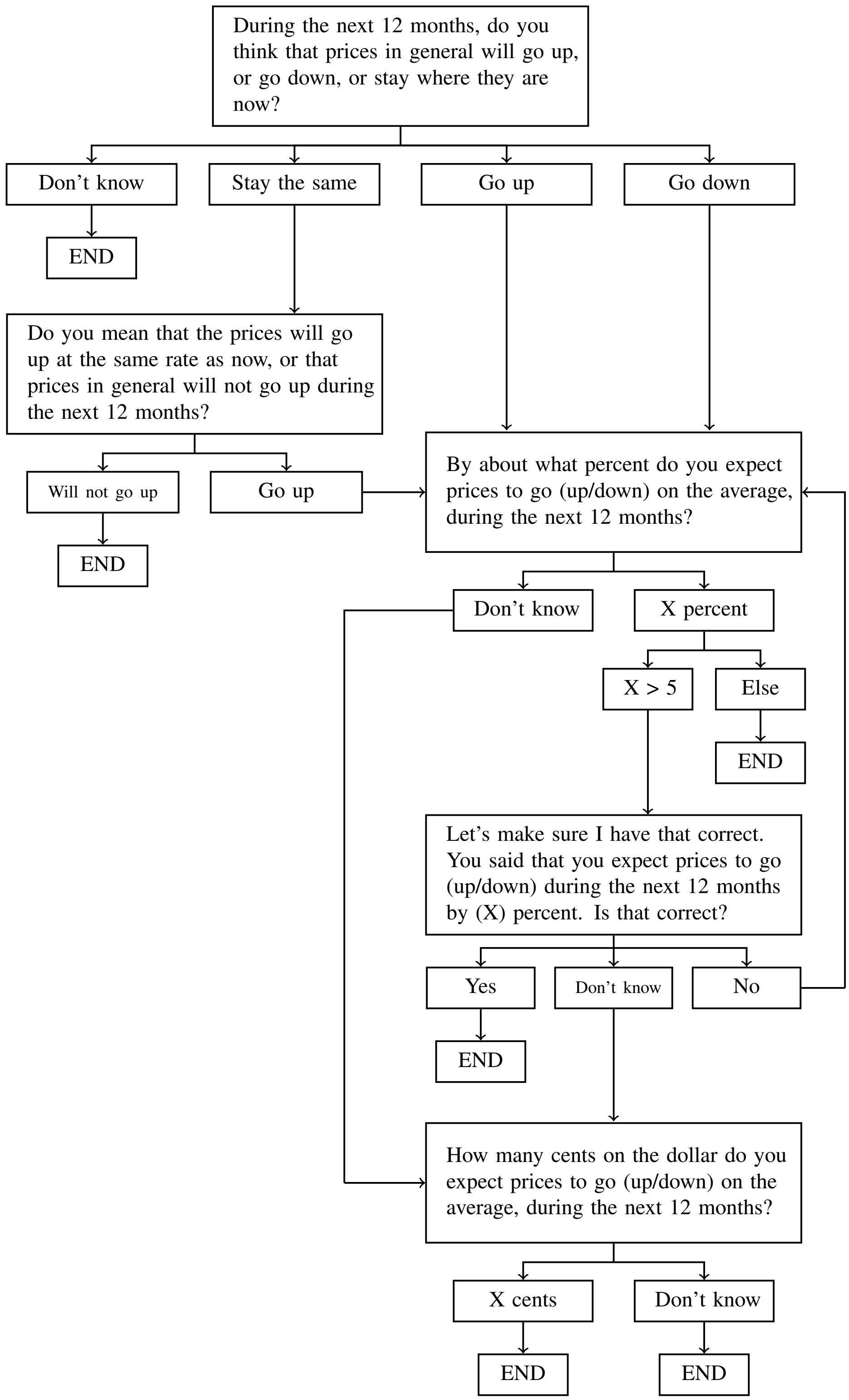


Figure A1.1: Questionnaire for short-run inflation expectations (px1)

B1 Direct effect of covariates

Table B1.1 displays the unreported coefficients from the maximum likelihood models on inflation (column 1), unemployment (column 2) and business expectations (column 3), respectively. All columns report the specification without heterogeneity in the experience effect (β) and the weighting parameter (λ), i.e. both parameters are modeled as constants. The estimates therefore correspond to the estimates from column 1 in Tables 1.3, 1.4 and 1.5, respectively.

Overall, Table B1.1 reports several parameter estimates. First, the direct effects of the covariates on expectations (γ) provide strong evidence for heterogeneity in expectations. Males, college graduates and the most affluent respondents are found to report lower inflation expectations, lower unemployment expectations and more optimistic expectations about future business conditions. These associations are all significant at the one percent level. Similar findings can be found in and are discussed by Manski (2004), Ranyard et al. (2008), Hobijn et al. (2009), Binder (2017) and others. Second, the estimates for the experience effect β and the weighting parameter λ, which are already discussed in detail in the main section, are shown for reasons of completeness. Third, the inflation model estimates the standard deviation of the error term (σ) as well as the constant in the covariate vector γ, whereas the model on unemployment and business expectations restricts the parameters to one and zero, respectively. It rather estimates the two cut-off parameters κ_1 and κ_2 which determine the frequency of the three outcome categories in the ordered variables on unemployment and business expectations. Still unreported are the coefficients for the year and age fixed effects.

Table B1.1: Unreported maximum likelihood estimates

	Expectations					
	(1) Inflation		(2) Unemployment		(3) Business conditions	
Direct effects ($\boldsymbol{\gamma}$)						
Constant	0.075***	[0.004]				
Male	-0.008***	[0.000]	-0.124***	[0.005]	0.150***	[0.005]
Partner	0.001***	[0.000]	-0.044***	[0.006]	0.006	[0.006]
College	-0.004***	[0.000]			0.069***	[0.006]
1st income quartile	0.014***	[0.000]				
2nd income quartile	0.008***	[0.000]				
3rd income quartile	0.003***	[0.000]				
West	-0.001	[0.000]	0.008	[0.007]	-0.006	[0.007]
Northcentral	-0.002***	[0.000]	0.017**	[0.007]	-0.028***	[0.007]
Northeast	-0.001***	[0.000]	0.034***	[0.008]	-0.007	[0.008]
Standard deviation (σ)						
Constant	0.056***	[0.000]				
Experience effect ($\boldsymbol{\beta}$)						
Constant	0.586***	[0.039]	0.069***	[0.011]	2.921***	[0.355]
Weighting parameter ($\boldsymbol{\lambda}$)						
Constant	3.619***	[0.383]	3.809***	[0.340]	0.520***	[0.077]
Cut-off parameter 1 (κ_1)						
Constant			-1.057***	[0.077]	-0.245***	[0.038]
Cut-off parameter 2 (κ_2)						
Constant			0.336***	[0.003]	0.355***	[0.003]
Year FE	yes		yes		yes	
Age FE	yes		yes		yes	
Observations	213,037		228,413		226,209	

Notes: This table reports the unreported coefficients from the maximum likelihood estimates for the model on (1) inflation, (2) unemployment and (3) business expectations. It is based on the specifications without heterogeneity in the experience effect (β) and the weighting parameter (λ). Time and age fixed effects are not reported. For details see text. Standard error in brackets are clustered at the individual level. *** p <0.01, ** p <0.05, * p <0.1.

C1 Estimation of the Lasso model

Section 1.5 is based on the Lasso methodology, as introduced by Tibshirani (1996). Applying the Lasso to the model on inflation expectations with fixed weighting parameter λ^{fixed} results in the following objective function for the penalized model:

$$\min_{(\beta,\gamma,\sigma)\in R^p} -\left[\sum_{i=1}^{N} \ln[\phi(y_{it}; \boldsymbol{w}_{it}\boldsymbol{\beta}A_{it}(\lambda^{fixed}) + \boldsymbol{x}_{it}\boldsymbol{\gamma}; \sigma)]\right] + \tau\left[||\boldsymbol{\beta}||_1 + ||\boldsymbol{\gamma}||_1\right] \tag{1.11}$$

where p denotes the number of coefficients which are to be estimated and $\phi(\cdot)$ the probability density function (p.d.f.) of the standard normal distribution. The other variables and coefficients are defined in the same way as in the main section. The first term of the objective function is given by the negative log likelihood function from Equation 1.6 under the restriction of a fixed weighting parameter λ^{fixed}. The second term adds an ℓ_1-norm penalization term, equal to the sum of the absolute value of the coefficients which are to be penalized (here $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$), multiplied by a shrinkage parameter τ, which controls the strength of the penalization. For a given shrinkage parameter τ, the Lasso estimator is then given by the solution to this minimization problem; several approaches for the specific choice of τ are discussed in Section 1.5. The Lasso analysis is implemented in R (version 3.5.2) using the `glmnet` package by Friedman et al. (2010) and in Stata®15 using the `lassopack` package by Ahrens et al. (2018).

D1 Additional Figures and Tables

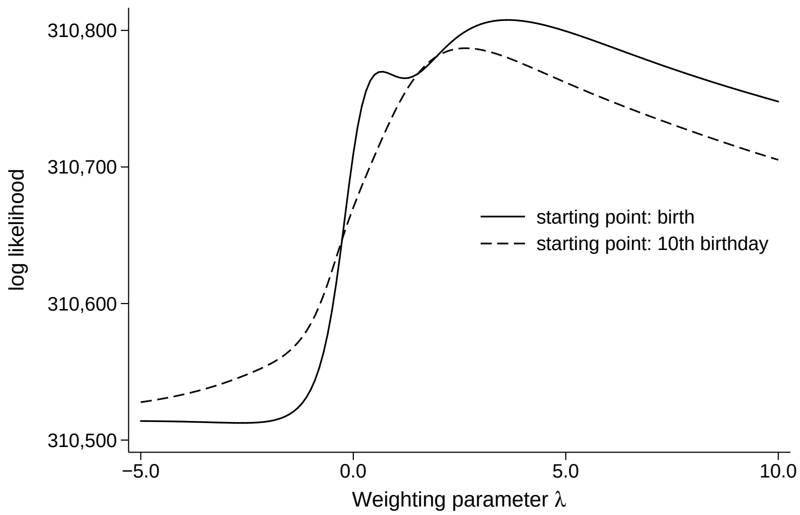


Figure D1.1: Log likelihood of model on inflation expectations for different values of the weighting parameter

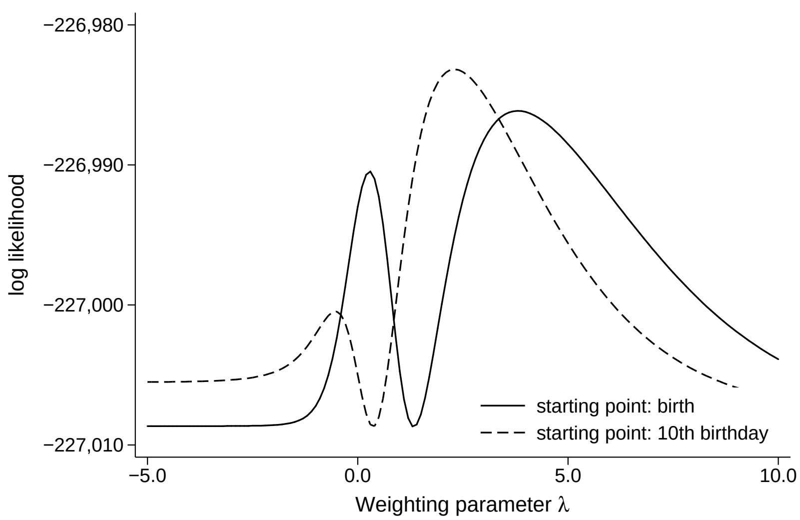


Figure D1.2: Log likelihood of model on unemployment expectations for different values of the weighting parameter

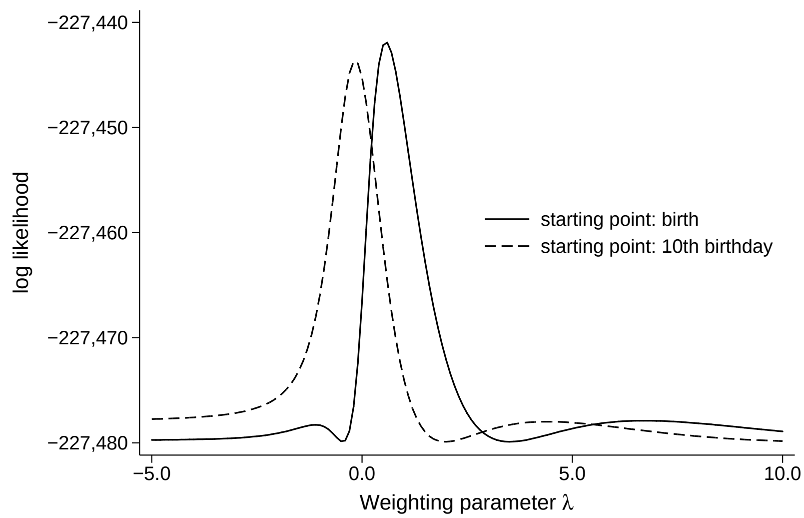


Figure D1.3: Log likelihood of model on business expectations for different values of the weighting parameter

Table D1.1: Model estimates with experience accumulation starting at age ten

	Expectations					
	(1) Inflation		(2) Unemployment		(3) Business conditions	
Experience effect ($\boldsymbol{\beta}$)						
Constant	0.407***	[0.048]	0.056***	[0.011]	1.916***	[0.264]
Male	-0.148***	[0.024]	0.007	[0.010]	-1.123***	[0.297]
Partner	0.040**	[0.020]	0.009	[0.010]	0.002	[0.252]
College	0.041**	[0.019]				
1st income quartile	0.177***	[0.044]				
2nd income quartile	0.093***	[0.033]				
3rd income quartile	0.024	[0.023]				
West	0.060**	[0.025]	0.019	[0.013]	-0.216	[0.337]
Northcentral	-0.055**	[0.023]	-0.009	[0.011]	-0.149	[0.286]
Northeast	0.049*	[0.027]	-0.009	[0.014]	-0.306	[0.348]
Weighting parameter ($\boldsymbol{\lambda}$)						
Constant	4.721***	[1.048]	3.701***	[0.850]	0.197	[0.203]
Male	0.001	[0.419]	-2.807***	[0.863]	-0.705***	[0.268]
Partner	-0.771***	[0.286]	0.510	[0.520]	0.072	[0.179]
College	0.466	[0.412]				
1st income quartile	-2.557***	[0.905]				
2nd income quartile	-1.830**	[0.863]				
3rd income quartile	-0.778	[0.714]				
West	-0.253	[0.443]	0.405	[0.523]	-0.057	[0.256]
Northcentral	-0.487	[0.374]	0.552	[0.555]	-0.393**	[0.190]
Northeast	-0.587	[0.372]	-0.538	[0.596]	-0.232	[0.315]
Avg. beta ($\bar{\beta}$)	0.443		0.065		1.230	
Avg. lambda ($\bar{\lambda}$)	3.045		2.783		-0.263	
Year FE	yes		yes		yes	
Age FE	yes		yes		yes	
Direct controls	yes		yes		yes	
Observations	213,037		228,413		226,209	

Notes: This table repeats the main analysis setting the starting point of experience accumulation at age ten. It reports maximum likelihood estimates for heterogeneity in the experience effect (β) and the weighting parameter (λ) with the dependent variables on expectations about inflation, unemployment and business conditions. Coefficients can be interpreted as interaction effects of the specific variable with the experience effect and the weighting parameter (both "Constant"), respectively. Table also reports model-implied averages for both parameters. Time and age fixed effects are included in the model. The estimated coefficients for the direct effect of the covariates on the expectations (γ) as well as the estimates of the two cut-off parameters κ_1 and κ_2 and the estimate of the standard deviation of the error term (σ) are not reported. For details see text in Section 1.6. Standard error in brackets are clustered at the individual level. *** p <0.01, ** p <0.05, * p <0.1.

Table D1.2: Model estimates for alternative outcomes measures of expectations

	Medium-run inflation expectations				Absolute business expectations			
	(1)		(2)		(3)		(4)	
Experience effect (β)								
Constant	0.885***	[0.058]	1.087***	[0.087]	0.805*	[0.425]	1.630***	[0.505]
Male			-0.305***	[0.046]			-0.723**	[0.299]
Partner			-0.007	[0.034]			-0.503	[0.349]
College			-0.206***	[0.049]			0.134	[0.277]
1st income quartile			0.268***	[0.081]				
2nd income quartile			0.113**	[0.056]				
3rd income quartile			0.041	[0.043]				
West			0.016	[0.045]			-0.364	[0.405]
Northcentral			-0.142***	[0.040]			0.240	[0.338]
Northeast			-0.063	[0.042]			-0.857	[0.575]
Weighting parameter (λ)								
Constant	2.547***	[0.297]	2.499***	[0.910]	0.544***	[0.180]	0.290	[0.247]
Male			0.569*	[0.318]			-1.178**	[0.486]
Partner			-0.065	[0.259]			2.639	[1.861]
College			0.658*	[0.337]			0.375	[0.372]
1st income quartile			-0.636	[0.718]				
2nd income quartile			-0.821	[0.616]				
3rd income quartile			-0.243	[0.491]				
West			0.025	[0.282]			0.219	[0.444]
Northcentral			0.212	[0.291]			0.724*	[0.383]
Northeast			0.512*	[0.297]			0.805	[1.021]
Avg. beta ($\bar{\beta}$)	0.885		0.891		0.805		0.854	
Avg. lambda ($\bar{\lambda}$)	2.547		2.793		0.544		1.874	
Year FE	yes		yes		yes		yes	
Age FE	yes		yes		yes		yes	
Direct controls	yes		yes		yes		yes	
Observations	163,269		163,269		210,032		210,032	

Notes: This table reports maximum likelihood estimates for the heterogeneity in the experience effect (β) and the weighting parameter (λ) with the two alternative dependent variables "px5" (medium-run inflation expectations) and "bus12" (absolute business expectations). For details see text in Section 1.6. Coefficients can be interpreted as interaction effects of the specific variable with the experience effect and the weighting parameter (both "Constant"), respectively. Table also reports model-implied averages for both parameters. Time and age fixed effects are included in the model. The estimated coefficients for the direct effect of the covariates on the expectations (γ) as well as the estimates for the cut-off parameters κ_1, κ_2, κ_3 and κ_4 and the estimate of the error term (σ) are not reported. Standard error in brackets are clustered at the individual level. *** p <0.01, ** p <0.05, * p <0.1.

Table D1.3: Model estimates for inflation expectations, excluding the most recent experiences

	Inflation expectations (px1)					
	Exclude last 3 years of inflation experience (1)		Exclude last 5 years of inflation experience (2)		Exclude last 10 years of inflation experience (3)	
Experience effect (β)						
Constant	0.434***	[0.059]	0.393***	[0.070]	0.281***	[0.042]
Male	-0.097***	[0.028]	-0.074***	[0.022]	-0.019	[0.019]
Partner	0.059**	[0.027]	0.049**	[0.023]	0.033	[0.021]
College	-0.143**	[0.056]	-0.123	[0.104]	-0.117***	[0.024]
1st income quartile	0.189***	[0.064]	0.186**	[0.093]	0.204***	[0.041]
2nd income quartile	0.041	[0.041]	0.034	[0.060]	0.034	[0.027]
3rd income quartile	-0.003	[0.027]	-0.005	[0.034]	-0.004	[0.020]
West	-0.005	[0.030]	0.004	[0.033]	-0.021	[0.024]
Northcentral	-0.020	[0.031]	0.002	[0.033]	0.036	[0.024]
Northeast	0.052	[0.033]	0.052	[0.032]	-0.004	[0.026]
Weighting parameter (λ)						
Constant	2.249**	[0.936]	3.335	[2.566]	5.226***	[0.965]
Male	-1.333***	[0.291]	-1.787***	[0.373]	-3.695***	[0.548]
Partner	-0.078	[0.297]	-0.041	[0.417]	0.108	[0.455]
College	2.638***	[0.615]	2.889**	[1.393]	3.284***	[0.953]
1st income quartile	-0.172	[0.654]	-0.602	[1.883]	-0.075	[0.708]
2nd income quartile	0.198	[0.472]	-0.118	[1.367]	0.196	[0.596]
3rd income quartile	0.191	[0.335]	0.089	[0.732]	0.249	[0.574]
West	0.239	[0.326]	0.356	[0.433]	0.941	[0.771]
Northcentral	-0.455*	[0.261]	-0.548	[0.348]	-0.784	[0.521]
Northeast	0.284	[0.327]	0.607	[0.459]	0.592	[0.731]
Avg. beta ($\bar{\beta}$)	0.412		0.390		0.294	
Avg. lambda ($\bar{\lambda}$)	2.658		3.528		5.010	
Year FE	yes		yes		yes	
Age FE	yes		yes		yes	
Direct controls	yes		yes		yes	
Log likelihood	310,878.5		310,859.3		310,783.6	
Observations	213,037		213,037		213,037	

Notes: This table repeats the main analysis on inflation expectations (px1), excluding the most recent experiences of inflation rates. It reports maximum likelihood estimates for heterogeneity in the experience effect (β) and the weighting parameter (λ). Coefficients can be interpreted as interaction effects of the specific variable with the experience effect and the weighting parameter (both "Constant"), respectively. Table also reports model-implied averages for both parameters. Time and age fixed effects are included in the model. The estimated coefficients for the direct effect of the covariates on the expectations (γ) as well as the estimate for the variance of the error term σ are not reported. Standard error in brackets are clustered at the individual level. *** p <0.01, ** p <0.05, * p <0.1.

Chapter 2

Dynamics and heterogeneity of subjective stock market expectations*

Abstract

Between 2004 and 2016, we elicited individuals' subjective expectations of stock market returns in a Dutch internet panel at bi-annual intervals. In this paper, we develop a panel data model with a finite mixture of expectation types who differ in how they use past stock market returns to form current stock market expectations. The model allows for rounding in the probabilistic responses and for observed and unobserved heterogeneity at several levels. We estimate the type distribution in the population and find evidence for considerable heterogeneity in expectation types and meaningful variation over time, in particular during the financial crisis of 2008/09.

* This chapter is based on joint work with Florian Heiß, Michael Hurd, Maarten van Rooij and Joachim Winter.

2.1 Introduction

Subjective expectations are crucial in all individual decisions where outcomes only materialize in the future and are subject to uncertainty. These include decisions regarding education, health, insurance, and household finance. One might argue that such intertemporal decisions are among the most important ones individuals make. In order to understand the determinants of subjective expectations and their role in decision-making, they must be measured at the individual level. Since the early 1990s, researchers have elicited subjective expectations of individuals in large-scale surveys (e. g., Dominitz and Manski, 1997).[1] For example, data on subjective stock market expectations contributed to the understanding of the stock market participation puzzle; see Dominitz and Manski (2007, 2011); Hudomiet et al. (2011); Hurd et al. (2011), *inter alia*. These papers document substantial heterogeneity of subjective expectations in the population and show that individuals' expectations predict their stock-market decisions. However, less is known about how individuals form and adjust their expectations.

This paper reports on findings from a study that collected data on subjective stock market expectations over a twelve-year period in a large, representative internet panel in the Netherlands. Expectations were elicited using a probabilistic format and refer to the one-year ahead rate of return of the Amsterdam Stock Exchange index (AEX), with four questions on gains and losses, respectively. We thus have, for each respondent and each interview date, eight responses that correspond to well-defined points on the subjective distribution of expected one-year rates of return. Results from the first two surveys, conducted in 2004 and 2006, are reported in Hurd et al. (2011); that paper documents substantial heterogeneity in stock market expectations.

[1] For comprehensive overviews of the measurement and analysis of subjective expectations, see Hurd (2009) and Manski (2004, 2018).

The present paper uses a much longer panel with data from follow-up surveys conducted in 2008, 2009, 2010, 2012, 2014, and 2016. These data are unique because they cover subjective expectations elicited with the same probabilistic format over a period of twelve years which includes the 2008/09 financial market crisis. As an important innovation in the econometric methodology for the analysis of subjective expectations, we propose a panel data model with a finite mixture of expectation types who differ in how they use past stock market returns to form current stock market expectations, following ideas by Dominitz and Manski (2011). The model allows for rounding in the probabilistic responses and for observed and unobserved heterogeneity at several levels.

We argue that individuals may differ in how they use past stock market returns when forming stock market expectations. Dominitz and Manski (2011) suggest that the population can be described by three latent expectation types. The first type (Random Walk, RW) believes that returns are independent and identically distributed (i.i.d.) over time and – given this belief – uses the long-run historical average return to predict returns. Type two (Mean Reversion, MR) believes that recent stock market changes will be reversed in the near future and type three (Persistence, P) believes that recent stock market changes will persist into the near future.

In this paper, we build on this insight and develop a panel data model with a finite mixture of three distinct expectation types who are allowed to differ in how they use the recent stock market performance to form expectations. Since individual type membership is not directly observed in the data, we model type probabilities and allow them to depend on both observed and unobserved individual-specific heterogeneity. The inclusion of year-fixed effects in the model also allows us to study the dynamics of the sample type distribution throughout the financial crisis. Our model includes two additional features. First, we specify an entire reporting model for subjective stock market expectations to capture different rounding patterns of individuals. Second, our model provides a sophisticated method to take use of the very detailed information on individuals' stock market expectations, i.e. all eight points on individuals' c.d.f. of expected one-year rates of return. The entire model is then estimated jointly to avoid selection bias (Kleinjans and van Soest, 2014).

Our results suggest that the population may indeed be described by three distinct expectation types who differ in how they use the past one-year AEX return to form expectations. While the first type does not seem to use this return, the second and third type do so in a negative and positive manner, respectively. These findings are in line with the Dominitz and Manski (2011) interpretation and allow us to label the three expectation types (RW,MR,P), as defined above. The implied distribution of these three types in the sample is given by (0.60,0.19,0.21), suggesting that most individuals do not use the past one-year AEX return when forming their expectations.

Further analysis reveals the existence of substantial individual-specific heterogeneity in the type probabilities. For example, females are significantly more likely to be type MR or type P than males. Similarly, highly educated respondents are more likely to be type RW. We also find evidence for the importance in accounting for unobserved factors. The model identifies several significant correlations between the individual effects, implying that, for example, individuals who are more likely to be type MR are also more likely to be type P.

We also use the coefficients of the year-fixed effects to predict the dynamics of the expectation type distribution in the sample. The results suggest that in years unaffected by the 2008 financial crisis, the type distribution is very similar. However, after the onset of the crisis, there is a substantial increase in the MR type share, which is followed by a large increase in the P type share. Both effects are, however, shown to be temporary, resulting in a 2016 type distribution which is close to the pre-crisis distributions of 2004 and 2006.

Moreover, our model confirms substantial heterogeneity in individuals' reported stock market expectations, as often found in the literature (cf. Dominitz and Manski, 2007; Hudomiet et al., 2011; Hurd et al., 2011). For example, males and more educated respondents have on average higher expectations than females and less educated respondents. Heterogeneity with respect to observable characteristics can also be found in our rounding model. Males tend to round less often than females; this also holds for young and highly educated respondents. Again, unobserved heterogeneity is found to be an additional important factor to account for. While we find evidence for different rounding behavior between questions on more or less extreme stock market changes, we find no differences between the gain and loss domain.

Our paper is related to several strands of the literature. Substantively, we add to the analysis of heterogeneity in subjective expectations, both with respect to the level and to updating of beliefs, specifically in the domain of stock market returns (Dominitz and Manski, 2007, 2011; Hudomiet et al., 2011; Hurd et al., 2011; Ameriks et al., 2018). We also extend the econometric toolkit for the analysis of subjective expectations data, in two directions. First, we embed the discrete type classification for belief updating proposed by Dominitz and Manski (2011) in a panel model. Second, we enrich this panel model by a response model that allows for nonresponse and rounding, inspired by Manski and Molinari (2010) and building on the parametric framework of Kleinjans and van Soest (2014). Our paper is also related to current research on response behavior in probabilistic expectations questions (Giustinelli et al., 2018) and the econometric modeling of stock market beliefs by Drerup et al. (2017) and von Gaudecker and Wogrolly (2018).

The remainder of this paper is organized as follows. We first describe our data and present basic descriptive analyses (Section 2.2). We then introduce our panel data model in Section 2.3 and present the results in Section 2.4. Robustness analyses are discussed in Section 2.5, while Section 2.6 concludes.

2.2 Data

The study was conducted using the CentER Panel, a household panel administrated by CentERdata at the University of Tilburg. About 2,000 Dutch households are interviewed online every spring in 2004, 2006, 2008, 2009, 2010, 2012, 2014 and 2016, making a total of eight waves (see Figure 2.1). While the majority of respondents participated right away, others who did not were contacted again three or four weeks later.

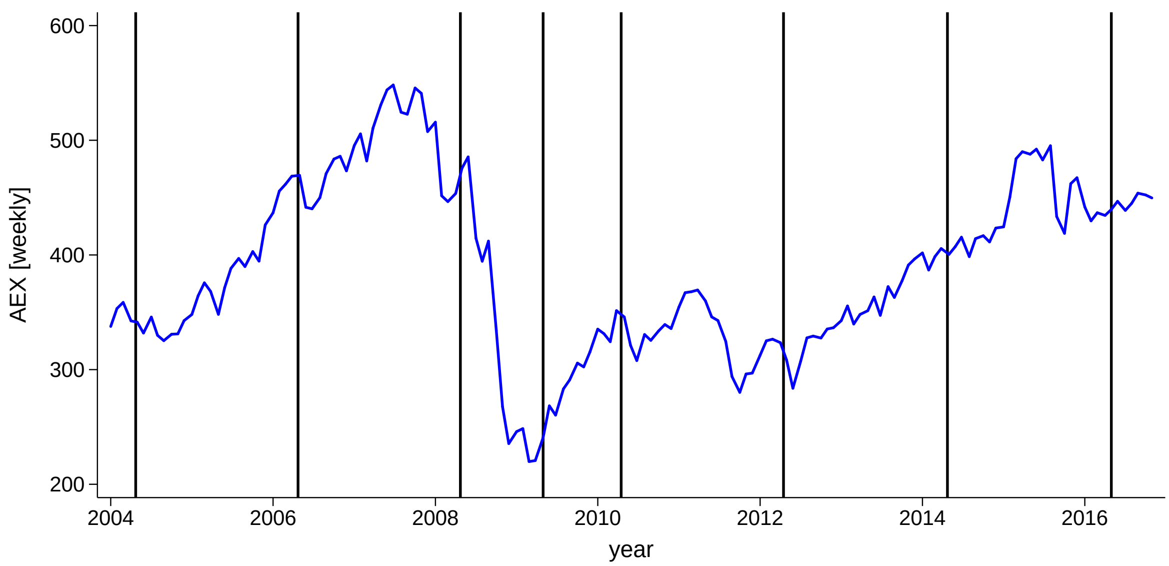


Figure 2.1: Amsterdam Stock Market Index (AEX) and spring interviews (vertical lines)

Most importantly, the questionnaire contains detailed probabilistic expectations questions on the stock market over a one-year horizon. The questions start with a short introduction explaining that the respondent has to imagine that she unexpectedly received 10,000 Euro from a rich relative and is thinking of putting the money into a mutual fund invested in "blue chip" stocks (like those in the Amsterdam AEX stock market index). We then ask for the chances that an investment in a broad investment fund will generate gains of more than 0%, 10%, 20% and 30%, as well as losses of more than 0%, 10%, 20% and 30% percent, for a total of eight questions. The four questions within each sequence (gain and loss) are always presented with increasing absolute threshold returns, but the gain and loss sequences are presented in random order. The wording of the first question in the gain sequence reads as follows:

> *Suppose you put the 10,000 Euro in the stock mutual fund and left it in for one year. What are the chances that you would make money where 0 means absolutely no chance and 100 means absolutely certain; that is what are the chances that in a year your investment would be worth more than 10,000 Euro?*

The other questions in this sequence use a very similar wording, with different numbers and adjusted to reflect the gain and loss sequence where appropriate. Moreover, the questionnaire in some years also contains questions on stock market experience, knowledge of average long-term returns for investment in risky and safe assets, and past trading history. For more detailed information, we refer the reader to Hurd et al. (2011).

Households from the CentER Panel also participate in the annual DNB Household Survey (DHS), formerly known as the CentER Savings Survey, which has two major advantages. First, we are able to merge our data with very detailed background information from the DHS. Second, since probabilistic questions have repeatedly been asked both in the DHS and in special purpose surveys run in the CentER panel, members of the panel are well acquainted with this question format.

Overall, our (unbalanced) panel data set contains 5,718 individuals who are observed in up to eight waves between 2004 and 2016, resulting in a total of 16,565 observations. Panel A of Table 2.1 displays standard summary statistics for the eight stock market expectations questions.[2] Overall, the respondents are quite pessimistic regarding the future stock market performance, confirming findings from earlier literature (Dominitz and Manski,

[2] Item non-response rates for subjective probability questions on the stock market are typically higher than for expectations questions in other domains (see, for example, Hurd, 2009). However, item non-response rates in our data are very similar to those from other surveys that include questions on stock market expectations, such as the Health and Retirement Survey (Kleinjans and van Soest, 2014).

Table 2.1: Summary statistics

	Mean	SD	Min	Max	Observations
A: Stock market expectations [%]					
Gain > 0%	42.70	27.03	0	100	13,940
Gain > 10%	22.77	21.65	0	100	13,666
Gain > 20%	12.76	16.77	0	100	13,569
Gain > 30%	7.31	13.39	0	100	13,510
Loss > 0%	40.91	25.55	0	100	13,936
Loss > 10%	29.55	25.64	0	100	13,541
Loss > 20%	20.40	23.64	0	100	13,417
Loss > 30%	14.94	22.42	0	100	13,281
B: AEX returns [%]					
One-year return	3.18	27.05	-48.91	46.65	16,565
One-month return	0.68	5.39	-11.31	10.08	16,565
One-week return	0.18	2.43	-4.23	4.02	16,565
C: Covariates [0/1]					
Female	0.47	0.50	0	1	16,554
Age > 64	0.25	0.44	0	1	16,565
Age < 45	0.33	0.47	0	1	16,565
Low education	0.30	0.46	0	1	16,547
High education	0.39	0.49	0	1	16,547
Partner	0.77	0.42	0	1	16,565
HH income: 1st quartile	0.25	0.43	0	1	16,565
HH income: 2nd quartile	0.25	0.43	0	1	16,565
HH income: 3rd quartile	0.25	0.43	0	1	16,565
HH income: 4th quartile	0.25	0.43	0	1	16,565
No. children in HH [#]	0.70	1.06	0	7	16,565
Riskaverse	0.84	0.36	0	1	9,856
Trust in other people	0.58	0.49	0	1	13,682

Notes: Sample consists of 5,718 individuals who are observed in up to eight waves between 2004 and 2016, $N = 16,565$. Varying number of observations due to item nonresponse. The dummy variable "Trust in other people" is not available in 2009, "Riskaverse" not in 2006, 2008 and 2009. For details see text.

2007; Hurd et al., 2011). The average subjective probability that the stock market will make any loss (Loss > 0%) is 40.9% and therefore almost as high as the average subjective probability that the stock market will make any gain (42.7%). For questions on more extreme changes in the stock market (gains and losses of more than 10, 20 and 30 percent), respondents assign on average even more probability mass to negative events than to positive events. For example, respondents report an average chance of 7.3% for the Gain > 30% question, compared to an average chance of 14.9% for the Loss > 30% question.

Panel B of Table 2.1 concentrates on three past returns of the Amsterdam Exchange index (AEX), which respondents experienced prior to their interview. Specifically, we use the respondents' interview week to calculate the experienced returns for one year, one month and one week, respectively.[3] On average, respondents experienced a one-year return of three percent prior to their interview date. However, these returns are also quite volatile, with a standard deviation of roughly 27 percent and a minimum (maximum) return of −48 (+46) percent in April 2009 (April 2010). The experienced returns over shorter periods are naturally smaller in magnitude, but on average positive.

Panel C of Table 2.1 describes our sample regarding several socio-economic dummy variables. Overall, there are slightly fewer females than males in the sample. One in three respondents is younger than 45 years, while one in four respondents is 65 or older. One third of the respondents completed no more than primary school or prevocational training (low education), while another third completed higher vocational training or university education (high education). The average household has 0.7 children. Our measure of risk aversion is based on a measure developed by Barsky et al. (1997), which asks if respondents prefer their current income above a gamble with equal probabilities on a 33% worse lifetime income and a doubling of the income. Using this methodology, the majority of

[3] Since the large majority of respondents are interviewed in the same week, the variation in these returns is mainly temporal rather than cross-sectional.

respondents are classified as risk averse. Unfortunately, this question is not asked in 2006, 2008 and 2009, leading to a substantial reduction in number of observations. In addition, respondents are asked whether they agree on that – generally speaking – *Most people can be trusted* rather than *One has to be very careful with other people.* Overall, 58% of the respondents agree on the former. Again, this question has not been asked in 2009.

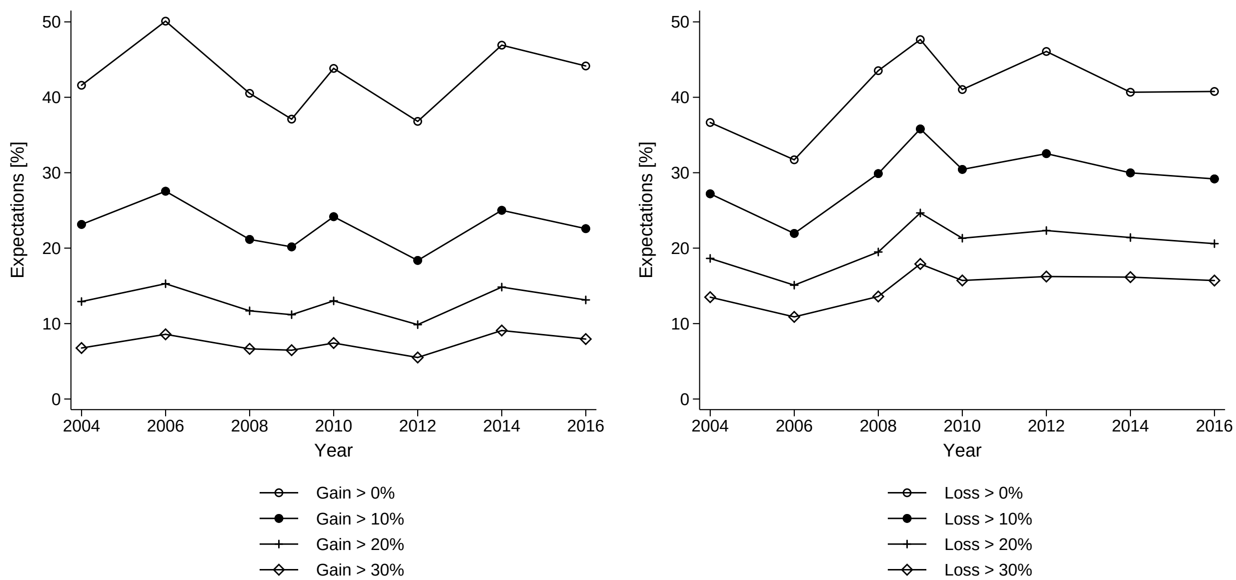


Figure 2.2: Descriptive time-series of subjective stock market expectations

Respondents' stock market expectations display considerable variation over time. Figure 2.2 displays average stock market expectations over time for each of the eight expectations questions. In general, expectations seem to follow the business cycle. The financial crisis in 2009 as well as the subsequent European sovereign debt crisis in 2012, coincide with dips in expectations in the gain domain (left panel) and peaks in the loss domain (right panel). Similarly, expectations are more optimistic during the boom of 2006. Overall, the largest changes in mean expectations can be found in the Gain > 0% and Loss > 0% question. If individuals are asked about more extreme events (gains and losses of more than 10, 20 or 30 percent), average expectations display considerably less variation over time. For example, the average probability that the AEX will increase by more than 30 percent in the next year varies only between 5.5% (in 2012) and 9% in (2014). For questions on the probability of more extreme loss events, there is more variation over time; in 2009, respondents shifted their entire distribution by roughly five percentage points upwards. Interestingly, the sovereign debt crisis in 2012 did not have such an effect. Overall, it seems as if during the financial crisis respondents systematically shifted probability mass to negative outcomes of the distribution. Additional descriptive analyses are reported in Appendix A2.

2.3 Model

2.3.1 Modeling the subjective mean

Following Dominitz and Manski (2011), we assume that the population can be described by three latent expectation types who differ in how they use past stock market returns to form their stock market expectations. The first type (Random Walk, RW) believes that returns are independent and identically distributed (i.i.d.) over time and – given this belief – uses the long-run historical average return to predict returns. Type two (Mean Reversion, MR) believes that recent stock market changes will be reversed in the near future and type three (Persistence, P) believes that recent stock market changes will persist into the near future. Note that the literature also refers to type P as "Momentum" type (see, for example, Armona et al., 2018).

Suppose that the (latent) mean μ^*_{itk} of the subjective year-ahead stock market return distribution of respondent i of type k in period t can be described by

$$\mu^*_{itk} = \alpha_i^{Mu} + \boldsymbol{x}_{it}\boldsymbol{\beta} + f_k(\mathcal{R}_t), \qquad k = 1, 2, 3 \tag{2.1}$$

where α_i^{Mu} is a respondent-specific, unobserved effect and $\boldsymbol{x}_{it}$ is a vector of potentially time-varying covariates including a constant. $f_k(\mathcal{R}_t)$ is an expectation type-specific function of the history of past stock market returns at period t, $\mathcal{R}_t$. This function captures how an individual of expectation type k processes past stock market information. In Equation 2.1, expectation types differ in $f_k(\mathcal{R}_t)$ only, while other influences on μ^*_{itk} are assumed to be the same across expectation types. While $f_k(\mathcal{R}_t)$ may in principle contain any past return, which respondents experienced prior to their interviews, our model assumes that individuals particularly focus on the past one-year AEX return in period t (r_t). This seems natural, because respondents are also asked about their one-year ahead stock market expectations. The past one-year AEX return should therefore be particularly salient.[4] We

[4] As a robustness check, we also estimate the model for other return lags in Section 2.5.

assume that the function $f_k(\cdot)$ takes the following linear form:

$$f_k(\mathcal{R}_t) = f_k(r_t) = \gamma_k r_t, \qquad k = 1, 2, 3 \tag{2.2}$$

This specification allows individuals to differ in their expectation type by different return coefficients γ_k. While the three return coefficients will later be unrestricted in the econometric model, the insights from Dominitz and Manski (2011) yield the following sign predictions:

- $k = 1$, Random Walk type. For these individuals, the return coefficient should be equal to zero, as they do not use the past one-year stock market to predict future returns, but rather focus on the long-run historical average return ($\gamma_1 = 0$).
- $k = 2$, Mean Reversion type. These individuals believe that recent stock market changes will be reversed in the near future, implying that the return coefficient should be negative ($\gamma_2 < 0$).
- $k = 3$, Persistence type. These individuals believe that recent stock market changes will persist into the near future, implying that the return coefficient should be positive ($\gamma_3 > 0$).

Since individuals' expectation type cannot be observed in the data, we use a standard random effects multinomial logit model with three possible outcomes to model individual type probabilities. Applying standard assumptions, these type probabilities are given by

$$P(D_{it} = k | \boldsymbol{x}_{it}, \alpha_i^2, \alpha_i^3) = \frac{\exp(\alpha_i^k + \tau_t^k + \boldsymbol{x}_{it}\boldsymbol{\beta}^k)}{\sum_{j=1}^{3} \exp(\alpha_i^j + \tau_t^j + \boldsymbol{x}_{it}\boldsymbol{\beta}^j)}, \qquad k = 1, 2, 3 \tag{2.3}$$

where α_i^k is an individual-specific unobserved effect for type k, and τ_t^k are type-specific time effects. Without loss of generality, α_i^1, τ_t^1 and $\boldsymbol{\beta}^1$ are normalized to zero. Note that the type probabilities are allowed to depend on a vector of covariates $\boldsymbol{x}_{it}$ and that by construction the three type probabilities for a given individual i in period t sum up to one.

2.3.2 Construction of subjective means from survey responses

As discussed earlier, the survey respondents are presented with a total of eight questions on the future performance of the stock market. Specifically, respondents are asked about the following eight subjective probabilities:

$$p_{its} = \begin{cases} P(z > \delta_s) & \text{for } \delta_s \in \{0, 0.1, 0.2, 0.3\}, \qquad s = 1,2,3,4 \\ P(z < \delta_s) & \text{for } \delta_s \in \{0, -0.1, -0.2, -0.3\}, \quad s = 5,6,7,8 \end{cases} \tag{2.4}$$

where p_{its} is the reported probability of respondent i in period t to question s that the future one-year stock market return (z) will be greater or smaller than some threshold δ_s. Importantly, these eight answers refer to well-defined points on individuals' subjective cumulative distribution function (c.d.f.). We follow the literature and assume that the one-year stock market returns roughly follow a normal distribution, allowing us to calculate a parametric counterpart $\tilde{p}_{its}$ (for a given subjective unobserved mean μ^*_{itk} and standard deviation σ^*_k) to every survey answer:[5]

$$\tilde{p}_{itks} = \begin{cases} P(z > \delta_s) = \Phi\left(\frac{\mu^*_{itk} - \delta_s}{\sigma^*_k}\right) & \text{for } \delta_s \in \{0, 0.1, 0.2, 0.3\}, \qquad s = 1,2,3,4 \\ P(z < \delta_s) = \Phi\left(\frac{\delta_s - \mu^*_{itk}}{\sigma^*_k}\right) & \text{for } \delta_s \in \{0, -0.1, -0.2, -0.3\}, \quad s = 5,6,7,8 \end{cases} \tag{2.5}$$

where $\Phi(\cdot)$ denotes the cumulative distribution function (c.d.f.) of the standard normal distribution. The existence of up to eight points on individuals' subjective distribution function over-identifies the model, as the normal distribution only depends on two parameters. While in Hurd et al. (2011) we estimate the parameters by non-linear least squares, our model estimates the two parameters by maximum likelihood. Specifically, we assume

[5] Other studies that use reported points on individuals' normal subjective distribution function to calculate individual-level means and standard deviations include, amongst others, Dominitz and Manski (2007) who exactly identify the two parameters, Hurd et al. (2011) who use non-linear least squares and Bellemare et al. (2012) who approximate the distribution non-parametrically using splines.

that respondents report unbiased expectations for all eight questions, i.e.

$$p_{itks} = \hat{p}_{itks} + u_{itks} \tag{2.6}$$

where u_{its} is normal with mean zero and variance σ^2 for all s: $u_{itks} \sim N(0, \sigma^2)$. For tractability reasons, we assume the variance of the error term to be identical across survey questions. However, an extension of our model could allow these variances to differ across questions, capturing potential differences between the gain and loss domain.

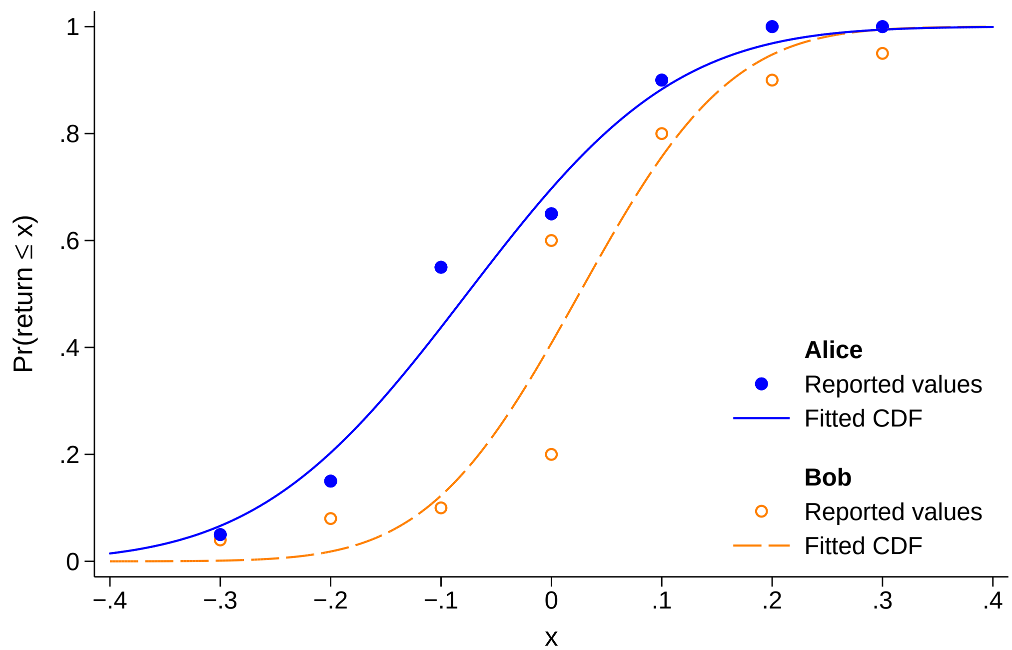


Figure 2.3: Fitting individual CDFs through the reported survey responses

Figure 2.3 illustrates how an individual's eight survey responses can be used to estimate the latent mean and standard deviation of her subjective distribution of future stock market returns. Consider two individuals, Alice and Bob. Alice (Bob) reports a 55% (10%) chance probability that the stock market will *decrease* by more than ten percent; for the probability that the stock market will *increase* by more than ten percent, the reported probabilities are 100%-90%=10% (Alice) and 100%-80%=20% (Bob). The fact that Bob's c.d.f. is shifted to the right indicates that his expectations regarding the future stock market performance are higher than those of Alice. Fitting a normal c.d.f. through these points by maximum likelihood (solid and dashed lines) yields estimated means of 2.34% for Bobs' c.d.f. and -8.60% for Alice. The mixture model we develop in this paper uses these ideas by averaging over the reported answers and allowing the parameters of the c.d.f. to differ across expectation types and to depend on socio-economic characteristics.

2.3.3 Rounding

The literature on subjective expectations has shown that individuals' survey responses are subject to rounding (cf. Manski and Molinari, 2010; Kleinjans and van Soest, 2014). Figure 2.4 plots the response distribution for two expectations questions, pooled across years. Clearly, there is evidence for considerable heaping at multiples of five and ten percent.[6] In the left panel (Gain > 0%), only 573 out of 13,940 respondents (4.1%) report a probability that is not a multiple of five. It is thus quite likely that at least some individuals do not report their true subjective probabilities p_{its}, but rather some rounded value. The same applies to the right panel, where respondents are asked about the probability that the stock market will increase by at least 20 percent (Gain > 20%). Here, the crude share of responses which are not multiples of five increases to 18% (2,449 out of 13,569 respondents). In addition, fewer respondents report a probability of 50% compared to the left graph.

Note that previous research often assumes that rounding patterns in probabilistic expectations questions are constant across domains. For example, using data from the Health and Retirement Survey (HRS), Giustinelli et al. (2018) make this assumption for different domains, such as health, personal finances and economic conditions. Our model, in contrast, assumes that rounding behavior is question-specific, even though the eight questions refer

[6] In addition, individuals also seem to round more in the center of the distribution than in the tails (cf. Giustinelli et al., 2018). For tractability reasons, however, we abstract from this phenomenon in our model.

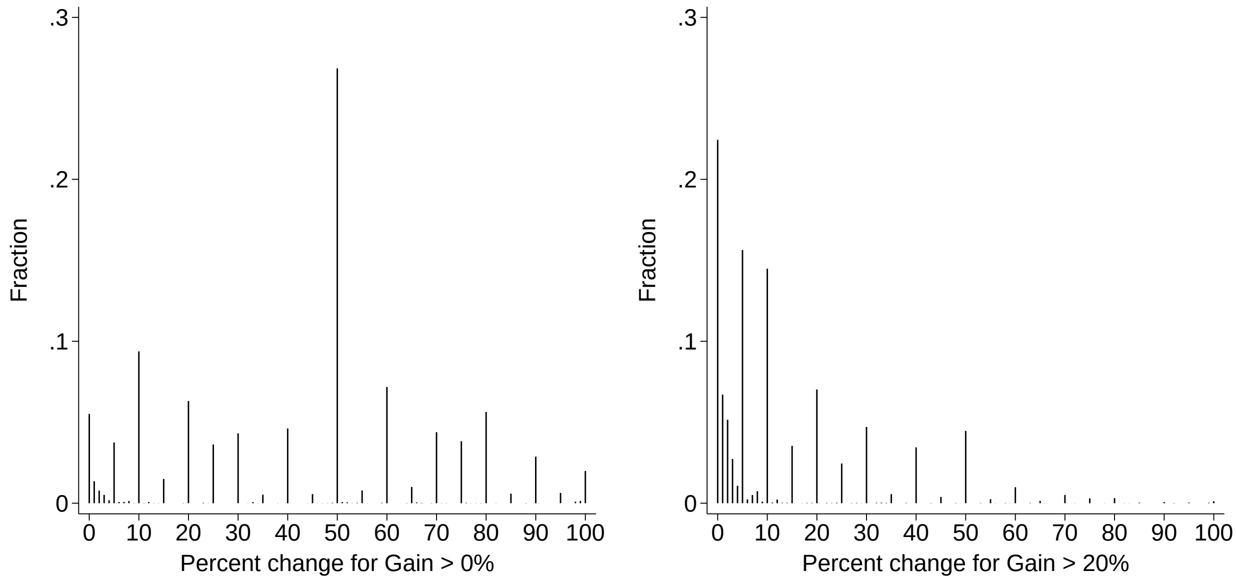


Figure 2.4: Response distribution for the Gain > 0% and Gain > 20% questions

to the same domain, namely stock market performance. The difference may be explained by the fact that the objective (retrospectively "correct") answers to the eight probability questions differ in magnitude (independent of expectation type). This might not be true in other settings, such as in Giustinelli et al. (2018), where the objective probabilities might be closer (even though in different domains). Moreover, question-specific rounding may be more suited to explain differences in rounding patterns, as depicted in Figure 2.4.

To model individuals' rounding behavior, we adjust a model by Kleinjans and van Soest (2014) and argue that the population can be described by the following three (latent) rounding types:[7]

[7] Note that our model could easily be extended to include additional rounding types who round to multiples of ten or twenty percent, or another type who uses 50 percent answers to express epistemic uncertainty rather than an actual probability of 50 percent (cf. Bruine de Bruin et al., 2000). However, as we allow the rounding types to vary across survey questions, each additional rounding type comes with a substantial increase in the number of parameters to be estimated. To reduce the computational burden, we thus restrict the number of rounding types to three.

$R_{its} = 1$ (type R1): the subjective probability is rounded to a multiple of 1 percent

$R_{its} = 2$ (type R5): the subjective probability is rounded to a multiple of 5 percent

$R_{its} = 3$ (type R50): the subjective probability is rounded to a multiple of 50 percent

where R_{its} represents the rounding type of individual i in period t in question s. Obviously, the three rounding types are increasing in their extent of rounding. As respondents only report integers, type R1 does in fact not round her expectations. Type R5 always rounds to the next multiple of five percent, while type R50 displays the strongest versions of rounding. She always rounds to the next multiple of 50 percent, which is equivalent to reporting 0, 50 or 100 percent.

Similar to the expectation types earlier, rounding types are generally unobserved in the data. For example, consider an individual who reports a subjective probability of 50% to the question of a positive stock market return (Gain > 0%). Clearly, her answer is consistent with all three rounding types. In contrast, a reported probability of 70% would identify her as either rounding type 1 or 2, while a reported probability of 18% exactly identifies her to be rounding type 1. This illustrates that individuals' rounding type is only partially revealed in the data.

Again, we use a finite mixture approach to model individual rounding type probabilities. Similar to Kleinjans and van Soest (2014), we model rounding behavior in a standard random effects ordered probit model with three possible categories. Applying standard assumptions, the rounding type probabilities are given by

$$P(R_{its} = r|\boldsymbol{x}_{it}, \alpha_i^R) = \Phi\left(m_{sr} - \alpha_i^R - \boldsymbol{x}_{it}\boldsymbol{\beta}^R\right) - \Phi\left(m_{sr-1} - \alpha_i^R - \boldsymbol{x}_{it}\boldsymbol{\beta}^R\right), \quad r = 1, 2, 3 \tag{2.7}$$

where α_i^R is a respondent-specific time-constant unobserved random effect that drives rounding behavior and $\boldsymbol{x}_{it}$ is a vector of potentially time-varying covariates (not including a constant). m_{sr} are the cut-off parameters for question s with the usual normalization $m_{s0} = -\infty$ and $m_{s3} = \infty$. For tractability reasons, we assume that differences in the rounding types probabilities across questions stem from the cut-offs only. We thus assume that the effect of the covariates and the random individual-specific effect on the rounding type probabilities are constant across the eight survey questions.

2.3.4 Distributional assumptions and likelihood function

In general, the likelihood function of the model depends on the unobserved individual random effects $\alpha_i^{Mu}, \alpha_i^2, \alpha_i^3$ and α_i^R, which we will denote by the vector of unobserved heterogeneity $\boldsymbol{\alpha}$. Using the assumptions from the previous sections, the likelihood function conditional on the unobserved heterogeneity, L^c, is given by:

$$L^c(\alpha_i^{Mu}, \alpha_i^2, \alpha_i^3, \alpha_i^R) = \prod_{i=1}^{N} \prod_{t=1}^{T} L_{it}^c(\alpha_i^{Mu}, \alpha_i^2, \alpha_i^3, \alpha_i^R) \tag{2.8}$$

where

$$L_{it}^c(\alpha_i^{Mu}, \alpha_i^2, \alpha_i^3, \alpha_i^R) = \sum_{k=1}^{3} P\left(D_{it} = k | \boldsymbol{x}_{it}, \alpha_i^2, \alpha_i^3\right) \cdot \prod_{s=1}^{8} L_{itks}^c(\alpha_i^{Mu}, \alpha_i^R). \tag{2.9}$$

The conditional likelihood contribution $L_{itks}^c(\alpha_i^{Mu}, \alpha_i^R)$ depends on the reported probabilities p_{its} as follows:

For $p_{its} \in \{0\%, 1\%, 2\%, ..., 100\%\}$ and $p_{its} \notin \{0\%, 5\%, 10\%, ..., 100\%\}$ (Rounding type 1):

$$L_{itks}^c(\alpha_i^{Mu}, \alpha_i^R) = P\left(R_{its}{=}1 | \boldsymbol{x}_{it}, \alpha_i^R\right) \left[\Phi\left(\frac{p_{its}{+}0.005{-}\tilde{p}_{itks}}{\sigma_u} | \boldsymbol{x}_{it}, r_t, \alpha_i^{Mu}\right) - \Phi\left(\frac{p_{its}{-}0.005{-}\tilde{p}_{itks}}{\sigma_u} | \boldsymbol{x}_{it}, r_t, \alpha_i^{Mu}\right)\right]$$

For $p_{its} \in \{0\%, 5\%, 10\%, ..., 100\%\}$ and $p_{its} \notin \{0\%, 50\%, 100\%\}$ (Rounding type 1 or 2):

$$\begin{aligned}
L^c_{itks}(\alpha_i^{Mu}, \alpha_i^R) = & P\left(R_{its}{=}1|\boldsymbol{x}_{it}, \alpha_i^R\right)\left[\Phi\left(\frac{p_{its}{+}0.005{-}\tilde{p}_{itks}}{\sigma_u}|\boldsymbol{x}_{it}, r_t, \alpha_i^{Mu}\right) - \Phi\left(\frac{p_{its}{-}0.005{-}\tilde{p}_{itks}}{\sigma_u}|\boldsymbol{x}_{it}, r_t, \alpha_i^{Mu}\right)\right] \\
& + P\left(R_{its}{=}2|\boldsymbol{x}_{it}, \alpha_i^R\right)\left[\Phi\left(\frac{p_{its}{+}0.025{-}\tilde{p}_{itks}}{\sigma_u}|\boldsymbol{x}_{it}, r_t, \alpha_i^{Mu}\right) - \Phi\left(\frac{p_{its}{-}0.025{-}\tilde{p}_{itks}}{\sigma_u}|\boldsymbol{x}_{it}, r_t, \alpha_i^{Mu}\right)\right]
\end{aligned}$$

For $p_{its} \in \{0\%, 50\%, 100\%\}$ (Rounding type 1, 2 or 3):

$$\begin{aligned}
L^c_{itks}(\alpha_i^{Mu}, \alpha_i^R) = & P\left(R_{its}{=}1|\boldsymbol{x}_{it}, \alpha_i^R\right)\left[\Phi\left(\frac{p_{its}{+}0.005{-}\tilde{p}_{itks}}{\sigma_u}|\boldsymbol{x}_{it}, r_t, \alpha_i^{Mu}\right) - \Phi\left(\frac{p_{its}{-}0.005{-}\tilde{p}_{itks}}{\sigma_u}|\boldsymbol{x}_{it}, r_t, \alpha_i^{Mu}\right)\right] \\
& + P\left(R_{its}{=}2|\boldsymbol{x}_{it}, \alpha_i^R\right)\left[\Phi\left(\frac{p_{its}{+}0.025{-}\tilde{p}_{itks}}{\sigma_u}|\boldsymbol{x}_{it}, r_t, \alpha_i^{Mu}\right) - \Phi\left(\frac{p_{its}{-}0.025{-}\tilde{p}_{itks}}{\sigma_u}|\boldsymbol{x}_{it}, r_t, \alpha_i^{Mu}\right)\right] \\
& + P\left(R_{its}{=}3|\boldsymbol{x}_{it}, \alpha_i^R\right)\left[\Phi\left(\frac{p_{its}{+}0.250{-}\tilde{p}_{itks}}{\sigma_u}|\boldsymbol{x}_{it}, r_t, \alpha_i^{Mu}\right) - \Phi\left(\frac{p_{its}{-}0.250{-}\tilde{p}_{itks}}{\sigma_u}|\boldsymbol{x}_{it}, r_t, \alpha_i^{Mu}\right)\right]
\end{aligned}$$

where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function (c.d.f.). i, t, k and s index respondents, periods, expectation types and survey questions, respectively. Recall that the (observed) reported subjective probabilities are denoted by p_{its}, while their parametric counterparts are denoted by $\tilde{p}_{itks}$. Note also that the likelihood function is written for a respondent who participates in every period and answers all eight probability questions. For the estimation, if a respondent does not answer one particular question, her likelihood contribution (L^c_{itks}) is replaced by one. Similarly, if a respondent did not participate in one particular period, her likelihood contribution for this period (L^c_{it}) is also replaced by one.

The unconditional likelihood function (L) can be derived by integrating out the individual effects:

$$L = \prod_{i=1}^{N} \int_{\mathbb{R}^4} \prod_{t=1}^{T} L^c_{it}(\alpha_i^{Mu}, \alpha_i^2, \alpha_i^3, \alpha_i^R) f(\boldsymbol{\alpha}) d\boldsymbol{\alpha}. \tag{2.10}$$

To avoid numerical integration in four dimensions, we use Maximum Simulated Likelihood (MSL) and replace the integral by a simulated mean. The simulated sample likelihood (SL) is then given by

$$SL = \prod_{i=1}^{N} \frac{1}{Q} \sum_{q=1}^{Q} \prod_{t=1}^{T} L_{it}^{c}(\alpha_{iq}^{Mu}, \alpha_{iq}^{2}, \alpha_{iq}^{3}, \alpha_{iq}^{R}) \tag{2.11}$$

where $\alpha_{iq}^{Mu}, \alpha_{iq}^{2}, \alpha_{iq}^{3}, \alpha_{iq}^{R}$ are simulated random effects for a given draw q. For the estimation, we assume that the unobserved heterogeneity follows a multivariate normal distribution with mean zero and arbitrary variance covariance matrix $\mathbf{\Sigma}$:

$$\boldsymbol{\alpha} \sim N(\mathbf{0}, \mathbf{\Sigma}). \tag{2.12}$$

Applying a Cholesky decomposition of $\mathbf{\Sigma}$, yields a positive semi-definite lower diagonal matrix $\mathbf{L}$ such that $\mathbf{\Sigma} = \mathbf{L}\mathbf{L}'$. For a given draw q, the unobserved heterogeneity is then calculated by $\boldsymbol{\alpha} = \mathbf{L}\boldsymbol{\tau}$, where $\boldsymbol{\tau}$ contains simulated vectors of the independent standard normal distribution. We follow Train (2003) and use draws from Halton sequences to obtain our independent standard normal variables $\boldsymbol{\tau}$.

2.4 Results

2.4.1 Heterogeneity in expectations, types, and rounding

We apply our model to data from the CentER panel, as described in Section 2.2. We generally present the results from three different model specifications, while several alternative specifications are discussed as robustness checks in Section 2.5. The first specification fits a model with constants and the three (unrestricted) return coefficients only, while the second specification adds several socio-economic covariates and in the random effects multinomial logit model also year fixed effects. The third specification adds sign restrictions to the three return coefficients, i.e. we enforce $\gamma_1 = 0$, $\gamma_2 < 0$ and $\gamma_3 > 0$, corresponding to the expectation types Random Walk (RW), Mean Reversion (MR) and Persistence (P), respectively. For the entire analysis, it is important to keep in mind that our model is estimated jointly, even though we report the model estimates – for illustrative reasons – in several tables.

Table 2.2 reports estimated coefficients for the subjective mean model (Equation 2.1). As shown in column 1, the model identifies three distinct expectation types whose return coefficients for the past year AEX return differ in both sign and magnitude. Specifically, the three (unrestricted) return coefficients $(\gamma_1, \gamma_2, \gamma_3)$ are given by $(0.027, -0.577, 0.658)$. While the estimate for type two is significantly negative, the type three estimate is significantly positive and of similar magnitude. The third estimate, for example, suggests that a one percentage point increase in the past year AEX return increases the expected mean return for the year ahead of type three by roughly 0.658 percentage points, *ceteris paribus*. For type three, higher past year returns of the AEX are therefore associated with higher expectations for the year ahead. Similarly, for type two, past year AEX returns are associated with lower stock market expectations. Even though the estimated coefficient for the first type (γ_1) is significantly positive, its magnitude is – compared to the other two – considerably smaller, differing by a factor of 20 and in fact being close to zero. In approximation, we therefore argue that type one does not use the past year AEX

Table 2.2: Model for the mean of the subjective distributions

	(1) Constants only		(2) Full model		(3) Restricted return coeff.	
γ_1: Return coeff. Cl1	0.0271***	[0.0015]	0.0286***	[0.0014]		
γ_2: Return coeff. Cl2	-0.5774***	[0.0167]	-0.5890***	[0.0166]	-0.5964***	[0.0185]
γ_3: Return coeff. Cl3	0.6576***	[0.0125]	0.7143***	[0.0127]	0.6154***	[0.0104]
Female			-0.0354***	[0.0023]	-0.0203***	[0.0024]
Age >64			-0.0014	[0.0016]	-0.0016	[0.0018]
Age <45			-0.0057***	[0.0017]	-0.0023	[0.0017]
Low education			-0.0103***	[0.0025]	-0.0257***	[0.0027]
High education			0.0134***	[0.0023]	0.0075***	[0.0028]
Partner			-0.0022	[0.0020]	0.0006	[0.0027]
HH income: 1st quart.			-0.0033	[0.0021]	-0.0000	[0.0027]
HH income: 2nd quart.			-0.0027	[0.0019]	-0.0013	[0.0022]
HH income: 3rd quart.			-0.0020	[0.0015]	0.0003	[0.0018]
No. children in HH			0.0007	[0.0008]	-0.0005	[0.0008]
Constant	-0.0386***	[0.0015]	-0.0114***	[0.0030]	-0.0128***	[0.0037]
σ_1^*	0.1176***	[0.0007]	0.1185***	[0.0007]	0.1167***	[0.0007]
σ_2^*	0.5445***	[0.0084]	0.5533***	[0.0087]	0.5767***	[0.0095]
σ_3^*	0.2775***	[0.0038]	0.2791***	[0.0037]	0.2601***	[0.0032]
σ_{CDFfit}	0.1597***	[0.0004]	0.1602***	[0.0004]	0.1596***	[0.0004]
LogLik	-332,714.34		-331,725.45		-331,997.03	
AIC	665,500.68		663,630.90		664,172.05	
Observations	14,282		14,264		14,264	

Notes: Table displays results for the subjective means model (Equation 2.1) as well as the type-specific estimates for the subjective standard deviations. For details see text. Standard errors in brackets; *** p <0.01, ** p <0.05, * p <0.1.

return when forming her expectations. Using our earlier definition of expectation types, we therefore label the three expectation types (1,2,3) as (RW,MR,P).

Adding several socio-economic variables to the model leaves the three return coefficients almost unchanged (specification 2). We find, however, that stock market expectations – here summarized by the mean of the expected return distribution – vary substantially across individuals. Similar to findings from the previous literature, males and more educated respondents have on average higher expectations than females and less educated respondents (cf. Dominitz and Manski, 2007, 2011; Hudomiet et al., 2011; Hurd et al., 2011).

In our third specification, we add sign restrictions to our return coefficients. Specifically, we restrict the first return coefficient (RW type) to be exactly zero. As the return coefficients of the second and third type are already negative and positive, the sign restrictions for those are actually non-binding. Overall, the estimates of the restricted model are almost identical to those of the unrestricted model, strengthening our interpretation of the three different expectation types.

The bottom part of Table 2.2 reports estimates for the type-specific standard deviations (σ_k^*) of the subjective return distributions. Throughout all specifications, the smallest dispersion in expectations can be found for type 1 (RW). Its estimate suggests a standard deviation of 0.12 for the expected year ahead return distribution. As one would expect, the return distribution is more volatile for the other two expectation types. While the distribution of type P has an estimated standard deviation of about 0.27, the estimate for type MR is equal to 0.55. This is in line with our interpretation that RW types base their expectations on the historical average return, while the other two types focus on recent changes and are thus subject to higher volatility. Last, Table 2.2 also reports the estimated standard deviation of the error term in Equation 2.6, σ_{CDFfit}, which is assumed to be constant across the eight probability questions.

We next turn to the estimates of the random effects multinomial logit model for the expectation type probabilities (Equation 2.3), which are reported in Table 2.3. Recall that the omitted category is type 1 (RW). Clearly, there is evidence for substantial heterogeneity in the type probabilities. For example, females are significantly more likely to be type 2 (MR) or type 3 (P) than males. Highly educated respondents are more likely to

Table 2.3: Random effects multinomial logit model for the expectation types

	(1) Constants only		(2) Full model		(3) Restricted return coeff.	
Class 2 (Mean Reversion)						
Female			0.6120***	[0.0713]	0.3394***	[0.0715]
Age >64			-0.5586***	[0.0901]	-0.5734***	[0.0936]
Age <45			0.6899***	[0.0747]	0.7835***	[0.0766]
Low education			0.0084	[0.0860]	0.2229**	[0.0889]
High education			-0.6089***	[0.0816]	-0.5621***	[0.0870]
Partner			0.2717***	[0.0878]	0.1975**	[0.0944]
HH income: 1st quart.			0.6510***	[0.1035]	0.5987***	[0.1070]
HH income: 2nd quart.			0.3570***	[0.0942]	0.3336***	[0.0974]
HH income: 3rd quart.			0.2764***	[0.0891]	0.2305**	[0.0919]
No. children in HH			-0.0152	[0.0333]	0.0011	[0.0338]
Constant	-1.3143***	[0.0421]	-1.9978***	[0.1467]	-1.9628***	[0.1543]
Class 3 (Persistence)						
Female			0.4790***	[0.0709]	0.2216***	[0.0661]
Age >64			-0.2835***	[0.0841]	-0.2922***	[0.0809]
Age <45			0.5440***	[0.0763]	0.5227***	[0.0733]
Low education			0.0870	[0.0872]	0.2687***	[0.0834]
High education			-0.3230***	[0.0811]	-0.2241***	[0.0795]
Partner			0.3157***	[0.0878]	0.2552***	[0.0879]
HH income: 1st quart.			0.4740***	[0.1036]	0.3926***	[0.1008]
HH income: 2nd quart.			0.2834***	[0.0934]	0.2189**	[0.0900]
HH income: 3rd quart.			0.2743***	[0.0867]	0.2341***	[0.0833]
No. children in HH			-0.0362	[0.0342]	-0.0154	[0.0322]
Constant	-1.1492***	[0.0444]	-2.2920***	[0.1532]	-2.0169***	[0.1497]
Implied Cl1 share	0.59		0.62		0.60	
Implied Cl2 share	0.20		0.19		0.18	
Implied Cl3 share	0.21		0.19		0.21	
LogLik	-332,714.34		-331,725.45		-331,997.03	
AIC	665,500.68		663,630.90		664,172.05	
Observations	14,282		14,264		14,264	

Notes: Table displays results for the random effects multinomial logit model for the expectation types (Equation 2.3). Baseline type 1 (Random Walk) is omitted. Specifications 2 and 3 also include year fixed effects. For details see text. Standard errors in brackets; *** p <0.01, ** p <0.05, * p <0.1.

be type 1 (RW). One interpretation could be that men and more educated respondents are usually found to be more informed about the stock market, hence more likely to have some information about the historical average return and therefore more likely to be type RW. The estimates also suggest the existence of an age gradient: younger respondents are more likely to be type 2 (MR) and type 3 (P), compared to older respondents. Overall, there is evidence for substantial heterogeneity in the expectation type probabilities.

Moreover, the model estimates can also be used to predict (unconditional) individual type probabilities.[8] The bottom part of Table 2.3 reports aggregated type probabilities, which can be interpreted as the (unconditional) sample distribution of expectation types. With only minor differences across specifications, our estimates suggest that the distribution of expectation types (RW,MR,P) is roughly (0.60,0.19,0.21). This indicates that most answers are actually in line with a RW type interpretation, while fewer responses are in line with type MR or type P. A detailed discussion of these type shares is presented in Section 2.4.2.

Table 2.4 reports coefficients of the random effects ordered probit model for the three rounding types R1, R5 and R50 (Equation 2.7). Recall that a higher rounding type is associated with a higher degree of rounding. Similar to Kleinjans and van Soest (2014), we find evidence for heterogeneity across the population. Males tend to round less often than females, as well as younger and highly educated people. In contrast, income is not associated with rounding behavior. The sixteen cut-off coefficients (two for each of the eight probability questions) are not reported, but used in order to determine the individual rounding type probabilities. Similar to the expectation type shares, we average the individual rounding type probabilities to predict the rounding type distribution in the population. Figure 2.5 displays these rounding type shares for each of the eight probability question. Clearly, there is evidence for less rounding in questions on more extreme

[8] The (unconditional) individual type probabilities are based on Equation 2.3, with the true parameter vectors τ_t^k and $\boldsymbol{\beta}_k$ being replaced by their respective estimates $\hat{\tau}_t^k$ and $\hat{\boldsymbol{\beta}}_k$ and the individual effects α^k being integrated out by simulation. Specifically, we use 71 draws from Halton sequences and simulate the normal individual effects with mean zero and a variance-covariance matrix which is given by the estimate of $\hat{\boldsymbol{\Sigma}}$.

Table 2.4: Random effects ordinal probit model for rounding types

	(1) Constants only	(2) Full model		(3) Restricted return coeff.	
Female		0.0848***	[0.0229]	-0.0154	[0.0209]
Age >64		0.0081	[0.0195]	0.0233	[0.0203]
Age <45		-0.0871***	[0.0192]	-0.0515***	[0.0188]
Low education		-0.0537**	[0.0261]	-0.0048	[0.0247]
High education		-0.0651***	[0.0227]	-0.0989***	[0.0248]
Partner		0.0317	[0.0243]	0.0005	[0.0268]
HH income: 1st quart.		0.0303	[0.0250]	-0.0294	[0.0275]
HH income: 2nd quart.		0.0270	[0.0217]	-0.0270	[0.0238]
HH income: 3rd quart.		-0.0201	[0.0194]	-0.0316	[0.0200]
No. children in HH		0.0123	[0.0086]	0.0113	[0.0090]
LogLik	-332,714.34	-331,725.45		-331,997.03	
AIC	665,500.68	663,630.90		664,172.05	
Observations	14,282	14,264		14,264	

Notes: Table displays results for the random effects ordinal probit model for the rounding types (Equation 2.7). Dependent variable is equal to 1 if the respondent does not round (R1), 2 if the respondent rounds to the next multiple of five (R5) and 3 if the respondent rounds to the next multiple of 50 (R50). Question type-specific cut-off parameters are not reported. For details see text. Standard errors in brackets; *** p <0.01, ** p <0.05, * p <0.1.

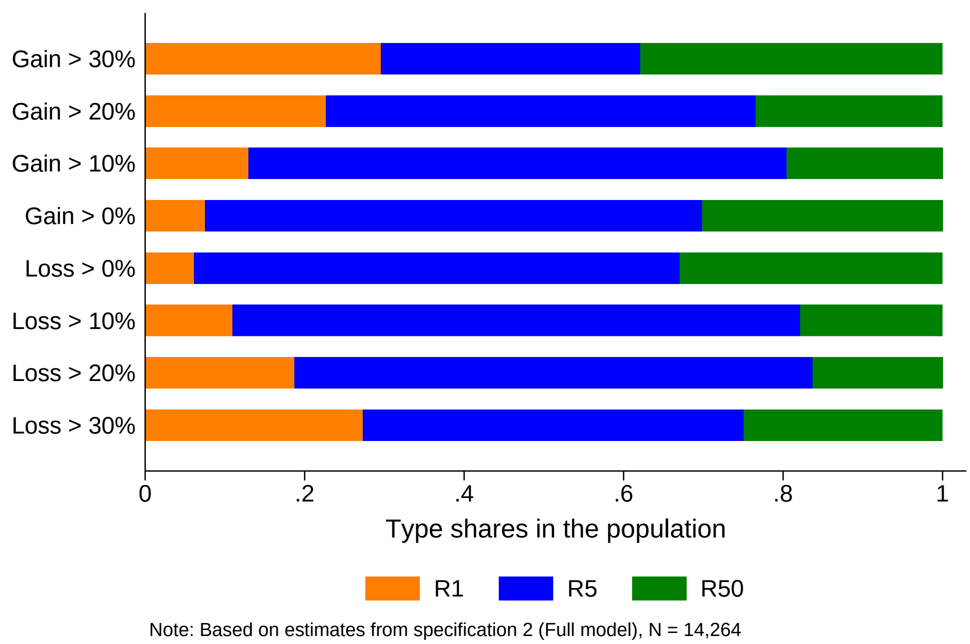


Figure 2.5: Rounding type distribution across questions

outcomes. While less than five percent of respondents are estimated to provide exact answers in the questions Gain $>$ 0% and Loss $<$ 0%, almost 30 percent of respondents do so for the questions Gain $>$ 30% and Loss $<$ 30%. Interestingly, there seems to be no difference between the gain and the loss domain. In fact, the shares are almost identical.

Last, Table 2.5 reports the variances and the correlations of the four random individual effects, which are derived from the estimated entries of the Cholesky matrix $\hat{\mathbf{L}}$. All four individual effects have in fact a variance significantly different from zero. In addition, their correlations are also significantly different from zero. The correlation between α^R and α^2 is, for example, significantly positive. This indicates that individuals who are more likely to round are also more likely to be of type 2 (MR). Applying the same logic, we also find that individuals who are more likely to round are also more likely to be of type 3 (P). The other interpretations are similar, but less intuitive.

2.4.2 Expectation type shares and the financial crisis

Note that the parameter estimates of the model can be used to predict individual unconditional type probabilities as well as posterior probabilities, i.e. conditional on the reported expectations. Figure 2.6 plots the sample distribution of both unconditional and posterior probabilities based on the results of the full model (Table 2.2, specification 2). As illustrated in the bottom panel, our model classifies respondents reasonably well. In fact, 11,022 out of 14,264 respondents (77%) are as good as uniquely classified, i.e. with a posterior probability of more than 90%, as either type RW, MR or P.

The upper panel of Figure 2.6 shows the unconditional sample contribution of type probabilities, averaged over individuals and time. The means of the three distributions are given by (0.60,0.19,0.21) for expectation types (RW,MR,P), as already reported in Table 2.3. This is somewhat in contrast to the findings by Dominitz and Manski (2011) who find that most individuals are found to be type P. Specifically, using a simple ordinal cri-

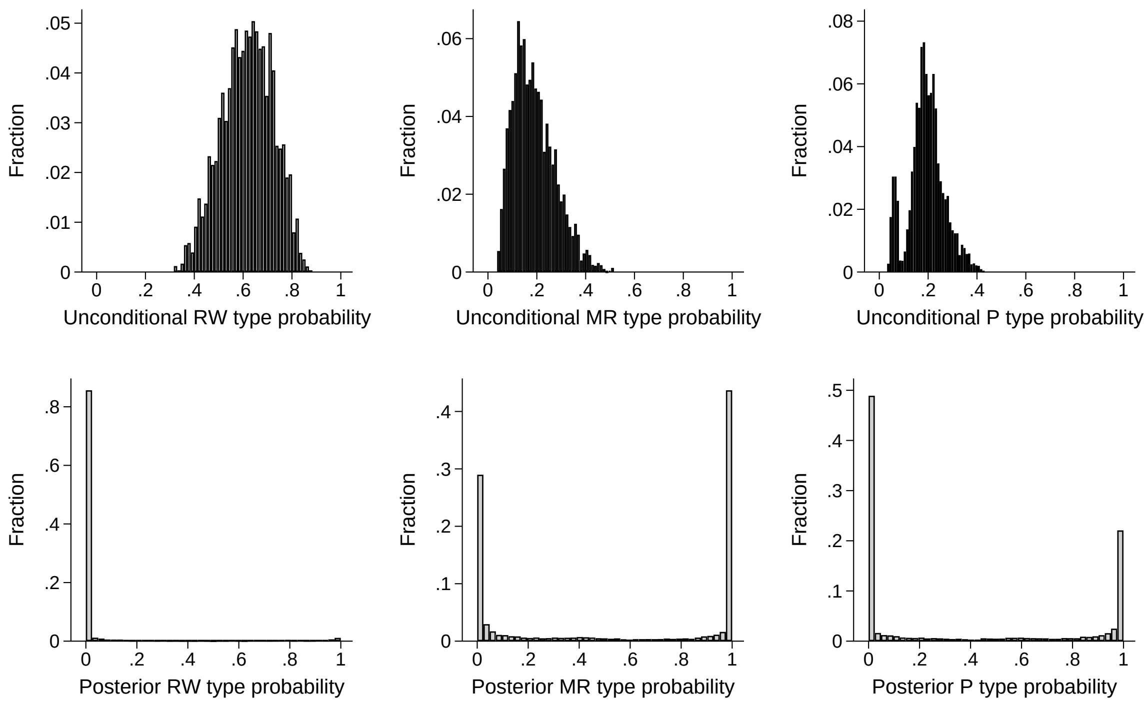
Table 2.5: Variances and correlations of the individual effects

	(1) Constants only		(2) Full model		(3) Restricted return coeff.	
Variances						
$V(\alpha^{Mu})$	0.0087***	[0.0002]	0.0071***	[0.0002]	0.0088***	[0.0003]
$V(\alpha^{2})$	2.8354***	[0.1777]	2.2242***	[0.1592]	2.6355***	[0.1771]
$V(\alpha^{3})$	2.2625***	[0.1559]	1.8099***	[0.1380]	1.6872***	[0.1330]
$V(\alpha^{R})$	0.6991***	[0.0180]	0.7345***	[0.0186]	0.7307***	[0.0188]
Correlations						
$Corr(\alpha^{Mu}, \alpha^{2})$	-0.9274***	[0.0100]	-0.9926***	[0.0071]	-0.8771***	[0.0147]
$Corr(\alpha^{Mu}, \alpha^{3})$	-0.9809***	[0.0054]	-0.9997***	[0.0012]	-0.9658***	[0.0083]
$Corr(\alpha^{Mu}, \alpha^{R})$	-0.1483***	[0.0140]	-0.3222***	[0.0121]	-0.2227***	[0.0187]
$Corr(\alpha^{2}, \alpha^{3})$	0.9824***	[0.0054]	0.9948***	[0.0040]	0.9708***	[0.0080]
$Corr(\alpha^{2}, \alpha^{R})$	0.5072***	[0.0240]	0.3239***	[0.0122]	0.6635***	[0.0224]
$Corr(\alpha^{3}, \alpha^{R})$	0.3377***	[0.0278]	0.3229***	[0.0123]	0.4663***	[0.0306]
Observations	14,282		14,264		14,264	

Notes: This table reports estimates for the variances of the four random effects and their correlations. α^{Mu} denotes the random effect in Equation 2.1. α^2 and α^3 are the random effects in the multinomial logit model for the expectation type probabilities, where α^1 is normalized to zero (Equation 2.3). α^R denotes the random effect in the ordered probit model for the rounding type probabilities (Equation 2.7). Standard errors in brackets; *** p <0.01, ** p <0.05, * p <0.1.

terion, the authors find the type distribution to be (0.27,0.32,0.41) for survey participants of the Michigan Survey of Consumers. We present two potential reasons for this difference.

First, our model assumes that type RW puts zero weight on recent stock market changes, because she uses the long-run historical average return rather than short-run fluctuations to form expectations. There may, however, also be other reasons not to use recent stock market returns when forming expectations. For example, respondents may form expectations intuitively or rely on heuristics (Drerup et al., 2017). The return coefficient of these respondents will also be zero. Unfortunately, these respondents are observationally equivalent to true RW types, explaining a higher RW share, compared to Dominitz and Manski (2011).



Note: Based on estimates from specification 2 (Full model), N = 14,264

Figure 2.6: Distribution of unconditional and posterior type probabilities

Second, while Dominitz and Manski (2011) base their classification on one probabilistic question only (Gain > 0%), we base the analysis on the entire distribution of future stock market returns, which is identified by the responses to the eight probability questions. As presented in Appendix B2, applying their original methodology to our Gain > 0% question yields an average type distribution of (0.30,0.26,0.44). This implied type distribution is extremely close to their original results using data on the S&P 500 index and from the Michigan Survey of Consumers between 2002 and 2004. However, applying the same methodology to questions on larger changes in the stock market, such as Gain > 30%, yields a share distribution which is actually very close to our results. In particular, the type distributions based on questions of more extreme changes in the stock market, such as Gain > 20% or Loss > 20%, yield substantially higher RW type shares. For more details, see Appendix B2.

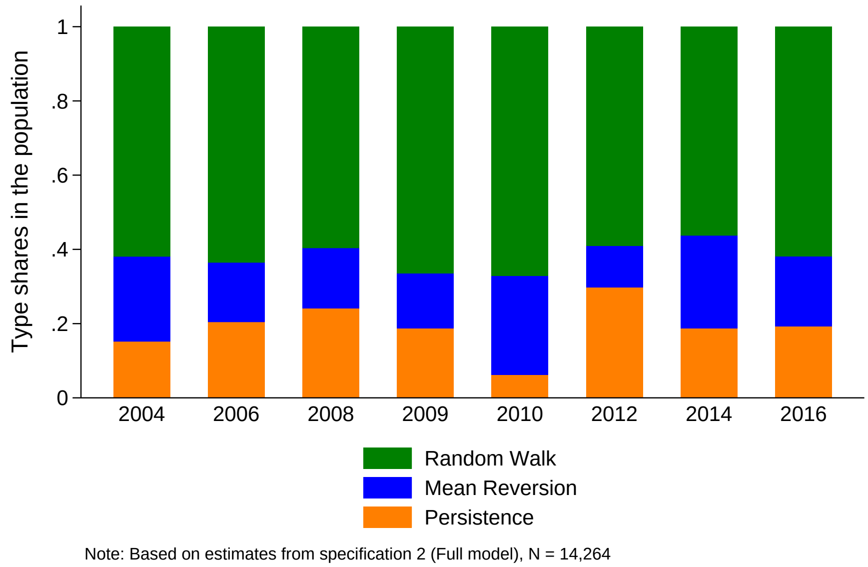


Figure 2.7: Expectation type distribution across years

Next, the inclusion of year-fixed effects in the random effects multinomial logit model for the type probabilities allows us to predict year-specific type distributions. As our sample covers the period between 2004 and 2016, we are able to analyze the effect of the 2008/09 financial crisis on the type distributions. Figure 2.7 plots the conditional type distribution over time, again based on the results of the full model (Table 2.2, specification 2); the graph for alternative specifications looks very similar. Clearly, there is evidence for variation over time. In years not affected by the financial crisis (2004, 06, 08, 14, 16) the type distribution looks similar.[9] In addition, there is little change at the onset of the financial crisis in 2009. In 2010, however, the MR share increases substantially. Two years later, the MR share drops again and is replace by a substantial increase in the P share. After 2012, the effect of the financial crisis seems to level off and the type share distribution returns to levels, which are similar to those of 2004. We therefore conclude that the effects of the financial crisis on the expectation type distribution were only temporary.

[9] Note that interviews are conducted in April and May of 2008. Since the financial crisis hit the Netherlands in June 2008, the first wave affected in our data is the 2009 wave. See also Figure 2.1.

2.5 Robustness

This section provides several robustness checks to variations in methodology and sample size. To reduce the computational burden, the specifications are estimated under the sign restrictions of the three return coefficients ($\gamma_1 = 0$,$\gamma_2 < 0$,$\gamma_3 > 0$) for the three expectation types (RW,MR,P). The results can thus be compared to the estimates from specification 3 in Tables 2.2, 2.3 and 2.4, respectively. The corresponding tables are presented in Appendix C2.

Monotonicity of probability responses. Similar to other surveys, some respondents in our data set report expectations which clearly violate basic laws of probabilities. For example, they report a higher chance that the stock market will increase by 20 percent than that the stock market will increase by 10 percent, clearly violating monotonicity. These respondents can actually be included in our main model, because we require monotonicity only at the aggregate, but not at the individual level.[10] Overall, roughly 20 percent of the observations violate (weak) monotonicity at least once. Excluding those from the estimation (Tables C2.1, C2.2 and C2.3), however, leaves the results unchanged. The (absolute) magnitude of the return coefficients decreases slightly, while the associations with the covariates as well as the implied type share distribution remain almost identical.

Answering all eight probability questions. We also estimate one specification that restricts the sample to respondents who answer all eight probability questions, resulting in a nine percent drop in the number of observations (Tables C2.1, C2.2 and C2.3). All the estimates are extremely close to our main specification, including the return coefficients. This ensures, in particular, that our finding that respondents round less when asked about more extreme changes in the stock market is not driven by the fact that some respondents only answer the questions Gain > 0% or Loss > 0%, potentially because the follow-up questions are too difficult for them to understand.

[10] As shown in Figure 2.2, aggregate monotonicity in our data set is fulfilled at any point in time.

50/50 answers and epistemic uncertainty. Bruine de Bruin et al. (2000) show that some respondents use 50/50 answers to express uncertainty rather than an actual probability of 50% (epistemic uncertainty). In principle, our model could also include another reporting type (next to R1, R5 and R50) which reports 50% to express uncertainty. However, in order to not further increase the complexity of our model, we rather estimate a specification which excludes all observations where at least one of the eight probability questions is answered with "50%" (Tables C2.1, C2.2 and C2.3). This almost halves our number of observations to 7,353. Surprisingly, the absolute magnitude of the return coefficients increases by a factor of five. More importantly, however, the sign of the return coefficients and thus the interpretation of our expectation types remains the same. The (RW,MR,P) type distribution is given by (0.82,0.08,0.10), thus predicting a considerably higher share of RW types.

Short-run returns. Our model assumes that respondents put a particular focus on the past one-year AEX return when forming their expectations. This assumption seems rather plausible, because respondents are also asked about their one-year ahead expectations. However, we also estimate the model under the assumption that respondents focus on the past one-month and one-week return (Tables C2.4, C2.5 and C2.6). Again, the magnitude of the return coefficients increases substantially, which can, however, be explained by the smaller magnitude of the short-term returns, as shown in Table 2.1. More importantly, the implied type share distributions for the one-month and the one-week return are given by (0.67,0.14,0.19) and (0.65,0.14,0.21), respectively, and are thus almost identical to our main specifications. The associations with the covariates are extremely similar to the main findings, the only exception being that the covariates seem to be less associated with individuals' rounding behavior.

Risk aversion and trust. We are also interested in how economic preferences, such as risk aversion and general trust in other people, affect type probabilities and expectations per se. Unfortunately, both variables have not been asked in all waves (cf. Section 2.2), leading to a substantial reduction in sample size (Tables C2.7, C2.8 and C2.9). Including both preference variables in the model (specification 1) shows that risk averse individuals have, on average, lower stock market expectations and are more likely to round. Risk aversion is, however, not related to individual expectation type probabilities. In contrast, individuals with higher levels of trust are more likely to be type RW than type MR or P. In addition, they also have higher expectations and are less likely to round. The magnitude of the type P return coefficient increases as well as the sample share of type RW (at the expense of type P). Both effects are shown to be driven by the reduction in sample size rather than by the inclusion of both economic preferences (specification 2).

2.6 Conclusion

This paper introduced a panel data model with a finite mixture of different expectation types who differ in how they take past returns into account when forming expectations. Such response types are not naturally given, and one could think of alternative definitions. We follow Dominitz and Manski (2011) and estimate the model for three expectation types that are governed by random walk, mean revision, and persistence updating, respectively. We find that most respondents report expectations which are in line with a random walk interpretation, while fewer answers are consistent with mean reversion or persistence updating. We find evidence for considerable heterogeneity in the type membership, which is predicted by observable characteristics, and also considerable variation over time.

We believe that our approach could be extended in several directions. Conceptually, it would be straightforward to add additional expectation types, even though they are not naturally given and it is unclear what would be gained from such an exercise. From a more technical perspective, the finite mixture model might get more unstable if too many types are added. One could also try to make the rounding model more realistic, for instance by adding additional types as in Kleinjans and van Soest (2014) or by using ideas developed in Giustinelli et al. (2018).

From a substantive perspective, the model might be used to study the determinants of heterogeneity in expectations formation, for instance by conditioning type membership on experiences individuals made over their life, as for example in Malmendier and Nagel (2011), Malmendier et al. (2017) or Rossmann (2019).

Appendix

A2 Additional descriptive analyses

In the following sections, we provide additional descriptive analyses of our data. While Figure 2.2 reported the cross-sectional means for the eight probability questions, we also report the cross-sectional standard deviations in Figure A2.1. Note that this measure is often used in the literature to measure disagreement among respondents and thus uncertainty (cf. Zarnowitz and Lambros, 1987; Bachmann et al., 2013).

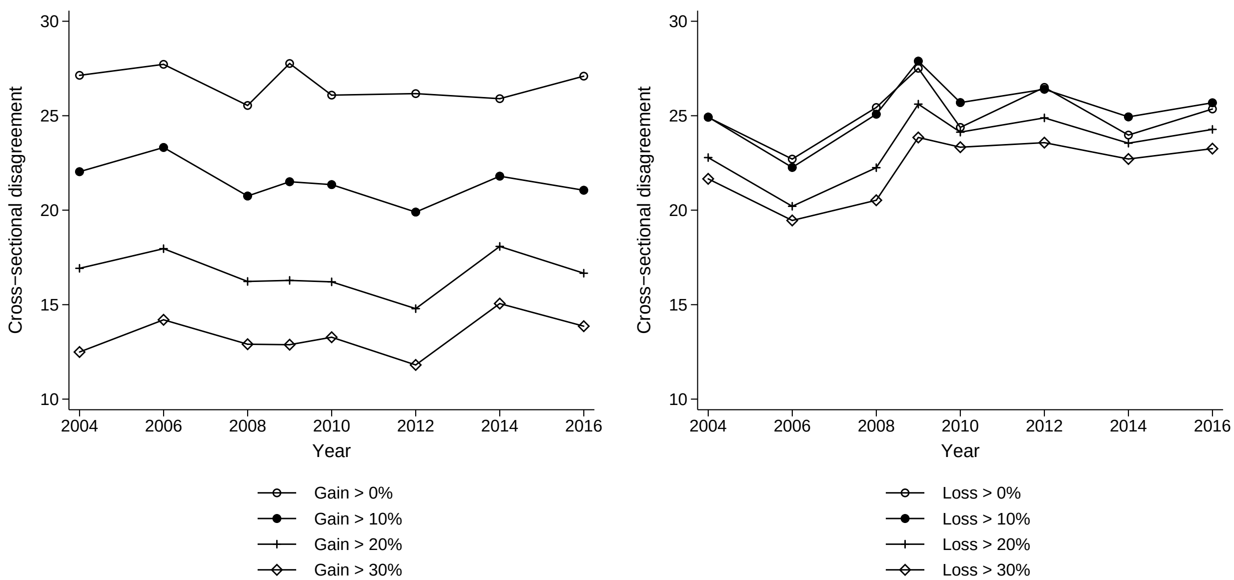


Figure A2.1: Cross-sectional disagreement of expectations over time

Overall, there are two striking differences between the gain and loss domain. First, the level of disagreement decreases if respondents are asked about more extreme changes in the AEX in the gain domain, but not in the loss domain. For example, the cross-sectional average standard deviation for the question Gain > 30% is only 13 percent, compared to 22 percent for the question Loss > 30%. In contrast, disagreement levels for the questions Gain > 0% and Loss > 0% are similarly high. This difference may be driven by the fact that many respondents agree on a zero percent chance for large gains, but they agree less on a zero percent chance for large losses. Second, our data supports the argument from the literature that respondents' disagreement may be used as an indicator for uncertainty, but only for questions in the loss domain. While in the loss domain, there is indeed a stark increase during the financial crisis in 2009, this increase is less pronounced or even absent for questions in the gain domain. The correlations between the four disagreement measures in the loss domain vary between 0.65 and 0.97. In contrast, the disagreement measures in the gain domain are rather uncorrelated, with correlation ranging between 0.03 (Gain $>$ 0% and Gain $>$ 30%) and 0.87 (Gain $>$ 20% and Gain $>$ 30%). These findings indicate that uncertainty measures based on questions in a loss framing might be more appropriate than from questions in a gain framing.

Another indicator for a stark difference between the gain and the loss domain can be found when looking at the within-respondent variation over time, for each of the eight survey questions. In particular, we are interested in how strongly respondents change their expectations between periods. We therefore estimate respondent-specific (sample) standard deviations of answers across periods for each of the eight questions separately. For clarification consider the following example. Respondent A (B) is observed in four (two) periods. The corresponding responses for the question on a positive stock market return (Gain $>$ 0%) are given by (70, 80, 60, 60) and (80, 80), respectively. The within-respondent (sample) standard deviation across periods for the question on positive stock market returns would then be 9.57 for respondent A and zero for respondent B. For each respondent, we calculate the standard deviation across periods for all of the eight expectations questions.[11]

Table A2.1 displays summary statistics for our measure of within-respondent disagreement. Again, the largest adjustments are made for questions on any gain or any loss. The

[11]Note that individuals have to be observed at least twice in order to calculates the (sample) standard deviation.

more extreme the outcome of the question gets, the less volatile are the answers to that particular question. More interestingly, however, is the difference between the gain and loss domain. While there is almost no difference for the question on any gain or loss, the picture changes when we look at questions on larger gains and losses. Here, answers in the loss domain are considerably more volatile than in the gain domain. For the questions on gains and losses of more than 30 percent, the difference in average standard deviation amounts to roughly five percentage points (12.06% versus 6.73%). In line with previous evidence, it seems that respondents tend to adjust their expectations more in the loss domain than the gain domain.

Table A2.1: Summary statistics for within-respondent disagreement (across years)

	Mean	p25	p50	p75	Min	Max	N
Gains							
Gain > 0%	18.58	9.57	18.35	26.15	0	70.71	2,783
Gain > 10%	14.80	7.07	13.45	21.21	0	70.71	2,732
Gain > 20%	10.03	2.89	7.07	15.00	0	67.18	2,709
Gain > 30%	6.73	0.71	3.21	9.06	0	70.71	2,701
Losses							
Loss > 0%	18.49	9.57	17.56	25.32	0	70.71	2,778
Loss > 10%	17.43	7.07	15.12	24.75	0	70.71	2,705
Loss > 20%	14.34	4.35	10.61	21.21	0	70.71	2,686
Loss > 30%	12.06	2.19	6.83	19.24	0	70.71	2,665

Notes: This table reports summary statistics for the within-respondent disagreement, i.e. sample standard deviation, across periods for each of the eight probabilistic questions on stock market returns. The across-period standard deviation is only defined if the respondent answers the question in at least two periods. For details see text.

B2 Ordinal methodology by Dominitz and Manski (2011)

Using the same definitions for the (RW,MR,P) expectation types as in the present paper, Dominitz and Manski (2011) propose an ordinal methodology to classify respondents. They argue that expectations of a given respondent are consistent with the RW type if and only if expectations hardly change between waves. Similarly, if a respondent adjusts her expectations by more than a certain cut-off, she can be classified as MR or P type, depending on the adjustment's direction and the recent short-term stock market performance.

For clarification, consider the following example. A respondent is interviewed on her stock market expectations in 2004 and 2006 – a period in which the AEX index increased almost monotonically (see Figure 2.1) and more importantly, the one-year return in 2006 was higher than the one-year return in 2004. If the respondent was a RW type, she would hardly adjust her expectations in 2006, as the long-run historical average return will only be marginally affected by those two additional years. In contrast, a P type would positively adjust her 2004 expectations, because she beliefs the (positive) recent stock market performance to persist into the near future. Similarly, if she was a MR type, she would lower her expectations in 2006. Note that this simple methodology uniquely classifies respondents into one of the three expectation types, while our panel data model avoids this classification by assigning individual probabilities for each of the three types.

Following Dominitz and Manski (2011), we measure recent stock market performance by the difference in the past one-year stock market returns between two waves and choose a cut-off of five percentage points. We apply this methodology to all eight probability questions on the stock market for every respondent who is observed in at least two subsequent waves. The results are summarized in Figure B2.1. Focusing on the question of a positive stock market return (Gain $> 0\%$), we get a type distribution of (0.29,0.26,0.45), which is extremely close to the findings by Dominitz and Manski (2011) using data from the Michigan Survey of Consumers and data on the S&P 500 index. However, this distribution differs somewhat from the results of our panel data model, which suggest a higher share of RW types. Potential reasons are discussed in Section 2.4.2. Applying the same methodology to questions on larger gains increases the share of RW types almost monotonically. In fact, responses to the question Gain > 30% imply a type distribution of (0.73,0.11,0.16) and therefore an even higher share of RW types as suggested in our model. Interestingly, at least in terms of the implied type distribution there seems to be absolutely no difference between the gain and the loss domain. Both the levels and the monotonic increase of the RW types are similar for both domains.

Similarly, also increasing the ad-hoc cut-off of five percentage points increases by definition the share of RW respondents, and can thus confirm our findings.

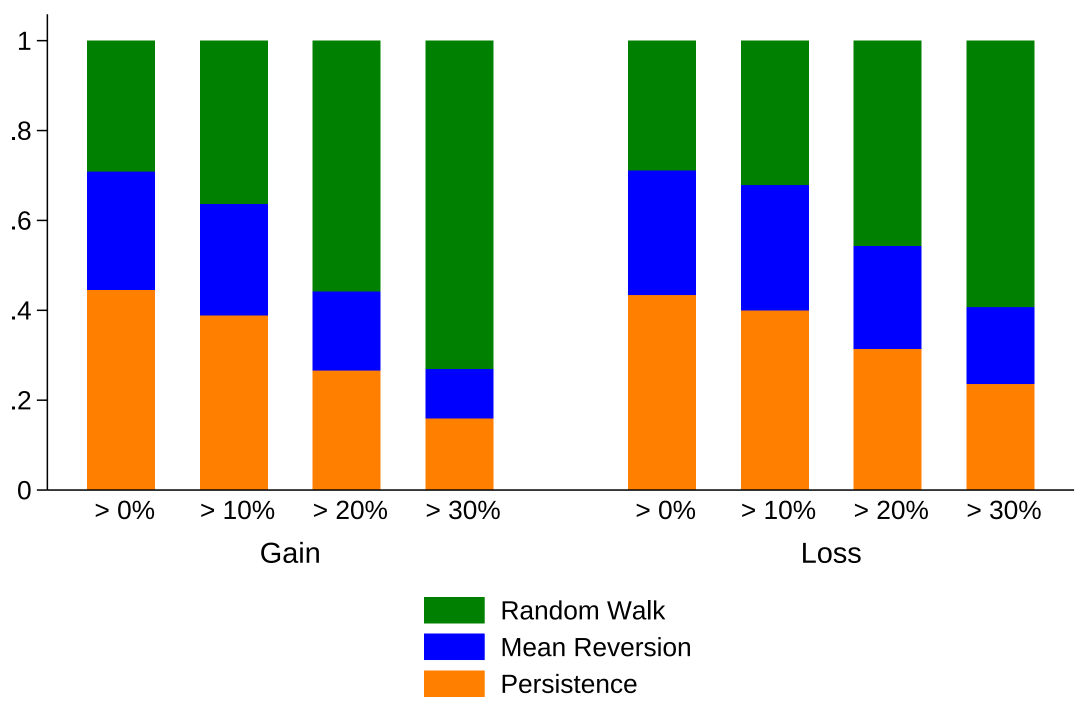


Figure B2.1: Type distributions with ordinal Dominitz and Manski (2011) criterion

C2 Additional Figures and Tables

Table C2.1: Model for the mean of the subjective distributions – robustness with respect to expectation response behavior

	(1) Only monotonic answers		(2) Eight probability questions		(3) Drop 50s	
γ_2: Return coeff. Cl2	-0.3200***	[0.0105]	-0.5801***	[0.0178]	-2.6640***	[0.1525]
γ_3: Return coeff. Cl3	0.4779***	[0.0080]	0.5898***	[0.0099]	2.5035***	[0.1108]
Female	-0.0116***	[0.0020]	-0.0229***	[0.0023]	-0.0128***	[0.0017]
Age >64	0.0003	[0.0015]	-0.0034**	[0.0016]	-0.0027*	[0.0016]
Age <45	0.0042***	[0.0016]	-0.0028	[0.0018]	0.0044***	[0.0017]
Low education	-0.0088***	[0.0022]	-0.0130***	[0.0024]	-0.0086***	[0.0020]
High education	0.0130***	[0.0021]	0.0060**	[0.0025]	0.0012	[0.0019]
Partner	0.0006	[0.0019]	-0.0026	[0.0031]	-0.0011	[0.0019]
HH income: 1st quart.	-0.0072***	[0.0022]	-0.0051**	[0.0026]	-0.0066***	[0.0022]
HH income: 2nd quart.	-0.0072***	[0.0019]	-0.0063***	[0.0020]	-0.0068***	[0.0019]
HH income: 3rd quart.	-0.0039***	[0.0015]	-0.0015	[0.0017]	-0.0032*	[0.0017]
No. children in HH	0.0000	[0.0009]	-0.0006	[0.0008]	-0.0027***	[0.0007]
Constant	-0.0166***	[0.0029]	-0.0058	[0.0048]	0.0188***	[0.0027]
σ_1^*	0.1026***	[0.0007]	0.1162***	[0.0007]	0.1063***	[0.0008]
σ_2^*	0.3963***	[0.0053]	0.5831***	[0.0098]	0.6436***	[0.0337]
σ_3^*	0.1894***	[0.0022]	0.2573***	[0.0031]	0.4237***	[0.0151]
σ_{CDFfit}	0.1401***	[0.0004]	0.1573***	[0.0004]	0.1777***	[0.0006]
LogLik	-252,684.91		-316,029.07		-182,140.62	
AIC	505,547.81		632,236.13		364,459.24	
Observations	11,402		12,973		7,353	

Notes: This table re-estimates the main model using only respondents who do not violate basic laws of probabilities (specification 1), who answer all eight expectations questions on the stock market performance (specification 2) and who do not report a probability of 50 percent to a specific expectations question (specification 3). Model uses sign restrictions for the return coefficients ($\gamma_1 = 0$, $\gamma_2 < 0$, $\gamma_3 > 0$). Table displays results for the subjective means model (Equation 2.1) as well as the type-specific estimates for the subjective standard deviations. For details see text. Standard errors in brackets; *** p <0.01, ** p <0.05, * p <0.1.

Table C2.2: Random effects multinomial logit model for the expectation types – robustness with respect to expectation response behavior

	(1) Only monotonic answers		(2) Eight probability questions		(3) Drop 50s	
Class 2 (Mean Reversion)						
Female	0.2432***	[0.0741]	0.4152***	[0.0701]	0.3926***	[0.1211]
Age >64	-0.7801***	[0.1037]	-0.5538***	[0.0962]	-0.7351***	[0.1750]
Age <45	0.7960***	[0.0814]	0.7650***	[0.0770]	0.3207**	[0.1383]
Low education	-0.2180**	[0.0963]	0.1743**	[0.0871]	0.2227	[0.1491]
High education	-0.5892***	[0.0854]	-0.4323***	[0.0831]	-0.5208***	[0.1497]
Partner	0.1961**	[0.0957]	0.3562***	[0.0961]	0.1558	[0.1617]
HH income: 1st quart.	0.6028***	[0.1150]	0.7227***	[0.1071]	0.5837***	[0.1910]
HH income: 2nd quart.	0.4355***	[0.1042]	0.3988***	[0.0974]	0.2023	[0.1784]
HH income: 3rd quart.	0.2446**	[0.0968]	0.2924***	[0.0920]	0.1128	[0.1685]
No. children in HH	-0.0120	[0.0383]	-0.0019	[0.0338]	0.0272	[0.0627]
Constant	-1.9476***	[0.1641]	-2.2393***	[0.1578]	-3.0667***	[0.2629]
Class 3 (Persistence)						
Female	0.1131	[0.0696]	0.2447***	[0.0657]	0.3960***	[0.1065]
Age >64	-0.3372***	[0.0891]	-0.2542***	[0.0820]	-0.3940***	[0.1414]
Age <45	0.4864***	[0.0801]	0.5218***	[0.0742]	0.5666***	[0.1250]
Low education	-0.0611	[0.0910]	0.1590*	[0.0831]	0.4030***	[0.1338]
High education	-0.2007**	[0.0812]	-0.1505*	[0.0779]	-0.2417*	[0.1337]
Partner	0.1835**	[0.0909]	0.3406***	[0.0916]	0.1361	[0.1424]
HH income: 1st quart.	0.4292***	[0.1089]	0.4950***	[0.1022]	0.5767***	[0.1725]
HH income: 2nd quart.	0.2640***	[0.0982]	0.2865***	[0.0904]	0.2559	[0.1590]
HH income: 3rd quart.	0.1960**	[0.0908]	0.2647***	[0.0839]	0.1313	[0.1494]
No. children in HH	-0.0087	[0.0370]	-0.0091	[0.0326]	0.0182	[0.0563]
Constant	-1.7239***	[0.1603]	-2.1845***	[0.1580]	-4.6496***	[0.3118]
Implied Cl1 share	0.59		0.61		0.82	
Implied Cl2 share	0.19		0.17		0.08	
Implied Cl3 share	0.22		0.22		0.10	
LogLik	-252,684.91		-316,029.07		-182,140.62	
AIC	505,547.81		632,236.13		364,459.24	
Observations	11,402		12,973		7,353	

Notes: This table re-estimates the main model using only respondents who do not violate basic laws of probabilities (specification 1), who answer all eight expectations questions on the stock market performance (specification 2) and who do not report a probability of 50 percent to a specific expectations question (specification 3). Model uses sign restrictions for the return coefficients ($\gamma_1 = 0$, $\gamma_2 < 0$, $\gamma_3 > 0$). Table displays results for the random effects multinomial logit model for the expectation types (Equation 2.3). Baseline type 1 (Random Walk) is omitted. Specifications 2 and 3 also include year fixed effects. For details see text. Standard errors in brackets; *** p <0.01, ** p <0.05, * p <0.1.

Table C2.3: Random effects ordinal probit model for rounding types – robustness with respect to expectation response behavior

	(1) Only monotonic answers		(2) Eight probability questions		(3) Drop 50s	
Female	-0.0016	[0.0240]	-0.0345*	[0.0202]	-0.0447	[0.0309]
Age >64	0.0081	[0.0210]	0.0505***	[0.0188]	0.0193	[0.0291]
Age <45	-0.0840***	[0.0217]	-0.0689***	[0.0189]	-0.1739***	[0.0298]
Low education	-0.0782***	[0.0297]	0.0537**	[0.0240]	0.0292	[0.0373]
High education	-0.1737***	[0.0259]	0.0092	[0.0227]	0.0329	[0.0370]
Partner	0.0724***	[0.0276]	0.0870***	[0.0241]	0.0326	[0.0342]
HH income: 1st quart.	0.0098	[0.0311]	0.0418*	[0.0253]	-0.0008	[0.0397]
HH income: 2nd quart.	0.0515*	[0.0269]	0.0262	[0.0214]	0.0260	[0.0342]
HH income: 3rd quart.	-0.0067	[0.0218]	-0.0025	[0.0190]	0.0010	[0.0307]
No. children in HH	0.0150	[0.0125]	0.0134	[0.0091]	0.0037	[0.0142]
LogLik	-252,684.91		-316,029.07		-182,140.62	
AIC	505,547.81		632,236.13		364,459.24	
Observations	11,402		12,973		7,353	

Notes: This table re-estimates the main model using only respondents who do not violate basic laws of probabilities (specification 1), who answer all eight expectations questions on the stock market performance (specification 2) and who do not report a probability of 50 percent to a specific expectations question (specification 3). Model uses sign restrictions for the return coefficients ($\gamma_1 = 0$, $\gamma_2 < 0$, $\gamma_3 > 0$). Table displays results for the random effects ordinal probit model for the rounding types (Equation 2.7). Dependent variable is equal to 1 if the respondent does not round (R1), 2 if the respondent rounds to the next multiple of five (R5) and 3 if the respondent rounds to the next multiple of 50 (R50). Question type-specific cut-off parameters are not reported. For details see text. Standard errors in brackets; *** p <0.01, ** p <0.05, * p <0.1.

Table C2.4: Model for the mean of the subjective distributions – robustness with respect to alternative returns

	(1) One-year return (main)		(2) One-month return		(3) One-week return	
γ_2: Return coeff. Cl2	-0.5964***	[0.0185]	-4.7453***	[0.1125]	-8.9345***	[0.2305]
γ_3: Return coeff. Cl3	0.6154***	[0.0104]	2.6610***	[0.0614]	6.7803***	[0.1311]
Female	-0.0203***	[0.0024]	-0.0187***	[0.0025]	-0.0212***	[0.0022]
Age >64	-0.0016	[0.0018]	-0.0035**	[0.0015]	-0.0003	[0.0016]
Age <45	-0.0023	[0.0017]	-0.0012	[0.0016]	-0.0007	[0.0016]
Low education	-0.0257***	[0.0027]	-0.0119***	[0.0025]	-0.0142***	[0.0031]
High education	0.0075***	[0.0028]	0.0049*	[0.0026]	0.0059**	[0.0026]
Partner	0.0006	[0.0027]	-0.0041**	[0.0020]	-0.0019	[0.0022]
HH income: 1st quart.	-0.0000	[0.0027]	-0.0057***	[0.0022]	-0.0045*	[0.0024]
HH income: 2nd quart.	-0.0013	[0.0022]	-0.0065***	[0.0019]	-0.0049**	[0.0020]
HH income: 3rd quart.	0.0003	[0.0018]	-0.0033**	[0.0016]	-0.0037**	[0.0017]
No. children in HH	-0.0005	[0.0008]	-0.0022***	[0.0008]	-0.0019**	[0.0008]
Constant	-0.0128***	[0.0037]	0.0031	[0.0034]	-0.0011	[0.0040]
σ_1^*	0.1167***	[0.0007]	0.1221***	[0.0007]	0.1194***	[0.0007]
σ_2^*	0.5767***	[0.0095]	0.3258***	[0.0055]	0.3394***	[0.0067]
σ_3^*	0.2601***	[0.0032]	0.5175***	[0.0082]	0.4516***	[0.0066]
σ_{CDFfit}	0.1596***	[0.0004]	0.1617***	[0.0004]	0.1600***	[0.0004]
LogLik	-331,997.03		-332,450.63		-331,660.91	
AIC	664,172.05		665,079.26		663,499.82	
Observations	14,264		14,264		14,264	

Notes: This table re-estimates the main model using different AEX returns. Specifications 1, 2 and 3 focus on the one-year, one-month and one-week AEX return, respectively. Model uses sign restrictions for the return coefficients ($\gamma_1 = 0$, $\gamma_2 < 0$, $\gamma_3 > 0$). Table displays results for the subjective means model (Equation 2.1) as well as the type-specific estimates for the subjective standard deviations. For details see text. Standard errors in brackets; *** p <0.01, ** p <0.05, * p <0.1.

Table C2.5: Random effects multinomial logit model for the expectation types – robustness with respect to alternative returns

	(1) One-year return (main)		(2) One-month return		(3) One-week return	
Class 2 (Mean Reversion)						
Female	0.3394***	[0.0715]	0.2945***	[0.0754]	0.4291***	[0.0761]
Age >64	-0.5734***	[0.0936]	-0.1697*	[0.0912]	-0.2188**	[0.0935]
Age <45	0.7835***	[0.0766]	0.3002***	[0.0852]	0.4295***	[0.0841]
Low education	0.2229**	[0.0889]	0.1784**	[0.0905]	0.2455**	[0.0978]
High education	-0.5621***	[0.0870]	-0.3865***	[0.0913]	-0.3411***	[0.0914]
Partner	0.1975**	[0.0944]	0.3286***	[0.0972]	0.2382**	[0.0992]
HH income: 1st quart.	0.5987***	[0.1070]	0.4760***	[0.1125]	0.4315***	[0.1141]
HH income: 2nd quart.	0.3336***	[0.0974]	0.1765*	[0.1041]	0.0931	[0.1052]
HH income: 3rd quart.	0.2305**	[0.0919]	0.1261	[0.0984]	0.1598	[0.0973]
No. children in HH	0.0011	[0.0338]	-0.0021	[0.0376]	0.0240	[0.0371]
Constant	-1.9628***	[0.1543]	-2.5656***	[0.1670]	-2.0716***	[0.1683]
Class 3 (Persistence)						
Female	0.2216***	[0.0661]	0.4165***	[0.0674]	0.3229***	[0.0655]
Age >64	-0.2922***	[0.0809]	-0.4785***	[0.0854]	-0.4331***	[0.0816]
Age <45	0.5227***	[0.0733]	0.8155***	[0.0700]	0.8097***	[0.0695]
Low education	0.2687***	[0.0834]	0.0790	[0.0800]	0.1326	[0.0839]
High education	-0.2241***	[0.0795]	-0.4224***	[0.0790]	-0.4575***	[0.0771]
Partner	0.2552***	[0.0879]	0.2496***	[0.0839]	0.2795***	[0.0836]
HH income: 1st quart.	0.3926***	[0.1008]	0.5211***	[0.0977]	0.5601***	[0.0969]
HH income: 2nd quart.	0.2189**	[0.0900]	0.2745***	[0.0884]	0.3583***	[0.0873]
HH income: 3rd quart.	0.2341***	[0.0833]	0.2464***	[0.0827]	0.2300***	[0.0821]
No. children in HH	-0.0154	[0.0322]	-0.0115	[0.0314]	-0.0230	[0.0311]
Constant	-2.0169***	[0.1497]	-2.2951***	[0.1469]	-2.2874***	[0.1546]
Implied Cl1 share	0.60		0.67		0.65	
Implied Cl2 share	0.18		0.14		0.14	
Implied Cl3 share	0.21		0.19		0.21	
LogLik	-331,997.03		-332,450.63		-331,660.91	
AIC	664,172.05		665,079.26		663,499.82	
Observations	14,264		14,264		14,264	

Notes: This table re-estimates the main model using different AEX returns. Specifications 1, 2 and 3 focus on the one-year, one-month and one-week AEX return, respectively. Model uses sign restrictions for the return coefficients ($\gamma_1 = 0$, $\gamma_2 < 0$, $\gamma_3 > 0$). Table displays results for the random effects multinomial logit model for the expectation types (Equation 2.3). Baseline type 1 (Random Walk) is omitted. Specifications 2 and 3 also include year fixed effects. For details see text. Standard errors in brackets; *** p <0.01, ** p <0.05, * p <0.1.

Table C2.6: Random effects ordinal probit model for rounding types – robustness with respect to alternative returns

	(1) One-year return (main)		(2) One-month return		(3) One-week return	
Female	-0.0154	[0.0209]	0.0359	[0.0234]	0.0251	[0.0230]
Age >64	0.0233	[0.0203]	0.0272	[0.0233]	0.0269	[0.0197]
Age <45	-0.0515***	[0.0188]	-0.0466**	[0.0193]	-0.0401**	[0.0192]
Low education	-0.0048	[0.0247]	-0.0386	[0.0267]	-0.0303	[0.0261]
High education	-0.0989***	[0.0248]	-0.0671**	[0.0293]	-0.0752***	[0.0257]
Partner	0.0005	[0.0268]	0.0497*	[0.0269]	0.0373	[0.0265]
HH income: 1st quart.	-0.0294	[0.0275]	0.0236	[0.0288]	0.0393	[0.0282]
HH income: 2nd quart.	-0.0270	[0.0238]	0.0201	[0.0263]	0.0242	[0.0237]
HH income: 3rd quart.	-0.0316	[0.0200]	-0.0093	[0.0202]	-0.0076	[0.0203]
No. children in HH	0.0113	[0.0090]	0.0108	[0.0094]	0.0114	[0.0090]
LogLik	-331,997.03		-332,450.63		-331,660.91	
AIC	664,172.05		665,079.26		663,499.82	
Observations	14,264		14,264		14,264	

Notes: This table re-estimates the main model using different AEX returns. Specifications 1, 2 and 3 focus on the one-year, one-month and one-week AEX return, respectively. Model uses sign restrictions for the return coefficients ($\gamma_1 = 0$, $\gamma_2 < 0$, $\gamma_3 > 0$). Table displays results for the random effects ordinal probit model for the rounding types (Equation 2.7). Dependent variable is equal to 1 if the respondent does not round (R1), 2 if the respondent rounds to the next multiple of five (R5) and 3 if the respondent rounds to the next multiple of 50 (R50). Question type-specific cut-off parameters are not reported. For details see text. Standard errors in brackets; *** p <0.01, ** p <0.05, * p <0.1.

Table C2.7: Model for the mean of the subjective distributions – robustness with respect to excluding survey years

	(1) Add preferences (no 2006,08,09)		(2) no 2006-2009		(3) Pre crisis (2004-2009)		(4) Post crisis (2010-2016)	
γ_2: Return coeff. Cl2	-0.7671***	[0.0251]	-0.7825***	[0.0245]	-0.9229***	[0.0503]	-0.5147***	[0.0225]
γ_3: Return coeff. Cl3	1.8050***	[0.0510]	1.8180***	[0.0534]	0.5141***	[0.0123]	0.6296***	[0.0176]
Female	-0.0128***	[0.0022]	-0.0116***	[0.0021]	-0.0165***	[0.0029]	-0.0165***	[0.0029]
Age >64	-0.0009	[0.0018]	-0.0001	[0.0018]	0.0024	[0.0031]	0.0081***	[0.0025]
Age <45	0.0023	[0.0020]	0.0001	[0.0019]	0.0015	[0.0030]	-0.0063**	[0.0029]
Low education	-0.0081***	[0.0027]	-0.0133***	[0.0027]	-0.0034	[0.0040]	-0.0206***	[0.0037]
High education	0.0088***	[0.0025]	0.0070***	[0.0024]	0.0119***	[0.0034]	0.0106***	[0.0032]
Partner	-0.0044*	[0.0023]	0.0026	[0.0023]	0.0059*	[0.0035]	0.0052*	[0.0030]
HH income: 1st quart.	-0.0036	[0.0026]	-0.0016	[0.0027]	-0.0034	[0.0039]	0.0067*	[0.0035]
HH income: 2nd quart.	0.0005	[0.0022]	0.0012	[0.0022]	-0.0074**	[0.0034]	0.0038	[0.0026]
HH income: 3rd quart.	-0.0016	[0.0019]	0.0008	[0.0019]	-0.0006	[0.0029]	0.0036	[0.0023]
No. children in HH	-0.0011	[0.0009]	-0.0003	[0.0009]	-0.0035***	[0.0013]	-0.0004	[0.0011]
Riskaverse	-0.0054***	[0.0018]						
Trust in other people	0.0065***	[0.0016]						
Constant	-0.0006	[0.0040]	-0.0050	[0.0035]	-0.0206***	[0.0057]	-0.0311***	[0.0048]
σ_1^*	0.1259***	[0.0009]	0.1249***	[0.0009]	0.1019***	[0.0012]	0.1219***	[0.0009]
σ_2^*	0.5365***	[0.0108]	0.5422***	[0.0104]	0.5302***	[0.0136]	0.6366***	[0.0155]
σ_3^*	0.3677***	[0.0090]	0.3649***	[0.0091]	0.2354***	[0.0055]	0.2917***	[0.0047]
σ_{CDFfit}	0.1589***	[0.0005]	0.1599***	[0.0005]	0.1536***	[0.0006]	0.1577***	[0.0005]
LogLik	-192,546.36		-211,164.38		-127,162.12		-203,456.82	
AIC	385,274.72		422,494.77		254,482.25		407,079.64	
Observations	8,339		9,214		5,356		8,908	

Notes: This table re-estimates the main model adding economic preferences as explanatory variables (specification 1) and excluding several survey years (specifications 2, 3 and 4). Model uses sign restrictions for the return coefficients ($\gamma_1 = 0$, $\gamma_2 < 0$, $\gamma_3 > 0$). Table displays results for the subjective means model (Equation 2.1) as well as the type-specific estimates for the subjective standard deviations. For details see text. Standard errors in brackets; *** p <0.01, ** p <0.05, * p <0.1.

Table C2.8: Random effects multinomial logit model for the expectation types – robustness with respect to excluding survey years

	(1) Add preferences (no 2006,08,09)		(2) no 2006-2009		(3) Pre crisis (2004-2009)		(4) Post crisis (2010-2016)	
Class 2 (Mean Reversion)								
Female	0.3852***	[0.0817]	0.3539***	[0.0770]	0.3730***	[0.1089]	0.3223***	[0.0912]
Age >64	-0.4853***	[0.1096]	-0.5584***	[0.1051]	-0.6795***	[0.1569]	-0.7778***	[0.1211]
Age <45	0.7078***	[0.0918]	0.7937***	[0.0867]	0.6297***	[0.1251]	0.7783***	[0.1022]
Low education	-0.1005	[0.1049]	-0.0068	[0.0991]	0.0643	[0.1364]	-0.0086	[0.1156]
High education	-0.5366***	[0.0971]	-0.5694***	[0.0923]	-0.5886***	[0.1360]	-0.5368***	[0.1052]
Partner	0.2295**	[0.1088]	0.2151**	[0.1023]	0.0863	[0.1463]	0.1770	[0.1205]
HH income: 1st quart.	0.5101***	[0.1269]	0.5322***	[0.1202]	0.7835***	[0.1721]	0.3734***	[0.1417]
HH income: 2nd quart.	0.2700**	[0.1132]	0.2655**	[0.1087]	0.4695***	[0.1608]	0.3112**	[0.1247]
HH income: 3rd quart.	0.1371	[0.1078]	0.1288	[0.1034]	0.3222**	[0.1530]	0.1648	[0.1180]
No. children in HH	-0.0244	[0.0407]	-0.0390	[0.0382]	0.0497	[0.0536]	0.0059	[0.0446]
Riskaverse	-0.0542	[0.1021]						
Trust in other people	-0.4113***	[0.0775]						
Constant	-1.6766***	[0.1967]	-2.0529***	[0.1640]	-1.7181***	[0.2235]	-2.4283***	[0.2025]
Class 3 (Persistence)								
Female	0.3106***	[0.0999]	0.2506***	[0.0938]	0.2416**	[0.1018]	0.1904**	[0.0833]
Age >64	-0.1083	[0.1274]	-0.1334	[0.1208]	-0.4836***	[0.1360]	-0.3461***	[0.1029]
Age <45	0.6714***	[0.1199]	0.6520***	[0.1127]	0.7028***	[0.1162]	0.5116***	[0.0978]
Low education	0.1069	[0.1254]	0.1471	[0.1178]	0.0566	[0.1338]	0.1336	[0.1063]
High education	-0.5708***	[0.1227]	-0.6074***	[0.1150]	-0.1512	[0.1232]	-0.2883***	[0.0985]
Partner	0.3291**	[0.1358]	0.2825**	[0.1274]	0.0391	[0.1352]	0.2711**	[0.1110]
HH income: 1st quart.	0.3779**	[0.1623]	0.3985***	[0.1523]	0.4123**	[0.1609]	0.2736**	[0.1319]
HH income: 2nd quart.	0.2041	[0.1426]	0.1785	[0.1365]	0.4294***	[0.1435]	0.0569	[0.1171]
HH income: 3rd quart.	0.1995	[0.1361]	0.1422	[0.1303]	0.0920	[0.1383]	0.1678	[0.1071]
No. children in HH	-0.0447	[0.0531]	-0.0314	[0.0494]	0.0074	[0.0509]	0.0071	[0.0428]
Riskaverse	0.0546	[0.1326]						
Trust in other people	-0.4445***	[0.0978]						
Constant	-3.5395***	[0.2717]	-3.6616***	[0.2311]	-1.4377***	[0.2173]	-1.7795***	[0.1800]
Implied Cl1 share	0.70		0.70		0.55		0.63	
Implied Cl2 share	0.20		0.20		0.16		0.17	
Implied Cl3 share	0.10		0.10		0.29		0.20	
LogLik	-192,546.36		-211,164.38		-127,162.12		-203,456.82	
AIC	385,274.72		422,494.77		254,482.25		407,079.64	
Observations	8,339		9,214		5,356		8,908	

Notes: This table re-estimates the main model adding economic preferences as explanatory variables (specification 1) and excluding several survey years (specifications 2, 3 and 4). Model uses sign restrictions for the return coefficients ($\gamma_1 = 0$, $\gamma_2 < 0$, $\gamma_3 > 0$). Table displays results for the random effects multinomial logit model for the expectation types (Equation 2.3). Baseline type 1 (Random Walk) is omitted. Specifications 2 and 3 also include year fixed effects. For details see text. Standard errors in brackets; *** p <0.01, ** p <0.05, * p <0.1.

Table C2.9: Random effects ordinal probit model for rounding types – robustness with respect to excluding survey years

	(1) Add preferences (no 2006,08,09)		(2) no 2006-2009		(3) Pre crisis (2004-2009)		(4) Post crisis (2010-2016)	
Female	-0.0262	[0.0269]	-0.0178	[0.0262]	0.0551*	[0.0287]	-0.0134	[0.0274]
Age >64	0.0286	[0.0252]	0.0190	[0.0244]	-0.0697**	[0.0354]	-0.0327	[0.0259]
Age <45	-0.1039***	[0.0258]	-0.0370	[0.0241]	-0.0951***	[0.0303]	-0.1300***	[0.0267]
Low education	-0.0256	[0.0330]	-0.0442	[0.0320]	0.0271	[0.0374]	-0.0928***	[0.0352]
High education	-0.0652**	[0.0310]	-0.0890***	[0.0310]	-0.1111***	[0.0339]	-0.0256	[0.0297]
Partner	0.0408	[0.0304]	0.0574**	[0.0282]	-0.1454***	[0.0358]	0.0730**	[0.0330]
HH income: 1st quart.	0.0046	[0.0347]	0.0017	[0.0335]	-0.0537	[0.0409]	-0.0089	[0.0371]
HH income: 2nd quart.	0.0344	[0.0299]	0.0325	[0.0300]	-0.0378	[0.0367]	0.0250	[0.0333]
HH income: 3rd quart.	-0.0338	[0.0266]	-0.0170	[0.0259]	0.0269	[0.0328]	-0.0445	[0.0284]
No. children in HH	0.0014	[0.0123]	-0.0168	[0.0117]	0.0335**	[0.0135]	0.0205	[0.0134]
Riskaverse	0.0859***	[0.0237]						
Trust in other people	-0.0898***	[0.0201]						
LogLik	-192,546.36		-211,164.38		-127,162.12		-203,456.82	
AIC	385,274.72		422,494.77		254,482.25		407,079.64	
Observations	8,339		9,214		5,356		8,908	

Notes: This table re-estimates the main model adding economic preferences as explanatory variables (specification 1) and excluding several survey years (specifications 2, 3 and 4). Model uses sign restrictions for the return coefficients ($\gamma_1 = 0$, $\gamma_2 < 0$, $\gamma_3 > 0$). Table displays results for the random effects ordinal probit model for the rounding types (Equation 2.7). Dependent variable is equal to 1 if the respondent does not round (R1), 2 if the respondent rounds to the next multiple of five (R5) and 3 if the respondent rounds to the next multiple of 50 (R50). Question type-specific cut-off parameters are not reported. For details see text. Standard errors in brackets; *** p <0.01, ** p <0.05, * p <0.1.

Chapter 3

Economic uncertainty and subjective inflation expectations

Abstract

In a seminal contribution, Binder (2017) shows that rounding patterns in individuals' reported inflation expectations can serve as measure of economic uncertainty. In this paper, I extend her econometric model by allowing for an additional panel dimension, individual-specific heterogeneity and item nonresponse and apply the model to data from the Michigan Survey of Consumers between 1978 and 2017. The results suggest that socio-demographic characteristics as well as unobserved heterogeneity are significant predictors for individuals' response behavior, i.e. whether or not they round or choose not to answer the question on inflation expectations at all. I also find evidence for intrapersonal response type stability over time. While the generalized model is shown to be crucial for the identification of these results, its superiority over the Binder (2017) model vanishes, when constructing the economic uncertainty index, measured by the monthly share of rounders in the sample.

3.1 Introduction

Inflation expectations of individuals are crucial for understanding the economy and economic policies. Individuals' expectations are directly linked to their decision-making regarding investments, savings, retirement planning and wage negotiations. Since these decisions again directly translate into real economy transactions, modern monetary policy relies to a large extent on individuals' inflation expectations (Sims, 2009; Galí, 2015). In fact, expected or perceived inflation is often thought to be more important for monetary policy than the actual, measured inflation rate (Bernanke, 2007; Blanchard et al., 2010).

When analyzing individual data on inflation expectations, macroeconomic studies usually focus on their predictive power for actual inflation and on interpersonal heterogeneity (see, amongst others, Souleles, 2004; Blanchflower and MacCoille, 2009; Hobijn et al., 2009). These studies usually take survey answers at face value, neglecting that responses may suffer from several reporting issues, such as rounding, measurement error and non-response. However, as shown in Kleinjans and van Soest (2014), these reporting issues may not only reduce data quality, but also lead to biases in the estimates induced by selection effects. Microeconomic studies have, in contrast, a longer tradition of rigorously modeling these reporting issues. For example, when analyzing (probabilistic) stock market expectations of private households, it is common to explicitly model measurement error, rounding behavior or both.[1] In a recent contribution, Manski (2018) gives an overview of how macroeconomics can benefit from microeconomic insights, when working with subjective expectations, and encourages interactions between both fields.

In this paper, I follow the call by Manski (2018) and propose a microeconometric panel data model for inflation point (rather than probabilistic) expectations of individuals, explicitly accounting for item nonresponse and rounding behavior.[2] Specifically, I generalize

[1] See, for example, Hudomiet et al. (2011), Ameriks et al. (2018) or Heiss et al. (2019).
[2] In this paper, I abstract from measurement error other than rounding.

a model by Binder (2017) who suggests that the population can be described by a mixture of two different response types. When asked about the year-ahead inflation expectations, type NR (non-rounder) reports her true expectation, while Type RD (rounder) rounds her answer to a multiple of five percent. Binder (2017) estimates monthly RD type shares in the US between 1978 and 2014 and shows that they can serve as measure of economic uncertainty. This paper builds on her model and extends it in several dimensions. First, I introduce a third response type DK for respondents, who choose a "don't know" option, when asked about their inflation expectations. Second, I add a panel dimension to the econometric model and estimate the uncertainty index by month-year fixed effects in the model for the type probabilities, rather than by hundreds of separate estimations. Third, I allow the type probabilities to depend on both observed and unobserved heterogeneity, rather than treating them as constant scalars. I therefore contribute to the literature by providing a rich, but tractable panel data model for inflation expectations, which – in contrast to previous studies, in particular Binder (2017) – allows for an additional panel dimension, individual-specific heterogeneity and item nonresponse.

I apply the model to monthly data from the Michigan Survey of Consumers (MSC) between 1978 and 2017. Assuming type RD rounds to the next multiple of five percent, the estimated population shares of types (NR,RD,DK) are (0.65,0.28,0.07). This implies that most respondents report their true inflation expectation, while only few choose a "don't know" response. The model also identifies considerable heterogeneity in individuals' type probabilities. For example, males and respondents with at least a college degree are significantly less likely to round or to choose a "don't know" option than females and respondents without a college degree. I also find evidence for the importance in accounting for unobserved factors. The unobserved, individual-specific (random) effects for types RD and DK are positively correlated, implying that respondents who are more likely to round are, in general, also more likely to choose a "don't know" option. This also suggests that discarding non-respondents – as often done in the literature and also in Binder (2017) – is invalid, because it would only be allowed if the individual effects were uncorrelated. In addition, my model identifies considerable heterogeneity across individuals' inflation expectations, confirming previous findings from the literature.

At the individual level, I find evidence for the persistence of response types over time. If respondents are interviewed twice, the probability of being a specific response type in the first interview is positively correlated with the probability of being the same type in the second interview and negatively correlated with the probability of being another type. Furthermore, model-implied posterior type probabilities, i.e. type probabilities conditional on the reported inflation expectation, suggest that roughly every second respondent who reports an inflation expectation of zero or five percent is rounding. Almost all respondents who report more extreme multiples of five, such as 25 or minus ten percent, are predicted to round.

I then follow the insight in Binder (2017) and construct a macroeconomic uncertainty index, which is given by the monthly share of rounders (RD) and respondents choosing the "don't know" option (DK). The resulting uncertainty index spikes during periods of arguably high uncertainty, such as the financial crisis, 9/11 or the Gulf War. However, the index is almost identical to the uncertainty index by Binder (2017). Even though it is more strongly correlated with alternative state-of-the-art uncertainty measures, the advantages of the generalized model therefore vanish – at least in terms of measuring macroeconomic uncertainty.

This paper is related to three different strands of the literature. First, several studies focus on heterogeneity of inflation expectations across individuals. Most prominently, females are found to systematically report higher inflation expectations than males. This is often explained by an argument of Jonung (1981), suggesting that females are on average more exposed to food prices than males and therefore more able to predict price changes. However, this view is challenged by Bryan and Venkatu (2001a,b), showing that gender differences can also be found between single females and single males as well as during periods where food prices actually increased less than prices for other goods. More generally, systematic differences in inflation expectations between different socio-economic subgroups of the population are often related to different consumption patterns, even though this is known not to be enough to explain all the variation (see for example, Ranyard et al., 2008; Hobijn et al., 2009; Georganas et al., 2014). Malmendier and Nagel (2016) show that experienced inflation rates during a respondent's lifetime are also strong predictors for inflation expectations. Indeed, research has shown that personal inflation experiences of members of the Federal Open Market Committee (FOMC) can be used to predict their voting behavior and consequently the federal funds target rate (Malmendier et al., 2017).

Second, the paper is related to several microeconometric papers focusing on measurement and modeling of probabilistic (rather than point) expectations. Comprehensive overviews are given by Manski (2004) and Hurd (2009). Kleinjans and van Soest (2014) show that expectations in various domains in the Health and Retirement Study (HRS) are subject to rounding, nonresponse and focal values and discuss potential implications. Heiss et al. (2019) elicit individual distributions of stock market expectations, analyze how individuals differ in using past stock market returns, when forming their expectations, and explicitly model rounding behavior. Drerup et al. (2017) argue that subjective stock market expectations might only be meaningful if they are precise. Expectations with low precision may indicate that individuals base their decisions not on expectations, but rather on heuristics or rules of thumb.

A third strand of the literature is concentrated on measuring general economic uncertainty. Traditional measures are given by the realized (or implied) volatility of stock market returns, the ex-ante cross-sectional dispersion of subjective forecasts by households or professional forecasters – often referred to as "disagreement" – and the ex-post cross-sectional dispersion of stock returns, productivity and forecast errors (see, amongst others, Bloom, 2009; Bachmann et al., 2013; Rossi and Sekhposyan, 2015; Rossi et al., 2017). In a recent contribution, Baker et al. (2016) show that using newspaper coverage frequencies of specific combinations of terms, such as “uncertainty”, “economic” and “deficit”, can also be used to construct a measure of economic uncertainty. Jurado et al. (2015) propose another measure which is based on whether the economy has become more or less predictable by focusing on the volatility of expected forecast errors. As mentioned earlier, Binder (2017) introduces an uncertainty measure which is based on rounding patterns in inflation expectations of US households.

The remainder of this paper is organized as follows. I first describe the data and present basic descriptive statistics in Section 3.2. The econometric model is introduced in Section 3.3. Section 3.4 applies the model to data from the Michigan Survey of Consumers and presents the results, while several robustness analyses are discussed in Section 3.5. Section 3.6 concludes.

3.2 Data

For information on subjective inflation expectations and socio-economic characteristics, I draw on data from the Michigan Survey of Consumers (MSC).[3] Starting in 1978, this nationally representative, monthly survey asks roughly 500 respondents on a variety of topics, including personal finances, unemployment, confidence in government and economic policies, personal attitudes and expectations.[4] Most prominently, answers to some of these questions are used to construct the University of Michigan Consumer Sentiment Index, one of the leading US indicators for consumer confidence.

In every month, respondents can be divided into three different groups. One third are new respondents who will be interviewed again in six months, while another third are new respondents who will not be contacted again. The last third consists of re-interviews of respondents who were already interviewed six months before. A substantial share of respondents is therefore interviewed twice, adding a panel dimension to the data, which will later be exploited by the econometric model. Focusing on the entire universe of interviews between January 1978 and December 2017, the data set contains 97,159 individuals who are interviewed twice and 77,630 individuals who are interviewed once, making a total of 271,948 observations. To reduce the computational burden, the main analysis concentrates on respondents who are interviewed twice, but the results are shown to be robust to including respondents with only one interview.[5]

As the focus of this paper lies on subjective inflation expectations, the following question from the MSC is of particular interest:

[3] After registration, the data is freely available at: https://data.sca.isr.umich.edu/ [accessed August 10, 2018].

[4] American households from Alaska and Hawaii are not included in the sample. Note also that some questionnaire items from the MSC date back to the late 1940s, when surveys were conducted on a yearly or quarterly basis. The systematic rotating panel design was incorporated in January 1978, which is also the earliest date available at the University of Michigan Survey Research Center. For more details on the survey and its design see Curtin (1982).

[5] For details, see Section 3.5 and Appendices B3 and F3.

Q1: *"During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now?"*

Respondents are asked about "prices in general" rather than "inflation" directly, the main reason being that researchers are afraid that "ordinary persons may not understand the professional economic use of the term [inflation]" (Manski, 2018, p.441). However, as discussed in Armantier et al. (2013), asking about "prices in general" might be problematic too, because respondents could interpret the term heterogeneously. Indeed, the authors find that some respondents focus on prices which they recently paid themselves rather than on actual inflation. While I assume that respondents think about actual inflation, this distinction becomes less important to the extent that the individual-specific (random) effects in the panel data model capture these interpersonal differences.[6]

If respondents' answer to question **Q1** is "stay where they are", their answer is coded as zero. If respondents choose "go up" or "go down", they are asked another question:

Q2: *By about what percent do you expect prices to go (up/down) on the average, during the next 12 months?*

Respondents are allowed to report any integer response. The answers to both questions are combined into an integer variable **px1**, measuring the subjective expected inflation rate in the year ahead. Note that both questions allow respondents to choose a "don't know" (DK) option, i.e. respondents are not forced to answer the questions if they cannot or do not want to.[7] Figure 3.1 shows the response distribution of individuals' inflation expectations (px1) in the year 2009. Overall, responses vary between −25 and 25 percent, with most respondents expecting a positive inflation rate. One quarter of respondents report an expected inflation rate of zero percent, i.e. no change in prices, and more than ten

[6] An in-depth analysis of the effect of the exact question wording on inflation expectations can also be found in Bruine de Bruin et al. (2010).

[7] There are also additional questions after a "don't know" response or an extraordinarily high inflation rate to ensure respondents' understanding of the question. The exact procedure is given by the interviewer instructions summarized in Appendix A3.

percent of respondents do not answer the questions at all (DK). Clearly, there is evidence for substantial heaping at multiples of five and ten percent, and focal values of zero, two or three percent. While these response patterns are often taken into account by microeconometric studies, they are usually neglected in macroeconomic studies that take responses at face value. However, as shown in Binder (2017), rounding is systematically related to economic uncertainty, indicating that temporal variation in these response patterns contains additional information by itself.

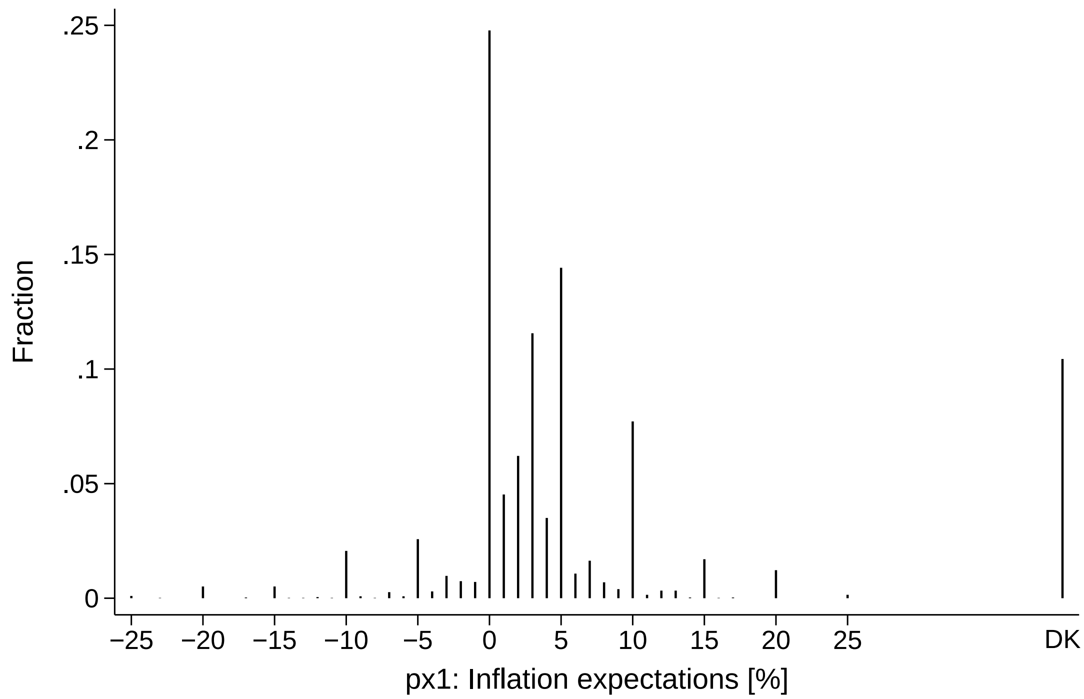


Figure 3.1: Response distribution of one-year inflation expectations (px1) in 2009

In addition, the questionnaire also includes questions about the average, yearly inflation rate over the next five years (px5). The elicitation and construction of these medium-run inflation expectations is almost identical to the procedure for short-run expectations and is presented in Appendix A3. However, questions for px5 have not been asked in all months and years, leading to several month-year combinations where data is missing. The main analysis therefore focuses on short-run inflation expectations (px1), while the results for medium-run inflation expectations (px5) are reported as robustness check in Section 3.5.

Table 3.1 reports standard summary statistics for the main sample, which consists of all respondents, who are interviewed twice between January 1978 and December 2017 (always with a six-month interval in between).[8] Panel A focuses on respondents' inflation expectations. On average, respondents expect an inflation rate of 3.92 percent for the year ahead and a slightly higher, yearly inflation rate of 3.97 percent over the next five years. The standard deviations are with 5.51 and 4.92 relatively large, hinting at substantial disagreement between respondents.

Panel B displays summary statistics regarding several binary socio-demographic characteristics. Overall, the sample contains slightly more females than males. One in five respondents is 65 or older; one in three respondents is younger than 40. 61 percent of respondents report to be living with a partner, and 40 percent to hold at least a college degree. Starting in October 1979, respondents are also asked about their total income (all sources including job) from the previous year. In every given month-year combination, this information is used to classify respondents into income quartiles, which are also presented in Panel B. Panel C reports coarse information on the region of residence at the time of the interview.[9]

Lastly, I draw on data on the official US inflation rate from the Organisation for Economic Co-operation and Development (OECD).[10] More specifically, I use monthly inflation rates between January 1956 and June 2018, measured by the annual growth rate of the US Consumer Price Index (CPI). Its time series is presented in Appendix C3.

[8] Table B3.1 in Appendix B3 reports summary statistics for the full sample, adding respondents who are interviewed only once. The results are very similar.
[9] US states are classified into the four statistical regions "West", "Northcentral", "Northeast" and "South", as defined by the United States Census Bureau.
[10] The data is freely available at https://data.oecd.org/price/inflation-cpi.html [accessed August 10, 2018].

Table 3.1: Summary statistics for the main sample

	Mean	SD	p5	p95	Min	Max	Observations
A: Inflation expectations [%]							
Short-run (px1)	3.92	5.51	0	11	-50	50	179,483
Medium-run (px5)	3.97	4.92	0	10	-50	50	139,897
B: Sociodemographics [0/1]							
Male	0.46	0.50	0	1	0	1	194,065
Partner	0.61	0.49	0	1	0	1	193,224
Age $>$ 64	0.21	0.41	0	1	0	1	193,379
Age $<$ 40	0.36	0.48	0	1	0	1	193,379
College	0.40	0.49	0	1	0	1	193,174
1st income quartile	0.20	0.40	0	1	0	1	183,104
2nd income quartile	0.21	0.41	0	1	0	1	183,104
3rd income quartile	0.28	0.45	0	1	0	1	183,104
4th income quartile	0.30	0.46	0	1	0	1	183,104
C: Regional information [0/1]							
West	0.20	0.40	0	1	0	1	194,269
Northcentral	0.27	0.45	0	1	0	1	194,269
Northeast	0.19	0.39	0	1	0	1	194,269
South	0.33	0.47	0	1	0	1	194,269

Notes: This table is based on all 97,159 respondents from the MSC who are interviewed twice within a six-month interval between January 1978 and December 2017, making a total of 194,318 observations. Number of observations differs due to item nonresponse. Panel B and C report dummy variables. Information on income (1st-4th quartile) not available before October 1979. For details see text.

3.3 Econometric model

In the following paragraphs, I introduce the econometric panel data model used in this paper and discuss the main differences to the model by Binder (2017).

3.3.1 Panel data model and likelihood function

Assume that the population can be described by three distinct response types, who differ in how they report their true inflation point expectation. Type NR (non-rounder) always reports her true inflation expectation. In contrast, type RD (rounder) always rounds to the next multiple of m, say for example five percent. Type DK chooses the "don't know" option, when asked about her one-year inflation expectation. Note that individuals' responses partially identify individuals' response types. For example, both reporting non-multiples of m and not answering at all uniquely classifies respondents as type NR and type DK, respectively. However, every individual reporting a multiple of m is always consistent with both type NR and type RD (but not with type DK).

I assume that the true inflation expectations of all individuals approximately follow a normal distribution, whose two parameters (mean μ and variance σ^2) are allowed to differ across types NR and RD:[11]

$$y_{it}^{*} \sim N(\mu^{R}, (\sigma^{R})^{2}), \qquad R \in \{NR, RD\} \tag{3.1}$$

where y_{it}^{*} is the true (and partially) unobserved inflation expectation of individual i in period t. The main difference between type NR and type RD is given by the mapping from the reported inflation expectation y_{it} to the true inflation expectation y_{it}^{*}. Abstracting from measurement error other than rounding, type NR reports *by definition* her true expectation, i.e. $y_{it}^{*} = y_{it}$. In contrast, type RD always reports a rounded value (to the

[11] In a robustness analysis, I later relax the normality assumption and report estimates under the assumption that inflation expectations follow alternative distributions (cf. Table F3.1).

next multiple of m), implying that we can only identify a symmetric interval for the true inflation expectation, i.e. $y_{it}^* \in [y_{it} - \frac{m}{2}; y_{it} + \frac{m}{2}]$. Using this insight as well as the fact that the reported values of y_{it} partially identify individuals' response types, the probabilities of observing y_{it} conditional on response type T_{it} are then given by:

$$
\begin{aligned}
P(y_{it}|T_{it}) &= \begin{cases} f_{NR}(y_{it}) & \text{if } T_{it} = NR \\ f_{RD}(y_{it}) & \text{if } T_{it} = RD \\ 0 & \text{if } T_{it} = DK \end{cases} && \text{\& } y_{it} \text{ is a multiple of } m \\
P(y_{it}|T_{it}) &= \begin{cases} f_{NR}(y_{it}) & \text{if } T_{it} = NR \\ 0 & \text{if } T_{it} = RD \\ 0 & \text{if } T_{it} = DK \end{cases} && \text{\& } y_{it} \text{ is not a multiple of } m \qquad (3.2) \\
P(y_{it}|T_{it}) &= \begin{cases} 0 & \text{if } T_{it} = NR \\ 0 & \text{if } T_{it} = RD \\ f_{DK}(y_{it}) & \text{if } T_{it} = DK \end{cases} && \text{\& } y_{it} \text{ is missing}
\end{aligned}
$$

with

$$
\begin{aligned}
f_{NR}(y_{it}) &= \phi(y_{it}; \mu^{NR}; \sigma^{NR}) \\
f_{RD}(y_{it}) &= \Phi\left(\frac{y_{it} + \frac{m}{2} - \mu^{RD}}{\sigma^{RD}}\right) - \Phi\left(\frac{y_{it} - \frac{m}{2} - \mu^{RD}}{\sigma^{RD}}\right) \qquad (3.3) \\
f_{DK}(y_{it}) &= 1
\end{aligned}
$$

where $\phi(\cdot)$ denotes the probability density function (p.d.f.) of the standard normal distribution and $\Phi(\cdot)$ denotes the standard normal cumulative distribution function (c.d.f.). Equation 3.2 illustrates the partial identification of reporting types. If an individual reports a missing value or an inflation expectation which is not a multiple of m, her type is uniquely identified as type DK or NR, respectively. Reporting a multiple of m, however, is consistent with two types, namely NR and RD. As shown in Equation 3.3, the p.d.f. for type NR, $f_{NR}(\cdot)$, is given by a Gaussian density function with mean μ^{NR} and standard deviation σ^{NR}, whereas the p.d.f. for type RD, $f_{RD}(\cdot)$, is given by the difference between two normal c.d.f.s with mean μ^{RD} and standard deviation σ^{RD} evaluated at $y_{it} \pm \frac{m}{2}$, respectively. For completeness, the p.d.f. for type DK, $f_{DK}(\cdot)$, is equal to one and therefore independent of any parameters.

In addition, the model allows the (type-specific) mean of the inflation expectation distribution to vary across individuals and time by using the following linear parameterization:

$$\mu_{it}^{R} = \boldsymbol{w}_{it}\boldsymbol{\beta}^{R}, \qquad R \in \{NR, RD\} \tag{3.4}$$

where $\boldsymbol{w}_{it}$ is a vector of potentially time-varying covariates of respondent i in period t. This formulation allows to capture systematic differences in inflation expectations between individuals, as often found in the literature.

I model response type probabilities in a standard random effects multinomial logit model with three outcomes:

$$\begin{aligned} u_{it}^{j} &= \boldsymbol{x}_{it}\boldsymbol{\beta}^{j} + \alpha_i^{j} + \varepsilon_{it}^{j}, && j = 1,2,3 \\ T_{it} &= j \text{ if } u_{it}^{j} \geq u_{it}^{k}, && k = 1,2,3 \\ P(\varepsilon_{it}^{j} \leq z) &= \exp(-\exp(-z)) && \text{(standard Gumbel)} \end{aligned} \tag{3.5}$$

where $\boldsymbol{x}_{it}$ is a vector of covariates of respondent i in period t, potentially including period fixed effects. α_i^{j} is an unobserved respondent-specific effect for type j and ε_{it}^{j} denotes an i.i.d. standard Gumbel error term. Without loss of generality, type NR is taken as benchmark outcome $T_{it} = 1$, leading to the standard normalizations $\boldsymbol{\beta}^{1} = 0$ and $\alpha_i^{1} = 0$. The other outcomes are type RD ($T_{it} = 2$) and type DK ($T_{it} = 3$). The response type probabilities conditional on the observed covariates $\boldsymbol{x}_{it}$ and the unobserved effects α_i^{2} and α_i^{3} can then be derived from the distributional assumptions on the error term ε_{it}^{j} and are given by:

$$P(T_{it} = j|\boldsymbol{x}_{it}, \alpha_i^2, \alpha_i^3) = \frac{\exp(\alpha_i^j + \boldsymbol{x}_{it}\boldsymbol{\beta}^j)}{\sum_{k=1}^{3} \exp(\alpha_i^k + \boldsymbol{x}_{it}\boldsymbol{\beta}^k)}; \qquad j = 1, 2, 3 \tag{3.6}$$

In addition to the previous assumptions, I impose the following assumption on the vector of unobserved heterogeneity $\boldsymbol{\alpha}$:

$$\boldsymbol{\alpha} = \begin{pmatrix} \alpha_i^2 & \alpha_i^3 \end{pmatrix} = \begin{pmatrix} \alpha_i^{RD} & \alpha_i^{DK} \end{pmatrix} \sim N(\mathbf{0}, \boldsymbol{\Sigma}) \tag{3.7}$$

Equation 3.7 implies that the individual (random) effects are i.i.d. jointly normal with mean zero and arbitrary variance-covariance matrix $\boldsymbol{\Sigma}$ and independent of x_{it} and ε_{is}^j for $j = 1, 2, 3$ and $s = 1, ..., T$. Note that both rounding and not answering at all can be seen as indicators for individual uncertainty. I therefore expect a positive correlation between α_i^{RD} and α_i^{DK}, indicating that individuals who do not answer at all are also more likely to round, unlike in a standard multinomial logit model.[12]

Under these assumptions the likelihood function conditional on the unobserved individual effects α_i^{RD} and α_i^{DK} can be written as:

$$L^c(\alpha_i^{RD}, \alpha_i^{DK}) = \prod_{i=1}^{N} \prod_{t=1}^{T} L_{it}^c(\alpha_i^{RD}, \alpha_i^{DK}) \tag{3.8}$$

with

$$\begin{aligned}
L_{it}^c(\alpha_i^{RD}, \alpha_i^{DK}) &= P\left(T_{it} = NR|\boldsymbol{x}_{it}, \alpha_i^{RD}, \alpha_i^{DK}\right) f_{NR}(y_{it}|\boldsymbol{w}_{it}) + \\
&+ P\left(T_{it} = RD|\boldsymbol{x}_{it}, \alpha_i^{RD}, \alpha_i^{DK}\right) f_{RD}(y_{it}|\boldsymbol{w}_{it}) \qquad \text{if } y_{it} \text{ is a multiple of } m \\
L_{it}^c(\alpha_i^{RD}, \alpha_i^{DK}) &= P\left(T_{it} = NR|\boldsymbol{x}_{it}, \alpha_i^{RD}, \alpha_i^{DK}\right) f_{NR}(y_{it}|\boldsymbol{w}_{it}) \qquad \text{if } y_{it} \text{ is not a multiple of } m \\
L_{it}^c(\alpha_i^{RD}, \alpha_i^{DK}) &= P\left(T_{it} = DK|\boldsymbol{x}_{it}, \alpha_i^{RD}, \alpha_i^{DK}\right) f_{DK}(y_{it}|\boldsymbol{w}_{it}) \qquad \text{if } y_{it} \text{ is missing}
\end{aligned}$$

[12] As shown by Revelt and Train (1998), adding unobserved heterogeneity to a multinomial logit model breaks the independence of irrelevant alternatives (IAA) assumption. See also Kleinjans and van Soest (2014) for a similar application.

where $f_{NR}(\cdot)$, $f_{RD}(\cdot)$ and $f_{DK}(\cdot)$ are given by Equation 3.3 and the conditional type probabilities $P(T_{it}|\cdot)$ by Equation 3.6. Again this conditional likelihood function illustrates the partial identification of response types, as already discussed before.

The unconditional likelihood function can be derived by integrating out the individual effects:[13]

$$L = \prod_{i=1}^{N} \int_{\mathbb{R}^2} \prod_{t=1}^{T} L_{it}^{c}(\alpha_i^{RD}, \alpha_i^{DK}) f(\boldsymbol{\alpha}) d\boldsymbol{\alpha}. \tag{3.9}$$

To avoid numerical integration in multiple dimensions, I use Maximum Simulated Likelihood (MSL) and replace the integral by a simulated mean. The simulated sample likelihood (SL) is then given by

$$SL = \prod_{i=1}^{N} \frac{1}{Q} \sum_{q=1}^{Q} \prod_{t=1}^{T} L_{it}^{c}(\alpha_{iq}^{RD}, \alpha_{iq}^{DK}) \tag{3.10}$$

where $\alpha_{iq}^{RD}, \alpha_{iq}^{DK}$ are simulated random effects for a given draw q. Applying a Cholesky decomposition of the variance-covariance matrix $\boldsymbol{\Sigma}$, yields a positive semi-definite lower diagonal matrix $\mathbf{L}$ such that $\boldsymbol{\Sigma} = \mathbf{L}\mathbf{L}'$, with the elements of $\mathbf{L}$ to be estimated. For a given draw q, the unobserved heterogeneity is then calculated by $\boldsymbol{\alpha} = \mathbf{L}\boldsymbol{\tau}$, where $\boldsymbol{\tau}$ contains simulated vectors of the independent standard normal distribution. As suggested by Train (2003), I use draws from Halton sequences to obtain the independent standard normal variables $\boldsymbol{\tau}$ to reduce the variance induced by the simulation.

Note that after solving the maximization problem the estimated parameter vector can be used to predict individual-specific (i) unconditional type probabilities as well as (ii) posterior type probabilities, i.e. response type probabilities conditional on the reported

[13] Appendix D3 discusses the derivation of the likelihood function in greater detail. Note also that the likelihood function is written for a respondent who participates in every period. If a respondent did not participate in one particular period, her likelihood contribution for this period (L_{it}^{c}) can be replaced by one.

value of y_{it}. The calculation of (i) is based on Equation 3.6 with the true parameter vectors $\boldsymbol{\beta}^j$ being replaced by their respective estimates $\hat{\boldsymbol{\beta}}^j$ and the individual effects being integrated out by simulation or quadrature methods. Specifically, I use 151 draws from Halton sequences and simulate the normal individual effects with mean zero and a variance-covariance matrix which is given by the estimates of $\hat{\boldsymbol{\Sigma}}$. (ii) can be calculated using Bayes' theorem. Not surprisingly, the posterior probability of being type DK is one if y_{it} is missing. Similarly, if the respondent does not report a multiple of m, her posterior probability of being type NR is one. In contrast, if she reports a multiple of m, the probability of being type NR and RD, respectively, is strictly between zero and one and can be calculated applying Bayes' theorem. See Appendix D3 for derivations, formulas and further details.

3.3.2 Comparison to Binder (2017)

This econometric panel data model is essentially a generalization of the model by Binder (2017) and nests it as a special case. First, Binder (2017) models the population as a mixture of two response types only (rounders and non-rounders) and drops respondents with missing information on inflation expectations.[14] This is equivalent to restricting the unconditional probability for type DK to zero in my model. Second, she does not allow for either observed or unobserved interpersonal heterogeneity in the type probabilities, which corresponds to restricting all coefficients other than the constants in the random effects multinomial logit model (Equation 3.6) to zero. Third and most importantly, she ignores the panel dimension of the data and rather estimates cross-sectional models, separately for every month between January 1978 and July 2014. This is equivalent to restricting the variances and covariances of the individual effects to zero, i.e. $\boldsymbol{\Sigma} = \mathbf{0}$, and applying the restricted model to each month separately. An important difference between both models is therefore that temporal variation in the unconditional rounding probabilities – which will later be used to construct the macroeconomic uncertainty index – comes from

[14] She does so for the estimation of her empirical model. For the construction of her uncertainty index, the DK share is added ad-hoc after the estimation.

hundreds of separate estimations in Binder (2017) and from the month-year fixed effects of the joint model in this paper.

My approach offers several advantages over the model by Binder (2017). First, one can expect considerable gains in efficiency, mainly stemming from two sources. On the one hand, the model additionally uses information of respondents with missing information on inflation expectations; on the other hand, the entire model is estimated jointly for all months in the estimation sample. Second, my approach allows for the identification of interpersonal heterogeneity in the response type probabilities. Third, leveraging the existence of the panel dimension in the MSC data also allows to model unobserved heterogeneity via the inclusion of individual-specific (random) effects. By allowing for arbitrary correlations between the individual effects, the model can actually test whether or not dropping respondents with missing responses – as often done in the literature – is valid. This will only be allowed if the individual-specific effects are uncorrelated.

3.4 Results

3.4.1 Interpersonal heterogeneity

I apply the econometric model to monthly data from the Michigan Survey of Consumers between 1978 and 2017.[15] Assuming that type RD rounds her true inflation expectation to the next multiple of five percent, i.e. $m = 5$, Table 3.2 reports one model specification excluding and one specification including month-year fixed effects in the random effects multinomial logit model (Equation 3.6), respectively.[16]

Columns 1a, 1b and 2a, 2b of Table 3.2 report coefficients of the random effects multinomial logit model for the type probabilities (Equation 3.6). Recall that the baseline category is type NR (non-rounder). Interestingly, males are found to be significantly less likely to round or report a "don't know" response than females. This finding could be driven by the fact that men are on average more financially literate than women and therefore more certain of and confident about their inflation predictions (see, for example, van Rooij et al., 2011). It could also correspond to general overconfidence of men, as often found in behavioral studies (cf. Niederle and Vesterlund, 2007). Unfortunately, the MSC does neither include a measure of financial literacy nor (over-)confidence to further analyze these patterns. Education is also significantly associated with type probabilities. Respondents holding at least a college degree are less likely type RD (rounder) or type DK (don't know), compared to respondents without a college degree. This seems intuitive, because more educated people are arguably more likely to know the concept of

[15] The estimation sample is based on all respondents, who are interviewed twice and who have full information on all socio-economic characteristics and the exact month and year of the interview. Note that respondents with missing information on inflation expectations via choosing a "don't know" option are explicitly allowed in the model and thus not excluded from the analysis. To make the results comparable to Binder (2017), I exclude extreme inflation expectations that are smaller than minus ten and larger than 25 percent. Including these outliers, however, yields almost identical results. These data requirements result in a total of 172,548 observations.

[16] As a robustness check, I also estimate the model for $m = 10$, i.e. type RD rounds her true inflation expectation to the next multiple of ten percent, as well as a model which includes both rounding types at the same time. Results are discussed in Section 3.5.

inflation. Wealthy individuals are more likely to be type NR, i.e. these individuals tend to provide exact answers, compared to less affluent respondents. Comparing specifications 1 and 2, the coefficients of the socio-economic covariates are remarkably similar. Therefore, including month-year fixed effects in the random effects multinomial logit model leaves the effects of the covariates on the type probabilities almost unchanged.[17] In summary, there is strong evidence for the fact that socio-economic characteristics predict individual type probabilities. Recall that Binder (2017) models these type probabilities as constant scalars, which would require all coefficients in columns 1a, 1b, 2a and 2b in Panel A of Table 3.2 other than the constants to be statistically indistinguishable from zero.

Columns 1c, 1d and 2c, 2d report estimates for the parameterized subjective mean of inflation expectations for type NR (non-rounder) and RD (rounder), respectively (Equation 3.4). Even though the magnitude of the coefficients slightly varies between both types, the effect of the covariates is qualitatively the same. Men report significantly lower inflation expectations than women, while less educated and less affluent respondents tend to report higher inflation expectations, independent of response type. Overall, these findings confirm findings from the previous literature (cf. Section 3.1).

Panel B focuses on the estimated standard deviation of the type-specific normal distribution of inflation expectations. Interestingly, rounders seem to have a more dispersed distribution of inflation expectations than non-rounders. The estimated standard deviations for both types differ, in fact, by a factor of two. This is in line with arguing that rounders perceive a higher level of uncertainty than non-rounders. It is, however, important to distinguish this estimated standard deviation from the cross-sectional standard deviation of individual beliefs, which is also often used in the literature as measure of uncertainty (see, for example, Bachmann et al., 2013).

[17]The results are also shown to be robust to including month-year fixed effects in the model of the parameterized mean of the normal inflation expectations (Equation 3.4). For further details, see Section 3.5.

Table 3.2: Model estimates

	Excluding month-year FE				Including month-year FE			
	P(T=RD) (1a)	P(T=DK) (1b)	Mean NR (1c)	Mean RD (1d)	P(T=RD) (2a)	P(T=DK) (2b)	Mean NR (2c)	Mean RD (2d)
Panel A								
Male	-1.00***	-1.40***	-0.12***	-1.10***	-0.93***	-1.40***	-0.12***	-1.12***
	[0.03]	[0.03]	[0.02]	[0.06]	[0.02]	[0.03]	[0.02]	[0.06]
Partner	-0.06**	-0.12***	-0.02	0.32***	-0.05*	-0.13***	-0.01	0.29***
	[0.03]	[0.03]	[0.02]	[0.06]	[0.02]	[0.03]	[0.02]	[0.06]
College	-0.66***	-0.58***	-0.12***	-0.37***	-0.55***	-0.67***	-0.13***	-0.39***
	[0.03]	[0.03]	[0.02]	[0.06]	[0.03]	[0.03]	[0.02]	[0.06]
1st income quartile	0.69***	1.76***	0.22***	1.37***	0.71***	1.71***	0.23***	1.37***
	[0.04]	[0.04]	[0.03]	[0.09]	[0.04]	[0.05]	[0.03]	[0.09]
2nd income quartile	0.26***	0.87***	0.01	1.14***	0.37***	0.81***	0.02	1.12***
	[0.03]	[0.04]	[0.03]	[0.09]	[0.03]	[0.04]	[0.03]	[0.09]
3rd income quartile	0.15***	0.33***	0.00	0.66***	0.18***	0.31***	0.00	0.67***
	[0.03]	[0.04]	[0.02]	[0.08]	[0.03]	[0.04]	[0.02]	[0.08]
West	-0.14***	-0.10***	0.06***	-0.01	-0.15***	-0.12***	0.06**	0.01
	[0.03]	[0.04]	[0.02]	[0.08]	[0.03]	[0.04]	[0.02]	[0.08]
Northcentral	-0.02	-0.21***	-0.01	-0.17**	-0.04	-0.20***	-0.01	-0.17**
	[0.03]	[0.04]	[0.02]	[0.07]	[0.03]	[0.04]	[0.02]	[0.07]
Northeast	0.16***	0.10***	0.03	-0.06	0.13***	0.10***	0.03	-0.05
	[0.03]	[0.04]	[0.02]	[0.08]	[0.03]	[0.04]	[0.02]	[0.08]
Constant	-0.70***	-2.92***	3.16***	4.84***	1.19***	-0.51*	3.17***	4.83***
	[0.04]	[0.05]	[0.03]	[0.09]	[0.24]	[0.31]	[0.03]	[0.09]
Panel B								
σ^{NR}	2.82***				2.81***			
	[0.00]				[0.00]			
σ^{RD}	5.87***				5.89***			
	[0.02]				[0.02]			
Panel C								
$Var(\alpha^{RD})$	3.46***				2.88***			
	[0.11]				[0.10]			
$Var(\alpha^{DK})$	4.24***				4.04***			
	[0.12]				[0.12]			
$Corr(\alpha^{RD}, \alpha^{DK})$	0.71***				0.71***			
	[0.01]				[0.01]			
Panel D								
Implied share NR	0.6485				0.6491			
Implied share RD	0.2834				0.2829			
Implied share DK	0.0681				0.0680			
Month-year FE	no				yes			
Observations	172,548				172,548			

Notes: This table reports model estimates for the dependent variable on short-run inflation expectations (px1). Response types are non-rounders (NR), rounders (RD) and respondents who choose a "don't know" answer (DK). Specification 1 (2) excludes (includes) month-year fixed effects in the random effects multinomial logit model for type probabilities (Equation 3.6). Panel A reports estimates for interpersonal heterogeneity. Columns a and b focus on the random effects multinomial logit model for type probabilities. Omitted category is type NR. Columns c and d report estimates for the parameterized mean of inflation expectations for type NR and RD (Equation 3.4), respectively. Panel B displays type-specific estimates for the standard deviation of the normal distribution of inflation expectations. Panel C reports the estimated variances of the individual specific random effects and its correlations. Panel D reports averages of model-implied unconditional type probabilities. For details see text. Standard errors in brackets. *** p <0.01, ** p <0.05, * p <0.1.

Panel C reports the estimated variances and correlation of the two random individual effects, which are derived from the entries of the estimated Cholesky matrix $\hat{\mathbf{L}}$. As shown, the variances of the individual effects are both significantly different from zero, confirming the importance in accounting for unobserved heterogeneity in the model. The individual effects are – as suspected in Section 3.3 – positively correlated ($\rho = 0.71$ in both specifications), implying that individuals who are more likely to round are also more likely not to respond at all. It is important to note that this correlation could not have been identified if type probabilities were modeled in a standard multinomial logit model. The positive correlation between the individual effects thus reinforces the necessity of joint estimation of the model. In fact, separate estimation – as often done in the literature by discarding item nonrespondents – would only be valid if the individual effects were uncorrelated.

Panel D displays the model-implied response type distribution in the sample, which is given by the unconditional type probabilities, averaged over time and individuals. With almost no differences between the two specifications, the average probability for type DK is given by 6.8 percent. This is almost identical to the crude DK share in the data set, which is given by 6.7 percent (11,490 out of 172,548 respondents choose the "don't know" option), strengthening the validity of the model. The average share of non-rounders is given by roughly 65 percent, implying that almost two in three respondents report an exact inflation expectation. The remaining 28 percent are consistent with type RD, implying that roughly one in four respondents rounds her inflation expectations to the next multiple of five percent. In comparison, the crude share of responses which are multiples of five percent is given by roughly 43 percent (74,161 out of 172,548 respondents) and clearly overestimates the true rounding share in the population, as identified by the model.

3.4.2 Type transitions and posterior probabilities

Recall that the methodology in this paper does not uniquely classify respondents into the three response types NR (non-rounder), RD (rounder) and DK (don't know), but rather assigns individual-specific probabilities to each of the three types. The panel dimension of the data allows me to analyze how these type probabilities change between the six-monthsapart interviews. Figure 3.2 plots individual, unconditional type probabilities for a specific response type in the first interview against the type probability of the same type in the second interview, based on the results of specification 2 of Table 3.2 (including month-year fixed effects). Clearly, there is evidence for a strong, positive correlation. For all three response types, the Pearson correlation coefficient is between 0.85 and 0.89. This indicates that, for example, individuals with a high probability of being type NR in the first wave, also have a high probability of being type NR in the second interview. The same applies to DK and RD type probabilities, even though the levels are considerably smaller. Overall, the strong, positive correlation across time can be explained by the fact that several covariates, such as gender and education, are time-constant for most respondents in the sample. Therefore, temporal variation in the unconditional type probabilities mainly stems from time-varying covariates and from the month-year fixed effects. Note that unobserved heterogeneity – modeled via the individual-specific random effects – only contributes to variation in the type probabilities across respondents, but not over time.

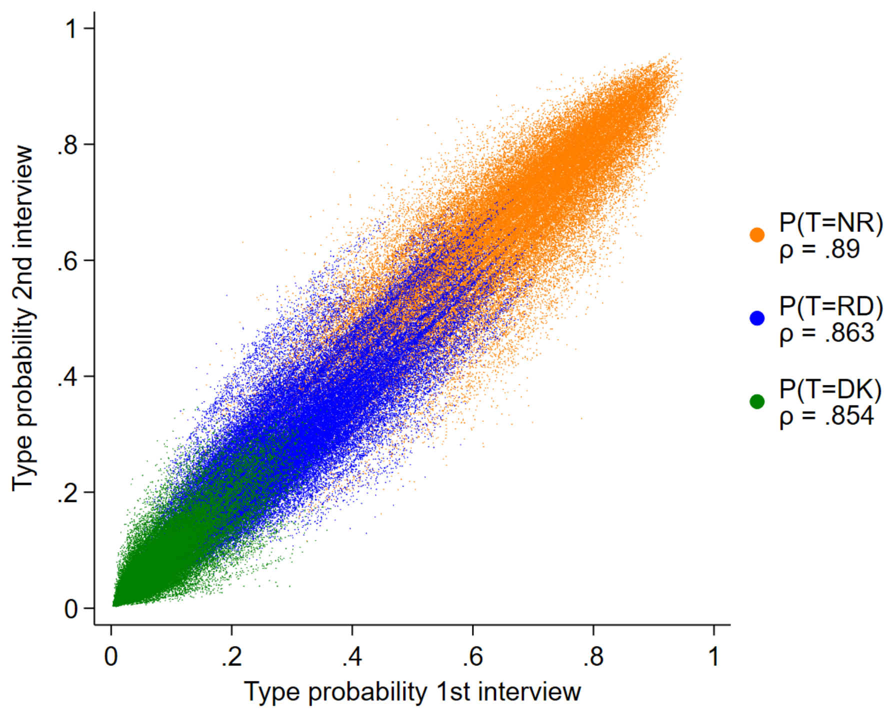


Figure 3.2: Type probability correlation between 1st and 2nd interview

Moreover, I am interested in how the probability of a specific type in the first interview is related to the probability of being another type in the second interview. Figure 3.3 therefore plots the RD probability in the first interview (horizontal axis) against the two other type probabilities (NR and DK) in the second interview (vertical axis). Mirroring the findings from the previous figure, there is a strong, negative correlation between types NR and RD. The lower the RD probability in the first interview, the higher the NR probability in the second interview ($\rho = -0.810$). The correlation with the type DK probability in the second interview is much weaker. Despite being slightly correlated ($\rho = 0.295$), a higher RD probability in the first interview seems to be rather unrelated to the DK probability in the second interview.

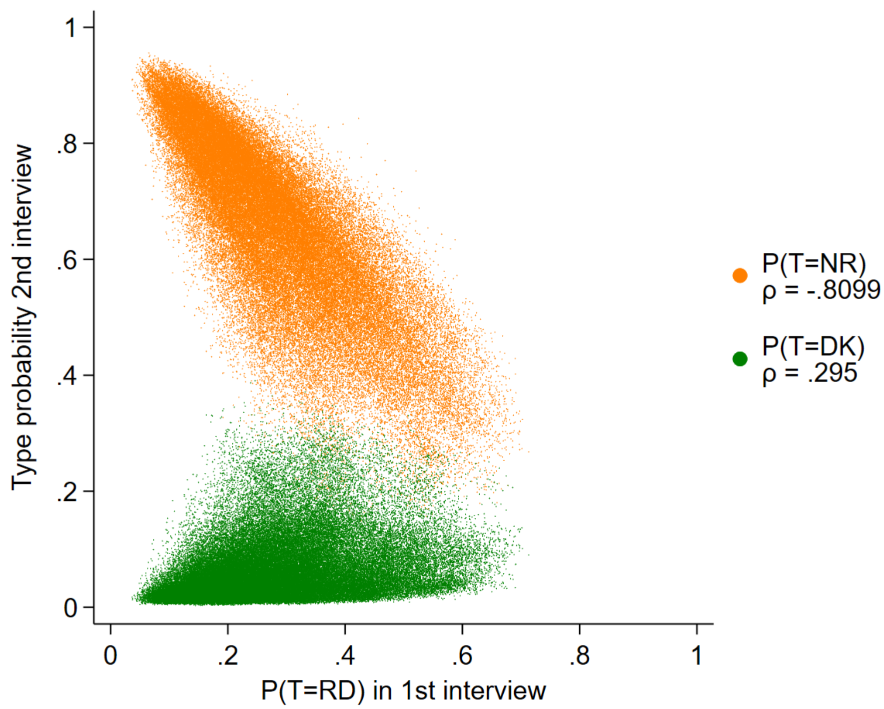


Figure 3.3: Type transition probabilities between 1st and 2nd interview

As highlighted in Figures 3.2 and 3.3, the levels of the unconditional type probabilities differ considerably across respondents and types. For example, the highest probability of being type DK is predicted to be "only" 0.390, the average being 0.0681 (cf. Table 3.2).

In contrast, the highest probability of being type RD is given by 0.722, with an average of 0.283 (cf. Table 3.2). However, the probabilities discussed so far are (individual-specific) unconditional type probabilities. Posterior probabilities, i.e. type probabilities conditional on the reported inflation expectations (px1), may in contrast be very different.[18]

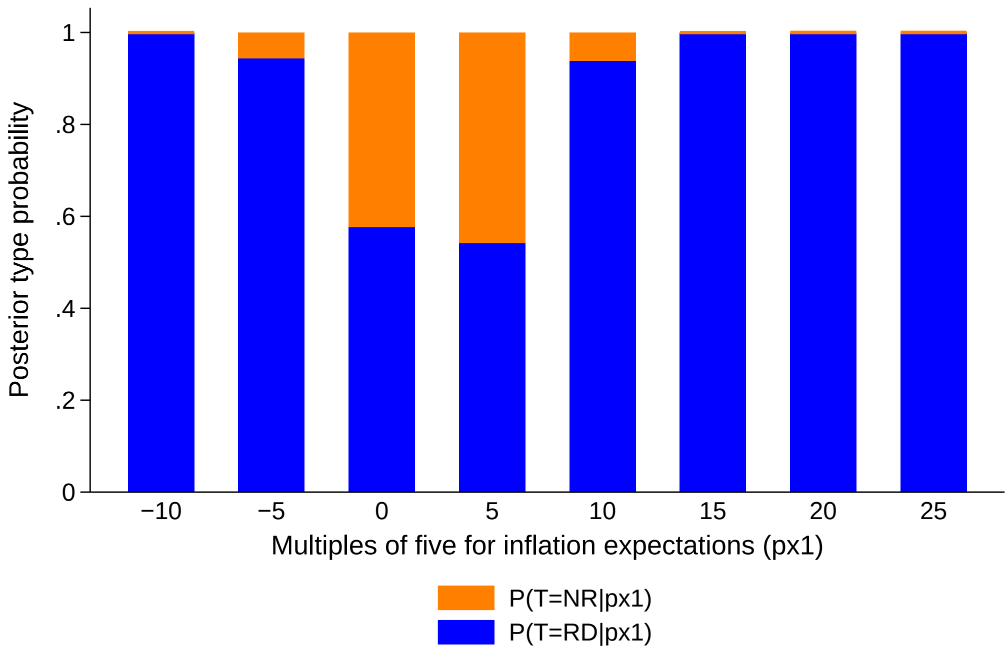


Figure 3.4: Posterior type probabilities conditional on reporting multiples of five

In fact, conditional on reporting a missing value, the posterior probability of type DK is one and, consequently, the posterior probabilities of types RD or NR are zero. For non-missing inflation expectations, there are two cases. First, if the respondent reports a non-multiple of five, the posterior probability of type NR is one; the posterior probabilities of type NR or DK are then zero. Second, if the reported value is a multiple of five, the posterior probability of being type DK is (exactly) zero, while the posterior probabilities of types RD and NR are strictly positive and can be calculated using Bayes' theorem. Figure 3.4 shows these probabilities for several multiples of five. To respondents reporting

[18]The exact calculation of the posterior probabilities is described in Section 3.3 and Appendix D3.

extreme expectations, such as a future inflation rate of 25 percent or minus ten percent (deflation), the model assigns a posterior RD probability of almost one, implying that these respondents are rounders with almost certainty. This pattern changes when looking at more moderate inflation expectations. For example, conditional on reporting a predicted inflation rate of zero (five) percent, the posterior probability of being type RD is 0.57 (0.54). This implies that every second respondent reporting an inflation prediction of zero (five) percent does not have an exact inflation expectation of zero (five) percent in mind, but rather some different value and reports a rounded value.

3.4.3 Uncertainty index

Next, I use the insight of Binder (2017) and argue that rounding patterns in individuals' inflation expectations can serve as measure of economic uncertainty. I follow her analysis and calculate an uncertainty index as average, unconditional rounding (RD) probability, augmented by the average unconditional probability for type DK. Thus, the index is essentially an estimate for the population shares of types RD and DK. While Binder (2017) estimates this index separately for each month, the temporal variation in my index comes from the month-year fixed effects in the random effects multinomial logit model.

Figure 3.5 plots the uncertainty index as well as the average DK share for every month between 1980 and 2017, based on the results from specification 2 of Table 3.2. The share of rounders (RD share) is implicitly given by the difference between both lines. Clearly, there is evidence for meaningful variation over time. Respondents' reported inflation expectations display more rounding in times of higher economic uncertainty, compared to times of lower uncertainty. For example, the uncertainty index increases shortly after the terrorist attacks in September 2001 or Hurricane Katrina in August 2005. Moreover, the variation in the index is almost exclusively driven by temporal variation in the RD share rather than variation in the DK share. In fact, the latter is relatively constant across time and on average around seven percent. Therefore, respondents seem to systematically use rounding rather than the "don't know" option to express uncertainty. These results confirm the findings in Binder (2017).

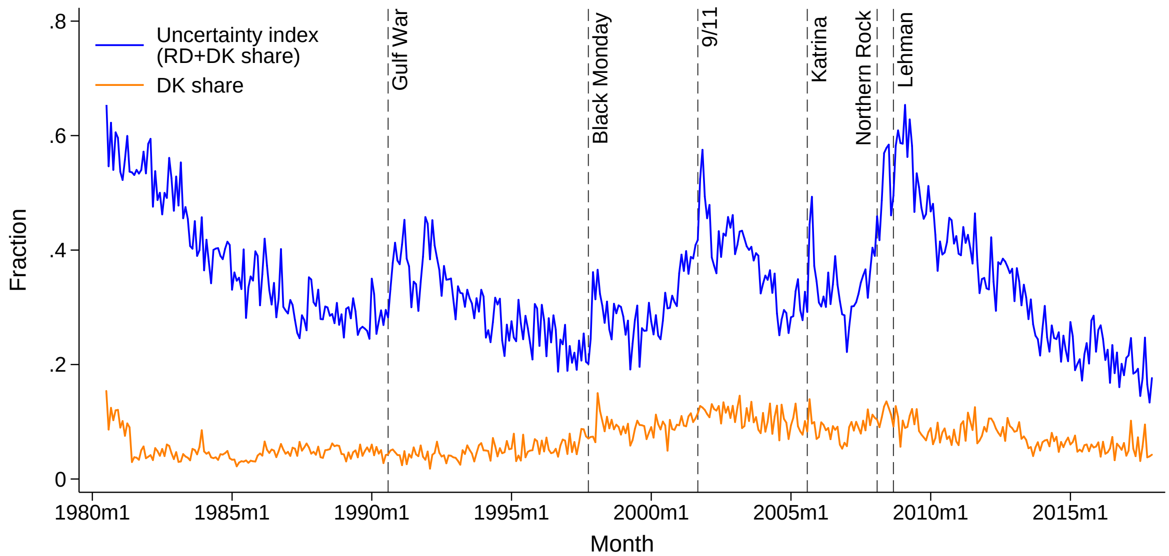


Figure 3.5: Model-implied uncertainty index over time

Figure 3.6 compares the uncertainty index to several other measures.[19] Most importantly, Panel A shows that the index is highly correlated with the original Binder (2017) index (Pearson's $\rho = 0.964$). Even though some minor differences exist, both indices display almost identical variation over time. My index is also shown to be correlated with two other measures of economic uncertainty (Panel B and C).[20] The first index by Baker et al. (2016) is based on newspaper coverage frequencies of specific combinations of terms, such as "uncertainty", "economic" and "deficit". In contrast to my uncertainty measure, this index does not spike after Hurricane Katrina, but does spike during the European sovereign debt crisis in 2012. The overall correlation between both indices is 0.527. The second index by Jurado et al. (2015) measures uncertainty by the volatility of expected forecast errors over a one-year horizon. The correlation with my measure of economic uncertainty

[19]Figure 3.6 is inspired by Figure 3 in Binder (2017, p.8).

[20]The data for both indices is freely available at the authors' websites: http://www.policyuncertainty.com and https://www.sydneyludvigson.com [accessed October 8, 2018].

is a lot higher with a correlation coefficient of 0.775. While the increase after 9/11 and Hurricane Katrina is less pronounced, the increase during the financial crisis in 2008 is similar. Overall, my uncertainty index shows a slightly higher correlation with the two alternative uncertainty measures than the original Binder (2017) index.[21]

Last, Panel D shows that there is only a small, positive correlation of the uncertainty index with the actual US inflation rate across time ($\rho = 0.357$). In particular, it is reassuring that the variation in the index is not driven by the level of the current inflation. The uncertainty index spikes during both times of high inflation, such as the Gulf War in late 1990, and times of low inflation, such as the financial crisis in 2008.

In summary, at least for the construction of the uncertainty index, the advantages of the generalized model introduced in this paper over the original Binder (2017) model become small. Both models yield almost identical uncertainty indices, with only minor advantages for my uncertainty index in terms of correlation with alternative uncertainty measures.

[21]The correlations of the original Binder index with the Baker et al. (2016) index and the Jurado et al. (2015) index are given by 0.470 and 0.755 (not reported), respectively.

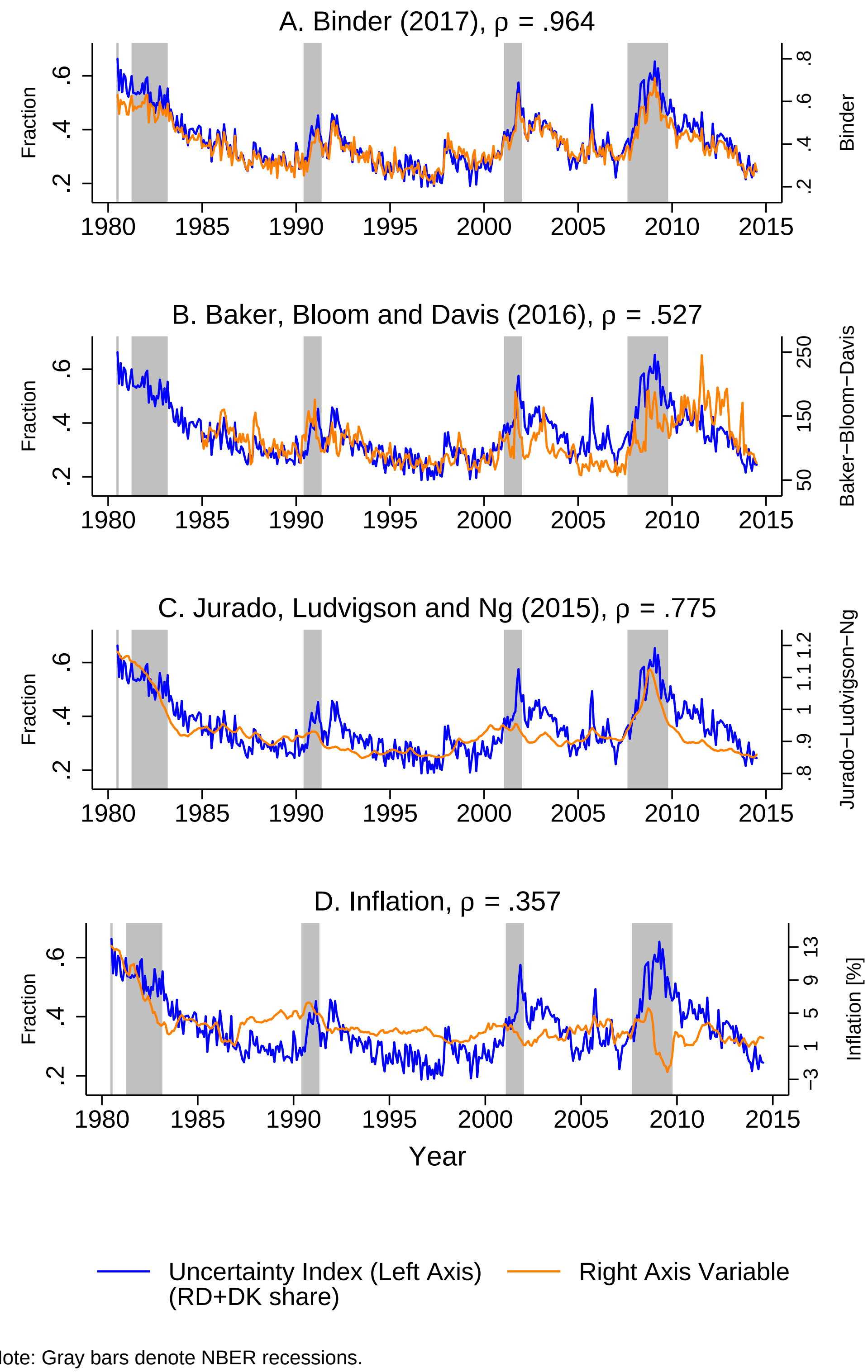


Figure 3.6: Comparison of the uncertainty index to other measures

3.5 Robustness

This section provides several robustness checks to variations in methodology and sample size. All tables and figures are presented in Appendix F3. To reduce the computational burden, some specifications are estimated under the restriction that the variances of the individual effects are zero, as indicated in the tables.[22]

Logistic inflation expectations. To check whether the results are sensitive to the assumption that inflation expectations follow a normal distribution, I repeat the analysis under the assumption of logistic inflation expectations (Table F3.1). The implied type distribution as well as the effects of the covariates on individual type probabilities and inflation expectations are almost unchanged.

Medium-run inflation expectations. I also use data on medium-run inflation expectations, which are based on the expected yearly inflation rate over the next five years (px5). Note, however, that I lose several month-year combinations, since this question is not asked throughout all waves. As shown in Table F3.2, the implied NR share increases to roughly 77 percent, implying that respondents round on average less when asked about medium-run inflation expectations, compared to short-run expectations (px1). In addition, the DK share increases to almost nine percent. Both effects are shown not to be driven by differences in sample size and periods, but rather by the difference between short-run and medium-run inflation expectations (not reported).

Rounding to multiples of ten. The main analysis assumes that type RD respondents round to the next multiple of five percent. I repeat the analysis for rounding to the next multiple of ten percent in Table F3.3. Since multiples of ten are by definition also multiples of five, the new share of rounders should decrease, as it does. In fact, the type shares are

[22] By restricting the variances of the individual effects to zero, these models ignore the panel structure of the data and essentially become pooled ordinary least squares models.

similar in magnitude to the ones from the analysis on medium-run inflation expectations. Again, the effects of the covariates on individual type probabilities and mean inflation expectations remain the same.

Two rounding types. I also estimate a variant of the model with two rounding types: type RD5 rounds to the next multiple of five percent, while type RD10 rounds to the next multiple of ten percent. Together with type NR and DK, this model is then a mixture of four different response types. Results are presented in Table F3.4, suggesting that the aggregated NR and DK share are 65% and 6.7%, respectively, and thus literally identical to the shares from the main model. The remaining 28% of rounders are split between 19% of respondents who round to the multiple of five, and 9% who round to the next multiple of ten percent. The effect of the covariates on the type probabilities is very similar for types RD5 and RD10 and qualitatively close to the main findings. Further analysis shows that the increase in the uncertainty index after 9/11 and the Lehman collapse are mainly driven by an increase in the RD10 share, while the increase after hurricane Katrina and Northern Rock is driven by an increase in the RD5 share (cf. Figure F3.1).

Level of current inflation. Rounding may also depend on the current level of the inflation rate. For example, one might to be more willing to round to five percent if the current inflation rate is given by 4.8 percent rather than 4.0 percent. Table F3.5 therefore includes month-year fixed effects not only in the random effects multinomial logit model, but also in the equation for the mean of the inflation expectation distribution (Equation 3.4). The time effects capture all variables affecting respondents similarly across time, such as the current inflation rate. The implied type distribution is literally unaffected by this specification and the associations with the covariates get even stronger.

Full sample. I also estimate the model for the full data set, i.e. I add data from the 77,630 respondents, who are interviewed only once (Table F3.6). The average NR share slightly decreases by two percentage points, while the RD and DK share increase by one percentage point each. The resulting type distribution is thus almost identical to the one from the main section. Due to the increase in sample size, the standard errors of the estimates get – as expected – even smaller. The other results are unchanged.

3.6 Conclusion

This paper introduces a microeconometric panel data model for inflation point expectations of US households. In contrast to previous studies, in particular Binder (2017), I explicitly model a panel dimension and allow for individual heterogeneity and item non-response. The population is described as a finite mixture of three distinct response types, who differ in how they report their inflation expectations: rounders (RD), non-rounders (NR) and respondents who choose a "don't know" response (DK). Type probabilities are allowed to depend on both observed and unobserved heterogeneity.

The estimated average population shares of types (NR,RD,DK) are given by (0.65,0.28,0.07), implying that most respondents actually report their true inflation expectation rather than some rounded value. However, the results suggest that more than a quarter of respondents round their inflation expectations to the next multiple of five, with meaningful variation over time. Rounding is more prevalent in times of higher economic uncertainty compared to times of lower economic uncertainty. Moreover, I find that response type probabilities can be predicted by both observed and unobserved heterogeneity. For example, males and respondents with at least a college degree are significantly less likely to round and to choose a "don't know" option than females and respondents without a college degree. Respondents who are more likely to round are also more likely to choose "don't know", questioning the standard procedure of dropping missing answers. I also find evidence for type stability across interviews.

This generalized model of Binder (2017) allows to increase efficiency of the estimates, to identify meaningful heterogeneity in the type probabilities and to explicitly take item non-response into account. However, in terms of the construction of the uncertainty index, there seems to be little difference across both models. In fact, the resulting uncertainty indices are almost identical.

This paper has several implications. For example, the insight that rounding behavior systematically varies with socio-economic characteristics may guide future survey design and improve data quality. Furthermore, since rounding patterns in inflation expectations are systematically linked with economic uncertainty over time, this information may be used to determine or at least improve existing estimates for the current level of uncertainty in the economy. Future research should, in addition, analyze if this also applies to other domains, i.e. if economic uncertainty is also related to rounding behavior in expectations questions in other domains or survey questions unrelated to expectations.

More generally, this paper demonstrates the usefulness of survey data, that goes beyond the face value of individuals' responses. Researchers have recently started to extensively rely on so-called paradata. This includes, for example, respondent-level information on the amount of time spent on a specific survey question, the number of adjustments, the number of mouse clicks as well as the exact mouse movement pattern. The latter, for example, has already been used for PC user verification (Pusara and Brodley, 2004; Zheng et al., 2011). Clearly, these novel approaches have the potential to improve not only data quality, but also the understanding of the decision-making process of individuals itself.

Appendix

A3 Questionnaire for price expectations

Figures A3.1 and A3.2 describe the exact procedure for the elicitation of inflation expectations in the short-run (px1) and the medium-run (px5), respectively. The entire questionnaire and interviewer instructions are available at the University of Michigan Survey Research Center and are described in Curtin (1996).

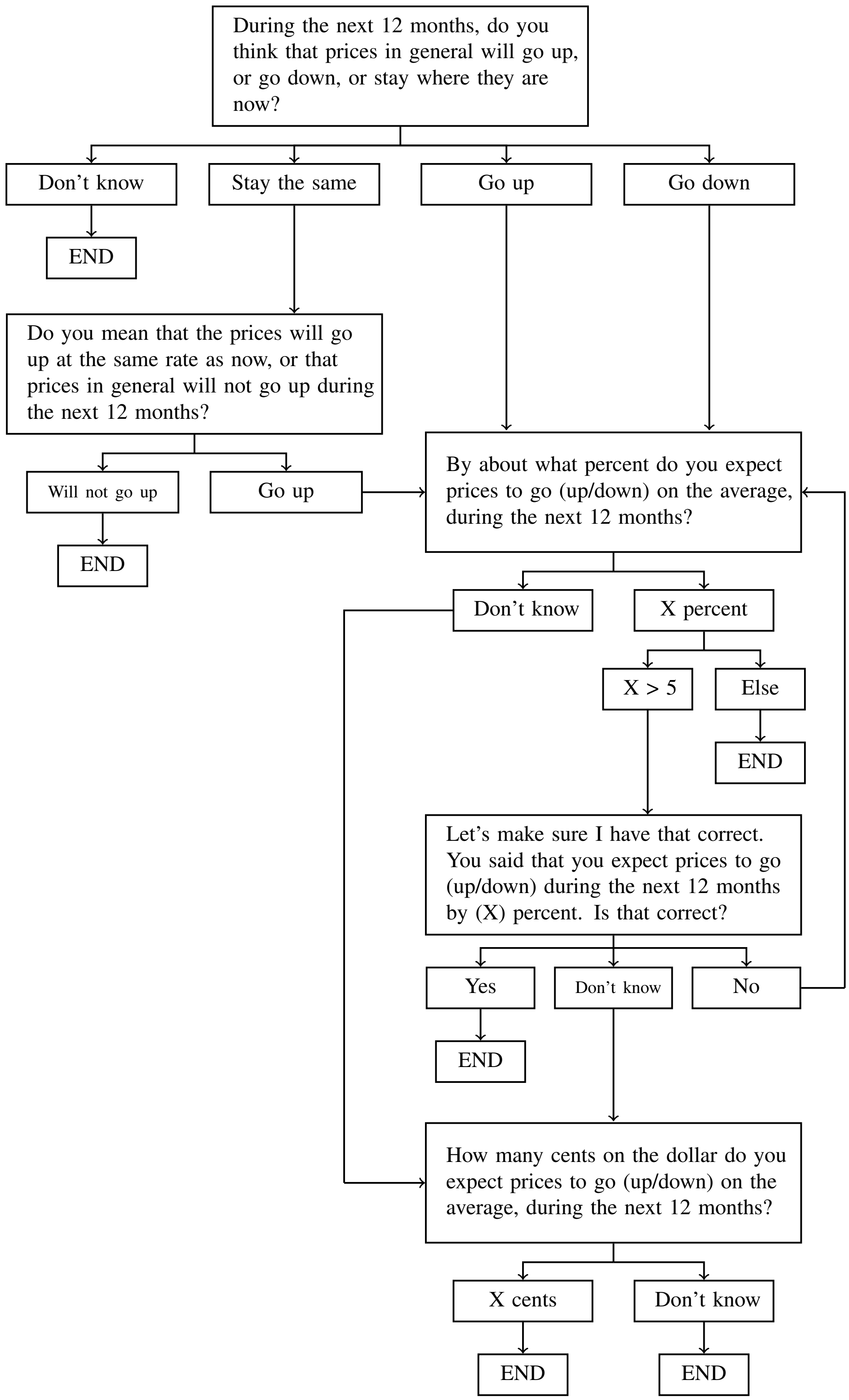


Figure A3.1: Questionnaire for short-run inflation expectations (px1)

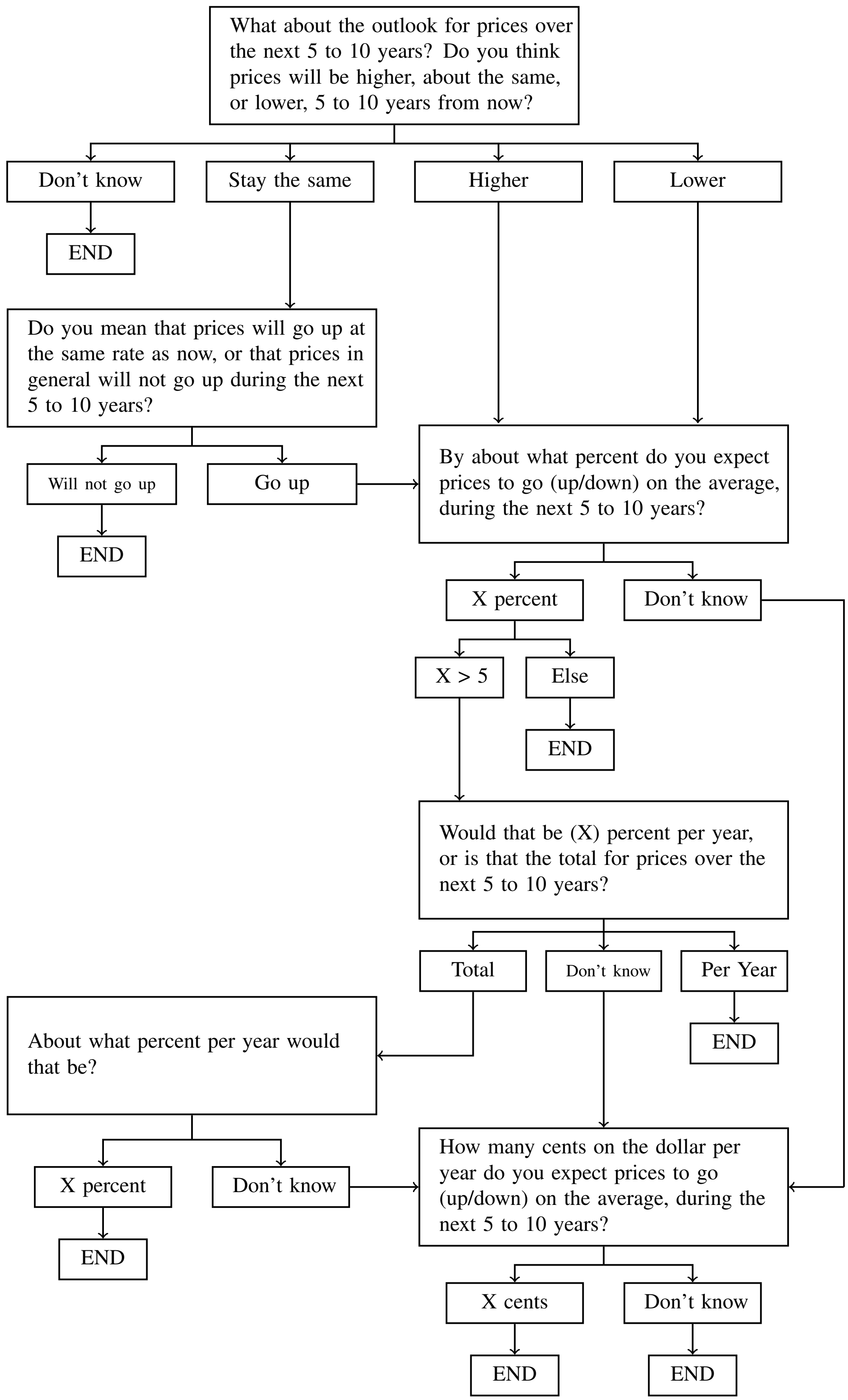


Figure A3.2: Questionnaire for medium-run inflation expectations (px5)

B3 Full sample summary statistics

Table B3.1: Summary statistics for the full sample

	Mean	SD	p5	p95	Min	Max	Observations
A: Inflation expectations [%]							
Short-run (px1)	4.55	6.30	0	15	-50	50	246,683
Medium-run (px5)	4.06	5.17	0	10	-50	50	176,177
B: Sociodemographics [0/1]							
Male	0.46	0.50	0	1	0	1	271,277
Partner	0.60	0.49	0	1	0	1	268,594
Age > 64	0.20	0.40	0	1	0	1	269,899
Age < 40	0.39	0.49	0	1	0	1	269,899
College	0.37	0.48	0	1	0	1	268,579
1st income quartile	0.21	0.41	0	1	0	1	234,095
2nd income quartile	0.21	0.41	0	1	0	1	234,095
3rd income quartile	0.28	0.45	0	1	0	1	234,095
4th income quartile	0.30	0.46	0	1	0	1	234,095
C: Regional information [0/1]							
West	0.20	0.40	0	1	0	1	271,853
Northcentral	0.27	0.44	0	1	0	1	271,853
Northeast	0.19	0.39	0	1	0	1	271,853
South	0.33	0.47	0	1	0	1	271,853

Notes: This Table is based on all 77,630 respondents who are interviewed once and all 97,159 respondents from the MSC who are interviewed twice between January 1978 to December 2017, making a total of 271,948 observations. Number of observations differ due to item nonresponse. Panel B and C report dummy variables if not indicated differently. Information on income (1st-4th quartile) not available before October 1979. For details see text.

C3 US inflation between 1978 and 2018

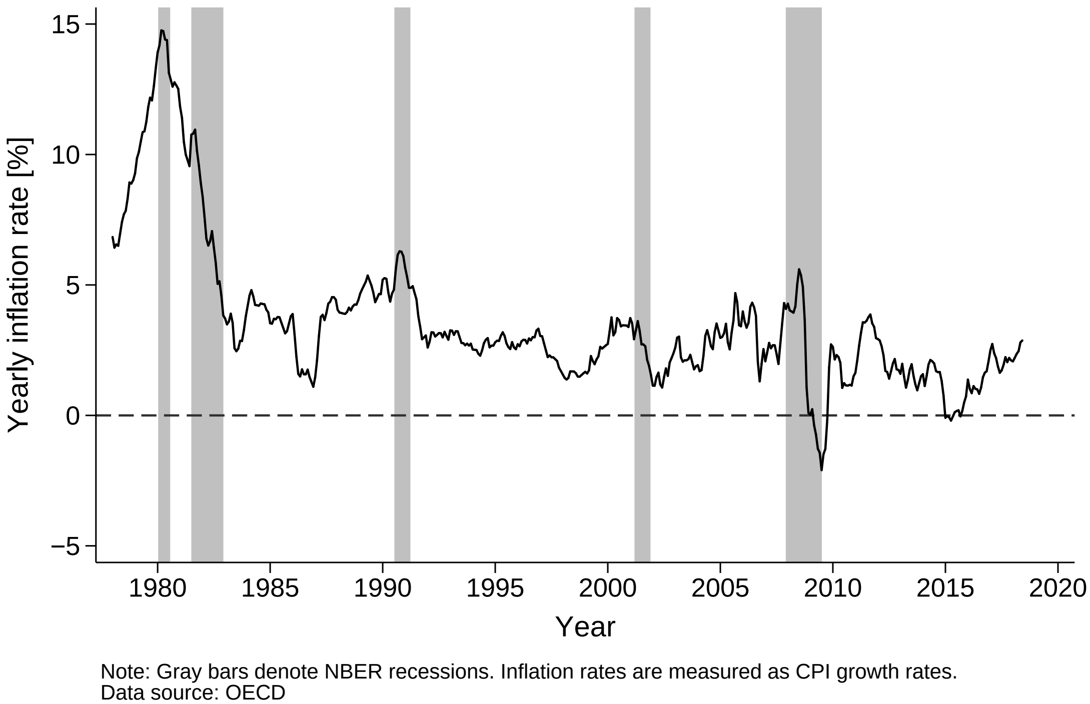


Figure C3.1: Yearly inflation rates in the US between 1978 and 2018

D3 Derivation of the likelihood function

Recall that the probabilities of observing y_{it} conditional on type T_{it} are given by:

$$P(y_{it}|T_{it}) = \begin{cases} f_{NR}(y_{it}) & \text{if } T_{it} = NR \\ f_{RD}(y_{it}) & \text{if } T_{it} = RD \\ 0 & \text{if } T_{it} = DK \end{cases} \qquad \&\ y_{it} \text{ is a multiple of } m$$

$$P(y_{it}|T_{it}) = \begin{cases} f_{NR}(y_{it}) & \text{if } T_{it} = NR \\ 0 & \text{if } T_{it} = RD \\ 0 & \text{if } T_{it} = DK \end{cases} \qquad \&\ y_{it} \text{ is not a multiple of } m$$

$$P(y_{it}|T_{it}) = \begin{cases} 0 & \text{if } T_{it} = NR \\ 0 & \text{if } T_{it} = RD \\ f_{DK}(y_{it}) & \text{if } T_{it} = DK \end{cases} \qquad \&\ y_{it} \text{ is missing}$$

with

$$\begin{aligned} f_{NR}(y_{it}) &= \phi(y_{it}; \mu^{NR}; \sigma^{NR}) \\ f_{RD}(y_{it}) &= \Phi\left(\frac{y_{it} + \frac{m}{2} - \mu^{RD}}{\sigma^{RD}}\right) - \Phi\left(\frac{y_{it} - \frac{m}{2} - \mu^{RD}}{\sigma^{RD}}\right) \\ f_{DK}(y_{it}) &= 1 \end{aligned}$$

By definition, the unconditional probability of observing y_{it} is given by:

$$\begin{aligned} P(y_{it}) = {} & P(y_{it}|T_{it} = NR) \cdot P(T_{it} = NR) + \\ & P(y_{it}|T_{it} = RD) \cdot P(T_{it} = RD) + \\ & P(y_{it}|T_{it} = DK) \cdot P(T_{it} = DK) \end{aligned}$$

which can then be simplified to:

$$P(y_{it}) \quad = \quad \begin{cases} P(T_{it} = DK) & \text{if } y_{it} \text{ is missing} \\ f_{NR} \cdot P(T_{it} = NR) & \text{if } y_{it} \text{ is not a multiple of } m \\ f_{NR} \cdot P(T_{it} = NR) + f_{RD} \cdot P(T_{it} = RD) & \text{if } y_{it} \text{ is a multiple of } m \end{cases}$$

Taking the product over individuals and time and parameterizing the type probabilities $P(T_{it} = j)$ results in the likelihood function presented in the main section. Note also that – after maximization of the likelihood function – the estimated (unconditional) individual type probabilities can be used to calculate posterior type probabilities conditional on the reported values of y_{it}. More specifically, those are given by Bayes' theorem:

$$P(T_{it} = j|y_{it}) = P(y_{it}|T_{it} = j)\frac{P(T_{it} = j)}{P(y_{it})}$$

Using the definitions introduced earlier, it is straightforward to show that

$$P(NR|y_{it}) \quad = \quad \begin{cases} 0 & \text{if } y_{it} \text{ is missing} \\ 1 & \text{if } y_{it} \text{ is not a multiple of } m \\ f_{NR} \cdot \frac{P(NR)}{f_{NR} \cdot P(NR) + f_{RD} \cdot P(RD)} & \text{if } y_{it} \text{ is a multiple of } m \end{cases}$$

$$P(RD|y_{it}) \quad = \quad \begin{cases} 0 & \text{if } y_{it} \text{ is missing} \\ 0 & \text{if } y_{it} \text{ is not a multiple of } m \\ f_{RD} \cdot \frac{P(RD)}{f_{NR} \cdot P(NR) + f_{RD} \cdot P(RD)} & \text{if } y_{it} \text{ is a multiple of } m \end{cases}$$

$$P(DK|y_{it}) \quad = \quad \begin{cases} 1 & \text{if } y_{it} \text{ is missing} \\ 0 & \text{if } y_{it} \text{ is not a multiple of } m \\ 0 & \text{if } y_{it} \text{ is a multiple of } m. \end{cases}$$

E3 Computational issues for the Hessian matrix

The default optimization method in Stata®15 is given by a (modified) Newton-Raphson algorithm, which is based on the calculation of the gradient and the Hessian matrix. While this algorithm is known to work fine for many applications, it becomes computationally very costly as the number of parameters increases. In fact, calculating the Hessian matrix for a k-dimensional parameter vector requires $O(k^2)$ evaluations of the log-likelihood function (Jeliazkov and Lloro, 2011). In the application of my model, I use monthly data over a 40-year period, which implies that adding month-year fixed effects increases the dimension of the parameter vector by almost 500 per response type. In combination with the Maximum Simulated Likelihood approach, which requires a repeated calculation of the likelihood function at every iteration, calculating the Hessian matrix and thus using the Newton-Raphson algorithm becomes computationally too costly and in fact infeasible.

I therefore rely on Quasi-Newton, gradient-based optimization methods, which replace the Hessian matrix by some other – computationally less costly – measure. For example, the Berndt-Hall-Hall-Hausmann (BHHH) algorithm replaces the negative Hessian by the outer product of the gradients. Similarly, the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm replaces the Hessian by a function of the gradient, which aims for an ever-improving estimate of the Hessian at every iteration.[23] One fundamental advantage of these algorithms is that they only require $O(k)$ evaluations of the likelihood function (Jeliazkov and Lloro, 2011). My specific optimization routine switches between the BHHH algorithm (5 iterations) and the BFGS algorithm (10 iterations) and focuses on BFGS only, when BHHH is not applicable.

By default, Stata declares convergence if the following two conditions are met: First, the scaled gradient is sufficiently small, i.e. $\boldsymbol{g}\boldsymbol{H}^{-1}\boldsymbol{g}' < 10^{-5}$, where $\boldsymbol{g}$ is the gradient (row) vector and $\boldsymbol{H}$ is the Hessian matrix of the parameter vector $\hat{\boldsymbol{\theta}}$. Second, either the relative

[23] See Gould et al. (2006) for more details on both algorithms.

change in the parameter vector $\hat{\boldsymbol{\theta}}$ or the relative change in the value of the log-likelihood function $L(\hat{\boldsymbol{\theta}})$ from one iteration to the next is sufficiently small. As the first criterion requires again the calculation of the Hessian matrix, I use Stata's `qtolerance()` option, which causes Stata to use the modified (gradient-based) version of the Hessian matrix as final check for convergence rather than the actual Hessian. Note that this procedure has been the default option in Stata until version 12. The second criterion remains unchanged.

Similarly, I estimate the variance-covariance matrix of my parameter vector and therefore the standard errors of my estimates by the outer product of the gradients (Gould et al., 2006). Again, Stata's default estimator would require the calculation of the Hessian matrix.

F3 Additional Figures and Tables

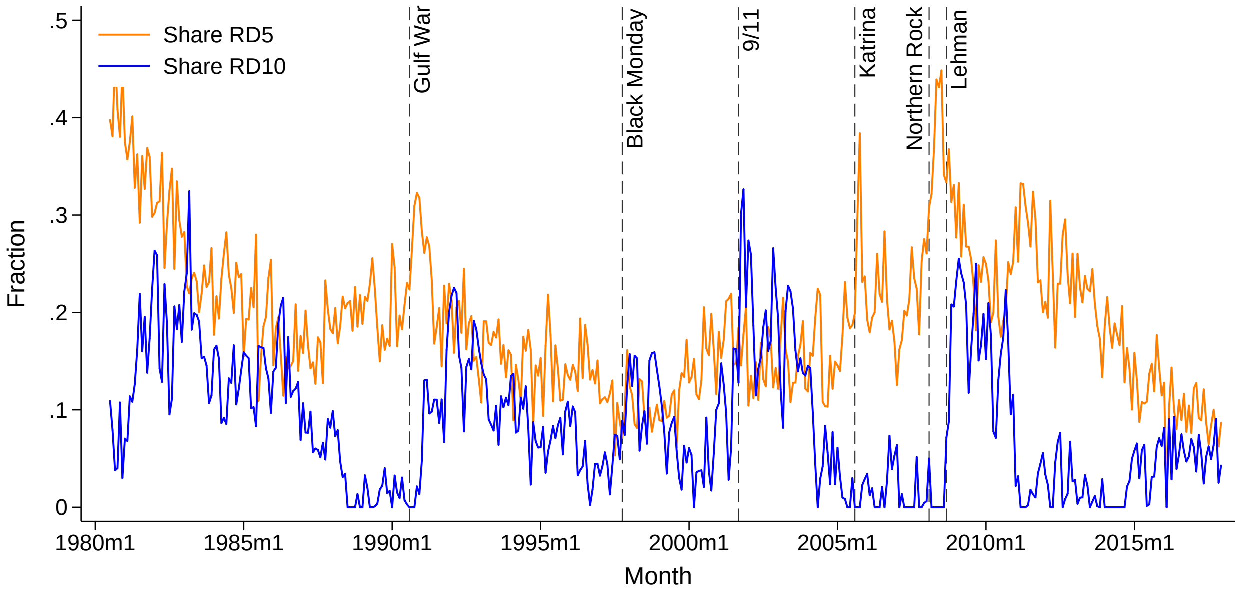


Figure F3.1: Rounding shares with two distinct rounding types

Table F3.1: Model estimates for logistic inflation expectations

	Logistic distribution				Normal distribution			
	Mean NR (1a)	Mean RD (1b)	P(T=RD) (1c)	P(T=DK) (1d)	Mean NR (2a)	Mean RD (2b)	P(T=RD) (2c)	P(T=DK) (2d)
Panel A								
Male	-0.01	-1.05***	-0.59***	-0.99***	-0.13***	-1.12***	-0.64***	-0.99***
	[0.02]	[0.06]	[0.01]	[0.02]	[0.02]	[0.06]	[0.02]	[0.02]
Partner	0.01	0.31***	-0.02	-0.06***	0.02	0.34***	-0.02	-0.06***
	[0.02]	[0.06]	[0.02]	[0.02]	[0.02]	[0.07]	[0.02]	[0.02]
Age	-0.01***	-0.02***	-0.00	0.02***	-0.01***	-0.02***	-0.00*	0.02***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
College	-0.01	-0.22***	-0.35***	-0.43***	-0.11***	-0.37***	-0.38***	-0.43***
	[0.02]	[0.06]	[0.02]	[0.02]	[0.02]	[0.07]	[0.02]	[0.02]
1st income quartile	0.15***	1.61***	0.44***	1.20***	0.30***	1.59***	0.49***	1.21***
	[0.03]	[0.09]	[0.02]	[0.03]	[0.03]	[0.10]	[0.03]	[0.03]
2nd income quartile	-0.01	1.27***	0.23***	0.58***	0.05*	1.22***	0.26***	0.59***
	[0.02]	[0.08]	[0.02]	[0.03]	[0.03]	[0.09]	[0.02]	[0.03]
3rd income quartile	-0.03	0.67***	0.10***	0.23***	0.01	0.67***	0.12***	0.24***
	[0.02]	[0.07]	[0.02]	[0.03]	[0.02]	[0.08]	[0.02]	[0.03]
West	0.06***	0.08	-0.10***	-0.06**	0.06**	-0.00	-0.10***	-0.06**
	[0.02]	[0.08]	[0.02]	[0.03]	[0.03]	[0.09]	[0.02]	[0.03]
Northcentral	0.03	-0.17**	-0.02	-0.16***	-0.02	-0.18**	-0.02	-0.16***
	[0.02]	[0.07]	[0.02]	[0.03]	[0.02]	[0.08]	[0.02]	[0.03]
Northeast	0.04	-0.02	0.08***	0.06**	0.02	-0.04	0.08***	0.06**
	[0.02]	[0.08]	[0.02]	[0.03]	[0.03]	[0.08]	[0.02]	[0.03]
Constant	3.09***	5.05***	0.68***	-1.35***	3.50***	5.78***	0.67***	-1.36***
	[0.03]	[0.11]	[0.17]	[0.23]	[0.04]	[0.12]	[0.18]	[0.23]
Panel B								
σ^{NR}	1.39***				2.81***			
	[0.00]				[0.01]			
σ^{RD}	3.10***				5.87***			
	[0.01]				[0.02]			
Panel C								
	Random effects are restricted to zero							
Panel D								
Implied share NR	0.629				0.652			
Implied share RD	0.305				0.281			
Implied share DK	0.067				0.067			
Month-year FE	yes				yes			
Observations	172,548				172,548			

Notes: This table repeats the main analysis under the assumption of logistic inflation expectations (specification 1). Dependent variable is short-run inflation expectations (px1). Response types are non-rounders (NR), rounders (RD) and respondents who choose a "don't know" answer (DK). All columns include month-year fixed effects in the random effects multinomial logit model for type probabilities (Equation 3.6). Panel A reports estimates for interpersonal heterogeneity. Columns a and b report estimates for the parameterized mean of inflation expectations for type NR and RD (Equation 3.4), respectively. Columns c and d focus on the random effects multinomial logit model for type probabilities. Omitted category is type NR. Panel B displays type-specific estimates for the standard deviation of the logistic or normal distribution, respectively. The individual effects are normalized to zero (Panel C). Panel D reports averages of model-implied unconditional type probabilities. For details see text. Standard errors in brackets. *** p <0.01, ** p <0.05, * p <0.1.

Table F3.2: Model estimates for medium-run inflation expectations

	Excluding month-year FE				Including month-year FE			
	Mean NR	Mean RD	P(T=RD)	P(T=DK)	Mean NR	Mean RD	P(T=RD)	P(T=DK)
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Panel A								
Male	0.02	-0.30***	-0.95***	-0.84***	0.00	-0.44***	-0.89***	-0.82***
	[0.02]	[0.11]	[0.02]	[0.02]	[0.02]	[0.11]	[0.02]	[0.02]
Partner	-0.02	0.46***	-0.08***	-0.10***	-0.02	0.43***	-0.05**	-0.08***
	[0.02]	[0.11]	[0.02]	[0.02]	[0.02]	[0.10]	[0.02]	[0.02]
Age	-0.01***	-0.06***	-0.01***	0.02***	-0.01***	-0.06***	-0.00***	0.02***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
College	-0.11***	-0.00	-0.84***	-0.43***	-0.13***	-0.08	-0.58***	-0.34***
	[0.02]	[0.12]	[0.03]	[0.02]	[0.02]	[0.11]	[0.03]	[0.02]
1st income quartile	0.03	-0.12	0.93***	1.09***	0.05*	0.10	1.05***	1.14***
	[0.03]	[0.16]	[0.04]	[0.03]	[0.03]	[0.16]	[0.04]	[0.03]
2nd income quartile	-0.15***	-0.26	0.44***	0.49***	-0.15***	-0.09	0.62***	0.54***
	[0.02]	[0.16]	[0.03]	[0.03]	[0.02]	[0.15]	[0.03]	[0.03]
3rd income quartile	-0.10***	-0.20	0.29***	0.21***	-0.10***	-0.07	0.35***	0.23***
	[0.02]	[0.15]	[0.03]	[0.03]	[0.02]	[0.15]	[0.03]	[0.03]
West	0.09***	0.12	-0.11***	-0.01	0.09***	0.11	-0.11***	-0.01
	[0.02]	[0.14]	[0.03]	[0.03]	[0.02]	[0.14]	[0.03]	[0.03]
Northcentral	-0.02	-0.06	-0.11***	-0.20***	-0.02	-0.14	-0.12***	-0.20***
	[0.02]	[0.12]	[0.03]	[0.03]	[0.02]	[0.12]	[0.03]	[0.03]
Northeast	0.02	-0.17	0.01	0.06**	0.03	-0.16	-0.05	0.04
	[0.02]	[0.14]	[0.03]	[0.03]	[0.02]	[0.14]	[0.03]	[0.03]
Constant	3.88***	10.31***	-1.01***	-3.02***	3.88***	10.22***	0.54***	-1.75***
	[0.03]	[0.21]	[0.05]	[0.05]	[0.03]	[0.20]	[0.17]	[0.22]
Panel B								
σ^{NR}	2.39***				2.39***			
	[0.01]				[0.01]			
σ^{RD}	5.76***				5.77***			
	[0.03]				[0.03]			
Panel C								
	Random effects are restricted to zero							
Panel D								
Implied share NR	0.777				0.774			
Implied share RD	0.134				0.137			
Implied share DK	0.089				0.089			
Month-year FE	no				yes			
Observations	136,264				136,264			

Notes: This table repeats the main analysis for the alternative dependent variable of medium-run inflation expectations (px5). Response types are non-rounders (NR), rounders (RD) and respondents who choose a "don't know" answer (DK). Specification 1 (2) excludes (includes) month-year fixed effects in the random effects multinomial logit model for type probabilities (Equation 3.6). Panel A reports estimates for interpersonal heterogeneity. Columns a and b report estimates for the parameterized mean of inflation expectations for type NR and RD (Equation 3.4), respectively. Columns c and d focus on the random effects multinomial logit model for type probabilities. Omitted category is type NR. Panel B displays type-specific estimates for the standard deviation of the normal distribution of inflation expectations. The individual effects are normalized to zero (Panel C). Panel D reports averages of model-implied unconditional type probabilities. For details see text. Standard errors in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table F3.3: Model estimates for rounding to the next multiple of ten percent

	Excluding month-year FE				Including month-year FE			
	Mean NR	Mean RD	P(T=RD)	P(T=DK)	Mean NR	Mean RD	P(T=RD)	P(T=DK)
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Panel A								
Male	-0.51***	-1.38***	-0.52***	-0.88***	-0.51***	-1.37***	-0.48***	-0.88***
	[0.02]	[0.08]	[0.02]	[0.02]	[0.02]	[0.08]	[0.02]	[0.02]
Partner	0.06***	0.33***	-0.03	-0.05**	0.07***	0.30***	-0.03	-0.06**
	[0.02]	[0.09]	[0.02]	[0.02]	[0.02]	[0.09]	[0.02]	[0.02]
Age	-0.01***	-0.03***	0.00***	0.02***	-0.01***	-0.03***	0.00***	0.02***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
College	-0.34***	-0.37***	-0.48***	-0.32***	-0.34***	-0.41***	-0.37***	-0.38***
	[0.02]	[0.09]	[0.02]	[0.02]	[0.02]	[0.09]	[0.02]	[0.02]
1st income quartile	0.62***	2.00***	0.32***	1.12***	0.64***	1.95***	0.32***	1.11***
	[0.04]	[0.13]	[0.03]	[0.03]	[0.04]	[0.12]	[0.03]	[0.03]
2nd income quartile	0.21***	1.54***	0.02	0.57***	0.22***	1.46***	0.09***	0.52***
	[0.03]	[0.12]	[0.02]	[0.03]	[0.03]	[0.12]	[0.03]	[0.03]
3rd income quartile	0.08***	0.85***	0.02	0.22***	0.09***	0.80***	0.03	0.21***
	[0.03]	[0.11]	[0.02]	[0.03]	[0.03]	[0.11]	[0.02]	[0.03]
West	-0.02	0.09	-0.09***	-0.05	-0.02	0.09	-0.10***	-0.05
	[0.03]	[0.11]	[0.02]	[0.03]	[0.03]	[0.11]	[0.02]	[0.03]
Northcentral	-0.05*	-0.16	-0.01	-0.17***	-0.04*	-0.18*	-0.01	-0.15***
	[0.03]	[0.10]	[0.02]	[0.03]	[0.03]	[0.10]	[0.02]	[0.03]
Northeast	0.03	0.09	0.10***	0.05	0.03	0.07	0.07***	0.05*
	[0.03]	[0.11]	[0.02]	[0.03]	[0.03]	[0.11]	[0.02]	[0.03]
Constant	4.35***	4.59***	-1.20***	-3.35***	4.33***	4.69***	-0.20	-1.81***
	[0.04]	[0.16]	[0.03]	[0.05]	[0.04]	[0.16]	[0.17]	[0.22]
Panel B								
σ^{NR}	3.55***				3.55***			
	[0.01]				[0.01]			
σ^{RD}	5.50***				5.47***			
	[0.03]				[0.03]			
Panel C								
	Random effects are restricted to zero							
Panel D								
Implied share NR	0.761				0.759			
Implied share RD	0.172				0.175			
Implied share DK	0.067				0.067			
Month-year FE	no				yes			
Observations	172,548				172,548			

Notes: This table repeats the main analysis under the assumption that rounders (RD) round to the next multiple of ten rather than five percent. Other response types are non-rounders (NR) and respondents who choose a "don't know" answer (DK). Dependent variable is short-run inflation expectations (px1). Specification 1 (2) excludes (includes) month-year fixed effects in the random effects multinomial logit model for type probabilities (Equation 3.6). Panel A reports estimates for interpersonal heterogeneity. Columns a and b report estimates for the parameterized mean of inflation expectations for type NR and RD (Equation 3.4), respectively. Columns c and d focus on the random effects multinomial logit model for type probabilities. Omitted category is type NR. Panel B displays type-specific estimates for the standard deviation of the normal distribution of inflation expectations. The individual effects are normalized to zero (Panel C). Panel D reports averages of model-implied unconditional type probabilities. For details see text. Standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table F3.4: Model estimates for four response types

	Excluding month-year FE						Including month-year FE					
	Mean NR (1a)	Mean RD5 (1b)	Mean RD10 (1c)	P(T=RD5) (1d)	P(T=RD10) (1e)	P(T=DK) (1f)	Mean NR (2a)	Mean RD5 (2b)	Mean RD10 (2c)	P(T=RD5) (2d)	P(T=RD10) (2e)	P(T=DK) (2f)
Panel A												
Male	-0.14***	-1.24***	0.27*	-0.77***	-0.32***	-0.98***	-0.15***	-1.21***	0.21*	-0.71***	-0.32***	-0.98***
	[0.02]	[0.09]	[0.15]	[0.02]	[0.03]	[0.02]	[0.02]	[0.09]	[0.13]	[0.02]	[0.03]	[0.02]
Partner	0.00	0.36***	0.00	0.00	-0.08**	-0.06**	0.02	0.35***	0.12	-0.01	-0.05*	-0.06***
	[0.02]	[0.10]	[0.17]	[0.02]	[0.03]	[0.02]	[0.02]	[0.09]	[0.14]	[0.02]	[0.03]	[0.02]
Age	-0.01***	-0.02***	0.00	-0.00***	0.00***	0.02***	-0.01***	-0.02***	-0.00	-0.00***	0.01***	0.02***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
College	-0.17***	-0.96***	-0.07	-0.36***	-0.59***	-0.36***	-0.16***	-0.76***	-0.25*	-0.36***	-0.33***	-0.43***
	[0.02]	[0.10]	[0.17]	[0.02]	[0.03]	[0.02]	[0.02]	[0.09]	[0.13]	[0.02]	[0.03]	[0.02]
1st income quartile	0.27***	1.37***	0.47*	0.64***	0.06	1.21***	0.27***	1.30***	-0.10	0.66***	0.01	1.21***
	[0.03]	[0.15]	[0.27]	[0.03]	[0.05]	[0.03]	[0.03]	[0.13]	[0.21]	[0.03]	[0.04]	[0.03]
2nd income quartile	-0.01	0.58***	0.40	0.40***	-0.32***	0.62***	0.01	0.69***	-0.07	0.44***	-0.18***	0.58***
	[0.03]	[0.13]	[0.26]	[0.03]	[0.05]	[0.03]	[0.03]	[0.12]	[0.19]	[0.03]	[0.04]	[0.03]
3rd income quartile	-0.02	0.41***	0.06	0.22***	-0.16***	0.25***	-0.01	0.49***	-0.06	0.21***	-0.10***	0.24***
	[0.02]	[0.13]	[0.17]	[0.03]	[0.04]	[0.03]	[0.02]	[0.12]	[0.15]	[0.03]	[0.03]	[0.03]
West	0.04	-0.17	0.08	-0.07**	-0.15***	-0.06**	0.04	-0.11	-0.30*	-0.07**	-0.19***	-0.06**
	[0.03]	[0.13]	[0.22]	[0.03]	[0.04]	[0.03]	[0.03]	[0.12]	[0.17]	[0.03]	[0.04]	[0.03]
Northcentral	-0.02	-0.21*	0.12	-0.03	0.01	-0.17***	-0.01	-0.14	0.02	-0.04*	0.03	-0.16***
	[0.02]	[0.11]	[0.17]	[0.03]	[0.04]	[0.03]	[0.02]	[0.11]	[0.15]	[0.02]	[0.03]	[0.03]
Northeast	0.02	-0.04	-0.30	0.13***	0.05	0.06**	0.02	0.01	-0.33**	0.09***	0.06*	0.06**
	[0.03]	[0.12]	[0.19]	[0.03]	[0.04]	[0.03]	[0.03]	[0.12]	[0.16]	[0.03]	[0.04]	[0.03]
Constant	3.72***	7.65***	0.30	-0.81***	-1.62***	-3.10***	3.71***	7.74***	0.00	0.78***	-0.95***	-0.75***
	[0.04]	[0.19]	[0.33]	[0.05]	[0.06]	[0.05]	[0.04]	[0.17]	[0.33]	[0.20]	[0.34]	[0.22]
Panel B												
σ^{NR}				2.79***						2.80***		
				[0.01]						[0.01]		
σ^{RD5}				5.95***						5.86***		
				[0.04]						[0.03]		
σ^{RD10}				3.15***						2.69***		
				[0.06]						[0.09]		
Panel C												
	Random effects are restricted to zero											
Panel D												
Implied share NR				0.646						0.645		
Implied share RD5				0.194						0.197		
Implied share RD10				0.093						0.091		
Implied share DK				0.067						0.067		
Month-year FE				no						yes		
Observations				172,548						172,548		

Notes: This table repeats the main analysis under the assumption of four response types: respondents who round to the next multiple of five (RD5) and ten (RD10), non-rounders (NR) and respondents who choose a "don't know" answer (DK). Dependent variable is short-run inflation expectations (px1). Specification 1 (2) excludes (includes) month-year fixed effects in the random effects multinomial logit model for type probabilities. Panel A reports estimates for interpersonal heterogeneity. Columns a, b and c report estimates for the parameterized mean of inflation expectations for type NR, RD5 and RD10, respectively. Columns d, e and f focus on the random effects multinomial logit model for type probabilities. Omitted category is type NR. Panel B displays type-specific estimates for the standard deviation of the normal distribution of inflation expectations. The individual effects are normalized to zero (Panel C). Panel D reports averages of model-implied unconditional type probabilities. For details see text. Standard errors in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table F3.5: Model estimates for full month-year fixed effects

	Excluding month-year FE				Including month-year FE			
	Mean NR (1a)	Mean RD (1b)	P(T=RD) (1c)	P(T=DK) (1d)	Mean NR (2a)	Mean RD (2b)	P(T=RD) (2c)	P(T=DK) (2d)
Panel A								
Male	-0.12***	-1.09***	-0.66***	-0.99***	-0.10***	-1.18***	-0.64***	-0.99***
	[0.02]	[0.06]	[0.02]	[0.02]	[0.02]	[0.06]	[0.02]	[0.02]
Partner	0.01	0.36***	-0.02	-0.06**	0.04*	0.31***	-0.01	-0.06**
	[0.02]	[0.07]	[0.02]	[0.02]	[0.02]	[0.06]	[0.02]	[0.02]
Age	-0.01***	-0.02***	-0.00***	0.02***	-0.00***	-0.03***	0.00	0.02***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
College	-0.10***	-0.35***	-0.45***	-0.37***	0.07***	-0.49***	-0.38***	-0.43***
	[0.02]	[0.07]	[0.02]	[0.02]	[0.02]	[0.07]	[0.02]	[0.02]
1st income quartile	0.28***	1.57***	0.48***	1.22***	0.36***	1.52***	0.50***	1.22***
	[0.03]	[0.10]	[0.02]	[0.03]	[0.03]	[0.09]	[0.02]	[0.03]
2nd income quartile	0.05*	1.21***	0.19***	0.62***	0.21***	1.13***	0.28***	0.59***
	[0.03]	[0.09]	[0.02]	[0.03]	[0.03]	[0.09]	[0.02]	[0.03]
3rd income quartile	0.00	0.68***	0.10***	0.25***	0.08***	0.65***	0.13***	0.24***
	[0.02]	[0.08]	[0.02]	[0.03]	[0.02]	[0.08]	[0.02]	[0.03]
West	0.06**	-0.00	-0.09***	-0.06**	0.05**	0.02	-0.10***	-0.06**
	[0.03]	[0.09]	[0.02]	[0.03]	[0.02]	[0.08]	[0.02]	[0.03]
Northcentral	-0.02	-0.16**	-0.01	-0.17***	-0.03	-0.24***	-0.02	-0.16***
	[0.02]	[0.08]	[0.02]	[0.03]	[0.02]	[0.07]	[0.02]	[0.03]
Northeast	0.02	-0.04	0.11***	0.06**	-0.03	-0.04	0.08***	0.06**
	[0.03]	[0.08]	[0.02]	[0.03]	[0.03]	[0.08]	[0.02]	[0.03]
Constant	3.50***	5.73***	-0.43***	-3.10***	7.13***	8.19***	0.63***	-1.37***
	[0.04]	[0.12]	[0.03]	[0.05]	[0.34]	[0.59]	[0.17]	[0.23]
Panel B								
σ^{NR}	2.82***				2.67***			
	[0.01]				[0.01]			
σ^{RD}	5.86***				5.67***			
	[0.02]				[0.02]			
Panel C								
	Random effects are restricted to zero							
Panel D								
Implied share NR	0.652				0.650			
Implied share RD	0.281				0.283			
Implied share DK	0.067				0.067			
Month-year FE	no				yes			
Observations	172,548				172,548			

Notes: This table repeats the main analysis and adds month-year fixed effects in the equation of the parameterized mean of inflation expectations for types NR and RD (Equation 3.4). Response types are non-rounders (NR), rounders (RD) and respondents who choose a “don’t know” answer (DK). Dependent variable is short-run inflation expectations (px1). Specification 1 (2) excludes (includes) month-year fixed effects in the random effects multinomial logit model for type probabilities (Equation 3.6). Panel A reports estimates for interpersonal heterogeneity. Columns a and b report estimates for the parameterized mean of inflation expectations for type NR and RD (Equation 3.4), respectively. Columns c and d focus on the random effects multinomial logit model for type probabilities. Omitted category is type NR. Panel B displays type-specific estimates for the standard deviation of the normal distribution of inflation expectations. The individual effects are normalized to zero (Panel C). Panel D reports averages of model-implied unconditional type probabilities. For details see text. Standard errors in brackets. *** p <0.01, ** p <0.05, * p <0.1.

Table F3.6: Model estimates for the full sample

	Excluding month-year FE				Including month-year FE			
	Mean NR	Mean RD	P(T=RD)	P(T=DK)	Mean NR	Mean RD	P(T=RD)	P(T=DK)
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Panel A								
Male	-0.12***	-1.03***	-0.65***	-0.95***	-0.13***	-1.03***	-0.63***	-0.96***
	[0.02]	[0.06]	[0.01]	[0.02]	[0.02]	[0.06]	[0.01]	[0.02]
Partner	0.03	0.36***	-0.02	-0.06***	0.04*	0.34***	-0.02	-0.06***
	[0.02]	[0.06]	[0.01]	[0.02]	[0.02]	[0.06]	[0.01]	[0.02]
Age	-0.01***	-0.03***	-0.00***	0.02***	-0.01***	-0.03***	-0.00**	0.02***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
College	-0.22***	-0.51***	-0.47***	-0.44***	-0.23***	-0.53***	-0.37***	-0.47***
	[0.02]	[0.06]	[0.01]	[0.02]	[0.02]	[0.06]	[0.02]	[0.02]
1st income quartile	0.23***	1.30***	0.44***	1.24***	0.25***	1.29***	0.50***	1.26***
	[0.03]	[0.08]	[0.02]	[0.03]	[0.03]	[0.09]	[0.02]	[0.03]
2nd income quartile	0.00	1.02***	0.17***	0.60***	0.01	1.01***	0.27***	0.59***
	[0.03]	[0.08]	[0.02]	[0.03]	[0.03]	[0.08]	[0.02]	[0.03]
3rd income quartile	-0.01	0.49***	0.09***	0.27***	-0.00	0.47***	0.13***	0.28***
	[0.02]	[0.07]	[0.02]	[0.03]	[0.02]	[0.07]	[0.02]	[0.03]
West	0.08***	-0.02	-0.08***	-0.08***	0.07***	-0.01	-0.09***	-0.09***
	[0.02]	[0.08]	[0.02]	[0.02]	[0.02]	[0.08]	[0.02]	[0.02]
Northcentral	-0.06**	-0.14**	-0.02	-0.19***	-0.05**	-0.16**	-0.03	-0.18***
	[0.02]	[0.07]	[0.02]	[0.02]	[0.02]	[0.07]	[0.02]	[0.02]
Northeast	0.03	-0.04	0.11***	0.02	0.03	-0.03	0.08***	0.02
	[0.03]	[0.08]	[0.02]	[0.02]	[0.03]	[0.08]	[0.02]	[0.02]
Constant	3.89***	6.61***	-0.33***	-2.81***	3.87***	6.72***	0.00	-1.66***
	[0.04]	[0.11]	[0.03]	[0.04]	[0.04]	[0.11]	[0.08]	[0.10]
Panel B								
σ^{NR}	3.06***				3.05***			
	[0.01]				[0.01]			
σ^{RD}	6.11***				6.14***			
	[0.02]				[0.02]			
Panel C								
	Random effects are restricted to zero							
Panel D								
Implied share NR	0.632				0.635			
Implied share RD	0.290				0.288			
Implied share DK	0.077				0.077			
Month-year FE	no				yes			
Observations	228,151				228,151			

Notes: This table repeats the main analysis for the full sample, thus adding respondents who are interviewed only once. Response types are non-rounders (NR), rounders (RD) and respondents who choose a "don't know" answer (DK). Dependent variable is short-run inflation expectations (px1). Specification 1 (2) excludes (includes) month-year fixed effects in the random effects multinomial logit model for type probabilities (Equation 3.6). Panel A reports estimates for interpersonal heterogeneity. Columns a and b report estimates for the parameterized mean of inflation expectations for type NR and RD (Equation 3.4), respectively. Columns c and d focus on the random effects multinomial logit model for type probabilities. Omitted category is type NR. Panel B displays type-specific estimates for the standard deviation of the normal distribution of inflation expectations. The individual effects are normalized to zero (Panel C). Panel D reports averages of model-implied unconditional type probabilities. For details see text. Standard errors in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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Eidesstattliche Versicherung

Ich versichere hiermit eidesstattlich, dass ich die vorliegende Arbeit selbstständig und ohne fremde Hilfe verfasst habe. Die aus fremden Quellen direkt oder indirekt übernommenen Gedanken sowie mir gegebene Anregungen sind als solche kenntlich gemacht. Die Arbeit wurde bisher keiner anderen Prüfungsbehörde vorgelegt und auch noch nicht veröffentlicht. Sofern ein Teil der Arbeit aus bereits veröffentlichten Papers besteht, habe ich dies ausdrücklich angegeben.

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