Does Experience Shape Subjective Expectations?

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Abstract: This paper documents that individuals' expectations about macroeconomic outcomes are systematically linked with the experiences of these macroeconomic outcomes they have made during life. Focusing on expectations about national inflation, national unemployment and national business conditions, I measure individual-specific experiences as weighted averages of these variables over the respondents' lifetime, respectively. I find that experience significantly predicts respondents' expectations in each of these domains and show that individuals generally put more weight on recent rather than distant years when aggregating past information. The 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 put relatively more weight on distant years when aggregating past information, and the association between expectations and past experiences is generally weaker for men.

Keywords: Expectations, Experience, Inflation, Unemployment, Business conditions
JEL classification: D84, E24, E31

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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 2, I introduce the econometric model in Section 3. The model estimates are presented and discussed in Section 4, while Section 5 concentrates on Lasso models. I then turn to additional robustness analyses in Section 6 and conclude in Section 7.

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

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[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 A.[6]

Table 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 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 percent

[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, response rates are, however, extremely high with values of 98.7% (unemp), 97.7% (bexp) and 90.7% (px1).

Table 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.

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. 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.

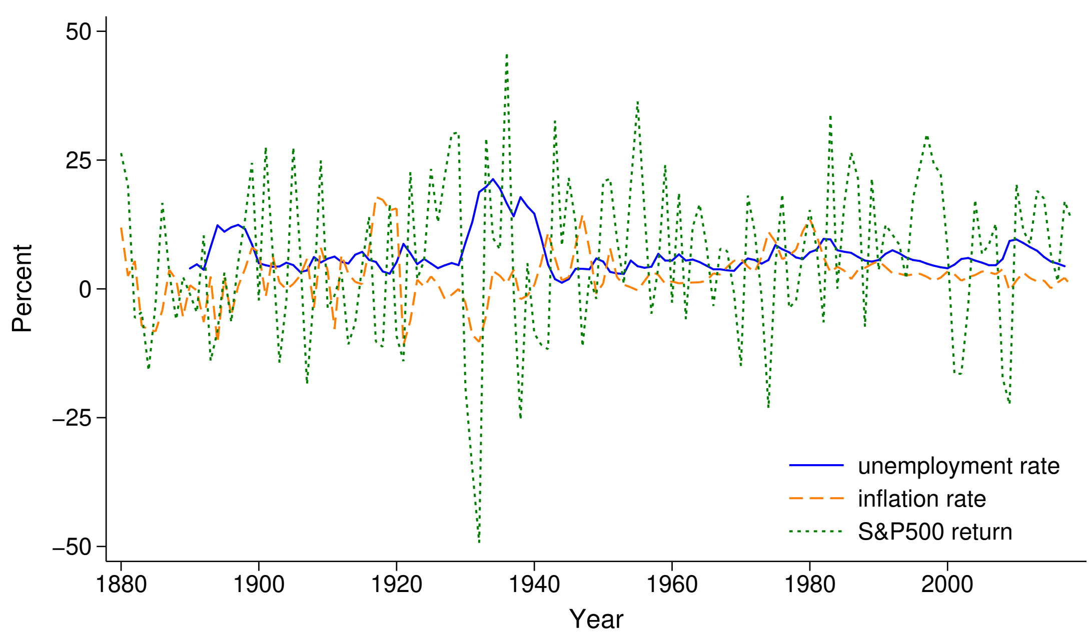

Figure 1: Historical data on US unemployment, inflation, and S&P 500 returns (1880-2017)

3 Model

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:

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

and

$$w_{it}(k,\lambda) = \frac{(age_{it}-k)^{\lambda}}{\sum\limits_{k=1}^{age_{it}-1} (age_{it}-k)^{\lambda}} \tag{2}$$

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 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 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.

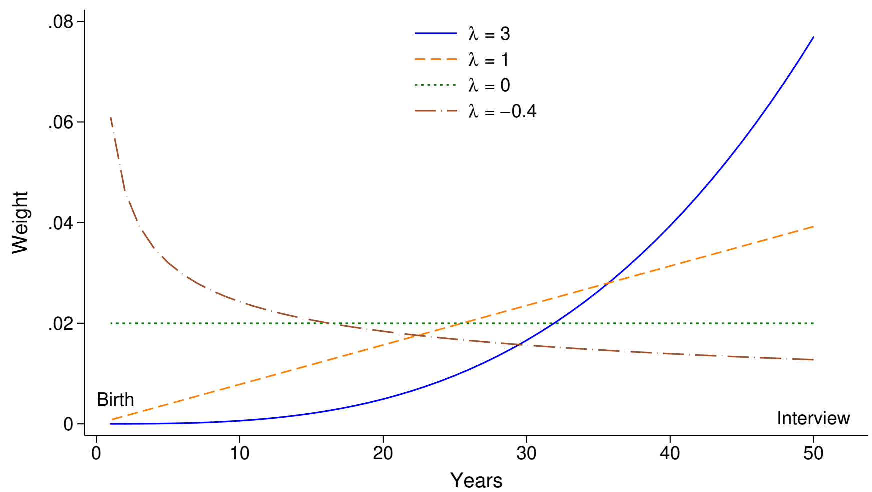

Figure 2: Weighting function of a 50-year-old respondent

Based on Equations 1 and 2, Table 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 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.

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:

$$y_{it} = \beta A_{it}(\lambda) + \boldsymbol{x}_{it}\boldsymbol{\gamma} + \varepsilon_{it} \tag{3}$$

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]

$$\beta = \beta_{it} = \boldsymbol{w}_{it}\boldsymbol{\beta} \tag{4}$$

and

$$\lambda = \lambda_{it} = \boldsymbol{w}_{it}\boldsymbol{\lambda} \tag{5}$$

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 5 for more details.

$$
\begin{aligned}
\mathcal{L}(\boldsymbol{\beta}, \boldsymbol{\lambda}, \boldsymbol{\gamma}, \sigma) &= \sum_{i=1}^{N} \ln[\phi(y_{it}; \beta A_{it}(\lambda) + \boldsymbol{x}_{it}\boldsymbol{\gamma}; \sigma)] \\
&= \sum_{i=1}^{N} \ln[\phi(y_{it}; \boldsymbol{w}_{it}\boldsymbol{\beta} A_{it}(\boldsymbol{w}_{it}\boldsymbol{\lambda}) + \boldsymbol{x}_{it}\boldsymbol{\gamma}; \sigma)] \qquad (6)
\end{aligned}
$$

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 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:

$$y^*_{it} = \beta A_{it}(\lambda) + \boldsymbol{x}_{it}\boldsymbol{\gamma} + \varepsilon_{it} \qquad (7)$$

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

$$y_{it} = j \quad \text{if} \quad \kappa_{j-1} < y^*_{it} \leq \kappa_j; \quad j = 1, 2, \ldots, m \qquad (8)$$

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]

$$
\begin{aligned}
P(y_{it} = j|\boldsymbol{x}_{it}, \boldsymbol{w}_{it}) &= P(\kappa_{j-1} < y^*_{it} \leq \kappa_j) \\
&= \Phi(\kappa_j - \beta A_{it}(\lambda) - \boldsymbol{x}_{it}\boldsymbol{\gamma}) - \Phi(\kappa_{j-1} - \beta A_{it}(\lambda) - \boldsymbol{x}_{it}\boldsymbol{\gamma}) \qquad (9) \\
&= \Phi(\kappa_j - \boldsymbol{w}_{it}\boldsymbol{\beta} A_{it}(\boldsymbol{w}_{it}\boldsymbol{\lambda}) - \boldsymbol{x}_{it}\boldsymbol{\gamma}) - \Phi(\kappa_{j-1} - \boldsymbol{w}_{it}\boldsymbol{\beta} A_{it}(\boldsymbol{w}_{it}\boldsymbol{\lambda}) - \boldsymbol{x}_{it}\boldsymbol{\gamma})
\end{aligned}
$$

and

$$
\mathcal{L}(\boldsymbol{\beta}, \boldsymbol{\lambda}, \boldsymbol{\gamma}, \kappa_1, \kappa_2, ..., \kappa_{m-1}) = \sum_{i=1}^{N} \sum_{j=1}^{m} \mathbb{1}(y_{it} = j) \cdot \ln[P(y_{it} = j|\boldsymbol{x}_{it}, \boldsymbol{w}_{it})] \qquad (10)
$$

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

3.3 Estimation and identification

The model is estimated jointly by maximizing the respective log likelihood function, as given in Equations 6 and 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 6 and Appendix D.

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.

4 Results

Tables 3, 4 and 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 B.

4.1 Inflation expectations

Table 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 2 and

Table 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.

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.

4.2 Unemployment expectations

Table 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 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 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.

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 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 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 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 3 summarizes the gender differences in the weighting parameter by plotting gender-specific and domain-specific weighting functions, implied by the estimates from Tables 3, 4 and 5 (column 3 each). Independent of gender, the graph illustrates the similar weighting

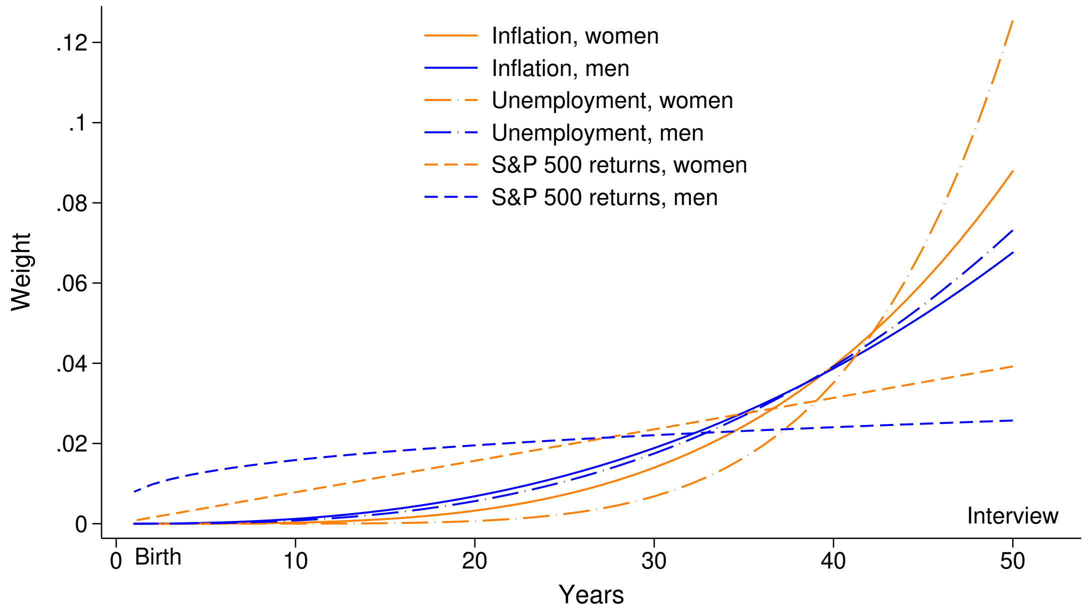

Figure 3: Model-implied gender differences in the weighting function of a 50-year-old respondent

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.

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 4 and 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 3, column 2). I estimate two different models: the

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

[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 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 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 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 6 and 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 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 ($\boldsymbol{\lambda}$)	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 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 3, column 2), providing additional support for the validity of the results.

Table 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 6 and 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 effect for

[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 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 ($\boldsymbol{\gamma}$) 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.

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.

6 Robustness

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

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, D2 and D3 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). 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 D2 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 D3 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.

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 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

A Questionnaire for price expectations

Figure A1 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).

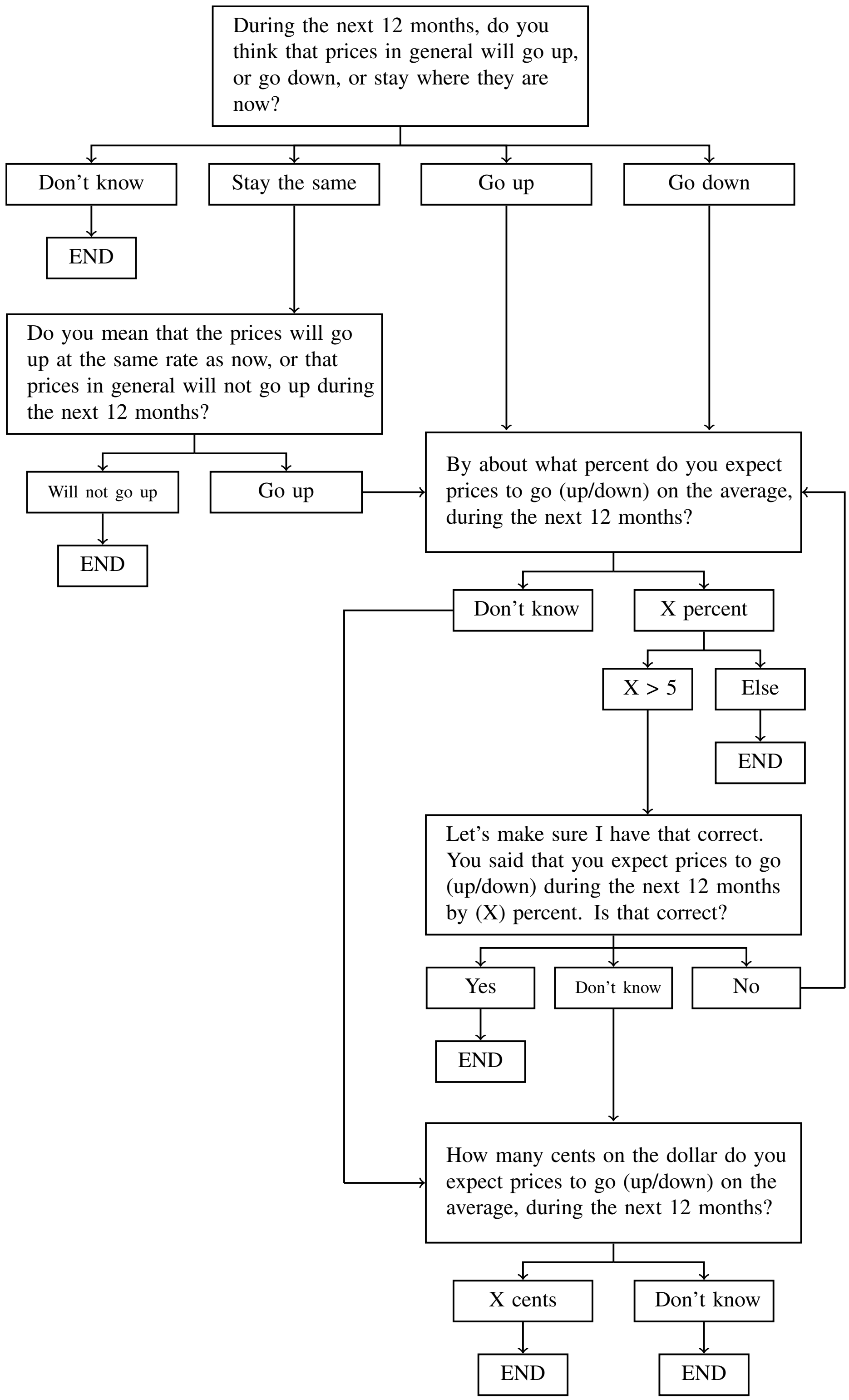

Figure A1: Questionnaire for short-run inflation expectations (px1)

B Direct effect of covariates

Table B1 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 3, 4 and 5, respectively.

Overall, Table B1 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: 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.

C Estimation of the Lasso model

Section 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:

$$\min_{(\beta,\gamma,\sigma)\in R^p} -\left[\sum_{i=1}^{N} \ln[\phi(y_{it}; \boldsymbol{w}_{it}\boldsymbol{\beta} A_{it}(\lambda^{fixed}) + \boldsymbol{x}_{it}\boldsymbol{\gamma}; \sigma)]\right] + \tau\left[||\boldsymbol{\beta}||_1 + ||\boldsymbol{\gamma}||_1\right] \tag{11}$$

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 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 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).

D Additional Figures and Tables

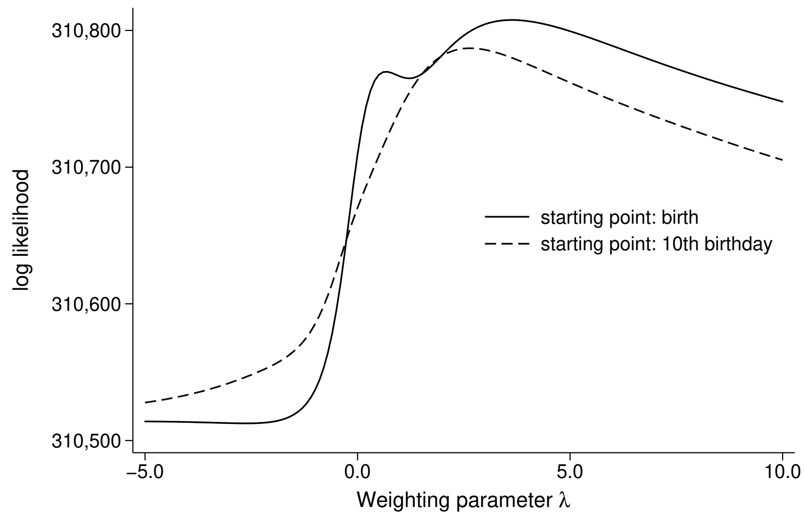

Figure D1: Log likelihood of model on inflation expectations for different values of the weighting parameter

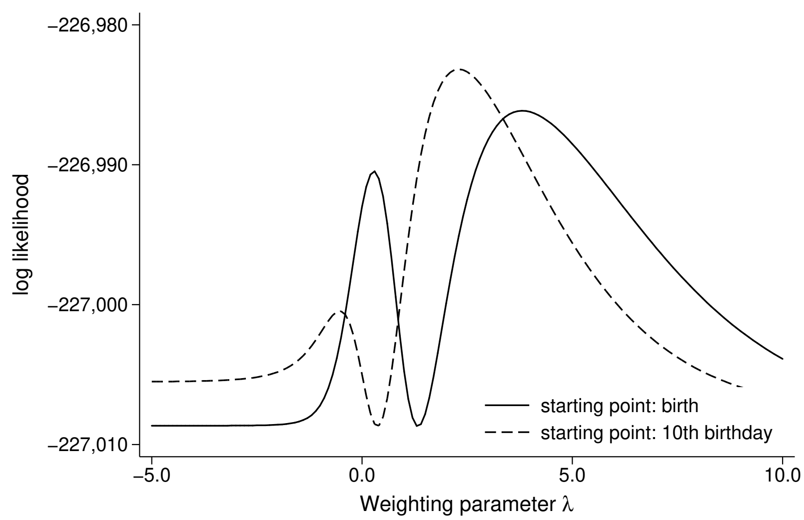

Figure D2: Log likelihood of model on unemployment expectations for different values of the weighting parameter

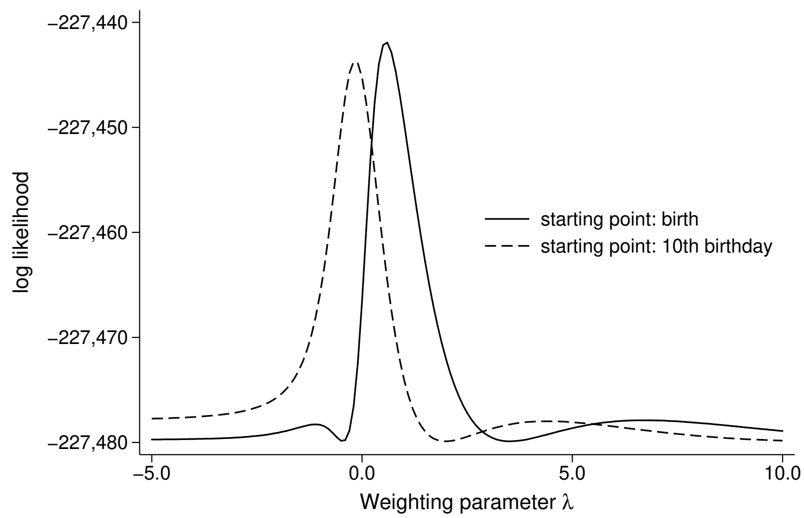

Figure D3: Log likelihood of model on business expectations for different values of the weighting parameter

Table D1: 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 6. Standard error in brackets are clustered at the individual level. *** p <0.01, ** p <0.05, * p <0.1.

Table D2: Model estimates for alternative outcomes measures of expectations

	Medium-run inflation expectations				Absolute business expectations			
	(1)		(2)		(3)		(4)	
Experience effect ($\boldsymbol{\beta}$)								
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 ($\boldsymbol{\lambda}$)								
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 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 D3: 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 ($\boldsymbol{\beta}$)						
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 ($\boldsymbol{\lambda}$)						
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.

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