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Beyond groceries: Forecasting confidence and the gender gap in inflation expectations

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Beyond Groceries: Forecast Confidence and the Gender Gap in Inflation Expectations*

Lovisa Reiche[†]

September 2025

This paper develops a theoretical framework to understand heterogeneity in inflation expectations. I integrate two mechanisms previously studied in isolation, exposure to salient prices and forecast confidence, within a Bayesian learning model. Empirically, I examine these mechanisms through the well-documented gender gap in inflation expectations. German and US household data confirm that forecast confidence is the dominant driver, while exposure to grocery prices matters only for low-confidence respondents. Forecast confidence is improved by financial literacy. Beyond gender, I provide a lens to study demographic heterogeneity, and show that salient prices exert greater influence during periods of elevated macroeconomic uncertainty.

Keywords Consumer Inflation Expectations, Gender, Confidence, Financial Literacy

JEL Codes E31, E71, G53, D84

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Introduction

The gender gap in inflation expectations is a well-documented phenomenon. Using Swedish survey data from 1977, Jonung (1981) first showed that women report significantly higher expected inflation. Subsequent research has confirmed the robustness of this finding across countries, survey methods, and experimental settings.¹ On average, the gender gap amounts to 2.6 percentage points in the US and 1.2 percentage points in Germany.² The prevailing explanation is that traditional gender roles expose women more to volatile grocery prices, leading them to overweight salient price increases (D’Acunto, Malmendier, & Weber, 2021). In this paper, I propose a complementary mechanism: forecast confidence. Consumers with low confidence hold flatter priors, making them more responsive to noisy signals. In this sense, traditional exposure matters only insofar as it interacts with confidence. Equalizing confidence could close the gender gap in expectations. Beyond gender, my mechanism offers a uniform lens through which heterogeneities in expectations can be understood and suggests that in times of low consumer confidence salient price signals play a larger role.

I formalize this intuition in a Bayesian framework with log-normally distributed signals and a conjugate log-normal prior. Exposure to higher grocery price volatility enters as higher signal variance, while flat priors correspond to low confidence. Volatile signals raise average expectations only when priors are flat, so low confidence amplifies the effect of noisy prices. Empirically, I use the Bundesbank Online Panel–Households (BOP-HH, 2019–2025), proxying forecast confidence via predicted rounding scores, motivated by linguistic evidence linking “round numbers” to “round interpretations” (C. C. Binder, 2017a; Krifka, 2007; Reiche & Meyler, 2022). Results show that equalizing confidence across genders closes the gap, while grocery shopping increases expectations primarily for low-confidence respondents. Findings are confirmed in the New York Fed Survey of Consumer Expectations (2013–2024) and the Michigan Survey of Consumers (1978–2025). Removing the top 20% of outliers eliminates the gender gap, consistent with the framework’s mechanism via the right-skew. Additional evidence shows that the gap persists among single households and does not widen during high food price inflation - both pointing towards a theory that does not rely solely on

¹See, e.g., Brischetto and de Brouwer (1999) for Australia; Bryan and Venkatu (2001) for Ohio; Palmqvist and Strömberg (2004) for Sweden; Pfajfar and Santoro (2010) for the US Michigan Survey; Blanchflower and MacCoille (2009) for the UK; Leung (2009) for New Zealand; Del Giovane et al. (2008) and Corduas (2022) for Italy; Bruine De Bruin et al. (2010) and Armantier et al. (2016) for the RAND American Life Panel; Arioli et al. (2017) and D’Acunto et al. (2024) for EU countries; D’Acunto, Malmendier, and Weber (2021) for the Chicago Booth Expectations and Attitudes Survey; Dräger and Nghiem (2020) for Germany; and Abildgren and Kuchler (2021) for Denmark.

²Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020–June 2025; Federal Reserve Bank of New York (FRBNY), SCE, June 2013–October 2024. Figure 1 illustrates the persistence of these gaps over time.

food price exposure.

Understanding the gender gap matters for both micro and macro outcomes. At the individual level, higher inflation expectations are linked to lower life satisfaction (Di Tella et al., 2001) and weaker retirement savings and stock market participation, with gender gaps well documented (Almenberg & Dreber, 2015; Cota et al., 2025; Lusardi & Mitchell, 2008; van Rooij et al., 2011). Higher expectations are also associated with greater perceived uncertainty (Reiche & Meyler, 2022), which can depress spending (Coibion, Georgarakos, Gorodnichenko, & van Rooij, 2023; Coibion et al., 2024). At the macro level, women account for roughly 70% of consumer spending in advanced economies (Silverstein & Sayre, 2009), making systematic differences salient for monetary policy. An emerging literature examines how central bank communication shapes household expectations (C. C. Binder, 2017b; Coibion, Georgarakos, Gorodnichenko, & Weber, 2023; Coibion, Gorodnichenko, et al., 2023; Coibion et al., 2020, 2022; Lamla & Vinogradov, 2019). Yet, women pay less attention to such communication and hold more negative views of central banks (McMahon & Reiche, 2024).

This paper contributes to two literatures: heterogeneity in inflation expectations due to signal exposure (Anesti et al., 2025; Cavallo et al., 2017; D’Acunto, Malmendier, Ospina, & Weber, 2021; D’Acunto & Weber, 2024; D’Acunto et al., 2024; Jonung, 1981; Malmendier & Nagel, 2016; Weber et al., 2022), and the role of education, financial literacy and uncertainty in shaping forecasts (Bruine De Bruin et al., 2010; Burke & Manz, 2014; D’Acunto, Hoang, et al., 2022; D’Acunto et al., 2019; Piccolo et al., 2025). I show empirically and theoretically that these strands are connected: the effect of exposure is conditional on confidence. More broadly, confidence gaps also arise across the age, income and education distribution (Bruine De Bruin et al., 2010; D’Acunto et al., 2023). I show that differences in forecast confidence explain a substantial fraction of expectation gaps also by other demographics. This suggests that the gender gap, while especially visible, is part of a broader pattern: forecast confidence acts as the common channel shaping heterogeneity in household expectations across demographic groups. In addition, my framework allows interpretation of other striking features in expectations surveys, such as the effect of incentivization on the demographic differences (Drobot et al., 2025) or how women’s beliefs typically are moved more in RCTs than men (Armantier et al., 2016; Coibion, Georgarakos, Gorodnichenko, & Weber, 2023; Coibion et al., 2022). Finally, I show that food prices, seen as the most important factor in forming expectations (Anesti et al., 2025), matter the most when macroeconomic uncertainty is high, in line with my framework. This adds to the literature on the formation of inflation expectations and monetary policy in different environments (Granziera et al., 2025; Pfäuti, 2024; Weber et al., 2025).

The remainder of the paper proceeds as follows. Section 1 introduces the Bayesian framework. Section 2 describes the data and measurement. Section 3 presents the main empirical results, highlighting confidence as the dominant driver and experience as secondary. Section 4 shows that financial literacy explains part of the confidence gap. Section 5 reports additional evidence in favor of the forecast confidence channel and Section 6 shows implications of the mechanism beyond gender. Section 7 concludes.

1 Bayesian Framework

I start with a Bayesian framework to illustrate the two hypothesized channels causing the gender gap in inflation expectations: exposure and confidence. I model differences in exposure, such as grocery shopping activity, as differences in the distribution of the signals received. An agent who visits grocery stores frequently observes more volatile prices as food prices are fundamentally more volatile than the core component of the consumption basket (see Appendix Figure B.1); hence, the agent will receive more volatile signals. On the other hand, I capture differences in confidence as differences in prior precision about future inflation. The framework highlights how these two channels work in isolation and that they interact. An agent with less confidence will place less weight on their own forecast and so signals matter more as they become the dominant source of information about inflation. I first present the basic framework and then explore the impact of changes in signal and prior precision. For simplification, the framework is shown for a representative agent.

Let θ denote inflation 12 months ahead, an unknown random variable. The representative agent’s prior belief about future inflation is assumed to follow a log-normal distribution, such that

$$\log \theta \sim \mathcal{N}\left(\mu_0, \frac{1}{\tau_0}\right).$$

Lower prior precision, i.e. a smaller τ_0 indicates lower confidence in the prior mean $\exp(\mu_0 + 1/(2\tau_0))$. The framework allows me to test the consequences of lower prior precision on the posterior mean and variance of an agent’s inflation expectation.

In addition, the agent receives a signal x about future inflation. Signals are unbiased but contain some noise, reflecting heterogeneity in inflation experiences given by heterogeneous consumption baskets,

$$\begin{aligned} \log x &= \log \theta + \epsilon, \\ \text{where } \epsilon &\sim \mathcal{N}\left(0, \frac{1}{\tau_x}\right). \end{aligned}$$

If the agent shops for goods with volatile prices (such as groceries, see Appendix Figure B.1)

she will receive signals with lower precision, i.e. with a smaller τ_x . Notice, that unbiasedness of signals allows me to show that signal volatility alone can affect mean expectations, such that purely by observing more volatile grocery prices an individual's inflation expectation can increase.

The log-normal prior is chosen because it is bounded at zero and features a heavy tail. This choice aligns with observations in the data: (1) there appears to be a zero lower bound in inflation expectations (Gorodnichenko & Sergeyev, 2021); (2) a majority of agents have expectations in line with central bank targets, but there are possible tail events to the right; (3) the average density forecast aligns with this choice (see Appendix Figure B.5). The right skew here serves a similar purpose as loss aversion in Dräger et al. (2014) where price increases contribute more to expectations such that variance increases the average. The signal about log inflation is unbiased and normally distributed. The asymmetry of the log-normal distribution is a key element of the framework. The framework can be extended to heterogeneous priors and biased signals as drivers of heterogeneous forecasts. The focus here is to show that gender gaps in precision of prior and signals are sufficient for gender gaps in expectations to emerge.

The agent updates her beliefs about θ based on the observed signal using Bayes' rule (see Appendix A),

$$\log \theta | x \sim \mathcal{N} \left(\hat{\mu}, \frac{1}{\hat{\tau}} \right),$$

where $\hat{\mu}$ represents the mean of the logged posterior inflation expectations and $\hat{\tau}$ the corresponding precision given by:

$$\hat{\mu} = \frac{\tau_0 \mu_0 + \tau_x \log x}{\tau_0 + \tau_x}, \quad (1)$$

$$\hat{\tau} = \tau_0 + \tau_x. \quad (2)$$

The expected value of θ under the posterior distribution is simply the mean of its posterior distribution. It depends directly on the precision of priors and signals and thus on the agents confidence in her own beliefs and the price signals she receives:

$$\mathbb{E}(\theta | x) = \exp \left(\hat{\mu} + \frac{1}{2\hat{\tau}} \right) = \exp \left(\frac{\tau_0 \mu_0 + \tau_x \log x + \frac{1}{2}}{\tau_0 + \tau_x} \right). \quad (3)$$

Similarly, the posterior variance is given by

$$\mathbb{V}ar(\theta|x) = \left[\exp\left(\frac{1}{\hat{\tau}}\right) - 1 \right] \exp\left(2\hat{\mu} + \frac{1}{\hat{\tau}}\right) \quad (4)$$

$$= \left[\exp\left(\frac{1}{\tau_0 + \tau_x}\right) - 1 \right] \exp\left(\frac{2\tau_0\mu_0 + 2\tau_x \log x + 1}{\tau_0 + \tau_x}\right). \quad (5)$$

The framework can be used to explain heterogeneity in observed point forecasts as well as density forecasts, particularly those between men and women. I show comparative statics for the effects of shocks to prior precision and signal variance. While using a representative agent framework for illustrative purposes, the framework can easily be interpreted as featuring two groups of agents. For instance, let women experience greater shocks to both prior precision and signal volatility due to lower forecast confidence and greater exposure to volatile food prices.

Beginning with the role of shopping experience, I assume that the composition of an agent's shopping basket may affect the signal precision parameter τ_x . Shopping for groceries is connected to a lower τ_x in line with historical food prices showing a larger variance than the overall basket. Further, the signal is assumed to be unbiased to reflect that groceries have the same level of inflation as other goods on average. The distribution of historical inflation of food prices and the total index for the US and Germany can be found in Appendix Figure B.1. The framework reveals that the expected inflation expectation as well as the variance thereof³ is increasing in signal volatility whenever $\log x$ exceeds μ_0 by less than half of the prior variance $\frac{1}{\tau_0}$.

$$\frac{d\mathbb{E}(\theta|x)}{d\tau_x} < 0 \iff \log x - \mu_0 < \frac{1}{2\tau_0} \quad (6)$$

Notice that the condition in (6) will always be satisfied when $\mu_0 > \log x$. This indicates that when consumers prior expectations exceed the signal, making the signal more volatile will always increase expectations since the signal becomes less reliable. In other words, those with high prior expectations do not revise them downwards if the price signals they receive become more volatile. Further, the condition relaxes when the prior is flat, i.e., prior precision τ_0 is small, such that the agent relies more on the signals received. When priors are sufficiently flat, the agent may revise her expectations upwards as signals become more volatile even when signals on average exceed the prior.

³Appendix A shows that the condition for the posterior variance to increase with signal volatility is weaker than for the posterior mean.

Further, equation 4 shows that under condition 6 it will also always be the case the variance is increasing in signal volatility. This is the case because the first term of equation 4 is monotonically increasing in $\frac{1}{\tau_x}$ while the second term is increasing under the same condition as the posterior mean in equation 3 (full proof in Appendix A).

Proposition 1.1 *Consumer inflation expectations (and the uncertainty thereof) are increasing in signal volatility whenever $\log x - \mu_0 < \frac{1}{2\tau_0}$. This condition has two features:*

1. *The condition is always satisfied when average prior expectations exceed the average of the signal $\mu_0 > \log x$.*
2. *The condition relaxes when priors are imprecise and τ_0 is small.*

In summary, under the assumption of a log-normal signal and its conjugate prior, increases in the noise of the signals can indeed increase the expected value of the posterior distribution. This is the case because it increases the variance of the right-skewed density forecast. This captures and formalizes the argument of the exposure hypothesis (D’Acunto, Malmendier, & Weber, 2021): women observing higher volatility through higher observed food prices have increased inflation expectations. However, this is facilitated by small prior precision. In contrast, a tight prior may cause mean expectations to decrease when the environment is noisier. Thus, it is important to analyze the consequences of prior heterogeneity, which may be caused by different levels of confidence.

Forecast confidence may impact the parameters of the prior distribution μ_0 and τ_0 such that an agent with lower confidence has a flatter prior, i.e. a lower τ_0 . It has been shown that women have lower financial confidence (Bucher-Koenen et al., 2024).⁴ Intuitively, individuals with low financial confidence may have a less formalized idea of price changes when observing prices. Subsequently, I will discuss the comparative statics of a decrease in τ_0 on $\mathbb{E}(\theta|x)$. The computations can be found in Appendix A.

$$\frac{d\mathbb{E}(\theta|x)}{d\tau_0} < 0 \iff \mu_0 - \log x < \frac{1}{2\tau_x} \quad (7)$$

Heterogeneity in priors can give rise to heterogeneous expectations even when signals received are identical. Reduced prior precision will always increase average expectations when signals exceed the prior. Similar to before, this makes the agent rely less on own forecasts and so the higher signals transmit directly to the expectations. Just as condition (6) relaxes with

⁴The authors show that women perform equally well in financial literacy tests when no “don’t know” answer is provided, but worse when such option is not available.

the prior being flat, condition (7) relaxes when signals are imprecise. Further, just as in the case of increased signal volatility, the same condition also ensures that the posterior variance will increase for the same reason as above.

Proposition 1.2 *Consumer inflation expectations (and uncertainty thereof) are increasing in prior imprecision whenever $\mu_0 - \log x < \frac{1}{2\tau_x}$. This condition has two features:*

1. *The condition is always satisfied when signals exceed the average of the prior $\log x > \mu_0$.*
2. *The condition relaxes when signals are volatile and τ_x is small.*

In the Bayesian framework with log-normal priors and signals, noisy environments caused by grocery shopping and low confidence can individually be a cause for higher inflation expectations. Moreover, they interact: The framework shows that noisy signals increase expectations when priors are flat. Simultaneously, low confidence (modeled as flat priors) increases expectations when signals are imprecise.

The conditions reveal that there is a combination of values for $\log x$, μ_0 , τ_x and τ_0 for which both conditions, (6) and (7) hold: $\mu_0 \in [\log x - \frac{1}{2\tau_0}, \log x + \frac{1}{2\tau_x}]$. Outside of this interval at least one of the conditions will always hold.

Proposition 1.3 *For a given $\log x$, whenever $\mu_0 \in [\log x - \frac{1}{2\tau_0}, \log x + \frac{1}{2\tau_x}]$ the agent's inflation expectation $\mathbb{E}(\theta|x)$ are increasing in both, higher signal volatility $\frac{1}{\tau_x}$ and prior imprecision $\frac{1}{\tau_0}$. Otherwise, the agent's inflation expectation $\mathbb{E}(\theta|x)$ are increasing in either higher signal volatility $\frac{1}{\tau_x}$ or prior imprecision $\frac{1}{\tau_0}$.*

The framework is well suited to explain the interaction of the two channels hypothesized to explain the gender gap in inflation expectations. It shows that if women on average observe more volatile price signals through greater involvement in grocery shopping, they may have higher expectations than men. Similarly, if women on average have lower confidence about their own forecasts they could also have higher expectations. Both channels complement each other: observing volatile prices will increase expectations when the individual is less confident. This makes sense intuitively if those confident about inflation rely more on aggregate news while others rely more on their day-to-day experiences.

1.1 Structural Calibration of Confidence

The Bayesian learning framework delivers sharp comparative statics: noisy food-price signals raise expected inflation only when priors are imprecise and right-skewed. To assess whether this mechanism can plausibly account for the observed gender gap in the data, I conduct a

simple calibration exercise. I map posterior mean and interquartile range (observed in the survey through point and density forecasts) to τ_0 and τ_x for men and women separately, holding μ_0 fixed at 2% inflation. I then test whether equalizing the prior precision for men and women (while holding the calibrated signal precision fixed) has the potential to close the gender gap and find that it does.

I target two moments of the cross-sectional distribution of expectations separately for men and women in Germany (BOP-HH) and the US (SCE): the mean of point forecasts, i.e. the average posterior mean and the mean individual interquartile range (IQR) of density forecasts, i.e. the average posterior interquartile range. The measurement of both variables will be explained in more detail in the next section. The model generates corresponding moments by simulating draws of the true inflation rate θ , signals x , and posterior beliefs. Specifically, I draw

$$\log \theta \sim \mathcal{N}(\mu_0, \frac{1}{\tau_0}), \quad \log x = \log \theta + \varepsilon, \quad \varepsilon \sim \mathcal{N}(0, \frac{1}{\tau_x}),$$

and compute the posterior mean

$$E[\theta \mid x] = \exp\left(\hat{\mu} + \frac{1}{2\hat{\tau}}\right),$$

as well as the posterior IQR

$$\text{IQR}(\theta \mid x) = \exp\left(\hat{\mu} + \frac{\Phi^{-1}(0.75)}{\sqrt{\hat{\tau}}}\right) - \exp\left(\hat{\mu} + \frac{\Phi^{-1}(0.25)}{\sqrt{\hat{\tau}}}\right),$$

from the lognormal distribution implied by $(\hat{\mu}, \hat{\tau})$ ⁵. I fix $\mu_0 = \log 2$ as the average prior mean of inflation and choose parameters (τ_0, τ_x) to minimize the squared distance between simulated and empirical moments.

The calibrated model reproduces the gender gap in average expectations with striking accuracy in both the US and Germany (Table 1). The empirical mean forecast of women exceeds that of men by 1.22 (Germany)/2.61 (US) percentage points. The model with gender-specific τ_0 values generates an actual gap of 1.24 (Germany)/2.35 (US) percentage points. When I equalize prior precision across genders (applying the estimated τ_0 for men) while holding signal precision fixed, the gap essentially disappears. This implies that differences in τ_0 , interpreted as forecast confidence, explain more than/almost the entire empirical gender gap: the share explained is 108% in Germany and 93% in the US. Bootstrap confidence

⁵ $\hat{\mu} = \frac{\tau_0 \mu_0 + \tau_x \log x}{\tau_0 + \tau_x}, \quad \hat{\tau} = \tau_0 + \tau_x$

intervals confirm the precision of these estimates: in Germany the share of the gap explained by τ_0 lies between 0.71 and 1.35 at the 95% level, while in the US the corresponding interval ranges from 0.79 to 1.06.

Table 1: Simulation Exercise

	BOP-HH, Germany		SCE, US	
	Men	Women	Men	Women
Model τ_0	0.57	0.45	0.60	0.40
Model τ_x	8.22	9.39	1.27	1.32
Model Actual Gap		1.24		2.35
Empirical Gap		1.22		2.61
Equalized Gap		-0.07		-0.07
Share Explained by τ_0		1.08		0.93

Notes: The table reports calibrated values of prior precision τ_0 and signal precision τ_x by gender, obtained by moment-matching the mean and interquartile range of inflation expectations in the BOP-HH and the SCE. “Model Actual Gap” is the difference in mean expectations generated by the calibrated model, “Empirical Gap” is the observed survey difference, and “Equalized Gap” sets women’s τ_0 equal to men’s while keeping τ_x fixed. The “Share Explained by τ_0 ” reports the proportion of the empirical gap accounted for by differences in prior precision.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; Federal Reserve Bank of New York (FRBNY), SCE, June 2013 - October 2024; own calculations

This calibration demonstrates that the mechanism proposed by the model is quantitatively consistent with the data. Lower prior precision among women suffices to reproduce the higher mean expectations observed in survey responses. Once priors are equalized, exposure to noisy food-price signals no longer generates a persistent gap. These results provide structural validation of the reduced-form evidence presented in the next section: forecast confidence is not only statistically but also quantitatively sufficient to account for the gender gap in inflation expectations.

2 Data and Estimation

My primary data source is the Bundesbank Online Panel of German consumers from April 2019 until June 2025 (Fischer et al., 2025).⁶ This survey is particularly suited to analyze the gender gap in inflation expectations because it contains individual-level data on household

⁶Disclaimer: The results published and the related observations and analysis may not correspond to results or analysis of the data producers.

Table 2: Features of the three surveys

Survey	Time/Place	Participants	Wording
BOP-HH	Apr.2020-Jun.2025, DE + Apr.2019-Jun.2019	2000/month	<i>inflation/deflation</i> + (definition) from 0-100 + Probabilistic bins for inflation + Financial literacy test + Household responsibilities
SCE	Jun.2013-Oct.2024, US	1200/month	<i>inflation/deflation</i> from 0-100 + Probabilistic bins for inflation + Financial literacy test
MSC	Jan.1978-Jan.2025, US	500/month	<i>prices in general</i> from 0-95, probing > 5%

responsibilities including grocery shopping alongside more standard questions such as a probabilistic elicitation of inflation expectations and a financial literacy test, thus allowing me to test all hypotheses on the same individuals. The BOP-HH has been conducted regularly since April 2020, and I use data up to June 2025. In addition, I include three months of pilot data collected from April to June 2019. Approximately 2000 participants are initially drawn randomly from a larger pool of candidates recruited via telephone. Participants complete an online survey with various questions ranging from macroeconomic assessments and expectations to political issues. Demographic characteristics are recorded by self-assessment; therefore, the terms “female” and “women” in my analysis refer to self-identified gender. The survey includes the option to not choose a binary gender and few candidates do so; these responses are excluded here. I also exclude all participants who do not give an inflation point forecast.

I complement this survey with two established consumer surveys, the Michigan Survey of Consumers in the US from June 1978 until January 2025 (MSC, Survey Research Center, 2025); and the Survey of Consumer Expectations in the US from June 2013 until October 2024 (SCE, Federal Reserve Bank of New York, 2024).⁷ Adding these surveys allows me to explore a longer time horizon than the short period of the BOP-HH, which was also heavily influenced by the Covid-19 pandemic, and provides external validity by benchmarking results for the US. All surveys are summarized in Table 2 and summary statistics of the demographics can be found in Table 3 Panel A. Women in all surveys have marginally lower education and substantially lower reported household incomes. They are of similar age as men in the surveys.

⁷Disclaimer: FRBNY did not participate in or endorse this work, and FRBNY disclaims any responsibility or legal liability for the administration of the survey and the analysis and interpretation of data collected.

2.1 Measuring inflation point forecasts and uncertainty

The literature has established that there are gender gaps in inflation point forecasts (Bryan & Venkatu, 2001; D’Acunto, Malmendier, & Weber, 2021; Jonung, 1981). The framework discussed above highlights that these gaps can arise through greater posterior variance in a right-skewed distribution caused by volatile signals or imprecise priors. Before discussing how to measure signals and priors, I focus on my measure of mean inflation expectations, i.e. posterior mean, and the uncertainty around them, i.e. a proxy measure of the posterior variance on the individual level.

Inflation expectations in all three surveys are measured quantitatively. In the BOP-HH, individuals are presented with a short definition of inflation⁸ and are asked if they expect inflation or deflation in the next 12 months. Subsequently, they indicate their anticipated inflation or deflation rate numerically. The answers are limited to a range of 0 to 100. The SCE skips this definition but the wording remains the same while the MSC instead asks for prices in general. This can cause respondents to increase their forecast and is a less precise measure of inflation expectations (Armantier et al., 2013). Further the MSC probes answers when respondents give a numerical value above 5%. I assume that the point forecast represents the mean of the respondents forecast in line with previous literature (Armantier et al., 2013).

Additionally, BOP-HH and SCE elicit uncertainty around the point forecast through probabilistic bins. Respondents are asked to assign probabilities to ranges or intervals of possible future inflation realizations. The lowest bin is smaller than -12% and the highest is higher than 12%. There are 10 bins in total. Appendix Figure B.5 shows the average density forecast in the BOP-HH. I use the probabilities of the reported bin to fit an underlying parametric density following the approach of Engelberg et al. (2009) and applied to the SCE as described in Armantier et al. (2017). My uncertainty measure is the interquartile range of the density forecast, defined as the difference between the third and first quartile. This is preferred to the standard deviation as it is more robust to outliers.

Table 3 compares mean (π^E_point) and interquartile range (π^E_intqr) of inflation forecasts in Panel B. As anticipated, women hold both substantially higher point forecasts as well as greater uncertainty around them. This is confirmed also in Figure 1 which shows the differences in means (purple line) over time. The gap shrinks when outliers are removed

⁸Inflation is the percentage increase in the general price level. It is mostly measured using the consumer price index. A decrease in the price level is generally described as “deflation”. The inflation question is asked before other questions in the survey.

(green line)⁹ but remains persistently positive even when controls for demographics such as age, income and education are included (yellow).

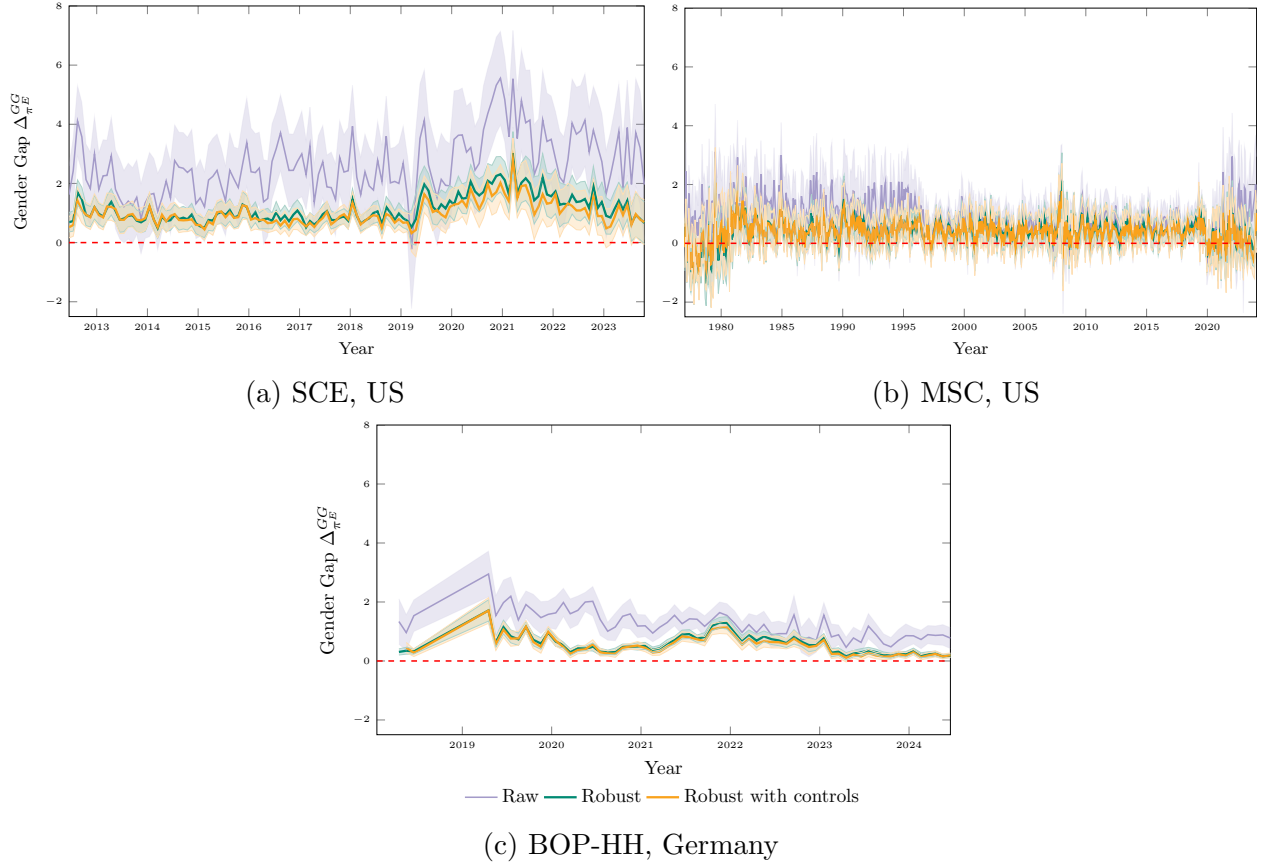


Figure 1: The gender gap raw, robust, and controlled for demographics over time

Notes: Estimated regression coefficients for the dummy variable *female* in an OLS regression with no controls (purple line), Huber robust regression with no controls (green line) and with all demographics controls available in a Mundlak CRE specification (yellow line). These include: age, income, education, single, unemployed, retired, full-time work, part-time work, homemaker, and region controls.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; Federal Reserve Bank of New York (FRBNY), SCE, June 2013 - October 2024; University of Michigan, Survey Research Center, MSC, January 1978 - January 2025; own calculations

Observation 2.1 *There is an gender gap in inflation expectations in both means (point forecasts) and uncertainty around those forecasts. The gap is robust to including demographic controls and removing outliers.*

⁹**female**-coefficient in Huber robust regression

2.2 Measuring experience

Inference of differentiated experience is possible in the BOP-HH due to a question regarding household responsibilities introduced in April 2021, namely everyday purchases (`shop_groceries`) and financial decisions (`decide_finance`). Respondents indicate whether they are not involved in the task (0), engage jointly with other household members (0.5) or are solely responsible for all work (1). I use the gradual ranking to differentiate between sole and joint responsibility as recommended in van Hove and Verbraecken (2025). The focus of this analysis is the variable `shop_groceries` as it is a direct measure of whether an individual frequently observes food prices. Since the question is only asked for the first time an individual participates in the survey, I must assume that household chores remain constant over time in the panel. Further, the variable is only asked for non-singles. Whenever grocery shopping is used in the analysis I include only households with more than one member. However, I use singles as an alternative robustness measure observed also in SCE and MSC as the men and women in the single sample are assumed to engage symmetrically in grocery shopping.

The data reveal that traditional gender norms are still present in German households. Table 3 Panel C compares grocery shopping and financial decision making for men and women. As expected, women appear significantly more involved in grocery shopping in households that involve more than one member. Men in the data are less likely to live alone. However, I note that financial decision making is split equal between German and US couples, hence women make most purchasing decisions and are equally involved in the spending and investment decisions, making them a relevant group to analyze.

Observation 2.2 *Traditional gender norms persist in Germany. Women in the BOP-HH are more often responsible for grocery shopping in households with more than one member.*

2.3 Measuring confidence and financial literacy

I measure individual forecast confidence using a simple proxy drawn from the linguistics literature: rounding to multiples of five. According to the “Round Numbers, Round Interpretations” hypothesis (Krifka, 2007), individuals with low confidence in their ability to provide a precise value tend to report the nearest round number. Applied to inflation expectations, this implies that less confident respondents may predict values in multiples of five such as 0, 5, or 10 rather than more precise figures. Building on this idea, C. C. Binder (2017a) and Reiche and Meyler (2022) use the share of “rounders” in survey data to construct indices of macroeconomic uncertainty. A similar application for professional forecasters can

be found in Glas and Hartmann (2022) though rounding is of smaller importance for professionals (Clements, 2021). I treat rounding, i.e. coarseness in forecasts, as a signal of low confidence in one’s own forecast, consistent with the notion of prior imprecision. The literature supports this measure: Ruud et al. (2014) show experimentally that (prior) uncertainty causes rounding and Reiche and Meyler (2022) show that, in a European survey, fewer than 2% of respondents who reported a multiple of five actually intended that number precisely, implying that classifying such responses as “low confidence” entails minimal misclassification. Rounding is also prevalent in probabilistic survey questions (Manski & Molinari, 2010) and for the BOP-HH, Dovern and Glas (2025) find that less than half of respondents insist that their rounded bin forecast reflects actual expectations. My measure of forecast confidence contrasts with posterior uncertainty, which I measure using the interquartile range of probabilistic bins, as described above. Further, forecast confidence differs slightly from concepts such as overconfidence in finance (Anderson et al., 2017; Moore & Healy, 2008) as it only measures the precision of prior beliefs and not the (mis)perceived precision of posterior forecasts. However, there are also known gender gaps in overconfidence (Barber & Odean, 2001) and precision in financial questionnaires (Anderson et al., 2017) which supports my findings. Most respondents provide non-rounded answers, but Table 3 reveals a clear gender gap, with women rounding more frequently in all three surveys.¹⁰

I use rounding as the baseline proxy for confidence but refine it by predicting rounding with other variables correlated with survey uncertainty, thereby filtering out influences unrelated to prior uncertainty, such as attention. Specifically, I incorporate responses to questions about how “easy” or “interesting” the survey was, as well as whether the respondent is a repeated participant (Kim & Binder, 2023) (summarized in $X_{i,t}$ in Equation 8). In addition, I include indicators of rounding in other questions—house price expectations, interest rate expectations (in the BOP-HH), and government debt expectations (in the SCE)—all asked 12 months ahead (summarized in $R_{i,t}$ in Equation 8). I then estimate a logistic regression predicting the probability of rounding in inflation expectations (coefficients reported in Appendix Table 10). The predicted probability exhibits a gender gap of similar magnitude to that found in the raw rounding measures. For the analysis that follows, I invert this measure

¹⁰This pattern differs from Reiche and Meyler (2022), who report that only about 25% of respondents gave precise forecasts in 2019 and later. One explanation may be data source differences: the European Commission Consumer Survey records an inflation expectation of zero for all respondents who qualitatively state that inflation will “stay about the same.” By contrast, the BOP-HH and SCE do not directly link qualitative and quantitative questions. This reduces the share of “zero” responses, which are classified as “rounders” in their analysis.

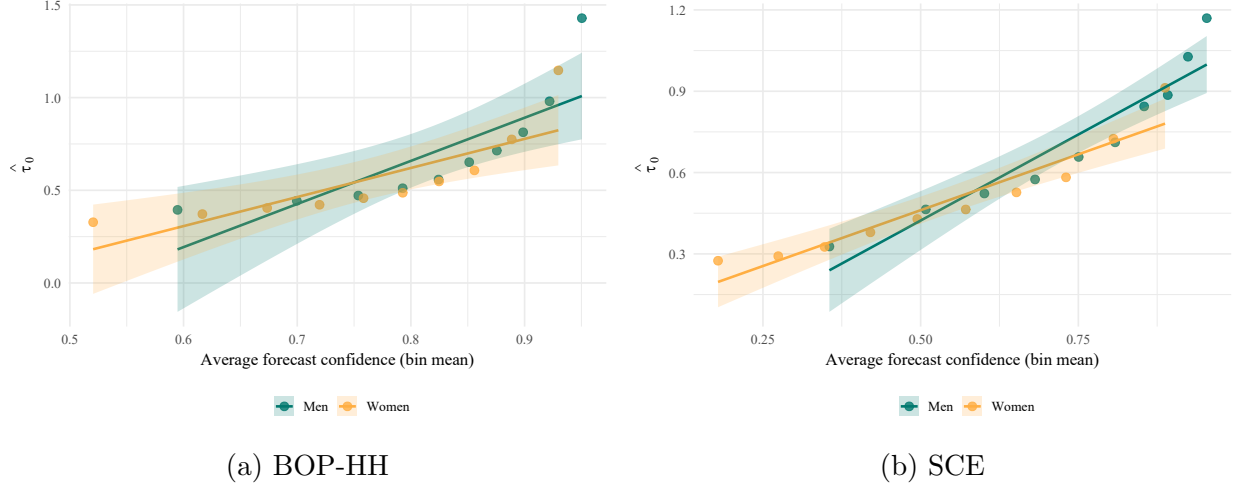


Figure 3: Confidence score and calibrated precision

so that higher values correspond to greater forecast confidence (i.e., 1 = high confidence).

$$\text{prob_confident}_i = 1 - \frac{1}{1 + e^{-(\hat{\alpha}_0 + R_{i,t}\hat{\beta} + X_{i,t}\hat{\gamma})}}. \quad (8)$$

I validate my measure of prior uncertainty by linking it to posterior uncertainty and to the model-implied prior precision. First, I test the correlation between my confidence score and posterior uncertainty, measured by the interquartile range (IQR) of density forecasts. As expected, the two are negatively and significantly correlated (Spearman's $r = -0.25$, $p < 0.001$; for the SCE $r = -0.37$, $p < 0.001$).

Second, I examine how my confidence index maps into the prior precision parameter τ_0 from the calibration exercise described above. To do so, I group respondents into deciles of forecast confidence, re-estimate the average τ_0 for each group, and plot the resulting relationship in Figure 3. The figure shows a strong and statistically significant positive correlation: higher values of my confidence index correspond to higher estimated prior precision, both in the BOP-HH and the SCE. This supports the interpretation of my confidence measure as capturing prior imprecision.

Table 3 Panel D shows that there are gender gaps in all confidence measures: actual rounding, predicted confidence measured as described above and survey feedback. While rounding is available also in the Michigan survey, the predicted confidence measure is not appropriate to be used in this context for two reasons. First, it probes everyone above 5% which leads to most responses being between 0 and 5 and thus by definition not rounded. Secondly, I am missing the other measures of survey uncertainty used above and thus cannot

filter out other factors causing rounding such as attention.

Finally, I show that a lack of confidence as measured by rounding is a symptom of lower financial literacy of women. I utilize data from the BOP-HH and SCE, which include micro-level financial literacy via a standardized financial literacy test (Lusardi & Mitchell, 2014).¹¹ I assign a score of 1 if a respondent answers all three questions covering compound interest, inflation, and risk correctly. Correct answers earn one point each, while “don’t know” responses are marked as incorrect. Table 3 Panel D confirms previous literature that has shown that women are significantly less likely to obtain three correct answers (Bucher-Koenen et al., 2017; Lusardi & Mitchell, 2008).

Observation 2.3 *Women have lower confidence in their survey forecasts, find surveys on inflation less interesting/easy and perform worse in standardized financial literacy tests.*

3 The Effects of Confidence and Grocery Price Exposure

Heterogeneity in experiences and in confidence are not mutually exclusive hypotheses for explaining the gender gap in inflation expectations. The Bayesian framework in Section 1 demonstrates that these parameters are complementary: low confidence increases the impact of experiences, and the effect of a flat prior is amplified when signals are noisy. I start by demonstrating that confidence is the dominating driver of the gender gap before showing that exposure does matter, but only through the lens of forecast confidence.

3.1 Forecast confidence dominates exposure

To test how the gender gap in inflation expectations evolves for different levels of forecast confidence and grocery price exposure, I interact predicted confidence with the female dummy. Similarly, I include grocery shopping and interact it with the female dummy:

$$\begin{aligned}\pi_{i,t}^E = & \beta_0 + \beta_1 female_i + \beta_2 prob_confident_{i,t} + \beta_3 shop_groceries_i \\ & + \beta_4 prob_confident_{i,t} \times female_i + \beta_5 shop_groceries_i \times female_i \\ & + X_{i,t}\gamma_1 + D_t\gamma_2 + R_i\gamma_3 + v_i + \rho_t.\end{aligned}\tag{9}$$

In the regression model above, $\pi_{i,t}^E$ denotes individual i ’s inflation expectations 12 months ahead (point forecast) at time t . The vector $X_{i,t}$ contains demographic characteristics (age, income, education, full-time, part-time, unemployed, retired, homemaker, refresher), D_t captures time dummies, and R_i includes regional dummies. I restrict the sample to respondents in non-single households, where the grocery shopping question is asked.

¹¹Questions in Appendix D

Table 3: Summary Statistics for Men and Women

	BOP-HH		SCE		MSC	
	Men	Women	Men	Women	Men	Women
Panel A: Demographics						
age	56.39 (15.46)	55.82 (15.64)	51.79 (15.24)	48.71 (15.57)	47.22 (17.22)	47.79 (17.51)
educ	8.83 (3.45)	8.11 (3.41)	4.55 (1.53)	4.36 (1.5)	4.17 (1.29)	3.99 (1.26)
hhinc	7.87 (25.52)	7.45 (61.82)	7.16 (2.65)	6.11 (2.75)	74 (28)	53 (60)
Panel B: Inflation forecasts						
π^E_point	4.78 (5.62)	6 (8.35)	4.63 (9.43)	7.24 (15.68)	4.06 (5.51)	5.01 (7.25)
π^E_intqr	2.07 (2.3)	2.49 (2.97)	3.63 (3.85)	5.27 (5.38)		
Panel C: Household responsibilities						
shop_groceries	0.6 (0.39)	0.83 (0.3)				
decide_finance	0.76 (0.28)	0.73 (0.31)	0.66 (0.21)	0.7 (0.25)		
single	0.22	0.3	0.28	0.45	0.21	0.3
Panel D: Financial literacy and survey confidence						
round. π^E_point	0.18	0.25	0.27	0.46	0.42	0.54
prob_confident	0.82 (0.11)	0.76 (0.12)	0.73 (0.19)	0.54 (0.22)	(0.21)	(0.2)
fin_lit	0.85 (0.36)	0.78 (0.42)	0.38 (0.49)	0.22 (0.42)		
qeasy	0.32 (0.3)	0.3 (0.31)				
qinterest	0.46 (0.33)	0.39 (0.34)	0.36 (0.5)	0.31 (0.52)		
refresher	0.78	0.76	0.87	0.86	0.37	0.37

Standard deviation in parentheses, omitted for dummy variables.

Notes: Panel A: Education is measured categorically from 1-14 in the BOP-HH where it is the sum of school education (1-6) and professional education (1-8), 1-8 in the SCE and 1-6 in the MSC. Household income is categorical for BOP-HH (1-13) and SCE (1-11) and in thousands for MSC.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; Federal Reserve Bank of New York (FRBNY), SCE, June 2013 - October 2024; University of Michigan, Survey Research Center, MSC, January 1978 - January 2025; own calculations

To address potential correlation between unobserved individual effects and the regressors in an unbalanced panel, I adopt the correlated random effects approach of Mundlak (1978). Concretely, I augment the specification with the individual-level means of the time-varying covariates in $X_{i,t}$. This allows consistent estimation of coefficients for both time-varying and time-invariant regressors (such as `femalei` or `shop_groceriesi`). For robustness, I estimate the models using Huber-robust regression (Huber, 1964), which down-weights the influence of outliers and relaxes the classical assumptions on the error term (e.g., homoskedasticity). Applying this robust estimator reduces the estimated gender gap by about 50%, implying that the baseline results should be interpreted as lower bounds (see Figure 1).

The results are summarized in Table 4. The interaction term of confidence and female is significantly negative in all three surveys. It shows that for average values of confidence for women (0.76 in the BOP-HH and 0.54 in the SCE, see Table 3) the gender gap is closed. This indicates that women with low confidence have much higher expectations than their male counterparts but those with high confidence behave similar to men. In addition, I find that grocery shopping on its own has a positive and significant effect on inflation expectations as estimated in D’Acunto, Malmendier, and Weber (2021) which is even stronger for women. Robustness checks with alternative measures for exposure and confidence that verify these results can be found in Appendix Table 13. For exposure, I test the interaction of `single` with `female` and find that male singles in the SCE actually have lower inflation expectations than those in larger households suggesting that being more exposed to supermarket prices has no positive effect for inflation expectations for men. In contrast, for alternative measures of forecast confidence, namely rounding and survey feedback, I find effects pointing in the same directions and my forecast confidence measure (though less sizable). The gender gap is larger among those who round and similarly, smaller among those who find the survey easier (both in line with being lower among those who are confident).

To assess the relative contributions of forecast confidence and grocery shopping to the gender gap, I implement a Kitagawa-Oaxaca–Blinder decomposition (Blinder, 1973; Kitagawa, 1955; Oaxaca, 1973) common in the literature on gender wage gaps (Blau & Kahn, 2017). Specifically, I estimate separate regressions for men and women, where individual i ’s inflation expectation at time t ($\pi_{i,t}^E$, point forecast 12 months ahead) is regressed on household characteristics $X_{i,t}$, along with time and regional fixed effects. Estimation is carried out using the Mundlak correlated random effects framework with Huber-robust regression. Let $\bar{W}$ and $\bar{M}$ denote the vectors of average covariate values for the female and male samples, respectively, and $\hat{\gamma}_w$ and $\hat{\gamma}_m$ the corresponding estimated coefficients. These inputs are then used to decompose the observed gender gap in expectations into parts attributable to

Table 4: Effect of confidence and grocery shopping on the gender gap

	Inflation expectation (12 months ahead, point estimate)			
	BOP-HH		SCE	
	(1)	(2)	(3)	(4)
female	0.36*** (0.07)	0.32*** (0.02)	0.23*** (0.08)	2.13*** (0.07)
prob_confident	-10.97*** (0.08)		-10.97*** (0.08)	-3.69*** (0.09)
prob_confident:female	-0.52*** (0.09)		-0.50*** (0.09)	-2.93*** (0.10)
shop_groceries		0.04** (0.02)	0.03* (0.02)	
shop_groceries:female		0.22*** (0.03)	0.14*** (0.03)	
Constant	11.28*** (0.20)	2.92*** (0.20)	11.27*** (0.20)	7.52*** (0.15)
Observations	155,203	155,202	155,202	108,961
Residual Std. Error	1.64	1.72	1.64	2.67

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

Robust Robust standard errors in parentheses.

Notes: Mundlak CRE specification; Huber-robust regression. All regressions incorporate demographic controls, regional controls and time fixed effects. Singles are excluded in all models.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; Federal Reserve Bank of New York (FRBNY), SCE, June 2013 - October 2024; own calculations

differences in characteristics versus a residual, unexplained gap:

$$\pi_{i,t}^E = \beta_0 + X_{i,t}\gamma_1 + D_t\gamma_2 + R_i\gamma_3 + v_i + \rho_t, \quad (10)$$

$$\bar{\pi}_w^E - \bar{\pi}_m^E = \underbrace{\hat{\gamma}_w(\bar{W} - \bar{M})}_{\text{explained by differences in } \bar{W}, \bar{M}} + \underbrace{\bar{M}(\hat{\gamma}_w - \hat{\gamma}_m)}_{\text{residual}}. \quad (11)$$

Figure 4a presents the Kitagawa–Oaxaca–Blinder decomposition for four model specifications in the BOP-HH. The first (baseline) model includes only demographic controls and a time dummy. In this case, the explained component reflects differences in age, education, or income distributions, while differences in grocery shopping involvement or forecast confidence fall into the unexplained component. The second model adds grocery shopping as a regressor, and the third adds forecast confidence. Grocery shopping alone accounts for roughly 11% of the total gender gap, while confidence alone explains about 110%—that is, it more than fully accounts for the observed difference. The fourth model includes both variables simultaneously. In this specification, the explained share rises but by less than the sum of the individual contributions, indicating that grocery shopping and confidence interact rather than contributing independently. This will be explored in more detail in the next section.

As a robustness check, I implement a parallel mediation model (MacKinnon, 2012; Tingley et al., 2014). Unlike the Kitagawa–Oaxaca–Blinder decomposition, this approach treats the total gender gap (β_1 in Equation 12) as being mediated by the explanatory variables in Equation 13, such that the mediated (indirect) effect is given by $\beta_1 - \beta'_1$. Equations 14 and 15 then attribute the mediated effect to each explanatory variable separately: the effect mediated through forecast confidence is $\alpha_1^c\beta_2$, while the effect mediated through grocery shopping is $\alpha_1^g\beta_3$.

$$\pi_{i,t}^E = \beta_0 + \beta_1 \text{female}_i + v_i + \rho_t \quad (12)$$

$$\pi_{i,t}^E = \beta'_0 + \beta'_1 \text{female}_i + \beta_2 \text{prob_confident}_{i,t} + \beta_3 \text{shop_groceries}_i + X_{i,t}\gamma_1 + D_t\gamma_2 + R_i\gamma_3 + v_i + \rho_t \quad (13)$$

$$\text{prob_confident}_{i,t} = \alpha_0^c + \alpha_1^c \text{female}_i + v_i + \rho_t \quad (14)$$

$$\text{shop_groceries}_i = \alpha_0^g + \alpha_1^g \text{female}_i + v_i + \rho_t \quad (15)$$

Although the mediation approach is fundamentally different from the Kitagawa–Oaxaca–Blinder decomposition, the results reported in Figure 4b are strikingly similar. Only about 4% of the

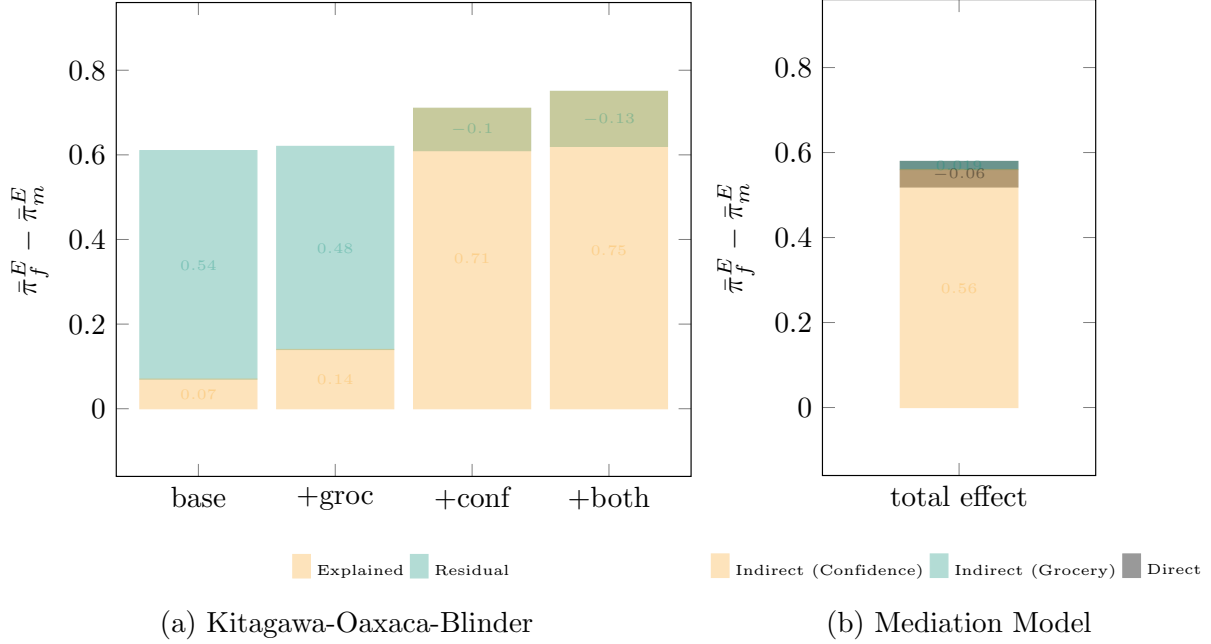


Figure 4: Decomposition of the Gender Gap

Notes: The left four columns show an Oaxaca-Blinder decomposition of the gender gap in inflation point forecasts when controlling for demographics only, grocery shopping, confidence or both. The right column decomposes the gender gap in raw data into a direct effect of gender on expectations (similar to a residual) and an indirect effect mediated through women's higher grocery shopping or confidence. Both are Mundlak CRE specification, Huber-robust regression.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; own calculations

total indirect effect is attributed to grocery shopping, with the remaining effect explained by my measure of forecast confidence. The direct effect is estimated negative, indicating that forecast confidence more than fully accounts for the gender gap. The regression results for these models are presented in Table 5.

Result 3.1 *Differences in exposure account for only a small part of the gender gap. By contrast, differences in forecast confidence fully explain the gap.*

3.2 Grocery price exposure matters when forecast confidence is low

While the confidence channel dominates the exposure channel individually, the framework does predict an interaction of the two. I test the interaction of the individual-level confidence

measure and grocery shopping with the following panel regression model:

$$\begin{aligned} \pi_{i,t}^E = & \beta_0 + \beta_1 \text{female}_i + \beta_2 \text{prob_confident}_{i,t} + \beta_3 \text{shop_groceries}_i \\ & + \beta_4 \text{prob_confident}_{i,t} \times \text{shop_groceries}_i + X_{i,t}\gamma_1 + D_t\gamma_2 + R_i\gamma_3 + v_i + \rho_t, \end{aligned} \quad (16)$$

where the variables are as explained above. Again, I exclude single households. Estimation is performed with the Mundlak correlated random effects approach, applying Huber-robust regression.

Table 5 shows that grocery shopping alone has a small positive effect on inflation expectations in columns (3) and (4), whereas forecast confidence consistently exhibits a substantial negative effect across all specifications, confirming that higher confidence is associated with lower expected inflation.

When the interaction between exposure and confidence is included (column 5), the results reveal that exposure does matter: the main effect of grocery shopping becomes significant only when combined with low forecast confidence, as indicated by the negative and significant interaction term. A simple calculation illustrates this pattern: for average confidence levels of men (0.82) and women (0.76), the predicted effect of grocery shopping is effectively negligible. The effect is statistically significant at the 95% level only for respondents with forecast confidence below 0.76, representing roughly 26% of the sample, with women disproportionately represented in this group.

Figure 6 visualizes this interaction, highlighting that the impact of grocery shopping on inflation expectations is conditional on the level of forecast confidence rather than uniform across all respondents.

I include robustness checks for these results which employ alternative measures for forecast confidence and grocery shopping in Appendix Table 12. I find that the interaction of `single` with `prob_confident` is insignificant. In contrast, a dummy for rounding yields similar results when interacted with `shop_groceries` as the preferred confidence measure.

Result 3.2 *Grocery shopping increases inflation expectations only for a small share of consumers with low forecast confidence ($\sim 26\%$) which is dominated by women.*

3.3 Verifying the mechanism

An implication of the confidence hypothesis is that the gender gap should disappear when the sample is trimmed to remove outliers in the right-skewed distribution. In the framework, the flat prior can affect the mean expectation only when the distribution is skewed to the right

Table 5: Effect of experience and confidence on point forecasts

	Inflation expectation (12 months ahead, point estimate)					prob.confident	shop.groceries
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
female	0.49*** (0.01)	−0.06*** (0.01)	0.47*** (0.01)	−0.08*** (0.01)	−0.08*** (0.01)	−0.05*** (0.0005)	0.26*** (0.002)
prob.confident		−11.20*** (0.06)		−11.20*** (0.06)	−10.76*** (0.10)		−0.08*** (0.01)
shop.groceries			0.11*** (0.02)	0.07*** (0.01)	0.66*** (0.10)	−0.004*** (0.001)	
prob.confident:shop.groceries					−0.72*** (0.12)		
Constant	2.93*** (0.20)	11.46*** (0.20)	2.88*** (0.20)	11.42*** (0.20)	11.07*** (0.21)	0.76*** (0.01)	0.51*** (0.04)
Observations	155,202	155,202	155,202	155,202	155,202	155,202	155,202
Residual SE	1.71	1.65	1.72	1.65	1.65	0.08	0.38

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses.

Notes: Mundlak CRE specification; Huber-robust regression. All regressions incorporate regional controls and time fixed effects. The full model is specified in Equation (16). Singles are excluded in all models.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; own calculations

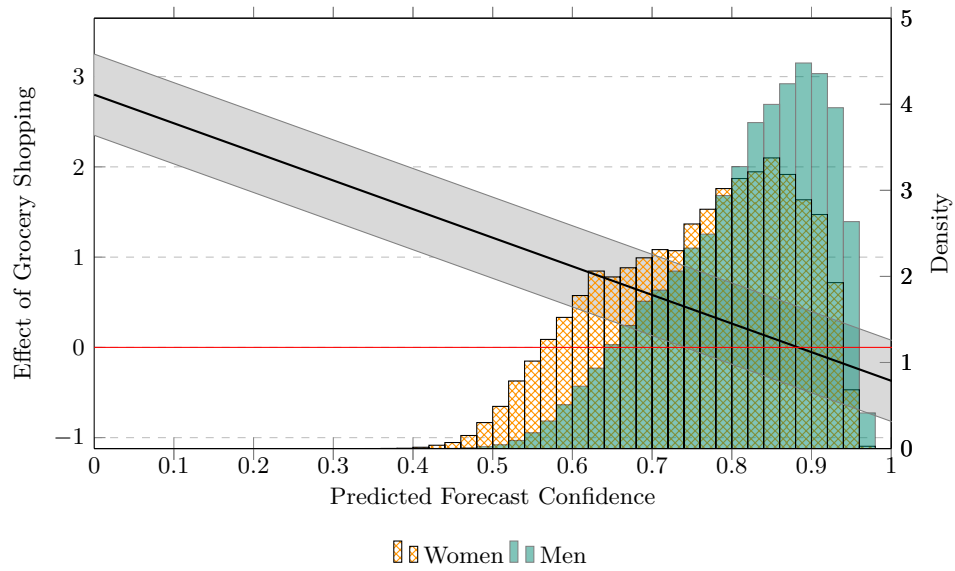


Figure 6: The effect of grocery shopping involvement on inflation expectations for different levels of forecast confidence

Notes: The predicted effect of participation in grocery shopping on inflation expectations for different levels of forecast confidence in the black line ($f(x) = 1.28 - 1.38x$). The complete regression results are shown in Table 5, column (5). The gray area indicates the 95% confidence interval. The way grocery shopping is measured will be explained in Section 2.2 and confidence in Section 2.3. The histograms show the density of the male (green) and female (orange, cross-hatched) distribution of forecast confidence.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; own calculations

asymmetrically. To test this, I compute the gender gap across deciles of the expectations distribution, controlling for demographics and time periods in the three surveys. I replicate model (1) in Table 5 for each decile of the expectations distribution and test whether the gender gap closes when outliers are removed. Figure 7 plots the coefficient of *female* across percentiles, showing a steady increase as predicted by the uncertainty hypothesis. In samples limited to inflation expectations below the 80th percentile, no positive gender gap is observed in any survey. Conversely, for lower percentiles, the gender gap is negative in both BOP-HH and SCE. This finding is in line with the confidence hypothesis as rounding for very low expectations can bias them downwards (saying 0% instead of 1 or 2%). The regression table is in the Appendix, Table 14.

Observation 3.3 *The gender gap in means is driven by the heavy tail in the female distribution. When the sample is restricted to the lowest 80% of inflation expectations, there is no positive gap and at lower percentiles a significantly negative gender gap emerges.*

4 Drivers of the Forecast Confidence Gap

Financial literacy is a potential driver of the forecast confidence gap between men and women. The SCE includes a standardized financial literacy test (Lusardi & Mitchell, 2014). It is well known that women perform worse in those tests (Bucher-Koenen et al., 2017), at least when “don’t know” answers are possible (Bucher-Koenen et al., 2024). The latter finding has been attributed to women being less confident when answering surveys about financial variables (Anderson et al., 2017). Table 3 Panel D confirms lower financial literacy for women in the SCE.

I test the effect of financial literacy on the gender gap in confidence through a simple regression of the predicted confidence on the female dummy, a range of demographics, and the test score of the financial literacy test. I also include an interaction of financial literacy and the female dummy. Table 6 column (3) shows that women with high financial literacy are less likely to round their point forecast on inflation. Further, when separating Table 4 by high and low financial literacy (columns (4) and (5) in Table 6), I find that the gender gap in inflation expectations disappears for those with high financial literacy. Confidence itself also has a larger impact irrespective of gender in the low literacy sample.

Result 4.1 *The gender gap in confidence is driven at least in parts by women’s lower financial literacy.*

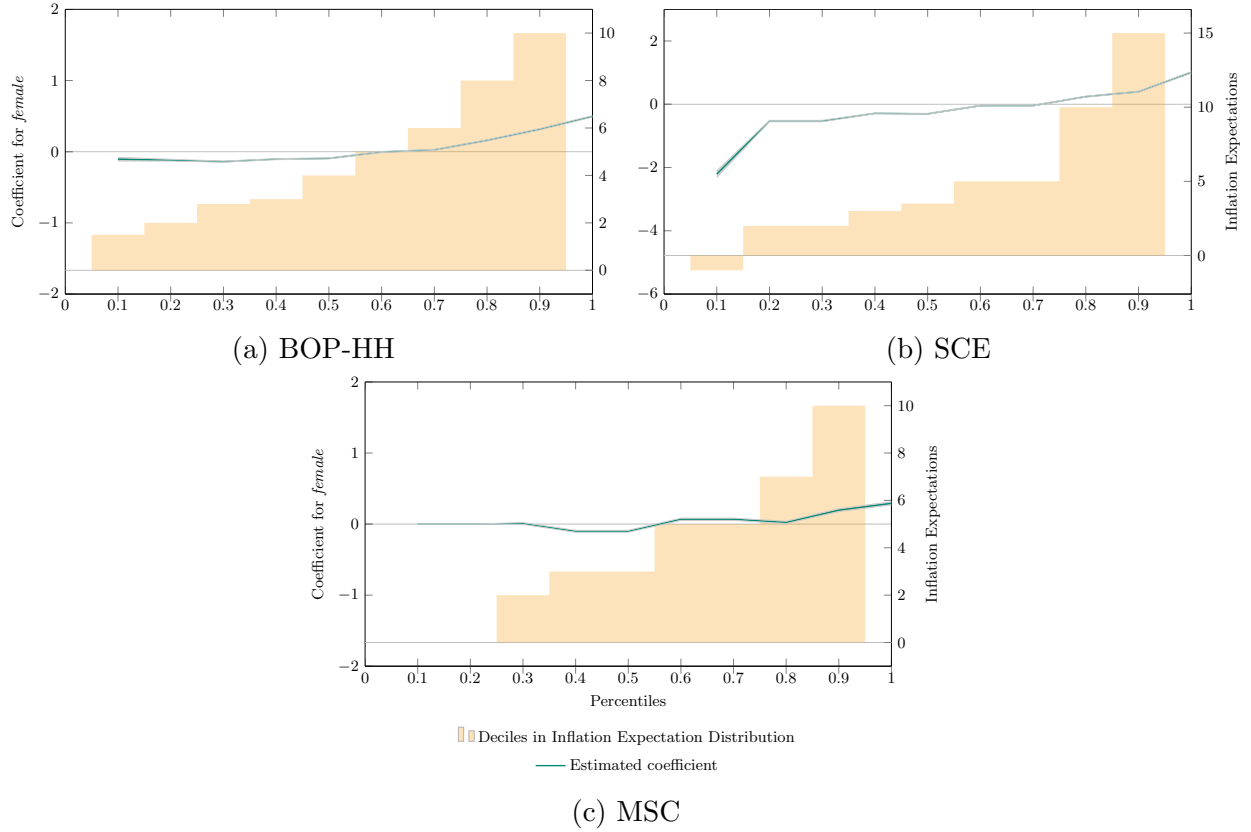


Figure 7: The gender gap along deciles in the inflation expectations distribution

Notes: Estimated regression coefficients for the dummy variable *female* in decile regressions of the inflation expectations distribution (0.1 to 0.9) across three surveys: BOP-HH, SEC, and MSC in the green line. 95% confidence bands are shaded in gray. Orange bars represent the percentiles in the inflation expectations distribution.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; Federal Reserve Bank of New York (FRBNY), SCE, June 2013 - October 2024; University of Michigan, Survey Research Center, MSC, January 1978 - January 2025; own calculations

Table 6: The impact of financial literacy

	Predicted confidence			Inflation point forecast	
				High literacy	Low literacy
	(1)	(2)	(3)	(4)	(5)
female	−0.16*** (0.001)	−0.16*** (0.001)	−0.17*** (0.001)	0.82*** (0.09)	2.72*** (0.10)
fin_lit		0.02*** (0.001)	0.001 (0.001)		
fin_lit:female			0.04*** (0.002)		
prob_confident				−2.57*** (0.10)	−4.86*** (0.14)
prob_confident:female				−1.23*** (0.13)	−3.69*** (0.15)
Constant	0.39*** (0.01)	0.39*** (0.01)	0.40*** (0.01)	4.84*** (0.39)	8.79*** (0.20)
Observations	145,452	145,452	145,452	46,252	99,200
Residual SE	0.18	0.18	0.18	2.11	3.75

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

Robust standard errors in parentheses.

Notes: Mundlak CRE specification; Huber-robust regression. All regressions include demographic controls, regional controls and time dummies.

Sources: Federal Reserve Bank of New York (FRBNY), SCE, June 2013 - October 2024; own calculations

5 Further Evidence in Support of the Forecast Confidence Hypothesis

I conduct two further robustness checks of the pure exposure hypothesis using all three available surveys:

1. **Singles Analysis:** I investigate whether the gender gap exists among singles. According to the experience hypothesis, there should be no gender gap among singles since both men and women engage symmetrically in grocery shopping when living alone. However, a financial confidence gap may still exist among singles, leading to asymmetric expectations despite symmetric shopping.
2. **Food Price Inflation Periods:** I assess whether the gender gap widens during periods of high food price inflation, i.e. when women in traditional gender roles observe even higher price increases. This does not necessarily hold if financial confidence is the main channel causing the gender gap.

The rejection of both supports the confidence hypothesis proposed in this paper as the dominant driver of the gender gap.

5.1 The gender gap among singles

One implication of the pure experience hypothesis is that there should be no gender gap in inflation expectations for single men and women, as singles are likely to engage in grocery shopping irrespective of gender and thus should experience similar inflation levels and volatility. To test this, I run a panel regression of inflation expectations on a female dummy and other demographics as in column (1) of Table 5. I split the sample by household size. Under the experience hypothesis, the gender gap should be larger in the non-single sample as traditional gender norms don't exist for singles.

Table 7 shows that for all surveys (a) there is a persistent and significant gender gap for both, singles and non-singles and (b) it is not statistically smaller for singles. In fact, in the SCE the gender gap is larger for singles. This is novel evidence as D'Acunto, Malmendier, and Weber (2021) show no evidence for non-married and single individuals, and Jonung (1981) shows no treatment of disaggregated data.

Observation 5.1 *The gender gap is significant and no different between singles and non-singles.*

Table 7: Comparing the gender gap in inflation expectations for singles and non-singles

	Inflation expectation (12 months ahead, point estimate)					
	BOP-HH		SCE		MSC	
	N	S	N	S	N	S
female	0.49*** (0.01)	0.46*** (0.02)	0.80*** (0.02)	1.67*** (0.07)	0.35*** (0.02)	0.33*** (0.03)
Constant	2.93*** (0.20)	2.75*** (0.17)	6.08*** (0.15)	7.84*** (0.43)	5.78*** (0.17)	5.62*** (0.36)
Δ female	<i>0.03</i> <i>(0.02)</i>		<i>-0.87***</i> <i>(0.08)</i>		<i>0.02</i> <i>(0.03)</i>	
Observations	155,203	55,022	108,961	36,491	207,312	69,781
Residual SE	1.71	1.88	2.76	5.08	3.11	3.34

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

Robust standard errors in parentheses.

Notes: Mundlak CRE specification; Huber-robust regression. All regressions include demographic controls, regional controls and time dummies. N indicates households with more than 1 member and S indicates single households. The italics below indicate the gap between the coefficient on female in non-single and single samples along with the robust standard error.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; Federal Reserve Bank of New York (FRBNY), SCE, June 2013 - October 2024; University of Michigan, Survey Research Center, MSC, January 1978 - January 2025; own calculations

5.2 The gender gap correlated with historical food prices

Under the experience hypothesis, the gender gap is expected to widen in periods of higher food price inflation or price volatility compared to CPI core. This is because in those periods, household members with grocery shopping exposure observe particularly high and volatile prices which increases the bias and noisiness of their signals in the Bayesian learning framework.

To test whether food price exposure contributes to the gender gap, I estimate a regression model similar to the previous setup but replace time dummies with measures of relative food price dynamics. Specifically, I include the difference between food price inflation and overall CPI inflation ($CPI_t^{food} - CPI_t^{total}$) and the difference in their 6-month moving coefficients of variation ($\rho_{t,6}^{food} - \rho_{t,6}^{total}$).¹² Under the exposure hypothesis, these interaction terms with female should be positive: women, due to greater grocery shopping experience, should respond more strongly to relative food price volatility.

The results, reported in Table 8, show little evidence in favor of this view. In the Michigan Survey of Consumers (MSC)—the longest-running dataset with the richest time variation—the coefficient on the interaction term with female are negative, suggesting that in fact, the gender gap shrinks when food price inflation is high. To align more closely with the confidence mechanism, I split the BOP-HH and SCE by forecast confidence. The results are striking. In the SCE, the interaction between food price volatility and gender is negative (and significant) for high-confidence respondents, and only marginally positive for low-confidence respondents. In the BOP-HH, the interaction is again insignificant at high confidence, while for low-confidence respondents it is small but positive. Taken together, these findings point away from a grocery-shopping channel and toward confidence as the operative mechanism. Food price signals matter only when respondents are uncertain about their forecasts. For confident households, food price volatility has no effect—or even a negative effect—on the gender gap.

Observation 5.2 *The gender gap in point forecasts reduces not increase in response to high or volatile food prices. It only increases for those with low confidence, who may pay more attention to signals.*

¹²The moving coefficient of variation is defined as $\rho_{t,n} = \frac{\sigma_{t,n}}{\bar{x}_{t,n}} \times 100$, where t denotes the current period, n the number of periods, $\bar{x}_{t,n}$ the moving average, and $\sigma_{t,n}$ the moving standard deviation, computed as $\sqrt{\frac{1}{n-1} \sum_{i=t-n+1}^t (x_i - \bar{x}_t)^2}$ with x_i the value at time i .

Table 8: Microlevel effects of high food prices

	Inflation expectation (12 months ahead, point estimate)				
	BOP-HH		SCE		MSC
	High conf.	Low conf.	High conf.	Low conf.	All
female	-0.002 (0.01)	0.22*** (0.03)	0.04** (0.02)	1.28*** (0.06)	0.30*** (0.01)
$CPI_t^{food} - CPI_t^{total}$	0.30*** (0.002)	0.30*** (0.003)	0.14*** (0.004)	0.14*** (0.02)	0.01** (0.004)
female x ($CPI_t^{food} - CPI_t^{total}$)	0.002	0.03***	-0.04***	0.04	-0.05***
$\rho_{t,6}^{food} - \rho_{t,6}^{total}$	0.08*** (0.004)	0.08*** (0.01)	-0.005* (0.003)	-0.02 (0.02)	-0.02*** (0.004)
female x ($\rho_{t,6}^{food} - \rho_{t,6}^{total}$)	-0.001 (0.01)	-0.01 (0.01)	-0.0001 (0.005)	0.02 (0.02)	-0.01 (0.01)
Constant	2.82*** (0.05)	5.29*** (0.07)	2.79*** (0.06)	8.97*** (0.19)	5.03*** (0.04)
Observations	98,825	104,599	72,726	72,726	277,092
Residual SE	1.52	2.84	1.89	6.17	3.43

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

Robust standard errors in parentheses.

Notes: Mundlak CRE specification; Huber-robust regression. All regressions include demographic and regional controls.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; Federal Reserve Bank of New York (FRBNY), SCE, June 2013 - October 2024; University of Michigan, Survey Research Center, MSC, January 1978 - January 2025; OECD, Prices: Consumer prices, Main Economic Indicators (database), January 1978 - January 2025; own calculations

6 Beyond Gender

The confidence hypothesis suggests two implications that go beyond gender: First, it offers a framework to understand heterogeneities beyond gender. While the gender gap is a particularly large and significant due to the amplification effects of traditional gender norms and lower forecast confidence on average, expectation differences between those on high and low incomes, high and low education or different age groups can also be explained through this lens. Forecasting confidence is likely to also vary along those dimensions and may interact with the different shopping baskets. Secondly, the framework implies that salient prices such as food or gasoline (irrespective of observed by men or women) play a larger role in times when forecast confidence is low. This speaks to the literature on exposure which found large effects of supermarket and gas prices on average (Anesti et al., 2025; C. C. Binder, 2018; Cavallo et al., 2017; Coibion & Gorodnichenko, 2015; D’Acunto, Malmendier, Ospina, & Weber, 2021). These effects are expected to be pronounced in times of macroeconomic uncertainty.

6.1 Confidence and other dimensions of heterogeneity

The framework developed above highlights forecast confidence as the central determinant of how noisy price signals are incorporated into household inflation expectations. While the gender gap provides a prominent and quantitatively large case—amplified by traditional gender norms and the systematically lower forecast confidence of women on average—the mechanism is not gender-specific. Rather, it offers a general lens for understanding the well-established expectation heterogeneities across demographic groups (Bruine De Bruin et al., 2010; D’Acunto et al., 2023)

In particular, forecast confidence is likely to vary systematically along dimensions such as income, education, and age. Households with lower income or education levels, or those at the tails of the age distribution, may hold flatter priors, face greater uncertainty in their economic environment, and have fewer opportunities to learn from reliable sources. In these cases, confidence interacts with the composition of shopping baskets: exposure to volatile prices differs not only between genders but also across income groups (e.g., a higher budget share of food or energy), education levels (e.g., reliance on different retail formats), or age cohorts (e.g., pensioners facing different consumption bundles).

To assess the extent to which confidence mediates these broader gaps, I apply a mediation analysis similar to that used in Section 3. This approach decomposes the raw differences in expectations between demographic groups into two parts: (i) the direct effect of a characteristic, which reflects differences in expectations not mediated by forecast confidence, and

(ii) the indirect effect, which operates through forecast confidence. If the proposed framework is correct, the indirect effect should explain a sizable share of observed heterogeneities, while the direct effect remains small once confidence is accounted for. The results in Figure 9 support the predicted role of forecast confidence as a mediator of socio-demographic effects on inflation expectations. The figure displays the effect of a one-standard-deviation change in key predictors—age, education (`educ`), and household income (`hhinc`)—on the outcome variable $\pi_{i,t}^E$, separated into indirect effects mediated by my confidence measure (`prob_confident`) and direct effects that do not pass through the mediator.

Standardization allows coefficients to be interpreted in terms of standard deviation changes, facilitating comparison across variables measured on different scales. The standardization procedure proceeds in two steps. First, the coefficients linking predictors to the mediator ($X \rightarrow M$) and the mediator to the outcome ($M \rightarrow Y$) are adjusted by the ratio of standard deviations of the relevant variables. Specifically, for each predictor X , the standardized indirect effect is computed as:

$$\text{indirect}_{std} = \left(\text{coef}_{X \rightarrow M} \times \frac{\text{sd}_X}{\text{sd}_M} \right) \times \left(\text{coef}_{M \rightarrow Y} \times \frac{\text{sd}_M}{\text{sd}_Y} \right),$$

where sd_X is the standard deviation of the predictor, sd_M is the standard deviation of the mediator (`prob_confident`), and sd_Y is the standard deviation of the outcome variable (inflation expectations, $\pi_{i,t}^E$). The direct effect is standardized as

$$\text{direct}_{std} = \text{coef}_{X \rightarrow Y|M} \times \frac{\text{sd}_X}{\text{sd}_Y},$$

and the total effect is the sum of the standardized direct and indirect effects.

This approach shows that a substantial portion of the influence of age, education and income operates through forecast confidence, while the remaining direct effects are smaller. Full regression coefficients underlying these calculations are reported in Appendix Table 15. For `educ` and `hhinc` in both SCE and BOP-HH, the standardized coefficients indicate sizable negative indirect effects via `prob_confident` and small direct effects on $\pi_{i,t}^E$. In contrast, `age` is included as a quadratic term to capture potential nonlinear effects (for example the youngest and oldest may be least confident). Its standardized effects are evaluated at three representative values corresponding to low (10th percentile), median, and high (90th percentile) ages. This allows the figure to show how both the indirect and direct effects of age change across the observed age range. At younger ages, the indirect effect through `prob_confident` is relatively small but positive in both surveys, while the direct effect is

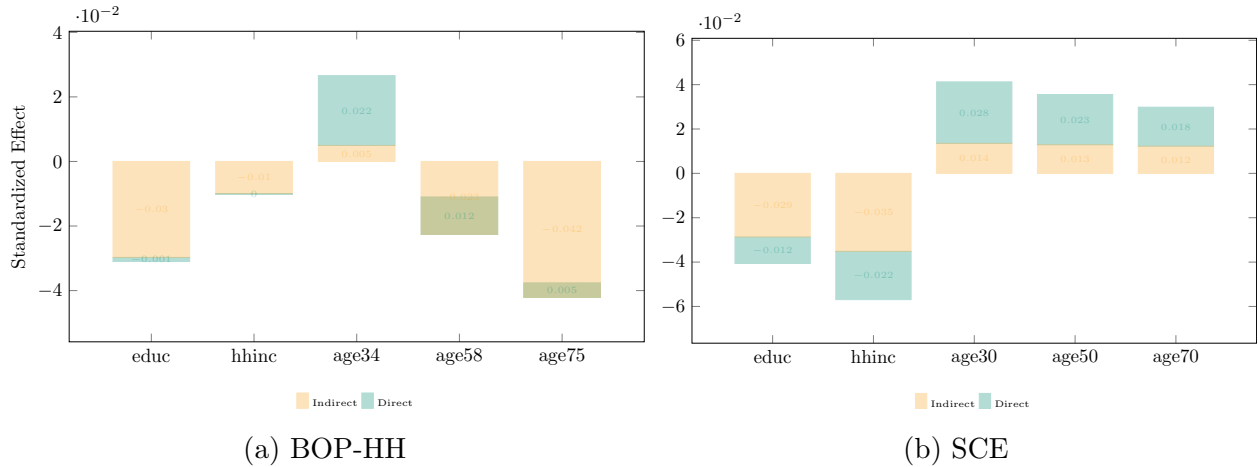


Figure 9: Mediation model for other dimensions of heterogeneity

Notes: The stacked bar chart summarizes these standardized effects in the mediation model, with indirect effects shown in orange and direct effects in green. For age, the three bars correspond to low, median, and high ages.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; Federal Reserve Bank of New York (FRBNY), SCE, June 2013 - October 2024; own calculations

larger and positive. As age progresses, in the US the total effect reduces driven mainly by the direct effect shrinking. However, in Germany the total effect reverses. At median and especially at old age there is a strongly negative indirect effect suggesting that at older ages, confidence falls while the direct effect remains small and positive mitigating the negative confidence response marginally.

Observation 6.1 *Differences in forecast confidence explain a substantial fraction of expectation gaps by income, education, and age.*

6.2 When do food prices matter?

A second key implication of the framework developed in Section 1 is that salient price signals, such as food prices, should have a stronger impact on expectations when macroeconomic uncertainty is high. When uncertainty is elevated, forecasting becomes inherently more difficult, which is reflected in lower forecast confidence. Consumers with flat priors—interpreted here as low confidence—place greater weight on noisy signals, so aggregate shocks to salient goods exert a larger influence on inflation expectations during periods of elevated uncertainty.

To examine this implication, I extend the empirical strategy of Coibion and Gorodnichenko (2015) and C. C. Binder (2018), who regress the change in respondent i 's expectation of one-year ahead inflation from six months prior on oil price inflation and find a positive

coefficient. Specifically, I replicate their baseline regression with food prices and augment it by interacting food price changes with the 6-months change in the Baker et al. (2016) economic policy uncertainty index (EPU). This design allows me to test directly whether the pass-through from salient price movements to expectations is state-dependent. In the specification all variables are the same as in previous models and $\Delta\pi_{i,t}^E$ is the change in inflation forecast of individual i over a 6 months time period.

$$\Delta\pi_{i,t}^E = \beta_0 + \beta_1\pi_t^{\text{food}} + \beta_2\pi_t^{\text{food}} \times \Delta\text{EPU}_t + \beta_3\Delta\text{EPU}_t + X_{i,t}\gamma_1 + R_i\gamma_3 + v_i + \rho_t, \quad (17)$$

The results in Table 9 strongly support the prediction. While the baseline effect of food price changes on expectations is modest and even negative in the US, the interaction with the EPU is positive and significant. Periods of heightened uncertainty amplify the effect of food price shocks on household inflation expectations, whereas in tranquil times food prices play a comparatively minor role. Put differently, consumers do not consistently overreact to grocery prices; rather, they rely on such signals disproportionately when uncertainty about the broader inflation environment is elevated. More generally, this result implies that central bank communication and policy credibility are especially important in periods of heightened uncertainty, when households are most susceptible.

Observation 6.2 *Consumers rely more on salient prices for forecasting inflation when macroeconomic uncertainty is increasing.*

7 Conclusion

This paper provides both theoretical and empirical insights into the determinants of inflation expectations, with a focus on the gender gap. Theoretically, I show that heterogeneity in point forecasts and forecast confidence can emerge from noise in priors and signals. Under a log-normal prior, increased noise raises average inflation expectations, consistent with the expoure hypothesis on the gender gap (D’Acunto, Malmendier, & Weber, 2021; Jonung, 1981), but only when priors are sufficiently flat. Low forecast confidence—captured through flat priors—produces similar effects in noisy environments, offering an alternative and equally plausible mechanism.

Empirically, using German household data, I find that grocery shopping alone does not explain inflation expectations. Instead, forecast confidence, proxied through rounding behavior in survey responses (C. C. Binder, 2017a; Reiche & Meyler, 2022), is central. If men and women had equal confidence, the gender gap would in fact be negative. Grocery

Table 9: EPU mitigates food prices

	Difference in inflation expectation (12 months ahead, point estimate)						
	BOP-HH			SCE		MSC	
	All	Singles	Grocery Shoppers	All	Singles	All	Singles
π_t^{food}	0.11*** (0.001)	0.11*** (0.003)	0.11*** (0.002)	-0.01*** (0.004)	-0.02 (0.01)	-0.02*** (0.004)	-0.01 (0.01)
ΔEPU_t	0.0004*** (0.0001)	0.0005*** (0.0002)	0.0003*** (0.0001)	-0.002*** (0.0003)	-0.002** (0.001)	-0.003*** (0.0003)	-0.002*** (0.001)
$\pi_t^{\text{food}} \times \Delta \text{EPU}_t$	0.001*** (0.0000)	0.001*** (0.0000)	0.001*** (0.0000)	0.001*** (0.0001)	0.001*** (0.0002)	0.0003*** (0.0001)	0.0001 (0.0002)
Constant	-0.43** (0.21)	-0.46 (0.43)	-0.50* (0.29)	-7.79*** (0.91)	-15.87*** (2.75)	-0.69*** (0.06)	-0.74*** (0.14)
Observations	100,482	25,054	52,714	57,122	14,215	99,379	24,424
Residual SE	2.37	2.47	2.52	2.72	4.26	2.95	3.10

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses.

Notes: Mundlak CRE specification; Huber-robust regression. All regressions include demographic and regional controls.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; Federal Reserve Bank of New York (FRBNY), SCE, June 2013 - October 2024; University of Michigan, Survey Research Center, MSC, January 1978 - January 2025; OECD, Prices: Consumer prices, Main Economic Indicators (database), January 1978 - January 2025; own calculations

shopping elevates expectations primarily among low-confidence respondents, with little effect on those with high confidence. U.S. data from the SCE and MSC confirm that higher point forecasts arise from uncertainty in a right-skewed posterior, and trimming the right tail significantly reduces the gender gap. Moreover, the gender gap does not appear among singles, does not increase with elevated food prices, and is absent when respondents are asked specifically about food inflation. These findings indicate that the exposure alone is insufficient in accounting for the gap: forecast confidence is pivotal. Forecast confidence is strongly correlated with financial literacy, which differs systematically by gender (Bucher-Koenen et al., 2017, 2024; Lusardi & Mitchell, 2008). The gender gap therefore reflects both traditional norms and lower financial literacy among women, leading to rounded and less precise forecasts. Importantly, forecast confidence also helps explain other demographic gaps in expectations, including age, education, and household income.

The policy implications are substantial. A sizable tail of low-confidence women produces imprecise expectations, affecting savings, investment, and responsiveness to policy communication (Lusardi & Mitchell, 2008; McMahon & Reiche, 2024). Improving financial literacy and increasing female representation in policy institutions could help mitigate these gaps (D’Acunto, Fuster, & Weber, 2022). More broadly, the mechanism has implications for survey-based measures of inflation: low-confidence individuals tend to overstate moderate

inflation but may understate high inflation, creating the appearance of more anchored expectations during high-inflation periods. Finally, easily observable price signals, such as food prices, become especially important during periods of heightened macroeconomic uncertainty providing a time varying element to the exposure literature.

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A Additional Material for Bayesian Framework

Algebraic manipulations to derive the log-normal posterior

The prior is defined as

$$\begin{aligned}\log \theta &\sim \mathcal{N}\left(\mu_0, \frac{1}{\tau_0}\right), \\ p(\theta) &= \frac{\sqrt{\tau_0}}{\theta\sqrt{2\pi}} \exp\left(-\frac{\tau_0(\log \theta - \mu_0)^2}{2}\right).\end{aligned}$$

The unbiased signal is defined as

$$\begin{aligned}\log x &= \log \theta + \epsilon, \\ \text{where } \epsilon &\sim \mathcal{N}\left(0, \frac{1}{\tau_x}\right), \\ p(x|\theta) &= \frac{\sqrt{\tau_x}}{x\sqrt{2\pi}} \exp\left(-\frac{\tau_x(\log x - \log \theta)^2}{2}\right)\end{aligned}$$

I compute the posterior following Bayesian updating:

$$\begin{aligned}p(\theta|x) &\propto p(\theta)p(x|\theta) \\ &= \frac{\sqrt{\tau_0}}{\theta\sqrt{2\pi}} \exp\left(-\frac{\tau_0(\log \theta - \mu_0)^2}{2}\right) \frac{\sqrt{\tau_x}}{x\sqrt{2\pi}} \exp\left(-\frac{\tau_x(\log x - \log \theta)^2}{2}\right) \\ &= \frac{\sqrt{\tau_0}\sqrt{\tau_x}}{\theta x 2\pi} \exp\left(-\frac{1}{2}\left[\tau_0((\log \theta)^2 - 2\mu_0 \log \theta + \mu_0^2) \right. \right. \\ &\quad \left. \left. + \tau_x((\log x)^2 - 2\log x \log \theta + (\log \theta)^2)\right]\right) \\ &\propto \frac{1}{\theta} \exp\left(-\frac{1}{2}\left[(\tau_0 + \tau_x)(\log \theta)^2 - 2(\tau_0\mu_0 + \tau_x \log x) \log \theta\right]\right).\end{aligned}$$

This is proportional to a log-normal distribution,

$$p(\theta|x) \propto \frac{1}{\theta} \exp\left(-\frac{\hat{\tau}(\log \theta - \hat{\mu})^2}{2}\right),$$

where

$$\hat{\mu} = \frac{\mu_0\tau_0 + \tau_x \log x}{\tau_x + \tau_0},$$

and $\hat{\tau} = \tau_0 + \tau_x$.

Comparative statics

The effect of increasing signal volatility

$$\begin{aligned}
\mathbb{E}(\theta|x) &= \exp\left(\hat{\mu} + \frac{1}{2\hat{\tau}}\right) \\
&= \exp\left(\frac{\tau_0\mu_0 + \tau_x \log x + \frac{1}{2}}{\tau_x + \tau_0}\right) \\
\frac{d\mathbb{E}(\theta|x)}{d\tau_x} &= \left(\frac{2\tau_0(\log x - \mu_0) - 1}{2(\tau_x + \tau_0)^2}\right) \times \mathbb{E}(\theta|x) \\
&< 0 \text{ whenever } 2\tau_0(\log x - \mu_0) - 1 < 0 \Rightarrow \log x - \mu_0 < \frac{1}{2\tau_0} \\
\mathbb{V}ar(\theta|x) &= \left[\exp\left(\frac{1}{\tau_0 + \tau_x}\right) - 1\right] \exp\left(\frac{2\tau_0\mu_0 + 2\tau_x \log x + 1}{\tau_0 + \tau_x}\right) \\
\frac{d\mathbb{V}ar(\theta|x)}{d\tau_0} &= \frac{2(\log x - \mu_0)\tau_0 - 2}{(\tau_0 + \tau_x)^2} \exp\left(\frac{2\tau_0\mu_0 + 2\tau_x \log x + 2}{\tau_0 + \tau_x}\right) \\
&\quad - \frac{2(\log x - \mu_0)\tau_0 - 1}{(\tau_0 + \tau_x)^2} \exp\left(\frac{2\tau_0\mu_0 + 2\tau_x \log x + 1}{\tau_0 + \tau_x}\right) \\
&< 0 \text{ whenever } \log x - \mu_0 < \frac{1}{2\tau_0} \underbrace{\frac{2 \exp \frac{1}{\tau_0 + \tau_x} - 1}{\exp \frac{1}{\tau_0 + \tau_x} - 1}}_{>1}
\end{aligned}$$

The effect of decreasing prior precision

$$\begin{aligned}
\frac{d\mathbb{E}(\theta|x)}{d\tau_0} &= \left(\frac{2\tau_x(\mu_0 - \log x) - 1}{2(\tau_x + \tau_0)^2}\right) \times \mathbb{E}(\theta|x) \\
&< 0 \text{ whenever } 2\tau_x(\mu_0 - \log x) - 1 < 0 \Rightarrow \mu_0 - \log x < \frac{1}{2\tau_x} \\
\frac{d\mathbb{V}ar(\theta|x)}{d\tau_0} &= \frac{2(\mu_0 - \log x)\tau_x - 2}{(\tau_0 + \tau_x)^2} \exp\left(\frac{2\tau_0\mu_0 + 2\tau_x \log x + 2}{\tau_0 + \tau_x}\right) \\
&\quad - \frac{2(\mu_0 - \log x)\tau_x - 1}{(\tau_0 + \tau_x)^2} \exp\left(\frac{2\tau_0\mu_0 + 2\tau_x \log x + 1}{\tau_0 + \tau_x}\right) \\
&< 0 \text{ whenever } \mu_0 - \log x < \frac{1}{2\tau_x} \underbrace{\frac{2 \exp \frac{1}{\tau_0 + \tau_x} - 1}{\exp \frac{1}{\tau_0 + \tau_x} - 1}}_{>1}
\end{aligned}$$

B Additional Figures

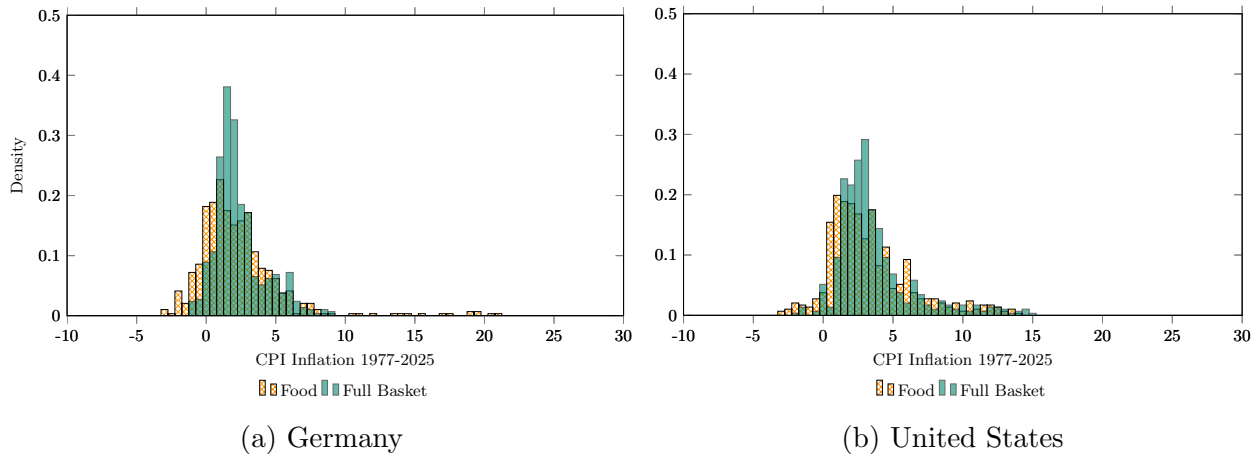


Figure B.1: Histogram of CPI Inflation

Sources: OECD, Prices: Consumer prices, Main Economic Indicators (database), January 1977 - July 2025; own calculations

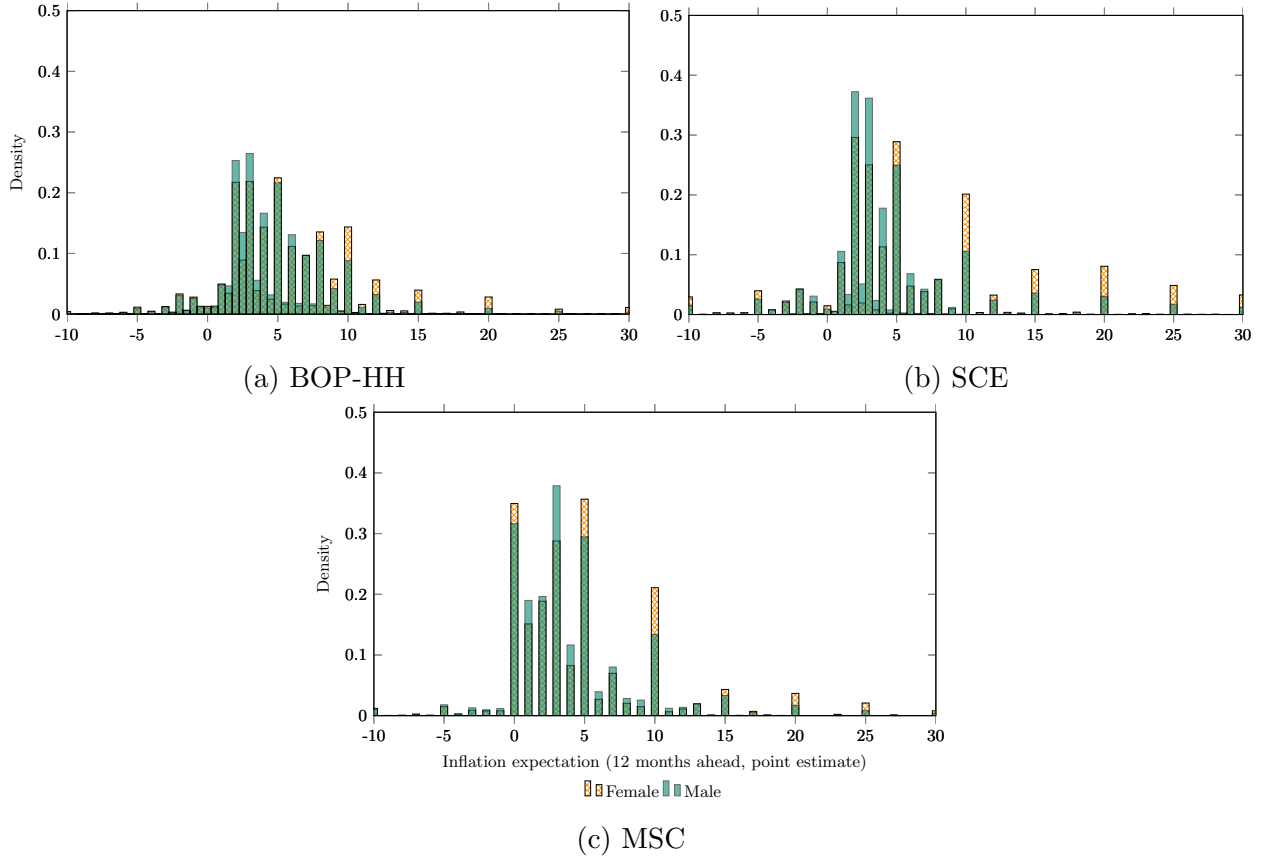


Figure B.3: Histogram of inflation expectation point forecasts of men and women

Notes: Distribution of male and female inflation expectations (measured as point forecasts over 12 months) pooled across all time periods. There is one plot per survey. The figures show that the distribution is more right skewed for women and rounded numbers (i.e. multiples of 5 or 10) are chosen more frequently.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; Federal Reserve Bank of New York (FRBNY), SCE, June 2013 - October 2024; University of Michigan, Survey Research Center, MSC, January 1978 - January 2025; own calculations

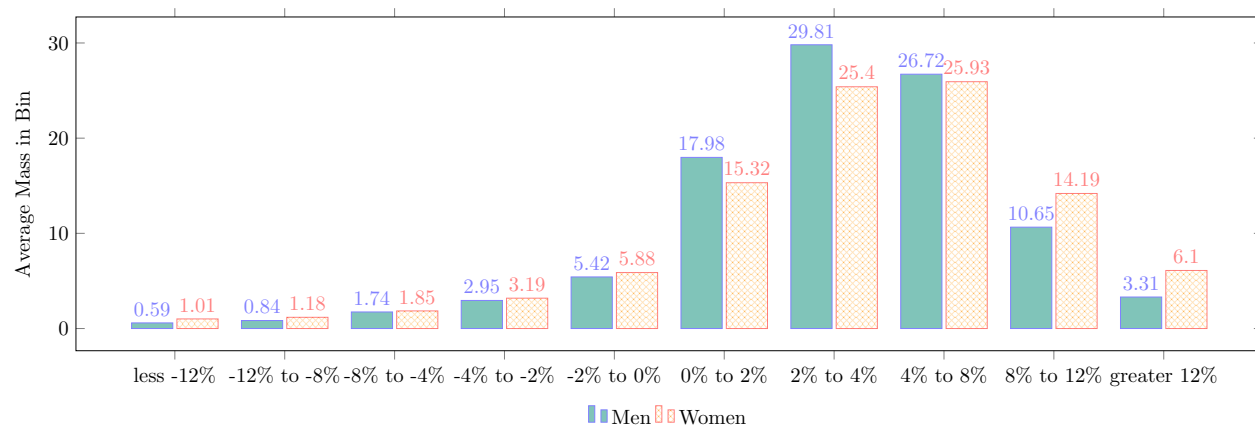


Figure B.5: Average density forecast of inflation 12 months ahead in the BOP-HH

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; own calculations

C Additional Tables

Table 10: Predicting confidence through rounding

	BOP-HH		round_inflexp_point		MSC	
	(1)	(2)	(3)			
infquali	0.63*** (0.01)		−0.06*** (0.01)		−2.79*** (0.02)	
round_exphp_point	0.17*** (0.02)		0.36*** (0.02)			
qeasy	−0.004 (0.02)					
qinterest	−0.03 (0.02)		−0.01 (0.02)			
decide_finance	−0.11** (0.05)		−0.28*** (0.03)			
Constant	−2.35*** (0.15)	−1.34*** (0.09)	−1.01*** (0.09)	0.56*** (0.08)	2.58*** (0.10)	0.13 (0.09)
McFadden R ²	0.08	0.049	0.181	0.096	0.161	0.038
Observations	210,225	229,869	145,452	171,607	277,093	277,093

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

Notes: Mundlak CRE specification; Huber-robust regression. All regressions include demographic controls, regional controls and time dummies. **infquali** is a dummy for increasing inflation expectations, **round_exphp_point** is a rounding dummy for point estimates for house price growth 12 months ahead, **decide_finance** measures involvement in financial decision making.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; ; Federal Reserve Bank of New York (FRBNY), SCE, June 2013 - November 2020; University of Michigan, Survey Research Center, MSC, January 1978 - January 2025; own calculations

Table 11: The gender gap and demographic controls

	Inflation expectation (12 months ahead, point estimate)					
	BOP-HH		SCE		MSC	
	(1)	(2)	(3)	(4)	(5)	(6)
female	0.50*** (0.01)	0.68*** (0.05)	1.01*** (0.02)	2.61*** (0.12)	0.33*** (0.01)	1.57*** (0.06)
age	0.01 (0.01)	0.01 (0.01)	−0.11 (0.33)	−0.10 (0.33)	−0.02*** (0.01)	−0.02** (0.01)
age:female		−0.0001 (0.001)		0.01*** (0.001)		−0.01*** (0.001)
hhinc	−0.004*** (0.0003)	−0.01*** (0.0004)	−0.25*** (0.01)	−0.22*** (0.01)	−0.0000 (0.0000)	0.0000 (0.0000)
female:hhinc		0.004*** (0.0003)		−0.08*** (0.01)		−0.0000*** (0.0000)
educ	0.01 (0.01)	0.02 (0.01)	−0.32*** (0.01)	−0.19*** (0.01)	−0.08 (0.05)	−0.01 (0.05)
female:educ		−0.02*** (0.003)		−0.31*** (0.02)		−0.14*** (0.01)
single	0.05 (0.04)	0.04 (0.04)	−0.10*** (0.03)	−0.30*** (0.04)	−0.05*** (0.02)	−0.02 (0.02)
female:single		0.01 (0.02)		0.32*** (0.06)		−0.03 (0.03)
full_time	−0.01 (0.05)	−0.01 (0.05)	0.08 (0.08)	0.08 (0.08)		
part_time	0.004 (0.05)	0.003 (0.05)	0.06 (0.07)	0.06 (0.07)		
retired	−0.06 (0.05)	−0.06 (0.05)	−0.10 (0.10)	−0.10 (0.10)		
homemaker	0.07 (0.09)	0.07 (0.09)	0.12 (0.11)	0.12 (0.11)		
unemployed	−0.03 (0.08)	−0.04 (0.08)	0.20** (0.10)	0.20** (0.10)		
refresher	−0.04** (0.02)	−0.04** (0.02)	−0.92*** (0.04)	−0.92*** (0.04)		
Constant	2.80*** (0.12)	2.76*** (0.12)	6.52*** (0.15)	5.89*** (0.16)	5.76*** (0.15)	5.22*** (0.16)
Observations	210,225	210,225	145,452	145,452	277,092	277,092
Residual SE	1.76	1.76	3.25	3.20	3.17	3.17

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

Standard errors in parentheses below.

Notes: Mundlak CRE specification; Huber-robust regression. All regressions include regional controls and time dummies.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; Federal Reserve Bank of New York (FRBNY), SCE, June 2013 - October 2024; University of Michigan, Survey Research Center, MSC, January 1978 - January 2025; own calculations

Table 12: Confidence and experience with alternative measures

	Inflation expectation (12 months ahead, point estimate)			
	(1)	(2)	(3)	(4)
female	0.47*** (0.01)	0.47*** (0.01)	0.37*** (0.01)	−0.06*** (0.01)
shop_groceries	0.11*** (0.02)	0.10*** (0.02)	−0.002 (0.02)	
round_inflexppoint			1.34*** (0.02)	
round_inflexppoint:shop_groceries			0.62*** (0.03)	
qeasy	0.03 (0.04)			
qeasy:shop_groceries	−0.003 (0.05)			
qinterest		−0.002 (0.03)		
qinterest:shop_groceries		0.01 (0.04)		
prob_confident				−11.22*** (0.06)
single				−0.11 (0.07)
prob_confident:single				0.11 (0.09)
Constant	2.83*** (0.20)	2.88*** (0.20)	2.68*** (0.19)	11.69*** (0.12)
Observations	155,202	155,202	155,202	210,224
Residual E	1.72	1.72	1.51	1.69

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

Robust standard errors in parentheses.

Notes: Replication of Table 5 with alternative measures. Mundlak CRE specification; Huber-robust regression. All regressions include demographic controls, regional controls and time dummies.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; own calculations

Table 13: Effect of confidence and grocery shopping on the gender gap

	Inflation expectation (12 months ahead, point estimate)								
	BOP-HH				SCE		MSC		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
female	0.49*** (0.01)	0.26*** (0.01)	0.51*** (0.02)	0.53*** (0.02)	0.88*** (0.03)	−0.04* (0.02)	0.80*** (0.03)	0.35*** (0.02)	−0.11*** (0.02)
single	0.05*** (0.01)				−0.39*** (0.04)			−0.02 (0.02)	
single:female	0.01 (0.02)				0.54*** (0.05)			−0.05 (0.03)	
round_π ^E _point		1.38*** (0.02)				3.36*** (0.03)			0.24*** (0.02)
round_π ^E _point:female		0.82*** (0.02)				1.60*** (0.04)			1.00*** (0.03)
qinterest			0.02 (0.02)				−0.11*** (0.03)		
qinterest:female			−0.04 (0.03)				−0.03 (0.04)		
qeasy				0.10*** (0.02)					
qeasy:female				−0.10*** (0.04)					
Constant	2.81*** (0.12)	2.69*** (0.19)	2.92*** (0.20)	2.90*** (0.20)	6.63*** (0.15)	4.44*** (0.13)	6.09*** (0.15)	3.71*** (0.18)	3.60*** (0.20)
Observations	210,225	155,203	155,203	155,203	145,452	108,961	108,961	78,076	63,638
Residual SE	1.76	1.53	1.71	1.71	3.24	2.36	2.76	2.84	2.36

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses.

Notes: Replication of Table 4 with alternative measures. Mundlak CRE specification; Huber-robust regression. All regressions include demographic controls, regional controls and time dummies.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; Federal Reserve Bank of New York (FRBNY), SCE, June 2013 - October 2024; University of Michigan, Survey Research Center, MSC, January 1978 - January 2025; own calculations

Table 14: Quantile regression

	Inflation expectations (12 months ahead, point estimate)				
	Bottom 20%	Bottom 40%	Bottom 60%	Bottom 80%	Full Sample
Survey: BOP-HH					
female	−0.12*** (0.01)	−0.10*** (0.01)	−0.004 (0.01)	0.16*** (0.01)	0.50*** (0.01)
single	0.04 (0.06)	0.03 (0.03)	0.03 (0.03)	0.01 (0.04)	0.05 (0.04)
age	0.04*** (0.01)	0.04*** (0.005)	0.03*** (0.01)	0.06*** (0.01)	0.01 (0.01)
educ	0.01 (0.01)	0.01* (0.01)	0.02** (0.01)	0.01 (0.01)	0.01 (0.01)
hhinc	−0.001 (0.01)	−0.001 (0.005)	−0.001 (0.01)	0.001*** (0.0004)	−0.004*** (0.0003)
Observations	41,192	79,904	129,691	175,103	210,225
Residual SE	0.96	0.84	1.10	1.40	1.76
Survey: SCE					
female	−0.53*** (0.02)	−0.29*** (0.01)	−0.04*** (0.01)	0.24*** (0.02)	1.01*** (0.02)
single	−0.05* (0.03)	−0.03* (0.02)	−0.07*** (0.02)	−0.04** (0.02)	−0.10*** (0.03)
age	0.11 (0.32)	0.04 (0.21)	0.05 (0.21)	−0.02 (0.23)	−0.11 (0.33)
educ	0.19*** (0.01)	0.10*** (0.005)	0.03*** (0.005)	−0.07*** (0.01)	−0.32*** (0.01)
hhinc	0.11*** (0.01)	0.07*** (0.003)	0.01*** (0.003)	−0.05*** (0.004)	−0.25*** (0.01)
Observations	47,398	71,259	102,115	125,646	145,452
Residual SE	1.80	1.43	1.68	2.20	3.25
Survey: MSC					
female	0.00*** (0.00)	−0.11*** (0.01)	0.04*** (0.01)	−0.01 (0.01)	0.33*** (0.01)
single	−0.00** (0.00)	−0.06*** (0.01)	−0.07*** (0.01)	−0.07*** (0.01)	−0.05*** (0.02)
age	0.00 (0.00)	−0.001 (0.01)	−0.01 (0.01)	−0.002 (0.01)	−0.02*** (0.01)
educ	0.00 (0.00)	0.01 (0.03)	−0.01 (0.03)	−0.04 (0.03)	−0.08 (0.05)
hhinc	0.00 (0.00)	−0.0000 (0.0000)	−0.0000 (0.0000)	0.0000 (0.0000)	−0.0000 (0.0000)
Observations	55,326	152,224	211,099	226,143	277,093
Residual SE	0.0000	1.79	2.45	2.67	3.17

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

Robust standard errors in parentheses.

Notes: Mundlak CRE specification; Huber-robust regression. All regressions include regional controls and time dummies. For BOP-HH and SCE also unemployment, full time, part time and homemaker dummies.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; Federal Reserve Bank of New York (FRBNY), SCE, June 2013 - October 2024; University of Michigan, Survey Research Center, MSC, January 1978 - January 2025; own calculations

Table 15: Confidence and other heterogeneities

	BOP-HH			SCE		
	Inflation expectations		prob.confident	Inflation expectations		prob.confident
female	0.50*** (0.01)	-0.06*** (0.01)	-0.05*** (0.0004)	1.00*** (0.02)	0.16*** (0.02)	-0.16*** (0.001)
age	0.03*** (0.002)	0.02*** (0.002)	-0.002*** (0.0001)	0.04*** (0.001)	0.03*** (0.001)	-0.002*** (0.0001)
age^2	-0.0003*** (0.0000)	-0.0001*** (0.0000)	0.0000*** (0.0000)	-0.0001*** (0.0000)	-0.0001*** (0.0000)	0.0000*** (0.0000)
educ	-0.06*** (0.001)	-0.003* (0.001)	0.01*** (0.0001)	-0.32*** (0.01)	-0.10*** (0.01)	0.04*** (0.0003)
hhinc	-0.0002 (0.0001)	-0.0000 (0.0001)	0.0001*** (0.0000)	-0.25*** (0.005)	-0.10*** (0.01)	0.03*** (0.0002)
prob.confident		-11.09*** (0.05)			-5.79*** (0.07)	
Constant	2.23*** (0.12)	11.20*** (0.13)	0.81*** (0.005)	6.18*** (0.15)	9.02*** (0.15)	0.40*** (0.01)
Observations	210,225	210,225	210,225	145,452	145,452	145,452
Residual SE	1.76	1.69	0.08	3.25	3.16	0.18

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

Notes: Mundlak CRE specification; Huber-robust regression. All regressions include regional controls and time dummies and unemployment, full time, part time and homemaker dummies.

Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BOP-HH, April 2020 - June 2025; Federal Reserve Bank of New York (FRBNY), SCE, June 2013 - October 2024; own calculations

D Financial Literacy Questionnaire (SCE)

QnumIntro. Next, we would like to ask you five questions to see how people use numbers in everyday life. Please answer the following questions by filling in the blank.

QNUM2. Let's say you have \$200 in a savings account. The account earns ten percent interest per year. Interest accrues at each anniversary of the account. If you never withdraw money or interest payments, how much will you have in the account at the end of two years?
\$

No answer

QNUM8. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After one year, how much would you be able to buy with the money in this account?

1. More than today
2. Just as much as today
3. Less than today

No answer

QNUM9. Please tell me whether this statement is true or false: Buying a single company's stock usually provides a safer return than a stock mutual fund.

1. True
2. False

No answer