Forecast Confidence and Exposure in Inflation Expectations: Evidence from the Gender Gap*

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Abstract

Do signals or priors matter more for household inflation expectations? I develop a Bayesian framework in which agents differ in prior precision ("forecast confidence") and observed signal volatility ("price exposure"), allowing me to assess their relative importance. Applying the framework to the persistent gender gap in survey expectations, I construct a novel, model-consistent measure of forecast confidence and show that confidence heterogeneity fully accounts for the gap.

Keywords Consumer Inflation Expectations, Gender, Forecast Confidence

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Introduction

Household inflation expectations are a fundamental driver of financial decision-making, shaping everything from consumption and saving trajectories to stock market participation and retirement planning. Within this context, the gender gap in inflation expectations, i.e. women reporting significantly higher expected inflation in household surveys, is a well-documented and persistent phenomenon.[1] On average, the gender gap amounts to 2.6 percentage points in the U.S. and 1.2 percentage points in Germany and is associated with higher forecast errors among women.[2] But why do consumers systematically differ in their inflation expectations? A leading explanation is lived experiences (D'Acunto, Malmendier, Ospina, & Weber, 2021). For the gender gap, seminal work suggests that traditional gender roles expose women more to volatile grocery prices which leads them to overweight salient price increases (D'Acunto, Malmendier, & Weber, 2021).

However, if a gendered division of labor were the primary driver, this gap should largely disappear among single-person households, where both men and women must manage their own grocery shopping. Yet, across three major micro-data sources across Germany and the U.S., I document that a persistent, statistically significant gender gap remains among singles (see Appendix Table A.1).[3] This poses an empirical puzzle for the "exposure-hypothesis". To resolve this puzzle, I turn to theory: For volatile price signals to alter inflation expectations, one must account for the structure of the agent's prior belief. This is the focus of this paper. I show both theoretically and empirically that price exposure matters, but only for a subset of consumers with low confidence in priors, many of whom are women. This provides a structural bridge to behavioral finance, where women consistently report lower confidence in financial literacy assessments and decision-making (Anderson et al., 2017; Barber & Odean, 2001; Bucher-Koenen et al., 2025).

[1] See, e.g. Bryan and Venkatu (2001), Corduas (2022), D'Acunto, Malmendier, and Weber (2021), Jonung (1981), and Kindermann et al. (2025)

[2] 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. Figure 1 illustrates the persistence of these gaps over time.

[3] Naturally, analyzing singles provides only a proxy for exposure. Recent evidence demonstrates that inflation experiences vary not just by what individuals consume, but also where they shop and which brands they choose (Kaplan & Schulhofer-Wohl, 2017). However, if these within-category shopping habits rather than the fundamental act of grocery shopping itself are driving the persistent gap among singles, it suggests that a pure exposure mechanism requires an exceptionally granular and unobserved set of assumptions.

Formally, in a Bayesian learning framework, agents observe a composite inflation signal in which frequent grocery shopping introduces transient, item-level price noise, directly reducing signal precision. To reflect historical inflation experiences accurately, I model grocery signals as unbiased. Forecast confidence is defined as prior precision, i.e. the sharpness of an agent's baseline belief about inflation. Because actual price distributions are right-skewed (Appendix Figure C.1), modeling beliefs as log-normal implies that lower precision in either the signal or the prior increases posterior variance, which mechanically elevates the posterior mean. Crucially, the two precisions interact: high prior precision acts as a cognitive anchor that heavily discounts noisy price signals. Consequently, volatile grocery shopping elevates mean inflation expectations only when an agent's prior precision is low. I extend this mechanism to a dynamic framework where past signals and priors affect the accumulation of prior precision over time. While existing work treats priors as exogenously tied to macroeconomic conditions and attributes the overweighting of salient supermarket prices to cognitive limitations (Cavallo et al., 2017), I provide a structural microfoundation for prior precision. This allows the weighting of salient price signals to vary endogenously across individuals within the exact same macroeconomic environment, while still implying that salient price shocks matter most during periods of heightened uncertainty.

Empirically, I construct a novel, model-consistent measure of forecast confidence using the Bundesbank Online Panel–Households (BOP-HH, 2019–2025). The index relies on two behavioral signals of confidence: less confident respondents give round poin forecasts (Binder, 2017; Krifka, 2007) and express wider ranges of possible inflation outcomes. Specifically, I estimate a logistic model that links point-forecast rounding to lagged belief dispersion, mapped through the theoretical law of motion where past posterior precision carries over into current prior precision. To isolate intrinsic confidence from personal price volatility, I extract a linear predictor of confidence while counterfactually holding grocery shopping frequency at zero. I establish two key empirical findings: (1) Equalizing forecast confidence across men and women fully accounts for the gender gap in inflation expectations. (2) Grocery shopping frequency elevates inflation expectations only for low-confidence respondents, confirming the theoretical interaction. Consistent with the mechanism via the right-skew, the gender gap is entirely an upper-tail phenomenon that vanishes below the 70th percentile of the expectations distribution, ruling out a uniform shift across all women. To verify

the model's structural logic, I confirm that backward-looking inflation perceptions depend strictly on prior precision and show zero interaction with grocery exposure. External validity is established using the New York Fed Survey of Consumer Expectations (2013–2024) and the Michigan Survey of Consumers (1978–2025).

My methodology makes use of Kitagawa-Oaxaca-Blinder decompositions (common in the literature on gender wage gaps, Blau & Kahn, 2017) and exploiting the panel dimension of the survey rather than experimental setups which have recently become more common in the literature on consumer inflation expectations (Armantier et al., 2016; Coibion, Georgarakos, Gorodnichenko, & van Rooij, 2023; Coibion, Georgarakos, Gorodnichenko, & Weber, 2023; Coibion & Gorodnichenko, 2025; Coibion et al., 2022, 2024; Haaland et al., 2023). While such RCTs can isolate causal effects for example of monetary policy communication on expectation formation or the effect of expectation changes and uncertainty on spending, they cannot quantify the relative accounting shares of a baseline gap nor test how prior precision and grocery price exposure interact in a natural environment. However, my results are complementary to this literature which has documented that incentivization reduces demographic differences in forecasts (Drobot et al., 2025), and that women's beliefs respond more strongly in randomized information treatments (Armantier et al., 2016; Coibion, Georgarakos, Gorodnichenko, & Weber, 2023; Coibion et al., 2022), both of which are results that follow naturally from lower prior precision.

Further, I reconcile my findings with financial literacy, another established driver of heterogeneities in inflation expectations (Bruine De Bruin et al., 2010). Recent work highlights that the observed gender gap in financial literacy is itself heavily driven by a confidence deficit rather than an absolute knowledge gap (Bucher-Koenen et al., 2025). Empirically, I show that my measure of forecast confidence mediates approximately 50% of the financial literacy effect on expectations. Yet, unlike confidence, financial literacy lacks the interaction with grocery shopping frequency. I formalize financial literacy therefore as reducing the prior mean directly (for example toward the objective inflation target). Because this channel acts as a location shift only, financial literacy systematically reduces average inflation expectations without altering how households process volatile everyday price signals. It's contribution to the gender gap is therefore smaller than that of forecast confidence.

Understanding this confidence channel is critical for household finance because subjective inflation expectations function as the implicit discount factor for real asset returns, directly shaping asset pricing dynamics and macro-financial transmission (D'Acunto & Weber, 2024; D'Acunto et al., 2024; Galashin et al., 2026; Leombroni et al., 2020; Malmendier & Nagel, 2016; Schnorpfeil et al., 2025; Vissing-Jorgensen, 2003). When exposure to price volatility and low forecast confidence systematically elevate expected inflation, they distort perceived real returns. This mechanism helps explain documented gender disparities in long-term wealth accumulation, stock market participation, retirement planning, and credit utilization (Almenberg & Dreber, 2015; Cota et al., 2025; Lusardi & Mitchell, 2008; van Rooij et al., 2011). The role of subjective confidence is thereby crucial: Consistent with evidence that subjective confidence and uncertainty governs how strongly beliefs transmit into financial choices (Coibion et al., 2024; Fermand et al., 2024; Giglio et al., 2021), I demonstrate that my proposed mechanism is not merely an abstract feature of survey responses, but actively maps into planned household balance-sheet decisions. Cross-sectional survey data reveal that the dampening effect of high inflation expectations on spending in line with an income channel (Coibion, Georgarakos, Gorodnichenko, & van Rooij, 2023; Galashin et al., 2026) is amplified for consumers with higher forecast confidence.

Additionally, the framework provides broader implications for macroeconomic policy. I show that forecast confidence acts as a unifying latent factor explaining expectation heterogeneities across age, education, and income cohorts. Furthermore, by interacting food price movements with the Economic Policy Uncertainty (EPU) index (Baker et al., 2016), I document that salient grocery price shocks pass through into expectations primarily during periods of heightened macroeconomic uncertainty, when baseline prior precision is cyclically depressed. Because central banks cannot alter physical exposure to supermarket prices, policy interventions aimed at anchoring beliefs are most effective when targeted at building forecast confidence and clarifying communication during turbulent economic environments (Coibion et al., 2022; Ehrmann & Fratzscher, 2007).

This paper contributes to the literature on the formation of household expectations by providing a unified mechanism through which lived exposure (Anesti et al., 2025; 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 prior beliefs jointly de-

termine expectations. Education, cognitive abilities and financial literacy (Bruine De Bruin et al., 2010; Burke & Manz, 2014; D'Acunto et al., 2019, 2022; Piccolo et al., 2025) can affect those priors. To my knowledge, the paper is the first to provide theoretical microfoundations for how grocery shopping affects inflation expectations but notes the conditionality of this channel on assumptions about the prior. In addition, the framework helps rationalize other features of survey data. For example, it reconciles evidence that gasoline prices strongly affect inflation expectations (Binder, 2018; Coibion & Gorodnichenko, 2015) with the gender gap: even when men and women face similar exposure to volatile prices (assuming men refuel at least as often as women), men with higher average forecast confidence adjust expectations less.

The paper proceeds as follows. Section 1 introduces the Bayesian framework. Section 2 describes the data and my novel forecast confidence measure. Section 3 presents the main empirical results: exposure matters when confidence is low, highlighting confidence as the dominant driver and exposure as secondary. Section 4 shows implications and applications of the mechanism beyond gender and Section 5 discusses the relationship between forecast confidence and financial literacy before 6 concludes.

1 Bayesian Framework

I start with a static Bayesian framework to illustrate the two hypothesized channels causing the gender gap in inflation expectations: exposure and forecast confidence. I model differences in exposure, such as grocery shopping activity, as differences in the distribution of a composite signal received. An agent who visits grocery stores frequently observes more volatile price signals as food prices are fundamentally more volatile than the core component of the consumption basket (see historical evidence in Appendix Figure C.1). Microfoundations of the signal structure will be discussed in Section 1.2. On the other hand, I capture differences in forecast confidence as differences in prior precision about future inflation. While I initially treat prior precision as exogenous, in Section 1.3 I endogenize the prior in a dynamic setting. The simple baseline framework is used to demonstrate how these two channels work in isolation and that they interact. An agent with less confidence will place less weight on their own forecast such that signals matter more as they become the dominant source of information about inflation. I first present the static framework and explore the

impact of changes in signal and prior precision. I calibrate the framework to the data to show that my framework can fully explain the gender gap in expectations. Afterwards, I develop micro-foundations of the composite signal and explore a dynamic version that will form the basis of my empirical identification of forecast confidence. For simplification, the framework is shown for a representative agent. Proofs are collected in Appendix B.

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

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

Lower prior precision, i.e. a smaller τ_0 indicates lower confidence in the prior.

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

$$\log x = \log \pi + \epsilon, \qquad \text{where } \epsilon \sim \mathcal{N}\left(0, \frac{1}{\tau_x}\right).$$

Signal-unbiasedness here is chosen to reflect that groceries have the same level of inflation as other goods on average. However, there has been greater volatility in the CPI food.[4] If the agent shops for goods with volatile prices she will receive signals with lower precision, i.e. with a smaller τ_x. While observing more grocery items eliminates idiosyncratic price noise, it cannot diversify away the common, highly volatile food-sector shock. As shopping frequency increases, agents place greater salience weight on their personal grocery experiences relative to broader macroeconomic news. Because food-sector volatility exceeds aggregate inflation noise, this cognitive weight shift increases the overall variance of the composite signal, structurally lowering its precision τ_x. More details can be found in Section 1.2. 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. Both assumptions are crucial for the mechanism discussed

[4]Historically, in fact food price inflation has been slightly lower than the total basket. See Appendix Figure C.1 for more details.

in D'Acunto, Malmendier, and Weber (2021) to operate.

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) Realized inflation outcomes match a right-skewed distribution with minimal observations below zero (see Appendix Figure C.1); (2) accordingly there appears to be a zero lower bound in inflation expectations (Gorodnichenko & Sergeyev, 2021); (3) tail prices to the right matter most for expectation formation (Chua & Tsiaplias, 2024); and finally, (4) the average density forecast (i.e. the average observed posterior forecast) aligns with this choice (see Appendix Figure C.3). 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 increasing the variance can increase the mean forecast. The asymmetry of the log-normal distribution is a key element of the framework.

The agent updates her beliefs about π based on the observed signal using Bayes' rule,

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

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

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

The expected value of π under the posterior distribution is simply the mean of its posterior distribution.[5] It depends directly on the precision of priors and signals and thus on the agent's confidence in her own beliefs and the price signals she receives:

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

[5] Alternatively, one may choose the mode of the distribution as a measure of central tendency. The intuition for the rest of the paper would follow through, but the mathematical conditions described in what follows differ slightly. Evidence on whether point forecasts align with mean or mode more are mixed (Armantier et al., 2013; Zhao, 2023)

Similarly, the posterior variance is given by

$$\begin{aligned}\mathbb{V}ar(\pi|x) &= \left[\exp\left(\frac{1}{\hat{\tau}}\right) - 1\right] \exp\left(2\hat{\mu} + \frac{1}{\hat{\tau}}\right) \\ &= \left[\exp\left(\frac{1}{\tau_0 + \tau_x}\right) - 1\right] \exp\left(\frac{2\tau_0\mu_0 + 2\tau_x \log x + 1}{\tau_0 + \tau_x}\right). \end{aligned} \tag{2}$$

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 lower prior precision ($\tau_0^{\text{female}} < \tau_0^{\text{male}}$) and higher signal volatility ($\tau_x^{\text{female}} < \tau_x^{\text{male}}$) 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. The framework reveals that the expected inflation as well as the variance thereof is increasing in signal volatility whenever $\log x$ exceeds μ_0 by less than half of the prior variance $\frac{1}{\tau_0}$.

$$\frac{d\mathbb{E}(\pi|x)}{d\tau_x} < 0 \iff \log x - \mu_0 < \frac{1}{2\tau_0} \tag{3}$$

Notice that condition (3) 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. However, assuming that signals are unbiased (as defined above), this would imply that the forecaster's prior is biased. A more interesting case arises when the prior is unbiased but imprecise and the condition relaxes such that the agent relies more on the signals received. When priors are sufficiently flat, the agent may revise her expectations upward as signals become more volatile even when signals on average exceed the rational, unbiased prior. Further, equation (2) shows that under condition (3) it will also always be true that the variance is increasing in signal volatility. This is the case because the first term

of equation (2) is monotonically increasing in $\frac{1}{\tau_x}$ while the second term is increasing under the same condition as the posterior mean in equation (1).

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 the prior mean of log inflation exceeds the log signal realization* $\mu_0 > \log x$.

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, Ospina, & Weber, 2021; 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 precision, here denoted as forecast confidence.

Subsequently, I will discuss the comparative statics of a decrease in the forecast confidence τ_0 on $\mathbb{E}(\pi|x)$.

$$\frac{d\mathbb{E}(\pi|x)}{d\tau_0} < 0 \iff \mu_0 - \log x < \frac{1}{2\tau_x} \tag{4}$$

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 (3) relaxes with the prior being flat, condition (4) 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 log 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 forecast confidence can individually be a cause of 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. It is thus well suited to explain the interaction of the two channels hypothesized to explain the gender gap in inflation expectations. 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.

Further, the conditions reveal that there is a combination of values for $\log x$, μ_0, τ_x and τ_0 for which both conditions, (3) and (4) 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* $\mathbb{E}(\pi|x)$ *are increasing in both, higher signal volatility* $\frac{1}{\tau_x}$ *and prior imprecision* $\frac{1}{\tau_0}$. *Otherwise, the agent's inflation expectation* $\mathbb{E}(\pi|x)$ *are increasing in either higher signal volatility* $\frac{1}{\tau_x}$ *or prior imprecision* $\frac{1}{\tau_0}$.

1.1 Structural calibration of confidence

The Bayesian learning framework delivers sharp comparative statics: if forecasters are unbiased, 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. 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 U.S. (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 π, signals x, and posterior beliefs. Specifically, I draw

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

and compute the posterior mean

$$\mathbb{E}(\pi \mid x) = \exp\Big(\hat{\mu} + \tfrac{1}{2\hat{\tau}}\Big),$$

as well as the posterior IQR

$$\mathbb{I}QR(\pi \mid x) = \exp\Big(\hat{\mu} + \frac{\Phi^{-1}(0.75)}{\sqrt{\hat{\tau}}}\Big) - \exp\Big(\hat{\mu} + \frac{\Phi^{-1}(0.25)}{\sqrt{\hat{\tau}}}\Big),$$

from the lognormal distribution implied by $(\hat{\mu}, \hat{\tau})$.[6] 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 Germany and the U.S. (Table 1). The empirical mean forecast of women exceeds that of men by 1.21 percentage points in Germany and 2.61 percentage points in the U.S.. The model with gender-specific precision parameters (τ_0, τ_x) generates a mean forecast gap of 1.12 (Germany) and 2.23 (U.S.) percentage points.

As a verification check, I evaluate the framework's performance on untargeted moments of

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

cross-sectional dispersion. Specifically, I test whether the model can predict the observed gender gap in the standard deviation of point forecasts, $\mathbb{S}D(\mathbb{E}(\pi \mid x))$. In the survey data, women exhibit substantially higher cross-sectional dispersion than men, with an empirical gap of 2.73 percentage points in Germany and 6.24 percentage points in the U.S.. Without being targeted in the optimization, the model naturally replicates this structural pattern, generating a dispersion gap of 3.98 percentage points in Germany and 8.88 percentage points in the U.S.. This confirms that lower prior precision among women not only shifts central tendency upward but also correctly predicts higher-order cross-sectional heterogeneity consistent with empirical data.

Finally, when I equalize prior precision across genders (setting women's τ_0 equal to men's while holding signal precision τ_x fixed at its calibrated level), the gap in mean expectations completely disappears (-0.06 pp in Germany and -0.03 pp in the U.S.). This implies that differences in τ_0, interpreted as forecast confidence, can explain virtually the entire empirical gender gap: the share explained is 97% in Germany and 87% in the U.S.. Once priors are equalized, exposure to noisy food-price signals no longer generates a persistent gap.

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.

1.2 Micro-foundation of the Composite Signal

A potential criticism of modeling exposure as a single composite signal is that in a standard Bayesian framework, receiving a larger quantity of signals should mechanically increase posterior precision through signal accumulation. If frequent grocery shopping simply provides additional independent price observations about aggregate inflation, frequent shoppers would become structurally more, rather than less, precisely informed.

To address this, I provide a micro-foundation showing how a single composite signal x arises when an agent observes both persistent macroeconomic news and transient, item-level grocery prices, but aggregates them into a single experienced signal before updating their macro expectations. This distinction formalizes not only the arguments for the grocery

Table 1: Simulation Exercise

	BOP-HH, Germany		SCE, U.S.	
	Men	Women	Men	Women
Model τ_0	0.57	0.45	0.61	0.40
Model τ_x	8.22	9.39	1.19	1.32
Targeted Moments				
Model Gender Gap in $E(\pi \mid x)$		1.12		2.23
Empirical Gender Gap in $E(\pi \mid x)$		1.21		2.61
Untargeted Moments				
Model Gap in $SD(E(\pi \mid x))$		3.98		8.88
Empirical Gap in $SD(E(\pi \mid x))$		2.73		6.24
Counterfactual				
Equalized Gender Gap ($\tau_0^f = \tau_0^m$)		-0.06		-0.03
Share Explained by τ_0		0.97		0.87

Notes: The table reports calibrated values of prior precision τ_0 and signal precision τ_x by gender, obtained by moment-matching the group-level mean point forecast and individual density uncertainty in the BOP-HH and SCE. All reported gaps are calculated as women minus men in percentage points. The untargeted moment, the cross-sectional standard deviation of point forecasts, serves as an out-of-sample validation of the model's predicted dispersion. "Equalized Gender Gap" sets women's τ_0 equal to men's while keeping τ_x fixed at its calibrated female value. "Share Explained by τ_0" measures the proportion of the empirical mean gap accounted for by prior precision differences.

shopping hypothesis (D'Acunto, Malmendier, Ospina, & Weber, 2021) but also recent work on local and global information (D'Acunto & Weber, 2026).

Suppose in any given period, an agent receives information from two distinct sources:

1. A persistent aggregate signal s_m (representing media coverage, professional forecasts, or non-volatile core basket components) given by:

$$\log s_m = \log \pi + \epsilon_m, \qquad \epsilon_m \sim \mathcal{N}\left(0, \frac{1}{\tau_m}\right). \tag{5}$$

2. A set of N transient grocery price signals $s_{g,i}$ for $i \in \{1, \ldots, N\}$ observed during

shopping trips. Each grocery signal reflects aggregate inflation π, a common volatile food-sector shock η, and idiosyncratic item-level noise ν_i:

$$\log s_{g,i} = \log \pi + \eta + \nu_i, \qquad \eta \sim \mathcal{N}\left(0, \frac{1}{\tau_f}\right), \quad \nu_i \sim \mathcal{N}\left(0, \frac{1}{\tau_v}\right). \tag{6}$$

Crucially, food prices exhibit structurally higher volatility than aggregate inflation, such that the sectoral noise variance exceeds aggregate media noise: $\frac{1}{\tau_f} > \frac{1}{\tau_m}$. The stochastic terms ϵ_m, η, and ν_i are assumed to be mutually independent.

Owing to cognitive limits or salience heuristics, the agent does not perform $N+1$ separate Bayesian updates. Instead, they first aggregate item-level shopping experiences into a single grocery basket signal:

$$\log \bar{s}_g = \frac{1}{N}\sum_{i=1}^{N} \log s_{g,i} = \log \pi + \eta + \bar{\nu}, \qquad \text{where } \bar{\nu} = \frac{1}{N}\sum_{i=1}^{N} \nu_i \sim \mathcal{N}\left(0, \frac{1}{N\tau_v}\right). \tag{7}$$

As shopping frequency $N \to \infty$, idiosyncratic item noise vanishes ($\frac{1}{N\tau_v} \to 0$), but the volatile sectoral shock η persists.

The agent then forms their single composite signal $\log x$ by taking an exposure-weighted average of the aggregate signal and grocery basket experiences:

$$\log x = (1 - \omega(N)) \log s_m + \omega(N) \log \bar{s}_g, \tag{8}$$

where $\omega(N) \in [0, 1]$ represents the salience weight assigned to grocery shopping, which increases in shopping frequency ($\omega'(N) > 0$).

Since both s_m and $\bar{s}_g$ are centered on $\log \pi$, the composite signal is strictly unbiased ($\mathbb{E}[\log x \mid \pi] = \log \pi$). However, its conditional variance $\frac{1}{\tau_x(N)} = \mathbb{V}ar(\log x \mid \pi)$ is given by:

$$\frac{1}{\tau_x(N)} = (1 - \omega(N))^2 \frac{1}{\tau_m} + \omega(N)^2 \left(\frac{1}{\tau_f} + \frac{1}{N\tau_v}\right). \tag{9}$$

Proposition 1.4 *Assume the structural volatility of the food sector strictly exceeds aggregate signal noise ($\frac{1}{\tau_f} > \frac{1}{\tau_m}$). As grocery shopping frequency N increases, shifting salience*

weight $\omega(N)$ toward grocery experiences, the variance of the composite signal strictly increases ($\frac{d}{dN}\frac{1}{\tau_x(N)} > 0$), resulting in a lower composite signal precision $\tau_x(N)$.

This micro-foundation confirms that frequent grocery shopping does not provide more structural signals about macroeconomic inflation. Rather, it shifts the composition of an agent's information basket toward a high-volatility sector, mapping directly into a lower single parameter τ_x in the baseline model.

1.3 Dynamic extension

While the baseline framework treats τ_0 and τ_x as static parameters, the panel dimension of the survey data allows for a recursive extension in which prior precision evolves endogenously over time. Embedding the learning problem in a dynamic environment transforms belief updating into a forecasting–updating recursion. This section shows how a prior imprecision can arise as the outcome of repeated exposure to noisy signals. The dynamic framework will be used to derive an estimate of $\tau_{0,i,t}$ from the panel data.

Let $z_t = \log \pi_t$ denote the log inflation state. I assume it follows an $AR(1)$ process:

$$z_t = (1-\rho)\bar{z} + \rho z_{t-1} + \eta_t, \quad \eta_t \sim \mathcal{N}(0, \frac{1}{\tau_\eta}), \tag{10}$$

where $\rho \in [0,1]$ captures the persistence of inflation and $\bar{z}$ is the long-run mean. This nests the static model discussed above for the case $\rho = 0$. The innovation variance τ_η^{-1} measures the degree of macroeconomic uncertainty. In more volatile environments, larger innovations to inflation reduce the informativeness of past observations and increase forecast dispersion. The signal structure remains:

$$\log x_t = z_t + \epsilon_t, \qquad \epsilon_t \sim \mathcal{N}\left(0, \frac{1}{\tau_x}\right).$$

Suppose that at the end of period $t-1$, beliefs are

$$\log \pi_{t-1} \mid x_{1:t-1} \sim \mathcal{N}\left(\hat{\mu}_{t-1}, \frac{1}{\hat{\tau}_{t-1}}\right),$$

where $x_{1:t-1}$ denotes the history of observed signals. Using the law of motion (10), the time-t

prior (before observing x_t) is:

$$\log \pi_t \mid x_{1:t-1} \sim \mathcal{N}\left(\mu_{0,t}, \frac{1}{\tau_{0,t}}\right),$$

with prior mean

$$\mu_{0,t} = (1-\rho)\bar{z} + \rho\hat{\mu}_{t-1}, \tag{11}$$

and prior variance

$$\frac{1}{\tau_{0,t}} = \rho^2 \frac{1}{\hat{\tau}_{t-1}} + \frac{1}{\tau_\eta}. \tag{12}$$

Equation (12) is the key dynamic result: in the static model prior uncertainty just reflected a constant macroeconomic uncertainty ($\rho = 0$,$\tau_0 = \tau_\eta$). In a dynamic model, past posterior precision ($\hat{\tau}_{t-1}$) increases prior precision.

Upon observing x_t, beliefs update according to the static Bayesian formula:

$$\hat{\tau}_t = \tau_{0,t} + \tau_x, \qquad \hat{\mu}_t = \frac{\tau_{0,t}\mu_{0,t} + \tau_x \log x_t}{\tau_{0,t} + \tau_x}.$$

Thus, learning remains conjugate and log-normal; what changes is that prior precision itself is now endogenous. Agents exposed to volatile and noisy price signals (low τ_x) fail to accumulate posterior precision $\hat{\tau}_{t-1}$, keeping $\tau_{0,t}$ persistently low. These agents enter each period with a flat prior and therefore overweight new noisy realizations. This further highlights the interaction between the two channels. The recursive structure of equation (12) implies that prior precision converges to a unique steady state $\bar{\tau}_0$, which characterizes the long-run confidence of the agent.

Proposition 1.5 *In the steady state of the dynamic learning process, the prior precision $\bar{\tau}_0$ is implicitly defined by:*

$$\bar{\tau}_0 = \left[\frac{\rho^2}{(\bar{\tau}_0 + \tau_x)} + \frac{1}{\tau_\eta}\right]^{-1}. \tag{13}$$

This yields a signal-prior complementarity where prior precision is strictly increasing in signal quality ($\frac{\partial \bar{\tau}_0}{\partial \tau_x} > 0$).

The comparative statics derived in Propositions 1.1–1.3 describe the direct effects of prior

precision and signal precision on inflation expectations, as well as their structural interaction, within the static Bayesian updating framework. Proposition 1.1 shows how noisier signals (lower τ_x) can increase expected inflation, while Proposition 1.2 demonstrates that lower prior precision (lower τ_0) can have a similar effect. Further, proposition 1.3 highlights that both channels may operate simultaneously. These static results treat τ_x and τ_0 as independent parameters. Proposition 1.4 suggests that τ_x can be modelled as a function of grocery shopping frequency and Proposition 1.5 shows that prior precision evolves endogenously over time. In particular, agents exposed to noisier signals accumulate less posterior precision, resulting in persistently flatter priors. Consequently, signal volatility may affect expectations both directly, through the updating equations characterized in Propositions 1.1–1.3, and indirectly, by shaping the evolution of prior precision.

Extending this framework to survey measurements reveals a structural distinction between historical perceptions and forward-looking expectations. When reporting past aggregate CPI, agents recognize that personal shopping experiences contain relative price noise rather than official historical data, causing reported perceptions to reflect the prior distribution. In contrast, when forecasting unobserved future inflation, agents actively integrate personal price signals with prior beliefs. Perceptions therefore function as a placebo exercise.

Proposition 1.6 *Let reported past inflation perceptions be given by* $\log \pi_t^P = \mu_{0,t} + \frac{1}{2\tau_{0,t}}$. *Unlike forward-looking expectations, past inflation perceptions depend strictly on prior precision* ($\frac{\partial \log \pi_t^P}{\partial \tau_{0,t}} < 0$) *and are independent of personal signal realizations* ($\frac{\partial \log \pi_t^P}{\partial \log x_t} = 0$).

In the empirical section I test the effect of current prior precision (forecast confidence) and signal precision (grocery shopping) on inflation forecasts and perceptions and show that forecast confidence is a dominant driver in explaining the gender gap in inflation expectations. This holds true even when removing the contribution of past signal volatility. However, while for forecasts signal volatility matters when confidence is low, in line with Proposition 1.6 for perceptions only confidence is significant.

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).[7] This survey is particularly suited to analyze the gender gap in inflation expectations because it contains individual-level data on household responsibilities including grocery shopping alongside the probabilistic elicitation of inflation expectations and a financial literacy test in selected survey waves, 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 participants do so; these responses are excluded here.

I complement this survey with two established consumer surveys from the U.S., the Michigan Survey of Consumers from June 1978 until January 2025 (MSC, Survey Research Center, 2025); and the Survey of Consumer Expectations from June 2013 until October 2024 (SCE, Federal Reserve Bank of New York, 2024).[8] 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 U.S.. In the analysis below, I focus on the BOP-HH and SCE which contain probabilistic forecasts, a central component to my analysis. For my analysis on implications beyond gender in Section 4.3 I also utilize the Michigan survey's longer time span. All surveys are summarized in Appendix Table D.1 and summary statistics of the demographics can be found in Table 2 Panel A. Women in the surveys have marginally lower education (`educ`) and substantially lower reported household incomes (`hhinc`). They are of similar age as men in the surveys. Throughout, I control for these demographics as well as observations on

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

[8] Disclaimer: 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.

employment.

2.1 Measuring inflation point forecasts and uncertainty

The literature has established that there are gender gaps in inflation point forecasts (Bryan & Venkatu, 2001; Corduas, 2022; D'Acunto, Malmendier, & Weber, 2021; Jonung, 1981; Kindermann et al., 2025). The framework discussed above highlights that these gaps can be caused by volatile signals or imprecise priors in a right-skewed distribution. 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 inflation[9] 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. I assume that the point forecast represents the mean of the respondents forecast in line with previous literature (Armantier et al., 2013). However, the intuition of the framework applies also to the mode, an alternative measure of central tendency that shows high consistency with probabilistic forecasts (Zhao, 2023). The non-response for inflation expectations in the surveys is very low, but in all surveys higher for women. This indicates that if confidence drives the gender gap, my estimates are a lower bound as those with the lowest confidence ('don't know') are not captured in the quantitative forecast.[10]

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 C.3 shows the average density forecast from both surveys. I use the probabilities of the reported bin to fit an underlying

[9]Inflation 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.

[10]While choosing 'don't know' can also reflect survey inattention (e.g., Bracha & Tang, 2025), a robust literature in behavioral finance frames it as a measure of low confidence (Bucher-Koenen et al., 2025).

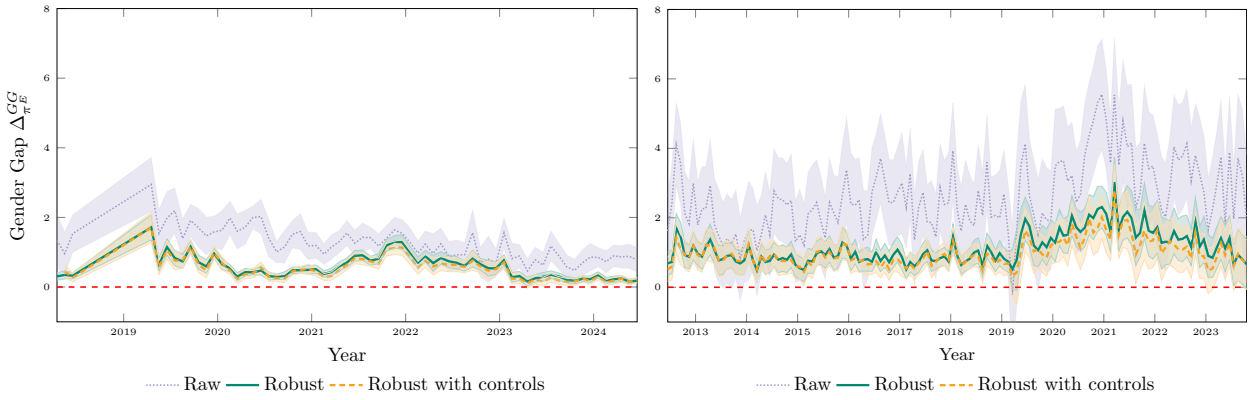
parametric density following the approach of Engelberg et al. (2009) and applied to the SCE as described in Armantier et al. (2017). My measure for posterior variance is the interquartile range of the density forecast, defined as the difference between the third and first quartile. This is preferred as it is more robust to outliers. The share of non-response to this measure is higher for all respondents than for the the point forecast, but especially so for women.

I denote the point forecast of inflation 12 months ahead at time t ($E(\pi \mid x)$ in the framework) as π_t^E and the posterior interquartile range around this forecast ($IQR(\pi \mid x)$ in the framework) as π_t^{IQR}. For the BOP-HH respondents also indicate their inflation perceptions, π_t^P, i.e. beliefs about inflation over the past 12 months. Table 2 compares π_t^P, π_t^E and π_t^{IQR} in Panel B. As anticipated, women hold both substantially higher point nowcasts and forecasts as well as greater uncertainty around them. This is confirmed also in Figure 1 which shows the differences in average π^E (purple line) over time. The gap shrinks when outliers are downweighted (green line)[11] but remains persistently positive even when controls for demographics such as age, income and education are included (yellow). The effect of demographics on the gender gap in inflation expectations is shown in Appendix Table D.2. Further, I test the accuracy of women and men's forecasts and find a larger forecast error measured as root mean squared error (*RMSE* in Table 2) for women. On average, women's higher forecasts lead to less accurate forecasts.

2.2 Measuring exposure

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 (1). Rather than a binary indicator, this scale acts as a chore intensity index. I use this gradual ranking to differentiate between sole and joint responsibility as recommended in van Hove and Verbraecken (2025). To provide further granular insights, I also construct two binary indicators: `any_groceries`, equal to 1 if an individual has either joint or sole responsibility and 0 otherwise; and `all_groceries`, equal to 1 only when an individual bears sole responsibility. Since the question is only asked for the first time an

[11] `female`-coefficient in Huber robust regression



(a) BOP-HH, Germany

(b) SCE, U.S.

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 on inflation point forecasts with no controls (purple line), Huber robust regression with no controls (green line) and with all demographics controls available (yellow line). These include: age, income, education, single, unemployed, retired, full-time work, part-time work, homemaker, and region controls.

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, in Appendix A I use singles as an alternative robustness measure for grocery shopping activity. Single men and women both need to visit grocery stores frequently despite maybe having different habits on food consumption.

The data reveal that traditional gender norms remain present in German households. Table 2 Panel C compares grocery shopping and financial decision-making for men and women. As expected, women exhibit significantly higher involvement in grocery shopping in multi-person households. Men report an average grocery chore intensity score of 0.60 (SD 0.39). Because a score of 0.5 denotes shared responsibility, this mean reflects that while a large majority of men (78%,) participate in grocery shopping to some degree, only 42% bear sole responsibility. In contrast, women average a chore intensity score of 0.83 (SD 0.30), with 94% involved in grocery shopping and 72% claiming sole responsibility. Furthermore, men in the sample are less likely to live alone than women. Assuming that single individuals naturally bear sole responsibility for their grocery shopping, extending these estimates to

the general population would further widen this gender gap. However, I note that financial decisions, i.e. investment and saving decisions, are split equal between German and U.S. couples, suggesting that women's expectations matter strongly for the financial behavior of household.

2.3 Measuring confidence

To empirically evaluate the role of exposure and forecast confidence, the central empirical object of interest is estimating the agent's latent prior precision, $\tau_{0,i,t}$. Recall that in the theoretical framework, prior precision evolves endogenously according to the law of motion in (12):

$$\frac{1}{\tau_{0,i,t}} = \rho^2 \frac{1}{\hat{\tau}_{i,t-1}} + \frac{1}{\tau_\eta},$$

where $\hat{\tau}_{i,t-1}$ denotes inherited posterior precision from the previous period. Intuitively, when previously accumulated information is imprecise, the agent enters the current period with a more diffuse prior distribution. In the panel data, I proxy inherited posterior variance, $1/\hat{\tau}_{i,t-1}$, using the interquartile range of respondent i's lagged probabilistic forecast, denoted $\pi^{IQR}_{i,t-1}$, which provides a robust, scale-consistent measure of subjective belief dispersion. However, using raw lagged belief dispersion $\pi^{IQR}_{i,t-1}$ to measure current prior confidence presents two key empirical challenges. First, $\pi^{IQR}_{i,t-1}$ conflates intrinsic prior confidence ($\tau_{0,i,t-1}$) with exposure to noisy price signals ($\tau_{x,i}$). Because frequent grocery shoppers are repeatedly exposed to volatile food price shocks, raw inherited dispersion risks misattributing price noise to low intrinsic forecast confidence. Second, while $\pi^{IQR}_{i,t-1}$ captures past belief spread, latent prior precision $\tau_{0,i,t}$ governs the agent's current state of confidence in wave t. To cleanly partial out personal price exposure and identify $\tau_{0,i,t}$, the empirical measurement model requires a contemporaneous behavioral choice through which current latent uncertainty is revealed.

To provide this observable outcome, I exploit respondents' state-dependent reporting choices in period t. Grounded in the "Round Numbers, Round Interpretations" hypothesis (Krifka, 2007), agents communicate subjective uncertainty by selecting coarser numerical reporting scales (i.e., rounding point forecasts to multiples of five). When prior beliefs are diffuse, mapping a wide distribution into a precise point forecast is cognitively costly and uninformative; respondents thus optimally report coarser figures. Rounding serves strictly as

a state-dependent behavioral choice through which the unobserved state $\tau_{0,i,t}$ is revealed. While recent literature uses rounding behavior to construct aggregate macroeconomic uncertainty indices (Binder, 2017; Reiche & Meyler, 2022) or to study professional forecasters (Clements, 2021; Glas & Hartmann, 2022), my approach differs in two key dimensions. First, I utilize individual-level reporting behavior to identify cross-sectional and temporal heterogeneity in individual prior precision. Second, rather than treating rounding as an ad hoc uncertainty proxy, I map this latent behavioral signal directly into the structural law of motion of a dynamic Bayesian learning model.

Let $R_{i,t} \in \{0, 1\}$ be an indicator equal to one if respondent i reports a rounded point forecast in wave t. Most respondents provide non-rounded answers but Table 2 reveals a clear gender gap, with women rounding more frequently in all surveys (share of rounders denoted $\bar{R}$). When prior beliefs are diffuse, mapping a wide distribution into a precise point forecast is cognitively costly and less meaningful; hence, respondents optimally provide coarser answers. Rounding behavior thus reveals latent forecast confidence $\tau_{0,i,t}$. Formally, the probability of rounding is assumed to depend on latent prior variance:

$$\Pr(R_{i,t} = 1) = \Lambda\left(\alpha + \beta \frac{1}{\tau_{0,i,t}}\right), \qquad \beta > 0, \tag{14}$$

where $\Lambda(\cdot)$ denotes the logistic cumulative distribution function.[12] The restriction $\beta > 0$ captures the theoretical prediction that higher prior variance (lower confidence) increases the probability of rounding.

In the dynamic model, prior precision evolves endogenously as a function of past posterior precision, which itself depends on signal precision ($\tau_{x,i}$). To isolate prior precision ($\tau_{0,i,t}$) from transient signal exposure ($\tau_{x,i}$), I include personal shopping frequency, $\text{shop_groceries}_{i,t}$, directly in the rounding measurement equation. Substituting the law of motion (12) into the

[12] I choose this functional form for two primary reasons: Econometrically, logistic functions act as a necessary link function that bound latent probabilities within their logical mathematical supports (between 0 and 1). Behaviorally, this transformation embeds realistic diminishing marginal returns.

measurement equation (14) yields the reduced-form estimation equation:

$$\Pr(R_{i,t}=1)=\Lambda\left(\underbrace{\left(\alpha+\frac{\beta}{\tau_\eta}\right)}_{\widetilde{\alpha}}+\underbrace{(\beta\rho^2)}_{\widetilde{\beta}}\pi_{i,t-1}^{IQR}+\delta\,\text{shop_groceries}_{i,t}+X_{i,t}\gamma\right), \tag{15}$$

Demographic controls are included in $X_{i,t}$, and $\Lambda(\cdot)$ denotes the logistic cumulative distribution function.[13] The restriction $\widetilde{\beta}>0$ captures the theoretical prediction that higher prior variance (lower confidence) increases the probability of rounding.

While the predicted probability of rounding provides an intuitive behavioral measure, the logistic transformation maps the latent state into the unit interval and attenuates variation at the tails. To preserve proportional variation in the underlying confidence state while purging the direct effect of grocery signal noise ($\tau_{x,i}$), I extract the counterfactual linear predictor (the log-odds of rounding) holding grocery exposure fixed at zero:

$$\hat{\theta}_{i,t}^{\text{purged}}=\hat{\widetilde{\alpha}}+\hat{\widetilde{\beta}}\pi_{i,t-1}^{IQR}+\delta\cdot(0)+X_{i,t}\hat{\gamma}.$$

I then define the primary Forecast Confidence Index ($FC_{i,t}$) as the standardized negative linear predictor:

$$FC_{i,t}=-\left(\frac{\hat{\theta}_{i,t}^{\text{purged}}-\mu_\theta}{\sigma_\theta}\right), \tag{16}$$

where μ_θ and σ_θ denote the sample mean and standard deviation of $\hat{\theta}_{i,t}^{\text{purged}}$. This transformation yields an easy-to-interpret index with mean zero and unit variance that is strictly increasing in prior precision. Higher values of $FC_{i,t}$ correspond to higher inherited precision and a lower predicted probability of rounding, purged of observed shopping volatility.

The validity of this index rests on a single monotonicity assumption: rounding is positively related to prior variance according to (14). $\beta>0$ implies the log-odds of rounding are strictly increasing in prior variance and strictly decreasing in prior precision. Empirically, $\hat{\widetilde{\beta}}>0$ (Table D.3), and since $\widetilde{\beta}=\beta\rho^2$ with $\rho^2>0$, this establishes $\beta>0$ in the data. Under this

[13] Logistic functions act as a necessary link function bounding latent probabilities within the unit interval while embedding realistic diminishing marginal returns to cognitive effort.

condition, the linear predictor is a monotonic transformation of prior precision and therefore preserves the model-implied ordering of respondent confidence. Thus, $FC_{i,t}$ is not an ad hoc proxy but a monotonic transformation of the latent state implied by the dynamic learning model. It captures relative variation in forecast confidence across individuals and over time, provided that rounding behavior is positively associated with prior variance.

I assess the validity of this measure empirically. First, I find a strong negative correlation between the *ex-ante* confidence score $FC_{i,t}$ and the *ex-post* posterior uncertainty $\pi_{i,t}^{IQR}$ (Spearman's $r = -0.37$, $p < 0.001$). This confirms that agents who enter the survey with a "flat prior" (as revealed by their rounding and previous information state) ultimately form more uncertain posterior beliefs after receiving new signals. Second, I examine how the confidence score maps into the calibrated static prior precision parameter $\tau_{0,i}$ from the simulation exercise in Section 1.1 (assuming $\rho = 0$ and $\bar{z} = \log 2$ for all observations). As robustness, I calibrate an alternative confidence measure as $\hat{\tau}_0$ from the posterior mean and interquartile range on the individual level. Figure 2 demonstrates that there is a robust positive relationship: respondents in the highest deciles of the confidence score exhibit significantly higher values of the structural precision parameter $\hat{\tau}_0$ from the static measure. This result supports the interpretation of the financial confidence index as a valid measure of the latent prior precision. Because $\hat{\tau}_0$ is very noisy on the individual level, I focus on the forecast confidence index $FC_{i,t}$ as my main measurement throughout though I report robustness using the individually estimated $\hat{\tau}_{0,i,t}$.

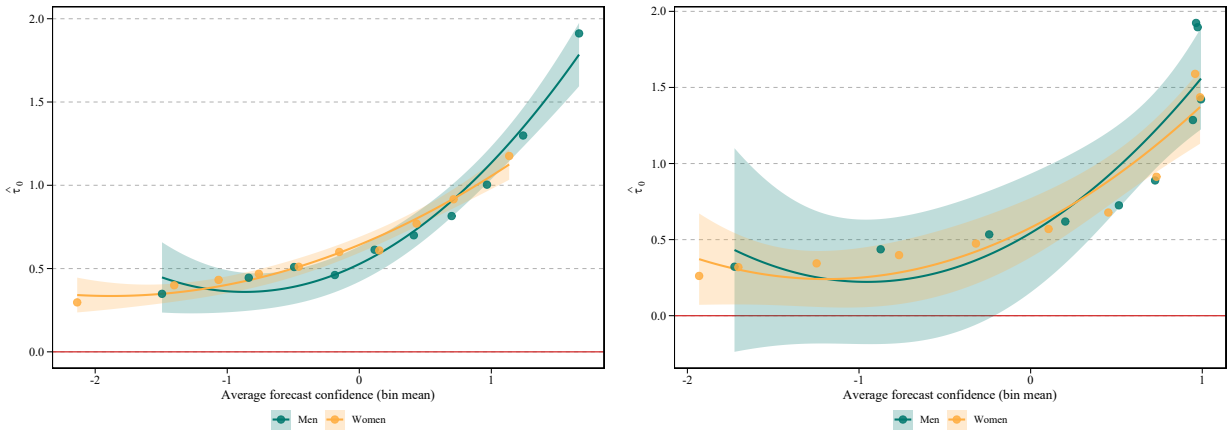
Because $FC_{i,t}$ requires lagged dispersion $\pi_{i,t-1}^{IQR}$, it is constructed only for respondents with prior survey participation. The analysis therefore focuses on tenured participants, which additionally mitigates potential "learning-through-survey" effects documented in Kim and Binder (2023). Notably, this concept of confidence captures variation in the precision of prior beliefs as implied by the model, rather than psychological misperceptions of posterior accuracy often discussed in the overconfidence literature (Anderson et al., 2017; Moore & Healy, 2008).

Finally, while $FC_{i,t}$ purges observed grocery shopping frequency in the BOP-HH, signal volatility ($\tau_{x,i}$) might also contain unobserved, time-invariant shopping routines or operate in survey datasets where direct shopping measures are unobserved (such as the SCE). To

address this, I construct an alternative fixed-effects confidence index, $FC_{i,t}^{\text{FE}}$, using a panel Linear Probability Model (LPM):

$$R_{i,t} = \mu_i + \beta_{\text{FE}} \pi_{i,t-1}^{IQR} + \varepsilon_{i,t}, \tag{17}$$

where μ_i represents individual fixed effects. By taking within-person variation over time ($\Delta R_{i,t}$), the individual fixed effect μ_i absorbs all time-invariant signal noise $\tau_{x,i}$. Consequently, β_{FE} is identified strictly off dynamic updates to prior precision ($\Delta\tau_{0,i,t}$). I extract the linear predictor $\hat{\theta}_{i,t}^{\text{FE}} = \widehat{\mu}_i + \hat{\beta}_{\text{FE}} \pi_{i,t-1}^{IQR}$ and define $FC_{i,t}^{\text{FE}}$ as its standardized negative counterpart. This measure confirms that all primary empirical findings are robust when sweeping out time-invariant signal exposure across both survey datasets.



(a) BOP-HH (b) SCE

Figure 2: Forecast confidence $FC_{i,t}$ and calibrated precision from the static model

Notes: Binscatter of forecast confidence and the model estimated $\hat{\tau}_0$. For the BOP-HH I use the baseline measure $FC_{i,t}$ with purged off grocery shopping. For the SCE I use the robustness measure $FC_{i,t}^{FE}$ which removes grocery shopping under the constant chores assumption.

Table 2 Panel D shows that there are gender gaps in all confidence measures: rounding behavior ($\bar{R}$), calibrated, individual-level $\hat{\tau}_0$ and predicted forecast confidence measured as described above (FC and FC^{FE}).

In addition, I provide evidence for financial literacy (FL) in my survey using the well established "Big 3"-Test (Kaiser et al., 2026; Lusardi & Mitchell, 2014). The financial literacy

score assigns 1 to each correct answer and is thus an index from 0 to 3. I replicate the finding that women perform worse than men in both, BOP-HH and SCE (Bucher-Koenen et al., 2017; Lusardi & Mitchell, 2008). I will revisit the role of financial literacy for forecast confidence in Section 5.

3 The Effects of Confidence and Grocery Price Exposure

Heterogeneity in exposure and in forecast 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. I test Propositions 1.1 and 1.2 directly in the data. I find direct evidence for the complementarity: grocery price exposure (i.e. observing imprecise signals) matters - but only to consumers with low forecast confidence.

3.1 Exposure matters when forecast confidence is low

The framework predicts an individual effect of at least one of exposure and confidence (Propositions 1.1-1.3). I test the individual effect and interaction of the individual-level confidence measure and grocery shopping with the following panel regression model:

$$\begin{aligned} \pi^E_{i,t} = \beta_0 + \beta_1 \text{female}_i + \beta_2 FC_{i,t} + \beta_3 \text{shop_groceries}_i \\ + \beta_4 FC_{i,t} \times \text{shop_groceries}_i + X_{i,t}\gamma_1 + D_t\gamma_2 + G_i\gamma_3 + \bar{X}_i\gamma_4 + \nu_{i,t}, \end{aligned} \tag{18}$$

In the regression model above, $\pi^E_{i,t}$ 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[14]), D_t captures time dummies, and G_i includes regional dummies. I restrict the sample to respondents in non-single households, where the grocery shopping question is asked.

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 $X_{i,t}$, denoted $\bar{X}_i$. This allows consistent estimation of coefficients for both

[14] A person who manages and takes primary responsibility for running a household, including tasks like cooking, cleaning, organizing, and caring for family members.

Table 2: Summary Statistics for Men and Women

	BOP-HH		SCE	
	Men	Women	Men	Women
Panel A: Demographics				
age	56.39	55.82	51.8	48.72
	(15.46)	(15.64)	(15.24)	(15.58)
educ	8.83	8.11	4.55	4.36
	(3.45)	(3.41)	(1.53)	(1.5)
hhinc	7.81	7.07	7.15	6.11
	(2.52)	(2.6)	(2.65)	(2.75)
Panel B: Inflation forecasts				
π^P	5.40	6.44		
	(4.82)	(7.54)		
π^E	4.78	6.00	4.63	7.24
	(5.62)	(8.35)	(9.43)	(15.68)
Don't know	0.03	0.06	0.003	0.005
RMSE	6.08	8.85	9.72	16.29
π^{IQR}	2.07	2.49	3.64	5.27
	(2.3)	(2.97)	(3.85)	(5.38)
Don't know	0.12	0.18	0.01	0.03
Panel C: Household responsibilities				
shop_groceries	0.6	0.83		
	(0.39)	(0.3)		
all_groceries	0.42	0.72		
any_groceries	0.78	0.94		
decide_finance	0.76	0.73	0.66	0.7
	(0.28)	(0.31)	(0.21)	(0.25)
single	0.22	0.3	0.28	0.45
Panel D: Financial literacy and survey confidence				
FC	0.21	−0.35		
	(0.95)	(0.98)		
FC^{FE}	0.07	−0.12	0.25	−0.27
	(0.94)	(1.08)	(0.89)	(1.04)
$\hat{\tau}_0$	5.73	5.71	2.32	2.11
	(6.83)	(6.95)	(2.66)	(2.6)
FL	2.83	2.74	1.8	1.48
	(0.42)	(0.52)	(1.11)	(1.09)
$\bar{R}$	0.18	0.25	0.27	0.46

Standard deviation in parentheses.

Notes: Panel A: Age is measured in years. Education (educ) 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) and 1-8 in the SCE. Household income (hhinc) is categorical for BOP-HH (1-13) and SCE (1-11). Standard deviations of dummy variables are omitted throughout.

time-varying and time-invariant regressors (such as `female` or `shop_groceries`). 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). All results are robust to alternative estimation strategies using simple OLS or excluding the correlated random effects.

Table 3 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 the average confidence levels in the forecast of men (0.21) and women (-0.35), the predicted effect of grocery shopping is significant but small in magnitude. The effect is statistically insignificant at the 95% level for respondents with forecast confidence above 0.50, representing roughly 35% of the sample, with women underrepresented in this group (44%). Figure 3 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 D.4. Using the `all_groceries` dummy instead of the scaled `shop_groceries` variable does not change the result. Further, for alternative measures of forecast confidence, namely actual rounding, π_t^{IQR} as measure of posterior uncertainty, the fixed effect measure of FC (where the fixed effect should cancel out time invariant grocery shopping) as well as the static prior $\hat{\tau}_0$ I find effects pointing in the same directions as my forecast confidence measure.

Additionally as placebo exercise, I empirically evaluate Proposition 1.6 using the BOP-HH survey data. Re-estimating specification (18) with perceived past 12-month inflation as the

Table 3: Effect of experience and confidence on point forecasts

	Inflation expectation (12 months ahead, point estimate)					Inflation perceptions (past 12 months, point estimate)
	(1)	(2)	(3)	(4)	(5)	(6)
female	0.45***	0.12***	0.44***	0.11***	0.11***	−0.10***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
FC		−0.73***		−0.73***	−0.65***	−0.62***
		(0.02)		(0.02)	(0.02)	(0.02)
FC × shop_groceries					−0.13***	0.01
					(0.02)	(0.02)
shop_groceries			0.03	0.03*	0.07***	0.02
			(0.02)	(0.02)	(0.02)	(0.02)
Constant	2.61***	2.71***	2.60***	2.69***	2.68***	2.48***
	(0.22)	(0.21)	(0.22)	(0.22)	(0.21)	(0.23)
Observations	72,162	72,162	72,162	72,162	72,162	41,977
Residual SE	1.56	1.55	1.56	1.55	1.55	1.30

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

Notes: Mundlak CRE specification; Huber-robust regression. All regressions incorporate demographics, regional controls and time fixed effects. The full model is specified in Equation (18). Singles are excluded in all models.

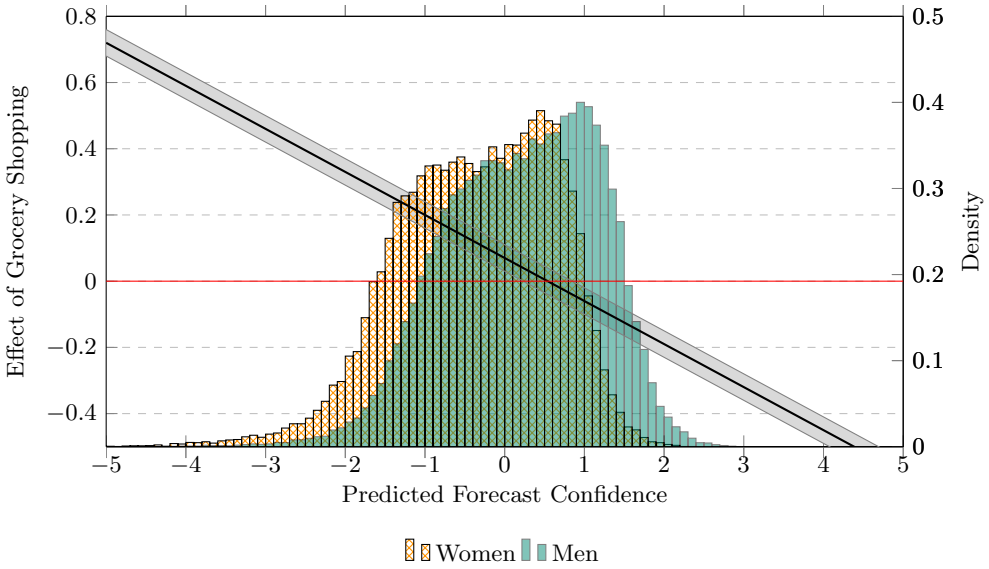


Figure 3: The effect of grocery shopping involvement on inflation expectations for different levels of forecast confidence

Notes: The predicted effect of participation in grocery shopping on inflation expectations for different levels of forecast confidence in the black line ($f(x) = 0.07 - 0.13x$). The complete regression results are shown in Table 3, column (5). The gray area indicates the 95% confidence interval. The histograms show the density of the male (green) and female (orange, cross-hatched) distribution of forecast confidence.

dependent variable confirms that perceptions are driven strictly by prior precision. Because perceptions reflect prior beliefs rather than forward-looking price signals, the model predicts no direct effect of grocery shopping exposure and no interaction term. This prediction is strongly confirmed by the data: Column (6) shows that while forecast confidence retains a significant negative effect on perceptions—just as it does for expectations—both grocery shopping frequency and its interaction with confidence are statistically insignificant.

3.2 Forecast confidence dominates exposure

After establishing the mechanisms of Propositions 1.1 and 1.2 and showing the complementarity of grocery shopping and forecast confidence, I next turn to the implications of these for the gender gap. According to Proposition 1.3 both can work simultaneously. However, a relevant question to ask is which of these channels dominates.

To test how the gender gap in inflation expectations evolves for different levels of forecast confidence and grocery price exposure, I interact the forecast confidence index $FC_{i,t}$ with the female dummy. Similarly, I include grocery shopping and interact with the female dummy:

$$\begin{aligned} \pi^E_{i,t} = \beta_0 + \beta_1 \text{female}_i + \beta_2 FC_{i,t} + \beta_3 \text{shop_groceries}_i \\ + \beta_4 FC_{i,t} \times \text{female}_i + \beta_5 \text{shop_groceries}_i \times \text{female}_i \\ + X_{i,t}\gamma_1 + D_t\gamma_2 + G_i\gamma_3 + \bar{X}_i\gamma_4 + \nu_{i,t}. \end{aligned} \tag{19}$$

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

The results are summarized in Table 4. The interaction term of the forecast confidence index and female is significantly negative in both surveys. This indicates that women with low forecast confidence have much higher expectations than their male counterparts but those with high forecast confidence behave similar to men. In addition, I find that grocery shopping on its own has no significant effect on inflation expectations for men but a positive effect for women. Robustness checks with alternative measures for exposure and confidence that verify these results can be found in Appendix Table D.5.

To assess the relative contributions of forecast confidence and grocery shopping to the gender

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	0.15***	0.31***	0.02	0.22***
	(0.02)	(0.03)	(0.03)	(0.02)
FC	−0.61***		−0.62***	−1.76***
	(0.02)		(0.02)	(0.01)
FC × female	−0.26***		−0.28***	−0.66***
	(0.02)		(0.02)	(0.02)
shop_groceries		−0.02	−0.01	
		(0.02)	(0.02)	
shop_groceries × female		0.19***	0.17***	
		(0.04)	(0.04)	
Constant	2.74***	2.63***	2.70***	4.89***
	(0.10)	(0.22)	(0.21)	(0.14)
Observations	74,891	72,162	72,162	86,151
Residual SE	1.54	1.56	1.54	2.15

*p<0.1; **p<0.05; ***p<0.01
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. While for the BOP-HH the purged, baseline FC measure is used, for the SCE I use FC^{FE} where the fixed effects should remove any time-invariant grocery exposure effect.

gap, I implement a Kitagawa-Oaxaca–Blinder (KOB) 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 ($\pi^E_{i,t}$, point forecast 12 months ahead) is regressed on demographics $X_{i,t}$, along with time and regional fixed effects. 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 differences in characteristics versus a residual, unexplained gap:

$$\pi^E_{i,t} = \beta_0 + X_{i,t}\gamma_1 + D_t\gamma_2 + G_i\gamma_3 + \bar{X}_i\gamma_4 + \nu_{i,t}, \tag{20}$$

$$\bar{\pi}^E_w - \bar{\pi}^E_m = \underbrace{\hat{\gamma}_w(\bar{W} - \bar{M})}_{\text{explained by differences in } \bar{W},\bar{M}} + \underbrace{\bar{M}(\hat{\gamma}_w - \hat{\gamma}_m)}_{\text{residual}}. \tag{21}$$

Figure 4a presents the KOB 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 4% of the total gender gap, while confidence in fact "overexplains the gap" such that the unexplained gap becomes negative. In other words, if men and women had the same forecast confidence, the gender gap in expectations would be negative. 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 - in line with the results of the previous section. Finally, I test using a dummy for rounding instead of my confidence measure. This explains substantially less, confirming that my result is not mechanically associated to rounding per se.

As a robustness check, I implement a parallel mediation model (MacKinnon, 2012; Tingley et al., 2014). Unlike the KOB decomposition, this approach treats the total gender gap (β_1

in Equation (22)) as being mediated by the explanatory variables in Equation (23), such that the mediated (indirect) effect is given by $\beta_1 - \beta_1'$. Equations (24) and (25) 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 $\alpha_1^g \beta_3$.

$$\pi_{i,t}^E = \beta_0 + \beta_1 \text{female}_i + \nu_{i,t} \tag{22}$$

$$\pi_{i,t}^E = \beta_0' + \beta_1' \text{female}_i + \beta_2 FC_{i,t} + \beta_3 \text{shop_groceries}_i + \nu_{i,t} \tag{23}$$

$$FC_{i,t} = \alpha_0^{fc} + \alpha_1^{fc} \text{female}_i + \nu_{i,t} \tag{24}$$

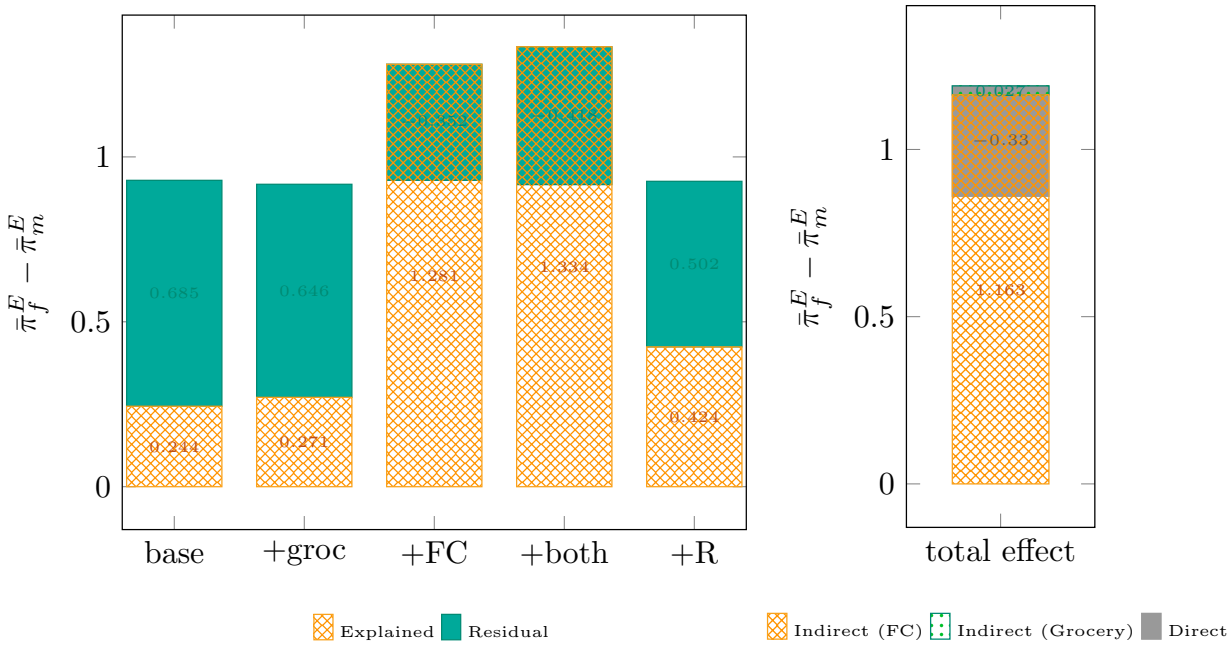
$$\text{shop_groceries}_i = \alpha_0^g + \alpha_1^g \text{female}_i + \nu_{i,t} \tag{25}$$

Although the mediation approach is fundamentally different from the KOB decomposition, the results reported in Figure 4b are strikingly similar. Only about 3% of the total indirect effect is attributed to grocery shopping, with the remaining effect explained by the measure of forecast confidence. The direct effect is estimated negative, indicating that forecast confidence more than fully accounts for the gender gap.

3.3 Verifying the mechanism

A core theoretical implication of the forecast confidence hypothesis is that the aggregate gender gap should be driven by the asymmetric right-skewness of the belief distribution, rather than a uniform location shift across all consumers. To empirically test whether the gender gap is a uniform shift or a tail phenomenon, I evaluate the gender gap across the entire belief distribution. Specifically, I replicate the baseline specification (Column (1) in Table 3) across percentiles of the inflation expectations distribution, controlling for demographics and time fixed effects.

Figure 5 plots the estimated coefficient for *female* across percentiles. The results reveal a striking pattern that directly supports the asymmetric tail hypothesis: the gender gap is not constant across the distribution. Instead, the *female* coefficient increases steadily across percentiles, providing clear evidence of an elongated right tail. Crucially, in subsamples restricted to inflation expectations below the 70th percentile, the positive gender gap com-



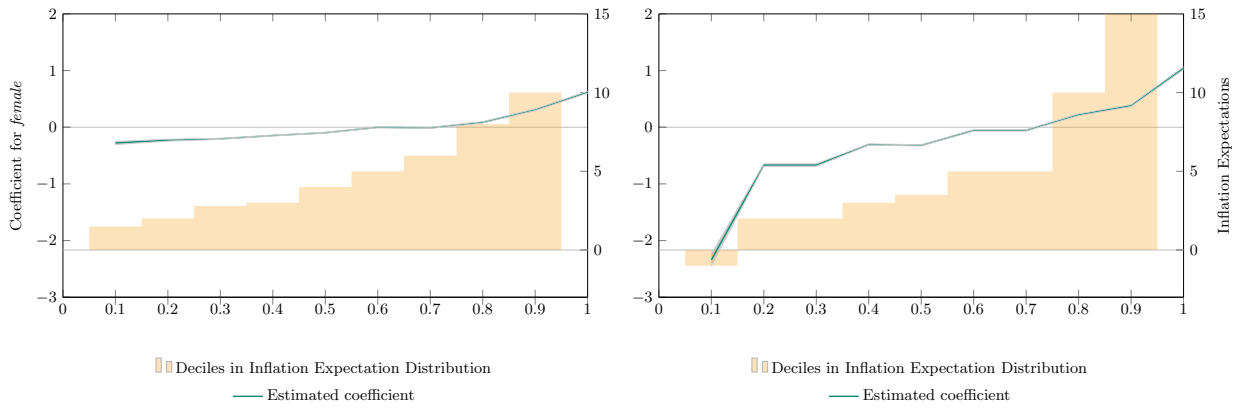
(a) Kitagawa-Oaxaca-Blinder (b) Mediation Model

Figure 4: Decomposition of the Gender Gap

pletely vanishes. If women held uniformly higher inflation expectations across the board, a significant and robust gap would persist even after truncating the upper tail. Its complete disappearance below the 70th percentile strongly confirms that the aggregate gap is entirely a tail phenomenon driven by a specific subset of consumers with highly elevated expectations. Conversely, at the lower percentiles of the distribution, the gender gap becomes negative. This finding is fully in line with the confidence framework when accounting for survey cognitive frictions; individuals with low forecast confidence who hold very low inflation expectations are more prone to rounding their answers downward (for instance, reporting 0% instead of a more precise 1% or 2%). The full regression results are reported in Appendix Table D.6.

4 Beyond Gender

Beyond the gender gap, the confidence hypothesis offers a parsimonious framework for understanding cross-sectional heterogeneity in belief formation more broadly. While gender



(a) BOP-HH (b) SCE

Figure 5: 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) in the green line. 95% confidence bands are shaded in gray. Orange bars represent the percentiles in the inflation expectations distribution.

norms and disparate forecast confidence provide a particularly stark empirical laboratory, the mechanism rationalizes the persistent heterogeneities observed across income, education, and age cohorts (D'Acunto et al., 2023; Das et al., 2020). These demographic groups do not only face different consumption baskets; they may also differ in the precision of their priors. My framework suggests that the interaction between these structural priors and lived price exposure is a fundamental driver of the demographic disparities. In Section 4.1 I confirm this empirically.

Moreover, forecast confidence matters for the pass-through of inflation expectations to consumer spending. This is in line with recent evidence on the effects on spending (Coibion et al., 2024) and portfolio choice (Giglio et al., 2021). I confirm this by exploiting the intentions to spend on various items from the BOP-HH in Section 4.2 and find that for lumpy and discretionary items, confidence plays a role.

Furthermore, the model implies that the sensitivity to salient price signals—such as gasoline or food prices (Anesti et al., 2025; Binder, 2018; Cavallo et al., 2017; Coibion & Gorodnichenko, 2015; D'Acunto, Malmendier, Ospina, & Weber, 2021)—is state-dependent. In periods of heightened macroeconomic uncertainty, even sophisticated agents experience a

decline in prior precision, leading them to overweight volatile, high-frequency price signals. This provides a theoretical bridge to the exposure literature by suggesting that the "salience bias" is a rational response to diminished forecast confidence. Consequently, in turbulent market environments, salient but idiosyncratic price shocks can disproportionately distort aggregate household expectations, with significant implications for market participation and the transmission of monetary policy. I confirm this empirically in Section 4.3.

4.1 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 (D'Acunto et al., 2023; Das et al., 2020)

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 (MacKinnon, 2012; Tingley et al., 2014) similar to the one in Section 3.2. 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 6 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[15] change in key predictors—age, education (`educ`), and household

[15]The standardization procedure proceeds in two steps. First, the coefficients linking predictors to the

income (`hhinc`)—on the outcome variable $\pi^E_{i,t}$, separated into indirect effects mediated by the confidence measure ($FC_{i,t}$) and direct effects that do not pass through the mediator.

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 D.8. For education and household income in both SCE and BOP-HH, the standardized coefficients indicate sizable negative indirect effects via forecast confidence. 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. I find a relatively consistent indirect effect, negative in Germany and positive in the U.S.. At younger ages, the direct effect is larger and positive. As age progresses, in the U.S. 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 direct effect.

4.2 Pass-through to household financial and spending intentions

A central question for household finance is whether the interaction of price exposure and forecast confidence influences actionable balance-sheet and consumption choices. While the link between inflation expectations and spending is weak and points to an income channel (Coibion, Georgarakos, Gorodnichenko, & van Rooij, 2023; Galashin et al., 2026), there is a stronger negative association between uncertainty and spending (Coibion et al., 2024) as

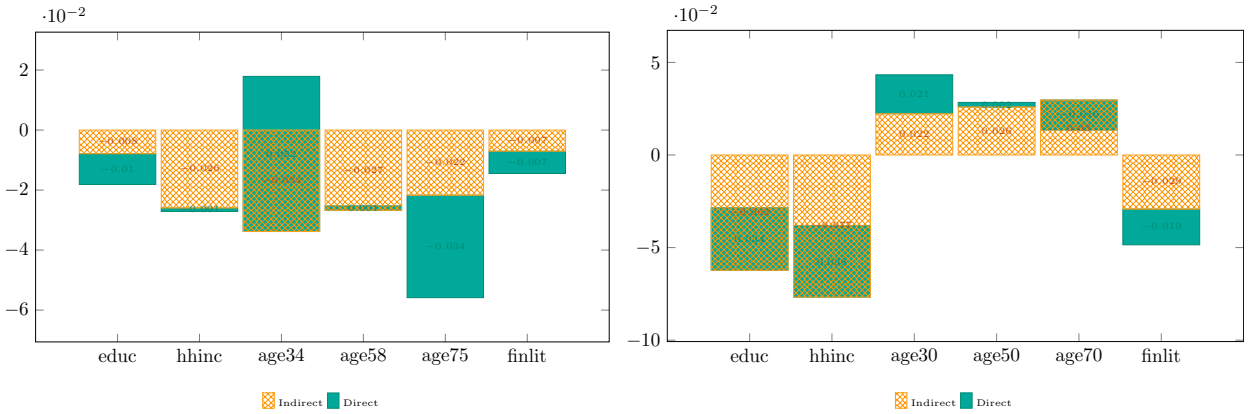
mediator ($X \to M$) and the mediator to the outcome ($M \to Y$) are adjusted by the ratio of standard deviations of the relevant variables. Specifically, for each predictor X, the standardized indirect effect is computed as:

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

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

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

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



(a) BOP-HH (b) SCE

Figure 6: 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. For financial literacy in the BOP-HH only the January 2022, October 2024 and April 2025 waves are used.

well as between subjective confidence and portfolio choice (Giglio et al., 2021).

To examine this in more detail, I exploit survey items in the BOP-HH regarding households' twelve-month forward-looking intentions across five key financial and consumption categories: (i) major purchases (e.g., consumer durables and appliances), (ii) discretionary entertainment expenditures, (iii) essential goods (e.g., food and everyday household items), (iv) housing expenses and (v) financial reserves. I estimate the following empirical specification for each outcome category $k \in \{\text{Major items}, \text{Entertainment}, \text{Essential items}, \text{Housing}, \text{Reserves}\}$ to test how subjective inflation expectations and forecast confidence jointly shape household balance-sheet and consumption choices:

$$\begin{aligned} \text{SpendIntent}_{i,t}^{k} = \alpha_0 + \alpha_1 \pi_{i,t}^{E} + \alpha_2 FC_{i,t} + \alpha_3 (\pi_{i,t}^{E} \times FC_{i,t}) \\ + X_{i,t}\gamma_1 + D_t\gamma_2 + G_i\gamma_3 + \bar{X}_i\gamma_4 + \varepsilon_{i,t}, \end{aligned} \tag{26}$$

where $\text{SpendIntent}_{i,t}^{k} \in \{-1, 0, 1\}$ denotes household i's reported intention at time t to decrease (-1), maintain (0), or increase (1) spending or reserve accumulation in category k. The primary variables of interest are subjective inflation expectations $(\pi_{i,t}^{E})$, forecast

confidence ($FC_{i,t}$), and their interaction term ($\pi^E_{i,t} \times FC_{i,t}$). As before, all models control for individual demographics ($X_{i,t}$), time fixed effects (D_t), regional fixed effects (G_i), and individual-level time-averaged demographics ($\bar{X}_i$).

Table 5 presents the estimates for the full sample (Panel A) and restricted to primary household financial decision-makers (Panel B). Notably, the main effects of both inflation expectations and forecast confidence are virtually identical across both samples. Baseline inflation expectations ($\pi^E_{i,t}$) consistently depress spending and savings intentions, confirming that households treat expected inflation primarily as a reduction in real income rather than an incentive for intertemporal substitution (Coibion, Georgarakos, Gorodnichenko, & van Rooij, 2023; Galashin et al., 2026). The only marginal positive effect can be found on housing expenses, in line with the expectation that higher inflation may increase interest payments on mortgages. Baseline forecast confidence ($FC_{i,t}$) on the other hand, displays a positive impact across both panels, underlining that more confidence households may be more willing to spend.

Where the full sample and financial decision-makers diverge is in the nuanced behavior of the interaction term ($\pi^E_{i,t} \times FC_{i,t}$). For lumpy and discretionary choices—major purchases and entertainment —the interaction term remains negative and statistically significant across both panels. High forecast confidence amplifies the reduction in discretionary spending among high-expectation households, consistent with subjective conviction governing the elasticity of balance-sheet adjustments (Giglio et al., 2021). However, focusing on primary financial decision-makers (Panel B) reveals a notable shift for non-discretionary baseline commitments, particularly housing expenses. While the interaction effect is statistically insignificant in the full sample, it becomes positive and statistically significant among financial decision-makers. This indicates that household members who actively manage financial planning and hold high inflation expectations with high confidence explicitly anticipate having to scale up nominal budget allocations to meet sticky, non-discretionary obligations like rent and housing costs.

4.3 When do food prices matter?

A final key implication of the dynamic Bayesian framework is that salient price signals, such as food prices, exert a stronger pass-through into expectations when macroeconomic uncertainty is high. In the law of motion (12), elevated macroeconomic uncertainty enters

Table 5: Effect of inflation expectations on spending

	Spending Intentions on				
	Major items	Entertainment	Essential items	Housing	Reserves
Panel A: Full Sample					
π^E	-0.01^{***}	-0.01^{***}	-0.001^{***}	0.001^{*}	-0.01^{***}
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0004)
$\pi^E \times FC$	-0.001^{**}	-0.001^{***}	0.0001	0.0002	0.0003
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
FC	0.06^{***}	0.05^{***}	0.02^{***}	0.03^{***}	0.02^{***}
	(0.01)	(0.01)	(0.004)	(0.004)	(0.005)
Constant	-0.24^{***}	-0.07^{***}	-0.02	0.07^{***}	0.26^{***}
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Observations	99,399	99,454	99,487	99,436	99,377
Residual SE	0.67	0.58	0.41	0.45	0.53
Panel B: Financial Decision Makers					
π^E	-0.01^{***}	-0.01^{***}	-0.002^{***}	0.001^{**}	-0.01^{***}
	(0.001)	(0.001)	(0.0004)	(0.0005)	(0.001)
$\pi^E \times FC$	-0.001^{*}	-0.001^{***}	-0.0001	0.001^{*}	0.0003
	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0004)
FC	0.06^{***}	0.05^{***}	0.02^{***}	0.03^{***}	0.02^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-0.23^{***}	-0.06	-0.01	0.09^{**}	0.26^{***}
	(0.06)	(0.05)	(0.03)	(0.04)	(0.05)
Observations	53,751	53,775	53,791	53,767	53,743
Residual SE	0.67	0.59	0.42	0.46	0.54
Note:					*p<0.1; **p<0.05; ***p<0.01

as an increase in $1/\tau_\eta$, which depresses agents' prior precision $\tau_{0,t}$ across the board. Following Proposition 1.1, a lower prior precision increases the pass-through parameter of signal volatility to expectations. Crucially, this mechanism governs the aggregate state-dependence of food price pass-through: when forecasting the broader macroeconomy becomes inherently more difficult, households compensate by relying more heavily on local, highly salient price signals.

To examine this implication, I extend the empirical strategy of Coibion and Gorodnichenko (2015) and 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 $\Delta\pi^E_{i,t}$ is the change in inflation forecast of individual i over a 6 months time period.

$$\Delta\pi^E_{i,t} = \beta_0 + \beta_1\pi^{\text{food}}_t + \beta_2\pi^{\text{food}}_t \times \Delta\text{EPU}_t + \beta_3\Delta\text{EPU}_t + X_{i,t}\gamma_1 + G_i\gamma_3 + \bar{X}_i\gamma_4 + \nu_{i,t}, \quad (27)$$

The results in Table 6 strongly support the prediction. While the baseline effect of food price changes on expectations is modest and even negative in the U.S., 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, consistent with evidence in Ehrmann and Fratzscher (2007) that communication has stronger effects in more uncertain environments.

Note that this prediction applies to the average household response and does not require a mechanical widening of cross-sectional demographic gaps. In fact, it may lead to the gender gap or other demographic gaps narrowing or widening depending on who's confidence is most

Table 6: Food prices and EPU

	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***	0.11***	0.11***	−0.01***	−0.01	−0.02***	−0.01
	(0.001)	(0.003)	(0.002)	(0.004)	(0.01)	(0.004)	(0.01)
Δ EPU$_t$	0.0004***	0.0004***	0.0003***	−0.002***	−0.001**	−0.003***	−0.002***
	(0.0001)	(0.0002)	(0.0001)	(0.0003)	(0.001)	(0.0003)	(0.001)
π_t^{food} x Δ EPU$_t$	0.001***	0.001***	0.001***	0.001***	0.0004***	0.0002**	0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Constant	−0.95***	−1.13***	−1.08***	−1.12***	−0.74***	−0.67***	−0.72***
	(0.07)	(0.14)	(0.10)	(0.10)	(0.19)	(0.06)	(0.14)
Observations	103,211	25,823	54,200	68,054	24,867	100,051	24,667
Residual SE	2.37	2.47	2.52	2.65	3.31	2.98	3.12

*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.

affected. The empirical evidence for the gender gap during one prominent uncertainty shock, the Covid-19 pandemic (Bracha & Tang, 2025; Weber et al., 2025), is mixed (Figure 1). In the U.S. it appeared to have increased the gender gap while it appears to have shrunk in Germany.

5 Disentangling Forecast Confidence from Financial Literacy

It is well-known that financial literacy affects inflation expectations (Bruine De Bruin et al., 2010) and that women achieve lower financial literacy in standardized financial literacy tests (Bucher-Koenen et al., 2017; Lusardi & Mitchell, 2014). A natural and important question is therefore whether my model-consistent measure of forecast confidence ($FC_{i,t}$) simply mirrors traditional measures of consumer financial literacy ($FL_{i,t}$). If forecast confidence were merely a repackaging of institutional economic knowledge or mathematical competence, the structural parameters estimated via the rounding-driven proxy would fail to capture a distinct behavioral mechanism. To address this concern, I exploit the financial literacy modules included in both the BOP-HH (only in January 2022, October 2024 and April 2025) and the SCE to construct an individual-level financial literacy index based on the standard "Big Three" questions mapping interest compounding, inflation mechanics, and risk diversification (Kaiser et al., 2026; Lusardi & Mitchell, 2008, 2014) and explicitly trace the joint relation-

ships between financial literacy, forecast confidence, grocery shopping and the formation of household inflation expectations.

I begin by examining the extent to which the expectations gap between high- and low-literacy consumers is mediated by forecast confidence. Following the empirical strategy outlined in Section 4.1, I perform a mediation analysis to identify whether the negative effect of financial literacy on inflation expectations is partially explained by forecast confidence. The results in Figure 7 reveal that my measure of forecast confidence explains approximately 50% of the aggregate inflation expectations gap across literacy levels in both surveys. These results are in line with the findings of Bucher-Koenen et al. (2025) who show that the gender gap in financial literacy is driven by confidence.

However, financial literacy and forecast confidence are far from completely interchangeable. If forecast confidence were simply a linear proxy for financial literacy, substituting $FL_{i,t}$ directly into the core interaction specifications should yield identical empirical patterns. To test this hypothesis, I replicate the interaction specification from Section 3 but replace the forecast confidence measure with the standardized financial literacy index:

$$\begin{aligned} \pi^{E}_{i,t} = \beta_0 + \beta_1 \text{female}_i + \beta_2 FL_{i,t} + \beta_3 \text{shop_groceries}_i \\ + \beta_4 FL_{i,t} \times \text{shop_groceries}_i + X_{i,t}\gamma_1 + D_t\gamma_2 + G_i\gamma_3 + \bar{X}_i\gamma_4 + \nu_{i,t}. \end{aligned} \tag{28}$$

As reported in column (5) in Table D.4, the results present a stark departure from the baseline findings. In contrast to the large, highly significant interaction documented between forecast confidence and grocery exposure in Table 3, the interaction coefficient β_4 on $FL_{i,t} \times \text{shop_groceries}_i$ is statistically insignificant. While low forecast confidence amplifies the impact of volatile everyday price signals, low financial literacy does not generate the same interaction with grocery shopping frequency.

The Bayesian framework developed in Section 1 provides a simple, structural reconciliation for this empirical divergence. In my log-normal setup, an agent's prior belief is fully characterized by two distinct parameters: the log-prior mean ($\mu_{0,i}$) and the prior precision ($\tau_{0,i}$). In contrast to confidence, financial literacy is assumed to operate through the prior mean:

$$\mu_{0,i} = g(FL_i, \dots) \quad \text{with} \quad \frac{\partial g}{\partial FL_i} < 0.$$

Higher financial literacy might shift the baseline log-prior mean ($\mu_{0,i}$) downward, for example placing it closer to the central bank's objective inflation target.

To see why this dual-channel mechanism rationalizes the absence of an interaction effect in Table D.4, recall from Equation (1) that the posterior expectation is given by:

$$\mathbb{E}(\pi_i|x_i) = \exp\left(\hat{\mu}_i + \frac{1}{2\hat{\tau}_i}\right) = \exp\left(\frac{\tau_{0,i}\mu_{0,i} + \tau_{x,i}\log x_i + \frac{1}{2}}{\tau_{0,i} + \tau_{x,i}}\right).$$

When evaluating the cross-partial derivative between a shift in the prior parameters and a change in signal volatility (where grocery shopping shifts the composition toward higher volatility, lower signal precision $\tau_{x,i}$), the prior mean $\mu_{0,i}$ enters strictly as a linear location shift within the weights of the exponential argument. $\mu_{0,i}$ does not enter the right-skewed tail-variance penalty term, $\frac{1}{2(\tau_{0,i}+\tau_{x,i})}$, which governs the non-linear amplification of volatile signals.

Consequently, an increase in financial literacy exerts a direct downward pressure on average inflation expectations via the anchoring of $\mu_{0,i}$. Confidence mediates around 50% of the overall affect through its weighting on $\mu_{0,i}$. The framework thus perfectly rationalizes why financial literacy lowers average expectations, why its effect is only partially mediated by confidence, and why it fails to interact with daily grocery exposure in the data.

The lack of interaction with grocery shopping results in financial literacy being a less important driver of the gender gap in inflation expectations. Restricting the sample to the three BOP-HH waves with financial literacy, I replicate the horse-race of Section 3.2 and compare the effect of forecast confidence and financial literacy in a Kitagawa-Oaxaca-Blinder decomposition. Figure 7 shows that while forecast confidence has a large impact also in this subsample, financial literacy explains only a small share of the gender gap.

6 Conclusion

Why do consumers systematically differ in their macroeconomic expectations? This paper integrates the widely documented phenomenon of lived price exposure with a novel, behavioral channel: forecast confidence. Using a Bayesian learning framework, I demonstrate that exposure to noisy, volatile price signals—such as frequent grocery shopping—raises inflation

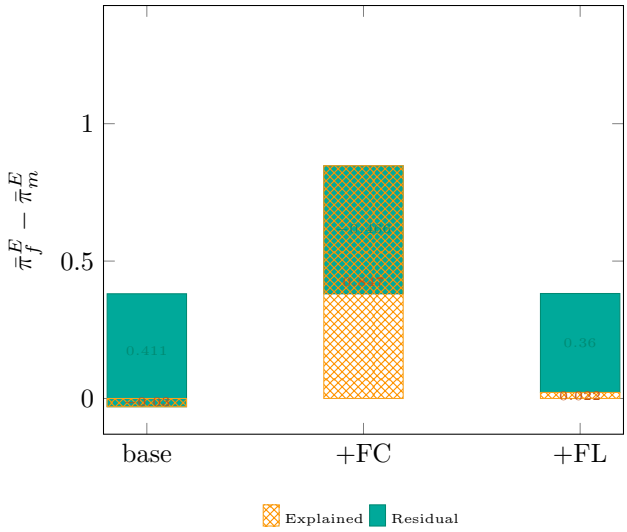


Figure 7: Decomposition of the Gender Gap with Financial Literacy

expectations only when a household's prior beliefs are sufficiently imprecise. This theoretical insight fundamentally recontextualizes the existing exposure hypothesis (D'Acunto, Malmendier, & Weber, 2021). It shows that it is not merely the salient price signals households receive that drive expectation gaps, but their underlying confidence in processing them.

Empirically, I construct a novel, model-consistent measure of forecast confidence using German and U.S. household data to test this mechanism, focusing on the persistent gender gap in inflation expectations. The results show that unequal forecast confidence accounts for the entirety of the gender gap. Strikingly, if men and women exhibited equal forecast confidence, the expectations gap would invert. Furthermore, exposure to salient grocery prices only elevates expectations among low-confidence consumers. Rather than acting as a standalone driver, exposure is conditional on individual-level confidence. This mechanism extends beyond gender; forecast confidence serves as a common latent factor explaining belief heterogeneity across age, education, and household income cohorts. Further, it amplifies the pass-through of expectations to spending and saving decisions.

The implications of this confidence channel extend beyond macroeconomic forecasting, providing insights for policy design. While a rich literature in behavioral finance documents that men often exhibit overconfidence (Anderson et al., 2017; Barber & Odean, 2001), my

structural and empirical findings indicate that the resulting wedge in expectations is driven by a genuine deficit in subjective confidence among a subset of consumers, manifesting in larger absolute forecast errors and an inflated right tail. From a policy perspective, this distinction offers a highly actionable view: while policy can do very little to alter consumers' daily physical exposure to volatile grocery prices, they can actively design interventions to boost forecast confidence. The framework also highlights a critical time-varying dynamic: salient consumer prices heavily distort expectations primarily during periods of elevated macroeconomic uncertainty.

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Appendix

A Motivation: Singles versus Non-singles

An implication of the pure exposure hypothesis relates to the household division of labor. If the gender gap were driven solely by traditional gender roles dictating that women do the grocery shopping, then the gap should be significantly muted or disappear entirely among single men and women, who must both manage their own grocery shopping regardless of gender.

To test this, I run a panel regression of inflation expectations on a female dummy and other demographics as in column (1) of Table 3. I split the sample by household size and test how the gender gap differs between singles and non-singles.

Table A.1: Singles and the gender gap

	Inflation expectation (12 months ahead, point estimate)					
	BOP-HH		SCE		MSC	
	N	S	N	S	N	S
female	0.51***	0.47***	0.79***	1.32***	0.33***	0.31***
	(0.01)	(0.02)	(0.02)	(0.04)	(0.02)	(0.03)
Constant	3.18***	2.64***	5.71***	6.08***	5.62***	5.35***
	(0.08)	(0.14)	(0.14)	(0.31)	(0.17)	(0.36)
Δ female	*0.04*		*-0.53****		*0.02*	
	(0.02)		*(0.05)*		*(0.03)*	
Observations	172,340	57,526	109,676	61,931	208,265	70,368
Residual SE	1.72	1.88	2.76	4.16	3.13	3.36

*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.

Table A.1 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.

B Supplemental Material for Bayesian Framework

Algebraic manipulations to derive the log-normal posterior

The prior is defined as

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

The unbiased signal is defined as

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

I compute the posterior following Bayesian updating:

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

This is proportional to a log-normal distribution,

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

where

$$
\begin{aligned}
\hat{\mu} &= \frac{\mu_0\tau_0 + \tau_x\log x}{\tau_x + \tau_0}, \\
\text{and } \hat{\tau} &= \tau_0 + \tau_x.
\end{aligned}
$$

Comparative statics

The effect of increasing signal volatility

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

The effect of decreasing prior precision

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

Proof of Proposition 1.4

Differentiating Equation (9) with respect to N yields:

$$\frac{d}{dN}\left(\frac{1}{\tau_x(N)}\right) = 2\omega'(N)\left[\omega(N)\left(\frac{1}{\tau_f}+\frac{1}{N\tau_v}\right)-(1-\omega(N))\frac{1}{\tau_m}\right]-\frac{\omega(N)^2}{N^2\tau_v}. \tag{29}$$

For $N \geq 1$, as item diversification reduces $\frac{1}{N\tau_v}$, the bracketed term simplifies to $\omega(N)\frac{1}{\tau_f}-(1-\omega(N))\frac{1}{\tau_m}$. Because $\frac{1}{\tau_f} > \frac{1}{\tau_m}$, for any non-trivial exposure weight satisfying $\omega(N) > \frac{\tau_f}{\tau_f+\tau_m}$, the weight-shift toward the volatile sector dominates the diversification of idiosyncratic item noise, establishing $\frac{d}{dN}\frac{1}{\tau_x(N)} > 0$.

Steady State of Dynamic Model

To solve for the steady-state prior precision $\bar{\tau}_0$, we seek the fixed point of the recursive system. Combining the equations for posterior dynamics and the law of motion, the prior precision evolves according to:

$$\tau_{0,t} = \left[\frac{\rho^2}{(\tau_{0,t-1}+\tau_x)}+\frac{1}{\tau_\eta}\right]^{-1} \equiv f(\tau_{0,t-1}).$$

The mapping $f(\cdot)$ is strictly increasing and concave in $\tau_{0,t-1}$ for $\rho \in (0,1]$. Note that

$$f(0) = \left[\frac{\rho^2}{\tau_x}+\frac{1}{\tau_\eta}\right]^{-1} > 0$$

and

$$\lim_{\tau\to\infty} f(\tau) = \tau_\eta.$$

Since $f(\cdot)$ is continuous, strictly increasing, there exists a unique steady state $\bar{\tau}_0 \in (f(0), \tau_\eta)$ such that $f(\bar{\tau}_0) = \bar{\tau}_0$.

To derive comparative statics, define the implicit function:

$$G(\bar{\tau}_0, \tau_x) = \frac{1}{\bar{\tau}_0}-\frac{\rho^2}{(\bar{\tau}_0+\tau_x)}-\frac{1}{\tau_\eta} = 0.$$

By the Implicit Function Theorem,

$$\frac{\partial \bar{\tau}_0}{\partial \tau_x} = -\frac{\partial G/\partial \tau_x}{\partial G/\partial \bar{\tau}_0}.$$

The partial derivatives are:

$$\frac{\partial G}{\partial \tau_x} = \frac{\rho^2}{(\bar{\tau}_0 + \tau_x)^2} > 0,$$

$$\frac{\partial G}{\partial \bar{\tau}_0} = -\frac{1}{\bar{\tau}_0^2} + \frac{\rho^2}{(\bar{\tau}_0 + \tau_x)^2}.$$

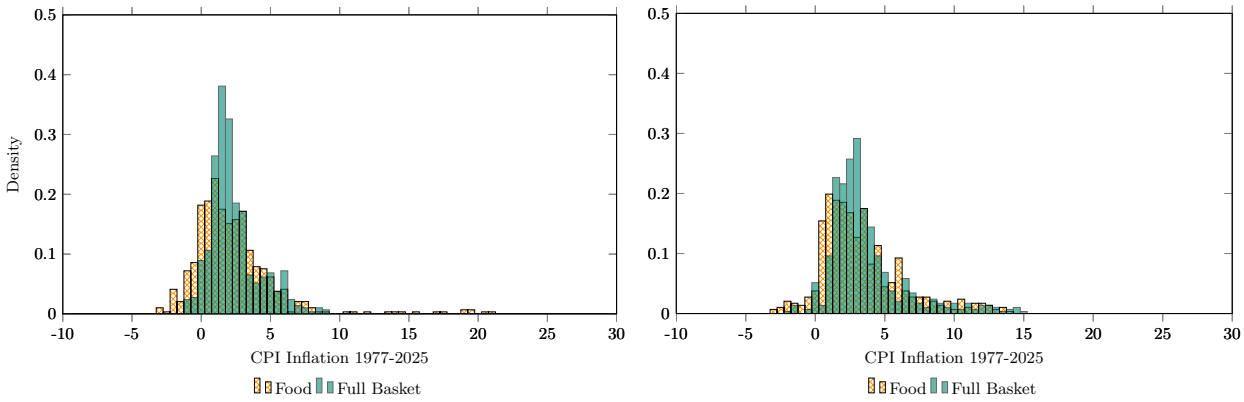
Local stability of the steady state requires $f'(\bar{\tau}_0) < 1$, which is equivalent to

$$\frac{\rho^2}{(\bar{\tau}_0 + \tau_x)^2} < \frac{1}{\bar{\tau}_0^2},$$

and hence to $\frac{\partial G}{\partial \bar{\tau}_0} < 0$. Under this condition,

$$\frac{\partial \bar{\tau}_0}{\partial \tau_x} = -\frac{(+)}{(-)} > 0,$$

C Supplemental Figures

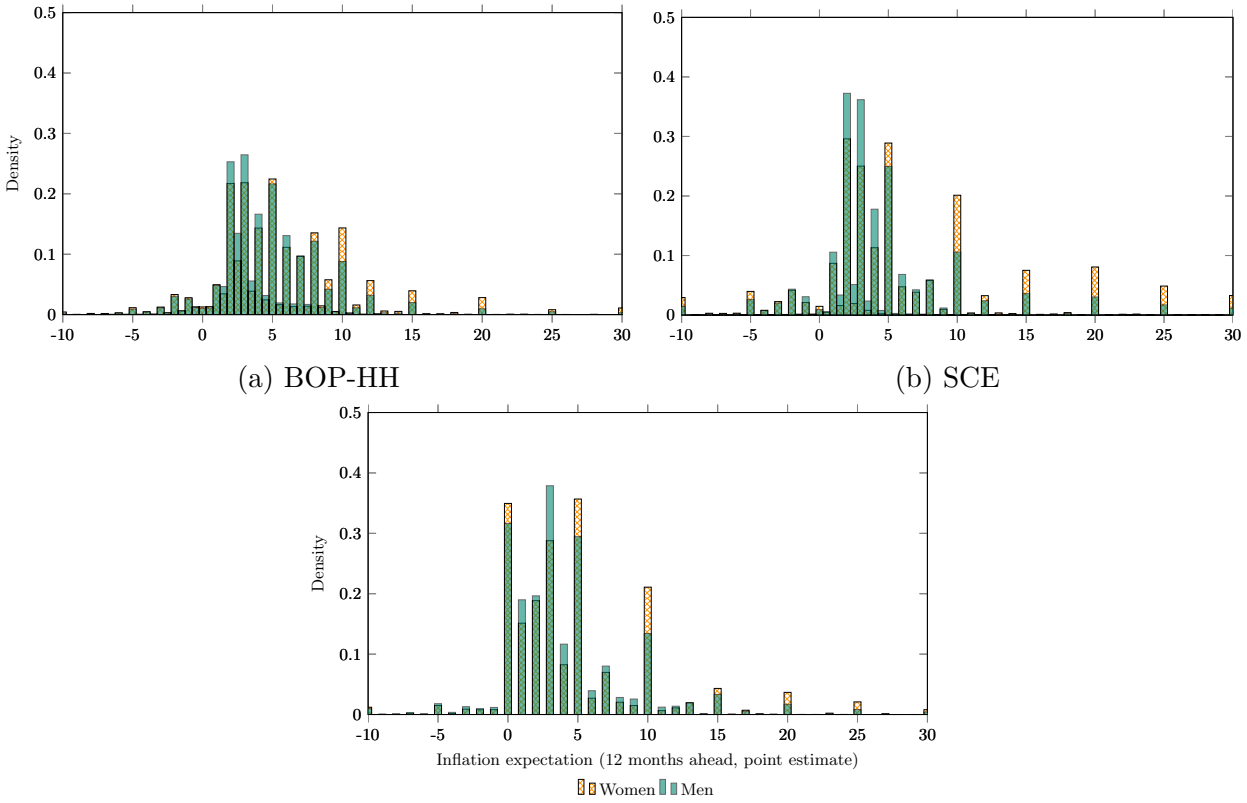


(a) Germany (b) United States

Figure C.1: Histogram of CPI Inflation

Average values of CPI: Germany Food: 2.31; Germany Total: 2.34; U.S. Food: 3.38; U.S. Total: 3.64.

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

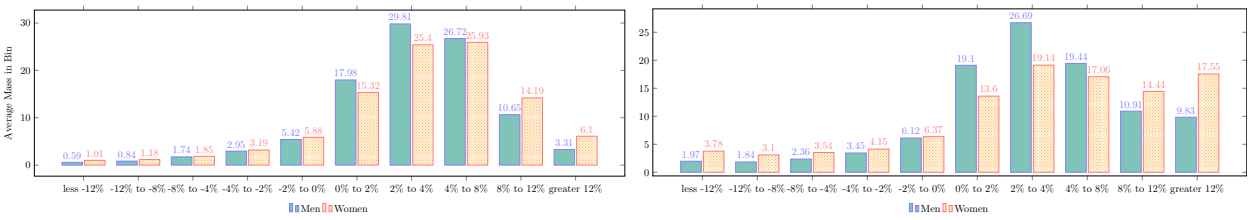


(a) BOP-HH (b) SCE

(c) MSC

Figure C.2: 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.



(a) BOP-HH (b) SCE

Figure C.3: Average density forecast of inflation 12 months ahead

Notes: Distribution of male and female inflation expectations (measured as density forecasts over 12 months) pooled across all time periods.

D Supplemental Tables

Table D.1: Features of the three surveys

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

Table D.2: 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***	0.68***	1.01***	2.61***	0.33***	1.57***
	(0.01)	(0.05)	(0.02)	(0.12)	(0.01)	(0.06)
age	0.01	0.01	−0.11	−0.10	−0.02***	−0.02**
	(0.01)	(0.01)	(0.33)	(0.33)	(0.01)	(0.01)
female × age		−0.0001		0.01***		−0.01***
		(0.001)		(0.001)		(0.001)
hhinc	−0.004***	−0.01***	−0.25***	−0.22***	−0.0000	0.0000
	(0.0003)	(0.0004)	(0.01)	(0.01)	(0.0000)	(0.0000)
female × hhinc		0.004***		−0.08***		−0.0000***
		(0.0003)		(0.01)		(0.0000)
educ	0.01	0.02	−0.32***	−0.19***	−0.08	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.05)	(0.05)
female × educ		−0.02***		−0.31***		−0.14***
		(0.003)		(0.02)		(0.01)
single	0.05	0.04	−0.10***	−0.30***	−0.05***	−0.02
	(0.04)	(0.04)	(0.03)	(0.04)	(0.02)	(0.02)
female × single		0.01		0.32***		−0.03
		(0.02)		(0.06)		(0.03)
full_time	−0.01	−0.01	0.08	0.08		
	(0.05)	(0.05)	(0.08)	(0.08)		
part_time	0.004	0.003	0.06	0.06		
	(0.05)	(0.05)	(0.07)	(0.07)		
retired	−0.06	−0.06	−0.10	−0.10		
	(0.05)	(0.05)	(0.10)	(0.10)		
homemaker	0.07	0.07	0.12	0.12		
	(0.09)	(0.09)	(0.11)	(0.11)		
unemployed	−0.03	−0.04	0.20**	0.20**		
	(0.08)	(0.08)	(0.10)	(0.10)		
refresher	−0.04**	−0.04**	−0.92***	−0.92***		
	(0.02)	(0.02)	(0.04)	(0.04)		
Constant	2.80***	2.76***	6.52***	5.89***	5.76***	5.22***
	(0.12)	(0.12)	(0.15)	(0.16)	(0.15)	(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.

Table D.3: Predicting rounding

	$R_t = 1$			
	BOP-HH		SCE	
π_{t-1}^{IQR}	0.07***	0.07***	0.15***	0.14***
	(0.003)	(0.02)	(0.002)	(0.002)
FL		-0.11		-0.26***
		(0.12)		(0.01)
easy	-0.08**	0.24		
	(0.04)	(0.23)		
interesting	-0.04	-0.10	0.03	0.02
	(0.04)	(0.24)	(0.02)	(0.02)
decide_finance	-0.10	-0.02	-0.19***	-0.16***
	(0.08)	(0.37)	(0.04)	(0.04)
$\uparrow \pi_{t+1}$	0.26***	0.46**	-0.03*	-0.03*
	(0.03)	(0.18)	(0.02)	(0.02)
age	-0.14***	-0.22**	0.31	0.32
	(0.02)	(0.10)	(0.21)	(0.21)
female	0.14***	0.15	0.60***	0.54***
	(0.02)	(0.13)	(0.01)	(0.01)
single	-0.03	0.03	-0.04*	-0.05**
	(0.03)	(0.17)	(0.02)	(0.02)
educ	0.05***	0.21	-0.14***	-0.12***
	(0.02)	(0.15)	(0.01)	(0.01)
hhinc	-0.01	-0.09	-0.09***	-0.08***
	(0.01)	(0.09)	(0.003)	(0.003)
full_time	0.18**	1.07*	-0.01	-0.01
	(0.09)	(0.64)	(0.05)	(0.05)
part_time	-0.08	0.69	0.04	0.04
	(0.09)	(0.66)	(0.05)	(0.05)
retired	0.03	-0.12	-0.14**	-0.14**
	(0.09)	(0.66)	(0.07)	(0.07)
homemaker	0.09	0.79	-0.02	-0.02
	(0.18)	(1.35)	(0.07)	(0.07)
unemployed	-0.14	-0.07	0.03	0.03
	(0.14)	(0.93)	(0.06)	(0.06)
Constant	-2.74***	-2.27***	-0.50***	-0.60***
	(0.23)	(0.63)	(0.14)	(0.14)
McFadden R2	0.08	0.142	0.15	0.155
Observations	95,690	3,534	115,908	115,908

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

Notes: Mundlak CRE specification; All regressions include regional controls and time dummies. `infquali` is a dummy for increasing inflation expectations, `decide_finance` measures involvement in financial decision making.

Table D.4: Confidence and experience with alternative measures

	Inflation expectation (12 months ahead, point estimate)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
female	0.36***	0.41***	0.32***	0.26***	0.09*	0.11***	0.10***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.05)	(0.02)	(0.02)
R	1.10***						
	(0.03)						
R × shop_groceries	0.54***						
	(0.04)						
π^{IQR}		0.20***					
		(0.01)					
π^{IQR}× shop_groceries		0.03***					
		(0.01)					
FC^{FE}			−0.56***				
			(0.01)				
FC^{FE}× shop_groceries			−0.26***				
			(0.02)				
$\hat{\tau}_0$				−0.31***			
				(0.01)			
$\hat{\tau}_0$× shop_groceries				−0.07***			
				(0.02)			
FL Test (3Q)					−0.03		
					(0.09)		
FL Test (3Q) × shop_groceries					−0.20		
					(0.13)		
shop_groceries	−0.05**	−0.03	0.07***	0.02	0.66*		
	(0.02)	(0.03)	(0.02)	(0.02)	(0.38)		
shop_groceries_robust						0.05***	
						(0.02)	
FC × shop_groceries_robust						−0.09***	
						(0.01)	
single							−0.22***
							(0.02)
FC × single							−0.04***
							(0.01)
FC						−0.69***	−0.75***
						(0.02)	(0.02)
Constant	2.59***	2.06***	2.90***	2.50***	4.72***	2.71***	2.57***
	(0.20)	(0.21)	(0.24)	(0.17)	(0.31)	(0.21)	(0.14)
Observations	72,162	67,681	69,512	48,307	3,250	72,162	96,645
Residual SE	1.42	1.52	1.49	1.17	1.00	1.55	1.59

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

Robust standard errors in parentheses.

Notes: Replication of Table 3 with alternative measures. Mundlak CRE specification; Huber-robust regression. All regressions include demographic controls, regional controls and time dummies.

Table D.5: Effect of confidence and grocery shopping on the gender gap

	Inflation expectation (12 months ahead, point estimate)									
	BOP-HH						SCE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
female	0.26***	0.26***	0.37***	0.36***	0.38***	0.45***	−0.07***	0.03	0.43***	0.72***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
R	1.25***						3.17***			
	(0.02)						(0.03)			
R × female	0.68***						1.54***			
	(0.03)						(0.04)			
π^{IQR}		0.18***						0.59***		
		(0.005)						(0.004)		
π^{IQR}× female		0.10***						0.15***		
		(0.01)						(0.005)		
$\hat{\tau}_0$			−0.05***						−0.33***	
			(0.001)						(0.003)	
$\hat{\tau}_0$× female			−0.02***						−0.07***	
			(0.002)						(0.004)	
FC^{FE}				−0.62***						
				(0.01)						
FC^{FE} × female				−0.27***						
				(0.01)						
all_groceries					−0.02					
					(0.02)					
all_groceries × female					0.13***					
					(0.03)					
single						−0.21***				−0.39***
						(0.02)				(0.03)
single × female						−0.04				0.34***
						(0.03)				(0.04)
Constant	2.69***	2.21***	2.78***	2.87***	2.63***	2.69***	3.86***	1.95***	4.31***	5.41***
	(0.10)	(0.10)	(0.08)	(0.15)	(0.22)	(0.09)	(0.14)	(0.14)	(0.08)	(0.15)
Observations	74,891	70,165	50,101	70,731	72,162	99,374	86,151	85,591	63,528	135,060
Residual SE	1.42	1.51	1.17	1.49	1.56	1.60	2.16	2.15	1.36	2.88

*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.

Table D.6: Truncated subsample regression

	Inflation expectations (12 months ahead, point estimate)				
	Bottom 20%	Bottom 40%	Bottom 60%	Bottom 80%	Full Sample
Survey: BOP-HH					
female	−0.23***	−0.15***	−0.001	0.09***	0.62***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
single	0.06***	0.05***	−0.05***	−0.10***	−0.34***
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
age	−0.001	0.003***	0.005***	0.01***	0.01***
	(0.001)	(0.0004)	(0.0005)	(0.001)	(0.001)
educ	0.03***	0.01***	0.01***	0.01***	−0.02***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
hhinc	0.03***	0.02***	−0.02***	−0.04***	−0.15***
	(0.004)	(0.002)	(0.002)	(0.003)	(0.004)
Constant	0.52***	1.54***	2.65***	3.30***	5.31***
	(0.06)	(0.03)	(0.03)	(0.04)	(0.05)
Observations	49,927	92,489	145,637	192,489	229,866
Residual SE	1.72	1.24	1.49	2.34	3.34
Survey: SCE					
female	−0.67***	−0.31***	−0.06***	0.22***	1.04***
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
single	−0.01	0.02	−0.01	−0.01	−0.19***
	(0.03)	(0.01)	(0.01)	(0.02)	(0.03)
age	−0.003***	0.01***	0.01***	0.02***	0.03***
	(0.001)	(0.0004)	(0.001)	(0.001)	(0.001)
educ	0.24***	0.10***	0.03***	−0.06***	−0.33***
	(0.01)	(0.004)	(0.004)	(0.01)	(0.01)
hhinc	0.08***	0.05***	0.01***	−0.04***	−0.22***
	(0.01)	(0.002)	(0.003)	(0.003)	(0.01)
Constant	−1.10***	0.58***	1.63***	2.63***	5.82***
	(0.07)	(0.04)	(0.04)	(0.05)	(0.07)
Observations	56,587	85,250	121,579	148,509	171,607
Residual SE	2.47	1.40	1.68	2.30	3.57

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

Robust standard errors in parentheses.

Notes: The regression model is the same as that used in Figure 1. Huber-robust regression with regional controls, unemployment, full time, part time and homemaker dummies.

Table D.7: Microlevel effects of high inflation

	Inflation expectation (12 months ahead, point estimate)				
	BOP-HH		SCE		MSC
	High conf.	Low conf.	High conf.	Low conf.	All
female	0.17^{***}	0.16^{**}	0.19^{***}	0.25^{**}	0.59^{***}
	(0.03)	(0.07)	(0.03)	(0.11)	(0.02)
CPI_t^{total}	0.53^{***}	0.62^{***}	0.33^{***}	0.37^{***}	0.50^{***}
	(0.004)	(0.01)	(0.005)	(0.02)	(0.003)
female x CPI_t^{total}	-0.04^{***}	0.04^{***}	-0.08^{***}	0.14^{***}	-0.09^{***}
	(0.01)	(0.01)	(0.01)	(0.02)	(0.004)
$\rho_{t,6}^{total}$	0.02^{***}	-0.01	-0.001	0.02	-0.03^{***}
	(0.005)	(0.02)	(0.005)	(0.04)	(0.01)
female x $\rho_{t,6}^{total}$)	-0.01	0.06^{*}	-0.01	-0.05	0.01
	(0.01)	(0.03)	(0.01)	(0.05)	(0.01)
Constant	1.49^{***}	3.46^{***}	1.96^{***}	7.06^{***}	2.29^{***}
	(0.05)	(0.11)	(0.06)	(0.21)	(0.04)
Observations	44,338	47,754	57,954	57,954	278,632
Residual SE	1.14	2.44	1.55	5.76	3.23

*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.

Table D.8: Forecast confidence and other heterogeneities

	Inflation expectations		FC	Inflation expectations		FC
	BOP-HH			SCE		
female	0.42^{***}	0.12^{***}	-0.43^{***}	0.71^{***}	0.47^{***}	-0.07^{***}
	(0.01)	(0.02)	(0.002)	(0.02)	(0.02)	(0.003)
age	0.04^{***}	0.05^{***}	0.01^{***}	0.06^{***}	0.04^{***}	-0.005^{***}
	(0.003)	(0.003)	(0.0004)	(0.005)	(0.004)	(0.001)
age^2	-0.0004^{***}	-0.0005^{***}	-0.0000^{***}	-0.0003^{***}	-0.0004^{***}	-0.0000^{***}
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
educ	-0.04^{***}	-0.02^{***}	0.02^{***}	-0.25^{***}	0.29^{***}	0.18^{***}
	(0.002)	(0.002)	(0.0002)	(0.01)	(0.01)	(0.001)
hhinc	-0.07^{***}	-0.003	0.10^{***}	-0.18^{***}	0.18^{***}	0.12^{***}
	(0.003)	(0.003)	(0.0003)	(0.004)	(0.004)	(0.001)
FL				-0.51^{***}	-0.22^{***}	0.12^{***}
				(0.01)	(0.01)	(0.002)
FC		-0.67^{***}			-2.92^{***}	
		(0.02)			(0.01)	
Constant	1.67^{***}	1.37^{***}	-0.35^{***}	4.42^{***}	1.55^{***}	-1.05^{***}
	(0.11)	(0.11)	(0.01)	(0.17)	(0.16)	(0.02)
Observations	99,523	99,523	103,154	136,887	136,887	137,206
Residual Std. Error	1.60	1.59	0.22	2.90	2.57	0.43

*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.