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

Lovisa Reiche†

April 2026

Do signals or priors matter more for inflation expectations? I develop a Bayesian learning framework in which agents differ in prior precision ("forecast confidence") and in the volatility of observed signals ("price exposure"). Lower prior precision and higher signal noise both increase expected inflation, but the exposure channel matters only when confidence is low. To assess their relative importance empirically, I apply the framework to a central puzzle: the persistent gender gap in inflation expectations. Using household survey data, I construct a novel, model-consistent measure of individual forecast confidence and show that heterogeneity therein fully accounts for the gap, while exposure to volatile grocery prices matters only among low-confidence consumers. Beyond gender, the framework provides a unified explanation for demographic heterogeneity in beliefs and implies stronger effects of salient price signals in periods of elevated macro uncertainty.

Keywords Consumer Inflation Expectations, Gender, Forecast Confidence

JEL Codes E31, E71, G53, D84

*I thank Michael McMahon and Alexandre Kohlhas for supervision and advice; and Ryan Rholes, Martin Weidner, Michael Ehrmann, Michael Weber, Tabea Bucher-Koenen, Annamaria Lusardi, Carly Urban, Roxana Mihet, Terrance Odean, Elisabeth Kempf, Josefina Cenzon, Dmitry Vinogradov, Maya Haran, Lea Weigand, Anders Anderson, Lisa Kramer, Camelia Kuhnen and Nicolò Maffei Faccioli for their excellent comments alongside the feedback of conference and seminar participants at the University of Oxford, the University of Copenhagen, the Royal Economic Society, Bocconi University, the University of Bamberg, the National Bank of Belgium, Norges Bank, the CEPR, Stanford University, University of Bergamo, the Mannheim Institute for Financial Education, the ifo Institute, Bundesbank, the European Central Bank, SAFE and the AFA. Declarations of interest: none.

†Department of Finance, BI Norwegian Business School, Nydalsveien 37, N-0484 Oslo
Email: lovisa.reiche@bi.no

Introduction

The gender gap in inflation expectations is a well-documented phenomenon. Using Swedish survey data from 1977, Jonung (1981) first showed that women report significantly higher expected inflation. Subsequent research has confirmed the robustness of this finding across countries, survey methods, and experimental settings.[1] On average, the gender gap amounts to 2.6 percentage points in the US and 1.2 percentage points in Germany and is associated with higher forecast errors among women.[2] A leading explanation is that traditional gender roles expose women more to volatile grocery prices, leading them to overweight salient price increases (D'Acunto, Malmendier, & Weber, 2021). This paper proposes a complementary mechanism: forecast confidence, defined as the precision of agents' priors over inflation. Individuals with lower forecast confidence optimally place greater weight on noisy signals. Hence, exposure affects expectations only through its interaction with confidence. Consistent with evidence that women exhibit lower confidence in financial literacy assessments (Bucher-Koenen et al., 2024), I construct a novel measure of forecast confidence to show that confidence matters also for inflation expectations.

I formalize this intuition in a Bayesian framework with log-normally distributed signals and a conjugate log-normal prior. Exposure to higher grocery price volatility enters as higher signal variance, while prior precision captures forecast confidence. In this setting, volatile signals raise mean expectations only when priors are sufficiently imprecise. I extend this framework to a dynamic setting in which past signal volatility endogenously affects current prior precision, generating persistent differences in forecast confidence over time. While Cavallo et al. (2017) show that consumers overweight salient supermarket prices due to cognitive limitations, they treat priors as linked to macroeconomic conditions. I instead provide a structural microfoundation for prior precision, allowing the weighting of salient signals to vary endogenously across individuals within the same macro environment. My mechanism provides a unified lens to understand heterogeneity in expectations and implies that salient price signals matter more in periods of heightened macroeconomic uncertainty.

[1] See, e.g. Arioli et al. (2017), Bryan and Venkatu (2001), Corduas (2022), and D'Acunto, Malmendier, and Weber (2021)

[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.

Empirically, I use the Bundesbank Online Panel–Households (BOP-HH, 2019–2025) and construct a novel measure of forecast confidence implied by the model. The results show that equalizing forecast confidence across men and women closes the expectation gap, while grocery shopping frequency affects expectations primarily for low-confidence respondents. I provide external validity using the New York Fed Survey of Consumer Expectations (2013–2024) and the Michigan Survey of Consumers (1978–2025). Removing the top 30% of outliers eliminates the gender gap, consistent with the model's emphasis on right-skewed beliefs. Further, the gap persists among single households and does not widen during high food price inflation, both of which cast doubt on a pure grocery-exposure explanation and instead support the role of forecast confidence as a mediating channel. Further, I argue that the gender gap, while especially visible, is part of a broader pattern: forecast confidence acts as a common latent factor shaping heterogeneity in household expectations across age, income, and education groups. Finally, I show that food prices—often cited as the most important factor in forming inflation expectations (Anesti et al., 2025)—matter most in periods of high macroeconomic uncertainty, consistent with the framework.

Understanding the gender gap matters for both micro and macro outcomes. At the individual level, higher inflation expectations are linked to lower life satisfaction (Di Tella et al., 2001) and weaker retirement savings and stock market participation, with gender gaps well documented (Almenberg & Dreber, 2015; Cota et al., 2025; Lusardi & Mitchell, 2008; van Rooij et al., 2011). Higher expectations are also associated with greater perceived uncertainty (Reiche & Meyler, 2022), which can depress spending (Coibion, Georgarakos, Gorodnichenko, & van Rooij, 2023; Coibion et al., 2024). At the macro level, women account for roughly 70% of consumer spending in advanced economies (Silverstein & Sayre, 2009), making systematic differences relevant for monetary policy. An emerging literature examines how central bank communication shapes household expectations (Binder, 2017b; Coibion, Georgarakos, Gorodnichenko, & Weber, 2023; Coibion, Gorodnichenko, et al., 2023; Coibion et al., 2020, 2022; Lamla & Vinogradov, 2019). Yet, women tend to pay less attention to such communication and hold more negative views of central banks (Garriga, 2026; McMahon & Reiche, 2024).

This paper contributes to two literatures: heterogeneity in inflation expectations driven by signal exposure and life experiences (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 the role of education, financial literacy, and uncertainty in shaping forecasts (Bruine De Bruin et al., 2010; Burke & Manz, 2014; D'Acunto, Hoang, et al., 2022; D'Acunto et al., 2019; Piccolo et al., 2025). I provide a unified mechanism through which exposure and individual-level confidence jointly determine expectations, and show both theoretically and empirically that these channels are tightly connected: the effect of exposure depends on forecast confidence. In addition, my framework helps rationalize other features of expectations data. It is consistent with findings 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 follow naturally from lower prior precision. It also 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 reports additional evidence in favor of the forecast confidence channel and Section 5 shows implications of the mechanism beyond gender. Section 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 the signals 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 Supplementary Appendix Figure B.1). 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 a later extension I endogenize the prior in a dynamic setting. The framework highlights how these two channels work in isolation and that they interact. An agent with less confidence will place less weight on their own forecast 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 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 the Supplementary Appendix (Section A).

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. The framework allows me to test the consequences of lower prior precision on the posterior mean and variance of an agent's inflation expectation.

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

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

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

The log-normal prior is chosen because it is bounded at zero and features a heavy tail. This choice aligns with observations in the data: (1) there appears to be a zero lower bound in inflation expectations (Gorodnichenko & Sergeyev, 2021); (2) tail prices to the right matter most for expectation formation (Chua & Tsiaplias, 2024); (3) the average density forecast aligns with this choice (see Supplementary Appendix Figure B.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. 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:

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

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. Shopping for groceries is connected to a lower τ_x in line with historical food prices showing a larger variance than the overall basket. Further, the signal is assumed to be unbiased to reflect that groceries have the same level of inflation as other goods on average. The 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, & 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.

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* $\frac{1}{\tau_0}$*.*

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

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 US (SCE): the mean of point forecasts, i.e. the average posterior mean and the mean individual interquartile range (IQR) of density forecasts, i.e. the average posterior interquartile range. The measurement of both variables will be explained in more detail in the next section. The model generates corresponding moments by simulating draws of the true inflation rate 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

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

as well as the posterior IQR

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

from the lognormal distribution implied by $(\hat{\mu}, \hat{\tau})$.[3] I fix $\mu_0 = \log 2$ as the average prior mean of inflation and choose parameters (τ_0, τ_x) to minimize the squared distance between simulated and empirical moments.

The calibrated model reproduces the gender gap in average expectations with striking accuracy in both the US and Germany (Table 1). The empirical mean forecast of women exceeds that of men by 1.22 (Germany)/2.61 (US) percentage points. The model with gender-specific τ_0 values generates a gap of 1.12 (Germany)/2.23 (US) percentage points. When I equalize prior precision across genders (applying the estimated τ_0 for men) while holding signal precision fixed, the gap disappears. This implies that differences in τ_0, interpreted as forecast confidence, can explain the entire empirical gender gap: the share explained is 97% in Germany and 87% in the US.

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 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

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

Table 1: Simulation Exercise

	BOP-HH, Germany		SCE, US	
	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
Model Actual Gap	1.12		2.23	
Empirical Gap	1.21		2.61	
Equalized Gap	-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 mean and interquartile range of inflation expectations in the BOP-HH and the SCE. "Model Actual Gap" is the difference in mean expectations generated by the calibrated model, "Empirical Gap" is the observed survey difference, and "Equalized Gap" sets women's τ_0 equal to men's while keeping τ_x fixed. All reported in percentage points. The "Share Explained by τ_0" reports the proportion of the empirical gap accounted for by differences in prior precision.

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:

$$z_t = (1-\rho)\bar{z} + \rho z_{t-1} + \eta_t, \quad \eta_t \sim \mathcal{N}(0, \frac{1}{\tau_\eta}), \tag{5}$$

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 (5), 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

$$\mu_{0,t} = (1-\rho)\bar{z} + \rho\hat{\mu}_{t-1}, \tag{6}$$

and prior variance

$$\frac{1}{\tau_{0,t}} = \rho^2 \frac{1}{\hat{\tau}_{t-1}} + \frac{1}{\tau_\eta}. \tag{7}$$

Equation (7) 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:

$$\hat{\tau}_t = \tau_{0,t} + \tau_x, \qquad \hat{\mu}_t = \frac{\tau_{0,t}\mu_{0,t} + \tau_x \log x_t}{\tau_{0,t} + \tau_x}. \tag{8}$$

Thus, learning remains conjugate and log-normal; what changes is that prior precision itself is now endogenous. The dynamic model yields an exposure trap. 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. The recursive structure of equations (8) implies that prior precision converges to a unique steady state $\bar{\tau}_0$, which characterizes the long-run confidence of the agent.

Proposition 1.4 *In the steady state of the dynamic learning process, the prior precision $\bar{\tau}_0$ is implicitly defined by:*

$$\bar{\tau}_0 = \left[\frac{\rho^2}{(\bar{\tau}_0 + \tau_x)} + \frac{1}{\tau_\eta}\right]^{-1}. \tag{9}$$

This yields a signal-prior complementarity where prior precision is strictly increasing in signal quality ($\frac{\partial \bar{\tau}_0}{\partial \tau_x} > 0$). Agents receiving noisier signals (lower τ_x) are trapped in a state of low prior confidence.

The comparative statics derived in Propositions 1.1-1.3 describe the direct effects of prior precision and signal precision on inflation expectations 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. Proposition 1.3 highlights that both channels may operate simultaneously, depending on the relative position of signals and priors. These results treat τ_x and τ_0 as independent parameters. The dynamic extension introduces an additional mechanism. Proposition 1.4 shows that prior precision evolves endogenously as a function of past posterior precision and therefore depends on signal quality. In particular, agents exposed to noisier signals accumulate less posterior precision over time, 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. In the empirical section I test the effect of current prior precision (forecast confidence) and signal precision (grocery shopping) on inflation forecast 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.

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).[4] 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 a probabilistic elicitation of inflation expectations, 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

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

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 US, 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).[5] Adding these surveys allows me to explore a longer time horizon than the short period of the BOP-HH, which was also heavily influenced by the Covid-19 pandemic, and provides external validity by benchmarking results for the US. In the analysis below, I focus on the BOP-HH and SCE which contain probabilistic forecasts, a central component to my analysis. For robustness exercises in Section 4 I also utilize the Michigan survey's longer time span. All surveys are summarized in Supplementary Appendix Table C.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.

2.1 Measuring inflation point forecasts and uncertainty

The literature has established that there are gender gaps in inflation point forecasts (Bryan & Venkatu, 2001; D'Acunto, Malmendier, & Weber, 2021; Jonung, 1981). The framework discussed above highlights that these gaps can 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-

[5] 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.

HH, individuals are presented with a short definition of inflation[6] 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). 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.

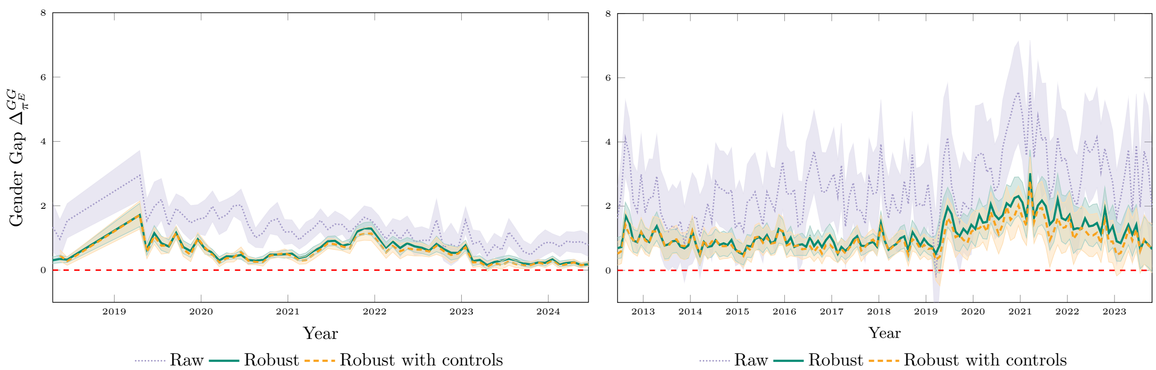
Additionally, BOP-HH and SCE elicit uncertainty around the point forecast through probabilistic bins. Respondents are asked to assign probabilities to ranges or intervals of possible future inflation realizations. The lowest bin is smaller than -12% and the highest is higher than 12%. There are 10 bins in total. Supplementary Appendix Figure B.3 shows the average density forecast from both surveys. I use the probabilities of the reported bin to fit an underlying parametric density following the approach of Engelberg et al. (2009) and applied to the SCE as described in Armantier et al. (2017). My 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}. Table 2 compares π_t^E and π_t^{IQR} in Panel B. As anticipated, women hold both substantially higher point forecasts as well as greater uncertainty around them. This is confirmed also in Figure 1 which shows the differences in means (purple line) over time. The gap shrinks when outliers are downweighted (green line)[7] 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 Supplementary

[6] 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.

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

Appendix Table C.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.



(a) BOP-HH, Germany

(b) SCE, US

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.

2.2 Measuring experience

Inference of differentiated experience is possible in the BOP-HH due to a question regarding household responsibilities introduced in April 2021, namely everyday purchases (`shop_groceries`) and financial decisions (`decide_finance`). Respondents indicate whether they are not involved in the task (0), engage jointly with other household members (0.5) or are solely responsible for all work (1). I use the gradual ranking to differentiate between sole and joint responsibility as recommended in van Hove and Verbraecken (2025).[8] The focus of this analysis is the variable `shop_groceries` as it is a direct measure of whether an individual frequently observes food prices. Since the question is only asked for the first time an individual participates in the survey, I must assume that household chores remain constant over time in the panel. Further, the variable is only asked for non-singles. Whenever grocery shopping is used in the analysis I include only households with more than one member. However, I use singles

[8] As robustness I also compute `all_groceries`= 1 only when `shop_groceries`=1 and 0 otherwise.

as an alternative robustness measure as the men and women in the single sample are assumed to engage symmetrically in grocery shopping.

The data reveal that traditional gender norms are still present in German households. Table 2 Panel C compares grocery shopping and financial decision making for men and women. As expected, women appear significantly more involved in grocery shopping in households that involve more than one member. Men in the data are less likely to live alone. However, I note that financial decisions, i.e. investment and saving decisions, are split equal between German and US couples, suggesting that women's expectations matter strongly for the financial behavior of household.

2.3 Measuring confidence

I construct a novel proxy for forecast confidence (i.e. the prior precision $\tau_{0,i,t}$) from the tendency to round numerical responses to multiples of five. This approach is grounded in the "Round Numbers, Round Interpretations" hypothesis (Krifka, 2007), which posits that agents communicate subjective uncertainty by selecting coarser numerical scales. While recent literature has used rounding to construct aggregate indices of macroeconomic uncertainty (Binder, 2017a; 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 rounding behavior to identify heterogeneity in individual-level prior precision. Second, I map this behavioral signal directly into the law of motion of a dynamic Bayesian learning model.

Recall that the dynamic model implies that prior precision evolves according to (7):

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

where $\hat{\tau}_{i,t-1}$ denotes posterior precision in the previous period. Current prior variance is therefore an increasing function of inherited posterior variance. Intuitively, when previously accumulated information is imprecise, the agent enters the next period with a more diffuse prior. In the panel data, I proxy inherited posterior variance, $1/\hat{\tau}_{i,t-1}$, using the interquartile range of respondent i's previous probabilistic forecast, denoted $\pi^{IQR}_{i,t-1}$, which provides a robust, scale-consistent measure of dispersion in subjective beliefs.

Rounding behavior is modeled as a state-dependent reporting choice. 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:

$$\Pr(R_{i,t} = 1) = \Lambda\left(\alpha + \beta \frac{1}{\tau_{0,i,t}}\right), \qquad \beta > 0, \tag{10}$$

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

Substituting the law of motion (7) into the measurement equation (10) yields the reduced-form estimation equation

$$\Pr(R_{i,t} = 1) = \Lambda\left(\underbrace{\left(\alpha + \frac{\beta}{\tau_\eta}\right)}_{\widetilde{\alpha}} + \underbrace{(\beta\rho^2)}_{\widetilde{\beta}} \pi^{IQR}_{i,t-1} + Z_{i,t}\delta + X_{i,t}\gamma\right), \tag{11}$$

where $Z_{i,t}$ includes survey-task controls such as perceived survey difficulty (`easy`), attention measured through survey interest (`interesting`), and survey fatigue measured through tenure (`survey_tenure`). The latter capture effects that can result in rounding outside of prior confidence, which I want to filter out. I include demographic controls in $X_{i,t}$.

While the predicted probability of rounding (denoted $\hat{p}_{i,t}$ in Table 2) provides an intuitive behavioral measure, the logistic transformation maps the latent state into the unit interval and therefore attenuates variation at the tails. To preserve the proportional variation in the underlying confidence state, I instead use the estimated linear predictor (the log-odds of rounding),

$$\hat{\theta}_{i,t} = \hat{\widetilde{\alpha}} + \hat{\widetilde{\beta}} \pi^{IQR}_{i,t-1} + \hat{\gamma} X_{i,t},$$

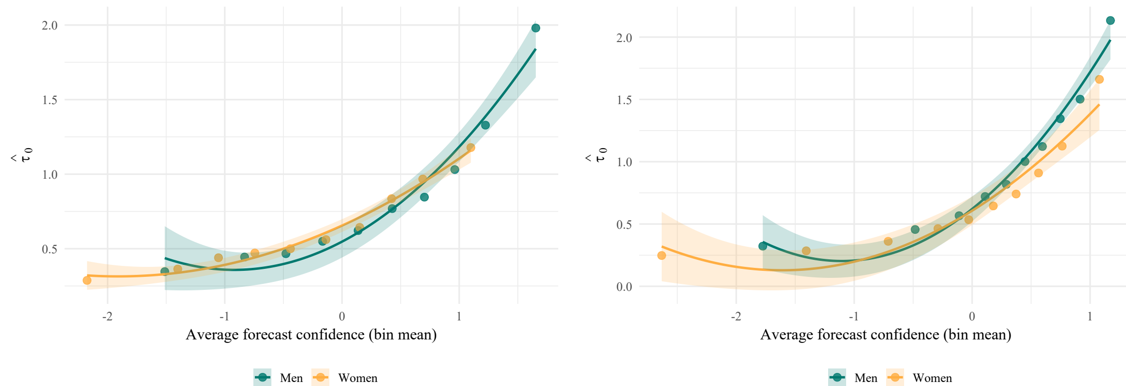
and define the forecast confidence index ($FC_{i,t}$) as the standardized negative linear predictor,

$$FC_{i,t} = -\left(\frac{\hat{\theta}_{i,t} - \mu_\theta}{\sigma_\theta}\right), \tag{12}$$

where μ_θ and σ_θ denote the sample mean and standard deviation of $\hat{\theta}_{i,t}$. This transformation yields an index with mean zero and unit variance that is increasing in prior precision. Higher values of $FC_{i,t}$ therefore correspond to higher inherited precision and a lower predicted probability of rounding. All empirical specifications use the standardized index so that coefficients can be interpreted in units of a one–standard-deviation change in forecast confidence.

The validity of this index rests on a single monotonicity assumption: rounding is positively related to prior variance according to (10). $\beta > 0$ implies the log-odds of rounding are strictly increasing in prior variance and strictly decreasing in prior precision. Empirically, $\hat{\widetilde{\beta}} > 0$ (Table C.3), and since $\widetilde{\beta} = \beta\rho^2$ with $\rho^2 > 0$, this establishes $\beta > 0$ in the data. Under this 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 $r = -0.37$ for BOP-HH; $r = -0.57$ for SCE, $p < 0.001$ for both). 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 results supports the interpretation of the financial confidence index as a valid proxy for the latent prior precision. Because this measure is very noisy on the individual level, I focus on the forecast confidence index FC as my main measurement throughout.



(a) BOP-HH (b) SCE

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

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).

In the dynamic framework, prior precision (τ_0) evolves endogenously as a function of past posterior precision, which itself depends on signal precision (τ_x). As shown in Proposition 1.4, signal volatility can therefore influence expectations not only directly (Proposition 1.1) but also indirectly via its effect on prior precision. To isolate the portion of prior precision that is independent of this direct signal effect, I construct an alternative measure of forecast confidence, $\widetilde{\mathrm{FC}}$, that removes the potential effect of grocery shopping exposure from the original measure. Specifically, I estimate the linear model

$$FC_{it} = \alpha + \delta\, \text{shop\_groceries}_{it} + u_{it},$$

where shop_groceries$_{it}$ captures the intensity of grocery shopping as described above.

I then define the purged forecast confidence as

$$\widetilde{FC}_{it} = FC_{it} - \hat{\delta}\,\text{shop\_groceries}_{it},$$

where $\hat{\delta}$ is the estimated coefficient on grocery shopping. This procedure allows me to separately evaluate the effects of prior confidence (τ_0) and signal volatility (τ_x) on inflation expectations. All analyses are repeated using $\widetilde{\text{FC}}$ to confirm robustness.

Table 2 Panel D shows that there are gender gaps in all confidence measures: rounding behavior ($\bar{R}$), predicted forecast confidence measured as described above (FC and $\widetilde{\text{FC}}$) as well as survey feedback.

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 interaction of the exposure and the confidence channel according to Propositions 1.1 and 1.2. I test the individual effect and interaction of the individual-level confidence measure and grocery shopping with the following panel regression model:

$$\begin{aligned}\pi^E_{i,t} &= \beta_0 + \beta_1\text{female}_i + \beta_2 FC_{i,t} + \beta_3\text{shop\_groceries}_i \\ &+\beta_4 FC_{i,t} \times \text{shop\_groceries}_i + X_{i,t}\gamma_1 + D_t\gamma_2 + G_i\gamma_3 + \bar{X}_i\gamma_4 + \nu_{i,t},\end{aligned} \tag{13}$$

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[9]), D_t captures time dummies, and G_i includes regional dummies. I restrict the

[9] 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^E	4.78	6	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)		
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
	(0.41)	(0.46)	(0.45)	(0.5)
Panel D: Financial literacy and survey confidence				
$\bar{R}$	0.18	0.25	0.27	0.46
	(0.38)	(0.43)	(0.44)	(0.5)
FC	0.21	−0.36	0.19	−0.21
	(0.95)	(0.98)	(0.85)	(1.1)
$\widetilde{FC}$	0.43	−0.03		
	(0.93)	(0.97)		
$1-\hat{p}$	0.86	0.83	0.69	0.63
	(0.06)	(0.08)	(0.15)	(0.2)
$\hat{\tau}_0$	5.73	5.71	2.32	2.11
	(6.83)	(6.95)	(2.66)	(2.6)
easy	0.32	0.3		
	(0.3)	(0.31)		
interesting	0.46	0.39	0.36	0.31
	(0.33)	(0.34)	(0.5)	(0.52)

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).

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 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 (-0.36), 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 Supplementary Appendix Table C.4.

Table 3: Effect of experience and confidence on point forecasts

	Inflation expectation (12 months ahead, point estimate)				
	(1)	(2)	(3)	(4)	(5)
female	0.45***	0.11***	0.44***	0.10***	0.10***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
FC		−0.76***		−0.76***	−0.68***
		(0.02)		(0.02)	(0.02)
FC × shop_groceries					−0.13***
					(0.02)
shop_groceries			0.03	0.03	0.07***
			(0.02)	(0.02)	(0.02)
Constant	2.61***	2.46***	2.60***	2.45***	2.44***
	(0.22)	(0.21)	(0.22)	(0.21)	(0.21)
Observations	72,172	72,172	72,172	72,172	72,172
Residual SE	1.56	1.55	1.56	1.55	1.55

*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 (13). Singles are excluded in all models.

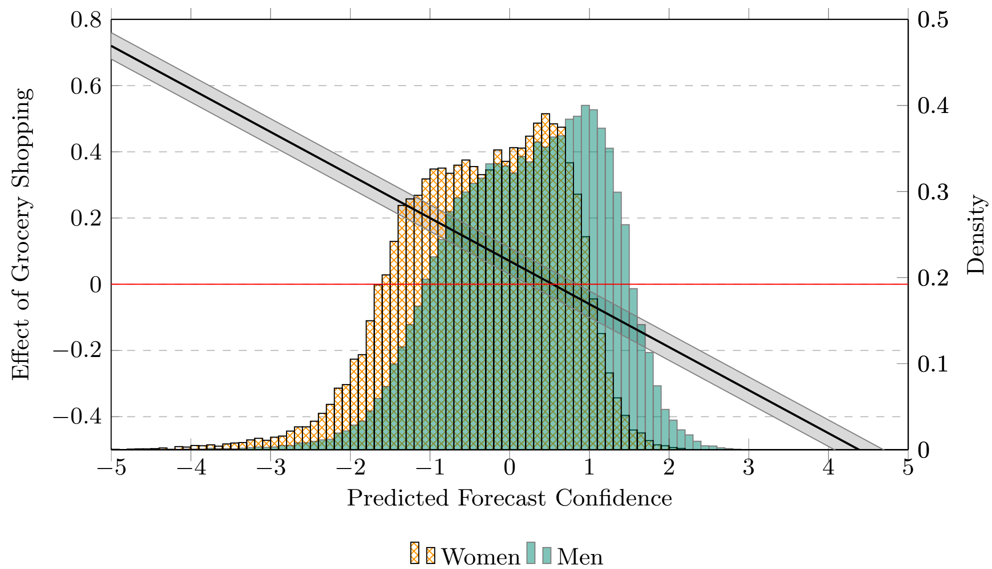


Figure 3: The effect of grocery shopping involvement on inflation expectations for different levels of forecast confidence

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.

Using the `all_groceries` dummy[10] 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 purged measure of FC (with no grocery effect) as well as the static prior $\hat{\tau}_0$ I find effects pointing in the same directions as my forecast confidence measure.

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:

$$\begin{aligned}\pi_{i,t}^{E} = \beta_0 + \beta_1 \text{female}_i + \beta_2 FC_{i,t} + \beta_3 \text{shop\_groceries}_i \\ + \beta_4 FC_{i,t} \times \text{female}_i + \beta_5 \text{shop\_groceries}_i \times \text{female}_i \\ + X_{i,t}\gamma_1 + D_t\gamma_2 + G_i\gamma_3 + \bar{X}_i\gamma_4 + \nu_{i,t}.\end{aligned} \tag{14}$$

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 Supplementary Appendix Table C.5.

[10] $\texttt{all\_groceries} = \begin{cases} 1 & \text{if } \texttt{shop\_groceries} = 1 \\ 0 & \text{otherwise} \end{cases}$

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	0.66***
	(0.02)	(0.03)	(0.03)	(0.02)
FC	−0.64***		−0.65***	−2.35***
	(0.02)		(0.02)	(0.02)
FC × female	−0.26***		−0.28***	−0.58***
	(0.02)		(0.02)	(0.02)
shop_groceries		−0.02	−0.01	
		(0.02)	(0.02)	
shop_groceries × female		0.19***	0.16***	
		(0.04)	(0.04)	
Constant	2.58***	2.63***	2.46***	2.70***
	(0.10)	(0.22)	(0.21)	(0.14)
Observations	74,901	72,172	72,172	87,352
Residual SE	1.54	1.56	1.53	2.30

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

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

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

$$\pi^E_{i,t} = \beta_0 + X_{i,t}\gamma_1 + D_t\gamma_2 + G_i\gamma_3 + \bar{X}_i\gamma_4 + \nu_{i,t}, \tag{15}$$

$$\bar{\pi}^E_w - \bar{\pi}^E_m = \underbrace{\hat{\gamma}_w(\bar{W} - \bar{M})}_{\text{explained by differences in } \bar{W},\bar{M}} + \underbrace{\bar{M}(\hat{\gamma}_w - \hat{\gamma}_m)}_{\text{residual}}. \tag{16}$$

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 the forecast confidence estimator purging grocery shopping ($\widetilde{FC}$) and find that it can still fully account for the gap, although less than before.

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 (17)) as being mediated by the explanatory variables in

Equation (18), such that the mediated (indirect) effect is given by $\beta_1 - \beta_1'$. Equations (19) and (20) 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 $\alpha_1^g \beta_3$.

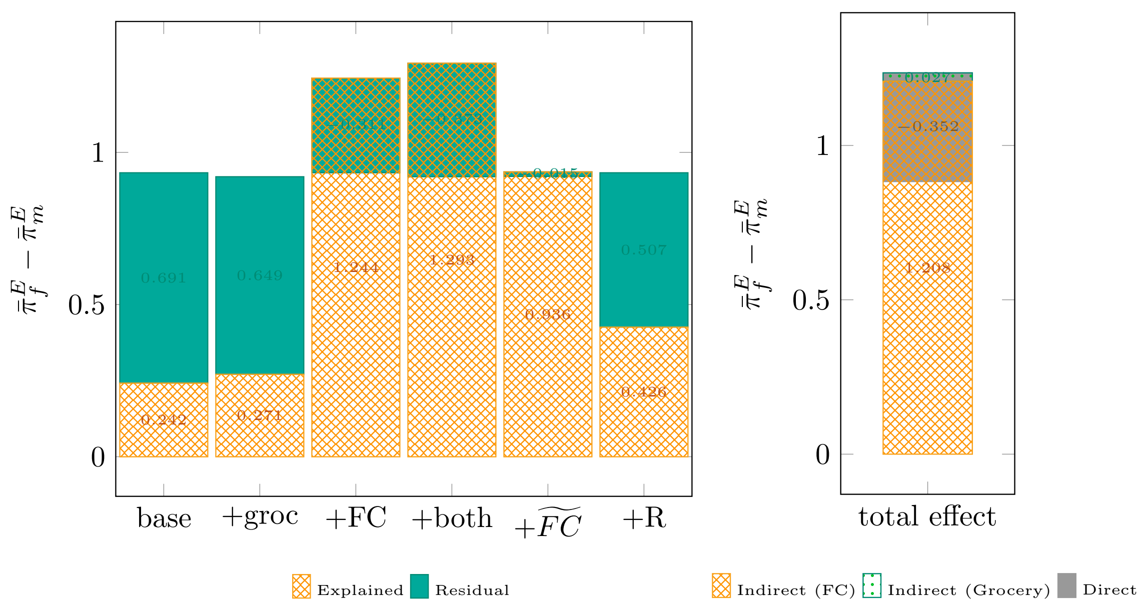
$$\pi_{i,t}^E = \beta_0 + \beta_1 \text{female}_i + \nu_{i,t} \tag{17}$$

$$\pi_{i,t}^E = \beta_0' + \beta_1' \text{female}_i + \beta_2 FC_{i,t} + \beta_3 \text{shop\_groceries}_i + \nu_{i,t} \tag{18}$$

$$FC_{i,t} = \alpha_0^{fc} + \alpha_1^{fc} \text{female}_i + \nu_{i,t} \tag{19}$$

$$\text{shop\_groceries}_i = \alpha_0^g + \alpha_1^g \text{female}_i + \nu_{i,t} \tag{20}$$

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.

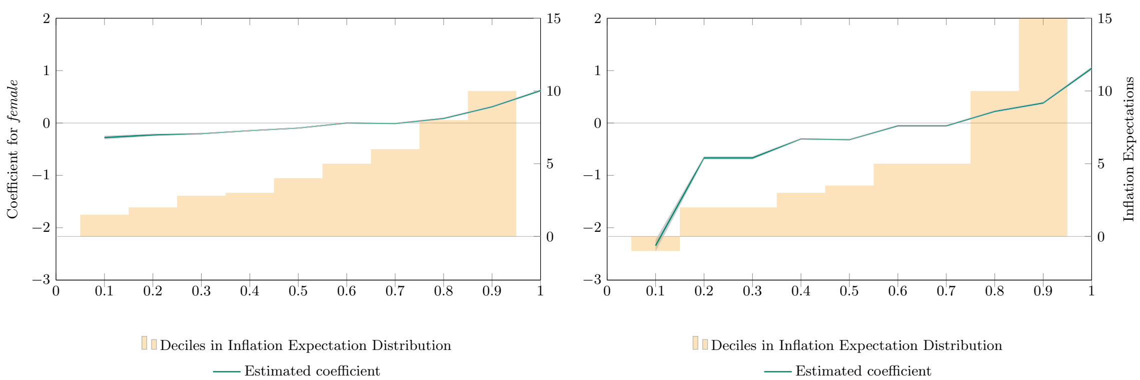


(a) Kitagawa-Oaxaca-Blinder (b) Mediation Model

Figure 4: Decomposition of the Gender Gap

3.3 Verifying the mechanism

An implication of the confidence hypothesis is that the gender gap should disappear when the sample is trimmed to remove outliers in the right-skewed distribution. In the framework, the flat prior can affect the mean expectation only when the distribution is skewed to the right asymmetrically. To test this, I compute the gender gap across deciles of the expectations distribution, controlling for demographics and time periods in the three surveys. I replicate model (1) in Table 3 for each decile of the expectations distribution and test whether the gender gap closes when outliers are removed. Figure 5 plots the coefficient of *female* across percentiles, showing a steady increase as predicted by the uncertainty hypothesis. In samples limited to inflation expectations below the 70th percentile, no positive gender gap is observed in any survey. Conversely, for lower percentiles, the gender gap is negative. This finding is in line with the confidence hypothesis as rounding for very low expectations can bias them downwards (saying 0% instead of 1 or 2%). The regression table is in the Supplementary Appendix, Table C.6.



(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.

4 Further Evidence

I conduct two robustness checks of the pure exposure hypothesis using the two main surveys (BOP-HH and SCE) as well as one additional survey, namely the Michigan

Survey of Consumers (MSC). Note that this survey elicits inflation expectations by asking about "general prices" and probes answers higher than 5%. This changes the magnitudes and distribution relative to the BOP-HH and SCE (Armantier et al., 2013) without affecting the observed gender gap.

1. **Food Price Inflation Periods**: I assess whether the gender gap widens during periods of high food price inflation, i.e. when women in traditional gender roles observe even higher price increases. In the framework this is a direct tests of Proposition 1.1 where τ_x is decreasing relative to before. Under the exposure hypothesis this must always increase expectations, while my framework allows for a weaker effect if forecast confidence is sufficiently high.

2. **Singles Analysis**: I investigate whether the gender gap exists among singles. According to the exposure hypothesis, there should be no gender gap among singles since both men and women engage symmetrically in grocery shopping when living alone. In my framework this refers to a situation where τ_x is identical for all agents. However, a forecast confidence gap may still exist among singles, leading to asymmetric expectations despite symmetric shopping according to Proposition 1.2.

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

4.1 The gender gap correlated with historical food prices

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

To test whether food price exposure contributes to the gender gap, I estimate a regression model similar to the previous setup but replace time dummies with measures of relative food price dynamics. Specifically, I include the difference between food price inflation and overall CPI inflation ($CPI_t^{food} - CPI_t^{total}$) and the difference in their 6-month moving coefficients of variation ($\rho^{food}_{t,6} - \rho^{total}_{t,6}$).[11] Under the exposure hypothesis, these interaction terms with female should be positive: women, due to greater grocery shopping experience, should respond more strongly to relative food price volatility.

The results, reported in Table 5, show little evidence in favor of this view. In the Michigan Survey of Consumers (MSC)—the longest-running dataset with the richest time variation—the coefficient on the interaction term with female are negative, suggesting that in fact, the gender gap shrinks when food price inflation is high. To align more closely with the confidence mechanism, I split the BOP-HH and SCE by forecast confidence. The results are striking: the interaction between food price volatility and gender is negative (and significant) for high-confidence respondents, and positive for low-confidence respondents. In addition, the effect of more volatile food prices is no different for men and women. In Supplementary Appendix Table C.7 I show that the gender gap in inflation expectations responds in a similar pattern to the level and volatility of overall inflation.

This finding point away from a grocery-shopping channel and toward forecast confidence as the operative mechanism. Food price signals matter more when respondents are hold less precise priors (Proposition 1.1 in the framework). For confident consumers, food price volatility has no effect—or even a negative effect—on the gender gap.

4.2 The gender gap among singles

Another implication of the pure exposure hypothesis is that if τ_x is identical across consumers, their forecasts should be the same. Hence, there should be no gender gap in inflation expectations for single men and women, as singles are likely to engage in grocery shopping irrespective of gender and thus should receive the same signals about inflation. 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. Under the experience hypothesis, the gender gap should be larger in the non-single sample as traditional gender norms don't exist for singles.

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

Table 5: Microlevel effects of high food prices

	Inflation expectation (12 months ahead, point estimate)				
	BOP-HH		SCE		MSC
	High conf.	Low conf.	High conf.	Low conf.	All
female	0.01	0.20^{***}	-0.15^{***}	0.34^{***}	0.28^{***}
	(0.02)	(0.04)	(0.02)	(0.07)	(0.01)
CPI_t^{food} - CPI_t^{total}	0.28^{***}	0.26^{***}	0.11^{***}	0.07^{***}	0.01^{*}
	(0.002)	(0.004)	(0.004)	(0.02)	(0.004)
female x (CPI_t^{food} - CPI_t^{total})	-0.03^{***}	0.04^{***}	-0.08^{***}	0.07^{***}	-0.05^{***}
	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)
$\rho_{t,6}^{food}$ - $\rho_{t,6}^{total}$	0.09^{***}	0.06^{**}	-0.004^{*}	-0.03	-0.02^{***}
	(0.01)	(0.03)	(0.002)	(0.02)	(0.004)
female x ($\rho_{t,6}^{food}$ - $\rho_{t,6}^{total}$)	-0.0004	-0.07^{*}	0.003	0.03	-0.004
	(0.01)	(0.03)	(0.004)	(0.03)	(0.01)
Constant	2.75^{***}	5.53^{***}	2.57^{***}	7.98^{***}	5.00^{***}
	(0.06)	(0.11)	(0.06)	(0.21)	(0.04)
Observations	44,338	47,754	57,954	57,954	278,632
Residual SE	1.31	2.62	1.66	5.92	3.44

*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 6: 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 6 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.

5 Beyond Gender

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

5.1 Confidence and other dimensions of heterogeneity

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

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

To assess the extent to which confidence mediates these broader gaps, I apply a mediation analysis (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[12] change in key predictors—age, education (`educ`), and household income (`hhinc`)—on the outcome

[12]The standardization procedure proceeds in two steps. First, the coefficients linking predictors to the mediator ($X \rightarrow M$) and the mediator to the outcome ($M \rightarrow Y$) are adjusted by the ratio of standard deviations of the relevant variables. Specifically, for each predictor X, the standardized

variable $\pi^E_{i,t}$, separated into indirect effects mediated by the confidence measure (FC) 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 Supplementary Appendix Table C.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 US. At younger ages, the direct effect is larger and positive. As age progresses, in the US the total effect reduces driven mainly by the direct effect shrinking. However, in Germany the total effect reverses. At median and especially at old age there is a strongly negative direct effect suggesting that at older ages.

5.2 When do food prices matter?

A second key implication of the dynamic Bayesian framework is that salient price signals, such as food prices, should have a stronger impact on expectations when macroeconomic uncertainty is high. This is because macroeconomic uncertainty will be reflected in increasing $1/\tau_\eta$ in (7) which has a decreasing effect on forecast confidence. Thus, following Proposition 1.1, τ_x has a larger effect on inflation expectations. In other words, when macroeconomic uncertainty is elevated, forecasting becomes in-

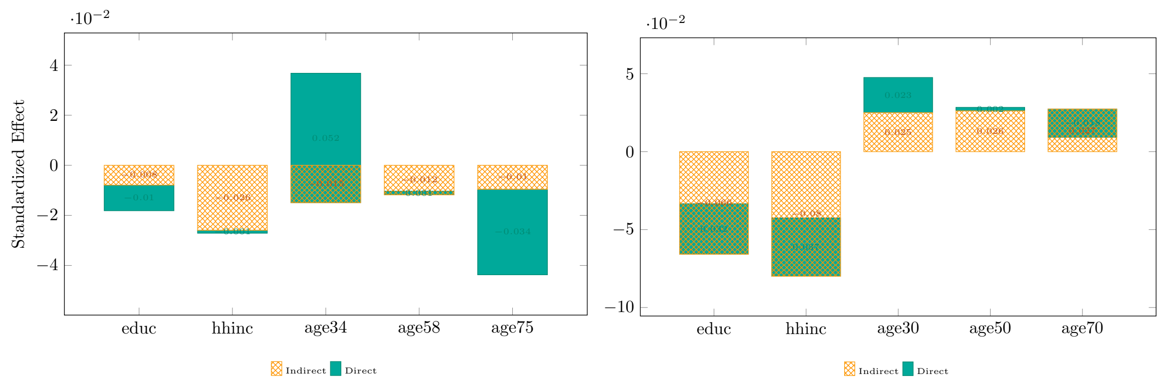
indirect effect is computed as:

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

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.

herently more difficult, which is reflected in lower forecast confidence. Consumers with imprecise priors—interpreted here as low confidence—place greater weight on noisy signals, so aggregate shocks to salient goods exert a larger influence on inflation expectations during periods of elevated uncertainty.

To examine this implication, I extend the empirical strategy of Coibion and Gorodnichenko (2015) and 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.

$$\Delta\pi^E_{i,t} = \beta_0 + \beta_1\pi^{\text{food}}_t + \beta_2\pi^{\text{food}}_t \times \Delta\text{EPU}_t + \beta_3\Delta\text{EPU}_t + X_{i,t}\gamma_1 + G_i\gamma_3 + \bar{X}_i\gamma_4 + \nu_{i,t}, \tag{21}$$

The results in Table 7 strongly support the prediction. While the baseline effect of food price changes on expectations is modest and even negative in the US, the inter-

Table 7: 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.

action 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.

6 Conclusion

This paper provides both theoretical and empirical insights into the determinants of inflation expectations, with a focus on the gender gap. Theoretically, I show that heterogeneity in point forecasts arises from variation in signal precision tied to heterogeneous consumption baskets. Under a log-normal prior, even unbiased but noisier signals raise average inflation expectations, but only when prior beliefs are sufficiently imprecise. This nests the exposure hypothesis on the gender gap (D'Acunto, Malmendier, & Weber, 2021; Jonung, 1981), which operates through differential exposure to price signals, but additionally shows that its effect is conditional on forecast confidence, which is the key mechanism emphasized in this paper. Low forecast confidence—captured through imprecise priors—produces similar effects in noisy environments, offering a complimentary and equally plausible mechanism.

Empirically, using German household data, I find that grocery shopping alone does not explain inflation expectations. I develop a measure of forecast confidence derived directly from my model and show that it is central to explain heterogeneity in inflation expectations. If men and women had equal forecast confidence, the gender gap would in fact be negative. Grocery shopping elevates expectations primarily among low-confidence respondents, with little effect on those with high confidence. I provide robustness exercises using U.S. data from the SCE and MSC. My findings indicate that exposure alone is insufficient in accounting for the gap: forecast confidence is pivotal. Importantly, forecast confidence also helps explain other demographic gaps in expectations, including age, education, and household income.

The policy implications are substantial. A sizable tail of low-confidence women produces imprecise expectations, affecting savings, investment, and attention to policy communication (Lusardi & Mitchell, 2008; McMahon & Reiche, 2024). Improving confidence in financial skills and increasing female representation in policy institutions could help mitigate these gaps (D'Acunto, Fuster, & Weber, 2022). More broadly, easily observable price signals, such as food prices, become especially important during periods of heightened macroeconomic uncertainty providing a time varying element to the exposure literature and guiding central bank communication.

References

Almenberg, J., & Dreber, A. (2015). Gender, stock market participation and financial literacy. *Economics Letters*, *137*, 140–142.

Anderson, A., Baker, F., & Robinson, D. T. (2017). Precautionary savings, retirement planning and misperceptions of financial literacy. *Journal of Financial Economics*, *126*, 383–398.

Anesti, N., Esady, V., & Naylor, M. (2025). Food prices matter most: Sensitive household inflation expectations. *Bank of England Staff Working Paper*, (1125).

Arioli, R., Lim, Y. C., Sek, S. K., Easaw, J., Golinelli, R., Malgarini, M., Morvan, C., Jenkins, B., Carroll, C. D., Axtell, R., Branch, W., Christ, C., Dickens, W., Dotsey, M., Epstein, J., Goodfriend, M., Manning, J., Mccallum, B., Mehra, Y., ... Schulhofer-Wohl, S. (2017). EU Consumers' Quantitative Inflation Perceptions and Expectations: an Evaluation. *ECB Occasional Paper Series*, *91*(186).

Armantier, O., Bruine De Bruin, W., Potter, S., Topa, G., Van Der Klaauw, W., & Zafar, B. (2013). Measuring inflation expectations. *Annual Review of Economics*, *5*, 273–301.

Armantier, O., Nelson, S., Topa, G., van der Klaauw, W., & Zafar, B. (2016). The price is right: Updating inflation expectations in arandomized price information experiment. *Review of Economics and Statistics*, *98*(3), 503–523.

Armantier, O., Topa, G., van der Klaauw, W., & Zafar, B. (2017). An Overview of the Survey of Consumer Expectations. *FRBNY Economic Policy Review*, *23*(2), 51–72.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty*. *The Quarterly Journal of Economics*, *131*, 1593–1636.

Binder, C. (2017a). Measuring uncertainty based on rounding: New method and application to inflation expectations. *Journal of Monetary Economics*, *90*.

Binder, C. (2017b). Fed speak on main street: Central bank communication and household expectations. *Journal of Macroeconomics*, *52*, 238–251.

Binder, C. (2018). Inflation expectations and the price at the pump. *Journal of Macroeconomics*, *58*, 1–18.

Blau, F. D., & Kahn, L. M. (2017). The Gender Wage Gap: Extent, Trends, and Explanations. *Journal of Economic Literature*, *55*(3), 789–865.

Blinder, A. S. (1973). Wage discrimination: Reduced form and structural estimates. *The Journal of Human Resources*, *8*, 436.

Bruine De Bruin, W., Van der Klaauw, W., Downs, J. S., Fischhoff, B., Topa, G., Armantier, O., Chien, S., Colvin, T., Forman, D., Fielding, P., Greenwald, D., Gutsche, T., Holbrook, M., & Weerman, B. (2010). Expectations of Inflation: The Role of Demographic Variables, Expectation Formation, and Financial Literacy. *Journal of Consumer Affairs*, *44*(2), 381–402.

Bryan, M., & Venkatu, G. (2001). The Curiously Different Inflation Perspectives of Men and Women. *Economic Commentary.*

Bucher-Koenen, T., Alessie, R., Lusardi, A., & van Rooij, M. (2024). Fearless Woman: Financial Literacy and Stock Market Participation. *Management Science*, *0*(0).

Burke, M. A., & Manz, M. (2014). Economic Literacy and Inflation Expectations: Evidence from a Laboratory Experiment. *Journal of Money, Credit and Banking*, *46*(7), 1421–1456.

Cavallo, A., Cruces, G., & Perez-Truglia, R. (2017). Inflation Expectations, Learning, and Supermarket Prices: Evidence from Survey Experiments. *American Economic Journal: Macroeconomics*, *9*(3), 1–35.

Chua, C. L., & Tsiaplias, S. (2024). The influence of supermarket prices on consumer inflation expectations. *Journal of Economic Behavior and Organization*, *219*, 414–433.

Clements, M. P. (2021). Rounding behaviour of professional macro-forecasters. *International Journal of Forecasting*, *37*, 1614–1631.

Coibion, O., Georgarakos, D., Gorodnichenko, Y., Kenny, G., & Weber, M. (2024). The Effect of Macroeconomic Uncertainty on Household Spending. *American Economic Review*, *114*(3), 645–677.

Coibion, O., Georgarakos, D., Gorodnichenko, Y., & van Rooij, M. (2023). How Does Consumption Respond to News about Inflation? Field Evidence from a Randomized Control Trial. *American Economic Journal: Macroeconomics*, *15*(3), 109–152.

Coibion, O., Georgarakos, D., Gorodnichenko, Y., & Weber, M. (2023). Forward Guidance and Household Expectations. *Journal of the European Economic Association*, *21*(5), 2131–2171.

Coibion, O., & Gorodnichenko, Y. (2015). Is the Phillips Curve Alive and Well after All? Inflation Expectations and the Missing Disinflation. *American Economic Journal: Macroeconomics*, *7*(1), 197–232.

Coibion, O., Gorodnichenko, Y., Knotek, E. S., & Schoenle, R. (2023). Average Inflation Targeting and Household Expectations. *Journal of Political Economy: Macroeconomics*, *1*(2), 403–446.

Coibion, O., Gorodnichenko, Y., Kumar, S., & Pedemonte, M. (2020). Inflation expectations as a policy tool? *Journal of International Economics*, *124*, 103297.

Coibion, O., Gorodnichenko, Y., & Weber, M. (2022). Monetary Policy Communications and their Effects on Household Inflation Expectations. *Journal of Political Economy*, *130*(6), 1537–1584.

Corduas, M. (2022). Gender differences in the perception of inflation. *Journal of Economic Psychology*, *90*, 102522.

Cota, M., Morazzoni, M., Frech, M., & Tallent, M. (2025). *Gender differences in savings over the lifecycle: The role of financial literacy.*

D'Acunto, F., Charalambakis, E., Geogarakos, D., Kenny, G., Meyer, J., & Weber, M. (2024). Household inflation expectations: an overview of recent insights for monetary policy. *ECB Discussion Paper*, (24).

D'Acunto, F., Fuster, A., & Weber, M. (2022). Diverse Policy Committees Can Reach Underrepresented Groups. *NBER Working Paper*, (29275).

D'Acunto, F., Hoang, D., Paloviita, M., & Weber, M. (2019). Cognitive Abilities and Inflation Expectations. *AEA Papers and Proceedings*, *109*, 562–66.

D'Acunto, F., Hoang, D., Paloviita, M., & Weber, M. (2022). IQ, Expectations, and Choice. *The Review of Economic Studies*, *90*(5), 2292–2325.

D'Acunto, F., Malmendier, U., Ospina, J., & Weber, M. (2021). Exposure to grocery prices and inflation expectations. *Journal of Political Economy*, *129*(5), 1615–1639.

D'Acunto, F., Malmendier, U., & Weber, M. (2021). Gender Roles produce divergent economic expectations. *Proceedings of the National Academy of Science*, *118*(21).

D'Acunto, F., Malmendier, U., & Weber, M. (2023). What Do the Data Tell Us About Inflation Expectations? In R. Bachmann, G. Topa, & W. van der Klaauw (Eds.), *Handbook of economic expectations* (pp. 133–161). Elsevier.

D'Acunto, F., & Weber, M. (2024). Why Survey-Based Subjective Expectations are Meaningful and Important. *Annual Review of Economics*, *16*(1), 329–357.

Di Tella, R., MacCulloch, R. J., & Oswald, A. J. (2001). Preferences over Inflation and Unemployment: Evidence from Surveys of Happiness. *American Economic Review*, *91*(1), 335–341.

Dräger, L., Menz, J. O., & Fritsche, U. (2014). Perceived inflation under loss aversion. *Applied Economics*, *46*(3), 282–293.

Drobot, S., Puzzello, D., Rholes, R., & Wabitsch, A. (2025). *Incentivizing inflation expectations.*

Ehrmann, M., & Fratzscher, M. (2007). The timing of central bank communication [Central bank transparency and central bank communication]. *European Journal of Political Economy*, *23*(1), 124–145.

Engelberg, J., Manski, C. F., & Williams, J. (2009). Comparing the Point Predictions and Subjective Probability Distributions of Professional Forecasters. *Journal of Business & Economic Statistics*, *27*(1), 30–41.

Federal Reserve Bank of New York. (2024). Survey of Consumer Expectations. Retrieved August 1, 2025, from http://www.newyorkfed.org/microeconomics/sce

Fischer, A.-K., Robert, C., Boddin, D., Dörner, M., Schmidt, T., Helmschrott, S., & Goldfayn-Frank, O. (2025). Bundesbank-Online-Panel-Households (BOP-HH). https://doi.org/10.12757/BBK.BOPHH.202503.01

Garriga, A. C. (2026). A gender gap in attitudes towards monetary policy? the case of satisfaction with the bank of england. *Political Studies*.

Glas, A., & Hartmann, M. (2022). Uncertainty measures from partially rounded probabilistic forecast surveys. *Quantitative Economics*, *13*, 979–1022.

Gorodnichenko, Y., & Sergeyev, D. (2021). Zero Lower Bound on Inflation Expectations. *NBER Working Paper Series*, (29496).

Huber, P. J. (1964). Robust estimation of a location parameter. *The Annals of Mathematical Statistics*, *35*, 73–101.

Jonung, L. (1981). Perceived and Expected Rates of Inflation in Sweden. *American Economic Review*, *71*(5), 961–968.

Kim, G., & Binder, C. (2023). Learning-through-survey in inflation expectations. *American Economic Journal: Macroeconomics*, *15*, 254–278.

Kitagawa, E. M. (1955). Components of a Difference Between Two Rates. *Journal of the American Statistical Association*, *50*(272), 1168.

Krifka, M. (2007). Approximate Interpretations of Number Words: A case for strategic communication. *Proceedings of the Colloquium*.

Lamla, M. J., & Vinogradov, D. V. (2019). Central bank announcements: Big news for little people? *Journal of Monetary Economics*, *108*, 21–38.

Lusardi, A., & Mitchell, O. S. (2008). Planning and Financial Literacy: How Do Women Fare? *American Economic Review*, *98*(2), 413–417.

MacKinnon, D. P. (2012, October). *Introduction to statistical mediation analysis*. Routledge.

Malmendier, U., & Nagel, S. (2016). Learning from Inflation Experiences. *The Quarterly Journal of Economics*, *131*(1), 53–87.

McMahon, M., & Reiche, L. (2024). Does the Bank of England need Gendered Communication. *National Institute Economic Review*, *269*, 29–46.

Moore, D. A., & Healy, P. J. (2008). The trouble with overconfidence. *Psychological Review*, *115*, 502–517.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica*, *46*, 69.

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International Economic Review*, *14*, 693.

Piccolo, J., Russo, A., Granziera, E., & Castelnuovo, E. (2025). *Households' Macroeconomic Beliefs: The Role of Education*.

Reiche, L., & Meyler, A. (2022). Making Sense of Consumer Inflation Expectations. *ECB Working Papers*, (2642).

Silverstein, M. J., & Sayre, K. (2009). The Female Economy. *Harvard Business Review*. Retrieved September 23, 2024, from https://hbr.org/2009/09/the-female-economy

Survey Research Center. (2025). University of Michigan Surveys of Consumers. Retrieved August 1, 2025, from https://sda.umsurvey.org/

Tingley, D., Yamamoto, T., Hirose, K., Keele, L., & Imai, K. (2014). Mediation: R package for causal mediation analysis. *Journal of Statistical Software*, *59*.

van Hove, L., & Verbraecken, R. (2025). Gender roles and inflation expectations: D'Acunto et al. revisited. *Review of Economics of the Household*, *23*, 797–818.

van Rooij, M., Lusardi, A., & Alessie, R. (2011). Financial literacy and stock market participation. *Journal of Financial Economics*, *101*, 449–472.

Weber, M., D'Acunto, F., Gorodnichenko, Y., & Coibion, O. (2022). The Subjective Inflation Expectations of Households and Firms: Measurement, Determinants, and Implications. *Journal of Economic Perspectives*, *36*(3), 157–184.

Supplemental Appendix

A Supplemental Material for Bayesian Framework

Algebraic manipulations to derive the log-normal posterior

The prior is defined as

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

The unbiased signal is defined as

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

I compute the posterior following Bayesian updating:

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

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

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

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

Comparative statics

The effect of increasing signal volatility

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

The effect of decreasing prior precision

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

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:

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

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

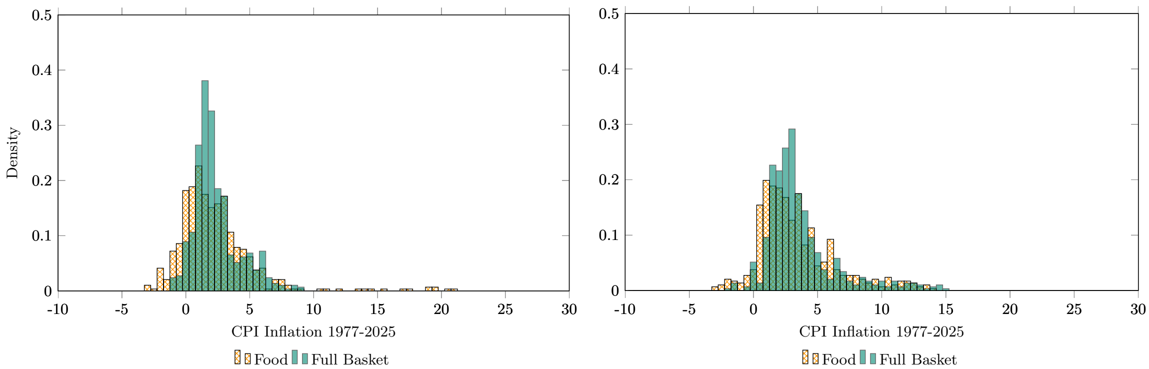
Local stability of the steady state requires $f'(\bar{\tau}_0) < 1$, which is equivalent to

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

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

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

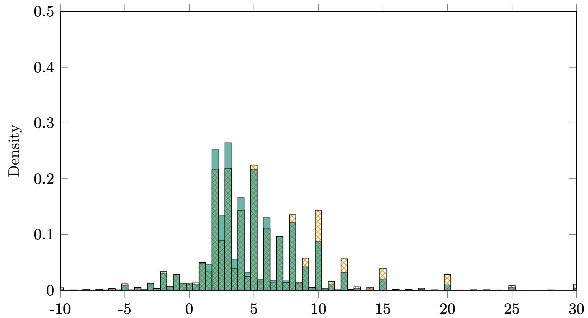
B Supplemental Figures



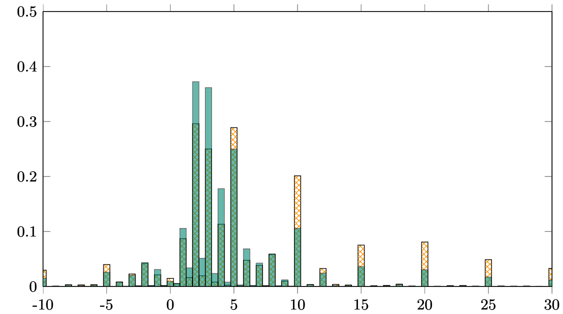
(a) Germany (b) United States

Figure B.1: Histogram of CPI Inflation

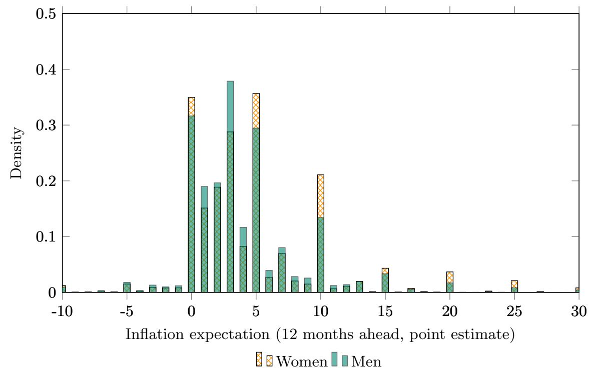
Sources: OECD, Prices: Consumer prices, Main Economic Indicators (database), January 1977 - July 2025.



(a) BOP-HH



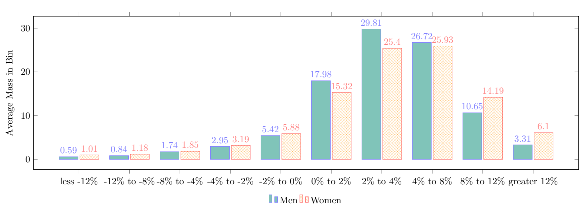
(b) SCE



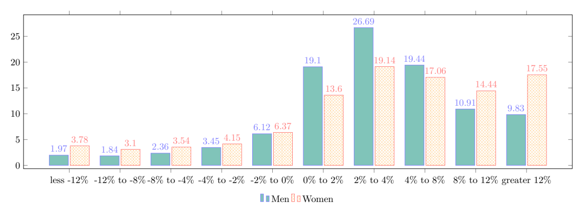
(c) MSC

Figure B.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 B.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.

C Supplemental Tables

Table C.1: Features of the three surveys

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

Table C.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 C.3: Predicting rounding

	$R_t = 1$			
	BOP-HH		SCE	
π^{IQR}_{t-1}	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 C.4: Confidence and experience with alternative measures

	Inflation expectation (12 months ahead, point estimate)					
	(1)	(2)	(3)	(4)	(5)	(6)
female	0.36***	0.41***	0.42***	0.26***	0.10***	0.09***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
R	1.10***					
	(0.03)					
R × shop_groceries	0.55***					
	(0.04)					
π^{IQR}		0.20***				
		(0.01)				
$\pi^{IQR}\times$ shop_groceries		0.03***				
		(0.01)				
$\widetilde{FC}$			−0.51***			
			(0.02)			
$\widetilde{FC}\times$ shop_groceries			−0.11***			
			(0.02)			
$\hat{\tau}_0$				−0.32***		
				(0.01)		
$\hat{\tau}_0\times$ shop_groceries				−0.05***		
				(0.02)		
shop_groceries	−0.05**	−0.03	0.06***	0.03*		
	(0.02)	(0.03)	(0.02)	(0.02)		
all_groceries					0.05***	
					(0.02)	
FC × all_groceries					−0.09***	
					(0.01)	
single						−0.22***
						(0.02)
FC × single						−0.04**
						(0.01)
FC					−0.73***	−0.77***
					(0.02)	(0.02)
Constant	2.59***	2.06***	3.02***	2.47***	2.46***	2.38***
	(0.20)	(0.21)	(0.22)	(0.17)	(0.21)	(0.14)
Observations	72,172	67,690	72,172	48,258	72,172	96,660
Residual SE	1.42	1.52	1.55	1.17	1.55	1.58

*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 C.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^{***}	0.36^{***}	0.34^{***}	0.38^{***}	0.45^{***}	-0.07^{***}	0.03	0.43^{***}	0.72^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
R	1.25^{***}						3.17^{***}			
	(0.02)						(0.03)			
R × female	0.68^{***}						1.55^{***}			
	(0.03)						(0.04)			
π^{IQR}		0.18^{***}						0.59^{***}		
		(0.005)						(0.004)		
$\pi^{IQR}\times$ female		0.10^{***}						0.15^{***}		
		(0.01)						(0.005)		
$\hat{\tau}_0$			-0.05^{***}						-0.33^{***}	
			(0.001)						(0.003)	
$\hat{\tau}_0\times$ female			-0.01^{***}						-0.07^{***}	
			(0.002)						(0.004)	
$\widetilde{FC}$				-0.49^{***}						
				(0.02)						
$\widetilde{FC}$ × female				-0.28^{***}						
				(0.02)						
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				0.35^{***}
						(0.03)				(0.04)
Constant	2.69^{***}	2.21^{***}	2.77^{***}	2.59^{***}	2.63^{***}	2.69^{***}	3.88^{***}	1.99^{***}	4.34^{***}	5.45^{***}
	(0.10)	(0.10)	(0.08)	(0.21)	(0.22)	(0.09)	(0.13)	(0.13)	(0.08)	(0.14)
Observations	74,901	70,174	50,045	72,172	72,172	99,389	87,352	86,753	64,308	136,876
Residual SE	1.42	1.51	1.17	1.54	1.56	1.60	2.17	2.16	1.36	2.90

*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 C.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 C.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 C.8: Forecast confidence and other heterogeneities

	Inflation expectations		FC	Inflation expectations		FC
		BOP-HH			SCE	
female	0.42^{***}	-0.17^{***}	-0.27^{***}	0.84^{***}	-1.08^{***}	-0.70^{***}
	(0.01)	(0.01)	(0.003)	(0.02)	(0.02)	(0.003)
age	0.04^{***}	0.04^{***}	-0.004^{***}	0.07^{***}	0.05^{***}	-0.01^{***}
	(0.003)	(0.003)	(0.001)	(0.01)	(0.005)	(0.001)
age^2	-0.0004^{***}	-0.0003^{***}	0.0001^{***}	-0.0004^{***}	-0.001^{***}	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
educ	-0.04^{***}	-0.01^{***}	0.01^{***}	-0.27^{***}	0.23^{***}	0.19^{***}
	(0.002)	(0.002)	(0.0004)	(0.01)	(0.01)	(0.001)
hhinc	-0.07^{***}	0.04^{***}	0.05^{***}	-0.23^{***}	0.10^{***}	0.12^{***}
	(0.003)	(0.003)	(0.001)	(0.01)	(0.01)	(0.001)
FC		-2.25^{***}			-2.74^{***}	
		(0.01)			(0.02)	
Constant	1.42^{***}	13.24^{***}	5.23^{***}	4.46^{***}	20.51^{***}	5.78^{***}
	(0.15)	(0.16)	(0.03)	(0.18)	(0.19)	(0.02)
Observations	95,690	95,690	95,690	115,908	115,908	115,908
Residual SE	1.60	1.56	0.40	2.94	2.69	0.41

*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.