DIVERGENT PERCEPTIONS, DIVERGENT PAY: INFLATION AND THE GENDER WAGE GAP*

Lovisa Reiche† Nicolò Maffei-Faccioli‡

July 2026

Abstract

Inflationary shocks do not affect all workers equally. Comparing men and women, we document two facts. First, both demand- and supply-driven inflationary shocks widen the gender wage gap within industries and occupations. Because these shocks imply opposite business-cycle conditions, their common effect points to inflation as the relevant force. Second, women and men perceive the same inflationary shocks as having different labor-market consequences: women expect conditions to worsen, while men expect them to improve. This asymmetry creates an expectations channel linking inflation to unequal wage growth. We formalize this channel in a New Keynesian search-and-matching model with male and female workers, imperfect information, and gender-specific ambiguity attitudes. Common macroeconomic signals lead ambiguity-averse women to place greater weight on adverse supply-driven states. For inflationary signals, this lowers their perceived outside options and wage demands relative to men's. Divergent perceptions translate common inflationary shocks into divergent pay.

JEL classification codes: C32, E24, E32, J16, J31.

Keywords: Consumer Expectations, Gender Wage Gap, Inflation, Business Cycle Dynamics.

*This paper should not be reported as representing the views of Norges Bank. The views expressed are those of the authors and do not necessarily reflect those of Norges Bank. We are grateful to Michael McMahon, Alexandre Kohlhas, Barbara Petrongolo, Martin Ellison, Britta Gehrke, Lea Weigand, Adrien Auclert, Sara Casella, Kurt Mitman, Per Krusell, Morten Ravn, Kjetil Storesletten, Jonna Olsson, Marianna Kudlyak, Jonathon Hazell, Jane Olmstead-Rumsey, Matthias Doepke, Francesca Monti, Evi Pappa, Riccardo Masolo, Domenico Giannone, Michael Ehrmann, Hie Joo Ahn, Ayşegül Şahin, Dirk Krüger, Christian Bayer, Francesco D'Acunto, Johannes Wohlfart, Chris Roth and Peter Andre for their insightful comments alongside conference and seminar participants at the SNDE, the Kiel Institute, CEPR, Bank of Finland, the ICEEE, the IAAE, the University of Oxford, NORMAC, the Oslo Macro Conference, Università Cattolica del Sacro Cuore, Norges Bank, University of Hamburg, the ASSA, the Federal Reserve Bank of Philadelphia, Bank of Italy, RWI Leibniz Institut, the University of Bonn, CEBRA, the CESifo, the CEF and the University of Heidelberg. We also thank an anonymous referee for the Norges Bank Working Paper Series for particularly helpful feedback. Declarations of interest: none.

†BI Norwegian Business School, Nydalsveien 37, 0484 Oslo, Norway. Corresponding author. Email: lovisa.reiche@bi.no.

‡Norges Bank, Bankplassen 2, 0151 Oslo, Norway. Email: nicolo.maffei-faccioli@norges-bank.no.

Introduction

Workers dislike inflation because it erodes purchasing power and makes wage adjustment costly (Guerreiro et al. 2026, Stantcheva 2024). We document a further distributional cost: the same inflationary shocks can generate different wage outcomes for otherwise comparable workers in the same industries and occupations. Why? Inflationary shocks can lead workers facing the same macroeconomic environment to draw systematically different conclusions about their labor-market prospects. These differences in perceptions shape workers' outside options and wage-setting behavior, translating common shocks into differences in pay. We study this channel through the gender wage gap (GWG), a central and persistent source of wage inequality.

Even after accounting for differences in worker demographics, industry, and occupation, men continue to earn more than women on average (Blau & Kahn 2017, Faberman et al. 2026, Goldin 2014, Ngai & Petrongolo 2017, Olivetti & Petrongolo 2016, 2017). In the United States, this adjusted gap narrowed in the 1980s and 1990s but has since remained above 10 percent, with sizable cyclical fluctuations (see Figure I). This makes the GWG an ideal empirical setting for our question: it is a key measure of wage inequality that exhibits cyclical variation and it allows us to compare men and women with similar characteristics working in the same industries and occupations. It is also a setting in which perceptions are likely to matter, since women and men form systematically different expectations about inflation (D'Acunto, Malmendier & Weber 2021, Reiche 2025). We ask whether inflationary shocks affect the GWG, and whether gender differences in perceptions help explain why.

We establish two empirical facts. First, both inflationary demand and supply shocks systematically widen the adjusted GWG. Because these shocks have opposite implications for real activity, their common effect points to inflation as the relevant force. We interpret this as a distinct equity cost of inflation: beyond eroding purchasing power, inflationary shocks widen pay differences even among comparable workers in the same industries and occupations. This mechanism differs from prior work emphasizing gender differences in industry composition and cyclical employment exposure (Albanesi & Şahin 2018, Bredemeier et al. 2017, Hoynes et al. 2012, O'Neill 1985). Second, women and men interpret the same inflationary shocks differently: after either type of shock, women expect labor-market conditions to worsen, whereas men expect them to improve.

We link these two empirical facts in a New Keynesian search-and-matching model with

male and female workers, imperfect information, and gender-specific ambiguity attitudes. Wage bargaining takes place separately through two gender-specific unions, one representing female workers and one representing male workers. Both observe the same noisy macroeconomic signal, which aggregates demand and supply shocks, but cannot identify its source. Supply shocks are the adverse regime: they move inflation and unemployment in the same direction, preventing monetary policy from stabilizing both simultaneously. The female union is ambiguity averse and thus overweights the worst-case supply-driven regime, while the male union is ambiguity seeking and overweights the favorable demand-driven regime. When the signal is inflationary, this asymmetry leads the female union to expect weaker outside options and demand lower nominal wage growth than the male union. The model reproduces the widening of the GWG after both supply- and demand-driven inflationary shocks: divergent perceptions of the same signal translate into divergent pay.

We begin by documenting how the GWG responds to inflationary shocks. Using the U.S. Current Population Survey (CPS) from 1982 onward, we construct a monthly time series of adjusted GWGs for full-time workers that control for worker characteristics, industry, and occupation using a Kitagawa-Oaxaca-Blinder decomposition (Blinder 1973, Kitagawa 1955, Oaxaca 1973). We embed this time series in a structural VAR with sign and zero restrictions to trace the response of the gap to inflationary demand and supply shocks. We uncover a clear and robust pattern: inflationary shocks, regardless of their source, systematically widen the adjusted GWG. The uniform response under both types of inflationary shocks suggests a mechanism directly tied to the inflation process itself rather than to standard business-cycle exposure. The widening is not driven by differential selection of women and men into employment over the cycle or by changes in workforce composition. It persists in gender-balanced matched samples constructed using nearest-neighbor matching on observables (Ñopo 2008), with exact matches on industry and occupation, and in within-individual wage-growth comparisons that exploit the rotating panel structure of the CPS under the same adjustments. The micro-level evidence points to wage renegotiation rather than mobility: the widening is not accompanied by gender-differentiated mobility responses and disappears among union-covered workers, whose collective agreements limit individual wage renegotiation but not mobility.[1] Consistent with this interpretation, decomposing the GWG reveals that after both types of inflationary

[1]This channel is also supported in the micro-literature where women's lower willingness to bargain has been identified as a core driver of the GWG in levels (Azmat & Petrongolo 2014, Babcock & Laschever 2003, Biasi & Sarsons 2022, Caldwell et al. 2025, Card et al. 2016, Exley et al. 2020, Leibbrandt & List 2015).

shocks women's real wages decline while men's remain largely unchanged. The effects are quantitatively important: inflationary shocks account for 12–25 percent of the forecast error variance of the GWG across alternative gap measures and identification schemes.

To understand why wage-setting behavior might differ across genders in response to inflation, we turn to the role of expectations. The idea that inflation shapes expectations about the labor market is well established. Hajdini et al. (2022) document a low inflation-to-wage expectations pass-through, while Kamdar & Rey (2025) show that consumers associate high inflation with high unemployment, coined the supply-side interpretation of inflation surges (Andre et al. 2022, 2025, Candia et al. 2020, D'Acunto & Weber 2024, Weber et al. 2022). Inflation expectations also influence labor-market behavior, for example job search (Pilossoph & Ryngaert 2024). These mechanisms plausibly differ by gender. Women tend to overestimate inflation (D'Acunto, Malmendier & Weber 2021, Reiche 2025), dislike inflation more (McMahon & Reiche 2024) and perceive a lower inflation-wage pass-through (Hajdini et al. 2022). If women associate inflation with weaker labor demand, they may perceive less room to ask for higher nominal pay, leading them to adjust nominal wages less aggressively than men and widening the GWG among otherwise similar workers.

We provide evidence on this expectations channel using microdata from the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE). We embed survey-based measures of labor-market expectations in the same SVAR to trace their responses to inflationary demand and supply shocks by gender. Focusing on full-time workers and controlling for demographic characteristics and industry sorting, we find a striking asymmetry. Following both types of inflationary shocks, women revise unemployment expectations upward and earnings-growth expectations downward. Men, in contrast, revise unemployment expectations downward and earnings-growth expectations upward. Job-finding expectations respond less uniformly, but they point in the same direction: after both shocks, men report stronger job-finding prospects than women. Overall, men respond to inflationary shocks with relative optimism about labor-market conditions, while women respond with relative pessimism. This pattern is consistent with well-documented gender differences in optimism and pessimism in economics and finance (Barber & Odean 2001, Bjuggren & Elert 2019, Dawson 2017, Garbarino & Strahilevitz 2004, Jacobsen et al. 2014). Our findings also complement the literature on consumer narratives (Andre et al. 2022, 2025, Binetti et al. 2024, Piccolo 2025, Shiller 2017, Stantcheva 2024) by moving from explicit scenarios to the average dynamic response of expectations after realized shocks. We doc-

ument substantial heterogeneity: women's responses to realized inflationary shocks are consistent with a supply-side interpretation, whereas men's responses are consistent with a demand-side interpretation. Nonetheless, we validate our evidence by showing that similar gender differences are present in revisions after hypothetical vignettes (Andre et al. 2022).

We develop a New Keynesian model with search-and-matching frictions (Blanchard & Galí 2010, Christiano et al. 2016, henceforth NKSM) and male and female workers as in Albanesi (2025).[2] We proceed in two steps. We first introduce a benchmark model under full-information rational expectations. In this environment, conventional explanations of the GWG, including discrimination, labor supply differences, and time-invariant bargaining frictions, imply that wage differentials move primarily with real activity. They predict opposite responses of the gap to demand- and supply-driven inflationary shocks and cannot explain why it widens after both. We resolve this tension by introducing imperfect information about the source of aggregate shocks and gender-specific ambiguity attitudes in the wage-setting block, while leaving households' consumption-saving decisions and firms' pricing decisions unchanged. Female (male) workers, represented by ambiguity-averse (-seeking) unions, overweight the adverse supply-driven (favorable demand-driven) regime. This asymmetry affects wage setting through perceived outside options: when the signal is inflationary, the pessimistic beliefs of ambiguity-averse unions lower their perceived outside options and wage demands relative to those of ambiguity-seeking unions. The model generates a widening of the GWG following both demand- and supply-driven inflationary shocks, and implies an insider–outsider pattern in unemployment: men's relative optimism sustains higher wages for those employed but leads to greater job losses during adverse shocks. Women's relative pessimism lowers wages but stabilizes employment, consistent with both our VAR evidence and the findings of Albanesi & Şahin (2018). Our model offers a structural interpretation of the data, complementing recent work on expectation-driven wage dynamics (Baek & Yaremko 2024, Balleer et al. 2026*a*,*b*, Menzio 2022, Mueller & Spinnewijn 2023, Pilossoph & Ryngaert 2024) and ambiguity (Baqaee 2020, Bhandari et al. 2025, Ilut & Schneider 2014, Masolo & Monti 2021, Michelacci & Paciello 2024).

The remainder of the paper is organized as follows. Section 1 constructs gender wage gaps from CPS data and examines their responses to inflationary shocks. Section 2 studies how these shocks affect labor-market expectations using SCE data. Section 3 introduces our NKSM model with two worker types and ambiguity attitudes. Section 4 concludes.

[2]This relates to a broader literature on gender in macroeconomics, including Albanesi & Olivetti (2009, 2016), Borella et al. (2018), Ngai & Petrongolo (2017), Olsson (2025).

1 Inflation and the Gender Wage Gap

We begin by documenting our first new empirical fact: the GWG widens in response to unanticipated increases in inflation, regardless of whether these are driven by demand or supply shocks, among women and men who are observationally similar in terms of demographics, industry, and occupation. This pattern, which has not been emphasized in the existing literature, suggests a macroeconomic dimension to gender wage disparities that goes beyond individual characteristics or sorting across industries and occupations. To establish this link, we combine detailed measures of the adjusted GWG from the CPS survey with a structural VAR model that allows us to analyze its cyclical behavior in response to inflationary demand and supply shocks.

We further complement this aggregate analysis with individual-level CPS panel evidence, exploiting within-worker wage growth to examine how the wages of the same men and women respond to inflationary shocks. By following incumbent workers over time, this approach allows us to directly isolate wage-setting responses from changes in workforce composition. The micro-level evidence confirms the aggregate results: when inflation rises, men experience higher wage growth than women, while declines in inflation are associated with lower wage growth for men. Importantly, this gender-inflation penalty does not appear to operate through differential labor-market mobility and disappears among workers covered by a trade union, whose collective agreements limit individual wage renegotiation.

1.1 Computation of the Adjusted Gender Wage Gap

We construct our measure of the adjusted GWG using monthly CPS data from January 1982 to December 2023 (Flood et al. 2025). Following standard practice in the literature (Blau & Kahn 2017), we restrict the sample of respondents to employed, full-time wage and salary workers, excluding the self-employed. This restriction serves two purposes. First, it ensures comparability across genders by focusing on workers whose pay is set through standard employer–employee wage-setting arrangements, rather than through self-employment or irregular hours. Second, it avoids conflating wage differences with gender gaps in hours worked or labor force attachment. Wages are measured as hourly earnings in respondents' current jobs. Throughout, we take hourly rather than weekly earnings as our baseline measure of wages, as this better captures variation along the intensive margin.[3]

[3]Nonetheless, our results are robust to using weekly earnings instead, as we show in the next subsection.

We define the adjusted GWG as the portion of the male–female difference in log hourly earnings that cannot be explained by observable worker characteristics, including industry, occupation, and demographics. We compute this measure using a standard Kitagawa–Oaxaca–Blinder (KOB) decomposition of log hourly wage differences into an explained component, attributable to these observed characteristics, and an unexplained component (Blinder 1973, Kitagawa 1955, Oaxaca 1973). The latter is our measure of interest. For any month t, we separately estimate male (m) and female (f) weighted ordinary least squares (OLS) wage regressions for individual i (the i and t subscripts are suppressed to simplify notation):

$$Y_m = X_m B_m + \gamma_m OCC1990_m + \zeta_m IND1990_m + u_m$$
$$Y_f = X_f B_f + \gamma_f OCC1990_f + \zeta_f IND1990_f + u_f,$$

where Y is the log of hourly earnings and X is a vector of demographic controls which includes age, age squared, education, race, children, marital status, region (state FIP code), an indicator for a single-person household and an indicator for high household income.[4] $OCC1990$ denotes a set of occupation dummies based on the 1990 Census Bureau occupational classification scheme, which distinguishes 389 detailed occupational categories. $IND1990$ is a corresponding set of industry dummies constructed from the 1990 Census Bureau industrial classification system, comprising 247 distinct industries.[5] The high granularity of these controls allows us to compare men and women within narrowly defined occupations and industries, ensuring that the estimated gap is not driven by broad sectoral or occupational composition differences. Finally, u is an error term.

Denote with hats the predicted coefficients from the regressions above and define:

$$\hat{Y}_{mm} = X_m \hat{B}_m + \hat{\gamma}_m OCC1990_m + \hat{\zeta}_m IND1990_m$$
$$\hat{Y}_{mf} = X_m \hat{B}_f + \hat{\gamma}_f OCC1990_m + \hat{\zeta}_f IND1990_m,$$

where $\hat{Y}_{mm}$ is the predicted log of hourly earnings of men using the estimated coefficients of the male regression, while $\hat{Y}_{mf}$ is the predicted log of hourly earnings of men using the estimated coefficients of the female regression. The demographics adjusted, intra-industry,

[4]The dummy for high household income is defined as total family income above 50000 dollars (CPS–IPUMS income category 800 or higher).

[5]See IPUMS occupation category description and IPUMS industry category description.

intra-occupation GWG is defined as:

$$\text{GWG}_t = \left[\exp\left(\sum_i (\hat{Y}_{mm,i,t} - \hat{Y}_{mf,i,t}) \times \omega_{i,t} \right) - 1 \right] \times 100, \tag{1}$$

where the sum is taken over all male individuals in period t and $\omega_{i,t}$ is individual i's sampling weight from the CPS survey. The gap measures the ratio of men's observed wages to the counterfactual wages they would earn if evaluated under women's wage coefficients. For example, a value of $\text{GWG}_t = 20$ means that men earn on average 20 percent more than they would if their characteristics were priced under women's wage structure. Equivalently, this implies that women earn about 17 percent less than men with the same characteristics. An increase in GWG_t indicates a larger wage penalty associated with being female, conditional on observables, while a decline reflects a narrowing of this differential.

We adopt the KOB decomposition as our baseline measure for two main reasons. First, unlike a simple female dummy in a linear regression (as in Penner et al. 2022), KOB allows the observables in X to have different effects on the wages of women and men, i.e. it does not impose $B_m = B_f$ (Bonaccolto-Töpfer & Satlukal 2024). For example, the return to education may differ between men and women, an effect the KOB framework captures but a pooled regression would constrain to be identical. Second, KOB decompositions are routinely used as the benchmark measure of adjusted GWGs (Blau & Kahn 2017). We define the GWG as male minus female wages.[6] This definition makes interpretation very intuitive: a widening gap means men's wages have risen further above women's, while a narrowing gap indicates convergence. That said, our findings are not sensitive to how the gap is measured and alternative specifications deliver the same results as our baseline.

In particular, we consider a non-parametric measure based on nearest-neighbor matching (NNM, Ñopo 2008). Regression-based counterfactual approaches, even with rich controls and a focus on full-time workers, may compare men and women in parts of the covariate space where they do not fully overlap. NNM addresses this by constructing gender-balanced samples at each point in time. Each employed woman is matched to the most similar employed man (and vice versa) using a rich set of predetermined demographic and job-related characteristics. Similarity is measured using Mahalanobis distance on the

[6] Blau & Kahn (2017) use the opposite sign convention. In Figure A.1 we replicate their exact definition using our CPS data, constructing the gap as predicted female minus male wages evaluated at the female covariate distribution. Because the CPS does not observe experience directly, we proxy it using age, education, and children. This yields estimates very similar to theirs.

same demographic controls as in the KOB decomposition, while requiring exact matches on occupation and industry.[7] By comparing observationally similar workers within the same regions of the covariate space, this approach limits composition bias. Unlike regression-based decompositions, it does not require estimating counterfactual wage equations or extrapolating beyond observed matches, avoiding functional-form assumptions. Thus, we use matching-based wage differences as a complementary measure of the adjusted GWG.

These methods yield monthly time series of demographically adjusted, intra-industry, intra-occupation GWGs. Figure I plots the resulting series constructed using both the baseline KOB decomposition and the NNM approach, alongside the unadjusted gap and year-on-year CPI inflation. Adjusted gaps have declined systematically since the 1980s, although the pace of convergence has slowed in recent years, consistent with Blau & Kahn (2017), Goldin (2014) and Olivetti & Petrongolo (2016). Adjusted gaps are smaller in level but exhibit stronger cyclical fluctuations than their unadjusted counterparts, which do not control for industry and occupation. All GWG measures are positively correlated with inflation, a pattern that motivates the formal analysis below. Figure A.1 in the Appendix additionally compares the KOB measure to alternative measures of the GWG, including the coefficient on the female dummy from a pooled linear regression (Penner et al. 2022), the GWG adjusted only for worker demographics, and the raw gap. Because these alternative measures are expressed as female-to-male earnings, their trends appear inverted relative to ours: when the KOB measure declines, the others rise. For comparability, the figure also reports the KOB-adjusted GWG expressed in female-minus-male terms, following Blau & Kahn (2017). Aside from this sign convention, the series display broadly similar dynamics, and both the KOB and NNM measures appear to provide conservative lower bounds on the overall magnitude of gender wage disparities.

1.2 Gender Wage Gap Response to Inflationary Shocks

We rely on a flexible time-series model in order to study the response of the adjusted GWG to inflationary demand and supply shocks. Consider the standard reduced-form VAR model with n variables and p lags:

$$Y_t = C + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + u_t$$

[7] Mahalanobis is preferred over Euclidean distance because it standardizes variables on different scales.

where Y_t is a $n \times 1$ vector of endogenous variables, $u_t \sim N(0_n, \Sigma)$ is a $n \times 1$ vector of reduced-form innovations, $A_1, ..., A_p$ are n x n coefficient matrices, and C is a n x 1 vector of constants. The reduced-form innovations u_t are linear combinations of structural, economic shocks: $u_t = B_0^{-1}\varepsilon_t$. B_0 is the $n \times n$ matrix of contemporaneous relationships between the endogenous variables in the system and $\varepsilon_t \sim N(0_n, I_n)$ is the $n \times 1$ vector of structural shocks, normalized to be of unit variance without loss of generality.

Y_t contains the following variables in levels, at the monthly frequency: CPI inflation, the unemployment rate and the adjusted GWG described in Equation 1.[8] This is arguably the simplest system of variables to identify the effects of demand and supply shocks on the GWG. We adopt this specification as our baseline because of its simplicity and interpretability. We include $p = 3$ lags of the dependent variable as suggested by the BIC criterion and estimate the VAR model using Bayesian methods, with standard NIW priors for the reduced-form parameters (see Arias et al. 2018). We estimate the VAR in levels, as our focus is on short-run fluctuations rather than long-run patterns. Johansen's trace test indicates the presence of two cointegrating relationships among the variables at the 5% significance level (see Table A.1 in the Appendix). In this setting, estimating the VAR in levels is appropriate and does not entail misspecification: it yields consistent inference for impulse responses even in the presence of cointegration, while avoiding distortions to short-run dynamics that may arise from differencing or detrending (Sims et al. 1990). Monthly data on CPI inflation and unemployment are obtained from the Bureau of Labor Statistics (BLS) and the Federal Reserve Economic Data (FRED), respectively. We exclude the COVID-19 period from our baseline analysis, as prior research has shown that the pandemic affected female labor markets in atypical ways, largely due to its asymmetric impact on different sectors and increased demands for home production (Albanesi & Kim 2021). We thus estimate the baseline VAR model on the sample spanning January 1982 - February 2020. Nonetheless, we assess the robustness of our findings to alternative specifications of the baseline model, including different measures of inflation, the business cycle, and the GWG, as well as higher-dimensional VARs with additional variables and lags, and including the COVID-19 period. As shown later in this section, these extensions yield consistent results, indicating that our baseline conclusions are not sensitive to alternative specifications of the VAR.

To identify the SVAR, we impose sign and zero restrictions on the matrix of contemporaneous responses B_0 (see Arias et al. 2018). We restrict the signs of the contemporaneous

[8] We use a trailing three-month moving average of the series to smooth its short-term volatility and improve model stability. Results using the original series are reported later in this section and are virtually identical.

responses of inflation and unemployment to distinguish between demand and supply shocks. Following standard practice, demand shocks generate a negative co-movement between inflation and unemployment, while supply shocks generate a positive co-movement. Both shocks are normalized to be inflationary, implying a positive impact response of inflation. This strategy allows us to study the effects of inflationary shocks while conditioning on the direction of real-side labor market conditions: demand and supply shocks share a common inflationary component by construction, but differ in their implications for unemployment. As our primary interest is the response of the GWG to these shocks, we leave its contemporaneous response unrestricted. Any observed movement in the GWG is thus an outcome of the estimated model. However, sign restrictions alone result in partial (set) identification, meaning the structural shocks are not uniquely determined. This limits the interpretability of the impulse responses and the attribution of observed dynamics to specific shocks. To achieve separate identification of the structural shocks, we introduce a third, residual shock using additional zero restrictions on B_0. This shock is defined as an innovation to the GWG that has no contemporaneous effect on inflation and unemployment. While we do not assign it a structural interpretation, its inclusion is necessary to fully identify the model. This approach is further justified by the fact that the GWG, constructed from micro-level hourly earnings in the CPS, may be influenced by idiosyncratic or institutional factors, such as survey-specific measurement factors, changes in workplace policies or discrimination, that can drive the GWG independently of aggregate macroeconomic conditions and are unlikely to have immediate effects on aggregate macroeconomic outcomes within a month. Table I summarizes the the identifying restrictions.

The first two columns of Panel (a) in Figure II present the estimated impulse response functions to inflationary demand and supply shocks. The x-axis indicates time in months following the shock, while the y-axis reports the impulse response in percentage point terms. For each horizon, the solid line shows the point-wise median response based on 10000 draws from the posterior distribution of impulse responses, while the shaded areas represent the 68% credible intervals. An inflationary demand shock leads to a persistent increase in inflation and a decline in unemployment. In contrast, an inflationary supply shock results in a persistent rise in both inflation and the unemployment rate. Although sign restrictions are imposed only on impact, these effects persist over time.

The novel contribution lies in the response of the adjusted GWG, which increases significantly and persistently following both types of inflationary shocks. Quantitatively, a

demand-driven inflationary shock that raises inflation by about 0.25 percentage points on impact leads to an increase in the GWG of approximately 0.19 percentage points after one year. Similarly, a supply-driven inflationary shock that increases inflation by about 0.22 percentage points on impact results in an increase in the GWG of roughly 0.18 percentage points after one year. The estimated impulse responses are persistent at monthly frequency, remaining economically and statistically significant for roughly three years before gradually converging back to their pre-shock level. Since the GWG is adjusted for individual characteristics, industry, and occupation, the observed responses cannot be explained by sectoral reallocation, occupational sorting, or differences in worker demographics. Instead, they reflect gender differences in how wages respond to inflationary shocks within similar jobs, sectors, and individual characteristics. That the adjusted GWG rises after both demand and supply shocks, despite their opposite effects on unemployment, isolates inflation as the common driver and suggests asymmetries in wage-setting behavior across gender.

Our baseline focuses on inflationary demand and supply shocks because this distinction allows us to differentiate between shocks that, by construction, increase inflation while either decreasing (demand) or increasing (supply) unemployment. This framing is informative for understanding the macroeconomic context in which the GWG evolves. However, the specific identification strategy is not central to our main results. While sign restrictions provide a clear macroeconomic interpretation, they imply set rather than point identification of the shocks. We thus complement our baseline analysis with an alternative approach that identifies inflationary shocks as those explaining the largest share of the unexplained variation in inflation over business-cycle frequencies, following the "max-share" approach of Angeletos et al. (2020). This strategy yields a uniquely identified inflationary shock and isolates the role of inflation more broadly, without imposing restrictions on unemployment responses. The third column of Figure II reports the corresponding impulse responses. A positive inflationary shock leads to a significant and persistent widening of the GWG, consistent with the baseline results.

A potential concern is that the KOB decomposition, even when conditioning on observables and using the sample on employed full-time workers, does not fully rule out differential selection into employment by gender over the business cycle. We therefore complement our results with the nearest-neighbor-matched sample GWG introduced in the previous section and re-estimate the SVAR identified with zero and sign restrictions and under the max-share approach. This alternative GWG is computed directly from matched

worker pairs and therefore does not involve estimation uncertainty from wage regressions. The results are unchanged: the GWG responds to inflationary shocks of either origin in the same way as in the baseline specification (Panel (b) of Figure II).[9]

Having established that inflationary shocks significantly widen the adjusted GWG, we next investigate whose real wage response drives this effect. We compute men's wages as $\hat{Y}_{mm}$ and women's wages as $\hat{Y}_{mf}$ from the KOB decomposition in Equation 1, comparing men to counterfactual individuals with identical characteristics priced under women's wage structure. Both series are deflated by the CPI index. We replace the adjusted GWG in our baseline VAR with $\hat{Y}_{mm}$ and $\hat{Y}_{mf}$, maintaining the same lag structure and identification strategy. This specification traces the response of each group's real wages to inflationary demand and supply shocks, conditional on identical observable characteristics, industries and occupations. Figure III reveals that the entire widening of the adjusted GWG can be traced to women's weaker protection of real earnings. Following both demand and supply shocks, consumer prices rise sharply. Men partially offset the resulting loss in purchasing power by securing higher nominal wages within the first months, leaving their real wages roughly unchanged or slightly higher. Women's nominal wages, by contrast, respond little, leading to a sizeable real-wage loss and a wider adjusted GWG. These findings dovetail with micro evidence that women are less likely to negotiate for raises (Azmat & Petrongolo 2014, Babcock & Laschever 2003, Biasi & Sarsons 2022, Caldwell et al. 2025, Card et al. 2016, Exley et al. 2020, Leibbrandt & List 2015) and thus cost-of-living adjustments. We examine this channel in more detail in Section 1.3, using individual-level wage growth from the same CPS data.

Figures A.4a and A.4b in the Appendix show that the responses of the unadjusted GWG, computed without controlling for industry and occupation, and the raw gap are more muted, particularly following supply shocks. This suggests that sectoral reallocation and exposure effects may offset part of the inflation-induced wage asymmetry in aggregate terms, but the underlying gender-based difference in wage adjustment emerges once those factors are controlled for. To further investigate this mechanism, we augment the baseline VAR with the unemployment gap between men and women as a direct measure of differential exposure (Albanesi & Şahin 2018, Bredemeier et al. 2017). The adjusted GWG response to both demand and supply shocks is stable across specifications (see Figure A.5a). In contrast, the unadjusted GWG response to supply shocks becomes positive and statistically

[9]Figure A.3 in the Appendix reports the full set of impulse responses and their comparison with the baseline. Inflation and unemployment responses are essentially identical across all inflationary shocks.

significant once gender-specific exposure is controlled for (see Figure A.5b). Both VARs feature an unemployment gap decreasing for inflationary demand shocks and increasing for inflationary supply shocks, a pattern consistent with the greater business-cycle sensitivity of male employment. Accounting for differential exposure reveals the inflation-induced widening of the GWG even in unadjusted specifications, supporting the interpretation that differences in wage-setting behavior across gender are central to the observed dynamics.

1.2.1 Alternative model and variable specifications

We perform a battery of robustness exercises to assess the sensitivity of our baseline finding, the widening of the GWG after inflationary shocks, to alternative specifications of the VAR model. For clarity of exposition, all corresponding figures are reported in the Appendix.

First, we test whether our results depend on the specific definitions of the key variables in the VAR. The widening of the GWG remains robust when we use alternative measures of inflation, including the PCE price index (Figure A.6a) and core CPI excluding food and energy (Figure A.6b), as well as when replacing the baseline business cycle indicator with industrial production (Figure A.7).[10] Results are similarly robust to using weekly rather than hourly earnings (Figure A.8a), suggesting that they are not sensitive to whether the wage measure captures intensive or extensive margin adjustments. We further explore alternative constructions of the GWG commonly used in the literature: computing the gap based on predicted women's wages using men's characteristics in the KOB decomposition (Blau & Kahn 2017, Figure A.8b), using median instead of mean wages (Figure A.8c), and estimating the gap as the coefficient on a female dummy in a wage regression with the same set of detailed controls as in our baseline specification (Penner et al. 2022, Figure A.8d). In these cases, the GWG is defined as female-minus-male, so impulse responses should be interpreted with the opposite sign relative to our baseline. Across all specifications, the positive relationship between inflation and the GWG remains robust. If anything, inflationary demand shocks produce larger effects under these alternative measures.

Second, we assess the robustness to changes in model specification. Our results are not driven by the application of the trailing moving average filter (Figure A.9a) or by lag selection (Figure A.9b). Moreover, our findings remain qualitatively unchanged when extending the sample to include the COVID-19 period (Figure A.10), suggesting that the

[10] In this exercise, inflationary demand shocks are identified by the positive co-movement between inflation and industrial production, while inflationary supply shocks are identified by their negative co-movement.

inflation-GWG relationship does not break if we include the pandemic period.

Third, we examine GWGs within demographic groups, assessing how the adjusted gap varies across and responds to shocks within categories such as age, parental and marital status. Figure A.2 shows that adjusted GWGs are larger among older workers and workers with children, but have been declining more rapidly over time. In the SVAR, younger workers (Figure A.11a) exhibit weaker responses to inflationary shocks, while older workers (Figure A.11a-A.11d) show stronger responses, consistent with larger gender differences in wage-setting behavior over the life cycle. Additionally, the gap response is larger for workers with young children (Figure A.12a), potentially reflecting differences in how inflationary shocks are incorporated into wage-setting decisions in the presence of caregiving responsibilities. We further estimate GWG responses separately for married individuals (Figure A.12b) and singles (Figure A.12c). While the response is larger among married workers, the widening of the gap following both inflationary shocks is also present among singles, indicating that the results are not driven solely by marital status. Section A.3.3 of the Appendix analyzes more in detail gender differences in characteristics, using the KOB decomposition to examine how observable attributes differ between men and women and how these differences contribute to the overall GWG's response.

A natural question is how much of the variation in the GWG can be attributed to inflationary shocks. We address this using forecast error variance decompositions of the adjusted GWG across our different SVAR model specifications and measurement approaches. We consider both the baseline SVAR with zero and sign restrictions and the alternative "max-share" identification of inflationary shocks. We perform this exercise using adjusted GWGs constructed with the baseline KOB decomposition, the NNM approach, and using the coefficient on the female dummy from a pooled linear regression. In the baseline SVAR, we aggregate the contributions of inflationary demand and supply shocks in order to measure their combined contribution to GWG fluctuations, making the results directly comparable to those obtained under the single max-share inflationary shock. Figure IV presents the results. The x-axis indicates time in months following the inflationary shocks, while the y-axis reports the percentage of forecast error variance explained by these shocks. Across specifications, inflationary shocks account for a substantial share of fluctuations in the GWG, ranging from approximately 12 to 25 percent of the forecast error variance. The magnitude is sizable given that the GWG is constructed from micro-level wage data and reflects a residualized measure that nets out detailed observable characteristics, including

industry, occupation, and demographics. It is influenced by a wide range of idiosyncratic and institutional factors that are not explicitly captured in the VAR and are expected to account for a large portion of residual variation. Against this backdrop, the fact that inflationary shocks account for up to one quarter of the variation in the GWG underscores their quantitative importance. The explained share is larger under the max-share identification, which captures inflationary disturbances more broadly and isolates the role of inflation more directly. Overall, these results indicate that inflationary shocks are a meaningful driver of GWG fluctuations across measures and identification strategies.

1.3 Micro-level Evidence: Individual Wage Growth and Composition

The baseline results show that inflationary shocks widen the GWG at the aggregate level. A concern is that this pattern may partly reflect compositional changes. If inflationary periods induce non-random entry into or exit from the labor force – for example, if low-wage men are more likely to leave employment following inflationary shocks – the observed increase in the aggregate gap could partly capture selection rather than changes in individual wage-setting behavior. Although our NNM analysis already mitigates these concerns by comparing gender-balanced samples of observationally similar workers in the same industries and occupations, we further complement the aggregate evidence with individual-level panel data from the CPS. By tracking individuals across the CPS's consecutive monthly surveys (the 4-8-4 rotation scheme), we can compute the wage growth of the same worker over a 12-month period.

We estimate the following micro-level regression:

$$\Delta \ln w_{i,t} = \alpha + \beta_1 \text{Female}_i + \beta_2 \Delta\pi_t + \beta_3 (\text{Female}_i \times \Delta\pi_t) + \Gamma \mathbf{X}_{i,t-12} + \beta_4 U_{t-12} + \beta_5 \pi_{t-12} + \epsilon_{i,t}, \quad (2)$$

where $\Delta \ln w_{i,t}$ is the log change in the nominal hourly wage for individual i between month $t-12$ and t. The vector $\mathbf{X}_{i,t-12}$ includes a comprehensive set of predetermined individual controls measured at the beginning of the wage-growth period: age, age squared, education levels, race, marital status, and the presence of children under five. To account for structural shifts in the labor market, we also include industry and occupation fixed effects, matching the control structure used in the computation of the adjusted GWGs above. We include the national unemployment rate U_{t-12} and CPI inflation π_{t-12} to control for the business cycle conditions at the start of the wage-growth period. Our primary independent variable is $\Delta\pi_t$, which denotes the change in the annual inflation rate over the same 12-month period.

We use changes rather than levels of inflation to capture the acceleration or deceleration of prices that trigger wage renegotiation or reveal nominal rigidities. A level-based approach would confound high but stable inflation with accelerating prices. For instance, during the Volcker disinflation of the early 1980s, inflation was high, but sharply falling. By focusing on $\Delta\pi$, our coefficients reflect the response to the direction and momentum of price changes, which are the key drivers of wage-setting revisions. The interaction term $\text{Female}_i \times \Delta\pi_t$ measures whether women's wage growth responds differently from men's to shifts in inflation. Because inflation dynamics are determined at the aggregate level, changes in inflation are unlikely to be driven by any individual worker's wage growth. However, inflation changes may co-move with broader macroeconomic conditions that also affect gender-specific wage growth.

To address this concern more directly, we also estimate IV specifications that use high-frequency external surprises as instruments for changes in inflation. This exercise complements, rather than mechanically replicates, the SVAR analysis. In the SVAR, inflationary demand and supply shocks are identified within a multivariate time-series system using sign and zero restrictions. In the micro regressions, by contrast, we rely on externally measured high-frequency surprises that provide plausibly exogenous sources of inflation variation. We use oil-supply news surprises to capture cost-push, supply-driven inflationary pressure, and monetary-policy surprises to capture demand-side inflationary variation. These specifications test whether the differential wage-growth response by gender persists when inflation movements are driven by specific external shocks rather than by broader macroeconomic conditions or by the identifying restrictions imposed in the SVAR.

The results of the micro-level estimation are presented in Table II. Column (1) reports the simple conditional association. The coefficient on the interaction term, β_3, is negative and statistically significant at the 1% level. A one-percentage-point increase in inflation is associated with a reduction in women's nominal wage growth relative to men's of approximately 0.1 percent, implying a relative "inflation penalty" of about \$0.01 per hour for every \$10 of hourly earnings. Because nominal wage setting is path dependent, even small asymmetries in short-run wage growth can translate into persistent differences in earnings levels. Column (2) shows that the result is robust to including month fixed effects and redefining $\Delta\pi_t$ as an indicator for periods of rising inflation. During periods of rising inflation, women's nominal wage growth is approximately 0.2 percentage points lower than men's, relative to periods in which inflation is not rising.

Columns (3) and (4) report the IV specifications. Column (3) instruments inflation changes using the moving sum of the high-frequency oil-supply news surprises of Känzig (2021), $\sum_{k=0}^{11}$ Oil Surprise$_{t-k}$, which captures unexpected oil-market news over the same annual horizon as $\Delta\pi_t$. Column (4) uses the moving sum of high-frequency monetary-policy surprises of Bauer & Swanson (2023), $\sum_{k=6}^{18}$ Monetary Policy Surprise$_{t-k}$, allowing for the delayed pass-through of monetary shocks to inflation. In both cases, summing shocks over the relevant window is natural because inflation changes are measured over a twelve-month horizon, while the shocks are observed at higher frequency and affect inflation cumulatively over time. The first-stage regressions also control for lagged macroeconomic conditions, namely unemployment and inflation at $t-12$, so the identifying variation comes from the accumulated high-frequency shocks conditional on the state of the economy one year earlier. The first stages support the interpretation of the two instruments: oil-supply surprises have a positive effect on inflation changes, while monetary-policy surprises have a negative effect, consistent with contractionary policy shocks lowering inflation (see Table A.2). The first-stage relationship is particularly strong for the oil-supply instrument, which we therefore use as our main IV specification. The monetary-policy instrument remains statistically significant, though less powerful, and is reported as a complementary demand-driven exercise. The second-stage estimates replace observed inflation changes with the component predicted by the corresponding high-frequency shock. In both IV specifications, the interaction between inflation and the female dummy remains negative, statistically significant, and economically relevant. These results indicate that women's relative wage growth declines when inflation rises due to externally measured inflationary shocks.

Appendix Table A.3 reports additional robustness exercises for both IV specifications. First, we augment the regression with changes in unemployment and their interaction with Female$_i$. The interaction terms are statistically insignificant, suggesting that the estimated gender-specific wage response is not capturing differential exposure to changes in aggregate labor-market slack. This is reassuring given that the baseline specification already controls for industry and occupation. Second, we show that the results are robust to the inclusion of the 2021–2023 inflationary episode and the exclusion of industry and occupation fixed effects. The estimates consistently indicate that inflation is associated with a statistically significant and economically relevant widening of the gender gap in nominal wage growth.

Figure V provides a non-parametric visualization of the relationship between gender, inflation regimes, and nominal wage adjustments. We plot the average 12-month log wage

growth for men and women, partitioned into periods of rising inflation (in red) and falling inflation (in blue). The figure reveals two key patterns. First, during periods of rising inflation, women experience systematically lower nominal wage growth than men, leading to a widening gender gap in wage growth even before conditioning on granular covariates. By contrast, during periods of falling inflation, men experience relatively weaker nominal wage growth, narrowing the differential. These non-parametric patterns are consistent with the linear structure of the VAR analysis: positive inflationary shocks widen the GWG, while negative shocks attenuate it. Second, the vertical error bars, representing the standard deviation of wage growth within each bin, show substantial idiosyncratic dispersion in wage adjustments. Yet, the "inflation penalty" for women reflects a broad distributional shift rather than the influence of a few extreme observations.

1.3.1 Renegotiation versus Labor-market Mobility

Our previous results establish that the gender gap in nominal wage growth widens during inflationary accelerations. A central question is whether disparities arise within stable employment relationships or through transitions across the labor market. This is a natural margin to consider, since a substantial portion of lifetime wage growth is realized through job-to-job transitions (Topel & Ward 1992). The focus on the search margin is also motivated by recent evidence that workers use on-the-job search to protect real earnings against inflationary shocks (Pilossoph & Ryngaert 2024). However, the ability to successfully navigate this transition is likely gendered. Women tend to accept job offers earlier than men, who exhibit greater overoptimism regarding prospective offers (Cortés et al. 2023). If men are more likely to use such transitions during inflationary episodes, then our estimates could reflect differential mobility rather than differential wage adjustment.

Our evidence does not support this interpretation. We begin with a placebo test for a wage-setting mechanism based on union coverage. This provides a particularly clean exercise because union contracts substantially reduce individual discretion in wage setting and wage renegotiation, thereby limiting the scope for gender differences in bargaining outcomes. At the same time, union coverage does not mechanically prevent workers from changing jobs, industries, or occupations. If our baseline results were primarily driven by differential mobility, they should remain present among union-covered workers. Columns (5)–(8) of Table II restrict the sample to workers covered by a trade union. In this sample, the interaction between inflation and the female dummy is small and statistically insignificant

across both the OLS and IV specifications. The disappearance of the gender-inflation penalty among union-covered workers points to individual wage setting and renegotiation, rather than pure job-to-job mobility, as the relevant margin.

We then examine mobility directly. In Appendix Table A.4 we test whether inflationary shocks induce men and women to move differently in the first place. We re-estimate the same micro-level specification used for wage growth, replacing the dependent variable with indicators for mobility between $t-12$ and t. We consider three margins: a broad transition, defined as changing both industry and occupation; remaining in the same industry, regardless of whether occupation changes; and remaining in the same occupation, regardless of whether industry changes. Under the oil-shock IV, inflation affects transition probabilities: it lowers the probability of a broad transition and raises the probability of remaining in the same industry. However, none of these mobility responses differs by gender. The interactions between inflation and the female dummy are small and statistically insignificant for all three outcomes. The monetary-policy specification yields the same conclusion for broad transitions. The only significant gender differential is that women become less likely than men to remain in the same occupation, which goes against the hypothesis, for example, that men move while women stay in response to inflation.

Taken together, these exercises show that job-to-job and other labor-market transitions are unlikely to drive our main result. The gender-inflation penalty does not appear among union-covered workers, and is not accompanied by gender-differential mobility responses to inflationary shocks. The evidence instead points to wage-setting and renegotiation as the relevant margin.

2 Inflation and Labor Market Expectations

We document our second new empirical fact: women interpret unexpected inflation, whether demand- or supply-driven, as a signal of deteriorating labor-market conditions, while men expect an improvement. That is, women revise their labor-market beliefs more pessimistically than men in response to inflationary shocks. The relationship between inflation and labor-market beliefs is central to understanding gender-specific economic behavior. We use data from the New York Fed Survey of Consumer Expectations (SCE, Federal Reserve Bank of New York 2024).[11] As in our analysis of the GWG, we focus on observationally

[11] 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.

comparable men and women, adjusting for differences in individual characteristics using both the KOB decomposition and NNM. We study how male and female expectations about inflation, unemployment, job-finding prospects, and earnings growth respond to inflationary demand and supply shocks using the same SVAR with sign and zero restrictions.

Our approach contributes to the literature on consumers' inflation narratives from a complementary perspective. Existing studies use survey experiments to provide rich evidence on how households reason about inflation under controlled informational environments (e.g., Andre et al. 2022, 2025, Piccolo 2025). We build on this insight but ask a distinct empirical question: how do average beliefs adjust after realized demand- and supply-driven inflationary shocks? By combining the SCE with SVAR-identified shocks, we move from experimentally elicited narratives to the dynamic response of beliefs following macroeconomic disturbances observed in the data. This allows us to trace belief responses over time and study transmission dynamics that may unfold gradually, making them difficult to capture using experimental vignettes or short-horizon panel revisions alone. Nonetheless, we show below that a very similar gender-specific pattern is also present in the survey data of Andre et al. (2022).

2.1 Construction of Time Series of Expectations

We construct time series of men's and women's inflation and labor-market expectations from the SCE, adjusting for differences in demographics and industry sorting. The SCE is a large and well-established survey of consumers in the US with around 1200 participants every month in a rotating panel since August 2013 (details of the survey can be found in Armantier et al. 2017). We restrict our sample to the pre-Covid period and to full-time employed workers (excluding the self-employed), consistent with our analysis of the adjusted GWG. The survey elicits inflation and unemployment expectations over a 12 months horizon, job finding probabilities over a 3 month horizon and earnings growth expectations over a 12 months horizon. All survey questions used in the analysis are reported in Appendix B.1. While the main survey does not capture the industry of the employee, we derive this information from the Labor Market Survey initiated in July 2014 and available every four months. For months in which the Labor Market Survey is not available, we assume industries to remain constant. There are 18 industry codes, thus the industry allocation is less granular than the CPS. Further, no occupation controls are available.

Our method resembles the KOB decomposition of Section 1. We recover separate

time series of expectations for observationally comparable men and women. For any month t, we separately estimate male (m) and female (f) weighted OLS expectations regressions for individual i (again, the i and t subscripts are suppressed to simplify notation):

$$Y_m = X_m B_m + \zeta_m IND18_m + u_m \qquad Y_f = X_f B_f + \zeta_f IND18_f + u_f,$$

where Y is the expectation about a given variable such as inflation, unemployment, job finding and earnings growth, X is a vector of demographic controls which includes age, age squared, education, numeracy, race, and region, and IND18 is a vector of 18 industry dummies. u is an error term. Denote with a hat the predicted coefficients from the regressions above and define:

$$\hat{Y}_{mm} = X_m \hat{B}_m + \hat{\zeta}_m IND18_m \qquad \hat{Y}_{mf} = X_m \hat{B}_f + \hat{\zeta}_f IND18_m.$$

where $\hat{Y}_{mm}$ represents predicted expectations of men and $\hat{Y}_{mf}$ represents the counterfactual expectations of men evaluated under women's expectation coefficients. This allows us to compare how men and women behave abstracting from the fact that they might be exposed differently to the economy through sorting in different industries. In what follows, we also summarize the implied expectations gap as the ratio between the two, namely $\frac{\hat{Y}_{mm}}{\hat{Y}_{mf}}$.

Figure VI plots the time series of expectations for observationally similar men and women ($\hat{Y}_{mm}$ and $\hat{Y}_{mf}$, respectively) for inflation, unemployment, job finding, and earnings growth. Our series replicates the well-known gender gap in inflation expectations, namely women having higher inflation expectations (D'Acunto, Malmendier & Weber 2021, Reiche 2025), and confirms that women also on average have lower earnings growth expectations. Overall, we find a general co-movement between male and female beliefs, but some cyclical differences.

2.2 Expectation Responses to Inflationary Shocks

We estimate a SVAR with the same sign and zero restrictions as in Section 1, replacing the adjusted GWG with the time series of expectations of interest. Lag length and prior specifications match the baseline model. Since the identified shocks jointly move inflation and unemployment by construction – demand shocks raise inflation and lower unemployment, while supply shocks raise both – men and women are exposed to the same inflation–labor

market signal.[12] Any differences in expectations reflect differences in how agents interpret this signal. The first two columns of Figure VII summarize the impulse responses of men's expectations (in blue) and women's expectations (in orange) to inflationary demand and supply shocks. The x-axis indicates time in months following the shock, while the y-axis reports the impulse response functions of the variables in percentage point terms. The full set of impulse responses is reported in Appendix Figure B.1.

The results reveal a striking and systematic gender asymmetry in expectation formation. For inflation expectations, women exhibit more volatile responses and react more strongly to inflationary supply shocks than men. Labor-market expectations reveal a pronounced gender difference in how workers interpret the macroeconomic environment. Women consistently interpret rising inflation as a signal of deteriorating labor-market conditions, consistent with a supply-side interpretation of inflation (Kamdar & Rey 2025). Men, by contrast, tend to view inflation as a signal of improving labor-market conditions, consistent with a demand-side interpretation. This divergence appears across both supply- and demand-driven inflationary shocks. Following supply-driven shocks, women revise aggregate unemployment expectations upward and revise both personal earnings-growth and job-finding expectations downward. Following demand-driven shocks, they again revise unemployment expectations upward and earnings-growth expectations downward, while leaving job-finding expectations largely unchanged. The increase in women's unemployment expectations is especially striking in this case, since unemployment falls in response to inflationary demand shocks in the same VAR by construction. Men display the opposite pattern. They revise aggregate unemployment expectations downward and personal earnings-growth expectations upward following both types of inflationary shocks. Their personal job-finding expectations are largely unchanged after supply shocks, but rise following demand-driven shocks. Appendix Figure B.2 shows that this gendered interpretation also extends to quit expectations: men revise quit expectations upward after both types of shocks, consistent with viewing inflation as a signal of stronger labor-market conditions, while women revise quit expectations downward, consistent with viewing inflation as a signal of weaker labor-market conditions. These results hold among observationally similar men and women, accounting for differences in demographics, numeracy, geographic region and industry, highlighting a robust and systematic gender difference in how inflationary shocks are mapped into labor-market expectations.

[12] Consistent with this, Appendix Figure B.1 shows that the inflation and unemployment impulse responses are essentially identical across specifications using men's and women's expectation measures.

Appendix Figure B.3 shows that these differences translate into a significant and persistent gap in expectations. Across all labor-market measures, women hold systematically more adverse views than men in response to inflation, expecting higher unemployment, lower earnings growth, and lower job-finding prospects relative to men. Consistently, the gender gap widens for earnings and job-finding expectations and narrows for unemployment expectations following any inflationary shock.[13] We call this a pessimism gap in response to inflation: women systematically place greater weight on adverse, supply-side interpretations of inflationary shocks, while men place relatively more weight on favorable, demand-side interpretations. This finding is consistent with a broad literature documenting gender differences in pessimism (Barber & Odean 2001, Bjuggren & Elert 2019, Dawson 2017, 2023, Jacobsen et al. 2014) and could reflect that women tend to follow more frequently the "good-bad" heuristic, assuming all negative things in the economy must move together (Candia et al. 2020, Kamdar & Rey 2025). Our results show that these belief differences become particularly salient in response to inflationary shocks with direct implications for labor-market prospects.

As with our analysis of the GWG, we assess the robustness of these expectation responses using alternative identification strategies for inflationary shocks and alternative measures of expectations. First, we identify an inflationary shock as the innovation that explains the largest share of residual variation in inflation at business-cycle frequencies. The third column of Figure VII reports the corresponding impulse responses for men's and women's expectations, and the third column of Figure B.3 for the gender gap in expectations. The baseline results remain virtually unchanged under this alternative specification. If anything, the gender asymmetries become more pronounced: differences in expectation responses widen, while continuing to move in the same direction as before. Second, we construct gender-balanced samples for each expectation variable at each point in time by matching each employed woman to the most similar employed man using NNM. Similarity is defined using Mahalanobis distance on raw covariates, with exact matches on region and industry. Figure B.4 in the Appendix shows that the gender-gap responses are robust to this alternative specification. Finally, we construct expectation gaps directly from the raw data, without applying the KOB decomposition or NNM. The raw gaps exhibit the same pattern of relative pessimism (Figure B.5): across all labor-market variables, women report more adverse expectations than men, and the gender gaps respond to inflationary shocks in the

[13] We obtain these results by including, for each variable, the expectations gap directly in the same SVAR with sign and zero restrictions.

same direction as in the baseline.

One possible interpretation is that gender differences in beliefs reflect differential past labor-market experience (Malmendier & Nagel 2016) or heterogeneous exposure to salient price categories (D'Acunto, Malmendier & Weber 2021, D'Acunto, Malmendier, Ospina & Weber 2021). Our evidence suggests that these channels are unlikely to be the primary drivers. Realized unemployment responds differently across shocks: the gender unemployment gap narrows following demand shocks but widens following supply shocks (see Figure A.5). By contrast, the unemployment expectations gap narrows for both inflationary shocks. Women expect higher unemployment after either inflationary shock, whereas men expect lower unemployment, even when realized outcomes for women improve relative to men, as after demand shocks. If beliefs were mainly shaped by past labor-market exposure, expectations should track these realized differences more closely. The uniform divergence in expectations points toward differences in how inflationary shocks are interpreted. Moreover, excluding food and energy prices from CPI leaves our results unchanged (Figure A.6b), suggesting that differential exposure to specific consumption categories is unlikely to fully account for the patterns we document. The gender expectation-gap responses are also nearly identical when we restrict the sample to single workers (Figure B.6), for whom household shopping responsibilities are less likely to be systematically allocated by gender.

2.3 Validation using Hypothetical Vignettes

Our empirical approach provides novel, complementary evidence to studies that directly elicit subjective narratives through hypothetical survey vignettes (e.g. Andre et al. 2022, Piccolo 2025). Rather than asking respondents to reason through predefined scenarios, our framework exploits macroeconomic disturbances identified in a structural VAR and traces how beliefs evolve following realized shocks. By linking these structural shocks to survey expectations, we recover dynamic belief updating over multiple periods after observed macroeconomic events. This approach avoids priming respondents with explicit shock scenarios that may correlate with past experiences (Andre et al. 2022) and are thus not representative of a general increase or decrease in inflation. Our estimated belief dynamics reflect *average historical responses* across business cycles rather than transient, episode-specific narratives.

Experimental vignette designs, however, offer a distinct advantage: by holding the

informational environment fixed, they isolate how individuals interpret the same macroeconomic event. We therefore use the household survey of Andre et al. (2022) as an external validation of our results. In the first two survey waves, conducted in February–March (wave 1) and July 2019 (wave 2), respondents were presented with different hypothetical macroeconomic shocks and asked to predict future inflation and unemployment. Specifically, we focus on two hypothetical vignettes: an unexpected increase in oil prices, representing a supply-side disturbance, and an unexpected increase in the federal funds rate, representing a contractionary monetary policy disturbance that operates primarily through aggregate demand (in line with our chosen instruments from the previous section). The full survey design and questionnaire are described in Andre et al. (2022) and their Supplementary Material. By splitting the household sample by gender, we test (a) whether belief asymmetries persist within their controlled framework and (b) which channels drive this difference.

We first study how respondents revise their inflation and unemployment expectations under the two hypothetical vignettes. Table C.1 shows that, on average, women expect a hypothetical oil price shock to raise both inflation (column 1) and unemployment (column 2) more than men, consistent with our finding that women hold a stronger supply-side view of inflation. Likewise, women are more likely to perceive a cost channel of monetary policy: relative to men, they expect inflation to increase following a federal funds rate hike (column 4). Columns 3 and 6 interact gender with whether respondents correctly predict the direction of inflation, showing how the gender gap in unemployment revisions varies with respondents' inflation beliefs. In the oil-price vignette, women who incorrectly expect inflation to fall also expect unemployment to fall, whereas women who correctly expect inflation to rise revise unemployment upward relative to men. A symmetric pattern emerges in the monetary-policy vignette: women who correctly expect a federal funds rate increase to lower inflation also expect unemployment to fall. Thus, regardless of whether their inflation response is correct, women are more likely than men to revise unemployment in the same direction as inflation. This systematic gender difference in perceived inflation–unemployment comovement is consistent with the mechanism identified in our SVAR. Naturally, gender differences are likely to be attenuated in this experimental setting, where respondents are explicitly prompted to consider a particular shock. By contrast, our SVAR evidence captures respondents who react to realized inflationary shocks without conditioning on a specific transmission mechanism. The fact that we nevertheless uncover similar gender differences in the perceived transmission of inflationary shocks to labor-market outcomes across these two very different empirical settings provides strong

external validation for our interpretation.

Next, we examine the narrative channels underlying these belief revisions. In a third wave of the same household survey, conducted in February 2021, respondents were presented with a structured list of seven to eight shock-specific propagation channels and asked which, if any, they had in mind when forming their predictions. The responses are summarized in Figure C.1. Following an oil price shock, women are more likely to emphasize negative labor market spillovers, such as cost-push layoffs and weaker demand, whereas men more frequently identify potential offsetting effects, including job creation in the oil sector or through the green transition. Under a contractionary monetary policy shock, men are also substantially more likely to attribute labor market weakness to reduced aggregate demand. These patterns reinforce the asymmetric narratives men and women use to interpret the labor market consequences of inflationary shocks.

Finally, we investigate why women and men form different expectations. In the same survey wave, respondents were asked in an open-ended question to describe how they "come up with [their] prediction." Figure C.2 reveals a clear gender difference. Women are considerably more likely to report relying on gut feeling, whereas men more often refer to past macroeconomic episodes, knowledge, or news. By contrast, only around 20% of respondents in either group mention personal experiences. These differences provide suggestive evidence on the reasoning process underlying the gender gap in expectations. Respondents relying less on structured macroeconomic reasoning and more on intuition may instead resort to simple heuristics when interpreting ambiguous inflationary developments. One such heuristic is a "good–bad" rule, in which higher inflation is more readily associated with adverse labor market outcomes. Such reasoning is consistent with ambiguity aversion: when the source of inflation is uncertain, respondents place greater weight on the downside interpretation.

Taken together, the evidence in Sections 1 and 2 shows that the GWG widens when inflation rises and that men and women update their labor-market expectations in systematically different ways in response to inflationary shocks. These gendered belief responses offer a plausible mechanism for women's reduced willingness to pursue higher nominal wages during periods of rising inflation, consistent with the observed patterns of wage adjustment in both aggregate and micro-level data. We formalize this mechanism in a structural model with belief heterogeneity and wage-renegotiation frictions, allowing us to study how informational biases can generate the gendered wage dynamics we document.

3 Theoretical Model

We develop a theoretical model that extends the standard New Keynesian framework with search-and-matching frictions (e.g., Blanchard & Galí 2010, Christiano et al. 2016). The model features male and female workers within a representative household as in Albanesi (2025) and allows for gender-specific wage-setting. Two gender-specific bargaining agents, which we refer to as unions, negotiate wages on behalf of female and male workers respectively. We proceed in two steps. First, we introduce the benchmark model under full-information rational expectations (FIRE). Second, motivated by our evidence on gender differences in labor-market expectations, we relax FIRE in the wage-setting block. Unions do not observe the source of macroeconomic shocks and form subjective beliefs about the prevailing macroeconomic regime.[14] The model is solved in two stages: first, unions form subjective beliefs and determine wage demands and participation. Second, taking these as given, the firms price-setting and the households' consumption-saving problem are solved under rational expectations, leaving intertemporal decisions unaffected by the ambiguity distortion.

We model gender differences in the perception of inflationary shocks through relative ambiguity aversion (Bhandari et al. 2025). The union representing female workers is relatively ambiguity averse and therefore attributes a greater share of any observed signal to the adverse supply-driven regime. Supply shocks represent the adverse regime because they break the divine coincidence, moving inflation and unemployment in the same direction and forcing a painful inflation-unemployment tradeoff that monetary policy cannot resolve simultaneously. The union representing male workers is relatively ambiguity seeking and attributes a greater share of any observed signal to the favorable demand-driven regime, under which rising prices reflect stronger labor demand and higher expected wage growth. Ambiguity distortions operate at the union level, leaving the household's intertemporal decision-making and firms' price-setting decisions unaffected. The model isolates how gender differences in the interpretation of inflationary shocks can generate gender-specific wage responses.

Under this belief structure, the model generates a GWG response to inflationary demand and supply shocks consistent with our empirical evidence. We compare our channel to several conventional sources of gender differences emphasized in the literature, including taste-based discrimination, statistical discrimination, differences in labor supply elasticities,

[14] This setup relates to Erceg et al. (2024), where agents face imperfect information about shock persistence.

lower bargaining power of women, and greater wage rigidity for women. We find that none of these mechanisms can replicate the empirical widening we document. These results point to belief frictions as a plausible and novel channel for explaining business-cycle fluctuations in the GWG.

3.1 Setup

The baseline NKSM framework provides a robust foundation for modeling labor market frictions and the joint dynamics of inflation, output, and unemployment. We extend the standard framework by incorporating a two-worker household and a production function with gender-specific labor inputs, following Albanesi (2025). Male and female workers, indexed by $g \in \{f, m\}$, coexist within a single household and consume collectively, yet supply two distinct types of labor. Wage bargaining takes place separately for each labor type through gender-specific wage-setting unions: one representing female workers and one representing male workers. These unions should be understood as representative bargaining units for each labor type, rather than as separate institutional unions with independent objectives or market power. Their role is to aggregate the surplus of workers of type $g \in \{f, m\}$ and bargain with firms over gender-specific wages. This structure allows for idiosyncratic wage-renegotiation processes driven by gender-specific beliefs, while preserving a standard representative-household consumption-saving problem.

Household We model a representative married household with one agent of type f (female) and one agent of type m (male).[15] As in Albanesi (2025), we abstract from home production (Albanesi & Olivetti 2009) and incomplete financial markets (Mankart & Oikonomou 2017) though we maintain perfect insurance. Since we are interested in the pure renegotiation effects of inflation and unemployment on the GWG, men and women start out identical in our benchmark model. They have joint preferences over consumption of a CES aggregate C_t of consumption goods $C_t(i)$ with elasticity of substitution ϵ and labor effort $L_{g,t}$, where $g = f, m$:

$$U_t = (\ln C_t - \frac{\chi L_{m,t}^{1+\varphi}}{1+\varphi} - \frac{\chi L_{f,t}^{1+\varphi}}{1+\varphi}) Z_t.$$

[15] Our empirical results hold for both married and single individuals (see Figures A.12 and B.6). We adopt a married-household structure to allow for joint consumption and perfect intra-household insurance in a tractable way.

We do not explicitly model intra-household bargaining. Instead, we assume that the household consumes jointly and supplies two types of labor. With identical preferences, this is equivalent to members bargaining with equal weights over an aggregated consumption good. We include a preference shock Z_t to model demand shocks in the economy, where $\ln Z_t = \rho_z \ln Z_{t-1} + \varepsilon_z$ and $\varepsilon_z \sim N(0, \sigma_z^2)$. Labor effort is defined as $L_{g,t} = N_{g,t} + \psi U_{g,t}$, where $N_{g,t}$ denotes the fraction of employed workers, $U_{g,t}$ is the fraction of unemployed workers, and ψ is the relative disutility generated by an unemployed household member. Employment and unemployment sum to labor force participation, $0 \leq N_{g,t} + U_{g,t} = F_{g,t} \leq 1$. Household members outside the labor force neither supply labor nor generate utility or disutility.

The household maximizes the expected lifetime utility cooperatively. Employed workers receive a nominal wage $W_{g,t}$ from their employer, which may differ by type $g = \{f, m\}$. The household is smoothing consumption through the purchase of bonds priced at Q_t and receives a lump-sum payment (i.e. from dividends or taxes). This yields the standard Euler equation for intertemporal consumption:

$$Q_t = \beta \mathbf{E}_t \left\{ \frac{C_t}{C_{t+1}} \frac{P_t}{P_{t+1}} \frac{Z_{t+1}}{Z_t} \right\}. \tag{3}$$

Final good firms There is a continuum of monopolistically competitive firms indexed by $i \in [0, 1]$. Each firm produces good $Y_t(i)$ according to

$$Y_t(i) = X_t(i)$$

and purchases the competitively produced intermediate goods $X_t(i)$ at price P_t^I.[16] The firm's price setting is assumed to be subject to Calvo frictions, where only fraction $1 - \theta^p$ of the producers can reset their prices in a given period. We introduce a cost-push shock to aggregate inflation given by $\ln U_t = \rho_u \ln U_{t-1} + \varepsilon_u$ and $\varepsilon_u \sim N(0, \sigma_u^2)$.

Intermediate goods firms Intermediate inputs are produced by a continuum of identical, perfectly competitive firms indexed by $j \in [0, 1]$ according to a CES production function that aggregates male and female labor with relative female productivity ζ and an elasticity of substitution between male and female labor σ (Albanesi 2025):

$$X_t(j) = A_t \left[\zeta \cdot N_{f,t}(j)^{\frac{\sigma-1}{\sigma}} + (1 - \zeta) \cdot N_{m,t}(j)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{(1-\alpha)\sigma}{\sigma-1}}.$$

[16] Perfect competition of intermediate goods implies that $P_t^I = MC_t(j)$ for an intermediate good firm j.

Technology A_t is assumed common across all firms and to remain at its steady state level $\bar{A} = 1$.[17] Employment for both types of workers $g = f, m$ in each firm evolves according to:

$$N_{g,t}(j) = (1 - \delta)N_{g,t-1}(j) + H_{g,t}(j). \tag{4}$$

where δ refers to exogenous job separation. $N_{g,t-1} \equiv \int_0^1 N_{g,t-1}(j)dj$ denotes aggregate employment and $H_{g,t-1} \equiv \int_0^1 H_{g,t-1}(j)dj$ denotes aggregate hiring for workers of type g. Firms hire out of a pool of jobless workers $U_{g,t}$. We assume full participation and that workers start working in the period they are hired. All firms incur a cost-per-hire:

$$G_{g,t} = \Gamma x_{g,t}^{\gamma}, \tag{5}$$

which depends on the aggregate job finding rate:

$$x_{g,t} \equiv \frac{H_{g,t}}{U_{g,t}}. \tag{6}$$

Vacancies are filled immediately upon payment of the hiring costs. This is a simplification of the original search-and-match framework (Diamond 1982, Mortensen 1982, Pissarides 1985) which abstracts from explaining vacancies but shares the same characteristics of the original framework (Blanchard & Galí 2010).

Intermediate goods firms maximize profit, taking their price and the wage as given. Optimality requires that the marginal revenue product of labor must equal the total cost to the firm of employing the worker:

$$\begin{aligned}\frac{P_t^I}{P_t} MPN_{g,t} &= A_t mc_t \zeta_g (1 - \alpha) N_{g,t}^{-\frac{1}{\sigma}} N_t^{-\alpha + \frac{1}{\sigma - 1}} (1 - d_g) \\ &= w_{g,t} + G_{g,t} - \beta(1 - \delta)\mathbf{E}_t \left\{ \frac{C_t}{C_{t+1}} \frac{P_{t+1}}{P_t} G_{g,t+1} \right\},\end{aligned}$$

where $\zeta_f = \zeta$ and $\zeta_m = 1 - \zeta$. In the full-information, rational expectations model, GWGs can arise in equilibrium in two main ways. Statically though taste-based discrimination (Becker 1971, Black 1995, Neyer & Stempel 2021) by assuming $d_f > d_m = 0$. This

[17] To keep the analysis focused, we restrict the model to one supply-side disturbance, cost-push shocks, and one demand-side disturbance, preference shocks. Since our question depends primarily on whether fluctuations originate on the supply or demand side, the qualitative implications would be unchanged if supply disturbances were modeled as technology shocks and demand disturbances as monetary policy shocks.

is the simplest way to generate an equilibrium GWG in the model and is supported by empirical evidence (Flabbi 2010, Maloney & Neumark 2025). Other mechanisms that generate persistent gender differences – such as women's stronger preferences for workplace amenities (Bolotnyy & Emanuel 2022, Faberman et al. 2026, Goldin 2014, Wiswall & Zafar 2018) or differences in personality traits like risk aversion (Azmat & Petrongolo 2014, Cortés et al. 2023, Flinn et al. 2025) – would produce equivalent reduced-form outcomes in equilibrium. Like taste-based discrimination, these are typically modeled as stable features rather than sources of short-run fluctuations.

Wage bargaining Wages are determined as the Nash bargaining outcome between gender-specific unions and firms. Each union aggregates the surplus of workers of type g and bargains with the firm on their behalf. We assume sticky wages (Barattieri et al. 2014, Gertler & Trigari 2009, Hall 2005), such that only a fraction of workers renegotiates their wages in a given period. The share of female workers able to readjust their wage is denoted by θ_f^w and the share of male workers by θ_m^w. This Calvo-like setup implies that the expectations of unions and firms matter in the bargaining process. Worker-representing unions and firms engage in Nash bargaining. Female and male unions can have different bargaining powers relative to the firm, denoted by $1-\xi_f$ and $1-\xi_m$ respectively. The target wage k periods ahead $\Omega^{tar}_{f,t+k|t}$ shares the surplus of the match between the worker and the firm and is thus a weighted average of the marginal rate of substitution of labor and consumption, and the marginal revenue product of labor:

$$\Omega^{tar}_{g,t+k|t} \equiv \xi_g \frac{C_{t+k}}{\chi L^{\varphi}_{g,t+k}} + (1-\xi_g)\frac{P^I_t}{P_t} MPN_{g,t+k|t}. \tag{7}$$

Market clearing We define aggregate output as $Y_t \equiv \left(\int_0^1 Y_t(i)^{\frac{\epsilon-1}{\epsilon}} di\right)^{\frac{\epsilon}{\epsilon-1}}$ and the demand for each final good as $Y_t(i) = \left(\frac{P_t(i)}{P_t}\right)^{-\epsilon}(C_t + G_{f,t}H_{f,t} + G_{m,t}H_{m,t})$. Thus, the aggregate goods market clearing condition is:

$$Y_t = C_t + G_{f,t}H_{f,t} + G_{m,t}H_{m,t}. \tag{8}$$

Since wage and price dispersion are assumed close to unity around a zero-inflation steady-state, we approximate further:

$$Y_t = A_t \left[\zeta \cdot N_{f,t}^{\frac{\sigma-1}{\sigma}} + (1-\zeta) \cdot N_{m,t}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{(1-\alpha)\sigma}{\sigma-1}}. \tag{9}$$

Finally, the model is closed through a standard monetary policy rule:

$$\frac{1+i_t}{1+\bar{i}_t} = \left(\frac{1+i_{t-1}}{1+\bar{i}_t} \right)^{\rho_i} \left[\left(\frac{1+\pi_t^p}{1+\bar{\pi}_t^p} \right)^{\phi_\pi} \left(\frac{U_{m,t}}{\bar{U}_{m,t}} \right)^{\phi_{u_m}} \left(\frac{U_{f,t}}{\bar{U}_{f,t}} \right)^{\phi_{u_f}} \left(\frac{Y_t}{\bar{Y}_t} \right)^{\phi_y} \right]^{1-\rho_i}. \tag{10}$$

3.2 Introducing Ambiguity Attitudes

To account for gender differences in the perception of macroeconomic shocks, we modify the baseline model so that female and male worker unions interpret identical aggregate signals under structural model uncertainty. While related work documents biased beliefs about labor market transitions (Balleer et al. 2026*a*,*b*, Spinnewijn 2015), we focus instead on how agents evaluate aggregate volatility. Our empirical evidence suggests that women systematically attribute inflationary shocks to supply-driven (cost-push) factors, which imply painful tradeoffs between inflation and unemployment, whereas men attribute them to demand-driven (preference) factors, which imply stronger labor demand.

We model this supply-biased attribution through ambiguity aversion over the underlying data-generating process, using a soft-min approximation of the Hansen–Sargent robust control framework (Cogley et al. 2008, Hansen & Sargent 2001).[18] In our setup, unions face uncertainty regarding the prevailing macroeconomic regime – whether the economy is predominantly supply-driven or demand-driven – rather than the specific realization of a period-by-period shock. An ambiguity-averse union, representing female workers, evaluates the unconditional welfare costs of different structural regimes and adopts a worst-case attribution, permanently tilting its perceived signal toward the harsher supply-driven regime. An ambiguity-seeking union, representing male workers, tilts toward the more favorable demand-driven regime. This approach differentiates our model from interval-based ambiguity frameworks (Baqaee 2020, Ilut & Schneider 2014, Masolo & Monti 2021, Michelacci & Paciello 2024), where uncertainty concerns the first moment (mean) of shocks. By

[18] Different from a min-max, the soft-min approximation allows for ambiguity seeking agents to also be present.

anchoring ambiguity to the unconditional regime tradeoffs rather than ex-post signal directions, our framework preserves linear signal extraction and ensures that ambiguity-averse agents consistently view supply shocks as the dominant driver of the economy, in line with the empirical evidence.

Our approach is closest to Bhandari et al. (2025), who introduce ambiguity aversion (subjective pessimism) into a NKSM framework to generate a supply-side bias in households' expectations. We depart from their framework by focusing on gender-specific wage setting: ambiguity attitudes are confined to the unions representing female and male workers in the first stage, while all other agents, including the household and firms, operate under rational expectations in the second stage. This mechanism allows identical macroeconomic information to generate systematically different wage-setting outcomes across genders without departing from rational expectations elsewhere in the economy.

Ambiguity aversion. Instead of evaluating the period-by-period realization of shocks, ambiguity-averse unions evaluate the unconditional macroeconomic regime. Before forming expectations, each union $g \in \{m, f\}$ evaluates the continuation value of the representative household under two distinct structural regimes, denoted $\bar{V}_s$ for $s \in \{z, u\}$. Here, regime z represents an economy dominated by preference (demand) shocks, and regime u an economy dominated by cost-push (supply) shocks. Let p_s denote the objective (prior) probability of regime s. Because supply shocks break the divine coincidence and force a painful tradeoff between inflation and unemployment, the unconditional expected welfare in the supply-driven regime is strictly lower than in the demand-driven regime ($\bar{V}_u < \bar{V}_z$).

We model ambiguity aversion as a smooth soft-min distortion of prior beliefs applied to these regime values. The distorted weights and the corresponding normalized subjective probabilities are:

$$m_g^s = p_s \exp\left(-\frac{\bar{V}_s}{\lambda_g}\right), \qquad w_g^s = \frac{m_g^s}{\sum_{s' \in \{z,u\}} m_g^{s'}}.$$

The parameter $\lambda_g \in \mathbb{R} \setminus \{0\}$ governs the degree and direction of belief distortion. Smaller absolute values of λ_g imply stronger sensitivity to adverse outcomes. We interpret $\lambda_m < 0$ as *ambiguity seeking* (overweighting favorable regimes) and $\lambda_f > 0$ as *ambiguity aversion* (overweighting unfavorable regimes). The normalization in w_g^s ensures $\sum_s w_g^s = 1$, such that $\{w_g^s\}$ defines a valid subjective probability measure. Because $\bar{V}_u < \bar{V}_z$ is a permanent structural feature of the economy, these ambiguity-distorted weights are time-invariant.

Signal extraction. Both unions observe a common but noisy composite signal that aggregates the underlying shocks:

$$s_t = \varepsilon_t^u + \varepsilon_t^z. \tag{11}$$

This informational friction is similar in spirit to that in Erceg et al. (2024), who model agents as unable to distinguish between persistent and transitory shocks. By contrast, we assume that agents cannot distinguish between demand and supply shocks. While both unions receive the same signal s_t, they do not exchange information and thus form beliefs independently, based on their gender-specific ambiguity attitudes.

Belief updating. We denote by $\tilde{\mathbb{E}}_{g,t}[\cdot]$ the conditional expectation operator of union g, formed under ambiguity-distorted beliefs using weights $\{w_g^s\}$. Unions use these beliefs to form subjective expectations about latent shocks:

$$\tilde{\mathbb{E}}_{g,t}[\varepsilon_t^z] = w_g^z \, s_t, \qquad \tilde{\mathbb{E}}_{g,t}[\varepsilon_t^u] = w_g^u \, s_t.$$

Crucially, because the distorted weight w_g^u is anchored to unconditional regime welfare rather than the directional sign of the current signal s_t, it preserves the linearity observed in our empirical results. An ambiguity-averse union permanently sets $w_f^u > p_u$. Consequently, whether a signal is inflationary ($s_t > 0$) or deflationary ($s_t < 0$), the female union consistently attributes a larger share of the variation to supply shocks, generating a persistent positive correlation between expected unemployment and expected inflation. To simplify notation, define the unions' subjective beliefs about the underlying state variables $z_t = \ln Z_t$ and $u_t = \ln U_t$ as

$$\tilde{z}_t^g \equiv \tilde{\mathbb{E}}_{g,t}[z_t], \qquad \tilde{u}_t^g \equiv \tilde{\mathbb{E}}_{g,t}[u_t].$$

These beliefs evolve according to the unions' perceived laws of motion:

$$\tilde{z}_t^g = \rho_z \, \tilde{z}_{t-1}^g + \tilde{\mathbb{E}}_{g,t}[\varepsilon_t^z], \qquad \tilde{u}_t^g = \rho_u \, \tilde{u}_{t-1}^g + \tilde{\mathbb{E}}_{g,t}[\varepsilon_t^u].$$

While households, firms, and the monetary authority observe the true shocks, unions solve the model following their subjective beliefs about the shock. Consistent with the empirical evidence motivating our framework, unions do not update their beliefs about the true shock realizations, giving rise to a persistent divergence in labor-market beliefs across genders.

Wage bargaining and labor participation. The optimal labor participation decision for each gender $g \in \{m, f\}$ is determined by equating the marginal disutility of labor with its expected marginal benefit. Formally, the participation condition can be written as

$$\psi_g \chi_g L_g^{\varphi_g} \frac{C_t}{Z_t} = \frac{x_g}{1 - x_g} \left[\frac{1 - \xi_g}{\xi_g} G_g - \pi_g^w \frac{\theta_g^w}{1 - \theta_g^w} \omega_{g,t-1} Q_g \right],$$

where

$$Q_g = 1 + \theta_g^w (1 - \delta_g) \beta \tilde{\mathbb{E}}_{g,t} \left[\frac{Z_{t+1}}{Z_t} \frac{C_t}{C_{t+1}} \frac{Q_{g,t+1}}{1 + \pi_t^p} \right].$$

Ambiguity aversion enters this condition indirectly through Q_g, which depends on subjective expectations about future productivity and consumption. Since $\tilde{\mathbb{E}}_{m,t}[\cdot] \neq \tilde{\mathbb{E}}_{f,t}[\cdot]$ whenever $\lambda_m \neq \lambda_f$, the perceived present value of expected wages differs across genders, even under identical institutional settings. Consequently, equilibrium labor participation rates may diverge between men and women as a function of their respective ambiguity attitudes.

This structure implies that gender differences in labor market outcomes can emerge endogenously from heterogeneity in ambiguity attitudes rather than from structural or policy asymmetries. Female unions, being ambiguity averse ($\lambda_f > 0$), place greater subjective weight on the adverse supply-driven regime and therefore anticipate weaker wage prospects in response to inflationary signals. Male unions, being ambiguity seeking ($\lambda_m < 0$), place greater weight on the favorable demand-driven regime and anticipate stronger wage growth. These divergent expectations alter wage demands and participation incentives, generating persistent differences in labor-market outcomes even in symmetric macroeconomic environments. The full set of equilibrium equations is reported in Section D.2 of the Appendix.

3.3 Calibration

We calibrate the model to the US economy using standard parameter values. Each period corresponds to a quarter. Following convention, we assign $\beta = 0.99$ and assume that prices and wages are reset on average once per year, such that $\theta^p = 0.75$ and $\theta_f^w = \theta_m^w = 0.75$. Equal wage-setting rigidity follows from Barattieri et al. (2014), who find little systematic heterogeneity across major occupational groups. Assuming 54% employment rate for women and 69% employment rate for men, as well as 6% unemployment[19] and a 0.7 job

[19]Employment rates are calibrated using the average employment-to-population ratios for men and women from FRED over our sample period (mnemonics LNS12300001 and LNS12300002, respectively). The unemployment rate is set to 6% for both groups, reflecting the near-identical average unemployment rates of

finding rate for both (Gertler & Trigari 2009), we obtain a quarterly separation rate of 0.20 for men and 0.26 for women. These values are slightly higher than the estimates in Gertler & Trigari (2009) and Hall (2005), but the higher separation rate for women is consistent with the patterns documented by Albanesi & Şahin (2018). In addition, we calibrate bargaining weights as $\xi_f = \xi_m = 0.6$ in accordance with Flinn (2006) who finds no significant bargaining differences between men and women. Following Blanchard & Galí (2010), we set $\gamma = 1$ to align the framework with the matching-function approach. We set $\Gamma = 0.013$ to match empirical results that the average cost of hiring a worker is 4.5% of the quarterly wage (Silva & Toledo 2009). For the production function, we assume $\alpha = 1/3$ to allow for a labor share of 2/3. We further set the elasticity of substitution of men and women to $\sigma = 4.3$, in line with empirical estimates (Acemoglu et al. 2004, Albanesi 2025). We assume a monetary authority that responds to inflation and unemployment with $\phi_\pi = 5$, $\phi_{u,g} = -0.8$ and $\phi_y = 0$ to match the simple optimal policy rule in Blanchard & Galí (2010). The interest rate smoothing parameter ρ_i is calibrated at 0.7. We include standard parameters for the shock processes, $\rho_z = 0.8$, $\sigma_z = 0.045$, $\rho_u = 0.9$ and $\sigma_u = 0.0003$.[20] The magnitude of the disturbance is calibrated to match the response of inflation in our SVAR. The full set of calibrated parameters is reported in Appendix Table D.1.

3.4 Cyclicality of the Gender Wage Gap

We first show that the model with no gender differences replicates the impulse responses of Blanchard & Galí (2010).[21] The black thin line in Figure VIII reports impulse responses to demand (preference) and supply (cost-push) shocks. As expected, inflationary demand shocks raise output and employment, whereas inflationary supply shocks reduce them. By construction, men and women respond identically.

Next, we introduce gender differences into our baseline calibration. We first include statistical discrimination through a productivity wedge ($\zeta = 0.49$, Olsson 2025), matching recent estimates of women's share in total hours of 49%.[22] In addition, we allow women to have a more elastic labor supply ($\varphi_f = 0.88 < \varphi_m = 2.64$, applying the calibration strategy

men and women over the sample period (mnemonics LNS14000001 and LNS14000002, respectively).

[20] For simplicity, we assume that technology is constant and there are no monetary policy shocks. An alternative specification would include a standard technology shock and a standard monetary policy shock, capturing supply and demand disturbances, respectively. The results would be the same in this scenario.

[21] Here, we calibrate employment of both men and women to 60% in the steady state.

[22] This corresponds to 7.9 hours relative to 8.2 hours per day among full-time workers in the 2024 American Time Use Survey.

in Albanesi (2025) to 2024 data). This means their work participation or hours respond more strongly to changes in wages, taxes, or work incentives than men's do. This could reflect, for example, women being more often the second-earner in a household. Finally, we introduce a steady-state GWG of roughly 11% (matching the average adjusted gap since 2010) through taste-based discrimination calibrated as $d_f = 0.11$. Because the disutility from hiring women enters the profit function proportionally to output, the additional cost of employing women scales with firm expansion and does not generate cyclical variation in the GWG. Hence, fluctuations in our baseline calibration (thick blue line in Figure VIII) are driven only by differences in labor hours and supply elasticities. The model replicates our empirical finding for demand shocks: the GWG increases with inflation when inflation is driven by a preference shock. By contrast, the wage gap falls following supply shocks, implying that it co-moves with output (and employment) rather than inflation.

To align the model with the empirical evidence, we introduce ambiguity aversion on top of our baseline calibration. We calibrate the gender-specific ambiguity parameters, λ_m and λ_f, such that the model-implied subjective wage expectations match the empirical 12-month wage growth expectations responses estimated from the Survey of Consumer Expectations (SCE) data following both inflationary demand and supply shocks. This empirical targeting yields $\lambda_m = -0.001$ and $\lambda_f = 0.001$. These values imply a substantially larger subjective weight on the adverse supply-side regime for women than for men ($w_f^u = 0.99 > w_m^u = 0.01$). Appendix D.4 describes the calibration procedure in detail and reports a grid-search analysis over alternative subjective regime weights.

Under this calibration, represented by the orange line in Figure VIII, inflationary shocks of either origin affect the expected present value of future wages differently for men and women as beliefs about future economic conditions diverge by genders. Women anticipate lower future outside options and accept lower target wages relative to men, widening the GWG. Importantly, the gap does not immediately revert to its pre-shock level. It remains elevated for an extended period as expectations adjust gradually. This persistence arises because Q_g, the discounted value of expected future wages, embeds forward-looking beliefs that evolve slowly over time, causing the wage differential to co-move with inflation and remain persistent after the initial shock. The persistence of ambiguity aversion reflects the persistence of divergent beliefs in the expectations data (Figures VII and B.3).

In addition to matching the widening of the GWG following inflationary demand and supply shocks, the model with gender differences in beliefs generates an unemployment gap

between men and women (Figure D.1) consistent with our empirical evidence (Figure A.5). The male–female unemployment gap decreases following inflationary demand shocks but increases following inflationary supply shocks. Because female-representing unions place greater subjective weight on adverse supply-driven states, they anticipate weaker future outside options and set lower target wages than male-representing unions when observing inflation. This moderates wage pressures for firms and reduces match destruction during adverse supply shocks, so female unemployment rises less than male unemployment in inflationary contractions over the impulse-response horizon. This mechanism implies heterogeneous welfare effects of beliefs. Male-representing unions' greater weight on favorable demand-driven states raises target wages and benefits employed male workers, but it also makes male matches more vulnerable to destruction when inflation reflects adverse supply conditions. Female-representing unions' greater weight on adverse supply-driven states lowers wages for workers who remain employed, but preserves more matches during supply-driven contractions. The resulting dynamics resemble an insider–outsider mechanism: more optimistic beliefs raise insider wages at the cost of higher unemployment risk, whereas more pessimistic beliefs protect employment at the cost of lower wages.

For robustness, we compare the effect of two alternative mechanisms (not directly supported in the literature) on our standard calibration excluding ambiguity attitudes. First, we allow for women's bargaining weights to be lower. While Flinn (2006) does not find large differences for men and women, he does for race. We use his bargaining weights estimated for non-whites as lower bound for women and bargaining weights for whites as upper bound for men, setting $\xi_m = 0.56 < 0.6 < \xi_f = 0.67$ (light blue, $\square$-marker). Second, we explore the possibility that women's wages are stickier than men's. While Barattieri et al. (2014) find little systematic heterogeneity across major occupational groups, we perform sensitivity analysis by setting $\theta_m^w = 0.6 < 0.75 < \theta_f^w = 0.9$. This approximates higher wage-resetting costs for women (light blue, $\diamond$-marker). Following Auclert et al. (2023), we maintain a Calvo-style framework, which provides a first-order approximation numerically equivalent to more complex menu-cost models. In both cases, the GWG widens during inflationary expansions (demand shocks) but narrows during inflationary contractions (supply shocks) contrasting with the empirical result.

One might ask whether gender differences in risk aversion could generate the same results. The answer is no, for a fundamental reason. Risk aversion governs how agents value uncertain outcomes but leaves their beliefs unchanged: under expected utility maximization,

all agents form expectations using the objective probability measure, regardless of their risk aversion. Differential risk aversion therefore predicts no divergence in labor-market expectations across genders – directly contradicted by our SCE evidence, which documents that women and men revise their labor-market expectations in opposite directions after both types of inflationary shocks. This divergence is evidence of gender-specific belief distortions rather than differences in outcome valuation. Gender-specific ambiguity attitudes generate exactly this pattern: by distorting the probability weights assigned to structural regimes, they cause the ambiguity-averse female union to expect worse labor-market conditions and the ambiguity-seeking male union to expect better ones, when the signal is inflationary.

Overall, the model links our two empirical findings: the widening of the adjusted GWG following both inflationary demand and supply shocks and women's relatively more pessimistic labor-market expectations in response to the same shocks. Standard mechanisms, such as taste-based discrimination, statistical discrimination, or differences in labor supply elasticity, can generate realistic steady-state GWGs but fail to reproduce the observed cyclical pattern. Under conventional calibrations, the GWG responds primarily to output fluctuations rather than inflation, contrary to the empirical evidence. Introducing gender differences in beliefs resolves this discrepancy. When women place greater weight on adverse, supply-side states, any inflationary disturbance reduces their expected future outside options relative to men's, leading to lower target wages and a widening of the GWG. These results show that our two empirical facts are plausibly connected: differential perceptions about inflation provide a mechanism to explain the observed cyclical behavior of the GWG.

4 Conclusion

Inflationary shocks can affect comparable workers differently when they interpret the same macroeconomic environment in different ways. We document two facts. First, both supply- and demand-driven inflationary shocks widen the adjusted gender wage gap in the U.S. Current Population Survey (CPS). Since these shocks have opposite implications for real activity, their common effect points to inflation as a driver of pay differences among otherwise similar workers. Second, men and women perceive both types of inflationary shocks very differently: women expect labor market conditions to worsen, while men expect them to improve. Women's expectation revisions are consistent with attributing inflationary shocks of either origin to supply-driven factors, while men's are consistent with attributing them to demand-driven factors. These asymmetries matter for wage setting, with women

requesting smaller nominal wage adjustments and experiencing weaker subsequent wage growth.

We rationalize these facts in a New Keynesian search-and-matching model with two worker types, imperfect information and gender-specific ambiguity attitudes. In the model, two gender-specific unions negotiate wages on behalf of female and male workers and observe the same noisy macroeconomic signal but cannot identify its source. Supply shocks represent the adverse regime: they break the divine coincidence, forcing a tradeoff between inflation and unemployment that demand shocks do not. The ambiguity-averse female union permanently overweights this worst-case regime, leading it to expect weaker outside options and demand lower nominal wage growth when the signal is inflationary. The ambiguity-seeking male union does the opposite. Common signals generate divergent beliefs, and divergent beliefs translate into divergent pay. The model reproduces the widening of the gender wage gap after both supply- and demand-driven inflationary shocks.

Our findings generalize beyond gender: we identify a belief channel through which macroeconomic shocks shape inequality. Our framework highlights how heterogeneity in expectations across demographic groups can generate persistent and systematic distributional effects of inflation, even among workers in the same industries and occupations. This mechanism has implications for both monetary policy design, by revealing hidden inequality trade-offs of inflation stabilization, and labor market policy, by emphasizing the importance of expectation management and communication in mitigating gendered outcomes of macroeconomic fluctuations.

References

Acemoglu, D., Autor, D. & Lyle, D. (2004), 'Women, War, and Wages: The Effect of Female Labor Supply on the Wage Structure at Midcentury', *Journal of Political Economy* **112**(3), 497–551.

Albanesi, S. (2025), 'Changing Business Cycles: The Role of Women's Employment', *American Economic Journal: Macroeconomics* **17**(4), 345–390.

Albanesi, S. & Kim, J. (2021), 'Effects of the COVID-19 Recession on the US Labor Market: Occupation, Family, and Gender', *Journal of Economic Perspectives* **35**(3), 3–24.

Albanesi, S. & Olivetti, C. (2009), 'Home production, market production and the gender wage gap: Incentives and expectations', *Review of Economic Dynamics* **12**(1), 80–107.

Albanesi, S. & Olivetti, C. (2016), 'Gender roles and medical progress', *Journal of Political Economy* **124**(3), 650–695.

Albanesi, S. & Şahin, A. (2018), 'The gender unemployment gap', *Review of Economic Dynamics* **30**, 47–67.

Andre, P., Haaland, I., Roth, C. & Wohlfart, J. (2025), 'Narratives About the Macroeconomy', *Review of Economic Studies* **forthcoming**.

Andre, P., Pizzinelli, C., Roth, C. & Wohlfart, J. (2022), 'Subjective Models of the Macroeconomy: Evidence From Experts and Representative Samples', *Review of Economic Studies* **89**(6), 2958–2991.

Angeletos, G.-M., Collard, F. & Dellas, H. (2020), 'Business-Cycle Anatomy', *American Economic Review* **110**(10), 3030–3070.

Arias, J. E., Rubio-Ramírez, J. F. & Waggoner, D. F. (2018), 'Inference Based on Structural Vector Autoregressions Identified With Sign and Zero Restrictions: Theory and Applications', *Econometrica* **86**(2), 685–720.

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.

Auclert, A., Rigato, R., Rognlie, M. & Straub, L. (2023), 'New pricing models, same old phillips curves?', *The Quarterly Journal of Economics* **139**(1), 121–186.

Azmat, G. & Petrongolo, B. (2014), 'Gender and the labor market: What have we learned from field and lab experiments?', *Labour Economics* **30**, 32–40.

Babcock, L. & Laschever, S. (2003), *Women Don't Ask* , 1 edn, Princeton University Press.

Baek, C. & Yaremko, V. (2024), Spillovers in Macroeconomic Expectations and Labor Supply: Implications for Wage Price Spirals.

Balleer, A., Duernecker, G., Forstner, S. & Goensch, J. (2026*a*), 'Biased expectations and labor market outcomes: Evidence from german survey data and implications for the east–west wage gap', *Journal of Monetary Economics* **159**, 103917.

Balleer, A., Duernecker, G., Forstner, S. & Goensch, J. (2026*b*), 'The effects of biased labor market expectations on consumption, wealth inequality, and welfare', *American Economic Journal: Macroeconomics* **18**(1), 297–335.

Baqaee, D. R. (2020), 'Asymmetric inflation expectations, downward rigidity of wages, and asymmetric business cycles', *Journal of Monetary Economics* **114**, 174–193.

Barattieri, A., Basu, S. & Gottschalk, P. (2014), 'Some Evidence on the Importance of Sticky Wages', *American Economic Journal: Macroeconomics* **6**(1), 70–101.

Barber, B. M. & Odean, T. (2001), 'Boys will be Boys: Gender, Overconfidence, and

Common Stock Investment', *The Quarterly Journal of Economics* **116**(1), 261–292.

Bauer, M. D. & Swanson, E. T. (2023), 'A reassessment of monetary policy surprises and high-frequency identification', *NBER Macroeconomics Annual* **37**(1), 87–155.

Becker, G. S. (1971), *The Economics of Discrimination*, 2 edn, Economic Research Studies.

Bhandari, A., Borovička, J. & Ho, P. (2025), 'Survey Data and Subjective Beliefs in Business Cycle Models', *Review of Economic Studies* **92**(3), 1375–1437.

Biasi, B. & Sarsons, H. (2022), 'Flexible Wages, Bargaining, and the Gender Gap', *The Quarterly Journal of Economics* **137**(1), 215–266.

Binetti, A., Nuzzi, F. & Stantcheva, S. (2024), 'People's understanding of inflation', *Journal of Monetary Economics* **148**, 103652.

Bjuggren, C. M. & Elert, N. (2019), 'Gender differences in optimism', *Applied Economics* **51**, 5160–5173.

Black, D. A. (1995), 'Discrimination in an Equilibrium Search Model', *Journal of Labor Economics* **13**(2), 309–334.

Blanchard, O. & Galí, J. (2010), 'Labor Markets and Monetary Policy: A New Keynesian Model with Unemployment', *American Economic Journal: Macroeconomics* **2**(2), 1–30.

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**(4), 436.

Bolotnyy, V. & Emanuel, N. (2022), 'Why Do Women Earn Less than Men? Evidence from Bus and Train Operators', *Journal of Labor Economics* **40**(2), 283–323.

Bonaccolto-Töpfer, M. & Satlukal, S. (2024), 'Gender differences in reservation wages: New evidence for Germany', *Labour Economics* **91**, 102649.

Borella, M., De Nardi, M. & Yang, F. (2018), 'The aggregate implications of gender and marriage', *The Journal of the Economics of Ageing* **11**, 6–26. Macroeconomics of Aging.

Bredemeier, C., Juessen, F. & Winkler, R. (2017), 'Man-cessions, fiscal policy, and the gender composition of employment', *Economics Letters* **158**, 73–76.

Caldwell, S., Haegele, I. & Heining, J. (2025), 'Bargaining and inequality in the labor market', *The Quarterly Journal of Economics* **141**(1), 315–371.

Candia, B., Coibion, O. & Gorodnichenko, Y. (2020), Communication and the Beliefs of Economic Agents, Working Paper 27800, National Bureau of Economic Research.

Card, D., Cardoso, A. R. & Kline, P. (2016), 'Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women', *The Quarterly*

Journal of Economics **131**(2), 633–686.

Christiano, L. J., Eichenbaum, M. S. & Trabandt, M. (2016), 'Unemployment and Business Cycles', *Econometrica* **84**(4), 1523–1569.

Cogley, T., Colacito, R., Hansen, L. P. & Sargent, T. j. (2008), 'Robustness and u.s. monetary policy experimentation', *Journal of Money, Credit and Banking* **40**(8), 1599–1623.

Cortés, P., Pan, J., Pilossoph, L., Reuben, E. & Zafar, B. (2023), 'Gender Differences in Job Search and the Earnings Gap: Evidence from the Field and Lab', *The Quarterly Journal of Economics* **138**(4), 2069–2126.

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 Science11818* **118**(21).

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

Dawson, C. (2017), 'The upside of pessimism biased beliefs and the paradox of the contented female worker', *Journal of Economic Behavior & Organization* **135**, 215–228.

Dawson, C. (2023), 'Gender differences in optimism, loss aversion and attitudes towards risk', *British Journal of Psychology* **114**, 928–944.

Diamond, P. A. (1982), 'Aggregate Demand Management in Search Equilibrium', *Journal of Political Economy* **90**(5), 881–894.

Erceg, C., Lindé, J. & Trabandt, M. (2024), Monetary Policy and Inflation Scares, Working Paper 2024/260, International Monetary Fund.

Exley, C. L., Niederle, M. & Vesterlund, L. (2020), 'Knowing When to Ask: The Cost of Leaning In', *Journal of Political Economy* **128**(3), 816–854.

Faberman, R. J., Mueller, A. I. & Şahin, A. (2026), Job search, job amenities and the gender pay gap, Working Paper 34877, National Bureau of Economic Research.

Federal Reserve Bank of New York (2024), 'Survey of Consumer Expectations'.

Flabbi, L. (2010), 'Gender discrimination estimation in a search model with matching and bargaining', *International Economic Review* **51**(3), 745–783.

Flinn, C. J. (2006), 'Minimum Wage Effects on Labor Market Outcomes under Search, Matching, and Endogenous Contact Rates', *Econometrica* **74**(4), 1013–1062.

Flinn, C. J., Todd, P. E. & Zhang, W. (2025), 'Labor Market Returns to Personality: A Job Search Approach to Understanding Gender Gaps', *Journal of Political Economy* **133**(4), 1169–1234.

Flood, S., King, M., Rodgers, R., Ruggles, S., Warren, R., Backman, D., Chen, A., Cooper, G., Richards, S., Schouweiler, M. & Westberry, M. (2025), 'IPUMS CPS: Version 13.0 [dataset]'.

Garbarino, E. & Strahilevitz, M. (2004), 'Gender differences in the perceived risk of buying online and the effects of receiving a site recommendation', *Journal of Business Research* **57**(7), 768–775.

Gertler, M. & Trigari, A. (2009), 'Unemployment fluctuations with staggered nash wage bargaining', *Journal of Political Economy* **117**(1), 38–86.

Goldin, C. (2014), 'A Grand Gender Convergence: Its Last Chapter', *American Economic Review* **104**(4), 1091–1119.

Guerreiro, J., Hazell, J., Lian, C. & Patterson, C. (2026), 'Why Do Workers Dislike Inflation? Wage Erosion and Conflict Costs', *Econometrica* **forthcoming**.

Hajdini, I., Knotek, E. S., Leer, J., Pedemonte, M., Rich, R. & Schoenle, R. (2022), Low Passthrough from Inflation Expectations to Income Growth Expectations: Why People Dislike Inflation, Working Paper 22-21, Federal Reserve Bank of Cleveland.

Hall, R. E. (2005), 'Employment Fluctuations with Equilibrium Wage Stickiness', *American Economic Review* **95**(1), 50–65.

Hansen, L. P. & Sargent, T. J. (2001), 'Robust Control and Model Uncertainty', *American Economic Review* **91**(2), 60–66.

Hoynes, H., Miller, D. L. & Schaller, J. (2012), 'Who Suffers During Recessions?', *Journal of Economic Perspectives* **26**(3), 27–48.

Ilut, C. L. & Schneider, M. (2014), 'Ambiguous Business Cycles', *American Economic Review* **104**(8), 2368–2399.

Jacobsen, B., Lee, J. B., Marquering, W. & Zhang, C. Y. (2014), 'Gender differences in optimism and asset allocation', *Journal of Economic Behavior & Organization* **107**, 630–651.

Kamdar, R. & Rey, W. (2025), Attention-Driven Sentiment and the Business Cycle.

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

Känzig, D. R. (2021), 'The macroeconomic effects of oil supply news: Evidence from opec announcements', *American Economic Review* **111**(4), 1092–1125.

Leibbrandt, A. & List, J. A. (2015), 'Do Women Avoid Salary Negotiations? Evidence from a Large-Scale Natural Field Experiment', *Management Science* **61**(9), 2016–2024.

Malmendier, U. & Nagel, S. (2016), 'Learning from Inflation Experiences', *The Quarterly*

Journal of Economics **131**(1), 53–87.

Maloney, M. & Neumark, D. (2025), Does the Gender Wage Gap Actually Reflect Taste Discrimination Against Women?, Working Paper 33405, National Bureau of Economic Research.

Mankart, J. & Oikonomou, R. (2017), 'Household Search and the Aggregate Labour Market', *The Review of Economic Studies* **84**(4), 1735–1788.

Masolo, R. M. & Monti, F. (2021), 'Ambiguity, Monetary Policy and Trend Inflation', *Journal of the European Economic Association* **19**(2), 839–871.

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

Menzio, G. (2022), Stubborn beliefs in search equilibrium.

Michelacci, C. & Paciello, L. (2024), 'Ambiguity Aversion and Heterogeneity in Households' Beliefs', *American Economic Journal: Macroeconomics* **16**(2), 95–126.

Mortensen, D. (1982), 'Property Rights and Efficiency in Mating, Racing, and Related Games', *American Economic Review* **72**(5), 968–979.

Mueller, A. I. & Spinnewijn, J. (2023), Expectations data, labor market, and job search, *in* 'Handbook of Economic Expectations', Elsevier, pp. 677–713.

Neyer, U. & Stempel, D. (2021), 'Gender discrimination, inflation, and the business cycle', *Journal of Macroeconomics* **70**, 103352.

Ngai, L. R. & Petrongolo, B. (2017), 'Gender gaps and the rise of the service economy', *American Economic Journal: Macroeconomics* **9**(4), 1–44.

Ñopo, H. (2008), 'Matching as a Tool to Decompose Wage Gaps', *Review of Economics and Statistics* **90**(2), 290–299.

Oaxaca, R. (1973), 'Male-Female Wage Differentials in Urban Labor Markets', *International Economic Review* **14**(3), 693.

Olivetti, C. & Petrongolo, B. (2016), 'The Evolution of Gender Gaps in Industrialized Countries', *Annual Review of Economics* **8**(1), 405–434.

Olivetti, C. & Petrongolo, B. (2017), 'The economic consequences of family policies: Lessons from a century of legislation in high-income countries', *Journal of Economic Perspectives* **31**(1), 205–30.

Olsson, J. (2025), 'Singles, couples, and their labor supply: Long-run trends and short-run fluctuations', *American Economic Journal: Macroeconomics* **17**(1), 1–34.

O'Neill, J. (1985), 'The Trend in the Male-Female Wage Gap in the United States', *Journal of Labor Economics* **3**(1, Part 2), 91–116.

Penner, A. M., Petersen, T., Hermansen, A. S., Rainey, A., Boza, I., Elvira, M. M., Godechot, O., Hällsten, M., Henriksen, L. F., Hou, F., Mrčela, A. K., King, J., Kodama, N., Kristal, T., Křížková, A., Lippényi, Z., Melzer, S. M., Mun, E., Apascaritei, P., Avent-Holt, D., Bandelj, N., Hajdu, G., Jung, J., Poje, A., Sabanci, H., Safi, M., Soener, M., Tomaskovic-Devey, D. & Tufail, Z. (2022), 'Within-job gender pay inequality in 15 countries', *Nature Human Behaviour* **7**(2), 184–189.

Piccolo, J. (2025), 'People's Understanding of Macroeconomic shocks'.

Pilossoph, L. & Ryngaert, J. (2024), Job Search, Wages, and Inflation, Working Paper 33042, National Bureau of Economic Research.

Pissarides, C. A. (1985), 'Short-Run Equilibrium Dynamics of Unemployment, Vacancies, and Real Wages', *American Economic Review* **75**(4), 676–690.

Reiche, L. (2025), Beyond Groceries: Forecasting Confidence and the Gender Gap in Inflation Expectations, Working Paper 11588, CESifo.

Shiller, R. J. (2017), 'Narrative Economics', *American Economic Review* **107**(4), 967–1004.

Silva, J. I. & Toledo, M. (2009), 'Labor turnover costs and the cyclical behavior of vacancies and unemployment', *Macroeconomic Dynamics* **13**(S1), 76–96.

Sims, C. A., Stock, J. H. & Watson, M. W. (1990), 'Inference in linear time series models with some unit roots', *Econometrica* **58**(1), 113–144.

Spinnewijn, J. (2015), 'Unemployed but optimistic: Optimal insurance design with biased beliefs', *Journal of the European Economic Association* **13**(1), 130–167.

Stantcheva, S. (2024), 'Why Do We Dislike Inflation?', *Brookings Papers on Economic Activity* pp. 1–46.

Topel, R. H. & Ward, M. P. (1992), 'Job mobility and the careers of young men', *The Quarterly Journal of Economics* **107**(2), 439–479.

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.

Wiswall, M. & Zafar, B. (2018), 'Preference for the Workplace, Investment in Human Capital, and Gender', *The Quarterly Journal of Economics* **133**(1), 457–507.

Tables

Table I: Impact Sign and Zero Restrictions in the SVAR

	Demand	**Supply**	**Residual**
Inflation	+	+	0
Unemployment	–	+	0
Gender wage gap	/	/	+

Table II: Gender Differences in Wage Growth and Inflation

	$\Delta \ln w_{i,t} \times 100$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	−0.833***	−0.751***	−0.828***	−0.875***	−0.243	−0.464*	−0.247	−0.367*
	(0.079)	(0.100)	(0.079)	(0.088)	(0.191)	(0.241)	(0.191)	(0.223)
$\Delta\pi$	0.366***	0.256‡	0.406***	0.372	0.231***	22.063‡	0.763***	0.632
	(0.030)	(0.854)	(0.079)	(0.250)	(0.062)	(60.169)	(0.167)	(0.560)
Female × $\Delta\pi$	−0.095***	−0.196*‡	−0.279***	−0.312***	0.111	0.419‡	−0.188	−0.215
	(0.036)	(0.115)	(0.069)	(0.066)	(0.086)	(0.276)	(0.171)	(0.162)
Month FE	No	Yes	No	No	No	Yes	No	No
IV	No	No	Oil Shock	MP Shock	No	No	Oil Shock	MP Shock
Period	1982-2020	1982-2020	1982-2019	1988-2020	1982-2020	1982-2020	1982-2019	1988-2020
Union Coverage					Yes	Yes	Yes	Yes
Observations	755,817	755,817	752,725	623,786	150,905	150,905	150,473	116,279
Adjusted R^2	0.010	0.011	0.010	0.010	0.012	0.013	0.012	0.011

*p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. Wage growth has been winsorized at the 5% level.

‡ Due to inclusion of time fixed effects, $\Delta\pi$ denotes a dummy for $\Delta\pi > 0$.

Figures

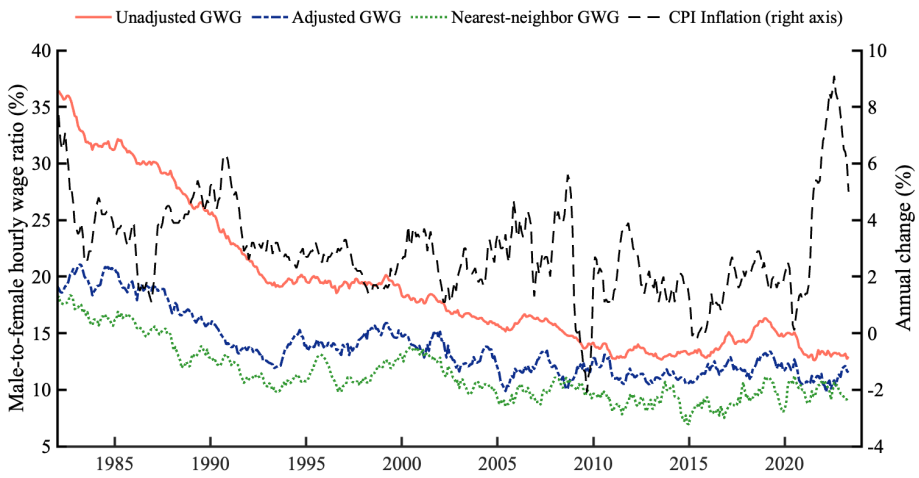
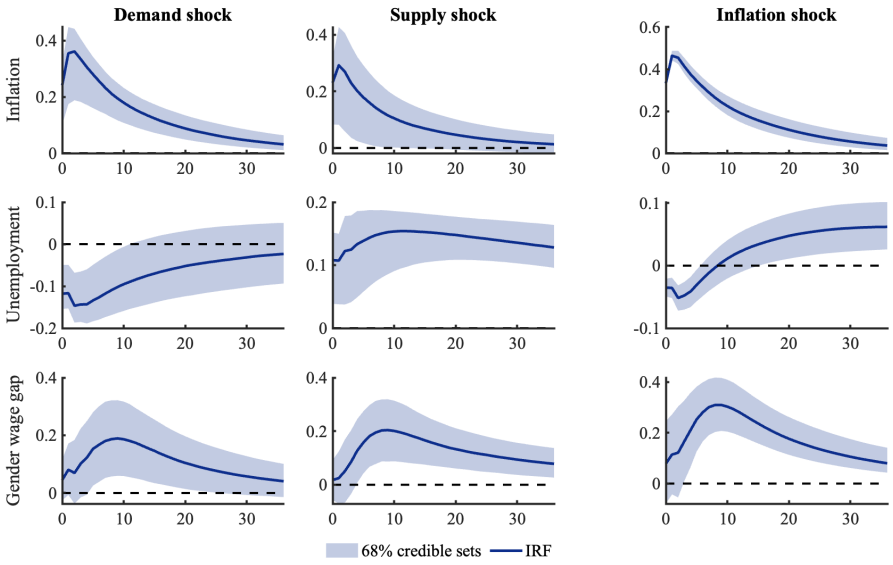
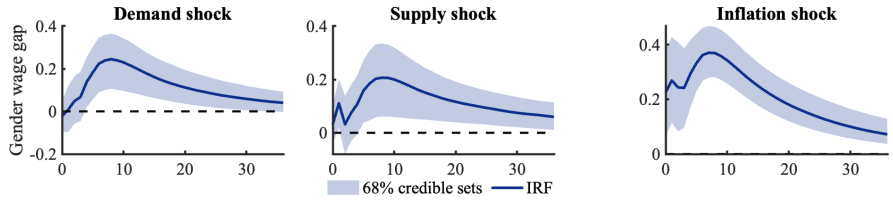


Figure I: Adjusted and unadjusted GWGs (1982-2023)

Notes: Adjusted GWGs are computed using a Kitagawa-Oaxaca–Blinder decomposition of male-female differences in log hourly wages controlling for worker characteristics, industry and occupation, as in Equation 1. Unadjusted GWG are computed in the same way, omitting industry and occupation controls. The figure shows 12-month moving averages to smooth the volatility of the series, allowing a cleaner comparison.



(a) Baseline with KOB decomposition



(b) Baseline with NNM

Figure II: Impulse Responses in the SVAR

Notes: Posterior distributions of impulse responses to estimated one-standard-deviation shocks. Median (solid line) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and the percentiles are computed pointwise. Adjusted GWGs computed using monthly data from January 1982–February 2020, 3-month trailing moving average. The two left columns present the aggregate demand and supply shocks identified using zero and sign restrictions. The third column presents an inflation shock identified using the "max-share" approach (Angeletos et al. 2020).

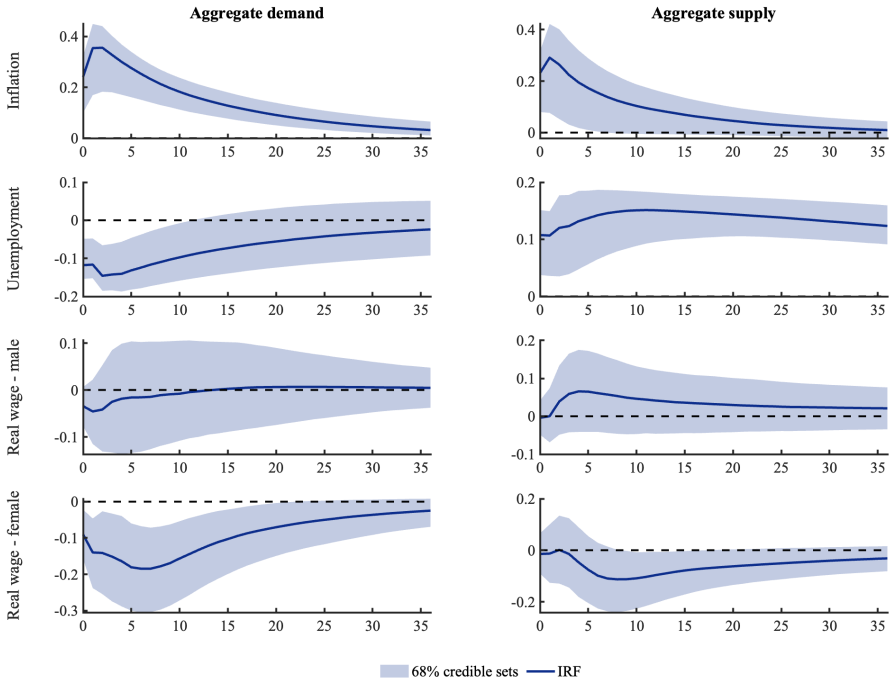


Figure III: Impulse Responses in the SVAR, GWG decomposed

Notes: Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid blue line) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and the percentiles are computed pointwise. Real wages computed using monthly data from January 1982 - February 2020, 3-month trailing moving average. Real wages are adjusted for industry, occupation and other demographics.

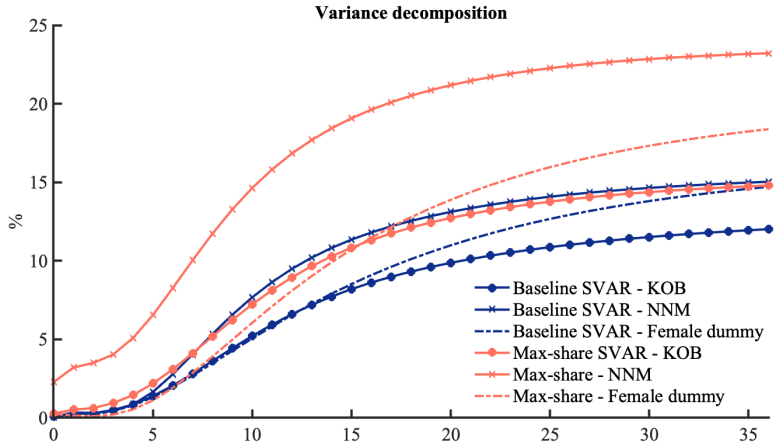


Figure IV: Forecast error variance decompositions

Notes: Forecast error variance decompositions constructed based on pointwise median estimates.

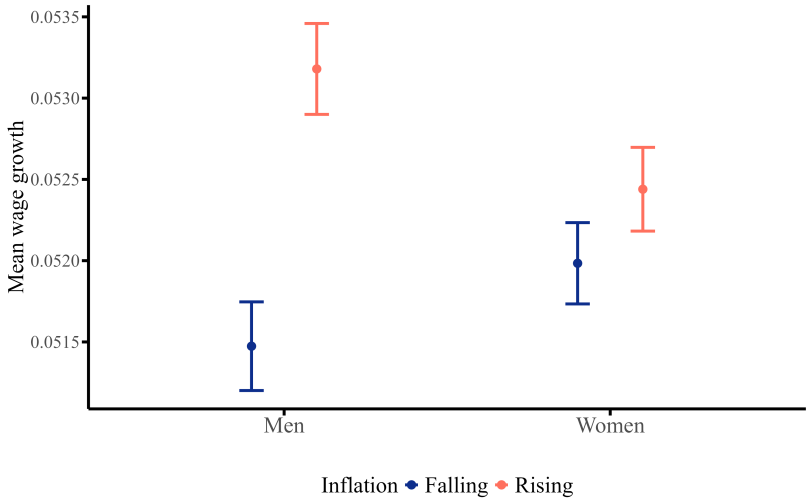


Figure V: Gender differences in Wage Growth by Inflation Regime

Notes: Average 12-month individual log wage growth ($\Delta \ln w_{i,t}$) for men and women, partitioned by the inflation regime. Rising inflation regimes (red) are defined as periods where $\Delta\pi_t > 0$, while falling regimes (blue) are defined as $\Delta\pi_t < 0$. Vertical error bars represent the standard deviation of wage growth within each bin, reflecting the dispersion of individual wage adjustments.

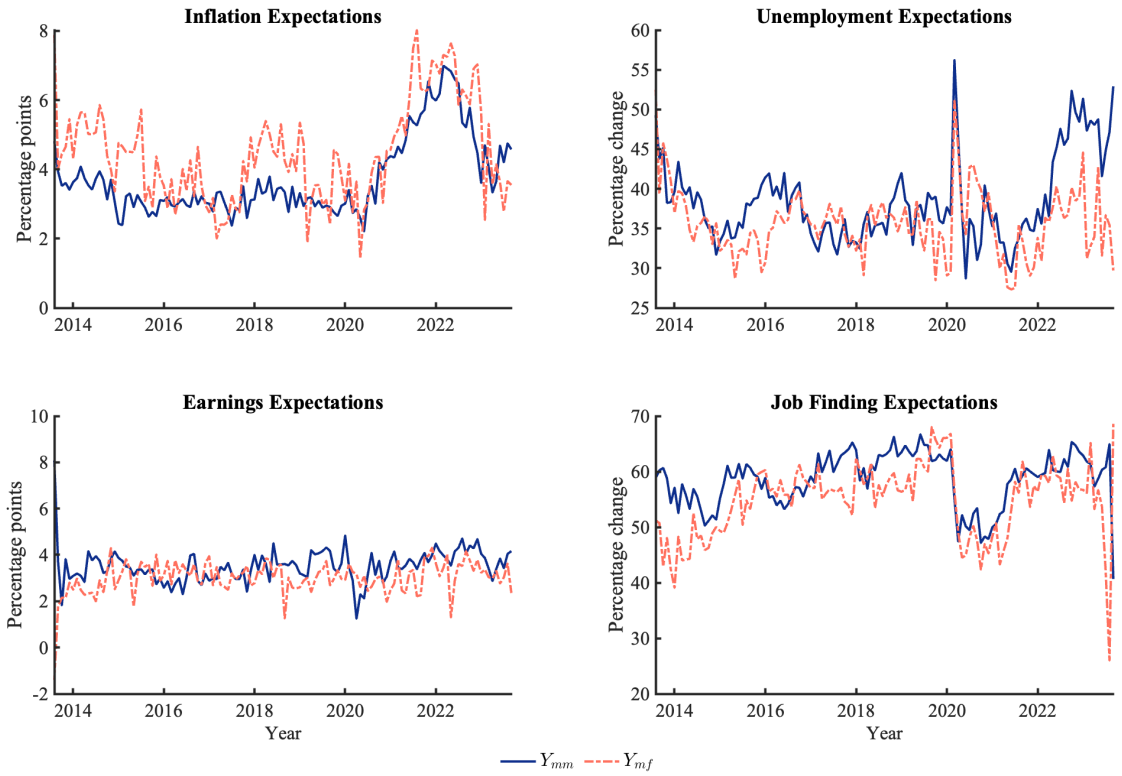
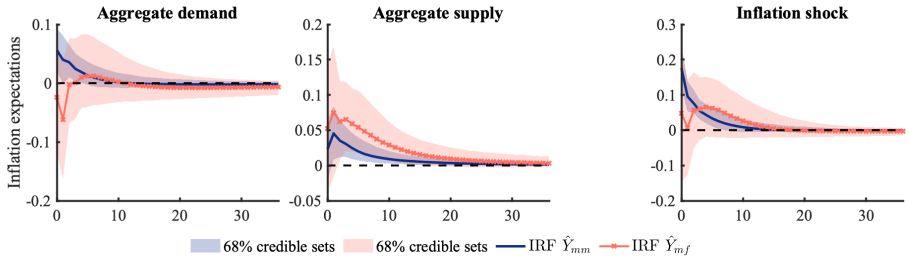
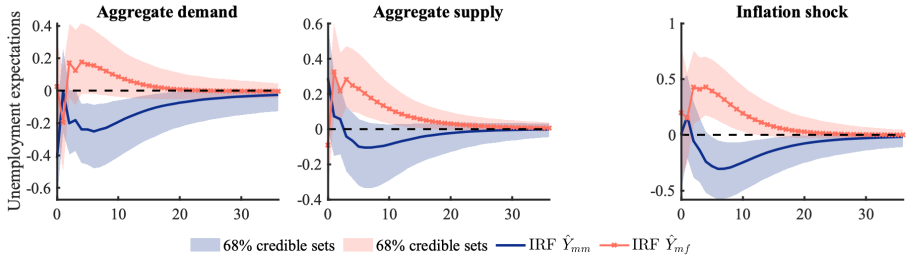


Figure VI: Survey Expectations in the SCE

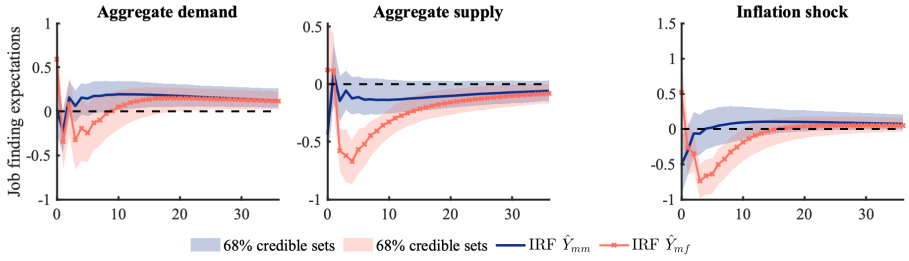
Notes: Women's expectations are plotted in dashed orange and men's expectations are plotted in solid dark blue. Both series stem from the Kitagawa-Oaxaca-Blinder decomposition. Monthly data from August 2013-December 2023.



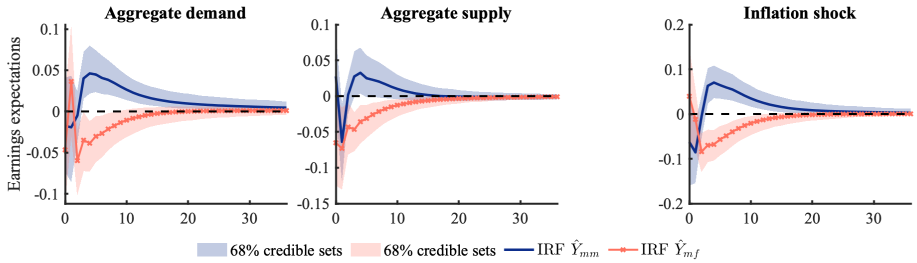
(a) Inflation (12 months)



(b) Unemployment (12 months)



(c) Job Finding (3 months)



(d) Earnings Growth (12 months)

Figure VII: Impulse Responses of Expectations in the SCE to Supply and Demand Shocks

Notes: Women's (orange crossed line) and men's (blue solid line) expectations computed using monthly data from August 2013-February 2020. Posterior distributions of impulse responses to estimated shocks of one standard deviation. Pointwise median (solid and crossed lines) and 68% probability density intervals (shaded areas) based on 10,000 draws. Medians and percentiles are computed pointwise.

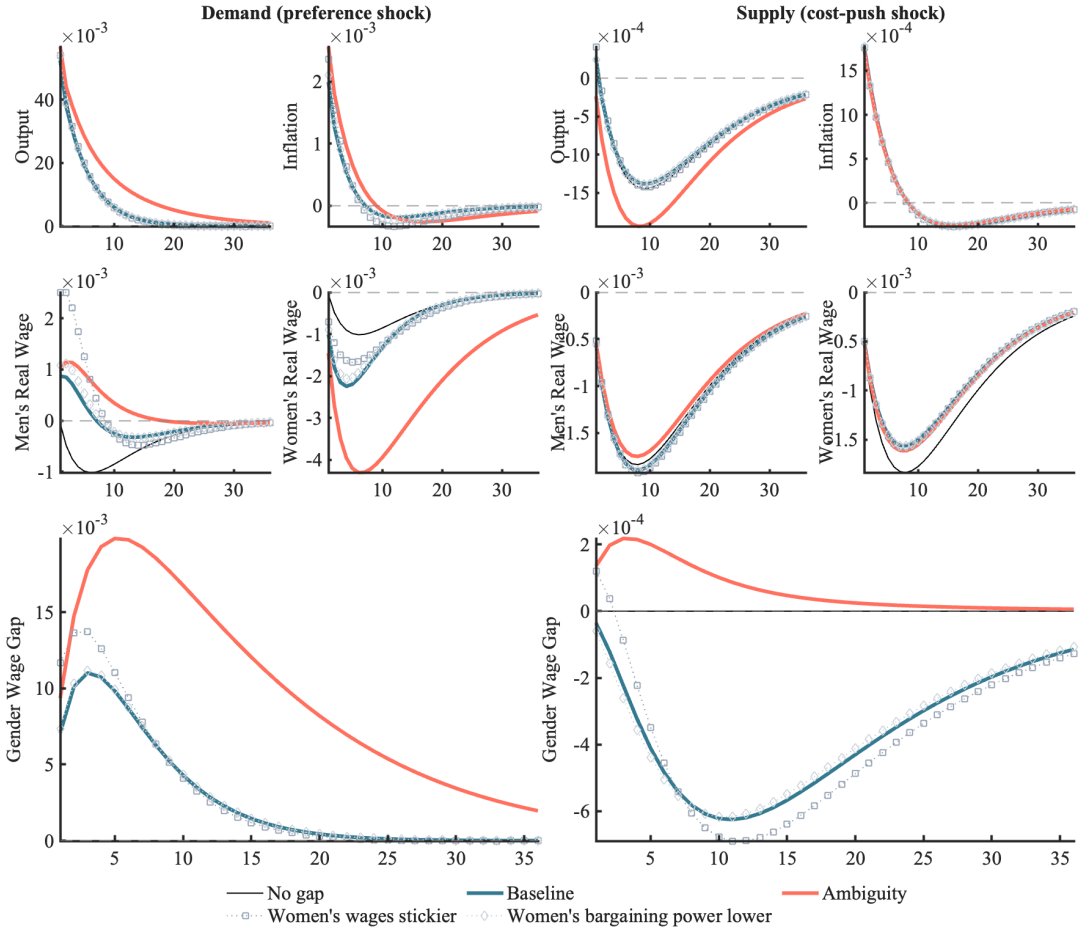


Figure VIII: Impulse responses from the theoretical model

Supplemental Appendix

A Gender wage gap supplementary material

A.1 Alternative measures of the gender wage gap

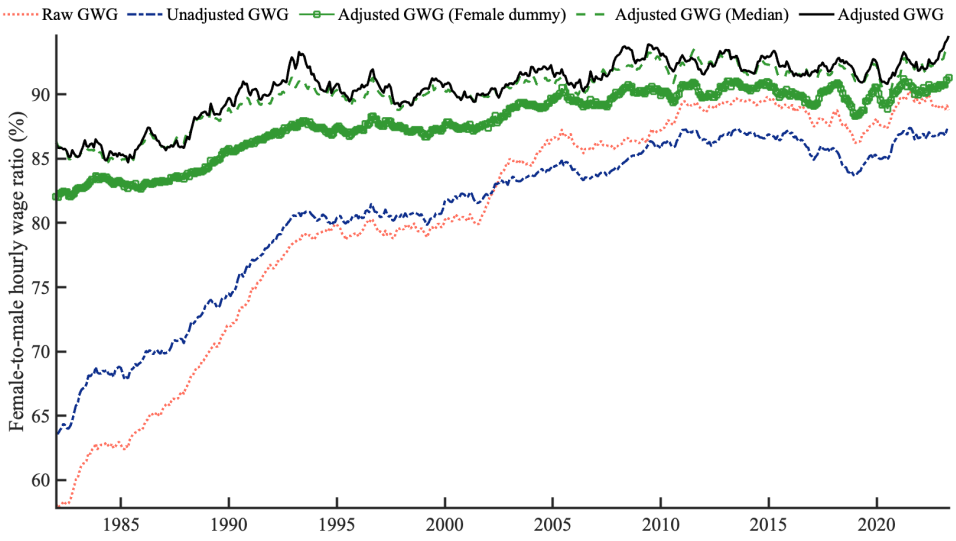


Figure A.1: Different measures of GWG (1982-2023) measured as female to male ratio

Notes: Adjusted GWGs are computed using a traditional Oaxaca–Blinder decomposition of female/male differences in log wages controlling for worker characteristics, industry and occupation computed as in Equation 1. The figure shows 12-month moving averages. Unadjusted GWG are computed in the same way omitting industry and occupation controls. Female coefficient describes 1 minus the female coefficient in a linear model on log wages with the same controls as the adjusted series. Median wage ratio is computed using log hourly earnings.

A.2 Gender wage gaps across demographic groups

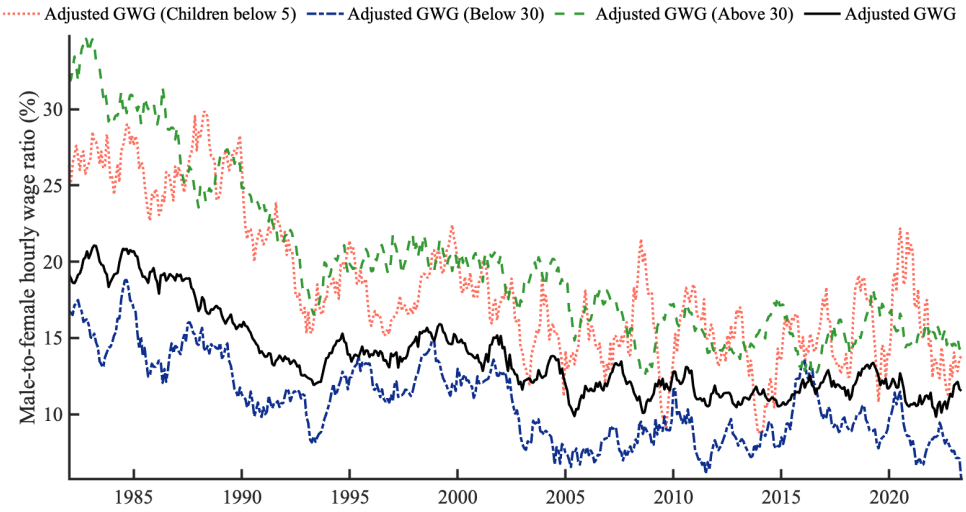


Figure A.2: Adjusted GWG (1982-2023) for different demographic groups

Notes: Adjusted GWGs are computed using the baseline Kitagawa-Oaxaca-Blinder decomposition of male-female differences in log wages controlling for worker characteristics, industry and occupation computed as in Equation 1. The figure shows 12-month moving averages.

A.3 Robustness checks on the SVAR

A.3.1 Cointegration test

Table A.1: Johansen cointegration (trace) test

No. of cointegrating relations r	test statistic	p-value	eigenvalue
$r = 0$	53.9461	0.0010	0.0792
$r = 1$	16.5835	0.0342	0.0225
$r = 2$	6.2743	0.0125	0.0138

Notes: The test assesses the null of at most r cointegrating relations for the baseline set of variables: CPI inflation, the unemployment rate and the adjusted GWG. The test includes 3 lags as in the baseline VAR specification.

A.3.2 Alternative model and variable specifications

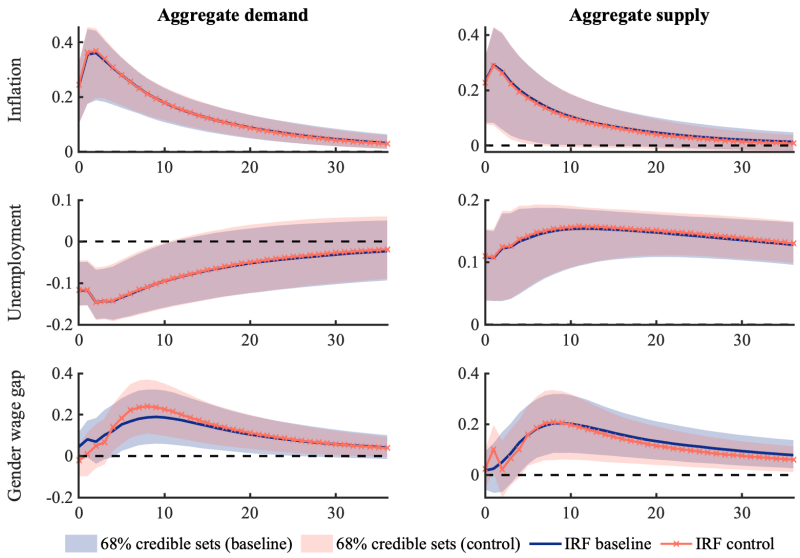
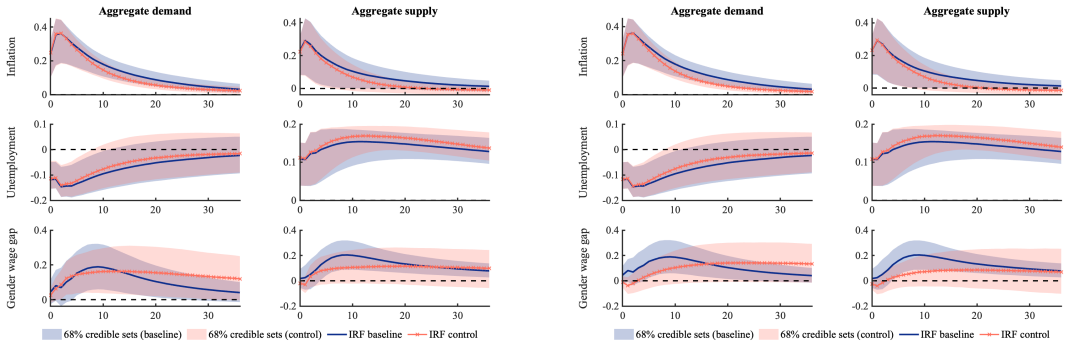


Figure A.3: Impulse Responses in the SVAR - baseline and NNM

Notes: Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid blue and crossed orange lines) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and the percentiles are defined at each point in time. Adjusted and matched GWGs are computed using monthly data from January 1982 - February 2020.

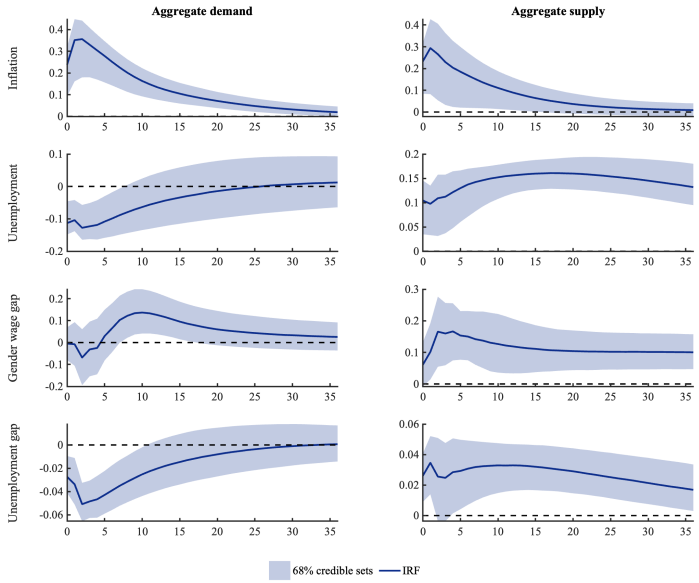


(a) Adjusted vs. unadjusted GWGs

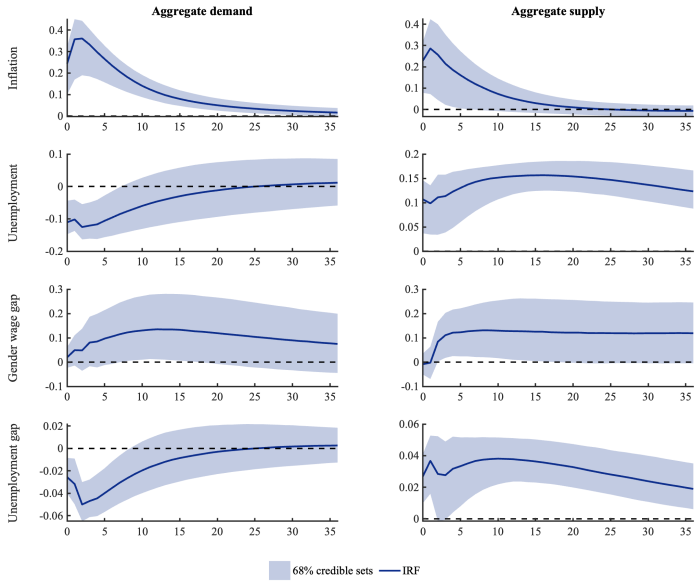
(b) Adjusted vs. raw GWGs

Figure A.4: Impulse Responses in the SVAR under Alternative GWG Measures

Notes: Adjusted, unadjusted, and raw GWGs computed using monthly data from January 1982–February 2020, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid and crossed lines) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and percentiles are defined at each point in time.



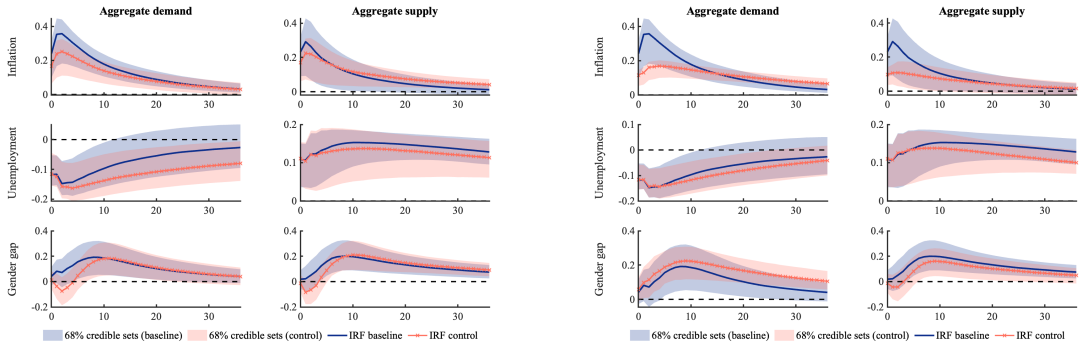
(a) Adjusted GWGs



(b) Unadjusted GWGs

Figure A.5: Impulse Responses in the SVAR Including the Unemployment Gap

Notes: Adjusted and unadjusted GWGs computed using monthly data from January 1982–February 2020, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid blue line) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and percentiles are defined at each point in time.



(a) PCE inflation

(b) Core CPI inflation (ex. food & energy)

Figure A.6: Impulse Responses in the SVAR

Notes: Adjusted GWGs computed using monthly data from January 1982–February 2020, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid and crossed lines) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and percentiles are defined at each point in time.

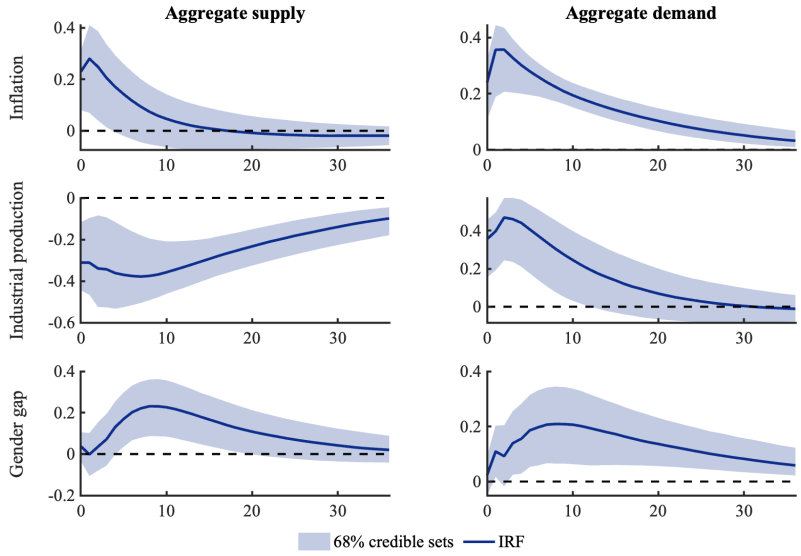
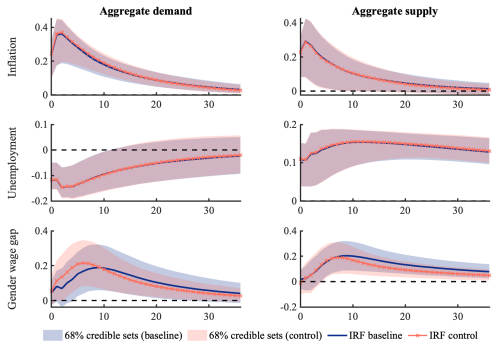
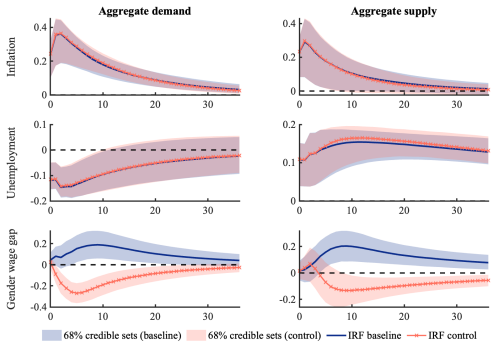


Figure A.7: Impulse Responses in the SVAR with Industrial Production

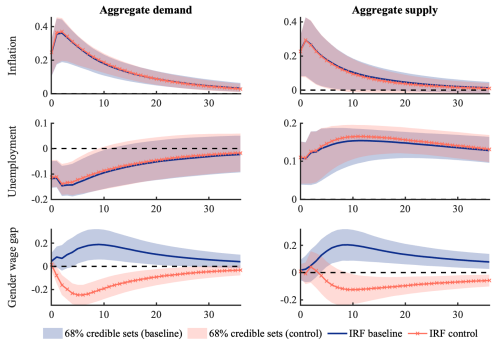
Notes: Adjusted GWGs computed using monthly data from January 1982 - February 2020, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid blue line) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and the percentiles are defined at each point in time.



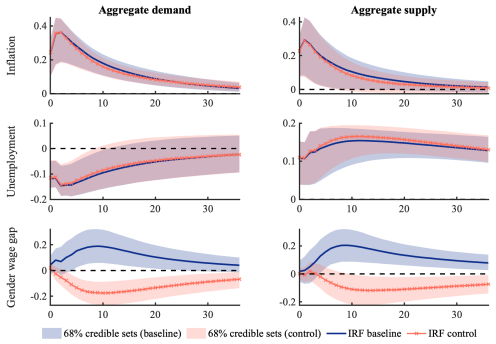
(a) Weekly earnings



(b) Inverted GWG (female characteristics)



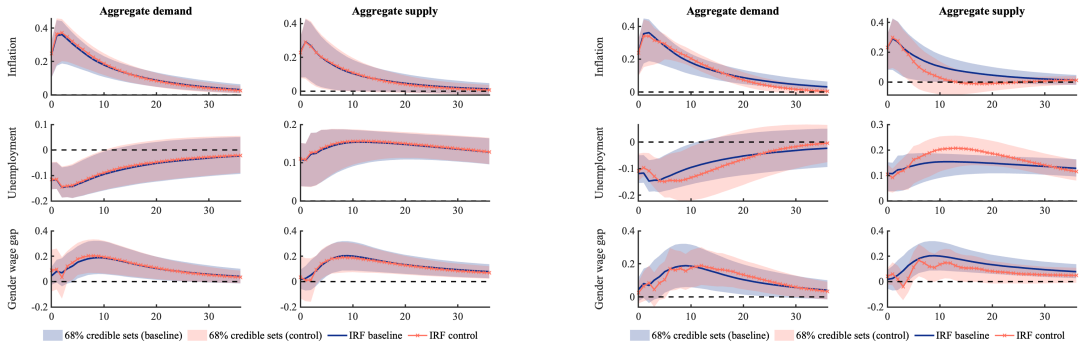
(c) Median GWG



(d) Alternative GWG (Penner specification)

Figure A.8: Impulse Responses in the SVAR under Alternative Gender Wage Gap Measures

Notes: Adjusted GWGs in hourly wages and weekly earnings computed using monthly data from January 1982–February 2020, 3-month trailing moving average. Specifications include inverted GWGs (men's wages with female characteristics), median-based GWGs, and the alternative construction following Penner (2022). Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid and crossed lines) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and percentiles are defined at each point in time.



(a) Without moving average (b) With 6 lags

Figure A.9: Impulse Responses in the SVAR under Alternative Specifications

Notes: Adjusted GWGs computed using monthly data from January 1982–February 2020. The moving-average specification uses a 3-month trailing average where indicated. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid and crossed lines) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and percentiles are defined at each point in time.

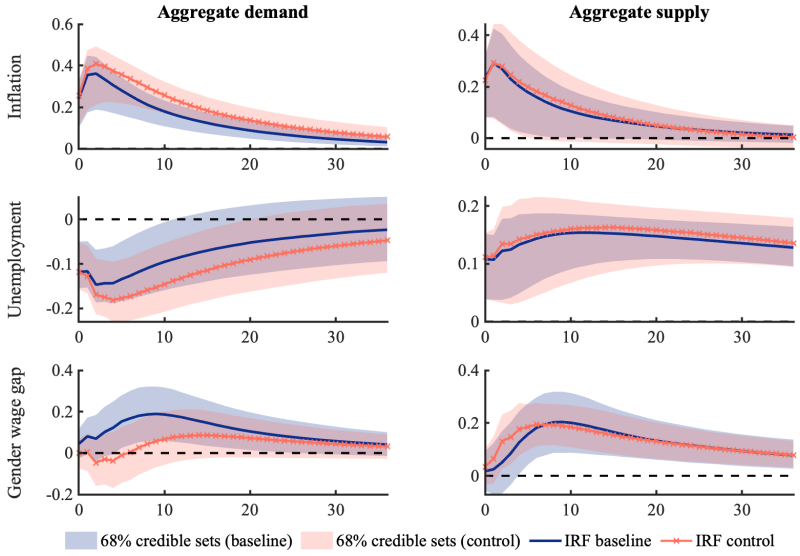
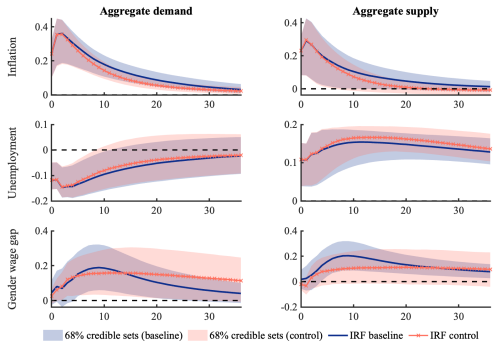
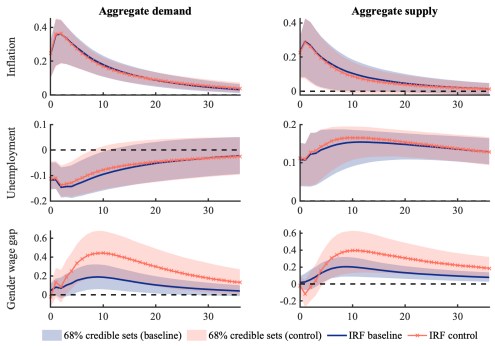


Figure A.10: Impulse Responses in the SVAR including Covid

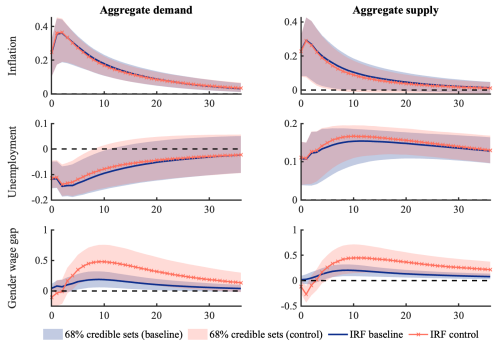
Notes: Adjusted GWGs computed using monthly data from January 1982 - December 2023, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid and crossed lines) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and the percentiles are defined at each point in time.



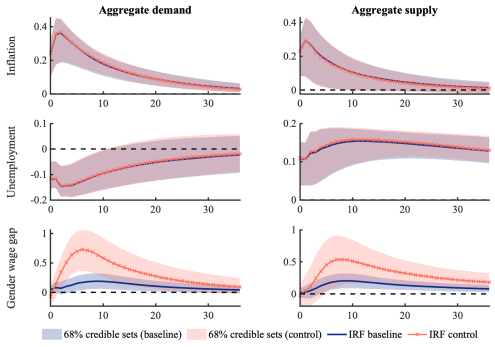
(a) Below 30



(b) Above 30



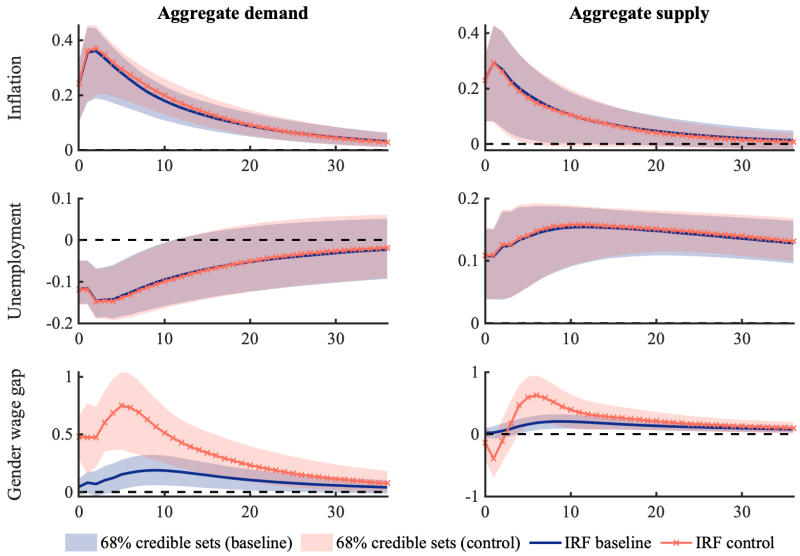
(c) Above 40



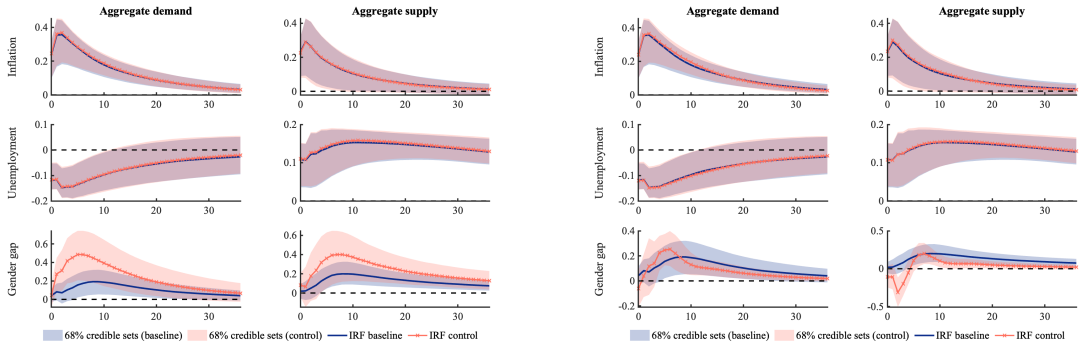
(d) Above 50

Figure A.11: Impulse Responses in the SVAR by Age Group

Notes: Adjusted GWGs computed using monthly data from January 1982–February 2020, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid and crossed lines) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and percentiles are defined at each point in time.



(a) Workers with children below 5 years old



(b) Married workers

(c) Single workers

Figure A.12: Impulse Responses in the SVAR by Family and Marital Status

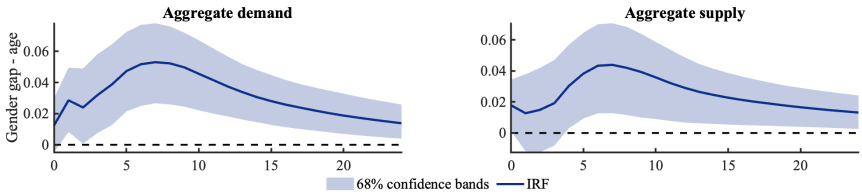
Notes: Adjusted GWGs of employees with children below 5 years and by marital status computed using monthly data from January 1982–February 2020, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid and crossed lines) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and percentiles are defined at each point in time.

A.3.3 Which characteristics drive the response?

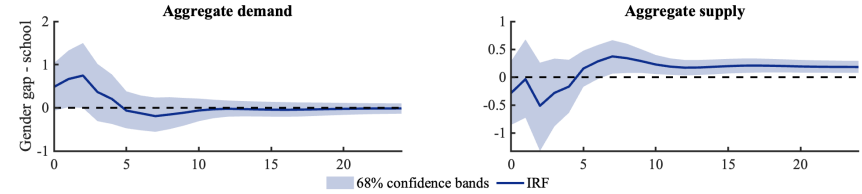
To understand which characteristics drive the response of the adjusted GWG to inflationary demand and supply shocks, we decompose the gap into its underlying sources by examining the dynamics of gender differences in the KOB coefficients. Specifically, we estimate separate VARs for each element of the wage structure – including returns to education, experience (age), race, marital status, occupation, and industry – using as dependent variables the time series of coefficient differences between men and women. This approach allows us to trace how gender-specific returns to observable characteristics respond to inflationary shocks and how each component contributes to the evolution of the adjusted GWG.

We begin by examining gender differences in the estimated coefficients on individual characteristics, as shown in Figures A.13 and A.14. Several individual characteristics contribute meaningfully to the inflation-induced widening of the adjusted GWG. In particular, the gender gap in returns to age and education (both general schooling and college) widens significantly following supply shocks, indicating that men's wages respond more strongly to inflation along these dimensions than women's, even conditional on observables. Similar patterns are also present following demand shocks, especially for age. In contrast, the coefficient gaps for Black workers respond negatively to both types of shocks, suggesting that women in these groups experience relatively more favorable wage dynamics than their male counterparts. Coefficient gaps associated with marital status are positive for both married and single individuals, implying that both groups contribute to the overall inflation-induced widening of the adjusted GWG. By contrast, the contribution of high household income is negative following supply shocks, indicating that the widening of the GWG in response to supply shocks is smaller for individuals in higher-income households. Taken together, these results suggest that the aggregate response of the adjusted GWG to inflationary shocks is primarily driven by gender asymmetries in the returns to experience and education, while race and household income partially offset these effects. For different industries (see Figures A.15 and A.16), the effects of inflationary shocks on the adjusted GWG are heterogeneous, both in magnitude and direction, and often differ across demand and supply shocks. In sectors like Business, Manufacturing, Mining, Public, Retail, Transport and Wholesale, the gender gap decreases following both types of shocks, suggesting a relative improvement in women's wage outcomes. By contrast, in Construction, the gap increases in response to both demand and supply shocks, pointing to a disproportionate negative impact on women. Other sectors, such as Entertainment and Finance, show more muted or short-lived effects,

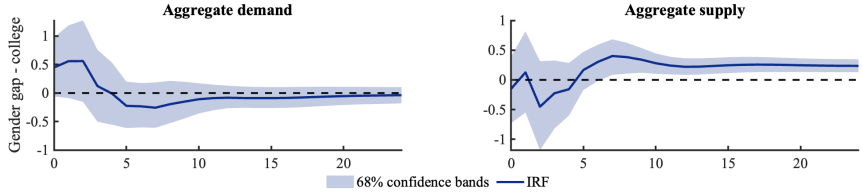
with generally negative but modest responses. These findings highlight that, unlike the consistent effects observed for individual characteristics such as education and experience, industry-level responses to inflation are more variable and can either exacerbate or narrow gender wage disparities depending on sector-specific labor dynamics.



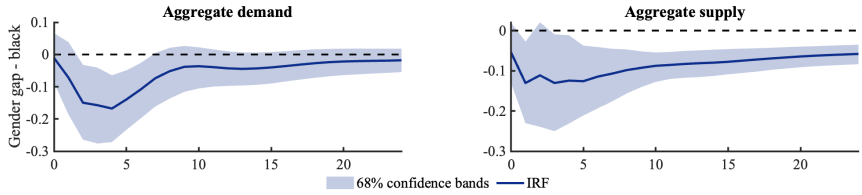
(a) Age



(b) School



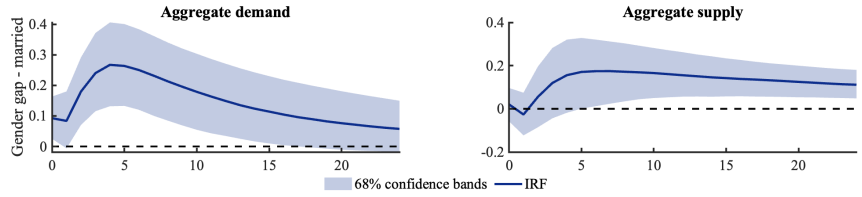
(c) College



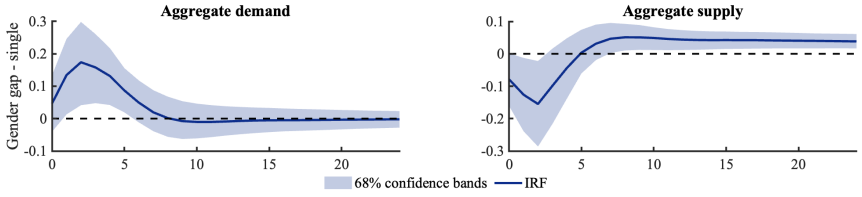
(d) Black

Figure A.13: Impulse Responses of the coefficients of the KOB decomposition to Supply and Demand Shocks

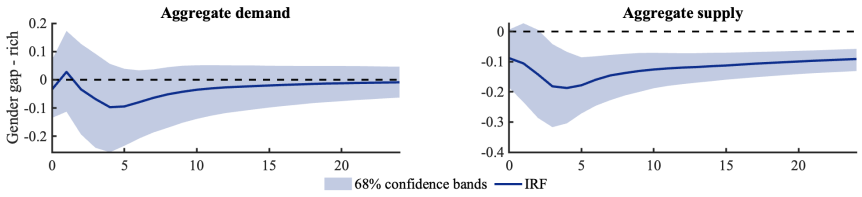
Notes: Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid line) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and the percentiles are defined at each point in time.



(a) Married



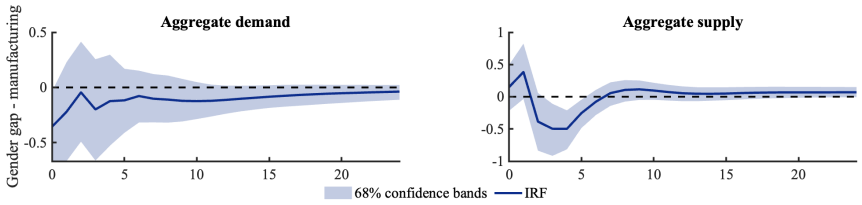
(b) Single



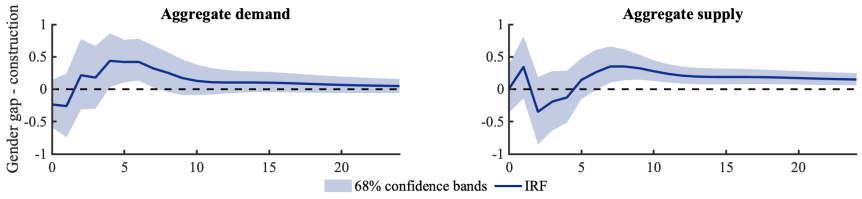
(c) High household income

Figure A.14: Impulse Responses of the coefficients of the KOB decomposition to Supply and Demand Shocks

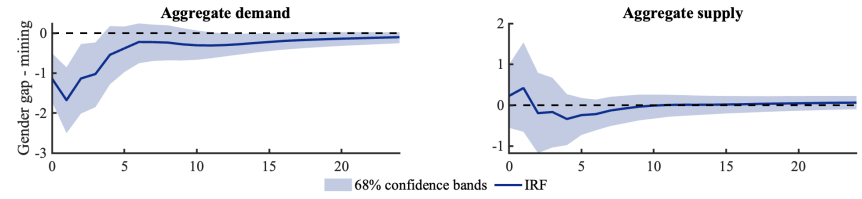
Notes: Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid line) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and the percentiles are defined at each point in time.



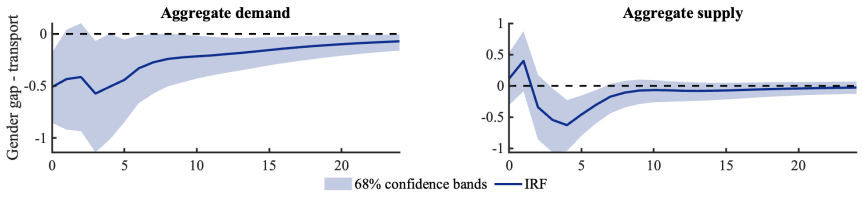
(a) Manufacturing



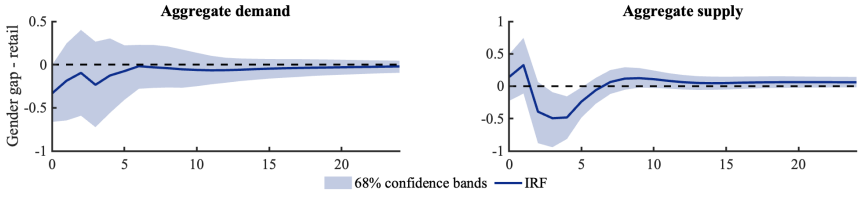
(b) Construction



(c) Mining



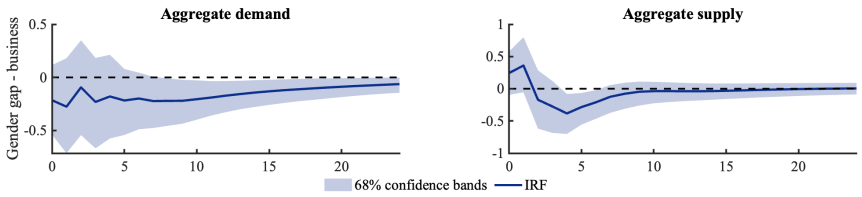
(d) Transport



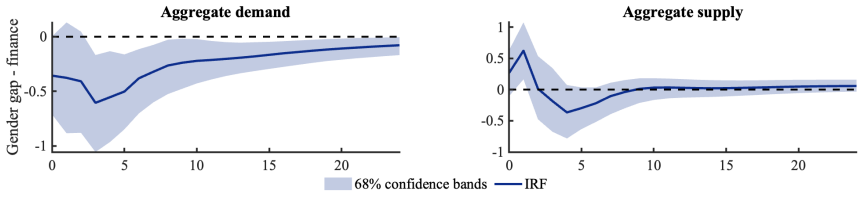
(e) Retail

Figure A.15: Impulse Responses of the coefficients of the KOB decomposition to Supply and Demand Shocks

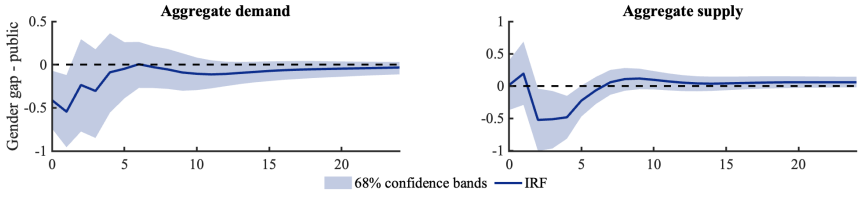
Notes: Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid line) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and the percentiles are defined at each point in time.



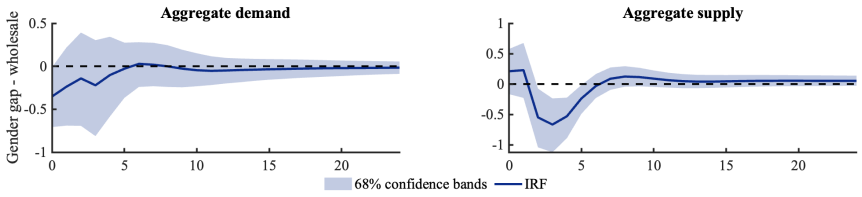
(a) Business



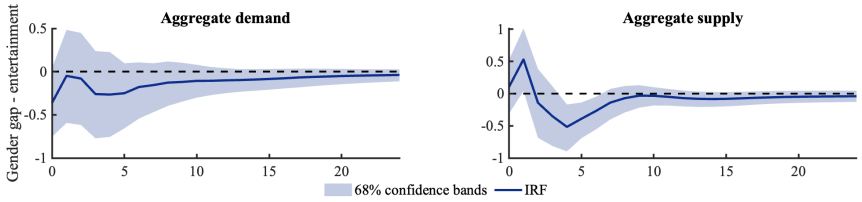
(b) Finance



(c) Public



(d) Wholesale



(e) Entertainment

Figure A.16: Impulse Responses of the coefficients of the KOB decomposition to Supply and Demand Shocks

Notes: Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid line) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and the percentiles are defined at each point in time.

A.4 Robustness on the micro data

Table A.2: First-Stage Regressions

	$\Delta\pi_{t-12}$			
	(1)	(2)	(3)	(4)
$\sum_{k=6}^{18}$ Monetary Policy Surprise$_{t-k}$	−0.937*	−0.959**		
	(0.537)	(0.456)		
$\sum_{k=0}^{11}$ Oil Surprise$_{t-k}$			0.123***	0.089***
			(0.014)	(0.013)
U_{t-12}	0.069	−0.065	0.050	0.007
	(0.048)	(0.042)	(0.036)	(0.036)
π_{t-12}	−0.636***	−0.745***	−0.485***	−0.469***
	(0.049)	(0.049)	(0.025)	(0.024)
Period	1988-2023	1988-2020	1982-2023	1982-2019
Observations	414	368	516	468
R^2	0.342	0.388	0.492	0.497
F Statistic	71.033***	76.830***	165.069***	152.625***
F Statistic (instrument only)	3.04*	4.41**	78.67***	45.64***

*p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.

Table A.3: Gender Differences in Wage Growth and Inflation, Extensions to Table II

	$\Delta \ln w_{i,t} \times 100$					
	(1)	(2)	(3)	(4)	(5)	(6)
Female	−0.813***	−0.770***	−0.078	−0.865***	−0.798***	−0.183***
	(0.080)	(0.077)	(0.059)	(0.088)	(0.085)	(0.066)
$\Delta\pi$	0.485***	0.500***	0.442***	0.208	0.400	0.362
	(0.079)	(0.056)	(0.079)	(0.251)	(0.248)	(0.248)
ΔU	−0.485***			−0.287***		
	(0.046)			(0.055)		
Female × $\Delta\pi$	−0.250***	−0.194***	−0.357***	−0.289***	−0.299***	−0.383***
	(0.071)	(0.053)	(0.069)	(0.071)	(0.061)	(0.066)
Female × ΔU	0.089			0.063		
	(0.062)			(0.075)		
IV	Oil Shock	Oil Shock	Oil Shock	MP Shock	MP Shock	MP Shock
Period	1982-2019	1982-2023‡	1982-2019	1988-2020	1988-2023‡	1988-2020
Industry FE	Yes	Yes	No	Yes	Yes	No
Occupation FE	Yes	Yes	No	Yes	Yes	No
Observations	752,725	805,982	752,725	623,786	673,951	623,786
Adjusted R^2	0.010	0.010	0.006	0.010	0.010	0.006

*p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. Wage growth has been winsorized at the 5% level.

‡ We include a dummy for the COVID period from March-August 2020.

Table A.4: Gender Differences in Labor Market Transitions

	Certain Transition	Same Industry	Same Occupation	Certain Transition	Same Industry	Same Occupation
	(1)	(2)	(3)	(4)	(5)	(6)
Female	−0.005***	0.005***	−0.0001	−0.004***	0.004**	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
$\Delta\pi$	−0.005***	0.006***	−0.0002	−0.014***	0.016***	0.012***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)
Female × $\Delta\pi$	−0.001	0.0001	−0.002	−0.001	0.001	−0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
IV	Oil Shock	Oil Shock	Oil Shock	MP Shock	MP Shock	MP Shock
Period	1982-2019	1982-20219	1982-2019	1988-2020	1988-2020	1988-2020
Observations	752,725	752,725	752,725	623,786	623,786	623,786
Adjusted R^2	0.092	0.117	0.121	0.090	0.116	0.121

*p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.

We define as a certain transition if a respondent is not in the same industry and is not in the same occupation.

B SCE Supplementary Material

B.1 Questionnaire

Next, we would like to ask you for your expectations about the economy. Of course, no one can know the future. These questions have no right or wrong answers - we are interested in your views and opinions.

Q4new
What do you think is the percent chance that 12 months from now the unemployment rate in the U.S. will be higher than it is now?
Ruler & box

Q8v2
The next few questions are about inflation. Over the next 12 months, do you think that there will be inflation or deflation? (Note: deflation is the opposite of inflation)

- Inflation
- Deflation (the opposite of inflation)

Q8v2part2
What do you expect the rate of [inflation (if Q8v2=inflation)/deflation (if Q8v2=deflation)] to be over the next 12 months? Please give your best guess.
Over the next 12 months, I expect the rate of [inflation/deflation] to be __ %

Q22new
Suppose you were to lose your ["main" if more than one] job this month. What do you think is the percent chance that within the following 3 months, you will find a job that you will accept, considering the pay and type of work?
Ruler & box

Q23v2
Please think ahead to 12 months from now. Suppose that you are working in the exact same ["main" if more than one] job at the same place you currently work, and working the exact same number of hours. What do you expect to have happened to your earnings on this job, before taxes and deductions?
Twelve months from now, I expect my earnings to have...

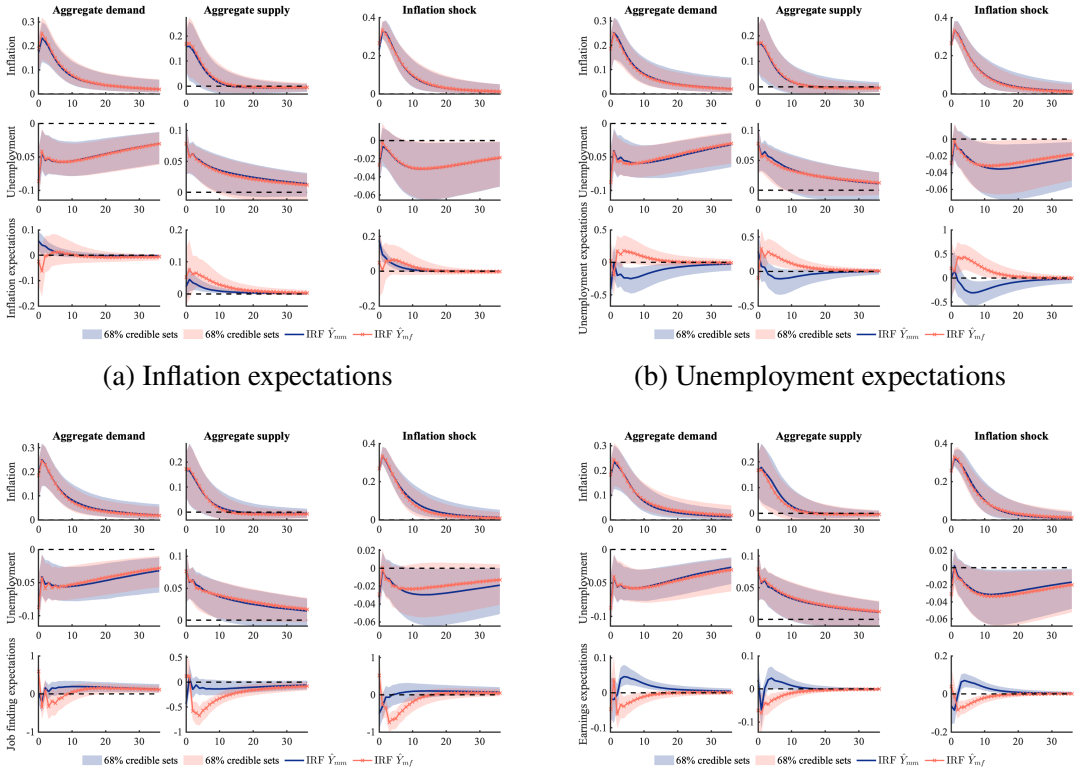
- increase by 0% or more

- decrease by 0% or more

Q23v2part2

By about what percent do you expect your earnings to have [increased/decreased as in Q23]? Please give your best guess. Twelve months from now, I expect my earnings to have [increased/decreased] by __ %

B.2 SCE survey responses



(a) Inflation expectations

(b) Unemployment expectations

(c) Job-finding expectations

(d) Earnings expectations

Figure B.1: Impulse Responses of SCE Expectations to Supply and Demand Shocks using NNM

Notes: Women's (orange crossed line) and men's (blue solid line) expectations computed using monthly data from August 2013–February 2020. Posterior distributions of impulse responses to estimated shocks of one standard deviation. Median (solid and crossed lines) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and percentiles are defined at each point in time.

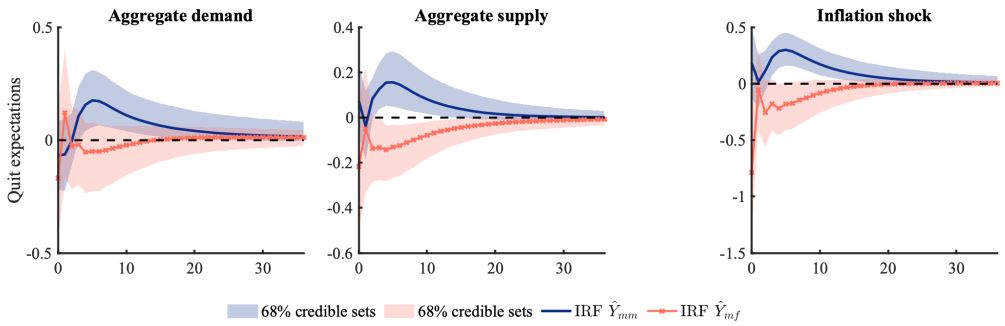
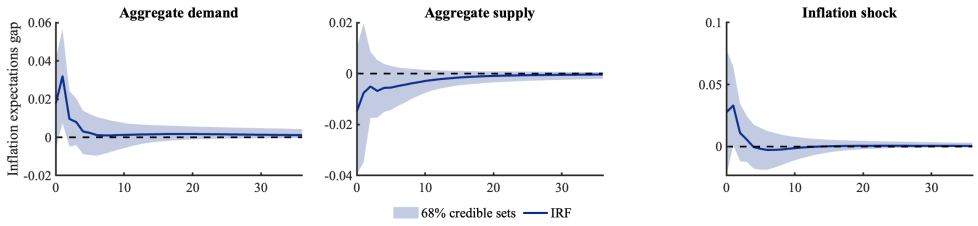
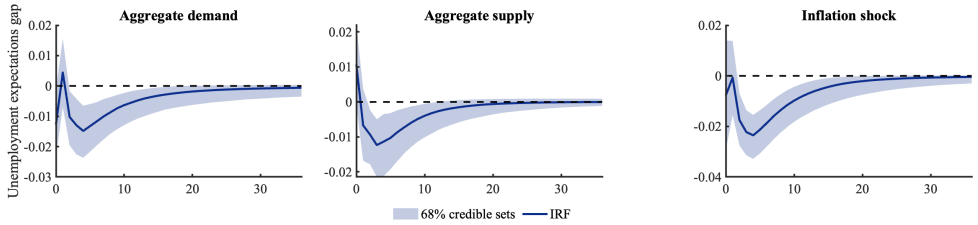


Figure B.2: Impulse Responses of SCE Expectations to Supply and Demand Shocks using KOB Decomposition

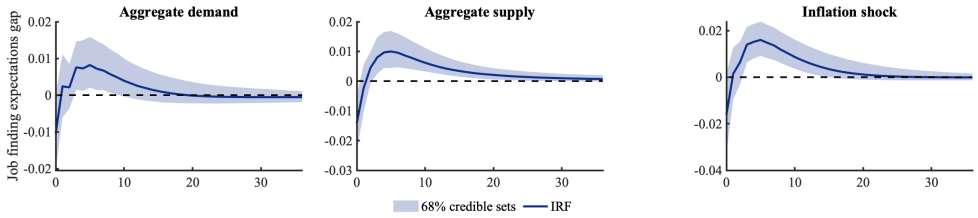
Notes: Women's (orange crossed line) and men's (blue solid line) expectations computed using monthly data from August 2013–February 2020. Posterior distributions of impulse responses to estimated shocks of one standard deviation. Median (solid and crossed lines) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and percentiles are defined at each point in time.



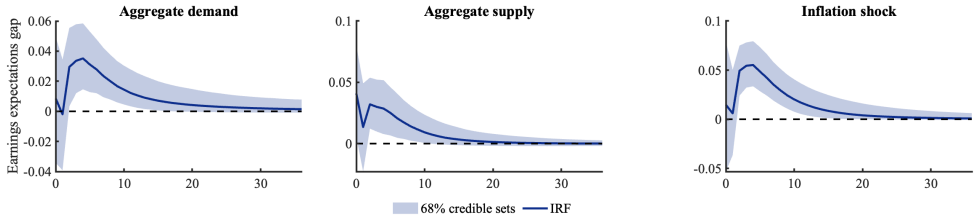
(a) Inflation (12 months)



(b) Unemployment (12 months)



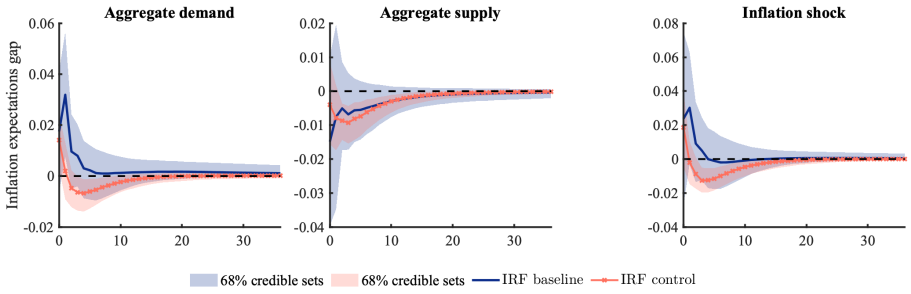
(c) Job Finding (3 months)



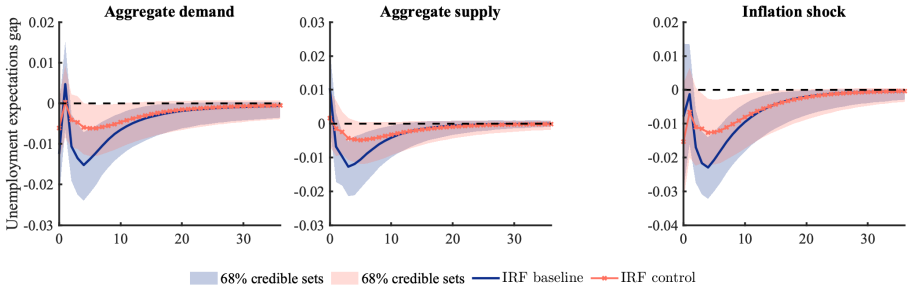
(d) Earnings Growth (12 months)

Figure B.3: Impulse Responses of Gender Gaps in Expectations in the SCE to Supply and Demand Shocks using KOB Decomposition

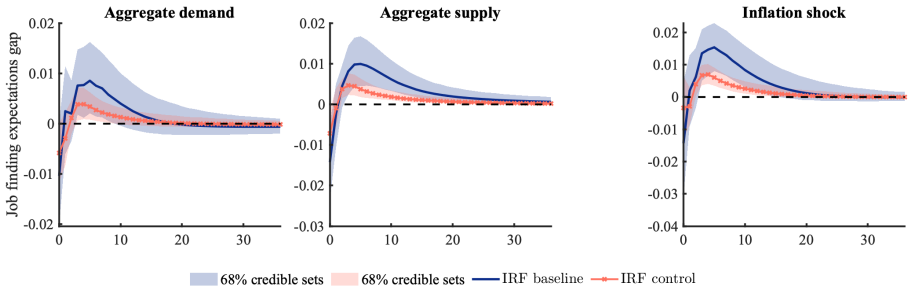
Notes: Posterior distributions of impulse responses to estimated shocks of one standard deviation. Median (solid line) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and the percentiles are defined at each point in time.



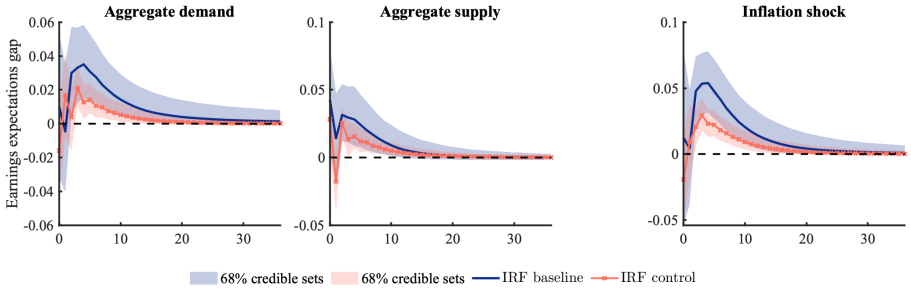
(a) Inflation (12 months)



(b) Unemployment (12 months)



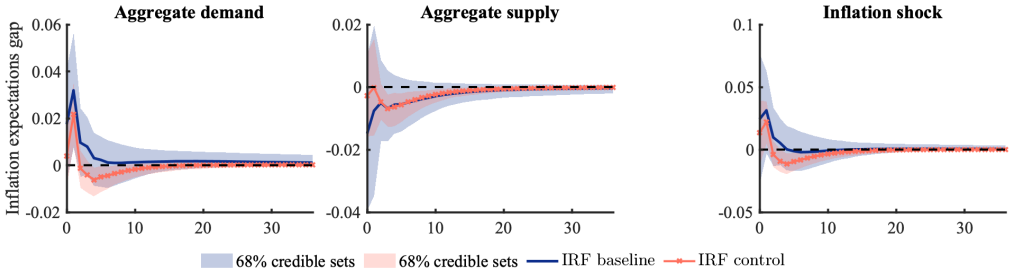
(c) Job Finding (3 months)



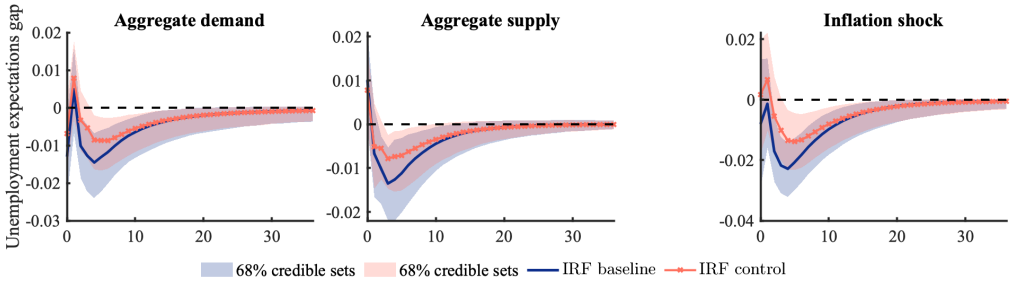
(d) Earnings Growth (12 months)

Figure B.4: Impulse Responses of Gender Gaps in Expectations in the SCE to Supply and Demand Shocks using NNM

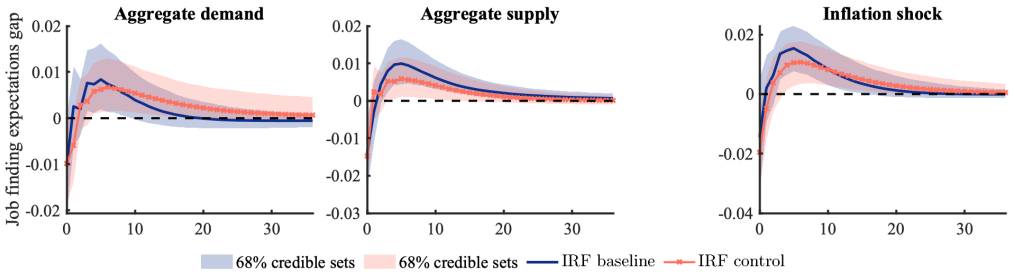
Notes: Posterior distributions of impulse responses to estimated shocks of one standard deviation. Median (solid line) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and the percentiles are defined at each point in time.



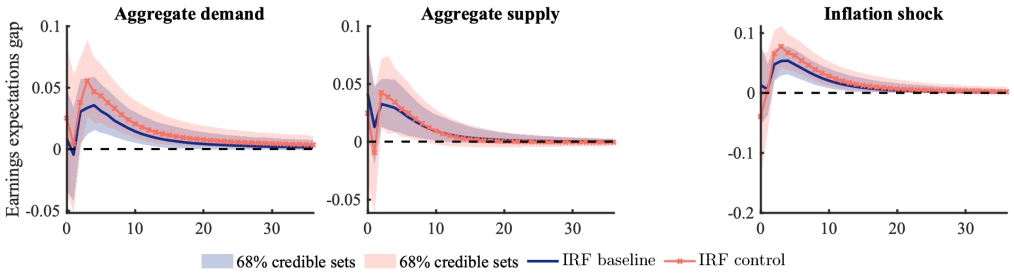
(a) Inflation (12 months)



(b) Unemployment (12 months)



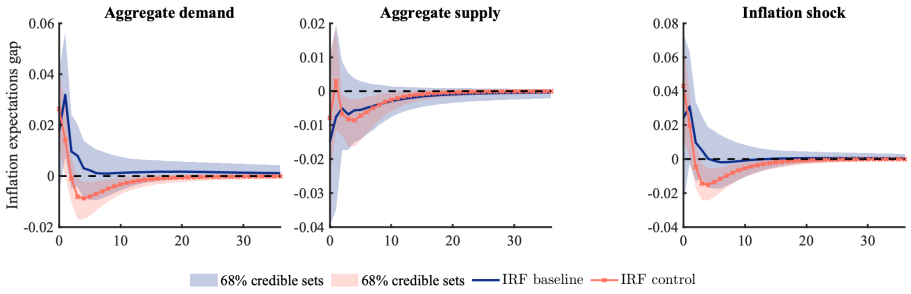
(c) Job Finding (3 months)



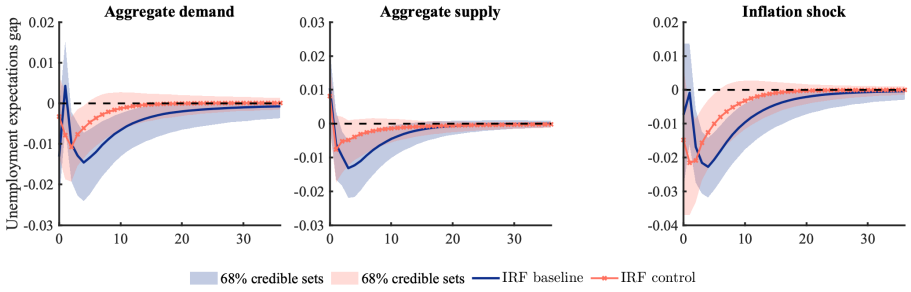
(d) Earnings Growth (12 months)

Figure B.5: Impulse Responses of Gender Gaps in Expectations in the SCE to Supply and Demand Shocks using Raw Data

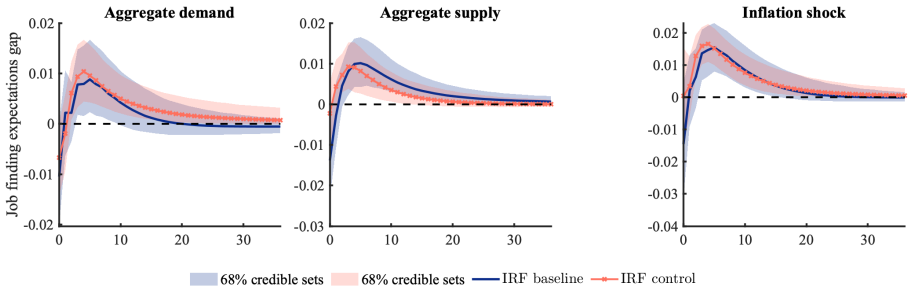
Notes: Posterior distributions of impulse responses to estimated shocks of one standard deviation. Median (solid line) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and the percentiles are defined at each point in time.



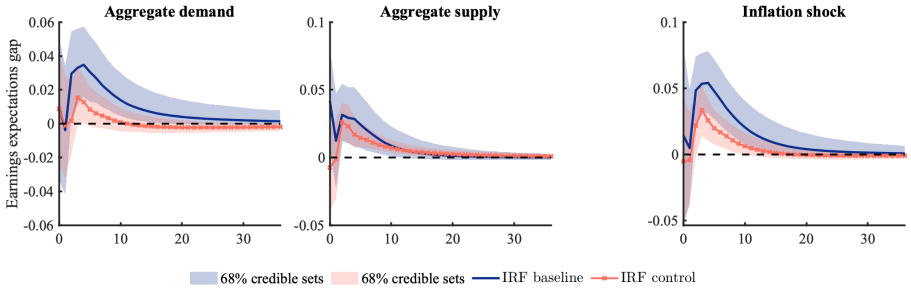
(a) Inflation (12 months)



(b) Unemployment (12 months)



(c) Job Finding (3 months)



(d) Earnings Growth (12 months)

Figure B.6: Impulse Responses of Gender Gaps in Expectations in the SCE to Supply and Demand Shocks among Singles

Notes: Posterior distributions of impulse responses to estimated shocks of one standard deviation. Median (solid line) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and the percentiles are defined at each point in time.

C Experimental Data

To benchmark our observational findings against controlled micro-evidence, we utilize the publicly available replication package for Andre et al. (2022).

To align their experimental dataset with our empirical focus on household belief dynamics, we apply two main modifications to the original replication code. While the original study surveys both U.S. households and professional macroeconomists/experts, we restrict the estimation sample strictly to households, dropping all expert respondents to isolate non-professional belief dynamics. We then partition the household sample by gender to separately evaluate the average subjective predictions and associated narrative channels for male and female respondents.

Table C.1: Gender gap in forecast revisions under hypothetical vignettes

	Oil price			Federal funds rate		
	$\Delta\pi$	Δu	Δu	$\Delta\pi$	Δu	Δu
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.143*	0.141**	−0.276**	0.142**	−0.063	0.091
	(0.074)	(0.069)	(0.111)	(0.061)	(0.063)	(0.065)
Female x $\Delta\pi$ correct			0.570***			−0.574***
			(0.112)			(0.100)
Constant	0.420***	0.250***	0.250***	0.094**	0.136***	0.136***
	(0.053)	(0.050)	(0.050)	(0.047)	(0.046)	(0.046)
Observations	1,099	1,099	1,099	1,123	1,123	1,123
R^2	0.003	0.004	0.030	0.005	0.001	0.033

*p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.

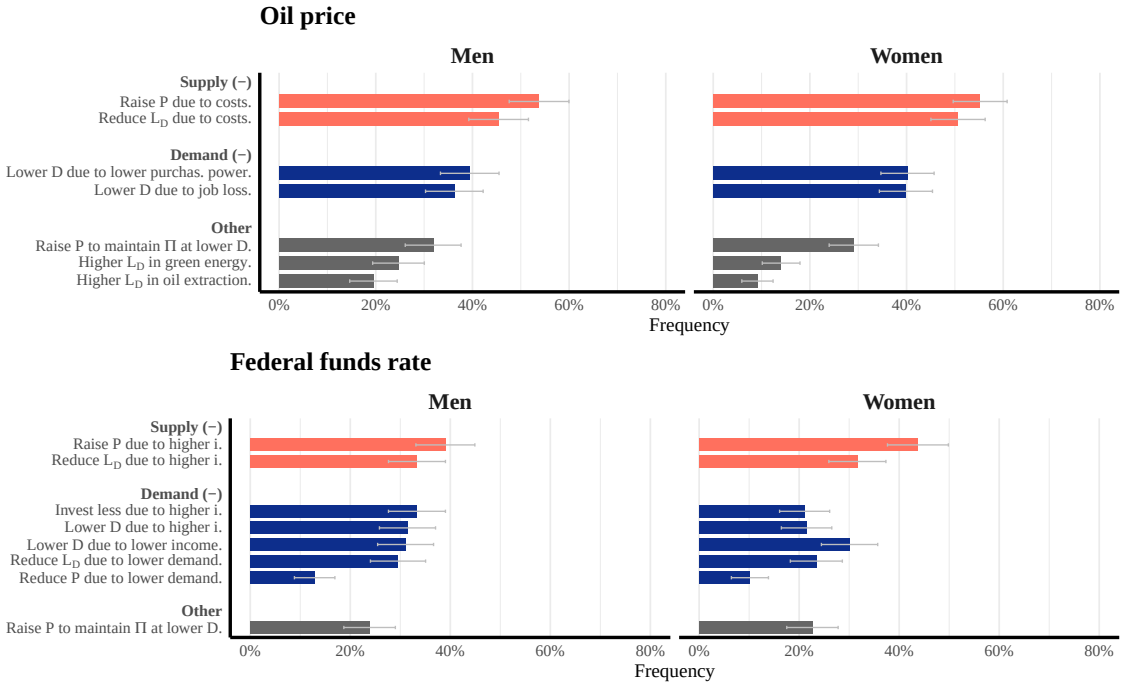


Figure C.1: Thoughts of propagation channels

Notes: This figure shows which propagation channels are on respondents' minds when they make their predictions, using Wave 3 data of Andre et al. (2022). Respondents can select the channels from a list. The results are displayed separately for each vignette and for men (left panel) and women (right panel). Error bars display 95 confidence intervals. The full wording of the channels is available in Supplementary Appendix E of the original paper.

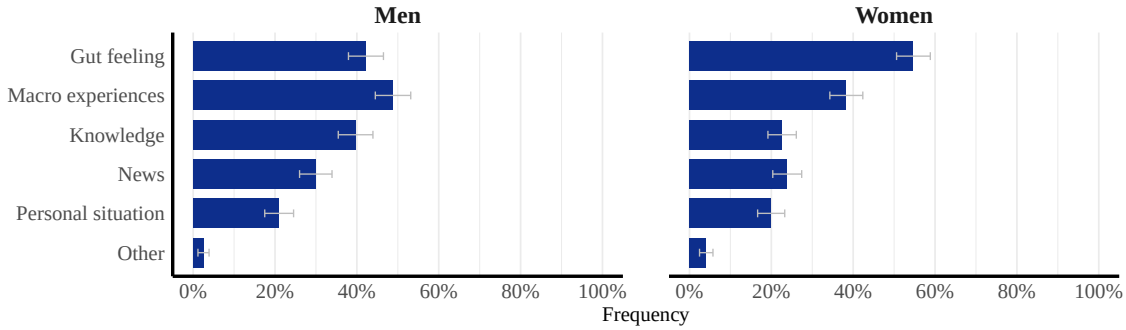


Figure C.2: Prediction approaches

Notes: This figure presents the prediction approaches by men and women in the household sample of Wave 3 in Andre et al. (2022), averaged across the oil shock and monetary policy shock vignettes. Respondents report which factors they thought most about when making their predictions. Survey questionnaire and answers can be found in the Online Appendix of the original paper. Error bars display 95% confidence intervals.

D Model Supplementary Material

D.1 Calibration

Parameter	Value	Description
α	0.333	exponent of labor in the production function
ζ	0.490	relative product of women in production
σ	4.300	elasticity of substitution between men and women in production
δ_m	0.203	separation rate men
δ_f	0.259	separation rate women
γ	1.000	coefficient of hiring cost function
ψ_m	0.046	coefficient of unemployment in the labor market effort men
ψ_m	0.051	coefficient of unemployment in the labor market effort women
β	0.990	discount rate
ρ_i	0.700	autocorrelation monetary policy
ρ_u	0.900	autocorrelation cost push shock
ρ_z	0.800	autocorrelation demand shock
φ_m	2.640	inverse Frisch elasticity of labor effort men
φ_f	0.880	inverse Frisch elasticity of labor effort women
ξ_m	0.600	bargaining power of firms over male workers
ξ_f	0.600	bargaining power of firms over female workers
θ_m^w	0.750	wage rigidities men
θ_f^w	0.750	wage rigidities women
θ_p	0.750	price rigidities
ϕ_π	5.000	Taylor rule coeff of inflation
ϕ_{u_m}	-0.800	Taylor rule coeff of male unemployment
ϕ_{u_f}	-0.800	Taylor rule coeff of female unemployment
ϕ_y	0.000	Taylor rule coeff of output
Γ_m	0.013	proportionality coefficient hiring cost men
Γ_f	0.013	proportionality coefficient hiring cost women
χ_m	1.134	labor disutility parameter men
χ_f	0.664	labor disutility parameter women
d_f	0.110	discrimination against women
$\bar{\pi}^p$	0.000	steady state price inflation
$\bar{\pi}^w$	0.000	steady state wage inflation
$\bar{U}_m$	0.060	steady state unemployment men

Table D.1 – Continued

Parameter	Value	Description
$\bar{U}_f$	0.060	steady state unemployment women
$\bar{N}_m$	0.690	steady state employment men
$\bar{N}_m$	0.540	steady state employment women
$\bar{Y}$	0.724	steady state output
$\bar{x}_m$	0.700	steady state job finding men
$\bar{x}_f$	0.700	steady state job finding women
ϵ	6.000	elasticity of substitution
$\bar{i}$	0.010	steady state nominal interest rate

D.2 Full model

Shock processes

$$\ln(Z_t) = \rho_z \ln(Z_{t-1}) + \varepsilon_t^z \tag{12}$$

$$\ln(U_t) = \rho_u \ln(U_{t-1}) + \varepsilon_t^u \tag{13}$$

Union receives signal

$$s_t = \varepsilon_t^u + \varepsilon_t^z \tag{14}$$

Union applies ambiguity loving/averse weights

$$\tilde{\mathbb{E}}_{mt}[\varepsilon_t^z] = s_t w_m^z \tag{15}$$

$$\tilde{\mathbb{E}}_{ft}[\varepsilon_t^z] = s_t w_f^z \tag{16}$$

$$\tilde{\mathbb{E}}_{mt}[\varepsilon_t^u] = s_t w_m^u \tag{17}$$

$$\tilde{\mathbb{E}}_{ft}[\varepsilon_t^u] = s_t w_f^u \tag{18}$$

Union forms beliefs about state variables

$$\ln\left(\tilde{\mathbb{E}}_{mt} Z_t\right) = \tilde{\mathbb{E}}_{mt}[\varepsilon_t^z] + \rho_z \ln\left(\tilde{\mathbb{E}}_{mt-1} Z_{t-1}\right) \tag{19}$$

$$\ln\left(\tilde{\mathbb{E}}_{ft} Z_t\right) = \tilde{\mathbb{E}}_{ft}[\varepsilon_t^z] + \rho_z \ln\left(\tilde{\mathbb{E}}_{ft-1} Z_{t-1}\right) \tag{20}$$

$$\ln\left(\tilde{\mathbb{E}}_{mt} U_t\right) = \tilde{\mathbb{E}}_{mt}[\varepsilon_t^u] + \rho_u \ln\left(\tilde{\mathbb{E}}_{mt-1} U_{t-1}\right) \tag{21}$$

$$\ln\left(\tilde{\mathbb{E}}_{ft} U_t\right) = \tilde{\mathbb{E}}_{ft}[\varepsilon_t^u] + \rho_u \ln\left(\tilde{\mathbb{E}}_{ft-1} U_{t-1}\right) \tag{22}$$

Euler equation

$$1 = \beta \frac{Z_{t+1}}{Z_t} \frac{C_t}{C_{t+1}} (1 + r_t) \tag{23}$$

Fisherian equation

$$1 + r_t = \frac{1 + i_t}{1 + \pi^p{}_{t+1}} \tag{24}$$

Price dispersion

$$v^p{}_t = \left((1 - \theta^p) \left(1 + \pi^{p,*}{}_t\right)^{\frac{(-\epsilon)}{1-\alpha}} (1 + \pi^p{}_t)^{\frac{\epsilon}{1-\alpha}} + \theta^p (1 + \pi^p{}_t)^{\frac{\epsilon}{1-\alpha}} v^p{}_{t-1}^{\frac{1}{1-\alpha}}\right)^{1-\alpha} \tag{25}$$

Aggregate inflation

$$(1 + \pi^p{}_t)^{1-\epsilon} = \theta^p + (1 - \theta^p) \left(1 + \pi^{p,*}{}_t\right)^{1-\epsilon} \tag{26}$$

Reset price inflation

$$\left(1 + \pi^{p,*}{}_t\right)^{1+\frac{\epsilon\,\alpha}{1-\alpha}} = u_t \frac{\epsilon}{\epsilon - 1} \frac{x1_t}{x2_t} (1 + \pi^p{}_t)^{1+\frac{\epsilon\,\alpha}{1-\alpha}} \tag{27}$$

$$x1_t = \frac{Z_t\, mc_t\, Y_t}{C_t} + \beta\, \theta^p (1 + \pi^p{}_{t+1})^{\epsilon + \frac{\epsilon\,\alpha}{1-\alpha}} x1_{t+1} \tag{28}$$

$$x2_t = \frac{Z_t\, Y_t}{C_t} + \beta\, \theta^p (1 + \pi^p{}_{t+1})^{\epsilon - 1} x2_{t+1} \tag{29}$$

Goods market clearing

$$Y_t = C_t + G_{mt}\, H_{mt} + G_{f_t}\, H_{f_t} \tag{30}$$

Labor index

$$N_t = \left(\zeta_f N_{f_t}^{\frac{\sigma-1}{\sigma}} + \zeta_m N_{m_t}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{31}$$

Aggregate production

$$Y_t = \frac{A_t N_t^{1-\alpha}}{v^p{}_t} \tag{32}$$

Aggregate hiring and employment

$$N_{mt} = H_{mt} + (1 - \delta_m)\ N_{mt-1} \tag{33}$$

$$N_{f_t} = H_{f_t} + \left(1 - \delta_f\right)\ N_{f_{t-1}} \tag{34}$$

Hiring costs

$$G_{mt} = \Gamma_m\, x_{m_t}^{\gamma} \tag{35}$$

$$G_{f_t} = \Gamma_f\, x_{f_t}^{\gamma} \tag{36}$$

Job finding rate

$$x_{mt} = \frac{H_{mt}}{U_{mt}^0} \tag{37}$$

$$x_{f_t} = \frac{H_{f_t}}{U_{f_t}^0} \tag{38}$$

Effective market effort

$$L_{mt} = N_{mt} + \psi_m\, U_{mt} \tag{39}$$

$$L_{f_t} = N_{f_t} + \psi_f\, U_{f_t} \tag{40}$$

Unemployment

$$U_{mt} = U_{mt}^0\ (1 - x_{mt}) \tag{41}$$

$$U_{f_t} = U_{f_t}^0\ \left(1 - x_{f_t}\right) \tag{42}$$

Marginal revenue product

$$MRPN_{mt} = (1 - \alpha)\ (1 - \zeta)\ A_t\, mc_t\, N_{m_t}^{\frac{-1}{\sigma}}\ N_t^{\frac{1}{\sigma-1}-\alpha} \tag{43}$$

$$MRPN_{f_t} = N_t^{\frac{1}{\sigma-1}-\alpha}\ (1 - \alpha)\ \zeta\, A_t\, mc_t\, N_{f_t}^{\frac{-1}{\sigma}}\ \left(1 - d_f\right) \tag{44}$$

Optimal hiring condition

$$MRPN_{mt} = \omega_{mt} + B_{mt} \tag{45}$$

$$MRPN_{f_t} = \omega_{f_t} + B_{f_t} \tag{46}$$

$$B_{mt} = G_{mt} - \frac{Z_{t+1}}{Z_t} \frac{C_t}{C_{t+1}} \beta \ (1 - \delta_m) \ G_{mt+1} \tag{47}$$

$$B_{f_t} = G_{f_t} - \frac{Z_{t+1}}{Z_t} \frac{C_t}{C_{t+1}} \beta \ \left(1 - \delta_f\right) \ G_{f_{t+1}} \tag{48}$$

Optimal participation condition[23]

$$\frac{C_t \, \psi_m \, \chi_m \, L_{m_t}^{\varphi_m}}{Z_t} = \frac{x_{mt}}{1 - x_{mt}} \left(G_{mt} \frac{1 - \xi_m}{\xi_m} - \pi_{mt}^w \frac{\theta_m^w}{1 - \theta_m^w} \omega_{mt-1} \, Q_{mt} \right) \tag{49}$$

$$\frac{C_t \, \psi_f \, \chi_f \, L_{f_t}^{\varphi_f}}{Z_t} = \frac{x_{f_t}}{1 - x_{f_t}} \left(G_{f_t} \frac{1 - \xi_f}{\xi_f} - \pi_{f_t}^w \frac{\theta_f^w}{1 - \theta_f^w} \omega_{f_{t-1}} \, Q_{f_t} \right) \tag{50}$$

$$Q_{mt} = 1 + \frac{\frac{\tilde{\mathbb{E}}_{mt} Z_{t+1}}{Z_t} \frac{C_t}{\tilde{\mathbb{E}}_{mt} C_{t+1}} \beta \ (1 - \delta_m) \ \theta_m^w}{1 + \pi^p{}_t} \tilde{\mathbb{E}}_{mt} Q_{mt+1} \tag{51}$$

$$Q_{f_t} = 1 + \frac{\frac{\tilde{\mathbb{E}}_{ft} Z_{t+1}}{Z_t} \frac{C_t}{\tilde{\mathbb{E}}_{ft} C_{t+1}} \beta \ \left(1 - \delta_f\right) \ \theta_f^w}{1 + \pi^p{}_t} \tilde{\mathbb{E}}_{ft} Q_{f_{t+1}} \tag{52}$$

Evolution of real wage

$$\omega_{mt} = \frac{\omega_{mt-1} \ \left(1 + \pi_{mt}^w\right)}{1 + \pi^p{}_t} \tag{53}$$

$$\omega_{f_t} = \frac{\omega_{f_{t-1}} \ \left(1 + \pi_{f_t}^w\right)}{1 + \pi^p{}_t} \tag{54}$$

Target (flex) wage

$$\omega_{m}^{tar}{}_t = \frac{C_t \, L_{m_t}^{\varphi_m} \, \chi_m \, \xi_m}{Z_t} + MRPN_{mt} \ (1 - \xi_m) \tag{55}$$

$$\omega_{f}^{tar}{}_t = \frac{C_t \, L_{f_t}^{\varphi_f} \, \chi_f \, \xi_f}{Z_t} + MRPN_{f_t} \ \left(1 - \xi_f\right) \tag{56}$$

Reset wage[24]

$$\omega_{mt}^* = \frac{h1_{mt}}{h2_{mt}} \tag{57}$$

[23] Ambiguity averse/seeking expectations in $\tilde{\mathbb{E}}_{g,t}$ are derived prior by the unions.

[24] See footnote 23.

$$\omega^*_{f_t} = \frac{h1_{f_t}}{h2_{f_t}} \tag{58}$$

$$h1_{mt} = \frac{Z_t\,\omega^{tar}_{m_t}}{C_t} + (1-\delta_m)\;\theta^w_m\beta\;\left\{\xi_m\left(1+\tilde{\mathbb{E}}_{mt}\pi^p{}_{t+1}\right)\;\tilde{\mathbb{E}}_{mt}h1_{mt+1} + (1-\xi_m)\,(1+\pi^p{}_{t+1})\;h1_{mt+1}\right\} \tag{59}$$

$$h2_{mt} = \frac{Z_t}{C_t} + (1-\delta_m)\;\theta^w_m\beta\;\left\{\xi_m\left(1+\tilde{\mathbb{E}}_{mt}\pi^p{}_{t+1}\right)\;\tilde{\mathbb{E}}_{mt}h2_{mt+1} + (1-\xi_m)\,(1+\pi^p{}_{t+1})\;h2_{mt+1}\right\} \tag{60}$$

$$h1_{f_t} = \frac{Z_t\,\omega^{tar}_{f_t}}{C_t} + \left(1-\delta_f\right)\;\theta^w_f\beta\;\left\{\xi_f\left(1+\tilde{\mathbb{E}}_{ft}\pi^p{}_{t+1}\right)\;\tilde{\mathbb{E}}_{ft}h1_{f_{t+1}} + (1-\xi_f)\,(1+\pi^p{}_{t+1})\;h1_{f_{t+1}}\right\} \tag{61}$$

$$h2_{f_t} = \frac{Z_t}{C_t} + \left(1-\delta_f\right)\;\theta^w_f\beta\;\left\{\xi_f\left(1+\tilde{\mathbb{E}}_{ft}\pi^p{}_{t+1}\right)\;\tilde{\mathbb{E}}_{ft}h2_{f_{t+1}} + (1-\xi_f)\,(1+\pi^p{}_{t+1})\;h2_{f_{t+1}}\right\} \tag{62}$$

Real wage inflation

$$\omega_{mt} = \theta^w_m\,\frac{\omega_{mt-1}}{1+\pi^p{}_t} + \left(1-\theta^w_m\right)\;\omega^*_{mt} \tag{63}$$

$$\omega_{f_t} = \theta^w_f\,\frac{\omega_{f_{t-1}}}{1+\pi^p{}_t} + \left(1-\theta^w_f\right)\;\omega^*_{f_t} \tag{64}$$

Interest rate rule

$$\frac{1+i_t}{1+\bar{i}} = \left(\frac{1+i_{t-1}}{1+\bar{i}}\right)^{\rho_i}\;\left(\left(\frac{1+\pi^p{}_t}{1+\bar{\pi}^p}\right)^{\phi_\pi}\;\left(\frac{U_{mt}}{\bar{U}_m}\right)^{\phi_{u,m}}\;\left(\frac{U_{f_t}}{\bar{U}_f}\right)^{\phi_{u,f}}\;\left(\frac{Y_t}{\bar{Y}}\right)^{\phi_y}\right)^{1-\rho_i} \tag{65}$$

Definition of GWG

$$GWG_t = \frac{\omega_{mt}}{\omega_{f_t}} \tag{66}$$

D.3 Impulse Responses

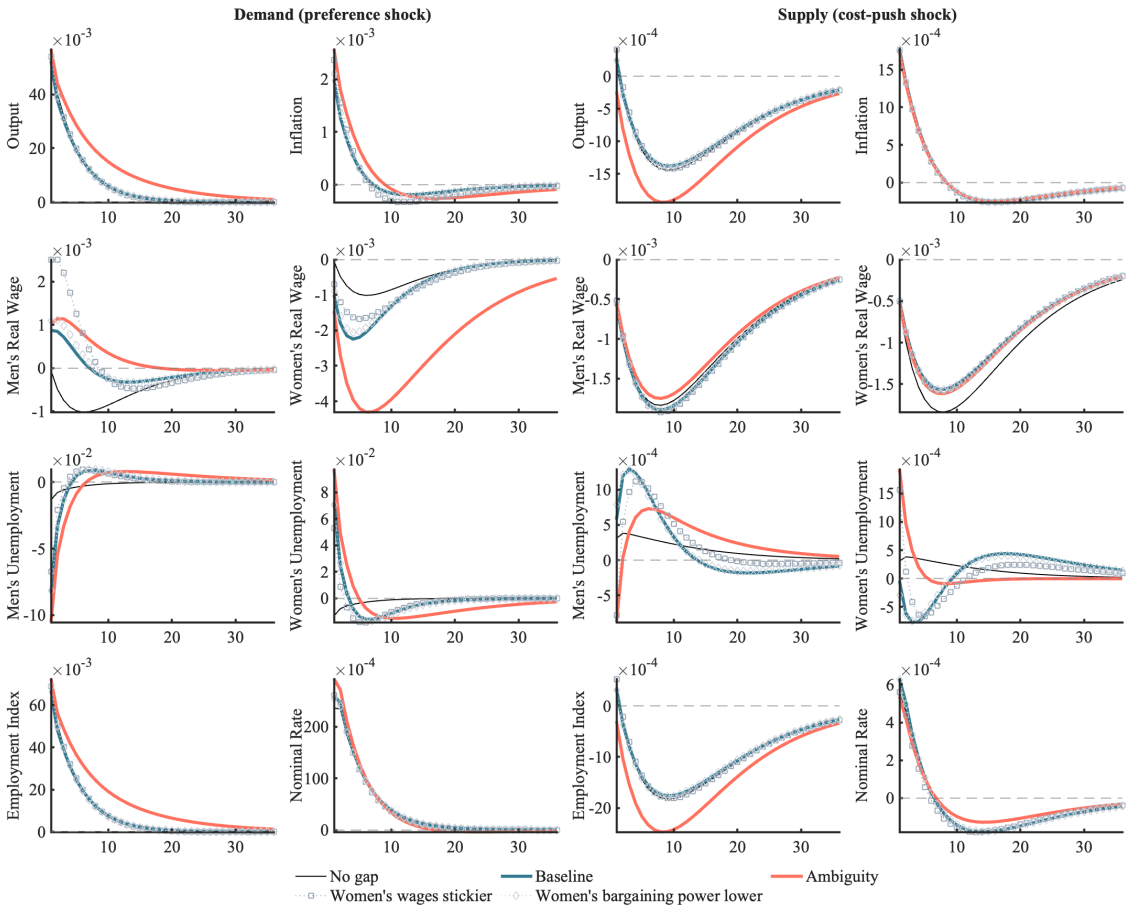


Figure D.1: Further impulse responses of the model

D.4 Calibration Strategy for Ambiguity Attitudes

To discipline the ambiguity parameters λ_m and λ_f, we directly map the expectation dynamics from our structural model to the empirical Survey of Consumer Expectations (SCE) data. We calibrate these parameters by matching the model's subjective wage expectations to empirical VAR estimates of how 12-month expected nominal wage growth responds to identified demand and supply shocks (Figure VII).

In the empirical VAR, we observe the expectation responses 3 months following the initial shock. In our quarterly model, this corresponds to evaluating the expectation at $t = 2$ (where $t = 1$ is the period of impact). We set empirical targets for the deviation in 12-month nominal wage growth expectations, measured in percentage points: following an

inflationary demand shock, men's expectations increase by 0.0477 percentage points, while women's expectations decrease by -0.0384 percentage points. Following an inflationary supply shock, men's expectations increase by 0.0325 percentage points, while women's expectations decrease by -0.0354 percentage points.

To construct the model-implied counterpart to the 12-month nominal wage growth, we consider the demand-driven regime (z) and the supply-driven regime (u) separately. If an agent knows they are in state $s \in \{z, u\}$, the rational expectation of their 12-month (4-quarter) nominal wage growth evaluated at $t = 2$ is the sum of the expected real wage growth and the accumulated expected inflation over the next four quarters:

$$W^s_{g,t=2} = \underbrace{\left(\log \omega^s_{g,t+4} - \log \omega^s_{g,t}\right)}_{\text{4-Quarter Real Wage Growth}} + \underbrace{\sum_{k=1}^{4} \pi^s_{t+k}}_{\text{4-Quarter Accumulated Inflation}}$$

where $\omega^s_{g,t}$ is the real wage for gender $g \in \{m, f\}$ and π^s_t is the quarterly inflation rate in regime s.

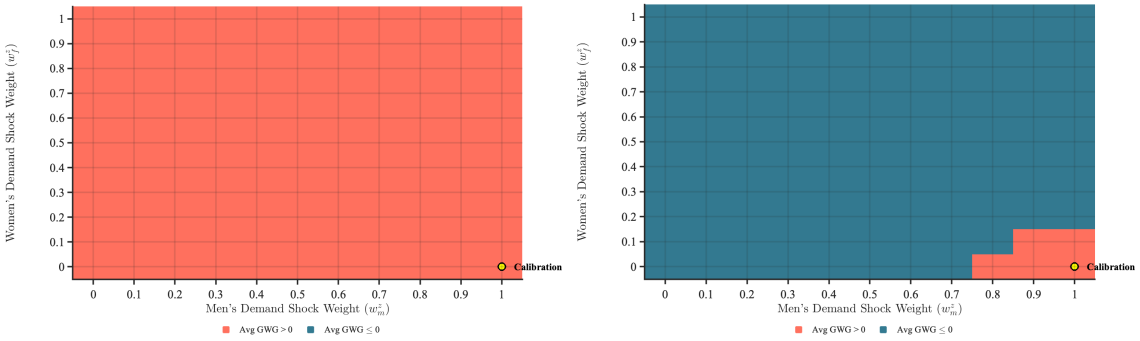
In the model, agents face Knightian uncertainty regarding the true underlying shock and formulate a single subjective expectation by applying Hansen-Sargent robust weights to the regime-specific paths. These weights, $w^z_g(\lambda_g)$ and $w^u_g(\lambda_g)$, are endogenous to the continuation values of each regime evaluated at $t = 1$ and the gender-specific ambiguity parameter λ_g. The subjective expected 12-month wage growth evaluated at $t = 2$ is thus the weighted average of the regime-specific growths:

$$\mathbb{E}^{\lambda_g}_{t=2}[W^g] = w^z_g(\lambda_g) W^z_{g,t=2} + w^u_g(\lambda_g) W^u_{g,t=2}$$

We choose λ_m and λ_f to minimize the joint sum of squared errors between this model-implied subjective expectation and the empirical VAR targets across both shock environments simultaneously. Formally, for each gender, we solve:

$$\min_{\lambda_g} \left(\mathbb{E}^{\lambda_g}_{t=2}[W^g] - \text{Target}^g_z\right)^2 + \left(\mathbb{E}^{\lambda_g}_{t=2}[W^g] - \text{Target}^g_u\right)^2$$

The optimization yields $\lambda_m = -0.001$ and $\lambda_f = 0.001$. This results in women endogenously assigning a dominant probability weight to the supply-shock regime ($w^u_f = 0.99$), reflecting a highly pessimistic outlook regarding cost-push environments, whereas



(a) Demand shock (b) Supply shock

Figure D.2: Sensitivity to Ambiguity Attitudes

men assign a much lower weight to this state ($w_m^u = 0.01$).

A central question is whether ambiguity parameters disciplined strictly by expectations data can generate divergent pay dynamics as an untargeted outcome. To verify this, we conduct a grid search over the entire feasible space of subjective demand-shock weights for both men (w_m^z) and women (w_f^z), mapping the region where the GWG widens following both type of shocks. Figure D.2 visualizes this parameter space. The orange shaded region denotes weight combinations that generate a positive average GWG response over the first 12 quarters following each shock. The marker identifies our baseline calibration. Notably, without explicitly targeting the wage gap itself, the empirically disciplined expectations place the model squarely inside the region that replicates the widening of the gender wage gap observed in the data.