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Divergent Perceptions, Divergent Pay: Inflation and the Gender Wage Gap*

Lovisa Reiche[†] Nicolò Maffei-Faccioli[‡]

February 2026

Abstract

This paper examines how inflation affects the gender wage gap. Using matched comparisons among observationally similar women and men, we document two empirical facts. First, the gender wage gap systematically widens when inflation rises, following both demand- and supply-driven shocks. Second, women revise their labor-market beliefs more pessimistically than men in response to these same inflationary shocks, particularly regarding their own job prospects. We propose a mechanism linking these belief differences to the widening gender wage gap: women's more pessimistic interpretation of inflationary shocks reduces their willingness to pursue nominal wage increases, slowing their wage growth relative to men when inflation rises. We formalize this mechanism in a two-agent New Keynesian search-and-matching model with imperfect information, in which women form pessimistic beliefs about underlying shocks. The model reproduces the observed inflation-induced widening of the gender wage gap, establishing a novel link between inflation and gender inequality.

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

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

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Introduction

Despite decades of convergence, a substantial wage gap between men and women persists even after accounting for differences in worker demographics, industry, and occupation (Blau & Kahn 2017, Goldin 2014, Olivetti & Petrongolo 2016). In the United States, this adjusted gap narrowed in the 1980s and 1990s but has since stabilized, remaining above 10% and showing marked cyclical fluctuations (see Figure 1). The persistence of this gap remains a central puzzle in labor economics, with implications for both gender inequality and labor market efficiency. While much is known about the long-run convergence of male and female wages, we know comparatively little about how the gap evolves over the business cycle and, in particular, how it responds to inflationary shocks.

This paper offers a new perspective by linking inflation dynamics to the evolution of the gender wage gap. Using matched comparisons among observationally similar women and men, we establish two empirical facts. First, the gender wage gap systematically widens when inflation rises, regardless of whether inflation is driven by demand or supply shocks. This finding implies that the costs of inflation extend beyond the aggregate loss in purchasing power: inflation also redistributes income across groups, exacerbating gender inequality in the labor market. This redistribution represents a distinct equity cost beyond existing explanations of the cyclical behavior of the gender wage gap. Rather than reflecting changes in industry composition or labor market attachment, the inflation-induced divergence we document persists among comparable workers and accounts for a sizable share of cyclical variation in the gap. Second, we document pronounced gender differences in how workers interpret inflationary surprises: women revise their labor-market beliefs pessimistically in response to inflationary shocks, particularly regarding their own job prospects, whereas men do not. We propose a mechanism that links these belief differences to the widening of the gender wage gap: women's more pessimistic interpretation of inflationary shocks reduces their willingness to pursue nominal wage increases, slowing their wage growth relative to men. We formalize this mechanism within a two-agent New Keynesian search-and-matching model with imperfect information in which women's pessimistic beliefs about underlying shocks generate their differential response to inflation. The model reproduces the empirical widening of the gender wage gap following inflationary shocks, providing a coherent explanation for the two empirical facts.

We begin by documenting the response of the gender wage gap to inflationary demand and supply shocks. Using the U.S. Current Population Survey (CPS) from 1982 onward, we construct a monthly time series of adjusted gender wage gaps that control for worker characteristics, industry, and occupation using a Kitagawa-Oaxaca-Blinder decomposition (Kitagawa 1955, Oaxaca 1973, Blinder 1973, Blau & Kahn 2017). Embedding this time series in a structural VAR with zero and sign restrictions, we study how the gender wage gap among comparable workers responds to inflationary shocks. We uncover a clear and robust pattern: inflation, regardless of its source, systematically widens the gender wage gap. This 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. Importantly, these results are not driven by differential selection of women and men into employment over the business cycle or changes in workforce composition: the widening of the gender wage gap persists in gender-balanced matched samples constructed using nearest-neighbor matching on observables (Ñopo 2008), with exact matches on industry and occupation, as well as in within-individual wage growth comparisons using the rotating panel structure of the CPS under the same adjustments. These effects are quantitatively important: inflationary shocks account for 12–25 percent of the forecast error variance of the gender wage gap across alternative gap measures and identification schemes. These results differ from previous work emphasizing differences in industry exposure (O'Neill 1985, Hoynes et al. 2012, Bredemeier et al. 2017, Albanesi & Şahin 2018) and countercyclical wage convergence (Kandil & Woods 2002, Kovalenko & Töpfer 2021). Once differences in industry, occupation, and demographics are netted out, the remaining explanation points to differences in wage-setting behavior: men adjust their nominal wages more aggressively to preserve real pay, while women do so less. Consistent with this interpretation, decomposing the gender wage gap reveals that after both types of inflationary shocks women's real wages decline while men's remain largely unchanged.

To understand why wage-setting behavior might differ across genders, we turn to the role of expectations. The idea that inflation shapes beliefs about the labor market is well established. For instance, Hajdini et al. (2023) document a low inflation-to-wage expectations pass-through, while Kamdar & Rey (2025) shows that consumers associate high inflation with high unemployment, coined the supply-side interpretation of inflation surges (Candia et al. 2020, Andre et al. 2022, Weber et al. 2022, D'Acunto & Weber 2024, Andre et al. 2025). This interpretation may also explain why workers dislike inflation, if they assume that nominal wages do not keep pace with rising prices (Stantcheva 2024, Guerreiro et al. 2024). Inflation expectations also influence consumption, savings (Coibion et al. 2023, 2022) and labor-market behavior. High inflation expectations can increase the likelihood for consumers to search for a new job (Pilossoph & Ryngaert 2024) and reduce their reservation wages (Baek & Yaremko 2024). In addition, women have been shown to overestimate inflation (D'Acunto, Malmendier & Weber 2021, Reiche 2025), dislike inflation more (McMahon & Reiche 2024), perceive a lower inflation-wage pass-through (Hajdini et al. 2023) and that gender gaps in wages can be traced to differences in bargaining behavior (Caldwell et al. 2025, Biasi & Sarsons 2022, Exley et al. 2020, Card et al. 2016, Leibbrandt & List 2015, Babcock & Laschever 2003, Azmat & Petrongolo 2014). Taken together, these findings suggest that women may interpret inflation more negatively than men in terms of labor-market outcomes. By associating inflation with weaker labor demand and expecting a smaller pass-through from prices to wages, women may perceive less room to bargain for higher nominal pay. As a result, when inflation rises, women adjust their nominal wages less aggressively than men, leading to a widening of the gender wage gap among workers with similar characteristics in the same industries and occupations.

We provide evidence on this belief channel by documenting our second empirical fact: women respond to inflationary shocks with systematically more pessimistic labor-market beliefs than men, particularly regarding their own job prospects. Using microdata from the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE), we embed survey-based measures of labor-market beliefs in the same structural VAR with sign and zero restrictions to trace their responses to inflationary demand and supply shocks across genders. Focusing on full-time workers and controlling for demographic characteristics and industry sorting as before, we find a striking asymmetry: following both types of inflationary shocks, women revise unemployment expectations upward and lower their job-finding and earnings expectations, whereas men revise unemployment expectations downward, leave job-finding expectations largely unchanged, and increase expected earnings growth. Overall, men respond to inflationary shocks with relative optimism about labor-market conditions, while women respond with relative pessimism. This pattern aligns with well-documented gender differences in optimism and pessimism in economics and finance (Dawson 2017, Jacobsen et al. 2014, Bjuggren & Elert 2019), as well as in psychology (Lin & Raghubir 2005, Dawson 2023) and political science (Gwartney-Gibbs & Lach 2016). Our contribution is to show that these gender differences in beliefs emerge sharply in response to inflationary shocks and are directly linked to expectations about labor-market outcomes. Our findings also complement the literature on consumer narratives (Shiller 2017, Stantcheva 2024, Andre et al. 2022, Binetti et al. 2024, Andre et al. 2025) by showing that the average "supply-side" interpretation of inflation in survey data coexists with substantial heterogeneity across individuals: women's responses are aligned with a supply-side view, whereas men's responses appear closer to a demand-side interpretation.

We develop a New Keynesian model with search-and-matching frictions (Diamond 1982, Mortensen 1982, Pissarides 1985), building on Thomas (2008), Faia (2008), Galí (2010), Blanchard & Galí (2010), Christiano et al. (2016), but featuring male and female workers. The purpose of the model is to formalize an expectation-driven channel through which inflationary shocks generate differential wage responses across genders, and to show that this mechanism can account for the observed widening of the gender wage gap, whereas alternative channels cannot. Within this framework, we first consider conventional explanations emphasized in the literature, including taste-based discrimination (Becker 1971, Black 1995, Charles & Guryan 2008, Neyer & Stempel 2021), perceived productivity differentials arising through statistical discrimination (Arrow 1971, Phelps 1972, Aigner & Cain 1977, Altonji & Pierret 2001) or statically less frequent (Leibbrandt & List 2015, Exley et al. 2020) and less aggressive (Artz et al. 2018, Babcock & Laschever 2003) wage negotiation. We show that none of these channels can replicate our empirical finding that the gender wage gap increases following both supply- and demand-driven inflationary shocks. In the model, these mechanisms instead imply opposite responses of the gender wage gap across the two shocks, because wage differentials are tied to the direction of output. Instead, we capture the empirically observed pattern through gender differences in subjective expectations: women assign greater posterior weight to adverse, supply-side interpretations of inflationary shocks. This leads to expectations of weaker labor-market conditions and, consequently, less aggressive wage renegotiation. This expectation-driven mechanism generates a widening of the gender wage gap following inflationary shocks of either origin, consistent with our empirical findings. Following Bhandari et al. (2025), we formalize these pessimistic beliefs through the lens of ambiguity aversion.

We solve the model in two stages. First, unions representing men and women in wage negotiations only observe imperfect signals about the nature of shocks and form beliefs about the underlying state of the economy (Erceg et al. 2025). They understand how the economy responds to each type of shock and compute continuation values accordingly. Household preferences are specified so that consumption losses from cost-push shocks dominate the associated reduction in the disutility of labor, implying that supply-side disturbances are perceived as more costly. We model pessimism through ambiguity aversion using the robust control framework of Hansen & Sargent (2001), in which continuation values are exponentially tilted toward adverse states ("softmin" weighting). Ambiguity-averse agents therefore behave as if facing worst-case scenarios. The model is then solved assuming rational expectations of households (where men and women form joint decisions) and firms, with ambiguity aversion affecting the beliefs of the union negotiating women's wages. Although output and inflation responses are broadly similar across belief regimes, differences in perceptions distort real wages: agents with pessimistic beliefs experience larger real wage losses for any inflationary shock. The model provides a structural interpretation of the empirical evidence, showing that gendered expectations shaped by pessimism can account for the observed dynamics of the gender wage gap, whereas traditional channels cannot. By embedding biased belief formation into an otherwise standard wage-setting framework, our analysis also contributes to the growing literature on expectation-driven wage dynamics (Baek & Yaremko 2024, Menzio 2022, Balleer et al. 2024, Pilossoph & Ryngaert 2024) and the role of ambiguity aversion in business cycles (Bhandari et al. 2025, Ilut et al. 2014, Masolo & Monti 2021, Baqaee 2020).

The remainder of the paper is structured as follows. Section 1 constructs gender wage gaps from CPS data and examines their responses to inflationary demand and supply shocks. Section 2 studies how inflationary shocks affect labor-market beliefs using data from the SCE. Section 3 introduces a New Keynesian search-and-matching model with two types of workers and ambiguity aversion. Section 4 concludes.

1 Inflation and the Gender Wage Gap

We begin by documenting our first new empirical fact: the gender wage gap 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 gender wage gap 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 inflation. 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.

1.1 Computation of the Adjusted Gender Wage Gap

We construct our measure of the adjusted gender wage gap 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.[1]

We define the adjusted gender wage gap (GWG) as the portion of the male–female difference in 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 (Kitagawa 1955, Oaxaca 1973, Blinder 1973). The latter is our measure of interest. For any month

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

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.[2] $OCC1990$ 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.[3] 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:

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

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, intra-occupation gender wage gap 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. Intuitively, 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 the adjusted

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

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

GWG therefore indicates that men's observed wages have moved further above this counterfactual benchmark. That is, the wage penalty associated with being female, conditional on observables, has grown. Conversely, a decline in the adjusted GWG reflects a narrowing of this differential, meaning that men's actual and counterfactual wages are becoming closer, or equivalently, that women's relative disadvantage is shrinking.

We adopt the KOB decomposition as our baseline measure of the gender wage gap 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 enjoy the status of "doubly robust" estimators of counterfactuals (Kline 2011) and are routinely used as the benchmark measure of adjusted gender wage gaps (Blau & Kahn 2017). We define the GWG as male minus female wages, whereas Blau & Kahn (2017) adopt the opposite sign convention. In Figure A.1 we replicate their exact definition of the gender wage gap using our CPS data, constructed as the difference between predicted female and male wages evaluated at the female covariate distribution.[4] Under this definition, we obtain very similar estimates to theirs. We adopt the male–female definition because it makes interpretation more 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. In the next subsection, we show that alternative measures deliver the same results as our baseline.

In particular, we also consider an alternative, non-parametric measure based on nearest-neighbor matching (Ñopo 2008). The motivation for doing so is that any regression-based counterfactual approach, even when conditioning on a rich set of observables and restricting attention to employed full-time workers, may implicitly rely on comparisons across regions of the covariate space where men and women do not fully overlap. If men and women sort differently across detailed occupation–industry–hours–tenure combinations, or if the composition of employed workers varies by gender over the business cycle, regression-based decompositions may partly attribute composition effects to wage differences. Nearest-neighbor matching addresses these concerns by constructing gender-balanced samples at each point in time in which each employed woman is matched to the most similar employed man (and vice versa) based on a rich set of predetermined demographic and job-related characteristics. Similarity is defined using Mahalanobis distance on the raw covariates – specifically, the same set of demographic controls used in the KOB de-

[4] Because the CPS does not observe experience directly, we proxy it using age, education, and children.

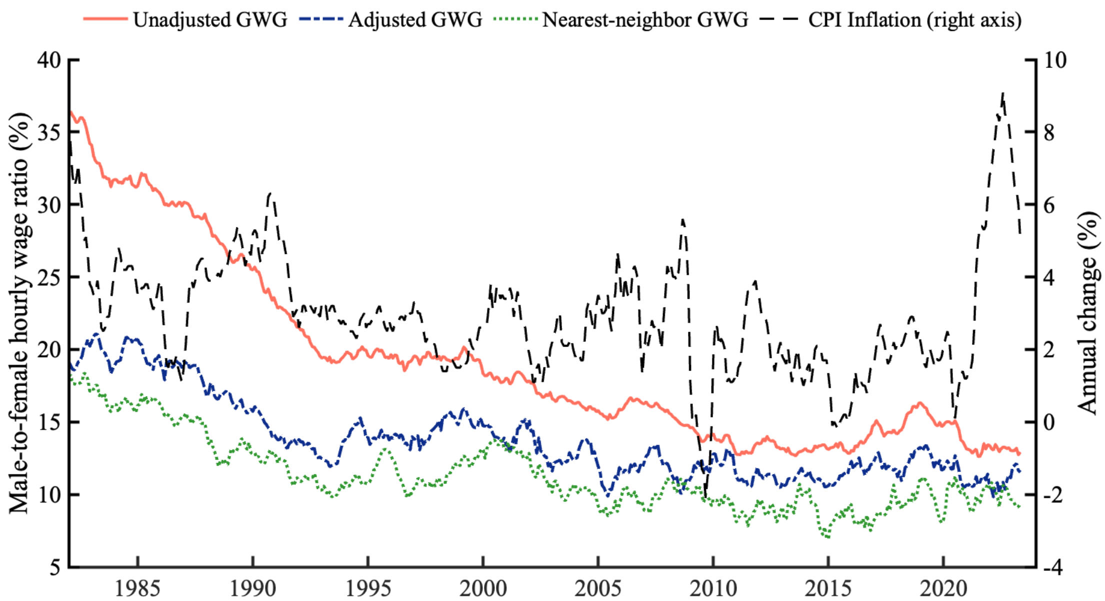


Figure 1: Adjusted and unadjusted gender wage gaps (1982-2023)

Notes: Adjusted GWGs are computed using a traditional Kitagawa-Oaxaca–Blinder decomposition of male-female differences in log wages controlling for worker characteristics, industry and occupation computed 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unadjusted, Adjusted and Nearest-neighbor GWG: CPS IPUMS, own calculations.

composition – while requiring exact matches on the detailed occupation and industry controls.[5] By restricting the comparison to observationally similar workers who coexist in the same regions of the covariate space, this approach enforces common support by construction and limits the scope for composition-driven bias. Moreover, unlike regression-based decompositions such as the KOB decomposition, nearest-neighbor matching does not require estimating counterfactual wage equations or extrapolating beyond observed matches and therefore avoids uncertainty arising from functional-form assumptions. We therefore use matching-based wage differences between men and women as a complementary measure of the adjusted gender wage gap in our empirical analysis.

These methods yield monthly time series of demographically adjusted, intra-industry, intra-occupation gender wage gaps. Figure 1 plots the resulting series constructed using both the baseline Kitagawa–Oaxaca–Blinder (KOB) decomposition and the nearest-neighbor matching approach, alongside the corresponding 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

[5] Mahalanobis is preferred to Euclidean distance as it automatically standardizes variables on different scales.

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 adjust for industry and occupation. Notably, all gender wage gap 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 gender wage gap, including the coefficient on the female dummy from a pooled linear regression (Penner et al. 2022), the gender wage gap 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 gender wage gap 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 nearest-neighbor 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 gender wage gap to inflationary demand and supply shocks. Consider the standard reduced-form VAR model with n variables and p lags:

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

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 associated with lagged variables, 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 a trailing three-month moving average of the adjusted gender wage gap constructed using the KOB decomposition described in Equation 1.[6] 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 given 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 specifying standard NIW priors for reduced-form parameters (see Arias et al. 2018).

[6] We use a moving average of the original series to smooth its short-term volatility and improve model stability. Later in this section, we also report results using the original series and find the results to be virtually identical.

We estimate the VAR in levels because our analysis focuses on explaining short- to medium-run fluctuations rather than long-run patterns. Johansen's trace test indicates two cointegrating relationships among the variables included in the VAR 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: as shown by Sims et al. (1990), VARs estimated in levels yield consistent inference for impulse responses even in the presence of cointegration, while avoiding potential distortions to short-run dynamics that may arise from unnecessary differencing or detrending. 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). Therefore, we 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 gender wage gap, 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 model.

To identify the SVAR, we impose sign and zero restrictions on the matrix of contemporaneous responses B_0 (see Arias et al. 2018). Specifically, we restrict the signs of inflation and unemployment responses to demand and supply shocks. Following standard practice in the literature, we impose that demand shocks generate a contemporaneous negative co-movement between inflation and unemployment, while supply shocks generate a positive co-movement. We normalize both demand and supply shocks to be inflationary, that is, with a positive sign on inflation. This identification strategy allows us to study the effects of inflationary shocks while explicitly 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 lies in the response of the GWG to these shocks, we leave its contemporaneous response unrestricted. Any observed movement in the GWG in response to demand and supply shocks is thus an outcome of the estimated model. However, sign restrictions alone generally 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 all three shocks, we introduce a third, residual shock using additional zero restrictions, setting certain elements of B_0 to zero to imply no contemporaneous effect. The residual shock is defined as an innovation to the GWG that has no contemporaneous effect on inflation and unemployment. While it is not assigned a structural

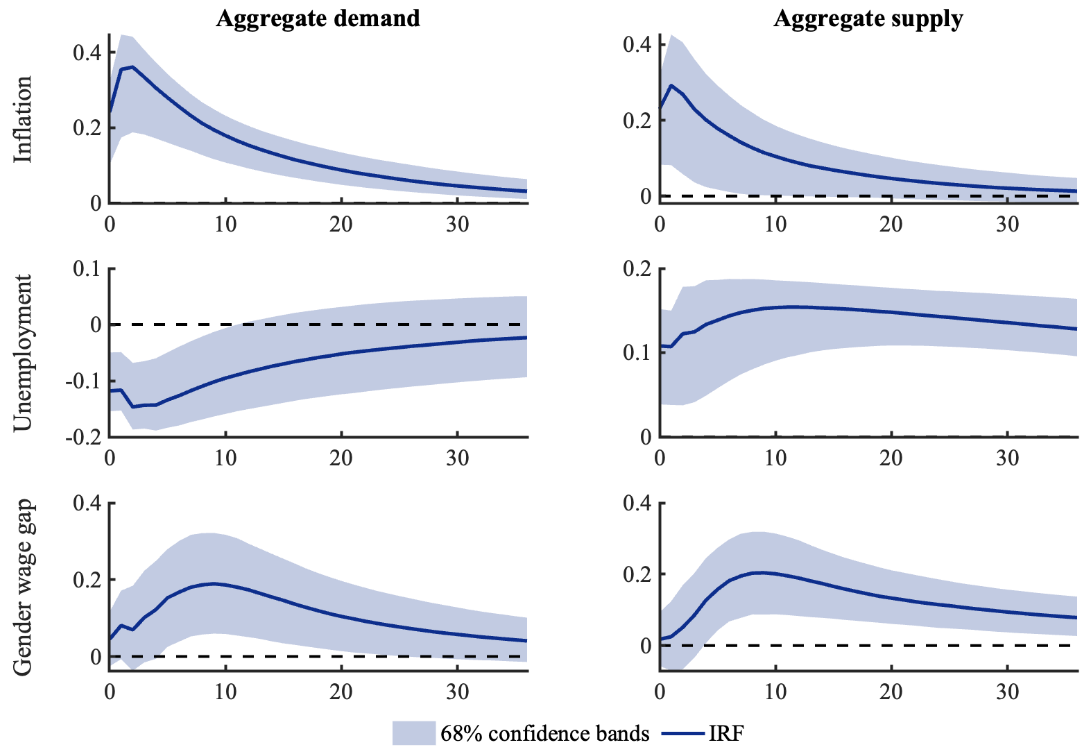
	Demand	Supply	Residual
Inflation	+	+	0
Unemployment	−	+	0
Gender wage gap	?	?	+

Table 1: Impact Sign and Zero Restrictions in the structural VAR

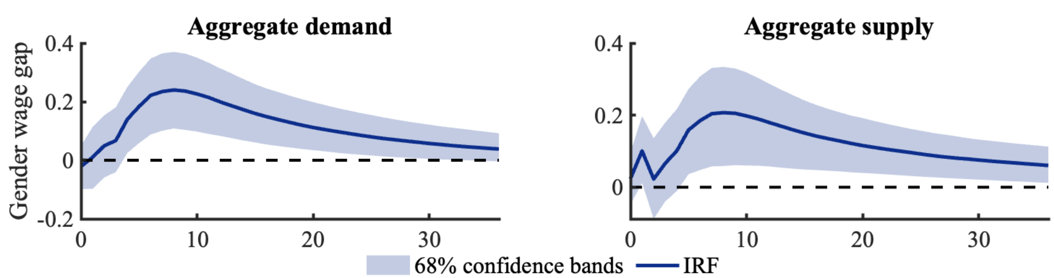
interpretation, its inclusion is necessary to fully identify the model. This approach is also justified by the fact that the GWG, constructed from micro-level hourly earnings from the CPS data, may be influenced by idiosyncratic or institutional factors, such as changes in workplace policies or discrimination, that are unlikely to have immediate effects on aggregate macroeconomic outcomes within a month. Table 1 summarizes the restrictions for the structural identification. Nonetheless, we show in the robustness below that alternative identification strategies for inflationary shocks deliver the same results.

Panel (a) of Figure 2 presents 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 functions of the variables 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 the sign restrictions are imposed only on impact, these effects persist over time.

The novel contribution lies in the response of the adjusted gender wage gap (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 indicate that these effects are persistent at monthly frequency, remaining economically and statistically significant for roughly three years. However, the responses gradually attenuate at longer horizons, with the gap converging back toward its 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



(a) Baseline with KOB decomposition



(b) Baseline with nearest-neighbor matching

Figure 2: Impulse Responses in the Structural VAR

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. Adjusted GWGs computed using monthly data from January 1982–February 2020, 3-month trailing moving average.

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.

One might be concerned 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. If inflationary shocks affect which men and women remain employed, the observed wage gap could partly reflect composition rather than within-worker wage adjustments. We address this by constructing gender-balanced samples using nearest-neighbor matching (Ñopo 2008). Unlike regression-based decompositions, this matching-based approach relies exclusively on observed wage comparisons among observationally similar workers and therefore does not hinge on parametric assumptions used to construct counterfactual wages. We then define the gender wage gap as the ratio of mean hourly earnings on the matched sample and substitute the adjusted gender wage gap with this measure in the baseline SVAR with zero and sign restrictions. The matched-sample GWG displays the same responses to inflationary shocks as in our baseline specification, as shown in Panel (b) of Figure 2.[7]

Having established that inflationary shocks significantly widen the adjusted gender wage gap, we next investigate whose real wage response drives this effect. We compute men's wages as $\hat{Y}_{mm}$ and women's wages as $\hat{Y}_{mm}$ from the KOB decomposition in Equation 1. We therefore compare men to individuals with the same characteristics as men but being treated like women. We replace the adjusted gender wage gap 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 3 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 align with micro evidence that women are less likely to negotiate for raises (Caldwell et al. 2025, Biasi & Sarsons 2022, Exley et al. 2020, Card et al. 2016, Leibbrandt & List 2015, Babcock & Laschever 2003, Azmat & Petrongolo 2014) and thus cost-of-living adjustments. To corroborate this explanation, we re-estimate the baseline SVAR including the GWG for unionized workers only (Figure A.3 in the Appendix), where wages are typically subject to collective bargaining, and observe little to no significant effect to inflationary demand and supply shocks. This suggests that wage-setting institutions that mitigate individual negotiation frictions can attenuate the inflation-induced widening of the GWG.

Figures A.5a and A.5b 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

[7] The full set of impulse responses and comparison with our baseline SVAR is presented in Figure A.4 in the Appendix. The responses of inflation and unemployment are essentially identical to those in the baseline specification for both shocks.

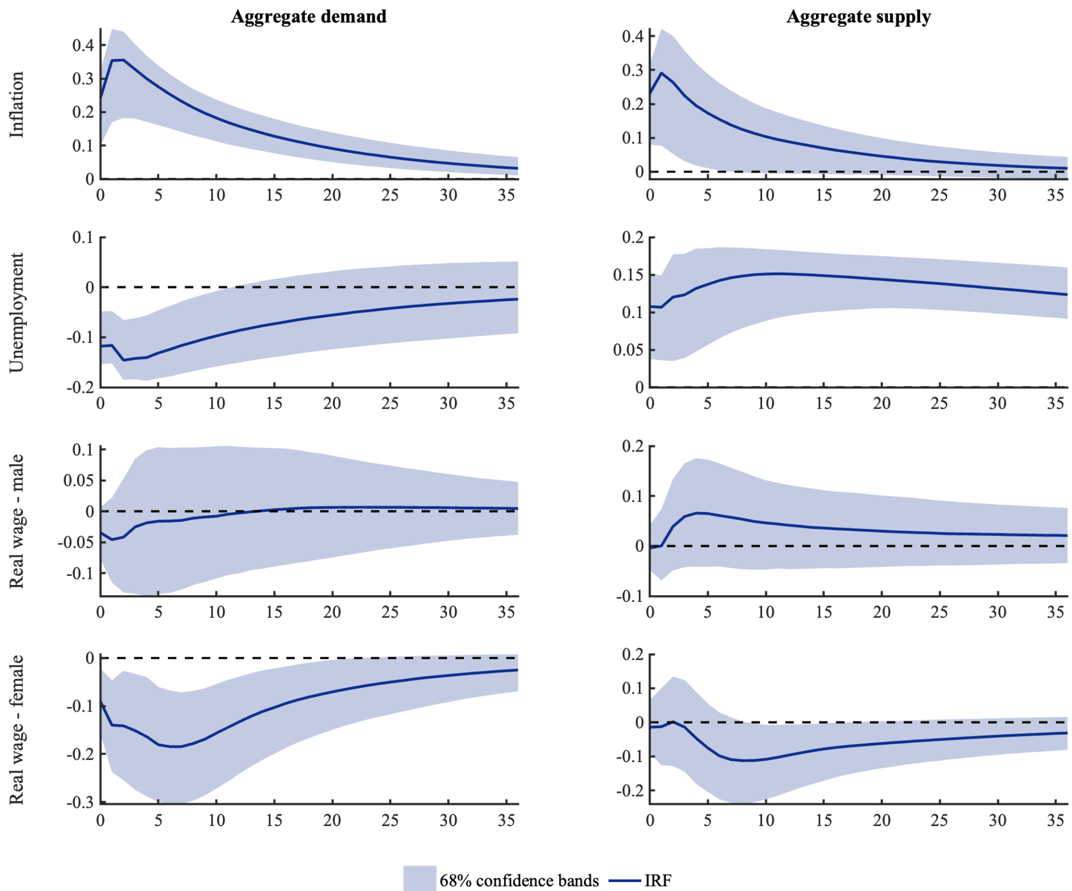


Figure 3: Impulse Responses in the Structural VAR, GWG decomposed

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 defined at each point in time. 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.

in wage adjustment remains visible 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 (Bredemeier et al. 2017, Albanesi & Şahin 2018). The adjusted GWG response to both demand and supply shocks is stable across specifications (see Figures A.6a and A.6b), whereas the unadjusted GWG response to supply shocks becomes positive and statistically significant once gender-specific exposure is controlled for. 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. Together, these results indicate that accounting for differential exposure reveals the inflation-induced widening of the gender wage gap 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

In addition, we perform a battery of robustness exercises to assess the sensitivity of our baseline finding – the widening of the gender wage gap after inflationary shocks – to alternative specifications of the VAR model. For clarity of exposition, all corresponding figures are reported in the Appendix.

First, we assess the robustness to alternative identification strategies for inflationary shocks. Our baseline focuses on inflationary demand and supply shocks because this distinction allows us to differentiate between shocks that 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. In particular, while sign restrictions provide a clear macroeconomic interpretation, they imply set identification 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 per se, though without imposing restrictions on unemployment responses. Figure A.7 shows the impulse response of the adjusted GWG (Panel (a)) and nearest-neighbor GWG (Panel (b)) to a positive inflationary shock. Consistent with the baseline, a positive inflationary shock produces a significant and persistent widening under both measures. If anything, the effect is larger and more precisely estimated than in the baseline, as reflected by narrower confidence bands.

Second, we test whether our results depend on the specific definitions of the key variables in the VAR. The co-movement between inflation and the GWG remains robust when we use alternative measures of inflation, including the PCE price index (Figure A.8a) and core CPI excluding food and energy (Figure A.8b). Similarly, we find consistent results when replacing the baseline business cycle indicator with industrial production (Figure A.9).[8] The results are also robust to using weekly earnings, rather than hourly, to compute the adjusted GWG (see Figure A.10a), suggesting that our findings are not sensitive to whether the wage measure captures intensive or extensive margin adjustments. We also explore alternative constructions of the GWG commonly used in the literature. These include computing the gap based on predicted women's wages using men's characteristics in the KOB decomposition as in Blau & Kahn (2017) (Figure A.10b), using median instead of mean wages (Figure A.10c), 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, following Penner et al. (2022) (Figure A.10d). In these cases, the GWG is defined as female-minus-male, in

[8] 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.

contrast to our baseline definition of male-minus-female. As such, the impulse responses should be interpreted with the opposite sign. Across all specifications, the positive relationship between inflation and the gender wage gap remains robust. If anything, inflationary demand shocks produce even larger effects under these alternative measures.

Third, we assess the robustness of our results to changes in model specification. We show that the results are not driven by the application of the trailing moving average filter (Figure A.11a) or by lag selection, with similar findings when including additional lags as suggested by the AIC criterion (Figure A.11b). Moreover, our findings remain qualitatively unchanged when extending the sample to include the COVID-19 period (Figure A.12), suggesting that the inflation-GWG relationship does not break if we include the pandemic period.

Fourth, we examine gender wage gaps within demographic groups, assessing how the adjusted GWG 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.13a) exhibit weaker responses to inflationary shocks, whereas older workers (Figure A.13a-A.13d) show stronger responses, consistent with lower bargaining power among older cohorts of women. Additionally, the gap response is larger for workers with young children (Figure A.14a), potentially reflecting reduced bargaining capacity among women with caregiving responsibilities or heightened wage responsiveness among men with young children. We also estimate GWG responses separately for married individuals (Figure A.14b) and singles (Figure A.14c). While the response of the GWG is larger among married workers, the widening of the GWG to both inflationary shocks is also present among single-person households, indicating that the inflation–GWG relationship is 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 that follows is how much of the variation in the gender wage gap can be attributed to inflationary shocks. We address this using forecast error variance decompositions of the adjusted gender wage gap across our different SVAR model specifications and measurement approaches of the gap. We consider both the baseline SVAR with zero and sign restrictions and the alternative "max-share" identification of inflationary shocks, and we perform this exercise using adjusted gender wage gaps constructed with the baseline Kitagawa–Oaxaca–Blinder decomposition (Blau & Kahn 2017), the nearest-neighbor matching approach (Ñopo 2008), and using the coefficient on the female dummy from a pooled linear regression (Penner et al. 2022). 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

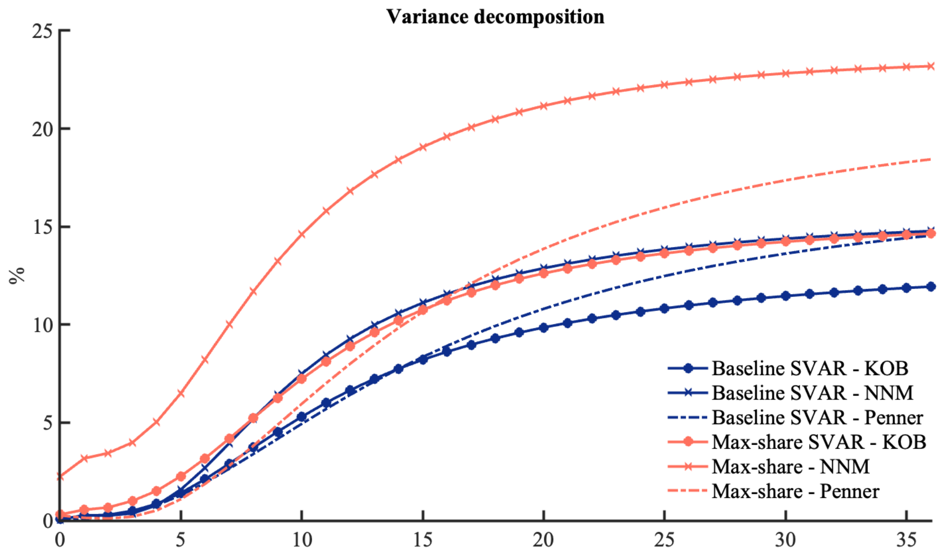


Figure 4: Forecast error variance decompositions

Notes: Forecast error variance decompositions constructed based on pointwise median estimates. The median is defined at each point in time.

those obtained under the single max-share inflationary shock. Figure 4 presents the corresponding forecast error variance decompositions. 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 gender wage gap, ranging from approximately 12 to 25 percent of the forecast error variance. This magnitude is sizable given that the gender wage gap is constructed from micro-level wage data and is therefore influenced by a wide range of idiosyncratic and institutional factors – such as changes in workplace policies, discrimination, and other unmodeled factors – that are not explicitly captured in the VAR and are expected to explain a large portion of residual variation. Against this backdrop, the fact that a single macroeconomic shock can account for up to one quarter of the variation in the adjusted gender wage gap underscores the quantitative importance of inflation for GWG dynamics. Consistent with this interpretation, the explained share is larger under the max-share identification, which captures inflationary disturbances more broadly and thus isolates the role of inflation per se. These results indicate that inflationary shocks are a quantitatively meaningful driver of gender wage gap fluctuations across measures and identification strategies.

1.3 Micro-level Evidence: Individual Wage Growth and Composition

The baseline SVAR results establish that inflationary shocks lead to a widening of the gender wage gap at the aggregate level. A potential concern, however, is that these findings may be confounded by composition effects. If inflationary periods are associated with non-random entry into or exit from the labor force – for example, if low-wage women are more likely to leave employment following inflationary shocks – the observed increase in the aggregate gap could partly reflect selection rather than changes in individual wage-setting behavior. While our nearest-neighbor matching analysis already mitigates these concerns by comparing gender-balanced samples of observationally similar workers, we further complement the aggregate evidence with individual-level panel data from the CPS. By matching individuals across the CPS's consecutive monthly surveys (the 4-8-4 rotation scheme), we can track the wage growth of the same worker over a 12-month period.

We estimate the following micro-level regression:

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

where $\Delta \ln w_{i,t}$ represents the log change in the real hourly wage for individual i between month $t-12$ and t. The vector $\mathbf{X}_{i,t}$ includes a comprehensive set of individual controls: 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. Together, these are the same controls as in the computation of the adjusted GWGs used 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 bargaining period. Our primary independent variable is $\Delta\pi_t$, which denotes the change in the annual inflation rate over the same period. We intentionally use changes rather than levels of inflation capture the acceleration or deceleration of prices that prompt wage renegotiation or expose nominal rigidities. Accordingly, the interaction term $\text{Female}_i \times \Delta\pi_t$ measures whether women's wage growth responds differently than men's to shifts in inflation. 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 the trend was sharply downward. By focusing on $\Delta\pi$, our coefficients reflect the labor market's response to the direction and momentum of price changes, which are the primary drivers of wage-setting revisions.

The results of the micro-level estimation are presented in columns (1)-(4) of Table 2. The coefficient on the interaction term (β_3) is negative and statistically significant, at the 1% level in our baseline specification (2). To contextualize the economic magnitude of our estimates, consider the implications of $\beta_3 = -0.105$. A one–percentage-point increase in inflation reduces women's nominal wage growth relative to men's by approximately 0.1 percent, implying a relative

Table 2: Gender Differences in Wage Growth and Inflation

	$\Delta \ln w_{i,t} \times 100$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.552^{***}	0.466^{***}	0.488^{***}	-0.152^{***}	0.152	0.029	1.717^{***}	-0.600^{**}
	(0.100)	(0.079)	(0.077)	(0.059)	(0.147)	(0.120)	(0.182)	(0.256)
$\Delta\pi$	$0.208^{\dagger}$	0.355^{***}	0.401^{***}	0.387^{***}	0.509^{***}	0.261^{***}	0.444^{***}	0.326^{***}
	(0.853)	(0.030)	(0.024)	(0.030)	(0.057)	(0.043)	(0.074)	(0.090)
Female x $\Delta\pi$	$-0.195^{*\dagger}$	-0.105^{***}	-0.050	-0.102^{***}	-0.211^{***}	-0.005	-0.221^{**}	-0.122
	(0.115)	(0.036)	(0.031)	(0.036)	(0.069)	(0.051)	(0.091)	(0.107)
Period	1982-2020	1982-2020	1982-2023	1982-2020	1982-2020	1982-2020	1982-2020	1982-2020
Month FE	Yes	No	No	No	No	No		
Industry FE	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Same Industry					Yes	Yes	No	No
Same Occupation					No	Yes	No	Yes
Observations	755,817	755,817	805,982	755,817	192,328	332,189	153,276	78,024
Adjusted R^2	0.013	0.012	0.012	0.006	0.020	0.004	0.060	0.007

*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 $\Delta\pi > 0$.

"inflation penalty" of \$0.01 per hour for every \$10 of hourly earnings. While small at the hourly level, this effect accumulates over the work year, corresponding to a \$20.80 reduction in annual earnings growth per \$10 of hourly pay for a full-time worker. Because nominal wage setting is path dependent, even small asymmetries in short-run growth permanently shift lifetime earnings levels. In column (1) we incorporate month fixed effects instead to absorb common seasonal shocks and redefine $\Delta\pi_{t-12}$ as a dummy where 1 indicates rising inflation. During periods of rising inflation, women's wage growth is on average 0.2 percent smaller. Column (3) shows that this result is robust to the exclusion of industry and occupation fixed effects.

Figure 5 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. Taken together, these non-parametric patterns are consistent with the linear structure of the VAR analysis: positive inflationary shocks widen the gender wage gap, 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. This pattern suggests that the "inflation

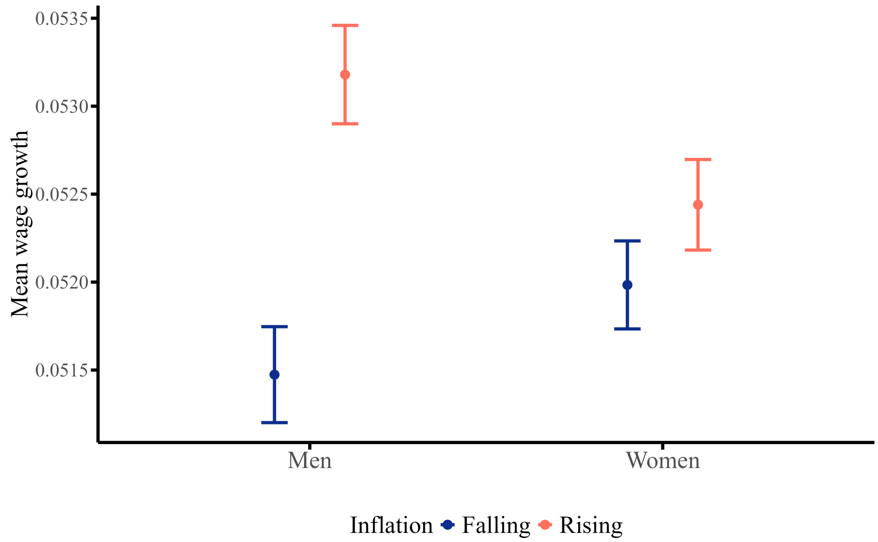


Figure 5: Gender differences in Wage Growth by Inflation Regime

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.

penalty" for women reflects a broad distributional shift rather than the influence of a small number of extreme observations.

1.3.1 Occupational Mobility and the Inflation Premium

A central question is whether disparities arise within stable employment relationships or through transitions across the labor market. Our previous results established that women's wages grow significantly slower than men's during inflationary accelerations. We investigate whether this is driven by workers who change jobs, a natural margin given that a substantial portion of lifetime wage growth is realized through job-to-job transitions (Topel & Ward 1992). The focus on the search margin is further motivated by recent evidence that workers actively utilize on-the-job search to protect real wages against inflationary shocks. Pilossoph & Ryngaert (2024) show that higher inflation expectations directly increase search effort to protect real earnings against wage erosion. However, the ability to successfully navigate this transition is likely gendered. Cortés et al. (2023) document that women tend to accept job offers significantly earlier than men, who exhibit greater overoptimism regarding prospective offers.

The CPS does not directly identify whether an individual remains with the same employer over a period of 12 months. We therefore proxy an occupational switch as a change in the respondent's three-digit occupation code over the 12-month observation window. This variable captures both external job-to-job transitions and significant internal promotions. We further define a certain job-to-job transition as a change in the three-digit industry code over the 12-month observation window. Table 2 reveals substantial heterogeneity in wage responses across workers. Columns (5)-(8) show that occupation switchers experience a stronger gender-inflation penalty. In contrast, we find no comparable heterogeneity between workers who remain in the same industry and those who certainly change employers. This suggests that the widening gender wage gap during inflation is fundamentally a story of *negotiated transitions*, such as promotions or role changes. Men appear more capable of extracting nominal wage premiums when shifting roles or securing promotions during inflationary shocks. Consistent with the mechanisms in Cortés et al. (2023), this may reflect women's relative pessimism when pursuing wage negotiations.

Because inflation shapes beliefs about future labor-market conditions (Pilossoph & Ryngaert 2024), potentially affecting wage-setting behavior differently across genders, we next examine how men and women form and update their labor-market expectations in response to inflationary shocks.

2 Inflation and Labor Market Expectations

We next document our second new empirical fact: women interpret unexpected inflation as a signal of deteriorating labor-market conditions, while men perceive mild improvement. That is, women revise their beliefs about labor-market conditions more pessimistically than men in the face of inflationary shocks. The relationship between inflation and labor-market beliefs is central to understanding gender-specific economic behavior. To this end, we use data from the New York Fed Survey of Consumer Expectations (SCE, Federal Reserve Bank of New York 2024).[9] As in our analysis of the gender wage gap, we focus on observationally comparable men and women, adjusting for differences in individual characteristics using both the KOB decomposition and the nearest-neighbor matching approach. We study how male and female expectations about unemployment, job-finding prospects, and earnings growth respond to inflationary demand and supply shocks using the same Structural VAR with zero and sign restrictions. This approach extends the existing literature on consumer expectations, which typically relies on micro-level revisions or survey experiments (e.g., Andre et al. 2022). Instead, we exploit inflationary demand and supply shocks to examine how average beliefs evolve over time, allowing us to capture transmission lags that panel revisions may miss.

[9] 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.

2.1 Construction of Time Series of Beliefs

We construct time series of men's and women's inflation and labor-market beliefs 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). As before, we restrict our sample to the pre-Covid period. 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. We restrict the sample to full-time employed workers and exclude the self-employed, consistent with our analysis of the adjusted gender wage gap. 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, there are no occupation controls available.

Our method resembles the Kitagawa-Oaxaca-Blinder decomposition employed in Section 1. However, rather than focusing on the gender gap itself, we recover separate time series of labor-market beliefs for observationally comparable men and women. For any month t, we separately estimate male (m) and female (f) weighted ordinary least squares (OLS) expectations regressions for individual i (again, the i and t subscripts are suppressed to simplify notation):

$$\begin{aligned} Y_m &= X_m B_m + \zeta_m IND18_m + u_m \\ Y_f &= X_f B_f + \zeta_f IND18_f + u_f, \end{aligned}$$

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:

$$\begin{aligned} \hat{Y}_{mm} &= X_m \hat{B}_m + \hat{\zeta}_m IND18_m \\ \hat{Y}_{mf} &\equiv X_m \hat{B}_f + \hat{\zeta}_f IND18_m. \end{aligned}$$

where $\hat{Y}_{mm}$ represents predicted expectations of men and $\hat{Y}_{mf}$ represents the counterfactual expectations of men if 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

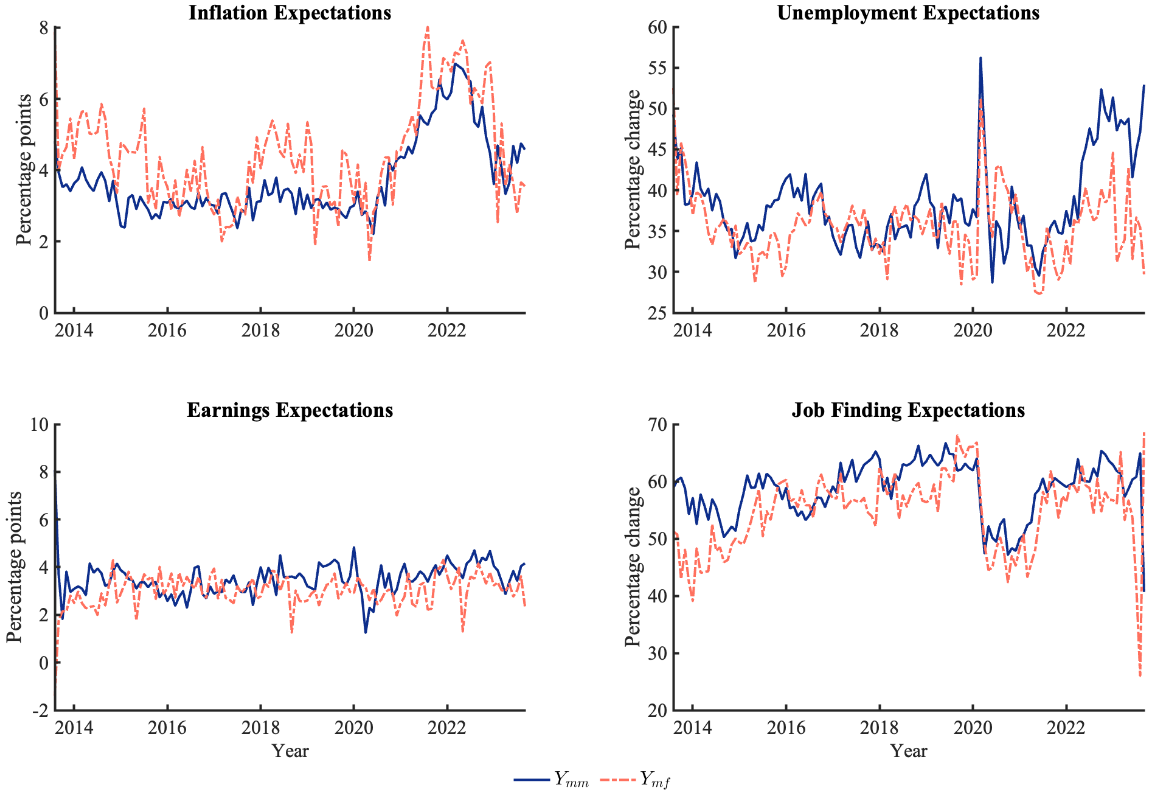


Figure 6: Survey Expectations in the SCE

Notes: Women's expectations are plotted in dashed orange and men's expectations are plotted in solid dark blue. Monthly data from August 2013-December 2023.

economy through sorting in different industries.

Figure 6 shows the time series of both series for inflation, unemployment, job finding and earnings growth expectations. Our series replicates the well-known gender gap in inflation expectations, namely women having higher inflation expectations (Reiche 2025, D'Acunto, Malmendier & Weber 2021), 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.

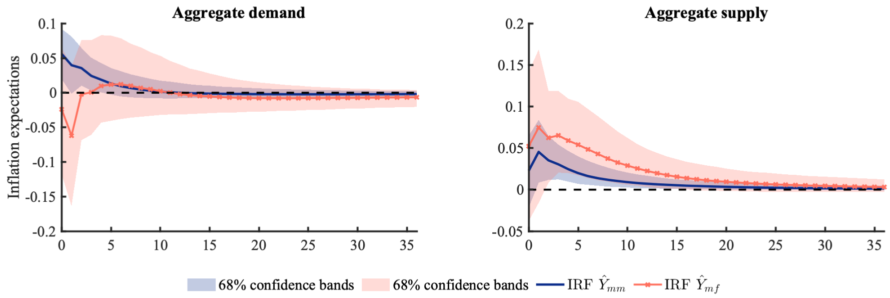
2.2 Belief Responses to Inflationary Shocks

We estimate a structural VAR 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. Figure 7 summarizes the impulse responses of men's predicted expectations, $\hat{Y}_{mm}$ (in blue), and the counterfactual $\hat{Y}_{mf}$ constructed using women's expectation coefficients (in orange), which we refer to as women's expectations in what follows, 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 for inflation and earnings expectations and percentage changes for unemployment and job-finding expectations. The full set of impulse responses for all variables is reported in the Appendix (see Figure B.1).

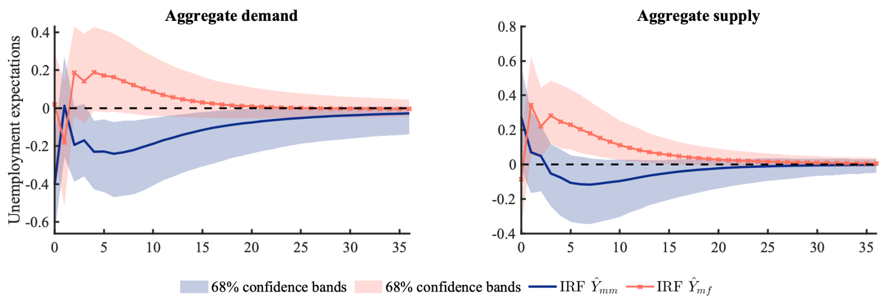
The results reveal a striking and systematic gender asymmetry in belief formation. For inflation expectations, women exhibit more volatile responses and react more strongly to inflationary supply shocks than men. For labor-market beliefs, women consistently respond to inflationary shocks with pessimism, interpreting rising inflation as a signal of deteriorating labor-market conditions (a supply-side interpretation of inflation). Men, by contrast, respond with relative optimism, viewing inflation as indicative of mild improvements in labor-market conditions (consistent with a demand-side interpretation). Specifically, women revise unemployment expectations upward and revise both earnings growth and job-finding expectations downward following both supply- and demand-driven inflationary shocks. Men, in contrast, revise job-finding and earnings expectations upward following expansionary demand shocks, while leaving job-finding expectations largely unchanged and revising earnings expectations upward following contractionary supply shocks. These results hold among observationally similar men and women, accounting for differences in demographics, numeracy, and industry, highlighting a robust and systematic gender difference in how inflationary shocks are mapped into labor-market expectations.

Taken together, these results provide direct evidence of a gendered pessimism channel in belief formation: women systematically place greater weight on adverse interpretations of inflationary shocks, while men place relatively more weight on favorable interpretations. This finding is consistent with a broad literature documenting gender differences in pessimism, optimism, and perceived downside risks in economics and finance (Dawson 2017, Jacobsen et al. 2014, Bjuggren & Elert 2019), as well as in psychology (Lin & Raghubir 2005, Dawson 2023) and political science (Gwartney-Gibbs & Lach 2016). Our results show that these belief differences become particularly salient in response to inflationary shocks with direct implications for labor-market prospects.

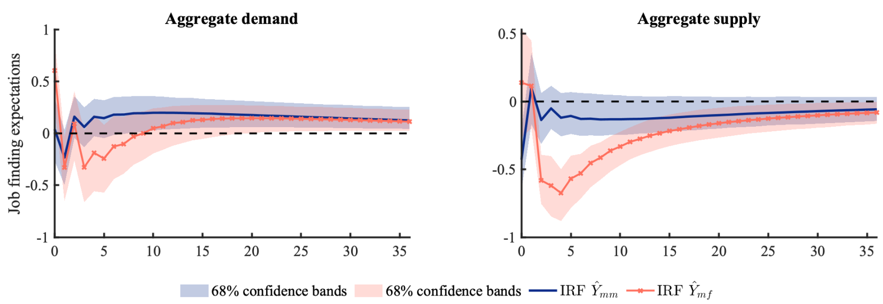
One possible interpretation is that gender differences in beliefs reflect differential past labor-market experience or heterogeneous exposure to salient price categories (Malmendier & Nagel 2016). Our evidence suggests that these channels are unlikely to be the primary drivers. Realized unemployment responds differently across shocks: the gender unemployment gap narrows following demand shocks but widens following supply shocks (see Figure A.6). Yet, expectations move in the same direction in both cases. Women expect higher unemployment after either inflationary shock, whereas men expect lower unemployment, even when realized outcomes for women improve, as after demand shocks. If beliefs were mainly shaped by past labor-market exposure, expectations would be expected to track these realized differences more closely. Instead, the uniform divergence



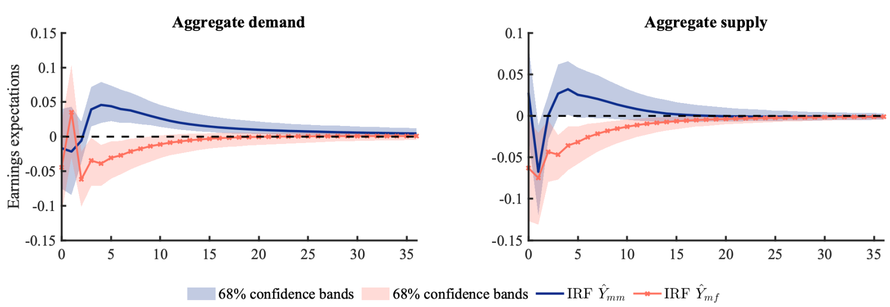
(a) Inflation (12 months)



(b) Unemployment (12 months)



(c) Job Finding (3 months)



(d) Earnings Growth (12 months)

Figure 7: 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 demand and supply shocks of one standard deviation. Median (solid and crossed lines) and 68% probability density intervals (shaded areas) are based on 10,000 draws and defined at each point in time.

in expectations points toward differences in how inflationary shocks are interpreted. Moreover, excluding food and energy prices from CPI (see A.8b) leaves our results essentially unchanged, suggesting that differential exposure to specific consumption categories (documented to matter for inflation expectations in D'Acunto, Malmendier, Ospina & Weber 2021, D'Acunto, Malmendier & Weber 2021) is unlikely to account for the patterns we document.

As with our analysis of the gender wage gap, we assess the robustness of these belief responses using alternative identification strategies for inflationary shocks and alternative measures of expectations constructed for observationally similar men and women. First, we identify an inflationary shock as the innovation that explains the largest share of residual variation in inflation at business-cycle frequencies. Figure B.2 in the Appendix reports the corresponding impulse responses. The baseline results remain virtually unchanged under this alternative specification. If anything, the gender asymmetries become even more pronounced: the differences between men's and women's belief responses are larger, yet they continue 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 nearest-neighbor matching. Similarity is defined using Mahalanobis distance on raw covariates, with exact matches on region and industry. Figure B.3 in the Appendix shows that the results are robust to this alternative specification. As for the max-share inflationary shock, the differences are even starker and more significant compared to our baseline, while preserving the same pattern.

Taken together, the evidence in Sections 1 and 2 shows that the gender wage gap widens when inflation rises and that men and women update their beliefs about labor-market conditions in systematically different ways in response to inflationary shocks. These gendered belief responses provide 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. To formalize this mechanism, we now turn to a structural model that incorporates belief heterogeneity and wage-renegotiation frictions, allowing us to study how informational biases can generate the gendered wage dynamics documented in the data.

3 Theoretical Model

In this section, we develop a model that extends the standard New Keynesian framework with search-and-matching frictions à la Diamond (1982), Mortensen (1982), Pissarides (1985) (DMP), as developed in Thomas (2008), Faia (2008), Galí (2010), Blanchard & Galí (2010), Christiano et al. (2016). The model features male and female workers within the household and allows for gender-specific wage-setting. We proceed in two steps.

We first introduce a benchmark Gender New Keynesian Search-and-Matching (Gender-NKSM) model under full-information rational expectations. Within this framework, we consider several conventional sources of gender differences emphasized in the literature, including taste-based discrimination, statistical discrimination, lower bargaining power of women, and greater wage rigidity for women. We assess how each of these mechanisms affects the response of the gender wage gap to supply- and demand-driven inflationary shocks. We find that none of these channels can replicate the empirical widening of the adjusted gender wage gap we document.

In a second step, motivated by our empirical evidence on gender differences in labor-market expectations, we relax full-information rational expectations. Wage-setting unions do not observe the true nature of inflationary shocks and must form beliefs about the underlying state of the economy.[10] We model the observed pessimism of women through relative ambiguity aversion using the robust control framework of Hansen & Sargent (2001), assuming that unions representing women are more ambiguity averse than those representing men. As a result, women's unions place greater weight on adverse, supply-driven interpretations of inflationary shocks and therefore expect weaker labor-market conditions regardless of the shock's origin. We show that, under this belief structure, the model generates a gender wage gap response to inflationary shocks in line with our empirical evidence.

3.1 The Gender-NKSM

The baseline NKSM framework provides a robust foundation for modeling labor market frictions and the joint dynamics of inflation, output, and unemployment (e.g., Galí 2010, Blanchard & Galí 2010, Christiano et al. 2016). We extend this framework by incorporating a two-agent household and a production function with gender-specific labor inputs, following Albanesi (2025). In our setup, male and female workers coexist within a single household and consume collectively, yet they supply labor through independent male and female unions. This structure allows for idiosyncratic wage-renegotiation processes driven by gender-specific beliefs.

Household The representative household consists of two members: one agent of type f (female) and one agent of type m (male). There are not many papers in macroeconomics looking inside families despite their importance in explaining macroeconomic trends (Doepke & Tertilt 2016). Browning & Chiappori (1998) introduce a collectivist view of households which Knowles (2013) applies to household bargaining and female labor supply to show how intra-family bargaining affects women's but not men's labor supply. Mankart & Oikonomou (2017) show that there may

[10]This setup is related to Erceg et al. (2025), where agents face imperfect information about the persistence of shocks.

be insurance effects between a primary and a secondary breadwinner when incomplete markets are present in a similar NKSM setup as ours and Neyer & Stempel (2021) incorporate unpaid domestic labor and discrimination into a New Keynesian framework to study gender differences in labor market participation.

As in Albanesi (2025), we abstract from domestic labor and incomplete financial markets though we maintain the perfect insurance setup. 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 $g = f, m$:

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

We do not explicitly model intra-household bargaining, instead we assume that the household consumes together but supplies two types of labor as in Ashenfelter & Heckman (1974). However, this is equivalent to members bargaining with equal weights over an aggregated consumption good when preferences are identical. 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 denotes 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) Π_t. The maximization problem of the houshold is:

$$\max \mathbf{E}_0 \sum_{t=0}^{\infty} \beta^t U(C_t, L_{m,t}, L_{f,t}; Z_t)$$

$$\text{subject to } P_t C_t + Q_t B_t \leq B_{t-1} + W_{f,t} N_{f,t} + W_{m,t} N_{m,t} + \Pi_t.$$

This yields the standard Euler equation for intertemporal consumption:

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

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.[11] 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 productivities ζ_m and ζ_f and an elasticity of substitution between male and female labor σ (Albanesi 2025):

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

Technology A_t is assumed common across all firms and its log follows an AR(1) process with autoregressive coefficient ρ_a and variance σ_a^2. 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 DMP framework which abstracts from explaining vacancies but shares the same

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

characteristics of the original framework (Galí 2010, 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:

$$\frac{P_t^I}{P_t} MPN_{g,t} = A_t mc_t \zeta_g (1-\alpha) N_{g,t}^{\frac{-1}{\sigma}} N_t^{-\alpha+\frac{1}{\sigma-1}} (1-d_g) \tag{7}$$

$$= w_{g,t} + G_{g,t} - \beta(1-\delta)\mathbf{E}_t \left\{ \frac{C_t}{C_{t+1}} \frac{P_{t+1}}{P_t} G_{g,t+1} \right\}. \tag{8}$$

Gender wage gaps in equilibrium can be introduced in two ways in our model. The first is taste-based discrimination (Becker 1971, Black 1995, Charles & Guryan 2008, Neyer & Stempel 2021) where $d_f > d_m = 0$. In contrast to standard models, we assume that the distaste is proportional to output rather than employment in the profit function to account for the effect of a general expansion on the distaste. An alternative way to model equilibrium gender wage gaps is statistical wage discrimination (Arrow 1971, Phelps 1972, Aigner & Cain 1977, Altonji & Pierret 2001), which results in lower perceived productivity of women such that $\zeta_m > \zeta_f$. There are also alternative ways to model gender wage gaps. For instance, women's greater preference for amenities (Wiswall & Zafar 2018, Goldin 2014, Bolotnyy & Emanuel 2022) and personality traits such as risk aversion (Azmat & Petrongolo 2014, Cortés et al. 2023, Flinn et al. 2025). However, there is evidence for prejudice dominating statistical differences between men and women in Flabbi (2010) and recent evidence in favor of the (Black 1995) model of taste-based discrimination in Maloney & Neumark (2025). Further, while amenities and personality differences may play a significant role, seminal work by Goldin & Rouse (2000) and Bertrand & Mullainathan (2004) shows that they cannot explain all of the differences observed. In fact, more recent evidence suggests that distaste and statistical discrimination remain prevalent in women's evaluation (Reuben et al. 2014, Hengel 2022) though initial biases can be overcome after repeated observation of performance (Bohren et al. 2019).

Wage bargaining Wages are determined as the Nash bargaining outcome between workers and firms. 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 households and firms matter in the bargaining process. Wage bargaining is symmetric across genders and follows the Nash bargaining framework in Blanchard & Galí (2010). This differs from Mankart & Oikonomou (2017) where agents only differ in their search effort but wages are bargained jointly. The value of an employment relationship to a worker of type g is given by their wage minus the disutility of labor plus the continuation value of keeping the job at the same wages or renegotiated wages:

$$V^N_{g,t+k|t} = \frac{W^*_{g,t}}{P_{t+k}} - MRS_{gt,t+k} + \mathbb{E}_{t+k}\left[\Lambda_{t+k,t+k+1}\left((1-\delta)\left((1-\theta^w_g)V^N_{g,t+k+1|t} + \theta^w_g V^N_{t+k+1|t+k+1}\right) + \delta V^U_{g,t+k+1}\right)\right].$$

Similarly, the value of an unemployment spell to a worker of type g is given by:

$$V^U_{g,t} = x_{g,t}\int_0^1 \frac{H_{g,t}(z)}{H_{g,t}} V^N_{g,t}(z)dz + (1-x_{g,t})\left(-\psi MRS_{g,t} + \mathbb{E}_t\left[\Lambda_{t,t+1}V^U_{g,t+1}\right]\right).$$

The surplus of a worker whose wages are currently being reset is given by:

$$\begin{aligned} S^H_{g,t|t} &= \mathbb{E}_t \textstyle\sum_{k=0}^{\infty}((1-\delta)(1-\theta^w_g))^k \Lambda_{t,t+k}\left(\frac{W^*_{g,t}}{P_{t+k}} - MRS_{g,t+k}\right) \\ &+ \theta^w_g(1-\delta)\mathbb{E}_t \textstyle\sum_{k=0}^{\infty}((1-\delta)(1-\theta^w_g))^k \Lambda_{t,t+k+1}\, S^H_{g,t+k+1|t+k+1}. \end{aligned}$$

Because optimal participation requires $V^U_{g,t} = 0$, we get the optimal participation condition:

$$\psi MRS_t = \frac{x_{g,t}}{1-x_{g,t}}\int_0^1 \frac{H_{g,t}(z)}{H_{g,t}} S^H_{g,t}(z)dz. \tag{9}$$

For firms, the surplus of a match is given by the marginal revenue product minus wages and plus the continuation value of the match, which saves the hiring costs of the firm in the next period:

$$\begin{aligned} S^F_{g,t|t} &= \mathbb{E}_t \textstyle\sum_{k=0}^{\infty}((1-\delta)(1-\theta^w_g))^k\, \Lambda_{t,t+k}\left(\left(\frac{P^I_t}{P_t} - d_g\right) MPN_{g,t+k|t} - \frac{W^*_{g,t}}{P_{t+k}}\right) \\ &+ \theta^w_g(1-\delta)\mathbb{E}_t \textstyle\sum_{k=0}^{\infty}((1-\delta)(1-\theta^w_g))^k\, \Lambda_{t,t+k+1}\, S^F_{t+k+1|t+k+1}. \end{aligned}$$

Workers and firms engage in Nash bargaining. We assume that female and male workers can have different bargaining powers relative to the firm denoted by $1-\xi_f$ and $1-\xi_m$ respectively. The Nash bargaining rule

$$\xi_g S^H_{g,t|t} = (1-\xi_g)\, S^F_{t|t},$$

yields the following condition for the newly set nominal wage:

$$\mathbb{E}_t \sum_{k=0}^{\infty}((1-\delta)(1-\theta^w_g))^k\, \Lambda_{t,t+k}\left(\frac{W^*_{g,t}}{P_{t+k}} - \Omega^{\text{tar}}_{g,t+k|t}\right) = 0.$$

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:

$$\Omega^{tar}_{g,t+k|t} \equiv \xi_g \frac{C_{t+k}}{\chi L^{\varphi}_{g,t+k}} + (1-\xi_g)\frac{P^I_t}{P_t} MPN_{g,t+k|t}. \tag{10}$$

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

$$Y_t = C_t + G_{f,t}H_{f,t} + G_{m,t}H_{m,t}. \tag{11}$$

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

$$Y_t = A_t \left[\zeta_f \cdot N_{f,t}^{\frac{\sigma-1}{\sigma}} + \zeta_m \cdot N_{m,t}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{(1-\alpha)\sigma}{\sigma-1}}. \tag{12}$$

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

$$\frac{1+i_t}{1+\bar{i}_t} = \left(\frac{1+i_{t-1}}{1+\bar{i}_t}\right)^{\rho_i} \left[\left(\frac{1+\pi^p_t}{1+\bar{\pi}^p_t}\right)^{\phi_\pi} \left(\frac{1+\pi^w_{m,t}}{1+\bar{\pi}^w_t}\right)^{\phi_{wm}} \left(\frac{1+\pi^w_{f,t}}{1+\bar{\pi}^w_t}\right)^{\phi_{wf}} \left(\frac{U_{m,t}}{\bar{U}_{m,t}}\right)^{\phi_{um}} \left(\frac{U_{f,t}}{\bar{U}_{f,t}}\right)^{\phi_{uf}} \left(\frac{Y_t}{\bar{Y}_t}\right)^{\phi_y}\right]^{1-\rho_i} \nu_t. \tag{13}$$

The full set of equilibrium equations can be found in Section C.2 of the Appendix.

3.2 Calibration

We calibrate the model to the US economy using standard parameter values. Each period corresponds to a quarter. Following convention, we assign $\beta = 0.99$, set a Frisch elasticity of 0.5 ($\varphi = 2$), and assume prices are set for about one year on average such that $\theta^p = 0.75$. Assuming around 60% employment rate, 6% unemployment[12] and a 0.7 job finding rate (Gertler & Trigari 2009) we arrive at a quarterly separation rate of 0.23, slightly higher than empirical estimates in Hall (2005) and Gertler & Trigari (2009). Following Galí (2010) and Blanchard & Galí (2010) we set $\gamma = 1$ to align the framework with the matching function approach in DMP style models and assign $\Gamma = 0.013$ 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. Further, we assume the elasticity of substitution of men and women to be $\sigma = 4.3$ in line with empirical estimates (Albanesi 2025, Acemoglu et al. 2004). We assume a monetary authority that responds to inflation and unemployment with $\phi_\pi = 2$, $\phi_y = 0$, $\phi_{w,g} = 0.005$ and $\phi_{u,g} = -0.0125$.

[12] BLS data indicates no meaningful differences in average unemployment rates by gender over the sample.

The values are taken from Faia (2008) who argues that central banks should not respond to output when labor market frictions are present to avoid excess volatility of unemployment. Further we assume persistence in monetary policy given by $\rho_i = 0.95$.

In our baseline calibration, we assume no differences between male and female workers. Hence, in the production function, $\zeta_m = \zeta_f = 0.5$, male and female wage-stickiness $\theta^w_m = \theta^w_f = 0.75$ and firms bargaining power relative to men and women $\xi_m = \xi_f = 0.6$. Wage stickiness is set to assume wages are being reset annually (Taylor 1998, Gottschalk 2005, Barattieri et al. 2014) and the average bargaining weight is taken from estimates in Flinn (2006), who finds strikingly small differences between men and women. We choose equal values as baseline not to match reality but to be able to single out the effects of varying parameters individually. We also start with assuming $d_f = 0$ such that there is no gender gap in equilibrium. We show the effect of a more realistic, gender divergent calibration in a second step. Finally, we include standard parameters for the shock processes, $\rho_z = 0.9$, $\sigma_z = 0.001$, $\rho_u = 0.9$ and $\sigma_u = 0.001$. For simplicity of presentation we assume $\sigma^2_a = 0$ and $\sigma^2_\nu = 0$ such that technology is assumed constant and there are no monetary policy shocks.[13] The full set of parameters and calibration is reported in Appendix Table C.1.

3.3 Gender wage gap dynamics under non-belief-frictions

In the baseline model, assuming no discrimination, symmetric bargaining power and symmetric wage rigidities across genders, no gender wage gap emerges. The black line in Figure 8 reports impulse responses to demand (preference) and supply (cost-push) shocks. As expected, inflationary demand shocks raise output, employment, and wages, whereas inflationary supply shocks reduce them. By construction, men and women respond identically, abstracting from differential exposure or wage renegotiation.[14]

Introducing taste-based discrimination ($d_f = 0.1$), which generates a steady-state GWG of roughly 11% in line with the data, produces negligible changes in the cyclical response of the GWG (lightest blue lines, + marker). This is unsurprising, as the additional cost of hiring women scales proportionally with output. We therefore retain d_f in all subsequent calibrations to ensure consistent steady-state wage gaps. Next, we calibrate relative productivity weights following Albanesi (2025) ($\zeta_f = 0.375 < 0.5$), amplifying the equilibrium GWG and generating weak cyclical patterns ($*$ marker). Statistical discrimination against women, interpreted as lower perceived productivity, makes the GWG slightly countercyclical: it declines under demand shocks and rises under supply shocks. This occurs because rising output reduces the relative cost of employing women, increasing

[13] An alternative specification would be to include a standard technology shock and a standard monetary policy shock calibrated as $\rho_a = 0.9$, $\sigma_a = 0.25$, $\rho_\nu = 0.9$, $\sigma_\nu = 1$ to represent the supply- and a demand-shock respectively. The results would be the same in this scenario.

[14] Further impulse responses are shown in Appendix Figure C.1.

their wages relative to men. Therefore, we rule out this channel as the primary driver of observed GWG cyclicality.

We then explore three alternative mechanisms linked to women's labor market behavior, each in isolation. First, higher female Frisch elasticity ($\varphi_f = 0.8 < 2 < \varphi_m = 2.399$) is considered (Albanesi 2025, Blundell & Macurdy 1999). Second, 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 such that $\xi_m = 0.56 < 0.6 < \xi_f = 0.67$. Finally, we explore the possibility that women's wages are stickier than men's. While Barattieri et al. 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 the assumption that women may experience higher wage-resetting costs. Following Auclert et al. (2023), we maintain a Calvo-style framework as it provides a first-order approximation that is numerically equivalent to more complex menu cost models. Across all three cases, the GWG widens during inflationary expansions (demand shocks) but narrows during inflationary contractions (supply shocks). These results suggest that during downturns, stickier wages, lower renegotiation capacity, or higher labor supply elasticity can mitigate the impact on women, partially shielding them from cyclical wage declines.

Since all five mechanisms fail to replicate the observed cyclical patterns of the gender wage gap, we turn to our second empirical fact. Women and men perceive inflationary shocks systematically differently: women appear to interpret shocks more pessimistically than men. We formalize this relative pessimism through ambiguity aversion (Bhandari et al. 2025). Women facing uncertainty over the nature of shocks may overweight adverse scenarios, generating gender-specific responses in wages and employment. By incorporating differential shock perceptions, the model can capture how identical aggregate disturbances may produce divergent outcomes across genders.

3.4 The model with pessimism

To account for gender differences in the perception of inflationary shocks, we develop a framework in which female and male worker unions interpret identical aggregate signals under structural model uncertainty. While related work documents biased beliefs about labor market transitions (Spinnewijn 2015, Balleer et al. 2024), we focus instead on how agents interpret aggregate volatility. Our empirical evidence points towards a pessimism gap: women's inflation expectations are consistent with a worst-case interpretation of supply-driven (cost-push) shocks, whereas men's expectations align more closely with demand-driven interpretations. We formalize this mechanism using the Hansen–Sargent robust control framework (Hansen & Sargent 2001, Cogley et al. 2008). In our setup, unions are uncertain about the structural interpretation of aggregate signals. An

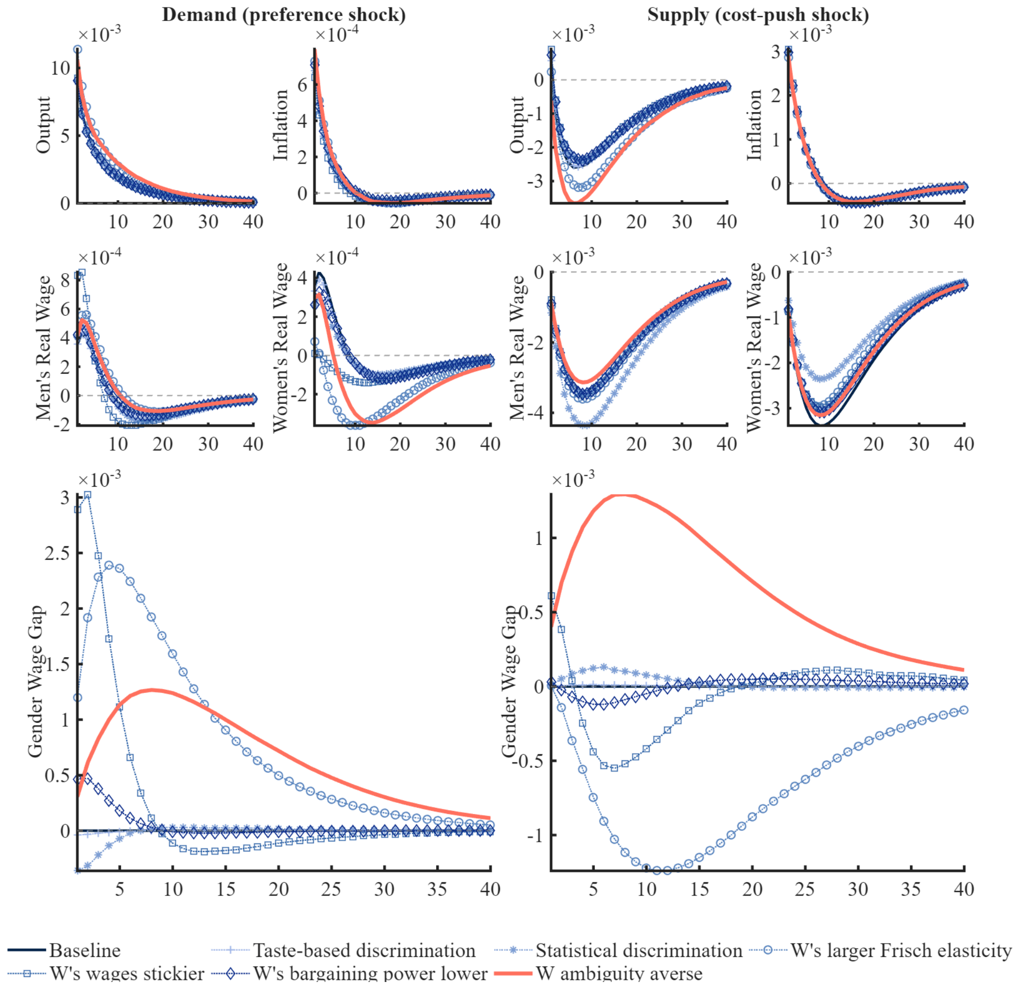


Figure 8: Impulse responses from the model

ambiguity-averse (female-representing) union therefore adopts a worst-case interpretation, tilting beliefs toward supply shocks, while a more optimistic (male-representing) union tilts beliefs toward demand shocks. This differs from the interval-based ambiguity in Ilut et al. (2014), Masolo & Monti (2021), Baqaee (2020), where uncertainty concerns the mean of shocks rather than their structural identification.

Our approach is most closely related to Bhandari et al. (2025), who introduce pessimism into a NKSM model. We depart from their framework by confining robust decision-making to the wage-setting process – implemented through gender-specific unions – while maintaining standard rational expectations for all other agents. This mechanism allows identical macroeconomic information to generate systematically different wage-setting across men and women without departing from rational expectations elsewhere in the economy.

Ambiguity aversion. Before forming expectations, each union $g \in \{m, f\}$ evaluates the continuation value of the representative household under each possible realization of the aggregate shocks, denoted $V_{s,t}$ for $s \in \{z, u\}$, where z represents a demand (preference) shock and u a cost-push (supply) shock. Let p_s denote the objective (prior) probability of shock s. Following the robust control framework (Hansen & Sargent 2001), we model ambiguity aversion as a smooth soft-min distortion of prior beliefs. The distorted (unnormalized) weights are given by

$$m_g^s = p_s \exp\left(-\frac{V_{s,t}}{\lambda_g}\right), \tag{14}$$

and the normalized subjective probabilities become

$$w_g^s = \frac{m_g^s}{\sum_{s' \in \{z,u\}} m_g^{s'}}. \tag{15}$$

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 *optimism* (overweighting favorable states) and $\lambda_f > 0$ as *pessimism* (overweighting unfavorable states). The normalization in w_g^s ensures $\sum_s w_g^s = 1$, such that $\{w_g^s\}$ defines a valid subjective probability measure. At the beginning of period t, prior to observing the realization of shocks, each union evaluates these distorted continuation values and forms beliefs about the likely nature of current disturbances.

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

$$s_t = \varepsilon_t^u + \varepsilon_t^z. \tag{16}$$

This informational friction is similar in spirit to Erceg et al. (2025), who model agents as unable to distinguish between persistent and transitory shocks. While both unions receive the same s_t, they do not exchange information and thus form beliefs independently, based on their gender-specific ambiguity attitudes.

Belief updating. Let $\tilde{\mathbb{E}}_{g,t}[\cdot]$ denote the conditional expectation operator of union g under its ambiguity-distorted beliefs, computed using weights $\{w_g^s\}$. Unions use these beliefs to infer the expected realizations of the latent shocks:

$$\tilde{\varepsilon}_{g,t}^z = w_g^z s_t, \tag{17}$$

$$\tilde{\varepsilon}_{g,t}^u = w_g^u s_t. \tag{18}$$

Subjective expectations about the underlying state variables evolve according to the perceived laws of motion:

$$\tilde{\mathbb{E}}_{g,t}[z_t] = \rho_z \, \tilde{\mathbb{E}}_{g,t-1}[z_{t-1}] + \tilde{\varepsilon}^z_{g,t}, \tag{19}$$

$$\tilde{\mathbb{E}}_{g,t}[u_t] = \rho_u \, \tilde{\mathbb{E}}_{g,t-1}[u_{t-1}] + \tilde{\varepsilon}^u_{g,t}. \tag{20}$$

The union's information set at time t excludes the true realizations of ε^z_t and ε^u_t, but includes all observable endogenous variables up to $t-1$ and the current composite signal s_t. Thus, while households, firms, and the monetary authority observe the actual shocks, unions operate under subjective and gender-specific belief distortions.

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 (9) can be rewritten as

$$\psi_g \, \chi_g L_g^{\varphi_g} \frac{C_t}{Z_t} = \frac{x_g}{1-x_g} \left[\frac{1-\xi_g}{\xi_g} G_g - \pi^w_g \frac{\theta^w_g}{1-\theta^w_g} \omega_{g,t-1} Q_g \right], \tag{21}$$

where

$$Q_g = 1 + \theta^w_g (1-\delta_g) \beta \frac{\tilde{\mathbb{E}}_{g,t}[Z_{t+1}]}{Z_t} \frac{C_t}{\tilde{\mathbb{E}}_{g,t}[C_{t+1}]} \frac{\tilde{\mathbb{E}}_{g,t}[Q_{g,t+1}]}{1+\pi^p_t}. \tag{22}$$

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 aversion rather than from structural or policy asymmetries. Consistent with our empirical analysis, male unions, being relatively optimistic ($\lambda_m < 0$), place higher subjective weight on favorable states and thus anticipate stronger future wage growth. Female unions, being relatively pessimistic ($\lambda_f > 0$), overweigh adverse shocks and anticipate weaker wage prospects. These divergent expectations alter wage demands and participation incentives, leading to persistent labor-supply differences even in symmetric macroeconomic environments.

The model with ambiguity aversion generates gender wage gaps that are sensitive to macroeconomic conditions, particularly inflation. In Figure 8, we calibrate $\lambda_m = -0.1$ and $\lambda_f = 0.1$ reflecting men's relative optimism and women's relative pessimism. This yields a weight on supply shocks for women of $w^u_f = 0.97 > w^u_m = 0.03$. Under this calibration, an inflationary shock increases the expected present value of future wages differently for men and women due to gender-specific beliefs. This divergence translates into lower expected outside options in the next period and thus lower target wages for women relative men, widening the gender wage gap. Importantly, the gap does not immediately revert to its pre-shock level; instead, 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 to display lasting effects after the initial shock.

In conclusion, our model highlights that relative pessimism of women, motivated by the survey evidence on labor market expectations after inflationary shocks, can replicate our empirical findings on the inflation-induced widening of the gender wage gap, while other common explanations cannot.

4 Conclusion

This paper establishes a new link between inflation dynamics and gender wage inequality. Using matched comparisons among observationally similar women and men drawn from the U.S. Current Population Survey (CPS), we show that the gender wage gap systematically widens following both supply- and demand-driven inflationary shocks. Inflation not only erodes purchasing power but also redistributes income across groups, amplifying gender disparities in the labor market. We trace this widening to gender differences in the interpretation of inflationary shocks. Women respond with relative pessimism, perceiving inflation as signaling weaker labor-market conditions, whereas men exhibit relative optimism, interpreting the same shocks as mild improvement. These asymmetric beliefs translate into unequal wage-setting behavior, with women pursuing smaller nominal wage increases and experiencing slower wage growth than men.

To formalize this mechanism, we develop a gendered New Keynesian search-and-matching model with informational frictions. Ambiguity-averse beliefs lead women to overweight adverse interpretations of shocks, generating systematically more pessimistic expectations. This framework replicates the empirical widening of the gender wage gap following inflationary shocks and links belief heterogeneity to aggregate wage dynamics, showing how differences in perceptions transform symmetric inflationary shocks into asymmetric distributional outcomes.

Our findings contribute to several strands of the literature. First, we add to the growing body of research on the distributional consequences of inflation (e.g., Auclert 2019, Kaplan et al. 2018, Cloyne et al. 2020, Doepke & Schneider 2006) by documenting a gender dimension of inflation's redistributive effects. Second, we connect to recent evidence on inflation narratives (Kamdar & Rey

2025, Candia et al. 2020, Andre et al. 2025, 2022, Shiller 2017, Stantcheva 2024) suggesting that narratives of inflation matter for macroeconomic outcomes and differ systematically across genders. Finally, we complement the literature on gender wage gaps (e.g., Goldin 2014, Blau & Kahn 2017, Biasi & Sarsons 2022, Card et al. 2016, Olivetti & Petrongolo 2016, Azmat & Petrongolo 2014) by showing how inflation can affect the cyclical evolution of gender wage gaps.

By linking inflation dynamics to gendered belief formation, the paper identifies a behavioral channel through which macroeconomic shocks shape inequality. In particular, our framework highlights how heterogeneity in expectations across demographic groups can generate persistent and systematic distributional effects of inflation. 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.

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Appendix

A Gender wage gap supplementary material

A.1 Alternative measures of the gender wage gap

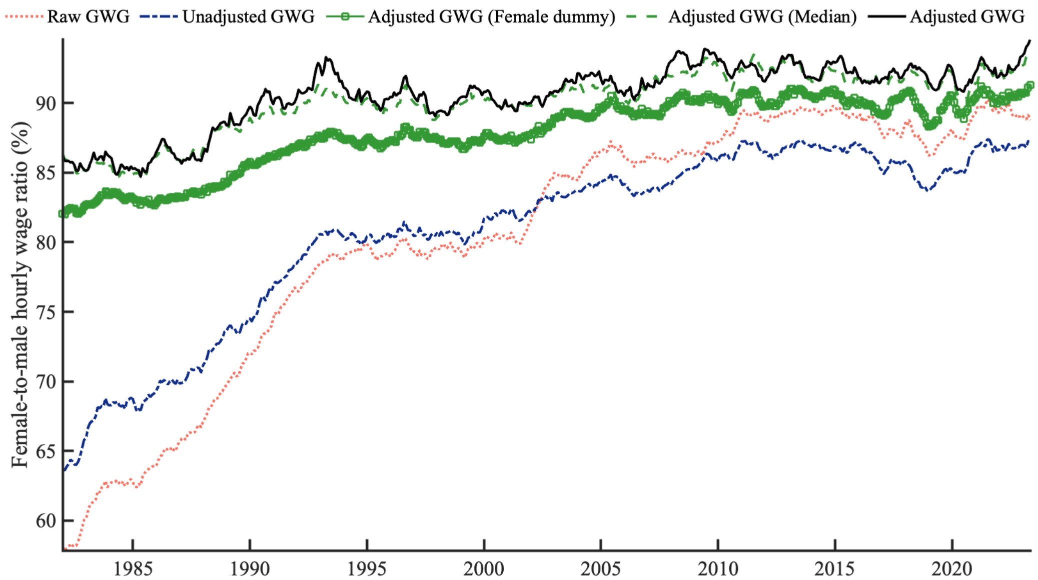


Figure A.1: Different measures of GWG (1982-2023) measured as female to male ratio

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 to smooth the volatility and seasonality. 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 weekly log earnings.

A.2 Gender wage gaps across demographic groups

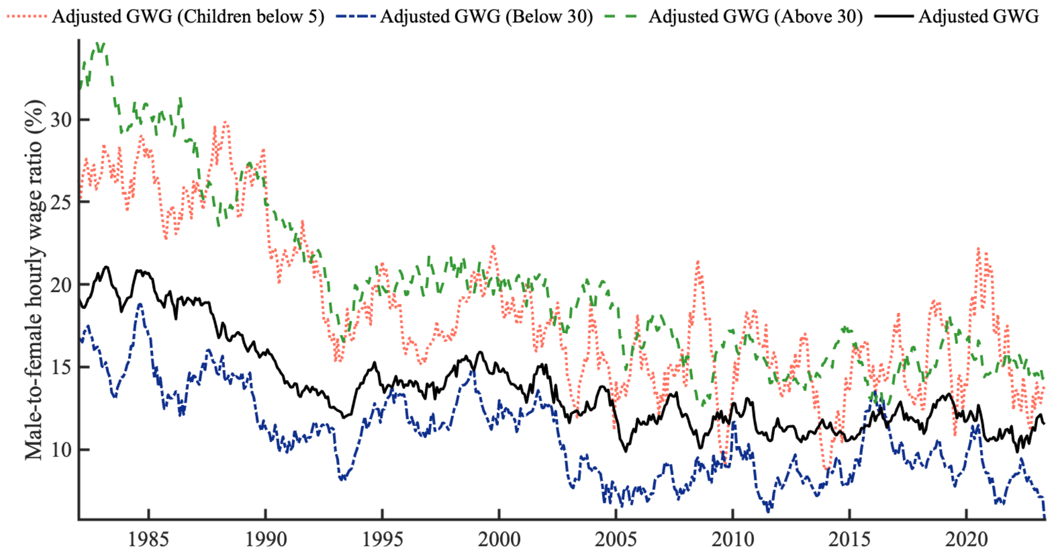


Figure A.2: Adjusted GWG (1982-2023) for different demographic groups

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 for a clean comparison.

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 gender wage gap. The test includes 3 lags as in the baseline VAR specification.

A.3.2 Alternative model and variable specifications

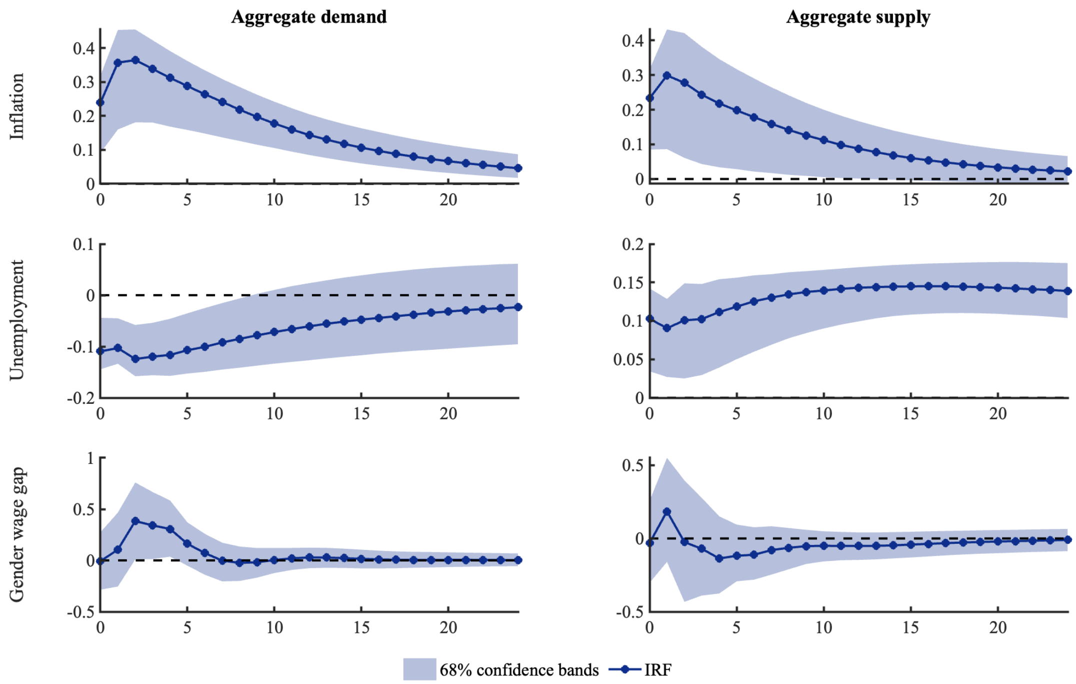


Figure A.3: Impulse Responses in the Structural VAR for unionised workers

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. Adjusted GWGs for unionised workers computed using monthly data from January 1982 - February 2020.

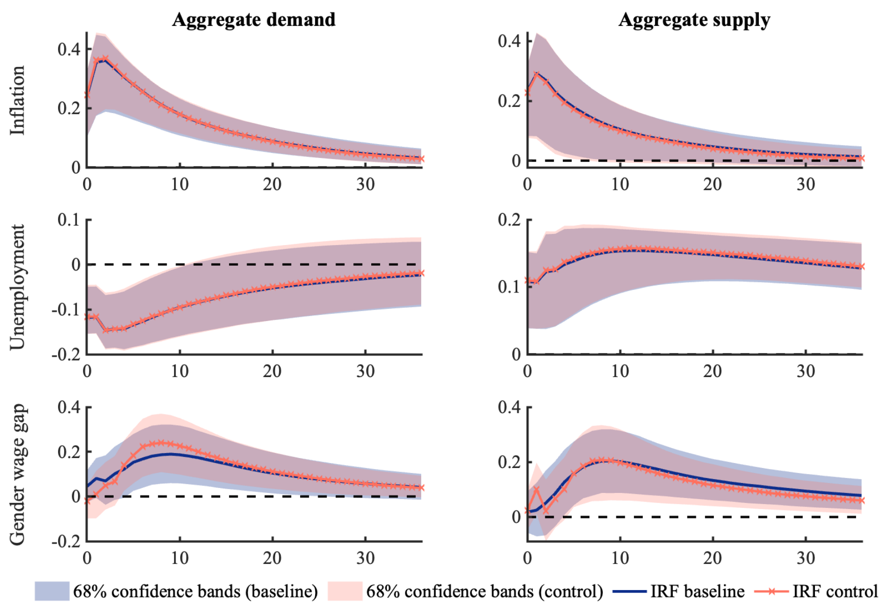
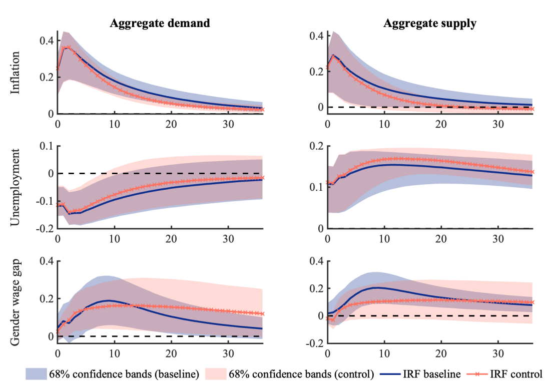
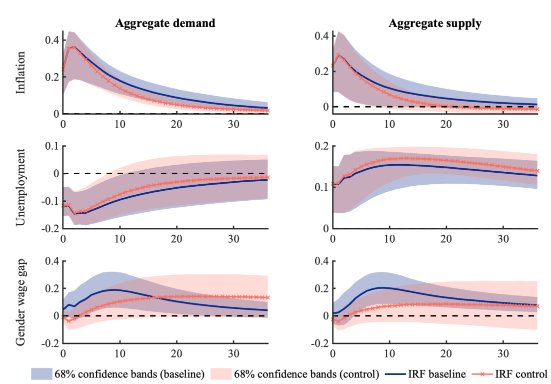


Figure A.4: Impulse Responses in the Structural VAR - baseline and nearest-neighbor matching

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.



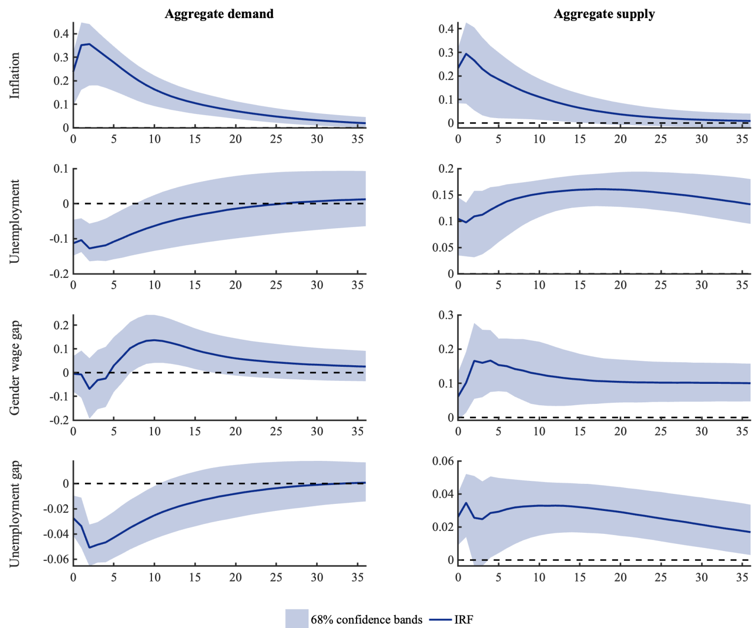
(a) Adjusted vs. unadjusted GWGs



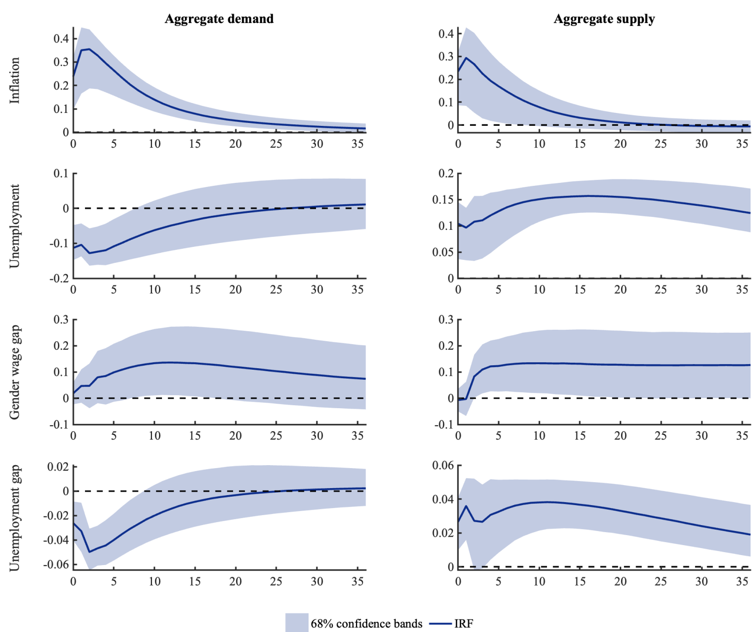
(b) Adjusted vs. raw GWGs

Figure A.5: Impulse Responses in the Structural VAR 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.



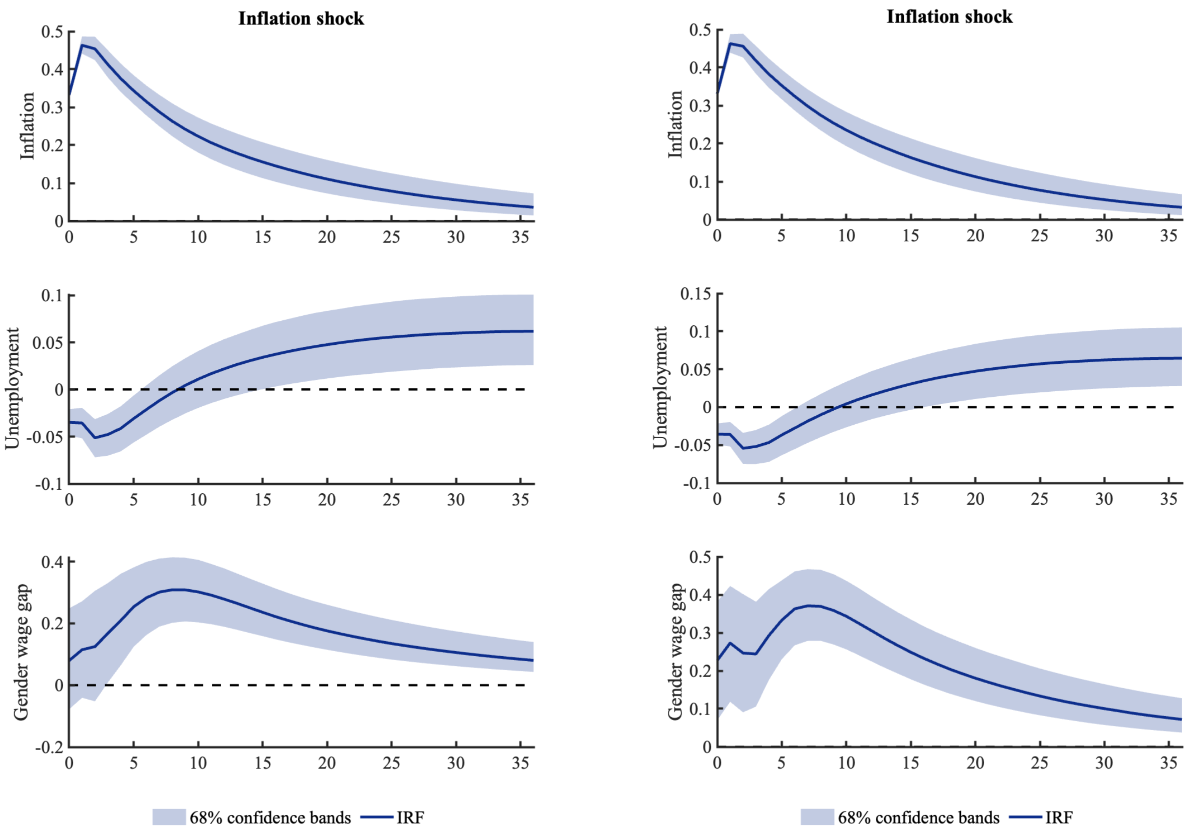
(a) Adjusted GWGs



(b) Unadjusted GWGs

Figure A.6: Impulse Responses in the Structural VAR Including the Unemployment Gap

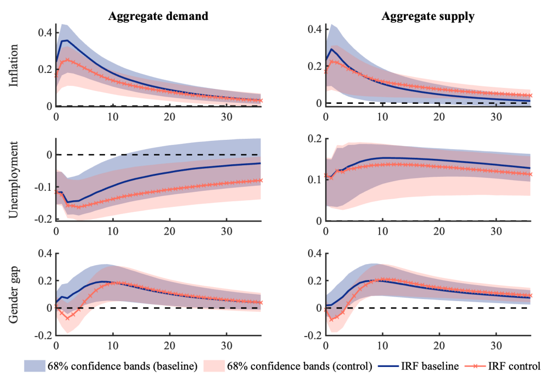
Notes: Adjusted and unadjusted GWGs computed using monthly data from January 1982–February 2020, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid blue line) and 68% probability density intervals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



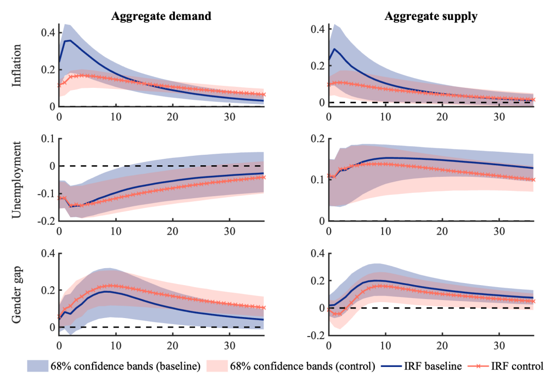
(a) KOB decomposition (b) Nearest-neighbor matching

Figure A.7: Impulse Responses in the Structural VAR using max-share identification

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 defined at each point in time. Adjusted GWGs are computed using monthly data from January 1982 – February 2020.



(a) PCE inflation



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

Figure A.8: Impulse Responses in the Structural VAR

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.

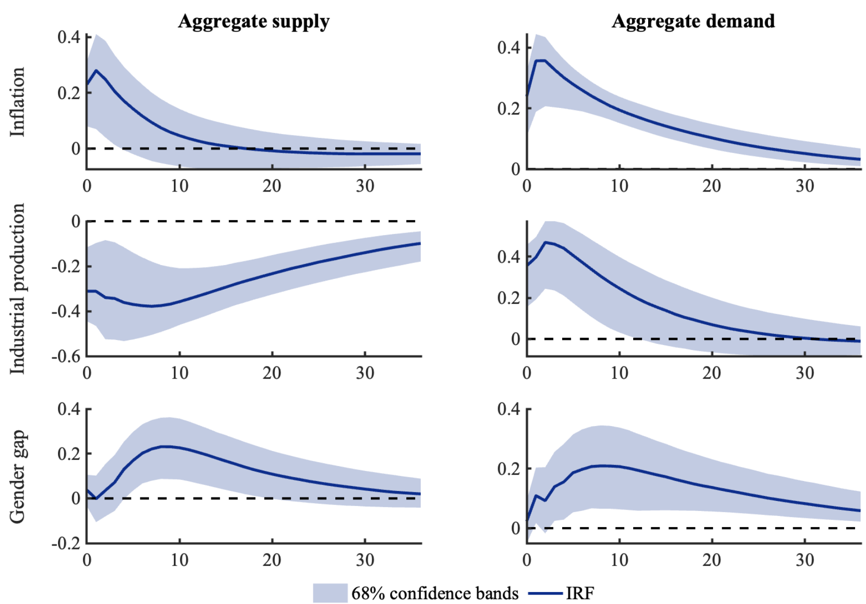
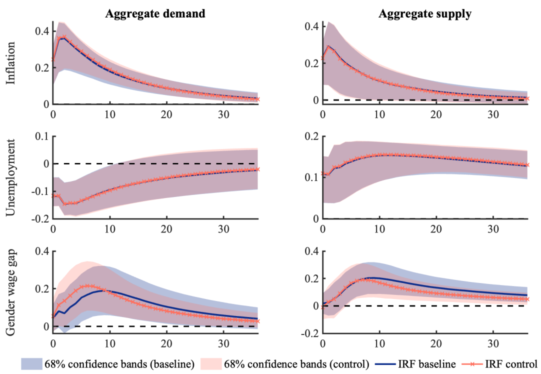
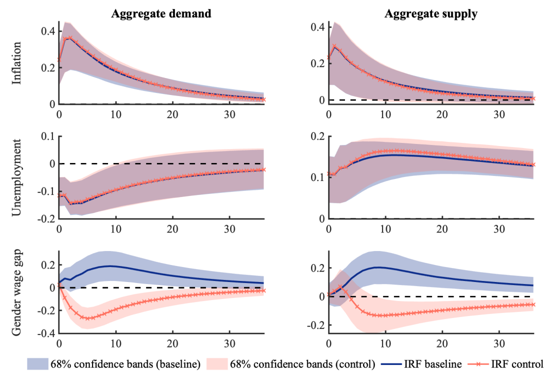


Figure A.9: Impulse Responses in the Structural VAR with Industrial Production

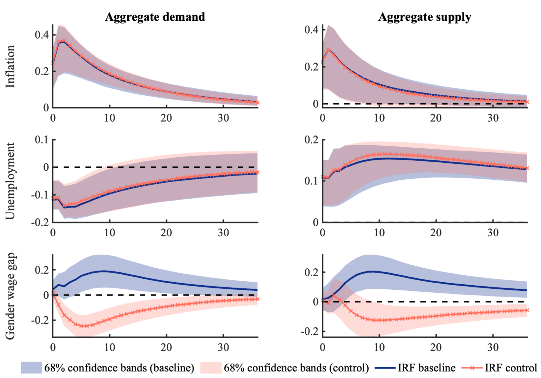
Notes: Adjusted GWGs computed using monthly data from January 1982 - February 2020, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid blue line) and 68% probability density intervals (shaded areas)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



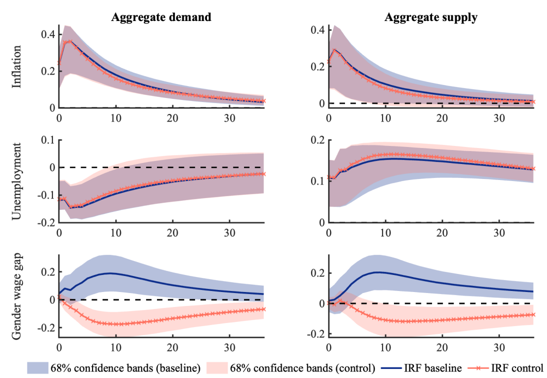
(a) Weekly earnings



(b) Inverted GWG (female characteristics)



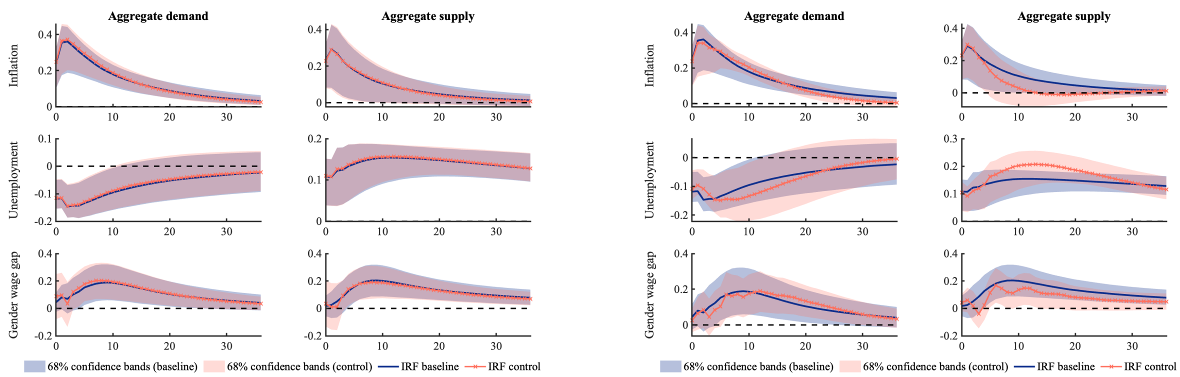
(c) Median GWG



(d) Alternative GWG (Penner specification)

Figure A.10: Impulse Responses in the Structural VAR 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.11: Impulse Responses in the Structural VAR 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.

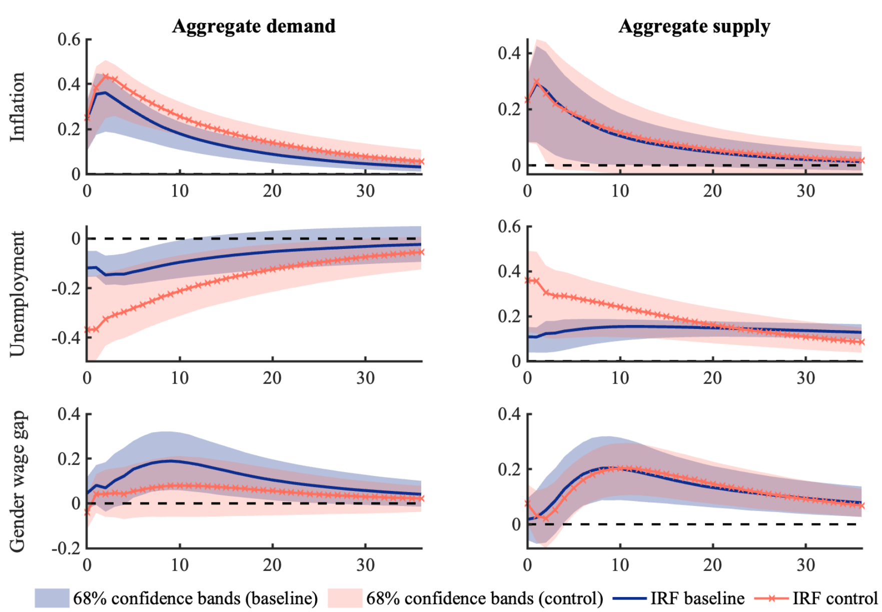
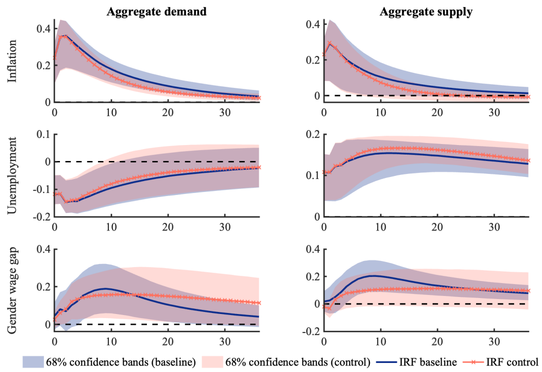
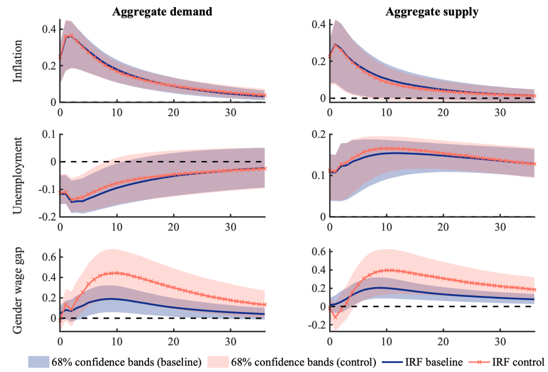


Figure A.12: Impulse Responses in the Structural VAR including Covid

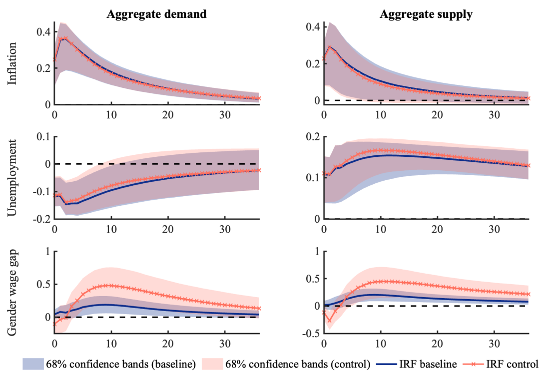
Notes: Adjusted GWGs computed using monthly data from January 1982 - March 2023, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid and crossed lines) and 68% probability density intervals (shaded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



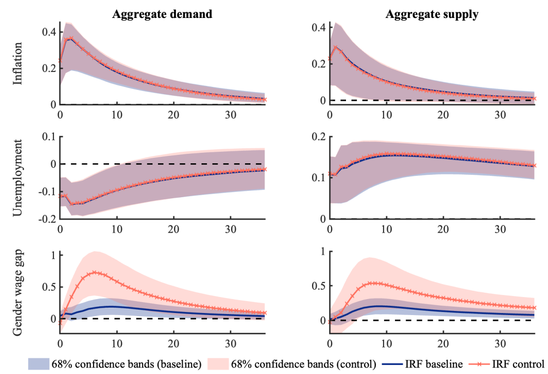
(a) Below 30



(b) Above 30



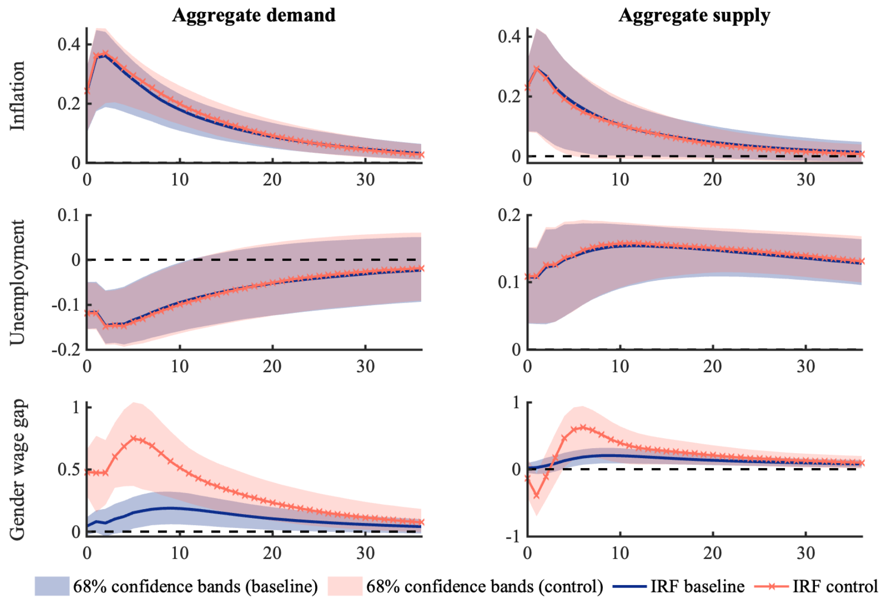
(c) Above 40



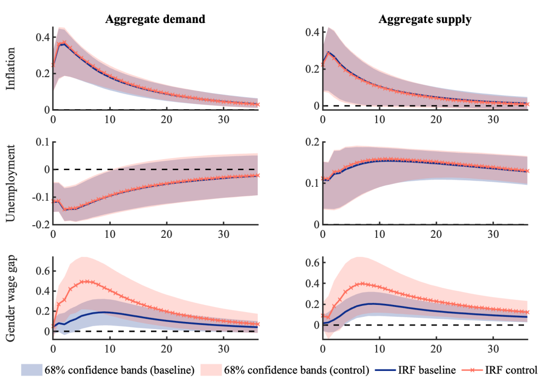
(d) Above 50

Figure A.13: Impulse Responses in the Structural VAR by Age Group

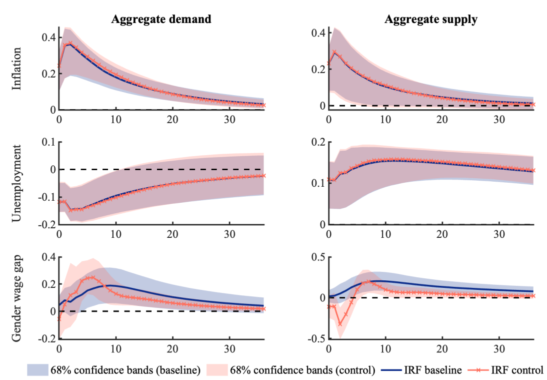
Notes: Adjusted GWGs computed using monthly data from January 1982–February 2020, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid and crossed lines) and 68% probability density intervals (shaded 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

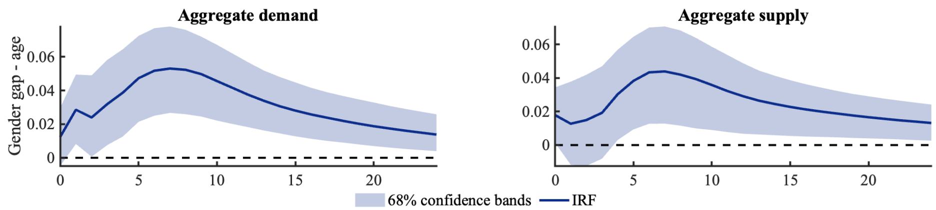
Figure A.14: Impulse Responses in the Structural VAR by Family and Marital Status

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.

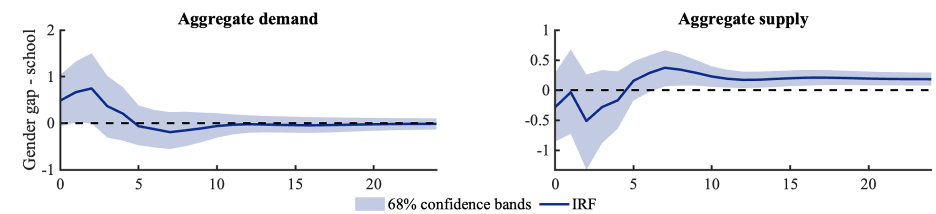
A.3.3 Which characteristics drive the response?

To better understand which characteristics contribute most to the response of the aggregate adjusted gender wage gap (GWG) to inflationary demand and supply shocks, we decompose the gap into its underlying sources by examining the dynamics of coefficient differences across genders in the KOB decomposition. Specifically, we estimate separate VARs for each element of the wage structure – including differences in returns to education, experience (age), race, marital status, occupation, and industry – where the dependent variables are the time series of estimated coefficient differences between men and women. This approach allows us to trace the response of each gender-specific return to inflationary shocks and assess how each component contributes to the evolution of the adjusted GWG over time. The analysis reveals whether the widening of the adjusted GWG is primarily driven by diverging returns to human capital (e.g., education), differences in occupational or sectoral wage premia, or other observed characteristics. By isolating these contributions, we identify the specific wage-setting channels through which inflation affects men and women differently.

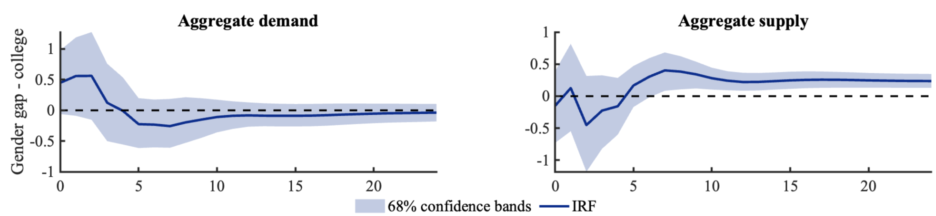
We begin by examining gender differences in the estimated coefficients on individual characteristics, as shown in Figures A.15 and A.16. The results indicate that several individual characteristics contribute meaningfully to the inflation-induced widening of the adjusted GWG. In particular, the gender 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 gender wage gap in response to supply shocks is smaller for individuals in higher-income households. Taken together, these results indicate that the aggregate response of the adjusted GWG to inflationary shocks is primarily driven by gender asymmetries in how the labor market rewards experience and education, while race and household income partially offset these effects. For different industries (see Figures A.17 and A.18), the effects of inflationary shocks on the adjusted gender wage gap 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.



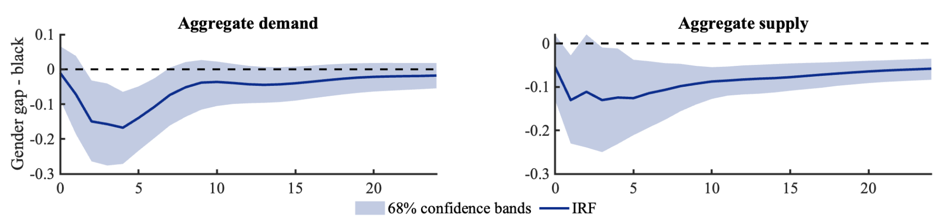
(a) Age



(b) School



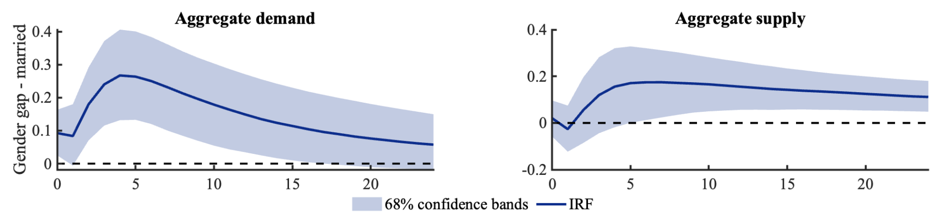
(c) College



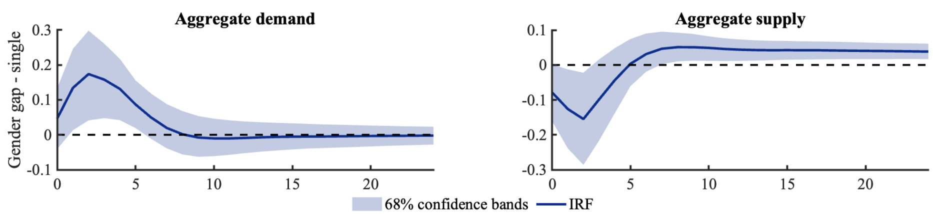
(d) Black

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

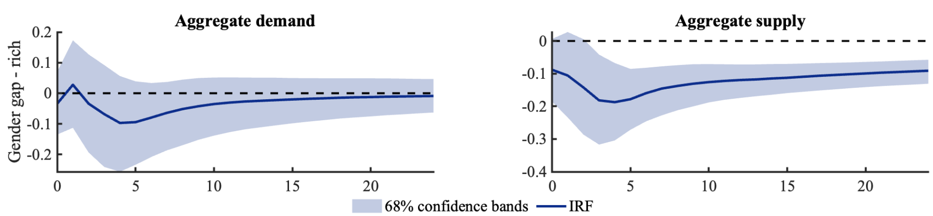
Notes: Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid line) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and the percentiles are defined at each point in time.



(a) Married



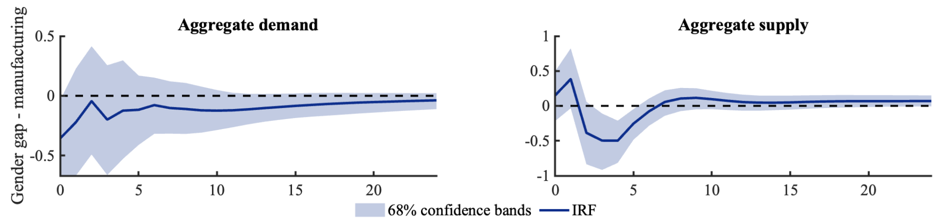
(b) Single



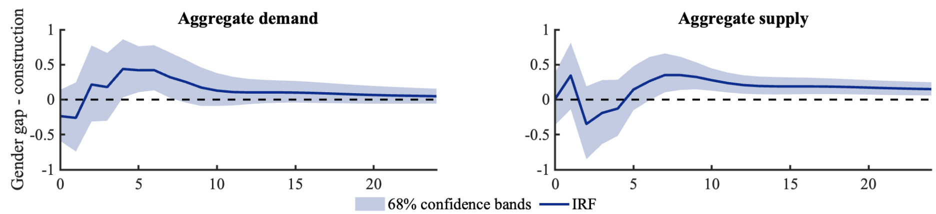
(c) High household income

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

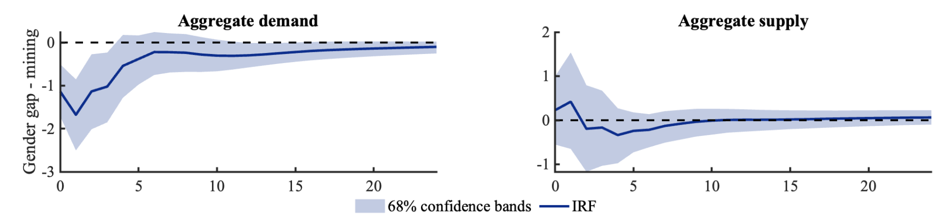
Notes: Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid line) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and the percentiles are defined at each point in time.



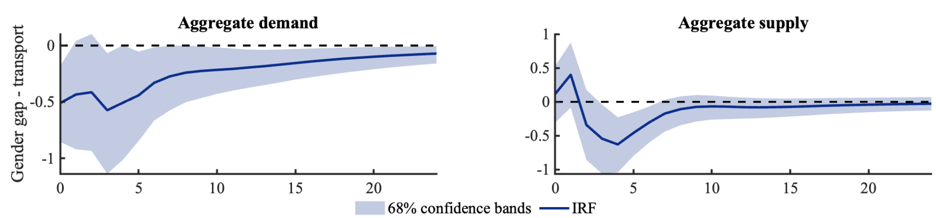
(a) Manufacturing



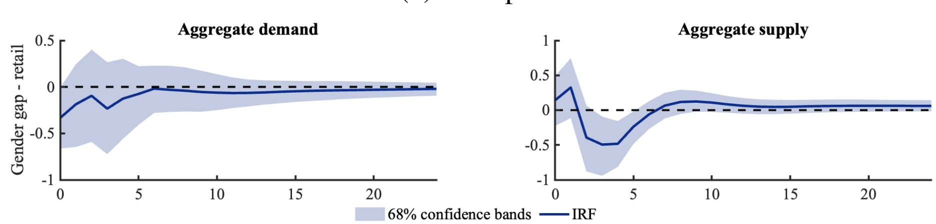
(b) Construction



(c) Mining



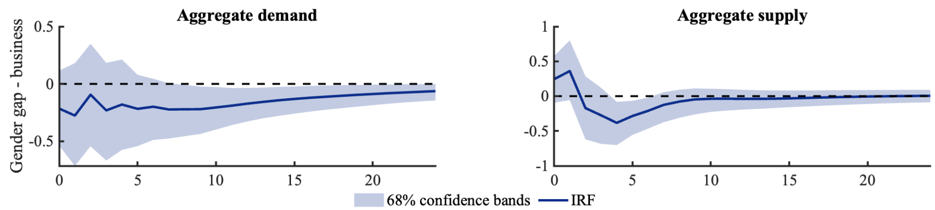
(d) Transport



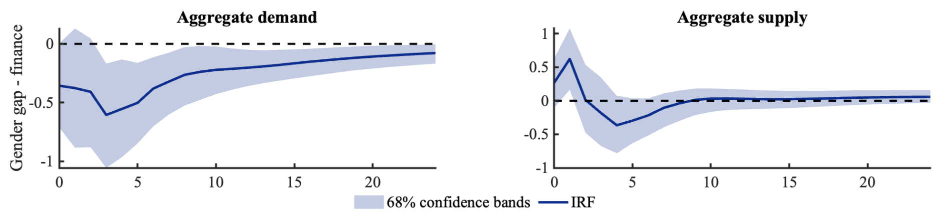
(e) Retail

Figure A.17: Impulse Responses of the coefficients of the KOB decomposition to Supply and Demand Shocks

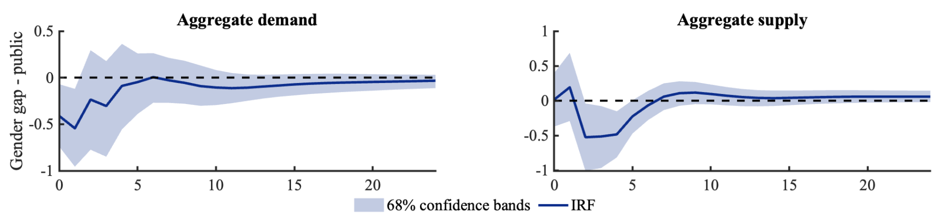
Notes: Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid line) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and the percentiles are defined at each point in time.



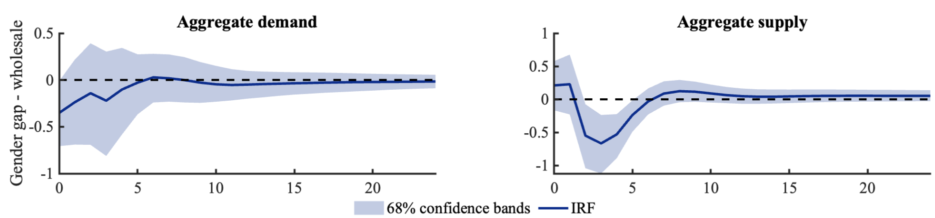
(a) Business



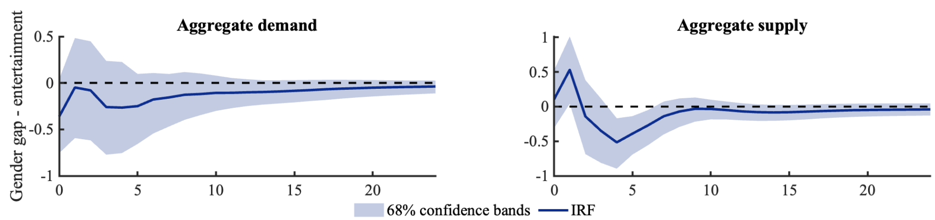
(b) Finance



(c) Public



(d) Wholesale



(e) Entertainment

Figure A.18: 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.

B SCE Supplementary Material

B.1 Questionnaire

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 __ %

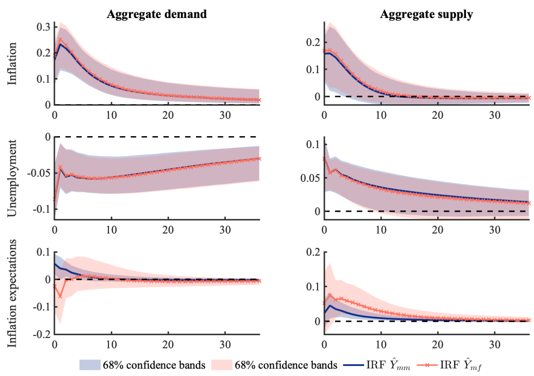
Q22new
Suppose you were to lose your ["main" if more than one] job this month. What do you think is the percent chance that within the following 3 months, you will find a job that you will accept, considering the pay and type of work?
Ruler & box

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...

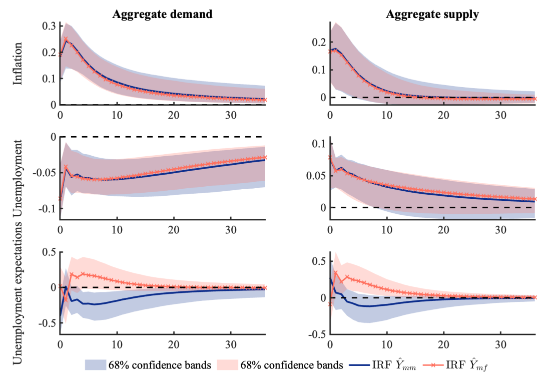
- increase by 0% or more
- decrease by 0% or more

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 __ %

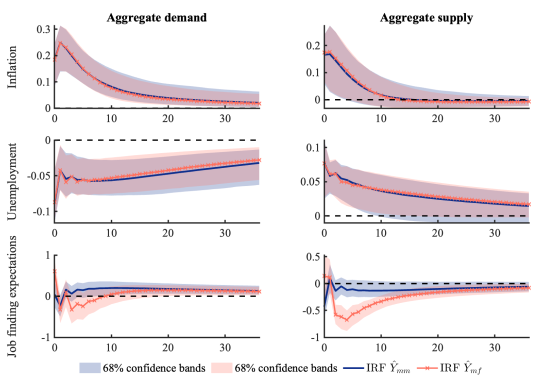
B.2 SCE survey responses



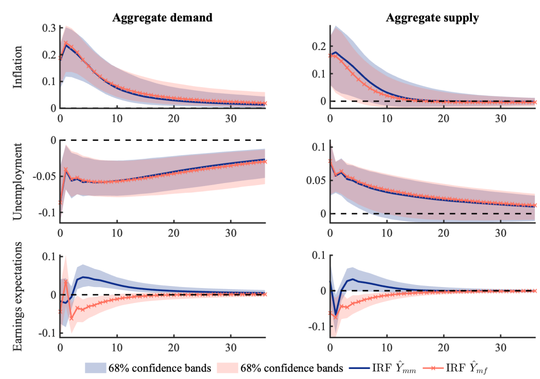
(a) Inflation expectations



(b) Unemployment expectations



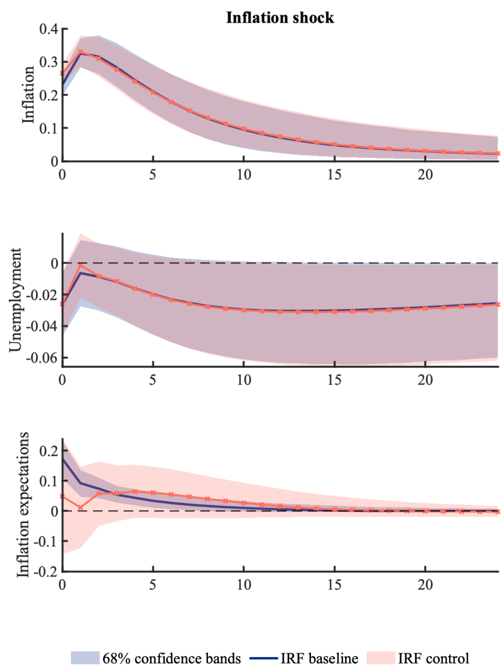
(c) Job-finding expectations



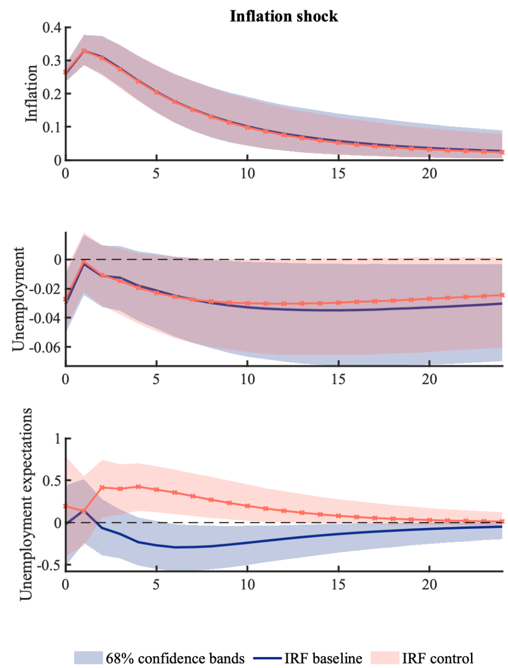
(d) Earnings expectations

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

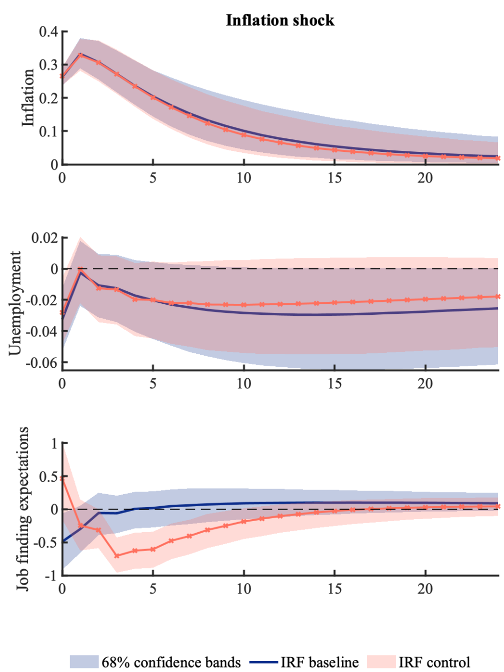
Notes: Women's (orange crossed line) and men's (blue solid line) expectations computed using monthly data from August 2013–February 2020. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid and crossed lines) and 68% probability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



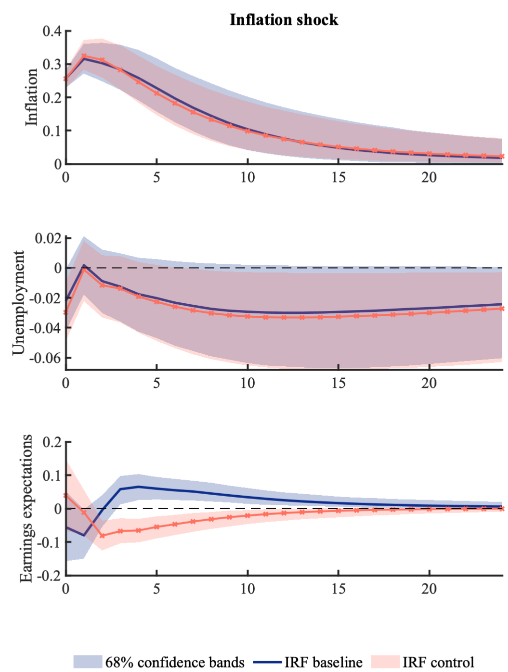
(a) Inflation expectations



(b) Unemployment expectations



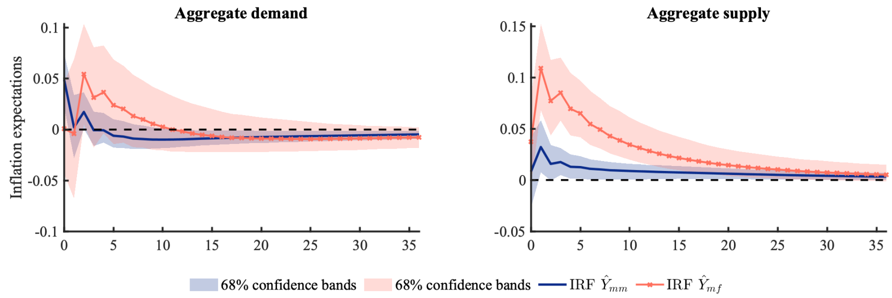
(c) Job-finding expectations



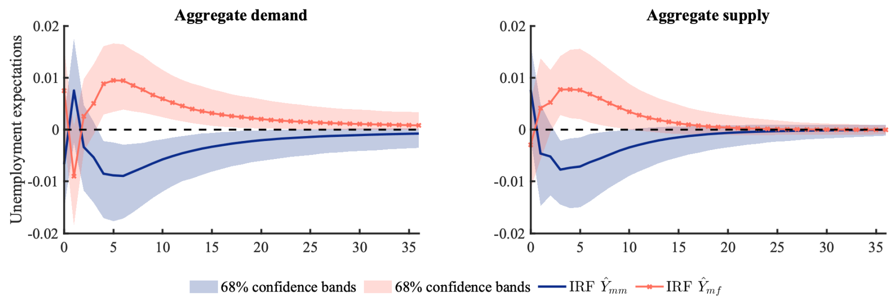
(d) Earnings expectations

Figure B.2: Impulse Responses of SCE Expectations to Inflation Shocks

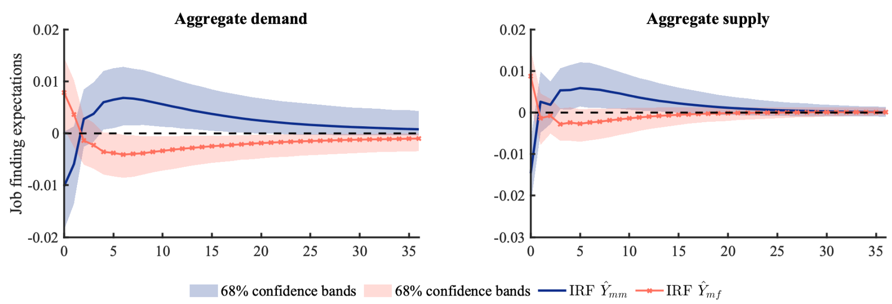
Notes: Women's (orange crossed line) and men's (blue solid line) expectations computed using monthly data from August 2013–February 2020. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid and crossed lines) and 68% probability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



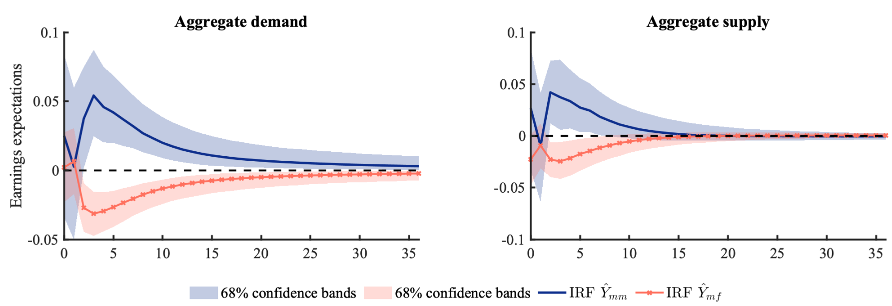
(a) Inflation (12 months)



(b) Unemployment (12 months)



(c) Job Finding (3 months)



(d) Earnings Growth (12 months)

Figure B.3: Impulse Responses of Expectations in the SCE to Supply and Demand Shocks using Nearest-Neighbor Matching

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 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.

C Model Supplementary Material

C.1 Calibration

Parameter	Value	Description
α	0.333	exponent of labor in the production function
ζ_f	0.500	relative product of women in production
σ	4.300	elasticity of substitution between men and women in production
δ_m	0.233	separation rate men
δ_f	0.233	separation rate women
γ	1.000	coefficient of hiring cost function
ψ_m	0.045	coefficient of unemployment in the labor market effort men
ψ_m	0.050	coefficient of unemployment in the labor market effort women
β	0.990	discount rate
ρ_i	0.950	autocorrelation monetary policy
ρ_u	0.900	autocorrelation cost push shock
ρ_z	0.900	autocorrelation demand shock
φ_m	2.000	inverse Frisch elasticity of labor effort men
φ_f	2.000	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	2.000	Taylor rule coeff of inflation
ϕ_{w_m}	0.005	Taylor rule coeff of male wage inflation
ϕ_{w_f}	0.005	Taylor rule coeff of female wage inflation
ϕ_{u_m}	-0.013	Taylor rule coeff of male unemployment
ϕ_{u_f}	-0.013	Taylor rule coeff of female unemployment
ϕ_y	0.000	Taylor rule coeff of inflation
Γ_m	0.013	proportionality coefficient hiring cost men
Γ_f	0.013	proportionality coefficient hiring cost women
χ_m	1.220	labor disutility parameter men
χ_f	1.095	labor disutility parameter women
d_f	0.100	discrimination against women
$\bar{\pi}^p$	0.000	steady state price inflation

Table C.1 – Continued

Parameter	**Value**	**Description**
$\bar{\pi}^w$	0.000	steady state wage inflation
$\bar{U}_m$	0.060	steady state unemployment men
$\bar{U}_f$	0.060	steady state unemployment women
$\bar{N}_m$	0.600	steady state employment men
$\bar{N}_m$	0.600	steady state employment women
$\bar{Y}$	0.711	steady state output
$\bar{x}_m$	0.700	steady state job finding men
$\bar{x}_f$	0.700	steady state job finding women
h	0.000	habits in household utility
ϵ	6.000	elasticity of substitution
$\bar{i}$	0.010	steady state nominal interest rate

C.2 Full model

Shock processes

$$\log\left(Z_t\right) = \rho_z\ \log\left(Z_{t-1}\right) + \varepsilon_{zt} \tag{23}$$

$$\log\left(u_t\right) = \rho_u\ \log\left(u_{t-1}\right) + \varepsilon_{at} \tag{24}$$

Union receives signal

$$s_t = \varepsilon_{ut} + \varepsilon_{zt} \tag{25}$$

Union applies ambiguity loving/averse weights

$$\tilde{\mathbb{E}}_{m,t}\varepsilon^z{}_t = s_t w_m^z \tag{26}$$

$$\tilde{\mathbb{E}}_{f,t}\varepsilon^z{}_t = s_t w_f^z \tag{27}$$

$$\tilde{\mathbb{E}}_{m,t}\varepsilon_{u_t} = s_t w_m^u \tag{28}$$

$$\tilde{\mathbb{E}}_{f,t}\varepsilon_{u_t} = s_t w_f^u \tag{29}$$

Union forms beliefs about state variables

$$\log\left(\tilde{\mathbb{E}}_{m,t} Z_t\right) = \tilde{\mathbb{E}}_{m,t}\varepsilon^{z}{}_t + \rho_z \, \log\left(Z_{t-1}\right) \tag{30}$$

$$\log\left(\tilde{\mathbb{E}}_{f,t} Z_t\right) = \tilde{\mathbb{E}}_{f,t}\varepsilon^{z}{}_t + \rho_z \, \log\left(Z_{t-1}\right) \tag{31}$$

$$\log\left(\tilde{\mathbb{E}}_{m,t} u_t\right) = \tilde{\mathbb{E}}_{m,t}\varepsilon_{u_t} + \rho_u \, \log\left(u_{t-1}\right) \tag{32}$$

$$\log\left(\tilde{\mathbb{E}}_{f,t} u_t\right) = \tilde{\mathbb{E}}_{f,t}\varepsilon_{u_t} + \rho_u \, \log\left(u_{t-1}\right) \tag{33}$$

Euler equation

$$1 = \beta \, \frac{\frac{Z_{t+1}}{Z_t} \, \left(C_t - h \, C_{t-1}\right)}{C_{t+1} - C_t \, h} \, \left(1 + r_t\right) \tag{34}$$

Fisherian equation

$$1 + r_t = \frac{1 + i_t}{1 + \pi^{p}{}_{t+1}} \tag{35}$$

Price dispersion

$$v^{p}{}_t = \left(\left(1 - \theta^p\right) \, \left(1 + \tilde{\mathbb{E}}_{m,t}\pi^{p,*}{}_t\right)^{\frac{(-\epsilon)}{1-\alpha}} \, \left(1 + \pi^{p}{}_t\right)^{\frac{\epsilon}{1-\alpha}} + \theta^p \, \left(1 + \pi^{p}{}_t\right)^{\frac{\epsilon}{1-\alpha}} \, v^{p}{}_{t-1}^{\frac{1}{1-\alpha}}\right)^{1-\alpha} \tag{36}$$

Aggregate inflation

$$\left(1 + \pi^{p}{}_t\right)^{1-\epsilon} = \theta^p + \left(1 - \theta^p\right) \, \left(1 + \pi^{p,*}{}_t\right)^{1-\epsilon} \tag{37}$$

Reset price inflation

$$\left(1 + \pi^{p,*}{}_t\right)^{1+\frac{\epsilon\,\alpha}{1-\alpha}} = u_t \, \frac{\epsilon}{\epsilon - 1} \, \frac{x1_t}{x2_t} \, \left(1 + \pi^{p}{}_t\right)^{1+\frac{\epsilon\,\alpha}{1-\alpha}} \tag{38}$$

$$x1_t = \frac{Z_t \, mc_t \, Y_t}{C_t - h \, C_{t-1}} + \beta \, \theta^p \, \left(1 + \pi^{p}{}_{t+1}\right)^{\epsilon+\frac{\epsilon\,\alpha}{1-\alpha}} \, x1_{t+1} \tag{39}$$

$$x2_t = \frac{Z_t\, Y_t}{C_t - h\, C_{t-1}} + \beta\, \theta^p\ \left(1 + {\pi^p}_{t+1}\right)^{\epsilon-1}\ x2_{t+1} \tag{40}$$

Goods market clearing

$$Y_t = C_t + G_{m\,t}\, H_{m\,t} + G_{f\,t}\, H_{f\,t} \tag{41}$$

Labor index

$$N_t = \left(\zeta_f\, {N_{f\,t}}^{\frac{\sigma-1}{\sigma}} + \zeta_m\, {N_{m\,t}}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{42}$$

Aggregate production

$$Y_t = \frac{A_t\, N_t^{1-\alpha}}{{v^p}_t} \tag{43}$$

Aggregate hiring and employment

$$N_{m\,t} = H_{m\,t} + (1 - \delta_m)\ N_{m\,t-1} \tag{44}$$

$$N_{f\,t} = H_{f\,t} + \left(1 - \delta_f\right)\ N_{f\,t-1} \tag{45}$$

Hiring costs

$$G_{m\,t} = \Gamma_m\, x_{m\,t}^{\gamma} \tag{46}$$

$$G_{f\,t} = \Gamma_f\, x_{f\,t}^{\gamma} \tag{47}$$

Job finding rate

$$x_{m\,t} = \frac{H_{m\,t}}{U^0_{m\,t}} \tag{48}$$

$$x_{f\,t} = \frac{H_{f\,t}}{U^0_{f\,t}} \tag{49}$$

Effective market effort

$$L_{m\,t} = N_{m\,t} + \psi_m\, U_{m\,t} \tag{50}$$

$$L_{f\,t} = N_{f\,t} + \psi_m\, U_{f\,t} \tag{51}$$

Unemployment

$$U_{m\,t} = U_{m\,t}^{0}\ (1 - x_{m\,t}) \tag{52}$$

$$U_{f\,t} = U_{f\,t}^{0}\ \left(1 - x_{f\,t}\right) \tag{53}$$

Marginal revenue product

$$MRPN_{m\,t} = (1-\alpha)\ (1-\zeta)\ A_t\, mc_t\, N_{m\,t}^{\frac{(-1)}{\sigma}}\ N_t^{\frac{1}{\sigma-1}-\alpha} \tag{54}$$

$$MRPN_{f\,t} = N_t^{\frac{1}{\sigma-1}-\alpha}\ (1-\alpha)\ \zeta\ A_t\, mc_t\, N_{f\,t}^{\frac{(-1)}{\sigma}}\ \left(1 - d_f\right) \tag{55}$$

Optimal hiring condition

$$MRPN_{m\,t} = \omega_{m\,t} + B_{m\,t} \tag{56}$$

$$MRPN_{f\,t} = \omega_{f\,t} + B_{f\,t} \tag{57}$$

$$B_{m\,t} = G_{m\,t} - \frac{\frac{Z_{t+1}}{Z_t}\ (C_t - h\, C_{t-1})}{C_{t+1} - C_t\, h}\, \beta\ (1-\delta_m)\ G_{m\,t+1} \tag{58}$$

$$B_{f\,t} = G_{f\,t} - \frac{\frac{Z_{t+1}}{Z_t}\ (C_t - h\, C_{t-1})}{C_{t+1} - C_t\, h}\, \beta\ \left(1-\delta_f\right)\ G_{f\,t+1} \tag{59}$$

Optimal participation condition

$$\frac{(C_t - h\, C_{t-1})\ \psi_m\ \chi_m\ L_{m\,t}^{\varphi_m}}{Z_t} = \frac{x_{m\,t}}{1-x_{m\,t}}\ \left(G_{m\,t}\ \frac{1-\xi_m}{\xi_m} - \pi_{m\,t}^{w}\ \frac{\theta_m^w}{1-\theta_m^w}\ \omega_{m\,t-1}\ Q_{m\,t}\right) \tag{60}$$

$$\frac{(C_t - h\, C_{t-1})\ \psi_m\ \chi_f\ L_{f\,t}^{\varphi_f}}{Z_t} = \frac{x_{f\,t}}{1-x_{f\,t}}\ \left(G_{f\,t}\ \frac{1-\xi_f}{\xi_f} - \pi_{f\,t}^{w}\ \frac{\theta_f^w}{1-\theta_f^w}\ \omega_{f\,t-1}\ Q_{f\,t}\right) \tag{61}$$

$$Q_{m\,t} = 1 + \frac{\frac{\frac{Z_{t+1}}{Z_t}\ (C_t - h\, C_{t-1})}{C_{t+1} - C_t\, h}\, \beta\ (1-\delta_m)\ \theta_m^w}{1 + \pi^{p}{}_t}\ \tilde{\mathbb{E}}_{m,t} Q_{m\,t+1} \tag{62}$$

$$Q_{f\,t} = 1 + \frac{\frac{\frac{Z_{t+1}}{Z_t}\,(C_t - h\,C_{t-1})}{C_{t+1} - C_t\,h}\,\beta\,\left(1-\delta_f\right)\,\theta_f^w}{1+\pi^p{}_t}\,\tilde{\mathbb{E}}_{f,t} Q_{f\,t+1} \tag{63}$$

Evolution of real wage

$$\omega_{m\,t} = \frac{\omega_{m\,t-1}\,\left(1+\pi^w_{m\,t}\right)}{1+\pi^p{}_t} \tag{64}$$

$$\omega_{f\,t} = \frac{\omega_{f\,t-1}\,\left(1+\pi^w_{f\,t}\right)}{1+\pi^p{}_t} \tag{65}$$

Target (flex) wage

$$\omega^{tar}_{m\ t} = \frac{(C_t - h\,C_{t-1})\,L_{m\,t}^{\varphi_m}\,\chi_m\,\xi_m}{Z_t} + MRPN_{m\,t}\,\left(1-\xi_m\right) \tag{66}$$

$$\omega^{tar}_{f\ \ t} = \frac{(C_t - h\,C_{t-1})\,L_{f\,t}^{\varphi_f}\,\chi_f\,\xi_f}{Z_t} + MRPN_{f\,t}\,\left(1-\xi_f\right) \tag{67}$$

Reset wage

$$\omega^*_{m\,t} = \frac{h1_{m\,t}}{h2_{m\,t}} \tag{68}$$

$$\omega^*_{f\,t} = \frac{h1_{f\,t}}{h2_{f\,t}} \tag{69}$$

$$h1_{m\,t} = \frac{Z_t\,\omega^{tar}_{m\ t}}{C_t - h\,C_{t-1}} + (1-\delta_m)\,\theta_m^w\,\beta\,\left\{\xi_m\,\left(1+\tilde{\mathbb{E}}_{m,t}\pi^p{}_{t+1}\right)\,\tilde{\mathbb{E}}_{m,t} h1_{m\,t+1} + (1-\xi_m)\,(1+\pi^p{}_{t+1})\,h1_{m\,t+1}\right\} \tag{70}$$

$$h2_{m\,t} = \frac{Z_t}{C_t - h\,C_{t-1}} + (1-\delta_m)\,\theta_m^w\,\beta\,\left\{\xi_m\,\left(1+\tilde{\mathbb{E}}_{m,t}\pi^p{}_{t+1}\right)\,\tilde{\mathbb{E}}_{m,t} h2_{m\,t+1} + (1-\xi_m)\,(1+\pi^p{}_{t+1})\,h2_{m\,t+1}\right\} \tag{71}$$

$$h1_{f\,t} = \frac{Z_t\,\omega^{tar}_{f\ \ t}}{C_t - h\,C_{t-1}} + \left(1-\delta_f\right)\,\theta_f^w\,\beta\,\left\{\xi_f\,\left(1+\tilde{\mathbb{E}}_{f,t}\pi^p{}_{t+1}\right)\,\tilde{\mathbb{E}}_{f,t} h1_{f\,t+1} + (1-\xi_f)\,(1+\pi^p{}_{t+1})\,h1_{f\,t+1}\right\} \tag{72}$$

$$h2_{f\,t} = \frac{Z_t}{C_t - h\,C_{t-1}} + \left(1 - \delta_f\right)\,\theta_f^w\,\beta\,\left\{\xi_f\,\left(1 + \tilde{\mathbb{E}}_{f,t}\pi^p{}_{t+1}\right)\,\tilde{\mathbb{E}}_{f,t}h2_{f\,t+1} + (1 - \xi_f)\,(1 + \pi^p{}_{t+1})\,\,h2_{f\,t+1}\right\} \tag{73}$$

Real wage inflation

$$\omega_{m\,t} = \theta_m^w\,\frac{\omega_{m\,t-1}}{1 + \pi^p{}_t} + \left(1 - \theta_m^w\right)\,\omega_{m\,t}^* \tag{74}$$

$$\omega_{f\,t} = \theta_f^w\,\frac{\omega_{f\,t-1}}{1 + \pi^p{}_t} + \left(1 - \theta_f^w\right)\,\omega_{f\,t}^* \tag{75}$$

Interest rate rule

$$\frac{1 + i_t}{1 + \bar{i}} = \nu_t\,\left(\frac{1 + i_{t-1}}{1 + \bar{i}}\right)^{\rho_i}\,\left(\left(\frac{1 + \pi^p{}_t}{1 + \bar{\pi}^p}\right)^{\phi_\pi}\,\left(\frac{1 + \pi_{m\,t}^w}{1 + \bar{\pi}^w}\right)^{\phi_{w,m}}\,\left(\frac{1 + \pi_{f\,t}^w}{1 + \bar{\pi}^w}\right)^{\phi_{w,f}}\,\left(\frac{U_{m\,t}}{\bar{U}_m}\right)^{\phi_{u,m}}\,\left(\frac{U_{f\,t}}{\bar{U}_f}\right)^{\phi_{u,f}}\,\left(\frac{Y_t}{\bar{Y}}\right)^{phi_y}\right)^{1-\rho_i} \tag{76}$$

Definition of GWG

$$GWG_t = \frac{\omega_{m\,t}}{\omega_{f\,t}} \tag{77}$$

C.3 Impulse Responses

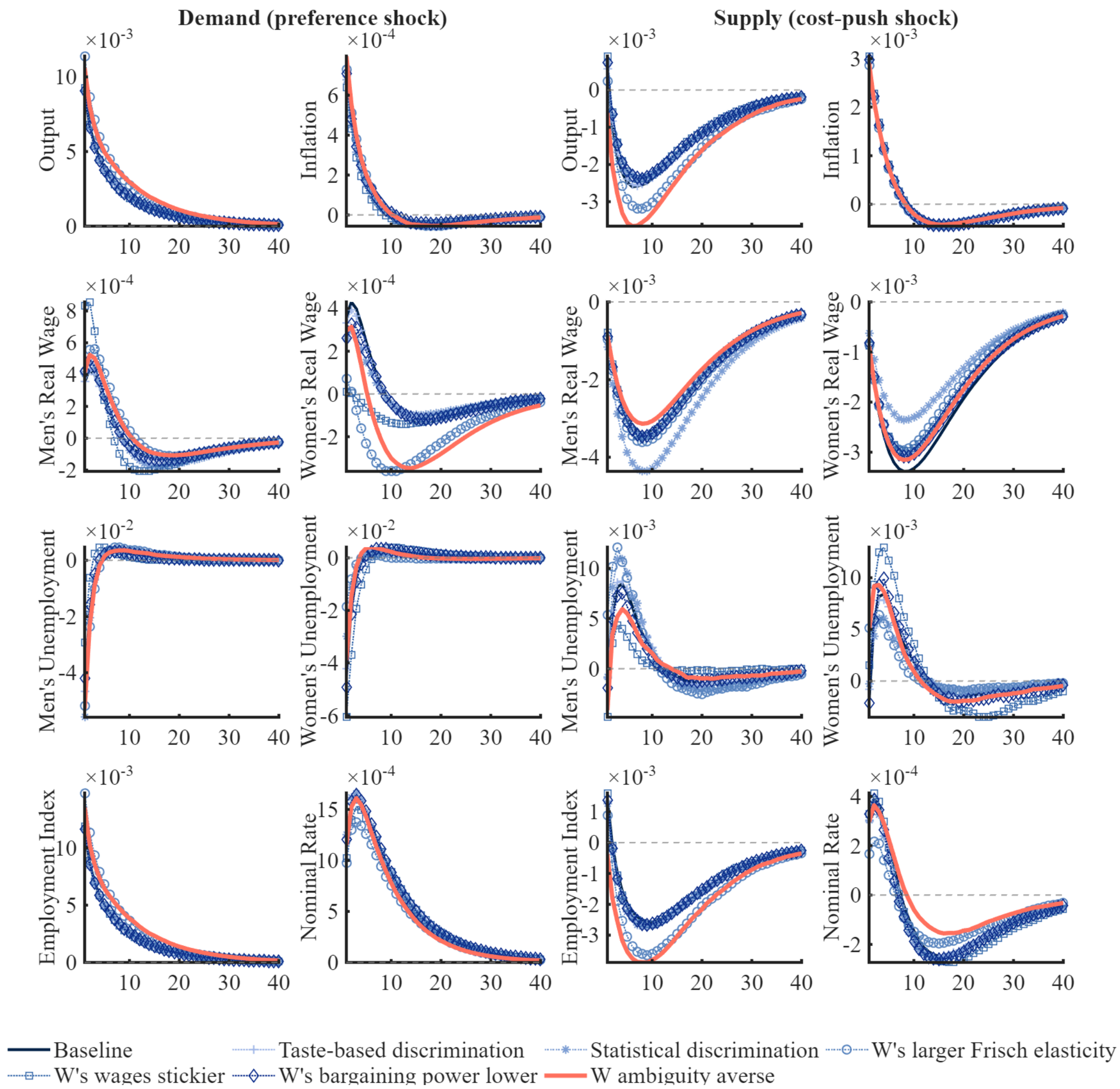


Figure C.1: Further impulse responses of the model