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

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Abstract

How does the gender wage gap respond to inflation? We show that it widens after both supply- and demand-driven inflationary shocks. This widening reflects gender differences in labor market perceptions: women interpret inflation as a signal of deteriorating conditions, while men perceive mild improvement. These divergent beliefs reduce women's willingness to pursue higher wages, slowing their nominal wage growth relative to men's. To formalize this mechanism, we develop a New Keynesian search-and-matching model where workers do not observe the true nature of the shock and women form ambiguity averse beliefs. The model replicates the observed cyclicality 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 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. In doing so, we establish two empirical facts. First, we show that the gender wage gap systematically widens during periods of rising inflation, 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, widening 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 widening 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 more 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 during inflationary episodes. We formalize this mechanism within a two-agent New Keynesian search-and-matching model in which women's ambiguity-averse beliefs generate their differential response to inflation. The model reproduces the empirical widening of the gender wage gap following inflationary shocks, thereby 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). Using this time series in a structural VAR with zero and sign restrictions, we study how the gender wage gap responds to inflationary demand and supply shocks.

The results reveal a robust and uniform pattern: inflation, regardless of its source, systematically widens the gender wage gap. The response is quantitatively important: inflationary shocks account for 12–25 percent of the forecast error variance of the gender wage gap across different model specifications. The widening of the gender wage gap 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 following inflationary shocks persists in gender-balanced matched samples that hold constant worker, industry, and occupation characteristics. 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 renegotiation behavior: men adjust their nominal wages more aggressively to preserve real pay, while women do so less. Consistent with this mechanism, decomposing the gender wage gap into real wages of women and men reveals that after both types of inflationary shocks, the real wages of women decrease while those of men remain largely unchanged.

To understand why wage renegotiation 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 and 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 may also explain why many workers dislike inflation, if they assume that nominal wages do not keep pace with rising prices (Stantcheva 2024, Guerreiro et al. 2024). Inflation expectations are also related to consumption and savings behavior (Coibion et al. 2023, 2022) as well as behavior in the labor market. For example, 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 et al. 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 a large extent 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 might interpret inflation more negatively than men in terms of labor market outcomes. Because they tend to associate inflation with weaker labor demand and expect a smaller pass-through from prices to wages, they 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 even among workers with similar characteristics in the same industries and occupations.

To provide evidence for this mechanism, we analyze how men and women revise their beliefs about the labor market in response to inflationary demand and supply shocks using microdata from the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE) within the same Structural VAR with sign and zero restrictions. This model allows us to study the responses of male and female survey beliefs to the same inflationary shocks we considered before. We focus on full-time workers, control for different demographic characteristics and industry sorting of male and female respondents as before. The results are striking: following both types of inflationary shocks, women's unemployment expectations rise, while men's fall. Women lower their job-finding and earnings expectations, while men leave their job-finding expectations unchanged and revise their earnings expectations upward. Overall, men respond to inflationary shocks with relative optimism about the labor market, while women react with relative pessimism. These systematic differences in expectations help explain why wage adjustments might differ across genders even among workers with comparable characteristics employed in similar industries. Our findings 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 observed in survey data may mask meaningful heterogeneity across individuals. The evidence is consistent with women responding to inflation historically in ways aligned with a supply-side interpretation, while men's reactions appear closer to a demand-side view.

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 show that an expectation-driven mechanism can explain the observed widening of the gender wage gap after inflationary shocks, while alternative channels fail to do so.

Within our baseline model, we first examine conventional explanations for the gender wage gap, 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. None of these channels can replicate our empirical finding that the gender wage gap widens following both supply- and demand-driven inflationary shocks. In particular, these mechanism imply opposite responses of the gender wage gap across the two shocks. We then turn to expectations: when women are more ambiguity averse than men, they place greater weight on adverse (supply-shock) interpretations, leading them to expect weaker labor market conditions and therefore renegotiate wages less aggressively. This mechanism generates a widening of the gender wage gap following any inflationary shock, consistent with our empirical findings. There is some evidence that suggests that women are more risk averse than men (Eckel & Grossman 2008, Azmat & Petrongolo 2014, Croson & Gneezy 2009) with weaker findings for ambiguity aversion (Borghans et al. 2009), though none of these papers focus on the interpretation of inflation.

Specifically, we solve the model in two stages. First, unions representing men and women in the wage negotiation observe only imperfect signals about the nature of shocks and must form beliefs about the underlying state of the economy (Erceg et al. 2025). They know how the economy will respond for each type of shock and compute the household value respectively. We specify household preferences such that lower consumption caused by a cost-push shock outweighs the reduced disutility from working and households perceive supply-side disturbances as more costly. We capture ambiguity aversion using the robust control framework of Hansen & Sargent (2001), in which continuation values are exponentially tilted ("softmin" weighting). This formulation implies that ambiguity-averse agents behave as if facing a worst-case scenario. The model is then solved assuming rational expectations of the household and firms but ambiguity aversion by the union negotiating women's wages. Although output and inflation responses remain broadly similar across belief regimes, these differences in perceptions distort real wages: agents with ambiguity-averse, supply-biased beliefs experience larger real wage losses for any inflationary shock. Hence, the model provides a structural interpretation of the data, showing that gendered expectations shaped by ambiguity aversion can account for the observed dynamics of the gender wage gap, while traditional channels cannot. By embedding biased belief formation into a 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 discusses the construction of gender wage gaps from CPS data and studies the response of these to inflationary demand and supply shocks. Section 2 presents evidence on the effect of inflationary shocks on labor-market beliefs in the SCE. Section 3 introduces a New Keynesian search and match 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 (GWG) widens in response to unanticipated increases in inflation, whether triggered by demand or supply shocks, even after controlling for worker 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 occupational sorting. To establish this link, we combine detailed measures of the GWG from the CPS survey with a structural VAR model that allows us to analyze its cyclical behavior in response to inflationary demand and supply shocks.

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] While we assume that most respondents interpret the earnings question as referring to their base pay, there is evidence that additional pay is strongly correlated (Caldwell et al. 2025).

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 characteristics such as differences in industry, occupation, educational attainment, working hours, and other demographics (as, for example, age, race, and region). 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 t, we estimate separately male (m) and female (f) weighted ordinary least squares (OLS) wage regressions for individual i (the i and t subscripts are suppressed to simplify

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

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, union coverage and total household income. $OCC1990$ denotes a set of occupation dummies based on the 1990 Census Bureau occupational classification scheme, which distinguishes 389 detailed occupational categories.[2] $IND1990$ 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, and its cyclicality, 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 GWG is defined as:

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

where the sum is taken over all male individuals in period t and $\omega_{i,t}$ is individual i's sampling weight from the CPS survey. 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 GWG therefore indicates that men's observed wages have moved further above this counterfactual

[2]See IPUMS variable description.
[3]See IPUMS variable description.

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.

More details on the estimation can also be found in Blau & Kahn (2017), who instead of industry and occupation controls include experience, not captured by the CPS. We include age, education and children as proxies for experience. When controlling for experience, the gap slightly narrows compared to our results, but their unadjusted specification matches our estimates, despite the use of different data sources. It is important to note that we define the GWG as male minus female wages, whereas Blau & Kahn (2017) define it as female minus male wages. 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.

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). That said, our main conclusions are not sensitive to this choice. In the next subsection, we show that alternative measures of the adjusted gender wage gap 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, while requiring exact matches on detailed occupation and industry.[4] By restricting the comparison to observationally similar workers who coexist in the same regions of the covariate space, this approach enforces common support by

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

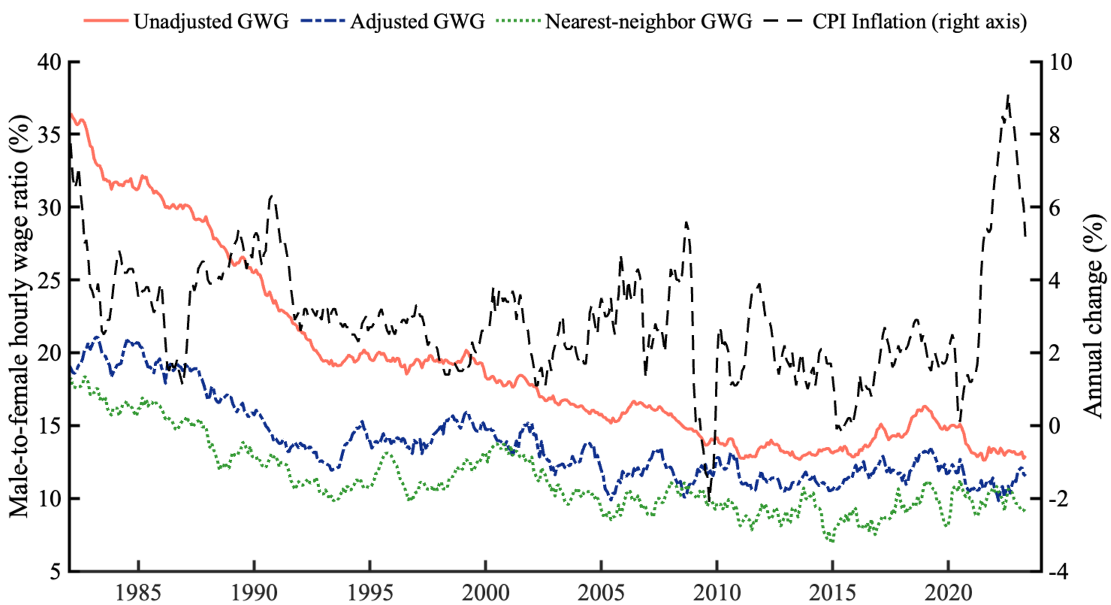


Figure 1: Adjusted and unadjusted GWG (1982-2023)

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 and Adjusted GWG: CPS IPUMS, own calculations.

construction and limits the scope for composition-driven bias. We therefore use matching-based estimates as a complementary measure of the adjusted gender wage gap.

These methods yield monthly time series of demographically adjusted, intra-industry, intra-occupation gender wage gaps. Figure 1 plots the resulting adjusted gender wage gaps constructed using both the baseline Kitagawa–Oaxaca–Blinder (KOB) decomposition and the nearest-neighbor matching estimator together with 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 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 omit industry and occupation controls. 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) and the official raw gaps published by the U.S. Census Bureau (Guzman & Kollar 2024). Because these alternative measures are expressed as female-minus-male earnings, their trends appear inverted relative to ours: when the KOB measure declines, the others rise. Aside from this sign convention, the series display broadly similar dynamics, and both the KOB and nearest-neighbor measures appear to provide a conservative lower bound 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.[5] 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). 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

[5] 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 (non-smoothed) series and find the results to be virtually identical, indicating that the main conclusions are not sensitive to this smoothing choice.

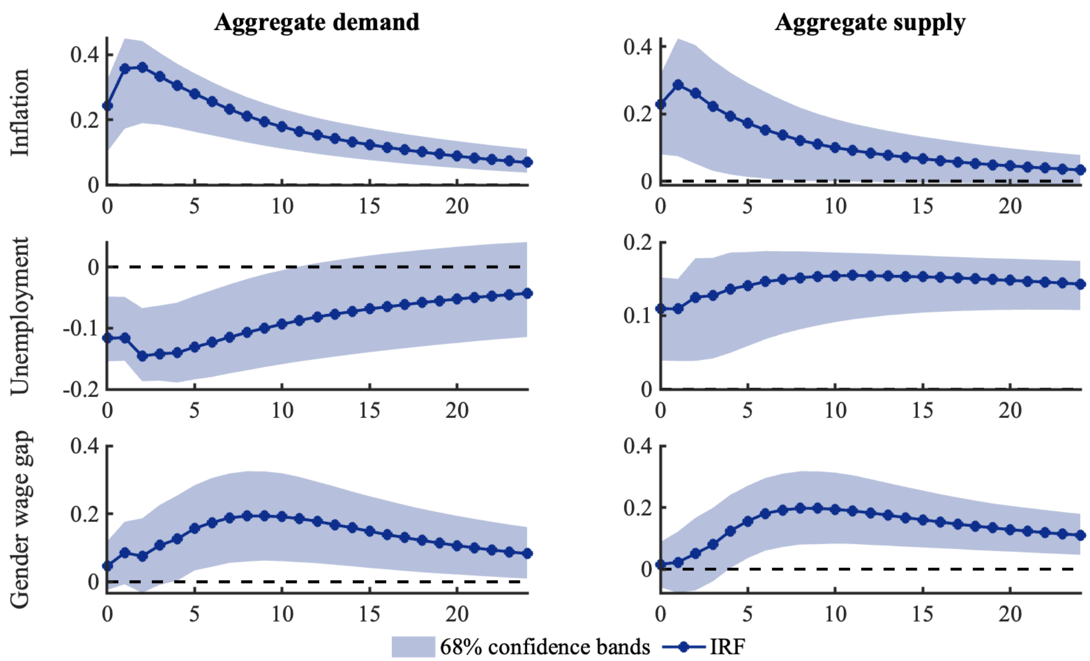
	Demand	**Supply**	**Residual**
Inflation	+	+	0
Unemployment	−	+	0
Gender wage gap	?	?	+

Table 1: Impact Sign and Zero Restrictions in the SVAR

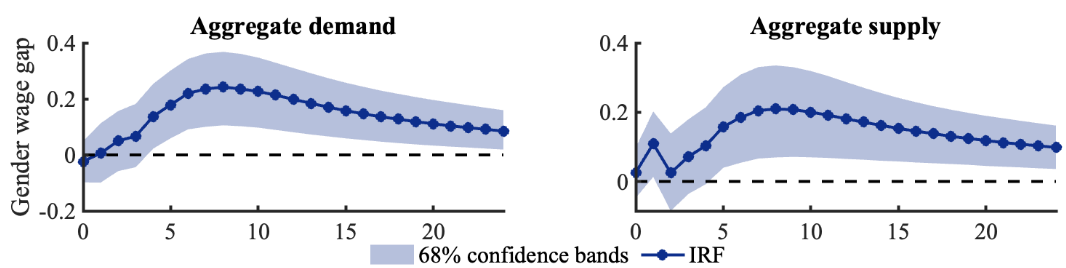
period. As shown later in this section, these extensions yield consistent results, indicating that our baseline conclusions about the effects of inflationary demand and supply shocks on the GWG are not sensitive to alternative specifications of the VAR model.

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. 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 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 dotted line shows the point-wise median response based on 10000 draws from the



(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 dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

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. Since the GWG is adjusted for individual characteristics, industry, and occupation, the observed response cannot be explained by sectoral reallocation, occupational sorting, or differences in worker demographics. Instead, it captures gender differences in how wages respond to inflationary shocks within similar jobs, sectors, and individual characteristics. The increase in the adjusted GWG following demand shocks suggests that inflation leads to asymmetric wage responses by gender even in comparable roles. The increase after inflationary supply shocks reinforces this interpretation and highlights the role of inflation itself as the common underlying mechanism. This finding suggests that gender asymmetries in wage-setting mechanisms are key. One possible explanation is that women may be less likely to renegotiate wages compared to men. This asymmetry would imply that inflation, whether demand- or supply-driven, reduces real wages more for women, thereby widening the adjusted GWG. To corroborate this explanation, we re-estimate the baseline SVAR including the gender wage gap for unionized workers only (see 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 gender wage gap.

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 differentially affect which women versus men remain employed (or enter/exit employment), the observed wage gap dynamics could reflect composition effects rather than a gender gap in within-person wage adjustments. To directly address this concern, we construct gender-balanced samples using nearest-neighbor matching (Ñopo 2008) as an alternative measure. This procedure ensures that men and women are comparable on key demographic and job-related characteristics that may jointly affect employment and wages. We then estimate 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. The matched-sample GWG displays the same responses to inflationary shocks as in our baseline specification, as shown in Panel (b) of Figure 2.[6] If anything, the estimated effects are slightly stronger. This indicates that our core results are not driven by differential selection of women and men into employment over the business cycle, but instead reflect genuine differences in

[6]The full set of impulse responses and comparison with our baseline SVAR is presented in Figure A.4 in the Appendix.

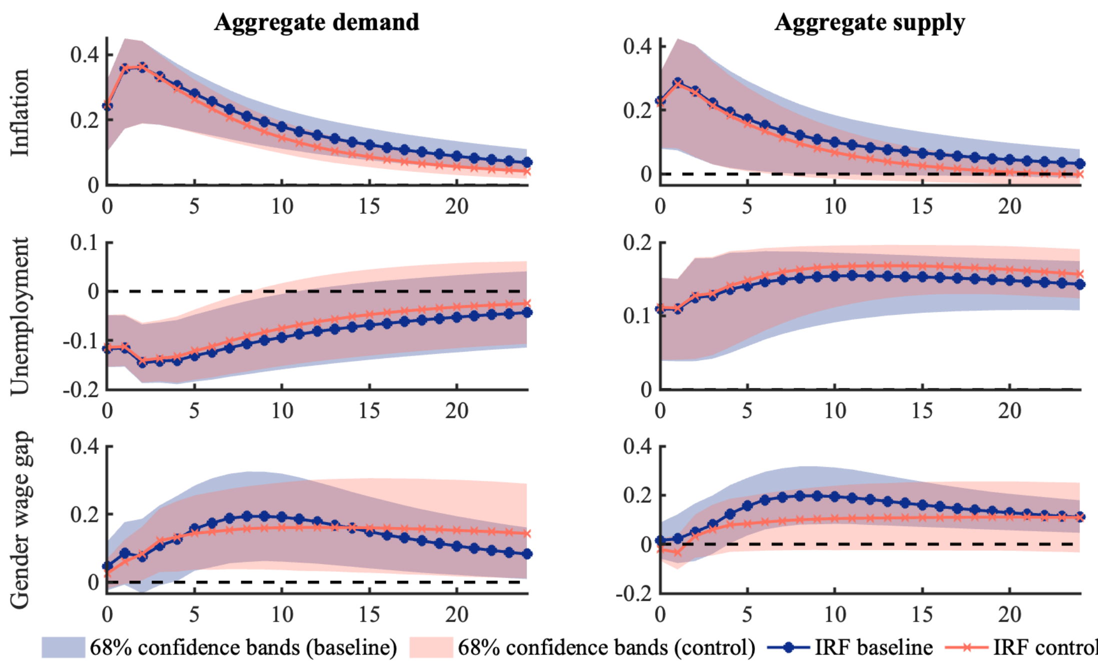


Figure 4: Impulse Responses in the Structural VAR of Adjusted and Unadjusted GWGs

Notes: Adjusted (blue) and undjusted (orange) 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 dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted and unadjusted GWG: CPS IPUMS, own calculations.

wage adjustment among comparable workers.

Figure 4 shows that the response of the unadjusted GWG is more muted, especially following supply shocks. This suggests that sectoral reallocation and exposure effects may offset part of the inflation-induced wage asymmetry in aggregate terms, but the underlying gender-based difference in wage adjustment 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). As shown in Figures A.5 and A.6, the adjusted GWG response to both demand and supply shocks remains robust and largely unchanged, while the response of the unadjusted GWG to supply shocks becomes positive and statistically significant. These results confirm that explicitly accounting for gender-specific exposure in the VAR reveals the inflation-induced widening of the GWG, even in unadjusted specifications, and further supports the interpretation that differences in wage-setting behavior across gender are central to the observed dynamics.

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. In our baseline, we focus 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. For this reason, we 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 allows us to isolate the role of inflation per se, albeit without imposing restrictions on the response of unemployment and therefore without the same macroeconomic context as in our baseline. Figure A.7 shows the impulse response to a positive inflationary shock. In line with our baseline findings, an unexpected increase in inflation leads to a significant and persistent widening of the gender wage gap. If anything, the resulting increase in the gender wage gap is even stronger than for the baseline and is estimated with greater precision, as reflected in substantially narrower confidence bands around the impulse response functions.

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.9) and core CPI excluding food and energy (Figure A.10). Similarly, we find consistent results when replacing the baseline business cycle indicator with industrial production (Figure A.14). 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 (Figure A.17), using median instead of mean wages (Figure A.18), and estimating the gap as the coefficient on a female dummy in a wage regression with detailed controls following Penner et al. (2022) (Figure A.19). In these cases, the GWG is defined as female-minus-male, in contrast to our baseline definition of male-minus-female. As such, the impulse responses should be interpreted with the opposite sign. Across all these variations, the underlying positive relationship between inflation and the widening of the gender wage gap between men and women remains stable. If anything, the effects of inflationary demand shocks are even greater using these alternative measures. The results are also robust to using weekly earnings, rather than hourly, to compute the adjusted GWG (see Figure A.15), suggesting that our findings are not sensitive to whether the wage measure captures intensive or extensive margin adjustments.

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.12) or by lag selection, with similar findings when including additional lags as suggested by the AIC criterion (Figure A.13). Moreover, our findings remain qualitatively unchanged when extending the sample to include the COVID-19 period (Figure A.11), 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 and parental status. Figure A.2 shows that adjusted GWGs are larger among older workers but have been declining more rapidly over time. In the SVAR, younger workers (Figure A.20) exhibit a weaker response of the GWG to inflationary shocks, while the response is stronger among older workers (Figure A.23), consistent with the idea that older cohorts of women may have had less bargaining power. Additionally, GWGs are more volatile for workers with young children (Figure A.24), suggesting greater responsiveness to shocks, potentially reflecting reduced bargaining capacity among women with caregiving responsibilities, or heightened wage responsiveness among men with young children. In what follows, in Section 1.2.2, we analyze more in detail gender differences in characteristics between groups, 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. To address this, we examine the forecast error variance decomposition (FEVD) of the adjusted gender wage gap across our different model specifications and measurement approaches. We consider both the baseline SVAR with zero and sign restrictions and the alternative "max-share" identification of inflationary shocks, and we perform this exercise using adjusted gender wage gaps constructed with both the Kitagawa–Oaxaca–Blinder decomposition and the nearest-neighbor matching estimator. In the baseline SVAR, we aggregate the contributions of inflationary demand and inflationary supply shocks in order to measure their combined contribution to gender wage gap fluctuations, making the results directly comparable to those obtained under the single max-share inflationary shock. Figure 5 presents the corresponding forecast error variance decompositions. The x-axis indicates time in months following the shock, while the y-axis reports the percentage of forecast error variance explained by inflationary shocks. Across specifications, we find that 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

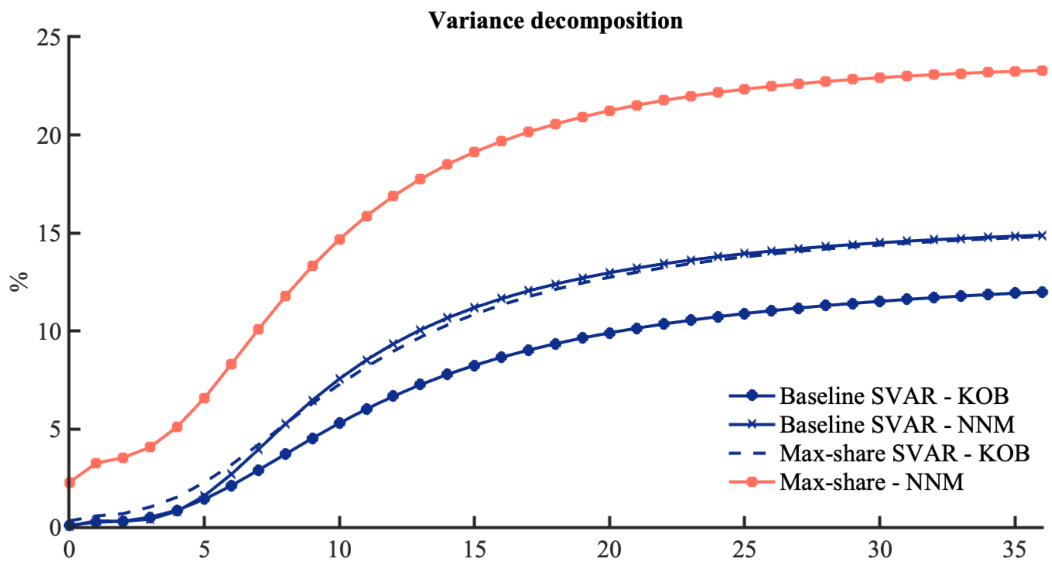


Figure 5: Forecast error variance decompositions

Notes: Forecast error variance decompositions constructed based on pointwise median estimates. The median is defined at each point in time.
Sources: Adjusted and matched GWG: CPS IPUMS, own calculations.

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 firm-level wage-setting practices, 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 gender wage dynamics. Consistent with this interpretation, the share of variance explained by inflationary shocks is systematically larger under the max-share identification, which is designed to capture inflationary disturbances in a broader sense and is therefore more directly interpretable as the contribution of inflation per se, abstracting from the specific macroeconomic channels emphasized in the baseline sign-restricted framework. Taken together, these results indicate that inflationary shocks are a quantitatively meaningful driver of fluctuations in the gender wage gap, even when measured using alternative constructions of the gap and across a range of identification strategies.

1.2.1 Whose wages respond?

Having established that inflationary shocks lead to a significant widening of the adjusted gender wage gap, we next investigate whose real wage response is driving this effect. To do so, we compute men's wages as $\hat{Y}_{mm}$ and women's wages as $\hat{Y}_{mm}$ from the KOB decomposition in Equation (1).

This can be interpreted as comparing men to individuals with the same characteristics as men but being treated like women. We then 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 allows us to trace the response of each group's real wages to inflationary demand and supply shocks, conditional on identical observable characteristics, industries and occupations.

Figure 6 reveals that the entire response of the adjusted GWG to both supply- and demand-side inflationary shocks can be traced to women's weaker protection of real earnings. Holding industry and occupation composition constant as before, women's nominal pay does not sufficiently increase following inflationary episodes, so that women experience real wage losses in either case. In both shocks, consumer prices surge immediately, but men partially offset the loss in purchasing power by renegotiating higher nominal wages within the first months such that their real wages do not respond, or mildly increase over time. Women's nominal wage growth, by contrast, remains virtually flat, implying a sizeable real-wage loss and a widening of the adjusted GWG. These findings dovetail 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. Taken together, the results suggest that real-wage preservation through renegotiation, and not sectoral exposure, might be the dominant channel linking macroeconomic shocks to the gender wage gap.

1.2.2 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, region, 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 observing the differences in coefficients for some individual characteristics in Figure A.25. The results reveal that several individual characteristics contribute meaningfully to the inflation-induced widening of the adjusted GWG. In particular, the gender gap in returns to

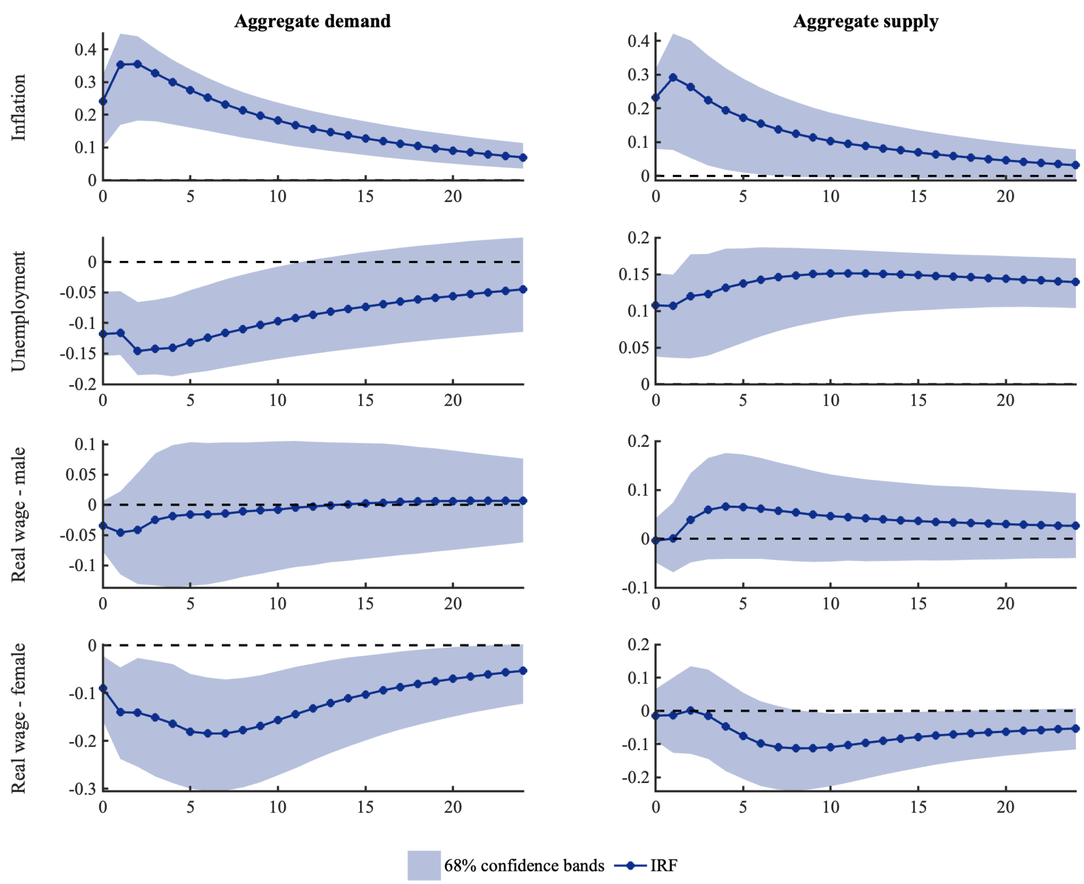


Figure 6: Impulse Responses in the Structural VAR, GWG decomposed

Notes: Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Real wages: CPS IPUMS, own calculations.

age and education (both general schooling and college) increases significantly following demand shocks, indicating that men's wages respond more strongly to inflation along these dimensions than women's, even conditional on observables. These effects are also present after supply shocks. In contrast, the coefficient gaps for black and unmarried individuals respond negatively to both types of shocks, suggesting that women in these groups experience relatively more favorable wage dynamics than their male counterparts. Taken together, these results indicate that the aggregate response of the adjusted GWG to inflationary shocks is primarily driven by asymmetries in how the labor market rewards experience and education by gender, while race and marital status partially offset these effects.

For different industries (see Figures A.27 and A.29), 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 Entertainment, Mining, and Transport, 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 Public, Retail, 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.

To understand why wage renegotiation might differ across genders, we examine how men and women form and update expectations about labor-market conditions.

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. The relationship between inflation and labor-market beliefs is central to understanding gender-specific economic behavior. To analyze it, we use data from the New York Fed Survey of Consumer Expectations (SCE, Federal Reserve Bank of New York 2020).[7] 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

[7]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.

survey experiments (e.g., Andre et al. 2022). Instead, we exploit exogenous macroeconomic shocks to examine how average beliefs evolve over time, allowing us to capture transmission lags that panel revisions may miss. Micro-level robustness checks using revisions in the SCE panel (Appendix Section B.2) confirm the same negative correlation between inflation and earnings-growth expectations for women.

2.1 Construction of Time Series of Beliefs

We construct a time series of mens' and womens' inflation and labor market beliefs from the SCE survey that controls 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 questions used here are shown in Appendix B.1. We restrict the sample to workers in full-time employment, excluding self-employed as for the analysis on 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, this time we are not interested in the gap and instead recover a series for men and women. For any month t, we estimate separately 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 and u is an error term.

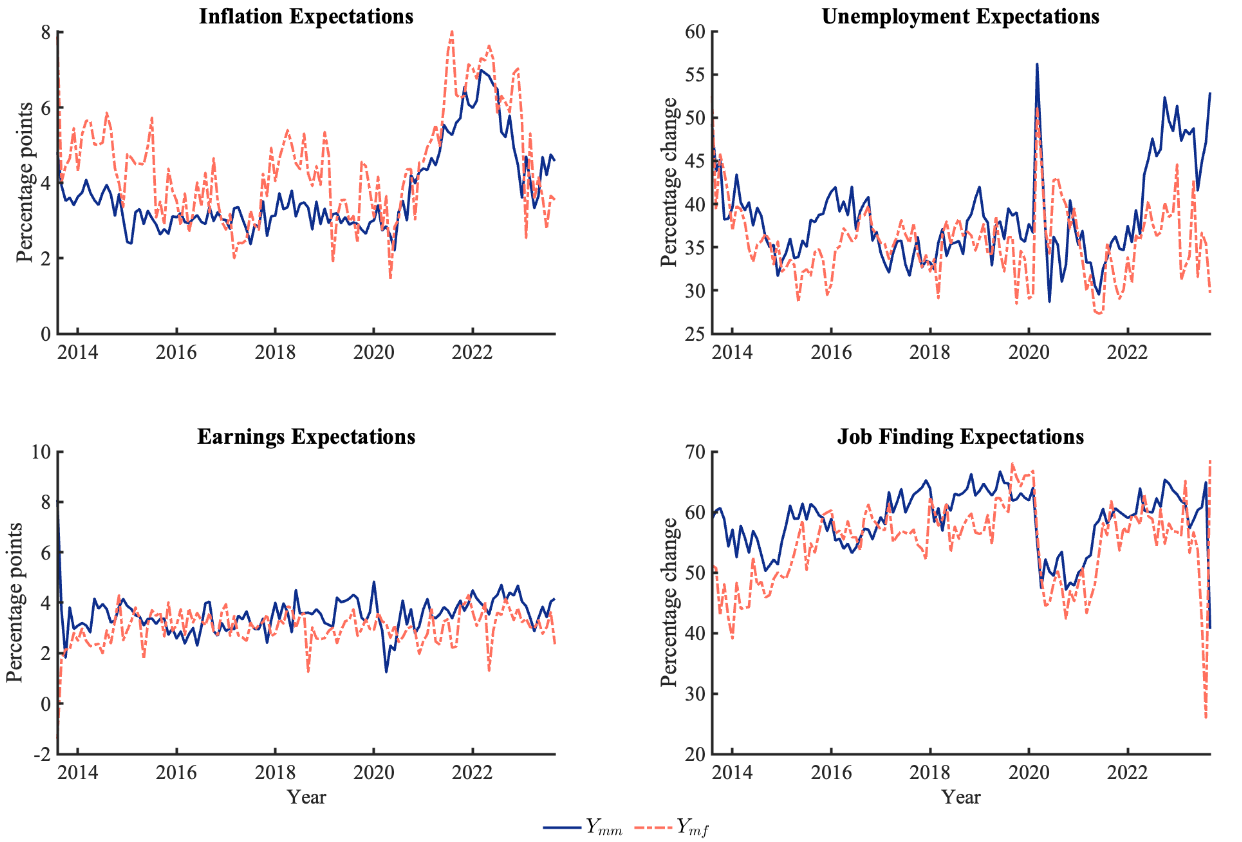


Figure 7: Survey Expectations in the SCE

Notes: Women's expectations are plotted in dashed orange and men's expectations are plotted in dark blue. Monthly data from August 2013-December 2023.
Sources: NYFED SCE, own calculations.

Denote with a hat the predicted coefficients from the regressions above and define:

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

where $\hat{Y}_{mm}$ represents predicted expectations of men and $\hat{Y}_{mf}$ represents the counterfactual expectations of men 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 economy through sorting in different industries.

Figure 7 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 et al. 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.

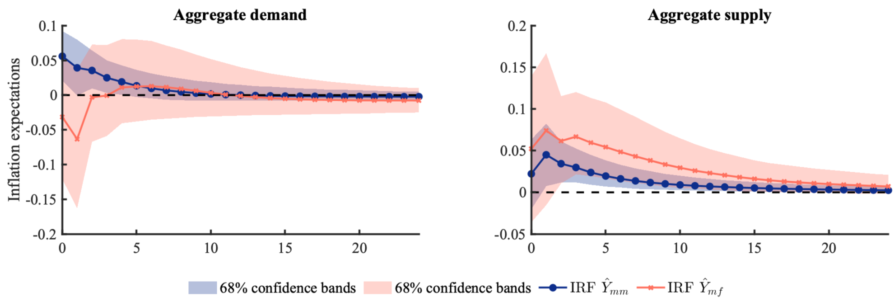
2.2 Belief Responses to Inflationary Shocks

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 are identical to those in the baseline model.

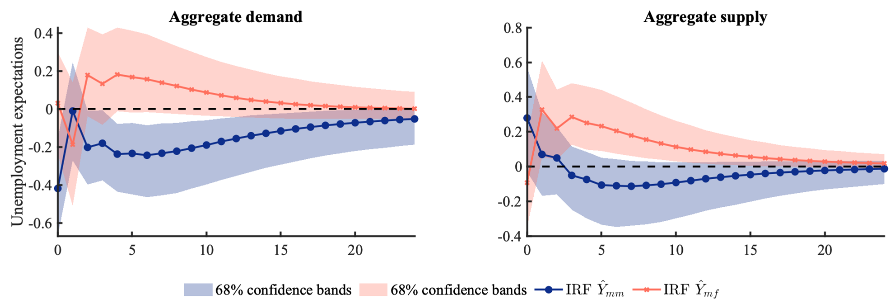
Figure 8 summarizes the impulse responses of men's predicted expectations, $\hat{Y}_{mm}$ (in blue), and the counterfactual $\hat{Y}_{mf}$ under women's expectations coefficients (in orange), to supply and demand shocks. The full set of impulse responses for all variables is provided in the Appendix. The results reveal a striking pattern of gender asymmetry in belief formation. If men behaved like women, their inflation expectations would be more volatile and would react more strongly to inflationary supply shocks. For labor-market beliefs, women consistently display pessimistic responses to inflation, interpreting it as a signal of deteriorating labor-market conditions (supply-side interpretation of inflation). Men, on the other hand, display optimistic responses, viewing inflation as a sign of mild improvement (demand-side interpretation of inflation). Specifically, women revise unemployment expectations upward and job-finding beliefs downward following both supply- and demand-driven inflationary shocks. Men, in contrast, revise job-finding and earnings expectations upward after expansionary demand shocks and leave them largely unchanged for job-finding and upward for earnings after contractionary supply shocks. These results hold even after controlling for demographics, numeracy, and industry, highlighting a robust and systematic difference in how men and women interpret inflation and its implications for labor-market prospects.

As for our first empirical fact, we re-estimate the SVAR model using an alternative identification strategy. Specifically, we identify the shock that explains the largest share of unexplained variation in inflation over business-cycle frequencies. Figures A.35, A.36, A.37, and A.38 in the Appendix present 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.

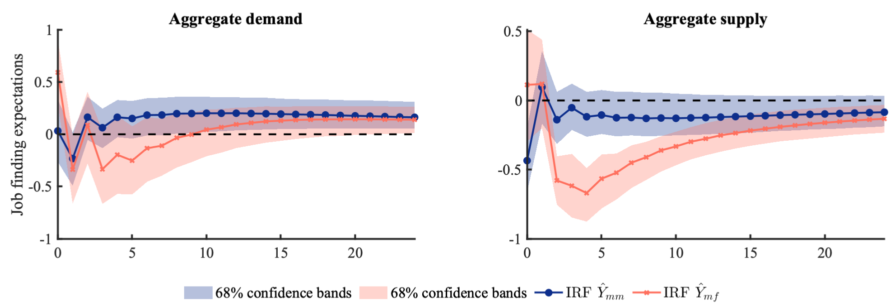
Together, our two empirical findings in Sections 1 and 2 reveal that the gender wage gap widens during inflationary surges and that men and women update their beliefs about labor market conditions differently in response to inflation. These asymmetries in expectations provide a plausible mechanism for women's reduced propensity to renegotiate wages during high-inflation periods, consistent with observed renegotiation behavior. To further explore and rationalize this mechanism, we now turn to a structural model that incorporates belief heterogeneity and wage-



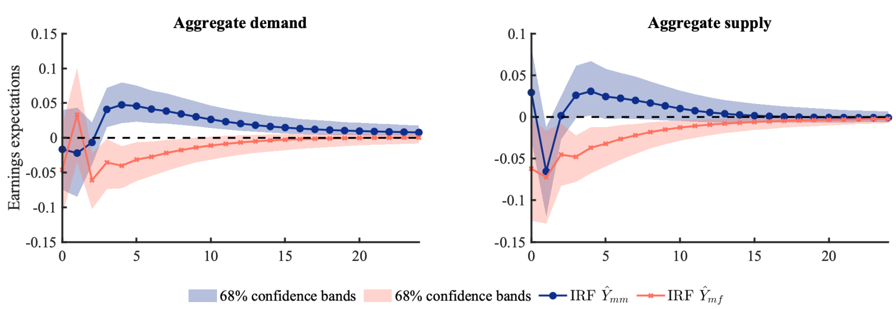
(a) Inflation (12 months)



(b) Unemployment (12 months)



(c) Job Finding (3 months)



(d) Earnings Growth (12 months)

Figure 8: Impulse Responses of Expectations in the SCE to Supply and Demand Shocks

Notes: Women's (orange crossed line) and men's (blue dotted line) expectations computed using monthly data from August 2013-February 2020, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Expectations: NYFED SCE, own calculations.

renegotiation frictions, allowing us to formally examine how informational biases can generate the gendered wage dynamics documented in the data.

3 Theoretical Model

In this section, we present a model that extends the standard New Keynesian framework with search and match frictions a la Diamond (1982), Mortensen (1982), Pissarides (1985) (DMP), as developed in Thomas (2008), Faia (2008), Galí (2010), Blanchard & Galí (2010), Christiano et al. (2016), by incorporating two agents within the household and introducing belief frictions in a second step. We first introduce the benchmark model (the Gender-NKSM) with full information rational expectations. In this model, we compare the effects of pure taste-based discrimination, statistical discrimination, lower bargaining power of women and stickier wages of women on the response of the GWG to supply and demand shocks. We find that none of these sources of gender differences replicates the empirical results on the cyclicality of the adjusted GWG.

In a second step, motivated by our empirical evidence on labor market expectations, we assume that wage setting unions depart from FIRE. They do not observe the true nature of the shock and must form beliefs.[8] We introduce ambiguity aversion of unions modeled using the robust control framework of (Hansen & Sargent 2001) and assume that unions representing women are more ambiguity averse than unions representing men. This results in the representative women's union to overweight the possibility of a supply-driven disturbance and therefore to expect deteriorating labor market conditions for any type of inflationary shock. We show that under such beliefs 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 effectively models labor market frictions and the interaction between inflation, output, and unemployment as in Galí (2010), Blanchard & Galí (2010), Christiano et al. (2016). However, to analyze the gender-specific effects of inflation expectations and job-finding perceptions, we introduce a two-agent structure in which both male and female agents co-exist within the same household. Both agents consume collectively, reflecting shared economic well-being, but negotiate wages independently through a men's and a women's union, allowing for divergent wage-renegotiation behavior influenced by their respective beliefs and expectations. We assume that the firm produces using inputs from both worker types.

[8] The setup resembles Erceg et al. (2025), where agents do not observe the true persistence of the shock.

Household The representative household consists of two representative 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 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) show the effect of unpaid domestic labor and discrimination in a standard New Keynesian model on female labor market participation.

Our household setup resembles most closely that of 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 and $U_{g,t}$ the fraction of unemployed workers and ψ denotes the relative disutility generated by an unemployed household member. It must be that $0 \leq N_{g,t} + U_{g,t} = F_{g,t} \leq 1$ and household members not part of the labor force don't generate any positive or negative utility.

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. 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 houseld is described by:

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

$$\text{subject to } P_tC_t + Q_tB_t \leq B_{t-1} + W_{f,t}N_{f,t} + W_{m,t}N_{m,t} + \Pi_t$$

This yields the standard Euler equation for intertemporal consumption:

$$Q_t = \beta \mathbf{E}_t \left\{ \frac{C_t}{C_{t+1}} \frac{P_t}{P_{t+1}} \frac{Z_{t+1}}{Z_t} \right\}. \tag{2}$$

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.[9] 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 productivity ζ_m, ζ_f and the elasticity of substitution between male and female labor σ:

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

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:

$$N_{g,t}(j) = (1-\delta)N_{g,t-1}(j) + H_{g,t}(j). \tag{3}$$

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

[9] Perfect competition of intermediate goods implies that $P_t^I = MC_t(j)$

they are hired. The firm incurs a cost-per-hire:

$$G_{g,t} = \Gamma x_{g,t}^{\gamma}, \tag{4}$$

which depends on the job finding rate:

$$x_{g,t} \equiv \frac{H_{g,t}}{U_{g,t}}. \tag{5}$$

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 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:

$$\frac{P_t^I}{P_t} MPN_{g,t} = A_t mc_t \zeta_g (1-\alpha) N_{g,t}^{\frac{-1}{\sigma}} N_t^{-\alpha+\frac{1}{\sigma-1}} (1-d_g) \tag{6}$$

$$= w_{g,t} + G_{g,t} - \beta(1-\delta)\mathbf{E}_t \left\{ \frac{C_t}{C_{t+1}} \frac{P_{t+1}}{P_t} G_{g,t+1} \right\}. \tag{7}$$

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 $d_f > 0$ and $d_m = 0$. 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 estimated 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 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 θ_m^w. This Calvo-like setup implies that the expectations of households and firms matter in the bargaining process. The bargaining here follows exactly the bargaining in Blanchard & Galí (2010) for both agents. 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 who's 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:

$$\psi MRS_t = \frac{x_{g,t}}{1-x_{g,t}}\int_0^1 \frac{H_{g,t}(z)}{H_{g,t}} S^H_{g,t}(z)dz. \tag{8}$$

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:

$$\mathbb{E}_t \sum_{k=0}^{\infty}((1-\delta)(1-\theta_g^w))^k \, \Lambda_{t,t+k} \left(\frac{W_{g,t}^*}{P_{t+k}} - \Omega_{g,t+k|t}^{\text{tar}}\right) = 0.$$

The target wage k periods ahead $\Omega_{f,t+k|t}^{tar}$ 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:

$$\Omega_{g,t+k|t}^{tar} \equiv \xi_g \frac{C_{t+k}}{\chi L_{g,t+k}^{\varphi}} + (1-\xi_g)\frac{P_t^I}{P_t} MPN_{g,t+k|t} \tag{9}$$

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

$$Y_t = C_t + G_{f,t}H_{f,t} + G_{m,t}H_{m,t}. \tag{10}$$

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

$$Y_t = A_t \left[\zeta \cdot N_{f,t}^{\frac{\sigma-1}{\sigma}} + (1-\zeta)\cdot N_{m,t}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{(1-\alpha)\sigma}{\sigma-1}}. \tag{11}$$

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

$$\frac{1+i_t}{1+\bar{i}_t} = \left(\frac{1+i_{t-1}}{1+\bar{i}_t}\right)^{\rho_i}\left[\left(\frac{1+\pi_t^p}{1+\bar{\pi}_t^p}\right)^{\phi_\pi}\left(\frac{1+\pi_{m,t}^w}{1+\bar{\pi}_t^w}\right)^{\phi_{wm}}\left(\frac{1+\pi_{f,t}^w}{1+\bar{\pi}_t^w}\right)^{\phi_{wf}}\left(\frac{U_{m,t}}{\bar{U}_{m,t}}\right)^{\phi_{um}}\left(\frac{U_{f,t}}{\bar{U}_{f,t}}\right)^{\phi_{uf}}\left(\frac{Y_t}{\bar{Y}_t}\right)^{\phi_y}\right]^{1-\rho_i} \nu_t. \tag{12}$$

The full set of equilibrium equations can be found in the Appendix Section C.1.

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, 0.06% unemployment[10] 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), Gertler & Trigari (2009). Following Galí (2010) and Blanchard & Galí (2010) we set $\gamma = 1$ to align

[10] Data from BLS - on average no differences between men and women.

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 in (Albanesi 2025, Acemoglu et al. 2004). We assume a monetary authority that responds to inflation and unemployment with $\phi^p = 2$, $\phi_y = 0$, $\phi_{w,g} = 0.005$ and $\phi_{u,g} = -0.0125$. 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 $\theta_m^w = \theta_f^w = 0.75$ 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 $\sigma_a^2 = 0$ and $\sigma_\nu^2 = 0$ such that technology is assumed constant and there are no monetary policy shocks.[11] The full set of parameters and their calibration can be found in Appendix Table C.1.1.

3.3 GWG dynamics under non-belief-frictions

In the baseline model, assuming no discrimination and symmetric bargaining power and wage rigidities across genders, no gender wage gap (GWG) emerges. The black line in Figure 10 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.[12]

Introducing taste-based discrimination ($d_f = 0.1$), generating a steady-state GWG of roughly 11% in line with empirical data, produces negligible changes in the cyclical response

[11]We also include robustness checks with a standard technology shock and a standard monetary policy shock calibrated as $\rho_a = 0.9$, $\sigma_a = 0.25$, $\rho_\nu = 0.9$, $\sigma_\nu = 1$ as alternatives for a supply- and a demand-shock.

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

of the GWG (lightest blue lines, +marker). This is expected, as the additional cost of hiring women is scaled with output. The discrimination parameter d_f is retained in all subsequent models to ensure consistent steady-state GWGs.

Next, we calibrate relative productivity weights following Albanesi (2025) ($\zeta_f = 0.375 < 0.5$), amplifying the equilibrium GWG and generating weak cyclical patterns (denoted with 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 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 also include women's wages to be stickier. We are not aware of any literature that has calibrated women's wages as stickier than men's. For illustration we set $\theta^w_m = 0.6 < 0.75 < \theta^w_f = 0.9$. Across all three cases, the GWG widens during inflationary expansions (demand shocks) but narrows during inflationary contractions (supply shocks). Larger female Frisch elasticity has the strongest effect, yet fails to replicate the observed response to 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. Evidence suggests that women and men may perceive inflationary shocks differently: women appear to interpret shocks more like supply (cost-push) shocks, while men perceive them as demand-driven. We formalize this idea using a framework of ambiguity aversion. Women facing uncertainty over the nature of shocks may overweight adverse scenarios, generating gender-specific responses in wages and employment. By incorporating differential shock perception, the model can capture how identical aggregate disturbances produce divergent outcomes across genders.

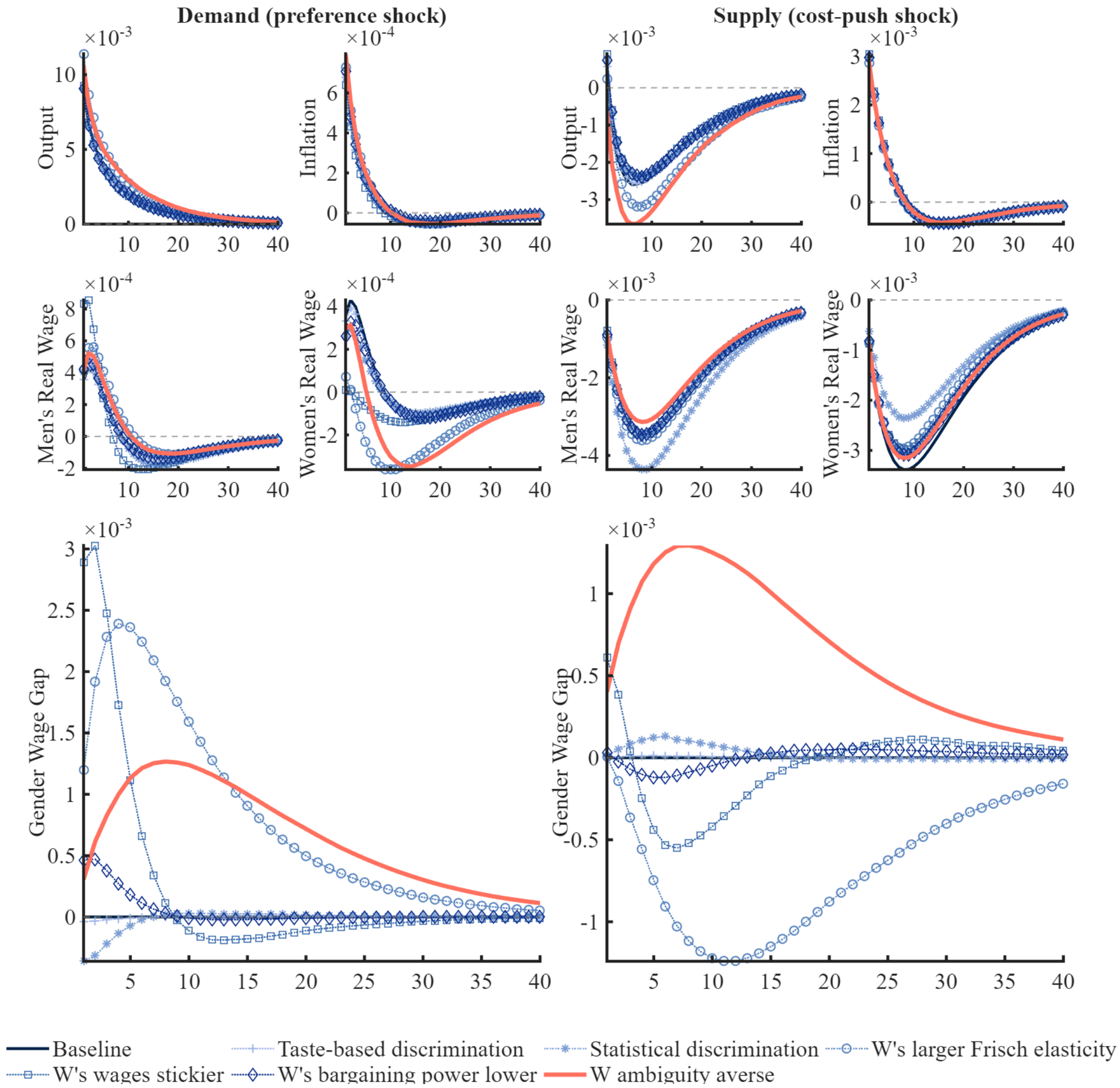


Figure 10: Impulse responses from the model

3.4 The model with ambiguity aversion

To account for gender differences in the perception of inflationary, macroeconomic shocks, we implement a framework in which women and men interpret identical shocks differently. There is some recent literature on biases in workers perceived job finding and job separation rates (Spinnewijn 2015, Menzio 2022, Mueller et al. 2021, Mueller & Spinnewijn 2023, Balleer et al. 2024). Our empirical evidence suggests that women perceive inflationary shocks primarily as *supply-driven* (cost-push), while men perceive them as *demand-driven*. We formalize this intuition using the *Hansen-Sargent robust control* approach (Hansen & Sargent 2001), which introduces ambiguity-averse beliefs into the baseline model. This setup differs slightly from the multiple prior preferences (Ilut et al. 2014, Masolo & Monti 2021, Baqaee 2020) as our agents are not ambiguity averse about one shock but about the type of shock. Our model resembles most closely Bhandari et al. (2025) who introduce pessimism (and pessimistic shocks) into a NK model with search and match frictions. Unlike their model which features ambiguity aversion in all economic agents, we introduce ambiguity aversion only for the wage-setting unions (one for men and one for women). This allows us to maintain full information rational expectations for the household problem and avoid aggregating women's and men's beliefs within the household. The unions do not observe the true nature of the shock and form expectations on the economy after observing a signal.

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

$$m_g^s = p_s \exp\left(-\frac{V_{s,t}}{\lambda_g}\right), \tag{13}$$

and the normalized subjective probabilities become

$$w_g^s = \frac{m_g^s}{\sum_{s' \in \{z,u\}} m_g^{s'}}. \tag{14}$$

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:

$$s_t = \varepsilon_t^u + \varepsilon_t^z. \tag{15}$$

The signal reflects that agents cannot perfectly identify whether contemporaneous fluctuations originate from demand or supply disturbances. 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:

$$\tilde{\varepsilon}_{g,t}^{z} = w_g^z\, s_t, \tag{16}$$

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

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

$$\tilde{\mathbb{E}}_{g,t}[z_t] = \rho_z\, \tilde{\mathbb{E}}_{g,t-1}[z_{t-1}] + \tilde{\varepsilon}_{g,t}^{z}, \tag{18}$$

$$\tilde{\mathbb{E}}_{g,t}[u_t] = \rho_u\, \tilde{\mathbb{E}}_{g,t-1}[u_{t-1}] + \tilde{\varepsilon}_{g,t}^{u}. \tag{19}$$

The union's information set at time t excludes the true realizations of ε_t^z and ε_t^u, 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 (8) can be rewritten as

$$\psi_g\, \chi_g L_g^{\varphi_g} \frac{C_t}{Z_t} = \frac{x_g}{1-x_g} \left[\frac{1-\xi_g}{\xi_g} G_g - \pi_g^w \frac{\theta_g^w}{1-\theta_g^w} \omega_{g,t-1} Q_g \right], \tag{20}$$

where

$$Q_g = 1 + \theta_g^w (1-\delta_g)\beta \frac{\tilde{\mathbb{E}}_{g,t}[Z_{t+1}]}{Z_t} \frac{C_t}{\tilde{\mathbb{E}}_{g,t}[C_{t+1}]} \frac{\tilde{\mathbb{E}}_{g,t}[Q_{g,t+1}]}{1+\pi_t^p}. \tag{21}$$

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.

Male unions, being relatively optimistic ($\lambda_m < 0$), place higher subjective weight on favorable states and thus anticipate stronger future wage growth, whereas 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 differences in labor supply even in symmetric macroeconomic environments.

The model with ambiguity aversion generates gender wage gaps that are sensitive to macroeconomic conditions, particularly inflation. In Figure 10 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 $w_f^u = 0.97 > w_m^u = 0.03$. 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 a belief-driven mechanism such as ambiguity aversion, motivated by survey expectations, can replicate our empirical findings on the cyclicality of the GWG while other, more static explanations cannot.

4 Conclusion

This paper establishes a new link between inflation dynamics and gender wage inequality. Using U.S. data, we show that the gender wage gap systematically widens following both supply- and demand-driven inflationary shocks, even after accounting for worker characteristics, industry, and occupation. 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 how workers interpret inflationary surprises: women perceive inflation as signaling weaker labor market conditions, while men interpret it as mild improvement. These asymmetric beliefs translate into unequal wage bargaining, with women negotiating smaller nominal wage increases and experiencing slower wage growth than men.

We formalize this mechanism within a two-agent New Keynesian search-and-matching model, where women's ambiguity-averse beliefs explain women's pessimistic interpretation of inflation and successfully replicate the empirical widening of the gender wage gap observed after inflationary shocks. The model links belief heterogeneity to aggregate wage dynamics, showing how differences in perceptions can 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 and the subsequent bargaining response 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 GWG Supplementary Material

A.1 Alternative measures of GWGs

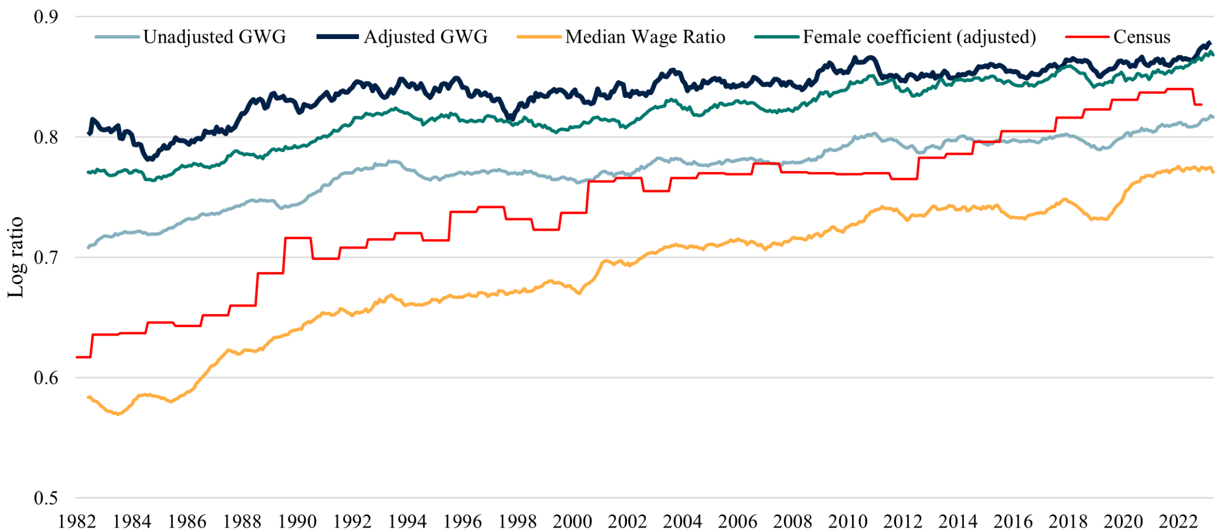


Figure A.1: Different measures of GWG (1982-2023) measured as female to male ratio

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 while the Census data uses the median annual wage ratio of year-round workers.
Sources: Unadjusted and Adjusted GWG, Median Wage Ratio and Female coefficient: CPS IPUMS, own calculations. Census: U.S. Census Bureau (Guzman & Kollar 2024).

A.2 GWGs across demographic groups

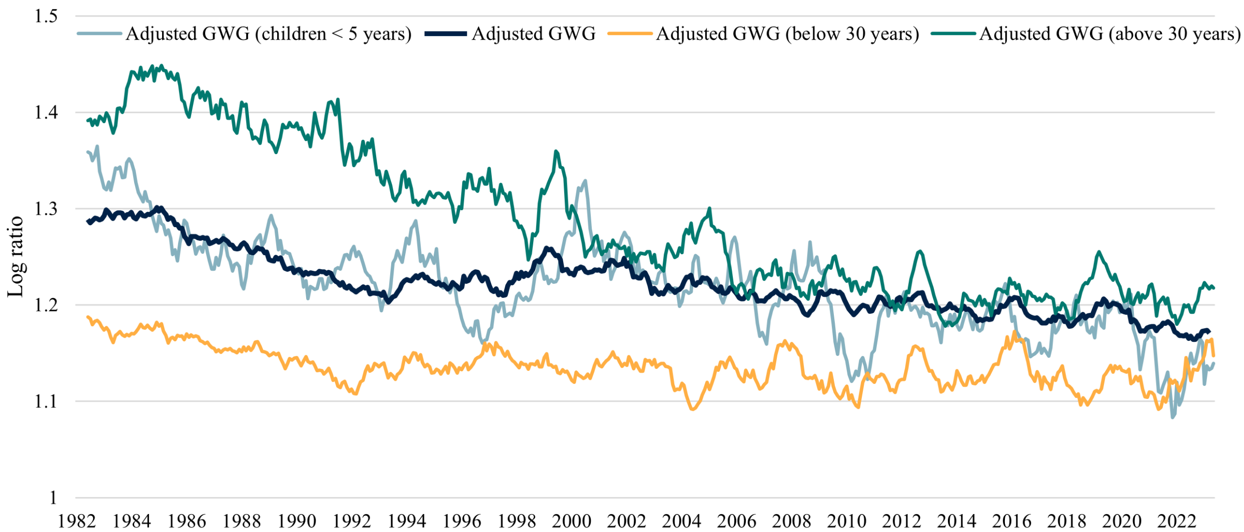


Figure A.2: Adjusted GWG (1982-2023) for different demographic groups

Notes: Adjusted GWGs are computed using a traditional 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 to smooth the volatility and seasonality.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unadjusted and Adjusted GWG: CPS IPUMS, own calculations.

A.3 Robustness checks on the SVAR

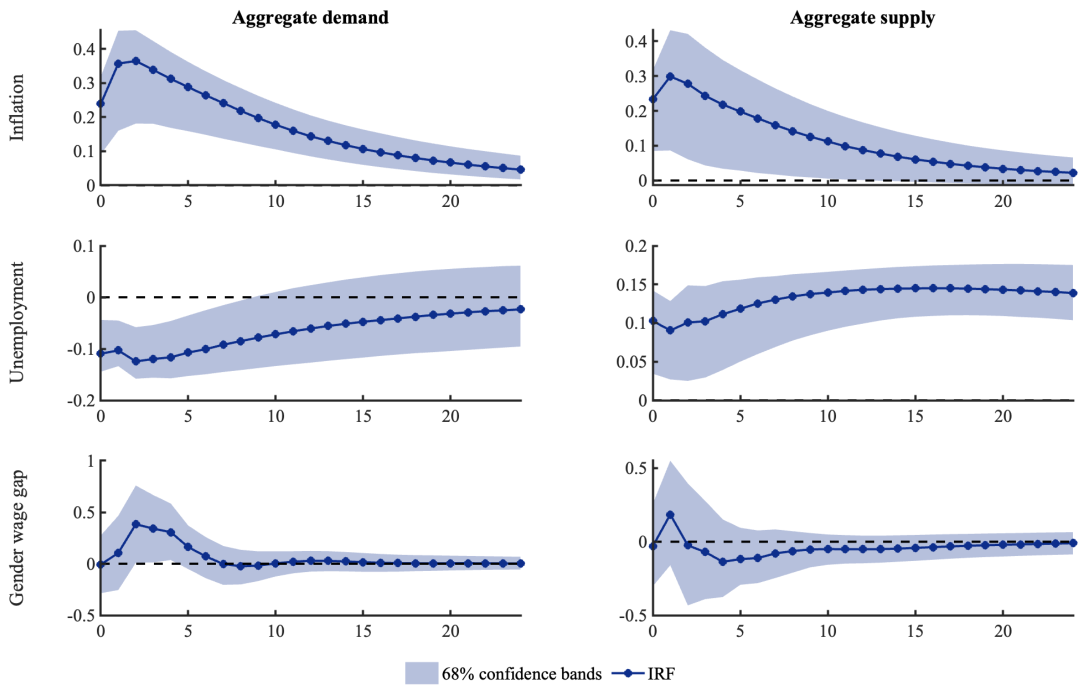


Figure A.3: Impulse Responses in the Structural VAR for unionised workers

Notes: Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

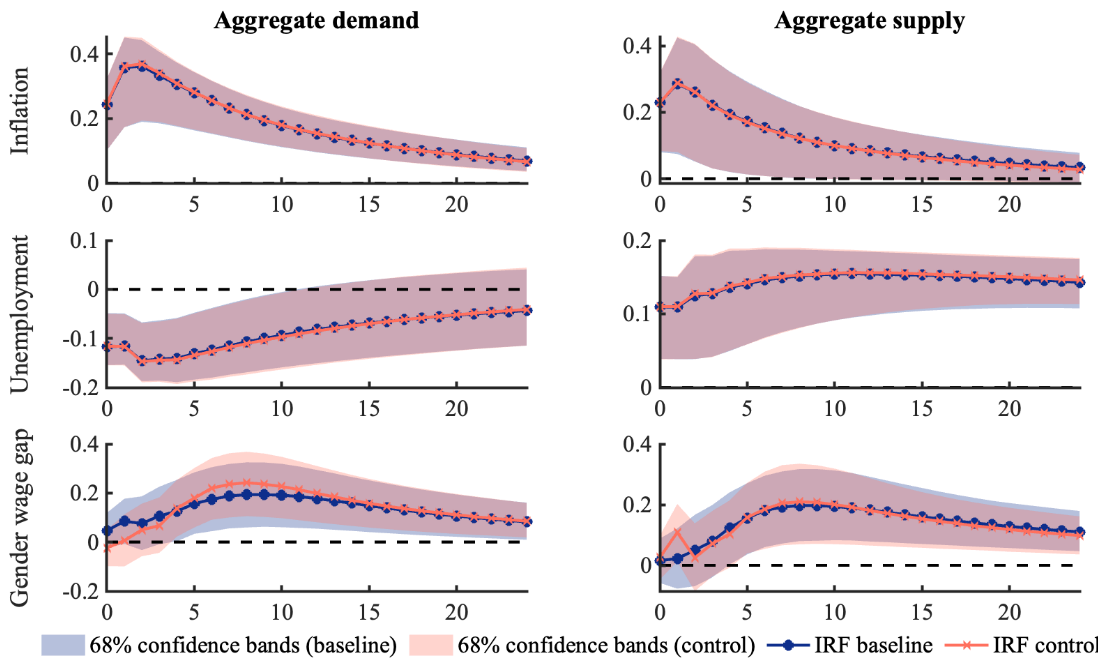


Figure A.4: Impulse Responses in the Structural VAR - baseline and nearest-neighbor matching

Notes: Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid dotted 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 and matched GWGs are computed using monthly data from January 1982 - February 2020.

Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

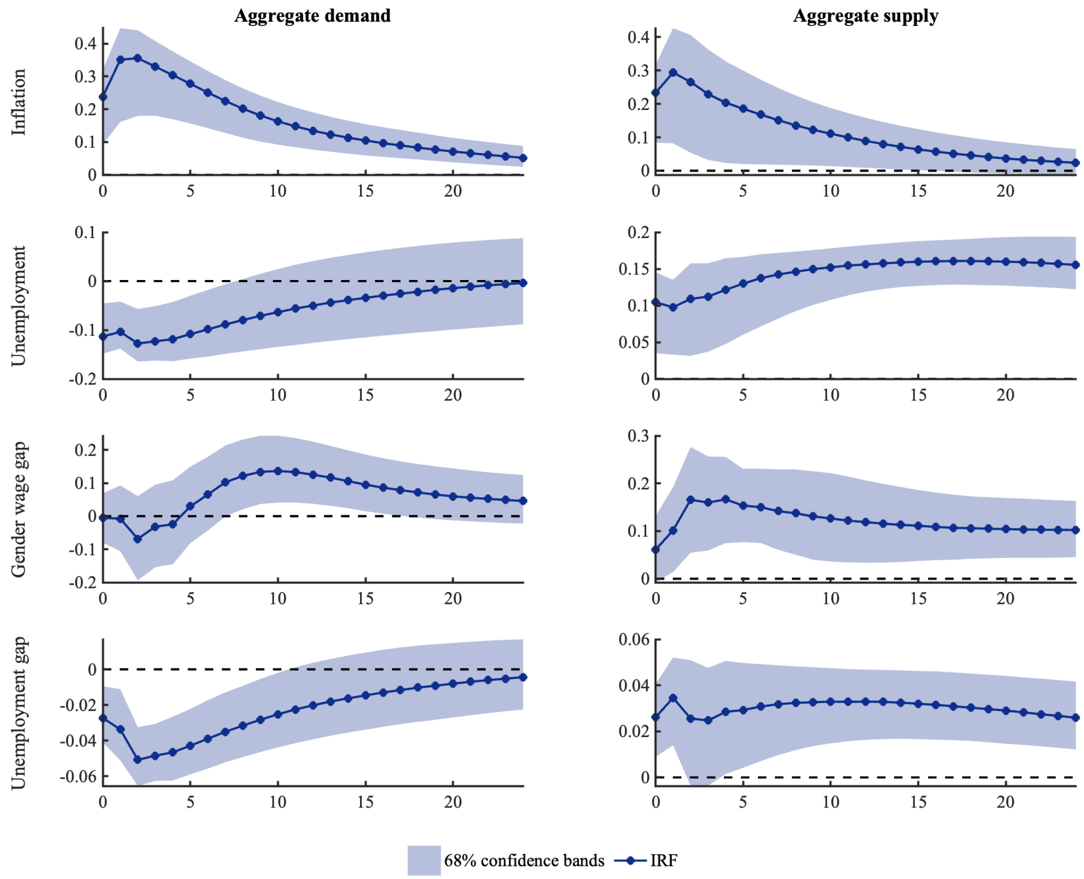


Figure A.5: Impulse Responses in the Structural VAR including unemployment gap

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 dotted 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.

Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations; Unemployment rate men: FRED LNS14000001, Percent, Seasonally adjusted; Unemployment rate women: FRED LNS14000002, Percent, Seasonally adjusted.

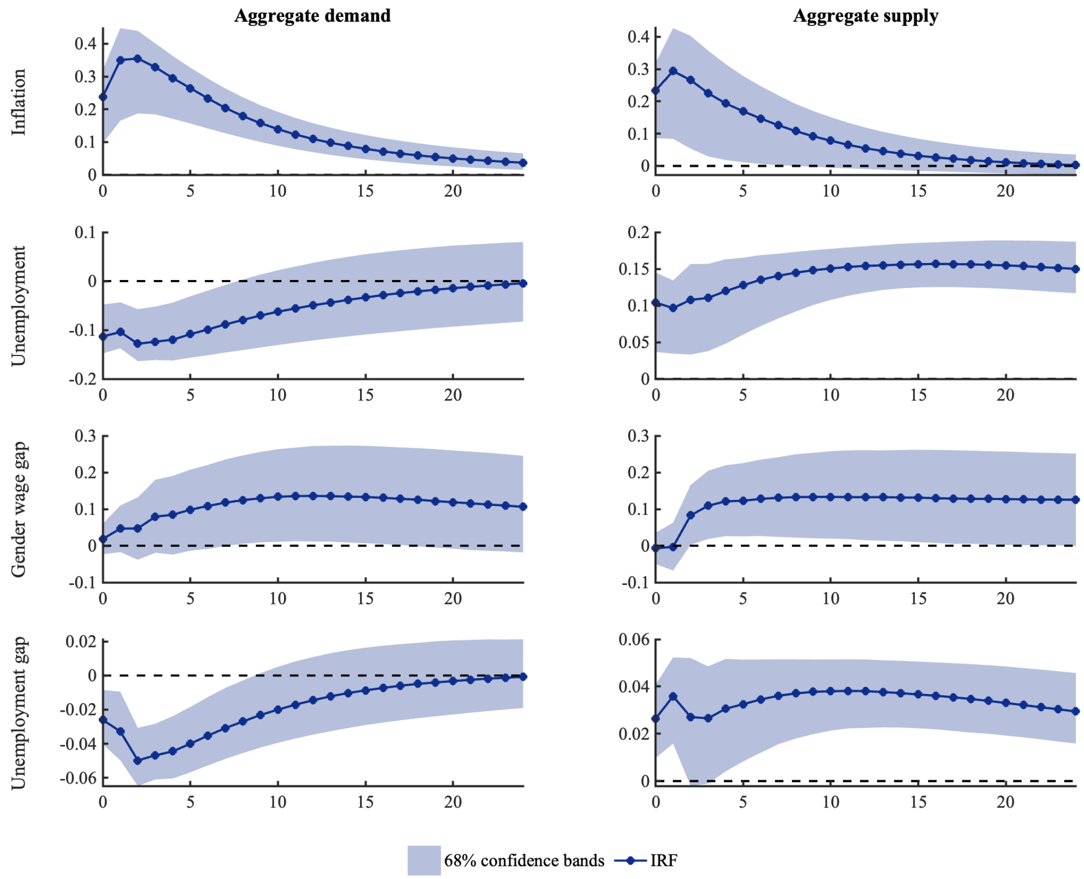
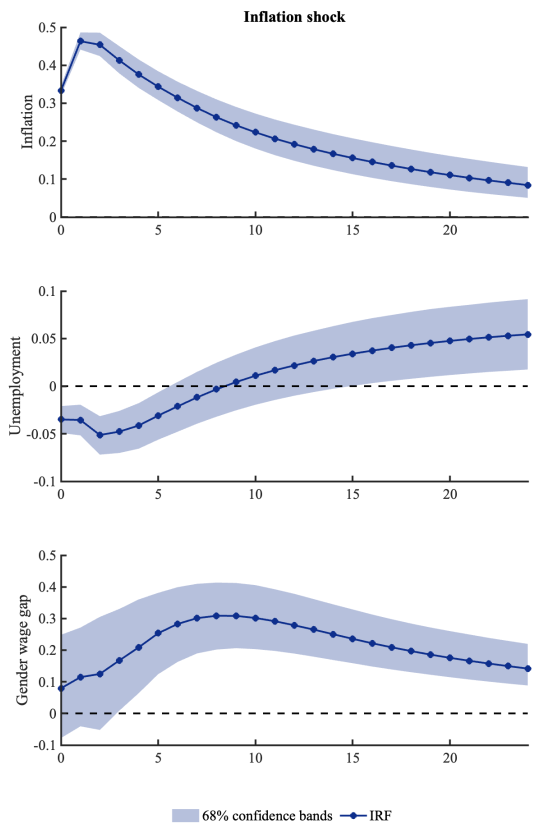
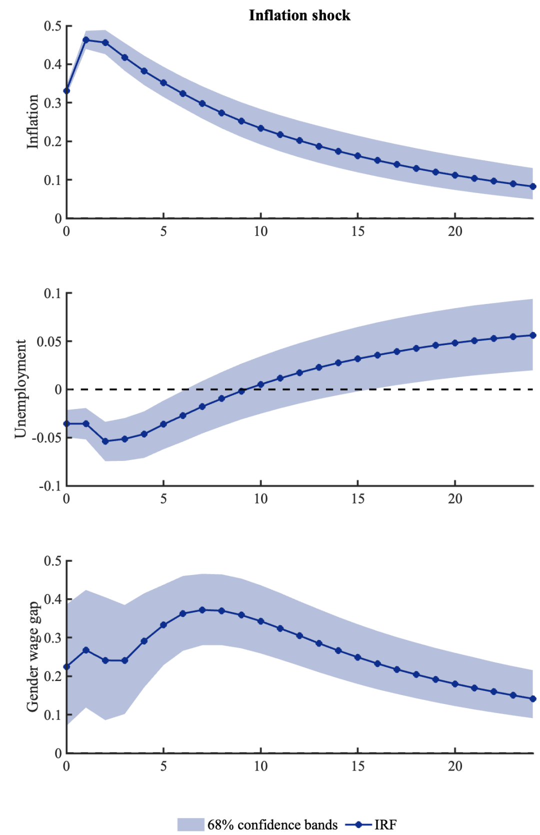


Figure A.6: Impulse Responses in the Structural VAR including unemployment gap

Notes: 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 dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations; Unemployment rate men: FRED LNS14000001, Percent, Seasonally adjusted; Unemployment rate women: FRED LNS14000002, Percent, Seasonally adjusted.



(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 dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

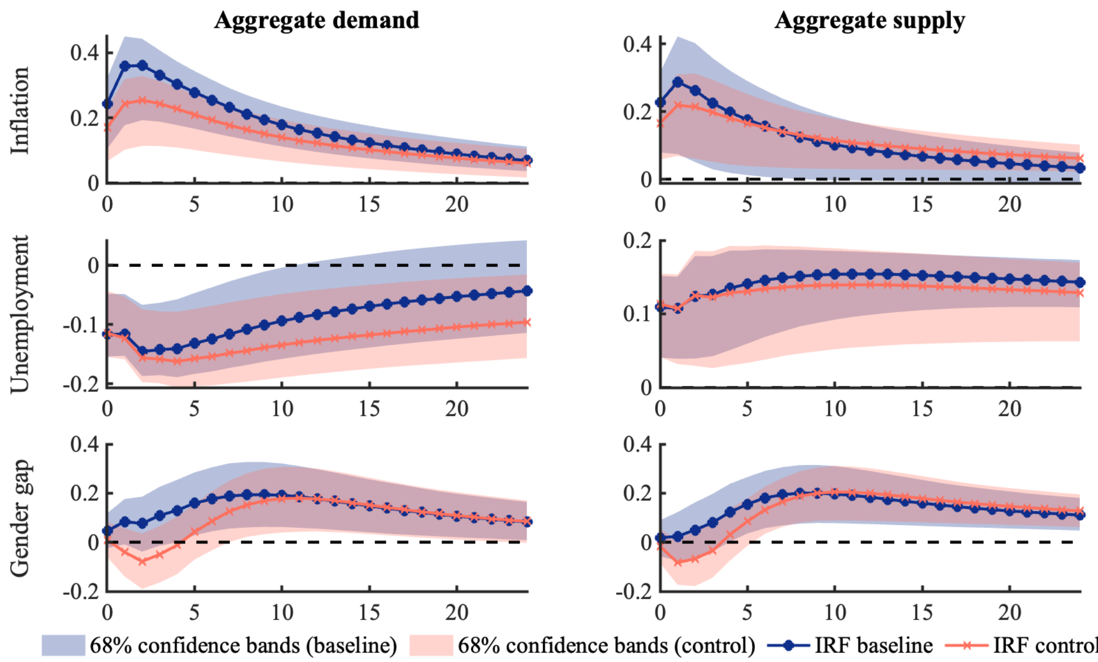


Figure A.9: Impulse Responses in the Structural VAR using PCE inflation

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 dotted 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.
Sources: Inflation: FRED PCEPILFE, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

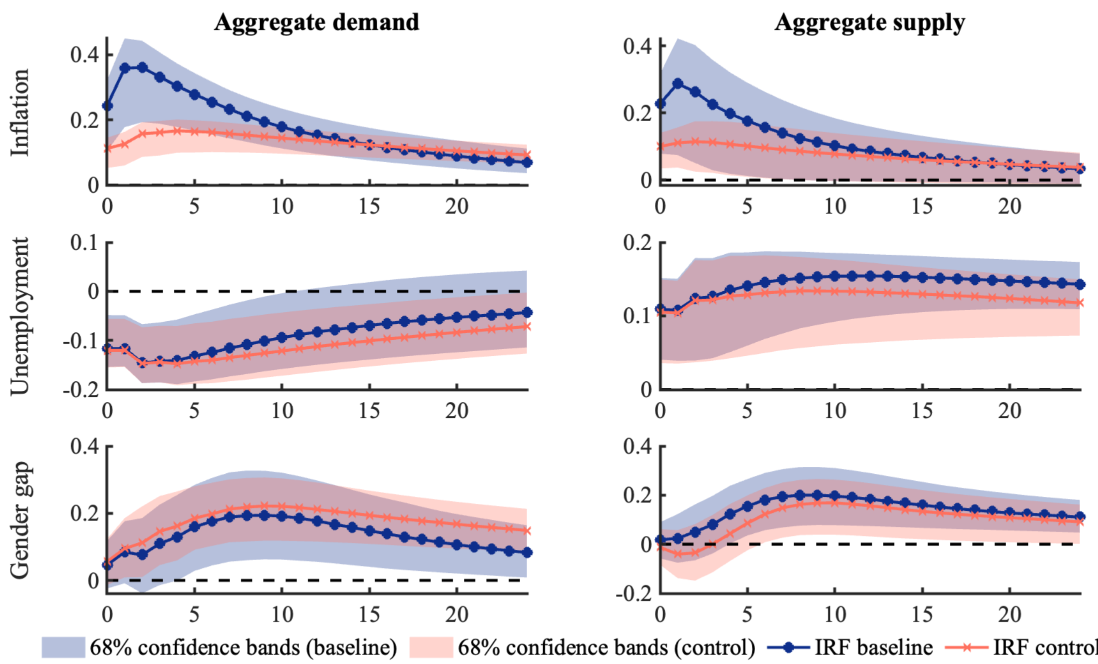


Figure A.10: Impulse Responses in the Structural VAR using CPI inflation excluding food and energy

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 dotted 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.
Sources: Inflation: FRED CPILFESL, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

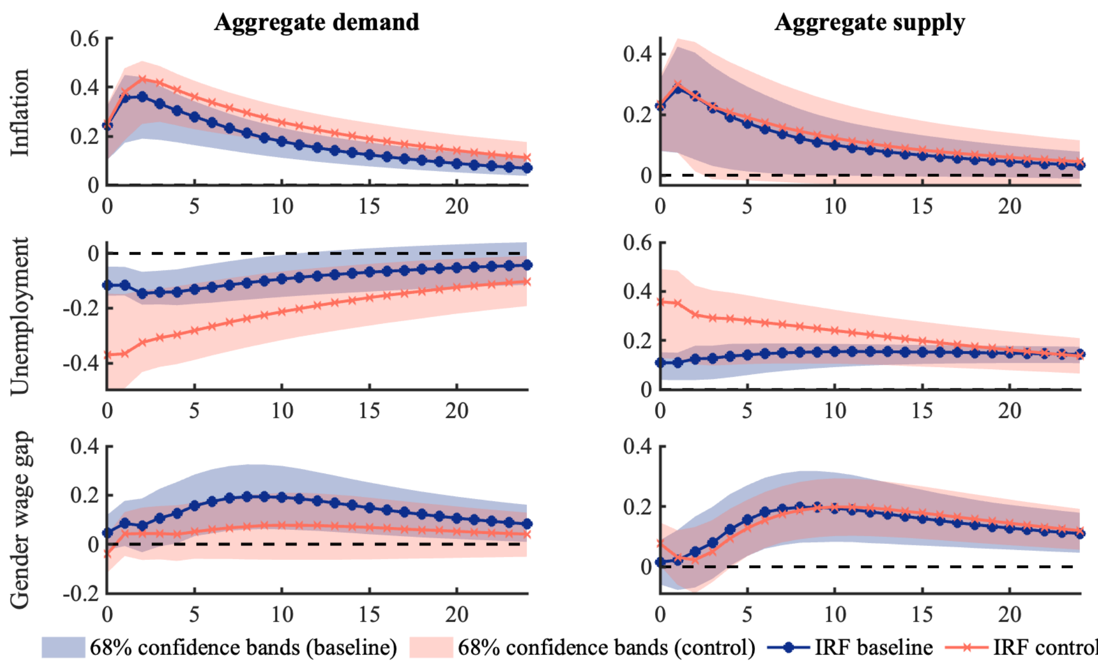


Figure A.11: Impulse Responses in the Structural VAR including Covid

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 dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

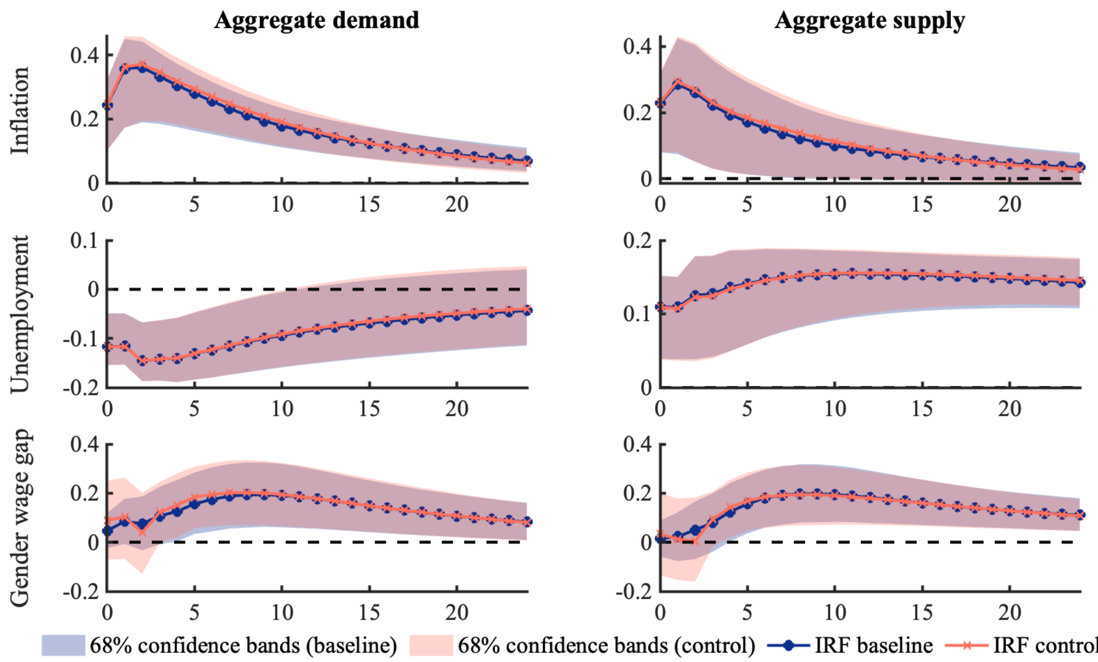


Figure A.12: Impulse Responses in the Structural VAR without moving average

Notes: Adjusted GWGs computed using monthly data from January 1982 - February 2020. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

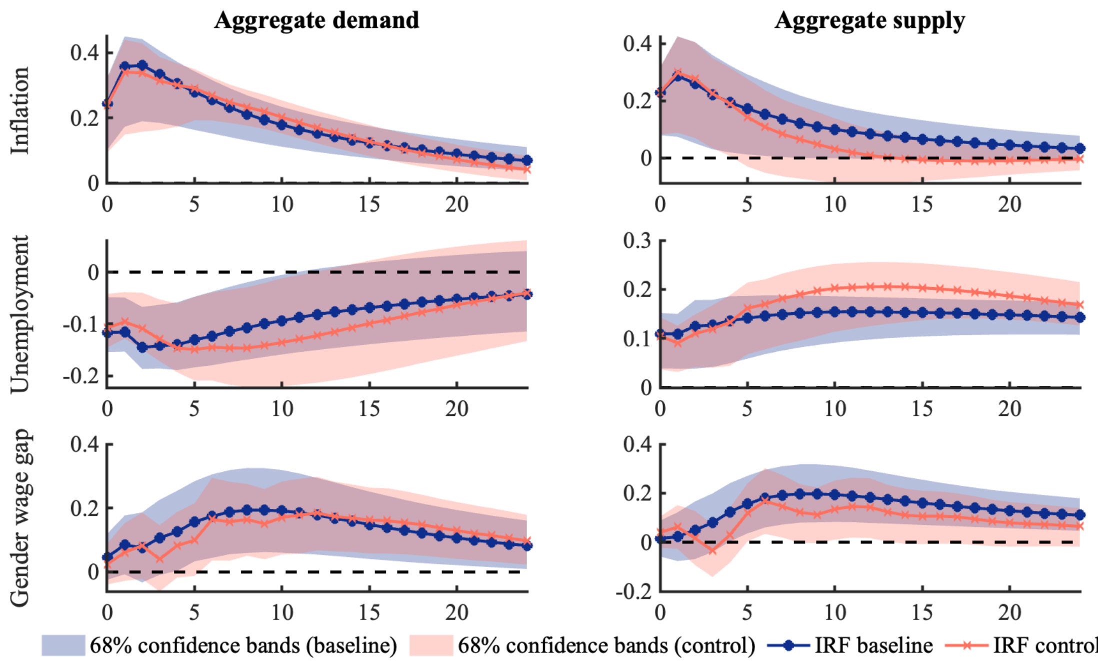


Figure A.13: Impulse Responses in the Structural VAR with 6 lags

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 dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

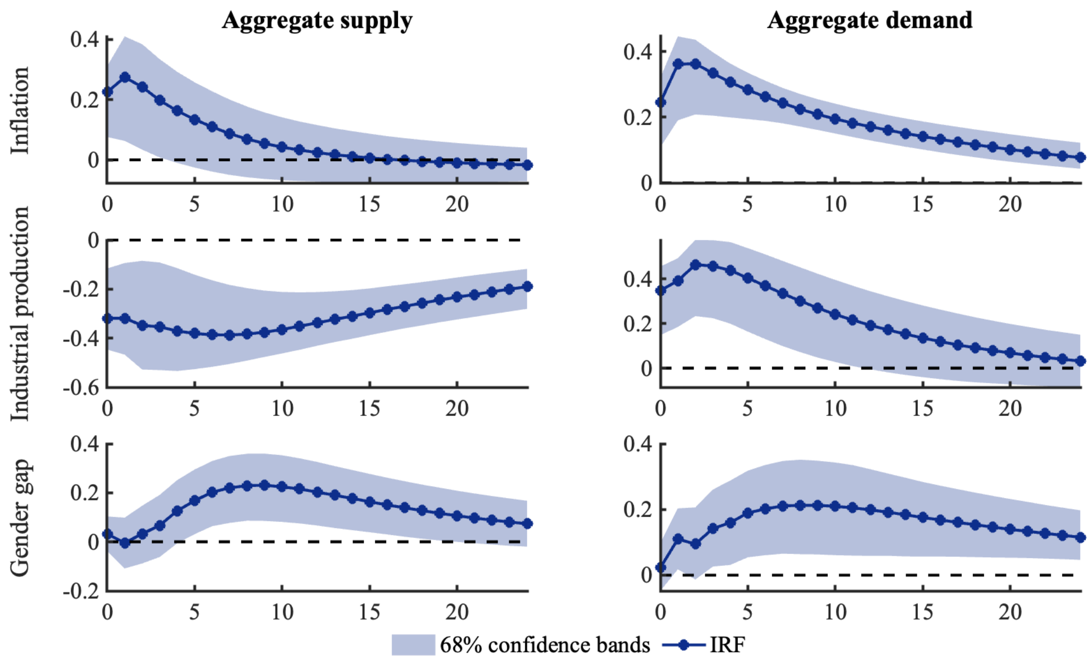


Figure A.14: Impulse Responses in the Structural VAR with Industrial Production

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 dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Industrial production: FRED INDPRO, Percent change, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

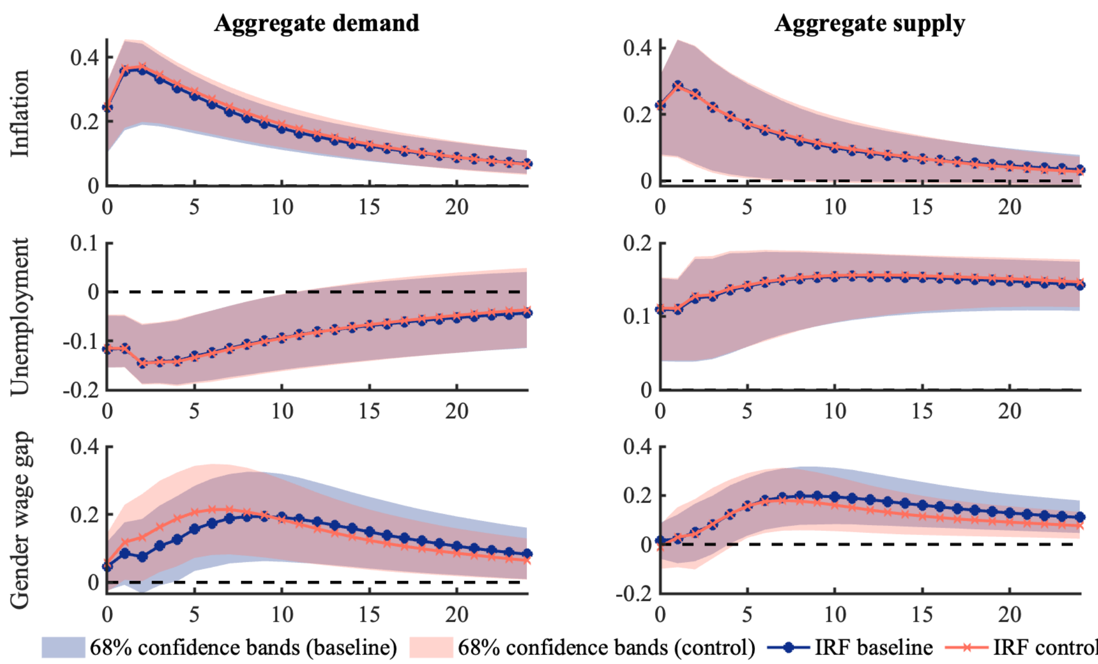


Figure A.15: Impulse Responses in the Structural VAR, weekly earnings

Notes: Adjusted GWG in hourly wages and weekly earnings 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 dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

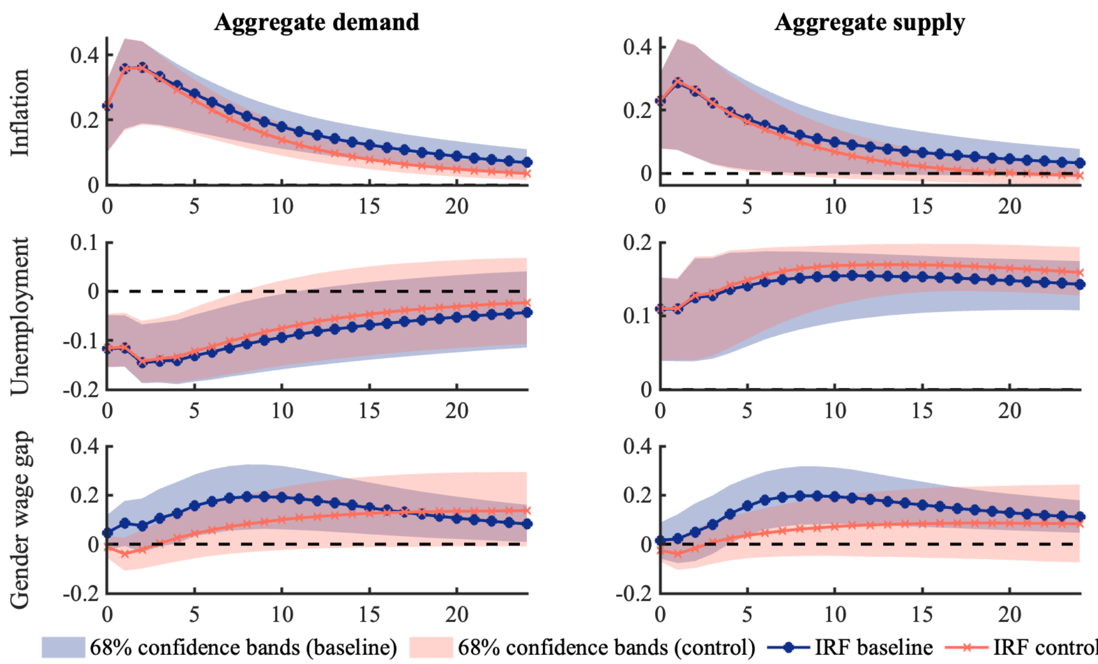


Figure A.16: Impulse Responses in the Structural VAR with raw GWG

Notes: 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 dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted and raw GWG: CPS IPUMS, own calculations.

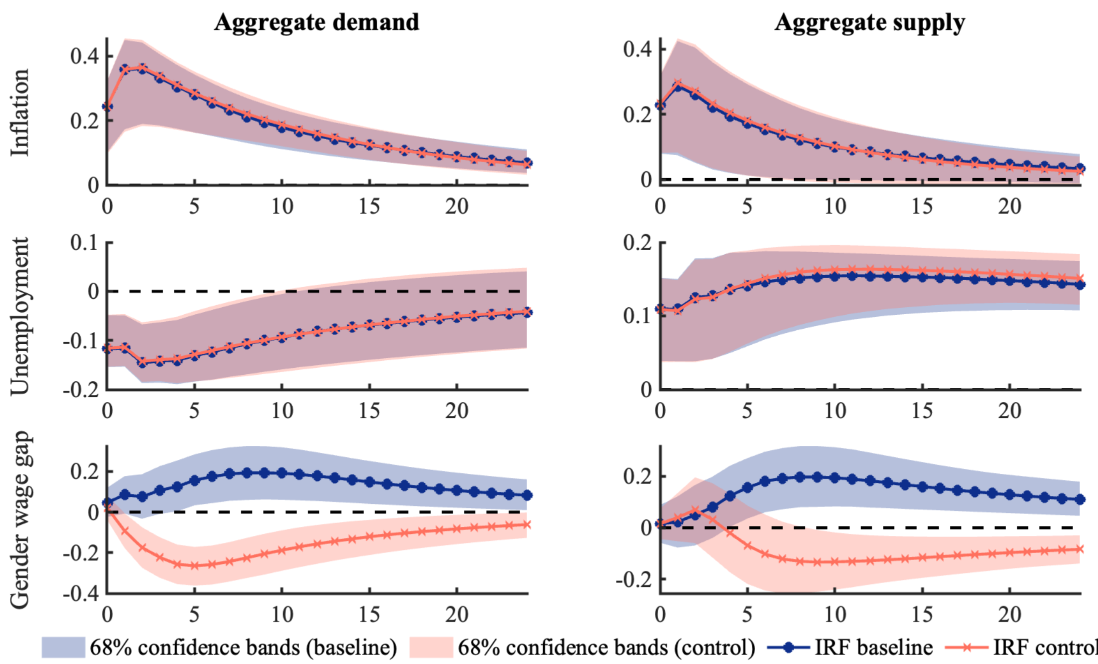


Figure A.17: Impulse Responses in the Structural VAR with inverted GWG

Notes: Adjusted GWGs (men's wages with female characteristics as in Blau & Kahn (2017)) 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 dotted 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.

Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

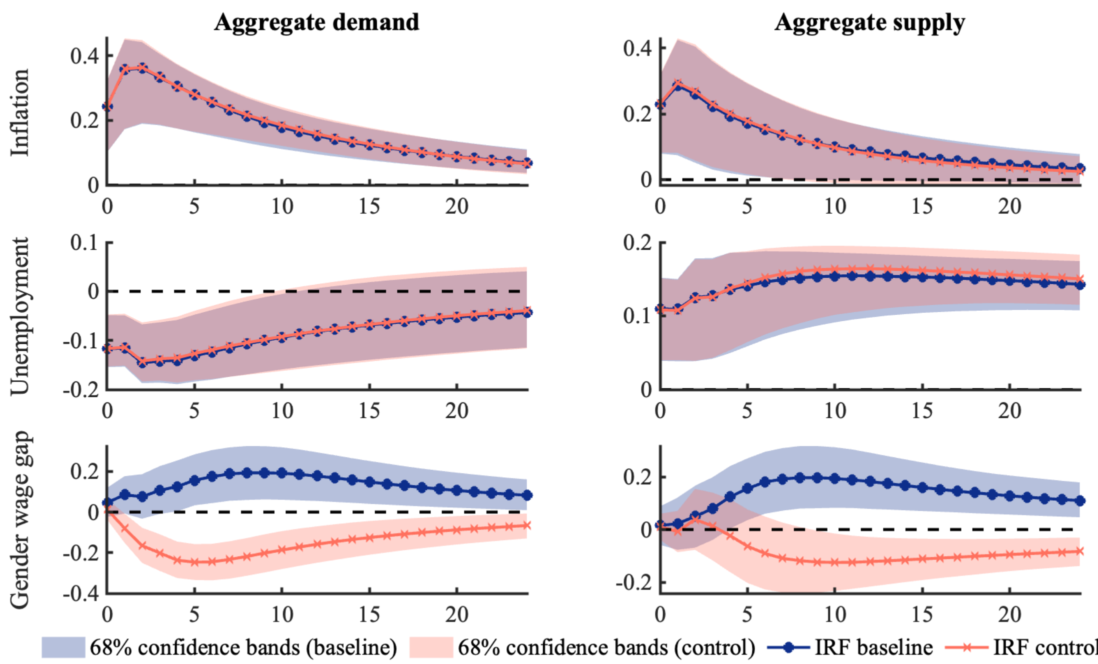


Figure A.18: Impulse Responses in the Structural VAR using Median

Notes: Adjusted GWGs (median) 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 dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

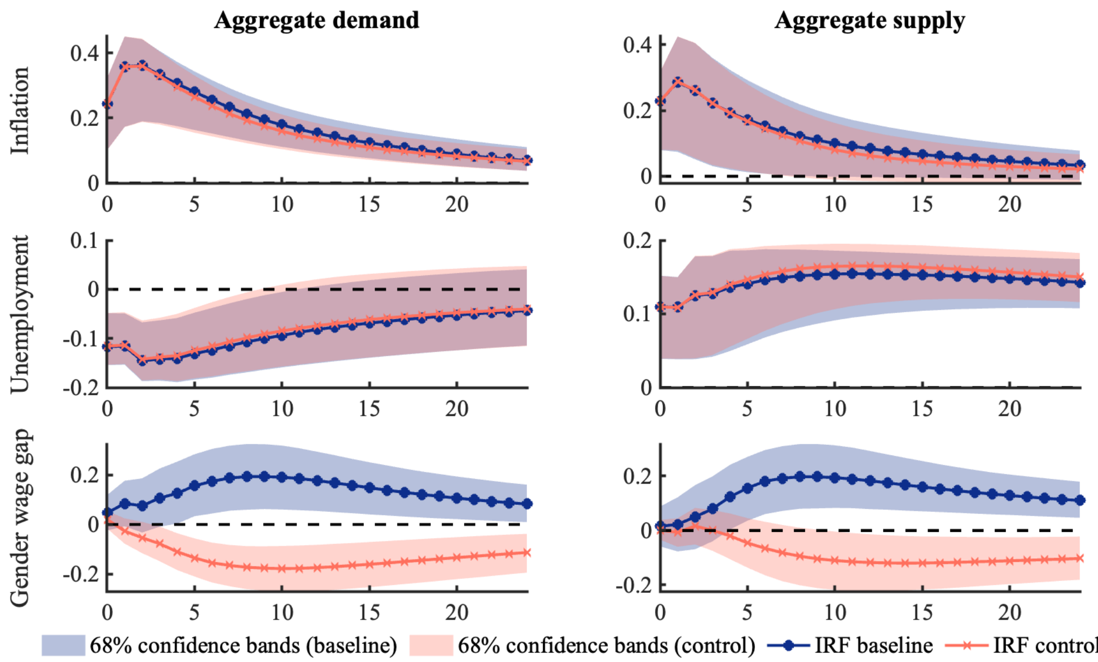


Figure A.19: Impulse Responses in the Structural VAR with Alternative GWG

Notes: Adjusted GWGs as in Penner et al. (2022) 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 dotted 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.

Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

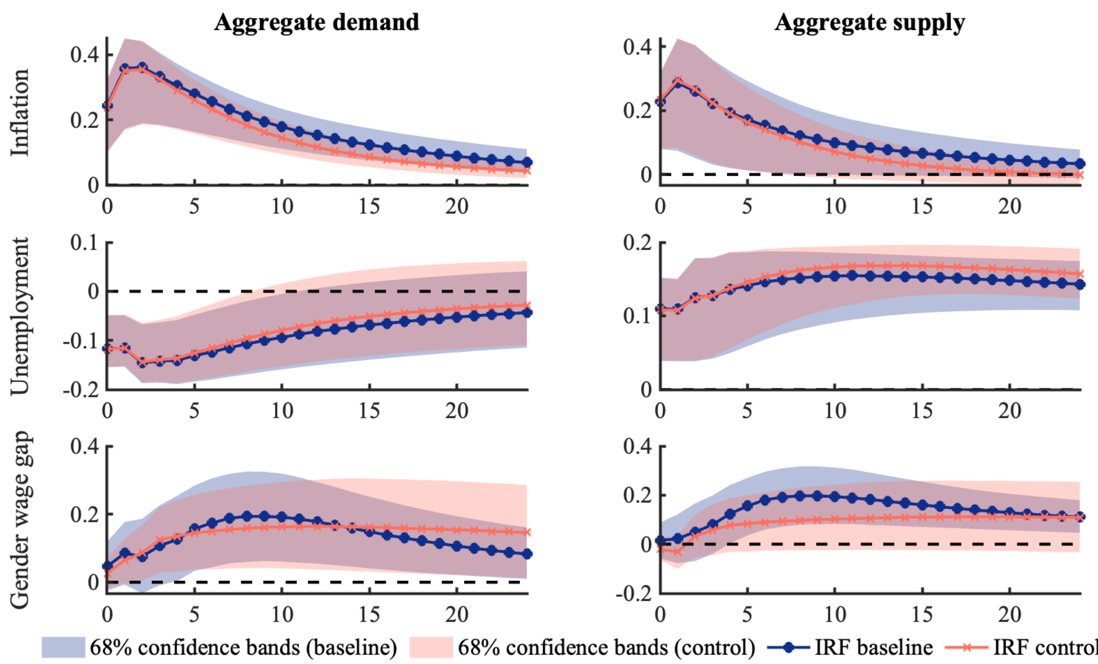


Figure A.20: Impulse Responses in the Structural VAR

Notes: Adjusted GWGs of employees below 30 years 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 dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

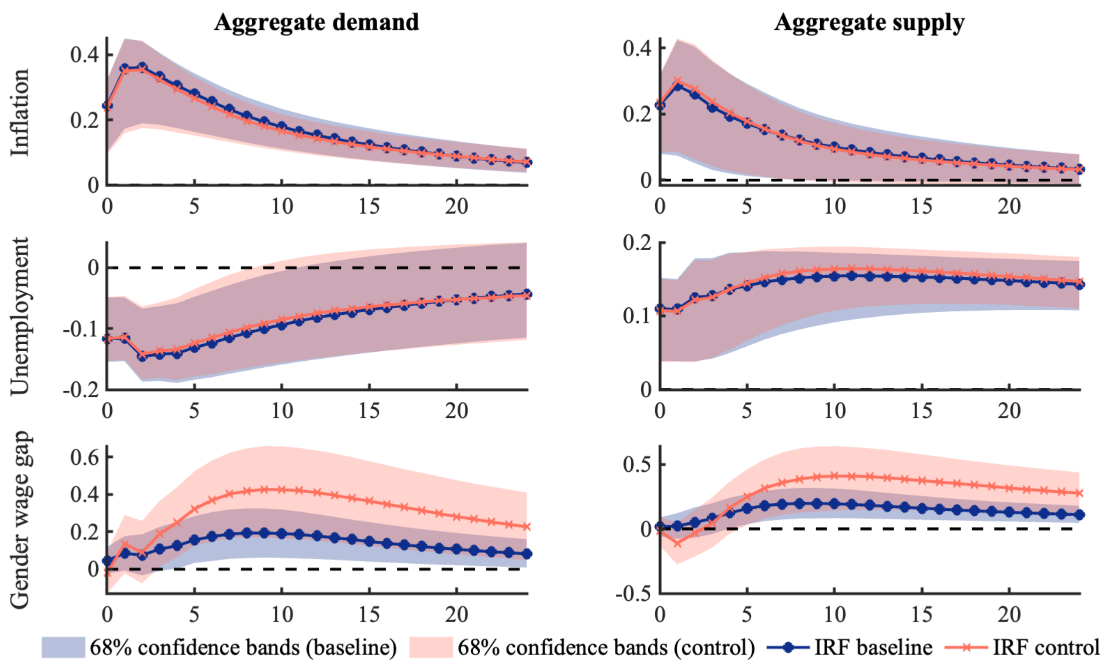


Figure A.21: Impulse Responses in the Structural VAR

Notes: Adjusted GWGs of employees above 30 years 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 dotted 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.

Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

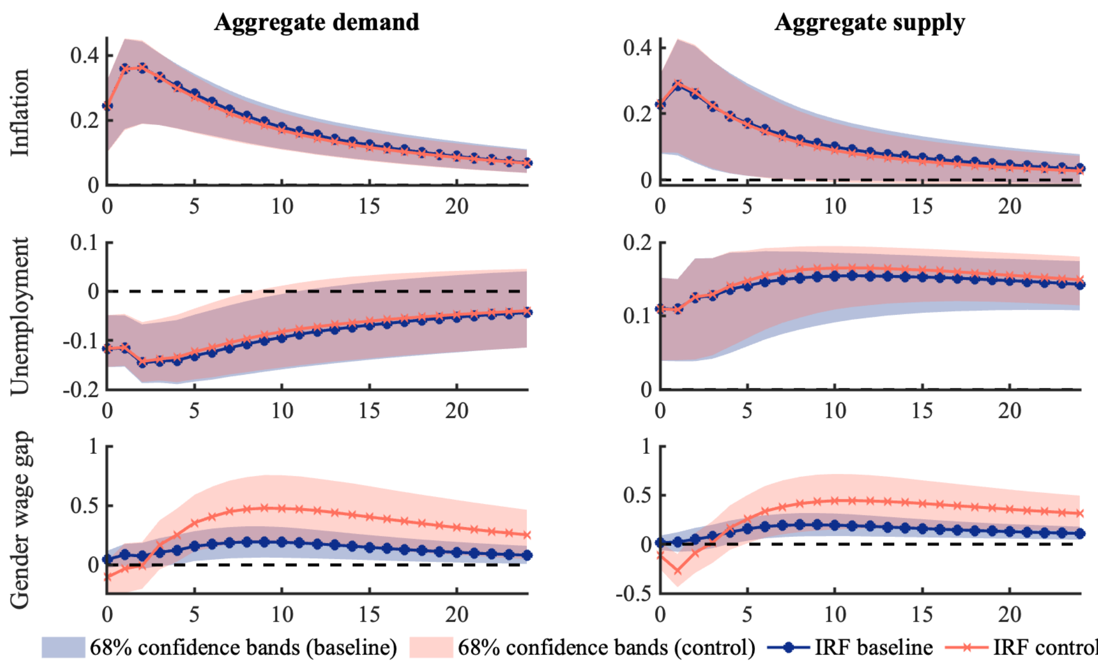


Figure A.22: Impulse Responses in the Structural VAR

Notes: Adjusted GWGs of employees above 40 years 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 dotted 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.

Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

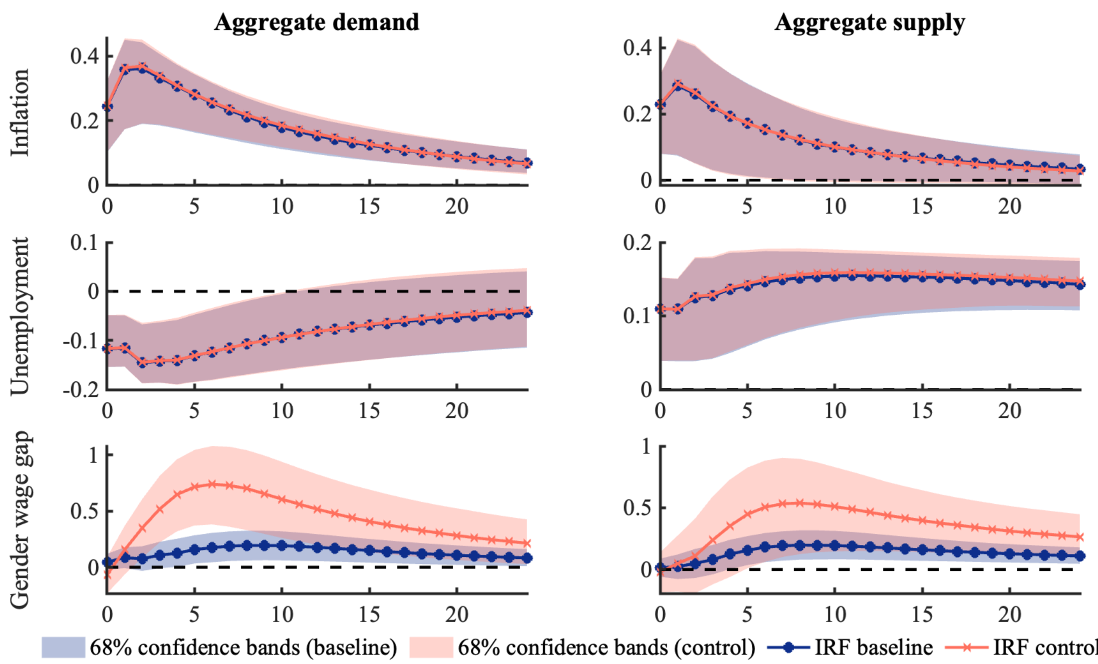


Figure A.23: Impulse Responses in the Structural VAR

Notes: Adjusted GWGs of employees above 50 years 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 dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

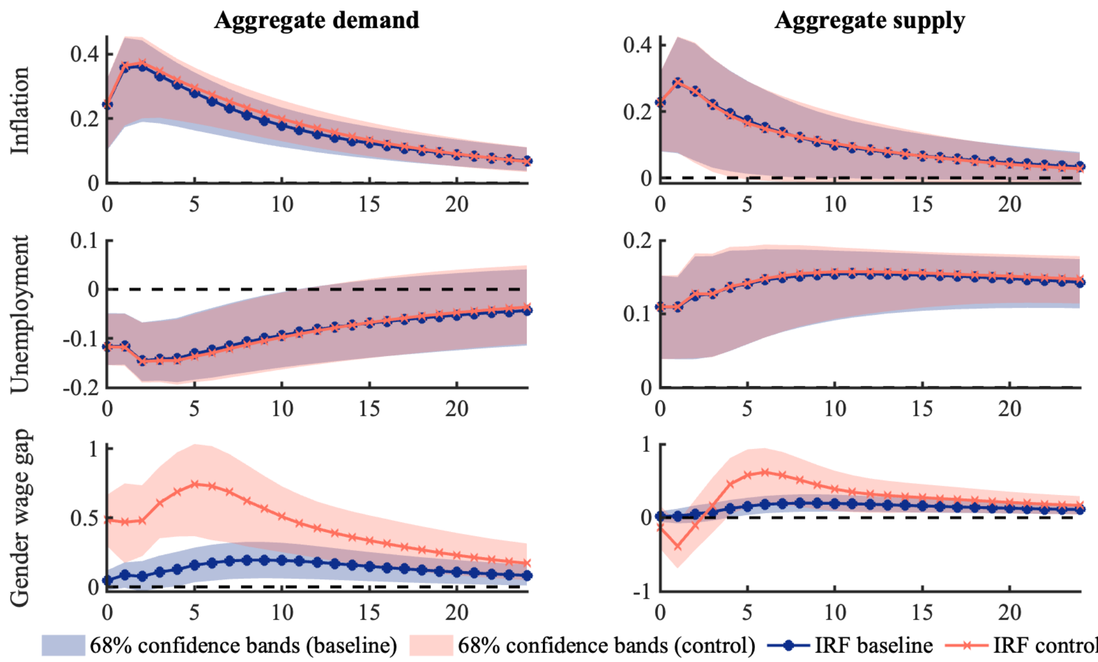
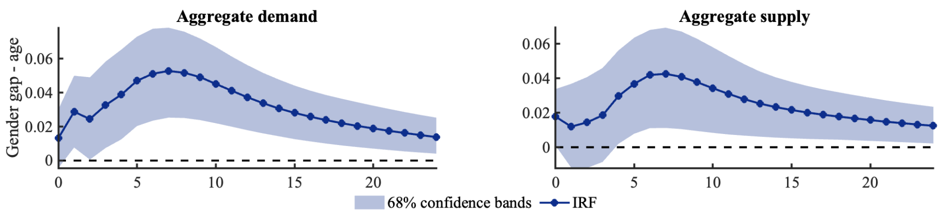


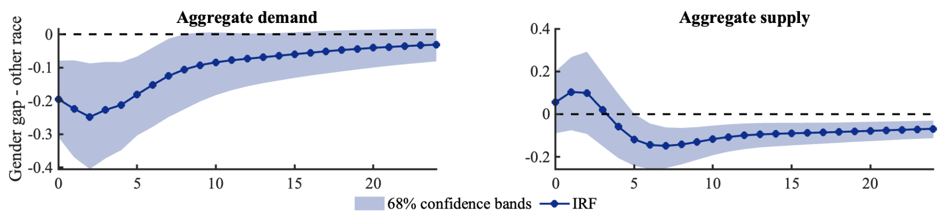
Figure A.24: Impulse Responses in the Structural VAR

Notes: Adjusted GWGs of employees with children below 5 years 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 dotted 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.

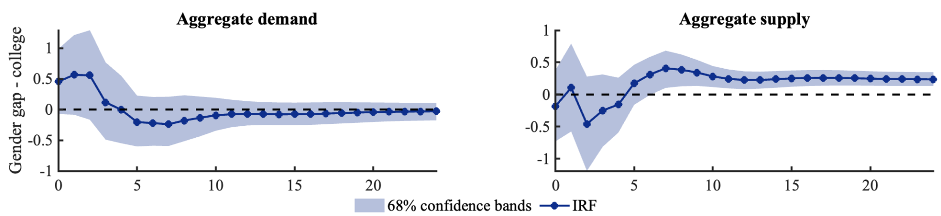
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.



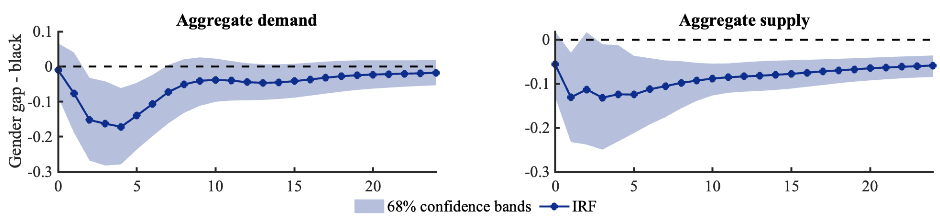
(a) Age



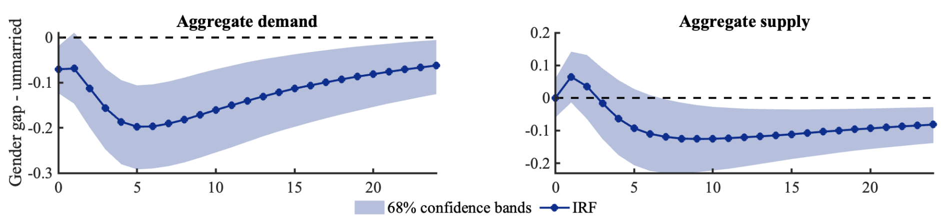
(b) School



(c) College



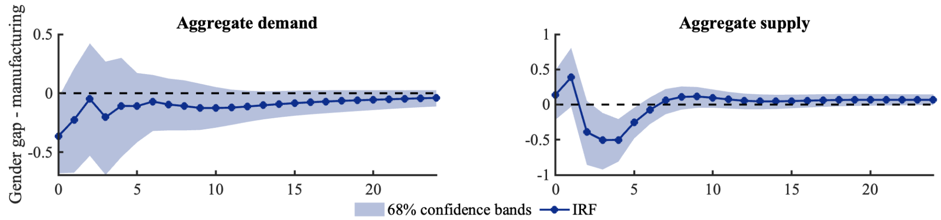
(d) Black



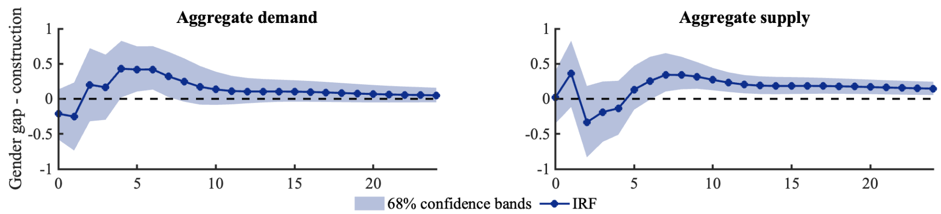
(e) Unmarried

Figure A.25: Impulse Responses of the coefficients of the KOB decomposition to Supply and Demand Shocks

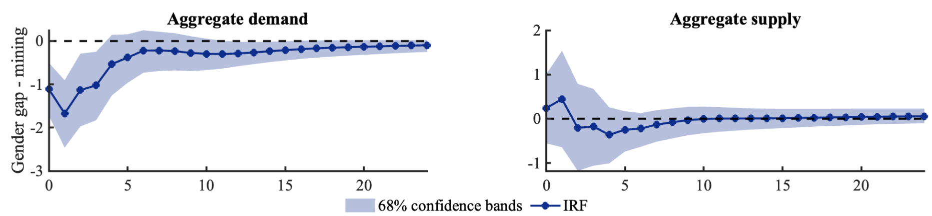
Notes: Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid dotted and crossed lines) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and the percentiles are defined at each point in time.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.



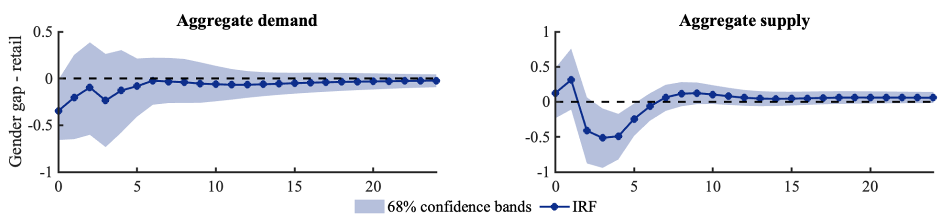
(a) Manufacturing



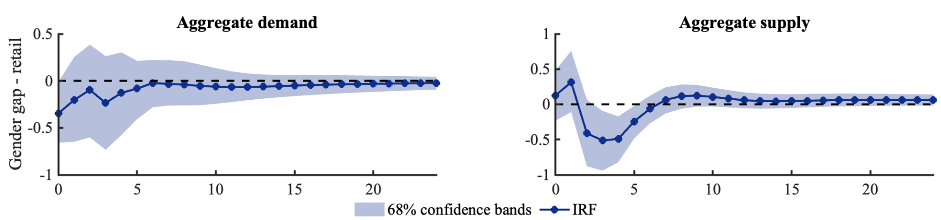
(b) Construction



(c) Mining



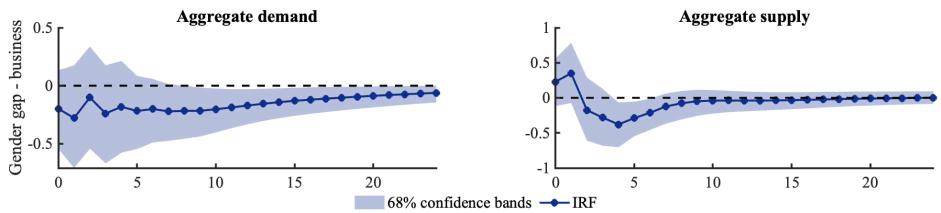
(d) Transport



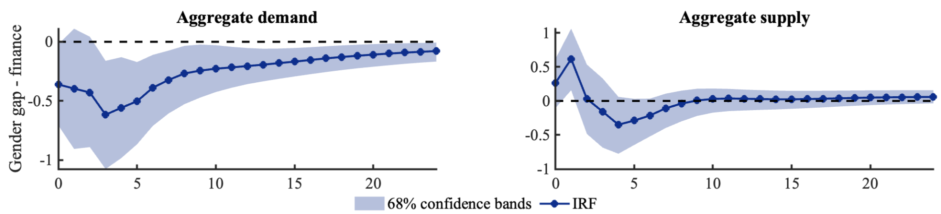
(e) Retail

Figure A.27: Impulse Responses of the coefficients of the KOB decomposition to Supply and Demand Shocks

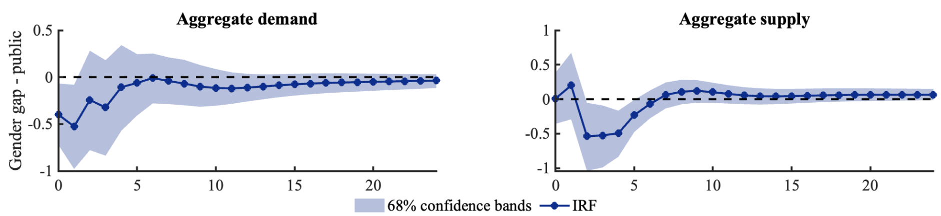
Notes: Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid dotted and crossed lines) and 68% probability density intervals (shaded areas) based on 10,000 draws. The median and the percentiles are defined at each point in time.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.



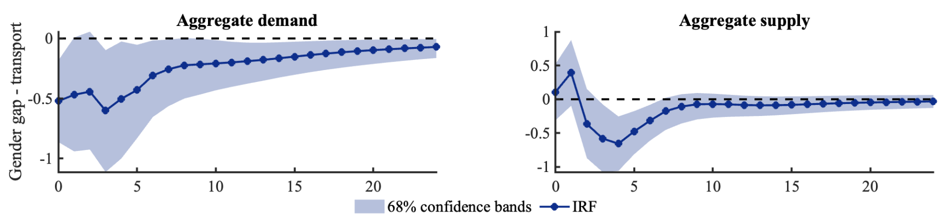
(a) Business



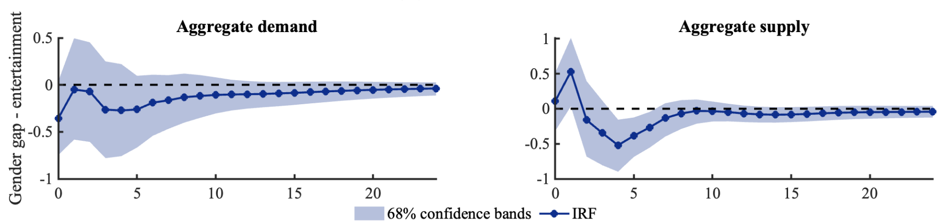
(b) Finance



(c) Public



(d) Wholesale



(e) Entertainment

Figure A.29: 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 dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Adjusted GWG: CPS IPUMS, own calculations.

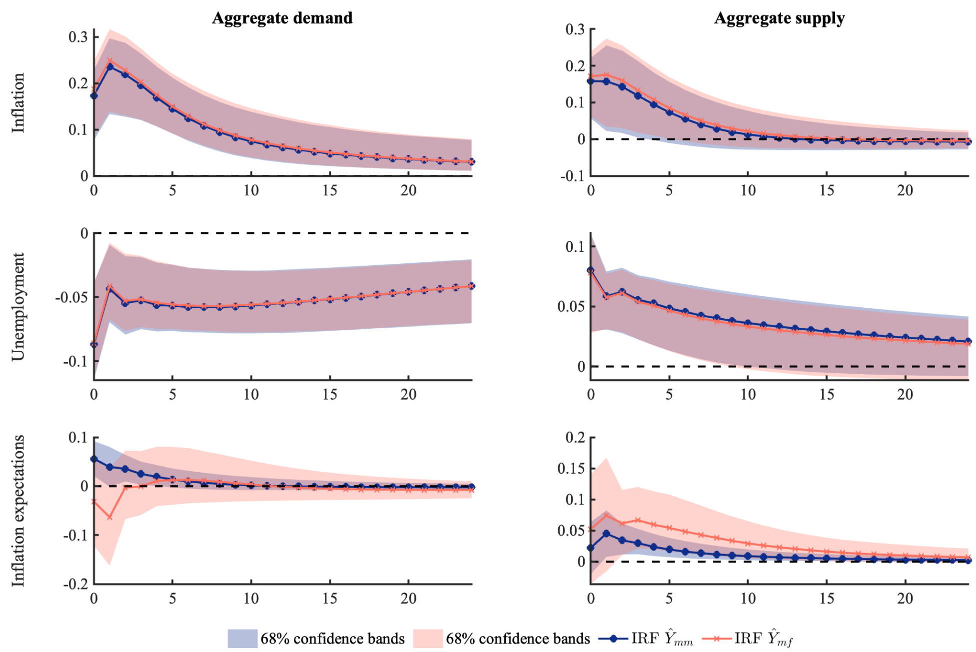


Figure A.31: Impulse Responses of Inflation Expectations in the SCE to Supply and Demand Shocks

Notes: Women's (orange crossed line) and men's (blue dotted line) expectations computed using monthly data from August 2013-February 2020, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Expectations: NYFED SCE, own calculations.

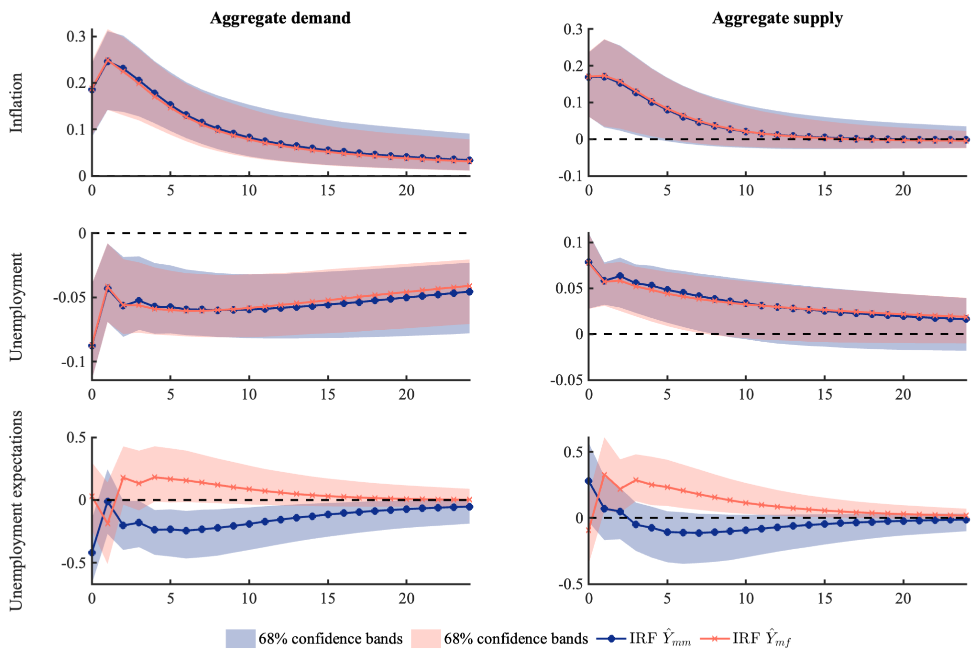


Figure A.32: Impulse Responses of Unemployment Expectations in the SCE to Supply and Demand Shocks

Notes: Women's (orange crossed line) and men's (blue dotted line) expectations computed using monthly data from August 2013-February 2020, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Expectations: NYFED SCE, own calculations.

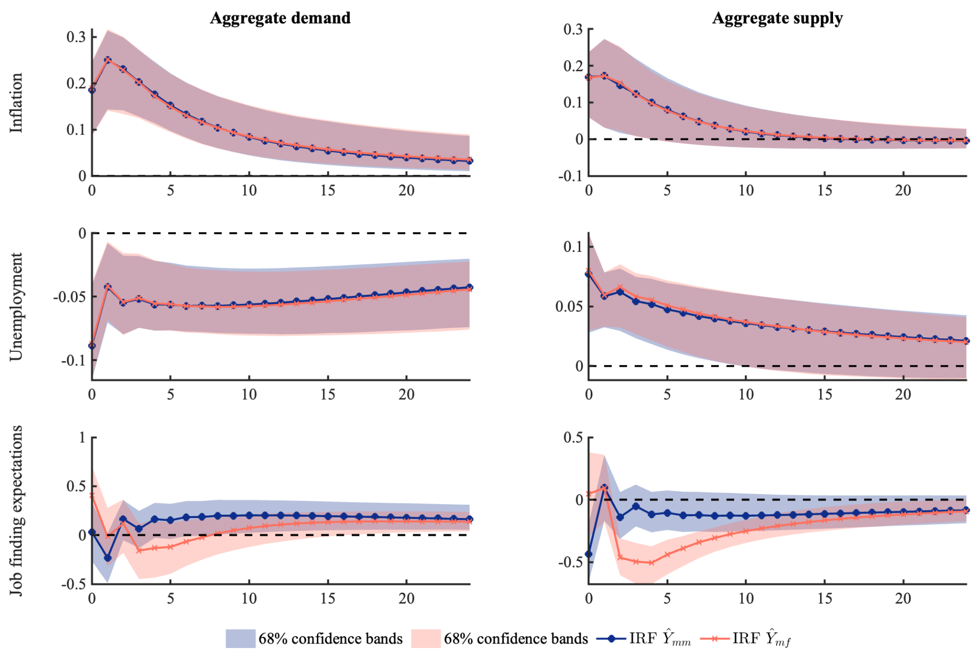


Figure A.33: Impulse Responses of Job-finding Expectations in the SCE to Supply and Demand Shocks

Notes: Women's (orange crossed line) and men's (blue dotted line) expectations computed using monthly data from August 2013-February 2020, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Expectations: NYFED SCE, own calculations.

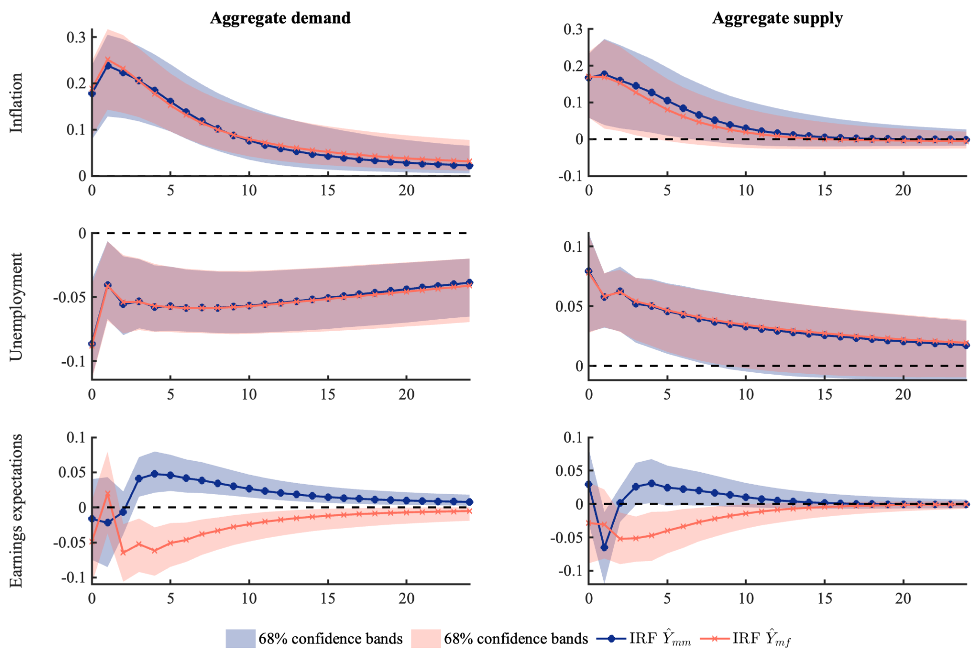


Figure A.34: Impulse Responses of Earnings Expectations in the SCE to Supply and Demand Shocks

Notes: Women's (orange crossed line) and men's (blue dotted line) expectations computed using monthly data from August 2013-February 2020, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Expectations: NYFED SCE, own calculations.

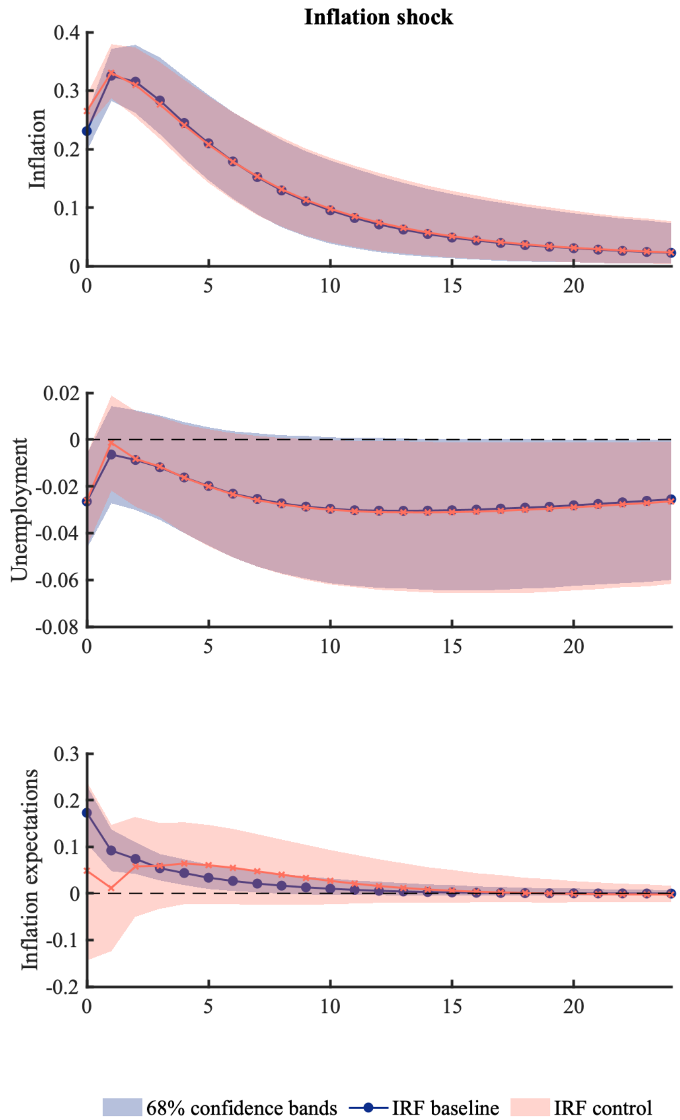


Figure A.35: Impulse Responses of Inflation Expectations in the SCE to Inflation Shocks

Notes: Women's (orange crossed line) and men's (blue dotted line) expectations computed using monthly data from August 2013-February 2020, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Expectations: NYFED SCE, own calculations.

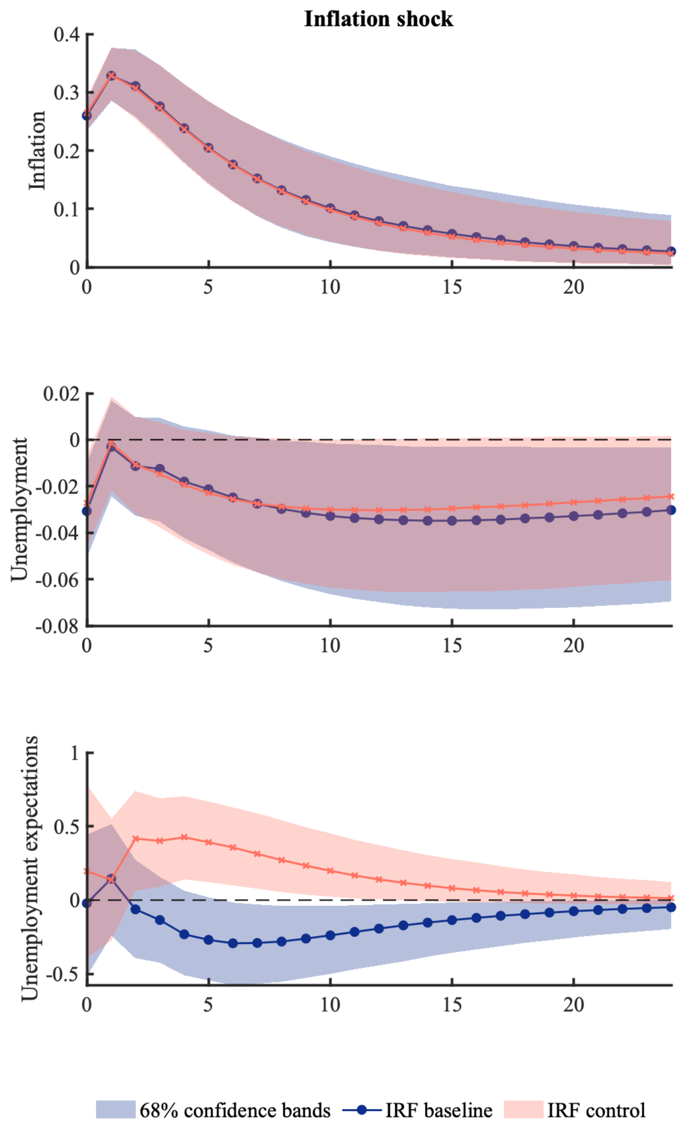


Figure A.36: Impulse Responses of Unemployment Expectations in the SCE to Inflation Shocks

Notes: Women's (orange crossed line) and men's (blue dotted line) expectations computed using monthly data from August 2013-February 2020, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Expectations: NYFED SCE, own calculations.

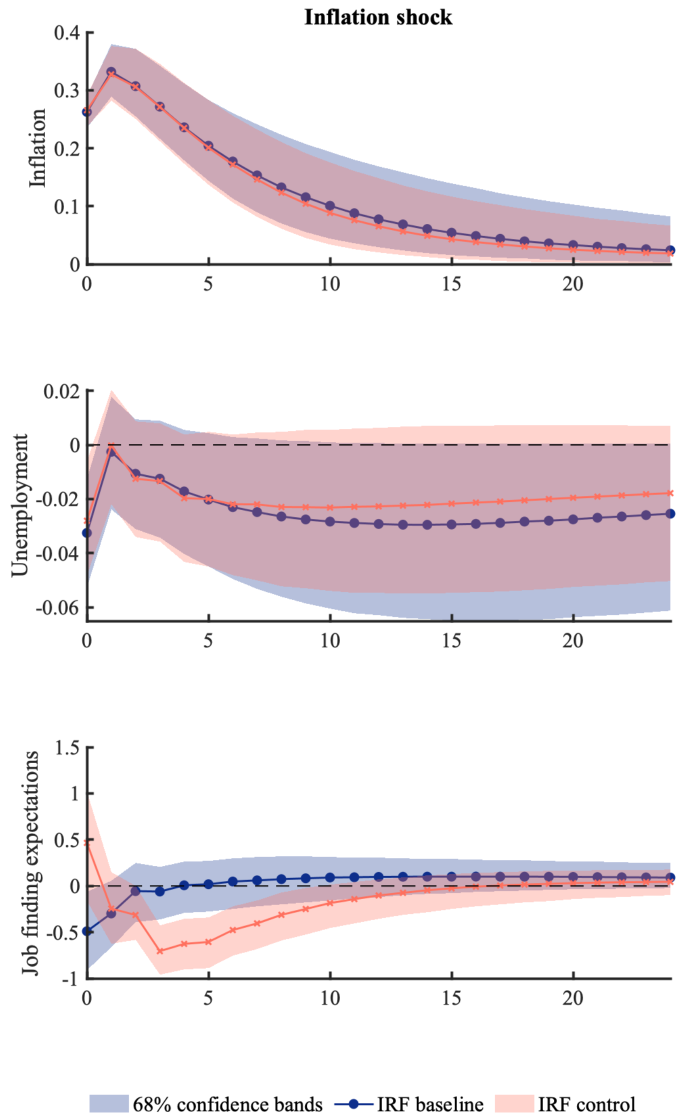


Figure A.37: Impulse Responses of Job-finding Expectations in the SCE to Inflation Shocks

Notes: Women's (orange crossed line) and men's (blue dotted line) expectations computed using monthly data from August 2013-February 2020, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid dotted 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.
Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Expectations: NYFED SCE, own calculations.

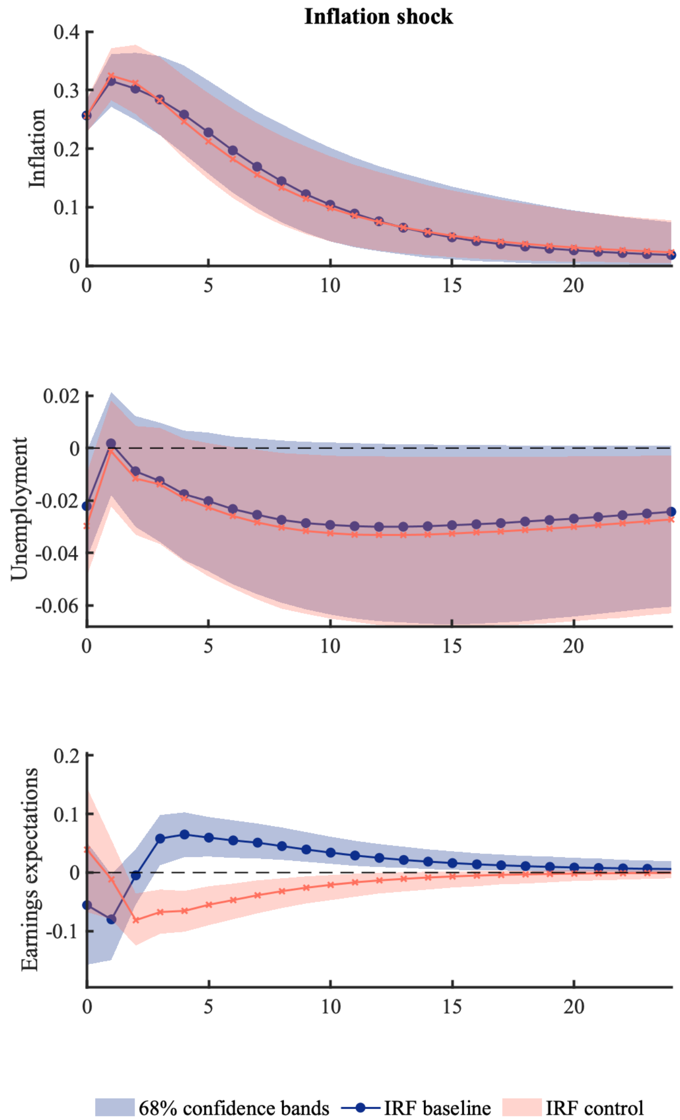


Figure A.38: Impulse Responses of Earnings Expectations in the SCE to Inflation Shocks

Notes: Women's (orange crossed line) and men's (blue dotted line) expectations computed using monthly data from August 2013-February 2020, 3-month trailing moving average. Posterior distributions of impulse responses to estimated demand and supply shocks of one standard deviation. Median (solid dotted 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.

Sources: Inflation: BLS CPI-U, 12-Month Percent Change; Unemployment: FRED UNRATE, Percent, Seasonally Adjusted; Expectations: NYFED SCE, own calculations.

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 Revisions in the Micro-Data

Using pooled OLS, we regress revisions in expectations on unemployment, job finding and earnings growth of individual i at time t on a dummy for identifying as female in the survey, revisions in inflation expectations at time t ($\Delta \mathbf{E}_t \pi_{t+12}$), the interaction term $\Delta \mathbf{E}_t \pi_{t+12} \times$ female controlling for date and industry fixed effects. We also control for age, income, education, numeracy and the respondents region. We cannot use fixed effect regression as we are interested in the time-invariant variable *female*. We use differencing to clean the data of other underlying behavioral factors that may cause correlation (i.e. gender differences in pessimism or uncertainty and rounding), our findings are thus more robust (Duca-Radu et al. 2020). Table 2 shows that men who revise their inflation expectations upwards from the previous survey wave on average increase their earnings expectations while women who revise inflation expectations upwards, do not. However, in the panel, other expectations do not respond to inflation expectations and there are no significant differences between men and women.

Table 2: Labor Market Beliefs and Inflation Expectations in the SCE

	$\Delta \mathbf{E}_t$ Wage$_{t+12}$	$\Delta \mathbf{E}_t$ Job Finding$_{t+3}$	$\Delta \mathbf{E}_t$ P(U↑)$_{t+12}$
	(1)	(2)	(3)
$\Delta \mathbf{E}_t \pi_{t+12}$	0.039**	-0.081	0.096*
	(0.017)	(0.061)	(0.057)
$\Delta \mathbf{E}_t \pi_{t+12} \times$ female	-0.049**	0.081	0.100
	(0.021)	(0.078)	(0.073)
female	-0.101	-0.558^*	-0.299
	(0.091)	(0.334)	(0.313)
Observations	19,385	19,385	19,375
R^2	0.003	0.002	0.008
Controls	Yes	Yes	Yes

Note: *p<0.1; **p<0.05; ***p<0.01

Controls include industry, age, education, income, numeracy, and time fixed effects.

C Model Supplementary Material

C.1 Full Linearized Model

C.1.1 Calibration

Table 3: Parameter Values

Parameter	Value	Description
α	0.333	exponent of labor in the production function
ζ	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

Table 3 – Continued

Parameter	Value	Description
d_f	0.100	discrimination against women
$\bar{\pi}^p$	0.000	steady state price inflation
$\bar{\pi}^w$	0.000	steady state wage inflation
$\bar{U}_m$	0.060	steady state unemployment men
$\bar{U}_f$	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.1.2 Full model

Shock processes

$$\log(Z_t) = \rho_z \log(Z_{t-1}) + \varepsilon_{zt} \tag{22}$$

$$\log(u_t) = \rho_u \log(u_{t-1}) + \varepsilon_{at} \tag{23}$$

Union receives signal

$$s_t = \varepsilon_{ut} + \varepsilon_{zt} \tag{24}$$

Union applies ambiguity loving/averse weights

$$\tilde{\mathbb{E}}_{m,t}\varepsilon^z{}_t = s_t w^z_m \tag{25}$$

$$\tilde{\mathbb{E}}_{f,t}\varepsilon^z{}_t = s_t w^z_f \tag{26}$$

$$\tilde{\mathbb{E}}_{m,t}\varepsilon_{u_t} = s_t w_m^u \tag{27}$$

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

Union forms beliefs about state variables

$$\log\left(\tilde{\mathbb{E}}_{m,t}Z_t\right) = \tilde{\mathbb{E}}_{m,t}{\varepsilon^z}_t + \rho_z\ \log\left(Z_{t-1}\right) \tag{29}$$

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

$$\log\left(\tilde{\mathbb{E}}_{m,t}u_t\right) = \tilde{\mathbb{E}}_{m,t}\varepsilon_{u_t} + \rho_u\ \log\left(u_{t-1}\right) \tag{31}$$

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

Euler equation

$$1 = \beta\,\frac{\frac{Z_{t+1}}{Z_t}\ \left(C_t - h\,C_{t-1}\right)}{C_{t+1} - C_t\,h}\ \left(1 + r_t\right) \tag{33}$$

Fisherian equation

$$1 + r_t = \frac{1 + i_t}{1 + {\pi^p}_{t+1}} \tag{34}$$

Price dispersion

$$ {v^p}_t = \left(\left(1-\theta^p\right)\ \left(1 + \tilde{\mathbb{E}}_{m,t}{\pi^{p,*}}_t\right)^{\frac{(-\epsilon)}{1-\alpha}}\ \left(1+{\pi^p}_t\right)^{\frac{\epsilon}{1-\alpha}} + \theta^p\ \left(1+{\pi^p}_t\right)^{\frac{\epsilon}{1-\alpha}}\ {v^p}_{t-1}^{\frac{1}{1-\alpha}}\right)^{1-\alpha} \tag{35}$$

Aggregate inflation

$$\left(1+{\pi^p}_t\right)^{1-\epsilon} = \theta^p + \left(1-\theta^p\right)\ \left(1+{\pi^{p,*}}_t\right)^{1-\epsilon} \tag{36}$$

Reset price inflation

$$\left(1+{\pi^{p,*}}_t\right)^{1+\frac{\epsilon\,\alpha}{1-\alpha}} = u_t\,\frac{\epsilon}{\epsilon-1}\,\frac{x1_t}{x2_t}\ \left(1+{\pi^p}_t\right)^{1+\frac{\epsilon\,\alpha}{1-\alpha}} \tag{37}$$

$$x1_t = \frac{Z_t\, mc_t\, Y_t}{C_t - h\, C_{t-1}} + \beta\, \theta^p\, \left(1 + {\pi^p}_{t+1}\right)^{\epsilon + \frac{\epsilon\, \alpha}{1-\alpha}}\, x1_{t+1} \tag{38}$$

$$x2_t = \frac{Z_t\, Y_t}{C_t - h\, C_{t-1}} + \beta\, \theta^p\, \left(1 + {\pi^p}_{t+1}\right)^{\epsilon - 1}\, x2_{t+1} \tag{39}$$

Goods market clearing

$$Y_t = C_t + G_{m\,t}\, H_{m\,t} + G_{f\,t}\, H_{f\,t} \tag{40}$$

Labor index

$$N_t = \left(\zeta\, {N_{f\,t}}^{\frac{\sigma-1}{\sigma}} + (1 - \zeta)\, {N_{m\,t}}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{41}$$

Aggregate production

$$Y_t = \frac{A_t\, N_t^{1-\alpha}}{{v^p}_t} \tag{42}$$

Aggregate hiring and employment

$$N_{m\,t} = H_{m\,t} + (1 - \delta_m)\, N_{m\,t-1} \tag{43}$$

$$N_{f\,t} = H_{f\,t} + \left(1 - \delta_f\right)\, N_{f\,t-1} \tag{44}$$

Hiring costs

$$G_{m\,t} = \Gamma_m\, x_{m\,t}^{\gamma} \tag{45}$$

$$G_{f\,t} = \Gamma_f\, x_{f\,t}^{\gamma} \tag{46}$$

Job finding rate

$$x_{m\,t} = \frac{H_{m\,t}}{U^0_{m\,t}} \tag{47}$$

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

Effective market effort

$$L_{m\,t} = N_{m\,t} + \psi_m \, U_{m\,t} \tag{49}$$

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

Unemployment

$$U_{m\,t} = U^0_{m\,t} \; (1 - x_{m\,t}) \tag{51}$$

$$U_{f\,t} = U^0_{f\,t} \; \left(1 - x_{f\,t}\right) \tag{52}$$

Marginal revenue product

$$MRPN_{m\,t} = (1-\alpha) \; (1-\zeta) \; A_t \, mc_t \, {N_{m\,t}}^{\frac{(-1)}{\sigma}} \; N_t^{\frac{1}{\sigma-1}-\alpha} \tag{53}$$

$$MRPN_{f\,t} = N_t^{\frac{1}{\sigma-1}-\alpha} \; (1-\alpha) \; \zeta \, A_t \, mc_t \, {N_{f\,t}}^{\frac{(-1)}{\sigma}} \; \left(1 - d_f\right) \tag{54}$$

Optimal hiring condition

$$MRPN_{m\,t} = \omega_{m\,t} + B_{m\,t} \tag{55}$$

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

$$B_{m\,t} = G_{m\,t} - \frac{\frac{Z_{t+1}}{Z_t} \; (C_t - h\,C_{t-1})}{C_{t+1} - C_t\,h} \beta \; (1-\delta_m) \; G_{m\,t+1} \tag{57}$$

$$B_{f\,t} = G_{f\,t} - \frac{\frac{Z_{t+1}}{Z_t} \; (C_t - h\,C_{t-1})}{C_{t+1} - C_t\,h} \beta \; \left(1-\delta_f\right) \; G_{f\,t+1} \tag{58}$$

Optimal participation condition

$$\frac{(C_t - h\,C_{t-1}) \; \psi_m \, \chi_m \, {L_{m\,t}}^{\varphi_m}}{Z_t} = \frac{x_{m\,t}}{1 - x_{m\,t}} \left(G_{m\,t} \, \frac{1-\xi_m}{\xi_m} - \pi^w_{m\,t} \, \frac{\theta^w_m}{1-\theta^w_m} \, \omega_{m\,t-1} \, Q_{m\,t} \right) \tag{59}$$

$$\frac{(C_t - h\,C_{t-1})\ \psi_m\,\chi_f\,{L_f}_t^{\varphi_f}}{Z_t} = \frac{{x_f}_t}{1 - {x_f}_t}\ \left({G_f}_t\,\frac{1 - \xi_f}{\xi_f} - {\pi^w_f}_t\,\frac{\theta^w_f}{1 - \theta^w_f}\,{\omega_f}_{t-1}\,{Q_f}_t\right) \tag{60}$$

$$Q_{m\,t} = 1 + \frac{\frac{\frac{Z_{t+1}}{Z_t}\,(C_t - h\,C_{t-1})}{C_{t+1} - C_t\,h}\,\beta\ (1 - \delta_m)\ \theta^w_m}{1 + {\pi^p}_t}\,\tilde{\mathbb{E}}_{m,t}Q_{m\,t+1} \tag{61}$$

$$Q_{f\,t} = 1 + \frac{\frac{\frac{Z_{t+1}}{Z_t}\,(C_t - h\,C_{t-1})}{C_{t+1} - C_t\,h}\,\beta\ \left(1 - \delta_f\right)\ \theta^w_f}{1 + {\pi^p}_t}\,\tilde{\mathbb{E}}_{f,t}Q_{f\,t+1} \tag{62}$$

Evolution of real wage

$$\omega_{m\,t} = \frac{\omega_{m\,t-1}\ \left(1 + \pi^w_{m\,t}\right)}{1 + {\pi^p}_t} \tag{63}$$

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

Target (flex) wage

$$\omega^{tar}_{m\ \ t} = \frac{(C_t - h\,C_{t-1})\ {L_m}_t^{\varphi_m}\,\chi_m\,\xi_m}{Z_t} + MRPN_{m\,t}\ (1 - \xi_m) \tag{65}$$

$$\omega^{tar}_{f\ \ t} = \frac{(C_t - h\,C_{t-1})\ {L_f}_t^{\varphi_f}\,\chi_f\,\xi_f}{Z_t} + MRPN_{f\,t}\ \left(1 - \xi_f\right) \tag{66}$$

Reset wage

$$\omega^*_{m\,t} = \frac{h1_{m\,t}}{h2_{m\,t}} \tag{67}$$

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

$$h1_{m\,t} = \frac{Z_t\, \omega^{tar}_{m\ t}}{C_t - h\, C_{t-1}} + (1 - \delta_m)\ \theta^w_m\, \beta\ \left\{\xi_m \left(1 + \tilde{\mathbb{E}}_{m,t} {\pi^p}_{t+1}\right)\ \tilde{\mathbb{E}}_{m,t} h1_{m\,t+1} + (1 - \xi_m)\,(1 + {\pi^p}_{t+1})\ h1_{m\,t+1}\right\} \tag{69}$$

$$h2_{m\,t} = \frac{Z_t}{C_t - h\, C_{t-1}} + (1 - \delta_m)\ \theta^w_m\, \beta\ \left\{\xi_m \left(1 + \tilde{\mathbb{E}}_{m,t} {\pi^p}_{t+1}\right)\ \tilde{\mathbb{E}}_{m,t} h2_{m\,t+1} + (1 - \xi_m)\,(1 + {\pi^p}_{t+1})\ h2_{m\,t+1}\right\} \tag{70}$$

$$h1_{f\,t} = \frac{Z_t\, \omega^{tar}_{f\ t}}{C_t - h\, C_{t-1}} + \left(1 - \delta_f\right)\ \theta^w_f\, \beta\ \left\{\xi_f \left(1 + \tilde{\mathbb{E}}_{f,t} {\pi^p}_{t+1}\right)\ \tilde{\mathbb{E}}_{f,t} h1_{f\,t+1} + (1 - \xi_f)\,(1 + {\pi^p}_{t+1})\ h1_{f\,t+1}\right\} \tag{71}$$

$$h2_{f\,t} = \frac{Z_t}{C_t - h\, C_{t-1}} + \left(1 - \delta_f\right)\ \theta^w_f\, \beta\ \left\{\xi_f \left(1 + \tilde{\mathbb{E}}_{f,t} {\pi^p}_{t+1}\right)\ \tilde{\mathbb{E}}_{f,t} h2_{f\,t+1} + (1 - \xi_f)\,(1 + {\pi^p}_{t+1})\ h2_{f\,t+1}\right\} \tag{72}$$

Real wage inflation

$$\omega_{m\,t} = \theta^w_m\, \frac{\omega_{m\,t-1}}{1 + {\pi^p}_t} + \left(1 - \theta^w_m\right)\ \omega^*_{m\,t} \tag{73}$$

$$\omega_{f\,t} = \theta^w_f\, \frac{\omega_{f\,t-1}}{1 + {\pi^p}_t} + \left(1 - \theta^w_f\right)\ \omega^*_{f\,t} \tag{74}$$

Interest rate rule

$$\frac{1 + i_t}{1 + \bar{i}} = \nu_t\ \left(\frac{1 + i_{t-1}}{1 + \bar{i}}\right)^{\rho_i} \left(\left(\frac{1 + {\pi^p}_t}{1 + \bar{\pi}^p}\right)^{\phi_\pi}\ \left(\frac{1 + \pi^w_{m\,t}}{1 + \bar{\pi}^w}\right)^{\phi_{w,m}}\ \left(\frac{1 + \pi^w_{f\,t}}{1 + \bar{\pi}^w}\right)^{\phi_{w,f}}\ \left(\frac{U_{m\,t}}{\bar{U}_m}\right)^{\phi_{u,m}}\ \left(\frac{U_{f\,t}}{\bar{U}_f}\right)^{\phi_{u,f}}\ \left(\frac{Y_t}{\bar{Y}}\right)^{phi_y}\right)^{1-\rho_i} \tag{75}$$

Definition of GWG

$$GWG_t = \frac{\omega_{m\,t}}{\omega_{f\,t}} \tag{76}$$

C.2 Impulse Responses

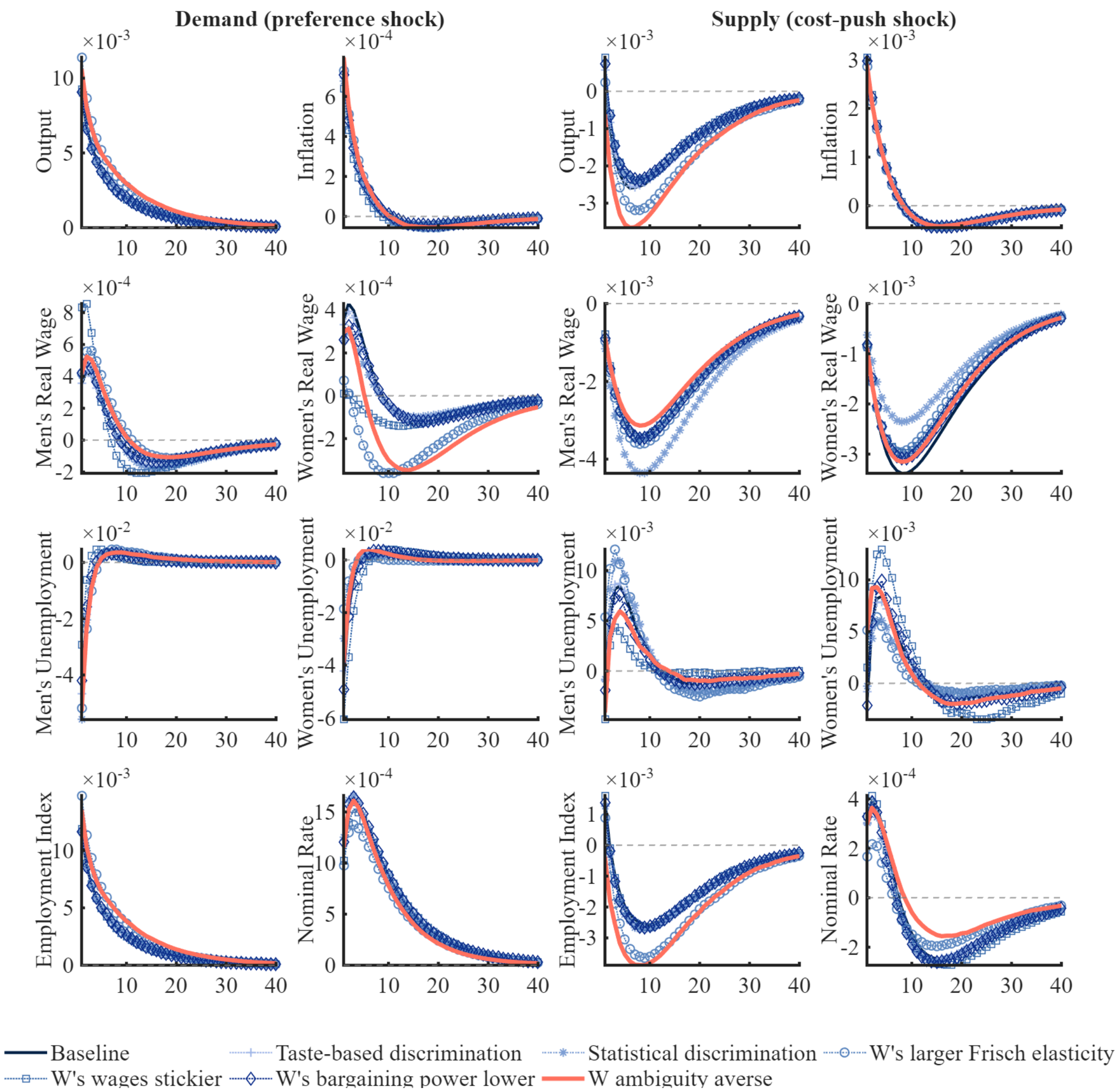


Figure C.1: Further impulse responses of the model