Cyclical dynamics and the gender pay gap: A structural VAR approach

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Abstract

Gender pay gaps persist worldwide despite political emphasis to close them. The literature found various drivers of the gaps but remained vastly silent about the role of cyclical dynamics. Using quarterly US data over the period 1979-2019, we study the effects of cyclical dynamics on the gender pay gap based on a structural vector auto-regression model with zero and sign restrictions. The results suggest that technology shocks lead to lower levels of the gender pay gap in the medium run, while higher wage bargaining power reduces the gap in the short run. However, these reductions of the gap come at the cost of increased unemployment. As a policy implication, these results imply a trade-off between lower gender pay gaps and higher unemployment.

Zusammenfassung

Trotz politischer Bestrebungen die Geschlechterlohnlücke zu beseitigen besteht sie weltweit fort. In der Literatur wurden verschiedene Treiber der Lohnlücke gefunden - die Rolle zyklischer Fluktuationen bleibt jedoch weitgehend unerwähnt. Unter Verwendung von vierteljährlichen US-Daten über den Zeitraum 1979-2019 untersuchen wir die Auswirkungen der zyklischen Fluktuationen auf die Geschlechterlohnlücke mithilfe eines strukturellen Vektor-Autoregressivem Modells mit Ausschluss- und Vorzeichenrestriktionen. Die Ergebnisse deuten darauf hin, dass Technologieschocks mittelfristig zu einem niedrigeren Niveau der Geschlechterlohnlücke führen, während eine höhere Lohnverhandlungsmacht die Lücke kurzfristig reduziert. Diese Verringerungen der Lücke gehen jedoch auf Kosten erhöhter Arbeitslosigkeit. Daher zeigen unsere Ergebnisse einen Trade-off zwischen geringeren Geschlechterlohnlücken und höherer Arbeitslosigkeit auf.

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1 Introduction

There is a huge literature on the Gender Pay Gap (GPG) finding various determinants of it (see Blau and Kahn, 2017, for an overview). However, so far the GPG has been considered mainly from a micro perspective. Traditional factors driving the wage gap are gender differences in labor market presence, human capital and occupational or industrial sorting (e.g. Fortin, 2005; Becker et al., 2010; Goldin, 2014; Blau and Kahn, 2017; Castagnetti and Giorgetti, 2019). Further, the GPG literature has started to examine the effects of societal norms, non-cognitive skills or psychological attributes on the pay gap (Mueller and Plug, 2006; Nyhus and Pons, 2012; Risse et al., 2018). Yet, little is known about how cyclical dynamics affect the GPG. Studies analyzing gender-specific effects of business cycle dynamics from a macro perspective suggest that men are hit harder during recessions ('men-cessions', e.g. Bredemeier et al., 2017; Albanesi and Şahin, 2018) but also pick up more quickly during recoveries ('he-coveries', Hoynes et al., 2012). Consequently, the question arises, which role cyclical fluctuations play for short, medium or long run variations of the GPG. From a policy perspective, it is important to learn more about effects of macroeconomic shocks on specific subgroups of the population (such as men and women) and, thus, to create effective and fair economic policies.

In this paper, we look at the GPG from a macro perspective using a Structural Vector Auto-Regression (SVAR) model with zero and sign restrictions. Our main interest lies in analyzing the response of the GPG to shocks associated with cyclical dynamics. We use quarterly data from the US Bureau of Labor Statistics and the Federal Reserve Bank of St. Louis between 1979-2019. As Blau and Kahn (2017) state, the case of the USA may be applicable to other industrial nations. Hence, potential policy insights drawn in this paper may be valid for other economically advanced countries as well.

In order to learn more about cyclical dynamics and the GPG, we estimate a SVAR with zero and sign restrictions to identify macroeconomic shocks and to analyze business cycle or short-term consequences of these shocks. We identify typical macroeconomic shocks affecting the labor market as well as two gender-specific shocks. These shocks are aggregate demand shocks, technology shocks, wage bargaining shocks, labor supply shocks and gender-specific labor supply shocks. Next, we investigate whether these shocks affect men and women differently in terms of their unemployment, their labor force participation and their wages. The responses of the identified shocks to the gender-specific unemployment rates, participation rates, wages and the GPG are shown via Impulse Response Functions (IRFs). The IRF is the reaction of any dynamic system in response to some external change. In our case, the external changes are macroeconomic shocks. We also look at reactions of GDP and prices.[1] Apart from looking at

[1] We present the IRFs of these remaining macroeconomic indicators (GDP and prices) in Appendix A.

short-run effects, the SVAR also allows us to consider medium- and long-run consequences.

In the macroeconomic literature, it is well known that unemployment, labor force participation and wages are affected by aggregate shocks (see e.g. Bredemeier et al., 2017; Foroni et al., 2018). The literature on the GPG and business cycle variations has found that the gap contracts during recessions and expands during expansions (Kandil and Woods, 2002; Finio, 2010). For example, if women choose industries that are less exposed to business cycles such as services or public administration, a portion of the GPG may be attributable to this behavior (Kandil and Woods, 2002; Hoynes et al., 2012). Moreover, also the effect of macroeconomic shocks to unemployment differs for men and women (Razzu and Singleton, 2016; Albanesi and Şahin, 2018). Potential explanations of this phenomenon are differences in labor supply elasticities (Hirsch et al., 2010), differences in demand for intellectual skills and physical strength (Blau and Kahn, 2006), occupational sorting (Solberg and Laughlin, 1995) and added or discouraged worker effects (Hoynes et al., 2012; Starr, 2014).

This paper contributes to the existing literature on gender-specific unemployment and labor force participation rates as well as the GPG by using a macroeconomic approach to explain short-term variations of the GPG in response to one-time macroeconomic shocks. As stated above, the SVAR allows us to consider also medium- and long-run effects of these shocks. To the best of our knowledge, this is the first paper that focuses on macroeconomic shocks and their effects on the overall GPG.[2] Short-term variations are generally neglected in the traditional microeconometric analysis of the GPG relying mainly on annual data. Cyclical shocks are – if accounted for – included via time dummies in the econometric analysis. Even though the literature identified gender-specific responses to business cycles (Hoynes et al., 2012; Razzu and Singleton, 2016), it often ignores the responses of gender-specific wages to macroeconomic shocks. Further, our analysis goes beyond studying the behavior of the GPG or macroeconomic indicators in (specific) recessions (Elsby et al., 2010; Albanesi and Şahin, 2018) by considering a bunch of shocks that may affect the business cycle. Thus, we can give a more detailed picture compared to looking only at particular recessions. Moreover, in contrast to standard microeconometric tools, the SVAR permits to take account of potential (gender-) cross effects that may be important for intra-household decisions. Additionally, in order to better understand the relevance of the macroeconomic shocks for gender-specific labor market outcomes, we conduct a Forecast Error Variance Decomposition (FEVD).

Our results suggest that aggregate demand shocks, labor supply shocks and male-specific labor supply shocks do not affect the GPG at any horizon. In contrast, wage bargaining shocks (i.e. declines in employees' wage bargaining power) and female-specific labor supply shocks

[2]For example, Kandil and Woods (2002) looked at the evolution of the GPG in eight sectors and Cortes et al. (2018) examined the effects of macroeconomic phenomena on labor market outcomes for high-skilled workers.

increase the GPG in the short run. Only technology shocks lead to a persistent reduction of the GPG. To be precise, technology shocks lead to lower GPGs but higher unemployment in the medium run. The reaction of unemployment is higher for men than for women. Moreover, we find that wage bargaining shocks reduce unemployment in the short run for both men and women. Again, the reaction is more pronounced for men. These findings represent a trade-off between unemployment and gender equality in pay. Such trade-offs are relevant for political decision makers. Similarly, responses to technology shocks may be of particular political interest given automatization and digitalization of the economy. When splitting the sample into the periods 1979-1999 and 2000-2019, we find that the recent productivity slowdown (Crafts, 2018) challenges a persistent reduction of the GPG. That is, we find no evidence that technology shocks reduce the GPG more recently – presumably due to a lack of diffusion of new technologies (e.g. artificial intelligence and robotics). Moreover, occupational sorting and (collective) wage bargaining have become less relevant for gender wage differentials since 2000. In the appendix, we provide further robustness tests including estimations with shocks identified only by sign restrictions or by relaxing a selected sign restriction.

This paper is organized as follows. Section 2 outlines the econometric model. Section 3 describes the data and parameters used and Section 4 discusses the estimation outcome. Section 5 shows results of the FEVD. Next, Section 6 presents robustness tests concerning trend treatment and different time periods. Finally, Section 7 concludes.

2 Methodology

The aim of this paper is to show the contribution of one-time structural shocks on the GPG and gender-specific unemployment and labor force participation rates in the short, medium and long run. The estimation strategy relies on a SVAR model with eight potential macroeconomic outcomes. To be precise, we look at the following eight outcome variables: male and female median wages, male and female unemployment rates, male and female labor force participation rates, real GDP and prices. We consider all variables in levels in the VAR model, i.e. not in first differences. In this way, we preserve cointegration relations in the system (Sims et al., 1990). For identification of the macroeconomic shocks of interest (demand, technology, wage bargaining and labor supply as well as male and female labor supply shocks), we use zero and sign restrictions.

All series enter the model in logs. Note that even though our variables may have stochastic trends and may be co-integrated, the log levels specification will give consistent estimates (Sims et al., 1990; Ramey, 2016). For robustness with respect to trend treatment, we repeat the analysis by including a linear time trend. To investigate if our results are driven by a specific time period, we repeat our analysis on samples split into the period 1979-1999 and 2000-2019, respectively (see Section 6).

2.1 Econometric model

We approximate the unknown data generating process by a K-dimensional VAR model with lag order p:

$$y_t = c + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t \tag{1}$$

where y_t is a $K \times 1$ vector of variables to be explained. We have sample size T for each of the K variables and p presample values for each variable, $y_{-p+1}, \ldots, y_0$. In our case, $T = 158$, $p = 4$ and $K = 8$ (i.e. the eight outcome variables stated above). Following the literature, we choose lag order four for quarterly series (Francis and Ramey, 2005; Fisher, 2006; Francis et al., 2014). The intercept vector is represented by c and has dimension $K \times 1$. $A_1, \ldots, A_p$ are $K \times K$ coefficient matrices and u_t is a $K \times 1$ vector of white noise innovations with zero mean and covariance matrix $E[u_t u_t'] = \Sigma_u$.

In general, Σ_u is not a diagonal matrix. The latter implies that innovations u_t are correlated and, hence, cannot be interpreted as (fundamental) economic shocks. In order to conduct thought experiments, where only one shock occurs at a time, u_t needs to be orthogonalized. Therefore, we seek for a linear combination of the structural shocks ε_t that gives the innovations $u_t = B\varepsilon_t$ such that $\Sigma_\varepsilon = E[\varepsilon_t \varepsilon_t'] = I_K$ and $E[B\varepsilon_t \varepsilon_t' B'] = BB' = \Sigma_u$, where B is the structural impact multiplier matrix.

A simple counting exercise shows that the system of equation $\Sigma_u = BB'$ contains K^2 parameters to estimate, but only $K(K+1)/2$ linear interdependent equations due to symmetry of the covariance matrix Σ_u (see Lütkepohl, 2005). To identify the $K \times K$ matrix B, we need to impose restrictions on the immediate responses to the structural shocks. We follow the framework of Arias et al. (2018) to combine zero with sign restrictions (Algorithm 2), i.e. we use a Bayesian estimation technique with a conjugate Normal-Inverse-Wishart prior on the reduced-form parameters $[c, A_1, \ldots, A_p]$ and Σ_u.[3] For implementation, we follow Kilian and Lütkepohl (2017) and use parts of the MatLab code provided by them.

The number of shocks in a SVAR model corresponds to the number of variables entering the model (eight in our case). We do not consider the GPG in the model but calculate the IRF of the GPG as the difference in the IRF of men's median (log) wages and the IRF of women's median

[3]We choose the OLS equivalents as our prior parameters for $[c, A_1, \ldots, A_p]$ and Σ_u. Moreover, we choose the shrinkage parameter to be rather weak such that the data is dominant in the estimation.

(log) wages in each period. Only the following six shocks are interpreted: aggregate demand, technology, wage bargaining, labor supply as well as gender-specific labor supply shocks. We have thus two shocks that we do not interpret. It is crucial that the shocks of interest can be distinguished from each other and from the remaining shocks (see Kilian and Lütkepohl, 2017, for details). Therefore, we do not allow the remaining shocks to resemble the restrictions of our six shocks of interest. In case of correct sign restrictions, the SVAR provides accurate dynamics in form of IRFs (Kilian and Lütkepohl, 2017, pp. 435-436), i.e. endogeneity is not an issue. In the following, we discuss the choice of the restrictions based on economic theory and the related literature.

2.2 Motivation of sign restrictions

Table 1 shows the sign restrictions used to identify the six shocks of interest. The six shocks of interest are aggregate demand, technology, wage bargaining, aggregate labor supply and male- and female-specific labor supply shocks. In case of the aggregate shocks, we generally follow the intuition of the sign restrictions for identification of the shocks in Foroni et al. (2018). Their identification is based on a typical New Keynesian Dynamic Stochastic General Equilibrium model with search and matching frictions (e.g. Galí, 2010; Foroni et al., 2018). In addition, we apply exclusion restrictions to be able to identify gender-specific shocks. For comparison and in order to further test the sign restrictions, we estimate a smaller model (without gender-specific shocks) using the same shocks and sign restrictions as in Foroni et al. (2018) (see Appendix B). Even though, this approach is closer related to previous SVAR estimations (e.g. Foroni et al., 2018), it comes at the cost of not being able to identify gender-specific labor supply shocks. A major advantage of this smaller model is that the approach uses the algorithm of Rubio-Ramirez et al. (2010). The latter, in contrast to the SVAR model with zero and sign restrictions, is invariant to the ordering of the variables (Rubio-Ramirez et al., 2010; Arias et al., 2018). The main insights do not change.

We assume that a positive, i.e. expansionary demand shock increases output and prices, while it reduces unemployment. Note that these effects are similar to effects of monetary or fiscal policy as well as to most financial shocks (Çebi, 2012; Bhattarai and Trzeciakiewicz, 2017; Foroni et al., 2018; Cavalcanti et al., 2018). We do not disentangle these shocks. As no further restrictions for separate identification of the demand shock from the remaining shocks are required, we set no sign restrictions on labor force participation and wages of both men and women on impact, i.e. in the first quarter after the shock.

Following most New Keynesian models, a positive technology shock moves output up and prices down, while it increases (real) wages. In fact, technology shocks such as digitalization may trigger production and consumption and thus GDP. At the same time, positive technology shocks are likely to reduce prices and to increase wages. The effect on unemployment and on labor force participation may go in either direction. Consequently, we do not set sign restrictions for these indicators.

An expansionary wage bargaining shock representing a decline in workers' bargaining power directly and negatively affects wages leading to lower marginal costs and thus lower prices. Lower marginal costs and prices imply that output and employment increase.[4] Thus, both male and female unemployment rates are affected negatively on impact. As a reduction in workers' bargaining power negatively affects wages, it presumably leads to a decrease in participation. The latter is a consequence of lower wages that reduce worker activity and may further decrease unemployment (due to individuals leaving the labor force). However, a decline in household or family income may yield to secondary earners entering the labor market through added worker or wealth effects. As women are mostly secondary earners within a household, we do not impose a restriction on female labor force participation, while we restrict male participation to decline after a wage bargaining shock.

A positive labor supply shock implies an increase in labor market participants and thus job seekers. The latter decreases wages and prices, while it increases output. In contrast to Foroni et al. (2018), we do not restrict unemployment to rise contemporaneously in response to this shock as we do not need this restriction for identification.

We assume that also gender-specific labor supply shocks increase output due to negative effects on at least one gender's wage level with having simultaneously more workers of the same gender in the labor market. We impose zero restrictions on the response of male- (female-) participation to a labor supply shock of women (men). That is, these shocks are restricted such that they have no immediate impact on the other gender's participation. This restriction implies that spillover effects on the opposite gender are allowed only with a lag of one quarter. The justification is a sluggish labor market, which does not allow for immediate adjustments of labor supply and participation. Another explanation is a sufficiently segregated labor market such that an increase in male labor supply does not affect female participation on impact and vice versa (see Bergmann, 1974). We do not impose a restriction on unemployment as it, on the one hand, may increase due to more men and women in the labor market that do not immediately find a job. On the other hand, employment may be stable at the macro level, while the composition of the workforce may have changed. For instance, better-educated workers may enter the workforce, while lower-educated workers may leave it. Using a macroeconomic

[4]As labor force participation decreases at the same time, one may argue that GDP decreases in response to a wage bargaining shock. Therefore, we repeat the analysis without a restriction on GDP in case of a positive wage bargaining shock in Appendix C.

model, we cannot disentangle such changes in workforce composition.

Table 1: Restrictions on the multiplier matrix B

Series ↓ / Shocks →	(1) Demand	(2) Technology	(3) Wage bargaining	(4) Labor supply	(5) Male-specific labor supply	(6) Female-specific labor supply
GDP	+	+	+	+	+	+
CPI	+	-	-	-	$*$	$*$
Male unemployment rate	-	$*$	-	$*$	$*$	$*$
Female unemployment rate	-	$*$	-	$*$	$*$	$*$
Male LFP	$*$	$*$	-	+	+	0
Female LFP	$*$	$*$	$*$	+	0	+
Male median wages	$*$	+	-	-	-	$*$
Female median wages	$*$	+	-	-	$*$	-

Notes: +/- signs indicate that the effect of a shock is positive/negative on impact and $*$ denotes an unrestricted parameter. A zero indicates that the effect of a shock on impact is zero. LFP = Labor Force Participation Rate.

Demand shocks may be relevant for the GPG as a change in demand (potentially) has quantitatively different impacts on male and female wages. The literature finds different male and female labor supply elasticities both at the firm- and market-level (e.g. Boal and Ransom, 1997; Blundell and Macurdy, 1999; Manning, 2003; Hirsch et al., 2010). Firms may anticipate this gender-specific behavior and, thus, demand shocks may change the GPG. Moreover, Clark and Summers (1981) found higher participation fluctuations for women. Hence, looking at gender-specific indicators (male and female unemployment, labor force participation as well as wages) may yield further insights on the effects of macroeconomic shocks for specific groups of the population (such as men and women). Another channel for an effect of demand shocks on the GPG may be added or discouraged worker effects, i.e. generally women either increase their labor supply in a recession to compensate for lost male wages or men decrease their labor supply (women even further) as wages decline. Men experience generally significant larger job losses than women during economic downturns such as the Great Recession 2007-2009 (Hoynes et al., 2012; Razzu and Singleton, 2016; Albanesi and Şahin, 2018). However, male employment recovers more quickly than female employment (Hoynes et al., 2012). The literature refers to these phenomena as 'men-cessions' or 'he-coveries', respectively (Hoynes et al., 2012; Bredemeier et al., 2017). Gender differences in cyclical responsiveness of employment are consistent with women being generally the added worker and men being mostly the discouraged worker. That is, male unemployment tends to increase more than female unemployment during recessions. Industrial gender segregation may also play a role for changes in the GPG after a demand shock. Men are more often employed in highly cyclical industries such as construction or manufacturing, while women are more likely to be employed in less cyclical industries such as public administration and services (Hoynes et al., 2012; Bredemeier et al., 2017). Consequently, the GPG may decrease in response to a demand shock. Changes in government spending, expansionary or restrictive monetary policy or financial shocks etc. cause demand shocks that are consistent to our (and Foroni et al. (2018)'s) restrictions.

Similarly, technology shocks may affect the GPG. Black and Spitz-Oener (2010) explained a substantial fraction of the closing of the GPG based on changes in job tasks. For example, women have experienced relative increases in non-routine analytic and interactive tasks, while at the same time, they experienced a pronounced relative decline in routine task inputs. The latter was at least partly driven by technological change (Black and Spitz-Oener, 2010).

In case of a positive (negative) wage bargaining shock, workers', unions' or collective bargaining power decreases (increases). Typically, trade unions fight for equal pay and against discrimination at the workplace. The latter implies that the GPG may be lower in firms covered by collective bargaining. Several studies find that collective bargaining coverage is related with lower GPGs (Stephan and Gerlach, 2005; Heinze and Wolf, 2010; Bruns, 2019). This finding would imply that decreases (increases) in wage bargaining power increase (reduce) the GPG. However, if a reduction in workers' bargaining power translates into equally lower wages for both men and women, the wages of both men and women are negatively affected and thus the GPG may not change. Similarly, increased bargaining power may result in equally higher wages for both men and women and thus may not affect the GPG. For example, Oberfichtner et al. (2020) found no statistically significant effect of collective bargaining on the GPG in Germany after accounting for time-constant firm-level heterogeneity.

Labor supply shocks are known to be important drivers of the labor market. For example, Chang and Schorfheide (2003) found that labor supply shocks account for 30% of the variation in aggregate US working hours. Men and women may respond differently to increased competition deriving from a positive labor supply shock (Niederle and Vesterlund, 2007). Moreover, women may be more willing to accept lower wages than men in a more competitive environment. Consider for example nursing, where wages are substantially lower compared to technical occupations. The latter is a typical male- and the former a typical female-dominated job. Overcrowding in jobs may occur because individuals prefer a particular occupation as an utility-maximizing alternative, or it may occur because employers behave in a way that restricts occupations to a certain type of individuals (Solberg and Laughlin, 1995). If there is occupational segregation by gender, an increase of gender-specific labor supply will only affect wages of the corresponding gender-specific occupation (overcrowding model). Thus, overcrowding may result in changes of the GPG. Moreso, if overcrowding is particularly present in either male- or female-dominated occupations, the GPG is affected (even more). For example, Solberg and Laughlin (1995) found no evidence of overcrowding in male-dominated occupations but did not exclude it in female-dominated jobs. This result suggests that gender differences in pay can be (inter alia) explained with overcrowding or occupational segregation. Further, we can think of a labor supply shock to consist of for example changes in tax incentives, changes in (dis-)utility of work or consumption as well as of changes in unemployment benefits. Gender-specific changes in the (dis-)utility of work, gender-specific changes in the attitude towards work, changes in family structures or moving away from traditional gender views etc. may induce gender-specific labor supply shocks.

Blau and Kahn (2006) argue that one reason for the slowing convergence of male and female wages in the 1990s are changes in prices for gender-specific skills and relevant labor market characteristics. According to studies in psychology and neuroscience, women have more pronounced social skills (see Cortes et al., 2018, and the references therein). Unfortunately, we can neither observe these skills and characteristics nor the corresponding prices. Yet, from simple market mechanisms, we know that a ceteris paribus increase in the supply of these skills decreases the prices for the corresponding skills. As the respective skills are gender-specific, it is enough to vary the gender-specific labor supply to generate variation in the prices for gender-specific skills. The prices for these skills can be assumed to be reflected in wages and, hence, have an effect on the GPG.

3 Data and descriptive statistics

We use quarterly data from the US Bureau of Labor Statistics from the first quarter of 1979 (1979Q1) to the second quarter of 2019 (2019Q2). All series are seasonally adjusted. The wage series is the weekly median log wage of full-time workers. The US Bureau of Labor Statistics (2019) defines full-time workers as workers that usually work 35 hours or more per week at their main job. Wages are before taxes and other deductions and include any overtime pay (at the main job). Self-employed persons are excluded (US Bureau of Labor Statistics, 2019). We observe wages, unemployment and labor force participation rates separately for men and women.

Besides male and female wages, unemployment and labor force participation rates, we include the non-gender-specific variables real GDP and prices (CPI) in our model. The non-gender-specific variables control for labor market conditions and general determinants of wages. We use data for all series, except GDP and CPI, from the US Bureau of Labor Statistics. The

GDP and CPI series come from the database of the Federal Reserve Bank of St. Louis. The Federal Reserve Bank of St. Louis provide quarterly GDP and CPI series, while the US Bureau of Labor Statistics provides no (for GDP) or only monthly (for CPI) information. In total, we have $T = 158$ observations (excluding four presample values).

Table 2 shows that female wages increased substantially over the entire period, while their increase was relatively less pronounced since 2000. This development led to a substantial reduction in the (median) GPG from 1979-2019 of almost 20 percentage points. Thus, the GPG in the first quarter of 2019 was only half the GPG in the first quarter of 1979.[5] While the decline in the median wage disparity between men and women in the USA during the last 50 years was tremendous (20 percentage points or 50%), the decline during the last 18 years was only about four percentage points or 18%. It is well known in the literature that there has been a grand convergence of the GPG in the 1980s that slowed down at the end of the last century (Blau and Kahn, 2006; Goldin, 2014; Blau and Kahn, 2017). By using data from 1979 onwards, we can observe this grand convergence as well as the slowdown afterwards.

Compared to the first quarter in 1979, unemployment is substantially lower in the same quarter in 2019 for both men (-22%) and women (-45%). Men's unemployment increased slightly over the last nine years (0.1%), while that of women decreased (-10%). As stated before, men's labor force participation rate decreased over both time spans, while that of women increased in total but decreased since the 2000s. GDP as well as CPI increased substantially since 1974 and relatively less since 2000.

4 Estimation outcome

We draw 2,500,000 reduced-form parameters from the posterior distribution. For each draw of the reduced-form parameter, we draw 1,000 candidates for the matrix B conditional on the zero restrictions. Only draws satisfying the sign restrictions are kept. The remaining draws are discarded (for more details see Kilian and Lütkepohl, 2017; Arias et al., 2018). For each matrix B satisfying the sign and zero restrictions, IRFs are computed. Recall that we do not consider the GPG in the VAR but calculate the IRF of the GPG as the difference of the IRF of men's median wages and the IRF of women's median wages in each period.

In the following, we discuss the IRFs of male and female unemployment rates, participation rates, median (log) wages and the GPG to aggregate demand, technology, wage bargaining, aggregate labor supply as well as gender-specific labor supply shocks. Responses of GDP and

[5] We use the first quarter of 2019 (even though our time series ends only in the second quarter of 2019) in order to circumvent potential seasonal effects on the change of the GPG. Note, however, that Table 2 represents merely a snapshot of the US labor market at the corresponding date (e.g. in 1979Q1).

Table 2: Descriptive statistics, selected data points

	(1)	(2)	(3)	(4)	(5)
				Change	
Series ↓	1979Q1	2000Q1	2019Q1	2019Q1-1979Q1 Difference (in %)	2019Q1-2000Q1 Difference (in %)
Male median wages (weekly)	965.88	884.81	930.06	-35.82 (-3.71)	22.62 (2.56)
Female median wages (weekly)	595.97	675.80	750.41	154.44 (25.91)	61.55 (9.11)
GPG (in %)	38.30	23.62	19.32	-18.98 (-49.56)	-4.30 (-18.2)
Male unemployment rate (in %)	5.10	3.90	4.00	-1.10 (-21.57)	0.10 (2.56)
Female unemployment rate (in %)	6.90	4.20	3.80	-3.10 (-44.93)	0.30 (-9.52)
Male LFP (in %)	78.20	75.20	69.20	-9.00 (-13.01)	-14.82 (-8.67)
Female LFP (in %)	50.80	60.10	57.40	6.60 (11.50)	-28.57 (-4.70)
GDP	6,742	12,924	18,927	12,185 (64.38)	6003.10 (31.72)
CPI	29.20	71.77	106.87	77.68 (72.68)	35.11 (32.85)

Notes: Own calculations on data from the US Bureau of Labor Statistics (for wages, labor force participation rates (LFP) and unemployment rates) and the Federal Reserve Bank of St. Louis (for GDP and Consumer Price Index (CPI)). The figures refer to data from the first quarter (Q1) in 1979, 2000 or 2019, i.e. one data point each. In total, we have $T = 158$ observations (excluding presample values). Wages are in constant US dollars (base year is 2014). The Gender Pay Gap (GPG) has been calculated as: $\frac{\text{Male Wages}_t \text{ - Female Wages}_t}{\text{Male Wages}_t}$, with t being the corresponding data point.

prices to the corresponding macroeconomic shocks are in line with the literature (e.g. Foroni et al., 2018) and, hence, provide support for our identification scheme. The IRFs of GDP and prices are shown in Appendix A (Figures A1-A6). Further, we show in Appendix B and Appendix C that the main insights do not change when using a smaller model without gender-specific labor supply shocks and when we drop the sign restriction of a wage bargaining shock on GDP.

Figure 1 shows the IRFs to a positive or expansionary demand shock. By definition (of the sign restriction in Table 1), both male and female unemployment decreases on impact in response to a positive labor demand shock. This reduction is statistically significant and amounts at most to 2% for men or to 1.5% for women. Thus, male unemployment is affected more by the shock. However, the male response crosses the zero line slightly before the female response returning about half-a-year earlier to its pre-shock level. The IRFs remain then above the zero line but are not statistically significantly different from zero (the error bands include the zero line). Labor force participation decreases on impact as well as in the medium or long run for both men and women. In the short run, we observe an increase in male and female participation. However, the responses in both directions are negligibly small. Further, the error bands include the zero line at each considered horizon. Demand shocks decrease male and female median wages by about 0.2% on impact. The decrease in wages is on average higher for females in the first two years resulting in a (slight) increase in the GPG in that period. The response of male median wages returns to its initial value faster than the response of female median wages. The latter results in a persistent, though tiny, decrease in the GPG starting four years after the shock. Ten years after the shock, the median response indicates that the GPG returns to its initial value. As the error bands do always include the zero line, the response of the GPG is statistically insignificant throughout.

In response to an expansionary demand shock, the GPG is thus not significantly affected. That is, wages of men and women respond similarly to a one-time labor demand shock. Similarly to wages or the GPG, labor force participation is not markedly affected by the shock. Unemployment is lower in the short run but not affected in the medium to long run. As the response for men is more pronounced, this result is in line with the 'men-cession' literature (e.g. Hoynes et al., 2012; Bredemeier et al., 2017). Male unemployment rates return slightly earlier to their pre-shock level than female unemployment rates. This finding is supported by the 'he-covery' literature (e.g. Hoynes et al., 2012).

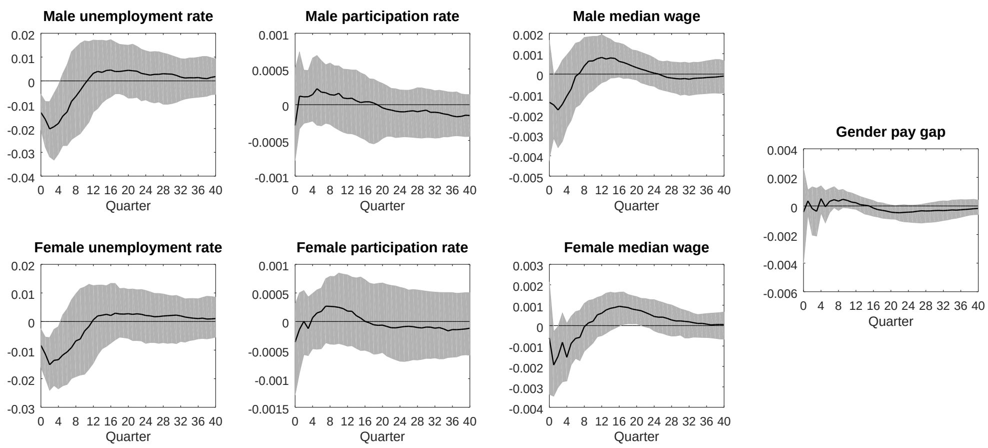


Figure 1: IRFs to a one standard deviation demand shock (1979Q1-2019Q2)
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

IRFs to a technology shock are shown in Figure 2. A one standard deviation technology shock lowers unemployment but increases both participation and wages on impact. The point estimates suggest a positive short-run effect on unemployment for both men and women, where the male response is again more pronounced than the corresponding female response. However, in both cases about four years after the shock, unemployment increases persistently. Again, the increase in male unemployment is more pronounced than that of their female colleagues. The effects are statistically significant. Even though the pattern of the participation response is similar for men and women, the male response is statistically significant and positive up to four years after the shock, while the error bands of the female response include the zero line throughout. The results suggest a negative response on participation in the long run (which is not statistically significant for women, however).

Male and female wages increase for six or eight years, respectively, and turn negative thereafter. This reduction is not statistically significant. As male wages respond more readily, we observe a slight, though statistically insignificant, increase in the GPG in the short run. Given that the increase in female wages is relatively more persistent (female wages turn below their initial values about two years later than male wages), we observe a statistically significant reduction in the GPG in the medium run. The decrease in the GPG is beyond 8.5 years after the shock no longer statistically significant. However, ten years after the shock, the IRF is still below the initial level of the GPG. The reduction in the GPG amounts to at most 0.1 percentage point, which implies a reduction of 0.5% in case of a GPG of 20% in one quarter. Consequently, positive technology shocks such as digitalization or automation of the industry may lead to a persistently lower GPG. This result is in line with findings from the literature based on microeconometric tools suggesting that technological change negatively affects the GPG (Black and Spitz-Oener, 2010).[6] Overall, technology improvements lead to a decline in the GPG. However, the results show that this comes at the cost of higher unemployment.

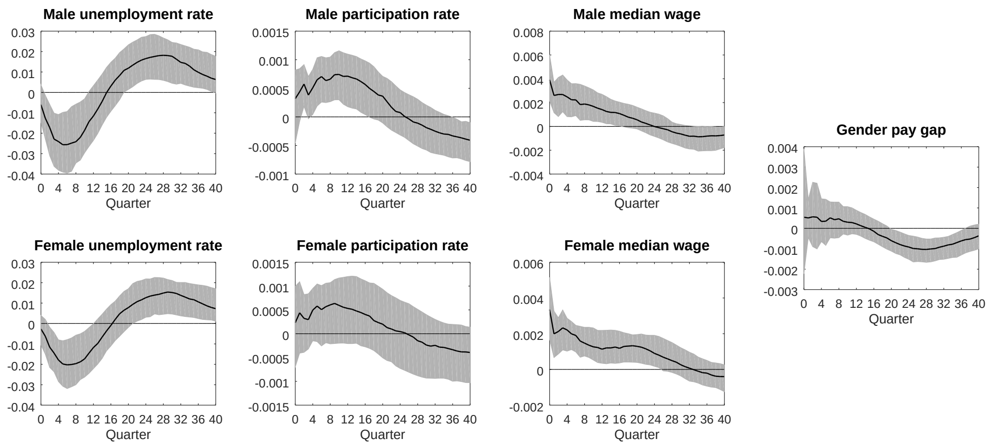


Figure 2: IRFs to a one standard deviation technology shock (1979Q1-2019Q2)
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

Figure 3 shows the IRF of an expansionary wage bargaining shock (i.e. a decrease in workers' bargaining power). The IRF of unemployment is substantially negative for both men and

[6] Black and Spitz-Oener (2010) look at the period 1979-1999. We repeat the analysis on this period as well as on the subsequent period in Section 6.

women. The male response is again more pronounced amounting to 2.5% at most, while the female response is highest with a reduction of approximately 2%. Yet, male unemployment returns to its pre-shock level about two years earlier than female unemployment. Participation declines on impact and converges already one year after the shock to its initial level. This result implies that we do not find increased female, i.e. secondary earner, labor force participation in response to a decrease in bargaining power representing a reduction in household income. Wages decrease on impact but increase statistically significantly three (male wages) or four (female wages) years after the shock. The median responses to wages remain statistically significant above the zero-line for about five years, before they converge to their initial value. These dynamics lead to a statistically significant increase in the GPG between year one to four. Since male wages approach the zero line more quickly, we see a small, though (just) statistically significant, decrease in the GPG seven years after the shock. However, this drop remains slightly statistically significant for only two years.

The latter suggests that it is important to distinguish between short, medium and long run effects when looking at gender differences in pay. According to most part of the literature on gender differences in pay and collective wage bargaining coverage (e.g. Stephan and Gerlach, 2005; Heinze and Wolf, 2010), an expansionary wage bargaining shock increases the GPG. This result is in line with our finding in the short to medium run. Corollary, an increase in bargaining power of workers would decrease the GPG in the short to medium run. As our estimation approach allows us to look at the dynamics of the GPG after a one-time macroeconomic shock, we can also make statements about the medium- and long-term response of the GPG to that shock. Our findings suggest that there is a reduction in the GPG in the medium to long run. However, the reduction is small and turns statistically insignificant nine years after the shock. Another benefit of our approach is that it allows us to consider the responses to a shock of several variables or indicators at the same time. This advantage comes into play here. Thus, from a policy perspective, we have a trade-off in the short run as an decrease in wage bargaining power increases the GPG but decreases unemployment.[7]

IRFs to a labor supply shock are shown in Figure 4. Male and female unemployment increases significantly only in the medium run by approximately 1%. According to the median response, a one standard deviation labor supply shock increases male and female labor force participation rates on impact by around 0.1%. The effects on labor force participation include the zero line two years after the shock. The responses of male and female workers are relatively equal and turn below the zero line after four to five years. A one standard deviation labor

[7]Figure A3 in the appendix shows the responses of the remaining variables to the wage bargaining shock. GDP increases in the short run in response to a decrease in wage bargaining power representing a further trade-off between increased output and employment but decreased gender equality in pay.

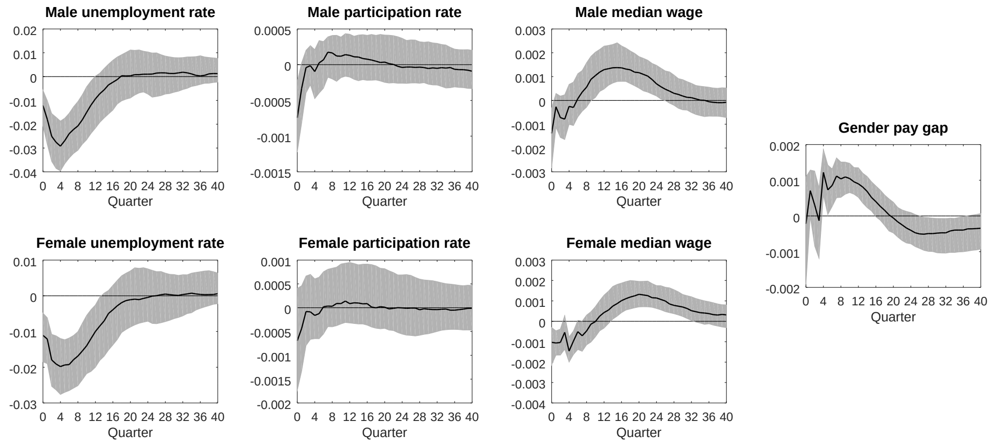


Figure 3: IRFs to a one standard deviation wage bargaining shock (1979Q1-2019Q2)
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

supply shock decreases both male and female median wages by 0.1% on impact. The median response of the female median wage is slightly more pronounced as well as slightly more persistent than the male response on impact. Moreover, the female response lags some quarters behind the male response. Nevertheless, the wage responses have similar shapes for men and women. Consequently, we do not find a marked impact of a one-time aggregate labor supply shock on the GPG. Indeed, the error bands of the GPG include the zero line at every considered horizon.

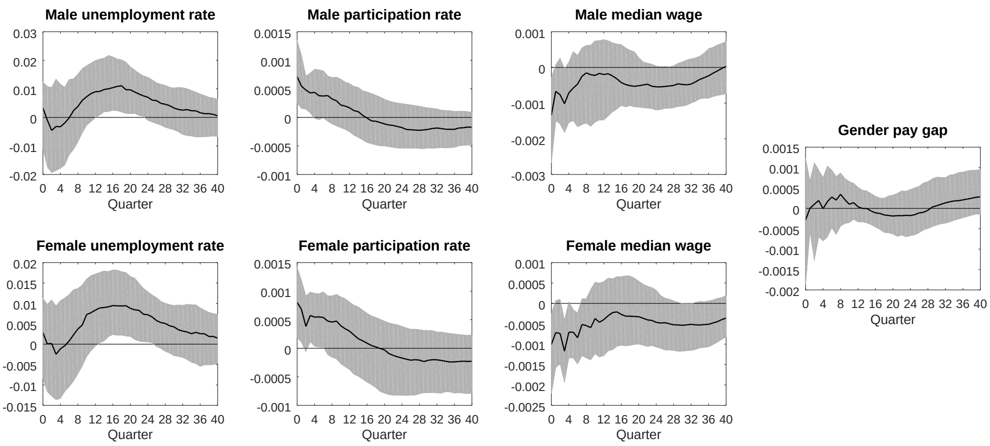


Figure 4: IRFs to a one standard deviation labor supply shock (1979Q1-2019Q2)
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

IRFs to a male-specific labor supply shock are shown in Figure 5. The response of unemployment is similar in shape for both men and women. The IRFs decrease for about two years after the shock, cross the zero line and remain above it until year nine before converging to their pre-shock levels. Note, however, that male unemployment is affected statistically significantly only directly after the shock, while female unemployment is never affected statistically significantly. Male participation increases on impact by 0.05%. This increase holds up to five years after the shock, then the median response crosses the zero line and becomes slightly negative. Interestingly, starting one period after the male-specific labor supply shock has appeared, female labor force participation rises and remains persistently above the zero line in response to a one-time male labor supply shock. However, at each horizon the error bands include the zero line. According to the median response, wages decrease on impact but converge to their initial levels about two years after the shock. In the first year, the male response is statistically significant, while the female wage response remains statistically insignificant throughout. Furthermore, as the decline in male wages is larger in magnitude in particular in the first year, we observe a decline in the GPG in this period. This pattern returns between year four and five leading again to a (slight) decrease in the GPG. The changes in the GPG are, however, never statistically significant. The main reason is that the shapes of the responses of male and female wages are similar.

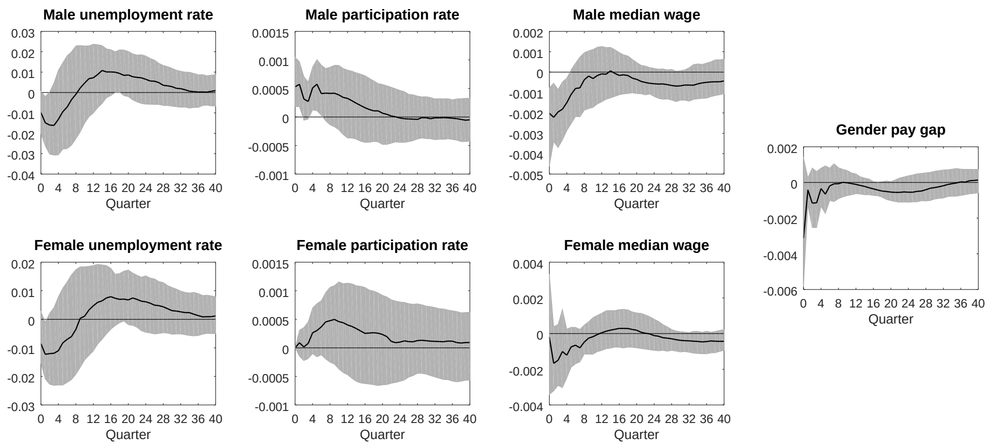


Figure 5: IRFs to a one standard deviation male-specific labor supply shock (1979Q1-2019Q2)
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

IRFs to a female-specific labor supply shock are shown in Figure 6. In contrast to the unemployment responses after a male-specific shock, the shapes of the IRFs for men and women differ on impact in case of a female-specific labor supply shock. Male unemployment decreases on impact, while the negative female response is negligible and crosses the zero line only one year after the shock has occured. Female unemployment remains then – in total – for about one year longer higher compared to male unemployment. In the long run, both IRFs return to their initial values. Again, the responses are never statistically significantly. The female labor force participation rate increases after the female-specific labor supply shock, but returns to its initial value (or even below) quickly. From more than one year after the shock, the error bands include the zero line. Interestingly, the male labor force participation rate increases slightly on impact but remains below its initial level in the long run. This response is never statistically significant. Thus, we find suggestive evidence that an increase in female labor supply negatively affects male labor supply but a male-specific labor supply shock has no effect on female labor supply in the long run (see Figure 5). The female median wage plummets on impact in response to a female-specific labor supply shock and remains below its initial value for about two years. The male median wage response increases on impact, but never statistically significantly diverges from its initial value and the error bands always include the zero line. The fall in female wages combined with an increase in male wages shortly after the shock results in an increase in the GPG (up to 0.4 percentage points), which declines to its initial value four years after the shock. The temporary increase in the GPG is statistically significant, while in the medium and long run, we find no effect. That is, a one-time female-specific labor supply shocks significantly increases the gap in the short run, but it has no effect on the GPG in the medium or long run. In contrast, a male-specific labor supply shock does not affect the GPG statistically significantly at any horizon. These results deliver support of the overcrowding model and gender segregation of the labor market that occur especially in female-dominated jobs (Bergmann, 1974; Solberg and Laughlin, 1995).

The findings underline again the importance of considering the responses to macroeconomic shocks on the GPG at different time horizons. Further, our results suggest that different labor supply shocks have distinct effects on the gap. Thus, it is also important to look separately at male- and female-specific one-time inflows of workers. An important implication of these results is that, in contrast to conventional wisdom, it is not enough to encourage women to participate in the labor market to reduce the GPG. In fact, an increase in female labor supply even increases the GPG – probably due to a segregated labor market. Moreover, women leave the labor market quickly after the shock (or replace other women such that the net effect is zero). Hence, to have a successful integration of women in the labor market and a reduction in the GPG, the labor market needs to be reformed first. Encouraging women to choose male-dominated jobs may be promising as it would tackle labor market segregation.

All in all, only technology shocks push the GPG persistently under its current level. Indeed, a one-time technology shock leads to a persistent lower GPG at the median of about 0.1 percentage points. A wage bargaining shock implies a decrease of the GPG by 0.04 percentage

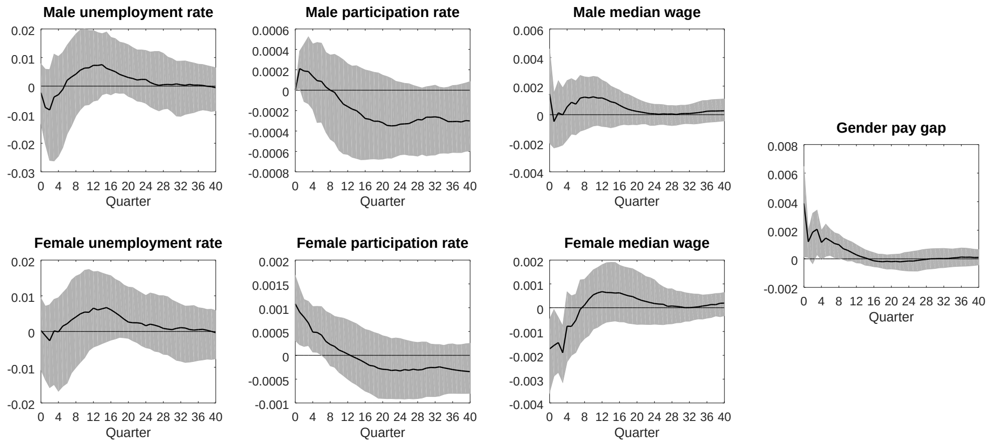


Figure 6: IRFs to a one standard deviation female-specific labor supply shock (1979Q1-2019Q2)
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

points in the medium to long run. Demand and labor supply shocks do not lead to a consistent reduction of the GPG. Short-term variation of the GPG can be explained with our model by wage bargaining and female-specific labor supply shocks. In the short to medium run, the GPG in the middle of the wage distribution increases temporarily by 0.1 percentage points in case of a wage bargaining shock. A female-specific labor supply shock increases the GPG in the short run by about 0.2 percentage points. These results imply that it is important to look at both short-, medium- and long-run effects of cyclical fluctuations on the GPG.

5 Forecast error variance decomposition

We conduct a FEVD to get an idea of how important the six macroeconomic shocks are for gender-specific labor market outcomes. A FEVD gives the proportion of the forecast error variance at forecasting horizons $h = 1, \ldots, H$ that can be attributed to a structural shock (Kilian and Lütkepohl, 2017).

Table 3 represents the contributions of the six shocks to the forecast error variance of gender-specific unemployment rates, labor force participation rates and wages for the horizons $h = 1, 8, 16, 24, 32, 40$.[8] The contributions are computed as the median contribution of a shock to the forecast error variance of the respective variable at each horizon based on the same posterior draws as the computation of the IRFs (Arias et al., 2018).

[8]We focus on the gender-specific outcome variables here as they are of main interest in the paper.

Demand shocks explain substantially more variation in the male unemployment rate (16%) than in the female unemployment rate (9%) in the first horizon after the shock. Again, this result is in line with the 'men-cession' literature. At later time horizons, the difference is markedly smaller (10% for men and 9% for women). Thus, the results of the FEVD are consistent with the presented IRFs. We find a significant response in the short run for men and women but no significant effect in the medium or long run. The FEVD suggests also no substantial gender difference in contributions at longer time horizons. For variations in participation rates and wages of both men and women, labor demand shocks are about equally important. With 4% to 12% of the explained variation, demand shocks are not the most important drivers of participation or wages.

Technology shocks are important drivers of the forecast error variance of unemployment rates in the medium and long run (15% to 20%). Similarly, out of the six identified shocks, technology shocks explain most of the forecast error variances of both male and female labor force participation rates at later time horizons. The FEVD shows that the technology shock is the most important driver of the forecast error variance of wages. At almost all horizons, technology shocks explain more than 20% of the forecast error variance of wages. Consistent with our results based on the IRFs presented in Section 4, the FEVD suggests that technology shocks are more important for male than female wages immediately after the shock, while the opposite holds at later horizons.

Wage bargaining shocks explain up to one-fifth of the forecast error variance of unemployment rates for both men and women at early time horizons. At later time horizons, the contribution of wage bargaining shocks to the forecast error variance of unemployment rates decreases (to about one-tenth). At most horizons, these shocks are more important for male unemployment, which may reflect higher union densities among men (for details on gender differences in unionism, see e.g. Schnabel, 2003, p. 27). In contrast, the contribution of these shocks to labor force participation is slightly higher for women than for men at almost all considered horizons. A one-time wage bargaining shock explains only a modest fraction of the forecast error variance of male (3%) and female (2%) wages at the first time horizon after the shock. The contribution to the forecast error variance of wages increases for men and women (up to 8% or 10%, respectively) at later time horizons. The latter implies that wage bargaining is more important in explaining forecast error variances in wages in the long run. This result is in line with New Keynesian models advocating that prices and wages adjust only slowly to short-term economic fluctuations (sticky wages).

Labor supply shocks explain a relatively stable fraction of all forecast error variances. Interestingly, in case of gender-specific shocks, the male-specific shock contributes always substantially more to the forecast error variance of male and female unemployment rates than the female-specific shock. The latter implies that the labor supply of men has a greater effect on employment fluctuations in the labor market. Further, female (male) labor supply shocks explain a larger fraction of the forecast error variance of female (male) labor force participation rates than male (female) labor supply shocks. While female-specific labor supply shocks are dominant for female wages, both gender-specific labor supply shocks are about equally important for male wages. The latter underlines the finding from the SVAR that only female-specific labor supply shocks statistically significantly affect the GPG.

Table 3: Forecast error variance decomposition 1979Q1-2019Q2, selected series

		(1)	(2)	(3)	(4)	(5)	(6)
Horizon →		$h = 1$	$h = 8$	$h = 16$	$h = 24$	$h = 32$	$h = 40$
Series ↓	Shock						
Male unemployment rate	Demand	0.16	0.09	0.10	0.10	0.10	0.10
	Technology	0.06	0.17	0.16	0.17	0.20	0.20
	Wage bargaining	0.12	0.19	0.16	0.14	0.13	0.12
	Labor supply	0.08	0.03	0.05	0.06	0.06	0.06
	Male labor supply	0.09	0.10	0.12	0.13	0.12	0.13
	Female labor supply	0.05	0.05	0.07	0.07	0.07	0.07
Female unemployment rate	Demand	0.09	0.10	0.09	0.09	0.09	0.09
	Technology	0.04	0.16	0.15	0.16	0.18	0.20
	Wage bargaining	0.17	0.18	0.13	0.13	0.12	0.11
	Labor supply	0.07	0.04	0.06	0.07	0.07	0.06
	Male labor supply	0.11	0.11	0.13	0.14	0.14	0.13
	Female labor supply	0.05	0.04	0.07	0.08	0.07	0.07
Male labor force participation rate	Demand	0.06	0.06	0.07	0.07	0.08	0.08
	Technology	0.05	0.14	0.16	0.16	0.15	0.18
	Wage bargaining	0.12	0.06	0.05	0.05	0.05	0.05
	Labor supply	0.10	0.10	0.08	0.08	0.10	0.10
	Male labor supply	0.06	0.12	0.13	0.13	0.12	0.12
	Female labor supply	0	0.03	0.04	0.06	0.08	0.08

Continued on next page

Horizon → Series ↓	Shock	$h=1$	$h=8$	$h=16$	$h=24$	$h=32$	$h=40$
Female labor force participation rate	Demand	0.04	0.05	0.06	0.06	0.06	0.07
	Technology	0.05	0.08	0.11	0.10	0.11	0.12
	Wage bargaining	0.11	0.11	0.08	0.07	0.07	0.06
	Labor supply	0.08	0.10	0.08	0.08	0.07	0.08
	Male labor supply	0	0.03	0.05	0.08	0.09	0.09
	Female labor supply	0.14	0.13	0.09	0.10	0.10	0.10
Male median wages	Demand	0.07	0.09	0.11	0.11	0.11	0.11
	Technology	0.21	0.22	0.20	0.21	0.21	0.21
	Wage bargaining	0.03	0.03	0.06	0.08	0.08	0.08
	Labor supply	0.02	0.03	0.03	0.04	0.05	0.05
	Male labor supply	0.10	0.13	0.11	0.11	0.12	0.12
	Female labor supply	0.06	0.1	0.12	0.12	0.12	0.11
Female median wages	Demand	0.08	0.11	0.11	0.12	0.12	0.12
	Technology	0.19	0.23	0.23	0.23	0.22	0.22
	Wage bargaining	0.02	0.05	0.06	0.09	0.1	0.1
	Labor supply	0.02	0.04	0.05	0.06	0.06	0.06
	Male labor supply	0.12	0.12	0.12	0.12	0.12	0.12
	Female labor supply	0.08	0.13	0.16	0.16	0.15	0.14

Notes: Forecast Error Variance Decomposition (FEVD) is based on the same posterior draws as the Impulse Response Functions (IRFs). The table shows the median contribution of the identified shocks to the respective variable at each horizon.

To sum up, the FEVD shows that there may be differences in contributions of distinct macroeconomic shocks on the error variance of specific indicators. This result underlines once more that it is important to consider gender-specific outcomes and shocks. Moreover, the proportion of explained variation in the forecast error variance changes across horizons implying that it is important to consider different time spans after a shock.

6 Robustness analysis: Trend specification and sample split

In order to show that the results are robust to different trend treatment and time periods, we estimate in this Section the model from the main analysis (Section 4) with a linear time trend and separately for the time spans 1979Q1-1999Q4 and 2000Q1-2019Q2, respectively. First, we present the results with a linear time trend. Second, we show the estimation outcome from the sample split.

Estimating the VAR model in levels represents one way of dealing with trending behavior of the variables (Sims et al., 1990; Ramey, 2016). However, we may think of different ways to address the treatment trend such as adding a linear trend or estimating the model in growth grates. We do not rely on the latter as estimation in growth rates may lead to biased estimates if the VAR includes cointegration relations. The bias occurs as using first differences eliminates the cointegration relations and therefore represents an omitted variable problem of the system (see Lütkepohl, 2005, p. 248). A linear trend is a popular way to deal with trending in time series (Ramey, 2016) accounting for deterministic trends of the variable, but leaving the stochastic trends in the system.

Figure 7 shows that our main results concerning the IRFs of the GPG are basically unaffected when including a linear trend. We present the IRFs of the remaining indicators in Appendix A (see Figures A7-A12). As a unit root process with an intercept is already able to generate time series with a linear trend, including a linear trend does not affect our results substantially.[9] A one-time technology shock leads again to a persistently lower GPG, while a wage bargaining shock increases the GPG in the short-run. Note that the effect of a wage bargaining shock on the GPG is negative, though negligible, at longer horizons. Female-specific labor supply shocks affect the gap only in the short run. Labor demand and other labor supply shocks do not affect the GPG statistically significantly. Thus, our results from the main analysis are robust to a different type of trend treatment (linear trend in our case).

In order to analyze whether our estimation results are driven by a particular time span, we repeat the analysis separately for the periods 1979Q1-1999Q4 (see Figure 8, Panel (a)) and the period 2000Q1-2019Q2 (see Figure 8, Panel (b)). That is, we conduct a sample split. Recall that Table 2 shows that the convergence of the GPG was stronger over the period 1979-1999 compared to the period 2000-2019. In the following, we outline the results from the sample split for the GPG (Figure 8). The IRFs of the remaining variables can be found in

[9] We find differences in the responses of GDP and CPI in the model with the linear trend compared to our main specification (see Appendix A). For example, in contrast to the main specification, in the linear trend specification, the results do not suggest a permanent effect of a technology shock on CPI. This finding is not surprising as GDP and CPI are the variables with the most obvious linear trend. Nevertheless, the overall shapes of the responses of GDP and CPI are robust to the inclusion of the trend.

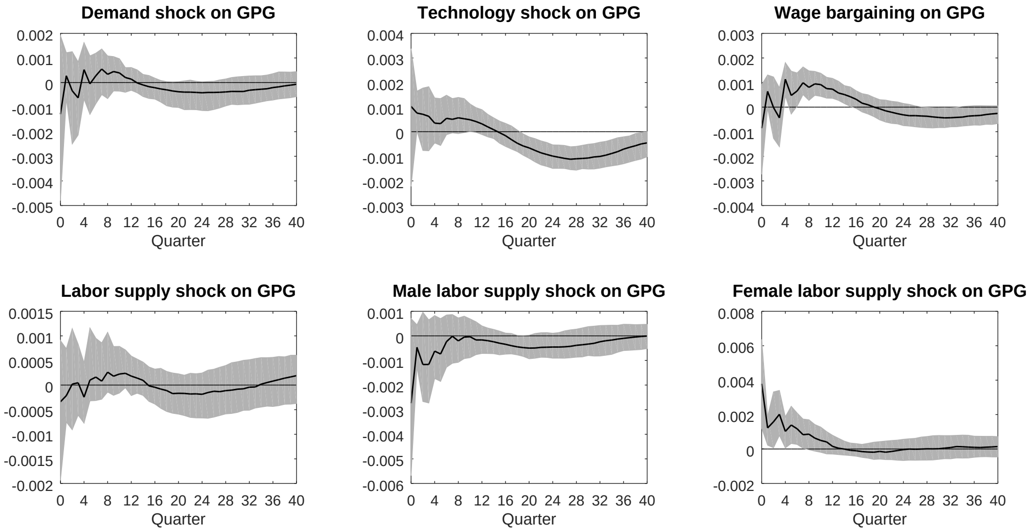


Figure 7: IRFs of the GPG – Trend treatment

Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively. Trend treatment is included in the model via a linear trend.

Appendix A (Figures A13-A18).

Figure 8 shows that demand shocks do again not affect the GPG at most horizons. In contrast to the main analysis, however, the shock enlarges the GPG slightly in the short run in both periods (statistically significantly only 1.5 years after the shock in the period 2000Q1-2019Q2). Similarly, the gap raises slightly in the medium run in the period 1979-1999. The latter increase is never statistically significantly, though.

Compared to the main analysis, we find interesting differences in the response of the GPG to technology shocks. Before 2000, the response is similar to the main results. We see again a drop in the GPG in the medium run. The response of unemployment is similar, too. Even though, the increase in the medium run is statistically insignificant (see Figure A14, Panel (a)), we see quantitatively again higher unemployment in the medium run. Turning to the results based on the sample 2000Q1-2019Q2, we observe a medium-run increase in the GPG in response to technology shocks, which we do not find in the main results. This increase in the GPG is associated with a delayed statistically significant increase in unemployment (see Figure A14, Panel (b)).

Reasons for this change may be the following. Technology shocks in the former period are mostly associated with advances in computer technology (Alexopoulos, 2011). Women executing generally more non-routine tasks benefited substantially from this computerization of the economy, which contributed to the closure of the GPG over that period (Black and Spitz-Oener, 2010). This finding is also consistent with Eden and Gaggl (2018) who showed that the labor share of non-routine occupations increased until 2000 but has been stable afterwards. Similarly, information and communication technologies' capital share rose until 2000 and has fluctuated around the 2000-level since then. In the more recent period, sources for technology shocks are more likely to be related to artificial intelligence, machine learning and robotics (Crafts, 2018). So far, these new technologies are mostly employed in sectors with a high share of male employees. For example, Acemoglu and Restrepo (2020) showed that the adoption of robots is particularly pronounced in industries like automotive, plastics and chemicals as well as metal products. The results of Acemoglu and Restrepo (2020) imply that the adoption of robots is associated with a reduction in employment in the medium to long run. Our estimated IRFs of unemployment and labor force participation for the period 2000Q1-2019Q2 (see Figure A14, Panel (a)) point in the same direction. As the above mentioned technologies need a considerable amount of time to become so-called general purpose technologies that affect all areas of the economy (Brynjolfsson and McAfee, 2014; Crafts, 2018), women may benefit from these technologies once they arrive at this stage. As a consequence, the implications for the GPG may be eventually similar as in case of computerization. From a policy perspective, accelerating the diffusion of these new technologies may help to combat gender inequality in the labor market. Moreover, encouraging women to enter also male-dominated industries may help to reduce the GPG. This association is also used to explain the productivity slowdown experienced in the US after 2000 (see e.g. Crafts, 2018). Thus, our results suggest that the productivity slowdown and the slowing convergence of the GPG have a similar background.

The response of the GPG to a wage bargaining shock in the earlier period is similar to the main analysis. That is, we see an increase after a wage bargaining shock in the short to medium run. In the period after 2000, we do not observe a statistically significant GPG response to this shock in the medium run, but only a short-lived drop in the short run. Thus, our result that a positive wage bargaining shock (resulting in a reduction of workers' bargaining power) increased the GPG (and vice versa) seems to be based on the period before 2000. This finding is in line with Oberfichtner et al. (2020) finding no effect of industrial relations institutions on the GPG in Germany over the period 1996-2014.

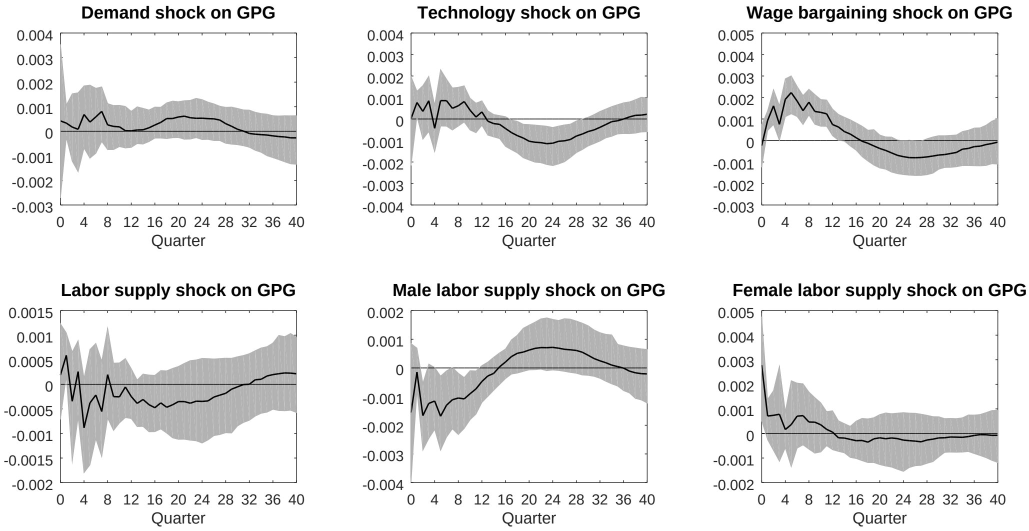
The response to a labor supply shock does – as in the main analysis – also in the period 1979Q1-1999Q4 not suggest a change in the GPG. Since 2000, we see a decrease in the GPG at longer horizons, which we do not observe in the main analysis. The reason may be that occupational segregation is weaker in more recent years leading to more women (men) in traditionally male and better-paying (female and lower-paying) jobs. The GPG-response to a male-specific labor supply shock does not differ substantially from their counterparts in the main analysis. In the earlier period, male wages decrease slightly more persistently resulting in a small short-run decrease in the GPG in response to the shock. As in the main results, the GPG does not change in response to the shock in the latter period. Female-specific labor supply shocks based on the period before 2000 suggest a less persistent increase in the GPG in this period. Similarly to the main results, after 2000, the GPG increases in the short run. However, in this period, we see a slight drop in the gap in the medium run indicating again that male wages are negatively affected by increased female labor supply in this time period. These results suggest that occupational segregation is weaker in more recent years and that (political) campaigns fighting sex segregation in the US labor market may start to pay off. Examples of such campaigns around the world are manifestations of Girls' and Boys' Days.

All in all, most insights from the IRFs are robust over different time periods. Nevertheless, the sample split with respect to different time periods allows us to disentangle the role of different time periods on the results. For instance, the result that technology shocks lead to lower GPGs in the medium run is driven by the period 1979-1999. Similarly, the results from the sample split suggest that decreases in workers' or collective bargaining power increase the GPG only before 2000 in the short run. In contrast, in the period after 2000, wage bargaining shocks affect the GPG even slightly negatively in the short run. This change may be associated with a substantial reduction in union power and collective bargaining coverage over time (Bryson and Blanchflower, 2003). Further, the sample split provides additional insights like the persistent drop in the GPG after a labor supply shock in the recent time period. This finding indicates that the labor market is less segregated and that females choose previously male-dominated higher-paying jobs.

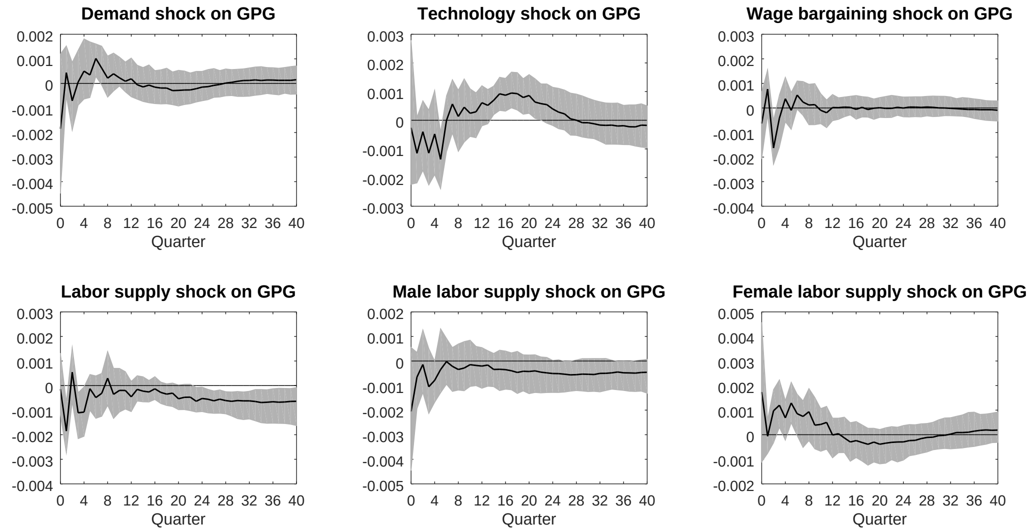
7 Conclusion

In this paper, we estimate the impact of both aggregate and gender-specific macroeconomic shocks on the variation of the US GPG in the short, medium and long run. Further, we disentangle the impact of demand, technology, wage bargaining and labor supply shocks on the wage gap. Thereby, we add to the small literature on cyclical dynamics and the GPG. To the best of our knowledge, this is the first paper that considers the effects of macroeconomic shocks on the aggregate GPG from a macro perspective using a SVAR model with zero and sign restrictions.

Demand and labor supply shocks do affect the gap only in the short or medium run (though statistically insignificantly). A female-specific labor supply shock increases the gap in the short run, while a male-specific labor supply shock does not affect the GPG statistically significantly at any time horizon. As neither labor supply nor female-specific labor supply shocks affect the GPG persistently, it is not enough to encourage women to enter the labor market to reduce



(a) IRFs of GPG (1979Q1-1999Q4)



(b) IRFs of GPG (2000Q1-2019Q2)

Figure 8: IRFs of GPG – Sample split

Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

gender wage inequality in the long run. The latter may be related to overcrowding and occupational sorting that is particularly present in female-dominated jobs (Bergmann, 1974; Solberg and Laughlin, 1995). After 2000, we find a persistent drop in the gap in response to a labor supply shock. The finding may indicate that occupational sorting of men and women in male- and female-dominated jobs, respectively, has become weaker recently. Since labor supply shocks have this effect, they may offer an effective policy tool to reduce gender wage differentials in the labor market. As a policy implication, promoting Girls' and Boys' Days represents a promising instrument for fighting occupational sorting by gender.

We find that a wage bargaining shock affects the GPG positively in the short and negatively in the medium run. However, the effect in the medium is negligibly small and both effects are driven by the period 1979-1999. The result suggests that after 2000, workers' wage bargaining power has only limited effects on the GPG. Our main results imply that a technology shock reduces the GPG persistently in the medium run. Hence, promoting innovation may not just trigger economic growth, but may also help to close the GPG. However, this finding is driven by the period 1979-1999, i.e. the era of computerization. A potential channel is the following. Advances in computer technology may have led to more women in non-routine tasks resulting in an increase in female wages and thus in a reduction of the GPG (Black and Spitz-Oener, 2010). Technological advances after 2000 (e.g. artificial intelligence, machine learning and robotics) do, so far, not trigger a transformation towards more gender equality as in case of computerization. A reason may be that these technologies lack diffusion throughout the economy compared to computer technology. In fact, modern technologies like robotics and artificial intelligence are mainly concentrated in male-dominated industries (Acemoglu and Restrepo, 2020; Varian, 2019). These results show that is important to track the sources of technological change (as done by e.g. Alexopoulos, 2011) in order to identify potential beneficiaries of the change. Doing so allows political decision makers to promote specific groups such as women and, thus, to combat gender-specific inequalities in the labor market. Additionally, the technological advances after 2000 have not been able to lift productivity growth to new heights resulting in a productivity slowdown (Crafts, 2018). Thus, our results indicate that the productivity slowdown and the stagnation of the GPG since the late 1990s go hand in hand. Policies promoting the diffusion of new technologies may not only help to overcome the productivity slowdown but may also represent a tool to reduce gender wage inequality consistently.

Overall, the results are robust to different trend treatment (linear time trend) and distinct model specifications (smaller model and different sign restriction on GDP after a wage bargaining shock). Additionally, using the SVAR, we can confirm the results of the 'men-cession' literature finding that male unemployment is more responsive than female unemployment to cyclical shocks. In contrast to this literature that generally looks at specific recessions, we can show that the result of a more pronounced male unemployment response holds in case of general aggregate demand, technology and wage bargaining shocks. Moreover, the results suggest a trade-off between lower levels of gender equality and higher levels of unemployment for both men and women. We find this trade-off in case of wage bargaining (in the short run) and technology shocks (in the medium run).A limitation of the macroeconometric analysis is that we cannot disentangle for example changes in workforce composition in response to a macroeconomic shock (Giavazzi and McMahon, 2013).

Finally, this paper helps to better understand the effects of cyclical dynamics on the GPG. The latter is particularly relevant in times of slowing convergence of male and female wages (Blau and Kahn, 2006). Our analysis helps to understand if men and women respond differently both in terms of magnitude and persistence to macroeconomic shocks and, therefore, shows which group (men or women) deserves special policy action after specific macroeconomic shocks. As economic downturns are costly (e.g. in terms of welfare costs; Tervala, 2021) but are generally not gender-neutral (Razzu and Singleton, 2016), identifying the most affected group is important in order to set-up stabilizing and gender-fair economic policies. A main insight is that technological change may offer a channel to reduce the GPG persistently. Further, fighting occupational gender segregation may also lead to lower levels of the gap, while (collective) wage bargaining seems to be no longer a powerful tool to fight gender-wage inequality.

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Appendix

A Remaining impulse response functions

A.1 Impulse response functions for GDP and CPI – Main analysis

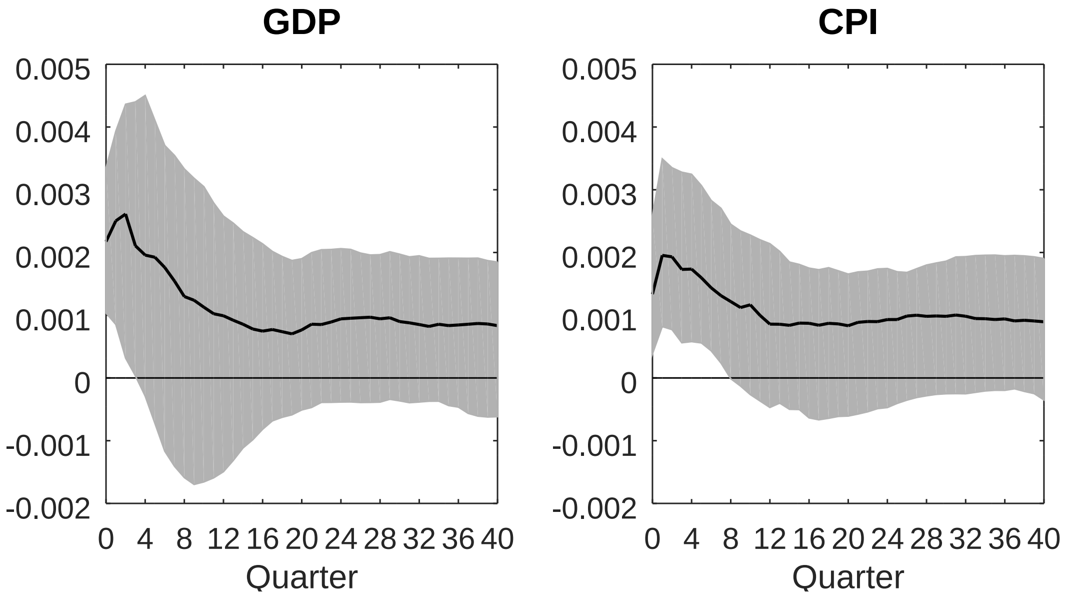


Figure A1: IRFs to a one standard deviation demand shock (1979Q1-2019Q2) – GDP and CPI
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

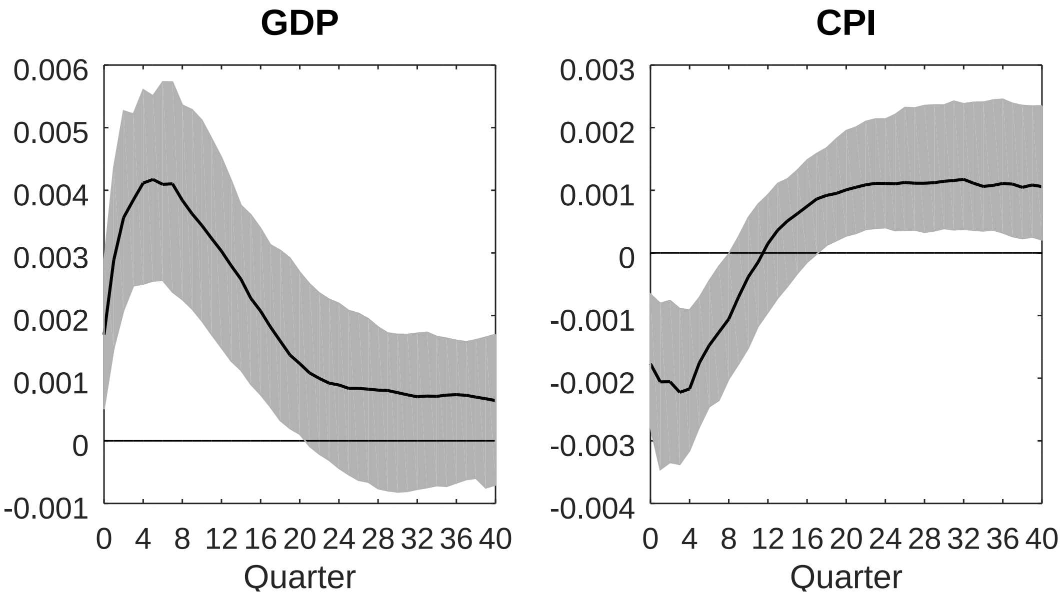


Figure A2: IRFs to a one standard deviation technology shock (1979Q1-2019Q2) – GDP and CPI

Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

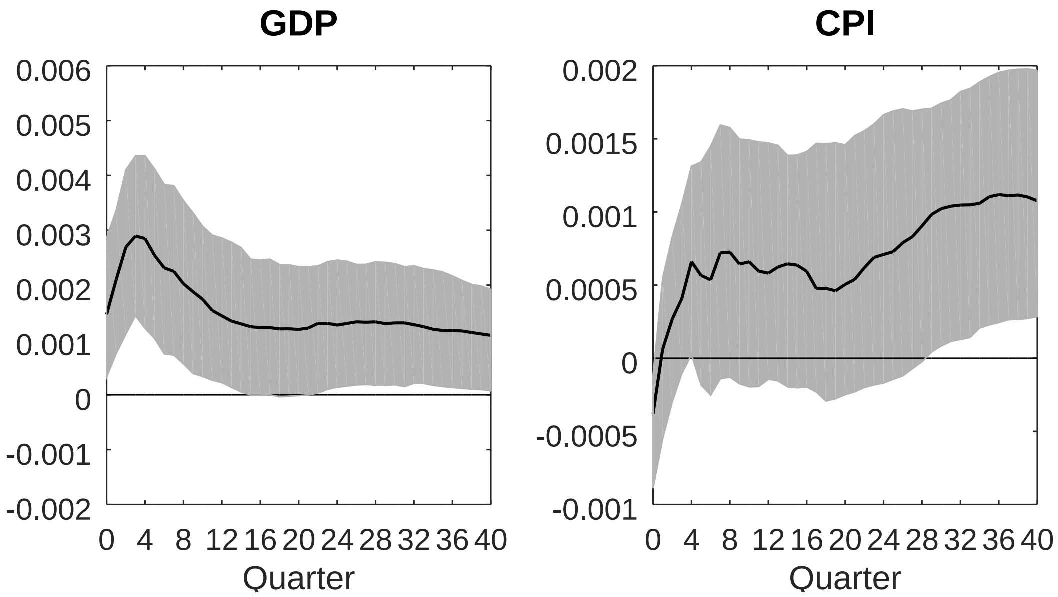


Figure A3: IRFs to a one standard deviation wage bargaining shock (1979Q1-2019Q2) – GDP and CPI

Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

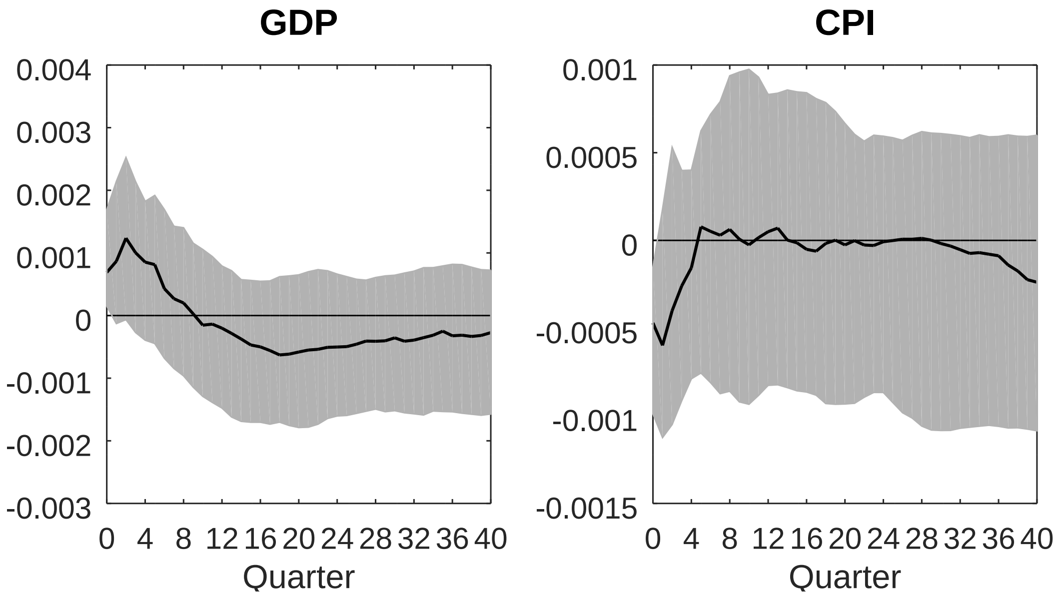


Figure A4: IRFs to a one standard deviation labor supply shock (1979Q1-2019Q2) – GDP and CPI

Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

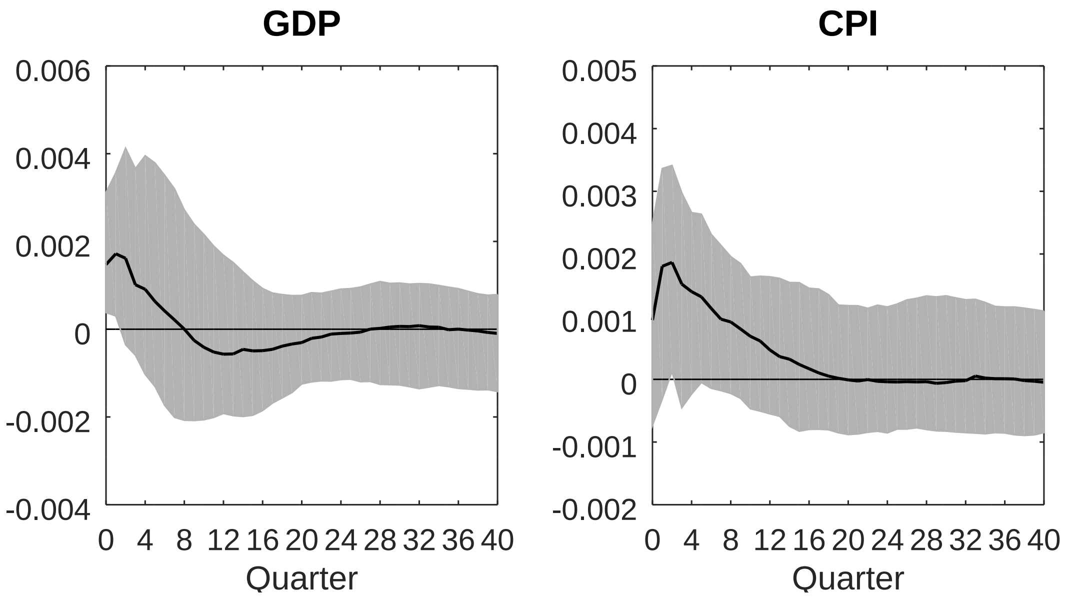


Figure A5: IRFs to a one standard deviation male-specific labor supply shock (1979Q1-2019Q2) – GDP and CPI

Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

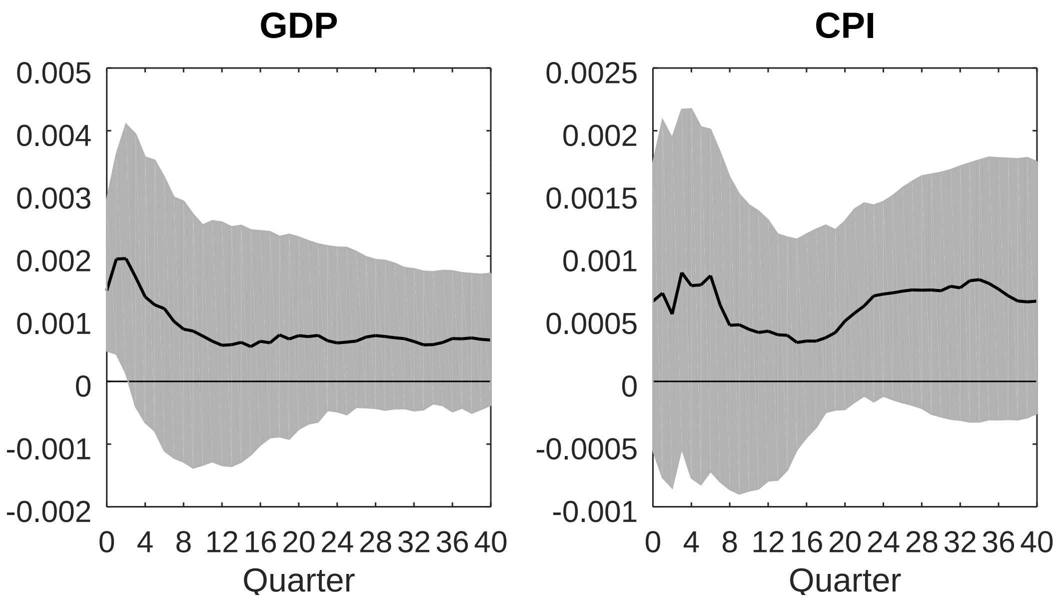


Figure A6: IRFs to a one standard deviation female-specific labor supply shock (1979Q1-2019Q2) – GDP and CPI

Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

A.2 Remaining impulse response functions – Linear trend

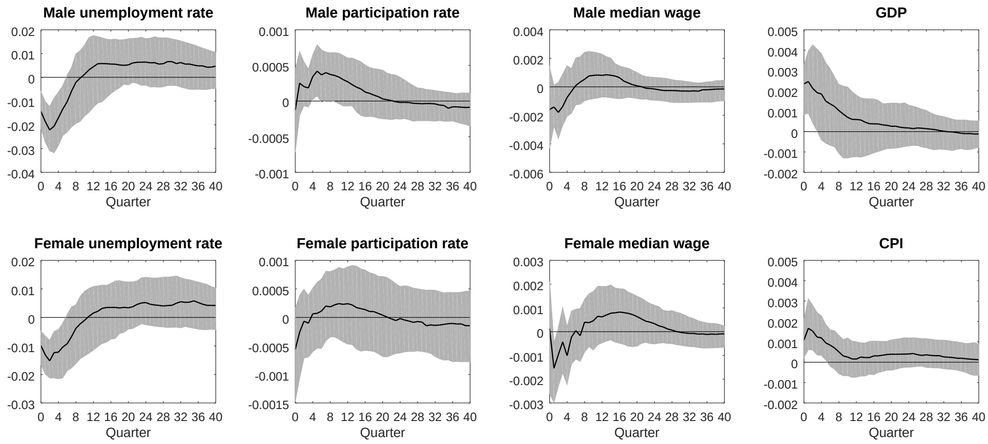


Figure A7: IRFs to a one standard deviation demand shock – Trend treatment

Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively. Trend treatment is included in the model via a linear trend.

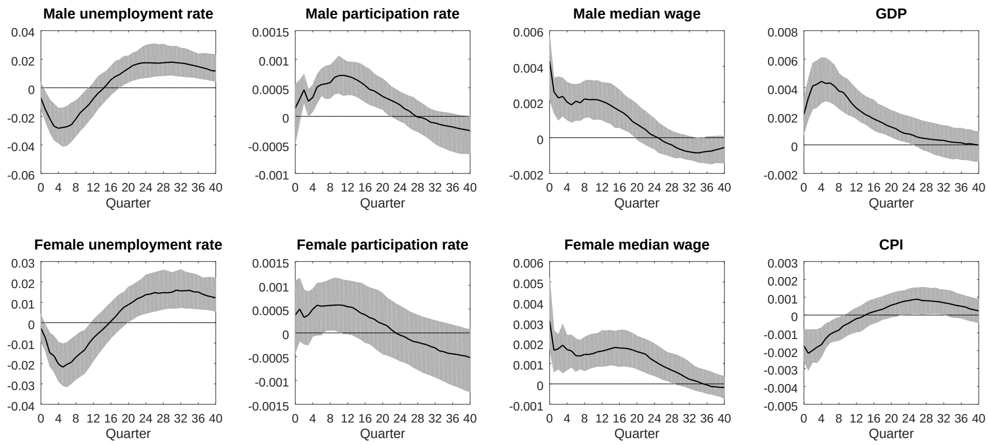


Figure A8: IRFs to a one standard deviation technology shock – Trend treatment

Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively. Trend treatment is included in the model via a linear trend.

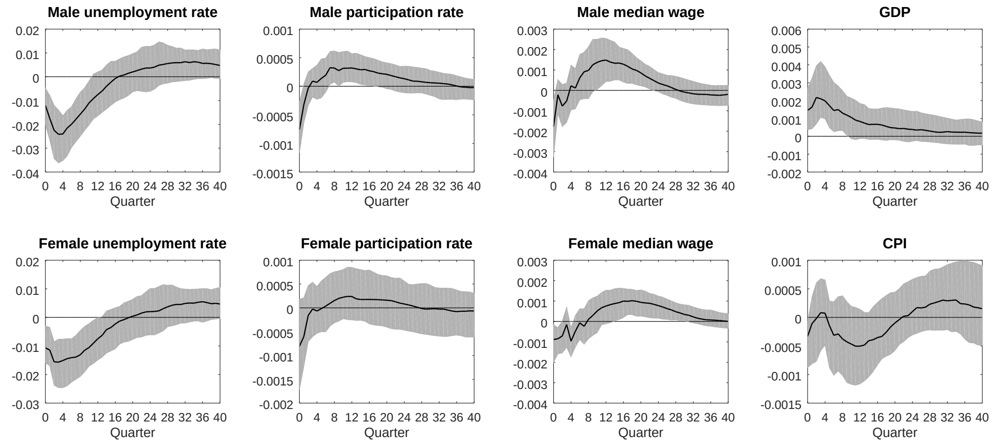


Figure A9: IRFs to a one standard deviation wage bargaining shock – Trend treatment
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively. Trend treatment is included in the model via a linear trend.

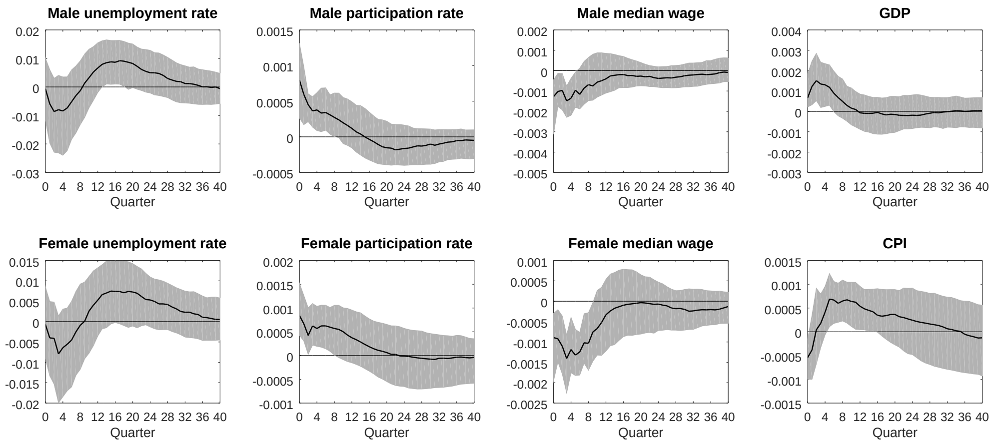


Figure A10: IRFs to a one standard deviation labor supply shock – Trend treatment
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively. Trend treatment is included in the model via a linear trend.

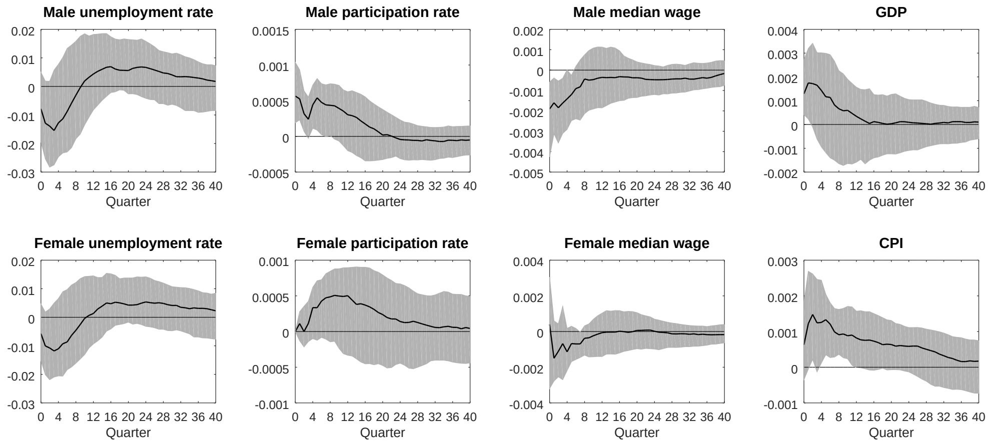


Figure A11: IRFs to a one standard deviation male-specific labor supply shock – Trend treatment
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively. Trend treatment is included in the model via a linear trend.

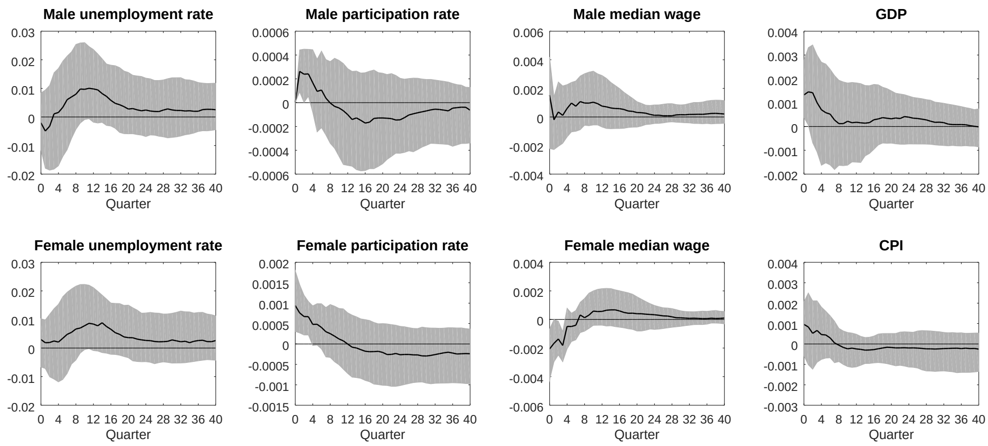
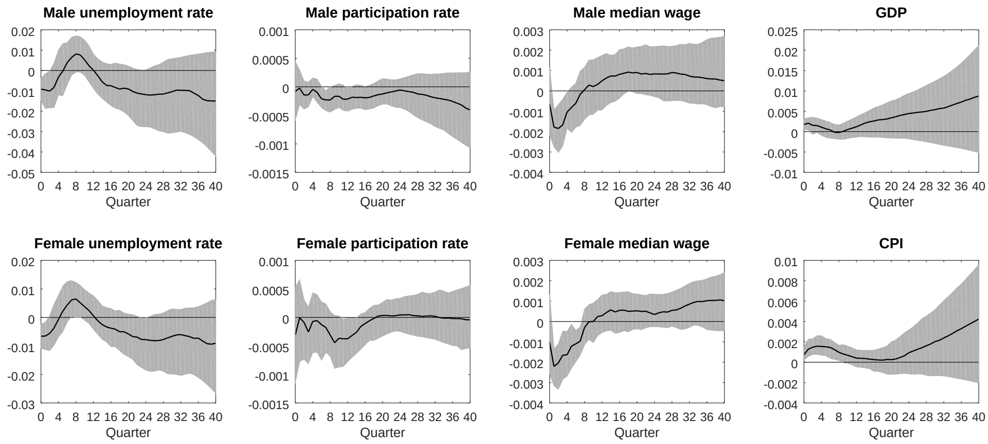
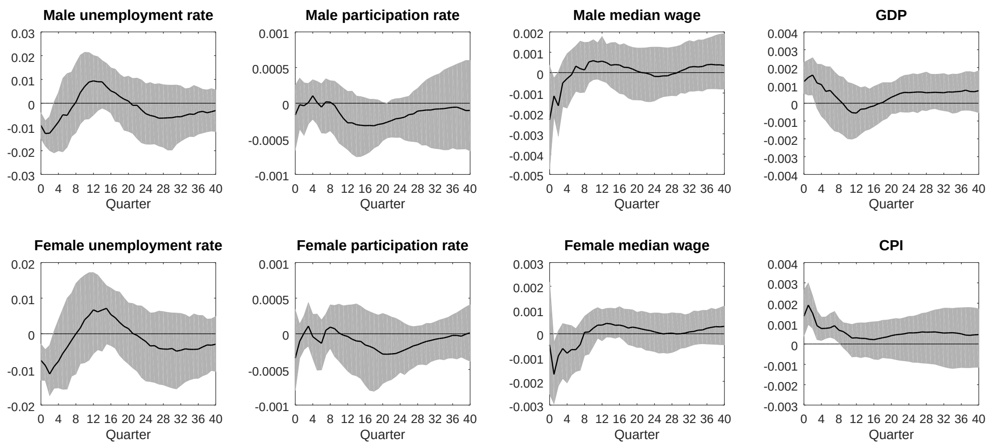


Figure A12: IRFs to a one standard deviation female-specific labor supply shock – Trend treatment
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively. Trend treatment is included in the model via a linear trend.

A.3 Remaining impulse response functions – Sample split



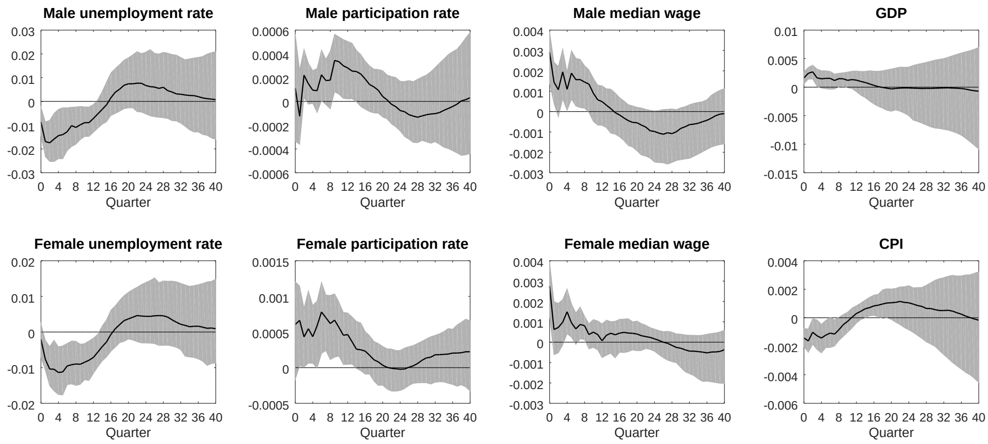
(a) IRFs to a one standard deviation demand shock (1979Q1-1999Q4)



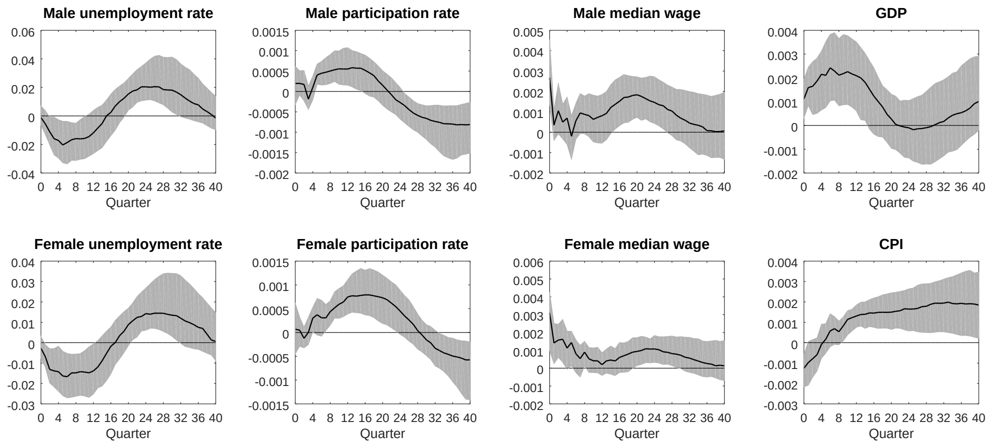
(b) IRFs to a one standard deviation demand shock (2000Q1-2019Q2)

Figure A13: IRFs to a one standard deviation demand shock – Sample split

Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.



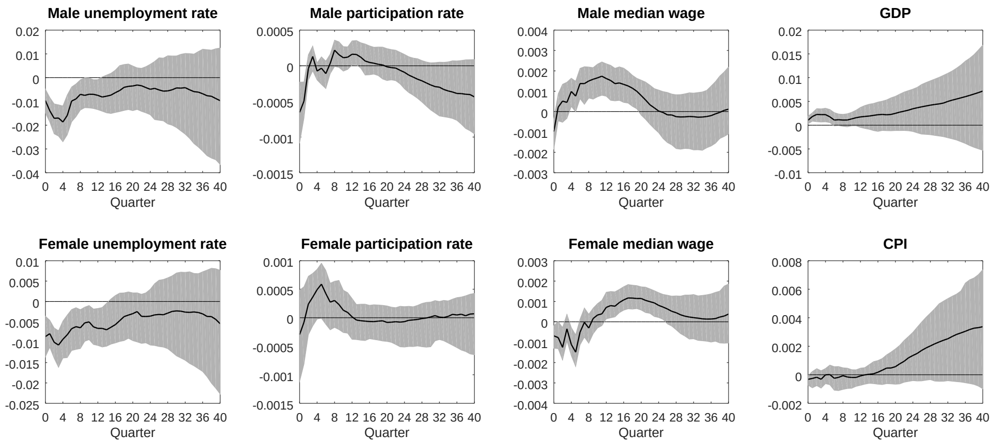
(a) IRFs to a one standard deviation technology shock (1979Q1-1999Q4)



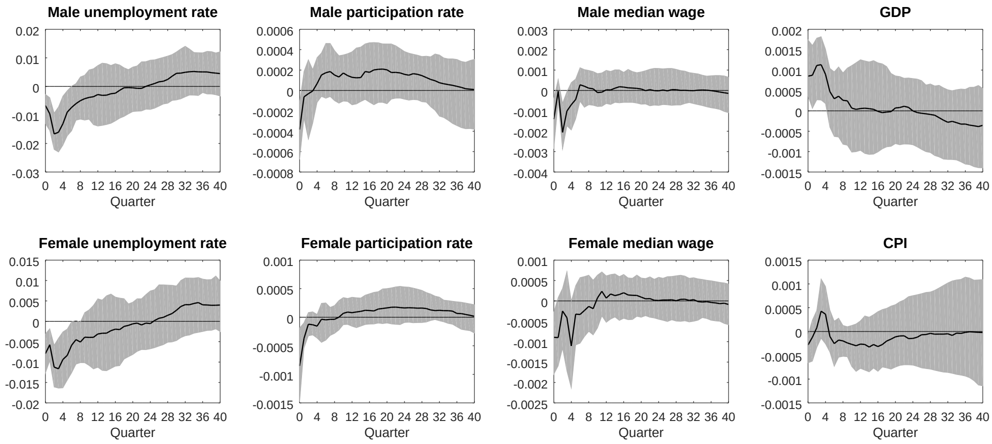
(b) IRFs to a one standard deviation technology shock (2000Q1-2019Q2)

Figure A14: IRFs to a one standard deviation technology shock – Sample split

Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.



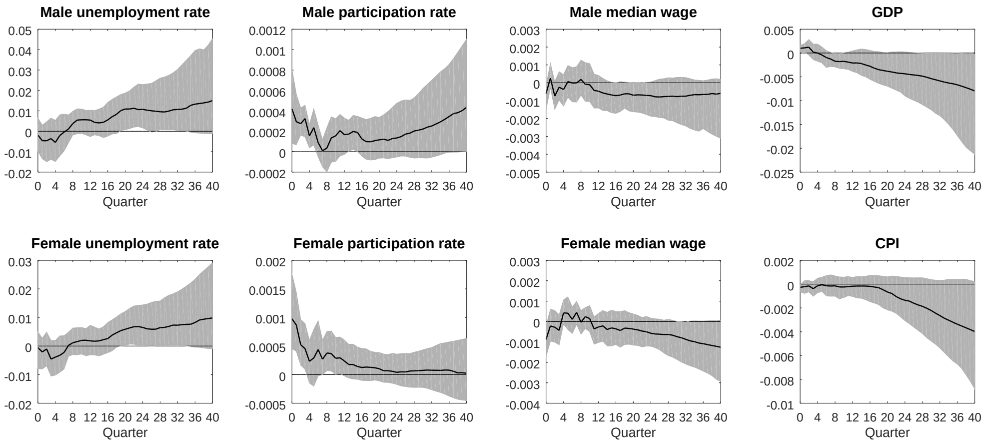
(a) IRFs to a one standard deviation wage bargaining shock (1979Q1-1999Q4)



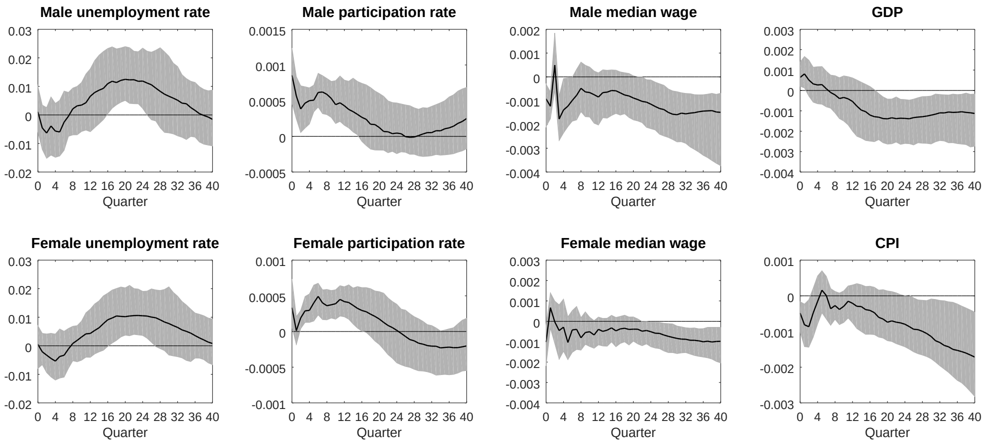
(b) IRFs to a one standard deviation wage bargaining shock (2000Q1-2019Q2)

Figure A15: IRFs to a one standard deviation wage bargaining shock – Sample split

Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.



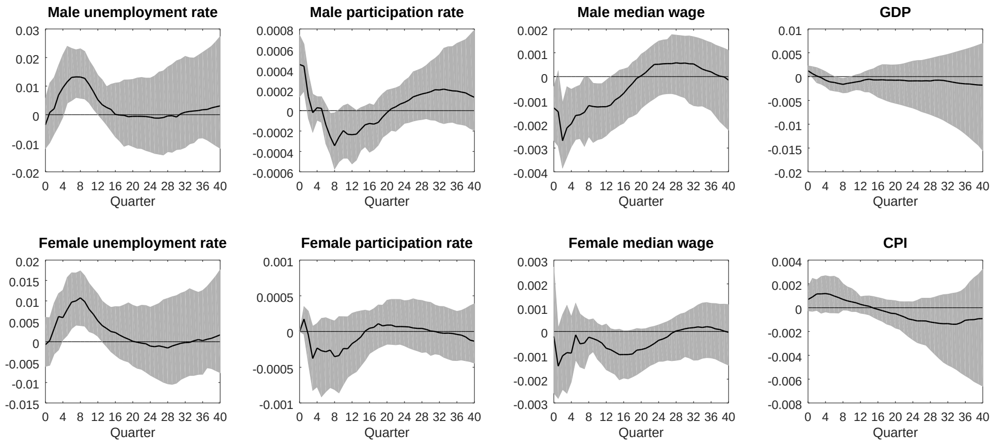
(a) IRFs to a one standard deviation labor supply shock (1979Q1-1999Q4)



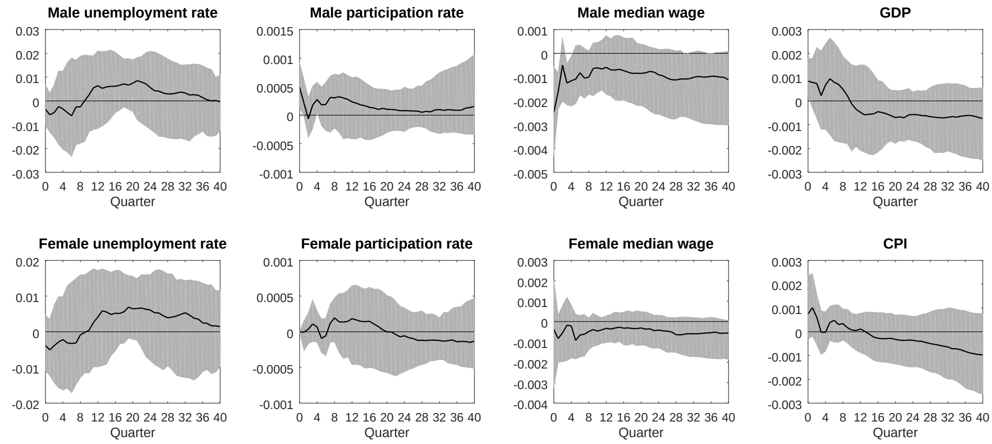
(b) IRFs to a one standard deviation labor supply shock (2000Q1-2019Q2)

Figure A16: IRFs to a one standard deviation labor supply shock – Sample split

Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.



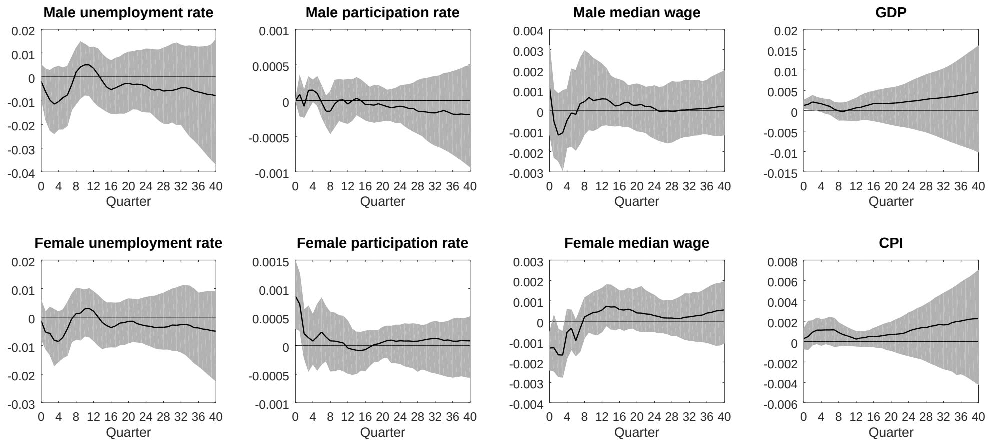
(a) IRFs to a one standard deviation male-specific labor supply shock (1979Q1-1999Q4)



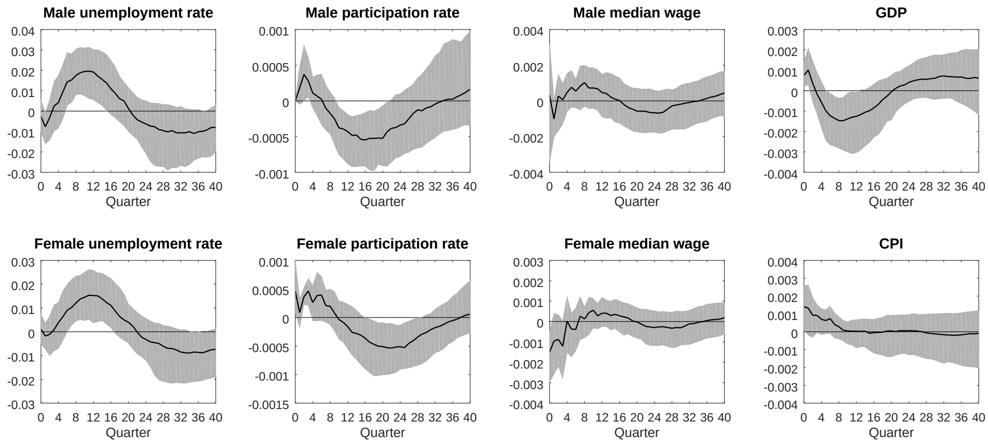
(b) IRFs to a one standard deviation male-specific labor supply shock (2000Q1-2019Q2)

Figure A17: IRFs to a one standard deviation male-specific labor supply shock – Sample split

Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.



(a) IRFs to a one standard deviation female-specific labor supply shock (1979Q1-1999Q4)



(b) IRFs to a one standard deviation female-specific labor supply shock (2000Q1-2019Q2)

Figure A18: IRFs to a one standard deviation female-specific labor supply shock – Sample split
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

B Smaller model of Foroni et al. (2018)

In Table B1, we present a smaller model using the same shocks as in Foroni et al. (2018). We interpret in our smaller model thus four instead of six shocks. To be precise, we identify aggregate demand, technology, wage bargaining and aggregate labor supply shocks, but we do not consider gender-specific labor supply shocks. In the smaller model, we have thus four shocks that we do not interpret.

Observe that additionally to the series in Foroni et al. (2018), we still have gender-specific series (unemployment rates, labor force participation rates and wages) as variables to be explained. For the general series (GDP and CPI) as well as the gender-specific series, we use the same sign restrictions as in the full model presented in Section 2. Note that this smaller model is based on the algorithm of Rubio-Ramirez et al. (2010) that is invariant to the ordering of the variables.

Table B1 presents the sign restrictions in line with Foroni et al. (2018, Table 1, p. 1494). Note that, again, we do not require a sign restriction of labor supply shocks on unemployment. Similarly, we need no sign restriction of wage bargaining shocks on female labor force participation. Therefore, in contrast to Foroni et al. (2018), we do not set a restriction in these cases. The results of the smaller model are shown in Figure B1-B4. The main insights do not change. As our analysis focuses one-time macroeconomic shocks on gender-specific variables, we present only the corresponding IRFs on male and female unemployment rates, participation rates, median wages as well as on the GPG.

Table B1: Restrictions on the multiplier matrix B, smaller model

Series ↓/Shocks→	(1) Demand	(2) Technology	(3) Wage bargaining	(4) Labor supply
GDP	+	+	+	+
CPI	+	-	-	-
Male unemployment rate	-	$*$	-	$*$
Female unemployment rate	-	$*$	-	$*$
Male LFP	$*$	$*$	-	+
Female LFP	$*$	$*$	$*$	+
Female wage	$*$	+	-	-
Male wage	$*$	+	-	-

Notes: +/- signs indicate that the effect of a shock is positive/negative on impact and $*$ denotes an unrestricted parameter. LFP = Labor Force Participation Rate.

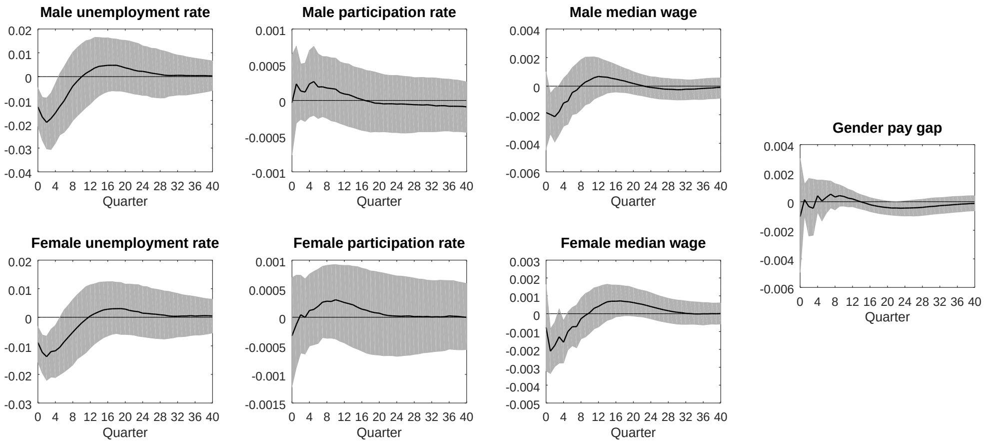


Figure B1: IRFs to a one standard deviation demand shock (1979Q1-2019Q2) – Smaller model
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

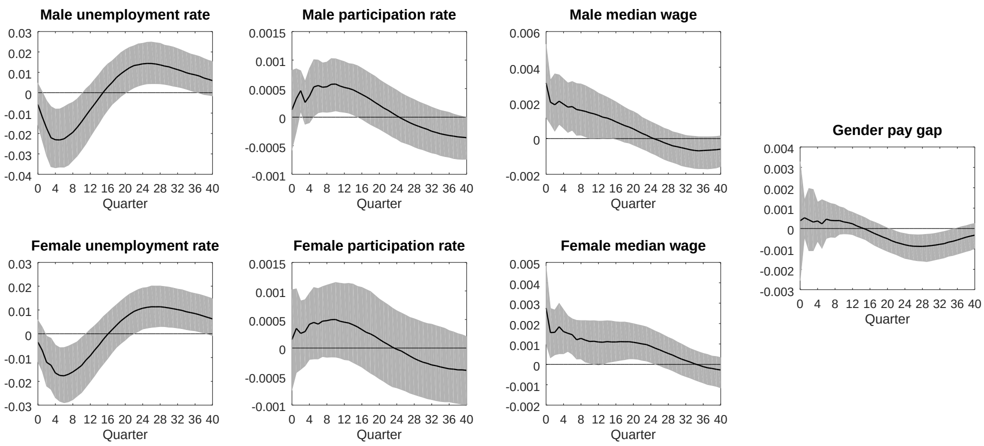


Figure B2: IRFs to a one standard deviation technology shock (1979Q1-2019Q2) – Smaller model
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

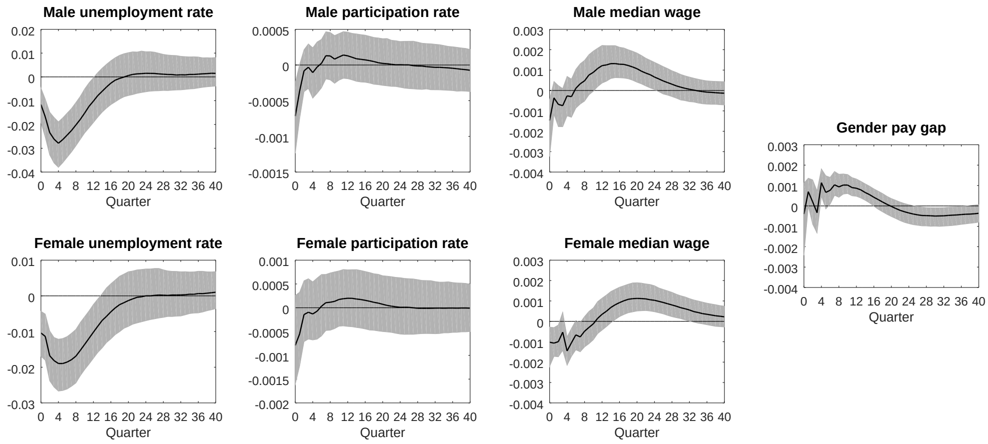


Figure B3: IRFs to a one standard deviation wage bargaining shock (1979Q1-2019Q2) – Smaller model
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

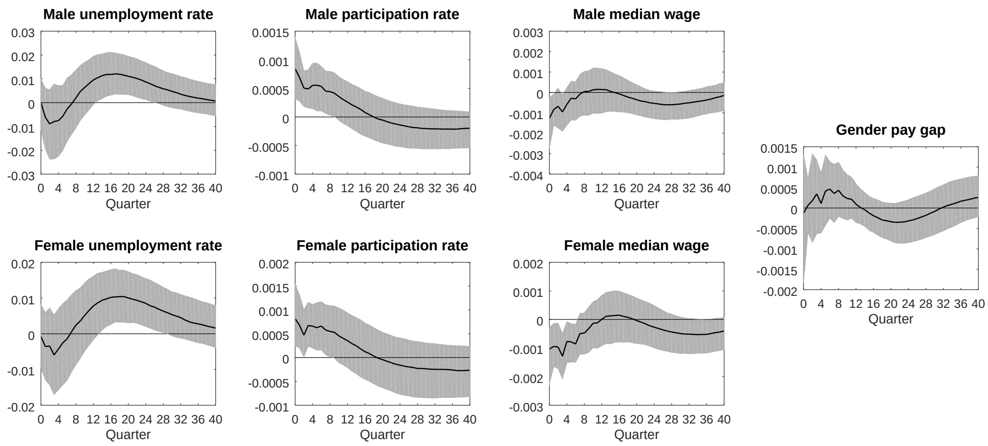


Figure B4: IRFs to a one standard deviation labor supply shock (1979Q1-2019Q2) – Smaller model
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

C No restriction on GDP after a wage bargaining shock

One may argue that GDP does not necessarily increase after a wage bargaining shock. For instance, because of increased labor costs that may have either a negative or no effect on GDP. Therefore, we repeat the main analysis without a sign restriction on the effect of a wage bargaining shock on GPD.

The results are shown in Figures C1-C6. The main insights do not change. Again, we present only the corresponding IRFs of the shocks of main interest. That is, the IRFs on male and female unemployment rates, participation rates, median (log) wages and the GPG. We show these IRFs on the following shocks: aggregate demand, technology, wage bargaining, aggregate labor supply and gender-specific labor supply.

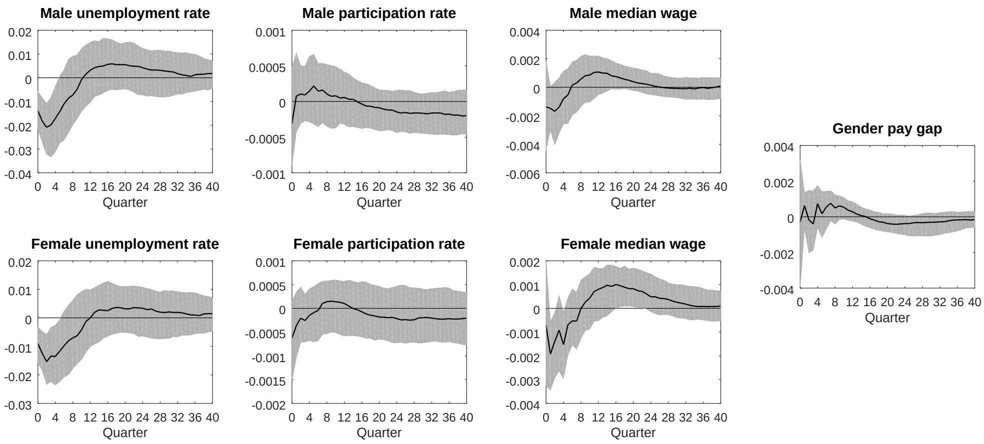


Figure C1: IRFs to a one standard deviation demand shock (1979Q1-2019Q2) – Model with no restriction on GDP after wage bargaining shock

Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

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Foroni, C., Furlanetto, F., and Lepetit, A., 2018, Labor supply factors and economic fluctuations. *International Economic Review*, 59(3), 1491-1510.

Rubio-Ramirez, J.F., Waggoner, D.F., and Zha, T., 2010, Structural vector autoregressions: Theory of identification and algorithms for inference. *The Review of Economic Studies*, 77(2), 665-696.

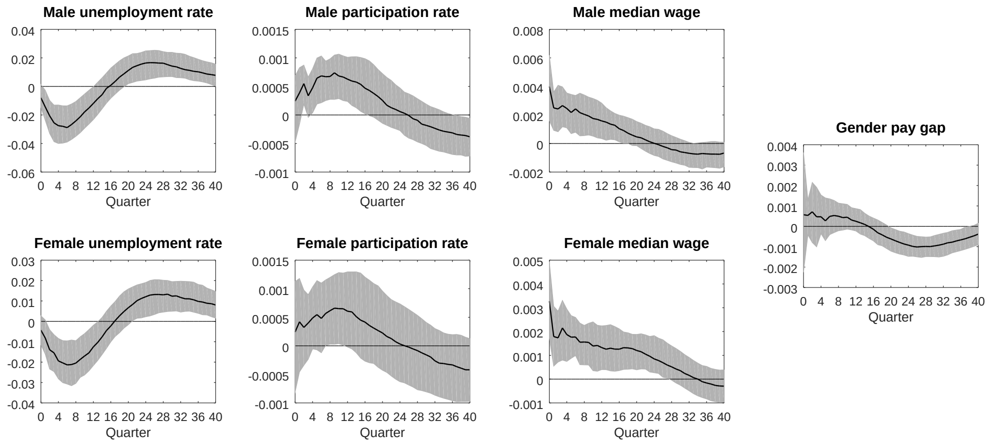

Figure C2: IRFs to a one standard deviation technology shock (1979Q1-2019Q2) – Model with no restriction on GDP after wage bargaining shock
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

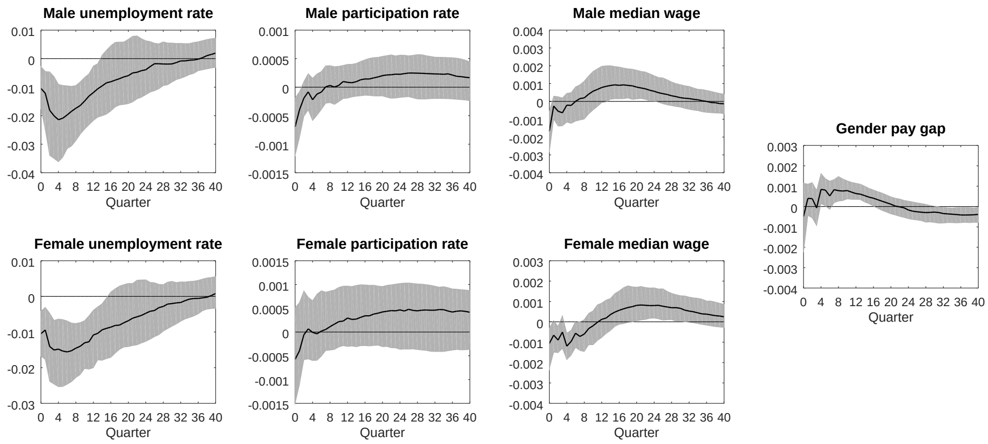

Figure C3: IRFs to a one standard deviation wage bargaining shock (1979Q1-2019Q2) – Model with no restriction on GDP after wage bargaining shock
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

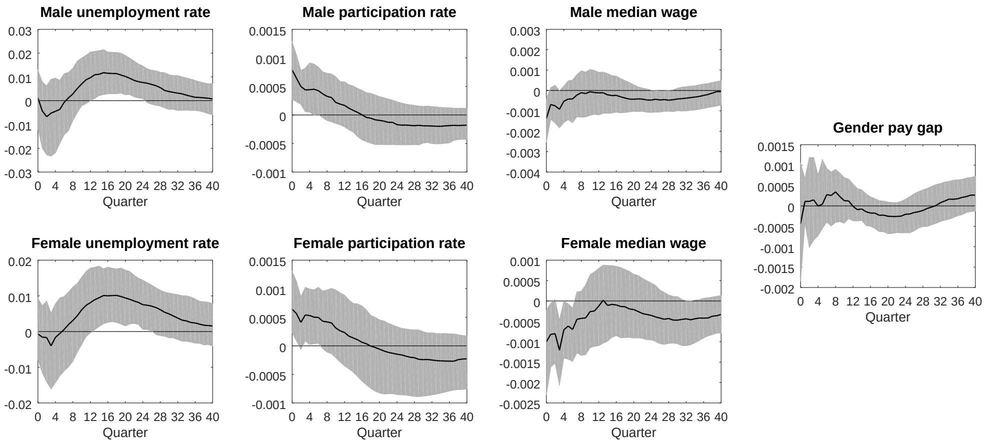

Figure C4: IRFs to a one standard deviation labor supply shock (1979Q1-2019Q2) – Model with no restriction on GDP after wage bargaining shock
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

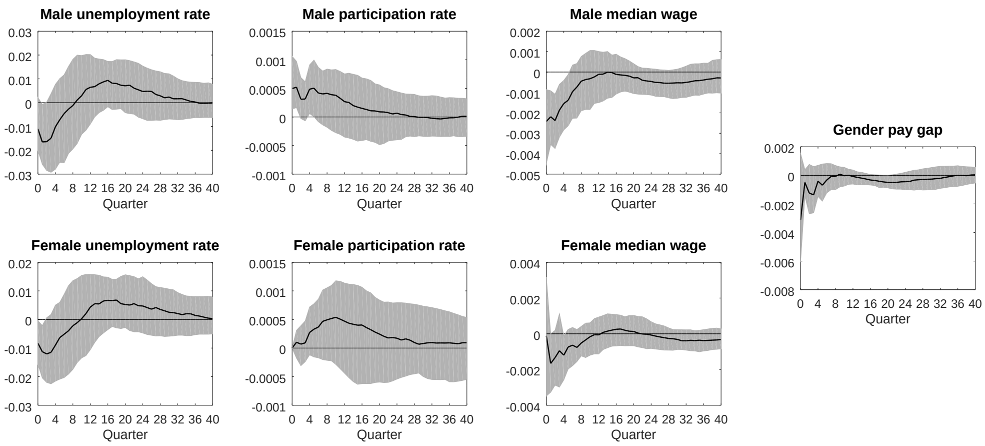

Figure C5: IRFs to a one standard deviation male-specific labor supply shock (1979Q1-2019Q2) – Model with no restriction on GDP after wage bargaining shock
Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.

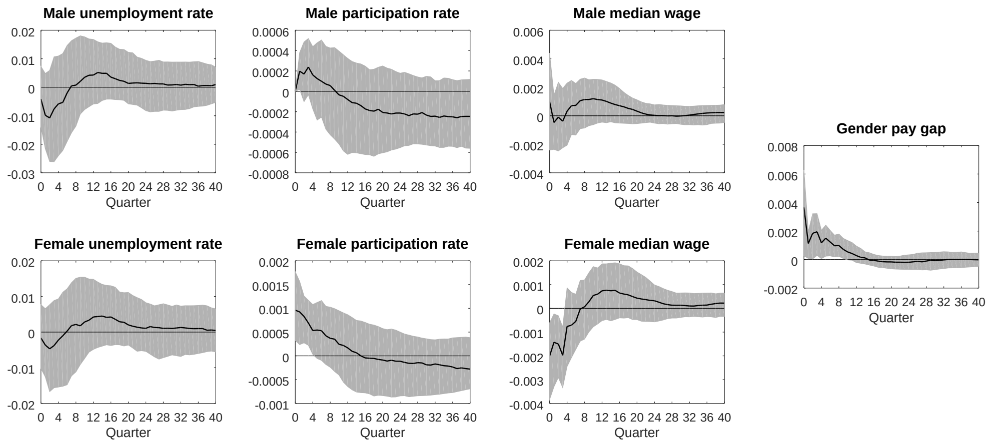

Figure C6: IRFs to a one standard deviation female-specific labor supply shock (1979Q1-2019Q2) – Model with no restriction on GDP after wage bargaining shock

Notes: The solid lines correspond to median responses, while gray shaded areas represent the 16th and 84th percentile of the posterior distribution, respectively.