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Age and Gender Differentials in Unemployment and Hysteresis*

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Abstract

We use a time-varying panel unobserved components model to estimate unemployment gaps disaggregated by age and gender. Recessions before COVID affected men's labor market outcomes more than women's; however, the reverse was true for the COVID recession, with effects amplified for younger workers. The aggregate Phillips curve flattens over time and hysteresis is countercyclical for all groups. We find heterogeneity in both the Phillips curve and hysteresis coefficients, with wages responding more to workers with an outside option (high school- and retirement-age) and larger effects of hysteresis for younger workers.
[JEL Codes: C32, E24]

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1 Introduction

Economists have long recognized fundamental differences in the labor market choices of men and women: in particular, their differences in education (Mincer and Ofek, 1982; Goldin et al., 2006); occupation (Polachek, 1981; Blau et al., 2013); and labor market participation (Becker, 1985; Burda et al., 2013; García-Mainar et al., 2011). Consequently, it may be important to consider these heterogeneities in evaluating how each gender's labor market experiences might vary over the business cycle. For example, the Great Recession affected men's labor market outcomes disproportionately more than women's, where, between 2007:IV to 2009:I, the unemployment rate for males rose from 4.9 percent to 8.9 percent and the rate for women rose from 4.7 percent to 7.2 percent. Much of this difference was attributed to differences in their chosen occupation: Two industries with the sharpest contractions were construction and manufacturing, both of which are male-dominated. On the other hand, industries where women are the majority—e.g., education and healthcare—are often deemed "recession-resistant."

And then came COVID-19. Industries viewed as the most vulnerable to COVID—either because they are high-contact, mandatory-attendance, or viewed as essential—also coincided, to a large extent, with the same industries that are majority-female. While the long-term effects of the entrenchment of the hybrid workforce on business cycle dynamics are as yet unknown, the COVID recession may have had different implications on male and female workers than previous recessions. In particular, the long "jobless recoveries" that followed the 1990, 2001, and 2008 recessions apparently did not occur following the COVID recession, as the unemployment shock was quickly reversed. This suggests that the unemployment hysteresis that might explain jobless recoveries either did not manifest or was quickly reversed.

The differences in unemployment rate dynamics by age have been well-documented—younger workers tend to have higher unemployment rates than older workers (Clark and Summers, 1981). With the aging of the Baby Boomers, the U.S. is experiencing an increase in the labor force participation of older workers (32.8% in 1980 to 40.2% in 2019 for workers 55+) and a decrease in younger workers (56.7% in 1980 to 35.3% in 2019 for workers 16-19 years old). Previous research focused on "correcting" estimates of the natural rate of unemployment for changing labor market shares (Perry et al., 1970); more recent work models age and gender changes directly by aggregating subgroups' natural rates (Crump et al., 2019; Hornstein and Kudlyak, 2019).

We document the demographic heterogeneity in workers' experiences across business cycles. Time-series models of the labor market experiences over the business cycle typically use the aggregate unemployment rate. However, modeling different genders and ages separately better accounts for the possibility that workers have different outside options—and, thus, different reservation wages—across their life cycles. For example, some might be secondary earners (Lundberg, 1985) or have school or retirement as outside options.

We estimate unemployment gaps jointly in a panel unobserved components model that incorporates both time-varying hysteresis and time-varying Phillips curve relationships. The labor market has undergone dramatic compositional changes (Aaronson et al., 2015), requiring time variation to capture the employment dynamics of the demographic subgroups. While we still estimate the policy-relevant aggregate unemployment gap, we also estimate the gaps for non-prime-age subgroups of both genders to capture the changing demographics of the labor force. Each of these groups have their own separately identifiable trend (natural rate) component and subgroup-specific, time-varying hysteresis effect. We exploit a time-varying wage Phillips curve to identify the natural rates of unemployment. All groups have an aggregate wage Phillips curve relationship and the age-gender subgroups have an additional time-varying effect of the cyclical unemployment gap relative to the aggregated cycle.

Because the COVID recession was sharper than past recessions, we estimate the model on two samples: (i) excluding COVID and (ii) a full sample that includes the COVID period. We find that the aggregate Phillips curve has flattened over time and varies across the business cycle with the coefficient being near zero during recessions. Additionally, we find heterogeneity across the subgroups with larger coefficients for subgroups with an outside option (high school- and retirement-age). We find that hysteresis is countercyclical, which helps explain jobless recoveries. Hysteresis also exhibits heterogeneity with larger effects for younger workers and smaller effects for older workers. When we estimate the model on the full sample, we see similarities in the estimated unemployment gaps relative to the previous sample. The time-varying nature of the model allows it to capture the uniqueness of the COVID recession. Unlike previous recessions, the Phillips curve coefficient during the COVID recession was large and positive, which is indicative of the unequal effect across industries. Additionally, during COVID, hysteresis appears to have affected women more than men, unlike in previous recessions.

The balance of the paper is as follows: Section 2 outlines the empirical model; Section 3 describes the data and the estimation; Sections 4 and 5 present the results for the sample truncated before and including COVID, respectively; and Section 6 concludes.

2 Setup

To capture the interaction between a gender-age subgroup's wage and unemployment gap, we assume that each gender-age subgroup has its own separately identifiable (trend) natural rate of unemployment. Each natural rate of unemployment is subject to its own (demographic-specific) hysteresis, where a portion of the subgroup's cyclical unemployment becomes permanent.

Consistent with other papers [e.g., Anderson et al. (2005) (henceforth ABB)], each subgroup's cyclical unemployment rate exerts pressure on its own wage growth, forming the basis for a wage Phillips curve. However, unlike ABB, we also allow *market* labor slack to exert wage pressure—that is, a subgroup's wage growth is a function of *both* the aggregate cyclical unemployment rate and the subgroup-specific cyclical unemployment rate.[1]

We differentiate between (both gender's) prime-age workers and other gender-age subgroups. Because the labor market is dominated by prime-age workers (in 2020, prime-age workers accounted for 65 percent of the U.S. population and 63.8 percent of the labor force), we assume that prime-age workers—male or female—have identical cyclical components to the aggregate.[2] Thus, our model consists of an aggregate unemployment equation, unemployment

[1] In their model, ABB include only the subgroup cyclical unemployment rate in that group's wage equation.

[2] While there may be small differences between the aggregate and prime-age cycles, these differences are

equations for non-prime-age workers of each gender, and wage equations for the aggregate and the subgroups.

To save on notation, we describe a model with (ungendered) prime-age workers (p) and one non-prime-age (np) worker group that can be thought of (generically) as any gender-age subgroup. Extension to the more general model that we estimate below is straightforward. Other non-prime groups will have the same basic DGP as the single non-prime-age group described here.

Each unemployment rate can be decomposed into a trend, u_t^N, and stationary cycle, u_t^C:

$$
\begin{aligned}
u_t &= u_t^N + u_t^C, \\
u_{p,t} &= u_{p,t}^N + u_{p,t}^C, \\
u_{np,t} &= u_{np,t}^N + u_{np,t}^C,
\end{aligned}
$$

where, as noted above, we assume that $u_t^C = u_{p,t}^C$. Each trend is assumed to follow a driftless unit root process:

$$
\begin{aligned}
u_t^N &= u_{t-1}^N + \alpha_t u_{t-1}^C + \varepsilon_t^N, \\
u_{np,t}^N &= u_{np,t-1}^N + \alpha_{np,t} u_{np,t-1}^C + \varepsilon_{np,t}^N,
\end{aligned}
$$

where the second term in each equation ($\alpha_t u_{t-1}^C$ or $\alpha_{np,t} u_{np,t-1}^C$) represents possible time-varying hysteresis, $\varepsilon_t^N \sim N\left(0, \sigma_N^2\right)$, and $\varepsilon_{np,t}^N \sim N\left(0, \sigma_{np,N}^2\right)$. We do not explicitly characterize the prime-age natural rate evolution but assume that any difference between each gender's prime-age unemployment rate and the aggregate rate is solely attributable to differences in their natural rates.

We allow for demographic-specific and time-varying hysteresis terms, α_t and $\alpha_{np,t}$. Thus,

sufficiently small that they affect separate identification of a prime-age Phillips curve parameter. We verified this by comparing separately estimated trend-cycle decompositions for aggregate and prime-age unemployment rates. Thus, to facilitate identification, we assume these two cyclical components are equal at the outset.

any group's cyclical unemployment rate affects their (future) trend unemployment rate. While the motivation for estimating hysteresis effects tends to be around periods of high unemployment (Blanchard and Summers, 1986; Blanchard, 2018), we do not take a one-sided stance on the effect (such as a threshold or a Markov-switching approach) and allow for the possibility of hysteresis increasing or decreasing trend similar to the idea of "reverse hysteresis" (Yellen, 2016).

We have just two cycle equations:

$$
\begin{aligned}
u_t^C &= \phi(L)\, u_{t-1}^C + \varepsilon_t^C, \\
u_{np,t}^C &= \phi_{np}(L)\, u_{np,t-1}^C + \varepsilon_{np,t}^C,
\end{aligned}
$$

where we assume that each $\phi_i(L)$ is of order $P > 1$ and has roots inside the unit circle, $\varepsilon_t^C \sim N\left(0, \sigma_C^2\right)$, and $\varepsilon_{np,t}^C \sim N\left(0, \sigma_{np,C}^2\right)$. We assume at the outset that the cycle innovations are contemporaneously uncorrelated.[3]

There are a number of ways of identifying the natural rate of unemployment. Often, the natural rate is defined as the steady-state unemployment rate, identified either through its effect on output (via an Okun's law-type relationship) or inflation (via a Phillips curve-type relationship). Neither of these relationships is useful for differentiating across demographic subgroups as we cannot identify the influence of each subgroup's effect on output or consumer prices. Instead, we exploit the relationship between cyclical unemployment and wage growth:

$$
\begin{aligned}
w_t &= \beta w_{t-1} + \delta_t u_{t-1}^C + \varepsilon_t^w, \\
w_{np,t} &= \beta_{np} w_{np,t-1} + \delta_t u_{t-1}^C + \delta_{np,t}\left(u_{np,t-1}^C - u_{t-1}^C\right) + \varepsilon_{np,t}^w,
\end{aligned}
$$

where $\varepsilon_t^w \sim N\left(0, \sigma_W^2\right)$, $\varepsilon_{np,t}^w \sim N\left(0, \sigma_{np,W}^2\right)$, and, because we have assumed $u_t^C = u_{p,t}^C$, the

[3]See Morley et al. (2003) for what allowing cross-component correlations does to the identification of the cycles.

equation for $w_{p,t}$ becomes essentially irrelevant.

Tightness in the aggregate labor market influences each subgroup's wages through a standard Phillips curve relationship reflected in the second term. Note that this effect is the same across all subgroups. Tightness in the subgroup labor market affects its own wages via the third term. The effect of the subgroup's labor market tightness on its wages is determined by its cycle relative to the aggregate cycle. Therefore, the subgroup's labor market tightness has an effect only when their own cycle differs from the aggregate cycle.

We allow both of these terms to vary over time. Time variation in the aggregate Phillips curve relationship (δ_t) is consistent with recent research finding that the Phillips curve has become flatter (see Galí and Gambetti (2019) for a review). Allowing for the demographic groups' Phillips curve coefficient to change over time recognizes the heterogeneity in demographic labor experiences (Perry et al., 1970; Summers et al., 1986).

The time-varying parameters, α_t, α_{it}, δ_t and δ_{it}, evolve as driftless unit roots, with variances σ_a^2, σ_{ia}^2, σ_d^2, and σ_{id}^2, respectively.

3 Empirical Approach

3.1 Data

The data used to estimate the model are the unemployment rates and year-over-year wage inflation rates. We use both national data and data for age-gender combinations obtained from the Bureau of Labor Statistics's (BLS) Current Population Survey (CPS). We consider non-prime-age groups by gender. Specifically, we include ages 16-19 (high school), 20-24 (college), 55-64 (pre-retirement), and 65 and older (retirement) for men and women. The unemployment rates are seasonally-adjusted and averaged across the quarter to match the wages. The wage data are seasonally-adjusted nominal median usual weekly earning for full-time workers.

The COVID recession was unlike previous recessions in term of depth (11.2 percentage points change in the unemployment rate during the COVID recession compared to an average change of 2.4 percentage points in the previous five recessions) and duration (3 months compared to an average of 12.2 months for the previous five recessions). Moreover, the recession occurred at the end of the sample. Both of these issues could lead to imprecision of the trend and cycle estimates (Staiger et al., 1997; Orphanides and Norden, 2002). Therefore, we estimate the model for two samples: (1) the pre-COVID sample from 1980:I to 2019:IV and (2) the full sample from 1980:I to 2022:I which includes the COVID recession.

3.2 Estimation

The model is estimated using MCMC and requires priors for most of the model parameters. The full set of priors and the prior hyperparameters are summarized in Table 1. In addition, we will treat the starting values of the latent series (the cycle terms) as parameters. The priors for each subgroups' cyclical AR parameters and the AR parameters in the Phillips curve equations are normal. Priors for the starting values of the latent series are also normal. Variances for innovations are assumed to be orthogonal and have inverse gamma priors.

Table 1: Priors for Estimation

Based on the prior, much of the algorithm is a straightforward application of the Gibbs sampler with conjugate priors. The algorithm partitions the set of model parameters into 5 blocks: (1) the natural rates and cycles for each subgroup, $\left[u_t^N, u_{np,t}^N, u_t^C, u_{np,t}^C\right]'$ for $t = 1, ..., T$; (2) the time-varying hysteresis and Phillips-curve coefficients, $[\alpha_t, \alpha_{np,t}, \delta_t, \delta_{np,t}]'$ for $t = 1, ..., T$; (3) the AR parameters in the Phillips curves, $[\beta, \beta_{np}]$; (4) the AR coefficients in the transition function, Φ; and (5) the variances of the natural rates, cycles, and time-varying Phillips-curve coefficients, $\left[\sigma_N^2, \sigma_{np,N}^2, \sigma_C^2, \sigma_{np,C}^2, \sigma_d^2, \sigma_{np,d}^2\right]$. In order to identify the scale of the cycles separately from the natural rates, we fix $\sigma_a^2 = \sigma_{np,a}^2 = 0.1$ and, therefore, do not draw the variances of the hysteresis terms.[4]

The natural rates and cycles are drawn from the Kalman filter posteriors. The disaggregate model with time-varying parameters requires two state space representations: one for the natural rate and one for the time-varying parameters. Conditional on the values of the

[4]Del Negro and Otrok (2008) argue that the prior for the time-varying parameter innovations should be tight with means very close to zero.

time-varying parameters, the state space for the natural rate is comprised of a measurement equation:

$$\begin{bmatrix} \Delta u_t \\ \Delta \mathbf{u}_{np,t} \\ w_t - \beta w_{t-1} \\ \mathbf{w}_{np,t} - \beta_{np} \mathbf{w}_{np,t-1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & \alpha_t - 1 & 0 \\ \mathbf{0} & \mathbf{1} & \mathbf{0} & \alpha_{np,t} - \mathbf{1} \\ 0 & 0 & \delta_t & 0 \\ \mathbf{0} & \mathbf{0} & \delta_t \mathbf{I} - vec\left(\delta_{np,t}\right) & vec\left(\delta_{np,t}\right) \end{bmatrix} \begin{bmatrix} u_t^C \\ \mathbf{u}_{np,t}^C \\ u_{t-1}^C \\ \mathbf{u}_{np,t-1}^C \end{bmatrix} + \begin{bmatrix} \varepsilon_t^N \\ \varepsilon_{np,t}^N \\ \varepsilon_t^w \\ \varepsilon_{np,t}^w \end{bmatrix},$$

where we assume that the measurement equation covariance matrix is diagonal. The transition equation is:

$$\begin{bmatrix} u_t^C \\ \mathbf{u}_{np,t}^C \\ u_{t-1}^C \\ \mathbf{u}_{np,t-1}^C \end{bmatrix} = \begin{bmatrix} \phi_1 & 0 & \phi_2 & 0 \\ \mathbf{0} & \phi_{np,1} & \mathbf{0} & \phi_{np,2} \\ 1 & 0 & 0 & 0 \\ \mathbf{0} & \mathbf{I} & \mathbf{0} & \mathbf{0} \end{bmatrix} \begin{bmatrix} u_{t-1}^C \\ \mathbf{u}_{np,t-1}^C \\ u_{t-2}^C \\ \mathbf{u}_{np,t-2}^C \end{bmatrix} + \begin{bmatrix} \varepsilon_t^C \\ \varepsilon_{np,t}^C \\ 0 \\ \mathbf{0} \end{bmatrix}$$

where we assume the transition equation covariance matrix is diagonal.

Conditional on these initial values and the draws of the natural rates and cycles, the time-varying parameters are also drawn from Kalman filter posteriors. The state space for the time-varying parameters has measurement and transition equations of the form:

$$\begin{bmatrix} \Delta u_t - u_t^C + u_{t-1}^C \\ \Delta \mathbf{u}_{np,t} - \mathbf{u}_{np,t}^C + \mathbf{u}_{np,t-1}^C \\ w_t - \beta w_{t-1} \\ \mathbf{w}_{np,t} - \beta_{np} \odot \mathbf{w}_{np,t-1} \end{bmatrix} = \begin{bmatrix} u_{t-1}^C & 0 & 0 & 0 \\ \mathbf{0} & vec\left(\mathbf{u}_{np,t-1}^C\right) & \mathbf{0} & \mathbf{0} \\ 0 & 0 & u_t^C & 0 \\ \mathbf{0} & \mathbf{0} & vec\left(\mathbf{u}_t^C\right) & vec\left(\mathbf{u}_{np,t}^C\right) - u_t^C \mathbf{I} \end{bmatrix} \begin{bmatrix} \alpha_t \\ \alpha_{np,t} \\ \delta_t \\ \delta_{np,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_t^N \\ \varepsilon_{np,t}^N \\ \varepsilon_t^w \\ \varepsilon_{np,t}^w \end{bmatrix}$$

and

$$\begin{bmatrix} \alpha_t \\ \alpha_{np,t} \\ \delta_t \\ \delta_{np,t} \end{bmatrix} = \begin{bmatrix} \alpha_{t-1} \\ \alpha_{np,t-1} \\ \delta_{t-1} \\ \delta_{np,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_t^a \\ \varepsilon_{np,t}^a \\ \varepsilon_t^d \\ \varepsilon_{np,t}^d \end{bmatrix}.$$

The initializations for the $\alpha's$ and $\delta's$ are treated as parameters, drawn from normal posterior distributions, conditional on their priors. The conditioning in these two quasi-linear steps is similar to the draws of latent factors and time-varying loadings described in Del Negro and Otrok (2008). The innovation variances are conjugate inverse gamma and the AR parameters are conjugate normal.

The sampler is then executed for 10,000 iterations after discarding the first 5,000 before forming the joint posterior. We choose two lags for the AR dynamics of the cycles (i.e., $P = 2$).

4 Pre-Covid Results

The size of the shock associated with the COVID shutdowns of 2020 may affect the overall results. Thus, we first analyze the results for the sample through the end of 2019. We then consider the full sample that includes the COVID period and the subsequent recovery.

4.1 Cyclical Components

Figure 1: Cycles

We decompose the data as described in Section 3.1 and obtain trends and cycles for the unemployment rates. Figure 1 graphs the cycles for all subgroups with the male non-prime-age workers in the left graph and the females on the right. The black line in both graphs is the aggregate unemployment cycle. Overall, we can see that all the cycles follow a familiar pattern of increasing during recessions and decreasing during expansions. Additionally, we see evidence of jobless recoveries in the 1990, 2001, and 2007 recessions with the cyclical unemployment rate staying positive during the beginning of the expansion (Engemann and Owyang, 2010; Panovska, 2017).

Men's cycles are generally more volatile than the female's cycles. This is consistent with the previous literature that finds that men experience higher unemployment rates during recessions but also have faster recoveries compared to women (Wall, 2009; Hoynes et al., 2012). Finally, the average magnitudes of the peaks and troughs vary across age groups. We find that cycles for younger workers are more volatile than older workers, which is a pattern consistent with the literature (Perry et al., 1970; Clark and Summers, 1981).

4.2 Time-varying Phillips Curve Coefficients

Figure 2: Time-varying Phillips Curve Coefficients

Figure 2 plots the Phillips curve coefficients. The negative coefficient implies that a decrease in last quarter's cyclical unemployment increases wage growth. The left panel shows how the national Phillips curve coefficient varies across the business cycle—becoming very close to zero during recessions and increasing in magnitude during expansions. The range of values (from basically 0 to -0.5) matches estimates from the existing literature that often assumes a constant coefficient.[5]

Prior to the Great Recession, the Phillips curve appears to flatten (Galí and Gambetti, 2019)—that is, the coefficient during successive expansions appears to decrease in magnitude. After the Great Recession, however, wages appear to be more responsive to labor market tightness.[6] The response of wages across the business cycle appear asymmetric (Donayre and Panovska, 2016). During recessions, the coefficient is near zero, suggesting downward nominal wage rigidities bend the short-run Phillips curve (Daly and Hobijn, 2014).

The middle and right panels show the non-prime-age male and female workers' coefficients, respectively. Recall that these coefficients are on the difference between the subgroup unem-

[5]Del Negro et al. (2015) argue the Phillips curve is basically flat, while Kumar and Orrenius (2016) find a slope of -0.55.

[6]This finding might suggest that the magnitude of the previous recession determines the steepness of the Phillips curve. This might be consistent with recent findings that wage changes are larger when workers change jobs (Grigsby et al., 2021).

ployment rate and the aggregate unemployment rate. For the most part, these coefficients are negative, suggesting that demographic-specific labor market tightness puts additional upward pressure on wages. This effect is most pronounced for high school-aged men; however, high school- and retirement-age (65+) subgroups of either gender have relatively large coefficients for at least some portion of the sample. These groups also have the most obvious outside options (school or retirement, respectively), which might explain why their wages are more responsive to labor market conditions. High school- and college-aged women do not see a weakening of the Phillips curve over time (Galí and Gambetti, 2019); instead, their wages are more sensitive to changes in unemployment. Younger women may be less attached to the labor market and more responsive to changes in wages and/or have education as an outside option.

4.3 Time-varying Hysteresis

Figure 3: Time-varying Hysteresis

Figure 3 plots the time-varying hysteresis coefficient (solid line, left axes) for the national/prime-age data (top), male subgroups (left column) and female subgroups (right column). Three features are readily apparent. The labor hysteresis coefficient: (i) is non-zero for all periods; (ii) is countercyclical; and (iii) exhibits heterogeneity across some subgroups. In particular, hysteresis is greater than average for the younger demographics (more for men than for women) and smaller than average for older demographics (for both men and women). Additionally, hysteresis is greater during deeper recessions (1981-82 and the Great Recession).

Previous studies found little evidence for hysteresis in the U.S. (Blanchard, 2018) or only during large economic downturns such as the Great Recession (Benati and Lubik, 2021; Cho and Rho, 2019). However, much of the previous research models hysteresis as a constant or tests for hysteresis using unit root tests.[7] Both of these require the hysteresis effect to be present and large for most of the sample. Compared to the constant parameter model, the

[7]In some of these papers, hysteresis is defined in goods markets rather than in labor markets. Specifically, hysteresis is the component of short-run aggregate demand shocks that eventually shift the aggregate supply curve.

larger hysteresis effects are concentrated during periods of recession. Thus, allowing for time variation in the hysteresis coefficient is important to identify the effect.

Time-varying hysteresis may also help explain jobless recoveries (Engemann and Owyang, 2010; Panovska, 2017). Adverse shocks to the cyclical unemployment rate increase the cyclical component of the unemployment rate but also, subsequently, increase the trend. Over time, this adverse shock filters out of the cycle's AR process, but leaves the trend at a (permanently) higher level. An increase in the hysteresis coefficient during recessions implies that the cycle has a larger effect on the trend during recessions (when the cyclical component of unemployment is positive) than during expansions (when the cyclical component of unemployment is negative). Consequently, hysteresis is more effective at increasing trend unemployment than decreasing it (the so-called "reverse hysteresis" effect (Yellen, 2016)).

The U.S. labor market has witnessed dramatic changes in composition (Aaronson et al., 2015); we investigate variation in hysteresis by gender-age groups. Figure 3 shows that the hysteresis coefficient is largest for high school- and college-aged men (especially during the Great Recession). Older men and women have more muted effects. Figure 3 (dashed line, right axes) also highlights the total effect of hysteresis ($\alpha_{k,t}U^C_{k,t}$) on the trend for each group, k. The smaller effect of hysteresis on the older population is consistent with labor-hoarding of the experienced workforce (less likely to be displaced) and the outside option to retire (if displaced) (Chéron et al., 2013). Based on these results, age appears to be more important than gender in explaining hysteresis. This is in contrast to previous work that found gender differences in hysteresis in OECD countries (Bakas and Papapetrou, 2014) once they allow for structural breaks. However, this paper used a different technique (panel unit root tests), region (OECD), and decomposition (gender only) for estimating hysteresis.

5 The COVID-19 Recession and Recovery

As mention above, one of the more pervasive narratives on the demographic composition of the business cycle is that men are often the losers from recession (Wall, 2009; Hoynes et al., 2012). One striking difference for the COVID recession (apart from its large magnitude) is that the industries that were most affected are majority female-employed. In this section, we highlight the differences in both the national and demographic subgroup results when we include the COVID recession and subsequent recovery.

5.1 Cycles

Figure 4: Cycles, Full Sample

Figure 4 plots the cycles for the full sample that includes the COVID period, with the male non-prime age groups in the left panel and the females on the right panel. The COVID recession was sharp compared to the previous recessions; however, the unemployment cycles follow the familiar pattern: positive during recessions and negative during expansions. By the end of the sample, many subgroups have recovered. This is because the hysteresis allows the cyclical component to fall faster than a model without hysteresis.

The COVID recession had a larger effect on women than men, a difference from previous recessions. While younger workers generally have higher cyclical unemployment, only college-aged men had higher cyclical unemployment than the aggregate. High school-, college-, and retirement-aged women experienced more cyclical unemployment than the aggregate during COVID. This outsized effect on women is also seen in the slower recovery at the end of the sample. These results are similar to the literature that found larger effects of the COVID recession on women and younger workers (Lee et al., 2021; Albanesi and Kim, 2021).

5.2 Time-Varying Phillips Curve Coefficients

Figure 5: Time-Varying Phillips Curve Coefficients, Full Sample

The estimate of the national (prime-age) Phillips curve coefficient in the left panel of Figure 5 exhibits two main features during the COVID recession and recovery: (i) at the outset of the pandemic, the coefficient spikes positive and relatively large (nearly twice as large in magnitude as any other period) and (ii) soon after the onset of the recession, the coefficient spikes negative until the end of the sample. The large, positive Phillips curve coefficient is likely caused by wages continuing to rise in a time of slack and may be indicative of the composition changes in the labor force during first months of the pandemic.[8] Unlike previous recessions, job losers during COVID were disproportionately low-wage workers (service industry); some higher-wage workers could more easily transition to working from home (Albanesi and Kim, 2021; Dingel and Neiman, 2020).

The center and right panels of Figure 5 show the heterogeneity across the demographic groups. Generally, younger groups, regardless of gender, have Phillips curve coefficients that reinforce the national coefficient. That is, high school- and college-age workers had more responsive wages than prime-age workers, albeit in a direction opposite of what we would think of as normal. Older men's wages, on the other hand, had a more muted response, while older women's wages were essentially the same as their prime-age counterparts.

5.3 Hysteresis

Figure 6: Time-varying Hysteresis, Full Sample

Figure 6 depicts the same information as Figure 3 but includes the COVID sub-sample. The sharpness of the COVID recession and the subsequent recovery have similarly dramatic effects on the hysteresis coefficient. The aggregate (prime-age) hysteresis coefficient rises just prior to the recession and falls precipitously at the onset of the downturn before recovering slightly. This fall of the hysteresis coefficient during the recession is inconsistent with a jobless recovery, as the unemployment rate fell by 50 percent in the six months following the trough. The total effect of hysteresis on the trend (dashed line, right axes) is near zero by the end of the sample. This indicates that there are no lingering effects of the Covid recession on the trend unemployment rate.[9]

While there is heterogeneity in the magnitudes of the hysteresis effect by demographic, the peak-reversal pattern is preserved for all of the groups except high school-aged males. For most non-prime groups, the hysteresis component is increasing by the end of the sample but

[8] Recall also that a number of states enacted increases in the minimum wage in 2019 and 2020.

[9] The narrative around hysteresis is often negative (about increases in the trend). However, hysteresis in times when the unemployment gap is negative could eventually lead to a lower trend unemployment rate (Yellen, 2016).

still below its long run average. Hysteresis affected women more than men during the COVID recession, consistent with the finding that majority-female industries were more heavily affected (Albanesi and Kim, 2021). The effect of hysteresis during COVID was the largest for younger women (high school- and college-aged) who may have worked in contact-intensive industries such as hospitality, education, or medicine. For these groups, the effect of hysteresis was also quickly reversed.

6 Conclusion

We examine various demographic groups for the presence of hysteresis in the unemployment rate. We estimate a time-varying panel unobserved components model, assuming *ex ante* that the cyclical component for prime-aged workers (of any gender) is essentially equal to the national cycle. This assumption allows us to estimate the model jointly for a number of demographic groups, assuming each groups wage dynamics are affected by the national cycle and the group's deviation from the national cycle.

We confirm evidence from past studies which argue that, before COVID, recessions affected men's labor market outcomes more than women's (Wall, 2009; Hoynes et al., 2012). On the other hand, we document that COVID affected women more than men. In addition, we find that these effects are amplified for young men and, respectively, young women during the COVID recession. The main source of demographic heterogeneity is across age groups, with high school- and college-aged men and women having different outcomes from their older counterparts.

Similar to previous studies, we find the Phillips curve flattening over time (Galí and Gambetti, 2019). Our estimates of the aggregate Phillips curve coefficient varies across the business cycle and is consistent with wage rigidities. In our estimates, the effect of hysteresis is countercyclical, which helps explain jobless recoveries. We find heterogeneities for both the Phillips curve and hysteresis coefficients with wages more responsive to workers with an outside option (high school- and retirement-age) and larger effects of hysteresis for younger workers workers.

Table 1: Priors for Estimation		
Parameter	Prior Distribution	Hyperparameters
$\sigma_N^2, \sigma_{np,N}^2$	$\Gamma^{-1}\left(\frac{v_{N0}}{2}, \frac{\delta_{N0}}{2}\right)$	$v_{N0} = 100$; $\delta_{N0} = 0.01$
$\sigma_C^2, \sigma_{np,C}^2$	$\Gamma^{-1}\left(\frac{v_{C0}}{2}, \frac{\delta_{C0}}{2}\right)$	$v_{C0} = 10$; $\delta_{C0} = 0.1$
β	$N\left(\mu_\beta, \Lambda_\beta\right)$	$\mu_\beta = 0.9$; $\Lambda_\beta = 0.01$
Φ	$N\left(\mu_\Phi, \Lambda_\Phi\right)$	$\mu_\Phi = [0.8, 0.1]'$; $\Lambda_\Phi = 0.01 I_P$
$\alpha_0, \alpha_{np,0}$	$N\left(0, \omega_\alpha^2\right)$	$\omega_\alpha^2 = 10$
$\delta_0, \delta_{np,0}$	$N\left(\mu_\delta, \omega_d^2\right)$	$\mu_\delta = -1$; $\omega_d^2 = 10$
$\sigma_a^2, \sigma_{np,a}^2$	Fixed at 0.1	–
$\sigma_d^2, \sigma_{np,d}^2$	$\Gamma^{-1}\left(\frac{v_{d0}}{2}, \frac{\delta_{d0}}{2}\right)$	$v_{d0} = 1000$; $\delta_{d0} = 0.01$

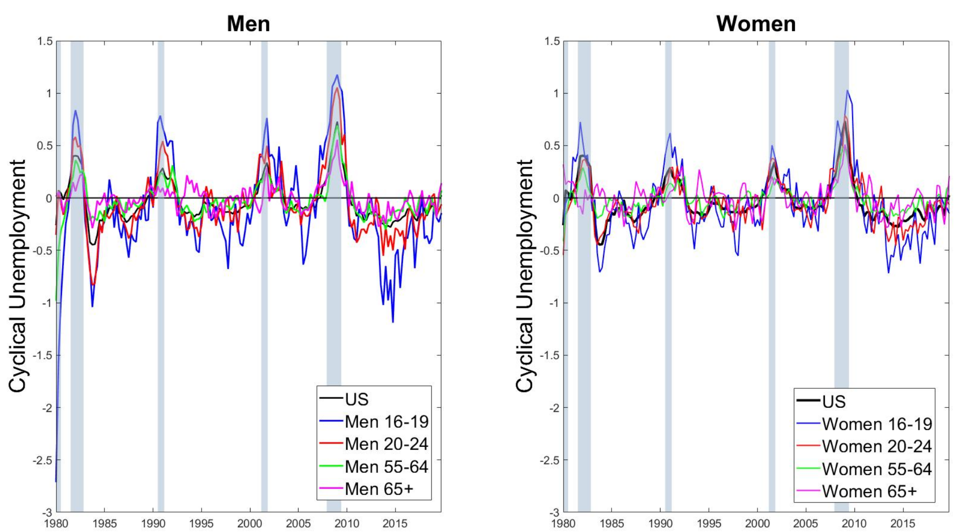

Figure 1: Posterior mean estimates of the cyclical components of the U.S. aggregate unemployment rate and the unemployment rate for each age-gender subgroup. The data span the period from 1980:I through 2019:IV.

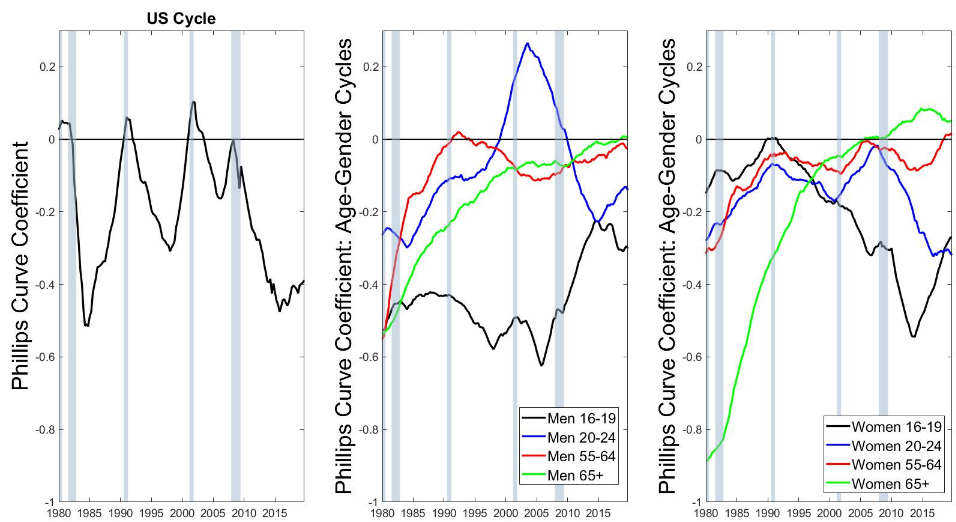

Figure 2: Posterior mean estimates of the time-varying Phillips curve coefficients on the U.S. aggregate cycle and on the deviation of the cycle for each age-gender subgroup from the aggregate cycle. The left panel displays the coefficient on the aggregate cycle that is consistent across all Phillips curve relationships. The middle and right panels display the male and female subgroup coefficients, respectively, which apply to how each demographic's cycle uniquely deviates from the aggregate cycle. The data span the period from 1980:I through 2019:IV.

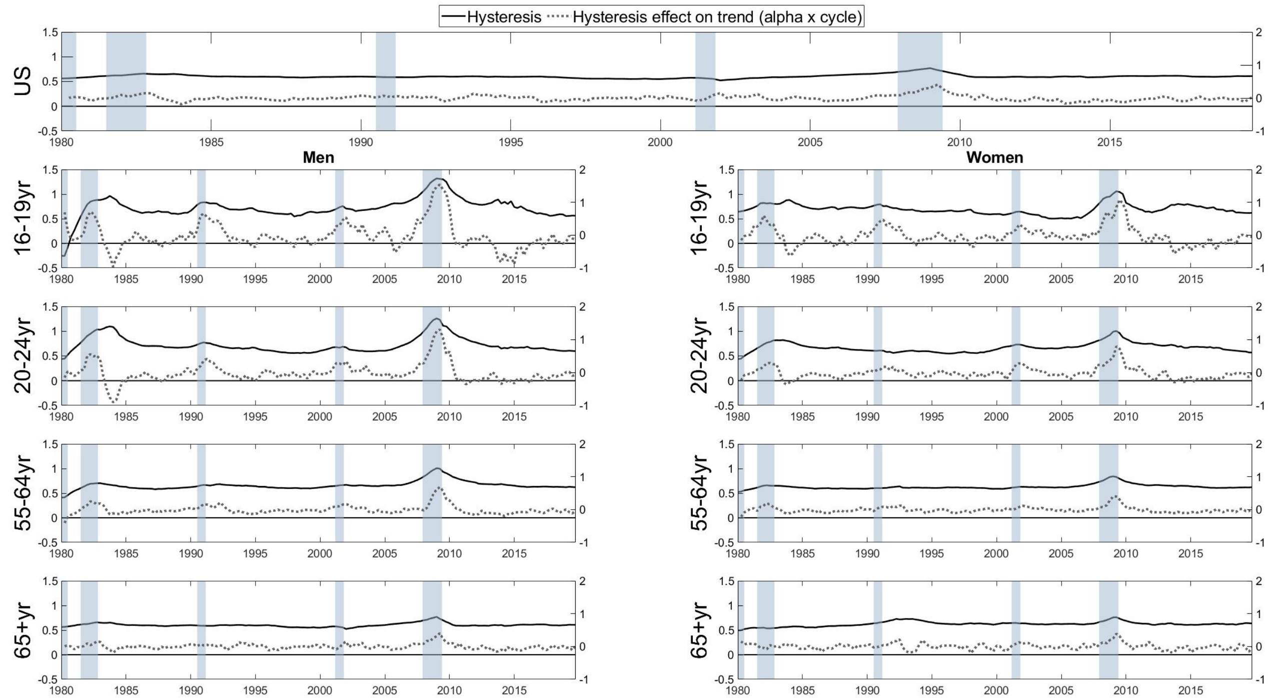

Figure 3: Posterior mean estimates of the time-varying hysteresis coefficients in the natural rates for the U.S. aggregate and each age-gender subgroup. The solid lines (left axis) represent the hysteresis coefficients alone. The dashed lines (right axis) illustrate the total effect on each demographic's natural rate, i.e. the product of the hysteresis coefficient and the unemployment cycle. The data span the period from 1980:I through 2019:IV.

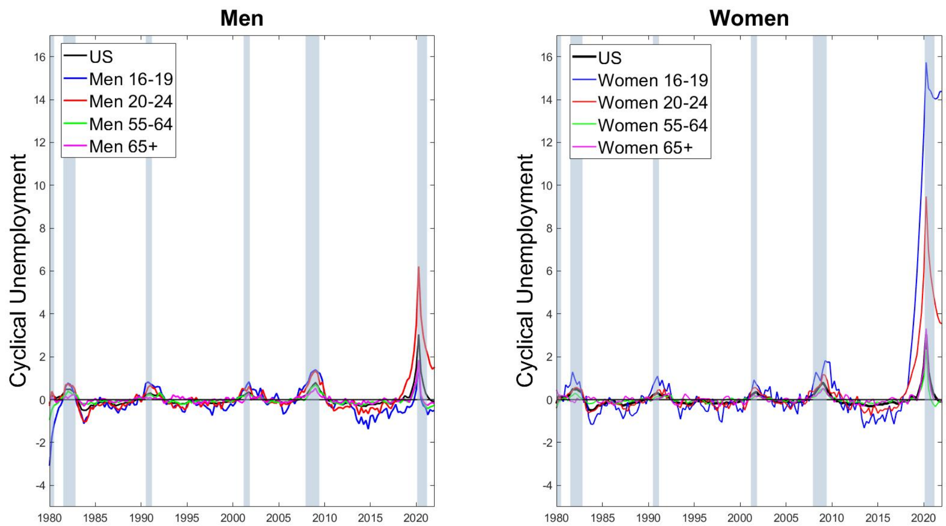

Figure 4: Full-Sample Results, including COVID: Posterior mean estimates of the cyclical components of the U.S. aggregate unemployment rate and the unemployment rate for each age-gender subgroup. The data are extended to include the COVID recession and thus cover the period from 1980:I through 2022:I.

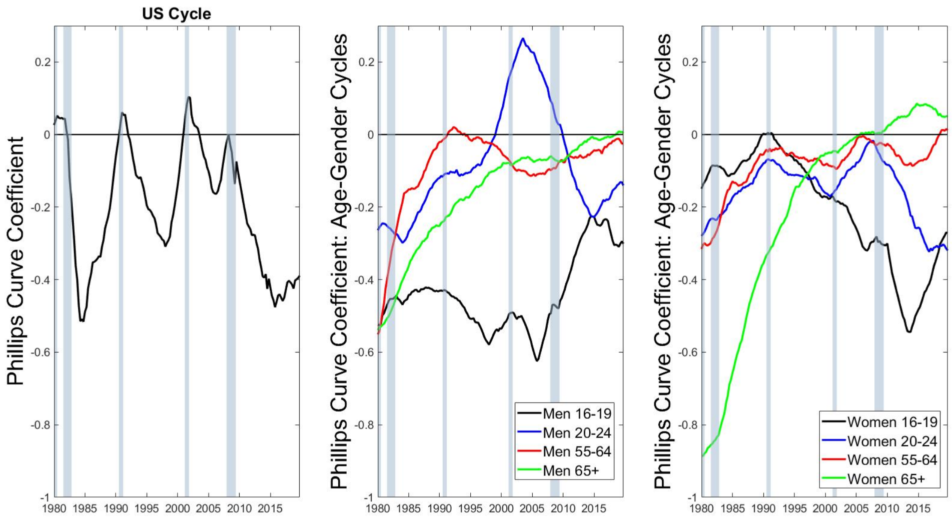

Figure 5: Full-Sample Results, including COVID: Posterior mean estimates of the time-varying Phillips curve coefficients on the U.S. aggregate cycle and on the deviation of the cycle for each age-gender subgroup from the aggregate cycle. The left panel displays the coefficient on the aggregate cycle that is consistent across all Phillips curve relationships. The middle and right panels display the male and female subgroup coefficients, respectively, which apply to how each demographic's cycle uniquely deviates from the aggregate cycle. The data are extended to include the COVID recession and thus cover the period from 1980:I through 2022:I.

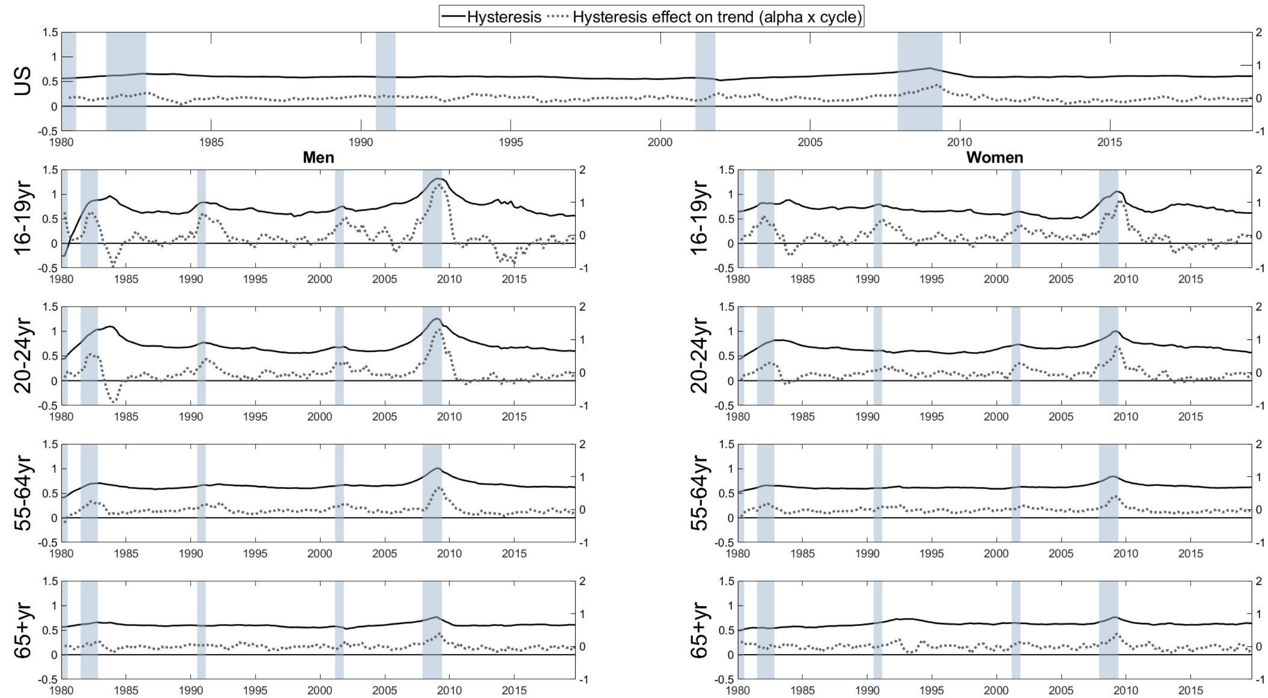

Figure 6: Full-Sample Results, including COVID: Posterior mean estimates of the time-varying hysteresis coefficients in the natural rates for the U.S. aggregate and each age-gender subgroup. The solid lines (left axis) represent the hysteresis coefficients alone. The dashed lines (right axis) illustrate the total effect on each demographic's natural rate, i.e. the product of the hysteresis coefficient and the unemployment cycle. The data are extended to include the COVID recession and thus cover the period from 1980:I through 2022:I.

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