Zooming in on Phillips Curve and Estimating NAIRU for Subgroups of Civilian Population

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Abstract

This paper presents evidence that the slope of the Phillips curve varies across subgroups of the civilian population. Based on the time-evolving subgroup-specific Phillips curve, we estimate the subgroup non-accelerating inflation rate of unemployment (NAIRU) using the Hodrick-Prescott filter, Band-Pass filter and the AR(4) forecast recommended by Hamilton (2018). Several empirical regularities of the disaggregate NAIRU are documented including how the Great Recession affects subgroups differently.

Keywords: Non-Accelerating Inflation Rate of Unemployment, NAIRU, Hodrick-Prescott Filter, Phillips Curve

JEL Classification: E24, E32, J21
1. Introduction

On 16 December 2015, the Federal Reserve announced for the first time in almost a decade that short-term interest rates will be raised, effectively terminating the zero interest rate policy that was implemented in 2009 in response to the Great Recession. This decision was motivated by an improving labor market and the recognition that it takes time before monetary policy is able to affect the real economy. There were pervasive doubts about the health of the labor market to accommodate an interest rate hike, and the concept of a non-accelerating inflation rate of unemployment (NAIRU) became integral to the debate. There still is wide disagreement about the current level of NAIRU and the position of labor market relative to it.

Discussions in media or academic publications usually center on the NAIRU for the total population. This aggregate measure has the limitation that it fails to account for the heterogeneity in subgroups of the population. First and foremost, a decline in aggregate NAIRU does not necessarily mean the labor market improves uniformly for all subgroups — we actually see that, for instance, employment for white and black workers has recovered at different rates since the Great Recession ended. In light of this, this paper makes a contribution to the literature by estimating the NAIRU for four classifications of the civilian population — gender, race, age and job type. There are other categorizations, but we think these four suffice for the purpose of highlighting the labor market fragmentation.

Following Ball and Mankiw (2002), we assume the NAIRU is slow-evolving, so the Hodrick–Prescott (HP) filter is employed in order to extract the smooth component and use it as the primary estimate for the subgroup-specific NAIRU. The second contribution

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1The literature on Phillips curve and NAIRU is vast. A symposium on the natural rate of unemployment is provided by Journal of Economic Perspectives (Vol.11, No.1). Important early works include Phelps (1967) and Friedman (1968). Authors such as Galbraith (1997) question the usefulness of NAIRU. King and Morley (2007) estimate the aggregate NAIRU as the time-varying steady state of a structural vector autoregression. Basistha and Startz (2008) provide more precise estimates of aggregate NAIRU using multiple indicators. Tramontana et al. (2010) investigate a nonlinear NAIRU model with regime switching. Kajuth (2012) makes use of heteroskedasticity to estimate the Phillips curve.
of this paper is relaxing the restrictive assumption of a time-invariant slope in the Phillips curve imposed by Ball and Mankiw (2002). We provide evidence that the Phillips curve can still be found in the most recent data, though the slope is hardly constant. Therefore, we are able to obtain more accurate results by letting both the intercept and slope vary over time, which reflects long-term structural changes in the labor market.

The third contribution is that we use the disaggregate NAIRU to sharpen our understanding of the Phillips curve. For example, we show that compared to full-time jobs, the price level is less sensitive to the tightness of the market for part-time jobs. Moreover, unlike the rising NAIRU of full-time jobs, the NAIRU of part-time jobs remained largely unchanged during the Great Recession. Jointly, those two findings lead to an explanation for the weakening Phillips curve which is overlooked in the literature.

We report four main findings. First, there is substantial variation, both over time and across groups, in the slope of the Phillips curve\(^2\). Second, for each classification, we detect a significant discrepancy in NAIRUs. For example, the average NAIRU is 5.3 percent for the white, but 11.7 for the black. It is not just the mean, but the volatility measured by the standard deviation also differs by a factor of more than two for the white and black. Third, there are varying degrees to which the subgroup NAIRUs are correlated with the aggregate NAIRU. For instance, the correlation is 0.96 between people of 20-24 years old and overall population, but is only 0.75 for people of 45-54 years old. Fourth, there is asymmetry in how the NAIRU for one group responds to the other. We find statistically significant responses of women’s NAIRU to men’s shock, young people’s NAIRU to the old people’s shock, the black’s NAIRU to the white’s shock, the part-time NAIRU to the full-time’s shock, but not vice versa.

\(^2\)There is theoretical foundation for interpretation of our findings. For instance, Thomas and Zanetti (2009) and Zanetti (2011a) attribute the shift in the Phillips Curve to the change in labor market institutions, Delacroix (2006) considers the effect of unions on the collective bargaining power, and Acemoglu and Restrepo (2018) show that automation can reduce the equilibrium wage.
Overall, those results point to a highly diverse labor market where a single aggregate NAIRU may be misleading and the same policy tool may affect each subgroup differently. Our findings are robust after a different smoothness parameter is used for the HP filter, the seemingly unrelated regression (SUR) is employed to account for the interdependence among subgroups, and the moving average filter and band-pass filter are used to construct the NAIRU. We carefully address the concerns about the HP filter raised by Hamilton (2018), and find no qualitative change in main results after using the AR(4) forecasting value as an alternative estimate for the NAIRU.

2. Phillips Curve

We download from Fred data the monthly seasonally adjusted civilian unemployment rates (defined as the U-3 measure of labor underutilization) from 1948 to 2016 for total population and for several subgroups — men and women, white and black people, workers in the age groups of 20 to 24 years old and 45 to 54 years old, and full-time and part-time workers. Given the low frequency nature of the NAIRU, we generate annual unemployment rates by averaging monthly observations\(^3\). The inflation rate is computed as the first difference of the natural logarithm of consumer price index. Table 1 reports the descriptive statistics for the annual series.

Notice that sample sizes vary across series because of different starting dates. In particular, the unemployment rates for the black are not available until 1972. The heterogeneity in subgroups is evident — for instance, the average unemployment rates are 9.38 percent for workers of 20 to 24 years old, and 12.1 percent for the black, both being well above the average total unemployment rate of 5.81 percent. In terms of dispersion, these two groups also show standard deviations much greater than the standard deviation for the total population. The maximum values for these two groups are noticeable as well.

\(^3\)There is no qualitative change in results if using the first or last monthly value as the annual value.
To visualize the heterogeneity in the labor market, Figure 1 plots the original unfiltered annual unemployment rates (percent) for each categorization. The short-run business cycle is evident in each panel, and whenever there is a recession, the gap between unemployment rates gets widened. We observe that after the 1980s the unemployment rates of the two genders seemed to largely overlap, except during recessions. However, that kind of convergence is missing, and persistent gaps are present for other sub-groups. For instance, both the average and dispersion of the unemployment rates for black people are consistently greater than white people.

Next we hope to reduce the amount of noise embedded in the raw series shown in Figure 1, and extract the underlying smooth trend with the HP filter. More explicitly, our estimation of the NAIRU is based on the expectation-augmented subgroup-specific Phillips Curve

\[ \Delta \pi_t = -\beta_{j,d}(u_{j,t} - u^n_{j,t}) + e_{j,t} \quad (\beta_{j,d} > 0) \] (1)

where \( t, d, j \) are indexes for year, decade, and subgroup, respectively. \( \pi \) is the inflation rate, \( u \) is the unemployment rate, and \( e \) represents the shock affecting the labor market. We add year subscript to the NAIRU \( u^n \) to emphasize that it is time-varying.

Equation (1) says that in the absence of a shock, when the unemployment rate equals its long-run natural level \( u_{j,t} = u^n_{j,t} \), the inflation rate (a proxy for the growth rate of wage) is stable \( \Delta \pi_t = 0 \), so the price level is not accelerating. On the other hand, there is tendency for the inflation rate to rise when the unemployment rate is below NAIRU. Basically, the Phillips curve describes how inflation rates react to the tightness of the labor market — the market gets tighter as the jobless rate falls, so there is more pressure of rising wage and the general price level. The Phillips curve is rationalized as long as such feedback exists.

\[^4\text{To derive this equation, start with } \pi_t = E(\pi_t | I_{t-1}) - \beta_{j,d}(u_{j,t} - u^n_{j,t}) + e_{j,t}. \text{ Then assume the adaptive expectation for the expected inflation: } E(\pi_t | I_{t-1}) = \pi_{t-1}. \text{ The adaptive expectation is close to the rational expectation when the inflation follows a random walk } \pi_t = \pi_{t-1} + \nu_t. \text{ For this sample, the Augmented Dickey-Fuller test with four and eight lags cannot reject the null hypothesis of a unit root for } \pi_t.\]
Notice that different subgroups may have different bargaining powers\(^5\) (think about skilled and unskilled workers), so their unemployment rates can exert different pressure on the price level, and that explains why \(\beta\) in (1) has the subgroup index \(j\). This is an important extension of the traditional Phillips curve, which ignores the heterogeneity in subgroups.

Meanwhile, it is desirable to help settle the debate about the Phillips curve\(^6\) by allowing for time-varying sensitivity of the price level to the market tightness (think of automation and globalization). That motivates adding the decade subscript \(d\) to the slope coefficient \(\beta\). By contrast, \(\beta\) is assumed to be fixed in Ball and Mankiw (2002), see the parameter \(\alpha\) in their equation on page 122. In this section we just regress \(\Delta \pi_t\) onto the observable \(u_{j,t}\), and focus on the estimated slope \(\hat{\beta}_{j,d}\).

Adding decade subscript \(d\) to \(\beta\) is supported by data. Figure 2 plots the first difference of the inflation rate (percent) against the unemployment rate of total population. To emphasize structural changes over time, we divide the whole sample into several decades\(^7\), and common scales in axes are used for easy comparison. The existence of the Phillips curve, i.e., the negative correlation between inflation and unemployment rates, is evident in all panels except in the 1990s during which the inflation rate was relatively stable. It is especially worth noting that, notwithstanding the outliers of 2010 and 2011, the Phillips curve can still be seen in the last 2000s panel.

Nevertheless, when it comes to the slope of the Phillips curve or how elastic the inflation rate is to the unemployment rate, we see that the inflation rate is not as responsive in the 2000s as in the 1970s. Possible explanations for this weakening trade-off between inflation and unemployment may include that workers have fewer bargaining powers thanks to glob-

\(^5\)See, for instance, Hernandez et al. (2018).

\(^6\)Most debates about the usefulness of the Phillips curve in fact is not about whether the overall price level responds to the market situation, but how strongly it responds. For example, the 2017 November 1st issue of the *Economist* publishes an article titled “The Phillips curve may be broken for good”, which discusses the recent shift of the Phillips curve.

\(^7\)We include years from 2000 to 2016 in the last panel in Figure 2.
alization, automation and weaker unions, there is deflationary pressures from China, or the Fed has done a better job of anchoring inflation expectations and making prices less sensitive to the business cycle.

To examine the disaggregate Phillips curve, Table 2 reports the estimated $\beta$ in (1) for total population and each subgroup over decades, with the R-squared (coefficient of determination) in brackets. For total population, $\beta$ decreases from 1.24 in 1970s to 0.66 in 2000s\(^8\). This falling $\beta$ seems to support arguments such as the Phillips curve is becoming outdated. Nevertheless, our view is that the Phillips curve remains its relevance given that the R-squared is 0.49 and $\beta$ is still statistically significant at the 5% level in the 2000s. It is economically significant as well: 0.66 is far from zero.

With regard to subgroup heterogeneity, we see remarkable gaps in $\beta$ between 20-24 years old and 45-54 years old workers, between white and black people, and between full-time and part-time jobs. If $\beta$ roughly measures the bargaining power, then in the 2000s female workers, old workers and white workers have more power than male workers, young workers and black workers.

It’s noteworthy to mention that for part-time jobs, $\beta$ is statistically insignificant most of the time. This fact may indicate an overlooked explanation for the weakening aggregate Phillips curve — as the share of part-time jobs rises, the overall price level becomes less responsive to the labor market. So the quantity of jobs matters, but quality matters more!

In short the variation in $\beta$ is substantial both over time and across subgroups. Despite that, Ball and Mankiw (2002) estimate the NAIRU by imposing the restriction that $\beta$ is decade-invariant and subgroup-invariant. Our results extend theirs by relaxing that restriction.

\(^8\)The outliers of 2010 and 2011 are excluded when estimating the 2000s regression.
3. HP Filter and NAIRU

Algebra rearrangement of (1) leads to

\[ u_{j,t} + \frac{\Delta \pi_t}{\beta_{j,d}} = u_{j,t}^n + \frac{e_{j,t}}{\beta_{j,d}}. \]  

(2)

Actual data and estimated \( \beta_{j,d} \) can be used to generate the left hand side of (2), which equals the right hand side — the combined shifts in the Phillips curve caused by the low frequency NAIRU \( u_{j,t}^n \) and the high frequency cyclical shocks \( e_{j,t} \). Following the decomposition approach of Ball and Mankiw (2002), we apply the HP filter of Hodrick and Prescott (1997) to the observable combined series \( u_{j,t} + \Delta \pi_t \beta_{j,d} \), and extract the slow-evolving trend component, which serves as the estimate for the unobservable NAIRU \( u_{j,t}^n \). Ball and Mankiw (2002) comment that the HP filter yields results similar to those obtained by more complicated methods such as the unobserved component model\(^9\).

Generally speaking, the HP filter produces a flexible trend with gradual changes in the slope. A strictly positive smoothing parameter \( \lambda \) is enforced to keep the trend smooth by minimizing the sum of squared errors between the actual series and the trend, with greater smoothness of the trend component series being achieved with higher values of \( \lambda \).

Figure 3 plots the estimated NAIRU for each subgroup based on the HP decomposition of (2) with \( \lambda = 100 \). We see a large gap between men and women NAIRUs before the 1980s; after that the NAIRUs of two gender groups tend to converge. By contrast, the NAIRU gaps between young and old workers, and between white and black workers are much more persistent without a clear tendency of convergence. As for the job type, there is a narrowing gap before 2000, and after that the converging pattern is reversed.

It is important to emphasize two findings associated with the Great Recession. First, relative to the full-time job, the NAIRU of the part-time job remains largely unchanged

\(^9\)For instance, see Gordon (1998).
during the Great Recession. Second, the Great Recession has uneven impact on subgroups — the rising NAIRUs for young, black, and full-time workers are especially noticeable in Figure 3.

Table 3 quantifies the variability in NAIRUs by reporting the descriptive statistics for the NAIRU of each subgroup and total population. For instance, the average NAIRU of 20-24 years old is close to three times of the 45-54 years old, and black workers have NAIRU that doubles white workers. It is not just the mean level, the standard deviations of NAIRUs also vary substantially across groups: the 45-54 years old have the most stable NAIRU, whereas black workers have the most variable NAIRU. All NAIRUs are the smooth trend components, so they should be highly serially correlated by construction. That is what the close-to-one first order autocorrelation coefficient $\rho_{x_t,x_{t-1}}$ indicates.

Finally, the contemporaneous correlation between the subgroup NAIRU and total NAIRU $\rho_{x_t,\text{total}}$ measures the degree to which the movement of the latter matches the former. We see that the 45-54 years old workers and part-time workers have the least correlation with the aggregate NAIRU. This finding is not surprising given that the skilled old workers are more immune to the business cycle, and part-time jobs are much less affected by the Great Recession than full-time jobs.

One benefit of obtaining disaggregate NAIRUs is that it enables us to look into the dynamic interactions between subgroup employment trends. Toward that end, and given the close-to-unity autocorrelation reported in Table 3, we take the first difference of subgroup NAIRU, and estimate a bivariate fourth order vector autoregression (VAR) for each pair of NAIRUs. Figure 4 displays the orthogonalized impulse responses with the 95% confidence intervals, i.e., it traces out how one subgroup NAIRU responds to a one-standard-deviation one-time shock of the other.

Figure 4 clearly shows asymmetry — we observe statistically significant responses of women’s NAIRU to men’s shock, young people’s NAIRU to the old people’s shock, the
black’s NAIRU to the white’s shock, the part-time NAIRU to the full-time’s shock, but not vice versa. All those significant impulse responses rise before they decay toward zero, which reflects the fact that most often the employment trends co-move in the same directions.

4. Robustness Check

4.1 Smoothness Parameter of the HP Filter

Following Ball and Mankiw (2002), we try two values of the smoothness parameter of the HP filter. Figure 5 plots the estimated subgroup NAIRU using $\lambda = 1000$. Except at the two ends of the sample where a filter typically performs less well, the extracted trends are alike. As expected using the bigger $\lambda = 1000$ generates a smoother NAIRU than $\lambda = 100$, but the average NAIRUs are similar\textsuperscript{10}.

4.2 Seemingly Unrelated Regression Estimation

The second robustness check is to utilize the interdependence between subgroups to obtain more efficient estimates by applying the Seemingly Unrelated Regression (SUR). For instance, it is easy to imagine that the job markets for female and male workers can be subject to common shocks such as an interest rate hike, which cause the error terms in the female and male Phillips curves to be contemporaneously correlated. SUR explicitly takes that cross-regression correlation into account to produce the Generalized Least Squares estimate. Figure 6 plots the disaggregate NAIRU obtained from applying the SUR to (1) for each pair of classification. Comparing Figure 6 to Figure 3, we see the overall pattern remains unchanged with the noticeable difference only before 1980s for the gender and after the 2000s for the job type.

\textsuperscript{10}An alternative way to show robustness is comparing the Log Periodograms of the cyclical component with $\lambda = 100, 1000$, which are very similar in this case.
4.3 Moving Average Filter

Finally, we apply the symmetric (two-sided) Moving Average (MA) filter with a span of 7 and equal weights to (2). Figure 7 displays the subgroup NAIRU based on the MA filter. The panels for race and job type are similar to those in Figure 3, though the MA trends are much choppier than the HP trends by construction. Because the MA filter involves the local averaging rather than the global smoothing, we see a different scale for the vertical axis in the gender and age panels in Figure 7 compared to Figure 3.

4.4 AR(4) Forecast

Hamilton (2018) summarizes several drawbacks of the HP filter. Nevertheless, here we argue that his concerns about the HP filter are largely irrelevant in our setting. First of all, we only assume the NAIRU is the smooth part of unemployment rate, and therefore our primary goal is to smooth out the combined series $\theta_{j,t} \equiv u_{j,t} + \Delta \pi_{j,t}$, which appears on the left hand in (2). Figures 3 and 5 clearly show that smoothness is adequately achieved by the HP filter. Our goal is not to extract the cyclical component that needs to be stationary, nor are we interested in using the cyclical component to make inference about the underlying data generating process.

Second, Hamilton emphasizes that applying the HP filter to a random walk time series may result in misleading artifacts observed in the filtered series. To mitigate that concern, we regress $\Delta \theta_{j,t}$ onto its first lag $\Delta \theta_{j,t-1}$ for eight subgroups. If $\theta_{j,t}$ were a random walk, then taking first difference would remove all predictability. However, we find for seven subgroups the coefficient of $\Delta \theta_{j,t-1}$ is statistically significant, meaning that $\Delta \theta_{j,t}$ is predictable, so $\theta_{j,t}$ is not a random walk.

Next we follow Hamilton (2018) and redefine the trend component as the two-year forecast
or the fitted value from the following AR(4) regression

\[
\hat{\theta}_{j,t} = \hat{\gamma}_{0,j} + \hat{\gamma}_{1,j} \theta_{j,t-2} + \hat{\gamma}_{2,j} \theta_{j,t-3} + \hat{\gamma}_{3,j} \theta_{j,t-4} + \hat{\gamma}_{4,j} \theta_{j,t-5}
\]  

(3)

where \( j \) is the index for subgroup. Hamilton suggests that the cyclical component is the main reason why the two-year forecast could be wrong. Figure 8 plots the alternative NAIRU estimated as the AR(4) forecast or the trend component \( \hat{\theta}_{j,t} \) in (3). Because the autoregression (3) imposes no restriction of smoothness, there is similarity regarding choppiness between the Moving Average NAIRU and AR(4) forecast, see Figure 7 and Figure 8.

Similarity can also be found in Table 3 where the descriptive statistics for the NAIRU estimated as the AR(4) forecast \( \hat{\theta}_{j,t} \) are reported in parentheses. We see that the mean and standard deviation of the HP NAIRU are very close to those of the AR(4) NAIRU. As expected, the AR(4) NAIRU is much less autocorrelated than the HP NAIRU because the former does not assume smoothness. It is noteworthy that the AR(4) NAIRUs for the black and part-time jobs are almost uncorrelated with the aggregate NAIRU, and this fact is indicative of even more heterogeneity in the labor market.

4.5 Band-Pass Filter

The final robustness check is applying the Band-Pass (BP) filter of Baxter and King (1999) to \( \theta_{j,t} \), where cyclical components at periods smaller than 2 and greater than 8 are filtered out (i.e., the remaining cycle is within a specified range of periods). Figure 9 plots the subgroup NAIRUs estimated as the BP trend components, and their descriptive statistics are in brackets in Table 3.

Comparing Figure 9 to Figure 3 and Figure 8 we see that in terms of smoothness the BP NAIRU is in between the HP NAIRU and AR(4) NAIRU. The overall pattern shown by the BP NAIRU is very similar to the HP NAIRU—for instance, the convergence of two genders
after 1980s, the persistent race gap, and the divergence between full-time and part-time jobs can be seen in both Figure 3 and Figure 9. Table 3 indicates the similarity between the BP and HP NAIRUs as well.

5. Conclusion and Discussion

This paper builds on previous research conducted by Ball and Mankiw (2002) and uses a variety of filters to estimate the NAIRU for subgroups of the civilian population. We extend their methodology by allowing both the intercept term and slope of the Phillips curve to vary over time and across subgroups. We provide evidence for the convergence in the NAIRUs of the two genders. On the other hand, the NAIRUs for black workers and young workers are consistently higher relative to white workers and old workers. We document the steep decline in the NAIRU for part-time workers after 1980 and show it is remarkably lower compared to full-time workers after the Great Recession.

We hope our new empirical regularities can lead to more theoretical modeling for the time-varying NAIRU. For instance, one promising area for future research may be investigating the slow-moving changes in labor market institutions as shown by Pissarides (2000) and Zanetti (2011b). We can gain greater insight and perspective into the job market by analyzing the NAIRU at the disaggregate level. We suggest that one possible explanation for the weakening Phillips curve is that the price level is less sensitive to the tightness of part-time job market relative to the full-time job. Improving our understanding of the labor market will be helpful for our policy makers to make sound economic decisions that will benefit the overall economy.
References


Table 1: Descriptive Statistics for Unemployment Rate

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Note: Obs is the sample size; Mean is the sample mean; SD is the standard deviation; Min is the minimum; Max is the maximum.
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<td>[0.50]</td>
<td>[0.17]</td>
<td>[0.23]</td>
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Note: We regress $\Delta \pi_t$ onto $u_{j,t}$. ** denotes statistical significance at the 5% level. The R-squared (coefficient of determination) is in brackets.
<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>$\rho_{\epsilon_t, \epsilon_{t-1}}$</th>
<th>$\rho_{\epsilon_t, \text{total}}$</th>
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<tr>
<td>Total</td>
<td>6.13</td>
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<td>(1.32)</td>
<td>(0.16)</td>
<td>(1.00)</td>
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<td>[1.45]</td>
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<td>[1.00]</td>
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<td>0.98</td>
<td>0.98</td>
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<td>(5.97)</td>
<td>(0.94)</td>
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<tr>
<td>Women</td>
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<td>1.75</td>
<td>0.97</td>
<td>0.88</td>
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<td></td>
<td>(6.88)</td>
<td>(2.55)</td>
<td>(0.27)</td>
<td>(0.96)</td>
</tr>
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<td>1.57</td>
<td>0.98</td>
<td>0.96</td>
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<td>(10.1)</td>
<td>(1.66)</td>
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<td>(0.67)</td>
<td>(0.15)</td>
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<td>0.86</td>
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<td>(0.52)</td>
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<td>(0.74)</td>
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<td></td>
<td>(6.40)</td>
<td>(1.04)</td>
<td>(0.69)</td>
<td>(0.07)</td>
</tr>
<tr>
<td></td>
<td>[6.50]</td>
<td>[1.33]</td>
<td>[0.98]</td>
<td>[0.81]</td>
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</table>

Note: Mean is the sample mean; $\rho_{\epsilon_t, \epsilon_{t-1}}$ is the first order autocorrelation coefficient; $\rho_{\epsilon_t, \text{NAIRU}}$ is contemporaneous correlation coefficient with total NAIRU. The descriptive statistics for the NAIRU estimated as the AR(4) forecast recommended by Hamilton (2018) and the trend component using the Baxter and King (1999) hand-pass filter are in parentheses and brackets, respectively.
Figure 1: Unemployment Rates

Gender

Age

Race

Job Type

Unemployment Rate

1940 1960 1980 2000 2020

Men

Women

20–24

45–54

White

Black

Full time

Part time

Unemployment Rate

1940 1960 1980 2000 2020

0 5 10 15

0 5 10 15

0 5 10 15

0 5 10 15

Unemployment Rate

1940 1960 1980 2000 2020

2 4 6 8 10

2 4 6 8 10

2 4 6 8 10

2 4 6 8 10

Unemployment Rate
Figure 2: Phillips Curves

1970—1979

Difference of Inflation Rate vs. Unemployment Rate (U3)

1980—1989

Difference of Inflation Rate vs. Unemployment Rate (U3)

1990—1999

Difference of Inflation Rate vs. Unemployment Rate (U3)

2000—2016

Difference of Inflation Rate vs. Unemployment Rate (U3)
Figure 3: Natural Unemployment Rates (NAIRU)

Gender

Age

Race

Job Type

[Graphs depicting unemployment rates by gender, age, race, and job type over time.]
Figure 4: Impulse Response Function

- m1: $D.t_{men} \rightarrow D.t_{women}$
- m2: $D.t_{2024} \rightarrow D.t_{4554}$
- m3: $D.t_{white} \rightarrow D.t_{black}$
- m4: $D.t_{fulltime} \rightarrow D.t_{parttime}$

Graphs showing the impulse response functions for the specified models.
Figure 5: NAIRU Using lambda=1000

Gender

- Men
- Women

Age

- 20–24
- 45–54

Race

- White
- Black

Job Type

- Full time
- Part time
Figure 6: NAIRU from SUR Estimation

Gender

Age

Race

Job Type

Figure 6: NAIRU from SUR Estimation
Figure 7: NAIRU Using MA Filter

Gender

Age

Race

Job Type

25
Figure 8: NAIRU Using AR(4) Forecast

Gender

Age

Race

Job Type
Figure 9: NAIRU Using BP Filter

**Gender**
- Men
- Women

**Age**
- 20–24
- 45–54

**Race**
- White
- Black

**Job Type**
- Full time
- Part time