Men are from Mars? Gender Differences in Business Cycle Dyanmics and Policy Implications*

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Abstract

While traditional macroeconomic models take individuals to be identical agents, the labor market is composed of many distinct groups that may have different reactions to policy. We compare a bivariate correlated unobserved components model against common filters in the literature to understand the business cycle dynamics of various groups. Our results show that the different filters provide conflicting results for the variability of the series components and the dominant force during recessions. According to our most general model, female unemployment is dominated by the permanent component during recession, while the transitory (or cyclical) component plays a larger role for male unemployment. Therefore, policy enacted to target either structural or cyclical unemployment will have unequal effects in reducing unemployment across genders. These results are robust to different disaggregate specifications and data simulations. Therefore, since males and females have separate and distinctive reactions to macroeconomic shocks, then policy may have unintentionally unequal effects.

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1 Introduction

While most traditional macroeconomic models take individuals to be identical agents, the labor market is composed of many distinct groups that may have different reactions to policy. There is a longstanding debate about the merits (or lack thereof) of aggregation (Grunfeld and Griliches, 1960; Theil, 1954). Some research suggests that we may lose information when we choose to aggregate across heterogeneous groups (Pesaran and Barker, 1990). Additionally, there is an extensive literature exploring the differences between males and females in the labor market. Since females historically have a shorter and discontinuous expected work life, their labor market choices differ from males when it comes to career choice (Blau et al., 2013; Polachek, 1981), education decisions (Mincer and Ofek, 1982; Pekkarinen, 2012), and labor market participation (Becker, 1985; Burda et al., 2007; García-Mainar et al., 2009). As women have entered the labor force in greater numbers over the last several decades, it is increasingly more crucial to disentangle the heterogeneous effects of macroeconomic shocks and policy on women and men.

Recently, there has been much debate over the role of structural versus cyclical unemployment in the Great Recession, with the research supporting both cyclical (Elsby et al., 2011; Lazear and Spletzer, 2012) and structural (Estevão and Tsounta, 2011; Katz, 2014; Kocherlakota, 2010) unemployment as the dominant force driving the high unemployment in the US. Identifying the relative importance of permanent and cyclical components has direct policy implications (Okun, 1962). While difficulty of estimating structural and cyclical unemployment has been well document (Diamond, 2013), the recent recession has also brought the relative labor market adjustments of demographic groups into discussion with many researchers arguing that the impacts of the Great Recession were larger for certain demographic groups, including men (Elsby et al., 2011; Engemann and Wall, 2009; Hoynes et al., 2012).

In this paper we extend our analysis beyond the traditional aggregate unemployment statistics to include other labor market indicators and disaggregated series by gender. We compare a bivariate correlated unobserved components model against alternative methods for identifying trend and cycle components including the Hodrick-Prescott filter (Hodrick and Prescott, 1997), and Baxter-King band-pass filter (Baxter and King, 1999) to better understand the business cycle dynamics of each group. Unlike Harvey (1985) and Clark (1989), we will allow for correlation between innovations of the components, where such empirical models have found that there is a statistically significant negative correlation between trend and cycle shocks for many macroeconomic series (Morley et al., 2003; Nelson and Plosser, 1982; Sinclair, 2009). These studies provide evidence that real shocks are the driving force behind movements in the economy with temporary adjustments to those shocks, consistent with the main mechanism in theoretical real business cycle models (Kydland and Prescott, 1982; Prescott, 1986).

Our results show that the different filters provide conflicting results for the variability of the series components and the dominant force during recessions, which supports research by Canova (1998) where different filters and detrending methods can differ in their results both quantitatively and qualitatively. However, we show that the bivariate unobserved components model that allows for correlation between any of the innovations is the most general model and thus nests the other filtering approaches within it. Additionally, there is wide variability of the relative movements of the components when looking at different subpopulations of the labor market. Specifically, during recessions female unemployment is dominated by the permanent component, while the transitory (or cyclical) component plays a larger role for male unemployment. Therefore, policy enacted to target either structural or cyclical unemployment will have unequal effects in reducing unemployment across genders. This result is also robust to data simulation exercises. Additionally, we estimated our models across other disaggregated subgroups emphasized in previous literature, including by age (Bell and

Blanchflower, 2011; O'Higgins, 2012) and duration of unemployment (Valletta et al., 2013, 2012). However, differences by gender were found to yield the most economically meaningful results. Therefore, since males and females have separate and distinctive reactions to macroeconomic shocks, then policy may have unintentionally unequal effects.

2 Empirical Model

Understanding the role of trends and cycles of various time series data is complicated by the fact that these movements within the data are not easily identifiable. Indeed there are many different types of filtering methods and empirical models that differ in the way trends and cycles are defined or how their underlying processes are determined or estimated. One way to go about this problem is to use data sources that already are already constructed for these purposes, such as the output gap being a measure of the cyclical component of GDP or the natural rate of unemployment being a measure of the permanent component of the unemployment rate. While these pre-constructed series exist for some national level time series, they do not exists for the disaggregated series we are interested in exploring in this paper.

We, therefore, have to estimate these latent series from time series. In line with the findings of Nelson and Plosser (1982), which showed that US macroeconomic time series are better characterized by a stochastic trend versus the linear trends, many researchers have created different filters and models, which all define the trend and cycle differently and can lead to deviations in their estimated components. This paper will analyze three different trend and cycle decompositions and compare the variability of the components for the disaggregated data. The three methods used are the Hodrick - Prescott filter, Baxter - King Band Pass filter, and the bivariate unobserved components model, and we will discuss each of them in turn.

2.1 Hodrick - Prescott Filter

The Hodrick-Prescott filter (Hodrick and Prescott, 1997) is a linear, two-sided filter that assumes that the trend is a smooth process and it is not correlated with cycle. Therefore, the smooth trend, s, of series q is found by minimizing the variance of q around s with a penalty to control the smoothness, λ.

$$\sum_{t=1}^{T} (q_t - s_t)^2 + \lambda \sum_{t=2}^{T-1} ((s_{t+1} - s_t) - (s_t - s_{t-1}))^2 \tag{2.1}$$

While this filter does not require a lot of data[1], the researcher must make choices about the definition of the cycle *a priori* by choosing λ, which effects the smoothness of the permanent component. The business cycle component is defined as the residual of the series minus the trend.

This filter was used in the seminal real business cycle paper by Kydland and Prescott (1982), and has since gained popularity has the workhouse filter used in macroeconomics, especially in theoretical models. Two reasons for the popularity of this method is the intuitive nature of the results, the trend is a smoother version of a linear, deterministic trend, and it's ease of implementation (Kydland and Prescott, 1990). However, other researchers have noted some shortcomings of the filter, by noting that the filter can create spurious cycles (Nelson and Kang, 1981) and generate cycles even when there are no cycles in the data (Cogley and

[1]It is a univariate filter and does not require a loss of data due to leads and lags for the model's fit, such as the Baxter-King Band Pass Filter (Baxter and King, 1999).

Nason, 1995). Others have also raised concerns over the consistency of the estimation near the endpoints (Mise et al., 2005; Razzak, 1997) and concerns over the optimal smoothing parameter (Harvey and Trimbur, 2008; King and Rebelo, 1993; Ravn and Uhlig, 2002). Despite these concerns, it still remains a popular filtering method in the literature.

2.2 Baxter-King Band-Pass Filter

The Baxter-King band-pass filter (Baxter and King, 1999) is a linear, fixed length symmetric filter. Where the lead and lag length and the duration range of the cycle is chosen beforehand by the researcher. The filter takes a two-sided moving average at the specified lag and lead of the data and extracts the cycles within the specified duration range. Following Baxter and King (1999), this paper defines the the lead and lag length to be 12 observations and the duration range to be between 6 and 32 observations for quarterly data.

Due to the multiple differencing operators, this method is robust to removing linear and quadratic time trends from the stationary component. However, due to the polynomial lag operator and the two-sided construction of the filter, it requires that observations at the beginning and end of sample are lost. Based on the recommendation from Baxter and King (1999) it requires the estimated components to be shorter than the original data by six years (three years at both the beginning and end of sample for quarterly data). Additionally, Murray (2003) has noted that due to the weighting scheme of this filter, it may overstate the transitory dynamics. While Baxter and King (1999) found that their filter provided quantitatively and qualitatively similar results for selected time series (notably, GNP) to the HP filter, their filtered results deviated more if the original data contains important high-frequency components.

2.3 Unobserved Components

The unobserved components model posits that any nonstationary time series can be decomposed into a permanent and a transitory component (Harvey, 1985), such as

$$x_t = \tau_t + c_t, \tag{2.2}$$

where x is a nonstationary time series, specifically in our case the unemployment indicator, τ is the permanent component, and c is the transitory component. The permanent component is modeled as a random walk with drift:

$$\tau_t = \mu + \tau_{t-1} + \eta_t, \tag{2.3}$$

where μ is the drift term, and η is the permanent innovation that is normally distributed with mean zero. The transitory component is modeled as a stationary process, more specifically as an autoregressive process of order two (AR(2)):

$$c_t = \phi_1 c_{t-1} + \phi_2 c_{t-2} + \varepsilon_t, \tag{2.4}$$

where the ϕ are the autoregressive coefficients and the ε is the temporary innovation that is normally distributed with mean zero.

Following Morley et al. (2003), we allow the innovations of the components to be correlated. Therefore, the covariance matrix for a univariate model can be defined as $\gamma = [\eta, \varepsilon]'$ and $E_t[\gamma\gamma'] = \Omega$, where

$$\Sigma = \begin{bmatrix} \sigma_\eta^2 & \sigma_{\eta\varepsilon} \\ \sigma_{\eta\varepsilon} & \sigma_\varepsilon^2 \end{bmatrix}. \tag{2.5}$$

Unlike earlier unobserved components models (e.g., Clark (1989)), the off-diagonal elements are not constrained to be zero; instead, this general framework allows for the correlation between the innovations. Therefore, this model can yield results for a linear trend specification (correlations are constrained to be zero as in Clark (1989)) or a Beveridge and Nelson (1981) decomposition (correlations between the permanent and transitory innovations are constrained to be negative one).

Following Sinclair (2009), this univariate model can be expanded into the bivariate case,

$$\begin{bmatrix} Y_t \\ u_t \end{bmatrix} = \begin{bmatrix} \tau_{y,t} \\ \tau_{u,t} \end{bmatrix} + \begin{bmatrix} c_{y,t} \\ c_{u,t} \end{bmatrix}, \tag{2.6}$$

In this bivariate case, where σ is the variance and ρ is the correlation, let $v_t = [\eta_{yt}, \eta_{ut}, \varepsilon_{yt}, \varepsilon_{ut}]'$ and $E_t[v_t v_t'] = \Sigma$, where

$$\Sigma = \begin{bmatrix} \sigma_{\eta y}^2 & \rho_{\eta y \eta u}\sigma_{\eta y}\sigma_{\eta u} & \rho_{\eta y \varepsilon y}\sigma_{\eta y}\sigma_{\varepsilon y} & \rho_{\eta y \varepsilon u}\sigma_{\eta y}\sigma_{\varepsilon u} \\ \rho_{\eta y \eta u}\sigma_{\eta y}\sigma_{\eta u} & \sigma_{\eta u}^2 & \rho_{\eta u \varepsilon y}\sigma_{\eta u}\sigma_{\varepsilon y} & \rho_{\eta u \varepsilon u}\sigma_{\eta u}\sigma_{\varepsilon u} \\ \rho_{\eta y \varepsilon y}\sigma_{\eta y}\sigma_{\varepsilon y} & \rho_{\eta u \varepsilon y}\sigma_{\eta u}\sigma_{\varepsilon y} & \sigma_{\varepsilon y}^2 & \rho_{\varepsilon y \varepsilon u}\sigma_{\varepsilon y}\sigma_{\varepsilon u} \\ \rho_{\eta y \varepsilon u}\sigma_{\eta y}\sigma_{\varepsilon u} & \rho_{\eta u \varepsilon u}\sigma_{\eta u}\sigma_{\varepsilon u} & \rho_{\varepsilon y \varepsilon u}\sigma_{\varepsilon y}\sigma_{\varepsilon u} & \sigma_{\varepsilon u}^2 \end{bmatrix}. \tag{2.7}$$

The above equations can be written in state space form and the Kalman filter can be applied to decompose the series into their permanent and transitory components using maximum likelihood estimation. The results reported in the next section use the basic Kalman filter, which uses only past information for estimation (unlike the Kalman smoother, which uses all information in the sample to obtain estimates). This method is appropriate for forecasting, as it uses only information available in time t.

3 Results

3.1 Data

This paper uses quarterly data from 1948 to 2015 for many different series. All data is seasonally-adjusted and natural logs are taken. The series used in this paper includes the real Gross Domestic Product in billions of chained 2009 dollars, the national unemployment level in thousands of persons, the national unemployment level dissaggregated by gender, civilians unemployed for less than five weeks, civilians unemployed for 27 weeks and over, and the unemployment level in the natual log of thousands of persons between the age of 20 to 24 years old.[2] All the data is available from FRED of the Federal Reserve Bank of St. Louis[3] and data from the Current Population Survey (CPS) from the Bureau of Labor Statistics[4]. The seasonally adjusted series is used in all cases, and the monthly unemployment statistic is averaged to yeild quarterly data. Summary statistics of the data is available in Table 6.1.

[2]Since this paper is interested in identifying differences in unemployment, all data is from the Current Populations Survey, which is a survey from the individual or worker's perspective. If we were intersted in employment, then we have another survey available from the firm's perspective, the Current Employment Statistics (CES). While both the CPS and the CES collects data on employment and hours worked there have been some discrepancies in the surveys (Abraham et al., 2013).

[3]https://research.stlouisfed.org/fred2/

[4]http://www.bls.gov/data/

3.2 Number of People Unemployed

Figure 1 graphs the series and components of the number of people unemployed using the Hodrick-Prescott (HP) filter. The permanent or trend component is represented by the dotted, red smooth line that follows the actual series (the blue, solid line). As stated in Section 2.1 the transitory or cyclical component is the difference between the actual series and the trend component. The cyclical component corresponds to the business cycle with the component increasing during NBER recessions (marked in the graph by the gray shaded regions), and decreasing during expansions. Unlike the transitory component, the permanent component is less volatile, but has fluctuations, such as during the end of the 1950s, from the 1970s to beginning of the 1980s, and, most recently, from the 2000s until near the end of the sample. This can be interpreted as the natural level of unemployment increasing during these time periods.

The estimated components for the Baxter-King Band-Pass (BP) filter are quantitatively and qualitatively similar to the HP filter. The BP filter has a smoother transitory component and a less smooth permanent component, than the HP filter, as seen in Figure 2. Also, this filter has a shorter sample by 24 quarters, due to the lead and lags necessary for estimating the components. However, the movements across the business cycle are similar between both filters, with the permanent component rising during recessions, and the transitory component moves from trough (and below the zero line) to peak (and above the zero line) during recessions.

The bivariate unobserved components (UC) model's movements of the transitory component are more variable than the previous two filters, as seen in Figure 3. Furthermore, the transitory component seems to dip during NBER recession periods (shaded area). While this result shows that the transitory component seems to play a larger role during recessions with this component moving from peak to trough during NBER recession periods (as denoted by the shaded regions in the figures). Note that this filter is different than the other two filters in two important ways. First this filter is bivariate rather than univariate, so that it uses more information, specifically real GDP, to help identify and estimate the components. Additionally, this filter allows for correlation between the components, which can be seen in the variance-covariance matrix, Equation 2.7. Column (1) in Table 6.2 provides the estimation results of the bivariate UC model. It is important to notice that the covariance of the permanent and transitory components of the number of unemployed people is -0.62 and statistically significant at the one percent level, which means that the correlation between the components is negative, which is consistent with findings of Morley et al. (2003) and Sinclair (2009).

These differences in the decomposition methods leads to the relative variation of the permanent component to the transitory component to be smaller for the bivariate UC model, than the other two filters, where the variation of the transitory component is the standard deviation of the stationary process and the variation of the permanent component is the standard deviation of the first-difference of the series. The BP filter has the largest relative variation at 0.27 and the UC filter has the least at 0.07. Overall, when comparing the different estimated components of the filters, the UC model provides the most variable transitory component. However, when looking that the national level of unemployed people, all three filters provide similar results overall, both quantitatively and qualitatively.

3.3 Disaggregated by Gender

Since previous studies have highlighted the difference between the genders in their labor market choices, such as career choice (Polachek, 1981), education decisions (Mincer and Ofek, 1982), and labor market participation (Becker, 1984). The model was estimated separately using the number of females unemployed and the number of males unemployed [5]. Comparing the disaggregated series, it is visually apparent that the level of unemployment for men is a more volatile series than for women with more peaks and toughs.

Similar to the previous section, Section 3.3, the HP and BP filters provide filtered components that are similar to the aggregated data within the gender breakdowns. Furthermore, the male relative variation for the components is quantitatively similar to the aggregate data and for the level of male unemployment with the relative variation being 0.11 for the HP filter and 0.27 for the BP filter (Table 6.3). While the relative variation of the components of the HP filter are almost identical across genders (0.11 for both), the BP filter estimates a higher relative variation is higher for unemployed females (0.36) than males (0.27). Additionally, the relative variation for males unemployed is almost identical to the aggregate (both estimated to be 0.27). Therefore, while the HP filter estimates the same relative variation across the components for the aggregate level of unemployed and for the data disaggregated by gender, the BP filter estimates a larger variation for the permanent component for the level of unemployment for women.

Unlike the pattern of the components for the disaggregated data using the HP or BP filters, the UC model estimates components that are visibly different for the data disaggregated by gender. Figure 6 graphs the estimated components of the UC model for the male unemployment level. Compared to the graphs of the male data using the other filters, the UC model estimates a more volatile transitory component, with the standard deviation being 26.67 compared to 15.50 and 15.15 for the HP and BP filters, respectively. However, when simply looking at the relative volatility of the components, this cross-filter comparison is masked since the standard deviation of the permanent component of the first-difference of the permanent component is also greater for the UC model (3.05) compared to the HP

[5] As in Section 3.3 the UC model uses real GDP to assist in identification.

(1.72). The greater volatility of the transitory component in the UC model indicates that this model estimates a larger role for adjustment of male unemployment to happen along the business cycle component. This implies that for male unemployment, policies that address short-term or cyclical unemployment will be effective in reducing the higher levels of unemployment seen during recessions.

While the UC model estimates a larger role for adjustment along the transitory component for males, the model does not estimate a similar pattern across genders. Figure 9 graphs the estimated components of the UC model for the female unemployment level. Compared to the estimated results for the male unemployment level (Figure 6), the estimated transitory component is much smaller and the permanent component is almost mirrors the movements of the series, which is consistent to the findings of Morley et al. (2003) and Sinclair (2009). While this result may seem contradictory to the typical view of business cycles being transitory, these results are consistent with the idea that permanent changes drive the business cycle (Kydland and Prescott, 1982). These results imply that the movements in the level of women unemployed is dominated by movements in the permanent component with the transitory component playing a small role in the adjustments across business cycles. Therefore, if policy makers want to reduce female unemployment, then they would prefer policies that address long-term or structural unemployment.

Overall, the HP filter estimated similar variation of the components regardless of whether the data was aggregated or disaggregated by gender, which implies that there is little difference by gender in the adjustment of the level of unemployment across time. This finding of various business cycle dynamics of unemployment by gender is similar to the findings of Peiró et al. (2012) in the US and Belaire-Franch and Peiró (2015) in the UK (although, they fail to find a similar pattern in the US). While the BP filter estimated a larger role for the adjustments of the permanent component for all data compared to the HP filter, the BP filter, also estimated a slight difference in the relative variation of the components by gender. The UC methodology, however, estimates a much larger standard deviation for the female permanent component and the male transitory component than the HP or BP filter. This deviation is the relative variation of the components, in Table 6.3, shows that even broad levels of disaggregation, such as by gender, can uncover divergent movements in the underlying series. As the permanent component plays a larger role for movements of the unemployment for women and the transitory component plays a larger role for men, policy enacted to target either structural or cyclical unemployment will have unequal effects in reducing unemployment across genders. This result is not robust across filters with only the UC model able to capture these dramatic differences in adjustment by gender.

4 Robustness

This next section will focus on exploring the robustness of the results in the previous section along two main fronts. One is to consider if disaggregation by gender is a particularly unique and important group breakdown or if other disaggregations are equally important. Therefore, we estimated our models across various other disaggregated subgroups emphasized in previous literature, including by age (Bell and Blanchflower, 2011; Jaimovich et al., 2013; O'Higgins, 2012) and duration of unemployment (Valletta et al., 2013, 2012). However, differences by gender were found to yield the most economically meaningful results. Another dimension to consider is that the difference in the estimated results of the filters are a statistical artifact of the data. Therefore, data was simulated given a true data generating process (DGP), and the filters were used to estimate the components. We show that the previous results are robust to these simulations.

4.1 Other Disaggregates

The previous section finds that aggregation can mask important group differences in the data. Specifically, Section 3.3 focuses on data disaggregated by gender and displays how optimal policy can differ by gender. While gender proves to be an important dimension to disaggregate data, previous research has focused on other labor market dimensions. This section will explore the possibility of different trend and cycle decompositions for data disaggregated by age and duration of unemployment, which were both found to be economically important during the Great Recession (Bell and Blanchflower, 2011; O'Higgins, 2012; Valletta et al., 2013, 2012).

Short-term unemployed is defined as the number of civilians unemployed for less than five weeks, whereas long-term unemployed is defined as the number of civilians unemployed for 27 weeks and over. During the Great Recession, the U.S. saw a huge increase in long-term unemployed with researchers finding small contributors of the rise due to an aging workforce (Aaronson et al., 2010) and extensions of unemployment insurance extensions (Daly et al., 2011; Stein, 2012). Larger contributors to this rise in the duration of unemployment has been linked to the widespread job losses across sectors (Aaronson et al., 2010; Valletta et al., 2013) and persistence of the recession were the major contributing factors (Valletta et al., 2012). Since the duration of unemployment has been an intriguing disaggregation in the last recession, this paper will investigate the importance of the relative components over a longer time period.

Table 6.4 displays the ratio of the standard deviation of the permanent component to the standard deviation of the transitory component for the three filters: UC, HP, and BP. For the long-term unemployed the results for the HP and BP filter are quantitatively similar to the national level of unemployed in Table 6.3 with the relative variation being 0.11 and 0.27, respectively. The UC model has a larger ratio, 0.26, than for the national level of unemployment, 0.07, meaning that the permanent component is playing a larger role for the level of long-term unemployment. This is consistent with the findings of Valletta et al. (2012) that persistence of unemployment plays an important role in downturns.

The relative variation of the short-term unemployment is greater than the long-term unemployment for each filter meaning that the permanent component is playing a larger role for short-term unemployment compared to long-term unemployed. The relative variation is largest for UC model (0.80) and least for the HP filter (0.12). However, unlike the disaggregation by gender, the relative variation of the components is not as dramatic when the level of disaggregation is by duration of unemployment.

While the Great Recession saw an increase in the long-term unemployment, it also saw a dramatic increase in the youth unemployment internationally (Bell and Blanchflower, 2011; O'Higgins, 2012; Scarpetta et al., 2010). There is some debate on whether youth unemployment has a small effect on total unemployment with the dynamics of youth unemployment dominated by the cyclical component (Clark and Summers, 1982) or that youth unemployment is a serious problem characterized by structural issues, such as inadequate skills (Scarpetta et al., 2010).

There are two main issues with disaggregating the data by age. First there is a question of how to define youth. Clark and Summers (1982) define youth as between 16 - 19, while Brown et al. (1983) distinguishes between teenagers and young adults (20 - 24) in the work force and Jaimovich et al. (2013) define "young" workers to be 15 to 29 years old. In explaining the importance of youth employment and unemployment for policy O'Higgins (2001) explains the difficulty of defining youth and chooses to explore youth by three different groups: 16 - 19, 20 - 24, 24 - 25 as he finds that these age groups have distinctive characteristics. Another issue to consider is the consistency of the definition across the sample. Previous research has shown that young workers are affected by changes in unions (Bertola et al., 2007), education decisions (Aaronson et al., 2006), and immigration policy (Borjas, 2001), all of which have not been stable in the US during the sample (Mosisa and Hipple, 2006).

Following the work by Brown et al. (1983); O'Higgins (2001), this paper will define youth unemployment as the unemployment level in thousands of persons between the age of 20 to 24 years old. The results for the relative variation of the components for youth is found in Table 6.4. While the HP filter estimates a very similar relative variation with the youth unemployment as the national level of unemployment (0.12 compared to 0.11), the BP filter estimates a larger role for the relative variation of youth unemployment (0.37 versus 0.27). Similar to most of the other disaggregated data, the UC model provides the highest ratio of the variation of the components (0.43). This implies that the UC model estimates the largest role for the permanent component, where optimal policies would address structural unemployment following Scarpetta et al. (2010). However, this relative variation is still less than half that of the UC model for females.

While looking at other disaggregates including youth unemployment and duration of unemployment provided different relative variation of the components across filters. The magnitude difference is not as dramatic as with the UC model disaggregated by gender. Therefore, while exploring other disaggregates provides a more complete picture of unemployment dynamics, the most economically dramatic disaggregation is by gender.

4.2 Data Simulations

Section 3.3 highlighted the ability of the UC model to identify different relative variation in the estimated components between gender. This difference between the genders was dramatic, and can lead to alternative policy recommendations. However, it is important to consider whether the different unemployment dynamics by gender is simply a statistical artifact of the data. To consider this uncertainty, this section simulates data under the assumption that the true data generating process (DGP) follows the parameters estimated by the unobserved components model for the national level of unemployment and disaggregated by gender. The simulated data is then filtered using HP and BP filters, and the relative variation of the filters is computed.

Under this exercise, we are assuming a very specific and known structure of the data. We are assuming that the DGP follows the bivariate UC model as specified in Section 2.3 and the parameters for each simulated data series will follow the estimates in Table 6.2. Therefore, we are seeing if we know the true DGP, can the HP filter or BP filter estimate the a difference in the relative volatility of the components that we saw with the UC model. The results can be found in Table 6.5. While the HP filter did estimate a higher relative volatility ratio for females versus males, the difference between the genders was not large, with the ratio being 0.09 for males and 0.17 for females. Therefore, while the relative direction was in the right direction, the magnitude was not arguably large enough to change the optimal policy between genders, as we saw with the UC model. Alternatively, the BP model estimated similar ratios between males and females, 0.41 and 0.39, respectively.

Therefore the structure of the UC model makes this method robust to estimating and identifying the underlying components of a series. The advantage of the UC model is twofold. First it is a bivariate model, which uses additional data, in this case real GDP, which assists in identifying the components. Additionally, the model allows for correlation between the components, by allowing for correlation between all the innovations of the components (permanent and transitory components of each series). While these correlations could be estimated to be zero, this specification is robust to other filtering methods that restrict the interaction between the components. Therefore, this section shows that the results of the filters are not due to a statistical artifact.

5 Conclusion

While most traditional macroeconomic models take individuals to be identical agents, the labor market is composed of many distinct groups that may have different reactions to policy. In this paper, we extend our analysis beyond the traditional aggregate unemployment statistics to include other labor market indicators and disaggregated series by gender, age, and duration of unemployment. We compare a bivariate correlated unobserved components model against an Hodrick - Prescott filter (Hodrick and Prescott, 1997) and Baxter - King band pass filter (Baxter and King, 1999) to better understand the business cycle dynamics of each group.

Our results show that the different filters provide conflicting results for the variability of the series components and the dominant force during the business cycle. According to our most general model, female unemployment is dominated by the permanent component during recession, while the transitory (or cyclical) component plays a larger role for male unemployment. Therefore, policy enacted to target either structural or cyclical unemployment will have unequal effects in reducing unemployment across genders. We estimated our models across various other disaggregated subgroups emphasized in previous literature; however, differences by gender were found to yield the most economically meaningful results. Therefore, since males and females have separate and distinctive reactions to macroeconomic shocks, then policy may have unintentionally unequal effects.

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6 Appendix

Table 6.1: Data Summary Statistics

	GDP	**Unemployed**	**Females**	**Males**	**Short Term**	**Long Term**	**Youth**
Mean	8.78	8.66	7.81	8.09	7.75	6.64	6.94
Median	8.79	8.80	8.02	8.16	7.86	6.71	7.11
Maximum	9.71	9.63	8.75	9.11	8.28	8.81	7.86
Minimum	7.60	7.40	6.31	6.99	6.94	4.16	5.41
Std. Dev.	0.63	0.51	0.58	0.49	0.33	1.02	0.58
Obs.	272	272	272	272	272	272	272

All data is seasonally-adjusted from 1948Q1 to 2015Q4, and available from FRED of the Federal Reserve Bank of St. Louis and the Current Population Survey (CPS) from the Bureau of Labor Statistics. GDP refers to the real Gross Domestic Product in the natural log of billions of chained 2009 dollars. Unemployed is the national unemployment level in the natural log of thousands of persons, and females and males are the national unemployment level dissaggregated by gender. Short term refers to the natural log of thousands of civilians unemployed for less than 5 weeks, and long term refers to the number of civilians unemployed for 27 weeks and over. Finally, youth is the unemployment level in the natual log of thousands of persons between the age of 20 to 24 years old.

Table 6.2: Unobserved Components

Parameter	Unemployed	Females	Males
llv	-1087.41	-1135.53	-1122.62
$\sigma_{\eta y}$	0.87	1.72	1.07
	(0.02)	(0.04)	(0.03)
$\sigma_{\eta u}$	2.23	9.19	4.45
	(0.15)	(0.73)	(0.15)
$\sigma_{\varepsilon y}$	0.79	1.76	1.02
	(0.03)	(0.03)	(0.03)
$\sigma_{\varepsilon u}$	5.62	7.21	6.21
	(0.13)	(0.41)	(0.32)
$\sigma_{\eta y \eta u}$	0.97	0.27	-0.24
	(0.02)	(0.03)	(0.00)
$\sigma_{\eta y \varepsilon y}$	-0.57	-0.94	-0.77
	(0.02)	(0.00)	(0.02)
$\sigma_{\eta y \varepsilon y}$	-0.29	-0.24	0.28
	(0.01)	(0.01)	(0.01)
$\sigma_{\eta u \varepsilon y}$	-0.37	-0.59	0.46
	(0.06)	(0.03)	(0.02)
$\sigma_{\eta u \varepsilon u}$	-0.47	-0.91	-0.54
	(0.06)	(0.01)	(0.02)
$\sigma_{\varepsilon y \varepsilon u}$	-0.62	0.52	-0.83
	(0.01)	(0.02)	(0.01)
μ_y	0.76	0.68	0.76
	(0.05)	(0.11)	(0.07)
μ_u	0.41	0.65	0.43
	(0.13)	(0.53)	(0.31)
ϕ_{1y}	1.46	1.34	1.42
	(0.04)	(0.03)	(0.02)
ϕ_{2y}	-0.54	-0.37	-0.51
	(0.03)	(0.03)	(0.02)
ϕ_{1u}	1.59	0.49	1.60
	(0.02)	(0.08)	(0.01)
ϕ_{2u}	-0.64	-0.15	-0.67
	(0.01)	(0.06)	(0.01)

The results are from a bivariate unobserved components model with a smooth two-way filter, using GDP and one labor market indicator noted at the top of the column. All data is seasonally-adjusted from 1948Q1 to 2015Q4 with a burn-in period of 4 quarters, so the estimated components are from 1949Q1 to 2015Q4. The data is available from FRED of the Federal Reserve Bank of St. Louis and the Current Population Survey (CPS) from the Bureau of Labor Statistics. GDP refers to the real Gross Domestic Product in the natural log of billions of chained 2009 dollars. Unemployed is the national unemployment level in the natural log of thousands of persons, and females and males are the national unemployment level dissaggregated by gender. Short term refers to the natural log of thousands of civilians unemployed for less than 5 weeks, and long term refers to the number of civilians unemployed for 27 weeks and over. Finally, youth is the unemployment level in the natural log of thousands of persons between the age of 20 to 24 years old.

Table 6.3: Relative Variation of the Components

Group	**UC**	**HP**	**BP**
Unemployed	0.07	0.11	0.27
Males	0.11	0.11	0.27
Females	1.03	0.11	0.36

Ratio of the standard deviation of the permanent component to the standard deviation of the transitory component. Unemployed is the national unemployment level in the natural log of thousands of persons, and females and males are the national unemployment level dissaggregated by gender. UC is the bivariate unobserved components model (using real GDP and the labor market indicator given), HP is the Hodrick Prescott filter, and BP is the Baxter-King band pass filter.

Table 6.4: Relative Variation of Other Unemployment Disaggregates

Group	**UC**	**HP**	**BP**
Long Term	0.26	0.11	0.27
Short Term	0.80	0.12	0.57
Youth	0.43	0.12	0.37

Ratio of the standard deviation of the permanent component to the standard deviation of the transitory component. Short term refers to the natural log of thousands of civilians unemployed for less than 5 weeks, and long term refers to the number of civilians unemployed for 27 weeks and over. Finally, youth is the unemployment level in the natural log of thousands of persons between the age of 20 to 24 years old. UC is the bivariate unobserved components model (using real GDP and the labor market indicator given), HP is the Hodrick Prescott filter, and BP is the Baxter-King band pass filter.

Table 6.5: Relative Variation of the Simulated Data Components

Group	**HP**	**BP**
Unemployed	0.09	0.22
Males	0.09	0.41
Females	0.17	0.39

Ratio of the standard deviation of the permanent component to the standard deviation of the transitory component. The data is simulated using the estimated parameters of the unobserved components model in Table 6.2. HP is the Hodrick Prescott filter, and BP is the Baxter-King band pass filter.

Figure 1: Hodrick - Prescott Filter: Number of Unemployed

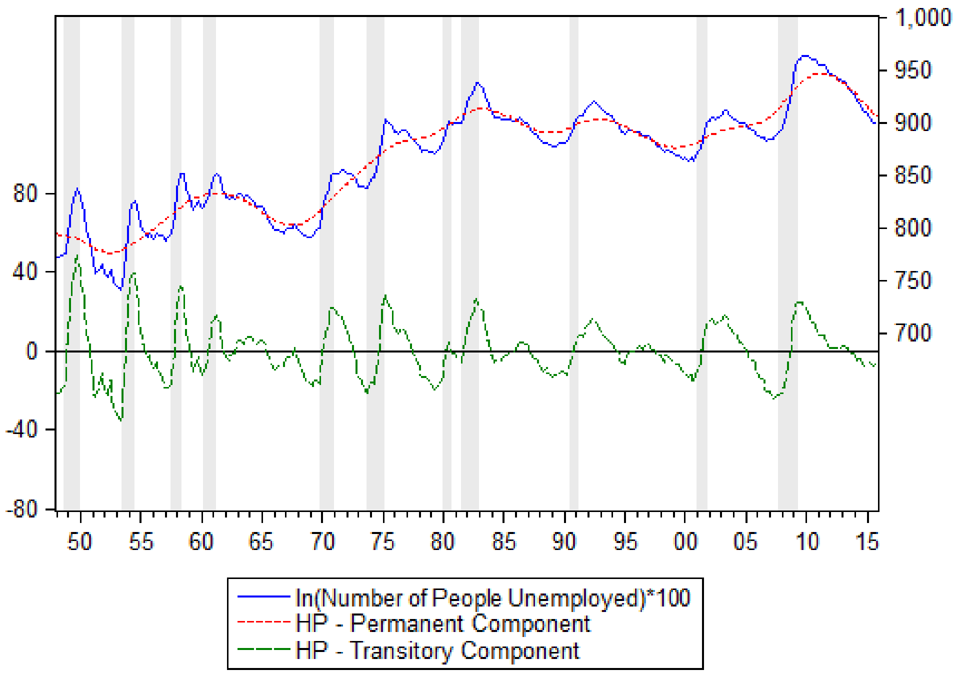

Figure 2: Baxter - King Band Pass Filter: Number of Unemployed

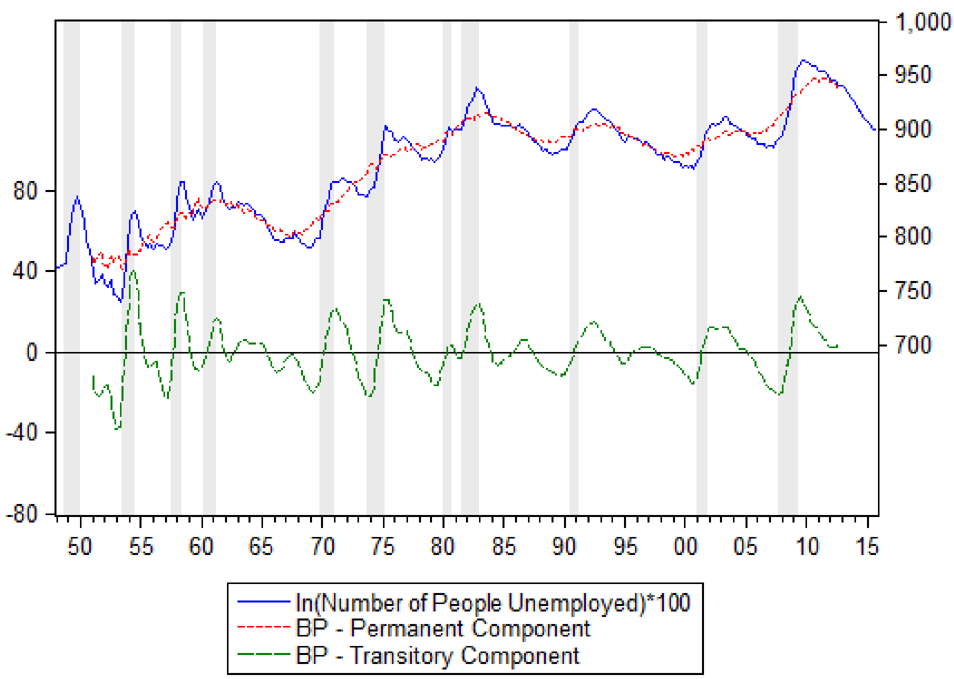

Figure 3: Unoberved Components: Number of Unemployed

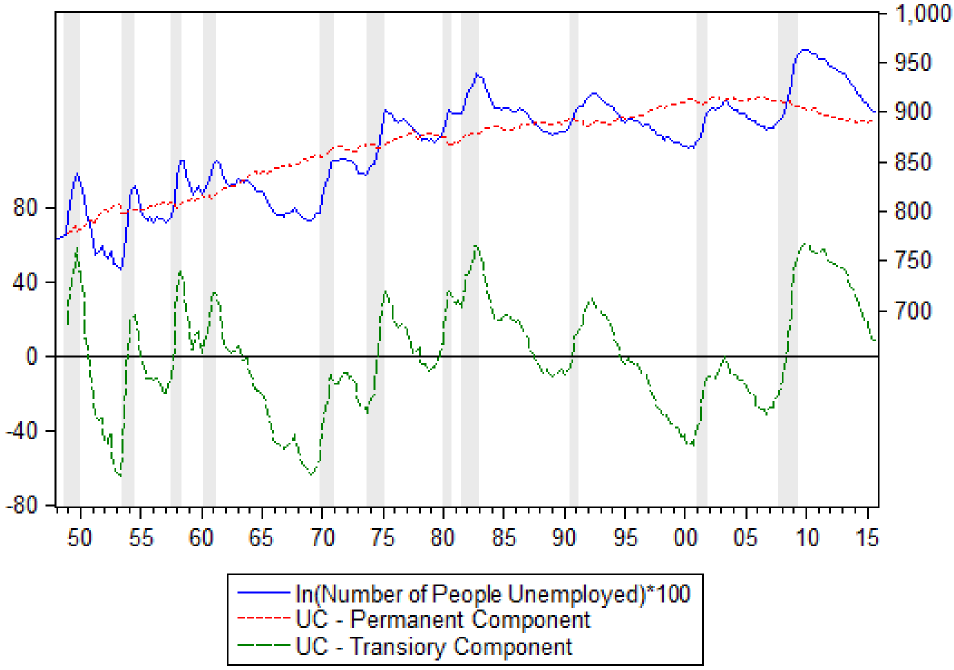

Figure 4: Hodrick - Prescott Filter: Number of Males Unemployed

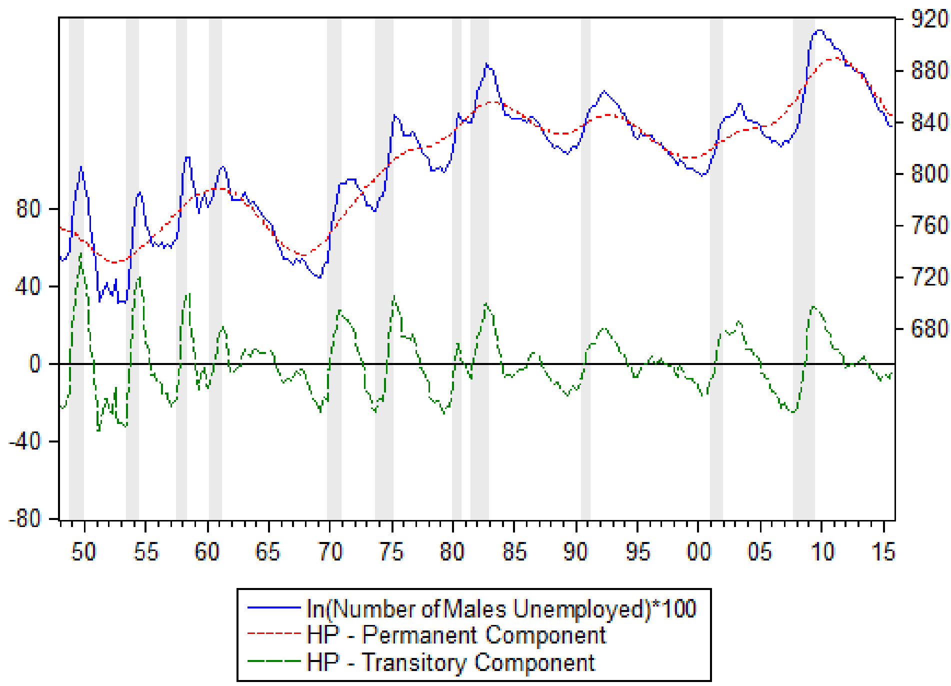

Figure 5: Baxter - King Band Pass Filter: Number of Males Unemployed

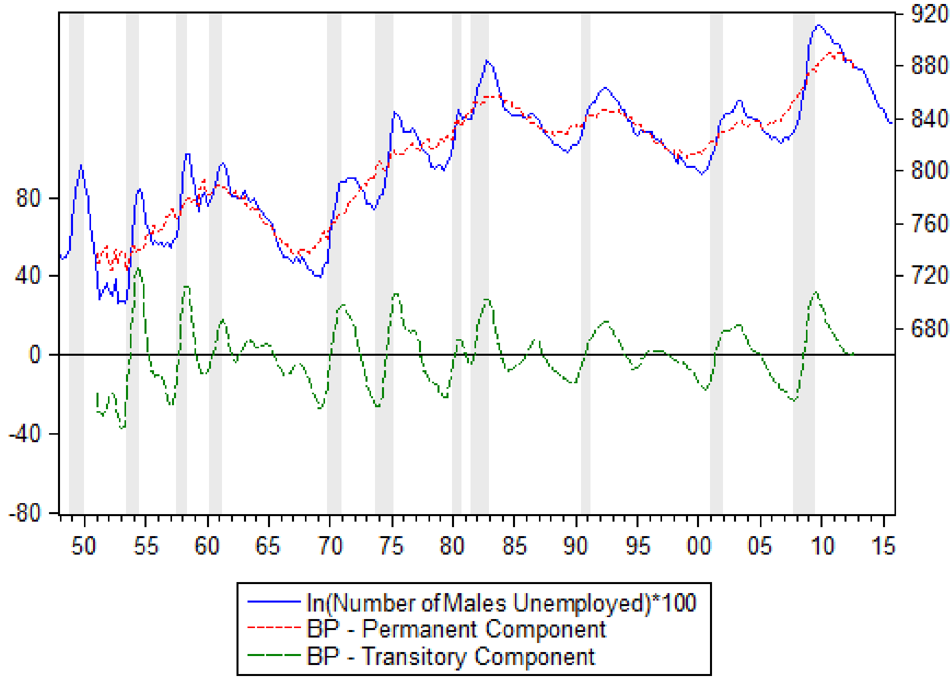

Figure 6: Unoberved Components: Number of Males Unemployed

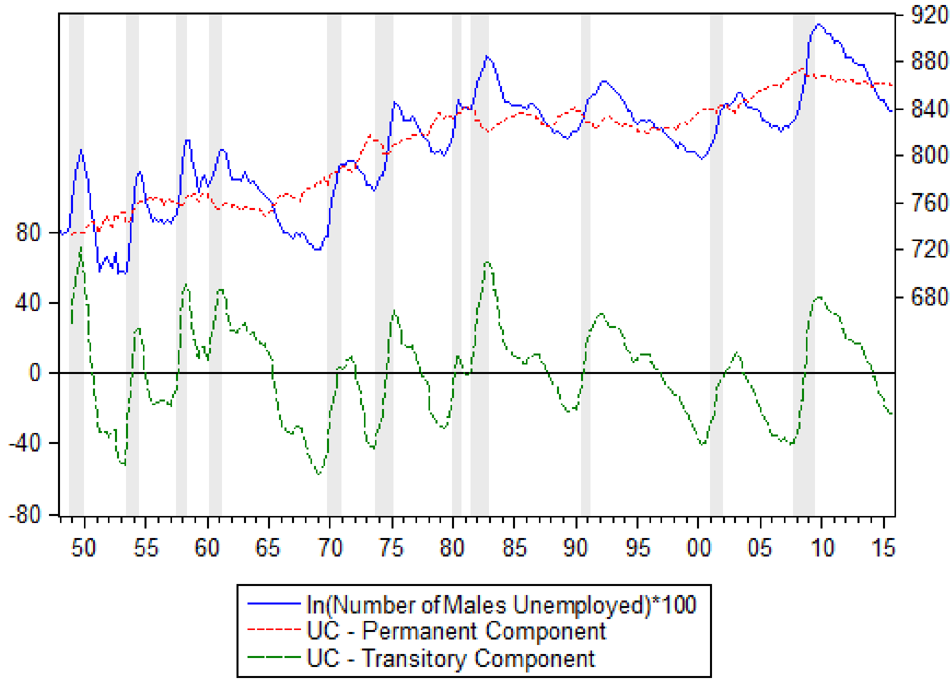

Figure 7: Hodrick - Prescott Filter: Number of Females Unemployed

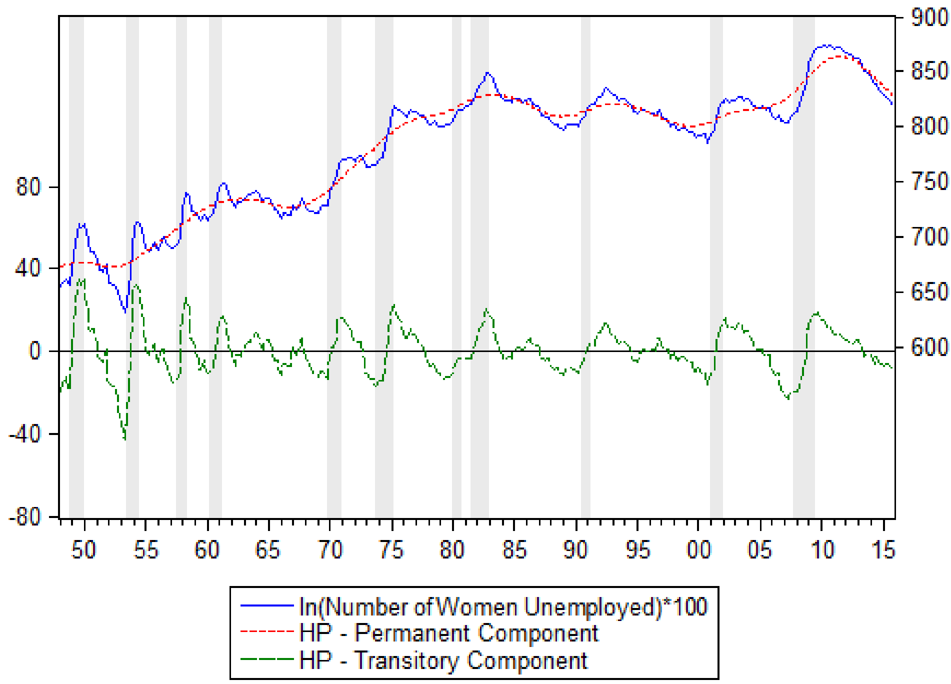

Figure 8: Baxter - King Band Pass Filter: Number of Females Unemployed

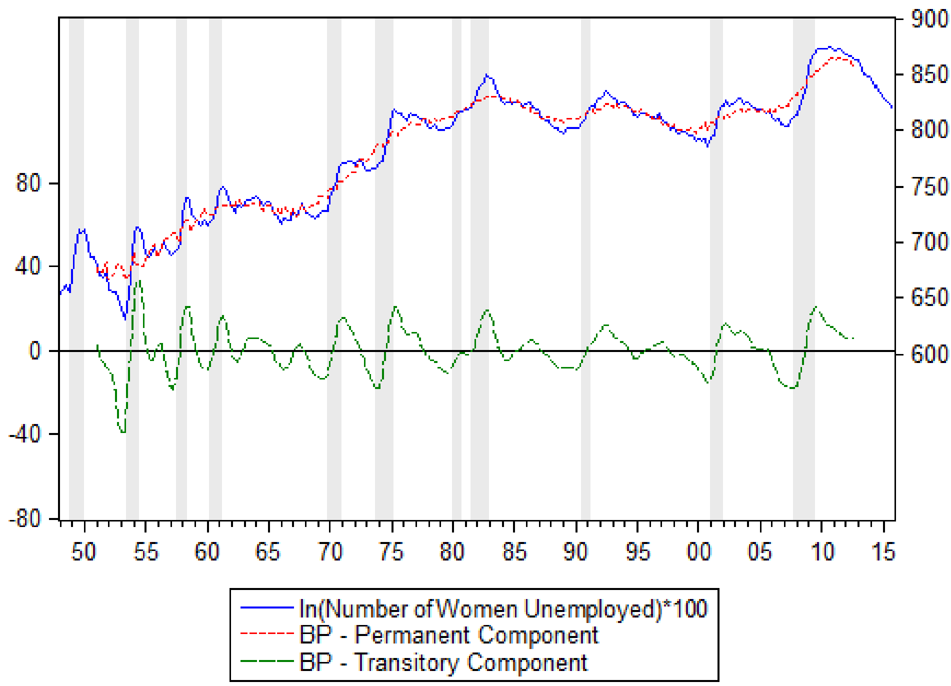

Figure 9: Unoberved Components: Number of Females Unemployed