Gender Differences in the Volatility of Work Hours and Labor Demand *

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Abstract

This paper examines the role of heterogeneity in a real business cycle model, which traditionally has not fully captured the relative volatility of hours to output. Men and women have different cyclical volatilities in hours worked, which is robust to different filtering methods. This empirical regularity is used to motivate a standard RBC model augmented to allow for two different agents following Jaimovich et al. (2013). These two agents have identical utility functions, but face different elasticities of labor demand due to their different complementarities with capital. These elasticities are estimated from the first order conditions of the firm's problem using person level data, which finds that women are more complementary to capital. The calibrated model generates the cyclical volatility of work hours by gender and for the total hours worked that matches the U.S. data better than the traditional representative agent model. I then explore other extensions to this model including investigating the stability of the estimated labor demand elasticities and allowing for various Frisch elasticities of labor supply. This paper demonstrates that allowing for even broad levels of heterogeneity in a simple framework can increase the model's tractability with the data. Since gender is important to explain U.S. business cycle dynamics, we need to carefully consider heterogeneity when analyzing counter-cyclical economic policy, as it may not have symmetric effects across assorted groups.

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1 Introduction

The Real Business Cycle (RBC) model created a framework that explained the business cycle relationships of key macroeconomic variables (Kydland and Prescott, 1982; Prescott, 1986). While the model has performed well in describing the co-movement of consumption and wages, it does not capture the relative volatility hours, defined as the standard deviation of work hours to the standard deviation of output. Many papers have tried to correct for this drawback by adding a fixed cost to labor supply (Cho and Rogerson, 1988; Cho and Cooley, 1994) and indivisible labor and lotteries (Hansen, 1985; Rogerson, 1988; Rogerson and Wright, 1988). Other additions to the RBC model includes capacity utilization, cash-in-advance, imperfect competition, and home production, which could be included to caputure other moments of the data.[1] In this paper, I show that the cycle of aggregate hours worked varies by gender. Motivated by this empirical result, I calibrate a model by Jaimovich et al. (2013), which expands on the classical RBC model to include two separate agents that make up a household, which I define as males and females.

Since men and women have different volatilities of cyclical hours, this paper investigates whether a model that accounts for these two different agents can better match the U.S. data. I use a two agent model as specified by Jaimovich et al. (2013). While this model was introduced to explain the differences of volatility by ages groups, this model can be calibrated to explain the differences generated by gender. The redefinition of these groups from "young" and "old" to "males" and "females" is an appropriate application because groups identified by gender do not suffer from the same definitional issues as groups disaggregated by age. While Jaimovich et al. (2013) define "young" workers to be 15 to 29 years old and "old" workers to be 30 to 64 years old, these cutoffs are not standard in the literature and could

[1] For more details about the RBC model and extensions see McCandless (2008).

induce some bias into their estimates. 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. Additionally, in explaining the importance of youth employment and unemployment for policy O'Higgins (2001) explains the difficulty of defining youth, especially across countries, which could be effected by different policies. While the United Nations defines youth to be between 15 and 24, the author 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 U.S. (Mosisa and Hipple, 2006). However, these definitional issues can be avoided when disaggregating the population by gender.

In macroeconomics, a widely used assumption is to characterize the world as being composed of many identical agents. However, there is a vast literature explaining the different labor decisions and dynamics based on different sub-populations, such as age, race, and gender. This paper focuses on the different labor market dynamics of men and women. There have been many studies that have shown men and women vary in occupation decisions (Blau et al., 2013; Polachek, 1981), educational decisions (Charles and Luoh, 2003; He et al., 2011; Pekkarinen, 2012), and time use (García-Mainar et al., 2009).[2] While many of the models have focused on the labor supply issues (Chiappori, 1992; Cho and Rogerson, 1988; Mulligan, 1998), this paper will focus on the labor demand differences between these two groups assuming they have the same utility functions and face the same budget constraint.

In order to provide evidence for the model specification, I first show that aggregate

[2]For a literature review of gender in the labor market see Altonji and Blank (1999).

hours varies by gender. Since this paper is concerned with the adjustments over the business cycle, it is important to use a data frequency appropriate to capture these dynamics. I use average hours for non-agricultural industries separated by gender from the Current Population Survey (CPS). This monthly series is transformed into a quarterly series of aggregate hours carefully taking into account possible outliers and seasonality issues following Cociuba et al. (2009). I find that the volatility of the cyclical component is greater for men than women using a sample from 1976Q3 to 2015Q2; this result is robust to different filtering methods. This is consistent with recent research that has found larger recessionary effects on men than women, which is not only a feature of the most recent recession (Engemann and Wall, 2009; Guisinger and Sinclair, 2015; Hoynes et al., 2012).

Therefore, as specified by Jaimovich et al. (2013), I set up a model with two different agents that compose a representative household. Since these agents have identical utility functions and additive separability, consumption is the same among household members. These agents are only different in the demand for their labor. Motivated by the capital and skill complementarity literature (Acemoglu, 1998; Krusell et al., 2000), which finds that differences in elasticities of substitution can explain a large portion of the wage differences between skilled and unskilled labor, I allow the elasticities of substitution to vary between men and women in the firms' production function. This specification is consistent with (Olivetti, 2006) who finds that the elasticity of labor demand has changed in favor of women as employers require more office work than manual labor. Additionally, allowing for different elasticities of men and women workers has been used in an overlapping generations model by (Galor and Weil, 1996) to explain fertility and growth within a country.

These labor demand elasticities are the key parameters in the model. Using annual person-level income data from the March supplement of the CPS and national data from the Bureau of Economic Analysis from 1964 to 2014, I am able to estimate the elasticities directly from the first order conditions of the representative firm's problem. I find that the elasticity of substitution between female workers and capital is greater than the elasticity between female workers and male workers, which is consistent with this explanation that women are more complementary with capital than men. Additionally, I explore the stability and sensitivity of these estimated elasticities. Using standard values for all other parameters, I compare the performance of the model with HP filtered U.S. data statistics, which is standard in the literature. I find that the relative volatility of hours for males and females generated by the model (1.34 and 1.19) closely matches the U.S. data (1.32 and 0.96). As a consequence of matching the volatilities of the gender groups, the model (1.24) generated relative volatility of aggregate hours that matches the data (1.12), as well. This result is much improved over the classical RBC model, which finds the volatility of hours to be around half the volatility of output (King et al., 1988). I then explore the concurrence of my baseline results to the estimated elasticities and to various Frisch elasticities taken from the literature. Therefore, accounting for difference in the labor demand for the two groups, specifically defining female labor as being more complementary to capital, resolves the classical RBC's inability to generate sufficient hours worked volatility.

The paper is organized as follows: Section 2 explores the gender differences of work hours using three different filtering methods. Section 3 describes the real business cycle model augmented to allow for two types of workers, men and women. Section 4 discusses the estimation and sensitivity of the elasticities of substitution on the labor demand side. Section 5 outlines the results of the baseline model and extensions of the model. Finally, Section 6 concludes.

2 Empirical Evidence

It has been well documented that Real Business Cycle models have not been able to generate the relative volatility of work hours with relation to output that is seen in the data (Kydland and Prescott, 1982; Prescott, 1986). While others have looked into adding different types of frictions to the model to generate more volatility in the labor market, this paper will look into the possible benefits of heterogeneity in explaining the labor market dynamics. 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). Therefore, this section will investigate the volatility of aggregate hours disaggregated by gender.

2.1 Aggregate Hours by Gender

As the focus of this paper is to explain the movement across the business cycle, it is important to use a data frequency that is appropriate to capture these dynamics. The Bureau of Labor Statistics (BLS) has seasonally unadjusted monthly data for average hours at work disaggregated by men and women from June 1976.[3] Following Cociuba et al. (2009) the average, monthly data is transformed into a seasonally adjusted, aggregate quarterly series. These data series contain outliers that could introduce bias if data is simply averaged across the months to create a quarterly series. The outliers tend to be a one month observation that is below the previous or following months, which could be due to a holiday falling on a reference week, thereby leading to an atypical number of hours reported for that month. Therefore, the average hours worked over the quarter is compared to the minimum hours

[3]The series used are LNU02033120, LNU02033510 (women), and LNU02033447 (men).

worked in that quarter. If the deviation is negligible, then the average is used. However, if the deviation is not negligible, then the minimum value is dropped and the average of the other two months is used. Specifically, if m_i is the monthly observation of average hours worked, then a quarterly observation is calculated as:

$$q = \begin{cases} \frac{3 \cdot \text{average}\{m_1, m_2, m_3\} - min\{m_1, m_2, m_3\}}{2}, & \text{if } d < 0.95 \\ \text{average}\{m_1, m_2, m_3\}, & \text{otherwise} \end{cases} \tag{2.1}$$

where d is the ratio of the minimum value over the average value. This method specifically corrects for the low outliers, or under-reporting hours worked.

Once the quarterly series is constructed, the data is seasonally adjusted using the Census deseasonalizer X12 method.[4] Total hours worked per quarter are then calculated by the employment level of the group[5] multiplied by the average hours worked multiplied by $\frac{52}{4}$.

2.2 Decomposition Methods

In order to evaluate the business cycle volatility, the data on aggregate hours worked by gender needs to be decomposed into a permanent or trend component and a transitory or cyclical component. Since all filters are modeled differently, they might lead to divergent decompositions of the same data series. This section will evaluate business cycle volatility by

[4]Seasonally adjustment was done using the X12 multiplicative deseasonalizing available in Eviews.

[5]The series used for employment is LNU02032187, LNU02032898 (men), and LNU02032998 (women). The method for converting this series into a quarterly seasonally adjusted series is the same as the method for hours worked explained above.

using three different types of filters or decomposition methods in order to extract a transitory or business cycle series of aggregate hours worked. The three types of filters used are the Hodrick-Prescott filter, the Baxter-King Band Pass Filter, and the univariate unobserved components model. Each model is discussed below, and the next section will evaluate and compare the results.

The Hodrick-Prescott (Hodrick and Prescott, 1997) filter is the most common filtering method used in the literature. The Hodrick-Prescott (HP) filter is a linear, two-sided filter that assumes that the trend is a smooth process and it is not correlated with the cycle. Therefore, the smooth trend, s, of the series, r, is found by minimizing the variance of r around s with a penalty to control the smoothness, λ:

$$\sum_{t=1}^{T}(r_t - s_t)^2 + \lambda \sum_{t=2}^{T-1}((s_{t+1} - s_t) - (s_t - s_{t-1}))^2. \tag{2.2}$$

While this filter does not require a lot of data[6], 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. While this method is an improvement over a deterministic, linear trend (Nelson and Plosser, 1982), this method can introduce spurious cycles into the resulting data (Cogley and Nason, 1995; Harvey and Jaeger, 1993b; Jaeger, 1994).

Another decomposition method considered is the Baxter-King Band Pass (BP) Filter (Baxter and King, 1999). This is a linear, fixed length symmetric filter. For this filter, the researcher must define the lead and lag length and the duration range of a cycle *a priori*.

[6]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).

Following Baxter and King (1999), the lead and lag length is set for 12 observations (or 3 years of data) and a cycle is expected to last between 6 and 32 observations. This filter takes a two-sided moving average at the specified lead and lag length of the data and extracts the cycles within the specified duration range. While this filter has been shown to be able to reproduce NBER business cycles for a variety of data series (Baxter and King, 1999), the research loses three years of data at the beginning and end of the sample for the estimation.

The final decomposition method considered is a univariate unobserved components model. Unlike the traditional specification (Clark, 1989; Harvey, 1985a), I allow for a correlation between innovations of the components following Morley et al. (2003). This specification nests the traditional model, as the correlation can be estimated to be any value between -1 and 1. Allowing for this correlation is consistent with many empirical models which have found a statistically significant negative correlation between trend and cycle shocks for many macroeconomic series (Beveridge and Nelson, 1981; Morley et al., 2003; Nelson and Plosser, 1982; Sinclair, 2009).

This method assumes that the I(1) series is a sum of an unobserved a permanent and transitory component. In order to estimate the model, the structural form of the permanent and transitory components need to be defined, and then the specific characteristics (i.e., parameters) are chosen by the data. The permanent component, ι is defined as a random walk with drift,

$$\iota_{jt} = \kappa_j + \iota_{jt-1} + \eta_{jt} \tag{2.3}$$

where j is the variable (i.e., aggregate hours worked, aggregate hours worked by females, and aggregate hours worked by males) and κ is the drift component. The innovation to the permanent component, η, is normally distributed with a mean of zero. The transitory component, c, is modeled as an autoregressive process of order two (AR(2)),[7]

$$c_{jt} = \phi_{1j} c_{jt-1} + \phi_{2j} c_{jt-2} + \nu_{jt} \tag{2.4}$$

where the ϕ are the autoregressive coefficients and ν is the innovation to the transitory component, which is normally distributed with a mean of zero. This stationary component is defined as the business cycle process for this model.

Following Morley et al. (2003) and Sinclair (2009), the innovations of the components are allowed to be correlated. As shown in Morley et al. (2003) this specification nests the traditional unobserved components model (Clark, 1987; Harvey, 1985b) in which the correlation between the innovations is restricted to be zero and the Beveridge-Nelson decomposition (Beveridge and Nelson, 1981) in which the correlation between the innovations is restricted to be -1. Therefore, the covariance matrix is

$$\Sigma = \begin{pmatrix} \sigma_\eta^2 & \sigma_{\eta\nu} \\ \sigma_{\eta\nu} & \sigma_\nu^2 \end{pmatrix} \tag{2.5}$$

where σ^2 is the variance and $\sigma_{\eta\nu}$ is the covariance. The above equations can be written in state space form and the Kalman filter can be applied to decompose the series into its permanent and transitory components using maximum likelihood estimation.

[7] Specifying the autoregressive lags to be greater than or equal to two is necessary for the cycle to be periodic (Clark, 1987; Harvey, 1985b; Harvey and Jaeger, 1993a).

2.3 Volatility Comparison by Gender

The the natural logs of the data series for total aggregate hours and aggregate hours by gender, as described in Section 2.1 are graphed on Figure 1, where the shaded regions are NBER U.S. recession dates. As can be seen in the figure, the aggregate hours worked does seem to fall sharply during the recessionary times for all groups. I then apply each of the filtering methods, described in the previous section, to extract the business cycle component of the series. Table 7.1 shows the standard deviation of the cyclical components of each series using the methods. The data used to estimate these models is from 1976Q3 to 2015Q2; however, since the Baxter-King Band Pass Filter required 12 observations at the beginning and end of sample for estimation, the sample presented is from 1979Q3 to 2012Q2.

It is important to note that the the aggregate cyclical variability in hours is relatively similar across between the HP and BP filtering methods, 1.61 and 1.49, respectively. However, the aggregate volatility for the univariate UC model is much less than the other two filters at 0.90. This may be due to the fact that this is the only filter than allows for the correlation between the innovations of the two components (trend and cycle). Table 7.2 shows the summary results for the univariate UC model. Consistent with Morley et al. (2003), I find that the covariance between the innovations of the components to be negative; although, the covariance for males is not statistically significant.

Comparing the relative volatilities between the gender groups by filtering methods in Table 7.1, we can see that the the univariate UC method estimated the largest volatility for both males and females, the BP filter estimated the smallest variability for both groups. However, despite the filtering method used, business cycle volatility for males is consistently greater than females.

While the HP filter has been shown to overstate the cyclical components in some cases (Cogley and Nason, 1995), the UC model has been shown to have poor end of sample properties (Orphanides and Norden, 2002). Since the relative percent deviations from the trend based on gender results are relatively consistent, this paper will motivate the model using the results from the HP filter, as is standard with the literature.[8] Figure 2 plots the HP cyclical component for men and women with NBER recessions displayed by the shaded area. These series can be interpreted as the percent deviations from the trend. As seen in the figure, male work hours falls by more than women work hours during recessions, but rises by more during expansions. These results are visually consistent with the estimated volatilities, which find that the volatility of the cyclical component is greater for men than women over the sample. This result is consistent with recent research that have found larger recessionary effects on men than women (Engemann and Wall, 2009; Guisinger and Sinclair, 2015; Hoynes et al., 2012) in the recent recessions.[9]

3 Model

This section describes an RBC model introduced by Jaimovich et al. (2013), which is augmented to include heterogeneity of workers, that I define as males and females, that form a representative household. While these household members are assumed to be identical on the supply side, the representative firm's elasticities of substitution on the demand side of the problem are allowed to vary, as male and female workers enter the production function

[8]Although, the empirical differences the filters is an interesting area of research, it is discussed more in Guisinger and Sinclair (2015).

[9]It is important to note that these results may be influenced by other differences that are manifested in gender, such as occupational differences (Blau et al., 2013; Polachek, 1981). Albanesi and Sahin (2013) find that males tend to have a higher share of workers in production occupations, while females tend to have a higher share of workers in sales and office occupations. However, how to appropriately define work, either by occupations, sectors, or tasks, has been an interesting topic of discussion (Acemoglu and Autor, 2011; Guvenen et al., 2015).

as separate labor inputs.

3.1 Households

The economy is populated with many identical, infinitely-lived households. The households are composed of family members, which sum to unity. Heterogeneity is introduced in the model by allowing for two types of family members, males and females, where the share of males is denoted by s_m and the share of females is $1 - s_m$. Family members derive utility from consumption, C_i and disutility from hours spent working, N_i, where $i \in \{m, f\}$. The representative household maximizes

$$E_t \sum_{\tau=t}^{\infty} \beta^{\tau-t}[s_m U_m(C_{m\tau}, N_{m\tau}) + (1 - s_m)U_f(C_{f\tau}, N_{f\tau})] \tag{3.1}$$

subject to

$$s_m C_{m\tau} + (1 - s_m)C_{f\tau} + K_{\tau+1} = (1 - \delta)K_\tau + r_\tau K_\tau + s_m W_{m\tau} N_{m\tau} + (1 - s_m)W_{f\tau} N_{f\tau} \tag{3.2}$$

for a date, t, where U_i is the utility function, K_t is capital, r_t is the rental rate of capital, and W_{it} is the wage rate (which can vary across members). I assume that households take all prices as given. The discount rate, β and the depreciation rate of capital, δ, is between 0 and 1.

The utility function is defined as:

$$U_i = logC_i - \frac{\psi_i N_i^{1+\theta_i}}{(1 + \theta_i)}, \tag{3.3}$$

where $\psi_i > 0$ is used to calibrate the steady-state hours worked for males and females and $\theta_i \geq 0$ are the Frisch elasticities of labor supply. The time endowment of the household is normalized to unity, such that $0 \leq N_m, N_f \leq 1$. As seen in Equation (3.3), the utility function for males and females has the same functional form. Therefore, differences between males and females are not arising from differences in their utility structure. However, this assumption is relaxed in Section 5.2, when I allow for different Frisch elasticities.

Since the preferences represented in the utility function are additively separable, and because the household is maximizing utility by choosing consumption, the optimal solution will have consumption equated across all household members:

$$C_{mt} = C_{ft} = C_t. \tag{3.4}$$

Households choose C_t, K_{t+1}, $N_{m,t}$, and $N_{f,t}$ to maximize Equation (3.1) subject to Equation (3.2). The first order conditions (FOCs) are:

$$\frac{1}{C_t} = \beta E_t[\frac{1}{C_{t+1}}(r_{t+1} + 1 - \delta)] \tag{3.5}$$

$$W_{it} = \psi_i C_t N_{it}^{\theta_i}, \tag{3.6}$$

where Equation (3.5) combines the first order conditions with respect to consumption and investment and Equation (3.6) is the FOC with respect to hours worked for males and females.

3.2 Firms

As members of the household are identical on the supply side, they must differ on the demand side in order to deviate from the typical represent agent model. Specifically, males and females enter into the production function as different factors of production. I assume a nested CES production function with multiple labor inputs following the capital skills literature (Krusell et al., 2000).[10] Goods in the economy are produced by perfectly competitive firms according to the following three-factor production function:

$$Y_t = [\mu(A_t H_{mt})^{\sigma} + (1-\mu)[\lambda K_t^{\rho} + (1-\lambda)(A_t H_{ft})^{\rho}]^{\sigma \backslash \rho}]^{1 \backslash \sigma}. \tag{3.7}$$

The three factors of production are labor hours of males (H_{mt}), labor hours of females (H_{ft}), and capital (K_t), and σ and ρ are the substitution parameters, which are less than unity in order for the isoquants to have the appropriate convexity (Solow, 1956). Unlike the standard Cobb-Douglas production funtion, this CES production function does not require that all factors inputs are necessary for production. The technology, A_t, evolves according to the following process:

$$A_t = exp(gt + z_t); z_t = \phi z_{t-1} + \varepsilon_t, \tag{3.8}$$

where g is the trend growth rate and z_t is the stationary shocks, where $E(\varepsilon_t) = 0$ and ϕ are the autoregressive coefficients that are between 0 and 1. These perfectly competitive

[10]Nested CES production functions have been found to lead to incongruous long-run predictions (Klump and de La Grandville, 2000; Klump et al., 2007). However, this paper's focus is in explaining the business cycle volatilities of hours worked.

firms choose the level of the factors in order to maximize profits, where the FOCs are:

$$r_t = Y_t^{1-\sigma}(1-\mu)\Omega_t \lambda K_t^{\rho-1} \tag{3.9}$$

$$W_{ft} = Y_t^{1-\sigma}(1-\mu)\Omega_t(1-\lambda)A_t^{\rho} H_{ft}^{\rho-1} \tag{3.10}$$

$$W_{mt} = Y_t^{1-\sigma}\mu A_t^{\sigma} H_{mt}^{\sigma-1} \tag{3.11}$$

where $\Omega_t \equiv [\lambda K_t^{\rho} + (1-\lambda)(A_t H_{ft})^{\rho}]^{(\sigma-\rho)\backslash\rho}$. As shown above, marginal revenues are set equal to factor prices.

As shown in (3.7), the substition parameters are allowed to vary; however, the elasticity between female workers and male workers is restricted to be the same as the elasticity between capital and male workers. This is similar to the specifications in the capital-skills complementarity literature where labor is disaggregated by education level, skill level, or experience level (Griliches, 1969; Jaimovich et al., 2013; Krusell et al., 2000), rather than gender. The elasticity of substitution between capital and female workers is given by $1/(1-\rho)$ and the elasticity of substitution between female workers (or capital) and male workers is $1/(1-\sigma)$. In order for the capital-skills complementary interpretation to hold, $\sigma > \rho$ must be true.

The conjecture that female labor is more complementary to capital than is male labor is consistent with recent research has shown that elasticity of labor demand has changed in the U.S. as jobs and requirements have changed for employers. Employers are demanding more office work, which favors the fine motor skills where females have a comparative advantage, over manual labor where males have a comparative advantage (Olivetti, 2006). This change in labor demand has been linked to a shift from the manufacturing sector and towards the services sector (Goldin, 1990), a change in society's attitudes towards females in the workplace (Fernández et al., 2004), and a rise in women's educational attainment (He et al., 2011). Additionally, allowing for men and women to be separate labor inputs in the production function and allowing for different elasticities of substitution has been implemented in an overlapping generations framework to explain the rapid decline in fertility and increase in output growth (Galor and Weil, 1996). Furthermore, Rendall (2010) argues that the recent labor demand changes that favor women are in part due to the job requirements shifting away from physical and toward intellectual attributes in conjunction with women overtaking men in college educational attainment. These two changes lead to what she coins as "brain biased technical change" that can explain the change in women's labor force participation, wages, and educational attainment.

In order to understand the mechanism at work to generate a greater volatility of hours, assume that female labor is a perfect complement to capital or that $1/(1-\rho)$ tends towards unity and male labor is not a perfect complement to capital or that $1/(1-\rho) > 1/(1-\sigma)$, so that the following holds: $\sigma > \rho$. If there is a productivity shock, then firms will want to reduce the amount of goods they are producing. Assuming that capital is inelastic in the short run, that leads firms to adjust the quantity of labor demanded. Since female workers and capital are perfect complements in production (in this example), this will lead firms to adjust the quantity of labor demanded of male workers. The result is that male workers will be more volatile over the business cycle than female workers.

3.3 Equilibrium

The competitive equilibrium is a set of quantities, $\{C_t, N_{mt}, N_{ft}, K_t, Y_t, H_{mt}, H_{ft}\}$ and prices, $\{r_t, W_{mt}, W_{ft}\}$, such that the representative household chooses C_t, N_{mt}, and N_{ft} given r_t, W_{mt}, and W_{ft}; the representative firm chooses K_t, Y_t, H_{mt}, and H_{ft} given r_t, W_{mt}, and W_{ft}; and all markets clear. In equilibrium, the following conditions hold:

$$K_0 > 0 \tag{3.12}$$

$$H_{mt} = s_m N_{mt} \tag{3.13}$$

$$H_{ft} = (1 - s_m) N_{ft} \tag{3.14}$$

$$C_t + K_{t+1} = Y_t + (1 - \delta) K_t, \tag{3.15}$$

for all t, such that the rental market, the labor markets, and the goods market clear. Aggregate hours worked in the economy is defined as the sum of female and male labor hours worked or $H_t = H_{ft} + H_{mt}$.

4 Estimation

I use standard calibrated values from the literature for the remaining parameters whenever possible. However, the main difference between the two types of labor in this model rests on the differences of the elasticities of substitution in the production function. Therefore, following Krusell et al. (2000) and Jaimovich et al. (2013), I estimate these values using the CPS March Supplement Survey (from IPUMS) and other macroeconomic data series from FRED[11] and the Bureau of Economic Analysis. This section describes the data used, the estimation specification, sensitivity analysis, and other calibrated values used for the model.

[11] Federal Reserve Bank of St. Louis, https://research.stlouisfed.org.

4.1 Data

While Section 2 uses a quarterly data series to explore the business cycle relationships of the data, due to data limitations this section uses an annual series.[12] Specifically, I use the CPS March Supplement Survey from IPUMS which includes annual individual observations on demographic characteristics, hours worked, weeks worked, and wage and salary income.[13] I keep only observations from non-self employed, civilians between the ages of 15 and 70 from 1964 to 2014.[14] While this section implicitly assumes that the elasticities are not changing over time,[15] this assumption is investigated in Section 4.3.

There are a few modifications I make to the data in order to exploit increased precision due to survey updates and to correct for reporting discrepancies. First, in 1976 the survey started recording the number of weeks worked the previous year (WKSWORK1) as two digit numeric values. Prior to this, the number of weeks worked the previous year (WKSWORK2) is recorded as an interval with eight bin options. In order to use the longest series possible and take advantage of the more precise estimates from 1976 onward, I use the median weeks worked in the interval prior to 1976 and use the numeric values from 1976 onward.

In a similar vein to the previous change, in 1976 a new question was included in the

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[12]While the Bureau of Labor Statistics provides aggregate monthly, average wages disaggregated by men and women starting in 1976, these series only includes full-time workers. Average wages for part time workers is not available until 2000. Therefore, it is necessary to use the micro-level data to explore the answer to this question.

[13]There was no correction for the top coding of wages. Although, it was adjusted for inflation using the CPI99 variable from IPUMS.

[14]The wage and salary income is for the previous year; therefore, the actual sample includes observations from 1963 to 2013.

[15]While this is a standard assumption in the literature, due to the difficult nature of estimating elasticities generally (Duffy et al., 2004), there is some research to believe that these elasticities may not be constant over time due to the changing work demand brought on by computerization of the workforce in the 1970s (Olivetti, 2006). However, since this data set is starting in 1965, the changes would have occurred during this sample period.

survey to ask what is the *usual* hours a week a person works, if they worked the previous year (UHRSWORK). Prior to this, the survey recorded just the hours worked last week (HRSWORK) during a given reference week. However, there could be some bias if the person happened to not work last week or worked less or more hours last week than usual. Therefore, for observations prior to 1976, I use the hours worked last week, and from 1976 onward I use the usual hours worked.

Finally, following Jaimovich et al. (2013), I correct for the consistency of reporting for hours worked using the workers' full-time or part-time status. Specifically, if a person claims to be part-time and has hours worked between 1 and 34 hours there is no change to the work hours; however, if they report 0 or more than 34 hours, they are given the group average of hours worked. Similarly, if a person claims to be full-time and has reported working 35 hours or more, then there is no change; however, if they report less than 35 hours, they are given the group average of hours worked. Similar to Krusell et al. (2000) and Jaimovich et al. (2013), I create groups based on age (eleven five-year age bins), education (five bins), gender, and race (2 bins). Therefore, there is a total of 220 possible group, g, where the weighted group average, h_g, of individual l's hours worked is given by:

$$h_g = \frac{\sum_{l=1}^{g} h_l \mu_l}{\sum_{l=1}^{g} \mu_l}, \tag{4.1}$$

where h_l is the hours worked reported by the individual, l, that matches the full-time or part-time status reported and μ_l is the CPS person-level weight. Jaimovich et al. (2013) find that this correction method avoids an under-reporting of hours when comparing the corrected hours to the usual hours a week a person works prior to 1976. This correction is similar in spirit to the correction in Section 2, due to the under-reporting of hours worked for a given reference week.

4.2 Elasticity Estimation Specification

This section discusses the methodology for estimating the substitution parameters from the production function, σ and ρ, which are the main differences between the two types of workers, males and females. In order to estimate the substitution parameters from the production function, I use the first order conditions from the firm's problem, Equations 3.9 through 3.11, following a similar methodology by Jaimovich et al. (2013). Starting with the estimation of σ, I take the logged first difference of Equation 3.11, which becomes

$$\Delta log W_{mt} = \alpha_0 + (1-\sigma)\Delta log Y_t + (\sigma - 1)\Delta log H_{mt} + \sigma\epsilon_t. \tag{4.2}$$

In this equation, *log* refers to the natural log, Δ refers to the first difference, α_0 is the constant term, and ϵ_t includes all the shock innovations. Since the annual CPS data does not include a wage variable for the whole series directly, I estimate the following variant:

$$\Delta log Inc_{mt} - \Delta log Y_t = \alpha_1 + \sigma(\Delta log H_{mt} - \Delta log Y_t) + \sigma\epsilon_t, \tag{4.3}$$

where Inc_{mt} is the labor income of men, which is equivalent to weekly hours multiplied by the number of weeks worked last year. With this specification, Y_t is available from FRED and Inc_{mt} and H_{mt} are available directly from the IPUMS CPS data.

I follow a similar procedure to estimate ρ. First I take the logged first difference of the first order conditions with respect to K_t and H_{ft}, Equations 3.10 and 3.9, and then take the difference of those two equations to get

$$\Delta logW_{ft} - \Delta logr_t = \alpha_2 + (\rho - 1)(\Delta logH_{ft} - \Delta logK_t) + \rho\epsilon_t. \tag{4.4}$$

Again in order to use data directly from the survey, I estimate a variation of the above equation:

$$\Delta logQ_{ft} - \Delta logQ_{Kt} = \alpha_3 + \rho(\Delta logH_{ft} - \Delta logK_t) + \rho\epsilon_t. \tag{4.5}$$

In this equation, Q_{ft} is the national income share of women and Q_{Kt} the national income share of capital, which can be estimated from data from the Bureau of Economic Analysis. Specifically, the national income share of labor (males and females combined) is estimated from the NIPA data from the BEA. The national income share of capital is defined as one minus the national income share of labor. Finally, the average of the percent of total income by gender from IPUMS is used to estimate male and female income shares.

Using the data described earlier, Equations (4.3) and (4.5) can be estimated to yield parameter values for σ and ρ. However, the equations above are assuming exogeneity of the right hand side variables. Table 7.3 shows the results of the estimates elasticities, σ and ρ, and their robust standard errors. I estimate σ to be 0.758 and ρ to be 0.697 with both estimated parameters are found to be statistically significant at the one percent level. These estimates are within the range of elasticities in found in other specifications.[16] It is important to note that the estimation method used in this paper does not put any restrictions of the values that σ and ρ can take. However, the estimated result that $\sigma > \rho$ is consistent with

[16]While Krusell et al. (2000) estimated demand elasticities between skilled and unskilled labor, σ, and equipment and unskilled labor, ρ, to be 0.401 and -0.495, respectively. Alternatively, Jaimovich et al. (2013) estimated demand elasticities between experienced and inexperienced labor, σ, and capital and inexperienced labor, ρ, to be 0.662 and 0.201, respectively.

the capital-skill complementarity literature (Krusell et al., 2000).

While the estimation method is assuming exogeneity of the right hand side variables, it is important to consider that there might be some endogeneity in the setup. Since the error term also includes all past technology shocks, there is a concern that the error term may be correlated with the explanatory variables or that there may be endogeneity with the specification. Following previous literature,[17] I investigate using lagged birthrates as a possible instrumental variable. Using data from the Census's Statistical Abstract of the United States, I construct a continuous series of birthrates in the U.S. from 1909. Using two-stage least squares, I estimate Equations (4.3) and (4.5) using one instrument at a time and conduct a test for exogeneity along with considering whether the instruments are weak. Table 7.4 shows the test for exogeneity by Durbin (1954) and Wooldridge (1995), where the null hypothesis is that the variables are exogeneous. While the null hypothesis was not rejected for most lagged instruments for σ, it was rejected for most lagged instruments of ρ.

Based on these results, it appears that I would want to use an IV for my specification of ρ; however, using weak IVs could be cause more harm than good due to a lack of consistency (Bound et al., 1993, 1995; Chao and Swanson, 2005). Following Staiger and Stock (1997), I should be concerned about weak instruments, if my first-stage F-statistic is less than 10. Table 7.5 reports the first-stage F-statistic, and none of the values reach the cutoff as defined by Staiger and Stock (1997). Therefore, using the weak instruments may lead to less stable and inconsistent estimates. I look into the stability of my results by conducting sensitivity tests to σ and ρ in Section 5.2.

[17]For some example of papers using lagged birthrates as an instrument, see Shimer (2001), Foote (2007), Beaudry and Green (2003), and Jaimovich et al. (2013).

4.3 Sensitivity Analysis

This section details the robustness of these estimated substitution parameters including checking the stability of these estimates over time and estimating the estimates under the reverse assumption (that the elasticity of male workers and female workers is restricted to be the same as the elasticity between capital and female workers.).

The first assumption of the model that I am investigating is the assumption that the elasticities are constant over time. While this is a standard assumption in the literature, there is some research to believe that these elasticities may not be constant over time due to the changing work demand brought on by computerization of the workforce in the 1970s (Olivetti, 2006). Therefore, I re-estimate Equations (4.3) and (4.5) using a rolling regression window, where I look at a sample window of 31 observations, that moves across full sample from 1964 to 2014. This technique has been used to investigate the stability of many macroeconomic relationships, including Okun's Law (Edward S. Knotek, 2008), inflation forecasts (Meese and Rogoff, 1988), and other univariate and bivariate forecasting relationships (Stock and Watson, 1996). The first regression estimates of σ and ρ are from 1964 to 1994 and the last estimates use a sample from 1984 to 2014, which leads to 21 estimates over the full sample.

Figure 3 graphs the point estimates of σ, the solid line, and the 95 percent confidence intervals, the dotted line. The year associated with each point estimate is the start of the sample. As can be seen in the figure, the estimate of σ stays relatively constant throughout the time period with a minimum estimate of 0.687 in 1984 and a maximum estimate of 0.924 of in 1976. This estimate is also statistically significant across the rolling regression horizon. Figure 4 graphs the point estimates of ρ, where the minimum estimated value is 0.614 in 1964 and a maximum value of 0.769 in 1984. Therefore, from the rolling regression analysis, both estimated elasticities remain relatively stable and statistically significant at the one percent significant level throughout the sample period.[18]

While it is important that the elasticities remain relatively constant throughout the full sample, this analysis also lends itself to test the hypothesis that the difference in labor demand is due to differing complementarity with capital, which requires that $\sigma > \rho$. It is important to note that the original methodology and the rolling regression methodology does not place any restrictions on the relative size of σ and ρ. Figure 5 plots both σ and ρ on the same graph. As can be seen in the graph, $\sigma > \rho$ for every estimate, except the last one with a sample from 1984 to 2014. Therefore, for 20 out of the 21 estimates, the explanation that the differences in labor demand is due to differing complementarity is not violated.

While there is recent literature to support the idea that women may be more complementary to capital than males (Galor and Weil, 1996; He et al., 2011; Olivetti, 2006), Polachek (1981) noted that women tend to have intermittent labor supply as opposed to men, who have continuous labor supply. Therefore, when women leave the labor market, they have an atrophy of skills, which causes them to return to the labor market at a lower wage and skill level. If this hypothesis is correct, then we would expect men to be more complementary with capital, since they will have more continuous on-the-job training and acquisition of skills. I estimate the elasticities assuming the opposite restriction, specifically, that the elasticity of substitution between males and females is the same as the elasticity of substitution between capital and females.

Under this identification scheme, the elasticity of substitution between capital and male workers is given by $1/(1-\gamma)$ and the elasticity of substitution between male workers (or capital) and female workers is $1/(1-\psi)$. In order for the capital experience complementary

[18] It is interesting that the last rolling regression, sample from 1984 to 2014, provided the extreme estimates for both σ and ρ with a lower limit for σ an upper limit for ρ. This may be due to the most recent recession, but it is an interesting topic for future research.

interpretation to hold, the following must be true $\psi > \gamma$. Therefore, following the similar methodology in Section 4.2, to estimate ψ, I can estimate the following equation, which is a modification of the firm's first order conditions:

$$\Delta logInc_{ft} - \Delta logY_t = \alpha_1 + \psi(\Delta logH_{ft} - \Delta logY_t) + \sigma\epsilon_t, \tag{4.6}$$

where Inc_{ft} is the labor income of women, which is equivalent to weekly hours multiplied by the number of weeks worked last year. With this specification, Y_t is available from FRED and Inc_{ft} and H_{ft} are available from the CPS.

In order to estimate γ, I can estimate the following variation from the first order conditions:

$$\Delta logQ_{ft} - \Delta logQ_{Kt} = \alpha_3 + \gamma(\Delta logH_{ft} - \Delta logK_t) + \rho\epsilon_t. \tag{4.7}$$

In this equation, Q_{mt} is the national income share of men and Q_{Kt} the national income share of capital, which can be estimated from data from the Bureau of Economic Analysis.

Table 7.6 shows the estimated substitution parameters under the assumption that men are more capital complementary. Both estimated parameters are significantly significant at one percent significance level with point estimates of 1.022 for ψ and 0.800 for γ. While the estimated coefficients displays the relative magnitudes necessary for capital experience complementarity, $\psi > \gamma$, the substitution parameters must be less than one to generate feasible elasticities of substitution. I can reject the null hypothesis that ψ is equal to one at the 5 percent significance level versus the alternative that ψ is greater than one.[19] Therefore, the assumption that men are more complementary than capital does not lead to feasible estimated elasticities, since an estimated substitution parameter greater than one leads to isoquants that have the wrong convexity (Solow, 1956).

4.4 Calibration

The remaining parameters use standard values or methods in the literature, and are summarized in Table 7.7. β and δ are set at 0.99 and 0.025, respectively, which is standard for quarterly time periods. The Frisch labor supply elasticities, θ_f and θ_m, are set to 0.00001 following Jaimovich et al. (2013), since there are many complications with the precision of the microeconomic estimates Rogerson (1988).[20] Following Krusell et al. (2000) and Jaimovich et al. (2013), I calibrate μ and θ to match national income shares using labor income from the NIPA from the BEA and the March supplement of the CPS from 1964 to 2014. Using these data series, I estimate the income share of capital to be 0.353[21] and the income share of female labor to be 0.228[22]. Finally, the persistence of the technology is set to 0.94 with a standard deviation of 0.0064, following Jaimovich et al. (2013).

[19]The stability of ψ was tested under various sample periods, and it was found to be relatively stable and greater than one in all estimates.

[20]Sensitivity tests to various microeconomic estimates of the Frisch elastiticies can be found in Section 5.2.

[21]This is similar to the estimate from Jaimovich et al. (2013) of 0.37 using data from 1964 to 2010.

[22]This would lead to an estimate of the income share of men to be 0.419, which means that the total income share of labor is 0.647, which is standard in the literature.

5 Results

This section evaluates the model with heterogeneity in household members, where household members vary due to differences in their complementarity with capital. The model's performance is evaluated on the ability to match the business cycle volatility of hours worked in the U.S., where the business cycle is defined as the cyclical component of the HP filter. Additional expansions to the model, analyzing the sensitivity of the model's results when changing the substitution parameters on the demand side and Frisch elasticities of labor supply, are also explored.

5.1 Baseline Results

The results are reported in Table 7.8, where the first column, Data, represents U.S. business cycle statistics. The standard deviation of hours worked are calculated from the BLS data referenced in Section 2 and the standard deviation of real GDP, Y, is from the Federal Reserve Bank of St. Louis's FRED database. As mentioned earlier, males have greater volatility in hours worked as compared with women. Additionally, the aggregate hours worked volatility, H, is greater than the volatility of real GDP, Y, which is the feature that traditional RBC models fail to predict. As a comparison, the third column, KPR, reports the relative volatility of hours worked and output from King et al. (1988). This statistic comes from a simplified version of the Kydland and Prescott (1982) model in which time-to-build in investment, non-separable utility in leisure, and technology shocks that include both a permanent and a transitory component are eliminated. Similar to the findings of other RBC models, the KPR model fails to capture the relative volatility of hours in the data with the standard deviation of hours being less than half of the standard deviation of output.

The second column of Table 7.8 reports the result of the model in Section 3. Assuming the standard calibration values outlined in Section 4.4, the model generates volatility of aggregate hours that are slightly above what is estimated in the data, 1.24 compared to 1.12. This slight over-prediction appears to come from the model generating a larger volatility of female hours than seen in the data, with the standard deviation of female hours relative to the standard deviation of output being 1.19 in the model and 0.96 in the data. However, the model is able to accurately predict the volatility of male hours with the standard deviation of male hours relative to the standard deviation of output being 1.34 in the model and 1.32 in the data. Despite this slight over prediction of the volatility of female hours, overall, the model is able to generate volatility of total hours worked that closely resemble the data, and is a large improvement over the standard RBC predictions.

5.2 Model Extensions

As noted in Section 4.2, the specification of σ and ρ may suffer from endogeneity, particularly ρ, based on the test of exogeneity (Durbin, 1954; Wooldridge, 1995). Therefore, I will investigate the model's ability to match the data if ρ is allowed to be smaller than the estimated value, which is consistent with other papers using nested CES production functions. In particular, I will set ρ to be 0.201 (which is the substitution parameter used in Jaimovich et al. (2013)) and -0.495 (which is the substitution parameter used in Krusell et al. (2000)). It is important to note that neither of these substitution parameters were estimated for a gender breakdown, but breakdowns by age and skill-level, respectively. In addition to the values mentioned above, ρ was also set to equal 0.449, which is half way between my estimate (0.697) and the estimate of Jaimovich et al. (2013).

The results for the model can be found in Table 7.9, where the Data and the Model columns are the same as from Table 7.8. As can be seen in the table, allowing the ρ to decrease leads to a lower relative volatility of female hours and a greater relative volatility of males hours. Additionally, Models (2) and (3) both find relative aggregate hour volatility greater than 1; however, Model (3) underestimates the females hours volatility and overestimates male hours of volatility. The rest of the statistics are fairly similar across all specifications. Therefore, it appears that an estimated ρ between 0.449 (Model 2) and 0.697 (baseline specification, Model 1) generates relative volatility of hours that matches the U.S. statistics.

Another interesting dimension to test the baseline model, is to relax the assumption forcing the Frisch elasticities to be equal to 0, but allow them to be deviate from zero and vary between agents. There has been a wide debate comparing macro and micro labor demand elasticities (Chetty, 2012; Chetty et al., 2011; Keane and Rogerson, 2012); it is well documented that macroeconomic RBC models have large elasticities compared to what is found in the micro literature. Breaking down aggregate hours labor supply elasticities into intensive and extensive margins, Chetty et al. (2011) find that macro models have a Frisch elasticity of aggregate hours of 2.84, compared with micro studies of 0.82. Additionally, there is no consensus about the estimated labor supply elasticities of men and women, with men having estimated elasticities between -0.07 and 0.45 (Pencavel, 1986), and women having -0.48 to 0.48 (Blundell and MaCurdy, 1999).

This paper will look at various Frisch labor supply elasticities for men and women. Specifically, I will investigate four specific combinations of elasticties by gender based on the micro literature. Following Jacobsen (2007), I will calibrate the model for the male elasticity of labor supply to be -0.09 and the female elasticity of 0.77. Blau and Kahn (2007) finds that female labor supply elasticities have been decreasing over time, while male elasticity have stayed relatively stable over the same time period. Therefore, I will use the mean of their model's estimates for the 1979 to 1981 period and the 1999 to 2001 period, which have elasticities of 0.825 and 0.386 for women and 0.040 and 0.072 for men, respectively. Finally, I will calibrate a model assuming that the Frisch elasticities of men and women are the same using the point estimates of 0.54 as documented by Chetty et al. (2011).

The results for the various Frisch elasticity specifications can be found in Table 7.10, where the U.S. moment estimates are followed by the baseline model results in Column (1), which has the same calibration as in Table 7.8. Column (2) shows the results using the estimates from Jacobsen (2007), which has the lowest elasticity for men and the second highest elasticity for women. This model underestimated the relative volatility of hours of women and overestimated the relative volatility of men. This pattern continued for most of the specifications with Column (4) generating the closest relative volatilities of hours worked, but still underestimated the volatility of hours worked for women. It is interesting to note that while Column (5), which specified the same micro founded elasticity, was able to generated relative hours volatility by gender ($\text{std}(H_f)/\text{std}(H_m)$), but underestimated both the relative male and female hours volatility with respect to output.

Similar to previous work by Jaimovich et al. (2013), I find that allowing the Frisch elasticities to deviate from zero generates more wage dynamics in the model. However, all the models generate relative volatility of wages that is greater for women than men, when the data finds the opposite result. This inconsistency could also be due to the lack of consistency in the data with women's wages increasing over the sample (Blau and Kahn, 2007; Olivetti, 2006). Additionally, these data statistics were calculated using annual level data, which is not ideal for business cycle dynamics. The BLS does produce a quarterly wage series disaggregated by gender from 1976; however, it only includes full-time workers.[23] Finally the investment and consumption volatilities remain comparatively stable across the different specifications.

[23]A series for the wages of part-time workers disaggregated by gender is available from 2000.

6 Conclusion

This paper examines the role of heterogeneity in a real business cycle model. Using quarterly data, this paper first shows that men and women have different cyclical volatilities in work hours. Specifically, using a Hodrick-Prescott filter (Hodrick and Prescott, 1997), Baxter-King Band Pass Filter (Baxter and King, 1999), and univariate unobserved components model, I find that the volatility of the cyclical component is greater for men than women over the sample of 1976Q3 to 2015Q2. This result is consistent with recent research that have found larger recessionary effects on men than women (Engemann and Wall, 2009; Guisinger and Sinclair, 2015; Hoynes et al., 2012) in the recent recessions.

Motivated by this empirical result, I utilize a model with a representative household that consists of two types of members from Jaimovich et al. (2013), which I characterize as males and females. These two members are identical in their utility functions. The difference between the members comes from different elasticities of labor demand, which is due to their different complementarity with capital. The elasticity between female workers and male workers is restricted to be the same as the elasticity between capital and male workers. This is similar to the specifications in the capital-skills complementarity literature where instead of labor disaggregated by gender, it is instead disaggregated by education, skill, or experience (Griliches, 1969; Jaimovich et al., 2013; Krusell et al., 2000). This specification of women being more capital complementary is consistent with recent research which has shown that the elasticity of labor demand has changed in the U.S. as jobs and employer requirements have evolved (Olivetti, 2006) due to shifts from manufacturing to services (Goldin, 1990), increase in computerization (Galor and Weil, 1996), change in society's attitudes (Fernández et al., 2004), and a rise in female educational attainment (He et al., 2011).

Once these elasticities are estimated from the first order conditions of the firm's problem, the model generates cyclical volatilities of hours worked that match the U.S. data better than the traditional representative agent model. Additional robustness checks were conducted on the substitution parameters including exploring an alternative specification of complementarity, examining instruments, and assessing the stability over time. After identifying a baseline model which is able to capture, not only, the relative volatilities of hours worked by gender, but also the relative volatility of the aggregate hours worked with respect to output. I then explore the sensitivity of the substitution parameter and the Frisch elasticities of substitution. While the discrepancies between micro and macro labor supply elasticities have been noted to be very large (Chetty, 2012; Chetty et al., 2011; Keane and Rogerson, 2012), I calibrate the model to various estimates from the micro literature, and find that allowing the Frisch elasticity of substitution to vary across agents leads to more wage dynamics.

Overall, I find that a simple RBC model augmented to allow for two types of workers, males and females, in a nested CES production function can not only match the relative volatility of hours by gender, but also for total hours. This paper emphasizes that males and females adjust differently across the business cycle in terms of the intensive margin of the labor market. These results accentuate the fact that the labor market consists of different agents, and allowing for even broad levels of heterogeneity can increase the model's tractability with the data. Therefore, policy may have an unequal effect on men and women, and we need to carefully consider heterogeneity when analyzing appropriate counter-cyclical economic policy decisions.

References

Aaronson, Daniel, Kyung-Hong Park, and Daniel G Sullivan, "The decline in teen labor force participation," *Economic Perspectives*, 2006.

Acemoglu, Daron, "Why do new technologies complement skills? Directed technical change and wage inequality," *Quarterly journal of economics*, 1998, pp. 1055–1089.

_ **and David Autor**, "Skills, tasks and technologies: Implications for employment and earnings," *Handbook of labor economics*, 2011, *4*, 1043–1171.

Albanesi, Stefania and Aysegul Sahin, "The gender unemployment gap," 2013.

Altonji, Joseph G and Rebecca M Blank, "Race and gender in the labor market," *Handbook of labor economics*, 1999, *3*, 3143–3259.

Baxter, Marianne and Robert G King, "Measuring business cycles: approximate band-pass filters for economic time series," *Review of economics and statistics*, 1999, *81* (4), 575–593.

Beaudry, Paul and David A Green, "Wages and employment in the United States and Germany: What explains the differences?," *The American Economic Review*, 2003, *93* (3), 573–602.

Bertola, Giuseppe, Francine D Blau, and Lawrence M Kahn, "Labor market institutions and demographic employment patterns," *Journal of Population Economics*, 2007, *20* (4), 833–867.

Beveridge, Stephen and Charles R Nelson, "A new approach to decomposition of economic time series into permanent and transitory components with particular attention to measurement of the business cycle," *Journal of Monetary economics*, 1981, *7* (2), 151–174.

Blau, Francine D and Lawrence M Kahn, "Changes in the Labor Supply Behavior of Married Women: 1980–2000," *Journal of Labor Economics*, 2007, *25* (3), 393–438.

_ **, Peter Brummund, and Albert Yung-Hsu Liu**, "Trends in occupational segregation by gender 1970–2009: Adjusting for the impact of changes in the occupational coding system," *Demography*, 2013, *50* (2), 471–492.

Blundell, Richard and Thomas MaCurdy, "Labor supply: A review of alternative approaches," *Handbook of labor economics*, 1999, *3*, 1559–1695.

Borjas, George J, *Heaven's door: Immigration policy and the American economy*, Princeton University Press, 2001.

Bound, John, David A Jaeger, and Regina Baker, "The cure can be worse than the disease: A cautionary tale regarding instrumental variables," 1993.

_ , _ , and Regina M Baker, "Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak," *Journal of the American statistical association*, 1995, *90* (430), 443–450.

Brown, Charles, Curtis Gilroy, and Andrew Kohen, "Time-Series Evidence of the Effect of the Minimum Wage on Youth Employment and Unemployment," *Journal of Human Resources*, 1983, pp. 3–31.

Chao, John C and Norman R Swanson, "Consistent estimation with a large number of weak instruments," *Econometrica*, 2005, *73* (5), 1673–1692.

Charles, Kerwin Kofi and Ming-Ching Luoh, "Gender differences in completed schooling," *Review of Economics and Statistics*, 2003, *85* (3), 559–577.

Chetty, Raj, "Bounds on elasticities with optimization frictions: A synthesis of micro and macro evidence on labor supply," *Econometrica*, 2012, *80* (3), 969–1018.

_ , Adam Guren, Day Manoli, and Andrea Weber, "Are micro and macro labor supply elasticities consistent? A review of evidence on the intensive and extensive margins," *The American Economic Review*, 2011, *101* (3), 471–475.

Chiappori, Pierre-Andre, "Collective labor supply and welfare," *Journal of political Economy*, 1992, pp. 437–467.

Cho, Jang-Ok and Richard Rogerson, "Family labor supply and aggregate fluctuations," *Journal of Monetary Economics*, 1988, *21* (2), 233–245.

_ and Thomas F Cooley, "Employment and hours over the business cycle," *Journal of Economic Dynamics and Control*, 1994, *18* (2), 411–432.

Clark, Kim B and Lawrence H Summers, "The dynamics of youth unemployment," in "The youth labor market problem: Its nature, causes, and consequences," University of Chicago Press, 1982, pp. 199–234.

Clark, Peter K., "The Cyclical Component of U.S. Economic Activity," *The Quarterly Journal of Economics*, November 1987, *102* (4), 797–814.

Clark, Peter K, "Trend reversion in real output and unemployment," *Journal of Econometrics*, 1989, *40* (1), 15–32.

Cociuba, Simona, Edward C Prescott, and Alexander Ueberfeldt, "VU. S. hours and productivity behavior using CPS hours worked data: 1947: III to 2009*II*,″ *VManuscript*, *FederalReserveBankofDallas*, 2009.

Cogley, Timothy and James M Nason, "Effects of the Hodrick-Prescott filter on trend and difference stationary time series Implications for business cycle research," *Journal of Economic Dynamics and control*, 1995, *19* (1), 253–278.

Duffy, John, Chris Papageorgiou, and Fidel Perez-Sebastian, "Capital-skill complementarity? Evidence from a panel of countries," *Review of Economics and Statistics*, 2004, *86* (1), 327–344.

Durbin, James, "Errors in variables," *Revue de l'Institut international de statistique*, 1954, pp. 23–32.

Engemann, Kristie and Howard J Wall, "The effects of recessions across demographic groups," *Available at SSRN 1490041*, 2009.

Fernández, Raquel, Alessandra Fogli, and Claudia Olivetti, "Mothers and sons: Preference formation and female labor force dynamics," *The Quarterly Journal of Economics*, 2004, pp. 1249–1299.

Foote, Christopher L, "Space and time in macroeconomic panel data: Young workers and state-level unemployment revisited," 2007.

Galor, Oded and David N Weil, "The Gender Gap, Fertility, and Growth," *The American Economic Review*, 1996, *86* (3), 374–387.

García-Mainar, Inmaculada, José Alberto Molina, and Victor Montuenga, "Intrahousehold time allocation: Gender differences in caring for children," 2009.

Goldin, Claudia, *The gender gap: An economic history of American women*, New York: Cambridge University Press, 1990.

Griliches, Zvi, "Capital-skill complementarity," *The review of Economics and Statistics*, 1969, pp. 465–468.

Grunfeld, Yehuda and Zvi Griliches, "Is aggregation necessarily bad?," *The Review of Economics and Statistics*, 1960, pp. 1–13.

Guisinger, Amy Y. and Tara M. Sinclair, "Men are from Mars? Gender Differences in Business Cycle Dynamics and Policy Implications," Technical Report 2015.

Guvenen, Fatih, Burhanettin Kuruscu, Satoshi Tanaka, and David Wiczer, "Multidimensional Skill Mismatch," Technical Report, National Bureau of Economic Research 2015.

Hansen, Gary D, "Indivisible labor and the business cycle," *Journal of monetary Economics*, 1985, *16* (3), 309–327.

Harvey, Andrew C, "Trends and cycles in macroeconomic time series," *Journal of Business & Economic Statistics*, 1985, *3* (3), 216–227.

Harvey, Andrew C., "Trends and Cycles in Macroeconomic Time Series," *Journal of Business & Economic Statistics*, July 1985, *3* (3), 216–227.

_ **and A. Jaeger**, "Detrending, Stylized Facts and the Business Cycle," *Journal of Applied Econometrics*, July / September 1993, *8* (3), 231–247.

Harvey, Andrew C and Albert Jaeger, "Detrending, stylized facts and the business cycle," *Journal of applied econometrics*, 1993, *8*, 231–231.

He, Hui et al., "Why Have Girls Gone to College? A Quantitative Examination of the Female College Enrollment Rate in the United States: 1955-1980," *Annals of Economics and Finance*, 2011, *12* (1), 41–64.

Hodrick, Robert J and Edward C Prescott, "Postwar US business cycles: an empirical investigation," *Journal of Money, credit, and Banking*, 1997, pp. 1–16.

Hoynes, Hilary W, Douglas L Miller, and Jessamyn Schaller, "Who suffers during recessions?," Technical Report, National Bureau of Economic Research 2012.

Jacobsen, Joyce P, *The economics of gender*, Blackwell Malden, MA, 2007.

Jaeger, Albert, "Mechanical detrending by Hodrick-Prescott filtering: A note," *Empirical Economics*, 1994, *19* (3), 493–500.

Jaimovich, Nir, Seth Pruitt, and Henry E Siu, "The demand for youth: explaining Age Differences in the Volatility of Hours," *The American Economic Review*, 2013, *103* (7), 3022–3044.

Keane, Michael and Richard Rogerson, "Micro and macro labor supply elasticities: A reassessment of conventional wisdom," *Journal of Economic Literature*, 2012, pp. 464–476.

King, Robert G, Charles I Plosser, and Sergio T Rebelo, "Production, growth and business cycles: I. The basic neoclassical model," *Journal of monetary Economics*, 1988, *21* (2), 195–232.

Klump, Rainer and Olivier de La Grandville, "Economic growth and the elasticity of substitution: Two theorems and some suggestions," *American Economic Review*, 2000, pp. 282–291.

_ **, Peter McAdam, and Alpo Willman**, "The long-term sucCESs of the neoclassical growth model," *Oxford Review of Economic Policy*, 2007, *23* (1), 94–114.

Knotek, II Edward S., "How Useful is Okun's Law?," *Federal Reserve Bank of Kansas City Economic Review*, 2008, *Fourth Quarter*, 73–103.

Krusell, Per, Lee E Ohanian, José-Víctor Ríos-Rull, and Giovanni L Violante, "Capital-skill complementarity and inequality: A macroeconomic analysis," *Econometrica*, 2000, *68* (5), 1029–1053.

Kydland, Finn E and Edward C Prescott, "Time to build and aggregate fluctuations," *Econometrica: Journal of the Econometric Society*, 1982, pp. 1345–1370.

McCandless, George, *The ABCs of RBCs*, Cambridge, Massachusetts, London: Harvard, 2008.

Meese, Richard and Kenneth Rogoff, "Was it real? The exchange rate-interest differential relation over the modern floating-rate period," *Journal of finance*, 1988, pp. 933–948.

Morley, James C, Charles R Nelson, and Eric Zivot, "Why are the Beveridge-Nelson and unobserved-components decompositions of GDP so different?," *Review of Economics and Statistics*, 2003, *85* (2), 235–243.

Mosisa, Abraham and Steven Hipple, "Trends in labor force participation in the United States," *Monthly Lab. Rev.*, 2006, *129*, 35.

Mulligan, Casey B., "Substitution over Time: Another Look at Life-Cycle Labor Supply," *NBER Macroeconomics Annual*, 1998, pp. 75–152.

Nelson, Charles R. and Charles R. Plosser, "Trends and Random Walks in Macroeconmic Time Series: Some Evidence and Implications," *Journal of Monetary Economics*, 1982, *10* (2), 139–162.

O'Higgins, Niall, "Youth unemployment and employment policy: A global perspective," 2001.

Olivetti, Claudia, "Changes in women's hours of market work: The role of returns to experience," *Review of Economic Dynamics*, 2006, *9* (4), 557–587.

Orphanides, Athanasios and Simon Van Norden, "The Unreliability of Output-Gap Estimates in Real Time," *Review of Economics and Statistics*, 2002, *84* (4), 569–583.

Pekkarinen, T, "Gender differences in higher education," Technical Report, IZA Discussion Paper 2012.

Pencavel, John, "Labor supply of men: a survey," *Handbook of labor economics*, 1986, *1* (Part 1), 3–102.

Pesaran, M Hashem and Terry Barker, *Disaggregation in Econometric Modelling*, Routledge, 1990.

Polachek, Solomon William, "Occupational self-selection: A human capital approach to sex differences in occupational structure," *The Review of Economics and Statistics*, 1981, pp. 60–69.

Prescott, Edward C, "Theory ahead of business-cycle measurement," in "Carnegie-Rochester Conference Series on Public Policy," Vol. 25 Elsevier 1986, pp. 11–44.

Rendall, Michelle, "Brain versus brawn: the realization of women's comparative advantage," *Available at SSRN 1635251*, 2010.

Rogerson, Richard, "Indivisible labor, lotteries and equilibrium," *Journal of monetary Economics*, 1988, *21* (1), 3–16.

_ **and Randall Wright**, "Involuntary unemployment in economies with efficient risk sharing," *Journal of Monetary economics*, 1988, *22* (3), 501–515.

Shimer, Robert, "THE IMPACT OF YOUNG WORKERS ON THE AGGREGATE LABOR MARKET.," *Quaterly journal of economics*, 2001, *116* (3), 969.

Sinclair, Tara M, "The relationships between permanent and transitory movements in US output and the unemployment rate," *Journal of Money, Credit and Banking*, 2009, *41* (2-3), 529–542.

Solow, Robert M, "A contribution to the theory of economic growth," *The quarterly journal* *of economics*, 1956, pp. 65–94.

Staiger, Douglas and James H Stock, "Instrumental Variables Regression with Weak Instruments," *Econometrica*, 1997, *65* (3), 557–586.

Stock, James H and Mark W Watson, "Evidence on structural instability in macroeconomic time series relations," *Journal of Business & Economic Statistics*, 1996, *14* (1), 11–30.

Theil, Henri, "Linear aggregation of economic relations," 1954.

Wooldridge, Jeffrey M, "Score diagnostics for linear models estimated by two stage least squares," *Advances in econometrics and quantitative economics*, 1995, pp. 66–87.

7 Appendix

Table 7.1: Variability in Hours

Group	**HP**	**BP**	**UC**
All	1.61	1.49	0.90
Males	1.91	1.77	2.20
Females	1.38	1.23	1.39
observations	131	131	131

All calculations are the standard deviations of the cyclical component. The first column (HP) shows the results for the Hodrick Prescott filter, the second column (BP) shows the results for the Baxter-King Band Pass filter, and the third column (UC) shows the results for the univariate unobserved components model. In order to have the same number of observations, the sample goes from 1979Q3 to 2012Q2.

Table 7.2: Parameters of the Univariate UC Model

Parameter	**All**	**Males**	**Females**
LLV	(-165.93)	(-184.31)	(-181.76)
σ_η	1.38	0.70	1.57
	(0.05)	(0.09)	(0.09)
σ_ν	1.10	0.39	1.14
	(0.02)	(0.09)	(0.05)
$\sigma_{\eta\nu}$	-1.51	-0.05	-1.75
	(0.07)	(0.12)	0.18
κ	0.34	0.26	0.44
	(0.11)	(0.06)	(0.13)
ϕ_1	1.38	1.76	1.37
	(0.03)	(0.04)	(0.03)
ϕ_2	-0.53	-0.80	-0.48
	(0.03)	(0.03)	(0.03)
observations	151	151	151

The models are estimated with the full sample and a four quarter burn-in. Therefore, the filtered data results cover 1977Q2 to 2015Q1. The standard errors are in the parenthesis below the parameter estimate.

Table 7.3: Substitution Parameter Estimates

Parameter	**Coefficient**	**Std Errors**
σ	0.758***	0.151
ρ	0.697***	0.071

Estimates are from Equations 4.3 and 4.5 using OLS. Robust standard errors are reported. The * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$.

Table 7.4: Substitution Parameter Estimates - Exogeneity

IV - Lagged Birth Rates	σ	ρ
15	1.574	6.974**
	(0.2158)	(0.011)
20	0.000	7.025**
	(0.997)	(0.011)
22	0.105	6.221**
	(0.748)	(0.016)
25	0.989	5.529**
	(0.325)	(0.02)
30	2.167	7.220***
	(0.148)	(0.010)
35	0.391	2.324
	(0.535)	(0.134)
40	2.527	2.561
	(0.119)	(0.116)
50	7.116**	0.460
	(0.010)	(0.501)

Estimates are from Equations 4.3 and 4.5 using 2SLS with the instrument being lagged birth rates. The first column indicates the number of years the birth rates are lagged for the IV. The next two columns indicate the robust regression F-statistic for the test of endogeneity, where the null hypothesis is that the variables are exogenous. The p-value is reported in parenthesis below the F-statistic. The * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$.

Table 7.5: Substitution Parameter Estimates - IV First-Stage

IV - Lagged Birth Rates	σ	ρ
15	4.957**	0.057
20	2.408	0.443
22	1.834	0.298
25	2.225	0.001
30	2.146	0.022
35	1.875	0.258
40	2.945*	0.442
50	1.141	0.002

Estimates are from Equations 4.3 and 4.5 using 2SLS with the instrument being lagged birth rates. The first column indicates the number of years the birth rates are lagged in the IV. The next two columns indicate the robust regression F-statistic for the first-stage regression. The * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$.

Table 7.6: Substitution Parameter Estimates - Counter Example

Parameter	**Coefficient**	**Std Errors**
ψ	1.022***	0.011
γ	0.800***	0.065

Estimates are from Equations 4.6 and 4.7 using OLS. Robust standard errors are reported. The * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$.

Table 7.7: Calibration

Parameter	**Value**	**Source**
β	0.99	Jaimovich et al. (2013)
δ	0.025	Jaimovich et al. (2013)
θ_i	0.00001	Jaimovich et al. (2013)
ϕ	0.94	Jaimovich et al. (2013)
Q_K	0.353	estimated from BEA
Q_f	0.228	estimated from CPS & BEA
s_m	0.570	estimated from CPS
σ	0.758	estimated March CPS & BEA
ρ	0.697	estimated March CPS & BEA

Above is a summary of the remaining parameters used to calibrate the baseline model, which are standard values or methods in the literature for quarterly time periods.

Table 7.8: Results

Parameter	**Data**	**Model**	**KPR**
Column	(1)	(2)	(3)
std(H_f)/std(H_m)	0.73	0.83	
std(H_f)/std(Y)	0.96	1.19	
std(H_m)/std(Y)	1.32	1.34	
std(H)/std(Y)	1.12	1.24	0.48
std(W_f)/std(W_m)	0.80	1.00	
std(W_f)/std(Y)	0.66	0.16	
std(W_m)/std(Y)	0.82	0.16	
std(I)/std(Y)	3.46	3.57	2.31
std(C)/std(Y)	0.76	0.16	0.64

This table focuses only on the cyclical component of the HP-filtered data. The Data column is calculated from CPS and BEA data. The KPR column reports values from King et al. (1988) (Table 4). Wages are from IPUMS data from 1976 to 2014. The data used to estimate investment is private nonresidential fixed investment and consumption is PCE from 1976Q3 to 2015Q2 available on FRED.

Table 7.9: Results - Changing ρ

Parameter	**Data**	**Model**	$\rho = 0.449$	$\rho = 0.201$	$\rho = -0.495$
Model		(1)	(2)	(3)	(4)
$\text{std}(H_f)/\text{std}(H_m)$	0.73	0.83	0.44	0.26	0.09
$\text{std}(H_f)/\text{std}(Y)$	0.96	1.19	0.66	0.40	0.15
$\text{std}(H_m)/\text{std}(Y)$	1.32	1.34	1.48	1.56	1.67
$\text{std}(H)/\text{std}(Y)$	1.12	1.24	1.10	1.02	0.91
$\text{std}(W_f)/\text{std}(W_m)$	0.80	1.00	1.00	1.00	1.00
$\text{std}(W_f)/\text{std}(Y)$	0.66	0.16	0.20	0.21	0.23
$\text{std}(W_m)/\text{std}(Y)$	0.82	0.16	0.20	0.21	0.23
$\text{std}(I)/\text{std}(Y)$	3.46	3.57	3.44	3.39	3.33
$\text{std}(C)/\text{std}(Y)$	0.76	0.16	0.20	0.21	0.22

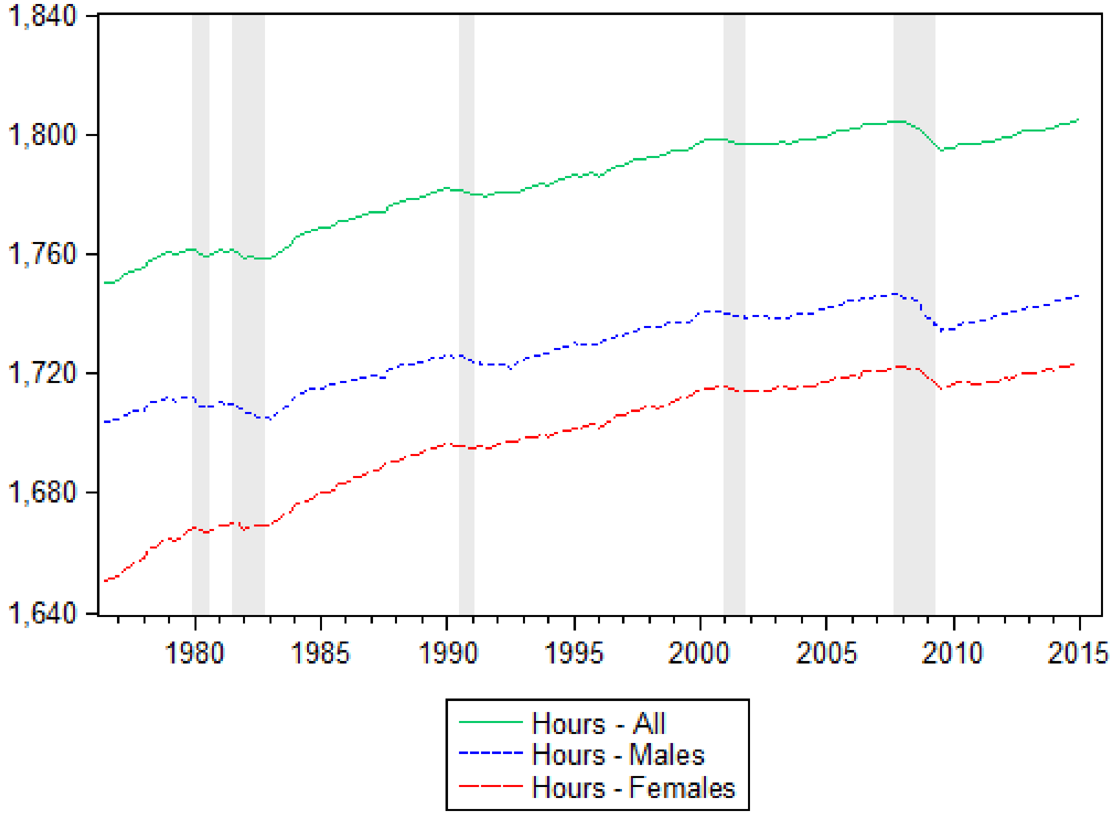
This table focuses only on the cyclical component of the HP-filtered data. The Data column is calculated from CPS and BEA data. Wages are from IPUMS data from 1976 to 2014. The data used to estimate investment is private nonresidential fixed investment and consumption is PCE from 1976Q3 to 2015Q2 available on FRED. ρ is allowed to be 0.201 following Jaimovich et al. (2013), -0.495 following Krusell et al. (2000), and 0.449, which is half way between my estimate (0.697) and the estimate of Jaimovich et al. (2013).

Table 7.10: Results - Changing Frisch Elasticity of Labor Supply

Parameter	**Data**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
θ_f	-	0.00001	0.77	0.825	0.368	0.54
θ_m	-	0.00001	-0.09	0.040	0.072	0.54
$\text{std}(H_f)/\text{std}(H_m)$	0.73	0.83	0.14	0.24	0.46	0.91
$\text{std}(H_f)/\text{std}(Y)$	0.96	1.19	0.27	0.36	0.62	0.71
$\text{std}(H_m)/\text{std}(Y)$	1.32	1.34	1.92	1.48	1.33	0.78
$\text{std}(H)/\text{std}(Y)$	1.12	1.24	1.16	0.96	1.00	0.74
$\text{std}(W_f)/\text{std}(W_m)$	0.80	1.00	3.18	1.89	1.43	0.94
$\text{std}(W_f)/\text{std}(Y)$	0.66	0.16	0.33	0.49	0.42	0.63
$\text{std}(W_m)/\text{std}(Y)$	0.82	0.16	0.11	0.26	0.29	0.66
$\text{std}(I)/\text{std}(Y)$	3.46	3.57	3.73	3.37	3.37	3.17
$\text{std}(C)/\text{std}(Y)$	0.76	0.16	0.14	0.20	0.21	0.26

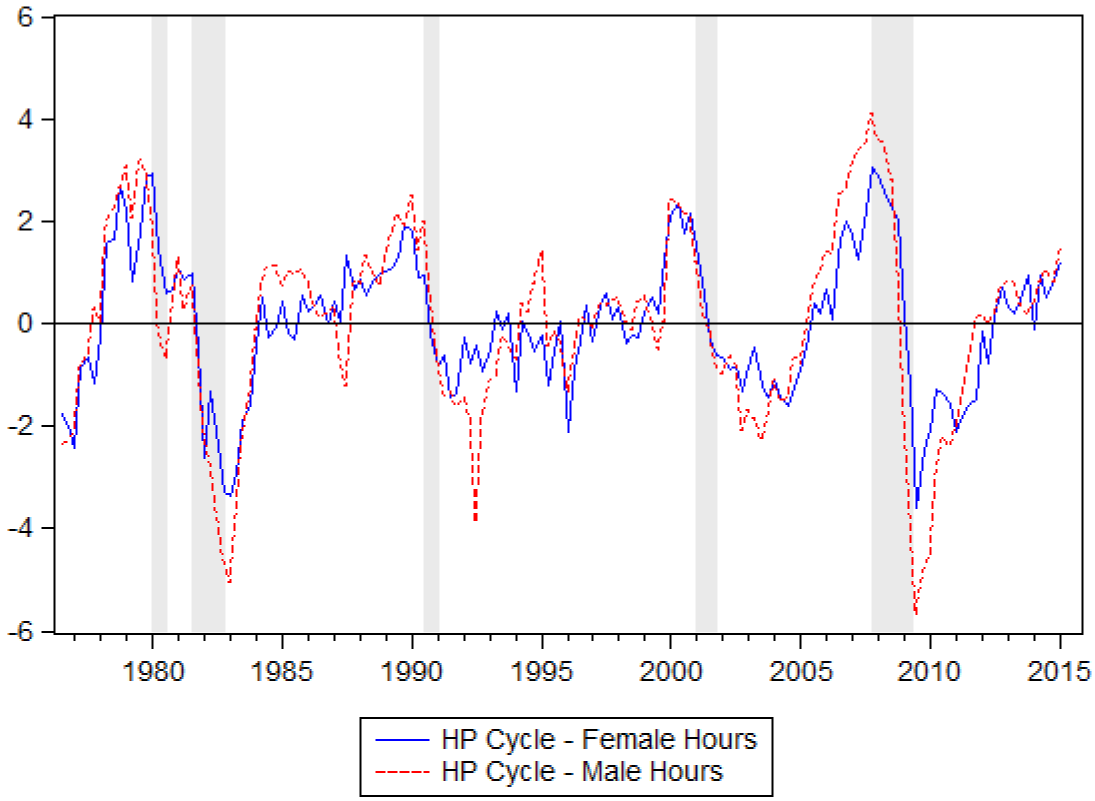
This table focuses only on the cyclical component of the HP-filtered data. The Data column is calculated from CPS and BEA data. Wages are from IPUMS data from 1976 to 2014. The data used to estimate investment is private nonresidential fixed investment and consumption is PCE from 1976Q3 to 2015Q2 available on FRED. Column (1) shows the baseline model with Frisch elasticities of labor supply equal to zero. Column (2) shows the model results when using elasticities from Jacobsen (2007). Column (3) uses elasticities from Blau and Kahn (2007) in 1980 and column (4) uses the elasticities from 2000. Column (5) uses the elasticities from Chetty et al. (2011).

Figure 1: Aggregate Hours Worked



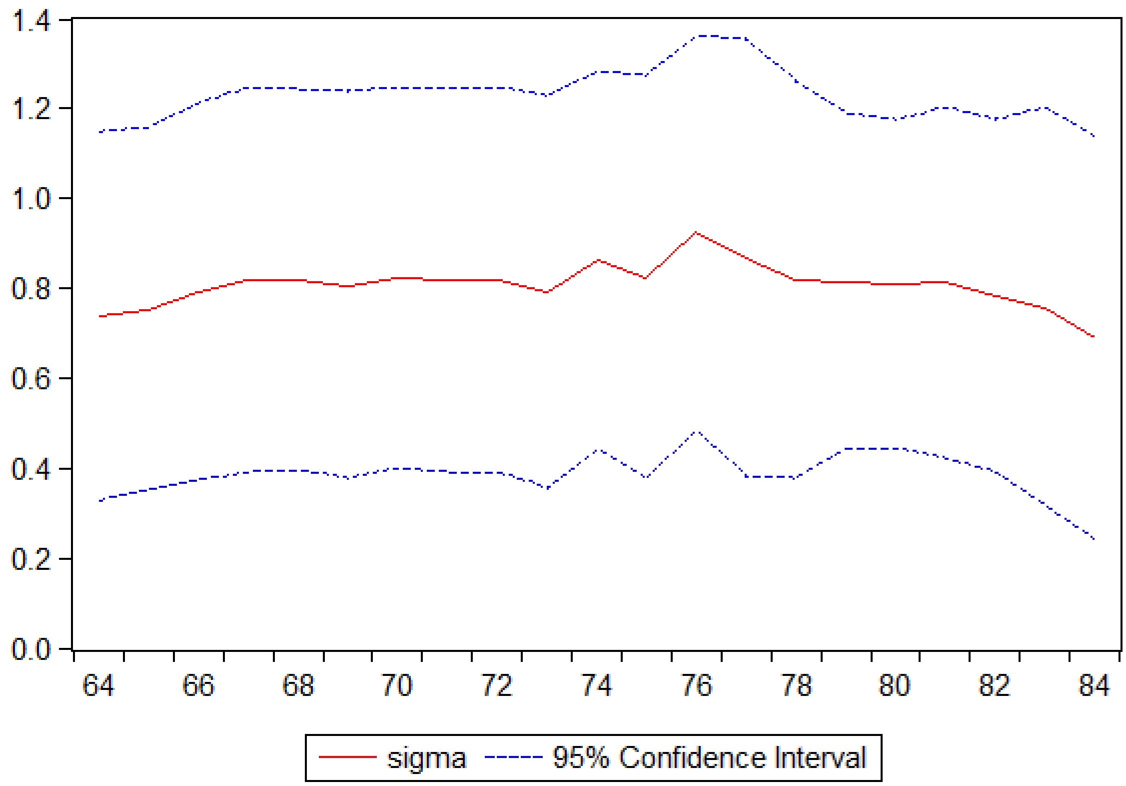
The the natural logs of the data series for total aggregate hours and aggregate hours by gender, as described in Section 2.1 are graphed above. The shaded regions indicate NBER U.S. recession dates.

Figure 2: Variability in Hours



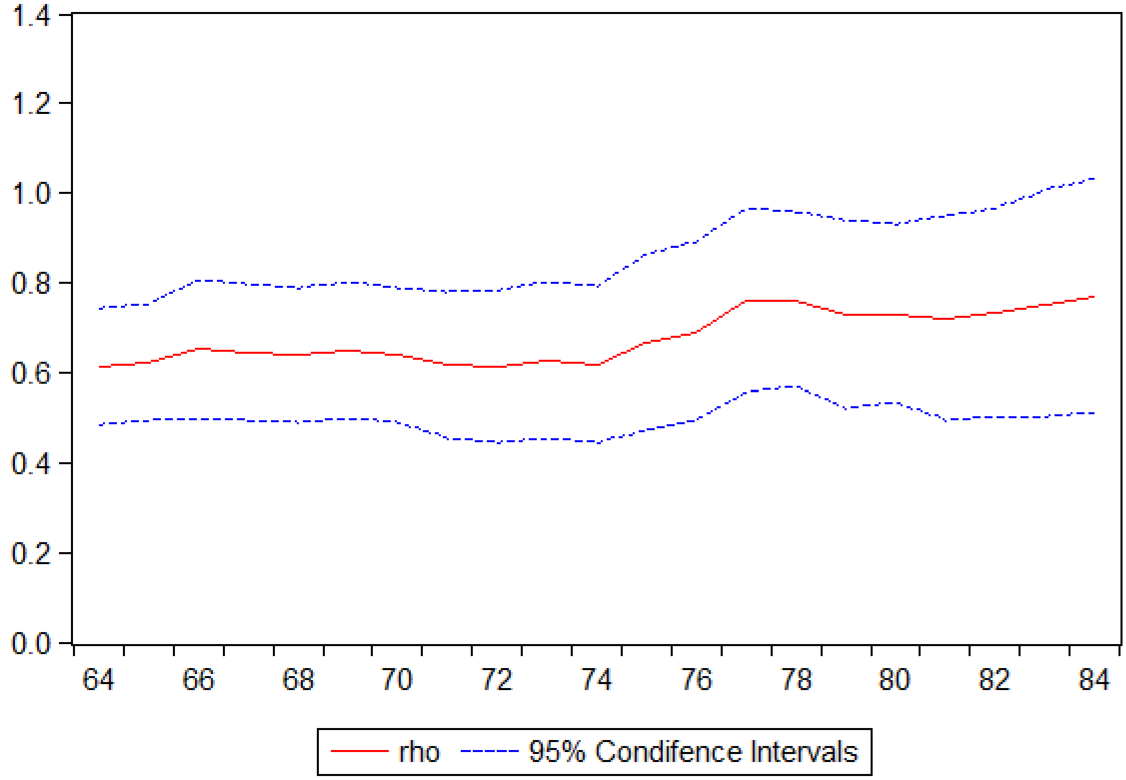
This figure plots the HP cyclical component for men and women with the NBER recessions displayed by the shaded area. These series can be interpreted as the percent deviations from the trend.

Figure 3: Stability of σ



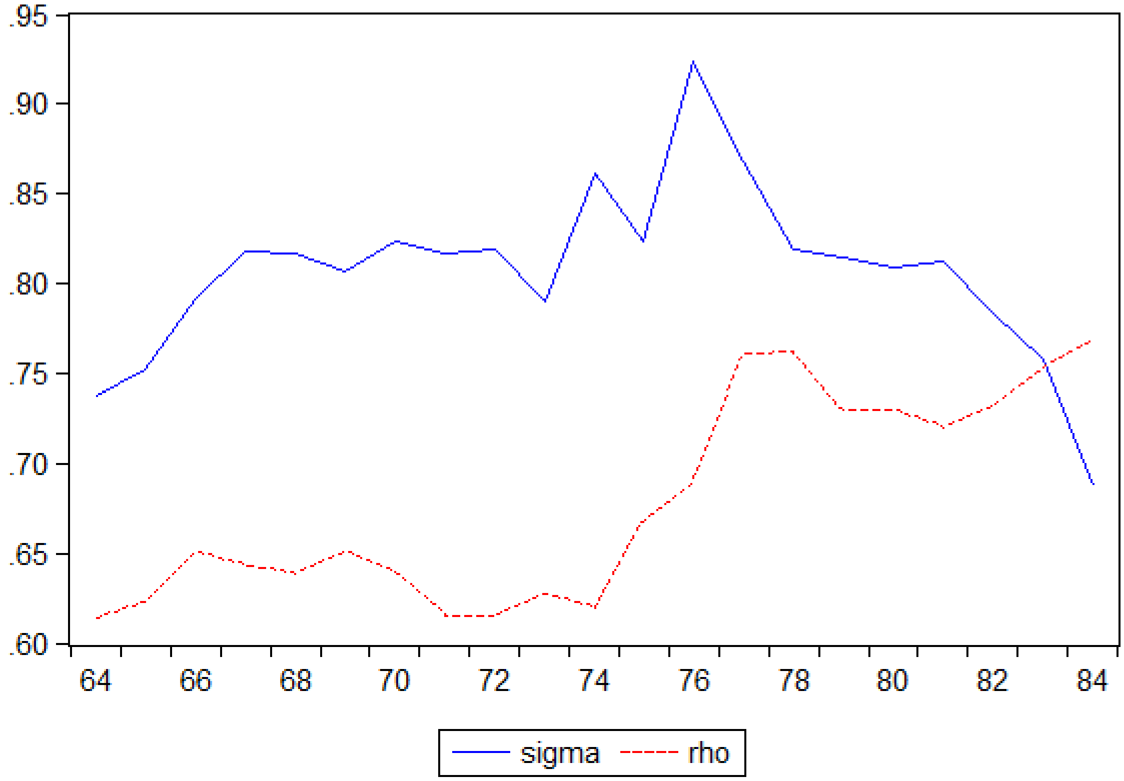
This graph plots the the rolling regression estimates for σ using a sample window of 31 observations across the full sample of 1964 to 2014, where σ is the substitution parameter between capital and female workers. The estimates are plotted corresponding to the start of the sample; therefore, the estimate for 1964 refers to the sample the from 1964 to 1994. The solid line represents the point estimates and the dotted line is the 95 percent confidence interval using annual data from IPUMS CPS and the BEA.

Figure 4: Stability of ρ



This graph plots the the rolling regression estimates for ρ using a sample window of 31 observations across the full sample of 1964 to 2014, where ρ is the substitution parameter between female workers (or capital) and male workers. The estimates are plotted corresponding to the start of the sample; therefore, the estimate for 1964 refers to the sample the from 1964 to 1994. The solid line represents the point estimates and the dotted line is the 95 percent confidence interval using annual data IPUMS CPS and the BEA.

Figure 5: Stability of Relative Magnitudes of σ and ρ



This graph plots the the rolling regression estimates for σ and ρ using a sample window of 31 observations across the full sample of 1964 to 2014. The estimates are plotted corresponding to the start of the sample; therefore, the estimate for 1964 refers to the sample the from 1964 to 1994. The solid line represents the point estimates for σ and the dotted line represents the point estimates for ρ using annual data from IPUMS CPS and the BEA.