Nonlinear Occupations and Female Labor Supply Over Time*

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Abstract

Long hours worked associated with higher hourly wages are common to many occupations, known as nonlinear occupations. Over the last four decades, both the share of workers in nonlinear occupations and their relative wage premium have been increasing. Females in particular have been facing rising experience premiums, especially in these types of occupations. We quantitatively explore how these changes have affected the female labor supply over time using a quantitative, dynamic general equilibrium model of occupational choice and labor supply at both the extensive and intensive margins. Our decomposition analysis finds that rising experience premiums are important in explaining the intensive margin of female labor supply, which has continued to increase even in the most recent period. Meanwhile, technical changes biased toward nonlinear occupations help to explain recent stagnating female employment rates. Finally, a counterfactual experiment suggests that, if the barrier aspects of nonlinearities had instead gradually vanished, female employment over this same time period would have been considerably higher at the expense of significantly lower labor supplies at the intensive margin.

Keywords: Female labor supply, occupational choice, Roy model, experience premium, gender gaps, structural change

JEL codes: E2, J2, J1

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1 Introduction

Nonlinear occupations describe a rather prevalent type of work in the modern economy, where employees receive higher hourly wages for longer hours of work (Goldin, 2014; Erosa, Fuster, Kambourov, and Rogerson, forthcoming). As these occupations provide greater rewards to individuals who work longer hours and penalize those who work shorter hours, earnings increase *nonlinearly* with hours worked. In this paper, we highlight several significant changes regarding these type of occupations.[1] The fraction of people—especially women—working in nonlinear occupations has increased over the last four decades, while positive wage premiums for these occupations have increased steadily. This suggests that the relative demand for nonlinear occupations has been increasing. Further, the large gender gaps in experience premiums that existed four decades ago have narrowed significantly, again especially for nonlinear occupations.

What are the implications of these changes to the relative demand for nonlinear occupations and to rising experience premiums on the recent evolution of female labor supply? In particular, we ask if these changes help to account for the ever-rising average number of hours worked per female worker (i.e., the intensive margin), which differs notably from the stagnating employment rate (i.e., the extensive margin) of recent years.[2] At first glance, and given that there are increasingly more women than men in these more remunerative nonlinear occupations, it may be expected that both changes have contributed to the shrinking gap in the wages of women relative to men. These factors in turn could induce greater female labor supply at both margins. On the other hand, the increasing importance of nonlinear occupations could hinder the participation of more women who would be unwilling to work long hours. We address this quantitative question using a version of the neoclassical growth model with heterogeneous agents in which occupational differences arise endogenously.

Specifically, we build upon the model of Erosa et al. (forthcoming) that combines occupational choice (Roy, 1951) and endogenous labor supply, whereby the two model occupations differ

[1] This terminology of "nonlinear" occupations versus "linear" occupations as well as the classification of occupations based on mean hours at the occupation level follows a recent quantitative theoretical analysis by Erosa et al. (forthcoming), who in turn were motivated by the empirical exploration of Goldin (2014).

[2] The sharp and steady increase in female labor force participation—one of the most remarkable changes in the US labor market during the postwar period—has stagnated in recent decades (Moffitt, 2012; Blau and Kahn, 2013). The literature does provide potential explanations for the stalling extensive margin (e.g., Fogli and Veldkamp, 2011; Fernandez, 2013; Albanesi and Prados, 2019), but these are at odds with the still-rising intensive margin.

by their degree of nonlinearity. Our model is essentially a dynamic version of their model, and is based on a standard heterogeneous agent incomplete markets framework (Huggett, 1993; Aiyagari, 1994)—a workhorse macroeconomic model used to study distributional issues.[3] Compared with the parsimonious static model of Erosa et al. (forthcoming), our dynamic environment is more advantageous as it enables us to specify origins for and the different nature of the nonlinearities in question.

Broadly speaking, nonlinearities are shaped by the dynamic returns to working long hours and the presence of part-time penalties. For each specific occupation, a worker can be upgraded stochastically if she worked in the same occupation during the previous period and worked greater than or equal to the (occupation-specific) upgrade threshold number of hours. Once a worker is upgraded, she additionally earns the (occupation-specific) return to experience. Similarly, part-time penalties also vary by occupation and are modeled as a proportional tax on earnings for those who work less than the full-time threshold number of hours. These thresholds are designed to capture the barrier nature of the nonlinearities. On the whole, these differences across occupations—along with individual state variables such as idiosyncratic productivity, comparative advantages, experience, household assets, and preference types—affect the employment decision, occupational choice, and hours of work conditional on occupational choice in the model.

We calibrate the model to US data using a standard approach by matching the relevant statistics obtained from the Current Population Survey (CPS) during the initial period of 1976–1985.[4] Following Erosa et al. (forthcoming), we categorize occupations found in the data into two groups based on mean hours worked at the occupational level. Without assuming any further conditions as part of this categorization, our calibration results distinguish those occupations with higher mean hours from those with lower mean hours along three dimensions: (i) the threshold number of hours for an upgrade is higher; (ii) the return to experience is higher; and (iii) the part-time penalty is higher. Since nonlinear occupations would indeed provide

[3] More precisely, our model framework builds on a standard general equilibrium incomplete-markets framework with production (Aiyagari, 1994), augmented with endogenous labor supply at both the intensive margin (e.g., Pijoan-Mas, 2006) and the extensive margin (e.g., Chang and Kim, 2006).

[4] We start from the 1976 CPS year because of the availability of data regarding occupational information. Since we are interested in long-run trends, we divide our sample period into four decades based on CPS years: 1976–1985; 1986–1995; 1996–2005; and 2006–2015.

greater compensation for working longer hours while disfavoring shorter hours (Goldin, 2014), our estimation and model calibration confirms that the occupations in the former group are more likely to be nonlinear and the latter more likely to be linear. We further confirm that our model can deliver the salient facts that nonlinear occupations have higher mean wages and higher wage dispersions.

Next, we use our model to quantify the role that changes in nonlinear occupations have in explaining the evolution of the female labor supply. We are particularly interested in the underlying factors responsible for the continued rise of the intensive margin labor supply and the stagnating employment rates of recent years. We investigate changes in select driving forces. These include not only the key interests of our paper—returns to experience and nonlinear-occupation-biased technical changes—but also factors that are known to be important for determining the female labor supply, such as relative wage changes (Heathcote, Storesletten, and Violante, 2010; Kaygusuz, 2010; Jones, Manuelli, and McGrattan, 2015; Bick, Brüggemann, Fuchs-Schündeln, and Paule-Paludkiewicz, 2019) and preference shifts (Fernández, Fogli and Olivetti, 2004, Fogli and Veldkamp, 2011; Fernández, 2013). This allows our model to replicate the observed changes in gender wage gaps and aggregate hours over time.

The first notable finding from our decomposition analysis is that rising returns to experience are quantitatively important when accounting for the rising intensive margin of the female labor supply. Specifically, our model predicts that the model-implied increment of 240 annual hours worked per worker from 1976–1985 to 2006–2015 (vs. 205 hours in the data) would be approximately 43% lower if the returns to experience were held fixed at their baseline levels (in 1976–1985). Secondly, our calibration results imply noticeable changes in demand factors that have increasingly favored nonlinear occupations over time. We find that this change naturally increases the share of women working in nonlinear occupations, but reduces the overall employment level—explaining why female employment has been stagnating in recent years. Quite a few women prefer short hours worked and would be willing to work in linear occupations. However, as linear occupations become less attractive due to technical changes favoring nonlinear occupations, more women are induced to leave the labor force altogether from linear occupations, as compared to those who leave them to work in nonlinear occupations. We also find that wage changes for women are very powerful in shifting more women to work (the extensive margin) but are not as important as the returns to experience in increasing labor supply at the intensive margin.

Finally, we conduct a counterfactual analysis by asking what would have happened to female labor supply trends if the barrier aspects of nonlinearities had gradually vanished. This analysis is motivated by Goldin (2014) who argues that these nonlinearities play the role of barriers in high-paying occupations and are thereby an important source of the gender wage gap—they prevent women from working in nonlinear occupations that pay higher average wages. In this experiment, we keep the changes in the returns to experience while adjusting for these nonlinearities by either (i) reducing the upgrade threshold number of hours or (ii) decreasing the full-time threshold number of hours.[5] We find that the level of female employment indeed could have been significantly higher, especially if the requirement of working long hours was eliminated. This could have led to a 12 percentage point higher employment rate in 2006–2015. Because returns to experience have been rising—especially in nonlinear occupations—our model predicts a significantly more prominent increase in the number of women working in such occupations. However, we also find that this change is accompanied by significantly lower labor supplies at the intensive margin (9.5% lower in 2006–2015). Our exercise suggests that, while nonlinearities are indeed a quantitatively important barrier that lead many women out of the labor force, they also play an important role in providing an incentive for women to supply long hours.

A large body of literature has investigated the determinants of changes in female labor supply over time, as reviewed recently by Doepke and Tertilt (2016) and Greenwood, Guner, and Vandenbroucke (2017).[6] Our results are closely related to Olivetti (2006), Attanasio, Low, and Sánchez-Marcos (2008), and Park (2018), all of whom consider that returns to experience are a major determinant of female labor supply in a structural environment. Relative to these papers, our work differs in that we consider returns to experience separately in different occupations categorized by nonlinearities. We also document differential trends by occupation, and we in-

[5] We keep the rising experience premiums because they are a beneficial feature of nonlinearities, unlike the hours thresholds that are essentially a form of barrier-like frictions.

[6] See also Adda, Dustmann, and Stevens (2017) who highlight the importance of career and occupational choices for women.

vestigate their implications for occupational choice—a channel that also shapes labor supply. Moreover, our findings shed light on the seemingly conflicting findings of Olivetti (2006) and Attanasio et al. (2008): the latter finds that returns to experience are unlikely to be quantitatively important factors in explaining the rising female labor supply, while the former finds a substantial role for returns to experience. Note that in our model incorporating both the intensive and extensive margins, we find that the effects of returns to experience work mostly through the intensive margin, with only limited effects on the extensive margin. Therefore, our results suggest that models without the intensive margin—as in Attanasio et al. (2008)—may understate the importance of returns to experience when accounting for overall female labor supply changes. At the same time—in comparison to Olivetti (2006)—our model incorporates idiosyncratic uncertainty and higher model frequency (annual vs. 10 years). With these features, we find that the role of returns to experience in explaining overall female labor supply is quantitatively not as strong, as compared to Olivetti (2006).

Erosa et al. (forthcoming) presented a model of occupational choice and labor supply, which they used to show that gender differences in home production responsibilities (in terms of time alone) can generate sizable gender gaps in various labor market outcomes like wages, hours, and occupational choice. As explained above, our model builds upon theirs by introducing the dynamic aspects necessary for us to specify the nonlinearities in more detail and to endogenize the labor supply decision along the extensive margin at the data frequency.[7] Based on their insight into nonlinear occupations and cross-sectional labor supply at a given time, our paper produces a further contribution by quantitatively investigating the implications of these factors on labor supply changes over time.

We highlight that our novel findings regarding the role of nonlinear occupations and experience premiums are based on a model where the effects of the other factors are quantitatively in line with the previous literature. In particular, and fitting in with earlier theory highlighting the role of learning in shifting women's disutility of work (Fogli and Veldkamp, 2011; Fernández, 2013), our decomposition exercise finds that the role of preference shifts in explaining overall

[7] Although our model is a dynamic version of this previous work, ours does not incorporate realistic lifecycles for computational tractability. Therefore, our model is not adequate to study issues related to age-specific factors such as the timing of birth and richer career dynamics.

increases in female labor supply became increasingly important until 1996–2005, while they then became much weaker in 2006–2015.

The reminder of this paper is organized as follows. The next section presents the stylized facts regarding how labor supply and occupations (nonlinear vs. linear) have evolved over the last four decades using data from the CPS. Section 3 presents the model economy and defines the equilibrium. Section 4 explains how the model is calibrated and presents some of the properties of the baseline economy. Section 5 presents our decomposition analysis showing how different factors affect the observed trends in labor supply and gender wage gaps. Section 6 conducts a counterfactual experiment to quantify what would have happened to labor supply trends if nonlinearities had gradually vanished. Section 7 contains our conclusions.

2 Trends in labor supply and nonlinear occupations

In this section, we present stylized facts regarding the evolution of labor supply and occupational choice using IPUMS-CPS files to obtain information on the 1976–2015 CPS. The CPS provides information not only on demographic characteristics but also on labor market outcomes, such as the number of weeks worked, the usual hours worked per week, total labor income, and occupations. We use the occupational classification of Autor and Dorn (2013) to generate occupational codes consistent over the whole sample period. Because the focus of this paper is on long-term changes, we divide the sample period into four 10-year intervals: 1976–1985 (baseline), 1986–1995, 1996–2005, and 2006–2015. In Appendix B, we also report the aggregate trend results based on annual data. We restrict our samples to households in which a male head and a female spouse cohabit because prominent changes in labor supply have been observed in married women (Jones et al., 2015). More details related to this data are provided in Appendix A.

For our definition of nonlinear occupations, we take the following steps. First, in the baseline period of 1976–1985, we rank all occupations according to their average working hours for males, using personal-level weights at the occupation level.[8] Second, we compute the size of these

[8] Despite using the same criterion to rank occupations, our approach slightly differs from Erosa et al. (forthcoming). Specifically, although they also computed average working hours for males at the occupational level,

occupations using personal-level weights for both male and female workers at the occupational level. Third, based on the size of the occupations, we evenly split them into two groups according to their occupational ranking, denoting the top and bottom 50% of occupations as nonlinear and linear, respectively. Finally, we apply this occupational grouping over the whole period consistently.[9]

Figure 1 shows the trend of the US labor supply by gender: total hours worked, in the extensive margin, and in the intensive margin. The top panel of Figure 1 shows that, although the male total hours worked remained stable over the entire period, the female total hours worked experienced an upward trend until the 1996–2005 period, with it subsequently leveling off. Consequently, the speed at which the gender gap in total hours worked is converging has slowed down significantly in recent years.

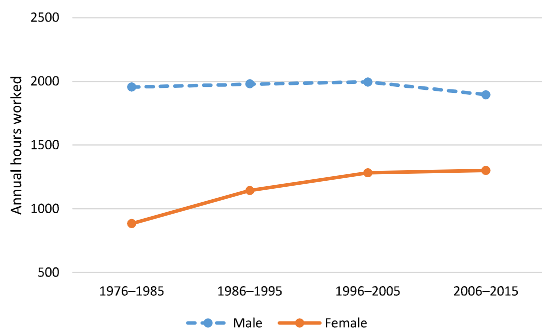
It is useful to analyze whether this slowdown in convergence is due to the evolution either of hours worked per worker (the intensive margin) or of employment (the extensive margin). The second and third panels of Figure 1 show that the evolution of labor supply differs sharply between the extensive and intensive margins, especially for females. Specifically, the female extensive margin had an upward trend until the 1996–2005 period but became stagnant afterward (e.g., Moffitt, 2012; Blau and Kahn, 2013). On the other hand, the female intensive margin shows a continually rising trend over the whole period. To explain both of these observations simultaneously, it would be necessary to delve into factors that might be driving differential dynamics between the extensive and intensive margins of labor supply. We argue that such factors are to be found in the evolution of nonlinear occupations, which we will now investigate.

Figure 2 presents the trends in the relative quantity and price of nonlinear occupations by gender. One can clearly notice steady increases in both the relative quantity and relative price of nonlinear occupations. The top panel of Figure 2 shows that, although the relative quantity of nonlinear occupations has had an upward trend in both genders, this trend is much steeper for females. Specifically, between the periods 1976–1985 and 2006–2015, the share of workers in

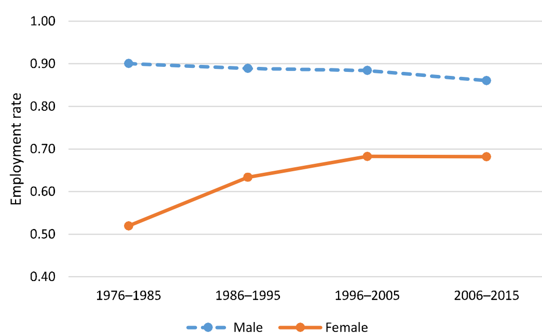
they did so for each period and updated their ranking accordingly. In contrast, we compute our occupational ranking for our 1976–1985 baseline period, and then apply this ranking over the other periods. We use such a time-invariant procedure because our paper is interested in changes in occupation composition over time.

[9] A few occupations were only observed after the baseline period. When these occupations were first observed in the data, we categorize them according to the threshold number of working hours of the occupational grouping in the baseline period. We then keep using this grouping for the subsequent periods.

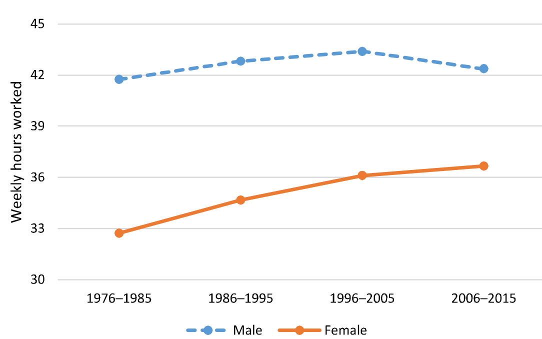
Figure 1: Trends in female labor supply in the US



(i) Total hours worked

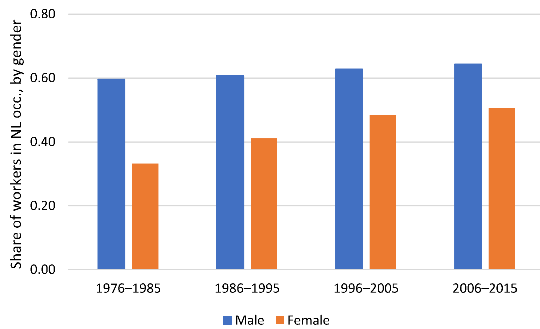


(ii) Extensive margin

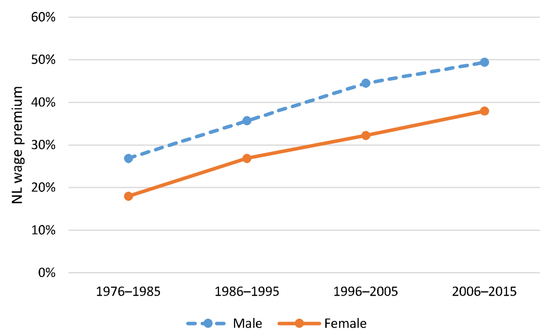


(iii) Intensive margin

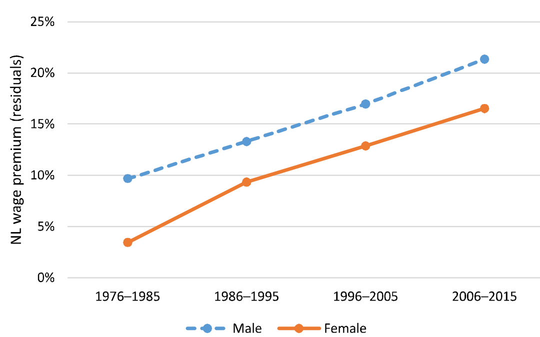
Figure 2: Trends in the relative quantity and price of nonliear occupations



(i) Share of workers in NL occupations, by gender



(ii) Nonlinear wage premium, by gender



(iii) Nonlinear (residual) wage premium, by gender

Note: Nonlinear vs. linear occupations are defined based on occupation-level mean hours in the base years of 1976–1985. We keep using the base-year occupation categorization for the following periods (1986–1995, 1996–2005, 2006–2015). The second panel is based on raw wages in two occupation groups, whereas the third panel is based on residual wages after controlling for age, education, race, industry, and the number of children under 5.

nonlinear occupations increased by nearly 4 percentage points for men and nearly 15 percentage points for women.

This increase in the relative quantity of nonlinear occupations could be driven by increases both in their relative demand and in the relative supply—such as a rising number of college-educated workers who are more likely go into nonlinear occupations.[10] However, the middle panel of Figure 2 shows that this rising relative quantity was accompanied by an increase in relative wages suggesting that demand-driven technological changes biased toward nonlinear occupations may potentially play an important role. As nonlinear wage premiums could also be due to factors such as education and selection, we also compute residual premiums by controlling for age, education, race, industry, and the number of children under age five. The bottom panel of Figure 2 shows that, although a quite significant portion of the observed nonlinear wage premiums can be explained by observables in each period, a rising trend is still clearly observed for both men and women. Intuitively, a rising demand for nonlinear occupations would increase the relative share of workers in them, while making linear occupations less attractive through even lower relative wages.

Having documented the trends in nonlinear occupations, we will now discuss how experience premiums have evolved over the same period in both occupation types. Note that relatively little attention has been paid to the rising trends in experience premiums, as pointed out by Heathcote, Perri, and Violante (2010). These trends are particularly relevant for our analysis because they may be shaping the observed changes in wage premiums for nonlinear occupations by affecting occupational choice and labor supply, especially when it comes to the question of how long one would like to work.

We compute occupation-specific experience premiums for females and males separately, based on wage differences between the age ranges 45–55 and 25–35, as in Heathcote, Perri, and Violante (2010) and Erosa et al. (forthcoming), but with some modifications. As a first step, we regress log wages on a quartic polynomial in age (Murphy and Welch, 1990), while controlling for education, race, industry, and the binary variables for having any child under either age eighteen or age

[10] In fact, Table A3 in Appendix E shows that, although nonlinear occupations have relatively more college-educated workers within each period, the share of college educated workers has been rising in both types of occupations for each gender in a parallel manner.

five. We do so for each occupation group and for each period. It is particularly important to control for education because it is systematically lower among older people within each period, due to the rising educational level over time. Further, since the presence of children is a strong predictor of female labor supply, it could mitigate biases that may arise due to selection. In the second step, we use the estimated coefficients for the polynomial in age to predict the age profile of wages, and use these residual age profiles to compute mean wages for the age groups 45–55 and 25–35. These are then used to compute the experience premiums.

Table 1 reports our experience premium estimates. First of all, we find that nonlinear occupations tend to have higher experience premiums regardless of gender.[11] Second, our results show that women used to have much lower experience premiums relative to men in both occupations, which is qualitatively consistent with Heathcote, Perri and Violante (2010). Most importantly, experience premiums for women have increased sharply, especially in nonlinear occupations, while those for men have been quite stable over time. In the specific case of nonlinear occupations, the 25.6 percentage point gender gap in experience premiums has narrowed substantially to only 6.9 percentage points from 1976–1985 to 2006–2015. By contrast, the initial 11.7 percentage point gap in linear occupations became just 7.3 percentage points over the same period. These shrinking gender gaps could be due to a cracking of the glass ceiling over time, as reviewed in Blau and Kahn (2017). This may especially the case in nonlinear occupations where long hours worked are more valued (e.g., see McDowell, Singell, and Ziliak 1999 for the evidence from the economics profession).

To sum up the situation when it comes to female labor supply, we would point to how the extensive margin became stagnant during the 2006–2015 period, while the intensive margin kept rising steadily. We can now document the evolution of variables related to nonlinear occupations. First, the relative quantity and price of nonlinear occupations have been increasing, suggesting technological changes biased toward such occupations. Second, the female experience premiums—which used to be quite small—have increased sharply, especially in nonlinear occupations, in contrast to stable male counterparts. In the next sections, we will explore the

[11] Although our methodology cannot exploit panel structures—as in Kambourov and Manovskii (2009b) who used the Panel Study of Income Dynamics—it is reassuring that our experience premium estimates for males (which are less likely to be subject to selection biases) are in the same ballpark as their estimates of 17–28% higher wages associated with 8 years of occupational tenure.

Table 1: Observed experience premiums over time, by gender and occupation

	1976–1985	1986–1995	1996–2005	2006–2015
Female				
Nonlinear occ.	.066	.117	.141	.222
Linear occ.	.035	.095	.146	.137
Male				
Nonlinear occ.	.322	.333	.292	.291
Linear occ.	.152	.241	.227	.210

Note: The observed experience premiums are computed as the difference in (residualized) wages between the age groups 45–55 and 25–35. To obtain the age profile of wages, we regress log wages on a quartic polynomial in age while controlling for education, race, industry and indicators for having any child under either age eighteen or age five.

implications of these changes regarding nonlinear occupations on female labor supply over time.

3 The model economy

In this section, we will describe the model that we use in our quantitative analysis. Building on an incomplete markets environment (Aiyagari, 1994), our model features adjustments along the intensive and extensive margins of female labor supply with occupational choice (in the spirit of Roy, 1951). The main endogenous decisions in our model, such as labor supply and occupational choice are for women only, with their male counterparts being simplified. A model period represents one year.

3.1 Households

There is a continuum of households comprised of married couples in our model, in accordance with our empirical analysis in Section 2.[12] We denote the household state vector by $(a, z, x, \grave{j}, \eta, \phi, j_m)$ where a is assets; z is female idiosyncratic productivity; $x \in \{0, 1\}$ is the occupational experience indicator (as in, e.g., Kambourov and Manovskii, 2009a); $\grave{j} \in \{0, 1, 2\}$ denotes the female occupational history in the last period, being either no relevant history

[12] It is common to model married women only for such studies on female labor supply, as most of the prominent variations in female labor supply exist among married women (e.g., Heathcote, Storesletten and Violante, 2010; Jones et al., 2015; Bick and Fuchs-Schündeln, 2018).

($\grave{j} = 0$), nonlinear occupation history ($\grave{j} = 1$), or linear occupation history ($\grave{j} = 2$); $\eta \in \mathbb{R}$ is Roy's comparative advantage (which we explain below) following a normal distribution $\mathcal{N}(0, \sigma_\eta^2)$; $\phi \in \{\phi_l, \phi_h\} > 0$ is a preference type regarding the disutility from hours worked, with each type having an equal mass; and $j_m \in \{0, 1, 2\}$ is a type of male occupation, where 0 means non-employed, 1 is a nonlinear occupation, and 2 a linear occupation. Households also face an exogenous positive probability of survival q. When a household dies with a probability of $1 - q$, it is replaced by a new household.

At the beginning of each period, the female member of the household chooses whether to work or not (the extensive margin labor supply), which is summarized by the following equation:

$$V(a, z, x, \grave{j}, \eta, \phi, j_m) = \max\{N(a, z, \eta, \phi, j_m), W(a, z, x, \grave{j}, \eta, \phi, j_m) - \xi \mathcal{I}_{j_m \neq 0}\} \tag{1}$$

where $N(a, z, \eta, \phi, j_m)$ is the value of not working and $W(a, z, x, \grave{j}, \eta, \phi, j_m)$ is the value of working. Participation costs $\xi \in \mathbb{R}$ are incurred if both spouses work (as in, e.g., Cho and Rogerson, 1988; Guner, Kaygusuz, and Ventura, 2012; and Erosa, Fuster, and Kambourov, 2016). We will first explain the value of working and then describe the value of non-working.

The value of working involves another discrete choice about occupation in the current period, as described by:

$$W(a, z, x, \grave{j}, \eta, \phi, j_m) = \max\left\{J_1(a, z, x, \grave{j}, \eta, \phi, j_m), J_2(a, z, x, \grave{j}, \eta, \phi, j_m)\right\} \tag{2}$$

where J_j is the value of working in occupation j at the beginning of the period before actually working in that period. When occupational choice j in this period is the same as in the last $\grave{j}$, she is eligible for an upgrade in her experience x. Specifically, with a probability of π, she becomes experienced ($x^{'} = 1$), with a probability that her experience does not change of $1 - \pi$. If her current occupation choice j is different from $\grave{j}$ in the previous period (e.g., she switched occupation or did not work), then her occupational experience is set to 0 (i.e., inexperienced).

Formally, the value of the occupation j is defined as:

$$
\begin{aligned}
& J_j(a, z, x, \grave{j}, \eta, \phi, j_m) && (3) \\
& = \pi P_j(a, z, 1, \eta, \phi, j_m) + (1-\pi) P_j(a, z, x, \eta, \phi, j_m) \quad \text{if } j = \grave{j} \\
& = P_j(a, z, 0, \eta, \phi, j_m) \quad \text{if } j \neq \grave{j}
\end{aligned}
$$

where P_j is the interim-period value of working in occupation j in the current period after the realization of the upgrade uncertainty.

Conditional on occupational choice and after the realization of experience relevant to this period, the female member chooses how many hours to work in occupation j. The value of working in occupation j at this stage, P_j, is given by:

$$
\begin{aligned}
& P_j(a, z, x, \eta, \phi, j_m) \\
& = \max_{\substack{c_f, c_m, a' \geq 0, \\ h \in [\underline{h}, 1-n]}} \left\{ u(c_f, n+h; \phi) + u(c_m, h_{j_m}; \phi_m) + \beta \left[\begin{array}{c} q \mathbb{E}_{z'|z} V(a', z', x, j', \eta, \phi, j_m) \\ +(1-q) \mathbb{E}_{z', \eta', \phi', j'_m} V(0, z', 0, 0, \eta', \phi', j'_m) \end{array} \right] \right\}
\end{aligned} \tag{4}
$$

subject to:

$$
\begin{aligned}
c_f + c_m + a' &\leq w_{j_f} z_j \left(1 + \mathcal{I}_{x=1} \chi_j - \mathcal{I}_{h<\mathcal{F}} \tau_j\right) h + w_{j_m} e_{j_m} h_{j_m} + (1+r) a + T && (5) \\
z_j &= \exp(\eta) z \quad \text{if } j = 1 \\
&= z \quad \text{if } j = 2 \\
j' &= j \mathcal{I}_{h \geq \mathcal{U}_j}. && (6)
\end{aligned}
$$

where c_f is female consumption, c_m is male consumption, n denotes housework hours, $a^{'}$ is asset holdings in the next period, β is the discount rate, r is the real interest rate, and $\phi_m > 0$ is a constant capturing the disutility from hours worked for males. The expected values in the next period show that households will survive with a probability of q and die with a probability of $1 - q$. The variable T refers to accidental bequest transfers redistributed from the assets of dying households, as in Conesa, Kitao, and Krueger (2009). The same measure is replaced by new households with zero assets and new draws of z', η', and husband $j_m' \in \{0, 1, 2\} \sim F_m(j_m)$. These new households have no female occupational experience ($x = 0$) and no female previous occupational career history ($\grave{j} = 0$).

Female labor income depends on the female market wage rate in occupation j (w_{j_f}), the labor productivity in that occupation z_j, an occupation-specific return to experience χ_j (available only for the experienced), a part-time penalty τ_j (applied to those who work less than the full-time threshold number of hours $\mathcal{F}$), and hours worked h. Unlike female labor income that involves various endogenous objects, male labor income is given simply: his labor income is exogenously determined by the male market wage rate in occupation j_m (w_{j_m}), the efficiency unit of a husband who works in that occupation e_{j_m} and his hours worked h_{j_m}.

We will now explain how we model labor productivity z_j in occupation j, especially compared to the closely related paper by Erosa et al. (forthcoming) that our model framework has built upon. They consider occupation-specific ability a_j with different means and variances in a static Roy model. There, those who draw a high a_1 compared to a_2 have a comparative advantage in occupation 1. In our model, z_1 is equal to $\exp(\eta)z$, where a positive η (or $\exp(\eta) > 1$) implies a comparative advantage in occupation 1 and the degree of this advantage increases with η. In addition, since our model is dynamic, we allow idiosyncratic productivity to evolve stochastically through z, which follows a standard AR(1) process in logarithms:

$$\log z^{'} = \rho_z \log z + \epsilon^{'}, \;\; \epsilon^{'} \sim \mathcal{N}(0, \sigma_z^2). \tag{7}$$

Next, it is also important to discuss how the degree of nonlinearity in an occupation is captured in our model. The first point concerns the differential dynamic returns to working long hours. As shown in (5), the return to experience χ_j differs across occupations. In our model, these differential dynamic returns are only eligible for those who work long enough hours (i.e., above the occupation-specific upgrade threshold number of hours $\mathcal{U}_j$). Thus, these thresholds essentially capture the barrier aspects of nonlinearity by prohibiting those who work relatively short hours from advancing their career. The second point is regarding the differential penalties for working part-time. As shown in (5), part-time penalties are modeled as a tax on earnings τ_j, which differs between occupations. They apply to those who choose to work less than the full-time threshold $\mathcal{F}$. This can capture the tendency of some firms to disfavor short hours (Goldin, 2014), which could be due to technology. From the worker perspective, $\mathcal{F}$ plays the role of another barrier because fewer people would be subject to part-time penalties if $\mathcal{F}$ were to decrease.

Finally, the value of non-working, which shares a number of elements that are also present in the value of working, is given by:

$$
\begin{aligned}
&N(a, z, \eta, \phi, j_m) \\
&= \max_{c_f, c_m, a' \geq 0} \left\{ u(c_f, n; \phi) + u(c_m, h_{j_m}; \phi_m) + \beta \left[\begin{array}{c} q\mathbb{E}_{z'|z} V(a', z', 0, 0, \eta, \phi, j_m) \\ +(1-q)\mathbb{E}_{z', \eta', \phi', j_m'} V(0, z', 0, 0, \eta', \phi', j_m') \end{array} \right] \right\}
\end{aligned} \tag{8}
$$

subject to:

$$c_f + c_m + a' \leq w_{j_m} e_{j_m} h_{j_m} + (1+r)a + T.$$

When women do not work, their experience in the next period is set to zero ($x^{'} = 0$), and this captures the negative aspects of career disruptions. The disutility of hours worked still occurs for non-working females due to the number of housework hours n.

3.2 The representative firm

The economy contains a representative firm, which solves the following:

$$\max_{L_{j_f}, L_{j_m}, K} \big(Y - w_{1_f} L_{1_f} - w_{1_m} L_{1_m} - w_{2_f} L_{2_f} - w_{2_m} L_{2_m} - (r+\delta)K\big) \tag{9}$$

where

$$
\begin{aligned}
Y &= AK^{\alpha}L^{1-\alpha} \\
L &= \left[\nu L_1^{\psi} + (1-\nu)L_2^{\psi}\right]^{\frac{1}{\psi}} \\
L_j &= \lambda_j L_{j_f} + (1-\lambda_j)L_{j_m}
\end{aligned}
$$

with Y being the aggregate output; L_{j_f} (L_{j_m}) being the female (male) aggregate labor in occupation j; δ being the depreciation rate of capital; A being the total factor productivity; K being the aggregate capital; and α being the capital share. Labor inputs from occupations are CES aggregated with ψ shaping the elasticity of substitution between occupations and ν capturing the relative demand for nonlinear occupations. Finally, λ_j captures the gender-biased demand in occupation j.

The first-order conditions yield the following equations characterizing the factor demands:

$$[K] : r + \delta = A\alpha K^{\alpha-1}L^{1-\alpha} \tag{10}$$

$$[L_{1_f}] : w_{1_f} = A(1-\alpha)K^{\alpha}L^{-\alpha}\frac{\partial L}{\partial L_1}\frac{\partial L_1}{\partial L_{1_f}} \tag{11}$$

$$[L_{1_m}] : w_{1_m} = A(1-\alpha)K^{\alpha}L^{-\alpha}\frac{\partial L}{\partial L_1}\frac{\partial L_1}{\partial L_{1_m}} \tag{12}$$

$$[L_{2_f}] : w_{2_f} = A(1-\alpha)K^{\alpha}L^{-\alpha}\frac{\partial L}{\partial L_2}\frac{\partial L_2}{\partial L_{2_f}} \tag{13}$$

$$[L_{2_m}] : w_{2_m} = A(1-\alpha)K^{\alpha}L^{-\alpha}\frac{\partial L}{\partial L_2}\frac{\partial L_2}{\partial L_{2_m}}. \tag{14}$$

Note that one can easily derive the following:

$$\frac{w_{1_f}}{w_{1_m}} = \frac{\lambda_1}{1-\lambda_1} \tag{15}$$

$$\frac{w_{2_f}}{w_{2_m}} = \frac{\lambda_2}{1-\lambda_2}, \tag{16}$$

which shows that the relative wages between females and males are shaped by the gender-biased demand parameter λ_j, as in Heathcote, Storesletten, and Violante (2010) and in Cerina, Moro, and Rendall (forthcoming).[13] Note that we allow the gender-biased demand λ_j to differ by occupation.

Similarly, the relative market wage of nonlinear occupations can be obtained as

$$\frac{w_{1_f}}{w_{2_f}} = \frac{\frac{\partial L}{\partial L_1}}{\frac{\partial L}{\partial L_2}} = \frac{\nu L_1^{\psi-1}}{(1-\nu)L_2^{\psi-1}}. \tag{17}$$

which shows that the nonlinear wage premiums would tend to increase with ν.

3.3 General equilibrium

The equilibrium definition used in our model is a standard one. The key objects in the stationary general equilibrium include the sets of prices that clear the goods market, the capital market, and the two labor markets in every period, as well as the stationary distribution. More precisely, we first define a measure space to describe the distribution. Let us denote $\mathbf{S} = \mathbf{A} \times \mathbf{Z} \times \mathbf{X} \times \grave{\mathbf{J}} \times \mathbf{E} \times \mathbf{\Phi} \times \mathbf{J_m}$ as the state space of households such that $(a, z, x, \grave{j}, \eta, \phi, j_m) = \mathbf{s} \in \mathbf{S}$. Then, a probability measure $F(\cdot)$ is defined on the Borel $\sigma-$algebra $\mathbb{B}(\mathbf{S})$ such that $F(\cdot) : \mathbb{B}(\mathbf{S}) \longrightarrow [0, 1]$. $F(B)$ represents the measure of households whose state lies in $B \in \mathbb{B}(\mathbf{S})$ as a proportion of all households.

A stationary recursive equilibrium is a set of factor prices $\big(r,\, w_{1_f},\, w_{2_f},\, w_{1_m},\, w_{2_m}\big)$; a set of female decision rules $\Big(g_n(a, z, x, \grave{j}, \eta, \phi, j_m),\, g_o(a, z, x, \grave{j}, \eta, \phi, j_m),\, \{g_{a,j}(a, z, x, \eta, \phi, j_m)\}_{j=0}^{2},$ $\{g_{h,j}(a, z, x, \eta, \phi, j_m)\}_{j=1}^{2}\Big)$; a set of value functions $\Big(V(a, z, x, \grave{j}, \eta, \phi, j_m)\ , N(a, z, \eta, \phi, j_m),$ $W(a, z, x, \grave{j}, \eta, \phi, j_m),\ \{P_j(a, z, x, \eta, \phi, j_m)\}_{j=1}^{2}\Big)$; the aggregate capital K, the aggregate labor L, and the aggregate labor by gender and occupation $L_{1_f},\, L_{2_f},\, L_{1_m},\, L_{2_m}$; the distribution of households $F(\cdot)$ such that

1. Given factor prices $\big(r,\, w_{1_f},\, w_{2_f},\, w_{1_m},\, w_{2_m}\big)$, the value functions $V(a, z, x, \grave{j}, \eta, \phi, j_m)$, $N(a, z, \eta, \phi, j_m)$, $W(a, z, x, \grave{j}, \eta, \phi, j_m)$, $\{P_j(a, z, x, \eta, \phi, j_m)\}_{j=1}^{2}$ solve the associated prob-

[13] In practice, this is similar to the gender-specific taxes introduced in Jones et al. (2015) without the subsequent redistribution of the tax revenue.

lems defined above, the associated decision rules are

$$g_n(a,z,x,\grave{j},\eta,\phi,j_m) = \arg\max\{N(a,z,\eta,\phi,j_m), W(a,z,x,\grave{j},\eta,\phi,j_m) - \xi\mathcal{I}_{j_m\neq 0}\} \tag{18}$$

$$g_o(a,z,x,\grave{j},\eta,\phi,j_m) = \arg\max\left\{J_1(a,z,x,\grave{j},\eta,\phi,j_m), J_2(a,z,x,\grave{j},\eta,\phi,j_m)\right\} \tag{19}$$

$$a^{'*} = g_{a,j}(a,z,x,\eta,\phi,j_m), : j \in \{0,1,2\} \tag{20}$$

$$h^* = g_{h,j}(a,z,x,\eta,\phi,j_m), : j \in \{1,2\}. \tag{21}$$

2. Given factor prices r, w_{1_f}, w_{2_f}, w_{1_m}, w_{2_m}, the representative firm optimally chooses K, L_{1_f}, L_{2_f} , L_{1_m}, and L_{2_m} following (10)-(14)

3. Markets clear:

$$K = \int a\,F(d\mathbf{s}) \tag{22}$$

$$\begin{aligned}
L_{j_f} = \int \mathcal{I}_{\{g_n(\mathbf{s})=W\}} \cdot z_j \cdot \Bigg(\mathcal{I}_{\{j=g_o(\mathbf{s})=\grave{j}\}} \cdot \Bigg(\pi \cdot \left(1+\chi_j - \tau_j \cdot \mathcal{I}_{\{g_{h,j}(\mathbf{s})<\mathcal{F}_j\}}\right) \cdot g_{h,j}(a,z,x^{'}=1,\eta,\phi,j_m) \\
+(1-\pi)\cdot(1+\chi_j\cdot\mathcal{I}_{x=1} - \tau_j\cdot\mathcal{I}_{\{g_{h,j}(\mathbf{s})<\mathcal{F}_j\}})\cdot g_{h,j}(a,z,x,\eta,\phi,j_m)\Bigg) \\
+\mathcal{I}_{\{j=g_o(\mathbf{s})\neq\grave{j}\}}\cdot(1-\tau_j\cdot\mathcal{I}_{\{g_{h,j}(\mathbf{s})<\mathcal{F}_j\}})\cdot g_{h,j}(a,z,x^{'}=0,\eta,\phi,j_m)\Bigg)\Bigg] F(d\mathbf{s}), : j\in\{1,2\}
\end{aligned}$$

$$L_{j_m} = \int e_{j_m} h_{j_m} F(d\mathbf{s}), : j \in \{1,2\} \tag{23}$$

where $\mathbf{s} = (a,z,x,\grave{j},\eta,\phi,j_m) \in \mathbf{S}$.

4. The household distribution $F(\cdot)$ is consistent with the household optimal choices defined

above. Specifically, for any $B \in \mathbb{B}(\mathbf{S})$,

$$
\begin{aligned}
F(B) =& q \cdot \int_{\{\mathbf{s}|(g_{a,j=0}(\mathbf{s}),z',x'=0,g_o(\mathbf{s})=0,\eta',\phi,j_m)\in B\}} \left[\pi_{z'|z} \cdot \pi_{\eta'|\eta} \cdot \mathcal{I}_{\{g_n(\mathbf{s})=N\}}\right] F(d\mathbf{s}) \\
&+ q \cdot \sum_{j=1}^{2} \Bigg\{ \int_{\{\mathbf{s}|(g_{a,j}(\mathbf{s}),z',x'=1,g_o(\mathbf{s})=j,\eta',\phi,j_m)\in B\}} \Big(\pi_{z'|z} \cdot \pi_{\eta'|\eta} \cdot \mathcal{I}_{\{g_n(\mathbf{s})=W)\}} \\
&\cdot \Big(\pi \cdot \mathcal{I}_{\{g_{h,j}(\mathbf{s})>\mathcal{U}_j\}} \cdot \mathcal{I}_{\{x=0\}} + \mathcal{I}_{\{g_{h,j}(\mathbf{s})>\mathcal{U}_j\}} \cdot \mathcal{I}_{\{x=1\}}\Big)\Big) F(d\mathbf{s}) \\
&+ \int_{\{\mathbf{s}|(g_{a,j}(\mathbf{s}),z',x'=0,g_o(\mathbf{s})=j,\eta',\phi,j_m)\in B\}} \Big(\pi_{z'|z} \cdot \pi_{\eta'|\eta} \cdot \mathcal{I}_{\{g_n(\mathbf{s})=W)\}} \\
&\cdot (1-\pi) \cdot \mathcal{I}_{\{g_{h,j}(\mathbf{s})>\mathcal{U}_j\}} \cdot \mathcal{I}_{\{x=0\}}\Big) F(d\mathbf{s}) \Bigg\} \\
&+ q \cdot \sum_{j=1}^{2} \Bigg\{ \int_{\{\mathbf{s}|(g_{a,j}(\mathbf{s}),z',x'=0,g_o(\mathbf{s})=j,\eta',\phi,j_m)\in B\}} \Big(\pi_{z'|z} \cdot \pi_{\eta'|\eta} \cdot \mathcal{I}_{\{g_n(\mathbf{s})=W)\}} \cdot \mathcal{I}_{\{g_{h,j}(\mathbf{s})\le\mathcal{U}_j\}}\Big) F(d\mathbf{s}) \Bigg\} \\
&+ (1-q) \cdot \int_{\{\mathbf{s}|(0,z',x'=0,j=0,\eta',\phi',j'_m)\in B\}} \pi^n_{z'} \cdot \pi^n_{\eta'} \cdot \pi^n_{\phi'} \cdot \pi^n_{j'_m} F(d\mathbf{s})
\end{aligned}
$$

where $\mathbf{s} = (a, z, x, \grave{j}, \eta, \phi, j_m) \in \mathbf{S}$ and $\pi_{z'|z}$ $(\pi_{\eta'|\eta})$ is the transitional probability from z to z' (from η to η'). $\pi^n_{z'}$, $\pi^n_{\eta'}$, $\pi^n_{\phi'}$, and $\pi^n_{j'_m}$ determine the distribution of newly-born households for z', η', ϕ' and j'_m, respectively.

4 Calibrating the model in the baseline period

In this section, we explain how our model is calibrated to US data from the baseline period (1976–1985). We will then discuss the properties of this calibrated model in relation to some stylized facts relating to nonlinear occupations. A set of parameters is calibrated externally without solving the model, and the other parameters are calibrated internally by matching relevant target statistics. All variables in the model with hours as their units are expressed as a fraction of total disposable annual hours (i.e., 105 weekly hours multiplied by 52 weeks).

4.1 Externally calibrated parameters

For the utility function, we use the same functional form as in Erosa et al. (forthcoming), which is standard in the literature:

$$u(c_g, h_g; \phi) = \log c_g - \phi \frac{h_g^{1+\gamma}}{1+\gamma}, \quad g = f, m. \tag{24}$$

We set $\gamma = 2$ so that the Frisch elasticity of labor supply at the intensive margin is 0.5, in line with the micro evidence (Chetty, Guren, Manoli, and Weber, 2011). Next, we set $q = 1 - 1/40$ to have an average of 40 years of life for work, and $\pi = 1/10$ such that it takes on average 10 years in an occupational career to become experienced (as in Kambourov and Manovskii, 2009a). The persistence of idiosyncratic shocks ρ_z is set to 0.94 (Jang, Sunakawa, and Yum, 2020), in line with standard values estimated in the literature (e.g., Heathcote, Storesletten, and Violante, 2010).[14] We set the minimum number of hours that can be supplied $\underline{h}$ to 0.0476 (or five weekly hours) to be consistent with the restriction imposed in our empirical analysis. We set $n = 0.289$, in line with the estimate of 30.3 weekly hours of housework performed by women (Ramey, 2009). We set the full-time threshold $\mathcal{F}$ to 0.286 (30 weekly hours) (Lagakos, Moll, Porzio, Qian, and Schoellman, 2018).

For the firm technology, we use a standard value of $\alpha = 0.36$ to be consistent with aggregate capital share. We set ψ to -0.5, implying that the elasticity of substitution between nonlinear and linear occupations is 0.67.[15] We set $A = 1$ for the baseline period. As for female weights in L_j, these parameters are not separately identified from the efficiency units of males in occupation j, which are internally calibrated to match the observed gender wage gaps. We fix $\lambda_1 = \lambda_2 = 0.4$ for the baseline period, implying that (without selection or any further forces) the gender wage gaps in each occupation are around 33%. Then, we allow them to change over time in the following quantitative exercises in Sections 5 and 6. Finally, the depreciation rate is set to $\delta = 0.096$.

There are several parameters related to husbands for us to consider. Firstly, the probability

[14] We use the method of Tauchen (1986) for our discretization with five grid points.

[15] This value implies that there is a moderate degree of complementarity between the nonlinear and linear occupations. We have also conducted sensitivity checks with $\psi = -0.25$, and our results are nearly unchanged. See Appendix E for details.

Table 2: Parameter values calibrated internally and target statistics

	Parameters		Target statistics		
	Value	Description	Model	Data	Description
$\beta =$	.9871	Discount factor	.040	.040	Real interest rate
$\mu_\phi =$	8.74	Disutility of work mean	.314	.312	Average hours per worker
$\Delta_\phi =$	.530	Disutility of work dispersion	.460	.487	$\mathbf{sd}(\log(h))$
$\xi =$	.055	Participation cost	.536	.520	Employment rate
$\sigma_z =$	.155	S.D. of innovations to $\ln z$	.453	.454	$\mathbf{sd}(\log(\text{wage}))$
$\sigma_\eta =$	.228	Variability of η	.496	.500	Share of all workers in NL
$\nu =$	.673	Weight of NL in prod.	.180	.179	$\mathbb{E}(\text{wage}\|\text{NL})/\mathbb{E}(\text{wage}\|\text{L}) - 1$
$e_1 =$	2.04	Eff. unit of husband in NL	.403	.410	Gender wage gap in NL
$e_2 =$	1.47	Eff. unit of husband in L	.372	.366	Gender wage gap in L
$\mathcal{U}_1 =$	.329	Hours for upgrading in NL	.430	.415	$\Pr(x = 1\|\text{NL})$
$\mathcal{U}_2 =$	.272	Hours for upgrading in L	.443	.443	$\Pr(x = 1\|\text{L})$
$\chi_1 =$	.047	Return to exp. in NL	.074	.066	Observed exp. premium in NL
$\chi_2 =$	.023	Return to exp. in L	.042	.035	Observed exp. premium in L
$\tau_1 =$	.179	Part-time penalty in NL	.792	.790	$\mathbb{E}(\text{wage}\|\text{PT})/\mathbb{E}(\text{wage}\|\text{FT})$ in NL
$\tau_2 =$	.113	Part-time penalty in L	.833	.917	$\mathbb{E}(\text{wage}\|\text{PT})/\mathbb{E}(\text{wage}\|\text{FT})$ in L

Note: $\mathbf{sd}(\log(h))$ and $\mathbf{sd}(\log(\text{wage}))$ denote the standard deviation of log hours worked and log wage, respectively. $\mathbb{E}(\text{wage}|\text{NL})$ and $\mathbb{E}(\text{wage}|\text{L})$ denote average hourly wage conditional on working in nonlinear occupations and linear occupations, respectively. $\Pr(x = 1|\text{NL})$ and $\Pr(x = 1|\text{L})$ refer to the share of the experienced workers conditional on working in nonlinear occupations and linear occupations, respectively. $\mathbb{E}(\text{wage}|\text{PT})$ and $\mathbb{E}(\text{wage}|\text{FT})$ denote average hourly wage conditional on working part-time and full-time, respectively.

mass of husbands $F_m(j_m)$ requires two parameters, p_1 and p_2, where p_{j_m} refers to the probability of the husband working in occupation j_m. These values are taken directly from the data, with $p_1 = 0.537$ and $p_2 = 0.364$ in the baseline period. The other two parameters regarding husbands are the occupation-specific intensive margins h_{j_m}, which are also directly taken from the data as $h_1 = 0.416$ and $h_2 = 0.370$.

4.2 Internally calibrated parameters

Table 2 summarizes 15 of the remaining parameters, which are calibrated internally to match the values present in the target statistics. We see that our model is able to match these target statistics quite successfully. We will now explain how each parameter is clearly linked to its target statistic, which explains the successful fit of our model.

The first parameter is the discount factor β, which is targeted to match the annual real interest rate of 4%. Next, there are three parameters related to the disutility of working: μ_ϕ, Δ_ϕ, and ξ. Since the female preference type takes two values, we assume that $\phi_l = \mu_\phi(1 - \Delta_\phi)$ and $\phi_h = \mu_\phi(1 + \Delta_\phi)$ and calibrate the two parameters: μ_ϕ and Δ_ϕ. Their relevant targets are the average hours worked per worker of 0.312 (or 1702 annual hours) and the standard deviation of log hours of 0.487. A constant for the male ϕ_m is set to μ_ϕ, and the participation cost ξ that is incurred when both spouses work is calibrated to match the female employment rate of 52.0%. The next parameter σ_z governs the degree of wage inequality in the model with its target set to the standard deviation of log wages of 0.454.

As discussed above, η captures the comparative advantage in nonlinear occupations, which follows a normal distribution with a mean of zero.[16] A higher σ_η implies a larger share of women choosing nonlinear occupations. This is because there are more people with stronger comparative advantages in nonlinear occupations. The share of both male and female workers in nonlinear occupations is used as the target for this parameter. Given the way we categorize nonlinear occupations, this target is exactly 0.5 in the baseline period (as discussed in Section 2). The next parameter ν describes the share of nonlinear occupations relative to linear occupations in the production technology. Holding all else fixed, a higher ν would increase the relative wage of nonlinear occupations, as shown in (17). Its target is thus set to the observed wage premium of nonlinear occupations: 17.9% in the baseline year (as documented in Section 2).

The next two parameters e_{j_m} are the efficiency units of husbands in each occupation. Although endogenous channels in our model have implications for gender wage gaps, there are numerous other channels that shape these gaps (as reviewed by Blau and Kahn, 2017) that are missing in our model. Thus, while allowing for endogenous channels to work, these two parameters are calibrated internally to match the observed gender wage gaps in each occupation: 41.0% in nonlinear occupations and 36.6% in linear occupations.

The next two parameters $\mathcal{U}_j$ are the upgrade thresholds. In essence, these parameters govern the barrier aspects of the nonlinearities in each occupation because higher values imply that longer working hours are required in order to be eligible for and maintain the returns to experi-

[16] As we have endogenous market wages in each occupation, a non-zero mean of η would be offset by adjustments to the relative wage in equilibrium.

ence. In the data, we calculate the share of experienced women relative to inexperienced women as the number of workers aged 45–55 divided by the sum of the number of workers aged 25–35 and those aged 45–55, in line with the definition in Heathcote, Perri and Violante (2010) and Erosa et al. (forthcoming). We find that this ratio is lower in nonlinear occupations (41.5%) compared to linear occupations (44.3%) in the baseline period (1976–1985). While allowing for other occupational differences such as returns to experience, we calibrate $\mathcal{U}_j$ internally to match these relative experience share ratios in each occupation group. Our calibration results indicate a higher threshold for the nonlinear occupation of $\mathcal{U}_1 = 0.329$, versus $\mathcal{U}_2 = .272$ for the linear occupation. This means that there are higher barriers in nonlinear occupations, which would prevent more women who are not willing to work long hours from working in these occupations.

The last four parameters—χ_1, χ_2, τ_1, and τ_2—shape the degree of nonlinearities in each occupation. Given the difficulties in estimating these deep structural parameters externally due to low female labor market attachment, we calibrate these internally within the model. This enables us to take into account various kinds of selection involved in work choices at the intensive and extensive margins, and in occupational choice. The relevant target statistics include the estimated experience premiums in each occupation in Section 2, as well as the observed part-time penalties. We compute the observed part-time penalties by regressing log hourly wages on a part-time dummy, which is set to one if weekly hours worked are less than 30. We do so for each occupation and period separately.[17] There is a clear pattern whereby nonlinear occupations tend to have higher part-time penalties for both men and women, and this is consistent with Goldin (2014). As there is no clear trend with regards to this penalty over time, we set the target statistics based on mean penalties for females over the whole period. As a result of the calibration, we do find that the nonlinear occupation group features a greater return to experience ($\chi_1 = 0.047 > \chi_2 = 0.023$) and a higher part-time penalty ($\tau_1 = 0.179 > \tau_2 = 0.113$) in terms of these structural parameters.

[17] Table A2 reports these estimates. We also estimate part-time penalties by using residual wages after controlling for age, education, race, industry, and the number of children under age five. The part-time penalties generally become lower, albeit not substantially.

Table 3: Wage and hours: Model vs. data

	All		**NL occ.**		**L occ.**	
	Model	Data	Model	Data	Model	Data
$\mathbb{E}$(wage)	1.0	1.0	1.114	1.113	.944	.944
$\mathbb{E}(h)$	.318	.312	.343	.324	.305	.306
sd(log(wage))	.453	.454	.455	.496	.443	.424
sd(log(h))	.460	.487	.444	.485	.462	.487
Gender wage gap	.419	.421	.403	.410	.372	.366

Note: $\mathbb{E}$(wage) and $\mathbb{E}(h)$ denote average hourly wage and average hours worked (conditional on working), respectively. **sd**(log(wage)) and **sd**(log(h)) refer to the standard deviation of log hourly wage and log hours worked, respectively. Gender wage gap denotes one minus the ratio of average wage for females to average wage for males. Wages are scaled such that its unconditional mean is one.

4.3 Properties of the model in the baseline period

Having discussed how we calibrate our model to the baseline period, we will now present how well our model is able to reproduce the salient facts with respect to the two occupation groups. Specifically, values for mean hours, mean wages, wage dispersion, and the gender wage gap in US data (1976–1985) are higher in nonlinear occupations, as shown in Table 3. Our model generates these patterns quite well. One interesting observation is that the overall gender wage gap is quite a bit higher than that seen within an occupation in the data, implying that features and choices related to occupation worsen the overall gender wage gap. As our model targets occupation-specific gender wage gaps, occupational premiums, and the relative share of nonlinear occupations, it ends up reproducing the overall gender wage gap (42%) found in the data.

Compared to Erosa et al. (forthcoming)—who also generate these patterns in a static environment—our dynamic environment enables us to microfound the nonlinearities through returns to experience χ_j and part-time penalties τ_j along with the hours thresholds $\mathcal{U}_j$ and $\mathcal{F}$. To illustrate how each of these occupation-specific features shapes labor market outcomes across occupations, we separately equalize $\chi_j, \mathcal{U}_j$, and τ_j at their linear occupation levels, while shutting down general equilibrium effects (i.e., prices are held constant at the baseline level).

Table 4 then reports how each parameter contributes to the differences observed in Table

Table 4: Sources of nonlinearity

	Baseline		$\chi_1 \downarrow$		$\mathcal{U}_1 \downarrow$		$\tau_1 \downarrow$	
	NL	L	NL	L	NL	L	NL	L
Emp. share	.175	.361	.169	.367	.184	.351	.207	.340
$\frac{\mathbb{E}(wage\|\text{NL})}{\mathbb{E}(wage\|\text{L})} - 1$	.180		.175		.168		.129	
$\mathbb{E}(h)$	.343	.305	.342	.306	.343	.306	.317	.313
sd(log(wage))	.455	.443	.454	.442	.448	.443	.470	.440
sd(log(h))	.444	.462	.450	.458	.425	.468	.473	.451

Note: $\mathbb{E}(wage|\text{NL})$ and $\mathbb{E}(wage|\text{L})$ denote average hourly wage conditional on working in nonlinear occupations and linear occupations, respectively. $\mathbb{E}(h)$ denote average hours worked (conditional on working). **sd**(log(wage)) and **sd**(log(h)) are the standard deviation of log wage and log hours worked, respectively. We separately set χ_1,$\mathcal{U}_1$, or τ_1 to χ_2, $\mathcal{U}_2$, or τ_2, respectively. In doing so, we shut down general equilibrium feedback by fixing prices at the baseline level.

3. When we first equalize the returns to experience at the linear occupation level, we find that the relative share of women working in nonlinear occupations decreases in response to a relatively lower incentive to work in such occupations. We also find that this would reduce the observed nonlinear occupation premium, and slightly reduce the positive gap in mean hours worked. Finally, because the lowered return to experience essentially shrinks the right tail of the wage distribution in nonlinear occupations, we can see that the positive gap in the dispersion of hourly wages becomes slightly smaller with this change.

Another important element of the nonlinearities present in our model is the occupation-specific upgrade threshold number of hours $\mathcal{U}_j$. Our calibration results produce a value for $\mathcal{U}_1$ that is greater than $\mathcal{U}_2$, implying that there are stronger barrier aspects in nonlinear occupations that only dynamically benefit those who work longer hours. When we reduce $\mathcal{U}_1$ to $\mathcal{U}_2$, this barrier to women is relaxed in nonlinear occupations. Table 4 indeed shows that this change would raise the share of women working in nonlinear occupations quite substantially (from 17.5% to 18.4%). In addition, we note that the positive wage premium for nonlinear occupations declines quite noticeably via selection effects, meaning that marginal women employed in nonlinear occupations tend to have lower productivity.

Finally, we also investigate how differences in part-time penalties affect labor market outcomes in each occupation group. When we reduce τ_1 in nonlinear occupations to the level of τ_2, Table 4 shows that this change substantially increases the share of women working in nonlinear occupations. This also raises their incentive to work short hours in nonlinear occupations, which in turn narrows the positive gap in mean hours worked considerably. By lowering the part-time penalty in nonlinear occupations, there will be more workers in those occupations who are willing to work less, which in turn increases the standard deviation of log hours worked in them.

5 Understanding the evolution of female labor supply

In this section, we investigate the forces at work behind the evolution of female labor supply through the lens of our model. For the decomposition exercise, we feed changes in selected driving forces into the model so that it could generate empirically plausible trends in key aggregate variables. These changes in driving forces are either estimated externally or calibrated internally following a calibration strategy equivalent to the one used in Section 4. Specifically, we externally recalibrate the four parameters related to male labor supply over time externally—p_1, p_2, h_1, and h_2—as reported in Table A1. Then, eight additional parameters—$A, \lambda_1, \lambda_2, s, \sigma_\eta, v, \chi_1$, and χ_2—are internally calibrated to match the target statistics over time, as reported in Table 5. All other parameters remain unchanged from the baseline period.[18]

5.1 Driving forces

We are interested in two main driving forces behind the observed changes in female labor supply over time. The first is the change in the returns to experience in each occupation: χ_1 and χ_2. With rising female employment and overall experience levels, selection makes it difficult to estimate these time-varying parameters externally. Therefore, we internally calibrate χ_1 and χ_2 to match the observed experience premiums, as is done for the baseline period. As reported in Table 5, our calibration recovers the result that returns to experience have been increasing (especially in nonlinear occupations), which is in line with the rising observed experience pre-

[18] We also consider perfect-foresight transitions in Appendix D. The main decomposition results are robust when temporally aggregated into 10 year periods, as in our main analysis.

Table 5: Parameters calibrated internally over time

	Parameter values			Target statistics						
	1986	1996	2006		1986–1995		1996–2005		2006–2015	
	–1995	–2005	–2015		Model	Data	Model	Data	Model	Data
$A =$	1.004	1.011	1.021	% change in overall wages	0.8	0.3	5.0	6.3	11.3	11.7
$\lambda_1 =$	.419	.438	.437	Gender wage gap in NL	.334	.332	.290	.289	.250	.246
$\lambda_2 =$	.430	.440	.454	Gender wage gap in L	.288	.286	.223	.223	.183	.183
$s =$	.882	.821	.856	% change in total hours	29.2	29.2	44.0	45.0	46.9	47.1
$\sigma_\eta =$	.284	.273	.307	Share of all workers in NL	.524	.526	.562	.565	.581	.582
$\nu =$	.710	.750	.781	$\mathbb{E}(\text{wage}\vert\text{NL})/\mathbb{E}(\text{wage}\vert\text{L}) - 1$	.269	.269	.319	.322	.389	.380
$\chi_1 =$	.178	.224	.301	Experience premium in NL	.104	.117	.143	.141	.220	.222
$\chi_2 =$	.130	.253	.228	Experience premium in L	.094	.095	.142	.146	.131	.137

miums in Table 1. These changes are likely driven by a reduction in discrimination regarding promotions (e.g., cracking the glass ceiling), which we take as given.

The second driving force of interest to us is structural changes captured by the change in v. This variable represents technical changes biased toward nonlinear occupations, as suggested by the empirical trends of Section 2 that showed how both the relative price and relative quantity of nonlinear occupations have been rising over time. Because these two trends are affected not only by technological change (demand) but also by other factors related to supply, we choose to recover the evolution of ν internally by targeting the nonlinear wage premiums in each of the three periods (1986–1995, 1996–2005, and 2006–2015), as in the baseline calibration in Section 4.[19]

Besides the two driving forces, there are others which we consider related to the evolution of wages. A crucial reason for including these in our model is to allow it to generate empirically reasonable price changes in terms of gender wage differences and overall wage changes, in addition to occupational wage differences. As equilibrium wages depend on the distribution of individual

[19] The relative importance of nonlinear occupations in the production technology (ν) affects the hourly wages of both men and women. Thus, when we identify ν, we also incorporate the observed changes in male employment rates and hours per male worker in each occupation, as reported in Table A1. This ensures that our value for ν is calibrated, while also taking into account general equilibrium feedback arising due to changes in the relative labor supply of males. Similarly, σ_η is re-calibrated to match the observed share of all workers in nonlinear occupations in addition to the nonlinear wage premium, as is done for the baseline period.

productivity among workers, selection issues related to participation and occupational choice make it impossible to externally feed in price changes into our model framework. Therefore, we use a calibration strategy equivalent to the one used for the baseline period. More precisely, we obtain the values of λ_1,λ_2, and A in each period by internally matching the observed gender wage gaps in each occupation and the observed overall wage changes.

Although price effects can be quantitatively strong, they may not be able to capture all of the changes in the labor supply observed in the data. An important alternative mechanism could be the intergenerational transmission of culture—as studied by Fernández et al. (2004), Fogli and Veldkamp (2011) and Fernández (2013)—that effectively reduces the utility costs of working. Hence, in addition to the above changes, we also consider a disutility-of-work shifter $s > 0$. Specifically, s gets multiplied by μ_ϕ and ξ, both of which capture the disutility of work. This parameter s is internally calibrated to generate the evolution of total hours worked, as observed in the data.

Before we move on, a brief discussion on some of the determinants we abstract from is in order. First, we do not consider changes to the number of hours women spent on housework over time. Figure A7 plots trends in homework hours in the postwar period, based on historical data from Ramey (2009). A noticeable decline in mean housework hours began in the mid-1960s, which was due to rapid changes in home production technology (Greenwood, Seshadri, and Yorukoglu, 2005). Subsequently, these numbers have gradually become stable since the 1980s. This relative stability in housework hours, especially conditional on employment status, suggests that it might not be one of the most relevant factors during the periods considered in our study. Still, technological changes in home production should be of first-order importance to our understanding of the female labor supply up until 1980. Secondly, we also do not explicitly consider changes in child care costs due to a lack of data availability, although these could potentially be an important quantitative factor (Attanasio et al., 2008). Finally, we abstract completely from medical progress— a factor found to be important when it comes to the labor supply of mothers (Albanesi and Olivetti, 2016). This factor is again more relevant for periods earlier than those we consider.

5.2 Trends implied by the model

We will first present the performance of our model, as measured by its ability to reproduce the empirically observed changes in female labor supply and occupational choice. This is necessary before we can conduct our decomposition exercises, as we would like to see whether our model captures the evolution of aggregate labor market variables reasonably well. We will then be in a position to understand how the underlying forces of interest shape the dynamics of female labor supply in labor market outcomes over time.

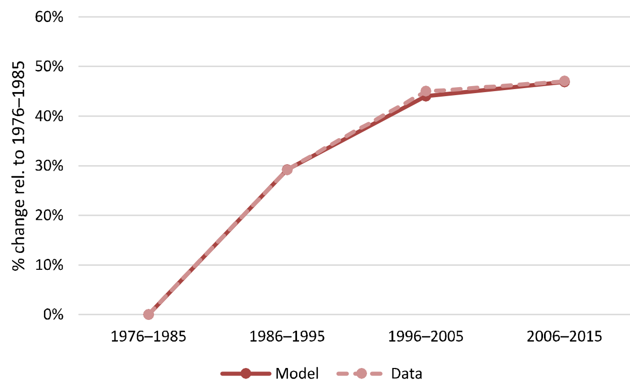
Figure 3 displays the model-generated trends and their empirical counterparts for total hours, the extensive margin, and the intensive margin for females. The top panel of Figure 3 shows that the model-generated trend in female total hours is, by construction, perfectly matched with its empirical counterpart. However, it is worth noting that both the extensive and intensive margins of female labor supply are not separately targeted. This means that it is more interesting to validate the model by comparing these two margins with their empirical counterparts.

Indeed, the middle and bottom panels of Figure 3 imply that the model does a good job of reproducing untargeted dynamics that sharply differ between the extensive and intensive margins. The middle panel of Figure 3 further implies that our model can capture the observed evolution of the female extensive margin very well. Not only does it generate the upward and concave trend in the female extensive margin until the period 1996–2005, but it also successfully reproduces the stagnating employment rate in the period 2006–2015. Furthermore, the bottom panel of Figure 3 shows that the model successfully reproduces the continually rising trend in the hours per worker.

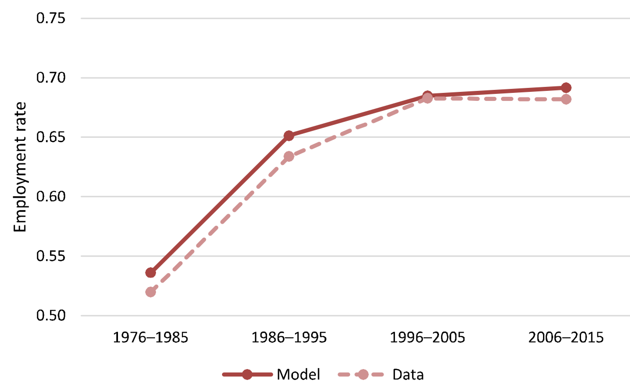
Figure 4 similarly presents the model-generated trends and their empirical counterparts related to female occupations. As can be seen, our model generally performs well at capturing the observed evolution of female occupational choice. The top and middle panels of Figure 4 show that the model-generated evolution of the share of workers in each occupation is empirically consistent. In other words, the model replicates the rising employment rate in nonlinear occupations and the inverse U-shaped employment rate in linear occupations.

What is even more noteworthy is the performance of our model in capturing the evolution of intensive margins conditional on occupation, which were not targeted. The bottom panel of Fig-

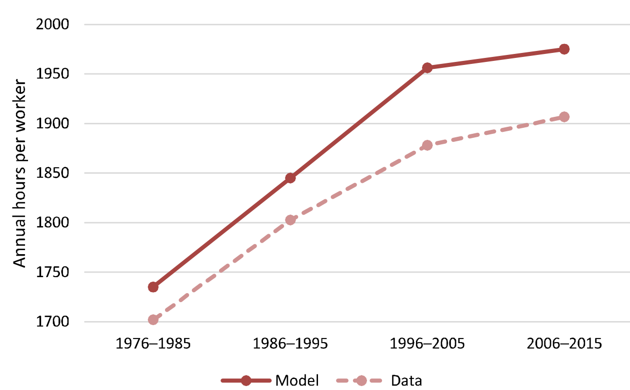
Figure 3: Trends in female labor supply: Model vs. data



(i) Total hours

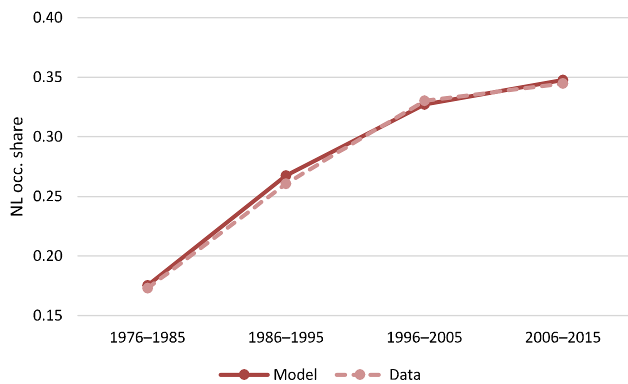


(ii) Extensive margin

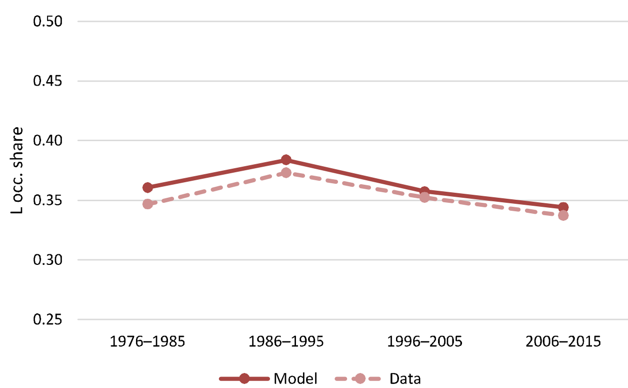


(iii) Intensive margin

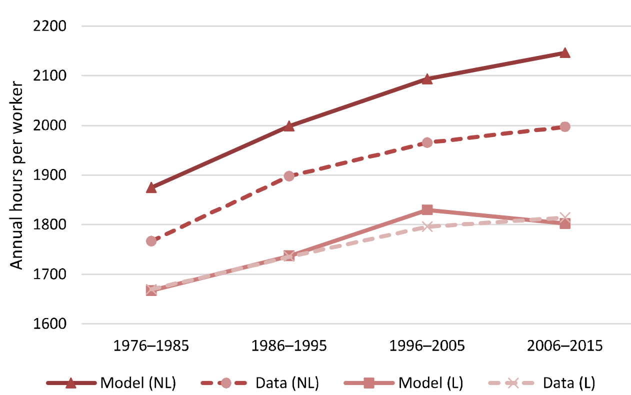
Figure 4: Female occupation-related trends: Model vs. data



(i) Nonlinear occupation



(ii) Linear occupation



(iii) Conditional intensive margins

ure 4 shows that it does a good job of replicating the trends in the conditional intensive margins in each occupation. Although the model has some difficulty in generating the continual upward trend in hours worked per worker in linear occupations, it does perform well in reproducing the same trend for nonlinear occupations.

Finally, we performed a validity check by computing trends in the second moments of wages and hours implied by the model, as reported in Table A4. In essence, our model successfully generate increasing trends in wage dispersion in line with the data, as also documented in Heathcote, Perri, and Violante (2010).

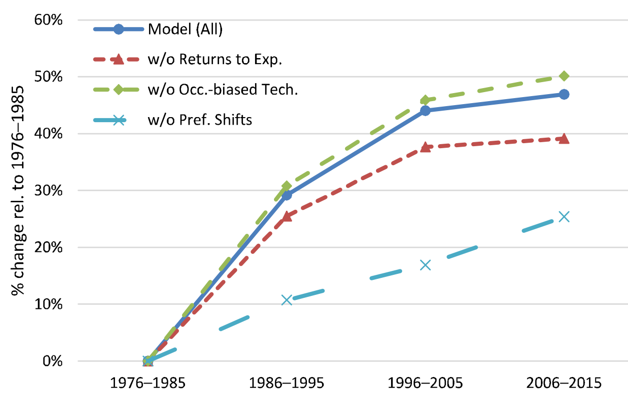
5.3 Underlying forces at work

In this subsection, we will investigate the underlying forces at work in the trends presented in the previous subsection. Specifically, we present counterfactual trends calculated when a driving force is assumed to be unchanged from its level in the baseline period (1976–1985). This allows us to quantify the role of each driving force by comparing such counterfactual trends to the trend visible when all forces are present (solid blue lines in the figures).

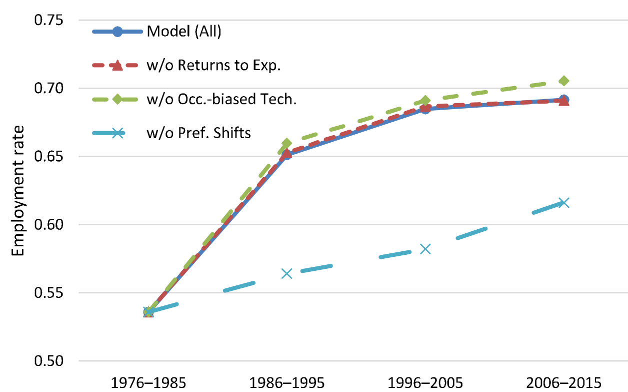
Returns to experience We begin with one of the two key driving forces of interest to us in this paper: returns to experience. As shown in Table 5, our calibration lead to the finding that χ_1 and χ_2 have increased substantially over time (more pronounced in nonlinear occupations). Such rising returns to experience increase the dynamic returns to long hours worked, giving women stronger incentives to increase the labor supply, especially in nonlinear occupations. To quantitatively investigate the implications of such a trend, we fix the values of χ_1 and χ_2 at the baseline period while allowing the other parameters to change.

Figure 5 displays the results from this decomposition exercise for the trends in three measures of female labor supply: total hours worked, the extensive margin, and the intensive margin. The dotted red lines show these trends in the absence of changes in returns to experience. The top panel of Figure 5 shows that, without the increase in returns to experience, the increase in female total hours worked over the last four decades would have been substantially lower. Specifically, had the returns to experience remained at their 1976–1985 levels over the whole period, the

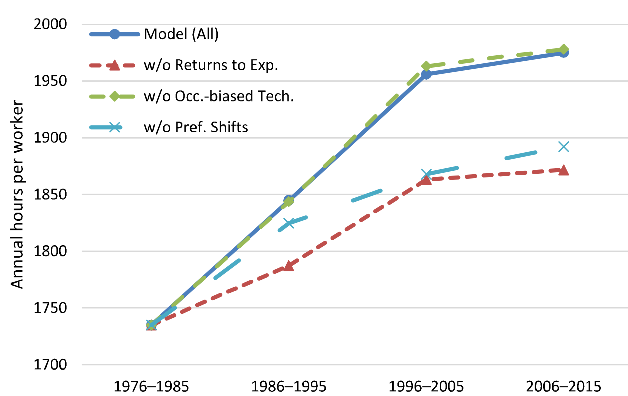
Figure 5: Decomposition: total hours and two margins of labor supply



(i) Total hours



(ii) Extensive margin



(iii) Intensive margin

model would have dampened the increment in the total hours worked over the entire period by 17% (i.e., 39.1% instead of 47.0%).

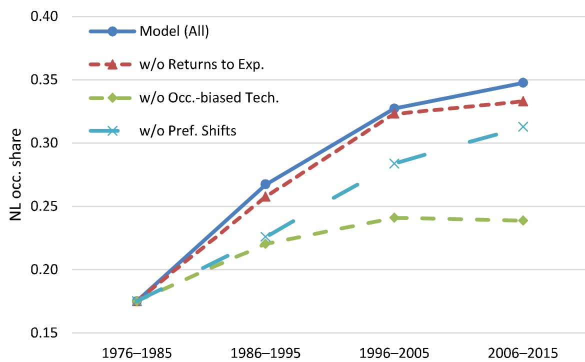
The middle and bottom panels of Figure 5 imply that the rising returns to experience have quantitatively differential effects on the two margins of labor supply. In the middle panel, the rising returns to experience are shown to have relatively negligible effects on the extensive margin, which is in line with Attanasio et al. (2008). On the other hand, the bottom panel shows that the rising returns to experience have played a significant role in accounting for the continual increases in the intensive margin that have occurred even until the most recent decade. Specifically, if the returns to experience were fixed at their baseline-period levels, our model predicts that the increment of 240 annual hours worked per worker would have been around 43% lower in the final period of 2006–2015.

Let us further note that the return to experience has increased significantly more in nonlinear occupations. As the return to experience is only available for those who advance their career by working longer hours, and this is especially the case in nonlinear occupations, it induces significant increases in hours worked per worker in such occupations. This can be seen in the left panel of Figure 7. More precisely, we find that the 272-hour increase in annual hours worked per worker in nonlinear occupations between 1976–1985 and 2006–2015 (as observed in the baseline model) would have been reduced by 47% in the absence of changes in returns to experience.

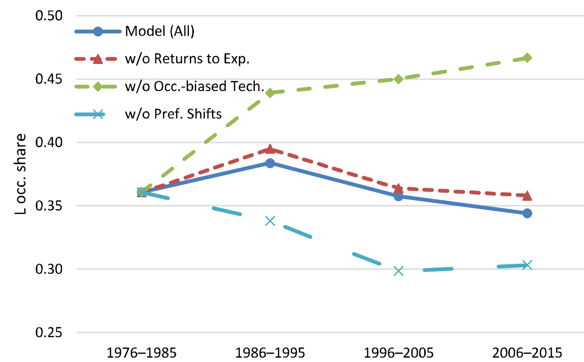
Technical changes biased toward nonlinear occupations As reported in Table 5, our calibration results imply that there has been a steady increase in the relative importance of nonlinear occupations in the technology of the firm with ν increasing from 0.673 in 1976–1985 to 0.781 in 2006–2015. One immediate impact of such a structural change would be higher wages in nonlinear occupations, which would shift people towards them and away from linear occupations. To quantitatively explore the consequences of such changes, we will now fix the value of v at its baseline-period level while allowing the other parameters to change.

We can clearly see in Figure 6 that this effect is quantitatively significant. Without allowing for the changes in ν, the nonlinear occupation share would have been nearly 10.9 percentage

Figure 6: Decomposition: occupation shares



(i) Nonlinear occupation

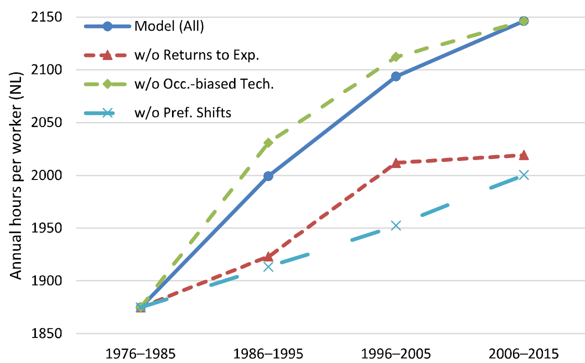


(ii) Linear occupation

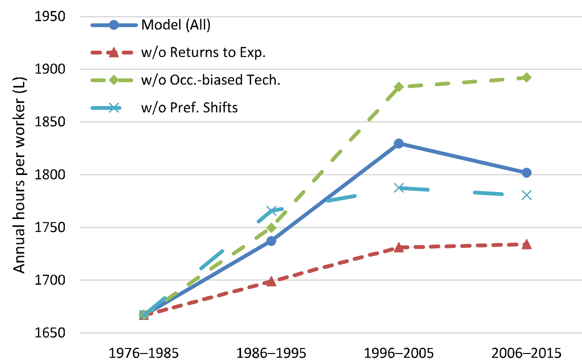
points lower in 2006–2015, whereas the linear occupation share would have been 12.3 percentage points higher. This implies that the overall female employment rate would have been higher by 1.4 percentage points in the absence of biased technical changes, and shows that such changes are partially responsible for the stagnating female employment level in recent periods. Consequently, and as shown in the top panel of Figure 5, the increment of total hours from the baseline period to the 2006–2015 period would have been 7% higher in the absence of this structural change (i.e., 50.1% instead of 46.9%).

On the other hand, the bottom panel of Figure 5 shows us that technical changes biased toward nonlinear occupations have negligible effects on the intensive margin, while Figure 7 simultaneously indicates that conditional hours worked per worker (especially in linear occupations) would have been much higher. This seemingly contradictory result can be understood by the large impact such a structural change has on the occupational shares shown in Figure 6. Because the share of nonlinear occupations tended to increase, the unconditional average hours worked per worker became increasingly more dependent on the average hours specifically in nonlinear occupations. Moreover, nonlinear occupations have a higher number of average hours worked per worker relative to linear occupations. This composition effect prevents the intensive margin labor supply from declining by overriding the decreases in conditional hours worked per

Figure 7: Decomposition: intensive margins conditional on occupation



(i) Nonlinear occupation



(ii) Linear occupation

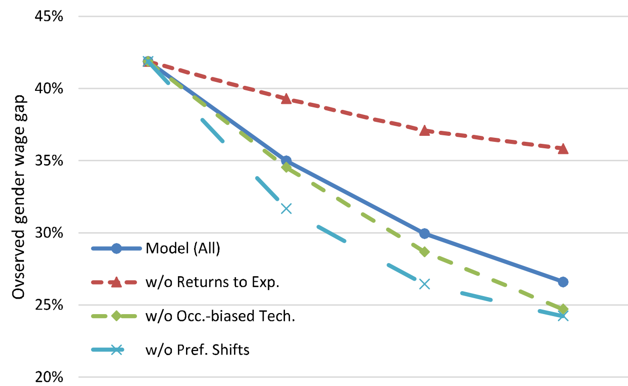
worker in each occupation.

Other factors Although preference shifts are not one of our key interests in this paper, it is still worth discussing their role given the interesting result of our analysis. As shown in Figure 5, the magnitude of the explanatory role of preference shifts has changed over time: their importance increased until the 1996–2005 period and then weakened in 2006–2015. This finding is in fact consistent with theory of cultural learning (Fogli and Veldkamp, 2011; Fernández, 2013) as preference shifts driven by an intergenerational learning process should initially cause its importance to grow, before slowing down over time. As in Fogli et al. (2011) and Fernández (2013), preference shifts can capture the stagnant pattern in the female extensive margin in the 2006-2015 period.

One should further note that there are still substantial parts of the rising trends in female labor supply that are not explained by the forces shown in Figure 5. These unexplained increases in female labor supply are largely due to the narrowing of exogenous gender wage gaps.[20] Such strong effects have been found in the existing literature (e.g., Heathcote, Storesletten and Violante, 2010; Kaygusuz, 2010; Jones et al., 2015; Bick et al., 2019), and our model relies on this

[20] More precisely, we are referring to the narrowing gender wage gaps that are unexplained by rising experience premiums since only about a half of the total decline in the final period is explainable by experience premium changes (as shown in Figure 8).

Figure 8: Decomposition: the observed gender wage gap



channel to generate the overall evolution of female labor supply.

As a final note, we have also investigated the role of changes in male labor supply. Their impact is much weaker relative to the major forces we have considered above. An exception is that male occupational supply shifts also affect female occupational shares through general equilibrium effects. In fact, this was the main reason why we included these changes in male labor supply in our calibration process. Further decomposition analysis results regarding the male labor supply are provided in Appendix C.

6 Nonlinearities in occupations and labor supply trends

Goldin (2014) argues that high nonlinearities in some occupations are an important source of the gender wage gap as they prevent women from working in these higher-paying occupations. In our theory, nonlinearities are captured by both the size of the returns to working long hours and the size of part-time penalties (intensities), but are also determined by the threshold numbers of hours beyond which these intensities operate. We may note that, if the first threshold relevant to upgrading $\mathcal{U}_j$ converges to zero, everyone working in the same occupation has an equal chance of enjoying experience premiums, regardless of their hours-worked history. If the second threshold for part-time penalties $\mathcal{F}$ converges to zero, part-time penalties would disappear entirely.

In this section, we will therefore conduct a counterfactual experiment motivated by Goldin

(2014) by gradually removing these barrier aspects of such nonlinearities. Specifically, we reduce the values of $\mathcal{U}_j$ and $\mathcal{F}$ smoothly through linear interpolation such that nonlinearities disappeared by the time we reached the most recent period. This enables us to quantify how important the barrier aspects of nonlinearities are for the evolution of the female labor supply. While doing so, we allow returns to experience to increase over time, and these became the more positive aspects of nonlinearities over time. We fix all other parameters except for the changing variables; these consisting of the four parameters related to male labor supply and the eight internally-calibrated parameters, discussed at the beginning of Section 5.

Table 6 reports the results for each counterfactual exercise alongside the benchmark results already presented in Section 5. For each, we report either percentage point differences relative to the benchmark trends for employment rates and occupational shares or percentage differences for the other variables.

The first three rows of this table show that the elimination of $\mathcal{U}_j$ and $\mathcal{F}$ is indeed a powerful mechanism that can boost the employment rate of women. If $\mathcal{U}_j$ had reached zero in 2006–2015, this rate could have been 12.2 percentage points higher than the benchmark value of 69.2%. The effect of reducing $\mathcal{F}$ is quantitatively smaller but is still quite sizable. Again if $\mathcal{U}_j$ were removed, the large effect on overall employment would have been driven by a disproportionately higher increase in the number of women working in nonlinear occupations, and expedited by its rapidly rising return to experience. These results so far appear to be consistent with the adverse role of nonlinearities illustrated by Goldin (2014).

However, we also find that this increase in female labor supply along the extensive margin is accompanied by significantly lower labor supplies at the intensive margin. For instance, if $\mathcal{U}_j$ had reached zero in 2006–2015, the average hours worked per female worker would have been 9.5% (or 188 annual hours) lower in 2006–2015. As a result, total hours worked (including both margins) would have increased in the same scenario by only around 1% in 2006–2015. Moreover, the observed gender wage gaps would even have been slightly higher because there would have been more women working with relatively lower productivity (selection) while facing lower hours thresholds, $\mathcal{U}_j$ and $\mathcal{F}$.

The key lesson of this exercise is now clear. While we quantitatively confirmed that non-

Table 6: Counterfactuals: nonlinearities and trends in labor supply and gender wage gaps

		1976–1985	1986–1995	1996–2005	2006–2015
Emp. rate	*Benchmark*	.536	.651	.685	.692
	$\mathcal{U}_j \to 0$		+2.9 pp	+9.2 pp	+12.2 pp
	$\mathcal{F} \to 0$		+2.5 pp	+3.9 pp	+5.6 pp
NL occ. share	*Benchmark*	.175	.267	.327	.348
	$\mathcal{U}_j \to 0$		+0.9 pp	+6.6 pp	+9.3 pp
	$\mathcal{F} \to 0$		+0.9 pp	+3.6 pp	+5.1 pp
L occ. share	*Benchmark*	.361	.384	.357	.344
	$\mathcal{U}_j \to 0$		+2.0 pp	+2.6 pp	+3.0 pp
	$\mathcal{F} \to 0$		+1.6 pp	+0.3 pp	+0.5 pp
Hours per worker	*Benchmark*	.318	.338	.358	.362
	$\mathcal{U}_j \to 0$		-1.6%	-6.8%	-9.5%
	$\mathcal{F} \to 0$		-1.7%	-2.8%	-4.0%
Total hours	*Benchmark*	100.0	129.2	144.0	146.9
	$\mathcal{U}_j \to 0$		+0.5%	+1.1%	+1.3%
	$\mathcal{F} \to 0$		+0.4%	+0.5%	+0.8%
Observed	*Benchmark*	.419	.350	.299	.266
gender wage	$\mathcal{U}_j \to 0$		+0.7 pp	+1.4 pp	+2.1 pp
gap	$\mathcal{F} \to 0$		+0.4 pp	+0.1 pp	+0.1 pp

Note: $\mathcal{U}_j \to 0$ decreases the upgrade threshold hours above which workers are eligible to become experienced in the next period, whereas $\mathcal{F} \to 0$ reduces the threshold hours below which part-time penalties are applied. Both $\mathcal{U}_j$ and $\mathcal{F}$ are set to converge linearly to zero in 2006–2015. Reported numbers are percentage point differences relative to the benchmark trends (Emp. rate, NL occ. share, L occ. share, and Observed gender wage gap) or percentage differences relative to the benchmark trends (Hours per worker and Total hours). Total hours are scaled to be 100 in the baseline year (1976–1985).

linearities are indeed an important form of barrier for a number of women, we also found that they play a significant role in providing an incentive scheme that maintains a high number of hours worked (conditional on working). Without these incentives, part-time work becomes more attractive, and those who work have fewer reasons to work long hours. On the other hand, when it comes to the intensive margin and gender wage gaps, the results of our decomposition analysis in the previous section suggest that further closing the gap in returns to experience is quantitatively more important. This could be achieved by reducing the degree of gender discrimination that occurs in promotions or career advancement.

7 Concluding remarks

In this paper, we have documented significant increases in the relative price and quantity of more nonlinear occupations, and that experience premiums for women have increased quite substantially—especially in such occupations. Motivated by the evidence, we built a quantitative, dynamic general equilibrium model of occupational choice and labor supply that we used to study how various changes related to nonlinear occupations have affected female labor supply over time. In our model, nonlinear occupations provide higher returns to working longer hours by penalizing part-time work and by only allowing workers to be eligible for greater returns to experience if they work long hours. We found that rising returns to experience have substantially contributed to the continued rise in the intensive margin, whereas structural changes biased toward nonlinear occupations are partially responsible for the stagnating extensive margin.

We then performed a counterfactual experiment in the spirit of Goldin (2014), who emphasizes the adverse role of nonlinearities in putting up barriers. The results of our experiment demonstrated important policy implications: removing the barrier aspects of nonlinearities may increase female employment rates at the expense of a sizable fall in labor supply along the intensive margin. In order to close the gender gaps in labor supply at both margins, further increases in female returns to experience therefore also seem necessary—even though this would ironically increase the observed degree of nonlinearities—while simultaneously removing the barrier aspects of these nonlinearities (such as the threshold number of hours required for career advancement).

Female labor supply has generally increased in many developed countries over the last few decades. However, the relative importance of the intensive versus the extensive margins vary substantially across countries. As documented by Bick et al. (2019), some countries such as Germany and the Netherlands have experienced quite noticeable decreases in hours worked per female worker, despite substantial increases in female employment. Our results in this paper suggest that changes in nonlinearities may account for such nontrivial variations. Another potentially relevant application of our framework is to account for the increasingly greater number of childless women in many developed countries, because the increasing share of women and the higher returns present in nonlinear occupations implies fewer women who would be willing to have a child. This further investigation would require a model that incorporates a more explicit lifecycle structure with endogenous fertility (e.g., Erosa, Fuster, and Restuccia, 2016). We leave these interesting investigations for future work.

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Appendix

A Data

To compute empirical statistics at the micro-level, we use the Current Population Survey (CPS) based on the 1976–2015 IPUMS-CPS files. The CPS is a nationally representative survey of individuals and their households. It provides information not only on demographic characteristics but also on labor market outcomes, such as the number of weeks worked in the last year, the usual hours worked per week, total labor income, and occupation. We choose the CPS waves from 1976 to 2015, and divide the sample periods into four groups: 1976–1985, 1986–1995, 1996–2005, 2006–2015. We regard the 1976–1985 period as our baseline period, and convert all the nominal values to the values in 1999 US dollar using the CPI-U.

We restrict our attention to married households only because prominent changes in labor supply have been observed in married women (Jones et al., 2015). Therefore, we select our samples from households in which a male head aged 22 to 64 and a female spouse cohabit—thereby excluding unmarried and single-parent households. In all calculations, we employ a household weight variable called *asecwt*.

We calculate our annual hours worked variable by multiplying the number of weeks worked by the usual hours worked per week. Hourly wage is constructed by dividing total labor income by annual hours worked. The intensive margin is measured by the average number of hours worked per worker. For the sake of interpretation, we convert the annual hours worked to the weekly one for the intensive margin. The extensive margin refers to the share of people with a positive number of annual hours worked. We then use the occupational classification method of Autor and Dorn (2013) to construct an occupational ranking over the sample period. We obtain occupation-specific hourly wage and hours worked variables by computing their averages for each occupation, as in Erosa et al. (forthcoming).

More specifically, we take the following steps. First, we rank all occupations present during the baseline period according to their average working hours for males at the occupational level, using personal-level weights. Second, we measure the size of these occupations in the baseline period by summing up all personal-level weights for both males and females at the occupational level. Third, we evenly divide the occupations in the baseline period into two groups, considering both their rank and size. The bottom and top 50% of occupations are then assigned as linear and nonlinear occupations, respectively. Finally, we apply this occupational grouping over the whole sample period.

One issue arising from this procedure is that several new occupations are observed after the baseline period. To address this, we compute the average hours worked for these new occupations at the occupational level in the period when they are first observed. They are then categorized according to the threshold number of hours worked for the occupational grouping in the baseline period, and we continue to use this occupational category in the subsequent periods. These procedures enable us to obtain hours worked and hourly wage both by gender and by time-invariant occupational group.

B Aggregate trends based on annual data

Section 2 presents the results based on 10-year averages in order to focus on long-term trends while smoothing out business cycle effects. In this section, we present the counterparts of Figures 1 and 2 by using the annual data to check the possibility that the documented aggregate trends are more or less affected by potential outliers (e.g., recessions). We first categorize nonlinear and linear occupations based on occupation-level mean hours in the baseline period of 1976–1985, as is done for the results in the main text. Then, we keep using the base-period occupation categorization for each year from 1976 to 2015.

Figure A1 plots the results for labor supply trends at different margins. Despite cyclical variations due to business cycle effects, the overall trends from the annual data are consistent with the trends based on 10-year averages in Figure 1. Specifically, the total hours worked for males have been weakly declining whereas those for females have been stagnating after they increased dramatically until 2000. The mid panel shows that the stagnating female labor supply is clearly visible in the extensive margin. On the other hand, the bottom panel shows that the female hours per worker (i.e., the intensive margin) has steadily been rising even in recent years.

These are generally in line with Figure 1.

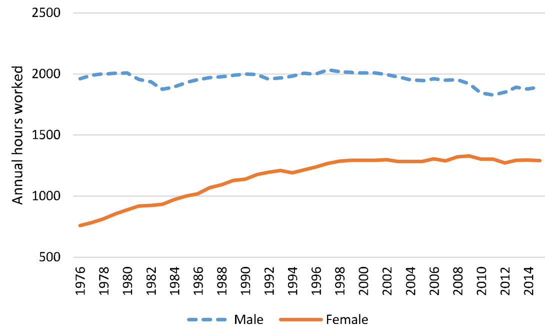
Figure A2 plots the results for occupational shares and nonlinear wage premiums over time using the annual data. The top panel shows that the share of women working in nonlinear occupations have been steadily rising, although it has become somewhat stagnant in recent years. The share of men working in nonlinear occupations have been increasing much weakly. In general, these patterns are consistent with the top panel of Figure 2. The other panels of Figure A2 plot the estimated nonlinear wage premiums over time at the annual frequency without controls (the mid panel) and with a set of control variables (the bottom panel). They show that the relative wages of nonlinear occupations have been generally increasing for both men and women, despite their cyclical fluctuations. These are also broadly consistent with the mid and bottom panels of Figure 2.

C The role of male labor supply and occupational choice

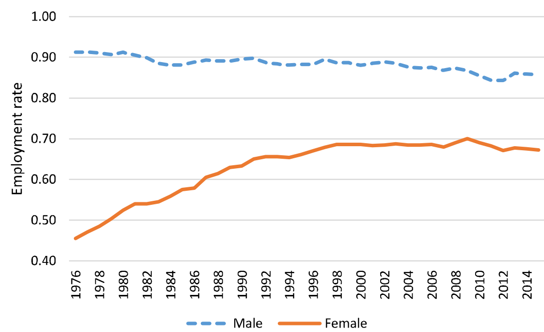
Male labor supply and occupational choice have changed alongside female counterparts, although in a much less noticeable way (as shown in Section 2). To take into account these changes in male labor supply in each occupation, we included their changing values (reported in Table A1) when calibrating the economies over time—as noted in the main text. Since a number of recent papers emphasize the role of interactions in labor supply within households (see e.g., Doepke and Tertilt, 2016, Alon, Coskun, and Doepke, 2018, Bick and Fuchs-Schündeln, 2018, and Erosa et al., forthcoming), we now present the same set of decomposition exercises with respect to these changes in male labor supply.

As can be seen in Figure A3, changes to the male labor supply and occupational choice yield relatively weaker impacts on total hours, employment, and the number of hours per worker among females. By assuming in our model that the male extensive margin labor supply does not change (as opposed to decreasing over time), we find that the female total hours worked would have been lower. According to the third panel of Figure A3, this effect is mostly driven by female intensive margin responses. However, its quantitative role is much smaller at only around 50 annual hours worked in the 2006–2015 period.

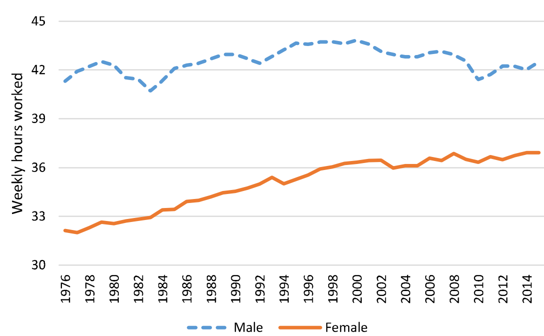
Figure A1: Trends in female labor supply in the US



(i) Total hours worked

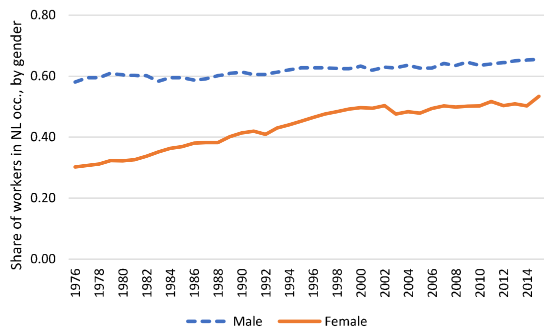


(ii) Extensive margin

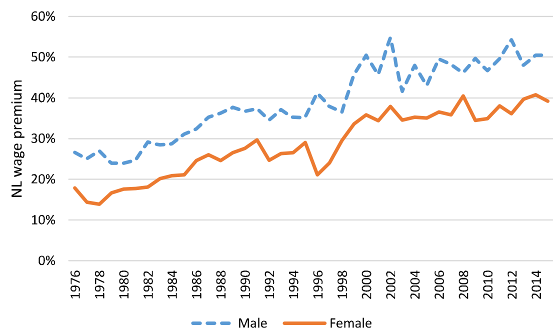


(iii) Intensive margin

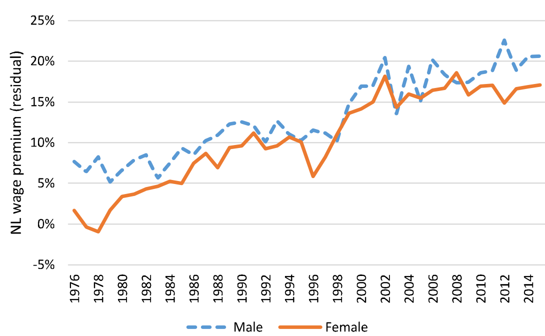
Figure A2: Trends in the relative quantity and price of nonliear occupations



(i) Share working in NL occupations, by gender



(ii) Nonlinear wage premium, by gender



(iii) Nonlinear (residual) wage premium, by gender

Note: Nonlinear vs. linear occupations are defined based on occupation-level mean hours in the base years of 1976–1985. We keep using the base-year occupation categorization for each year. The second panel is based on raw wages in two occupation groups, whereas the third panel is based on residual wages after controlling for age, education, race, industry, and the number of children under 5.

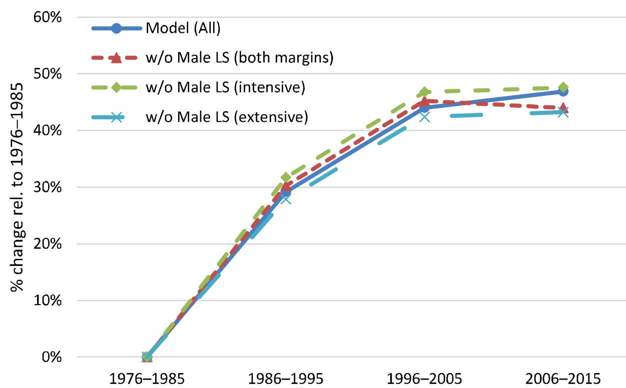
Table A1: Changes related to husbands over time

	j_m	1976–1985	1986–1995	1996–2005	2006–2015
p_{j_m}	1	.537	.540	.555	.554
	2	.364	.349	.329	.307
h_{j_m}	1	.416	.427	.429	.418
	2	.370	.379	.386	.377

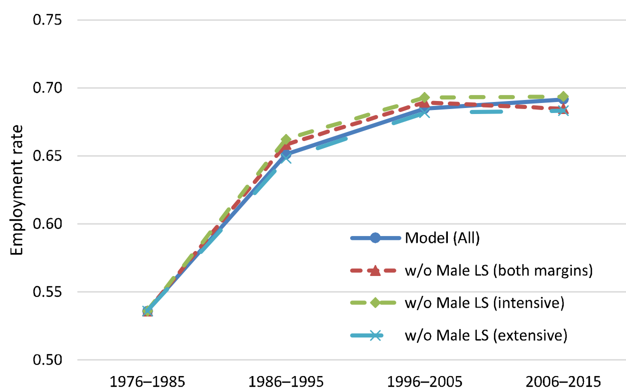
More importantly, Figure A4 shows that the role of changes in the male labor supply and occupational choice is quantitatively visible when it comes to female occupational composition. A closer look reveals that most of these effects are due to changes in the male occupational share (the extensive margin). When p_1 and p_2 are held fixed at their baseline-period levels, we find that a substantial fraction of women working in linear occupations would have moved to nonlinear occupations, and its occupational share would have risen by around 5 percentage points in the 2006–2015 period. Note that this is precisely why our calibration included these changing moments when identifying occupation-biased technical changes: because they closely interact through general equilibrium effects.

Finally, we emphasize that a more comprehensive analysis on the role of male labor supply and occupational choice should include both directions: (i) how changes related to female (e.g., female returns to experience) would affect male labor supply and occupational choice; and (ii) how such male responses would affect female choices. Our analysis above focuses on the latter, given the heavy computational burden required for us to include various dimensions of state variables and endogenous choices for the male members of households. Although the overall effects are still to be explored, the former channel might reinforce our main findings on the role of returns to experience. This is because favorable changes to females are likely to reduce the male labor supply (through income effects within households) as well as the share of male workers in nonlinear occupations (through general equilibrium effects). Both of these consequences would reduce household income, which in turn gives women a stronger incentive to work more hours (again through within-household income effects).

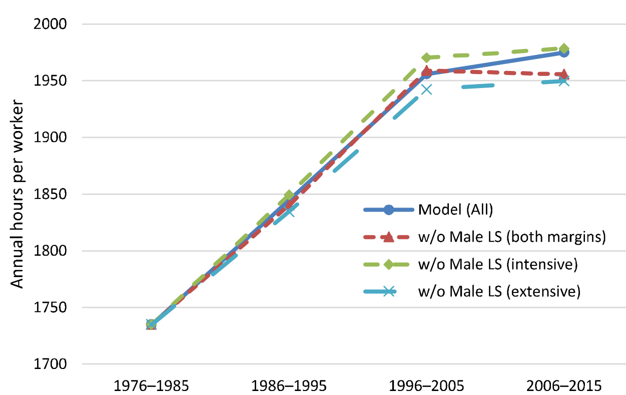
Figure A3: Decomposition: total hours and two margins of labor supply



(i) Total hours

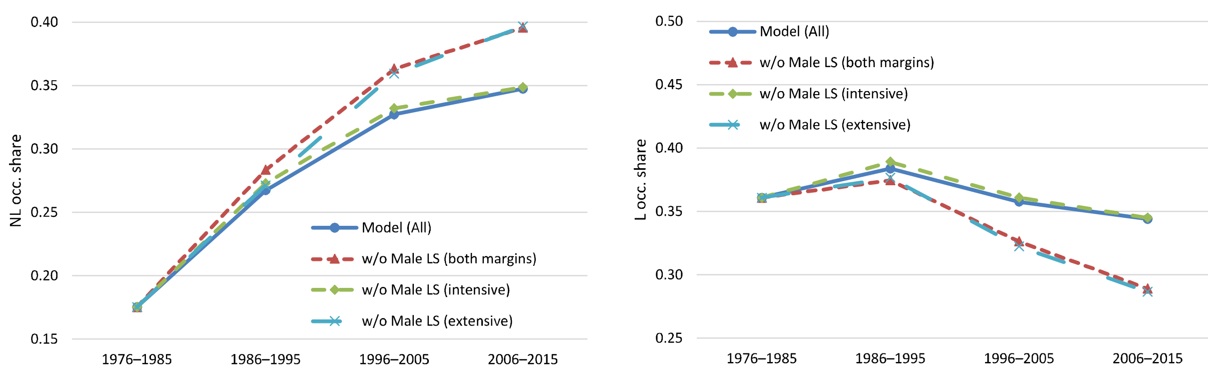


(ii) Extensive margin



(iii) Intensive margin

Figure A4: Decomposition: occupation shares



(i) Nonlinear occupation

(ii) Linear occupation

D Transitional dynamics

Our analysis in the main text is carried out by comparing steady states in ten-year intervals. We will now perform the same analysis for when the economy moves from its initial steady state to its final steady state along the perfect foresight transition path at the annual frequency. Then, the annual data along the transition are aggregated at ten-year intervals, as is done for the empirical and model counterparts in the main text.

We will first describe the definition of equilibrium along the transitional paths. The economy is initially in a steady state $t = ..., -2, -1$, as described in Section 3.3. In period $t = 0$ (or the year 1986), agents learn that the economy will evolve according to the driving forces described in Section 5.1. For the annual sequences of driving forces, we use the piecewise linear interpolation such that the annual values in 1990 and 2000 are equal to the steady-state values in the 1986–1995 and 1996–2005, respectively. From 2006 on, the sequences take on the steady-state values of 2006-2015. Agents optimize under the condition of perfect foresight on these sequences.

More formally, given an initial distribution $F^*(\cdot)$ and a sequence of $\{A_t, \{\lambda_{j,t}, \chi_{j,t}\}_{j=1}^2, P_t(\cdot), \nu_t\}_{t=0}^{\infty}$, a recursive competitive equilibrium is a sequence of factor prices $\{r_t,\ w_{1_f,t},\ w_{2_f,t},\ w_{1_m,t},\ w_{2_m,t}\}_{t=0}^{\infty}$; a sequence of female decision rules $\Big\{g_{n,t}(a,z,x,\grave{j},\eta,\phi,j_m),\ g_{o,t}(a,z,x,\grave{j},\eta,\phi,j_m),\ \{g_{a,j,t}(a,z,x,\eta,\phi,j_m)\}_{j=0}^2,$ $\{g_{h,j,t}(a,z,x,\eta,\phi,j_m)\}_{j=1}^2\Big\}_{t=0}^{\infty}$; a sequence of value functions $\Big\{V_t(a,z,x,\grave{j},\eta,\phi,j_m)\ ,N_t(a,z,\eta,\phi,j_m),$

$W_t(a,z,x,\grave{j},\eta,\phi,j_m),\ \{P_{j,t}(a,z,x,\eta,\phi,j_m)\}_{j=1}^{2}\Big\}_{t=0}^{\infty}$; the aggregate capital $\{K_t\}_{t=0}^{\infty}$, the aggregate labor $\{L_t\}_{t=0}^{\infty}$, and the aggregate labor by gender and occupation $\{L_{1_f,t},\ L_{2_f,t},\ L_{1_m,t},\ L_{2_m,t}\}_{t=0}^{\infty}$; the distribution of households $\{F_t(\cdot)\}_{t=0}^{\infty}$ such that, for all t

1. Given factor prices $\big(r_t,\ w_{1_f,t},\ w_{2_f,t},\ w_{1_m,t},\ w_{2_m,t}\big)$, the value functions $V_t(a,z,x,\grave{j},\eta,\phi,j_m)$, $N_t(a,z,\eta,\phi,j_m)$, $W_t(a,z,x,\grave{j},\eta,\phi,j_m)$, $\{P_{j,t}(a,z,x,\eta,\phi,j_m)\}_{j=1}^{2}$ solve the associated problems, the associated decision rules are

$$g_{n,t}(a,z,x,\grave{j},\eta,\phi,j_m) = \arg\max\{N_t(a,z,\eta,\phi,j_m), W_t(a,z,x,\grave{j},\eta,\phi,j_m) - \xi\mathcal{I}_{j_m\neq 0}\} \tag{A1}$$

$$g_{o,t}(a,z,x,\grave{j},\eta,\phi,j_m) = \arg\max\Big\{J_{1,t}(a,z,x,\grave{j},\eta,\phi,j_m), J_{2,t}(a,z,x,\grave{j},\eta,\phi,j_m)\Big\} \tag{A2}$$

$$a^*_{t+1} = g_{a,j,t}(a,z,x,\eta,\phi,j_m), : j\in\{0,1,2\} \tag{A3}$$

$$h^*_t = g_{h,j,t}(a,z,x,\eta,\phi,j_m), : j\in\{1,2\}. \tag{A4}$$

2. Given factor prices $r_t,\ w_{1_f,t},\ w_{2_f,t},\ w_{1_m,t},\ w_{2_m,t}$, the representative firm optimally chooses $K,\ L_{1_f,t},\ L_{2_f,t}\ ,\ L_{1_m,t}$, and $L_{2_m,t}$ following (10)-(14).

3. Markets clear:

$$K_t = \int a\,F_t(d\mathbf{s}) \tag{A5}$$

$$\begin{aligned} L_{j_f,t} = \int \mathcal{I}_{\{g_{n,t}(\mathbf{s})=W_t\}}\cdot z_j\cdot\Bigg(\mathcal{I}_{\{j=g_{o,t}(\mathbf{s})=\grave{j}\}}\cdot\Bigg(\pi\cdot\big(1+\chi_{j,t}-\tau_j\cdot\mathcal{I}_{\{g_{h,j,t}(\mathbf{s})<\mathcal{F}_j\}}\big) \\ \cdot g_{h,j,t}(a,z,x'=1,\eta,\phi,j_m) + (1-\pi)\cdot(1+\chi_{j,t}\cdot\mathcal{I}_{x=1}-\tau_j\cdot\mathcal{I}_{\{g_{h,j,t}(\mathbf{s})<\mathcal{F}_j\}})\cdot g_{h,j,t}(a,z,x,\eta,\phi,j_m)\Bigg) \\ +\mathcal{I}_{\{j=g_{o.t}(\mathbf{s})\neq\grave{j}\}}\cdot(1-\tau_j\cdot\mathcal{I}_{\{g_{h,j.t}(\mathbf{s})<\mathcal{F}_j\}})\cdot g_{h,j,t}(a,z,x'=0,\eta,\phi,j_m)\Bigg)\Bigg]F_t(d\mathbf{s}), : j\in\{1,2\} \end{aligned} \tag{A6}$$

$$L_{j_m,t} = \int e_{j_m}h_{j_m}F_t(d\mathbf{s}), : j\in\{1,2\} \tag{A7}$$

where $\mathbf{s} = (a,z,x,\grave{j},\eta,\phi,j_m)\in\mathbf{S}$.

4. The household distribution $F_{t+1}(\cdot)$ is consistent with the household optimal choices defined

above. Specifically, for any $B \in \mathbb{B}(\mathbf{S})$,

$$
\begin{aligned}
F_{t+1}(B) = & q \cdot \int_{\{\mathbf{s} | (g_{a,j=0,t}(\mathbf{s}), z', x'=0, g_{o,t}(\mathbf{s})=0, \eta', \phi, j_m) \in B\}} \left[\pi_{z'|z} \cdot \pi_{\eta'|\eta} \cdot \mathcal{I}_{\{g_{n,t}(\mathbf{s})=N_t\}} \right] F_t(d\mathbf{s}) \\
& + q \cdot \sum_{j=1}^{2} \Bigg\{ \int_{\{\mathbf{s} | (g_{a,j,t}(\mathbf{s}), z', x'=1, g_{o,t}(\mathbf{s})=j, \eta', \phi, j_m) \in B\}} \Big(\pi_{z'|z} \cdot \pi_{\eta'|\eta} \cdot \mathcal{I}_{\{g_{n,t}(\mathbf{s})=W_t)\}} \\
& \cdot \left(\pi \cdot \mathcal{I}_{\{g_{h,j,t}(\mathbf{s}) > \mathcal{U}_j\}} \cdot \mathcal{I}_{\{x=0\}} + \mathcal{I}_{\{g_{h,j,t}(\mathbf{s}) > \mathcal{U}_j\}} \cdot \mathcal{I}_{\{x=1\}} \right) \Big) F_t(d\mathbf{s}) \\
& + \int_{\{\mathbf{s} | (g_{a,j,t}(\mathbf{s}), z', x'=0, g_{o,t}(\mathbf{s})=j, \eta', \phi, j_m) \in B\}} \Big(\pi_{z'|z} \cdot \pi_{\eta'|\eta} \cdot \mathcal{I}_{\{g_{n,t}(\mathbf{s})=W_t)\}} \\
& \cdot (1-\pi) \cdot \mathcal{I}_{\{g_{h,j,t}(\mathbf{s}) > \mathcal{U}_j\}} \cdot \mathcal{I}_{\{x=0\}} \Big) F_t(d\mathbf{s}) \Bigg\} \\
& + q \cdot \sum_{j=1}^{2} \Bigg\{ \int_{\{\mathbf{s} | (g_{a,j,t}(\mathbf{s}), z', x'=0, g_{o,t}(\mathbf{s})=j, \eta', \phi, j_m) \in B\}} \left(\pi_{z'|z} \cdot \pi_{\eta'|\eta} \cdot \mathcal{I}_{\{g_{n,t}(\mathbf{s})=W)\}} \cdot \mathcal{I}_{\{g_{h,j,t}(\mathbf{s}) \leq \mathcal{U}_j\}} \right) F_t(d\mathbf{s}) \Bigg\} \\
& + (1-q) \cdot \int_{\{\mathbf{s} | (0, z', x'=0, j=0, \eta', \phi', j_m') \in B\}} \pi^n_{z'} \cdot \pi^n_{\eta'} \cdot \pi^n_{\phi'} \cdot \pi^n_{j_m'} F_t(d\mathbf{s})
\end{aligned}
$$

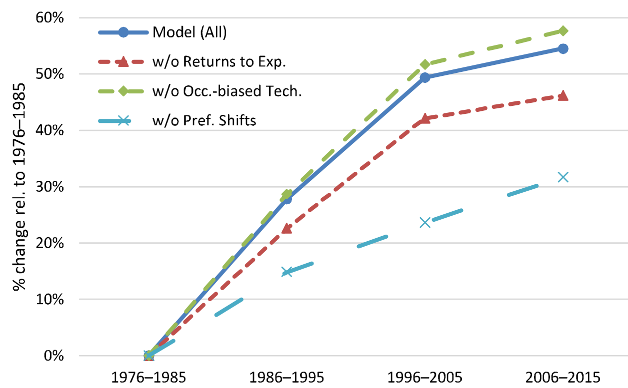
where $\mathbf{s} = (a, z, x, \grave{j}, \eta', \phi, j_m') \in \mathbf{S}$, $\pi_{z'|z}$ is the transitional probability from z to z' and $\pi_{\eta'|\eta}$ is the transitional probability from η to η'. $\pi^n_{z'}$, $\pi^n_{\eta'}$, $\pi^n_{\phi'}$ and $\pi^n_{j_m'}$ determine the distribution of newly-born households for z', η', ϕ' and j_m', respectively.

Figures A5 and A6 report the decomposition analysis results, corresponding to Figures 5 and 6, respectively. We find that the trends based on perfect-foresight transitions are closely in line with their counterparts in the main text. Despite the somewhat overstated increases in female labor supply in 2006–2015, we find that our main decomposition results are very robust. Changes in returns to experience are still largely responsible for the increases in labor supply at the intensive margin, as shown in Figure A5. Occupation-biased technical changes have significant impacts on occupational composition, as shown in Figure A6. Importantly, this contributes negatively to the extensive margin, as in the main text. All these results are quantitatively very similar to their counterparts in the main text.

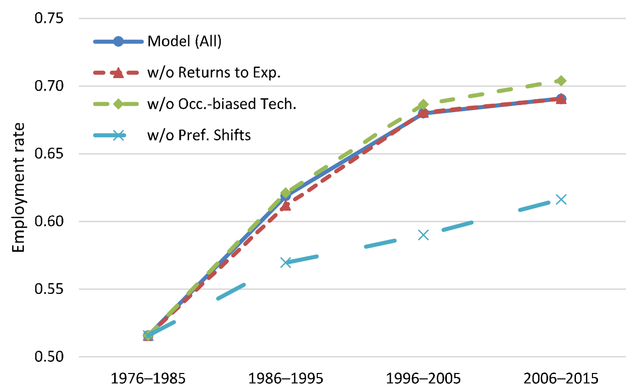
E Additional tables and figures

Table A2 reports the estimates of part-time penalties. Part-time is defined as hours less than 30 weekly hours (Lagakos et al., 2018). We control for age, education, race, industry, and the

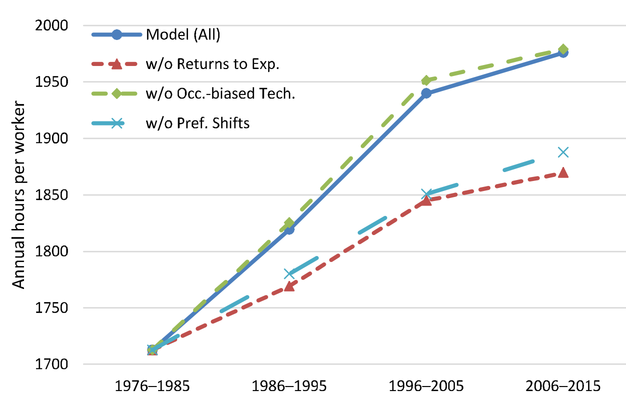
Figure A5: Decomposition based on perfect-foresight transition equilibrium: total hours and two margins of labor supply



(i) Total hours

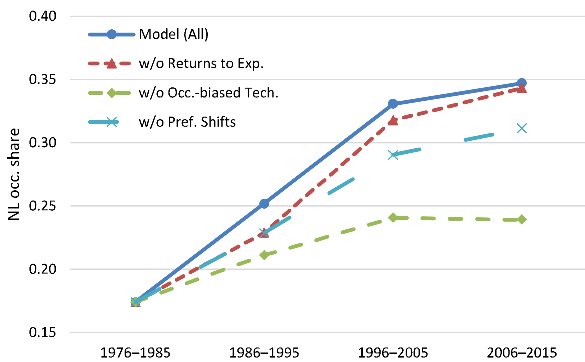


(ii) Extensive margin

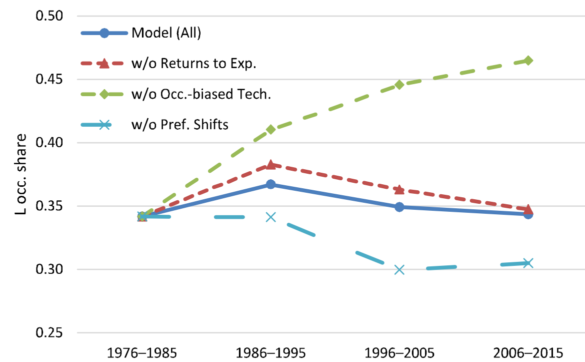


(iii) Intensive margin

Figure A6: Decomposition based on perfect-foresight transition equilibrium: occupation shares



(i) Nonlinear occupation



(ii) Linear occupation

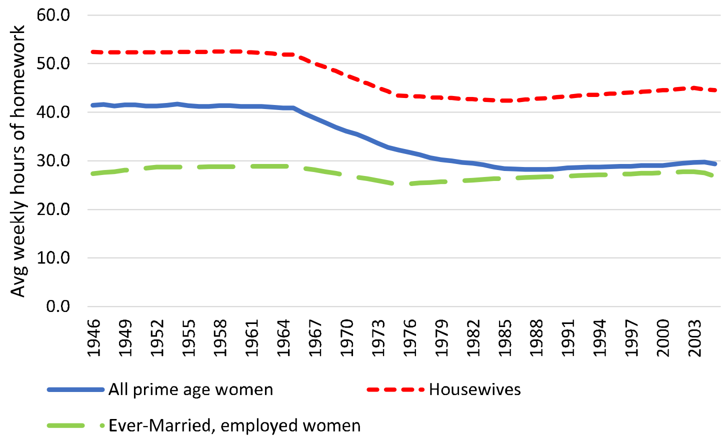
number of children under age 5. The estimates show that nonlinear occupations have higher part-time penalties in general. Another observation worth noting is that there is no clear trend.

Table A3 reports the share of college-educated workers in each occupation by gender and time period. We can clearly see that nonlinear occupations tend to have more college educated workers in each period. However, both occupations had more college-educated workers in them over time, especially among women. In other words, linear occupations are also increasingly being filled with college-educated workers, suggesting that the rising number of skilled workers is not particularly biased toward nonlinear occupations.

Table A4 shows how the variables for dispersion of wages and hours worked have changed in our model, compared to their data counterparts. The reported numbers are percentage changes relative to their values in the baseline period (1976–1985). They show our model correctly predicting a substantial increase in the volatility of wages over time, alongside a decrease in the volatility of hours worked. Quantitatively, our model explains a substantial portion of the changes in the second moments of wages.

Table A5 reports our results when we set ψ to -0.25 instead of -0.5. In that case, the elasticity of substitution between nonlinear and linear occupations increases to 0.8, and our model is then recalibrated to each period accordingly. Since the decomposition results from

Figure A7: Home production hours over time



Note: The data source is Ramey (2009)

Section 5 barely change, we only report our results from the exercise in Section 6. Even here, we obtain results very similar to our baseline ones.

Figure A8 shows that the model replicates the trend in the observed gender wage gap very well. Note that the trend of this aggregate gender wage gap is not directly targeted because gender wage gaps within occupations are only targeted.

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Table A2: Part-time penalties over time

		1976–1985	1986–1995	1996–2005	2006–2015
Panel A: Observed wage gap					
Female	NL	-.227	-.231	-.181	-.198
	L	-.079	-.096	-.060	-.099
Male	NL	-.194	-.256	-.201	-.244
	L	-.111	-.194	-.148	-.159
Panel B: Residual wage gap					
Female	NL	-.170	-.179	-.148	-.151
	L	-.080	-.104	-.068	-.092
Male	NL	-.113	-.184	-.146	-.176
	L	-.089	-.162	-.126	-.135

Note: The reported values are percentage deviations in hourly wages for part-time workers. Part-time is defined as hours less than 30 weekly hours (Lagakos et al. 2018). The bottom panel is based on residual wages after controlling for age, age squared, years of schooling, race, industry, and the number of children under age 5. All estimates are highly statistically significant.

Table A3: Share of college educated workers, by occupations over time

	1976–1985	1986–1995	1996–2005	2006–2015
Female				
Nonlinear occ.	36.6%	39.9%	44.5%	55.0%
Linear occ.	9.4%	14.9%	19.9%	27.8%
Male				
Nonlinear occ.	36.2%	43.6%	47.3%	52.4%
Linear occ.	6.5%	9.7%	12.2%	16.5%

Table A4: Percentage changes in second moments of wages and hours: model vs. data

		1986–1995	1996–2005	2006–2015
sd(log(wage))				
All	*Data*	15.5%	23.1%	29.2%
	Model	9.1%	12.5%	16.1%
NL	*Data*	10.9%	16.1%	19.7%
	Model	9.4%	9.8%	15.8%
L	*Data*	14.8%	21.1%	27.7%
	Model	6.3%	9.5%	8.3%
sd(log(h))				
All	*Data*	-8.2%	-14.5%	-18.5%
	Model	7.6%	6.3%	5.3%
NL	*Data*	-12.3%	-17.9%	-22.6%
	Model	9.1%	2.1%	-0.7%
L	*Data*	-6.1%	-12.3%	-15.7%
	Model	6.9%	9.9%	9.2%

Note: Reported numbers are percentage changes relative to their values in the baseline period, 1976–1985.

Figure A8: Trends in the observed gender wage gap: Model vs. data

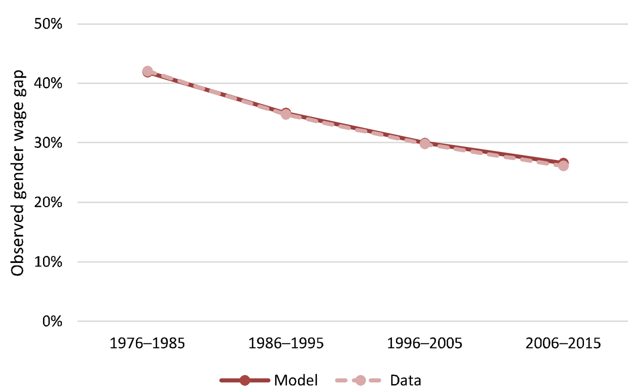

Table A5: Nonlinearity experiment in Section 6 with an alternative value of ES between NL and L occupations

$\psi = -0.25$		1976–1985	1986–1995	1996–2005	2006–2015
Emp. rate	*Benchmark*	.536	.652	.685	.692
	$\mathcal{U}_j \to 0$		+2.8 pp	+9.1 pp	+12.2 pp
	$\mathcal{F} \to 0$		+2.4 pp	+3.8 pp	+5.6 pp
NL occ. share	*Benchmark*	.175	.267	.327	.348
	$\mathcal{U}_j \to 0$		+1.5 pp	+6.6 pp	+9.9 pp
	$\mathcal{F} \to 0$		+0.9 pp	+3.6 pp	+5.1 pp
L occ. share	*Benchmark*	.361	.384	.358	.344
	$\mathcal{U}_j \to 0$		+1.3 pp	+2.5 pp	+2.3 pp
	$\mathcal{F} \to 0$		+1.6 pp	+0.3 pp	+0.5 pp
Hours per worker	*Benchmark*	.318	.338	.358	.362
	$\mathcal{U}_j \to 0$		-1.5%	-6.7%	-9.5%
	$\mathcal{F} \to 0$		-1.6%	-2.8%	-4.0%
Total hours	*Benchmark*	100.0	129.2	144.1	146.9
	$\mathcal{U}_j \to 0$		+0.5%	+1.7%	+2.0%
	$\mathcal{F} \to 0$		-0.7%	+1.1%	+1.4%
Observed	*Benchmark*	.419	.350	.299	.266
gender wage	$\mathcal{U}_j \to 0$		+0.6 pp	+1.4 pp	+2.1 pp
gap	$\mathcal{F} \to 0$		+0.3 pp	+0.1 pp	+0.0 pp

Note: The elasticity of substitution between nonlinear (NL) and linear (L) occupations is set to be higher at 0.8, and the model is re-calibrated accordingly. $\mathcal{U}_j \to 0$ decreases the upgrade threshold hours above which workers are eligible to become experienced in the next period, whereas $\mathcal{F} \to 0$ reduces the threshold hours below which part-time penalties are applied. Both $\mathcal{U}_j$ and $\mathcal{F}$ are set to converge linearly to zero in 2006–2015. Reported numbers are percentage point differences relative to the baseline trends (Emp. rate, NL occ. share, L occ. share, and Observed gender wage gap) and percentage differences relative to the baseline trends (Hours per worker and Total hours). Total hours are scaled to be 100 in the baseline year (1976–1985).

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