The Quiet Revolution and the Decline of Routine Jobs*

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Abstract

What is the contribution of changes in female labor supply to the decline of employment in routine jobs in the U.S. between 1970 and 2000? While typically attributed to changes in labor demand, the decline in routine employment has been larger for women than for men, as women moved out of routine clerical roles and into high-skill professions. This paper assess the contribution of the Quiet Revolution—a shift in women's life-cycle labor supply from intermittent to continuous—to the reallocation of aggregate employment from routine to abstract jobs over this period. The Quiet Revolution plausibly contributed to women's movement out of routine and into abstract occupations because the latter feature stronger human capital dynamics, offering returns to continuous work. I develop and calibrate an equilibrium model of the labor market that incorporates both the Quiet Revolution and changes in production technology. Counterfactual analyses reveal that while the Quiet Revolution accounts for 12% of the drop in the aggregate routine employment share, technology is the dominant force in explaining changes in the overall distribution of employment. Nonetheless, the Quiet Revolution is essential for gender-specific trends: without it, women would neither have entered the labor force nor transitioned into abstract occupations to the extent observed.

Keywords: Quiet Revolution; Routine jobs; Occupational choice; Female labor supply; Human capital; Technological change.
JEL codes: E24; J16; J21; J22; J24; O33.

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1 Introduction

It is well-known that employment in routine task-intensive jobs has declined in the U.S. since the 1970's. This trend is commonly attributed to the arrival of automation technology—such as computers—that can substitute for labor in performing routine tasks, thus reducing relative demand for such work.

However, less widely known is that the shift away from routine employment has been much larger for women than for men (see Figure 1). Motivated by this gender difference, I investigate in this paper to what extent changes in female labor supply—rather than technology alone—can explain the aggregate decline of routine employment.

Figure 1: Routine Share of Employment

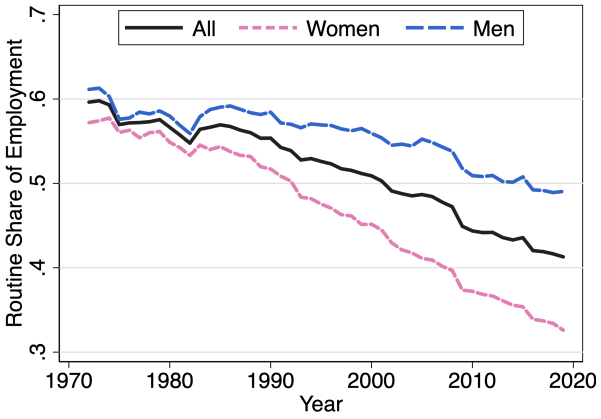
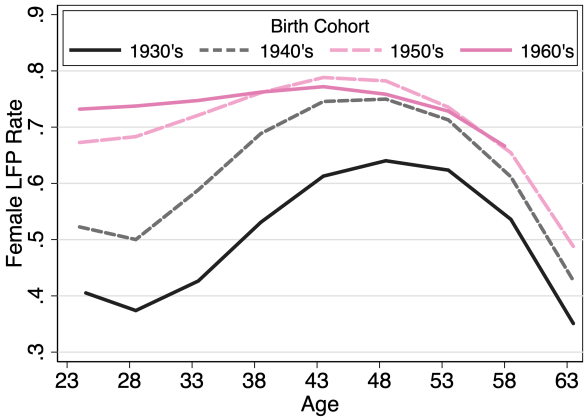


Figure 2: Female LFP Over the Life-Cycle



Notes: The left figure plots the share of employed individuals aged 18-55 in routine occupations, on aggregate and by gender. The classification is that of Cortes, Jaimovich, Nekarda, and Siu (2020). They consider routine occupations to be sales, clerical, production, craft and repair, operators, transportation, and moving. The right figure plots labor force participation at different ages for synthetic cohorts of women by decade of birth. Both figures use CPS ASEC data from Flood et al. (2025).

During this same period, female labor supply was undergoing a qualitative change that Goldin (2006) called the Quiet Revolution. This change was qualitative in the sense that it was not

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readily apparent in extensive-margin participation, but rather in how women worked: a shift in women's life-cycle labor supply from intermittent to continuous, facilitated by changing social norms around maternal employment and increased access to birth control. The Quiet Revolution is evident among women born after 1950, who would have entered the labor force beginning in the 1970s (see Figure 2). This change in women's work horizons is plausibly related to their exit from routine jobs, such as clerical and administrative roles, and their entry into abstract, non-routine professions, because these professions reward experience and require substantial educational investments, making them more suited to continuous work.

In this paper, I develop and calibrate a quantitative equilibrium life-cycle Roy model which I use to decompose the observed decline in routine employment between 1970 and 2000, as well as the rise of non-routine abstract employment, into labor supply vs. labor demand forces. I focus on the contribution of the Quiet Revolution as a labor supply change, shifting women's work horizon from intermittent to continuous. On the labor demand-side, I also model technological change which reduces relative demand for routine labor and increases the relative demand for abstract labor.

I begin by presenting four motivating facts that guide the modeling choices. First, women's intermittent work horizon prior to the Quiet Revolution centered on child-rearing, and women anticipated this horizon when making human capital and occupation choices. Second, the decline of routine employment and rise of abstract employment, as classified by Autor and Dorn (2013), were more pronounced among women than among men. Third, markers of women's work horizons correlate with their occupational sorting across routine and abstract work. Fourth, abstract occupations differ from routine and manual occupations in their human capital dynamics.

With this motivation in hand, I develop a model building on that of Hsieh, Hurst, Jones, and Klenow (2019), but incorporating two novel ingredients: women's labor force participation varies over the life-cycle, and occupations differ in human capital dynamics. I model the

former parsimoniously: women face an exogenous probability that they are not able to work during the period of life associated with child-rearing. This probability falls with the Quiet Revolution, as a reduced-form representation of factors like changing social norms, access to birth control, and childcare availability. I show theoretically how this intermittent work horizon faced by women interacts with occupation-specific characteristics to affect their occupational sorting relative to men. When women face an intermittent work horizon, they shift into occupations which feature lower returns to experience, lower skill depreciation, and lower educational requirements. Thus, work horizon drives a wedge between male and female occupational sorting, which has a clear economic logic, can be quantified and distinguished from the "black box" of wage gaps and preferences, and falls over time.

I use U.S. Census data to calibrate the model to 1970, a starting point chosen because it precedes both the Quiet Revolution and widespread automation technology. I recalibrate parameters governing the Quiet Revolution and technological change to match the year 2000, by which point most working-age women were from post–Quiet Revolution cohorts. I then use the model to conduct counterfactual analysis, starting in 1970 and turning on different forces individually to assess their contributions.

In a first exercise, I show that the shift in women's work horizon from intermittent to continuous increased the incentives for women to enter abstract occupations and leave routine jobs. On its own, the Quiet Revolution can explain over 80% of the change in women's employment shares in partial equilibrium.

I then turn to my main exercise: decomposing the decline in aggregate routine employment in equilibrium. I find that the Quiet Revolution can explain 12% of the decline in the routine employment share, and 8% of the rise in the abstract employment share. By contrast, technological change, especially improvement in automation technology that substitutes for routine labor, is the dominant contributor to these trends.

While technology is thus needed to generate the "what," I find the Quiet Revolution critical for the "how." Without the Quiet Revolution, women's entry to the labor force between 1970 and 2000 would not have risen as much as observed.Moreover, without the Quiet Revolution, the model cannot generate the observed increase in the female share of abstract employment: the Quiet Revolution explains 58% of the rise, while technology alone accounts for at most 16%. I conclude that although technological change explains the trends in the aggregate distribution of employment, the Quiet Revolution was a concurrent labor supply shift that played a central role in shaping how these trends unfolded.

This paper proceeds as follows. Section 2 describes the data, and Section 3 presents the motivating facts. Section 4 outlines the model, and Section 5 details the calibration. Section 6 presents the results of the quantitative exercise. Section 7 concludes.

1.1 Contribution

This paper draws a novel link between research on automation, gender, and the (mis-)allocation of talent and makes three main contributions.

First, despite gender difference in routine employment trends being documented since Autor, Levy, and Murnane (2003), this paper is the first to investigate to what extent these trends may be driven by changes in labor supply, rather than purely labor demand. Recently, a number of papers have posited that women may have responded more strongly to the arrival of automation technology because of gender differences in skill endowments (Beaudry & Lewis, 2014; Black & Spitz-Oener, 2010; Chuan & Zhang, 2025; Cortes, Jaimovich, & Siu, 2023; Cortés, Feng, Guida-Johnson, & Pan, 2024; Hsieh, Hurst, Jones, & Klenow, 2019). However, these studies do not take into account the myriad evidence that female labor supply was independently evolving during this period, due to factors like changing social norms, childcare availability, and access to birth control pills (Albanesi & Olivetti, 2016; Attanasio, Low, & Sánchez-Marcos, 2008; Bailey, 2006; Fernández, 2013; Fernández, Fogli, & Olivetti, 2004;

Goldin & Katz, 2002; Greenwood, Seshadri, & Yorukoglu, 2005; Stevenson, 2008). I develop a quantitative equilibrium framework that accounts for technological change, gender differences in comparative advantage, and evolving female labor supply, allowing me to decompose the relative importance of these factors in explaining the aggregate trend of employment away from routine occupations.

Second, this paper provides a macroeconomic analysis of the impact of the Quiet Revolution, as a distinct phenomenon from growth in extensive margin participation or average work hours of women. While there are a number of recent studies of the macroeconomic implications of the growth in women's labor force participation, these papers do not take into account the changing nature of women's life-cycle labor supply (Fukui, Nakamura, & Steinsson, 2023; Heathcote, Storesletten, & Violante, 2017; Hsieh, Hurst, Jones, & Klenow, 2019; Kuhn, Manovskii, & Qiu, 2024; Ngai & Petrongolo, 2017; Rendall, 2017). A key characteristic of the Quiet Revolution is that women started working continuously rather than intermittently (Goldin, 2021). This paper is the first to study the quantitative implications of this particular change—not just whether women work, but how they work over the life-cycle—in an equilibrium model of the labor market.

Third, I make a theoretical contribution in showing how work horizon interacts with occupation-specific "skill-dynamics" to impact female occupational sorting within the context of a Roy model: how women work matters for what they do. My model provides an analytically tractable representation of the logic expressed in Adda, Dustmann, and Stevens (2017), Goldin, Katz, and Kuziemko (2006), Olivetti (2006), and Polachek (1981) that career interruptions may impact women's occupation choices, and embeds it within a quantitative equilibrium framework. Relative to the literature quantifying exogenous wedges between male and female occupational sorting, I show how the interaction between intermittency and human capital dynamics leads women to make different occupation choices than men (Chiplunkar & Kleineberg, 2023; Hsieh, Hurst, Jones, & Klenow, 2019; Lee, 2024). This

enables me to micro-found and quantify part of the "black-box" gender wedges with a clear economic mechanism, and provide some empirical evidence in support of the mechanism. This is similar in spirit to Erosa, Fuster, Kambourov, and Rogerson (2022), who focus on the quantitative implications of occupational differences in the the convexity of wages with respect to hours worked when men and women differ in home production demands. I focus on life-cycle labor force participation instead of hours worked, as this the core change at the heart of the Quiet Revolution between 1970 and 2000, but remains under-studied in the macroeconomic literature.

2 Data

I use three publicly-available data sources to document the empirical facts which motivate the model.

The main data set that I use to document US employment trends as well as differences in educational attainment and income growth by occupation is the US Census between 1970 and 2000, as well as the American Community Survey for 2010 (Ruggles et al., 2025). For both men and women, I restrict to ages 18 and 55. I create a wage sample by restricting the sample to currently employed men who worked full-time, full-year in the pervious year .

To illustrate women's work horizon prior to the Quiet Revolution, I use data from Great Aspirations, a nationally-representative survey of college students who graduated in 1961.[0] The first wave of the survey was conducted prior to graduation and 4 follow-up surveys took place . The 1964 follow-up wave included a women's supplement, which asked women a variety of questions regarding gender roles, including their expectations of working in the future.[1] I keep women who attended universities, liberal arts colleges, and teacher colleges.

Finally, I use the General Social Survey to document a correlation between women's occupa-

[0]The data have been made available by Claudia Goldin on the Inter-university Consortium for Political and Social Research.

[1]While the full sample of *Great Aspirations* consists of around 35,000 individuals, approximately 8,000 women responded to the 1964 supplement.

tional sorting and their own attitudes toward mothers working. This is a cross-sectional data set which includes respondent's attitudes on social questions as well as basic demographic and economic information. I use the 1977 wave, which is the first year in which respondents were asked about their attitudes regarding mothers working. In particular, I use the question which asked respondents whether they agree with the statement, *"A working mother can form as warm a connection with her children as a mother who does not work."*, creating an indicator for having progressive views (i.e., agree or strongly agree with the statement). I keep working age employed individuals in the sample.

2.1 Classification of occupational tasks

To determine the task content of occupations, I take the 1980 task measures from Autor and Dorn (2013), which, for a set of 331 occupations harmonized across Census years, provide a score of routine, abstract, and manual tasks based on the Department of Labor's 1977 *Dictionary of Occupational Titles* (DOT). For each occupation and for each task, these provide a score on the scale of 0 to 10 which captures the level of complexity of different occupation requirments in DOT. While there are many occupation requirements listed in DOT, the literature has settled on the average score of "set limits, tolerances, and standards" and "finger dexterity" as reflecting routine tasks. Abstract tasks are captured by the average score of "direction control and planning" and "GED math", while manual tasks are captured by the score for "eye-hand-foot coordination."

For each occupation j, I calculate the task k share for routine, abstract, or manual, as:

$$OccTaskShare_j^k = \frac{TaskScore_j^k}{\sum_{m\in\{R,A,M\}} TaskScore_j^m} \tag{1}$$

Within occupation, the task shares for R, A, and M sum to 1. While the underlying task scores do not have a cardinal interpretation, the occupation task shares are widely used in the literature to classify occupations (see discussion in Acemoglu and Autor, 2011). Moreover, my

goal in this paper is to decompose the *change* in the task content of employment over time, rather than speak to the *levels*, so this measure is sufficient for my purposes. The underlying occupation-specific task scores are fixed at the 1980 level, thus for the following analysis, any change in the overall task content of work stems from changes in the occupational composition of employment.

3 Motivating Facts

In this section, I document four descriptive facts. These serve to motivate the model, which follows in Section 4.

Fact 1: Women's life-cycle labor force attachment shifted from intermittent to continuous with the Quiet Revolution.

As evident in Figure XX, women born before approximately 1950 worked intermittently, while those born after 1950 started working continuously over the life-cycle. A key reason that women worked intermittently in the past was child-rearing; factors like social norms and childcare availability led women with young kids to drop out of the labor force in the past, although they often reentered later in life. Indeed, the key statistic of the Quiet Revolution that Goldin (2006) emphasizes is labor force participation of women with a child under the age of 5, which grew from 29% to 59% between 1970 and 1990.[2]

Importantly, prior to the Quiet Revolution, women expected and planned for an intermittent work horizon over their life-cycle–even highly educated women. Table 1 reports the share of college-educated women in the 1964 wave of *Great Aspirations* who that they expected to work or not to work in each future phase of life. There is a clear U-shape in expected labor force participation, tied strongly to the presence and age of children. After marriage but before children, 84% of these women expected to work. However, once women would have a child under the age of 5, the vast majority (over 60%) expected not to work (not even part

[2]Author's own calculation using Census data.

time). Once the youngest child would be in elementary school or beyond, the majority again expected to work.

Table 1: Share Expecting to Work or Not Work in Future Life Phases

	Work	Not Work	Unsure
After marriage, before children	0.84	0.12	0.04
Between pregnancies	0.25	0.61	0.14
Youngest child under 3	0.21	0.69	0.10
Youngest child 3-5	0.25	0.63	0.12
Youngest child 6-12	0.53	0.31	0.15
Youngest child in high school	0.64	0.16	0.20
All children working/married	0.65	0.09	0.26

Notes: This table reports the results of Question 60 of the Woman's Role supplement to the 1964 wave of the Great Aspirations survey. The number of individuals responding for each phase of life varies slightly due to the survey implementation; for each row in the table, the number of respondents ranges from 7744 to 7846. The column "Work" shows the share of respondents who report they expect to work (either full-time or part-time), while the column "Not Work" shows the share who expect not to work.

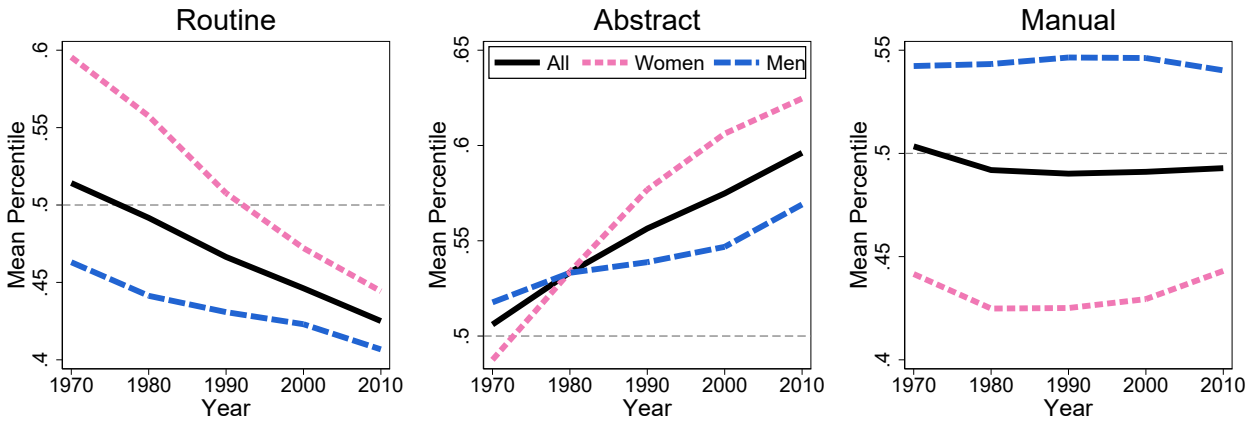
Fact 2: During the same period, women's employment shifted out of routine task-intensive jobs, and into abstract task-intensive jobs.

The decline in routine work and rise of abstract work since 1970 are trends that have been driven by women; for men, employment has shifted much less. To document this, I assign each of the 331 occupations from Autor and Dorn (2013) to a percentile of routine, abstract, or manual task share, weighting by 1970 employment. I hold the task percentiles for each occupation fixed thereafter. By construction, the mean percentile for each task in 1970 is approximately 50 for the aggregate labor force.[3]

Figure 3 illustrates trends in the mean task percentiles of employment over time, for the aggregate labor force as well as separately by gender. An increase in the mean percentile for a given task means employment has shifted on average toward occupations which have a higher task share for that task. The percentiles for each occupation are held fixed over time, so any change in the mean percentile reflects changes in the distribution of employment across occupations.

[3]I use percentiles to follow Autor, Levy, and Murnane (2003) in documenting these trends, although the same qualitative patterns emerge if I instead use the mean of the occupation-specific task shares themselves.

Figure 3: Mean Task Percentile of Employment Over Time



Notes: Each panel shows the mean task percentile of employment, on aggregate and separately by gender, across Census years. Occupations are assigned a task percentile based on the 1970 aggregate distribution of employment. These percentiles are held fixed within-occupation over time. By construction, the mean task percentile for the full labor force (black line) is approximately 0.50 in 1970.

Several patterns emerge in Figure 3. The decline in routine work and rise of abstract work on aggregate are pronounced, while there has been less change over time in manual work. Conditioning on gender, there are level differences: women are more likely than men to be in routine occupations, and less likely than men to be in manual occupations. However, there are also gender differences in the trends: routine employment has fallen more precipitously among women than among men. At the same time, women experienced rapid growth in the abstract intensity of their employment, surpassing men in the abstract task intensity of their work. Overall, the pattern of relocation of employment from routine occupations toward abstract has been stronger among women than among men.

Fact 3: Women's own social norms are correlated with entry into abstract task-intensive jobs and exit from routine task-intensive jobs.

Fact 3 suggests a link between between Facts 1 and 2, using within-women variation in markers of work horizon and occupational sorting. Given the central role of child-rearing in women's historical intermittent life-cycle labor supply, I use as a marker of worker horizon women's own self-reported social norm regarding whether children suffer if their mother works from the General Social Survey; the underlying assumption is that a woman who reports

progressive views on working mothers is more likely to have a continuous work horizon that a woman with traditional views. This assumption rests on the argument of Goldin (2021) that social norms are a key driver of the Quiet Revolution, as well as a large body of evidence of a causal effect of norms on the rise of labor force participation of mothers and, by extension, the increase in women's life cycle labor force attachment (Fernández, 2013; Fernández & Fogli, 2009; Fernández, Fogli, & Olivetti, 2004; Fogli & Veldkamp, 2011).

I use data on social norms from the 1977 cross-section of the GSS, keeping individuals aged 22-65 who were employed at the time of the survey. I generate an indicator variable for progressive responses to a question which asked whether respondents agreed with the statement: *A working mother can establish just as warm and secure a relationship with her children as a mother who does not work.* The variable (Progressive$_i$) takes the value 1 for respondents who say they "agree" or "strongly agree." I regress an indicator for having a non-routine cognitive occupation on (Progressive$_i$), as in equation (2):

$$OccTaskShare_i^k = \alpha + \beta_0 \text{Progressive}_i + \boldsymbol{\beta_1 X_i} + \epsilon_i \tag{2}$$

where $\boldsymbol{X_i}$ is a vector of control variables, including race, decade of birth, marital status, and presence of children under 6 in the household. The results from this regression are shown in Table 2.

Panel A presents the results for women. Columns (1), (2), and (3) show the estimated β_0 for abstract, routine, and manual task content from equation 2. There is a positive correlation between a woman's progressivity toward working mothers and her entry into abstract and out of routine occupations. This is consistent with the hypothesis that a woman's work horizon matters for the type of work she performs.

These results indicate merely a correlation and I do not interpret them as a causal relationship. However, one might dispute that the channel through which the correlation operates is work

Table 2: Correlation between Social Norms and Occupation Task Share

	Abstract (1)	Routine (2)	Manual (3)	Abstract (4)	Routine (5)	Manual (6)
Panel A: Women						
Progressive	0.0937***	-0.0633**	-0.0304	0.0706***	-0.0443*	-0.0263
	(0.0252)	(0.0263)	(0.0195)	(0.0239)	(0.0263)	(0.0193)
Education Controls	No	No	No	Yes	Yes	Yes
Dep Var Mean	0.315	0.558	0.127	0.315	0.558	0.127
R-sq	0.0874	0.0459	0.0630	0.175	0.100	0.0688
N	352	352	352	352	352	352
Panel B: Men						
Progressive	0.0283	-0.0223	-0.00605	-0.00180	-0.00755	0.00935
	(0.0263)	(0.0212)	(0.0179)	(0.0232)	(0.0207)	(0.0170)
Education Controls	No	No	No	Yes	Yes	Yes
Dep Var Mean	0.359	0.460	0.181	0.359	0.460	0.181
R-sq	0.0402	0.0313	0.0432	0.224	0.0983	0.150
N	435	435	435	435	435	435

Notes: This table presents estimated regression coefficients from equation (**??**). The sample is a cross section of employed individuals aged 22-55 in the 1977 GSS. Columns (1) and (2) run the regression using women only, while columns (3) and (4) use men only. "Progressive" is an indicator which takes the value 1 respondents who said they "agree" or "strongly agree" with the statement: *A working mother can establish just as warm and secure a relationship with her children as a mother who does not work.* The outcome for each column is an indicator for a non-routine cognitive occupation, as defined in Table **??**. Standard errors are reported in parentheses. * indicates significance at $p < 0.10$, ** indicates significance at $p < 0.05$, and *** indicates significance at $p < 0.01$.

horizon; perhaps attending college makes women more progressive and enables them to access non-routine cognitive jobs. In columns (4)-(6), I control additionally for education. While this slightly reduces the magnitude of the estimated coefficient on the progressive indicator, a positive correlation remains between progressivity and abstract task content. This suggests that these norms are related to female occupational sorting even independently of education, strengthening the work horizon interpretation.

Another concern may be that high-skill workers are simply more progressive in general. To mitigate this concern, I repeat the exact same regression using employed men in Panel B. There is no correlation between male views on the acceptability of working mothers and their occupational sorting. This indicates that the correlation documented in Panel A operates through a channel that uniquely affects women, such as expected work horizon.

In Appendix A, Table A.1 I show robustness of the correlation between progressivity and abstract occupation task share using an alternative measure of social norms from the GSS. In Appendix A, Table A.2 I show that the qualitative results in Table 2 hold when I use the occupation task percentile instead of the occupation task share as the outcome variable.

Fact 4: Abstract task-intensive occupations feature greater life-cycle income growth and are associated with higher human capital investments.

The final motivating fact provides an economic reason why women's work horizon would be related to entry to non-routine abstract occupations: they differ from other types of work in human capital dynamics, such as life-cycle income growth and required human capital investments. I document that this was true even in 1970, before widespread automation technology is thought to have changed the nature of work. Abstract occupations are thus more compatible with a continuous work horizon.

First, to illustrate different income growth over the lifecycle for abtract vs. routine or manual occupations, I use 1970 Census data and employed men aged 22 to 54 who worked at least 48

weeks and 35-48 hours per week in the previous year. I regress the log of each respondent's annual pre-tax wage and salary income on his occupation-specific task share for routine, abstract, and manual, in addition to an interaction of each task share with an indicator variable for age bin. The un-interacted task shares capture differences in the levels of income for occupations with different task intensities, whereas the age- and task-specific coefficients Γ capture the growth in income for each age bin, relative to a baseline age (the youngest).

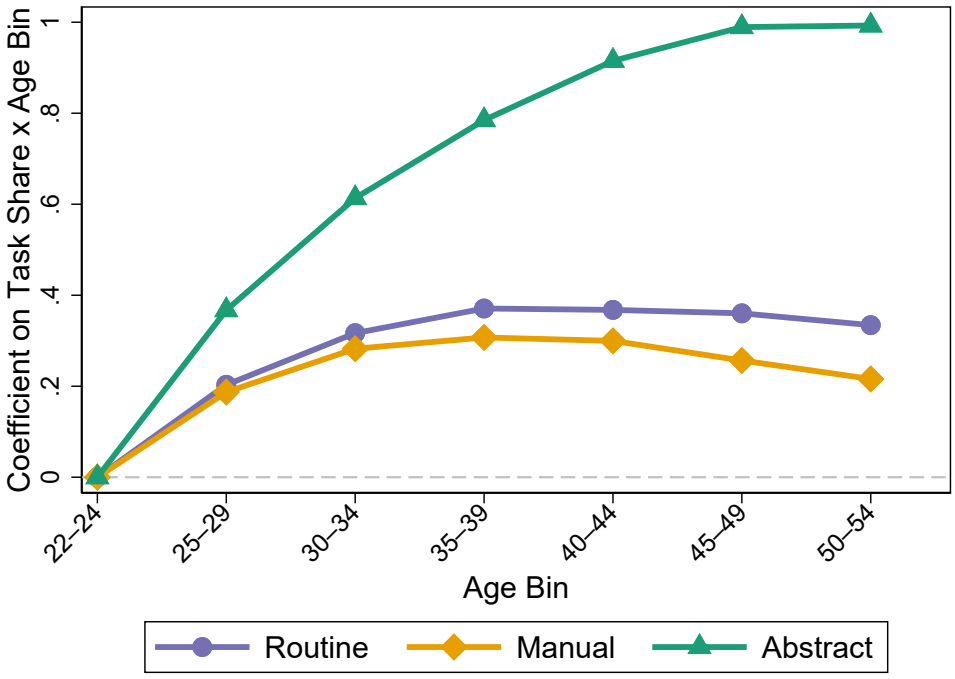
$$\begin{aligned} \ln(income)_i \quad &= \sum_{k\in\{A,R,M\}} \beta_k \cdot OccTaskShare_i^k \\ &+ \sum_{k\in\{A,R,M\}} \sum_{b\in B} \Gamma_{k,b} \cdot \mathbf{1}\{AgeBin_i = b\} \times OccTaskShare_i^k + \epsilon_i \end{aligned} \tag{3}$$

The estimated Γ coefficients for the interactions by task types are plotted in Figure 4. These show income growth over the life-cycle by occupation task content; for example, $\gamma_{R,b}$ shows how much higher income is for someone at age b relative to the youngest age bin, in the hypothetical "extreme" occupation which involves only routine tasks. As can be seen, the abstract task content of an occupation exhibits the highest life-cycle growth. Both manual and routine task content is exhibit much flatter life-cycle income profiles.

Next, I show that not only is income growth more pronounced in abstract occupations, but also they are markedly different in terms of the educational attainment of workers, suggesting differences in educational requirements or returns of the various occupation types. Figure 5 plots the mean occupation task share for employed individuals aged 22-55 in the 1970 Census. College educated workers tend to do occupations higher in abstract tasks and lower in both routine and manual tasks, compared to non-college workers.

These patterns together suggest that abstract occupations are associated with higher income growth over the life-cycle as well as larger human capital requirements, such as a college degree. Such occupational skill dynamics will feature prominently in my model, which follows next, and form the key channel through which the Quiet Revolution shifts female employment

Figure 4: Income Growth Over the Lifecycle by Occupation Task Share



Notes: This figure plots the estimates of $\Gamma_{k,b}$ from the regression specified in equation 3. The youngest age bin is omitted due to co-linearity. The sample consists of employed men aged 22 to 54 who worked at least 48 weeks and 35-48 hours per week in the previous year from the 1970 Census. Following Hsieh, Hurst, Jones, and Klenow (2019) I keep top-coded observations, but drop observations with annual labor income less than 1000 in 2010 dollars.

away from routine jobs and toward abstract jobs.

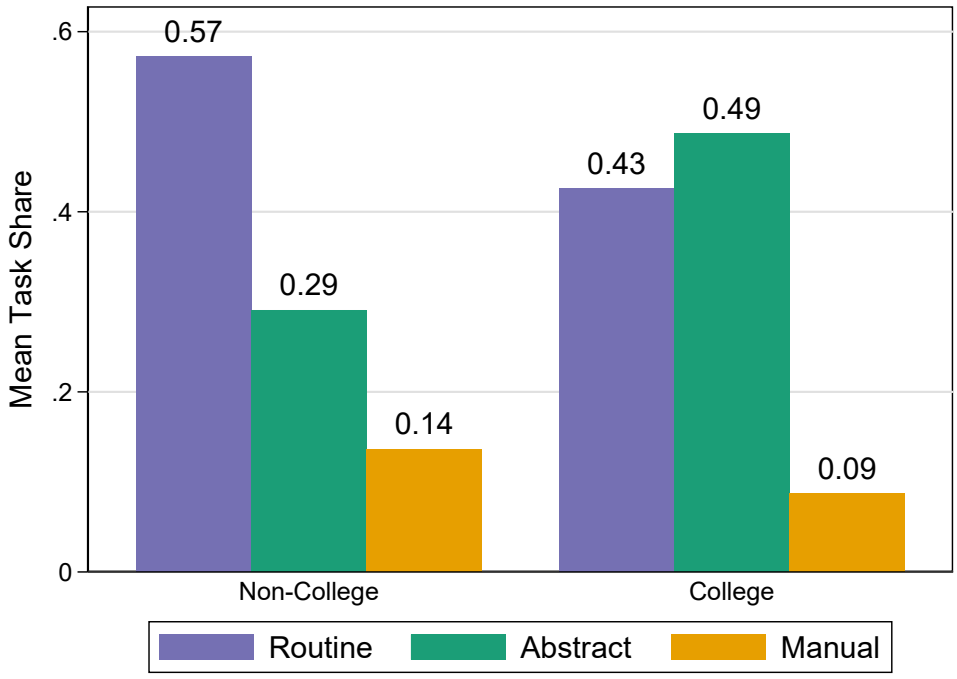
4 Model

The model builds on the framework of Hsieh, Hurst, Jones, and Klenow (2019), a life-cycle Roy model of occupational choice with human capital investment. I add two features: (1) female labor force participation varies over the life-cycle, and (2) occupations differ in human capital dynamics. The labor demand-side of the model allows for technological change to shift the relative demand for different occupations.

4.1 Labor Supply

There are equal-sized populations of men and women who live for three working periods representing the stages of life: single, married with young children, and old. Individuals

Figure 5: Mean Occupation Task Share by College Attainment



Notes: This figure plots the mean task share of occupation for employed individuals aged 22-55 in the 1970 Census. Both men and women are included in the calculation. College workers are defined as having at least four years of college education, whereas non-college workers do not.

are born with a 4-dimensional innate skill vector $\epsilon \sim G(.)$, comprised of skill in the market occupations R, A, M as well as the home sector H (which serves as the extensive margin). These individuals anticipate future wages across the occupations and make two simultaneous choices when they are young, before entering the first working period: a discrete occupation choice $j \in \{H, M, R, A\}$, and a continuous human capital investment h. They then proceed deterministically through the periods of life. Each period, workers simply consume their labor income (there are no savings or assets in the model). The per-period utility function is logarithmic.

4.1.1 Gender Differences

There are four gender differences in the model. The first is that women face an intermittent work horizon, while men do not. There is some probability represented by parameter $\rho_w > 0$ that women will be unable to work in the market in the second period of life, that associated

with childbearing. By contrast, men never leave the labor force during this period, meaning ρ_m is effectively 0. A decrease in ρ_w will capture the Quiet Revolution. For simplicity, I will drop the gender superscript and refer to ρ_w as ρ.

Second, women and men may differ in productivity in the three market occupations. For $j \in \{M, R, A\}$, women's skill ϵ_j is multiplied by a scalar a_{wj}, while men simply have ϵ_j (i.e., $a_{mj} = 1 \ \forall \ j$). This generates a difference in both absolute and comparative advantage of women vs. men in market occupations. There are no productivity differences in the home sector $a_{mH} = a_{wH} = 1$.[4]

Third, women face a wage gap relative to men in each market occupation. Following Hsieh, Hurst, Jones, and Klenow (2019), this is captured by a "tax" that women pay on the wage per efficiency unit. While men earn w_j in occupation j, women earn $(1 - \tau_{wj})w_j$. There is no wage gap in the home sector (i.e., $\tau_{wH} = 0$).

Finally, men and women obtain non-monetary utility from working in the different market occupations and home sector, which is added to their per-period log utility of consumption. Workers of gender g receive extra utility of $\log(b_{gj})$ each period they work in sector $j \in \{H, M, R, A\}$.

4.1.2 Human Capital Dynamics

A worker's efficiency units in occupation j and period t, ℓ_{jt}, evolve over the life cycle ($t \in \{1, 2, 3\}$) according to 3 skill dynamics, which differ across the market occupations. The skill dynamics are:

1. Required human capital investments (ϕ_j): Individuals choose how much to invest in human capital h before they start working. Efficiency units in the chosen occupation in period 1 become $\ell_{j,1} = \epsilon_j e^{h\eta}$, where η governs the returns to education, akin to a

[4] I make this assumption because there is no income observed in the home sector to identify productivity differences. However, I allow gender differences in non-monetary preferences to enter the home sector.

Mincer coefficient, and $\eta \geq 0$. However, acquiring h imposes a utility cost of $\frac{h^\zeta}{\zeta \phi_j}$ with $\zeta > 1$ and $\phi_j > 0$. Occupations differ in ϕ_j, with high values implying large required investments in human capital.

2. Returns to experience (γ_{tj}): A worker who performs occupation j at age t will see his or her efficiency units in that occupation scale up by a factor $\gamma_{t+1,j} \geq 1$ if he or she continues to work at age $t+1$. Formally, $\ell_{j,t+1} = \gamma_{t+1,j}\ell_{j,t}$. (There is a t subscript on γ to allow for different income growth between ages 1 and 2 and between ages 2 and 3.)

3. Skill depreciation (δ_j): A worker who exits the labor force the child-rearing period will lose efficacy in their chosen occupation. Effective skills are scaled down by factor $(1-\delta_j)$ upon returning to work, with $\delta_j \in [0,1]$. Formally, $\ell_{j,t+1} = (1-\delta_j)\ell_{j,t-1}$ if the worker did not work at t.

Anticipating the calibration results below, and consistent with the motivating evidence, I find that the N job features stronger skill dynamics along all three dimensions than the R or M jobs.

I assume H does not feature skill dynamics (i.e., $\phi_H = 0, \gamma_H = 1$, and $\delta_H = 0$). As such, a worker's efficiency units at home are fixed at $\ell_{Ht} = \epsilon_H$.

4.1.3 The Workers' Problem

A worker born with innate skills $\epsilon = \{\epsilon_M, \epsilon_R, \epsilon_N, \epsilon_H\}$, anticipating an age 2 interruption with probability ρ, and observing wages per efficiency unit across occupations $w =$

(w_H, w_M, w_R, w_A), solves the problem:

$$\max_{j\in\{H,M,R,A\}} \left\{ \max_{h\geq 0} \quad \underbrace{\beta_1 \log\left((1-\tau_{gj})w_j a_{gj}\epsilon_j e^{h\eta} b_{gj}\right)}_{\text{Age 1}} \quad - \quad \underbrace{\frac{h^\zeta}{\zeta\phi_j}}_{\text{Investment}} \right.$$
$$+ \underbrace{(1-\rho)\Big(\beta_2 \log\left((1-\tau_{gj})w_j a_{gj}\epsilon_j e^{h\eta}\gamma_{2j} b_{gj}\right) + \beta_3 \log\left((1-\tau_{gj})w_j a_{gj}\epsilon_j e^{h\eta}\gamma_{2j}\gamma_{3j} b_{gj}\right)\Big)}_{\text{Work Continuously}} \tag{4}$$
$$\left. + \underbrace{\rho\Big(\beta_2 \log(\epsilon_H b_{gH}) + \beta_3 \log\left((1-\tau_{gj})w_j a_{gj}\epsilon_j e^{h\eta}(1-\delta_j) b_{gj}\right)\Big)}_{\text{Work Intermittently}} \right\}$$

where the outer maximization captures the discrete choice across occupations, while the inner maximization captures the continuous choice of skill investment within the chosen occupation. Time subscripts are omitted, because the model is solved in an overlapping generations steady state in which equilibrium wages do not change. The home sector wage is normalized as $w_H = 1$. The weights for each period of life, β_1, β_2, and β_3, are set to 1 for the rest of the model exposition in Section 4.

4.2 Labor Demand

A representative firm produces a numeraire final consumption good, Y, by hiring labor across the three occupations, M, R, and A. Factor markets are perfectly competitive. Occupation-specific labor combines in a nested CES production function. I assume male and female efficiency units of labor are perfect substitutes within each market occupation.

The outer nest of the production function is given by:

$$Y = Z\left(A^{\frac{\lambda-1}{\lambda}} + Z_M M^{\frac{\lambda-1}{\lambda}} + \tilde{R}^{\frac{\lambda-1}{\lambda}}\right)^{\frac{\lambda}{\lambda-1}}$$

where A and M are the total efficiency units of labor in abstract and manual jobs, while $\tilde{R}$ is total routine tasks, defined below. The parameter Z captures total factor productivity, while Z_M denotes the relative productivity of M occupations compared to A.

The routine tasks $\tilde{R}$ are performed by either routine labor R or computers C, which are gross substitutes. These combine in a second production nest given by:

$$\tilde{R} = \left(R^{\frac{\psi-1}{\psi}} + C^{\frac{\psi-1}{\psi}} \right)^{\frac{\psi}{\psi-1}} \qquad \text{with} \quad \psi > 1$$

where C denotes a technology which substitutes for routine labor ("computers") and R is total efficiency units of routine labor. The cost of computers in terms of final output is denoted p_C, which is exogenously given and represents the state of automation capabilities. All else equal, a decline in p_C reduces relative demand for R workers by providing a cheaper substitute.

As factor markets are perfectly competitive, the representative firm takes wages w_j for $j \in \{M, R, A\}$ as well as p_C as given and chooses labor and computers to maximize net output $Y - p_C \times C$.

4.3 Steady-State Equilibrium

The model is solved in an overlapping generations steady state, in which three identical cohorts who differ only in age coexist, and workers have rational expectations about future wages. Equilibrium consists of an allocation (M^*, R^*, A^*, C^*) and wages $w^* = (w_M^*, w_R^*, w_A^*)$ such that:

1. Given w^*, workers optimally pick their occupation and human capital investment.
2. Given w^*, firms optimally hire labor and purchase computers.
3. The labor market clears.

4.4 Implications of the Quiet Revolution

In this subsection, I show how women's work horizon interacts with the human

4.4.1 The Quiet Revolution Increases Women's Human Capital Investments

Given the properties of the log utility function, the human capital investment problem in equation (4) can be simplified to:

$$\max_{h \geq 0} \quad (3-\rho)\eta h \quad - \quad \frac{h^{\zeta}}{\phi_j \zeta}$$

Proposition 1. *The optimal choice of human capital is:*

$$h^*(\phi_j, \rho) = ((3-\rho)\eta\phi_j)^{\frac{1}{\zeta-1}} \tag{5}$$

For any given $\phi_j > 0$, the optimal human capital choice is strictly decreasing in ρ.

Proof. See Appendix B.1. □

The parameters which influence the optimal choice of skill investment in equation (5) are intuitive: workers invest more when the utility cost of h is low (low ζ), when the returns to education are high (high η), and when the given occupation j requires more investment (high ϕ_j). Additionally, the expected work horizon matters for the optimal skill investment: workers invest less when they expect a high probability of not working at age 2 (high ρ).

Intermittency thus implies that women have less effective skill within an occupation than men, due to lower human capital investment, and this contributes to a gender gap in labor income. Therefore, as the Quiet Revolution progresses and ρ falls, the gender gap in human capital investment and income within each occupation falls. Proposition 1 additionally implies that the gender gap in education investment within an occupation j, $h^*(\phi, \rho) - h^*(\phi, 0)$, rises with ϕ. Because h increases efficiency units of labor by $\exp(h\eta)$ as in Section 4.1.2, the upshot is that higher ρ makes women less productive than men due to lower human capital in all occupations, but especially less productive in high ϕ occupations. As I show next, this is one channel through which the Quiet Revolution shifts women's labor supply toward occupations

with high education requirements, namely abstract work.

4.4.2 The Quiet Revolution Shifts Women into Dynamic Jobs

Proposition 1 shows that intermittency leads women to invest less in their human capital, conditional on choosing a given occupation, compared to men, thus generating a gender gap in effective skill. Next, I show that intermittency also affects the propensity of women to sort across occupations, relative to men.

After accounting for the optimal choice of skill investment in equation (5), $h^*(\phi_j, \rho)$, the worker's problem in equation (4) can be written succinctly as:

$$\max_{j \in \{H,M,R,A\}} (3-\rho) \log \left(a_{gj} \epsilon_j (1-\tau_{gj}) w_j b_{gj} \gamma_{2j}^{\frac{2-2\rho}{3-\rho}} \gamma_{3j}^{\frac{1-\rho}{3-\rho}} (1-\delta_j)^{\frac{\rho}{3-\rho}} e^{\frac{\eta(\zeta-1)}{\zeta} h^*(\phi_j,\rho)} \right)$$

where for men, $\rho = 0$, while for women, $\rho \geq 0$. This formulation enables the derivation of the occupational sorting condition between any two occupations in partial equilibrium, taking wages as given. Define $\tilde{\gamma}_j = \gamma_{2j}^2 \gamma_{3j}$, the product of income growth between ages 1 and 2 and between ages 2 and 3. A worker of gender g prefers occupation j over occupation k if $\frac{\epsilon_j}{\epsilon_k} \geq \chi_{jk}^g$ where:

$$\chi_{jk}^g = \underbrace{\frac{a_{gk} w_k (1-\tau_k)}{a_{gj} w_j (1-\tau_j)}}_{\substack{\text{Wages} \\ \text{Net of Wage Gaps}}} \times \underbrace{\frac{b_{gk}}{b_{gj}}}_{\text{Pref.}} \times \underbrace{\left(\frac{\tilde{\gamma}_k}{\tilde{\gamma}_j}\right)^{\frac{1-\rho}{3-\rho}} \times \left(\frac{1-\delta_k}{1-\delta_j}\right)^{\frac{\rho}{3-\rho}} \times e^{\frac{\eta(\zeta-1)}{\zeta}(h^*(\phi_k,\rho) - h^*(\phi_j,\rho))}}_{\substack{\text{Human capital dynamics \&} \\ \text{intermittency}}} \quad (6)$$

That is, for a worker of gender g to prefer j to k, their innate skill in j relative to k must be higher than the threshold χ_{jk}^g. Equation (6) highlights that occupation sorting is based on three considerations: wages (net of wage gaps), preferences, and human capital dynamics, which interact with intermittency. The first two considerations are standard in Roy models: occupation j is more attractive—that is, χ_{jk}^g falls, drawing in more workers—when its relative wage or non-monetary preferences are higher.

The third consideration, skill dynamics, is novel to this paper and forms the channel through which intermittency affects occupational sorting, which is characterized by the set of χ^g_{jk} across all possible occupation pairs. As can be seen in equation (6), ρ affects χ^g_{jk}, but only if occupations j and k differ in at least one skill dynamic parameter: $\tilde{\gamma}, \delta$, or ϕ. This means that if occupations differ in skill dynamics and men and women face different ρ, they will sort differently across occupations, even absent gender differences in productivity, preferences, or discrimination. By contrast, if occupations do not differ in skill dynamics, then intermittency does not impact the occupational sorting of women versus men.

Proposition 2. *Suppose occupation j is more dynamic than occupation k, that is, $\tilde{\gamma}_j \geq \tilde{\gamma}_k$, $\delta_j \geq \delta_k$, and $\phi_j \geq \phi_k$, with at least one inequality holding strictly. Then, χ^g_{jk} increases with ρ, holding wages and all other parameters fixed.*

Proof. See Appendix B.2. □

The intuition behind Proposition 2 is that when women face $\rho > 0$, they more or less sensitive to differences in skill dynamics across occupations, all else equal, and thus enter different occupations than men do. The resulting gender difference in the relative attractiveness of occupations is intuitive. While χ^g_{jk} rises with $\frac{\gamma_k}{\tilde{\gamma}_j}$, meaning workers prefer occupations with high returns to experience, all else equal, it rises *less* when ρ is high. This reflects the fact that when women expect that they will not be able to accumulate returns to experience, they put less value on this characteristic of an occupation. The same pattern emerges for occupational differences in education requirements ϕ, as can be seen from the $h^*(\phi_k, \rho) - h^*(\phi_j, \rho)$ term in equation 6, but the opposite happens with depreciation: as men face no risk of leaving the labor force and incurring depreciation, they do not care about occupational differences in δ (i.e., δ does not affect χ^m_{jk}). However, when $\rho > 0$, a high $\frac{1-\delta_k}{1-\delta_j}$ raises χ^w_{jk}. Intermittency leads women to prefer low δ occupations, all else equal, because they risk losing their effective skills.

5 Calibration

I calibrate the model parameters to 1970 as a starting equilibrium, reflecting the economy before both the Quiet Revolution and automation technology. I assume the economy to be in an overlapping generations steady state, where the three coexisting generations are identical, except for their age and accumulated experience. Workers have rational expectations over wages when choosing their occupation and skill investment.

I assume worker skills ϵ are drawn from an i.i.d. Fréchet distribution with shape parameter θ. There are 5 sets of parameters to calibrate: the skill distribution parameters (θ and a_{wj} for $j \in \{M, R, A\}$), the Quiet Revolution parameter (ρ), the skill dynamics parameters (η, ζ, $\phi_j, \gamma_j, \delta_j$ for $j \in \{M, R, A\}$), the wage gap j (τ_{wj} for $j \in \{M, R, A\}$) and gender-specific preference parameters (b_{wj}, b_{mj} for $j \in \{H, M, R, A\}$) and the technology parameters (λ, ψ, Z, Z_M, p_C). I proceed in two steps. First, I set some parameters exogenously based on commonly accepted values in the literature. Second, I calibrate the remaining parameters simultaneous by matching moments between the model and the data. The model structure provides in most cases a one-to-one mapping between a particular empirical moment and an unknown parameter.

In order to perform the decomposition, I recalibrate a subset of these parameters to reflect the post-Quiet Revolution and post-automation world, which I take to be the year 2000.[5] I again solve the model for 2000 as an overlapping generations steady-state, so my decomposition is a comparison of steady-states, in the spirit of Heathcote, Storesletten, and Violante (2017) and Olivetti (2006). The parameters which I recalibrate for 2000 are intended to capture the salient labor supply and labor demand forces which changed over these decades: (1) the Quiet Revolution (ρ), (2) technological change(Z_M, p_C, Z), and (3) wage gaps and non-monetary preferences (τ, b). Changes in the latter, while not the focus of this paper, are needed to

[5]This year was chosen because by 2000, almost all working age women 18-55 would have been born after 1950, and therefore "post-Quiet Revolution" women, as 1950 is the turning point birth year associated with the change in women's work horizon.

match employment shares and mean wages by gender in 2000.

5.1 Data

For both the 1970 and 2000 calibrations, I use U.S. Census data and restrict the sample to the working-age population (ages 18 to 55). I retain variables on labor force participation, occupation, educational attainment, family status (marital status and age of children, if any), wage and salary income earned last year, typical number of hours worked last year, and number of weeks worked last year.

Separately by gender, I calculate occupational employment shares among employed individuals across all ages. One challenge is that in the model, occupations are a discrete choice across manual, routine, and abstract, while in reality, occupations consist of varying shares of these tasks. To map the model to the data, I calculate in the Census task employment shares from the occupation task shares, weighting by occupational employment shares:

$$TaskEmpShare_k = \sum_j OccTaskShare_j^k \times OccEmpShare_j \quad \text{for } k \in \{M, R, A\}$$

where $OccTaskShare_{oj}$ refers to the occupation-specific manual, routine, or abstract task share from Autor and Dorn (2013), while the $OccEmpShare_o$ is the share of employed individuals in occupation o. I convert these task employment shares into task population shares by accounting for the extensive margin: I multiply them by the labor force participation rate for each gender to obtain the share of the population working in each type of task. This assumes the task content of individuals who are out of the labor force is 0 for all three tasks. Therefore I obtain populations shares, which I denote π_{gj} for $g \in \{m, w\}$ and $j \in \{H, M, R, A\}$.

To measure education in the data, I use years of schooling after grade 10, when legal requirements to attend school end. I assign individuals with grade 10 or less 0 years of

education, and increase this value by 1 for every year up to 5 years of university.[6]

Because the model structure and core mechanism concerns women's labor force intermittency associated with child-rearing, I use data on family status to inform the definition of periods in the model as well as the life-cycle variability of FLFP. I assign individuals in the Census to "model period 1" if they are single (never married), "model period 2" if they are married and have a child under the age of 5, and "model period 3" if they are married but do not have a child under the age of 5. While there is of course some variation in actual ages observed within each of these life phases in the data, Table 3 shows that the model structure is capturing on average a natural life cycle: individuals in period 1 tend to be in their early- to mid-20's, those in period 2 tend to be in their late 20's or early 30's, and those in period 3 tend to be late 30's or older. I use the 25^{th}-75^{th} percentile age ranges reported in Table 3 to define the lengths of the periods in the model.

Table 3: Statistics by Model Period from 1970 Census

Model Age	Life Phase	Mean Age	25^{th} – 75^{th} Pctile	FLFP	Pop. Weight
1	Single	25	19 – 28	0.65	0.24
2	Married w. kid ≤ 5	31	25 – 35	0.28	0.31
3	Other married	41	35 – 49	0.52	0.45

Notes: This table presents statistics for individuals assigned to each model period from the 1970 Census. The sample includes men and women aged 18-55 for all statistics, except for the female labor force participation rate, which is calculated using women only.

When calculating statistics based on labor earnings, I restrict the sample to employed individuals who worked 48+ weeks last year and between 35-48 hours per week. I use the variable corresponding to wage and salary income, convert it to real income in 2010 dollars, and drop observations with annual real income below 1000.[7]

[6]The education variable harmonized across Census years gives integer values for years of education up to 5 years of university, corresponding to a maximum value of education of 7 years post-grade 10.

[7]Following Hsieh, Hurst, Jones, and Klenow (2019), I include top-coded values when calculating the average income of full-time, full year workers by age and gender.

5.2 Exogenously-set parameters

The exogenously-set parameters are outlined in Table 4. I take values of the production elasticity of substitution between non-routine labor and routine tasks (λ) from Goos, Manning, and Salomons (2014), and between routine workers and computer technology (ψ) from Eden and Gaggl (2018). I take the shape of the Fréchet skill distribution from Hsieh, Hurst, Jones, and Klenow (2019), although I explore robustness of the main results to alternative values of this parameter in Section 6.5.

Table 4: Exogenously-Set Parameters

Parameter	Meaning	Value	Source
λ	EOS outer nest	0.9	Goos, Manning, and Salomons (2014)
ψ	EOS inner nest	2.5	Eden and Gaggl (2018)
θ	Fréchet shape parameter	2	Hsieh, Hurst, Jones, and Klenow (2019)
η	Mincer return to education	0.08	Acemoglu (2008)
δ_M	Depreciation in M	0.32	Adda, Dustmann, and Stevens (2017)
δ_R	Depreciation in R	0.05	Adda, Dustmann, and Stevens (2017)
δ_A	Depreciation in A	0.54	Adda, Dustmann, and Stevens (2017)
a_{wj}	Productivity Differences	1	Assumption

Notes: This table outlines the parameters that are set exogenously. Sources for parameter values are provided where applicable.

I take the values of skill depreciation for the different market occupations from Adda, Dustmann, and Stevens (2017). In their Table 3, they provide annual skill depreciation rates in routine (0.5%), abstract (6.9%), and manual jobs (3.45%), which are estimated using a panel dataset of German women. The context of their estimates suits my model very well: depreciation in my model is incurred only by women as men face $\rho = 0$, and the mean age of labor market exit in their sample is age 26, which corresponds exactly to the age of transition between periods 1 and 2 in my model, when depreciation kicks in. Table 4 reports the full period 2 depreciation rates I derive from their estimates. As expected, skill atrophy is highest in abstract and lowest in routine occupations.

My calibration strategy does not permit separate identification of wage gaps (τ's) in both 1970 and 2000, as well as gender differences in productivity (a's). For my baseline calibration,

I follow Hsieh, Hurst, Jones, and Klenow (2019) and assume no productivity differences between men and women (i.e., $a_{wj} = 1$ for $j \in \{M, R, A\}$). In Section 6.5, I show sensitivity of the main results to an alternative calibration which assume no wage gaps in 2000, but allows productivity differences between men and women.

5.3 Labor supply parameters

The remaining 22 parameters are calibrated simultaneously to match model moments with their empirical counterparts, under the assumption of the model being in equilibrium (see Table 6 for a summary of identification).

The Quiet Revolution parameter, ρ, which is key to my analysis and captures the probability that a woman works intermittently, is identified by the observed U-shape in female labor force participation over the typical life cycle. I calculate ρ according to the equation:

$$\rho = \frac{\text{LFP}_{1,3} - \text{LFP}_2}{\text{LFP}_{1,3}}$$

where $\text{LFP}_{1,3}$ is the weighted average of LFP for women in model periods 1 and 3 from Table 3, while LFP_2 is the value for women in model period 2. This procedure yields a value of $\rho = 0.50$ for 1970, meaning that half of women who start working in a market occupation in period 1 will stay at home in period 2, before returning to work in period 3.

I identify the income growth parameters between ages 1 and 2 and between ages 2 and 3 using a similar procedure as in equation 3 in Section 3. For full-time, full-year working men in the Census, I assign them into three age bins, defined as five-year ranges centered at the mean age for each model period in Table 3. I regress for each individual i in one of these bins the log annual income on the manual, routine, and abstract task content of i's occupation,

plus an interaction between task shares and age bins $b \in \{1, 2, 3\}$, according to:

$$\begin{aligned} \ln(income)_i \quad &= \sum_{k \in \{A,R,M\}} \beta_k \cdot OccTaskShare_i^k \\ &+ \sum_{k \in \{A,R,M\}} \sum_{b \in \in \{1,2,3\}} \Gamma_{k,b} \cdot \mathbf{1}\{AgeBin_i = b\} \cdot OccTaskShare_i^k + \epsilon_i \end{aligned} \tag{7}$$

As in equation 3 in Section 3, the coefficients $\Gamma_{k,b}$ capture income growth over life life-cycle by occupation task content k. From this regression, I infer the model parameter γ_{2j} from the estimated coefficient $\Gamma_{j,2}$ as well as parameter γ_{3j} from the estimated coefficients $\Gamma_{j,2}$ and $\Gamma_{j,3}$. Table 5 reports the estimated parameter values for returns to experience by occupation type. Income growth is faster between ages 1 and 2 than between 2 and 3 for all occupations. Consistent with Figure 4 in Section 3, abstract occupations feature the highest income growth.

Table 5: Calibrated Values of Returns to Experience

Occupation	γ_2 (Age 1 to 2)	γ_3 (Age 2 to 3)
Manual M	1.11	0.97
Routine R	1.13	1.03
Abstract A	1.41	1.23

Notes: This table shows the estimated returns to experience parameters from equation 7. Formally, γ_2 is $\exp(\Gamma_{k,2})$ for each task $k \in \{M, R, A\}$, while γ_3 is $\exp(\Gamma_{k,3} - \Gamma_{k,2})$. The sample is full-time, full-year employed men in the 1970 Census.

In a similar vein, I calculate mean years of education after grade 10 by occupation task among employed individuals in the Census data, separately by gender. I run the following regression:

$$YearsEdu_i = \beta_M \cdot OccTaskShare_i^M + \beta_R \cdot OccTaskShare_i^R + \beta_A \cdot OccTaskShare_i^A + \epsilon_i$$

where $OccTaskShare$ is individual i's occupation task share from Autor and Dorn (2013).[8] The coefficients β_M, β_R, and β_A, represent the means years of schooling by occupation in the model (h). See Figure 6 for the coefficient estimates by gender. I calibrate the human capital requirements ϕ_j for $j \in \{M, R, A\}$, as well as the convexity of the dis-utility of schooling

[8] I additionally control for age fixed effects, to control for differences across cohorts in educational attainment.

parameter ζ to jointly match these 6 moments.

The wage gap parameters τ_{wj} for $j \in \{M, R, A\}$ are identified from the ratio of mean income earned by young men vs. women in each occupation, after accounting for differences in human capital investments and adjusting for selection on skill.[9] As shown in Appendix B.4, this ratio is:

$$\frac{\text{Mean income of young men in } j}{\text{Mean income of young women in} j} = \frac{w_j \pi_{mj}^{-\frac{1}{\theta}} e^{\eta h^*(\phi_j,0)}}{w_j(1-\tau_{wj})\pi_{wj}^{-\frac{1}{\theta}} e^{\eta h^*(\phi_j,\rho)}} = \frac{1}{(1-\tau_{wj})} \cdot \frac{\pi_{mj}^{-\frac{1}{\theta}}}{\pi_{wj}^{-\frac{1}{\theta}}} \cdot \frac{e^{\eta h^*(\phi_j,0)}}{e^{\eta h^*(\phi_j,\rho)}}$$

where π_{gj} is the share of the gender g population in occupation j. It is related to mean income because of selection on skill.[10]

The technology parameters, p_C and Z_M, are calibrated to match relative mean earnings of young men across the different occupations. The TFP parameter Z is calibrated so the model matches real GDP per working age population.[11]

Finally, to calibrate the gender-specific occupation preference terms, $b_{gj}$for $g \in \{m, w\}, j \in \{H, M, R, A\}$, I impose that the model matches the observed aggregate share of men and women in the home sector H π_{gH} (accounting for ρ) as well as the aggregate task population shares of men and women across the three market occupations $\pi_{gM}, \pi_{gR}, \pi_{gA}$, given wages and other parameters. These task population shares are calculated for all individuals in the data and are not segmented by model period/age. Intuitively, the b's capture whatever is needed, after accounting for the economy forces, to ensure the model matches the data in terms of the share of the male and female population engaged in each occupation type.

[9] I use only the young for these calculations as they have not yet accumulated experience or incurred depreciation of their skills.

[10] Because some women leave the labor force at period 2, π_{wH} is not the complement of the labor force participation rate, but the share of women who choose to stay home in period 1 and thus never work. I adjust the female labor force participation rate in the data using the calibrated value of ρ to get π_{wH}.

[11] Data from the Federal Reserve Economic Data maintained by the Federal Reserve Bank of St. Louis.

Table 6: Full List of Internally-Calibrated Parameters for 1970

Parameter	Meaning	Value	Source
Panel A: Skill Dynamics			
γ's	Returns to Experience	Table 5	Male Income Growth
ϕ_M, ϕ_R, ϕ_N	Education Requirements	0.20,0.38,1.14	Education by Occupation
ζ	Schooling Dis-utility	1.67	Gender Gap in Education
Panel B: Labor Supply			
ρ	Intermittency Probability	0.50	FLFP Over Life Cycle
τ_M, τ_R, τ_N	Wage Gaps	0.66,0.35,0.38	Income of Young Women vs. Men
b's	Non-Monetary Preferences	Table C.1	Task Population Shares
Panel C: Technology			
p_C	Price of Automation	0.57	Male Earnings in A vs. R
Z_M	Manual Productivity	0.41	Male Earnings in A vs. M
Z	Total Factor Productivity	3.043×10^3	Real GDP per Working Age Pop.

Notes: This table presents the full set of internally calibrated parameters and the moments from which they are identified.

5.4 Calibrating model to 2000

For the 2000 calibration, I keep all but 3 sets of parameters at their 1970 level. Using Census data from 2000 and the same calibration procedure to identify (1) the intermittency parameter (ρ), (2) the technology parameters (p_C, Z_M, Z), (3) the wage gaps and preference parameters (τ, b). While the latter are not a focus of my analysis, they are needed so that the model matches the data in terms of task population shares and earnings.

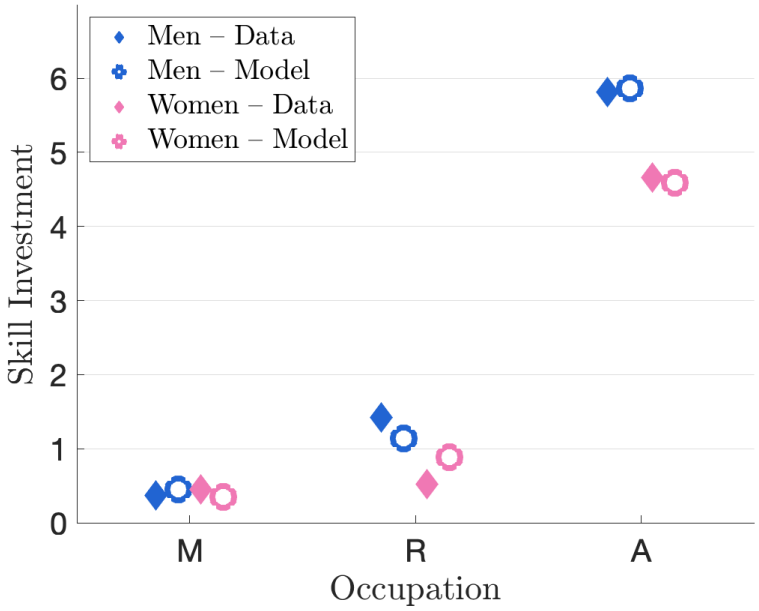
The Quiet Revolution is evident in a decline of ρ from 0.50 to 0.20. Technological shifts away from both routine and manual occupations are captured by a decline in p_C from 0.57 to 0.34 and in Z_M from 0.41 to 0.34. Finally, the calibration indicates that wage gaps τ fell in all occupations between 1970 and 2000.[12]

[12]Specifically, they fell from 0.66, 0.35, and 0.38 to 0.45, 0.10, and 0.14 in manual, routine, and abstract occupations, respectively.

5.5 Model fit

While most parameters in Table 6 are identified via a one-to-one mapping between a particular empirical moment, implying an exact match between the data and the model, the education parameters are over-identified, as I target 6 moments for 4 parameters. Figure 6 shows the model fit for these targeted moments (mean years of education after grade 10, for men and women by occupation, in 1970). Notably, the prediction of equation 5—that the gender gap in educational attainment widens with educational requirements ϕ—is borne out in the data.

Figure 6: Skill Investment by Occupation



Notes: This figure plots h by occupation and gender, in both the model and the data.

The model replicates several non-targeted moments well, especially those pertaining to women's the share of the female population engaged in different types of work over the life-cycle, as well as income growth over the life-cycle for women. This is important validation for the model, because the core mechanism of has to do with women's life-cycle behavior.

First, I show that the assumption of exogenous ρ fits the data on women's employment shares in both 1970 and 2000 remarkably well. One concern with modeling ρ as an exogenous

probability, rather than a choice to leave the labor force, is that women in different occupations may differentially select to work during period 2. For example, the women who enter the abstract occupation may stay in the labor force due to the returns to continuous work, and thus have a shallower U-shape in life-cycle labor force participation. To the contrary, in Figure 7 and 8, I show that the model with exogenous ρ fits the data on women's life-cycle population shares remarkably well: the observed U-shape in labor force participation is equally pronounced across all three occupation types. Importantly, I do not target the task population shares of women by age, only on aggregate. These figures provide validation that the exogenous ρ is a reasonable reduced-form representation of the factors which lead women to work intermittently.

Figure 7: Female Task Pop. Shares (1970)

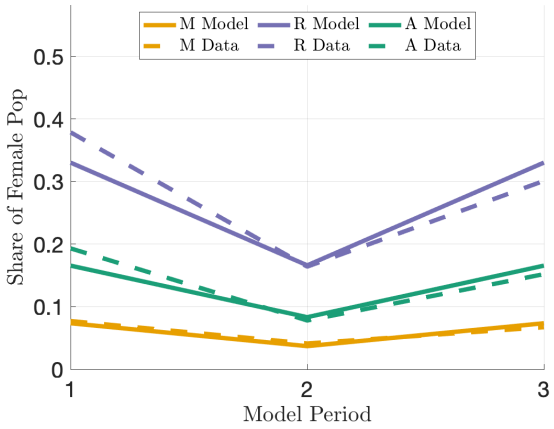
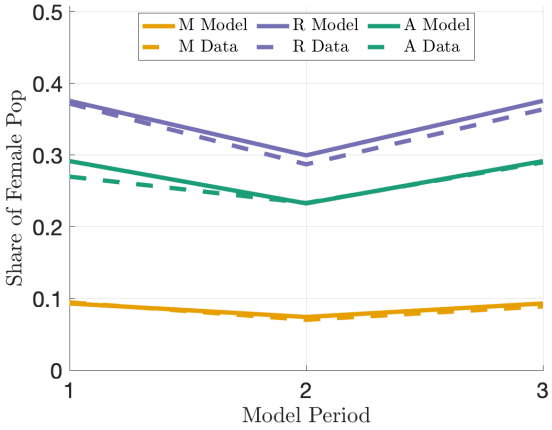


Figure 8: Female Task Pop. Shares (2000)



Notes:

Second, while the model explicitly targets male income growth between ages 1 and 3 in the calibration, it does not target female income growth. Table 7 shows the income growth for women in each occupation in both the model and the data. Compared to men, women's life-cycle income growth was flat in each occupation in 1970—a pattern captured well by the calibrated model. The model even captures negative income growth with age for women in manual-intensive occupations.

Additionally, the 2000 calibration exhibit substantially smaller widening of the gender wage gap with age. This is generated exclusively by the Quiet Revolution force increasing women's

Table 7: Life-cycle income growth in 1970, by gender and occupation.

Occupation	Male (Data=Model)	Female (Model)	Female (Data)
Manual	8.3	-11.7	-28.5
Routine	15.7	5.2	8.4
Abstract	76.7	11.5	4.0

Notes: This table shows the percentage increase in mean income between ages 1 and 3 by occupation, in both the model and the data. Male income growth is targeted in the calibration, while female income growth is not.

attachment to the labor force, because women of all ages experience the same exogenous wage gap τ. XXXXXXXXXX

Finally, the model generates an increase in computer expenditure as a share of GDP, $\frac{p_C C}{Y}$, by XX% between the 1970 and 2000 steady states. This is in line with the substantial growth in IT-related spending observed in the data, even though this moment is not targeted in the calibration.[13] While private fixed investment in information processing equipment and software as a share of GDP grew more, approximately doubling, over this period, it is important to note that C in my model is not literally computers, but rather represents a specific technology that can substitute for labor in performing routine tasks. Therefore it is not expected that the model would exactly replicate this statistic.

6 Quantitative Exercise

6.1 Partial Equilibrium Effects of the Quiet Revolution

I start the quantitative analysis by showing the implications of intermittency, as well as wage gaps and preferences, for female occupational sorting in partial equilibrium. Holding wages and parameters fixed at their 1970 levels, I individually turn on (one at a time) the Quiet Revolution (change in ρ), changes in the wage gaps (τ), and changes in preferences (b).

The left-most bar in Figure 9 (Figure 10) plots the total change in the female routine (abstract) employment share between 1970 and 2000. The remaining bars show the change under the

[13] `https://fred.stlouisfed.org/series/A679RC1Q027SBEA`

counterfactual where only one force changes, with all other parameter remaining at 1970 levels.

Figure 9: Change in Routine Emp. Share

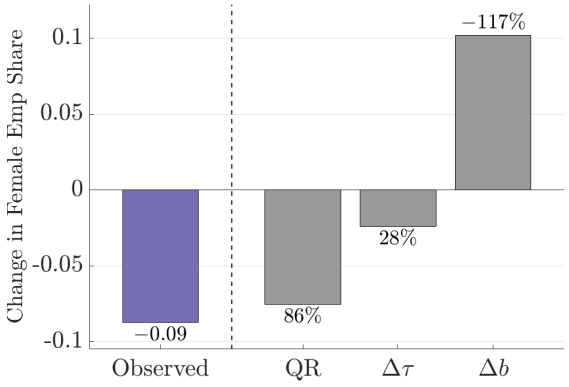
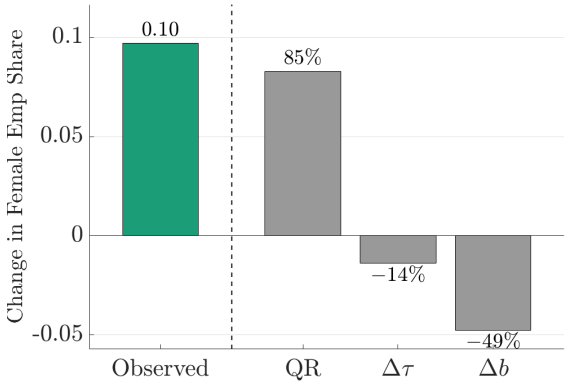


Figure 10: Change in Abstract Emp. Share



Notes: These figures show the change in the female routine and abstract employment share between 1970 and 2000 (leftmost colored bars). The gray bars in show the counterfactual change in the employment shares, if only one set of parameters changed from the 1970 to 2000 values, with all other parameters remaining at the 1970 values. The percentages displayed on top of each bar indicate the percent of the total observed change generated under that counterfactual.

The Quiet Revolution by itself can generate nearly the entire decline in women's routine and abstract employment shares. Abstract human capital dynamics are stronger than those in routine occupations, and the Quiet Revolution corresponds to a sufficiently large reduction in the parameter ρ to match these patterns. This highlights the quantitative importance of this labor-supply shift not only for whether women work, but also for which occupations they enter.

By contrast, falling wage gaps play a much smaller role in reallocating female employment across occupations. Because wage gaps decline in all three market occupations, their effect on relative incentives is limited. Interestingly, changes in the non-monetary preference parameters b actually push against the movement of women from routine to abstract occupations: if only these parameters changed, the female routine employment share would have increased. The same pattern holds for men (not shown). Since relative wages in routine occupations fall substantially, the 2000 calibration requires an increase in non-monetary preference for routine work for both women and men to match data on employment shares. While I refer to b as "preferences," in practice it captures any non-wage factor affecting occupational choice,

including barriers to reallocation.

6.2 Aggregate Employment Shares in Equilibrium

While the Quiet Revolution can explain much of the shift of female employment from routine to abstract in partial equilibrium, it's impact on the aggregate employment shares is less clear. While it directly affects female employment shares, it will also affect both women and men indirectly via equilibrium wage adjustments. It can also change the weighting of female and male labor when calculating aggregate employment shares, both by drawing more women into market occupations, and by mechanically increasing the number of women who remain in the labor market during period 2.

Figures 11 and 12 show the decomposition of the change in the aggregate routine and abstract employment share accounted for by both labor supply and labor demand forces, in equilibrium. The Quiet Revolution accounts for only 12% and 8%, respectively, of these.

Figure 11: Change in Routine Emp. Share

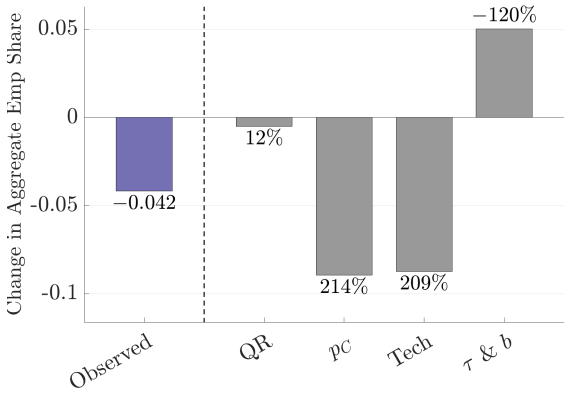
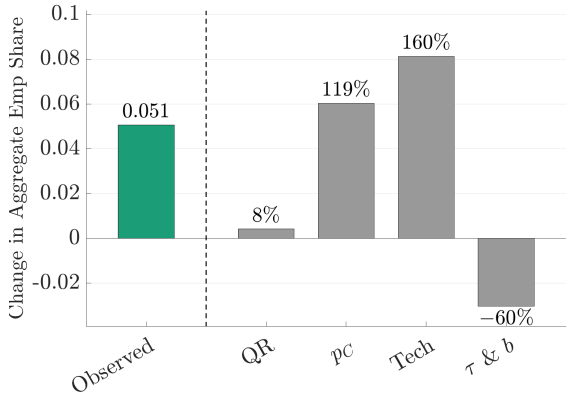


Figure 12: Change in Abstract Emp. Share



Notes: These figures show the change in the aggregate routine and abstract employment share between 1970 and 2000 (leftmost colored bars). The gray bars in show the counterfactual change in the employment shares, if only one set of parameters changed from the 1970 to 2000 values, with all other parameters remaining at the 1970 values. QR refers to the Quiet Revolution (change in ρ), p_C refers to the change in the computer price p_C, Tech refers to a change in all technology parameters (p_C, Z_M, Z), while $\tau + b$ refers to a change in the wage gap and preference terms. The percentages displayed on top of each bar indicate the percent of the total observed change generated under that counterfactual.

Technology plays a dominant role in explaining the aggregate employment shares: the fall in p_C alone explains over 100% of the aggregate decline (rise) in routine (abstract) employment. The counterfactual labeled "Tech" allows all technology parameters to evolve (p_C, Z_M, and

Z). The main difference between p_C and Tech counterfactuals is that the former reduces relative demand for routine labor, whereas the latter reduces relative demand for both routine and manual labor, compared to abstract.

6.3 Female LFP and Female Share of Abstract Employment

The counterfactuals illustrated in Figures 11 and 12 indicate that technology is the dominant force behind explaining the distribution of aggregate employment across routine and abstract jobs. Nonetheless, technology alone is not sufficient to generate the fact that most of the rise of abstract employment is attributable to women. Rather, the Quiet Revolution is needed to help explain why women entered the labor force over this period, and especially to explain the increase in the female share of abstract workers over this period. In terms of explaining changes in aggregate employment shares, technology explains the "what," while the Quiet Revolution is critical for the "how."

Figure 13 decomposes the change in the share of women who ever enter the labor market. I use this statistic, defined as the complement of π_{wH}, to avoid conflating the impact of the Quiet Revolution on occupational sorting with the mechanical impact of allowing women to work in period 2. The Quiet Revolution alone explains 29% of the increase in the share of women who choose in period 1 to enter the labor market; when women can work continuously, that makes market work more attractive in general. The decline in the computer price is only half as impactful as the Quiet Revolution, while the full technology counterfactual is approximately equal in magnitude.

Figure 14 shows the change the share of total abstract workers who are female. Again, to avoid conflating the contribution of the Quiet Revolution with it's mechanical effect, I focus on the change in $\frac{\pi_{wA}}{\pi_{wA}+\pi_{mA}}$–that is, the female share of individuals who enter the abstract occupation when young, regardless of whether they are in the labor force in period 2. This share increases by 14 percentage points between 1970 and 2000, and the Quiet Revolution

Figure 13:

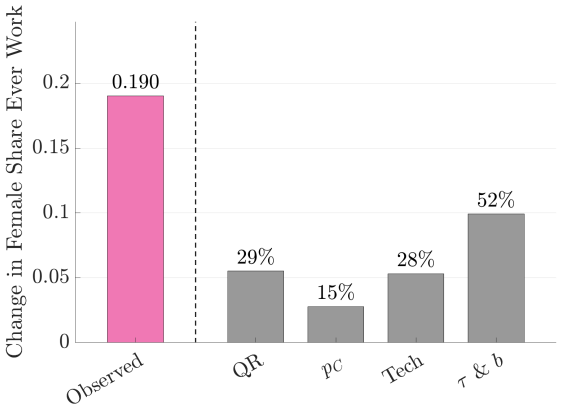
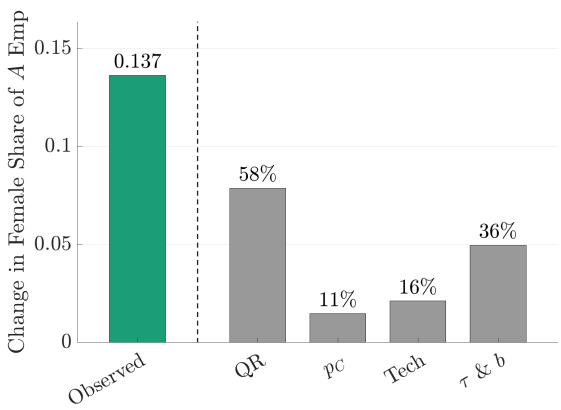


Figure 14:



Notes: The left figure shows the change in the share of women who ever enter market work in the model (i.e., the change in the complement of 1-π_{wH}). The right figure shows the change in the share of abstract workers who are female.

contributes 58% of that change. Technological change alone leaves the gender ratio of abstract employment almost unchanged.

6.4 Productivity & Automation Adoption

As a final exercise, I use the calibrated model to decompose the contribution of the Quiet Revolution to aggregate productivity, defined as GDP per working age population or GDP per worker. I find the Quiet Revolution explains 23% of the increase in market output per working-age population. By contrast, falling wage gaps τ explain 9% of the increase. The main difference is that the Quiet Revolution draws more women into the labor force, but increases their labor efficiency dramatically via human capital investment and returns to experience; falling wag gaps only draw more women into the labor market, but do not improve their efficiency. The combine technological forces explain the vast majority—70%—of the increase in market output per working age population.

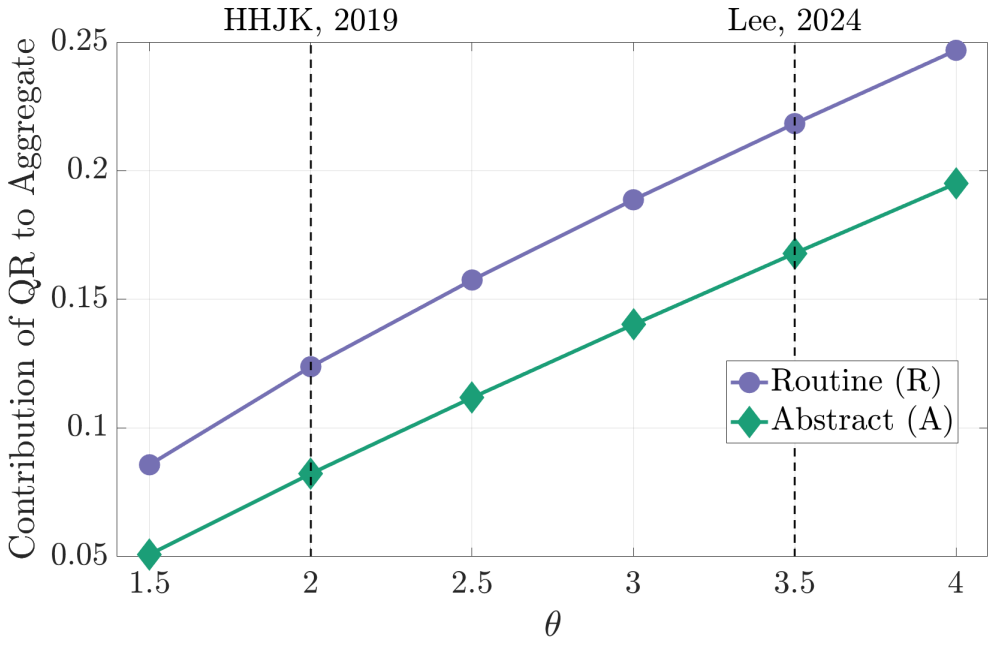
I also examine the share of GDP on computer investment, $\frac{p_C C}{Y}$. This is endogenous in the model because amount of computers used depends on relative factor prices, particularly that of routine workers. While technological change explains most of the increase in computer investment, I find that the Quiet Revolution explains 5% of the increase. This suggests an intriguing possibility of technology responding to the Quiet Revolution, such as via a directed

technical change mechanism.

6.5 Additional Results

In Figure 15, I show sensitivity of the main result, the contribution of the Quiet Revolution to the change in the routine or abstract employment share in equilibrium, to the parameter governing dispersion of the Fréchet skill distribution. The vertical lines are set at two values of θ which have been used in similar models from Hsieh, Hurst, Jones, and Klenow (2019) and Lee (2024). My baseline value was $\theta = 2$, but one can see that the contribution of the Quiet Revolution to the aggregate change in routine (abstract) employment may reasonably range between 12% and 22% (8% and 17%). Therefore, technology remains the dominant force in explaining the aggregate change in employment shares, regardless of the value of θ.

Figure 15: Contribution of Quiet Revolution to Change in Aggregate Employment Share



Notes: This figure plots the share of the change in the aggregate routine or abstract employment share between 1970 and 2000 that can be explained by the Quiet Revolution alone, for different values of the Fréchet parameter θ.

7 Conclusion

This paper provides the first macroeconomic analysis of the Quiet Revolution, focusing on how this shift in female labor supply reshaped the aggregate distribution of employment. Using a calibrated equilibrium model, I show that the Quiet Revolution had a substantial effect on female occupational sorting—facilitating women's entry into abstract occupations and their exit from routine work. While the Quiet Revolution accounts for roughly 12% of the aggregate decline in routine employment, technological change remains the primary driver of changes in the overall employment distribution between 1970 and 2000.

Nevertheless, the Quiet Revolution is essential for understanding how these aggregate shifts occurred, particularly their gender incidence. The results in this paper demonstrate that technological change and evolving labor supply worked in tandem to produce the decline in routine employment over this period.

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A Additional Results from Motivating Facts

Table A.1: Correlation between Social Norms and Occupation Task Share

	Abstract (1)	Routine (2)	Manual (3)	Abstract (4)	Routine (5)	Manual (6)
Panel A: Women						
Progressive	0.0552**	-0.0276	-0.0276	0.0454*	-0.0196	-0.0258
	(0.0263)	(0.0272)	(0.0170)	(0.0249)	(0.0265)	(0.0167)
Education Controls	No	No	No	Yes	Yes	Yes
Dep Var Mean	0.315	0.558	0.127	0.315	0.558	0.127
R-sq	0.0636	0.0331	0.0622	0.164	0.0945	0.0691
N	352	352	352	352	352	352
Panel B: Men						
Progressive	-0.0162	0.00765	0.00853	-0.0228	0.0109	0.0119
	(0.0281)	(0.0231)	(0.0197)	(0.0244)	(0.0221)	(0.0185)
Education Controls	No	No	No	Yes	Yes	Yes
Dep Var Mean	0.359	0.460	0.181	0.359	0.460	0.181
R-sq	0.0380	0.0288	0.0434	0.225	0.0985	0.150
N	435	435	435	435	435	435

Notes: This table presents estimated regression coefficients from equation (**??**). "Progressive" is an indicator which takes the value 1 respondents who said they "agree" or "strongly agree" with the statement: . The outcome for each column is an indicator for a non-routine cognitive occupation, as defined in Table **??**. Standard errors are reported in parentheses. * indicates significance at $p < 0.10$, ** indicates significance at $p < 0.05$, and *** indicates significance at $p < 0.01$.

Table A.2: Correlation between Social Norms and Occupation Task Percentile

	Abstract (1)	Routine (2)	Manual (3)	Abstract (4)	Routine (5)	Manual (6)
Panel A: Women						
Progressive	0.115***	-0.0800**	-0.0336	0.0815**	-0.0557	-0.0246
Education Controls	No	No	No	Yes	Yes	Yes
Dep Var Mean	0.503	0.568	0.435	0.503	0.568	0.435
R-sq	0.0714	0.0401	0.0449	0.176	0.0881	0.0521
N	352	352	352	352	352	352
Panel B: Men						
Progressive	0.0353	-0.0282	-0.0204	-0.00486	-0.00900	0.00739
	(0.0342)	(0.0273)	(0.0289)	(0.0300)	(0.0266)	(0.0265)
Education Controls	No	No	No	Yes	Yes	Yes
Dep Var Mean	0.522	0.427	0.563	0.522	0.427	0.563
R-sq	0.0357	0.0295	0.0415	0.230	0.0984	0.177
N	435	435	435	435	435	435

Notes: This table presents estimated regression coefficients from equation (**??**). Standard errors are reported in parentheses. * indicates significance at $p < 0.10$, ** indicates significance at $p < 0.05$, and *** indicates significance at $p < 0.01$.

B Mathematical Appendix

B.1 Proof of Proposition 1

The derivative of $h(\phi_j, \rho)$ with respect to ρ is: $-\frac{1}{\zeta-1}(3-\rho)^{\frac{2-\zeta}{\zeta-1}}(\eta\phi_j)^{\frac{1}{\zeta-1}}$. As $\zeta > 1$ and $\eta > 0$, when $\phi_j > 0$, this is strictly negative. This means $h(\phi_j, 0) > h(\phi_j, \rho)$ when $\rho \in (0, 1]$ and $\phi_j > 0$. If $\phi_j = 0$, then $h(\phi_j, 0) = h(\phi_j, \rho) = 0$.

B.2 Proof of Proposition 2

Proposition 2 states that the derivative of χ^g_{jk} (the innate skill threshold $\frac{\epsilon_j}{\epsilon_k}$ to prefer occupation j over occupation k) with respect to ρ is positive, all else equal, as long as occupation j is more dynamic than occupation k ($\tilde{\gamma}_j \geq \tilde{\gamma}_k$, $\delta_j \geq \delta_j$, and $\phi_j \geq \phi_k$, with at least one inequality

holding strictly). Equation (6) in the main text defines χ^g_{jk} as:

$$\chi^g_{jk} = \underbrace{\frac{a_{gk}w_k(1-\tau_k)}{a_{gj}w_j(1-\tau_j)}}_{\substack{\text{Wages} \\ \text{Net of Gaps}}} \times \underbrace{\frac{b_{gk}}{b_{gj}}}_{\text{Pref.}} \times \underbrace{\left(\frac{\tilde{\gamma}_k}{\tilde{\gamma}_j}\right)^{\frac{1-\rho}{3-\rho}} \times \left(\frac{1-\delta_k}{1-\delta_j}\right)^{\frac{\rho}{3-\rho}} \times e^{\frac{\eta(\zeta-1)}{\zeta}(h^*(\phi_k,\rho)-h^*(\phi_j,\rho))}}_{\substack{\text{Human capital dynamics \&} \\ \text{intermittency}}}$$

To prove this result, it is sufficient to show that the last part of the equation, highlighted as "Skill dynamics & intermittency", increases with ρ, because the rest of the equation does not depend on ρ. I will consider the impact of ρ on each of the factors, which each correspond to different skill dynamics.

1. Returns to experience γ:

$$\frac{\partial}{\partial\rho}\left(\frac{\gamma_k}{\gamma_j}\right)^{\frac{1-\rho}{3-\rho}} = \left(\frac{\gamma_k}{\gamma_j}\right)^{\frac{3-3\rho}{3-\rho}} \times \ln\left(\frac{\gamma_k}{\gamma_j}\right) \times -\frac{2}{(3-\rho)^2}$$

   If $\gamma_j = \gamma_k$, then $\frac{\partial}{\partial\rho}\left(\frac{\gamma_k}{\gamma_j}\right)^{\frac{1-\rho}{3-\rho}} = 0$. If $\gamma_j > \gamma_k$, then $\frac{\partial}{\partial\rho}\left(\frac{\gamma_k}{\gamma_j}\right)^{\frac{1-\rho}{3-\rho}} > 0$, as $\ln\left(\frac{\gamma_k}{\gamma_j}\right) < 0$. Thus, $\frac{\partial}{\partial\rho}\left(\frac{\gamma_k}{\gamma_j}\right)^{\frac{1-\rho}{3-\rho}} \geq 0$ if $\gamma_j \geq \gamma_k$.

2. Depreciation δ:

$$\frac{\partial}{\partial\rho}\left(\frac{1-\delta_k}{1-\delta_j}\right)^{\frac{3-3\rho}{3-\rho}} = \left(\frac{1-\delta_k}{1-\delta_j}\right)^{\frac{3-3\rho}{3-\rho}} \times \ln\left(\frac{1-\delta_k}{1-\delta_j}\right) \times \frac{3}{(3-\rho)^2}$$

   If $\delta_j = \delta_k$, then $\frac{\partial}{\partial\rho}\left(\frac{1-\delta_k}{1-\delta_j}\right)^{\frac{\rho}{3-\rho}} = 0$. However, if $\delta_j > \delta_k$, then $\frac{\partial}{\partial\rho}\left(\frac{1-\delta_k}{1-\delta_j}\right)^{\frac{\rho}{3-\rho}} > 0$, as $\ln\left(\frac{1-\delta_k}{1-\delta_j}\right) > 0$. Thus, $\frac{\partial}{\partial\rho}\left(\frac{1-\delta_k}{1-\delta_j}\right)^{\frac{3-3\rho}{3-\rho}} \geq 0$ if $\delta_j \geq \delta_k$.

3. Skill requirements ϕ: From Proposition 1, the optimal choice of human capital is $h^*(\phi,\rho) = ((3-\rho)\eta\phi)^{\frac{1}{\zeta-1}}$, so $h^*(\phi_k,\rho) - h^*(\phi_j,\rho) = (\eta(3-\rho))^{\frac{1}{\zeta-1}}(\phi_k^{\frac{1}{\zeta-1}} - \phi_j^{\frac{1}{\zeta-1}})$. Then $\frac{\partial}{\partial\rho}e^{\frac{\eta(\zeta-1)}{\zeta}(h^*(\phi_k,\rho)-h^*(\phi_j,\rho))}$ is:

$$e^{\frac{\eta(\zeta-1)}{\zeta}(\eta(3-\rho))^{\frac{1}{\zeta-1}}(\phi_k^{\frac{1}{\zeta-1}}-\phi_j^{\frac{1}{\zeta-1}})} \times \frac{\eta(\zeta-1)}{\zeta}\eta^{\frac{1}{\zeta-1}}(\phi_k^{\frac{1}{\zeta-1}} - \phi_j^{\frac{1}{\zeta-1}}) \times -\frac{1}{\zeta-1}(3-\rho)^{\frac{2-\zeta}{\zeta-1}}$$

If $\phi_j = \phi_k$, then $\frac{\partial}{\partial \rho} e^{\frac{\eta(\zeta-1)}{\zeta}(h^*(\phi_k,\rho)-h^*(\phi_j,\rho))} = 0$. If $\phi_j > \phi_k$, then $\frac{\partial}{\partial \rho} e^{\frac{\eta(\zeta-1)}{\zeta}(h^*(\phi_k,\rho)-h^*(\phi_j,\rho))} > 0$.

B.3 Occupation Population Shares

Recall that skill vector $\boldsymbol{\epsilon} = (\epsilon_H, \epsilon_M, \epsilon_R, \epsilon_A)$ is distributed i.i.d. Fréchet where the shape parameter is θ, where the joint cumulative distribution function is:

$$F(\boldsymbol{\epsilon}) = \exp\left(-\sum_s \epsilon_s^{-\theta}\right)$$

Following the worker's problem in equation (4) in the main text, denote:

$$X_{gj}(\rho) = a_{gj}(1-\tau_{gj}) w_j b_{gj} \tilde{\gamma}_j^{\frac{1-\rho}{3-\rho}} (1-\delta_j)^{\frac{\rho}{3-\rho}} e^{\frac{\eta(\zeta-1)}{\zeta} h^*(\phi_j,\rho)}$$

For occupation $j \in \{1, ..., J\}$ and group $g \in \{\text{men, women}\}$, an individual will pick occupation j if for all $s \neq j$: $\epsilon_j X_{gj}(\rho) > \epsilon_s X_{gs}(\rho)$. Without loss of generality, order occupations such that $j = 1$. The probability that an individual picks occupation 1 is:

$$\begin{aligned}
& Pr(\epsilon_1 X_{g1}(\rho) > \epsilon_s X_{gs}(\rho)) && \forall s > 1 \\
= \; & Pr\left(\epsilon_s < \frac{X_{g1}(\rho)}{X_{gs}(\rho)} \epsilon_1\right) && \forall s > 1 \\
= \; & \int_0^\infty F_1\left(\epsilon_1, \frac{X_{g1}(\rho)}{X_{g2}(\rho)}\epsilon_1, \frac{X_{g1}(\rho)}{X_{g3}(\rho)}\epsilon_1, \frac{X_{g1}(\rho)}{X_{g4}(\rho)}\epsilon_1\right) d\epsilon_1
\end{aligned}$$

where $F_1(\boldsymbol{\epsilon})$ denotes the derivative of $F(\boldsymbol{\epsilon})$ with respect to the first element of $\boldsymbol{\epsilon}$. Define $\alpha_s = \frac{X_{g1}(\rho)}{X_{gs}(\rho)}$. Then this can be written as:

$$\begin{aligned}\int_0^\infty F_1(\alpha_1\epsilon_1, \alpha_2\epsilon_1, \alpha_3\epsilon_1, \alpha_4\epsilon_1)\, d\epsilon_1 &= \int_0^\infty \theta\epsilon_1^{-\theta-1} \exp\left(-\sum_{s=1}^{J} \alpha_s^{-\theta}\epsilon_1^{-\theta}\right) d\epsilon_1 \\ &= \int_0^\infty \theta\epsilon_1^{-\theta-1} \exp\left(-\epsilon_1^{-\theta}\alpha\right)\, d\epsilon_1\end{aligned}$$

where $\alpha = \sum_{s=1}^{J} \alpha_s^{-\theta}$. This can be rewritten as:

$$\begin{aligned}&= \frac{1}{\alpha}\int_0^\infty \theta\epsilon_1^{-\theta-1}\alpha \exp\left(-\epsilon_1^{-\theta}\alpha\right)\, d\epsilon_1 \\ &= \frac{1}{\alpha} \\ &= \frac{(X_{g1}(\rho))^\theta}{\sum_{s=1}^{J}(X_{gs}(\rho))^\theta}\end{aligned}$$

I denote the population share for group g in occupation j as π_{gj}.

B.4 Mean Skill in Chosen Occupation

Denote by y^* the maximized value of $y_j = \epsilon_j X_{gj}(\rho)$:

$$y^* = \max_{j\in J} y_j = \max_{j\in J} \epsilon_j X_{gj}(\rho) = \epsilon^* X_g(\rho)^*$$

Then y^* also follows an extreme value distribution with CDF $G(.)$:

$$\begin{aligned} Pr(y^* < z) &= Pr(y_j < z) \quad \forall j \\ &= Pr\left(\epsilon_j < \frac{z}{X_{gj}(\rho)}\right) \quad \forall j \\ &= F\left(\frac{z}{X_{g1}(\rho)}, \frac{z}{X_{g2}(\rho)}, \frac{z}{X_{g3}(\rho)}, \frac{z}{X_{g4}(\rho)}\right) \\ &= \exp\left(z^{-\theta} \sum_s (X_{gs}(\rho))^\theta\right) \end{aligned}$$

So $G(z) = \exp(-mz^{-\theta})$ where $m = \sum_s (X_{gs}(\rho))^\theta$.

Denote by $H(.)$ the CDF of ϵ^*, the innate skill in the chosen occupation. Using the change of variables result for a CDF, it is straightforward to derive $H(.)$ from $G(.)$:

$$\begin{aligned} H(q) &= G(X_g(\rho)^* q) \\ &= \exp(-m(X_g(\rho)^*)^{-\theta} q^{-\theta}) \\ &= \exp(-m^* q^{-\theta}) \end{aligned}$$

where $m^* = \sum_s \left(\frac{X_{gs}(\rho)}{X_g(\rho)^*}\right)^\theta$. Note that $m^* = \frac{1}{\pi_{gj}}$ when j is the chosen occupation (i.e., it is the inverse of the employment share in the chosen occupation).

The mean of ϵ^* is then $= m^{*(1/\theta)} \Gamma\left(1 - \frac{1}{\theta}\right)$, where $\Gamma(.)$ is the gamma function. Therefore, the mean ϵ^* is inversely proportional to the employment share for a given group, as it can be expressed as ${\pi_{gj}}^{(-1/\theta)} \Gamma\left(1 - \frac{1}{\theta}\right)$. This captures the effect of selection on skill.

C Additional Calibration Results

In calibrating the non-monetary preference parameters, I impose the restriction that $b_{gH} + b_{gM} + b_{gR} + b_{gA} = 1$ for $g \in \{m, w\}$. This normalization is feasible because it is the relative preference parameters that matter, not the levels.

C.1 Calibrated Values of Preference Parameters

Table C.1: Calibrated Preference Parameters for Women and Men

	1970 Value	2000 Value
Panel A: Women		
b_{wH}	0.1177	0.1363
b_{wM}	0.2627	0.2108
b_{wR}	0.3915	0.4383
b_{wN}	0.2281	0.2146
Panel B: Men		
b_{mH}	0.1033	0.1390
b_{mM}	0.1971	0.1722
b_{mR}	0.4722	0.4861
b_{mA}	0.2274	0.2027

Notes: This table presents the calibrated value of the non-monetary preference terms (b's) for men and women in each occupation.