The Quiet Revolution and the Decline of Routine Jobs

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Abstract

What role have factors affecting female labor supply, such as social norms and discrimination, played in the decline of routine jobs in the U.S. since the 1970's? While typically attributed to changes in labor demand, the decline in routine employment has been larger for women than men, reflecting a shift of female employment out of routine clerical jobs and into non-routine professions. This paper presents a quantitative analysis of the impact of falling labor market distortions faced by women in explaining the trend. One observable manifestation of these falling distortions is the Quiet Revolution, which refers to a shift in women's life cycle labor force attachment from intermittent to continuous after 1970; it spurred the rise of female non-routine employment because these are long-term careers that reward experience. I develop and calibrate an equilibrium model of the labor market featuring the Quiet Revolution, discrimination, and improvement in automation. Counterfactual analyses reveal that the Quiet Revolution and reduced discrimination explain 21% and 59%, respectively, of the growth of non-routine relative to routine white-collar employment among women between 1970 and 2000. Together, they explain 36% of the aggregate increase, while automation explains 56%. Finally, the Quiet Revolution raised output per worker by 3% via increased female experience.

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1 Introduction

In recent decades, employment has shifted out of routine jobs and into non-routine jobs.[1] Automation technology, which can substitute for routine labor, is thought to be the driving force behind this trend, sparking concern about the displacement of workers.

Less widely known, however, is that the decline in routine employment since the 1970's has been substantially larger for women than for men, as illustrated in Figure 1. Despite starting from similar levels, the percentage point drop in women's routine employment share has been more than twice that of men. This gender gap emerges within white-collar occupations, where a substantial decline in female employment in routine clerical jobs has been matched by a dramatic rise in non-routine managerial and professional careers.

Figure 1: Routine Share of Employment

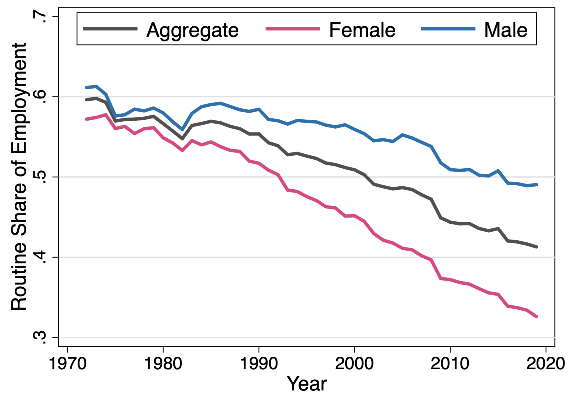
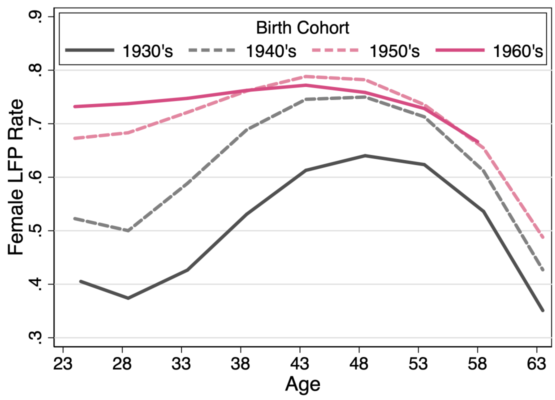


Figure 2: Female LFP Over the Life-Cycle



Notes: The left figure plots the share of employed individuals aged 18-55 in the CPS ASEC 1972-2019 in routine occupations, as classified by Cortes, Jaimovich, Nekarda, et al. (2020). See Table 1 for the classification. The right figure plots labor force participation at different ages for synthetic cohorts of women, constructed using the CPS ASEC 1962-2019.

In this paper, I investigate the role of falling labor market distortions—social norms and discrimination—faced by women as an alternative explanation for the trend. One observable manifestation of these falling barriers is a qualitative change in female labor supply itself, which Goldin (2006) calls the Quiet Revolution. The Quiet Revolution refers to an increase in life cycle labor force attachment among women born after 1950, who would enter the labor force starting in the 1970's (see Figure 2). Goldin (2021) attributes this shift in women's work horizon from intermittent, often with extended breaks to raise children, to continuous to changing social norms regarding the acceptability of working mothers and access to birth control pills.[2] The fact that non-routine jobs—especially professional and managerial—reward experience and require costly education forms the key link between the Quiet Revolution and the entry of women to non-routine jobs. The work horizon of women born in the 1930's and 1940's in Figure 2 was well-suited to routine clerical jobs, like secretaries, but not to non-routine careers, such as law or medicine.

I develop a new quantitative framework to study the impact of falling distortions affecting female labor supply on both the decline of routine employment and aggregate productivity,

[1]Routine jobs refer to clerical, administrative, sales, production, and operator roles, while non-routine jobs comprise managers, professionals, technicians, and low-skill services (Acemoglu and Autor 2011).

[2]Indeed, the most "revolutionary" statistic of the Quiet Revolution is labor force participation of women with children under the age of 5, which grew from 29% to 59% between 1970 and 1990.

with a particular emphasis on the Quiet Revolution. My analysis also incorporates wage discrimination faced by women, which is thought to have fallen specifically in high-skill non-routine professions (Hsieh et al. 2019). Additionally, I allow for exogenous technological change, specifically automation, as it is the standard explanation for the decline of routine employment. I develop an equilibrium model of the labor market featuring changes in women's life-cycle labor supply, reductions in residual wage discrimination, and exogenous improvements in automation technology. Using this model, I quantify the role of falling labor market distortions in explaining the decline of routine employment and rise of non-routine employment, particularly within a white-collar setting.

A novel aspect of my approach in incorporating the Quiet Revolution is the ability to micro-found part of the labor market distortions faced by women, offering a clear economic rationale for why these distortions disproportionately affected non-routine occupations. Moreover, I provide direct empirical evidence supporting the existence of these distortions. I begin by demonstrating a robust empirical link between the Quiet Revolution and the occupational sorting of women into non-routine rather than routine jobs. The pivotal shift of the Quiet Revolution was that women began working continuously, even when they had young children. Using survey data from the National Longitudinal Survey of Young Women (NLS-YW) and the General Social Survey, I show that women's expectations of future work and personal attitudes toward working mothers are strongly correlated with entry into non-routine professional occupations.

Next, I propose a model of life cycle labor supply which rationalizes this correlation and in which the Quiet Revolution plays a central role. The model builds on Hsieh et al. (2019) in that women face a wage discrimination "tax" that varies across occupations, but it adds the realistic feature that female labor force participation varies over the life cycle. Additionally, occupations differ in characteristics like required educational investments and returns to experience, which makes them better or worse suited to an intermittent work horizon, as has been argued by Polachek (1981) and Adda, Dustmann, and Stevens (2017). Workers make human capital investments and choose their occupation "once-and-for-all" when young to maximize expected life-time utility.

I model intermittency in a parsimonious way: 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 changing social norms and access to birth control. I show theoretically how expected work horizon interacts with occupation characteristics—human capital requirements, returns to experience, and skill depreciation—to drive a wedge between female and male skill acquisition and occupational sorting. For example, a woman expecting a high probability of leaving the labor force to raise children has less incentive to invest in her human capital and enter a high returns-to-experience non-routine occupation, such as law or medicine, preferring instead a low returns-to-experience occupation, such as routine clerical work.

On the labor demand-side, firms hire routine and non-routine labor and can purchase computers to substitute for routine workers. I focus on the distinction between routine and non-routine *cognitive* jobs (i.e., white-collar work) in the model, as this is where the gender divergence emerges empirically. The notion of automation in the model thus captures technologies like electronic filing or automated phone answering systems, which automate tasks that typically women used to perform in office settings.[3] Improved automation capabilities are modeled as an exogenous decline in the real price of computers. The fact that automation is endogenous and depends on factor prices means that firms may respond to changes in labor supply by automating more of the routine tasks.

I calibrate the model to 1970 initially, before the Quiet Revolution happened and before automation technology became widely available. The model structure provides a one-to-one mapping between key parameters and empirical moments, enabling me to separately identify the effects of intermittency and discrimination on occupational sorting and selection-adjusted earnings. I use data on the variability of female labor force participation over the life cycle as well as gender differences in educational attainment and income growth to inform occupation-specific characteristics, like education requirements, returns to experience, and skill depreciation. This enables me to quantify the effects of intermittency on women's earnings and occupational sorting. The remaining gender wage gap is assigned to a discrimination wedge, as in Hsieh et al. (2019). I employ an indirect inference technique to inform the parameters which govern the elasticity of labor supply across occupations, leveraging within-women variation in expected work horizon and occupational sorting from the NLS-YW.

I use the calibrated model to perform counterfactual analyses. First, I investigate how much of the increase in non-routine relative to routine employment in a white-collar setting over the period 1970 to 2000 can be attributed to falling distortions faced by women—the Quiet Revolution and falling discrimination—vis-à-vis improvements in automation. Second, I quantify the implications of the Quiet Revolution for aggregate productivity.

I find that falling labor supply distortions are the primary driver of the shift of female employment from routine cognitive to non-routine cognitive occupations in the model: together, falling discrimination and the Quiet Revolution explain 76% of the change, with the Quiet Revolution alone explaining 21%. If only technology changed, the model would generate only 24% of the shift of female employment across routine and non-routine white-collar jobs, and there would have been a substantial counterfactual shift of men across these occupation categories as well. The fact that technology changed while the Quiet Revolution happened and discrimination fell meant that male employment was stabilized across occupations, as women met the increased demand for non-routine labor.

Turning to the aggregate, I find that the Quiet Revolution and falling discrimination together explain 36% of the rise of white-collar non-routine relative to routine employment. Importantly, this is net of the equilibrium effect of crowding-out of men, generated from the shift of female labor supply toward non-routine jobs with both the Quiet Revolution and falling discrimination. Improvement in automation technology explains only 56% of the growth in non-routine relative to routine employment on aggregate, highlighting the salience of non-technological factors for this trend. The Quiet Revolution has a smaller impact on the aggregate employment shares than discrimination, because while it shifts female employment toward non-routine jobs, it also increases the share of the workforce who are female via labor force continuity. As women have a higher white-collar routine employment share than men to begin with, this effect partly offsets the extent to which

[3]While manual occupations are present in the model and are subject to shifting labor demand via technological change, I do not formulate this explicitly as automation, as it may also reflect forces such as trade competition or structural transformation.

changes in female employment translates to aggregate employment shares.

Despite a smaller impact on aggregate employment shares than changes in discrimination, the Quiet Revolution has a larger impact on aggregate productivity. The Quiet Revolution raises market output per worker by 3%, whereas the decline in discrimination causes output per worker to fall. Both the Quiet Revolution and falling discrimination lower the innate skill threshold at which women enter market occupations, which drives down the mean innate skill of workers. However, the Quiet Revolution additionally enables women with high innate skills to remain in the labor force and increases female human capital investment and accumulated experience. The latter are the main contributing factors to the productivity gains.

Finally, the counterfactual analyses also reveals an intriguing complementarity between labor supply changes and labor demand changes. The decline in labor market distortions faced by women amplifies the extent of substitution of automation for routine labor in the model, as routine labor becomes scarce. This finding suggests a new perspective of automation as filling gaps left after improvement in the allocation of female labor.

1.1 Related Literature

This paper draws a link between three sets of literature: (1) automation and the decline of routine jobs, (2) the macroeconomic implications of changes in female labor force participation, and (3) the misallocation of labor.

The dominant paradigm in the literature studying the decline of routine jobs is that this trend is a demand-side phenomenon, primarily driven by automation technology (Autor, Levy, and Murnane 2003; Acemoglu and Autor 2011; Acemoglu and Restrepo 2020; Autor and Dorn 2013; Acemoglu and Restrepo 2022; Cortes, Jaimovich, and Siu 2017). While it is known that the decline in routine employment has been more pronounced for women than for men, this trend has not, to the best of my knowledge, been explicitly connected to the various changes affecting female labor supply during this period, in particular the Quiet Revolution and other falling distortions (Autor, Levy, and Murnane 2003; Black and Spitz-Oener 2010; Cortés et al. 2024). In this paper, I provide quantitative estimates of the relative importance of both demand- and supply-side factors in explaining the overall trend. In taking a quantitative approach, my work connects with prior structural analyses of the decline of routine jobs and the implications of automation (Bárány and Siegel 2018; Beraja and Zorzi 2024; Goos, Manning, and Salomons 2014; Cortes, Jaimovich, and Siu 2017; Guerreiro, Rebelo, and Teles 2022).

There are many recent contributions to our understanding of the macroeconomic implications of changes in female labor supply (Cerina, Moro, and Rendall 2021; Acemoglu, Autor, and Lyle 2004; Ngai and Petrongolo 2017; Fukui, Nakamura, and Steinsson 2023; Heathcote, Storesletten, and Violante 2017; Kuhn, Manovskii, and Qiu 2024; Rendall 2017; Hsieh et al. 2019). A key contribution of this paper is to study the macroeconomic implications of the Quiet Revolution, a shift in women's life cycle work horizon, as distinct from growth in extensive margin labor force participation. The shift in women's life cycle employment from intermittent to continuous is well-documented in the labor economics literature, and supply-side factors such as access to birth control and evolving social norms have been shown to have caused women to work more continuously (Goldin 2006; Goldin and Mitchell 2017; Olivetti 2006; Attanasio, Low, and Sánchez-Marcos 2008; Fernández, Fogli, and Olivetti 2004; Goldin and Katz 2002; Bailey 2006; Fernández 2013). Moreover, it has been proposed that women, facing a more intermittent work horizon than men, may invest in different types of human capital and enter different occupations (Polachek 1981; Lazear and Rosen 1990; Adda, Dustmann, and Stevens 2017). This paper synthesizes these concepts within an equilibrium model of the labor market to quantify how the Quiet Revolution affected not only women's occupational sorting but also, taking into account equilibrium effects, how it impacted aggregate employment and productivity.

Finally, this paper relates to the existing literature on the aggregate implications of labor market distortions and misallocation, particularly along gender lines (Hsieh et al. 2019; Chiplunkar and Kleineberg 2023; Lee 2024).While distortions are often modeled as "black-box" wedges, I contribute to recent work which micro-founds distortions leading to misallocation of resources (Erosa et al. 2022). By focusing on an observable change in how women work over the life-cycle—the Quiet Revolution—I am able to provide both a theoretical micro-foundation of a distortion faced by women, as well as direct empirical evidence of it using survey data. Existing frameworks tend to focus on static distortions, but the Quiet Revolution is inherently a dynamic distortion with real productivity consequences: when women work intermittently they are less effective at work which rewards returns to experience, even if they have high innate skill.

The paper is structured as follows. Section 2 describes the Quiet Revolution and shows a direct empirical connection to women's entry into non-routine cognitive professions. In Section 3, I develop the equilibrium model of the labor market, which serves as the foundation for the analysis. Section 4 details the model calibration, while Section 5 presents the results of the quantitative exercises. Finally, Section 6 concludes.

2 The Quiet Revolution and Non-Routine Work

In this section, I provide empirical evidence to motivate the hypothesis of this paper. The hypothesis is intuitive: if women expect to work intermittently, they have little incentive to accumulate human capital or to sort into occupations with high returns to experience. As their work horizon expands and becomes more continuous, as with the Quiet Revolution, they undertake more education and start to enter these occupations. Since the rise of non-routine employment has been larger for women and these occupations tend to be better suited to a long and continuous work horizon, the Quiet Revolution may contribute to the observed trend in aggregate employment. I present three pieces of empirical evidence in support of this argument:

1. Women used to work intermittently, with long gaps out of the labor force associated with child-rearing. They expected this work horizon when they were young and undertaking human capital investments. With the Quiet Revolution, women entering the labor force around 1970 onward started working continuously over the life cycle.

2. The widening gender gap in the routine employment share emerges within cognitive occupations: it reflects a shift of female employment away from routine cognitive jobs (clerical, administrative, and sales) towards non-routine cognitive careers (professional, managerial, and technical). The latter require more human capital investment and exhibit stronger returns to experience, which make these occupations better suited to a continuous work horizon.

3. Within-women variation in markers of a continuous work horizon — expectations of future labor force attachment reported during teenage years, and social attitudes toward working mothers — are correlated with entry to non-routine cognitive professions. This provides a direct link between facts 1 and 2.

I document these facts using a variety of data sources. To illustrate women's historical intermittent work horizon in fact 1, I use data from *Great Aspirations*, a large, nationally-representative survey of college students who graduated in 1961.[4] This survey started following students who were on the cusp of graduating from college in 1961, and followed them for 4 years. The 1964 follow-up wave included a women's supplement, which asked women specifically about gender roles and balancing work and family. While the full sample size of *Great Aspirations* is around 35,000 individuals, approximately 8,000 women responded to the 1964 supplement. To illustrate fact 1, I focus on a particular question from the women's supplement that asked respondents whether they expected to work at various stages of their lives.

Fact 2, the shift of female employment from routine cognitive to non-routine cognitive occupations, is illustrated using the annual Current Population Survey March Supplement (CPS ASEC) between 1976 and 2019, obtained from IPUMS (Flood et al. 2022). I restrict the samples to employed civilian individuals aged 18 to 55. I use a routine/non-routine, cognitive/manual job classification analogous to that used by Acemoglu and Autor (2011) and Cortes, Jaimovich, Nekarda, et al. (2020). Table 1 illustrates how occupations are broadly grouped into these categories. Appendix B provides more details on the exact mapping of occupation codes to these categories. Additionally, I use the 1970 Census to illustrate occupational differences in skill requirements and returns to experience.

Table 1: Classification of Occupation Groups

Category	**Broad Occupation Groups Included**
Non-Routine Cognitive	Managers, Professionals, Technicians
Routine Cognitive	Clerical, Administrative, Sales
Routine Manual	Production, Operators
Non-Routine Manual	Personal Services, Food/Cleaning, Protective Services

Notes: This table shows the categorization of broad occupational groups into routine/non-routine, cognitive/manual categories, based on the approach of Acemoglu and Autor (2011) and Cortes, Jaimovich, Nekarda, et al. (2020). The specific 3-digit occupation codes which are included in each category are detailed in Appendix B.1.

Finally, the link between women's expected work horizon and occupational sorting in fact 3 is established using data from the National Longitudinal Survey of Young Women

[4] I thank Claudia Goldin for sharing *Great Aspirations* and providing instructions on how to use and analyse the data.

(NLS-YW) as well as the General Social Survey (GSS). The NLS-YW was a longitudinal survey (conducted every 1-2 years) which followed women who were aged 14-24 in 1968 through their adult lives, tracking education, economic, and family outcomes. The survey asked women a forward-looking question, whether they expected to work or "keep house," at age 35. I keep all individuals who responded to this question at ages 16, 17, and 18 (i.e., prior to college or to labor force entry) and create a panel of their labor market outcomes when they are 22 or older. This enables me to examine the correlation between work expectations stated and fixed as teenagers, with eventual occupation in adulthood, conditional on working.

For social norms, I turn to the GSS, which, by contrast is a cross-sectional data set on views and attitudes on social questions. It also includes basic demographic and economic information on respondents. I use the 1977 wave, which is the first year in which respondents were asked about their attitudes regarding child-rearing. 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 keep employed individuals aged 22-55 in the sample, and examine the correlation between their views on this question and the type of occupation that they have, conditional on working.

Fact 1: From Intermittent to Continuous Work Horizon

The defining characteristic of the Quiet Revolution pertains to women's work horizon. Before 1970, it was typical for women – even college educated women – to leave the labor force for many years in order to raise children. This U-shape in labor force participation over the life cycle was something that women expected and planned for, as unique evidence from the survey *Great Aspirations* shows. Women who had graduated from college in 1961 were asked about their expectations of working at various periods of life as part of the 1964 follow-up survey.[5] The stages of life and expectations are reported in Table 2.

Table 2: Work Expectations of Women in *Great Aspirations* by Life Phase

Period of Life	Share Expect to Work	Share Expect Not to Work
After marriage, before children	0.84	0.12
Youngest child under 3 yrs old	0.20	0.70
Youngest child 3-5 yrs old	0.24	0.64
Youngest child 6-12 yrs old	0.52	0.32
Youngest child in high school	0.64	0.16

Notes: This table shows the share of non-missing respondents to the *Women's Role* supplement to the 1964 wave of the *Great Aspirations* survey. The question posed to respondents was, "For each of the following periods of your life, circle whether you expect to be working full time, part time, or not at all." Approximately 8,000 women answered the question, although the exact number varies slightly for the period of life. Survey weights are used in calculating the shares. "Expect to Work" includes women who anticipate either full-time or part-time work. "Expect Not to Work" includes women who reported that they expect not to work at all. The remaining category, not shown in the table, is women who reported that they were unsure.

[5] In the case that a woman had already entered one of these stages of life, she was asked to report what she actually did, rather than her expectation.

Table 2 shows clear evidence of an intermittent work horizon: 84% of these young women expected to work before having children, and 64% expected to do so after their children were sufficiently grown up. However, when their children were young, the vast majority expected not to work at all—not even part-time—thus generating a U-shape in expected labor force participation over the life cycle. Given the timing of the survey, we know that this work horizon was expected when these women were young and choosing a career path and human capital investments. The fact that the women included in the survey all had a college degree is particularly striking and suggestive of a deep-seated social norm; even high human capital women anticipated exiting the labor force when their children were young.

A major change was about to unfold with subsequent generations of women. As evidenced in Figure 2, women born approximately 1950 onward started to work continuously over the life cycle. Unsurprisingly, given the evidence in Table 2, labor force participation of mothers of young children was the key driver of this shift toward continuity: labor force participation of adult women with children under the age of 5 grew from 29% to 59% between 1970 and 1990.[6]

Fact 2: Women Shifting into Non-Routine Cognitive Professions

For the Quiet Revolution to plausibly explain the disproportionate rise of non-routine employment among women compared to men, it must be that the non-routine occupations that women start entering during this time differ in horizon-relevant attributes, such as requisite educational investment or returns to experience. Indeed, that is the pattern exhibited in the data. The widening gender gap in routine employment in Figure 1 emerges *within* cognitive occupations. In particular, it reflects a dramatic shift of female employment out of routine clerical, administrative, and sales roles, and into non-routine managerial, professional, and technical roles. Figures 3 and 4 show that the aggregate decline in routine clerical, administrative and sales roles, and the aggregate rise of non-routine professional and managerial employment, over the past 50 years have been driven by women.

While over 40% of employed women in the 1970's were in routine cognitive jobs, since the 1980's this figure has plummeted by 16 percentage points, as evidenced in Figure 3. By contrast, the share of employed men in routine cognitive occupations exhibits no trend over this period and has remained relatively constant around 15%.[7] Therefore, the decline of aggregate employment in routine cognitive jobs reflects the fact the women are less likely to be in this type of work, conditional on working.

Similarly, Figure 4 shows that the share of employed women in non-routine professional, managerial, and technical occupations has more than doubled since 1972, from 22% to 46%. Again, the share of employed men in this type of work has remained stable, with a slight uptick since the 2010's. The aggregate rise in non-routine cognitive employment is thus almost entirely driven by women.

[6] Author's own calculations, using data from the U.S. Census.

[7] The discontinuity evident between 1982-1983 is due to a reclassification of some occupation codes in the CPS, and appears also in Cortes, Jaimovich, Nekarda, et al. (2020).

Figure 3: Routine Cognitive Share of Total Employment

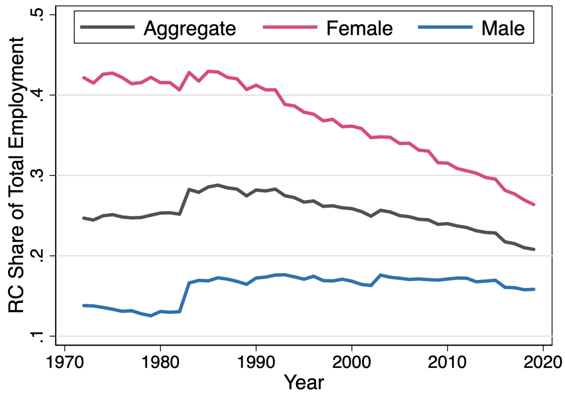
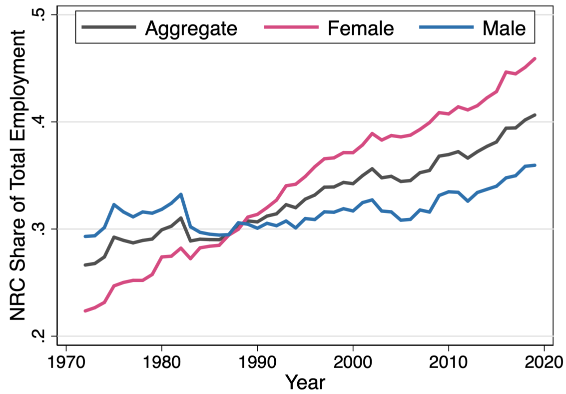


Figure 4: Non-Routine Cognitive Share of Total Employment



Notes: These figures plot the share of total employed individuals — on aggregate and by gender — in routine cognitive jobs (left) and non-routine cognitive jobs (right). The shares are calculated using working-age employed individuals aged 18-55 in CPS ASEC between 1972-2019. Employment in routine and non-routine manual jobs are not depicted in these figures, hence the black (or pink or blue) lines in the left figure and right figure do not sum to 1. See Appendix B.2 for the analogous figures for manual jobs. See Appendix B.1 for the full occupation classification.

The employment shares for men and women in routine and non-routine manual jobs have followed almost identical trends since the 1970's, and thus do not contribute to the widening gender gap in the routine employment share (see Appendix B.2). The routine employment share for women has declined more than that for men because women have disproportionately shifted out of routine cognitive jobs into non-routine cognitive jobs, while men have not.

The Quiet Revolution may explain this shift of female employment, because non-routine cognitive occupations are uniquely compatible with a continuous work horizon. Table 3 shows evidence of this from the 1970 Census: non-routine cognitive occupations use cognitive skill investments more intensively and exhibit higher returns to experience. In 1970, the share of non-routine cognitive workers who had four or more years of college education was 49%, while in all other occupation categories it was less than 10%. Additionally, income growth between ages 25 and 45 was over 50% in non-routine cognitive for men, who have high attachment to the labor force. It was substantially lower for other occupations, especially manual jobs, which tend to have a flat earnings-age profile.

Table 3: Income Growth and Education in Different Occupation Groups

Occupation Type	Income Growth (Ages 25-45)	Share with College Degree
Non-Routine Cognitive	53%	49%
Routine Cognitive	33%	9%
Routine Manual	14%	2%
Non-Routine Manual	6%	2%

Notes: This table shows patterns of income growth and educational attainment among employed individuals in different occupation groups using the 1970 Census. Income growth between ages 25 and 45 is calculated for full-time, full-year employed men. The share of workers with a college degree is calculated using all employed individuals aged 18-55 within each occupation group. Employed individuals who report 4 years or more of college are classified as having a college degree.

Fact 3: Correlation between Work Horizon & Occupation

The final motivating fact draws a direct link between the previous two: women who either expect to work continuously, or who have more progressive social norms regarding mothers working, are more likely to sort into non-routine cognitive occupations than other women, conditional on working.

Expected Work Horizon & Occupation Conditional on Working

First, I document a correlation between expected work horizon and occupational sorting in the NLS-YW, a longitudinal survey of women who were age 14-24 in 1968. The survey asked these young women annually whether they expected to work or "keep house" when they were 35 years old. While the phrasing of the question did not explicitly mention children, given the cultural context at the time of the survey, responses likely capture whether women expected to work continuously or intermittently, as in Table 2.

I create a sample of women who answered this question at ages 16, 17, and 18. This would typically be prior to labor market entry and investment in human capital via college. I create a variable called (Prob in LF at 35_i), which is an average of the responses across ages 16-18 of each woman in the sample. This variable takes the value 1 for women who report in all three years that they expect to work at age 35, and 0 for those who consistently report that they do not expect to work at age 35. Women who changed their responses across survey years have an intermediate value for this variable, reflecting plausible uncertainty about their future participation. I link these expectations with demographic variables, including fertility histories, as well as an unbalanced panel of labor market outcomes when the respondents were age 22 and older, up until the survey year 1993.

First, I show that the expectations variable, (Prob in LF at 35_i), is associated with higher labor force participation of women when they have children. I run a regression of labor force participation on expectations in which the unit of observation is the woman-year. Equation (1) shows the regression specification. I include an indicator for whether a woman has a child under the age of 5 in a given year, (Child Under 5_{it}), as well as an interaction of this indicator with (Prob in LF at 35_i). The latter is the coefficient of interest: if positive, it indicates that a woman who reported as a teenager that she expected to work at age 35 is more likely to work when she has a young child, compared to a woman who had different expectations as a teenager. Additionally, I control for individual fixed effects, α_i and age fixed effects, γ_{age}.

$$\text{LFP}_{it} = \beta_1 \cdot \text{Child Under } 5_{it} + \beta_2 \cdot (\text{Child Under } 5_{it} \times \text{Prob in LF at } 35_i) + \alpha_i + \gamma_{\text{age}} + \epsilon_{it} \quad (1)$$

The result of this regression is reported in column (1) of Table 4. The estimated coefficients indicate that having a young child is associated with a 26 percentage point decline in labor force participation. However, the decline is substantially attenuated among women who as teenagers had a higher expectation of working in the future, as evidenced by the positive coefficient on the interaction term. Thus, women who reported as teenagers a higher expectation of working at age 35 are less likely to drop out of the labor force when they have children.

Table 4: Women's Expected Work Horizon and Labor Market Outcomes

		Occupation Conditional on Working		
	(1) In Labor Force	(2) Non-Routine Cog.	(3) Routine Cog.	(4) Manual
Child Under 5	-0.256***			
	(0.016)			
Child Under 5 × Prob in LF at 35	0.096***			
	(0.024)			
Prob in LF at 35		0.187***	-0.082***	-0.105***
		(0.016)	(0.017)	(0.015)
Dep. Var. Mean	0.76	0.33	0.39	0.28
No. Women-Years	7118	5417	5417	5417
No. Women	752	747	747	747
R^2	0.442	0.061	0.022	0.078

Notes: This table presents estimated regression coefficients from Equations (2). The sample is an unbalanced annual panel of women aged 22 and older in the NLS-YW. The women were aged 15-16 in 1968 and responded to the question regarding what they expected to be doing at age 35 at age 16, 17 and 18. The unit of observation is the woman-year. Columns (2) to (4) include only years when a woman was in the labor force. (Prob in LF at 35) is the average expectation of being in the labor force at age 35, across responses given between ages 16-18. The outcome for column (1) is an indicator for being in the labor force. The outcomes for columns (2) to (4) are indicators for having an occupation in each group presented in Table 1. I combine both routine and non-routine manual jobs for the manual category in column (4). Standard errors are reported in parentheses. * indicates significance at $p < 0.10$, ** indicates significance at $p < 0.05$, and *** indicates significance at $p < 0.01$.

Next, I examine how these expectations stated as a teenager relate to the types of occupations which women enter later in life. To that end, I restrict the sample to woman-year observations in which the woman is in the labor force. I regress an indicator for occupation type on the variable (Prob in LF at 35_i), as in Equation (2). Additionally, I control for age fixed effects, to capture the fact that there may be occupational differences in the job ladder, and year fixed effects, to capture time-varying factors which affect all women, such as technological change or discrimination. Finally, I control for race, as Asian and black women faced other forms of labor market discrimination.

$$\text{Occ. Type}_{it} = \beta_0 + \beta_1 \text{Prob in LF at } 35_i + \mathbf{X}_{it}\boldsymbol{\beta} + \gamma_t + \epsilon_{it} \tag{2}$$

The results from this regression are shown in columns (2) to (4) of Table 4. Women who as teenagers expected a higher probability of working continuously are significantly more likely to be observed in a non-routine cognitive, conditional on working at any given age and in any given year. This expectation has a negative impact on female employment shares both in routine cognitive and manual jobs. This correlation is consistent with the hypothesis of this paper, that the Quiet Revolution, in expanding women's work horizons, shifted female labor supply toward non-routine jobs, especially the high-skill managerial and professional occupations.

The regression coefficients in columns (2) to (4) will be used in the calibration of my model, as described below in Section 4.

Social Norms & Occupation Conditional on Working

To corroborate this pattern, I additionally show a correlation between progressive social norms regarding working mothers and entry to non-routine professions. Changing social norms regarding the acceptability of mothers working are, according to Goldin (2021), a key driver of the Quiet Revolution. They have been shown to be an important driver of the rise of labor force participation of mothers and, by extension, the increase in women's life cycle labor force attachment (Fernández, Fogli, and Olivetti 2004; Fernández and Fogli 2009; Fernández 2013; Fogli and Veldkamp 2011).

I use data on social norms from the 1977 cross-section of the GSS, keeping individuals aged 22-55 who were currently 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 (3):

$$\text{NRC}_i = \alpha + \beta_0 \text{Progressive}_i + \boldsymbol{\beta_1 X_i} + \epsilon_i \tag{3}$$

where $\boldsymbol{X_i}$ is a vector of control variables, including race, age, marital status, spouse's employment status, and presence of children. The results from this regression are shown in Table 5.

Table 5: Social Norms & Occupational Sorting

	Women		Men	
	(1)	(2)	(3)	(4)
Progressive	0.241***	0.191***	0.0441	-0.0175
	(0.0484)	(0.0480)	(0.0503)	(0.0467)
Education Controls	No	Yes	No	Yes
Dep. Var. Mean	0.24	0.24	0.34	0.34
Observations	301	301	373	373
R^2	0.143	0.261	0.095	0.247

Notes: This table presents estimated regression coefficients from equation (3). 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 1. Standard errors are reported in parentheses. * indicates significance at $p < 0.10$, ** indicates significance at $p < 0.05$, and *** indicates significance at $p < 0.01$.

Column (1) shows the results for women. There is a strong correlation between a woman's attitudes toward working mothers and her entry to non-routine cognitive occupations. This is consistent with the hypothesis that a woman's work horizon matters for the type of work she performs. However, one might dispute that the channel is work horizon; perhaps attending college makes women more progressive and enables them to access non-routine cognitive jobs. To illustrate that education does not drive this correlation, I include in column (2) a control for education. While this slightly reduces the magnitude of the estimated coefficient on the progressive indicator, a positive correlation remains. This suggests that these norms are related to female occupational sorting even independently of education, strengthening the work horizon interpretation.

To address an additional concern that high-skill workers are simply more progressive in general, I repeat the exact same regression on a sample of employed men in columns (3) and (4). There is no correlation between male views on the acceptability of working mothers and their entry to non-routine professions. This suggests that the correlation in columns (1) and (2) operates through a channel that uniquely affects women, such as expected work horizon.

3 Theory

I develop a general equilibrium model of the labor market to study the aggregate impact of the Quiet Revolution. Workers pick their human capital investment and occupation at the beginning of life, taking into account their expected work horizon. Women face a higher probability of work interruptions than men do, and this probability falls as the Quiet Revolution progresses. Routine and non-routine jobs differ in "skill dynamics" (educational requirements, returns to experience, and skill depreciation), making them more or less suitable to an intermittent work horizon. The key aspect of the theory is that individuals choose their occupation and education investment up front, hence if they expect to work intermittently, this affects the *ex ante* human capital investment and occupation choice. Additionally, women are subject to occupation-specific wage discrimination, which drives a further wedge between women's and men's occupational sorting. Finally, firms can substitute automation technology for routine workers.

3.1 Labor Supply

The model of labor supply builds on that of Hsieh et al. (2019). There are equal-sized populations of men and women, who live for 3 periods and are born with heterogeneous innate skills ϵ across a set J of occupations, which includes several market occupations as well as the home sector H. The market occupations consist of white-collar non-routine and routine jobs, denoted N and R, as well as a manual job M. Individuals solve a life cycle Roy model, where at the beginning of life, they pick their occupation and choose how much to invest in human capital, "once and for all." Each period thereafter, they consume the income they earn in their chosen occupation, with a per-period utility function of $\log(c)$. Workers do not save or borrow. Utility in each model period is assigned a weight, denoted β_1, β_2, and β_3, which captures the length of that phase of life.

For model exposition, I assume innate skills $\epsilon = \{\epsilon_M, \epsilon_R, \epsilon_N, \epsilon_H\}$ are drawn from a joint independent and identically distributed (i.i.d.) Fréchet distribution with shape parameter θ, scale equal to 1, and minimum at 0. Later for the quantitative model, I will relax the i.i.d. assumption and allow for correlation in innate skills, which I describe below in Section 3.7. The efficiency units of a worker in his or her chosen occupation in period t, denoted ℓ_{jt}, depend on this innate skill draw, but also on human capital investments undertaken and accumulated work experience, described below.

The utility of a worker of gender $g \in \{m, w\}$ in occupation j in period t is $\log(w_{jt}(1 - \tau_{gjt})a_{gj}\ell_{jt}b_{gjt})$. Here, w_{jt} is the wage per efficiency unit in occupation j, τ_{gjt} is occupation-specific wage discrimination faced only by women ($\tau_{mjt} = 0 \; \forall \; j$), a_{gj} reflects gender-specific productivity in occupation j, and b_{gjt} capture gender-specific non-monetary preferences for occupation j. The home sector H has wages normalized to 1 and features neither wage discrimination ($\tau_{wHt} = 0$) nor gender differences in productivity ($a_{mH} = a_{wH}$).

The 3 model periods correspond to typical phases of life: young & single, married with young children, and older married. Individuals are assumed to move deterministically through these phases of life, but couple formation and fertility are not modeled.

Men and women differ in their work horizon. With exogenous probability $\rho \in [0, 1]$, women are unable to work in period 2, the typical child-rearing period. The realization of the shock is unknown *ex ante*, so women make their choice of occupation and skill investment expecting that with probability ρ they will face a work interruption in period 2. Men do not face the risk of an interruption in period 2, which is equivalent to $\rho = 0$ for men. The Quiet Revolution will be modeled as a decline in ρ, which is meant to capture in a reduced-form way changing social norms and access to birth control.

3.1.1 Skill 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 Mincerian 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 signaling large required investments in human capital.

2. Returns to experience (γ_j): A worker who performs occupation j at age t will see his or her efficiency units in that occupation scale up by a factor $\gamma_j \geq 1$ if he or she continues to work at age $t + 1$. Formally, $\ell_{j,t+1} = \gamma_j \ell_{j,t}$.

3. Skill depreciation (δ_j): A worker who exits the labor force for a 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.

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 $\ell_{Ht} = \epsilon_H$.

3.1.2 The Worker's 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, solves the problem:

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

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 over time. 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 3.

3.2 Labor Demand

A representative firm produces a numeraire final consumption good, Y, by combining output from two intermediate sectors, a manual sector and a cognitive sector. These intermediates combine in a CES production function with elasticity of substitution $\sigma < 1$:

$$Y = Z\left((A_M M)^{\frac{\sigma-1}{\sigma}} + S_{net}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

where $A_M M$ is the output of the manual sector, which uses only manual workers M. S_{net} is the net output of the cognitive ("white-collar") sector. The parameter A_M captures the labor productivity of manual work M, while Z represents total factor productivity.

Service output S is produced using both non-routine labor N as well as routine tasks $\tilde{R}$, which combine in a second CES nest and are assumed to be gross complements:

$$S = \left(N^{\frac{\lambda-1}{\lambda}} + \tilde{R}^{\frac{\lambda-1}{\lambda}}\right)^{\frac{\lambda}{\lambda-1}} \qquad \text{with} \quad \lambda < 1$$

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

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

Computers C are produced using intermediate output of the service sector S. The cost of computers in terms of S is denoted p_C, which is exogenously given and represents the state of automation capabilities.[8]

As factor markets are perfectly competitive, the representative firm takes wages as given and solves:

$$\begin{aligned} \max_{M,R,N,C} \quad & Z \left((A_M M)^{\frac{\sigma-1}{\sigma}} + (S_{\text{net}}(N,R,C))^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \\ \text{where} \quad & S_{\text{net}}(N,R,C) = S(N,R,C) - p_C C \end{aligned} \tag{5}$$

3.3 Steady State Equilibrium

The model is solved in an overlapping generations steady state, in which workers have rational expectations about future wages. Equilibrium consists of an allocation (M^*, R^*, N^*, C^*) and wages $w^* = (w_M^*, w_R^*, w_N^*)$ 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.

3.4 Implications of the Quiet Revolution for Labor Supply

The Quiet Revolution reflects a shift in women's work horizon from intermittent (high ρ) to continuous (low ρ). This change matters for the supply of female efficiency units to different occupations because occupations differ in skill dynamics. The Quiet Revolution affects both women's propensity to enter different occupations, as well as their investments in human capital and accumulated returns to experience.

To capture the intuition behind the effect of intermittency and skill dynamics on the occupation choice, consider a simple comparison of an occupation with strong dynamics and an occupation without dynamics. Figure 5 plots utility over the life cycle in these two hypothetical occupations for a continuous worker (recall that there is no saving in the model, so per-period utility is an increasing function of current labor income). The black dots are utility if the worker enters the non-dynamic occupation, while the blue are utility in the dynamic occupation. The dynamic occupation features returns to experience,

[8] The assumption that C is derived from service output only, rather than from the final consumption good, is adopted to ensure the decision to automate depends on the relative wages of the white-collar workers, R and N, but not on that of the manual workers, M. This means that the extent of white-collar automation, C, is self-contained to that sector.

captured by the upward slope of the blue line: labor income, and hence consumption and utility, grows over the life cycle. This also requires a human capital investment, h, which imposes an up-front utility cost, represented as a downward shift of the blue line. The continuous worker chooses his occupation to maximize the sum of the dots; in this example, he prefers the dynamic occupation.

Figure 5: Life Cycle Utility of Continuous Worker

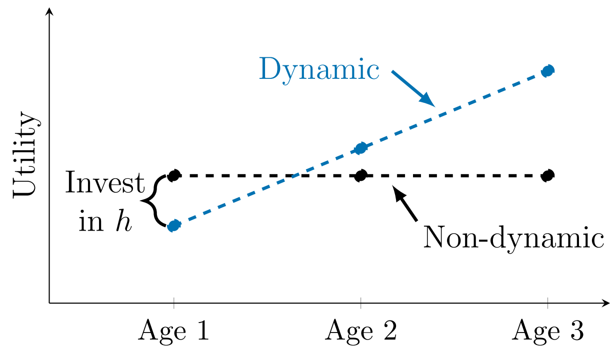
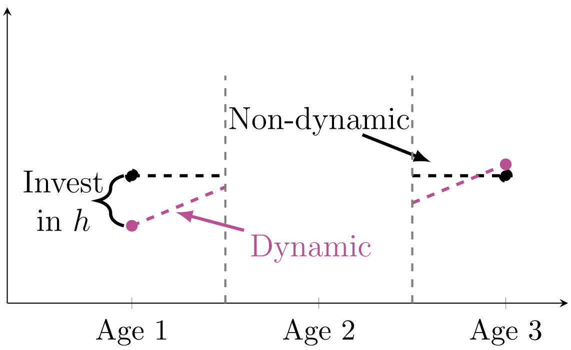


Figure 6: Life Cycle Utility of Intermittent Worker



Notes: These figures show a comparison of life cycle utility in a dynamic vs. a non-dynamic occupation for a continuous worker (left) and an intermittent worker (right). The dynamic occupation is assumed to have human capital requirements, returns to experience, and skill depreciation. The other occupation does not.

By contrast, the life cycle utility of an intermittent worker—one who gets the ρ shock in the model—is depicted in Figure 6. This worker is unable to work at age 2, hence does not get utility from labor income at that stage. The non-dynamic occupation is again represented in black, while the dynamic occupation is represented in pink. If the intermittent worker chooses the dynamic occupation, she not only forgoes returns to experience during age 2, but she also incurs depreciation: her flow utility at age 3 in the dynamic occupation is lower than it would have been at age 2, had she continued working. In this example, total life-time utility is higher under the non-dynamic occupation than the dynamic occupation, hence the intermittent worker prefers the former.

This intuition underpins the following three propositions, which formally show the effects of the Quiet Revolution on female labor supply in the quantitative model.

The Quiet Revolution Increases Women's Human Capital Investments

Given the properties of the log utility function, the human capital investment decision from 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:*

$$h^*(\phi_j, \rho) = ((3-\rho)\eta\phi_j)^{\frac{1}{\zeta-1}} \tag{6}$$

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

Proof. See Appendix A.1. □

The parameters which influence the optimal choice of skill investment in equation (6) 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. Proposition 1 additionally implies that as the Quiet Revolution progresses and ρ falls, the gender gap in human capital investment and income within each occupation falls.

It is worth noting that neither wages nor wage discrimination in a given occupation affects the optimal choice of human capital. Mathematically, this result stems from the per-period log utility of consumption specification. Intuitively, this means that marginal utility benefit of investment in human capital in a given occupation does not depend on the level of wages or discrimination. If women face wage discrimination $\tau_{wj} > 0$ and earn less than men in occupation j, a marginal increase in human capital investment h increases their per-period income by less than it would for men. However, because women have a lower level of earnings, there is an income effect, encouraging human capital investment among women. These forces offset each other and the marginal utility benefit of human capital investment for women is equivalent to that of men.

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 (6), $h^*(\phi_j, \rho)$, the worker's problem in equation (4) can be written succinctly as:

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

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. A worker of gender g prefers occupation j over occupation k if $\frac{\epsilon_j}{\epsilon_k} \geq \chi^g_{jk}$ where:

$$\chi^g_{jk} = \underbrace{\frac{a_{gk} w_k (1-\tau_k)}{a_{gj} w_j (1-\tau_j)}}_{\substack{\text{Wages \&} \\ \text{Discrimination}}} \times \underbrace{\frac{b_{gk}}{b_{gj}}}_{\text{Pref.}} \times \underbrace{\left(\frac{\gamma_k}{\gamma_j}\right)^{\frac{3-3\rho}{3-\rho}} \times \left(\frac{1-\delta_k}{1-\delta_j}\right)^{\frac{\rho}{3-\rho}} \times e^{\frac{\eta(\zeta-1)}{\zeta}(h^*(\phi_k,\rho)-h^*(\phi_j,\rho))}}_{\substack{\text{Skill dynamics \&} \\ \text{intermittency}}} \quad (7)$$

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^g_{jk}. Equation (7) highlights that occupation sorting is based on three considerations: wages (net of discrimination), preferences, and skill dynamics, which interact with intermittency. The first two considerations are standard in Roy models: occupation j is more attractive—that is, χ^g_{jk} 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 (7), ρ affects χ^g_{jk}, but only if occupations j and k differ in at least one skill dynamic parameter, γ, δ, 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, $\gamma_j \geq \gamma_k$, $\delta_j \geq \delta_k$, 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 A.2. □

The intuition behind Proposition 2 is that when women face $\rho > 0$, they respond more or less 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 $\frac{\gamma_k}{\gamma_j}$, 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, but opposite happens with depreciation: as men face no risk of leaving the labor force and incurring depreciation, occupational differences in δ do 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.

To quantify the impact of intermittency on the occupational sorting of women versus men, I define an "intermittency wedge," χ^ρ_{jk}, between occupation j and k as:

$$\chi^\rho_{jk} = \left(\frac{\gamma_k}{\gamma_j}\right)^{\frac{2\rho}{3-\rho}} \times \left(\frac{1-\delta_k}{1-\delta_j}\right)^{-\frac{\rho}{3-\rho}} \times e^{\eta^{\frac{\zeta}{\zeta-1}} \frac{(\zeta-1)}{\zeta} \left(3^{\frac{1}{\zeta-1}} - (3-\rho)^{\frac{1}{\zeta-1}}\right)\left(\phi_k^{\frac{1}{\zeta-1}} - \phi_j^{\frac{1}{\zeta-1}}\right)} \tag{8}$$

The intermittency wedge χ^ρ_{jk} captures how gender differences in work horizon affect the relative attractiveness of occupations j and k for women compared to men. Formally, it indicates how differences in work horizon—separately from discrimination and preferences—affect the ratio of χ^m_{jk} to χ^w_{jk}, which are defined in equation (7). Notice that $\chi^\rho_{jk} = 1$ if men and women have the same work horizon (i.e., $\rho = 0$). When $\chi^\rho_{jk} < 1$, it means that occupation j is better suited to a continuous work horizon than occupation k, all else equal. Men more readily enter occupation j versus k than women who face $\rho > 0$.

In Section 5, I will use equation (8) to quantify the impact of intermittency on women's occupational sorting as its own channel, distinct from discrimination and preferences.

Because the home sector is assumed to have no skill dynamics, a corollary to proposition 2 is:

Corollary 1. *Intermittency makes market work less attractive for women than for men.*

Corollary 1 implies that as the Quiet Revolution progresses, it can increase extensive margin participation of women beyond the mechanical decline in ρ, which directly increases the participation of women in period 2. Anticipating a higher probability of a long-term career, more women choose to enter market work in period 1.

The Quiet Revolution Affects Aggregate Efficiency Units Across Occupations

The Quiet Revolution impacts the aggregate supply of labor efficiency units to different occupations directly, as well as indirectly through changes in equilibrium wages. Only women are directly affected by a decline in ρ, while both men and women are affected indirectly through equilibrium wages, which changes their occupational sorting in period 1. Both indirect and direct effects need to be taken into account to determine how a decline in ρ affects the supply of female labor to different occupations and, ultimately, aggregate output.

There are four direct effects of a decline in ρ on female labor supply, taking as given wages. First, it induces greater human capital investments among women, as in Proposition 1. Second, a decline in ρ affects the occupational sorting and extensive margin choice of women in period 1, as in Proposition 2. Third, it mechanically increases the number of women working, by increasing participation of women specifically in period 2. Fourth, by enabling women to work continuously, a decline in ρ increases women's efficiency units of labor via accumulated experience. All of these factors

The aggregate supply of efficiency units of labor to market occupation j for gender g, as a function of wages w in all occupations as well as the probability of intermittency for g ($\rho \geq 0$ for women and $\rho = 0$ for men), is:

$$Q_{gj}(w,\rho) = a_{gj} \times \underbrace{e^{\eta h^*(\phi_j,\rho)}}_{\text{Investment}} \times \underbrace{\left(\pi_{gj}(w,\rho)\right)^{\frac{\theta-1}{\theta}}}_{\substack{\text{Selection-Adjusted}\\ \text{Population Share}}} \times \underbrace{\left(1+\gamma_j+\gamma_j^2+\rho(1-\delta_j-\gamma_j-\gamma_j^2)\right)}_{\substack{\text{Period 2 Employment \&}\\ \text{Accumulated Experience}}} \quad (9)$$

where π_{gj} denotes the share of the population of gender g who enters occupation j.[9] Closed-form expressions for π_{gj} are derived in Appendix A.3.

[9]Given the assumption of no occupational switching, π_{mj} is the share of the total male population in any occupation j. However, because share ρ of women who entered the labor force at period 1 will be out of the labor force at period 2, π_{wj} will be accurate for women at period 1 and 3 only, but will overstate the share of women in market occupations at age 2.

As intermittency declines with the Quiet Revolution, it increases the human capital investments undertaken by women, affecting the first component of equation (9) as in Proposition 1.

The second component of equation (9), the selection-adjusted population share, captures the contribution of occupational sorting to aggregate efficiency units. When more people enter occupation j, the effective units of labor supply increase, however the increase is not one-for-one due to selection on innate skill. As π_{gj} rises—that is, more individuals of gender g enter occupation j—the mean innate skill of the workers falls. Given the assumption of i.i.d. Fréchet skills, there is a closed-form expression for the mean innate skill of workers who select into occupation j, and it is inversely proportional to π_{gj}. The mean skill is $\bar{\epsilon}_{gj} = (\pi_{gj})^{-\frac{1}{\theta}}\Gamma(1-\frac{1}{\theta})$ (see Appendix A.4).

Finally, a decline in ρ means that more women are able to work at period 2, and that women are able to accumulate more experience and avoid skill depreciation. The last component of equation (9) captures these effects.

Proposition 3. *Suppose occupation j is more dynamic than occupation k, that is, $\gamma_j \geq \gamma_k$, $\delta_j \geq \delta_k$, and $\phi_j \geq \phi_k$, with at least one inequality holding strictly. Then, holding wages and other parameters fixed, $\frac{\partial \log Q_{wj}(w,\rho)}{\partial \rho} < \frac{\partial \log Q_{wk}(w,\rho)}{\partial \rho}$. That is, as ρ falls, $Q_{wj}(w,\rho)$ increases by a greater percentage than does $Q_{wk}(w,\rho)$.*

Proof. See Appendix A.5. □

Proposition 3 implies that in partial equilibrium, the Quiet Revolution will increase female efficiency units supplied to dynamic jobs by a greater percentage than less-dynamic jobs. The efficiency units supplied by men, $Q_{mj}(w,0)$, are unaffected in partial equilibrium by a decline in ρ. Ultimately, the extent to which this change in female labor supply across occupations in response to a decline in ρ translates to a change in *aggregate* efficiency units will depend on two factors.

First, it will depend on the share of total efficiency units in an occupation that are supplied by women. The aggregate supply of labor efficiency units to occupation j is the sum of that for men and women, $Q_j(w,\rho) = Q_{wj}(w,\rho) + Q_{mj}(w,0)$. Therefore, the percentage change in total efficiency units in any occupation j, $Q_j(w,\rho)$, induced by a percentage change in female efficiency units to that occupation, $Q_{wj}(w,\rho)$, will depend on the gender breakdown of the total efficiency units. If $Q_{mj}(w,0)$ is high relative to $Q_{wj}(w,\rho)$—meaning men supply more of the total efficiency units to j than women do—then a given percentage change in $Q_{wj}(w,\rho)$ will generate a substantially muted percentage change in total $Q_j(w,\rho)$, even in partial equilibrium.

Second, the full effect of the Quiet Revolution on the aggregate supply of efficiency units to each occupation must take into account equilibrium effects. As female labor supply to an occupation grows, this may put downward pressure on the relative wage in that occupation, causing men to leave. Such equilibrium effects will attenuate the direct effects of a decline in ρ highlighted in Proposition 3.

For these reasons, the impact of the Quiet Revolution on total efficiency units of labor in equilibrium is *ex ante* uncertain. My equilibrium model incorporates all these forces.

3.5 Implications of the Quiet Revolution for Productivity

The Quiet Revolution influences aggregate productivity, defined as market output per worker, by altering the mean effective skill across all workers within each market occupation. Effective skill combines innate skill with human capital investments and accumulated experience. The Quiet Revolution impacts mean effective skill in each occupation through three channels: sorting in period 1, labor force continuity in period 2, and human capital investments.

The first channel, sorting, affects mean effective skill by altering innate skill alone. Recall that the mean innate skill of workers of gender g in occupation j is given by $\bar{\epsilon}_{gj} = (\pi_{gj})^{-\frac{1}{\theta}}\Gamma(1-\frac{1}{\theta})$, where π_{gj} is the share of the population entering occupation j in period 1 (see Appendix A.4). As the Quiet Revolution draws more women into dynamic occupations, both from less dynamic sectors and from the home, it lowers the mean innate skill of women in these occupations through selection. However, if women's entry into a dynamic occupation displaces less skilled men, the overall mean innate skill of workers in that occupation may increase.

The second channel, increased labor force continuity, changes the mean innate skill of workers in an occupation via a composition effect, and additionally enables women to accumulate more experience. The composition effect arises as women make up a larger share of the workforce due to more continuous employment in period 2. For a given occupational sorting in period 1, a reduction in ρ increases the share of the workforce who are women, simply because more women work in period 2. If women have higher average innate talent in an occupation than men, this increased attachment will raise the mean innate skill of all workers. Moreover, as women work more continuously, they gain experience, enhancing their effective skill independent of their innate skill. The extent to which this experience increases the mean effective skill across all workers in an occupation depends on the share of occupational employment that is female.

The third channel follows from Proposition 1: women invest more in education with a more continuous career horizon, increasing their effective skill, particularly in occupations with high education requirements (high ϕ_j). Again, the female share of occupational employment will influence the extent to which this channel increases the mean effective skill of all workers.

Unlike the productivity effects of the Quiet Revolution, a reduction in wage discrimination against women only induces changes in the mean effective skill of workers via occupational sorting at age 1. Because τ_{wj} does not affect women's human capital investment or her propensity to accrue experience, there is no further change in the mean effective skill per worker, besides that induced by changes in mean innate skill. This highlights a key difference between the productivity gains induced by the Quiet Revolution and falling discrimination. The former has dynamic implications, while the latter is purely static.

3.6 Changes in Labor Supply Trigger Endogenous Automation

The firm's problem in equation (5) can be split into two steps: first the maximization of $S_{net}(N, R, C)$, given wages for N and R, denoted in terms of S_{net}, and p_C, which is already in terms of S_{net}; and second, the maximization of final output with respect to M and S_{net}. Intuitively, the choice of how to run the "white collar" sector—the relative demand for N, R, and C—can be separated from the choice of how many manual workers to hire.

Denoting the wages of R and N workers in terms of S_{net} as $\tilde{w}_R$ and $\tilde{w}_N$, respectively, the first step is for the firm to solve:

$$\max_{R,N,C} \quad S(N, R, C) - p_C C - \tilde{w}_R R - \tilde{w}_N N$$

where $\tilde{w}_R$, $\tilde{w}_N$, and p_C are taken as given. This is equivalent to the firm taking w^R, w^N, p_S, and p_C as given, because $\tilde{w}_R = \frac{w_R}{p_S}$ and $\tilde{w}_N = \frac{w_N}{p_S}$.

Combining the first-order conditions for routine labor and computers yields $\frac{C}{R} = \left(\frac{\tilde{w}_R}{p_C}\right)^{\psi}$. Firms substitute computers for routine workers in performing the routine task when p_C is lower or when $\tilde{w}_R$ is higher. Given that $\lambda < 1$—that is, that non-routine labor and routine tasks are complementary—$\tilde{w}_R$ falls in R and rises in N. Therefore, if the Quiet Revolution sufficiently changes the supply of N and R labor, this can stimulate firms to automate more of the routine tasks (i.e., increase the ratio of $\frac{C}{R}$), which amplifies the shift in employment toward non-routine jobs.

3.7 Relaxing the Assumption of I.I.D. Innate Skills ϵ

In the next section, in which I calibrate the model, I allow for correlation in innate cognitive skills (ϵ_R and ϵ_N). To do this, I assume that the innate skill draw occurs in two stages. First, workers receive an i.i.d. Fréchet draw ϵ over the set $\{H, M, S\}$, where S refers to cognitive ("service") skill, which can be applied to either R or N. Based on this initial draw, workers decide whether to stay at home, enter manual jobs, or pursue white-collar/service occupations. The shape parameter of this first draw is θ_1.

Conditional on choosing a white-collar job, workers then receive a second i.i.d. draw from a Fréchet distribution with shape parameter θ_2, determining their skill in either R or N. The realized innate skill in these occupations is $\epsilon_S \epsilon_R$ for R and $\epsilon_S \epsilon_N$ for N. If $\theta_2 > \theta_1$, this indicates a positive correlation between innate skills in R and N. See Appendix A.6 for details on the formal implementation.

4 Model Calibration

I calibrate the model parameters to 1970 as an initial steady state, because this is before both the Quiet Revolution happened and automation technology became available. Later, I re-calibrate a subset of these parameters for the post-Quiet Revolution and post-automation era, which I take to be 2000, to capture the salient labor supply and labor demand forces which changed over these decades. The forces that evolve are: (1) the Quiet Revolution (ρ); (2) technological change, particularly increasing automation capabilities (Z, A_M, p_C); and (3) wage discrimination and non-monetary preferences (τ, b).

In calibrating the model, I assume the economy to be in an overlapping generations steady state, where the three coexisting generations are identical within-gender, except for the period of life and their accumulated experience or skill depreciation. Workers have rational expectations (i.e., they expect wages stay constant) when choosing their occupation and skill investment.

This section proceeds as follows. First, I describe the data used for calibration. Second, I describe how I calibrate the model parameters to 1970. Third, I show that the model fits several non-targeted moments well. Fourth, I discuss how I re-calibrate key parameters governing labor supply and labor demand to the post-Quiet Revolution, post-automation world.

4.1 Data

For both the 1970 and 2000 calibrations, I use U.S. Census data from IPUMS and restrict the sample to the working-age population (ages 18 to 55). I retain variables on employment status, 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, and number of weeks worked last year.

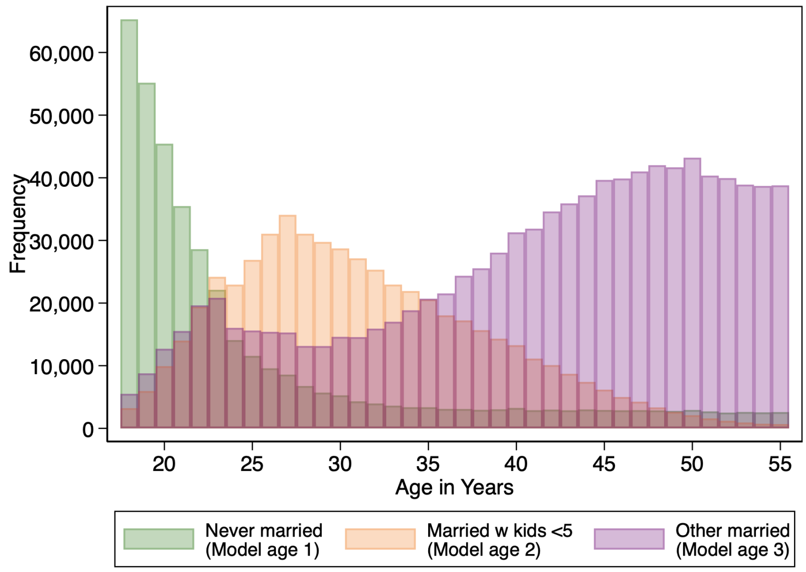
I assign individuals who are not employed to the home sector H, and employed individuals to one of the occupational groups $j \in \{M, R, N\}$ based on their 3-digit Census occupation codes, following the same occupation classification as in table 1. Using all employed individuals in the data, I calculate employment shares across the three market occupations by gender, as well as the the mean years of education beyond high school by gender and occupation.[10] Additionally, I calculate the share of men at home H.

Because the model structure and core mechanism concerns the work intermittency faced by women associated with child-rearing, I use data on family status to inform the extent of intermittency faced by women, as well as to define period weights in the individual's problem and population weights for aggregate labor supply. To do this, I assign individuals in the Census to model period 1 if they have never married, model period 2 if they are

[10] For the education statistics only, I use the 1980 Census because the 1970 Census truncates educational attainment at 6 years after high school. This is problematic for workers in the N jobs, because a large share attend graduate/professional school. In calculating the average years of education beyond high school, I assign individuals with high school or less 0 years of education, individuals with one year of college 1 year, etc., and then take the average.

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. Figure 7 plots a histogram of age in the Census within each of these life phases for both men and women. While there is some variation in ages within each of these life phases, the model structure is clearly 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 30's, and those in period 3 tend to be 40 or older.

Figure 7: Histogram of Ages within Each Model Period in 1970



Notes: The figure shows the distribution of actual ages (in years) reported by individuals in the 1970 Census who fall into each of the phases of life in the model. The sample includes men and women aged 18-55 who are not in the military or on a farm in the 1970 Census.

Table 6 presents statistics for each of these phases of life. I use the female labor force participation rate across these model periods to inform the Quiet Revolution parameter, ρ. The 25-75 percentile range of ages informs period weights $(\beta_1, \beta_2, \beta_3)$ in the individual's problem, which capture the typically length of each period of life. Additionally, I calculate population weights for aggregating labor supply.

Table 6: Statistics by Model Period from 1970 Census

Model Period	Mean Age	25^{th} Pctile.	75^{th} Pctile.	FLFP Rate	Pop. Weight
1	25	19	27	0.65	0.20
2	31	26	36	0.30	0.28
3	41	34	49	0.56	0.51

Notes: This table presents statistics for individuals assigned to each model period from the 1970 Census. The sample included men and women aged 18-55 for all statistics, except for the female labor force participation rate, which is calculated using women only. Period 1 is never-married, period 2 is married with a child < 5, and period 3 is other married.

Finally, I calculate wage and salary income earned last year by occupation, model period, and gender. To do so, I restrict the sample to individuals who reported working full-year, full-time. Since there is heterogeneity in actual ages within each model phase, I calculate mean income for individuals in the Census sample in 5-year age bins starting at the mean numeric age for each model period, as reported in table 6. For example, I calculate the mean income for model age 1 men in N occupations using the mean income of men aged 25-29 in employed in N jobs, and the mean income of model age 3 men in N using the mean income of men aged 41-45 employed in N jobs.

4.2 Calibrating the Model to 1970

There are 5 sets of parameters to calibrate: the skill distribution parameters (θ_1, θ_2, $\{a_{gj}\}_{j\in J, g\in\{m,w\}}$), the Quiet Revolution parameter (ρ), the skill dynamics parameters ($\{\phi_j, \gamma_j, \delta_j\}_{j\in J}$, η, ζ), the discrimination and preference parameters ($\{\tau_{gj}, b_{gj}\}_{j\in J, g\in\{m,w\}}$) and the technology parameters (σ, λ, ψ, Z, A_M, p_C). I proceed in four steps. First, I set some parameters exogenously based on commonly accepted values in the literature. Second, I calibrate the Quiet Revolution parameter ρ using the variability of female labor force participation over the life phases in the model. Third, I calibrate the occupational skill dynamics parameters using growth in income over the life cycle and years of education by occupation, as implied by the model. Finally, I calibrate the preference, discrimination, and technology parameters to rationalize the observed employment shares and wages earned by men and women.

4.2.1 Exogenously-Set Parameters

Several parameters are set exogenously, either based on estimates in the literature or by assumption. These are outlined in Table 7. I take values of the production elasticities of substitution between manual work and cognitive work (σ), between non-routine work and routine tasks (λ), and between routine workers and computer automation (ψ) from the literature. Additionally, I take the shape of the Fréchet skill distribution for the first skill draw from Hsieh et al. (2019) and a commonly accepted value of the returns to education, as cited by Acemoglu (2008).

Table 7: Exogenously-Set Parameters

Parameter	Meaning	Value	Source
σ	EOS b/t M and S	0.88	Rendall (2017)
λ	EOS b/t N and $\tilde{R}$	0.9	Goos, Manning, and Salomons (2014)
ψ	EOS b/t R and C	2.5	Autor, Levy, and Murnane (2003)
η	Mincer Return to Education	0.08	Acemoglu (2008)
a's	Productivity Differences	1	Assumption
ϕ_H	Skill Requirement in H	0	Assumption
γ_H	Returns to Experience in H	1	Assumption
δ_H	Depreciation in H	0	Assumption
τ_H	Wage Gap in H	0	Assumption

Notes: This table outlines the parameters that are set exogenously. Sources for parameter values are provided where applicable. The last four parameters are based on model assumptions, with no wage discrimination ($\tau_H = 0$) and no skill dynamics in the home sector ($\gamma_H = 1$, $\phi_H = 0$, $\delta_H = 0$).

Because I cannot separately identify gender differences in occupation-specific productivity (a) from wage discrimination faced by women (τ), I follow the baseline assumption of

Hsieh et al. (2019) and assume no gender differences in productivity.[11]

The final four parameters in Table 7 are set based on assumptions specific to the home sector. I assume there is no wage discrimination in the home sector ($\tau_H = 0$) and that the home sector is not dynamic, with no returns to experience ($\gamma_H = 1$), no skill requirements ($\phi_H = 0$), nor skill depreciation ($\delta_H = 0$).

4.2.2 Calibrated Parameters

The remaining 25 parameters are calibrated simultaneously to match model moments with their empirical counterparts, under the assumption of being in equilibrium. There is a direct mapping between each parameter and a particular empirical moment (see Table 9 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 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 6, while LFP_2 is the value for women in model period 2. This procedure yields a value of $\rho = 0.49$ 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.

Next I determine the skill dynamics parameters, which form the channel through which a change in ρ affects the economy. Given the assumption of no occupational switching, the parameters governing returns to experience (γ) and depreciation (δ) map directly to wage growth over the life cycle by occupation for men and women. Table 8 shows these empirical moments and the calibrated parameter values. As men face no risk of intermittency in the model, they always accumulate experience, thus $\{\gamma_j\}_{j\in J}$ are identified from observed male income growth between model periods 1 and 3 for each occupation. Similarly, because only women incur skill depreciation in the model, I calibrate $\{\delta_j\}_{j\in J}$ to match observed female income growth over the life cycle by occupation, given ρ and $\{\gamma_j\}_{j\in J}$. Share ρ of women incur depreciation over their lives, while share $1-\rho$ accumulate experience; thus, mean observed income growth of women between model periods 1 and 3 in each occupation is an average of these two groups.

The identification of $\{\delta_j\}_{j\in J}$ is based on the assumption that skill depreciation and forgone returns to experience when out of the labor force are the only drivers of the divergent gender wage gap over the life cycle. In other words, the assumption that the occupational wage discrimination terms, $\{\tau_j\}_{j\in J}$, affect the income of women relative to men at all ages equally is critical for identifying the depreciation parameters.[12]

[11]Alternatively, I could assume that there is no wage discrimination in the later period, and use the gender wage gap to inform differences in innate productivity of men and women across occupation.

[12]This assumption is consistent with prior work which has found that a large share of the gender wage gap in the late 20th century can be attributed to differences in accumulated work experience between men

Table 8: Experience and Depreciation Parameters: Targeted Moments and Values

Occupation	Male Inc. Growth	Estimate of $\boldsymbol{\gamma}$	Female Inc. Growth	Estimate of $\boldsymbol{\delta}$
N	1.51	1.23	1.05	0.43
R	1.30	1.14	0.99	0.27
M	1.12	1.06	0.99	0.20

Notes: This table presents the empirical moments used for calibrating the returns to experience γ and depreciation δ by occupation, in addition to the calibrated parameter values. Income growth for men and women is calculated as the ratio of mean income for workers in each occupation aged 41-45 compared to those aged 25-29 in the 1970 Census, as described in section 4.1.

To calibrate the 3 occupation-specific human capital requirement parameters, $\{\phi_j\}_{j\in J}$, and the convexity of the dis-utility of schooling, ζ, I minimize the sum of squared differences between the model-implied educational investment for men and women, $h(\phi_j, 0)$ and $h(\phi_j, \rho)$, and empirical mean years of education beyond high school by gender and occupation. That is, I target 6 moments to pin down 4 parameters. I obtain $\phi_M = 2.9$, $\phi_R = 5.5$, and $\phi_N = 9.4$.

Given $\{\phi_j\}_{j\in J}$ and the results in Table 8, it is clear that non-routine jobs are the most dynamic and in the sense that $\gamma_N > \gamma_R > \gamma_M$, $\delta_N > \delta_R > \delta_M$, and $\phi_N > \phi_R > \phi_M$. This is consistent with the hypothesis of this paper as well as the motivating evidence presented in Section 2.

The identification of the wage discrimination and non-monetary preference terms, $\{\tau_j\}_{j\in J}$ and $\{b_{gj}\}_{g\in\{m,w\},j\in J}$, follows the strategy of Hsieh et al. (2019). Wages in the home sector are normalized to unity as there is no measure of income for people out of the labor force and as such, w_H cannot be separately identified from preferences b_{gH}.

The discrimination parameters $\{\tau_j\}_{j\in J}$ in each market occupation are identified from the difference in mean income earned by young men and women in each occupation, after accounting for differences in human capital investments and adjusting for selection on skill.[13] The mean income for young men in each occupation is:

$$w_j \bar{\epsilon}_{mj} e^{\eta h(\phi_j,0)} = w_j \pi_{mj}^{-\frac{1}{\theta}} \Gamma(1 - \frac{1}{\theta}) e^{\eta h(\phi_j,0)} \tag{10}$$

Equation (10) uses the result from Appendix A.4 that the mean skill $\bar{\epsilon}_{gj}$ of gender g in occupation j is declining in the share of the population in occupation j, denoted π_{gj}. Similarly, the mean income of young women in the model is:

$$(1 - \tau_j) w_j \bar{\epsilon}_{wj} e^{\eta h(\phi_j,\rho)} = (1 - \tau_j) w_j \pi_{wj}^{-\frac{1}{\theta}} \Gamma(1 - \frac{1}{\theta}) e^{\eta h(\phi_j,\rho)} \tag{11}$$

Given observed population shares as well as the calibrated values of $\{\phi_j\}_{j\in J}$ and η, equation (10)—mean income of young men—enables me to back out equilibrium wages per efficiency unit in each occupation. Then, using both the calibrated parameters as

and women (Blau and Kahn 2017). However, if wage discrimination widened over the life cycle, or if it prevented women from entering higher returns to experience occupations within the broad categories N, R, and M, then my calibrated model will overstate the impact of the Quiet Revolution on occupational sorting, and understand the impact of changes in τ.

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

well as the equilibrium wages, equation (11)—mean income of young women—enables me to determine the wage discrimination $\{\tau_j\}_{j\in J}$ faced by women in each occupation to rationalize the observed gender gap in mean income by occupation.

To calibrate the gender-specific occupation preference terms, $\{b_{gj}\}_{g\in\{m,w\},j\in J}$, I impose that the model matches the observed aggregate share of men and women in the home sector H, accounting for ρ, as well as the aggregate employment shares of men and women across the three market occupations, given wages and parameters. These statistics are calculated for all individuals in the data and are not segmented by model period. I normalize preferences for the N occupation $b_{g,N} = 1$ for $g \in \{m, w\}$, because it is the relative preference terms that matter.

The parameters θ_1 and θ_2, which govern the dispersion of innate skills and thus the elasticity of labor supply across occupations, are calibrated via indirect inference to replicate the correlation between expected work horizon and occupational sorting reported in Table 4. In particular, holding fixed the wages and parameters in 1970, I pick θ_1 and θ_2 so that the model replicates these regression coefficients as the difference in female employment shares if women faced $\rho = 0$ vs. $\rho = 1$. Intuitively, the independent variable in regression equation (2) is an empirical counterpart to ρ in the model: women's expected probability of working continuously or intermittently over the life cycle. Thus, the correlation between future work expectations and the propensity to enter different occupations is informative about the elasticity of female labor across occupations. The calibrated values of θ_1 and θ_2 are reported in Table 9.

Table 9: Full List of Internally-Calibrated Parameters

Parameter	**Meaning**	**Value**	**Source**
Panel A: Skill Dynamics			
γ's	Returns to Experience	Table 8	Male Income Growth
δ's	Skill Depreciation Rate	Table 8	Female Income Growth
ϕ_M, ϕ_R, ϕ_N	Education Requirements	2.9, 5.5, 9.4	Education by Occupation
ζ	Schooling Dis-utility	1.63	Gender Gap in Education
Panel B: Labor Supply			
ρ	Probability of Intermittency	0.49	FLFP Over Life Cycle
θ_1	Fréchet Dispersion H, M, C	1.87	Table 4 Coefficients
θ_2	Fréchet Dispersion R, N	4.13	Table 4 Coefficients
τ's	Wage Discrimination	Table 11	Income of Women vs. Men
b's	Non-Monetary Preferences	Appendix C.2	Employment Shares
Panel C: Technology			
p_C	Price of Automation	0.0029	N vs. R Wages & Emp.
A_M	Manual Labor Productivity	0.0017	N vs. M Wages & Emp.
Z	Total Factor Productivity	13.1×10^5	Level of Real Wages

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

Finally, the technology parameters, p_C, A_M, and Z, are calibrated in a way similar to that used by Beraja and Zorzi (2024).[14] The intuition behind identification is that p_C

[14] Beraja and Zorzi (2024) use a production function with only two types of labor, routine and

determines the equilibrium ratio $\frac{w_N}{w_R}$ for a given amount of efficiency units in N and R. Similarly, A_M pins down the equilibrium ratio $\frac{w_M}{w_N}$, for a given amount of total efficiency units in M and N. Total factor productivity Z determines the level of wages in all occupations. Under the assumption of the skill distribution, I compute the aggregate efficiency units of labor in each occupation, N, R, and M, using the calibrated skill dynamics and intermittency parameters and the observed employment shares. Then, p_C, A_M, and Z are set so that the wages per efficiency unit determined from equation (10) satisfy market clearing at this allocation. Details are provided in Appendix C.1.

4.3 Model Fit

The calibrated model is able to replicate several important patterns—both targeted and non-targeted—in the data well. First, I show how the model fits the mean years of education by gender and occupation, which are used to calibrate the 4 education parameters (ϕ's and ζ). As Figure 8 shows, the model fits these moments in the data very closely. Further, it is clear that Proposition 1 is born out in the data: even conditional on working in the same occupation category, women had a smaller amount of formal skill investment than their male counterparts in the pre-Quiet Revolution world. Note that in my model, the only driver of differences in education investment between men and women within occupation is intermittency.

Figure 8: Skill Investment by Occupation

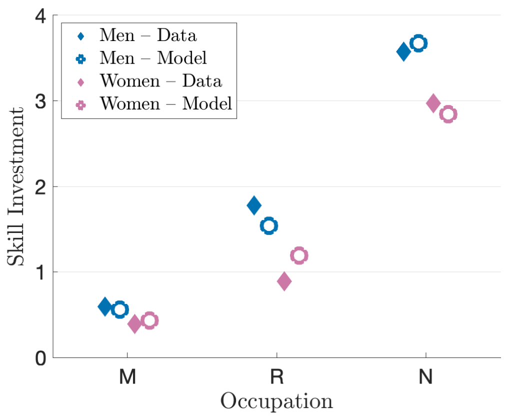


Table 10: Partial Equilibrium Effect of ρ on Female Employment Shares

	M	R	N
Panel A: Model			
$\rho = 0$ Emp. Share	0.308	0.392	0.300
$\rho = 1$ Emp. Share	0.414	0.474	0.112
Difference	-0.105	-0.082	0.187
Panel B: Regression Coefficients			
Regression Coef.	-0.105	-0.082	0.187

Notes: Figure 8 shows how the model fits the targeted moments in the calibration of the education parameters, ϕ's and ζ. Skill investment is measured in the Census as years of education beyond high school. Table 10 shows the model fit of the moments which inform the Fréchet dispersion parameters, θ_1 and θ_2. The regression coefficients reported in Panel B come from Table 4. The coefficients pertain to the difference in the employment shares of women who reported in the NLS-YW that they expected to work at age 35, compared to those who did not. Holding fixed wages and model parameters in the 1970 calibration, I calculate a model-analogue to this by measuring the difference in employment shares of women when I set $\rho = 0$ and $\rho = 1$.

Second, I show the model fit for the moments which inform the dispersion of the Fréchet skills across occupations, θ_1 and θ_2, which determine the elasticity of labor supply. I choose these parameters such that, at the 1970 calibrated parameters and in partial equilibrium, female employment shares evolve in response to ρ in the same way as the

non-routine, and assume that any changes in relative demand are driven by a decline in the price of computers.

regression coefficients reported in Table 4 from Section 2. Table 10 shows the moments in the model (Panel A) and the data (Panel B) used to calibrate θ_1 and θ_2. The first two rows show the employment share of women across the three market occupations in the model holding at 1970 parameters and holding wages fixed, when $\rho = 1$ or $\rho = 0$. The third row calculates the difference between the first two rows. The θ's are calibrated such that the partial equilibrium effect of changing ρ on employment shares in the model exactly replicates the regression results in Table 4, which are displayed in the bottom panel of Table 10.

Third, I show in Figure 9 that the calibrated model replicates the female population shares in each occupation across the periods of life. This serves as justification for the assumption that all women—regardless of education or skill level—experience the same probability of interruptions and hence are not strongly selected into the labor force in period 2.[15] The age-specific population shares in each occupation are non-targeted; recall that ρ is calibrated to match the variability of labor force participation over the life cycle for women, whereas other labor supply parameters are calibrated to match the employment shares of women across all ages. Thus, if it were the case that the U-shape in labor force participation were driven by low-skill women (e.g., manual workers, for whom interruptions are less costly in terms of forgone experience), the model would fail to replicate the share of the female population in each model period in each occupation.

Figure 9: Female Population Shares over Life Cycle

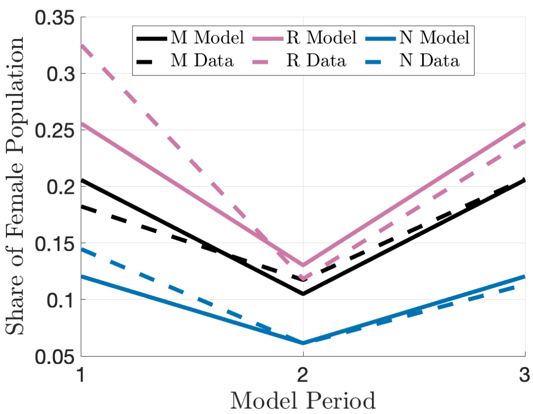
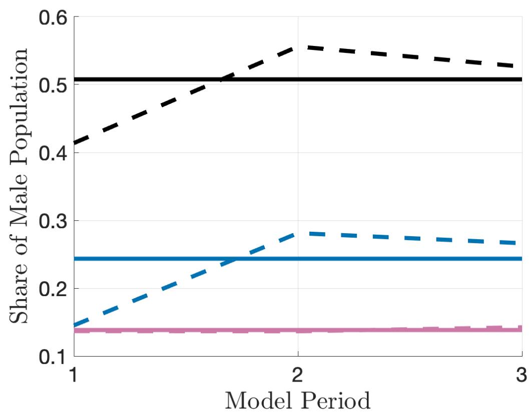


Figure 10: Male Population Shares over Life Cycle



Notes: These figures show the share of the female and male population in each occupation in each period of life in the 1970 steady state. The data is the 1970 Census and I restrict to individuals aged 18-55. The model periods map to the data as follows: 1 is never-married, 2 is married with children < 5, and 3 is other married.

Figure 10 shows the analogous moments for men. It can be seen immediately that in the data, labor force participation of men in period 1 is lower than in other periods of life, and that this reduces in particular the share of the male population in manual and non-routine jobs in that period. This may be due to positive selection of men into marriage, which is the distinguishing feature of period 1. As the model time structure is designed to capture the U-shape of labor force participation over the life cycle for women, the fact that it does not perfectly match male employment across these periods will not affect the core mechanisms pertaining to female labor supply.

[15]Recall that even college-educated women expected an intermittent work horizon, as late as the mid-1960's, as evidenced in Table 2.

Finally, while to the best of my knowledge, there are no estimates of the routine and non-routine occupation-specific returns to experience or skill depreciation parameters, Dinerstein, Megalokonomou, and Yannelis (2022) estimate returns to experience and depreciation for teachers, which would be a non-routine occupation. Their estimate for annual depreciation would imply a 36% depreciation rate over the horizon considered in my model. My estimate of 43% thus seems in a reasonable range, as teaching is likely to involve less skill atrophy than other non-routine occupations, such as medicine.

4.4 Calibrating the Model to 2000

In order to provide a quantitative assessment of the role of the impact of Quiet Revolution, I re-calibrate a subset of parameters using Census data from 2000 to capture the key labor demand and labor supply forces which are changing over time. These are: (1) the Quiet Revolution (ρ); (2) technology (p_C, A_M, Z) ; and (3) wage discrimination and non-monetary preferences (τ, b). The identification of these parameters follows the same procedure as I used for the 1970 calibration, but with Census data from 2000.

Table 11: Comparison of Paramater Values for 1970 and 2000

Parameter	**1970 Value**	**2000 Value**
Intermittency ρ	0.49	0.19
Manual Discrim. τ_M	0.67	0.54
Routine Discrim. τ_R	0.27	0.09
Non-Routine Discrim. τ_N	0.28	-0.12
Automation Price p_C	0.0048	0.0022

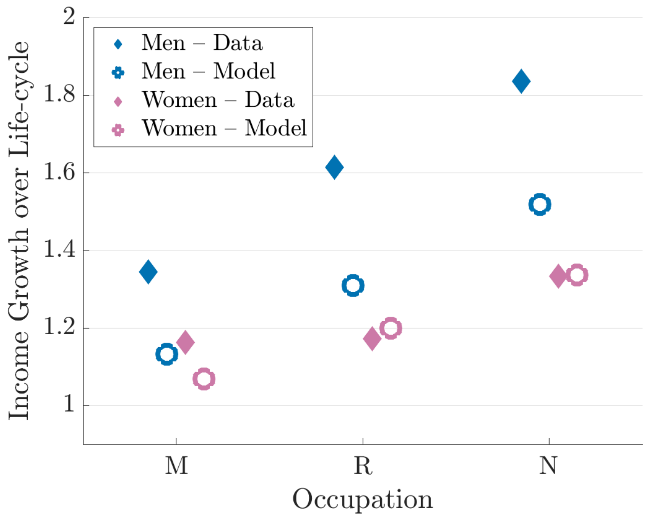
Notes: This table shows how the key parameters pertaining to the Quiet Revolution, discrimination, and automation technology change over time between 1970 and 2000.

Table 11 shows how the key parameters for my quantitative analysis change. All three forces—intermittency, discrimination, and the price of automation—decline, as expected. The parameters indicate that in the later period, women do not face discrimination in the non-routine occupations at all; if anything, they are subsidized, with a negative τ_{wN}.

In calibrating the model to 2000, I hold the skill dynamics parameters fixed at their 1970's levels. By simply changing ρ, the model is able to replicate income growth over the life cycle for women in each of the occupations remarkably well, as illustrated in Figure 11. This highlights that changes in women's work continuity are important for explaining the increase in life cycle income growth for women over this period.

However, Figure 11 shows evidence of an increase in returns to experience over this period for men. While my model doesn't capture this, the fact that it occurs fairly evenly across all occupations means that this is unlikely to impact occupational sorting in my model.

Figure 11: Income Growth over Life Cycle in 2000



Notes: This figure shows average income growth over the life cycle for men and women in the model vs. the 2000 Census data, by occupation. Income growth in the data is calculated between ages 25-29 and 41-45.

5 Quantitative Exercise

In this section, I turn to the main exercise of this paper: quantifying the impact of the Quiet Revolution on occupational sorting and aggregate productivity. First, I quantify the occupation sorting distortions faced by women; I show that in 1970, the intermittency wedge was almost equivalent in magnitude to wage discrimination in reducing the attractiveness of non-routine occupations for women. Second, I show that the rise of non-routine relative to routine employment for women between 1970 and 2000 in the model can be accounted for primarily by the Quiet Revolution and falling discrimination. Even on aggregate, the decline of routine relative to non-routine employment in the model is only partly explained by the decline in the price of automation, implying that labor supply factors matter for understanding this trend. Third, I highlight the implications of the Quiet Revolution for aggregate productivity, particularly in contrast to falling discrimination: the former raises output per worker by 3%, while the latter reduces it by almost 4%. Finally, I quantify the interaction between changes affecting female labor supply and the decline in the price of automation in accelerating the adoption of routine-substituting technology.

5.1 Quantifying the Intermittency Wedge in Occupational Choice

The effect of intermittency on occupation choice manifests in different sorting thresholds, χ^g_{jk} as in equation (7), for men and women across all pairs of market occupations and the home sector. Because the home sector H does not feature skill dynamics and is undistorted by discrimination, it serves as a suitable reference point for quantifying the attractiveness of market occupations for women relative to men.

Consider χ^g_{jH} (the minimum skill threshold $\frac{\epsilon_j}{\epsilon_H}$ for a worker of gender g to prefer market occupation j over H), which, for convenience, I state here:

$$\chi^g_{jH} = \frac{b_{gH}}{b_{gj}} \times \frac{1}{w_j(1-\tau_j)} \times \left(\frac{1}{\gamma_j}\right)^{\frac{3-3\rho}{3-\rho}} \times \left(\frac{1}{1-\delta_j}\right)^{\frac{\rho}{3-\rho}} \times e^{-\frac{\eta(\zeta-1)}{\zeta}h^*(\phi_j,\rho)}$$

Define $\chi_j = \chi^{men}_{jH}/\chi^{women}_{jH}$. The lower is this ratio, the higher is men's propensity to pick occupation j over the home sector, compared to women's. χ_j can be expressed using the intermittency wedge, χ^ρ_{jH}, as defined in equation (8):

$$\chi_j \quad = \quad \frac{b_{mH}}{b_{mj}} \cdot \frac{b_{wj}}{b_{wH}} \quad \times \quad (1-\tau_j) \quad \times \quad \chi^\rho_{jH}$$

Table 12 shows χ_j, the attractiveness of each market occupation for women relative to men, in the 1970 and 2000 calibrations. The total χ_j is reported in the first column. Columns 2 to 4 show the multiplicative decomposition of the total χ_j into there three factors: preference differences; wage discrimination; and the intermittency wedge, χ^ρ_{jH} (i.e, the product of Columns 2 to 4 yields Column 1). The final 3 columns further break down the intermittency wedge, χ^ρ_{jH}, into its constituent parts, pertaining to the skill dynamics, where ϕ refers to the education requirements, γ refers to returns to experience, and δ refers to skill depreciation. Again this is a multiplicative decomposition, where the product of the final three columns yields the χ^ρ_{jH} column.

Table 12: Relative Attractiveness of Market Occupation for Women vs. Men

Occupation	**Total** χ_j	$\frac{b_{mH}}{b_{mj}} \cdot \frac{b_{wj}}{b_{wH}}$	$(1-\tau_j)$	χ^ρ_{jH}	ϕ	γ	δ
Panel A: 1970 Calibration							
Manual M	0.30	1.00	0.33	0.91	1.00	0.97	0.94
Routine R	0.57	0.91	0.73	0.85	0.99	0.94	0.92
Non-Routine N	0.41	0.75	0.72	0.76	0.97	0.90	0.86
Panel B: 2000 Calibration							
Manual M	0.54	1.21	0.46	0.97	1.00	0.99	0.98
Routine R	1.02	1.18	0.91	0.94	1.00	0.98	0.97
Non-Routine N	0.90	0.89	1.12	0.90	0.99	0.96	0.95

Notes: This table reports the total $\chi_j = \chi^{men}_{jH}/\chi^{women}_{jH}$ in each market occupation, at both the 1970 as well as the 2000 calibrated parameters. The first column reports the total χ_j. Columns 2-4 show the multiplicative decomposition of the total χ_j into preferences b, discrimination τ, and the intermittency wedge, χ^ρ_{jH} . The intermittency wedge is further multiplicatively decomposed into the contribution of each of the skill dynamics in the final three columns: education (ϕ), returns to experience (γ), and skill depreciation (δ).

As is evident in Table 12, in 1970, all market occupations were less attractive for women than men, as $\chi_j < 1$ for all j. This is expected, as women are 4 times more likely than men to pick the home sector at period 1. By 2000, all forms of market work have become more attractive for women, reflecting both growth in extensive margin participation for women, as well as a decline for men. In both calibrations, the routine jobs are the most attractive for women, out of all the market occupations, while the manual jobs are the least attractive. This rationalizes the fact that women are over-represented in routine employment relative to manual employment in the data.

Columns 2 to 4 of Table 12 highlight that there are different reasons that women are less attracted to each market occupation compared to men. Wage discrimination, τ, has the biggest effect in manual jobs, reducing their attractiveness to women by a factor of 3. Intermittency, by contrast, disproportionately affects N jobs, both in 1970 and in 2000. This is consistent with Proposition 2, as intermittency impacts the occupational sorting of women via skill dynamics and N jobs featured the strongest dynamics. However, all occupations are impacted by intermittency to some degree, as none of the market occupations is entirely "non-dynamic." Columns 5 to 7 show that of the skill dynamics parameters which contribute to the intermittency wedge, depreciation has the biggest impact, followed by returns to experience γ and finally educational requirements ϕ.

To put in context the intermittency wedge faced by women in 1970: it reduced the attractiveness of N jobs by 24% for women relative to men, whereas wage discrimination reduced the attractiveness of these jobs by 28%. Thus, the intermittency wedge was nearly equivalent in magnitude to the discrimination wedge at this point in time.

However, the change in the intermittency wedge between 1970 and 2000 is small relative to the change in discrimination, especially for non-routine work. Intermittency reduced the attractiveness of the non-routine occupation for women by 24% in 1970, and this figure falls to 10% in 2000. By contrast, as shown in Table 12, discrimination reduced the attractiveness of the non-routine occupation for women by 28% in 1970, but by 2000, women are actually 12% more attracted to this occupation than men. I will show in the next section that this result from the model calibration implies that the Quiet Revolution has a smaller impact on the rise of non-routine employment among women, compared to falling discrimination.

5.2 Explaining the Decline of Routine Cognitive Employment

Next, I ask how much of the decline in routine relative to non-routine employment can be explained by the Quiet Revolution, both by gender and on aggregate. Since my model distinguishes routine and non-routine jobs in the *white-collar* sector only, and the notion of automation in the model (C) substitutes specifically for workers in clerical and sales settings, the decomposition in this section examines the change in the difference between the non-routine cognitive employment share and the routine cognitive employment share. I call this difference the $N - R$ employment gap. For $g \in \{women, men\}$, the $N - R$ employment gap is:

$$\frac{\pi_{gN} - \pi_{gR}}{1 - \pi_{gH}}$$

where π_{gN} is the share of g who sort into N at period 1, π_{gR} is the share who sort into R, and π_{gH} is the share who do not enter the labor force.

I start with the model calibrated to 1970 and then allow the three main forces of interest to evolve: the Quiet Revolution happens (ρ falls), discrimination changes ($\Delta\tau$), and the price of automation falls (Δp_C). I examine how the $N - R$ employment gap evolves under each counterfactual scenario, separately for women, for men, and on aggregate. The results are shown in Figures 12, 13, and 14.

The first bar in each of Figures 12, 13, and 14 shows the observed change in the $N - R$ employment gap between 1970 and 2000. The second bar in each figure shows the

Figure 12: Change in Female $N-R$ Employment Share Under Counterfactuals

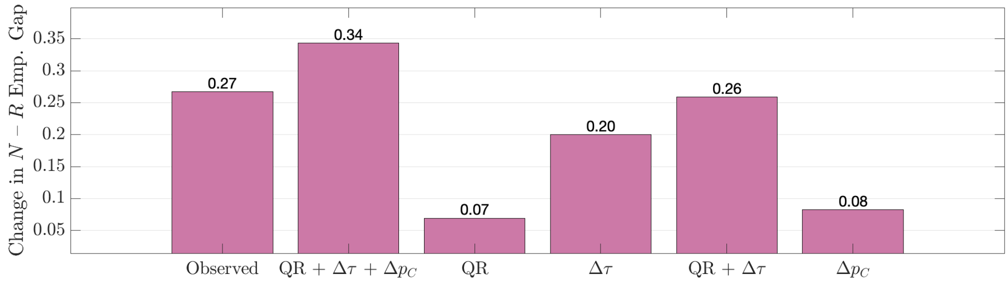


Figure 13: Change in Male $N-R$ Employment Share Under Counterfactuals

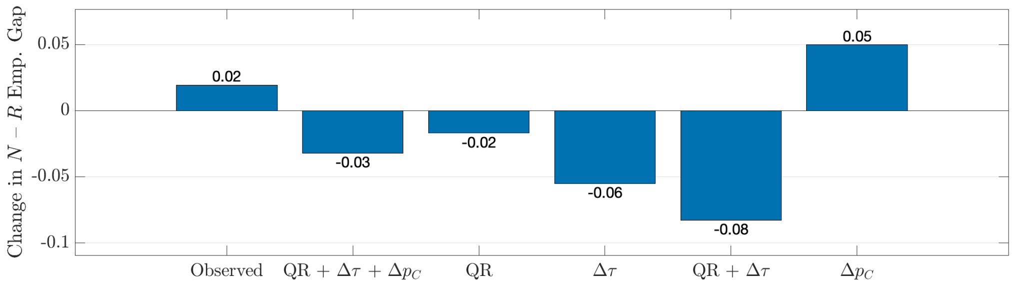
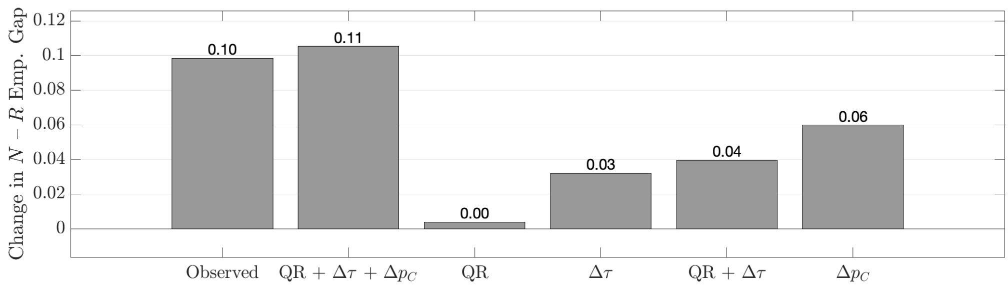


Figure 14: Change in Aggregate $N-R$ Employment Share Under Counterfactuals



Notes: Figures 12, 13, & 14 plot the change in the gap between the non-routine N employment shares and the routine R employment share for women, men, and aggregate, respectively, in the data and under various counterfactual scenarios in the model. The employment shares in 1970 serve as the reference point for all bars. "Observed" shows the change in the $N-R$ employment share gap between 1970 and 2000 in the data. "QR + $\Delta\tau$ + Δp_C" shows the change in the $N-R$ employment share gap when all three key forces are allowed to change in the model relative to 1970. The remaining bars break down the individual contributions of "QR", "$\Delta\tau$" , and "Δp_C", starting from the model calibrated to 1970.

change implied by starting from 1970 and turning on these three key forces in the model. The "QR + $\Delta\tau$ + Δp_C" bars differ from the "Observed" bars because they do not take into account changes in non-monetary preferences for occupations (b) or changes in technology parameters unrelated to automation (Z, A_M). However, the "QR + $\Delta\tau$ + Δp_C" counterfactual serves as a useful benchmark to understand the relative contribution of each of these three main forces. Because I do not interpret changes in the non-monetary preference terms and treat them as a residual to enable the model to match observed employment shares, I compare the contribution of each force independently to the full "QR + $\Delta\tau$ + Δp_C" counterfactual.

Figure 12 reveals that both the Quiet Revolution and falling discrimination are critical for understanding why the shift from routine to non-routine white-collar work has been so large for women. The Quiet Revolution explains 21% and falling discrimination, 59%, of the widening of the $N - R$ employment gap for women.[16] The impact of the Quiet Revolution is almost equivalent to the impact of the decline in the price of automation alone on this statistic; if only the latter had taken place, only 24% of the widening $N - R$ employment gap for women would have occurred.

Not only are the Quiet Revolution and falling discrimination important the key drivers of the dramatic rise of non-routine cognitive employment among women, but also they explain why male employment across occupations has been relatively stable. If only automation technology had become cheaper, not only would the shift in employment from routine to non-routine jobs have been small for women, widening by only 8 percentage points, but also this shift would have been born more equally by both genders, with the male $N - R$ employment gap widening by 5 percentage points, as shown in Figure 13. The Quiet Revolution and the decline in discrimination both crowd-out men from the non-routine occupation and generate a reduction in the $N - R$ employment gap for men. The fact that the Quiet Revolution occurred and discrimination fell while automation was getting cheaper stabilized male employment across these occupation categories, as the increased demand for non-routine work could be met by women.

Taking into account the effects on both women and men, can these non-technological factors—the Quiet Revolution and falling discrimination—explain the decline of routine employment on aggregate, for both genders combined? When it comes to the rise of the aggregate $N - R$ employment gap, Figure 14 reveals that these factors affecting the allocation of female labor together (the "QR + $\Delta\tau$" counterfactual) explain 36% of the change under the full "QR + $\Delta\tau$ + Δp_C" counterfactual, while the decline in the price of automation alone explains 55%. Independently, the contribution of the Quiet Revolution is much smaller than that of falling discrimination: it induces less than half a percentage point increase in the aggregate $N - R$ employment share gap, despite the non-trivial impact on female employment shares in Figure 12. A striking result from this exercise is that improvement in automation technology alone is not sufficient to explain the rise of non-routine relative to routine cognitive employment, contrary to the standard explanation for the decline of routine employment in the literature. As illustrated in Figure 14, declining barriers faced by women—arguably a change in labor supply rather than labor demand—are also an important driver of this observed trend within the white-collar

[16] The combined effect is nearly equal to the sum of the individual effects, suggesting that there is not a substantial interaction of the QR and $\Delta\tau$.

setting.

To understand why the Quiet Revolution alone has less impact on the aggregate $N - R$ employment gap than falling discrimination, despite these two forces having qualitatively similar effects on this statistic for women, it is necessary to consider the channels through which these forces affect the aggregate employment shares. First, both the Quiet Revolution and a decline in wage discrimination directly change the occupational sorting of women in period 1, as in Proposition 2. Second, both forces also indirectly affect male occupational sorting in period 1, via equilibrium wages. Finally, the Quiet Revolution has a third effect: because it enables women to work continuously in period 2, it increases the share of employed who are women, for a given set of occupation choices made in period 1. It is actually possible that the Quiet Revolution shifts female employment from R to N, while shifting aggregate employment in the opposite direction; this can occur if women are substantially more likely than men to be in R jobs in the first place.

Table 13 provides a decomposition of the effects of the Quiet Revolution and falling discrimination on aggregate employment shares into these three channels. My discussion focus on the $N - R$ employment gap in Panel C, which is the same statistic reported in Figures 12 to 14. For reference, Panels A and B show the effects on the aggregate employment share in N and R jobs separately. Column 1 reports the total change in the aggregate statistic under the counterfactual. Column 2, "Women Sorting," shows what the change would be if the counterfactual only affected women's occupational sorting in period 1. Column 3, "Men Sorting," shows the change in the aggregate statistic if only male occupational sorting changed as it did in response to equilibrium wages. Finally, Column 4, "Continuity," shows the change in the aggregate statistic if only women's attachment to the labor force in period 2 changed, holding period 1 occupational sorting fixed; this is relevant only for the Quiet Revolution counterfactual, as discrimination does not affect the propensity of women to work in period 2.

Table 13: Aggregate Employment Shares Under Counterfactuals, Relative to 1970

Counterfactual	**Change**	**Women Sorting**	**Men Sorting**	**Continuity**
Panel A: Aggregate Employment Share in Non-Routine N Jobs				
QR	0.002	0.014	-0.012	-0.001
$\Delta\tau$	0.019	0.037	-0.019	–
Panel B: Aggregate Employment Share in Routine R Jobs				
QR	-0.002	-0.006	-0.001	0.006
$\Delta\tau$	-0.013	-0.028	0.016	–
Panel C: Aggregate $N - R$ Employment Gap				
QR	0.004	0.020	-0.011	-0.008
$\Delta\tau$	0.032	0.065	-0.035	–

Notes: Panels A and B show the change in aggregate non-routine and routine employment shares under the Quiet Revolution and falling discrimination counterfactuals, relative to 1970. Panel C shows the change in the $N - R$ employment gap, which is the same statistic as in Figures 12 – 14. The column "Change" shows the total change, which is then broken down into different components in Columns 2 to 4. The column "Women Sorting" shows the change in the aggregate if only female occupational sorting at age 1 changes. "Men Sorting" shows the contribution of changes in male employment shares, which are induced by changes in equilibrium wages. "Continuity" shows the impact on the aggregate if only intermittency declined (ρ fell), enabling more women to work at period 2 for a given occupational sorting.

Mirroring Figure 14, Panel C of Table 13 shows that the Quiet Revolution induced a small increase in the aggregate $N - R$ employment gap, while falling discrimination widened this gap by 3.2 percentage points. However, if only women's occupational sorting in period 1 changed, then the Quiet Revolution would have induced a 2 percentage point widening of the aggregate $N - R$ employment gap, while falling discrimination would have led to a change of 6.5 percentage points. The direct effects of changes in female occupational sorting on aggregate employment shares are partly offset because both counterfactuals generate crowding out of men; if only male occupations choices in period 1 changed, the Quiet Revolution would have reduced the aggregate $N - R$ employment gap by 1.1 percentage points and falling discrimination, by 3.5. On top of this, the Quiet Revolution mechanically increases the share of workforce who are women via higher participation in period 2, which actually reduces the aggregate $N - R$ employment gap, holding fixed occupational sorting in period 1. The intuition is that women have a higher employment share in the routine occupation than men to begin with, so if women comprise a greater share of the workforce, this increases the aggregate employment share in routine jobs.

In summary, my counterfactual analyses indicate that the Quiet Revolution has a similar magnitude effect as improvements in automation on the shift of female employment from routine to non-routine white-collar work. Falling discrimination plays an even larger role in explaining the change for women. Turning to the aggregate, I find that non-technological factors—the Quiet Revolution and falling discrimination combined—explain approximately a third of the rise of non-routine relative to routine employment, contrary to the dominant explanation in the literature that this trend has resulted from changes in technology. However, the Quiet Revolution alone does not explain much of the aggregate rise of non-routine relative to routine employment, as the shift of female employment toward non-routine work is offset by crowding out of men and the increased continuity of female workers, who are more likely to do non-routine work in general. While the Quiet Revolution alone does not explain the aggregate changes in employment shares, this does not mean it did not have implications for the broader economy: in the next section, I show that the Quiet Revolution had a large effect on aggregate productivity and the aggregate supply of efficiency units, particularly in non-routine occupations.

5.3 Productivity Implications of the Quiet Revolution

The Quiet Revolution affects the mean effective skill of workers in each market occupation via three channels, with implications for aggregate productivity, which is defined as market output per worker. As outlined in Section 3.5, the Quiet Revolution: (1) changes the period 1 occupational sorting of women and men, drawing less-innately skilled women into dynamic jobs and potentially crowding-out less innately-skilled men; (2) allows more women to stay in the workforce in period 2, which enables them to accumulate experience and increases the mean innate skill of workers in an occupation if women are under-represented relative to men; and (3) increases the human capital investment of women, as in Proposition1.

The impact of the Quiet Revolution on the mean innate and effective skill of workers in each occupation is reported in Table 14, along with a decomposition into the three channels. Each entry in Table 14 is the percentage change in mean skill among all workers—both genders combined—in each occupation under the Quiet Revolution counterfactual relative to the 1970 calibration. For example, the first entry under Panel A indicates that the mean innate skill of non-routine workers under the Quiet Revolution counterfactual is 99.8% of that in the model calibrated to 1970.

Table 14: Percentage Change in Mean Skill Under Quiet Revolution Relative to 1970

Skill Type	**Total Change**	**Sorting**	**Continuity**	**Investment**
Panel A: Mean Skill of Non-Routine Workers N				
Innate	-0.002	-0.003	0.004	–
Effective	0.046	-0.016	0.044	0.011
Panel B: Mean Skill of Routine Workers R				
Innate	-0.013	-0.009	-0.003	–
Effective	0.047	-0.008	0.048	0.009
Panel C: Mean Skill of Manual Workers M				
Innate	-0.010	-0.020	0.010	–
Effective	0.011	-0.020	0.029	0.002

Notes: This table shows the percentage change in mean innate skill and mean effective skill among workers in each market occupation under the Quiet Revolution counterfactual, relative to the model calibrated to 1970. Mean skill is calculated across all workers—female and male—in an occupation. The column "Total Change" shows the percentage change in the mean skill, relative to the 1970 calibration. The column "Sorting" shows the impact of changes in female and male occupational sorting in period 1, holding everything else fixed. "Continuity" shows the effect of more women being able to work in period 2 and thus accumulating experience, holding fixed the period 1 occupational sorting and skill investment. "Investment" shows the effect of women changing their human capital investment in response to a decline in ρ, with everything else staying the same.

The Quiet Revolution decreases the mean innate skill of workers in each occupation. This is primarily driven by changes in the sorting of workers, particularly the fact that less innately-skilled women are drawn in to each market occupation as the intermittency wedge falls. In the non-routine and manual occupations, where women are under-represented compared to men and thus more innately talented on average, the continuity channel somewhat offsets this, pushes up the mean innate skill as talent women are able to remain in the labor force in period 2.

However, the most significant effects of the Quiet Revolution are on the mean effective skill of workers, rather than mean innate skill. Despite drawing workers with lower innate talent, the Quiet Revolution substantially increases mean effective skill across all occupations. As indicated in Table 14, the mean effective skill of non-routine workers and routine workers increases by 4.6% and 4.7%, respectively, relative to the model calibrated to 1970. This results from the continuity and investment channels, as women gain more experience and achieve higher educational attainment. Given that non-routine occupations offer higher returns to experience than routine ones, one might expect that women's increased work continuity would lead to a greater rise in mean effective skill in non-routine roles. Yet, because women make up a larger share of routine employment, even after the Quiet Revolution, the percentage change in mean effective skill is almost equivalent in non-routine and routine occupations. By contrast, the mean effective skill of manual workers rises by only 1.1%. Manual occupations, being less dynamic and having a smaller proportion of female workers, experience a more limited impact from the Quiet Revolution on mean effective skill.

Naturally, as the mean effective skill of workers rises, so does aggregate productivity. Panel A of Table 15 shows the percentage change in market output per worker under the Quiet Revolution counterfactual, compared to the model in 1970. The Quiet Revolution increases market output per worker by 3%. The contribution of each channel is reported in Columns 2 to 4; consistent with Table 14, the fact that women work continuously and are able to accumulate experience is the driving force behind this result.

Table 15: Percentage Change in Output Per Worker and Aggregate Efficiency Units

Counterfactual	**Total Change**	**Sorting**	**Continuity**	**Investment**
Panel A: Market Output Per Worker				
QR	0.030	-0.015	0.036	0.006
$\Delta\tau$	-0.039	-0.039	–	–
Panel B: Aggregate Efficiency Units of Non-Routine Labor N				
QR	0.125	0.021	0.074	0.011
$\Delta\tau$	0.074	0.074	–	–
Panel C: Aggregate Efficiency Units of Routine Labor R				
QR	0.108	-0.009	0.110	0.009
$\Delta\tau$	0.006	0.006	–	–
Panel D: Aggregate Efficiency Units of Manual Labor M				
QR	0.076	0.018	0.055	0.002
$\Delta\tau$	0.039	0.039	–	–

Notes: This table shows the aggregate efficiency units in each occupation and output per worker under the Quiet Revolution (QR) and falling discrimination ($\Delta\tau$) counterfactuals, relative to the 1970 baseline. Total refers to the ratio of the given variable under the counterfactual relative to the 1970 value. Sorting allows the counterfactual to affect the outcome through the occupation sorting of workers at age 1. Continuity allows for the change in women working at age 2, which generates both more workers as well as more accumulated experience. Investment allows only the human capital investment decision before working to change.

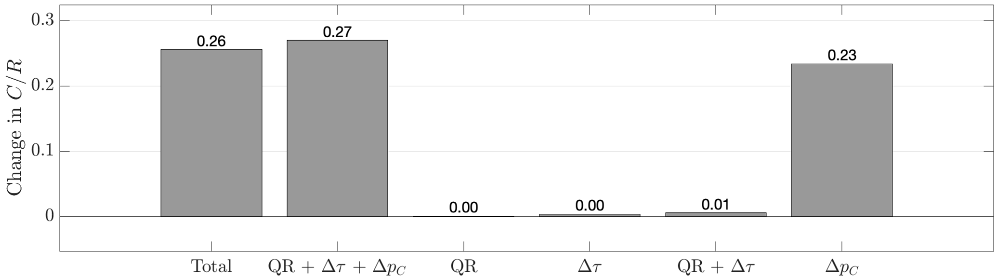
For comparison, in Table 15, I also show the effect of a decline in discrimination on this aggregate statistic. The decline in discrimination faced by women reduces output per worker by almost 4%. Falling discrimination draws women with lower innate skills in to each market occupation. However, without the Quiet Revolution, they are unable to accumulate experience or invest more in their human capital. This comparison highlights that the productivity gains from the Quiet Revolution are dynamic rather than static; they result from women accumulating experience over time, rather than from the static reshuffling of individuals across occupations.

Finally, Panels B to D of Table 15 show the change in the aggregate efficiency units of labor for each occupation, which are affected by both by the number of bodies in those occupations, as well as the mean effective skill per worker. The Quiet Revolution has a large impact on the aggregate efficiency units in each occupation, raising it by 12.5%, 10.8%, and 7.6% in the non-routine, routine, and manual occupations, respectively. Thus, the Quiet Revolution shifts the aggregate supply of efficiency units of labor in the economy toward non-routine work. The decline in discrimination also leads to growth in the aggregate non-routine efficiency units, although by only 7.4%, which comes entirely from changes in occupational sorting.

5.4 Quantifying the Endogenous Adoption of Automation

In my model, automation is an endogenous choice and firms may choose to have computers perform more of the routine tasks, depending on factor prices. This raises the possibility that the Quiet Revolution and falling discrimination, in affecting the aggregate efficiency units supplied to the different occupations, encourage greater substitution of computers for routine workers for a given p_C. To investigate this, I examine changes in the ratio $\frac{C}{R}$ in the model under various counterfactual scenarios. The results are shown in Figure 15.

Figure 15: Change in Model-Implied Computer Substitution for Routine Workers $\left(\frac{C}{R}\right)$



Notes: This figure plots the percentage point change in the ratio of computers to routine worker efficiency units, C/R, under various counterfactual scenarios in the model. The model-implied ratio of C/R in 1970 serves as the reference point for all bars; it's value is 0.14. "Total" shows the change in the ratio C/R between 1970 and 2000, as implied by the model calibrated to both periods. "QR + $\Delta\tau$ + Δp_C" shows the change in C/R when all three key forces are allowed to change in the model, relative to C/R in 1970. The remaining bars break down the individual contributions of "QR", "$\Delta\tau$" , and "Δp_C", starting from the model calibrated to 1970.

The vast majority of the increase in $\frac{C}{R}$ in the model, specifically 85%, comes from the decline in p_C. However, p_C alone clearly does not explain the full increase observed in the "QR + $\Delta\tau$ + Δp_C" counterfactual. The Quiet Revolution and falling discrimination taken together without technological change can explain only about 4% (0.01/0.27) of the rise in this ratio. This means the remaining 11% must arise via an interaction of the factors affecting the allocation of female labor and improvements in technology. This highlights a complementarity between these factors affecting female labor supply and technological change. Firms have a stronger incentive to substitute automation for workers in performing white-collar routine tasks when technological improvements coincide with these factors affecting female labor supply.

6 Concluding Remarks

This paper provides the first macroeconomic analysis of the shift in female life cycle labor force attachment from intermittent to continuous since the 1970's, which Goldin (2006) named the Quiet Revolution. By incorporating gender differences in work horizon and quantifying how these interact with various occupational attributes, my model sheds light on the "black box" of distortions faced by women in the labor market and the implications for the distribution of employment and aggregate productivity.

Through the lens of my calibrated model, I show that shifts affecting female labor supply significantly contribute to the observed decline in routine employment since the 1970's, a phenomenon which is typically attributed to changes in labor demand. Focusing on routine and non-routine cognitive occupations—which constitute a larger share of women's employment than manual jobs and have shown divergent trends between men and women over time—I use a calibrated model to reveal that the Quiet Revolution explains 21% of the rise in non-routine cognitive employment relative to routine cognitive employment among women between 1970 and 2000, while falling discrimination explains 59%. Changes in technology alone are not sufficient to replicate the fact that the shift of employment across these categories has happened mostly among women. On aggregate, the Quiet Revolution and falling discrimination together explain 36% of the total decline in routine relative to non-routine white-collar employment. While in this counterfactual analysis, the decline in wage discrimination contributes more than the Quiet Revolution in explaining the changes in employment shares, I find that the Quiet Revolution has a substantial impact on aggregate productivity: it increases output per worker by 3%, primarily through the increase in work experience accumulated by women.

Furthermore, the model suggests that these changes in female labor supply complemented the increase in computer efficiency during this period. Specifically, the Quiet Revolution and declining barriers faced by women account for 15% of the model-implied rise in computers substituting for routine cognitive workers, taking into account both independent effects and interactions with technological change. This occurs because the supply of non-routine labor, which is complementary to computers, became more abundant and relatively cheaper as the Quiet Revolution happens and discrimination falls.

These findings suggest several avenues for future research, which I plan to explore in future work. First, this paper highlights that at least part of the decline in routine employment relative to non-routine reflects shifts in female labor supply and a decline in discrimination. While concerns over worker displacement often guide proposed policy responses to increasing automation, my findings suggest a need for nuance: the optimal response to industrial robots that replace manual workers might differ significantly from that to software that automates traditionally female roles, especially when labor market distortions are also present (Guerreiro, Rebelo, and Teles 2022; Beraja and Zorzi 2024).

Second, while my analysis in Section 5.4 indicates that changes affecting the allocation of female labor—the Quiet Revolution and falling discrimination—created conditions conducive to the adoption of automation technologies, it assumes that the underlying technological improvements are exogenous. However, these same conditions may have created the incentive for innovation in software that replaces workers in traditionally female tasks, such as automated phone answering systems or booking platforms (Caselli and Coleman II 2006; Acemoglu and Zilibotti 2001; Acemoglu 2007). Understanding whether changes in female labor supply may have induced innovation, as in the directed technical change literature, is a natural next line of inquiry.

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A Mathematical Appendix

A.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 $h(\phi_j, 0) = h(\phi_j, \rho) = 0$.

A.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 ($\gamma_j \geq \gamma_k$, $\delta_j \geq \delta_j$, and $\phi_j \geq \phi_k$, with at least one inequality holding strictly). Equation (7) in the main text defines χ^g_{jk} as:

$$\chi^g_{jk} = \underbrace{\frac{a_{gk}w_k(1-\tau_k)}{a_{gj}w_j(1-\tau_j)}}_{\substack{\text{Wages \&}\\ \text{Discrimination}}} \times \underbrace{\frac{b_{gk}}{b_{gj}}}_{\text{Pref.}} \times \underbrace{\left(\frac{\gamma_k}{\gamma_j}\right)^{\frac{3-3\rho}{3-\rho}} \times \left(\frac{1-\delta_k}{1-\delta_j}\right)^{\frac{\rho}{3-\rho}} \times e^{\frac{\eta(\zeta-1)}{\zeta}(h^*(\phi_k,\rho)-h^*(\phi_j,\rho))}}_{\substack{\text{Skill dynamics \&}\\ \text{intermittency}}}$$

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:

$$\frac{\partial}{\partial\rho}\left(\frac{\gamma_k}{\gamma_j}\right)^{\frac{3-3\rho}{3-\rho}} = \left(\frac{\gamma_k}{\gamma_j}\right)^{\frac{3-3\rho}{3-\rho}} \times \ln\left(\frac{\gamma_k}{\gamma_j}\right) \times -\frac{6}{(3-\rho)^2}$$

   If $\gamma_j = \gamma_k$, then $\frac{\partial}{\partial\rho}\left(\frac{\gamma_k}{\gamma_j}\right)^{\frac{3-3\rho}{3-\rho}} = 0$. If $\gamma_j > \gamma_k$, then $\frac{\partial}{\partial\rho}\left(\frac{\gamma_k}{\gamma_j}\right)^{\frac{3-3\rho}{3-\rho}} > 0$, as $\ln\left(\frac{\gamma_k}{\gamma_j}\right) < 0$. Thus, $\frac{\partial}{\partial\rho}\left(\frac{\gamma_k}{\gamma_j}\right)^{\frac{3-3\rho}{3-\rho}} \geq 0$ 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 $\frac{\partial}{\partial\rho} e^{\frac{\eta(\zeta-1)}{\zeta}(h^*(\phi_k,\rho)-h^*(\phi_j,\rho))} > 0$.

A.3 Occupational Employment Shares

Recall that skill vector $\boldsymbol{\epsilon} = (\epsilon_H, \epsilon_M, \epsilon_R, \epsilon_N)$ 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:

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

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 employment share for group g in occupation j as $\pi_g j$.

A.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 $G(.)$:

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

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 $G(.)$:

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

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.

A.5 Proof of Proposition 3

Assume that occupation j is more dynamic than occupation k along all three dimensions; that is, $\phi_j > \phi_k$, $\gamma_j > \gamma_k$, and $\delta_j > \delta_k$. The result in proposition 3$\frac{\partial \log S_{wj}(w,\rho)}{\partial \rho} < \frac{\partial \log S_{wk}(w,\rho)}{\partial \rho}$ is equivalent to $\frac{\partial \log\left(\frac{S_{wj}(w,\rho)}{S_{wk}(w,\rho)}\right)}{\partial \rho} < 0$.

$$\log\left(\frac{S_{wj}(w,\rho)}{S_{wk}(w,\rho)}\right) = \log\left(\frac{a_{wj}}{a_{wk}}\right) + \log\left(\frac{\pi_{wj}}{\pi_{wk}}\right) + \eta^{\frac{\zeta}{\zeta-1}}(3-\rho)^{\frac{1}{\zeta-1}}(\phi_j^{\frac{1}{\zeta-1}} - \phi_k^{\frac{1}{\zeta-1}}) \\ + \log\left(\frac{1+\gamma_j+\gamma_j^2+\rho(1-\delta_j-\gamma_j-\gamma_j^2)}{1+\gamma_k+\gamma_k^2+\rho(1-\delta_k-\gamma_k-\gamma_k^2)}\right)$$

The last three terms on the right-hand side are strictly decreasing in ρ, while the first is non-increasing in ρ.

1. $\log\left(\frac{a_{wj}}{a_{wk}}\right)$ does not change with ρ.

2. $\log\left(\frac{\pi_{wj}}{\pi_{wk}}\right)$ falls with ρ. Using the expression for the population shares in A.3:

$$\frac{\pi_{wj}}{\pi_{wk}} = \frac{a_{gj}(1-\tau_{gj})w_j b_{gj}\gamma_j^{\frac{3-3\rho}{3-\rho}}(1-\delta_j)^{\frac{\rho}{3-\rho}}e^{\frac{\eta(\zeta-1)}{\zeta}h^*(\phi_j,\rho)}}{a_{gk}(1-\tau_{gk})w_k b_{gk}\gamma_k^{\frac{3-3\rho}{3-\rho}}(1-\delta_k)^{\frac{\rho}{3-\rho}}e^{\frac{\eta(\zeta-1)}{\zeta}h^*(\phi_k,\rho)}}$$

   Plugging in the optimal human capital choice (h^* as a function of ρ and ϕ), taking log's, and differentiating with respect to ρ yields $\frac{\partial \frac{\pi_{wj}}{\pi_{wk}}}{\partial \rho} < 0$. As the log function is monotonically increasing, $\frac{\partial \log\left(\frac{\pi_{wj}}{\pi_{wk}}\right)}{\partial \rho} < 0$

3. $\eta^{\frac{\zeta}{\zeta-1}}(3-\rho)^{\frac{1}{\zeta-1}}(\phi_j^{\frac{1}{\zeta-1}} - \phi_k^{\frac{1}{\zeta-1}})$ falls with ρ: As $\zeta > 1$, $\eta > 0$, and $\phi_j > \phi_k$, $\eta^{\frac{\zeta}{\zeta-1}}(\phi_j^{\frac{1}{\zeta-1}} - \phi_k^{\frac{1}{\zeta-1}})$ is positive. The derivative of $(3-\rho)^{\frac{1}{\zeta-1}}$ is negative: $-\frac{1}{\zeta-1}(3-\rho)^{\frac{-\zeta}{\zeta-1}} < 0$.

4. $\log\left(\frac{1+\gamma_j+\gamma_j^2+\rho(1-\delta_j-\gamma_j-\gamma_j^2)}{1+\gamma_k+\gamma_k^2+\rho(1-\delta_k-\gamma_k-\gamma_k^2)}\right)$ falls with ρ: Consider an intermediate occupation m, with $\gamma_m = \gamma_j$ and $\delta_m = \delta_k$. Then, re-write $\log\left(\frac{1+\gamma_j+\gamma_j^2+\rho(1-\delta_j-\gamma_j-\gamma_j^2)}{1+\gamma_k+\gamma_k^2+\rho(1-\delta_k-\gamma_k-\gamma_k^2)}\right)$ as:

$$\log\left(\frac{1+\gamma_j+\gamma_j^2+\rho(1-\delta_j-\gamma_j-\gamma_j^2)}{1+\gamma_m+\gamma_m^2+\rho(1-\delta_m-\gamma_m-\gamma_m^2)}\right) + \log\left(\frac{1+\gamma_m+\gamma_m^2+\rho(1-\delta_m-\gamma_m-\gamma_m^2)}{1+\gamma_k+\gamma_k^2+\rho(1-\delta_k-\gamma_k-\gamma_k^2)}\right)$$

The derivative of each term with respect to ρ is < 0. Starting with the first term:

$$\frac{\partial}{\partial\rho}\log\left(\frac{1+\gamma_j+\gamma_j^2+\rho(1-\delta_j-\gamma_j-\gamma_j^2)}{1+\gamma_m+\gamma_m^2+\rho(1-\delta_m-\gamma_m-\gamma_m^2)}\right)=\frac{1}{\frac{1+\gamma_j+\gamma_j^2}{1-\delta_j-\gamma_j-\gamma_j^2}+\rho}-\frac{1}{\frac{1+\gamma_m+\gamma_m^2}{1-\delta_m-\gamma_m-\gamma_m^2}+\rho}$$

As $\frac{1+\gamma_m+\gamma_m^2}{1-\delta_m-\gamma_m-\gamma_m^2}=\frac{1+\gamma_j+\gamma_j^2}{1-\delta_k-\gamma_j-\gamma_j^2}>\frac{1+\gamma_j+\gamma_j^2}{1-\delta_j-\gamma_j-\gamma_j^2}$, this is < 0. By similar reasoning, the derivative of the second term is also < 0. Hence, $\frac{\partial}{\partial\rho}\log\left(\frac{1+\gamma_j+\gamma_j^2+\rho(1-\delta_j-\gamma_j-\gamma_j^2)}{1+\gamma_k+\gamma_k^2+\rho(1-\delta_k-\gamma_k-\gamma_k^2)}\right)<0$.

A.6 Allowing Correlation in Innate Skills

In taking the model to the data, I break the innate skill draw into two steps to allow for correlation in cognitive skills, which can be applied to the routine R or non-routine N jobs. Workers get an initial i.i.d. Fréchet draw over $\{\epsilon_H, \epsilon_M, \epsilon_S\}$, where the shape parameter is θ_1. Conditional on entering the service sector S, workers get a second i.i.d. Fréchet draw over $\{\epsilon_R, \epsilon_N\}$, with shape parameter θ_2. A worker's skill in R or N is $\epsilon_S\epsilon_R$ or $\epsilon_S\epsilon_N$, respectively.

At the first draw, workers anticipate an expected value of the second draw equal to $\log\epsilon_S+\frac{1}{\theta_2}\log(X_{gR}(\rho)^{\theta_2}+X_{gN}(\rho)^{\theta_2})$, where $X_{gR}(\rho)$ and $X_{gN}(\rho)$ are defined as in Appendix A.3. Define $X_{gS}(\rho)=\exp(\frac{1}{\theta_2}\log(X_{gR}(\rho)^{\theta_2}+X_{gN}(\rho)^{\theta_2}))$. Therefore, at the first draw, workers pick over $j\in\{H,M,S\}$ to maximize $\log(\epsilon_j X_{gj})$. The choice probabilities are the same as in Appendix A.3.

Conditional on entering "services" S, workers get the second draw over $\{R,N\}$. From that point on, they choose between R and N; the option of returning to M or R is shut down. They pick over $k\in\{R,N\}$ to maximize $\log(\epsilon_k X_{gk})$.

The full choice probability to enter $k\in\{R,N\}$ is:

$$\pi_{kg}(\rho)=\underbrace{\frac{(X_{gS}(\rho))^{\theta_1}}{(X_{gS}(\rho))^{\theta_1}+(X_{gM}(\rho))^{\theta_1}+(X_{gH}(\rho))^{\theta_1}}}_{\text{Enter services } S}\times\underbrace{\frac{(X_{gk}(\rho))^{\theta_2}}{(X_{gR}(\rho))^{\theta_2}+(X_{gN}(\rho))^{\theta_2}}}_{\text{Conditional on } S\text{, enter } k}$$

B Data Appendix

B.1 Classification of Occupation Codes

Table B.1 shows the mapping between the Census occupation coding systems and the broad occupation groups considered for the empirical results. This mapping is borrowed from Cortes, Jaimovich, Nekarda, et al. (2020). The coding system changes in the CPS over time, so when I use the CPS data, I use the classification relevant for that year. In the Census data downloaded from IPUMS, I use the harmonized `occ1990` variable, which is based on the 1990 Census coding system.

Table B.1: Mapping of Detailed Census Occupation Codes to Occupational Groups

Occupation Group	**Census Coding System**			
	1970	**1980/1990**	**2002**	**2010**
Non-Routine Cognitive	001-100, 102-162, 165, 171, 173-216, 222-225, 230, 235-245, 321, 326, 363, 382, 426, 506, 801-802, 924, 926	003-225, 228-229, 234-235, 473-476	0010-3540	0010-3540
Non-Routine Manual	101, 505, 740, 755, 901-923, 925, 931-984	403-469, 486-487, 773	3600-4650	3600-4650
Routine Cognitive	220, 231-233, 260-285, 301-305, 310-320, 323-325, 330-362, 364-381, 383-395	243-389	4700-5930	4700-5940
Routine Manual	163-164, 170, 172, 221, 226, 401-425, 430-446, 452-504, 510-575, 601-624, 626-715, 750-751, 753-754, 760, 762-785	226-227, 233, 503-769, 774-799, 803-869, 873-889	6200-9750	6200-9750
Farming, Military	450, 580, 600, 625, 752, 761, 821-824	477-485, 488-499, 905	6000-6130, 9800-9840	6005-6130, 9800-9840

Notes: This table shows the classification of 3-digit occupation codes into the routine/non-routine and cognitive/manual job categories used in this paper. The classification of occupations into these groups is borrowed from Cortes, Jaimovich, Nekarda, et al. (2020).

B.2 Employment in Routine and Non-Routine Manual Jobs

Figures B.1 and B.2 show the share of aggregate employment as well as female and male employment in routine and non-routine manual jobs. These figures are analogous to figures 3 and 4, which show employment in routine and non-routine cognitive jobs. Summing the black (or pink or blue) lines in all 4 figures yields 1.

Figure B.1: Routine Manual Share of Total Employment

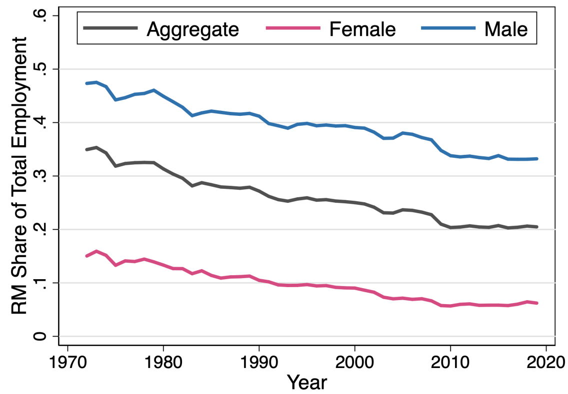
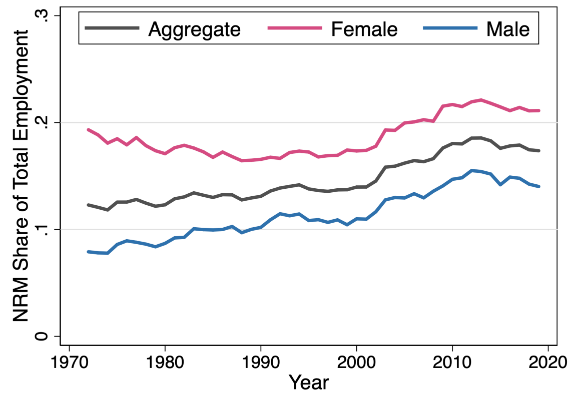


Figure B.2: Non-Routine Manual Share of Total Employment



Notes: These figures plot the share of total employed individuals — on aggregate and by gender — in routine manual jobs (left) and non-routine manual jobs (right). The shares are calculated using working-age employed individuals aged 18-55 in CPS ASEC between 1972-2019. See Appendix B.1 for the full occupation classification.

C Calibration Appendix

C.1 Calibrating Technology Parameters

Given the skill distribution assumption, the male and female population shares in each occupation, the skill dynamics parameters, and the intermittency parameter, I can calculate aggregate efficiency units of labor in each market occupation, M, R, N, summing equation (9) for men and women. Additionally, I have wages per efficiency unit in each occupation, calculated based on young men's mean income in each occupation. The technology parameters are chosen to rationalize this allocation and these wages, in accordance with the first order conditions to the firm's problem in equation (5).

First, I calculate the value of the automation price, p_C, which is needed to rationalize the allocation and wages of the routine relative to non-routine jobs. To calculate this, I solve for C as a function of N, R, p_C which maximizes S_{net} in the firm's problem laid out in equation (5). Combing R and the optimal $C(N, R, p_C)$ yields a value of $\tilde{R}(N, R, p_C)$. The p_C is chosen such that the allocation N and R satisfies the relative demand at the given wages for these types of labor, derived by taking the first-order conditions from the firm's problem:

$$\frac{w_R}{w_N} = \left(\frac{N}{\tilde{R}(N, R, p_C)}\right)^{\frac{1}{\lambda}} \times \tilde{R}(N, R, p_C)^{\frac{1}{\psi}} \times R^{\frac{-1}{\psi}}$$

Next, I calculate the value of manual labor productivity, A_M, which is needed to rationalize the allocation of manual relative to non-routine jobs. Given R, N and p_C, I calculate the optimal S_{net}. I then find the value of A_M which makes the given allocation and wages satisfy the firm's relative demand for manual and non-routine workers:

$$\frac{w_M}{w_N} = A_M^{\frac{\sigma-1}{\sigma}} \times \left(\frac{S_{net}(N,R,p_C)}{M}\right)^{\frac{1}{\sigma}} \times (S_{net}(N,R,p_C) + p_C C(N,R,p_C))^{\frac{-1}{\lambda}} \times N^{\frac{1}{\lambda}}$$

Finally, I pick the value of total factor productivity to match the level of real wages in the manual job, again using the first-order condition from the firm's problem:

$$Z = w_M \times M^{\frac{1}{\sigma}} \times A_M^{\frac{1-\sigma}{\sigma}} \times \left((A_M M)^{\frac{\sigma-1}{\sigma}} + S_{net}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{-1}{\sigma-1}}$$

C.2 Calibrated Values of Preference Parameters

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

	1970 Value	**2000 Value**
Panel A: Women		
b_{wH}	18.60	20.85
b_{wM}	1.50	1.65
b_{wR}	1.19	1.31
b_{wN}	1	1
Panel B: Men		
b_{mH}	13.97	18.49
b_{mM}	1.13	1.21
b_{mR}	0.98	0.98
b_{mN}	1	1

Notes: This table presents the calibrated value of the non-monetary preference terms (b's) for men and women in each occupation. The preference for the non-routine occupation, N, is normalized to 1 as it is the relative preferences that matter in determining the employment shares.