Dual Income Earners and Productivity

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Abstract

We examine when joint households contribute towards productivity improvements. Motivated by the increasing share of females in joint households employed in full-time non-routine cognitive jobs, we develop a directed search model with heterogeneous job choice. Income pooling and consumption security afforded by one's partner affect the decision of whether to accept a risky job that grows one's productivity. Using our estimated model, we find that females in joint households contributed the most to productivity improvements. Declining non-employment risk was a significant factor driving these gains, while changes in the marginal distributions of underlying types played a smaller role.

Keywords: Joint Household Search, Female Labor Supply, Job Allocation, Productivity
JEL Codes: E24, J24, J64

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1 Introduction

When do dual-income earners give rise to productivity improvements? Apriori, an increase in dual-income earners need not give rise to productivity gains. If workers and jobs are homogeneous, then one more employed person in a household contributes the same amount of output per unit labor, leaving labor productivity unchanged. The 1970s productivity slowdown, however, occurred alongside both a rising share of dual income earners and rapidly increasing female labor supply. Moreover, the above-trend productivity observed in the post-2000 period was accompanied by a significant shift in the *composition* of jobs held by females in joint households, with an increasingly larger share of them selecting into full-time jobs. Both observations are at odds with the assumption of homogeneous jobs and workers, and suggest that the focus on extensive margin measures of labor supply alone may miss how changes in job composition matter for productivity outcomes. Because the decision of which job to select is determined at the *household* level[1], we ask in this paper what conditions enable members within the joint household to select into jobs that raise productivity.

We make three contributions. First, we document novel facts concerning the employment outcomes and job allocation of females in joint households over time. We focus on females in joint households as the rise in dual income earners is largely driven by their increased employment. Our examination of job outcomes suggests that female engagement with the labor market can still be increasing even when employment and participation measures have leveled off. As we show, this is especially true for females in joint households who were not only increasingly employed in full-time work in the post-2000 period but also in jobs that typically involved more complex and abstract tasks. Second, we build on the literature on joint search, and develop a model with heterogeneous job choice. Agents in our model can choose to search for risky jobs that provide the potential for human capital growth, or safe jobs that provide a steady stream of consumption. While greater selection of jobs that grow one's human capital contributes towards raising aggregate productivity, these decisions within the joint household are contingent on not only the individual's characteristics, but also the partner's attributes. Third, we estimate our model to match labor market moments, and use it to quantify the disparate productivity gains across individuals in different household types. We further use our model to uncover the factors which drive females in joint households to select into the kinds of jobs which promote productivity improvements. We find that declining non-employment risk among joint household females contributes the most towards increasing productivity. Conversely, we find a small role for improvements in the marginal

[1]This is especially pertinent when jobs are heterogeneous in their returns as well as their risk profile, as members of the household determine which risks are worth taking based on total resources as well as relative market opportunities of the couple.

distributions of workers.

In terms of our empirical findings, we first show how labor productivity has evolved over time alongside coincident changes in the share of dual income earners. Because changes in the share of dual-income earners mimic changes in female labor supply, we next highlight that females in joint households – as opposed to single females –are the main drivers behind the movements in aggregate female employment outcomes. As measures of the extensive margins of female labor supply only provide a partial picture of females' engagement with the labor market, we then detail how the composition of jobs among employed females has changed over time. In doing so, we highlight that employment in full-time non-routine cognitive jobs (FT-NRCOG) rose disproportionately among females in joint households in the post-2000s, overtaking that of single females. Finally, we document how the average wage income of each group relative to the economy-wide average wage has varied over time given these changes in job composition. Overall, our findings complement existing empirical work on female labor supply. By segmenting the data by household type, we provide additional insight on the role that household structure can have on the job allocation decisions of individuals and its implications for productivity dynamics.

Given our empirical observations, we develop a directed search model with heterogeneous workers and jobs for both the single and the joint household. In our model, there are two types of jobs, a *dead-end* job which provides no opportunity for human capital accumulation and productivity growth, and a *learning* job which provides the opportunity to gain human capital and grow productivity. An individual's underlying type determines how quickly they gain human capital. The learning job, however, is risky as human capital is match-specific and non-transferable across jobs. In the event of a separation, human capital gained at a learning job completely depreciates. We use our model to study how income pooling affects job selectivity and wage choices: given anticipated disruptions to their careers, individuals choose between dead-end jobs which provide a steady stream of consumption and risky learning jobs which offer the potential for human capital and income growth.

Income pooling and relative exposure to non-employment risk within the joint household impact the decisions of which job to choose and what wage to accept. A partner's relative level of non-employment risk and their type affect the amount of expected income within the joint household. On one hand, added expected income from a partner reduces the marginal benefit of an extra dollar, making the worker more likely to search for less risky jobs that offer more consumption with greater certainty. On the other hand, added expected income from a partner can also reduce the marginal cost of searching for high-paying jobs, as enlarged outside options and a bigger consumption buffer enable the worker to take on more risk and hold out for hard-to-get high-paying jobs. These opposing forces affect both the job selection margin and the choice of wage. The former (job selection) impacts the worker's likelihood of growing productivity, while the latter (wage choice) affects the worker's likelihood of employment and thus contribution to aggregate productivity. These forces are absent in the single household's problem, underscoring the fact that the household structure is an important factor behind job allocation decisions and productivity outcomes. In this sense, our work is complementary to the literature on the added-worker effect (AWE) (See Bacher et al. [2025], Birinci [2019], Ellieroth [2019] for recent examples), which shows how household structure can affect female labor supply in response to business cycle shocks. Our focus, however, on how the same decision-making affects the type of jobs held emphasizes its impact on productivity.

Having developed our framework, we take our model to the data. We consider two time periods, pre- and post-2000, resembling the break in the empirical facts we present on labor productivity and labor market moments. In estimating our model, we focus on the parameters that play a key role in affecting the composition of jobs and employment outcomes. We find that the parameters that varied a lot over the two time periods, are those that govern separation rates and the unconditional distribution of types. Movements in these parameters *jointly* affect the share of employed in learning jobs – which in our estimation corresponds to the share employed in FT-NRCOG jobs – and the extent of continuous market attachment, both of which increased significantly in the data for females in joint households.

Given these parameters, our estimated model predicts that higher productivity outcomes in the post-2000s period are largely explained by the labor market outcomes of females in joint households. Qualitatively, our model also matches untargeted moments such as the changes in wage income ratios over time. Turning to our model's predictions, we find that the rise in productivity over the two time periods stems mostly from the increased propensity of females in joint households to be employed in risky learning jobs which grow their productivity. In this sense, our findings accord with that of Albanesi [2025] who finds that increases in females' relative productivity added positively to aggregate productivity outcomes. We find that lower non-employment risk for females in joint households is the main factor driving a larger share of employed females to select into learning jobs. Intuitively, learning jobs provide the potential for higher income growth, but individuals only find it worthwhile to search for such jobs if they are likely to be continuously employed, as 1) the human capital gained in such jobs is non-transferable and 2) the rate at which one gains this human capital is stochastic. Improvements in the marginal distributions of members within joint households play a smaller role in promoting productivity improvements, as the marginal worker indifferent between selecting into a learning job vs. a dead-end job is increasing in the partner's type. That is, individuals matched to high partner types are more likely to opt for dead-end jobs which offer a steadier stream of consumption.

In sum, our model sheds light on why an increase in the share of dual income earners and in female labor supply need not translate into productivity gains. Rather, it is the composition of jobs which matter for productivity outcomes. Within the joint household, these decisions on job allocation are dependent on the relative risk and degree of consumption security provided by the partner. As such, our model provides new insights on how household structure shapes job allocation decisions, which in turn determine productivity outcomes.

The rest of the paper proceeds as follows. Section 2 discusses the related literature. Section 3 documents the motivating facts on female labor supply, and job composition by household status. Section 4 presents the model while Section 5 provides some comparative statics detailing the forces at play. Section 6 quantifies the model and evaluates how decisions in the joint household, especially among females, contribute to long-run productivity trends. Finally, Section 7 provides a summary conclusion and direction for future research.

2 Literature Review

Our paper connects three distinct strands of the macroeconomic literature: the literature on family economics and labor supply, the analysis of structural transformation and labor productivity trends, and the theory of frictional labor markets with joint search.

First, we contribute to the family macroeconomics literature, which has long emphasized that labor supply decisions are often made jointly within households rather than by isolated individuals. Doepke and Tertilt [2016] provide a comprehensive review of this approach, arguing that accounting for family dynamics is crucial for understanding aggregate economic outcomes. Attanasio et al. [2008] and Heathcote et al. [2010] document the life-cycle profiles and secular trends of female labor supply. We contribute to this literature by developing a model where the insurance effect of spousal income influences not just whether females work, but also the type of job they select, a margin that is critical for productivity outcomes.

Second, our work relates to the literature on structural transformation and female labor supply. Ngai and Petrongolo [2017] and Olivetti and Petrongolo [2016] have documented how the rise of the service economy and the marketization of home production have fundamentally shifted the demand for female labor. Similarly, Goldin [2006] documents how females were initially secondary earners in a joint household and that a 'quiet revolution' in females' expectations about future employment as well as the introduction of contraceptives led to their increased realized continuous attachment to the labor market. In closely related work, Uniat [2025] examines how various factors affecting female labor supply contributed to the decline in routine employment and the rise of female employment in non-routine jobs. Our work is complementary to these sets of empirical observations and quantitative findings. We provide additional insight on how it is females in joint households that have been a major driver of these trends, and offer a novel explanation as to how female employment and job allocation outcomes can depend on risk-sharing within the joint household.

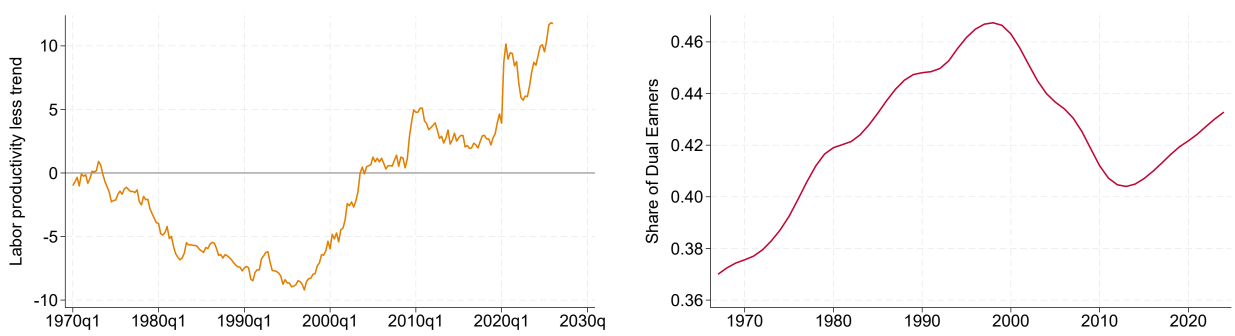
Third, we build on the theoretical literature on household search. The canonical framework by Guler et al. [2012] and Flabbi and Mabli [2018] shows how joint household reservation wage and search decisions can differ from that of single households. Fernández-Blanco [2022] extends the joint household search model to study optimal public insurance for couples while Pilossoph and Wee [2021] show how joint household search can impact the sign of wage premia. A large strand of the literature on joint household search has studied the "added-worker-effect" and has examined how spousal labor supply can be used to partially insure the household against income shocks (See Mankart and Oikonomou [2017], Wang [2019], Birinci [2019], Ellieroth [2019], Casella [2022], and Bacher et al. [2025] for example). We depart from these frameworks by introducing a directed search model with distinct job types, some of which provide the opportunity for human capital accumulation and thus productivity gains. Our focus on how both the job selection margin and wage choice are affected by the relative skill and non-employment risk of members within the joint household allows us to study how household decisions can affect aggregate productivity outcomes. This connects our work to Jang and Yum [2022] and Erosa et al. [2022], who investigate the relationship between hours worked, occupation types, and aggregate productivity. In contrast, our model provides a mechanism that connects labor productivity outcomes with household search, and shows how income pooling can impact the sorting into risky, high-return jobs.

Finally, we relate to the debate on productivity fluctuations and female employment. Albanesi [2025] and Fukui et al. [2023] analyze how female employment has shaped the volatility of business cycles, the emergence of jobless recoveries and measured productivity. In closely related work, Ellieroth and Michaud [2024] show how changes in female career paths can predict the evolution of aggregate employment volatility over business cycles, even as participation levels remain fairly constant. We contribute to this debate by focusing, instead, on the long-run, and highlighting that the *composition* of jobs held by females in joint households is a key determinant of aggregate productivity outcomes, distinct from the pure extensive margin effect of entering the labor force.

3 Motivating Facts

We provide some new stylized facts motivating our analysis. First, we examine movements in labor productivity (relative to its linear trend) and how these varied alongside changes in the share of households which are dual-income earners. Because females in joint households are the drivers of movements in the share of dual-income earners, we next show how employment-to-population (EPOP) ratios for prime-age females have evolved over time[2], and show how these differences vary across household type, i.e., for singles vs females in joint households. Next, we document how the job allocation of females by household type has evolved over time, as well as its implications for income earned.

Labor Productivity and Dual Income Earners Figure 1a shows the deviation in labor productivity from trend. Labor productivity was below trend starting in the 1970s and above-trend in the latter part of the 2000s. Alongside these changes, the share of dual-income earners rose rapidly in the 1970s and largely stabilized in the late 2000s (Figure 1b). As aforementioned, these coincident changes stand at odds with the assumption of homogeneous workers and jobs. In what follows, we focus on the employment outcomes of females in joint households as the variation in dual-income earners largely reflects changes in the employment of this group. More importantly, and as we discuss next, we go beyond extensive margin measures of labor supply and focus on how the composition of jobs for this group has evolved over time. We highlight the implications such a change may suggest for productivity outcomes.



(a) Labor productivity less trend

(b) Share of dual-income earners

Figure 1: Labor productivity and share of dual income-earners

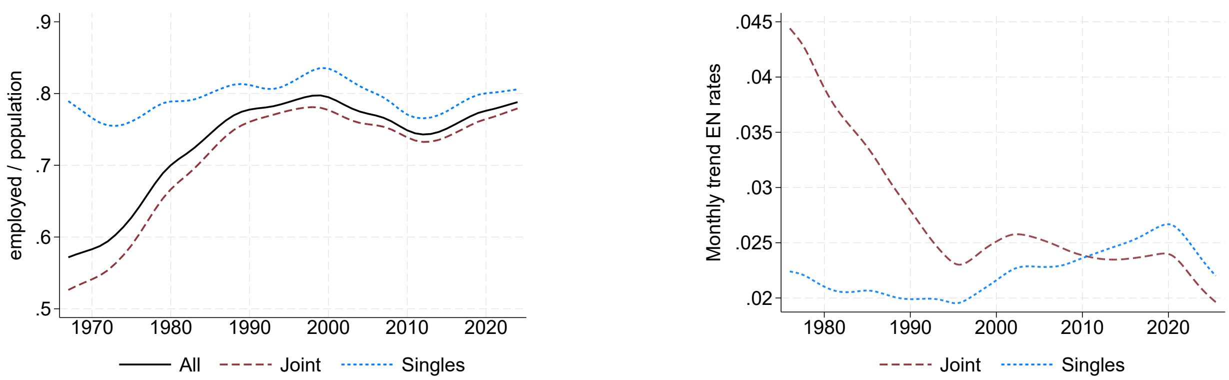
Notes: Labor productivity data is taken from U.S. Bureau of Labor Statistics (BLS), Nonfarm Business Sector: Labor Productivity for All Workers. The figure plots the deviation of the labor productivity from its fitted linear trend. Data on the share of household that are dual-income earners are taken from the CPS, March Supplement. See Appendix B for further details.

Labor Supply & Extensive Margin To study the extensive margin of women's employment trends, we focus on the EPOP ratio of prime-age females, as depicted in Figure 2a.[3] The female EPOP ratio in the US rose rapidly between the 1970s to 1990s, before peaking in

[2]We focus on prime-age workers as this abstracts from other trends like an aging population. We highlight the moments for females as the trends for males are either stable (as observed for those in joint households) or declining over time (as observed for singles).

[3]It should be noted that the literature has highlighted similar trends in female labor force participation rates (LFPR) over the same time period (See for example Albanesi and Prados [2022] and Albanesi [2025]).

the 2000s and then stabilizing. As in Olsson [2025], we find that the changes in the aggregate female EPOP ratio largely reflect movements in the EPOP ratio for females in joint households. The increase and subsequent stabilization in EPOP ratios were accompanied by a large decrease in the Employment to Non-Employment (EN) rate of females in joint households, followed by a period of relative stabilization post-2000, as depicted in Figure 2b. Overall, these patterns suggest that the 1970s slowdown in labor productivity was accompanied by significant changes in the labor market attachment of females in joint households. The latter in turn was likely driven by a reduction in non-employment risk, as evidenced by their falling EN rates. In stark contrast, both the EPOP ratio and EN rate for single females were fairly stable over time.[4] We next examine how the job allocation of females varied over time.



(a) EPOP Rate

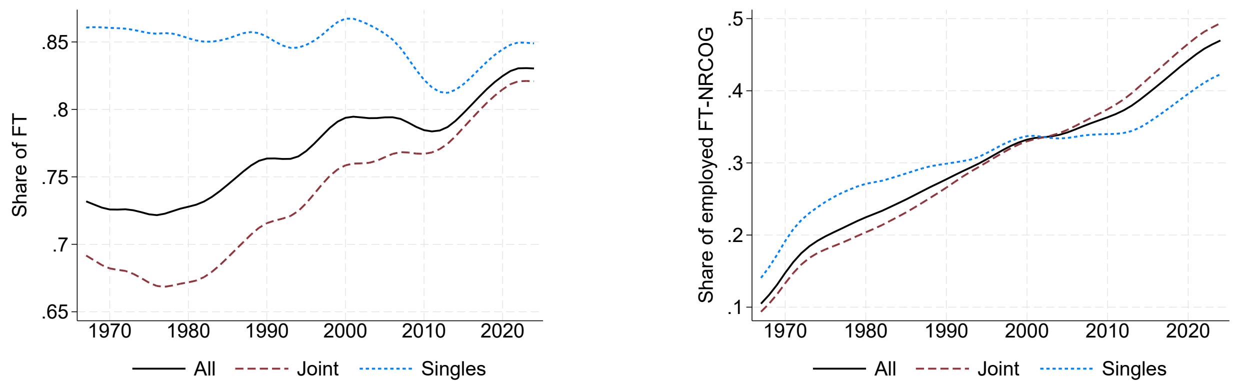
(b) EN Rate

Figure 2: Labor Force Trends by Household Type - Females.
Notes: Data is taken from CPS. Trend component of EPOP and EN rate are derived by HP-filtering the respective series with smoothing parameter 6.25 and 129600, respectively. See Appendix B for further details.

Job Allocation and Income The next set of facts relates to females' job allocation by household type. We examine the shares of employed prime-age females working in full-time (FT) jobs as well as the type of jobs they hold. In particular, we focus on how the share of employed prime-age females working in full-time non-routine cognitive (FT-NRCOG) jobs has changed over time, and whether this is different for females in joint households. We focus on FT-NRCOG jobs as these jobs have typically been identified by the literature to involve abstract tasks, and represent jobs with skilled human capital (see Acemoglu and Autor [2011]).[5]

[4]Appendix B.2 shows that no discernible trends emerge for males in joint households and that single males actually observe falling employment rates.

[5]In this sense, and foreshadowing our model in Section 4, FT-NRCOG jobs correspond to the learning jobs that raise one's productivity.



(a) Share of FT

(b) Share of FT-NRCOG

Figure 3: Job Allocation Trends by Household Type - Females.
Notes: Figure 3a shows the trend component of the fraction of employed prime-age females who work full-time. Figure 3b shows the trend component of the fraction of employed prime-age females who work full-time in non-routine cognitive jobs. Data derived from CPS and HP-filtered with smoothing parameter 6.25. See Appendix B for further details.

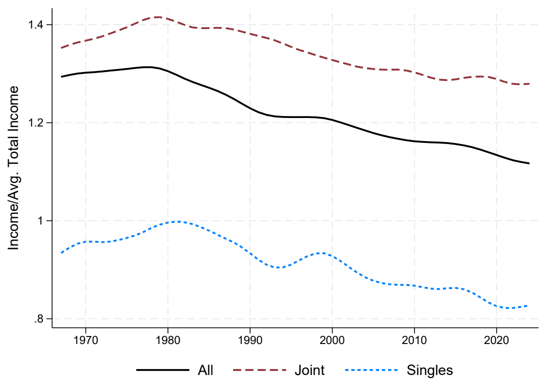
Figure 3 shows the share of employed prime-age females working in FT jobs (left panel) and in FT-NRCOG jobs (right panel) over time. Figure 3a shows that while the share of employed working in FT jobs has increased over time for females, this increase is uniquely due to females in joint households. The increased propensity of females in joint households to work in FT jobs also implies that labor supply measured in terms of hours per capita was continually rising for this group of females.[6] In this sense, engagement with the labor market was continuously increasing for females in joint households, a facet of the data that is obscured when only extensive margin measures of employment are used.

Delving deeper into the types of jobs held, Figure 3 shows that conditional on employment, females in joint households have been increasingly more likely to be represented in FT-NRCOG jobs. In fact, in the post-2000 period, employed females in joint households were more represented in FT-NRCOG jobs than their single counterparts. These patterns suggest that household structure can affect not only a female's employment decision, but also the types of jobs she selects. To the best of our knowledge, this latter fact is new and complements the quantitative evidence on labor market attachment of women with more qualitative evidence on the *type* of jobs they select.

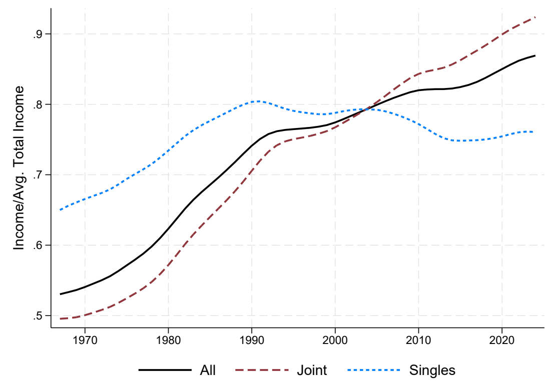
Figure 4 concludes the empirical section by plotting the trends in (annual) wage income earned (normalized by the economy-wide average wage income) for men (left panel) and for women (right panel) by household type. While the trend for males has largely stagnated, the right panel shows that until the 1990s, (detrended) income ratios for females increased

[6]Appendix B shows the variation in hours per capita for females in joint households over time.

for all household types. Thereafter, the income ratio for single females largely stagnated, but the income ratio continued to increase for females in joint households. These differential income trends which are particularly pronounced in the post-2000 period mirror the trends in job allocation presented in Figure 3b. Our empirical findings suggest that household status matters for the type of jobs individuals choose, and thus for their amount of income earned.



(a) Males



(b) Females

Figure 4: Income Trends.

Notes: The figure plots average annual wage income for each group divided by average wage income for the pooled all-population benchmark in the same year. Wage income is based on CPS ASEC wage-and-salary income. The benchmark is constructed from the corresponding all-group wage components pooled across genders. The plotted lines are HP-filtered with smoothing parameter 6.25. See Appendix B for further details.

To the extent that the composition of workers across jobs of different productivity and with different potential for human capital growth matters for productivity gains, it is useful to understand what drives the variation in employment outcomes and job allocation between females in joint households and their single counterparts. To examine this question, we next introduce a model to illustrate the forces which drive differential job choices between single females and females in joint households.

4 Model

Environment Time is continuous. The economy is composed of risk-averse single and joint households as well as risk-neutral firms, all of whom discount the future at rate ρ. Joint households are households with exactly two members. There exists a measure 1 of singles for each gender and a measure 1 of joint households.

Households Within a household, individuals are ex-ante heterogeneous and differ by their gender, their household type (single or joint) and their individual learning ability, x. In what follows, we denote $s \in \{m, f, a, b\}$ as the status of an individual by gender-household type.

That is, a single male household is denoted by $s = m$, a single female household is denoted by $s = f$, a male in a joint household is denoted by $s = a$, and a female in a joint household is denoted by $s = b$.

Individuals are also distinguished by their individual type x. An individual's type x is permanent, and drawn from an exogenous distribution $F_s(x)$ with associated density $f_s(x)$. An individual's type x determines the rate at which they learn and gain human capital at a job. Formally, we denote $\gamma(x)$ as the rate at which an individual of type x gains human capital, and assume that an individual's rate of growing human capital is increasing in their type, i.e., $\gamma'(x) > 0$. We allow the distribution of x to differ by one's gender and household status. In addition, job separation rates, δ_s, as well as home production values, z_s, also vary by one's gender and household status.

Individuals are also ex-post heterogeneous and can differ by their employment status. An employed individual earns their wage, which is the product of their contracted wage share η and the output produced in the match. A non-employed individual in a gender-household combination s observes income from home production z_s. There is no savings technology and all households consume their current income.

Jobs A job is a single firm-worker pair. There are two types of jobs in this economy: (1) a *dead-end* job which offers no growth in human capital and (2) a *learning* job which offers an opportunity for human capital growth. A firm matched to a worker in a dead-end job produces y_D units of output in each period throughout the duration of their match. In contrast, a firm matched to a worker in a learning job initially produces $y_L < y_D$ units of output. At rate $\gamma(x)$, the worker gains human capital at this learning job and thereafter produces $y_H > y_D$ units of output each period for the duration of the match. Human capital in the learning job is match-specific, implying that if a worker is displaced from her job at rate δ_s, the next time this worker is re-employed at a learning job, they again initially only produce y_L units of output until they regain human capital and become skilled at rate $\gamma(x)$. In this sense, human capital at a learning job is risky as it is non-transferable across jobs and completely depreciates upon job loss.

Search and matching Search is directed with the markets segmented into sub-markets which vary by (i) the type of job $k \in \{D, L\}$, where D refers to dead-end job and L refers to the learning job, (ii) by the individual's gender-household combination s, (iii) by the individual's type x, (iv) by the posted wage share η and by (v) the employment status of the household. We denote these characteristics as $\mathbf{C}$.[7] Firms post a vacancy at cost κ and select which

[7]In Proposition 1, we show in equilibrium that the characteristics of the sub-market $\mathbf{C}$ can be summarized by just $\{k, s, x, \eta\}$.

sub-market to post a vacancy. Within a sub-market $\mathbf{C}$, search is random and total matches follow a Cobb-Douglas matching function:

$$M(\mathbf{C}) = \xi \ell(\mathbf{C})^{\alpha} v(\mathbf{C})^{1-\alpha}$$

where $\ell(\mathbf{C})$ and $v(\mathbf{C})$ refer to the job-seekers and vacancies in the sub-market with characteristics $\mathbf{C}$. ξ refers to the matching efficiency and α is the elasticity of the matching function with respect to job-seekers. Denote labor market tightness, $\theta(\mathbf{C})$, as the ratio of vacancies to job-seekers in that sub-market, i.e., $\theta(\mathbf{C}) = {}^{v(\mathbf{C})}/_{\ell(\mathbf{C})}$. Then, workers find jobs at rate $p(\theta[\mathbf{C}])$ and firms in that sub-market fill jobs at rate $q(\theta[\mathbf{C}]) = {}^{p(\theta[\mathbf{C}])}/_{\theta(\mathbf{C})}$.

Having described the model set-up, we now turn to the individual problems. We start with single households, due to the simplicity of their problem relative to joint households.

4.1 Single households

Non-employed single The value of a non-employed single of gender-household combination $s \in \{m, f\}$ and type x is given by:

$$\rho U_s(x) = u(z_s) + R_s(x)$$

where

$$R_s(x) = \max\{R_s^D(x), R_s^L(x)\} \tag{1}$$

and for $k \in \{D, L\}$

$$R_s^k(x) = \max_{\eta} p(\theta(\mathbf{C})) \left[W_s^k(\eta, x, y_k) - U_s(x)\right] \tag{2}$$

$W_s^k(\eta, x, y_k)$ is the value of the employed single of type x in job k producing output y_k with wage-share η. The value of a non-employed single is given by their flow utility in home production and their maximized value of search $R_s(x)$. The worker's search problem is twofold, first they choose which job – dead-end or learning – to search. Second, within a job type, they choose the wage-share that maximizes their expected gain to matching.

Employed single The value of an employed single of gender-household combination s, type x with η wage share in a dead-end job is given by:

$$\rho W_s^D(\eta, x, y_D) = u(\eta y_D) - \delta_s \left[W_s^D(\eta, x, y_D) - U_s(x)\right]$$

The employed worker gets flow utility from their wage income ηy_D, and is displaced from their job at rate δ_s, at which point they observe the change in value $-\left[W_s^D(\eta, x, y_D) - U_s(x)\right]$. As aforementioned, dead-end jobs do not provide any avenue for human capital growth, and thus the worker produces y_D each period until the match dissolves.

Conversely, the employed single at a learning job can grow their human capital. Consider the value of a single of gender-household combination s, type x, with wage share η and who is employed at a learning job but has not yet gained human capital. Their value is given by:

$$\rho W_s^L(\eta, x, y_L) = u(\eta y_L) - \delta_s \left[W_s^L(\eta, x, y_L) - U_s(x)\right] + \gamma(x) \left[W_s^L(\eta, x, y_H) - W_s^L(\eta, x, y_L)\right]$$

where

$$W_s^L(\eta, x, y_H) = \frac{u(\eta y_H) + \delta_s U_s(x)}{\rho + \delta_s}$$

In addition to their flow utility from consuming their wage income and the change in value they observe from a separation shock, the individual in a learning job who currently produces y_L units of output grows their human capital at rate $\gamma(x)$ and produces y_H units of output thereafter. In such an event, the individual receives the change of value $\left[W_s^L(\eta, x, y_H) - W_s^L(\eta, x, y_L)\right]$ where $W_s^L(\eta, x, y_H)$ is the value of an employed single in a learning job who has gained human capital.

4.2 Joint Households

Joint households can be (i) dual non-employed, (ii) a worker-searcher household where only one member is employed and (iii) dual employed. We outline their problems below.

Dual non-employed household The problem of a dual non-employed household with pair types $\mathbf{x} = (x_a, x_b)$ is given by:

$$\rho\mathcal{U}(\mathbf{x}) = u(z_a + z_b) + \mathcal{R}_a^{uu}(\mathbf{x}) + \mathcal{R}_b^{uu}(\mathbf{x})$$

where for $s \in \{a, b\}$

$$\mathcal{R}_s^{uu}(\mathbf{x}) = \max\{\mathcal{R}_s^{D,uu}(\mathbf{x}), \mathcal{R}_s^{L,uu}(\mathbf{x})\} \tag{3}$$

and for $k \in \{D, L\}$

$$\mathcal{R}_s^{k,uu}(\mathbf{x}) = \max_{\eta} p(\theta(\mathbf{C})) \left[\mathcal{W}_s^k(\eta, \mathbf{x}, y_k) - \mathcal{U}(\mathbf{x})\right] \tag{4}$$

$\mathcal{W}_s^k(\eta, \mathbf{x}, y_k)$ is the value of a worker-searcher household of pair-type $\mathbf{x}$ and where member s is employed in job-type k producing output y_k with wage-share η. The problem of the dual non-employed household is similar to that of a non-employed single except for the fact that joint household members get utility from consuming their pooled income and both members of the joint household can search. $\mathcal{R}_s^{uu}(\mathbf{x})$ represents the maximized value of search for non-employed member $s \in \{a, b\}$ and this is similar to the maximized value of search for the non-employed single: $R_s(x)$ for $s \in \{m, f\}$. A key difference is that the search problem of the joint household depends not just on the individual's characteristics x_s, but rather on the characteristics of both members, $\mathbf{x}$.

Worker-searcher household In what follows, we focus on the value of a worker-searcher household where only member a is employed. Analogous expressions exist for worker-searcher households where b is instead employed.

Consider a worker-searcher household where member a is employed in job-type k producing output $y_a \in \{y_L, y_D, y_H\}$ with wage-share η_a. This household's value is given by:

$$
\begin{aligned}
\rho \mathcal{W}_a^k(\eta_a, \mathbf{x}, y_a) &= u(\eta_a y_a + z_b) - \delta_a \left[\mathcal{W}_a^k(\eta_a, \mathbf{x}, y_a) - \mathcal{U}(\mathbf{x})\right] + \mathcal{R}_b^{eu}(\eta_a, \mathbf{x}, y_a) \\
&\quad + \mathbb{I}(y_a = y_L)\gamma(x_a)\left[\mathcal{W}_a^L(\eta_a, \mathbf{x}, y_H) - \mathcal{W}_a^L(\eta_a, \mathbf{x}, y_L)\right]
\end{aligned}
$$

where the search problem of the non-employed b in such a household is given as:

$$
\mathcal{R}_b^{eu}(\eta_a, \mathbf{x}, y_a) = \max\{\mathcal{R}_b^{D,eu}(\eta_a, \mathbf{x}, y_a), \mathcal{R}_b^{L,eu}(\eta_a, \mathbf{x}, y_a)\} \tag{5}
$$

and for $k, j \in \{D, L\}$

$$
\mathcal{R}_b^{j,eu}(\eta_a, \mathbf{x}, y_a) = \max_{\eta} p(\theta(\mathbf{C}))\left[\mathcal{T}(\eta_a, \eta, \mathbf{x}, y_a, y_j) - \mathcal{W}_a^k(\eta_a, \mathbf{x}, y_a)\right] \tag{6}
$$

where $\mathcal{T}(\eta_a, \eta, \mathbf{x}, y_a, y_j)$ is the value of dual employment. The joint household gets flow utility from their combined income. At rate δ_a, the worker-searcher household observes a separation shock and observes the change in value from transitioning to a dual non-employed household. Unlike single employed households, the worker-searcher household's non-employed member can continue to search for a job. This search value is represented by $\mathcal{R}_b^{eu}(\eta_a, \mathbf{x}, y_a)$. This search value, $\mathcal{R}_b^{eu}(\eta_a, \mathbf{x}, y_a)$, for the non-employed member in a worker-searcher household depends not only on the characteristics of the joint household but also on the income of member a which is summarized by their η_a and their output produced at their current job. Finally, if member a is currently employed at a learning job but has not yet gained human capital – i.e., the case where $\mathbb{I}(y_a = y_L)$ is equal to 1 – then at rate $\gamma(x_a)$, the household transitions to a worker-searcher household where a has gained human capital and now produces y_H. The value of a worker-searcher household where a has already gained human capital and produces output y_H is given by:

$$
\mathcal{W}_a^L(\eta_a, \mathbf{x}, y_H) = \frac{u(\eta_a y_H + z_b) + \delta_a \mathcal{U}(\mathbf{x}) + \mathcal{R}_b^{eu}(\eta_a, \mathbf{x}, y_H)}{\rho + \delta_a}
$$

Dual employed household Denote $\mathbf{n} = (\eta_a, \eta_b)$ and $\mathbf{y} = (y_a, y_b)$. Then the value of a dual employed household where both a and b are employed in job-types k and j with wage-shares η_a and η_b, respectively, and producing $y_a, y_b \in \{y_L, y_D, y_H\}$ is given by:

$$\begin{aligned}
\rho\mathcal{T}(\mathbf{n},\mathbf{x},\mathbf{y}) \quad = \quad & u(\eta_a y_a + \eta_b y_b) \\
& -\delta_a \left[\mathcal{T}(\mathbf{n},\mathbf{x},\mathbf{y}) - \mathcal{W}_b^j(\eta_b,\mathbf{x},y_b)\right] - \delta_b \left[\mathcal{T}(\mathbf{n},\mathbf{x},\mathbf{y}) - \mathcal{W}_a^k(\eta_a,\mathbf{x},y_a)\right] \\
& +\mathbb{I}(y_a = y_L)\gamma(x_a)\left[\mathcal{T}(\mathbf{n},\mathbf{x},y_H,y_b) - \mathcal{T}(\mathbf{n},\mathbf{x},y_L,y_b)\right] \\
& +\mathbb{I}(y_b = y_L)\gamma(x_b)\left[\mathcal{T}(\mathbf{n},\mathbf{x},y_a,y_H) - \mathcal{T}(\mathbf{n},\mathbf{x},y_a,y_L)\right]
\end{aligned}$$

The dual employed household gets flow utility from their joint wage income. At rate δ_s for $s \in \{a, b\}$, member s is separated from their job and they transition to a worker-searcher household where only their partner is employed. If either member a or b or both a and b are in a learning job and currently producing y_L, then at rate $\gamma(x_s)$ for $s \in \{a, b\}$, they gain human capital and transition to a dual employed household where member s now produces y_H units of output.

4.3 Firms

The value of a matched firm depends on its worker's type x, the worker's gender-household combination s, the job type k, and the output that the worker is currently able to produce, $y \in \{y_L, y_D, y_H\}$. Proposition 1 makes clear that the firm's value only depends on the characteristics of its own worker, and not on the partner's traits.

Proposition 1. *In equilibrium, the matched firm's value depends only on its worker's characteristics, and not on the characteristics of the partner in a joint household. Thus, the value of a matched firm attached to a worker of type x, of gender-household combination s, in job-type k with wage-share η is given by:*

$$\rho J_s^k(\eta,x,y) = (1-\eta)y - \delta_s J_s^k(\eta,x,y) + \mathbb{I}(y = y_L)\gamma(x)\left[J_s^k(\eta,x,y_H) - J_s^k(\eta,x,y)\right] \tag{7}$$

where $y \in \{y_L, y_D, y_H\}$.

Further, the characteristics of the sub-markets can be summarized by $\mathbf{C} = \{k, s, \eta, x\}$. For an active sub-market, $\theta_s^k(\eta, x) \geq 0$, the following free entry condition must hold:

$$\theta_s^k(\eta,x) = \left[\frac{\xi}{\kappa} J_s^k(\eta,x,y_k)\right]^{1/\alpha} \tag{8}$$

Proof. See Appendix A.1 □

Intuitively, in our model, the only events that can cause a change in the firm's value are the incidence of an exogenous separation shock, and for a learning job, the growth in the worker's human capital such that she goes from producing y_L to producing y_H units of output. These events only depend on the worker's gender-household combination type, s, and the worker's learning ability, x. Consequently, the firm's value is independent of the partner's characteristics. Because the firm's value is independent of such characteristics, the sub-markets are also independent of the partner's characteristics.[8]

While the partner's characteristics do not affect the value of the firm and thus the manner in which markets are segmented, the partner's characteristics do affect the outside option of the worker and the choice of sub-market to search. In Section 5, we show how the partner's type x and relative exposure to non-employment risk affects job selection, the wage-share workers seek, their corresponding employment outcomes and thus their impact on productivity.

4.4 Closing the model

Closing the model, Appendix A.2 describes the laws of motion and characterizes the steady state measure of each household type by employment status. Equilibrium in the model is then given by the following proposition.

Proposition 2. *In steady state, equilibrium is characterized by the solution to equations 1, 2, 3, 4, 5, 6, the free entry condition 8 and the equations A.2-A.15 contained in Appendix A.2 which describe the laws of motion for each household type.*

Crucially, the key decisions in this model which affect the resultant aggregate productivity in the economy concern the type of job – the solutions to equations 1, 3, 5 – as well as the optimal wage-share, where the latter is given by the solutions to equations 2, 4 and 6. The former determines whether individuals are employed in jobs which can grow their human capital while the latter determines their likelihood of employment and thus whether they can contribute to aggregate productivity. In the joint household, job selection and wage choices depend on the expected income of the partner, and thus on their partner's type x, and their relative exposure to non-employment risk. The following Section 5 outlines how these partner attributes influence the optimal job and wage-share choice of the worker.

[8] Crucially, our assumptions of no on-the-job search and no quits are key to this outcome. If on-the-job search and/or quits into non-employment are allowed, then the rate at which firm's profits are discounted is dependent on the partner's characteristics, as the partner's expected income affects the outside option of the joint household and thus the rate at which the matched worker quits and accepts a new job.

5 Characterization

For the following exercises, we focus on the decisions of member b in a dual non-employed joint household. To highlight the role of relative exposure to non-employment risk, we assume that $\delta_b > \delta_a$ and all other parameters are the same unless otherwise stated.

5.1 Optimal job choice

Consider member b in a dual non-employed household. Suppose that in one household, member b is attached to a partner who has a high $x_a = x_H$ while in another household, member b is attached to a partner who has a low $x_a = x_L < x_H$. Figure 5 shows how the partner's type affects the optimal job choice. The dashed blue line represents the benefit of selecting a learning job, $\mathcal{R}_b^{L,uu}(x_L, x_b)$, for a household where member b is attached to a partner with a low $x_a = x_L$. This line is upward-sloping as higher x_b types have a higher rate of growing human capital ($\gamma'(x) > 0$), raising the value of searching for a learning job. The solid blue horizontal line represents the cost of searching for a learning job in terms of the foregone opportunity of searching for a dead-end job, $\mathcal{R}_b^{D,uu}(x_L, x_b)$. Finally, the vertical dotted blue line represents the marginal x_b type attached to a low $x_a = x_L$ partner who is exactly indifferent between a learning job and a dead-end job.

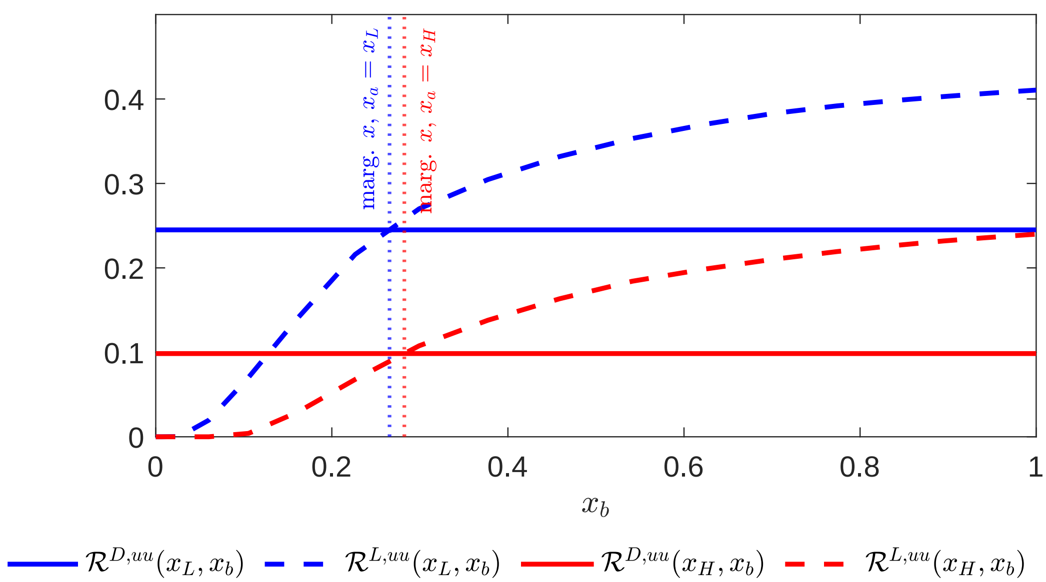


Figure 5: Marginal x type is in increasing in partner's type

Notes: The blue (red) solid line refers to the value of search in a dead-end job for non-employed member b attached to a partner with low $x_a = x_L$ (high $x_a = x_H$). The blue (red) dashed line refers to the value of search in a learning job for non-employed member b attached to a partner with low $x_a = x_L$ (high $x_a = x_H$). The vertical dotted blue (red) line represents the marginal x_b type that is indifferent between a learning and a dead-end job when the partner is of type $x_a = x_L$ ($x_a = x_H$).

The lines in red are exactly the same except they are for a member b in a dual non-employed household with a partner of a high $x_a = x_H$ type, where $x_H > x_L$. The red lines lie below their counterparts in blue. Intuitively, this is because a partner with a higher x_a offers a higher expected stream of income, implying a larger outside option for the joint household, $\mathcal{U}(x_H, x_b) > \mathcal{U}(x_L, x_b)$. Since outside options are larger when the partner's x_a type is higher, this implies a smaller gain to matching and hence the maximized values of $\mathcal{R}_b^{D,uu}(\mathbf{x})$ and $\mathcal{R}_b^{L,uu}(\mathbf{x})$ are both lower. The benefit of searching for a learning job, however, falls more than the cost when the partner's type increases from x_L to x_H, implying that the marginal x_b is increasing in their partner's type. Although the risky job offers the potential for future income growth, higher expected income from a high partner type reduces the marginal value of an extra dollar and thus the value of searching for a job with risky but high returns. Consequently, more x_b types select into the dead-end job that offers more consumption with greater certainty when their partner's type is higher. Overall, the marginal x_b type is increasing in their partner's x_a type.

5.2 Optimal wage share

To note how the optimal wage-share varies by the partner's type, consider member b's search problem in a dual non-employed household. Using the free entry condition 8, the solution to 4 for member b can be characterized as:

$$\frac{1-\alpha}{\alpha}\frac{1}{1-\eta}\left[\mathcal{W}_b^k(\eta, \mathbf{x}, y_k) - \mathcal{U}(\mathbf{x})\right] = \frac{\partial \mathcal{W}_b^k(\eta, \mathbf{x}, y_k)}{\partial \eta} \tag{9}$$

The LHS of Equation 9 represents the marginal cost of searching for a higher wage-share η while the RHS represents the associated marginal benefit. Similar expressions exist for the singles' optimal search problem, and for the non-employed member in a worker-searcher household. Both the LHS and RHS are functions of $\mathbf{x}$ and are thus affected by the partner's type x_a. On one hand, added expected income from a partner reduces the marginal value of an extra dollar, i.e., the RHS of equation 9, lowering the benefit of searching for very high-paying jobs. On the other hand, added expected income from one's partner also provides consumption security, lowering the marginal cost of holding out for a high-paying job, i.e., the LHS of equation 9. We illustrate how both the marginal cost and benefit vary with x_a in Figure 6. For this exercise, we fix the x_b type to the mean x which in our example optimally selects a learning job. We show how the wage-share choice of a single household – with the same $x = x_b$ and who faces the same exact parameters as b – varies relative to the wage-share choices of a joint household member b attached to different partners.

The black solid line in Figure 6 represents the marginal cost of searching for a higher η

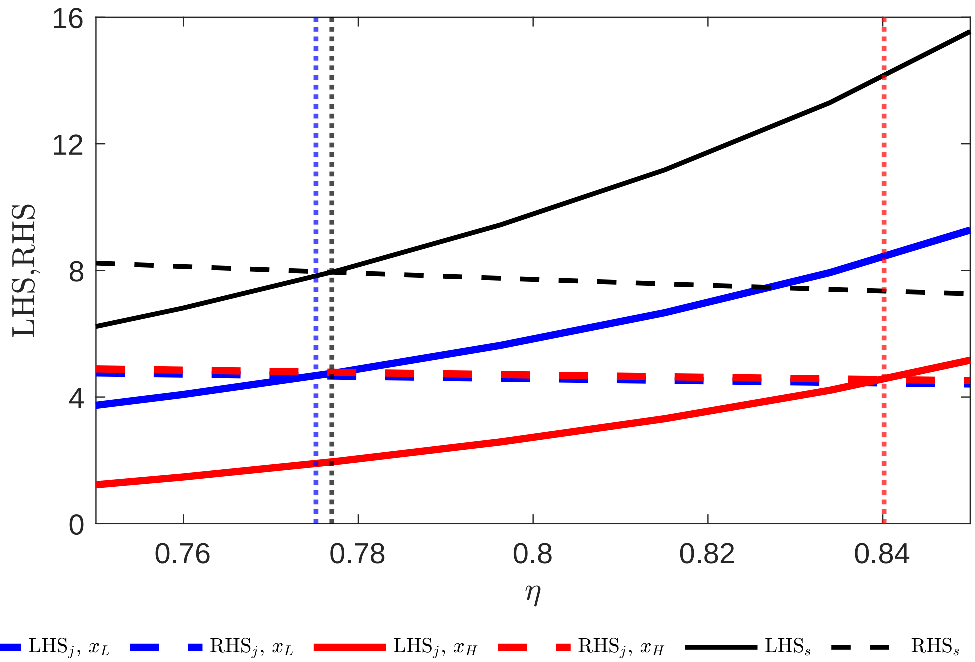


Figure 6: Relative to singles, optimal η can be higher or lower depending on partner's x
Notes: The black, blue and red solid lines represent the marginal cost of searching for a higher η for a single household, for a member b attached to a partner of type x_L and for a member b attached to a partner of type x_H, respectively. The black, blue and red dashed lines represent the corresponding marginal benefit while the black, blue, and red vertical lines denote the optimal η chosen for the aforementioned household types. The single household and member b are fixed to the mean x type.

(LHS) for a single household. Because a higher wage-share implies lower values for the firm, fewer jobs are created when η is high. Consequently, the black solid line is upward-sloping as searching for a higher η is associated with lower job-finding rates. The black dashed line represents the marginal benefit of searching for a higher η for a single household. Because marginal utility is decreasing in consumption, the black dashed line is downward sloping. The vertical black dotted line highlights the optimal η chosen by the single household.

The blue solid and dashed lines represent the same marginal cost and benefit curves, but for a member b in a dual non-employed household attached to a partner with a low $x_a = x_L$. Both curves for this member b (blue lines) lie below the corresponding curves for a single household (black lines). The marginal cost is lower as joint household members observe a smaller gain to matching given their larger outside options. The marginal benefit is also lower since higher pooled income within the joint household lowers the marginal utility from an additional dollar. When the partner's type is low, the marginal benefit of searching for a higher η falls more than the marginal cost. Income pooling within the joint household lowers the marginal value of an extra dollar. As such, member b who is attached to a low x_a partner prefers to search for lower wages in equilibrium so as to increase their employment probability and ensure a higher stream of consumption.

In contrast, the joint household where member b is attached to a partner with a high $x_a = x_H > x_L$ observes its marginal cost of searching for a higher η falling by a greater extent (red solid line in Figure 6). Intuitively, when the partner has a high x_a, their high expected stream of income implies a significant consumption buffer for the joint household. Member b is thus now willing to take on more risk and hold out for higher-paying jobs that are harder to find. Consequently, the large fall in the marginal cost leads member b to search for a much higher η, as depicted by the vertical red dotted line.

These comparative statics highlight that within the joint household, the partner's x type matters for both job selection and wage choice. Income pooling and the degree of consumption security is increasing in the partner's type, reducing the value of searching for a risky learning job. Conditional on selecting into the learning job, a high partner type provides a strong consumption buffer, making it worthwhile for individuals to hold out for higher-paying jobs, and thus affecting their wage choice. Both job-selection and the wage choice affect productivity, the former through the potential for human capital growth, the latter through the probability of employment and the likelihood that an individual contributes towards aggregate productivity.

5.3 Optimal search given differential non-employment risk

So far, we have only shown how member b searches within the dual non-employed joint household. We now consider how the household specializes given their type x and their differential exposure to non-employment risk. To highlight how the joint household makes its decisions, we again focus on the search decisions within a dual non-employed household. We assume in this exercise that i) separation risks differ across members, specifically $\delta_b > \delta_a$, and ii) the partner in the joint household observes the mean x, while the searching member's x is allowed to vary. All other parameters are otherwise the same between the two household members. Figure 7 plots how the optimal choice of η in a learning job varies with the searching member's x for differential non-employment risk.

The red solid line plots how the optimal choice of η in a learning job varies with x for a joint household member b who faces a higher $\delta_b > \delta_a$ and whose partner observes the mean x. The black dashed line plots the same curve but for member a who faces lower non-employment risk. The vertical lines indicate the marginal x type that is exactly indifferent between choosing a learning vs. a dead-end job. Relative to member a, member b who faces a higher δ_b is less likely to select into a learning job. Intuitively, household members that face high separation risk are less likely to benefit from selecting into a learning job where workers initially produce low output $y_L < y_D$. Since such workers could separate from a learning job

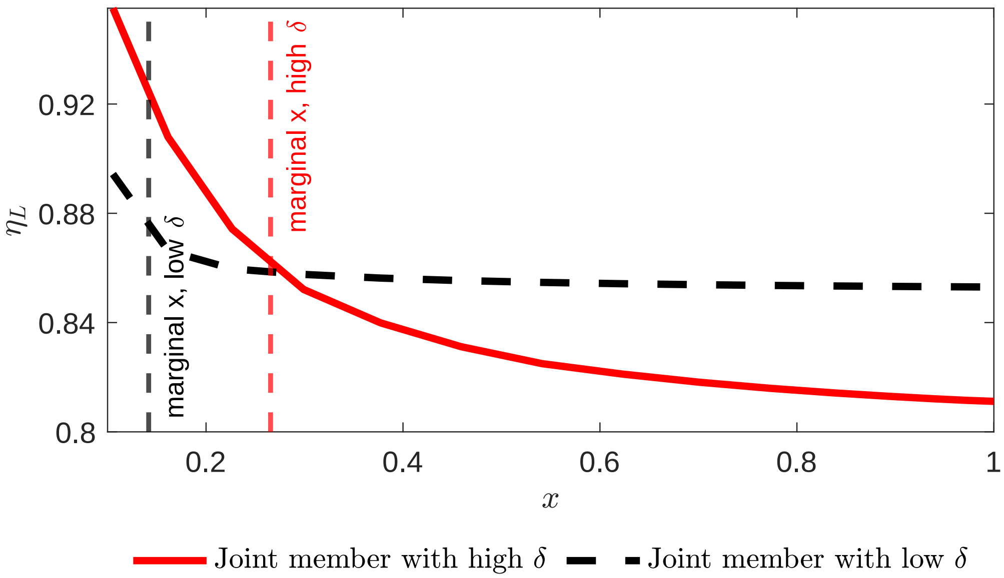


Figure 7: Higher δ members less likely to select learning jobs, more likely to seek lower wages
Notes: The black (red) downward-sloping lines represent the optimal wage-share η chosen in a learning job for a worker of type x in a joint household with low (high) separation risk and attached to a partner with mean x. The vertical black (red) dashed line represents the marginal x type that is indifferent between a learning job and a dead-end job for a worker who observes low (high) separation risk and whose partner's type is of the mean x.

before ever gaining human capital, such jobs would actually provide lower streams of income. Conditional on searching for a learning job, however, members with high non-employment risk actually seek lower wage-shares than members with low δ_a. This is partly due to the fact that in equilibrium, fewer jobs are created for individuals with higher separation risk. Seeking lower wages allows these workers to be employed faster and thus raises their expected gains from searching for learning jobs.

In summary, our comparative static exercises shed light on how insurance and risk affect the job selection and wage choices within the joint household. Members with high non-employment risk, or who are matched to a partner with a high x are less likely to select into learning jobs. The degree of non-employment risk faced and amount of consumption buffer provided by the partner in turn shape the wage choices of the household, impacting their likelihood of being employed and their contribution to aggregate productivity. Having described the forces inherent in our model, we now turn to our quantitative model to explore how these forces shaped productivity changes in the economy.

6 Quantitative

6.1 Estimation

Overview The singles model can be solved as a separate block from that of joint households so long as we target moments that apply to that gender-household type specifically. In what follows, we first estimate the model for single females and males. We then estimate the model for joint households, again targeting gender-specific moments that apply to that household type. In doing so, we are implicitly making the assumption that certain key parameters are gender-household-specific. We estimate the model over two periods, pre-2000 (1967-1999) and post-2000 (2000-2024), given the break in labor market and productivity trends we documented earlier.

Data The dataset is the Current Population Survey, CPS (March Supplement). The sample is restricted to prime-age individuals, ages 25-54. Wage moments are constructed from CPS wage-and-salary income.[9] Details on the sample construction are reported in Appendix B.1.

Externally Set Parameters and Functional Forms A model period is a quarter. We set the quarterly discount rate to $\rho = 0.012$, consistent with an annual interest rate of approximately 5 percent. We also make the following functional form assumptions. First, we assume utility is logarithmic in consumption, $u(c) = \log(c)$. Second, we assume that the rate at which workers gain human capital in the learning job takes the form of $\gamma(x) = 1 - \exp(-x)$. Next, we assume that the distribution of x types follows that of a Beta distribution: $x \sim \mathbb{B}(1, \beta)$, where the first shape parameter is normalized to one and the second shape parameter β is to be estimated. With regards to output, we normalize initial output in the learning job, $y_L = 1$, and assume that output in the dead-end job and output produced once one has gained human capital in the learning job is equal to $y_D = y_L + \Delta$ and $y_H = y_D + \Delta$, respectively. We further assume $\Delta = 1$. The matching function is set to be Cobb-Douglas, with matching efficiency $\xi = 1$ and elasticity parameter $\alpha = 0.5$, as is standard in the literature. Finally, for $\delta_{s,t}$ for $s \in \{m, f, a, b\}$, we impose the EN transition rates we observe in the data for each gender-household combination type.[10] These transition rates imply that apart from females in joint households, separation rates rose for all other groups. Table 1 summarizes the parameters set externally.

[9] When hourly wages are used, they are computed as annual wage income divided by annual hours, where annual hours are measured using weeks worked last year and weekly hours.

[10] Given monthly EN probabilities, we calculate the quarterly EN probability as $EN_{quarterly} = 1 - (1 - EN_{monthly})^3$. To then convert this into a rate, we calculate the quarterly EN rate as $EN_{rate} = -\ln(1 - EN_{quarterly})$ as in Shimer [2012].

Object	Value	Description
ρ	0.012	Quarterly discount rate.
α	0.5	Matching elasticity.
ξ	1	Matching efficiency normalization.
y_L	1	Low-productivity level.
Δ	1	Productivity increment.
	Pre-2000	
δ_m	0.075	EN rate for male singles
δ_f	0.063	EN rate for female singles
δ_a	0.036	EN rate for male in joint households
δ_b	0.094	EN rate for female in joint household
	Post-2000	
δ_m	0.083	EN rate for male singles
δ_f	0.074	EN rate for female singles
δ_a	0.042	EN rate for male in joint households
δ_b	0.073	EN rate for female in joint household

Notes: The table reports the externally set parameters.

Table 1: Fixed parameters

Singles Having specified functional forms and externally set parameters, this leaves the following key parameters to be estimated: $\Xi_t^s = \{\kappa_t, z_{s,t}, \beta_{s,t}\}$ for $s \in \{m, f\}$ and $t \in$ {pre-2000,post-2000}. These parameters are key in affecting labor market moments, and as such, we discipline the parameters in the following manner. First, κ_t is chosen to match the aggregate EPOP among singles in the associated time period. Second, for $s \in \{m, f\}$, $\beta_{s,t}$ is chosen to match the share of employed in a learning job by gender and the associated time period. To pin down the share employed in a learning job, we use information on the share of employed in FT-NRCOG jobs. Intuitively, the distribution of x types would affect the measure of individuals who work in a learning job since the rate at which one grows their productivity in such jobs is dependent on their $\gamma(x)$. Third, we assume that home production values $z_{s,t}$ replaces 40% of that group's average wage, as per Shimer [2005].

Joint households For joint households, we estimate the following set of gender-specific parameters:

$$\Xi_t^J = (z_{a,t},\, z_{b,t},\, \beta_{a,t},\, \beta_{b,t}), \qquad \text{where } a = m, \quad b = f.$$

We assume joint households face the same vacancy posting cost κ_t as singles. The remaining parameters are estimated to match the same analogous moments as in the estimation for singles: for $s \in \{a, b\}$, $\beta_{s,t}$ is pinned down by the share of employed in learning jobs, and $z_{s,t}$ replaces 40% of the average wages within that gender-household type. Targeting moments by gender-household type allows us to recover the implied marginal distributions of x types, and because we assume random matching, the joint distribution of household pairs.

SMM We estimate both the singles model and joint household model by the method of simulated moments. Let m_t^{data} denote the vector of targeted moments in period t, and let $m_t^{model}(\Xi)$ denote the corresponding model moments. We estimate parameters by minimizing

$$\widehat{\Xi} = \arg\min_{\Xi} \left(m^{model}(\Xi) - m^{data}\right)' W \left(m^{model}(\Xi) - m^{data}\right),$$

where W is a positive definite weighting matrix. Details on the estimation procedure are reported in Appendix C.1.

Estimated parameters Panel A of Table 2 reports the estimated parameters for singles, while Panel B reports the corresponding estimates for joint households. Overall, the model matches the data moments very well. The following variations in parameters are worth noting. First, the vacancy posting cost κ rose across the two time periods in order to match the decline in aggregate EPOP. Second, there was an improvement in the marginal distributions of x types for all groups, as exhibited by the decline in $\beta_{s,t}$ for $s \in \{m, f, a, b\}$ across time periods. Given our assumption that $x \sim \mathbb{B}(1, \beta)$, a decline in β implies on average, a shift in the distribution towards higher x types.

The movements in observed separation rates and in the estimated distribution of x types are particularly significant for individuals in joint households. For example, the separation rate for females in joint household fell by 22%, reminiscent of the steep decline documented in Figure 2b. The estimated distribution of x types for males in joint households also improves significantly, with the mean x type rising by 49%. The significant shifts in these parameters suggest a non-trivial impact on the decisions within the joint household of how to specialize according to relative learning ability (x) and relative non-employment risk (δ).

As a validation exercise, we report the model's predictions for wage ratios, a moment which is untargeted in our estimation. Table C.1 in Appendix C.2 shows that despite its parsimony, the model qualitatively gets correct movements in the wage ratios, defined as average wages by gender and household status divided by the economy-wide average wage. Interestingly, our model predicts that males in joint households earn a premium relative to males in single households. Females in joint households initially observe a wage penalty relative to single females in the pre-2000s, which is later reversed to a wage premium in the post-2000s, similar to findings in Pilossoph and Wee [2021]. Moreover, our model predicts a narrowing in the gender wage gap over time, from 0.96 to 0.99.[11] These differences

[11] In our model, we assumed measure 1 of single males, measure 1 of single females and measure 1 of joint households. The gender wage gap is the average of female wages across all household types divided by the

Panel A: Singles				
Pre 2000s				
Parameter	Value	Target	Data	Model
κ	10.49	Aggregate EPOP	0.84	0.83
z_m	0.72	40% of mean wage	0.40	0.40
z_f	0.74	40% of mean wage	0.40	0.40
β_m	9.72	Share employed in learning job	0.25	0.25
β_f	9.38	Share employed in learning job	0.27	0.27
Post 2000s				
κ	14.09	Aggregate EPOP	0.81	0.78
z_m	0.70	40% of mean wage	0.4	0.41
z_f	0.75	40% of mean wage	0.4	0.41
β_m	9.32	Share employed in learning job	0.26	0.27
β_f	7.33	Share employed in learning job	0.35	0.36
Panel B: Joint Households, a =male,b =female				
Pre 2000s				
Parameter	Value	Target	Data	Model
z_a	0.80	40% of mean wage	0.40	0.40
z_b	0.71	40% of mean wage	0.40	0.40
β_a	12.95	Share employed in learning job	0.33	0.32
β_b	4.12	Share employed in learning job	0.22	0.22
Post 2000s				
z_a	0.79	40% of mean wage	0.40	0.40
z_b	0.75	40% of mean wage	0.40	0.40
β_a	8.35	Share employed in learning job	0.39	0.39
β_b	4.02	Share employed in learning job	0.41	0.41

Notes: The table reports the estimated parameters by gender-household combination.

Table 2: Estimated Parameters

arise not from any imposition of differing marginal products of labor for singles vs. joint household members or males vs. females. In our model, conditional on the job type chosen, all individuals produce the same output once they have the same level of human capital. Wage differences in our model arise across household types and gender because of the job choices made. Because the parameters for members of joint households are more similar in the post-2000 period, gender gaps in incomes naturally shrink.[12]

average of male wages across all household types.

[12] In this respect, the model provides an alternative and complementary story for declining gender gaps relative to those typically emphasized in the literature, pointing broadly to declining labor market and hours barriers for women, as in Erosa et al. [2022] and Hsieh et al. [2019].

6.2 Aggregate Implications

Having estimated our model to match labor market moments by gender-household combination type $s \in \{m, f, a, b\}$, we now examine our model's implications for labor productivity. Table 3 highlights the percentage change in labor productivity, employment-to-population and the share of employed in learning jobs by gender-household combination type. Matching labor market moments, our estimated model predicts that labor productivity gains were observed for individuals in joint households and for single females, while male singles observed a labor productivity decline.

Crucially, Table 3 demonstrates that the largest increase in labor productivity came from females in joint households. Table 3 also makes clear that the reason why females in joint households recorded the largest increase in labor productivity stems not from their increased employment alone, but rather from the type of jobs they chose, since the largest increase in the share employed in learning jobs was recorded for females in joint households. In our model, individuals only find it worthwhile to engage in these learning jobs if they anticipate a high likelihood of growing their human capital while employed. In the estimated model, this effect is strongest for females in joint households for two reasons. First, the distribution of x types improved for all gender-household combinations, with the mean x type rising by about 2% for females in joint households to about 49% for males in joint households. The improvement in the distribution of x types implies that there are more individuals with high x in the post-2000 period relative to the pre-2000s. These higher x individuals are more likely to select into learning jobs. Second, the fall in the separation rates for females in joint households, δ_b, was especially large, representing a significant decline in non-employment risk. All other groups saw an increase in their separation rate. Alongside the improvement in the distribution of x types, increased continuous attachment and lower non-employment risk made learning jobs substantially more attractive to females in joint households, and thus caused their share of employed in learning jobs to increase the most.

Percent Change across two periods				
	Male joint	Male single	Female joint	Female single
Labor productivity	2.18	-0.17	5.50	1.48
EPOP	-4.65	-6.17	1.14	-6.52
Share employed in learning jobs	21.00	6.11	86.35	34.58
Wage ratio	0.40	-3.35	4.80	-1.81

Notes: The table reports the percent change in outcomes by gender-household combination.

Table 3: Increase in productivity driven by joint households females

These differences in job selection and productivity outcomes in turn translate into differential wage outcomes. The last row of Table 3 shows that the ratio of the average wage in a gender-household combination type relative to the economy-wide average wage increased the most for females in joint households. While the share employed in learning jobs grew for all groups, only members in joint households observed an increase in their wage ratios, consistent with the incomes trends in Figure 4, where the wage ratios declined over time mostly for individuals in single households. Despite only matching labor market moments, our model-implied wage-ratios qualitatively match these trends of negative growth in wage ratios for individuals in single households, negligible growth for males in joint households and significant growth in the wage ratio of females in joint household. This happens as a direct consequence of the differential job choices that these households make over time.

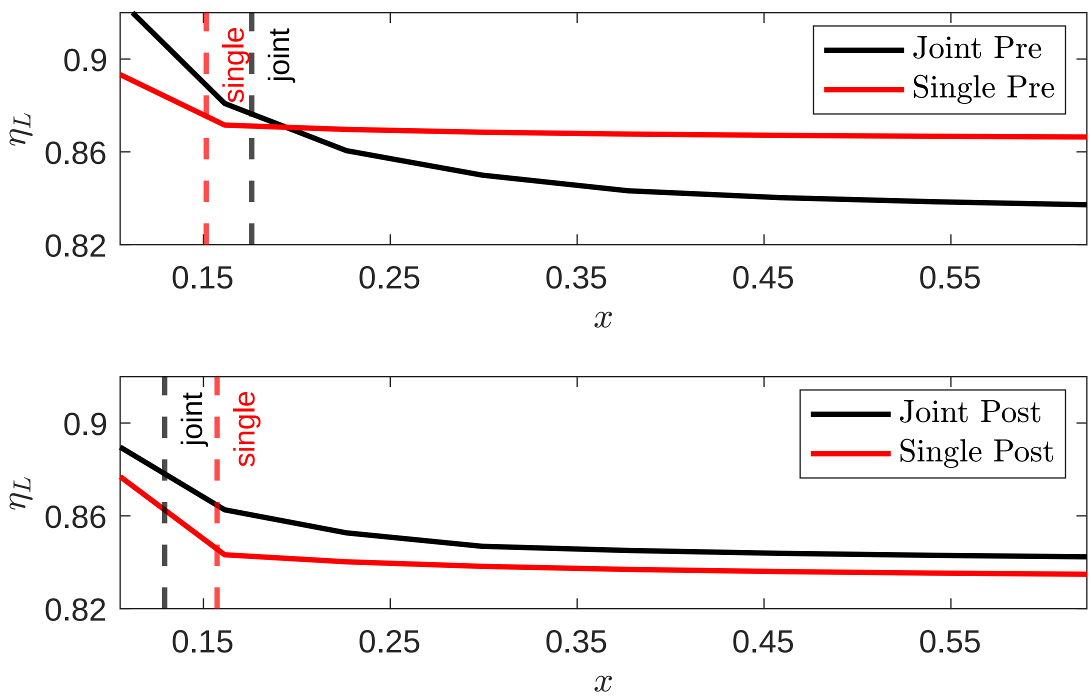


Figure 8: Job selection and wage choice for single vs. joint household females

Notes: The black (red) downward-sloping lines represent the optimal wage-share chosen in a learning job for a worker of type x in a joint (single) household whose partner's type is of mean x. The vertical black (red) dashed line represents the marginal x type that is indifferent between a learning job and a dead-end job for a worker in a joint (single) household. The top panel shows the choices for the pre-2000 period, the bottom panel for the post-2000 period.

Unpacking the changes across time Why have wage ratios declined for singles when their share of employed in learning jobs has increased? To understand this phenomenon, it is first useful to focus on the differences between single and joint household females. For this exercise, we fix the partner of the joint household female to be the mean x type of joint household males in the corresponding period. Figure 8 shows the selection into learning jobs and the associated wage-share choice in the pre- and post-2000 period. Across the two time periods, females in joint households were more likely to select into learning jobs as the marginal x type who is indifferent between the two types of jobs fell from the pre-2000 to the post-2000 period, as depicted by the black dashed lines in the top and bottom panel of Figure 8. This greater selection into learning jobs, together with the distribution of x types improving and shifting more towards high types, accounts for the large increase in the share employed in learning jobs for females in joint households. At the same time, the marginal x type for single females increased slightly. The concurrent decline and rise in the marginal x type for females in joint households and single females, respectively, led to the former being more likely than the latter to be employed in learning jobs in the post-2000 period, a reversal from the patterns observed pre-2000 and similar to the trends documented in Figure 3b.

The marginal x type for single females was higher in the post-2000 period due to an increase in their separation rate, δ_f. Although the marginal x type for singles increased, the share of single females employed in learning jobs still rose across the two time periods, as the unconditional distribution of x types improved across time. Nonetheless, the rise in separation risk for single females meant that for the same wage-share, the firm's value of matching to such a worker is lower in the post-2000 period. This in turn implies that for the same wage, fewer vacancies are created for a single female. Consequently, conditional on selecting a learning job, single females searched for lower wage-share jobs in the post-2000 period.[13] Even though a larger share of single females are employed in a learning job post-2000 relative to pre-2000, their higher non-employment risk and consequently, lower vacancy creation for this group induces single females to search for lower wages, resulting in a decline in their model-predicted wage ratios. In contrast, our model predicts that wage ratios increase for females in joint households because lower non-employment risk together with an improvement in the distribution of x types implies that not only are more of them are employed in learning jobs which provide income growth, but they are also searching for higher wages. Conditional on selecting into a learning job, both a decline in non-employment risk and an improvement in their *partner's* type drive the increase in wage ratios. In contrast, optimal wage-share choices are declining in an individual's own x type, as depicted in Figure 8. Since females in joint households in the post-2000s have a higher propensity to search for higher wage shares, this weighs negatively on their job-finding probability as these higher paying jobs are harder to find. As such, the increase in employment for females in joint

[13] This can be seen by the fact that red solid line (which represents the optimal wage-share choice of a single female in a learning job) is lower than 0.86 for all those who select into a learning job in the bottom panel (post-2000), while the optimal wage share is above 0.86 for all the single females who select into a learning job in the top panel (pre-2000).

Percent Change across two periods				
	δ only		β only	
	Male	Female	Male	Female
Labor productivity	-1.21	5.29	5.09	0.40
EPOP	-2.38	6.55	-0.26	-0.55
Share employed in learning jobs	-6.07	83.28	49.40	6.72
Wage ratios	-2.88	4.33	3.58	-1.10

Notes: The table reports the percent change in outcomes. The first counterfactual only allows (δ_a, δ_b) to be updated to their post-2000 values. The second counterfactual only allows the distribution parameter (β_a, β_b) to be updated to their post-2000 values.

Table 4: Change in separation rates drive most of increase in productivity

households is tempered.

While we have largely focused on the wage dynamics of females, similar forces are at play behind the wage growth of males. Although the separation rate increased for both single males and males in joint households, single males observed a much smaller improvement in their distribution of x types relative to males in joint households. Consequently, single males experienced a decline in their wage ratios as they search for lower wages since more firms find hiring such a worker unattractive with the rise in separation risk. Males in joint households observe negligible changes in their wage ratio over time as the significant improvement in their distribution of x types implies that a much larger share of them select into learning jobs despite the increase in their separation rate, δ_a.

Overall, our model estimated to match labor market moments suggests that females in joint households contribute significantly to labor productivity gains, and that differential changes in employment risk and in the marginal distributions of types are key factors behind this result. We now perform some counterfactual exercises to identify which factor contributed the most to productivity gains *within* the joint household across time.

6.3 Counterfactual exercises

In the following counterfactual exercises, we only allow one set of parameters to be updated to its post-2000 values, leaving all others constant. Given our estimation, we focus on the relative exposure to non-employment risk, and the marginal distribution of x types within joint households, both of which changed significantly across the two time periods. Table 4 shows the counterfactual results.

Non-employment risk Our first set of results focuses on the role of non-employment risk as represented by (δ_a, δ_b).[14] Across the two time periods, δ_a increases and δ_b falls while all other

[14]We are agnostic about what causes the change in non-employment risk across time. The literature has suggested that a decline in the motherhood penalty and changing norms positively affected females'

parameters are held constant. In this case, the changes in separation rates cause the EPOP ratios for males and females in joint households to decline and rise, respectively. Clearly, a rise in the separation rate diminishes the firm's value and reduces the degree of vacancy creation for that worker, impacting their likelihood of employment. These changes in the degree of non-employment risk also affect job selection by both members. Figure 9 shows the job selection decisions and wage choice in a learning job for the male and female in a joint household whose partner observes the average x for their gender-household combination type. The top panel represents the results for the pre-2000 period while the bottom panel represents the results for our counterfactual where only (δ_a, δ_b) are updated to their post-2000 values. The vertical dashed lines represent the marginal x type who is indifferent between a learning and dead-end job while the solid downward sloping lines shows how the optimal wage-share choice is changing with the individual's x.

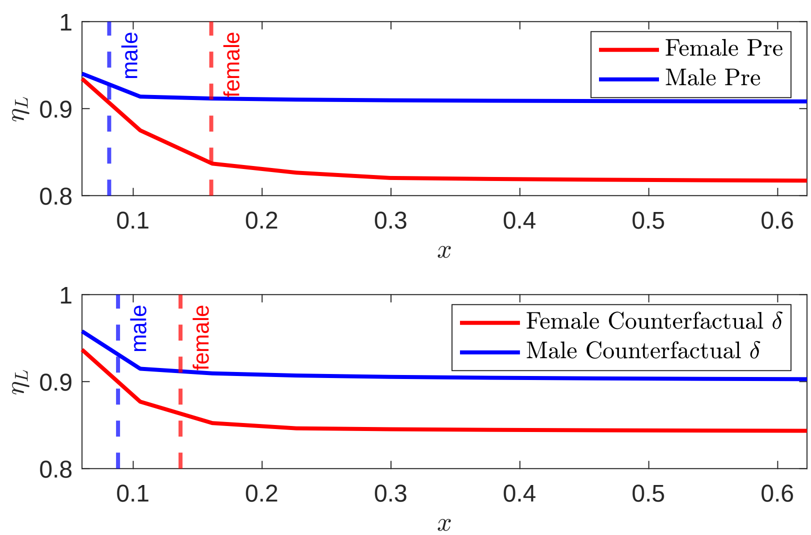


Figure 9: Job and wage selection when only (δ_a, δ_b) change.

Notes: The blue (red) downward-sloping lines represent the optimal wage-share chosen in a learning job for a male (female) worker of type x in a dual non-employed household whose partner's type is the mean x. The vertical blue (red) dashed line represents the marginal x type that is indifferent between a learning job and a dead-end job for a male (female) worker in a dual non-employed household. The top panel shows the choices for the pre-2000 period while the bottom panel shows the choices in our counterfactual where only (δ_a, δ_b) are updated to their post-2000 values.

Focusing first on job-selection, changes in (δ_a, δ_b) translate into more females selecting into learning jobs, and a slight decrease in the propensity of males to select into learning jobs. The change for males is small as males still bear lower separation risk than females within the joint households. As such, overall the share employed in learning jobs for males

continuous attachment to the labor market. See Olivetti et al. [2024] for a comprehensive overview.

in joint households falls by about 6 percent and this reduces their labor productivity by about 1 percent. For females, it is the opposite. As aforementioned, our model estimates imply that the females in joint households actually observe a distribution of x types that first order stochastically dominates (FOSD) that of males in joint households in the pre-2000 period. The reason why more of them are not employed in learning jobs is precisely because of their high separation risk. Our counterfactual exercise shows that the mere decline in δ_b leads fewer of them to specialize in dead-end jobs for insurance reasons, resulting in a large increase in the share employed in learning jobs and explaining almost all of the rise in labor productivity as observed in our baseline results.

Notably, in this counterfactual, EPOP for females in joint households also rises by a significant extent, despite females demanding higher wage-shares in learning jobs as δ_b declines, where the latter is depicted by the higher red line in the bottom panel of Figure 9 as opposed to its counterpart in the top panel of the same figure. The first reason for this is because the mean x type for females in joint households in the pre-2000 period is about 0.19. Larger changes in the demanded wage-share stem from very high x types of which there are few in the population of females in joint households. As such, despite higher demanded wage-shares, wage ratios for females in joint households increase by less across the two time periods relative to our baseline results. The second reason is that in this counterfactual, marginal distributions remained the same, while in our baseline, the marginal distributions of types varied across time. Improvements in the partner's x type *together* with a decline in non-employment risk implies that females in joint households have a stronger consumption buffer and can hold out for higher wages. Absent the change in the distributions of types, the change in average wage-shares is smaller, leading EPOP to rise by more in our counterfactual exercise where only (δ_a, δ_b) changes. This points to the effects of changing marginal distributions across the two periods, which we highlight next.

Marginal distributions Under this counterfactual, only the parameters, (β_a, β_b), affecting the unconditional distribution of x types for both males and females in joint households change. This implies that conditional on a pair $\mathbf{x} = (x_a, x_b)$, changes in the marginal distribution of x types do not impact the joint household's decisions of what job and wage to select. Instead, movements in the marginal distributions of males and females in joint households affect the *aggregation* of these choices, and thus the outcomes we report in Table 4. The table shows that in this case labor productivity increases for both males and females in joint households as the marginal distribution of both genders shifts towards higher x values. This improvement in the marginal distributions leads to an increase in the share employed in learning jobs for both genders, as higher x types benefit more from learning jobs with their faster rate of gaining human capital, and thus productivity improves overall.

EPOP falls for both genders in this counterfactual, but the wage ratio falls marginally only for females. Conditional on selecting a particular job type, a higher x type partner leads workers to hold out for better paying jobs which are harder to get, as previously explained in Section 5.2. Holding out for these higher-paying jobs causes EPOP to fall. Why then does the wage ratio for females in joint households not rise? This is largely because being matched to higher x types also changes the job selection margin. As highlighted in Section 5.1, individuals matched to higher x types observe lower values of searching for a learning job. In other words, the marginal x_b type who is indifferent between the learning and dead-end job is increasing in their partner's x_a type. The greater shift in the marginal distribution of males (relative to females) towards higher x types implies that more joint households are comprised of females attached to high x partners. Conditional on being matched to a partner who has the average x_a in that economy, the marginal x_b-type among such females rises from 0.16 in the pre-2000 period to about 0.18 in our counterfactual.[15] Thus the improvement in the marginal distribution of males implies that, holding all else constant, females are more likely to select into the dead-end jobs which provide no income growth over time. The main reason why the realized share of employed in learning jobs also rises in our counterfactual is because the female marginal distribution has *also* improved.Crucially, our results highlight that a mere change in the distribution of types alone is not sufficient to guarantee wage gains alongside productivity gains. This is precisely because the expanded outside option that comes from being matched to a higher partner x type and specialization among joint household members can actually reduce the propensity of workers to select into learning jobs.

Overall, we find that changes in non-employment risk were a key factor encouraging the rise in labor productivity among females in joint households, suggesting that dual income earners contribute most significantly to productivity when females in such households anticipate more continuous attachment. In contrast, improvements in the marginal distributions of types especially among males imply a higher likelihood of a female in a joint household being attached to a partner with high x. This in turn lowers the propensity of females to select into learning jobs, dampening the contribution of dual income earners towards aggregate productivity.

7 Conclusion

This paper has examined when dual income households can give rise to productivity gains, and if so, under what conditions. Motivated by our empirical findings, we develop a model where joint households pool income to share labor-market risk, and choose which jobs and wages to select. The extent to which productivity gains can arise within joint households

[15] The average x_a type rises from 0.07 in the pre-2000 period to about 0.11 in our counterfactual.

depends crucially on members' relative level of non-employment risk and on their relative types. Income pooling and the degree of consumption security afforded by one's partner can affect the propensity of workers to select into jobs with higher future returns, even if those jobs are riskier or have lower current pay.

The main implication is that household structure can be a channel through which labor-market risk affects aggregate productivity. Previous literature has emphasized how embedding joint earners in standard macro models is key to understanding employment over business cycles. Our paper complements this literature by extending these considerations to the long run. In addition to the existing literature that has focused on how productivity growth is affected by technology and firm dynamism, we argue that one should also take into account how household decision-making and risk-sharing affect the selection into jobs which provide the potential for human capital growth.

We kept the model simple enough that it can be extended in several directions, potentially tackling different questions. Recent literature has argued that educational sorting over time seems to explain only a limited part of the rise in household income inequality (See [Eika et al., 2019] for example). In our model, matching to a higher partner type has two opposing effects on wage incomes. It reduces the likelihood of selecting into a learning job which implies lower income growth. Conditional on selecting a learning job, a higher partner type also raises the optimal wage choice, raising wage incomes. Our framework can thus be used to explain why increased marital sorting is associated with limited income sorting, complementing work done by Calvo et al. [2024] and Pilossoph and Wee [2025]. We have also abstracted from on-the-job search, a margin of interest but that gives rise to non-trivial considerations on both the worker and the firm side. With on-the-job search, the firm's value is also dependent on partner characteristics, and as such the decisions within the joint household also bear on the firm's hiring decisions and on matters of pay, as in Di Nola et al. [2026]. We leave all these questions for future research.

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A Theory Appendix

A.1 Proof for Proposition 1

Consider two firms matched to member a from a dual non-employed joint household where for the first firm, member a is from a dual non-employed household with $\mathbf{x} = (x_a, x_b = x_L)$, and for the second firm, member a is from a dual non-employed household with $\mathbf{x} = (x_a, x_b = x_H)$ and $x_H > x_L$. First, it is useful to note that for $k \in \{D, L\}$ and $y \in \{y_D, y_H\}$, the value of a matched firm is given by:

$$J_a^k(\eta, x_a, y \mid x_b = x_L) = \frac{(1-\eta)y}{\rho + \delta_a} = J_a^k(\eta, x_a, y)$$

and

$$J_a^k(\eta, x_a, y \mid x_b = x_H) = \frac{(1-\eta)y}{\rho + \delta_a} = J_a^k(\eta, x_a, y)$$

In words, the only event that causes a change in value for the matched firm is a separation shock when the worker is either producing $y = y_D$ or $y = y_H$. Because we have assumed that there is no on-the-job search and no quits, the partner's characteristics do not affect the value of the firm. Further for matched firms in learning jobs whose worker currently produces y_L, we have:

$$J_a^L(\eta, x_a, y_L \mid x_b = x_L) = \frac{(1-\eta)y_L + \gamma(x_a) J_a^L(\eta, x_a, y_H)}{\rho + \delta_s + \gamma(x_a)} = J_a^L(\eta, x_a, y_L)$$

and

$$J_a^L(\eta, x_a, y_L \mid x_b = x_H) = \frac{(1-\eta)y_L + \gamma(x_a) J_a^L(\eta, x_a, y_H)}{\rho + \delta_s + \gamma(x_a)} = J_a^L(\eta, x_a, y_L)$$

Consequently, the above shows that the matched firm's value is independent of the partner characteristics.

Next we look at free entry. Because the matched firm's value is independent of partner characteristics, then from free entry, the labor market tightness in each market is independent of partner's characteristics. That is, for a firm seeking a worker of gender-household combination s and type x, under-free entry, we have:

$$\kappa \geq q(\theta(\mathbf{C})) J_s^k(\eta, x, y_k) \quad \text{for } k \in \{D, L\} \tag{A.1}$$

where the above holds with equality for active sub-markets, $\theta(\mathbf{C}) > 0$. Since the value of the firm only depends on (k, s, η, x) and using the Cobb-Douglas matching function, one can show solving equation A.1 gives us $\theta_s^k(\eta, x)$ as defined in equation 8. Thus, in equilibrium

$\theta(\mathbf{C})$ can be characterized as $\theta_s^k(\eta, x)$.

A.2 Labor market flows

In this section, we detail the equations that characterize the steady state measures of employed and non-employed within each household type.

A.2.1 Single household flows

Non-employed singles Denote $n_s(x)f_s(x)$ as the measure of single households of gender-household combination $s \in \{m, f\}$ and of type x. In steady state, the measure of non-employed singles of combination (s, x) satisfies:

$$\delta_s\left[1 - n_s\left(x\right)\right] = \left\{\mathbb{I}_s^D\left(x\right) p\left(\theta_s^D\left[\eta_{s,D}^*\left(x\right), x\right]\right) + \left(1 - \mathbb{I}_s^D\left(x\right)\right) p\left(\theta_s^L\left[\eta_{s,L}^*\left(x\right), x\right]\right)\right\} n_s(x) \quad \text{(A.2)}$$

where $\eta_{s,D}^*(x)$ and $\eta_{s,L}^*(x)$ are the optimal wage-shares chosen by the worker in each type of job given (s, x) and represents the wage share that maximizes Equation 2.[16] $\mathbb{I}_s^D(x)$ is an indicator function that is equal to one if $R_s^D(x) > R_s^L(x)$. The LHS of the above equation describes all the inflows into non-employment from exogenous separations while the RHS of the above equation represents all the outflows from non-employment which occur when the non-employed single successfully finds a job.

Employed singles Denote $e_s^D(x)f_s(x)$ as the measure of employed singles of type x of gender-household combination $s \in \{m, f\}$. In steady state, the measure of employed singles is implicitly characterized by:

$$\mathbb{I}_s^D\left(x\right) p\left(\theta_s^D\left[\eta_{s,D}^*\left(x\right), x\right]\right) n_s\left(x\right) = \delta_s e_s^D\left(x\right) \quad \text{(A.3)}$$

The LHS of Equation A.3 represents the inflows from non-employed singles who choose to search for dead-end jobs and who are successfully hired. The RHS represents the outflows from exogenous separations. Similarly, denoting $e_s^L(x)f_s(x)$ as the measure of employed in learning jobs who have yet to gain human capital, Equation A.4 characterizes its steady state level. The LHS of Equation A.4 represents the inflows from non-employed singles who choose to search for learning jobs and who are successfully hired, while the RHS represents outflows from exogenous separations *and* from the currently employed in learning jobs who gain human capital at rate $\gamma(x)$.

$$\left[1 - \mathbb{I}_s^D\left(x\right)\right] p\left(\theta_s^L\left[\eta_{s,L}^*\left(x\right), x\right]\right) n_s\left(x\right) = \left[\delta_s + \gamma(x)\right] e_s^L(x) \quad \text{(A.4)}$$

[16]While the measure of non-employed singles of type (s, x) is given by $n_s(x)f_s(x)$, it should be noted multiplying both sides by $f_s(x)$ leaves Equation A.2 unchanged.

Finally the measure of employed single households of type x and gender-household combination s in learning jobs who have gained human capital, $e_s^H(x)f_s(x)$ is given by:

$$\gamma(x)e_s^L(x) = \delta_s e_s^H(x) \tag{A.5}$$

Inflows into this measure stem from the unskilled employed at learning jobs who gain human capital at rate $\gamma(x)$ while outflows stem from exogenous separations.

To arrive at the aggregate non-employed singles of gender-household combination s, we simply aggregate across x, that is:

$$n_s = \int n_s(x)f_s(x)dx$$

We do the same aggregation across x to get the measure of employed in each job-type and skill-status: e_s^D, e_s^H, e_s^L.

A.2.2 Joint household flows

Throughout, we assume that there is random matching among joint households, and that the joint distribution of pair types $g(x_a, x_b) = f_a(x_a)f_b(x_b)$. While a large literature (See Calvo et al. [2024] and Pilossoph and Wee [2025] for example) has looked into explaining how changing labor market returns can lead to increased positive sorting among joint households and focused on the endogenous distribution of households, we treat the distribution of types here as exogenous.

Dual non-employed Denote $nn(\mathbf{x})f_a(x_a)f_b(x_b)$ as the measure of dual non-employed of type $\mathbf{x} = (x_a, x_b)$. Then in steady state, this measure is characterized by:

$$\begin{aligned} \delta_a \sum_{k\in\{D,L,H\}} e^k n\left(\mathbf{x}\right) \quad &= \quad \Big\{\mathbb{I}_a^D(\mathbf{x})p(\theta_a^D[\eta_{a,D}^*(\mathbf{x}), x_a]) + [1-\mathbb{I}_a^D(\mathbf{x})]p(\theta_a^L[\eta_{a,L}^*(\mathbf{x}), x_a]) \\ +\delta_b \sum_{k\in\{D,L,H\}} ne^k\left(\mathbf{x}\right) \quad & \qquad +\mathbb{I}_b^D(\mathbf{x})p(\theta_b^D[\eta_{b,D}^*(\mathbf{x}), x_b]) + [1-\mathbb{I}_b^D(\mathbf{x})]p(\theta_b^L[\eta_{b,L}^*(\mathbf{x}), x_b])\Big\}nn(\mathbf{x}) \end{aligned} \tag{A.6}$$

The LHS of Equation A.6 denotes all the inflows into dual non-employment stemming from the event when the employed in a worker-searcher household observes a separation shock. The RHS denotes the outflows from dual non-employment which occurs whenever a member from the dual non-employed household finds a job.

Worker-searcher with a employed in dead-end job Denote $e^D n(\eta_a, \mathbf{x})f_a(x_a)f_b(x_b)$ as the measure of worker-searcher households of pair-type $\mathbf{x} = (x_a, x_b)$ with member a employed in a dead-end job at wage share η_a. The steady state measure of this group is characterized by:

$$\begin{aligned}\mathbb{I}_a^D(\mathbf{x})\mathbb{I}(\eta_{a,D}^*(\mathbf{x})=\eta_a)p[\theta_a^D(\eta_a,x_a)]nn(\mathbf{x}) \quad &= \quad \Big\{\mathbb{I}_b^D\left(\eta_a,\mathbf{x},y_D\right)p\left[\theta_b^D\left(\eta_{b,D}^*\left[\eta_a,\mathbf{x},y_D\right],x_b\right)\right] \\ +\delta_b\sum_{k\in\{D,L,H\}}e^De^k(\eta_a,\mathbf{x}) \quad & \qquad +\left[1-\mathbb{I}_b^D\left(\eta_a,\mathbf{x},y_D\right)\right]p\left[\theta_b^L\left(\eta_{b,L}^*\left[\eta_a,\mathbf{x},y_D\right],x_b\right)\right] \\ & \qquad +\delta_a\Big\}e^Dn(\eta_a,\mathbf{x})\end{aligned} \tag{A.7}$$

where $e^De^k(\eta_a,\mathbf{x})$ represents the measure of households where member a is employed in a dead-end job with wage share η_a, and member b is employed in a job produce output y_k for $k\in\{D,L,H\}$.[17] The LHS represents inflows from member a in the dual non-employed household whose optimal search decision is a dead-end job with wage share η_a and who successfully finds a job with those characteristics. Inflows also stem from separations of member b in dual employed households where member a is employed in a dead-end job with wage share η_a and member b is employed in any job at any wage. The first two lines of the RHS represent the outflows that occur when non-employed member b finds a job in the worker-searcher household where a is currently employed in a dead-end job with wage-share η_a. The last line on the RHS represents outflows from exogenous separations. An analogous expression exists for $ne^D(\eta_b,\mathbf{x})f_a(x_a)f_b(x_b)$ which is the measure of worker-searcher households of pair-type $\mathbf{x}=(x_a,x_b)$ with member b employed in a dead-end job at wage-share η_b.

Worker-searcher with a employed in a learning job but who has yet to gain human capital Denote $e^Ln(\eta_a,\mathbf{x})f_a(x_a)f_b(x_b)$ as the measure of worker-searcher households of pair-type $\mathbf{x}=(x_a,x_b)$ with member a employed in a learning job at wage share η_a, and who has yet to gain human capital.

$$\begin{aligned}\left[1-\mathbb{I}_a^D(\mathbf{x})\right]\mathbb{I}(\eta_{a,L}^*(\mathbf{x})=\eta_a)p[\theta_a^L(\eta_a,x_a)]nn(\mathbf{x}) \quad &= \quad \Big\{\mathbb{I}_b^D\left(\eta_a,\mathbf{x},y_L\right)p\left[\theta_b^D\left(\eta_{b,D}^*\left[\eta_a,\mathbf{x},y_L\right],x_b\right)\right] \\ +\delta_b\sum_{k\in\{D,L,H\}}e^Le^k(\eta_a,\mathbf{x}) \quad & \qquad +\left[1-\mathbb{I}_b^D\left(\eta_a,\mathbf{x},y_L\right)\right]p\left[\theta_b^L\left(\eta_{b,L}^*\left[\eta_a,\mathbf{x},y_L\right],x_b\right)\right] \\ & \qquad +\delta_a+\gamma(x_a)\Big\}e^Ln(\eta_a,\mathbf{x})\end{aligned} \tag{A.8}$$

[17] This implicitly sums across all possible wage-shares for member b.

where $e^L e^k(\eta_a, \mathbf{x})$ is the measure of dual employed households where a is employed in a learning job with wage-share η_a without human capital and b is employed at any job producing output y_k for $k \in \{D, L, H\}$ The LHS represents inflows from member a in the dual non-employed household whose optimal search decision is a learning job with wage share η_a and who successfully finds a job with those characteristics. Inflows also arise when separations occur for member b in a dual employed household with a employed in a learning job without human capital and at wage-share η_a and b employed at any job. The first two lines of the RHS represent the outflows that occur when non-employed member b finds a job in the worker-searcher household where a is currently employed in a learning job with wage-share η_a. The last line on the RHS represents outflows from exogenous separations and from the event where the worker gains human capital at a learning job at rate $\gamma(x_a)$ and produces y_H. An analogous expression exists for $ne^L(\eta_b, \mathbf{x}) f_a(x_a) f_b(x_b)$ which is the measure of worker-searcher households of pair-type $\mathbf{x} = (x_a, x_b)$ with member b employed in a learning job without human capital at wage-share η_b.

Worker-searcher with a employed in a learning job with human capital Denote the measure of worker-searcher households of pair-type $\mathbf{x} = (x_a, x_b)$ with member a employed in a learning job at wage share η_a, and who has gained human capital as $e^H n(\eta_a, \mathbf{x}) f_a(x_a) f_b(x_b)$. This measure is implicitly given by:

$$\begin{aligned}
\gamma(x_a) e^L n(\eta_a, \mathbf{x}) + \delta_b \sum_{k \in \{D,L,H\}} e^H e^k(\eta_a, \mathbf{x}) \quad = \quad & \Big\{ \mathbb{I}_b^D\left(\eta_a, \mathbf{x}, y_H\right) p\left[\theta_b^D\left(\eta_{b,D}^*\left[\eta_a, \mathbf{x}, y_H\right], x_b\right)\right] \\
& + \left[1 - \mathbb{I}_b^D\left(\eta_a, \mathbf{x}, y_H\right)\right] p\left[\theta_b^L\left(\eta_{b,L}^*\left[\eta_a, \mathbf{x}, y_H\right], x_b\right)\right] \\
& + \delta_a \Big\} e^H n(\eta_a, \mathbf{x})
\end{aligned} \tag{A.9}$$

where $e^H e^k(\eta_a, \mathbf{x})$ refers to the measure of dual employed households where a is employed at a learning job with human capital, and b is employed at any job producing output y_k for $k \in \{D, L, H\}$. The LHS represents inflows from this group which stem from worker-searcher households with member a employed in a learning job at wage-share η_a gaining human capital at rate $\gamma(x_a)$. Inflows also arise when separations occur for member b in dual employed households with a employed in a learning job with human capital and at wage-share η, and for b employed in any job. Outflows from this group stem from non-employed member b finding a job and exogenous separations as exemplified by the RHS of the above equation.

Dual employed households, both employed in dead-end jobs Consider households whose members are both employed at dead-end jobs. Denote $e^D e^D(\mathbf{n}, \mathbf{x}) f_a(x_a) f_b(x_b)$ as the measure of dual employed households of pair-type $\mathbf{x} = (x_a, x_b)$, with wage-shares $\mathbf{n} = (\eta_a, \eta_b)$ and who produce output $\mathbf{y} = (y_a, y_b)$ for $y_a, y_b = y_D$. This measure, in steady state, is implicitly given by

$$\begin{aligned} \mathbb{I}_b^D(\eta_a, \mathbf{x}, y_D)\mathbf{I}(\eta^*_{b,D}(\eta_a, \mathbf{x}, y_D) = \eta_b)p(\theta_b^D(\eta_b, x_b))e^D n(\eta_a, \mathbf{x}) &= (\delta_a + \delta_b)e^D e^D(\mathbf{n}, \mathbf{x}) \\ + \mathbb{I}_a^D(\eta_b, \mathbf{x}, y_D)\mathbf{I}(\eta^*_{a,D}(\eta_b, \mathbf{x}, y_D) = \eta_a)p(\theta_a^D(\eta_a, x_a))ne^D(\eta_b, \mathbf{x}) & \end{aligned} \tag{A.10}$$

The LHS represents inflows from the non-employed member of a worker-searcher household optimally choosing a dead-end job with wage-share equal to η_i for $i \in \{a, b\}$ and successfully finding a job. The RHS represents outflows from exogenous separations.

Dual employed: a **employed in dead-end job,** b **in a learning job with human capital** Denote $e^D e^H(\mathbf{n}, \mathbf{x}) f_a(x_a) f_b(x_b)$ as the measure of dual employed households of pair-type $\mathbf{x} = (x_a, x_b)$, with wage-shares $\mathbf{n} = (\eta_a, \eta_b)$ and who produce output $\mathbf{y} = (y_a, y_b)$ for $y_a = y_D, y_b = y_H$. This measure, in steady state, is implicitly given by

$$\begin{aligned} \gamma(x_b)e^D e^L(\mathbf{n}, \mathbf{x}) &= (\delta_a + \delta_b)e^D e^H(\mathbf{n}, \mathbf{x}) \\ + \mathbb{I}_a^D(\eta_b, \mathbf{x}, y_H)\mathbf{I}(\eta^*_{a,D}(\eta_b, \mathbf{x}, y_H) = \eta_a)p(\theta_a^D(\eta_a, x_a))ne^H(\eta_b, \mathbf{x}) & \end{aligned} \tag{A.11}$$

The first line of the LHS represents the inflows that occur when member b in a dual-employed household with a employed in a dead-end job, gains human capital at her learning job at rate $\gamma(x_b)$. The second line of the LHS represents the inflow when the non-employed member a in a worker-searcher household where b is employed in a learning job with human capital finds a dead-end job at wage η_a. The RHS represents the outflows from this measure which stem only from exogenous separations. An analogous expression exists for the measure of dual-employed household where a is employed in a learning job with human capital, and b is employed in a dead-end job, i.e., $e^H e^D(\mathbf{n}, \mathbf{x})$.

Dual employed: a **employed in dead-end job,** b **in a learning job without human capital** Denote $e^D e^L(\mathbf{n}, \mathbf{x}) f_a(x_a) f_b(x_b)$ as the measure of dual employed households of pair-type $\mathbf{x} = (x_a, x_b)$, with wage-shares $\mathbf{n} = (\eta_a, \eta_b)$ and who produce output $\mathbf{y} = (y_a, y_b)$ for $y_a =$

$y_D, y_b = y_L$. This measure, in steady state, is implicitly given by

$$\begin{aligned}[1-\mathbb{I}_b^D(\eta_a,\mathbf{x},y_D)]\mathbf{I}(\eta^*_{b,L}(\eta_a,\mathbf{x},y_D)=\eta_b)p(\theta_b^L(\eta_b,x_b))e^D n(\eta_a,\mathbf{x}) &= (\delta_a+\delta_b+\gamma[x_b])e^De^L(\mathbf{n},\mathbf{x}) \\ +\mathbb{I}_a^D(\eta_b,\mathbf{x},y_L)\mathbf{I}(\eta^*_{a,D}(\eta_b,\mathbf{x},y_L)=\eta_a)p(\theta_a^D(\eta_a,x_a))ne^L(\eta_b,\mathbf{x}) & \end{aligned} \tag{A.12}$$

The LHS of the above equation indicates all the inflows from worker-searcher households whose non-employed member a (b) finds a dead-end (learning) job paying wage-share η_a (η_b) and where employed member b (a) is currently working in a learning (dead-end) job. The RHS indicates the outflows from this group from exogenous separations and when member b gains human capital at rate $\gamma(x_b)$ at their learning job. An analogous expression exists characterizing $e^Le^D(\mathbf{n},\mathbf{x})$.

Dual employed: a and b both employed in learning jobs with human capital Denote $e^He^H(\mathbf{n},\mathbf{x})f_a(x_a)f_b(x_b)$ as the measure of dual employed households of pair-type $\mathbf{x}=(x_a,x_b)$, with wage-shares $\mathbf{n}=(\eta_a,\eta_b)$ and who produce output $\mathbf{y}=(y_a,y_b)$ for $y_a,y_b=y_H$. This measure, in steady state, is implicitly given by

$$\gamma(x_b)e^He^L(\mathbf{n},\mathbf{x})+\gamma(x_a)e^Le^H(\mathbf{n},\mathbf{x})=(\delta_a+\delta_b)e^He^H(\mathbf{n},\mathbf{x}) \tag{A.13}$$

The LHS represents the inflows whenever the member who has yet to gain human capital at their learning job gains human capital at rate $\gamma(x_i)$ for $i\in\{a,b\}$. The RHS represents outflows from exogenous separations.

Dual employed: a and b both employed in learning jobs without human capital and with human capital, respectively. Denote $e^Le^H(\mathbf{n},\mathbf{x})f_a(x_a)f_b(x_b)$ as the measure of dual employed households of pair-type $\mathbf{x}=(x_a,x_b)$, with wage-shares $\mathbf{n}=(\eta_a,\eta_b)$ and who produce output $\mathbf{y}=(y_a,y_b)$ for $y_a=y_L, y_b=y_H$. This measure, in steady state, is implicitly given by

$$\begin{aligned}\gamma(x_b)e^Le^L(\mathbf{n},\mathbf{x}) &= (\delta_a+\delta_b)e^Le^H(\mathbf{n},\mathbf{x}) \\ +[1-\mathbb{I}_a^D(\eta_b,\mathbf{x},y_H)]\mathbf{I}(\eta^*_{a,L}(\eta_b,\mathbf{x},y_H)=\eta_a)p(\theta_a^L(\eta_a,x_a))ne^H(\eta_b,\mathbf{x}) &\quad +\gamma(x_a)e^Le^H(\mathbf{n},\mathbf{x})\end{aligned} \tag{A.14}$$

The LHS represents inflows from worker-searcher households where member a finds a learning job and b is already employed in a learning job with human capital, as well as inflows from dual employed households where both a and b are in learning jobs without human capital and b gains human capital. The RHS represents outflows from this group stemming from exogenous separations and when a gains human capital. An analogous expression exists for $e^H e^L(\mathbf{n}, \mathbf{x})$.

Dual employed: a and b both employed in learning jobs without human capital. Denote $e^L e^L(\mathbf{n}, \mathbf{x}) f_a(x_a) f_b(x_b)$ as the measure of dual employed households of pair-type $\mathbf{x} = (x_a, x_b)$, with wage-shares $\mathbf{n} = (\eta_a, \eta_b)$ and who produce output $\mathbf{y} = (y_a, y_b)$ for $y_a, y_b = y_L$. This measure in steady state is characterized by:

$$\begin{aligned} [1 - \mathbb{I}_b^D(\eta_a, \mathbf{x}, y_L)]\mathbf{I}(\eta_{b,L}^*(\eta_a, \mathbf{x}, y_L) = \eta_b) p(\theta_b^L(\eta_b, x_b)) e^L n(\eta_a, \mathbf{x}) &= (\delta_a + \delta_b) e^L e^L(\mathbf{n}, \mathbf{x}) \\ +[1 - \mathbb{I}_a^D(\eta_b, \mathbf{x}, y_L)]\mathbf{I}(\eta_{a,L}^*(\eta_b, \mathbf{x}, y_L) = \eta_a) p(\theta_a^L(\eta_a, x_a)) n e^L(\eta_b, \mathbf{x}) &\quad + [\gamma(x_a) + \gamma(x_b)]\, e^L e^L(\mathbf{n}, \mathbf{x}) \end{aligned} \tag{A.15}$$

The LHS represents inflows from worker-searcher households where the employed member is in a learning job without human capital and the non-employed member also searches for a learning job. The RHS represents outflows from the dual-employed household stemming from exogenous separations and from either member gaining human capital.

B Data Appendix

Details of the sample construction are detailed here.

B.1 Sample Construction

Overview. The main empirical series are constructed from the IPUMS CPS Annual Social and Economic Supplement (ASEC). Most labor-market variables used here refer to the previous calendar year. The cleaned ASEC sample covers reference years 1967 to 2024. Unless otherwise noted, all statistics use the person weight. The baseline demographic sample consists of individuals aged 25-54. Individuals are grouped by gender and household type. The baseline joint-household definition is married with spouse present.

Definitions Employment is measured as having worked at any point during the previous calendar year. The employment-to-population ratio is the weighted share of individuals who worked last year. Full-time status is based on the CPS full-time/part-time variable. Learning jobs are measured as full-time non-routine cognitive jobs, using last-year occupation. The main job-composition moments are therefore

$$P(\text{FT} \mid \text{employed}) \quad \text{and} \quad P(\text{FT \& NRCOG} \mid \text{employed}),$$

computed separately by gender and household type.

College attainment is measured as having completed at least four years of college. The college-share series report the weighted college share by gender and household type.

Dual-earner status is defined for joint households as both partners having worked during the previous calendar year.

Wages and Income Annual wage income is measured using CPS wage-and-salary income. The wage-income series are computed for workers with positive wage income. We also construct hourly wages by dividing annual wage income by annual hours, where annual hours are approximated using weeks worked last year and weekly hours.

The wage series are trimmed to avoid artificially low or high wages, given that our measure of hourly wages is derived from income and hours and therefore subject to measurement error; the trimmed series use a two-sided 5 percent trim within year, gender, and household type, removing the lower and upper tails of the wage distribution before computing averages.

Wages are normalized by aggregate wages in the same year. Specifically, each group is divided by the average wage for the pooled population. These normalized series remove common aggregate wage-growth components and emphasize relative differences across household types and gender.

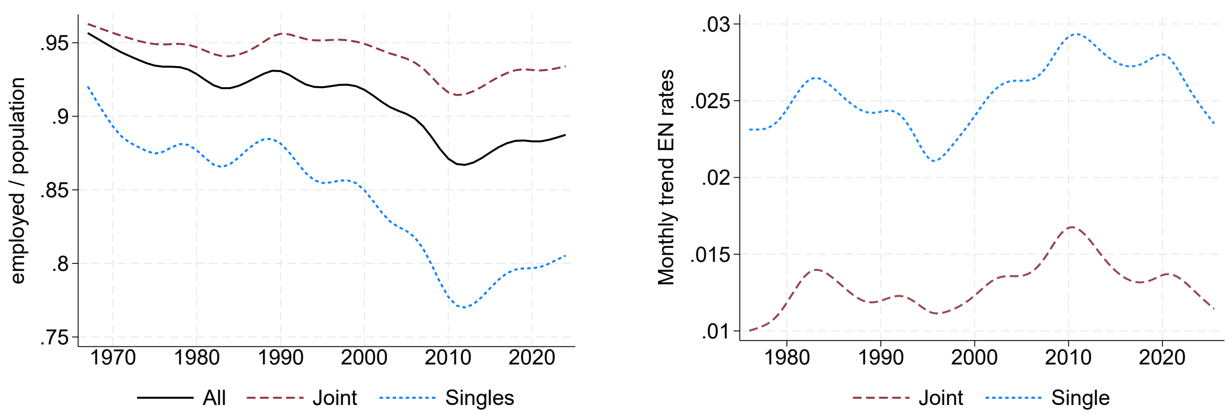
EN Rates The monthly employment-to-nonemployment transition series are constructed from CPS monthly data. These series are reported separately for joint and single households, by gender.

Labor productivity. Labor productivity is measured using the BLS nonfarm business sector output-per-hour index. The deviation from trend is the difference between labor productivity and its linear trend.

B.2 Additional Evidence

In this section, we present additional and complementary evidence to the one presented in the main text.

Figures B.1 and B.2 are the analogue of Figures 2 and 3, respectively. For males, we observe that their EPOP ratios and share of employed who work full-time are declining, especially for single males. EN rates are relatively stable, albeit slightly higher in the post-2000 period. Across the two time-periods, this group observes a mild increase in the share employed in FT-NRCOG jobs.

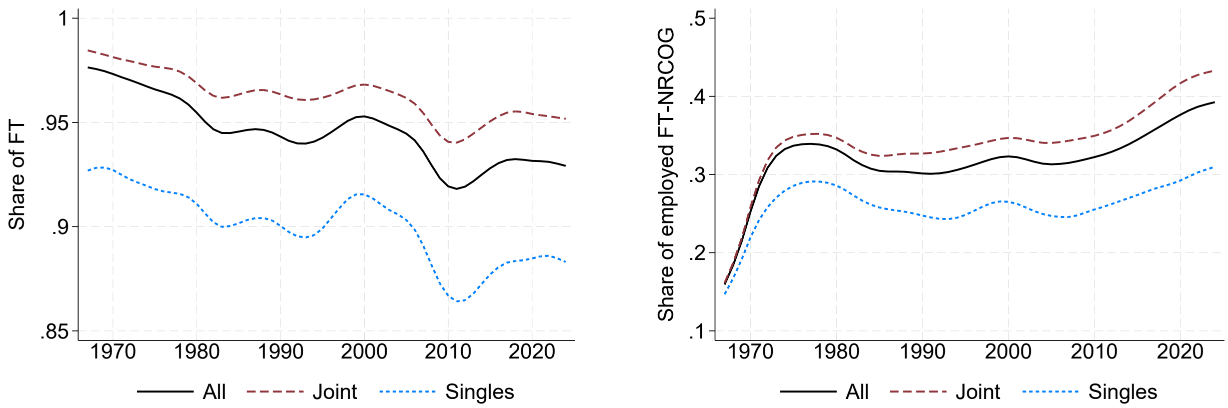


(a) EPOP Rate

(b) EN rate

Figure B.1: Labor Force Trends by Household Type - Males.
Notes: Data are from CPS ASEC for prime-age adults ages 25–54. The series reports EPOP ratios and EN rates for prime-age males for each household type. The EPOP ratios are HP-filtered with smoothing parameter 6.25 while the monthly EN rates are HP-filtered with smoothing parameter 129600.

Figure B.3 shows how the hours per capita has varied over time for females in joint households. Reflecting their continual rise into full-time work, hours per capita has risen for females in joint households.



(a) Full-time share of employment

(b) FT non-routine cognitive share

Figure B.2: Job Allocation Trends by Household Type - Males.

Notes: Data are from CPS ASEC for prime-age males ages 25–54. The left panel reports the share of employed males working full-time. The right panel reports the share of employed males working in full-time non-routine cognitive jobs. Series are HP-filtered with smoothing parameter 6.25.

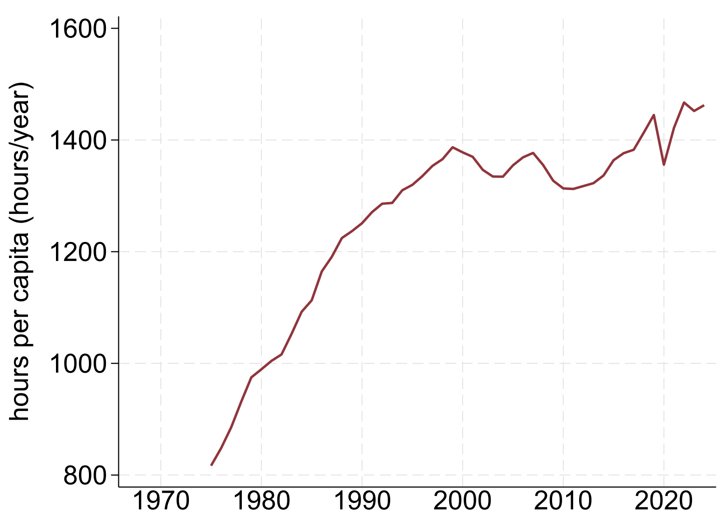


Figure B.3: Hours per capita of joint household females

Notes: Data are from CPS ASEC for prime-age females ages 25–54 in joint households. The figures report the total hours worked by females in joint households, divided by the population of females in joint households. Series are HP-filtered with smoothing parameter 6.25.

C Quantitative Appendix

Details of the quantitative appendix and additional model results are detailed here.

C.1 SMM Details

Overview The empirical moments are computed separately for two periods, a pre-2000 period and a post-2000 period. In the baseline implementation, the pre period is 1967–1999 and the post period is 2000–2024. For each period, we compute averages of the corresponding annual moments.

Single households We first estimate the singles model separately by period. Let

$$\Xi^S = \left(\kappa_{pre}, \beta^S_{m,pre}, \beta^S_{f,pre}, z^S_{m,pre}, z^S_{f,pre}, \kappa_{post}, \beta^S_{m,post}, \beta^S_{f,post}, z^S_{m,post}, z^S_{f,post}\right)$$

denote the vector of singles estimates. The first and sixth elements of this vector discipline the vacancy-posting costs in the pre and post periods, respectively. These values are imposed in the joint-household estimation. This restriction ensures that differences between singles and joint households do not arise from different vacancy-posting technologies, but instead from household structure, income pooling, and the endogenous search choices of household members.

For the singles, the moment vector is

$$m^{S,data} = \left(e^{S,data}_{pre}, s^{L,S,data}_{m,pre}, s^{L,S,data}_{f,pre}, 0, 0, e^{S,data}_{post}, s^{L,S,data}_{m,post}, s^{L,S,data}_{f,post}, 0, 0\right)'.$$

Here $e^{S,data}_t$ is aggregate EPOP among singles in period t, and $s^{L,S,data}_{g,t}$ is the share of employed single workers of gender $g \in \{m, f\}$ employed in learning jobs.

The zero moments impose the restrictions

$$z^S_{g,t} = 0.4 \times \overline{w}^{S,model}_{g,t}, \qquad g \in \{m, f\}, \quad t \in \{pre, post\}.$$

Equivalently, the corresponding model moments are written as gaps,

$$z^S_{g,t} - 0.4 \times \overline{w}^{S,model}_{g,t},$$

with target equal to zero.

Joint Households For the joint-household estimation, the targeted data moments are

$$m^{J,data} = \left(s^{L,data}_{m,pre}, s^{L,data}_{f,pre}, 0, 0, s^{L,data}_{m,post}, s^{L,data}_{f,post}, 0, 0\right)'.$$

Here $s_{g,t}^{L,data}$ denotes the share of employed workers of gender $g \in \{m, f\}$ in period $t \in \{pre, post\}$ who are employed in learning jobs.

The third, fourth, seventh, and eighth moments impose the restrictions

$$z_{g,t} = 0.4 \times \overline{w}_{g,t}^{model},$$

where $b_{g,t}$ is the flow value of non-employment for gender g in period t, and $\overline{w}_{g,t}^{model}$ is the model-implied average wage for that gender-period cell.

Conditional on the first-stage singles estimates, we estimate the joint-household parameters

$$\Xi^J = (\beta_{m,pre}, \beta_{f,pre}, z_{m,pre}, z_{f,pre}, \beta_{m,post}, \beta_{f,post}, z_{m,post}, z_{f,post})'.$$

The parameters $\beta_{g,t}$ govern the distribution of learning ability for gender g in period t. Specifically, we assume

$$x_{g,t} \sim \mathbb{B}(1, \beta_{g,t}),$$

so that changes in $\beta_{g,t}$ shift the distribution of learning ability and therefore affect selection into learning jobs. The parameters $z_{g,t}$ are the flow values of non-employment.

The joint-household separation rates are not estimated in this step. Instead, they are fixed to their empirical or baseline values:

$$\delta_{a,pre} = 0.036, \qquad \delta_{b,pre} = 0.094,$$

and

$$\delta_{a,post} = 0.042, \qquad \delta_{b,post} = 0.073.$$

The vacancy costs are also fixed at the singles-estimated values. All remaining fixed primitives are held at the values reported in Table 1.

Objective Function Let $m^{model}(\Xi^J)$ denote the vector of model moments implied by parameter vector Ξ^J. The estimator solves

$$\widehat{\Xi}^J = \arg\min_{\Xi^J} Q(\Xi^J),$$

where

$$Q(\Xi^J) = \left[m^{model}(\Xi^J) - m^{data}\right]' W \left[m^{model}(\Xi^J) - m^{data}\right].$$

W is the identity matrix. The joint-household estimation is exactly identified: the eight estimated parameters are disciplined by eight moments.

Two-Steps Strategy We use a two-step numerical strategy to estimate the model parameters; the strategy used is identical for singles and joint households estimation.

First, we perform a global search over the bounded parameter space using a Sobol sequence to uniformly cover the parameters space. For each candidate vector Ξ, we solve the model, compute the model moments, and evaluate $Q(\Xi)$. We then rank all Sobol candidates by their objective value.

The second step of the algorithm is a refinement of the first, global step. In particular, we refine the best Sobol candidate using a local optimizer.

C.2 Additional model predictions

Table C.1 shows our model predictions for untargeted wage moments. In general, our model gets right the direction of the change in wage moments, as well as the size of the change.

Wage ratios, pre- and post-2000					
		Male joint	Male single	Female joint	Female single
Model	Pre	1.07	0.97	0.96	1.00
Model	Post	1.08	0.93	1.01	0.98
Model	Difference	4e-3	-0.03	0.05	-0.02
Data	Pre	1.30	1.01	0.69	0.82
Data	Post	1.29	0.86	0.86	0.77
Data	Difference	-0.01	-0.14	0.17	-0.05

Notes: The table reports untargeted wage-ratio moments. For each period, the wage ratio is the average wage of a gender-household group divided by the economy-wide average wage in that period. Difference denotes the post-2000 value minus the pre-2000 value.

Table C.1: Untargeted Moments