On-the-Job Search, Human Capital Formation, and Lifecycle Wages

Matthew J. Millington*

March 17, 2024

Click here for latest version.

Abstract

I build an equilibrium lifecycle model of wages in which heterogeneous workers endogenously invest in human capital accumulation and on-the-job search effort while firms post jobs. The model is disciplined using microdata from the SIPP. The calibrated model shows that on-the-job search is the driving force behind lifecycle wage growth while heterogeneous human capital accumulation is the driving force behind lifecycle wage dispersion. Then, I use the model as a laboratory to study the effects of tax and transfer progressivity. An increase in progressivity decreases wages, primarily due to reduced on-the-job search effort. Interactions between human capital, search, and job posting amplify the decrease in wages. An increase in progressivity has little effect on wage dispersion because the effects from the human capital and search channels offset each other.

*Arizona State University, W.P. Carey School of Business, Department of Economics, 501 E. Orange St. 415B, Tempe, AZ 85281, United States (email: mmilling@asu.edu). I am grateful to Domenico Ferraro, Gustavo Ventura, and Hector Chade for their guidance. I am also grateful to Murat Çelik, Victoria Gregory, Michael Keane, Andreas Kostøl, David Splinter, Xincheng Qui, and Galina Vereshchagina for helpful comments.

1 Introduction

Contemporary macroeconomists tend to focus on two general theories for wage growth: human capital theory and job ladder theory. In human capital theory (Ben-Porath, 1967), workers increase their wages by accumulating human capital. As a worker accumulates human capital, he becomes more productive, and his wage increases.

In job ladder theory, workers increase their wages by making job-to-job transitions. When a worker moves to a new firm, he and the firm negotiate over a new, higher wage. The theory relies on search frictions; there would be no wage growth if workers could start in the most productive firm.

In this paper, I develop an equilibrium model where both channels interact endogenously. Altogether, the model combines endogenous human capital accumulation, endogenous on-the-job search, endogenous job posting, and a life cycle. Going forward, I refer to the human capital part as the "human capital channel" and the job ladder part as the "search channel." Firms choose how many job vacancies to post in equilibrium, and workers choose how much effort to invest in human capital accumulation and job search effort. For workers, both types of investment increase wages, and workers choose an optimal mix of investments according to their fixed learning ability, their current state, and the state of the labor market.

What is the benefit of endogenizing all of these elements? Empirical research (cited below) shows that both the human capital and search channels are necessary to account for wage levels, lifecycle wage growth, and wage inequality. It follows that both channels will play a role in responding to policy. In this paper, I use the model to evaluate tax and transfer progressivity. Progressive labor taxation is a natural choice for counterfactual policy experiments. It is well established that tax progressivity differs vastly across developed countries (Guvenen et al., 2014) and that labor markets operate very differently across countries (for example, with respect to lifecycle wage growth, job-to-job transitions, and unemployment (Engbom, 2022)). Thus, I contribute to an important question: To what extent are the differences across labor markets attributable to tax policy?

In the model, workers are heterogeneous at the beginning of life in fixed learning ability and initial human capital. Firms are heterogeneous in productivity. Human capital and firm productivity are complements in production. When employed by a firm, a worker earns a wage that is the product of three components: the worker's human capital, the firm's productivity, and an endogenous bargaining component. The bargaining component arises from a surplus sharing rule following Cahuc et al. (2006).

Workers are risk averse and maximize their lifetime utility. To do so, workers choose how much effort to invest in accumulating human capital and searching for a new job. When a worker invests in human capital accumulation, he increases his stock of human capital as in Ben-Porath (1967); when a worker invests in search effort, he increases his probability of meeting an outside firm. Both activities are costly in the sense that the worker experiences disutility. However, both activities are beneficial because they lead to wage growth and increased future consumption.

Workers also face negative risk from exogenous unemployment shocks. Low-wage workers are more likely to become unemployed, and a worker's human capital depreciates while he is unemployed.

Firms enter the model by posting job vacancies, and meeting probabilities are determined by an aggregate matching function. In equilibrium, the number of vacancies satisfies a free entry condition such that firms are indifferent toward posting the marginal vacancy. From the firm's perspective, the benefit of posting a vacancy depends on the distribution of human capital and search effort in the labor market.

Workers face a clear tradeoff: if a worker invests in human capital accumulation or job search effort today, he may increase his wage tomorrow. His optimal mix of human capital investment and search effort depends on his learning ability, age, and current levels of human capital, firm productivity, and the bargaining term.

For example, consider how fixed learning ability affects investment decisions.[1] Analytically, I show that a worker with high learning ability will invest more in human capital

[1] In the calibrated model, heterogeneity in learning ability turns out to be a key variable in accounting for wage dispersion.

accumulation and less in job search. The opposite is true for workers with low learning ability. In a sense, workers *substitute* between investment in human capital and search. I also analytically show that tax progressivity disincentivizes both human capital accumulation and search effort.

I calibrate the model using microdata from the Survey of Income and Program Participation (SIPP) for 1990-2019. The SIPP is a large panel data set that tracks respondents for several years at a time. It is particularly useful for this paper because wages and jobs are reported monthly. The calibrated model successfully replicates lifecycle profiles for mean wages, wage dispersion, and job-to-job transitions. It also matches monthly wage growth rates for workers who stay at the same job or switch jobs.

Since I experiment with tax progressivity, I also calibrate a government sector. I estimate an average tax function over wages that replicates income taxes and means-tested transfer payments for an average household in the US. Some workers pay negative taxes; such workers receive more in transfers than they pay in taxes. In counterfactual exercises, I increase the progressivity of the system. Greater progressivity implies that low-wage workers receive more transfers while high-wage workers pay more taxes.

Before I conduct policy experiments, I derive insights from the calibrated benchmark model. On average, the search channel is the largest driver of lifecycle wage growth; about 70% of lifecycle wage growth comes from workers climbing the job ladder, with the remaining coming from an increase in human capital.

However, there is significant heterogeneity across workers. Heterogeneity in fixed learning ability generates different relative returns to human capital investment versus search effort, and workers with greater learning ability will invest more in human capital accumulation, especially at the beginning of life. Across learning abilities, I observe vast differences in human capital accumulation, but roughly equal job ladder outcomes. The result is that workers with high learning ability accumulate wages faster than those with low learning ability, and the difference is driven by human capital. Thus, over the life cycle, the increase in wage dispersion is driven by an increase in the dispersion of human capital. Taken together, my results suggest that wage growth comes from the job ladder while wage dispersion comes from human capital. Finally, human capital and firm productivity are positively correlated in the calibrated model.

I then turn to counterfactual tax policy experiments. Greater tax progressivity implies that when a worker increases his wage, he will take home a smaller part of the wage increase. Thus, workers are disincentivized from growing their wages, which puts downward pressure on both human capital investment and search effort. There is also an equilibrium effect; because workers have less human capital and exert less search effort, firms are discouraged from posting jobs, leading to fewer open vacancies in equilibrium, which further decreases investment in human capital accumulation and search effort.

I perform a simple tax policy experiment where I increase the progressivity of the tax and transfer system from the US benchmark to that of a typical Nordic country. As a result, the wage level in the economy decreases by about 4%. Approximately 2/3 of the decrease comes from the job search channel, inclusive of the job posting effect, and the remaining 1/3 comes from the human capital channel. Since job-to-job transitions are the primary method for generating wage growth for the average worker in the benchmark model, search effort is the most relevant margin for adjustment. Furthermore, interactions between human capital, search, and job posting amplify the decrease in wages. Thus, a model that does not endogenize each channel will understate the decrease in the wage level. 15% of the decrease comes from a decrease in vacancy posting, which suggests that equilibrium effects are also significant.

Surprisingly, increasing tax progressivity has no effect on the variance of pretax wages. Again, the result is due to interactions between the human capital and search channels. It turns out that the effects of the human capital and search channels offset one another. A human capital model predicts that an increase in tax progressivity will decrease the variance of wages; since an increase in progressivity has more “bite" at the top of the wage distribution, workers with high wages are relatively more disincentivized from accumulating human capital. So, wages at the top of the distribution decrease more than wages at the bottom, and the gap between high wages and low wages decreases.

In contrast, in a job ladder model, an increase in tax progressivity increases wage dispersion. In my model (and as is typical in job ladder models), workers meet firms from a fixed productivity distribution. Over the life cycle, workers progressively move to firms with more productivity, and workers eventually bunch up near the top of the distribution. With more tax progressivity, workers exert less search effort and make fewer job-to-job transitions. So, there is less bunching at high-productivity firms, and the variance of wages is more spread. Simply put, since there are fewer job-to-job transitions, workers are more likely to remain at unproductive firms that would otherwise not be able to retain workers. Alternately stated, decreasing search effort increases the importance of luck in the labor market. Taken together, the result casts some doubt on the notion that increasing tax progressivity can decrease pretax wage inequality.

Finally, I perform horse race experiments where I compare the effects of tax progressivity in my model with simplified, recalibrated models where certain channels are removed. In response to an increase in progressivity, a pure human capital model will understate the decrease in wage levels and overstate the decrease in lifecycle wage growth. The opposite is true for a pure job ladder model.

The remainder of the paper proceeds as follows. First, I contextualize my paper within the literature in Section 2. Section 3 presents the model. I analytically investigate the model mechanisms in Section 4. My calibration strategy is described in Section 5. I analyze the benchmark model in Section 6 before analyzing counterfactual taxation experiments in Section 7. Section 8 concludes.

2 Related Literature

To my knowledge, my model is the first to combine a life cycle, endogenous human capital accumulation, endogenous search effort, and endogenous job posting. My model is most similar to the model in Engbom (2022), which features endogenous human capital accumulation and job posting. In addition to the framework in Engbom (2022), my model includes two key features: endogenous search effort, and heterogeneity in learning ability and initial human capital. And I use my model to investigate tax policy, whereas Engbom (2022) investigates wedges to job creation. In response to tax policy, I show that search effort is the more relevant margin of adjustment for most workers.

Bowlus and Liu (2013) analyzes a model with endogenous human capital accumulation and endogenous search effort, but does not do policy analysis. I add firms, which requires that I adopt a wage bargaining scheme. The inclusion of firms allows for more careful counterfactual policy experiments, and I show that endogenous job posting amplifies the effects of tax progressivity. Rauh and Santos (2022) builds a search-and-matching model with human capital accumulation, endogenous job posting, and a carefully-calibrated government sector, and use the model to investigate transfer payments. However, human capital accumulation is exogenous and there is no on-the-job search. Hubmer (2018) shows that job ladder and unemployment dynamics are vital for generating the observed earnings process in the data with negative skewness and high kurtosis (Guvenen et al., 2021). As in this paper, Hubmer (2018) finds that search effort is crucial relevant factor. Since I also endogenize human capital accumulation and job posting in equilibrium, I can perform policy experiments.[2]

I rely on well-established methods for modeling human capital accumulation and job search, which is intentional; it allows me to easily isolate the effects of their interaction. With regard to human capital accumulation, my model builds on Ben-Porath (1967) and Huggett et al. (2011). For modeling on-the-job search, the model borrows from Burdett and Mortensen (1998)[3] and Bagger et al. (2014). I model endogenous search effort and job posting as in Pissarides (2000) and Mortensen and Pissarides (1994). Finally, the wage bargaining protocol comes from Cahuc et al. (2006) and Bagger et al. (2014).

Quantitative human capital models, such as those in Huggett et al. (2011) and Badel et al. (2020), often rely on idiosyncratic shocks to match wage dispersion. Such idiosyn-

[2]On the other hand, in the models in Rauh and Santos (2022) and Hubmer (2018), workers can save across periods, which is a potentially important feature that I do not incorporate.

[3]See also Mortensen (2003).

cratic shocks are thought to represent unemployment spells or job-to-job transitions. In a sense, my model provides an explicit theory for such idiosyncratic shocks.

My paper also draws from a literature that decomposes wage growth and inequality between the human capital and search channels (Ozkan et al., 2023; Gregory, 2021; Taber and Vejlin, 2020; Bagger et al., 2014; Pavan, 2011; Carrillo-Tudela, 2012; Veramendi, 2012; Omer, 2004; Schönberg, 2007; Dustmann and Meghir, 2005).[4,5] In particular, my model closely resembles Ozkan et al. (2023) and Gregory (2021).[6] Generally, my findings from my benchmark calibration are in line with the literature: both human capital and on-the-job search are important in accounting for wage dynamics, with on-the-job search the largest contributor to lifecycle wage growth and human capital dispersion the largest contributor to wage inequality. My contribution is to apply a decomposition-type framework to policy analysis. As such, in my model, human capital accumulation, job finding rates, and labor market tightness are endogenously determined and, thus, responsive to policy.

In counterfactual experiments, I make a unique contribution to the literature on the effects of progressive taxes and transfers on lifecycle wage growth and inequality. One strand of literature investigates labor taxation in models with endogenous on-the-job search and job posting but fixed human capital (Bagger et al., 2021, 2019; Sleet and Yazıcı, 2017; Kreiner et al., 2015; Gentry and Hubbard, 2004). Another strand investigates labor taxation in human capital models without labor market frictions (Badel et al., 2020; Guvenen et al., 2014; Blandin, 2018; Kapička, 2015, 2006).[7] I show that both channels interact in meaningful ways in response to a change in tax policy and that a model without both

[4] In a slightly different vein, Acabbi et al. (2023) investigates how human capital and job search interact over the business cycle, and Faberman et al. (2022) calibrates a model with endogenous on-the-job search effort using survey data on search behavior and also find that search effort plays a prominent role over the business cycle.

[5] In addition to human capital and the job ladder, Taber and Vejlin (2020) incorporates worker and firm types which can be complementary in production (which generates comparative advantage) and in the worker's utility (which generates compensating differentials).

[6] Ozkan et al. (2023) incorporates sophisticated worker heterogeneity while Gregory (2021) studies firms as heterogeneously promoting human capital accumulation.

[7] In these papers, workers make human capital decisions each period. One can also study progressive taxation in a model with an endogenous education choice that only occurs at the beginning of the life cycle (Heathcote et al., 2020, 2017; Esfahani, 2020; Krueger and Ludwig, 2016).

will misstate the effects of tax progressivity.

3 Model

3.1 Life Cycle

For computational efficiency, the model is in continuous time. I model overlapping generations using a stochastic life cycle.[8] Life consists of $I+1$ stages of life, I working stages and a retirement stage. For $i \in \{1, 2, ..., I\}$, workers transition from stage i to stage $i+1$ with probability ζ. Retired workers die with probability $\overline{\zeta}$, after which they are replaced by newborns in the first working stage. To fix ideas, when I calibrate the model, I set $I = 4$ and calibrate the working part of life to ages 23 to 65. So, each stage of working life is approximately a decade. I focus on the recursive stationary equilibrium, which I define in Appendix C.

3.2 Wages

Workers are heterogeneous in human capital h, and firms are heterogeneous in productivity p. A match between a worker with human capital h and a firm with productivity p produces hp of the numeraire consumption good. Note that human capital and firm productivity are complements in production. Of the total production of the match, workers earn a piece-rate $r \in [0, 1]$. Therefore, before taxes and transfers, the worker earns the wage hpr and the firm earns profit $hp(1-r)$. r is endogenously negotiated between workers and firms as described below.

3.3 Utility

Workers discount the future at discount rate ρ. They enjoy utility from consumption which equals the worker's after-tax-and-transfer wage. I assume that utility of consump-

[8]One can think of the life cycle as perpetual youth with multiple stages.

tion is logarithmic, $\ln(c)$. Given the wage hpr and the average tax rate function $T(hpr)$ (explained below), $c = [1 - T(hpr)]hpr$.

Workers are employed or unemployed. Employed workers choose how much effort to invest in human capital accumulation, l (for "learning"), and job search, s. Unemployed workers can search but cannot accumulate human capital.

Both types of investment are costly in that workers experience disutility from effort. Disutility of effort is a convex function over $l + s$. For the employed, disutility of effort is $\phi(l+s)^{1+\gamma_E}$ with $\phi > 0$ and $\gamma_E > 0$, and for the unemployed, disutilty of effort is $\phi s^{1+\gamma_U}$ with $\gamma_U > 0$.[9]

3.4 Human Capital Accumulation

Workers accumulate human capital as in Ben-Porath (1967). From birth, workers are heterogeneous in fixed learning ability, $a > 0$. Human capital evolves according to the law of motion

$$\dot{h} = a(lh)^{\omega} - \delta h \tag{1}$$

where $\omega \in (0, 1)$ governs the level of decreasing returns to human capital accumulation and $\delta \in [0, 1]$ is the human capital depreciation rate. Thus, a is the worker's efficiency of human capital accumulation.

3.5 Labor Market Frictions

All workers, employed and unemployed, meet open vacancies at the rate $sm(\theta)$ where s is search effort as described above, $m(\theta)$ is an aggregate meeting function, and θ is the labor market tightness ratio. Therefore, when a worker exerts search effort, he increases

[9]Later, I estimate $\gamma_U > \gamma_E$, which means that unemployed workers can exert relatively more search effort before their disutility of effort gets prohibitively steep. Therefore, unemployed workers will tend to exert more search effort and get more job offers, and the model replicates higher job finding rates for unemployed workers than employed workers.

his probability of meeting an outside firm.[10] θ is defined as the number of vacancies v per unit of aggregate search effort S, $\theta = v/S$.[11] Search is random in the sense that workers and firms randomly meet in a single market and neither can direct their search toward certain types of firms or workers.

Upon meeting an open vacancy, the worker observes the firm's productivity, p, drawn from a distribution $F(p)$ over $[\underline{p}, \overline{p}]$. The worker and firm then bargain over the wage. Since h and p are fixed at this point, wage bargaining is over the piece rate r. They will form a match if the worker is better off with the new firm.

Firms post and maintain jobs at cost κ. From the firm's perspective, an open job vacancy meets a worker with probability $m_f(\theta)$. Matches are subject to exogenous job destruction shocks which are a decreasing function of wage, $\Lambda(hpr)$. I assume that the job destruction rate depends on the wage for two reasons: (1) it is clearly true in the data, and (2) the increased risk of unemployment for low-wage workers is key for accounting for increasing wage dispersion over the life cycle (Ozkan et al., 2023; Jarosch, 2023).

3.6 Government

I model both income taxes and means-tested transfers in a single average tax equation with the functional form from Bénabou (2002). At wage hpr, workers pay the average tax rate

$$T(hpr) = 1 - \tau_0 (hpr)^{-\tau_1} \tag{2}$$

which subsumes both income taxes paid and means-tested transfers received. It is possible that workers with low wages pay negative taxes. If so, then transfers received exceed taxes paid. Going forward, I refer to Equation (2) as a tax function for simplicity, though it should be understood that the function is carefully calibrated to combine progressive taxation and means-tested transfers.

[10] Mukoyama et al. (2018) shows empirically that greater search effort (in the form of time spent searching for a job) is significantly and positively correlated with the probability of finding a job.

[11] For completeness, S is mathematically defined in Appendix A.1 Equation (24), but it does not need to be solved in computing the model; the relevant object is θ.

The two parameters of the tax function are easily interpretable: τ_1 determines the progressivity of the tax and transfer system while τ_0 determines its level. Later in the paper, I will experiment with adjusting τ_1, and I let τ_0 adjust so that the government budget constraint holds in equilibrium.

Unemployed workers earn unemployment benefits $B(w)$ where w is the most recent wage the worker earned before becoming unemployed. Unemployment benefits expire with probability χ, after which the worker gets a transfer payment T_0. I denote whether unemployed workers qualify for unemployment benefits with the indicator $\iota \in \{0,1\}$. Finally, retired workers receive a flat social security payment SS.

3.7 Wage Bargaining

I adopt the wage bargaining protocol of Cahuc et al. (2006) as applied in Bagger et al. (2014). The protocol determines the endogenous values of r as well as the worker's reservation strategies for accepting a new job. Every resulting object is a function that depends on the characteristics of the worker and firm(s). Behind every function is a surplus sharing rule where, if the worker has the opportunity to go to a new firm, he extracts the total surplus from his outside option plus a fraction $\eta \in [0,1]$ of the additional worker surplus at the winning firm.

Let $W_{ai}(h,p,r)$ be the value of employment for a worker with learning ability a, in stage of life i, with human capital h, and currently working for a firm with productivity p at the piece rate r. I define $W_{ai}(h,p,r)$ mathematically in Section 3.8. Currently, the worker earns the wage hpr. The greatest wage that the worker can earn while working at the current firm is hp, the wage when $r=1$, and the firm makes zero profit. In equilibrium, the value of the firm's outside option is zero. So, if $r=1$, the firm is indifferent toward continuing the match.

Wage bargaining arises when an employed worker meets an outside firm and when an unemployed worker meets a firm. Consider first the scenario of a meeting between an employed worker with value $W_{ai}(h,p,r)$ and an outside firm with productivity p'. The incumbent firm and the outside firm will commence Bertrand competition for the worker, making alternating bids on the worker's wage. As the firms offer progressively higher wages, they reach a point where the firm with lower productivity cannot pay the worker a higher wage without earning negative profit. For the firm with lower productivity, that wage is given by $r = 1$. At that point, the firm with higher productivity can offer a marginally larger wage and win the worker.

Within the scenario of an employed workers meeting an outside firm, there are three possible outcomes. First, suppose that the outside firm has greater productivity than the incumbent firm, $p' > p$. In this case, the worker will be poached and make a job-to-job transition to the outside firm. The poaching firm will pay the worker a piece rate $R_{ai}^{P}(h, p, p')$ which solves

$$W_{ai}\left(h, p', R_{ai}^{P}(h, p, p')\right) = W_{ai}(h, p, 1) + \eta\left[W_{ai}(h, p', 1) - W_{ai}(h, p, 1)\right]. \tag{3}$$

After getting poached by the firm with productivity p', the worker earns a piece rate $r = R_{ai}^{P}(h, p, p')$ such that the value of employment equals the maximum surplus possible from the incumbent firm, $W_{ai}(h, p, 1)$, plus a fraction η of the additional worker surplus from the match.[12]

Next, suppose that the outside firm has lower productivity than the incumbent firm, $p' < p$. Regardless of the exact value of p', the incumbent firm will retain the worker because it can pay the worker a greater wage while remaining profitable. However, if the outside firm has a high enough p', it is possible that the outside firm could pay the

[12] A slight clarification is in order. The worker earns a fraction η of the additional *potential worker* surplus from the match, not the additional *total* surplus from the match. This is slightly different from the original scheme in Cahuc et al. (2006) which uses a version of the Rubinstein (1982) infinite-horizon alternating-offers bargaining game. In Cahuc et al. (2006), workers and firms have linear utility over wages. Thus, $W_{ai}(h, p, 1)$ is equivalent to the total surplus of the match, regardless of how the total surplus is shared. So, Equation (3) states that the worker earns a fraction η of the additional total surplus of the match. The same is true in Engbom (2022). However, as Bagger et al. (2014) points out, when workers have curvature in utility and firms have linear utility, the total amount of surplus from the match is not independent of r and, therefore, not fixed, and the present scheme may not be a Nash equilibrium. My case is further complicated by the fact that workers also have disutility over effort. I elect to follow Bagger et al. (2014) and impose this wage structure even with curvature in utility and disutility over effort. For an approach which uses total surplus but allows for curvature in utility, see Lise et al. (2016).

worker a greater wage than it earns now. This is the second possible outcome. In this case, the outside firm triggers a renegotiation between the worker and the incumbent firm. Again, the firms will make alternating bids over the worker until the firm with lower productivity (in this case, the outside firm) earns zero profit. The worker will stay at the current firm but get a wage increase; the worker will earn a piece rate $R^R_{ai}(h,p,p')$ which solves

$$W_{ai}\left(h,p,R^R_{ai}(h,p,p')\right) = W_{ai}(h,p,'1) + \eta\left[W_{ai}(h,p,1) - W_{ai}(h,p',1)\right]. \tag{4}$$

Now, the worker's outside option is the maximum surplus from the unsuccessful outside firm. So, the worker earns a piece rate $r = R^R_{ai}(h,p,p')$ such that value of employment is the maximum that the outside firm could offer, $W_{ai}(h,p',1)$, plus a fraction of the additional worker surplus.

The third and final outcome is that the outside firm has lower productivity than the incumbent firm, $p' < p$, and the outside firm cannot pay the worker a greater wage even if it offers the worker the maximum $r = 1$. In this case, the worker ignores the outside firm and stays at the current firm at the same piece rate.

$q_{ai}(h,p,r)$ defines the minimum p' such that, if the worker meets an outside firm with $p' \in [q_{ai}(h,p,r),p]$, the meeting will trigger a renegotiation with the current firm. $q_{ai}(h,p,r)$ solves

$$W_{ai}(h,p,r) = W_{ai}\left(h,q_{ai}(h,p,r),1\right) + \eta\left[W_{ai}(h,p,1) - W_{ai}\left(h,q_{ai}(h,p,r),1\right)\right]. \tag{5}$$

To summarize the scenario where an employed worker meets an outside firm: if $p' > p$, the worker is poached, and the worker earns the piece rate $R^P_{ai}(h,p,p')$; if $q_{ai}(h,p,r) < p' < p$, the worker stays at their current firm but leverages the outside offer into a greater piece rate $R^R_{ai}(h,p,p')$; and if $p' < q_{ai}(h,p,r)$, the outside firm cannot compete with the current firm and the worker stays with the same firm at the same piece rate.

Next, consider the scenario of a meeting between an unemployed worker and a firm with productivity p'. In this case, the firm is not competing against another firm, but rather is competing against the worker's outside option of remaining unemployed. Let $U_{ai}(h, w, \iota)$ be the value of unemployment for a worker with learning ability a, in stage of life i, with human capital h, who previously earned the pre-tax wage w, and is eligible for unemployment benefits with indicator ι. Suppose that the outside firm has a high enough p' such that it can make an offer that will entice the worker to leave unemployment and form a match. The worker will earn the piece rate $R^U_{ai}(h, w, \iota, p')$ which solves

$$W_{ai}\left(h, p', R^U_{ai}(h, w, \iota, p')\right) = U_{ai}(h, w, \iota) + \eta\left[W_{ai}(h, p', 1) - U_{ai}(h, w, \iota)\right]. \tag{6}$$

The piece rate is set such that the worker gets the value of his outside option, $U_{ai}(h, w, \iota)$, plus a fraction η of the additional worker surplus from the match.

It is possible that a firm cannot make the unemployed worker better off, even if the firm pays the worker $r = 1$. Let $z_{ai}(h, w, \iota)$ be the lowest value of p' that will entice the worker to leave unemployment. If $p' = z_{ai}(h, w, \iota)$, then the unemployed worker is indifferent between remaining unemployed and working for the firm at the highest possible wage. So,

$$U_{ai}(h, w, \iota) = W_{ai}\left(h, z_{ai}(h, w, \iota), 1\right). \tag{7}$$

3.8 Hamilton-Jacobi-Bellman Equations for Workers

The value of employment for a worker with learning ability a, in stage of life i, with human capital h, and currently working for a firm with productivity p at the piece rate r

solves

$$\rho W_{ai}(h,p,r) = \max_{l,s}\; u(c) - d_E(l+s) + (a(lh)^{\omega} - \delta h)\,\frac{\partial W_{ai}(h,p,r)}{\partial h}$$
$$+\Lambda(hpr)\left[U_{ai}(h,hpr,1) - W_{ai}(h,p,r)\right] + \zeta\left[W_{ai}(h,p,r) - W_{ai}(h,p,r)\right]$$
$$+sm(\theta)\Bigg(\int_{q_{ai}(h,p,r)}^{p}\left[W_{ai}\left(h,p,R^{R}_{ai}(h,p,p')\right) - W_{ai}(h,p,r)\right]dF(p') \tag{8}$$
$$+\int_{p}^{\overline{p}}\left[W_{ai}\left(h,p',R^{P}_{ai}(h,p,p')\right) - W_{ai}(h,p,r)\right]dF(p')\Bigg)$$

subject to

$$c = [1 - T(hpr)]hpr. \tag{9}$$

An employed worker chooses how much effort to invest in human capital accumulation l and search s. The worker consumes the value of his after-tax-and-transfer wage and experiences the disutility associated with human capital accumulation and search effort. He accumulates human capital as in Equation (1). With probability $\Lambda(hpr)$, the match is destroyed and the worker becomes unemployed with unemployment benefits. With probability ζ, the worker ages to the next stage of life. And with probability $sm(\theta)$, the worker meets an outside firm with productivity p' drawn from the distribution $F(p')$. If $p' \in (q_{ai}(h,p,r), p]$, the worker leverages the outside offer and renegotiates a higher piece rate with the incumbent firm. If $p' \in (p, \overline{p}]$, the worker is poached.

The value of unemployment for a worker with learning ability a, in stage of life i, with human capital h, who previously earned the pre-tax wage w, and earns unemployment benefits with indicator ι solves

$$\rho U_{ai}(h,w,\iota) = \max_{s}\; u(c) + d_U(s) - \delta h\frac{\partial U_{ai}(h,w,\iota)}{\partial h}$$
$$+\zeta\left[U_{a,i+1}(h,w,\iota) - U_{ai}(h,w,\iota)\right] + \chi\left[U_{ai}(h,w,\iota) - U_{ai}(h,w,0)\right] \tag{10}$$
$$+sm(\theta)\int_{z_{ai}(h,w,\iota)}^{\overline{p}}\left[W_{ai}\left(h,p',R^{U}_{ai}(h,w,p')\right) - U_{ai}(h,w,\iota)\right]dF(p')$$

subject to

$$c = \iota\left[1 - T(B(w))\right]B(w) + (1-\iota)T_0 \tag{11}$$

An unemployed worker chooses how much effort to invest in search, enjoys utility from consumption, endures disutility from search effort, and experience human capital depreciation. The worker's consumption level depends on if he still qualifies for unemployment benefits. With probability ζ, the worker ages to the next stage of life, and with probability χ, his unemployment benefits expire (if they have not already). With probability $sm(\theta)$, the worker meets an outside firm with productivity p', and if $p \in (z_{ai}(h, w, \iota), \overline{p}]$, the worker will accept a job from the firm. Unemployed workers pay taxes on their unemployment benefits while unemployment workers without unemployment benefits do not pay taxes.

Finally, the value of retirement, $\overline{W}$, solves

$$\left(\rho + \overline{\zeta}\right) \overline{W} = u(SS). \tag{12}$$

Employed and unemployed workers transition to retirement according to

$$W_{ai}(h, p, r) = \overline{W}. \tag{13}$$

and

$$U_{a,I+1}(h, w, \iota) = \overline{W}. \tag{14}$$

3.9 Firms

Firms are modeled as one worker-one job matches. Firms have linear utility over after-tax profit. There is a flat tax on profits τ_b, so after-tax profits are $(1 - \tau_b)hp(1 - r)$.

I assume free entry in the labor market. In equilibrium, firms post a quantity of vacancies such that firms are indifferent toward to the marginal job posting. Thus, the equilibrium level of job vacancies will depend on the distribution of workers in the economy. All else equal, if all workers in the economy increase their human capital, then, because h and p are complements, filled jobs become more profitable, the benefit of job posting increases, and firms will post more jobs. Similarly, if workers increase search effort, then firms have a greater probability of converting an open vacancy to a filled job, the benefit of job posting increases, and firms will post more jobs.

Let $l_{ai}(h,p,r)$, $s_{Eai}(h,p,r)$, and $s_{Uai}(h,w,\iota)$ denote the policy functions for employed workers' human capital investment, employed workers' search effort, and unemployed workers' search effort, respectively. For a firm with productivity p, the value of a filled job with a worker of learning ability a, in stage of life i, with human capital h, and with the worker earning the piece rate r solves

$$\begin{aligned}\Big[\rho + s_{Eai}(h,p,r)m(\theta)\left(F(\overline{p}) - F(p)\right) + \Lambda(hpr)\Big] J_{ai}(h,p,r) = (1-\tau_b)hp(1-r) + \\ (a(l_{ai}(h,p,r)h)^{\omega} - \delta h)\frac{\partial J_{ai}(h,p,r)}{\partial h} + \zeta\left[J_{a,i+1}(h,p,r) - J_{ai}(h,p,r)\right] \\ + s_{Eai}(h,p,r)m(\theta)\int_{q_{ai}(h,p,r)}^{p}\Big[J_{ai}\left(h,p,R^{R}_{ai}(h,p,p')\right) - J_{ai}(h,p,r)\Big]\,dF(p')\end{aligned} \tag{15}$$

Except for the additional probabilities of the match dissolving on the left hand side, Equation (15) closely resembles Equation (8).

If the match is destroyed, the firm is left with zero profit. There are three ways the match can be destroyed: (1) the worker is poached by a firm with higher productivity, which occurs if the worker meets an outside firm with greater productivity at probability $s_{Eai}(h,p,r)m(\theta)\left(F(\overline{p}) - F(p)\right)$; (2) the job is exogenously destroyed at rate $\Lambda(hpr)$; or (3) the worker retires. The latter is made explicit by

$$J_{a,I+1}(h,p,r) = 0. \tag{16}$$

Let $\Psi_E(h,p,r|a,i)$, $\Psi_U(h,w|a,i,\iota)$, and $\Psi_R(a)$ denote the distributions of employed, unemployed, and retired workers, respectively. These distributions are defined such that

$$1 = \sum_{a,i}\int_{\Psi_E} d\Psi_E(h,p,r|a,i) + \sum_{a,i,\iota}\int_{\Psi_U} d\Psi_U(h,w|a,i,\iota) + \sum_{a}\Psi_R(a). \tag{17}$$

The free entry condition is

$$\begin{aligned}\kappa = m_f(\theta) \Bigg[\sum_{a,i} \int_{\Psi_E} s_{Eai}(h,p,r) \int_{p}^{\overline{p}} J_{ai}\left(h, p', R_{ai}^{P}(h,p,p')\right) dF(p') d\Psi_E(h,p,r|a,i) \\ + \sum_{a,i,\iota} \int_{\Psi_U} s_{Uai}(h,w) \int_{z_{ai}(h,w)}^{\overline{p}} J_{ai}\left(h, p', R_{ai}^{U}(h,w,p')\right) dF(p') d\Psi_U(h,w|a,i,\iota) \Bigg].\end{aligned} \tag{18}$$

The left hand side of Equation (18), κ, is the cost of posting and maintaining a vacancy. The right hand side is the expected benefit of posting a vacancy. It consists of two terms, both multiplied by the $m_f(\theta)$ (the probability that an open job vacancy meets a worker). The first term is the probability and expected value of poaching an employed worker; the second is the probability and expected value of hiring an unemployed worker. In equilibrium, the cost of posting a vacancy equals the benefit.

3.10 Government Budget Constraint

When I perform counterfactual experiments with tax policy, I discipline the model such that a government budget constraint must hold in equilibrium. Mathematically, the government budget constraint is

$$\begin{aligned}\sum_{a,i} \int_{\Psi_E} T(hpr)hpr\, d\Psi_E(h,p,r|a,i) + \sum_{a,i} \int_{\Psi_U} T(bw)bw\, d\Psi_U(h,w|a,i,\iota=1) \\ + \sum_{a,i} \int_{\Psi_E} \tau_b(1-r)hp\, d\Psi_E(h,p,r|a,i) = \sum_{a,i} \int_{\Psi_U} bw\, d\Psi_U(h,w|a,i,\iota=1) \\ + \sum_{a,i} \int_{\Psi_U} T_0\, d\Psi_U(h,w|a,i,\iota=0) + \sum_{a} \Psi_R(a) SS + \overline{g}.\end{aligned} \tag{19}$$

The left hand side consists of tax revenue from employed workers, unemployed workers, and firms. Strictly speaking, since those at the low end of the wage distribution pay negative taxes (receive means-tested transfers), there are also government outlays in the left hand side of (19). The right hand side consists of other outlays in the form of unemployment benefits, transfers to workers without unemployment benefits, social security payments, and public consumption, $\overline{g}$. I calculate $\overline{g}$ in my benchmark economy such that the government budget constraint holds, and I assume that the government must spend $\overline{g}$ in counterfactual experiments.

4 Mechanisms in Simplified Model

Before proceeding to quantitative exercises, I analytically inspect the economics of the worker's problem. To do so, I use a slightly simplified discrete-time two-period model. Suppose workers live for two periods and discount the second period at discount factor β. They experience utility from consumption both periods, but can only invest in human capital accumulation or job search in the first period. Workers earn a constant piece rate $r = 1$ and there is no human capital depreciation. With probability $sm(\theta)$, workers move from firm productivity p to $p + \Delta_p$. I write the worker's problem in Appendix B.

For a worker in the first period of life, the first order conditions state that the optimal choices for human capital effort l and search effort s solve

$$\phi(1+\gamma)(l+s)^{\gamma} = \frac{\beta(1-\tau_1)\omega}{(lh)^{1-\omega}/a + l} = \frac{\beta(1-\tau_1)}{p/(m(\theta)\Delta_p) + s}. \tag{20}$$

The left hand side of this equation is the marginal cost of investing in human capital or search effort,[13] the middle part is the marginal benefit of human capital accumulation, and the right hand side is the marginal benefit of search effort. When the worker is behaving optimally, all three are equal. Note that tax progressivity, τ_1, enters directly in the marginal benefit of human capital accumulation and search effort.[14]

Consider two otherwise identical workers except that one has greater learning ability than the other, $a_1 > a_0$. The marginal benefit of human capital investment, the middle

[13]Because disutility is simply a function of $l + s$, the marginal cost of investing in either activity will always be equivalent.

[14]The tax level, τ_0, has no effect on worker decisions in the simplified model because I use log utility of consumption. With log utility of consumption, if the tax level changes, the income and substitution effects perfectly offset each other. The result is analogous to how the tax level does not affect labor supply in a model with log utility of consumption.

part of Equation (20), is greater for the worker with high a. In order for Equation (20) to hold, the worker must increase l and decrease the middle part. However, by increasing l, the worker increases the marginal cost of effort on the left hand side. Thus, for Equation (20) to hold, the worker must also decrease s. (In any case, the worker will not adjust l or s without adjusting the other.)

It can be shown that the optimal decision rules for the two workers satisfy $l_1 > l_0$, $s_1 < s_0$, and $l_1 + s_1 > l_0 + s_0$.[15] In words, the agent with more learning ability will invest more in human capital accumulation, less in search, and more overall. So, the worker with greater learning ability will substitute away from search toward human capital, but the substitution is imperfect (the increase in l exceeds the decrease in s.) Within the period, it follows that human capital and job search investment are akin to imperfect substitutes. One implication is that, compared to a pure human capital model, endogenous search effort has an equalizing force in my model. Instead of struggling to accumulate human capital, workers with low learning ability can direct their efforts toward on-the-job search.

On the other hand, Equation (20) also features some complementarity between human capital and search in a dynamic sense. Consider two otherwise identical workers except that one worker works for a more productive firm, $p_1 > p_0$. It can be shown that $l_1 > l_0$, $s_1 < s_0$, and $l_1 + s_1 < l_0 + s_0$. In words, the worker at the more productive firm will invest more in human capital accumulation, less in search, and less overall. Recall that h and p are complements in production. So, at a more productive firm, the benefit of increasing human capital is greater, and the worker at the high-productivity firm is incentivized to invest in h such that the level of h “catches up" with the level of p. The same logic holds for differences in h. Therefore, contrary to the substitution story above, it may be the case that workers with high human capital may work at more productive firms.

Finally, note that if τ_1 is greater, then the marginal benefits of human capital and search investment both decrease. The result is that both l and s will be lower in an economy with higher tax progressivity. More progressive taxes discourage wage growth in all of its

[15]The mathematical proof follows from the fact that all other possibilities lead to a contradiction.

forms because, either way, when the worker's wage increases, the benefit of the increased wage is smaller.

5 Calibration

5.1 Data

To parameterize the model, I rely on microdata from the Survey of Income and Program Participation (SIPP). The SIPP is a panel data set with interviews every four months.[16] Within interviews, respondents report on what occurred in the months between interviews. I use every SIPP panel between the years 1990 and 2019, 12 panels in total.[17]

Two features of the SIPP make it convenient for my setting. First, respondents report their earnings and hours every month, which allows me to observe hourly wage growth across months. Second, the SIPP tracks worker-job matches, which allows me to observe job switches. I convert monthly transfer rates (unemployment to employment, employment to unemployment, and job switching) to continuous-time arrival rates and correct for time aggregation bias using the methods developed in Mukoyama (2014).

I restrict the data to males between the ages of 23 and 65 who are never out of the labor force, I convert earnings data to hourly wages, and I drop the self-employed. Observations with wages below the federal minimum wage are dropped. For every statistic, I calculate the weighted mean within the panel using panel weights, then take the weighted mean across panels where each panel is weighted by the number of months it covers. I drop the first two and last two months of each panel. Though the SIPP has weekly labor force indicators, I aggregate to a monthly frequency and use the labor force indicator for the second week of the month to mirror the CPS.[18]

[16] In 2018, the SIPP transitioned from interviewing respondents every four months to interviewing respondents every year with an event history design. I use three panels with such a design.

[17] I use the 1990, 1991, 1992, 1993, 1996, 2001, 2004, 2008, 2014, 2018, 2019, and 2020 panels.

[18] Unemployment-to-employment and employment-to-unemployment rates in the SIPP are consistently lower than the familiar values in the CPS. See the discussion in Footnote 16 in Menzio et al. (2016).

5.2 Functional Forms and Distributions

I use a Cobb-Douglas matching function. From the perspective of a worker, the probability of meeting an open vacancy per unit of search effort is $m(\theta) = \xi\theta^{1-\alpha}$ with $\xi > 0$ and $\alpha \in (0, 1)$. For a firm, the probability of meeting a worker is $m_f(\theta) = \xi\theta^{-\alpha}$.

I assume that the distribution of firm productivity, $F(p)$, is Pareto with level parameter μ_p and tail parameter $1/\lambda_p$. The distributions for learning ability and initial human capital follow Badel et al. (2020). Thus, learning ability a is drawn from a Pareto lognormal distribution, $a \sim PLN(\mu_a, \sigma_a, 1/\lambda_a)$, where μ_a is the level parameter, σ_a is the dispersion parameter, and $1/\lambda_a$ is the tail parameter.[19] The distribution of initial human capital, h_0, is a linear function of a,

$$\ln(h_0) = \beta_0 + \beta_1 \ln(a) + \ln(\varepsilon)$$

with $\varepsilon \sim LN(0, \sigma_\varepsilon)$. Badel et al. (2020) shows that h_0 is also distributed Pareto lognormally. Appendix D.2 documents how I discretize the distribution of a.

To help the model fit the data, I make one final adjustment to include "godfather shocks." With probability ψ, an employed worker experiences a godfather shock, which means that he meets an outside firm and must accept a job at the new firm.[20] Though ad-hoc, godfather shocks are useful for generating one feature in the data: of workers who switch jobs, 30% earn a lower wage in their new job compared to their old job. In my model, it is impossible for a worker to make a job-to-job transition without a wage increase.[21] Quantitatively, I estimate a small value for ψ, but it is very helpful in matching this fact. All equations which are affected by godfather shocks are updated in Appendix A.2.

[19]There is more than one type of Pareto lognormal distribution (Hajargasht and Griffiths, 2013). I am referring to the distribution that consists of a lognormal distribution with a Pareto right tail.

[20]The worker is made "an offer he can't refuse."

[21]See Dorn (2018) and Tjaden and Wellschmied (2014) for investigations into job-to-job transitions with a wage decrease, and see Moscarini and Postel-Vinay (2018) for another example of godfather shocks in use.

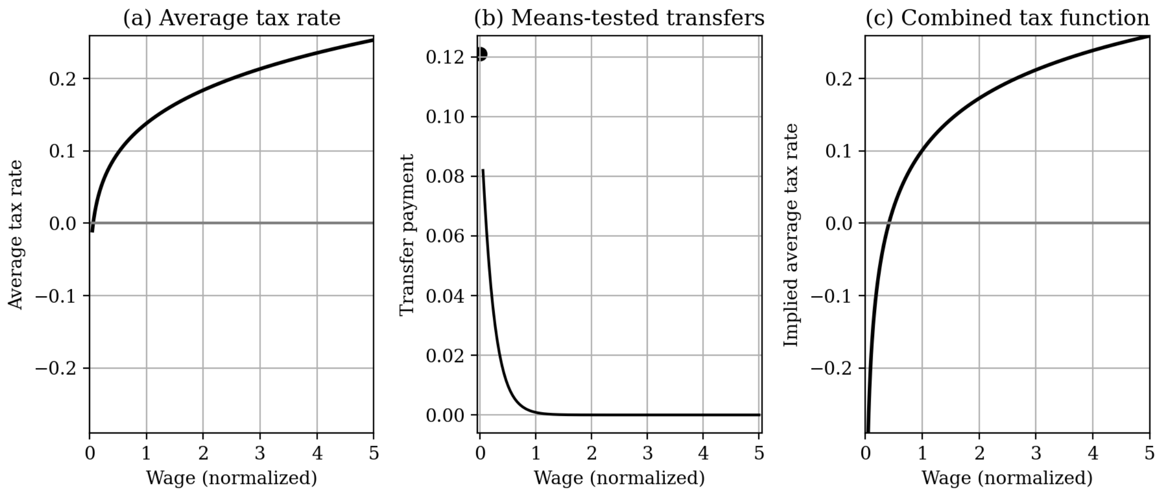

Figure 1: Combined tax function and its ingredients

Panel (a): average tax rate function as estimated in Guner et al. (2014). Panel (b): means-tested transfer function as estimated in Guner et al. (2023). Panel (c): combined average tax function with combines panels (a) and (b) and re-estimates an average tax function with the form of Equation (2). Wage is normalized such that the mean wage equals one.

5.3 Taxes and Transfers

My goal in calibrating taxes and transfers is to accurately represent the US system while maintaining a simple structure. I therefore estimate Equation (2) such that it fits both the progressive income tax and means-tested transfer systems in the US. My strategy consists of borrowing an estimated average tax function and an estimated means-tested transfer function from the literature, then re-estimating Equation (2) on the combination of both functions. Each function is over wage hpr normalized such that the mean wage is one.

For taxes, I use an estimate of federal income taxes from Guner et al. (2014) for all households (married and unmarried) which takes the earned income tax credit (EITC) into account.[22] To this function, I add a flat state and local income tax rate of 5%.[23] Using

[22]I use the power function specification in Table A5 in the appendix.

[23]I take the value of 5% from (Guner et al., 2022). The notion of a flat state and local income tax rate is supported by Fleck et al. (2021).

these estimates, the average tax rate is

$$Tax(y) = -0.294 + 0.382(hpr)^{0.164} + 0.05.$$

The average tax function is plotted in Panel (a) of Figure 1.

For transfers, I use an estimated means-tested transfer function for all households from (Guner et al., 2023). The means-tested transfer function takes the following programs into account: WIC (the Special Supplemental Nutrition Program for Women, Infants, and Children), SSI (Supplemental Security Income, for those with disabilities), SNAP (Supplemental Nutrition Assistance Program, formerly known as Food Stamps), TANF (Temporary Assistance for Needy Families), and housing. For a discussion of these programs, see Guner et al. (2023). The estimated transfer function is

$$Tr(hpr) = \begin{cases} e^{-2.122}e^{-4.954(hpr)}(hpr)^{0.044}, & y > 0 \\ 0.121, & y = 0 \end{cases} \tag{21}$$

and is plotted in Panel (b) of Figure 1. I use the zero-wage case (0.121) to parameterize transfers for the unemployed without unemployment benefits, T_0.

When I combine taxes and transfers and estimate the parameters of Equation (2), I get $\tau_0 = 0.899$ and $\tau_1 = 0.120$.[24] The new tax function is plotted in Panel (c) of Figure 1. Comparing Panel (c) and Panel (a), it is clear that including transfers significantly increases progressivity.

5.4 External Parameters

External parameter choices are summarized in Table 1. The model is period is monthly. Working life is ages 23 to 65, 42 years total, and I set the number of working stages of life to $I = 4$. So, each stage is $(42 \times 12)/4 = 126$ months and the rate of transitioning from one stage of life to the next is $\zeta = 1/126$. Retirement is 10 years, so $\overline{\zeta} = 1/(10 \times 12)$.

[24] These estimates are similar to Holter et al. (2019).

Table 1: Externally calibrated parameters

Parameter	Meaning	Value	Explanation/source
Lifecycle			
I	Stages of life	4	By choice
ζ	Transition pobability from one stage to the next	$\left(\frac{42\times 12}{I}\right)^{-1}$	Working for 42 years on average (ages 23-65)
$\overline{\zeta}$	Probability of death for the retired	$(10 \times 12)^{-1}$	Retired for 10 years on average
Policy			
τ_0	Tax+transfer progressivity	0.899	Guner et al. (2014, 2023)
τ_1	Tax+transfer level	0.120	Guner et al. (2014, 2023)
T_0	Transfer for worker without UI	0.121	Guner et al. (2023)
τ_b	Business tax rate	0.243	Cooper et al. (2016)
b	Unemployment benefit replacement rate	0.5	Standard in US
$\overline{b}$	Unemployment benefit maximum	0.5	Standard in US
χ	Unemployment benefit expiration rate	1/6	Standard US maximum of 6 months
SS	Social security payment	0.5	Normalization
$\overline{g}$	Public consumption	0.084	Equalizes government budget constraint in benchmark equilibrium
Search			
α	Meeting function elasticity	0.5	Petrongolo and Pissarides (2001)
η	Worker's bargaining power	0.4	Bagger et al. (2014)
κ	Job posting cost	0.124	Normalizes benchmark equilibrium θ to 1
Other			
ρ	Discount rate	0.00330	4 percent annual interest rate
δ	Human capital depreciation rate	0.00116	Matches decline of wages in last stage of life
β_0	Initial human capital intercept	0.305	Normalized such the lowest h_0 is the bottom point on the h grid

Parameters set outside the model.

Unemployment benefits pay a fraction b of the previous wage up to a maximum, $\bar{b}$. So, $B(w) = \min\left\{bw, \bar{b}\right\}$. In accordance with typical unemployment benefits in the US, I set $b = 0.5$ and $\bar{b} = 0.5$. The expiration rate of unemployment benefits is $\chi = 1/6$ in keeping with the typical rule that unemployment benefits can be collected for a maximum of six months. I normalize $SS = .5$.[25] The flat tax rate on firm profit is $\tau_b = 0.243$, the estimated average tax on business income in Cooper et al. (2016).

As for other parameters, I set $\alpha = 0.5$ (Petrongolo and Pissarides, 2001) and $\eta = 0.4$ (Bagger et al., 2014).[26] κ is chosen such that equilibrium θ is normalized to one. I set $\rho = 0.0033$ in accordance with a 4% risk-free annual real interest rate, and I set $\delta = 0.00116$ to match the decline in wages at the end of life.[27] β_0 is normalized such that the lowest possible h_0 is the bottom point on the human capital grid.

Finally, I estimate the job loss function $\Lambda(hpr)$ directly from the SIPP. $\Lambda(hpr)$ is presented graphically in Appendix D.1.

5.5 Targeted Moments

I am left with 13 parameters to calibrate internally. I jointly estimate Internal parameters using simulated method of moments such that the simulated model matches 16 moments from the SIPP.[28]

I target the lifeycle profiles of the mean log wage, variance of log wages, and the job switching rate. For each profile, I target the starting point, the ending point, and the midpoint. I also target five moments that are not associated with the life cycle: the average unemployment to employment rate, cross-sectional log wage skewness, monthly wage

[25]The choice of SS is immaterial to my results. Since social security payments are equal across workers and workers have no choice but to transition to retirement eventually, retirement does not affect choices during working life.

[26]Engbom (2022) estimates a similar value for η.

[27]Assume that workers do not invest in human capital in the last stage of life, $i = I$. Without job switching or unemployment, wages are multiplied by $1 - \delta$ every month. If there are x months in the last stage of life, then $\frac{w_I}{w_{I-1}} = (1 - \delta)^x$. Since each working stage is 126 months on average, and given that $w_I / w_{I-1} = 0.864$ in the data, we have $\delta = 0.00116$.

[28]I solve the SMM minimization problem using MIDACO, a general-purpose ant colony optimization algorithm (Schlüter et al., 2009).

growth for those who stay in the same job, monthly wage growth for those who switch jobs, and monthly wage growth for those who switch jobs and increase their wage. Finally, I target two normalizations: I normalize the mean wage to 1 (in order to be consistent with the job destruction function and tax function), and I normalize mean $l + s_E$ to equal 0.1.[29]

5.6 Identification

Since I use simulated method of moments, all parameters are jointly determined, and most parameters affect more than one moment. Nevertheless, I will describe how each parameter relates to moments in the data with the goal of arguing that my internal parameters are well-identified. The 13 internal parameters are listed and described in Table 3.

First, there are some clear one-to-one relationships between moments and parameters. γ_U pins down the unemployment-to-employment rate. And the level parameter for the firm productivity distribution, μ_p, is immaterial except for establishing the mean wage in the economy. So, μ_p is used to normalize mean log wages to 1.

The two moments associated with wage growth for job switchers are determined by two parameters, λ_p and ψ. λ_p determines the size of wage jumps that workers experience while changing jobs. Conditional on λ_p, ψ identifies the difference between wage growth for those switching jobs with a wage increase and those switching jobs with a wage decrease. In other words, the frequency of godfather shocks is pinned down by the relative wage growth from switching jobs when the wage decreases.

Next, the level parameter of the learning ability distribution, μ_a, pins down the mean monthly wage increase for job stayers. This leaves ω as the parameter most closely related to the concave shape of wages over the life cycle.[30]

[29] The final normalization is not necessary, but it is convenient because it keeps other parameter levels contained. Since I have level parameters on the disutility of effort (ϕ), the return to human capital investment (a), and the return to job search effort (ξ), l and s can be any level and these three parameters will adjust to get an equally tight fit.

[30] One difficulty with identification is that both the human capital and search channels are generate cur-

Following the logic of Huggett et al. (2011) (and given the parameters and moment accounted for to this point), I associate the parameters of the learning ability and initial human capital distributions $(\sigma_a, \lambda_a, \beta_1, \sigma_\varepsilon)$ with the variance of wages, skewness of wages, and lifecycle profile of the variance of wages. Given that it determines the skewness of a, λ_a is mostly closely related to the skewness of wages. With λ_p accounted for, σ_a is identified by the overall level of variance of wages. The lifecycle profile of wage variance is thus identified by σ_ε, the dispersion of human capital at birth, and β_1, the correlation between human capital at birth and learning ability.

We are left with three parameters, ϕ, γ_E, and ξ, for the level of the job switching rate, the lifecycle profile of the job switching rate, and the normalized of mean human capital investment plus mean search effort for the employed. Since ϕ and γ_E parameterize the function for total disutility, $\phi(l+s)^{1+\gamma_E}$, they are strongly related to the level of total wage investment, but immaterial to the mix of human capital investment and search investment. Therefore, ϕ and γ_E are closely related with the normalization of $s_E + l$. ξ determines the relative benefit of search investment compared to human capital investment, and thus is associated with the job switching rate.

It is crucial that I match monthly wage growth for job stayers versus job switchers. The difference allows me to differentiate the month-to-month wage growth that comes from the human capital channel versus the search channel. One may object that in my wage bargaining protocol, workers who stay at the same firm can experience wage growth from human capital accumulation or from renegotiation, the latter of which is part of the search channel. However, we know that the wage growth for job switchers is due to search. So, for job stayers, the residual wage growth that is unidentified from the search channel comes from human capital growth.

vature in lifecycle wages. Because I use the Ben-Porath (1967) human capital accumulation function, there are decreasing returns to human capital investment given by ω, which generates concavity in the lifecycle human capital profile. Similarly, since the distribution of firm productivity $F(p)$ is fixed, we would expect to see greater wage increases at the beginning of life (as workers pick the "low hanging fruit" of firms), but wage growth will become slower as workers move up the job ladder. This curvature is determined by λ_p. However, λ_p is also closely related to monthly wage growth for job switchers. Thus, we can say that the residual curvature in lifecycle wages is identified by ω.

Table 2: Fit between data and model, non-lifecycle moments

Moment	Target	Model
Unemployment to employment rate	0.283	0.327
Wage growth, stayers	0.008	0.007
Wage growth, switchers	0.106	0.107
Wage growth, switchers with increase	0.350	0.421
Log wage skewness	0.412	0.408

Model values are from calibrated benchmark model. Targets are calculated from SIPP data. Unemployment to employment rate and wage growth rates are monthly. Unemployment to employment rate is a continuous-time arrival rate.

5.7 Calibration Results

Figure 2 illustrates the fit between the model and lifecycle moments. The model successfully replicates the hump shape of wages, the steady increase in the variance of wages, and the convex decrease in the job switching rate over the life cycle. Table 2 presents the fit between the model and non-lifecycle moments. The parameters which deliver the fit are listed in Table 3.

A handful of calibration results deserve a brief discussion. First, my estimate of the curvature parameter in the human capital production function, $\omega \approx 0.5$, is in line with micro estimates.[31] Second, $\gamma_U > \gamma_E$; in words, the disutility function has significantly more curvature for unemployed workers than employed workers. Thus. unemployed workers exert more search effort before the marginal cost becomes prohibitively large, which allows the model to match the fact that the unemployment-to-employment rate is much greater than the job switching rate. Third, my calibrated value for the dispersion of learning ability, σ_a, is relatively large.[32] I attribute my large σ_a value to the fact — described in Section 4 — that endogenous search acts as an equalizer; compared to a model without endogenous search, in order to generate the same level of wage dispersion, I need more dispersion in learning ability.

[31] For discussions of the human capital curvature parameter, see Blandin (2018) and Browning et al. (1999).
[32] See Badel et al. (2020) and Esfahani (2020).

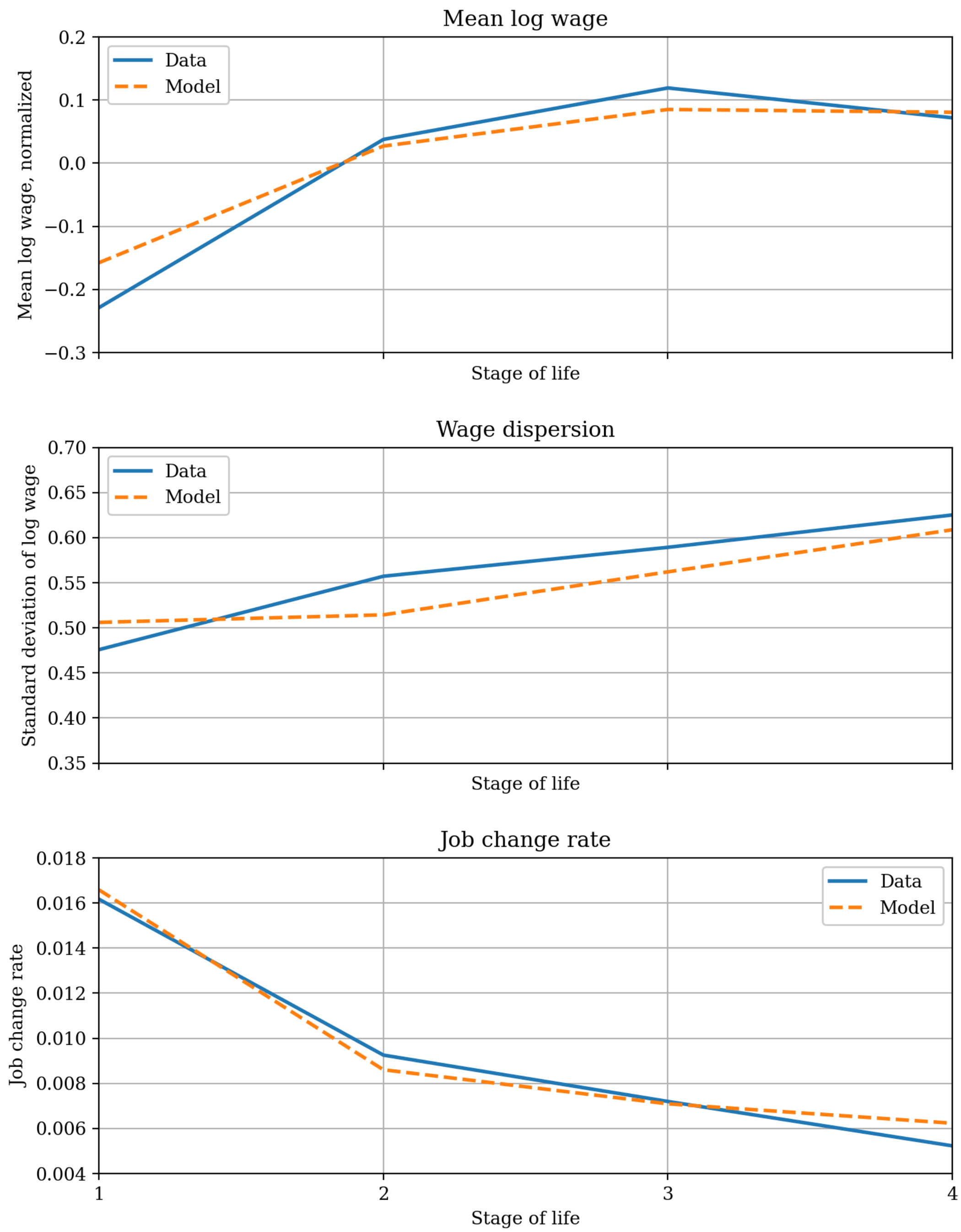

Figure 2: Fit between data and model, lifecycle moments

Model values are from calibrated benchmark model. Data source: SIPP. The mean wage is normalized such that the mean wage equals 1. The job change rate is monthly.

Table 3: Internally calibrated parameters

Parameter	Meaning	Value
ϕ	Disutility level	6.56
γ_E	Disutility curvature, employed	1.53
γ_U	Disutility curvature, unemployed	3.84
ω	Human capital investment curvature	0.48
ξ	Meeting efficiency	1.69
μ_p	Firm productivity distribution, level	0.23
λ_p	Firm productivity distribution, tail	0.36
μ_a	Learning ability distribution, level	0.0044
σ_a	Learning ability distribution, dispersion	0.67
λ_a	Leaning ability distribution, tail	0.06
β_1	Correlation between a and h_0	0.0025
σ_ε	h_0 dispersion	0.10
ψ	Godfather shock rate	0.0003

Values for parameters which generate best model fit with SIPP data.

6 Properties of Benchmark Model

Before experimenting with taxes, I describe properties of the benchmark model that are vital for understanding how the model works and how it will respond to policy changes.

6.1 Mean Wages

Recall that the wage equals hpr. Given its structure, I can easily decompose log wages between human capital h, firm productivity p, and the bargained piece rate r. The log wage is the sum of the log of the three components,

$$\ln(wage) = \ln(h) + \ln(p) + \ln(r).$$

The mean log wage follows is the sum of the mean log of each component,

$$\mathrm{E}[\ln(wage)] = \mathrm{E}[\ln(h)] + \mathrm{E}[\ln(p)] + \mathrm{E}[\ln(r)]. \tag{22}$$

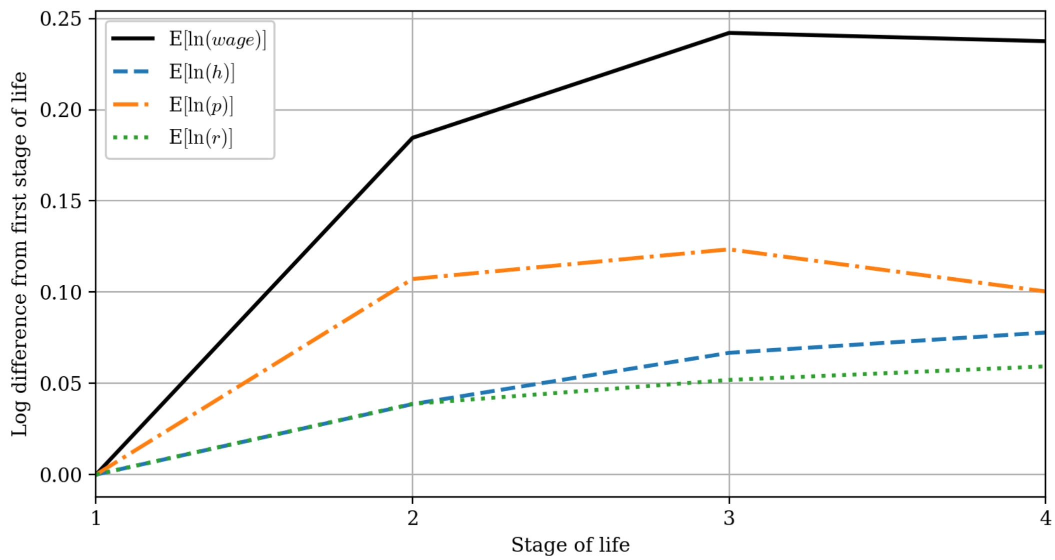

Figure 3: Mean log wage lifecycle decomposition

Additive decomposition of mean log wage as in Equation (22). Mean log wage is the sum of mean log human capital h, firm productivity p, and piece rate r. Dashed colored lines sum to black line. Computed in benchmark calibrated model.

Taken together, p and r comprise the search channel, and h represents the human capital channel.[33]

In the benchmark model, lifecycle wage growth is mostly driven by workers moving up the job ladder to more productive firms. Figure 3 plots the growth of mean log wages over the life cycle along with its three additive components. All three components contribute to lifecycle wage growth, but approximately 2/3 of lifecycle wage growth comes from the search channel and 1/3 comes from human capital accumulation.[34]

However, the average masks significant heterogeneity in the ways that workers grow wages. Recall that a worker's choice of l and s depend on his state, age, and fixed learning ability. In practice, learning ability is especially important. As described in Section 4, workers with high learning ability will substitute away from search effort toward human

[33]The decomposition is somewhat compromised by the fact that h, p, and r all interact with each other. However, I show later that the implications of this decomposition are the same as when I take a more careful approach in Section 7.5, and this additive decomposition is far more intuitive.

[34]Bayer and Kuhn (2019) finds a similar result.

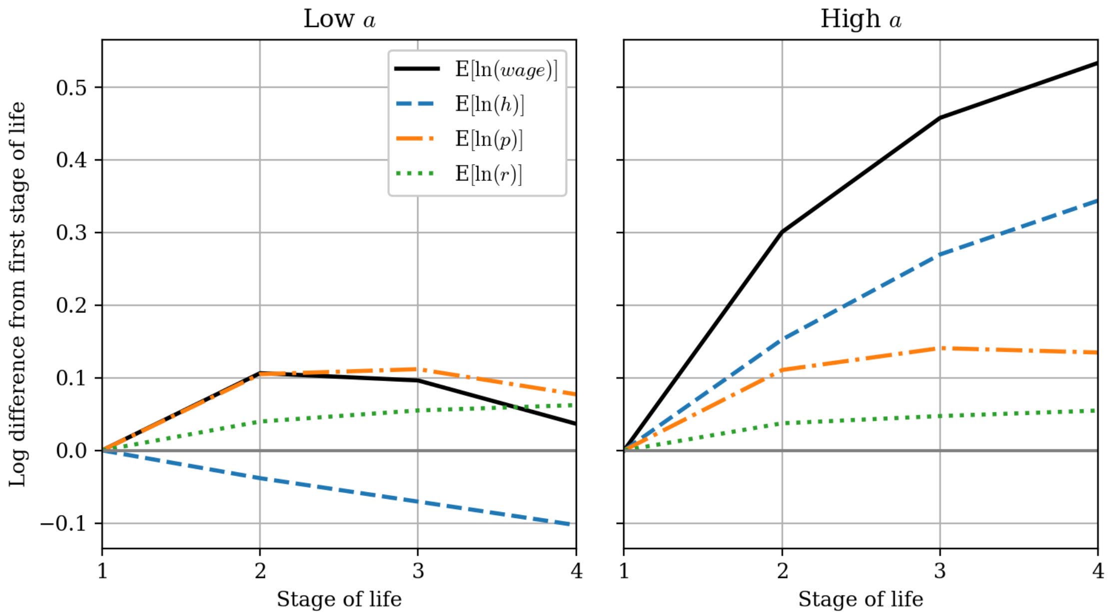

Figure 4: Mean log wage lifecycle decomposition by learning ability

Additive decomposition of mean log wage as in Equation (22) and Figure 3 split by learning ability. Learning ability a is split between lower 60% and upper 40% of a values. Computed in benchmark calibrated model.

capital accumulation and vice versa.

The result is that wage growth is significantly heterogeneous, and the heterogeneity is driven by human capital. In Figure 4 and going forward, I split my distribution of a values into two bins: the lower 60% and the upper 40%.[35] Figure 4 replicates the same decomposition of mean log wages for both learning ability bins. Clearly, human capital growth differentiates the two groups. In fact, the growth of p and r is quite similar across groups. However, those with high learning ability rely mostly on human capital for wage growth, while those with low learning ability rely entirely on search. (In fact, those with low learning ability experience a net loss of human capital over the life cycle.) In general, these findings support the conclusions in Ozkan et al. (2023) and Bagger et al. (2014) which argue that the search channel is the largest determinant of wage growth for the lower part of the wage distribution, while human capital growth is the largest determi-

[35]These values translate conveniently to how I discretize the distribution of a. See Appendix D.2.

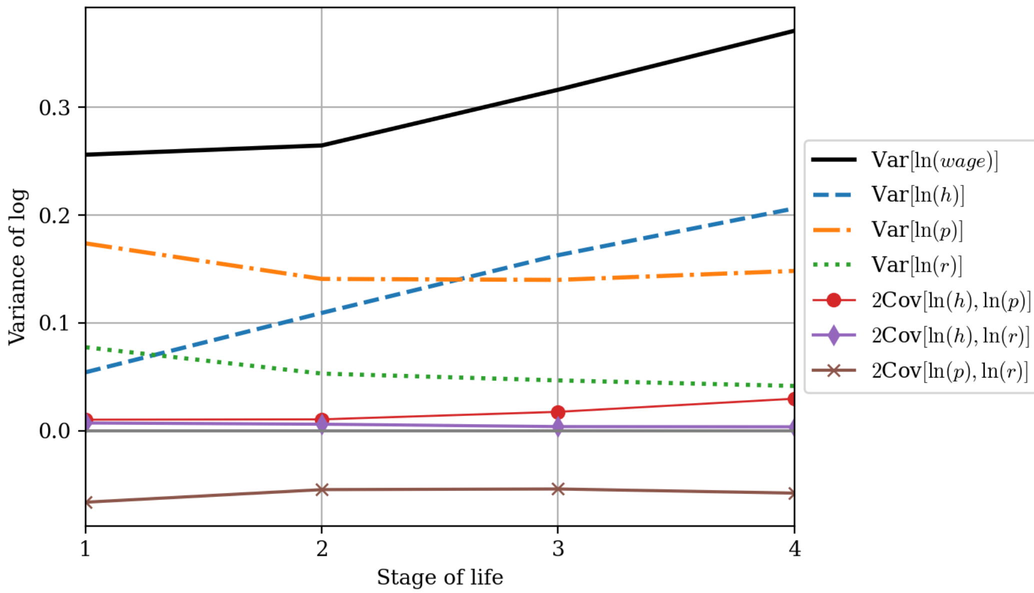

Figure 5: Variance of log wage lifecycle decomposition

Additive decomposition of the variance of log wage as in Equation (23). Colored lines sum to black line. Computed in benchmark calibrated model.

nant of wage growth for the upper part of the wage distribution.

6.2 Lifecycle Wage Dispersion

6.2.1 Benchmark Model

As with mean log wages, the structure of the model implies a straightforward decomposition for the variance of log wages. The variance of the log wage is the sum of the variance of each log component plus an interaction term for each pair of log components,

$$\begin{aligned} \text{Var}[\ln(wage)] &= \text{Var}[\ln(h)] + \text{Var}[\ln(p)] + \text{Var}[\ln(r)] \\ &\quad + 2\,\text{Cov}[\ln(h), \ln(p)] + 2\,\text{Cov}[\ln(h), \ln(r)] + 2\,\text{Cov}[\ln(p), \ln(r)]. \end{aligned} \tag{23}$$

Using Equation (23), I find that the increase in wage dispersion over the life cycle is completely driven by an increase in human capital dispersion. I decompose wage dispersion over the life cycle into the six terms in Equation (23) in Figure 5. In the cross section, variance in human capital accounts for about half of the variance of log wages. But over the life cycle, the increase in variance of human capital is solely responsible for the increase in wage dispersion.

As Huggett et al. (2011) shows, two key ingredients are required to generate increasing wage dispersion in a human capital model: heterogeneity in learning ability and positive correlation between learning ability and initial levels of human capital. With heterogeneity in learning ability, those with high learning ability accumulate human capital faster than those with low learning ability. And if initial human capital and learning ability are positively correlated, then the gap between workers with high and low learning ability will increase over the life cycle.

The benchmark model can be summarized as follows: wage growth is generally a function of the job ladder, while inequality is generally a function of human capital.

6.2.2 Restricted Models

I now introduce "restricted models" where I shut down certain channels. By shutting down channels, I will show how different features of the model generate different results with respect to lifecycle wage inequality in Figure 6. For now, I use the same benchmark parameters for all models. (Later, in Section 7.6, I recalibrate each restricted model and perform a "horse race" experiment.)

There are four restricted models. First, I shut down the search channel but keep the rest of the model the same. I refer to this as the "pure human capital + heterogeneity" model. Then, I also shut down heterogeneity in learning ability and refer to this model as the "pure human capital" model. Returning to the benchmark model, I then shut down the human capital channel but keep the rest the same. This is the "pure job ladder + heterogeneity" model. Then, I shut down all heterogeneity in initial human capital and refer to it as the "pure job ladder" model.[36]

[36] I also shut down heterogeneity in learning ability, but it is immaterial in a model without human capital accumulation.

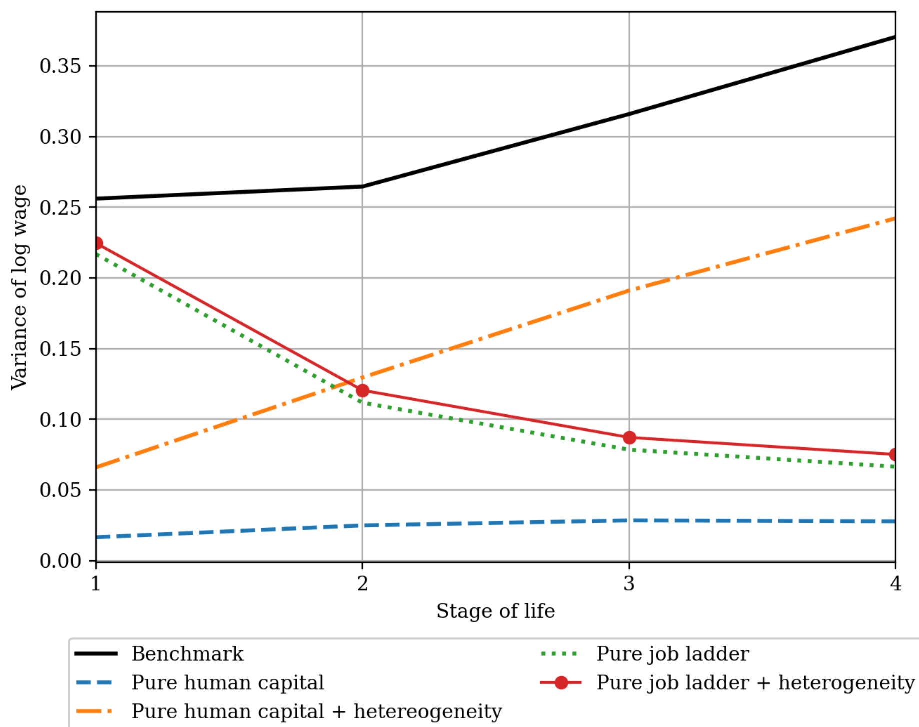

Figure 6: Lifecycle wage dispersion when channels are shut down

Lifecycle variance of log wage in models where channels are shut down. All models are computed using the benchmark calibration. Pure human capital models shut down the search channel, and pure job ladder models shut down the human capital channel. In both cases, “heterogeneity" refers to heterogeneity in initial human capital h_0 and learning ability a.

First, in Figure 6, note how lifecycle wage dispersion behaves when I shut down the search channel in pure human capital models. Clearly, the search channel adds a significant amount of wage dispersion to the model. Also, note how a pure human capital without heterogeneity has far less wage dispersion as well as hardly any increase in wage dispersion over the life cycle. Again, as pointed out in Huggett et al. (2011), in a human capital model, heterogeneity in learning ability and initial human capital are vital ingredients for generating an increase in wage dispersion over the life cycle.

When I shut down the human capital channel in pure job ladder models, wage dispersion *decreases* over the life cycle. To understand why, recall how on-the-job search works in the model. At the beginning of life, workers randomly meet a firm with productivity p drawn from the fixed distribution $F(p)$. Thus, the newborn distribution of p roughly mirrors $F(p)$. As workers search on the job, they meet more firms, and if they meet a firm with higher productivity than their current firm, they switch. As workers move up the job ladder, workers tend to bunch more at the top of the wage distribution, and the variance of firm productivity decreases.[37]

Thus, the human capital and search channels have opposite predictions for lifecycle wage dispersion. Following this logic, when I increase tax progressivity in the model, the two channels will have opposite effects.

6.3 Interaction of Human Capital and On-the-Job Search

In Section 4, I show that human capital and job search may be positively or negatively correlated in the model. Quantitatively, the benchmark model suggests that the two channels are substitutes within the individual worker's decision problem, but positively correlated on an aggregate level.

In Figure 7, I plot mean policy functions for human capital investment l and search effort s across workers in the two learning ability bins described earlier. Overall, the figure suggests that workers substitute between l or s. At the beginning of life, workers with low

[37]The mechanism is common to any framework that models on-the-job search as climbing a fixed job ladder, including Bagger et al. (2014) and related models.

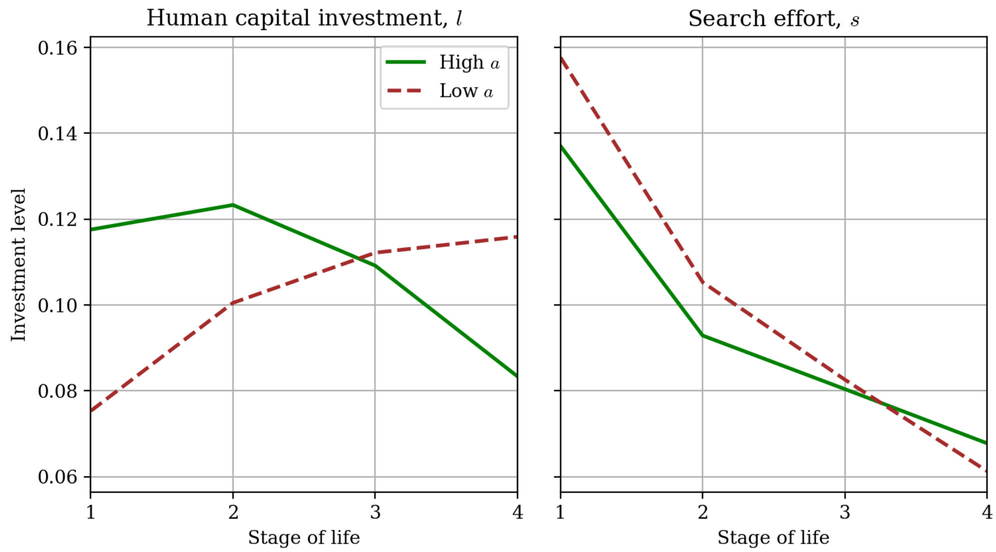

Figure 7: Mean policy functions by learning ability

Mean policy functions for human capital investment l and search effort s over life cycle. Learning ability a is split between lower 60% and upper 40% of the a distribution.

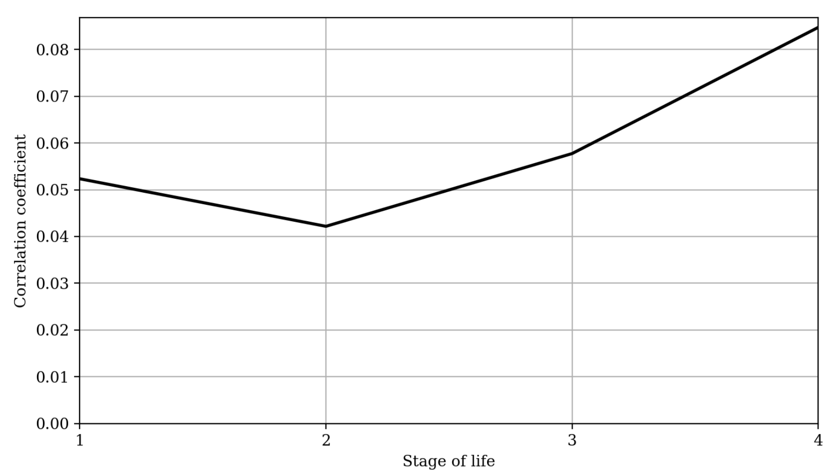

Figure 8: Correlation of $\ln(h)$ and $\ln(p)$

Weighted correlation coefficient of log human capital and log firm productivity over the life cycle. Computed in benchmark calibrated model.

learning ability tend to invest more in job search while workers with high learning ability tend to invest more in human capital accumulation. By the end of life, the relationship flips.

Despite the substitutability of human capital and search, Figure 8 shows that, at the aggregate level, the correlation between h and p is positive and increasing over the life cycle.[38] There are at least two forces at work. First, as shown in Section 4, since h and p are complements in production, workers will make investments in h and p such that h and p become positively correlated over the life cycle. Second, workers are heterogeneous in unemployment risk; because low-wage workers are more likely to lose their job, they do not climb the job ladder as quickly (Jarosch, 2023). Thus, workers with high human capital are less likely to fall down the job ladder, and the correlation between h and p increases over the life cycle.

Why does the correlation between h and p matter? The extent to which high-skill workers tend to work at high-productivity firms can help explain the extent of wage inequality we observe in the data. For example, in a search-and-matching model using the same on-the-job search apparatus as my model, Bagger and Lentz (2019) find that a substantial portion of wage dispersion is due to positive sorting. My findings support this argument even with many potentially confounding features in the model. Furthermore, using the lifecycle feature in my model, I show that the increasing correlation of h and p over the life cycle contributes to increasing wage dispersion over the life cycle.

7 Tax Progressivity Experiments

To demonstrate the usefulness of the model, I perform counterfactual experiments on tax progressivity. From Section 4 alone, we know that an increase in tax progressivity will decrease wages. Facing greater tax progressivity, if a worker increases their wage, then they take home a smaller part of the wage increase. Since the benefit of investment

[38]The literature following Abowd et al. (1999) has tended to find a positive correlation between estimated worker and firm productivity (though the original study did not); see Card et al. (2018) for a discussion.

decreases while the cost of investment is unchanged, l and s will decrease, and wages decrease as well. What is unclear is the magnitude of the effect and how the channels interact quantitatively.

In counterfactual experiments, I feed the model new values of tax progressivity, τ_1. There are two objects that adjust so that the model is in equilibrium under the new τ_1: labor market tightness θ, which adjusts such that the free entry condition (18) holds, and the tax level τ_0, which adjusts such that government budget constraint (19) holds.

First, I provide an overview on how the model responds when I change tax-and-transfer progressivity. Then, I investigate the machinery behind the results for the mean wage level, wage dispersion, and lifecycle wage growth. I then compare my results with recalibrated restricted models where I turn off certain channels.

7.1 Overview of Results

In the benchmark model, the level of tax progressivity, $\tau_1 = 0.12$, reflects the combined progressivity of the tax system and means-tested transfers in the US. I compare $\tau_1 = 0.12$ with flat taxes, $\tau_1 = 0$, and with twice as much progressivity, $\tau_1 = 0.24$. Setting $\tau_1 = 0.24$ puts the level of tax-and-transfer progressivity in line with countries such as Denmark, Finland, Germany, the Netherlands, and Sweden.[39]

I plot the average tax rate for each tax system in Panel (a) Figure 9. As τ_1 increases, the average tax curve increases in curvature; those with low wages earn more transfers, and those with high wages pay more taxes. The increase in τ_1 also increases the threshold at which workers are net tax payers from 1/3 of the mean wage to 2/3 of the mean wage. Marginal tax rates are plotted in Panel (b) of Figure 9. If $\tau_1 = 0.12$, the marginal tax rate at the mean wage is 21%; when $\tau_1 = 0.24$, it is 30%.

The counterfactual results from adjusting tax progressivity are summarized in Table 4 and Figure 10. In Figure 10, I plot the mean log wage and variance of log wage over the life cycle for all three values of τ_1. In Table 4 and going forward, I only compare the

[39] See the appendix of Holter et al. (2019).

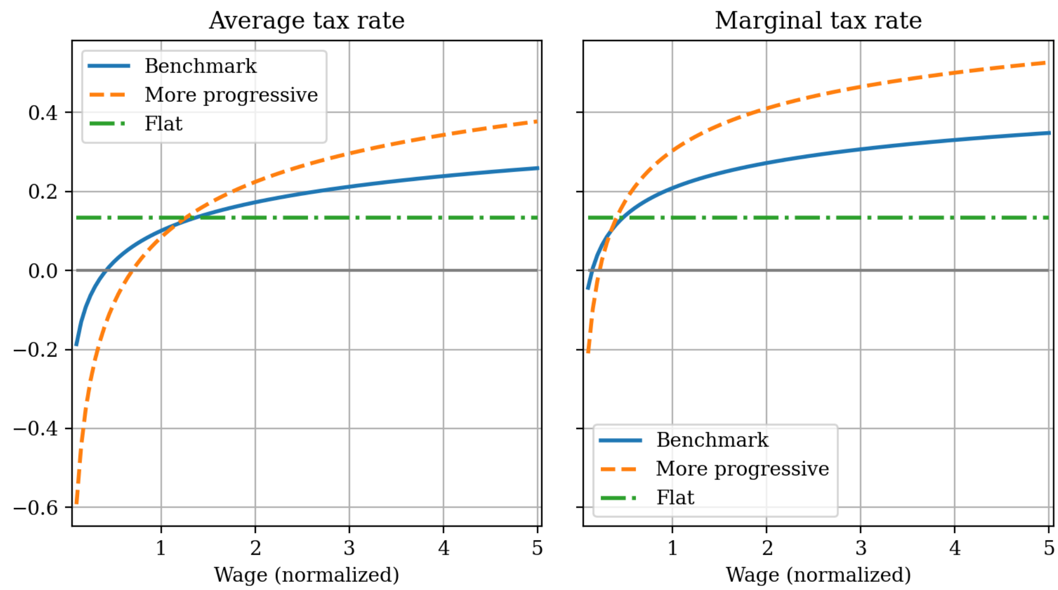

Figure 9: Tax rates by wage

The benchmark model uses progressivity parameter $\tau_1 = 0.12$, the “more progressive" model uses $\tau_1 = 0.24$, and the “flat" model uses $\tau_1 = 0$. Wage is normalized such that the mean wage equals one in the benchmark model. Each model is in equilibrium; thus, the tax level parameter τ_0 is set such that the government budget constraint holds.

Table 4: Summary of effects from increasing tax progressivity

	Benchmark	More progressive	Difference
Labor market tightness, θ	1.00	0.97	-0.03
Tax level, τ_0	0.90	0.92	0.02
Mean log wage	0.01	-0.03	-0.04
Variance of log wage	0.31	0.31	0.00
90-50 interdecile wage ratio	2.01	1.96	-0.05
Lifecycle growth of mean log wage	0.24	0.23	-0.01
Lifecycle growth of variance of log wage	0.11	0.11	-0.01
Unemployment rate	0.0181	0.0166	-0.0015
Job switching rate	0.0096	0.0100	0.0004
Mean consumption	1.02	0.98	-0.05
Variance of consumption	0.50	0.28	-0.22
Mean human capital investment, l	0.104	0.099	-0.005
Mean search effort, s, for employed workers	0.099	0.094	-0.005

“Lifecycle growth" refers to the difference between the last stage and the first stage of the life cycle. The benchmark model uses progressivity parameter $\tau_1 = 0.12$ and the “more progressive" model uses $\tau_1 = 0.24$. θ and τ_0 are solved for in equilibrium.

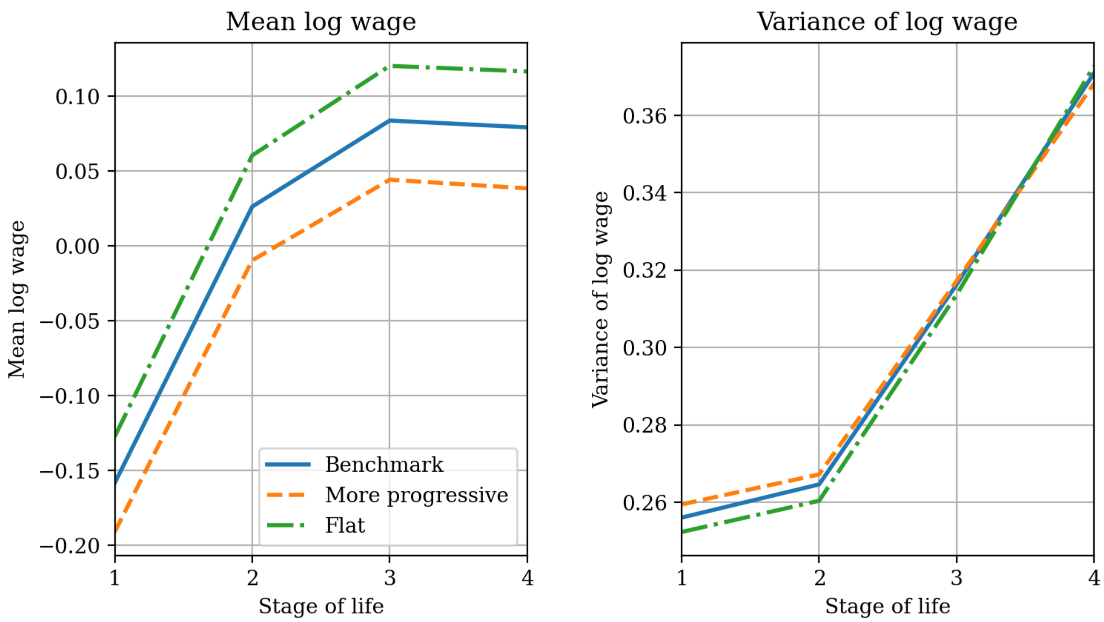

Figure 10: Effect of tax progressivity on lifecycle mean wage and wage dispersion

The benchmark model uses progressivity parameter $\tau_1 = 0.12$, the “more progressive" model uses $\tau_1 = 0.24$, and the “flat" model uses $\tau_1 = 0$.

Table 5: Decomposing effect of tax progressivity on mean log wage

	Benchmark	More progressive	Difference
$\mathrm{E}[\ln(wage)]$	0.008	-0.030	-0.037
$\mathrm{E}[\ln(wage)]$, low a	-0.186	-0.219	-0.033
$\mathrm{E}[\ln(wage)]$, high a	0.294	0.251	-0.043
$\mathrm{E}[\ln(h)]$	0.374	0.364	-0.010
$\mathrm{E}[\ln(h)]$, low a	0.183	0.178	-0.005
$\mathrm{E}[\ln(h)]$, high a	0.658	0.641	-0.017
$\mathrm{E}[\ln(p)]$	-0.167	-0.193	-0.026
$\mathrm{E}[\ln(p)]$, low a	-0.167	-0.193	-0.026
$\mathrm{E}[\ln(p)]$, high a	-0.168	-0.193	-0.025
$\mathrm{E}[\ln(r)]$	-0.199	-0.201	-0.001
$\mathrm{E}[\ln(r)]$, low a	-0.201	-0.203	-0.002
$\mathrm{E}[\ln(r)]$, high a	-0.196	-0.197	-0.001

$\mathrm{E}[\ln(wage)]$ is decomposed as in Equation (22). Learning ability a is split between the lower 60% and upper 40% of the a distribution. The benchmark model uses progressivity parameter $\tau_1 = 0.12$ and the "more progressive" model uses $\tau_1 = 0.24$. "Difference" is "more progressive" minus benchmark.

benchmark model ($\tau_1 = 0.12$) with the more progressive model ($\tau_1 = 0.24$).

In total, Table 4 shows that increasing tax progressivity decreases the mean wage by 4%. Figure 10 shows that the change in wages is constant over the life cycle, generating parallel lines and no difference in lifecycle growth for the mean log wage. Regarding inequality, increasing tax progressivity has no effect on the variance of log wages, but significantly decreases the variance of consumption. θ adjusts as expected in equilibrium; with lower levels of human capital and search effort in the labor pool, firms post fewer jobs, and labor market tightness decreases by 3%. There is no change in the unemployment rate or the job switching rate.

7.2 Mean Wage Level

If I increase progressivity, the wage level decreases mostly because workers make fewer job-to-job transitions and, therefore, are employed at less productive firms. In Table 5, I compare log wages using the mean log wage decomposition in Equation (22). According

Table 6: Decomposing effect of tax progressivity on variance of log wage

	Benchmark	More progressive	Difference
$\mathrm{Var}[\ln(wage)]$	0.312	0.312	0.000
$\mathrm{Var}[\ln(h)]$	0.134	0.128	-0.006
Variance from search channel	0.152	0.158	0.007
$\mathrm{Var}[\ln(p)]$	0.153	0.158	0.005
$\mathrm{Var}[\ln(r)]$	0.055	0.059	0.003
$2\,\mathrm{Cov}[\ln(p), \ln(r)]$	-0.056	-0.058	-0.002
Variance from interaction	0.026	0.026	0.000
$2\,\mathrm{Cov}[\ln(h), \ln(p)]$	0.019	0.020	0.001
$2\,\mathrm{Cov}[\ln(h), \ln(r)]$	0.006	0.006	-0.000

$\mathrm{Var}[\ln(wage)]$ decomposed as in Equation (23). The benchmark model uses progressivity parameter $\tau_1 = 0.12$ and the "more progressive" model uses $\tau_1 = 0.24$. "Difference" is "more progressive" minus benchmark.

to the overall differences of $\mathrm{E}[h]$, $\mathrm{E}[p]$, and $\mathrm{E}[r]$ (in the top line of each block), the decrease in log wages is mostly driven by a decrease in firm productivity, followed by human capital, and then the piece rate. In the fact, the decrease in $\mathrm{E}[\ln(p)]$ over is twice as large as the decrease in $\mathrm{E}[\ln(h)]$.

Earlier in the paper, I showed that job-to-job transitions are the primary driver of lifecycle wage growth for the average worker. Since job search is the most relevant margin for wage growth for most workers, the fact that job search is the driving force behind the policy response is unsurprising.

Also, the effect on the search channel is universal. In Table 5, the decrease in $\mathrm{E}[\ln(h)]$ is over three times larger for the group with high a than the group with low a. In contrast, the decrease in $\mathrm{E}[\ln(p)]$ is relatively similar across groups. Recall that workers with high learning ability rely heavily on accumulating human capital for lifecycle wage growth while all workers are roughly equally successful in climbing the job ladder. Thus, taxes affect all workers through the search channel, but only some workers through the human capital channel.

7.3 Wage Dispersion

An increase of tax progressivity has no effect on the variance of wages. In response to an increase in tax progressivity, the human capital channel pushes wage dispersion down while the search channel pushes wage dispersion up. Together, the effects offset each other. These effects are quantified in Table 6, where I decompose the effects of increased tax progressivity on the variance of log wages using Equation (23). For simplicity, I group the additive components of wage variance on the right hand side of Equation (23) into three parts: (1) the variance from the human capital channel, $\text{Var}[\ln(h)]$; the variance from the search channel, $\text{Var}[\ln(p)] + \text{Var}[\ln(r)] + 2\,\text{Cov}[\ln(p), \ln(r)]$; and the variance from interactions between human capital and search, $2\,\text{Cov}[\ln(h), \ln(p)] + 2\,\text{Cov}[\ln(h), \ln(r)]$.

Table 5 illustrates why the variance of human capital decreases. Human capital levels decrease for all workers, but the magnitude of the decrease is larger for workers with high learning ability. Therefore, the gap in human capital between workers with high a and low a decreases, decreasing the variance of human capital. Wage dispersion decreases primarily because high wages decrease; so, we can say that the human capital channel decreases wage dispersion from above.

Why do workers with high learning ability experience a larger decrease in human capital? There are two reasons. First, increasing tax progressivity has more "bite" at the top of the wage distribution, so high-wage workers are more disincentivized to grow their wages. Second, those at the higher end of the distribution are the same workers who invest more in human capital, so their relevant margin for adjustment is human capital.

However, the decrease in variance from the human capital channel is offset by an increase in wage dispersion from the search channel. Recall from Figure 6 that, because of on-the-job search, the variance of firm productivity decreases over the life cycle. The same logic is at work when I increase tax progressivity. When tax progressivity increases, workers exert less search effort, are less likely to meet outside firms, and do not climb the job ladder as quickly. The result is less bunching at high levels of p. Intuitively, with more tax progressivity, workers exert less search effort, so unproductive firms are more likely to

Table 7: Decomposing effect of tax progressivity on lifecycle wage growth

	Benchmark	More progressive	Difference
Lifecycle growth of E[ln($wage$)]	0.238	0.229	-0.008
Lifecycle growth of E[ln(h)]	0.078	0.069	-0.009
Lifecycle growth of E[ln(p)]	0.100	0.103	0.003
Lifecycle growth of E[ln(r)]	0.059	0.057	-0.002

Decomposes the log of lifecyle wage growth to the growth of its three additive components; see Equation (22). Lifecycle log growth is defined as the difference between the log value in the last stage of life and the first stage of life. The benchmark model uses progressivity parameter $\tau_1 = 0.12$ and the "more progressive" model uses $\tau_1 = 0.24$. "Difference" is "more progressive" minus benchmark.

retain workers. Another intuitive interpretation is that, with fewer job-to-job transitions, the luck of the draw of firms is more important. In any case, wage dispersion increases from below, and when both channels are combined, the gap between high and low wages is the same, but the level of wages has decreased.

7.4 Lifecycle Wage Growth

The slight decrease in lifecycle wage growth is driven by a decrease in human capital accumulation. Table 7 illustrates the result by taking Equation 22 one step further and decomposing log wage growth into the log growth of human capital, firm productivity, and the piece rate. When progressivity increases, lifecycle wage growth decreases by 3%[40], and the difference is entirely driven by a decrease in the lifecycle growth of human capital.[41] However, an increase in tax progressivity has little effect on lifecycle wage growth from the search channel. Likewise, in the next section, I show that the decrease in lifecycle wage growth is relatively small compared to a pure human capital model. Taken together, I conclude that the presence of the search channel mitigates the decrease in lifecycle wage growth.

[40] $0.008/0.238 \approx 3\%$.

[41] Taken together, the search channel, which includes p and r, sums to nearly zero.

7.5 The Role of Interaction Between Endogenous Channels

In this section, I show how the human capital, search, and job posting channels interact by progressively shutting down the channels' endogeneity. I focus on two main results, both of which deal with the mean log wage following an increase in tax progressivity. First, the human capital and search channels amplify one another such that the mean log wage decreases more when both channels are endogenous than when one channel is exogenous. Second, firms respond the policy change by posting fewer jobs in equilibrium, which further decreases wages. Altogether, this section shows that a model that does not simultaneously endogenize each channel will under-predict the negative effect of tax progressivity on the wage level.

I experiment with disallowing the following objects to adjust to the increase in tax progressivity: equilibrium labor market tightness θ^*, workers' policy functions for human capital accumulation l^*, and workers' policy functions for job search effort (for both employed and unemployed workers) s^*. I consider three out-of-equilibrium models between the benchmark equilibrium and the more progressive equilibrium. For each, I impose the policy change of $\tau_1 = 0.24$ and the equilibrium value of τ_0. The in the more progressive equilibrium, all of l^*, s^*, and θ^* are flexible and adjust to policy. In out-of-equilibrium models, a subset of the three objects are held fixed.

In the first out-of-equilibrium model, I fix s^* and θ^* to their values in the benchmark model, thereby only allowing l^*, human capital accumulation, to respond to the policy change. Thus, search effort, and therefore the probability of switching jobs, cannot respond to policy, and we can say that the search channel is exogenous.[42,43] In the second out-of-equilibrium model, I fix l^* and θ^*, generating a model where the path of human capital is fixed, and workers can only respond to policy changes by adjusting search effort. Finally, in the third out-of-equilibrium model, I only fix θ^* so that workers can adjust human capital and search effort in response to the change in tax policy, but firms cannot

[42]This roughly corresponds to a human capital model with exogenous shocks (Badel et al., 2020; Huggett et al., 2011).

[43]I also hold $z_{ai}(h, w)$ constant so that unemployment-to-employment transition rates are the same.

Table 8: Out-of-equilibrium decomposition from increase in tax progressivity

	Benchmark	Flexible l $-$benchmark	Flexible s $-$benchmark	Flexible (l, s) $-$benchmark	Flexible (l, s, θ) $-$benchmark
Labor market tightness, θ	1.000	0.000	0.000	0.000	-0.029
Mean log wage	0.008	-0.014	-0.027	-0.033	-0.037
$\mathrm{E}[\ln(h)]$	0.374	-0.013	-0.004	-0.010	-0.010
$\mathrm{E}[\ln(p)]$	-0.167	-0.001	-0.021	-0.021	-0.026
$\mathrm{E}[\ln(r)]$	-0.199	-0.000	-0.002	-0.001	-0.001
Variance of log wage	0.312	-0.006	0.005	0.000	0.000
Lifecycle growth of mean log wage	0.238	-0.013	-0.002	-0.008	-0.008
Mean human capital investment, l	0.104	-0.005	-0.002	-0.005	-0.005
Mean search effort, s, for employed workers	0.099	-0.001	-0.005	-0.005	-0.005

Analyzes out-of-equilibrium models between the equilibrium benchmark ($\tau_1 = 0.12$) and “more progressive" ($\tau_1 = 0.24$) models. Benchmark column is in levels; all other columns are in differences relative to the benchmark.

adjust the number of open vacancies.

I summarize the decomposition in Table 8. In the interest of readability, I do not report the levels of each variable for each model; I only report the difference between the value from the model in question and the value in the benchmark model.

Compared to a model where only l or s can respond to policy, the decrease in the wage level is larger when both channels respond simultaneously. If only human capital is endogenous, then wages decrease 1.4%; if only search effort is endogenous, then wages decrease 2.7%; and if both are endogenous, then wages decrease by 3.3%. Thus, the negative effect of tax progressivity on wages is greater when human capital and search interact with one another. However, the interaction is less than additive; if the effects were additive, then the result of endogenous human capital and search would be $-1.4\% - 2.7\% = -4.1\%$. So, if workers can only adjust along one channel, the workers will adjust that on that channel more dramatically. If workers can adjust along both channels, workers will make smaller adjustments along each channel, but taken together, the effect is greater.

When firms are allowed to adjust job posting, the negative effect on the wage level is further amplified. If workers have less human capital and exert less search effort, then the benefit of posting a job decreases, and firms post fewer jobs in equilibrium. Quantitatively, θ decreases by 3%. Because there are fewer job vacancies, the marginal benefit of search decreases, and workers exert less search effort. In addition, since h and p are complements in production and workers are less likely to transition to more productive firms, then the benefit of human capital decreases as well, and workers also accumulate less human capital. Taken together, because firms post fewer jobs, the wage level in the economy will be lower. Indeed, in Table 8, when firms adjust θ, the decrease in the wage goes from -3.3% to -3.7%.

Two additional results in Table 8 support earlier findings. First, the search channel is more responsive when l is exogenous than is the human capital channel when s is exogenous. This supports the notion that, on average, search effort is more responsive to policy

Table 9: Effect of increasing tax progressivity in re-calibrated restricted models

Model	Log wage difference	Lifecycle wage growth difference
Benchmark*	-0.031	-0.007
Pure human capital	-0.029	-0.025
Pure human capital + heterogeneity	-0.012	-0.012
Pure job ladder	-0.039	0.030
Pure job ladder + heterogeneity	-0.035	-0.002

The effect of increasing tax progressivity in restricted models. Restricted models are described in Section 6.2.2. "Heterogeneity" refers to heterogeneity in learning ability and initial human capital. Lifecycle wage growth is defined as the difference between the log wage in the first stage of life and the last stage of life.
*In only this table, the benchmark model is not in equilibrium with respect to θ after the tax policy changes.

changes. Second, depending on which channel is exogenous, increasing tax progressivity has opposite effects on the variance of wages. Thus, regarding wage dispersion, it is clear that the two channels offset one another.

7.6 Horse Race Results from Recalibrated Restricted Models

As a final experiment, I pit my model in a horse race against the restricted models described in Section 6.2.2. To do so, I recalibrate each restricted model to match the lifecycle profile of mean wages. The calibration results are in Figure 12 in Appendix E. I then feed each calibrated model the same change in tax policy parameters (τ_1, τ_0). I do not find a new equilibrium θ. I document the effect of the increase in tax-and-transfer progressivity for each model in Table 9 along two dimensions: the mean log wage level and lifecycle log wage growth. Each column displays the change in each object as a result of the policy change.

My findings can be summarized as follows: As a result of increasing tax progressivity, a pure human capital model (without the search channel) will *understate* the effect on the mean wage level and *overstate* the effect on lifecycle wage growth. The opposite is true for models without a human capital channel: as a result of increasing tax progressivity, a pure job ladder model (without the human capital channel) will *overstate* the effect on the mean wage level and *understate* the effect on lifecycle wage growth.

These results in Table 9 are consistent with the rest of this paper. Recall that the search channel is the driving force behind the decrease in the mean wage level and that the human capital channel is the driving force behind a decrease in lifecycle wage growth. So, a model without both channels will misstate the effects of tax progressivity in the same direction. More generally, these results suggest that the rich interactions in my model are necessary for accurately predicting the effects of policy.

8 Conclusion

This paper develops and studies a rich lifecycle model of wages. Existing literature mostly consists of models where either the human capital channel or the search channel is endogenous. I endogenize human capital accumulation, on-the-job search, and job posting. I argue that these elements interact in ways that are quantitatively important.

In the benchmark calibration, job search is the driving force of lifecycle wage growth for the average worker. However, human capital is the driving force of wage dispersion, particularly at the top of the wage distribution. Workers take different approaches to increasing their wages. In particular, workers who are young and have low learning ability invest more in search effort, while workers with high learning ability invest more in human capital accumulation.

I demonstrate the usefulness of the model by reinvestigating the effects of progressive taxes and transfers on wage levels and wage inequality. I find that increasing tax progressivity from its current level in the US to a level roughly in line with some European countries would decrease the mean wage by 4%, decrease lifecycle wage growth by 4%, and have no effect on wage dispersion. The lack of a response in the variance of wages is a unique feature arising from the combination of both channels. Finally, I show that models without both channels will misstate the effects of progressive taxes and transfers.

Appendix

A Equations

A.1 Aggregate Search Effort

Aggregate search effort is defined as

$$S = \sum_{a,i} \int_{\Psi_E} s_{Eai}(h,p,r) d\Psi_E(h,p,r|a,i) + \sum_{a,i,\iota} \int_{\Psi_U} s_{Uai}(h,w) d\Psi_U(h,w|a,i,\iota). \tag{24}$$

A.2 Equations Updated with Godfather Shocks

Godfather shocks arrive at rate ψ. When a worker experiences a godfather shock, he randomly meets a firm and is forced to accept an offer with that firm. When we include godfather shocks in the employed worker's Hamilton-Jacobi-Bellman equation (Equation (8)), the worker's problem adds a new line like so:

$$\begin{aligned}
\rho W_{ai}(h,p,r) &= \max_{l,s} u(c) - d_E(l+s) + (a(lh)^{\omega} - \delta h) \frac{\partial W_{ai}(h,p,r)}{\partial h} \\
&+ \Lambda(rhp) \left[U_{ai}(h, hpr, \iota) - W_{ai}(h,p,r) \right] + \zeta \left[W_{ai}(h,p,r) - W_{ai}(h,p,r) \right] \\
&+ sm(\theta) \Bigg(\int_{q_{ai}(h,p,r)}^{p} \left[W_{ai}\left(h, p, R^R_{ai}(h,p,p')\right) - W_{ai}(h,p,r) \right] dF(p') \\
&\quad + \int_{p}^{\overline{p}} \left[W_{ai}\left(h, p', R^P_{ai}(h,p,p')\right) - W_{ai}(h,p,r) \right] dF(p') \Bigg) \\
&+ \psi \int_{\underline{p}}^{\overline{p}} \left[W_{ai}\left(h, p', R^G_{ai}(h, hpr, p')\right) - W_{ai}(h,p,r) \right] dF(p')
\end{aligned} \tag{25}$$

subject to

$$c = [1 - T(hpr)]hpr.$$

where $R^G_{ai}(h, hpr, p')$ is the endogenous piece rate arising from a godfather shock.

Firms have an additional risk of losing their worker to a godfather shock, which adds

ψ to the bottom line of Equation (15) like so:

$$\begin{aligned}\rho J_{ai}(h,p,r) = hp(1-r)(1-\tau_b) + (a(l_{ai}(h,p,r)h)^{\omega} - \delta h)\,\frac{\partial J_{ai}(h,p,r)}{\partial h}\\ +\zeta\left[J_{a,i+1}(h,p,r) - J_{ai}(h,p,r)\right]\\ +s_{Eai}(h,p,r)m(\theta)\int_{q_{ai}(h,p,r)}^{p}\left[J_{ai}\left(h,p,R^{R}_{ai}(h,p,p')\right) - J_{ai}(h,p,r)\right]dF(p')\\ +\left[s_{Eai}(h,p,r)m(\theta)\left(F(\overline{p})-F(p)\right)+\Lambda(hpr)+\psi\right](-J_{ai}(h,p,r))\end{aligned} \tag{26}$$

Firms also have an additional channel for filling job vacancies; an employed worker might experience a godfather shock and land with the firm. Thus, the free entry condition gets a new term,

$$\begin{aligned}\kappa = m_f(\theta)\Bigg[\sum_{a,i}\int_{\Psi_E} s_{Eai}(h,p,r)\int_{p}^{\overline{p}} J_{ai}\left(h,p',R^{P}_{ai}(h,p,p')\right)dF(p')d\Psi_E(h,p,r|a,i)\\ +\sum_{a,i}\int_{\Psi_U} s_{Uai}(h,w)\int_{z_{ai}(h,w)}^{\overline{p}} J_{ai}\left(h,p',R^{U}_{ai}(h,w,p')\right)dF(p')d\Psi_U(h,w|a,i)\Bigg]\\ +\psi\sum_{a,i}\int_{\Psi_E}\int_{\underline{p}}^{\overline{p}} J_{ai}\left(h,p',R^{G}_{ai}(h,hpr,p')\right)dF(p')d\Psi_E(h,p,r|a,i).\end{aligned} \tag{27}$$

Finally, I assume that when bargaining over wages, the outside option for workers who have been subject to a godfather shock is unemployment without unemployment benefits. It is impossible that the worker goes to this state, but the worker's outside option is necessary for determining r after godfather shocks. So, $R^{G}_{ai}(h,hpr,p')$ solves

$$W_{ai}\left(h,p',R^{G}_{ai}(h,hpr,p')\right) = U_{ai}(h,hpr,0) + \eta\left[W_{ai}(h,p',1) - U_{ai}(h,hpr,0)\right]. \tag{28}$$

B Simple Two-Period Model

I write this version of the model in discrete time. Agents live for two periods, $i = \{0,1\}$, and discount the second period at discount factor β. In the first period, agents work, consume, and make investments in human capital accumulation and job search effort; in the second, agents only work and consume.

Assume that workers earn the piece rate $r = 1$ and that there is no human capital depreciation, $\delta = 0$. Otherwise, the human capital accumulation equation is as in the full model. If workers exert search effort s, then, with probability $sm(\theta)$, they move from their current p to $p + \Delta_p$.

In the first period, an employed worker with learning ability a, human capital h, and firm productivity p solves

$$E_{a0}(h, p) = \max_{l,s} u(c) - d_E(l + s) + \beta E_{a1}(h', p') \tag{29}$$

subject to

$$c = [1 - T(hp)]hp$$
$$h' = h + a(lh)^{\omega}$$
$$p' = p + sm(\theta)\Delta_p.$$

In the second period, the worker simply enjoys the fruits of his labor,

$$E_{a1}(h, p) = u(c)$$

where

$$c = [1 - T(hp)]hp.$$

When we solve for the first order conditions for Equation (29), we get Equation (20).

C Equilibrium Definition

The recursive stationary equilibrium consists of a set of value functions $\{W_{ai}(h, p, r),$ $U_{ai}(h, w, \iota)$, $\overline{W}$, $J_{ai}(h, p, r)\}$, a human capital investment policy function $l_{Eai}(h, p, r)$, a set of search effort policy functions $\{s_{Eai}(h,p,r), s_{Uai}(h,w,\iota)\}$, a set of job search cutoff rules $\{q_{ai}(h,p,r), z_{ai}(h,w,\iota)\}$, a set of wage functions $\{R^P_{ai}(h,p,p'), R^R_{ai}(h,p,p'), R^U_{ai}(h,w,\iota,p'), R^G_{ai}(h,hpr,p')\}$, vacancies v, aggregate search effort S, labor market tightness $\theta = v/S$, a distribution of workers $\Psi = \{\Psi_E(h,p,r|a,i), \Psi_U(h,w|a,i,\iota), \Psi_R(a)\}$, and a set of government policy parameters $\mathcal{G} = \{\tau_0, \tau_1, \tau_b, b, \chi, SS, \overline{g}\}$ which satisfy:

1. Employed worker optimization: Given $R^P_{ai}(h,p,p')$, $R^R_{ai}(h,p,p')$, $R^G_{ai}(h,hpr,p')$, $q_{ai}(h,p,r)$, θ, and $\mathcal{G}$, $W_{ai}(h,p,r)$ solves (25) subject to (9) and (13) with associated decision rules $l_{Eai}(h,p,r)$ and $s_{Eai}(h,p,r)$.

2. Unemployed worker optimization: Given $R^U_{ai}(h,w,p')$, $z_{ai}(h,w,\iota)$, θ, and $\mathcal{G}$, $U_{ai}(h,w,\iota)$ solves (10) subject to (11) and (14) with associated decision rule $s_{Uai}(h,w)$.

3. Retired workers: $\overline{W}$ solves (12).

4. Filled jobs: Given $R^R_{ai}(h,p,p')$, $l_{ai}(h,p,r)$, $s_{Eai}(h,p,r)$, θ, and $\mathcal{G}$, $J_{ai}(h,p,r)$ solves (26) and (16).

5. Wage equations: Given $W_{ai}(h,p,r)$ and $U_{ai}(h,w,\iota)$,

   (a) $R^P_{ai}(h,p,p')$ solves (3),

   (b) $R^R_{ai}(h,p,p')$ solves (4),

   (c) $R^U_{ai}(h,w,\iota,p')$ solves (6), and

   (d) $R^G_{ai}(h,hpr,p')$ solves (28).

6. Job search cutoff rules: Given $W_{ai}(h,p,r)$ and $U_{ai}(h,w,\iota)$,

   (a) $q_{ai}(h,p,r)$ solves (5) and

   (b) $z_{ai}(h,w,\iota)$ solves (7).

7. Free entry: Given $J_{ai}(h,p,r)$, $R^P_{ai}(h,p,p')$, $R^U_{ai}(h,w,\iota,p')$, $R^G_{ai}(h,hpr,p')$, $s_{Eai}(h,p,r)$, $s_{Uai}(h,w,\iota)$, S, Ψ, and $\mathcal{G}$, θ solves (27).

8. Government budget constraint: $\mathcal{G}$ satisfies (19).

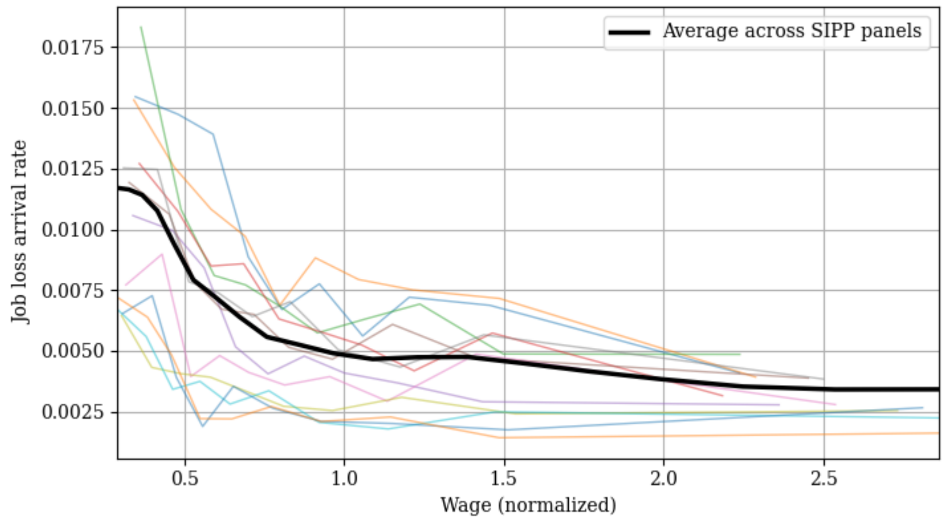

Figure 11: Estimate of exogenous job destruction function, $\Lambda(wage)$

Estimates of the employment-to-unemployment rate in the SIPP by hourly wage. Each colored line represents a different SIPP panel. For each panel, I estimate the employment-to-unemployment rate for 10 hourly wage deciles, then interpolate between points. The thick black line is the resulting weighted average job loss function by wage, $\Lambda(wage)$. I flatly extrapolate the edges of Λ. Wage is normalized such that the mean hourly wage equals one. The monthly employment-to-unemployment rate is converted to a continuous time arrival rate as in Mukoyama (2014).

9. Aggregate search effort: Given $s_{Eai}(h,p,r)$, $s_{Eai}(h,w)$, and Ψ, S satisfies (24).

10. Consistency: Ψ, as defined in (17), is the stationary distribution.

D Calibration Details

D.1 Λ Function

I estimate the exogenous job destruction function, $\Lambda(hpr)$, directly from SIPP data. See Figure 11 for an illustration. As with the tax function, the mean wage is normalized to one.

D.2 Learning Ability Distribution

I discretize the learning ability distribution as follows. The grid of a points is $\{a_1, ..., a_J\}$ where $a_j = \mathrm{E}[a|a_{P_j} \leq a < a_{P_{i+1}}]$ and a_{P_j} is the P_j-th percentile of the ability distribution. I take the expectation using $PLN(\mu_a, \sigma_a, 1/\lambda_a)$. To calculate the PLN distribution, I use analytical expressions in Hajargasht and Griffiths (2013). Percentiles are chosen to be $(0.0, 0.3, 0.6, 0.9, 0.99, 1.0)$.

E Restricted Model Details

Figure 12 illustrates the calibrated lifecycle profiles of the mean log wage in each restricted model.

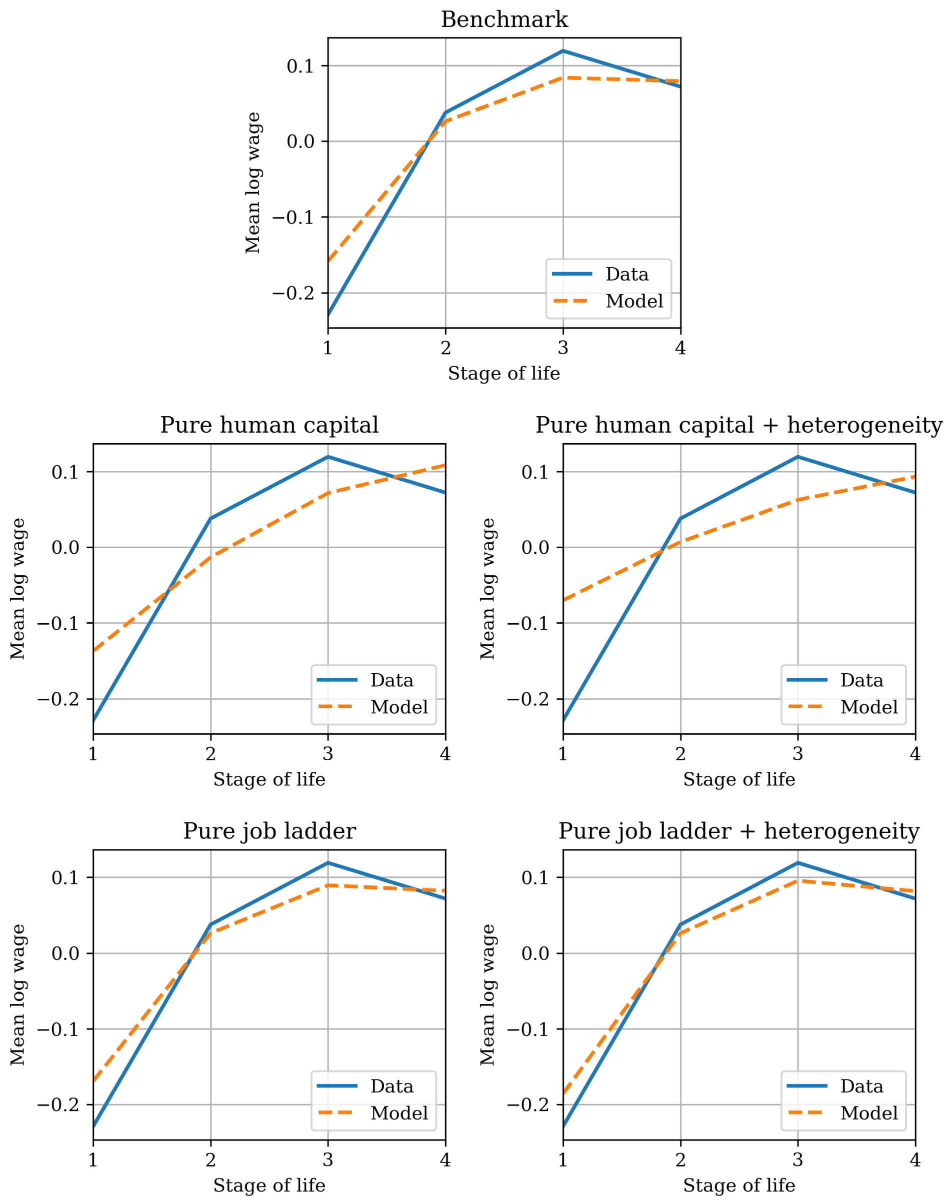

Figure 12: Mean lifecycle wage calibrations for restricted models

Calibrated lifecycle profile for mean log wage in the benchmark model and each restricted model. The restricted models are described in Section 6.2.2. The benchmark calibration in this figure is identical to Figure 2.

References

Abowd, J. M., F. Kramarz, and D. N. Margolis (1999). High Wage Workers and High Wage Firms. *Econometrica 67*(2), 251–333.

Acabbi, E. M., A. Alati, and L. Mazzone (2023). A Labor Market Sorting Model of Hysteresis and Scarring.

Badel, A., M. Huggett, and W. Luo (2020). Taxing Top Earners: a Human Capital Perspective. *The Economic Journal 130*(629), 1200–1225.

Bagger, J., F. Fontaine, F. Postel-Vinay, and J.-M. Robin (2014). Tenure, Experience, Human Capital, and Wages: A Tractable Equilibrium Search Model of Wage Dynamics. *The American Economic Review 104*(6), 1551–1596.

Bagger, J., R. Holloway, M. Hejlesen, K. Sumiya, and R. Vejlin (2019). Income Taxation and the Equilibrium Allocation of Labor.

Bagger, J. and R. Lentz (2019). An Empirical Model of Wage Dispersion with Sorting. *The Review of Economic Studies 86*(1), 153–190.

Bagger, J., E. R. Moen, and R. Vejlin (2021). Equilibrium Worker-Firm Allocations and the Deadweight Losses of Taxation.

Bayer, C. and M. Kuhn (2019). Which Ladder to Climb? Decomposing Life Cycle Wage Dynamics.

Ben-Porath, Y. (1967). The Production of Human Capital and the Life Cycle of Earnings. *Journal of Political Economy 75*(4, Part 1), 352–365.

Blandin, A. (2018). Learning by Doing and Ben-Porath: Life-cycle Predictions and Policy Implications. *Journal of Economic Dynamics and Control 90*(C), 220–235.

Boskin, M. J. (1975). Notes on the Tax Treatment of Human Capital. In *Conference on Tax Research 1975*, Washington, D.C.

Bowlus, A. J. and H. Liu (2013). The contributions of search and human capital to earnings growth over the life cycle. *European Economic Review 64*, 305–331.

Browning, M., L. P. Hansen, and J. J. Heckman (1999). Micro data and general equilibrium models. In *Handbook of Macroeconomics*, Volume 1, pp. 543–633.

Burdett, K. and D. T. Mortensen (1998). Wage Differentials, Employer Size, and Unemployment. *International Economic Review 39*(2), 257–273.

Bénabou, R. (2002). Tax and Education Policy in a Heterogeneous-Agent Economy: What Levels of Redistribution Maximize Growth and Efficiency? *Econometrica 70*(2), 481–517.

Cahuc, P., F. Postel-Vinay, and J.-M. Robin (2006). Wage Bargaining with On-the-Job Search: Theory and Evidence. *Econometrica 74*(2), 323–364.

Card, D., A. R. Cardoso, J. Heining, and P. Kline (2018). Firms and Labor Market Inequality: Evidence and Some Theory. *Journal of Labor Economics 36*(S1), S13–S70.

Carrillo-Tudela, C. (2012). Job Search, Human Capital and Wage Inequality.

Cooper, M., J. McClelland, J. Pearce, R. Prisinzano, J. Sullivan, D. Yagan, O. Zidar, and E. Zwick (2016). Business in the United States: Who Owns It, and How Much Tax Do They Pay? *Tax Policy and the Economy 30*(1), 91–128.

Cubas, G. and P. Silos (2020). Social Insurance and Occupational Mobility. *International Economic Review 61*(1), 219–240.

Dorn, A. (2018). How Dangerous is Godfather? Job-to-Job Transitions and Wage Cuts.

Dustmann, C. and C. Meghir (2005). Wages, Experience and Seniority. *The Review of Economic Studies 72*(1), 77–108.

Engbom, N. (2022). Labor Market Fluidity and Human Capital Accumulation.

Esfahani, M. (2020). Inequality Over the Life-cycle: U.S. vs Europe.

Faberman, R. J., A. I. Mueller, A. Şahin, and G. Topa (2022). Job Search Behavior Among the Employed and Non-Employed. *Econometrica 90*(4), 1743–1779.

Fleck, J., J. Heathcote, K. Storesletten, and G. L. Violante (2021). Tax and Transfer Progressivity at the US State Level.

Gentry, W. M. and R. G. Hubbard (2004). The effects of progressive income taxation on job turnover. *Journal of Public Economics 88*(11), 2301–2322.

Gregory, V. (2021). Firms as Learning Environments: Implications for Earnings Dynamics and Job Search.

Guner, N., R. Kaygusuz, and G. Ventura (2014). Income Taxation of U.S. Households: Facts and Parametric Estimates. *Review of Economic Dynamics 17*(4), 559–581.

Guner, N., R. Kaygusuz, and G. Ventura (2022). The Looming Fiscal Reckoning: Tax Distortions, Top Earners, and Revenues.

Guner, N., C. Rauh, and G. Ventura (2023). Means-Tested Transfers in the US: Facts and Parametric Estimates.

Guvenen, F., F. Karahan, S. Ozkan, and J. Song (2021). What Do Data on Millions of U.S. Workers Reveal About Lifecycle Earnings Dynamics? *Econometrica 89*(5), 2303–2339.

Guvenen, F., B. Kuruscu, and S. Ozkan (2014). Taxation of Human Capital and Wage Inequality: A Cross-Country Analysis. *The Review of Economic Studies 81*(2 (287)), 818–850.

Hajargasht, G. and W. E. Griffiths (2013). Pareto–lognormal distributions: Inequality, poverty, and estimation from grouped income data. *Economic Modelling 33*, 593–604.

Heathcote, J., K. Storesletten, and G. L. Violante (2017). Optimal Tax Progressivity: An Analytical Framework. *The Quarterly Journal of Economics 132*(4), 1693–1754.

Heathcote, J., K. Storesletten, and G. L. Violante (2020). How Should Tax Progressivity Respond to Rising Income Inequality? *Journal of the European Economic Association 18*(6), 2715–2754.

Holter, H. A., D. Krueger, and S. Stepanchuk (2019). How do tax progressivity and household heterogeneity affect Laffer curves? *Quantitative Economics 10*(4), 1317–1356.

Hubmer, J. (2018). The job ladder and its implications for earnings risk. *Review of Economic Dynamics 29*, 172–194.

Huggett, M., G. Ventura, and A. Yaron (2011). Sources of Lifetime Inequality. *American Economic Review 101*(7), 2923–2954.

Jarosch, G. (2023). Searching for Job Security and the Consequences of Job Loss. *Econometrica 91*(3), 903–942.

Kapička, M. (2006). Optimal income taxation with human capital accumulation and limited record keeping. *Review of Economic Dynamics 9*(4), 612–639.

Kapička, M. (2015). Optimal Mirrleesean Taxation in a Ben-Porath Economy. *American Economic Journal: Macroeconomics 7*(2), 219–248.

Kreiner, C. T., J. R. Munch, and H. J. Whitta-Jacobsen (2015). Taxation and the long run allocation of labor: Theory and Danish evidence. *Journal of Public Economics 127*, 74–86.

Krueger, D. and A. Ludwig (2016). On the optimal provision of social insurance: Progressive taxation versus education subsidies in general equilibrium. *Journal of Monetary Economics 77*(C), 72–98.

Lise, J., C. Meghir, and J.-M. Robin (2016). Matching, sorting and wages. *Review of Economic Dynamics 19*, 63–87.

Menzio, G., I. A. Telyukova, and L. Visschers (2016). Directed search over the life cycle. *Review of Economic Dynamics 19*, 38–62.

Mortensen, D. T. (2003). *Wage Dispersion: Why Are Similar Workers Paid Differently?* Cambridge: The MIT Press.

Mortensen, D. T. and C. A. Pissarides (1994). Job Creation and Job Destruction in the Theory of Unemployment. *The Review of Economic Studies 61*(3), 397–415.

Moscarini, G. and F. Postel-Vinay (2018). The Cyclical Job Ladder. *Annual Review of Economics 10*(1), 165–188.

Mukoyama, T. (2014). The cyclicality of job-to-job transitions and its implications for aggregate productivity. *Journal of Economic Dynamics and Control 39*, 1–17.

Mukoyama, T., C. Patterson, and A. Şahin (2018). Job Search Behavior over the Business Cycle. *American Economic Journal: Macroeconomics 10*(1), 190–215.

Omer, V. (2004). Wage Growth, Search and Experience: Theory and Evidence.

Ozkan, S., J. Song, and F. Karahan (2023). Anatomy of Lifetime Earnings Inequality: Heterogeneity in Job-Ladder Risk versus Human Capital. *Journal of Political Economy Macroeconomics 1*(3), 506–550.

Pavan, R. (2011). Career Choice and Wage Growth. *Journal of Labor Economics 29*(3), 549–587.

Petrongolo, B. and C. A. Pissarides (2001). Looking into the Black Box: A Survey of the Matching Function. *Journal of Economic Literature 39*(2), 390–431.

Pissarides, C. A. (2000). *Equilibrium Unemployment Theory* (Second ed.). Cambridge: The MIT Press.

Rauh, C. and M. R. Santos (2022). How Do Transfers and Universal Basic Income Impact the Labor Market and Inequality?

Rubinstein, A. (1982). Perfect Equilibrium in a Bargaining Model. *Econometrica 50*(1), 97–109.

Schlüter, M., J. A. Egea, and J. R. Banga (2009). Extended ant colony optimization for non-convex mixed integer nonlinear programming. *Computers & Operations Research 36*(7), 2217–2229.

Schönberg, U. (2007). Wage Growth Due to Human Capital Accumulation and Job Search: A Comparison Between the United States and Germany. *ILR Review 60*(4), 562–586.

Sleet, C. and H. Yazıcı (2017). Taxation, Redistribution and Frictional Labor Supply.

Taber, C. and R. Vejlin (2020). Estimation of a Roy/Search/Compensating Differential Model of the Labor Market. *Econometrica 88*(3), 1031–1069.

Tjaden, V. and F. Wellschmied (2014). Quantifying the Contribution of Search to Wage Inequality. *American Economic Journal: Macroeconomics 6*(1), 134–161.

Veramendi, G. (2012). Labor Market Dynamics: A Model of Search and Human Capital Accumulation.