What can explain the hump-shaped job search intensities over the life-cycle?

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Abstract

This paper explores the puzzling hump-shaped job-search profile in U.S. data, which the standard life-cycle incomplete-markets model fails to explain. Using the ATUS, NJS, and SCE, I document the profile and show that search effort declines with measured uncertainty and wealth. I develop a life-cycle incomplete-markets model combining dispersed worker–occupation matches, Bayesian learning, an age-dependent value of non-employment, wealth accumulation, and Epstein–Zin preferences. The calibrated model jointly matches search, offer arrival, acceptance, reservation wages, and wealth. The high value of non-employment accounts for much of young workers' low search, while wealth accumulation and the shrinking career horizon reduce search later in life. Learning mainly governs offer selectivity: fully revealing match quality preserves the hump, whereas eliminating match dispersion substantially flattens it.

JEL Classification: D52, D83, D91, E21, J64
Keywords: Job search intensity, Occupational match uncertainty, Bayesian learning, Incomplete markets

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1 Introduction

This paper asks what explains the puzzling hump-shaped profile of job-search intensity over the life cycle in the United States. Using the American Time Use Survey (ATUS), Aguiar et al. (2013) show that unemployed workers aged 46–50 spend roughly three times as much time searching as those aged 21–25, and that even workers aged 61–65 search more than the youngest group. The same qualitative pattern appears in the more recent ATUS and in the New Jersey Survey (NJS). This pattern is difficult to reconcile with the standard life-cycle incomplete-markets model. In that model, workers accumulate precautionary wealth as they age, improving their outside option and generating a declining search profile through the wealth effect. The empirical hump therefore requires forces that raise the net value of finding a job early in the life cycle and forces that lower it later.

I argue that the profile reflects the interaction of four forces: dispersion in worker–occupation matches, an age-dependent value of non-employment, wealth accumulation in an incomplete market, and the shrinking career horizon. Workers initially have imperfect information about a new occupational match and learn from realized earnings, but the analysis distinguishes this information problem from the underlying dispersion of match quality. This distinction is quantitatively important. Holding realized match dispersion fixed, fully revealing the match at entry does not eliminate the hump; it raises the peak-to-first search ratio from 1.70 to 1.84. By contrast, eliminating match heterogeneity lowers the ratio to 1.258 and makes offer acceptance nearly universal. Occupational learning therefore matters primarily for offer selectivity and reservation wages, whereas the search profile is generated jointly by the age profile of the outside option, realized match dispersion, wealth accumulation, and the remaining career horizon.

The mechanism is intuitive. Young workers have little wealth, face dispersed employment opportunities, and place a relatively high value on non-employment because schooling, home production, parental co-residence, and family insurance are more important early in life. The high outside option depresses their search effort despite their limited wealth. As both the value of non-employment and the dispersion of newly drawn matches decline, the net benefit of employment rises and search increases. Later in life, accumulated wealth improves the value of remaining unemployed, while a shorter career reduces the return to finding a job; search consequently declines. Imperfect information affects this process by changing how workers value and screen offers. A favorable earnings signal raises the perceived match and the value of employment, whereas unresolved downside risk makes workers more selective. Learning is thus consequential for acceptance behavior even though it is not necessary for the hump itself.

I first establish the wealth and uncertainty channels in a two-period search model. Search effort is increasing in the expected net value of receiving an acceptable offer. Greater wealth raises the value of unemployment relative to employment and therefore reduces search. A mean-preserving spread in offers also reduces search when the spread occurs within the acceptance region, where the employment surplus is concave. The qualification is important: dispersion that moves probability across the reservation threshold also creates an option-value effect and need not reduce search. The full quantitative model contains both margins and uses acceptance and reservation-wage moments to discipline their relative importance.

I then examine these channels using three complementary data sets. The ATUS provides a nationally representative life-cycle profile of search time. The NJS follows unemployment-insurance claimants weekly and contains search time, offer arrival, offered wages, acceptance, reservation wages, assets, household income, and family circumstances. In the NJS, wealth and other measures of the outside option are negatively associated with search effort. A realized squared gap between offered and reservation wages, used as a descriptive proxy for uncertainty rather than a causal measure of ex ante risk, is also negatively associated with search. Finally, the Survey of Consumer Expectations (SCE) Job Search Supplement provides an external check because it is nationally representative, was fielded in normal times, and differs sharply from the NJS in sampling and survey design. The implied weekly offer measures for non-employed workers are nevertheless similar, at 0.057 in the NJS and 0.068 in the SCE. The SCE also supplies a reservation-wage-to-previous-wage ratio that disciplines the model's acceptance rule.

The quantitative framework is a life-cycle McCall model with endogenous search intensity, incomplete asset markets, and recursive preferences. Earnings contain a dispersed worker–occupation match with an intercept and a growth component, as in Chang, Hong and Karabarbounis (2018), together with the persistent and transitory worker-level shocks of Guvenen and Smith (2014). When a worker enters a new occupation, she observes earnings but not the components of match quality and updates her beliefs through a Kalman filter. Epstein–Zin preferences separate risk aversion, which prices the occupational-match gamble, from the elasticity of intertemporal substitution, which governs consumption smoothing and wealth accumulation. This separation is important: under additively separable CRRA preferences, the saving motive becomes strong enough to increase wealth accumulation and reverse the model's cross-sectional relationship between beliefs and search.

The model is disciplined jointly by moments that capture different margins of behavior. The curvature of the search profile disciplines the search-cost curvature parameter, while the magnitude of the young-to-midlife decline in the value of non-employment is selected from the corresponding portion of the profile; external evidence disciplines its sign and qualitative pattern rather than its numerical value. By contrast, the age gradient in new-match dispersion is selected using the acceptance rate and the reservation-wage ratio. Offer arrival and separation discipline the transition block, and the wealth-to-income ratio informs the intertemporal elasticity. This assignment of moments matters because several specifications generate similar search profiles but sharply different acceptance and reservation-wage behavior.

The calibrated model reproduces the smooth hump in the ATUS and lies within the sampling bands of both the ATUS and the NJS profiles. It generates a peak-to-first ratio of about 1.70, compared with 1.80 in the ATUS and 1.84 in the NJS. It also produces an acceptance rate of 0.69 against 0.79 in the NJS and a reservation-wage ratio of 0.89 against 0.96 in the SCE. The decomposition shows that the age gradient in the value of non-employment accounts for much of the low search effort of the young. Removing it lowers the peak-to-first ratio to about 1.23. Removing the age gradient in match dispersion has a smaller effect on the profile but raises acceptance substantially and lowers reservation wages, confirming that this component is identified mainly by offer selectivity. Wealth accumulation and the shortening horizon generate the declining portion of the profile.

The model also yields cross-sectional implications that complement the life-cycle results. Among young workers, search is more closely related to the perceived occupational match than to its true value because information is incomplete. These relationships converge with age as workers learn. Conditional on beliefs, wealth reduces search for both young and prime-age workers, even though the unconditional relationship can be positive when favorable signals jointly raise beliefs and accumulated wealth. The distinction between beliefs, realized match quality, and wealth therefore clarifies both when search is greatest over the life cycle and who searches more within an age group.

This paper makes three contributions. First, it provides a quantitatively disciplined explanation of the hump-shaped job-search profile that is evaluated not only against search time but also against offer arrival, acceptance, reservation wages, and wealth. These additional moments distinguish mechanisms that fit the profile similarly. Second, it separates uncertainty about a match from the underlying dispersion of realized match quality. The results narrow the role of learning: it is not necessary for the hump, and its primary quantitative role is screening offers. Third, the paper connects life-cycle search to market incompleteness while separating the pricing of match risk from the consumption-smoothing motive. This separation permits the model to account jointly for life-cycle and cross-sectional search behavior without forcing a single preference parameter to govern both risk and saving.

Related literature. This paper is most closely related to work on life-cycle job search. Aguiar et al. (2013) document the U.S. hump and show that the wealth effect in a standard incomplete-markets model pushes search downward with age. He et al. (2017) emphasize the interaction between age-dependent labor efficiency and reservation-wage strategies. I instead study how dispersed occupational matches, incomplete information, the value of non-employment, and wealth jointly affect the intensive search margin. Lise (2013) analyzes precautionary saving and search dynamics with on-the-job search in an infinite-horizon model, and Lentz and Tranæs (2005) studies the wealth effect on job-search behavior. Relative to these papers, the present analysis uses acceptance and reservation-wage evidence to distinguish information about a match from match dispersion itself.

The paper is also related to models of learning and labor-market transitions. Treating a new occupation as an experience good builds on Jovanovic (1979). Menzio et al. (2016) show that learning about worker–firm match quality is important for life-cycle transitions in an on-the-job search framework. The occupational-learning block here follows Chang, Hong and Karabarbounis (2018), who introduce an unobserved occupation-specific intercept and growth component that are redrawn at occupational changes and learned from earnings. I bring this structure to unemployed workers' search intensity and offer-acceptance decisions. The model also relates to the heterogeneous income profile literature: Guvenen (2007,0) study life-cycle income risk and imperfect information, while Guvenen and Smith (2014) estimate a life-cycle earnings process using earnings and consumption data. Recursive preferences follow Epstein and Zin (1989) and Weil (1990) and allow the risk and saving channels to be disciplined separately.

Finally, the empirical analysis contributes to evidence on job-search effort and outcomes. The NJS has been used to study unemployment duration, benefits, search time, reservation wages, and non-wage job values (Krueger and Mueller, 2010,0,0; Hall and Mueller, 2018). The SCE Job Search Supplement of Faberman, Mueller, Şahin and Topa (2022) provides nationally representative evidence on search effort and outcomes for employed and non-employed workers. I use the SCE to cross-validate the NJS offer measure and to discipline the reservation-wage and acceptance margins. Evidence on the age profile of the value of non-employment draws on Michelacci and Ruffo (2015), Aguiar et al. (2013a), and Kaplan (2012a), who emphasize age-dependent unemployment insurance, home production and education, and parental co-residence, respectively.

The remainder of the paper is organized as follows. Section 2 presents the empirical evidence. Section 3 isolates the wealth and uncertainty effects in a two-period model. Section 4 introduces the life-cycle model, and Section 5 describes the calibration. Section 6 reports the quantitative results and decomposition, and Section 7 concludes.

2 Empirical analysis

In this section, I examine the hump-shaped job-search profile using the American Time Use Survey (ATUS) and the New Jersey Survey (NJS). Aguiar et al. (2013) and He et al. (2017) study the profile in detail using the ATUS.[1] The NJS provides additional evidence on the uncertainty and wealth effects. The two data sets have complementary advantages. I also use a third source, the Survey of Consumer Expectations (SCE) Job Search Supplement of Faberman, Mueller, Şahin and Topa (2022), a nationally representative panel fielded by the Federal Reserve Bank of New York between 2013 and 2017. The SCE is too small in the non-employed dimension to estimate a nine-bin life-cycle profile, but it supplies level moments that the other two sources cannot. Because it differs from the NJS in every design dimension, it provides a demanding external-validity check on the NJS, which Section 2.3 reports.

First, I re-examine the hump-shaped job search profile using the recent version of the ATUS and the NJS. In Aguiar et al. (2013), they use the ATUS from 2003 to 2011. I call the ATUS from 2003 to 2011 as ATUS 0311. To confirm the hump-shaped job search profile in the recent ATUS, I use Multi-Year ATUS from 2003 to 2016, and I will call it ATUS 0316.

Job-search profiles are hump-shaped over the life cycle in both ATUS 0316 and the NJS, although their curvature is more moderate. The ratio of the maximum to the minimum search measure is almost 3 in ATUS 0311, as shown by Aguiar et al. (2013), compared with 1.7957 in ATUS 0316 and 1.8429 in the NJS. I use both ATUS 0316 and the NJS in the calibration because they produce similar profiles, while the NJS also provides offer-arrival and acceptance rates.

I next provide evidence on the uncertainty and wealth effects. The NJS covers job seekers who receive unemployment insurance benefits in New Jersey. Its sample of approximately 37,000 observations includes search behavior and outcomes, specifically job offers, offered wages, offer acceptance, and reservation wages. This information permits an empirical analysis of both channels.

In order to measure uncertainty, I set a proxy variable $d_2 = (\log(y) - \log(r))^2$, where y is an offered wage and r is a reservation wage in the NJS. I assume that r, the reservation wages reflect job seekers' beliefs and y, the offered wage reflect job seekers' true labor productivity.[2] Assumptions imply that unemployed job seekers would not know an exact market value of productivity. As theory predicts, the measured uncertainty decreases search intensities in regression analysis.

[1] ATUS data can be found at `https://www.bls.gov/tus/data.htm`.

[2] d_2 can be interpreted as an proxy of $\mathbb{E}[(y_t - \hat{y}_{t|t-1})^2]$.

For the wealth effect, I show that unemployed workers search jobs less intensively as they have better outside options using the NJS. Not only wealth, I also identify the role of family insurance. For example, Aguiar et al. (2013) shows that single workers devote more time than married in ATUS. Because NJS includes whether spouses have a paid job or not, top-coded and categorical savings and household income, whether they have mortgage debts or not, and the number of households, I can identify the role of each outside options. Results show that job seekers find jobs more intensively if spouses do not have jobs (lower spouses' income), they have lower savings and household income. The number of family members increases search intensities but mostly statistically insignificant.

Lastly, in Section A.4 and Section A.5, I study aggregate time effects on the job-search profile and on-the-job search in the ATUS. Since the ATUS covers the period from 2003 to 2016, I compare the profile in normal periods (2004 $\sim$ 2006) and crisis periods (2007 $\sim$ 2009). The hump-shaped profile holds in both periods. I also examine the time employed workers spend searching for jobs. The level of on-the-job search in the ATUS is quite low[3] and follows a U-shaped profile, consistent with the findings of Topel and Ward (1992).

2.1 Re-examination of hump-shaped job search profile

• **ATUS 0311** Aguiar et al. (2013) and Aguiar et al. (2013a) provide following categories of job search intensities in the ATUS 0311. A- "sending out resumes, going on job interviews, researching details about a job, asking about job openings or looking for jobs in the paper or on the Internet". ATUS codes are ATUS code 05-04 and ATUS code 18-05-04. For the more recent ATUS, the paper just follows their classification of job search intensities.

Figure 1 is the result of age-dummy regression (1).

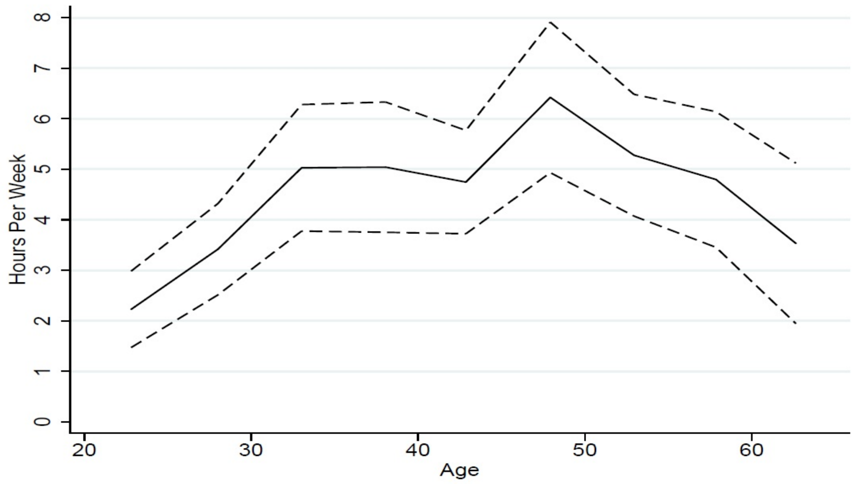
$$Y_{ia}^{j} = \sum_{a=1}^{9} \beta_a^j D_{ia}^j + \varepsilon_{ia}^j \tag{1}$$

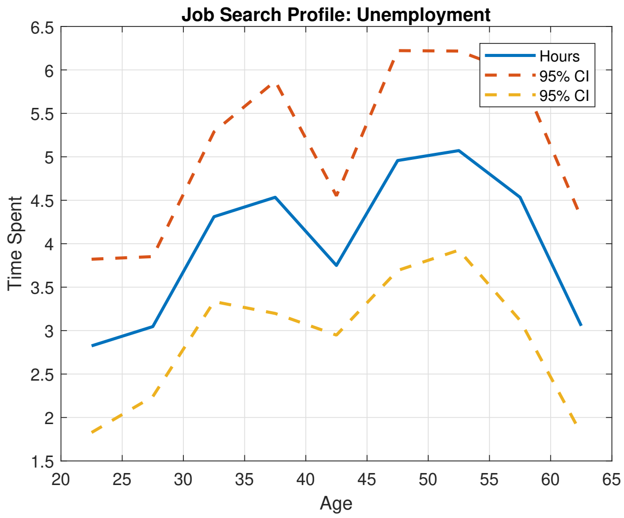
where $j \in \{employed, unemployed\}$, $a \in \{21-25, 26-30, 31-35, 36-40, 41-45, 46-50, 51-55, 56-60, 61-65\}$, Y_{ia}^j is time (minutes per day)[4] to spend finding jobs of individual i belongs to age group a and D_{ia}^j is a dummy variable which takes one if it belongs to the age group a or zero otherwise. To handle the measurement error, they use the sample weight provided by BLS.

[3]This does not necessarily mean that employed workers devote no effort to moving up the job ladder. For example, they may use headhunters because the opportunity cost of their time is higher, but the data do not identify this channel.

[4]Thus, to translate to hours per week, took a multiplication 7/60.

Figure 1: Source-Aguiar et al. (2013): Age-Dummy Regression





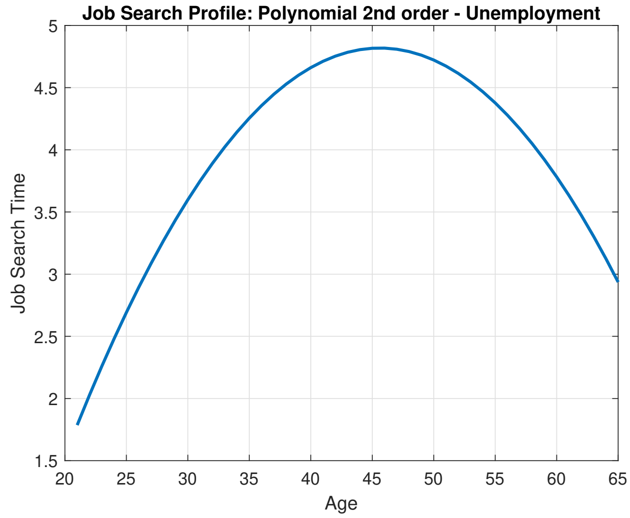


Figure 2: ATUS 2003∼2016

Figure 3: ATUS 2003∼2016: Age Polynomial

• **Reexamination: Hump-shaped profile in ATUS 0316** Following Aguiar et al. (2013), I estimate age-dummy and age-polynomial regressions, choosing the polynomial order that minimizes the mean squared error (MSE). The quadratic specification minimizes the MSE. The hump-shaped profile holds across demographic groups, and I report the aggregate result. Figure 2 presents the age-dummy estimates, Figure 3 presents the quadratic age-polynomial estimates, and Table 1 reports the age-dummy regression results. The hump-shaped profile therefore remains present in the more recent data, although with moderate curvature similar to that in the NJS.

Coefficient	Estimate	Coefficient	Estimate
β_{2125}	2.8242^{***} (0.5088)	.	.
β_{2630}	3.0459^{***} (0.4109)	$\beta_{2630} - \beta_{2125}$	0.2217 (0.6540)
β_{3135}	4.3107^{***} (0.4985)	$\beta_{3135} - \beta_{2125}$	1.4865^{**} (0.7123)
β_{3640}	4.5342^{***} (0.6822)	$\beta_{3640} - \beta_{2125}$	1.7100^{**} (0.8510)
β_{4145}	3.7496^{***} (0.4090)	$\beta_{4145} - \beta_{2125}$	0.9254 (06528)
β_{4650}	4.9569^{***} (0.6455)	$\beta_{4650} - \beta_{2125}$	2.1327^{***} (0.8219)
β_{5155}	5.0713^{***} (0.5845)	$\beta_{5155} - \beta_{2125}$	2.2471^{***} (0.7749)
β_{5660}	4.5342^{***} (0.7233)	$\beta_{5660} - \beta_{2125}$	1.7099^{*} (0.8843)
β_{6165}	3.0551^{***} (0.6341)	$\beta_{6165} - \beta_{2125}$	0.2309 (0.8130)

Table 1: Age dummy regression in the ATUS 0316. Numbers in parenthesis represent standard deviations. $*$ represents that estimates are significant in 10%, $**$ represents that estimates are significant in 5% and $***$ represents that estimates are significant in 1%.

2.2 New Jersey Survey

The survey collected weekly data from job seekers in New Jersey who are receiving unemployment benefit for several months. NJS is on-line survey and it was administered by the Cornell Survey Research Institute in collaboration with the Princeton Survey Research Center. As a recent work, the data set is used in Hall and Mueller (2018).[5]

I first examine whether the NJS also exhibits a hump-shaped life-cycle profile. I then present empirical evidence on the uncertainty and wealth effects in Section 2.4 and Section 2.5.

Descriptions for job search behavior and age groups in the NJS are as follows:

• **Job Search Behavior** In the NJS, it asks to respondents how many hours and minutes did they spend in the last 7 days. With questionnaire numbers in parenthesis, methods for search jobs include 1) contacted employer directly (q10a1_1 in the survey questionnaire), 2) contacted public employment agency ($q10a1_2$), 3) contacted private employment agency (q10a1_3), 4) contacted friends or relatives (q10a1_4), 5) contacted school/university employment center (q10a1_5), 6) checked union/professional registers (q10a1_6), 7) attended job training programs/courses (q10a1_7), 8) placed or answered ads (q10a1_8), 9) want to interview (q10a1_9), 10) sent out resumes/filled out applications (q10a1_10), 11) looked at

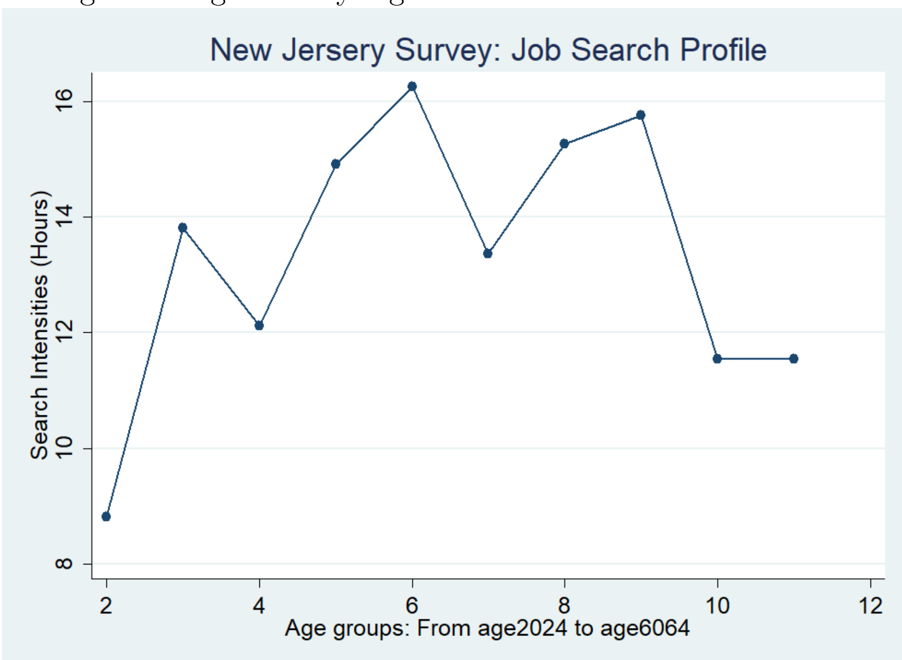
[5]The NJS can be obtained by registering to the Princeton Survey Research Center. Or, they can be found in Andria Mueller's website: `https://www0.gsb.columbia.edu/faculty/amueller/research.html`

ads (q10a1_11) and 12) other (q10a1_12). Search intensities are evaluated by the sum of all and I scale them in hours.

• **Age and sampling weight** The survey reports age categorically in the following bins: 20–24, 25–29, 30–34, 35–39, 40–44, 45–49, 50–54, 55–59, 60–64, and 65–69. I construct age indicators directly from these bins. Because the NJS provides sampling weights, as does the ATUS, I use them throughout the empirical analysis.

The job search profile implied by NJS with dummy regression (1) is as follows. Figure 4 represents the graph and Table 2 represents results of age dummy regression. Since I aggregate ages between 60 and 64 and ages between 6569, the last two points in Figure 4 are the same. Result is consistent with Aguiar et al. (2013).

Figure 4: Age dummy regression: Job Search Profile in NJS



2.3 The SCE Job Search Supplement: cross-validation and new moments

The NJS has an obvious external-validity vulnerability: it covers a single state, October 2009 to April 2010, and only UI claimants, who at entry had been receiving benefits for 45 weeks on average. The SCE Job Search Supplement is close to its design opposite: a nationally

Coefficient	Estimate	Coefficient	Estimate
β_{2024}	8.8163*** (0.5722)	.	.
β_{2529}	13.8022*** (0.9512)	$\beta_{2529} - \beta_{2024}$	4.9859*** (1.1100)
β_{3034}	12.1134*** (0.5746)	$\beta_{3034} - \beta_{2024}$	3.2971*** (0.8110)
β_{3539}	14.9013*** (0.5732)	$\beta_{3539} - \beta_{2024}$	6.0850*** (0.8099)
β_{4044}	16.2477*** (0.7665)	$\beta_{4044} - \beta_{2024}$	7.4314*** (0.9565)
β_{4549}	13.3647*** (0.5040)	$\beta_{4549} - \beta_{2024}$	4.5484*** (0.7625)
β_{5054}	15.2667*** (0.4359)	$\beta_{5054} - \beta_{2024}$	6.4504*** (0.7194)
β_{5559}	15.7595*** (0.6582)	$\beta_{5559} - \beta_{2024}$	6.9432*** (0.8722)
β_{6064}	11.5436*** (0.3909)	$\beta_{6064} - \beta_{2024}$	2.7273*** (0.5722)

Table 2: Age dummy regression in NJS. Numbers in parenthesis represent standard deviations. $*$ represents that estimates are significant in 10%, $**$ represents that estimates are significant in 5% and $***$ represents that estimates are significant in 1%.

representative annual panel (5,951 person-years over 2013–2017), fielded in normal times, covering employed, unemployed and non-participating respondents. If a moment agrees across the two surveys, it is unlikely to be an artefact of either. The profile itself is also robust to cyclical conditions: Section A.4 shows the same hump in the pre-crisis ATUS (2004–06) and in the crisis ATUS (2007–09).

	reference window	raw p	implied weekly	implied annual
NJS, non-employed	1 week	0.0573	**0.0573**	0.950
SCE, non-employed	4 weeks	0.2460	**0.0682**	0.975
SCE, employed	4 weeks	0.1167	0.0305	0.801

Table 3: Empirical job-offer measures in the NJS and the SCE. Weekly and annual hazards are computed as $1-(1-p)^{1/k}$ and $1-(1-p)^{52/k}$ for a k-week survey window. These survey-frequency measures are not the model-period normalization 0.164 used in the annual quantitative program.

Table 3 reports the central result. Using the four-week reference window stated in the SCE, the implied weekly job-offer measure of the non-employed is 0.068, compared with 0.057 in the NJS. The two values are of the same order despite differences in coverage, calendar time, and cyclical conditions. The NJS was fielded when New Jersey unemployment was almost twice the rate prevailing over the SCE sample, while NJS claimants search harder than the average SCE non-employed respondent (13.3 versus 8.3 hours per week). I therefore treat the NJS as informative about the level and age profile of search frictions, while using the SCE as an external check.

Three further SCE moments are used below. First, the real reservation wage of non-employed respondents is 96% of their previous real wage, direct evidence that job seekers apply a reservation rule to observed offers, which disciplines the acceptance protocol of the model in Section 4. Second, the acceptance rate conditional on receiving an offer is 0.79 in the NJS (weekly observation, excluding undecided spells); the SCE bounds it from below at 0.52, with the difference attributable to the four-week window and a 55% still-undecided share. Third, the SCE records applications alongside hours: non-employed workers aged 20–34 file 0.32 applications per search hour against 0.17 for ages 50–64, while offers *per application* are nearly flat in age. The decline of the offer rate with age is therefore a decline in applications, not in the return to an application, a fact I return to when interpreting the age profile of the search technology.

Finally, the two profile sources measure different margins. In the ATUS, a single-day diary in which 84% of unemployed respondents record zero search, 78% of the log variation of the profile is the *extensive* margin (whether one searched that day). In the weekly NJS, in which 80% of claimant-weeks record positive search, the hump is almost entirely the *intensive* margin (hours conditional on searching). Since search intensity s_t in the model is a continuous choice, the NJS is its closer conceptual counterpart and supplies the intensive-margin level moments, while the nationally representative ATUS is the profile the calibrated model matches most tightly (Section 6.1); I report the model against both. Bootstrap standard errors on the NJS profile (clustered by respondent) are roughly half those on the ATUS profile.

2.4 Empirical evidence: Uncertainty effect

For job offers, offered wages and reservation wages in the NJS, I follow methods used in Hall and Mueller (2018).

• **Job Offer** The NJS asked respondents each week: "In the last 7 days, did you receive any job offers? If yes, how many?" (q12_1_a,q12_1_b in the survey questionnaire) and "Since you last filled out this web survey, did you receive any other job offers that you did not include on the previous pages? If yes, how many?" (q12_2_a,q12_2_b). For 37,126 (24,413) observations, 1,806 (285) said 'yes' for q12_1_a and (q12_2_a respectively. The respondents in our sample received a total of 2,174 job offers in 37,609 reported weeks of job search.

• **Offered wages** For respondents who received job offers, the survey asked "What was the wage or salary offered (before deductions)? Is that per year, per month, bi-weekly, weekly or per hour?" (q13_1_a and q13_1_b1 in last 7 days and q13_2_a and q13_2_b1 since the last interview)

• **Reservation wages** For all respondents, the survey asked "Suppose someone offered you a job today. What is the lowest wage or salary you would accept (before deductions) for the type of work you are looking for?" (q7_1_a). I here use the same sample restrictions as in Krueger and Mueller (2011b) and Hall and Mueller (2018).[6]

• **Measured Uncertainty** Based on the model, agents do not know their true type, thus they predict earnings offer and update their mean belief. In this sense, not exactly the same, but roughly, the distance between offered wages (a proxy of realized earnings reflects true type) and reservation wages (a proxy of agents mean belief) $d_2 = (\log(y) - \log(r))^2$ can be interpreted as agents' perceived uncertainty. Because this variable is observed only after an offer arrives and is a realized squared gap rather than an ex ante variance, I use it as descriptive evidence consistent with the uncertainty channel rather than as a causal measure of perceived risk. See Section A.1 how this proxy can be justified.

• **Selection bias** All respondents in the survey are job seekers who receive unemployment benefits. Offered wages, however, are observed only for workers who receive offers, so the uncertainty proxy d may be subject to selection bias. I therefore compare the reservation wages of workers who receive offers with those of workers who do not. Unconditionally, reservation wages are statistically higher among workers who do not receive offers, and the difference remains after controlling for observable characteristics. The observed value of d may consequently be upward biased. Within the offer group, however, offered wages are positively correlated with reservation wages.[7] If this positive relationship also holds for workers who do not receive offers, the upward bias may be attenuated. This pattern can be rationalized by the McCall model or a directed-search framework: workers with higher reservation wages may enter submarkets with better offers but longer queues. Because the purpose of this exercise is to provide descriptive evidence on the uncertainty channel, I do not interpret the estimates causally.

[6] They only use the first reservation wage observation available for each worker in the survey to make the sample be representative and exclude respondents who reported working in the last 7 days or accepted a job offer at the time of the interview.

[7] The reservation-wage specification controls for age, gender, race, spousal income, mortgage debt, household income, savings, and education. The positive relationship between offered and reservation wages is robust in a parametric linear regression with 1,000 bootstrap replications and in a nonparametric analysis. The two log wages exhibit a strong linear relationship in the nonparametric analysis. Additional results are available upon request.

	(1)	(2)	(3)	(4)
uncertainty	-1.3779 (.9738)	-3.7478^{***} (1.0653)	-4.2780^{***} (1.1318)	-2.3627^{*} (1.3318)
duration	.	-0.0052 (0.0511)	-0.0194 (0.0498)	-0.0252 (0.0806)
savings	.	-0.3906 (0.8049)	-1.1621 (0.8981)	1.3149 (1.3106)
age	.	.	1.4472^{**} (0.5755)	1.3966 (1.1146)
spouse	.	.	.	4.5038 (4.2811)
mortgage	.	.	.	3.4806 (4.6578)
constant	14.8976^{***} (1.2380)	17.2824^{***} (3.0164)	10.57878^{***} (3.17071)	-3.9751 (12.3777)

Table 4: Uncertainty effect. Note: The analysis here considers the offered wage got in last 7 days because it for since last interview has too small sample size. $*$ represents that estimates are significant in 10%, $**$ represents that estimates are significant in 5% and $***$ represents that estimates are significant in 1%

• **Endogeneity** Lastly, in the regression, it might be worried if there exists an endogeneity between search intensities and measured uncertainty. First, the McCall model predicts that both offered wages and reservation wages are exogenous in optimal search intensities. Second, the Hausman test cannot reject the null-hypothesis. Thus, I here simply use the ordinary least square (OLS) estimation (2). The Hausman result is treated as a robustness check and not as proof that the realized offer–reservation gap is exogenous.

$$\text{SearchIntensity}_i = \beta d_i + \gamma X_i + u_i \tag{2}$$

where X_i includes control variables, unemployment duration, age and savings. Table 4 shows the result. The empirical study implies that higher uncertainty decreases job search intensities except the case if it is not controlled by any other variables.

2.5 Empirical Evidence: Wealth effect and outside option

Another crucial mechanism is the wealth effect. In the McCall model, unemployed workers with greater wealth exert less effort because better outside options reduce the net benefit of finding a job. I examine this mechanism together with broader measures of the outside option, particularly family insurance and mortgage debt.[8] The NJS reports household income, spousal income, household size, savings, and mortgage debt, allowing me to examine

[8]Lentz (2009) studies related mechanisms.

the role of each component. I estimate regression (3).

$$\text{Intensity}_i = \beta_1 \text{Savings}_i + \beta_2 \text{Spouse}_i + \beta_3 \text{Mortgage}_i + \beta_4 (\#\text{ of Household}) + \beta_5 \text{HouseholdIncome} + \beta_6 X_i + u_i \tag{3}$$

where X_i includes age, education, gender, race, the number of children, unemployment duration, and an indicator for positive search. Table 12 in Section A.3 reports the results. Although savings are categorical, search effort declines clearly across higher savings categories; the result also holds when each category enters as a separate indicator. Search effort is also lower when the worker has an employed spouse or higher household income. These findings indicate that workers search less when their outside options are better. Mortgage debt and a two-person household are associated with greater search effort, although several household-size coefficients are imprecisely estimated.[9] Overall, the estimated outside-option effects are consistent with the McCall model.

3 Analytical Analysis: Wealth and Uncertainty

In this section, I use a simple two-period model to isolate the wealth and uncertainty effects. The analytical result shows why declining perceived risk can, in principle, raise search as workers learn. It does not establish that learning is quantitatively necessary for the life-cycle hump. In the benchmark model, workers initially face uncertainty about an occupational match and update it from earnings, while accumulated wealth and the remaining horizon also change search over the life cycle. The quantitative information experiment in Section 6.2 separates these channels.

Workers are risk averse and have access to a risk-free asset and unemployment insurance. Employed workers have an incentive to accumulate the risk-free asset because their wages may decline even if they retain their jobs. Unemployed workers choose search effort optimally because offer arrival increases with search and search is costly. There is no on-the-job search.[10] As in the standard McCall model, unemployed workers search more intensively when the expected net benefit of finding a job is higher. The analysis therefore compares the value of employment with the value of remaining unemployed. Risk aversion is central to the value of the outside option.

Let first consider the wealth effect. Suppose unemployed workers have large wealth at the beginning period. If they are risk neutral, this does not necessarily mean that they have

[9] A larger household may increase the need to find a job quickly, but it may also provide more family insurance.

[10] Time-varying earnings during employment can be interpreted indirectly as a wage ladder.

better outside options for the next period. Since they are risk averse, i.e., the utility function is concave, they have an incentive to purchase risk free assets for consumption smoothing. Large wealth here implies that they save more. It increases both values of being employed and staying unemployed but more the value of staying unemployed because of concavity. Thus, as risk averse agents have higher wealth, optimal job search intensities decrease because it decreases (increases) the net benefit of finding jobs (value of outside options)[11]

I also show that higher uncertainty decreases optimal job search intensities. I here assume the prudence of utility function. Uncertainty is defined by the variance of wage offer distribution. The wage/earning distribution here has the lower bound that is smaller than the reservation wage, and this is supported by empirical findings.[12] Intuitively, the higher variance is risky for risk averse workers even in the two-period model since offered earning is more likely lower than reservation wages, even if they found jobs.

More specifically, there are two channels for higher uncertainty and they unambiguously decrease optimal job search intensities. First, the expected utility is lower under higher variance due to concavity of utility function. Also, under prudence utility, it increases precautionary savings. Since the offered wage could be more likely lower than reservation wages, they would reject job offers more likely. With the similar logic, employed workers increase precautionary savings if the job separation rate is higher. Thus, the uncertainty effect decreases optimal search intensities.

3.1 Environment

• **Time** Discrete and $t \in \{1, 2\}$.

• **Agents** Employed and unemployed. Agents are risk averse so the model is McCall job search model with consumption-saving choice problem.

• **Market** Incomplete. There is only risk free asset with fixed return r. For unemployed workers, they have fixed value of b which represents unemployment benefit, home production or leisure.

[11] See also Lentz and Tranæs (2005) for the wealth effect on the job search behavior.

[12] The NJS provides the information whether respondents got job offers and if they accepted or not. If the lower bound of offered wage is higher than the reservation wage, the acceptance rate conditional on getting job offer should be unity but this does not hold. Also, if we just simply compare between the offered wage and reservation wage, the offered wage is somewhat frequently lower than the reservation wage. To be precise, with the measurement error issue in reservation wage, the non-wage job values would is also crucial as shown by Hall and Mueller (2018).

• **Search Intensity** At the initial period, unemployed agent devotes search effort to get a job offer in the next period. Job arrival rate, or the probability of finding job is the function of job search intensities.

• **Earnings Offer** The labor earnings offer y' in $t = 2$ has a support $[0, \bar{y}]$ with a distribution function $F(y')$ and for simplification, assume that it is independent to the initial earnings offer y. In the standard life-cycle incomplete market model, y' follows the first order auto-regressive (AR(1)) process.

3.2 Value functions and job search intensities

• **Terminal period** Given the risk-free return rate r, the asset holding level a' determined at $t = 1$ and the labor earning y', employed worker's value function at the terminal period $V_2^E(a', y')$ is

$$V_2^E(a', y') = \max_{c'} u(c')$$

subject to

$$c' = y' + (1 + r)a'$$

where c' is the consumption level at $t = 2$ and $u(c)$ is the utility function for the consumption which is strictly increasing and strictly concave. The paper considers prudence class of utility functions. And unemployed worker's value function $V_2^U(a')$ is

$$V_2^U(a') = \max_{c'} u(c')$$

subject to

$$c' = b + (1 + r)a'$$

where b is the value of unemployment which could include the level of unemployment benefit or home-production. Thus they are nothing but

$$\begin{aligned} V_2^E(a', y') &= u(y' + (1 + r)a') \\ V_2^U(a') &= u(b + (1 + r)a') \end{aligned} \tag{4}$$

• **Unemployed worker's problem** Given the initial wealth a and the risk-free return r, unemployed workers or job seekers at initial period $t = 1$ solve following value function optimally:

$$V_1^U(a) = \max_{\{c,s,a'\}} \left\{ U(c,s) + \delta \left[p(s) \int \max \left\{ V_2^E(a',y'), V_2^U(a') \right\} dF(y') + (1-p(s)) V_2^U(a') \right] \right\} \tag{5}$$

subject to

$$c + a' = b + (1+r)a$$

where c is the consumption level, s is the effort level of finding jobs and a' is the savings level. δ represents the time discount factor with $\delta \in [0,1]$ and $p(s)$ represents job search technology which is the strictly increasing and strictly concave function of the level of job search effort s. With a probability $p(s)$, agents can get a job offer and take a decision whether accept or not. The paper considers following functional form of $p(s)$ used in Aguiar et al. (2013).

$$p(s) = \frac{m}{\pi} s^{\pi} \tag{6}$$

where m is the productivity of the job search technology and π is the share of job search effort. $U(c,s)$ is the utility function for c and s and we consider the additively separable utility function such that

$$U(c,s) = u(c) - v(s) = \frac{c^{1-\gamma}}{1-\gamma} - B \frac{s^{1+\psi}}{1+\psi} \tag{7}$$

where $u(c)$ is the constant relative risk aversion (CRRA) utility function with risk aversion parameter γ and $v(s)$ is a convex utility function with the weight for job search effort disutility B and the elasticity ψ.

• **Employed worker's problem** Given the initial wealth a and the risk-free return r,, employed workers at initial period $t = 1$ solve following value function optimally:

$$V_1^E(a,y) = \max_{\{c,a'\}} \left\{ u(c) + \delta \left[(1-\theta) \int V_2^E(a',y') dF(y') + \theta V_2^U(a') \right] \right\} \tag{8}$$

subject to

$$c + a' = y + (1+r)a$$

where θ is an exogenous job separation rate.

• **Optimal Job Search Intensity** From (5), (6) and (7), the first order optimality condition for the optimal policy function $g_s(a)$ with respect to the job search effort s is

$$g_s(a) = \left[\delta m \int_0^{\bar{y}} \max\left\{V_2^E(g_a^u(a), y') - V_2^U(g_a^u(a)), 0\right\} dF(y')\right]^{\frac{1}{1-\pi+\psi}}$$

where $g_a^u(a)$ is an unemployed worker's optimal saving policy function. More compact representation would be following:

$$g_s(a) = \left[\delta m \int_{y^*}^{\bar{y}} J(g_a^u(a), y') dF(y')\right]^{\frac{1}{1-\pi+\psi}} \tag{9}$$

where y^* is the reservation earnings offer such that $V_2^E(a', y^*) = V_2^U(a')$ and $J(a', y') = V_2^E(a', y') - V_2^U(a')$ is the net benefit from finding jobs.

Likewise the standard McCall model, the optimal job search intensity is positively proportional to the net benefit of finding jobs, which is $J(g_a^U(a), y')$.[13] Note that the sufficient statistics of the net benefit of finding jobs are the current asset holding a and the distribution function F. The initial wealth a (so thus optimal savings $g_a^u(a)$) implies the value of outside option and the distribution function F implies how the earnings will be beneficial for (risk-averse) agents, roughly in senses of the first order moment and the second order moment.

We now have following two propositions.

Proposition 3.1. ***(Wealth Effect)*** *For any concave function of $u(c)$ and convex function of $v(s)$, given the distribution function $F(y')$,*

$$g_s(a_i) \leq g_s(a_j)$$

for any $a_i \geq a_j$.

Proof. See the Section C.1. □

Proposition 3.2. ***(Uncertainty Effect)*** *Suppose that $G(y')$ is a mean preserving spread of $F(y')$, and that the spread is confined to the acceptance region, i.e., supp$(F) \cup$ supp$(G) \subseteq [y^*, \bar{y}]$ where $y^* = b$ is the reservation earnings offer. Then,*

$$g_s^F(a) \geq g_s^G(a)$$

[13] The convexity of utility function with respect to job search effort and the concavity of the job search technology guarantee that $1 - \pi + \psi > 0$.

where g_s^X for $X \in \{F, G\}$ is the optimal job search intensity policy function under the distribution function X.

Proof. See the Section C.2. $\square$

Remark 3.3. *The support restriction in Proposition 3.2 is not innocuous. The integrand of the net benefit,* $\max\{J(a', y'), 0\}$*, is zero below the reservation offer $y^* = b$ and strictly concave above it, so it is* convex *at the reservation margin: its derivative jumps from* 0 *to* $u'((1+r)a' + b) > 0$ *at $y' = b$. A mean preserving spread that moves probability mass* across *the margin therefore has two opposing effects. It spreads accepted offers, which risk-averse searchers dislike (the risk margin), but it also fattens the upside relative to a truncated downside, which any searcher likes (the option margin). For utility close to linear the option margin dominates and greater dispersion* raises *search, the classic option-value result of the reservation-wage literature. The restriction to spreads within the acceptance region shuts down the option margin and isolates the risk margin, which is the effect the paper emphasizes. Empirically the restriction is mild: the acceptance rate conditional on an offer is* 0.79 *in the NJS and* 0.69 *in the calibrated benchmark model of Section 4, so the bulk of the offer distribution indeed lies inside the acceptance region and the risk margin carries the quantitative weight. The full model prices both margins, and Section 6.2 uses the acceptance rate and the reservation-wage moment to discipline their relative strength.*

The wealth effect is the key channel in the standard life-cycle incomplete-markets model. Agents face three sources of risk: persistent earnings shocks, job separation, and retirement. Because markets are incomplete, workers accumulate precautionary wealth as they age. The standard model therefore predicts a declining search profile through the wealth effect.

The uncertainty effect implies that, under the support condition of Proposition 3.2, smaller uncertainty raises search. A process of resolving uncertainty can therefore contribute to a rising search profile. This is a theoretical comparative static, not an identification result: Section 6.2 shows that the calibrated hump survives full information when realized match dispersion is held fixed. The risk margin that Proposition 3.2 isolates is nevertheless present in the quantitative model, and Table 9 measures its strength. Raising risk aversion strengthens it relative to the option and selection margins until, at $\gamma = 8$, it dominates and full information flattens the profile rather than steepening it. At the risk aversion the remaining moments support, it does not. The two-period result therefore identifies a force that operates in the calibrated model; what the quantitative analysis settles is its relative magnitude.

4 Benchmark Model

The model combines occupational-match dispersion, Bayesian learning, an age-varying value of non-employment, and wealth accumulation in an incomplete market. When a worker enters a new occupation, she does not know its match-specific intercept and growth component and learns from realized earnings. This information structure affects risk pricing and offer selectivity. The quantitative experiment in Section 6.2, however, shows that learning is not required for the hump: full revelation of the same dispersed match preserves and slightly steepens it. The young end is chiefly shaped by the outside-option profile and realized match dispersion, while wealth and the shorter remaining horizon lower search later in life. The unknown component of earnings is attached to the *occupation* rather than to the worker, following Chang, Hong and Karabarbounis (2018). Two considerations motivate this. First, uncertainty about a person-level type enters the values of employment and unemployment nearly symmetrically, because the type follows the worker whether or not she takes a job, and therefore largely cancels out of the net benefit of finding a job. Uncertainty about an occupational match, by contrast, is borne only by taking a job and is therefore priced asymmetrically. Second, the speed at which perceived risk is resolved is disciplined by the observed decline in occupational mobility with age rather than by the Kalman filter alone. Preferences belong to the recursive class of Epstein and Zin (1989), allowing risk aversion, which prices match risk, and the elasticity of intertemporal substitution, which governs the wealth effect, to vary independently. The model also allows the value of non-employment to vary with age, a channel supported by the outside-option evidence in Section 2.5. The remainder of this section states the environment, belief dynamics, preferences, and value functions.

4.1 Environment

Many features of the benchmark model are similar to the two-period model except Bayesian learning. The benchmark model considers 1) the life-cycle incomplete market model 2) imperfect information about an occupational match, which generates age- and tenure-dependent perceived risk, and 3) retirement stage.

• **Age** Agents can work for $t = 1, \dots, T^R$. During the working age, agents could be employed and unemployed. At $t = T^R + 1$, agents retire and die at $t = T$ with probability 1.

• **Earnings** If agents are in an unemployment state at age t, they receive the value of non-employment b_t^U (below). If agent i is employed, her log labor earnings consist of a common life-cycle component, an *occupational match*, and worker-level shocks:

$$\begin{aligned} y_t^i &= \underbrace{g(\Theta,t)}_{\text{Common life-cycle component}} + \underbrace{a_o + b_o\, t}_{\text{Occupational match}} + \underbrace{z_t^i + \varepsilon_t}_{\text{Random shocks}} \\ z_t^i &= \rho z_{t-1}^i + \eta_t^i, \qquad z_1^i \sim \mathbb{N}\left(0, \frac{\sigma_\eta^2}{1-\rho^2}\right) \end{aligned} \tag{10}$$

The pair (a_o, b_o) is an intercept and a growth rate specific to the worker–occupation pair. It is redrawn whenever the worker changes occupation, which happens to employed workers with the age-declining probability λ_t estimated by Chang, Hong and Karabarbounis (2018), and a job offer received while unemployed is drawn from a new occupation with probability κ:

$$a_o' = \rho_a a_o + \nu_a, \qquad b_o' = \rho_b b_o + \nu_b, \qquad \nu_a \sim \mathbb{N}(0, \sigma_{\nu a}^2),\ \nu_b \sim \mathbb{N}(0, \sigma_{\nu b}^2). \tag{11}$$

Neither a_o nor b_o is observed: the worker sees only realized earnings, and only in years actually worked, so the match must be inferred while it is also confounded with the persistent shock z_t^i. As in the heterogeneous income profile (HIP) literature (Guvenen, 2007; Guvenen and Smith, 2014), this confounding is what makes learning slow. The difference here is that the panel from which the worker learns is truncated by her own occupational mobility, so young workers, who change occupations most, remain the least informed. The entry match uses the CHK initial variances $(\sigma_{a0}^2, \sigma_{b0}^2)$. For a match generated by a later occupational transition, the dispersion of the *level innovation* is allowed to decline with age, $\sigma_{\nu a}(t) = \sigma_{\nu a}\left[1 + \chi\,(T^R - t)/T^R\right]$, with $\chi = 0$ reproducing Chang, Hong and Karabarbounis (2018) exactly. This expression scales the standard deviation; the innovation variance entering the state transition is $\sigma_{\nu a}^2(t)$. Thus χ changes total realized match dispersion after occupational transitions; it is not a parameter of the worker's initial signal. The motivation is the sorting evidence of Topel and Ward (1992) and the career-experimentation literature, and Section 6.2 disciplines χ by the reservation-wage and acceptance moments instead of the search profile itself.

In the retirement period, agents receive annual pension payments that mimics features of U.S. Social Security Administration (SSA) system. This paper follows Storesletten et al. (2004) and Guvenen and Smith (2014)'s formula.

• **Bayesian Learning** When agent i takes a job in a new occupation she does not know (a_o, b_o): the occupation is an experience good in the sense of Jovanovic (1979), revealed only by working. Define the composite match state $q_t \equiv a_o + b_o t$. Within an occupation the system is then a *local linear trend* with constant coefficient matrices,

$$\underbrace{\begin{bmatrix} q_{t+1} \\ b_{t+1} \\ z_{t+1} \end{bmatrix}}_{S_{t+1}} = \underbrace{\begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \rho \end{bmatrix}}_{F} \begin{bmatrix} q_t \\ b_t \\ z_t \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \eta_{t+1} \end{bmatrix}, \qquad \tilde{y}_t = \underbrace{\begin{bmatrix} 1 & 0 & 1 \end{bmatrix}}_{H'} S_t + \varepsilon_t, \tag{12}$$

where $\tilde{y}_t \equiv y_t^i - g(\Theta, t)$ is the observed earnings residual. The middle state component b_t denotes the occupational growth component and is distinct from the value of non-employment b_t^U. Beliefs $\hat{S}_{t|t-1} = [\hat{q}, \hat{b}, \hat{z}]'$ evolve by the standard Kalman recursion

$$\begin{aligned} \text{Updating: } \hat{S}_{t|t} &= \hat{S}_{t|t-1} + K_t \, \hat{\xi}_t^i, \qquad \hat{\xi}_t^i = \tilde{y}_t^i - H' \hat{S}_{t|t-1} \\ \text{Forecasting: } \hat{S}_{t+1|t} &= F \hat{S}_{t|t}, \qquad P_{t+1|t} = F P_{t|t} F' + Q, \end{aligned} \tag{13}$$

with Kalman gain $K_t = P_{t|t-1} H \left[H' P_{t|t-1} H + \sigma_\varepsilon^2 \right]^{-1}$. At an occupational change between t and $t+1$ the intercept must be rotated back before the AR(1) of equation (11) applies, $q'_{t+1} = \rho_a (q_t - b_t t) + \rho_b b_t (t+1) + \nu_a + \nu_b (t+1)$ and $b'_{t+1} = \rho_b b_t + \nu_b$, and occupational tenure resets.

Formation of the initial belief. The composite match state is $q_t = a_o + b_o t$, so at labor-market entry $q_1 = a_o + b_o$. Before the first earnings observation the benchmark worker has received no private signal about (a_o, b_o); hence $\hat{q}_{1|0} = \mathbb{E}[a_o + b_o] = 0$, $\hat{b}_{1|0} = 0$, and $\hat{z}_{1|0} = 0$. The entry prior is therefore

$$\hat{S}_{1|0} = \begin{bmatrix} 0 & 0 & 0 \end{bmatrix}', \qquad P_{1|0} = \begin{bmatrix} \sigma_{a0}^2 + \sigma_{b0}^2 & \sigma_{b0}^2 & 0 \\ \sigma_{b0}^2 & \sigma_{b0}^2 & 0 \\ 0 & 0 & \sigma_\eta^2 / (1 - \rho^2) \end{bmatrix}. \tag{14}$$

The first realized earnings signal updates this zero prior mean through equation (13). This is the incomplete-information branch (PIM $= 0$) in the supplied Chang, Hong and Karabarbounis (2018) code: CHK's σ_{a0}^2, σ_{b0}^2, $\sigma_{\nu a}^2$ and $\sigma_{\nu b}^2$ govern total cross-sectional dispersion, while PIM switches only what the worker initially knows. The benchmark adopts the unknown branch exactly.

For the information experiments, write each occupational innovation as $\nu_j = \nu_j^K + \nu_j^U$, $j \in \{a, b\}$, where the known component shifts the prior mean and only the unknown component enters the covariance. If ℓ is the unknown standard-deviation share, then

$$\text{Var}(\nu_j^U) = \ell^2 \sigma_{\nu j}^2(t), \qquad \text{Var}(\nu_j^K) = (1 - \ell^2) \sigma_{\nu j}^2(t). \tag{15}$$

The notation is mapped once and used throughout: the CHK switch PIM $= 0$ corresponds to $\ell = 1$ (no private information), while PIM $= 1$ corresponds to $\ell = 0$ (full information). The continuous ℓ is used only to construct intermediate information experiments while preserving total realized dispersion. The partial-information value $\ell = 0.438$ follows the interpretation of the initial-signal parameter in Guvenen and Smith (2014): it is a ratio of conditional to unconditional standard deviations, so the unknown *variance* share is $\ell^2 = 0.438^2 = 0.191844$. This GS value is used only in the information experiment, not to calibrate the benchmark. In particular, χ controls the age profile of total level-innovation dispersion, whereas ℓ controls how much of that dispersion is initially unknown.

Two properties of this structure do all the work. First, because F and H are constant within an occupation and the only event that resets the filter is an occupational change, the belief covariance P is a *deterministic function of age and occupational tenure*: it is computed once, before the dynamic program, as a table $P(t, \tau)$ by iterating the Riccati recursion over the ergodic tenure distribution implied by λ_t. Perceived risk is therefore never a state variable, yet its resolution is interrupted by every occupational change. Second, a single scalar innovation $\hat{\xi}_{t+1}$ drives realized earnings and all three belief components with known loadings, so the expectation in the Bellman equation reduces to a one-dimensional quadrature, the dimensional collapse of Guvenen and Smith (2014). Perceived uncertainty is the sum of match uncertainty $H'P(t, \tau)H$ and the shock variances; because occupational mobility falls steeply with age, so does the rate at which the match is re-randomized, and perceived risk resolves over the life cycle.

• **Preferences** Preferences are the recursive class of Epstein and Zin (1989) and Weil (1990). Let $\varrho = 1 - 1/\text{EIS}$ and $\alpha = 1 - \gamma$. The period index and the recursion are

$$u(c, s)^{\varrho} = c^{\varrho} - \varrho B \frac{s^{1+\psi}}{1+\psi}, \qquad V_t = \Big[(1-\delta)\, u(c_t, s_t)^{\varrho} + \delta\big(\mathbb{E}_t[V_{t+1}^{\alpha}]\big)^{\varrho/\alpha}\Big]^{1/\varrho}, \tag{16}$$

so that V is measured in consumption units. Placing the search cost inside the period index in the ϱ-power makes the specification nest the additively separable CRRA model *exactly*: at $\varrho = \alpha$ (i.e., EIS $= 1/\gamma$), the transformation $W \equiv V^{\varrho}/[(1-\delta)\varrho]$ turns (16) into $W = \frac{c^{1-\gamma}}{1-\gamma} - B\frac{s^{1+\psi}}{1+\psi} + \delta\, \mathbb{E}[W']$, so every policy function coincides; this identity is used to validate the computation. The motivation is specific to the question of this paper: under CRRA a single parameter prices both the occupational match gamble (the uncertainty effect) and the consumption-smoothing motive that generates wealth accumulation (the wealth effect). Separating them lets the data on wealth-to-income ratios speak to the EIS while γ continues to price risk, and Section 6.2 shows the separation matters quantitatively. The feasible set additionally requires $c^{\varrho} - \varrho B s^{1+\psi}/(1+\psi) > 0$ and $0 \leq p_t(s) \leq 1$.

• **Value of non-employment** The flow value of non-employment contains a mean-preserving age tilt and the pre-retirement floor used in the quantitative code,

$$\widetilde{b}_t^U = \varrho_b \left[1 + \kappa_b \left(\frac{T^R - t}{T^R - 1} - \frac{1}{2} \right) \right] \bar{Y}, \qquad b_t^U = \begin{cases} \widetilde{b}_t^U, & \text{age} < 62, \\ \max\{\widetilde{b}_t^U, \varrho_{62}\bar{Y}\}, & \text{age} \geq 62, \end{cases} \tag{17}$$

where $\varrho_b = 0.42$, $\kappa_b \geq 0$, and $\varrho_{62} = 0.50$. The parameters have separate roles. The unfloored component $\widetilde{b}_t^U$ preserves its life-cycle average by construction, and κ_b controls its young-to-midlife decline. The distinct parameter ϱ_{62} applies the age-62 floor. Consequently, the implemented b_t^U is U-shaped near retirement and its final average need not equal $\varrho_b \bar{Y}$ exactly. I do not identify κ_b from a young-to-old endpoint ratio. I select its magnitude from the young-to-midlife portion of the search profile; external evidence disciplines only its sign and qualitative age pattern. Michelacci and Ruffo (2015) find that optimal unemployment replacement rates decline with age, Aguiar et al. (2013a) document substantial home production and education among the unemployed, and Kaplan (2012a) show that moving into and out of the parental home insures young workers against labor-market risk. The NJS evidence in Section 2.5 adds within-sample support from spousal employment, savings, and household income. These sources motivate a broader value of non-employment, not a literal UI benefit, but do not independently identify its numerical slope. The age-62 timing is separately aligned with the earliest eligibility age for U.S. Social Security retirement benefits; it is not evidence for κ_b.[14]

4.2 Value functions

• **Unemployment** For each age t, an unemployed agent i chooses consumption c, savings a' and search effort s, given the risk-free rate r, current assets a, the belief $\hat{S}^i_{t|t-1} = [\hat{q}^i_{t|t-1}, \hat{b}^i_{t|t-1}, \hat{z}^i_{t|t-1}]'$ and its covariance $P_{t|t-1}$. Together with occupational tenure τ_t, these variables define the formal state $X_t^U = (a, \hat{S}^i_{t|t-1}, \tau_t)$; the arguments of the value functions are suppressed below to keep the notation compact.[15] Writing $\alpha = 1 - \gamma$ and $\varrho = 1 - 1/\text{EIS}$, let $\mathcal{C}_t^j \equiv \left(\mathbb{E}_t[(V^j_{t+1})^{\alpha}]\right)^{1/\alpha}$ be the certainty equivalent of the next-period value. Under the

[14]The Social Security Administration states that retirement benefits may begin at age 62, subject to an actuarial reduction; see `https://www.ssa.gov/benefits/retirement/planner/applying2.html`.

[15]The belief covariance is a deterministic function of age and occupational tenure (Section 4); with $\chi = \kappa_b = 0$ and a single lifetime occupation it collapses to the age-only sufficient statistic of Chang, Hong and Karabarbounis (2018).

recursive preferences of equation (16) the unemployment problem is

$$V_t^U = \max_{\{c,s,a'\}} \left\{ (1-\delta) \left[c^{\varrho} - \varrho B \frac{s^{1+\psi}}{1+\psi} \right] + \delta \left(Q_t^U(s) \right)^{\varrho/\alpha} \right\}^{1/\varrho}, \tag{18}$$

where the continuation certainty-equivalent argument mixes the no-offer and offer branches,

$$Q_t^U(s) = \big(1 - p_t(s)\big)\, \mathbb{E}_t\big[(V_{t+1}^U)^{\alpha}\big] + p_t(s)\, \mathbb{E}_t\big[\big(\max\{V_{t+1}^E, V_{t+1}^U\}\big)^{\alpha}\big], \tag{19}$$

each V_{t+1}^j evaluated at $(a', y_{t+1}^i, \hat{S}_{t+1|t}^i)$. The accept/reject decision is a reservation rule on the *value*: a worker who receives an offer accepts if and only if $V_{t+1}^E \geq V_{t+1}^U$ at the realized earnings draw, so the maximum is taken over values before the α-power is applied. This ordering matters because $\alpha = 1 - \gamma < 0$: applying the power first would reverse the comparison. subject to

$$c + a' = b_t^U + (1+r)a$$

and the Kalman recursion (13), where b_t^U is the value of non-employment (equation (17)) and $p_t(s) = \frac{m_t}{\pi} s^{\pi}$ is the age-dependent job-offer technology, increasing and weakly concave in s, with $m_t > 0$ and $0 < \pi \leq 1$; the benchmark has $\pi = 1$. In the nested additively separable case ($\varrho = \alpha$), define $W_t^j \equiv (V_t^j)^{\alpha}/[(1-\delta)\alpha]$. The first order condition for search then takes the familiar additive-CRRA form

$$s = \left[\frac{m_t \delta}{B} \mathbb{E}_t \max\left\{ W_{t+1}^E - W_{t+1}^U, 0 \right\} \right]^{\frac{1}{1-\pi+\psi}} \tag{20}$$

As in the standard job search model, optimal job search effort s_t is increasing in the net benefit of finding a job. The Kalman filter affects this benefit through two channels: the posterior covariance determines how perceived risk changes over the life cycle, while the posterior mean determines which workers search more within an age group. The first channel is related to when workers search more and the second to who searches more.

Three remarks characterize the search and acceptance decisions. First, under Epstein–Zin preferences the continuation values are aggregated by the certainty equivalent: writing $Q \equiv \mathbb{E}_t[V_{t+1}^{\alpha}] = Q^U + p_t(s)\left(Q^{acc} - Q^U\right)$, where $Q^U \equiv \mathbb{E}_t[(V_{t+1}^U)^{\alpha}]$ and $Q^{acc} \equiv \mathbb{E}_t[(\max\{V_{t+1}^E, V_{t+1}^U\})^{\alpha}]$, the first order condition generalizes to

$$s = \left[\frac{\delta\, m_t \left(Q^{acc} - Q^U\right) Q^{\varrho/\alpha - 1}}{(1-\delta)\,\alpha\, B} \right]^{\frac{1}{1-\pi+\psi}}, \tag{21}$$

which is positive since $Q^{acc} - Q^U \leq 0$ and $\alpha < 0$, and which collapses to (20), expressed in the transformed value W, at $\varrho = \alpha$. Second, the accept/reject margin is a *reservation rule on observed earnings*: an offer arrives with the realized first-period earnings draw attached, the worker updates beliefs on it, and accepts if and only if the updated value of employment exceeds the value of remaining unemployed, so the max sits inside the expectation, exactly as in equation (9) of the two-period model. The empirical basis for this protocol, rather than acceptance on the prior, is the reservation-wage evidence of Section 2.3: non-employed workers report reservation wages equal to 96% of their previous wage, and reservation wages could not be elicited at all if new matches were accepted sight unseen. Third, with probability κ the offer is drawn from a new occupation, in which case the observed first-period earnings reveal the match only partially, since the growth rate b_o remains to be learned by working, so accepted offers restart occupational tenure and re-open the learning problem. The interaction of these margins with the age profiles of λ_t, of match dispersion (χ), and of the outside option (κ_b) is quantified in Section 6.2.

• **Employment** An employed agent chooses c and a', with belief state $\hat{S}^i_{t|t-1} = [\hat{q}^i_{t|t-1}, \hat{b}^i_{t|t-1}, \hat{z}^i_{t|t-1}]'$ and covariance $P_{t|t-1}$. The problem is

$$\begin{aligned} V^E_t &= \max_{\{c,a'\}} \left\{ (1-\delta)\, c^{\varrho} + \delta \left(Q^E_t\right)^{\varrho/\alpha} \right\}^{1/\varrho}, \\ Q^E_t &= \mathbb{E}_t \Big[\theta_t (V^U_{t+1})^{\alpha} + (1-\theta_t) \left\{ (1-\lambda_t)(V^{E,S}_{t+1})^{\alpha} + \lambda_t (V^{E,N}_{t+1})^{\alpha} \right\} \Big] . \end{aligned} \tag{22}$$

subject to

$$c + a' = Y^i_t + (1+r)a$$

and the Kalman recursion (13), where θ_t is the exogenous job separation rate. The superscripts are transition labels: $V^{E,S}$ means employment after *staying* in the current occupation, whereas $V^{E,N}$ means employment in a *new* occupation with the prior reset described above. The comma distinguishes the label S from the belief-state vector $\hat{S}_{t|t-1}$. Finally, $Y^i_t = \exp(y^i_t)$ is earnings, with the log earnings y^i_t given by equation (10), which already contains the common life-cycle component $g(\Theta, t)$.

•**Retirement** After retire, for $t = T^R + 1, \ldots, T$, agent i chooses optimally the consumption c and the savings a' by solving the following bellman equation optimally:

$$V^i_t(a) = \max_{\{c,a'\}} \left\{ (1-\delta)\, c^{\varrho} + \delta \left(V^i_{t+1}(a')\right)^{\varrho} \right\}^{1/\varrho} \tag{23}$$

subject to

$$
\begin{aligned}
c + a' &= (1+r)a + Y^i \\
Y^i &= \Phi\left(\exp\left(y^i_{T^R}\right)\right)
\end{aligned}
\tag{24}
$$

where Y^i is the retirement pension for retirement agent i. The formulation to mimic US social security system, I follow Storesletten et al. (2004)'s one. This formula is also used in Guvenen (2007), Guvenen and Smith (2014) and many other life cycle studies. To simplify notation, define $\tilde{Y}_{T^R} \equiv Y_{T^R}/\bar{Y}_{T^R}$ to be an individual's income at age T^R relative to the average income at that age Y_{T^R}. The retirement replacement rate is a concave function of $\tilde{Y}_{T^R}$ given by

$$
\Phi(\tilde{Y}_{T^R}) = \bar{\Phi}
$$

$$
\times \begin{cases} 0.9\tilde{Y}_{T^R} & \text{if } \tilde{Y}_{T^R} < 0.3 \\ 0.27 + 0.32(\tilde{Y}_{T^R} - 0.3) & \text{if } \tilde{Y}_{T^R} \in (0.3, 2] \\ 0.81 + 0.15(\tilde{Y}_{T^R} - 2) & \text{if } \tilde{Y}_{T^R} \in (2, 4.1] \\ 1.1 & \text{if } \tilde{Y}_{T^R} > 4.1 \end{cases}
$$

where $\bar{\Phi} = 1/1.4$ is a scaling parameter.[16]

5 Calibration

Table 5 represents parameters used in the model. Most of values are commonly used in life-cycle literature and job search intensity literature.

• **Occupational uncertainty** All parameters of the occupational process (the mobility profile λ_t, the new-occupation share κ, the persistence pair (ρ_a, ρ_b), the innovation variances and the entry dispersion) are taken from Chang, Hong and Karabarbounis (2018) without adjustment, as is the worker-level income process of Guvenen and Smith (2014) and the age profiles of productivity and separations. The only departures from their estimates are the two age gradients χ and κ_b, which are new parameters and both nest the original at zero. Risk aversion is fixed at $\gamma = 5$ as in Chang, Hong and Karabarbounis (2018) so that the risk pricing of the occupational gamble remains comparable to theirs.

• **Identification** The average unemployment rate does not identify the search-technology

[16] See Storesletten et al. (2004), Guvenen (2007) and Guvenen and Smith (2014) for more detail

Parameter	Value	Description	Targets/Reference
γ	5.000	Risk aversion	Chang, Hong and Karabarbounis (2018)
EIS	**1.200**	**Elast. of intertemporal substitution**	Broad comparison: CHK $K/Y = 3.2$; SCF mean WTI 5.6–7.0; model 4.81
r	0.030	Risk-free rate	Annual rate
δ	0.950	Time-discount factor	Standard annual value
T^R	66	Retirement Age	
T	80	Terminal Age	
ψ	2.500	Elasticity of job search intensity	Curvature of search profile
m	0.253	Search-technology scale	Model-period normalization 0.164; survey weekly measures: NJS 0.057, SCE 0.068
π	1.000	Share of job search effort	Linear Technology
B	1.000	Disutility weight of job search	Normalized m
θ_t		Job separation rate profile	Chang, Hong and Karabarbounis (2018); average 1.43%, externally calibrated
ϱ_b	0.420	Average replacement rate	Standard
ϱ_{62}	0.500	Non-employment-value floor from age 62	Separate schedule parameter; age-62 timing aligns with SSA eligibility
$\boldsymbol{\kappa_b}$	**1.000**	**Young-to-midlife tilt of non-employment value**	Profile-selected magnitude; sign/pattern disciplined by Michelacci and Ruffo (2015), Aguiar et al. (2013a), and Kaplan (2012a)
$\boldsymbol{\chi}$	**2.000**	**Age gradient of new-match dispersion**	Model selection: acceptance (0.79, model 0.69); res. wage (0.96, model 0.89)
κ	0.520	New-occupation share of offers	Chang, Hong and Karabarbounis (2018)
λ_t		Occupational mobility (cubic in age)	Chang, Hong and Karabarbounis (2018)
$\rho_a,\ \rho_b$	0.502, 0.177	Persistence of match (a_o, b_o)	Chang, Hong and Karabarbounis (2018)
$\sigma_{a0}^2,\ \sigma_{b0}^2$	0.160, 1.3e-4	Entry match/prior variances	Chang, Hong and Karabarbounis (2018), PIM = 0
$\sigma_{\nu a}^2,\ \sigma_{\nu b}^2$	0.035, 6.6e-5	Match innovation variances	Chang, Hong and Karabarbounis (2018)
ℓ	1.000	Unknown standard-deviation share	PIM $= 0 \Leftrightarrow \ell = 1$; $\ell = 0.438$ only in robustness
ρ	0.756	AR(1) coefficient of persistent shock	Guvenen and Smith (2014)
σ_η	0.227	Std. dev. in persistent shock	Guvenen and Smith (2014)
σ_ε	0.100	Std. dev. in transitory shock	Guvenen and Smith (2014)

Table 5: Calibration. EIS: elasticity of intertemporal substitution; WTI: wealth-to-income ratio; SCF: Survey of Consumer Finances; CHK denotes Chang, Hong and Karabarbounis (2018).

scale. I use the NJS offer information in two distinct ways. First, the age profile of offer incidence disciplines the relative age profile of m_t. Second, the scalar scale is normalized so that the mean model-period offer probability is 0.164, the mean across the age-bin targets used in the computation. This 0.164 normalization is not a frequency conversion of either empirical weekly survey measure: NJS 0.057 and SCE 0.068 are reported separately as external arrival-rate evidence (Table 3). Because consumption, earnings, and learning are annual in the model, the per-period offer probability should not be read as an annual transition probability. The offer and separation profiles discipline the search block, while the unemployment rate is reported as an outcome. The remaining parameters enter the calibration as follows: ψ targets the peak-to-first search ratio; κ_b is profile-selected from the young-to-midlife search decline, with only its sign and qualitative age pattern externally disciplined; ϱ_{62} separately governs the late-career floor; χ is selected using the acceptance rate and reservation-wage ratio; and the EIS is disciplined by the wealth-to-income comparison. Thus κ_b is partially identified by the profile and is not calibrated from a young-to-old outside-option ratio.

• **Frequency and the unemployment rate** The unemployment rate is reported as an outcome, not a target, and the annual period is dictated by the estimated inputs rather than chosen for convenience. The worker-level income process is estimated at annual frequency by Guvenen and Smith (2014), and the occupational-learning block – the mobility profile λ_t, the persistence and innovation variances of the match, and the entry dispersion – is estimated at annual frequency by Chang, Hong and Karabarbounis (2018). A monthly or quarterly model would require re-estimating both processes at that frequency, which panels with annual earnings observations do not support, and pairing an annual earnings-and-learning block with a sub-annual search block would be internally inconsistent: the Kalman filter updates on a once-a-year earnings signal, so the speed of information updating is defined at annual frequency. Refining only the search period would therefore misstate the information block even though learning is not necessary for the hump. The model is kept annual, and as a robustness check Section 6.2 shows that the level gap is not an artifact of the annual period and that the hump is invariant to whether the offer rate or the unemployment rate disciplines the calibration.

• **Elasticity of job search intensity** ψ is an inverse of job search elasticity as in the equation (20). The value used in this paper, 2.5, is standard in Macro-Labor literature, as used in Chang and Kim (2006). I choose ψ to match the ratio $\max s_t / \min s_t$ in the data, which is 1.7957 in ATUS 0316 and 1.8429 in the NJS. The value in the model 1.7650.

Lise (2013) structurally estimates the search-elasticity parameter, obtaining $\psi = 0.168$ for high-school workers and $\psi = 0.268$ for college workers. These estimates imply substantially greater search elasticity than the calibration used here. Even targeting the steeper curvature in ATUS 0311, whose peak-to-trough ratio is 2.9967 in Aguiar et al. (2013), would require less elasticity than the estimates in Lise (2013). I target the similar, more moderate curvature in ATUS 0316 and the NJS because a high value of $1/\psi$ also makes it difficult to match life-cycle job-finding rates.

• **Linear job-search technology and age-dependent search productivity** The NJS reports whether an offer arrives over the survey reference period by age. Given the benchmark linear technology ($\pi = 1$), I choose the age profile of m_t to reproduce the age profile of offer arrival, not the job-finding rate; job finding also depends on the acceptance decision. Because the model allows at most one offer in a period, the empirical offer measure is treated as a binary arrival indicator.

One may argue that an age-dependent m_t mechanically generates the hump in search. The data imply the opposite pattern: the offer-arrival measure falls with age while search time is hump-shaped. Hence the implied $m_t \propto p_t / s_t^{\pi}$ declines with age, and using the offer profile in the calibration does not generate the hump in search effort.

The SCE helps interpret this decline. Young searchers file twice as many applications per hour of search (0.32 against 0.17 for ages 50–64), while offers per application are nearly flat in age. Thus, the falling offer rate mainly reflects fewer applications per hour rather than a lower return to an application. I report the implied m_t profile as a calibration input and do not interpret it as the mechanism generating the hump.

Related to job search productivity, the weight of disutility parameter B is not identified separately with search productivity m. Thus, as in other literature, I set $B = 1$ to normalize

m as in Lise (2013) and Lentz (2009).

• **Income process** I use estimated values in Guvenen and Smith (2014) for ρ, σ_β, σ_η and σ_ε. Rigorously, Guvenen and Smith (2014)'s estimates are based on *employed* workers' earnings data. Thus, those values could be biased in the model since the model considers unemployed workers' latent earnings process. In standard life-cycle literatures, those values are calibrated/estimated usually to match the increasing consumption inequality. The simulated result shows the increasing consumption inequality over the life-cycle.

• **Job separation rate** The age profile and average scale of the exogenous separation rate θ_t are taken from Chang, Hong and Karabarbounis (2018) without adjustment. The unemployment rate is therefore not used to calibrate θ_t and is reported as an untargeted outcome.

Again, we can consider age-dependent job separation rate and check whether it could affect search intensities. As shown by many literature[17], the employment to unemployment (EU) rate is decreasing profile over the life-cycle. Note that the job search effort in the model is robust to search productivity, which affects relatively more significantly. Even if I computed the model with age-dependent job separation rates, it does not affect job search profile[18]

• **Time Discount and the intertemporal elasticity** With annual risk free rate $r = 0.03$, the discount factor is set to the standard annual value $\delta = 0.950$, and the wealth-to-income (WTI) ratio is disciplined through the EIS instead. Under CRRA the WTI ratio could only be moved by distorting either δ or γ, both of which also price the occupational gamble; under Epstein–Zin the EIS moves saving while leaving risk pricing at $\gamma = 5$ untouched. The model statistic is aggregate risk-free assets relative to aggregate income. The capital–output ratio of 3.2 targeted by Chang, Hong and Karabarbounis (2018) and the SCF household mean net-worth-to-income ratios between 5.6 (Gálvez and Paz-Pardo, 2025) and 7.0 are not identical empirical objects; I therefore use them as a broad comparison rather than as a single literal target. The benchmark EIS of 1.2, a standard value, yields an aggregate model ratio of 4.81, between the CHK and SCF benchmarks but below the SCF-only mean range. The corresponding median WTI is 3.18, higher than the Panel Study of Income Dynamics (PSID) median of about 1.1 (Guvenen and Smith, 2014) because the single risk-free asset and the absence of a housing or retirement saving motive compress the lower tail of the wealth dis-

[17]See Choi et al. (2015) and Menzio et al. (2016). They use Current Population Survey (CPS) and U.S. Census' Survey of Income and Program Participation (SIPP).

[18]Moderate but the job separation rate affects employed workers' saving choice as discussed in Section 3. If θ is large, the precautionary savings increase.

tribution. Setting the EIS to the CRRA value $1/\gamma = 0.2$ would raise the aggregate ratio to 6.02. That is still within the SCF range, but the precautionary motive is then strong enough to dominate the cross-section of search (Figure 8), so the benchmark keeps the standard EIS.

6 Quantitative Analysis

In this section, I report performance of the quantitative model and implement various quantitative studies. In Section 6.1, I report how the quantitative model fits the hump-shaped job search profile, unemployment rate over the life-cycle, job finding rate and job acceptance rate. In Section 6.3, I study how information and uncertainty affect to job acceptance rate to have better and deeper understanding of uncertainty effect and wealth effect. In Section 6.4, I study cross-sectional perspectives of job search intensities with respect to type, updated belief and wealth.

6.1 Quantitative Result: Benchmark

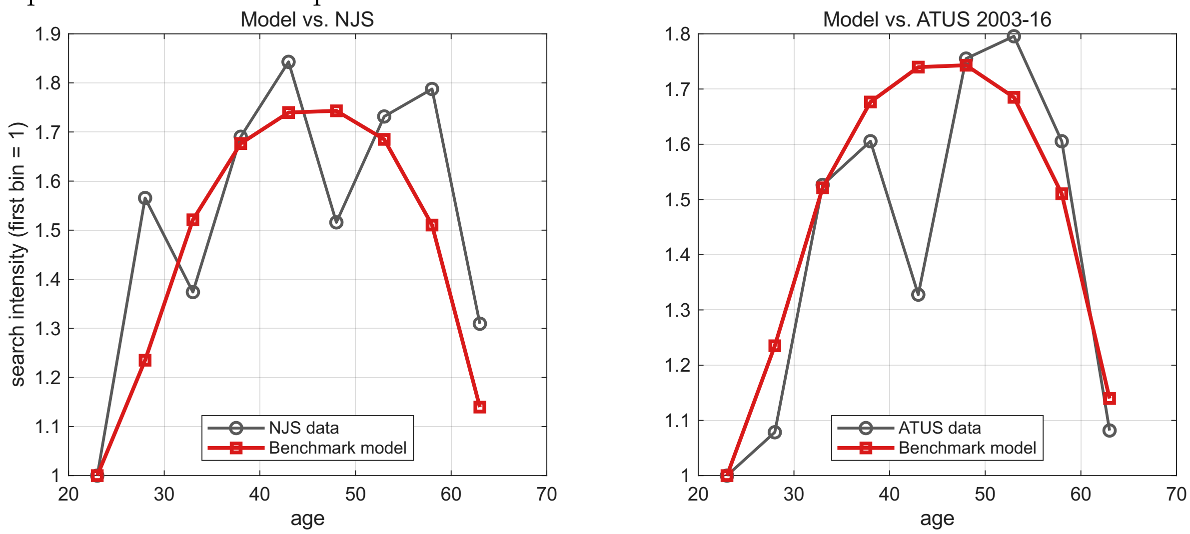
This section shows the quantitative results of the model. Figure 5 shows that the benchmark model explains the hump-shaped job search profile. The left panel plots the benchmark against the NJS profile together with its 95% bootstrap band (clustered by respondent); the right panel repeats the comparison for the ATUS 2003–16. The model reproduces the rise of roughly 55 log points from the first bin, places the peak in the 46–50 range, between the NJS peak at 41–45 and the ATUS peak at 51–55, and turns down thereafter; everywhere it lies within the sampling bands of both data sets. The fit to the ATUS is the tighter of the two, with a sum of squared errors (SSE) of 0.22 against 0.30 for the NJS, because the model produces a smooth hump that matches the ATUS shape closely and cannot reproduce the sharp single-bin spike at ages 26–30 in the NJS. I take the ATUS as the primary profile reference, since it is a nationally representative time-use measure and the benchmark matches its smooth hump most closely. The NJS, though limited to one state, supplies the offer, acceptance and reservation-wage moments that discipline the mechanism and provides an independent check on the profile shape. Table 6 collects the corresponding moments.

Two remarks on the relationship to the data. First, the model's peak-to-first ratio of 1.70 on the common 70×60 grid sits within one bootstrap standard error of both data profiles: the NJS point estimate is 1.84 (s.e. 0.23, 95% CI $[1.55, 2.44]$ on the peak) and the ATUS ratio is 1.80, so the profile is not rejected by either source. Second, the required amplification is itself smaller than the raw profile suggests, because the SCE decomposition

Moment	Data	Model	Source / status
Empirical weekly offer measures	NJS 0.057; SCE 0.068	N/A	Survey-frequency external cross-validation
Model-period offer normalization	0.164	matched	Computational normalization from NJS age-bin targets; disciplines m_t
Average separation rate	0.0143	matched	Chang, Hong and Karabarbounis (2018); targets scale of θ_t
Search profile, peak bin	41–45 / 51–55	46–50	NJS / ATUS; untargeted
Search profile, peak/first ratio	1.84 / 1.80	1.70	NJS / ATUS; targets ψ
Search profile, SSE vs. ATUS (NJS)	N/A	0.22 (0.30)	ATUS, NJS; untargeted
Acceptance rate given an offer	0.79	0.69	NJS; identifies χ
Reservation wage / previous wage	0.96	0.89	SCE; identifies χ
Aggregate asset/income comparison	CHK $K/Y = 3.2$; SCF WTI 5.6–7.0	4.81	broad comparison; disciplines EIS
Average unemployment rate	0.065	0.122	outcome (frequency caveat, Section 5)

Table 6: Benchmark fit. The "Source / status" column records how each moment enters the calibration or model-selection exercise: ψ is set to the search-profile curvature; κ_b is selected from the young-to-midlife profile, with its direction externally disciplined; ϱ_{62} separately governs the late-career floor; χ is selected by the acceptance rate and reservation-wage ratio; the EIS is disciplined by the asset/income comparison; and the peak bin, remaining profile SSE, and unemployment rate are untargeted outcomes. NJS 0.057 and SCE 0.068 are weekly survey measures used only as external comparisons, whereas 0.164 is the model-period computational normalization. SSE is the sum of squared errors over the nine age bins.

Figure 5: Benchmark model: Hump-shaped job search profile. Shaded areas are 95% bootstrap bands on the data profiles.



of Section 2.3 shows that roughly half of the age variation in search *time* reflects time per application rather than applications, so the effort object the model prices needs to rise by less than the measured hours profile.

The unemployment-rate comparison over the life cycle is omitted: as discussed in Section 5, at annual frequency the offer-rate, separation-rate and unemployment-rate levels are not simultaneously attainable, and the model is calibrated to the first two. The average simulated unemployment rate, the mean over working ages of the non-employed share of the labor force, is 12.2% against 6.5% in the data; reconciling the levels requires a quarterly or monthly time period and is deferred. Section 6.2 shows as a robustness check that the hump is unchanged whether the offer rate or the unemployment rate disciplines the calibration.

In the model, even if agents found jobs, if the value of being employed based on offered earnings is lower than the value of staying in unemployment, they can reject the job offer. Since the NJS includes the information that 1) whether survey respondents got job offers and 2) whether they accepted or not, we can see how the model fits job finding rates and job acceptance rates separately.

The acceptance rate and reservation-wage ratio are model-selection moments rather than purely untargeted validation moments. Conditional on receiving an offer, the NJS acceptance rate is 0.79, and the benchmark delivers 0.69. Under acceptance on the prior, with no reservation rule for new matches, the model's acceptance rate exceeds 0.94 in every specification examined, which performs poorly relative to the data. The reservation-wage level is the

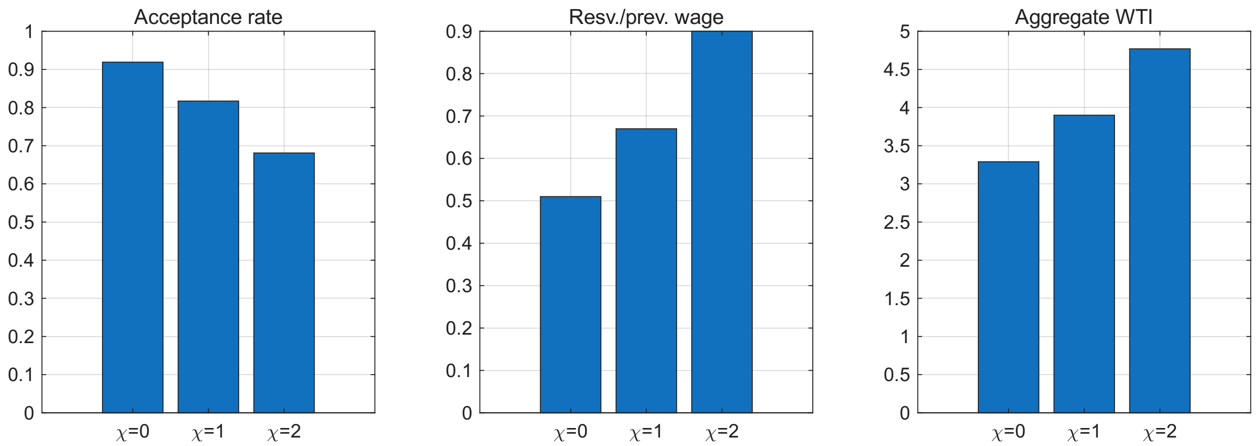


Figure 6: Model selection across specifications. Bars are three calibrated specifications that fit the search profile comparably well; dashed lines are the data. The benchmark is chosen because it brings the reservation-wage ratio closest to the SCE value and places the asset/income ratio between the CHK and SCF comparison benchmarks, at a moderate undershoot of the acceptance rate.

harder moment, and the benchmark reaches 0.89 against the SCE ratio of 0.96. Section 6.2 uses these two moments jointly, together with the asset/income comparison, to select the dispersion gradient χ.

In Section 6.3, I study what determines the job acceptance rate in the model by using a locally weighted regression (LOWESS) as in Hall and Mueller (2018). Specifically, I study how the information adjustment (ξ), the wealth level and uncertainty affect the job acceptance decision. Because the job acceptance implies the relative value of being employed, it is also directly related to job search intensities.

6.2 Model Selection, Validation and Decomposition

This subsection documents why the benchmark is the specification it is, and what each channel contributes. Three calibrated specifications ($\chi = 0, 1, 2$, each with $\kappa_b = 1$) fit the search profile with losses that, given the bootstrap bands of Figure 5, cannot be sharply separated on the profile alone, so the selection comes from the non-profile moments (the acceptance rate and the reservation-wage ratio) in Figure 6. Raising the dispersion gradient χ from 0 to 2 moves the acceptance rate from 0.93 down through the NJS value of 0.79 to 0.69, lifts the reservation-wage ratio from 0.50 toward the SCE value of 0.96 (reaching 0.89), and raises the aggregate asset/income ratio from 3.3 to 4.8, between the CHK and SCF comparison benchmarks but below the SCF-only mean range. The reservation wage is the moment the screening protocol is built to address, and the one the specifications without a dispersion gradient miss most badly. The benchmark $(\chi, \kappa_b) = (2, 1)$ brings it almost to the data and places the asset/income ratio between the comparison benchmarks, at the cost of a moderate undershoot of the acceptance rate (0.69 against 0.79). Two conclusions follow. The specification without any dispersion gradient performs poorly on the non-profile moments ($\chi = 0$: acceptance far too high, reservation wages far too low), and it is the reservation-wage evidence, not the profile, that identifies χ.

Table 7 makes this identification explicit and separates the roles of the two age gradients. Within each κ_b block, raising χ from 0 to 2 moves the acceptance rate monotonically from 0.93 to 0.69 and the reservation-wage ratio from 0.50 to 0.89, so these two non-profile moments, and not the profile, pin down χ; the data values (0.79 and 0.96) bracket $\chi \in [1, 2]$ and select $\chi = 2$ on the reservation wage. The outside-option gradient κ_b behaves differently: within each χ column it barely moves the acceptance rate, the reservation wage or the wealth ratio (at $\chi = 2$ the triple is $(0.66, 0.95, 4.79)$ at $\kappa_b = 0$ and $(0.69, 0.89, 4.79)$ at $\kappa_b = 1$), while it sharply lowers the profile loss. This is partial rather than external point identification. The magnitude of κ_b is selected from the young-to-midlife portion of the search profile; the literature and NJS family-insurance evidence discipline its sign and qualitative pattern, not its numerical value. Mechanically, $\kappa_b = 1$ gives the *unfloored* component an endpoint ratio of $(1 + \kappa_b/2)/(1 - \kappa_b/2) = 3.0$, but that ratio is neither a calibration target nor the ratio in the implemented schedule. The separate age-62 floor binds: in units of average earnings, b_t^U is about 0.63 at age 21, around 0.42 in midlife, roughly 0.25 immediately before age 62, and 0.50 thereafter. The resulting schedule is U-shaped near retirement. Hence I do not describe $\kappa_b = 1$ as a young-to-old external calibration.

Two features of the calibration deserve emphasis. The acceptance rate conditional on an offer is a moment the life-cycle search literature rarely reports because most data do not separate offer arrival from acceptance. Here it enters the joint model-selection exercise with the reservation-wage ratio: the benchmark delivers 0.69 against 0.79 for acceptance and 0.89 against 0.96 for the reservation-wage ratio. More broadly, the benchmark is evaluated jointly against the search profile, the offer-arrival profile, acceptance, reservation wages, wealth, and occupational mobility. Reproducing the search profile is not by itself decisive; the additional margins distinguish mechanisms that otherwise generate similar humps.

Table 8 separates two objects that the decomposition groups together: the actual cross-sectional dispersion of occupational matches and the share of that dispersion initially unknown to the worker. The benchmark corresponds to PIM $= 0$ and $\ell = 1$: actual match dispersion is fixed at its calibrated value and the entire match is initially unknown. The partial-information experiment keeps the same actual dispersion but sets $\ell = 0.438$, so the unknown variance share is $\ell^2 = 0.438^2$. Full information corresponds to PIM $= 1$ and $\ell = 0$,

χ	κ_b	acceptance (data 0.79)	resv./prev. wage (data 0.96)	aggregate WTI (CHK/SCF comparison)	profile SSE (vs NJS)
0	0.0	0.91	0.53	3.24	3.66
0	0.5	0.92	0.51	3.27	2.63
0	1.0	0.93	0.50	3.30	1.58
1	0.0	0.82	0.68	3.88	3.17
1	0.5	0.82	0.66	3.89	2.01
1	1.0	0.83	0.65	3.91	0.90
2	0.0	0.66	0.95	4.79	2.06
2	0.5	0.68	0.92	4.81	0.73
2	**1.0**	**0.69**	**0.89**	**4.79**	**0.32**

Table 7: Model selection for the two age gradients. Every cell recalibrates the search-technology scale to the model-period normalization 0.164. The acceptance rate, reservation-wage ratio, and asset/income ratio are model-selection moments for χ. The magnitude of κ_b is profile-selected from the young-to-midlife segment, while external evidence disciplines only its sign and qualitative pattern; the separate age-62 floor is held fixed in every cell. The benchmark is $(\chi, \kappa_b) = (2, 1)$. Profile SSE is the sum of squared errors against the NJS profile over the nine age bins. Every cell is computed on the production grid ($n_x = 70$, $n_a = 60$, seven quadrature nodes, 30,000 workers, seed 2026).

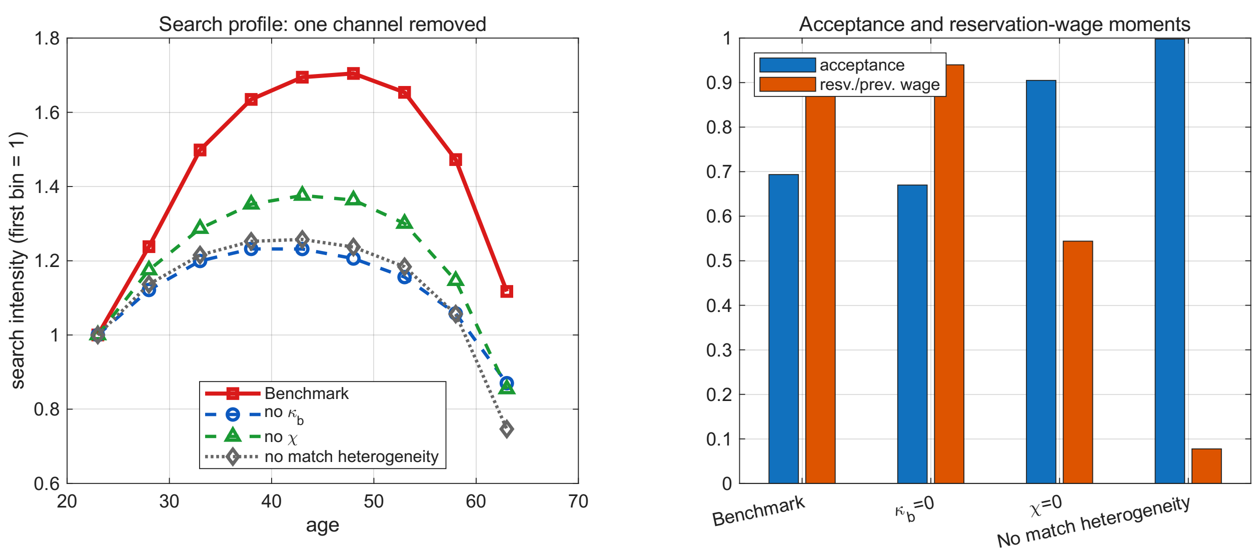


Figure 7: Decomposition of the benchmark. Left: search profiles when one channel at a time is removed and m is recalibrated to the offer rate. Right: the acceptance rate and the reservation-wage ratio across the same counterfactuals. The final specification removes match heterogeneity, rather than merely revealing the realized match.

Initial information structure	Actual match dispersion	Unknown variance share ℓ^2	Peak/ first	Acceptance rate	Reservation-wage ratio
No private information	Fixed	1	1.705	0.694	0.882
Partial information	Fixed	$0.438^2 = 0.192$	1.772	0.711	0.834
Full information	Fixed	0	1.837	0.720	0.776
No match heterogeneity	0	0	1.258	0.998	0.078

Table 8: Information structure and quantitative outcomes. At entry $q_1 = a_o + b_o$. The benchmark maps PIM $= 0$ to $\ell = 1$ (no private information), whereas full information maps PIM $= 1$ to $\ell = 0$; the table reports the unknown variance share ℓ^2. "Fixed" holds the calibrated cross-sectional dispersion of realized occupational matches constant; its simulated mean variance is 0.29674 in each of the first three rows. Each entry and occupational-switch innovation is decomposed into independent known and unknown components: the known component shifts the prior mean, and only the unknown component enters the Kalman covariance. Each row uses the same 70×60 asset grid, seven-node signal quadrature, seed 2026, and 30,000 simulated workers; the search-technology scale is adjusted to the model-period offer normalization of 0.164 (realized means range from 0.162 to 0.165). This normalization is distinct from the NJS and SCE weekly survey measures 0.057 and 0.068.

again holding actual dispersion fixed. In the code, each entry and occupational-switch innovation is split into independent known and unknown components; the known draw shifts the prior mean, whereas only the unknown component enters the Kalman covariance. The simulated mean variance of the realized match remains 0.29674 in all three rows. By contrast, the no-match-heterogeneity experiment sets both realized dispersion and initial uncertainty to zero.

The results show that learning is not required for the hump. As initial information increases, the peak-to-first ratio rises from 1.705 to 1.772 and then 1.837 under full information. Acceptance rises more modestly, from 0.694 to 0.711 and 0.720, while the reservation-wage ratio falls from 0.882 to 0.834 and 0.776. Thus, revealing a dispersed match changes selectivity but does not remove the hump. Removing match heterogeneity itself is much stronger: the peak-to-first ratio falls to 1.258, acceptance rises to 0.998, and the reservation-wage ratio falls to 0.078. The relevant distinction is therefore not simply information versus no information, but information about a dispersed match versus elimination of the match distribution.

One might ask whether a higher coefficient of relative risk aversion would deliver the opposite conclusion, since γ prices the match gamble. Table 9 repeats the information experiment for higher γ, holding the elasticity of intertemporal substitution fixed and recalibrating the search-technology scale to the model-period normalization in every cell. The uncertainty effect does strengthen with γ, and at $\gamma = 8$ the sign reverses: full information then flattens the profile rather than steepening it. That configuration is not a viable benchmark, however.

At $\gamma = 8$ the model already produces a peak-to-first ratio of 2.54 without any information channel, against 1.80–1.84 in the data, the acceptance rate falls to 0.58 against 0.79, and the reservation wage exceeds the previous wage. The profile loss rises by an order of magnitude, and it rises further at $\gamma = 12$. Higher risk aversion also raises precautionary saving, so γ moves the profile, the acceptance margin and the wealth ratio together rather than isolating perceived risk. I therefore retain $\gamma = 5$, which is the value used by Chang, Hong and Karabarbounis (2018) and the most coherent of these specifications across the profile and the non-profile moments.

γ	peak/first no private info.	peak/first full info.	difference	acceptance (data 0.79)	resv./prev. wage (data 0.96)	profile SSE (vs ATUS)
5	**1.71**	**1.84**	+0.14	**0.69**	**0.89**	**0.20**
8	2.54	2.35	−0.19	0.58	1.10	4.25
12	3.60	4.14	+0.54	0.44	1.43	19.03

Table 9: Sensitivity of the information experiment to risk aversion. Each cell recalibrates the search-technology scale to the model-period offer normalization 0.164, with the elasticity of intertemporal substitution held at its benchmark value. “Difference” is the change in the peak-to-first ratio when initial information is raised from none to full, holding realized match dispersion fixed; a negative entry means that information flattens the hump. The acceptance rate and the reservation-wage ratio are reported for the no-private-information column. The data peak-to-first ratio is 1.80–1.84. The benchmark is $\gamma = 5$.

Figure 7 reports the one-channel-at-a-time decomposition. Removing the outside-option gradient ($\kappa_b = 0$) flattens the young end of the profile almost completely, lowering the peak-to-first ratio from about 1.70 to 1.23, so κ_b carries much of the *young* end of the hump. Removing the dispersion gradient ($\chi = 0$) has a smaller effect on the profile (a fall to 1.38) but raises acceptance to 0.90 and lowers the reservation-wage ratio to 0.55. The information experiment in Table 8 sharpens the interpretation of the final counterfactual. Revealing the realized match leaves both its unconditional distribution and a pronounced hump in place; removing match heterogeneity eliminates the distribution itself and produces the much larger change in acceptance and reservation wages. Occupational learning affects selectivity, while the profile is jointly generated by the outside-option gradient, realized match dispersion, wealth, and the remaining career horizon.

In terms of the net benefit of finding a job $\mathcal{J}_t$ that drives the first order condition (20), matching the peak-to-first ratio of about 1.8 common to the two data sets requires $\mathcal{J}$ to rise by a factor of $1.8^{\psi} \approx 4.3$ over the life cycle. The benchmark's two age gradients jointly deliver about $1.70^{\psi} \approx 3.8$; removing either one drops the factor to 1.7 ($\kappa_b = 0$) or 2.2 ($\chi = 0$), and the SCE applications evidence implies the effective requirement is roughly half of 4.3 once time per application is accounted for. The information experiment shows that this amplification cannot be attributed to unresolved uncertainty alone: the outside option, realized match dispersion, wealth, and the horizon jointly shape the net surplus.

Figure 8 isolates the role of Epstein–Zin preferences. Setting EIS $= 1/\gamma = 0.2$ recovers the additively separable CRRA model at the same $\gamma = 5$, $\chi = 2$, $\kappa_b = 1$ and the same offer-rate target. The CRRA profile (left panel) fits the search profile about as well in levels, with a peak-to-first ratio that is if anything slightly higher, because the low intertemporal elasticity forces a strong consumption-smoothing motive that amplifies the transmission of the age gradients. That same low elasticity over-accumulates wealth, and it also distorts the cross-section. The CRRA aggregate wealth-to-income ratio is 6.0, against 4.8 under Epstein–Zin, and its precautionary motive is strong enough to *reverse* the sign of the cross-sectional relationship between search and the belief. Under CRRA search falls in both the belief and the true occupational match, because the dominant wealth effect swamps the learning channel and the positive correlations of Figure 10 turn negative, while the acceptance rate falls to 0.59. CRRA thus conflates the two effects the paper separates: one parameter must both price the occupational gamble and govern saving, so fitting the time-series profile forces a wealth effect strong enough to overturn the cross-sectional evidence. Epstein–Zin holds risk pricing fixed at $\gamma = 5$, comparable to Chang, Hong and Karabarbounis (2018), and sets the saving motive to a standard elasticity that places the aggregate asset/income ratio between the broader CHK and SCF comparison benchmarks and keeps the cross-section intact. That is why it is the benchmark.

A second experiment addresses the acceptance protocol directly. Allowing endogenous separation in the spirit of Jovanovic (1979) and Mortensen and Pissarides (1994), so that workers may quit into unemployment after observing the year's earnings and forfeit UI, leaves the profile essentially unchanged at the calibrated offer rate: re-employment is slow enough that the option to experiment is nearly worthless, and endogenous quits substitute almost one-for-one for exogenous separations. The natural question "why can a bad match not simply be discarded?" is thus answered within the model: it can, and at the observed offer arrival rate almost no one does.

Robustness: frequency and the unemployment rate. Two checks bear on the unemployment rate, which the calibration reports as an outcome rather than a target. First, the offer-rate/unemployment tension is not an aggregation artifact that a higher frequency would remove. The NJS weekly offer hazard of 0.057 and the benchmark acceptance of 0.69 imply a weekly job-finding rate of 0.039, which with a weekly separation rate of 0.0143/52 produces a steady-state unemployment rate below one percent; the annual model, at the other extreme, saturates the offer probability and produces twelve percent. Neither brackets

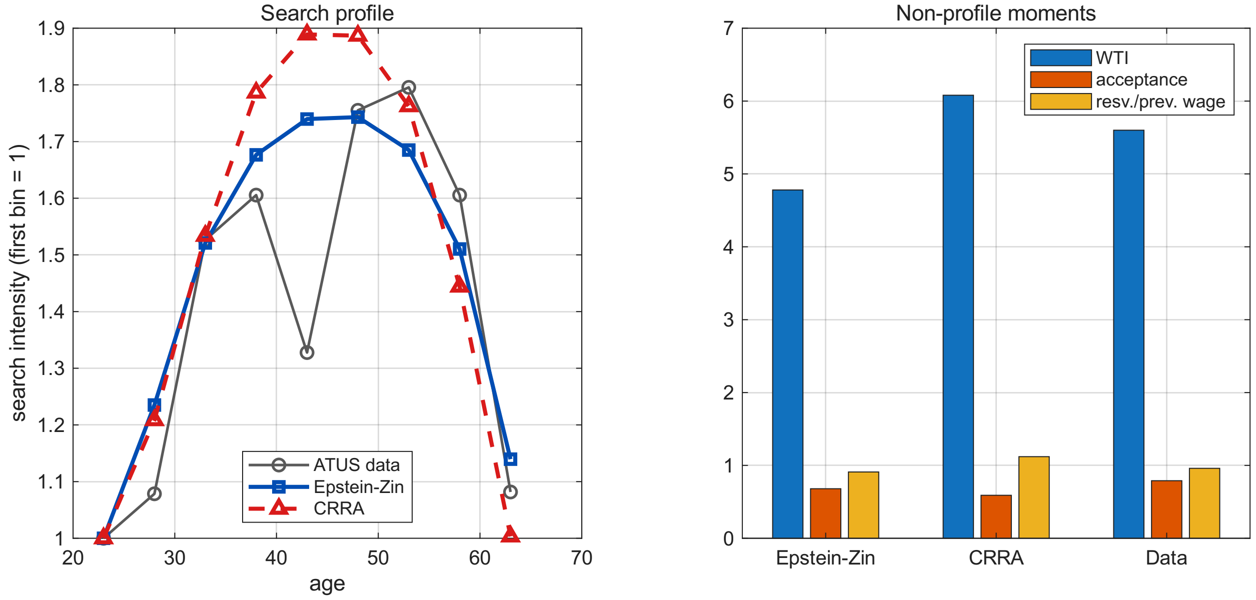


Figure 8: Epstein–Zin versus CRRA at the benchmark specification ($\chi = 2$, $\kappa_b = 1$, screened acceptance, $\gamma = 5$; CRRA sets EIS $= 1/\gamma = 0.2$). Left: the search profile against the ATUS. Right: the non-profile moments, where the two preferences differ; CRRA over-accumulates wealth and reverses the cross-sectional belief–search relationship. Dashed lines are the data values.

6.5%, because an offer hazard this high is inconsistent with a 6.5% unemployment rate at any frequency given the observed separation rate, a gap familiar from the job-finding literature rather than a consequence of the annual period. A genuinely higher-frequency structural model is left to future work because the earnings and learning processes are estimated at annual frequency. Second, the hump is invariant to which level moment pins the model down. If the unemployment rate is matched directly, by scaling the separation rate so that $u = 6.5\%$ while the offer probability is held at the model normalization of 0.164, the search profile is essentially unchanged (peak-to-first 1.76 against the benchmark's common-grid value of about 1.70, and profile SSE 0.32 against 0.30), because the profile shape is governed by the age gradients, realized match dispersion, wealth, and the remaining horizon rather than by the level of m or of the separation rate. The hump therefore survives whether the offer rate or the unemployment rate disciplines the calibration.

6.3 Job Acceptance: Information and Uncertainty

This section studies how information and uncertainty affect the value of employment, acceptance, and search intensity.[19] The results establish that information is important for selectivity and for cross-sectional differences in search. They do not imply that learning is necessary for the life-cycle hump; the full-information experiment in Section 6.2 rejects that stronger interpretation.

Job seekers are more likely to accept an offer when employment has a higher value conditional on offered earnings and the updated belief. The first-order condition (20) also implies that optimal search intensity increases with this value. Studying acceptance as a function of the information adjustment ($\xi_{i,t} = y_{i,t} - \hat{y}_{t|t-1}$) and uncertainty $\sigma_{y_{t+1|t}}$ therefore also helps explain search effort. Following Hall and Mueller (2018), I estimate a locally weighted regression (LOWESS) with bandwidth 0.3.

• **Information and Job Acceptance** Under imperfect information, job seekers update beliefs to infer the true occupational match. It is important because the match contains a level and a growth component that affect permanent income.

When a job seeker observes a signal above her prior prediction, rejecting the offer becomes more costly. A positive information adjustment, $\xi > 0$, therefore increases the probability of acceptance, particularly for a worker with little wealth. Even without a current offer, a positive ξ raises the expected benefit of finding a job and increases search effort. Consistent with the permanent-income hypothesis, the worker also consumes more and saves less, which further raises the value of employment relative to unemployment. Figure 9 reports the LOWESS estimate of the acceptance rate against ξ. More favorable signals raise acceptance, but at a diminishing rate. The absolute value of ξ can increase over the life cycle because the occupational match includes the growth component b_o. Wealth accumulation in the incomplete market also contributes to the diminishing response.[20]

• **Uncertainty and Job Acceptance** The preceding discussion concerns the mean belief. Job seekers also respond to uncertainty about future earnings, measured by the forecast standard deviation $\sigma_{y_{t+1|t}}$. When greater uncertainty raises the probability that future earnings fall below the value of unemployment, a risk-averse worker is less likely to accept an offer.

[19] The figures in this and the next subsection are produced from the benchmark occupational-learning model; here "belief" is the perceived occupational match $\hat{q}$, "type" is the true match $a_o + b_o t$, ξ is the signal surprise, and "uncertainty" is the forecast standard deviation, which is a deterministic function of age and occupational tenure. The simulation panels and the scripts that generate these figures are provided in the replication package (`run_figures.m`, `run_figures.do`).

[20] A sixth-degree polynomial specification also produces a declining segment.

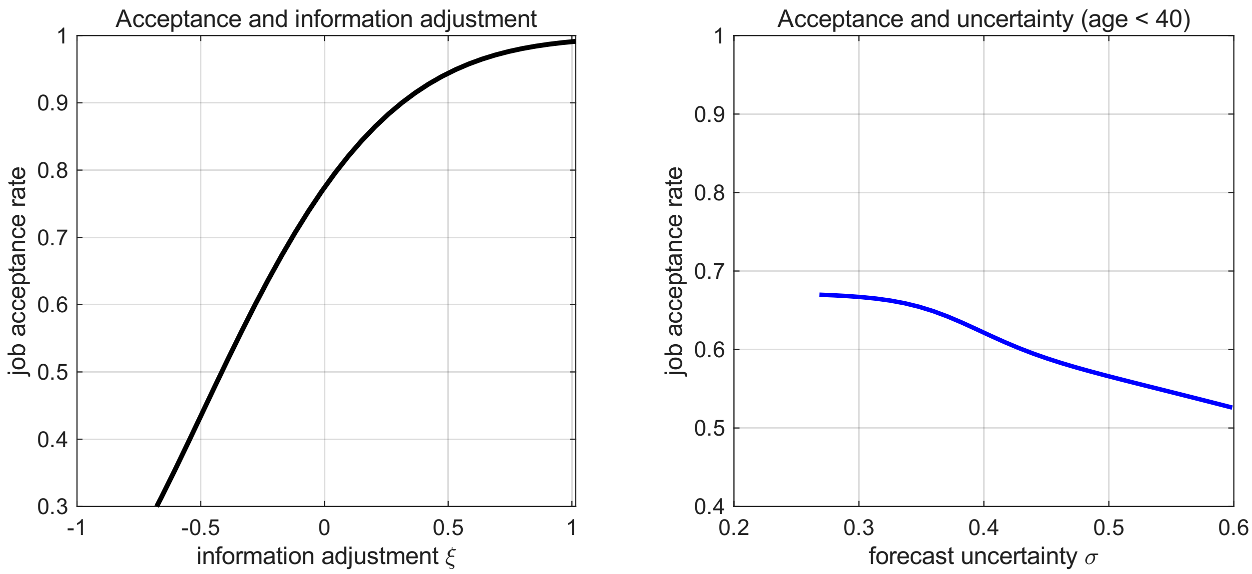


Figure 9: Left: job acceptance rate against the information adjustment ξ (kernel regression); more optimistic signals raise acceptance with diminishing returns. Right: job acceptance rate against forecast uncertainty for young job seekers (age <40); higher perceived uncertainty lowers acceptance. Prime-age job seekers face little residual uncertainty and are omitted for sparsity.

In the incomplete-markets McCall model, this relationship varies with age and wealth. Young workers face greater perceived risk and have accumulated little wealth to insure against persistent adverse shocks. Greater uncertainty therefore lowers both acceptance and search effort for these workers. Once workers are better informed and have sufficient wealth to absorb adverse shocks, a wider distribution also provides more upside potential and may increase acceptance.

The right panel of Figure 9 shows the effect of forecast uncertainty on acceptance for young job seekers (younger than age 40): higher perceived uncertainty makes them accept offers less likely, because they lack the accumulated wealth to insure a bad match. Prime-age job seekers, by contrast, have largely resolved their occupational uncertainty. The forecast standard deviation is a deterministic function of age and tenure and is compressed at older ages, so there is little residual variation to trace out, and they are omitted from the panel. The same forces operate on job search intensity through the first order condition (20), since search effort is proportional to the same net benefit that governs acceptance. The information experiment shows, however, that this channel is most clearly identified by acceptance and reservation wages; a hump persists even when the realized match is fully revealed.

6.4 Occupational Match, Belief and Job Search: Cross-Sectional Analysis

In this section, I study the cross-sectional properties of search intensity in the simulated data. Explaining the hump-shaped profile addresses when agents search more; the analysis here addresses who searches more at each age. It therefore provides a different perspective on the interaction between learning and the wealth effect.

At early ages, search intensity is more closely correlated with the updated belief than with the true occupational match because information is imperfect. Learning also affects the cross section through consumption-saving decisions. When a worker receives a favorable signal relative to her prior prediction, she updates her belief upward. This first-order effect raises search effort. Given current wealth, the worker also consumes more and saves less, which further raises search through the wealth channel. The information adjustment therefore has a stronger relationship with search intensity than either wealth or the true occupational match early in the life cycle.

At the latter stage of life cycle, job search intensities over mean belief (and the true occupational match) show an inverted-V shape. This is because of an interaction between Bayesian learning and accumulated wealth with finer information. Obviously, high- (low-) match experienced agents have accumulated large (less) wealth. This implies that the higher expected earnings from finding jobs makes low-match agents search jobs more intensively because they have lower value of outside options. However, from the threshold level, because high-match experienced agents have accumulated large wealth, they search jobs less intensively as they have higher future expected earnings. This implies that the simple correlation could have opposite sign with the marginal effect. The marginal effect of the true occupational match at the later stage of life-cycle is larger than it at the early stage as implied by Bayesian learning.

• **Early stage of the life cycle** Because information is imperfect, a young job seeker's decision is more closely related to her belief than to her true occupational match. The top row of Figure 10 represents this for young job seekers. While job search intensities over the true occupational match are dispersed and only weakly related (corr = 0.28), job search intensities over the updated belief are a clearly increasing function of it (corr = 0.43). As one would expect, the relationship between the information adjustment ξ and search intensities is similar to that of the updated belief (corr = 0.29), as shown in the right panel of Figure 11.

• **Later stage of life-cycle** One might expect experienced job seekers' search intensities

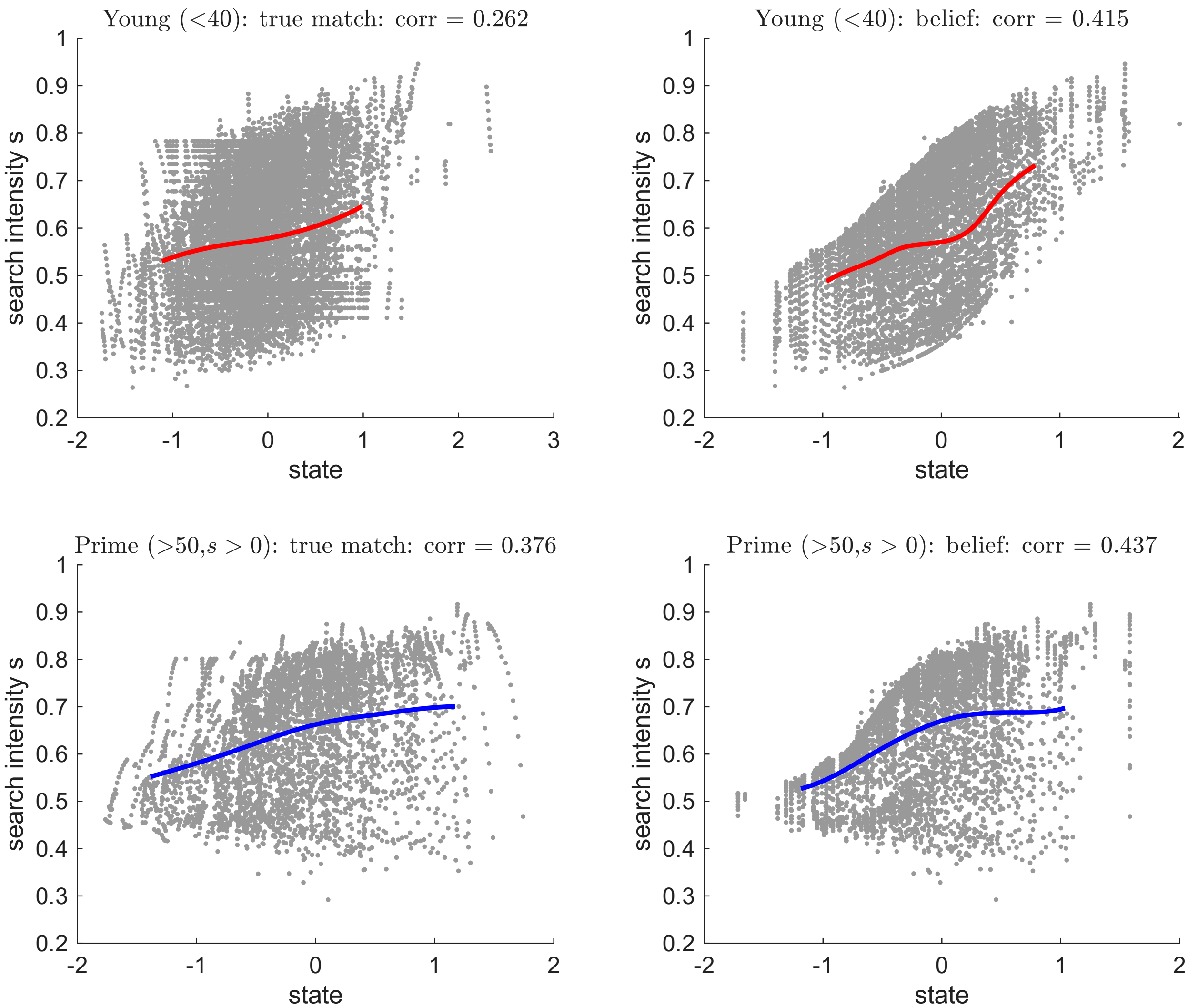


Figure 10: Cross-section of job search intensity against the true occupational match (left column) and the updated belief (right column), for young (<40, top) and prime (>50, bottom) job seekers. For the young, search tracks the belief (corr = 0.43) more closely than the true match (corr = 0.28), reflecting imperfect information; for prime-age job seekers the two correlations converge once the terminal-age (65) non-searchers are excluded (0.45 and 0.38), the cross-sectional signature of resolved uncertainty.

to increase in both the true match and the updated belief, since they are better informed. The bottom row of Figure 10 shows that, taken over all prime-age (>50) job seekers, both relationships appear to flatten (the correlations are 0.19 with the true occupational match and 0.24 with the belief). This apparent flattening is largely a composition effect. Every prime-age job seeker with zero search intensity is exactly at the terminal working age of 65, where search carries no payoff because the worker retires the following period, and it is these mechanical non-searchers, not the very wealthy, that depress the correlations. Excluding them, the correlations rise to 0.38 with the true occupational match and 0.45 with the belief. Once the terminal-age agents are set aside, well-informed prime-age job seekers track the true match nearly as closely as the belief, and the wide young gap between the two (0.28 against 0.43) has all but closed. This convergence of the type and belief correlations with age is the cross-sectional signature of resolved uncertainty; the residual, offsetting role of wealth is documented in Table 10 and Figure 11.

This pattern reflects an interaction between the wealth effect and the learning effect. Risk-averse experienced agents with high (low) matches accumulate large (small) wealth through consumption smoothing, and the better outside option that wealth affords pulls their search down, partly offsetting the learning effect. Under the recursive preferences of the benchmark this wealth effect is present but does not dominate: a higher elasticity of intertemporal substitution weakens the precautionary motive relative to CRRA, so the search–belief relationship stays positive at every age, and it is the terminal-age non-searchers, not wealth, that flatten the raw prime-age correlations. Table 10 isolates the two forces.

• **Marginal effect** Disentangling the wealth effect from the learning effect requires the joint distribution. Table 10 reports linear regressions of job search intensity in the simulated cross-section on the perceived match (the belief) or the true occupational match, together with log wealth.[21] The results imply the following. The wealth effect is negative wherever the perceived state is controlled, at -0.017 for the young and -0.025 for the prime in the belief specifications, and the young, who hold less wealth, respond more strongly relative to their holdings. The belief coefficient exceeds the true-match coefficient at every age, so search responds to the *perceived* match rather than the true one. That excess is widest for the young, whose belief coefficient (0.186) is more than double their true-match coefficient (0.081), and it narrows for the experienced (0.140 against 0.096) as beliefs converge on the truth, the signature of resolving uncertainty. Once the belief is controlled the true occupational match carries no marginal effect at any age: a joint regression that includes both puts the match coefficient at -0.001, insignificant, for both groups, so what reads as a "match

[21] Since many agents hold zero wealth, wealth enters as $\log(1 + a)$.

	Belief	True match	Wealth
Young	0.186^{***} (0.001)	.	-0.017^{***} (0.001)
Prime	0.140^{***} (0.002)	.	-0.025^{***} (0.001)
Young	.	0.081^{***} (0.001)	0.011^{***} (0.001)
Prime	.	0.096^{***} (0.002)	-0.013^{***} (0.001)

Table 10: Marginal Effect: $JS_{i,t} = \beta_{0,t} + \beta_1 Belief(\text{Match})_{i,t} + \beta_2 Wealth_{i,t} + u_{i,t}|_{t\in\{\text{Young,Prime}\}}$. JS is job search intensity and $Wealth$ enters as $\log(1+a)$; standard errors in parentheses; *** denotes significance at the 1% level.

effect" in the separate regressions is the belief acting through its correlation with the true match.

- **Wealth Effect and Information adjustment** Figure 11 plots job search intensity against log wealth (left) and against the information adjustment ξ (right), separately for young and prime job seekers. In the cross-section young search *rises* with wealth, because the wealthier young are disproportionately those who have drawn favorable signals and hold more optimistic beliefs; holding the belief fixed, the direct wealth effect is negative (Table 10). Search rises in ξ as well, most steeply for the young, while for the prime-age the relationship flattens as beliefs converge on the truth.

7 Conclusion

This paper shows that the hump-shaped life-cycle job-search profile reflects forces that the model disciplines jointly. The age gradient in the value of non-employment accounts for much of the low search effort of the young, while wealth accumulation and the shrinking career horizon lower search later in life. Occupational information shapes acceptance and reservation wages, but it is not necessary for the hump: holding realized match dispersion fixed, full information raises the peak-to-first ratio from 1.70 to 1.84. Removing match heterogeneity itself instead lowers the ratio to 1.258 and makes acceptance nearly universal. Reproducing the profile is therefore not decisive by itself. The joint behavior of search, acceptance, and reservation wages distinguishes learning about a dispersed match from eliminating match dispersion, and the paper also explains the cross-sectional implications of search effort based on the true occupational match and the updated belief.

This study suggests several directions for future research. First, the imperfect-information framework may help explain another life-cycle labor-supply pattern. As perceived risk is re-

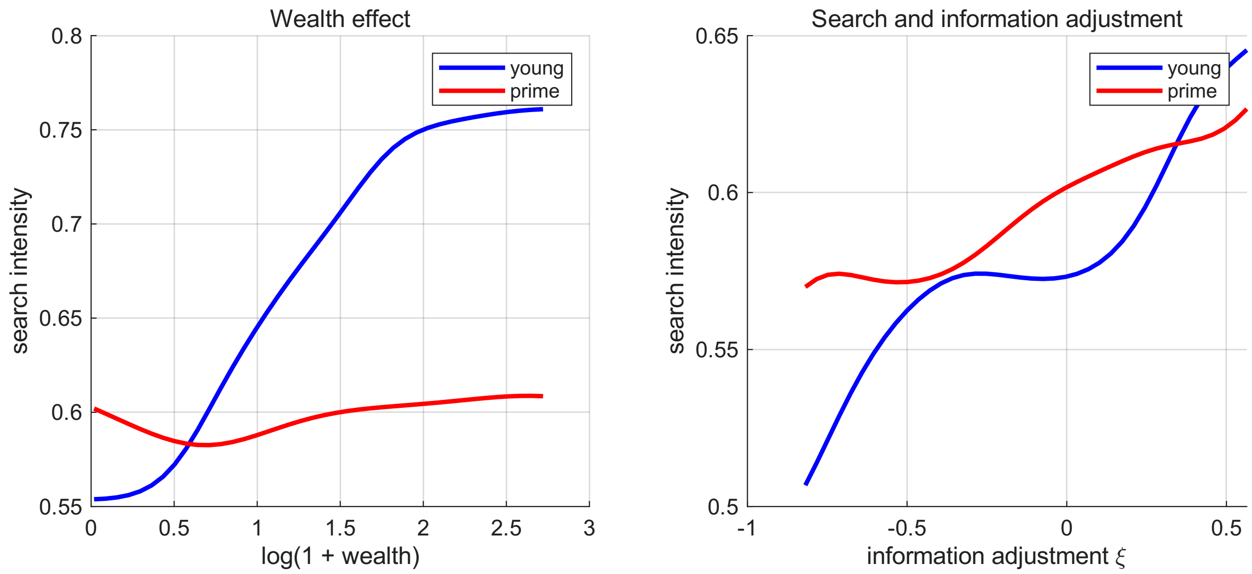


Figure 11: Left: job search intensity against log wealth for young and prime job seekers; the unconditional relationship is positive for the young, reflecting the correlation between wealth and optimistic beliefs, whereas the wealth effect holding beliefs fixed is negative (Table 10). Right: job search intensity against the information adjustment ξ; young job seekers with more optimistic signals search more intensively, while for prime-age job seekers the relationship flattens as beliefs converge on the truth.

solved, the precautionary labor-supply motive weakens, potentially generating a declining expected-hours profile over the life cycle.[22] Jointly identifying the dynamics of hours and job-search effort would therefore be useful. Second, Aguiar et al. (2013) document a declining life-cycle search profile in European data. Embedding country-specific estimates of the HIP process in the model would allow the information mechanism to be assessed before introducing differences in fiscal policy between the United States and European countries. Third, the SCE shows that the age decline in job-offer rates reflects applications per hour of search rather than the return to an application. Endogenizing the choice between the number and quality of applications, and linking it to reservation wages, is a natural extension. Finally, reconciling the levels of offer, separation, and unemployment rates requires a quarterly or monthly model, which the deterministic belief-covariance structure of the occupational block makes computationally feasible.

[22] See Flodén (2006) for the precautionary labor-supply mechanism and Rogerson and Wallenius (2009); Kaplan (2012); Badel and Huggett (2014) for life-cycle labor-supply dynamics.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the author used Claude Cowork and ChatGPT Codex for proofreading and for developing, debugging, and validating computational code. The author reviewed and edited the output as needed and takes full responsibility for the content of the published article.

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Appendices

A Supplement of empirical analysis

A.1 Measured Uncertainty: How reliable?

In this section, I provide indirect evidence on the relationship between $(y-r)^2$ and job search. Figure 12 shows a negative age-profile association between job search intensity and the realized offer–reservation gap. The figure is descriptive and should not be interpreted as showing that the realized gap is an exact measure of ex ante perceived uncertainty.

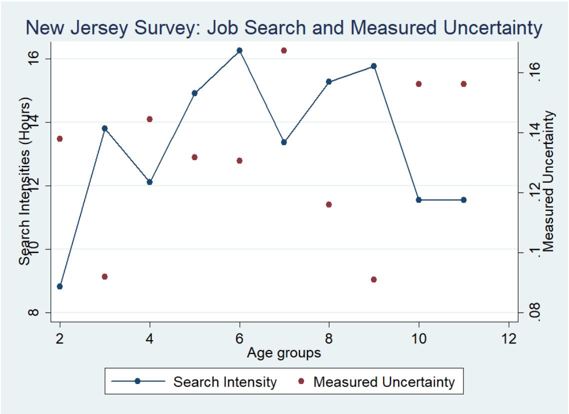

Figure 12: NJS: Job Search and Measured Uncertainty over the life-cycle

A.2 Uncertainty effect: Reservation wage and Offered wage

I here provide 1) the difference between job seeker's reservation wage who have a job offer and it who does not have a job offer without any control 2) the difference after control and 3) the positive relationship between offered wage and reservation wage.

Table 11 represents the difference between job seeker's reservation wage who have a job offer and it who does not have a job offer before the control and after the control. The reservation wage is controlled by age, gender, race, spouse's income, mortgage debts, household income, savings and education. And Figure 13 is the fitted value from A locally weighted regression (LOWESS) with bandwidth 0.3. The estimated coefficient in the linear regression with 1,000 bootstrap replications is 0.9641 with 0.0298 standard error and it is robust to various alternative specifications.

	Before control		After control	
Group	Mean	Std. Dev	Mean	Std. Dev
Non-offer	6.6748	0.0032	6.9107	0.0045
Offer	6.5939	0.0076	6.8259	0.0181
Difference	0.1009	0.0082	0.0848	0.0187

Table 11: Log of reservation Wage: Offer vs Non offer. Assumed unequal variance

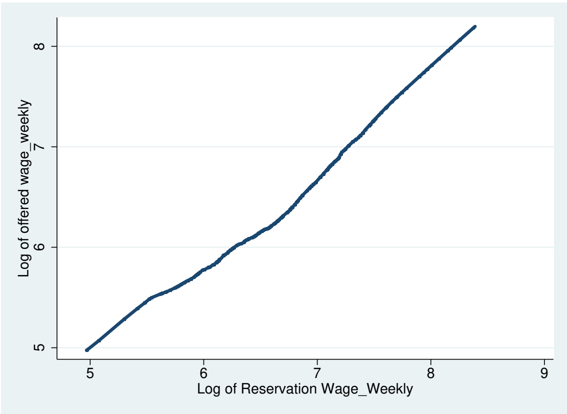

Figure 13: A locally weighted regression (LOWESS) with bandwidth 0.3. Dependent variable is a log of offered wage and an independent variable is a log of reservation wage. The estimated coefficient in the linear regression with 1,000 bootstrap replications is 0.9641 with 0.0298 standard error.

A.3 Wealth Effect: Fully specified estimation result

Table 12 represents the empirical evidence of wealth effect and other outside options to search intensities.

A.4 Time effect in the data: Normal vs. Recession

What we would need to consider is that time effect on the job search profile, i.e., whether there could be different job search dynamics in the boom and recession.[23] Because the ATUS is available only for 13 years, it is hard to handle the small sample issue. Thus, as an indirect evidence, I simply compare job search profiles in the normal period (2003 $\sim$ 2005) and in the crisis period (2007 $\sim$ 2009). Both of them show the hump-shaped profile but the job search profile in the crisis period look more close to the aggregated one (2003 $\sim$ 2011 or 2015). Because of the short time periods, it is hard to study the life-cycle dynamics in the business cycle dimension. One possible conjecture is that there was a structure break during the financial crisis and its effect dominates dynamics before the financial crisis. However, again, because we do not have long time series data, it cannot be identified whether it would be just because we have longer time series after the financial crisis in the ATUS or not. Also, since identifying aggregate shocks is not focus of this paper, I will not deeply study for this.

The results have two main features. First, the full-sample estimates are closer to those from the crisis period. Second, workers search more intensively during the recession, consistent with the broader empirical literature. Figure 14 presents the job-search profile for 2007 $\sim$ 2009, and Figure 15 presents the profile for 2004 $\sim$ 2006. Both figures use quadratic specifications selected by the same criterion as in Aguiar et al. (2013).

A.5 Search on the job in the data

Neither Aguiar et al. (2013) nor the model in this paper considers employed workers' search effort. This section provides supporting evidence on on-the-job search. First, employed workers search much less than unemployed workers, spending about eight minutes per week on average.[24] Second, their search profile is U-shaped, in contrast to the hump-shaped profile among unemployed workers. This pattern is qualitatively consistent with Topel and Ward (1992), who show that about two-thirds of occupational changes occur during workers' first ten years in the labor market. The evidence is descriptive and does not identify the

[23] See Mukoyama et al. (2018) for studies in the business cycle frequency.

[24] Employed workers seeking to change jobs may use intermediaries such as headhunters because their opportunity cost of time is higher. The ATUS does not identify this channel, and the associated fees would also constitute search costs.

Variable	Estimate
Savings	-0.9583^{***} (0.2667)
Spouse	-4.1520^{***} (0.8476)
Mortgage	1.9570^{**} (0.9134)
Number of household 1	1.8635 (2.6455)
Number of household 2	7.1823^{***} (2.7949)
Number of household 3	4.0834 (2.6221)
Number of household 4	0.1831 (2.8300)
Number of household 5	-4.5957 (2.9343)
Household Income 1	-18.2953^{***} (4.5678)
Household Income 2	-4.3828^{***} (2.7182)
Household Income 3	-11.4515^{***} (2.3425)
Household Income 4	-5.6947^{**} (2.2886)
Household Income 5	-7.8152^{***} (2.3764)
Household Income 6	-6.9023^{***} (2.3092)
Household Income 7	-7.2315^{***} (2.1524)
Household Income 8	-7.6098^{***} (2.3542)
Household Income 9	-8.1745^{***} (2.3542)
Household Income 10	-3.4271 (2.2939)
Household Income 11	-2.9058 (2.4407)

Table 12: Wealth Effect. Spouse=1 if a respondent's spouse has a paid job, Mortgage=1 if she has a mortgage debt and the number of household i=1 if the number of household is i. Savings is the categorical variable with 1= savings account is less than \$10,000, 2=\$10,000 $\sim$ \$24,999, 3=\$25,000 $\sim$ \$49,999, 4=\$50,000 $\sim$ \$99,999 and 5=more than \$100,000. Household income is also the categorical data such that 0=less than \$10,000, 1=\$10,000 $\sim$ \$19,999 , 2= \$20,000 $\sim$ \$29,999 , 3=\$30,000 $\sim$ \$39,999 and i=\$$i \times 10,000 \sim \$(i+1) \times 10,000 - 1$. $*$ represents that estimates are significant in 10%, $**$ represents that estimates are significant in 5% and $***$ represents that estimates are significant in 1%.

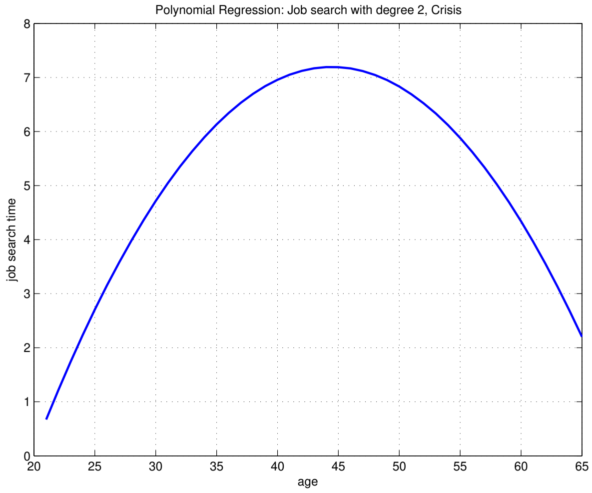

Figure 14: Crisis periods: 2007 ∼ 2009

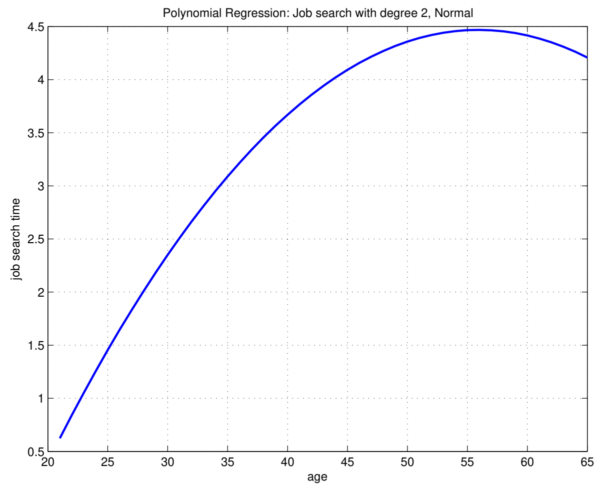

Figure 15: Normal periods: 2004 ∼ 2006

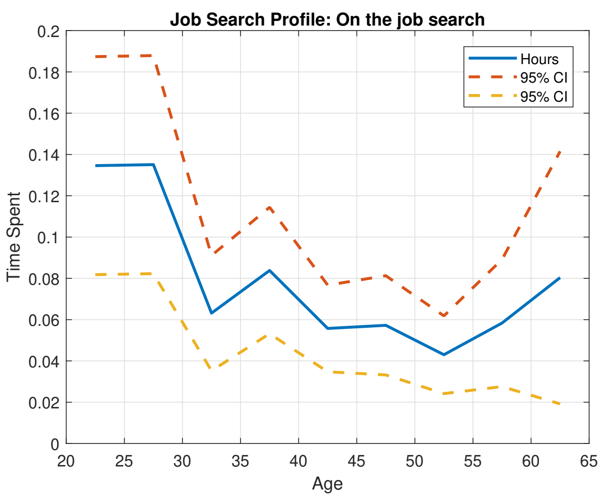

Figure 16: On the job search: 2003 ∼ 2016

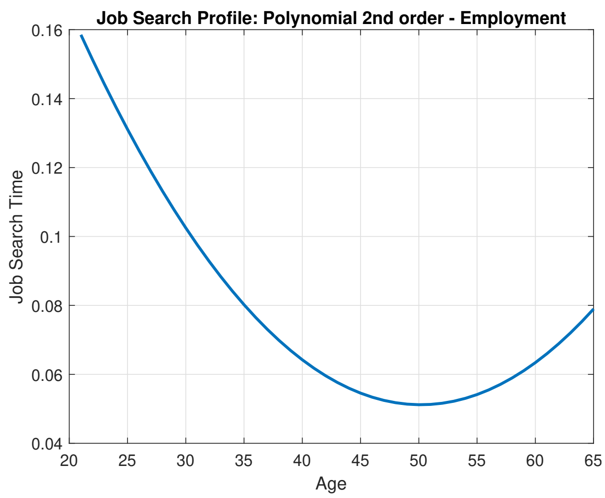

Figure 17: On the job search: 2003 ∼ 2016

underlying mechanism. Figure 16 presents the age-dummy estimates, and Figure 17 presents the quadratic age-polynomial estimates.

B Computational Appendix

Initial-information notation. The code and text use the same mapping. The entry match is $q_1 = a_o + b_o$, with $\hat{q}_{1|0} = 0$ before any private earnings signal. The benchmark is PIM $= 0$ and $\ell = 1$; full information is PIM $= 1$ and $\ell = 0$. The implementation stores ℓ as lam_pr, and lam_pr^2 is the unknown variance share. This convention also applies when an occupational transition draws a new match. The employment-transition labels E, S and E, N mean stay and new occupation, respectively, and are not components of the belief state

$\hat{S}$. The state vector is cash on hand, the three belief components $(\hat{q}, \hat{b}, \hat{z})$ and occupational tenure; the belief covariance $P(t, \tau)$ is precomputed as described in Section 4, so perceived risk never enters the state. The expectation in the Bellman equation is a one-dimensional Gauss–Hermite quadrature in the scalar innovation. Two computational results are worth recording. First, the Epstein–Zin recursion is validated against the additively separable CRRA program at $\varrho = \alpha$, where the two must coincide exactly: on the risk-free retirement block, where grid refinement isolates interpolation error, both converge to the same values to five digits at $n_x = 800$. Second, the Epstein–Zin formulation is not only more general but numerically better conditioned: it interpolates the value function in consumption units, a nearly linear object, whereas the CRRA program interpolates the utility-valued function, which behaves like x^{-4} at $\gamma = 5$. The CRRA program's calibrated moments have not converged even at $n_x = 140$ cash-on-hand nodes, whereas the Epstein–Zin program is stable over the same refinement, as Table 13 shows. Holding the benchmark parameters fixed and refining the grid, the search margins move negligibly from $n_x = 70$ (the peak-to-first ratio within 0.02, the acceptance rate within 0.01, the unemployment rate within 0.003), and the maximum deviation of the nine-bin search profile from the finest grid falls monotonically to zero. The aggregate wealth-to-income ratio, a wealth-tail statistic, is the most grid-sensitive: it rises from 4.79 at $n_x = 70$ to 4.97 at $n_x = 140$ and settles by $n_x = 100$, so the benchmark value is a mild underestimate that remains inside the target range either way. All results in the paper are computed at the benchmark grid $(n_x, n_a) = (70, 60)$ with the Epstein–Zin code, setting EIS $= 1/\gamma$ whenever the CRRA model is required. Replication codes (Julia and MATLAB) and all data-processing scripts are provided in the replication package.

n_x	n_a	n_q	peak/first	acceptance	res./prev.	WTI	u	max $\lvert\Delta$prof.$\rvert$
45	38	7	1.720	0.682	0.904	4.30	0.123	0.041
70	60	7	1.701	0.684	0.894	4.79	0.122	0.034
100	85	9	1.708	0.693	0.864	4.95	0.120	0.021
140	119	15	1.697	0.687	0.883	4.97	0.120	0.000

Table 13: Grid convergence of the benchmark ($\chi = 2$, $\kappa_b = 1$, EIS $= 1.2$, $\gamma = 5$, with $m = 0.2527$ held fixed). n_x cash-on-hand nodes, n_a savings-choice nodes, n_q Gauss–Hermite quadrature nodes; res./prev. is the reservation-to-previous-wage ratio, WTI the aggregate wealth-to-income ratio, and the last column the maximum absolute deviation of the nine-bin normalized search profile from the finest ($n_x = 140$) grid.

C Proofs

C.1 Proposition 3.1

Proof. What we need to show is

$$\int_{y_i^*}^{\bar{y}} J(g_a^U(a_i), y')dF(y') \geq \int_{y_j^*}^{\bar{y}} J(g_a^U(a_j), y')dF(y')$$

for any $a_i \leq a_j$ where $g_a^U(a)$ is an unemployed worker's saving policy function and y_k^* for $k \in \{i, j\}$ is the reservation earning for the state variable a_k. First, we will show following claim.
Claim: The reservation earning $y^* = b$ for any strictly increasing and strictly concave function of u and for any distribution function F.

Proof is simple. Because we are considering two-period model, we have $V^E(a', y^*) = V^U(a')$. i.e., $u(y^* + (1+r)a') = u(b + (1+r)a')$. Thus, regardless of the distribution function F, under given properties of utility function u, $y^* = b$ regardless of asset level. This result is identical with Proposition 1 in Lise (2013). This implies $y_i^* = y_j^* = b$. Thus, since the reservation earning y^* is fixed for all asset a, we just need to consider how the savings affect to the net benefit of finding jobs.

Then what we need to show is following:

$$\frac{\partial}{\partial a} \int_{y*}^{\bar{y}} J(g_a^U(a), y')dF(y') \leq 0$$

Given $J(g_a^U(a), y') = u(g_a^U(a) + y') - u(g_a^U(a) + b)$, since $\frac{d}{da} g_a^U(a) \geq 0$, the above inequality holds by Jensen's inequality and this completes the proof of the proposition. □

C.2 Proposition 3.2

Proof. What we need to show is

$$\int_{y_F^*}^{\bar{y}} J(g_{F,a}^U(a), y')dF(y') \geq \int_{y_G^*}^{\bar{y}} J(g_{G,a}^U(a), y')dG(y')$$

for $F \succeq_{S.S.D} G$. First, as shown in the proof of Proposition 3.1, $y_F^* = y_G^* = b$. Under the support restriction $\mathrm{supp}(F) \cup \mathrm{supp}(G) \subseteq [b, \bar{y}]$, every offer is accepted, so on the relevant domain the integrand equals $J(a', y') = u((1+r)a' + y') - u((1+r)a' + b)$, which is strictly concave in y' for strictly concave u. Second-order stochastic dominance therefore delivers $\int J(a', y')dF(y') \geq \int J(a', y')dG(y')$ at any fixed a'. Without the support restriction the integrand is $\max\{J(a', y'), 0\}$, which is convex at the kink $y' = b$, and the inequality can fail; see Remark 3.3. Then, what remains is $g^U_{F,a}(a) \leq g^U_{G,a}$ and this is shown by Flodén (2006). This completes the proof.

$\square$