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

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Abstract

This paper explores the puzzling inverted U-shape job search profile for U.S. data. It is well established that the standard life-cycle incomplete market model is incapable of explaining this phenomenon because of the wealth effect. I argue two channels to explain the puzzle: (i) the resolution of perceived risks through Bayesian learning, and (ii) wealth accumulation in the incomplete market over the life-cycle. To support this, I empirically and analytically show that unemployed job seekers devote less efforts to find jobs under higher uncertainty and wealth.

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1 Introduction

This paper explores what can explain the puzzling inverted U-shape (hump-shaped) job search profile for U.S. data. Aguiar et al. (2013) find that unemployed between the ages 46 and 50 spend three times more time to find jobs than ones between the ages 21 and 25, and even unemployed between the ages 61 and 65 spend more time than between the ages 21 and 25 in the American Time Use Survey (ATUS).[1] However, it is well established that the standard life-cycle incomplete market model (SIM), which is characterized by persistent earnings shocks and partial insurance, is incapable of explaining it because of the wealth effect. That is, more experienced agents in the SIM have higher outside options for finding jobs as they have accumulated large wealth by the precautionary saving motivations.

In this paper, I propose two channels to explain the hump-shaped job search profile: i) the resolution of age-dependent risk through Bayesian learning for true type (productivity) of workers, and ii) the wealth accumulation in the SIM. The calibrated model fits not only the hump-shaped job search profile but also life-cycle labor market outcomes such as unemployment rates and job-finding rates for each age. In order to support the argument, I provide analytical analysis and empirical evidence of those effects. That is, this paper shows that the risk from imperfect information is more relevant to study behaviors of unemployed workers than it from bad persistent shocks. The nature of risk over the life-cycle is crucial as it is closely related to optimal unemployment insurance benefits.

Main intuition is as follows. Young workers[2] who just enter the labor market face large perceived uncertainty as they do not know their true type which is labor productivity in the model. It implies that finding jobs is less beneficial for young risk-averse job seekers. Thus, they devote less effort to search for jobs as predicted by the standard McCall job search model. Over the life-cycle, they learn about their types through Bayesian learning. The resolution of perceived risks explains an increasing part of the job search profile as the net expected benefit of finding jobs increases over the life-cycle. However, once workers are informed enough, they devote less effort as they have accumulated wealth to insure risks — persistent bad income shock, job separation, and retirement.

Theoretically, I first analytically show that risk-averse unemployed workers devote less effort if 1) they face higher uncertainty, which is defined by the variance of earnings shocks, or 2) have larger wealth using the simple two-period model. The first effect is called *Uncertainty effect* and the second effect is called *Wealth effect* in this paper. And then, I show that

[1] The hump-shaped profile is robust. I show that it holds in both the more recent ATUS and the other data — New Jersey Survey. More details will be discussed in Section 4.

[2] I do not consider on-the-job search in this paper. Thus, *workers* in this paper without additional explanations refer unemployed workers.

Bayesian learning and wealth accumulations explain the puzzle and the reasonably calibrated model fits labor market outcomes as well using the fully characterized life-cycle model. The full model consists of four main ingredients: 1) McCall model with endogenous search intensity, 2) the incomplete market as in Huggett (1993), 3) life-cycle risks — unemployment risk, persistent income shock and retirement, and 4) the imperfect information on the earnings process, that is, the heterogeneous income profile (HIP) in Guvenen and Smith (2014).

I also study who search more for each stage of life-cycle. At the early stage of life-cycle, optimal search intensities of unemployed workers are more closely related to their beliefs rather than true types due to the imperfect information. That is, even if a worker had high labor productivity, she would devote less effort if she had a low mean belief. In the later stage, once workers are informed, the elasticity of job search effort with respect to the mean belief converges to it with respect to the true type. The more interesting implication of the model is that the relationship between job search intensities and (true) types at the later stage of life-cycle is not monotonic but it depends on the history of workers.

To support the theoretical uncertainty and wealth effects empirically, I provide empirical evidence using New Jersey Survey (NJS).[3] I measure the empirical uncertainty by calculating a distance between offered wages and reservation wages. The offered wages reflect the true market value of true types of workers, and the reservation wages reflect the lowest value of mean beliefs of job seekers. I find that higher measured uncertainty and wealth reduce job search effort in the data. Further, they could be sufficient variables to explain the hump-shaped job search effort.

This paper has two main contributions. First, this paper helps to identify the nature of life-cycle risk. I show that the risk from imperfect information is more relevant to explain responses of unemployed workers with respect to unemployment shocks than it from bad persistent earnings shocks. To my best knowledge, this is the first paper to show the relevance of HIP to explain life-cycle dynamics by analyzing unemployed workers. Even though this paper does not attempt to investigate policy implications, the design of optimal insurance deeply depends on the nature of risk.[4] Second, the paper presents a tractable economic theory to explain the puzzling hump-shaped job search profile quantitatively with empirical evidence. To my best knowledge, this is the first paper to provide uncertainty effect theoretically *and* empirically. It is important that those effects are sufficient to understand the hump-shaped job search profile in the data.

[3]See Krueger and Mueller (2010, 2011b), Hall and Mueller (2017), or Section 4.1 for more details of NJS.

[4]For example, if we need to worry about bad persistent shocks, than it would be beneficial to provide generous unemployment insurance benefits for consumption smoothing and having less precautionary savings. However, if we need to worry about imperfect information on fitness of career, it would be beneficial to improve education system or job training.

Related literature This paper is related to the job search study and the life-cycle study with incomplete market and earnings process. For the job search, Aguiar et al. (2013) provides the main motivated question of this paper. Aguiar et al. (2013) reports the puzzling hump-shaped job search profile in the U.S. and show how the wealth effect affects to job search intensities in the model. He et al. (2017) studies the hump-shaped job search profile in the U.S. with this paper. They focus on the interaction between the age-dependent labor efficiency and reservation wage strategies. This paper focuses sources of uncertainty - imperfect information, bad persistent shock and retirement - and the wealth effect raised from the incomplete market. Also, Lise (2013) studies job search dynamics with precautionary savings with on the job search in infinite horizons. Main distinctions of this paper with Lise (2013)'s work are the nature of risk and search on the job. Not only because this paper considers various sources of risks - including job separations, imperfect information, persistence of shocks and retirement risks - but because Lise (2013) considers wage ladders, the wealth effect in this paper could be quantitatively more significant. But mainly, consumption smoothing is the key dynamics for both. Lentz and Tranæs (2005) also studies the wealth effect on the job search behavior.

Also, Menzio et al. (2016) studies the labor market over the life-cycle. Based on efficient search on the job in Menzio and Shi (2011), it explains labor market transitions over the life-cycle. Menzio et al. (2016) shows that the learning friction for matched quality between workers and firms is also crucial to explain the labor market transition over the life-cycle. While Menzio et al. (2016) studies transitions of labor market over the life-cycle, this paper studies how workers react to risks through search intensities in the incomplete market. For counter-cyclical job search intensities, Shimer (2004) and Mukoyama et al. (2018) study empirically and suggest theoretical frameworks. Aguiar et al. (2013a) studies how unemployed people use forgone hours work in the recession by using ATUS.

Also, the paper is related to the life-cycle literature. There are two strands of literature for the life-cycle study. One is to consider the heterogeneous income profile (HIP) process, i.e., stochastic individual type components in log labor earnings which implies the imperfect information and the restricted income profile (RIP) with very persistent shocks. This paper considers the HIP process to embed the age-dependent uncertainties. For the HIP, Guvenen (2009) estimates the HIP empirically and Guvenen (2007) embeds the HIP in the life-cycle incomplete market model. By using both earnings and consumption data, Guvenen and Smith (2014) estimates standard parameters in the life-cycle model structurally with the indirect inference. Also, Chang et al. (2017) studies the life-cycle portfolio choice problem based on the extended version of the HIP specifications.

This paper provides additional empirical facts by using the NJS data. This novel data is used in Krueger and Mueller (2010, 2011a,b) and Hall and Mueller (2017). Krueger and Mueller (2010, 2011a) study great details of unemployed people's unemployment durations, unemployment benefits and job search time. Hall and Mueller (2017) studies great details of reservation wages, job acceptance and non-wage values by using the same data set.

The rest of paper is organized as follows. Section 2 studies the uncertainty effect and the wealth effect analytically using the simple two-period model. Section 3 introduces the fully characterized quantitative life-cycle model and provides quantitative results. Section 4 provides empirical evidence of uncertainty and wealth effects identified in the theoretical model. Section 5 concludes the paper.

2 Analytical Analysis: Wealth and Uncertainty

In this section, using the simple two-period model, I theoretically show that unemployed workers devote less effort searching for jobs if they hold larger asset holdings or face higher uncertainty.

2.1 Environment

Risk-averse agents live two periods and they could be employed and unemployed workers as the labor market is decentralized as in the McCall model. Since the asset market is incomplete, there exists only one risk-free asset. And there is no search on-the-job, and the job arrival rate is endogenous for unemployed workers as it is positively proportional to job search intensities of unemployed workers.

At the initial period $t = 1$, unemployed workers with the value of unemployment b choose savings a' and search effort s optimally. As they devote more effort s, they can get a job offer at the beginning of the second period more likely but it is costly. Further, even if unemployed workers got a job offer, they could reject it. Employed workers with labor earnings y at the initial period choose savings a' optimally given the exogenous job separation rate θ. I assume that both employed and unemployed workers face the same random earnings offer at time $t = 2$ with the distribution $F(y')$. The model can be summarized as follows.

Time Discrete and the economy ends at the second period.

Agents Employed and unemployed and they are risk-averse. Employed workers earn y units of consumption good by providing labor services and unemployed workers earn b units of consumption good. b here can be broadly interpreted as the whole value of home-production and unemployment insurance benefit.

Labor Market This paper considers the simple one-side McCall labor search model with an endogenous job arrival rate. Unemployed workers at the initial period could get a job offer with a probability $p(s)$ where s is job search effort. As in the standard literature, I assume that p is a strictly increasing and weakly concave function with respect to search effort s. With the probability p, if the worker get a job offer y' units of consumption good which is drawn from a cumulative distribution function F, they can either accept or reject the job offer. For simplicity, I assume that y' is drawn from the uniform distribution function. The more generalized job offer process will be covered in Section 3.

Asset Market There is no complete state contingent asset but there is only one risk-free asset. Thus, the market is incomplete. Since workers are risk-averse, they have incentives to purchase a' units of consumption goods as savings with the net risk-free return r for consumption smoothing.

2.2 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

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

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:

$$V_1^U(a) = \max_{\{c,s,a'\}} \left\{ U(c,s) + \delta \left[p(s) \int \max \left\{ V_2^E(a', y'), V_2^U(a') \right\} dF(y') + (1 - p(s)) V_2^U(a') \right] \right\} \tag{2}$$

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).

$$p(s) = \frac{m}{\pi} s^{\pi} \tag{3}$$

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

$$U(c,s) = u(c) - v(s) = \frac{c^{1-\gamma}}{1-\gamma} - B\frac{s^{1+\psi}}{1+\psi} \tag{4}$$

where $u(c)$ is the CRRA utility function with risk aversion parameter γ and $v(s)$ is a convex utility function with the weight for job search effort dis-utility 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:

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

subject to

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

where θ is an exogenous job separation rate.

Optimal Job Search Intensity From (2), (3) and (4), the first order optimality condition for the optimal policy function $g_s(a)$ with respect to the job search effort s is

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

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

$$g_s(a) = \left[\frac{\delta m}{B}\int_{y^*}^{\bar{y}} J(g_a^u(a), y')dF(y')\right]^{\frac{1}{1-\pi+\psi}} \tag{6}$$

where y^* is the reservation earnings 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 $J(g_a^U(a), y')$.[5] 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 2.1. ***(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 Appendix B.1.[6] □

[5]The strictly convex function of utility and the weakly concave job search technology guarantee that $1 - \pi + \psi > 0$.

[6]See also Lentz and Tranæs (2005) for the wealth effect.

Proposition 2.2. ***(Uncertainty Effect)*** *Suppose that $G(y')$ is a mean preserving spread of $F(y')$. Then,*

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

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 Appendix B.2. □

In particular, the uncertainty effect implies that if agents face smaller uncertainties, they will devote more effort for finding jobs. That is, technically, if the distribution function of earnings offer at $t+1$ is the second order stochastic dominance of t, it explains an increasing part of the hump-shaped job search profile.

3 Quantitative Analysis

This section investigates the fully-fledged quantitative life-cycle model. In the fully-fledged life-cycle model, I incorporate Bayesian learning to the standard incomplete market model of Bewley (1977). In the model, agents do not know whether she is a good type worker or a bad type worker when they enter the labor market. Thus, agents face large perceived risks initially and the perceived risks are resolved through Bayesian learning. By the uncertainty effect, agents devote more effort searching for jobs over the life-cycle as perceived risks are resolved. However, once they learn enough, the wealth effect dominates the previous channel as the market is incomplete.

3.1 Environment

Age Agents can work for $t = 1, \ldots, T^R$. During the working age, agents could be employed and unemployed as in the McCall model. At $t = T^R + 1$, agents retire and die at $t = T$ as deterministic events.

Earnings process The paper follows Guvenen (2007) and Guvenen and Smith (2014)'s heterogeneous income profile (HIP) process to embed Bayesian learning over the life-cycle. For $t = 1, \ldots, T^R$, if agents are in an unemployment state, they will have the value of unemployment b. If agents are in an employment state, agent i's log labor earning at age t,

y_t^i consists of

$$y_t^i = \underbrace{g(\Theta, t)}_{\text{Common life-cycle component}} + \underbrace{\alpha^i + \beta^i t}_{\text{Individual specific type}} + \underbrace{z_t^i + \varepsilon_t}_{\text{Random shocks}} \tag{7}$$
$$z_t^i = \rho z_{t-1}^i + \eta_t^i, \qquad \eta \sim \mathbb{N}(0, \sigma_\eta^2), \qquad z_0^i = 0$$

where $g(\Theta, t)$ is the common life-cycle component with observable characteristics θ. Here, $g(\Theta, t)$ is the quadratic polynomial in age t. α^i and β^i are the time invariant individual specific components. If agents have full information, they are deterministic type components. If not, agents need to learn about them. z_t^i is the persistent shock which follows the first order Markov process, and ε_t is the temporary shock.

As in Guvenen (2007) and Guvenen and Smith (2014), I assume that agents can observe not each α^i, β^i, z_t^i, and ε_t, but only the sum of them y_t^i. Due to this feature, even if the agent have good earnings for several periods in a row, they can still not sure whether they are good type or bed type since it could be just due to good persistent luck. This makes the speed of learning be slow.[7]

Bayesian Learning The agent i has an initial mean belief $\hat{\alpha}_{1|0}^i, \hat{\beta}_{1|0}^i$ and $\hat{z}_{1|0}^i$. As time goes by, $\hat{\alpha}_{t|t-1}^i$ and $\hat{\beta}_{t|t-1}^i$ for the individual type converge to the true values of α^i and β^i. And also, the perceived risk, the sum of variance mean belief and truly random components,[8] converge to the variance of stochastic components only, z_t^i and ε_t.

Bayesian learning is implemented through the Kalman filter as in Guvenen and Smith (2014). For simplicity and computational issue, the paper considers $\sigma_\alpha \equiv 0$. i.e., no heterogeneity/uncertainties on the intercept term α^i. Instead, let the life-cycle component $g(\theta, t)$ captures $\bar{\alpha}$ the mean of the α^i and the result is robust to the value of $\bar{\alpha}$.[9] Given this structure, the imperfect information only come from the slope term β^i.

At time 0,[10] the individual specific component β^i drawn with $\beta^i \equiv \beta_k^i + \beta_u^i$, where k represents *known* and u represents *unknown*, and β_k and β_u are orthogonal. Each individual i knows β_k^i at the time 0 thus initial mean belief $\hat{\beta}_{1|0}^i = \beta_k^i$. Due to the orthogonality, σ_β^2, the cross-sectional dispersion of type β^i is the sum of the variation of known part, $\sigma_{\beta_k}^2$, and the

[7]See more details in Guvenen (2007), Guvenen and Smith (2014) and Chang et al. (2017) for the learning procedure and the speed of learning.

[8]The uncertainty can be measured by the variance due to the normality assumption

[9]This can be partially justified by the result of Guvenen (2007) and Guvenen and Smith (2014). Guvenen (2007) shows that the uncertainties from α^i resolved immediately. Guvenen and Smith (2014) does not include α^i in the Kalman filter but it is included as agents' deterministic heterogeneity. Unlike them, the paper ignores even the heterogeneity for the intercept term.

[10]All explanations here related to Kalman filter are in Guvenen (2007) and Guvenen and Smith (2014). See those papers for more detail

variation of unknown part $\sigma^2_{\beta_u}$. i.e., $\sigma^2_\beta = \sigma^2_{\beta_k} + \sigma^2_{\beta_u}$ If agents have full information, $\hat{\beta}^i_{1|0} = \beta^i$, and the cross-sectional dispersion of β^i is fully explained by the cross-sectional dispersion of β^i_k, $\sigma^2_\beta = \sigma^2_{\beta_k}$. Then, the degree of initial uncertainty λ is defined by as follows:

$$\lambda = \frac{\sigma^2_{\beta_u}}{\sigma^2_\beta} \tag{8}$$

Thus if the $\lambda = 1$, agents do not have any private information thus $\hat{\beta}^i_{1|0}$ is degenerated to the cross-sectional mean $\bar{\beta}$. Thus, computationally, each known part and unknown part of the individual type β^i will be drawn $\beta^i_k \sim \mathbb{N}(0, (1-\lambda)\sigma^2_\beta)$ and $\beta^i_u \sim \mathbb{N}(0, \lambda\sigma^2_\beta)$. The variance of the mean belief at the beginning of the period $P_{1|0}$ is

$$P_{1|0} = \begin{pmatrix} \lambda\sigma^2_\beta & 0 \\ 0 & \sigma^2_\eta \end{pmatrix} \tag{9}$$

In order to implement the Kalman recursion, we need to set the state equation and the observational equation. The state equation and the observational equation are defined by[11]

State equation:

$$\underbrace{\begin{bmatrix} \beta^i \\ z^i_t \end{bmatrix}}_{S^i_t} = \underbrace{\begin{bmatrix} 1 & 0 \\ 0 & \rho \end{bmatrix}}_{F} \underbrace{\begin{bmatrix} \beta^i \\ z^i_{t-1} \end{bmatrix}}_{S^i_{t-1}} + \underbrace{\begin{bmatrix} 0 \\ \eta^i_t \end{bmatrix}}_{\nu^i_t} \tag{10}$$

Observation equation:

$$y^i_t = \underbrace{\begin{bmatrix} t & 1 \end{bmatrix}}_{H'_t} \underbrace{\begin{bmatrix} \beta^i \\ z^i_t \end{bmatrix}}_{S^i_t} + \varepsilon^i_t \tag{11}$$

Let $P_{t|t-1}$ be the variance of $\hat{S}^i_{t|t-1}$ where $\hat{S}_{t|t-1}$ is the predicted mean belief in the previous period $t-1$. Note that the sufficient statistics of the variance of the mean belief is just the

[11] The common life-cycle component $g(\theta, t)$ is not included in these equations. But in the actual computation, they will be included.

age, t. The Kalman recursions are as follows.

$$\begin{aligned}
\text{Updating Mean belief: } & \hat{S}^i_{t|t} = \hat{S}^i_{t|t-1} + K_t \times \hat{\xi}^i_t \\
\text{Updating Variance: } & P_{t|t} = (I - K_t H'_t) \times P_{t|t-1} \\
\text{Forecasting Mean belief: } & \hat{S}^i_{t+1|t} = F \hat{S}^i_{t|t} \\
\text{Forecasting Variance: } & P_{t+1|t} = F P_{t|t} F' + Q \\
\text{Expectation: } & y^i_{t+1} | \hat{S}_{t+1|t} \sim \mathbb{N}\left(H'_{t+1}\hat{S}_{t+1|t}, H'_{t+1}P_{t+1|t}H_{t+1} + \sigma^2_\varepsilon\right)
\end{aligned} \tag{12}$$

where $\hat{\xi}^i_t = (y^i_t - H'_t \hat{S}_{t|t-1})$ is the forecasting error, Q is the covariance matrix of the ν_t in the (10), $K_t = P_{t|t-1}H_t[H'_t P_{t|t-1} H_t + \sigma^2_\varepsilon]^{-1}$, the Kalman gain.

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

3.2 Value functions

Unemployment For each age t, an unemployed agent i chooses optimally the consumption level c, savings a' and the job search effort s by solving following bellman equation given the risk free rate r, the current asset holding a, the predicted mean belief $\hat{S}^i_{t|t-1} = [\hat{\beta}^i_{t|t-1}, \hat{z}^i_{t|t-1}]'$ and the variance of mean belief $P_{t|t-1}$.[12]

$$\begin{aligned}
V^U_t(a, y^i_t, \hat{S}^i_{t|t-1}) = \max_{\{c,s,a'\}} \Bigg\{ & \frac{c^{1-\gamma}}{1-\gamma} - B\frac{s^{1+\psi}}{1+\psi} + \delta[p(s)\mathbb{E}_t \max\left\{V^E_{t+1}(a', y^i_{t+1}, \hat{S}^i_{t+1|t}), V^U_{t+1}(a', y^i_{t+1}, \hat{S}^i_{t+1|t})\right\} \\
& + (1-p(s))V^U_{t+1}(a', y^i_{t+1}, \hat{S}^i_{t+1|t})]\Bigg\}
\end{aligned} \tag{13}$$

subject to

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

and the Kalman recursion (12), and where δ is a time discount factor, b is a value of unemployment - value of leisure or home-production and $p(s)$ is the job search technology which

[12] With the basic Kalman filter, the age t is the sufficient statistics of the variance of the mean belief. See Chang et al. (2017) for more general discussion.

is a strictly increasing and strictly concave function of s such that

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

where $m > 0$ is a job search productivity and $\pi \in [0, 1)$ is a share of job search effort. Based on specific functional forms of the (additively separable) utility function and the job search technology, we have the following the first order optimality condition:

$$s = \left[\frac{m\delta}{B} \mathbb{E}_t \max \left\{ V^E_{t+1}(a', y^i_{t+1}, \hat{S}^i_{t+1|t}) - V^U_{t+1}(a', y^i_{t+1}, \hat{S}^i_{t+1|t}), 0 \right\} \right]^{\frac{1}{1-\pi+\psi}} \tag{14}$$

As in the standard job search model, the optimal job search effort s_t is positively proportional to the net benefit of finding jobs. The learning effect, the Kalman filter affects to the optimal job search effort through two channels, updating of the variance of the mean belief, i.e., being resolved perceived risk, and updating of the mean belief. First effect related to the when searches more and the second effect related to who searches more.

Employment For each age t, an employed agent i chooses optimally the consumption level c and savings a' by solving following bellman equation given the risk free rate r, the current asset holding a, the predicted mean belief $\hat{S}^i_{t|t-1} = [\hat{\beta}^i_{t|t-1}, \hat{z}^i_{t|t-1}]'$ and the variance of mean belief $P_{t|t-1}$.

$$V^E_t(a, y^i_t, \hat{S}^i_{t|t-1}) = \max_{\{c,a'\}} \left\{ \frac{c^{1-\gamma}}{1-\gamma} + \delta \mathbb{E}_t \left[\theta V^U_{t+1}(a', y^i_{t+1}, \hat{S}^i_{t+1|t}) + (1-\theta) V^E_{t+1}(a', y^i_{t+1}, \hat{S}^i_{t+1|t}) \right] \right\} \tag{15}$$

subject to

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

and the Kalman recursion (12) and where δ is a time discount factor, θ is an exogenous job separation shock and $Y^i_t = \exp(y^i_t + g(\Theta, t))$, earnings for an agent i.

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:

$$V^i_t(a) = \max_{\{c,a'\}} \left\{ \frac{c^{1-\gamma}}{1-\gamma} + \delta V^i_{t+1}(a') \right\} \tag{16}$$

subject to

$$\begin{aligned} c + a' &= (1+r)a + Y^i \\ Y^i &= \Phi\left(\exp\left(y^i_{T^R}\right)\right) \end{aligned} \tag{17}$$

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.[13]

3.3 Calibration

Table 1 represents parameters used in the model. Most of values are commonly used in life-cycle literature and job search intensity literature.

Initial uncertainty λ represents how much agents have private information for their type. I assume that $\lambda = 1$ which represents no private information at all. i.e , $\hat{\beta}^i_{1|0} = \bar{\beta}(=0)$ for all i. The main result of the model still holds to the structural estimate in Guvenen and Smith (2014) $\lambda = 0.438$.

Elasticity of job search intensity ψ is an inverse of job search elasticity as in the equation (14). 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.

As a recent study, Lise (2013) estimates structurally ψ. In his estimate, the elasticity $\psi = 0.168$ for high school and $\psi = 0.268$ for colleges, which are much higher than the

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

Parameter	Value	Description	Targets/Reference
$\boldsymbol{\lambda}$	**1.000**	**Initial uncertainty**	No private information
γ	2.000	Risk aversion	Standard
r	0.030	Risk-free rate	Annual rate
δ	0.963	Time-discount factor	Wealth-to-income ratio
T^R	66	Retirement Age	
T	80	Terminal Age	
$\boldsymbol{\psi}$	**2.500**	**Elasticity of job search intensity**	Curvature of search profile.
$\mathbf{m}$		**Searching productivity**	Job finding rates for each ages (NJS)
$\boldsymbol{\pi}$	**1.000**	**Share of job search effort**	Linear Technology
B	1.000	Disutility weight of job search intensities	Normalized m
θ	0.006	Job Separation Rate	Average unemployment rate
b		Value of unemployment	40 % replacement ratio
ρ	0.756	AR(1) coefficient of persistent shock	Guvenen and Smith (2014)
σ_β	1.764%	Std. dev of β^i	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 1: Calibration

calibration in this paper. Even if I target much steeper curvature as in ATUS 0311 -the value is 2.9967- used in Aguiar et al. (2013), still, needed elasticity is lower than estimates in Lise (2013). Because both two additional data sets - ATUS 0316 and NJS - show similar curvature and it is hard to match job finding rates over the life-cycle with too high elasticity (i.e., too high $1/\psi$, I target those two data sets and use the standard elasticity in labor supply.

Linear Job search technology and Age dependent search productivity Because the NJS includes information of how many offers respondents get during the survey period with their age, I can also match the job finding rate over the life-cycle. Given the linear search technology, I calibrate m_t to match the job finding rate for each age t. Because we can see only extensive margin of offers in the data, i.e., the model does not consider multiple job offers at each period, I consider the job offer in the NJS as a binary variable. The model matches the job finding rate for each ages well given the calibration.

One may argue that the hump-shaped job search profile is the result of age dependent job search productivity, i.e., roughly speaking if m_t is the hump-shaped over the life-cycle, so would job search profile. Theoretically, this is reasonable conjecture. However, first of all, the calibrated age-dependent job search productivities m_t show U-shape profile with hump-shaped profile. Furthermore, even if I computed the model with constant job search productivity, for example, average of m_t, it does not affect curvature nor shape significantly.

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 I calibrate an exogenous job separation rate θ to match the average unemployment during the working period. The calibrated θ matches well not only average of it but unemployed rates over the life-cycle for each age.

Again, we can consider age-dependent job separation rate and check whether it could affect search intensities. As shown by many literature,[14] 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.[15]

Time Discount With annual risk free rate $r = 0.03$, I choose the time discount rate $\delta = 0.963$ to match the wealth-to-income (WTI) ratio. I here follow Guvenen and Smith (2014)'s calibration strategy. I target the WTI ratio 1.31, which is the average of values in the Panel Study of Income Dynamics (PSID) 1984 and 1984 for all households up to age 65.

3.4 Quantitative Result: Benchmark

This section shows the quantitative results of the model. In order to compare the curvature in the data and the model, the paper considers two normalized graphs: One is normalized by the job search intensities of the first age bin (age 21-25) and the second one is normalized by the average value of total average job search intensities.

Figure 1 and Figure 2 represent it by comparing with the NJS. Red lines represent the simulated data from the model and circles represent estimates of age-dummy regression for the NJS.

[14]See Choi et al. (2014) and Menzio et al. (2016). They use Current Population Survey (CPS) and U.S. Census' Survey of Income and Program Participation (SIPP).

[15]Moderate but the job separation rate affects employed workers' saving choice as discussed in section 2. If θ is large, the precautionary savings increase.

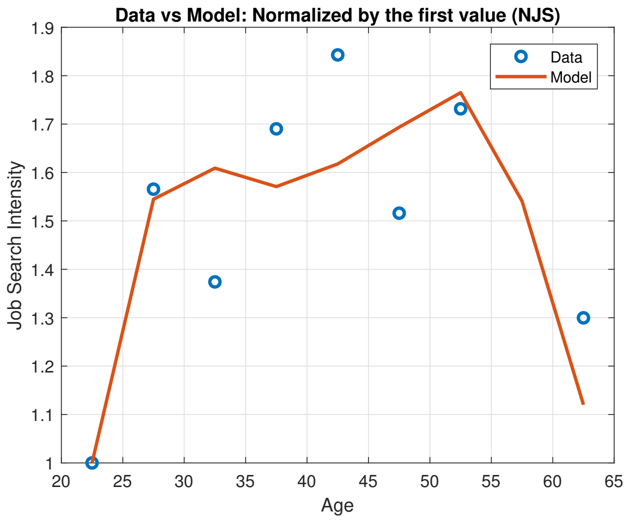


Figure 1: Data - NJS. Normalized by $JS_{21\sim25}$

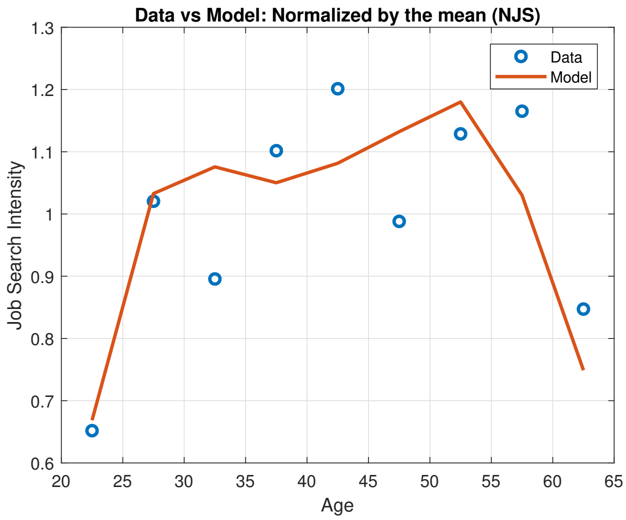
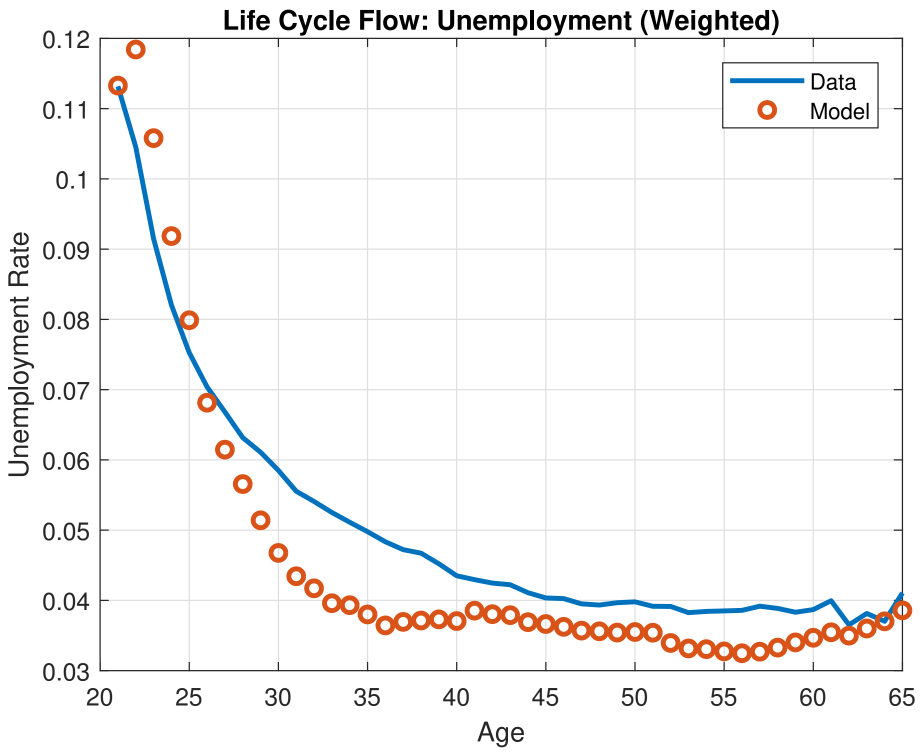


Figure 2: Data - NJS. Normalized by $\mathbb{E}JS$

Figure 3: Data vs Model: Unemployment rate over the life cycle



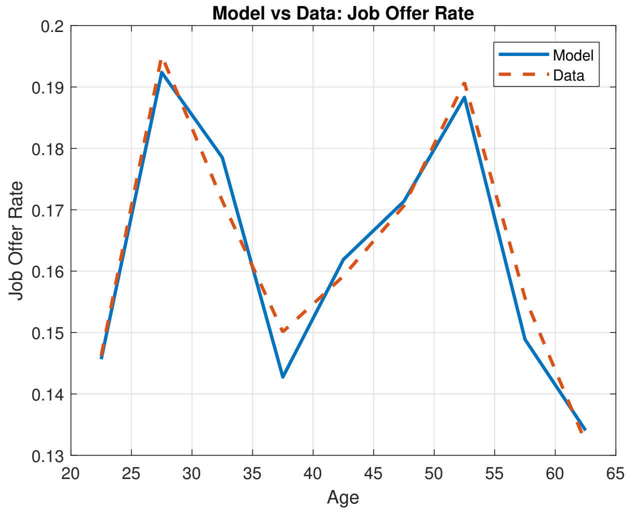


Figure 4: Data vs Model: Job finding

Figure 5: Data vs Model: Job acceptance

Also, Figure 3 shows the performance of the model to match the unemployment rate over the life-cycle. Blue line represents the simulated data from the model and circles represent data which is the result of Choi et al. (2014).

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.

Figure 4 and Figure 5 represent the performance of the model to match job finding rate and job acceptance rate respectively. Solid line represents the simulated data from the model and dotted line represents the job finding rate and the unconditional job acceptance rate in the NJS which are results of the linear probability regression. Since I calibrate the job search productivity m_t to match the job finding rate for each age t, the model fits it well. However, it cannot match the job acceptance rate well as much as job finding rate. However, since the average of job acceptance rate in the model is 16.26% and it in the NJS is 14.29%, it can be partially justified.

In subsection 3.5, I study what determines the job acceptance rate in the model by using a locally weighted regression (LOWESS) as in Hall and Mueller (2017). 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.

3.5 Job Acceptance: Information and Uncertainty

Analysis in this section gives better and deeper understanding how learning and uncertainty affect the value of being employment and thus job search intensities. Results of quantitative analysis here imply that learning or uncertainty effect is crucial to understand the hump-shaped job search profile.

Job seekers accept job offers more likely if the value of employment conditional on offered earnings, and updated belief, is larger. And the optimal job search intensity is an increasing function of it by the first order condition (14). This implies that analyzing the acceptance frequency with information adjustment ($\xi_{i,t} = y_{i,t} - \hat{y}_{t|t-1}$) and uncertainty $\sigma_{y_{t+1|t}}$ is beneficial not only by itself but in understanding of job search effort. In order to analyze the job acceptance frequency, I follow Hall and Mueller (2017)'s method: A locally weighted regression (LOWESS) with the bandwidth 0.3.

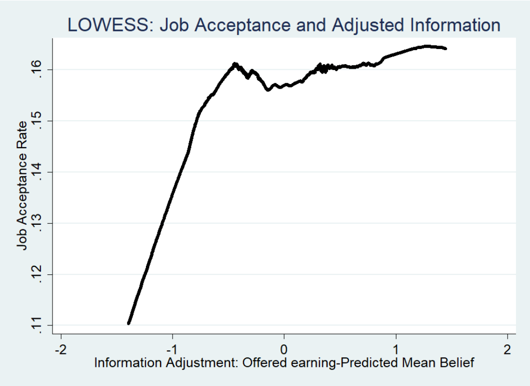
Information and Job Acceptance Under imperfect information, job seekers update beliefs to infer true type. It is important because the true type determines earnings growth rate which is directly related to permanent income.

If a job seeker observe signals which is greater than her predicted belief, the opportunity cost of rejecting the job offer becomes larger. Thus, if she does not hold large wealth, the information adjustment in positive way, i.e., $\xi > 0$, will make her accept offers more likely. Also, even if she did not get job offer, if she has the positive ξ, this makes her expected benefits of getting job be higher, she will devote more effort to find jobs. For job search intensities, related to the permanent income hypothesis, she consumes more and save less for consumption smoothing and it makes the value of being employed be higher. Thus, she will devote more effort to find jobs. Figure 6 is the result of LOWESS, job acceptance rate on the information adjustment ξ. It shows that job seekers who have more optimistic information accept job offers more likely. It shows diminishing return of optimistic updating. Because of earnings growth component β^i, the absolute value of ξ could be larger over the life-cycle. Also, since the market is incomplete, agents have incentives to accumulate wealth. This is why we have the diminishing.[16]

Uncertainty and Job Acceptance The above discussion is related to the first moment. However, what job seekers consider also is uncertainty in their jobs. In this section, I consider the standard deviation in forecasting future earnings $\sigma_{y_{t+1|t}}$. If risk averse agents expect that future earnings would be lower than the value of being unemployed more likely, they less likely accept the job offer.

[16] In 6th degree polynomial regression, we can see the decreasing part which implies hump-shaped pattern.

Figure 6: Job Acceptance and Information adjustment



However, once we consider the standard prediction in the McCall model with the incomplete market model, the dynamics of uncertainty would be more complicated. For risk averse young agents, since 1) they have higher perceived risk and 2) they do not have accumulated wealth to insure (moderate but still persistent) bad shocks, the higher uncertainty makes job seekers accept the job offer less likely. Same logic is applied to job search intensities. However, once they are informed and they have enough wealth to insure bad shocks, the higher variance implies higher future earnings. i.e., the moderate risk with savings buffer makes agents accept offers more likely.

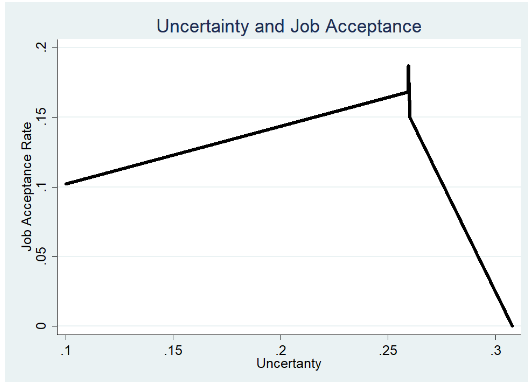
The above argument implies that we need to see the effect of uncertainty for each age. First, when we see just whole sample of job seekers, it shows the hump-shaped pattern as in Figure 7, which is the result of LOWESS. And then, I study the effect of uncertainty on job acceptance for young agents (who are younger than age 40) and experienced agents (who are older than age 50). Each result shows that while higher uncertainty with high absolute value makes young agents accept job offers less likely but it with low absolute value makes experienced agents behave in opposite ways. Figure 8 and Figure 9 show results of this.

Not surprisingly, we have the same dynamics on job search intensities as shown in Figure 10 and Figure 11. Thus, resolving perceived risk under imperfect information with wealth effect is one crucial channel to explain the hump-shaped job search profile.

3.6 Type, Belief and Job Search: Cross-Sectional Analysis

In this section, I study cross-sectional properties of job search intensities from the simulated data. While explaining the humps-shaped job search profile is related to the question 'when do agents search jobs more', analysis in this section is related to questions who searches more at each ages. We can see different perspective of interaction between the learning effect and

Figure 7: Job Acceptance and Uncertainty



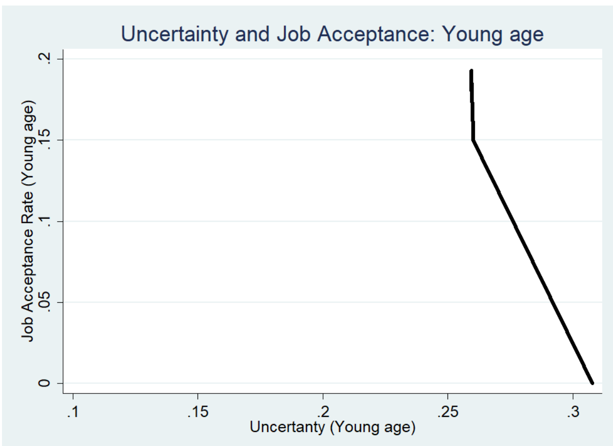


Figure 8: Job Acceptance and Uncertainty: Age<40

Figure 9: Job Acceptance and Uncertainty: Age>50

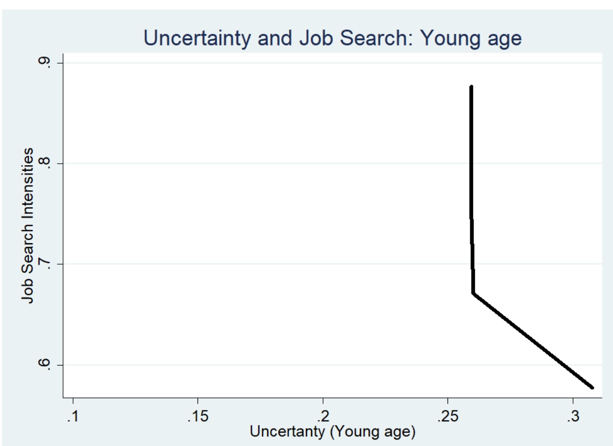


Figure 10: Job Search and Uncertainty: Age<40

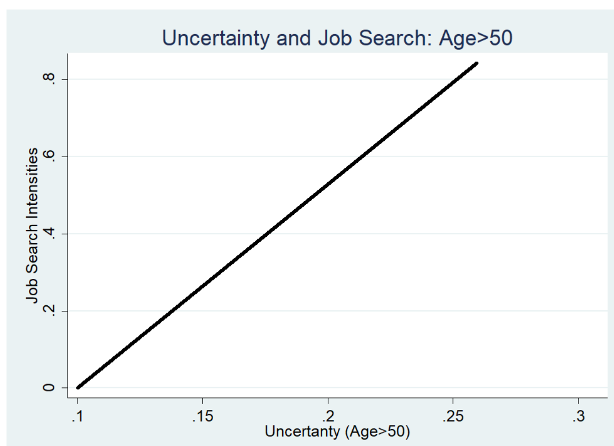


Figure 11: Job Search and Uncertainty: Age>50

the wealth effect cross-sectionally.

At early ages, agents' job search intensities are more closely correlated with their updated belief rather than true type due to imperfect information. Not only updated belief, the learning process itself is also crucial through consumption-saving dynamics. For example, if agents experienced high forecasting errors which are difference between signals (realized earnings) and predicted mean beliefs, agents update belief optimistically. The first order effect makes agents exert more efforts to find jobs. Also, agents consume more and save less given the wealth and it makes agents exert more efforts to find jobs as the second order effect. Thus, the information adjustment affects more significantly to job search intensities than wealth and true types at the early stage of the life cycle.

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

Early stage of life-cycle Because of imperfect information, young job seeker's job finding decision is more closely related to her belief rather than her true type. Figure 12 and Figure 13 represent results of them for age 22 job seekers. While job search intensities over true types are dispersed, job search intensities over updated belief are clearly increasing function of it. As we can expect, the dynamics of the information adjustment ξ and search intensities is similar with it of updated belief as shown in Figure 18.

Later stage of life-cycle Based on the above discussion, what we can expect is that experienced job seeker's job search intensities will be an increasing function for both of true type and updated belief because they will be informed. However, as shown in Figure 14 and Figure 15, they show similar dynamics but both of them show inverted V shape.

This is because of an interaction between the wealth effect and the learning effect. Risk averse high (low) type experienced agents have accumulated large (less) wealth from consumption smoothing motivation. Given this, if an agent's true earning growth rate is lower than the threshold level (roughly, it is zero), because they have low value of outside option,

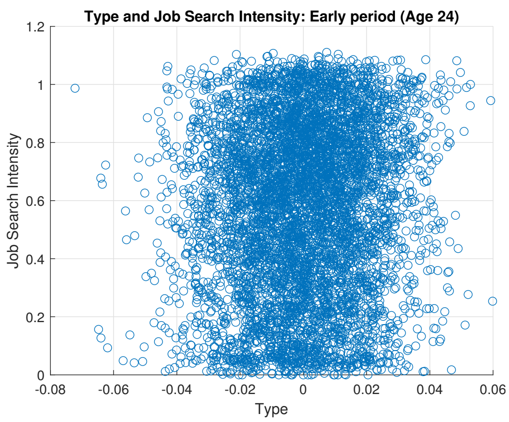


Figure 12: Young Age: True type $Corr = 0.0847$

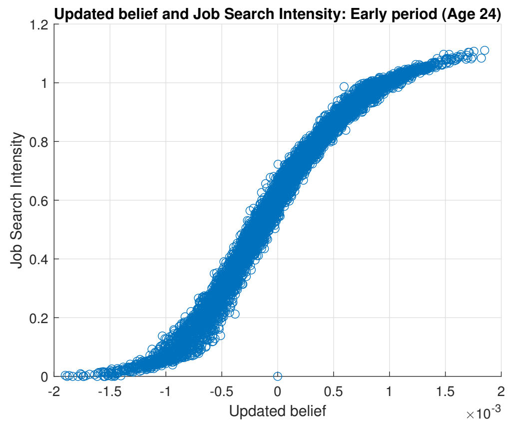


Figure 13: Young Age: Updated Belief $Corr = 0.9763$

Figure 14: Prime Age: True type $Corr = -0.4665$

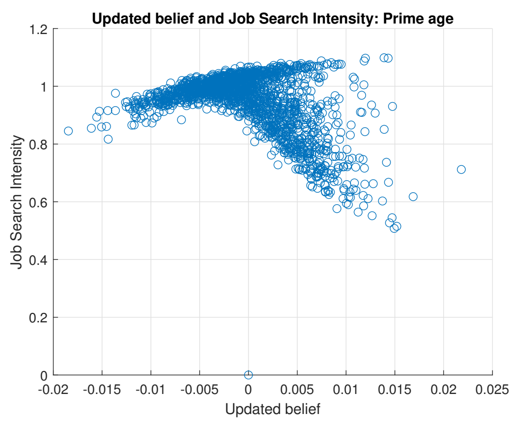


Figure 15: Prime Age: Updated Belief $Corr = -0.4650$

they have a stronger incentive to find jobs as they have higher type. However, since high type experience agents have large accumulated wealth over the life-cycle, they will search less because the wealth effect dominates. Because of the strong wealth effect, the overall correlations are negative.

Marginal effect The above discussion implies that we need to consider the joint distribution in order to see the true marginal effect. In order to see the marginal effect, I run the simple linear regression. Table 2 shows results. Dependent variable is job search intensities in the simulated data, and dependent variables are logarithm of wealth.[17] Results in Table 2 clearly imply that 1) wealth effect exists for all workers 2) but young job seekers are more sensitive because they have lower wealth 3) the value of true type for young agents does not have significant effect which is implied by imperfect information 4) the value of true type

[17]Since many agents have zero wealth, I take logarithm to $1 + a$.

	Belief	Type	Wealth
Young	414.52^{***} (5.954)	.	-1.42^{***} (0.102)
Prime	6.70^{***} (0.184)	.	-0.13^{***} (0.001)
Young	.	0.01 (0.078)	-9.44^{***} (0.047)
Prime	.	1.95^{***} (0.053)	-0.13^{***} (0.001)

Table 2: Marginal Effect: $JS_{i,t} = \beta_{0,t} + \beta_1 Belief(Type)_{i,t} + \beta_2 Wealth_{i,t} + u_{i,t}|_{t\in\{\text{Young,Prime}\}}$

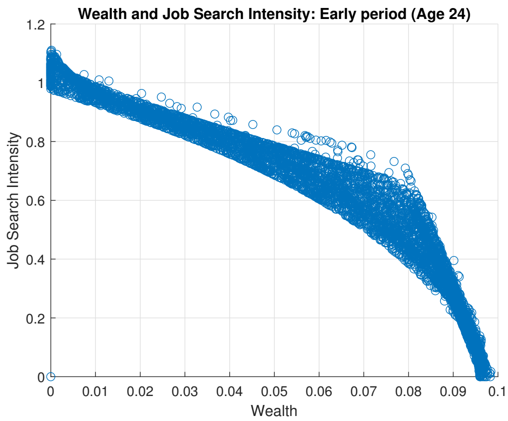


Figure 16: Wealth Effect (Young)

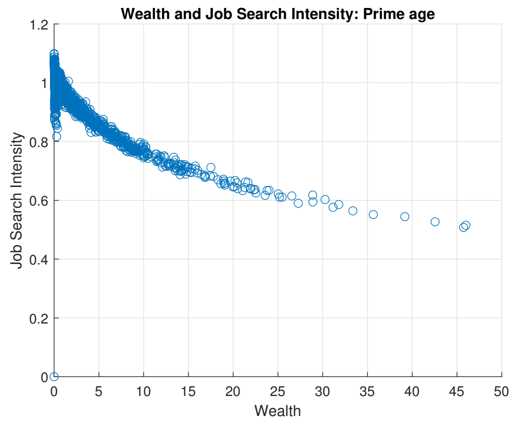


Figure 17: Wealth Effect (Prime)

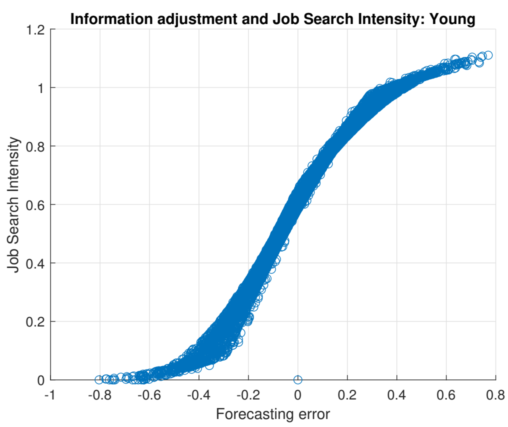


Figure 18: Young Age: $Corr(\xi, s_t) = 0.9787$

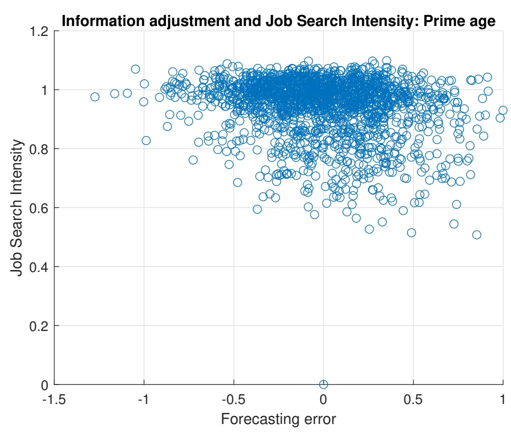


Figure 19: Prime Age: $Corr(\xi, s_t) = -0.2071$

has a significant effect for experienced job seekers but still not as much as belief.

Wealth Effect and Information adjustment Figure 16 and Figure 17 show the relationship between the wealth and job search intensities, and Figure 18 and Figure 19 show the relationship between the information adjustment ξ and job search intensities. Results are consistent with the above discussion.

4 Empirical Analysis

In this section, I re-examine the hump-shaped job search profile of unemployed workers using the different data source, New Jersey Survey (NJS), and more recent American Time Use Survey (ATUS). And I provide empirical evidence of theoretical channels − uncertainty and wealth effects using NJS.

4.1 Data

NJS 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. This data set is novel since it includes unemployed job seekers' job search behavior and outcomes - job offer, offered wages, job acceptance and reservation wages with large sample size - the sample size is 36,639 even after the sample restriction below.[18] Since the ATUS provides only job search effort, not the outcome of it and other related information, it is beneficial to use NJS and ATUS together.

To measure job search effort, I use the information of spending time on contacting people or agencies related to job searching, checking union/professional registers, attending job traning programs, placing/answering ads, interviewing, sending/filling out applications, looking at ads, and etc. See Appendix A.1 for more details related to measuring job search effort. Further, I consider the following sample restrictions in NJS. To be consistent with the analysis of Aguiar et al. (2013), I exclude samples if respondents respond they are not willing to find jobs. Unlike ATUS, the age information in NJS is the categorical data and it covers from 17 year-old to above 70. I consider only the age from 20 to 64.

ATUS The ATUS is conducted by the Bureau of Labor Statistics (BLS) and individuals are sub-samples of the Current Population Survey (CPS). Survey respondents are sampled approximately three months after completion of their final CPS survey on average. The ATUS in this paper covers from 2003 to 2018. Each wave is based on 24-hour time diaries where respondents report the activities from the previous day in detailed time intervals. Since we can combine the ATUS with CPS, the data also provides rich demographic information. For more information on the types of activities that are recorded in the ATUS, see Hamermesh et al. (2005).

[18]As a recent work, the data set is used in Hall and Mueller (2017), and I use their method to clean the data. NJS can be obtained by registering to the Princeton Survey Research Center: http://opr.princeton.edu/archive/njui/ or found in Andreas I. Mueller's website: https://sites.google.com/view/andreasimueller/research.

To be consistent with Aguiar et al. (2013), I focus on unemployed workers between the ages 21 and 65. I use categories of job search intensities in the ATUS code t05-04.[19] It includes the time spent on job interviewing, waiting associated with job search or interview, contacting employer, sending out resumes, filling out applications, looking at ads and etc. Note that the time categories are similar to those in the NJS. I use the sample weight provided by ATUS in the analysis to smooth our measurement errors. See Appendix A.3 for time use categories that I use in this paper.

4.2 Hump-Shaped Job Search Profile in ATUS and NJS

In this section, I show that the hump-shaped job search profile holds in both NJS and ATUS. For each NJS and ATUS, I run (18) to investigate the job search profile for unemployed workers.

$$Y_{ia}^{j} = \sum_{a=1}^{A} \beta_a^j D_{ia}^j + X_{ia}^j + \varepsilon_{ia}^j \tag{18}$$

Y_{ia}^{j} is time (minutes per day) to spend finding jobs of individual i belongs to age group a with A age bins and labor status j, D_{ia}^j is a dummy variable which takes one if it belongs to the age group a or zero otherwise, and X includes demographic controls.[20]

As shown in Figure 20 and Table 3, the job search profile over life-cycle is hump-shaped for both NJS and ATUS even we control observable characteristics. Table 3 summarizes results of (18) with and without demographic controls for each ATUS and NJS, and Figure 20 are figures of them. The first and fourth columns represent $\hat{\beta}_a$ in (18), that is, the difference between age group a and youngest age group. To control observable characteristics, I include gender, employment status of spouse, the number of households, and unemployment duration with year fixed effect for NJS, and gender, education level, the number of children, the presence of married/unmarried partner, employment status of partners, hours for home-production, and dummies of regional state with year fixed effect for ATUS.[21]

[19]ATUS can be found in https://www.bls.gov/tus/data.htm. Note that while the recent ATUS 2003 – 2018 does not provide the information of the ATUS code 18-05-04 (the time spent traveling for job search), the previous ATUS 2003 – 2011 did. Thus, I do not include the time spent traveling for job search in measuring job search effort.

[20]To translate to hours per week, took a multiplication 7/60. Further, I consider $A = 9$ age bins. In the ATUS, I consider between the ages 21 and 25, 26 and 30, 31 and 35, 36 and 40, 41 and 45, 46 and 50, 51 and 55, 56 and 60, and 61 and 65. Similarly, in the NJS, I consider those between 20 and 24, 25 and 29, 30 and 34, 35 and 39, 40 and 44, 45 and 49, 50 and 54, 55 and 59, and 60 and 64. In the regression analysis, I take an initial age bin ($21-25$ in the ATUS and $20-24$ in the NJS) as a base group.

[21]I report job search profiles in normal (2003 – 2005) and crisis (2007 – 2009) periods using the ATUS.

	New Jersey Survey (NJS) Base Age Group: 20−24			ATUS: 2003−2018 Base Age Group: 21−25	
Difference	Baseline (1)	Demographics with FE (2)	Difference	Baseline (3)	Demographics with FE (4)
β_{2529}	3.716***	4.502***	β_{2630}	1.636*	1.525*
β_{3034}	2.949***	3.944***	β_{3135}	1.395**	1.832***
β_{3539}	5.522***	6.537***	β_{3640}	1.055	1.481**
β_{4044}	4.461***	5.515***	β_{4145}	0.919	1.486***
β_{4549}	4.019***	4.974***	β_{4650}	1.739***	1.958***
β_{5054}	5.740***	6.442***	β_{5155}	2.122***	2.250***
β_{5559}	5.289***	5.839***	β_{5660}	1.553**	1.633**
β_{6064}	2.908***	3.033***	β_{6165}	0.213	0.0855
Demographic Control	No	Yes		No	Yes
Year Fixed Effect	No	Yes		No	Yes

*: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$, ****: $p < 0.001$

Table 3: Job search profile in NJS and ATUS: Estimates represent the difference of job search effort between age group a and base age group. (1) and (3) represent the result of baseline regression without controlling anything for NJS and ATUS, respectively. (2) includes demographic control variables with the survey year fixed effect (FE) in NJS, and (4) includes those with year fixed effect (FE), and state dummies.

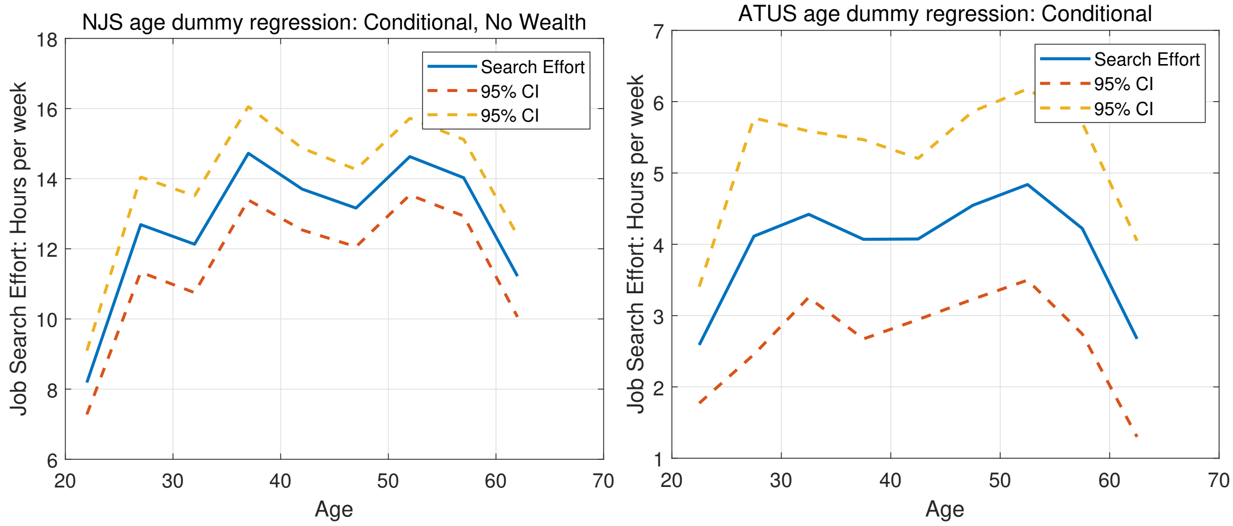
It is noteworthy to note two points. First, I do not include wealth effect or measured uncertainty, which are key effects of this paper yet for NJS. I will discuss how it changes once I control them, and argue that they would be sufficient factors to explain job search profile in the later section. Second, compared to the result of Aguiar et al. (2013), the curvatures of job search profile in NJS and recent ATUS $(2003-2018)$ are not exactly the same. In the calibration, I mainly target results of NJS as 1) I target several moments from NJS such as job acceptance rate for each age, 2) the curvature of NJS is more close to the result of Aguiar et al. (2013), and 3) the estimated earnings process in Guvenen and Smith (2014) would be more relevant to explain the periods of NJS $(2010-2011)$.

4.3 Empirical Evidence: Uncertainty and Wealth Effects

In this section, I provide empirical evidence to support theoretical uncertainty and wealth effects using NJS.

Measured Uncertainty Theoretically, uncertainty is defined by $\xi = \mathbb{E}[\big(y_t - \hat{y}_{t|t-1}\big)^2]$, where y_t is log earnings at age t and $\hat{y}_{t|t-1}$ is the predicted mean belief of job seeker at age $t-1$. To measure uncertainty from the data which is consistent with the model, I compute the distance between offered earnings and reservation wages. The offered earnings represent true market values of worker productivity, and reservation wages reflect objective lowest

See Appendix A.5 for more details. Also, I show that the effort level in search on-the-job is very small in Appendix A.6 using the ATUS. See Faberman et al. (2019) for the performance of ATUS measuring search effort on-the-job.



(a) NJS: Demographic controls (b) ATUS: Demographic controls

Figure 20: Results of age dummy regressions: Figure 20a is the result of (2), and Figure 20b is the result of (4) in Table 3. Solid lines are $\hat{\beta}_a$s for each NJS and ATUS, and dashed lines are confidence intervals of $\hat{\beta}_a$s.

willingness to work of job seeker given her belief.

Since the NJS asks the best offered earning of job seekers for both the last seven days and since the last interview, I first compute two-type of distances. Let y_1 and y_2 be log offered earnings for the last interview and the last seven days, respectively. And let Let r_1 and r_2 be log reservation wages for the correspondent period of y_1 and y_2, respectively. I use those values computed in Hall and Mueller (2017). Then, the measured uncertainty $\tilde{\xi}_k$ is

$$\tilde{\xi}_k = (y_k - r_k)^2 \qquad \text{for } k = 1, 2 \tag{19}$$

Moreover, I compute the distance between reservation wages of current period and those of last interview as a compliment. Since the distance can be interpreted as learning on types of job seekers once we control for unemployment duration, I also use this distance as measured uncertainty. That is,

$$\tilde{\xi}_3 = (r_2 - r_1)^2 \tag{20}$$

I now consider the following regression model.[22]

$$\text{Search Effort} = \tilde{\xi}\beta + \text{Wealth} \times \delta + \gamma X + \lambda_t + \varepsilon_i \tag{21}$$

[22]See Appendix A.1 NJS codes of job offer with offered wages and reservation wages, and see Appendix A.2 for the discussion of potential selection bias and endogeneity.

where the Wealth is the matrix of related variables − the amount of savings, mortgage debt, X includes other control variables − unemployment duration, gender, education, the number of households, age, and λ_t is the survey year fixed effect.

Dependent Variable: Job Search Effort			
	$k=1$	$k=2$	$k=3$
Measured Uncertainty (β_k)	-4.025**	-4.552**	-3.896***
Savings	-5.292***	-4.717***	-0.606***
Mortgage	0.00119***	0.000956***	0.000531***
Demographic Control	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

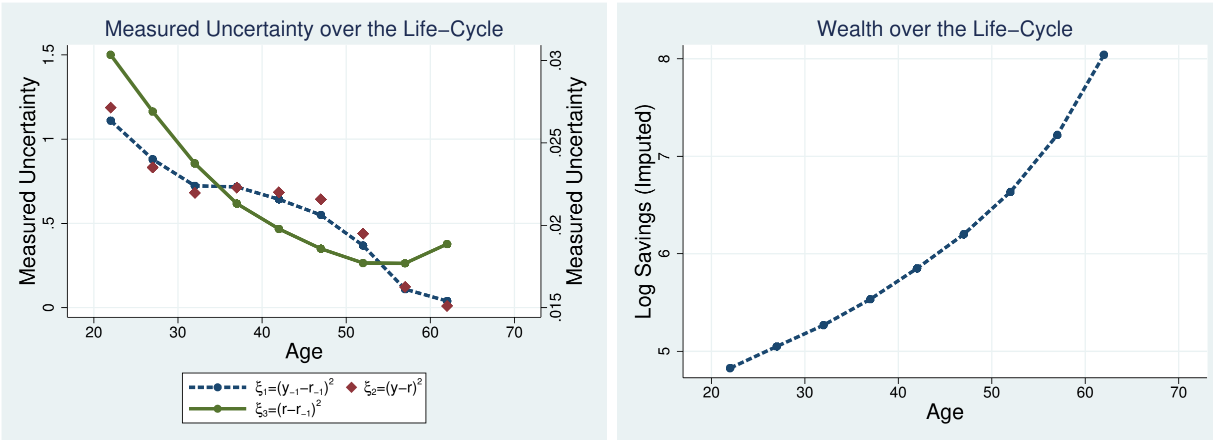
Table 4: Uncertainty and Wealth Effects. $k = 1$ and $k = 2$ represent results of regression for $\tilde{\xi}_1$ and $\tilde{\xi}_2$ in (19), $k = 3$ represents results of regression for $\tilde{\xi}_3$ in (20). The full table will be provided upon request.

Table 4 shows results of interest in (21). Consistent with the theory, the job search effort decreases as job seekers have higher savings and lower mortgage debts, and face larger uncertainty.[23]

And then, I investigate age profiles of the measured uncertainty and wealth, and show that the implications are consistent with the theory of this paper. First, I show that while measured uncertainty is decreasing, the wealth (savings) is increasing over the life-cycle in Figure 21. Figure 21 represents results of a locally weighted regression (LOWESS) with the default bandwidth 0.8. With results in Table 4, Figure 21 says that the learning or resolving uncertainty explain the increasing part, and wealth accumulates explain the decreasing part of the job search profile.

Lastly, I show that it would be enough considering measured uncertainty and wealth accumulates with general outside options to understand the hump-shaped job search profile. As shown in Table 5, the systematic pattern of job search over the life-cycle disappear once I control for both measured uncertainty and wealth. This result suggests that the argued channels are at least as strong as other candidates to explain the data. Overall, empirical evidence discussed supports the theory of this paper: Job search effort decreases as wealth and uncertainty increase. And while the measured uncertainty decreases, wealth accumulates increase over the life-cycle. Thus, Bayesian learning explains the increasing part, and savings due to the incomplete market explain the decreasing part. Table 5 supports the argument empirically.

[23] I also investigate empirical effects of general outside options. See Appendix A.4 for more details.



(a) Measured Uncertainty over the Life-Cycle

(b) Wealth over the Life-Cycle

Figure 21: Age Profiles of Measured Uncertainty and Wealth: Figure 21a represents age profiles of $\tilde{\xi}_k$s. Dashed line represents measured uncertainty $\tilde{\xi}_1$ based on last interview, diamond represents $\tilde{\xi}_2$ based on last 7 days interview, and solid line represents $\tilde{\xi}_3$, the difference of reservation wages for the last interview and current week with right y-axis scale. Figure 21b represents an age profile of wealth in the NJS. Log of savings on the vertical axis are imputed values given following categorical data. 1: Less than \$10,000, 2: $\$10,000 - \$24,999$, 3: $\$25,000 - \$49,999$, 4: $\$50,000 - \$99,999$, and 5: $\$100,000$ or more. The bandwidth of LOWESS is 0.8.

5 Conclusion

This paper shows that the hump-shaped job search profiles over the life-cycle in the US data is the result of the imperfect information on individuals' type and accumulated savings in the incomplete market. Not only along the time-series dimension, but the paper explains the cross-sectional implication of job search effort based on the true type and the updated belief.

This study leads following future interesting research topics. First, we can consider another puzzle for life-cycle labor supply dynamics. Under the imperfect information structure, i.e., the process of resolving perceived risk, the expected dynamics of labor supply is decreasing shape over the life-cycle. As a well-known theory, the labor supply increases when there exist higher uncertainties for future periods as a precautionary motive.[24] Thus, under the imperfect information with Bayesian learning framework, expected hours work profiles would be monotonically decreasing curve due to resolving uncertainties and precautionary savings. Identifying dynamics of labor supply and job search supply would be an interesting topic. Second, the additional finding in Aguiar et al. (2013) is that the job search profile in the

[24] See Flodén (2006) for detail. And see Rogerson and Wallenius (2009), Kaplan (2012), Badel and Huggett (2014) to study life-cycle labor supply dynamics.

Base Age Group: 20−24		
Difference	Demographics (1)	Uncertainty + Wealth (2)
β_{2529}	4.502***	22.18
β_{3034}	3.944***	7.621
β_{3539}	6.537***	4.047
β_{4044}	5.515***	8.410
β_{4549}	4.974***	-1.198
β_{5054}	6.442***	9.643
β_{5559}	5.839***	18.54
β_{6064}	3.033***	16.72
Demographic + Year	Yes	Yes
Wealth	No	Yes
Uncertainty	No	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Decomposition: The second column Demographics (1) represents the different of job search effort between the age group a and the age group $20-24$ as in Table 3. The third column Uncertainty + Wealth (2) controls demographics, measured uncertainty in the case of $\tilde{\xi}_1 = (y_1 - r_1)^2$.

Europe data shows decreasing trend over the life cycle. By embedding the empirical estimates of the HIP processes to this model, we can test whether this framework works without considering significant differences of fiscal policies in the US and the Europe countries.

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Appendices

A Supplement of Empirical Analysis

A.1 Data Appendix: NJS

1. **Job Search Effort**: contacted employer directly (q10a1_1 in the survey questionnaire), contacted public employment agency ($q10a1_2$), contacted private employment agency (q10a1_3), contacted friends or relatives (q10a1_4), contacted school/university employment center (q10a1_5), checked union/professional registers (q10a1_6), attended job training programs/courses (q10a1_7), placed or answered ads (q10a1_8), want to interview (q10a1_9), sent out resumes/filled out applications (q10a1_10), looked at ads (q10a1_11) and other (q10a1_12). Search intensities are evaluated by the sum of all and I scale them in hours.

2. **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.

3. **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)

4. **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 (2017).[25]

[25] 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.

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

A.2 Selection Issue in Measuring Uncertainty

Since the offered earning y is observed only if workers get job offers, there would be selection issues. Thus, I check if job seekers who got job offers have higher or lower reservation wages than them who did not get job offers during the survey period. I find that reservation wages of job seekers who did not get job offers are statistically higher than those who get, unconditionally and conditionally. This implies that observed $\tilde{\xi}$ might be upward biased. However, the offered wages *within the group* are positively correlated with reservation wages. The reservation wage is controlled by age, gender, race, spouse's income, mortgage debts, household income, savings and education. The positive correlation between offered wage and reservation wage is robust to both of parametric linear regression with 1,000 bootstrap replications and non-parametric analysis. Even in non-parametric analysis, logarithm of offered wages and logarithm of reservation wages show very strong linear relationship. If we can assume that the positive correlation holds for job seekers who did not get job offers, the upward bias can be weak or canceled out. Theoretically, it can be rationalized by prediction of the directed search model. Job seekers who are on long queues of the submarket with better offers would take longer time to get job offers than those who are on the submarekt with lower offers. Additionally, the Hausman test cannot reject the null hypothesis (no endogeneity) in the main analysis. To support the above argument, I 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 6 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 22 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.

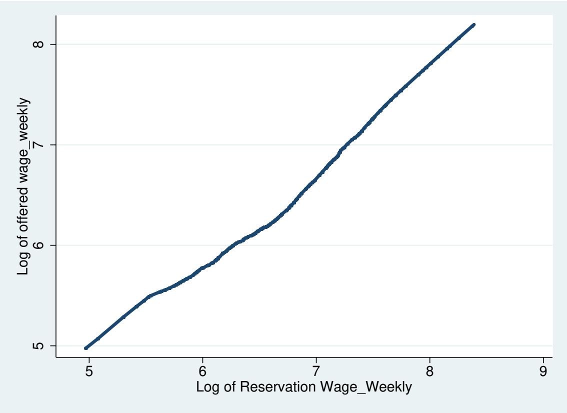

Figure 22: A locally weighted regression (LOWESS) with bandwidth 0.3. Dependent variable is a log of offered wage and an independent variable is a log of reservation wage. The estimated coefficient in the linear regression with 1,000 bootstrap replications is 0.9641 with 0.0298 standard error.

A.3 Data Appendix: ATUS

In the regression analysis, I exclude samples which exceed more than 60 hours per week for job search. For example, while the average hour of job search activity (t050481) is around 0.3 hours per day, the maximum is around 16.3 hours per day for unemployed workers. Since the average share of job search activity is not quite large, it is beneficial to control those outliers. As the result, I exclude 30 samples. This sample restriction does not harm any main result qualitatively.

1. **Job Search Effort**: job Interviewing (t050403), Waiting associated with job search or interview (t050404), security procedures related to job search/interviewing (t050405), job search activities (t050481), and job search and interviewing, n.e.c. (t050499).

2. **Core Home Production**: Interior cleaning (t020101), Laundry (t020102), Sewing, Repairing and Maintaining textiles (t020103), Storing interior hh items, including foods (t020104), Housework, n.e.c. (t020199), Food and drink preparation (t020201), Food presentation (t020202), Kitchen and food clean up (t020203), Food and drink preparation & Clean up, n.e.c. (t020299), Building and repairing furniture (t020302), Heating and cooling (t020303), Interior maintenance, repair & decoration, n.e.c., (t020399), Vehicle repair and maintenance by self (t020701), Vehicles, n.e.c. (t020799), Appliance, tool, and toy set-up, repair & maintenance by self (t020801), Appliance and tool, n.e.c. (t020899), Financial management (t020901), Household & personal mail & messages except e-mail (t020903), Home security (t020905), and Travel related to household activity (t180280)

A.4 Wealth Effect: Fully specified estimation result

Table 7 represents the empirical evidence of wealth effect and other outside options to search intensities.

A.5 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.[26] 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.

Results can be characterized by as follows. First, results in the paper are more close to the crisis periods results. Second, as shown by many other empirical results, people devotes more efforts in the recession. Figure 23 represents job search profile in the crisis periods 2007 $\sim$ 2009 and Figure 24 represents job search profile in the normal periods 2004 $\sim$ 2006. Those are results of polynomial degree 2 and the selection criteria of choosing polynomial degree is the same as Aguiar et al. (2013).

A.6 Search on the job in the data

Both Aguiar et al. (2013) and this paper do not consider employed worker's search efforts. In this section, empirical characteristics of the search on the job can justify them and give interesting consistency with other literature. Empirical characteristics of on-the-job search can be summarized as follows. First, the level of search effort is much smaller. Roughly, on-the-job search is about 8 minuets in a week.[27] Second, the job search profile for employed workers is the U-shaped curve, which is opposite the job search profile for unemployed

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

[27] This could be because more employed workers who want to change jobs would use institutions like head-hunter companies. Of course, theoretically, fees for using them also should be taken into account for search effort.

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 7: 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%.

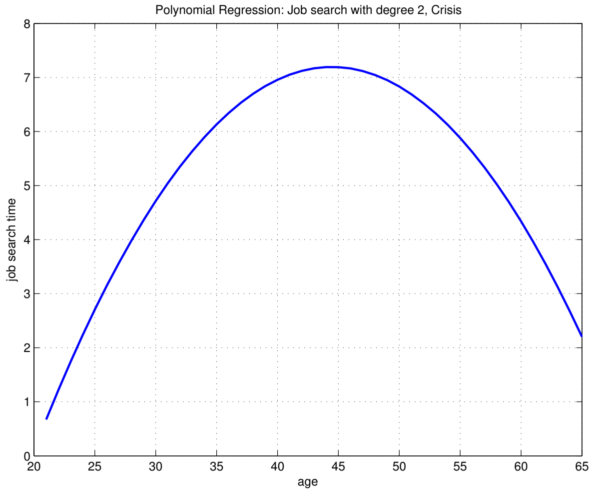

Figure 23: Crisis periods: 2007 ∼ 2009

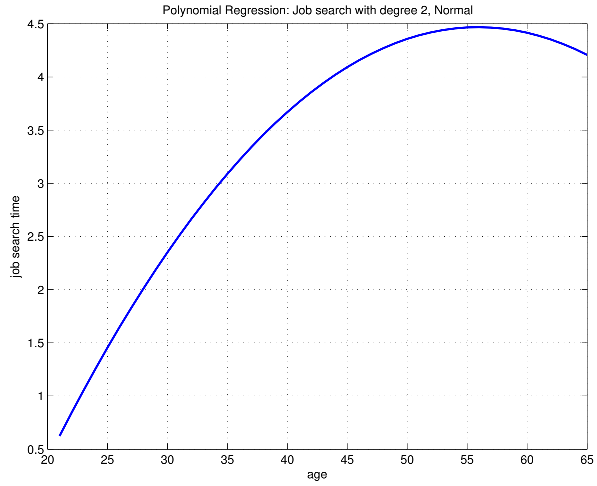

Figure 24: Normal periods: 2004 ∼ 2006

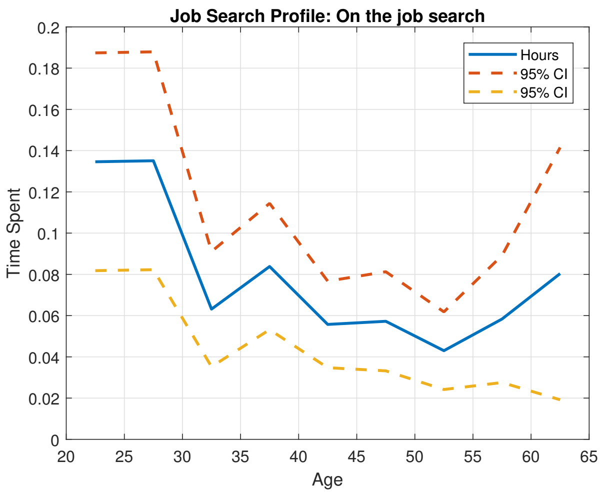

Figure 25: On the job search: 2003 ∼ 2016

Figure 26: On the job search: 2003 ∼ 2016

workers. Qualitatively, this result could be partially consistent to Topel and Ward (1992)'s result. Topel and Ward (1992) shows that about two-thirds of occupational changes in the life-cycle are implemented during workers' first ten years in the labor market. We need more rigorous identification in the data in order to argue the above claim but this section just studies time spent for search jobs by employments as supplements of the paper. Figure 25 shows estimated job search profile from age-dummy regression and Figure 26 shows estimated job search profile from polynomial regression with degree 2.

B Proofs

B.1 Proposition 2.1

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. □

B.2 Proposition 2.2

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 2.1, $y_F^* = y_G^* = b$ Then, given strictly increasing and strictly concave utility function u, since $\int_{y^*}^{\bar{y}} J(a', y')dF(y') \geq \int_{y^*}^{\bar{y}} J(a', y')dG(y')$, what we need to show is $g_{F,a}^U(a) \leq g_{G,a}^U$ and this is shown by Flodén (2006). This completes the proof.

□