Job Hunting: A Costly Quest*

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Abstract

Searching for a job requires, among other resources, money, which unemployed often lack. To study the implications of pecuniary search costs, which mostly affect search decisions of liquidity-constrained individuals, we embed them in a general equilibrium model featuring incomplete markets and search-and-matching frictions with endogenous job search decisions. In the model, the elasticity of the likelihood of job search decisions to unemployment insurance benefits identifies the quantitative impact of pecuniary search costs. To empirically estimate this moment, we use administrative data from random job-search audits of unemployed individuals claiming benefits, exploiting exogenous variation in such benefits due to their formulas. After matching this elasticity in the model, we analyze policies aimed at alleviating the adverse effects of such costs on allocations and welfare. We find the endogenous response of the assets' distribution is key for policy evaluation, highlighting the disparity between our reduced form estimates and the full equilibrium analysis.

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1 Introduction

Unemployed individuals who actively search for a job incur different types of costs that can be expressed in terms of time, which they typically have to spare, and of monetary resources, which they often lack. With imperfect insurance and credit markets, the latter costs —*"pecuniary search costs"*— may prevent individuals from searching, and eventually from participating in the labor market altogether. Moreover, such costs can impose a significant financial burden on low-asset unemployed individuals facing liquidity constraints, who are limited in their ability to smooth consumption.[1] Indeed, a vast literature documents that a nontrivial share of the unemployed has limited liquid assets to tap into to replace lost income (see, e.g., Sullivan, 2008; Chetty, 2008), and more generally the existence of liquidity constraints (see, e.g., Jappelli, 1990; Jappelli and Pistaferri, 2010; Kaplan and Violante, 2014; Kaplan, Violante and Weidner, 2014; Jappelli and Pistaferri, 2014). Against this background, it is natural to view pecuniary search costs as a potential barrier to gainful employment, with adverse welfare consequences for liquidity-constrained unemployed individuals and the economy as a whole.

In this paper, we study the aggregate and distributional impact of pecuniary search costs and policies aimed at alleviating their adverse effects in terms of both allocations and welfare. We do so in three steps. First, we develop a novel general equilibrium heterogeneous-agent search-and-matching model with both pecuniary and non-pecuniary costs and endogenous search decisions. Second, to quantitatively discipline the pecuniary search channel we use indirect inference methods; we use administrative data of random job-search audits of unemployed individuals from the U.S. Department of Labor[2] and exploit quasi-exogenous variation in unemployment insurance (UI) benefits to estimate their impact on the likelihood of unemployed individuals engaging in active search. As we show, this is an informative moment with respect to the relative importance of pecuniary vs. non-pecuniary search cost. Third, we employ our general equilibrium model as a "laboratory" to evaluate the economic and welfare impact of different government policies.

Hence, in this paper we study an under-researched aspect of UI benefits, namely that they allow liquidity constrained unemployed to keep searching. Importantly, from a policy perspective, such

[1] Examples of pecuniary search costs include those for "presentation of self" (e.g., clothing and personal grooming), transportation, home computer, and internet access, resumé service or employment agency fees, and child care. In fact, until 2018, the U.S. tax code permitted deductions of items related to job search, thus recognizing the importance of pecuniary job search.

[2] Such data has also been used by Fuller, Ravikumar and Zhang (2015) in the context of the optimal design of unemployment insurance.

frictions might give a rationale for government intervention aimed at facilitating search. Although job search is central to models of unemployment and is typically a prerequisite for collecting benefits, theoretical (both positive and normative) and empirical evidence about the cost of search, the search decision, and their relation to UI benefits is scant. To fill these gaps we offer novel facts related to a new empirical scheme to exploit quasi-exogenous variation in UI benefits. Theoretically, we develop a rich general equilibrium model which allows us to analyze the impact of pecuniary search costs on search decisions of unemployed individuals and to consider the impact of policy reforms. Importantly, the policy reforms analysis actually overturns what one might have concluded from our micro evidence results alone. In what follows, we discuss these contributions in detail.

Our model economy, presented in Section 2, which is calibrated in Section 3, features incomplete markets where individuals are subject to uninsurable unemployment risk and face search frictions in the labor market. To self-insure against such risk, individuals accumulate assets, such that the distribution of asset holdings is an object determined in general equilibrium. What distinguishes our model from previous work that shares these features (see, e.g., Krusell, Mukoyama and Şahin, 2010; Setty and Yedid-Levi, 2020) is the view that job searching entails both pecuniary and non-pecuniary costs. As a result, the exit rate from unemployment depends on whether unemployed individuals *endogenously* decide to engage in search, and on the equilibrium probability of finding a job conditional on searching.[3]

To quantitatively discipline the margin of pecuniary job search, we rely on indirect inference. Specifically, as we argue in Section 4, the elasticity of the likelihood that unemployed individuals engage in active job search with respect to UI benefits is a moment that identifies the quantitative impact of pecuniary search costs on search decisions. Importantly, this elasticity captures an effect of UI benefits on the decision to search or not search (a dichotomous choice) that is distinct from the UI benefits effect on the exit probability from unemployment that is commonly estimated in the literature; we discuss how these two measures relate in this same section.

In order to estimate this elasticity we rely on administrative data and cross-sectional variation in *actual search decisions* of the unemployed and UI benefit amounts. The data, from the U.S. Department of Labor, contains information on (i) random job-search audits of unemployed individuals collecting UI benefits, (ii) whether the UI benefit recipient has engaged or not in active search, and (iii) administrative records on the amount of benefits, previous wages, and various demographic

[3] See also Lentz and Tranaes (2005) who study a partial equilibrium savings problem of a risk-averse worker who moves back and forth between employment and unemployment and faces leisure, non-pecuniary, search costs.

and labor market variables.

We leverage two sources of cross-sectional variation for the estimation. First, a nontrivial fraction of almost 9% of unemployed individuals do *not* actively look for a job, although they are required to do so by UI state laws. Naturally, the presence of variation in search decisions is a necessary condition for estimating the elasticity of search with respect to UI benefits in the first place. Second, in several U.S. states the amount of UI benefits partially rely on a random timing criteria, which generates plausibly exogenous variation in benefits among individuals with the same wages. Overall, we estimate a positive elasticity of the likelihood of search to UI benefits, which allows us to quantify the pecuniary search cost in the model.

We note that gauging the "importance" of pecuniary search costs from this 9% figure would be misleading. The search costs are paid by all searchers, who are the majority of the unemployed individuals. Since the unemployed tend to be low-asset individuals facing liquidity constraints, the search cost incidence is disproportionately large for them as they are limited in their ability to smooth consumption. That is, what makes pecuniary search costs fundamentally different from the more standard non-pecuniary ones is that they subtract resources, that could be otherwise used for consumption or asset accumulation, especially for individuals with a high marginal utility of consumption; hence, the decision to search for a job entails a drop in consumption from a level that is low to begin with.

We then use our empirical results to discriminate between the two sources of costs. Specifically, in Section 5 we use our estimated elasticity as an auxiliary moment which we ask our model to match. We further evaluate the model along several untargeted moments and show its success with respect to these.

We then turn in Section 6 to our policy evaluation. We first consider a UI benefit reform. We do so, since in the context of the consumption cost of pecuniary search, UI benefits can play a big role in mitigating the consumption loss arising from search which can be extremely painful for those who are already liquidity-constrained. Indeed, our empirical findings discussed above, would suggest, prima facie, that raising UI benefits would lead to increase in the share of unemployed individuals engaged in active search. However, perhaps surprisingly, we find that an increase in UI benefits leads in fact to a *reduction* in the share of unemployed individuals engaged in active search, and consequently a fall in the exit rate from unemployment. Hence, the economic impact of a UI benefit reform, our first policy experiment, cannot be gleaned from the empirical estimates alone. In other words, while our reduced-form estimates of the impact of UI benefits on the likelihood of search are an essential input to discipline the relative importance of the two types of search costs, they are misleading in terms of their implications for the potential impact of policy reforms.

The discrepancy between the empirical estimates and model's predictions arises from the behavioral response of the individuals in the model: after a policy reform, individuals change their savings, fueling an across-the-board adjustment in the asset holding distribution, which in turn impacts the likelihood of the average unemployed individual to engage in costly search. Naturally, such an endogenous change in the asset distribution cannot be simply gauged from the cross-sectional variation in our data. As such, from a policy perspective, our model highlights the importance of including a motive for self-insurance in the presence of pecuniary search costs. Indeed, Engen and Gruber (2001) supports the view that the generosity of UI benefits affects saving decisions by lessening the precautionary saving motive. More generally, the evidence suggests that the existence of a distribution of asset holding among the unemployed is empirically relevant. On the one hand, a significant fraction of the unemployed has access to credit markets (see, e.g., Herkenhoff, 2019; Braxton, Herkenhoff and Phillips, 2020), suggesting that they can partly smooth income shocks, while on the other hand, the evidence suggests that there is a non-negligible fraction of households with few assets who do not have sufficient access to these markets to smooth consumption (see, e.g., Sullivan, 2008). It is the interaction between this distribution of asset holdings and the pecuniary search costs that is crucial for the policy impact.

Armed with this result we then show that due to the endogenous adjustment in the asset holding distribution a wide range of UI benefit *reductions* in fact increase the fraction of searchers, and consequently increase the exit rate from unemployment. However, we demonstrate that UI benefits can only be reduced to a certain limit, since the fraction of searchers starts to decline when benefits fall below a critical threshold. Moreover, in terms of welfare we show that this policy reform reduces the welfare in the economy.

Hence, to summarize, in the model the relation between the generosity of UI benefits and job search is hump-shaped. Moreover, changes in the economy's welfare and in the fraction of searchers are inversely related.

We then continue by analyzing the impact of a different policy, a job search subsidy. As with the UI benefits reforms, we are especially interested in the impact of this program on the fraction of searchers and welfare. Our motivation to study this policy stems from the fact (i) in the U.S. the tax code allowed for deductions associated with job search until 2018, (ii) a job search subsidy represents a more direct way to foster search at the individual level than UI benefits do in the presence of pecuniary search costs.

The analysis of this policy reform delivers a key message. As we show in Section 6 there is a range of search subsidies that achieves both an increase in welfare *and* an increase in the fraction of searchers. However, there is a limit to this; if the subsidies are high enough such that all unemployed search, then aggregate welfare declines due to the greater tax burden required to fund the subsidies. Moreover, importantly, we show that such subsidies unambiguously lead to an overall *increase* in the unemployment rate in the economy.

Our paper is organized as follows. Sections 2-3 present our model and the benchmark calibration. Section 4 presents our data and empirical findgins. Section 5 shows how our estimates are useful in evaluating the relative importance of the two search costs. Section 6 discusses the implications of policy reforms. Section 7 concludes. Appendices A-F include further details and additional results related to the theoretical and empirical analysis.

2 Model

Our quantitative model is a stationary equilibrium hybrid of the Bewley-Huggett-Aiyagari (BHA) incomplete-markets model and the Diamond-Mortensen-Pissarides (DMP) model of unemployment with search costs and endogenous search decisions. Specifically, the paper shares many of the features in Krusell, Mukoyama and Şahin (2010) and Setty and Yedid-Levi (2020) as follows. The economy is populated by a measure one of infinitely-lived risk-adverse individuals who face uninsurable unemployment risk and search frictions in the labor market. Asset holdings and the rate of return on assets (claims to firms' profits), wages, and the probability of finding a job are endogenous objects determined in general equilibrium.

The model's key novel feature is that job search is endogenous. Specifically, searching for a job entails, potentially, two types of costs; a payment of a pecuniary search cost making it painful for liquidity-constrained individuals, and a non-pecuniary utility cost. In a nutshell, a job search is akin to "buying a lottery ticket;" incurring the search cost is tantamount to buying a chance to win a job. The trade-off is that, in order to buy such lottery ticket, the individual has to incur a cost. We emphasize that we model search as a $\{0,1\}$ decision, abstracting from the intensive margin of search effort due to the data on job-search audits which we use to quantitatively discipline the model; as we discuss in Section 4, our data has information on whether or not unemployed individuals engaged in job search without information on the intensity of the search. As such, in order to have a direct mapping between the model and the data we formulate search decisions to be dichotomous.[4]

2.1 Firms

Production requires the match between one firm and one individual. When a match (or "job") is created, output y is produced with a linear production function. The matching process between unemployed searchers and vacancy-posting firms is subject to a search friction; job vacancies, V, and unemployed searchers, U_S, are randomly matched each period according to a standard constant-returns-to-scale matching function that gives $M(U_S, V)$ matches in a period. In this context, the probability that an unemployed searcher finds a job λ_w is equal to $M(U_S, V)/U_S = M(1, V/U_S) = M(1, \theta)$, where $\theta \equiv V/U_S$ is the tightness ratio. Similarly, the probability that a job vacancy is filled λ_f is equal to $M(U_S, V)/V = M(U_S/V, 1) = M(1/\theta, 1) = \lambda_w/\theta$. We assume that a match is destroyed with an exogenous and constant probability σ in each period.

On the production side firms face the same problem as in the standard DMP model adjusted for the fact that a fraction of the unemployed is not searching, which the firm takes as a given equilibrium object. Formally, there is a continuum of firms posting job vacancies whose mass is determined in free-entry equilibrium. We assume that firms discount future values by $\frac{1}{1+r}$, which corresponds to the marginal rate of substitution of equity holders.

The value of posting a vacancy is

$$V = -k + \frac{[\lambda_f J + (1 - \lambda_f)V]}{1 + r}, \tag{1}$$

where k is the unit cost of posting a vacancy and J is the value of a filled job, which is given by

$$J = y - w + \frac{[\sigma V + (1 - \sigma)J]}{1 + r}, \tag{2}$$

where w is the wage rate whose determination we discuss below. In free-entry equilibrium, firms post new vacancies until $V = 0$, so that the cost equals the expected benefit of posting a vacancy, $k = \lambda_f J/(1 + r)$.

[4] See Appendix A for a simplified partial equilibrium version of the model in which we derive several theoretical and qualitative results, including a Baily-Chetty-type formula for optimal benefits. The formula highlights the trade-offs from insurance provision faced by a social planner in the presence of pecuniary search costs.

2.2 Individuals' Dynamic Program

Individuals discount future streams of utility by a discount factor $0 < \beta < 1$. Their preferences over current consumption c are described by a strictly increasing and concave utility function $u(c)$. They face unemployment idiosyncratic shocks not fully insurable by the government; the government provides UI benefits that partially replace the wage.

We assume that individuals can be in one of three labor market states: employed, unemployed searcher, or unemployed non-searcher. As discussed above, and as is common in the DMP model, the transition from employment to unemployment occurs at the time an employed individual is hit by a random job destruction shock, σ. The transition from unemployment to employment depends on two elements. First, the endogenous decision of the unemployed, which is the key focus of our model, of whether to search or not. Second, conditional on searching, as discussed above, all unemployed face the same job finding probability, λ_w which is naturally an equilibrium object.

Guided by the data discussed below in Section 4 we assume that UI benefits are (i) constant within an unemployment spell, and (ii) random at the time an employed individual is hit by a job destruction shock; as we discuss at length in Section 4, in many U.S. states, the "randomness" in UI benefits is a result of the UI benefit rules, so that individuals with the same total amount of past wages receive different benefits. Here, for model's simplicity, we bypass the formalization of the specific details of the UI benefit rules altogether, but, consistently with the data, in the model individuals with the same wage can draw different benefit amounts.

We write the individual's problem in recursive form. As we focus on a stationary equilibrium, we omit aggregate state variables from the individual's state vector to streamline exposition. Let $V_e(a)$ denote the value function of an employed individual who holds equity shares a, which are claims to the overall firms' profits in the economy. Similarly, $V_{u,S}(a,b)$ and $V_{u,N}(a,b)$ denote the value functions of an unemployed searcher and non-searcher, respectively, with assets a and current level of benefits b. Individuals allocate their available resources between consumption and accumulation of assets, and decide whether to search, to maximize their discounted value of lifetime utility.

Formally, the employed individual's problem is given by

$$V_e(a) = \max_{a' \geq 0} u(c_e) + \beta \left[\sigma \mathbb{E} V_u(a', b) + (1-\sigma) V_e(a')\right], \tag{3}$$

subject to $c_e + pa' = w + (p+d)a - T$, where c_e is consumption of the employed, T is labor taxes, p denotes the value of equity shares, and d is the dividend payout to shareholders.[5] Also, we impose the common in the literature no short selling constraint on equity, $a' \geq 0$. Finally, the wage w is determined via Nash bargaining as described below.[6]

Turning to unemployed individuals, we note that job searching is described by a discrete choice, so that the value of an unemployed individual is

$$V_u(a,b) = \max\left\{V_{u,S}(a,b), V_{u,N}(a,b)\right\}. \tag{4}$$

At each point in time, an unemployed individual, searcher and non-searcher, decides whether to continue searching or to start searching, respectively, given the current level of assets and UI benefits.

We specify the unemployed searcher's problem as

$$V_{u,S}(a,b) = \max_{a' \geq 0}\ u(c_{u,S}) - \Phi + \beta\left[\lambda_w V_e(a') + (1-\lambda_w)V_u(a',b)\right], \tag{5}$$

subject to $c_{u,S} + pa' + \Psi = b + (p+d)a$, where $c_{u,S}$ is consumption of the unemployed searcher, and Φ and Ψ are non-pecuniary and pecuniary search costs, respectively.

Similarly, the unemployed non-searcher's problem is

$$V_{u,N}(a,b) = \max_{a' \geq 0}\ u(c_{u,N}) + \beta V_u(a',b), \tag{6}$$

subject to $c_{u,N} + pa' = b + (p+d)a$, where $c_{u,N}$ is consumption of the unemployed non-searcher. Hence, note that we assume for simplicity in this version of our model that individuals receive these benefits even if they are not engaged in active job search.[7] This is consistent with our data on job-search audits from the U.S. Department of Labor where, as we show below, individuals, in violation of state laws, receive UI benefits even if they are not searching.

[5]Thus, the gross rate of return to equity is $1 + r = (d + p')/p$, where d is the dividend payout to equity holders. In a stationary environment, there are no capital gains, so that $p' = p$ and $r = d/p$.

[6]As is common in the literature, we assume that the individuals are not allowed to hold the claims to the profit of individual firms; rather they can only hold claims to the aggregate profits of a "representative firm" with a continuum of jobs. Without loss of generality, we normalize the total amount of equity to one.

[7]Hence in this version of the model we abstract from issues related to detection technologies and auditing probabilities altogether. See Appendix F for a version of this model where individuals face a detection probability and Ravikumar and Zhang (2012), Fuller, Ravikumar and Zhang (2015), and Setty (2019) for work that discusses detection probabilities in the context of optimal unemployment insurance.

2.3 Wage Determination

As is standard in the DMP literature, we assume that the wage is determined by period-by-period Nash bargaining. We assume that bargaining is based on the *mean* net surplus from accepting a job rather than the individual surplus. Under this solution concept there is only one equilibrium wage. Formally, let $\overline{V}_e$ and $\overline{V}_{u,S}$ denote the mean values of employed and unemployed searchers. We specify the bargaining problem as

$$w = \arg\max \left(\overline{V}_e - \overline{V}_{u,S}\right)^{\eta} J^{1-\eta}, \tag{7}$$

where $0 < \eta < 1$ is the worker's bargaining weight.[8]

We opt for this approach since it greatly simplifies computation; instead of solving for a large set of wage functions for all combinations of asset holdings, benefits, and, most importantly, endogenous search decisions, we only have to solve for one wage. Moreover, while the assumption of a common wage simplifies computation, perhaps more importantly, our approach is consistent with our empirical analysis in the next section. In the regressions we estimate the empirical relationship between UI benefit generosity and search, controlling for past wages. In other words, in the data we compare two unemployed individuals collecting UI benefits who are the same in all observables, including their pre-unemployment spell wages, but who differ in the amount of benefits they collect. Notably, we will make the same comparison among the individuals in the stationary equilibrium of the model.

2.4 Equilibrium

We consider a stationary equilibrium in which aggregate variables are constant and refer the reader to Appendix C for a detailed discussion of the solution algorithm. At the stationary equilibrium, individuals transit across all labor market states with positive probability. A Recursive Stationary Equilibrium consists of a set of value functions, $\{V_e(a), V_{u,S}(a,b), V_{u,N}(a,b), J, V\}$, a set decision rules for consumption, $c(a,e,S)$, asset accumulation, $a'(a,e,S)$, and search decision $S(a,e)$,[9] prices, $\{w, p\}$, job vacancies v, tightness ratio θ, dividends d, government policy $\{b, T\}$, and a stationary distribution of assets $F(a,e,S)$, such that:

[8] In our simulations, we verify that the wage remains in the bargaining set for all asset levels. This implies there are no endogenous job separations induced by the assumption of a common wage. All job separations come from the exogenous and constant job destruction shock, σ.

[9] We define $S(a,e) = 1$ to denote a searcher and $S(a,e) = 0$ to denote a non-searcher.

1. Individual decision rules solve the value functions (3)-(6).

2. Posted job vacancies are consistent with free entry $V = 0$ and with the fraction of searchers derived from the individual decision rules.

3. The asset market clears: $\int adF(a,e,S) = 1$.

4. Matching probabilities are functions of V and U_S as implied by the matching function.

5. The wage is consistent with Nash bargaining.

6. The government budget is balanced.

7. The aggregate resource constraint holds.

3 Calibration of Standard Parameters

To parametrize the model, we proceed as follows. First, to facilitate comparison with previous work, we set the value of a subset of parameters based on common values or data moments used in the literature. Second, to measure the empirical counterpart of the fraction of unemployed searchers in the model (which is an equilibrium object), and the relation of UI benefits to search decisions, we rely on an administrative data we discuss below in Section 4.

A period in the model is a month and we set the constant exogenous job-separation rate σ to 0.02 (see, e.g., Krusell et al., 2017). Given this value for σ, we then target an unconditional job-finding probability of 0.38 so that the unemployment rate equals 5%. We choose the value of the unit vacancy cost k so that the probability of finding a job conditional on searching is $\frac{0.38}{\text{Fraction of Searchers}}$, where the "Fraction of Searchers" is the fraction of unemployed who engage in active search which we discuss below. Since we assume a Cobb-Douglas matching function, and set the elasticity of matches with respect to vacancies α to 0.5 (see, e.g., Petrongolo and Pissarides, 2001), then given that there is a fraction of the unemployed that does not search, the tightness ratio θ is defined over the relevant measure of searchers implying that in the steady state $\theta = \lambda_w^{1/\alpha} = \left(\frac{0.38}{\text{Fraction of Searchers}}\right)^{\frac{1}{\alpha}}$. This pins down λ_f. Of course, in our policy experiments in Section 6, θ, λ_w, and λ_f are equilibrium objects that change in response to changes in the environment. Finally, the worker's bargaining weight η is set to 0.5 implying symmetric Nash bargaining. The overall parameter values, sources, and data targets are summarized in Table 1.

Table 1: Model Parametrization

Parameter	Description	Value	Target/Source
Preferences			
β	Time discount factor (monthly frequency)	0.995	Annual interest rate (5%)
γ	Relative risk aversion	2	Kydland and Prescott (1982)
Labor-market frictions			
σ	Exogenous separation rate	0.02	Krusell et al. (2017)
α	Elasticity of matches w.r.t. vacancies	0.5	Petrongolo and Pissarides (2001)
η	Worker's bargaining weight	0.5	Symmetric Nash bargaining
κ	Unit vacancy cost	1.08	Job-finding rate (0.38)
Taxes and UI benefits			
τ	Labor tax rate	0.015	Government budget balance
b_{low}	UI benefits: Low	0.4098	10%, average, and 90% of the
b_{mid}	UI benefits: Mid	0.4553	replacement rate distribution
b_{high}	UI benefits: High	0.5009	in BAM data

In terms of preferences, we assume a CRRA utility function, $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$, where γ is the coefficient of relative risk aversion. We set the value of γ to the standard value in the literature of 2, which implies an intertemporal elasticity of substitution (IES) of 0.5 (see, e.g., Kydland and Prescott, 1982).

The last two parameters that need to be assigned values are the search cost parameters Φ and Ψ. We discuss our procedure to do so in the next section.

4 Data and Estimation

In this section, we present our empirical findings on the fraction of unemployed individuals engaged in active job search. This statistic informs the calibration of the search cost parameters Φ and Ψ in a way we make clear below.

Our measure of the share of unemployed who do not search for a job is based on data from the Benefit Accuracy Measurement (BAM) program, which we briefly discuss below, see Appendix B for further details.[10] The time period in the data is between 1988 and 2006. For each unemployed

[10]Data from BAM has also been used by Fuller, Ravikumar and Zhang (2015) in the context of the optimal design of unemployment insurance.

individual in the data set there is information about their age, gender, education, race, and state of residence. In terms of work history, the data includes information regarding the last industry and occupation in which they worked prior the the unemployment spell, their recall status, and administrative records of their base period wage (i.e. the wage prior to the unemployment spell). Moreover the data includes administrative information about the individual's UI benefit amount.

Our outcome variable of interest, "Active Job Search," is a dichotomous variable S = 0, 1, which is not self-reported; rather it is a determination by the auditor that a UI recipient met state search requirements. Specifically, since 1988, the U.S. Department of Labor has organized *random audits* of UI benefit payments, investigating claimant's efforts to find suitable work (see Department of Labor and Administration, 2005). State UI investigators, who are regular UI case file workers, examine payment records and interview claimants and employers to verify all aspects of the claim that could affect benefit eligibility. Essentially, in order to qualify for UI benefit payments, unemployed individuals are asked to describe their job search contacts and then, in turn, the employers are contacted to verify that indeed such job contacts were made.

We find that, overall, a nontrivial fraction of 8.6% of unemployed individuals in our sample does *not* actively look for a job, although they are required to do so by UI state laws. To provide some context to this number we note that using survey data, Chodorow-Reich and Karabarbounis (2016) estimate that "the share of UI income accruing to non-unemployed is 8.4% percent" (see discussion on page 1579, and Table 1, page 1580, which is based on the CPS and SIPP). Hence, our 8.6% figure based on a different administrative data is very close to this estimate.

Armed with this measure of non-searchers, our calibration of the search cost parameters Φ and Ψ is as follows. We solve two versions of the model, one with $\Phi > 0$ and $\Psi = 0$ (non-pecuniary job search), and another for $\Psi > 0$ and $\Phi = 0$ (pecuniary job search). In each case we iteratively search for the parameter value such that in equilibrium 8.6% of the unemployed do not search. For the pecuniary search model we set $\Psi = 1.06$ in order to match the fraction of searchers of 8.6%, while for the non-pecuniary search model we set $\Phi = 9.652$ in order to match the same fraction of searchers. We then also solve for various combinations of $\Psi > 0$ and $\Phi > 0$ such that we continue to match the same share of unemployed non-searchers in the data.

4.1 UI Benefits and the Likelihood of Search

Since different combination of the search cost parameters can match the mean fraction of the unemployed who do not search, we need an additional data moment. This moment will be used to identify which of the various combinations of the search costs fits the data better. We are interested in doing so because in the model the impact of a policy change on aggregate outcomes, including welfare, depends on the relative importance of the two costs.

A natural candidate is the empirical relation between the likelihood that an unemployed individual engages in job search and the generosity of UI benefits. As we show below, in the model, the sign of such relationship flips when we compare the two versions of the model with pecuniary and non-pecuniary job search. We thus proceed to estimate this new moment with the BAM data. We then proceed in Section 5 to analyze the predictions of the non-pecuniary and pecuniary search cost models with respect to this moment. This allows us to calibrate the relative importance of the two search cost.

We note that this elasticity captures an effect of UI benefits on the decision to search or not search (a dichotomous choice) that is distinct from the UI benefits effect on the exit probability from unemployment that is commonly estimated in the literature. After presenting our empirical findings, below we discuss how these two measures relate.

4.1.1 Identification

The fundamental challenge to identifying the effect of UI benefits on the likelihood of searching for work stems from the fact that benefits are a function of past earnings; since UI benefits depend partially on past wages, simply analyzing the link between benefits and the likelihood of a job search may fail to identify the effect of interest for two reasons. First, past wages may directly influence the decision to look for work: due to the positive correlation between wages and benefits, one could then erroneously associate the job search decision with benefits. Second, and more broadly, unobserved variables correlated with past wages (and hence benefits), which also factor into the search decision, generate well-known omitted variable bias.

To address the first challenge, we note that our BAM data discussed above includes detailed administrative information both on base period wages (BPW) and on UI benefits, allowing us to control for the former in our estimation.[11] Sections 4.1.2-4.1.3 address the second challenge.

[11]Commonly used datasets to study the effects of UI benefits, such as the Current Population Survey (CPS), the Survey of Income and Program Participation (SIPP), and the Panel Study of Income Dynamics (PSID) contain neither individuals' qualifying income nor reliable information on the benefit amounts. To overcome these issues, early studies based on those datasets rely on estimates of benefit eligibility and amounts, not on the actual amount of benefits collected (Blank and Card, 1991; Gruber, 1997; Chetty, 2008).

Controlling for BPW and UI benefits A natural question that follows is then whether UI benefits exhibit variation once the BPW is controlled for. Our identification makes use of the fact that, in most U.S. states, UI benefits that individuals receive depend on their *highest quarter* (HQ) of earnings during the previous year, and thus on the *dispersion* of earnings across quarters. As the Department of Labor and Administration (2005) notes, "*depending on the distribution of wages in the base period, workers with the same total base period wages can have... different weekly benefit amounts.*" Hence, due to the presence of the HQ rule, benefits are not a deterministic function of BPW. Rather, the UI benefit amount is a *deterministic* function of the HQ wage, with the function itself varying across states and over time within a given state, allowing us to control both for the UI benefits and the BPW in our regressions.[12]

As an example, consider the state of Arizona, which uses a formula where the weekly UI benefits equal to 0.04 of HQ earnings.[13] The left panel of Figure 1 depicts for each individual collecting benefits the average monthly wage prior to the unemployment spell (BPW/12) on the x-axis and the corresponding HQ on the y-axis. As evident from the scatter plot, individuals with the same BPW have vastly different HQ earnings, which generates variation in benefits for given BPW. Indeed, the right panel of Figure 1 shows how individuals with the *same* BPW receive different UI payments. This is the kind of variation that enables us to control for both the UI benefits and the BPW. In what follows we restrict our focus to states that use the HQ system.

4.1.2 Results

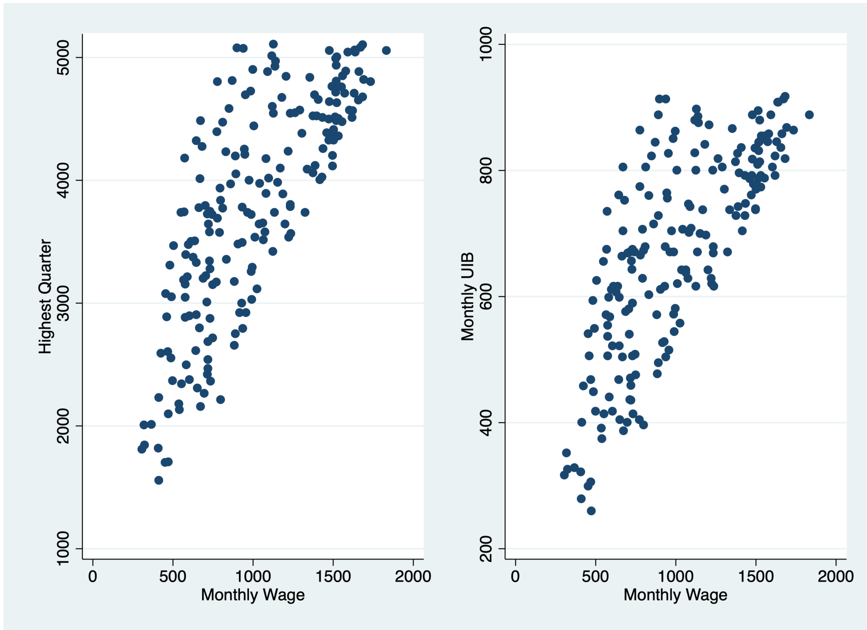
To recap, our dataset offers the following unique advantages over others. First, information on job search activity is not self-reported but based on the conclusion of an auditor's independent investigation. Second, BPW and UI benefit amounts alike come from administrative records. Third, by centering our analysis on states that use the HQ, our identification strategy relies on the fact that UI benefits are determined not only as a function of BPW, but also of earnings dispersion over quarters; it is this rule that importantly allows us to control for the BPW. Overall we are left with 24 states in our sample that use this HQ system.

It is natural to wonder whether the variation in HQ earnings, conditional on BPW and the other observable covariates, is plausibly exogenous. Our baseline analysis relies on a "selection on ob-

[12] To the best of our knowledge, this source of variation in the generosity of UI conditional on BPW has not been exploited before for the purpose of estimating the effect of UI benefits on the likelihood of search.

[13] As an example, consider the case of an individual with a constant monthly wage. She gets a weekly UI benefit that equals 0.04 of her HQ, or on a monthly basis 16% of her HQ earnings. This figure translates into a replacement rate of 48% of her monthly wage.

Figure 1: Variation in Replacement Rates



Notes: Data is for the state of Arizona from 2002 and 2003 for which UI benefits are below the maximum weekly amount of $205. Outliers below the 1% and above the 99% of the HQ distribution are removed for expositional purposes.

servables" assumption where we condition on a rich set of covariates:[14] should any unobservable variable that affects the decision to look for work have a bearing both on the temporal distribution of wages and, hence, on UI benefits, only because of the variable's influence on past wages and on the other covariates that we condition on, our estimates will reveal the effect of UI benefits on search.[15]

We study the sensitivity of our results on this assumption in three ways: first, we document in Table 2 that our results are stable and robust as we include a larger and arguably relevant set of covariates in the analysis. Second, below we provide two further sensitivity tests and we find that our results are arguably insensitive to plausible deviations from the selection on observables assumption.

[14] Table B.1 in Appendix B reports sample averages of the variables in our dataset.

[15] To emphasize that our identification is solely due to the HQ rule, we run our analysis on the subsample of individuals with UI benefits below the state's maximum UI benefits, as it is only for these individuals that the variation in earnings dispersion translates into variation in UIB. Including observations with UI benefits at the maximum level does not alter our findings in any significant way.

Our estimating model is the following Probit specification:

$$S_{i,z,t} = \mathbf{1}(\alpha_0 + \alpha_1 UIB_{i,z,t} + \alpha_2 BPW_{i,z,t} + \alpha_3 \vec{X}_{i,z,t} + \delta_z + \eta_t + \epsilon_{i,z,t} \geq 0), \tag{8}$$

where $S_{i,z,t}$ is a dichotomous search variable $\{0 = \text{Non-Searcher}, 1 = \text{Searcher}\}$ for individual i, in state z, in period t and $\text{UIB}_{i,z,t}$ is the amount of UI benefits for such an individual. In our analysis, in an attempt to reduce concerns that omitted variables such as individual skills may be biasing our results, we always control for the base period wages (BPW) which are the wages earned in the year prior to the spell of unemployment. The vector $\vec{X}_{i,z,t}$ is an additional vector of covariates chosen to control, to the extent possible, for individuals' earning *potential* and includes: demographic characteristics (age, age-squared, gender, and race), education dummies for the highest educational degree attained, last occupation and industry the individual worked in prior to the unemployment spell, recall status of the previous job, and the number of weeks remaining until benefit expiration. We note that since U.S. states vary in their definition of what constitutes "active job search," we include throughout state fixed effects, denoted by δ_z; these serve as additional controls that take into account any state specific unobservables that are constant across individuals in that state. We also control for time fixed effects η_t, and cluster standard errors at the state level and deflate all monetary variables, such as UI benefits and BPW, by the CPI converting them to real values.

Table 2 presents our regression results. The first column reports the estimates from a specification with UIB and BPW as covariates, including state and time fixed effects. This simple regression yields a coefficient on UIB that is positive and significant at the 5% level. Different covariates are then added progressively in columns (2)-(8) and several columns are of particular interest since they control for potential channels that could be affecting search decisions and be related to the variability in the HQ. In column (5) we include a recall status, which addresses the concern that those who could be recalled to their former employers may systematically differ from those who do not. In column (6) we include the number of weeks of UI benefits left; doing so controls for potentially different channels. For example, the incentive to search for work in individuals with fewer weeks of benefits remaining may be higher since they will run out of wage replacement sooner. Conversely, they might become discouraged and stop searching altogether. Alternatively, such individuals also face a lower probability of being audited: because audits are random and occur each week, having fewer weeks of benefits left translates into a lower auditing probability for them and may lessen their incentive to search.

Finally, in column (8) we include dummy variables for the occupation and industry that an individual used to work in prior to the unemployment spell. Doing so addresses the concern that those working in specific industries and occupations may face higher variability in their HQ (e.g., seasonal workers), and also differ in their unobservable characteristics from individuals in other occupations or industries.[16] Overall, the estimate of the UIB coefficient remains positive, statistically significant, and fairly stable, throughout the incremental inclusion of covariates. Had the coefficient estimates varied considerably across specifications, it would have been prima facie evidence of potential omitted variable bias.

Table 2: Probit Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UI Benefits	2.208**	2.537**	2.470**	2.302**	2.231**	2.456***	2.254**	2.075**
	(1.093)	(1.017)	(1.014)	(1.030)	(0.871)	(0.922)	(0.931)	(0.866)
Gender	✗	✓	✓	✓	✓	✓	✓	✓
Age	✗	✗	✓	✓	✓	✓	✓	✓
Education	✗	✗	✗	✓	✓	✓	✓	✓
Recall	✗	✗	✗	✗	✓	✓	✓	✓
Weeks Left	✗	✗	✗	✗	✗	✓	✓	✓
Race	✗	✗	✗	✗	✗	✗	✓	✓
Occ & Ind FE	✗	✗	✗	✗	✗	✗	✗	✓
BPW	✓	✓	✓	✓	✓	✓	✓	✓
State & Time FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Results are based on 102,983 observations from the 1988-2006 Benefit Accuracy Measurement program. See Appendix B for further details on the data.

4.1.3 Further Sensitivity Analysis

While our empirical analysis controls for many potential confounding factors, it is natural to wonder whether the results are sensitive to other possible omitted variables. In what follows we discuss two sensitivity analysis highlighting the robustness of our empirical findings.

Further sensitivity analysis - I Our first sensitivity analysis takes advantage of the fact that UI benefits received by individuals are not only a function of their HQ earnings during the previous year, but also of the state they work in and the year, as replacement rates differ across states and time. Assuming that individuals do not choose which state to work in based on states' replacement rates, this gives us an additional plausibly exogenous source of variation in UIB.

[16]To highlight that our results are not driven by a specific occupation we show in Figure B.1 that the variation in the HQ earnings within occupations is similar across the different occupations.

Hence, to address the concern that despite controlling for many plausible sources of variation in HQ that might correlate with search behavior, others remain unaccounted for, we run an additional robustness check, including the HQ variable as an additional covariate to the specification of column (8) of Table 2. In this case we identify the effect of UIB on search exploiting state and time variation in replacement rates; specifically, in this specification, since the UI benefits are a *product* of the HQ and the state's specific replacement rate (which can also vary over time), we can identify the estimate of the UI benefits while also controlling in the regression for HQ. We find the coefficient on UI benefits to remain remarkably similar to what we estimated before: column (8) of Table 2 reported an estimate of 2.075 with a standard error of 0.866; in this specification we get an estimate of 1.963 with a standard error of 1.029, which implies a p-value of 5.7%.

Further sensitivity analysis - II Next, we introduce an econometric model to formally assess the sensitivity of our results to omitted variables under specific assumptions. Formally, our selection on observables assumption requires

$$S_{i,z,t}(b) \perp UIB_{i,z,t} | \vec{W}_{i,z,t} \ \ \forall b \in \mathcal{B}, \tag{9}$$

where $S(b)$ is the potential outcome (search/don't search) associated with a given benefit level b, $\vec{W}_{i,z,t} \equiv [BPW_{i,z,t}, \vec{X}_{i,z,t}, \{\text{state dummies}\}, \{\text{time dummies}\}]$, and $\mathcal{B} = [0, b_{\max,z,t}]$ with $b_{\max,z,t}$ is state z's maximum UI benefits in year t. The concern is that for equation (9) to hold, one might need to condition on additional variables not included in $\vec{W}_{iz,t}$. Notationally, we collect all such variables in a single potential (unobserved) omitted variable $V_{i,z,t}$.

A rich literature is concerned with how to carry out sensitivity analysis to the possible omission of relevant conditioning covariates in equation (9). Part of this literature leverages results for ordinary least squares to benchmark sensitivity parameters using R^2 coefficients, see, e.g., Imbens (2003), Cinelli and Hazlett (2020), and references therein. Another part of the literature provides semi and nonparametric assessments of the sensitivity of, e.g., average treatment effect estimates to the selection on observables assumption, see, e.g., Franks, D'Amour and Feller (2018) and references therein. Unfortunately, neither approach is immediately applicable in our context: we work with a binary outcome variable where the probability of search is sufficiently small that a linear probability model could introduce substantial bias, so we cannot rely on benchmarks of sensitivity parameters based on the R^2 measure. And our analysis conditions on a large number of covariates, rendering nonparametric methods inapplicable due to the curse of dimensionality.

We therefore assess the sensitivity of our results to possible omitted variables as follows. Suppose that the true data generating process were

$$S_{i,z,t} = \mathbf{1}(\alpha_0 + \alpha_1 UIB_{i,z,t} + \alpha_2 BPW_{i,z,t} + \alpha_3 \vec{X}_{i,z,t} + \gamma V_{i,z,t} + \delta_z + \eta_t + \epsilon_{i,z,t} \geq 0), \tag{10}$$

where V is the unobserved *omitted variable* (our main specification assumes $\gamma = 0$) and $\epsilon_{i,z,t}|UIB_{i,z,t}, \vec{W}_{i,z,t}, V_{i,z,t} \sim \mathcal{N}(0,1)$. Following Yatchew and Griliches (1985), we further assume that $S_{i,z,t}$ are drawn independently given $[UIB_{i,z,t}\ \vec{W}_{i,z,t}]$ and that the conditional distribution of $V_{i,z,t}$ given $[UIB_{i,z,t}\ \vec{W}_{i,z,t}]$ depends on $[UIB_{i,z,t}\ \vec{W}_{i,z,t}]$ only through a linear regression function:

$$V_{i,z,t} = \pi_0 + \pi_1 UIB_{i,z,t} + \pi_2 BPW_{i,z,t} + \pi_3 \vec{X}_{i,z,t} + \phi_z + \psi_t + \omega_{i,z,t}, \tag{11}$$

$$\omega_{i,z,t}|UIB_{i,z,t}, \vec{W}_{i,z,t} \sim \mathcal{N}(0, \sigma^2_\omega), \tag{12}$$

with $\omega_{i,z,t}$ and $\epsilon_{i,z,t}$ jointly distributed bivariate normal with zero correlation. Then the model for $S_{i,z,t}$ can be rewritten as

$$\begin{aligned} S_{i,z,t} = \mathbf{1}((\alpha_0 + \pi_0) + (\alpha_1 + \gamma\pi_1) UIB_{i,z,t} + (\alpha_2 + \gamma\pi_2) BPW_{i,z,t} + (\alpha_3 + \gamma\pi_3)\vec{X}_{i,z,t} \\ + \varphi_z + v_t + \gamma\omega_{i,z,t} + \epsilon_{i,z,t} \geq 0). \end{aligned} \tag{13}$$

Under the normality assumption for ω and ϵ, equation (13) yields a valid probit model. The Maximum Likelihood estimator of the coefficient on UIB then converges to

$$\frac{\alpha_1 + \gamma\pi_1}{\sqrt{\gamma^2\sigma^2_\omega + 1}}.$$

This expression yields an omitted variable bias result for probit models.[17]

In Figure 2 below we report bias contours parametrized by values of (π_1, γ); each subplot corresponds to a different choice of $\sigma^2_\omega \in \{0.1, 0.5, 1, 2\}$. In the figure we also plot additional coefficient pairs as follows. Let $W_{i,z,t,[j]}$ denote the j-th variable in $\vec{W}_{i,z,t}$, and $\vec{W}_{i,z,t,[-j]}$ all other variables. Using OLS, we compute the coefficient on $UIB_{i,z,t}$ from a regression of $W_{i,z,t,[j]}$ on a constant and $[UIB_{i,z,t}\ \vec{W}_{i,z,t,[-j]}]$. This mimics the coefficient π_1 for each of the observed covariates. We then plot the pair given by this coefficient, and the Probit regression coefficient for variable $W_{i,z,t,[j]}$ that results from estimating model (10) with $\gamma = 0$ (this mimics the coefficient α_1 in our main specification

[17] It is easy to show that this omitted variable bias formula is not affected by the scale used to measure $V_{i,z,t}$.

(8) for each of the observed covariates).

Doing so allows us to benchmark the strength of association with $S_{i,z,t}$ and $UIB_{i,z,t}$ that the omitted variable should have relative to the included variables, to overturn our result. As illustrated in Figure 2, the omitted variable should display a much larger effect on search, and/or be much more correlated with UIB, then any of the variables that we already control for. Hence, we conclude that our results are not very sensitive to the selection on observables assumption.

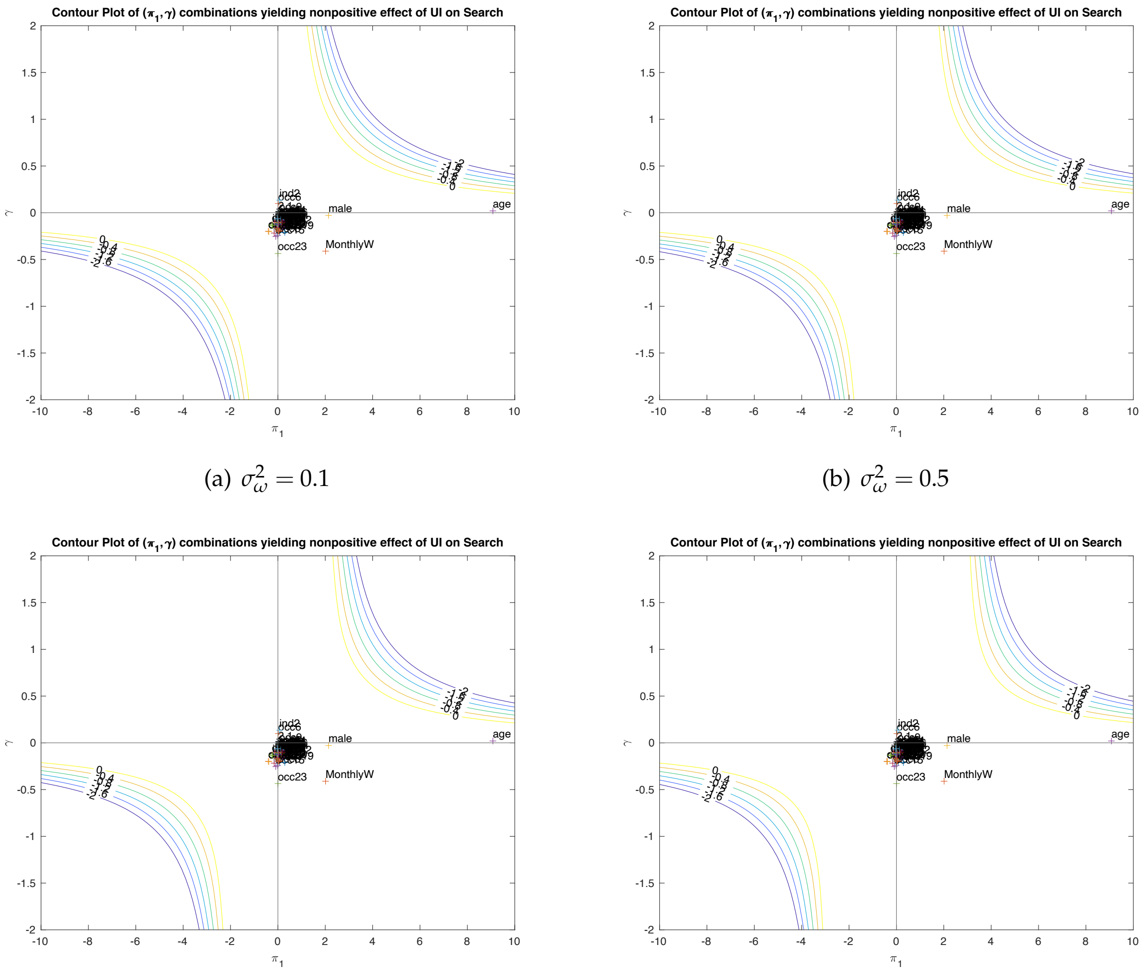
4.2 Relation of Empirical Findings to Previous Empirical Work

Our empirical analysis zooms in on the dichotomous decision of whether or not unemployed UI benefit recipients engage in search. Doing so provides novel evidence on *actual job-search* decisions about which direct evidence is scant. To connect our empirical findings to those in the existing literature, which focuses on exit rates from unemployment and unemployment duration, it is useful to think of the average exit rate from unemployment as the product of two objects, both being potentially affected by changes in UI benefit levels, b: (i) the fraction of searchers, or, one minus the fraction of non-searchers $G(b)$, whose determination we discuss further below; and (ii) the job-finding rate conditional on searching, $\lambda_w(b)$. It then follows that the elasticity of the exit rate from unemployment with respect to UI benefits, denoted by ξ, equals the elasticity of the fraction of searchers plus the elasticity of the job-finding rate conditional on searching:

$$\xi \equiv -\frac{G'(b)b}{1-G(b)} + \frac{\lambda_w'(b)b}{\lambda_w(b)} \gtreqless 0. \tag{14}$$

In our empirical analysis we estimate a positive elasticity of search to benefits, implying that $G'(b) < 0$. This suggests that the elasticity of the fraction of searchers to UI benefits, the first term on the right-hand side of (14), is positive. Through the lens of our model, such elasticity will prove to be a useful moment informing the quantitative relevance of pecuniary job search.

However, we note that taken at face value our estimates are not readily comparable to those in the literature, which are invariably about the exit rate elasticity ξ, as it is the sum of the two elasticities. Indeed, the important body of work that aims at credibly estimating the overall elasticity of the exit rate from unemployment, i.e., ξ in our notation, is extensive and summarizing it is beyond the scope of this paper, so we only offer a short discussion here and below we relate this literature to our modelling choices and results. While the exact magnitudes of the effects vary by study, a consensus view has emerged that: (i) a higher replacement rate (the ratio



(a) $\sigma_\omega^2 = 0.1$

(b) $\sigma_\omega^2 = 0.5$

(c) $\sigma_\omega^2 = 1$

(d) $\sigma_\omega^2 = 2$

Figure 2: Sensitivity Analysis: Contour plots of (π_1, γ) pairs such that $\alpha_1 \leq 0$, compared to Probit regression coefficients of the impact of other variables on search and OLS coefficients of a regression of these variables on UIB and other covariates.

of benefits to base period wage) increases unemployment duration (see, e.g., Carling, Holmlund and Vejsiu (2001), Røed and Zhang (2002), Lalive, Van Ours and Zweimüller (2006)) and (ii) the exit rate from unemployment spikes at the time benefits expire (see, e.g., Moffitt and Nicholson (1982), Moffitt (1985), Grossman (1989), Katz and Meyer (1990*a*,*b*), Meyer (1990), Card and Levine (2000), Lalive and Zweimüller (2004), Lalive, Van Ours and Zweimüller (2006), Landais (2015), Schmieder, Von Wachter and Bender (2012), and Johnston and Mas (2018)). These findings have typically been interpreted as evidence of the disincentive effect of UI benefits (see, e.g., Krueger and Meyer (2002), for a survey article, and Feldstein (2005)).

Related research focuses on the *equilibrium* response of wages, job creation, and labor market tightness. It highlights the general equilibrium effects of UI benefits. Hagedorn et al. (2013) estimate a large and positive macro elasticity of unemployment with respect to a change in UI benefits generosity in the U.S. Consistent with these results, Johnston and Mas (2018) look at the unexpected cut in potential benefit duration that took place in Missouri in April 2011. They discover a significant positive effect on job creation. In contrast, Chodorow-Reich, Coglianese and Karabarbounis (2018) exploit cross-state variation in UI benefits extensions caused by measurement error in within-state unemployment rates and argue for a small or even negative effect of UI benefit extensions on unemployment.

Our model relates to these strands of the literature as follows. Given that our main object of interest is whether or not the unemployed engage in costly search, the extensive margin of search takes centre stage in the model. As such, we make the simplifying assumption that unemployed individuals search in the same labor market and hence they all face *identical* exit probabilities from unemployment conditional on searching. Importantly, as we discuss in Section 6, when we consider the aggregate impact of a UI benefit reform, the overall exit rate from unemployment, ξ, will endogenously change through both components that determine it.

5 Discriminating between the Models

Armed with the empirical results from Section 4.1, we go back to the model predictions for the two calibrations of the search cost parameters. To discriminate between the pecuniary and the non-pecuniary costs we first calculate the implied empirical search probabilities; these are calculated as the average of the marginal probabilities for different values of UI benefits implied by our Probit estimates from column (8) in Table 2. These are reported in the first column in Table 3. We then construct the same object in the non-pecuniary and pecuniary search models.

5.1 Search Cost: Non-Pecuniary

Consider first the case where the search cost is solely non-pecuniary. What are the model's implications for the relation between search activity and UI benefits? As the second column in Table 3 shows, in this model the search likelihood *decreases* the higher the UI benefits are.[18]

Table 3: Fraction of Non-Searchers

	(1)	(2)	(3)
Fraction of Non-Searchers	Data	Model Non-Pecuniary Search	Model Pecuniary Search
Targeted			
Unconditional	8.60%	8.60%	8.60%
Non-targeted			
UI Benefits: Low	8.91%	0%	9.02%
UI Benefits: Average	8.68%	0%	8.60%
UI Benefits: High	8.45%	22.12%	8.17%

Notes: Column (1) presents the implied empirical search probabilities reported for the average and $\pm 10\%$ of the average UI benefit levels. These values cover about 90% of the replacement rate distribution in our data. Columns (2)-(3) show the fraction of non-searchers by the level of UI benefits for the two models, for the same UI benefits range of $\pm 10\%$ of the average. Both models target the unconditional fraction of unemployed who do not search.

This stands in sharp contrast to our empirical estimates. Moreover, not only is the sign of the slope of the relation between UI benefits and the search likelihood counterfactual, the levels of the search probabilities in the model deviate greatly from their respective empirical counterparts, which are reported in the first column in Table 3.

To understand this result, which we formally derive in a simplified version of the model in Appendix F, consider the scenario of two individuals with the same amount of assets whose UI benefits differ. In our model, conditional on searching, and incurring the same non-pecuniary search cost, both individuals face the same probability of transitioning into employment. In this

[18]To allow for variability in UI benefits in our model, and hence be able to compute this moment, we assume that there are three levels of UI benefits in the model: one corresponds to the average of UI benefits in our sample while the other two values are set as $\pm 10\%$ of the average. We chose these values as they cover about 90% of the replacement rate distribution in our data, where importantly we note that in our data, as we discuss below, there is variation in the degree of UI benefits for the same wage level. We then compute the search probabilities generated by the model associated with each benefit level.

case, the individual with higher UI benefits is always less likely to engage in search than her counterpart receiving lower benefits. While both face the same cost of exiting unemployment, the "benefit" of remaining unemployed is always higher the higher the UI benefits are. These forces lead to the prediction that individuals receiving higher UI benefits are less likely to engage in active search. This is depicted in the search policy functions in Appendix Figure D.1.

5.2 Search Cost: Pecuniary

Next, we consider the case where the search cost is solely pecuniary, $\Psi > 0$. As the third column in Table 3 reveals, in contrast to the version of the model discussed above, the search likelihood in this version of the model *increases* with higher UI benefits. Thus, this version of the model, is consistent with our empirical findings. In addition, the search probabilities in the model square well with their respective empirical values reported in the first column of the table.

To understand this result, note that in the model with a pecuniary cost of search, everything else equal, the higher the UI benefits are, the less costly it is to engage in search. In other words, the incidence of the search cost decreases with the generosity of UI benefits. This is depicted in the search policy functions in Figure D.2 in Appendix D.

To further highlight that the non-pecuniary search model cannot match the data, we present in Appendix F a version of this model where individuals face a detection probability. In this model, all individuals are required to search, and those who get detected not doing so loose their benefits. This model addresses the hypothesis that it is the presence of this threat that generates the positive relation between UI benefits and the search likelihood; yet, as we show in Appendix F, even with a detection probability mechanism, the model with a non-pecuniary search cost cannot account for the empirical relation we estimate.

Hence, to conclude, the impact of UI benefits on the likelihood of engaging in active search is a useful moment that allows us to differentiate between the relative importance of the two search costs. Overall, the pecuniary search model comes very close to replicating the empirically *untargeted* moments reported in the first column of Table 3.[19] As such we continue our analysis with the pecuniary search cost version of the model as our favourite setting for policy analysis.[20]

[19] We also experimented with models which included both search costs. Not surprisingly, the relationship between UI benefits and the search probability that results from such mixed models lies in between the two models with a non-pecuniary or a pecuniary search cost. Since the model with solely pecuniary search comes very close to account for the estimated relation between UI benefits and search in the data, we opt to focus on the pecuniary cost specification and abstract from non-pecuniary search costs altogether.

[20] We note that in Appendix E we show that the sign of the relation between the degree of UI benefits and the

5.3 Exit Rates from Unemployment by Assets

The discussion in the previous subsection was concerned with the model's ability to account for the estimated relationship between the level of UI benefits and the likelihood of actively searching for a job. In this subsection we consider the model's predictions for the pattern of exit rates from unemployment to employment (UE) by assets. As we discuss below, our model has clear predictions regarding this relation.

The search policy function in Figure D.2 provides a simple characterization of the mechanism in the model; for a given level of UI benefits, the fraction of unemployed searchers is

$$\text{Fraction of Searchers} = \int_{a^*}^{\infty} S(a)dG(a), \tag{15}$$

where $G(a)$ is the endogenous CDF of asset holdings, $S(a)$ is the search policy function (again, for a given level of benefits) and a^* is the endogenous cutoff above (below) which unemployed individuals do (not) search. Since the job search decision is described by a cutoff rule, in the pecuniary search model the expression for the fraction of searchers simplifies to

$$\text{Fraction of Searchers} = 1 - G(a^*). \tag{16}$$

It is the interaction between a^* and the mass of searchers that determines the measure of searchers in the second and third column of Table 3. Moreover, this interaction highlights that the model has a tight relation between an individual asset holding and the likelihood of exit rates from unemployment.

Table 4: Exit Rates by Wealth Quintile Relative to the Aggregate

UE Flow Rate by Quintiles	Q1	Q2	Q3	Q4	Q5
Model: Pecuniary Search	0.883	1.095	1.095	1.095	1.095
Data	0.880	1.080	1.040	1.100	1.060

Notes: Data on UE flow rates are taken from Table 6 of Krusell et al. (2017). Data statistics are based on the 1990-2008 SIPP panels.

likelihood of search is robust to different values of the search cost; Table E.1 shows that when calibrating both the non-pecuniary and pecuniary search cost models to match a smaller fraction of non-searchers, the non-pecuniary search model continues to counterfactually predict a negative relation between UI benefits and the search likelihood. In contrast, the pecuniary search model continues to correctly predict a positive relation between these two. As such, the underlying relation between the generosity of UI benefits and the search likelihood is robust to different parametrizations of the search cost.

In Table 4, we report UE flow rates by asset quintiles relative to the aggregate exit rate implied by the model and those calculated from the SIPP.[21] The model successfully accounts for the *untargeted* pattern of exit rates by wealth in the data; it essentially matches the exit rate at the first quintile, and, as in the data, the job-finding rate increases with wealth, being approximately flat from the second to the fifth quintile.

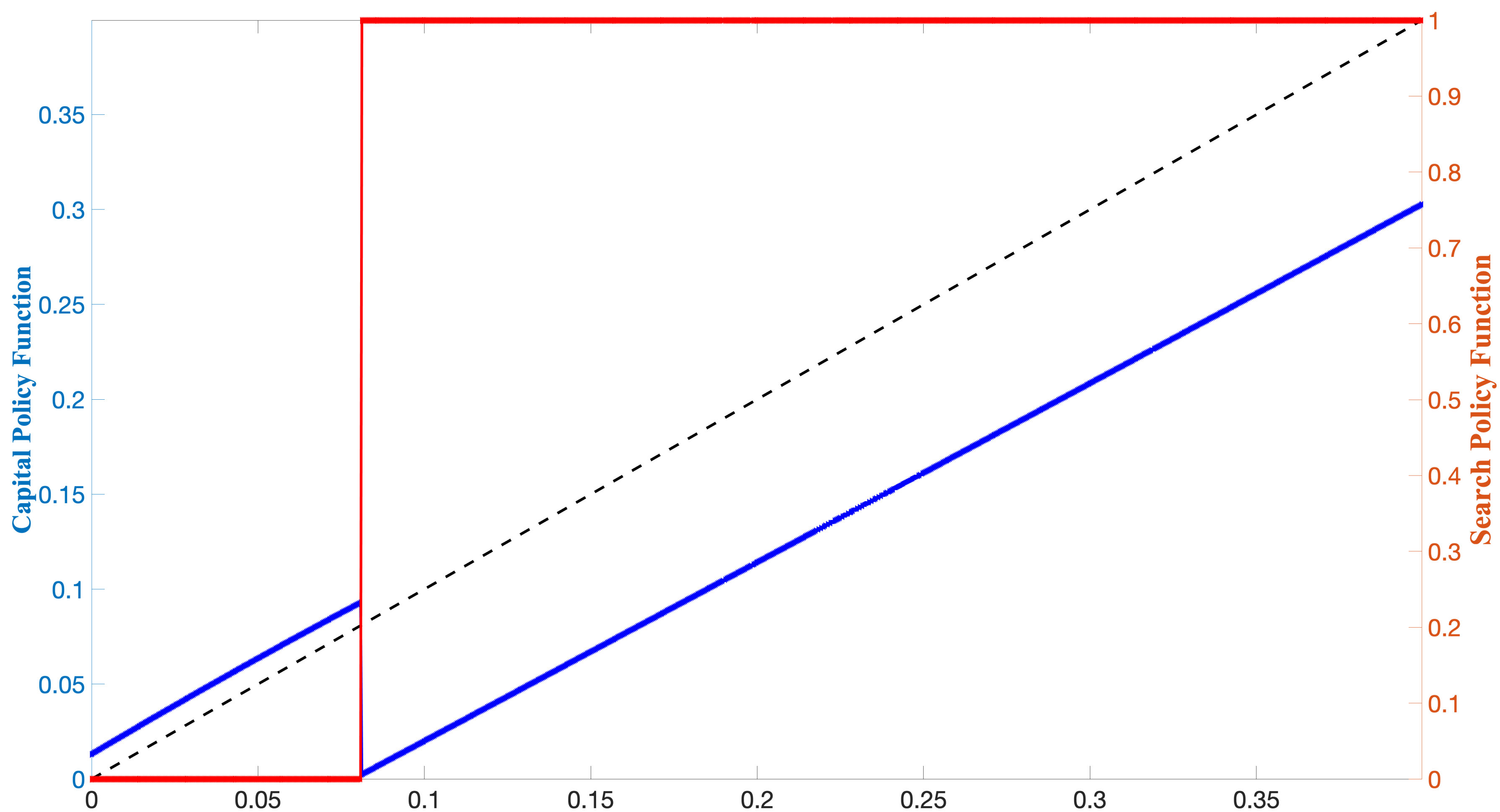
What are mechanics of the model that gives rise to this pattern? In the model this is driven by the presence of the pecuniary search cost: individuals with more assets have more resources to incur the pecuniary cost and so are more likely to exit unemployment. This can be seen in Figure 3 which depicts the asset and search policy functions for the pecuniary search model. It is those individuals with sufficiently high assets that search and thus have a possibility to exit unemployment. In contrast, the model with a non-pecuniary search cost predicts a counterfactual negative relationship between exit rates and assets; recall from Figure D.1 that in that model it is only those individuals with high assets and high UI benefits that do *not* search, and thus do not exit unemployment.

We also note that our model accounts for the fact that a very small share of the net worth is held by the unemployed; 3.9% in the model, which is very close to the empirical counterpart of 1.8%.[22] Admittedly, the model we set up here cannot, and purposely was not built to generate an overall realistic asset holding distribution. In the model, the sole source of risk is related to the possibility of persistent unemployment. There is no aggregate risk, nor other sources of idiosyncratic risk that typically drive precautionary saving decisions in real-world economies, let alone retirement, bequests, and entrepreneurship, all factors that the literature has shown to be quantitatively important drivers of why people accumulate assets. It is also well-known that the BHA models have a hard time generating the observed concentration and right skewness in the U.S. wealth distribution (see, e.g., Quadrini and Ríos-Rull, 1997). In this respect, our model shares the same shortcomings of this type of model and the vast literature that builds on it. Yet, we do not view it as a major concern for two reasons.

[21] Our dataset does not contain information on individual asset holdings, so here we compare the model's predictions regarding the relationship between job-finding rates, often referred to as unemployment-to-employment (UE) flow rates, and wealth from the SIPP. As discussed in Fujita, Nekarda and Ramey (2007) the UE flow rates calculated using the CPS and SIPP differ in levels. Since our model is calibrated to standard CPS levels, to ease comparison of the model with the data, we report the flow rates for each quintile relative to the average flow rate.

[22] This statistic is based on the biannual 2001-2015 waves of the PSID for household heads of 25-65 years old.

Figure 3: Asset and Search Policy Functions for Unemployed Individuals



Notes: The blue line on the left vertical axis depicts the asset policy function for the unemployed individual as a function of current assets. The right vertical axis in red depicts the dichotomous search policy function for the unemployed individual as a function of current assets. For simplicity's sake we depict the policy functions for the UI benefit level that is at its mid value on the grid. The same patterns hold for all levels of UI benefits. The black dashed line shows the 45° line for asset holdings.

First, as argued above, pecuniary search costs matter most for low-asset individuals facing liquidity-constraints, who have limited ability to smooth consumption; they are instead likely to represent a trivial cost for wealthy individuals who are searching for a job. That is, the key margin where the search adjusts is at the bottom of the asset distribution. And as discussed above, our model matches the fact that a very small share of the net worth is held by the unemployed. As such, our model, which by construction lacks many of the features that are required to account for the right tail of the asset distribution, is well equipped to deal with the left tail of the asset distribution, which again, is arguably where pecuniary search matter.

Second, recent empirical evidence strongly corroborates the view that the flows in and out of unemployment are largely composed of individuals who frequently switch jobs, circling through multiple short-lived jobs with intervening unemployment spells, who represent a small subset of the population (Hall and Kudlyak, 2019; Gregory, Menzio and Wiczer, 2021; Morchio, 2020). Such labor market histories are inconsistent with sustained asset accumulation. Taken together these facts suggest that getting the right tail of the asset distribution right is not of first-order importance for the question we tackle in this paper.

6 Policy Analysis

Given the success of the pecuniary search model in accounting for various non-targeted moments, in this section we use it for policy analysis. Specifically, our goal is to quantify the effects of several policies aimed at increasing the fraction of the unemployed who actively search for a job. Our first policy experiment is a tax-financed UI benefit reform. In this respect, we note that our estimates from Table 2 and the implied search probabilities are *not* readily portable to policy valuation: the general equilibrium effects on the share of searchers, wages, asset prices, the asset holding distribution, and exit rates from unemployment cannot be gauged from those estimates. We then continue by considering a policy based on a tax-financed job search subsidy targeted at individuals engaged in search.

6.1 UI Benefits Reform

In this subsection, we study the effects of a once-and-for-all tax-financed increase in UI benefits.[23] The reform entails an across-the-board increase in replacement rates financed by a labor tax levied

[23]See Mitman and Rabinovich (2015) and Mitman and Rabinovich (2019) on the implications of UI benefit extensions for business cycle dynamics.

on the employed. When computing the effects of this policy reform we solve for the new values of the following equilibrium objects: wage, equity price, tightness ratio, balanced-budget tax rate, measure of searchers, and unemployment rates.[24]

Table 5 reports the results of this experiment. To ease exposition, column (1) reports statistics for the benchmark economy prior to the reform. Consider as an example column (2) in which UI benefits increase by 20%, i.e., the benefit schedule goes from a triplet of $(0.409, 0.455, 0.500)$ to $(0.491, 0.546, 0.600)$. The headline result in column (2) implies that in the new equilibrium of the model, the fraction of non-searchers in fact *increases* by about 3 percentage points. Again, we stress that this result holds in the aggregate despite of the positive cross-sectional relation between search probabilities and UI benefits. Similarly, columns (3)-(4) show an even higher rise in the percentage of non-searchers when benefits increase above their pre-reform levels by 30% and 40% respectively.[25]

Why does an increase in liquidity, in the form of more generous benefits that presumably facilitate job search, leads instead to a drop in the fraction of searchers? Again, it is useful to consider Figure D.2 which shows the cutoff values for different values of UI benefits, or Figure 3 where the asset policy function illustrates the individual dynamics of asset accumulation and its interaction with the search decision. In the pecuniary search model, in a partial equilibrium sense, any type of "liquidity injection" is akin to moving the unemployed to a higher asset position. In this scenario, if the increase in benefits is sufficiently large, the individual moves over the asset threshold value, switching from not-searching to searching.

However, this partial equilibrium argument does not capture the endogenous changes in the cutoff value, and most importantly the changes in the asset holding distribution. Specifically, recall that in the model the expression for the fraction of searchers is simply

$$\text{Fraction of Searchers} = 1 - G(a^*), \tag{17}$$

where $G(a)$ is the endogenous CDF of asset holdings, $S(a)$ is the search policy function and a^* is the endogenous cutoff above (below) which unemployed individuals do (not) search.

From this expression it is evident that the policy effects on the mass of searchers operate through two channels; first, changes in the value of the cutoff a^*, and second through changes in the distribution of asset holdings that determines the mass of unemployed to the left of the cutoff, $G(a^*)$.

[24] See Appendix C for a detailed discussion of the solution algorithm implemented for the policy reform analysis.
[25] In Appendix E we show that these results are robust to alternative calibrations of the search cost parameters.

Table 5: Aggregate Effects of UI Benefits Reform

	(1)	(2)	(3)	(4)
	Benchmark	Increase 20%	Increase 30%	Increase 40%
Fraction of non-searchers				
Unconditional UIB	8.60%	11.56%	14.28%	18.52%
Low UIB	8.91%	12.05%	14.80%	18.95%
Mean UIB	8.68%	11.54%	14.23%	18.35%
High UIB	8.17%	11.07%	13.74%	17.97%
Unemployment statistics				
JFR: unconditional	0.380	0.356	0.3391	0.3253
JFR: conditional on searching	0.409	0.402	0.3956	0.4003
Unemployment Rate	5.00%	5.32%	5.57%	5.79%
Prices				
Wage	0.895	0.898	0.900	0.9031
Equity Price	10.693	9.472	8.881	7.5709
Tax	0.02	0.025	0.027	0.029
Welfare: Consumption equivalents				
Weighted Avg. of Unemployed		1.47%	2.17%	2.86%
Weighted Avg. of Employed		0.59%	0.92%	1.12%
Weighted Avg. Overall		0.63%	0.98%	1.20%

Armed with the characterization of equation (17), we continue by implementing a number of exercises. These are aimed at assessing the relative contribution of the different forces that lead to a fall in the fraction of searchers after an increase in UI benefits. For each experiment we discuss below, we present in panels A through C of Table 6 the mass of unemployed below the asset cutoff and the cutoff value itself; given the discussion surrounding equation (17) these are the key objects that determine the fraction of unemployed who search.[26]

6.1.1 Partial Equilibrium I

Our first step is to re-solve the individual's search decision problem after the benefit change, keeping (i) the wage, (ii) the equity price, and (iii) the distribution of asset holdings at their original steady state values. This allows us to highlight the sole *partial equilibrium* effect of changes in UI benefits on search decisions.

Not surprisingly, we find that the cutoff value a^* falls. Thus, individuals with few assets who prior to the increase in the UI benefits did not search, now engage in active search. Simply put, in the presence of pecuniary search costs, higher UI benefits facilitate job search by mitigating the consumption loss incurred by the payment of the search cost. Everything else equal, this would increase the fraction of searchers overall. The column labeled "PE1" in Table 6 shows the results of such an exercise. Again, by the nature of this experiment the asset distribution remains unchanged.

6.1.2 Partial Equilibrium II

Next, we keep on holding the wage and equity price at their original steady state values implying that the cutoff value a^* remains the same as in the PE1 case. However, we compute the new ergodic asset distribution implied by the model after the change in benefits. This experiment highlights the key role that the change in the asset holding distribution has on the fraction of searchers.

The results for this exercise are shown in the column labeled "PE2" in Table 6. To clarify the forces in this case, it is useful to consider the changes in the policy functions under this experiment; Figure 4 shows (i) the search policy function in the steady state and in the PE2 economy, and (ii) the asset policy functions for the employed and unemployed in the steady state and in the PE2 economy.

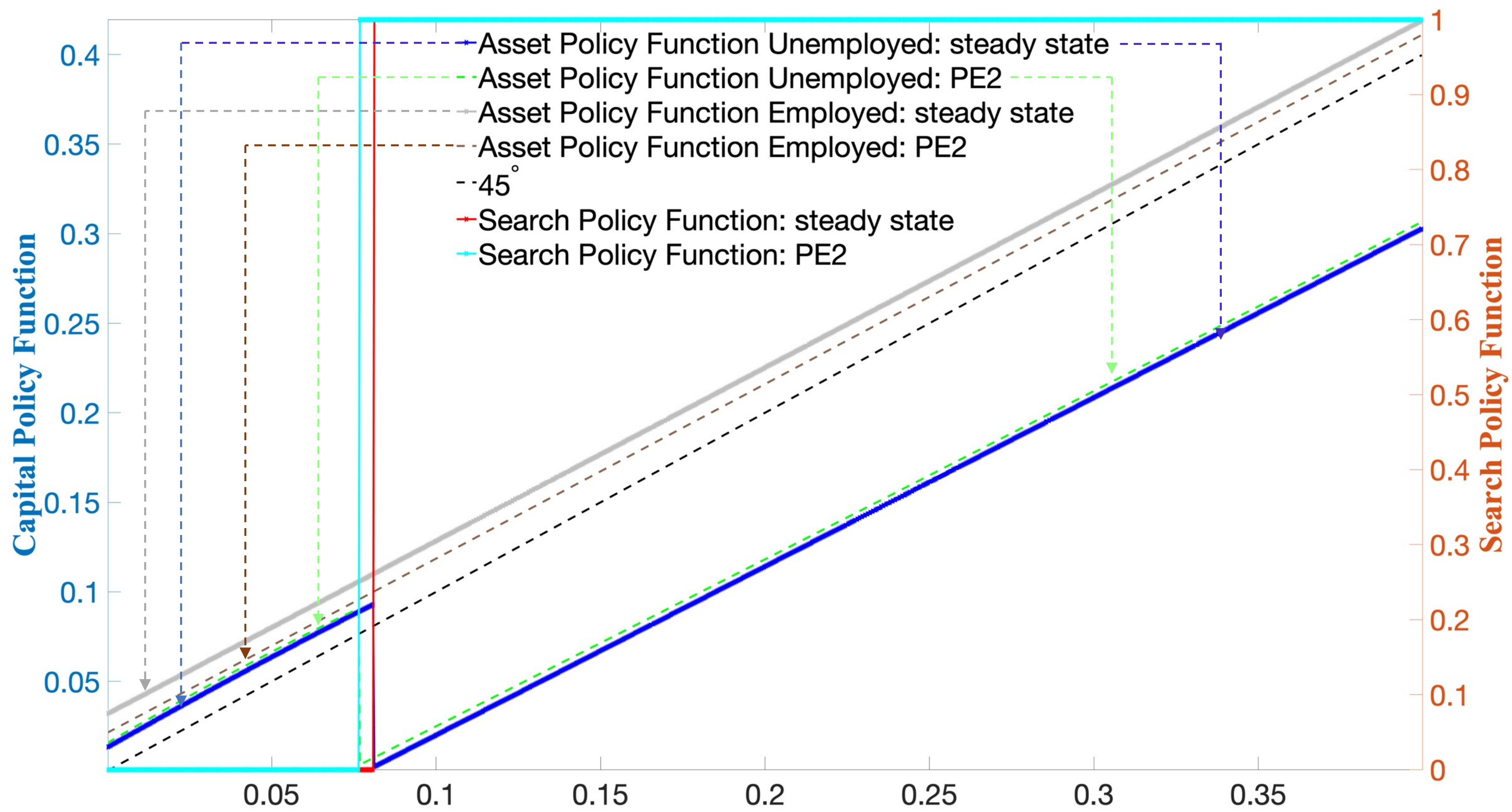
[26] To streamline exposition, the discussion focuses on the case of a 20% increase in benefits, even though the same forces apply for benefit changes of different sizes as well.

Table 6: Inspecting the Mechanism

	(1)	(2)	(3)	(4)	(5)
	Benchmark	PE1	PE2	PE3	GE
Panel A: Cutoff values					
$a^*_{L_{new}}$	0.0808	0.0780	0.0780	0.0892	0.0880
$a^*_{M_{new}}$	0.0792	0.0768	0.0768	0.0876	0.0868
$a^*_{H_{new}}$	0.0780	0.0764	0.0764	0.0872	0.0860
Panel B: CDF at original steady-state cutoff values					
$G(a^*_{L_{old}})$	0.0891%	NA	0.1232%	0.1129%	0.1205%
$G(a^*_{M_{old}})$	0.0868%	NA	0.1182%	0.1074%	0.1154%
$G(a^*_{H_{old}})$	0.0817%	NA	0.1131%	0.1025%	0.1107%
Panel C: CDF at new cutoff values					
$G(a^*_{L_{new}})$	0.0891%	NA	0.1232%	0.1131%	0.1204%
$G(a^*_{M_{new}})$	0.0868%	NA	0.1182%	0.1080%	0.1150%
$G(a^*_{H_{new}})$	0.0817%	NA	0.1131%	0.1033%	0.1103%
Panel D: Fraction of non-searchers					
$G(a^*)$	0.0860	0.0859	0.1182	0.1081	0.1156
Panel E: Equity price					
Equity Price	10.693	10.693	10.693	9.366	9.472

Notes: $G(a^*_{L_{new}}), G(a^*_{M_{new}}), G(a^*_{H_{new}})$ denote the CDF of unemployed, for the low, medium, and high UI benefits levels at the new asset cutoff values respectively. Similarly, $G(a^*_{L_{old}}), G(a^*_{M_{old}}), G(a^*_{H_{old}})$ denote the CDF of unemployed, for the low, medium, and high UI benefits levels at the original steady-state asset cutoff values respectively.

Figure 4: Policy Function: Steady State and PE2



Notes: The figure depicts the search and asset policy function in the steady state and the PE2 for unemployed and employed individuals. To ease the interpretation of the figure it includes arrows that link the legend entry with the specific policy function with matching colors.

First we note that the figure shows a reduction in the asset cutoff value in the face of higher UI benefits; this is depicted as the horizontal movement to the left in the cutoff value and can be read also from panel A of Table 6 which reports the new, lower, cutoff values. In terms of asset holdings, note from the asset policy function of the employed that these individuals, in the face of higher public insurance, reduce their savings. That is, these individuals, in the face of higher UI benefits, optimally choose to hold fewer assets since the provision of public insurance through UI benefits crowds out asset accumulation (see, e.g., Braxton, Herkenhoff and Phillips, 2020; Engen and Gruber, 2001; Herkenhoff, 2019). As such, upon transitioning to unemployment, they start, on average, with a lower asset position than they had prior to the policy reform. Overall, this leads to a "shift to the left" of the asset holding distribution. We note that the unemployed individuals do slightly increase their asset savings following the policy reform, but since the majority of the economy is employed, it is the effect on the employed individuals that dominates the change in the asset distribution.

What is the implication of this new asset distribution for the fraction of unemployed who search? At this new asset distribution, which again is still not the equilibrium one, the mass of non-searchers $G(a^*)$ increases across all benefit levels. Since the search policy function is such that below the cutoff value individuals do not search for work, this shift in the CDF implies that overall the probability of search in the economy should decline. Indeed we find the fraction of non-searchers to increase to 11.82%. In other words, the key message of this partial equilibrium exercise is that the provision of public insurance reduces the demand for self-insurance; this endogenous change in the asset holding distribution overshadows the change in the search policy function discussed in the PE1 economy resulting in a jump of roughly three percentage points in the share of non-searchers.[27]

[27] We relate these partial equilibrium results to Chetty (2008) who shows that individuals who receive severance payments or higher UI benefits exit at a lower rate from unemployment. While we do not formally model severance payments in our framework, the extra liquidity individuals get in the PE2 experiment is similar in spirit. And indeed, in this PE2 experiment, following the increase in UI benefits, the individuals are less likely to engage in active search. Since in the PE2 economy, conditional on searching there is no change in the job finding rate, then overall, unconditionally, there is a fall in the exit rate from unemployment. Thus, our framework is consistent with the empirical findings in Chetty (2008) which are, by construction, of a partial equilibrium nature. Our framework provides in fact a mechanism that rationalizes the findings in Chetty (2008) as to why these individuals are less likely to exit unemployment. Relatedly, Card, Chetty and Weber (2007) leverage a discontinuity from the eligibility rule for severance payments in Austria, and in the context of a regression-discontinuity (RD) approach find that laid-off individuals right after the cutoff for severance payment eligibility have on average a higher nonemployment duration than individuals right before the cutoff. Interpreting such estimates in the context of our model is not immediate as we do not have severance payments, let alone the type of discontinuity present in the Austrian UI system. However, for well-understood reasons we can safely argue that whether an individual gets the severance payment or not will affect the time path of savings right after entering unemployment; this happens because the one-time transfer induces income effects and with incomplete markets the presence of severance payments itself alters the precautionary saving motive. Overall, it would thus seem

6.1.3 Partial Equilibrium III

As both the PE1 and PE2 experiments are partial equilibrium in nature, we proceed next by clearing the asset market while keeping the wage at its original value in the benchmark economy. In this case, the firm's free entry condition implies that the tightness ratio is unchanged vis-à-vis the benchmark economy, so that the job-finding rate conditional on searching does not change as well. The results of this exercise are shown in the "PE3" column in Table 6.

Given the reduced demand for assets discussed above in the context of PE2, it is unsurprising that in this experiment the equilibrium equity price falls to clear the asset market. The fall in the equity price has two counteracting forces. First, the fall in the asset price per se induces individuals to increase asset holdings. The implication of this right shift in the asset distribution is that the mass of unemployed non-searchers at the same cutoffs as in the original steady state is lower in this economy relative to PE2. On the other hand, the fall in the equity price leads to an increase in the cutoff value, a^*. This occurs because the fall in the equity price implies that for any level of asset holdings, an unemployed individual now has less asset income to rely on than in the benchmark economy. As such, the incidence of the pecuniary search cost raises.

Overall, the results suggest that the first force dominates and that clearing the asset market and allowing the equity price to fall attenuates the increase in the measure of non-searchers. Yet, we note that vis-à-vis the original steady state prior to the policy reform, the asset distribution shifts to the left. The increase in the mass below the cutoff, reduces the fraction of searchers and implies that relative to the original steady state the fraction of searchers is lower by about two and half percentage points.

6.1.4 General Equilibrium

In our final experiment, we allow the wage to adjust as implied by Nash bargaining. This allows us to assess the role of asset market clearing vs. wage flexibility. We note that the bulk of the overall impact of the reform on the fraction of searchers is *not* due to the assumption of flexible wages; about 75% of the increase in the fraction of non-searchers is present even with perfectly sticky wages as in PE3. This last result is important since it suggests that the key mechanism is the adjustment in the equilibrium asset holding distribution and that it does not depend on assumptions regarding the flexibility of wages. Similarly, it highlights that the impact of the moral hazard induced by the raise in UI benefits (manifested in the DMP framework by an increase in

unlikely that the wealth distribution evolves smoothly at the discontinuity.

bargained wages and a fall in the exit rate from unemployment) is much smaller than the impact of the asset market channel discussed above.

A natural concern with the results in the GE and PE3 the plausibility of the drop in the stock price after the increase in UI benefits. In this regard, we emphasize that the UI benefit reform represents a permanent increase in the generosity of the UI system, financed with distortionary labor taxes. Specifically, we compute the stock prices in two stationary equilibria before and after the policy reform, accounting for general equilibrium effects and government budget balance. To be sure, the effects of a UI benefit reform would naturally unfold and accumulate over time; the figures we report in the table can then be interpreted as the long-run outcome of a long process of dynamic adjustment. Arguably, reforms of such type are likely to have nontrivial aggregate effects, that cannot be gauged from reduced-form estimates alone. In this resepct, the experiment in PE2 might be a better approximation of "short term" dynamics without a change in the stock market value.

6.1.5 Connecting the Model to Existing Empirical Literature

In connecting the model's predictions to the existing empirical literature, it is useful to draw a distinction between the micro and macro effects of UI benefit changes, where the former refers to the effects of benefit changes on job searching, keeping the tightness ratio fixed, and the latter refers to the effect on job searching and unemployment rates, allowing the tightness ratio to change.

Focusing on the macro effect, in the model, the aggregate unemployment rate unambiguously rises after a UI benefit increase. The fall in the average exit rate from unemployment comes about two forces: (i) a reduction in job vacancies as in the standard DMP model (see Hagedorn et al., 2013, for evidence on this mechanism); and (ii) a reduction in savings induced by a lesser precautionary saving motive (Engen and Gruber, 2001), which reduces the mass of searchers who can afford the pecuniary search cost.

Overall, the available evidence on the macro effect supports the negative effect of UI benefit increases on the average exit rate from unemployment, even though there is yet no consensus on its magnitude (see Schmieder and Von Wachter, 2016, for a survey article).

6.2 Welfare

The analysis above centred on the impact of UI benefits reform on the fraction of searchers. While we found that higher UI benefits reduce this fraction, they naturally provide insurance in the context of an incomplete markets framework, allowing for consumption smoothing across the asset distribution and across the unemployment and employment states. At the same time, the increased taxation that is required to pay for the higher benefits hurt the employed.

The last row in Table 5 reports the consumption equivalent welfare measures. In calculating these values we adopt the welfare criterion and methodology used in Krusell, Mukoyama and Şahin (2010) and Setty and Yedid-Levi (2020).

First, we calculate the consumption equivalent welfare change associated with the policy change; to do so, we let $V \equiv E_0\left[\Sigma_{t=0}^{\infty}\beta^t \frac{C_t^{1-\gamma}}{1-\gamma}\right]$ denote the value function in the benchmark economy before the reform, and $\tilde{V} \equiv E_0\left[\Sigma_{t=0}^{\infty}\beta^t \frac{C_{t,\text{ after change}}^{1-\gamma}}{1-\gamma}\right]$ denote the value function after the reform. We then look for the change in consumption, λ, so that at each node in the distribution the values before and after the reform equal each other, i.e., $E_0\left[\Sigma_{t=0}^{\infty}\beta^t \frac{((1+\lambda)C_t)^{1-\gamma}}{1-\gamma}\right] = E_0\left[\Sigma_{t=0}^{\infty}\beta^t \frac{C_{t,\text{ after change}}^{1-\gamma}}{1-\gamma}\right]$.[28]

Second, again, as in Krusell, Mukoyama and Şahin (2010) and Setty and Yedid-Levi (2020), for each counterfactual economy we sum over the individual λ's using the distribution in the benchmark economy. This procedure gives a measure of the aggregate welfare gain or loss in consumption equivalent terms.[29]

To streamline exposition, here we only discuss the welfare consequences of a 20% increase in benefits.[30] We find that the reform increases the welfare of the unemployed by 1.47 percent (i.e., $\lambda = 0.0147$). For the employed, there are two counteracting forces. On one hand, they receive higher insurance in the event they become unemployed (naturally the value function takes into account such an event through the continuation value term). On the other hand, while employed they face higher taxation which is required to fund the increased UI benefits. These opposing forces imply that the rise in welfare for employed individuals is much smaller ($\lambda = 0.0059$) than the welfare gain of the unemployed. Overall, given the higher share of employed in the economy, the welfare in the economy increases by 0.63 percent. Hence, overall, an increase in the generosity of UI benefits yields a tradeoff between a lower fraction of unemployed who engage in active search, and a higher economy-wide welfare due to enhanced public insurance.

[28]For each individual, the consumption equivalent is calculated as $\lambda = \exp\left[\frac{1}{1-\gamma} \times \log\left(\frac{\tilde{V}}{V}\right)\right] - 1$.

[29]We note that we do not consider the entire transition path for all our results. However, Setty and Yedid-Levi (2020) show in the context of their DMP with incomplete markets economy that this welfare metric yields very similar results to when the full transition path is taken into account.

[30]Qualitatively, similar results hold for UI benefit increases of different size.

6.3 UI Benefits Reform: Redux

Overall, the experiments in the previous subsection suggest that, if a policy maker aims to increase the fraction of searchers in the economy, a *reduction* in the generosity of UI benefits could achieve that goal. At the same time, consider an extreme policy that eliminates UI benefits altogether. Unemployed individuals unable to find work for some time despite being engaged in pecuniary job search would deplete their asset holdings. Eventually, such unlucky individuals would cross the search cutoff value on assets and stop searching altogether. In this extreme policy scenario, then, there are unemployed who are unable to engage in search as they run out of liquidity. Hence a reduction in UI benefits generate two counteracting forces, which hints at the possibility of a hump-shaped relationship between benefit generosity and the percentage of those searching for employment. Table 7 reports the results for different experiments in which we reduce UI benefits.

Consider for example the second column where we cut them by 20%. Indeed, the fraction of searchers increases by about two and half percentage points relative to the benchmark economy, with a reduction in the unemployment rate. Columns (3)-(7) progressively reduce the UI benefits showing that the share of searchers continues to rise for the same reasons discussed in the previous subsection; the demand among the unemployed to accumulate assets rises and is manifested in an increase in the equity price. This increase in the asset holding of the unemployed implies that there is a larger mass of them above the asset cutoff search value. However, we find that once UI benefits are reduced by 85% or more, the fraction of searchers starts to decline for the reasons discussed above. Thus, the equilibrium relation between a reduction in benefit generosity and the fraction of searchers is non-monotonic.

To sum up, reductions in public insurance provision via less generous UI benefits foster asset accumulation shifting the distribution of asset holdings for the unemployed to the right. This in turn leads to an increase in the fraction of unemployed engaged in pecuniary job search. This mechanism has a natural limit though: when benefits fall below a critical threshold, the mass of searchers begins to fall.[31]

6.4 Job Search Subsidy

Our second policy experiment is based on a subsidy targeted at unemployed searchers financed via a labor tax on the employed. We consider this policy since (i) the U.S. tax code allowed for

[31] Again, in Appendix E we show that these results are robust to alternative calibrations of the search cost parameters.

Table 7: Aggregate Effects of UI Benefits Reform: Redux

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Benchmark	Decrease 20%	Decrease 40%	Decrease 50%	Decrease 80%	Decrease 85%	Decrease 90%
Fraction of non-searchers							
Unconditional UIB	8.60%	6.16%	4.20%	3.48%	1.82 %	2.22%	5.90%
Low UIB	8.91%	6.85%	4.58%	3.99%	2.17%	2.53%	6.81%
Mean UIB	8.68%	5.93%	4.08%	3.40%	2 1.65%	2.42%	5.41%
High UIB	8.17%	5.67%	3.93%	3.05%	1.59%	1.73%	5.21%
Unemployment statistics							
JFR: unconditional	0.380	0.400	0.422	0.426	0.429	0.4509	0.4508
JFR: conditional on searching	0.415	0.427	0.440	0.442	0.463	0.461	0.479
Unemployment Rate	5.00%	4.67%	4.55%	4.48%	4.21%	4.24	4.25%
Prices							
Wage	0.895	0.892	0.888	0.886	0.882	0.881	0.88
Equity Price	10.693	12.033	13.508	16.35	18.14	19.30	19.37
Tax	0.025	0.015	0.012	0.01	0.008	0.004	0.003
Welfare: Consumption equivalents							
Weighted Avg. of Unemployed		−0.97%	−3.29%	−4.80%	−11.04%	−12.57%	−14.79%
Weighted Avg. of Employed		0.25%	−0.35%	−0.59%	−0.49%	−0.33%	−0.68%
Weighted Avg. Overall		0.19%	−0.49%	−0.81%	−1.02%	−0.94%	−1.38%

deductions associated with job search until 2018, and (ii) a subsidy represents a more direct way to foster search at the individual level. Formally, we re-formulate the unemployed searcher's problem as

$$V_{u,S}(a,b) = \max_{a' \geq 0} u(c_{u,S})\beta \left[\lambda_w V_e(a') + (1-\lambda_w)V_{u,S}(a',b)\right], \tag{18}$$

subject to $c_{u,S} + pa' + \Psi \times (1-\tau_s) = b + (p+d)a$, where τ_s is the fraction of the pecuniary search cost that unemployed individuals are allowed to deduct. Job search subsidies are financed by levying additional taxes on employed individuals.

Naturally, a 100% search subsidy would imply that all individuals engage in active search. However, such a policy would come with a significant increase in the tax burden on the employed. As such our interest lies in whether a less-than-full subsidy encourages all the unemployed to engage in search. Table 8 reports the results for various subsidy experiments.

As we progressively increase the size of the subsidy, the fraction of non-searchers decreases. Notably, we find that all unemployed individuals search when the subsidy rate takes a value of 85%. At the same time, though, the unemployment rate increases because the before-tax wage rises as a result of the improved bargaining position that the unemployed enjoy due to a higher search subsidy which implies that the outside option of remaining unemployed is less costly. Given that the productivity on the job is fixed, a higher wage must result in a fall in vacancy posting and thereby in a lower job finding rate.

In terms of welfare, we find that the search subsidy has a differential impact on the unemployed vis-à-vis employed individuals. Consider first the unemployed who, unsurprisingly, experience an increase in their welfare. The reduction in the cost of search mitigates the negative effect of the decline in the exit probability from unemployment and the lower after-tax wage. For the employed we find that for big enough subsidies they suffer a welfare loss because the after-tax wage decreases as the search subsidy increases. For example, consider the case of a 85% subsidy, which is the required subsidy to incentive all unemployed to search: after-tax wage falls by about five percent. Overall, for such big subsidies we find the aggregate welfare to decrease; simply put, the additional tax burden required to fund the search subsidies outweighs the benefit from having more unemployed searching for a job.

Hence, to summarize, job-search subsidies can indeed increase the fraction of unemployed who engage in search. However, such interventions lead to an overall increase in the unemployment rate, and for big enough subsidies, lead to a decline in the aggregate welfare in the economy.

Table 8: Aggregate Effects of Job Search Subsidy

	(1)	(2)	(3)	(4)	(5)
	Benchmark	Subsidy 40%	Subsidy 60%	Subsidy 80%	Subsidy 85%
Fraction of non-searchers					
Unconditional UIB	8.60%	4.44%	2.72%	0.25%	0%
Low UIB	8.91%	4.72 %	3.15%	0.75%	0%
Mean UIB	8.68%	4.44 %	2.90%	0% %	0%
High UIB	8.17%	4.15 %	2.12%	0%%	0%
Unemployment statistics					
JFR: unconditional	0.380	0.3297	0.2970	0.2537	0.2421
JFR: conditional on searching	0.415	0.3450	0.3053	0.2534	0.2421
Unemployment Rate	5.00%	5.72%	6.31%	7.31%	7.63%
Prices					
Wage	0.895	0.9124	0.9229	0.9355	0.9391
Equity Price	10.693	7.4946	6.7826	4.9797	4.3080
Tax	0.025	0.05	0.07	0.102	0.11
Welfare: Consumption equivalents					
Weighted Avg. of Unemployed		1.63%	2.02%	1.49%	1.51%
Weighted Avg. of Employed		0.32%	-0.12%	-1.61%	-1.91%
Weighted Avg. Overall		0.39%	0.13%	-1.46%	-1.74%

7 Conclusion

Searching for a job requires monetary resources. With imperfect insurance and credit markets, such pecuniary search costs may prevent liquidity-constrained unemployed individuals from engaging in job search. Moreover, such costs can impose a significant financial burden on low-asset unemployed individuals facing liquidity constraints, who are limited in their ability to smooth consumption.

From a policy perspective such frictions might give a rationale for government intervention aimed at facilitating search. Overall, we believe this issue to be overlooked in the literature. To fill this gap and study this topic, we analyze the impact of pecuniary search costs on search decisions of unemployed individuals, and the impact of two policies aimed at increasing the fraction of searchers. We do so through the lens of a new heterogeneous-agent search-and-matching model with incomplete markets and endogenous job search decisions in the presence of pecuniary search costs. To quantitatively discipline the model we require it to match our empirical estimates from administrative data of random job-search audits.

Through the lens of our UI benefit reform experiments we note that, even though the model matches the estimated positive cross-sectional relation between benefits and job search, the aggregate effects of an increase in the UI benefits nonetheless reduce the fraction of unemployed engaging in search. As such, it is reduced UI benefits that increase the share of searchers, but only up to a certain limit since the equilibrium relation between benefit reduction and the fraction of searchers is non-monotonic.

We then consider the impact on search decisions and on the overall economy of a search subsidy. In this analysis we highlight the tradeoff that more generous subsidies lead to. On the one hand, they raise the fraction of unemployed who search for a job. On the other hand, aggregate welfare declines and the unemployment rate increase due to the tax burden needed to fund such job-search subsidies.

The results in this paper suggest that pecuniary search costs are important to consider when examining why unemployed individuals do not search for a job. Moreover, from a normative point of view, our policy experiments suggest that these costs are crucial to take into account when designing a UI system and essential for policy analysis at large.

References

Blank, Rebecca M., and David E. Card. 1991. "Recent Trends in Insured and Uninsured Unemployment: Is There an Explanation?" *Quarterly Journal of Economics*, 106(4): 1157–1189.

Braxton, J. Carter, Kyle F Herkenhoff, and Gordon M. Phillips. 2020. "Can the Unemployed Borrow? Implications for Public Insurance." *NBER Working Paper*, 27026.

Card, David, and Phillip B. Levine. 2000. "Extended Benefits and the Duration of UI Spells: Evidence from the New Jersey Extended Benefit Program." *Journal of Public Economics*, 78(1-2): 107–138.

Card, David, Raj Chetty, and Andrea Weber. 2007. "Cash-on-Hand and Competing Models of Intertemporal Behavior: New Evidence from the Labor Market." *Quarterly journal of economics*, 122(4): 1511–1560.

Carling, Kenneth, Bertil Holmlund, and Altin Vejsiu. 2001. "Do Benefit Cuts Boost Job Finding? Swedish Evidence from the 1990s." *Economic Journal*, 111(474): 766–790.

Chetty, Raj. 2008. "Moral Hazard versus Liquidity and Optimal Unemployment Insurance." *Journal of Political Economy*, 116(2): 173–234.

Chodorow-Reich, Gabriel, and Loukas Karabarbounis. 2016. "The Cyclicality of the Opportunity Cost of Employment." *Journal of Political Economy*, 124(6): 1563–1618.

Chodorow-Reich, Gabriel, John Coglianese, and Loukas Karabarbounis. 2018. "The Macro Effects of Unemployment Benefit Extensions: A Measurement Error Approach." *Quarterly Journal of Economics*, 134(1): 227–279.

Cinelli, Carlos, and Chad Hazlett. 2020. "Making Sense of Sensitivity: Extending Omitted Variable Bias." *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 82(1): 39–67.

Department of Labor, Employment, and Training Administration. 2005. "Monetary Entitlement." *Comparison of State Unemployment Laws*.

Engen, Eric M., and Jonathan Gruber. 2001. "Unemployment Insurance and Precautionary Saving." *Journal of Monetary Economics*, 47(3): 545–579.

Feldstein, Martin. 2005. "Rethinking Social Insurance." *American Economic Review*, 95(1): 1–24.

Franks, Alexander M., A. D'Amour, and A. Feller. 2018. "Flexible Sensitivity Analysis for Observational Studies Without Observable Implications." *Journal of the American Statistical Association*, 115: 1730 – 1746.

Fujita, Shigeru, Christopher J. Nekarda, and Garey Ramey. 2007. "The Cyclicality of Worker Flows: New Evidence from the SIPP." *FRB of Philadelphia Working Paper No. 07-5*.

Fuller, David L., B. Ravikumar, and Yuzhe Zhang. 2015. "Unemployment Insurance Fraud and Optimal Monitoring." *American Economic Journal: Macroeconomics*, 7(2): 249–290.

Gregory, Victoria, Guido Menzio, and David Wiczer. 2021. "The Alpha Beta Gamma of the Labor Market." *NBER Working Paper*, , (28663).

Grossman, Jean Baldwin. 1989. "The Work Disincentive Effect of Extended Unemployment Compensation: Recent Evidence." *Review of Economics and Statistics*, 71(1): 159–64.

Gruber, Jonathan. 1997. "The Consumption Smoothing Benefits of Unemployment Insurance." *American Economic Review*, 87(1): 192.

Hagedorn, Marcus, Fatih Karahan, Iourii Manovskii, and Kurt Mitman. 2013. "Unemployment Benefits and Unemployment in the Great Recession: The Role of Macro Effects." *NBER Working Paper*, 19499.

Hall, Robert E., and Marianna Kudlyak. 2019. "Job-Finding and Job-Losing: A Comprehensive Model of Heterogeneous Individual Labor-Market Dynamics." *NBER Working Paper*, , (25625).

Herkenhoff, Kyle F. 2019. "The Impact of Consumer Credit Access on Unemployment." *Review of Economic Studies*, 86(6): 2605–2642.

Imbens, Guido W. 2003. "Sensitivity to Exogeneity Assumptions in Program Evaluation." *American Economic Review*, 93(2): 126–132.

Jappelli, Tullio. 1990. "Who is Credit Constrained in the U.S. Economy?" *Quarterly Journal of Economics*, 105(1): 219–234.

Jappelli, Tullio, and Luigi Pistaferri. 2010. "The Consumption Response to Income Changes." *Annu. Rev. Econ.*, 2(1): 479–506.

Jappelli, Tullio, and Luigi Pistaferri. 2014. "Fiscal Policy and MPC Heterogeneity." *American Economic Journal: Macroeconomics*, 6(4): 107–36.

Johnston, Andrew C., and Alexandre Mas. 2018. "Potential Unemployment Insurance Duration and Labor Supply: The Individual and Market-Level Response to a Benefit Cut." *Journal of Political Economy*, 126(6): 2480–2522.

Kaplan, Greg, and Giovanni L. Violante. 2014. "A Model of the Consumption Response to Fiscal Stimulus Payments." *Econometrica*, 82(4): 1199–1239.

Kaplan, Greg, Giovanni L. Violante, and Justin Weidner. 2014. "The Wealthy Hand-to-Mouth." *Brookings Papers on Economic Activity*, 77–138.

Katz, Lawrence F., and Bruce D. Meyer. 1990*a*. "The Impact of the Potential Duration of Unemployment Benefits on the Duration of Unemployment." *Journal of Public Economics*, 41(1): 45–72.

Katz, Lawrence F., and Bruce D. Meyer. 1990*b*. "Unemployment Insurance, Recall Expectations, and Unemployment Outcomes." *Quarterly Journal of Economics*, 105(4): 973–1002.

Krueger, Alan B., and Bruce D. Meyer. 2002. "Labor Supply Effects of Social Insurance." *Handbook of Public Economics*, 4: 2327–2392.

Krusell, Per, Toshihiko Mukoyama, and Ayşegül Şahin. 2010. "Labour-Market Matching with Precautionary Savings and Aggregate Fluctuations." *Review of Economic Studies*, 77(4): 1477–1507.

Krusell, Per, Toshihiko Mukoyama, Richard Rogerson, and Ayşegül Şahin. 2017. "Gross Worker Flows over the Business Cycle." *American Economic Review*, 107(11): 3447–3476.

Kydland, Finn E., and Edward C. Prescott. 1982. "Time to Build and Aggregate Fluctuations." *Econometrica*, 1345–1370.

Lalive, Rafael, and Josef Zweimüller. 2004. "Benefit Entitlement and Unemployment Duration: The Role of Policy Endogeneity." *Journal of Public Economics*, 88(12): 2587–2616.

Lalive, Rafael, Jan Van Ours, and Josef Zweimüller. 2006. "How Changes in Financial Incentives Affect the Duration of Unemployment." *Review of Economic Studies*, 73(4): 1009–1038.

Landais, Camille. 2015. "Assessing the Welfare Effects of Unemployment Benefits using the Regression Kink Design." *American Economic Journal: Economic Policy*, 7(4): 243–78.

Lentz, Rasmus, and Torben Tranaes. 2005. "Job Search and Savings: Wealth Effects and Duration Dependence." *Journal of Labor Economics*, 23(3): 467–489.

Meyer, Bruce D. 1990. "Unemployment Insurance and Unemployment Spells." *Econometrica*, 58(4): 757–782.

Mitman, Kurt, and Stanislav Rabinovich. 2015. "Optimal Unemployment Insurance in an Equilibrium Business-cycle Model." *Journal of Monetary Economics*, 71(C): 99–118.

Mitman, Kurt, and Stanislav Rabinovich. 2019. "Do Unemployment Benefit Extensions Explain the Emergence of Jobless Recoveries?" *Available at SSRN 3401133*.

Moffitt, Robert. 1985. "Unemployment Insurance and the Distribution of Unemployment Spells." *Journal of Econometrics*, 28(1): 85–101.

Moffitt, Robert, and Walter Nicholson. 1982. "The Effect of Unemployment Insurance on Unemployment: The Case of Federal Supplemental Benefits." *Review of Economics and Statistics*, 64(1): 1–11.

Morchio, Iacopo. 2020. "Work Histories and Lifetime Unemployment." *International Economic Review*, 61(1): 321–350.

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

Quadrini, Vincenzo, and José-Víctor Ríos-Rull. 1997. "Understanding the U.S. Distribution of Wealth." *Federal Reserve Bank of Minneapolis Quarterly Review*, 21(2): 22–36.

Ravikumar, B., and Yuzhe Zhang. 2012. "Optimal Auditing and Insurance in a Dynamic Model of Tax Compliance." *Theoretical Economics*, 7(2): 241–282.

Røed, Knut, and Tao Zhang. 2002. "Does Unemployment Compensation Affect Unemployment Duration?" *Economic Journal*, 113(484): 190–206.

Schmieder, Johannes F., and Till Von Wachter. 2016. "The Effects of Unemployment Insurance Benefits: New Evidence and Interpretation." *Annual Review of Economics*, 8: 547–581.

Schmieder, Johannes F., Till Von Wachter, and Stefan Bender. 2012. "The Effects of Extended Unemployment Insurance over the Business Cycle: Evidence from Regression Discontinuity Estimates over 20 Years." *Quarterly Journal of Economics*, 127(2): 701–752.

Setty, Ofer. 2019. "Optimal Unemployment Insurance with Monitoring." *Quantitative Economics*, 10(2): 693–733.

Setty, Ofer, and Yaniv Yedid-Levi. 2020. "On the Provision of Unemployment Insurance when Workers are Ex-Ante Heterogeneous." *Journal of the European Economic Association*, fothcoming.

Sullivan, James X. 2008. "Borrowing During Unemployment Unsecured Debt as a Safety Net." *Journal of Human Resources*, 43(2): 383–412.

Yatchew, Adonis, and Zvi Griliches. 1985. "Specification Error in Probit Models." *Review of Economics and Statistics*, 67(1): 134–139.

Online Appendix

A Simple Pecuniary Search Model

There is a unit mass of risk-adverse individuals, each endowed with assets $a \geq 0$. Assets are drawn from the distribution $G(a)$ where $a \in [0, \bar{a}]$. In this simple model we take $G(a)$ to be exogenous, but in the main body of the paper, endogenizing it is crucial with regard to the impact of policy reforms aimed at changing the fraction of searchers in the economy.

Individuals can be in three labor market states: employed, unemployed searcher, and unemployed non-searcher where search entails a pecuniary search cost $\Psi > 0$. Individuals start out being unemployed and receive UI benefits funded by a government that collects labor taxes τ. Within this period, there are two stages. In the first stage, individuals decide whether to search or not to search. They do so by comparing the expected value of searching and not-searching, before the realization of the idiosyncratic shocks. In the second stage, conditional on searching, idiosyncratic job finding shocks realize: with probability p a searcher bumps into a job and becomes employed, and with probability $1-p$, she remains unemployed searcher.[32] In a nutshell, pecuniary job search is akin to "buying a lottery ticket," in that incurring the search cost Ψ is tantamount to buying a chance to win a job. The trade-off is that, in order to buy such lottery ticket, the individual has to forgo consumption.

Job search is a discrete choice, i.e., $s \in \{0,1\}$. If the individual searches, her expected utility is $V_S = pu(c_e) + (1-p)u(c_{u,S})$, where $c_e = a + w - \tau - \Psi$ is consumption of the employed, and w denotes the wage.[33] Similarly, the consumption of the unemployed searcher is $c_{u,S} = a + b - \Psi$, and b denote UI benefits. If the individual does not search, her expected utility is $V_N = u(c_{u,N})$, where $c_{u,N} = a + b$.[34] An individual searches if $V_S(a) > V_N(a)$.

As we formally show below, under suitable conditions, a unique reservation asset level $a^* \geq 0$ exists such that $s(a) = 1$ if $a > a^*$, and $s(a) = 0$ if $a \leq a^*$. This result provides an important insight; in the presence of pecuniary search costs, liquidity, in the forms of more assets, facilitates job

[32] To abstract from the inherently dynamic aspect of job search, we measure transitions in this simple model as changes in labor market states that occur within the period between the end and the beginning of the period.

[33] Without loss of generality we normalize the return on the asset to be equal to 1 in this simple model.

[34] Consistent with our data on job-search audits from the U.S. Department of Labor, throughout the simple model in this section and the general equilibrium model in the next section, we assume that individuals receive UI benefits even if they are not engaged in active job search, abstracting from issues related to detection technologies and auditing probabilities altogether (see, e.g., Ravikumar and Zhang, 2012; Fuller, Ravikumar and Zhang, 2015; Setty, 2019).

search, so that unemployed individuals with more assets are likelier to search.

A.1 Reservation Asset Level

An individual searches if and only if $V_S(a) > V_N(a)$, that is, $pu(c_e) + (1-p)u(c_{u,S}) > u(c_{u,N})$, where $c_e = a + w - \Psi$, $c_{u,S} = a + b - \Psi$, and $c_{u,N} = a + b$, with $c_e > c_{u,N} > c_{u,S}$. To establish the existence and uniqueness of an intersection between the value of searching and not-searching, $V_S(a^*) = V_N(a^*)$, and so of the reservation asset level $a^* > 0$, it is useful to work with $\tilde{V}(a) \equiv V_S(a) - V_N(a)$, defined as the *difference* between the value of searching and not-searching, so that the reservation asset level is now implicitly determined by $\tilde{V}(a^*) = 0$. With this change of variable, the existence and uniqueness of a^* requires that the difference function $\tilde{V}(a)$ crosses the x-axis, either from above or from below, once. Whether such single crossing exists depends on suitable slope and intercept conditions.

Let $\tilde{V}_a(a) \equiv \partial\tilde{V}(a)/\partial a = pu'(c_e) + (1-p)u'(c_{u,S}) - u'(c_{u,N})$. We consider two cases, one in which $\tilde{V}_a(a)$ is monotonically increasing or decreasing, another in which $\tilde{V}_a(a)$ has an inflection point at $\bar{a}$. First, $\tilde{V}_a(a) > 0$ for all $a \geq 0$ is ruled out as inconsistent with $\lim_{a\nearrow\infty}\tilde{V}(a) = 0$. In the case in which $\tilde{V}_a(a) < 0$ for all $a \geq 0$: (a) if $\tilde{V}(0) < 0$, the value of searching is always below the value of not-searching, so *no intersection exists*; (b) if instead $\tilde{V}(0) > 0$, given $\lim_{a\nearrow\infty}\tilde{V}(a) = 0$, the value of searching is always above the value of not-searching so that, again, *no intersection exists*.[35]

Second, in the case in which $\tilde{V}_a(a) < 0$ for $a < \bar{a}$, and $\tilde{V}_a(a) > 0$ for $a > \bar{a}$: (a) if $\tilde{V}(0) < 0$, given $\lim_{a\nearrow\infty}\tilde{V}(a) = 0$, the value of searching is below the value of not-searching for all asset levels, thus *no intersection exists*; (b) if instead $\tilde{V}(0) > 0$, the difference function crosses the x-axis from above, so that *a unique intersection exists*. In the case in which $\tilde{V}_a(a) > 0$ for $a < \bar{a}$, and $\tilde{V}_a(a) < 0$ for $a > \bar{a}$: (a) if $\tilde{V}(0) < 0$, the difference function crosses the x-axis from below, thus *a unique intersection exists*; (b) if instead $\tilde{V}(0) > 0$, given $\lim_{a\nearrow\infty}\tilde{V}(a) = 0$, the value of searching is above the value of not-searching for all asset levels, so that *no intersection exists*.

In sum, there are in principle two cases consistent with the existence of a unique reservation asset level. One in which $\tilde{V}(a)$ crosses the x-axis from above, so that $V_S(a) > V_N(a)$ for all $a < a^*$; another in which $\tilde{V}(a)$ crosses the x-axis from below, so that $V_S(a) > V_N(a)$ for all $a > a^*$. While we cannot generically rule out the case of a intersection from above, we can provide a set of sufficient conditions for which such an intersection does *not* exist. First, for a sufficiently large

[35] As a reference, we note that in the case of zero or approximately zero pecuniary search costs, $\tilde{V}(0) > 0$, and $\tilde{V}_a(a) < 0$, so that the difference function is monotonically decreasing, with the value of searching above the value of not-searching for all asset levels.

pecuniary search cost, $\Psi > \overline{\Psi}$, given the convexity of the marginal utility of consumption with $\lim_{c \searrow 0} u'(c) = \infty$, as the assets approach zero, c_e and $c_{u,S}$ become sufficiently small, $u'(c_e)$ and $u'(c_{u,S})$ sufficiently large, so that $\tilde{V}(a) > 0$ for low asset values. Second, similarly, for sufficiently small UI benefits, $b < \overline{b}$, as the asset level approaches zero, $c_{u,S}$ becomes sufficiently small, $u'(c_{u,S})$ sufficiently large, so that again $\tilde{V}(a) > 0$ for sufficiently small asset values. Third, for a sufficiently small probability of finding a job, $p < \overline{p}$, $V_S'(a) > V_N'(a)$, given that $u'(a + b - \Psi) > u'(a + b)$, so that $\tilde{V}(a) > 0$. Fourth, if $b \leq \Psi$, as the asset level approaches $\overline{a} = \Psi - b$, again, $\tilde{V}(a) > 0$.

Figure A.1: Pecuniary Search Model and Risk Aversion

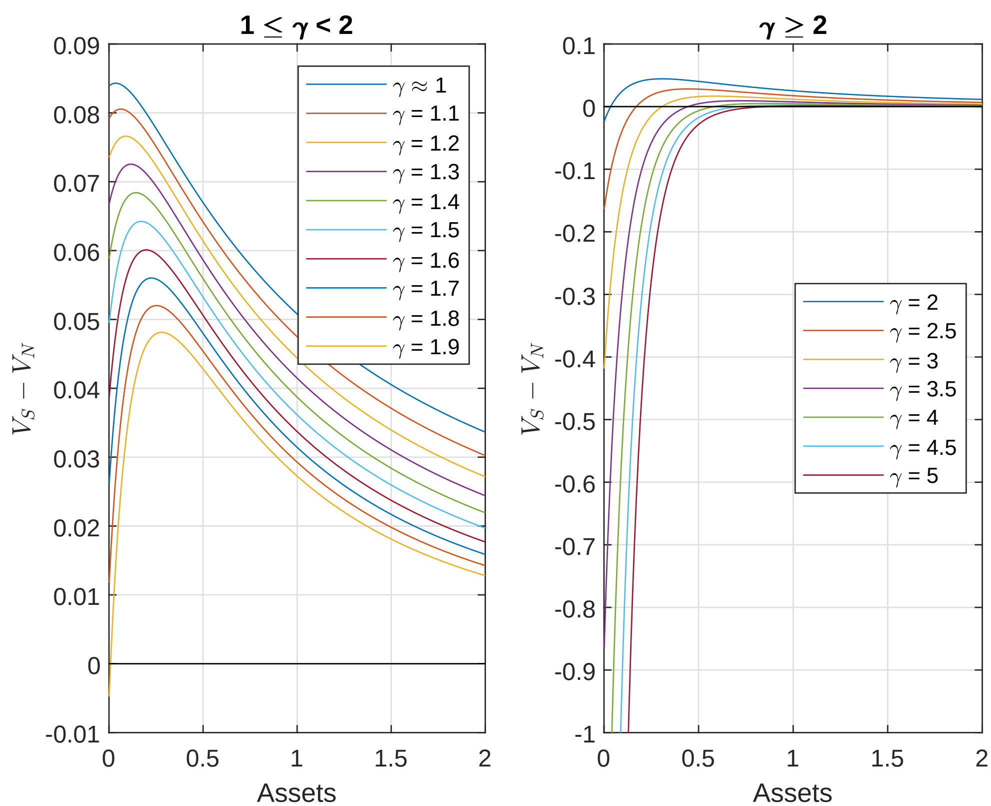
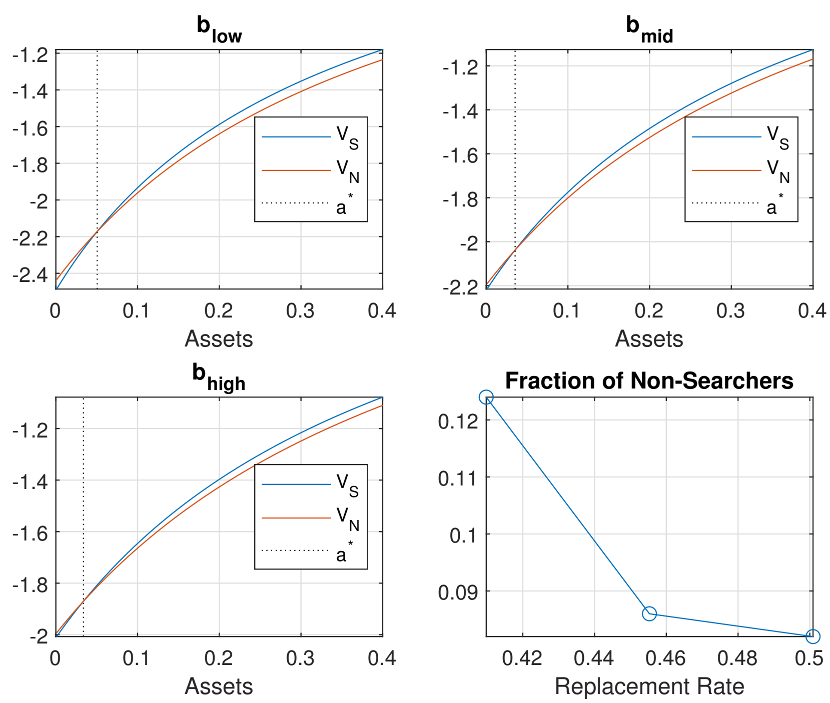


Figure A.1 shows $\tilde{V}(a)$ for a reasonable calibration of the simple pecuniary search model and several values of the risk-aversion parameter. Specifically, we assume a CRRA utility function $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$ and vary the parameter γ from a value of approximately 1 (logarithmic case) to 1.9 in the left panel, and from 2 to 5 in the right panel. Across all parametrizations of risk aversion, $\tilde{V}(a)$ takes a hump-shaped form, such that if an intersection exists, it is unique. For all the values of $\gamma \geq 1.9$, a single crossing exists, and in all such cases $V_S(a) > V_N(a)$ for $a > a^*$.

To further illustrate the role pecuniary search costs in this simple model, we assign parameter values, form grids for assets and UI benefits, and calculate the fraction of non-searchers for each value of UI benefits. We exogenously set the values of a subset of parameters, taken from our baseline calibration of the full-blown general-equilibrium model, and choose the values of the search costs so that the fraction of non-searchers is 8.6%, the same target used for our baseline calibration. We set the probability of finding a job to $p = 0.38$.

We assume a CRRA utility function $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$ and set $\gamma = 2$. For each model, we consider the three values of UI benefits used for the baseline calibration, i.e., $b_{\text{low}} = 0.4098$, $b_{\text{mid}} = 0.4553$, and $b_{\text{max}} = 0.5009$. Finally, the grid for assets $a \in [a_{\text{min}}, a_{\text{max}}]$ consists of $n_a = 500$ points, evenly spaced between the lower bound $a_{\text{min}} = 2^{-10}$ and an upper bound $a_{\text{max}} = 0.4$. Here we assume that individuals are uniformly distributed over the grid of assets, so that the mass of individuals with assets a is simply $1/n_a$. Figure A.2 show results for a parametrized version of the pecuniary search model. The key lesson from the bottom-right panels of the figures is that the models has the empirically correct prediction for the *negative sign* of the relationship between the fraction of non-searchers and the generosity of benefits.

Figure A.2: Fraction of Non-Searchers and UI Benefits in the Pecuniary Search Model



A.2 Baily-Chetty-type Formula

What are the tradeoffs that a UI benefit system balances in the presence of pecuniary search costs? To answer this question, we note that in a second-best allocation, the government can set the policy parameters (b, τ), but it cannot dictate a^*. Thus, the problem of the government is to maximize the expected discounted utility of individuals taking in account the individual's best response $a^*(b, \tau)$, with the requirement that the government budget is balanced:

$$\max_{b,\tau} V(b,\tau) \equiv \int_0^{a^*(b,\tau)} V_N(a,b)dG(a) + \int_{a^*(b,\tau)}^{\bar{a}} V_S(a,b,\tau)dG(a), \tag{A.1}$$

subject to $\tau E(a^*(b,\tau)) = bU(a^*(b,\tau))$, where $E(a^*)$ and $U(a^*)$ denote the mass of employed and unemployed, respectively. Letting $\tau^*(b) = bU(a^*)/E(a^*)$ denote the tax required to finance the benefit level b, the problem in (A.1) reduces to

$$\max_{b} V(b,\tau^*(b)) \equiv \int_0^{a^*(b,\tau^*(b))} V_N(a,b)dG(a) + \int_{a^*(b,\tau^*(b))}^{\bar{a}} V_S(a,b,\tau)dG(a), \tag{A.2}$$

where $a^*(b, \tau^*(b))$ captures the direct effect of benefits on a^*, as well as the indirect effect of taxes due to the requirement of a balanced government budget. At an interior optimum, one can show that an optimal benefit level satisfies the following Baily-Chetty-type formula:

$$\frac{\int_0^{a^*} u'(c_{u,N}(a))dG(a) + (1-p)\int_{a^*}^{\bar{a}} u'(c_{u,S}(a))dG(a)}{p\int_{a^*}^{\bar{a}} u'(c_e(a))dG(a)} = \frac{U(a^*)}{E(a^*)}\left[1 + \frac{\eta_b^U}{E(a^*)}\right], \tag{A.3}$$

where η_b^U on the right-hand side is the elasticity of unemployment with respect to benefits.

Hence, according to the formula, not surprisingly, the optimal benefits trade off the gain from consumption smoothing across the asset distribution with the cost of providing insurance. Search is painful in that it requires a drop in consumption, which with risk aversion, manifests itself in a high marginal utility of consumption for unemployed searchers. On the cost side, Ψ affects, both the tax base $E(a^*)$ and the spending base $U(a^*)$ of unemployed individuals collecting benefits.

The value of a^* and the shape of the asset distribution are key elements of the formula. They affect the weighting of the marginal utilities and the unemployment elasticity to benefits. To see this, it is useful to write the elasticity as $\eta_b^U \equiv \frac{\partial U(a^*)}{\partial a^*} \cdot \frac{\partial a^*}{\partial b} \cdot \frac{b}{U(a^*)}$, where the term $\frac{\partial U(a^*)}{\partial a^*} = pg(a^*) \geq 0$ depends on the mass of individuals at the cutoff, $g(a^*)$.

B Data and Variables' Construction

Dataset construction The underlying row data has 635,940 observations covering the years 1988-2006.[36] We remove 171,500 observations of individuals who for different reasons are not required to engage in search and are left with 438,980 observations. We then remove observations that belong to states that do not use the HQ system and observations for which we have missing information (such as information about occupations and industries worked, HQ, education, maximum benefit amount in the state year, recall status, weeks left, age, race) and are left with 167,609 individuals. Out of these 102,983 are unemployed individuals who are below the unemployment state cap in a given year, while the remaining 64,626 are unemployed individuals who are at the unemployment state cap in a given year. Our HQ states include Alabama, Arkansas, Arizona, Georgia, Idaho, Indiana, Kansas, Minnesota, Missouri, Mississippi, North Carolina, Nebraska, Nevada, New York, Oklahoma, South Carolina, South Dakota, Texas, Utah, Virginia, Vermont, Washington, Wisconsin, Wyoming.[37]

BPW and HQ Because BPW in the data are censored at $100,000, our analysis centers on the subpopulation of individuals whose BPW is below this threshold. With respect to the HQ variable we note that our data only includes information regarding the single highest quarter during the year prior to the unemployment spell.

Search Each payment error in the BAM data is assigned a code. Our search variable is based on "a lack of eligibility" due to lack of active work search.

Two-digit occupations & SOC codes 11 Management Occupations, 13 Business and Financial Operations Occupations,15 Computer and Mathematical Occupations, 17 Architecture and Engineering Occupations, 19 Life, Physical, and Social Science Occupations, 21 Community and Social Services Occupations, 23 Legal Occupations, 25 Education, Training, and Library Occupations, 27 Arts, Design, Entertainment, Sports, and Media Occupations, 29 Healthcare Practitioners and Technical Occupations, 31 Healthcare Support Occupations, 33 Protective Service Occupations, 35 Food Preparation and Serving Related Occupations, 37 Building and Grounds Cleaning and Maintenance Occupations, 39 Personal Care and Service Occupations, 41 Sales and Related Occu-

[36] Though the BAM program continued to be run past 2006 we only have access to data up to 2006.
[37] For Washington we exclude the year 2005 since in that year Washington did not have the HQ system.

pations, 43 Office and Administrative Support Occupations, 45 Farming, Fishing, and Forestry Occupations, 47 Construction and Extraction Occupations, 49 Installation, Maintenance, and Repair Occupations, 51 Production Occupations, 53 Transportation and Material Moving Occupations, 55 Military Specific Occupations.

Two-digit industries & SOC codes 11 Agriculture, Forestry, Fishing, Hunting, 21 Mining, 22 Utilities, 23 Construction, 31-33 Manufacturing, 42 Wholesale Trade, 44-45 Retail Trade, 48-49 Transportation and Warehousing, 51 Information, 52 Finance and Insurance, 53 Real Estate, Rental and Leasing, 54 Professional, Scientific, and Technical Services, 55 Management of Companies and Enterprises, 56 Administrative Support, Waste Management and Remediation Services, 61 Education Services, 62 Health Care and Social Assistance, 71 Arts, Entertainment and Recreation, 72 Accommodation and Food Services, 81 Other Services (except Public Administration), 92 Public Administration.

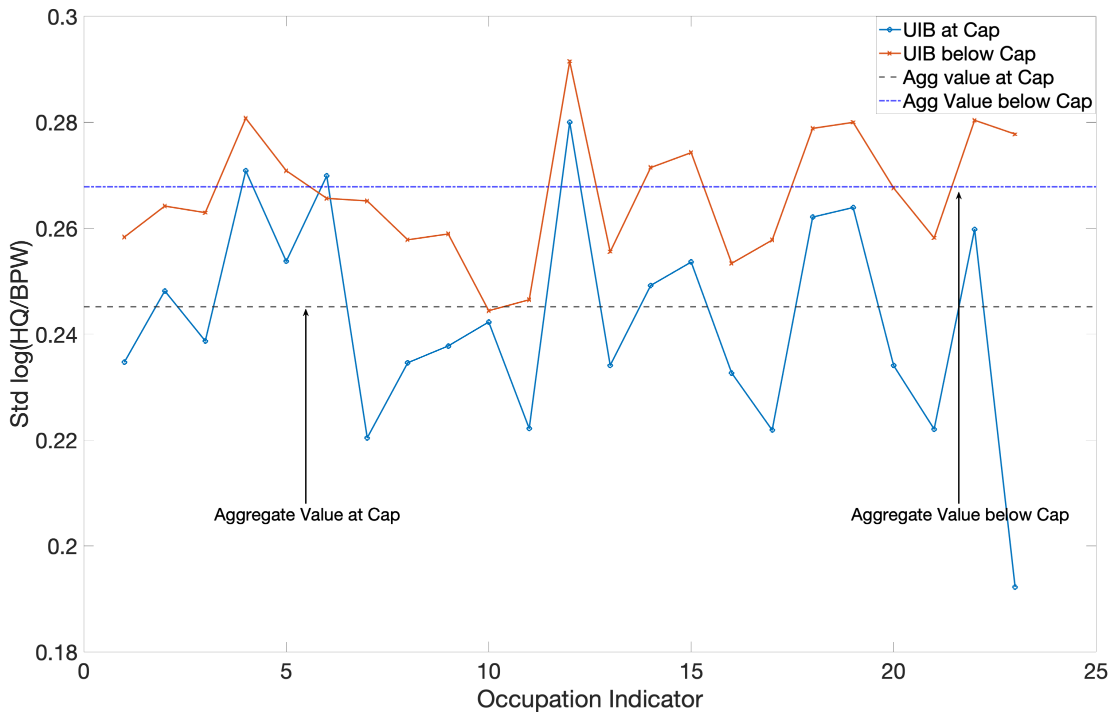
Summary Stats Sample averages of the variables in our dataset for the full sample and by quintiles of the BPW are reported in Table B.1 in the next page.

Table B.1: Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
Fraction of searchers	0.914	0.903	0.916	0.922	0.918	0.928
Weekly UI benefits	208	138	198	245	297	319
Monthly wage	1417	685	1222	1728	2315	3668
Fraction of male	0.466	0.416	0.44	0.47	0.555	0.715
Age	38.483	37.325	38.385	39.047	39.395	41.788
Fraction on recall	0.139	0.162	0.150	0.120	0.102	0.104
Weeks of benefits left	12.415	10.526	12.595	13.705	13.917	13.111
Fraction of high school	0.460	0.459	0.466	0.474	0.450	0.371
Fraction of some college	0.264	0.235	0.255	0.278	0.312	0.321
Fraction of college	0.068	0.042	0.056	0.066	0.109	0.213
Fraction of Blacks	0.226	0.269	0.235	0.206	0.169	0.134
Fraction of Hispanics	0.070	0.087	0.076	0.061	0.043	0.035
Fraction of Asians	0.005	0.004	0.004	0.005	0.006	0.003
Fraction of Indians	0.024	0.029	0.024	0.021	0.021	0.014

Notes: Data are based on 102,983 observations from the 1988-2006 Benefit Accuracy Measurement program.

Figure B.1: Variability of HQ Earnings



Notes: The figure reports the variability of the ratio of the HQ earnings to the base period wages. This ratio is bounded between 0.25 (for individuals who receive an equal salary in each quarter) and 1 (for individuals who receive all their annual salary in a given quarter). The figure shows that the standard deviation of the log of this ratio is quite similar across the different occupations in our sample both when considering individuals whose UI benefits are below the cap as well as for individuals who are at the UI cap.

C Computational Algorithm

The individual value functions have four "productivity" states (one for the employed and three values of UI benefits for the unemployed). We discretize the asset holding grid with 5,000 grid points with distance of 0.0004000800160032 between two adjacent grid points.

For the stationary equilibrium of the model in Section 2 we proceed as follows. Our target is for the model to match the measure of non-searchers (17.17%) and we do it twice; once for the pecuniary search cost and another for the non-pecuniary search cost.

The computation algorithm is as follows:

1. Guess p, w, r, θ, T, and Ψ (or Φ depending on which type of search cost we are solving for):

(a) Solve the firm's value of a filled job;

(b) Guess the individuals' value functions (i.e., matrices of size 4×5000 each);

(c) Solve the individual's maximization problem and derive the asset policy function $a' = h(a,e,s)$ and the search policy function $s = s(a,e)$.

2. Market clearing:

(a) Solve for the stationary distribution $F(a,e,s)$ induced by the policy functions $a' = h(a,e,s)$ and $s = s(a,e)$ such that

$$F\left(a',e',s\right) = \sum_e g\left(e' \mid e\right) \int_{\{a:h(a,e,s),\ s:s(a,e)\}} dF(a,e,s);$$

(b) Check asset market clearing: $\int adF(a,e,s) = 1$;

(c) Check that the Nash-bargaining solution is consistent with the guess for the wage;

(d) Check that the government budget clears.

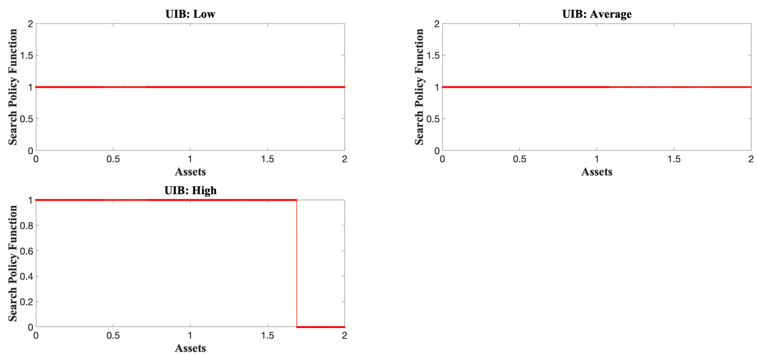
3. Calculate the measure of non-searchers; if it differs from the target, go back to step 1 and repeat until targeted moment is matched.

For the policy experiments in Section 6, we proceed as follows. We keep the pecuniary search cost value and the unit cost of posting vacancies at their baseline values; the former is the output of the algorithm above, the latter is directly solved for by targeting an unconditional job finding rate as discussed in Section **??**. Operationally, we guess a value for the job finding rate (which endogenously changes for each policy we consider) and for the fraction of unemployed who do not search. We then use the algorithm above with the two additional conditions that the guesses for the job finding rate and the fraction of unemployed who do not search are indeed the equilibrium outcomes induced by the firms' entry decisions and individuals' policy functions.

D Search Policy Functions

D.1 Non-Pecuniary Search Cost

Figure D.1: Search Policy Functions for Unemployed Individuals: Non-Pecuniary Search Cost

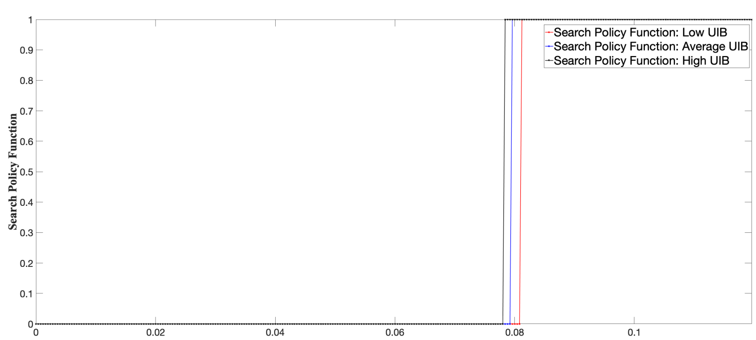


Notes: The three panels depict the search policy function for the three different levels of the UI benefits as a function of current asset holdings for the unemployed individual. A value of $S = 1$ implies the individual searches while a value of $S = 0$ implies the individual does not search.

The three panels show the search decision for the three different levels of UI benefits in our full-blown non-pecuniary search model. Indeed, for the low and average levels of UI benefits, individuals across all the asset distribution engage in active search. In contrast, for the highest level of UI benefits, there are individuals above a certain asset cutoff value who do not search.

D.2 Pecuniary Search Cost

Figure D.2: Search Policy Functions for Unemployed Individuals: Pecuniary Search Cost



Notes: The graph depicts the search policy function for the three different levels of the UI benefits as a function of current asset holdings for the unemployed individual.

The three graphs show the search decision for the three different levels of UI benefits in our full-blown pecuniary search model. This figure shows that the higher the UI benefits are, the lower the asset cutoff value above which the unemployed engage in search is.[38]

E Alternative Targets for Pecuniary Search Costs

In our data sample, on average 8.6% of UI benefit claimants do not actively look for a job. In the main body of the paper, we used this figure to discipline the value of the pecuniary search cost. To validate the robustness of our model's predictions, here we consider alternative targets for the fraction of non-searchers. These are based on moments of the distribution of non-searchers across U.S. states in the following way. We calculate for each state in our sample the fraction of unemployed non-searchers. We then target two different moments of these state distribution; in the median and upper quartile of the states in our sample, respectively 5.35% and 2.95% of the unemployed do not search.

For each of these targets, we solve the model using the same computation algorithm discussed in Appendix C. Specifically, we keep the parameters at their baseline values and determine two new values of the pecuniary search cost for the model to match the two alternative targets for the fraction of non-searchers. We repeat the same steps for the non-pecuniary search cost model, and similarly we determine the values of the non-pecuniary search cost so that the non-pecuniary search model as well matches the targets of 5.35% and 2.95%.

As Table E.1 below reports, for each of the alternative calibrations, the pecuniary search model continues to generate a downward-sloping relationship between UI benefits and the fraction of non-searchers when the search cost is modelled as pecuniary search cost. This is consistent with our empirical findings. In contrast, when the search cost is modelled as non-pecuniary, the relation between the UI benefits and the search likelihood is counterfactual.

Finally, we redid all of our policy analysis (UI benefits reforms, and job search subsidies) for each of these two alternative calibrations presented in Table E.1. Reassuringly, we note that all of the main policy conclusions from the baseline calibration continue to hold.

[38] To visually clarify this point we zoom in on the x-axis around the cutoff values implied by the model.

Table E.1: Different Targets for the Fraction of Non-Searchers

	(1)	(2)
Fraction of Non-Searchers	Model Non-Pecuniary Search	Model Pecuniary Search
Panel A: **Mean of non-searchers in the data**		
Targeted: Unconditional	8.6%	8.6%
Non-targeted:		
UI Benefits: Low	0%	9.02%
UI Benefits: Average	0%	8.60%
UI Benefits: High	22.12%	8.17%
Panel B: **Median of non-searchers in the data**		
Targeted: Unconditional	5.35%	5.35%
Non-targeted:		
UI Benefits: Low	0%	5.68%
UI Benefits: Average	0%	5.38%
UI Benefits: High	14.53%	5.06%
Panel C: 75^{th} **percentile of non-searchers in the data**		
Targeted: Unconditional	2.95%	2.95%
Non-targeted:		
UI Benefits: Low	0%	3.81%
UI Benefits: Average	0%	2.54%
UI Benefits: High	8.40%	2.36%

Notes: In panel A, for the baseline calibration in which the fraction of non-searchers is 8.6%, the non-pecuniary cost is $\Phi = 9.652$ while the pecuniary cost is $\Psi = 1.06$ such that $\Psi/w = 1.2$. In panel B, for the first alternative calibration in which the fraction of non-searchers is 5.35%, the non-pecuniary cost is $\Psi = 9.199$ while the pecuniary cost is $\Psi = 0.80$ such that $\Psi/w = 0.87$. In panel C, for the second alternative calibration in which the fraction of non-searchers is 2.95%, the non-pecuniary cost is $\Psi = 8.877$ while the pecuniary cost is $\Psi = 0.57$ such that $\Psi/w = 0.62$.

F Non-Pecuniary Search Cost

In this appendix we study a simple partial equilibrium model with a *non-pecuniary search cost*. This is a simplified version of the non-pecuniary search model discussed in Section 5.1 and it allows us to highlight the mechanism which counterfactually predicts that higher UI benefits lead to a lower search probability. We then consider below in Section F.2 an extension of this model which allows for a *detection probability*. The goal of this extension is to show that even in the presence of a detection probability, a model driven by non-pecuniary search costs is inconsistent with our empirical findings.

F.1 Non-Pecuniary Search Cost

We consider a model where individuals can be in three labor market states: employed, unemployed searcher, unemployed non-searcher. The utility function $u(c)$ is strictly increasing and concave, i.e., $u'(\cdot) > 0$ and $u''(\cdot) < 0$. We normalize the wage to one, and interpret the UI benefits as a replacement rate.

Search entails a non-pecuniary search cost, Φ. The value of searching remains the same as in the model without a detection probability, that is $V_S = pu(c_e) + (1-p)u(c_{u,S}) - \Phi$, where p is the probability that a searcher finds a job, $1-p$ is the probability a searcher remains unemployed, and $c_e = a + w$ and $c_{u,S} = a + b$ are the values of the consumption of the employed and unemployed searcher, respectively. If the individual does *not* search, she does not get detected and she collect benefits. Hence, the value of non-searching is $V_N = u(c_{u,N})$, where $c_{u,N} = a + b$ is consumption of a non-searcher.

This model implies that an individual searches if and only if

$$pu(a+w) + (1-p)u(a+b) - \Phi > u(a+b). \tag{F.1}$$

First, note that the slope of the left-hand side of (F.1) is *smaller* than the slope of the right-hand side, $\frac{\partial V_S(a)}{\partial a} < \frac{\partial V_N(a)}{\partial a}$, for all $a \geq 0$: given $w > b$, $u'(a+w) < u'(a+b)$ for all $a \geq 0$ by the concavity of the utility function. Second, since $V_S(a)$ and $V_N(a)$ are monotonically increasing and concave, and $\frac{\partial V_S(a)}{\partial a} < \frac{\partial V_N(a)}{\partial a}$, for all $a \geq 0$, the necessary and sufficient condition for the existence and uniqueness of an intersection at $a^* > 0$ is that $V_S(0) > V_N(0)$, i.e., $u(w) > u(b) + \Phi/p$.

The indifference condition $V_S(a^*) = V_N(a^*)$ can be rewritten as $u(a^* + w) = u(a^* + b) + \Phi/p$, which yields that the reservation asset level is decreasing in the level of benefits:

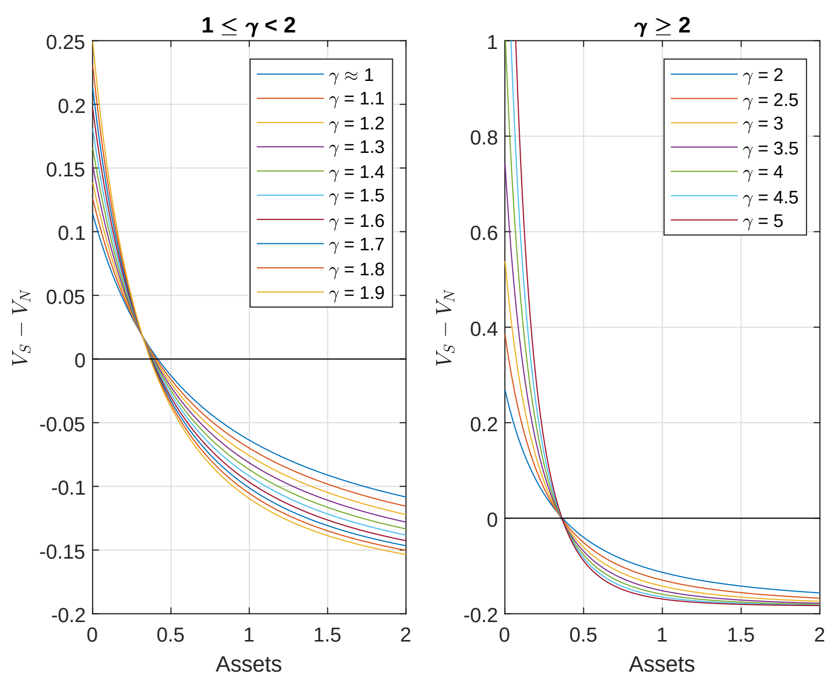
$$\frac{\partial a^*}{\partial b} = \frac{u'(a^* + b)}{u'(a^* + w) - u'(a^* + b)} < 0, \tag{F.2}$$

where $u'(a^* + w) < u'(a^* + b)$, again, by the concavity of the utility function.

Note that since in the non-pecuniary search model, the value of not-searching cuts the value of searching from below, the search decision rule is such that $s(a) = 1$ if $a < a^*$, and $s(a) = 0$ if $a \geq a^*$. Hence, the fraction of non-searchers is $1 - G(a^*)$, which is counterfactually *increasing* in UI benefits.

As a way to illustrate such analytical properties, Figure F.1 shows the "difference function," $\tilde{V}(a) \equiv V_S(a) - V_N(a)$, defined as the difference between the value of searching and not-searching, by asset levels. Specifically, we assume a CRRA utility function $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$ and vary the parameter γ from a value of approximately 1 (logarithmic case) to 1.9 in the left panel, and from 2 to 5 in the right panel. Across all parametrizations of the risk aversion parameter, $\tilde{V}(a)$ is monotonically decreasing, intersecting the x-axis from above, such that $V_S(a) > V_N(a)$ for $a < a^*$.

Figure F.1: Non-Pecuniary Search Model and Risk Aversion



F.2 Non-Pecuniary Search Cost with Detection Probability

We now extend the model above and consider a model where individuals can be in four labor market states: employed, unemployed searcher, unemployed non-searcher detected, and undetected. Relative to the model above we now assume that if the individual does *not* search, two events can occur. With probability $d \in [0,1]$ the individual is detected as non-searcher and thus does not collect benefits. With probability $1-d$, the individual goes undetected and collects benefits. Hence, the value of non-searching is $V_N = du(c_{u,N,d}) + (1-d)u(c_{u,N})$, where $c_{u,N,d} = a$ and $c_{u,N} = a+b$ are consumption of a non-searcher detected and undetected, respectively. As in the model with $d=0$, there exists a reservation asset level a^* that is implicitly determined by the search indifference condition $V_S(a^*) = V_N(a^*)$.

An individual searches if and only if

$$pu(a+w) + (1-p)u(a+b) - \Phi > du(a) + (1-d)u(a+b), \tag{F.3}$$

$$\rightarrow \quad u(a+w) > u(a+b) + \tilde{\Phi} + \tilde{d}\left[u(a) - u(a+b)\right], \tag{F.4}$$

where $\tilde{\Phi} \equiv \Phi/p$ and $\tilde{d} \equiv d/p$. Note that the slope of the left-hand side of (F.4) is *smaller* than the slope of the right-hand side: $u'(a+w) < u'(a+b)$ for all $a \geq 0$ as $w > b$ and $u'(a) > u'(a+b)$. Thus, the necessary and sufficient intercept condition for the existence and uniqueness of an intersection at $a^* > 0$ requires that $u(w) > u(b) + \tilde{\Phi} + \tilde{d}[u(0) - u(b)]$ at $a = 0$.

The indifference condition $u(a^*+w) = u(a^*+b) + \tilde{\Phi} + \tilde{d}[u(a^*) - u(a^*+b)]$ yields that the reservation asset level is decreasing in the level of benefits:

$$\frac{\partial a^*}{\partial b} = \frac{\left(1-\tilde{d}\right)u'(a^*+b)}{u'(a^*+w) - u'(a^*+b) + \tilde{d}\left[u'(a^*+b) - u'(a^*)\right]} < 0, \tag{F.5}$$

where $u'(a^*+w) < u'(a^*+b)$ and $u'(a^*+b) < u'(a^*)$ for all $a \geq 0$ by the concavity of the utility function given $w > b$.

Finally, note that as in the non-pecuniary search model without detection, here as well the search decision rule is such that $s(a) = 1$ if $a < a^*$, and $s(a) = 0$ if $a \geq a^*$. Hence, the fraction of non-searchers equals $1 - G(a^*)$, which remains *increasing* in UI benefits.

F.3 A Numerical Illustration

To further illustrate the role of non-pecuniary vs. pecuniary search costs, and that of the detection probability, here we provide some numerical results. To proceed, we assign parameter values, form grids for assets and UI benefits, and calculate the fraction of non-searchers for each value of UI benefits. We exogenously set the values of a subset of parameters, taken from our baseline calibration of the full-blown general-equilibrium model, and choose the values of the search costs so that the fraction of non-searchers is 8.6%, the same target used for our baseline calibration. We set the probability of finding a job to $p = 0.38$.

We assume a CRRA utility function $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$ and set $\gamma = 2$. For each model, we consider the three values of UI benefits used for the baseline calibration, i.e., $b_{\text{low}} = 0.4098$, $b_{\text{mid}} = 0.4553$, and $b_{\text{max}} = 0.5009$. Since we do not have reliable information to pin down the value of the detection probability, we consider a grid of six values, $d \in \{0.02, 0.002, 0.0002, 0.00002, 0.000002, 0\}$, that includes the baseline of no detection ($d = 0$). Finally, the grid for assets $a \in [a_{\text{min}}, a_{\text{max}}]$ consists of $n_a = 500$ points, evenly spaced between the lower bound $a_{\text{min}} = 2^{-10}$ and an upper bound $a_{\text{max}} = 0.4$. Here we assume that individuals are uniformly distributed over the grid of assets, so that the mass of individuals with assets a is simply $1/n_a$.

Figure F.2 show results for parametrized versions of the non-pecuniary model. In line with the analysis above, the relationship between the fraction of non-searchers and UI benefits remains positive in the non-pecuniary search model.

Figure F.2: Fraction of Non-Searchers and UI Benefits in the Non-Pecuniary Search Model

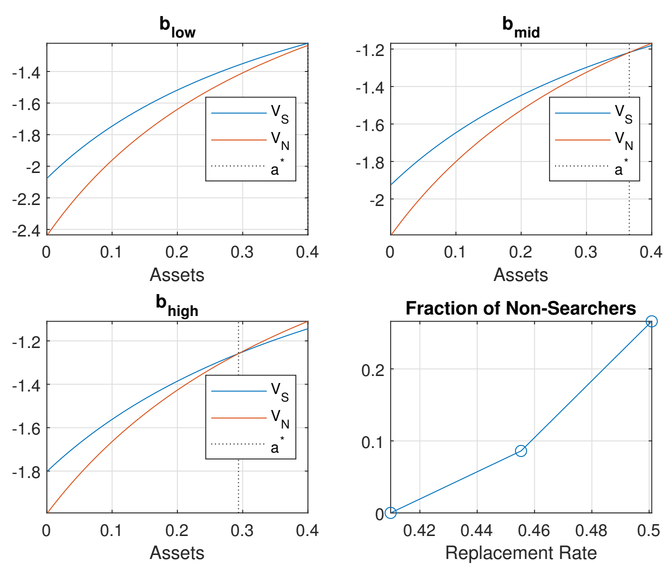


Figure F.3 below shows results for parametrized versions of the non-pecuniary model for several values of the detection probability. Again, in line with the analysis above, the relationship between the fraction of non-searchers and UI benefits remains positive in the non-pecuniary search model even in the presence of a detection probability.

Figure F.3: Non-Pecuniary Search Model with Detection Probabilities