THE ACTIVE SEARCH PREMIUM

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Abstract. We document that the job-finding premium for non-employed active searchers relative to comparable nonparticipants is surprisingly small, strongly procyclical, and declining in the aggregate quantity of active search. This pattern does not support the standard assumption of perfect substitutability between active and passive search; it instead identifies a crowding-out of active search—the relative return to search effort falls as aggregate search effort rises. We develop a matching framework in which the elasticity of substitution is estimated from the premium's response to the extensive and intensive margins of active search. At the estimated elasticity, aggregate search effort responds less to an economy-wide change in unemployment insurance benefits than micro-data estimates would imply. We formulate sufficient statistics for the extent of crowding-out, characterize its implications for unemployment insurance within a standard Baily–Chetty formula, and quantify the mechanism in an equilibrium business-cycle model.

1. Introduction

There are two ways an individual can find a job: by actively searching for a job (e.g., directly contacting firms about employment opportunities), or passively waiting for a job to find them (e.g., through referrals from friends, family, and former colleagues). Insofar as all workers can be thought of as being engaged in some form of passive search, engaging in active search serves to increase a worker's overall job-finding probability beyond that associated with purely passive search.

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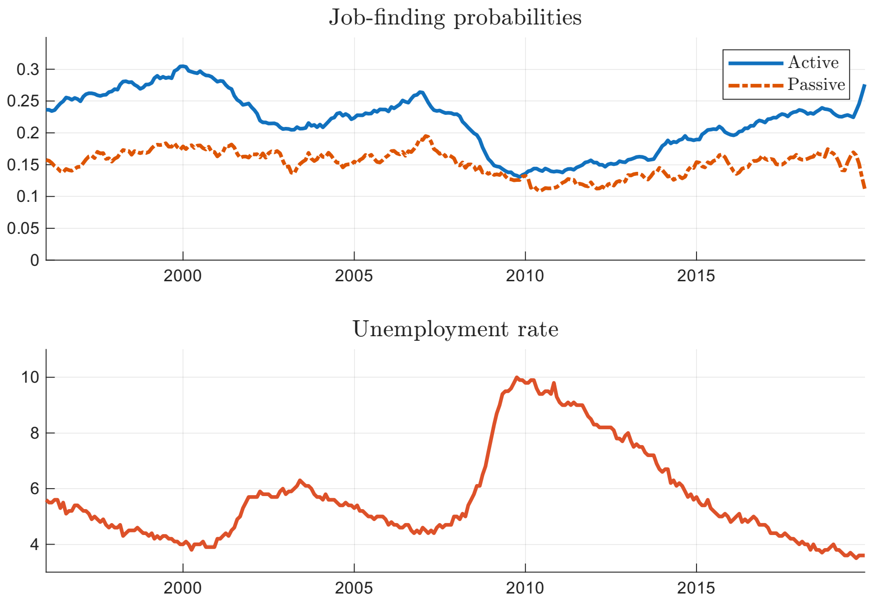
This paper studies the size and cyclicality of the return to active search for workers in non-employment. In the United States, this distinction is embedded in the official labor force statistics: an individual is classified as unemployed, rather than as a nonparticipant, precisely when she engages in active search. We document new findings on the *active search premium*, defined here as the job-finding rate of the unemployed relative to a reference group of passive searchers among nonparticipants. The premium is small; it falls in recessions; and it declines with the aggregate quantity of active search. This pattern is inconsistent with the longstanding assumption that active and passive search are perfect substitutes; it instead identifies a crowding-out of active search during downturns. We develop a general matching framework that measures how steeply the return to active search falls as aggregate active search rises: during the Great Recession, we estimate that this return fell by almost two-thirds. A significant implication of this estimated degree of crowding-out is that aggregate search effort responds far less to an economy-wide change in unemployment insurance (UI) benefits than the individual responses measured in micro data would imply.

The distinction between active and passive search dates to Blanchard and Diamond (1989), who decompose new hires by the search status of the hired worker under the assumption that the unemployed and nonparticipants who want a job are perfect substitutes in an aggregate matching function. Perfect substitutability is a natural benchmark, and the subsequent literature has effectively adopted it in formal models of matching with active and passive search (e.g., Krusell et al., 2017; Faberman et al., 2022; Graves, Huckfeldt and Swanson, 2024). Yet Blanchard and Diamond themselves noted that the data did not appear to support the specification: hires from the two pools respond differently to vacancies than they would under perfect substitutability (p. 34)—an observation not pursued in the subsequent literature. This paper writes down the search structure implicit in their exercise and provides a direct test of the perfect substitutes restriction. The restriction fails; relaxing it yields an estimated elasticity of substitution well below one. Both the test and the estimate rest on the same measurements: the job-finding rates of active and passive searchers, and how the active search premium varies with the aggregate quantity of active search—the objects to which we now turn.

Using data from the Current Population Survey (CPS), we document that, when defined against a reference group of nonparticipants who are comparable to the unemployed in their willingness and availability to work—differing primarily in whether they engage in active search—the active search premium is surprisingly modest in

FIGURE 1. Job-finding probabilities of active and passive searchers



Note: Monthly job-finding probabilities of unemployed workers (active searchers) and of nonparticipants who want a job and are available for work (passive searchers), from the CPS, 1996–2019. The difference between the two series shrinks during periods of high unemployment, approaching zero in the recovery from the Great Recession. Construction detailed in Section 2. Bottom panel: the unemployment rate. Plotted series in the top panel are smoothed using a centered five-month moving average.

size. Whereas the job-finding probabilities of the unemployed are nearly four times larger than those of the entire population of nonparticipants, they are only 67% larger than those of nonparticipants who report wanting a job, and only 42% larger than those of nonparticipants who want a job and are available for work, the reference group that serves as our baseline. Taken on its own, the baseline estimate implies that, on average, active search accounts for roughly 30 percent of an unemployed worker's job-finding. Thus, even for workers classified as unemployed precisely because they engage in active search, the majority of job-finding appears to operate through channels that do not require it. The active search premium is also highly procyclical: during the labor market recovery from the Great Recession, for example, our baseline measure fell to approximately zero, implying roughly equal job-finding probabilities for active and passive searchers (Figure 1).

We further document that, among the non-employed who want a job, the fraction of workers engaged in active search is strongly countercyclical, as is the intensity of active search among active searchers (Osberg, 1993; Shimer, 2004; Mukoyama, Patterson and Şahin, 2018). Together, these findings indicate that the returns to active search decrease as overall active search increases, an empirical pattern that is consistent with a "crowding-out" of active search during recessions.

We first interpret our findings under the standard assumption of perfect substitutes, under which the marginal return to active search is constant and does not depend on the aggregate quantity of active search. From this restriction on the technology, we derive a structural restriction on the active search premium: it should exhibit a unit elasticity with respect to the average active search effort of the unemployed. In other words, the active search premium should be higher when the unemployed actively search more. Potential aggregate confounders—market tightness, match efficiency—are differenced out of the restriction and need not be observed.

Returning to the data, we strongly reject this restriction, instead recovering an elasticity that is negative and large in magnitude. We show that our rejection is robust across different reference groups of passive searchers, to restricting the passive group to workers who were also nonparticipants in the prior month, and to controlling for time aggregation bias, cyclical composition, and unemployment duration. That the active search premium is *decreasing* in average active search is at odds with the standard framework, but arises naturally under imperfect substitutes, where the marginal return to active search declines as more workers search actively.

Accordingly, we generalize the matching framework to allow for a finite elasticity of substitution between active and passive search via a constant elasticity of substitution (CES) aggregator, nesting the standard perfect substitutes specification as a special case. Under the CES aggregator, we derive a generalized restriction for the active search premium in which the fraction of active searchers among the non-employed enters as an additional term, and the elasticities with respect to both average active search and the fraction of active searchers are governed by the inverse of the elasticity of substitution. Moreover, the generalized equation delivers an over-identifying restriction between the two coefficients, providing a means by which the CES structure itself (and other identifying assumptions) can be rejected.

In contrast to the standard model, we are unable to reject the over-identifying restriction from the CES model. We estimate an elasticity of substitution between active and passive search of approximately 1/5, starkly different from the infinite elasticity implied under perfect substitutes. For a non-employed individual, this implies a crowding-out of active search: the premium from active search is greater when fewer other workers are engaged in active search. For the firm, the low elasticity of substitution is consistent with a recruiting process where the average value of external applicants declines as applications increase—for example, as marginal applicants extend their search effort to jobs for which they are a progressively worse fit, lowering the quality of the pool of external applicants—leading firms to tilt their recruiting toward referrals and internal channels.

We then turn to the implications of our estimates. First, we provide a simple representation theorem showing that a CES aggregator over active and passive search entering a *single* matching function is equivalent to active and passive search being intermediated by *separate* matching functions, with each search input weighted by its marginal efficiency and market tightness equalized across submarkets. Using this representation, we show that both the marginal efficiency of active search and the implied active search share of vacancies fall dramatically during a recession. During the Great Recession, the marginal efficiency of active search declined by almost two-thirds and the active search share of vacancies by roughly half, similar in magnitude to the drop in aggregate match efficiency estimated by Gavazza, Mongey and Violante (2018). The estimates from the CES aggregator imply that the role of active search in aggregate matching is modest even on average: among the non-employed who want a job, the active channel accounts for roughly one quarter of hires, in line with survey evidence that many job offers arrive without active search (Faberman et al., 2022). During the Great Recession, the share fell to roughly half that level. Thus, even though recessions are periods when the fraction of the non-employed engaged in active search and the intensity of that search are both at their peak, they are also the periods when active search plays the smallest role in matching workers with jobs.

These estimates have implications for the disincentive effects of UI over the business cycle. Using the Baily–Chetty sufficient statistics framework for optimal unemployment insurance, we show that the micro-elasticity of unemployment with respect to the replacement rate depends on the elasticity of job-finding with respect to active search effort, which under our estimates declines when active search increases. Thus, UI has a smaller distortionary effect on job-finding during recessions. A back-of-the-envelope calculation implies that the time-varying elasticity narrows the optimal consumption gap between employed and unemployed workers from around 30% before the Great Recession to around 20% at its trough—a drop of one-third.[1]

[1]This channel operates independently of market tightness—and hence of assumptions about surplus splitting and the cyclicality of wages.

The final part of the paper embeds the estimated search technology in a full quantitative equilibrium model of the business cycle in which both margins of active search are endogenous: non-employed individuals choose whether to engage in active search and, conditional on searching, how intensively. Countercyclical search effort naturally emerges in the quantitative model from a procyclical opportunity cost of employment à la Chodorow-Reich and Karabarbounis (2016), as an increasing marginal utility of consumption during a downturn diminishes the value workers place on leisure. The estimated degree of crowding-out dampens but does not overturn the countercyclicality of search effort relative to a benchmark of perfect substitutability. The model thus reproduces the joint cyclical behavior at the center of the paper—search effort rises in recessions, exactly when job-finding collapses, and the active search premium falls—while remaining consistent with standard business-cycle moments.

The model also isolates the aggregate consequences of the crowding-out of active search. The low estimated elasticity of substitution between active and passive search implies that there is a wedge between the micro and macro elasticities of search effort: an aggregate increase in search effort lowers the return to active search, whereas an idiosyncratic increase does not. We illustrate the wedge with a change in UI benefits: holding market tightness fixed, aggregate search effort responds by roughly one quarter of the individual response at our estimated elasticity. Moreover, we use the estimates from the empirical section as sufficient statistics that bound the effective elasticity of aggregate search effort—for any elasticity of individual search—strictly below the elasticities implied by micro evidence on UI responses. Crucially, this force operates on the search response itself, and is accordingly complementary to the general-equilibrium effects of UI emphasized elsewhere in the literature (e.g., Landais, Michaillat and Saez, 2018b; Hagedorn et al., forthcoming). In general equilibrium, the same force dampens the response of unemployment duration to temporary benefit expansions by roughly 40 to 60 percent, and to a permanent expansion by roughly one-quarter, relative to the standard specification in the literature, in which active and passive search are perfect substitutes and crowding-out is absent.

Related literature.— The paper provides additional evidence for the importance of nonparticipation in understanding the dynamics of unemployment. Although models in the tradition of Diamond, Mortensen, and Pissarides typically exclude a role for nonparticipation, the importance of nonparticipants for broader labor market dynamics is well documented: for example, Blanchard and Diamond (1989) estimate that roughly half of all new hires from non-employment originate from nonparticipation.

The same paper also documents the importance of nonparticipants for explaining the cyclical behavior of vacancies and new hires, emphasizing the empirical relevance of the distinction between nonparticipants who want a job and those who do not (p. 32). More recently, Faberman et al. (2022) show the importance of unsolicited employer contacts for job-finding, empirically validating that workers do indeed find jobs via passive search. Lester, Rivers and Topa (2023) provide further worker-side evidence on the role of referrals for job-finding, while Davis, Macaluso and Waddell (2021) provide firm-side evidence documenting the extent to which employers rely on referrals and internal channels in their recruiting.

Motivated by these patterns, a recent literature has incorporated a role for labor force inactivity—and the coexistence of active and passive search—into frictional models of equilibrium unemployment, including Krusell et al. (2017, 2020), Cairó, Fujita and Morales-Jiménez (2022), Ferraro and Fiori (2023), Faberman et al. (2022), and Graves et al. (2024). While implementations differ, each implies that the relative return per unit of effort is constant—a property that Section 3 shows obtains only under perfect substitutability of active and passive search.

We show that this restriction can be rejected, and that the elasticity of substitution is well below one—implying that the composition of active and passive searchers among the non-employed affects the marginal return to active search. More broadly, our findings suggest that passive search is quantitatively important for job-finding, and that abstracting from it—as is common in models of unemployment—may miss a significant channel through which labor market conditions affect the matching process.

This paper also relates to the empirical literature evaluating the response of unemployment to variation in unemployment insurance benefits over the business cycle. Chodorow-Reich, Coglianese and Karabarbounis (2019) isolate UI extensions triggered by measurement error in recorded unemployment to estimate the causal impact of increased UI durations during the Great Recession, finding negligible effects on unemployment. Similar estimates from Rothstein (2011) and Farber and Valletta (2015) suggest that increases in UI benefits during recessions have smaller effects on job-finding probabilities than during normal times. Acosta et al. (2023) show that UI extensions at long baseline durations—as during the Great Recession—have minimal macroeconomic effects, while extensions at short baseline durations have substantial effects. Of particular relevance is Kroft and Notowidigdo (2016), who exploit cross-state variation in the interaction of UI benefit levels with local unemployment rates to estimate that the effect of UI on unemployment is smaller when unemployment is high.[2]

This paper takes a different and complementary approach, structurally estimating the search aggregator entering the matching function in order to recover the elasticity of substitution between active and passive search. In this respect, our approach is in the tradition of structural matching function estimation, as in Blanchard and Diamond (1989), Davis, Faberman and Haltiwanger (2013), and Borowczyk-Martins, Jolivet and Postel-Vinay (2013). Whereas Borowczyk-Martins et al. (2013) estimate matching function elasticities and Davis et al. (2013) estimate recruiting intensity, our focus is on the substitutability of different types of search within the matching function. A key innovation of our approach is that comparing the job-finding rates of active and passive searchers within the same matching function differences out aggregate match efficiency—the unobserved object that creates the central identification problem in matching function estimation, which Borowczyk-Martins et al. (2013) address through instrumental variables.

The structural estimates deliver a rationale for the reduced-form findings described above. In particular, the finding of Kroft and Notowidigdo (2016) that UI has a smaller effect on unemployment during periods of high unemployment is consistent with the procyclical elasticity of search efficiency with respect to active search estimated here: during recessions, when active search increases relative to passive, the diminished marginal efficiency of active search implies that the disincentive effect of UI on active search matters less for the probability of finding a job.

Our paper similarly relates to the theoretical literature studying unemployment insurance over the business cycle, including Mitman and Rabinovich (2015) and Landais, Michaillat and Saez (2018a); Landais et al. (2018b), which emphasizes how the effects of UI vary with aggregate conditions through job creation and market tightness. In contrast, we study cyclical variation in the disincentive effects of UI. The procyclical elasticity of search efficiency described above implies a microelasticity of unemployment duration in the Baily–Chetty formula that declines during recessions—even absent general equilibrium effects.[3] In our quantitative model, which incorporates these effects, crowding-out bounds the effective elasticity of aggregate

[2]Kroft and Notowidigdo (2016) interpret their finding through the lens of procyclical moral hazard costs of UI. Our explanation is complementary: both offer accounts of why UI has a smaller effect on unemployment during recessions, through different channels.

[3]See Section IV of Landais et al. (2018b) for a helpful discussion of the role of general equilibrium effects in sufficient-statistics formulas.

search effort with respect to benefits strictly below the elasticity implied by micro evidence. Both results operate through the matching process, independently of market tightness—and hence of assumptions about surplus splitting and the cyclicality of wages.

This paper argues that the increase in active search during downturns drives the decline in the active search premium at such times through crowding-out. Direct evidence of countercyclical active search along the extensive and intensive margins comes from Osberg (1993), Shimer (2004), Elsby, Hobijn and Şahin (2015), Mukoyama et al. (2018), and Faberman and Kudlyak (2019).

Finally, the paper relates to a literature documenting the "failure of the matching function" during the Great Recession, including Şahin et al. (2014) and Gavazza et al. (2018), who document large recessionary declines in aggregate match efficiency. Our results offer a complementary perspective: the decline in aggregate match efficiency can be understood in part as a decline in the marginal efficiency of active search driven by the recessionary increase in active search. In other words, the matching function did not become uniformly less efficient; rather, the return to active search declined as the matching process was flooded with active applicants.

The remainder of the paper proceeds as follows. Section 2 documents the size and cyclicality of the active search premium. Section 3 derives and rejects the restriction on the premium implied by perfect substitutes. Section 4 estimates the CES search aggregator and develops its implications, including for the disincentive effects of UI. Section 5 develops the quantitative model. Section 6 shows that the model reproduces the cyclical behavior of search effort and the active search premium, and quantifies the micro and macro elasticity of search effort with respect to UI benefits. Section 7 concludes.

2. Measurement of the Active Search Premium

This section uses data from the CPS over the period 1996 to 2019 to study job-finding outcomes of active and passive searchers.[4] We document that (i) the active search premium is small and procyclical, (ii) among the population of non-employed individuals who are willing to work, the fraction of workers engaged in active search is countercyclical, and (iii) conditional on engaging in active search, the intensity of active search among the non-employed is also countercyclical.

[4]The estimation samples below are monthly, 1995m9–2019m12; business-cycle statistics are quarterly averages over 1996–2019. Exhibit notes state the sample used.

In its 1994 redesign, the CPS introduced a series of questions that allow researchers to identify non-employed individuals who are not searching but would be willing to accept a job.[5] Conditional on (*a*) not being employed or on temporary layoff, and (*b*) being willing to accept work, non-employed individuals are asked which of a series of nine methods of active search they are engaged in. Workers engaged in at least one method of active search meet the Bureau of Labor Statistics (BLS) definition of unemployment; workers engaged in no active search methods are considered out of the labor force, although they may be eligible for inclusion in broader measures of unemployment as "discouraged workers."

We classify all unemployed workers not on temporary layoff as belonging to the active non-employed. We exclude workers on temporary layoff from the sample, as the majority of these workers are recalled to their previous employer (Fujita and Moscarini, 2017; Gertler, Huckfeldt and Trigari, 2026), and thus their reemployment outcomes are largely mediated by recall rather than the matching process relevant for other non-employed individuals. Furthermore, the CPS does not collect information on search activity for workers on temporary layoff, precluding measurement of their active search effort.

We classify a worker as belonging to the passive non-employed if the worker indicates willingness to work, is not engaged in active search, and reports that the reason for not searching relates to the availability of work ("believes no work available," "couldn't find any work") rather than to their ability to supply labor (e.g., "family responsibilities," "ill-health, physical disability") or to perceived discrimination (e.g., "employers think too young or too old"). If an individual provides no reason for not searching, we classify that individual as passive non-employed. Workers who report willingness to work but do not meet the criteria for the passive non-employed are included among the inactive. The classification thus generates five distinct labor force states: employment, temporary layoff, active non-employment, passive non-employment, and inactivity. We consider alternative definitions of the passive non-employed—including broader definitions that encompass all nonparticipants who report wanting a job—as robustness exercises in Appendix C, where we also report summary statistics under each definition.

[5]1996 is the first year after the redesign for which it is possible to merge each of the twelve monthly basic files to study gross worker flows. Consecutive monthly files can be matched from September 1995, following the phase-in of the redesigned sample; this sets the start of the monthly estimation samples.

Table 1. Summary Statistics: Job-Finding Rates and Active Search

Panel A: Job-finding rates

	Monthly job-finding probability		
	Active (f_A)	Passive (f_P)	Ratio (f_A/f_P)
mean(x)	0.218	0.153	1.430
std(x)/std(Y)	8.218	7.655	8.032
corr(x,Y)	0.846	0.421	0.461

Panel B: Active search

	Active non-employed	Passive non-employed	Fraction active	Avg. # of search methods
mean(x)	5.01	1.41	0.77	1.88
std(x)/std(Y)	10.88	5.51	1.56	2.23
corr(x,Y)	−0.89	−0.71	−0.76	−0.85

Note: f_A and f_P are monthly transition probabilities to employment from active and passive non-employment, under our baseline definition of passive non-employment (nonparticipants who want a job and are available for work). Active and passive non-employed are expressed in percent of the population base implied by the definition—the population aged 16+, net of the inactive and of temporary layoffs—as in Table C.4 of the appendix. Y indicates quarterly real GDP. For the second and third rows, series are taken as (1) quarterly averages of seasonally adjusted monthly series, (2) logged, then (3) HP-filtered with smoothing parameter of 1600; volatilities relative to Y. CPS, 1996–2019.

We use the number of active search methods as a measure of the intensive margin of active search. Such a measure has been used and validated elsewhere in the literature. Osberg (1993) reports that the number of active search methods is countercyclical using data from Canada. Shimer (2004) reports the same for the United States from the post-1994 CPS. Mukoyama et al. (2018) study the extent to which an increase in the number of search methods corresponds to an increase in time spent searching, finding that time spent searching is essentially linear in the number of search methods, and they too find that the intensive margin of active search is countercyclical.[6]

Job-finding rates. Table 1 provides summary statistics. Panel A reports that the monthly job-finding probabilities of the active non-employed are roughly 40 percent

[6]See Figure 1, pg. 198 of Mukoyama et al. (2018). There is a slight break in linearity when the number of search methods reaches five. In practice, however, very few active searchers are observed using this many search methods within this range.

larger than those of the passive non-employed: 0.22 versus 0.15.[7] Although the passive non-employed have lower job-finding probabilities than the active non-employed, their average job-finding probabilities are substantially higher than those of all non-participants, estimated here to be 0.05 (see Table C.4 of the Appendix). Although the job-finding probabilities of the active and passive non-employed are similarly volatile, the job-finding probabilities of the passive non-employed are substantially less correlated with GDP. As a result, the active search premium is strongly procyclical.

The top panel of Figure 2 illustrates the cyclical behavior of the job-finding probabilities of the active and passive non-employed. At the onset of a recession, job-finding probabilities from both active and passive non-employment decline, with a slow subsequent recovery. However, the extent of the recessionary decline is much greater for the active non-employed: the gap between the two job-finding rates shrinks during recessions, with the active search premium approaching zero during the recovery from the Great Recession.

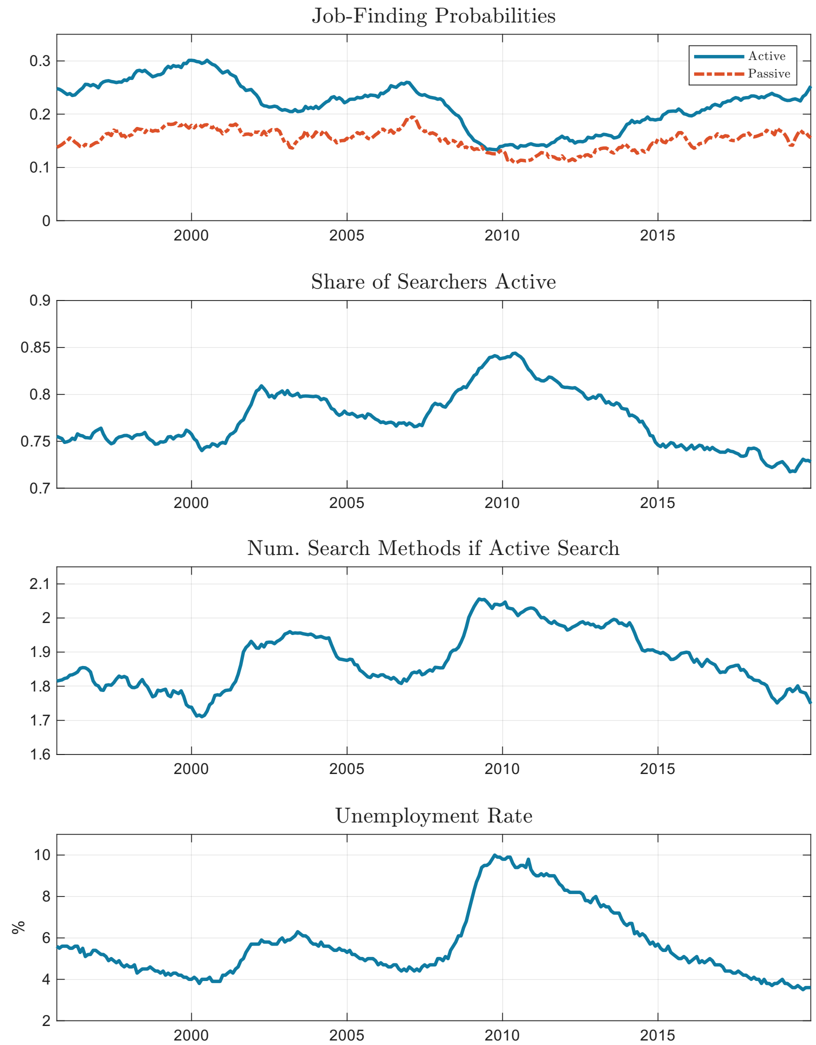
Active search. Panel B of Table 1 gives descriptive statistics of the extensive and intensive margins of active search. The fraction of the non-employed engaged in active search is countercyclical, as is the average number of search methods conditional on active search. The second and third panels of Figure 2 plot the extensive and intensive margins of active search over time. Active search rapidly increases along both margins at the onset of a recession, and then gradually subsides. Thus, the returns to active search decline precisely when active search increases—a pattern consistent with a crowding-out of active search.

3. Testing Perfect Substitutes in the Matching Function

This section develops a restriction on the active search premium implied by the standard assumption that active and passive search are perfect substitutes in the matching function. We show that the restriction is strongly rejected in the data, motivating the more general CES framework developed in Section 4. The restriction relates the active search premium to the average active search effort of the active non-employed. Notably, all other aggregate variables—including labor market tightness and match efficiency—are differenced out of the expression. Thus, the restriction can

[7]The job-finding probability of the active non-employed is comparable to other estimates of the job-finding probability from unemployment produced by procedures that acknowledge inactivity as a distinct labor market state, e.g., Krusell et al. (2017). In general, such estimates are lower than those produced from the procedure proposed by Shimer (2012), which effectively treats flows from unemployment to inactivity as flows from unemployment to employment.

Figure 2. Job-Finding Probabilities and Active Search Over Time



Note: Top panel: monthly job-finding probabilities of active and passive searchers. Second and third panels: the fraction of the non-employed engaged in active search, and the average number of search methods among active searchers. Bottom panel: the unemployment rate. Plotted series in the top three panels are smoothed using a centered five-month moving average. CPS, 1996–2019.

be tested independently of a particular surplus-splitting mechanism, and independently of the "unemployment volatility puzzle" à la Shimer (2005) and Hall (2005).

A standard approach in the search and matching literature is to model the job-finding rate as the product of an individual's search efficiency and the aggregate job-finding rate per efficiency unit of search. Specifically, let the job-finding rate of non-employed individual i at time t be

$$f_{i,t} = s_{i,t} \cdot \frac{m_t(\bar{s}_t, v_t)}{\bar{s}_t}, \tag{1}$$

where $m_t(\cdot)$ is a constant-returns-to-scale matching function defined over aggregate effective search $\bar{s}_t$ and vacancies v_t. Individual effective search $s_{i,t}$ is a composite of active and passive search effort. Following the literature, we assume that non-employed individuals inelastically supply one unit of passive search effort, while also choosing $e_{A,i,t}$ units of active search effort.

Aggregating across the distribution Γ_t^{ne} of active and passive searchers, we define total active and passive search effort as follows:

$$\bar{s}_{A,t} = \int_i e_{A,i,t}\, d\Gamma_t^{ne}(i) \qquad \text{and} \qquad \bar{s}_{P,t} = \int_i d\Gamma_t^{ne}(i) = ne_t, \tag{2}$$

where ne_t is the total number of active and passive searchers. We take aggregate effective search to be a weighted sum of total active and passive search effort—the specification effectively assumed by Krusell et al. (2017), Faberman et al. (2022), and others:

$$\bar{s}_t = \omega \cdot \bar{s}_{A,t} + (1-\omega) \cdot \bar{s}_{P,t} \tag{3}$$

This implies that individual effective search is defined as follows:

$$s_{i,t} = \omega \cdot e_{A,i,t} + (1-\omega), \tag{4}$$

and consequently that the job-finding probability of an individual can be written

$$f_{i,t} = (\omega \cdot e_{A,i,t} + (1-\omega)) \frac{m_t(\bar{s}_t, v_t)}{\bar{s}_t} \tag{5}$$

Equations (4) and (5) restate the textbook efficiency-units formulation (Pissarides, 2000): an individual's job-finding probability is her search efficiency times the market job-finding rate per efficiency unit of search. The weights in (4) are constants only because the aggregator (3) is linear—that is, only in a setup that implicitly assumes that active and passive search are perfect substitutes.

This formulation can be used to develop a sharp restriction implied by this standard matching framework. Let $f_{A,t}$ denote the average job-finding probability of active searchers, and $f_{P,t}$ denote the average job-finding probability of passive searchers. Using equation (5) we derive the following restriction on the active search premium:

$$\frac{f_{A,t}}{f_{P,t}} - 1 = \frac{\left(\omega \cdot \bar{e}^*_{A,t} + (1-\omega)\right)\left(\frac{m_t(\bar{s}_t, v_t)}{\bar{s}_t}\right)}{(1-\omega)\left(\frac{m_t(\bar{s}_t, v_t)}{\bar{s}_t}\right)} - 1 = \frac{\omega}{1-\omega} \cdot \bar{e}^*_{A,t} \tag{6}$$

where $\bar{e}^*_{A,t}$ is the average level of active search effort conditional on active search.

This expression has several notable features. First, it depends only on the structural parameter ω and the average intensity of active search. Second, it implies that the active search premium exhibits a unit elasticity with respect to $\bar{e}^*_{A,t}$: periods when active searchers are more engaged in active search should be periods when the active search premium is larger. Equivalently, the restriction states that the return earned per unit of active search effort, relative to passive search, is constant. Third, aggregate match efficiency and labor market tightness have been differenced out of the expression, so that the restriction can be tested without taking a stand on these unobservables. This identification relies on the assumption that active and passive searchers have common acceptance probabilities. Our baseline definition of passive searchers—nonparticipants who want a job and report being available for work—is designed to select workers whose acceptance probabilities are most comparable to those of active searchers. We assess sensitivity to this choice below.

Estimation. We estimate the following equation by OLS:

$$\log\left(\frac{f_{A,t}}{f_{P,t}} - 1\right) = \beta_0 + \beta_T\, t + \beta_{ASP} \cdot \log \bar{e}^*_{A,t} + \epsilon_t, \tag{7}$$

where ϵ_t is an *iid* error term and the linear time trend absorbs secular change in the relative weight of active search. Under perfect substitutes with operative extensive and intensive margins of active search à la Faberman et al. (2022), the estimated coefficient β_{ASP} should be equal to one. Under perfect substitutes with only an extensive margin of search à la Krusell et al. (2017), the coefficient β_{ASP} should be zero—i.e., a constant active search premium.

Table 2 reports estimates across three definitions of the passive non-employed. Column (1) uses our baseline measure: nonparticipants who want a job and report being available for work. Column (2) broadens the definition to all nonparticipants who want a job, and column (3) broadens further to all nonparticipants. The baseline point estimate for the elasticity in column (1) is −7.66 with a standard error of 1.02. Thus, a one percent increase in average active search effort is associated with an approximately eight percent *reduction* in the active search premium—whereas the theory predicts an elasticity of one (under intensive and extensive margins of active search) or zero (with only an extensive margin). Given the procyclical active search premium and countercyclical active search documented in Section 2, the rejection of the theoretical restriction should come as no surprise.

An important feature of these results is that the estimated elasticity is *largest* in magnitude under the narrowest definition of passive search (column 1) and smallest under the broadest (column 3). The framework underlying equation (6) assumes that all non-employed individuals who receive a job offer accept it. If nonparticipants were instead to become less selective about accepting offers during recessions, we could mechanically reject the restriction even in the absence of crowding-out. However, the pattern across columns works against this concern: our results are strongest when we condition on workers who are most plausibly willing and able to accept a job offer, i.e., those who report both wanting a job and being available to start work.

We subject this finding to a battery of robustness checks. As detailed in Appendix C, the rejection of the standard restriction is robust to: alternative definitions of the passive non-employed; adjustment for time-aggregation bias in measured transition probabilities; restricting the sample of passive searchers to those who were also non-participants at $t-1$; controlling for cyclical composition using shift-share estimators with up to 360 subgroups defined by reason for unemployment, education, age, gender, and prior-year labor force status; and restricting the sample of active searchers to only the short-term unemployed to control for duration dependence.

4. An Unrestricted CES Search Aggregator: Estimates and Implications

The linear aggregator in equation (3) imposes that active and passive search are perfect substitutes in generating matches. We now relax this assumption by replacing the linear aggregator with a CES structure that nests equation (3) as a special case.

4.1. **A generalized active search premium.**

Let aggregate effective search $\bar{s}_t$ be given by a CES aggregator over total active search $\bar{s}_{A,t}$ and total passive search $\bar{s}_{P,t}$:

$$\bar{s}_t = \left(\omega\, \bar{s}_{A,t}^{\frac{\nu-1}{\nu}} + (1-\omega)\, \bar{s}_{P,t}^{\frac{\nu-1}{\nu}}\right)^{\frac{\nu}{\nu-1}}, \tag{8}$$

where $\nu \in (0,\infty]$ is the elasticity of substitution between active and passive search and ω continues to govern the relative weight on active search. When $\nu = \infty$, active and passive search are perfect substitutes and (8) reduces to the linear aggregator in (3). Values of $\nu < \infty$ imply that active and passive search are imperfect substitutes, and thus that the return to each type of search will depend on its relative prevalence.

TABLE 2. Elasticity of the Active Search Premium

Dependent variable: Log active search premium			
	(1)	(2)	(3)
Log # of search methods	-7.655^{***}	-5.642^{***}	-3.488^{***}
	(1.0226)	(0.4354)	(0.1441)
β_T	$-1.7\text{e-}3^{***}$	$-1.1\text{e-}3^{***}$	$-4.5\text{e-}4^{***}$
	(4.2e-4)	(1.8e-4)	(7.2e-5)
Constant	3.820^{***}	3.096^{***}	3.511^{***}
	(0.6322)	(0.2682)	(0.0898)
$Pr(H_0 : \beta_{ASP} = 1)$	0.000	0.000	0.000
Observations	287	292	292
Passive searchers:	N + want job + available	N + want job	All nonparticipants (N)

Note: OLS estimates of equation (7). Dependent variable is the log active search premium. Each column varies the definition of passive searchers—the non-employed treated as searching passively in constructing both active search premium. Column (1): nonparticipants who report wanting a job and being available to work; column (2): nonparticipants who report wanting a job; column (3): all nonparticipants. N denotes nonparticipation (not in the labor force). All regressions include a constant and a linear time trend (centered at the sample mean); robust standard errors in parentheses. CPS, 1995m9–2019m12.

Differentiating (8), we define the marginal efficiencies of active and passive search as follows:

$$ME_{A,t} = \frac{\partial \bar{s}_t}{\partial \bar{s}_{A,t}} = \omega \left(\frac{\bar{s}_t}{\bar{s}_{A,t}} \right)^{\frac{1}{\nu}} \qquad \text{and} \qquad ME_{P,t} = \frac{\partial \bar{s}_t}{\partial \bar{s}_{P,t}} = (1-\omega) \left(\frac{\bar{s}_t}{\bar{s}_{P,t}} \right)^{\frac{1}{\nu}}. \tag{9}$$

By linear homogeneity of the aggregator, individual effective search can be written as:

$$s_{i,t} = \underbrace{ME_{A,t} \cdot e_{A,i,t}}_{\equiv\, s_{A,i,t}} + \underbrace{ME_{P,t}}_{\equiv\, s_{P,t}}. \tag{10}$$

The person-level decomposition mirrors the aggregate one: $s_{A,i,t}$ is the individual's active-channel effective search—her own effort, converted at the aggregate efficiency—and $s_{P,t}$ her passive-channel effective search, common to all non-employed workers since passive effort is supplied inelastically. Because job-finding is linear in individual effort, the restriction developed below depends only on average effort among active searchers, $\bar{e}^*_{A,t}$; no assumption on the distribution of effort across individuals is required.

Using this, we can formulate a new restriction for the active search premium in this extension of the model:

$$\frac{f_{A,t}}{f_{P,t}} - 1 = \frac{\left(ME_{A,t} \cdot \bar{e}^*_{A,t} + ME_{P,t}\right)\left(\frac{m_t(\bar{s}_t, v_t)}{\bar{s}_t}\right)}{ME_{P,t}\left(\frac{m_t(\bar{s}_t, v_t)}{\bar{s}_t}\right)} - 1 = \frac{ME_{A,t}}{ME_{P,t}} \cdot \bar{e}^*_{A,t}. \tag{11}$$

The second equality in (11) shows that the active search premium is the product of two objects: average active search effort, and the ratio $ME_{A,t}/ME_{P,t}$—the *relative return per unit of effort*, the additional job-finding probability that a unit of active search effort earns over the passive endowment. The premium is the relative return per unit of effort, times the number of units. Under perfect substitutes the relative return is the constant $\omega/(1-\omega)$; under $\nu < \infty$ it declines with the aggregate active search of the non-employed.

Note that total active search can be written as $\bar{s}_{A,t} = \check{\mathcal{G}}_t \, ne_t \, \bar{e}^*_{A,t}$, where $\check{\mathcal{G}}_t$ is the fraction of the non-employed who are actively searching for work. Using this and substituting the expressions for the marginal efficiencies from (9) into (11) yields:

$$\frac{f_{A,t}}{f_{P,t}} - 1 = \frac{\omega}{1-\omega}\left(\frac{1}{\check{\mathcal{G}}_t \cdot \bar{e}^*_{A,t}}\right)^{\frac{1}{\nu}} \cdot \bar{e}^*_{A,t}. \tag{12}$$

There are two key differences between this and the restriction in equation (6). First, the active search premium now no longer depends only on $\bar{e}^*_{A,t}$, but is also affected by the share of the non-employed who actively search, $\check{\mathcal{G}}_t$. Second, the elasticity of the active search premium with respect to $\bar{e}^*_{A,t}$ is no longer unity. Taking logs:

$$\log\left(\frac{f_{A,t}}{f_{P,t}} - 1\right) = \log\left(\frac{\omega}{1-\omega}\right) - \frac{1}{\nu} \cdot \log \check{\mathcal{G}}_t + \left(1 - \frac{1}{\nu}\right) \cdot \log \bar{e}^*_{A,t}. \tag{13}$$

Equation (13) delivers three testable implications. First, the elasticity of the active search premium with respect to average active search effort is $1 - 1/\nu$, which equals unity only when $\nu = \infty$, i.e., the perfect substitutes case. Second, the fraction of non-employed who actively search, $\check{\mathcal{G}}_t$, now enters the premium with an elasticity of $-1/\nu$, which vanishes only in the case of perfect substitutes. Third, the two elasticities are linked: the elasticity with respect to average active search exceeds the elasticity with respect to the active search fraction by exactly one. These restrictions can be tested and the structural parameters ω and ν estimated using data on job-finding rates by search status, the fraction of non-employed who actively search, and average search effort among active searchers.

4.2. **Estimation.** We estimate the parameters of the CES aggregator from equation (13). We allow the weight on active search to vary over time,

$$\frac{\omega_t}{1-\omega_t} = \frac{\omega}{1-\omega}\, e^{\beta_T t},$$

which changes the estimation equation only by adding a linear time trend:[8]

$$\log\left(\frac{f_{A,t}}{f_{P,t}} - 1\right) = \beta_0 + \beta_T\, t + \beta_e \cdot \log \bar{e}^*_{A,t} + \beta_{\check{\mathcal{G}}} \cdot \log \check{\mathcal{G}}_t + \epsilon_t \tag{14}$$

We consider three specifications. First, we leave the regression unrestricted and test the over-identifying restriction $\beta_e = \beta_{\check{\mathcal{G}}} + 1$. The restriction rests jointly on the CES structure and on the assumptions underlying the differencing—common match efficiency and acceptance rates across the two groups. Second, we impose this restriction to recover the structural parameters ν and ω. Third, we consider the case in which there is no operative intensive margin of active search by imposing $\beta_e = 0$.

The test is related in structure to the original exercise of Blanchard and Diamond (1989), who estimate matching functions separately for the unemployed and for nonparticipants who want a job. Under perfect substitutability, the two regressions should return identical parameters—a restriction they note the data did not appear to satisfy (p. 34). The active-search-premium-based test conducted here differs in what it holds fixed: because the premium compares the two groups within the same matching function at each date, aggregate match efficiency differences out, whereas hiring functions estimated in levels confound variation in relative search efficiency with variation in aggregate match efficiency. The over-identifying restriction $\beta_e = \beta_{\check{\mathcal{G}}} + 1$ thus serves the role of their cross-equation parameter equality, with aggregate match efficiency differenced out.

Table 3 presents results. In the unrestricted specification, the point estimates of $\beta_{\check{\mathcal{G}}}$ and β_e are qualitatively consistent with the restriction implied by the CES aggregator, and we cannot reject the null hypothesis that $\beta_e = \beta_{\check{\mathcal{G}}} + 1$. Imposing the restriction, we can strongly reject the null hypothesis that $\nu = \infty$—i.e., that active and passive search are perfect substitutes—with a p-value that is essentially zero. The estimated elasticity of substitution is approximately $1/5$ when both intensive and extensive margins of active search are operative. Panel C of Table 3 reports the results using only the extensive margin. This specification is the limiting case in which diminishing

[8]The estimated change in the relative weight is -2.9 percent per year; the cyclical movements we emphasize are unaffected by the trend. The trend identifies only the relative effectiveness of active versus passive search; it can equivalently be attributed to growth in the effective quantity of active search per measured unit, at rate $\pi = \hat{\beta}_T\, \nu/(\nu-1) \approx +0.7$ percent per year.

individual returns leave the intensive margin uninformative. The implied elasticity of substitution falls further, to approximately 1/10; thus, diminishing returns at the individual level do not substitute for a diminishing marginal efficiency of active search at the aggregate level.[9]

The pattern across columns is familiar from Table 2: the estimated elasticity of substitution rises from 0.201 to 0.392 as the definition of the passive pool broadens, and the CES restriction is rejected under the broadest definition. The same pattern appears in Panel C, where the implied elasticity rises from 0.115 to 1.510. Broader samples of passive searchers include a greater fraction of individuals who remain nonparticipants regardless of labor market conditions; their presence mutes the measured responsiveness of the active search premium, mechanically biasing the estimated elasticity toward substitutability. Consistent with this interpretation, Blanchard and Diamond (1989) estimate that nonparticipants who want a job enter a pooled matching function with roughly half the weight of the unemployed, while nonparticipants as a whole enter with essentially zero weight (p. 32).

Rather than being perfect substitutes with an infinite elasticity of substitution as assumed in the existing literature, active and passive search are estimated to be close complements. For the non-employed individual, this implies a crowding-out of active search: the job-finding rate from active search relative to passive search is greater when fewer other workers are engaged in active search. For the firm, the low elasticity of substitution is consistent with a recruiting process that favors a relatively stable ratio of outside applicants to referrals and known candidates.[10]

4.3. **Cyclicality of the marginal efficiency of active search.** The estimates of the CES search aggregator allow us to recover the time series of the marginal efficiency of active search, $ME_{A,t}$, directly from the data. Using the expression for $ME_{A,t}$ from equation (9) and the definition of total active search $\bar{s}_{A,t} = \check{\mathcal{G}}_t \cdot ne_t \cdot \bar{e}^*_{A,t}$, the marginal efficiency of active search can be written as a function of observables and the estimated structural parameters:

$$ME_{A,t} = \omega \cdot \left(\frac{\left(\omega \cdot \left(\check{\mathcal{G}}_t \cdot \bar{e}^*_{A,t} \right)^{\frac{\nu-1}{\nu}} + (1-\omega) \right)^{\frac{\nu}{\nu-1}}}{\check{\mathcal{G}}_t \cdot \bar{e}^*_{A,t}} \right)^{\frac{1}{\nu}} \tag{15}$$

[9]Appendix C.2 re-estimates ν by GMM and instrumental variables, instrumenting each margin of search with the other; the estimates lie within 0.01 of the restricted regression, suggesting a limited role for measurement error in either margin.

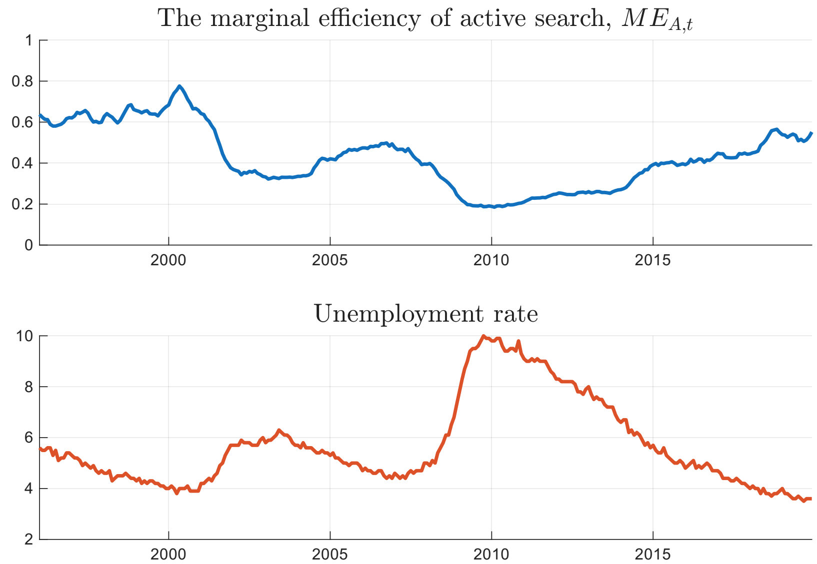
[10]As $\nu \to 0$, the aggregator approaches Leontief.

Table 3. Estimates of a CES Search Aggregator

Dependent variable: Log active search premium			
	(1)	(2)	(3)
Passive searchers:	N + want job + available	N + want job	All nonparticipants (N)
	A. Unrestricted		
$\beta_{\check{\mathcal{G}}}$	-5.244^{***}	-2.531^{***}	-0.549^{***}
	(1.3945)	(0.3887)	(0.0460)
β_e	-3.738^{***}	-1.590^{***}	-0.710^{***}
	(1.3378)	(0.6051)	(0.2496)
$p(\beta_e = \beta_{\check{\mathcal{G}}} + 1)$	0.840	0.950	0.000
Observations	287	292	292
	B. Restricted: $\beta_e = \beta_{\check{\mathcal{G}}} + 1$		
$\beta_{\check{\mathcal{G}}}$	-4.976^{***}	-2.552^{***}	—
	(0.5546)	(0.1546)	
β_e	-3.976^{***}	-1.552^{***}	—
	(0.5546)	(0.1546)	
Implied ν	0.201	0.392	—
Implied ω (sample mean)	0.554	0.325	—
$p(\nu = \infty)$	0.000	0.000	—
Observations	287	292	—
	C. Extensive margin only ($\beta_e = 0$)		
$\beta_{\check{\mathcal{G}}}$	-8.721^{***}	-3.297^{***}	-0.662^{***}
	(1.0965)	(0.2363)	(0.0197)
Implied ν	0.115	0.303	1.510
Observations	287	292	292

Note: OLS estimates of equation (14). Each column varies the definition of passive searchers—the nonemployed treated as searching passively in constructing both the active search premium and the fraction actively searching. Column (1): nonparticipants who report wanting a job and being available to work; column (2): nonparticipants who report wanting a job; column (3): all nonparticipants. N denotes nonparticipation (not in the labor force). Restricted estimates omitted where the CES restriction is rejected. All regressions include a constant and a linear time trend (centered at the sample mean), with trend coefficients reported in Appendix C.1; robust standard errors in parentheses. Implied ω is the weight on active search in (8), evaluated at the sample mean of the estimated trend. CPS, 1995m9–2019m12.

FIGURE 3. Marginal efficiency of active search



Note: The figure plots the marginal efficiency of active search $ME_{A,t}$ computed from equation (15) using estimated parameters from Table 3 and data on the extensive and intensive margins of active search from the CPS, 1996–2019. Plotted series in the top panel are smoothed using a centered five-month moving average.

Given $\nu < \infty$, the marginal efficiency of active search $ME_{A,t}$ is strictly decreasing in the average active search effort of the non-employed, $\check{\mathcal{G}}_t \cdot \bar{e}^*_{A,t}$. The marginal efficiency of passive search, $ME_{P,t}$, is increasing in the same quantity.

Figure 3 plots the implied time series of $ME_{A,t}$. The plotted time series holds the estimated trend in the relative weight of active search at its sample mean, so the constructed series varies only with the cyclical composition of search. The marginal efficiency of active search exhibits large reductions during recessions, with slow recoveries that mirror those of unemployment. During the Great Recession, the marginal efficiency of active search declined by almost two-thirds—similar in magnitude to the drop in aggregate match efficiency estimated by Gavazza et al. (2018).

The cyclical behavior of $ME_{A,t}$ helps account for the convergence of job-finding probabilities from active and passive non-employment documented in Section 2. The sharp recessionary decline in the average job-finding probability from active non-employment $f_{A,t}$ reflects not only the decline in the aggregate job-finding probability, but also the decline in the marginal efficiency of active search. The weaker recessionary decline in the job-finding probability from passive non-employment $f_{P,t}$ reflects the countercyclical increase in the marginal efficiency of passive search.

4.4. **Interpreting the CES search aggregator.** The notion of a CES aggregator over different types of search entering a matching function may seem somewhat unfamiliar. The following proposition offers an equivalent and more intuitive representation.

Proposition 1 (Equivalence result). *A CES aggregator over active and passive search entering a single matching function is equivalent to active and passive search entering separate matching functions, weighted by their marginal efficiencies:*

$$m_t(\bar{s}_t, v_t) = m_t(ME_{A,t} \cdot \bar{s}_{A,t}, \alpha_{A,t} \cdot v_t) + m_t \left(ME_{P,t} \cdot \bar{s}_{P,t}, (1 - \alpha_{A,t}) \cdot v_t\right), \tag{16}$$

where $\alpha_{A,t}$ is the active search share of vacancies, i.e. the fraction of vacancies posted in the submarket for active search, and we write $\alpha_{P,t} \equiv 1 - \alpha_{A,t}$ for the passive counterpart:

$$\alpha_{A,t} = \frac{ME_{A,t} \cdot \bar{s}_{A,t}}{\bar{s}_t} = \frac{\left(\frac{\omega}{1-\omega}\right)\left(\check{\mathcal{G}}_t \cdot \bar{e}^*_{A,t}\right)^{\frac{\nu-1}{\nu}}}{1 + \left(\frac{\omega}{1-\omega}\right)\left(\check{\mathcal{G}}_t \cdot \bar{e}^*_{A,t}\right)^{\frac{\nu-1}{\nu}}}. \tag{17}$$

Proof. By constant returns to scale of the CES search aggregator, $\bar{s}_t = ME_{A,t} \cdot \bar{s}_{A,t} + ME_{P,t} \cdot \bar{s}_{P,t}$. Exploiting linear homogeneity of the matching function,

$$\begin{aligned} m_t(\bar{s}_t, v_t) &= \left(\frac{ME_{A,t} \cdot \bar{s}_{A,t}}{\bar{s}_t}\right) \cdot m_t(\bar{s}_t, v_t) + \left(\frac{ME_{P,t} \cdot \bar{s}_{P,t}}{\bar{s}_t}\right) \cdot m_t(\bar{s}_t, v_t) \\ &= m_t\left(ME_{A,t} \cdot \bar{s}_{A,t}, \alpha_{A,t} \cdot v_t\right) + m_t\left(ME_{P,t} \cdot \bar{s}_{P,t}, (1 - \alpha_{A,t}) \cdot v_t\right) \end{aligned}$$

where $\alpha_{A,t}$ is defined as in (17). □

The active search share of vacancies $\alpha_{A,t}$ is analogous to a factor share from a production function, and thus inherits the standard properties. When $\nu < 1$—as is the case under our estimates—the vacancy share of active search is *decreasing* in the average active search effort of the non-employed, $\check{\mathcal{G}}_t \cdot \bar{e}^*_{A,t}$. Given that both $\check{\mathcal{G}}_t$ and $\bar{e}^*_{A,t}$ are countercyclical, the active search share of vacancies is procyclical: during recessions, even though a greater share of the non-employed are searching via active methods and the intensity of active search is higher, firms allocate a *smaller* share of their vacancies to the active search channel. In the language of the submarket representation from Proposition 1, the share of new hires coming through active search declines during a recession. In other words, firms substitute toward referrals and other passive hiring channels precisely when active search—and thus the number of external applications—is most abundant.

The next corollary establishes that market tightness is equalized across the two notional submarkets, and that the share of new hires intermediated through active search is given by $\alpha_{A,t}$.

Corollary 1.1 (Equal market tightness across matching functions)**.** *Under the representation in Proposition 1, the ratio of vacancies to search inputs (market tightness) is the same in the aggregate matching function as in the separate matching functions intermediating active and passive search. Moreover, the fraction of new hires formed via the matching function intermediating active search is equal to $\alpha_{A,t}$.*

Proof. Market tightness $\theta_{A,t}$ for the matching function intermediating active search is $\theta_{A,t} \equiv \alpha_{A,t} \cdot v_t/(ME_{A,t} \cdot \bar{s}_{A,t})$. Using the definition of $\alpha_{A,t}$ from (17), $\theta_{A,t} = v_t/\bar{s}_t = \theta_t$. A similar argument establishes $\theta_{P,t} = \theta_t$. Given equal tightness, vacancy-filling probabilities are equalized across submarkets, and the share of new hires matched via active search equals $\alpha_{A,t}$. □

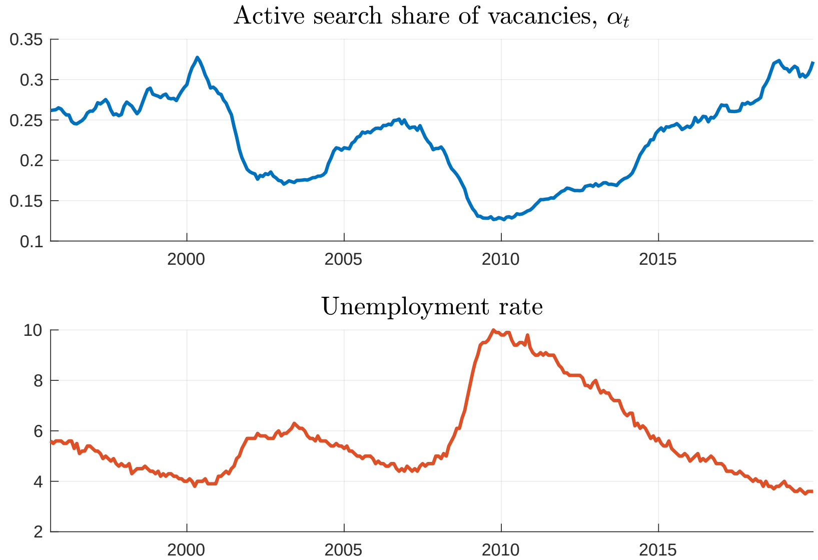
Figure 4 plots the implied time series of the active search share of vacancies, $\alpha_{A,t}$. The active search share exhibits large and persistent recessionary declines. During the Great Recession, the active search share fell from around 0.23 to approximately 0.12—a nearly 50 percent decline in the share of vacancies notionally intermediating active search.

This finding helps explain a growing body of evidence suggesting that increases in unemployment insurance benefits have smaller impacts on job-finding probabilities during recessions than during normal times (Rothstein, 2011; Farber and Valletta, 2015; Kroft and Notowidigdo, 2016; Chodorow-Reich et al., 2019; Acosta et al., 2023), though estimates of larger effects exist (Hagedorn et al., forthcoming; Johnston and Mas, 2018). Increased UI benefits are thought to discourage active search effort. However, even if the disincentive effect of UI on active search is as large during a recession as during an expansion, active search is less important for job-finding during a recession due to the reduction in both the marginal efficiency of active search and the active search share of vacancies.

4.5. **Implications for optimal unemployment insurance.** Our findings have implications for the optimal design of unemployment insurance over the business cycle. A useful benchmark comes from the Baily–Chetty formula (Baily, 1978; Chetty, 2006), which implicitly defines the welfare-maximizing replacement rate R:

$$\frac{1}{1-u} \cdot \frac{d \log u}{d \log R} = \frac{U'(c^u)}{U'(c^e)} - 1, \tag{18}$$

FIGURE 4. Active search share of vacancies



Note: The figure plots the active search share of vacancies $\alpha_{A,t}$ computed from equation (17) using estimated parameters from Table 3 and data on the extensive and intensive margins of active search from the CPS, 1996–2019. Plotted series in the top panel are smoothed using a centered five-month moving average.

where c^e and c^u denote the consumption of the employed and unemployed, $U'(\cdot)$ is the marginal utility of consumption, and $\frac{d\log u}{d\log R}$ is the micro-elasticity of unemployment with respect to the replacement rate. The left-hand side captures the cost of expanding UI through reduced job search; the right-hand side captures the benefit of consumption smoothing.

The micro-elasticity is typically taken to be constant, implying a constant optimal replacement rate (Cohen and Ganong, 2026). However, the micro-elasticity can be decomposed as follows:

$$\frac{d\log u}{d\log R} = \underbrace{\frac{d\log u}{d\log f}}_{\approx -(1-u)} \cdot \underbrace{\frac{d\log f}{d\log \bar{s}}}_{\text{match elas.}} \cdot \underbrace{\frac{d\log \bar{s}}{d\log \bar{s}_A}}_{\text{search elas.}} \cdot \underbrace{\frac{d\log \bar{s}_A}{d\log R}}_{\text{behav. response}} . \tag{19}$$

The first term is the elasticity of unemployment with respect to the job-finding rate, which can be closely approximated by $-(1-u)$ given the rapid dynamics of flows in and out of unemployment (Landais et al., 2018a). The second term is the matching function elasticity, typically taken as constant. The fourth term is the behavioral response of active search effort to a change in benefits. These three terms are standard in the literature.

The third term—the elasticity of effective search with respect to active search effort—is the novel object. Taking the CES search aggregator from equation (8), this elasticity is given by

$$\frac{d\log\bar{s}}{d\log\bar{s}_A} = \omega\cdot\left(\frac{\bar{s}_A}{\bar{s}}\right)^{\frac{\nu-1}{\nu}}. \tag{20}$$

Under the typical assumption that all search is active (i.e., $\omega = 1$, so that $\bar{s} = \bar{s}_A$), this elasticity equals one and is constant. In contrast, under our estimates of $\omega < 1$ and $\nu < 1$, the elasticity varies over time with the ratio of active to passive search. Given the countercyclical ratio of active to passive search, the elasticity is procyclical: it declines during recessions.[11] Thus, even if the behavioral response of active search to UI ($d\log\bar{s}_A/d\log R$) is constant, the overall micro-elasticity of unemployment with respect to UI is lower during recessions.

To quantify these implications, we proceed as follows. We take an estimate of the average micro-elasticity from the existing literature: Cohen and Ganong (2026) conduct a meta-analysis and find that the mean estimated elasticity of unemployment duration with respect to the replacement rate is 0.44. Because expected unemployment duration is the inverse of the job-finding rate, $dur_t = 1/f_t$, the duration elasticity identifies the elasticity of job-finding:

$$\frac{d\log dur}{d\log R} = -\frac{d\log f}{d\log R} = 0.44.$$

We then compute the average value of the elasticity of search efficiency with respect to active search implied by our estimates, which we find to be 0.224. Given these, the product of the remaining terms in equation (19) is pinned down:

$$\frac{d\log f}{d\log\bar{s}}\cdot\frac{d\log\bar{s}_A}{d\log R} = -\frac{0.44}{0.224} = -1.96. \tag{21}$$

We hold this product constant and allow the two remaining terms of equation (19), $d\log u_t/d\log f_t \approx -(1-u_t)$ and the elasticity of search efficiency, to vary over time, yielding a time-varying micro-elasticity:

$$\left.\frac{d\log u}{d\log R}\right|_t = (1-u_t)\cdot 1.96\cdot\left.\frac{d\log\bar{s}}{d\log\bar{s}_A}\right|_t. \tag{22}$$

[11] With a passive channel ($\omega < 1$), the elasticity is constant only in the Cobb–Douglas case $\nu = 1$. When active and passive act as substitutes ($\nu > 1$), the elasticity is increasing with the relative quantity of active search, and it is thus countercyclical.

The construction is deliberately simple: the $(1 - u_t)$ term cancels from the optimal-benefit formula below, so the time variation in the optimum reflects only the channel identified in this paper.

Assuming log preferences, the Baily–Chetty formula (18) implies that the optimal unemployed-employed consumption ratio $\Delta_t^* \equiv c_t^{u,*}/c_t^{e,*}$ is

$$\Delta_t^* = \left(\frac{1}{1-u_t} \cdot \left. \frac{d \log u}{d \log R} \right|_t + 1 \right)^{-1}. \tag{23}$$

Figure 5 plots the implied time series for Δ_t^* alongside the counterfactual in which the elasticity of search efficiency with respect to active search is held at its sample mean; because the $(1 - u_t)$ term cancels from (23), this counterfactual is constant.

The optimal consumption ratio is countercyclical: the social planner prescribes a smaller gap between employed and unemployed consumption during recessions. The intuition is straightforward: even if UI has the same disincentive effect on active search during a recession as during an expansion, the reduction in active search does less to lower job-finding probabilities when the marginal efficiency of active search is diminished. Thus, the policymaker can do more to smooth consumption without raising unemployment.

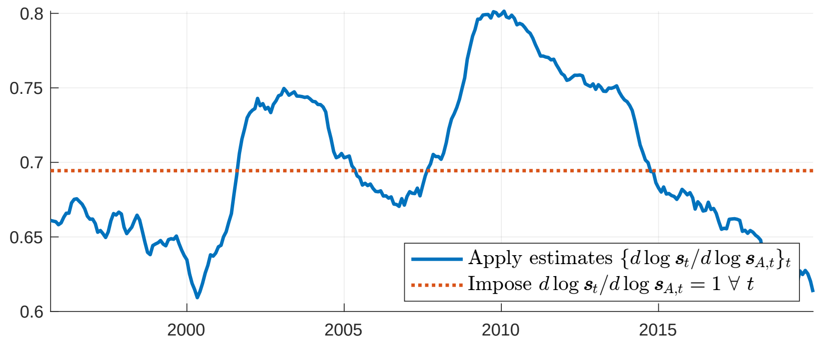
We note that this analysis abstracts from the macro-elasticity, which describes how UI affects job-finding rates through market tightness. Landais et al. (2018b) show that optimal UI incorporating a macro-elasticity prescribes less generous UI during recessions if wages are flexible, acyclical UI if wages are rigid, and more generous UI if wages are rigid and firms face capacity constraints. The time-varying micro-elasticity identified here operates independently of market tightness.

5. A Quantitative Model

We consider how a standard search model can rationalize our central finding of Section 2: that, during a recession, active search increases along both the intensive and extensive margins, despite the fall in the active search premium. Our model features equilibrium unemployment à la Diamond–Mortensen–Pissarides with sticky wages in a real business cycle framework with perfect risk-sharing within a representative family, à la Andolfatto (1996); Merz (1995). In addition, we allow for staggered Nash wage bargaining, as in Gertler and Trigari (2009).

We add two key ingredients to the model: endogenous active search along the extensive and intensive margins; and curvature in the aggregate relative return to active search, through an unrestricted CES aggregator over active and passive search, as in

FIGURE 5. Optimal unemployed-employed consumption ratio Δ_t^*



Note: The solid line plots the optimal unemployed-employed consumption ratio Δ_t^* from equation (23), computed using the time-varying micro-elasticity from equation (22). The dotted line shows the fixed optimum associated with the standard formula. The constructed series holds the estimated trend in the relative weight of active search at its sample mean, so only the cyclical composition of search varies. Log preferences assumed. Plotted series are smoothed using a centered five-month moving average. CPS, 1996–2019.

Section 4. The calibrated model successfully generates countercyclical active search and a procyclical active search premium (in addition to replicating standard business cycle moments). Countercyclical active search arises from the combination of (*i*) a procyclical opportunity cost of employment à la Chodorow-Reich and Karabarbounis (2016) and (*ii*) sticky wages, which generates a robustly countercyclical surplus from employment. In other words, workers search more during a recession because the value they obtain from employment relative to unemployment is sufficiently high to offset the higher cost of search from the lower aggregate job-finding rate.

Given countercyclical active search, the model generates the procyclical active search premium: as active search increases during a downturn, the relative return to active search declines under the calibrated (finite) elasticity of substitution between active and passive search, decreasing the active search premium.

To illustrate the connection between active search incentives and the relative return to active search, we decompose the increase in the unemployment rate after an increase in UI benefits into the contributions from changes in (a) active search and (b) the relative return to active search. An increase in UI benefits reduces the relative value of employment, directly reducing active search effort, and thus raising unemployment. But, as an indirect effect, the reduction in active search effort *increases* the relative return to active search, offsetting the overall increase in unemployment.

5.1. **Setting: matching with active and passive search.** Time is discrete. Each period is divided into four subperiods: (*i*) aggregate productivity z_t is realized, and each firm learns whether it may renegotiate its wage contract; (*ii*) production and wage bargaining occur; (*iii*) each non-employed individual draws a fixed cost γ of engaging in active search; and (*iv*) separations, search, and matching occur.

There is a unit measure of firms and workers. For each firm j operating at the beginning of period t, denote ℓ_t as beginning-of-period employment and υ_t as the total number of vacancies posted. Then, total employment in period t is given by $\bar{\ell}_t = \int_j \ell \, dj$ and total vacancies are given by $\bar{\upsilon}_t = \int_j \upsilon \, dj$. Total non-employment ne_t is defined by

$$ne_t = 1 - \bar{\ell}_t. \tag{24}$$

The aggregate number of new hires $\bar{m}_t$ is given by a constant returns to scale matching function in aggregate vacancies $\bar{\upsilon}_t$ and aggregate efficiency units of search $\bar{s}_t$,

$$\bar{m}_t = \sigma_m \, \bar{s}_t^{\sigma} \bar{\upsilon}_t^{1-\sigma}, \tag{25}$$

where $\bar{s}_t$ is defined below. The probabilities f_t and q_t that an efficiency unit of search finds a vacancy and that a vacancy finds an efficiency unit of search are given by

$$f_t = \frac{\bar{m}_t}{\bar{s}_t} \quad \text{and} \quad q_t = \frac{\bar{m}_t}{\bar{\upsilon}_t}. \tag{26}$$

Given an average level of active search effort $\bar{e}^*_{A,t}$ from workers engaged in active search, the job-finding probabilities of the active and passive non-employed, $f_{A,t}$ and $f_{P,t}$, satisfy

$$f_{A,t} = \left(ME_{A,t} \, \bar{e}^*_{A,t} + ME_{P,t} \right) f_t \quad \text{and} \quad f_{P,t} = ME_{P,t} \, f_t, \tag{27}$$

where the marginal efficiencies of active and passive search are those of the CES search technology introduced in Section 4: aggregate effective search $\bar{s}_t$ aggregates total active and passive search effort according to the CES aggregator in equation (8), and $ME_{A,t}$ and $ME_{P,t}$ are its partial derivatives, given by equation (9) and reproduced here for convenience:

$$ME_{A,t} = \omega \left(\frac{\bar{s}_t}{\bar{s}_{A,t}} \right)^{\frac{1}{\nu}} \qquad \text{and} \qquad ME_{P,t} = (1-\omega) \left(\frac{\bar{s}_t}{\bar{s}_{P,t}} \right)^{\frac{1}{\nu}}.$$

Workers and firms take the aggregate objects f_t, q_t, $ME_{A,t}$, and $ME_{P,t}$ as given.

The central object of Section 4 reappears here as an aggregate conversion rate. A marginal unit of active search effort raises a worker's job-finding probability by $ME_{A,t} \, f_t$—equivalently, by the relative return per unit of effort applied to the passive job-finding rate, $(ME_{A,t}/ME_{P,t})\, f_{P,t}$. The relative return has a closed form:

$$\frac{ME_{A,t}}{ME_{P,t}} = \frac{\omega}{1-\omega}\left(\check{\mathcal{G}}_t\, \bar{e}^*_{A,t}\right)^{-\frac{1}{\nu}}, \tag{28}$$

where $\check{\mathcal{G}}_t$ is the endogenously determined proportion of non-employed individuals engaged in active search (derived from the optimal active search decision of the non-employed, as shown below). The relative return, denominated in job-finding probabilities, declines in the aggregate active search effort of the non-employed with elasticity $1/\nu$; each worker takes its path as given. The empirical relative return per unit of effort—the measured active search premium divided by average active search effort—follows the same construction.[12]

The average job-finding probability among the non-employed, $\bar{f}_t$, is then given by

$$\bar{f}_t = \check{\mathcal{G}}_t\, f_{A,t} + (1-\check{\mathcal{G}}_t)\, f_{P,t}. \tag{29}$$

Substituting the definitions of $f_{A,t}$ and $f_{P,t}$ from (27) into (29) and applying Euler's theorem to the linearly homogeneous CES aggregator, $ME_{A,t}\,\bar{s}_{A,t} + ME_{P,t}\,\bar{s}_{P,t} = \bar{s}_t$, delivers the identity

$$\bar{f}_t = f_t \cdot \frac{\bar{s}_t}{ne_t}: \tag{30}$$

the average job-finding probability among the non-employed equals the matching rate per efficiency unit of search, multiplied by average search efficiency units per non-employed individual. Equivalently, substituting the definition of f_t from (26) into (30) gives $\bar{f}_t = \bar{m}_t/ne_t$, so that $\bar{f}_t$ coincides with the conventional definition of the aggregate job-finding probability: total new hires divided by the stock of non-employed individuals.

Finally, the law of motion for the number of non-employed individuals is given by

$$ne_{t+1} = \left(1-\bar{f}_t\right) ne_t + (1-\rho)\,\bar{\ell}_t, \tag{31}$$

where $1-\rho$ is the exogenous probability that a match dissolves.

5.2. **Workers.** Let $V_{E,t}(w)$ be the value of employment at wage w and $V_{NE,t}$ be the value of non-employment, reflecting worker values immediately after the realization of the aggregate shock (but prior to the realization of worker-specific shocks and

[12]By the active search premium equation (11), $ME_{A,t}/ME_{P,t} = (f_{A,t}/f_{P,t} - 1)/\bar{e}^*_{A,t}$.

search).[13] Then,

$$V_{E,t}(w_t) = w_t + \beta\,\mathbb{E}_t\,\Lambda_{t,t+1}\left[\rho\,V_{E,t+1}\left(w_{t+1}\right) + (1-\rho)\,V_{NE,t+1}\right] \tag{32}$$

where ρ is the probability a worker retains her job and $\Lambda_{t,t+1}$ represents the stochastic discount factor of the household (derived below). For now, we assume that households and firms take the path of the wage w_t as given.

Developing an expression for the value of non-employment $V_{NE,t}$ at the beginning of the period requires solving for the optimal active search policies of a non-employed individual. Define the auxiliary value function $\mathcal{V}_{NE,t}(\gamma)$ as the value of non-employment immediately after the realization of the worker's idiosyncratic fixed active search cost, γ. Accordingly,

$$\mathcal{V}_{NE,t}(\gamma) = \max\Big\{\mathcal{V}^{s}_{NE,t}(\gamma),\ \mathcal{V}^{ns}_{NE,t}\Big\}, \tag{33}$$

where $\mathcal{V}^{s}_{NE,t}(\gamma)$ and $\mathcal{V}^{ns}_{NE,t}$ reflect the values of non-employed individuals who actively search and those who do not. The ex-ante value of non-employment $V_{NE,t}$—the object relevant for consumption, saving, and wage bargaining—integrates over the search cost draws:

$$V_{NE,t} = \int_{\gamma} \mathcal{V}_{NE,t}(\gamma')\,d\mathcal{G}(\gamma'). \tag{34}$$

The value of the non-employed individual not engaged in active search is given by

$$\mathcal{V}^{ns}_{NE,t} = \xi_t + \beta\,\mathbb{E}_t\Big[\Lambda_{t,t+1}\Big\{f_{P,t}\,\bar{V}_{E,t+1} + (1-f_{P,t})\,V_{NE,t+1}\Big\}\Big], \tag{35}$$

where $\bar{V}_{E,t}$ is the expected value of being a new hire.[14] The object ξ_t is the flow value of non-employment gross of search costs—comprising unemployment benefits and the consumption value of leisure—defined within the household problem below. Because a worker who does not search actively pays no search costs, her flow benefit is exactly ξ_t.

A non-employed individual engages in active search by paying the fixed search cost γ and optimally chooses a level of active search effort $e_{A,t} \geq 0$ to balance the higher job-finding probability from greater active-channel effective search $s_{A,t} = ME_{A,t}\,e_{A,t}$ against leisure costs $\psi(e_{A,t})$. Thus, the value of a non-employed individual at time t

[13] Whereas Section 3 tracks individuals i with heterogeneous search intensities, non-employed individuals in the model differ only in their current draw of the search cost γ; we accordingly suppress individual indices. As shown below, the optimal search effort is common across active searchers, so the model's $e^{*}_{A,t}$ corresponds directly to its empirical counterpart in Section 2, the average intensity among active searchers.

[14] Under staggered bargaining, wages differ across firms by contract vintage, and a new hire is matched to firms in proportion to their hiring, so $\bar{V}_{E,t}$ averages $V_{E,t}(w)$ over the wages of hiring firms (Appendix D.1).

with fixed search cost γ engaged in active search is given by

$$\mathcal{V}^{s}_{NE,t}(\gamma) = \max_{e_{A,t}} \Bigg\{ \xi_t - \frac{\psi(e_{A,t}) + \gamma}{\mu_t} + \beta\, \mathbb{E}_t \Big\{ \Lambda_{t,t+1} \Big[\Big(ME_{A,t}\, e_{A,t} + ME_{P,t} \Big) f_t\, \bar{V}_{E,t+1} + \Big[1 - \Big(ME_{A,t}\, e_{A,t} + ME_{P,t} \Big) f_t \Big] V_{NE,t+1} \Big] \Big\} \Bigg\}, \tag{36}$$

where

$$\psi\left(e_{A,t}\right) = \frac{\psi_0}{1 + \frac{1}{\varepsilon_s}}\, e_{A,t}^{1+\frac{1}{\varepsilon_s}}, \tag{37}$$

and μ_t is the household's marginal utility of consumption, defined below. From inspection of (36), we see that the non-employed worker engaged in active search sacrifices additional flow value $\left(\psi(e_{A,t}) + \gamma\right)/\mu_t$ for a higher job-finding probability, in the amount $s_{A,t}\, f_t = ME_{A,t}\, e_{A,t}\, f_t$: her own effort, converted into effective search at the aggregate efficiency, and matched at the aggregate rate.

The optimal level of active search effort $e^*_{A,t}$ that solves the problem of the non-employed active searcher is given by the first-order condition to equation (36):

$$\psi_0 \cdot {e^*_{A,t}}^{1/\varepsilon_s} = \beta\, \mathbb{E}_t \Big[\mu_{t+1} \cdot ME_{A,t} \cdot f_t \cdot \bar{H}_{t+1} \Big], \tag{38}$$

where $\bar{H}_{t+1} \equiv \bar{V}_{E,t+1} - V_{NE,t+1}$ is the expected surplus of a new hire: the expected value of employment for a newly matched worker, net of the value of remaining non-employed. Each worker takes the marginal efficiency of active search $ME_{A,t}$ in (38) as given and does not internalize the contribution of her own effort to the aggregate $\bar{s}_{A,t}$ (nor, therefore, to $ME_{A,t}$). As we will see in Section 6.5, this matters for the response of aggregate search. When all workers reduce their search effort in response to, say, an increase in benefits, the marginal efficiency of active search rises, which induces them to search more. This offsetting feedback makes aggregate search effort less responsive to a change in benefits than the effort of a single worker facing the same change alone.

A non-employed individual engages in active search if $\mathcal{V}^{s}_{NE,t}(\gamma) \geq \mathcal{V}^{ns}_{NE,t}$. From equations (35) and (36), we obtain that the participation cutoff γ^*_t satisfies

$$\gamma^*_t = \beta\, \mathbb{E}_t \Big[\mu_{t+1}\, ME_{A,t}\, e^*_{A,t}\, f_t\, \bar{H}_{t+1} \Big] - \psi(e^*_{A,t}). \tag{39}$$

For a worker to be indifferent to engaging in active search, the fixed cost of search must exactly equal the benefit obtained from the optimal level of active search (conditional on paying the fixed cost γ^*_t).

Combining (38) and (39), we obtain

$$\gamma_t^* \;=\; e_{A,t}^* \, \psi'(e_{A,t}^*) - \psi(e_{A,t}^*) \;=\; \frac{\psi_0 \cdot {e_{A,t}^*}^{1+1/\varepsilon_s}}{1+\varepsilon_s}. \tag{40}$$

Then,

$$\mathcal{G}\left(\gamma_t^*\right) \;\simeq\; \text{const} \cdot \left(e_{A,t}^*\right)^g, \qquad g \equiv \kappa_{\mathcal{G}}\left(1 + \tfrac{1}{\varepsilon_s}\right), \tag{41}$$

up to a first-order approximation of the participation-cost CDF around the steady-state cutoff, where $\kappa_{\mathcal{G}} = \frac{d \ln \mathcal{G}}{d \ln \gamma^*}\Big|_{s.s.}$. Equation (41) holds period by period, tying the extensive margin of active search to the intensive margin with elasticity g. In particular, countercyclical search effort among active searchers implies a countercyclical fraction of the non-employed engaged in active search, consistent with the findings of Section 2.

The participation cutoff completes the characterization of the search behavior of the non-employed: the proportion of non-employed individuals engaged in active search is given by $\check{\mathcal{G}}_t = \mathcal{G}(\gamma_t^*)$, so that the average job-finding probability $\bar{f}_t$ defined in (29) is now fully determined by the intensive and extensive margins of active search, $e_{A,t}^*$ and γ_t^*. Using $\bar{f}_t$, we can derive an analytic expression for the ex-ante value of non-employment, $V_{NE,t}$:

$$V_{NE,t} = \xi_t - \frac{\mathcal{G}(\gamma_t^*)\, \psi(e_{A,t}^*) + \bar{\Gamma}_t}{\mu_t} + \beta\, \mathbb{E}_t \Lambda_{t,t+1} \left[\bar{f}_t\, \bar{V}_{E,t+1} + \left(1 - \bar{f}_t\right) V_{NE,t+1} \right] \tag{42}$$

The flow term represents the ex-ante flow value of non-employment: the gross flow value ξ_t, net of the expected intensive and extensive margin costs of search, $\mathcal{G}(\gamma_t^*)\psi(e_{A,t}^*)$ and $\bar{\Gamma}_t \equiv \int^{\gamma_t^*} \gamma' d\mathcal{G}(\gamma')$.

Finally, the surplus that the worker obtains from employment at wage w_t relative to non-employment (expressed in terms of worker values after the realization of the aggregate shock) is given by

$$H_t(w_t) = w_t - \xi_t + \frac{\mathcal{G}(\gamma_t^*)\, \psi(e_{A,t}^*) + \bar{\Gamma}_t}{\mu_t} + \beta\, \mathbb{E}_t \Lambda_{t,t+1} \Big[\rho\, H_{t+1}(w_{t+1}) - \bar{f}_t\, \bar{H}_{t+1} \Big]. \tag{43}$$

The surplus form makes transparent that the flow value of employment is the wage net of the term

$$\xi_t^o \equiv \xi_t - \frac{\mathcal{G}(\gamma_t^*)\, \psi(e_{A,t}^*) + \bar{\Gamma}_t}{\mu_t}, \tag{44}$$

the flow opportunity cost of employment in the sense of Chodorow-Reich and Karabarbounis (2016): the gross flow value of non-employment ξ_t—unemployment benefits and the consumption value of leisure—net of the expected intensive and extensive margin costs of active search.

For the reasons emphasized by Chodorow-Reich and Karabarbounis (2016), the opportunity cost of employment is procyclical; through the optimality conditions (38) and (39), its cyclicality passes directly into countercyclical active search along both margins.[15] We return to the mechanism when evaluating the model, where the measurements of Chodorow-Reich and Karabarbounis (2016) discipline both the level and the cyclicality of the opportunity cost.

5.3. **Firms.** The problem of the firm is standard: each firm produces output y_t from a Cobb–Douglas production function in labor and capital, with

$$y_t = z_t k_t^{\alpha} \ell_t^{1-\alpha} \tag{45}$$

where z_t represents total factor productivity.

We define the hiring rate of a firm, x_t, as the ratio of new hires $q_t\, \upsilon_t$ to the firm's existing workforce:

$$x_t = \frac{q_t\, \upsilon_t}{\ell_t} \tag{46}$$

Given x_t, we can write the law of motion for the firm's labor force as the sum of (exogenously) retained workers and new hires:

$$\ell_{t+1} = (\rho + x_t)\ell_t. \tag{47}$$

We assume that firms face labor adjustment costs that are quadratic in the hiring rate and proportional to the size of their existing labor force.

As the firm's value $F_t(w_t, \ell_t)$ is linearly homogeneous in its labor input, we express the firm's value-per-worker as $J_t(w_t) \equiv F_t(w_t, \ell_t)/\ell_t$. Denote r_t as the rental rate of capital, w_t as the prevailing wage rate at the firm, and $\check{k}_t = k_t/\ell_t$ as the firm's capital-per-worker. Then, the firm's value of a worker can be expressed as

$$J_t(w_t) = \max_{x_t, \check{k}_t} \left\{ z_t \check{k}_t^{\alpha} - r_t \check{k}_t - w_t - \frac{\kappa_t}{2}\, x_t^2 + (\rho + x_t)\, \beta\, \mathbb{E}_t \Lambda_{t,t+1} J_{t+1}(w_{t+1}) \right\} \tag{48}$$

subject to (47), for now taking the path of the firm's wage as given. Following Sala, Söderström and Trigari (2013), we allow hiring costs to comprise both vacancy-posting costs and post-match costs incurred when incorporating a new worker:

$$\kappa_t = \kappa \left(\bar{\upsilon}_t / \bar{\upsilon} \right)^{\gamma_\upsilon}, \tag{49}$$

[15]The induced search costs could in principle offset or amplify the procyclicality of the opportunity cost through the terms $\mathcal{G}(\gamma_t^*)\, \psi(e_{A,t}^*)$ and $\bar{\Gamma}_t$ in (44). We show below that the effect is quantitatively minimal.

where $\bar{v}$ denotes steady-state vacancies and $\gamma_v \in [0,1]$ is the vacancy-posting share of hiring costs: by the firm's optimality condition for vacancies, the elasticity of hiring costs with respect to aggregate vacancies equals the share of recruitment costs attributable to vacancy posting.[16]

The first-order conditions to the firm's problem give

$$r_t = \alpha z_t \check{k}_t^{\alpha-1} \tag{50}$$

$$\kappa_t x_t = \beta \mathbb{E}_t \Lambda_{t,t+1}\, J_{t+1}(w_{t+1}) \tag{51}$$

Thus, firms rent capital so that the marginal product of capital equals the rental rate, and hire until the marginal cost of hiring equals the discounted present value of a new worker to the firm.

5.4. **Wage bargaining.** Following Gertler and Trigari (2009), we assume that a firm and its workers bargain over wages on a multiperiod, staggered basis. Let $1-\lambda$ denote the probability that the parties negotiate a new contract in a given period, drawn independently across time and firms. When negotiating, the parties bargain over a new contract wage w_t^*, which then remains in place until the firm and its workers are next able to renegotiate. Workers hired between renegotiations receive the firm's prevailing contract wage.

Bargaining occurs after the realization of the aggregate shock but prior to the realization of the idiosyncratic search costs of the non-employed. Accordingly, the relevant surpluses for bargaining are the firm's value of a worker $J_t(w)$, defined in (48), and the worker's surplus from employment $H_t(w)$, defined in (43). The contract wage maximizes the Nash product

$$\max_{w_t^*} \; H_t(w_t^*)^{\eta}\, J_t(w_t^*)^{1-\eta}, \tag{52}$$

where η is the bargaining weight of the worker, subject to the law of motion of the firm's wage,

$$w_{t+1} = \begin{cases} w_t & \text{with probability } \lambda \\ w_{t+1}^* & \text{with probability } 1-\lambda. \end{cases} \tag{53}$$

We relegate the full characterization of the contract wage and the evolution of the average wage across firms to Appendix D.2.

[16] $\gamma_v = 1$ corresponds to pure vacancy-posting costs, and $\gamma_v = 0$ to pure post-match hiring costs à la Gertler and Trigari (2009).

5.5. **Household.** We embed the labor market in a real business cycle framework by adopting the representative family construct of Merz (1995) and Andolfatto (1996), allowing for perfect consumption insurance across members. The family pools the wage and benefit income of its members, owns diversified stakes in firms, and saves through capital, which it rents to firms at rate r_t and which depreciates at rate δ.

As in Chodorow-Reich and Karabarbounis (2016), non-working time yields utility: each non-employed member contributes the pure leisure flow ξ^l, net of the utility costs of active search where relevant. The family's period utility is accordingly

$$u(c_t) + \left(\xi^l - \mathcal{G}(\gamma_t^*)\,\psi(e_{A,t}^*) - \bar{\Gamma}_t\right) ne_t, \tag{54}$$

where $u(c)$ is increasing and strictly concave.

The household's problem determines two objects that appear throughout the model: the marginal utility of consumption, $\mu_t \equiv u'(c_t)$, which converts utility flows into consumption equivalents,[17] and the stochastic discount factor $\Lambda_{t,t+1} \equiv \mu_{t+1}/\mu_t$, which prices future flows. The first-order condition for saving yields the standard Euler equation,

$$1 = \beta\,\mathbb{E}_t[\Lambda_{t,t+1}\,(1 - \delta + r_{t+1})]\,. \tag{55}$$

The marginal utility of consumption also determines the flow value of non-employment gross of search costs, the object ξ_t introduced in Section 5.2:

$$\xi_t \equiv b + \frac{\xi^l}{\mu_t}, \tag{56}$$

unemployment benefits plus the value of leisure, converted at the marginal utility of consumption.

6. Model evaluation

6.1. **Calibration.** The model is calibrated at a monthly frequency. Of the 21 parameters in the model, we set 13 directly, as listed in Table 4; three more are implied by steady-state restrictions described below; and the remaining five are calibrated jointly to match moments from the data. Preferences over consumption are CRRA with curvature $\sigma_c = 4$ and the monthly discount factor is $\beta = 0.9967$.[18] We set $\lambda = 11/12$,

[17]The worker value functions of Section 5.2 correspond to marginal values of members to the family, expressed in consumption equivalents through normalization by μ_t; we present the household's problem, along with this correspondence, in Appendix D.3.

[18]The curvature of preferences matters for the volatility of the household's opportunity cost of employment, which transmits to the search decisions of non-employed individuals. Because this parameter governs the transmission at the center of the paper, we hold it to the micro evidence: our value implies an intertemporal elasticity of substitution of 1/4, between the bias-corrected estimates

implying an average contract duration of twelve months; and the vacancy-posting share of hiring costs is $\gamma_v = 1/2$, following evidence from Sala et al. (2013). Participation costs γ are drawn from a lognormal distribution $\mathcal{G}$ with dispersion σ_γ. The remaining externally set parameters are standard in the business-cycle literature and take conventional values (Table 4).

We set the separation rate to be $1 - \rho = 0.035$, so that employment spells last roughly 2.4 years. The model's non-employed correspond to the non-employed who want a job, as measured in Section 2; flows to and from inactivity are conditioned out, as is standard in two-state calibrations of matching models (Shimer, 2005, 2012; Gertler et al., 2026). Accordingly, we assign active searchers—the model counterpart of measured unemployment—a steady-state job-finding probability of 0.45, the value estimated by Shimer (2005).

The parameters governing active and passive search follow the measurements of Sections 2 and 4. The relative job-finding rates of active and passive searchers match the estimates of Section 2, $f_A/f_P = 1.43$, and the CES weight on active search is set to its sample-mean estimate, $\omega = 0.554$ (Table 3, column (1)). Among the non-employed who want a job, the share engaged in active search, $\check{\mathcal{G}} = 0.774$ in the CPS, pins the location μ_γ of the participation-cost distribution. Given these restrictions, the hiring-cost scale κ is implied by the hiring-rate condition, solved jointly with the steady-state wage, surplus, and marginal utility, and the search-cost scale ψ_0 follows from the search first-order condition. The pecuniary component of the opportunity cost of employment is set to $b = 0.16$ of the marginal product of labor: a statutory replacement rate of 0.40, as in Shimer (2005), adjusted for a benefit take-up rate of 0.40 à la Chodorow-Reich and Karabarbounis (2016).

The five remaining parameters are calibrated jointly to five moments; Table 5 lists the parameters and Table 6 the targets. Although computed as a joint fit, the mapping from moments to parameters is block-recursive. The three search-block parameters are pinned sequentially, and in closed form: the duration elasticity of unemployment with respect to UI benefits identifies the elasticity of search costs, ε_s, on its own. Given ε_s, the relative volatility of the two search margins identifies σ_γ through the participation elasticity g of equation (41), which in turn pins down $\kappa_{\mathcal{G}}$,

of the Havránek (2015) meta-analysis, which center on 0.3–0.4, and the quasi-experimental estimate of roughly 0.1 from mortgage notches (Best et al., 2020). The model's aggregate behavior is standard at this value — consumption remains smooth and investment volatile (Table 7) — and the calibration is unaffected by the choice: the targets of Table 6 are invariant to σ_c. In untabulated results, repeating the analysis at the common macro value $\sigma_c = 2$ yields the same qualitative patterns, with a less volatile opportunity cost and correspondingly less volatile active search.

TABLE 4. Calibration: assigned parameter values

Parameter	Value	Source / interpretation
β	0.9967	Monthly discount factor
σ_c	4.0	CRRA curvature
ρ	0.965	Job survival; 3.5% monthly separation
λ	11/12	Twelve-month average contract duration
γ_v	0.50	Vacancy-posting share of hiring costs (Sala et al., 2013)
α	1/3	Capital share
δ	0.0083	Monthly depreciation; 2.5% quarterly
ρ_z	0.9830	Monthly TFP persistence; 0.95 quarterly
σ_z	0.0075	St. dev. of monthly TFP innovation
η	0.50	Nash bargaining weight
b	0.16	Statutory 0.40 $\times$ take-up 0.40
ω	0.554	CES weight on active search (Table 3)
σ_m	1.0	Matching-function constant (normalization)
κ	38.4	Scale, hiring costs
ψ_0	0.013 $\times$ MPL	Scale, search costs
e^{μ_γ}	0.007 $\times$ MPL	Scale, participation costs

Note: Externally set parameters and parameters implied by the steady-state restrictions (the job-finding rate of active searchers, f_A/f_P, $\check{\mathcal{G}}(\gamma^*)$, ω) described in the text. ψ_0 and e^{μ_γ} are expressed in units of the marginal product of labor, ψ_0 as the implied search cost at the optimum.

the elasticity measuring the mass of workers near the participation threshold in steady state. Then, given g, the elasticity of the active search premium identifies ν: the model counterpart of the premium regression coefficient of Section 3 is $\beta_{ASP} = 1-(1+g)/\nu$.[19] The calibration recovers $\nu = 0.196$, close to the 0.201 estimated from the restricted regression of Section 4. The remaining two parameters each solve a single equation given the search block: ξ^l is set so that the flow value of non-employment matches its target, and σ to reproduce the measured matching elasticity.

6.2. **Aggregate labor-market moments.** Before turning to the implications of our findings for the comovement of the active search premium with search effort over the business cycle, we verify that the model provides a reasonable description of aggregate labor-market volatility. We compare the model to quarterly U.S. data. As the model is monthly, we take quarterly averages of the simulated monthly series; data and model

[19]Within the model the two search margins carry the same information, so ν could equivalently be identified from the elasticity of the active search premium with respect to the extensive margin, $\mathcal{G}(\gamma^*)$; the choice is immaterial.

Table 5. Calibration: jointly fitted parameters

Parameter	Value	Description
ε_s	0.557	Elasticity of intensive-margin search cost $\psi(s)$
σ_γ	1.552	Dispersion of participation-cost draws γ
ν	0.196	CES elasticity of substitution, active vs. passive search
σ	0.525	Matching-function elasticity (structural)
ξ^l	0.013	Leisure flow (utility units; ξ^l/μ_{ss} per MPL = 0.72)

Note: Parameters calibrated jointly to match the moments in Table 6.

Table 6. Calibration: targeted moments

Target	Data	Model	Source
Duration elasticity to UI	0.45	0.45	Micro UI literature
$\mathrm{sd}(\log \check{\mathcal{G}})/\mathrm{sd}(\log e_A^*)$	0.70	0.70	CPS (Section 2)
ASP elasticity β	−7.66	−7.65	Table 2, col. (1)
Measured matching elasticity	0.50	0.50	Estimated on model-simulated data
Opportunity cost / MPL	0.86	0.86	CRK (2016) leisure + UI

Note: Moments targeted by the joint calibration. Business-cycle moments are computed from quarterly averages of model-simulated monthly data, logged and HP-filtered with smoothing parameter 1600.

output are logged and detrended with an HP filter with the conventional smoothing parameter.

Table 7 compares business-cycle statistics from the model with the data. Overall, the model with staggered contracting does a reasonable job of accounting for the relative volatility of unemployment, with vacancies and market tightness somewhat more volatile than in the data, and wages somewhat smoother. As the flexible-wage rows show, the wage inertia induced by staggered contracting is critical for the volatility of unemployment: under period-by-period bargaining, unemployment volatility collapses to roughly one-eighth of its measured value, the familiar result of Hall (2005) and Shimer (2005). Notably, the model preserves these standard implications of wage rigidity while incorporating our additions—endogenous active search along the extensive and intensive margins, and a finite elasticity of substitution between active and passive search in matching—and while accommodating a procyclical opportunity cost of employment, which Chodorow-Reich and Karabarbounis (2016) show undermines labor-market volatility in leading models. Under staggered bargaining, the wage does not track the opportunity cost, so the surplus that drives firms' hiring remains volatile

Table 7. Aggregate business-cycle moments

	y	w	u	v	θ	c	i
	U.S. Data						
Relative St. Dev.	1.00	0.44	7.89	8.98	16.63	0.80	4.51
Autocorrelation	0.87	0.91	0.93	0.93	0.93	0.88	0.84
Correlation with y	1.00	0.35	−0.86	0.90	0.90	0.87	0.90
	Model, $\lambda = 11/12$ (4Q-Sticky)						
Relative St. Dev.	1.00	0.25	8.42	12.08	19.75	0.23	3.40
Autocorrelation	0.88	0.96	0.91	0.82	0.88	0.82	0.89
Correlation with y	1.00	0.41	−0.88	0.92	0.97	0.96	1.00
	Model, Flex wages						
Relative St. Dev.	1.00	0.92	0.92	1.25	2.12	0.29	3.30
Autocorrelation	0.80	0.80	0.94	0.89	0.93	0.81	0.80
Correlation with y	1.00	1.00	−0.73	0.66	0.71	0.98	1.00

Note: Quarterly averages of monthly series, logged and HP(1600)-filtered; standard deviations relative to output. Model: baseline (capital), under staggered and flexible wages. Data: output = real GDP (GDPC1); wage = average hourly earnings of production and nonsupervisory workers (AHETPI), deflated by core PCE; unemployment = UNRATE; vacancies = the composite help-wanted index of Barnichon (2010); consumption = real PCE (PCECC96); investment = real gross private domestic investment (GPDIC1). Aggregate series 1964–2019.

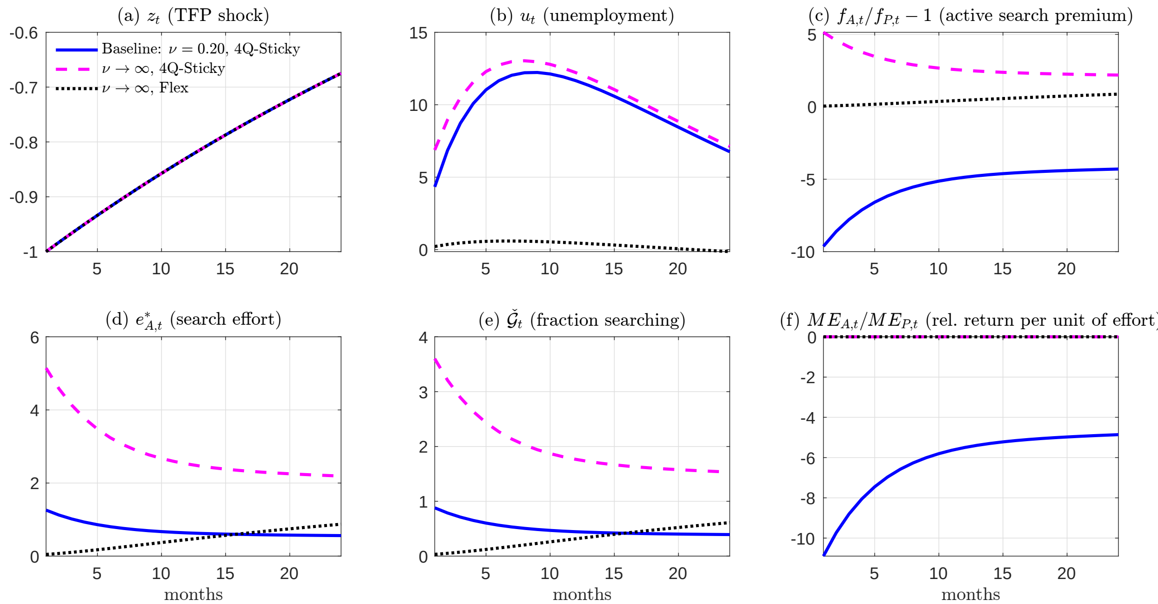
even as the opportunity cost moves procyclically. The procyclical opportunity cost, in turn, will be crucial for replicating the countercyclical intensive and extensive margins of search in the data.

6.3. **Search effort and the active search premium.** Next, we evaluate the model's ability to generate the observed cyclical co-movements of search effort and the active search premium.

Impulse responses.—Figure 6 presents impulse responses to a negative one percentage point TFP shock; panel (a) displays the shock itself. The remaining panels show unemployment, the active search premium $f_{A,t}/f_{P,t} - 1$, the active search effort of active searchers $e^*_{A,t}$, the fraction of non-employed engaged in active search $\check{\mathcal{G}}_t$, and the relative return per unit of effort $ME_{A,t}/ME_{P,t}$. We consider three cases: (*i*) our baseline, with an elasticity of substitution $\nu = 0.20$ and sticky wages; (*ii*) the same model, recalibrated to the perfect-substitutes case ($\beta_{ASP} = +1$, i.e., $\nu = \infty$), with sticky wages; and (*iii*) the perfect-substitutes case with flexible wages.

We take the three cases in turn, starting with the outcomes under the baseline model. Panel (b) shows a persistent rise in unemployment in response to the decline

FIGURE 6. Impulse responses to a −1pp TFP shock



Note: Responses to a negative one percentage point TFP innovation, in percent deviations from steady state. Solid: baseline (staggered wages, $\nu = 0.20$). Dashed: perfect substitutes ($\nu \to \infty$), staggered wages. Dotted: perfect substitutes, flexible wages.

in TFP. Panel (c) shows the active search premium falling alongside it: the model replicates the premium's procyclicality. And yet, as shown in panels (d) and (e), both margins of search rise while the labor market deteriorates and the active search premium falls: active search effort, and the fraction of the non-employed searching actively. The decline in the active search premium can thus be understood as the product of the endogenous increase in search effort and the premium elasticity calibrated to its empirical counterpart. Panel (f) shows the implied response of the relative return per unit of effort, $ME_{A,t}/ME_{P,t}$: as shown in equation (11) of Section 4 and equation (28) of Section 5, this object captures both the cyclical behavior of the active search premium and the crowding of that return by aggregate search effort.

The perfect-substitutes case shows how the crowding of the active channel restrains the search response itself. As in the baseline, unemployment rises in response to the fall in productivity. Calibrated to $\beta_{ASP} = +1$, however, the model shows a counterfactual increase in the active search premium, in panel (c), reflecting a constant—rather than declining—relative return per unit of effort, in panel (f). With the relative return no longer falling as aggregate search rises, search effort increases by more along both margins, shown in panels (d) and (e). Hence, under the baseline calibration, the decline in the relative return $ME_{A,t}/ME_{P,t}$ acts as a feedback mechanism that moderates the overall responsiveness of search effort to deteriorating labor market conditions.

The case with flexible wages and perfect substitutes shows that the unemployment volatility puzzle à la Shimer (2005) and Hall (2005) extends to search effort and the active search premium. Panel (b) shows only a minor increase in unemployment under flexible wages. Panels (d) and (e) show a similarly modest response of search effort. Given the constant relative return per unit of effort implied by perfect substitution, the mild response of search effort implies an equally mild response of the active search premium. Across the three cases, then, the ingredients divide the labor: wage rigidity supplies the amplitude of the responses—of unemployment and of search alike—while imperfect substitutability disciplines their composition, delivering the falling premium and the damped effort response of the baseline.

Comparison to U.S. data: search behavior.—Table 8 compares the responses of the search variables of Figure 6 with their measured counterparts. The first row reproduces the measurements of U.S. data from Section 2; the second row reports the same moments from the baseline model.

The baseline model generates the same comovement of active search and the active search premium as in the data: search effort increases even as the relative job-finding rate from active search falls. Both the intensive and extensive margins of search effort are countercyclical, with correlations roughly matching the data; whereas the relative job-finding rate, f_A/f_P, is procyclical, with a correlation higher than that of the data. However, the model fails to generate the full amplitude measured in the data: in particular, the volatility of the two margins of search effort is roughly one-quarter of that in the data. The relative job-finding rate falls short by more; as we document below, this failure is inherited from the lack of volatility in search effort itself.

The third row of Table 8 reports the same statistics for the perfect-substitutes recalibration shown as case (*ii*) of Figure 6 ($\beta_{ASP} = +1$, with the remaining calibration targets re-fit). The comovement of search effort is similar to that of the baseline, with far greater volatility: 2.17 against 2.23 in the data. As in the impulse responses, the relative return per unit of effort is constant, so it no longer dampens the recessionary increase in search effort. Although this calibration closes nearly all of the volatility gap, it does so by counterfactually reversing the cyclicality of the relative job-finding

Table 8. Search moments: data and model

	e_A^*		$\check{\mathcal{G}}$		f_A/f_P	
	s.d.	corr	s.d.	corr	s.d.	corr
U.S. Data	2.23	−0.85	1.56	−0.76	8.03	0.46
Baseline	0.52	−0.84	0.37	−0.84	1.21	0.84
No crowding ($\beta_{ASP} = 1$)	2.17	−0.84	1.52	−0.84	0.65	−0.84
Volatile μ_t ($\zeta = 3.93$)	2.23	−0.94	1.56	−0.94	5.15	0.94

Note: Standard deviations relative to output; correlations with output. Quarterly averages of monthly series, logged and HP(1600)-filtered. Data: CPS, 1996–2019. Model rows, all under staggered wages: the baseline; perfect substitutes ($\nu \to \infty$: $\beta_{ASP} = +1$ imposed in place of the premium-elasticity target, with the remaining targets re-fit), which removes the cyclical crowding of active search; and the volatile-μ experiment, in which ζ is chosen to match the volatility of e_A^* alone.

rate: with the premium inheriting the sign of search effort, its correlation with output is −0.84, against +0.46 in the data—the restriction rejected in Section 3.

In the fourth row, we explore whether the missing volatility of search effort can come from the relative value of a job (i.e., the worker surplus), rather than the return per unit of effort. The value of non-employment moves with the marginal utility of consumption: the flow value of leisure is priced by $1/\mu_t$ in the opportunity cost of employment (equation (44)), the channel of Chodorow-Reich and Karabarbounis (2016). We therefore allow the cyclical deviations of searching workers' marginal utility to exceed those of the representative household:

$$\hat{\mu}_t^s = \hat{\mu}_t - \zeta \hat{z}_t, \tag{57}$$

where hats denote log deviations from steady state, thus introducing a reduced form of limited consumption insurance within the household. The parameter ζ governs only the cyclicality of the wedge: in recessions, the marginal utility of searching workers rises by more than that of the household, raising the value of a job and hence search effort.[20] We set $\zeta = 3.93$ to match the volatility of search effort; the volatility of the relative job-finding rate—untargeted—then rises to 5.15, covering most of the remaining distance to the measured 8.03. Thus, the consumption of searching workers

[20]The wedge enters only the search decision and the worker's surplus; aggregate consumption and the household's Euler equation are unchanged. Its steady-state level is normalized to unity and is not separately identified: a constant difference in marginal utility between searching workers and the household would be absorbed into the calibration of steady-state search costs and leave the model's first-order dynamics unchanged.

must fall by roughly one percent for each percent decline in output, against 0.23 for aggregate consumption.[21]

Exposure of this size is in line with the evidence on the consumption of job losers. Displacement generates large and persistent earnings losses, which roughly double for job loss in recessions (Davis and von Wachter, 2011; Huckfeldt, 2022), and persistent income shocks transmit roughly two-thirds into consumption (Blundell, Pistaferri and Preston, 2008; Kaplan and Violante, 2010). Combined, these estimates imply a large and persistent consumption decline at job loss. Direct measurement finds exactly that: Gruber (1997) shows spending falling at job loss, and Stephens Jr. (2001) shows the spending of displaced workers remaining below its pre-displacement level after reemployment—a response to the persistent component of the earnings loss rather than to a temporary interruption of income. Given that the earnings losses from displacement are markedly larger in recessions, this transmission implies that the consumption exposure of job losers is concentrated precisely in downturns. In an economy in which this risk is imperfectly insured, the consumption of searching workers accordingly falls relative to that of the household during recessions; to a first order, and with a single aggregate shock, any such gap is proportional to $\hat{z}_t$, so that the wedge in equation (57) is its reduced form, with ζ measuring the combined strength of the earnings loss and its transmission into consumption. A model in which workers face imperfectly insured unemployment risk is a natural candidate for generating the full volatility of search effort (e.g., Krusell et al., 2017; Graves et al., 2024).

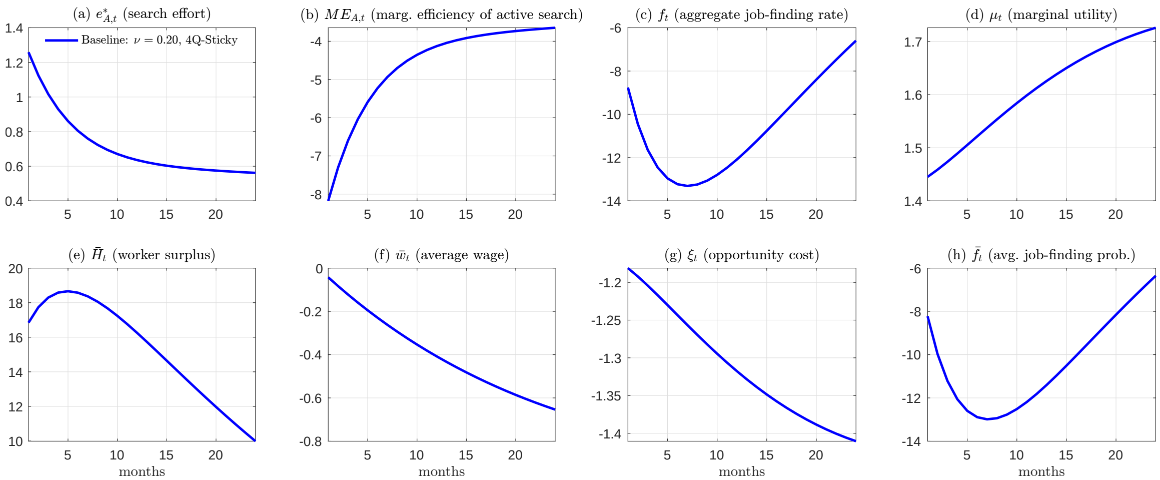
6.4. **Decomposing the response of search effort.** In the previous sections, we showed that search effort unambiguously increases in response to a negative productivity shock, but that the degree of crowding out—dictated by the elasticity of substitution between active and passive search—controls the amplitude of the response of search effort.

To understand how search can increase amid a decline in labor market conditions, consider the log-linearized optimality condition for search effort:

$$\hat{e}^{*}_{A,t} = \varepsilon_s \, \mathbb{E}_t\Big[\widehat{ME}_{A,t} + \hat{f}_t + \hat{\mu}_{t+1} + \widehat{\overline{H}}_{t+1}\Big] \,, \tag{58}$$

[21]Equivalently, the implied volatility of the searcher's stochastic discount factor is roughly 14 percent annualized, against the 40 to 50 percent demanded by the Hansen–Jagannathan bound from equity returns.

FIGURE 7. The mechanism: the search FOC and the surplus



Note: Responses to a negative one percentage point TFP innovation. Top row: search effort $e^*_{A,t}$ and the objects of the search first-order condition (58)—the marginal efficiency of active search $ME_{A,t}$, the job-finding probability f_t, and the marginal utility of consumption μ_t. Bottom row: the surplus $\bar{H}_t$ and the objects of (59)—the average wage $\bar{w}_t$, the opportunity cost ξ^o_t, and the job-finding rate from non-employment $\bar{f}_t$.

where ε_s represents the elasticity of search costs, and the job-finding rate per unit of search effort, $ME_{A,t}\, f_t$, is split into its two components: the marginal efficiency of active search and the aggregate job-finding probability.

Figure 7 plots the response of search effort together with the four terms of (58): the top row displays search effort, the marginal efficiency of active search, the job-finding probability, and the marginal utility of consumption; the surplus, the remaining term, leads the bottom row, followed by its components. The marginal efficiency of active search falls as aggregate active search rises (panel b). The job-finding rate similarly falls (panel c), as firms post fewer vacancies. Together, these objects put downward pressure on equilibrium search effort. However, they are more than offset by an increasing marginal utility of consumption (panel d) and an increase in the expected surplus from employment (panel e).

To understand why the worker's employment surplus increases, consider its log-linearized form:

$$\widehat{\bar{H}}_t = \omega_w\, \widehat{\bar{w}}_t \;-\; \underbrace{\left(\omega_l\, \widehat{(\xi^l/\mu_t)} \;-\; \omega_\psi\, \widehat{\Psi}_t\right)}_{=\,\omega_o\, \hat{\xi}^o_t} + \beta\, \mathbb{E}_t\Big[(\rho - \tilde{f})\, \widehat{\bar{H}}_{t+1} - \tilde{f}\, \widehat{\bar{f}}_t\Big], \qquad (59)$$

with

$$\omega_w = \tilde{w}/\tilde{H}, \quad \omega_l = (\xi^l/\tilde{\mu})/\tilde{H}, \quad \omega_\psi = \tilde{\Psi}/\tilde{H}, \quad \omega_o = \tilde{\xi}^o/\tilde{H}$$

where tildes denote steady-state values, and $\Psi_t \equiv [\mathcal{G}(\gamma_t^*)\,\psi(e_{A,t}^*) + \bar{\Gamma}_t]/\mu_t$ represents the expected search costs recouped upon employment.

The term in braces, $\omega_o \cdot \widehat{\xi}_t^o$, represents the cyclical component of the opportunity cost of employment. Following Chodorow-Reich and Karabarbounis (2016), the opportunity cost of employment largely comprises the flow value of leisure, expressed as consumption equivalents through normalization by the marginal utility of consumption, i.e., ξ^l/μ_t. During a downturn, when consumption falls, the marginal utility of consumption rises (panel d), and the household places less value on leisure. Thus, a falling opportunity cost (panel g) increases the household's flow surplus from employment. Meanwhile, the average wage falls only sluggishly (panel f), putting only minimal downward pressure on the flow surplus. Finally, the falling average job-finding rate from non-employment $\bar{f}_t$ increases the surplus by reducing the value of unemployment (panel h).

A cursory inspection of (58) reveals why the counterfactual $\beta_{ASP} = +1$ calibration of Figure 6 and Table 8 generates a greater responsiveness of search effort. Under the $\beta_{ASP} = +1$ calibration, $\widehat{ME}_{A,t} = 0$ for all t, thus suppressing an otherwise procyclical force that moderates the overall responsiveness of search effort.

6.5. **The micro and macro elasticity of search effort.** Thus far, we have seen that, during a recession, the crowding out of search effort reduces the marginal efficiency of active search (and the relative return per unit of effort), thereby compressing the active search premium. Next, we examine how these same forces mute the response of search effort to an aggregate transfer.

Rewrite the search optimality condition (58), isolating the source of crowding out—the marginal efficiency of active search—from the remaining forcing terms:

$$\frac{1}{\varepsilon_s}\,\hat{e}_{A,t}^* = \mathbb{E}_t\Big[\widehat{ME}_{A,t} + \hat{D}_t\Big], \qquad \hat{D}_t \equiv \hat{f}_t + \hat{\mu}_{t+1} + \hat{\bar{H}}_{t+1}. \tag{60}$$

where

$$\begin{aligned} \widehat{ME}_{A,t} &= -\frac{\tilde{\alpha}_P}{\nu}\left(\hat{\bar{\mathcal{G}}}_t + \hat{\bar{e}}_{A,t}^*\right) \\ &= -\frac{\tilde{\alpha}_P}{\nu}\,(1+g)\,\hat{\bar{e}}_{A,t}^*, \end{aligned} \tag{61}$$

the first equality follows from log-linearizing the marginal efficiency of active search, equation (9), and the second from the optimality equation linking the extensive and intensive margins of search effort (41). Here $\tilde{\alpha}_P$ is the CES share of passive search in the aggregator, evaluated at steady state—by Proposition 1, the share of hires arriving through the passive channel.

Active searchers are identical, so equilibrium requires $\hat{e}^*_{A,t} = \widehat{\bar{e}}^*_{A,t}$. Substituting into (60), the crowding term—which each searcher treats as independent of her own effort—moves one-for-one with it, damping the equilibrium response:

$$\widehat{\bar{e}}^*_{A,t} = \varepsilon_s^{\text{eff}}\, \mathbb{E}_t[\hat{D}_t], \qquad \varepsilon_s^{\text{eff}} = \frac{\varepsilon_s}{1 + \frac{\tilde{\alpha}_P}{\nu}\,(1+g)\,\varepsilon_s}. \tag{62}$$

Equation (62) suggests that, holding the terms entering $\hat{D}_t$ fixed, search effort is more responsive to an idiosyncratic transfer than to an aggregate transfer. We formalize this below:

Proposition 2 (The micro and macro elasticity of search effort)**.** *Consider a permanent marginal change in benefits, holding the wage, market tightness—and with it the job-finding rate f_t—and the marginal utility of consumption μ_t fixed.*[22] *Whether the change is idiosyncratic or aggregate, the surplus from employment falls by*

$$\frac{d \ln \bar{H}}{d \ln b} = -\,\sigma_b, \qquad \sigma_b \equiv \frac{b}{\tilde{\Delta}\,\tilde{H}} = \frac{b}{\tilde{w} - \tilde{\xi}^o}, \tag{63}$$

where $\tilde{\Delta} \equiv 1 - \beta(\rho - \tilde{f})$, and search effort responds by

$$\left.\frac{d \ln e^*_A}{d \ln b}\right|_{\textit{one worker}} = -\,\varepsilon_s\,\sigma_b, \tag{64}$$

$$\left.\frac{d \ln \bar{e}^*_A}{d \ln b}\right|_{\textit{all workers}} = -\,\varepsilon_s^{\text{eff}}\,\sigma_b. \tag{65}$$

The ratio of the macro to the micro response is $\varepsilon_s^{\text{eff}}/\varepsilon_s < 1$ for every $\nu < \infty$, with equality if and only if $\nu = \infty$.

Proof: See Appendix D.4.

Equation (64) follows directly from the envelope theorem: at the optimum, neither a worker's effort nor her participation cutoff has a first-order effect on her surplus, so only the direct effect of the benefit remains. To establish (65), we take into account the response of the marginal efficiency of active search to aggregate active search—the integral of all workers' choices—which contributes the crowding feedback $\frac{\tilde{\alpha}_P}{\nu}(1+g)$ and turns ε_s into $\varepsilon_s^{\text{eff}}$.

[22]Constant tightness corresponds to perfectly elastic vacancy creation: vacancies scale with effective search $\bar{s}_t$, leaving f_t and q_t unchanged while the composition of search—and with it $ME_{A,t}$—moves freely.

Corollary 2.1 (Sufficient statistics for the macro elasticity)**.** *By the active search premium identity $\beta_{ASP} = 1 - (1+g)/\nu$—the same identity that identified ν in the calibration—the macro elasticity takes a measured form:*

$$\varepsilon_s^{\text{eff}} = \frac{\varepsilon_s}{1 + \tilde{\alpha}_P \left(1 - \beta_{ASP}\right) \varepsilon_s}. \tag{66}$$

Conditional on ε_s, the premium slope β_{ASP} and the passive share $\tilde{\alpha}_P$ are sufficient statistics for $\varepsilon_s^{\text{eff}}$.

Corollary 2.2 (Bound on the macro elasticity)**.** *For $\beta_{ASP} < 1$,*

$$\varepsilon_s^{\text{eff}} \; < \; \min\left\{\varepsilon_s, \; \frac{1}{\tilde{\alpha}_P \left(1 - \beta_{ASP}\right)}\right\}. \tag{67}$$

At $\beta_{ASP} = 1$, $\varepsilon_s^{\text{eff}} = \varepsilon_s$.

Proofs: See Appendix D.4.

The proposition and corollaries place bounds on the aggregate response of search effort to a transfer, holding aggregate prices and market tightness fixed. Under the standard case from the literature—perfect substitutability of active and passive search, under which $\beta_{ASP} = +1$—the two elasticities coincide. Any estimate $\beta_{ASP} < 1$ implies $\varepsilon_s^{\text{eff}} < \varepsilon_s$, and the wedge grows as β_{ASP} falls. At our estimates, Corollary 2.2 bounds $\varepsilon_s^{\text{eff}}$ by $1/\Big(\tilde{\alpha}_P(1 - \beta_{ASP})\Big) = 1/(0.699 \times 8.655) = 0.165$, against a computed value of 0.12.

These results relate to a literature on the macro elasticity of unemployment with respect to a change in benefits. The macro elasticity is typically decomposed into two components: the micro-elasticity—matched in the calibration of our model—which describes the response of an individual worker's search effort, and thus unemployment duration, to a change in benefits holding all else fixed; and general equilibrium effects, such as the changes in wages and vacancy posting that arise from an aggregate change in benefits.[23] Implicit in this decomposition is the assumption that the micro elasticity remains the relevant object for describing a worker's search response to an aggregate change in benefits. Our results suggest otherwise: for sufficient crowding-out, the relevant elasticity, $\varepsilon_s^{\text{eff}}$, falls substantially below ε_s.

We next turn to a full general equilibrium analysis, accounting for both the effective elasticity of search and general equilibrium forces.

[23]See Landais et al. (2018b) for an example.

Table 9. Duration elasticity of a K-month UI expansion

K (months)	Baseline ($\beta_{ASP} = -7.7$) Full	ME_A, ME_P fixed	Difference	Counterfactual ($\beta_{ASP} = +1$) Full	Difference
3	0.022	0.048	−54%	0.053	−59%
6	0.053	0.104	−49%	0.117	−55%
9	0.088	0.146	−40%	0.164	−46%
12	0.116	0.175	−34%	0.196	−41%
24	0.160	0.214	−25%	0.237	−33%
permanent	0.117	0.154	−24%	0.158	−26%

Note: Elasticity of unemployment duration with respect to an anticipated increase in UI benefits lasting K months, perfect-foresight transition. Baseline: the calibrated model, solved with and without the marginal efficiencies $ME_{A,t}$, $ME_{P,t}$ held at their steady-state values. Counterfactual: a recalibrated perfect-substitutes economy ($\nu \to \infty$) matching the same steady-state and search-elasticity targets. Each Difference column reports the percent gap of the full baseline elasticity (first column) from the column preceding it.

6.6. **The macro effects of unemployment insurance.** To this point, we have studied the crowding out of active search without considering how it might interact with general equilibrium effects. Here, we consider both: we solve for the response of the economy to anticipated increases in UI generosity lasting K months, as perfect-foresight transitions in which all prices and quantities respond, and report the elasticity of expected non-employment duration with respect to the benefit increase, for a worker entering non-employment at the onset of the policy. We compare outcomes across two economies. The first is the baseline model, for which we also report a counterfactual in which the marginal efficiencies $ME_{A,t}$ and $ME_{P,t}$ do not respond to the policy, shutting off the crowding channel while all other prices and quantities adjust. The second is a perfect-substitutes economy with $\beta_{ASP} = +1$, recalibrated to the same steady-state and search-elasticity targets.

Table 9 reports the results. In the full baseline, the elasticity is 0.022 at three months, 0.116 at a year, and 0.117 for a permanent expansion. With ME_A and ME_P held fixed, the elasticity rises to 0.048 at three months and 0.175 at a year: the crowding channel dampens the response by 54 percent at three months and 34 percent at a year. The mechanism operates through the return to active search. More generous benefits reduce the surplus from employment, so both search intensity and participation fall; with $\nu < 1$, the decline in aggregate active search raises the return to each worker's active search, partially offsetting the effect of reduced effort on the job-finding rate of the active non-employed.

The perfect-substitutes economy delivers elasticities of 0.053 at three months and 0.196 at a year. At every temporary horizon, the recalibrated economy responds roughly ten percent more strongly than the fixed-ME benchmark, so the measured damping is larger against perfect substitutes—59 versus 54 percent at three months, 41 versus 34 percent at a year—with the two benchmarks nearly coinciding only for a permanent expansion (0.158 against 0.154). Crowding dampens the response substantially under either benchmark.

7. Conclusion

This paper documents that the active search premium is small, procyclical, and declining in the aggregate quantity of active search. This pattern is inconsistent with the standard assumption that active and passive search enter the matching function as perfect substitutes; we estimate an elasticity of substitution of roughly one fifth, implying a substantial crowding-out of active search. The estimates imply that the disincentive effects of UI on job-finding are weakest precisely when unemployment is high.

The quantitative model embeds the estimated search technology in general equilibrium. Search effort rises in recessions, as an increasing marginal utility of consumption raises the value of employment, and the resulting increase in active search reduces its return, as in the data. Because an aggregate increase in search effort lowers the return to active search whereas an idiosyncratic increase does not, the macro elasticity of search effort with respect to UI benefits falls below the micro elasticity, and crowding-out dampens the response of unemployment duration to a temporary benefit expansion by roughly 40 to 60 percent—and to a permanent expansion by roughly one-quarter—relative to perfect substitutes.

Four extensions strike us as natural: on-the-job search, where the same crowding-out would operate on the employed margin; multiple applications, as a microfoundation for the declining return to active search; a richer specification of passive search, beyond the single inelastic unit assumed here; and a heterogeneous-agent model with imperfect consumption insurance among searchers, consistent with the evidence on the consumption of job losers discussed in Section 6. We leave these for future work.

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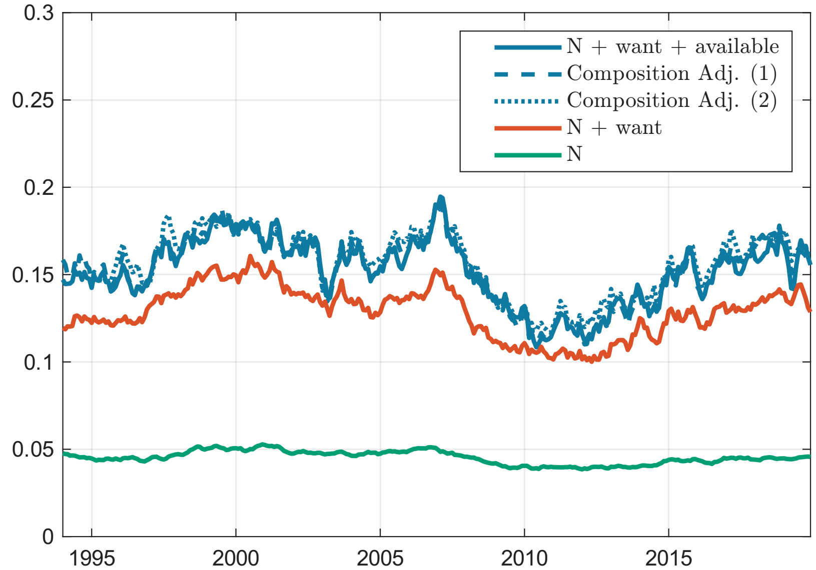
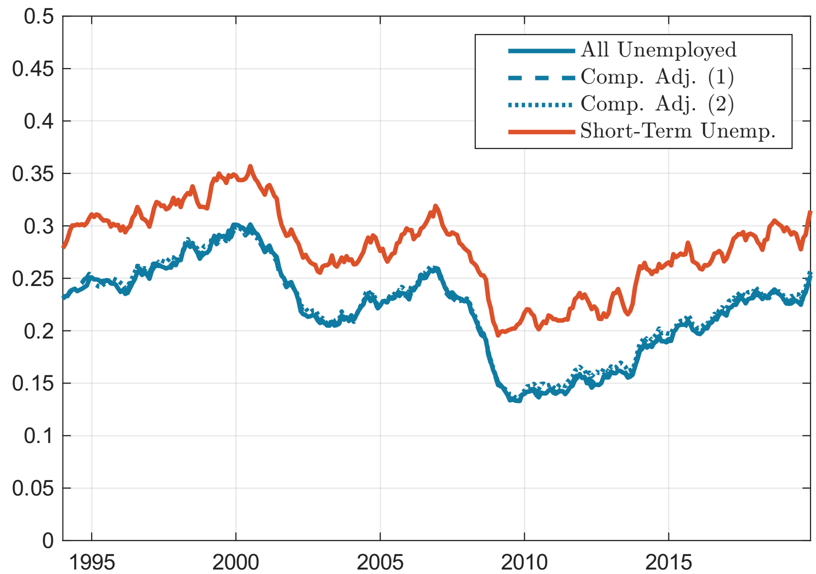
Appendix A. Additional Figures

Figure A.1. Job-finding probabilities of alternative passive search groups



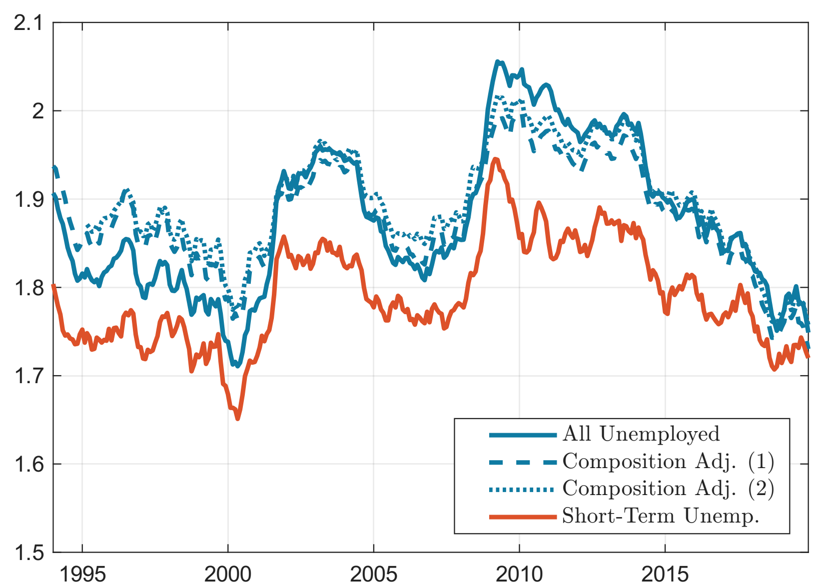
Note: The figure plots the job-finding probabilities for different groups of passive searchers. The dashed and dotted series report the baseline definition of passive search using 72 or 360 groups for composition adjustment, respectively. Plotted series are smoothed using a centered five-month moving average. CPS, 1996–2019.

FIGURE A.2. Job-finding probabilities of alternative active search groups



Note: The figure plots the job-finding probabilities for different groups of active searchers. The dashed and dotted series use all active searchers and 72 or 360 groups for composition adjustment, respectively. Plotted series are smoothed using a centered five-month moving average. CPS, 1996–2019.

FIGURE A.3. Number of search methods for alternative active search groups



Note: The figure plots the number of active job search methods used by different groups of active searchers. The dashed and dotted series use all active searchers and 72 or 360 groups for composition adjustment, respectively. Plotted series are smoothed using a centered five-month moving average. CPS, 1996–2019.

Appendix B. Characteristics of Active and Passive Searchers

Table B.1. Demographics by Labor Market Group

	Non-participants (N)	N + Want job	N + Want + Available	Active searchers
Mean Age	53.1	38.3	42.4	34.7
Share Male	0.39	0.45	0.53	0.54
Share Married	0.49	0.35	0.37	0.32
Share LHS	0.28	0.30	0.25	0.24
Share HS	0.32	0.30	0.34	0.34
Share Some Coll.	0.23	0.24	0.23	0.26
Share College+	0.17	0.15	0.19	0.16
Share White	0.80	0.71	0.71	0.70
Share Black	0.13	0.21	0.21	0.22
Observations	11,489,206	641,578	304,887	1,001,977

Table C.1. Estimates of the CES Search Aggregator: Baseline Passive Group

	(1)	(2)	(3)
$\beta_{\breve{\mathcal{G}}}$	-5.244^{***}	-4.976^{***}	-8.721^{***}
	(1.3945)	(0.5546)	(1.0965)
β_e	-3.738^{***}	-3.976^{***}	—
	(1.3378)	(0.5546)	
β_0	-0.002	0.217	-3.255^{***}
	(1.1190)	(0.1945)	(0.3005)
β_T	$-2.5\text{e-}3^{***}$	$-2.4\text{e-}3^{***}$	$-3.2\text{e-}3^{***}$
	(4.6e-4)	(3.6e-4)	(3.5e-4)
Passive searchers:		N + want job + available	
Constrain $\beta_e = \beta_{\breve{\mathcal{G}}} + 1$?	No	Yes	—
F-test	$p(\beta_e = \beta_{\breve{\mathcal{G}}} + 1)$	$p(\nu = \infty)$	$p(\nu = \infty)$
	$= 0.840$	$= 0.000$	$= 0.000$
Observations	287	287	287
Implied ν	—	0.201	0.115
Implied ω (sample mean)		0.554	0.037

Note: OLS estimates of equation (14), with passive searchers defined as nonparticipants who report wanting a job and being available to work. Column (1): unrestricted; column (2): imposes the CES restriction $\beta_e = \beta_{\breve{\mathcal{G}}} + 1$; column (3): no operative intensive margin ($\beta_e = 0$). The implied ω in column (3) is not comparable to the restricted estimate: absent a search-effort measure, it absorbs the average level of $\bar{e}_A^*$. All regressions include a constant and a linear time trend (centered at the sample mean); robust standard errors in parentheses. CPS, 1995m9–2019m12.

Appendix C. Robustness of the Rejection of Perfect Substitutes

This appendix provides a range of robustness checks for the rejection of the perfect substitutes restriction reported in Section 3 of the main text.

C.1. **CES estimation detail.**

Tables C.1 and C.2 report the full three-specification CES estimates summarized in Table 3 of the main text: unrestricted, restricted ($\beta_e = \beta_{\breve{\mathcal{G}}} + 1$), and extensive-margin only ($\beta_e = 0$), for the baseline passive group and for the broader group of nonparticipants who report wanting a job.

C.2. **GMM estimation of the elasticity of substitution.**

The restricted regression of Table 3 is one member of a family of estimators. Imposing the CES restriction

Table C.2. Estimates of the CES Search Aggregator: Nonparticipants Wanting a Job

	(1)	(2)	(3)
$\beta_{\check{\mathcal{G}}}$	-2.531^{***}	-2.552^{***}	-3.297^{***}
	(0.3887)	(0.1546)	(0.2363)
β_e	-1.590^{***}	-1.552^{***}	—
	(0.6051)	(0.1546)	
β_0	-0.697	-0.732^{***}	-2.075^{***}
	(0.5468)	(0.0213)	(0.1229)
β_T	$-1.4\text{e-}3^{***}$	$-1.5\text{e-}3^{***}$	$-1.6\text{e-}3^{***}$
	(1.7e-4)	(1.6e-4)	(1.6e-4)
Passive searchers:		N + want job	
Constrain $\beta_e = \beta_{\check{\mathcal{G}}} + 1$?	No	Yes	—
F-test	$p(\beta_e = \beta_{\check{\mathcal{G}}} + 1)$	$p(\nu = \infty)$	$p(\nu = \infty)$
	$= 0.950$	$= 0.000$	$= 0.000$
Observations	292	292	292
Implied ν	—	0.392	0.303
Implied ω (sample mean)		0.325	0.112

Note: OLS estimates of equation (14), with passive searchers defined as nonparticipants who report wanting a job. Column (1): unrestricted; column (2): imposes the CES restriction $\beta_e = \beta_{\check{\mathcal{G}}} + 1$; column (3): no operative intensive margin ($\beta_e = 0$). The implied ω in column (3) is not comparable to the restricted estimate: absent a search-effort measure, it absorbs the average level of $\bar{e}^*_A$. All regressions include a constant and a linear time trend (centered at the sample mean); robust standard errors in parentheses. CPS, 1995m9–2019m12.

$\beta_e = \beta_{\check{\mathcal{G}}} + 1$ and rearranging (14) gives

$$\log\left(\frac{f_{A,t}}{f_{P,t}} - 1\right) - \log \bar{e}^*_{A,t} = c + \beta_T\, t - \frac{1}{\nu}\left(\log \check{\mathcal{G}}_t + \log \bar{e}^*_{A,t}\right) + u_t, \tag{C.1}$$

a single equation in the log of aggregate active search per non-employed individual. Instrumenting the composite with either margin alone gives a just-identified estimator—robust to classical measurement error in the other margin, since the number of search methods and the fraction searching actively are separately measured; using both leaves one over-identifying restriction. Table C.3 reports the four members: instrumenting with either margin alone, restricted OLS, and two-step efficient GMM. Every member of the family lands within 0.01 of $\nu = 0.20$; none approaches $\nu = \infty$; and the Hansen J-statistic does not reject the over-identifying restriction

Table C.3. GMM and IV Estimates of the Elasticity of Substitution

Estimator	$\hat{\nu}$	s.e.
IV, instrument $\ln \bar{e}$	0.202	(0.023)
IV, instrument $\ln \check{\mathcal{G}}$	0.200	(0.022)
Restricted OLS	0.201	(0.022)
Two-step GMM, both instruments	0.201	(0.022)
Hansen J (1 d.o.f.)	0.04	[$p = 0.84$]
Observations	287	

Note: Estimates of equation (C.1). All regressions include a constant and a linear time trend (centered at the sample mean). The restricted OLS row coincides with the restricted estimate for the baseline passive group in Panel B of Table 3. Robust standard errors in parentheses. CPS, 1995m9–2019m12.

($p = 0.84$), matching the F-test of Table 3. In particular, restricted OLS is not attenuated relative to either just-identified estimator, so classical measurement error in the survey-based margins appears to have little effect on the estimated elasticity. The restricted estimate pools the two margins' information about $1/\nu$: its slope lies between the two single-margin estimates implied by the unrestricted coefficients of Table 3 ($-1/\beta_{\check{\mathcal{G}}} = 0.191$ and $1/(1-\beta_e) = 0.211$).

C.3. **Summary statistics by definition of passive search.** Table C.4 reports the summary statistics of Table 1 under each definition of the passive non-employed used in the regressions: the baseline, nonparticipants who report wanting a job, and all nonparticipants.

C.4. **Time aggregation bias.** First, we address the issue of time-aggregation bias as monthly transition probabilities computed from the CPS will miss transitions that occur at higher frequencies. For example, an individual who is laid off but finds a job quickly will be recorded as employed in consecutive surveys and thus the E-to-U and U-to-E transitions are missed. To account for this, we construct continuous-time flow hazard rates following the equivalent procedures of Shimer (2012) and Elsby et al. (2015).

Table C.5 reports estimates of equation (7) using monthly transition probabilities constructed using these continuous-time hazard rates. The results are essentially unchanged: the estimated elasticity remains large, negative, and precisely estimated across all definitions of the passive non-employed, and we continue to strongly reject the restriction implied under perfect substitutes.

C.5. **Restricting passive searchers to those who were nonparticipants at $t-1$.** A potential concern is that some workers classified as passive non-employed at time t may have recently transitioned from unemployment. In this case, such workers may re-enter employment due to their active job search in prior months, rather than due to their passive job search in month t.

Table C.4. Summary Statistics by Definition of Passive Search

	mean(x)	std(x)/std(Y)	corr(x, Y)	corr(x, x_{-1})
	A. Baseline: passive = N + want job + available			
f_A	0.218	8.22	0.85	0.82
f_P	0.153	7.66	0.42	0.22
f_A/f_P	1.430	8.03	0.46	0.17
u (active, % of pop.)	5.01	10.88	−0.89	0.94
ne (passive, % of pop.)	1.41	5.51	−0.71	0.73
Fraction active	0.774	1.56	−0.76	0.77
	B. Passive = N + want job			
f_A	0.218	8.22	0.85	0.82
f_P	0.129	5.36	0.53	0.32
f_A/f_P	1.674	6.69	0.62	0.40
u (active, % of pop.)	4.93	10.86	−0.89	0.94
ne (passive, % of pop.)	2.94	3.80	−0.64	0.75
Fraction active	0.616	3.08	−0.83	0.89
	C. Passive = all nonparticipants (N)			
f_A	0.218	8.22	0.85	0.82
f_P	0.045	3.27	0.60	0.57
f_A/f_P	4.777	6.62	0.76	0.64
u (active, % of pop.)	3.31	10.82	−0.89	0.94
ne (passive, % of pop.)	34.84	0.47	−0.41	0.90
Fraction active	0.086	9.56	−0.90	0.94
	Common across definitions			
Avg. # of search methods	1.88	2.23	−0.85	0.79

Note: As in Table 1, under each definition of the passive non-employed. Quarterly averages of monthly series, logged and HP(1600)-filtered; volatilities relative to GDP. The job-finding rate of active searchers does not depend on the definition of passive search and is reported under *Common across definitions.* Unemployment and non-employment rates are expressed as a percent of the population base implied by each definition. CPS, 1996–2019.

To address this, we restrict the sample of passive searchers to those who were also classified as nonparticipants at $t-1$. This restriction excludes workers who may have

TABLE C.5. Elasticity of the Active Search Premium: Time-Aggregation Adjusted Rates

Dependent variable: Log active search premium			
	(1)	(2)	(3)
Log # of search methods	-7.705^{***}	-6.857^{***}	-3.633^{***}
	(0.9735)	(0.6883)	(0.1497)
β_T	$-2.2\text{e-}3^{***}$	$-1.4\text{e-}3^{***}$	$-5.0\text{e-}4^{***}$
	(4.2e-4)	(2.2e-4)	(7.5e-5)
Constant	3.677^{***}	3.752^{***}	3.708^{***}
	(0.5940)	(0.4195)	(0.0931)
$Pr(H_0 : \beta_{ASP} = 1)$	0.000	0.000	0.000
Observations	276	292	292
Passive searchers:	N + want job + available	N + want job	All nonparticipants (N)

Note: OLS estimates of equation (7) using transition probabilities adjusted for time-aggregation bias following Shimer (2012) and Elsby et al. (2015). Each column varies the definition of passive searchers—the non-employed treated as searching passively in constructing both the active search premium and the fraction actively searching. Column (1): nonparticipants who report wanting a job and being available to work; column (2): nonparticipants who report wanting a job; column (3): all nonparticipants. N denotes nonparticipation (not in the labor force). All regressions include a constant and a linear time trend (centered at the sample mean); robust standard errors in parentheses. CPS, 1995m9–2019m12.

recently transitioned out of active search, ensuring that the passive non-employed in our sample are more plausibly engaged in purely passive search.

Table C.6 reports estimates of equation (7) using this restricted sample. The estimated elasticity remains large, negative, and precisely estimated, and we continue to reject the perfect substitutes restriction. This suggests that our results are not driven by recent transitions from active to passive non-employment contaminating the job-finding probabilities of the passive non-employed.

C.6. **Cyclical composition.** One possible explanation for the findings in Table 2 is that recessions are times when the pool of active searchers shifts toward individuals with lower job-finding rates, all else equal (or the converse happens among passive searchers). To address this possibility, we employ a shift-share approach following Elsby et al. (2015). For a set of observable characteristics defining subgroups indexed by j, we compute job-finding probabilities and active search effort within each subgroup, and then construct re-weighted aggregates using time-invariant population weights. Specifically, the re-weighted job-finding probability for the active

Table C.6. Elasticity of the Active Search Premium: Passive Searchers Nonparticipant at $t-1$

	Dependent variable: Log active search premium		
	(1)	(2)	(3)
Log # of search methods	-5.518^{***}	-4.566^{***}	-2.731^{***}
	(0.9337)	(0.5037)	(0.1700)
β_T	-4.0e-4	2.3e-4	-1.0e-4
	(4.1e-4)	(3.1e-4)	(1.7e-4)
Constant	3.380^{***}	2.976^{***}	3.676^{***}
	(0.5783)	(0.3135)	(0.1086)
$Pr(H_0 : \beta_{ASP} = 1)$	0.000	0.000	0.000
Observations	291	292	292
Passive searchers:	N + want job + available	N + want job	All nonparticipants (N)

Note: OLS estimates of equation (7), restricting the sample of passive non-employed to workers who were also nonparticipants at $t-1$. Each column varies the definition of passive searchers—the non-employed treated as searching passively in constructing both the active search premium and the fraction actively searching. Column (1): nonparticipants who report wanting a job and being available to work; column (2): nonparticipants who report wanting a job; column (3): all nonparticipants. N denotes nonparticipation (not in the labor force). All regressions include a constant and a linear time trend (centered at the sample mean); robust standard errors in parentheses. CPS, 1995m9–2019m12.

non-employed is

$$\tilde{f}_{A,t} = \sum_j \bar{\pi}_{A,j} \cdot f_{A,j,t}, \tag{C.2}$$

where $\bar{\pi}_{A,j}$ is the average fraction of workers of type j in the population of active searchers over time, and $f_{A,j,t}$ is the job-finding probability for the active non-employed of subgroup j at time t. We similarly construct re-weighted measures of passive job-finding probabilities and average active search effort.

We then re-estimate equation (7) using the re-weighted series. To the extent that our benchmark estimates are driven by the cyclical recomposition of the active and passive non-employed across observable groups, the shift-share correction should attenuate the estimated elasticity toward the values predicted under perfect substitutes.

We consider two levels of disaggregation. In the first, we define 72 subgroups based on reason for unemployment (if unemployed), education level, age group, and gender. In the second, we expand to 360 subgroups by additionally conditioning on labor market status one year prior (employed, temporary layoff, unemployed, passive searcher, or other nonparticipant). The job-finding rates and average active search effort calculated holding composition constant are shown in Figures A.1, A.2 and A.3.

TABLE C.7. Elasticity of the Active Search Premium: Shift-Share with 72 Subgroups

Dependent variable: Log active search premium			
	(1)	(2)	(3)
Log # of search methods	-7.159^{***}	-5.497^{***}	-3.403^{***}
	(0.9356)	(0.4747)	(0.1779)
β_T	$-2.8\text{e-}3^{***}$	$-1.6\text{e-}3^{***}$	$-6.2\text{e-}4^{***}$
	(3.9e-4)	(2.0e-4)	(7.6e-5)
Constant	3.514^{***}	3.030^{***}	3.437^{***}
	(0.5904)	(0.2998)	(0.1124)
$Pr(H_0 : \beta_{ASP} = 1)$	0.000	0.000	0.000
Observations	289	292	292
Passive searchers:	N + want job + available	N + want job	All nonparticipants (N)

Note: OLS estimates of equation (7) using shift-share re-weighted job-finding probabilities and active search effort. Population weights of 72 subgroups held constant, where subgroups are defined by reason for unemployment (if unemployed), education level, age group, and gender. Each column varies the definition of passive searchers—the non-employed treated as searching passively in constructing both the active search premium and the fraction actively searching. Column (1): nonparticipants who report wanting a job and being available to work; column (2): nonparticipants who report wanting a job; column (3): all nonparticipants. N denotes nonparticipation (not in the labor force). All regressions include a constant and a linear time trend (centered at the sample mean); robust standard errors in parentheses. CPS, 1995m9–2019m12.

Tables C.7 and C.8 report results of estimating equation (7) using these adjusted series. Under both levels of disaggregation, the estimated elasticity remains large, negative, and precisely estimated. In every case, we can easily reject the null hypothesis that the elasticity equals one.

These findings are consistent with Mueller (2017), who studies the cyclicality of separation and job-finding rates across groups defined by various observable characteristics, finding that the cyclicality of job-finding rates is essentially uniform across groups—including groups sorted by residual wages, which would capture a role for unobserved heterogeneity.

C.7. **Duration dependence among active searchers.** It is well established that exit rates from unemployment decline with the duration of non-employment (e.g., Kroft, Lange and Notowidigdo, 2013). If the source of such duration dependence is a declining return to active search over a non-employment spell, this could confound our estimates. A lower return to active search during recessions could simply reflect the fact that these are periods with higher average unemployment durations.

We attempt to control for this by restricting the sample of active searchers to those reporting an unemployment duration of 8 weeks or less. Note, this adjusts both our job-finding rate for active searchers as well as the number of search methods used by active searchers. The time series are shown in Figures A.2 and A.3: the short-term

TABLE C.8. Elasticity of the Active Search Premium: Shift-Share with 360 Subgroups

Dependent variable: Log active search premium			
	(1)	(2)	(3)
Log # of search methods	-8.119^{***}	-5.220^{***}	-3.310^{***}
	(1.2162)	(0.4684)	(0.1743)
β_T	$-2.8\text{e-}3^{***}$	$-1.6\text{e-}3^{***}$	$-7.0\text{e-}4^{***}$
	(5.1e-4)	(2.0e-4)	(7.4e-5)
Constant	4.136^{***}	2.913^{***}	3.414^{***}
	(0.7782)	(0.3001)	(0.1116)
$Pr(H_0 : \beta_{ASP} = 1)$	0.000	0.000	0.000
Observations	288	292	292
Passive searchers:	N + want job + available	N + want job	All nonparticipants (N)

Note: OLS estimates of equation (7) using shift-share re-weighted job-finding probabilities and active search effort. Population weights of 360 subgroups held constant, where subgroups are defined by reason for unemployment (if unemployed), education level, age group, gender, and labor market status one year prior (employed, temporary layoff, unemployed, passive searcher, other nonparticipant). Each column varies the definition of passive searchers—the non-employed treated as searching passively in constructing both the active search premium and the fraction actively searching. Column (1): nonparticipants who report wanting a job and being available to work; column (2): nonparticipants who report wanting a job; column (3): all nonparticipants. N denotes nonparticipation (not in the labor force). All regressions include a constant and a linear time trend (centered at the sample mean); robust standard errors in parentheses. CPS, 1995m9–2019m12.

unemployed have higher job-finding rates and use slightly fewer search methods than the full set of active searchers, but the cyclicality of these series is little changed by focusing on the narrower group.

It is important to note that this is an imperfect correction, as it only adjusts the job-finding rate and search effort for active searchers. Ideally, we would also control for the non-employment duration of passive searchers. However, this data is not collected in the CPS survey. To the extent that long-duration non-employed individuals who are not actively searching have lower job-finding probabilities, failing to adjust the denominator of the active search premium would dampen its cyclicality, biasing the estimated elasticity *upward*. Thus, the partial correction that we consider here provides an upper bound on the elasticity of the active search premium to the search effort of active searchers.

With this caveat in mind, Table C.9 reports results. While the point estimates of the elasticity are smaller in magnitude than in the benchmark specification, they remain negative, precisely estimated, and far from the values predicted under perfect substitutes. In all cases, we can reject the null hypotheses that the elasticity

Table C.9. Elasticity of the Active Search Premium: Short-Term Unemployed Only

Dependent variable: Log active search premium			
	(1)	(2)	(3)
Log # of search methods	-1.588^{***}	-1.527^{***}	-1.847^{***}
	(0.4117)	(0.2559)	(0.1288)
β_T	$-4.1\text{e-}4^{*}$	$-2.5\text{e-}4^{*}$	$-5.5\text{e-}5$
	(2.3e-4)	(1.4e-4)	(7.2e-5)
Constant	0.774^{***}	1.080^{***}	2.789^{***}
	(0.2603)	(0.1618)	(0.0814)
$Pr(H_0 : \beta_{ASP} = 1)$	0.000	0.000	0.000
Observations	292	292	292
Passive searchers:	N + want job + available	N + want job	All nonparticipants (N)

Note: OLS estimates of equation (7), restricting the sample of active non-employed to those reporting an unemployment duration of 8 weeks or less. This provides an imperfect control for duration dependence, as non-employment duration for passive searchers is not observed in the CPS. The resulting estimates are biased upward (toward zero); see text for discussion. Each column varies the definition of passive searchers—the non-employed treated as searching passively in constructing both the active search premium and the fraction actively searching. Column (1): nonparticipants who report wanting a job and being available to work; column (2): nonparticipants who report wanting a job; column (3): all nonparticipants. N denotes nonparticipation (not in the labor force). All regressions include a constant and a linear time trend (centered at the sample mean); robust standard errors in parentheses. CPS, 1995m9–2019m12.

equals one. We conclude that duration dependence alone cannot explain the negative elasticities estimated in Table 2.

Appendix D. Model Appendix

D.1. **Worker value functions: additional equations.** Let $\bar{V}_{E,t+1}$ denote the expected value of being a new hire. New hires are allocated across firms in proportion to hires $x_t(w)\,\ell_t(w)$. Accordingly,

$$\bar{V}_{E,t+1} = \int_w V_{E,t+1}(w_{t+1})\,\frac{x_t(w)}{\bar{x}_t}\,d\mathcal{W}_t(w), \tag{D.3}$$

where $\mathcal{W}_t$ denotes the employment-weighted distribution of wages across firms, $\bar{x}_t$ denotes the average hiring rate, and the wage w_{t+1} at each firm evolves according to (53).[24] The expected surplus of a new hire follows as $\bar{H}_{t+1} \equiv \bar{V}_{E,t+1} - V_{NE,t+1}$.

[24]Following Gertler and Trigari (2009), to a first order $\bar{V}_{E,t+1}$ equals the average value of employment across existing workers, $\int_w V_{E,t+1}(w_{t+1})\,d\mathcal{W}_t(w)$.

D.2. **Wages.** Given that firms and workers have an approximately similar horizon,[25] the following first-order necessary condition pins down the contract wage w_t^*:

$$\eta\, J_t(w_t^*) = (1-\eta)\, H_t(w_t^*). \tag{D.4}$$

Given that all renegotiating firms set the same contract wage w_t^*, we can express the evolution of the average wage across firms, $\bar{w}_t$, as

$$\bar{w}_{t+1} = (1-\lambda)\, w_{t+1}^* + \lambda \int_w w\, \frac{\rho + x_t(w)}{\rho + \bar{x}_t}\, d\mathcal{W}_t(w). \tag{D.5}$$

The second term on the right is the employment-weighted average wage across firms that do not renegotiate in the current period; it captures the inertia in wage adjustment.

D.3. **Households: consumption and saving.** There is a measure one of families, each comprised of a measure one of workers. Each family pools the wage and benefit income of its members, owns diversified stakes in firms that pay out profits Π_t, and receives lump-sum transfers T_t from the government. The family assigns consumption c_t to its members and saves in the form of capital k_t, which is rented to firms at rate r_t and depreciates at rate δ.

Utility from consumption is common across members. Non-working time yields the utility flow ξ^l; non-employed members with search cost draws $\gamma \le \gamma_t^*$ additionally incur the utility costs $\gamma + \psi(e_{A,t})$ of active search. The family's problem is

$$\Omega_t = \max_{c_t,\, k_{t+1}} \left\{ u(c_t) + \left(\xi^l - \mathcal{G}(\gamma_t^*)\, \psi(e_{A,t}^*) - \bar{\Gamma}_t\right) ne_t + \beta\, \mathbb{E}_t\, \Omega_{t+1} \right\} \tag{D.6}$$

subject to the budget constraint

$$c_t + k_{t+1} - (1-\delta)\, k_t = \bar{w}_t\, \bar{\ell}_t + b\, ne_t + r_t\, k_t + T_t + \Pi_t, \tag{D.7}$$

the law of motion for non-employment (31), and the optimal search policies $e_{A,t}^*$ and γ_t^* of its non-employed members.

The first-order conditions for consumption and saving give $\mu_t = u'(c_t)$ and the Euler equation (55), where $\Lambda_{t,t+1} \equiv \mu_{t+1}/\mu_t$.

The worker value functions of Section 5.2 follow from the family's problem: $V_{E,t}(w)$ and $V_{NE,t}$ correspond to the marginal values to the family of a member employed at wage w and of a non-employed member, expressed in units of market consumption through division by the marginal utility of market consumption μ_t. The normalization by μ_t of the leisure flow ξ^l and of the search costs $\psi(e_{A,t})$ and γ in the value functions of the non-employed reflects precisely this conversion of utility flows into units of market consumption; and the family's stochastic discount factor $\beta\, \Lambda_{t,t+1}$ prices future flows for workers and firms alike. Formally, $V_{E,t}(w) = \mu_t^{-1}\, \partial\Omega_t/\partial\ell_t(w)$ and $V_{NE,t} = \mu_t^{-1}\, \partial\Omega_t/\partial ne_t$, so that the surplus (43) is the marginal value to the family of moving a member from non-employment to employment at wage w—the analog, with wage heterogeneity, of the marginal value of employment derived by Chodorow-Reich and

[25]See Gertler and Trigari (2009) for a discussion of the "horizon" effect in the context of staggered Nash bargaining and of its quantitative irrelevance.

Karabarbounis (2016) from the household problem (their equation (10)). Gertler and Trigari (2009) define worker values in consumption equivalents directly within the same family construct; see also Gertler, Huckfeldt and Trigari (2020); Gertler et al. (2026).

D.4. **The micro and macro elasticity of search effort to a transfer.** This appendix proves Proposition 2 and its corollaries, which compare the response of search effort to a change in benefits across two experiments: a change in one worker's benefits, and a change in everyone's. As we show below, a transfer affects search effort through the return $ME_{A,t}\, f_t\, \bar{H}_{t+1}$. The response of the surplus does not drive the difference between the two elasticities—it is identical in both experiments—but rather the response of the marginal efficiency of active search.

Both experiments are comparative statics on a small permanent change in b, holding the wage, market tightness and the marginal utility μ_t fixed. Tildes denote steady-state values. Write $\tilde{F} \equiv \tilde{w} - \tilde{\xi}^o$ for the flow surplus, so that $\tilde{H} = \tilde{F}/\tilde{\Delta}$ with $\tilde{\Delta} \equiv 1 - \beta(\rho - \tilde{f})$, and $\sigma_b \equiv b/\tilde{F}$.

Lemma D.1 (Composition and the marginal efficiencies)**.** *For any small change in the aggregate inputs* $(\bar{s}_{A,t}, \bar{s}_{P,t})$*:*

(i)

$$d\ln ME_{A,t} = -\frac{\alpha_{P,t}}{\nu}\Big(d\ln \bar{s}_{A,t} - d\ln \bar{s}_{P,t}\Big) \quad \textit{and} \quad d\ln ME_{P,t} = +\frac{\alpha_{A,t}}{\nu}\Big(d\ln \bar{s}_{A,t} - d\ln \bar{s}_{P,t}\Big);$$

(ii) $\alpha_{A,t}\, d\ln ME_{A,t} + \alpha_{P,t}\, d\ln ME_{P,t} = 0.$

Proof. From (9), $\ln ME_{A,t} = \ln \omega + \frac{1}{\nu}(\ln \bar{s}_t - \ln \bar{s}_{A,t})$, and Euler's theorem for the linearly homogeneous aggregator gives $d\ln \bar{s}_t = \alpha_{A,t}\, d\ln \bar{s}_{A,t} + \alpha_{P,t}\, d\ln \bar{s}_{P,t}$; hence $\partial \ln ME_{A,t}/\partial \ln \bar{s}_{A,t} = (\alpha_{A,t} - 1)/\nu = -\alpha_{P,t}/\nu$ and $\partial \ln ME_{A,t}/\partial \ln \bar{s}_{P,t} = \alpha_{P,t}/\nu$; symmetrically for $ME_{P,t}$. Substituting (i) into (ii), the terms cancel. □

Part (i) says the marginal efficiencies are homogeneous of degree zero—only the composition $\bar{s}_{A,t}/\bar{s}_{P,t}$ matters, so the pool ne_t drops out of everything below. Part (ii) is Euler's theorem differentiated: a composition shift redistributes effective search between the two channels one-for-one; it neither creates nor destroys it.

Aggregation. Each non-employed worker takes $ME_{A,t}$, $ME_{P,t}$, and f_t as given, and her optimality conditions are

$$\psi'(e^*_{A,t}) = \beta\, \mathbb{E}_t\Big[\mu_{t+1}\, ME_{A,t}\, f_t\, \bar{H}_{t+1}\Big], \qquad \gamma^*_t = \beta\, \mathbb{E}_t\Big[\mu_{t+1}\, ME_{A,t}\, e^*_{A,t}\, f_t\, \bar{H}_{t+1}\Big] - \psi(e^*_{A,t}). \tag{D.8}$$

Differentiating (2), the aggregate active input moves through both margins: active searchers adjust their effort, and the moving threshold adds searchers at the margin,

$$d\ln \bar{s}_{A,t} = \underbrace{\int_{i:\, \gamma_{i,t} \le \gamma^*_t} \frac{e_{A,i,t}}{\bar{s}_{A,t}}\, d\ln e_{A,i,t}\, di}_{\text{intensive}} \;+\; \underbrace{\kappa_{\mathcal{G}}\, d\ln \gamma^*_t}_{\text{extensive}} = d\ln \bar{e}^*_{A,t} + d\ln \check{\mathcal{G}}_t, \tag{D.9}$$

The first term weights each searcher's effort change by her share of the aggregate input. The second term is Leibniz's rule at the participation boundary: the mass

$ne_t\, \mathcal{G}'(\gamma_t^*)\, d\gamma_t^*$ of marginal participants each enters with effort $\bar{e}^*_{A,t}$, and dividing by $\bar{s}_{A,t} = \check{\mathcal{G}}_t\, ne_t\, \bar{e}^*_{A,t}$ gives $\kappa_{\mathcal{G}}\, d\ln\gamma_t^*$, with $\kappa_{\mathcal{G}} \equiv d\ln\mathcal{G}/d\ln\gamma^*$. The second equality uses common effort across active searchers.

This leaves two variables measuring search effort, $\bar{e}^*_{A,t}$ and γ_t^*. It is more convenient to work with $\bar{e}^*_{A,t}$ alone, so we express the responses of the cutoff and of participation in terms of it, using elasticities familiar from the main text (equation (41)). Combining the two conditions in (D.8), and using the isoelastic cost function (37), $\gamma_t^* = e^*_{A,t}\,\psi'(e^*_{A,t}) - \psi(e^*_{A,t}) \propto (e^*_{A,t})^{1+1/\varepsilon_s}$, so $d\ln\gamma_t^* = (1+\frac{1}{\varepsilon_s})\, d\ln\bar{e}^*_{A,t}$ and

$$d\ln\check{\mathcal{G}}_t = g\, d\ln\bar{e}^*_{A,t}, \qquad g \equiv \kappa_{\mathcal{G}}\Big(1+\frac{1}{\varepsilon_s}\Big): \tag{D.10}$$

any equilibrium movement of effort drags participation with it, and by (D.9) the aggregate input moves by $d\ln\bar{s}_{A,t} = (1+g)\, d\ln\bar{e}^*_{A,t}$.

Proposition D.2 (Aggregate search moves the marginal efficiency of active search). *Within the search subperiod, with the pool predetermined:*

- *(i)* (individual) *A single worker's search decision leaves the marginal efficiencies unchanged:* $\partial\ln ME_{A,t}/\partial\ln e_{A,i,t} = -\frac{\alpha_{P,t}}{\nu}\, e_{A,i,t}\, di/\bar{s}_{A,t} = 0$ *in the continuum, and likewise for her participation decision and for* $ME_{P,t}$ *and* f_t*.*
- *(ii)* (aggregate) *A common movement of search behavior moves them:*

$$d\ln ME_{A,t} = -\frac{\alpha_{P,t}}{\nu}\,(1+g)\, d\ln\bar{e}^*_{A,t}, \qquad d\ln ME_{P,t} = +\frac{\alpha_{A,t}}{\nu}\,(1+g)\, d\ln\bar{e}^*_{A,t}. \tag{D.11}$$

- *(iii) The crowding coefficient* $\frac{\alpha_{P,t}}{\nu}(1+g)$ *is nonzero if and only if* $\nu < \infty$ *and* $\alpha_{P,t} > 0$*; equivalently, by the premium identity* $\nu = (1+g)/(1-\beta_{ASP})$*, if and only if* $\beta_{ASP} < 1$*, in which case* $\frac{\alpha_{P,t}}{\nu}(1+g) = \alpha_{P,t}(1-\beta_{ASP})$*.*
- *(iv) In either experiment,* $\alpha_{A,t}\, d\ln ME_{A,t} + \alpha_{P,t}\, d\ln ME_{P,t} = 0$*: crowding redistributes hires between channels; it does not change their total.*

Proof. (i): by Lemma D.1(i), $\partial\ln ME_{A,t}/\partial\ln e_{A,i,t} = -\frac{\alpha_{P,t}}{\nu}\,\partial\ln\bar{s}_{A,t}/\partial\ln e_{A,i,t}$, and the weight is $e_{A,i,t}\, di/\bar{s}_{A,t}$; a worker starting or stopping active search moves $\bar{s}_{A,t}$ by $\bar{e}^*_{A,t}\, di$, of the same order. (ii): substitute (D.9) and (D.10) into Lemma D.1(i) with $d\ln\bar{s}_{P,t} = 0$. (iii) is immediate from $\alpha_{P,t} \in [0,1]$ and the premium identity. (iv) is Lemma D.1(ii). □

Evaluated at steady state, (D.11) is equation (61) of the main text.

The response of the surplus. The surplus responds to the benefit through three channels:

$$\frac{d\bar{H}_i}{db} = \underbrace{\frac{\partial\bar{H}_i}{\partial b}}_{\text{direct}} + \underbrace{\frac{\partial\bar{H}_i}{\partial e_{A,i}}\frac{de_{A,i}}{db} + \frac{\partial\bar{H}_i}{\partial\gamma_i^*}\frac{d\gamma_i^*}{db}}_{=0}. \tag{D.12}$$

Her effort and cutoff enter $\bar{H}_i = \bar{V}_E - V_{NE,i}$ only through her value of non-employment, which her choices maximize; both partials in the second bracket therefore vanish—the envelope theorem, with the zeros given by the two conditions in (D.8). The direct effect is $-1/\tilde{\Delta}$ per unit of benefits, so in logs the discounting cancels:

$$\frac{d\ln \bar{H}}{d\ln b} = -\,\frac{b/\tilde{H}}{\tilde{\Delta}} = -\,\frac{b}{\tilde{F}} = -\,\sigma_b.$$

In the aggregate experiment, everyone's search also moves the marginal efficiencies. Her surplus depends on them only through her total job-finding rate, and by Proposition D.2(iv) crowding leaves that total unchanged. So $d\ln \bar{H}/d\ln b = -\sigma_b$ in both experiments.

The two experiments. **Proposition 2 (restated).** *Consider a permanent marginal change in benefits under the experiments described above. Whether the change is idiosyncratic or aggregate, the surplus falls by* (63)*, and search effort responds by*

$$\left.\frac{d\ln e_A^*}{d\ln b}\right|_{\textit{one worker}} = -\,\varepsilon_s\,\sigma_b,$$

$$\left.\frac{d\ln \bar{e}_A^*}{d\ln b}\right|_{\textit{all workers}} = -\,\varepsilon_s^{\text{eff}}\,\sigma_b, \qquad \varepsilon_s^{\text{eff}} = \frac{\varepsilon_s}{1+\frac{\tilde{\alpha}_P}{\nu}\,(1+g)\,\varepsilon_s}.$$

The ratio of the macro to the micro response is $\varepsilon_s^{\text{eff}}/\varepsilon_s < 1$ for every $\nu < \infty$, with equality if and only if $\nu = \infty$.

Proof. Log-differentiating the first-order condition in (D.8) with f and μ fixed,

$$\frac{1}{\varepsilon_s}\,d\ln e_A^* = d\ln ME_A + d\ln \bar{H}. \tag{D.13}$$

Idiosyncratic: $d\ln ME_A = 0$ by Proposition D.2(i); substituting (63) gives (64). *Aggregate:* identical active searchers move together, $d\ln e_A^* = d\ln \bar{e}_A^*$, so Proposition D.2(ii) makes the crowding term move one-for-one with the response:

$$\left(\frac{1}{\varepsilon_s} + \frac{\tilde{\alpha}_P}{\nu}\,(1+g)\right) d\ln \bar{e}_A^* = -\,\sigma_b\,d\ln b, \tag{D.14}$$

which is (65). The ratio is $1/\left[1+\frac{\tilde{\alpha}_P}{\nu}(1+g)\,\varepsilon_s\right] < 1$ for every $\nu < \infty$, with equality if and only if $\nu = \infty$. □

Corollary 2.1 (restated). *Substituting the premium identity $(1+g)/\nu = 1-\beta_{ASP}$ into* (65)*,*

$$\varepsilon_s^{\text{eff}} = \frac{\varepsilon_s}{1+\tilde{\alpha}_P\,(1-\beta_{ASP})\,\varepsilon_s}:$$

conditional on ε_s, the premium slope β_{ASP} and the passive share $\tilde{\alpha}_P$ are sufficient statistics for $\varepsilon_s^{\text{eff}}$.

Corollary 2.2 (restated). *For $\beta_{ASP} < 1$,*

$$\varepsilon_s^{\text{eff}} \;<\; \min\left\{\varepsilon_s,\; \frac{1}{\tilde{\alpha}_P\,(1-\beta_{ASP})}\right\}.$$

At $\beta_{ASP} = 1$, $\varepsilon_s^{\text{eff}} = \varepsilon_s$.

Proof. Taking reciprocals in (66), $1/\varepsilon_s^{\text{eff}} = 1/\varepsilon_s + \tilde{\alpha}_P\,(1 - \beta_{ASP})$. For $\beta_{ASP} < 1$ both terms are positive, so $1/\varepsilon_s^{\text{eff}}$ exceeds each of them; the second bound is approached as $\varepsilon_s \to \infty$. At $\beta_{ASP} = 1$ the crowding term vanishes. $\square$