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Passive Search and Jobless Recoveries

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Abstract

For employed workers, passive search is as important as active search. Passive search implies costly poaching by firms. I introduce poaching and passive search into a random matching model of the labor market. In the model, some firms switch from poaching to vacancy posting in recessions. Employed workers respond by increasing active search. By doing so, they crowd out unemployed workers both amplifying and propagating the reaction of unemployment to aggregate shocks. This mechanism can explain the counter-cyclicality of relative on-the-job search inferred from aggregate data. I provide cross-state empirical evidence supporting the mechanism.

Keywords: unemployment, passive search, jobless recoveries, on-the-job search

JEL: E24, E32, J62, J63, J64

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1 Introduction

The labor market search is a two-way search, workers search for jobs and firms search for employees. It is important to distinguish who makes the first move to facilitate a match. A firm might post a vacancy but it is a worker who will apply for the job facilitating a match. At the same time, a firm can contact a candidate directly, asking the candidate to apply, or just making an offer straight away. The latter becomes more and more common, especially for already employed workers, with the success of headhunters and numerous online platforms, such as LinkedIn.[1] I say that a worker *searches actively* if she applies for jobs and *searches passively* if she agrees to consider an offer when being contacted by a potential employer.

In this paper, I show that passive on-the-job search is as important as active on-the-job search and that introducing passive on-the-job search as an endogenous margin for workers and firms alters the dynamics of the labor market. Changes of firms' and workers' strategies over the business cycle can generate jobless recoveries due to a counter-cyclical on-the-job search and crowding out of unemployed workers during recoveries.

First, using the job search survey by the Federal Reserve Bank of New York, I show that passive search is as important for employed workers as active search. Moreover, workers at different parts of the wage distribution rely on different search strategies. Workers with lower wages are more likely to search actively, applying for jobs, and do it with a higher search effort, applying for more jobs. Workers with higher wages, instead, are more likely to have unsolicited contacts with potential employers, searching passively. To provide empirical evidence on the cyclicality of on-the-job search, I use a simple model to infer the average search effort of employed workers relative to unemployed from aggregate data. I use data for total hires and total quits from JOLTS, as well as the unemployment rate from BLS. I show that the on-the-job search has to be counter-cyclical to fit the data.[2]

Second, I extend the random matching model of the labor market to feature endogenous decisions in terms of both active and passive on-the-job search similar to Gorn (2021). The model features two-sided heterogeneity, two channels for labor market matching, and

[1] Carrillo-Tudela et al. (2015) show that 77.6% of hires coming from employment are workers who report no search activity prior to the hire.

[2] My empirical strategy is not informative about the reason for counter-cyclicality, whether it is driven by the extensive or the intensive margin of search, but infers an aggregate measure of search by all employed workers combined relative to the aggregate search by all unemployed.

aggregate shocks. The first labor market channel is the standard channel where firms post vacancies and workers apply for jobs randomly. The second labor market channel is the poaching channel where firms can directly contact exclusively high-skilled workers. Workers receive unsolicited offers from firms through this channel. The cost structure is such that the firms have to pay a higher cost in order to poach a high-skilled worker. Participating in the first channel represents the workers' active search strategy, while the second channel represents the workers' passive search strategy. I calibrate the model to match the aggregate statistics on skill and occupation distributions and the relevant statistics that I observe from the micro data on search strategies.

Third, I show that the extended model generates a large amplification of the labor market reaction to aggregate shocks relative to a standard one-channel model. The amplitude of the unemployment response increases by 2 to 8 times depending on the shock and the half-life of the response of unemployment increases by 25% to 33%. There are two channels through which the mechanism operates. First, the high-productivity firms react to a negative shock by switching from poaching to the cheaper standard channel. This amplifies the negative effect on vacancy posting due to a larger decrease in expected vacancy value as the cheaper channel also brings lower expected return. Second, the high-skilled employed workers adjust their search decision by searching less passively and more actively.[3] As a result, the employed workers crowd out the unemployed workers from the active search channel. The job finding rate falls and the response of unemployment increases and becomes more persistent. I assess the relative importance of on-the-job search adjustment by fixing the level of on-the-job search at the steady-state level. I show that the model generates a significant amplification in terms of the magnitude of the response but not in terms of persistence. It is the second channel that generates the most amplification and persistence. However, without the first channel, the second channel would work in the opposite way. I show that in a model with one channel, where firms don't have the second margin to adjust, on-the-job search is pro-cyclical and it dampens the response of the labor market to aggregate shocks. Importantly, the model with two channels generates counter-cyclical implied on-the-job search computed in a way consistent with my empirical inference and can explain the observed behavior.

[3] The passive search decreases because the firms stop poaching, but because the firms post vacancies instead of poaching, the benefits of active search increase relative to passive search since there are more good vacancies in the active search channel.

I then discuss the implications of the extended model for cyclicality of inequality and misallocation. In the model, the wage inequality is strongly pro-cyclical. In booms, most of the high-skilled workers are hired by high-productivity firms through the poaching channel. This improves the assortative matching between workers and firms and, due to complementarity of the production technology, wage inequality. Another consequence of this is that the misallocation is counter-cyclical. Because more high-skilled workers are poached by high-productivity firms in booms, the misallocation decreases. The model with poaching also predicts the behavior of implied recruiting intensity, skill requirements in posted vacancies and probability of moving up the job ladder that are consistent with the data.

Finally, I use state-level data on unemployment and enforceability of non-compete agreements to study the mechanism of the model. I interpret the enforceability of non-compete agreements as a fixed cost of poaching. Non-compete agreements create legal obstacles for job-to-job transitions and equally affect all firms in a state. In the model, a higher fixed cost of poaching implies that firms' search strategies are more sensitive to the aggregate state of the economy. In states with a higher fixed cost, more firms switch from poaching to the standard channel in response to a negative aggregate shock. This leads to more employed workers switching to active search and crowding out the unemployed workers, thus amplifying the shocks. In the data, states with a higher non-compete enforceability index exhibit a higher volatility of unemployment and a larger increase of unemployment during the Great Recession, consistent with the model predictions.

This paper contributes to the literature studying the effects of on-the-job search on labor market dynamics. Eeckhout and Lindenlaub (2019) is the closest study. Eeckhout and Lindenlaub (2019) show that when the active on-the-job search decision has only an extensive margin the model features multiple equilibria. They consider two equilibria, one with no active on-the-job search and one with on-the-job search by all employed workers. They show that an expectations shock can shift the equilibrium of the model. If the economy is in an equilibrium without on-the-job search during a recession and a positive expectations shock hits in the beginning of the recovery, their model will generate a jobless recovery. Employed workers will switch from the no-search strategy to the search strategy and crowd out the unemployed from the labor market. The main mechanism of Eeckhout and Lindenlaub (2019) is very similar to the mechanism in this paper, however, this paper features a model with endogenous changes in search strategies and the reasons for the mechanism are very different. Importantly, Eeckhout and Lindenlaub (2019) also find that the stock of on-the-job searchers is countercyclical in CPS data consistent with empirical and quantitative predictions in this paper.[4]

In another related study, Faberman et al. (2021) document the extent of on-the-job search and the differences in the effectiveness of search between employed and unemployed workers. They show that employed workers are more efficient in their search and receive a wage premium relative to unemployed workers. They develop a model with on-the-job search in order to explain the differences. They further show that the model calibrated to match the micro elasticity of on-the-job search to wages generates amplification and propagation of the reaction on vacancies, labor market tightness and job-to-job transitions to aggregate shocks. Moscarini and Postel-Vinay (2018) also propose a mechanism through which on-the-job search amplifies and propagates the labor market fluctuations. They argue that accounting for on-the-job search increases the estimated elasticity of the matching function and this increases the fluctuations of the job finding rate with the same effect on vacancies. They also argue that firms prefer to hire unemployed workers rather than employed workers as they have to pay more to employed workers due to competition, so that the distribution of employed workers over wages matters for job creation. The latter effects dampen but propagate the response of the labor market to aggregate shocks. The mechanisms of Faberman et al. (2021) and Moscarini and Postel-Vinay (2018) are very different from this paper, they don't take into account passive search and rely on the opposite cyclicality of on-the-job search.

Gertler, Huckfeldt and Trigari (2020) show that adding on-the-job search to a model with staggered wage bargaining helps to account for the observed excess wage cyclicality of new hires. In their framework, the excess wage cyclicality of new hires comes from the cyclical job quality upgrading by already employed workers. Accounting for the composition, the wages of new hires are as cyclical as the wages of existing workers. The model presented in this paper predicts pro-cyclical job upgrading in line with Gertler, Huckfeldt and Trigari (2020) despite the counter-cyclical active on-the-job search. This happens be-

[4]The presence of two channels in my model makes the direct comparison of the stock of searchers in two frameworks difficult. I distinguish between the stock of active searchers and the stock of workers available for another job (through passive search). The former is counter-cyclical while the latter is pro-cyclical in the model. The comparison between the stock of searchers in Eeckhout and Lindenlaub (2019) with the former measure is more correct because they apply for jobs, have a higher job finding rate and are in a more direct competition with the unemployed.

cause pro-cyclical poaching has a larger contribution to the cyclicality of job upgrading.

Finally, this paper can be also related to the earlier literature on the volatility of the labor market including Shimer (2005), Hall (2005), Hagedorn and Manovskii (2008), Gertler and Trigari (2009), as well as more recent contributions focusing more on the appearance of jobless recoveries such as Hagedorn et al. (2016), Chodorow-Reich, Coglianese and Karabarbounis (2018), and Mitman and Rabinovich (2019).

The remainder of the paper is organized as follows. Section 2 presents the empirical evidence on on-the-job search. Section 3 discusses the model. Section 4 presents the quantitative results. Section 5 presents the cross-state evidence. Section 6 concludes.

2 Empirical Evidence

2.1 Micro Evidence on Passive Search

In this section I use the Survey of Consumer Expectations (SCE) job search survey by the Federal Reserve Bank of New York to estimate the extent of passive search in the data. The survey asks a wide range of questions about employment and job search.[5] I focus on the responses by employed workers and study the responses to questions related to their job search and search outcomes. I use the 2013-2017 surveys, I exclude workers without a job, self-employed, employed part-time, and workers reporting more than one job. This leaves between 400 and 600 observations per year in the reduced sample.

The benefit of the survey is that it allows to distinguish between active and passive on-the-job search, as well as to determine the success of the search. The active search can be measured by the number of jobs the worker applied to (if any) over the last 4 weeks. The passive search, instead, can be measured by the number of unsolicited contacts (including referrals). The success of the search can be measured by the total number of contacts and offers received. The survey also includes information about the accepted offers or the offers the worker intends to accept.

Table 1 presents the share of workers answering positively to the questions regarding on-the-job search in the pooled sample. The first row represents all workers in the reduced sample across all five years. 17.4% of workers applied to other jobs, representing the active on-the-job search. 17.7% of workers had unsolicited contacts by potential employers,

[5] Faberman et al. (2021) provide a detailed discussion of the dataset.

half of those being through referrals, representing the passive on-the-job search. 7.5% of workers received another offer in a given month and 2.3% accepted the offer, being very close to the quit rate reported by JOLTS. One third of those workers who accepted an offer (0.77%) had an unsolicited contact by an employer during that month.

	Share (%)						
Sample	Applied	Contacted	Uns Cont	Referral	Offer	Accepted	Acc*Uns
All	17.43	23.94	17.71	8.84	7.49	2.28	0.77
Below M	20.10	19.77	12.29	7.73	9.36	3.25	0.90
Above M	14.75	28.12	23.15	9.94	5.62	1.3	0.65
Q1	24.64	20.77	11.20	9.37	11.81	5.09	1.43
Q2	18.33	19.35	13.44	7.13	8.55	2.04	0.81
Q3	16.67	22.15	14.84	7.32	6.50	1.83	0.20
Q4	12.80	24.59	20.53	6.91	4.47	0.61	0.41
Q5	14.87	32.79	28.51	13.44	6.11	1.83	1.02

Table 1: SCE survey tabulations for employed workers, shares of workers

To study which workers apply and which workers are being contacted, I split the sample by annual wage.[6] Rows 2 and 3 of Table 1 show the statistics for workers with wages below and above the median, respectively. More lower-paid workers apply to jobs themselves, while a higher share of high-paid workers have unsolicited contacts. More lower-paid workers accept an offer, while the share of workers accepting an offer who had an unsolicited contact is much lower (0.9 out of 3.25 for workers paid below the median vs 0.65 out of 1.3 for workers paid above the median). Rows 4 through 8 show the same statistics for the quintiles of the wage distribution. The general pattern remains, even though it is much noisier due to small sample size. The lower-paid workers rely more on active on-the-job search while higher-paid workers are targeted more by potential employers.

Table 2 presents the measures of intensity of the search. The first column presents the average number of applications by applicants, the second, third, and fourth columns show the average number of contacts, unsolicited contacts, and contacts through referrals, for workers with at least one contact. Finally, the fifth column presents the average number of offers for workers with at least one offer. Workers apply to 5.4 jobs on average, are con-

[6] The survey reports annual, weekly, or hourly wage for each worker as well as number of weeks worked and hours per week. I construct annual wages for all workers using the corresponding rates and hours. I drop outliers and clear coding errors.

tacted by 3 employers on average, with most of the contacts being unsolicited. Studying the same measures by wage, it is evident that also the search intensity changes with wage. Lower-paid workers put more effort into active search applying to a higher number of jobs while higher-paid workers rely more on passive search.

	Conditional Average				
Sample	Applied	Contacted	Uns Cont	Referral	Offer
All	5.3598	2.9983	2.1361	0.6207	1.9076
Below Median	6.1660	2.4650	1.5185	0.6173	2.0174
Above Median	4.2597	3.3739	2.5710	0.6232	1.7246
Q1	6.1818	3.1373	1.8725	0.7647	2.6034
Q2	4.5111	1.8421	1.2421	0.5263	1.3095
Q3	6.3415	3.2018	1.5046	0.4954	1.5000
Q4	5.2540	2.9504	2.5455	0.4711	2.000
Q5	3.9863	3.4907	2.9503	0.7826	1.7667

Table 2: Measures of search intensity

2.2 Cyclicality of On-the-job Search

In this section, I propose a way to infer the cyclicality of on-the-job search relative to the search by unemployed using aggregate data. I use JOLTS data for the total quits, the total hires and the unemployment rate. The calculation relies on three assumptions: 1) hires in JOLTS data are only from unemployed and employed workers (there is no flow from out of the labor force); 2) all (or most) quits are job-to-job transitions; 3) job finding rate per unit of search effort is the same for employed and unemployed workers. I proceed in the following way. I start with the identity:

$$\text{Total hires} = \text{Total quits} + \text{Total hires from unemployment}, \tag{1}$$

that is simply a formulation of my first assumption. First, I write the hires from unemployment as the product of the stock of unemployed, their average search effort, and the job finding rate per unit of search effort:

$$\text{Total hires from unemployment} = u \cdot L \cdot s_u \cdot f, \tag{2}$$

where u is the unemployment rate, L is the labor force, s_u is the average search effort of unemployed, and f is the job finding rate per unit of search effort. Note that because JOLTS doesn't report a separate measure for the hires from unemployment, I have to use the difference between total hires and quits from equation (1).

Second, similar to hires from unemployment, I write total quits as the product of the stock of all employed, their average search effort, and the job finding rate per unit of search effort:

$$\text{Total quits} = (1-u) \cdot L \cdot s_e \cdot f, \tag{3}$$

where s_e is the average search effort of the employed. With this formulation, s_e is a measure of search effort by all employed regardless of individual search status and includes many workers who do not search at all. This is beneficial relative to estimation of search effort by employed searchers because the aggregate measure of employed searchers is not directly observable.

Finally, I solve equations (2) and (3) for f, combine them, substitute the hires from unemployment from (1), and solve the resulting equation for s_e/s_u:

$$\frac{s_e}{s_u} = \frac{u}{1-u} \frac{\text{Total quits}}{\text{Total hires} - \text{Total quits}}. \tag{4}$$

This measure represents the average search effort among all employed who can be searching or not relative to the average search effort among all unemployed. If the job finding rate per unit of search effort is different for employed and unemployed (i.e. assumption 3 is not satisfied), this measure will include the differences not only in search effort but also in search efficiency.

Figure 1 plots the resulting series computed using JOLTS data. On average, the search effort by employed workers is 15 times lower than that by the unemployed.[7] Most of this difference comes from the fact that not all employed workers are looking for a job. The previous section shows that only 17% of workers search actively while employed and 24% of workers have contacts with other employers. Taking that into account, it is possible to say that the search effort by the employed, conditional on search, is around 2-3 times lower. This number is consistent with the observation from Faberman et al. (2021) that unemployed workers apply to twice as many jobs as employed workers looking for another job.

[7] The estimate is very close to the micro estimate by Mukoyama, Patterson and Şahin (2018) who report that the unemployed workers spend on average 30.4 minutes per day on search while the employed workers spend on average 1.9 minutes.

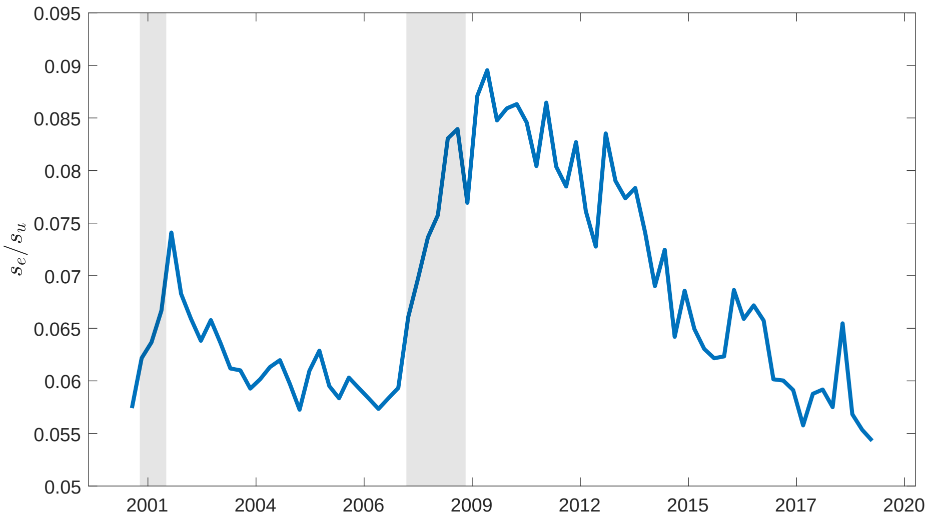


Figure 1: Implied on-the-job search

The most important observation from Figure 1 is that this measure appears to be counter-cyclical. There are several reasons for why the implied on-the-job search might increase in recessions, the most important distinction being between the intensive and extensive margins.[8] For example, the employed workers can be applying to more jobs or there might be more employed workers who apply to the same (or smaller) number of jobs. The extensive margin can also vary for several reasons. Among other reasons, it can increase because there are more employed who are mismatched during recessions, or it can increase because more employed want an extra job offer in case they will be made redundant on their current job. My empirical strategy is not informative about what reason was behind the observed increase during recessions. In the model that I develop in this paper, the extensive margin will be the main driving force of the cyclicality of average search effort by employed workers. In recessions, there will be more workers who search actively and fewer workers who search passively, and active search implies a higher effort from the side of the workers and a higher job-finding rate. The increase of the active search will dominate the decrease in the passive search resulting in the observed increase of implied average search effort.

The observed counter-cyclicality of on-the-job search is consistent with the results in Ahn and Shao (2020) and Eeckhout and Lindenlaub (2019) among other contributions.

[8]The relative on-the-job search can be also counter-cyclical due to pro-cyclicality of search by unemployed workers. However, there is little evidence for this in the data, Mukoyama, Patterson and Şahin (2018), instead, find evidence for counter-cyclicality of the search effort by nonemployed.

Ahn and Shao (2020) study the cyclicality of on-the-job search in the American Time Use Survey and show that both extensive and intensive margins of on-the-job search are counter-cyclical[9], contrary to the conventional view. Moreover, they show that the extensive margin is more important in generating the counter-cyclical on-the-job search. Eeckhout and Lindenlaub (2019), instead, use CPS data and infer the stock of on-the-job searchers and their search effort. They find that the stock is counter-cyclical while the effort is pro-cyclical. The counter-cyclicality of the stock of searchers is consistent with my results.

3 The Model

3.1 Environment

The economy is populated by workers and firms. There is a continuum of workers of measure 1 and a continuum of firms. There are two types of workers - high-skilled and low-skilled, and two types of firms - high-productivity and low-productivity. There are two channels for matching workers and firms. The channels differ in regards of who has to make the first move - workers or firms. In the standard, or vacancy, channel, the workers have to apply for a job in order to be matched, or search actively, while firms just post vacancies. In the second, or poaching, channel, the firms have to contact the worker directly and the worker is searching passively, deciding whether to accept the new job or not. The second channel is more expensive for firms but they can contact exclusively high-skilled workers.

For tractability, I assume that only high-skilled workers employed in low-productivity firms can search on-the-job. If a high-skilled worker is employed in a low-productivity firm, the worker draws an idiosyncratic productivity shock every period. The draw affects the worker's search strategy because if the worker moves to another low-productivity firm within the period the worker will draw a new realization of the shock (the shock is match-specific). This formulation, as opposed to full ex ante heterogeneity as in Gorn (2021), is chosen for analytical tractability purposes and can be generalized.

[9] Braun (2020) also finds counter-cyclical on-the-job search using the ATUS and CPS data.

3.2 Matching

Let v_i and s_i be the number of vacant positions and the number of searchers in channel $i \in \{V, H\}$, and $\theta_i \equiv \frac{v_i}{s_i}$ be the market tightness. Vacant positions and searchers are matched with a standard matching technology where the number of matches m_i is determined via a function $m_i(s_i, v_i) = \chi s_i^{\alpha} v_i^{1-\alpha}$. The searchers' job finding rate is $f_i(\theta_i) = m_i(1, \theta_i)$ and the job filling rate is $q_i(\theta_i) = \frac{f_i(\theta_i)}{\theta_i}$.

3.3 Firms

To open a vacant position a firm has to pay a fixed cost $\overline{F}$. The vacant position exists only for one period. If the position is not filled during the period, the firm has to pay the fixed cost again next period. After paying the fixed cost the firm draws a productivity level of this position from an exogenous distribution. After the productivity is drawn, the firm decides how to fill this position, posting a vacancy or trying to poach a worker.

Assume that only the high-productivity firms can poach workers (this will also be an equilibrium outcome with a reasonable calibration of the parameters). A low-productivity firm with a vacant position has to post a vacancy. The vacancy cost is c_{fV}. The firm is matched with a worker with probability $q_V(\theta_V)$ and the match is accepted by the worker with probability $P(A)$. If the match is accepted, the firm receives the value of a job this period (the hiring is instant), $J(p_L, e, a, \Omega)$, that depends on the firm's productivity, p_L in this case, worker's skill, e, idiosyncratic shock, a, and exogenous aggregate state, Ω. If the firm is not matched with a worker, the firm has to pay the fixed cost and draw a new productivity again next period, receiving 0 payoff this period. The value of a vacancy is:

$$V_V(p_L, \Omega) = -c_{fV} + q_V(\theta_V) E_{e,a|V} \{P(A) J(p_L, e, a, \Omega)\}.$$

A high-productivity firm can either post a vacancy or try to poach a worker. The value of posting a vacancy is similar to the one of a low-productivity firm with the difference that all matches will be accepted by workers:

$$V_V(p_H, \Omega) = -c_{fV} + q_V(\theta_V) E_{e,a|V} \{J(p_H, e, a, \Omega)\}.$$

A high-productivity firm that considers to poach a worker, instead, has to draw an idiosyncratic poaching cost shifter, c_{fN}.[10] The total cost of poaching for this firm will be

[10]Uniformly distributed over $[0, 1]$.

$c_{fV} + \overline{c_{fH}} + c_{fN} \cdot c_{fH}$. The poaching will be successful with probability $q_H(\theta_H)$ and the firm will be matched with a high-skilled worker. The value of poaching is:

$$V_H(p_H, c_{fN}, \Omega) = -\left(c_{fV} + \overline{c_{fH}} + c_{fN} \cdot c_{fH}\right) + q_H(\theta_H) J(p_H, e_H, a, \Omega).$$

The expected value of a high-productivity vacant position is the expectation of the maximum of the values of posting a vacancy and poaching over the poaching cost shifter:

$$\tilde{V}(p_H, \Omega) = E_{c_{fN}}\left\{\max\left\{V_V(p_H, \Omega); V_H\left(p_H, c_{fN}, \Omega\right)\right\}\right\}.$$

The expected value of a low-productivity vacant position is exactly the value of posting a vacancy: $\tilde{V}(p_L, \Omega) = V_V(p_L, \Omega)$. The free-entry condition can, therefore, be written as:

$$E_p\left\{\tilde{V}(p, \Omega)\right\} = \overline{F}.$$

Define $\overline{c_{fN}}$ as the poaching cost shifter that makes the firm indifferent between poaching and posting a vacancy[11]:

$$V_V(p_H, \Omega) = V_H\left(p_H, \bar{c}_{fN}, \Omega\right). \tag{5}$$

Firms with the cost below this threshold will be poaching workers while firms with the cost above will be posting vacancies. The reaction of this threshold to the aggregate shocks will be one of the key determinants of labor market dynamics.

The firms will open v vacant positions in order to satisfy the free-entry condition. $v \cdot F_H$ of these positions will be for high-productivity jobs and $v \cdot F_L$ will be for low-productivity jobs with F_H and F_L being the exogenous probabilities of opening a high- or a low-productivity job, respectively. High-productivity firms with a low poaching cost will be poaching with the total number of poaching firms being $v_H = vF_H P\left(c_{fN} \leq \bar{c}_{fN}\right)$ and the rest will post vacancies: $v_{VH} = vF_H P\left(c_{fN} > \bar{c}_{fN}\right)$. Low-productivity firms will only post vacancies: $v_{VL} = vF_L$. The total number of vacancies posted is $v_V = vF_H P\left(c_{fN} > \bar{c}_{fN}\right) + vF_L$.

A firm with productivity $p \in \{p_L, p_H\}$ matched with a worker with skill $e \in \{e_L, e_H\}$ produces $a \cdot z \cdot y(e, p)$ each period. For tractability, only matches of low-productivity firms and high-skilled workers draw an idiosyncratic shock, while $a = 1$ for all other matches. The firm then pays the wage to the worker, $a \cdot z \cdot w(e, p)$. The match survives to the next period if it is not exogenously destroyed or if the worker stays with the firm. The match

[11] $\overline{c_{fN}}$ will depend on the aggregate state as well as on the labor market conditions in both channels.

survives the exogenous separation with probability $(1 - s(\Omega'))$ and the endogenous separation with probability $\left(1 - s_Q(.)\right)$, defined formally in the Appendix. If the match does not survive, the firm disappears, or equivalently, the firm has to open a new vacancy paying the fixed cost under zero-profit condition and payoff of 0. The firm discounts the future with an exogenous discount factor $\beta(\Omega)$. The value of a job is:

$$\begin{aligned} J(p,e,a,\Omega) = \; & a \cdot (z(\Omega) \cdot y(e,p) - w(e,p,\Omega)) \\ & +\beta(\Omega) E\left\{\left(1 - s_Q(.)\right)(1 - s(\Omega')) J(p,e,a',\Omega')\right\}. \end{aligned}$$

3.4 Workers

A worker with skill e who is unemployed at the end of the period collects the unemployment benefits, $b(e)$, and searches for a job next period. The search from unemployment brings the value S_U. The workers discount the future with the same exogenous discount factor as firms, $\beta(\Omega)$. The value of unemployment, U, is:

$$U(e,\Omega) = b(e) + \beta(\Omega) E\left\{U\left(e,\Omega'\right) + S_U\left(e,\Omega'\right)\right\}.$$

A worker with skill e who is employed in a firm with productivity p at the end of the period receives the total wage $a \cdot w(e,p,\Omega)$ this period. Next period the match can be exogenously separated with probability $s(\Omega)$ in which case the worker will be unemployed. If the match is not separated exogenously, the worker can search on-the-job. The on-the-job search brings the value S_E. The value of work, W, is:

$$\begin{aligned} W(e,p,a,\Omega) = \; & a \cdot w(e,p,\Omega) \\ & +\beta(\Omega) E\{s(\Omega) U(e,\Omega') \\ & + (1 - s(\Omega))(W(e,p,a',\Omega') + S_E(e,p,a',\Omega'))\}. \end{aligned}$$

Consider the search behavior of a low-skilled worker. Because firms poach only high-skilled workers, the low-skilled worker can only search actively. Therefore, the value of search from unemployment for a low-skilled worker is the following:

$$S_U(e_L,\Omega) = \max\{S_{UV}(e_L,\Omega), 0\} = S_{UV}(e_L,\Omega),$$

where S_{UV} is the value of search through the vacancy channel. If an unemployed worker searches actively for a job, with probability $f_V(\theta_V)$ the worker will be matched with a vacancy and the worker will choose whether to accept the match or not. The worker also pays an active search cost, c_{wV}, every period of search. The value of active search is:

$$S_{UV}(e_L,\Omega) \equiv f_V(\theta_V) E_{p|V}\{\max\{E_a\{W(e_L,p,a,\Omega)\} - U(e_L,\Omega), 0\}\} - c_{wV}.$$

For simplicity, I assume that low-skilled workers do not search on the job. The assumption can be easily relaxed and the on-the-job search by low-skilled workers does not affect the main mechanism as they can only search actively, hence their decision will follow the predictions of a standard model. Therefore, $S_E(e_L, p, \Omega) = 0$.

Consider now the search behavior of a high-skilled worker. Because a high-skilled worker can search both actively and passively, an unemployed high-skilled worker will participate in both channels:

$$S_U(e_H, \Omega) = \max\{S_{UV}(e_H, \Omega), S_{UH}(e_H, \Omega), S_{UVH}(e_H, \Omega), 0\} = S_{UVH}(e_H, \Omega),$$

where S_{UV}, S_{UH}, and S_{UVH} are the values of search from unemployment actively, passively, and both. If the worker is searching both actively and passively, with probability $f_H(\theta_H)$ the worker matches with a poaching firm[12] in which case she pays the passive search cost, c_{wH}, and decides whether to accept a match or not.[13] If the worker is not being poached she may be matched through the vacancy channel with probability $f_V(\theta_V)(1 - f_H(\theta_H))$. The worker also has to pay the active search cost every period. The value of search through both channels is:

$$\begin{aligned} S_{UVH}(e_H, \Omega) \equiv \;& f_H(\theta_H)\Big(E_{p|H}\{\max\{E_a\{W(e_H, p, a, \Omega)\} - U(e_H, \Omega), 0\}\} - c_{wH}\Big) \\ & + f_V(\theta_V)(1 - f_H(\theta_H)) \\ & \cdot E_{p,a|V}\{\max\{W(e_H, p, a, \Omega) - U(e_H, \Omega), 0\}\} - c_{wV}. \end{aligned}$$

An employed high-skilled worker chooses whether to search actively, passively, both, or not to search at all. The value of search from employment is:

$$S_E(e_H, p, a, \Omega) = \max\{S_{EV}(e_H, p, a, \Omega), S_{EH}(e_H, p, a, \Omega), S_{EVH}(e_H, p, a, \Omega), 0\}.$$

If the worker is already employed in a high-productivity firm, there is no incentive to search for another job and the value of search is 0: $S_E(e_H, p_H, 1, \Omega) = 0$. The values of

[12] It is assumed that a worker will always accept an offer from a poaching firm if she meets two high-productivity firms at the same time.

[13] In equilibrium, all matches from unemployment will be accepted.

other search strategies are the following:

$$S_{EV}\left(e_H,p_L,a,\Omega\right) \equiv f_V\left(\theta_V\right)\left(1-f_H\left(\theta_H\right)\right)\cdot E_{p'|V}\left\{\max\left\{E_{a'}\left\{W\left(e_H,p',a',\Omega\right)\right\}-W\left(e_H,p_L,a,\Omega\right),0\right\}\right\} - c_{wV} \tag{6}$$

$$S_{EH}\left(e_H,p_L,a,\Omega\right) \equiv f_H\left(\theta_H\right)\left(\left[W\left(e_H,p_H,1,\Omega\right)-W\left(e_H,p_L,a,\Omega\right)\right]-c_{wH}\right) \tag{7}$$

$$S_{EVH}\left(e_H,p_L,a,\Omega\right) \equiv f_H\left(\theta_H\right)\left(W\left(e_H,p_H,1,\Omega\right)-W\left(e_H,p_L,a,\Omega\right)-c_{wH}\right)+ f_V\left(\theta_V\right)\left(1-f_H\left(\theta_H\right)\right)\cdot E_{p'|V}\left\{\max\left\{E_{a'}\left\{W\left(e_H,p',a',\Omega\right)\right\}-W\left(e_H,p_L,a,\Omega\right),0\right\}\right\} - c_{wV}. \tag{8}$$

The search strategy of a worker will depend on the current realization of the idiosyncratic productivity shock. Workers with a very high realization will not search at all this period, $S_E\left(e_H,p_L,a,\Omega\right)=0$ for a high enough. Workers with a medium realization of the shock will search only passively with the optimal strategy being $S_E\left(e_H,p_L,a,\Omega\right)=S_{EH}\left(e_H,p_L,a,\Omega\right)$. Workers with a low realization of the shock will search both actively and passively, $S_E\left(e_H,p_L,a,\Omega\right)=S_{EVH}\left(e_H,p_L,a,\Omega\right)$. Moreover, workers with the realization of the shock below the average will be accepting the matches with both high- and low-productivity firms and workers with the realization above the average will accept only the matches with high-productivity firms. Figure 2 illustrates the point, it plots the values of search as a function of the realization of the idiosyncratic shock. The value of search actively and passively (red dashed line) is the highest for low values of a as the worker will accept matches with other low-productivity firms and with the high-productivity firms. The function also has a kink at $a=1$ (average value in this case) as the worker stops accepting the matches with other low-productivity firms but still wants to search for a high-productivity firm both actively and passively. The value of search both actively and passively is decreasing with a and at some point it intersects the value of passive search (blue solid line) and the worker stops searching actively. The value of passive search also decreases but at a slower rate.[14] For a high enough, the value of passive search becomes negative and the worker does not search on-the-job. Note that searching only actively (green dotted line) is never optimal.

[14]One can see from equations (7) and (8) that the value of passive search is decreasing with a at a rate $f_H\left(\theta_H\right)W'_a\left(e_H,p_L,a,\Omega\right)$ while the value of search both actively and passively decreases at a faster rate $\left(f_H\left(\theta_H\right)+f_V\left(\theta_V\right)\left(1-f_H\left(\theta_H\right)\right)\right)W'_a\left(e_H,p_L,a,\Omega\right)$.

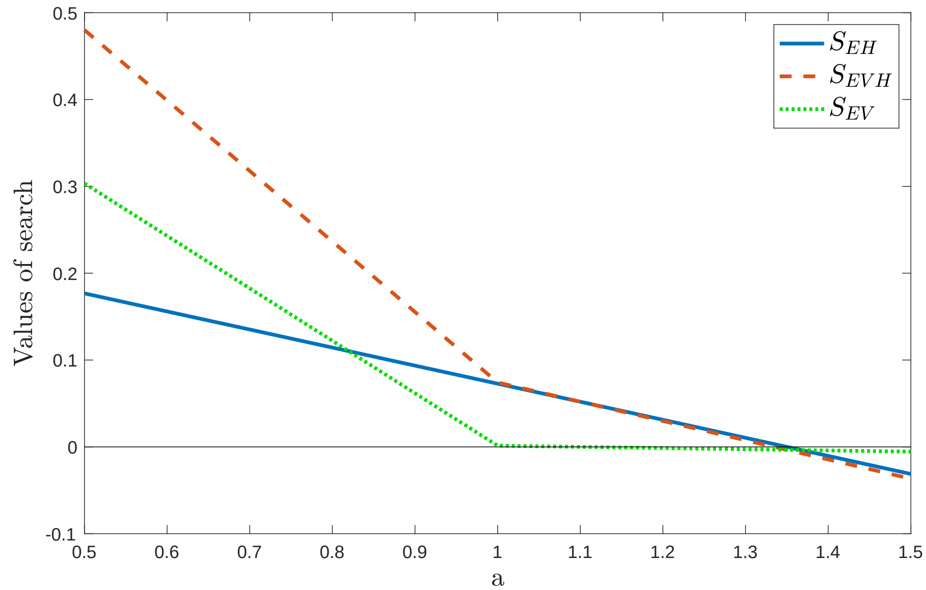


Figure 2: Values of search

It is useful to define three search thresholds. The passive search threshold, $\bar{a}_{HL}^{H}$, is such that:

$$S_{EH}\left(e_H, p_L, \bar{a}_{HL}^{H}, \Omega\right) = 0, \tag{9}$$

the active search for high-productivity firms threshold, $\bar{a}_{HL}^{VH}$, is such that:

$$S_{EVH}\left(e_H, p_L, \bar{a}_{HL}^{VH}, \Omega\right) = S_{EH}\left(e_H, p_L, \bar{a}_{HL}^{VH}, \Omega\right),$$

and the active search for any firm threshold, $\bar{a}_{HL}^{VH-}$, is such that:

$$W\left(e_H, p_L, \bar{a}, \Omega\right) = W\left(e_H, p_L, \bar{a}_{HL}^{VH-}, \Omega\right),$$

if it is below $\bar{a}_{HL}^{VH}$, $\bar{a}_{HL}^{VH-} = \min\left\{\bar{a}, \bar{a}_{HL}^{VH}\right\}$. Similar to the firms' hiring strategy, the response of the workers' search strategies to the aggregate shocks will determine the behavior of the labor market.

3.5 Distributions

Define as ϕ_{ij} the measure of workers with skill $i \in \{H, L\}$ employed in firms with productivity $j \in \{H, L\}$ in the end of the previous period. The low-skilled workers do not search on the job and the corresponding measures evolve similarly to the employment level in a standard search and matching model. Next period measure is equal to the measure of this period net of separations plus the new hires from unemployment:

$$\phi'_{LL} = \phi_{LL}\left(1 - s\left(\Omega\right)\right) + u_L f_V\left(\theta_V\right) \frac{v_{VL}}{v_V},$$

$$\phi'_{LH} = \phi_{LH} \left(1 - s\left(\Omega\right)\right) + u_L f_V \left(\theta_V\right) \frac{v_{VH}}{v_V},$$

where u_L is the measure of unemployed low-skilled workers.

The measures for the high-skilled workers depend also on the quits and the inflow of workers from other firms (the quits are partially offset by the inflow from similar firms for low-productivity firms). The next period measure of high-skilled workers in low-productivity firms depends on this period measure net of exogenous separations and quits plus the inflow from unemployment and the inflow of workers from similar firms through the vacancy channel:

$$\phi'_{HL} = \phi_{HL} \left(1 - s\left(\Omega\right)\right) \left(1 - s_{Q,HL}\right) + \left(u_H + \lambda_{HL}^{VH-}\right) f_V \left(\theta_V\right) \frac{v_{VL}}{v_V} \left(1 - f_H\left(\theta_H\right)\right),$$

where u_H is the measure of high-skilled unemployed workers and λ_{HL}^{VH-} is the measure of high-skilled employed workers who accept a job in a low-productivity firm.

Similarly, the next period measure of high-skilled workers in high-productivity firms depends on this period measure net of exogenous separations plus the inflow from unemployment and the inflow of workers from low-productivity firms through both channels:

$$\begin{aligned} \phi'_{HH} = \; & \phi_{HH} \left(1 - s\left(\Omega\right)\right) + \left(u_H + \lambda_{HL}^{VH}\right) f_V \left(\theta_V\right) \tfrac{v_{VH}}{v_V} \left(1 - f_H\left(\theta_H\right)\right) \\ & + \left(u_H + \lambda_{HL}^{H}\right) f_H \left(\theta_H\right), \end{aligned}$$

where λ_{HL}^{VH} is the measure of workers employed in low-productivity firms searching both actively and passively and λ_{HL}^{H} is the measure of workers employed in low-productivity firms and searching passively (including the workers using both channels).

The measures of on-the-job searchers can be defined using the search decision thresholds as follows:

$$\lambda_{HL}^{VH} = \phi_{HL} P\left(a < \bar{a}_{HL}^{VH}\right) \left(1 - s\left(\Omega\right)\right)$$

$$\lambda_{HL}^{VH-} = \phi_{HL} P\left(a < \bar{a}_{HL}^{VH-}\right) \left(1 - s\left(\Omega\right)\right)$$

$$\lambda_{HL}^{H} = \phi_{HL} P\left(a < \bar{a}_{HL}^{H}\right) \left(1 - s\left(\Omega\right)\right).$$

3.6 Wages

The wage of a high-skilled worker in a high-productive firm is determined via wage bargaining. The wages of workers in other matches are scaled down proportionally to the productivity of the match.

The wage of a high-slkilled worker in a high-productivity firm, $w(e_H, p_H, \Omega)$, is a solution to the Nash bargaining problem:

$$w(e_H, p_H, \Omega) = \arg\max_{w} \left(W(e_H, p_H, 1, \Omega, w) - U(e_H, \Omega)\right)^{\gamma} \left(J(e_H, p_H, 1, \Omega, w)\right)^{1-\gamma},$$

where γ is the bargaining power of the workers. The solution implies a standard sharing rule:

$$(1-\gamma)\left(\tilde{W}(e_H, p_H, 1, \Omega, w(e_H, p_H, \Omega)) - U(e, \Omega)\right) = \gamma \tilde{J}(e_H, p_H, 1, \Omega, w(e_H, p_H, \Omega)).$$

Wages of other matches are set according to the following rule:

$$w(e, p, \Omega) = w(e_H, p_H, \Omega) \frac{y(e, p, \Omega)}{y(e_H, p_H, \Omega)}.$$

3.7 Equilibrium

In the equilibrium, the workers' and firms' value functions satisfy the corresponding Bellman equations, the search decisions by workers and firms satisfy the corresponding optimality conditions, the firms' free-entry condition is satisfied, and the measures of workers evolve according to the laws of motion.

3.8 Calibration

The model is calibrated to monthly frequency. There are four parameters set exogenously - the steady-state discount factor, β, is set to 0.997; the workers bargaining power, γ, is set to 0.5; the elasticity of the matching function, α, is set to 0.5; the firms' search cost shifter, $\overline{c_{fH}}$, is set to 7.5. There are three sets of parameters to jointly calibrate internally: the distributions and productivity parameters; the labor market transitions; and the search costs. I choose the share of high-skilled workers to match the share of population with a college degree and the relative productivity of high-skilled workers to match the college wage premium estimated in Valletta (2016). To determine the probability of opening a high-productivity position, I match the share of workers employed in high-productivity jobs ($\frac{\phi_{LH}+\phi_{HH}}{\sum \phi_{i,j}}$) to the share of workers employed in high-skilled occupations in the BLS data.[15] To determine the firms' productivity, I match the raw occupational wage premium

[15] I use the 2016 Occupational Employment Statistics program data. I sort the occupations by wage. I define the occupations paying more than $40,000 per year as high-skilled.

from the BLS data.[16] I choose the exogenous steady-state separation rate to match the steady-state unemployment and the matching efficiency to match the job finding rate. I calibrate the search costs for workers and firms by matching the aggregate quit rate and the share of quits that result from unsolicited contacts. The results of the calibration are presented in Table 3.

Variable	Value	Target	Data	Model
Share of HS workers	0.44	College degree	0.44	0.44
Relative productivity HS	1.7	College skill premium	1.7	1.7
Share of HP vacancies	0.085	Share of HS occupations	0.40	0.40
Relative productivity HP	1.5	Occupational premium raw	2.2	2.32
Separation rate	0.03	SS unemployment	5%	5.09%
Matching efficiency	0.35	Job finding rate	0.5	0.52
Search thresholds (costs)	1.35/1.1	Quit rate	2%	2%
Share of HP poaching	0.75	Unsolicited quits	0.77%	0.75%

Table 3: Calibration

I use a simple production function $y(e,p) = e \cdot p$. For the idiosyncratic shock I use a uniform distribution over $[0.5, 1.5]$. Finally, I use AR(1) processes for the aggregate shocks.

4 Results

4.1 Responses to Shocks

In this section, I compare the response of the model to aggregate shocks for three versions of the model: the baseline model, the model with two channels and active search fixed at the steady-state level, and the model with one channel and no on-the-job search. This comparison demonstrates how different margins of the baseline model affect the aggregate dynamics.

[16] I compute the average wage of high- and low-skilled occupations as defined above and target the ratio of the two.

Productivity Shock

Figure 3 plots the impulse responses of key variables to a productivity shock for three versions of the model. Output drops significantly in response to a decrease in the productivity in all three models. Unemployment increases and vacancies drop sharply. The increase in unemployment in the baseline model is around four times larger than in the model with one channel. The peak of the response is also later, the unemployment starts to decrease 7 months after the initial shock in the baseline model, comparing to 5 months in the model with one channel. Therefore, the response of unemployment also becomes more persistent. There are two reasons for this amplification. First, as can be seen in the bottom right panel, the firms switch from poaching to the vacancy channel in response to a negative shock. Because of this switch, the expected value of a vacancy drops by more and the vacancy posting reacts stronger in the model with two channels. Second, active on-the-job search increases in the baseline model (bottom left panel) because the value of search through both channels drops by less than the value of passive search. The number of active on-the-job searchers increases and they crowd out the unemployed workers from this labor market channel. As a result, the job finding rates fall more in both channels and stay much lower than in the other specifications of the model for a prolonged period.

The comparison of the three models demonstrates the relative importance of the two ingredients of the mechanism. Comparing the impulse responses of the model with two channels and no active search reaction (red dotted lines) to the model with one channel (yellow dashed lines) reveals the importance of the firms' endogenous switch between two channels. In the model with two channels, the firms switch to the cheaper hiring channel (bottom right panel). This switch decreases the average value of posting a vacancy by more because the cheaper channel also brings lower expected return due to absence of targeting in the hiring. Hence, the vacancy posting falls by more with the endogenous switching (upper right panel) and this translates into a larger decrease in job finding rate (middle left panel) and a larger increase in unemployment. However, without a reaction of the active on-the-job search, this switch is relatively short-lived and it does not affect the persistence of the response.

Comparing the responses of the model with two channels and with (blue solid lines) or without (red dotted lines) active on-the-job search reaction, instead, reveals the effect of the active search. This is where the main difference comes from. When firms switch to posting vacancies, the value of passive search drops and passive search decreases (bottom

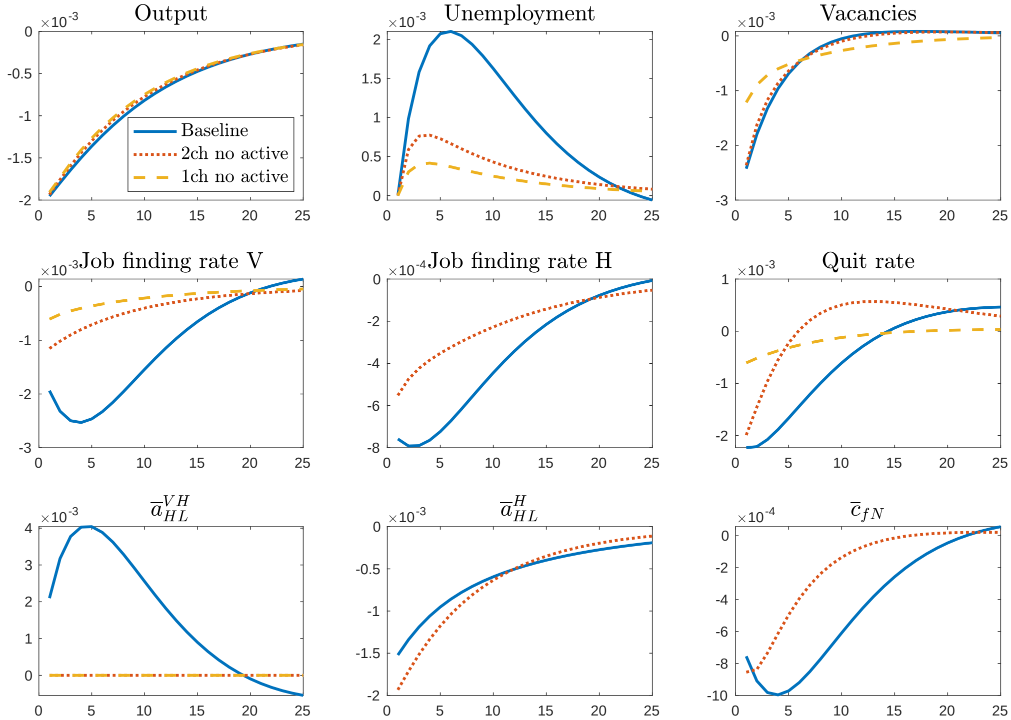


Figure 3: Impulse responses, productivity shock

center panel). The value of active search also decreases because there are fewer vacancies overall, but because there are relatively more high-paying vacancies (due to the firms' switch), the value of active search decreases by less than the value of passive search. As a result, the intercept between the two moves to the right and active search by the employed workers increases. The increase in the on-the-job search then increases congestion on the standard labor market and the unemployed workers are crowded out. The reaction of the active search and the resulting crowding out of the unemployed increases the magnitude of the response of unemployment even more and, more importantly, increases the persistence of the responses. For this mechanism to operate, both effects are needed, as without the firms switching the active search wouldn't be counter-cyclical as will be argued in the next section.

Another way to see the difference between the versions of the model is to look at the implied Beveridge curves (Figure 4). All three models feature an outward shift in the Beveridge curve as is common in this type of models. The magnitude of the shift and the speed of the return are different across the three. The model with one channel (dashed line) generates the smallest outward loop. The model with two channels and fixed active search (dotted line) features a similar loop but about twice larger in scale showing that the firms' switching changes the amplitude of the responses rather than the nature of the behavior of the labor market. Finally, the full model (solid line) features a much more pronounced outward loop that is not only larger but also has a different shape. In this case, after the initial drop in vacancies and the increase in unemployment, the unemployment keeps rising significantly while the vacancies pick up. The unemployment starts to go down only when the vacancies are almost back at the steady-state level.

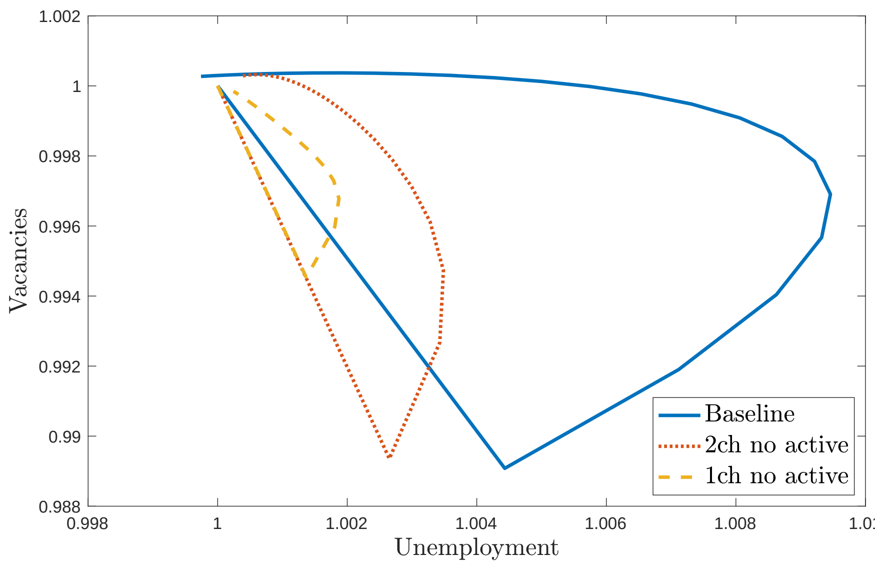


Figure 4: Normalized Beveridge curves, productivity shock

Separation Shock

Figure 5 presents the results for a separation shock. Output drops in response to an increase in the separation rate with the baseline model featuring the largest and the most persistent drop in output. Unemployment increases and vacancies drop initially and then increase. The increase in unemployment in the baseline model is around two times larger than in the model with one channel. The response of unemployment is also more persistent in the baseline model with a 33% increase in the half-life of the response. Again, the effects of two channels are evident. The model with two channels and fixed active search features responses similar to the model with one channel but they are amplified due to firms' strategy switch and a stronger reaction of vacancies. Active on-the-job search adds to the amplification due to the crowding out of the unemployed.

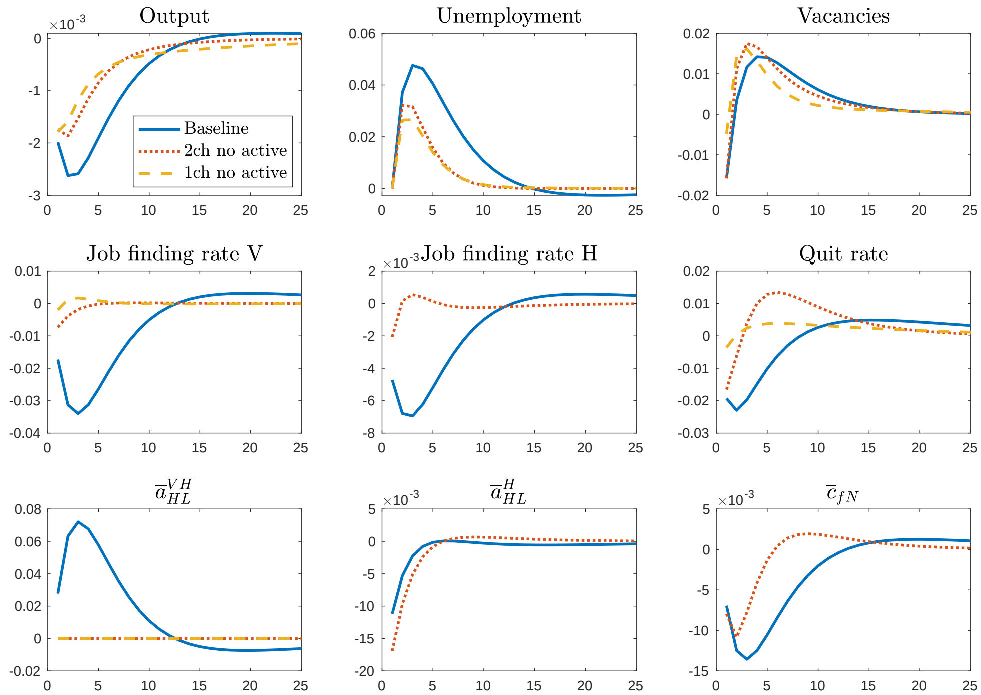


Figure 5: Impulse responses, separation shock

Discount Factor Shock

Figure 6 presents the results for the discount factor shock. As in the case of the productivity and the separation shocks, the model with two channels amplifies the reaction of the model to a discount factor shock. In this case the amplification is even stronger with the unemployment reaction increasing by around 8 times relative to the model with one channel and the persistence of the response increasing by 25%. The peak of the response is also much later in this case, the full model peaks after 9 months while the one-channel model peaks after 5. Here the differences between the three models are even more pronounced. Both firms and workers react to a discount factor shock stronger. This happens because the discount factor affects all value functions directly, making the future considerations less important for present decisions. Therefore, more firms switch to the cheaper channel and more workers want to increase their chance for a new productivity draw this period.

Figure 7 plots the Beveridge curves for the three models for the case of a discount factor shock. Again, the model with fixed active search and the model with one channel feature similar shapes of the curves with the loop of the model with two channels being around four times larger. The model with two channels and variable active search features a more

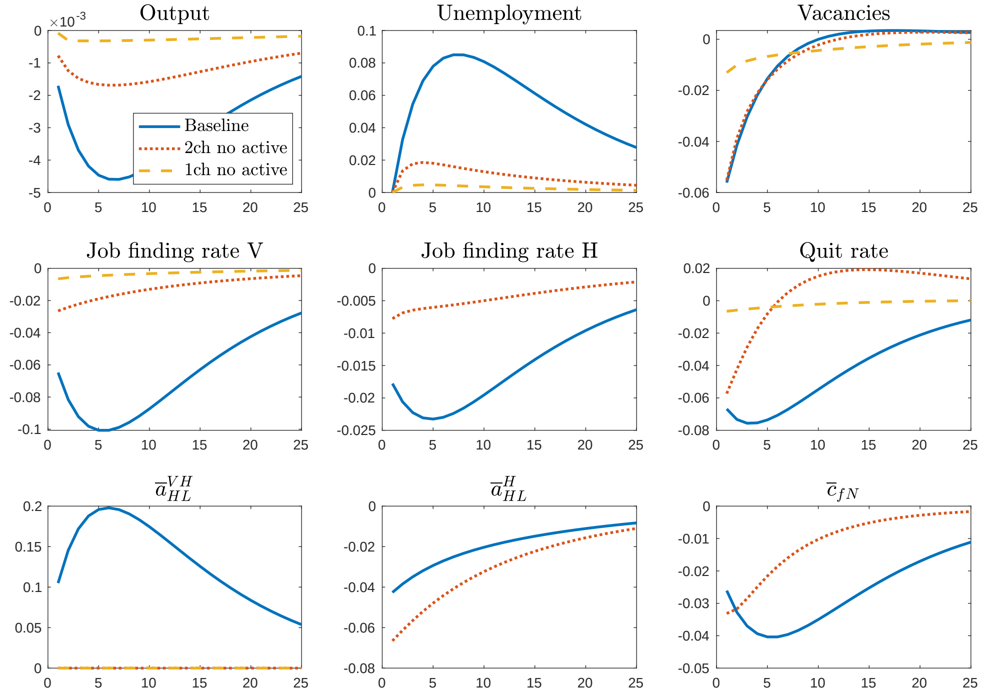


Figure 6: Impulse responses, discount factor shock

pronounced outward shift and a slower convergence back to the steady state, especially for unemployment. The unemployment is still 10% higher than the steady-state level 2 years after the shock.

4.2 On-the-job Search in a Model with One Channel

In this section, I analyze the behavior of the model with one channel with and without active on-the-job search. I also compare it to the baseline model. The one-channel model is presented in the Appendix.

Figure 8 plots the responses of key variables to a separation shock in the model with one channel with and without active search reaction and the baseline model. The most important observation here is that active on-the-job search falls in the model with one channel. In response to an increase in the separation rate firms post fewer vacancies and employed workers have lower incentives to search on-the-job. Because of this, the unemployment increases by less when the active search is present. This effect is even stronger in the cases of a productivity or discount factor shocks presented in Figures D.1 and D.2 in the Appendix, respectively. Unemployment even decreases in response to a contractionary productivity or discount factor shock when active search is present in the one-

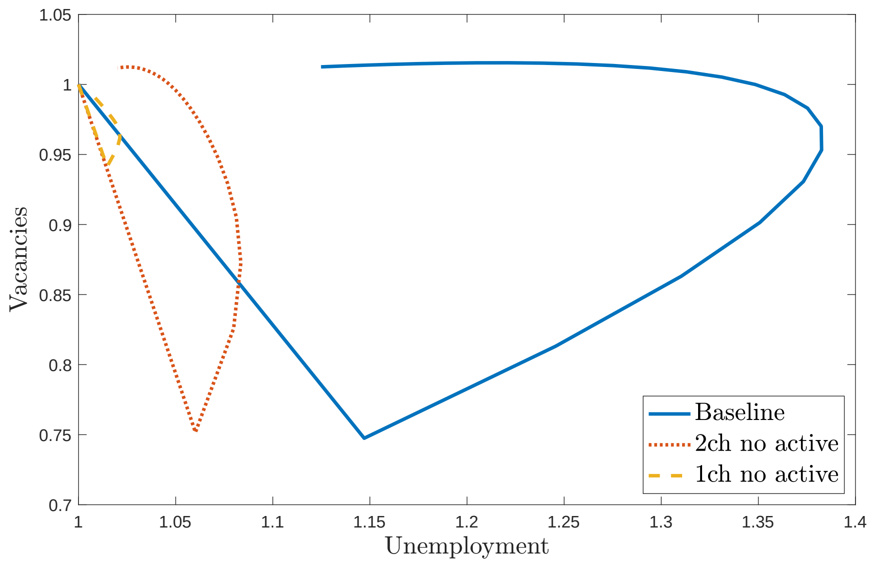


Figure 7: Normalized Beveridge curves, discount factor shock

channel model despite a significant drop in the vacancy posting. This happens because of a drop in on-the-job search that leaves more job opportunities for unemployed workers.

These results are very different from the model with two channels where active search amplifies the response of unemployment. In the model with two channels, firms have two margins to adjust the search after aggregate shocks: the aggregate vacancy posting and the search channel of the high-productivity firms. Similarly, employed high-skilled workers not only decide whether to search or not, but they also decide through which channel to search. In a model with one channel, both such decisions are one-dimensional. In the one-channel model, on-the-job search generally follows the vacancy posting and is very pro-cyclical. This link is hard to separate in models with an endogenous on-the-job search decision. Hence, on-the-job search generally dampens the fluctuations of the labor market. The presence of the second channel allows to separate the link. In the model with two channels, the overall on-the-job search is still strongly pro-cyclical as can be seen in the response of the passive search threshold in the bottom middle panels. However, the overall on-the-job search is not the relevant measure for the job prospects of unemployed as unemployed workers compete for jobs mainly through the active search channel.

It is also important to relate the response of the on-the-job search in different versions of the model to its empirical counterpart. Section 2.2 demonstrates that the implied on-the-job search increased by around 50% during the Great Recession. Figure 9 plots the implied on-the-job search for the three models computed similar to the data.[17] The fig-

[17] I compute the implied on-the-job search in the model with two channels as $s_e = (1 - f_H)\lambda_{HL}^{VH}/(1-u) +$

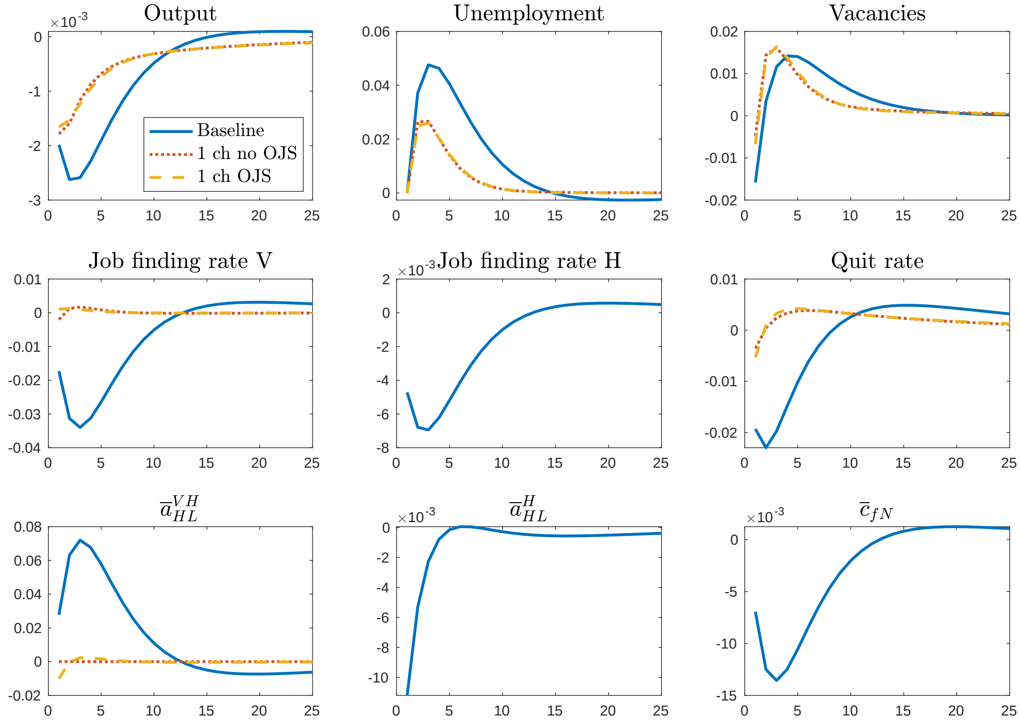


Figure 8: Impulse responses, separation shock

ure shows that the implied on-the-job search rises significantly and persistently only in the model with two channels. In this model, the implied on-the-job search increases after a negative shock for two reasons. First, there are more workers who are in the low-productivity firms and have incentives to search for a better job. Second, more of such workers search actively since the active search threshold increases and because the job-finding rate is higher for active search, the calculation picks it up as a higher on-the-job search. The model with one channel fails to generate such increase with or without variable on-the-job search. When variable, the active search threshold decreases in the model with one channel and this initially dominates the increase in the number of workers in bad matches when the shock hits. This shows that the model with two channels can explain the observed cyclicality of implied on-the-job search without relying on other margins such as endogenous search intensity.

$f_H/f_V * \lambda^H_{HL}/(1-u)$ and in the model with one channel as $s_e = \lambda^V_{HL}/(1-u)$.

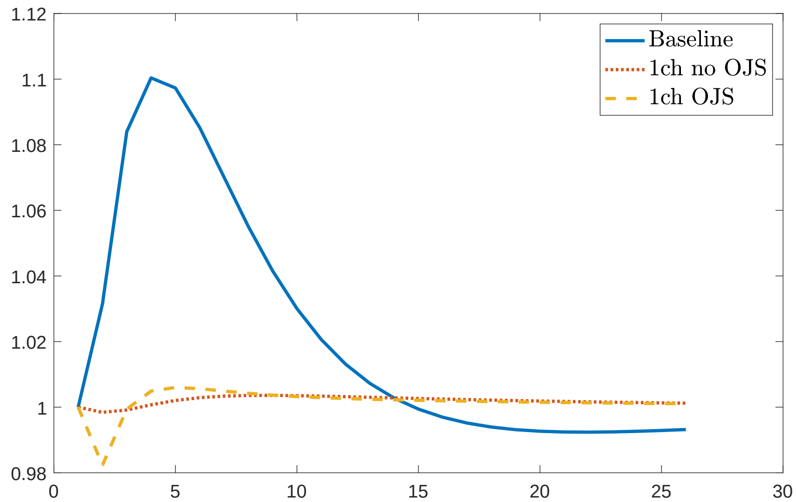
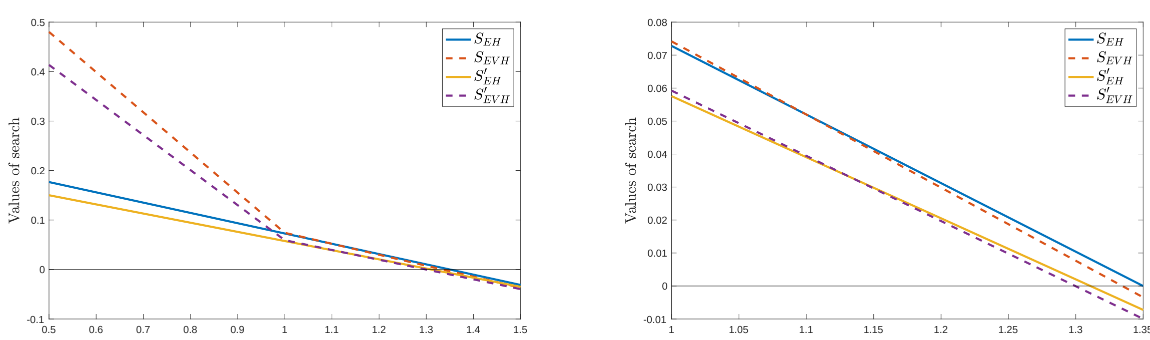


Figure 9: Implied on-the-job search, separation shock

4.3 Mechanism

The responses of on-the-job search decisions depend on the responses of values of search. In the model with one channel, there is only one decision - to search or not to search. During a recession, the value of search decreases as the benefits of a new match are lower and the chances of finding a new match are scarce due to lower job creation. In the model with two channels, both effects - lower benefits and lower job creation - are still in place so the values of search decrease (Figure 10a). Because the value of passive search decreases, the intercept of the value of passive search with 0 moves to the left. Overall on-the-job search decreases as in a model with two channels. The value of passive search decreases by more than the value of searching both actively and passively and the intercept between them moves to the right (Figure 10b). The threshold for active on-the-job search increases.



(a) Full support of *a*

(b) Relevant region

Figure 10: Change in values of search in a recession

To understand why active on-the-job search increases in a recession, focus on the difference between the value of passive search and the value of searching both actively and passively in the region where the workers accept only matches with high-productivity firms:

$$S_{EVH}(e_H, p_L, a, \Omega) - S_{EH}(e_H, p_L, a, \Omega) = f_V(\theta_V)(1 - f_H(\theta_H)) \cdot \frac{v_{VH}}{v_V}(W(e_H, p_H, 1, \Omega) - W(e_H, p_L, a, \Omega)) - c_{wV}.$$

As in a standard model, the benefit of the move (the difference between the value functions) and the probability of finding a match, $f_V(\theta_V)$, decrease putting downward pressure on the difference and active on-the-job search. But at the same time, high-productivity firms switch from poaching to posting vacancies. The switch affects the difference in two ways. First, it decreases the chance of being poached increasing the need for active search if the worker wasn't poached, $(1 - f_H(\theta_H))$. Second, it increases the chance of meeting a high-productivity firm through the standard channel, $\frac{v_{VH}}{v_V}$. The increase in these two components counteracts the decrease in the two standard components and shifts the difference between the two values of search up if enough firms switch from poaching to posting vacancies.[18]

Why do firms switch from poaching to posting vacancies? When an aggregate shock hits the economy, the value of a job of a high-productivity firm with a high-skilled worker is affected by more than the value of a job of a high-productivity firm with a low-skilled worker. The productivity shock affects the HH match more because $y(e_H, p_H) > y(e_L, p_H)$ and the discount factor and the separation shocks affect it more because the continuation value of an HH match is higher. Therefore, other things being equal, the initial impact of the shock affects the value of poaching more than the value of posting a vacancy and firms respond by switching away from poaching. When workers respond to the switch by adjusting their search strategy, the relative value of posting a vacancy increases even more as there are more high-skilled workers in the pool of applicants (due to higher active on-the-job search). The response of workers amplifies the firms' switch away from poaching. This effect can be seen from the following equation determining the poaching

[18] If the firms do not change their hiring decision, active search would still be pro-cyclical as in a standard model.

cost threshold:

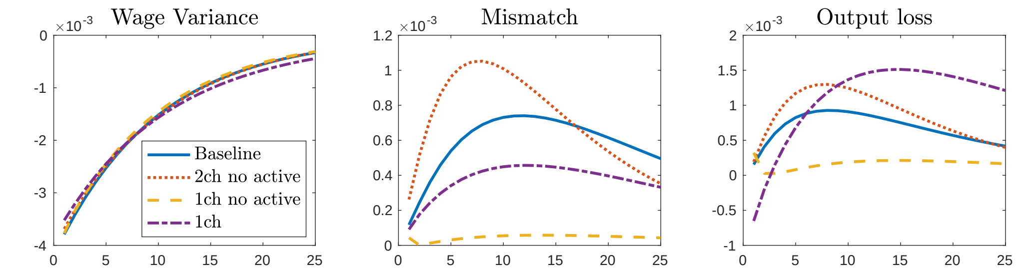
$$\overline{c_{fN}} = \frac{1}{c_{fH}} \cdot \Bigg(-\overline{c_{fH}} + q_H(\theta_H) J(p_H, e_H, \Omega) - \\ q_V(\theta_V) \left[\frac{\lambda^{HL} + u^H}{s^V} (1 - f_H(\theta_H)) J(p_H, e_H, \Omega) + \frac{u^L}{s^V} J(p_H, e_L, \Omega) \right] \Bigg)$$

Initially, $J(p_H, e_H, \Omega)$ decreases by more than $J(p_H, e_L, \Omega)$ and the poaching cost threshold goes down. When the poaching cost threshold is lower, there are fewer firms that will draw the cost low enough to poach and the share of poaching firms will decrease. After workers respond by increasing active on-the-job search, λ^{HL} will increase and the chance to meet a high-skilled worker by posting a vacancy will increase putting even more downward pressure on the poaching cost threshold and the share of poaching firms.

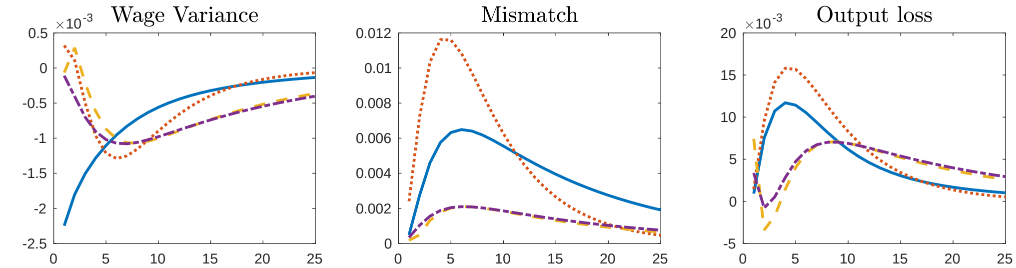
4.4 Implications for Inequality and Misallocation

In this section I study implications of the model for dynamics of inequality and misallocation. Figure 11 presents impulse responses of inequality, misallocation and output loss due to misallocation. In the model, inequality is strongly pro-cyclical as can be seen from the left panels. The inequality decreases in recessions for the following reason. When firms stop poaching and switch to posting vacancies, high-productivity firms will have a higher probability of matching with a low-skilled worker. There will be relatively more low-skilled workers employed in high-productivity firms and more high-skilled workers in low-productivity firms. Therefore, the wage inequality will decrease due to the compositional changes of the existing matches. At the same time, the wage schedule also compresses in recessions. It is especially pronounced in case of a productivity shock that has the most direct effect on wages (left panel of Figure 11a).

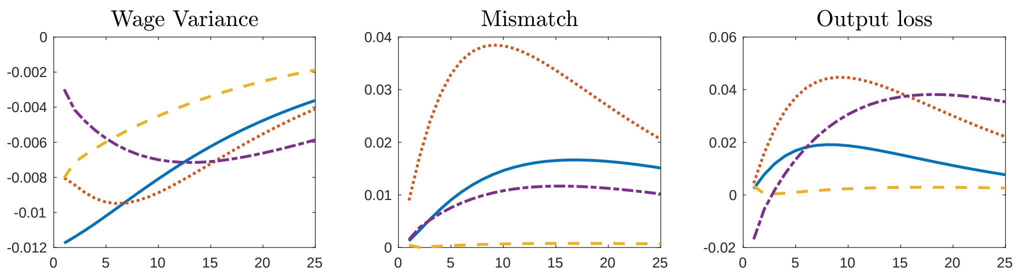
Lower inequality, however, comes with a cost. The decrease in wage inequality due to change in the composition of the existing matches is driven by the increasing mismatch (middle panels of Figure 11). The mismatch is calculated as the share of high-skilled workers in low-productivity firms plus the share of low-skilled workers in high-productivity firms. The mismatch increases in recessions. The increase in mismatch is larger in the model with two channels comparing to the model with one channel. In the model with one channel and no active search decision, the mismatch increases because firms create fewer vacancies that decreases the job finding and quit rates. In the model with two channels, there is an additional effect. When many high-productivity firms poach workers,



(a) Productivity shock



(b) Separation shock



(c) Discount factor shock

Figure 11: Response of inequality and misallocation

they know that they poach high-skilled workers. When poaching decreases, the probability that a high-productivity firm will hire a high-skilled worker decreases opening possibility for a mismatch. Counter-cyclical active on-the-job search partly offsets the drop in poaching because more employed high-skilled workers apply for jobs. We can see this in the difference between the model with optimal active search (solid blue lines) and the model with fixed active search (dotted red lines).

The mismatch contributes to the decrease in output. Right panels of Figure 11 plot the responses of the output loss due to mismatch. The output loss due to mismatch is calculated as a percentage difference of actual output from the output that would result from a perfect assortative matching equilibrium (all employed high-skilled workers employed in high-productivity firms and all low-skilled workers employed in low-productivity firms). The output loss due to mismatch calculated this way increases relative to the steady state output loss in recessions. It follows closely the response of the mismatch in general. The difference is that the contribution of the mismatched high-skilled workers to the output loss is larger relative to the one of the low-skilled workers. The composition of the mismatch matters for the output loss.

4.5 Implications of Pro-cyclical Poaching

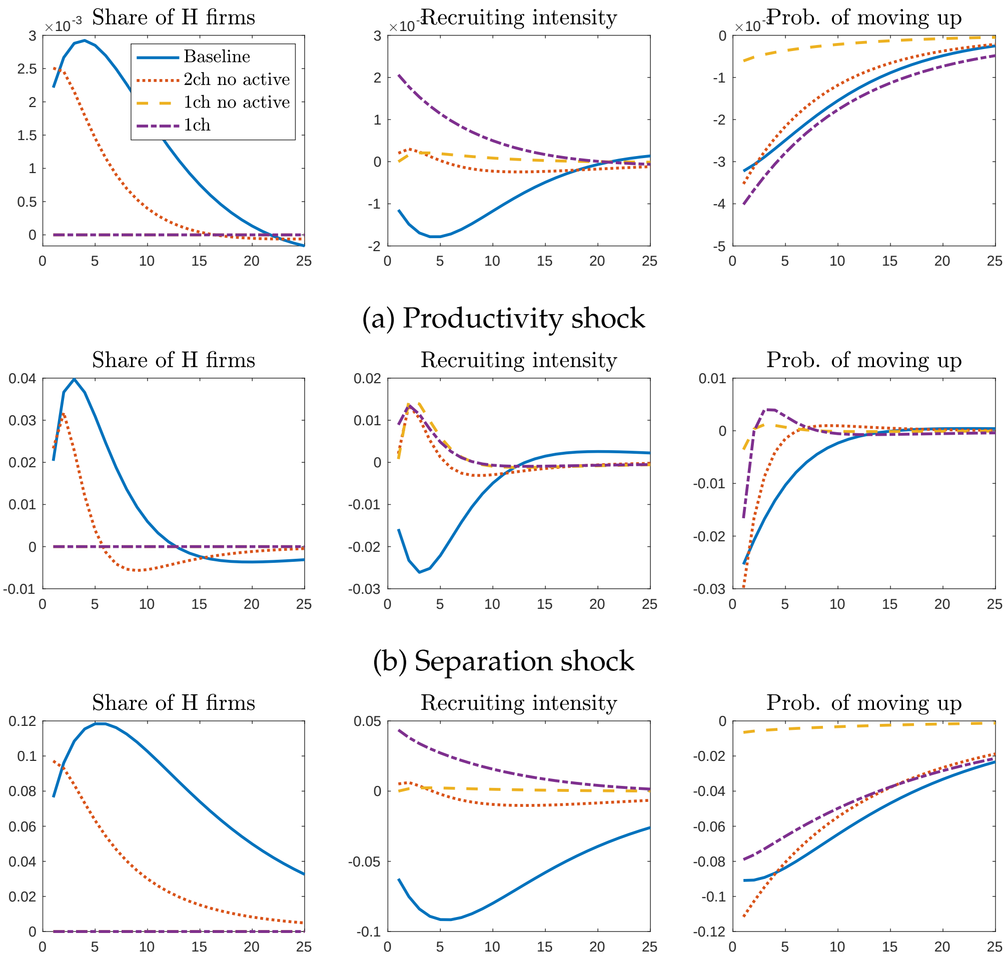
In this section I show that the model with two channels is able to match several features of the response of the labor market to aggregate shocks observed in the data. First, there is a growing empirical literature studying the cyclicality of skill requirements in the job ads. The studies normally find that the skill requirements are counter-cyclical. The share of job ads that require a certain level of education is higher in recessions. In one of such studies, Hershbein and Kahn (2018) find that the ads in a hard-hit metro area are more likely to include educational or experience requirements. In another study, Modestino, Shoag and Ballance (2019) come to the same conclusion.[19] They argue that this finding can be explained by a higher supply of unemployed workers during recessions.

The model presented in this paper provides an additional explanation for the observed counter-cyclicality of skill requirements. The model predicts that the share of high-productivity firms which fill their vacancies by active poaching is pro-cyclical. Instead of poaching, the high-productivity firms switch to posting vacancies. The share of high-productivity firms among the posted vacancies is counter-cyclical. If the vacancies posted by the high-productivity firms are more likely to include some skill requirements than the vacancies posted by low-productivity firms, the skill requirements are counter-cyclical.[20] In the model, the share of high-productivity firms among the posted vacancies is strongly counter-cyclical, consistent with the empirical findings. The impulse responses of the share of high-productivity vacancies to a negative aggregate shock is presented on the left panels of Figure 12. As it can be seen from the figures, the share of top vacancies is counter-cyclical in the model with two channels. The model with one channel features acyclical share as it is determined by an exogenous productivity draw and does not respond to shocks.

Another important implication of pro-cyclical poaching is the cyclicality of implied recruiting intensity. Davis, Faberman and Haltiwanger (2013) find that implied recruit-

[19] Choi, Figueroa and Villena-Roldán (2020) also find counter-cyclical skill requirements in Chile.

[20] Assuming that the firms that actively poach workers do not advertise the position for which they are poaching.



(a) Productivity shock

(b) Separation shock

(c) Discount factor shock

Figure 12: Implications of poaching

ing intensity is strongly pro-cyclical in the data. In the model, there are two factors affecting the implied recruiting intensity. First, poaching delivers a higher job-filling rate. When poaching is high, the average job-filling rate is also high even for the same number of unemployed and employed job seekers and vacancies posted. Therefore, cyclicality of poaching translates to the cyclicality of implied recruiter intensity. Second, the cyclicality of on-the-job search is attributed to the cyclicality of implied recruiting intensity. Because active on-the-job search is counter-cyclical, the implied recruiting intensity from unemployment is pro-cyclical. As it can be seen from the middle panels of Figure 12[21],

[21] I compute the implied recruiting intensity as the ratio of hires from unemployment to a standard matching function including only unemployment:

$$Q_t = \left(\frac{u_L f_V + u_H \left(f_H + (1 - f_H) f_V \right)}{\chi u^{\alpha} v_V^{1-\alpha}} \right)^{\frac{1}{1-\alpha}}.$$

only the model with two channels and active on-the-job search is able to generate strong pro-cyclicality of implied recruiting intensity. The model with one channel and active on-the-job search generates a strongly counter-cyclical implied recruiting intensity. In this model, on-the-job search is pro-cyclical and the crowding out of unemployed decreases in recessions implying that the recruiting intensity from unemployment increases.

Finally, cyclicality of poaching also has implications for the cyclicality of the job ladder. Haltiwanger et al. (2018) show that the job ladder is pro-cyclical. They find that the probability of a worker moving up the job ladder falls by 40% during recessions. In the model, most of the moves up the job ladder are made by workers being poached by high-productivity firms. There are only few high-productivity firms that hire through the standard channel, so that the probability to move up the job ladder through the standard channel is rather small. Because the poaching drops during a recession, the probability of moving up the job ladder is also decreasing. A higher number of high-productivity vacancies posted does not compensate for the lower poaching. The right panels of Figure 12 present the probability of moving up the job ladder in different versions of the model.[22] Both the model with one and two channels generate a pro-cyclical job ladder. The reasons behind, however, are very different. The model with two channels generates a pro-cyclical job ladder due to the response of poaching by firms. The effect is present with or without the active on-the-job search reaction. The model with one channel, instead, generates the pro-cyclical job ladder due to a pro-cyclical active on-the-job search.

As shown in this section, the three empirical facts would not be matched by a model with one channel under standard assumptions. The model with one channel is able to match the pro-cyclicality of the job ladder but fails to reproduce the other two features of the data.

5 Cross-state Evidence

In this section I analyze how the labor market dynamics in different U.S. states depend on the enforceability of the non-compete agreements and compare it to the predictions of the model. I use the state-level unemployment rates from BLS and non-compete enforceability index (NCEI) from Starr (2019).

[22] The probability of moving up the job ladder in the model is computed as the probability of a high-skilled worker moving from a low- to a high-productivity firm within a period.

Figure 13 plots the state-level volatility of unemployment against the NCEI.[23] The two are positively correlated.[24] The states with a higher enforceability on average exhibit a higher volatility of unemployment. One can interpret this correlation through the lens of the model presented in this paper in the following way. Stronger enforceability of non-compete agreements makes it more difficult and costly for firms to poach workers. A higher poaching cost means that more firms will switch to the standard channel when a negative shock hits the economy. Because more firms switch to the standard channel, more employed workers find it profitable to start searching actively. Because more employed workers search actively, the crowding out of unemployed workers is stronger and unemployment reacts more to aggregate shocks. Volatility of unemployment increases.

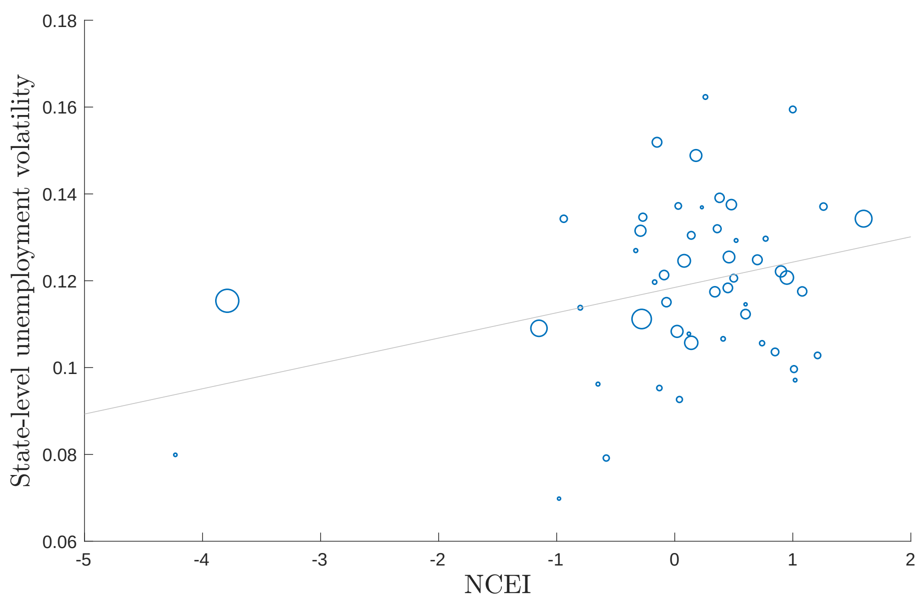


Figure 13: NCEI and unemployment volatility by state

Figure 14 studies the behavior of unemployment in different states during the Great Recession. It plots the maximum increase of unemployment during the Great Recession relative to the pre-recession level in each state against the NCEI. Again, there is a positive correlation. The states with a higher NCEI saw a larger increase of unemployment during the Great Recession. A higher NCEI implies a higher cost of poaching, a stronger reaction of search strategies and results in a larger crowding out of unemployed workers.

To show the effect of NCEI more formally, I regress the state-level unemployment volatility or the increase in unemployment during the Great Recession on NCEI control-

[23] One circle is one state and the size of the circle is proportional to the state labor force.

[24] It is robust to excluding the outliers - California and North Dakota

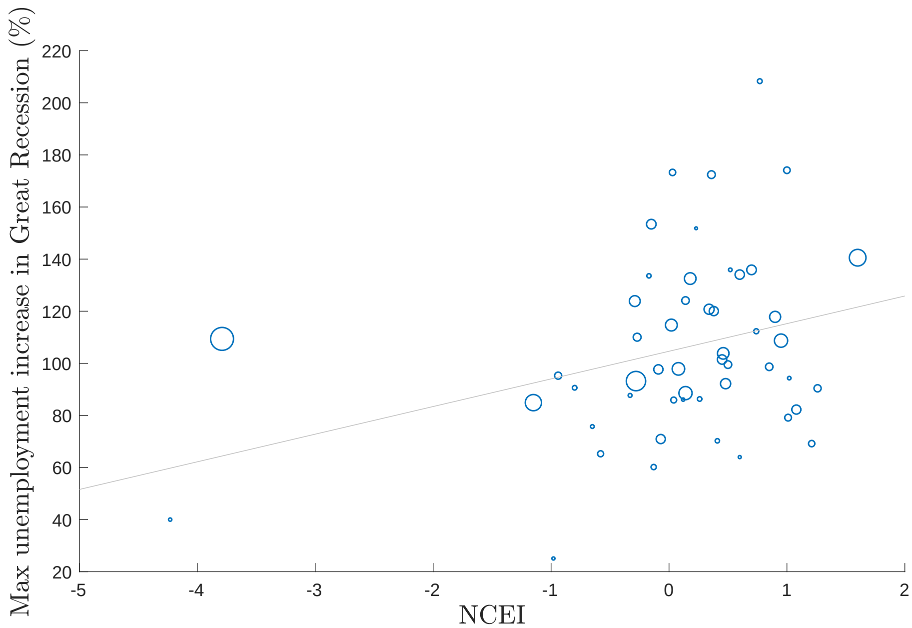


Figure 14: NCEI and maximum unemployment increase during the Great Recession

ling for the size of the state (measured by the labor force) and the average unemployment. The results are presented in Table 4. The first three columns present the results for the log of unemployment volatility and the last three columns present the results for the log of the increase in unemployment during the Great Recession. NCEI has a positive and significant coefficient in all specifications.

To illustrate that the mechanism also works in the model, I vary the fixed cost of poaching, $\overline{c_{fH}}$, and compare the impulse responses of the model. The fixed cost of poaching is the relevant cost for measuring the non-compete agreements enforceability as the enforceability in the state affects all firms equally. Enforceability of the non-compete agreements is determined by the laws and legal framework of each state so all firms in the state should be exposed to the associated constraints similarly. Therefore, the firms in the states with a higher NCEI have a higher fixed cost of poaching. Figure 15 plots the impulse responses of key variables to a productivity shock for different values of the poaching cost. It is evident that a higher cost is associated with a stronger reaction of output, unemployment and vacancies. Importantly, a higher cost is also associated with a more persistent increase in unemployment. This amplification comes from a stronger reaction of firms to a negative shock. Because the fixed cost is higher, more firms switch to the cheaper channel after a negative aggregate shock. Because more firms switch, more employed workers also switch to the standard channel and crowding out of unemployed increases.

A higher sensitivity of firms' strategy with a higher fixed poaching cost requires certain

	Log volatility			Log increase during GR		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-2.1475	-1.9461	-2.1688	4.5884	5.0654	5.3238
	(0.0227)	(0.0973)	(0.3201)	(0.0482)	(0.2043)	(0.6746)
NCEI	0.0561	0.0556	0.0553	0.1322	0.1310	0.1313
	(0.0221)	(0.0214)	(0.0215)	(0.0470)	(0.0448)	(0.0453)
Log labor force	-	0.0455	0.0504	-	0.1077	0.1020
		(0.0214)	(0.0226)		(0.0449)	(0.0475)
Log unemployment	-	-	-0.0863	-	-	0.1001
			(0.1181)			(0.2489)
R^2	0.12	0.19	0.20	0.14	0.23	0.23
Number of observations	51	51	51	51	51	51

Table 4: Effect of NCEI on state-level unemployment volatility and unemployment increase during the Great Recession

assumptions for the distribution of the idiosyncratic poaching costs. In order to generate this result, the CDF of the distribution of idiosyncratic costs must be concave in the relevant region (for example, a Pareto distribution). An increase in the fixed cost shifts the distribution of the total cost to the right. Such shift moves the threshold idiosyncratic cost to the left. Due to the concavity of the CDF, the slope of the CDF will be higher at the new intercept (and the average number of firms poaching will be lower). Because of the higher slope, an aggregate shock that moves the idiosyncratic cost threshold by the same amount would affect the share of poaching firms by more ensuring higher sensitivity. In the baseline calibration, however, the distribution of the idiosyncratic costs is uniform, featuring a CDF with a constant slope. To achieve the change in the sensitivity, I recalibrate the variable cost of poaching to keep the steady-state share of the poaching firms constant. This changes the slope of the CDF artificially. This assumption is made both to simplify the computations and to assure that the slope of the CDF is the only parameter that changes while comparing the responses of the model. This helps to isolate the effect of the sensitivity from the effect of the average reliance of poaching. In general, the concavity of the CDF of the cost distribution seems like a natural assumption. Therefore, the results presented here are not the artifact of the particular choice of cost structure.

Figures D.3 and D.4 in the Appendix show similar results for a negative separation and discount factor shocks, respectively. A higher cost is associated with a stronger and more

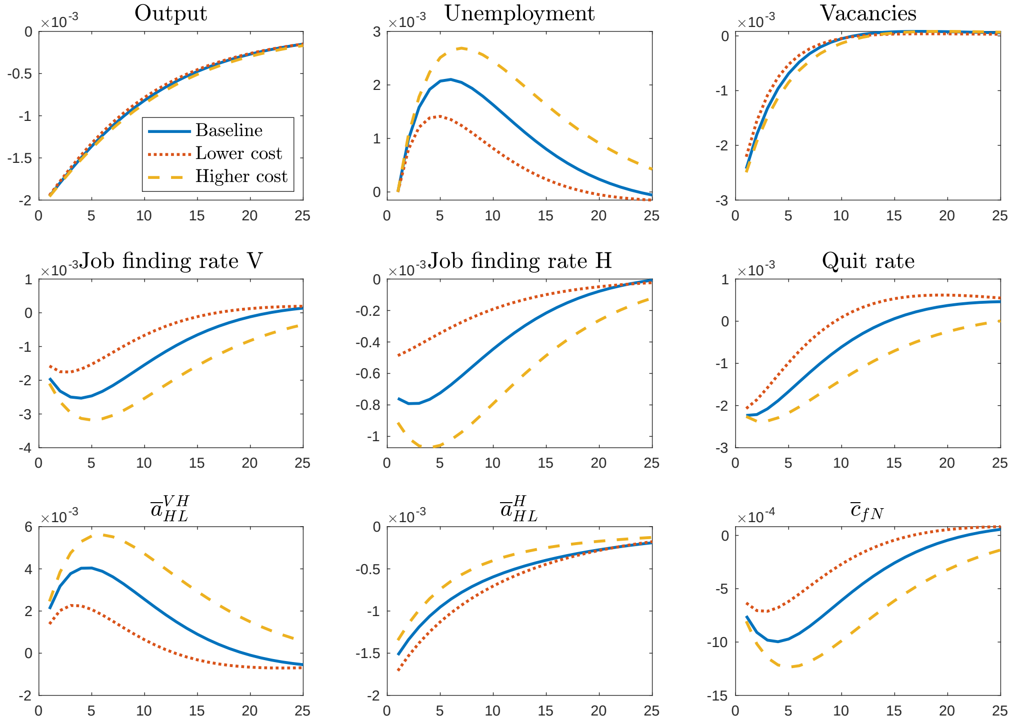


Figure 15: Sensitivity to poaching cost, productivity shock

persistent response of output and unemployment. This effect is generated by a stronger and more persistent reaction of firms' and workers' decisions. These results show that the states where the fixed cost of poaching is higher should experience larger increases in unemployment during recessions and higher volatility of unemployment in general.

6 Conclusion

I show that introducing the worker poaching by firms and the resulting passive search by workers into a relatively standard random matching model of the labor market generates amplification and propagation of aggregate shocks. In response to a negative aggregate shock, firms change their hiring strategy towards the cheaper standard option. Because the standard option also brings a lower gain, the aggregate hiring decreases by more than if there was just one channel. In response to lower poaching, employed workers choose to search more actively and crowd out the unemployed workers from the standard channel. The job finding rate drops by more and stays lower longer because more workers get stuck in low-productivity jobs and so continue searching actively on-the-job.

I calibrate the model to the U.S. economy and show that the mechanism generates 2-8 times increase in the response of unemployment and 25-33% increase in the persistence of the response. The major part of this effect comes from the adjustment of the active on-the-job search. The model with two channels also generates a counter-cyclical behavior of implied on-the-job search explaining such behavior in the data.

References

Ahn, Hie Joo, and Ling Shao. 2020. "The Cyclicality of On-the-Job Search Effort." *The BE Journal of Macroeconomics*, 1(ahead-of-print).

Braun, Christine. 2020. "Look Who's Searching: Revisiting the Stocks and Flows of the Labor Market." *Unpublished manuscript*.

Carrillo-Tudela, Carlos, Bart Hobijn, Patryk Perkowski, Ludo Visschers, et al. 2015. "Majority of hires never report looking for a job." *FRBSF Economic Letter*, 10.

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

Choi, Sekyu, Nincen Figueroa, and Benjamin Villena-Roldán. 2020. "Wage Cyclicality Revisited: The Role of Hiring Standards."

Davis, Steven J, R Jason Faberman, and John C Haltiwanger. 2013. "The establishment-level behavior of vacancies and hiring." *The Quarterly Journal of Economics*, 128(2): 581–622.

Eeckhout, Jan, and Ilse Lindenlaub. 2019. "Unemployment cycles." *American Economic Journal: Macroeconomics*, 11(4): 175–234.

Faberman, R. Jason, Andreas I. Mueller, Ayşegül Şahin, and Giorgio Topa. 2021. "Job Search Behavior among the Employed and Non-Employed." .

Gertler, Mark, and Antonella Trigari. 2009. "Unemployment fluctuations with staggered Nash wage bargaining." *Journal of political Economy*, 117(1): 38–86.

Gertler, Mark, Christopher Huckfeldt, and Antonella Trigari. 2020. "Unemployment fluctuations, match quality, and the wage cyclicality of new hires." *The Review of Economic Studies*, 87(4): 1876–1914.

Gorn, Alexey. 2021. "The role of headhunters in wage inequality: It's all about matching." *Review of Economic Dynamics*, 40: 309–346.

Hagedorn, Marcus, and Iourii Manovskii. 2008. "The cyclical behavior of equilibrium unemployment and vacancies revisited." *American Economic Review*, 98(4): 1692–1706.

Hagedorn, Marcus, Fatih Karahan, Iourii Manovskii, and Kurt Mitman. 2016. "Unemployment benefits and unemployment in the great recession: the role of macro effects." National Bureau of Economic Research.

Hall, Robert E. 2005. "Employment fluctuations with equilibrium wage stickiness." *American economic review*, 95(1): 50–65.

Haltiwanger, John C, Henry R Hyatt, Lisa B Kahn, and Erika McEntarfer. 2018. "Cyclical job ladders by firm size and firm wage." *American Economic Journal: Macroeconomics*, 10(2): 52–85.

Hershbein, Brad, and Lisa B Kahn. 2018. "Do recessions accelerate routine-biased technological change? Evidence from vacancy postings." *American Economic Review*, 108(7): 1737–72.

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

Modestino, Alicia Sasser, Daniel Shoag, and Joshua Ballance. 2019. "Upskilling: do employers demand greater skill when workers are plentiful?" *Review of Economics and Statistics*, 1–46.

Moscarini, Giuseppe, and Fabien Postel-Vinay. 2018. "On the Job Search and Business Cycles." .

Mukoyama, Toshihiko, Christina Patterson, and Ayşegül Şahin. 2018. "Job search behavior over the business cycle." *American Economic Journal: Macroeconomics*, 10(1): 190–215.

Shimer, Robert. 2005. "The cyclical behavior of equilibrium unemployment and vacancies." *American economic review*, 95(1): 25–49.

Starr, Evan. 2019. "Consider this: Training, wages, and the enforceability of covenants not to compete." *ILR Review*, 72(4): 783–817.

Valletta, Robert G. 2016. "Recent Flattening in the Higher Education Wage Premium: Polarization, Skill Downgrading, or Both?" IZA Discussion Papers.

A Data

In my analysis, I keep only workers employed full-time, with only one job and not self-employed in the sample. I construct a measure of the annual wage for each worker given the information provided, weekly or hourly wages and weeks and hours worked. I drop outliers and clear coding errors, for example, weekly wages likely reported as hourly. I use the following variables: L1a, L2a, L4, L10, L11, JS14, JS15, JS16, JS17a, JS18, JS19, and JS23.

Table A.1 reports the results by year of the study. Unfortunately, the sample is too small and the results are too noisy to draw any conclusion.

	Share (%)						
Sample	Applied	Contacted	Uns Cont	Referral	Offer	Accepted	Acc*Uns
2013	17.92	22.78	15.75	9.55	6.53	1.84	0.34
2014	17.42	27.25	21.31	9.84	9.02	2.66	0.82
2015	18.49	22.83	16.89	9.13	7.76	2.74	1.37
2016	18.75	24.58	17.92	8.13	5.00	1.67	0.63
2017	14.35	22.30	17.00	7.28	9.49	2.65	0.88
	Conditional Average						
2013	5.3178	2.8529	2.1103	0.9118	1.2564		
2014	7.2000	2.9248	2.3835	0.5113	1.4091		
2015	5.8642	2.6700	1.9200	0.6400	1.7941		
2016	4.2889	2.3983	1.7458	0.4576	1.5417		
2017	3.8769	4.3168	2.5149	0.5446	3.3023		

Table A.1: Results by year

B Additional Model Equations Used in the Solution

It is convenient to derive explicit equations for the search thresholds. First, to derive the threshold of passive search, $\bar{a}^H_{HL}$, one can use the optimality condition (9) and the expressions for the value of search and the value of work:

$$\begin{aligned} S_{EH}\left(e_H, p_L, \overline{a}^H_{HL}, \Omega\right) &= 0 \\ f_H\left(\theta_H\right)\left(\left[W\left(e_H, p_H, \Omega\right) - W\left(e_H, p_L, \overline{a}^H_{HL}, \Omega\right)\right] - c_{wH}\right) &= 0 \\ W\left(e_H, p_H, \Omega\right) - \overline{a}^H_{HL} \cdot z\left(\Omega\right) \cdot w\left(e_H, p_L\right) & \\ -c_{wH} - \beta\left(\Omega\right) E\left\{s\left(\Omega\right) U\left(e_H, \Omega'\right)\right. & \\ \left. + \left(1 - s\left(\Omega\right)\right)\left(W\left(e_H, p_L, a', \Omega'\right) + S_E\left(e_H, p_L, a', \Omega'\right)\right)\right\} &= 0 \end{aligned}$$

Solving for $\overline{a}^H_{HL}$:

$$\begin{aligned} \overline{a}^H_{HL} = \; & \frac{1}{z(\Omega)\cdot w(e_H, p_L)} \cdot \Bigg(W\left(e_H, p_H, \Omega\right) - c_{wH} - \\ & \beta\left(\Omega\right) E\left\{s\left(\Omega\right) U\left(e_H, \Omega'\right)\right. \\ & \left. + \left(1 - s\left(\Omega\right)\right)\left(W\left(e_H, p_L, a', \Omega'\right) + S_E\left(e_H, p_L, a', \Omega'\right)\right)\right\}\Bigg) \end{aligned}$$

One can derive the active search threshold, $\overline{a}^{VH}_{HL}$, in a similar way using the fact that workers on the threshold accept only matches with high-productivity firms.Resulting $\overline{a}^{VH}_{HL}$ is:

$$\begin{aligned} \overline{a}^{VH}_{HL} = \; & \frac{1}{z(\Omega)\cdot w(e_H, p_L)} \cdot \Bigg(W\left(e_H, p_H, \Omega\right) - \frac{c_{wV}}{f_V(\theta_V)(1 - f_H(\theta_H))\frac{v^{VH}}{v}} - \\ & \beta\left(\Omega\right) E\left\{s\left(\Omega\right) U\left(e_H, \Omega'\right)\right. \\ & \left. + \left(1 - s\left(\Omega\right)\right)\left(W\left(e_H, p_L, a', \Omega'\right) + S_E\left(e_H, p_L, a', \Omega'\right)\right)\right\}\Bigg) \end{aligned}$$

As before, $\overline{a}^{VH-}_{HL} = \min\left\{\overline{a}, \overline{a}^{VH}_{HL}\right\}$.

Using the distributions and workers' decisions, the expected value of search can be written as:

$$\begin{aligned} & E_a S_E\left(e_H, p_L, a, \Omega\right) = \\ & f_H\left(\theta_H\right)\left(W\left(e_H, p_H, \Omega\right) - W\left(e_H, p_L, \overline{a}, \Omega\right) - w\left(e_H, p_L\right) z\left(\Omega\right)\left(\frac{\overline{a}^H + \underline{a}}{2} - \overline{a}\right) - c_{wH}\right) \cdot \\ & \left(\overline{a}^H - \underline{a}\right) + f_V\left(\theta_V\right)\left(1 - f_H\left(\theta_H\right)\right)\frac{v^{VL}}{v}\left[w\left(e_H, p_L\right) z\left(\Omega\right)\left(\overline{a} - \frac{\overline{a} + \underline{a}}{2}\right)\right]\left(\overline{a} - \underline{a}\right) + \\ & f_V\left(\theta_V\right)\left(1 - f_H\left(\theta_H\right)\right)\frac{v^{VH}}{v} \cdot \\ & \left[W\left(e_H, p_H, \overline{a}, \Omega\right) - W\left(e_H, p_L, \overline{a}, \Omega\right) - w\left(e_H, p_L\right) z\left(\Omega\right)\left(\frac{\overline{a}^{VH} + \underline{a}}{2} - \overline{a}\right)\right]\left(\overline{a}^{VH} - \underline{a}\right) \\ & -c_{wV}\left(\overline{a}^{VH} - \underline{a}\right) \end{aligned}$$

And the average quit rate as:

$$\begin{aligned} s_Q = \; & f_V\left(\theta_V\right)\left(1 - f_H\left(\theta_H\right)\right)\left(\overline{a} - \underline{a}\right) \\ & + f_V\left(\theta_V\right)\left(1 - f_H\left(\theta_H\right)\right)\frac{v^{VH}}{v}\left(\overline{a}^{VH} - \underline{a}\right) + f_H\left(\theta_H\right)\left(\overline{a}^H - \underline{a}\right) \end{aligned}$$

I can also explicitly derive the poaching cost threshold from (5):

$$\overline{c_{fN}} = \frac{1}{c_{fH}} \cdot \Bigg(-\overline{c_{fH}} + q_H(\theta_H) J(p_H, e_H, \Omega) - \\ q_V(\theta_V) \left[\frac{\lambda^{HL} + u^H}{s^V} (1 - f_H(\theta_H)) J(p_H, e_H, \Omega) + \frac{u^L}{s^V} J(p_H, e_L, \Omega) \right] \Bigg)$$

To compute the free-entry condition, define $VH(c)$ as the vacancy value for poaching firms as a function of the cost:

$$VH(c) = -\left(c_{fV} + \overline{c_{fH}} + c \cdot c_{fH}\right) + q_H(\theta_H) J(p_H, e_H, \Omega)$$

$$\int_0^{\overline{c_{fN}}} VH(c) \frac{1}{\overline{c_{fN}}} dc = \int_0^{\overline{c_{fN}}} \left[q_H(\theta_H) J(p_H, e_H, \Omega) - \left(c_{fV} + \overline{c_{fH}} + c \cdot c_{fH}\right) \right] \frac{1}{\overline{c_{fN}}} dc$$

$$\int_0^{\overline{c_{fN}}} VH(c) \frac{1}{\overline{c_{fN}}} dc = q_H(\theta_H) J(p_H, e_H, \Omega) - \left(c_{fV} + \overline{c_{fH}} + \frac{\overline{c_{fN}}}{2} \cdot c_{fH} \right)$$

The free-entry condition can be written as:

$$F_L V_V(p_L, \Omega) + F_H \left[\left(1 - \overline{c_{fN}}\right) V_V(p_H, \Omega) + \overline{c_{fN}} \int_0^{\overline{c_{fN}}} VH(c) \frac{1}{\overline{c_{fN}}} dc \right] = \overline{F}$$

C Model with One Channel

C.1 Firms

The values of a vacancy and a job simplify to:

$$V_V(p, \Omega) = -c_{fV}(p) + q_V(\theta_V) E_{e,a|V} \{P(A) J(p, e, a, \Omega)\}$$

$$J(p, e, a, \Omega) = a \cdot z(\Omega) \cdot (y(e, p) - w(e, p)) \\ + \beta(\Omega) E \left\{ \left(1 - s_Q(.)\right) (1 - s(\Omega)) J(p, e, a', \Omega') \right\}$$

C.2 Workers

The workers' value functions simplify to:

$$U(e, \Omega) = b(e) + \beta(\Omega) E\left\{ U\left(e, \Omega'\right) + S_U\left(e, \Omega'\right) \right\}$$

$$W(e, p, a, \Omega) = a \cdot z(\Omega) \cdot w(e, p) + \\ \beta(\Omega) E\{s(\Omega) U(e, \Omega') \\ + (1 - s(\Omega)) (W(e, p, a', \Omega') + S_E(e, p, a', \Omega'))\}$$

$$S_U(e,\Omega) = \max\{S_{UV}(e,\Omega), 0\} = S_{UV}(e,\Omega)$$

$$S_{UV}(e,\Omega) \equiv f_V(\theta_V) E_{p,a|V}\{\max\{W(e,p,a,\Omega) - U(e,\Omega), 0\}\}$$

$$S_E(e,p,a,\Omega) = \max\{S_{EV}(e,p,a,\Omega), 0\}$$

$$S_{EV}(e,p,a,\Omega) \equiv \quad f_V(\theta_V) E_{p',a'|V}\{\max\{W(e,p',a',\Omega) - W(e,p,a,\Omega), 0\}\} - c_{wV}$$

C.3 Distributions

The laws of motion for the distribution are:

$$\phi'_{LL} = \phi_{LL}(1 - s(\Omega)) + u_L f_V(\theta_V) \frac{v_{VL}}{v_V}$$

$$\phi'_{LH} = \phi_{LH}(1 - s(\Omega)) + u_L f_V(\theta_V) \frac{v_{VH}}{v_V}$$

$$\phi'_{HL} = \phi_{HL}(1 - s(\Omega))\left(1 - s_Q\right) + u_H f_V(\theta_V) \frac{v_{VL}}{v_V} + \lambda^{V-}_{HL} f_V(\theta_V) \frac{v_{VL}}{v_V}$$

$$\phi'_{HH} = \phi_{HH}(1 - s(\Omega)) + u_H f_V(\theta_V) \frac{v_{VH}}{v_V} + \lambda^{V}_{HL} f_V(\theta_V) \frac{v_{VH}}{v_V}$$

with

$$\lambda^V_{HL} = \phi_{HL} P\left(a < \overline{a}^V_{HL}\right)(1 - s(\Omega))$$
$$\lambda^{V-}_{HL} = \phi_{HL} P\left(a < \overline{a}^{V-}_{HL}\right)(1 - s(\Omega))$$

The search threshold, $\overline{a}^{VH}_{HL}$, is defined from:

$$S_{EV}\left(e_H, p_L, \overline{a}^{VH}_{HL}, \Omega\right) = 0$$

and $\overline{a}^{V-}_{HL}$ from:

$$W(e_H, p_L, \overline{a}, \Omega) = W\left(e_H, p_L, \overline{a}^{VH-}_{HL}, \Omega\right)$$

Number of vacancies:

$$v_V = vF_H + vF_L$$

$$v_{VH} = vF_H$$

$$v_{VL} = vF_L$$

D Additional Figures

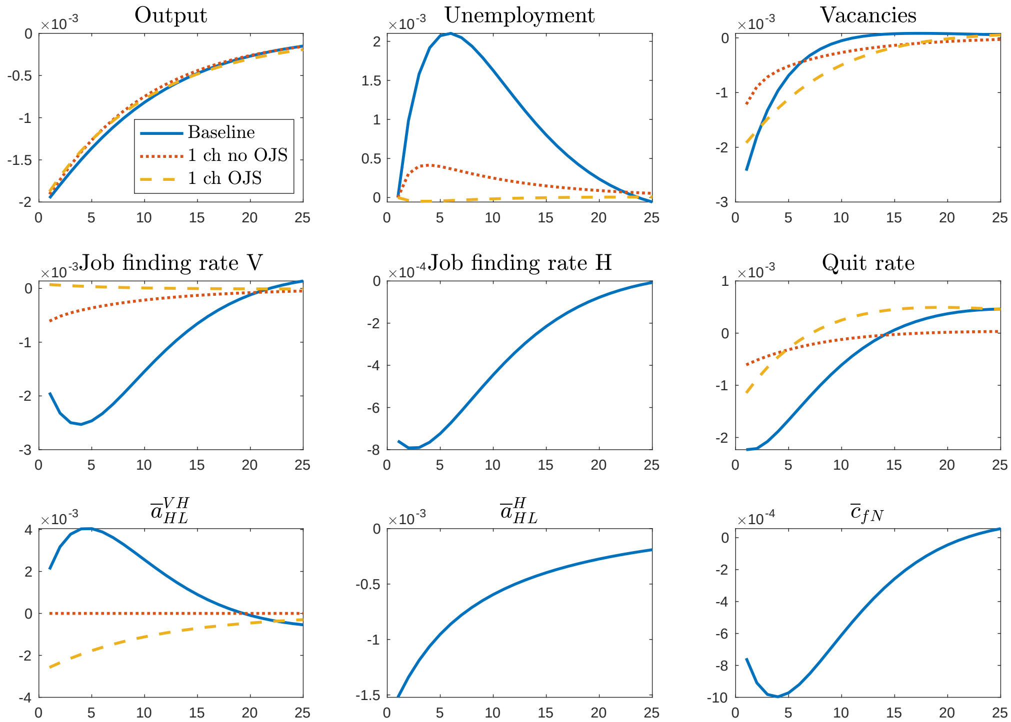


Figure D.1: Impulse responses, productivity shock

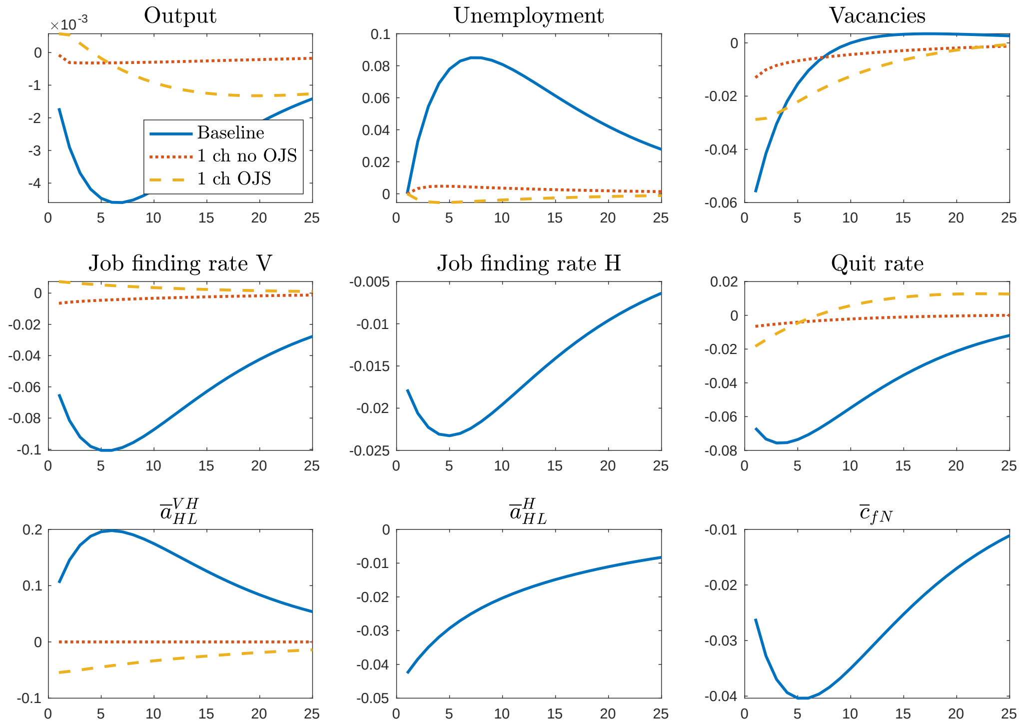


Figure D.2: Impulse responses, discount factor shock

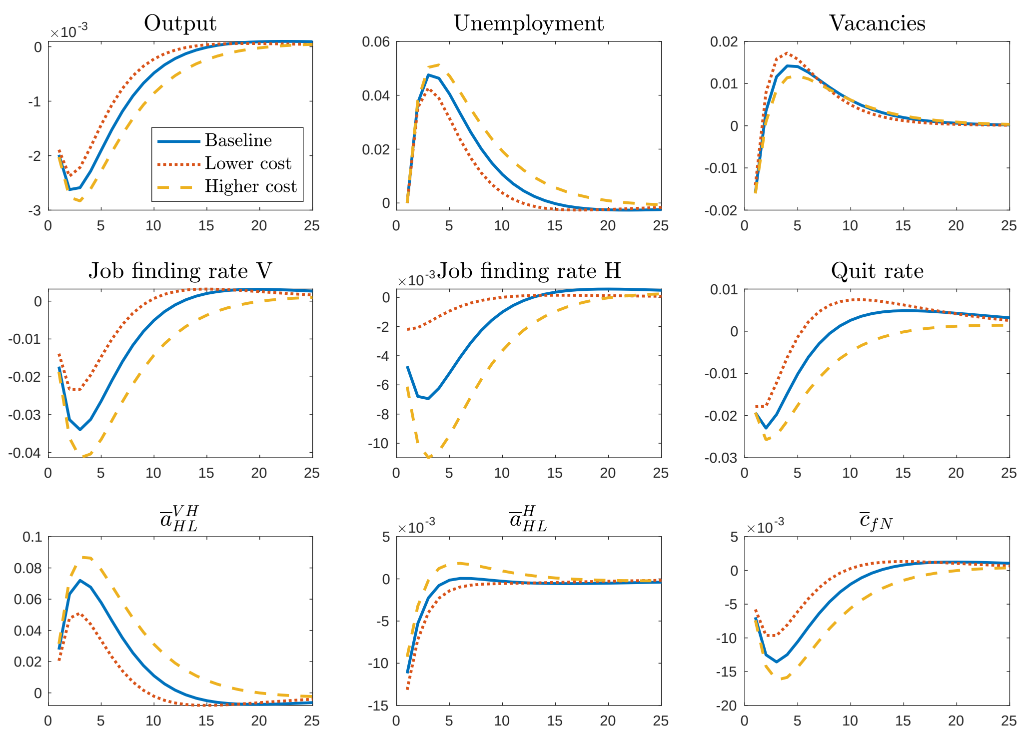


Figure D.3: Sensitivity to poaching cost, separation shock

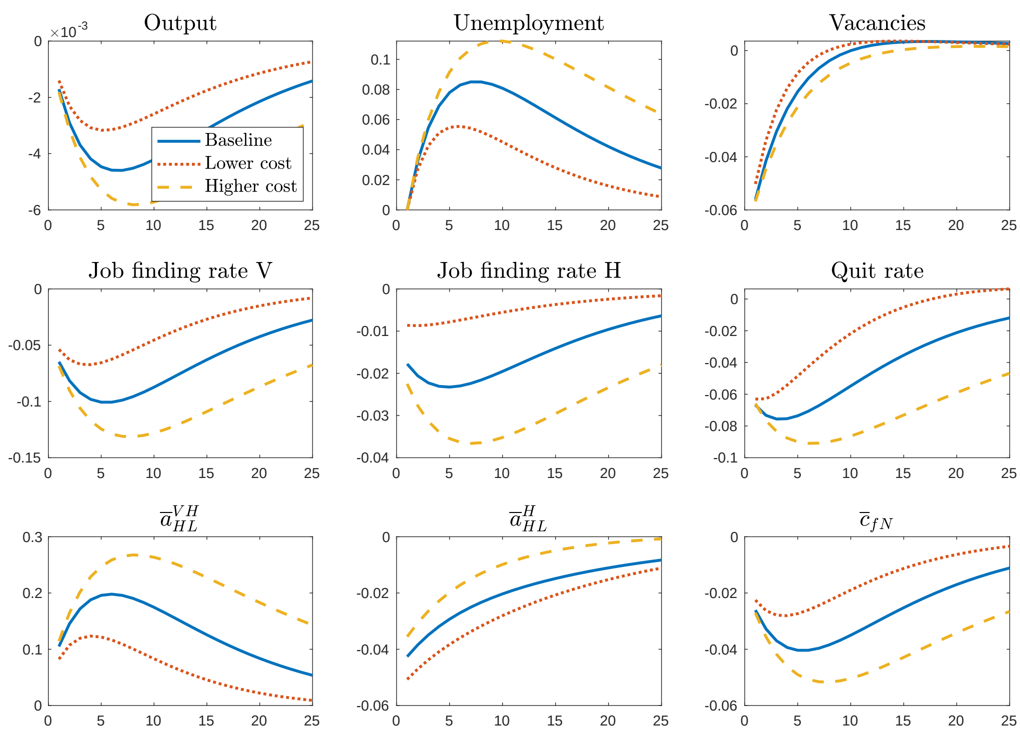


Figure D.4: Sensitivity to poaching cost, discount factor shock