Aggregate Labor Market Dynamics and Micro Behavior: A Data-Driven Perspective

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Abstract

Whether driven by recessions, industrial policy, or structural shifts in labor demand, economic change is inevitably accompanied by labor market frictions. These frictions vary across occupations, increasing the risk of certain groups of workers being left behind in times of economic transformation. Such challenges to labor market stability are often studied as exogenous shocks, taking the preferences and actions of workers to be fixed or negligible. However, incorporating the adaptive behavior of workers in the labor market to cope with uncertainty is critical to understanding both aggregate labor market fluctuations and adverse labor market outcomes related to wage and unemployment duration. We extend a leading data-driven network model of occupational mobility by embedding empirically grounded dynamics in search effort, reservation wages, belief updating, and competition-reactive on-the-job search, grounded in U.S. micro data. By incorporating a more comprehensive representation of worker decision-making, we enable a deeper exploration of critical labor market phenomena, including long-term unemployment dynamics, gender wage disparities, and the uneven distribution of wage gains during periods of economic recovery.

1 Introduction

1.1 Motivation

Periods of economic change, driven by recessions, technological disruptions, industrial policy, or structural shifts in labor demand, require workers to relocate across jobs and occupations. Whether labor markets absorb these shocks smoothly or instead generate persistent unemployment, slow recoveries, uneven re-employment timelines, and unequal wage outcomes depends critically on how workers search for jobs and compete for vacancies [34, 77, 91, 46].

Consider, for instance, an individual who has recently been laid off and embarks on a job search process. They likely start by setting a reservation wage similar to their previously held wage, primarily explore vacancies well-suited to their skill-sets through known search channels, and preferably entertain the possibility of a more optimal match than the role they were separated from. As unemployment persists and signals from the market accumulate, through rejections, missed interviews, or a lack of offers, job-seekers adjust their behavior. They could take constructive action, increasing search effort and casting a wider net to consider jobs less similar to their former one [71, 66, 55, 59]. They could reassess their chosen trade-off between wage expectations and re-employment probability [11, 2, 12]. In the most extreme cases, emotional affect and psychological pressure from repeated failure might bring workers to restrict their search effort as their expected gains from search drop below search costs [3, 7, 48, 66].

These are not negligible behavioral facts, but rather a feature of the adjustment process itself, with recent work finding these behavioral regularities to be both constructive and obstructive to aggregate labor market adjustment [77, 34]. These adjustments also reflect learning, reference dependence, and responses to uncertainty, and they differ markedly across individuals. A growing empirical literature supports this picture, finding that job search unfolds gradually.[1] Workers adapt their effort and wage expectations over the unemployment spell, and competition for jobs changes over the business cycle as employed workers enter and exit the market.

Nonetheless, though canonical search-and-matching models provide a tractable equilibrium framework for labor market adjustment, they often treat search behavior as fixed or fully optimized under rational expectations and represent wages through bargaining rules that adjust smoothly with aggregate conditions. These simplifications can make it harder to capture the aggregate impacts of gradual learning over the unemployment spell, changing competition (including on-the-job search), and reallocation across occupational structures. In turn, they can obscure how decentralized search decisions and evolving competitive pressures shape employment recovery pathways after shocks to or fluctuations in labor demand.

As a result, existing frameworks struggle to jointly account for several empirical facts: strong duration dependence in unemployment exits, persistent long-term unemployment following shocks, the loosening of the vacancy–unemployment relationship during recoveries, and heterogeneous wage losses after displacement [48, 75, 93, 17, 21, 71, 66, 2, 24, 90, 55, 67, 12]. Capturing these patterns requires models in which adaptation is a core mechanism through which shocks propagate and persist, linking individual search behavior to both aggregate fluctuations and distributional consequences.

Altogether, this suggests that incorporating adaptive job search behavior into labor market models is a natural next step to reconcile the asymmetry between the literature from behavioral labor economics and labor market modeling. Responding to this need, this work proposes a method for incorporating data-driven behavioral micro foundations to enrich labor market models in their ability to match micro moments and distributions that comprise aggregate macro series such as unemployment and vacancy rates.

1.2 Methodological Approach

The puzzle at hand is not whether job search behavior matters when modeling aggregate labor market outcomes, this is well established empirically. Rather, the outstanding question is how best to incorporate this insight into labor market models to ensure that they reflect the reality of slow and uneven re-employment across the business cycle. Therefore, this paper develops a data-disciplined framework to study labor market adjustment in which job search behavior is adaptive, heterogeneous, and embedded in an occupational network, and in which aggregate shocks propagate through decentralized individual searches rather than equilibrium reallocation.

More specifically, we ask whether empirically grounded behavioral search rules - specifically, slow (concave) updating of subjective job-finding beliefs, duration-dependent reservation wages and search effort, and cyclical on-the-job (OTJ) search - can jointly account for observed unemployment dynamics, vacancy-unemployment decoupling, and unequal labor market outcomes over the business cycle. Our approach is deliberately comparative: we evaluate what is gained by introducing behavioral dynamics relative to models in which search behavior is fixed, when subjected to similar forces of occupational restructuring and aggregate demand forces.

To accommodate these behavioral mechanisms, we adopt an agent-based modeling approach in which micro decisions produce macro realities, rather than abstracting from the processes of labor market

[1] A large empirical literature documents that job search is a dynamic process of learning and adaptation. Job-seekers revise beliefs about callback and offer probabilities only gradually [93, 75, 2], and react to rejections or uncertainty (discouragement, loss aversion) via their expended search effort [48, 75, 93, 17, 21, 71, 66]. Reservation wages decline slowly with duration and income losses [57, 62, 30, 50] and search effort varies over the unemployment spell and over the business cycle [56, 55, 37, 100, 67]. At the same time, job-to-job transitions and on-the-job search play a central role in reallocation [49, 38], intensifying during recoveries and altering competition for vacancies faced by the unemployed [34, 10].

churn. Agent-based modeling (ABM) is well suited to this task by accommodating heterogeneous agents, adaptive rules [88, 4, 86], and out-of-equilibrium interactions while generating macro regularities from micro behavior [22, 27, 63, 79].[2] Furthermore, we contribute to the growing field of data-driven agent-based models, tempered by real-world data rather than pure theory [81, 73].

Principally, we build on a leading data-driven model of occupational mobility [28] that represents the labor market as a network of occupations linked by empirically observed worker transition patterns. We extend this framework by micro-founding worker search behavior using empirically estimated relationships drawn from U.S. microdata. Workers differ by occupation-specific human capital, unemployment duration, and demographics. In each period, unemployed (and a subset of employed) agents choose an application bundle in line with reservation wages and desired effort over adjacent occupations. To account for the non-negligible influence of competition from employed job-seekers, employed agents endogenously (re-)enter the labor market in response to perceived competition, endogenously rising in recoveries and receding in downturns, so the composition of job-seekers shifts over the cycle. Additionally, we incorporate data on occupational wage distributions and microdata on duration-dependent reservation wage satisficing, to arrive at a micro-founded mechanism for potentially frictional wage preferences during periods of labor market adjustment.

Labor demand evolves with occupation-specific demand drawn from the evolution of value added across 19 US industries. Wages emerge from decentralized matching, evolving reservation wages, and endogenous competition across occupations rather than from Nash bargaining or market-clearing conditions. The model is calibrated and validated against both macro aggregates and micro moments (duration distributions, separation and hire rates, wage distributions) drawn from public use data.

As a complement, to illuminate the interactions between the micro-founded behavioral rules proposed, we also develop a simple model of job search under uncertainty in which workers hold subjective beliefs about job finding prospects that update concavely with experience. These beliefs jointly determine reservation wages and search effort. In the computational model, belief "updating" is implicit: we discipline effort and reservation wage rules directly with microdata because outcomes (applications, effort, wage expectations) are observed reliably. The formalization therefore clarifies the behavioral mechanisms underlying the empirical relationships we impose in the computational model, ensuring internal coherence between observed behavior and underlying learning dynamics.

1.3 Contributions

Our contributions are fourfold. **First**, we introduce empirically grounded behavioral search dynamics into a network-based labor market model, allowing search effort, wage expectations, and competition to evolve endogenously over the business cycle. We document how this adaptive search behavior and endogenous competition from on-the-job seekers interact with occupational structure to generate persistence in unemployment and heterogeneous wage outcomes following shocks without relying on ad hoc frictions, equilibrium selection, or mere occupational proximity. **Second**, the data basis for these incorporated behavioral rules suggest a concave shape of search effort and a duration-dependent downward pressure on reservation wages. These empirical contributions speak to two frequently cited puzzles in the behavioral labor economics literature regarding the dynamics of search effort and reservation wages [48, 17, 57, 52]. **Third**, we develop a calibration and validation pipeline that jointly targets micro moments and macro series, bridging reduced form job-search evidence and structural modeling. **Fourth**, we present a small behavioral framework that clarifies how learning and discouragement can generate

[2] Agent-based models (ABMs) have emerged as a useful tool for modeling labor market dynamics and macro-economic adjustment processes [22, 27, 63, 79]. Examples of applications include studies on the effect of structural reform policy on unemployment and income inequalities [31]; the relationship between employment protection legislation and unemployment with an endogenized institutional setting in which workers can vote to influence the employment protection legislation [69]; and an investigation of the effect of social networks on job market and upskilling effort [47]. They provide considerable flexibility in comparison to classical models by accommodating non-linearities, interactive or feedback effects, and behavioral heterogeneity [22]. Some notable examples include [31, 47, 85, 69, 5]. More broadly, agent-based modeling provides a useful vehicle through which to integrate insights from multiple disciplines beyond economics into our understanding of societal adaptation to change [88]. Indeed, agent-based modeling might provide one of the more straight-forward ways in which to do so as it requires incorporating insights from macro, meso, and micro level disciplines to understand the interactions between individuals, their networks, and the macro-economy they navigate [19, 70]. Furthermore, they provide a practical infrastructure for defining agent-specific behavioral rules though this potential has thus far been under-utilized [79].

the adaptive rules governing search effort and reservation wages used in the ABM. Albeit partial, it can be integrated into broader models of labor market adjustment.[3]

Our results demonstrate that embedding behavioral mechanisms - specifically, concave job-search effort, reservation wage satisficing, and learning dynamics - enhances the capacity of search models to replicate observed labor market fluctuations rather than merely matching the lowest order moments. By incorporating both unemployed and employed job-seekers alongside occupation-level heterogeneity, we better capture the cyclicality of effort, long-term unemployment dynamics, and post-displacement wage losses across the business cycle. These findings underscore the necessity of modeling competitive pressures and heterogeneity in search behavior to achieve empirically consistent and policy-relevant representations of labor market adjustment.

Furthermore, the behavioral rules endogenously produce cyclicality in search effort of employed and unemployed workers in relation to the business cycle, results that have been demonstrated empirically in other works [77, 34]. These dynamics arise endogenously from interactions between individual adaptation, occupational structure, and aggregate demand, rather than from imposed frictions or equilibrium selection. In addition, this work highlights the potential for over-fitting in calibrated macro models in the absence of more detailed behavioral agent rules. The model matches both aggregate fluctuations and the dispersion of outcomes across workers more closely than comparable models with static or fully rational search behavior. The framework additionally enables analysis of distributional outcomes such as gender wage disparities and the uneven distribution of wage gains during structural change within the same behavioral-network environment.[4]

1.4 Outline

In what follows, we present first, the underlying network model and agent behavior in Section 2; second, the methods and data employed for calibration in Section 3; third, an overview of validation exercises to assess model performance in Section 4. Fourth, in Section 5, we present a tractable theoretical framework representing the behavioral adjustments made to job search in the network model. Finally, Section 6 concludes with a discussion of the potential for this work to inform labor market modeling with greater simulation fidelity and an inventory of potential avenues for future research.

2 The Model

We describe the model by first outlining the non-seeker component of the labor market model (ie. vacancy creation, separation rates, and business cycle dynamics), followed by an explanation of the core behavioral additions which comprise majority of this work's novelty.

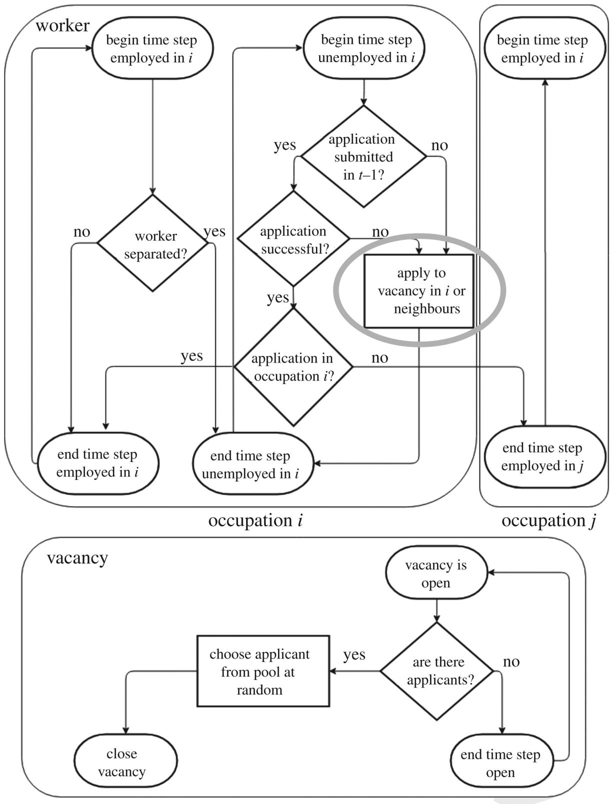
2.1 The Market

In this work, we expand del Rio-Chanona et al's occupational mobility network model to an agent-based framework [28]. The original model simulates the search-and-matching process of a labor market in which unemployed workers in various occupations search and fill available vacancies, akin to search-and-matching models proposed by other authors [83, 74]. The original execution of the model in del Rio-Chanona et al. is represented in Figure 1 below.

[3] An important yet often underexplored benefit of working with agent-based models is precisely the ability to incorporate more realistic behavioral rules into economic agents. This freedom naturally comes with the important responsibility on the modeller to ensure such behavioral rules are meticulously chosen, informed by data, and free of researcher bias. Therefore, we aim to demonstrate, wherever relevant, any non-data-driven (either due to a lack of data or purely theory-based justifications) decisions and suggestions for alternative approaches that merit testing as foils to the following approach.

[4] Heterogeneous preferences and constraints are also known to shape search strategies. Women and men differ in reservation wages, search radius, and job applications, with consequences for wages and timing of exit [19, 36, 61, 9, 44]. Location matters via mobility costs and local tightness [18, 68], while social networks affect the search channels used, reservation wages, and match quality [20, 45, 99]. Meta-analyses synthesize these patterns and emphasize dynamic, self-regulatory search and learning [92, 98]. These findings justify our heterogeneous state space and the distributional analyses we highlight though could be extended in further work.

Figure 1: Model Search and Matching Process



As shown in Figure 1, the central entities represented in the model are workers and vacancies. Workers have state variables for their current or latest held occupation, a record of the amount of time periods spent unemployed, their current or latest held wage, gender, and age. Vacancies have state variables for the relevant occupation and its wage distribution. All workers and vacancies are linked to occupations that represent nodes in a network A where edges are weighted by the revealed probability of transitioning between them. These transition probabilities are drawn from observed worker transitions as reported in US Current Population Survey using the methodology of [72, 28].

At each time step, occupations first set target labor demand, which determines desired employment levels for the period. Given these targets, separations occur as a subset of employed workers lose or leave their jobs, after which occupations open vacancies to close the gap between current and desired employment. Workers then search and submit applications to the set of open vacancies. Demographic turnover is captured next: older workers exit the labor market through retirement, while new entrants join by flowing into entry-level occupations. Finally, vacancies process their applicant pools and hire, updating employment and unemployment stocks going into the next period.

Target Demand To be more specific, first, target demand $d^{\dagger}_{i,t}$ reflects the desired employment level of occupation i at time t. Target demand for occupation i at time t is the product of a fixed baseline occupational demand $d^{\dagger}_{i}$ and sum of marginal occupational demand shocks across all industries j in the US economy at time t.

$$d^{\dagger}_{i,t} = d^{\dagger}_{i} \sum_{j=1}^{n} \hat{d}_{ijt} \tag{1}$$

...where $\hat{d}_{ijt}$ is the industry-level demand shift for occupation i at time t defined as:

$$\hat{d}_{ijt} = \sum_{j=1}^{n} \bar{d}_{ij}\theta_{jt} \tag{2}$$

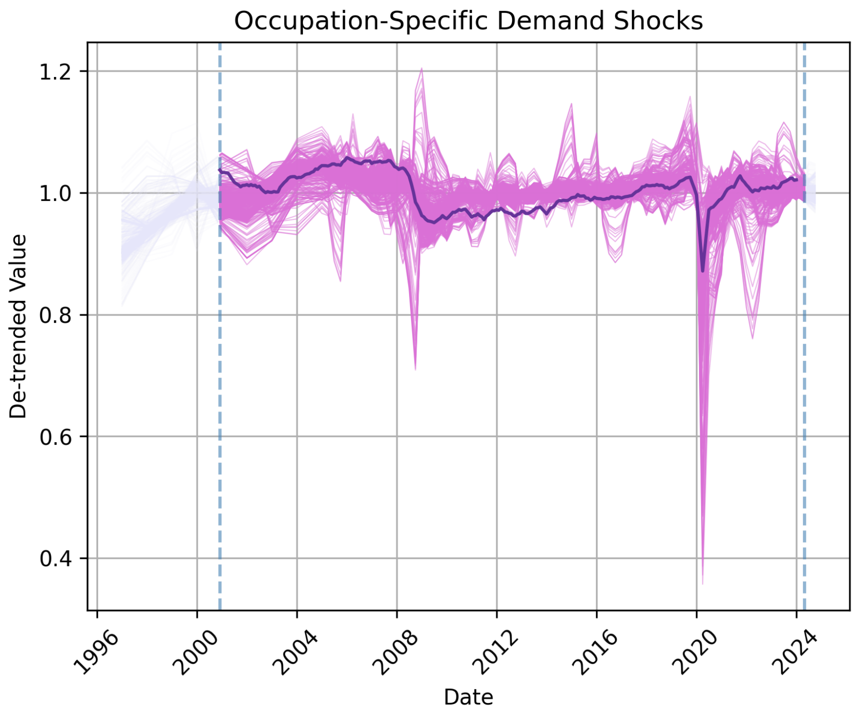
...where θ_{jt} is a de-trended value added shock in industry j and $\bar{d}_{ij}$ represents the fixed demand for occupation i in industry j calculated as:

$$\bar{d}_{ij} = \frac{1}{T}\sum_{T=2012}^{2018} \frac{d_{ijT}}{d_{iT}} \tag{3}$$

Thus, we obtain occupation-specific fluctuations in demand dependent on their "exposure" or the share of a specific occupation in industry j. These occupation-specific demand shocks are represented in Figure 2.

To calculate target demand, we use the reported occupational shares of industry employment from the Bureau of Labor Statistics' Occupational Employment and Wages dataset to define $\bar{d}_{ij}$ and quarterly industry value added data to define θ_{jt}. We de-trend the value added using a Hodrick-Prescott filter. We initialize $d_i^{\dagger}$ as the occupation-specific demand in 2016 as reported by the US Census Bureau and Bureau of Labor Statistics [43]. More detail about the data and methods used to derive the occupational-specific demand shocks is presented in Appendix B.

Figure 2: Occupation-specific Demand Shocks



Separations Second, workers are separated from jobs at a rate of π_{it}^{u} which is a function of both a spontaneous base rate δ_u independent of economic conditions and a state-dependent factor α_u which adjusts to close the gap between occupation-specific target demand $d_{i,t}^{\dagger}$ and realized demand d_{it}.[5] d_{it} is defined as the sum of employed persons e_{it} and vacancies v_{it} in a given occupation i at time t, as follows:

[5]Optionally, to account for occupational heterogeneity in separation hazard rates, we additionally incorporate occupation-specific separation rates ω_i such that occupations are not uniformly affected by industry-level value added shocks (i.e., it is unlikely that a manager will be fired with the same likelihood as a factory worker). We draw occupation-specific separation rates ω_i from employment-to-unemployment transitions rates drawing on CPS microdata, such that Equation 6 becomes $\pi_{i,t}^{u} = \omega_i\delta_u + (1-\delta_u)\alpha_{u,i,t}$. We do not employ these occupation-specific hazard rates in the main text of this document, but the model can be adjusted to accomodate them.

$$d_{i,t} = e_{i,t} + v_{i,t} \tag{4}$$

α_u is defined as:

$$\alpha_{u,i,t} = \gamma_u \frac{\max\{0, d_{i,t} - d^{\dagger}_{i,t}\}}{e_{i,t}} \tag{5}$$

whereby α_u satisfies $0 \leq \alpha_{u,i,t} \leq 1$, γ_u is the sensitivity of an occupation's adjustment response to over-employment, or a positive gap between d_{it} and $d^{\dagger}_{i,t}$. Thus, the probability that a worker is separated $\pi_{u,i,t}$ is given by

$$\pi^{u}_{i,t} = \delta_u + (1 - \delta_u)\alpha_{u,i,t} \tag{6}$$

Vacancy Creation Next, occupations open vacancies. The probability that a vacancy opens is simply the difference between the national vacancy rate at time t and the vacancy rate coming out of the previous period $t - 1$ such that we impose vacancy rates explicitly as follows:

$$\pi^{v}_{it} = max\{0, \bar{v}_t - \pi^{v}_{it-1}\} \tag{7}$$

Vacancy rate $\bar{v}_t$ is drawn from the Job Openings and Labor Turnover Survey from the Bureau of Labor Statistics. Each vacancy is associated with a wage offer drawn from a log-normal distribution around occupational wage quantiles available from the BLS Occupational Employment and Wage Statistics program (OEWS). Drawn wage offers are restricted to between \$15,080 and \$250,000, where the minimum bound is equivalent to the federal minimum annual wage and the upper bound is the maximum reported salary value in the OEWS data.

Applications Next, workers apply to available open vacancies in occupations with which they share a non-zero transition probability in network A. This search and apply method is described in Section 2.2.

Entry and Exit Next, any workers over the age of 65 $W^{\leftarrow}_t$ retire from the labor force and are replaced by $W^{\rightarrow}_t$ workers who enter into entry-level occupations $\mathcal{E}$ with probability s_{it} proportional to each occupation's share of entry-level demand at time t.

$$s_{i,t} \;=\; \frac{d^{\dagger}_{i,t}}{\sum_{k\in\mathcal{E}} d^{\dagger}_{k,t}} \tag{8}$$

The new entrants are allocated proportionally:

$$W^{\rightarrow}_{it} \;=\; W^{\leftarrow}_{it} \cdot s_{i,t}, \quad \forall i \in \mathcal{E} \tag{9}$$

By design, $\sum_{i\in\mathcal{E}} W^{\rightarrow}_{it} = W^{\leftarrow}_t$ such that the labor market size is fixed. Each occupation's definition as either entry-level or not is drawn from the Bureau of Labor Statistics' Employment Projections Program's "Education and training assignments by detailed occupation" table and the entry-level worker's age is assigned according to the "typical education needed for entry" field from the same source.

Hiring Finally, open vacancies hire a single applicant at random from the applicant pool.

As described above, the model is initialized with two adjustable economy-wide parameters governing worker flows, δ_u and γ_u. δ_u captures the spontaneous separation rate while γ_u governs how sensitively the separation rate responds to fluctuations in demand. The model is then calibrated using occupation-specific inputs, including baseline employment and unemployment levels, the gender composition of employment, median wages, minimum experience requirements (to distinguish entry-level occupations), median age, and observed separation rates.

Finally, the model takes as given an occupational mobility network constructed following the methodology reported in [28, 72]. The occupational mobility network's nodes represent different occupations connected by edges that correspond to the probability that workers transition between them, ρ_{ij}. These transition probabilities are drawn CPS microdata that reports realized worker transitions between 2011-2019. In this particular occupational mobility network, there are 528 occupational nodes corresponding to the 2010 ACS Occupational Classification framework and the edge weights were derived using the baseline methodology of [72] adapted slightly to account for potential selection effects or measurement error as indicated by population weights provided by the CPS and restrict the sample to workers over the age of 18.

2.2 Agents

Until this point, the model's functionality can be reduced to a set of deterministic equations as it does not incorporate behavioral heterogeneity. However, a wealth of theoretical and, more recently, empirical literature proposes that the search behavior of labor market participants can not only influence individual labor market success but also broader labor market outcomes like post-recession unemployment rate recovery and long-term unemployment rate [75, 77, 34, 54]. In other words, labor market performance at the macro level is not a purely deterministic process but rather influenced heavily by the participants in that market. Therefore, the following section sets out a framework for incorporating insights from general and behavioral labor economics into the above outlined model.

The wealth of literature available from the field of behavioral economics offers both a challenge and an opportunity. A growing base of empirical evidence triangulating the role of relevant behavioral biases on job search effort and employment success provides baseline parameter values on which to ground the behavioral rules economic agents are endowed with. However, this literature explores human behavior across a wide variety of axes beyond just cognitive biases. It illuminates the diverse presentation of these biases across demographics, business cycle states, and their interactions. In other words, arriving at truly time- and demographic-invariant behavioral rules is seemingly made more difficult as more evidence comes to light.

Therefore, we draw on the measured *behaviors* that these biases and their heterogeneous presentation affect, namely: search effort (represented by applications sent) and wage expectations. Throughout investigations of how human behavior influences job search behavior and outcomes these were the most frequently used outcome metrics (apart from employment attainment itself). Additionally, majority of the evidence on demographic heterogeneity of behavior focused on these outcome metrics such that the implementation that follows could be adapted to study transition-related outcomes across gender, age, income, skills, and level of education, for example.

We outline below the core behavioral mechanisms incorporated in the model and the empirical data sources used to discipline their implementation.

2.2.1 Application Effort and Learning Dynamics

The effort an individual exerts in a job search process is determined by individual idiosyncrasies, meso-level competition for relevant vacancies within a network of attainable occupations, and the broader macroeconomic conditions. While job seekers cannot directly control whether an application results in an offer, since outcomes are constrained by competition and aggregate labor market health, they do retain agency over how intensively and strategically they search. In this work, we model search effort as the outcome of a dynamic learning process that evolves over the unemployment spell [71, 38, 95, 56, 55, 30, 64, 58, 66, 97, 53, 25, 65, 29, 100, 67, 92, 99, 2, 101], incorporating data from the Bureau of Labor Statistics to inform dynamic search effort on the part of job-seekers.

We incorporate data from a supplementary survey conducted as part of the US Current Population Survey to deduce the magnitude and dynamics of this learning process. More precisely, we estimate the probability distribution over reported job application intensity during unemployment using pooled microdata from the 2018 and 2022 waves of the CPS in which the Bureau of Labor Statistics conducted a Job Search Supplement [13, 14]. This probability distribution allows us to draw a likely application effort for each additional month of unemployment.

The survey asks unemployed respondents who are actively searching for work the amount of job applications they have sent. Respondents report job application counts in ordinal bins: "0", "1–10", "11–20", "21–80", and "81 or more". To account for the lack of a continuous dependent variable, we estimate a series of ordinal logistic regression models to recover the conditional probability of each response bin as a function of unemployment duration and various demographic characteristics. We test model specifications along three dimensions: (i) link function, comparing logistic, probit, complementary log-log (cloglog), and log-log links; (ii) linear, quadratic, and cubic specifications of unemployment duration; and (iii) models with and without demographic covariates (education, gender, age, and family income; race was excluded due to lack of statistical significance across models). Formally, the model estimates $\Pr(Y_i \leq j \mid X_i)$, the cumulative probability of observing response category Y_i for individual i below j where j represents the five ordinal bins given various transformations of the vector X_i of independent variables (unemployment duration and demographic controls).

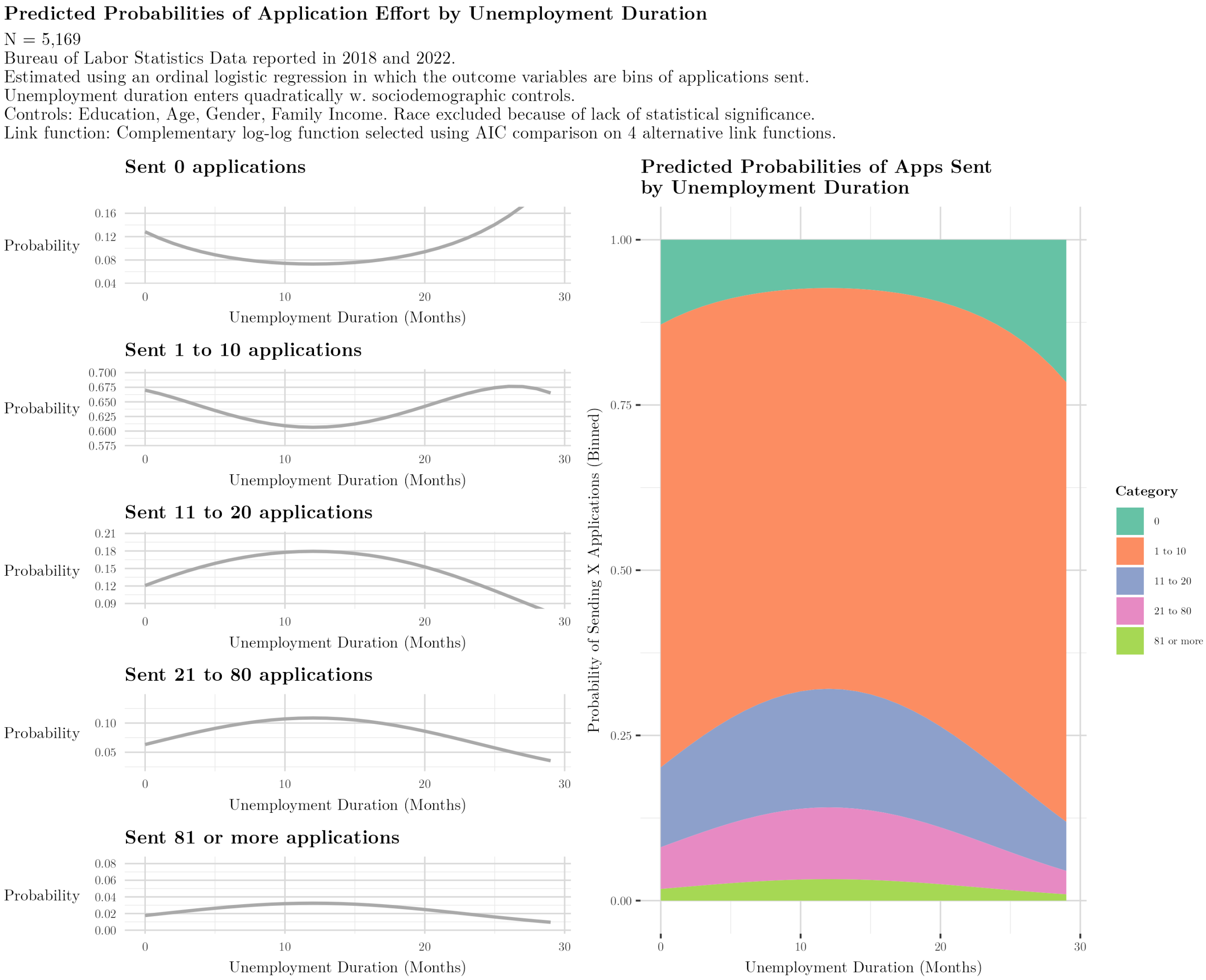
Thus, employing a complementary log-log link function, quadratic unemployment duration, and full demographic controls,[6] we generate predicted probabilities over the five application bins for unemployment spells ranging from 0 to 36 months. These fitted probabilities serve as the empirical foundation for modeling job search effort in the agent-based simulation. In our chosen specification, the odds of reporting a lower application bin increases by approximately 0.1% per additional month unemployed, a relationship statistically significant at the 0.1% level.

Figure 3a demonstrates the predicted probability distribution of application effort by unemployment duration indicating a non-linear concave search effort. We believe this contributes to an open debate in the job search literature regarding the shape of search effort over the unemployment spell. The concave application effort emerging from this data aligns with previous observations about unemployed workers engaging in delayed search while either grieving job loss or engaging in job search planning [3, 92, 96] and adjusting expectations about their re-employment prospects [75].

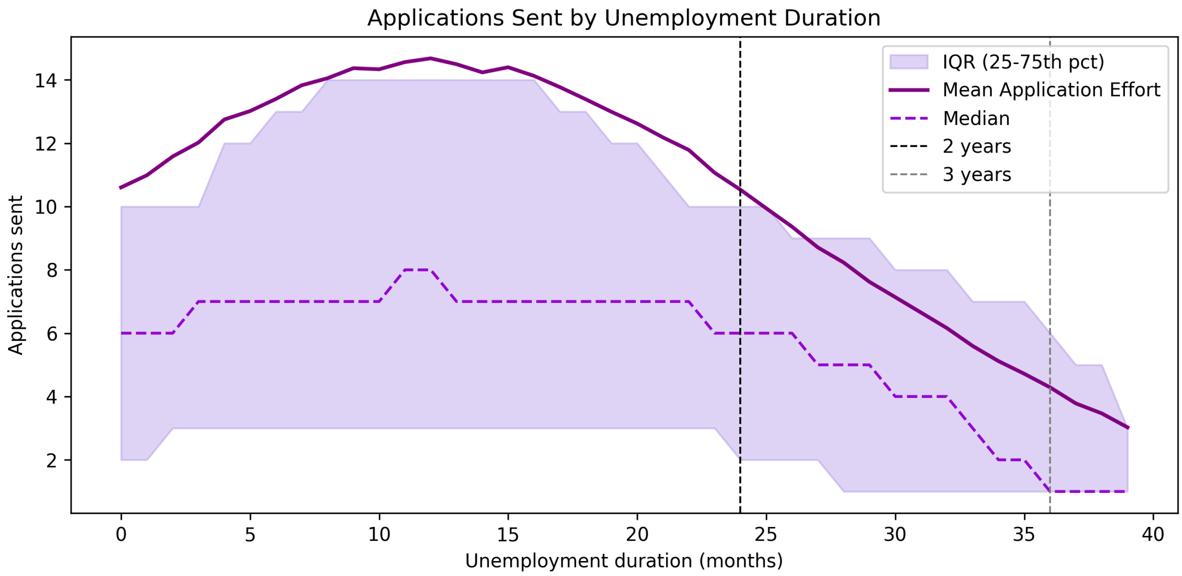
[6]This specification was chosen using an Akaike Information Criterion.

Figure 3: Observed and imposed application effort.

(a) Application effort: Observed



(b) Imposed application effort as a function of unemployment duration.



In relation to the agent-based simulation, we introduce stochasticity by allowing individuals to sample from the relevant probability distribution at each simulated month of unemployment. More precisely, unemployed workers draw an application effort bin according to the probability distribution across bins at their current unemployment duration. Within each bin, the worker draws a precise application effort from a uniform distribution, with a maximum application effort of 100. Figure 3b demonstrates the number of applications sent by an agent for each month of unemployment in expectation.

We provide additional detail about the data, survey questions, and various robustness checks applied in Appendix A.

2.2.2 Wage Expectations and Satisficing

Next, we focus on the evolution of wage expectations as a dynamic criterion applied by workers to available vacancies. Reservation wages act as heterogeneous acceptance thresholds shaped by a range of observable and unobservable worker characteristics [19, 44, 24]. At the same time, a consistent finding in the job-search literature is that reservation wages decline with unemployment duration as workers adjust expectations and engage in satisficing to avoid the costs of prolonged joblessness [48, 2, 95].

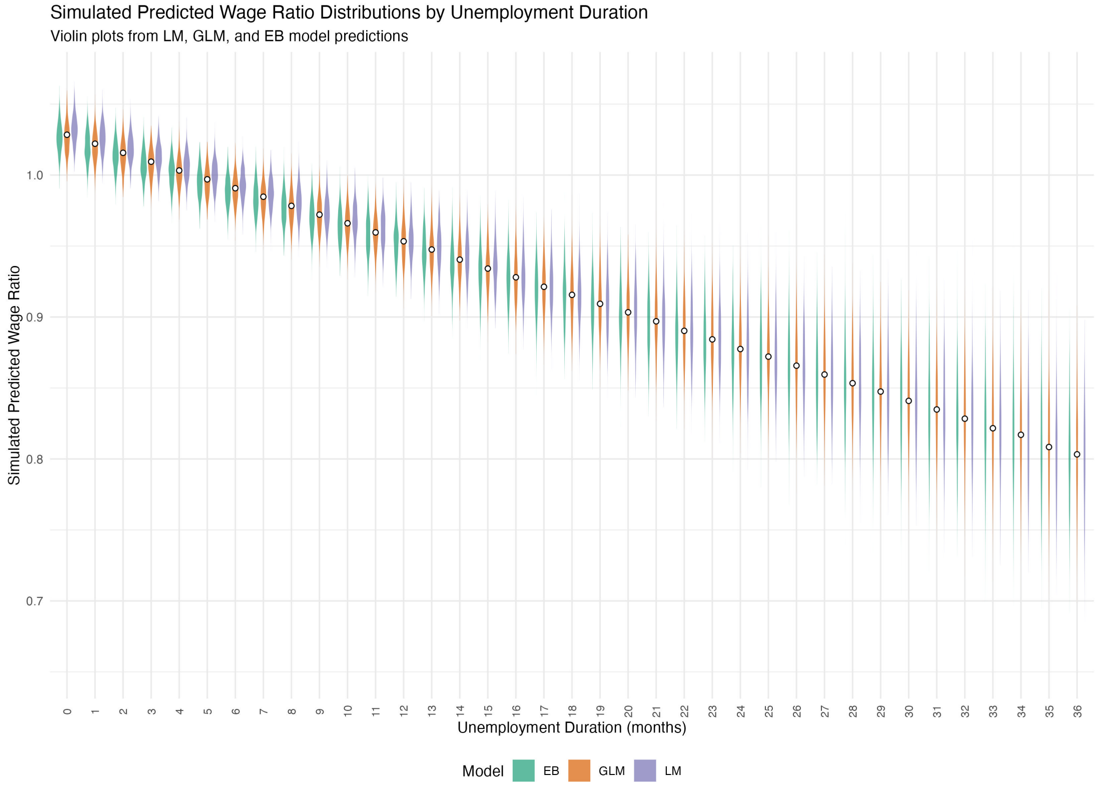
To quantify this duration dependence, we use microdata from the Displaced Worker Supplement (DWS) of the Current Population Survey spanning 2000–2025. We estimate how an unemployed individual's reservation wage, measured relative to their pre-displacement wage, changes with the length of their unemployment spell, controlling for demographic and labor market covariates. More specifically, the analysis estimates cross-sectional regressions of the log ratio of post-displacement to pre-displacement wages on the duration of unemployment allowing for linear and non-linear effects and controlling for observable covariates including age, sex, race, education, marital status, unemployment insurance receipt, and the wage level of their previously held position.

Wage data are not reported uniformly across respondents (hourly, weekly, or both). Our baseline specification therefore uses the maximum reported re-employment wage, whether expressed as hourly or weekly earnings, to minimize measurement error from partial reporting. We also restrict the sample by trimming observations with wage ratios outside the [0.25, 2] range and unemployment durations exceeding 96 weeks. Recognizing that the distribution of unemployment duration is heavily right-skewed and that unemployment duration might suffer from selection effects, we employ three alternative weighting schemes to assess the robustness of our baseline regression estimates: (i) a Heckman two-step correction for potential selection bias, (ii) entropy balancing , and (iii) generalized linear model-based propensity scores to re-weight the sample to achieve representativeness over unemployment duration bins. The latter two are motivated by concerns about non-random attrition and survey sampling imbalances. The preferred specification yields a robust estimate of a ~ 1 percentage point decline in the re-employment reservation wage ratio per additional month of unemployment. We predict the re-employment wage ratio for 36 months of unemployment (the maximum unemployment duration reported in the survey). Supplementary analyses assess the representativeness of the unweighted and weighted samples across key demographic and labor market dimensions and find consistent results. The final sample includes $\sim$ 4,900 individuals. We provide additional information on the data cleaning, sample trimming, econometric model selection, selection correction and sample-rebalancing methods in Appendix A.

Ultimately, we choose to calibrate our reservation wage adjustment rate to a linear function with a lower limit set to the minimum predicted wage ratio for unemployment durations longer than 36 months. The variation in the magnitude of the regression coefficient across the linear and quadratic estimators is feasibly small to justify this decision. The cubic relationship between unemployment duration and reservation wage is characterized by poor goodness-of-fit across several measures, allowing us to rule it out.

Figure 4 shows the predicted wage ratios arising from the linear regression with associated confidence intervals across the linear models that employ either the raw sample (LM) or the rebalanced samples using entropy balancing (EB) or a GLM propensity score matching. We use the predicted probability distributions at each month of unemployment duration from these regressions to inform our agent behavior with the confidence intervals allowing for data-informed noise.

Figure 4: Reservation Wage (as proportion of previously held wage) by Unemployment Duration



We acknowledge the challenges of relying on the ratio of pre-and post-displacement wages as an effective reservation wage, particularly in terms of potential selection effects. First, pre-displacement wages are not a clean proxy for reservation wages. More fundamentally, observed post-displacement wages or accepted wage offers provide only an upper bound on workers' true reservation wages rather than a direct measure. Any individual's accepted wage reveals merely that it exceeded their reservation threshold, not the reservation wage itself. In other words, due to data constraints, we are inferring latent preferences from realized outcomes. We describe these concerns in greater detail in Appendix A.

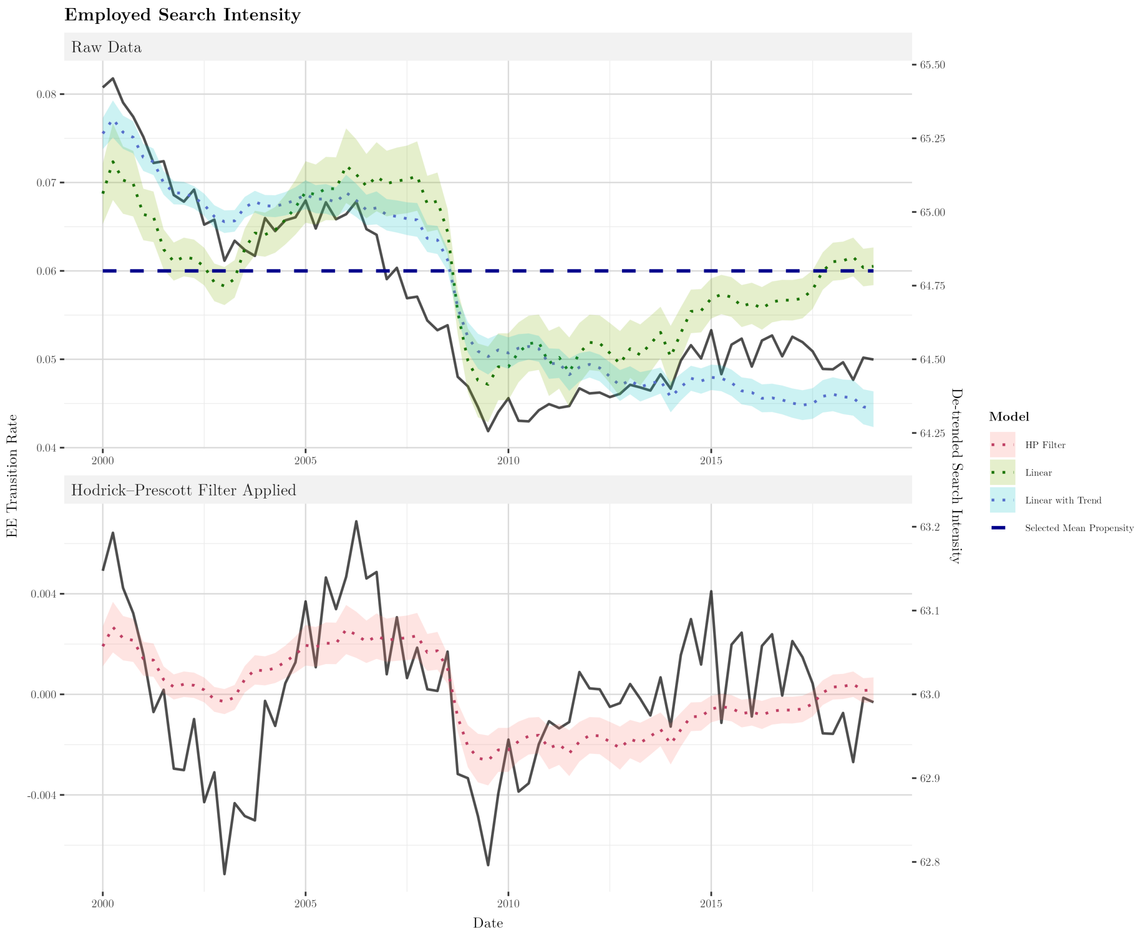
Furthermore, we provide a discussion on the embedded assumption regarding the orthogonality of wage preferences and realized occupational transitions embodied in the occupational mobility network in Appendix C. The section includes two alternative networks drawn from the O*NET Related Occupations Network framework. The first replaces the occupational mobility network with the raw Related Occupations Network and the second with a version of the Related Occupations Network that adds reciprocal edges between occupations that are only connected via a directed edge from a lower- to a higher-wage occupation, aiming to correct for the bias in the relatedness measure in favor of low-high wage connections.

2.2.3 On-the-job Search and Competition Effects

Finally, compelling evidence suggests that the presence of employed job-seekers creates significant competition in the labor market not least due to their quantity but also the fact that their employment provides a positive signal of productivity and skill to potential re-employers [35, 34, 94, 23]. Furthermore, Eeckhout et al provide evidence that the pro-cyclical nature of the magnitude of on-the-job seekers present in the labor market can endogenously create cyclical outcomes [34].

Therefore, our picture of the labor market is incomplete without consideration of the varying degree of competition between unemployed and employed job-seekers. Using data from the IPUMS-CPS from 2000 to 2020, we triangulate an estimate for the search propensity of employed workers using employment-to-employment transition rates following the flow calculation conventions outlined [39]. More precisely, we draw a mean propensity to engage in job search from the employment-to-employment transition rate

Figure 5: Employed Search Effort Drawn from E-E Transitions



The above are predicted values of employment-employment (EE) transitions as a function of the HP-filtered GDP cycle. The grey line represents the real and de-trended EE transition rate (calculated as the ratio of EE transitions to number of employed persons in the labor force) using the Current Population Survey and tabulation method from Eeckhout et al. 2019. The green and blue lines represent the fitted/predicted values using a linear predictor and linear predictor with a linear trend component, respectively. The red line demonstrates the fitted values of the HP filtered EE series using a linear predictor on the HP-filtered GDP series.

(EE) of those workers who transitioned to a 5% higher wage in line with the convention employed in [34]. We focus on employment-to-employment transitions that result in wage increases, as such transitions are more likely to be voluntary and thus reflect active rather than passive search behavior, aligning more closely with our on-the-job search mechanism.

We explore both a simplified heuristic rule through a fixed share of employed workers engaging in on-the-job search and a probabilistic decision rule whereby workers decide to engage in active on-the-job search as a function of perceived market tightness. As demonstrated in Figure 5, we draw a mean probability that an employed person engages in active job seeking which serves as the complete basis for our heuristic rule and partial basis for our agent decision rule. This value is represented by the dashed blue line in Figure 5.

Figure 5 demonstrates this time series in raw (grey) and fitted form (blue, green, red). The fitted series are calculated by regressing the EE transition rate on US real GDP over the time period using either a linear regression or a linear regression with a deterministic time trend. These fitted series are presented to display the cyclicality of E-E transitions, though the raw series is ultimately used to draw the mean propensity with which employed seekers engage in OTJ search.

2.2.4 Operationalising Agent behavior

Finally, we turn to the operationalisation of this agent behavior. We outline the job search behavior of unemployed and employed job-seekers separately.

Unemployed Search behavior An unemployed worker enters a time step unemployed with memory of the wage and occupation of their latest held job, awareness of the amount of time spent unemployed and a risk preference value. First, an unemployed worker b finds a subset of vacancies $\{1, ...n\}$ by sampling from occupations that share a non-zero weighted edge ($\rho_{ij} > 0$). Assuming that workers do not have perfect information on all available vacancies, n is smaller than the total available vacancies in the economy, workers sample a maximum of 30 vacancies that exist within neighboring occupations, and their likelihood of "finding" a given vacancy in occupation j is given by ρ_{ij}.

At this point, the behavioral attributes outlined above enter the stylized process where R^i_t is drawn from Section 2.2.2 and A^i_t is drawn from Section 2.2.1.

First, workers restrict their "found" vacancy set to those vacancies whose wage offers are greater than $R_{i,t}$. To accommodate challenges with small occupations, we relax this reservation wage such that individuals will apply to vacancies below R^i_t with a relatively low probability p_r. This parameter is time-invariant and common to all job-seekers. In the simulation results presented here, $p_r = 0.15$.

Next, within the sample of remaining vacancies, workers rank the vacancies according to a scaled wage differential equation (Equation 10). As the model is currently designed, the worker's utility function represents a wage differential scaled by occupational similarity ρ to proxy the extent to which a vacancy matches an applicant's job content criteria, where w_i represents their most recently held wage and w_j represents the wage offer of vacancy v_j. Each ranked vacancy is then assigned an index k.

$$u(v_j) = \rho_{ij}(w_j - w_i) \tag{10}$$

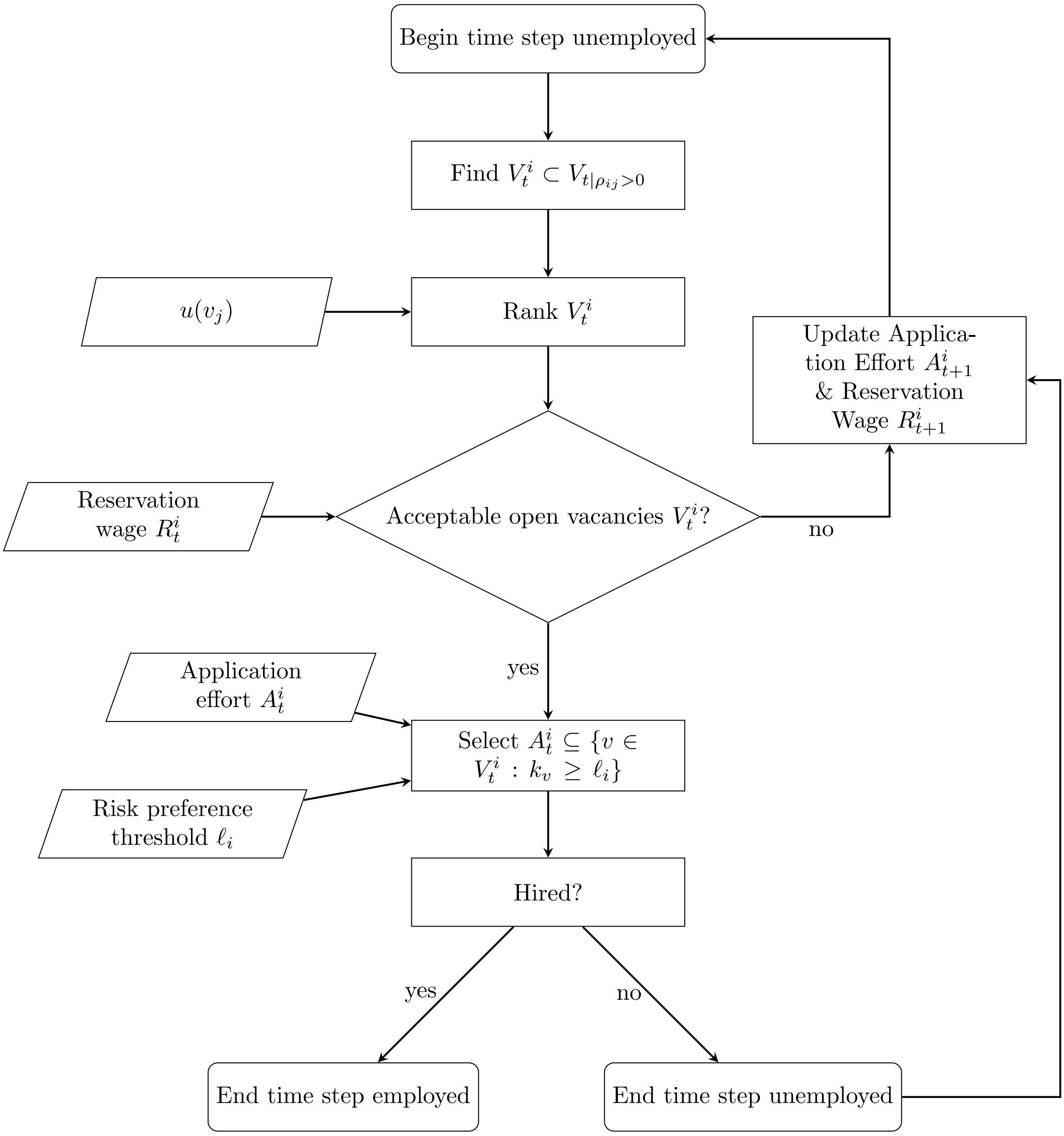
Next, they select A^i_t vacancies from the ranked vacancy set starting from index $k = \ell_i$. The value of ℓ_i represents a worker-specific risk preference, with risk-loving (averse) workers holding lower (higher) values of ℓ_i.

We do not allow for unemployed job-seekers to apply to zero vacancies. Therefore, the search effort of an unemployed worker is:

$$A_{it} = \max\{1, A^i_t\}$$

Figure 6 represents the proposed decision-making process of an unemployed worker when searching for a job.

Figure 6: Search Process of Unemployed Job-Seekers



Employed Search behavior Second, employed workers decide to search for work with probability p_t^{OTJ} which is either a function of a mean proportion of employed workers engaging in active search ϕ drawn from Section 2.2.3:

$$p_t^{OTJ} = \phi$$

...or a more precise agent decision rule whereby employed agents engage in active search as a function of perceived competition:

$$p_{it}^{OTJ}(comp_{jt}) = \frac{1}{1 + \exp\Big(- \big[\phi + \beta_C comp_{jt}\big]\Big)}$$

Perceived competition is defined as:

$$comp_{jt} = \frac{U_{j,t-1}}{V_{j,t-1}}$$

...ensuring that workers are responsive to market conditions experienced in the previous month.[7]

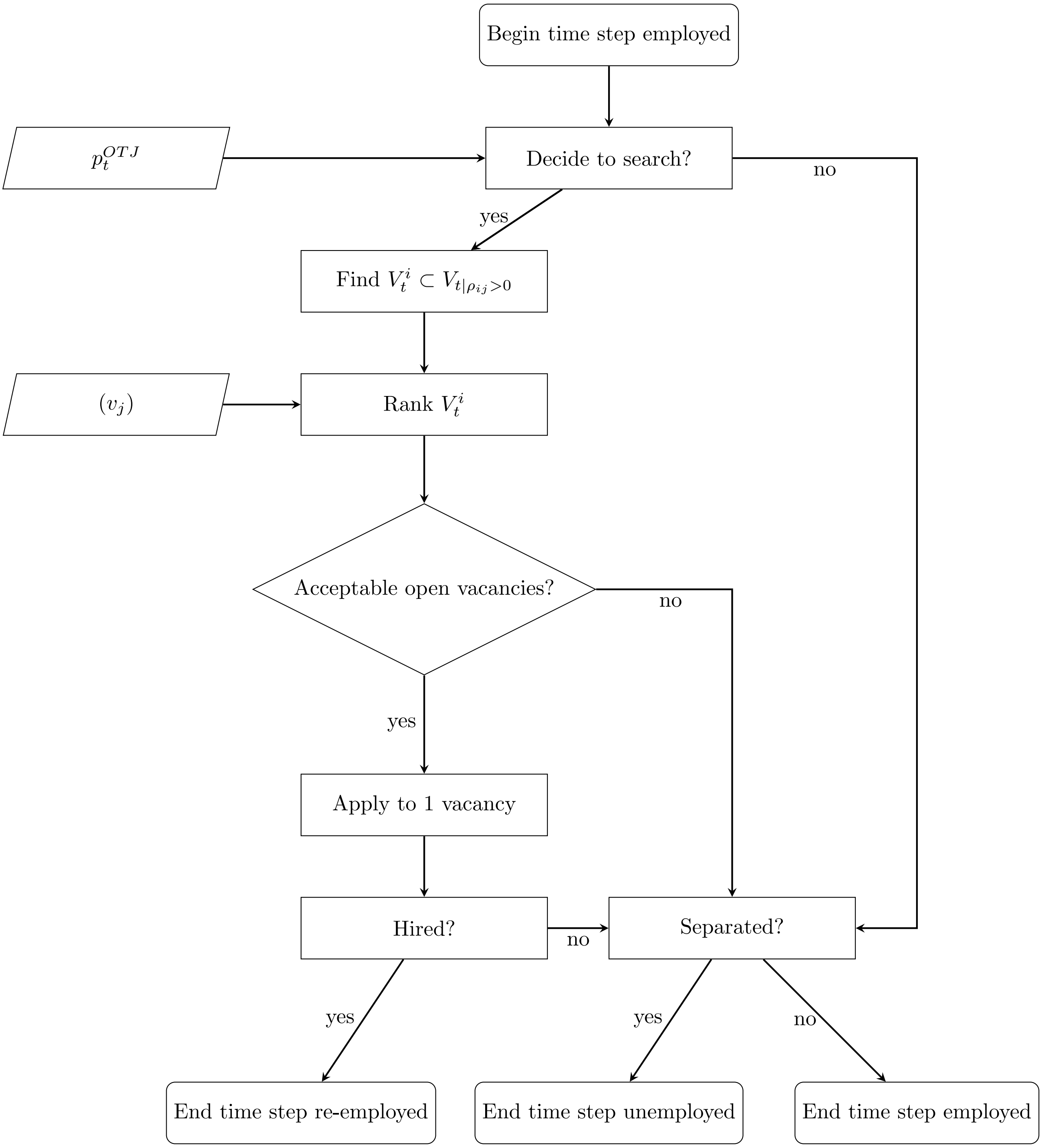
Let $p_t^i \sim \text{Bernoulli}(p_{it}^{OTJ})$ be a binary indicator of whether employed individual i decides to apply for A_t^i jobs, where:

$$A_t^i = \begin{cases} 1 & \text{with probability } p_{it}^{OTJ} \\ 0 & \text{with probability } 1 - p_{it}^{OTJ} \end{cases}$$

Similar to unemployed workers, they "find" a sample of vacancies, rank them according to Equation 10. We impose that employed workers will only apply to those vacancies for which $w_j \geq X \sim \mathcal{N}(w_i,\, 0.05 * w_i)$. To avoid purely deterministic outcomes, we incorporate noise to the wage preferences of employed seekers which is drawn from a normal distribution around their previously held wage. We represent the above search process of employed job-seekers in Figure 7.

[7] Alternative methods for calculating a valid competition metric could use (1) applications per vacancy $\frac{A_{j,t-1}}{V_{j,t-1}}$, to account for competition from job-seekers in other occupations; (2) or either $\frac{A_{i|\rho_{ij}>0,t-1}}{V_{i|\rho_{ij},t-1}}$ or $\frac{U_{i|\rho_{ij}>0,t-1}}{V_{i|\rho_{ij},t-1}}$, calculating the total competition across vacancies in all neighboring occupations.

Figure 7: Search Process of Employed Job-Seekers



Thus, in addition to the two baseline economic parameters, the model is instantiated with a set of behavioral parameters from empirically grounded behavioral inputs.[8] These include ϕ which governs the average propensity of employed workers to engage in on-the-job search, β_c which captures how sensitive that search decision is to competitive conditions in the relevant labor market. On the unemployed side, job-search intensity is disciplined by A, a probability distribution over application effort that varies with unemployment duration, while wage expectations are governed by R, a duration dependent reservation wage schedule (represented as a wage ratio). Finally, individual heterogeneity in preferences is introduced via ℓ, a risk aversion parameter drawn from a normal distribution, which adds stochastic variation to workers' vacancy valuation and, consequently, to the search processes.[9]

In the following sections, we display the results for six separate models with relevant features as outlined below. Table 1 indicates the labels used to distinguish the models in the following section, the various behavioral attributes (if any) enabled in each model, and the justification for presenting the model. The justification for presenting each model draws on the importance of isolating specific behavioral mechanisms to understand their contribution to the model's functionality, unconfounded by others.

Description	Employed Workers Search	Employed Workers Search Dynamically	Dynamic Application Effort	Reservation Wage Adjustment	Justification
Non-behavioral					Non-behavioral benchmark
Non-behavioral w. OTJ	✓				Competition from OTJ seekers might be sufficient to better match aggregate outcomes.
Behavioral w. Cyc. OTJ	✓	✓	✓	✓	"Full" behavioral model
Behavioral w. Cyc. OTJ w.o RW	✓	✓	✓		
Behavioral w.o. Cyc. OTJ	✓		✓	✓	Determining the importance of the imposed cyclicality of the OTJ search and whether this might be superfluous.
Behavioral w.o. Cyc. OTJ w.o RW	✓		✓		Determining the effects of effort adjustment absent reservation wage conditions.

Table 1: Model Description

[8]As noted, the wealth of evidence proposed by behavioral labor economics on the topic of job search poses a challenge to the principle of parsimony and its relevance to ensuring the tractability of modelled outcomes. We explore additional dimensions of job search behavior considered during the execution of this work in the Appendices of this article but focus on the above outlined given their demonstrated relative importance.

[9]The original model incorporated an endogenous vacancy creation process which was similarly subject to state-dependent and spontaneous forces. In order to test the validity of our behavioral mechanisms more concretely, we chose to exogenize this vacancy creation process to ensure the improved matching rate in our model would be attributable to mechanisms added and not confounded by an inability to accurately model occupation-specific vacancy creation processes. Such vacancy creation processes are difficult to both calibrate and validate using data due to considerable discrepancies in different accounts of both national and occupation-specific vacancy rates stemming from inconsistent or broad definitions, inclusions and exclusions of different types of vacancies, and considerable changes in vacancy posting and recruitment behavior on the part of firms [76]

3 Calibration

We calibrate our behavioral parameters (except β_c) as outlined above using microeconomic data and the economic parameters and β_c to macroeconomic data to ensure the model's credible simulation fidelity.[10] To calibrate the economic parameters, we employ approximate Bayesian computation methods which rely on Monte Carlo simulations drawing from defined prior distributions of each parameter to triangulate the parameter combination that best replicates relevant empirical relationships [33, 32]. We perform this calibration using the *pyabc* package in Python [89, 51].

We calibrate our economic parameters for each model exploring either the joint parameter space of δ_u and γ_u or δ_u, γ_u and β_c, by minimising the distance between the model's simulated unemployment rate and that observed between 2000-2019 (Figure 9a) and, by extension, the Beveridge curve relationship between the unemployment rate and observed vacancy rate from the same time period, represented in Figure 9b.

3.1 Economic Parameters

We calibrated our two economic parameters using Approximate Bayesian Computation with Sequential Monte Carlo (ABC-SMC), as implemented in the `pyabc` Python library [89, 51]. The goal of calibration is to align the model's simulated unemployment dynamics with observed macroeconomic data.

3.1.1 Priors and Calibrated Values

The following model parameters were subject to calibration:

- **Spontaneous separation rate**, $\delta_u \sim \mathcal{U}(0.001, 0.9)$
- **State-dependent separation rate**, $\gamma_u \sim \mathcal{U}(0.001, 0.9)$
- **Employed responsiveness to perceived competition**, $\beta_c \sim \mathcal{U}(0.001, 0.9)$

3.1.2 Observed Data and Summary Statistics

When calibrating only economic parameters δ_u and γ_u, the calibration targeted the monthly time series of national-level unemployment rate data from the U.S. labor market between 2000-2019 (prior to Covid). When calibrating β_c in addition to the economic parameters, the calibration additionally targeted a time series of the share of employed seekers in the labor market as derived in Eeckhout et al [34].

3.1.3 ABC-SMC Algorithm

Model fit was assessed using a variance-normalized sum of squared errors (SSE) distance:

$$d(y^{sim}, y^{obs}) = \sqrt{\frac{1}{\sigma^2} \sum_{t=1}^{T} (y_t^{sim} - y_t^{obs})^2}$$

[10] Unsurprisingly, actions and interactions of interest within social dynamical systems are not always, and in fact rarely, directly observed. In such cases, calibration is relatively difficult. Several options are available that vary both in sophistication and data requirements. [84] provide a comprehensive overview of available calibration methods divided into three distinct classes: direct observation, analytical methods, and simulation-based methods. The latter of the three is further sub-categorized into frequentist (distance- or likelihood-based) versus Bayesian (likelihood-based) methods. In the case in which the output of a proposed model is observable, for example via detailed microdata, graph neural networks could aid simulation-based inference methods as proposed in [33].

where y_t^{sim} is the simulated unemployment rate at time t, y_t^{obs} is the observed unemployment rate, and σ^2 is the variance of the observed series. Where multiple time series were matched, sum of the SSE of each simulated series was minimized.

Let $\theta \in \Theta$ denote the vector of parameters and y^{obs} the observed data. Standard Bayesian inference defines the posterior as:

$p(\theta \mid y^{obs}) \propto p(y^{obs} \mid \theta), p(\theta)$

ABC approximates the posterior using Monte Carlo simulations with the rejection algorithm proceeds as follows:

1. Sample $\theta \sim p(\theta)$
2. Simulate $y^{\text{sim}} \sim \mathcal{M}(\theta)$ using Model $\mathcal{M}$
3. Accept θ if $d(s(y^{\text{sim}}), s(y^{\text{obs}})) \leq \epsilon$

This yields an approximate posterior:

$$p_\epsilon(\theta \mid y^{\text{obs}}) \propto \int \mathbb{I}[d(s(y^{\text{sim}}), s(y^{\text{obs}})) \leq \epsilon]\, p(y^{\text{sim}} \mid \theta)\, p(\theta)\, dy^{\text{sim}}$$

To improve efficiency, we used the ABC-SMC variant, which iteratively updates the posterior over T populations by lowering the tolerance ϵ_t:

1. Sample $\theta_{t-1}^{(i)}$ from previous weighted population
2. Perturb: $\theta_t^{(i)} \sim K_t(\theta \mid \theta_{t-1}^{(i)})$
3. Simulate $y_t^{\text{sim}} \sim \mathcal{M}(\theta_t^{(i)})$
4. Accept if $d(s(y_t^{\text{sim}}), s(y^{\text{obs}})) \leq \epsilon_t$
5. Weight:
   $w_t^{(i)} \propto \frac{p(\theta_t^{(i)})}{\sum_j w_{t-1}^{(j)} K_t(\theta_t^{(i)} | \theta_{t-1}^{(j)})}$

The final weighted particle set $\{(\theta_T^{(i)}, w_T^{(i)})\}_{i=1}^N$ approximates the posterior $p(\theta \mid y^{\text{obs}})$.

3.1.4 Implementation Details

The ABC-SMC procedure was configured with the following settings:

- Population size: 50 particles per generation
- Sampler: `MulticoreEvalParallelSampler` with 40 parallel cores
- Minimum threshold: $\epsilon_{\text{min}} = 0.1$
- Maximum number of populations: 15

Posterior means were estimated from the final population using:

$\hat{\theta} = \sum_{i=1}^N w^{(i)} \theta^{(i)}$

Posterior distributions and model fit diagnostics were visualized using kernel density estimates (KDE) and time series overlays of simulated versus observed data. In the case of each model, the maximum population threshold was reached prior to the minimum ϵ threshold.

3.1.5 Calibration Results

Figure 8 demonstrates the kernel density of the selected posterior distributions of the three economic parameters. In both the behavioral and non-behavioral models, the parameters are well-identified, although the uncertainty around the value of γ_u is considerably greater than δ_u. Figure 9 demonstrates the simulated vacancy and unemployment rates using the calibrated parameter estimates. All models demonstrate stability using these parameter estimates, though the non-behavioral model without OTJ search exhibits greater amplitude in the unemployment rate compared to the other models and observed data. In the behavioral models, the amplitude exhibits more realistic dynamics; however, the slope of economic recovery following the unemployment rate spike of 2008 is inconsistent with real data. Notably, the incorporation of dynamic search effort without cyclical OTJ search exhibits the most realistic unemployment rate trajectory, indicating that the incorporation of dynamic search effort generates a more realistic unemployment rate recovery following the 2008 financial crisis.

By extension, we replicate the directionality of the Beveridge curve, a negative empirical relationship between the US vacancy rate and unemployment rate [6]. We display the simulated Beveridge curve alongside the observed values. Given the nature of the calibration exercise, all models fit the Beveridge curve well.

Figure 8: Calibration Results: Kernel Density Estimates of Economic Parameters

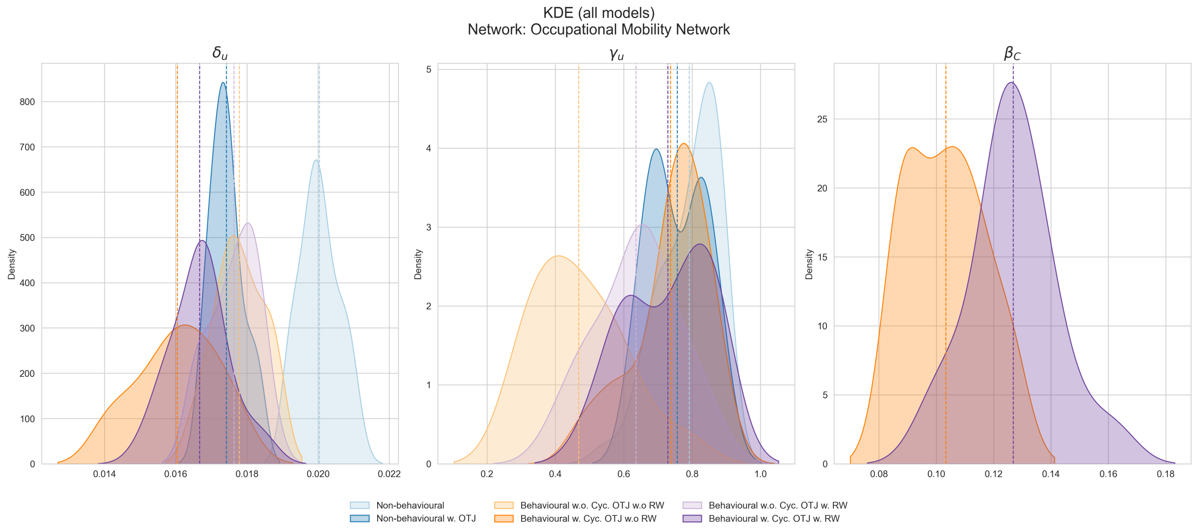
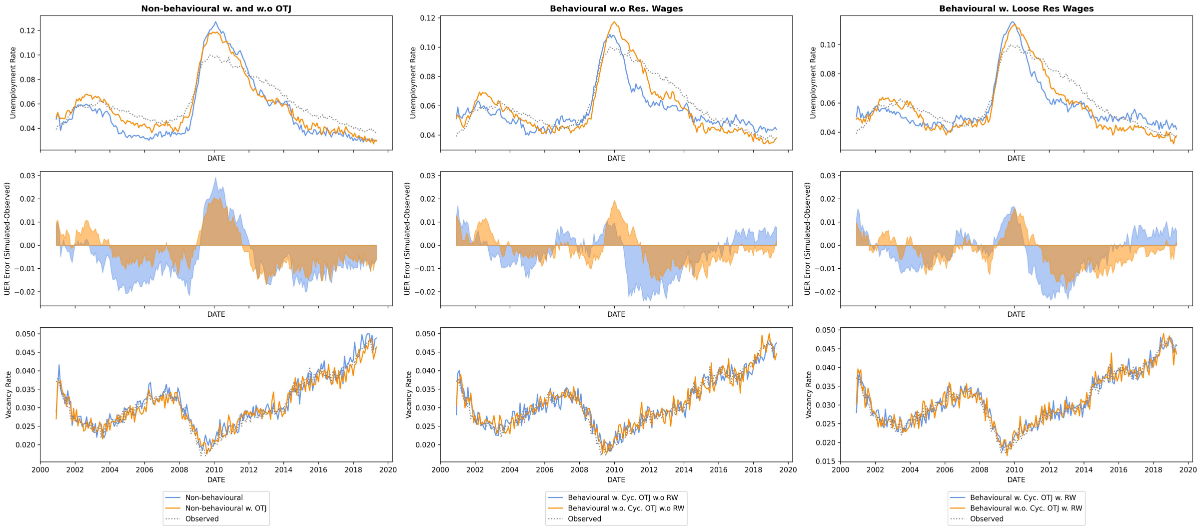
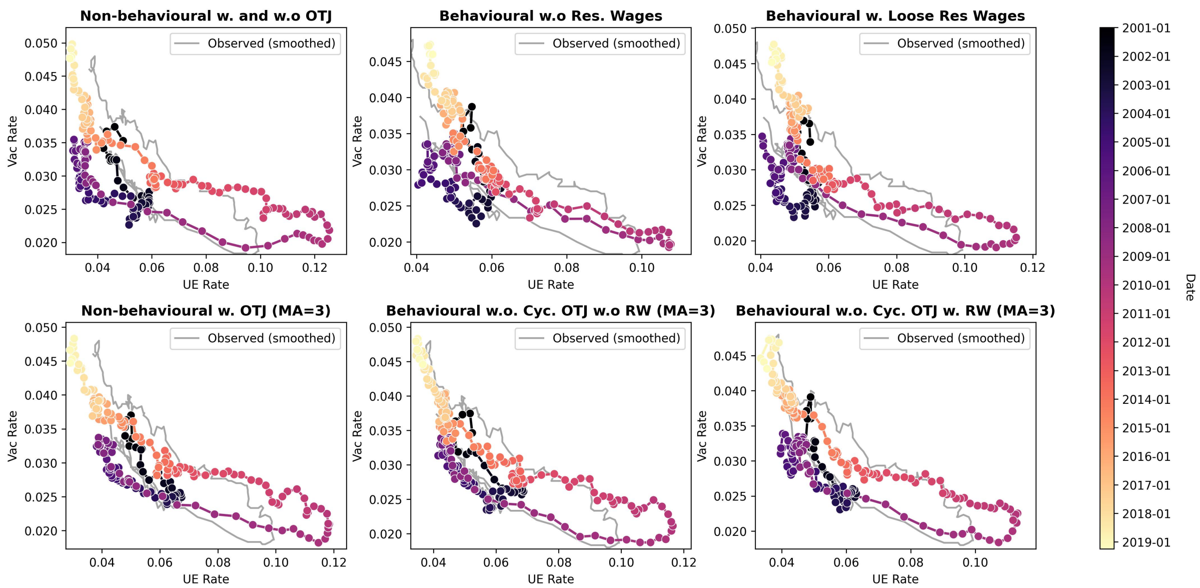


Figure 9: Comparison of simulation outputs.



(a) Simulated UER and vacancy rates compared to real data.



(b) Simulated Beveridge curve compared to real data.

Parameter	Prior Distribution	Model Category					
		Non-behavioural	Non-behavioural w. OTJ	Behavioural w. Cyc. OTJ w.o RW	Behavioural w.o. Cyc. OTJ w.o RW	Behavioural w. Cyc. OTJ w. RW	Behavioural w.o. Cyc. OTJ w. RW
δ_u	$U(0.0001, 0.9)$	0.02	0.017	0.016	0.018	0.017	0.018
γ_u	$U(0.0001, 0.9)$	0.792	0.756	0.737	0.468	0.729	0.636
β_c	$U(0.0001, 0.9)$			0.103		0.127	

Table 2: Prior distribution and parameter estimates for all models. $U(a, b)$ denotes a uniform distribution on $[a, b]$.

In Appendix G, we demonstrate that the calibrated parameter sets across all models yield stable steady states near the US mean unemployment rate (between 4.5-5.5%), absent target demand fluctuations.

4 Model Fit and Validation

4.1 Data

We outline the data sources used in this work in Table 3 including the level of observation (occupation, national), source, and any relevant methodology used to process the raw data from the source. If parameter data is derived using the methodology of other authors, they are labeled "empirical estimates" with the relevant citation.

Variable	***Granularity***	***Source***	***Methodology***
Input data			
Gender share of employment	Occupation	Current Population Survey (CPS), Bureau of Labor Statistics (BLS)	
Wages	Occupation	Occupational Employment and Wage Statistics	[16]
E-U Transition Rates	Occupation	IPUMS CPS Data [43]	
Separation Rates	Occupation	IPUMS CPS Data [43]	
Employment levels	Occupation	IPUMS CPS Data [43]	[28]
Unemployment levels	Occupation	IPUMS CPS Data [43]	[28]
Vacancy levels	Occupation	IPUMS CPS Data [43]	[28]
Occupational mobility network	Occupation	IPUMS CPS Data [43]	[28]
Entry level	Occupation	Education and training assignments by detailed occupation	[15]
Calibration data			
Unemployment rate	National	BLS	
Vacancy rate	National	Job Openings & Labor Turnover Survey (JOLTS), BLS	
Parameter data			
Applications Sent	Microdata	2018 and 2022 Supplement to the Current Population Survey	Author's own analysis
Reservation Wage	Microdata	Displaced Workers Supplement to the Current Population Survey	Author's own analysis
Composition of job-seekers by employment status	Empirical estimate	CPS & JOLTS	[34]
Validation Data			
Unemployment rate	National	CPS via Bureau of Labor Statistics and the Federal Reserve Bank of St. Louis	
Unemployment rate	Occupation	CPS	
Long-term unemployment rate	National	CPS via Bureau of Labor Statistics and the Federal Reserve Bank of St. Louis	
Long-term unemployment rate	Occupation	CPS	
Gender wage gap	National	BLS	
Separation and Hires Rates	National	JOLTS	
Intensive Search Effort	National		[77]
Composition of job-seekers	National		[34]

Table 3: Input data, empirical parameter values, and calibration and validation data benchmarks.

4.2 Validation

In the following section we present both macro and micro validation of model outputs. We validate our model across aggregate and disaggregated labor market statistics. First, Table 4.2 demonstrates the relative accuracy of the various models by comparing the difference in mean, sum of squared errors, and correlation coefficients between simulated model output and observed time series to demonstrate the model's ability to target the level and dynamics of various relevant labor market statistics. When a model's statistic is highlighted in red, it outperforms the other models by at least 5%. When a statistic is highlighted in yellow, it is no greater than 5% higher or lower than the best-performing model. In other words, statistics highlighed in red outperform other models whereas those highlighted in yellow are comparable to the best performing model. We find comparable ability to match the mean of various rates across the models. However, importantly, models with more detailed behavioral rules allow for greater fidelity to the *dynamics* of these time series measured as the sum of squared errors and correlation coefficients. The non-behavioral models (with and without competition from employed job-seekers) struggle to replicate any statistics beyond the national unemployment rate and vacancy rate to which it was calibrated. Notably, the behavioral models without reservation wages are the only models that 'outperform' other models. We believe that this speaks to the challenge of incorporating reservation wage dynamics in general, rather than a denunciation of the models incorporating wage preferences as compared to the other behavioral models.

Model	Variable	Mean (Sim)	Mean (Obs)	SSE	Correlation
Non-behavioural	Vacancy Rate	0.032	0.031	0.001	0.960
	Unemployment Rate	0.054	0.060	0.036	0.950
	Long-term Unemployment Rate	0.107	0.264	6.357	0.760
	Hires Rate	0.029	0.036	0.015	0.471
	Separations Rate	0.031	0.036	0.008	0.368
	UE Transition Rate	0.027	0.014	0.049	-0.464
	EE Transition Rate	0.000	0.019	0.080	–
	Application Effort (U)	–	–	–	-0.047
	Seeker Composition	0.000	0.410	37.974	–
Non-behavioural w. OTJ	Vacancy Rate	0.031	0.031	0.001	0.956
	Unemployment Rate	0.058	0.060	0.018	0.946
	Long-term Unemployment Rate	0.128	0.264	4.960	0.768
	Hires Rate	0.031	0.036	0.011	0.541
	Separations Rate	0.034	0.036	0.008	0.409
	UE Transition Rate	0.024	0.014	0.029	-0.450
	EE Transition Rate	0.006	0.019	0.043	0.017
	Application Effort (U)	–	–	–	0.154
	Seeker Composition	0.495	0.410	2.384	0.803
Behavioural w. Cyc. OTJ w. RW	Vacancy Rate	0.031	0.031	0.001	0.961
	Unemployment Rate	0.058	0.060	0.021	0.860
	Long-term Unemployment Rate	0.166	0.264	2.853	0.814
	Hires Rate	0.031	0.036	0.011	0.549
	Separations Rate	0.034	0.036	0.009	0.429
	UE Transition Rate	0.024	0.014	0.028	-0.473
	EE Transition Rate	0.006	0.019	0.043	0.056
	Application Effort (U)	–	–	–	0.221
	Seeker Composition	0.431	0.410	3.226	0.792
Behavioural w.o. Cyc. OTJ w. RW	Vacancy Rate	0.031	0.031	0.001	0.953
	Unemployment Rate	0.057	0.060	0.013	0.942
	Long-term Unemployment Rate	0.164	0.264	2.934	0.801
	Hires Rate	0.031	0.036	0.011	0.557
	Separations Rate	0.033	0.036	0.007	0.436
	UE Transition Rate	0.023	0.014	0.025	-0.408
	EE Transition Rate	0.006	0.019	0.041	0.061
	Application Effort (U)	–	–	–	0.095
	Seeker Composition	0.493	0.410	2.046	0.811
Behavioural w. Cyc. OTJ w.o RW	Vacancy Rate	0.031	0.031	0.001	0.948
	Unemployment Rate	0.057	0.060	0.021	0.858
	Long-term Unemployment Rate	0.093	0.264	7.594	0.681
	Hires Rate	0.032	0.036	0.011	0.558
	Separations Rate	0.034	0.036	0.009	0.451
	UE Transition Rate	0.023	0.014	0.026	-0.403
	EE Transition Rate	0.007	0.019	0.040	0.064
	Application Effort (U)	–	–	–	0.217
	Seeker Composition	0.429	0.410	3.268	0.793
Behavioural w.o. Cyc. OTJ w.o RW	Vacancy Rate	0.031	0.031	0.001	0.953
	Unemployment Rate	0.058	0.060	0.012	0.940
	Long-term Unemployment Rate	0.130	0.264	4.607	0.836
	Hires Rate	0.031	0.036	0.010	0.584
	Separations Rate	0.034	0.036	0.007	0.448
	UE Transition Rate	0.022	0.014	0.020	-0.362
	EE Transition Rate	0.007	0.019	0.035	0.047
	Application Effort (U)	–	–	–	0.375
	Seeker Composition	0.487	0.410	1.875	0.798

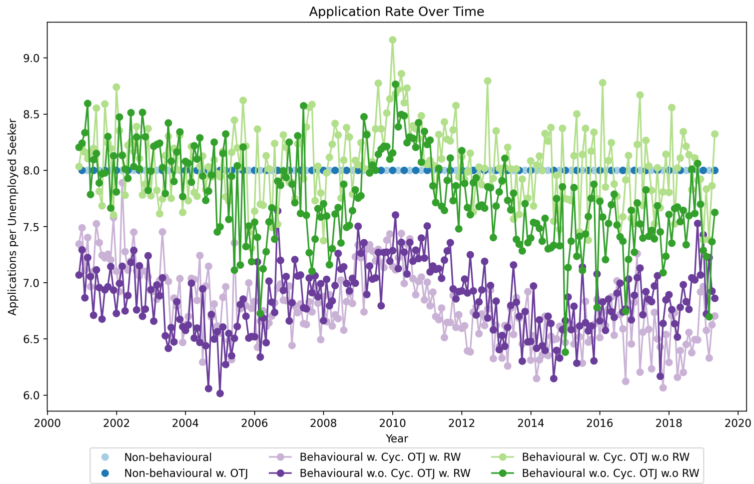
4.2.1 Micro-economic Data

Notably, our model reproduces two critical emergent/endogenous cyclicalities in the behavior of employed and unemployed seekers. We draw on insights from [77], and [34] to validate these micro-behavioral outcomes of our model. These two works stand out within the canon that seeks to disentangle the determinants of labor market matching as a result of job search behavior leveraging micro-level data.

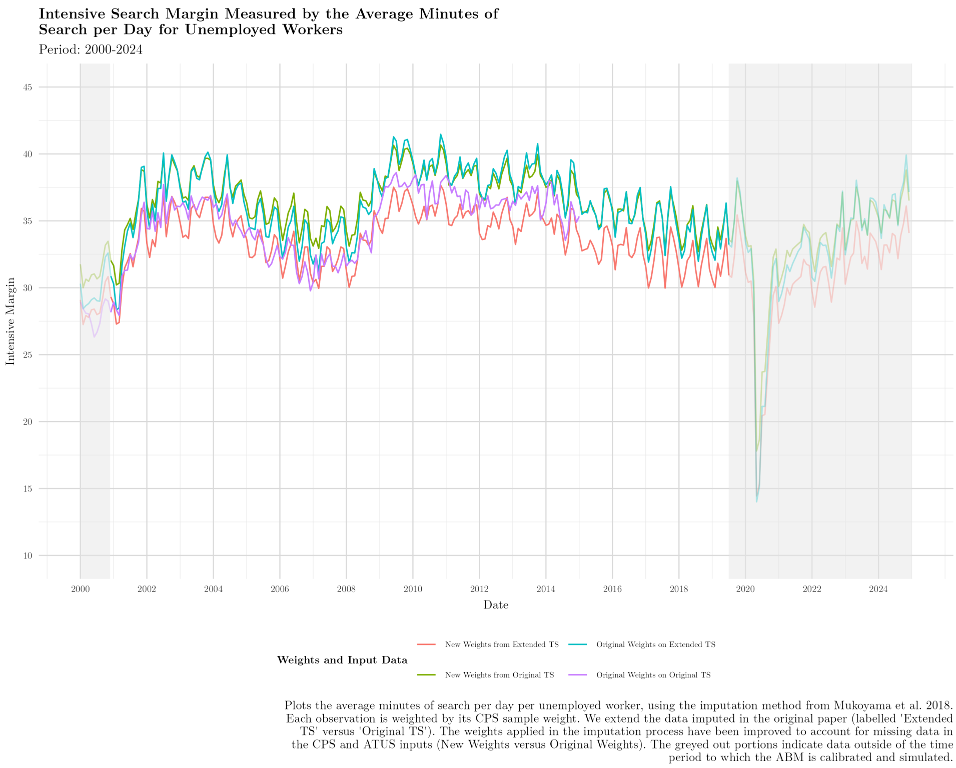
First, the **job search behavior of unemployed workers is anti-cyclical**. More precisely, it has been found that unemployed job-seekers exert greater effort at the intensive margin in economic downturns [77]. The individual agents in our model demonstrate such counter-cyclical search effort in that their effort at the intensive margin increases during busts and decreases during booms. In Figure 10, we demonstrate the average applications sent by unemployed individuals, a series that follows the periodicity of the measure of intensive search effort that Mukoyama et al derive as represented in Figure 10b [77]. Notably, this cyclical intensive search effort emerges within our model as a product of the incorporated behavioral rules and network competition in bust periods, demonstrating the relevance of incorporating duration-dependent search effort as a critical feature of unemployed search behavior.

Figure 10: Simulated versus Observed Job Search Effort

(a) Application Effort by Unemployed Seekers in the Model



(b) Unemployed Search Effort - Intensive Margin (Mukoyama et al.

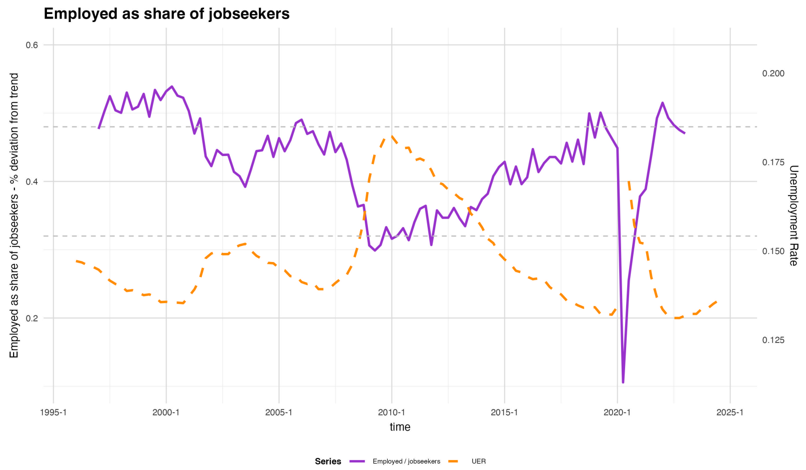


Plots the average minutes of search per day per unemployed worker, using the imputation method from Mukoyama et al. 2018. Each observation is weighted by its CPS sample weight. We extend the data imputed in the original paper (labelled 'Extended TS' versus 'Original TS'). The weights applied in the imputation process have been improved to account for missing data in the CPS and ATUS inputs (New Weights versus Original Weights). The greyed out portions indicate data outside of the time period to which the ABM is calibrated and simulated.

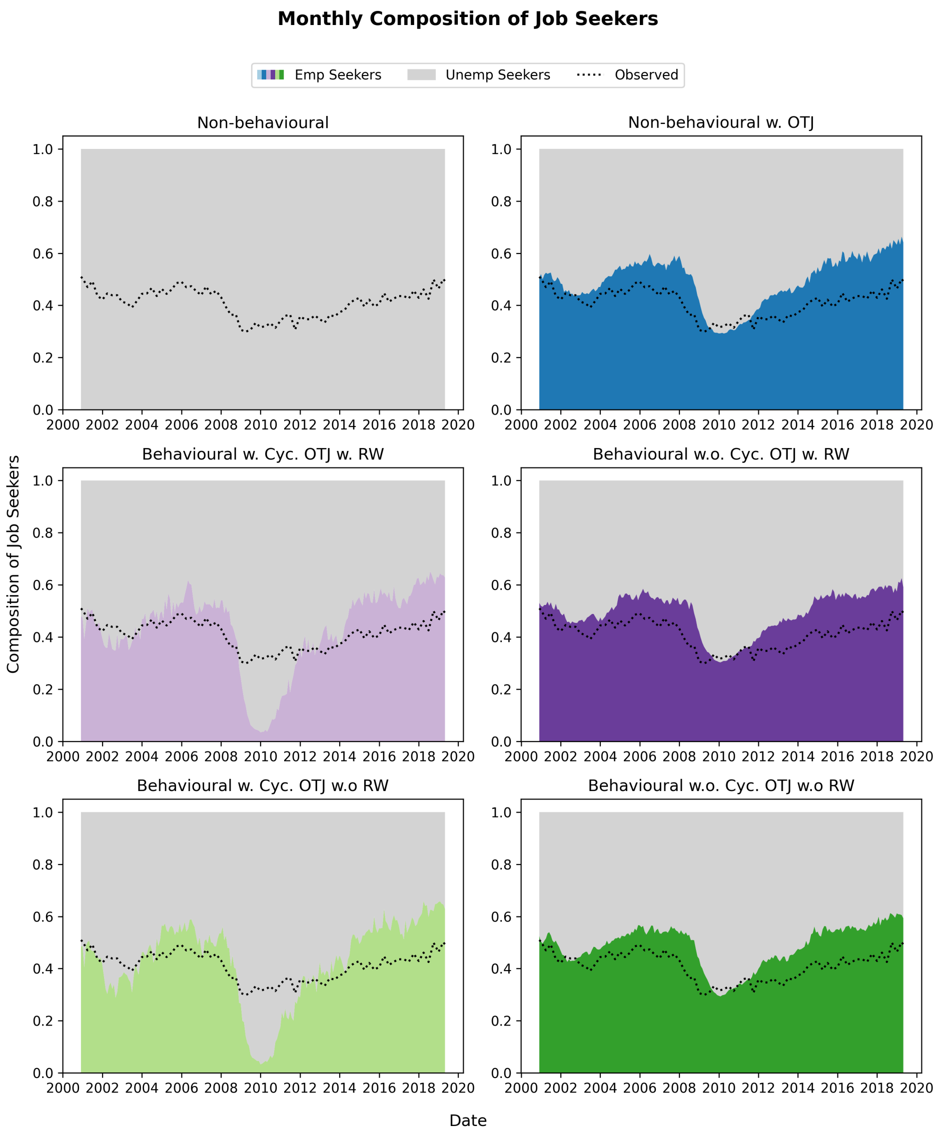
Second, the propensity for employed job-seekers to enter the job search demonstrates a pro-cyclical relationship, leading to greater competition in times of economic recovery or booms [34]. To validate this outcome, we have replicated and extended the data used in [34] to measure the search intensity of employed workers and employment status composition of job-seekers. We use this replicated and extended dataset to validate the population-level behavior of employed job-seekers in the model. As described in Section 2.2.3, OTJ search behavior is either defined as a static mean propensity (denoted as "w.o. Cyc. OTJ") or in response to perceived competition (denoted as "w. Cyc. OTJ" in the models below). Figure 11 demonstrates the simulated share of employed and unemployed persons competing in the market in the shaded colors, where the dashed line represents the observed value of this share as derived in Eeckhout et al [34]. Notably, incorporating a simple mean propensity to participate generates a reasonable share of employed job-seekers. However, the models that include a method for competition-sensitive OTJ search, perform significantly worse in matching this time series. This indicates that, though the presence of OTJ seekers has important consequences for the accuracy of the model, incorporating further behavioral rules for employed job-seekers is less important than the rules defined for unemployed job-seekers.

Figure 11: Simulated versus Observed Job-Seeker Composition

(a) Observed composition of job-seekers (violet) and UER (orange)



(b) Simulated composition of job-seekers.



4.2.2 Labor Market Inefficiencies

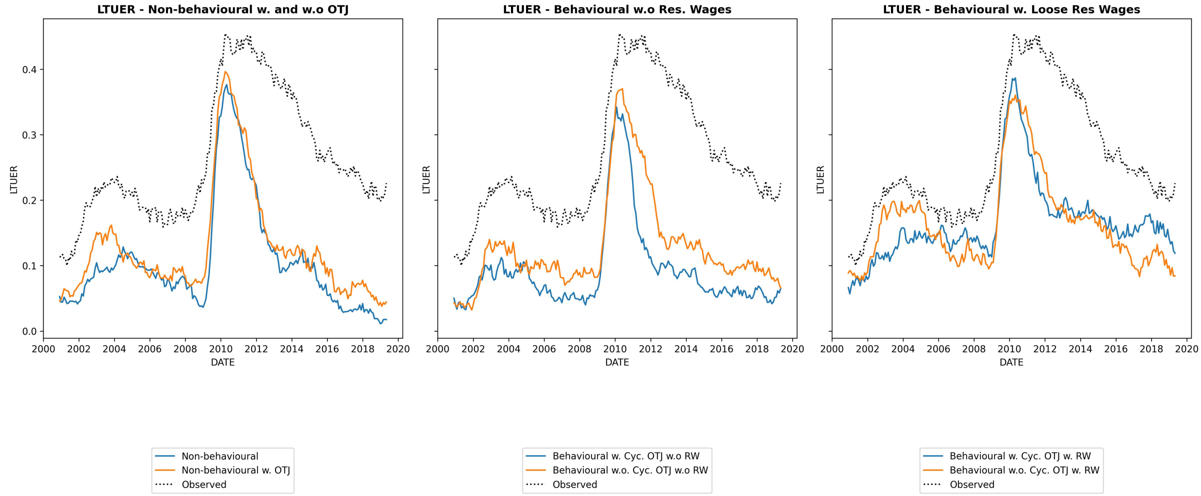
Finally, a further potential benefit of incorporating behavioral heterogeneity into an agent-based labor market model draws from the proven contribution of such heterogeneity to unequal labor market outcomes. Thus, we evaluate the performance of our model by its ability to reproduce three patterns: the distribution of unemployment duration, the relationship between the business cycle and re-employment wages, and gender wage gaps. We find that the (1) incorporation of concave search effort and wage preferences improves the matching of the distribution of unemployment duration; (2) dynamic reservation wage adjustment better matches the cyclicality of relative re-employment wage gains over the business cycle; and (3) the incorporation of data on the gender share of occupations, varying risk aversion between male and female job-seekers, and wage preferences allows a gender wage gap to emerge.

Long-Term Unemployment First, long-term unemployment, defined as the state of being unemployed for a period of at least 27 weeks by the Bureau of Labor Statistics and one year by the OECD, is a persistent challenge across economies [80, 8]. Long-term unemployment is of considerable concern as it can both indicate economic ill health, while also potentially causing poor economic, mental, or even physical health consequences for those individuals or communities experiencing it [1]. However, long-term unemployment persists even during periods of macro-economic health. In other words, despite the existence of suitable open vacancies, a significant proportion of a labor market remains in unemployment. Our mechanism for dynamic search effort informed by insights from [75] directly influences the long-term unemployment rate in our behavioral models.

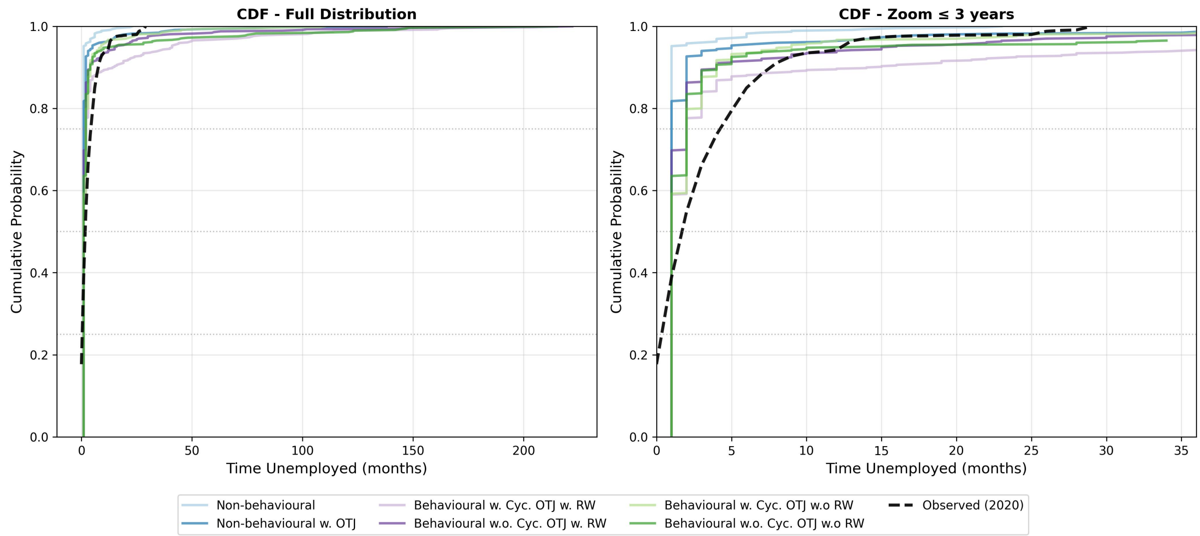
In Figure 12a we compare the performance of our various models against the observed long-term unemployment rate time series as well as the distribution available from the Current Population Survey for the period 2000-2019. Models in which individuals have a duration-dependent search effort and wage preferences more closely match the observed long-term unemployment rate from 2000-2019. The simulated long-term unemployment rate dynamics of our non-behavioral models fluctuate more dramatically than real-world values indicate, underscoring the important role of increased search effort at the intensive margin during busts [77]. We still significantly underestimate the long-term unemployment rate following the 2008 financial crisis. We attribute this finding to a lack of attention to the role of unemployment insurance on unemployment duration, as several studies have found that UI benefit extensions following the Great Recession had a significantly positive effect on unemployment duration and kept long-term unemployed workers in the labor force that would have otherwise exited [54, 42, 87].

Finally, Figure 12b compares the simulated to the observed distribution of unemployment duration at the end of the simulation (2019). The observed values are drawn from the Current Population Survey. Comparing the cumulative distribution function of the simulated and observed data, we find that the simulated models approach the CDF of the observed data in 2019 as each behavioral component is added. The non-behavioral models exhibit CDFs that are significantly shallower than the CDF of the observed data. Whereas the incorporation of dynamic search effort and reservation wages leads to distributions that better match the long tails of unemployment duration present in the real-world data. However, the model with cyclical OTJ search and reservation wages exaggerate this distribution, indicating a slower probability saturation than the data suggests.

Figure 12: LTUER Results



(a) Simulated long-term unemployment in behavioral versus non-behavioral model.



(b) End-of-simulation (2019Q2) distribution of unemployment duration for unemployed agents.

Re-Employment Wage Gains and Losses Third, we investigate whether the incorporation of wage data and data-informed reservation wage setting results in meaningful movements in relative re-employment wages. Empirically, individuals displaced or involuntarily separated from their jobs experience wage losses upon re-employment [40, 60, 50, 26]. The severity of these wage losses is mediated by the characteristics of employers and employees as well as the timing of displacement in relation to the business cycle.[11]

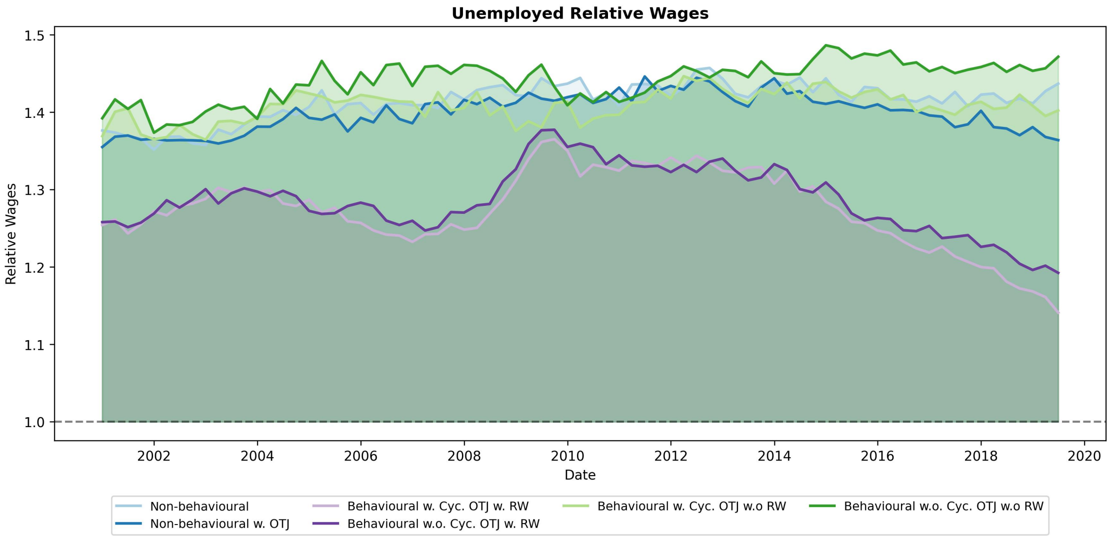
In our model, we can assess the accepted wage offers of workers across occupational or demographic characteristics. The combined effect of variable competition between employed and unemployed workers and a reservation wage adjustment mechanism produces a series of re-employment wage ratios correlated with real-world series of proportional changes in real weekly earnings for full-time job losers between 2000-2018. Both competition between employed and unemployed workers as well as wage satisficing is at play: wage satisficing is a negative pressure and decreased competition is a positive pressure in bad times. Only models in which dynamic search effort and employed search effort is cyclical manage to correlate positively with the movements of observed data on the changes in real weekly earnings for full-time workers [41]. The non-behavioral models and the behavioral models without wage preferences exhibit limited cyclicality whatsoever. However, a challenge that remains to be investigated in this work is the fact that simulated re-employment wages do not recover in the later portion of the simulated time

[11] Periods with elevated layoff rates correlate with slow wage growth speaking to the relevance of layoff timing [26].

period, which contrasts with real-world data.

Figure 13: Re-Employment Relative Wages

(a) Simulated Wage Losses



(b) Observed post-separation wage losses

Taken from Henry S. Farber, Employment, Hours, and Earnings Consequences of Job Loss: US Evidence from the Displaced Workers Survey. *Journal of Labor Economics* 2017.

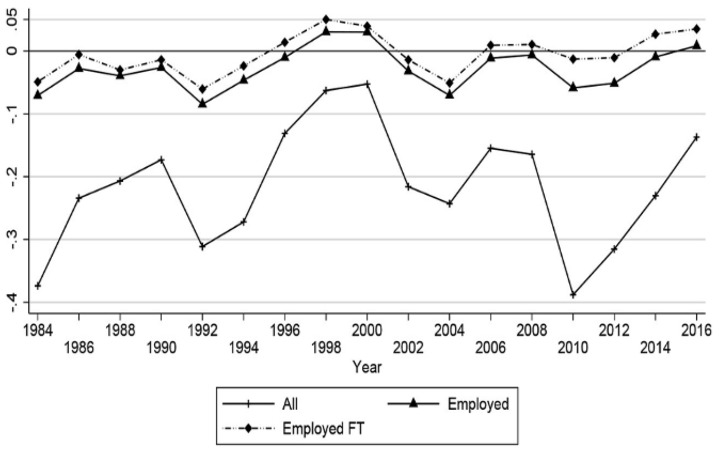
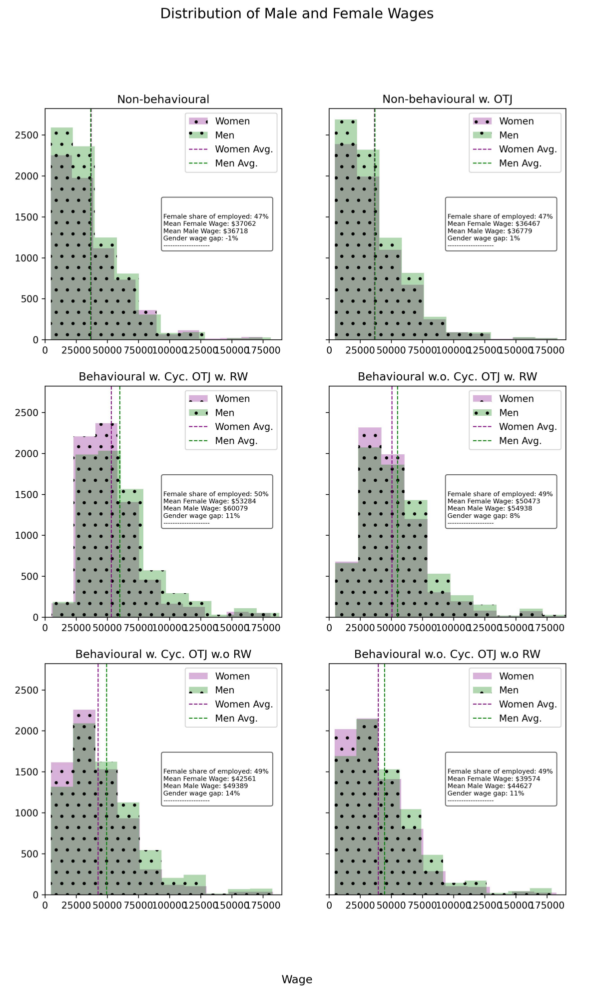


Fig. 13. Proportional change in real weekly earnings for full-time job losers. Year effects from DWS earnings change regressions at medians: ages 35–44, tenure 1–3 years, white, female, ED = 12, lost job 2 years ago.

Gender Wage Gaps Finally, the US faces a persistent gender wage gap of 13%. Although several factors contribute to its existence including workplace and recruitment discrimination, entrenched gender roles in relation to caring responsibilities, motherhood penalties, occupational choice, and gendered patterns in job search behavior [19, 24, 44, 61, 70, 36]. Thus, we make a preliminary attempt to incorporate gendered search behavior into this model by varying the risk aversion between male and female workers in the model. Practically, this means that male workers will aim higher by applying to jobs that yield a higher relative utility gain than those applied to by women in our behavioral models. In other words, men set the top rank of their application bundle at a value of ℓ greater than that of women. The resulting wage gap from this implementation is displayed below. This work is still in a preliminary stage, but we believe that incorporating insights from behavioral labor economics into how job search patterns differ between men and women can allow for an evaluation of relative wage gains in

Figure 14: Simulated gender wage gap in behavioral versus non-behavioral model.



the eventual application of this model to a policy analysis scenario.

When initialized, the input data on occupational gender shares leads to an initial 10% gender wage gap across all models. Figure 14 demonstrates the wage distributions of men and women in the model at the end of the simulation period (2019). Notably, the absence of wage preferences in the non-behavioral model leads to an evening out of the initialized wage gap. The persistence of the gender wage gap in the behavioral models is sensitive to parameter choices across the model. If workers can optimize near-perfectly in terms of their wage preferences, the wage gap decreases, whereas adding stochasticity to this wage optimization process, the resulting wage gap shrinks. This difference is evident when comparing the results for the behavioral models with and without wage preferences in Figure 14.

5 Formalising A Dynamic Job Search Model

In the agent-based modeling framework, job search behavior evolves according to data-driven rules. In other words, empirically estimated probability distributions are drawn for application effort and reservation wage adjustment. However, underlying this process is a central belief mechanism which is therefore abstracted from by design. We have data on realized outcomes rather than underlying beliefs, allowing for more explicit modeling of relevant job search behavior.

However, returning to the understanding of job search as an adaptive learning process, considerable evidence suggests that much of what regulates the realized behavior imposed in the agent-based model, is a subjective learning process in which individual job-seekers revise their beliefs about their re-remployability in relation to the state of the labor market they are facing.

Therefore, in the following section, we develop a simple model of job search under uncertainty in which workers hold subjective beliefs about job-finding prospects that update concavely with experience. These beliefs jointly determine reservation wages and search effort. In the computational model, belief "updating" is implicit: we discipline effort and reservation-wage rules directly with microdata because outcomes (applications, effort, wage expectations) are observed reliably. The formalization therefore clarifies the behavioral mechanisms underlying the empirical relationships we impose in the computational model, ensuring internal coherence between observed behavior and underlying learning dynamics.

5.1 Model

Time is discrete, indexed by $t = 0, 1, 2, \dots$. The labor market contains a finite set of occupations $\mathcal{I}$, and a worker is characterized by an origin occupation $i \in \mathcal{I}$. At month t the economy comprises unemployed workers $\mathcal{U}_t$, employed workers $\mathcal{E}_t$ and vacancies $\mathcal{V}_t$. Labor-market tightness is defined broadly as:

$$\varphi_t \equiv \frac{|\mathcal{V}_t|}{|\mathcal{U}_t|}$$

and, analogously, for specific occupation i as:

$$\varphi_{i,t} = \frac{V_{i,t}}{\mathcal{U}_{i,t}}$$

All occupations $\mathcal{I}$ are situated in a network where directed edges from occupation i to j are weighted by their occupational similarity $\rho_{ij} \in [0, 1]$. In the agent-based model, this occupational similarity is drawn from realized transitions, but in this more general form, this occupational similarity index should be considered a measure of "transition-ability" between occupation i and j, indicating the extent to which a worker from occupation i could take on the tasks and work of occupation j. All occupations $\mathcal{I}$ are additionally characterized by a wage w_j which sets the wage offer of any open vacancies in occupation j.

5.2 Unemployed Search

In each period t, an unemployed worker b chooses how many applications to submit to ranked vacancies to maximize their expected utility. Applications incur a fixed per-application cost $c > 0$. The worker's optimization problem is therefore to select the number of applications $A_t \in \{0, 1, \dots, \bar{A}\}$ to send at time t to maximize their expected utility, where $\bar{A}$ is finite. Seekers are subject to a budget constraint such that $Ac < C$, where C is their total budget.

In addition to their most recently held occupation i, the unemployed worker b is characterized by their unemployment duration $\tau_{b,t}$, utility function defined by constant relative risk aversion attenuated by parameter λ_b, reservation wage $R_{b,\tau}$, and a subjective re-employment success belief $\beta_{b,\tau} \in [0, 1]$, each of which is explained below. Variables are denoted using t (τ) when their values are subject to time-specific (individual unemployment duration-specific) variation.

Let $V_t^i \subseteq \mathcal{V}_t$ denote vacancies in the economy relevant to occupation i where relevance is defined by $\rho_{ij} > 0$. Let $A_t^b \subseteq V_t^i$ denote the subset of these relevant vacancies that an individual job-seeker b chooses to apply to.

Reservation wage. First, worker b restricts the observed vacancy set to V_t^i to those vacancies where the vacancy's wage $w_{j,t} \geq R_{b,t}$. Reservation wage $R_{b,t}$ is defined as follows:

$$R_{b,t} = \max\left\{\underline{w}\ , (1 - \psi\tau_{b,t})w_b^{\text{ref}}\right\} \tag{11}$$

where ψ captures general disutility from unemployment (stemming from stigma, loss of confidence, financial precarity), $\tau_{b,t}$ is the worker's current unemployment duration, and w_b^{ref} is their latest held wage in occupation i. The reservation wage has a minimum bound $\underline{w}$.

Vacancy valuation. Next, worker b ranks available vacancies according to a risk-adjusted utility function. Wage preferences are defined by constant relative risk aversion (CRRA), mediated by match quality or occupational similarity ρ_{ij} :

$$u_b(w_{j,t}) = \begin{cases} \dfrac{(\rho_{ij} w_{j,t})^{1-\lambda_b}}{1-\lambda_b}, & \lambda_b \neq 1, \\ \ln(\rho_{ij} w_{j,t}), & \lambda_b = 1. \end{cases} \tag{12}$$

where λ_b represents agent b's risk aversion:
$\lambda_b > 0$: risk averse (concave utility)
$\lambda_b < 0$: risk seeking (convex utility)
$\lambda_b = 0$: risk neutral (linear utility)

Per-application subjective success probabilities. Next, we extend this utility function to an expected utility framework through the incorporation of a subjective belief updating process, allowing the worker's subjective beliefs to factor into the decision-making process.

Let $p_{a,t}$ denote the worker's *subjective belief* about the probability that the a-th application submitted (in rank order according to Equation 12) in period t yields a job offer. This probability is jointly determined by the worker's subjective belief $\beta_{b,t} \in [0,1]$ (a reflection of confidence or self-efficacy) of their re-employability, an indicator of match likelihood $m_{ij,t}$, and a probability decay parameter γ which reflects the decreasing probability of a match as a worker descends their ranked application set. $m_{ij,t}$ is a function of competition in the target occupation j ($\varphi_{j,t}$) such that:

$$m_{ij,t} = f(\varphi_{j,t})$$

As such, $m_{ij,t} \in [0,1]$.

In this expected utility framework, the similarity index ρ_{ij} modifies the utility directly by adjusting for match *quality* (a higher ρ_{ij} implies a better match and thus greater value derived from the job), whereas $m_{ij,t}$ adjusts for match *likelihood* given competition effects. This version formalizes the idea that both *uncertainty* via $m_{ij,t}$ and *match quality* via ρ contribute to how the worker perceives the value of a job offer, while remaining grounded in von Neumann–Morgenstern expected utility theory.

As such, the subjective probability of success of the a-th application ($p_{a,t}$) is a value that decreases in relation to the subjective probability of success of the top vacancy in the ranked set $p_{1,t}$. $p_{a,t} \in [0,1]$to ensure valid probabilities.

$$p_{1,t} = \beta_{b,\tau}\, m_{i(1),t}^{\eta}, \tag{13}$$

$$p_{a,t} = \max\{p_{1,t} - \gamma(a-1),\, 0\} \tag{14}$$

Sticky belief updating. Beliefs are updated according to Equation 15

$$\beta_{b,\tau} \;=\; \beta_{b,\tau-1} \;+\; \alpha_\tau \big(h_{b,\tau-1} - r\big), \qquad \alpha_\tau \;=\; e^{-\omega\tau} \tag{15}$$

where $h_{b,\tau-1} = 1$ if the previous application succeeded (and 0 otherwise), r is the benchmark learning rate, $\omega > 0$ is a curvature parameter, and α_τ delivers concave (saturating) learning.

This functional form for α implies diminishing sensitivity over time, consistent with concave learning in line with the findings of [75] who demonstrate that job seekers' beliefs are sticky and adjust slowly downward over time.

Marginal benefit of the a-th application. Thus, if the worker submits applications in a ranked order $a = 1, 2, \ldots$, and the per-rank success probabilities in period t are $p_{1,t}, p_{2,t}, \ldots$, then the *marginal* probability that the a-th application yields the *first* success is

$$\Delta P_t(a) \;=\; \left(\prod_{j=1}^{a-1}(1 - p_{j,t})\right)\, p_{a,t}, \tag{16}$$

and if we use $u_b(v_a) - u_b(B^U)$ to represent the utility surplus of gaining employment in vacancy a relative to remaining unemployed, then the expected utility from applying to A applications is:

$$EU_t(A) = u_b(B^U) - cA + \sum_{a=1}^{A} \Delta P_t(a)(u_b(v_a) - u_b(B^U)) \tag{17}$$

Discrete marginal-cost decision rule. Thus, the perceived marginal gain from adding an additional application a is

$$\Delta EU_t(a) = P_t(a)(u_b(v_a) - u_b(B^U)) - c \tag{18}$$

Then, the decision rule is:

$$A_t^\star \;=\; \arg\max\Big\{\, a \le \bar{A} \;: MB_t(a) \ge c \,\Big\}, \tag{19}$$

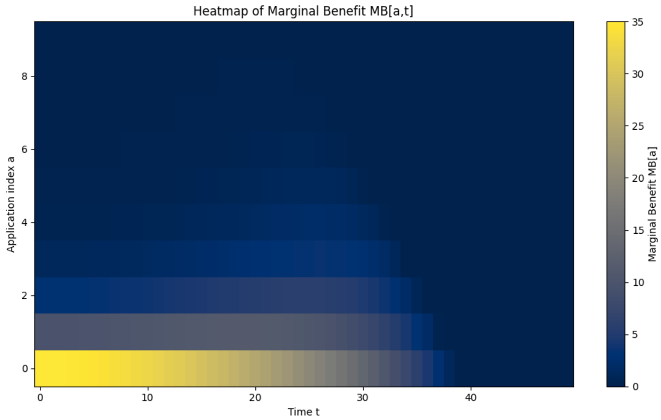
where

$$\mathrm{MB}_t(a) \;=\; \Delta P_t(a)(u_b(v_a) - u_b(B^U)). \tag{20}$$

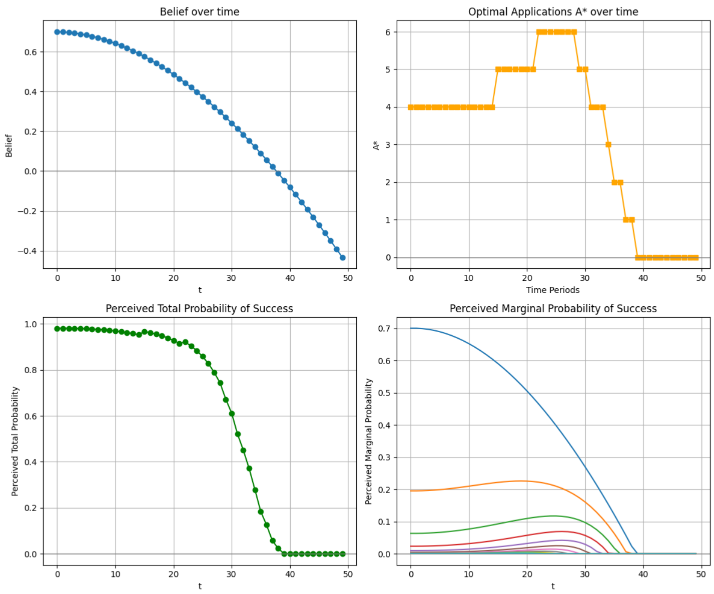
Thus, the worker applies until the perceived marginal expected utility of the next application a falls below the cost per application c. Because applications are discrete and limited by an upper bound $\bar{A}$, the optimal number of applications in period t is $A_t^\star$.

These rules impose that our incorporated forms of adaptive behavior (reservation wages and search effort) operate differently to increase the chances of re-employment. The reservation wage broadens the available application set of the agent and sticky beliefs influence application effort through an adaptive learning process.

The below plots demonstrate initial comparative statics about this decision rule using the following parameter values: $T = 50, \beta_0 = 0.7, \omega = 0.01, r = 0.1, \bar{A} = 10, \Delta B = 50$. Figure 15b demonstrates the trajectories of parameter β_b and its effect on the size of the optimal application set, perceived probability of success, and marginal probability of success. The incorporation of slowly decaying beliefs induces concavity in search effort, as represented in sub-figure (a) and the top right panel of sub-figure (b).



(a) Heatmap of marginal benefits by duration and cost.



(b) Value trajectories in stylized model with fixed parameters.

Figure 15

5.3 Employed Search

Participation decision. Employed individuals are subject to a different decision relative to unemployed workers because they retain an outside option, i.e., remaining in their current job. Though they are similarly affected by their subjective beliefs about their re-employability, their initial decision about whether to actively engage in on-the-job search P_{it}^{OTJ} is driven by their perceived labor market tightness. In particular, an employed worker i with current wage w_i decides whether to search on the job as a function of market tightness and beliefs. This means that their probability of searching is:

$$P_{i,t}^{\mathrm{OTJ}}(\varphi_t) \; = \; \frac{1}{1 + \exp\Big(- \big[\delta + \beta_i \, \varphi_t\big] \Big)}, \tag{21}$$

where, as in the model above, $\beta_i \in [0,1]$ is the worker's subjective confidence in re-employment success (confidence) which either increases or decreases the pressure of competition φ_t and δ is a fixed likelihood of search across all employed workers. Search occurs when $P_{i,t}^{\mathrm{OTJ}} \geq \kappa$, for some threshold $\kappa \in (0,1)$, implying a saturating (logistic) relationship between market conditions and search participation. This rule enforces that, as in the ABM, employed seekers exhibit diminishing marginal likelihood of search as a function of competition.

Application Decision Conditional on searching, the worker observes the set of relevant vacancies $V_t^i \subseteq \mathcal{V}_t$ (defined as in the unemployed case by $\rho_{ij} > 0$) and restricts attention to vacancies that constitute an "upgrade" over the current job.

The worker ranks vacancies in V_t^i in the same way unemployed workers do according to Equation 12. The worker then chooses whether to apply to the top-ranked vacancy in the set or not, maximizing perceived marginal benefit. Let c again denote the cost of applying to vacancy a. In order to align with the functionality in the ABM, where employed workers only send one application per time period, the decision is now binary rather than targeting an application count. This could feasibly be extended to a multiple-application case as in the formulation for unemployed workers above.

In the one-application case, we capture this via a simple employed reservation rule:

$$V_{i,t}^E \; = \; \{\, v \in V_t^i : w_v \geq w_i \,\}. \tag{22}$$

Employed workers are not subject to duration-dependent reservation wage dynamics in this model; rather, they only consider vacancies that weakly dominate the current wage.

Vacancies in $V_{i,t}^E$ are valued using the same match-quality-adjusted CRRA utility as for unemployed workers (see Equation 12), with match quality proxied by occupational similarity ρ_{ij}. Let j denote the occupation associated with vacancy v.

The utility gain from switching to vacancy v relative to remaining employed in i is

$$\Delta u_i(v) \; = \; u_i(w_v, \rho_{i\,j}) \; - \; u_i(w_i, 1). \tag{23}$$

As in the unemployed case, workers form a subjective probability of receiving an offer. Let $m_{i\,j(v),t} \in [0, 1]$ denote a match-likelihood term (increasing in destination-market tightness, as specified earlier), and let $\eta > 0$ be a curvature parameter. Then the perceived success probability for applying to v is

$$p_{i,t}(v) \; = \; \beta_{i,t}\, m^{\eta}_{i\,j(v),t}. \tag{24}$$

Let $c > 0$ denote the per-application cost. Conditional on searching, the worker selects at most one vacancy to apply to. The expected utility from applying to vacancy v (and accepting the offer if received) is

$$EU^S_{i,t}(v) \; = \; (1 - p_{i,t}(v_a))\, u_i(v_a) \; + \; p_{i,t}(v_a)\, u_i(v_a) \; - \; c. \tag{25}$$

Subtracting the outside option of not applying, $u_i(w_i, 1)$, yields the expected surplus from applying:

$$\Delta EU_{i,t}(v) \; = \; p_{i,t}(v)\, \Delta u_i(v) \; - \; c. \tag{26}$$

Define the marginal benefit of applying to vacancy v as

$$MB_{i,t}(v) \; = \; p_{i,t}(v)\, \Delta u_i(v). \tag{27}$$

The worker applies to the vacancy that maximizes this expected benefit, provided it exceeds the application cost. That is, conditional on searching,

$$A^\star_{i,t} = \begin{cases} 1, & \text{if } \max\limits_{v \in \mathcal{V}^E_{i,t}} MB_{i,t}(v) \; \geq \; c, \\ 0, & \text{otherwise,} \end{cases} \qquad\qquad v^\star_{i,t} \in \arg\max_{v \in \mathcal{V}^E_{i,t}} MB_{i,t}(v). \tag{28}$$

Thus, employed workers first decide whether to engage in OTJ search via Equation 21 and, if they search, submit a single application to the vacancy offering the highest perceived expected surplus, net of application cost.

Testable implications. (i) $R_{i,t}$ declines linearly, expanding the acceptable set $\{j : w_j \geq R_{i,t}\}$ and raising exit hazards. (ii) OTJ participation is pro-cyclical (increasing in φ_t), altering the composition of applicants over the cycle and crowding queues faced by the unemployed. (iii) Search effort of the unemployed is concave.

Symbol	Meaning
$\mathcal{I}$	Set of occupations
$\mathcal{U}_t$	Set of unemployed workers at time t
$\mathcal{V}_t$	Set of vacancies at time t
$\mathcal{E}_t$	Set of employed workers at time t
φ_t	Market tightness $\lvert\mathcal{V}_t\rvert/\lvert\mathcal{U}_t\rvert$
w	Wage offered by vacancy (occupation and/or time specific)
Worker-related variables	
B^U	Value of unemployment
$\beta_{b,t}$	Subjective belief of worker from occupation i about job-finding
β_i	Fixed subjective belief of worker from occupation i about job-finding
$\tau_{b,t}$	Unemployment duration of worker b at time t
$h_{b,\tau-1}$	Job-finding outcome (1 if hired, 0 otherwise)
$P_{i,t}^{OTJ}$	Probability of engaging in job search
$V_{i,t}^{E}$	Acceptable vacancy set for employed workers
w_b^{ref}	Reference wage (latest held) for unemployed workers
A_t	Number of vacancies to apply to at time t
a	Vacancy rank in worker's preference ordering
$\bar{A}$	Maximum possible applications per period
λ_b	Risk aversion parameter
ψ	Disutility to unemployment
$A_t^\star$	Optimal number of applications / chosen set size
Probabilities	
$p_{a,t}$	Success probability for vacancy of rank a at time t
$p_{1,t}$	Baseline success probability for top-ranked vacancy
γ	Suitability / decay profile across ranked applications
ρ_{ij}	Occupational similarity between occupations i and j
$m_{ij,t}$	Matching probability of worker i with vacancy j
η	Elasticity of matching w.r.t. occupational similarity
$\mathrm{MB}_t(a)$	Marginal benefit of applying to vacancy rank a
Belief updating	
α_τ	Learning-rate parameter
ω	Curvature parameter in belief updating function
r	Benchmark learning rate
Costs, budgets, and constraints	
c	Per-application search cost
C	Total application/search-time budget in period t
$R_{b,t}$	Reservation wage of worker b
$\underline{w}$	Minimum reservation wage requirement
Decision and participation	
δ	The fixed propensity to search by employed workers
κ	Threshold for on-the-job search participation

Table 4: Notation and Definitions Used in the Model

6 Discussion

In this work, we demonstrate the utility of incorporating data-driven behavioral rules into labor market models. Doing so raises an immediate design tension: the behavioral economics literature documents many interacting mechanisms, but adding them all quickly undermines parsimony and tractability. We therefore take a deliberately selective approach, disciplining the model with data on the key *actions* workers directly control, how intensively they search and which wages they are willing to accept, while leaving scope for these behavioral rules to be heterogeneous across demographic groups in future applications.

A first set of results demonstrate that the inclusion of more detailed, data-driven behavioral rules materially improve the model's ability to match the *dynamics* of various labor market statistics, that simpler models only match in levels. We provide two empirical contributions in this respect. First, we provide evidence on the concave shape of search effort (abstracting from unemployment insurance) wherein seekers exhibit declining search effort following a period fo strategy adjustment. In relation to existing literature, we propose that this concavity is an interaction between a learning and discouragement process wherein in individuals adapt to new information about the state of the labor market.

Second, we provide additional evidence of satisficing in reservation wage behavior: unemployment duration exerts sustained downward pressure on wage expectations, in line with existing findings [48, 17, 57, 52]. Furthermore, unemployment-duration dependent reservation wage adjustments allow us to more accurately model the relationship between post-displacement wage losses and the business cycle. Additionally, we find that these behavioral margins also matter for aggregate adjustment. Allowing application effort to evolve over the unemployment spell improves the fit of the unemployment-rate response following the 2008 financial crisis relative to a non-behavioral benchmark. In other words, the incorporation of a learning process throughout an unemployment spell in relation to job search strategy corroborate the findings of [77] regarding the cyclicality of job search effort. Similar to the findings of Mukoyama et al. we find that agent search effort dampens the amplitude of the unemployment rate's relationship to the business cycle, avoiding over-estimated peaks and near-zero unemployment rate measurement during economic booms. modeling belief updating and effort choices therefore helps the simulated labor market adjust in a way that resembles observed recoveries.

Additionally, as has been advocated for by [34], the inclusion of employed job-seekers provides key improvements to our ability to fit a model with just two economic parameters (δ_u and γ_u). Their considerable share of the job-seekers induces significant competition in boom periods which allows us to triangulate a more realistic unemployment rate. We provide additional evidence of the imperative to incorporate competition into studies of unemployed search behavior and transformation-related frictions. Similarly, we find that the combination of agent learning in relation to their reservation wage and required application effort allows us to more realistically emulate the distribution and time series of long-term unemployment rate. A natural extension is to incorporate unemployment insurance explicitly, since the empirical literature suggest it shifts effort and reservation behavior in systematic ways.

6.1 Limitations and Potential for Future Work

This work could benefit significantly from further exploration of the following dimensions, categorized by data and modeling needs. First, the model does not accommodate skill deterioration during unemployment spells which have been found to affect re-employment prospects of the unemployed [82, 78, 94]. Second, the model does not currently incorporate geographical frictions in labor market re-allocation. Third, the entry and exit protocol within the model could serve as an additional engine to accommodate structural transformation forces, in which mismatches between educational investments and labor market realities might affect over- or under-supply of certain occupational groups. Fourth, the scale at which the model is simulated influences the appropriate economic parameter values given the network effects at play. The model reported in the main text uses a scaled down representation of the US economy (1/10,000th of the US labor force). This leads to challenges in the vacancy creation process in which very small occupations rarely open vacancies. Though this mismatch is likely in line with supply and demand dynamics in smaller occupations, mismatch in the current model is at least partly defined by this challenge rather than true mobility frictions. Finally, the occupational wage distributions that wage offers are drawn from are fixed throughout the simulation period. Though this choice might be justified via an argument about the offers representing real rather than nominal wage offers, this assumption is potentially unrealistic. Greater consideration of wage offer dynamics (i.e., employer decision-making) could inform a wage mechanism responsive to changes in labor supply and demand. Not only would such an incorporation bring greater realism to the model but could similarly inform discourse on wage dispersion and displacement-related wage losses.

Furthermore, the work was aided by the availability of public use microdata. However, the quality of data available on the behavior of jobseekers was nonetheless limited. Most significantly, lack of longitudinal data impeded investigation of the business cycle effects on the job search behavior incorporated in this work. We assume that the data used to inform the behavioral rules in the model are consistent across various stages of the business cycle, which is a restrictive, and perhaps unrealistic assumption.

7 Conclusion

Within labor ABMs, prior work studies structural reform, institutions, and network effects, but search behavior is typically represented by fixed heuristics rather than empirically estimated rules. Relative to these previous studies, our contribution is integrative and structural. First, we translate separately documented behaviors - biased belief updating, wage expectations, and dynamic search effort - into an internally consistent set of rules and embed it in a market environment allowing us to estimate the importance of these behavioral margins jointly rather than one-by-one. We endogenize on-the-job search alongside unemployed search. This generates vacancy–unemployment decoupling via crowding in and not only vacancy posting. We allow heterogeneity in both states and behavioral parameters, so distributional outcomes (e.g., gender wage disparities; uneven wage gains during structural change) arise endogenously rather than being imposed as fixed gaps.

Additionally, we propose an accompanying theoretical framework formalising an analogous job search model in which individuals choose an application bundle over adjacent occupations to attain a target success probability subject to heterogeneity in subjective beliefs, learning rates, dynamic search effort and reservation wage-setting. Applications generate offers with arrival intensity increasing in effort and local tightness. Beliefs update from realized outcomes via a concave learning rule; reservation wages evolve with time out of work.

8 Inventory of Remaining Work

Below, we outline the remaining work planned prior to pursuing journal submission. In addition to cosmetic improvements to the manuscript, we intend to:

- Run sensitivity analyses varying the scale of the model (i.e., size of the population).
- Incorporate out-of-sample testing over the COVID-19 period.
- Incorporate statistics for model performance comparison rather than relying on visual comparison.
- Reconsider calibration of OTJ search propensity as the fit is currently poor.
- Generalize the behavior in the theoretical job search model formulation to apply more uniformly across unemployed and employed job-seekers. This will be achieved by incorporating the propensity for on the job search into the utility maximization problem faced by employed seekers, rather than allowing this propensity to act as a strict gate. We could additionally consider generalizing the employed job search to allow for multiple applications.
- Include additional appendices:
  - Document the calculation of occupational gender shares which requires various assumptions to account for missing occupational categories.

– Documentation of entry-exit indicators used from BLS to define the entry-exit protocol in the model.
– Provide greater detail in the documentation of the data basis for the behavioral mechanisms.
– Provide greater detail in the documentation of O*NET Related Occupations Network including the work done to draw reciprocal edges from higher- to lower-wage related occupations.
– Document the procedure for drawing occupational wage distributions from the BLS Occupational Employment and Wage Statistics database.

Use of AI

- Used ChatGPT to aid translation of Stata replication code from [34, 77, 75] to R.
- Used ChatGPT to improve spacing, legend placement, and provide suggestions for improving plot readability in Python.
- Used Claude to create code automating plot generation across model versions (rewriting repetitive code as functions and for loops).
- Used Claude for debugging and diagnostics of ABM functions.
- Used Claude for advice on unit testing placement.
- Used Claude to verify consistent and non-repetitive notation in theoretical model formulation in Section 5.

Code and Data Availability

All public use data used in this work is cited in Section 4.1. All replication code will be made available via Zenodo link. The current version of the code can be found on Github.

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Appendices

A Calibrating Behavioral Parameters

The model's central functionality relies on a variety of behavioral mechanisms that are parametrised econometrically using micro data. Furthermore, the model relies on additional sources of micro data for validation. In the following section we outline, first, the data and analysis used to derive the model's behavioral parameters, followed by an inventory of the data used to validate various model outputs. We note where we make use of methodology employed or constructed by other authors.

Application Effort and Learning Dynamics: Applications Sent

First, we employ data from the US Bureau of Labor Statistics and the Curren Population Survey on the application effort of unemployed job-seekers to discipline our behavioral mechanism for search. More specifically, in 2018 (May, September) and 2020 (February, May), the Bureau of Labor Statistics ran the "Unemployment Insurance Nonfilers" supplemental survey to the monthly Current Population Survey run by the US Census Bureau. The survey's stated intent was to "obtain information on the characteristics of people who do not file for Unemployment Insurance benefits as well as their reasons for not doing so." The survey was conducted for all persons responding the the monthly Current Population Survey which encompasses "all persons in the civilian non-institutional population of the United States living in households. The probability sample selected to represent the universe consists of approximately 54,000 households."

Relevant to our work, survey respondents were asked the following two questions:

PRUNEDUR	3	DURATION OF UNEMPLOYMENT FOR LAYOFF AND LOOKING RECORDS	407 - 409

EDITED UNIVERSE: PEMLR = 3-4

<u>VALID ENTRIES</u>

0 MIN VALUE
119 MAX VALUE

Topcoded consistent with PELAYDUR or PELKDUR, as appropriate, starting April 2011.

Figure 1: Survey Question: Unemployment Duration

A1 Now, we also have a few questions about your experience looking for a new job over the last 2 months. How many jobs (have you/has name) applied for, if any, in the last 2 months?

(Do not read the answer choices aloud)

(0) 1
(1) 1 to 10
(2) 11 to 20
(3) 21 to 80
(4) 81 or more

Figure 2: Survey Question: Applications Sent

Overview of Survey Results

First, we replicate figures produced for a 2020 Bureau of Labor Statistics "Beyond the Numbers" issue 2020 "Beyond the Numbers" issue, illustrating some high-level results from the survey, prior to describing the econometric specifications employed using the raw survey data. As seen in the image above, the survey responses regarding applications sent are "binned" into intervals (ie. number of people sending 81 or more applications or unemployment duration of between 5 and 14 weeks) which means that any line plots (or linear interpretation of the bar graph) should be done with caution.

In Figure 1, the top left panel shows the proportion of all individuals sending X amount of applications receiving Y amount of interviews. The plot indicates a "consistent" return to sending more applications, although as demonstrated in the bottom left plot, the number of applications sent is not a linear predictor of job offers received. More precisely, the bottom left plot demonstrates that the percentage of jobseekers receiving an offer seems to increase as a function of the number of applications sent, until a certain point.Next, the right plot demonstrates the number of applications sent (red), interviews received (green), average interview:application ratio (blue), and probability of receiving a job offer (purple) by individuals in each category of unemployment duration. There is some indication that both effort and success seem to increase and then decline with time spent in unemployment, apart from success as measured by receiving a job offer which seems to consistently decline with time spent in unemployment.

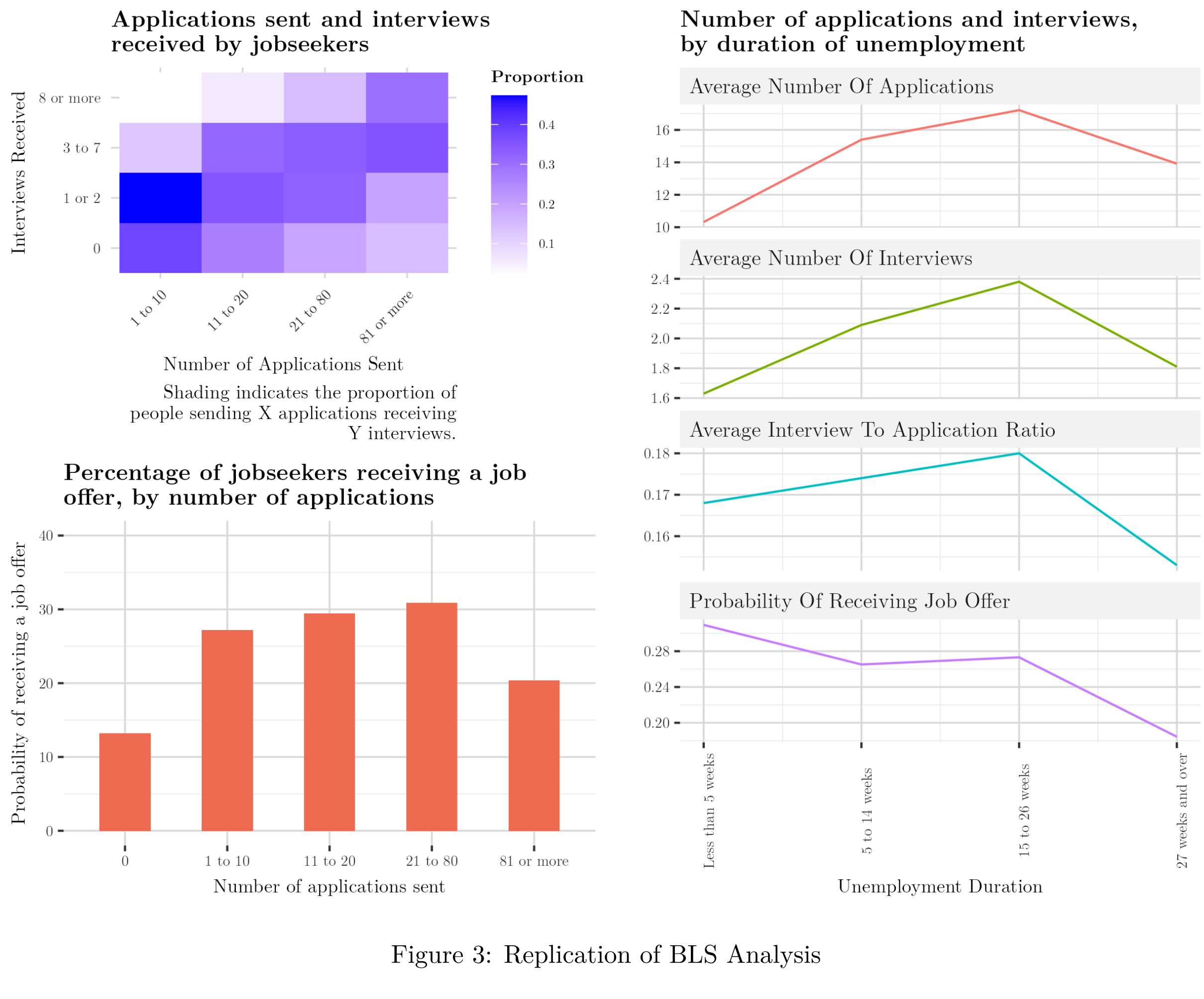
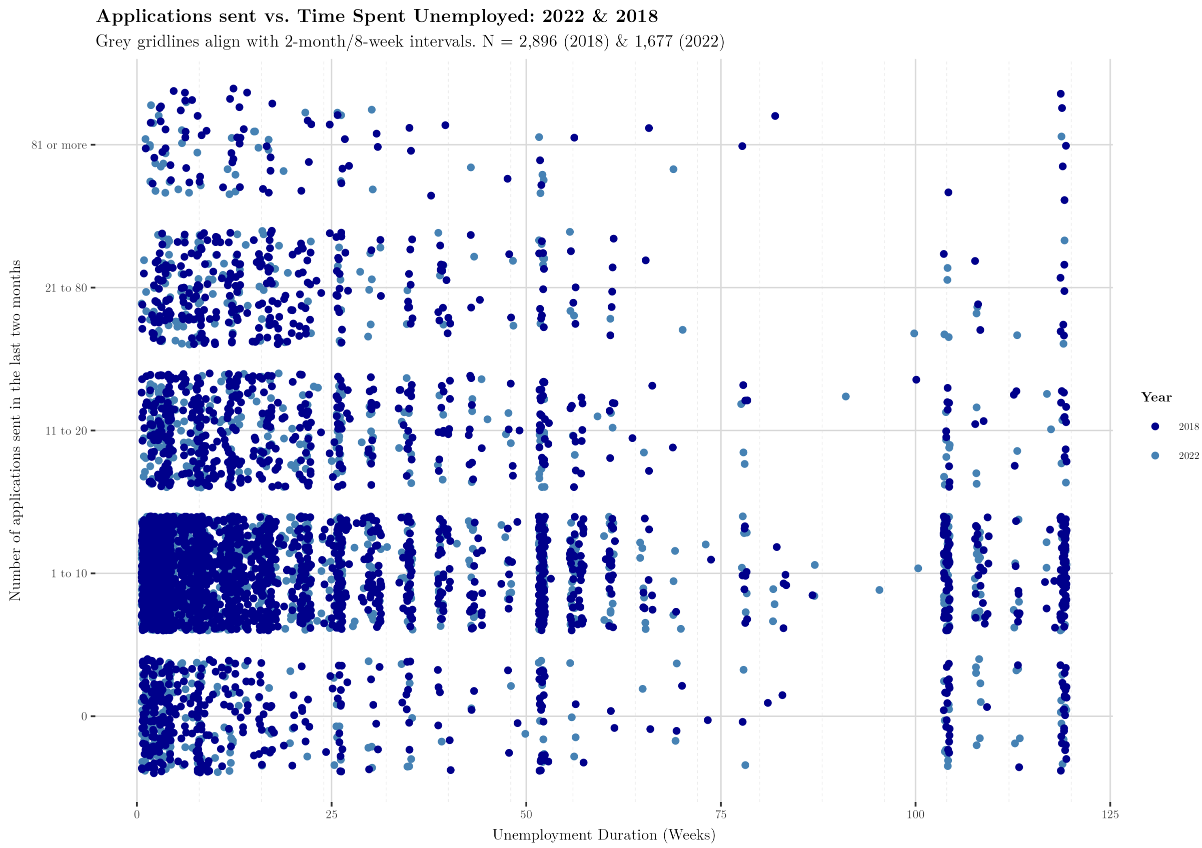


Figure 3: Replication of BLS Analysis

Econometric Specification Using Raw Data



To inform our agent behavior, we derive an unemployment-duration dependent measure of application effort, reporting in applications sent. More precisely, we estimate the probability distribution over reported job application intensity during unemployment using pooled micro data from the 2018 and 2022 waves of the CPS in which the Bureau of Labor Statistics conducted a Job Search Supplement. The survey asks unemployed respondents who are actively searching for work the amount of job applications they have sent. Respondents report job application counts in ordinal bins: 0'',1–10’‘, 11-20'',21–80’‘, and “81 or more’’. To account for the lack of a continuous dependent variable, we estimate a series of ordinal logistic regression models to recover the conditional probability of each response bin as a function of unemployment duration and various demographic characteristics. We test model specifications along three dimensions: (i) link function, comparing logistic, probit, complementary log-log (cloglog), and log-log links; (ii) linear, quadratic, and cubic specifications of unemployment duration; and (iii) models with and without demographic covariates (education, gender, age, and family income; race was excluded due to lack of statistical significance across models). Formally, the model estimates $\Pr(Y_i \leq j \mid X_i)$, the cumulative probability of observing response category Y_i for individual i below j where j represents the five ordinal bins given various transformations of the vector X_i of independent variables (unemployment duration and demographic controls).

Below, we display the results of an exploration of the probability of reporting a specific number of applications sent (in the bins as in the survey question above) using various specifications of an ordinal logistic regression. Wetest specifications varying three different model parameters:
1. link function
2. linear vs. quadratic unemploymentduration,
3. with and without demographic control variables (education, gender, age, family income - race excluded because of lack of statistical significance though this can be revisited.)

We estimate an ordinal logistic regression model for reported applications sent Y_i in $0, 1, 2, 3, 4$ testing four different link functions: the complementary log-log (cloglog), logistic, log-log, and probit link functions. Let $X_i^\top \beta$ denote the predictor variable. The cumulative probability of observing response category j or below, $\Pr(Y_i \leq j \mid X_i)$, is modeled as follows for each link function:

$$\begin{aligned}
\text{Complementary log-log (cloglog):} \quad & \Pr(Y_i \leq j \mid X_i) = 1 - \exp\left(-\exp\left(\tau_j - X_i^\top \beta\right)\right) \\
\text{Logistic (logit):} \quad & \Pr(Y_i \leq j \mid X_i) = \frac{1}{1 + \exp\left(-(\tau_j - X_i^\top \beta)\right)} \\
\text{Loglog:} \quad & \Pr(Y_i \leq j \mid X_i) = \exp\left(-\exp\left(-(\tau_j - X_i^\top \beta)\right)\right) \\
\text{Probit:} \quad & \Pr(Y_i \leq j \mid X_i) = \Phi(\tau_j - X_i^\top \beta)
\end{aligned}$$

Here, $\Phi(\cdot)$ denotes the cumulative distribution function of the standard normal distribution. The estimated coefficients β are interpreted conditional on the choice of link function where X_i is either:

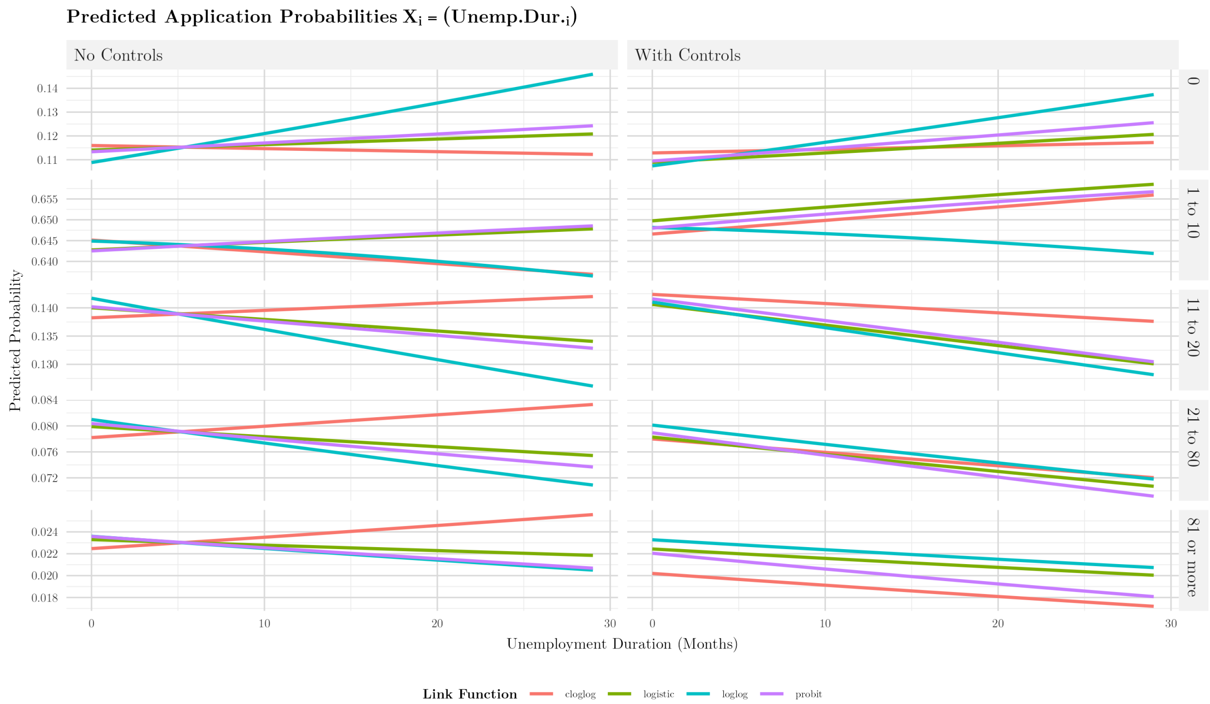
$X_i = (\text{Unemp.Dur.}_i)$

$X_i = \left(\text{Unemp.Dur.}_i^2\right)$

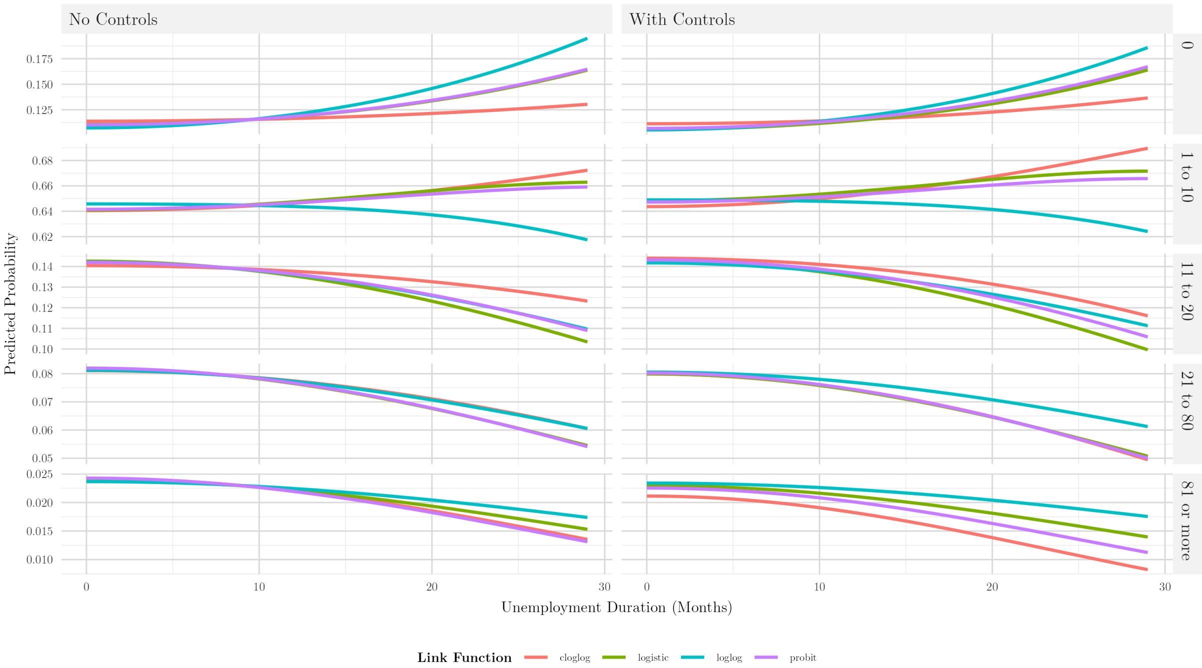
$X_i = \left(\text{Unemp.Dur.}_i, \text{Unemp.Dur.}_i^2\right)$

with and without control variables (education, gender, age, family income).

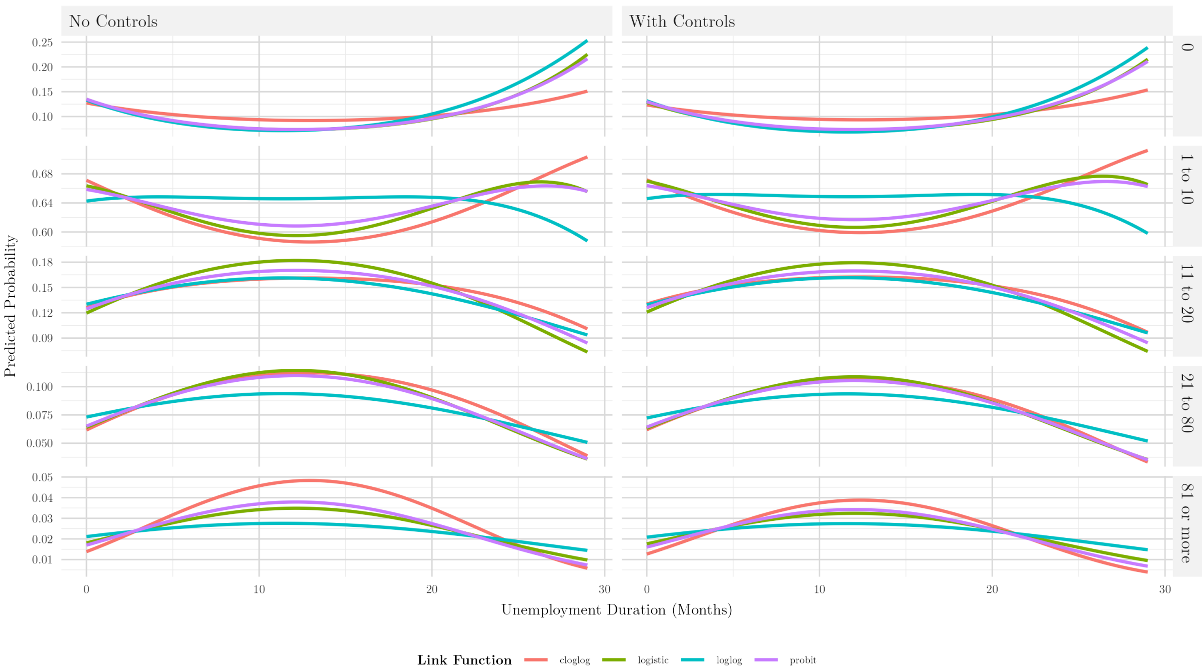
Assumptions about the probability distribution of the errors associated with each link function:
- *Logit:* Useful when responses are evenly distributed across categories.
- *Probit:* Useful when latent variable is assumed to be normally distributed.
- *Complementary log-log:* Useful when higher categories are more probable.
- *Log-log:* When early categories are of more importance or more probable.



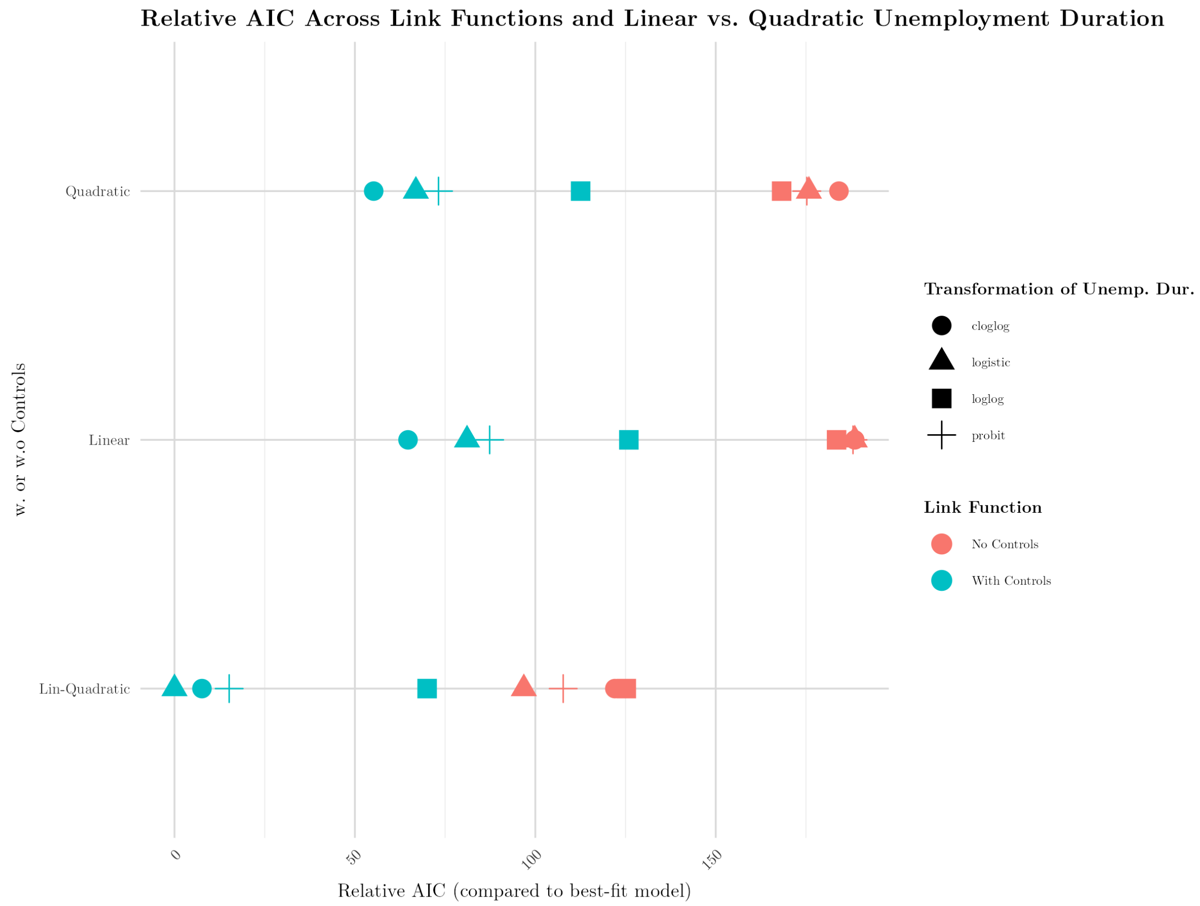
Predicted Application Probabilities $X_i = (\text{Unemp.Dur.}_i^2)$



Predicted Application Probabilities $X_i = (\text{Unemp.Dur.}_i, \text{Unemp.Dur.}_i^2)$



Using an AIC information criterion to compare the fit across all models, clear results emerge. Models including socio-demographic controls consistently outperform unadjusted models (blue versus red dots in the figure below) and the inclusion of a quadratic transformation (labelled "Lin-Quadratic" in the plot below) of unemployment duration better captures the non-linear relationship between unemployment duration and application effort. Among link functions, the complementary log-log specification performs best across model comparisons. Though the logistic link function emerges as slightly superior in the specification incorporating a linear and quadratic term, we choose to employ the complementary log-log link function to align with the hypothesis that fine-grained resolution is needed among low application effort categories, which dominate the data. Thus, employing a complementary log-log link function, quadratic unemployment duration, and full demographic controls, we generate predicted probabilities over the five application bins for unemployment spells ranging from 0 to 36 months. These fitted probabilities serve as the empirical foundation for modeling job search effort in the agent-based simulation. In our chosen specification, the odds of reporting a lower application bin increase by approximately 0.1% per additional month unemployed, a relationship statistically significant at the 0.1% level. However, the inclusion of a quadratic term allows for a concave shape to emerge, better fitting the non-linearity of this relationship between unemployment duration and applications sent.

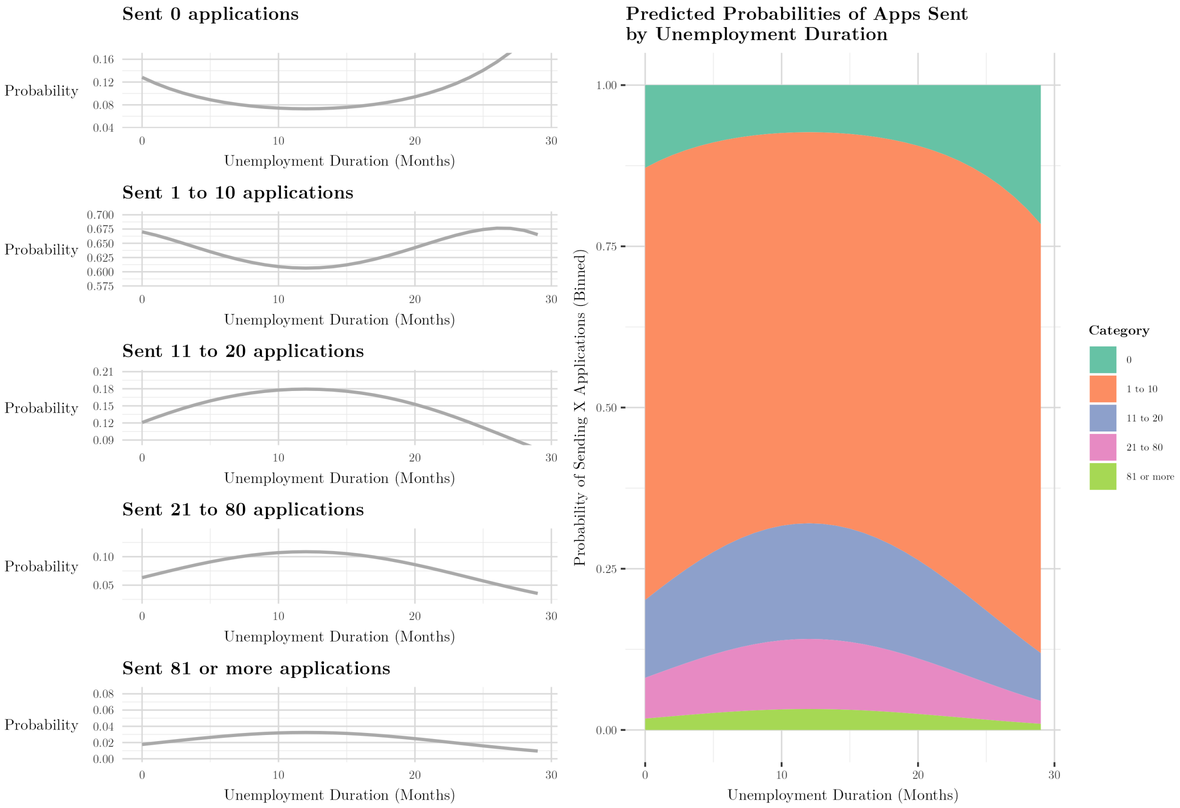


The figure below demonstrates the predicted probability distribution of application effort by unemployment duration indicating a non-linear concave search effort. We believe this contributes to an open debate in the job search literature regarding the shape of search effort over the unemployment spell. The concave application effort emerging from this data aligns with previous observations about unemployed workers engaging in delayed search while either grieving job loss or engaging in job search planning and adjusting expectations about their re-employment prospects, as described in the main text.

The final result is that for each additional quarter of unemployment, an individual's odds of dropping to a lower-level application category decreases by ~.1%. This is statistically significant across all specifications at the 0.1% level.

Predicted Probabilities of Application Effort by Unemployment Duration

N = 5,169
Bureau of Labor Statistics Data reported in 2018 and 2022.
Estimated using an ordinal logistic regression in which the outcome variables are bins of applications sent.
Unemployment duration enters quadratically w. socio-demographic controls.
Controls: Education, Age, Gender, Family Income. Race excluded because of lack of statistical significance.
Link function: Complementary log-log function selected using AIC comparison on 4 alternative link functions.



Wage Expectations and Satisficing: Reservation Wage Adjustment

As part of the Current Population Survey, the US Census Bureau conducts an annual Displaced Worker Supplement in which workers who have lost their job in the last three years are asked additional questions about their unemployment experiences and (if re-employed) their re-employment conditions. From this we draw a reservation wage adjustment rate as a function of unemployment duration. We compare various econometric specifications across several samples that correct for selection effects that typically confound studies of duration-dependent employment outcomes.

As part of the Current Population Survey, the US Census Bureau conducts an annual Displaced Worker Supplement in which workers who have lost their job in the last three years are asked additional questions about their unemployment experiences and (if re-employed) their re-employment conditions.

As reported in the survey documentation linked above, "the universe for the Displaced Workers Supplement is civilians 20 or older. Respondents are further categorized as a 'displaced worker' if they meet additional characteristics (see DWSTAT). Users should note that there is an important difference in definition of displaced worker across samples. Before 1994, displaced workers are those who lost or left a job during the past 5 years. After 1994, displaced workers are those who lost or left a job due to layoffs or shutdowns within the past 3 years. For 1998 on, respondents are only considered displaced workers if they had lost or left a job due to layoffs or shutdowns within the past 3 years, were not self-employed, and did not expect to be recalled to work within the next six months. Self-response was not required for this supplement after 1994, so often one individual answered for all household members."

We utilize the information reported on an individual's weekly wage at their lost job, wage at their new job, and the time spent unemployed to derive a measure of duration-dependent reservation wage adjustment. More precisely, we regress the ratio of the new wage to the wage at the lost job on unemployment duration and various control variables in a cross-sectional setting. We compare the model fit across linear, quadratic, and cubic specifications, with and without various combinations of control variables (whether or not an individual received unemployment compensation, age, race, sex, marital status, education, previous wage level). Note that wages are reported in hourly and weekly values but this reporting is inconsistent across observations. In other words, though most individuals (4600/6198) report their wage in both units, 270 report only hourly and 1328 report only weekly. To be able to combine information on all workers to one value, we select the present statistic for those missing one and retain either the minimum, maximum, or mean of the hourly versus weekly wage for those reporting both. We display box plots of these wage ratios across unemployment duration bins for the different methods of reconciling the missing data later in this document. The data used below is from annual survey responses between 2000-2025. We use the supplement sample weights in all results below.

We note where the sample has been trimmed for outliers (wage ratio between [0.25, 2] and unemployment duration less than 96 weeks (~24 months). All analysis below uses Displaced Worker Sample Weights to ensure appropriate weighting of survey responses and reduce any influence of selection bias.

Below, we outline the data cleaning procedure, provide descriptive figures and statistics, outline the econometric estimation strategy, provide regression results using the raw sample and reweighted samples addressing selection issues and non-uniformity, and provide information on the representativeness of the raw sample. The sample is non-uniform in unemployment duration (less observations are observed for higher values of unemployment duration). We employ three methods of reweighting to address these selection issues (Heckman Selection correction, entropy-balancing, and propensity score matching) to deal with representativeness issues of across values of unemployment durations. These re-weighting and sample balancing methods confirm the directionality of the regression results in the non-uniform sample, providing greater confidence in the triangulated reservation wage adjustment rate.

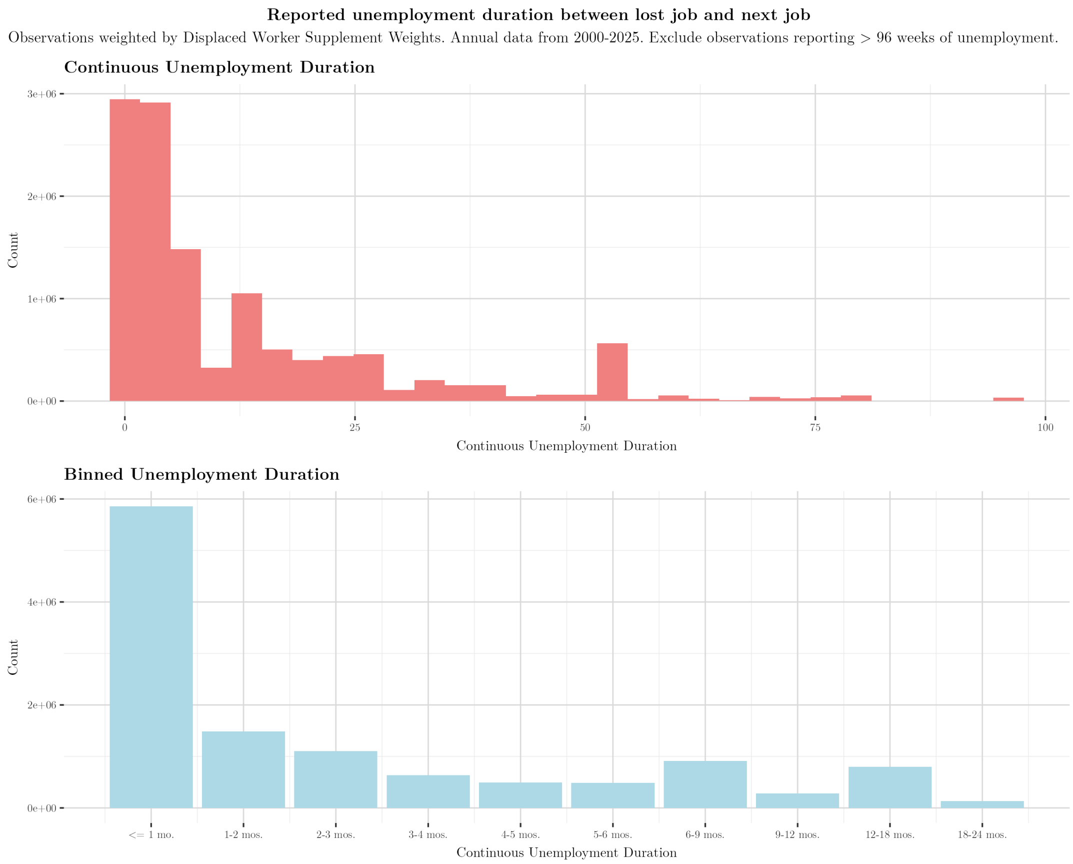
Overall, we find that individuals accept a ~1-percentage point decrease in the wage ratio per additional month of unemployment. Variations using model reweighting, different samples, combinations of control variables, reported hourly and weekly wage ratios do not seem to affect the result. However, the data seems to follow a non-linear relationship (we see little satisficing until around ~12 months of unemployment) after which the wage ratio begins to decrease. Individuals seem to accept a below-1 relative wage ratio (current wage:wage at lost job) following a year of unemployment.

Potential Limitations:

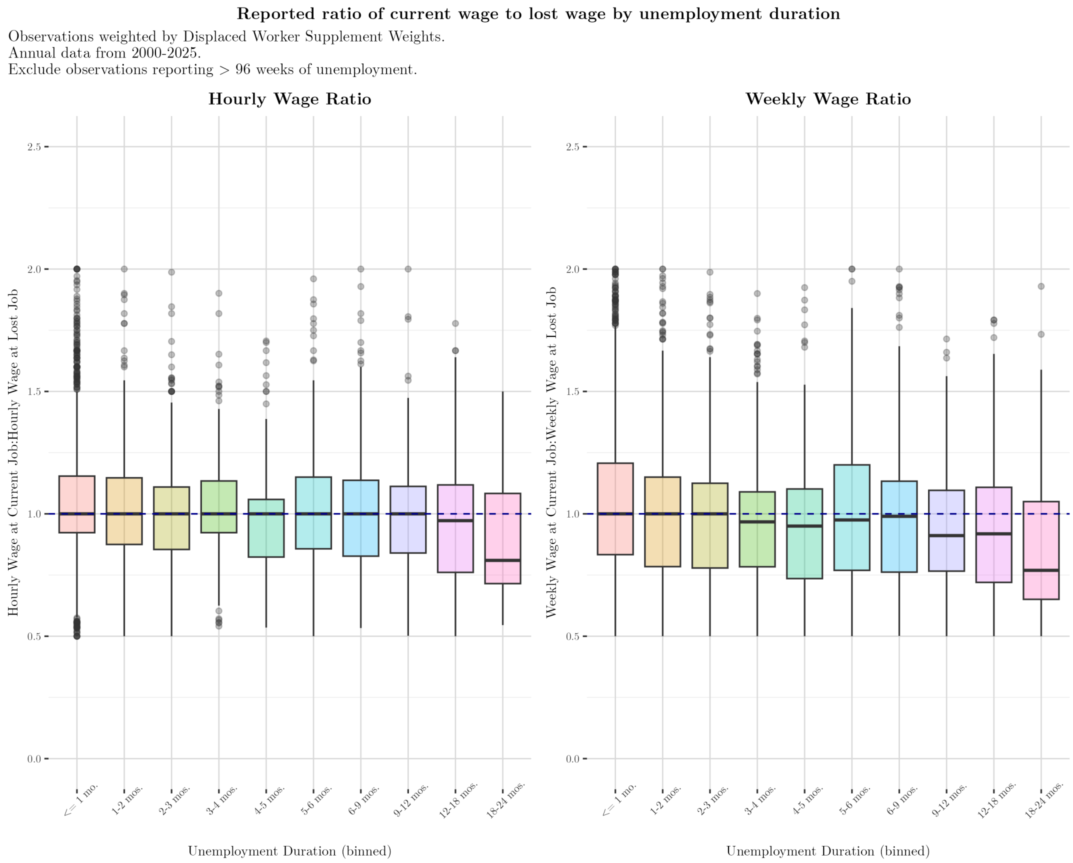
1. **Displaced worker classification as outlined above.** We do not distinguish between workers in our model that are voluntarily or involuntarily separated from their jobs. Therefore, the displaced worker classification outlined above does not represent individuals unemployed voluntarily.
2. **The reported 'current wage' is not necessarily the realised wage post-re-employment.** Individuals report the wage at their lost job, the amount of time unemployed until they were re-employed, and the wage they hold at their current job. However, it is not indicated whether the current job is the same job as the first they were re-employed at. As such, there is uncertainty in the measurement of this outcome as an accepted wage that is relatively low compared to an individual's previous wage might be a temporary reality rather than a true re-employment wage (i.e., an individual finding stop-gap employment).
3. **Outcome variable:** The outcome variable does not adequately handle fundamentally different wage scales (i.e., a 10% wage increase would likely be more or less devastating depending on the initial wage level). We control for wage levels in various specifications listed below. We find that controlling for wage levels does not significantly impact our results.

Descriptives

First, we display the distribution of continuous (red) and binned (blue) unemployment duration. The distribution is, as expected, heavily skewed, with more individuals concentrated at low unemployment durations. The binned values in the blue histogram are the binned values later employed as an outcome variable in various regressions.



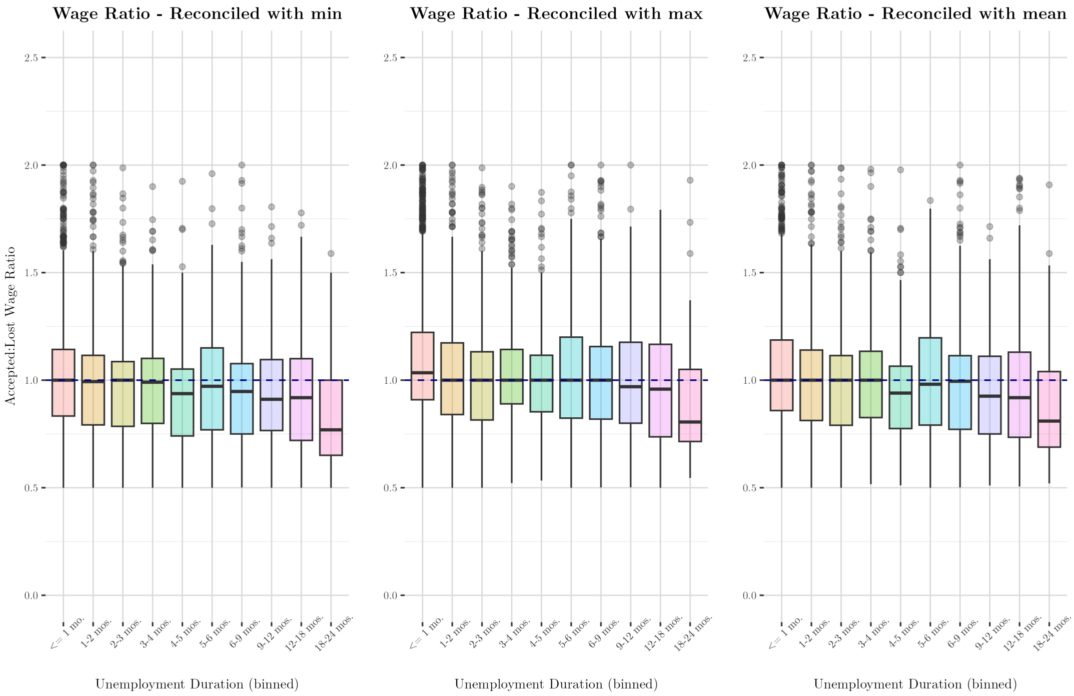
Next, looking at the reported wage ratios in weekly and hourly values (without reconciling the missing data), the mean is fixed near 1 until >12 mos of unemployment in hourly wage reporting. In weekly wage reporting, the "satisficing" seems to start earlier in unemployment duration, indicating that the relationship is potentially negative and non-linear.

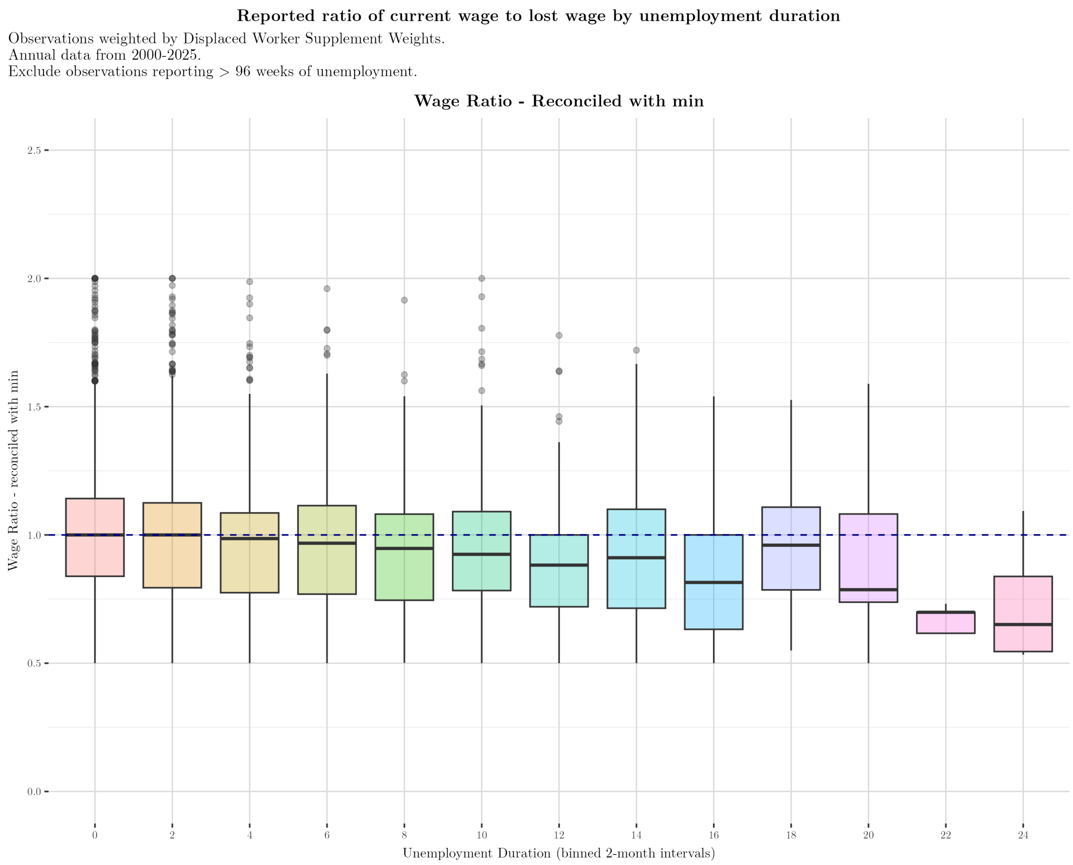


Next, we compare the various options for reconciling missing data across survey responses (i.e., when either weekly or hourly wage is reported but not both.) Notably, reconciling the reported data by taking the minimum (left panel) or mean (right panel) across reported wage values for those individuals that report both do not lead to meaningful differences in the distribution, visually. However, reconciling with the max (middle panel) value leads to slightly less dramatic declines in accepted wage ratios than in the other two cases. In the following sections, we proceed with the method that reconciles mutliple reported values using the minimum value of the wage ratio.

Reported ratio of current wage to lost wage by unemployment duration

Observations weighted by Displaced Worker Supplement Weights. Annual data from 2000-2025. Exclude observations reporting > 96 weeks of unemployment. In many cases, only hourly OR weekly wages are reported. To be able to combine information on all workers to one value, we select the present statistic for those missing one and retain either the minimum, maximum, or mean of the hourly versus weekly wage for those reporting both.

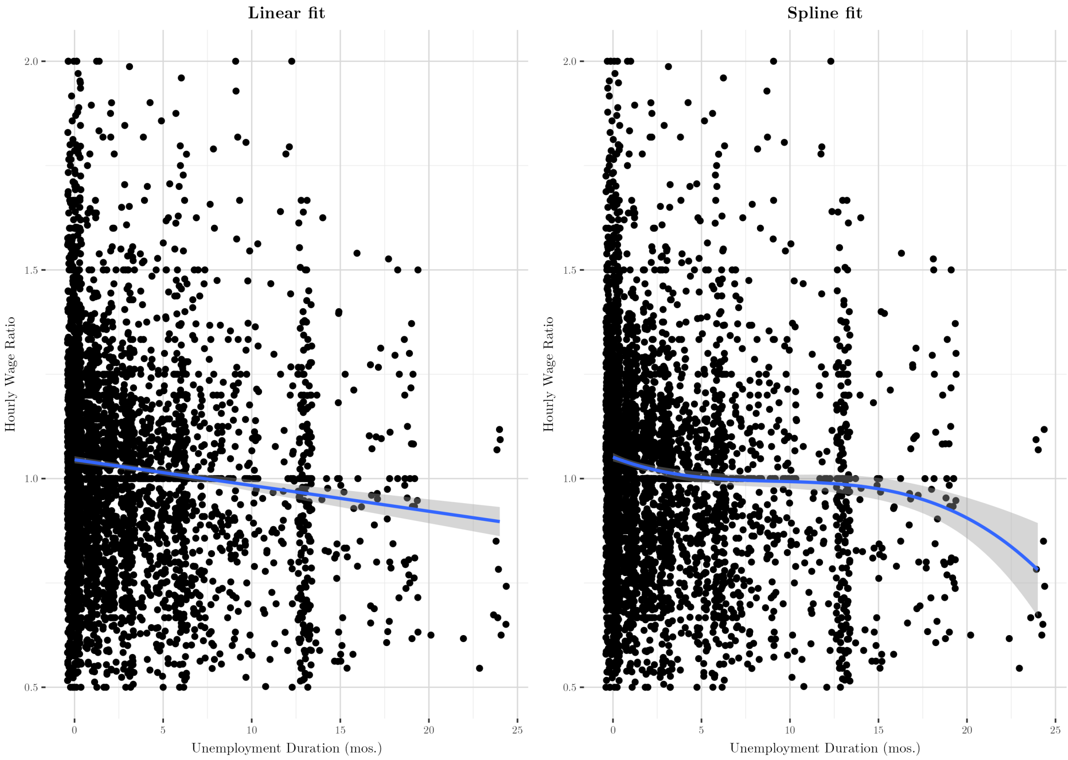




Next, we fit a linear and spline fit to the scatted plot of the wage ratio to unemployment duration before employing any regressions. These plots both visually indicate a decline in the wage ratio with unemployment duratio, with the spline fit indicating a potentially non-linear fit (not yet accounting for selection effects).

Linear and spline fit to scatter plot of wage ratio vs. unemployment duration in months.

Observations weighted by Displaced Worker Supplement Weights. Annual data from 2000-2025. Exclude observations reporting > 96 weeks of unemployment and wage ratios below 0.5 and above 2.



Regressions (non-uniform sample)

Next, before correcting for the non-uniformity of the sample (i.e., that there are less observations present for higher unemployment durations), we employ the following cross-sectional econometric specifications (with various modifications to sample and control variables).

$W_i = \alpha_i + \beta_1 d_i + \beta_2 UI_i + \beta_3 X_i + \epsilon_i$

where W_i: Ratio of accepted wage to wage at lost job (hourly values).

d_i: Unemployment duration in continuous (months) or binned values.

UI_i: Control variable for having used or exhausted unemployment benefits.

X_i: Vector of control variables (sex, age, race, marital status, education level, and previous wage level).

We present and compare ~72 variations on the above model present with all combinations of the following:

- **Continuous vs. Discrete Treatment Variable (2 alternatives):** Continuous (monthly) versus binned unemployment duration.
- **Linear vs. Quadratic vs. Cubic representation of the principal treatment variable (3 alternatives):** We allow the treatment variable to enter non-linearly by testing the presence of quadratic or cubic relationships (with the lower-order transformations entering in all models). We do not include any non-linear representation of the binned unemployment duration as the bins are uneven and would thus require additional assumptions for validity.

- **w. UI vs w. Exhausted UI (3 alternatives):** The survey includes a variable for whether individuals USE and/or EXHAUST unemployment benefits. We run the regressions without these UI controls, with the control for having used UI, or with the control for having exhausted UI.
- **w. Controls (2 alternatives):** With or without additional demographic controls (sex, age, race, married, education).
- **w. Wage Level (2 alternatives):** With or without wage level of lost job to control for income and the relationship between wage levels and the outcome wage ratio itself.
- **Outlier clipped sample (2 alternatives):** We either remove outliers where the wage ratio is within [0.25, 2.5] and reported unemployment duration is below 96 weeks (~ 2 years), or employ the raw sample.

In each regression table, we include the full set of coefficients to allow for examination of the regression coefficients on the controls as well as the principal variables of interest. In each table, we highlight β_1 as this is the main regression coefficient of interest. We employ the *check_model()* function from the *performance* package in R to display visual checks of various model assumptions.

Across all models (except those that include a control for having exhausted UI benefits) in the tables below we see a consistently negative coefficient on unemployment duration (~0.5-1 percentage point increase in the wage ratio for each additional month spent in unemployment). These coefficients are all statistically significant at the 0.1% level. Interestingly, this coefficient loses statistical significance in any model that controls for having exhausted UI benefits. Otherwise, examining the performance of our model with continuous unemployment duration, UI use (not exhaustion), all controls, wage levels, and outlier correction we see that the model performs passably across various diagnostic tests.

In the sections that follow, we report all regression results in regression tables. Additionally, we display model diagnostic plots for the specification with continuous unemployment duration, UI control, demographic controls, using the clipped sample, and assuming linearity in the relationship between unemployment duration and the accepted re-employment wage ratio. The quantile-quantile plots below reveal that residuals are approximately normally distributed, though there is evidence of heavy-tailed behavior in the upper quantiles.

Continuous UE Duration

Continuous UE duration treatment is reported in monthly values. A one-unit increase in the treatment variable = 1 additional month of unemployment.

Table 1: Continuous UE Duration w.o Wage Level Control (Clipped Sample)

	Cont. (clipped)	Cont. w. UI (clipped)	Cont. w. exhausted UI (clipped)	Cont. Sq (clipped)	Cont. Sq w. UI (clipped)	Cont. Sq w. exhausted UI (clipped)	Cont. w. controls (clipped)	Cont. w. UI w. controls (clipped)	Cont. w. exhausted UI w. controls (clipped)	Cont. Sq w. controls (clipped)	Cont. Sq w. UI w. controls (clipped)	Cont. Sq w. exhausted UI w. controls (clipped)
Intercept	1.045***	1.045***	1.006***	1.046***	1.046***	1.001***	1.163***	1.163***	1.113***	1.163***	1.163***	1.108***
	(0.004)	(0.004)	(0.007)	(0.005)	(0.005)	(0.008)	(0.021)	(0.021)	(0.023)	(0.021)	(0.021)	(0.023)
Unemployment Duration (Months)	−0.006***	−0.006***	−0.004***	−0.007**	−0.007**	−0.001	−0.006***	−0.006***	−0.004***	−0.006**	−0.006**	−0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Received Unemployment Compensation		0.000			0.000			0.000			0.000	
		(0.001)			(0.001)			(0.001)			(0.001)	
Exhausted Unemployment Compensation			0.001***			0.001***			0.000***			0.001***
			(0.000)			(0.000)			(0.000)			(0.000)
Unemployment Duration (Months²)				0.000	0.000	0.000				0.000	0.000	0.000
				(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
Female							−0.003	−0.003	−0.003	−0.003	−0.003	−0.003
							(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age							−0.002***	−0.002***	−0.002***	−0.002***	−0.002***	−0.002***
							(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White							−0.052**	−0.052**	−0.051**	−0.052**	−0.052**	−0.051**
							(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Black							−0.057**	−0.057**	−0.055**	−0.057**	−0.057**	−0.056**
							(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Mixed							−0.070**	−0.070*	−0.068*	−0.070**	−0.070*	−0.068*
							(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Married							0.011	0.011	0.012+	0.011	0.011	0.012+
							(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
High School							0.001	0.001	0.005	0.001	0.001	0.005
							(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Associate's Degree							−0.009	−0.009	−0.005	−0.009	−0.009	−0.005
							(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Bachelor's Degree							0.066***	0.066***	0.070***	0.066***	0.066***	0.070***
							(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Postgraduate Degree							0.030	0.030	0.037	0.030	0.030	0.037
							(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Num.Obs.	4644	4644	4644	4644	4644	4644	4644	4644	4644	4644	4644	4644
R2	0.012	0.012	0.022	0.012	0.012	0.023	0.032	0.032	0.040	0.032	0.032	0.040
R2 Adj.	0.012	0.011	0.022	0.011	0.011	0.022	0.029	0.029	0.037	0.029	0.029	0.038
RMSE	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 2: Continuous UE Duration w.o Wage Level Control (Full Sample)

	Cont.	Cont. w. UI	Cont. w. exhausted UI	Cont. Sq	Cont. Sq w. UI	Cont. Sq w. exhausted UI	Cont. w. controls	Cont. w. UI w. controls	Cont. w. exhausted UI w. controls	Cont. Sq w. controls	Cont. Sq w. UI w. controls	Cont. Sq w. exhausted UI w. controls
Intercept	1.053***	1.053***	1.006***	1.055***	1.055***	1.002***	1.180***	1.180***	1.119***	1.180***	1.180***	1.116***
	(0.006)	(0.006)	(0.010)	(0.007)	(0.007)	(0.011)	(0.031)	(0.031)	(0.033)	(0.031)	(0.031)	(0.033)
Unemployment Duration (Months)	−0.007***	−0.007***	−0.005***	−0.009***	−0.009***	−0.003	−0.006***	−0.006***	−0.004***	−0.008**	−0.008**	−0.003
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Received Unemployment Compensation		0.000			0.000			0.000			0.000	
		(0.001)			(0.001)			(0.001)			(0.001)	
Exhausted Unemployment Compensation			0.001***			0.001***			0.001***			0.001***
			(0.000)			(0.000)			(0.000)			(0.000)
Unemployment Duration (Months^2)				0.000	0.000	0.000				0.000	0.000	0.000
				(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
Female							0.003	0.003	0.003	0.003	0.003	0.003
							(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Age							−0.003***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***
							(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White							−0.035	−0.035	−0.033	−0.035	−0.035	−0.033
							(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Black							−0.048+	−0.048+	−0.045+	−0.048+	−0.048+	−0.045+
							(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Mixed							0.014	0.014	0.017	0.014	0.014	0.016
							(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Married							0.005	0.005	0.005	0.005	0.005	0.005
							(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
High School							0.005	0.005	0.011	0.006	0.006	0.011
							(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Associate's Degree							0.032	0.032	0.038+	0.032	0.032	0.037+
							(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Bachelor's Degree							0.079***	0.079***	0.085***	0.080***	0.080***	0.084***
							(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Postgraduate Degree							0.114*	0.114*	0.122**	0.115*	0.115*	0.122**
							(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Num.Obs.	4870	4870	4870	4870	4870	4870	4870	4870	4870	4870	4870	4870
R2	0.009	0.009	0.017	0.010	0.010	0.017	0.025	0.025	0.030	0.025	0.025	0.030
R2 Adj.	0.009	0.009	0.016	0.009	0.009	0.016	0.022	0.022	0.028	0.022	0.022	0.027
F	46.344	23.169	41.487	23.546	15.694	27.802	11.151	10.220	12.521	10.252	9.462	11.589
RMSE	0.38	0.38	0.37	0.38	0.38	0.37	0.37	0.37	0.37	0.37	0.37	0.37

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

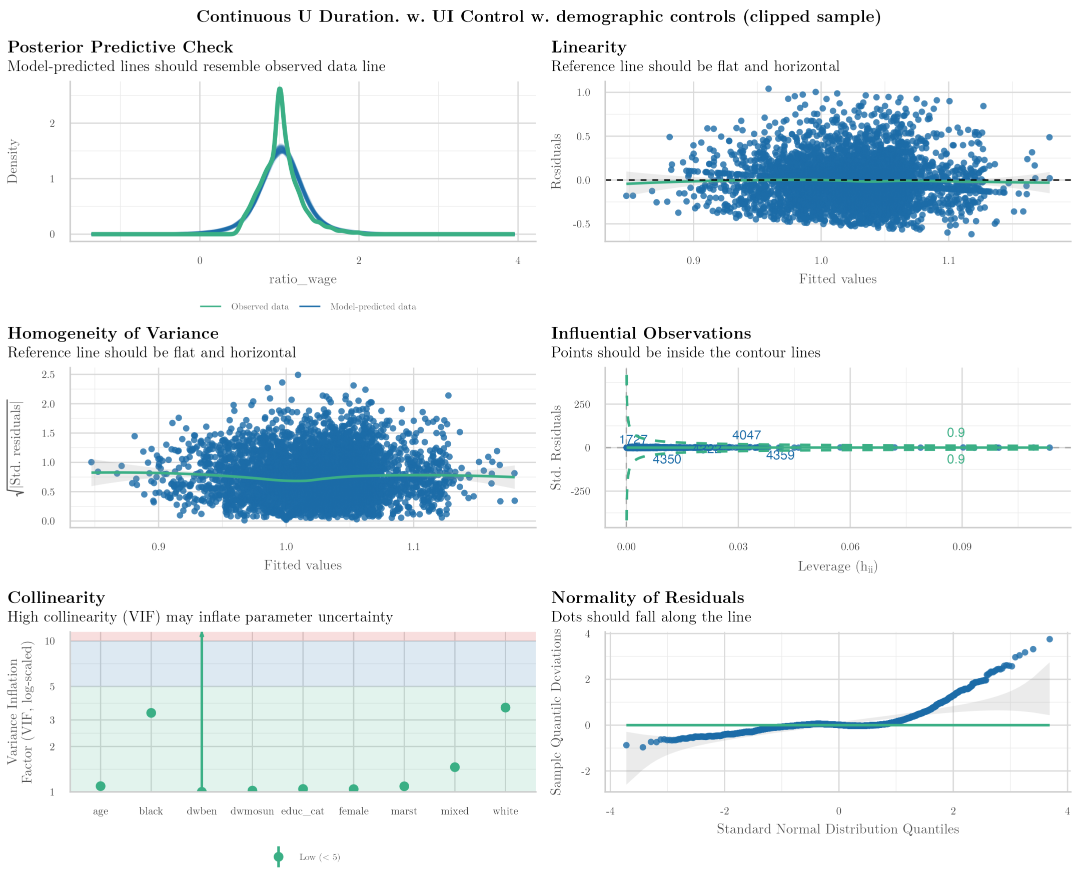


Table 3: Continuous UE Duration w. Wage Level Control (Clipped Sample)

	Cont. (clipped)	Cont. w. UI (clipped)	Cont. w. exhausted UI (clipped)	Cont. Sq (clipped)	Cont. Sq w. UI (clipped)	Cont. Sq w. exhausted UI (clipped)	Cont. w. controls (clipped)	Cont. w. UI w. controls (clipped)	Cont. w. exhausted UI w. controls (clipped)	Cont. Sq w. controls (clipped)	Cont. Sq w. UI w. controls (clipped)	Cont. Sq w. exhausted UI w. controls (clipped)
Intercept	1.131***	1.130***	1.094***	1.131***	1.131***	1.090***	1.217***	1.217***	1.173***	1.217***	1.217***	1.169***
	(0.008)	(0.008)	(0.010)	(0.008)	(0.008)	(0.011)	(0.021)	(0.021)	(0.022)	(0.021)	(0.021)	(0.023)
Hourly Wage of Lost Job	−0.006***	−0.006***	−0.006***	−0.006***	−0.006***	−0.006***	−0.007***	−0.007***	−0.007***	−0.007***	−0.007***	−0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Duration (Months)	−0.006***	−0.006***	−0.004***	−0.006**	−0.006**	−0.002	−0.006***	−0.006***	−0.004***	−0.006**	−0.006**	−0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Received Unemployment Compensation		0.000			0.000			0.000			0.000	
		(0.001)			(0.001)			(0.001)			(0.001)	
Exhausted Unemployment Compensation			0.000***			0.000***			0.000***			0.000***
			(0.000)			(0.000)			(0.000)			(0.000)
Unemployment Duration (Months²)				0.000	0.000	0.000				0.000	0.000	0.000
				(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
Female							−0.023**	−0.023**	−0.023**	−0.023**	−0.023**	−0.023**
							(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age							−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
							(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White							−0.050**	−0.050**	−0.049**	−0.050**	−0.050**	−0.050**
							(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Black							−0.061***	−0.061***	−0.060***	−0.061***	−0.061***	−0.060***
							(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Mixed							−0.067*	−0.067*	−0.065*	−0.067*	−0.067*	−0.066*
							(0.027)	(0.027)	(0.026)	(0.027)	(0.027)	(0.026)
Married							0.018*	0.018*	0.018*	0.018*	0.018*	0.018*
							(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
High School							0.019+	0.019+	0.022*	0.019+	0.019+	0.022*
							(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Associate's Degree							0.027+	0.027+	0.029*	0.027+	0.027+	0.030*
							(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Bachelor's Degree							0.121***	0.121***	0.123***	0.121***	0.121***	0.123***
							(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Postgraduate Degree							0.120***	0.120***	0.123***	0.120***	0.120***	0.123***
							(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Num.Obs.	4644	4644	4644	4644	4644	4644	4644	4644	4644	4644	4644	4644
R2	0.046	0.046	0.053	0.046	0.046	0.053	0.073	0.073	0.079	0.073	0.073	0.079
R2 Adj.	0.046	0.046	0.053	0.046	0.045	0.053	0.071	0.071	0.077	0.071	0.071	0.077
RMSE	0.24	0.24	0.24	0.24	0.24	0.24	0.23	0.23	0.23	0.23	0.23	0.23

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Predicted Wage Ratios by Unemployment Duration

From non-reweighted regressions: linear, quadratic, and cubic specifications

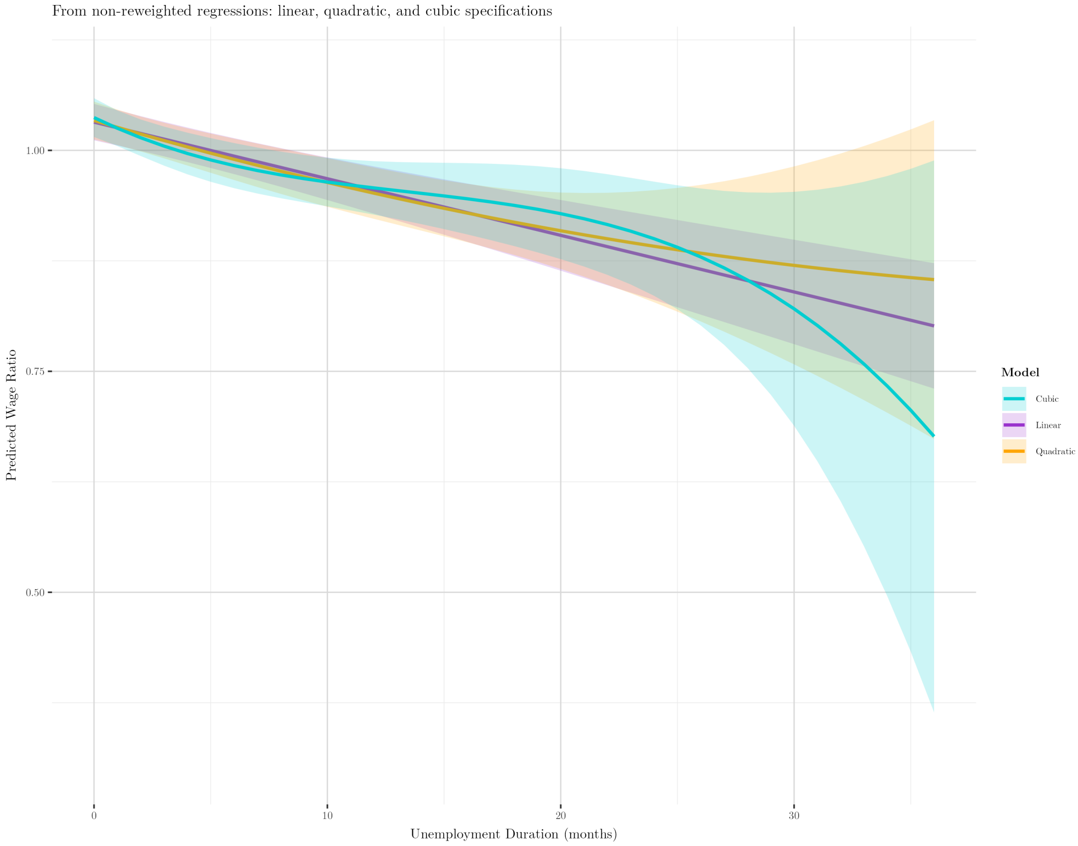


Table 4: Continuous UE Duration w. Wage Level Control (Full Sample)

	Cont.	Cont. w. UI	Cont. w. exhausted UI	Cont. Sq	Cont. Sq w. UI	Cont. Sq w. exhausted UI	Cont. w. controls	Cont. w. UI w. controls	Cont. w. exhausted UI w. controls	Cont. Sq w. controls	Cont. Sq w. UI w. controls	Cont. Sq w. exhausted UI w. controls
Intercept	1.185***	1.186***	1.145***	1.186***	1.187***	1.141***	1.263***	1.263***	1.213***	1.263***	1.263***	1.210***
	(0.011)	(0.011)	(0.014)	(0.012)	(0.012)	(0.015)	(0.031)	(0.031)	(0.033)	(0.031)	(0.031)	(0.033)
Hourly Wage of Lost Job	−0.009***	−0.009***	−0.009***	−0.009***	−0.009***	−0.009***	−0.011***	−0.011***	−0.011***	−0.011***	−0.011***	−0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment Duration (Months)	−0.007***	−0.007***	−0.005***	−0.007**	−0.007**	−0.003	−0.006***	−0.006***	−0.005***	−0.007**	−0.007**	−0.003
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Received Unemployment Compensation		0.000			0.000			0.000			0.000	
		(0.001)			(0.001)			(0.001)			(0.001)	
Exhausted Unemployment Compensation			0.001***			0.001***			0.000***			0.000***
			(0.000)			(0.000)			(0.000)			(0.000)
Unemployment Duration (Months^2)				0.000	0.000	0.000				0.000	0.000	0.000
				(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
Female							−0.028**	−0.028**	−0.028**	−0.028**	−0.028**	−0.028**
							(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Age							−0.002***	−0.002***	−0.001***	−0.002***	−0.002***	−0.001***
							(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White							−0.034	−0.034	−0.032	−0.034	−0.034	−0.032
							(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Black							−0.058*	−0.058*	−0.055*	−0.057*	−0.057*	−0.055*
							(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Mixed							0.016	0.016	0.019	0.016	0.016	0.018
							(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Married							0.013	0.013	0.013	0.013	0.013	0.014
							(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
High School							0.033*	0.033*	0.037*	0.033*	0.033*	0.037*
							(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Associate's Degree							0.084***	0.084***	0.088***	0.084***	0.084***	0.087***
							(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Bachelor's Degree							0.161***	0.161***	0.164***	0.161***	0.161***	0.163***
							(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Postgraduate Degree							0.244***	0.244***	0.248***	0.245***	0.245***	0.248***
							(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Num.Obs.	4870	4870	4870	4870	4870	4870	4870	4870	4870	4870	4870	4870
R2	0.048	0.048	0.052	0.048	0.048	0.052	0.069	0.069	0.073	0.069	0.069	0.073
R2 Adj.	0.047	0.047	0.051	0.047	0.047	0.051	0.067	0.067	0.070	0.067	0.067	0.070
F	121.551	81.034	88.352	81.047	60.784	66.451	30.216	27.890	29.347	27.893	25.899	27.287
RMSE	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Binned UE Duration

Binned UE duration treatment is reported in bins as indicated in the box plots and code cleaning above.

Table 5: Binned UE Duration w.o Wage Level Control (Clipped Sample)

	Disc. (clipped)	Disc. w. UI (clipped)	Disc. w. exhausted UI (clipped)	Disc. w. controls (clipped)	Disc. w. UI w. controls (clipped)	Disc. w. exhausted UI w. controls (clipped)
Intercept	1.055***	1.055***	1.010***	1.170***	1.170***	1.116***
	(0.005)	(0.005)	(0.008)	(0.021)	(0.021)	(0.023)
Unemployment Duration (Binned)	−0.009***	−0.009***	−0.005***	−0.008***	−0.008***	−0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Received Unemployment Compensation		0.000			0.000	
		(0.001)			(0.001)	
Exhausted Unemployment Compensation			0.001***			0.001***
			(0.000)			(0.000)
Female				−0.003	−0.003	−0.003
				(0.007)	(0.007)	(0.007)
Age				−0.002***	−0.002***	−0.002***
				(0.000)	(0.000)	(0.000)
White				−0.052**	−0.052**	−0.050**
				(0.016)	(0.016)	(0.016)
Black				−0.056**	−0.056**	−0.055**
				(0.018)	(0.018)	(0.018)
Mixed				−0.070**	−0.070*	−0.068*
				(0.027)	(0.027)	(0.027)
Married				0.011	0.011	0.012
				(0.007)	(0.007)	(0.007)
High School				0.001	0.001	0.005
				(0.011)	(0.011)	(0.011)
Associate's Degree				−0.009	−0.009	−0.005
				(0.014)	(0.014)	(0.014)
Bachelor's Degree				0.067***	0.067***	0.071***
				(0.015)	(0.015)	(0.015)
Postgraduate Degree				0.030	0.030	0.038
				(0.031)	(0.031)	(0.031)
Num.Obs.	4644	4644	4644	4644	4644	4644
R2	0.011	0.011	0.021	0.031	0.031	0.039
R2 Adj.	0.011	0.010	0.021	0.028	0.028	0.036
RMSE	0.24	0.24	0.24	0.24	0.24	0.24

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

Table 6: Binned UE Duration w.o Wage Level Control (Full Sample)

	Disc.	Disc. w. UI	Disc. w. exhausted UI	Disc. w. controls	Disc. w. UI w. controls	Disc. w. exhausted UI w. controls
Intercept	1.069***	1.069***	1.016***	1.190***	1.190***	1.127***
	(0.008)	(0.008)	(0.012)	(0.031)	(0.031)	(0.034)
Unemployment Duration (Binned)	−0.013***	−0.013***	−0.008***	−0.011***	−0.011***	−0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Received Unemployment Compensation		0.000			0.000	
		(0.001)			(0.001)	
Exhausted Unemployment Compensation			0.001***			0.001***
			(0.000)			(0.000)
Female				0.003	0.003	0.003
				(0.011)	(0.011)	(0.011)
Age				−0.003***	−0.003***	−0.003***
				(0.000)	(0.000)	(0.000)
White				−0.035	−0.035	−0.033
				(0.023)	(0.023)	(0.023)
Black				−0.047+	−0.047+	−0.045+
				(0.026)	(0.026)	(0.026)
Mixed				0.014	0.014	0.017
				(0.040)	(0.040)	(0.040)
Married				0.004	0.004	0.005
				(0.011)	(0.011)	(0.011)
High School				0.006	0.006	0.012
				(0.016)	(0.016)	(0.016)
Associate's Degree				0.033	0.033	0.038+
				(0.021)	(0.021)	(0.021)
Bachelor's Degree				0.082***	0.082***	0.087***
				(0.021)	(0.021)	(0.021)
Postgraduate Degree				0.116**	0.116**	0.124**
				(0.045)	(0.045)	(0.045)
Num.Obs.	4870	4870	4870	4870	4870	4870
R2	0.010	0.010	0.016	0.025	0.025	0.030
R2 Adj.	0.009	0.009	0.016	0.022	0.022	0.027
F	47.638	23.816	40.199	11.165	10.232	12.314
RMSE	0.37	0.37	0.37	0.37	0.37	0.37

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

Table 7: Binned UE Duration w. Wage Level Control (Clipped Sample)

	Disc. (clipped)	Disc. w. UI (clipped)	Disc. w. exhausted UI (clipped)	Disc. w. controls (clipped)	Disc. w. UI w. controls (clipped)	Disc. w. exhausted UI w. controls (clipped)
Intercept	1.139***	1.139***	1.098***	1.224***	1.224***	1.176***
	(0.008)	(0.008)	(0.011)	(0.021)	(0.021)	(0.023)
Hourly Wage of Lost Job	−0.006***	−0.006***	−0.006***	−0.007***	−0.007***	−0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Duration (Binned)	−0.009***	−0.009***	−0.005***	−0.008***	−0.008***	−0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Received Unemployment Compensation		0.000			0.000	
		(0.001)			(0.001)	
Exhausted Unemployment Compensation			0.000***			0.000***
			(0.000)			(0.000)
Female				−0.023**	−0.023**	−0.023**
				(0.007)	(0.007)	(0.007)
Age				−0.001***	−0.001***	−0.001***
				(0.000)	(0.000)	(0.000)
White				−0.050**	−0.050**	−0.049**
				(0.016)	(0.016)	(0.016)
Black				−0.061***	−0.061***	−0.059***
				(0.018)	(0.018)	(0.018)
Mixed				−0.067*	−0.067*	−0.065*
				(0.027)	(0.027)	(0.026)
Married				0.017*	0.017*	0.018*
				(0.007)	(0.007)	(0.007)
High School				0.019+	0.019+	0.022*
				(0.011)	(0.011)	(0.011)
Associate's Degree				0.027+	0.027+	0.030*
				(0.014)	(0.014)	(0.014)
Bachelor's Degree				0.122***	0.122***	0.124***
				(0.015)	(0.015)	(0.015)
Postgraduate Degree				0.120***	0.120***	0.124***
				(0.031)	(0.031)	(0.031)
Num.Obs.	4644	4644	4644	4644	4644	4644
R2	0.045	0.045	0.052	0.072	0.072	0.078
R2 Adj.	0.045	0.045	0.051	0.070	0.070	0.076
RMSE	0.24	0.24	0.24	0.23	0.23	0.23

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

Table 8: Binned UE Duration w. Wage Level Control (Full Sample)

	Disc.	Disc. w. UI	Disc. w. exhausted UI	Disc. w. controls	Disc. w. UI w. controls	Disc. w. exhausted UI w. controls
Intercept	1.198***	1.199***	1.154***	1.272***	1.272***	1.220***
	(0.012)	(0.012)	(0.016)	(0.031)	(0.031)	(0.034)
Hourly Wage of Lost Job	−0.009***	−0.009***	−0.009***	−0.011***	−0.011***	−0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment Duration (Binned)	−0.011***	−0.011***	−0.008***	−0.011***	−0.010***	−0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Received Unemployment Compensation		0.000			0.000	
		(0.001)			(0.001)	
Exhausted Unemployment Compensation			0.000***			0.000***
			(0.000)			(0.000)
Female				−0.028**	−0.028**	−0.028**
				(0.011)	(0.011)	(0.011)
Age				−0.002***	−0.002***	−0.001***
				(0.000)	(0.000)	(0.000)
White				−0.034	−0.034	−0.032
				(0.023)	(0.023)	(0.023)
Black				−0.057*	−0.057*	−0.054*
				(0.026)	(0.026)	(0.026)
Mixed				0.017	0.017	0.019
				(0.039)	(0.039)	(0.039)
Married				0.013	0.013	0.013
				(0.010)	(0.010)	(0.010)
High School				0.034*	0.034*	0.038*
				(0.015)	(0.015)	(0.015)
Associate's Degree				0.085***	0.085***	0.088***
				(0.021)	(0.021)	(0.021)
Bachelor's Degree				0.163***	0.163***	0.166***
				(0.022)	(0.022)	(0.022)
Postgraduate Degree				0.246***	0.246***	0.250***
				(0.045)	(0.045)	(0.045)
Num.Obs.	4870	4870	4870	4870	4870	4870
R2	0.047	0.047	0.051	0.069	0.069	0.072
R2 Adj.	0.047	0.047	0.050	0.067	0.067	0.070
F	120.632	80.422	86.995	30.090	27.774	29.084
RMSE	0.37	0.37	0.37	0.37	0.37	0.37

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

Next, we provide results for the econometric specifications listed above with better balanced survey samples. We outline the various procedures employed for dealing with selection issues and non-uniformity in the sample.

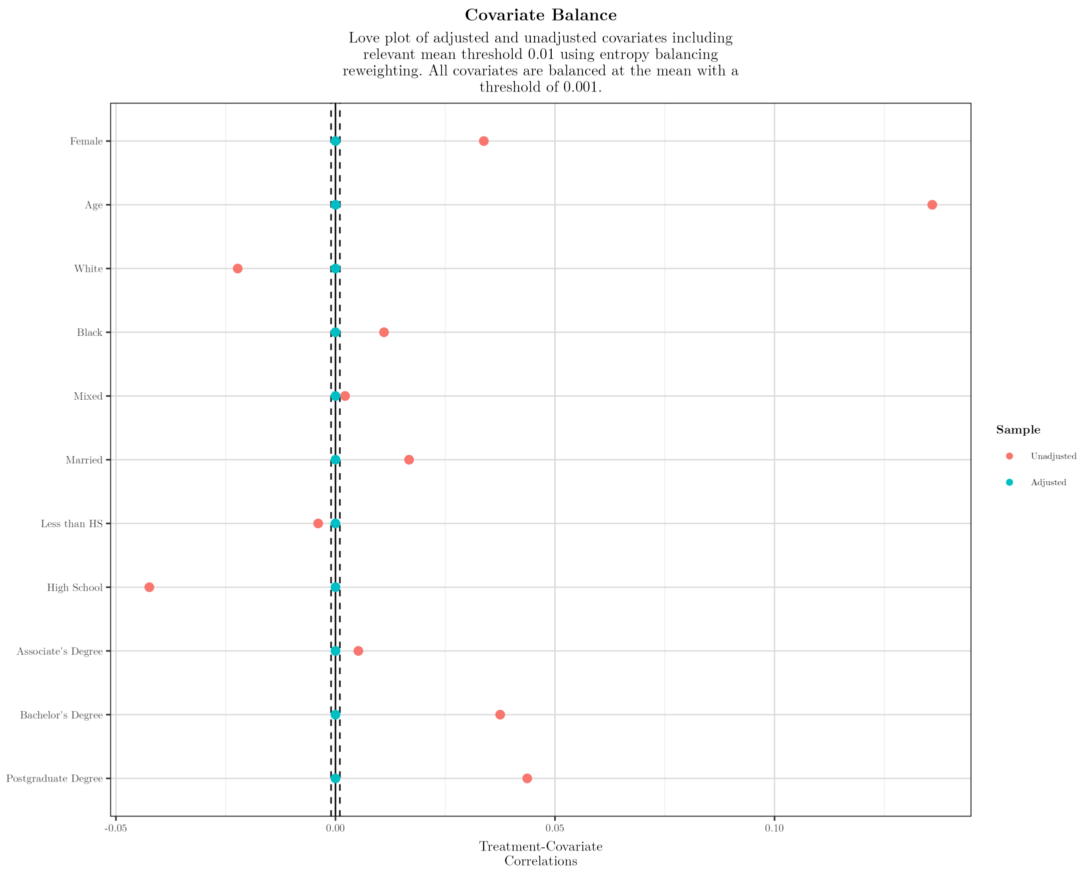
Regressions with Selection Correction of Non-Random Sample

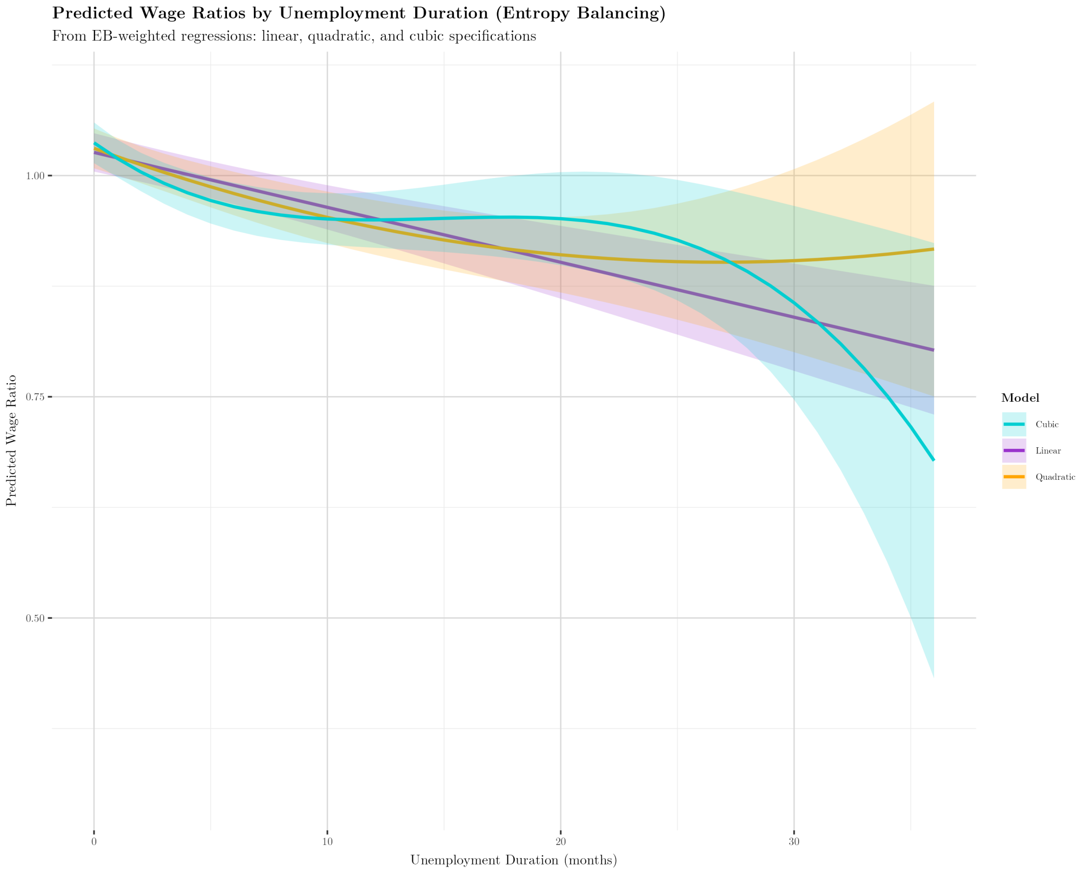
One of the challenges with this data is that the sample grows significantly smaller for higher reported of unemployment duration (see scatter plots in section above). Therefore, we re-weight our survey sample (beyond the census weights already employed) to ensure population similarity across bins. More precisely, we employ propensity score matching using a generalised linear model, entropy-balancing, and Heckman selection correction.

Overall, we find the econometric results reported earlier to be consistent across these implementations, with the coefficients on unemployment duration remaining somewhat stable.

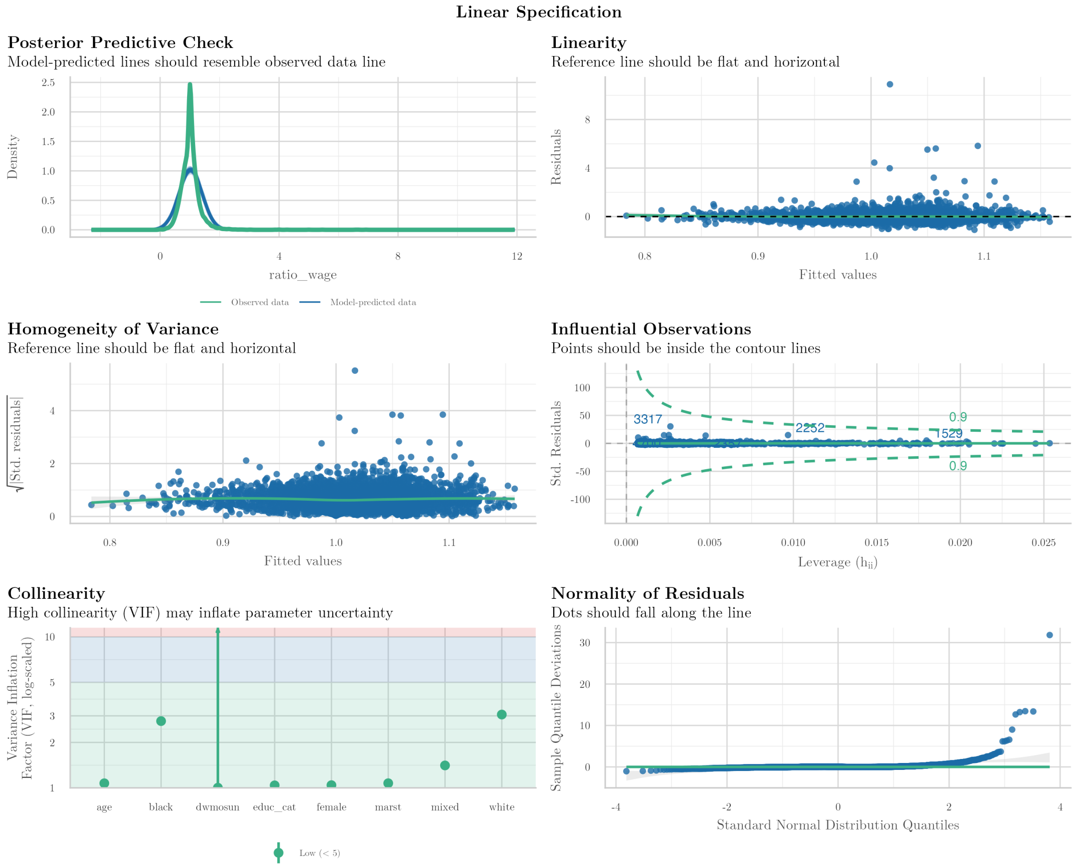
Entropy Balancing

First, entropy balancing simply reweights observations to ensure population matching across the key dependent variable.




Predicted Wage Ratios by Unemployment Duration (Entropy Balancing)
From EB-weighted regressions: linear, quadratic, and cubic specifications
Predicted Wage Ratio
1.00
0.75
0.50
0
10
20
30
Unemployment Duration (months)
Model
Cubic
Linear
Quadratic

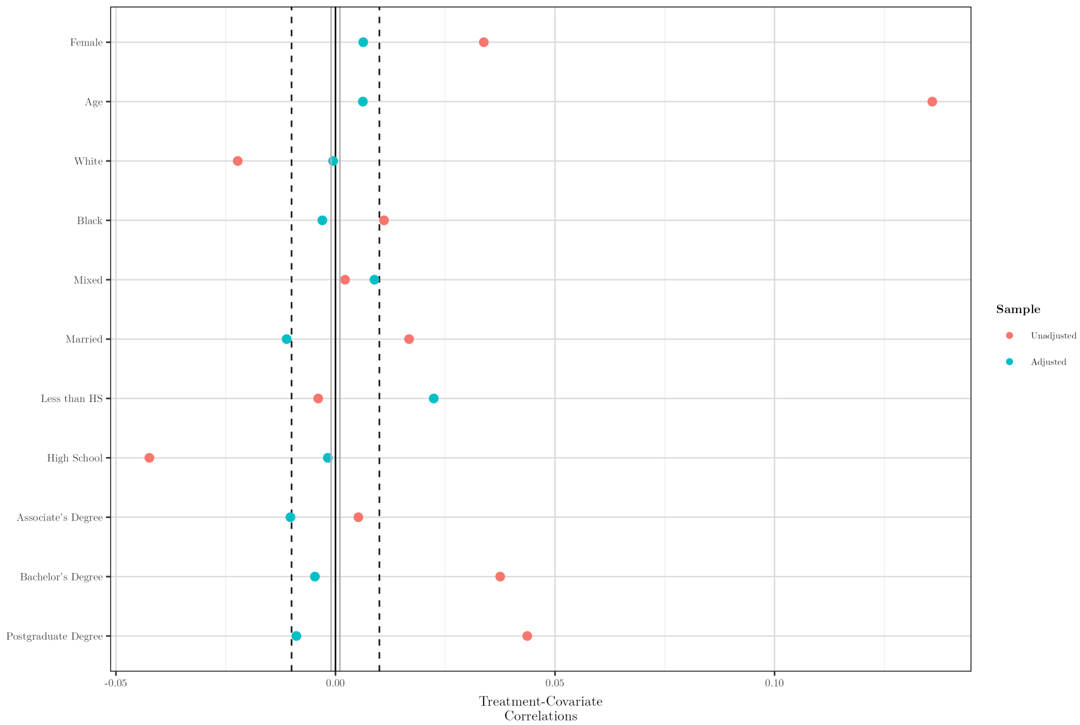
Diagnostic Tests for Entropy-balanced Reweighted Sample



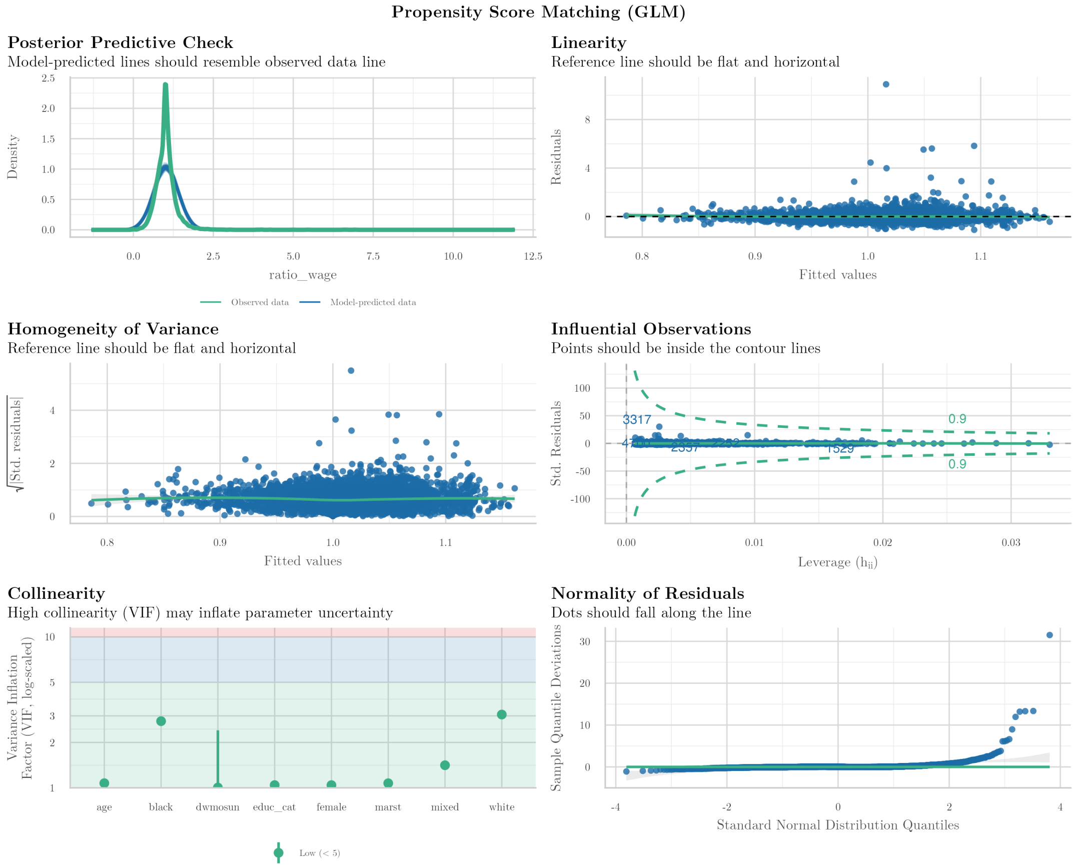
Propensity Score Weighting with GLM Estimator

Covariate Balance

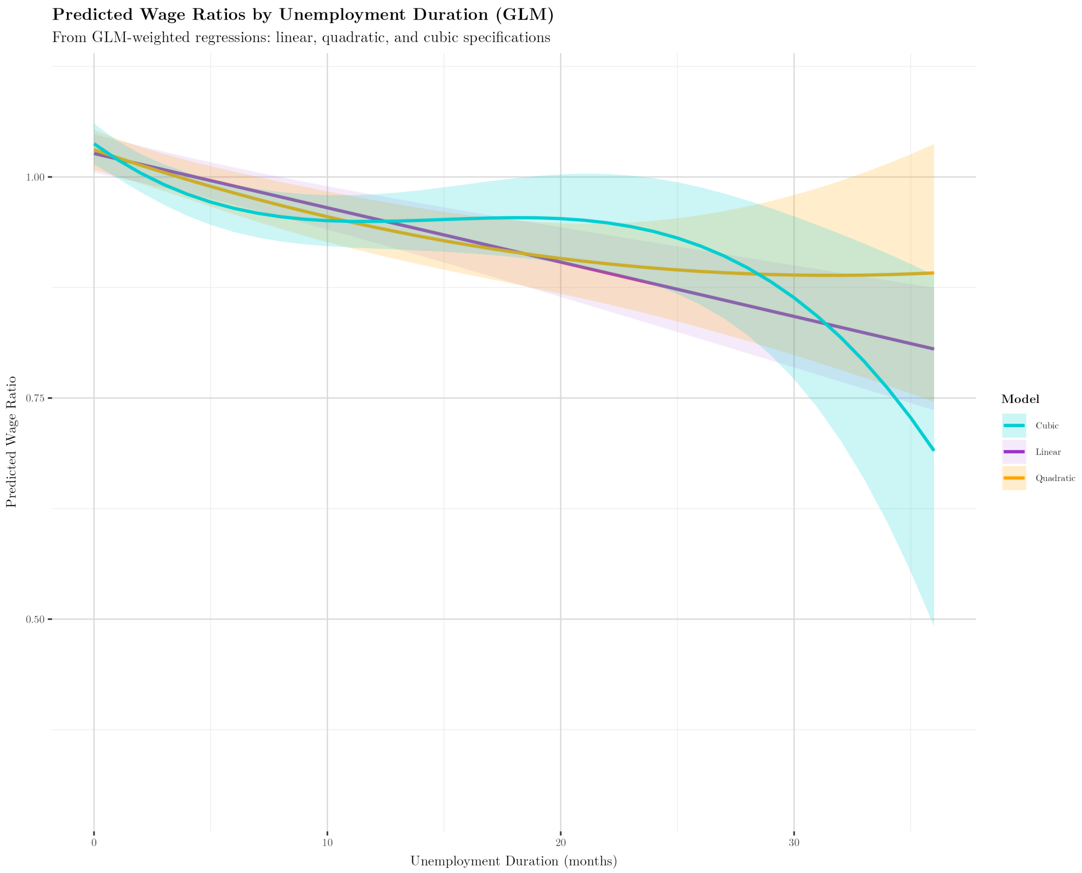
Love plot of adjusted and unadjusted covariates including relevant mean threshold 0.01 using a GLM estimator. All covariates except the binary indicator for having less than a HS degree level of education are balanced at the mean with a threshold of 0.01 (black dashed line) whereas very few variables pass at a tighter threshold 0.001 with the GLM estimator.



Diagnostic Tests for Propensity Score Matching (GLM) Reweighted Sample

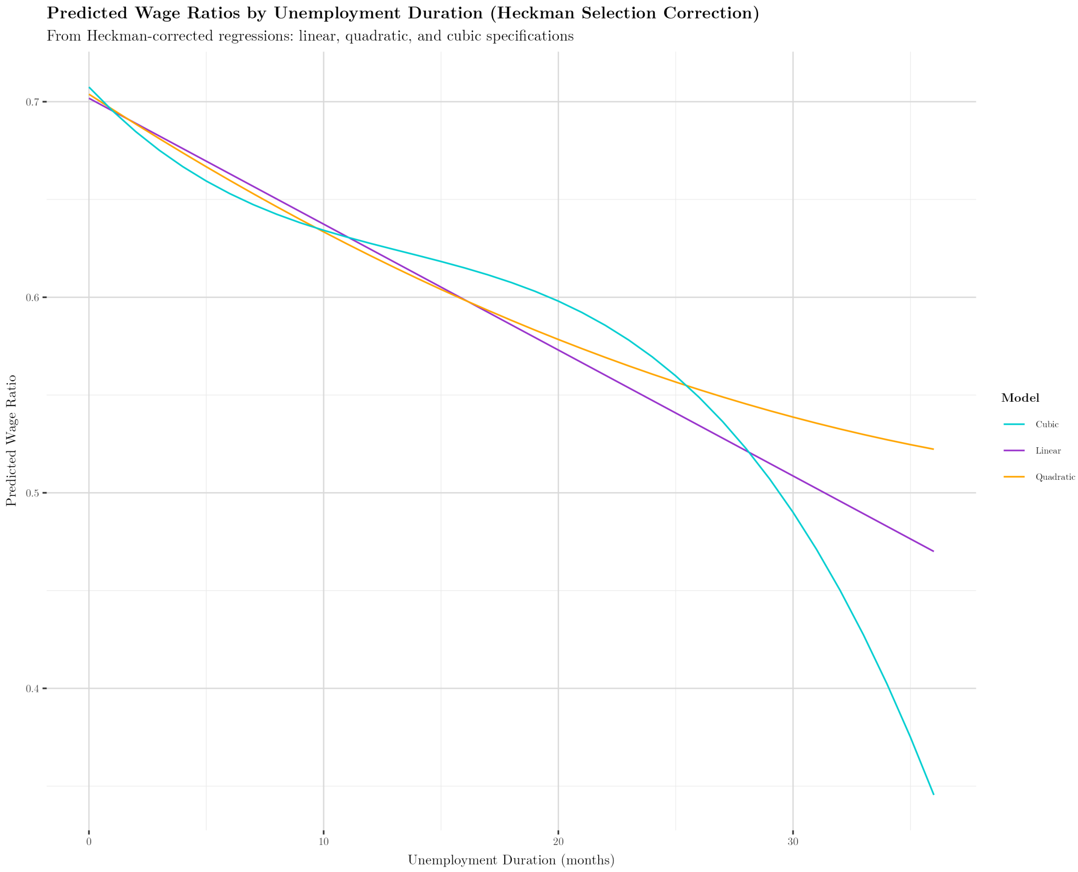


Predicted Reservation Wage using GLM Reweighted Sample



Heckman Selection

Additionally, we employ a Heckman Selection correction to correct for likely selection effects in the data. We correct for selection effects by balancing across the various control variables (gender, age, race, marital status, and level of eduction).



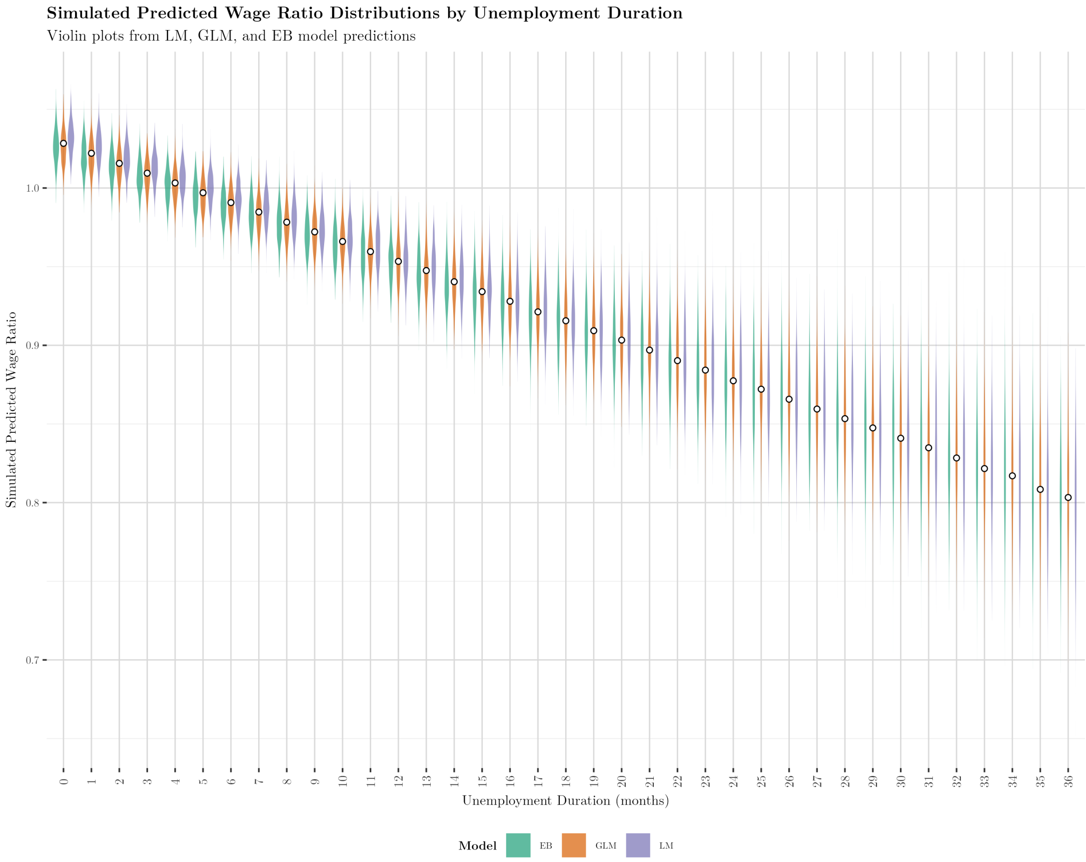
Regression Results with Sample Reweighting

Finally, we provide a comparison of the regression coefficients of the unbalanced, Heckman corrected, entropy balanced, and GLM reweighting using propensity score matching. Most importantly, the regression coefficient on unemployment duration is consistent across specifications indicating that the consequences of non-uniformity and selection effects in our sample are minimal. We incorporate the

Next, we predict the value of the accepted wage ratio using each of the models, incorporating 95% confidence intervals to allow for stochasticity to enter the behavioral mechanism itself. Essentially, as an agent in our model enters an additional period of unemployment, they will draw their reservation wage ratio from the mean and 95% confidence interval at each unemployment duration value represented in the figure below. We assume a uniform distribution around the regression estimate when drawing these values.

	Unabalanced LM	Heckman Correction	Entropy Balanced Reweight	GLM Reweight
Intercept	1.180***	1.131***	1.147***	1.143***
	(0.031)	(0.041)	(0.033)	(0.033)
Unemployment Duration (Months)	−0.006***	−0.006***	−0.006***	−0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Received Unemployment Compensation	0.000			
	(0.001)			
Female	0.003	0.018	0.001	0.001
	(0.011)	(0.014)	(0.011)	(0.011)
Age	−0.003***	−0.007***	−0.002***	−0.002***
	(0.000)	(0.002)	(0.000)	(0.000)
White	−0.035	−0.162*	−0.027	−0.023
	(0.023)	(0.074)	(0.025)	(0.025)
Black	−0.048+	−0.125*	−0.040	−0.036
	(0.026)	(0.050)	(0.030)	(0.030)
Mixed	0.014	−0.054	0.003	0.007
	(0.040)	(0.055)	(0.044)	(0.044)
Married	0.005	0.003	0.005	0.004
	(0.011)	(0.011)	(0.011)	(0.011)
High School	0.005	−0.014	−0.014	−0.014
	(0.016)	(0.019)	(0.017)	(0.017)
Associate's Degree	0.032	−0.078	0.007	0.006
	(0.021)	(0.064)	(0.022)	(0.022)
Bachelor's Degree	0.079***	−0.217	0.054*	0.054*
	(0.021)	(0.165)	(0.023)	(0.023)
Postgraduate Degree	0.114*	−0.479	0.083+	0.086+
	(0.045)	(0.330)	(0.048)	(0.047)
Inverse Mills Ratio		0.870+		
		(0.479)		
Num.Obs.	4870	4870	4870	4870
R2	0.025	0.893	0.014	0.015
R2 Adj.	0.022	0.893	0.012	0.013
F	10.220		6.487	6.798
RMSE	0.37	0.37	0.37	0.37

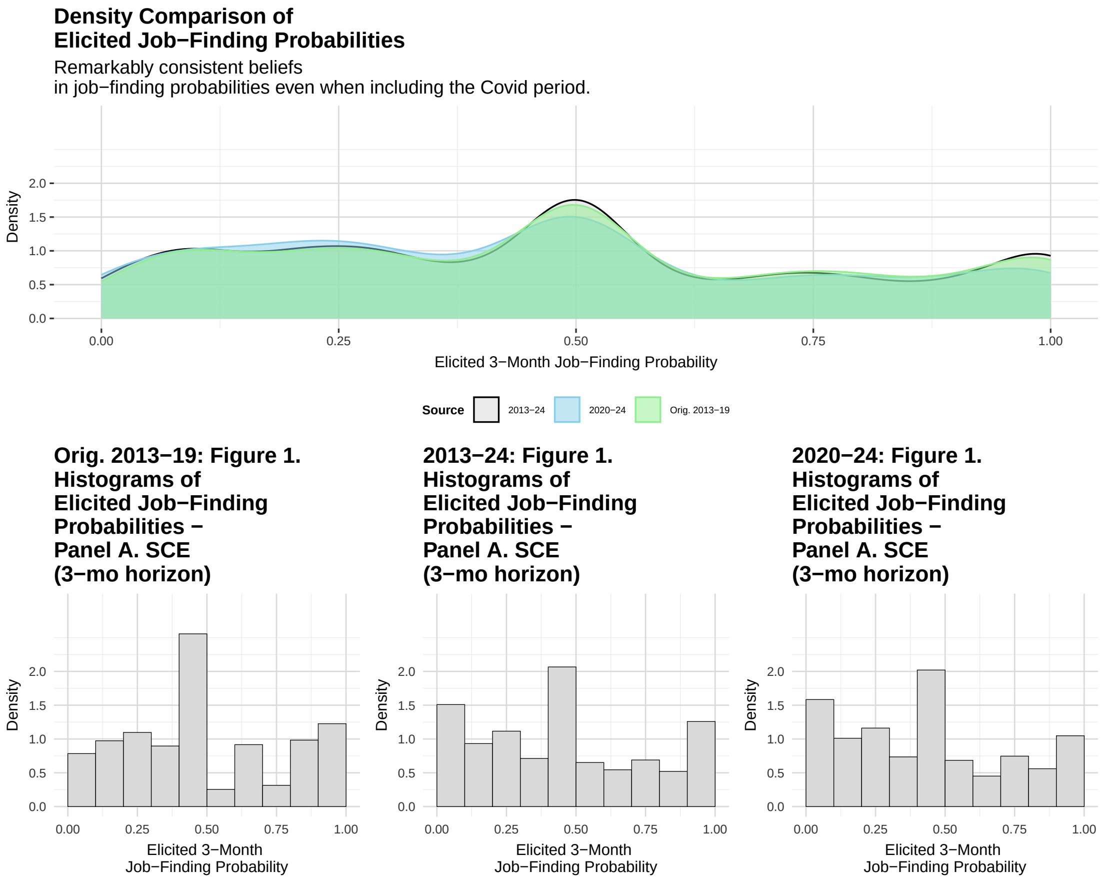
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$



Additional Considerations

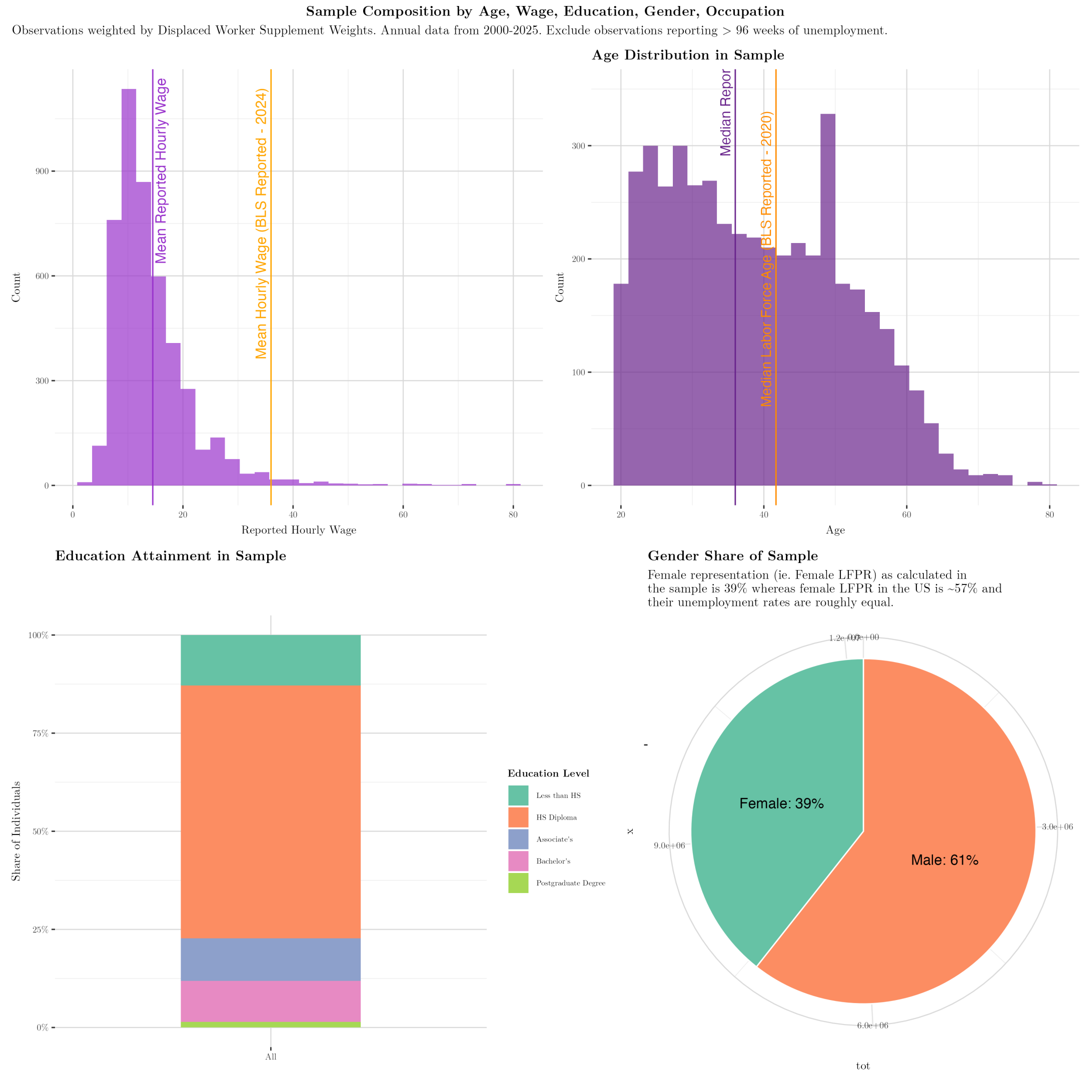
Job Tenure

We have information on the tenure spent at the last job which could impact the result. This could speak to the "adaptability" of individuals. Wage ratio seems to decrease (although not sure if meaningfully) with tenure at previous job.



Representation

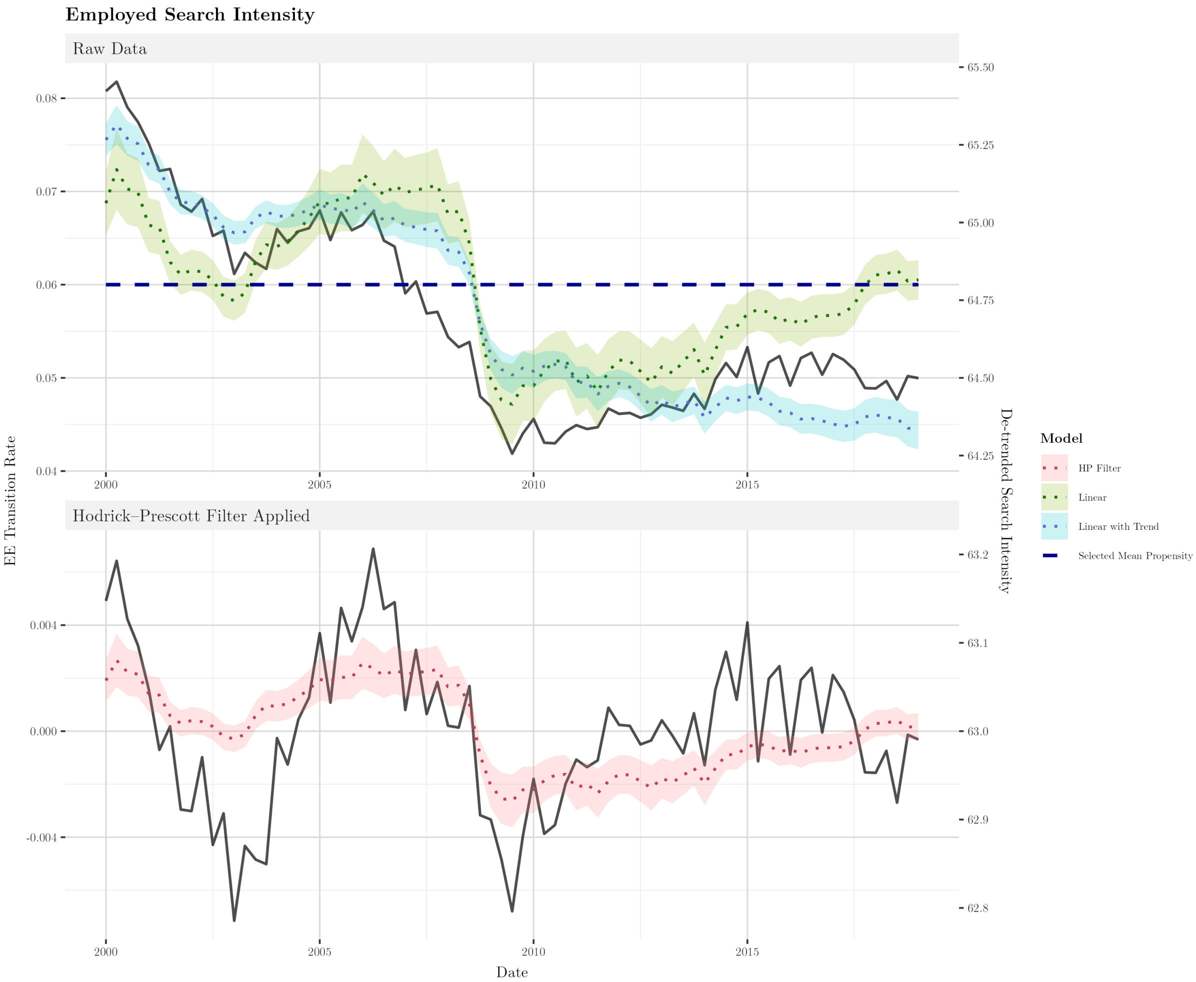
Although the survey does provide sample weights which we use above, it's still likely that those who are laid off might be systematically more susceptible to layoffs (lower-wage, low-skill occupation, male, etc). Below, we provide some descriptive graphs to illustrate what the sample looks like. First, the sample over-represents below-mean wage earners and men. The median age of survey respondents is near the mean age of the US labor force as reported by the Bureau of Labor Statistics in 2024. Individuals with only a HS diploma represent a strong majority in the sample.



OTJ Search Propensity

A key improvement in this model is the incorporation of on-the-job seekers. Eeckhout et al. 2019 demonstrate that the flow of employed job-seekers into the pool of job-seekers can generate increased competition in boom periods. Therefore, we derive a mean value for the propensity of employed job-seekers to engage in search using the methodology and data presented in Eeckhout et al. 2019. In other words, we derive the sensitivity of employed job seekers to the business cycle from the employment-to-employment transitions data as used in Eeckhout et al. Due to unreliable component parts of the Eeckhout analysis, we decided to abandon using their estimated parameters (search intensity for employed workers), and instead rely on their series of employment-to-employment (EE) transition rate which resulted in wage increases. This series is plotted in the top panel of the following figure. We draw the mean propensity to search from the average EE transition rate ~6%, represented by the dark blue dashed line in the top panel.

We provide additional indicators of the cyclicality of this series by plotting fitted values of the EE transition rate as a function of national real GDP. These fitted values are derived from a linear regression in which the EE transition rate is regressed on national real GDP, optionally incorporated a deterministic linear trend. Furthermore, we provide the Hodrick-Prescott filtered series in the bottom panel, both as the raw de-trended series, and as a fitted series to real GDP.



The above are predicted values of employment-employment (EE) transitions as a function of the HP-filtered GDP cycle. The grey line represents the real and de-trended EE transition rate (calculated as the ratio of EE transitions to number of employed persons in the labor force) using the Current Population Survey and tabulation method from Eeckhout et al. 2019. The green and blue lines represent the fitted/predicted values using a linear predictor and linear predictor with a linear trend component, respectively. The red line demonstrates the fitted values of the HP filtered EE series using a linear predictor on the HP-filtered GDP series.

Figure 4: Employed Search Effort Fit

Supporting Data for Validation

Intensive Search Effort: Mukoyama et al. 2018 *Job Search and the Business Cycle*

We use evidence from Mukoyama et al. 2018 regarding the cyclicality of unemployed job search effort to validate the micro behavior of our agents. This is a foundational paper within the literature that explores the relationship between search effort and business cycles. The authors provide new data on the intensive margin of unemployed search effort (in minutes searched) over the business cycle by linking date from the American Time Use Survey (ATUS) and Current Population Survey (CPS). We employ the methods and data presented in their work in a validation exercise of the emergent micro behavior of unemployed job-seekers.

More specifically, the authors provide a novel measure of job search effort exploiting the American Time Use and Current Population Surveys which can be reduced to just the intensive margin (changes in search effort by worker). Typically, this is an extremely challenging measure to approximate due to data availability and survey design. In general, surveys measure actions taken (i.e., applications sent, interviews completed) but these indicators can abstract from the fundamental intensive margin of search effort. In other words, the most common metrics that measure search effort can result from passive search or intrinsic advantageous worker characteristics, obscuring any sense of real search "effort" or urgency with which individuals apply their search strategies. This intensive margin underlies the motivation behind our dynamic search effort rule, making this data a valuable source of validation data for the model's output.

Methodologically, the authors construct this time series measure of job search intensity by linking the American Time Use Survey (ATUS) and Current Population Survey (CPS). While the ATUS directly measures minutes spent on job search activities but has limited sample size and coverage (2003-2014), the CPS reports the number and types of search methods used over larger samples beginning in 1994. Both surveys ask similar questions about search methods employed in the previous month. The authors exploit this overlap by first estimating the relationship between reported search time and search methods in the ATUS using a Heckman selection model—estimating both the probability of positive search time and the number of minutes conditional on searching, controlling for demographics, occupation, and unemployment duration. They then apply these estimated coefficients to impute daily search time for all CPS unemployed respondents based on their reported search methods, generating a monthly intensive margin series from 1994-2014. This approach weights each search method by its estimated time intensity and allows baseline search effort to vary by demographic characteristics, producing a more nuanced measure than simply counting the number of methods used.

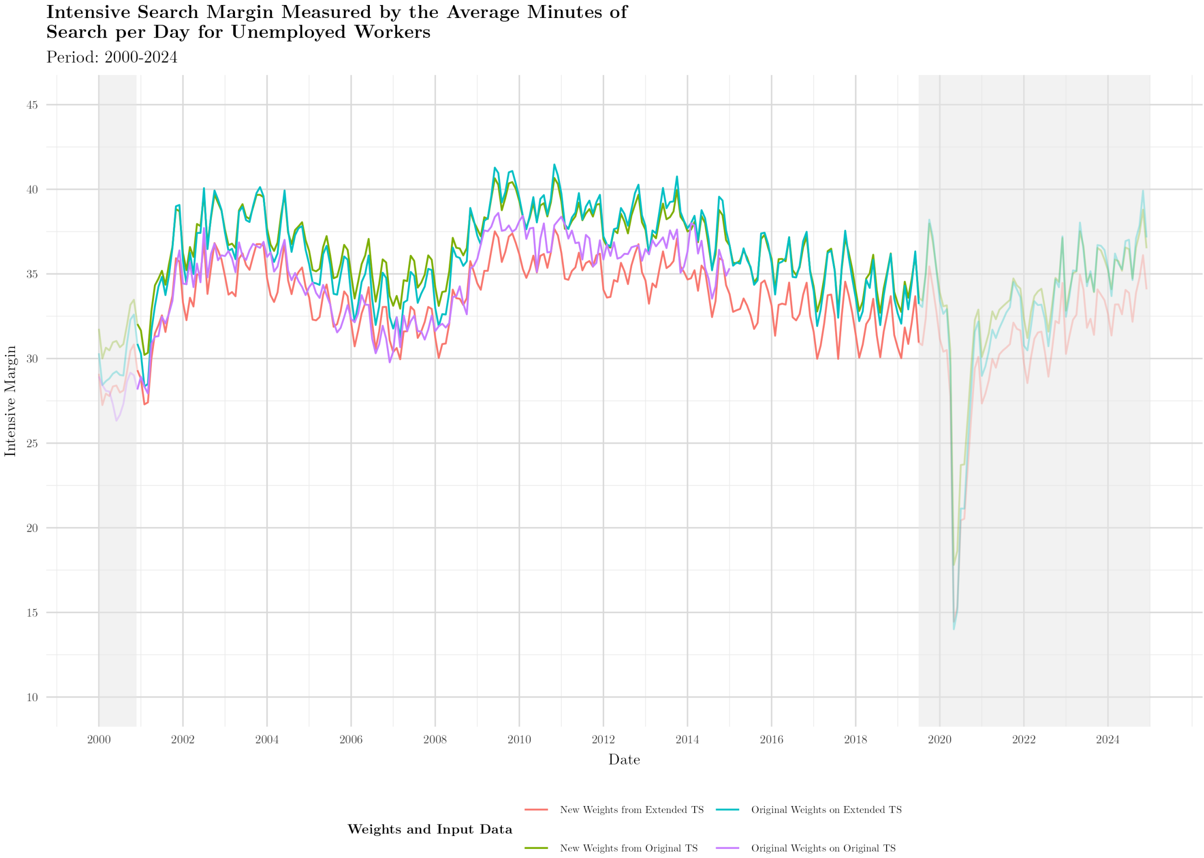
The figure below represents the intensive search margin time series as calculated by the authors. This data is drawn from the replication code provided by the authors. We have translated the code from Stata to R, and the time series represented in the figure below relies on the methodology outlined by Mukoyama et al. We indicate in the caption and legend where we have incorporated new data by extending the time series to include additional years or applied an alternative weighting scheme to the data to account for missing data. The citation for this work can be found in the bibliography of the main text.

Learning Rate - Mueller et al. Job Seekers' Perceptions and Employment Prospects: Heterogeneity, Duration Dependence and Bias

Given, the theoretical job search model presented in the main text relies additionally on a learning rate. We consider drawing this learning rate from work by Mueller et al, though this has not been incorporated in the main text thus far.

In this work, the authors claim to disentangle the effects of duration dependence and dynamic selection by using job seekers' elicited beliefs about job-finding. Assuming (and confirming empirically) that job-seekers have realistic initial beliefs about job-finding they isolate the heterogeneity in job-seekers from true duration dependence. Ultimately, they find that dynamic selection selection explains most of the negative duration dependence (rather than pure, true duration dependence).

We replicate and extend the analysis using replication code made available by the autors. The figures and econometric specification choices are crafted by Mueller et al, and several of the below plots are present in the main text of their work as well. Plot and regression table titles have been maintained for easy comparison.



Plots the average minutes of search per day per unemployed worker, using the imputation method from Mukoyama et al. 2018. Each observation is weighted by its CPS sample weight. We extend the data imputed in the original paper (labelled 'Extended TS' versus 'Original TS'). The weights applied in the imputation process have been improved to account for missing data in the CPS and ATUS inputs (New Weights versus Original Weights). The greyed out portions indicate data outside of the time period to which the ABM is calibrated and simulated.

Figure 5: Mukoyama Validation Series

We provide additional evidence regarding the stability of their estimates across a longer time series that includes six additional years of data from 2019-2024.

We find that their results are remarkably consistent even when including additional data from 2019-2024. We aim to include this information in our theoretical model of the job search effort as a learning rate (ie. individuals learn about their re-employment probability with repeated failures in the job search).

Table 9: Descriptive Statistics (SCE)

Variable	Orig. 2013-19	2013-24	2020-24
High-School Degree or Less	44.5	40.6	36.9
Some College Education	32.4	34.9	37.6
College Degree or More	23.1	24.6	25.6
Age 20-34	25.4	27.2	30.0
Age 35-49	33.5	33.6	35.3
Age 50-65	41.1	39.2	34.8
Female	59.3	61.2	60.8
Black	19.1	17.9	16.4
Hispanic	12.5	13.0	12.6
UE transition rate	18.7	19.1	18.2
UE transition rate: ST	25.8	26.5	24.3
UE transition rate: LT	12.7	12.7	12.3
# respondents	948	$1,367$	433
# respondents w/ at least 2 u obs	534	780	252
# observations	$2,597$	$3,926$	$1,347$

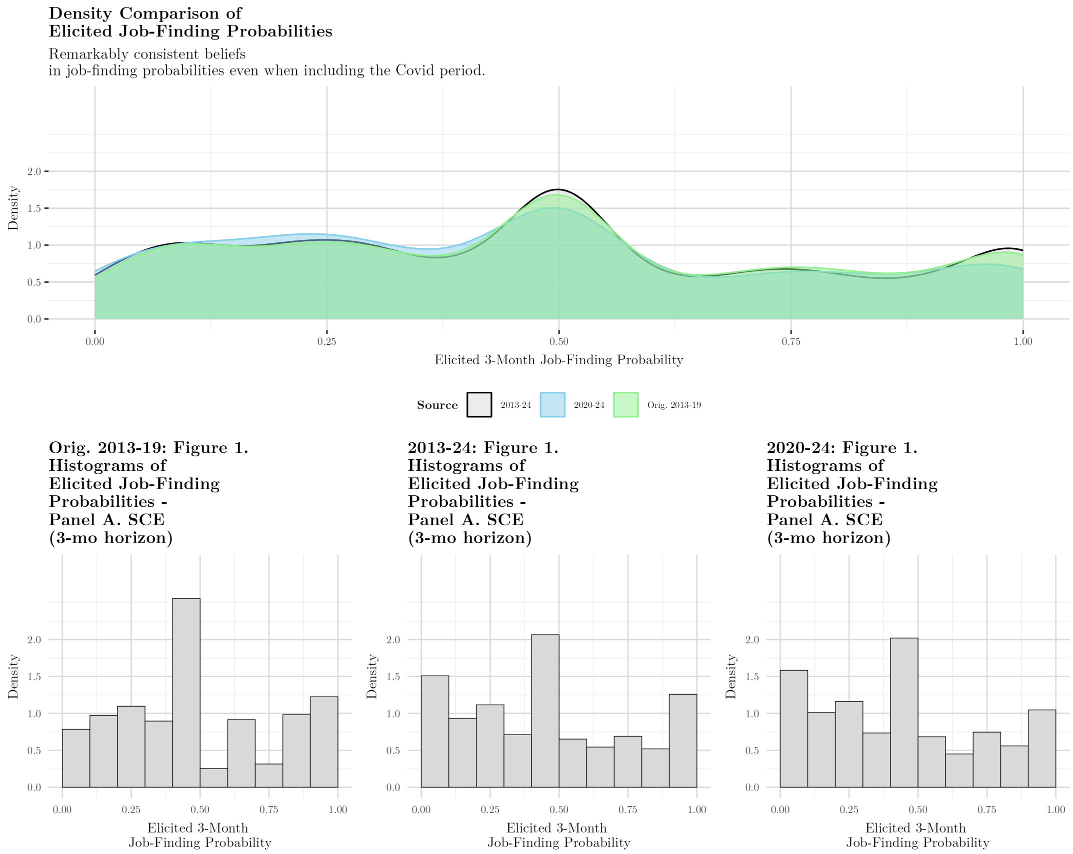

Density Comparison of
Elicited Job-Finding Probabilities
Remarkably consistent beliefs
in job-finding probabilities even when including the Covid period.
Density
Elicited 3-Month Job-Finding Probability
Source
2013-24
2020-24
Orig. 2013-19
Orig. 2013-19: Figure 1. Histograms of Elicited Job-Finding Probabilities - Panel A. SCE (3-mo horizon)
2013-24: Figure 1. Histograms of Elicited Job-Finding Probabilities - Panel A. SCE (3-mo horizon)
2020-24: Figure 1. Histograms of Elicited Job-Finding Probabilities - Panel A. SCE (3-mo horizon)
Elicited 3-Month
Job-Finding Probability

Figure 2: Averages of Realized Job-Finding Rates, by Bins of Elicited Probabilities (SCE)

Demonstrates the predictive power of beliefs. Remarkably consistent even when including the Covid period except for those who were perhaps overly optimistic.

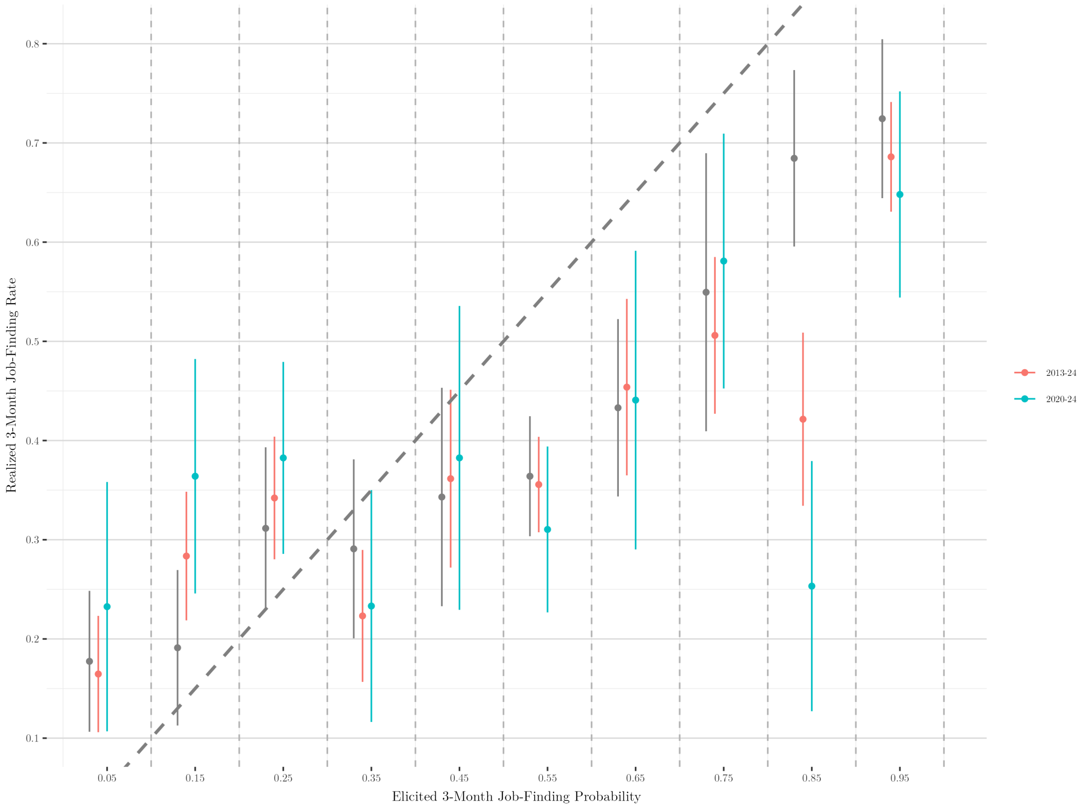


Table 10: Table 2—Regressions of Realized on Elicited 3-Month Job-Finding Probabilities (SCE): Contemporaneous elicitations

	Dependent variable:		
	T+3 UE Transitions (3-Months)		
	Orig. 2013-19	2013-24	2020-24
	(1)	(2)	(3)
find_job_3mon	0.464***	0.396***	0.265***
	(0.045)	(0.036)	(0.067)
1 |userid	−0.104		−0.136
	(0.169)		(0.267)
Constant		−0.080	
		(0.137)	
Observations	1,201	1,911	673
R^2	0.218	0.139	0.105
Adjusted R^2	0.207	0.132	0.083
Residual Std. Error	0.467 (df = 1184)	0.475 (df = 1894)	0.478 (df = 656)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 11: Table 2—Regressions of Realized on Elicited 3-Month Job-Finding Probabilities (SCE): Contemporaneous elicitations

	Dependent variable:		
	T+3 UE Transitions (3-Months)		
	Orig. 2013-19	2013-24	2020-24
	(1)	(2)	(3)
find_job_3mon	0.501^{***}	0.418^{***}	0.391^{***}
	(0.061)	(0.051)	(0.094)
findjob_3mon_longterm	-0.258^{***}	-0.170^{**}	-0.360^{***}
	(0.088)	(0.071)	(0.133)
longterm_unemployed	-0.078	-0.127^{***}	-0.043
	(0.051)	(0.041)	(0.075)
1 |userid			
Constant	-0.062	-0.063	-0.402
	(0.175)	(0.139)	(0.266)
Observations	1,201	1,911	673
R^2	0.259	0.182	0.155
Adjusted R^2	0.248	0.174	0.132
Residual Std. Error	0.455 (df = 1182)	0.464 (df = 1892)	0.465 (df = 654)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 12: Table 2—Regressions of Realized on Elicited 3-Month Job-Finding Probabilities (SCE): Lagged elicitations

	Dependent variable:		
	T+3 UE Transitions (3-Months)		
	Orig. 2013-19	2013-24	2020-24
	(1)	(2)	(3)
tplus3_percep_3mon	0.332^{***}	0.241^{***}	0.203^{**}
	(0.067)	(0.056)	(0.102)
1 |userid			
Constant	0.304	0.490^{**}	0.451
	(0.270)	(0.207)	(0.394)
Observations	474	798	300
R^2	0.168	0.090	0.179
Adjusted R^2	0.139	0.071	0.132
Residual Std. Error	0.398 (df = 457)	0.436 (df = 781)	0.447 (df = 283)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 13: Table 2—Regressions of Realized on Elicited 3-Month Job-Finding Probabilities (SCE): Lagged elicitations

	Dependent variable:		
	T+3 UE Transitions (3-Months)		
	Orig. 2013-19	2013-24	2020-24
	(1)	(2)	(3)
find_job_3mon	0.301***	0.205***	−0.035
	(0.069)	(0.058)	(0.110)
1 |userid			
Constant	0.201	0.422**	0.361
	(0.274)	(0.207)	(0.400)
Observations	474	798	300
R^2	0.159	0.083	0.168
Adjusted R^2	0.129	0.064	0.121
Residual Std. Error	0.400 (df = 457)	0.437 (df = 781)	0.450 (df = 283)
Note:			*p<0.1; **p<0.05; ***p<0.01

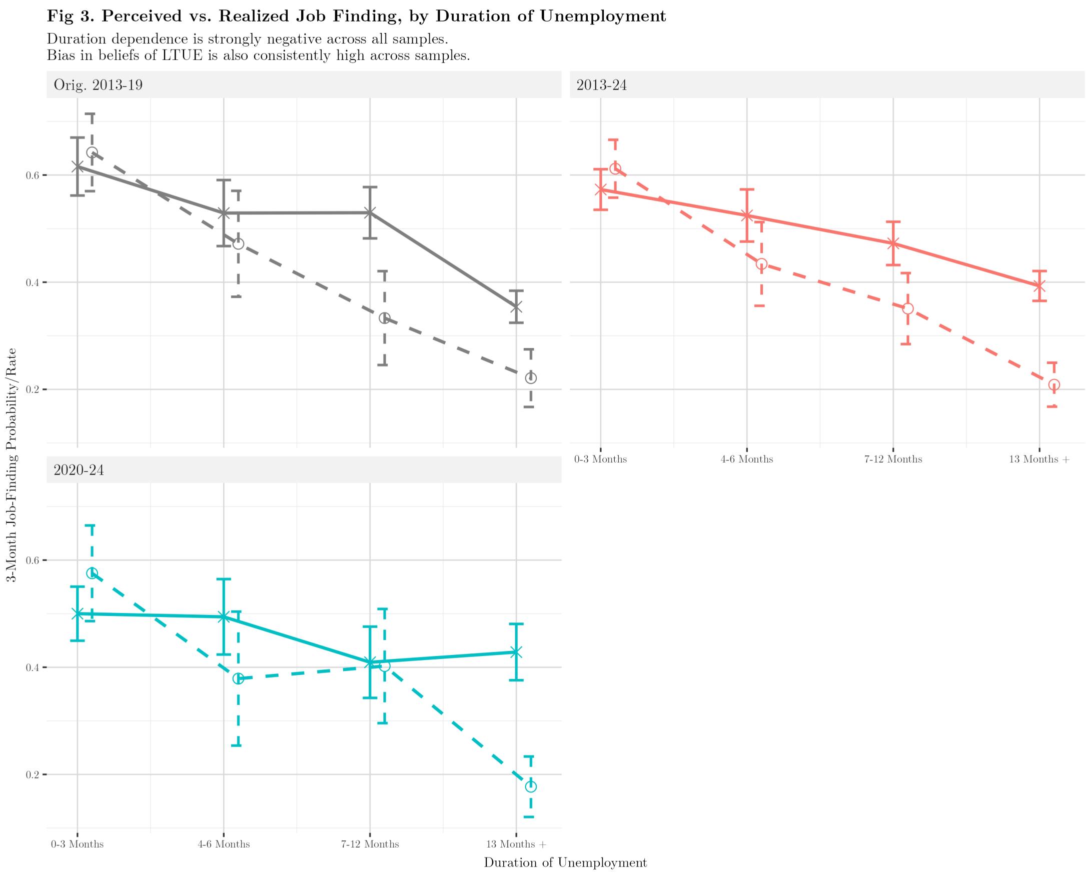


Fig 3. Perceived vs. Realized Job Finding, by Duration of Unemployment

Duration dependence is strongly negative across all samples.
Bias in beliefs of LTUE is also consistently high across samples.

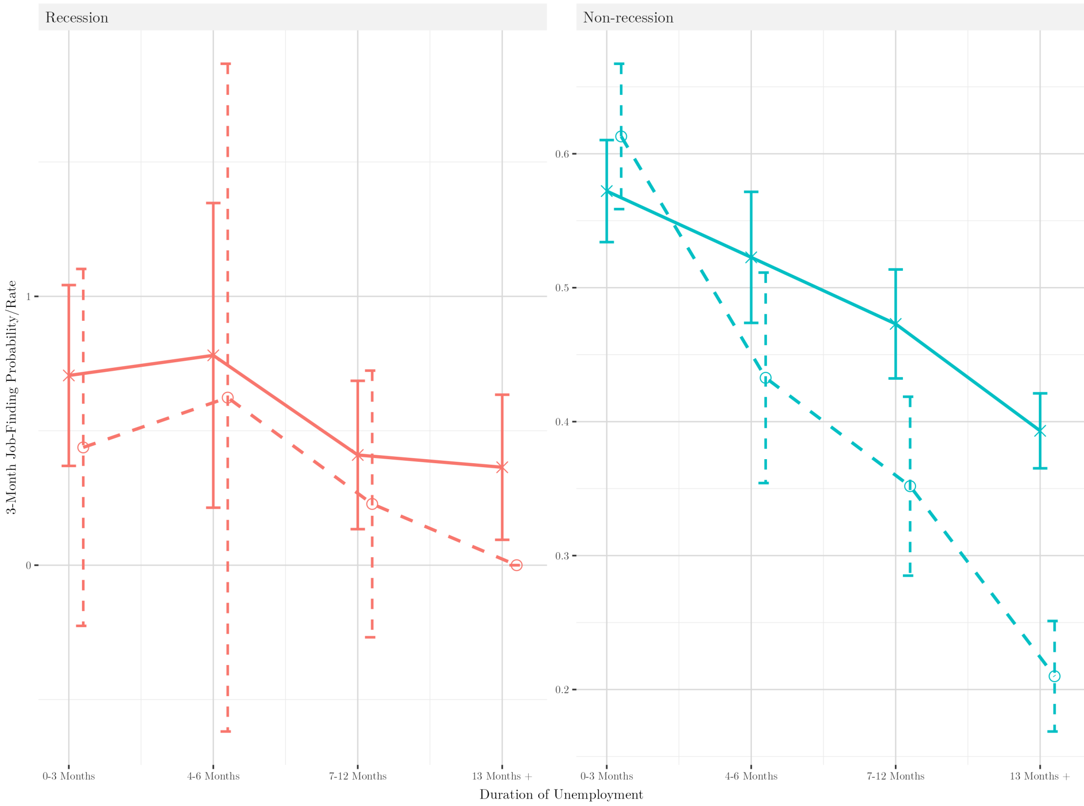


Fig 4. Changes in Job-Finding Probability Across and Within Spells

Figure 4 illustrates the difference between the observed (cross-sectional - left panel) duration dependence and the true (individual-level - right panel) duration dependence in the reported beliefs graphically.

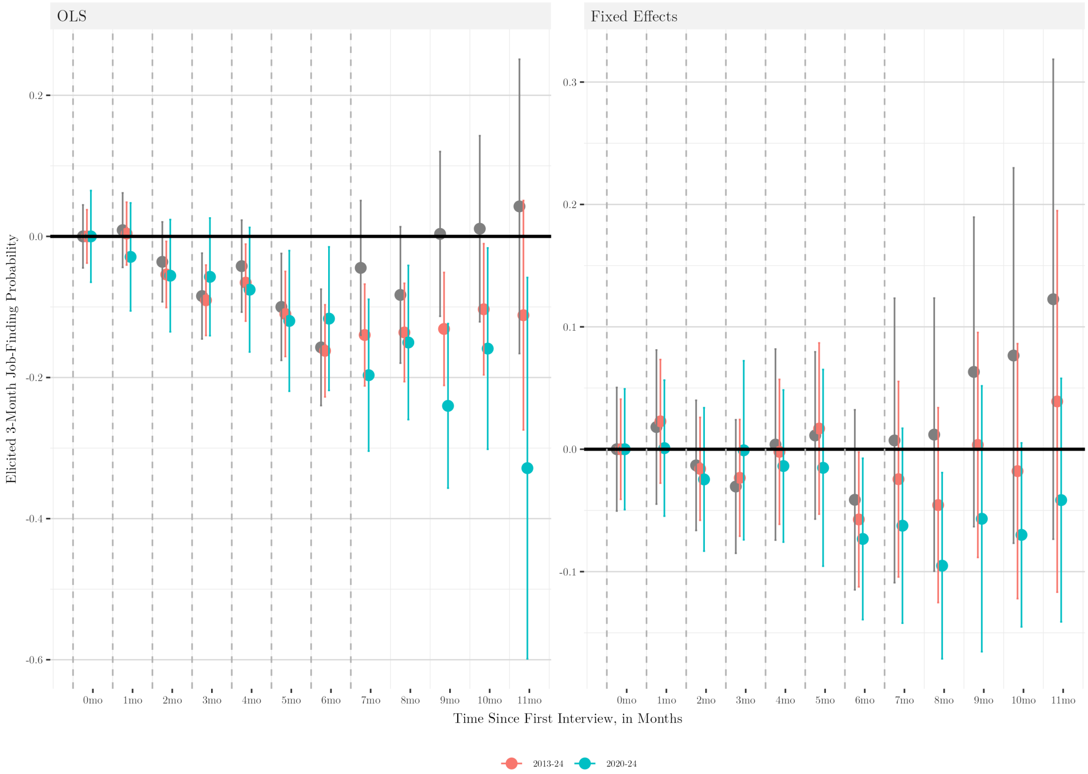


Fig 3. Perceived vs. Realized Job Finding, by Duration of Unemployment

Duration dependence is strongly negative across all samples.
Bias in beliefs of LTUE is also consistently high across samples.

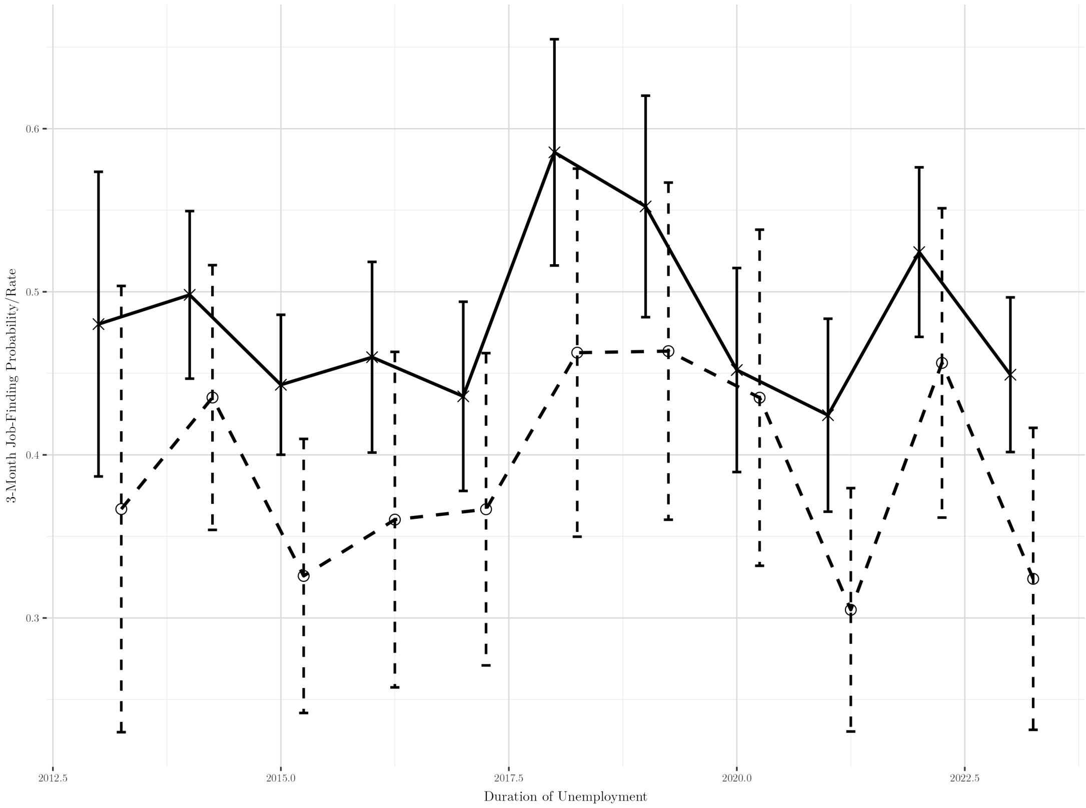
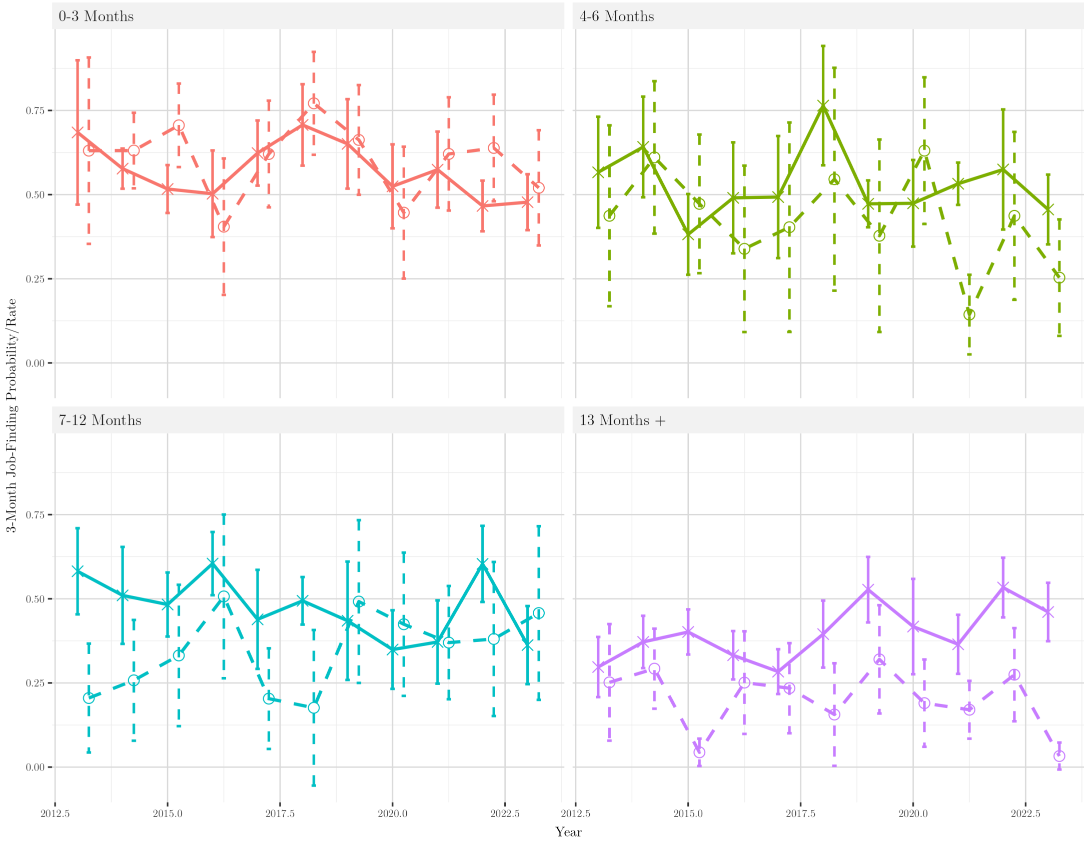


Fig 3. Perceived and Realized Job Finding, by Year



B Setting Occupational Target Demand

Setting Occupational Target Demand

The impetus for agents to act within our model relies on non-static target demand across occupations. In other words, occupational demand for workers needs to fluctuate during the simulation. We define such movements at the occupational level by drawing on the share of occupations employed across various US industries and interact these shares with the real value added of each industry. As such, we arrive at occupational target demand profiles that fluctuate in line with real-world target demand over the simulated time period. Important future work should aim to accommodate shifts in labor productivity of different industries and/or shifting industry-specific occupational shares to account for additional sources of structural transformation beyond those explored in this work.

First, using reported occupational shares of industry employment from the Bureau of Labor Statistics' Occupational Employment and Wages dataset and the industry Value Added (quarterly data available from 2005 and annual data available from 1999), we calculate the occupational employment composition across 19 US industries at NAICS 2-digit code level.

First, assume that the baseline de-trended demand for occupation i in the economy D_i is:

$D_i = \sum_{j=1}^{n} \bar{d}_{ij} = 1$

where the de-trended fluctuating demand (i.e., demand at time t for occupation i) is:

$D_{it} = \sum_{j=1}^{n} \hat{d}_{ijt}$

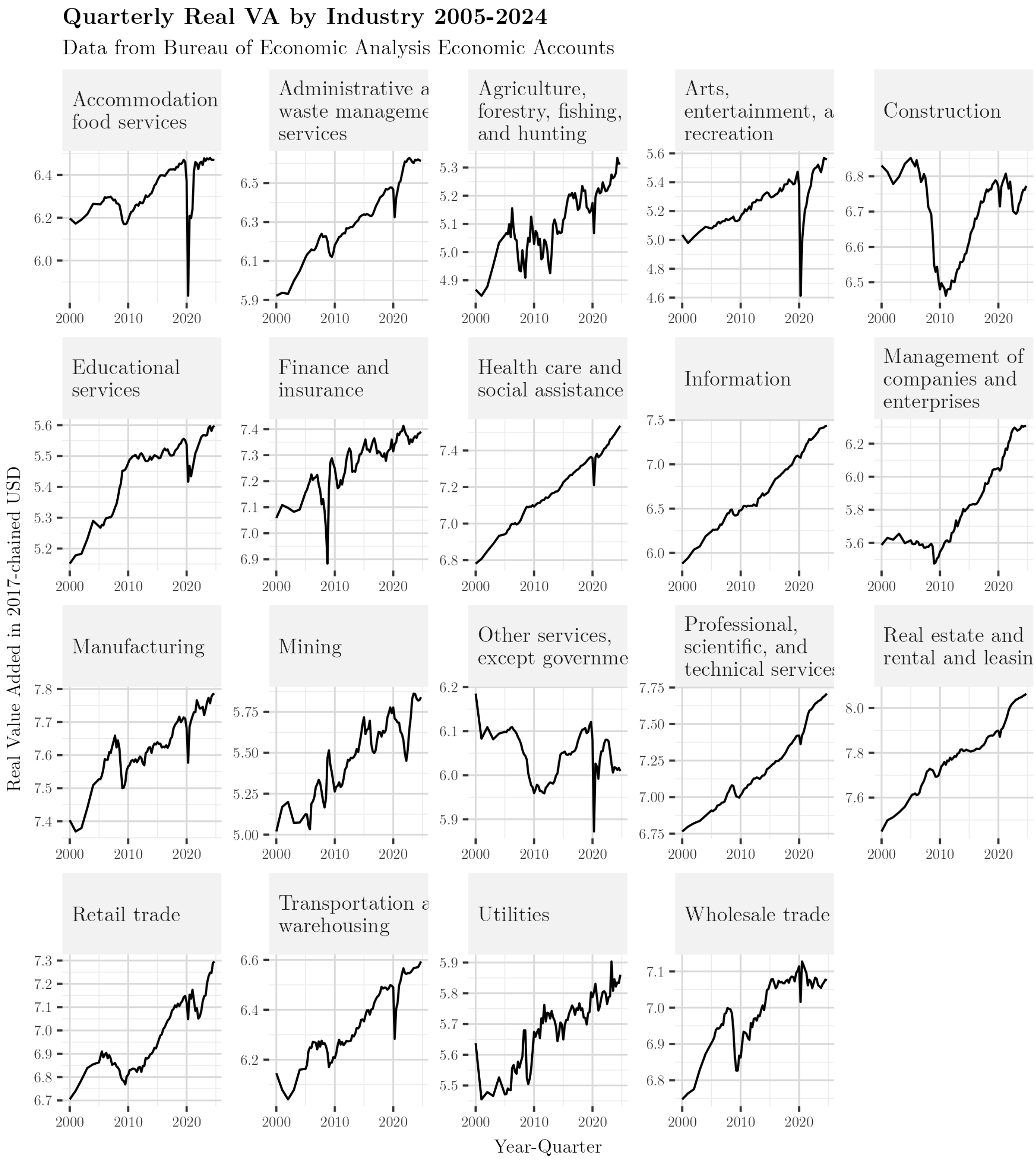
$\hat{d}_{ijt} = \sum_{j=1}^{n} \bar{d}_{ij}\theta_{jt}$

in which $\bar{d}_{ij}$ is the average share of occupation i in industry j and θ_{jt} is the de-trended value-added of industry j at time t. Thus, we obtain occupation-specific fluctuations in demand dependent on their "exposure" or the share of a specific occupation in industry j. We de-trend the value added using a Hodrick-Prescott filter to obtain occupational target demand as a fluctuation around a mean. This allows for an interpretation of demand fluctuations as either an upward or downward pressure on occupational employment levels.

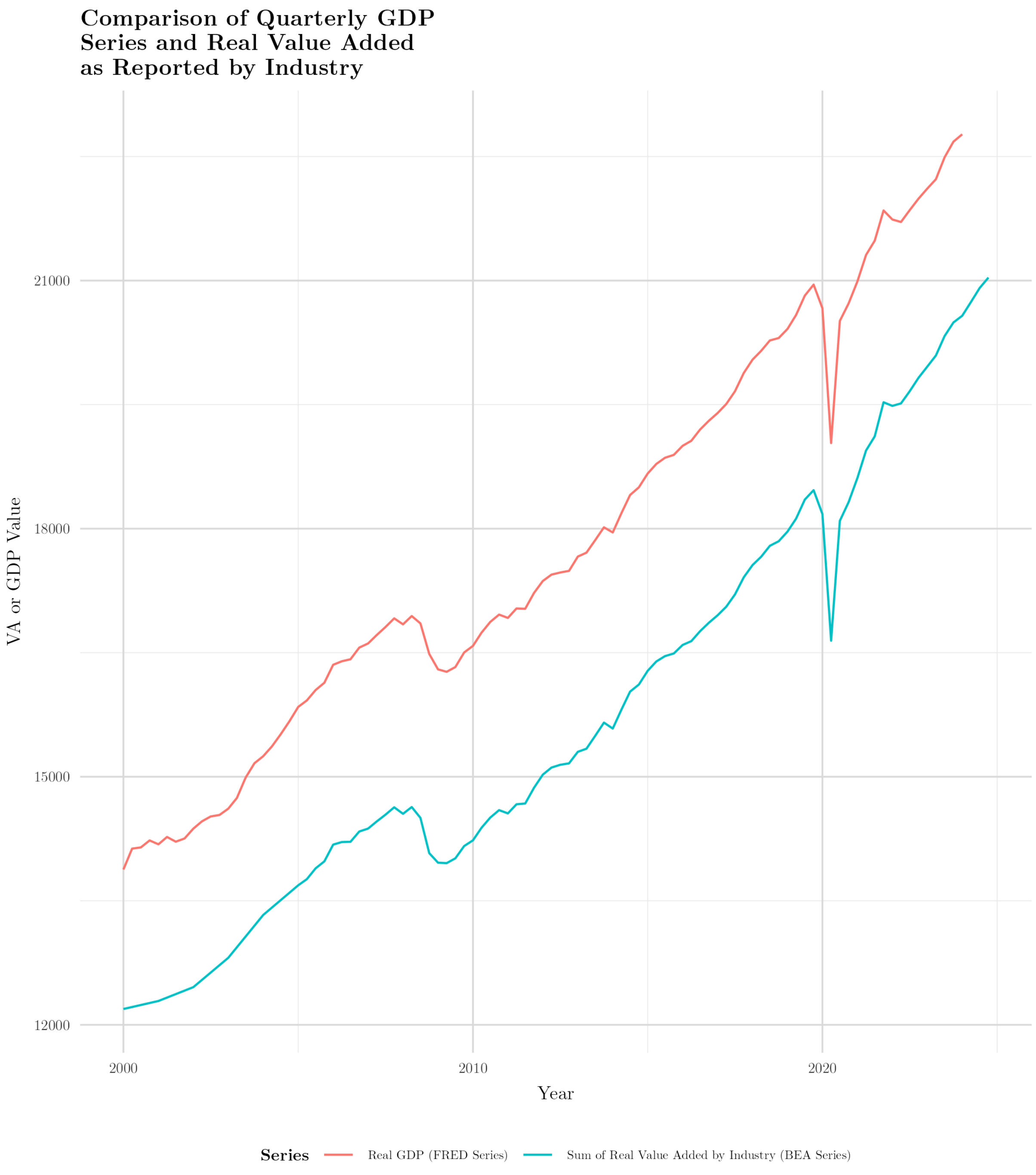
In the following sections, we describe the data used, provide visualizations of the series as well as the imputed occupational target demand series.

Value Added by Industry

We use industry value added data from the US Bureau of Economic Analysis (using annual data from 2000-2004 and quarterly data available from 2005) to define θ_{jt} to create these occupation-specific target demand trajectories. We de-trend the value added using a Hodrick-Prescott filter. Below, we present the industry real value added and demonstrate that these disaggregated series closely follow the national real GDP series.



nnual data prior to 2005 is linearly interpolated to achieve a quarterly frequency matching the later portion of each time series.



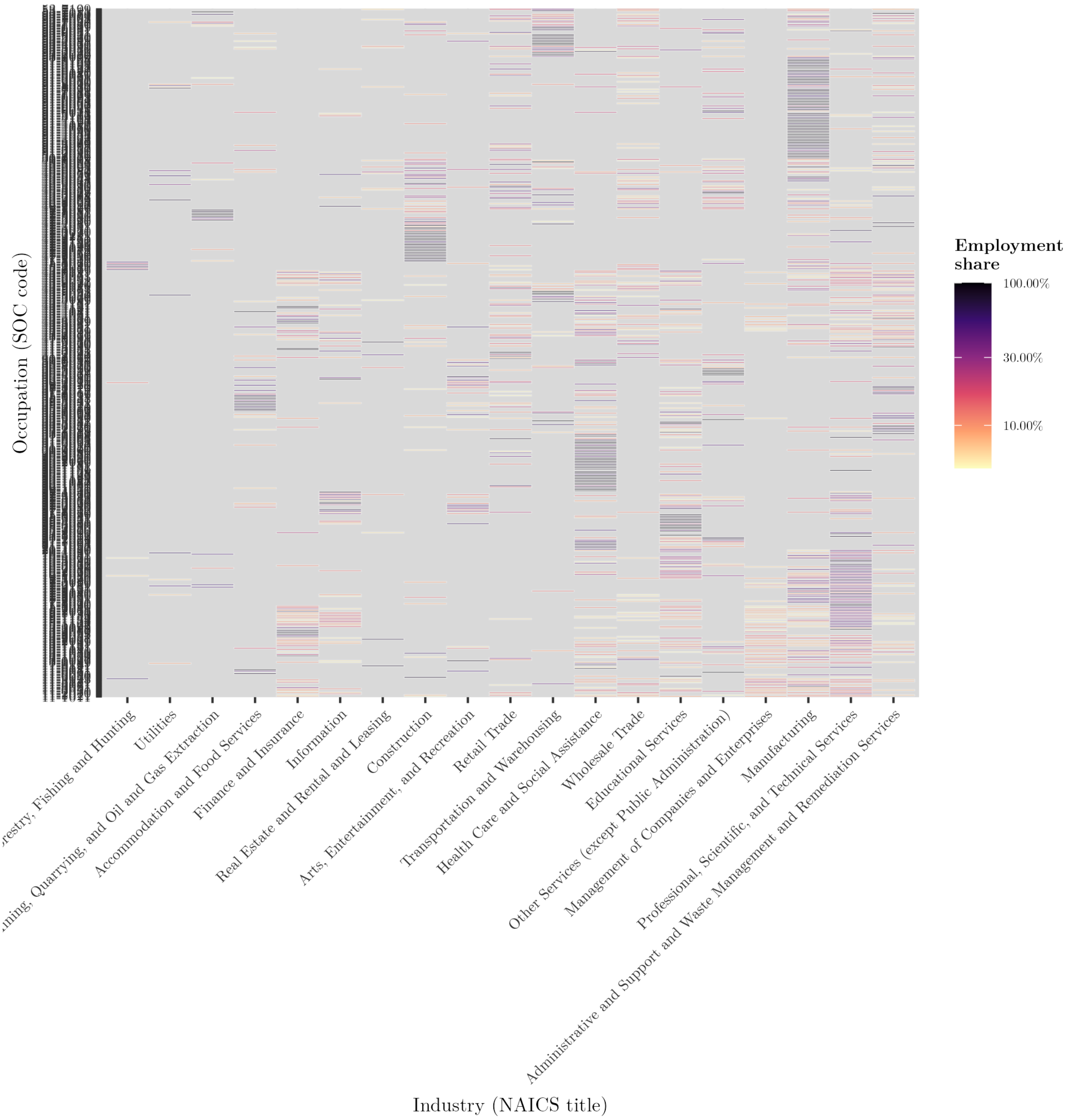
Occupational shares of industry-level emloyment

We use annual occupational shares of employment from the Occupational Employment and Wage Statistics database from the US Bureau of Labor Statistics to derive our $\bar{d}_{ij}$. The first figure shows the share of occupations within each industry, drawn from the OEWS data. The gaps in the figure is due to a reshuffling of occupational codes in 2010 and 2018. To deal with this challenge, we take the mean industry-share of occupational employment reported in the years where majority (>97%) of our occupational codes are present (2012-2018 - after and before SOC reorganization of 2010 and 2018). We display the occupation-industry employment shares in a gridded format as well.

Note that the procedure we employ to arrive at consistent occupational shares of industry-level employment results in 6 occupational categories that have a sum of their mean shares greater than 1.1.

Occupation–Industry Employment Shares

The colors display the share of total occupational employment in each industry.
Industries are ordered by the total number of occupations they employ in ascending order.
We display only those occupations whose industrial-level employment share is at least 5%.



[1] "6 occupational categories have a sum of mean shares > 1.1:"

SOC2010 Occupational Code	Occupational Label	Sum of Mean Shares
53-4041	Subway, streetcar, and other rail transportation workers	1.374194
49-9093	Other installation, maintenance, and repair workers	1.254556
43-2099	Communications equipment operators, all other	1.180072
37-2021	Pest control workers	1.135526
53-6011	Bridge and lock tenders	1.132450
53-6041	Other transportation workers	1.121672

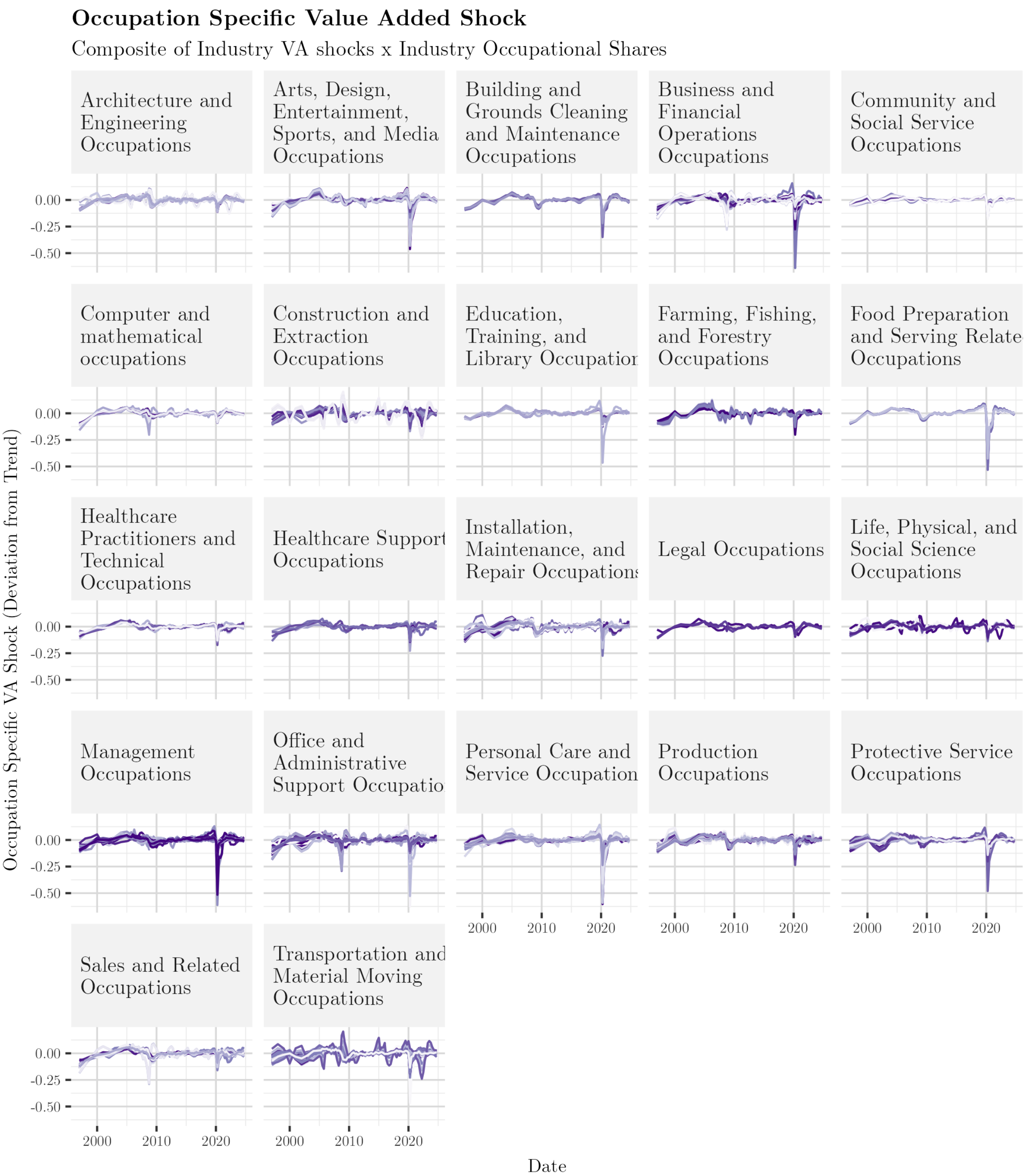
Bringing them together

We bring these values together by adding the product of industry-level real-value added and the fixed occupational employment shares across all industries as in the formulation above, repeated here for ease: $\hat{d}_{ijt} = \sum_{j=1}^{n} \bar{d}_{ij}\theta_{jt}$. This yields occupation-specific target demand profiles that respond to disaggregated industrial productivity movements.

Note that we are missing information on occupation code 13-2081 (Tax examiners and collectors, and revenue agents) which are present in our occupational network but not in our VA data as they are only employed in public administration. VA information does not exist for public administration. For now, we use the shocks to 13-2082 as the shocks to 13-2081 though this could potentially be adjusted such that public administration fluctuations depend on overall GDP fluctuations.

Furthermore, in the case of the full OMN we are missing both 13-2081 and 33-3031 (Fish and Game Wardens). We assign the fish and game wardens the same occupational shocks as 33-9011 (Animal Control Workers) within the same broad category grouping of SOC codes.

Finally, in the case of the O*NET Related Occupations Network both of the above are missing in addition to 45-3021 (hunters and trappers). We assign hunters and trappers the same occupational shocks as the only other occupation in the same Minor SOC Group (45-3011 - Fishers and Related Fishing Workers). They are both categorized within the same "Fishing and Hunting Workers" Minor SOC Group (45-3000).


Occupation Specific Value Added Shock
Composite of Industry VA shocks x Industry Occupational Shares
Architecture and Engineering Occupations
Arts, Design, Entertainment, Sports, and Media Occupations
Building and Grounds Cleaning and Maintenance Occupations
Business and Financial Operations Occupations
Community and Social Service Occupations
Computer and mathematical occupations
Construction and Extraction Occupations
Education, Training, and Library Occupation
Farming, Fishing, and Forestry Occupations
Food Preparation and Serving Relate Occupations
Healthcare Practitioners and Technical Occupations
Healthcare Support Occupations
Installation, Maintenance, and Repair Occupations
Legal Occupations
Life, Physical, and Social Science Occupations
Management Occupations
Office and Administrative Support Occupatio
Personal Care and Service Occupation
Production Occupations
Protective Service Occupations
Sales and Related Occupations
Transportation and Material Moving Occupations
0.00
-0.25
-0.50
2000
2010
2020
Occupation Specific VA Shock (Deviation from Trend)
Date

C On the orthogonality of preferences and occupational mobility

Preferences are not orthogonal to realised occupational transitions. Occupational transitions observed in our data are outcomes of processes in which individuals act upon their preferences for job characteristics such as location, wages, tasks, etc. This complicates the task of incorporating wage preferences and dynamic reservation wage setting in our model. Therefore, we replace the occupational mobility network with the O*NET Related Occupations Network wherein related occupations are linked by job similarity. We create two variants of an occupational similarity network using the O*NET related occupations framework. First, we use the raw O*NET Related Occupations Network, crosswalking from O*NET SOC Codes to SOC Codes. Second, we draw additional edges between higher-wage occupations to lower-wage occupations to account for the asymmetry in "relatedness" as defined in the Related Occupations Network. One of the challenges with the O*NET Related Occupations Network is that it only provides the top 20 occupational connections. As such, "related" occupations are often more likely to be connected directionally from lower- to higher-wage occupations, meaning that the network potentially under-reports the similarity between occupations situated at higher levels of the occupational ladder with those below. Therefore, we add reciprocal links between related occupations where only the "relatedness" between the lower-wage node in the direction of the higher-wage node is present. Correcting these "wage asymmetries" allow us to better reflect the fact that individuals can potentially feasibly transition from higher-wage occupations to related lower-wage occupations.

C.1 O*NET Related Occupations Network

First, O*NET uses a variant of the standard occupational classification (SOC) system to describe occupations. By definition, O*NET-SOC codes are more detailed than SOC codes and have an additional two digit suffix as compared to SOC codes. Therefore, to arrive at a network with occupations similar to those used in the occupational mobility network (OMN) in the main text, we convert the O*NET SOC codes to 2010 SOC codes using two intermediate crosswalks, allowing us to link these to the supporting data that we require from the CPS (employment, unemployment, gender share, etc.) to inform the creation of the occupational network.

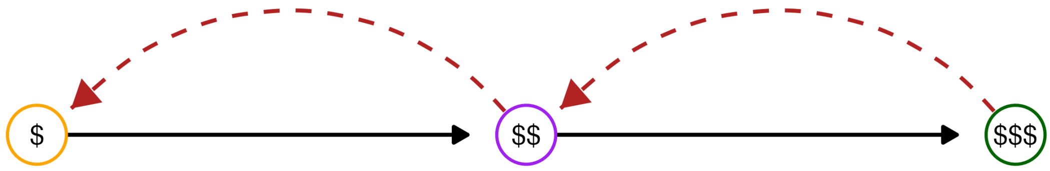
We first use a crosswalk from O*NET to SOC2010 Codes (ONET-SOC to Occupational Outlook Handbook Crosswalk) available from O*NET and next, employ the National Employment Matrix (SOC to ACS Crosswalk) crosswalk to translate the SOC2010 codes to American Community Survey (ACS) occupational codes, which align with the occupational codes used in our occupational mobility network in the main text. We guard all intermediate network formations for potential additional.

Crosswalking and aggregating occupations in this way requires reconciling duplicate occupational connections. For example, an occupation might have initially been linked to two O*NET-SOC occupations that fall under the same higher-level occupational category. In these cases, we reconcile the weight of the edge by taking the mean of the weights of multiple, now identical, edges.

C.2 O*NET Network with Adjusted Wage Asymmetries

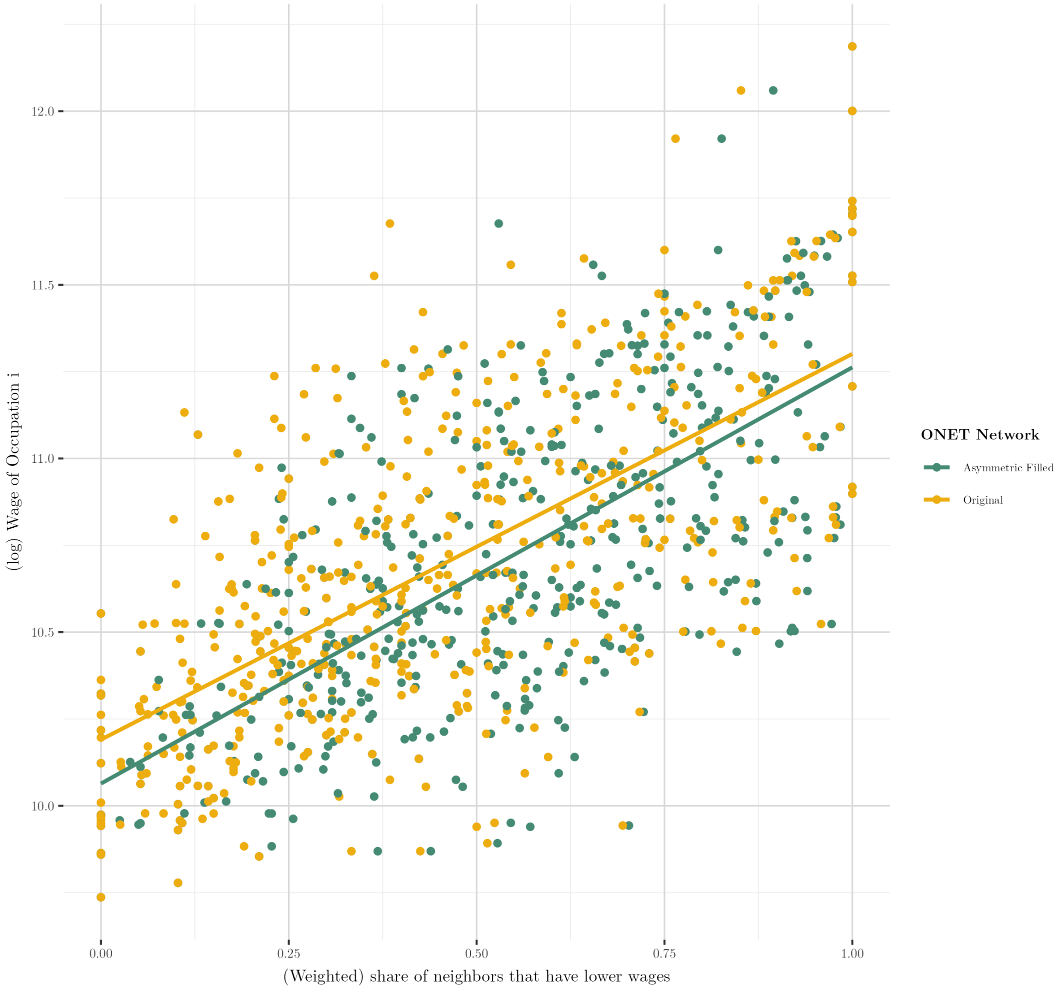
Furthermore, the related occupations network is likely biased in the direction of the occupational ladder. In other words, occupations on relatively higher rungs of the occupational ladder are likely over-represented in an occupation's "related occupations." This is likely exacerbated by the fact that the Related Occupations Network only reports the top 20 most likely related occupations. As a result, potential but under-weighted potential transitions from higher-wage occupations to lower-wage occupations are excluded from our network. Therefore, we systematically augment the related occupations network, adding reciprocal connections from higher-wage neighbors to new lower-wage neighbors where a relationship of the opposite direction already exists. The figure below represents the relationship, where black solid (red dashed) lines represent existing (new) links from lower- (higher-) to higher- (lower-) wage neighbors.

Representation of Added Links



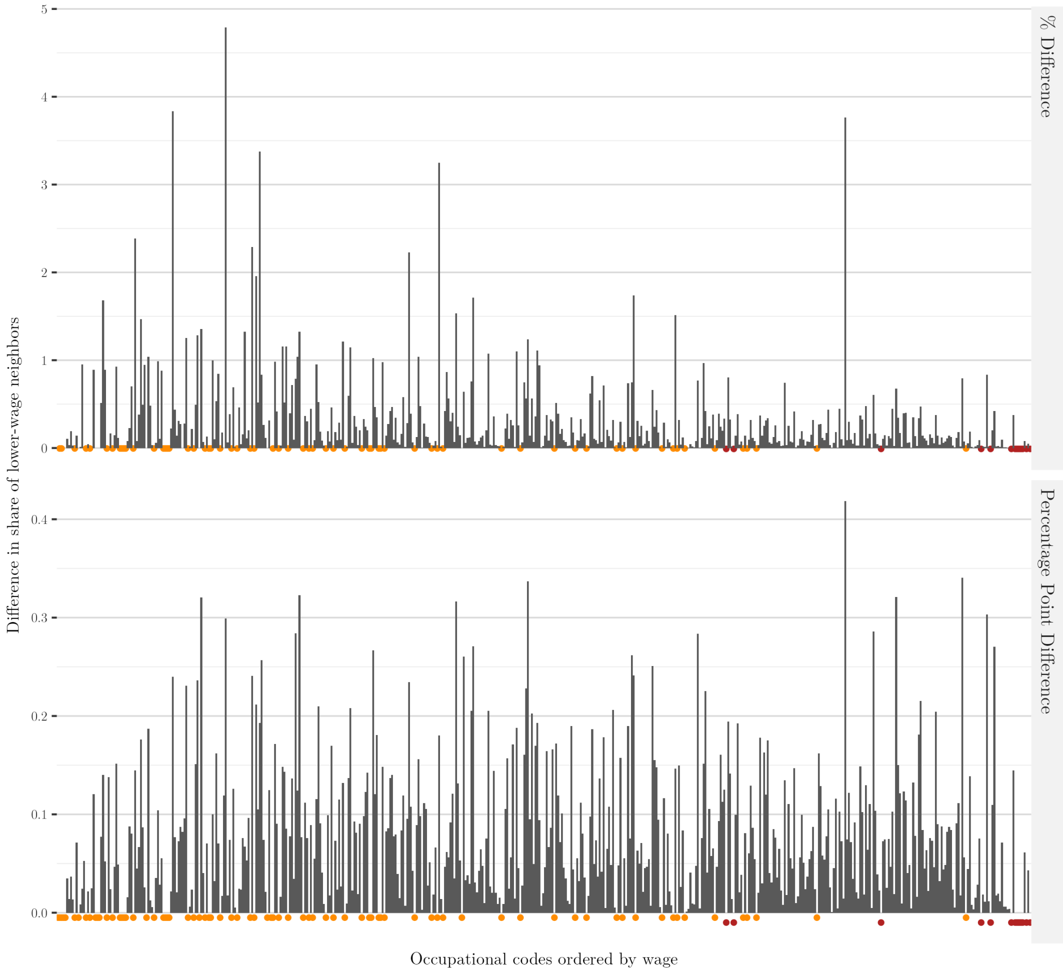
Relationship between Occupation i's Wage and Share of Lower-wage Neighbors

The colors represent the network used (ONET Related Occupations Network vs.
Augmented Network with Corrected Wage Asymmetries



Percentage Point Increase in Low-wage Neighbor Share After Reweighting

Orange dots represent those occupations that are not assigned any new neighbors conditional on the original share of low-wage neighbors being less than 1 (ie. all neighbors were already low-wage) (n = 76). Red dots represent occupations that only had lower-wage neighbors (n = 13).



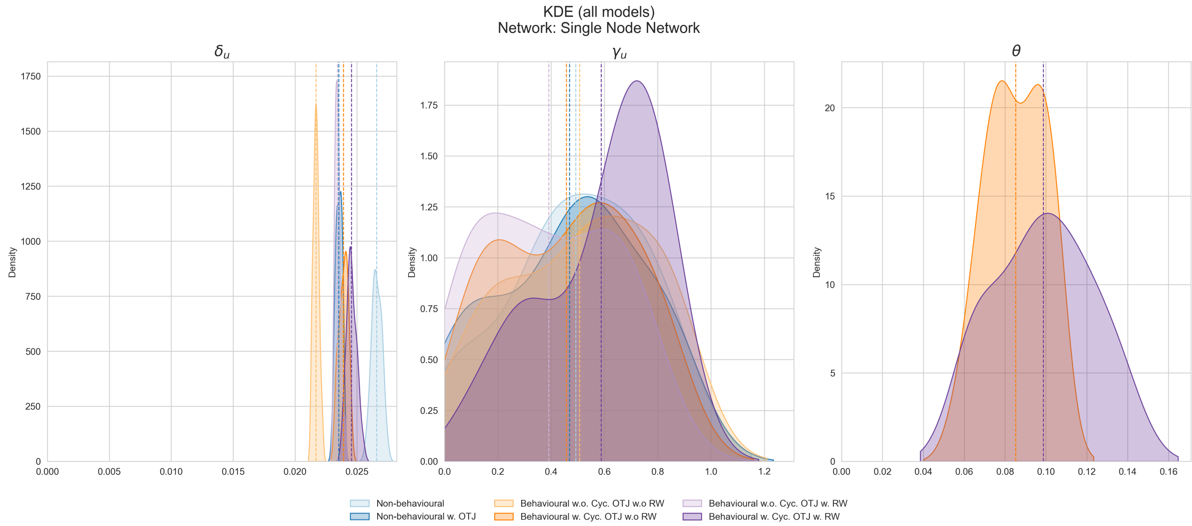
C.3 O*NET Network

Model Parameters

Parameter	Prior Distribution	Model Category							
		Non-behavioural	Non-behavioural w. OTJ	Behavioural w. Cyc. OTJ w.o RW	Behavioural w.o. Cyc. OTJ w.o RW	Behavioural w. Cyc. OTJ w. RW	Behavioural w.o. Cyc. OTJ w. RW	Behavioural w. Cyc. OTJ w. Strict RW	Behavioural w.o. Cyc. OTJ w. Strict RW
d_u	$U(0.0001, 0.9)$	0.02	0.017	0.016	0.017	0.015	0.017	0.007	0.012
gamma_u	$U(0.0001, 0.9)$	0.848	0.763	0.683	0.6	0.773	0.709	0.113	0.033
theta	$U(0.0001, 0.9)$			0.111		0.149		0.455	

Table 5: Prior distribution and parameter estimates for all models. $U(a, b)$ denotes a uniform distribution on $[a, b]$.

Figure 16: ABC Calibration Results: Jointly minimizing unemployment rate loss



Time Series Metrics

Model	Variable	Mean (Sim)	Mean (Obs)	SSE	Correlation
Non-behavioural	Vacancy Rate	0.032	0.031	0.001	0.959
	Unemployment Rate	0.058	0.060	0.036	0.956
	Long-term Unemployment Rate	0.103	0.264	6.499	0.832
	Hires Rate	0.029	0.036	0.015	0.496
	Separations Rate	0.031	0.036	0.008	0.400
	UE Transition Rate	0.027	0.014	0.048	-0.465
	EE Transition Rate	0.000	0.019	0.080	–
	Application Effort (U)	–	–	–	-0.780
	Seeker Composition	0.000	0.410	37.974	–
Non-behavioural w. OTJ	Vacancy Rate	0.031	0.031	0.001	0.944
	Unemployment Rate	0.059	0.060	0.017	0.935
	Long-term Unemployment Rate	0.131	0.264	4.820	0.774
	Hires Rate	0.032	0.036	0.011	0.558
	Separations Rate	0.034	0.036	0.007	0.440
	UE Transition Rate	0.024	0.014	0.028	-0.458
	EE Transition Rate	0.006	0.019	0.041	0.033
	Application Effort (U)	–	–	–	-0.623
	Seeker Composition	0.488	0.410	2.022	0.796
Behavioural w. Cyc. OTJ w. RW	Vacancy Rate	0.031	0.031	0.001	0.952
	Unemployment Rate	0.060	0.060	0.014	0.892
	Long-term Unemployment Rate	0.162	0.264	3.106	0.771
	Hires Rate	0.031	0.036	0.011	0.538
	Separations Rate	0.033	0.036	0.008	0.400
	UE Transition Rate	0.024	0.014	0.028	-0.465
	EE Transition Rate	0.006	0.019	0.043	0.038
	Application Effort (U)	–	–	–	-0.802
	Seeker Composition	0.416	0.410	1.944	0.760
Behavioural w.o. Cyc. OTJ w. RW	Vacancy Rate	0.031	0.031	0.001	0.962
	Unemployment Rate	0.061	0.060	0.013	0.944
	Long-term Unemployment Rate	0.176	0.264	2.745	0.746
	Hires Rate	0.031	0.036	0.011	0.575
	Separations Rate	0.033	0.036	0.007	0.451
	UE Transition Rate	0.023	0.014	0.023	-0.414
	EE Transition Rate	0.006	0.019	0.039	0.082
	Application Effort (U)	–	–	–	-0.693
	Seeker Composition	0.478	0.410	1.605	0.801
Behavioural w. Cyc. OTJ w.o RW	Vacancy Rate	0.031	0.031	0.001	0.958
	Unemployment Rate	0.061	0.060	0.016	0.879
	Long-term Unemployment Rate	0.112	0.264	6.027	0.746
	Hires Rate	0.032	0.036	0.012	0.557
	Separations Rate	0.034	0.036	0.009	0.420
	UE Transition Rate	0.023	0.014	0.025	-0.455
	EE Transition Rate	0.007	0.019	0.039	0.061
	Application Effort (U)	–	–	–	-0.639
	Seeker Composition	0.416	0.410	2.177	0.792
Behavioural w.o. Cyc. OTJ w.o RW	Vacancy Rate	0.031	0.031	0.001	0.950
	Unemployment Rate	0.059	0.060	0.013	0.918
	Long-term Unemployment Rate	0.120	0.264	5.520	0.741
	Hires Rate	0.031	0.036	0.010	0.575
	Separations Rate	0.033	0.036	0.007	0.458
	UE Transition Rate	0.022	0.014	0.021	-0.454
	EE Transition Rate	0.007	0.019	0.035	0.072
	Application Effort (U)	–	–	–	-0.532
	Seeker Composition	0.483	0.410	1.664	0.782

Unemployment and Vacancy Rates

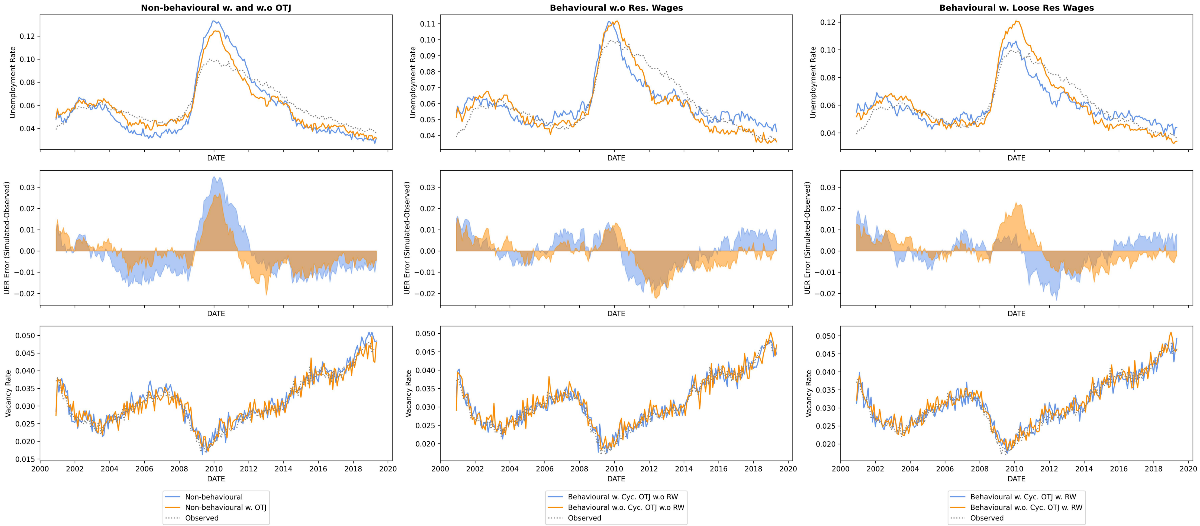


Figure 17: Unemployment and Vacancy Rates

Beveridge Curves

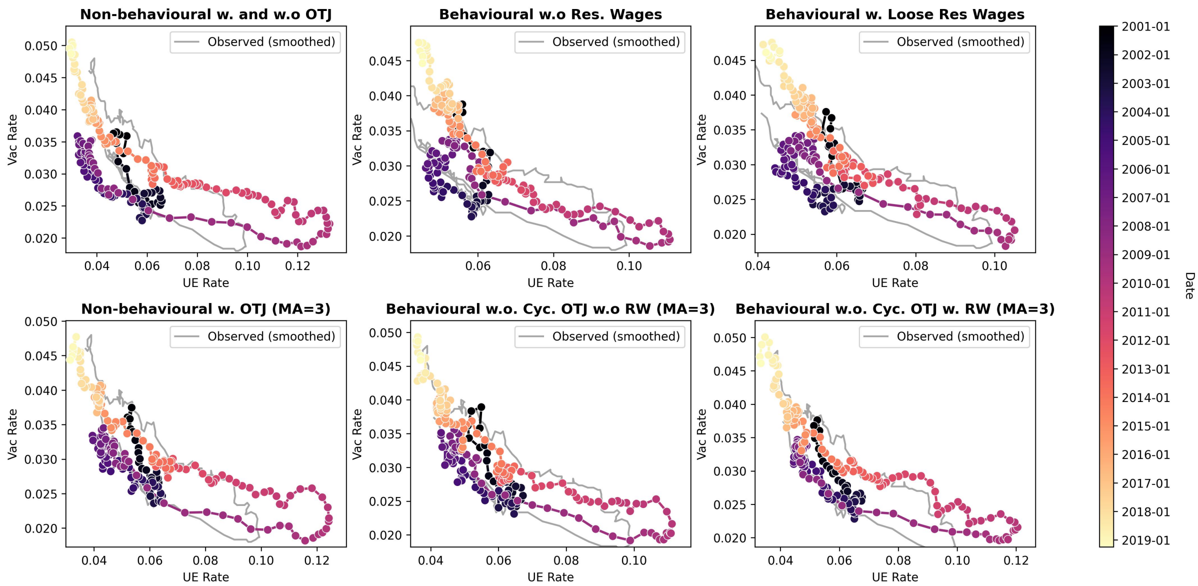


Figure 18: Beveridge Curves

Long-Term Unemployment

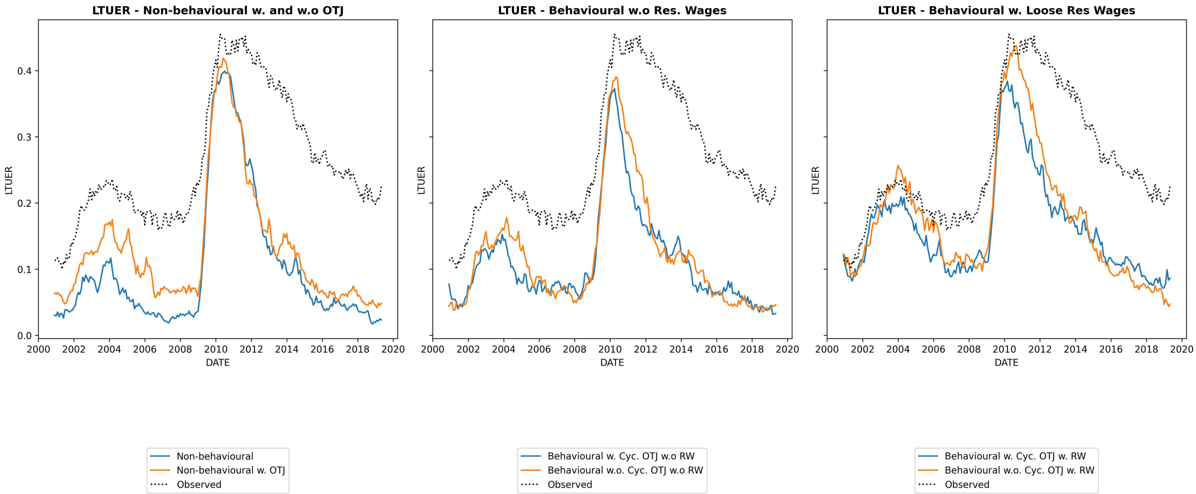


Figure 19: Long-Term Unemployment Rate

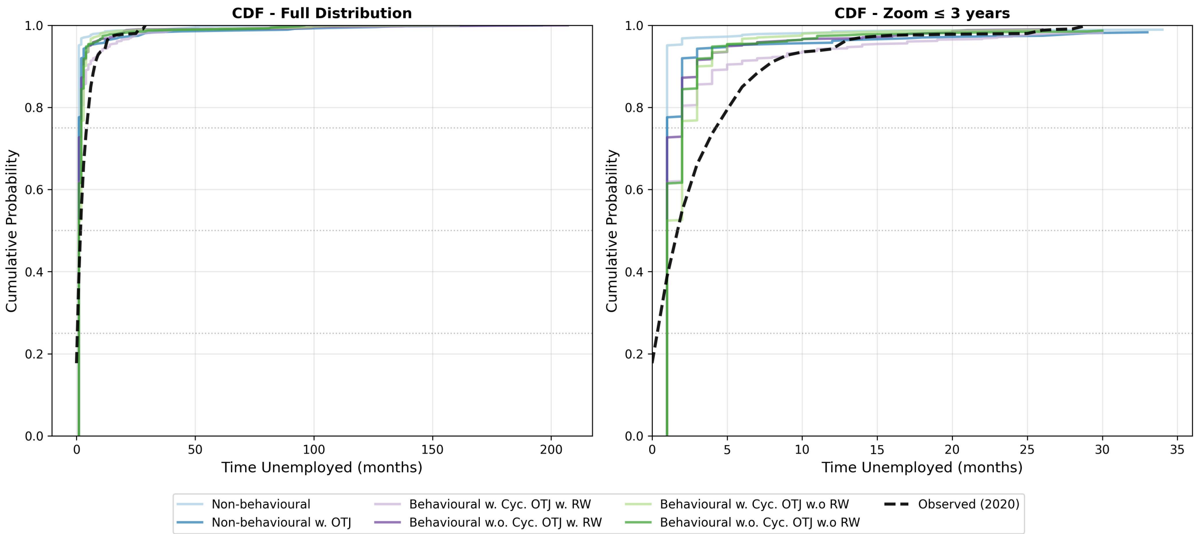


Figure 20: Long-Term Unemployment Rate

Applications per Unemployed Seeker

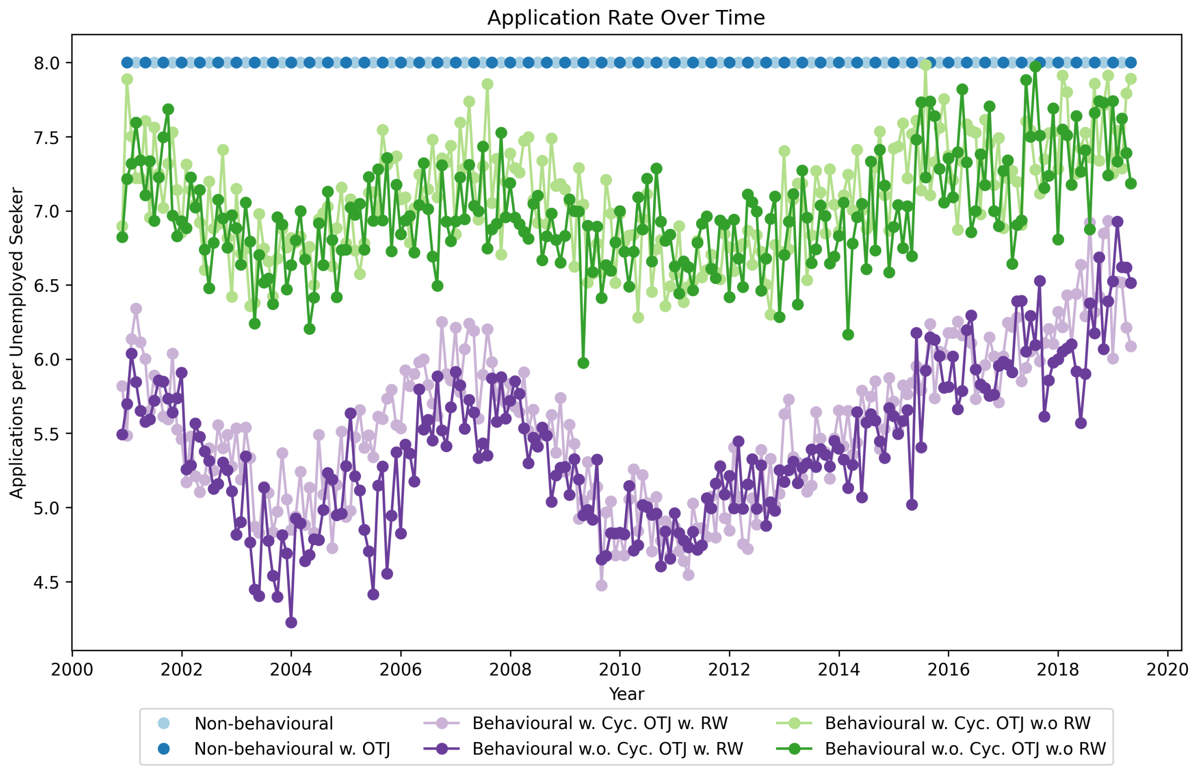


Figure 21: Applications per Unemployed Seeker

C.4 O*NET Wage Asymmetric Network

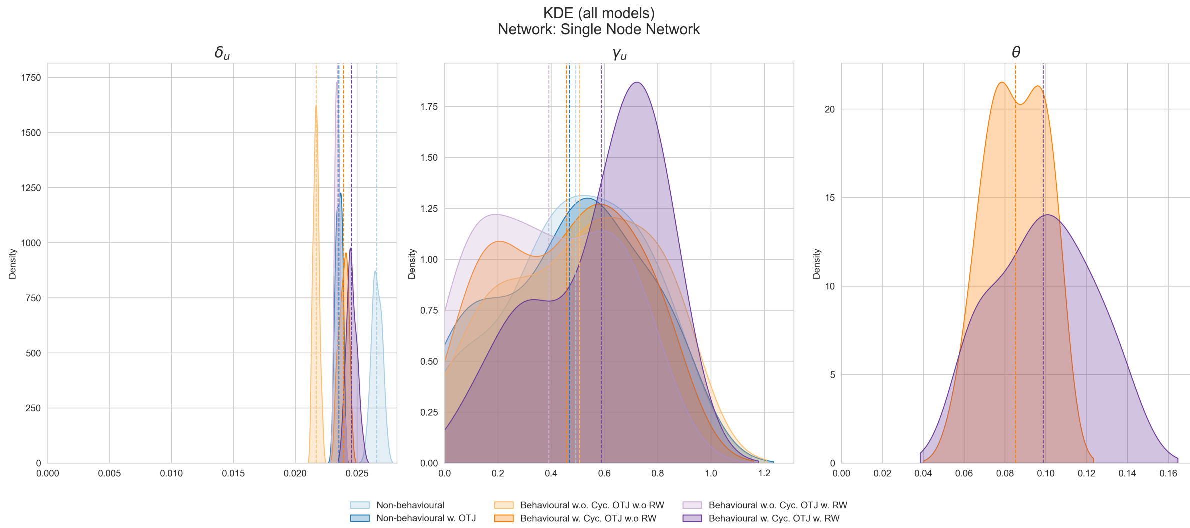
Model Parameters

Parameter	Prior Distribution	Model Category							
		Non-behavioural	Non-behavioural w. OTJ	Behavioural w. Cyc. OTJ w.o RW	Behavioural w.o. Cyc. OTJ w.o RW	Behavioural w. Cyc. OTJ w. RW	Behavioural w.o. Cyc. OTJ w. RW	Behavioural w. Cyc. OTJ w. Strict RW	Behavioural w.o. Cyc. OTJ w. Strict RW
d_u	$U(0.0001, 0.9)$	0.02	0.018	0.016	0.017	0.017	0.018	0.007	0.015
gamma_u	$U(0.0001, 0.9)$	0.851	0.786	0.747	0.729	0.783	0.774	0.195	0.028
theta	$U(0.0001, 0.9)$			0.092		0.119		0.345	

Table 6: Prior distribution and parameter estimates for all models. $U(a, b)$ denotes a uniform distribution on $[a, b]$.

Time Series Metrics

Figure 22: ABC Calibration Results: Jointly minimizing unemployment rate loss



Model	Variable	Mean (Sim)	Mean (Obs)	SSE	Correlation
Non-behavioural	Vacancy Rate	0.031	0.031	0.001	0.957
	Unemployment Rate	0.057	0.060	0.038	0.948
	Long-term Unemployment Rate	0.061	0.264	10.159	0.761
	Hires Rate	0.029	0.036	0.013	0.487
	Separations Rate	0.031	0.036	0.007	0.368
	UE Transition Rate	0.028	0.014	0.052	-0.463
	EE Transition Rate	0.000	0.019	0.080	–
	Application Effort (U)	–	–	–	-0.693
	Seeker Composition	0.000	0.410	37.974	–
Non-behavioural w. OTJ	Vacancy Rate	0.031	0.031	0.001	0.953
	Unemployment Rate	0.059	0.060	0.019	0.954
	Long-term Unemployment Rate	0.076	0.264	8.790	0.774
	Hires Rate	0.032	0.036	0.010	0.560
	Separations Rate	0.034	0.036	0.007	0.440
	UE Transition Rate	0.025	0.014	0.032	-0.492
	EE Transition Rate	0.005	0.019	0.045	0.019
	Application Effort (U)	–	–	–	-0.802
	Seeker Composition	0.492	0.410	2.355	0.800
Behavioural w. Cyc. OTJ w. RW	Vacancy Rate	0.031	0.031	0.001	0.956
	Unemployment Rate	0.060	0.060	0.015	0.895
	Long-term Unemployment Rate	0.090	0.264	7.866	0.689
	Hires Rate	0.032	0.036	0.011	0.573
	Separations Rate	0.034	0.036	0.009	0.451
	UE Transition Rate	0.025	0.014	0.033	-0.501
	EE Transition Rate	0.005	0.019	0.046	0.074
	Application Effort (U)	–	–	–	-0.738
	Seeker Composition	0.420	0.410	2.588	0.804
Behavioural w.o. Cyc. OTJ w. RW	Vacancy Rate	0.031	0.031	0.001	0.948
	Unemployment Rate	0.059	0.060	0.019	0.938
	Long-term Unemployment Rate	0.097	0.264	7.436	0.723
	Hires Rate	0.031	0.036	0.010	0.569
	Separations Rate	0.033	0.036	0.007	0.448
	UE Transition Rate	0.024	0.014	0.029	-0.494
	EE Transition Rate	0.005	0.019	0.044	0.059
	Application Effort (U)	–	–	–	-0.678
	Seeker Composition	0.487	0.410	2.037	0.791
Behavioural w. Cyc. OTJ w.o RW	Vacancy Rate	0.031	0.031	0.001	0.950
	Unemployment Rate	0.061	0.060	0.016	0.879
	Long-term Unemployment Rate	0.066	0.264	9.894	0.656
	Hires Rate	0.032	0.036	0.011	0.547
	Separations Rate	0.034	0.036	0.009	0.438
	UE Transition Rate	0.024	0.014	0.028	-0.437
	EE Transition Rate	0.006	0.019	0.041	0.072
	Application Effort (U)	–	–	–	-0.365
	Seeker Composition	0.423	0.410	2.693	0.793
Behavioural w.o. Cyc. OTJ w.o RW	Vacancy Rate	0.031	0.031	0.001	0.956
	Unemployment Rate	0.060	0.060	0.012	0.935
	Long-term Unemployment Rate	0.076	0.264	9.016	0.705
	Hires Rate	0.031	0.036	0.011	0.564
	Separations Rate	0.033	0.036	0.008	0.433
	UE Transition Rate	0.023	0.014	0.024	-0.452
	EE Transition Rate	0.007	0.019	0.039	0.026
	Application Effort (U)	–	–	–	-0.335
	Seeker Composition	0.482	0.410	1.670	0.798

Unemployment and Vacancy Rates

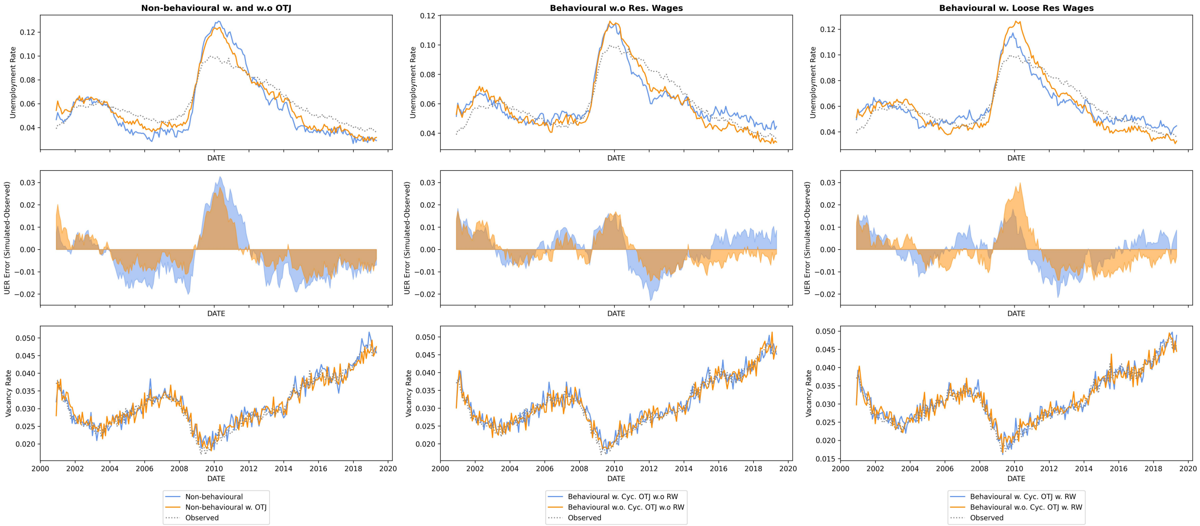


Figure 23: Unemployment and Vacancy Rates

Hires and Separations Rates

Beveridge Curves

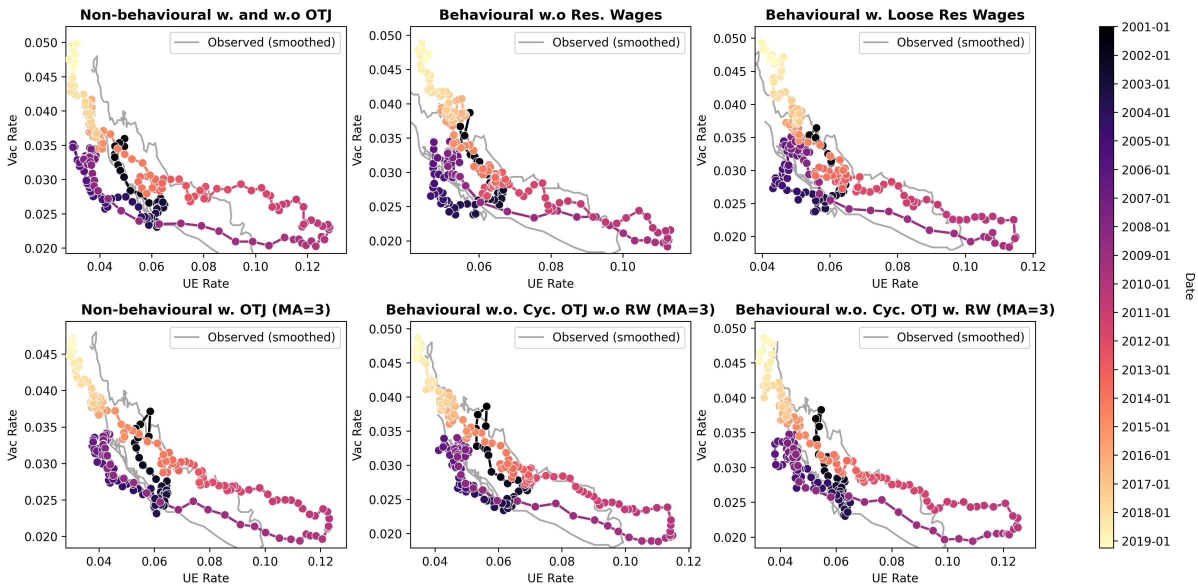


Figure 24: Beveridge Curves

Long-Term Unemployment

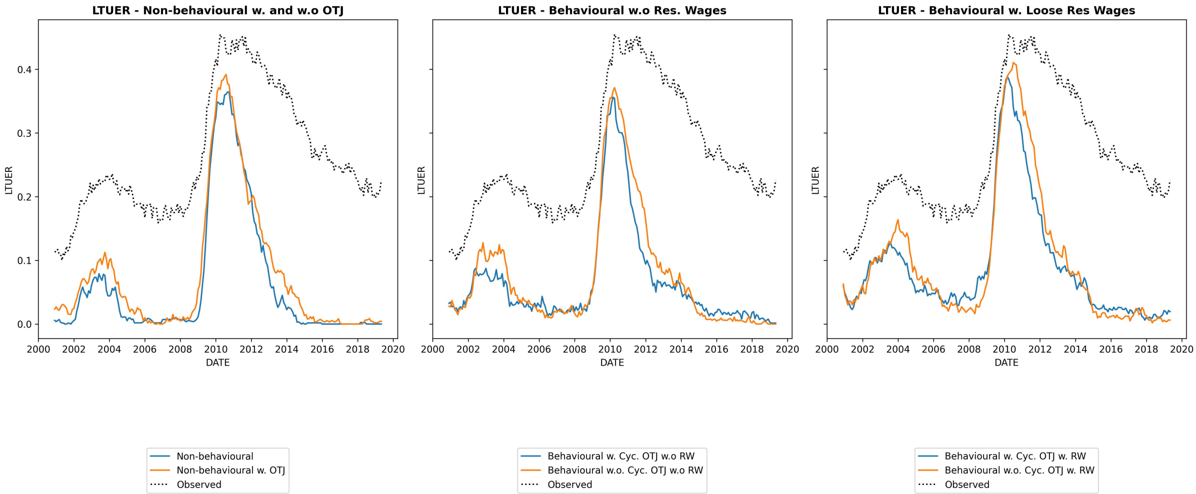


Figure 25: Long-Term Unemployment Rate

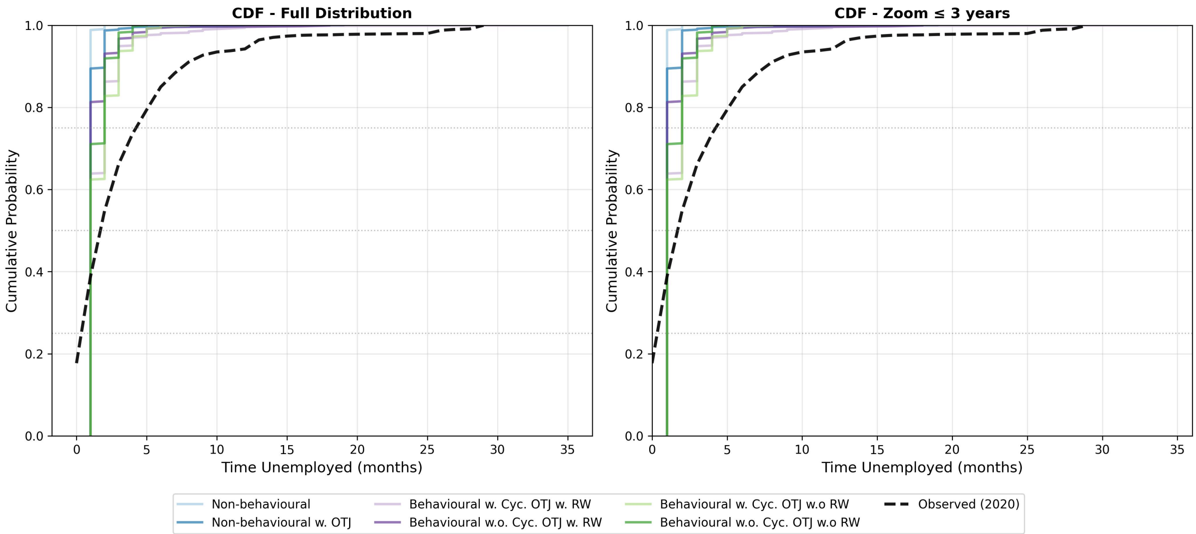


Figure 26: Long-Term Unemployment Rate

Applications per Unemployed Seeker

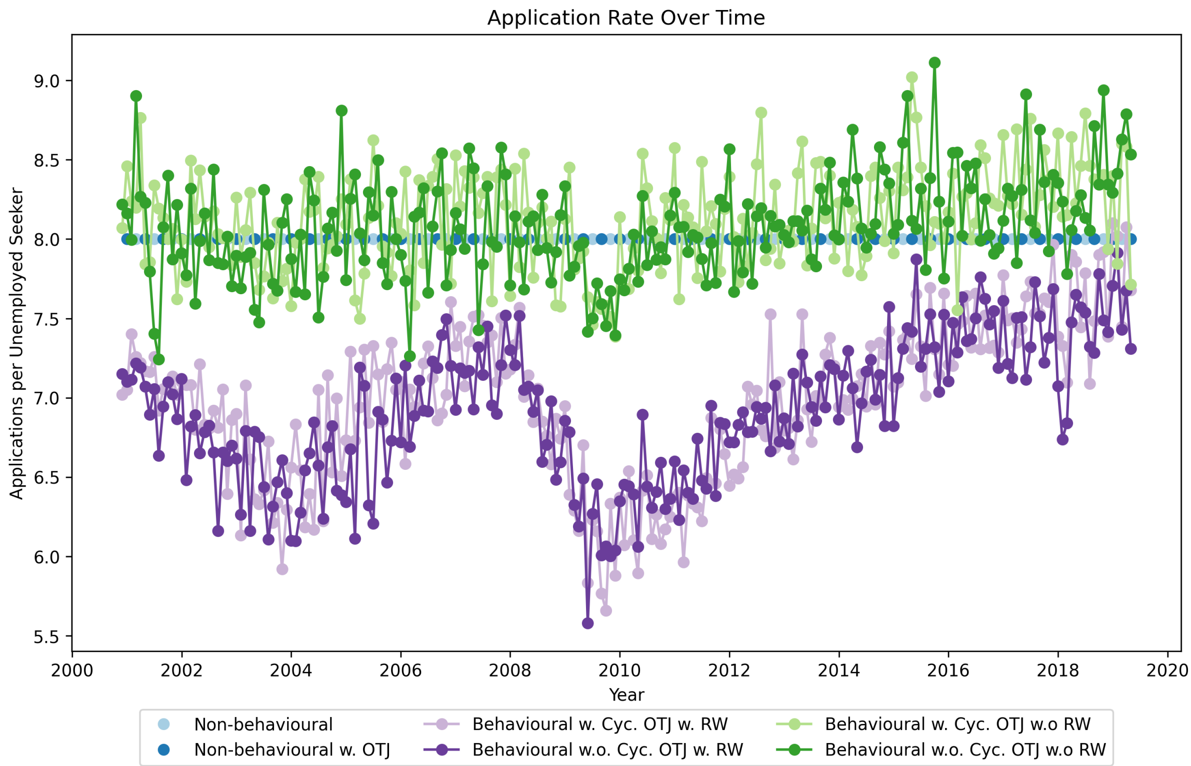


Figure 27: Applications per Unemployed Seeker

D Preliminary Out of Sample Validation

We allow the model to run until 2024 using the calibrated parameter values highlighted in the main text. Below, we display the simulated unemployment and vacancy rates, separation rates, hires rates, quits rates, layoff rates, the long-term unemployment rate, and the applications sent per unemployed job-seekers.

Unemployment and Vacancy Rates

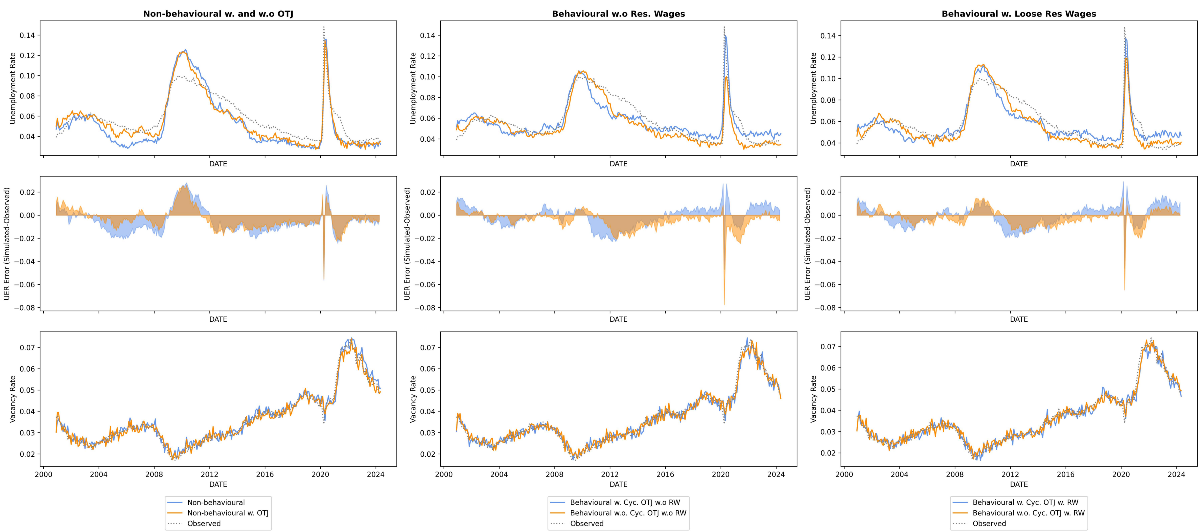


Figure 28: Unemployment and Vacancy Rates

Hires and Separations Rates

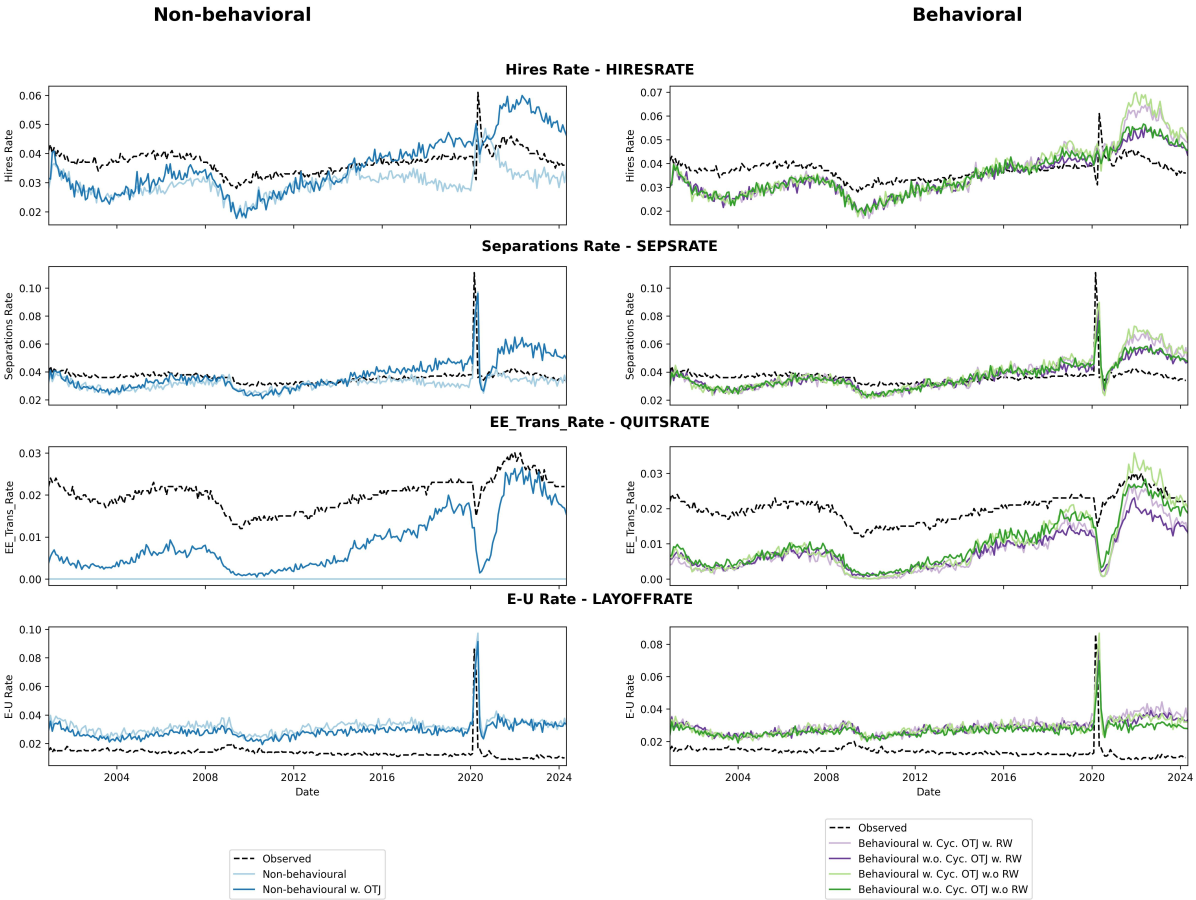


Figure 29: Hires and Separations Rate Grid

Long-Term Unemployment

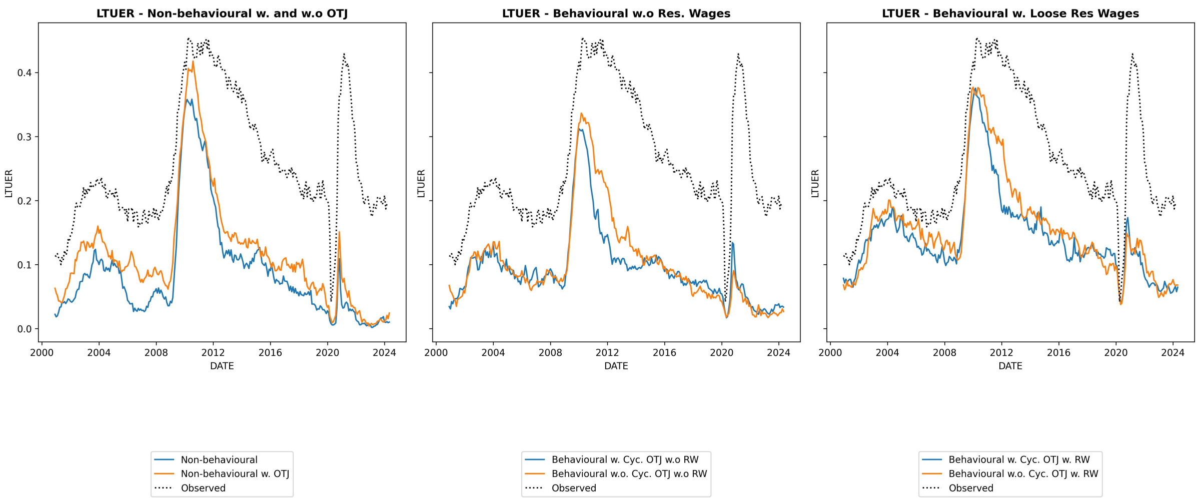


Figure 30: Long-Term Unemployment Rate

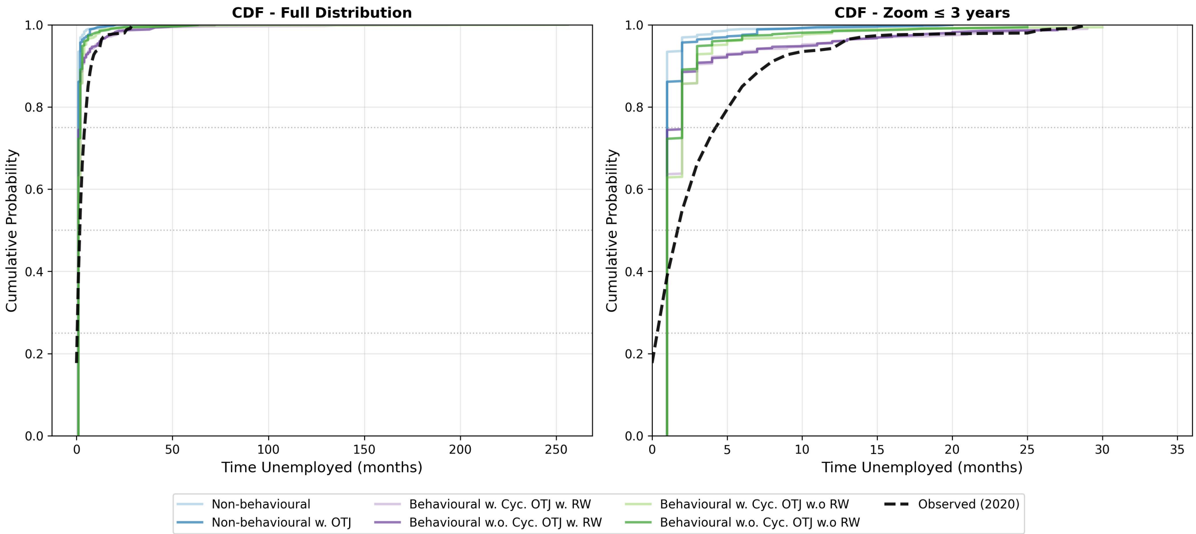


Figure 31: Long-Term Unemployment Rate

Applications per Unemployed Seeker

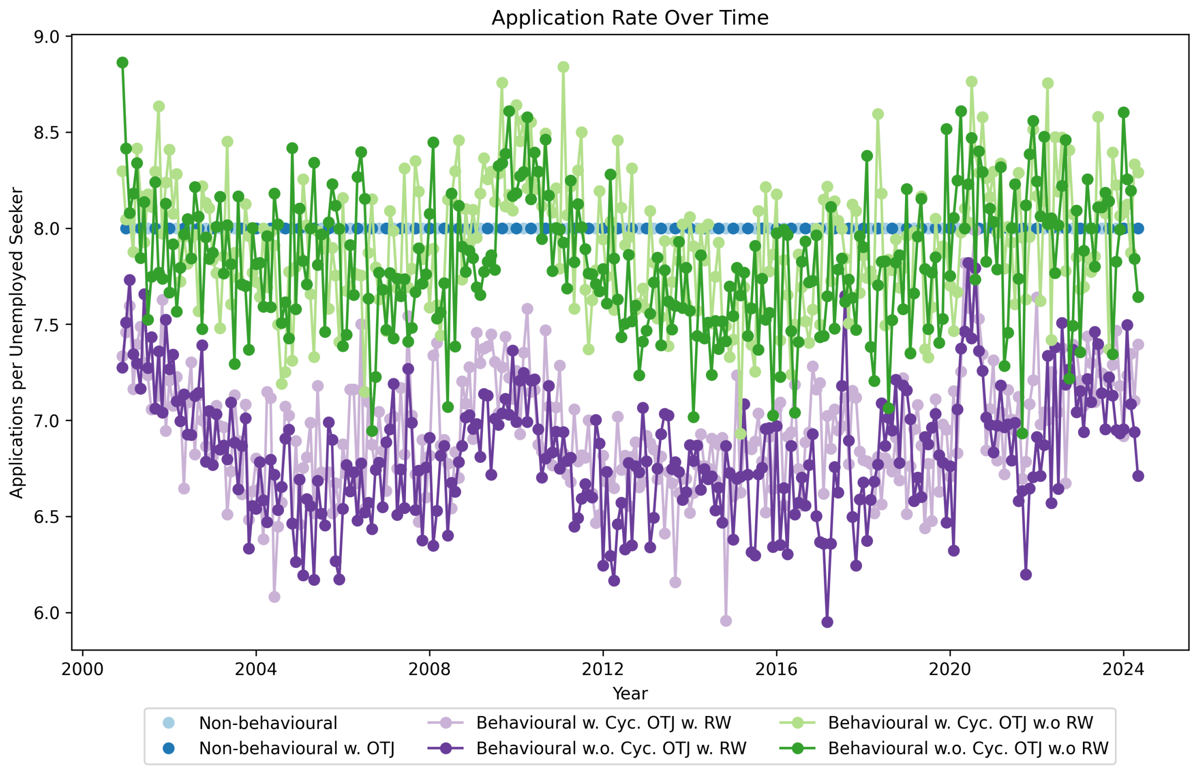
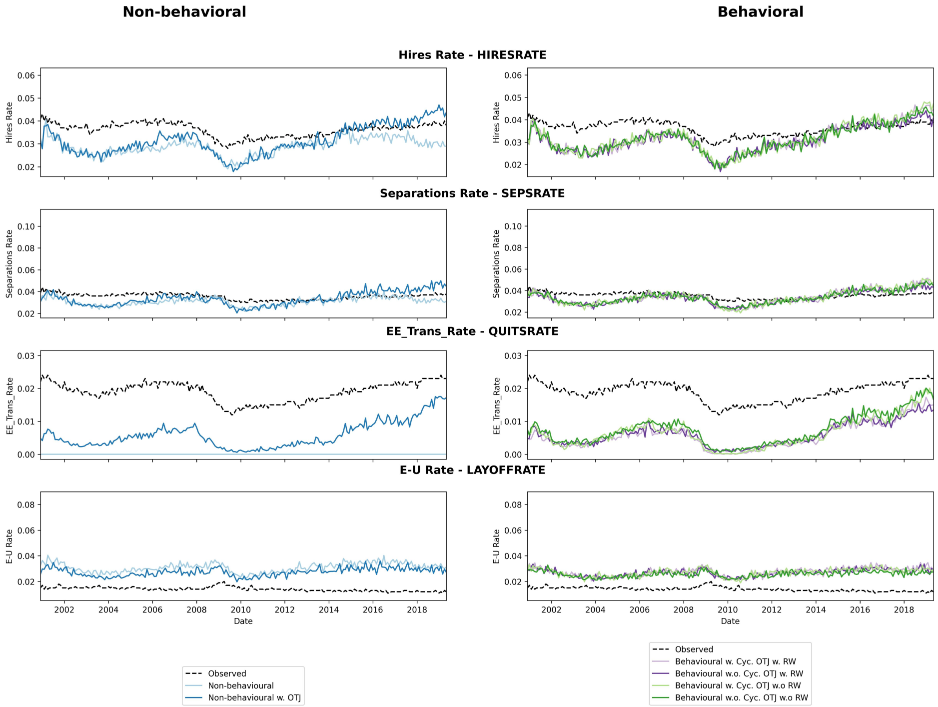


Figure 32: Applications per Unemployed Seeker

E Labor Turnover

Aggregate unemployment and vacancy rate statistics obscure labor market churn necessitating a validation of the transitions occurring in the simulated labor market. Therefore, we first evaluate the simulated hiring and separations rates in relation to observed values as reported by the Job Openings and Labor Turnover Survey Figure 33 displays the hiring, separations, layoffs, and quits of the non-behavioral (left) and behavioral (right). Notably though, we match the hiring rate in the behavioral model considerably better than in the non-behavioral model. We match each rate well in levels across the models, however as displayed in Table 4.2 our behavioral models perform remarkably better in terms of matching the volatility and cyclicality of these series.

Figure 33: Simulated vs. Observed Hires and Separations Rates



F Single Node Case

To test the utility of the network, we provide a simulation in which the network is replaced by a single node. In other words, this simulation assumes all workers are employed in the same occupation implying no occupational frictions. Occupational target demand in set using the de-trended real GDP series of the US from 2000-2019. We observe that considerable frictions remain as a result of shifts in target demand, indicating that the network frictions do not overwhelm other dynamics in the model. Importantly though, in the single-node case, the behavioral model struggles to match the unemployment rate time series, where the simulated series has a higher amplitude than the real-world data. Additionally, absent on-the-job search, the single-node network achieves complete employment in boom periods, which is highly unrealistic. This demonstrates that the behavioral mechanisms matter crucially in a model that abstracts from occupational frictions (the unemployment rate is matched reasonably well in all behavioral models). Though all models appear to hit a near-zero level of long-term unemployment in boom periods of the business cycle, indicating the importance of the network frictions for achieving a realistic long-term unemployment rate and distribution of unemployment duration.

F.1 Model Results

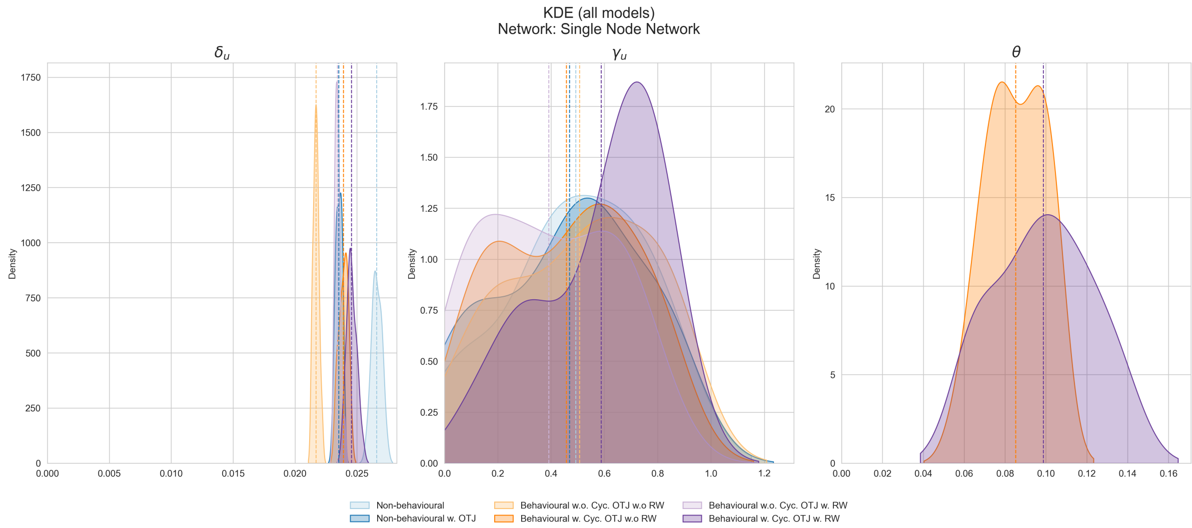
Model Parameters

Parameter	Prior Distribution	Model Category							
		Non-behavioural	Non-behavioural w. OTJ	Behavioural w. Cyc. OTJ w.o RW	Behavioural w.o. Cyc. OTJ w.o RW	Behavioural w. Cyc. OTJ w. RW	Behavioural w.o. Cyc. OTJ w. RW	Behavioural w. Cyc. OTJ w. Strict RW	Behavioural w.o. Cyc. OTJ w. Strict RW
d_u	$U(0.0001, 0.9)$	0.027	0.024	0.024	0.022	0.025	0.024	0.016	0.015
gamma_u	$U(0.0001, 0.9)$	0.513	0.62	0.419	0.556	0.515	0.548	0.447	0.467
theta	$U(0.0001, 0.9)$			0.078		0.138		0.175	

Table 7: Prior distribution and parameter estimates for all models. $U(a, b)$ denotes a uniform distribution on $[a, b]$.

Time Series Metrics

Figure 34: ABC Calibration Results: Jointly minimizing unemployment rate loss



Model	Variable	Mean (Sim)	Mean (Obs)	SSE	Correlation
Non-behavioural	Vacancy Rate	0.031	0.031	0.001	0.941
	Unemployment Rate	0.052	0.060	0.153	0.905
	Long-term Unemployment Rate	0.061	0.264	9.887	0.850
	Hires Rate	0.027	0.036	0.023	0.177
	Separations Rate	0.029	0.036	0.013	-0.191
	UE Transition Rate	0.025	0.014	0.034	-0.320
	EE Transition Rate	0.000	0.019	0.080	–
	Application Effort (U)	–	–	–	–
	Seeker Composition	0.000	0.410	37.974	–
Non-behavioural w. OTJ	Vacancy Rate	0.031	0.031	0.001	0.945
	Unemployment Rate	0.053	0.060	0.060	0.902
	Long-term Unemployment Rate	0.064	0.264	9.820	0.755
	Hires Rate	0.032	0.036	0.011	0.550
	Separations Rate	0.034	0.036	0.008	0.366
	UE Transition Rate	0.023	0.014	0.021	-0.225
	EE Transition Rate	0.008	0.019	0.038	-0.017
	Application Effort (U)	–	–	–	–
	Seeker Composition	0.583	0.410	8.642	0.694
Behavioural w. Cyc. OTJ w. RW	Vacancy Rate	0.031	0.031	0.001	0.948
	Unemployment Rate	0.050	0.060	0.056	0.885
	Long-term Unemployment Rate	0.043	0.264	11.741	0.734
	Hires Rate	0.030	0.036	0.012	0.564
	Separations Rate	0.032	0.036	0.007	0.388
	UE Transition Rate	0.024	0.014	0.026	-0.189
	EE Transition Rate	0.005	0.019	0.048	0.013
	Application Effort (U)	–	–	–	0.366
	Seeker Composition	0.417	0.410	10.115	0.691
Behavioural w.o. Cyc. OTJ w. RW	Vacancy Rate	0.031	0.031	0.001	0.945
	Unemployment Rate	0.054	0.060	0.055	0.874
	Long-term Unemployment Rate	0.062	0.264	9.995	0.748
	Hires Rate	0.031	0.036	0.010	0.601
	Separations Rate	0.033	0.036	0.006	0.433
	UE Transition Rate	0.023	0.014	0.022	-0.259
	EE Transition Rate	0.006	0.019	0.040	0.036
	Application Effort (U)	–	–	–	0.456
	Seeker Composition	0.573	0.410	7.770	0.651
Behavioural w. Cyc. OTJ w.o RW	Vacancy Rate	0.031	0.031	0.001	0.942
	Unemployment Rate	0.058	0.060	0.023	0.842
	Long-term Unemployment Rate	0.056	0.264	10.708	0.672
	Hires Rate	0.032	0.036	0.011	0.561
	Separations Rate	0.034	0.036	0.008	0.404
	UE Transition Rate	0.022	0.014	0.020	-0.199
	EE Transition Rate	0.008	0.019	0.038	-0.034
	Application Effort (U)	–	–	–	0.313
	Seeker Composition	0.450	0.410	6.403	0.621
Behavioural w.o. Cyc. OTJ w.o RW	Vacancy Rate	0.031	0.031	0.001	0.936
	Unemployment Rate	0.059	0.060	0.032	0.861
	Long-term Unemployment Rate	0.075	0.264	9.017	0.704
	Hires Rate	0.031	0.036	0.011	0.573
	Separations Rate	0.033	0.036	0.007	0.401
	UE Transition Rate	0.021	0.014	0.015	-0.289
	EE Transition Rate	0.009	0.019	0.032	0.016
	Application Effort (U)	–	–	–	0.504
	Seeker Composition	0.544	0.410	5.217	0.616

Unemployment and Vacancy Rates

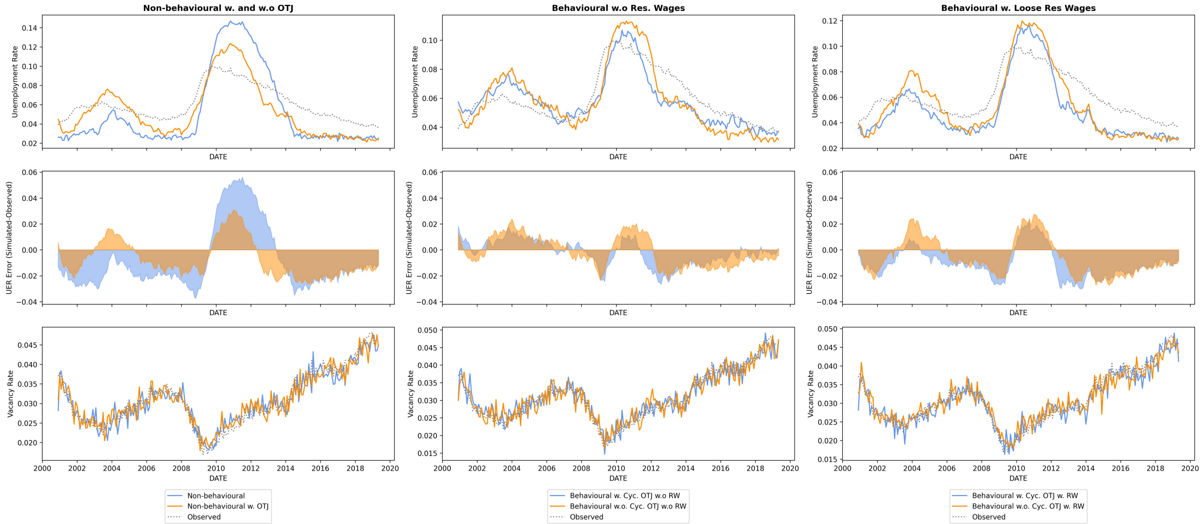


Figure 35: Unemployment and Vacancy Rates

Hires and Separations Rates

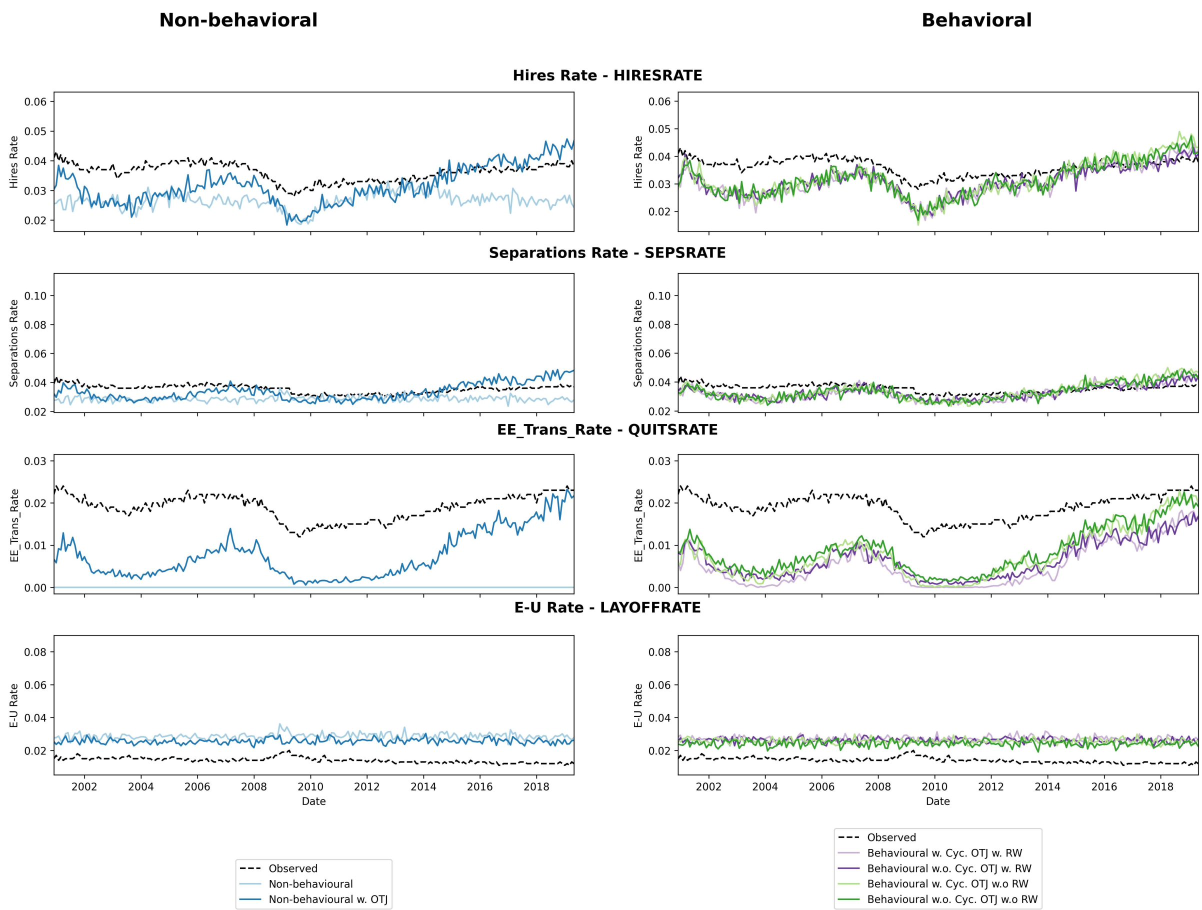


Figure 36: Hires and Separations Rate Grid

Beveridge Curves

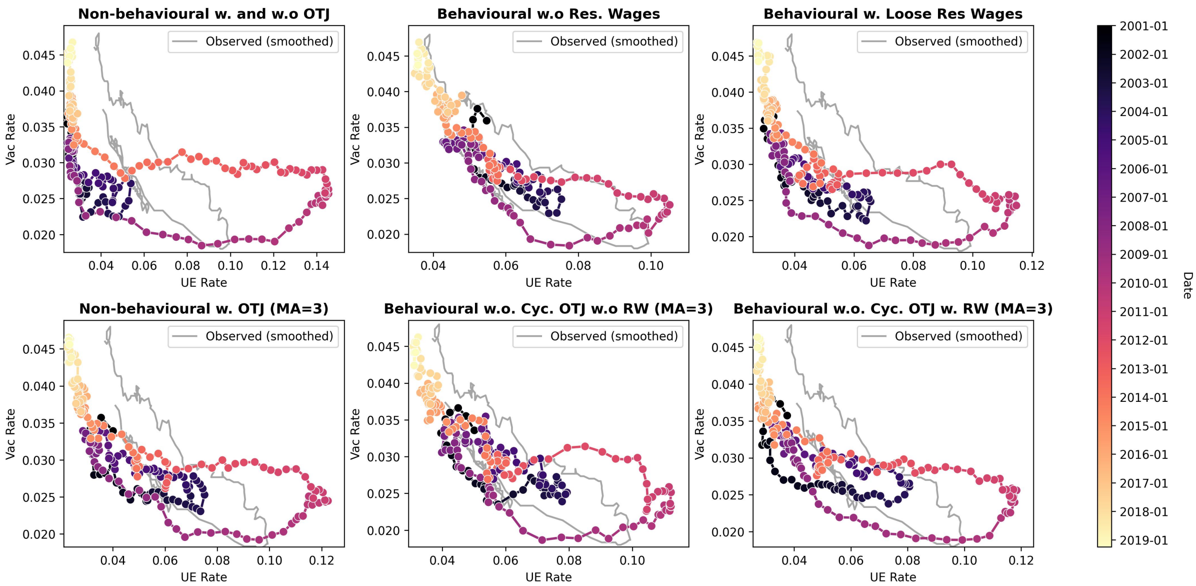


Figure 37: Beveridge Curves

Long-Term Unemployment

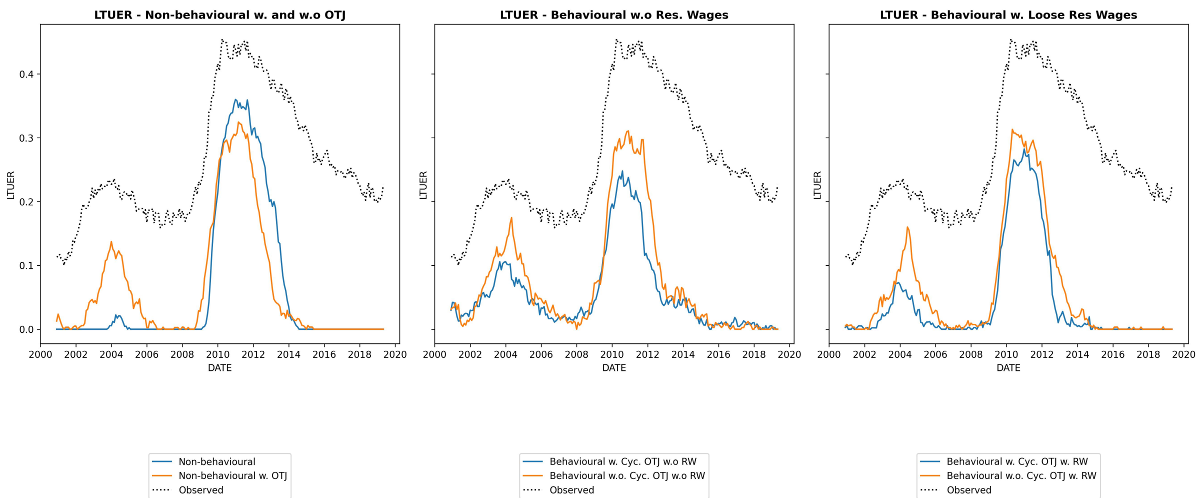


Figure 38: Long-Term Unemployment Rate

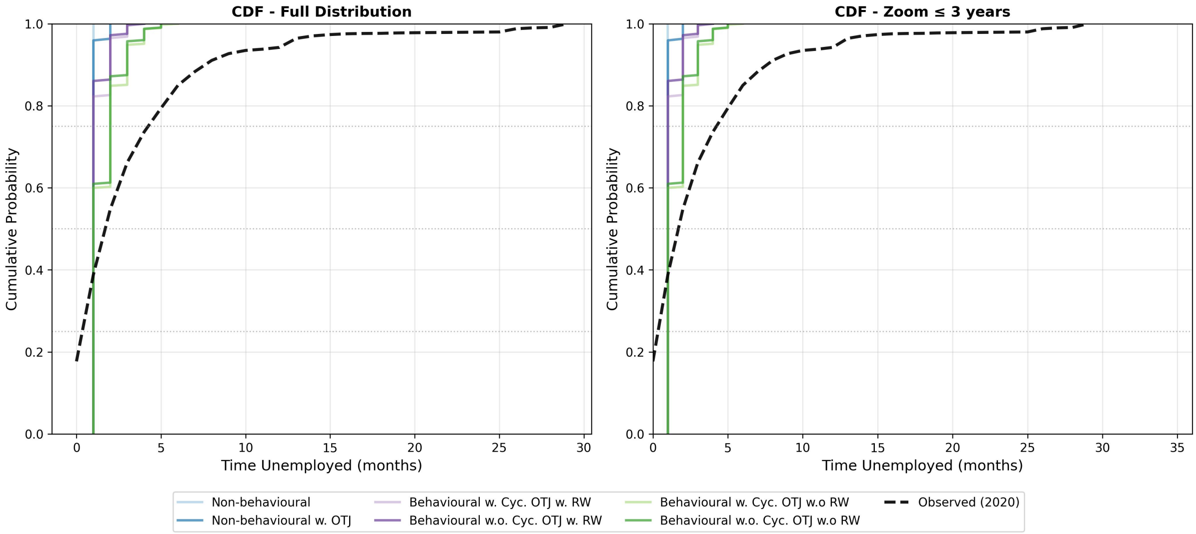


Figure 39: Long-Term Unemployment Rate

Applications per Unemployed Seeker

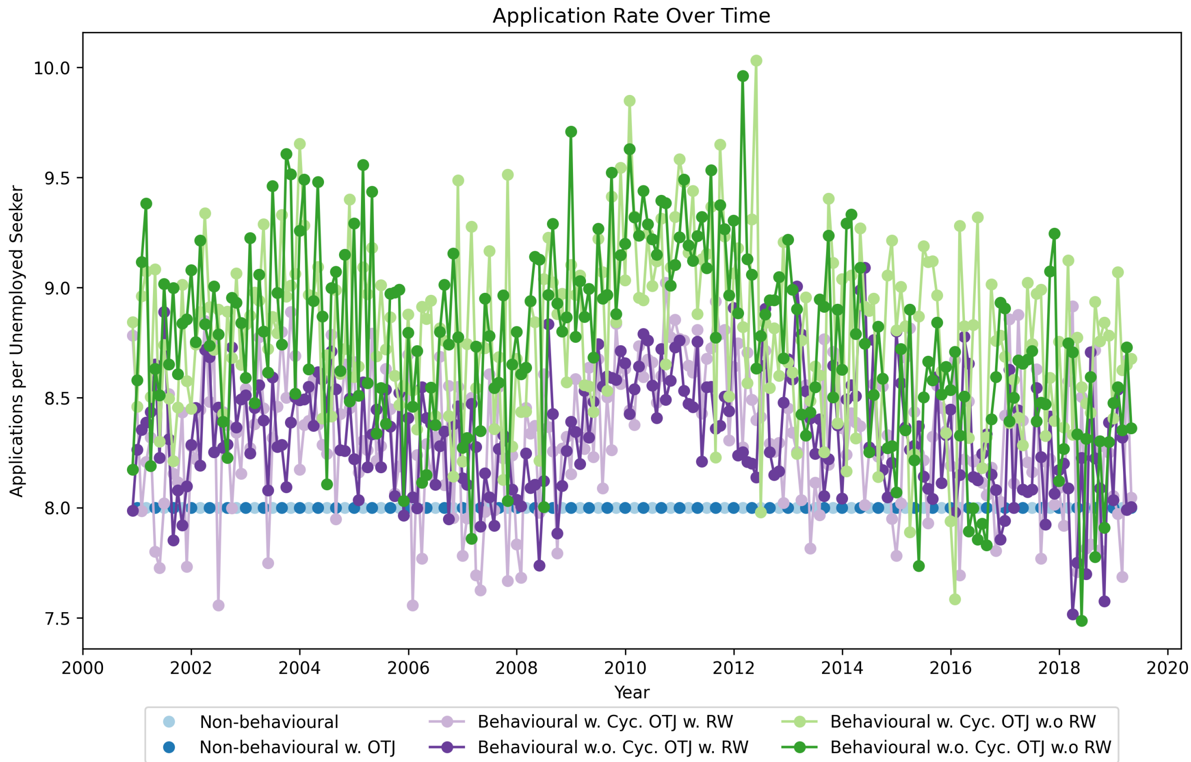


Figure 40: Applications per Unemployed Seeker

G Steady State

Below we display the steady state unemployment rate of each model by allowing the model to run for a period of 1,000 months using a variety of networks the model is equipped to handle (full occupational mobility network as reported in the main text, O*NET related occupations network, O*NET related occupations network with added reciprocal links from high- to low-wage occupations, and the single node network). The steady state is imposed by setting target demand equal to 1, rather than allowing target demand to fluctuate around 1 in line with changes in occupation specific value added or national GDP (in the single node case). All models achieve a stable steady state following a brief delay (all results presented in this work allow for the model to reach a steady-state by allowing the model to run for a period of 25 months prior to imposing any fluctuations in target demand). We represent the start of the target demand imposition with the vertical black dashed line, and provide the observed unemployment rate series for the simulated period with the grey dotted line.

G.1 Full Occupational Mobility Network

Figure 41: Unemployment Rate in Steady State

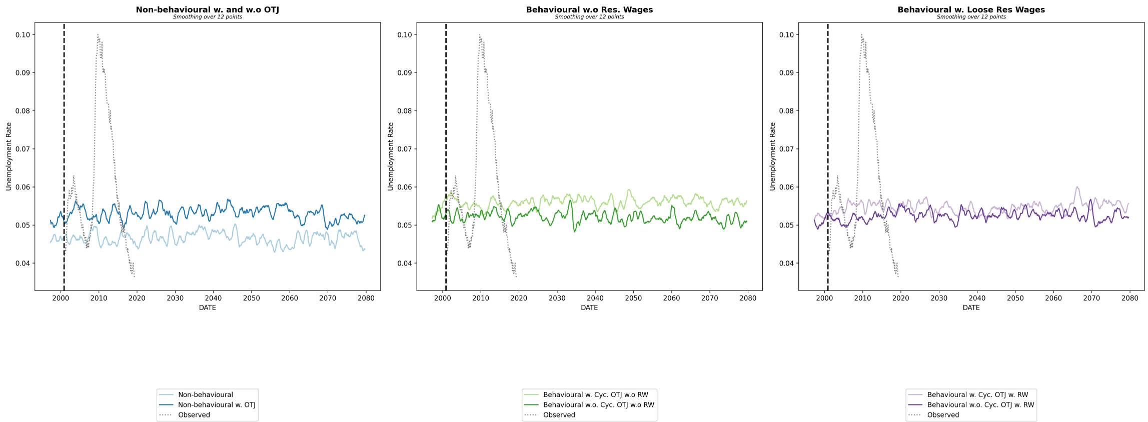
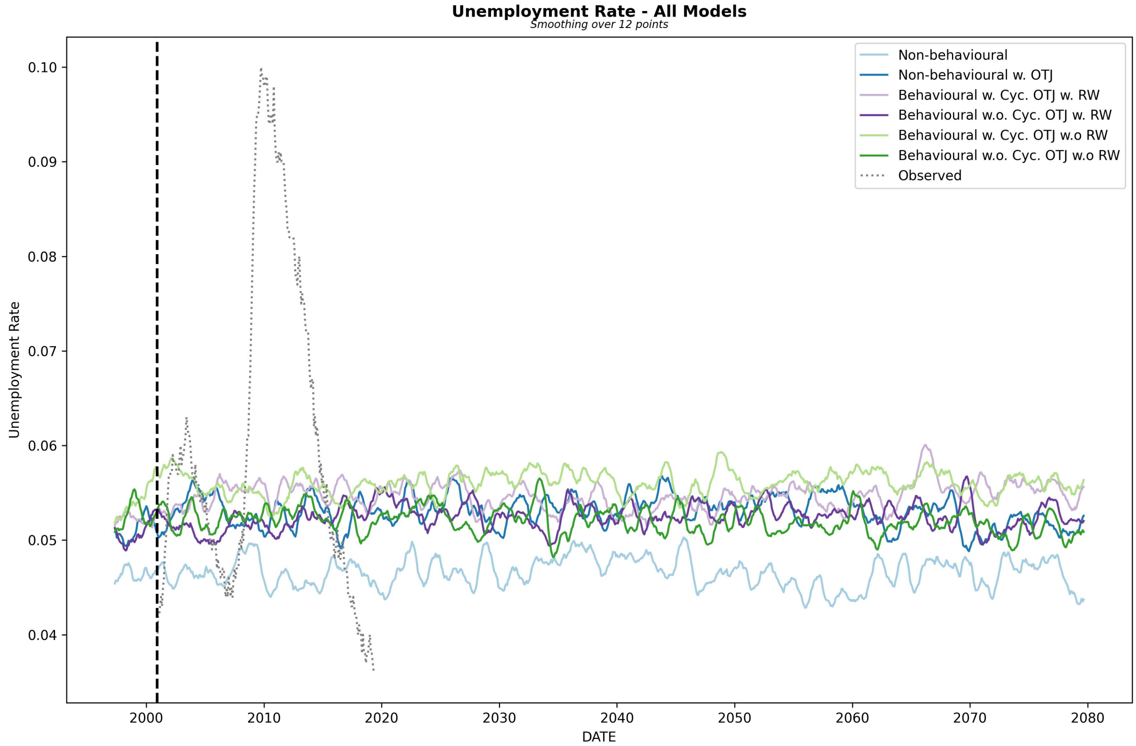


Figure 42: Unemployment Rate in Steady State



G.2 O*NET Related Occupations Network

Figure 43: Unemployment Rate in Steady State

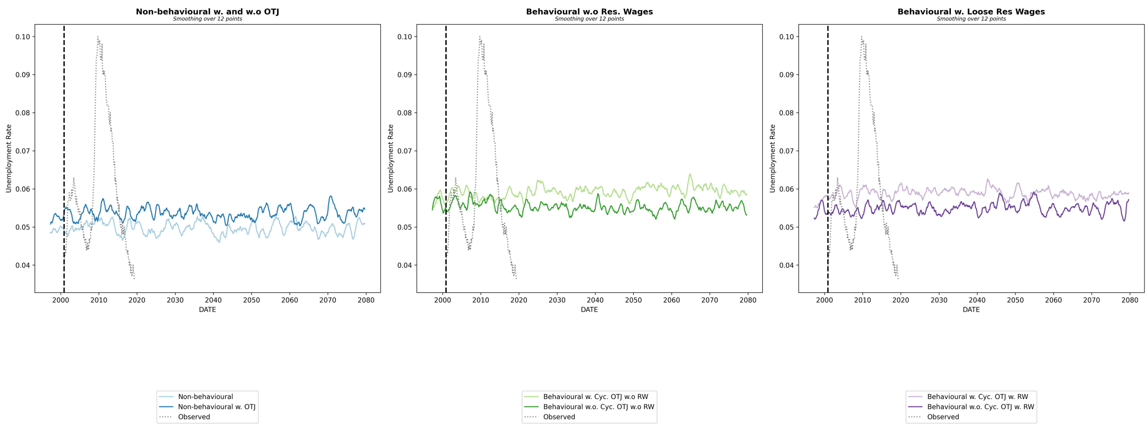
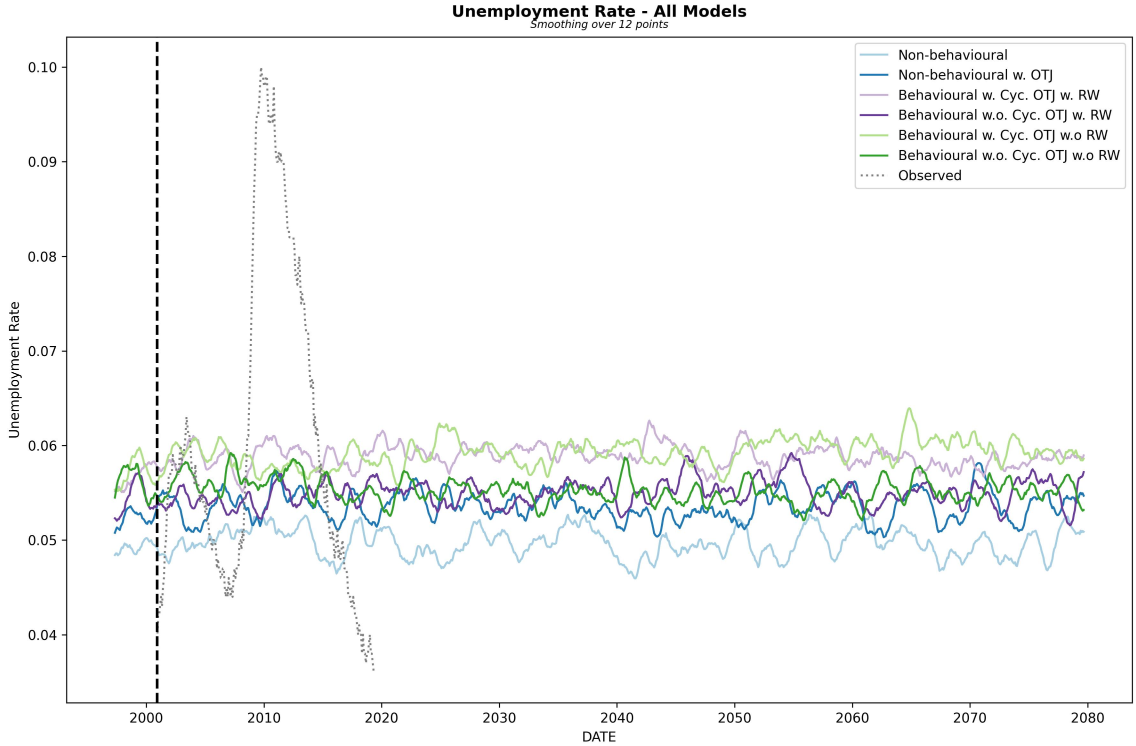


Figure 44: Unemployment Rate in Steady State



G.3 O*NET Related Occupations Network with Wage Asymmetry Correction

Figure 45: Unemployment & Vacancy Rate in Steady State

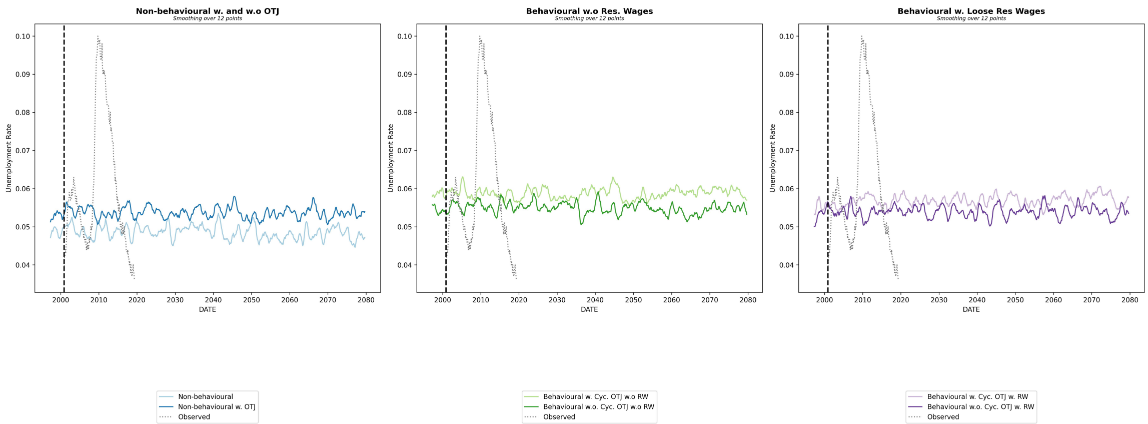
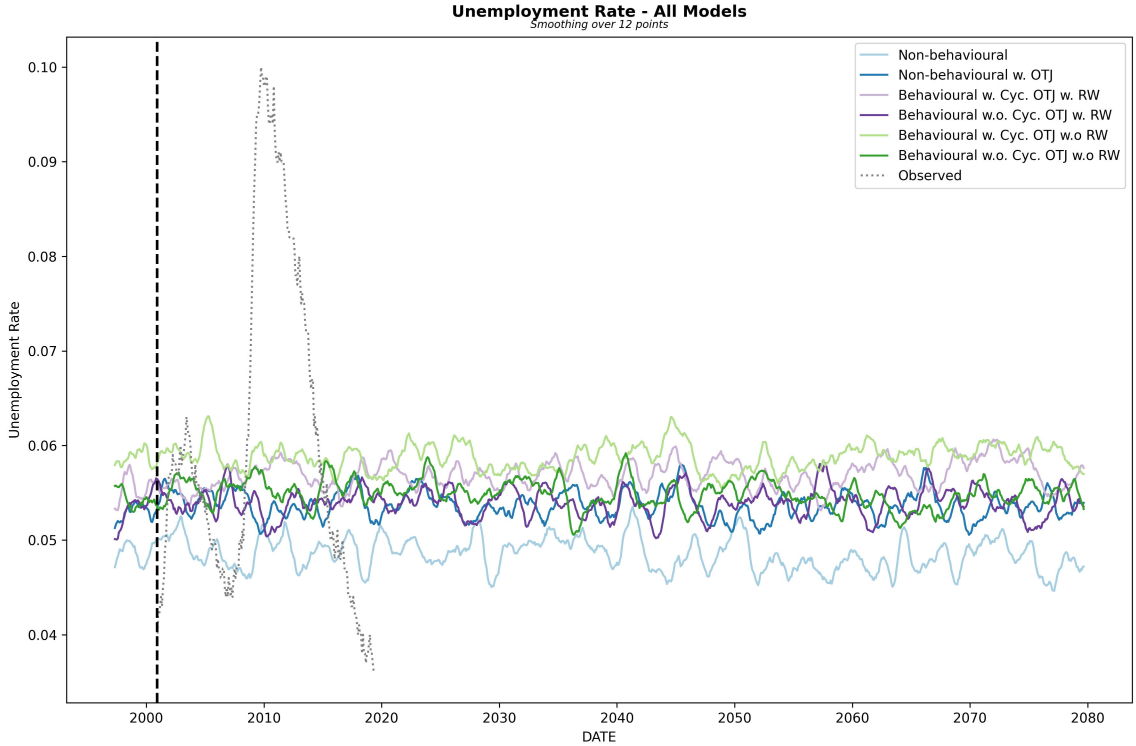


Figure 46: Unemployment & Vacancy Rate in Steady State



G.4 Single Node Network

Figure 47: Unemployment & Vacancy Rate in Steady State

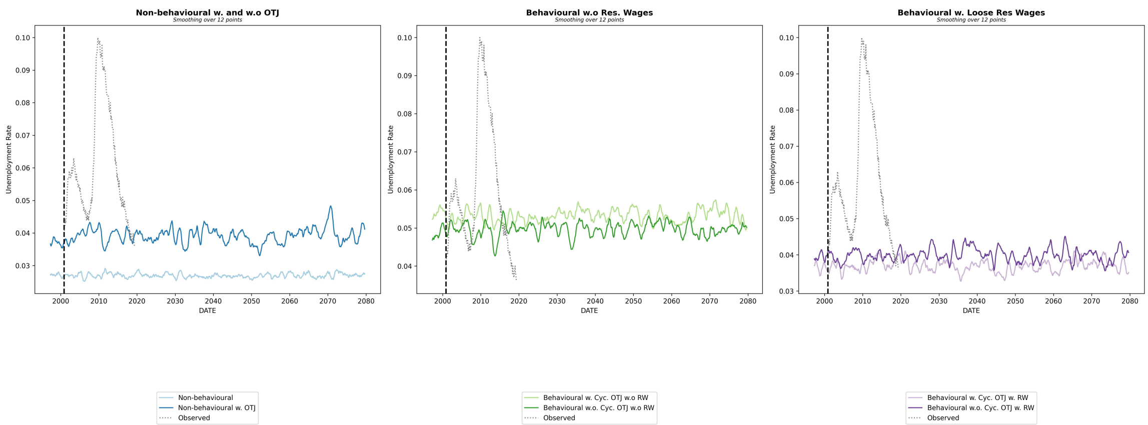


Figure 48: Unemployment & Vacancy Rate in Steady State