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

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Abstract

Economic change generates labor market frictions that vary across occupations and workers, yet most models abstract from how job search behavior adapts to uncertainty over the unemployment spell. This paper studies how adaptive search interacts with occupational structures and aggregate conditions to shape labor market adjustment. 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 on U.S. micro data. Incorporating adaptive behavior improves the model's ability to replicate persistent long-term unemployment, vacancy–unemployment decoupling in recoveries, and heterogeneous wage outcomes following displacement. In doing so, we shed light on the role of behavioral adaptation in shaping labor market persistence and inequality.

Contents

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 [32, 75, 89, 44].

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 [69, 64, 53, 57]. 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, 46, 64].

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 [75, 32]. 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 pressure shape employment recovery pathways after shocks.

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 [46, 73, 91, 15, 19, 69, 64, 2, 22, 88, 53, 65, 12]. Capturing these patterns requires models in which adaptation is a core mechanism through which shocks propagate and persist, linking individual search behaviour 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 modelling. 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] 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 [91, 73, 2], and react to rejections or uncertainty (discouragement, loss aversion) via their expended search effort [46, 73, 91, 15, 19, 69, 64]. Reservation wages decline slowly with duration and income losses [55, 60, 28, 48] and search effort varies over the unemployment spell and over the business cycle [54, 53, 35, 98, 65]. At the same time, job-to-job transitions and on-the-job search play a central role in reallocation [47, 36], intensifying during recoveries and altering competition for vacancies faced by the unemployed [32, 10].

1.2 Methodological Approach

The puzzle at hand is not whether job search behavior matters when modelling 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 modelling approach in which micro decisions produce macro realities, rather than abstracting from the processes of labor market churn. Agent-based modeling (ABM) is well suited to this task by accommodating heterogeneous agents, adaptive rules [86, 4, 84], and out-of-equilibrium interactions while generating macro regularities from micro behavior [20, 25, 61, 77].[2] Furthermore, we contribute to the growing field of data-driven agent-based models, tempered by real-world data rather than pure theory [79, 71].

Principally, we build on a leading data-driven model of occupational mobility [26] 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 micro data 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 proposed behavioral rules are motivated by empirical relationships drawn from US micro data on wage expectations and search effort as a function of unemployment duration. We do not attempt to model entry, exit, or inflation expectations. While incomplete, this parsimonious approach allows us to study how adaptive search behavior translates into persistent wage losses and unequal gains during recoveries in a non-equilibrium setting. 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.

[2] Agent-based models (ABMs) have emerged as a useful tool for modeling labor market dynamics and macro-economic adjustment processes [20, 25, 61, 77].Examples of applications include studies on the effect of structural reform policy on unemployment and income inequalities [29]; the relationship between employment protection legislation and unemployment with an endogenised institutional setting in which workers can vote to influence the employment protection legislation [67]; and an investigation of the effect of social networks on job market and upskilling effort [45]. They provide considerable flexibility in comparison to classical models by accommodating non-linearities, interactive or feedback effects, and behavioral heterogeneity [20]. Some notable examples include [29, 45, 83, 67, 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 [86]. 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 [17, 68]. Furthermore, they provide a practical infrastructure for defining agent-specific behavioral rules though this potential has thus far been under-utilised [77].

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 micro data 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 unemployment spell and the business cycle. We document how this adaptive search behavior and endogenous competition from on-the-job searchers interact with occupational structure to generate persistence in unemployment and heterogeneous wage outcomes following shocks. By allowing employed and unemployed job seekers to compete endogenously for vacancies, the model generates long-term unemployment and post-displacement wage losses without relying on ad hoc frictions, equilibrium selection, or mere occupational proximity. **Second**, the data basis for these incorporated behavioral rules demonstrate the 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 [46, 15, 55, 50]. **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 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 - such as 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 modelling 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 [75, 32]. 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 likelihood of over-fitting in calibrated macro models in the absence of more detailed behavioral agent rules. As a result, 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]

[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 [17, 34, 59, 9, 42]. Location matters via mobility costs and local tightness [16, 66], while social networks affect the search channels used, reservation wages, and match quality [18, 43, 97]. Meta-analyses synthesize these patterns and emphasize dynamic, self-regulatory search and learning [90, 96]. These findings justify our heterogeneous state space and the distributional analyses we highlight though could be extended in further work.

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.

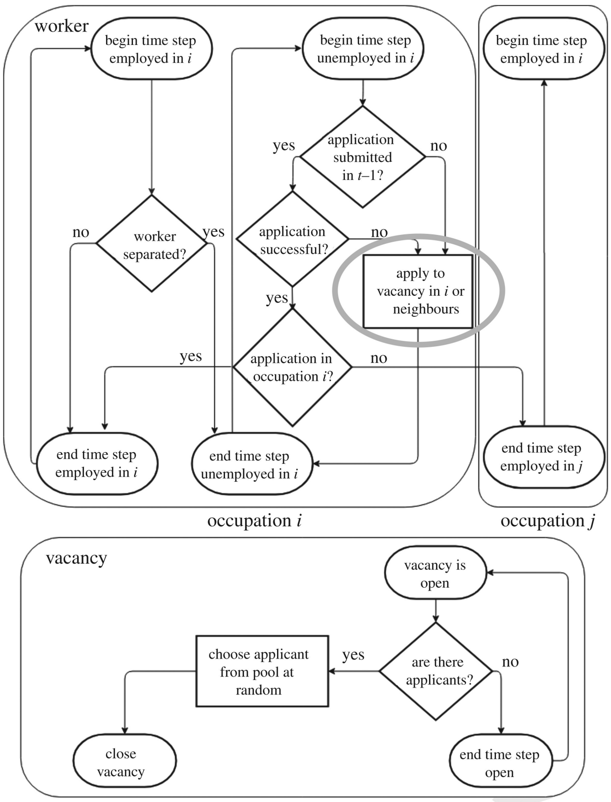
2 The Model

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 [26]. 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 [81, 72]. The original execution of the model in del Rio-Chanona et al. is represented in Figure 1 below.

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, 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 [70, 26].

At each time step, occupations first set target labour 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 labour 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.

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 baseline occupational demand $d^{\dagger}_{i}$ and sum of occupational demand shocks across all industries j in the US economy.

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

where $\hat{d}_{ijt}$ is the industry-level demand shift for occupation i as a product of the mean share of industry j in total employment of occupation i ($\bar{d}_{ij}$) in the period when there is full coverage of occupational employment in the network's occupations (2012-2024) and an indicator of industrial health θ_{jt} at time t.

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

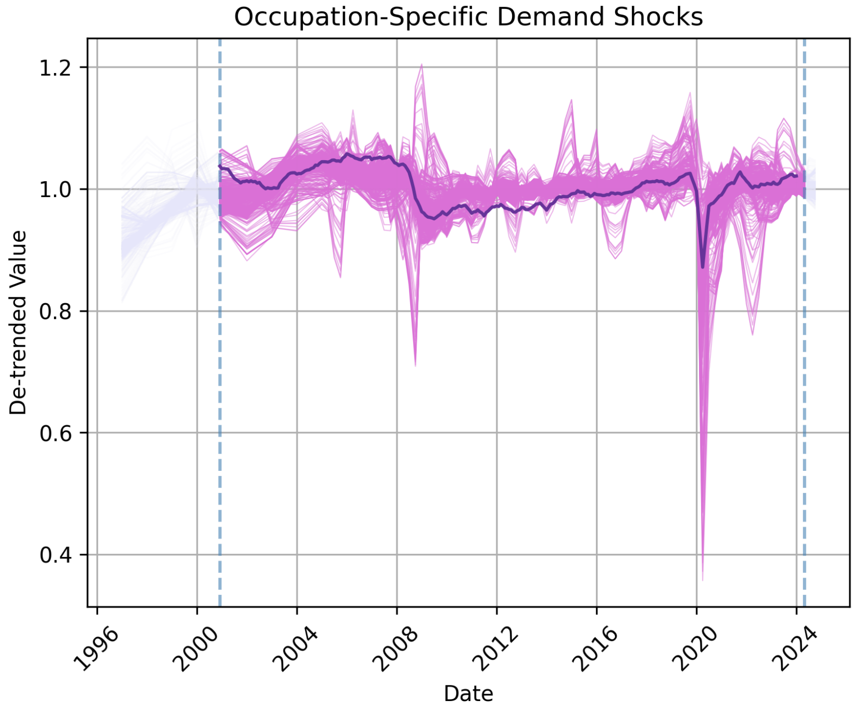
Fixed demand for occupation i in industry j is calculated as:

$$\bar{d}_{ij} = \frac{1}{T} \sum_{T=2012}^{2024} \frac{d_{ijT}}{d_{iT}} \tag{3}$$

in which $\bar{d}_{ij}$ is the average share of industry j in occupation i . Thus, we obtain occupation-specific fluctuations in demand dependent on their "exposure" or the share of a specific occupation in industry j.

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 industry value added data (using annual data from 1999-2004 and quarterly data available from 2005) to define θ_{jt} to create these occupation-specific target demand trajectories which are presented in Figure 2. We de-trend the value added using a Hodrick-Prescott filter. We initialise $d^{\dagger}_{i}$ as the occupation-specific demand in 2016 as reported by the US Census Bureau and Bureau of Labor Statistics [41]. 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



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 realised 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:

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

α_u is defined as:

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

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 $d_{i,t}^{\dagger}$. Thus, the probability that a worker is separated $\pi_{u,i,t}$ is given by

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

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:

[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 micro data, such that Equation 6 becomes $\pi_{i,t}^{u} = \omega_i \delta_u + (1 - \delta_u)\alpha_{u,i,t}$.

$$\pi_{it}^{v} = \bar{v}_t - \pi_{it-1}^{v} \tag{7}$$

Vacancy rate $\bar{v}_t$ is drawn from the Job Openings and Labor Turnover Survey from the Bureau of Labor Statistics.

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.

Next, any workers over the age of 65 $W_t^{\leftarrow}$ retire from the labor force and are replaced by $W_t^{\rightarrow}$ workers who enter into entry-level occupations $\mathcal{E}$ with probability s_{it} proportional to each occupation's share of entry-level demand.

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

The new entrants are allocated proportionally:

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

By design, $\sum_{i\in\mathcal{E}} W_{it}^{\rightarrow} = W_t^{\leftarrow}$ such that the labor market size is fixed. Each occupation's definition as either entry-level or not is drawn from the "work experience in a related occupation" field of 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.

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

As such, the model is initialised with a small set of economy-wide parameters governing worker flows. In particular, 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 the model takes as given an occupational mobility network constructed following the methodology reported in [26, 70], adapted to consider additional sample restrictions and survey weights. The occupational mobility network's nodes represent different occupations connected by edges that correspond to the probability that workers transition between them. These transition probabilities are drawn CPS micro data that reports realised 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 [70] 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 [73, 75, 32, 52]. 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 less possible 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 behavioural mechanisms incorporated in the model and the empirical 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 labour 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 [69, 36, 93, 54, 53, 28, 62, 56, 64, 95, 51, 23, 63, 27, 98, 65, 90, 97, 2, 99], 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 micro data from the 2018 and 2022 waves of the CPS in which the Bureau of Labor Statistics conducted a Job Search Supplement [13, 14]. 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).

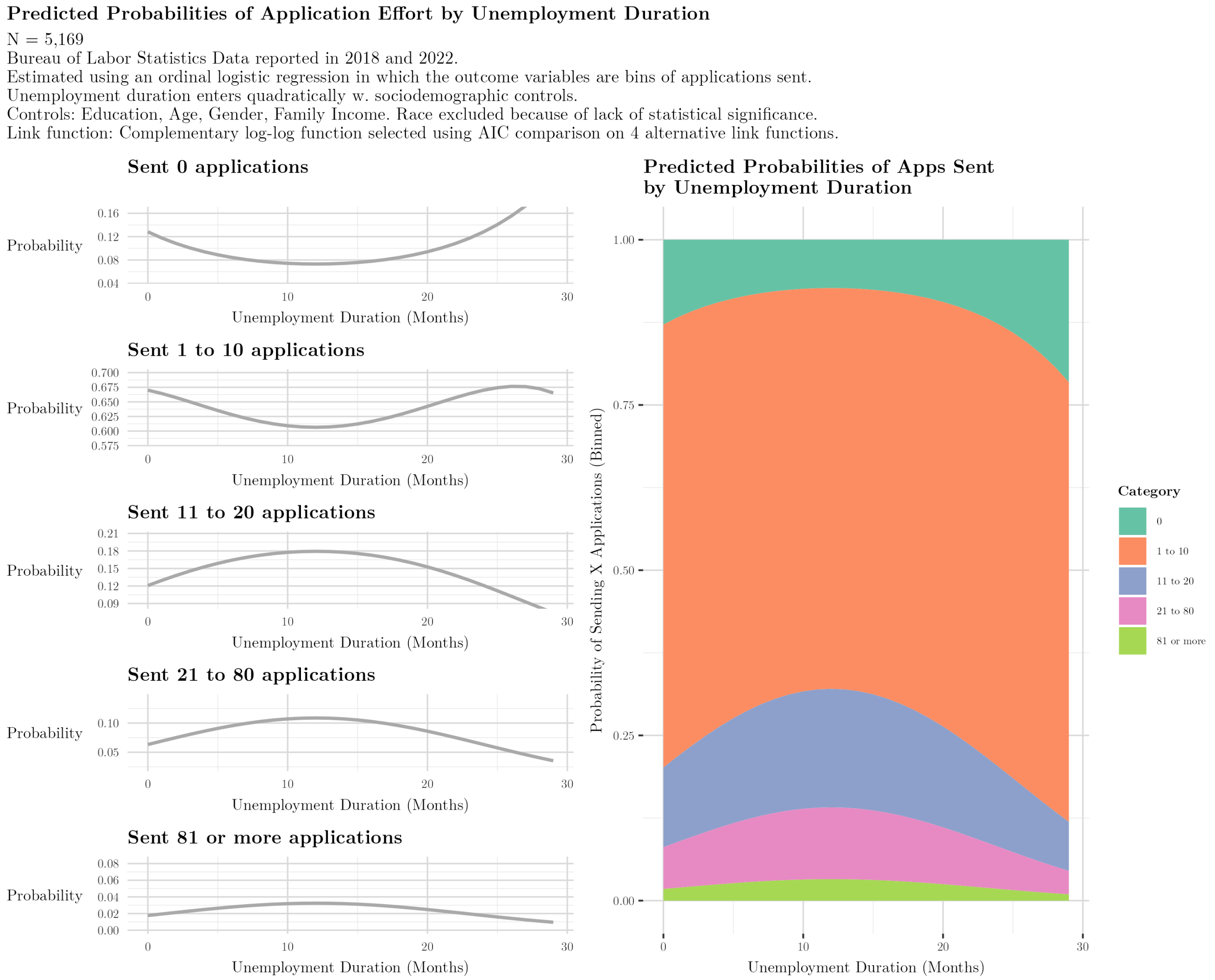
Models including sociodemographic controls consistently outperform unadjusted models and the inclusion of a quadratic transformation of unemployment duration better captures the non-linear relationship between unemployment duration and application effort. Among link functions, the complementary log-log specification performs best across model comparisons, aligning 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 200 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.

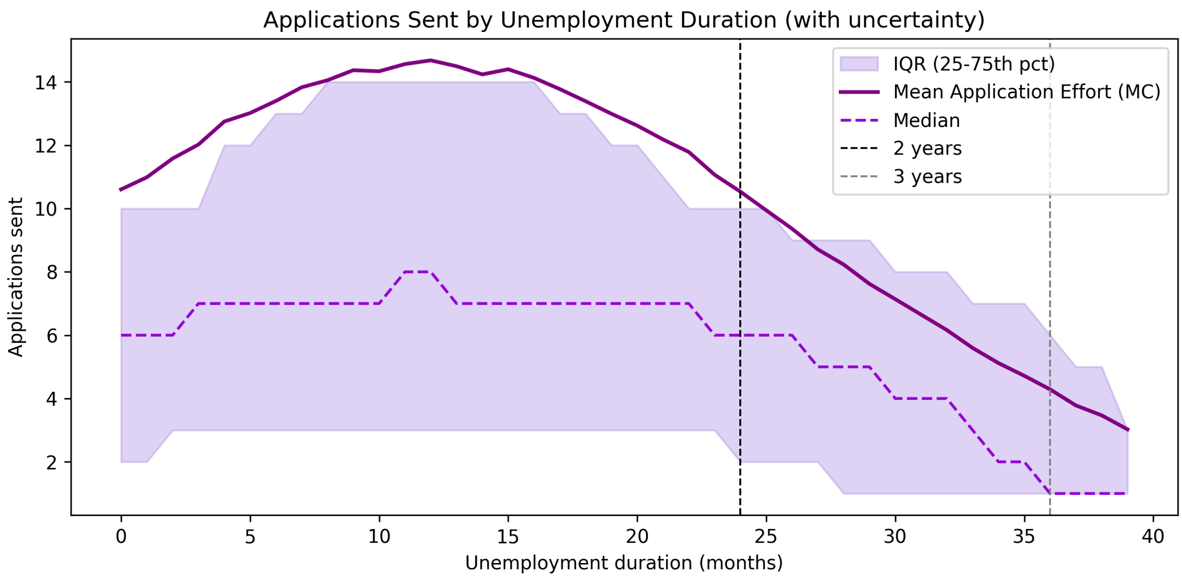
Figure 3a demonstrates the predicted probability distribution of application effort by unemployment duration indicating a non-linear concave search effort. We believe this contributes to an open debate in the job search literature regarding the shape of search effort over the unemployment spell. The 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, 90, 94] and adjusting expectations about their re-employment prospects [73].

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, workers draw an application effort from a uniform distribution within the interval of each discrete effort bin according to the estimated probability distribution at each unit of employment duration in months 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 [17, 42, 22]. 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[46, 2, 93].

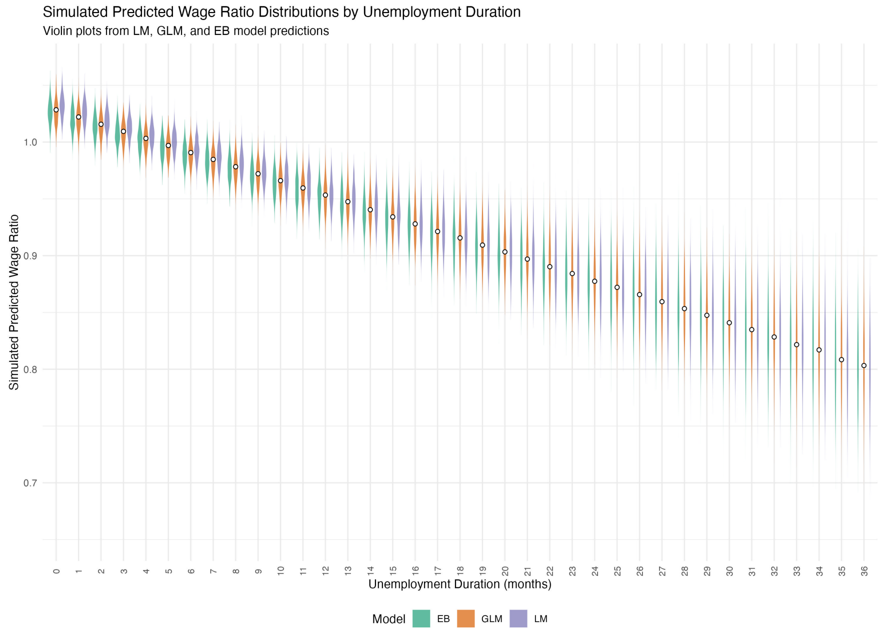
To quantify this duration dependence, we use microdata from the Displaced Worker Supplement (DWS) of the Current Population Survey spanning 2000–2025. We estimate how an unemployed individual's reservation wage, measured relative to their pre-displacement wage, changes with the length of their unemployment spell, controlling for demographic and labour 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 minimise measurement error from partial reporting. We also restrict the sampletrimming 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 duration. 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 characterised 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. In Appendix A we outline other data sources considered to inform this parameter and the motivation for foregoing them in lieu of the data and estimation reported here.

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. 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.

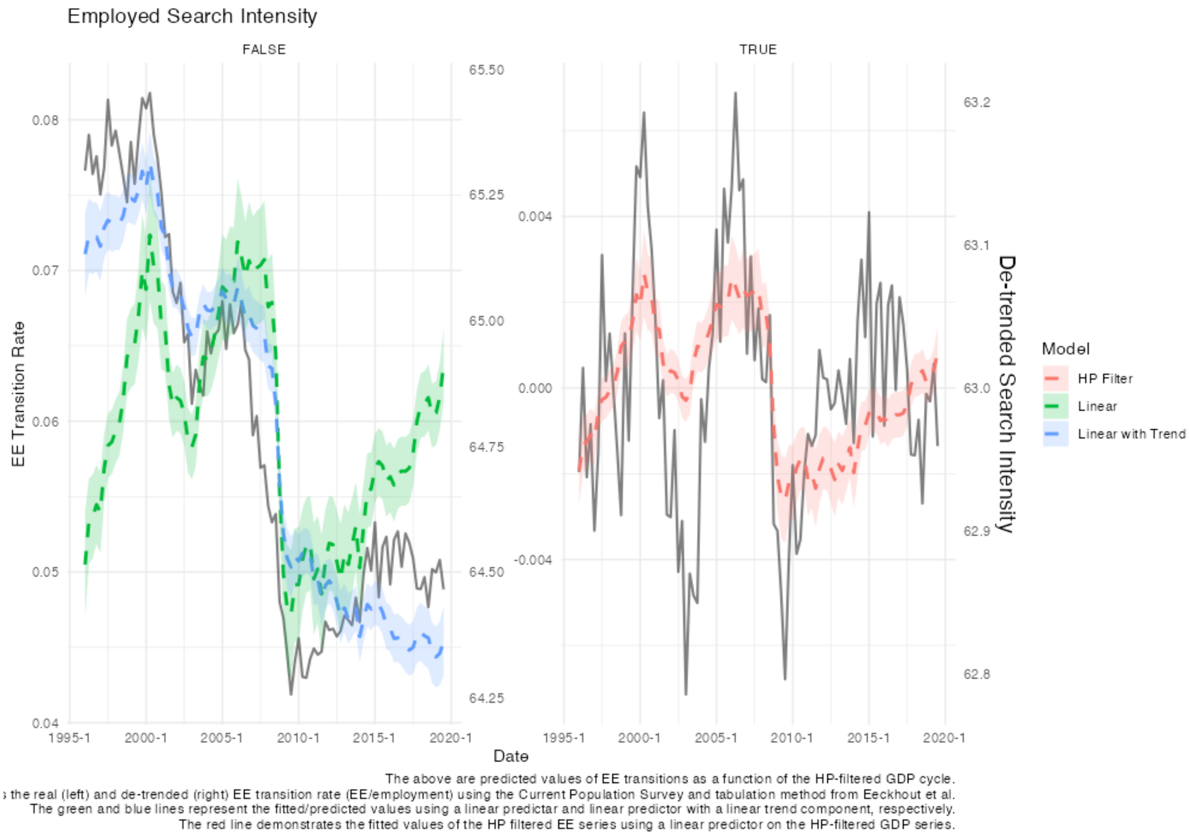
2.2.3 On-the-job Search and Competition Effects

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 [33, 32, 92, 21]. Furthermore, [32] 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.

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 1996 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 [37]. More precisely, we observe the employment-to-employment transition rate as well as the rate of those who transitioned to a 5% higher wage in line with the convention employed in [32].

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.

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



As demonstrated in Figure 5, we draw a mean probability that an employed person engages in active job seeking as ϕ_w which serves as the complete basis for our heuristic rule and partial basis for our agent decision rule.

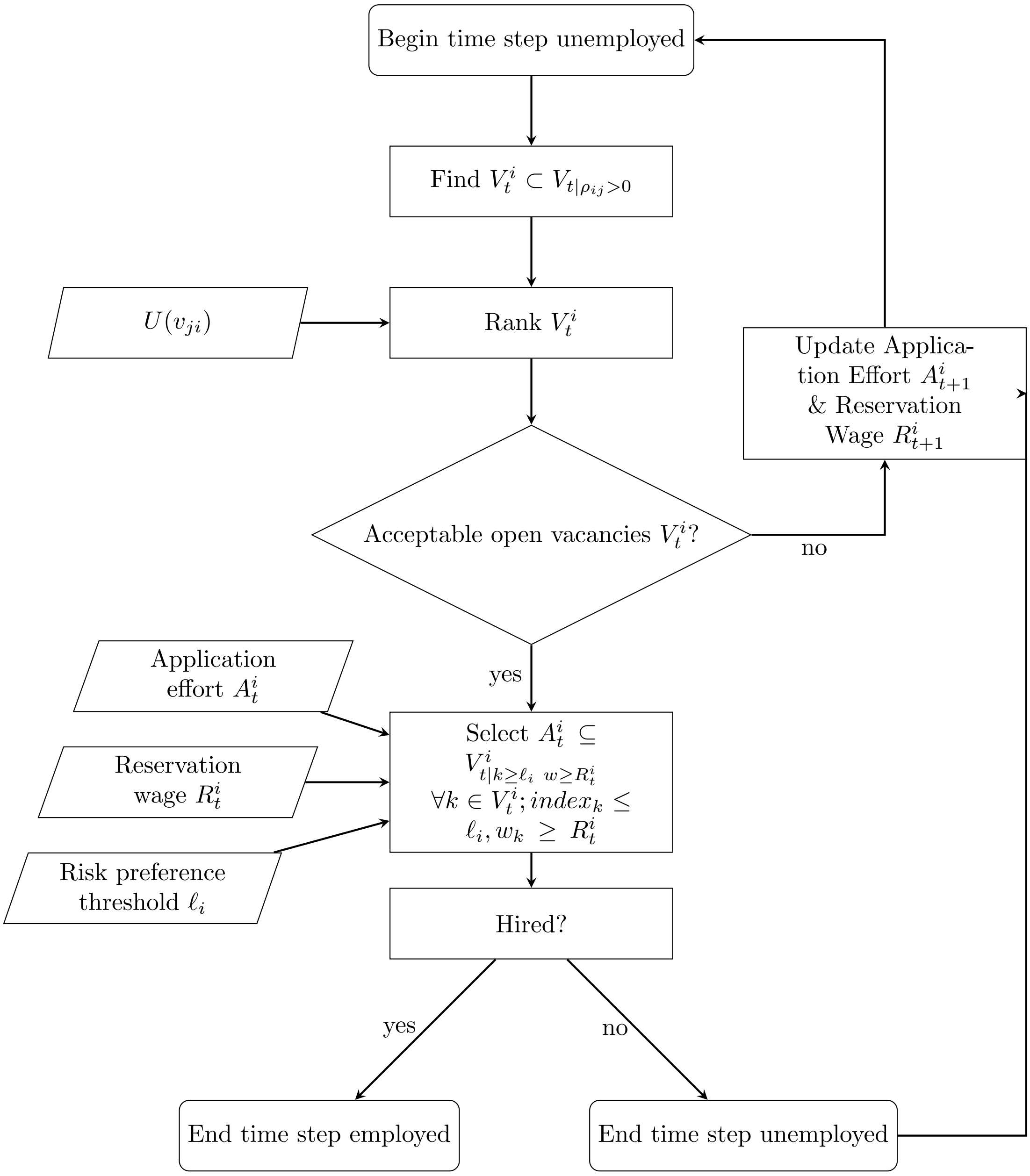
2.2.4 Operationalising Agent behavior

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

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



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 w finds a subset of vacancies $\{1, ..., n\}$ by sampling from occupations that share a non-zero weighted edge with their latest held occupation with probability ρ_{ij} . Assuming that workers do not have perfect information on all available vacancies, n is smaller than the total available vacancies in the economy that exist within neighboring occupations and their likelihood of "finding" a given vacancy in occupation j is given by ρ_{ij}.

Within this sample of found 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.

$$U(v_{ji}) = \rho_{ij}(w_j - w_i) \tag{10}$$

At this point, the behavioral attributes outlined above enter the stylized process where:

- R^i_t is drawn from Section 2.2.2
- A^i_t is drawn from Section 2.2.1

Workers select A^i_t vacancies from the ranked vacancy set starting from index ℓ_i whose wage is at least 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, $p_r = 0.15$.

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

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

<u>Employed Search behavior</u>

Second, employed workers decide to search for work with probability p^{OTJ}_t which is either a function of a mean proportion of employed workers engaging in active search drawn from Section 2.2.3...:

$$p^{OTJ}_t = \phi$$

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

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

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.[6]

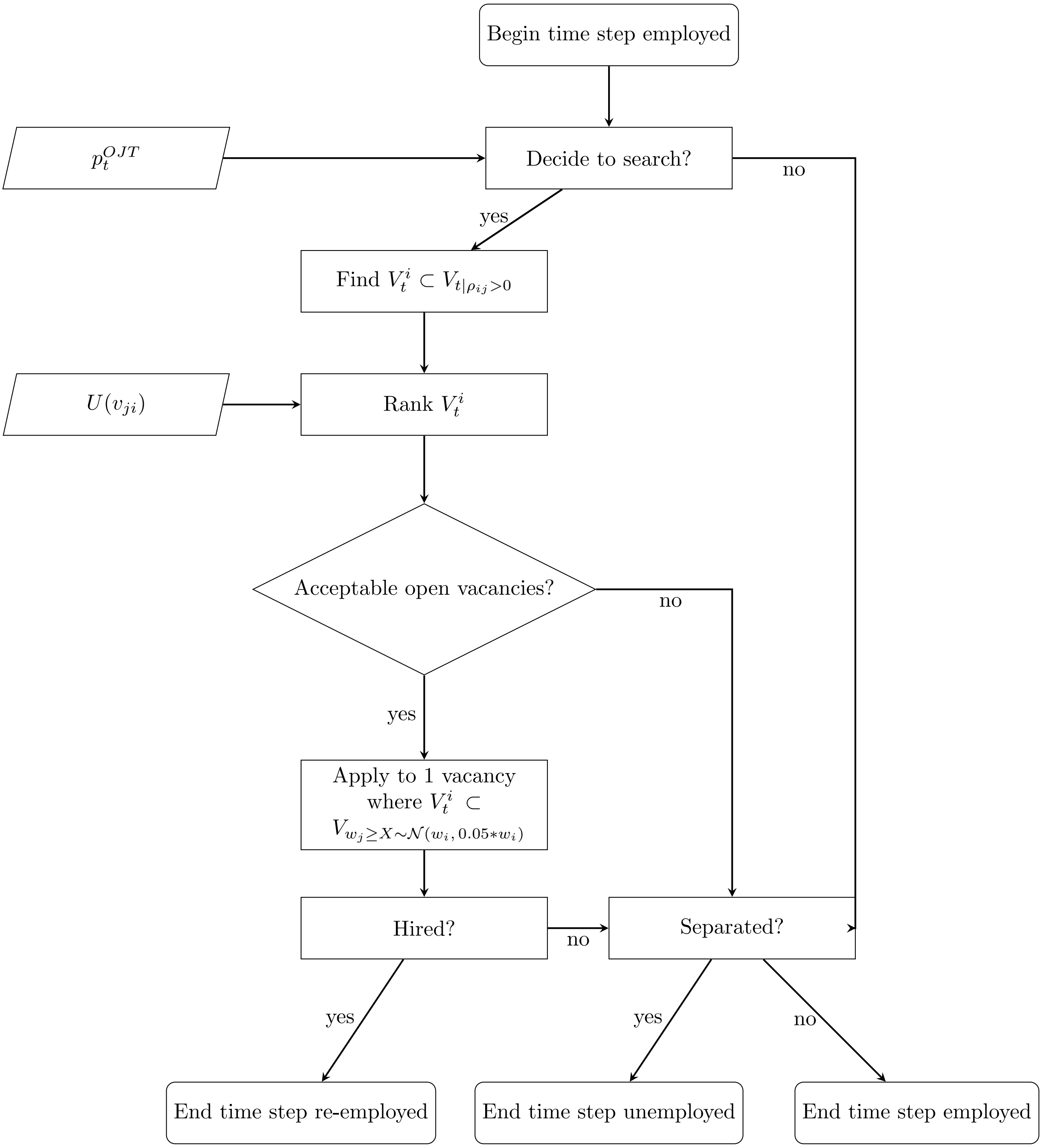
[6] Alternative methods for calculating a valid competition metric could use (1) applications per vacancy $\frac{A_{j,t-1}}{V_{j,t-1}}$, to account for competition from job-seekers in other occupations; (2) or either $\frac{A_{i|\rho_{ij}>0,t-1}}{V_{i|\rho_{ij},t-1}}$ or $\frac{U_{i|\rho_{ij}>0,t-1}}{V_{i|\rho_{ij},t-1}}$,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

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 add some noise to the wage preferences of employed seekers which is drawn from a normal distribution around their previously held wage.

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 behavioural parameters and empirically grounded behavioural inputs. [7] 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.[8]

In the following sections, we display the results for four separate models with relevant features as outlined below.

Description	Employed Workers Search	Employed Workers Search Cyclically	Application Effort Adjustment	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.

3 Calibration

We calibrate our behavioral parameters as outlined above using microeconomic data and the economic parameters to macroeconomic data to ensure the model's credible simulation fidelity. [9]

[7] 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.

[8] 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 exogenise 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 [74]

[9] 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. [82] 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-categorised 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 micro data, graph neural networks could aid simulation-based inference methods as proposed in [31].

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 [31, 30]. We perform this calibration using the *pyabc* package in Python [87, 49].

We calibrate our economic parameters for each model exploring the joint parameter space of δ_u and γ_u 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 [87, 49]. 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**, $\gamma_u \sim \mathcal{U}(0.001, 0.9)$

The prior distributions were chosen to reflect economically plausible ranges, while ensuring broad support for parameter exploration.

3.1.2 Observed Data and Summary Statistics

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).

3.1.3 ABC-SMC Algorithm

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

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

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.

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. 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 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 though the Beveridge curve is inadequately steep in the non-behavioral models.

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

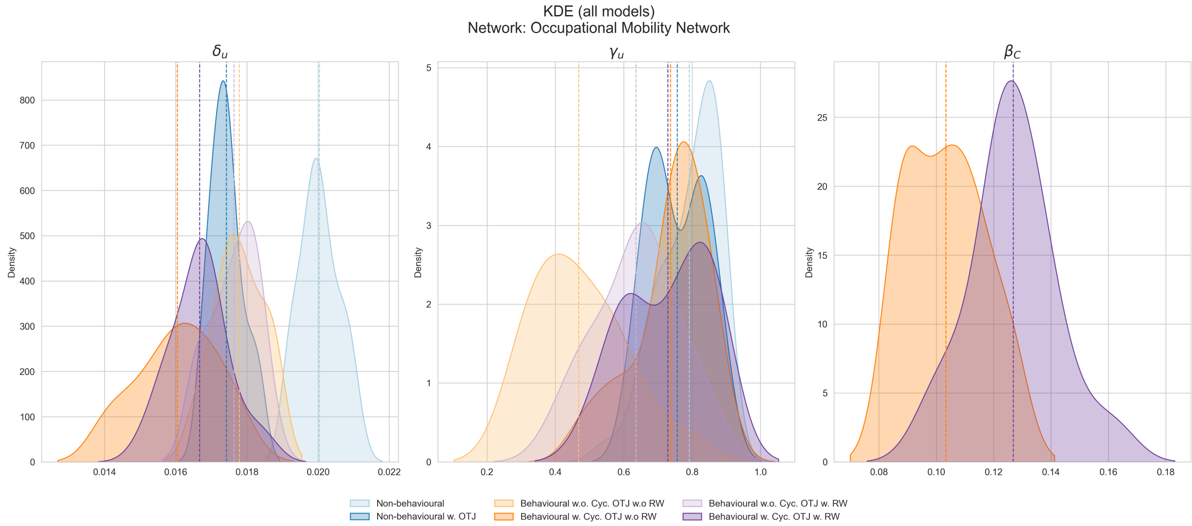
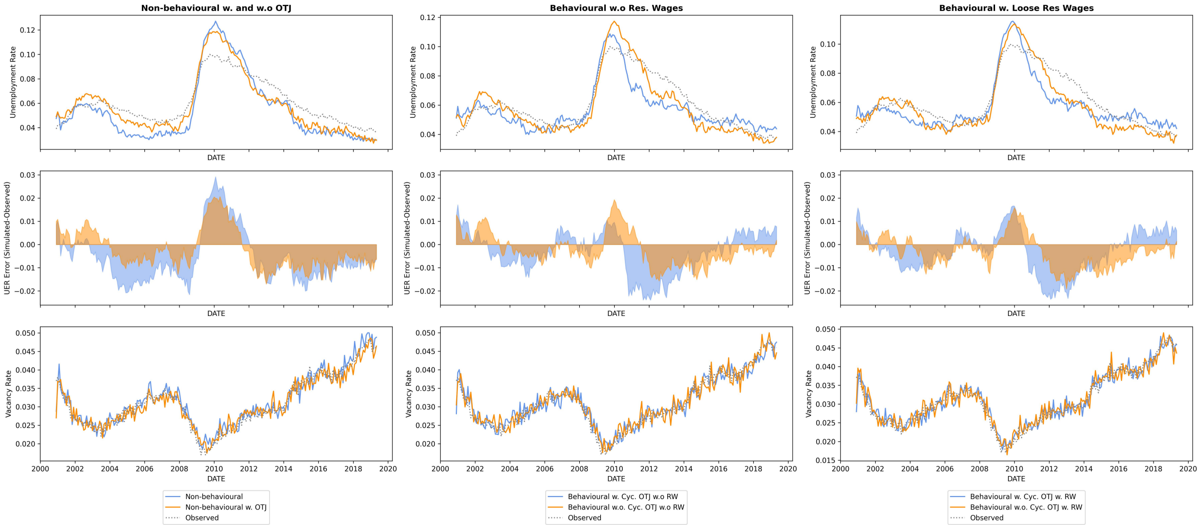
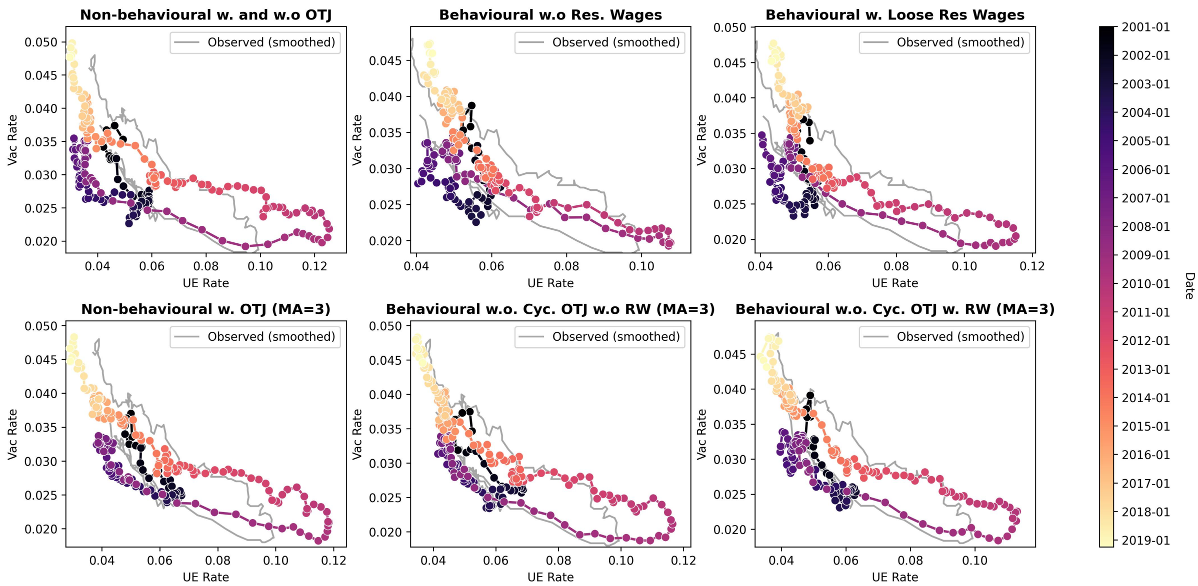


Figure 9: Comparison of simulation outputs.



(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	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	0.018	0.017	0.018	0.007	0.014
gamma_u	$U(0.0001, 0.9)$	0.792	0.756	0.737	0.468	0.729	0.636	0.085	0.025
theta	$U(0.0001, 0.9)$			0.103		0.127		0.396	

Table 1: Prior distribution and parameter estimates for all models. $U(a, b)$ denotes a uniform distribution on $[a, b]$.

In Appendix F, 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 2 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	[41]	[26]
E-U Transition Rates	Occupation	IPUMS CPS Data [41]	
Separation Rates	Occupation	IPUMS CPS Data [41]	
Employment levels	Occupation	IPUMS CPS Data [41]	[26]
Unemployment levels	Occupation	IPUMS CPS Data [41]	[26]
Vacancy levels	Occupation	IPUMS CPS Data [41]	[26]
Occupational mobility network	Occupation	IPUMS CPS Data [41]	[26]
Entry level	Occupation	Education and training assignments by detailed occupation	BLS
Calibration data			
Unemployment rate	National	BLS	
Vacancy rate	National	Job Openings & Labor Turnover Survey (JOLTS), BLS	
Parameter data			
Applications Sent	Micro data	2018 and 2022 Supplement to the Current Population Survey	Author's own analysis
Reservation Wage	Micro data	Displaced Workers Supplement to the Current Population Survey	Author's own analysis
Composition of job-seekers by employment status	Empirical estimate	CPS & JOLTS	[32]
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		[75]
Composition of job-seekers	National		[32]

Table 2: 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 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

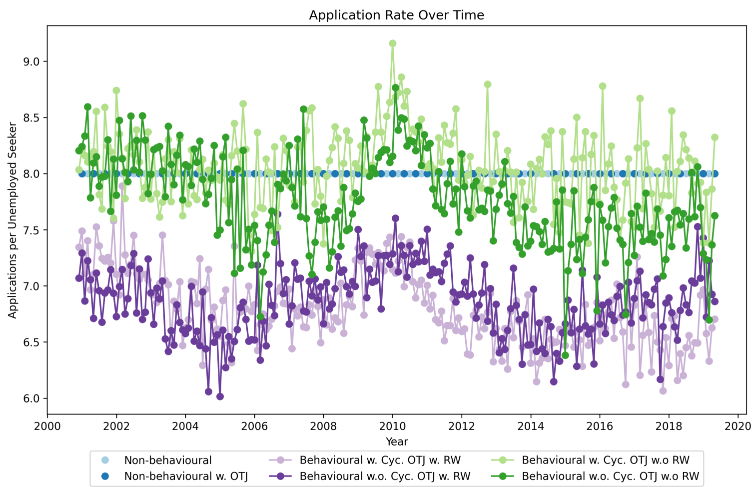
4.2.1 Micro-economic Data

At each time step, workers face labor market states defined by different degrees of competition and employment availability. Notably, our model reproduces two critical emergent/endogenous cyclicalities in the behavior of employed and unemployed seekers. We draw on insights from [75], and [32] 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.

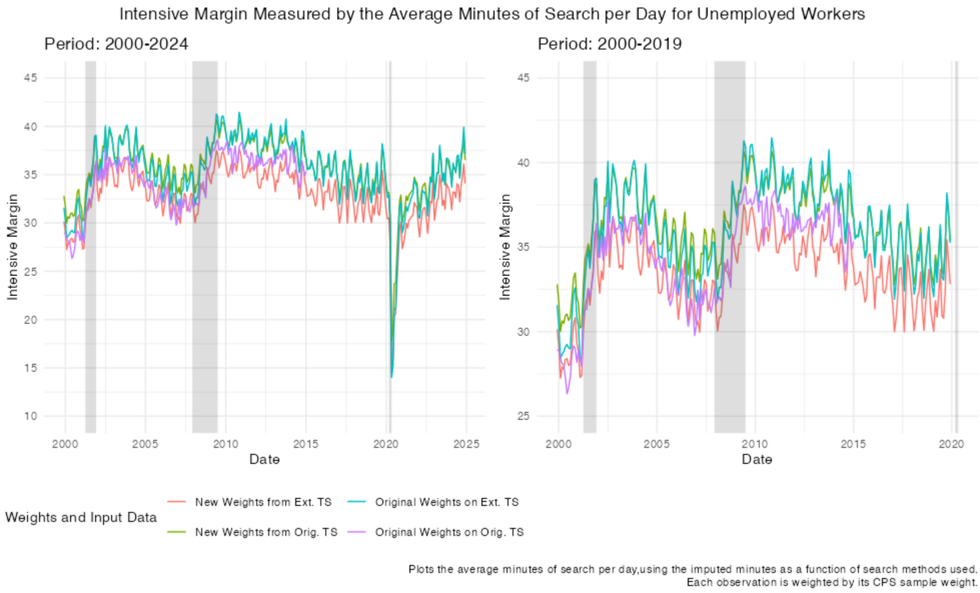
First, the **job search behavior of unemployed workers is anti-cyclical**. More precisely, it has been found that unemployed job-seekers exert greater effort at the intensive margin in economic downturns [75]. The individual agents in our model demonstrate such counter-cyclical search effort in that 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 [75]. 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



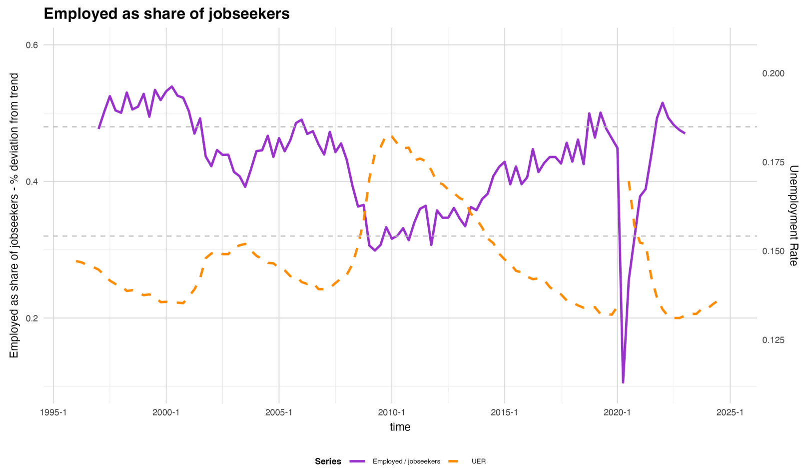
(b) Unemployed Search Effort - Intensive Margin (Mukoyama et al.



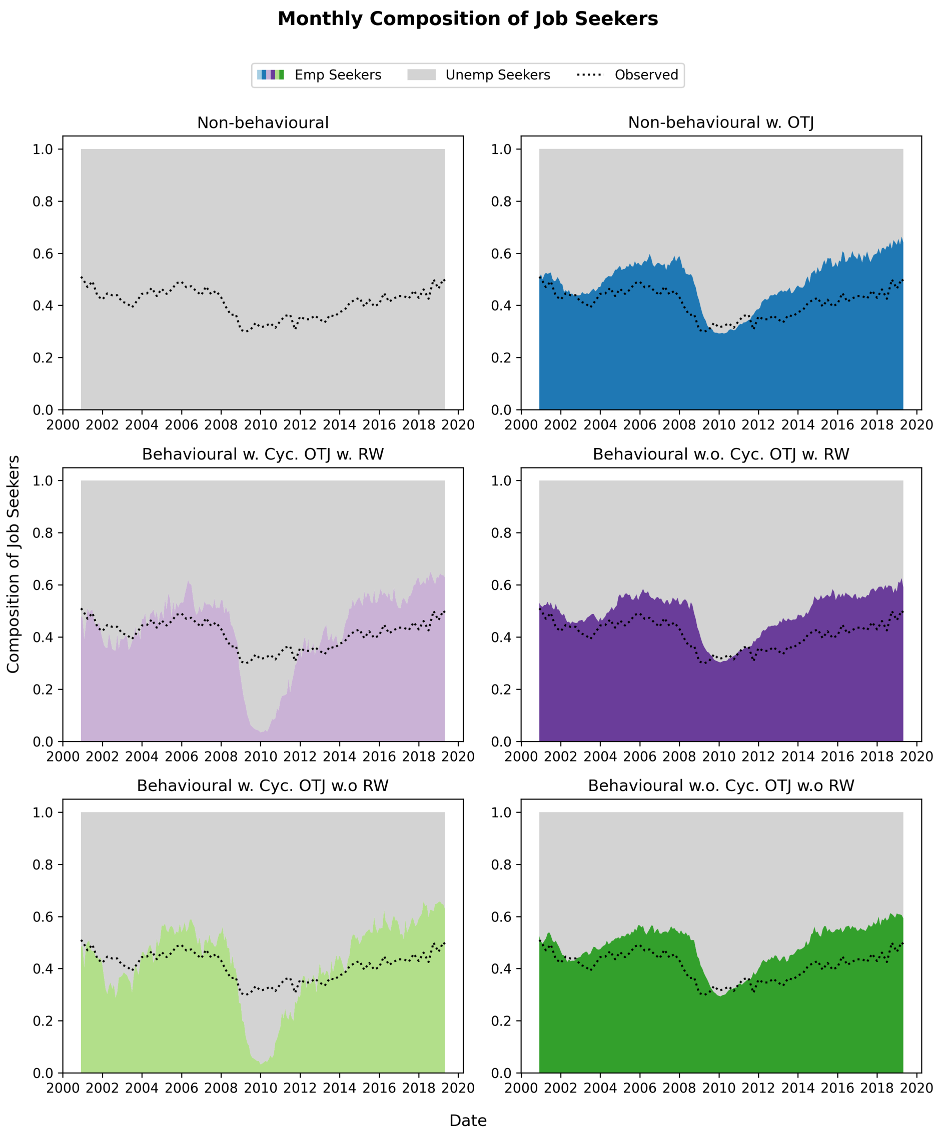
Second, the propensity for employed job-seekers to enter the job search demonstrates a pro-cyclical relationship, leading to greater competition in times of economic recovery or booms [32]. To validate this outcome, we have replicated and extended the data used in [32] to measure the search intensity of employed workers and employment status composition of job-seekers and use this to validate the population-level behavior of employed job-seekers in the model. As described in subsubsection 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 [32]. 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

Next, we examine a set of labor market inefficiencies potentially illuminated by the incorporation of the data-driven behavioral rules. 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 as well as varying risk aversion between male and female job-seekers allows a gender wage gap to emerge.

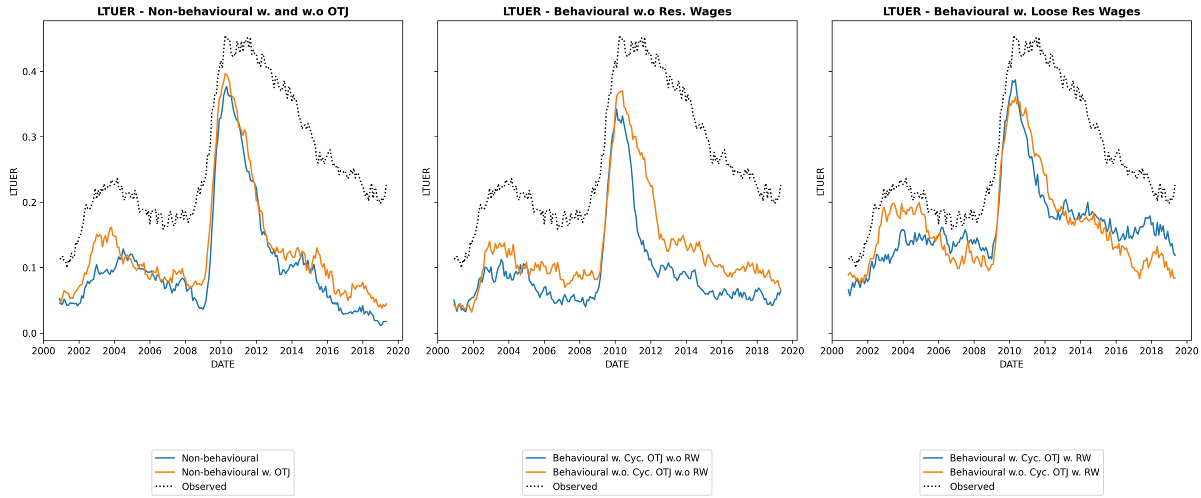
Long-Term Unemployment

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 [78, 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 [73] directly influences the long-term unemployment rate in our behavioral models.

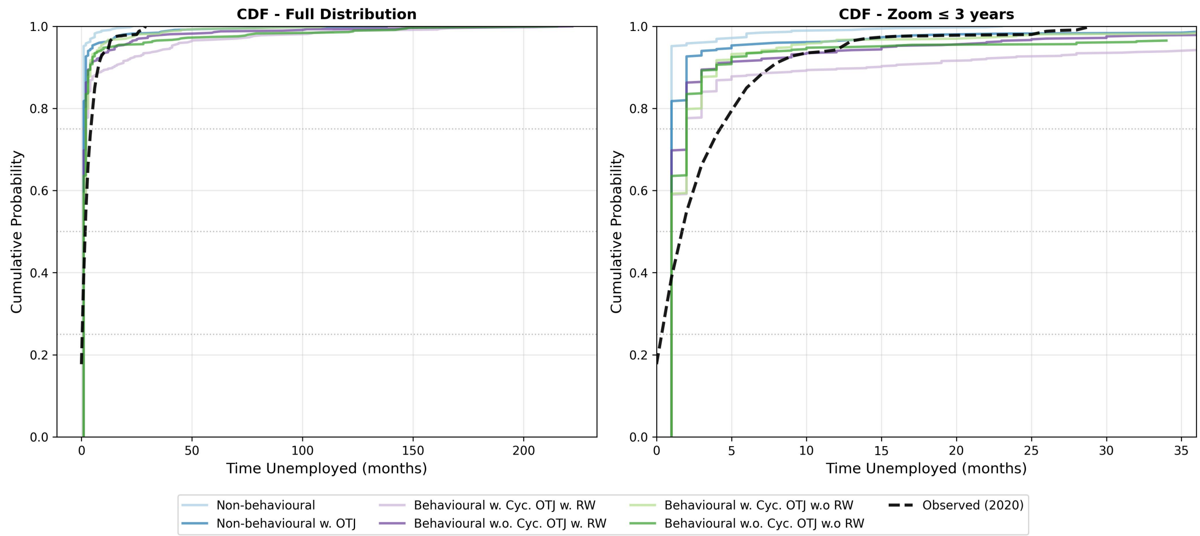
In Figure 12a we compare the performance of our various models against the observed long-term unemployment rate time series as well as the distribution available from the Current Population Survey for the period 2000-2019. Evidently, the incorporation of on-the-job search allows the long-term unemployment rate to more closely follow the shape of observed long-term unemployment rate. However, the majority of meaningful improvements in our matching of the observed long-term unemployment rate comes from the incorporation of our behavioral mechanisms. Models in which individuals have a duration-dependent search effort 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 [75]. We still significantly under-estimate 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 [52, 40, 85].

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 [38, 58, 48, 24]. 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.[10]

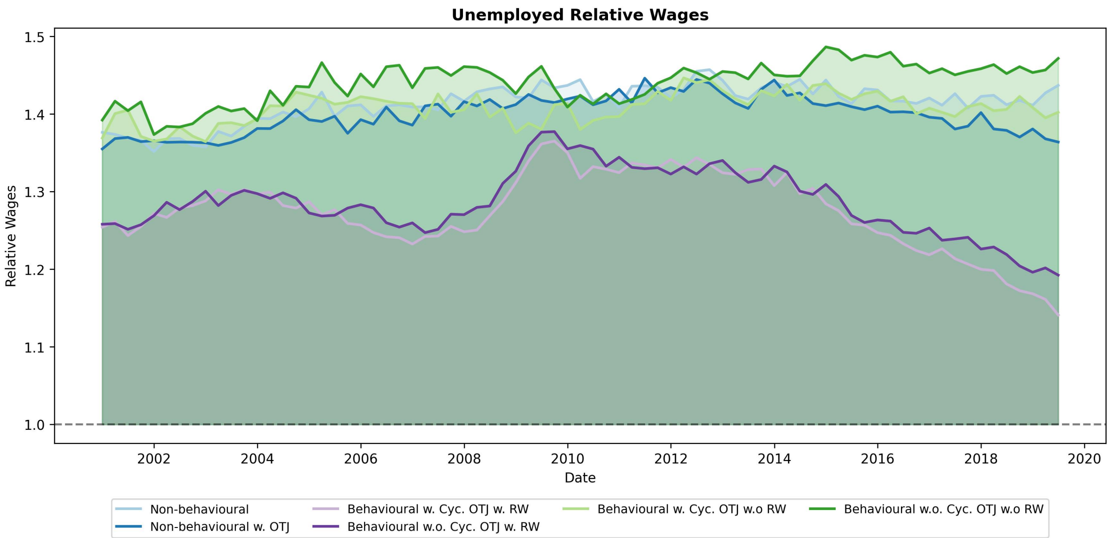
In our model, we can assess the accepted wage offers of workers across occupational or demographic characteristics. The combined effect of variable competition between employed and unemployed workers and a reservation wage adjustment mechanism produces a series of re-employment wage ratios correlated 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 [39]. The model supports these empirical findings as demonstrated in Figure 13a, where the pattern of re-employment wage gains and losses for unemployed workers in relation to the business

[10]Periods with elevated layoff rates correlate with slow wage growth speaking to the relevance of layoff timing [24].

cycle is only correlated with real data in Figure 13b in the models in which behavioral mechanisms are included. The non-behavioral models and the behavioral models without wage preferences exhibit limited cyclicality. However, a challenge that remains to be investigated in this work is the fact that simulated re-employment wages do not recover 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.

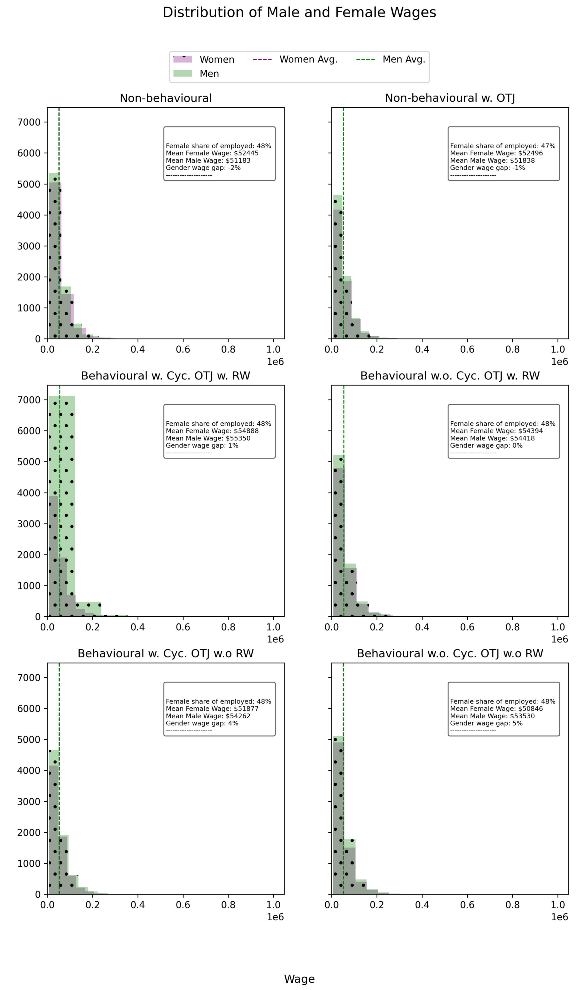
Fig. 13. Proportional change in real weekly earnings for full-time job losers. Year effects from DWS earnings change regressions at medians: ages 35–44, tenure 1–3 years, white, female, ED = 12, lost job 2 years ago.

Gender Wage Gaps

Finally, 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 3 patterns: the distribution of unemployment duration, gender wage gaps, and the relationship between the business cycle and re-employment wages.

First, 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

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



caring responsibilities, motherhood penalties, occupational choice, and gendered patterns in job search behavior [17, 22, 42, 59, 68, 34].

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

When initialised, the input data on occupational gender shares leads to an initial 10% gender wage gap across all models. Notably, the absence of wage preferences in the non-behavioral model leads to an evening out of this wage gap. The persistence of the gender wage gap in the behavioral models is sensitive to parameter choices across the model. If workers can optimise near-perfectly in terms of their wage preferences, the wage gap increases, whereas adding stochasticity to this wage optimisation process, the resulting wage gap shrinks.

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 realised 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 micro data 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 $t = 0, 1, 2, \ldots$. 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 $A_t \in \{0, 1, \ldots, \bar{A}\}$ 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 [73] 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:

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

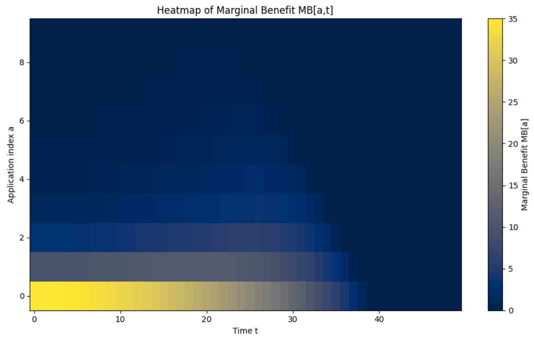
where

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

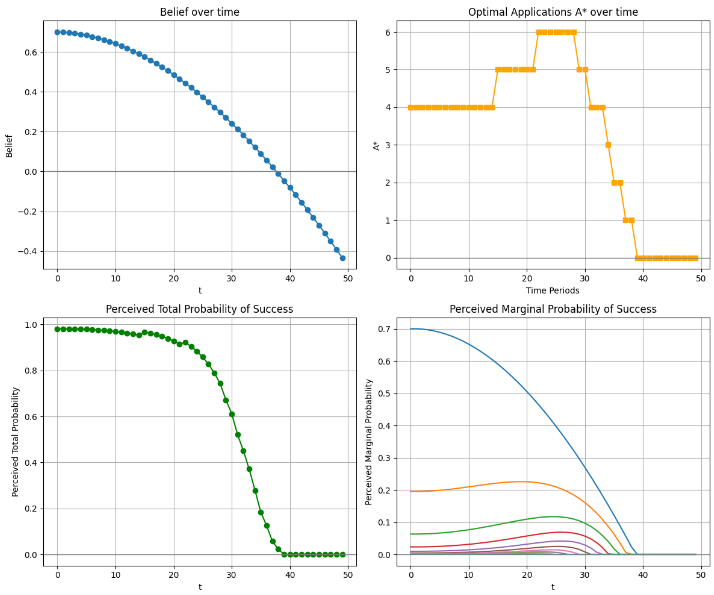
Thus, the worker applies until the perceived marginal expected utility of the next application a falls below the cost per application c. Because applications are discrete and limited by an upper bound $\bar{A}$, the optimal number of applications in period t is $A_t^\star$.

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 these 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.



(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:

$$P_{i,t}^{\mathrm{OTJ}}(\varphi_t) \;=\; \frac{1}{1+\exp\Bigl(-\bigl[\delta+\beta_{i,t}\,\varphi_t\bigr]\Bigr)}, \tag{21}$$

where, as in the model above, $\beta_{i,t} \in [0, 1]$ 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, though this can 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:

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

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 $\mathcal{V}_{i,t}^E$ 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 $j(v)$ denote the occupation associated with vacancy v.

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

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

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

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

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

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

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,

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

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.

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 $\lvert\mathcal{V}_t\rvert/\lvert\mathcal{U}_t\rvert$
$w_{j,t}$	Wage offered by vacancy in occupation j at time t
Worker-related variables	
B^U	Value of unemployment
E^i	Value of employment in occupation i
$\beta_{b,t}$	Subjective belief of worker from occupation i about job-finding
β_i	Fixed subjective belief of worker from occupation i about job-finding
$P(h_{i,t}=1)$	Job-finding outcome (1 if hired, 0 otherwise)
w_b^{ref}	Reference wage (latest held) for unemployed workers
A_t	Set of vacancies found to apply to at time t
a	Vacancy rank in worker's preference ordering
$\bar{A}$	Maximum possible applications per period
$A_t^\star$	Optimal number of applications / chosen set size
Matching and success 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
$\mathrm{MB}_t(a)$	Marginal benefit of applying to vacancy rank a
Belief updating	
α	Learning-rate parameter
ω	Curvature parameter in belief updating function
r	Weight on application outcome ($P(h_{i,t}=1)$)
Costs, budgets, and constraints	
c	Per-application search cost
C	Total application/search-time budget in period t
$R_{b,t}$	
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 3: 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 behavioural 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 behavioural 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 labour 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 behaviour: unemployment duration exerts sustained downward pressure on wage expectations, in line with existing findings [46, 15, 55, 50]. 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 behavioural 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-behavioural benchmark. In other words, the incorporation of a learning process throughout an unemployment spell in relation to job search strategy corroborate the findings of [75] 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. Modelling belief updating and effort choices therefore helps the simulated labour market adjust in a way that resembles observed recoveries.

Additionally, as has been advocated for by [32], 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 behaviour in systematic ways.

Critical to this work was the incorporation of data to better model occupation-level heterogeneity. The improved simulation fidelity of our behavioral models is largely attributable to better matching of transition rates between occupations at the lower end of the wage spectrum. By contrast, the model struggles to replicate the precise movements of workers in higher-wage and highly skilled occupations. One interpretation is that the behavioural pressures we model are unevenly salient across the wage spectrum and that high-skill occupation transitions are shaped by additional margins (e.g. non-wage amenities) not yet captured here. While this mismatch highlights a limitation of the current framework, the stronger performance for lower wage workers is also substantively relevant, since these are often most exposed to displacement risk and most dependent on continuous wage income and therefore a key policy priority.

6.1 Limitations and avenues for Further Work

This work could benefit significantly from further exploration of the following dimensions, categorized by data and modelling needs. First, the model does not accommodate skill deterioration during unemployment spells which have been found to affect re-employment prospects of the unemployed [80, 76, 92].

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 enginge 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 results in the main text of the model, 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 micro data. 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 Inventory of Remaining Work

What needs to be done:

- Sensitivity analyses regarding the scale of the model (ie. size of the population).

8 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 endogenise on-the-job search alongside unemployed search and let its intensity vary with perceived competition, so the composition of searchers shifts. 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.

Acknowledgments

Jonas Kurle, Complexity Economics Programme at INET, Doyne Farmer, François Lafond, Robert Axtell, and Vasco Carvalho. Calleva Research Centre for funding.

Use of AI

- Used ChatGPT to aid translation of Stata replication code from [32, 75, 73] 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.

Code availability statement

All replication code will be made available via Zenodo link. The current version of the code can be found on Github.

Appendices

A Calibrating Behavioral Parameters

Calibrating Behavioural Mechanisms

The model's central functionality relies on a variety of behavioural 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. We conclude with an inventory of other data sources considered for behavioral parameter calibration ultimately disregarded due to lack of statistical power.

Application Effort and Learning Dynamics: Applications Sent

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 person 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."

This 2020 "Beyond the Numbers" issue distills insights from a 2018 Supplement to the Current Population Survey. The below plots show the highlights relevant to our decision-making on the job search process.

In nearly all cases, the results 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 carefully. We employ the raw data informing thsee figures. The description of our analysis of the raw data is found in the next section.

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.

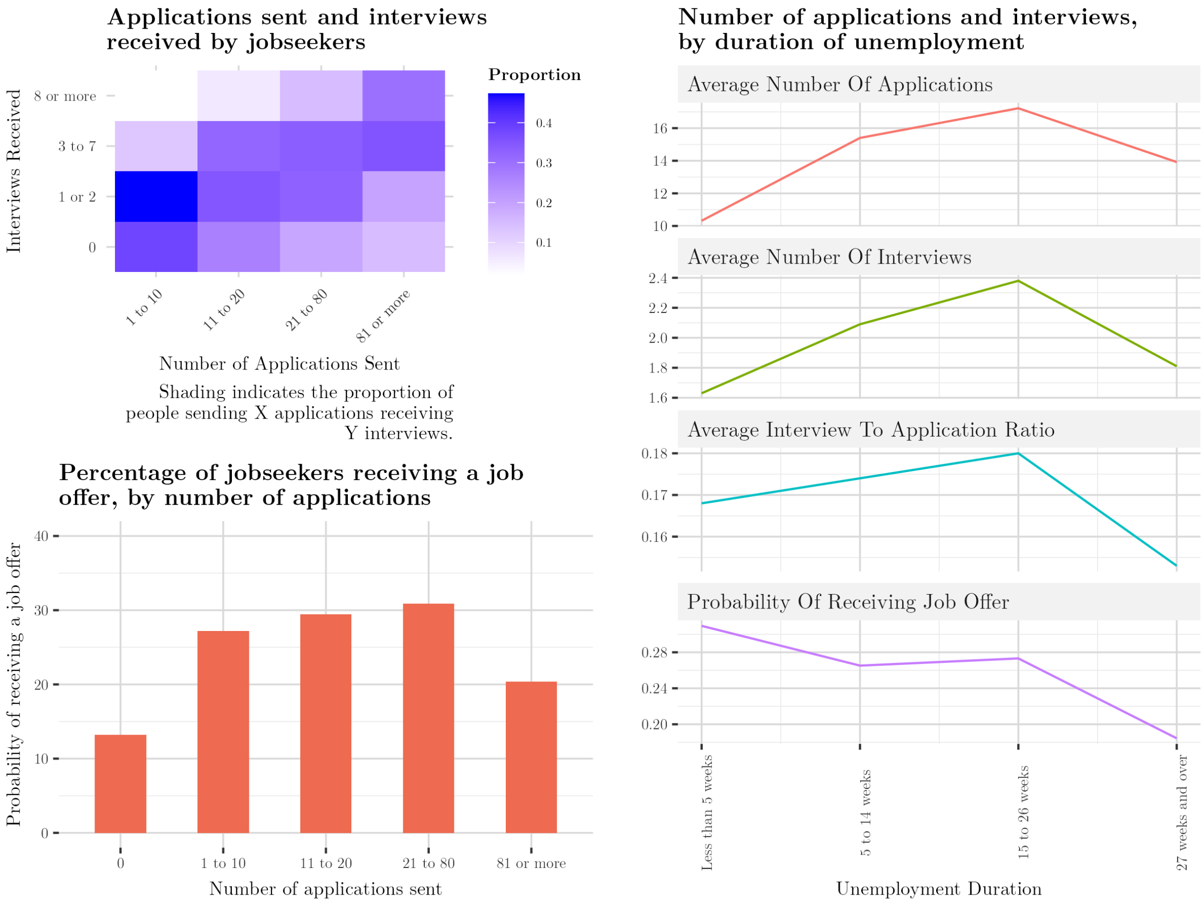
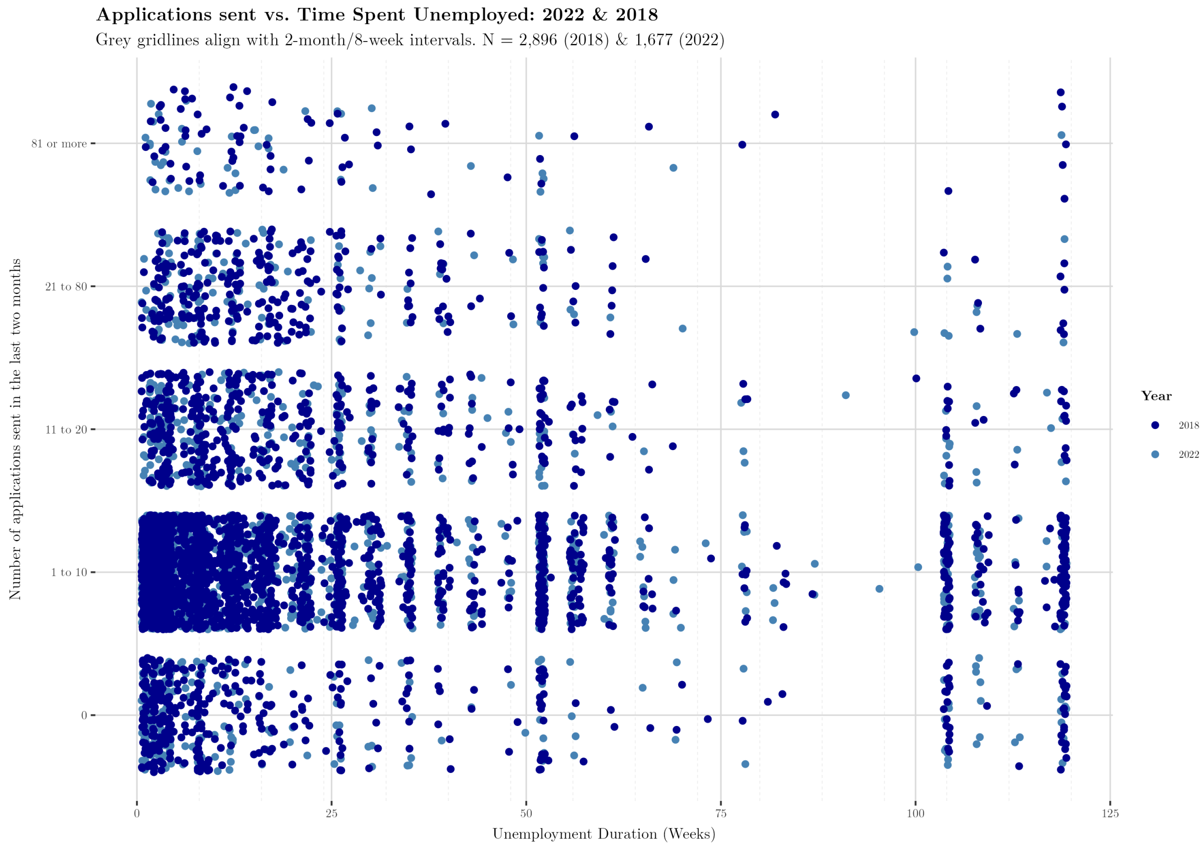


Figure 1: Replication of BLS Analysis



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. I test 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:

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

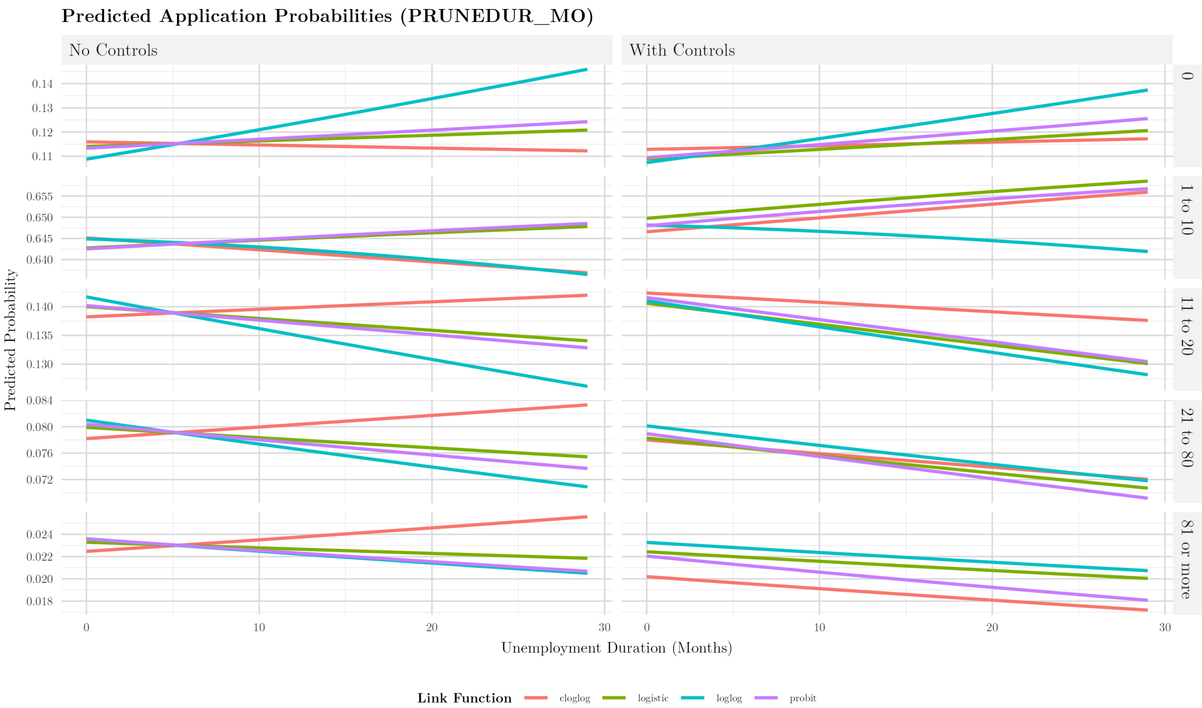
$$X_i = \left(\text{Unemp.Dur.}_i^2\right)$$

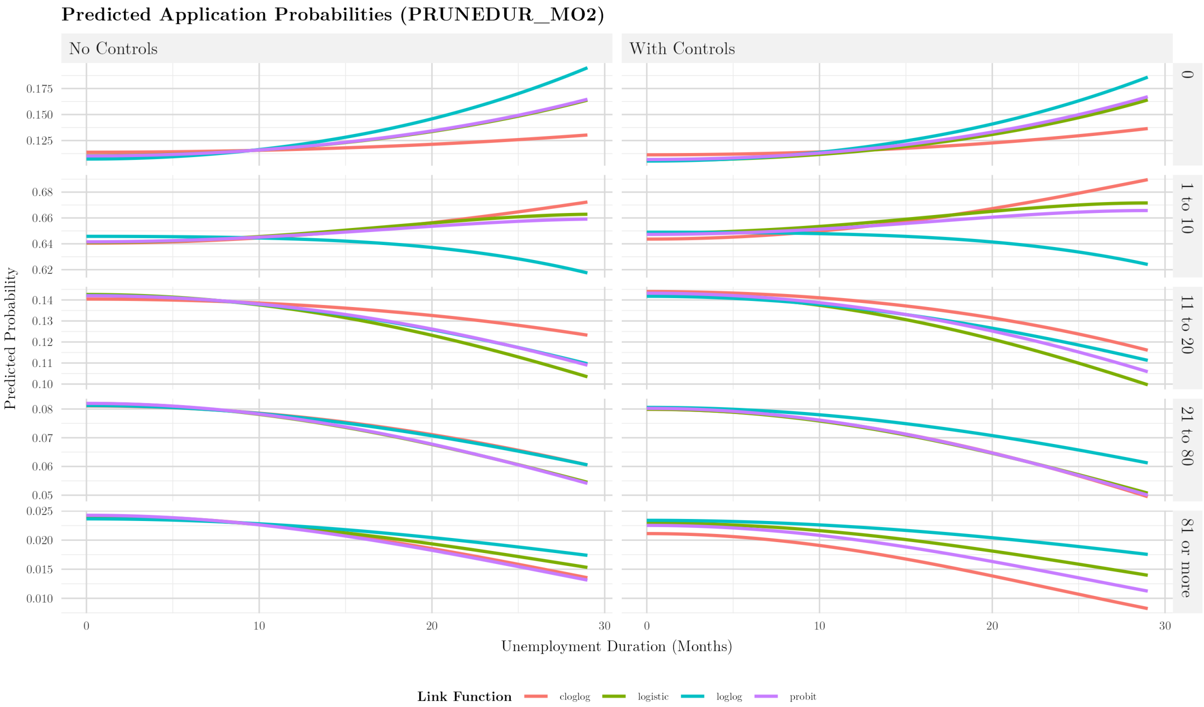
$X_i = \left(\text{Unemp.Dur.}_i, \text{Unemp.Dur.}_i^2\right)$

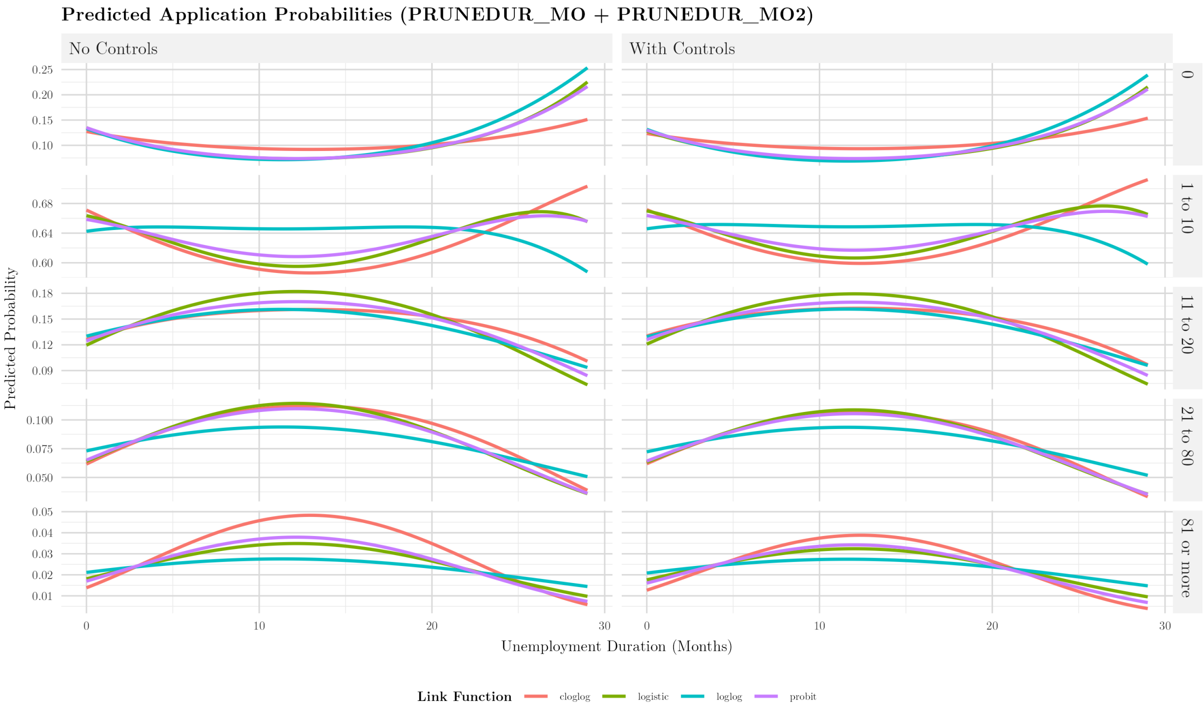
with and without control variables (education, gender, age, family income).

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.

Preliminary hypothesis: Best fit will be with a complementary log-log as we care more about distinguishing between lower-level bins and there are few observations in the highest-level bins.



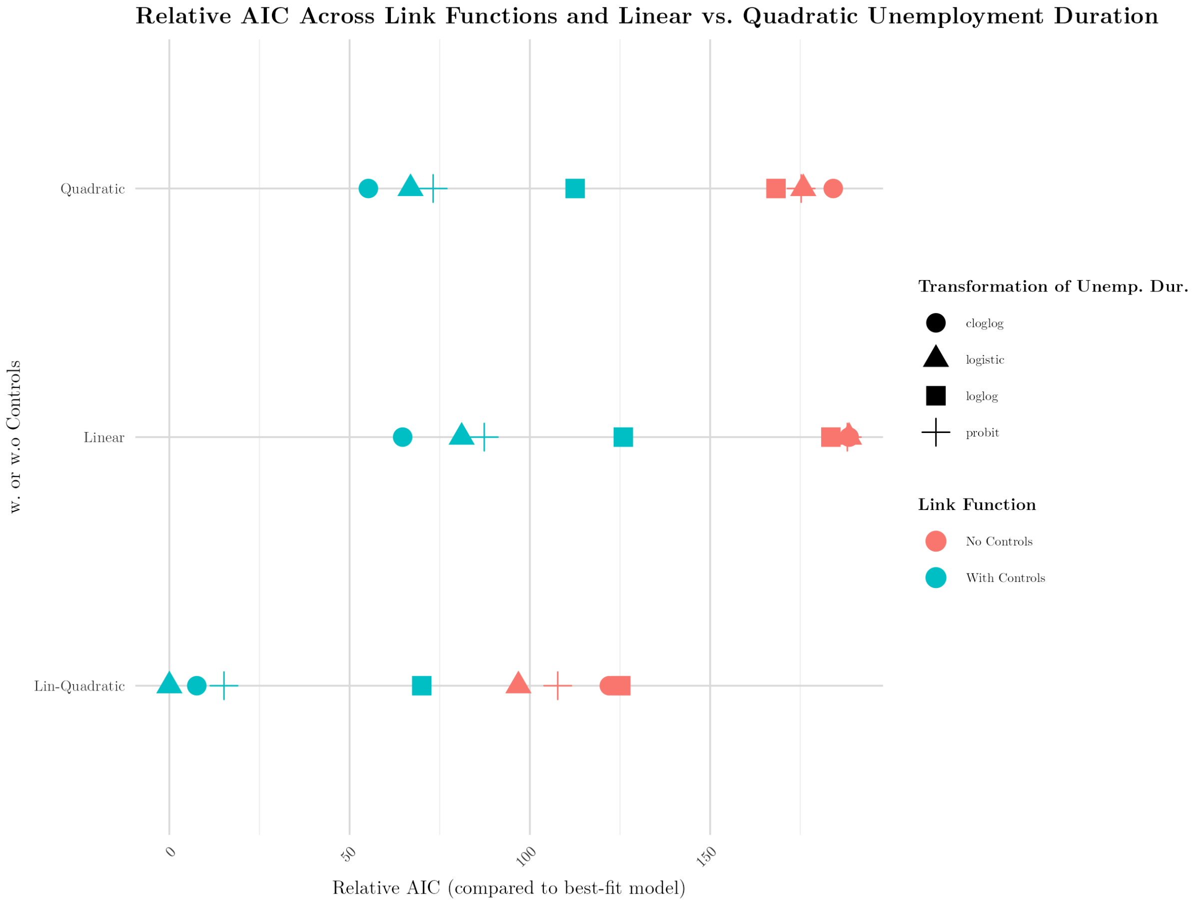


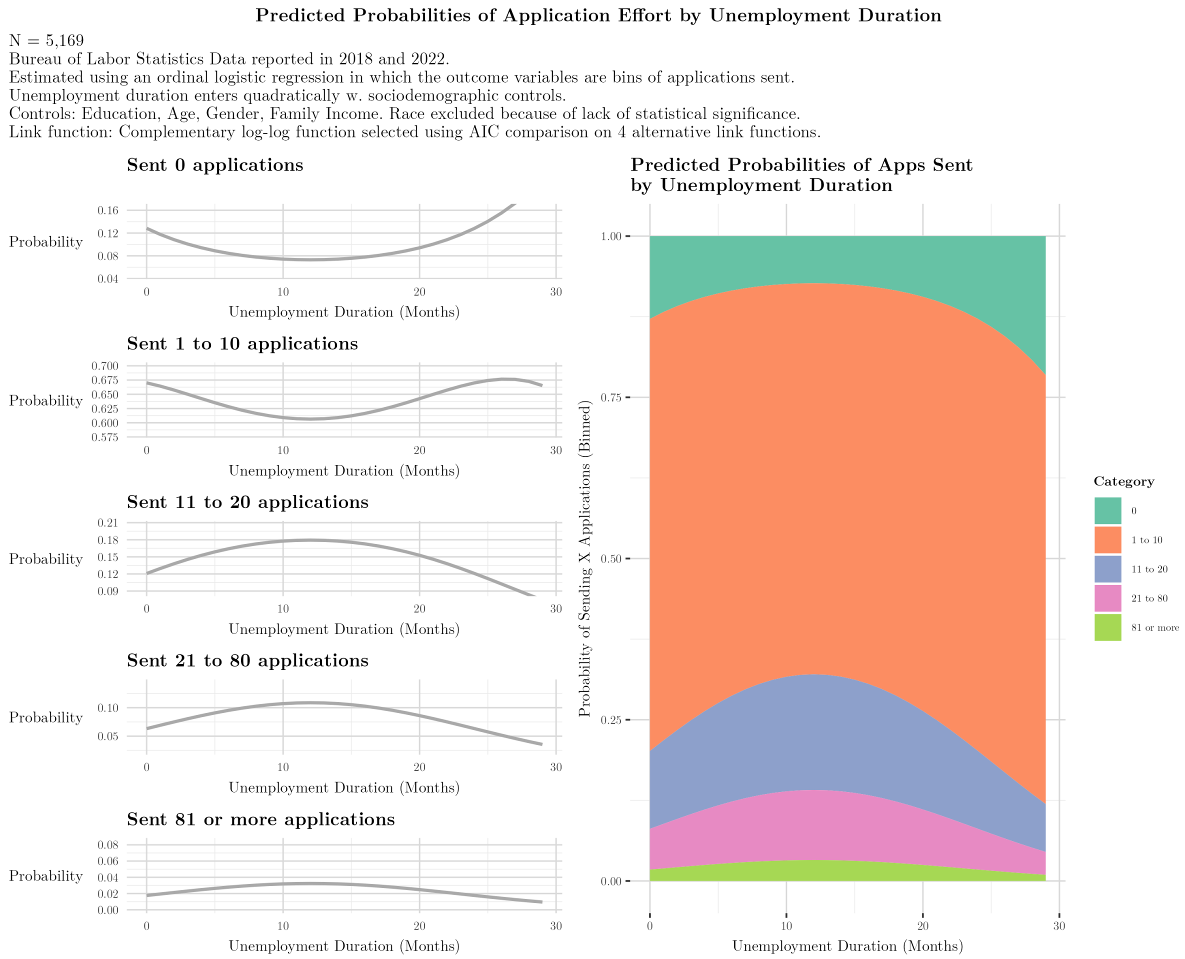


Using an AIC information criterion to compare the fit across all models, the following results are clear:
1. Models with control variables consistently perform better than those without.
2. Looking at the plots above, the relationship between unemployment duration and the predicted probability of reporting each application effort bin is very consistent except in the case of the log-log link function (blue in the panels above). In the plot below comparing the AIC the log-log link function (represented by the square symbol below) is consistently worse than all other link functions. This indicates consistency in

the results reported above. Intuitively, the log-log link function is likely to be an unreasonable fit for the latent variable as we care more about shifts in the lower-level categories than higher-level categories.
3. A complementary log-log specification for the latent variable is most suitable. This follows logically from the fact that the probability of being in the highest-level categories is relatively low.
4. Finally, a specification with a linear and quadratic estimator is consistently better than either the specification with simply a linear OR quadratic unemployment duration estimator indicating that the probability distributions represented in the final panel above are likely to be the best fit.

Result: 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.





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 specificaitions, 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. We reconcile this by converting reported hourly wages to weekly wages, where weekly values are not reported. The data used below is from annual survey responses between 2000-2025. We use the supplement sample weights in all results below. In the 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).

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.

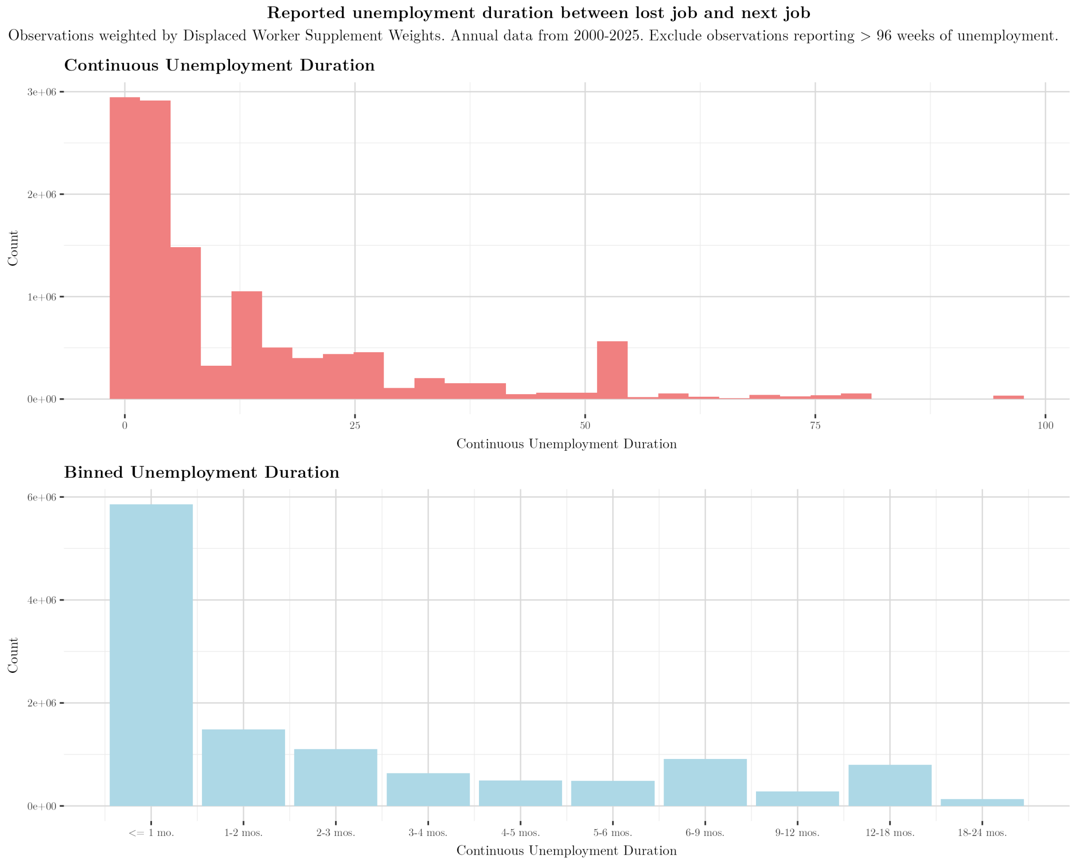
Descriptives

All descriptives below use the Displaced Worker Sample Weights.

Histogram: sample is skewed (see reweighting alternatives at end of document).

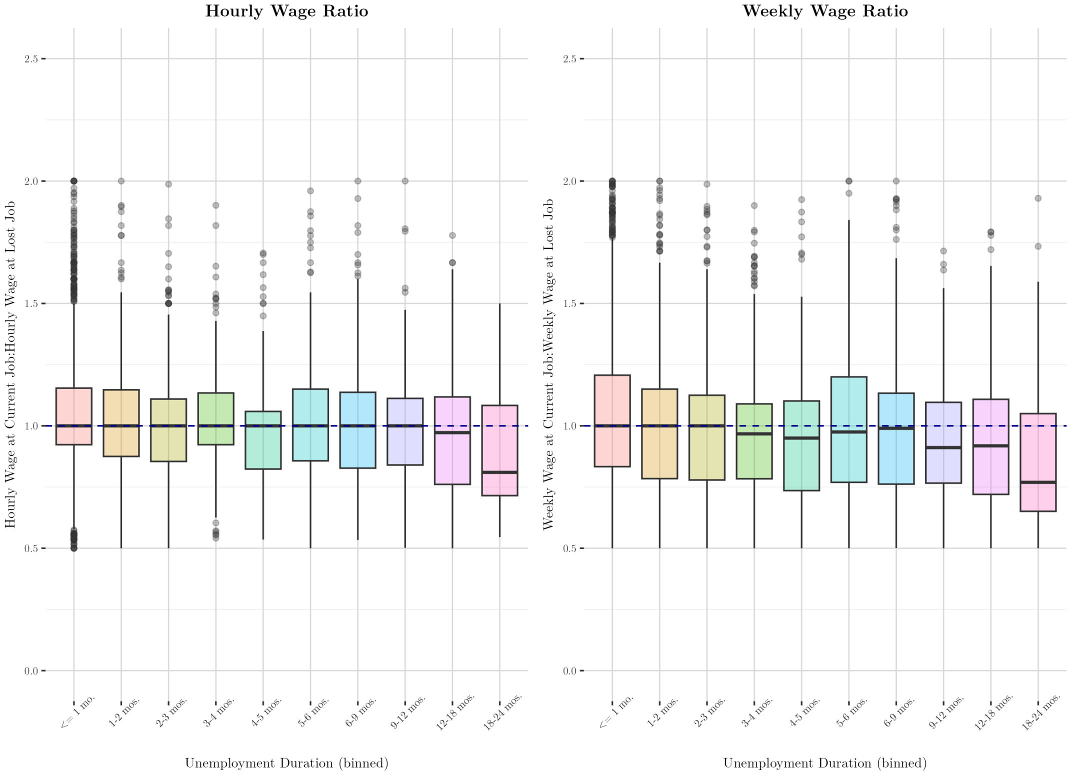
Box plots: Looking at the reported wage ratios in weekly and hourly values, the mean is fixed near 1 until >12 mos of unemployment in hourly wage reporting. In weekly wage reporting, the "satisficing" seems to start earlier in unemployment duration (sample size is larger for weekly reporting - might be worth focusing on those wages).

Scatter plot: I fit a linear and spline fit to the scatted plot of the wage ratio to unemployment duration before using the regression. Indicates decline in the wage ratio with unemployment duration that has a potentially non-linear fit.



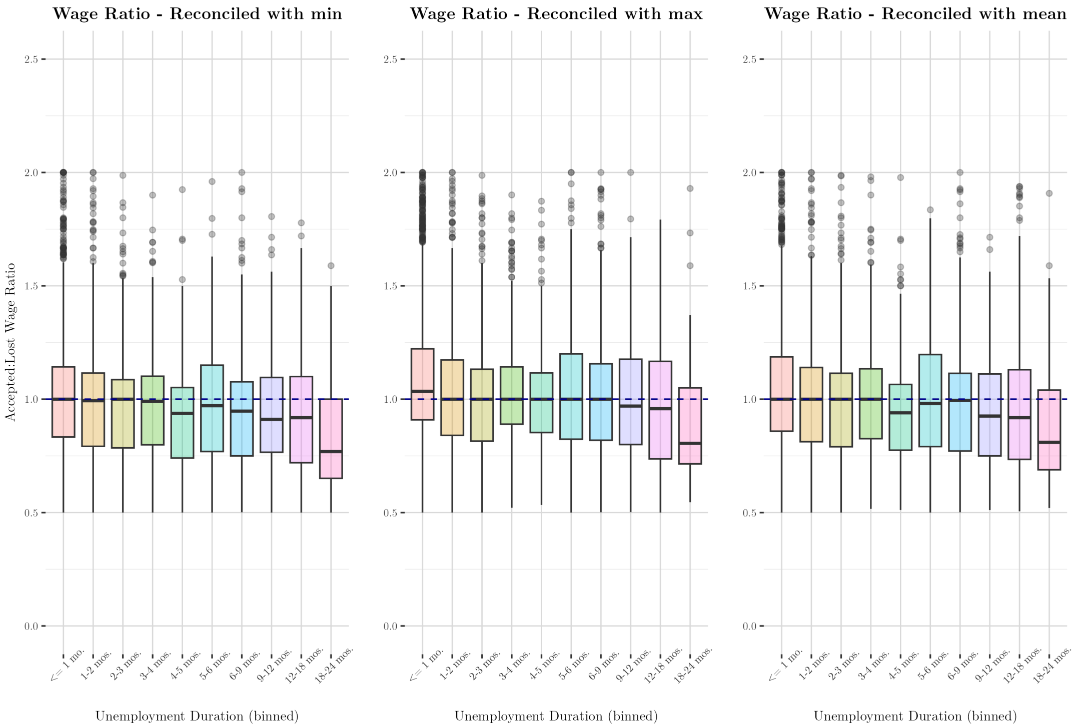
Reported ratio of current wage to lost wage by unemployment duration

Observations weighted by Displaced Worker Supplement Weights.
Annual data from 2000-2025.
Exclude observations reporting > 96 weeks of unemployment.



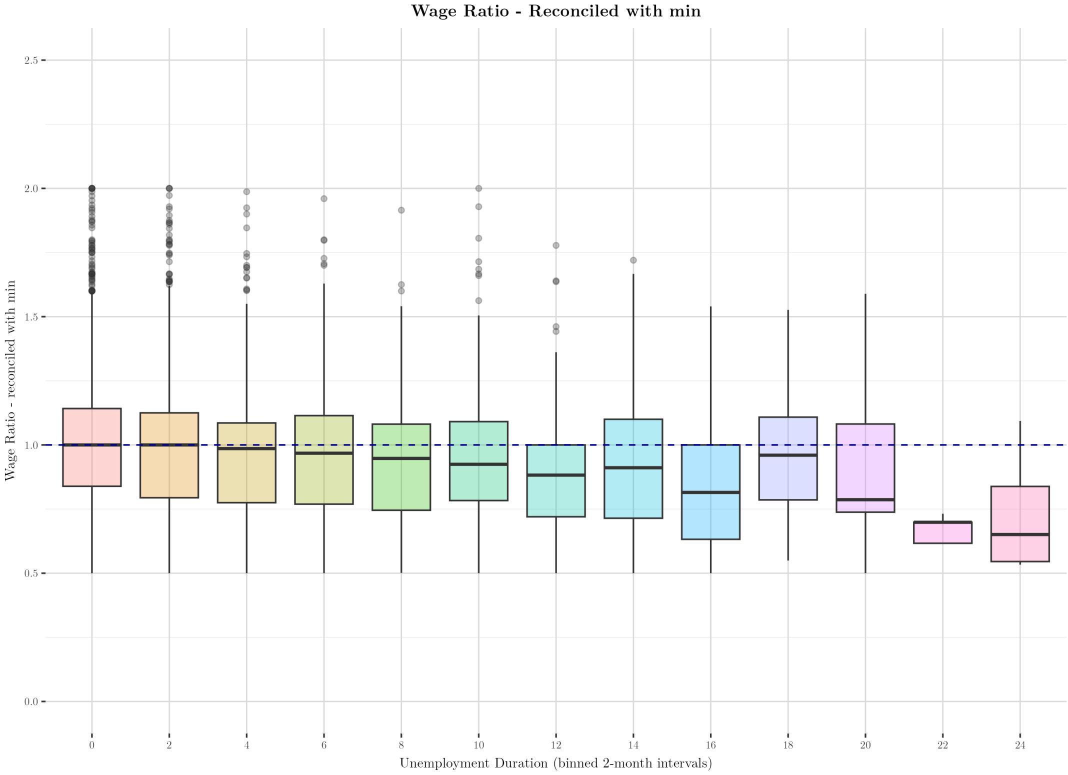
Reported ratio of current wage to lost wage by unemployment duration

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.



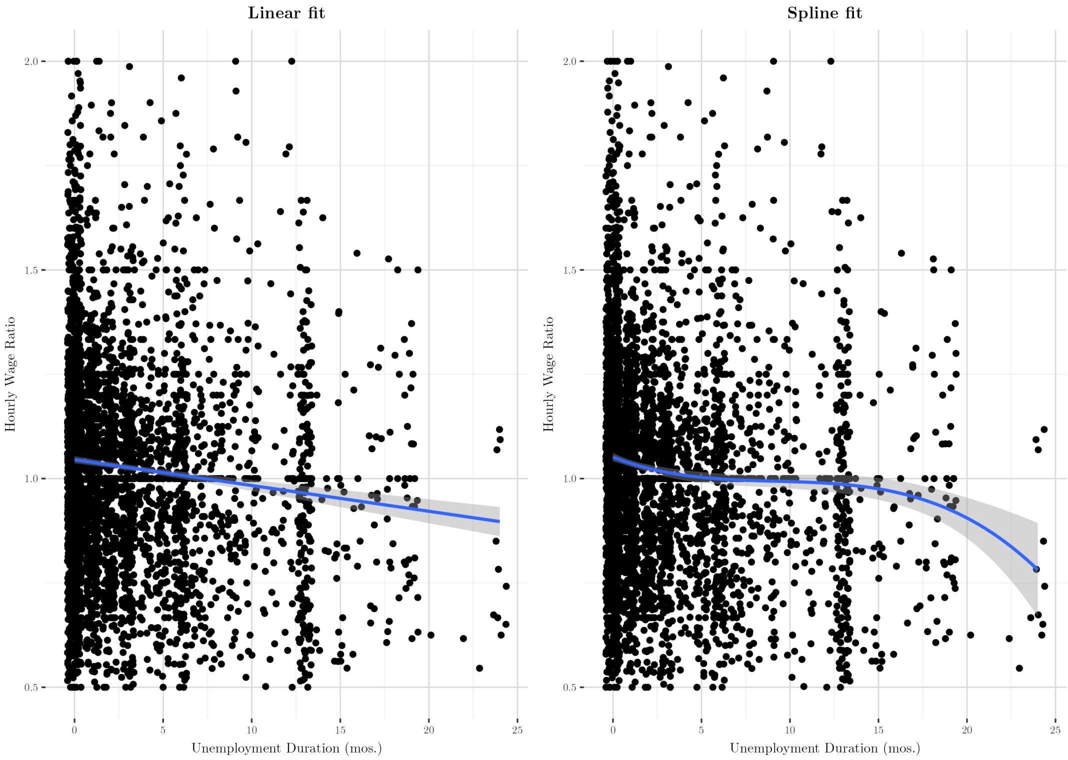
Reported ratio of current wage to lost wage by unemployment duration

Observations weighted by Displaced Worker Supplement Weights.
Annual data from 2000-2025.
Exclude observations reporting > 96 weeks of unemployment.



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 econometric specificaitons (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).

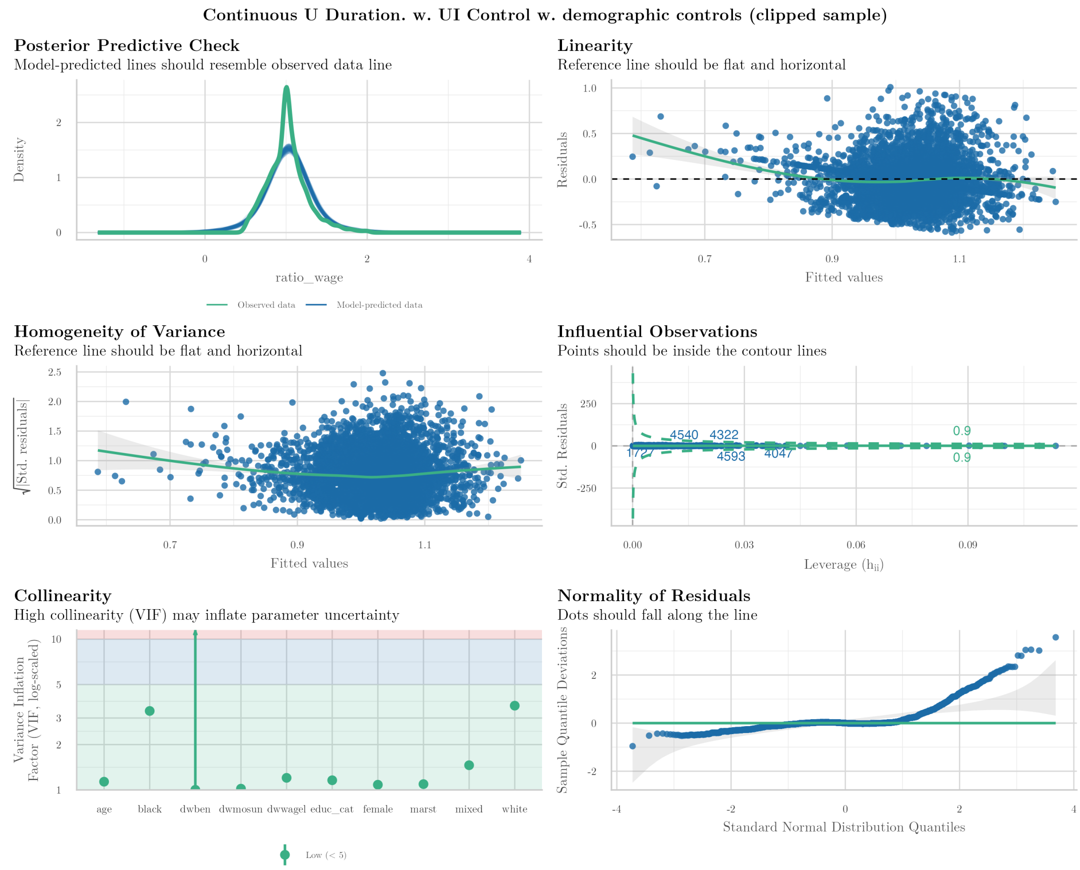
We present and compare 48 variations on the above model present with all combinations of the following:

- **Continuous vs. Discrete Treatment Variable (2 alternatives):** Continuous (monthly) versus binned unemployment duration.
- **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):** 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 in the tables below we see a consistently negative coefficient on unemployment duration (~0.7-1 percentage point increase in the wage ratio for each additional month spent in unemployment). If we look more closely at 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.



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 (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
							(0.011)	(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

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

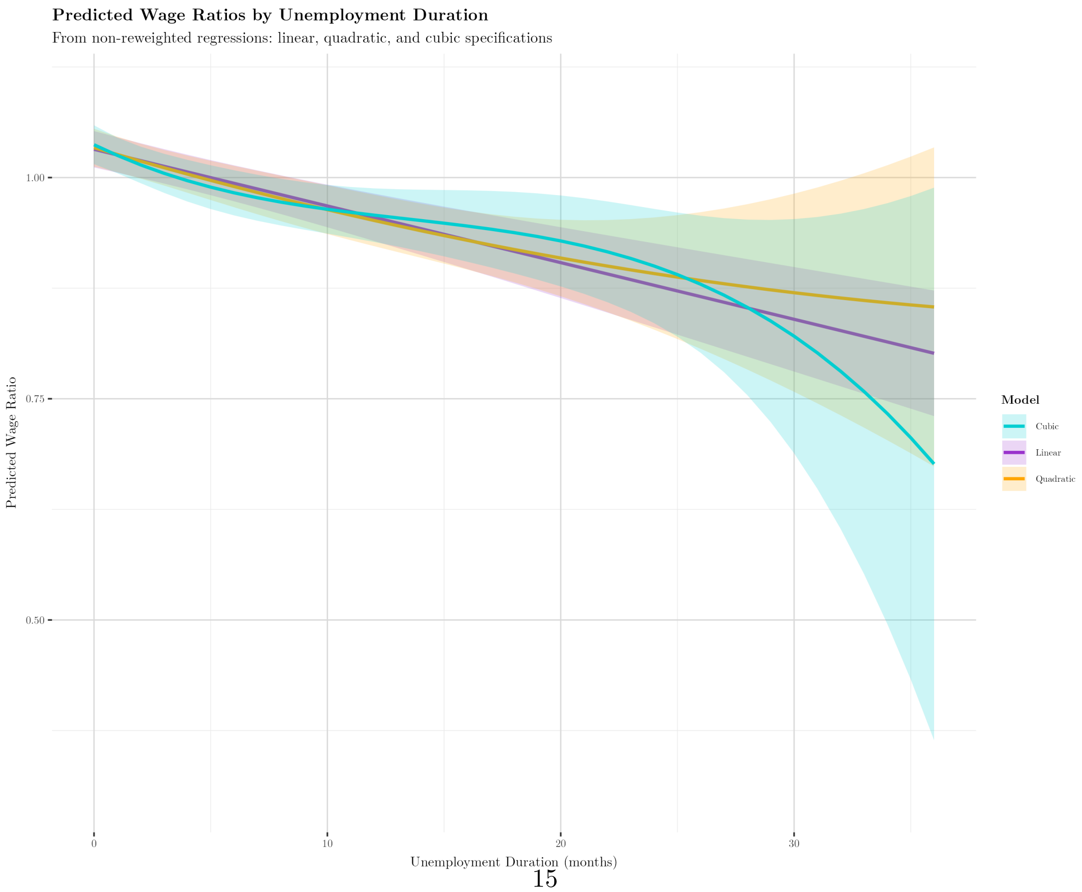


Table 3: Continuous UE Duration w. Wage Level Control (Clipped Sample)

	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

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 (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							−0.028**	−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.

Additional Considerations

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.

Selection Issues with 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.

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)

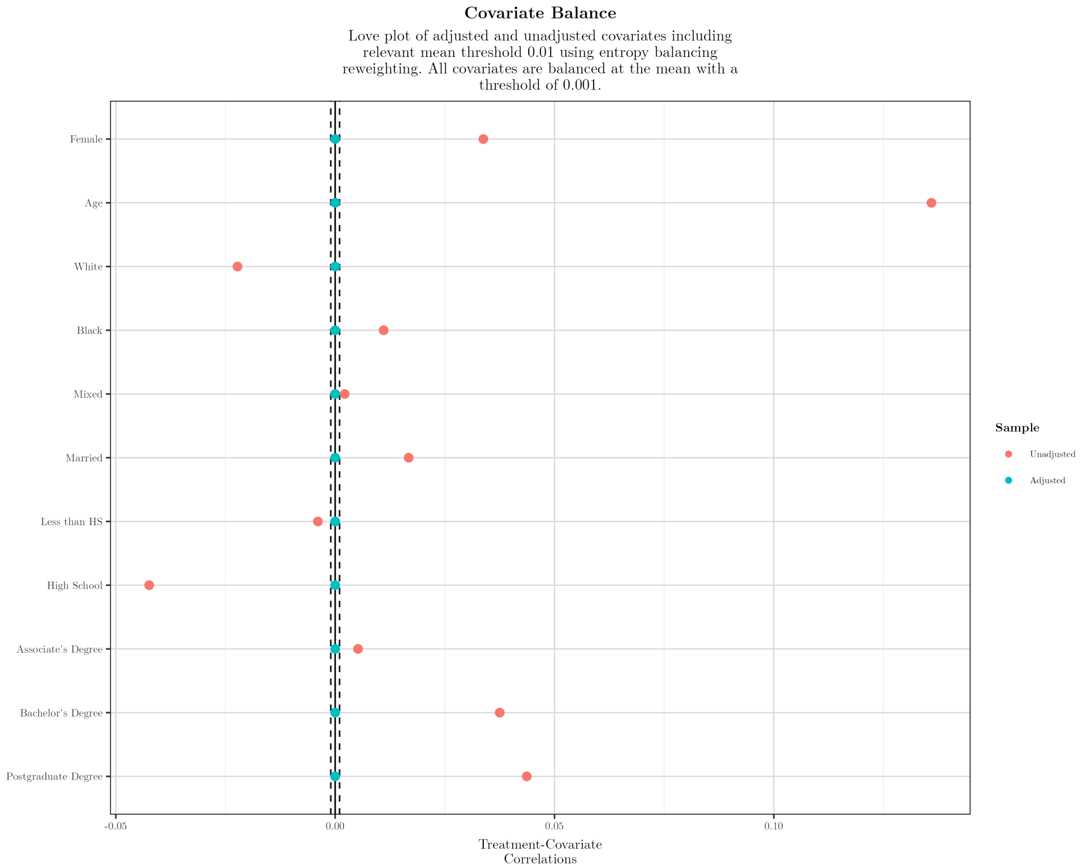
	Disc. (clipped)	Disc. w. UI (clipped)	Disc. w. exhausted UI (clipped)	Disc. w. controls (clipped)	Disc. w. UI w. controls (clipped)	Disc. w. exhausted UI w. controls (clipped)
Intercept	1.139***	1.139***	1.098***	1.224***	1.224***	1.176***
	(0.008)	(0.008)	(0.011)	(0.021)	(0.021)	(0.023)
Hourly Wage 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

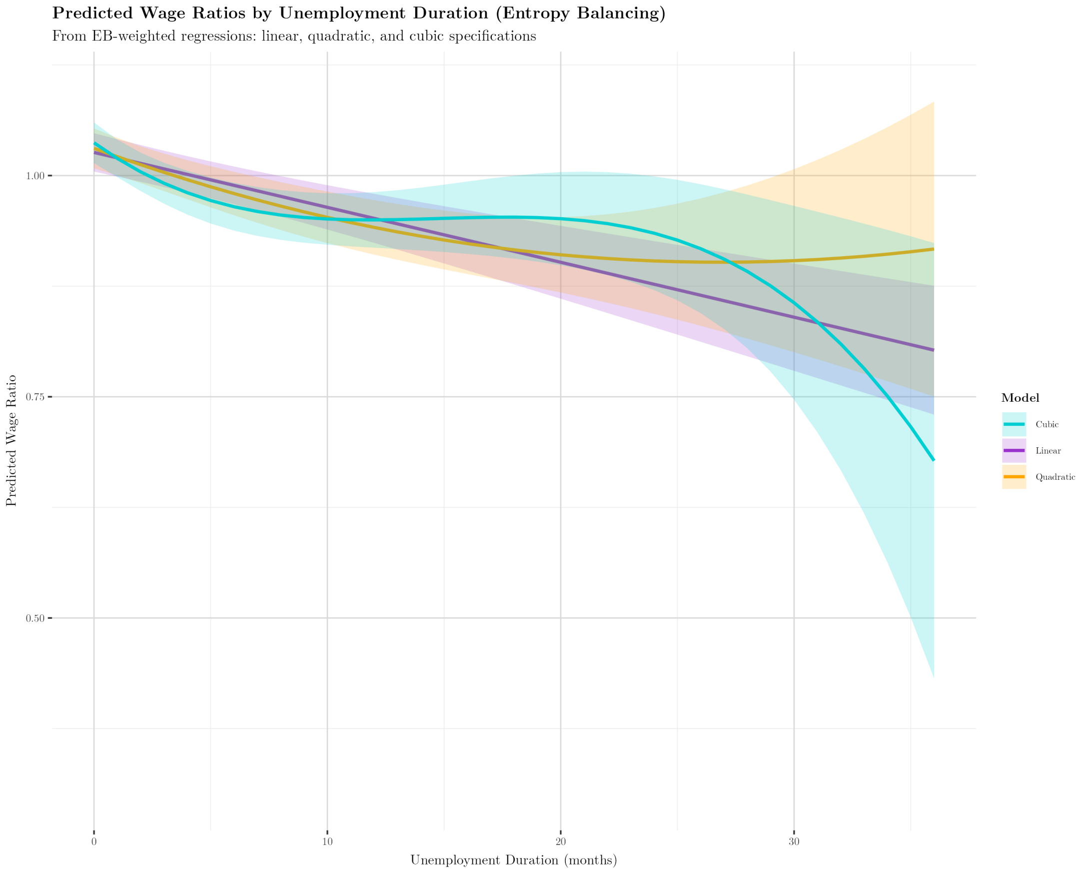
Table 8: Binned UE Duration w. Wage Level Control (Full Sample)

	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

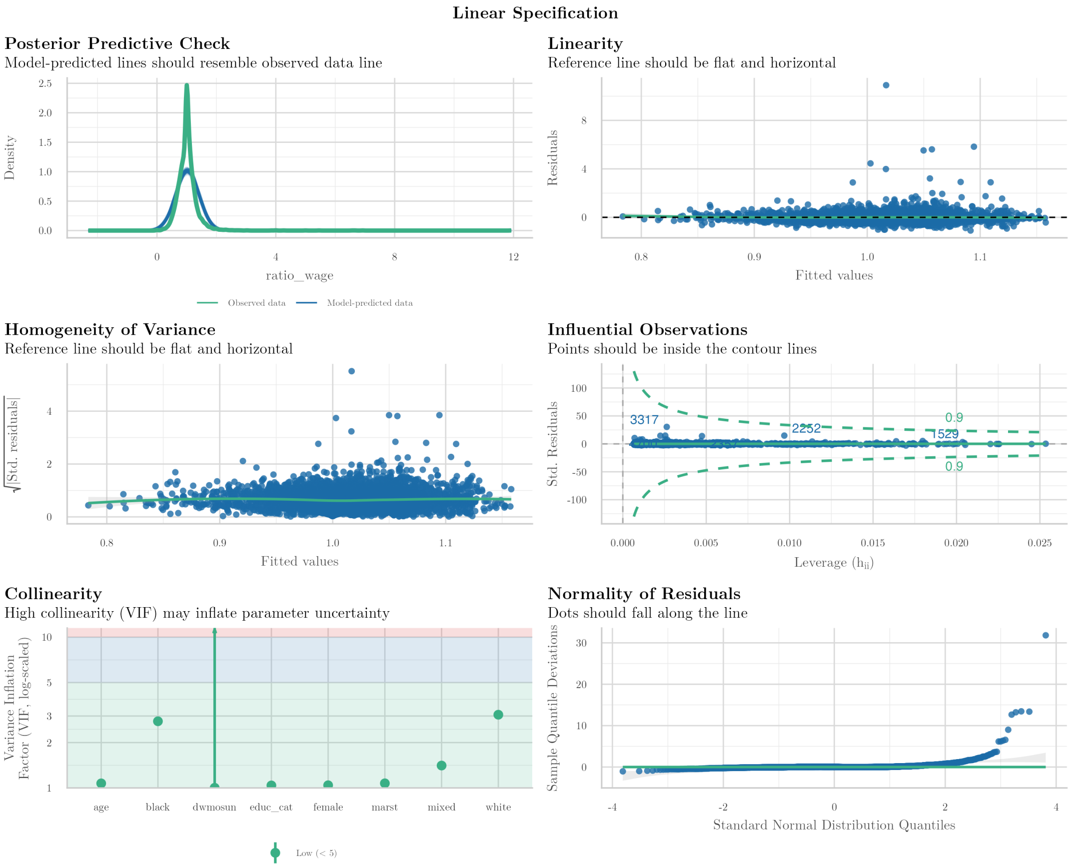
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

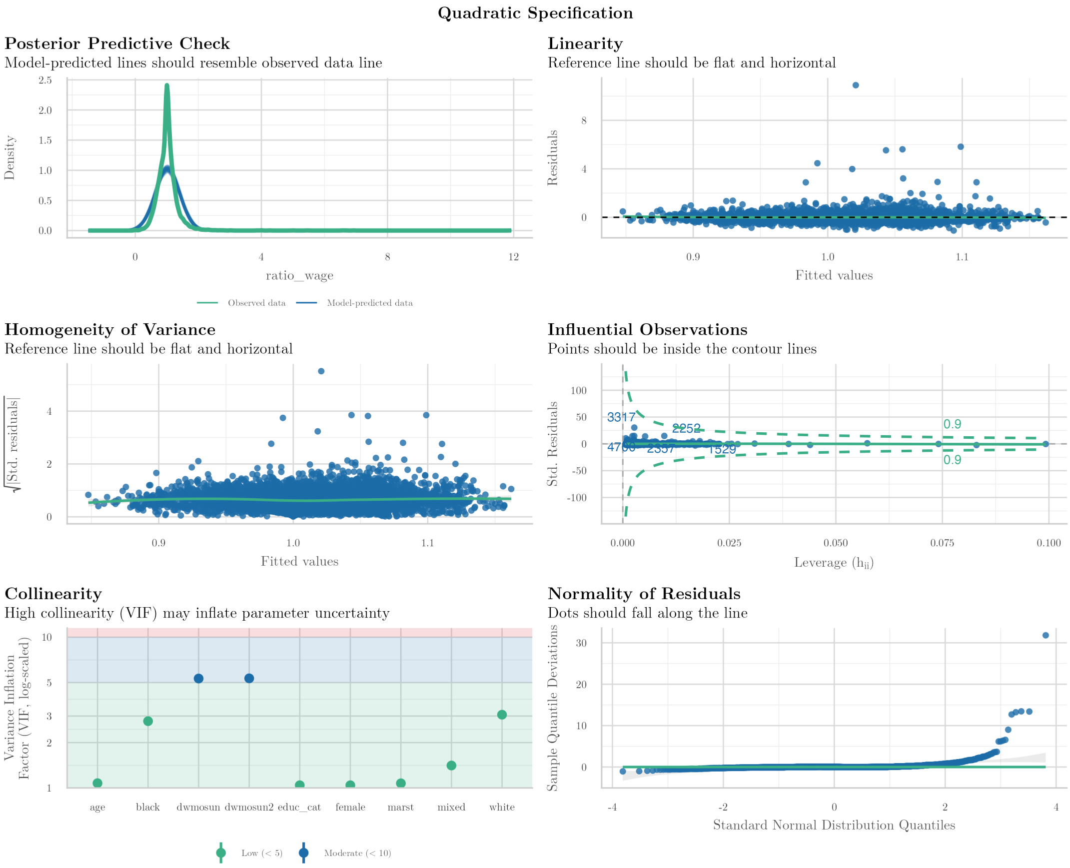


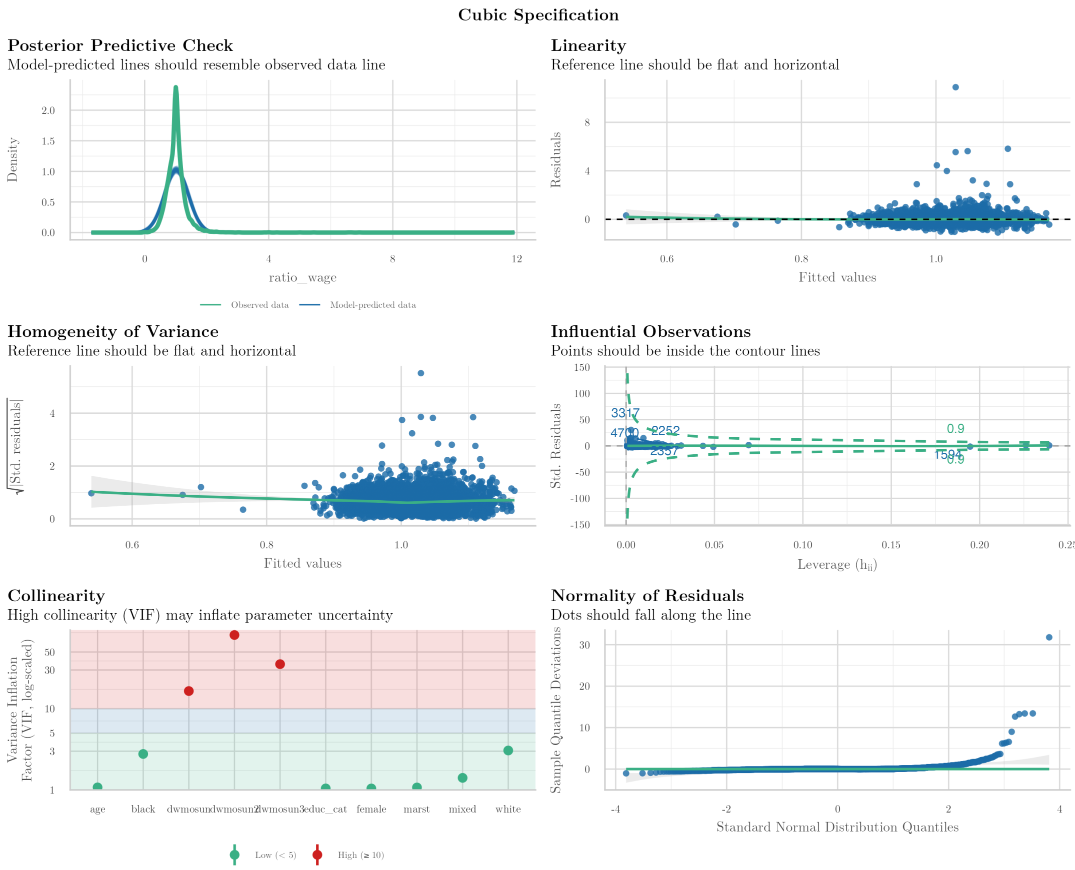
Covariate Balance
Love plot of adjusted and unadjusted covariates including relevant mean threshold 0.01 using entropy balancing reweighting. All covariates are balanced at the mean with a threshold of 0.001.
Female
Age
White
Black
Mixed
Married
Less than HS
High School
Associate's Degree
Bachelor's Degree
Postgraduate Degree
-0.05
0.00
0.05
0.10
Treatment-Covariate Correlations
Sample
Unadjusted
Adjusted



Diagnostic Tests for Entropy-balanced Reweighted Sample


Linear Specification
Posterior Predictive Check
Model-predicted lines should resemble observed data line
Density
ratio_wage
Observed data
Model-predicted data
Linearity
Reference line should be flat and horizontal
Residuals
Fitted values
Homogeneity of Variance
Reference line should be flat and horizontal
√|Std. residuals|
Fitted values
Influential Observations
Points should be inside the contour lines
Std. Residuals
Leverage (hii)
3317
2252
1529
0.9
0.9
Collinearity
High collinearity (VIF) may inflate parameter uncertainty
Variance Inflation Factor (VIF, log-scaled)
age
black
dwmosun
educ_cat
female
marst
mixed
white
Low (< 5)
Normality of Residuals
Dots should fall along the line
Sample Quantile Deviations
Standard Normal Distribution Quantiles

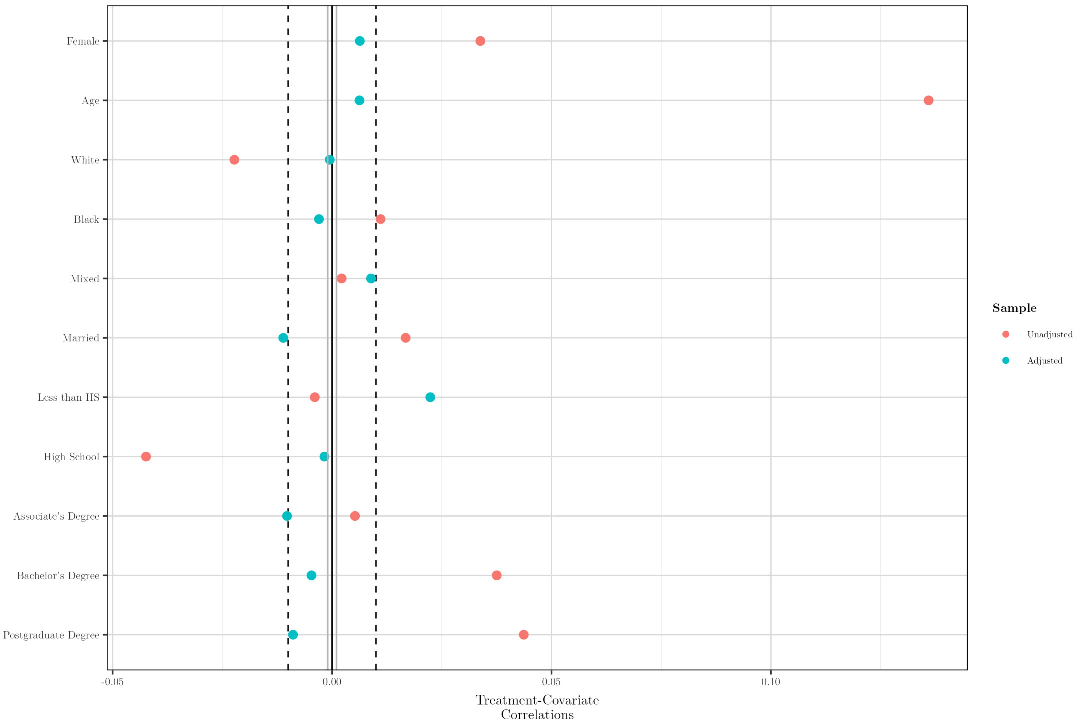

Quadratic Specification
Posterior Predictive Check
Model-predicted lines should resemble observed data line
Density
ratio_wage
Observed data
Model-predicted data
Linearity
Reference line should be flat and horizontal
Residuals
Fitted values
Homogeneity of Variance
Reference line should be flat and horizontal
√|Std. residuals|
Fitted values
Influential Observations
Points should be inside the contour lines
Std. Residuals
Leverage (hii)
Collinearity
High collinearity (VIF) may inflate parameter uncertainty
Variance Inflation Factor (VIF, log-scaled)
age
black
dwmosun
dwmosun2
educ_cat
female
marst
mixed
white
Low (< 5)
Moderate (< 10)
Normality of Residuals
Dots should fall along the line
Sample Quantile Deviations
Standard Normal Distribution Quantiles


Cubic Specification
Posterior Predictive Check
Model-predicted lines should resemble observed data line
Density
ratio_wage
Observed data
Model-predicted data
Linearity
Reference line should be flat and horizontal
Residuals
Fitted values
Homogeneity of Variance
Reference line should be flat and horizontal
√|Std. residuals|
Fitted values
Influential Observations
Points should be inside the contour lines
Std. Residuals
Leverage (h_{ii})
Collinearity
High collinearity (VIF) may inflate parameter uncertainty
Variance Inflation Factor (VIF, log-scaled)
age
black
educ_cat
female
marst
mixed
white
Low (< 5)
High (≥ 10)
Normality of Residuals
Dots should fall along the line
Sample Quantile Deviations
Standard Normal Distribution Quantiles

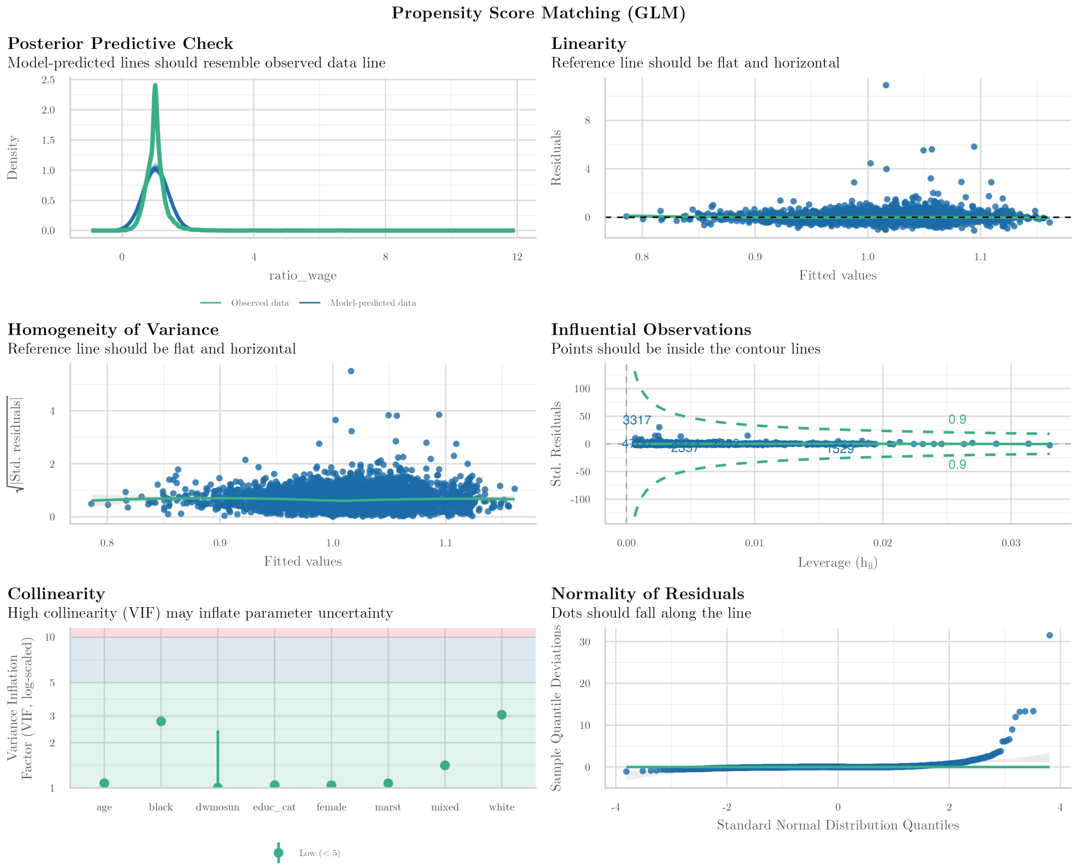
Propensity Score Weighting with GLM Estimator

Covariate Balance

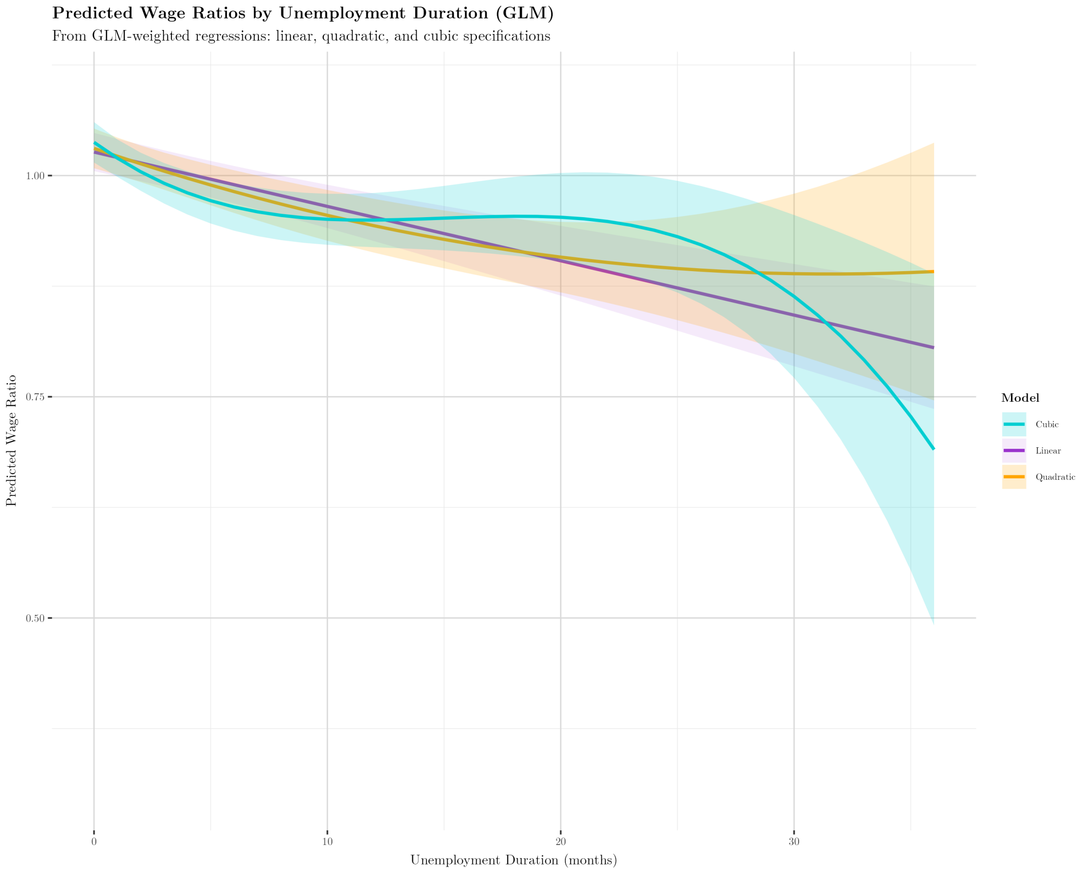
Love plot of adjusted and unadjusted covariates including relevant mean threshold 0.01 using a GLM estimator. All covariates except the binary indicator for having less than a HS degree level of education are balanced at the mean with a threshold of 0.01 (black dashed line) whereas very few variables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



Diagnostic Tests for Propensity Score Matching (GLM) Reweighted Sample

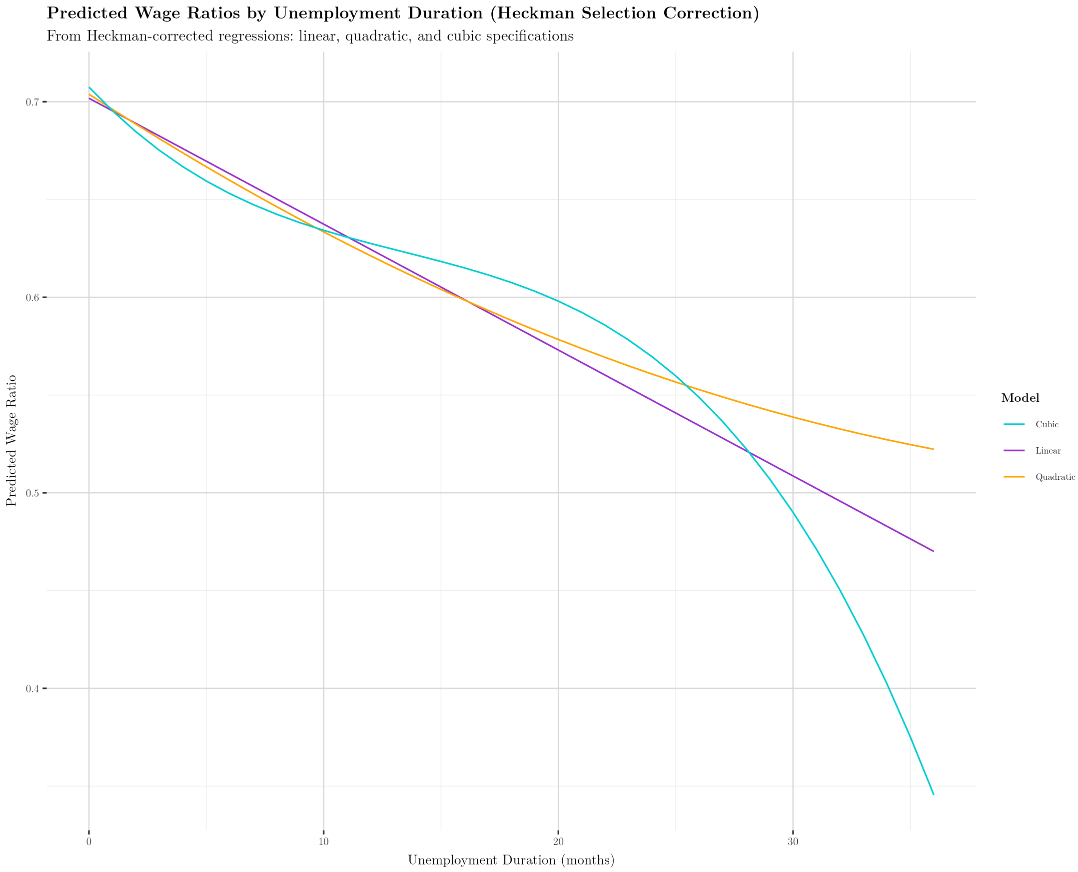


Predicted Reservation Wage using GLM Reweighted Sample



Heckman Selection

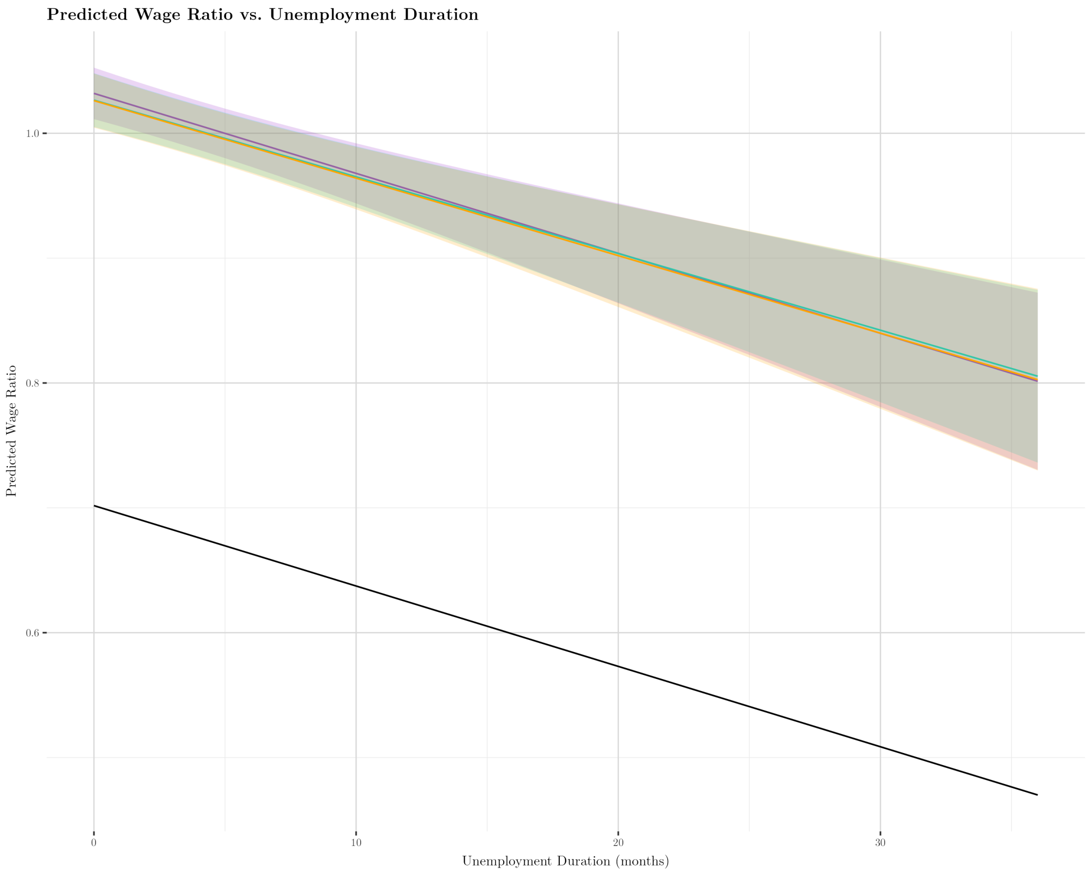
Another option is a Heckman Selection correction though I do not think this addresses the particular selection concern we have where there are simply less observations in longer unemployment durations.

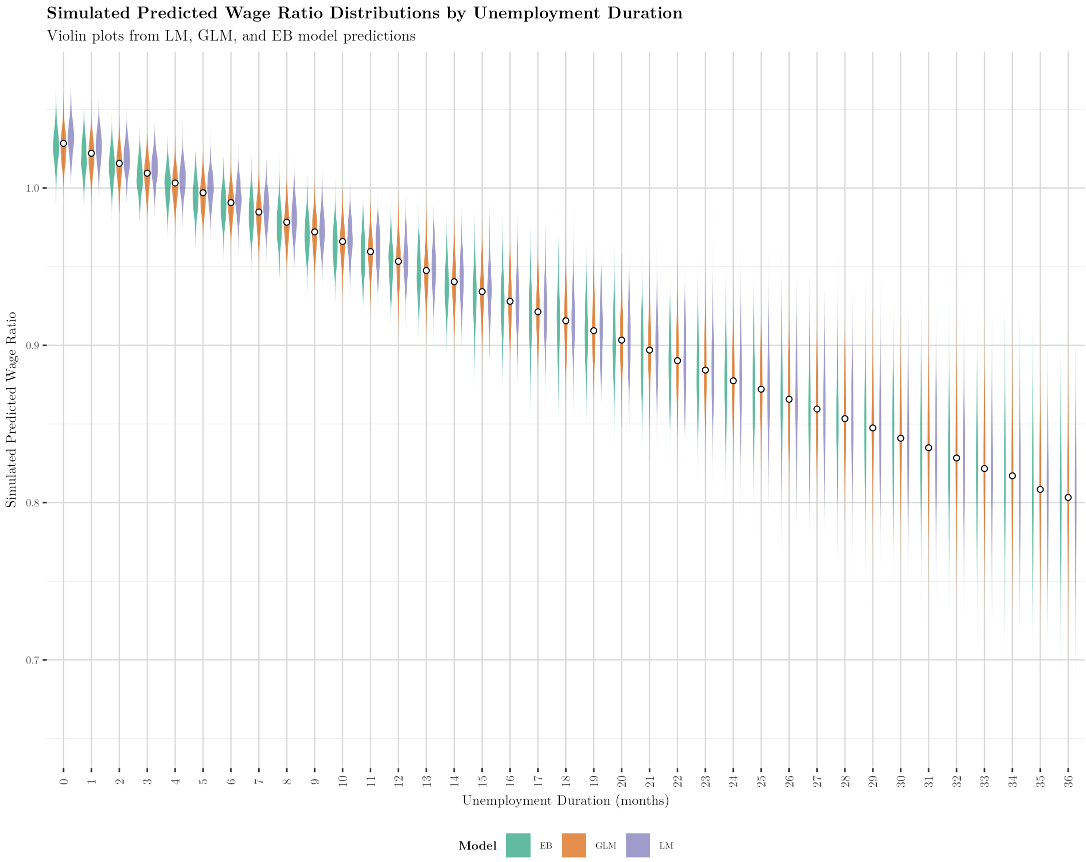

Predicted Wage Ratios by Unemployment Duration (Heckman Selection Correction)
From Heckman-corrected regressions: linear, quadratic, and cubic specifications
Predicted Wage Ratio
0.7
0.6
0.5
0.4
0
10
20
30
Unemployment Duration (months)
Model
Cubic
Linear
Quadratic

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

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

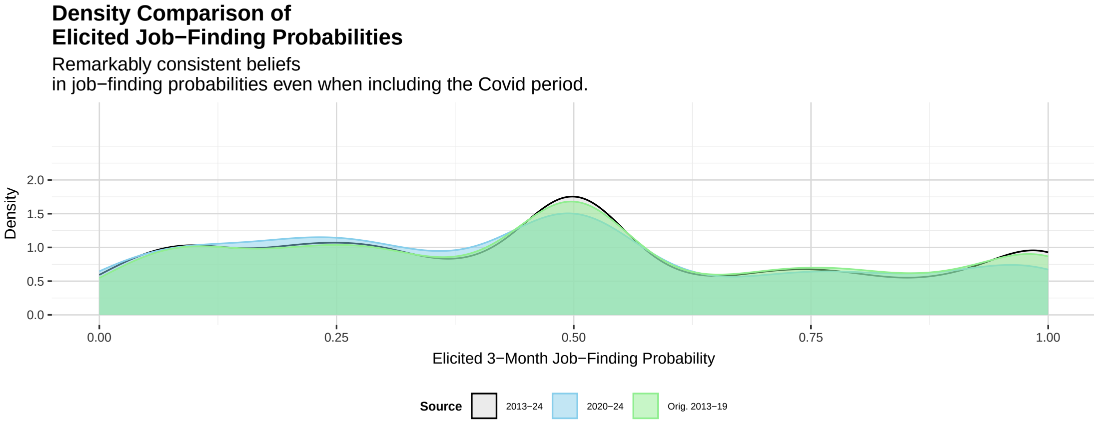
Regression Results with Sample Reweighting

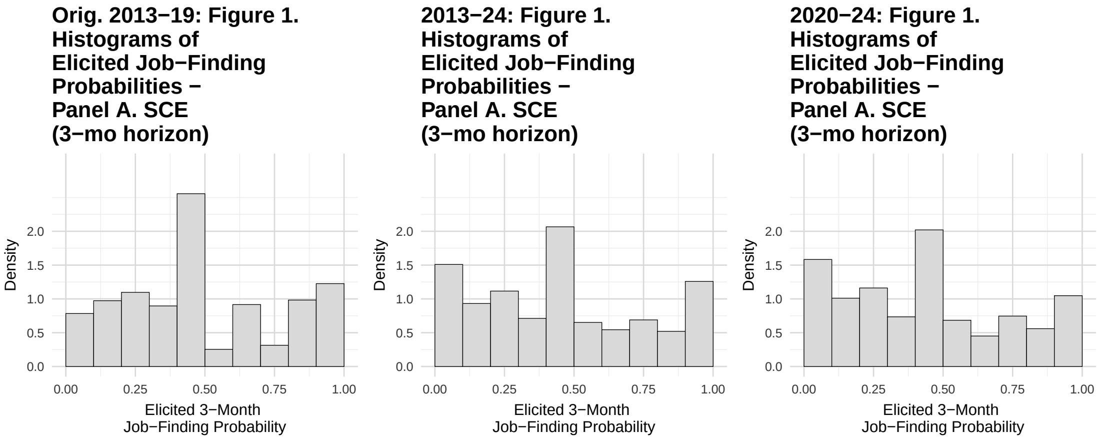




Job Tenure

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.



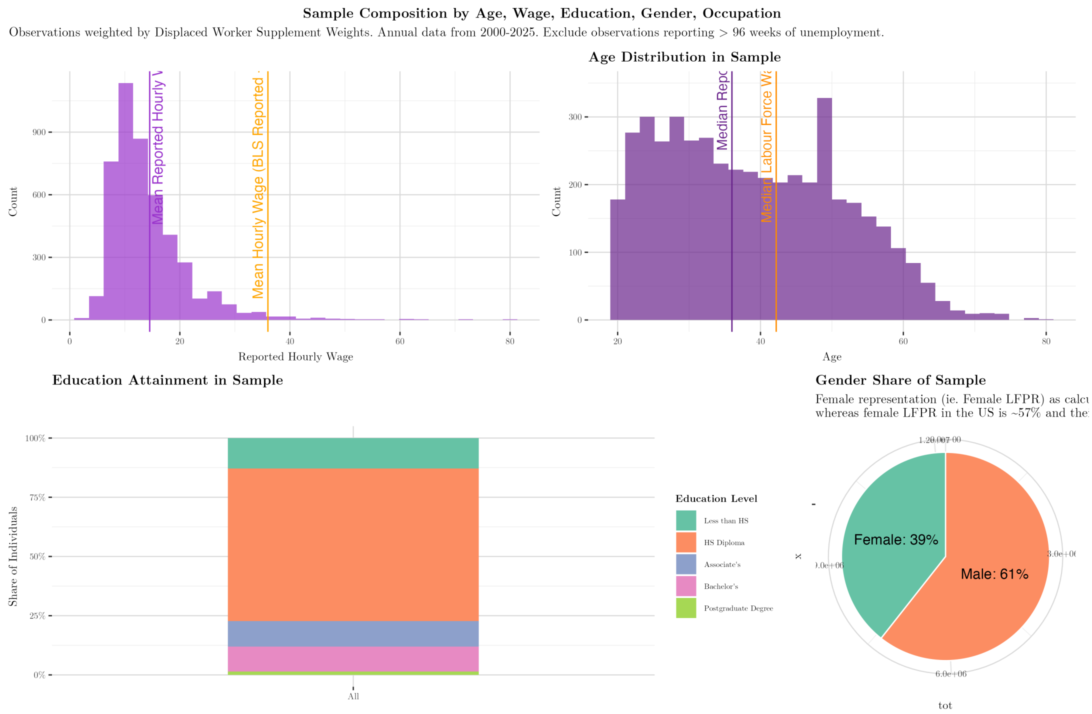


Representation

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, some (very rough) graphs to indicate what the sample looks like.

Headline result: it seems the sample over-represents below-mean wage earners and women. Age looks reasonably accurate (in relation to a simple median though....have not checked spread). Have not yet checked match to educational attainment. Individuals with only a HS diploma is strong majority in sample - not sure how accurate this is (likely correlated with wage however...so this might be cause for concern and confirm a skewed sample in that sense).

If we wish to pursue this data, I could improve on the below but it will have to do for now.



OTJ Search

Eeckhout et al. 2019 Unemployment Cycles

Source

3. Eeckhout et al. 2019 Unemployment Cycles: 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).

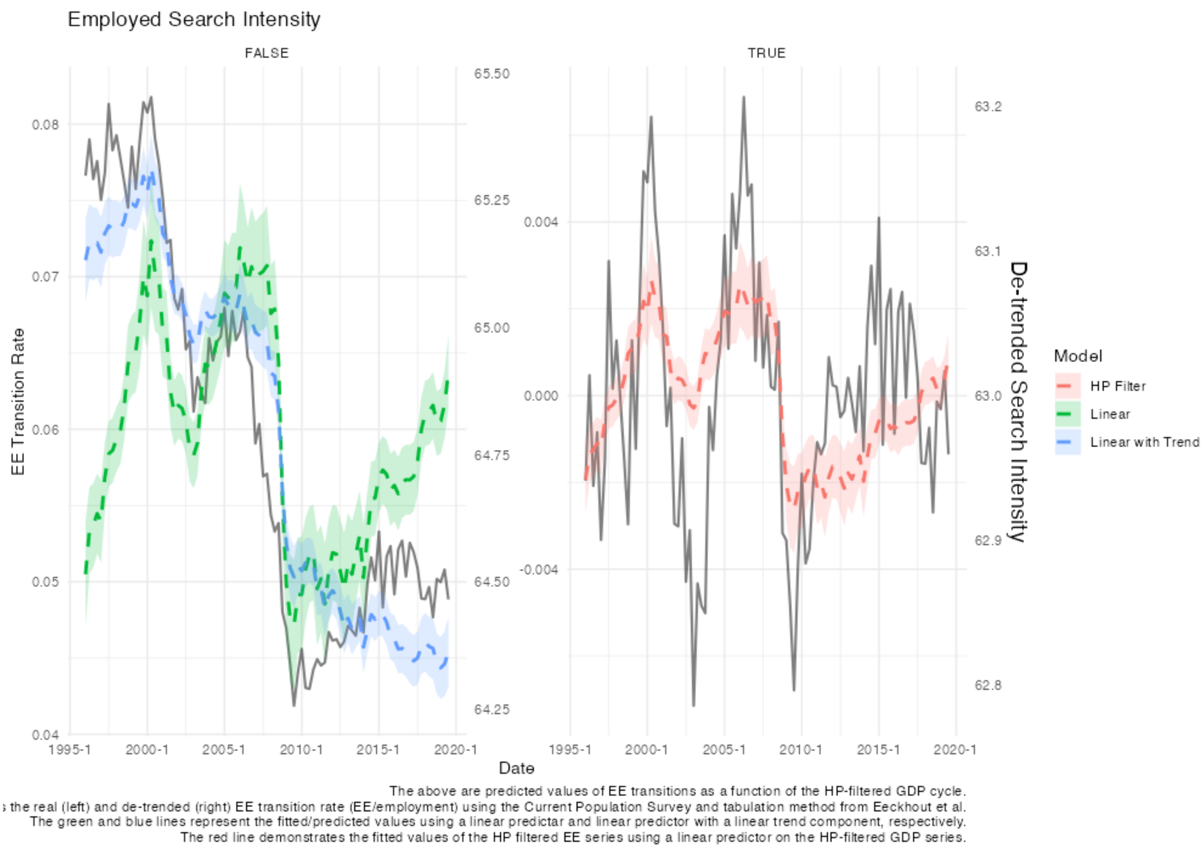
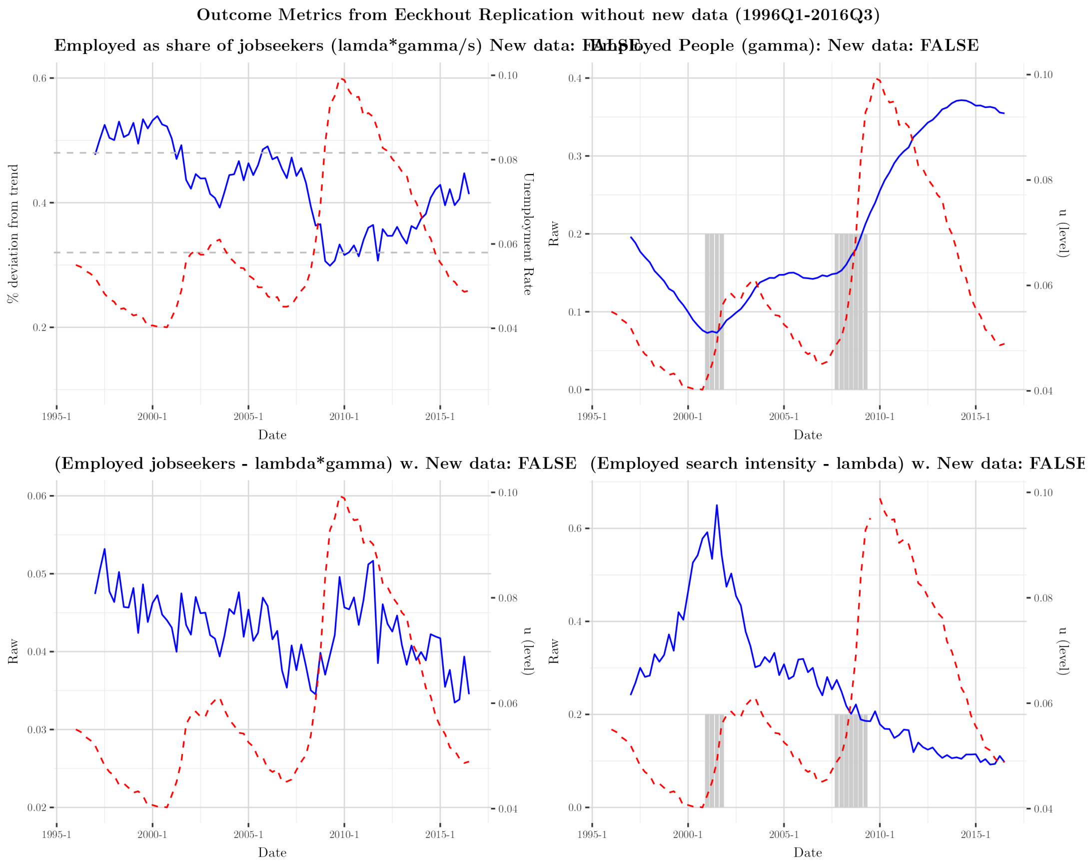
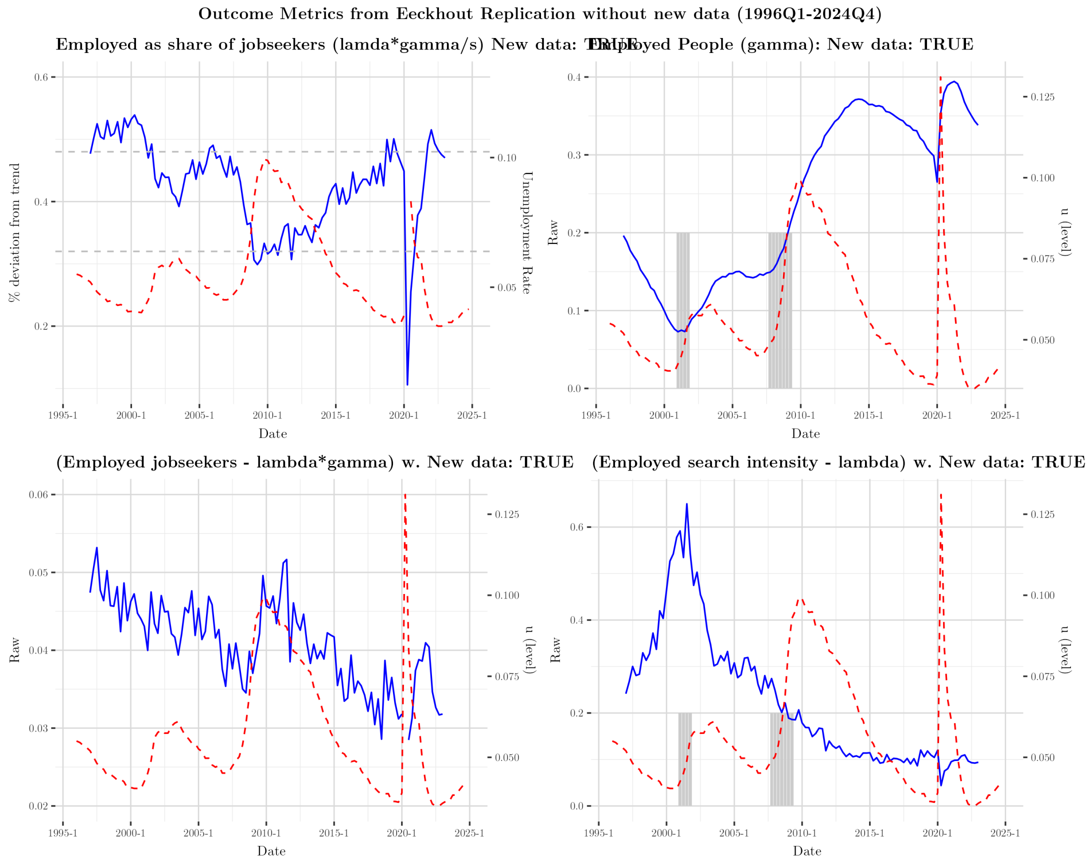


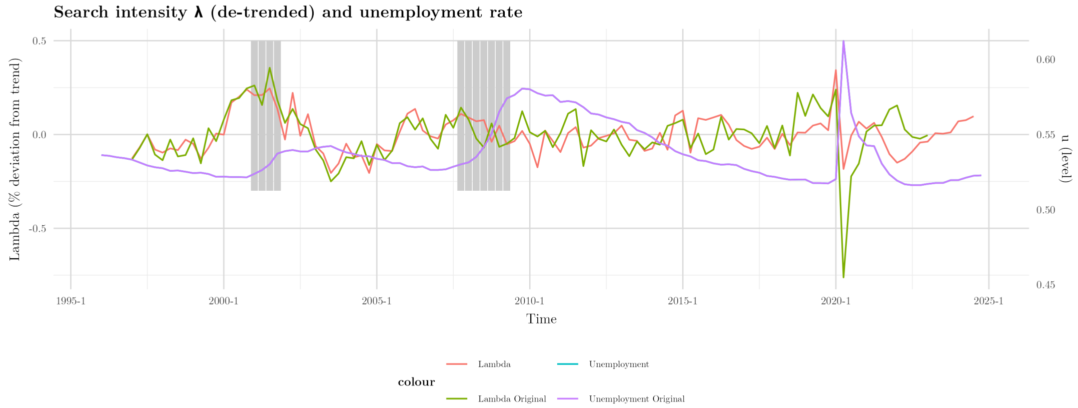
Figure 2: Employed Search Effort Fit

	Linear	Linear with Trend	HP Filter
(Intercept)	−0.174***	−0.053**	−0.049***
	(0.035)	(0.018)	(0.008)
x	0.233***	0.129***	0.049***
	(0.035)	(0.017)	(0.008)
trend		0.000***	
		(0.000)	
Num.Obs.	95	95	95
R2	0.323	0.854	0.282
R2 Adj.	0.315	0.851	0.275
AIC	−594.7	−738.3	−872.6
BIC	−587.0	−728.1	−865.0
Log.Lik.	300.334	373.173	439.307
F	44.309	268.734	36.593
RMSE	0.01	0.00	0.00

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




Outcome Metrics from Eeckhout Replication without new data (1996Q1-2024Q4)
Employed as share of jobseekers (lamda*gamma/s) New data: TRUE
Employed People (gamma): New data: TRUE
% deviation from trend
Unemployment Rate
Raw
u (level)
Date
(Employed jobseekers - lambda*gamma) w. New data: TRUE
(Employed search intensity - lambda) w. New data: TRUE
1995-1
2000-1
2005-1
2010-1
2015-1
2020-1
2025-1



Supporting Data for Validation

Mukoyama et al. Job Search and the Business Cycle

4. (Validation) Mukoyama et al. data on the intensive margin of unemployed search effort (in minutes searched) over the business cycle. We have chosen to include this as a validation exercise of our application effort imposition.

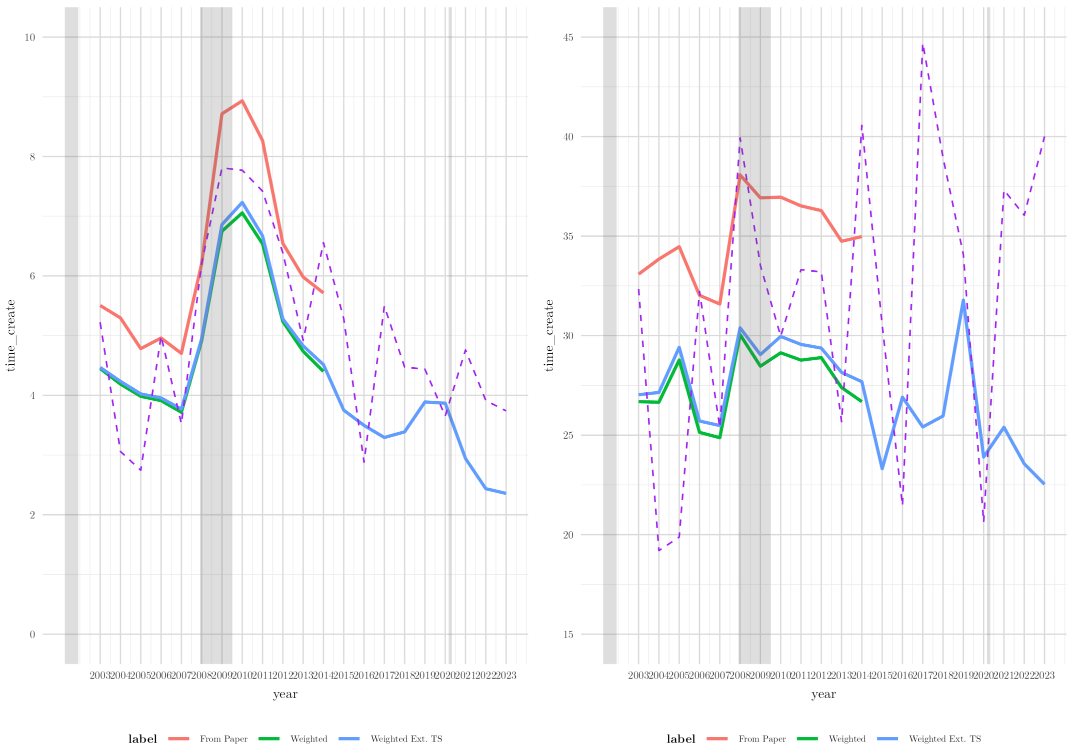
We use evidence from Mukoyama et al regarding the cyclicality of unemployed job search effort to validate the micro behaviour of our agents. I will provide more explanation on this...

(Replicated with additional data for unemployed jobseekers) **Mukoyama et al. 2018: Job Search Over the Business Cycle**

They 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!). At the moment, I think this will be the most useful input for our model.

Abstract: We examine the cyclicality of search effort using time-series, cross-state, and individual variation and find that it is countercyclical. We then set up a search and matching model with endogenous search effort and show that search effort does not amplify labor market fluctuations but rather dampens them. Lastly, we examine the role of search effort in driving recent unemployment dynamics and show that the unemployment rate would have been 0.5 to 1 percentage points higher in the 2008–2014 period had search effort not increased.

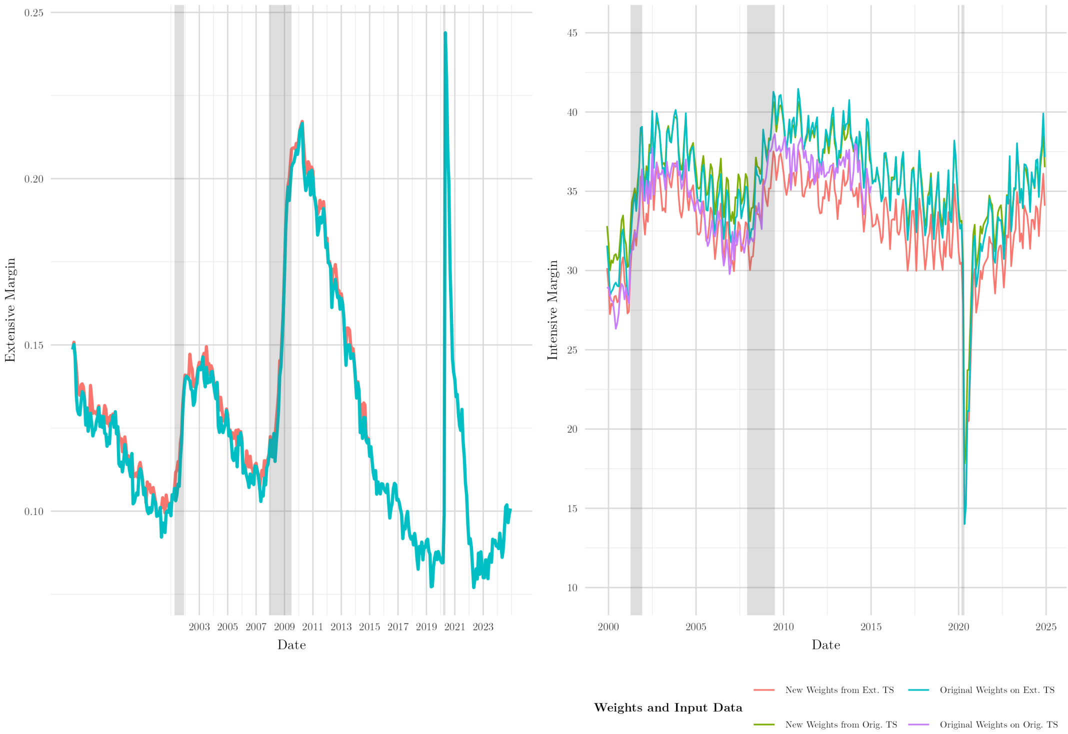
**Figure 2. Actual and Imputed Average Search Time (minutes per day)
for All Nonemployed Workers (panel A) and Unemployed Workers (panel B)**



Notes: Regressions are estimated in the ATUS from 2003–2014.
:ls A and B plot the fitted values from the sample regression, panel A plots the actual and imputed search time for all nonemployed, while panel B plots them for just the unemployed.
Observations are weighted by their ATUS sample weight.

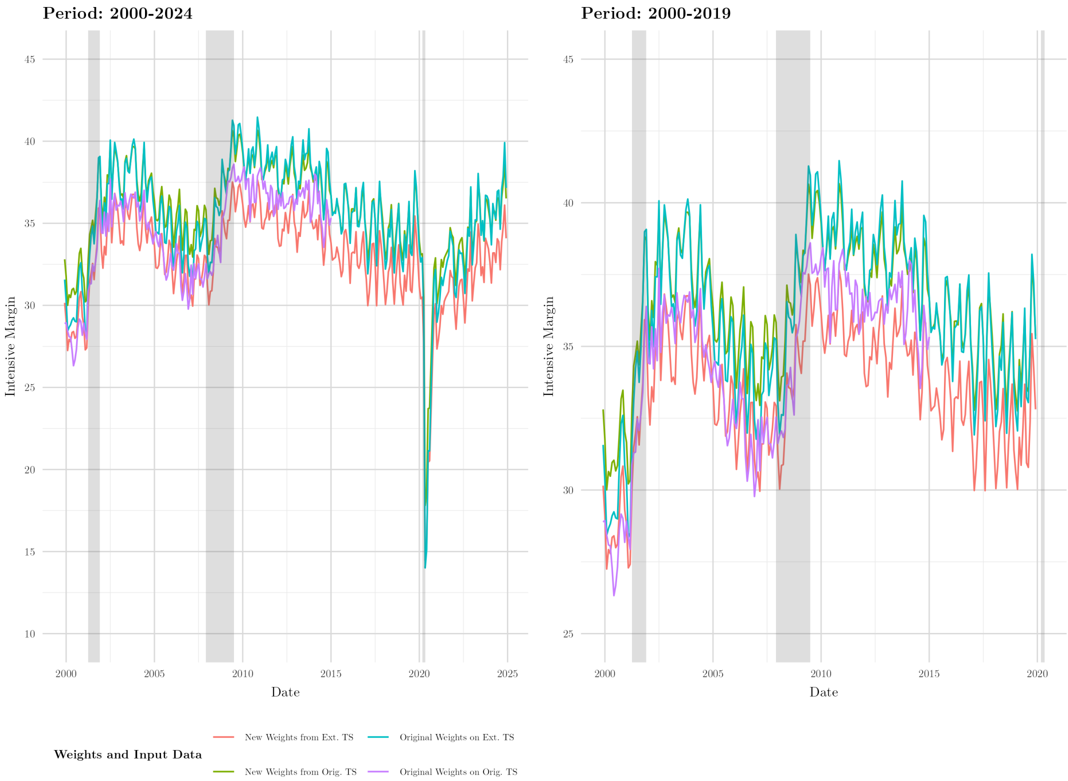
Figure 3. The Time Series of the Extensive Margin (U/(U + N)) (panel A) and the Intensive Margin (panel B), Measured by the Average Minutes of Search per Day for Unemployed Workers

Period: 2000-2024



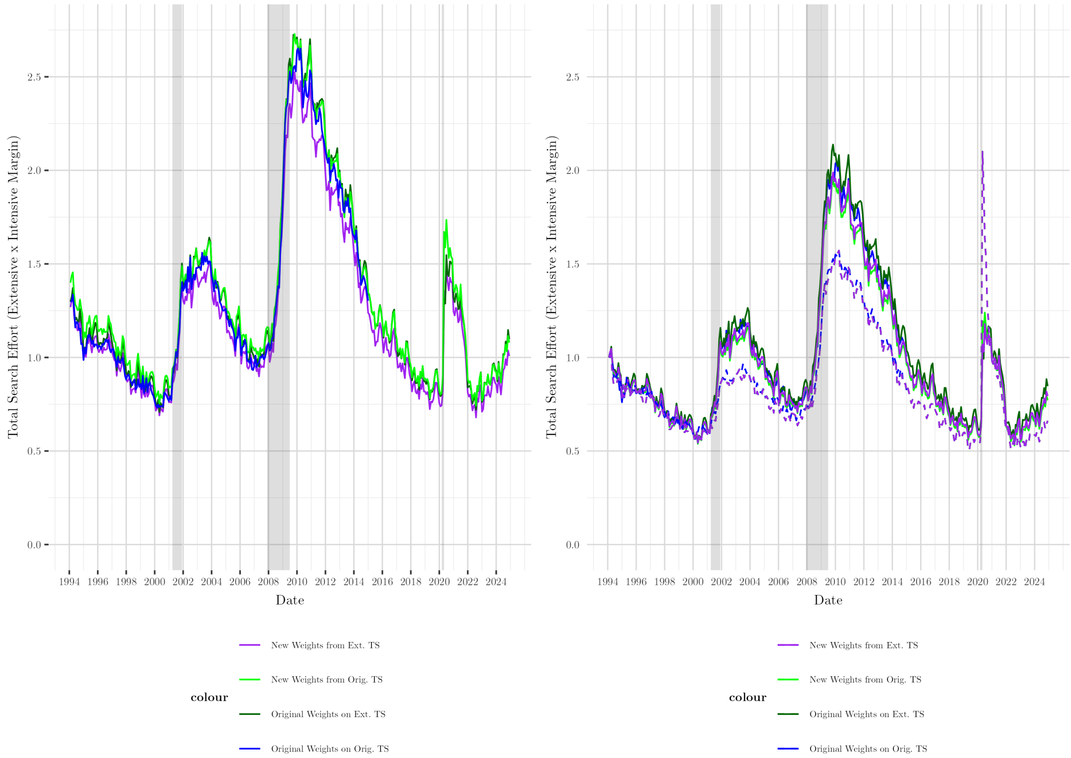
Red data is new data. Notes: Panel A plots the monthly ratio of the number of unemployed (U) to the total number of unemployed (U + N) in the CPS from 1994–2014.

Intensive Margin Measured by the Average Minutes of Search per Day for Unemployed Workers



Plots the average minutes of search per day,using the imputed minutes as a function of search methods used. Each observation is weighted by its CPS sample weight.

Figure 4. Time Series of (Panel A) Total Search Effort and (Panel B) Total Search Effort Using the Search Time of Unemployed Workers [solid: (s*(U/(E + U + N))] versus Using the Number of Unemployed Workers [dashed: U/(E + U + N)) (panel B)



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

Mueller et al: Job Seekers' Perceptions and Employment Prospects

5. **Mueller et al. 2021: Job Seekers' Perceptions and Employment Prospects: Heterogeneity, Duration Dependence and Bias**

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 jobseekers from true duration dependence. Ultimately, they find that dynamic selection selection explains most of the negative duration dependence (rather than pure, true duration dependence).

Findings: Results are remarkably consistent even when including additional data from 2019-2024. The below results replicate the findings in Mueller et al and extend the analysis to include a longer time series. Plot and regression table titles have been maintained for easy comparison.

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 created by stargazer v.5.2.3 by Marek Hlavac, Social Policy Institute. E-mail: marek.hlavac at gmail.com % Date and time: Tue, Jan 06, 2026 - 04:21:21

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

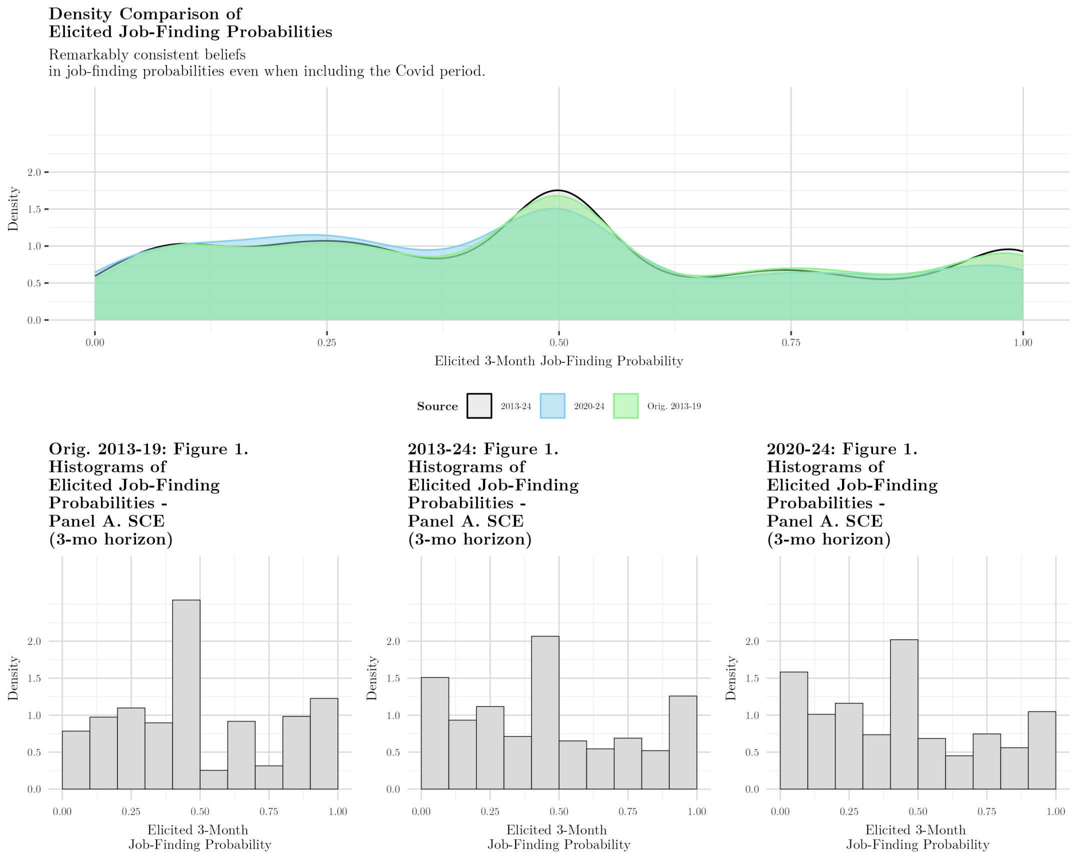
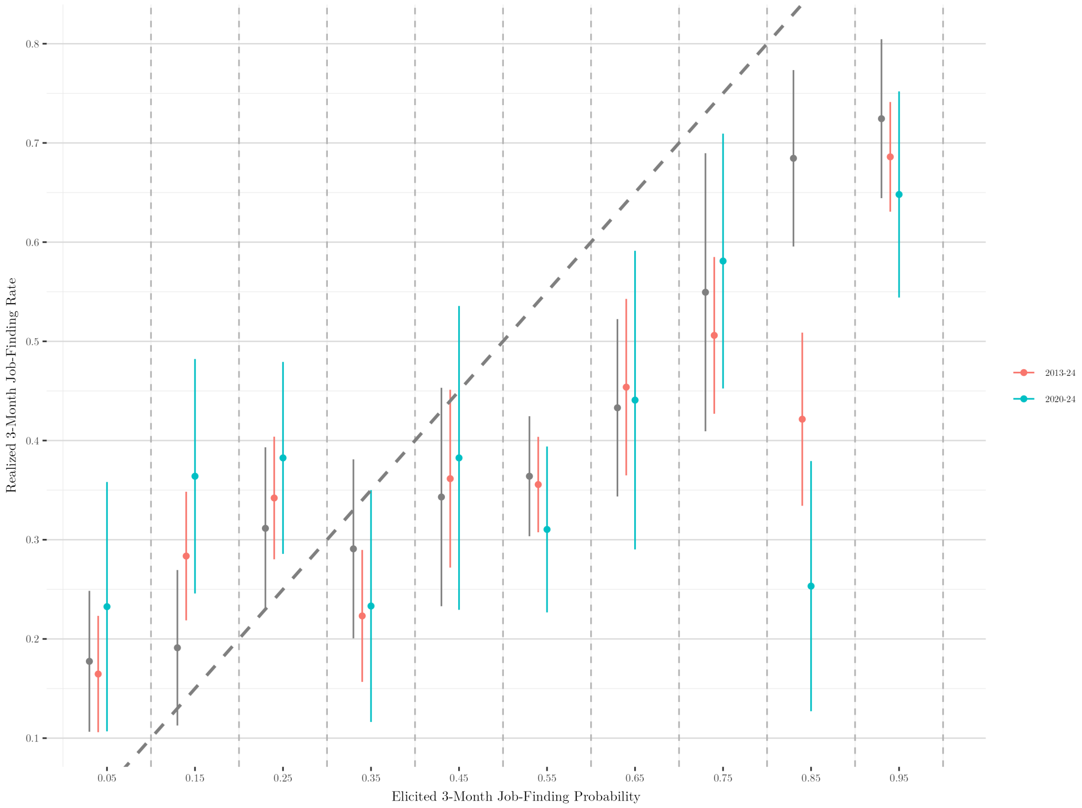


Figure 2: Averages of Realized Job-Finding Rates, by Bins of Elicited Probabilities (SCE)

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



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% Table created by stargazer v.5.2.3 by Marek Hlavac, Social Policy Institute. E-mail: marek.hlavac at gmail.com % Date and time: Tue, Jan 06, 2026 - 04:21:22

% Table created by stargazer v.5.2.3 by Marek Hlavac, Social Policy Institute. E-mail: marek.hlavac at gmail.com % Date and time: Tue, Jan 06, 2026 - 04:21:22

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.

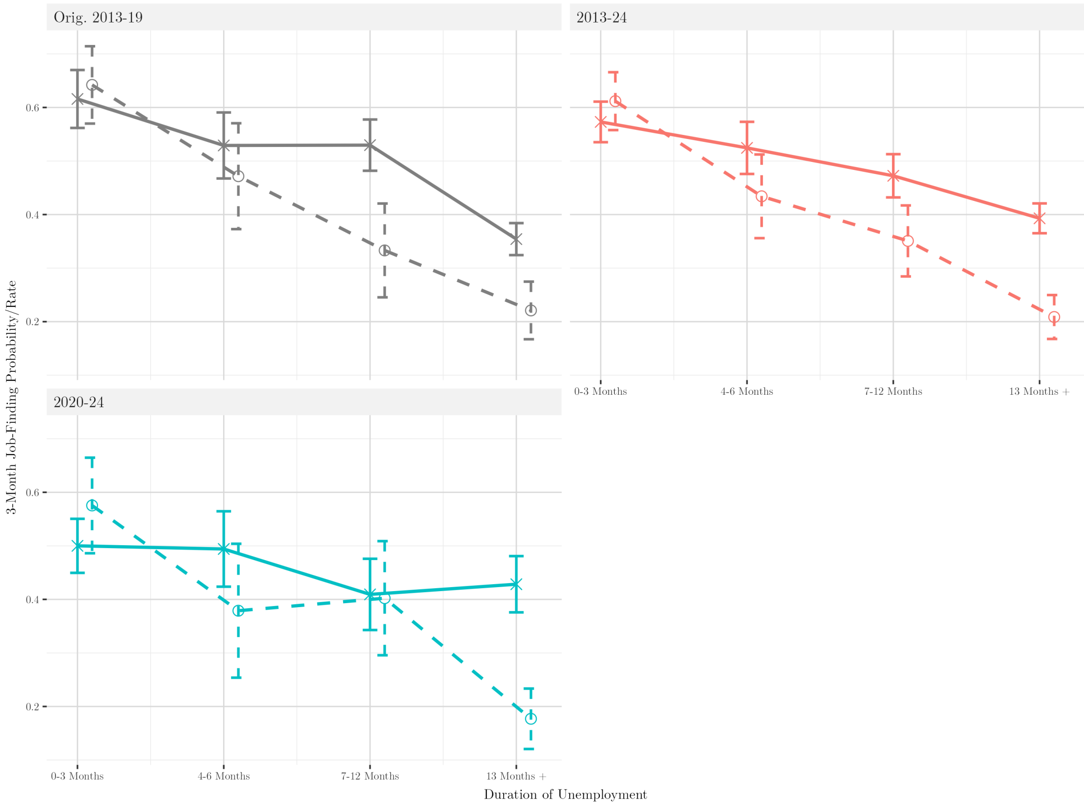


Fig 3. Perceived vs. Realized Job Finding, by Duration of Unemployment

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

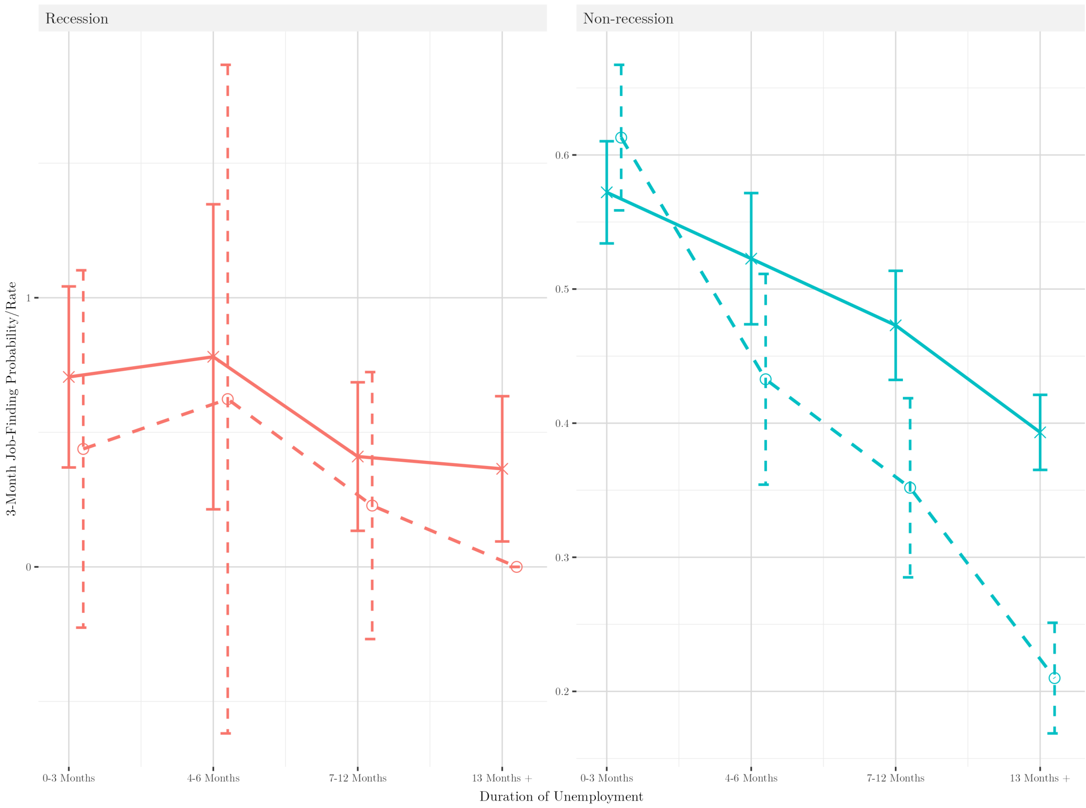


Fig 4. Changes in Job-Finding Probability Across and Within Spells

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.

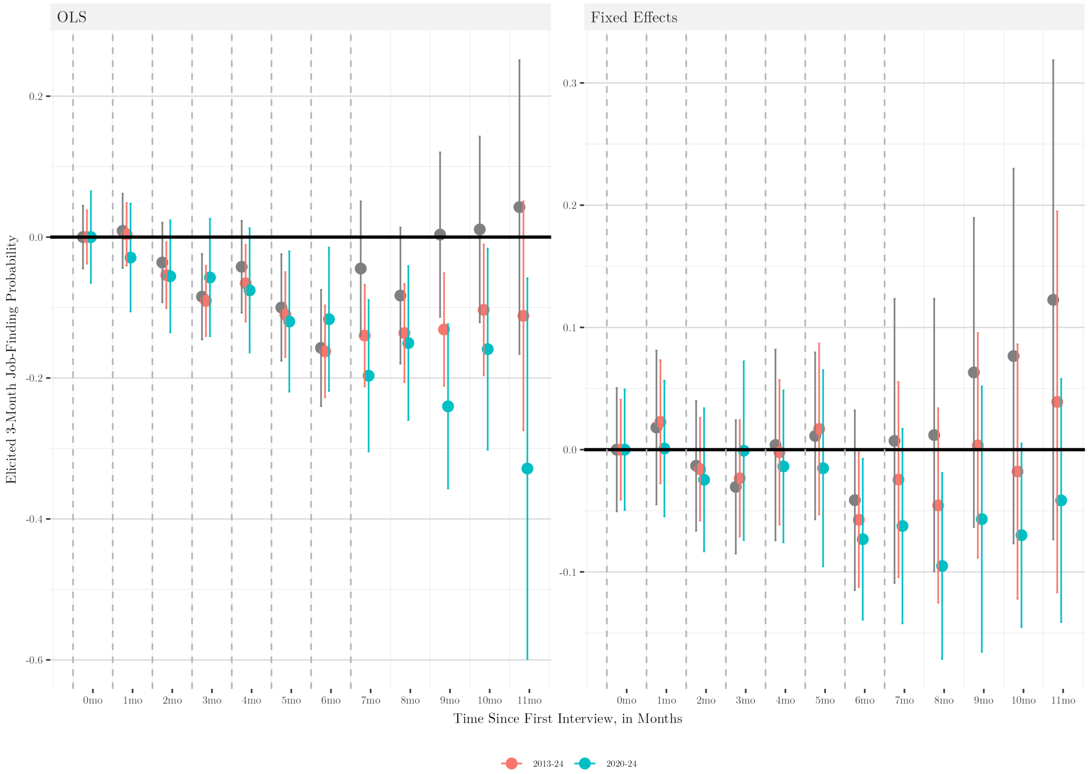


Fig 3. Perceived vs. Realized Job Finding, by Duration of Unemployment

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

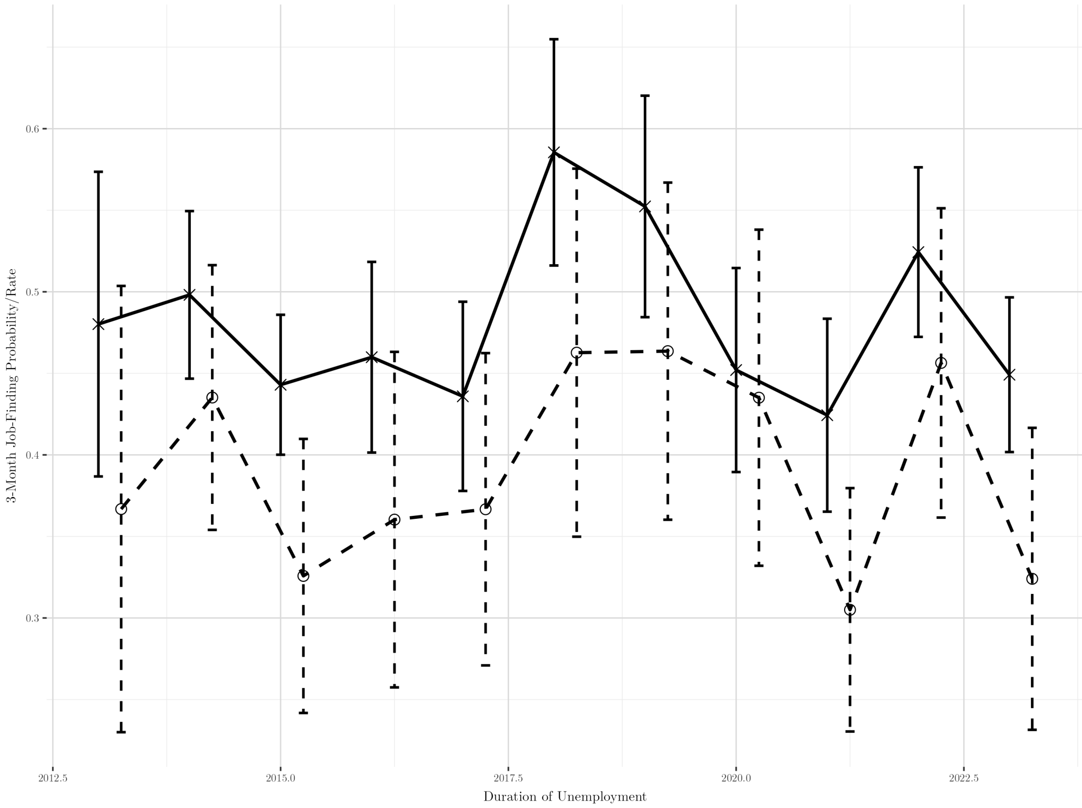
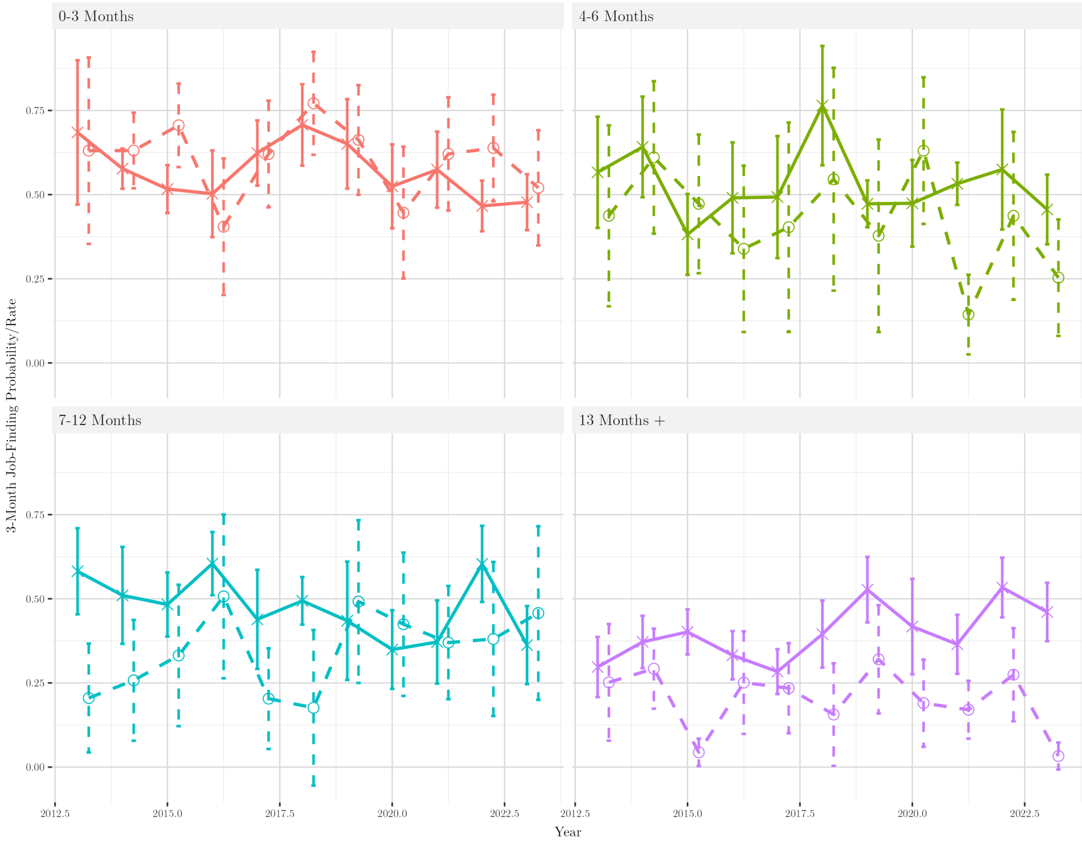


Fig 3. Perceived and Realized Job Finding, by Year



Additional Analyses

SCE Labor Market Survey: Reservation Wages

Survey of Consumer Expectations Reservation Wages, Accepted Wages, and Wage Expectations The data is unfortunately sparse and linking outcomes to reservation wages is difficult. However, in a cross-sectional setting we are able to deduce some weak relationships between Unemployment Duration and Absolute Reservation Wages and Wage Expectations.*

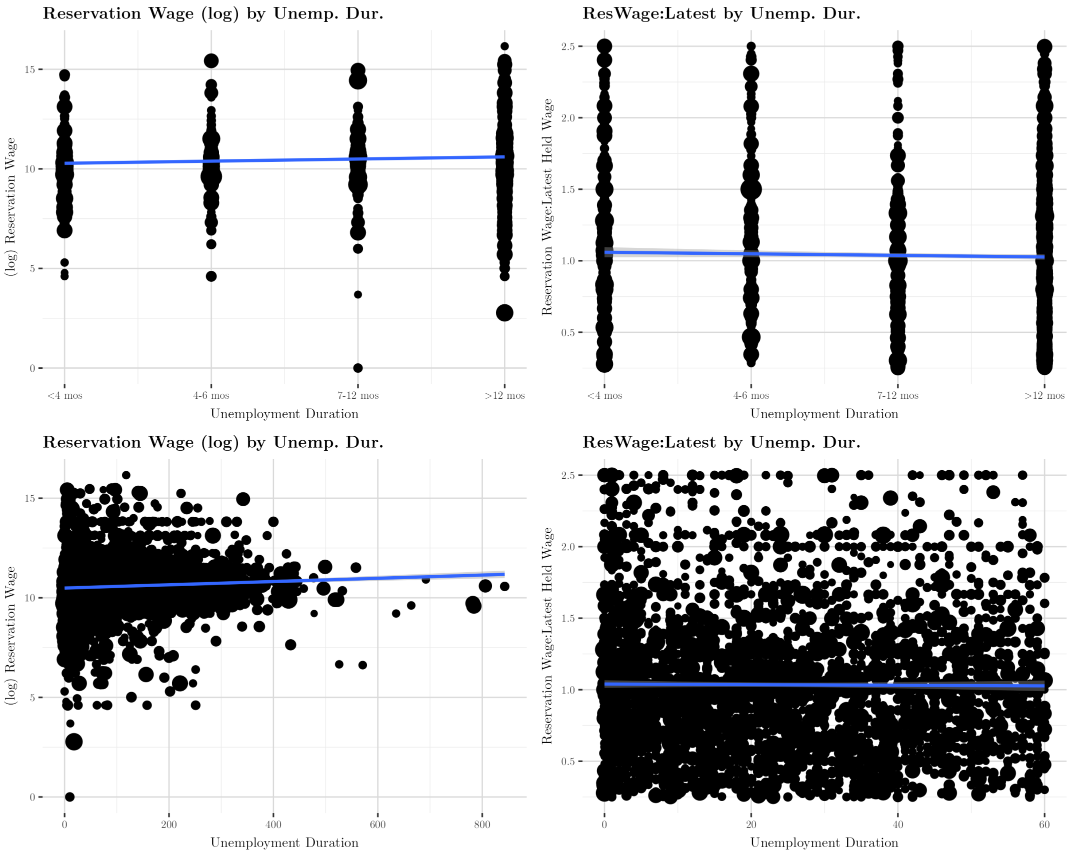
Exploring the effect of unemployment duration on reservation wages, accepted wages, and expected wage offers.

Survey of Consumer Expectations Reservation Wages, Accepted Wages, and Wage Expectations (2014-2022) *The data is unfortunately sparse and linking outcomes to reservation wages is difficult. However, in a cross-sectional setting we are able to deduce some weak relationships between Unemployment Duration and Absolute Reservation Wages and Wage Expectations.*

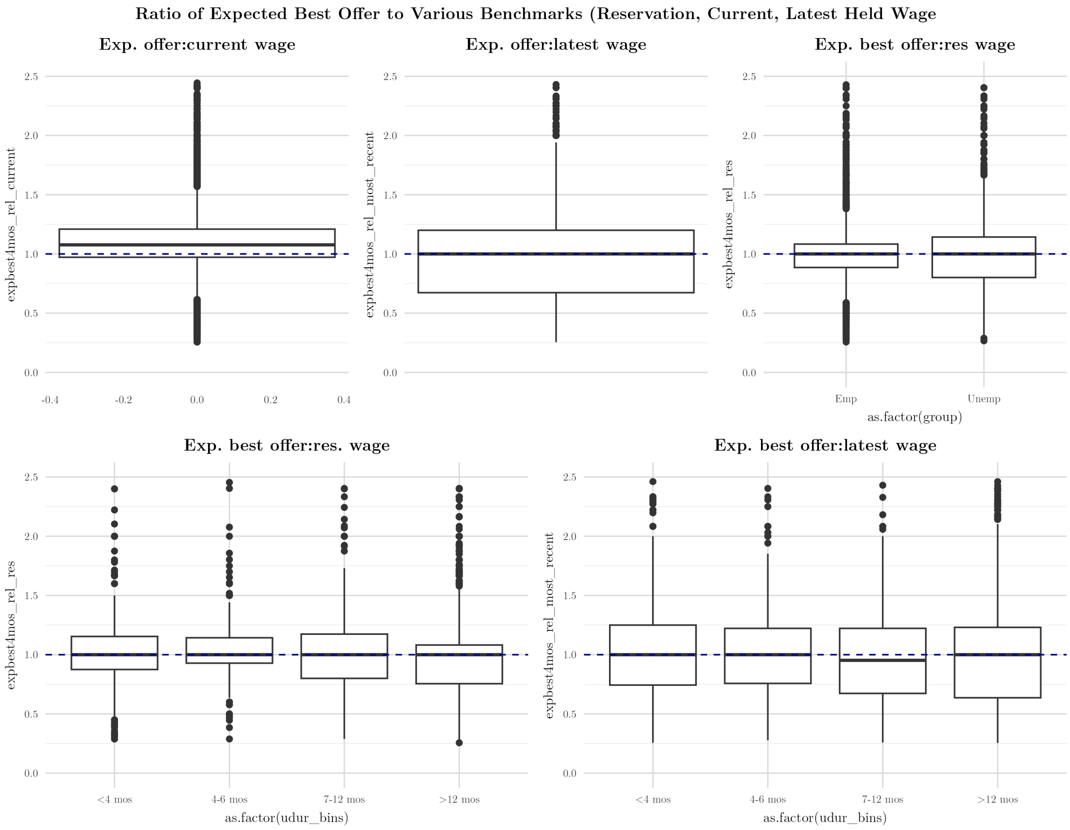
[1] “Plots of RESERVATION WAGE versus latest, current wage”

Reservation Wage as proportion of Current Wage

Reservation Wage as proportion of Latest Held Wage

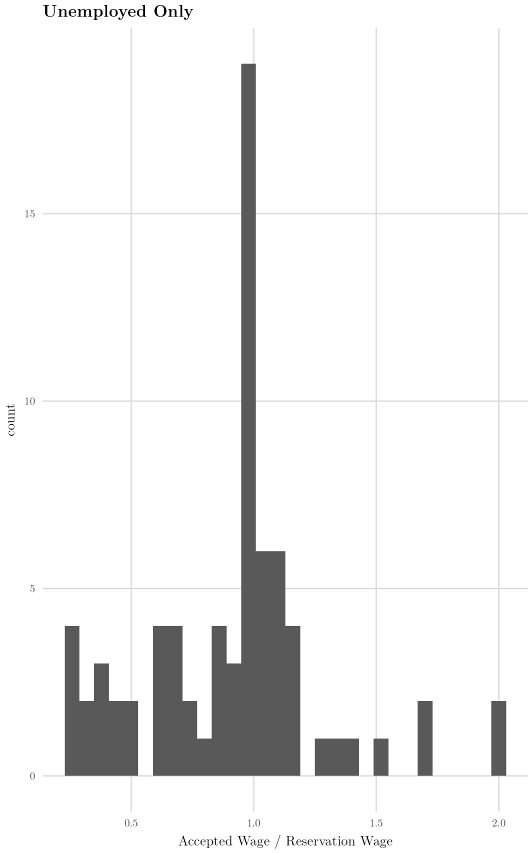


[1] "Plots of EXPECTED OFFER versus latest, current, reservation wage"

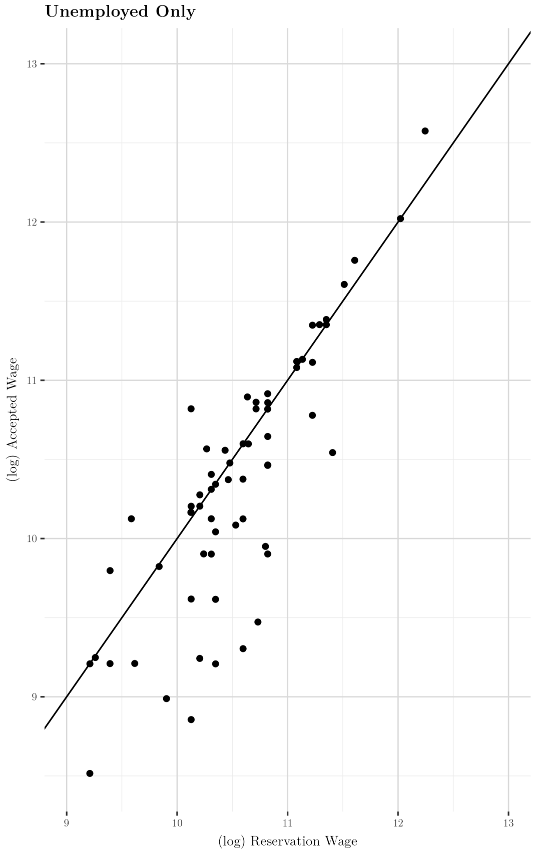


Notes: Regressions are estimated in the Survey of Consumer Expectations between 2014-2022.
Observations are weighted by their SCE sample weight.

[1] “Plots of ACCEPTED SALARY versus latest, current, reservation wage”



Unemployed Only
count
Accepted Wage / Reservation Wage

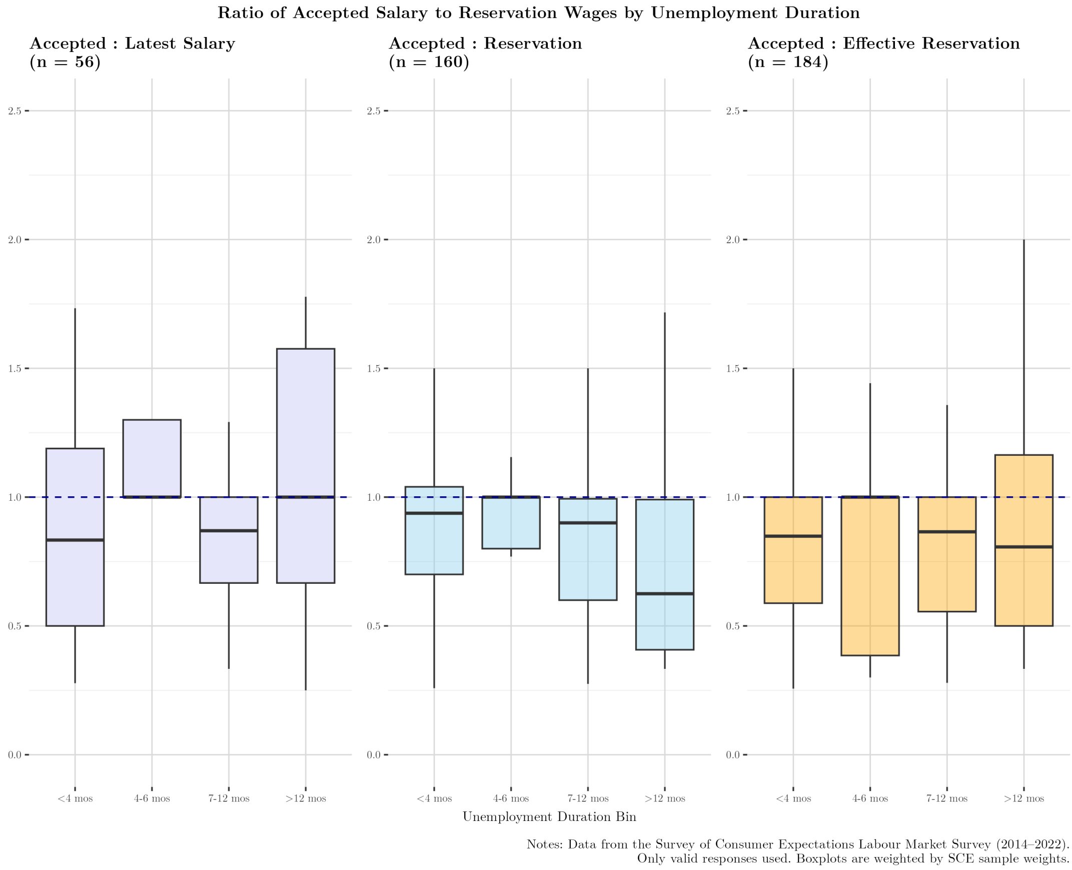


Unemployed Only
(log) Accepted Wage
(log) Reservation Wage

Table 14: Accepted Wages and Unemployment Duration

	Accpt:Latest	AccptWage w.c	Accpt:ResWage	AccptWage:ResWage w.c	Accpt:EffResWage	AccptW
(Intercept)	0.826***	1.743***	0.933***	1.199***	0.826***	
	(0.108)	(0.260)	(0.045)	(0.141)	(0.051)	
udur_bins	0.050	−0.005	−0.048*	−0.053**	0.008	
	(0.045)	(0.048)	(0.019)	(0.020)	(0.023)	
Num.Obs.	56	56	160	159	184	
R2	0.022	0.430	0.040	0.118	0.001	
RMSE	0.40	0.35	0.30	0.30	0.34	

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



SCE Job Search Supplement:

The Federal Reserve Bank of New York compiles the nationally representative Survey on Consumer Expectations annually in October. Since 2013, they have run a Job Search Supplement which includes questions on the time spent searching for work, and unemployment duration. The job search supplement has plenty more questions that we can look at incorporating, listed here. For now, I plot the relationship between time spent searching and time out of work. The table below also indicates the number of people unemployed in the dataset and the number of people unemployed and searching.

Table 15: Reservation Wages and Unemployment Duration

	ResWage	ResWage w.c	ResWage/LastWage	ResWage/LastWage w.c
(Intercept)	10.173***	9.945***	0.825***	0.750***
	(0.044)	(0.071)	(0.022)	(0.040)
udur_bins	0.107***	0.083***	0.027***	0.023***
	(0.012)	(0.011)	(0.006)	(0.006)
female		−0.275***		0.009
		(0.022)		(0.012)
age		0.005***		0.001*
		(0.001)		(0.000)
hhinc_2		0.230***		−0.008
		(0.026)		(0.014)
hhinc_3		0.427***		−0.017
		(0.030)		(0.017)
hhinc_4		0.759***		−0.008
		(0.033)		(0.019)
education_2		−0.247***		0.050+
		(0.045)		(0.026)
education_3		−0.122**		0.007
		(0.047)		(0.027)
education_4		−0.046		0.052+
		(0.051)		(0.029)
education_5		0.027		0.008
		(0.049)		(0.028)
education_6		0.111*		0.054+
		(0.054)		(0.031)
Num.Obs.	7937	7824	6294	6224
R2	0.010	0.169	0.003	0.007
R2 Adj.	0.010	0.168	0.003	0.005
AIC	191 435.4	187 281.4	9054.4	8961.7
BIC	191 456.4	187 372.0	9074.6	9049.3
Log.Lik.	−11 923.451	−11 075.843	−4524.195	−4467.857
RMSE	0.98	0.90	0.44	0.44

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

Table 16: Accepted Wages and Unemployment Duration

	AccptWage	AccptWage w.c	AccptWage/ResWage	AccptWage/ResWage w.c
(Intercept)	10.568***	11.705***	0.924***	1.303***
	(0.106)	(0.255)	(0.048)	(0.132)
udur_bins	−0.006	−0.037	−0.031+	−0.036+
	(0.040)	(0.037)	(0.018)	(0.018)
female		−0.164		−0.073
		(0.102)		(0.050)
age		−0.008*		−0.005**
		(0.004)		(0.002)
hhinc_2		0.260+		0.043
		(0.139)		(0.067)
hhinc_3		0.272+		0.042
		(0.138)		(0.069)
hhinc_4		0.377*		−0.052
		(0.150)		(0.075)
education_2		−0.996***		−0.043
		(0.224)		(0.122)
education_3		−0.940***		−0.128
		(0.223)		(0.122)
education_4		−1.036***		−0.176
		(0.226)		(0.123)
education_5		−0.827***		−0.141
		(0.224)		(0.124)
education_6		−0.551*		−0.095
		(0.228)		(0.127)
Num.Obs.	127	126	164	163
R2	0.000	0.299	0.017	0.133
R2 Adj.	−0.008	0.232	0.011	0.070
AIC	2933.2	2884.9	110.6	109.9
BIC	2941.7	2921.7	119.9	150.1
Log.Lik.	−123.204	−99.911	−52.283	−41.957
RMSE	0.58	0.53	0.32	0.32

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

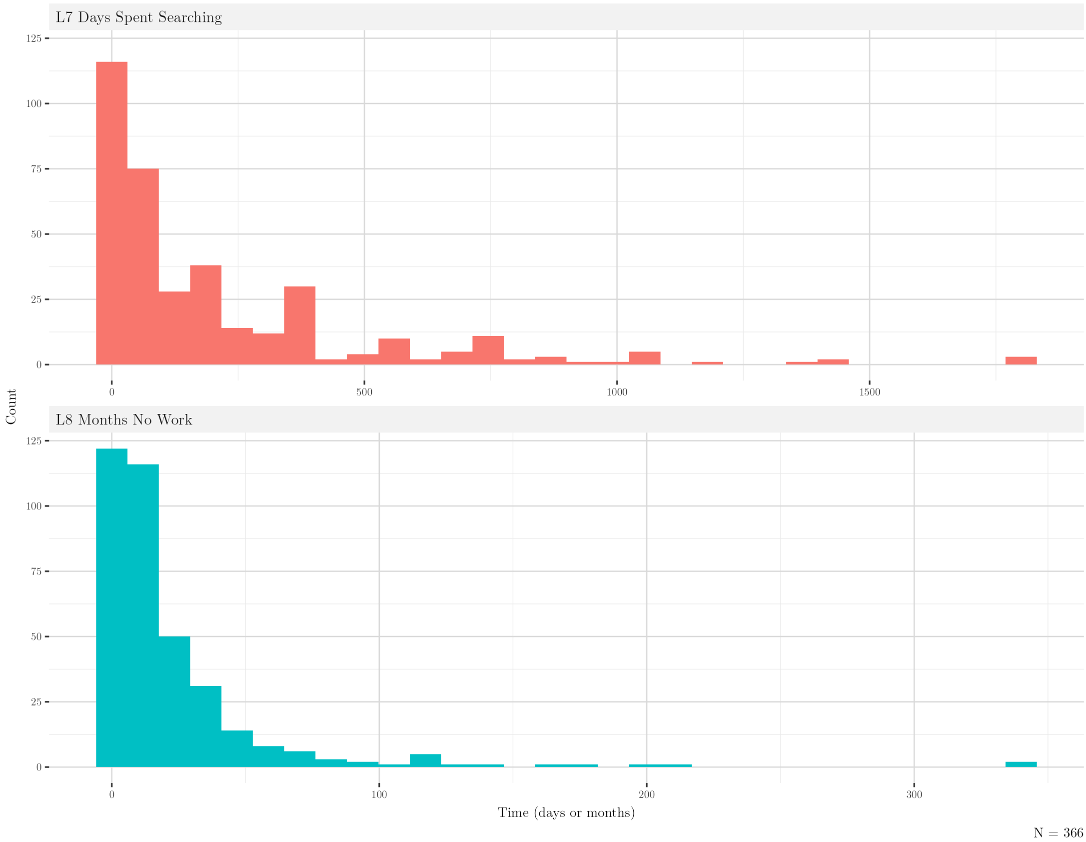
Table 17: Expected Wages and Unemployment Duration

	ExpWage/ResWage	ExpWage/ResWage w.c	ExpWage/LastWage	ExpWage/LastWage w.c
(Intercept)	1.057***	1.226***	1.087***	1.257***
	(0.020)	(0.040)	(0.029)	(0.059)
udur_bins	−0.022***	−0.009	−0.024**	−0.008
	(0.006)	(0.006)	(0.008)	(0.009)
female		−0.022+		0.064***
		(0.013)		(0.019)
age		−0.003***		−0.004***
		(0.000)		(0.001)
hhinc_2		0.004		−0.038
		(0.016)		(0.023)
hhinc_3		0.004		−0.001
		(0.018)		(0.026)
hhinc_4		0.000		−0.005
		(0.019)		(0.027)
education_2		−0.035		−0.032
		(0.027)		(0.040)
education_3		−0.008		−0.056
		(0.028)		(0.041)
education_4		0.004		−0.031
		(0.030)		(0.044)
education_5		0.011		−0.090*
		(0.029)		(0.042)
education_6		0.021		0.002
		(0.032)		(0.046)
Num.Obs.	3114	3070	2721	2690
R2	0.005	0.028	0.003	0.029
R2 Adj.	0.005	0.024	0.003	0.025
AIC	2803.9	2733.2	4079.4	3986.5
BIC	2822.1	2811.6	4097.2	4063.1
Log.Lik.	−1398.968	−1353.588	−2036.722	−1980.241
RMSE	0.34	0.34	0.46	0.45

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

Year	N Unemployed	N Unemp & Searching
2014	383	70
2015	321	44
2016	339	46
2017	350	38
2018	354	41
2019	343	32
2020	304	45
2021	330	50

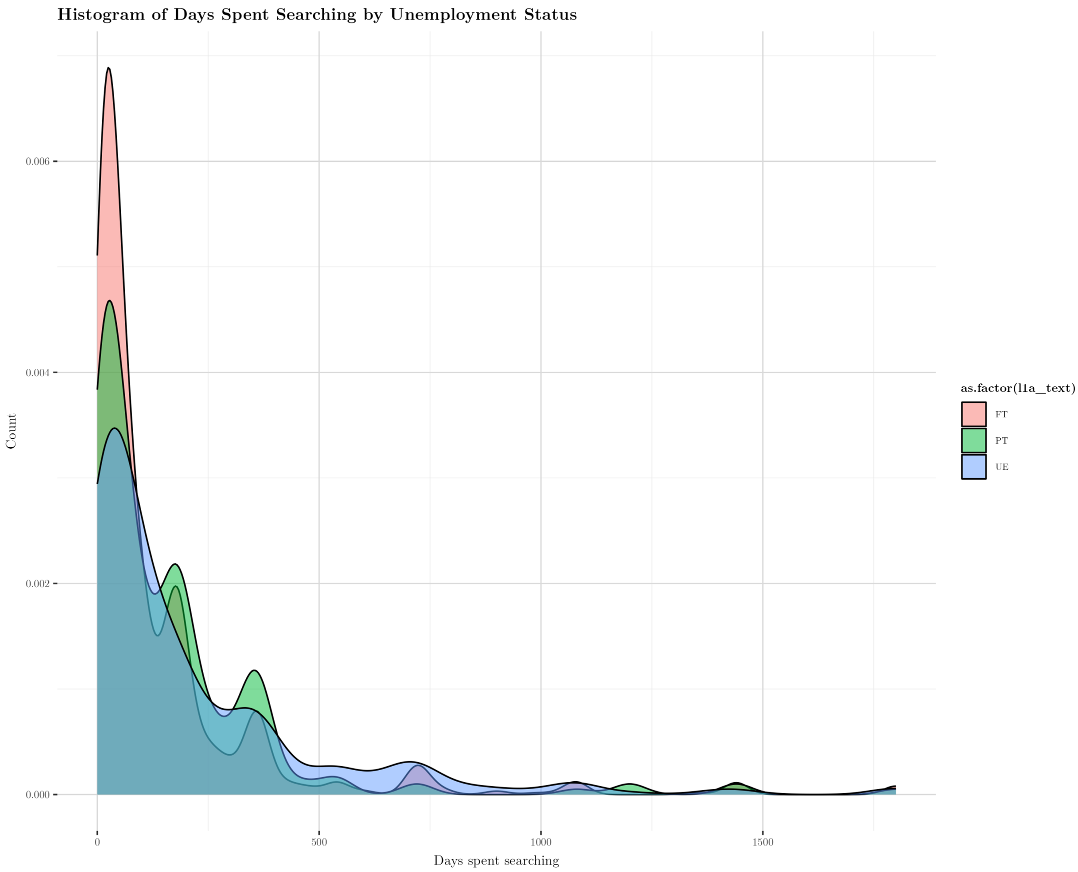
Histogram of time spent searching and out of work.



Time dedicated to searching versus time spent unemployed

Blue line indicates best fit line. Grey dashed line indicates 45 degree line. N = 366

On-the-Job Search



B Setting Target Demand

Setting Occupational Target Demand

2025-08-01

Setting Occupational Target Demand

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).

Assume that the baseline de-trended demand for occupation i in the economy D_i is:

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

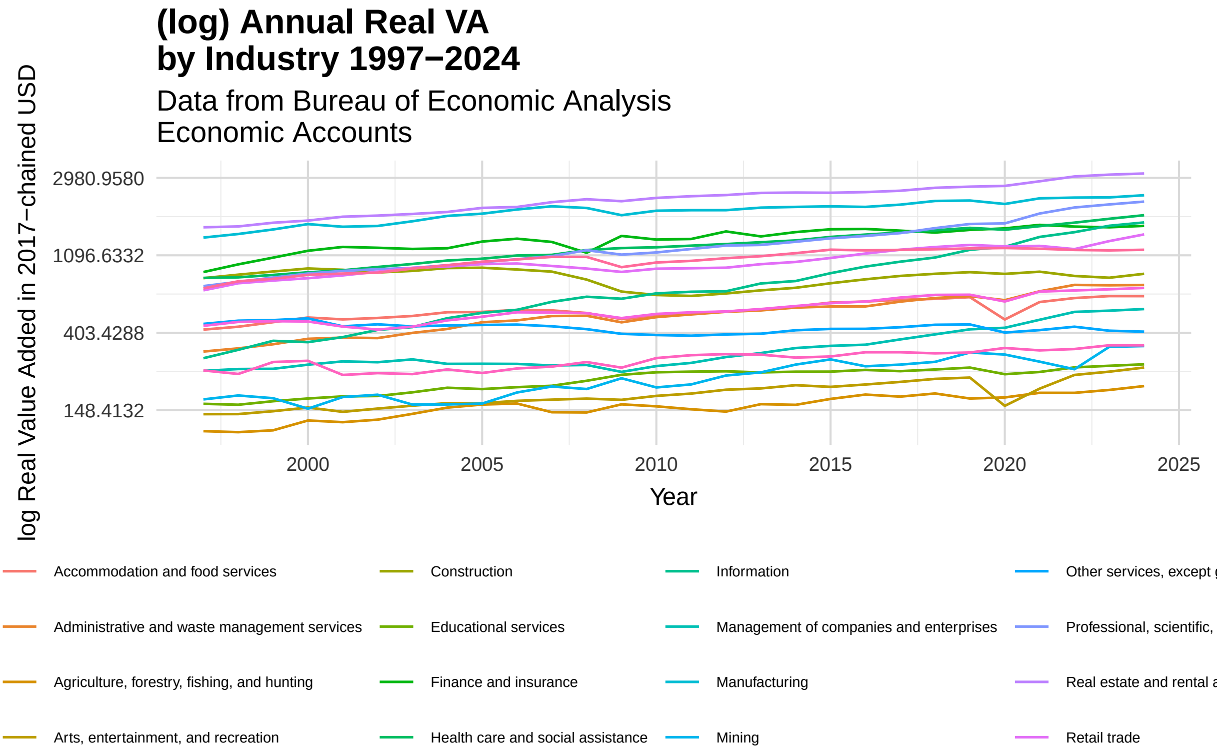
where the de-trended fluctuating demand (ie. demand at time t for occupation i) is:

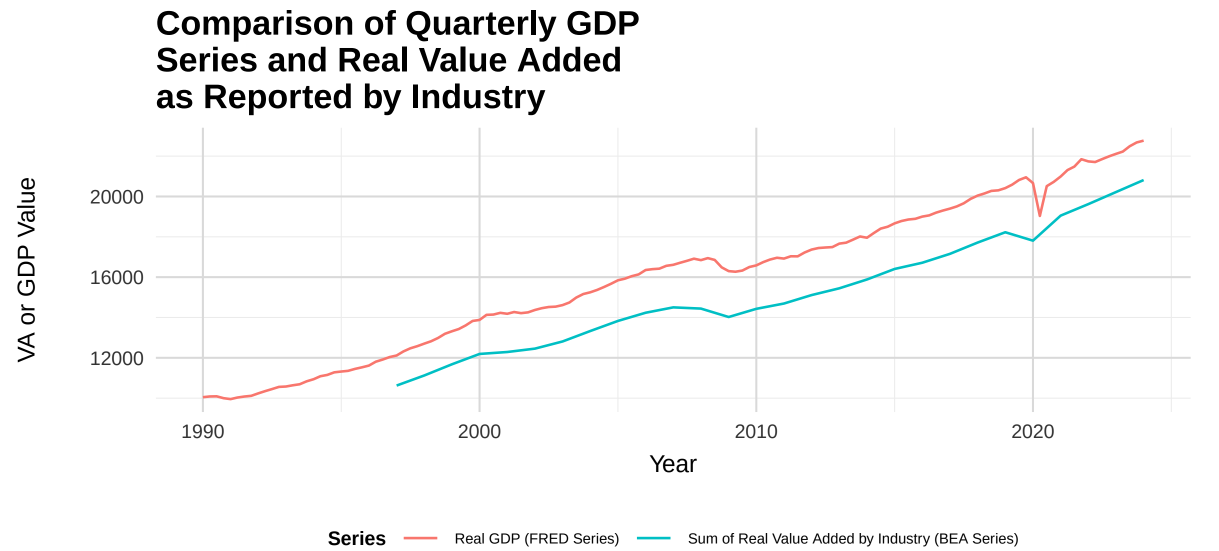
$D_{it} = \sum_{j=1}^{n} \hat{d}_{ijt}$

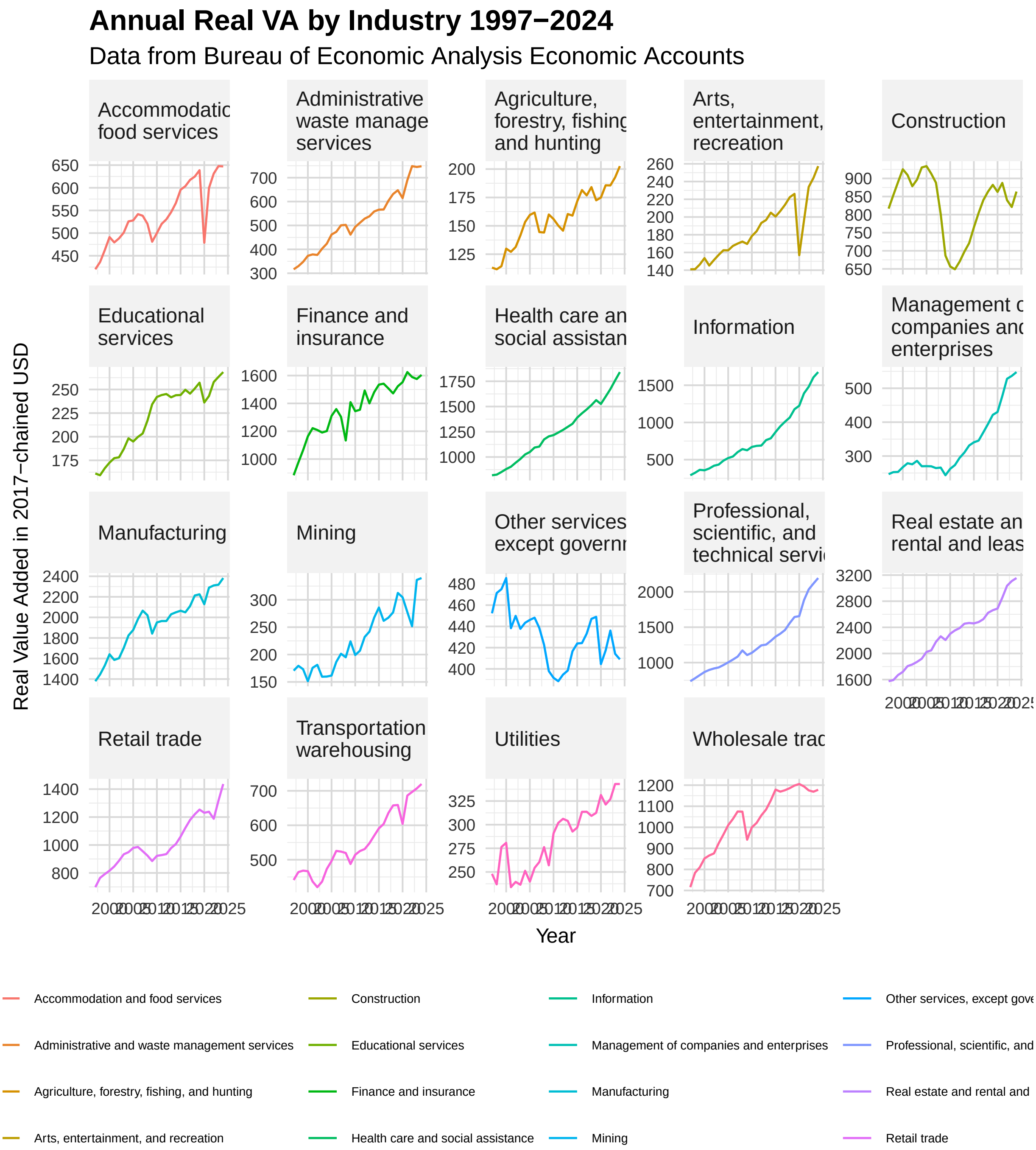
$\hat{d}_{ijt} = \sum_{j=1}^{n} \bar{d}_{ij}\theta_{jt}$

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 in the same way as in the GDP series such that we obtain the fluctuation around a mean.

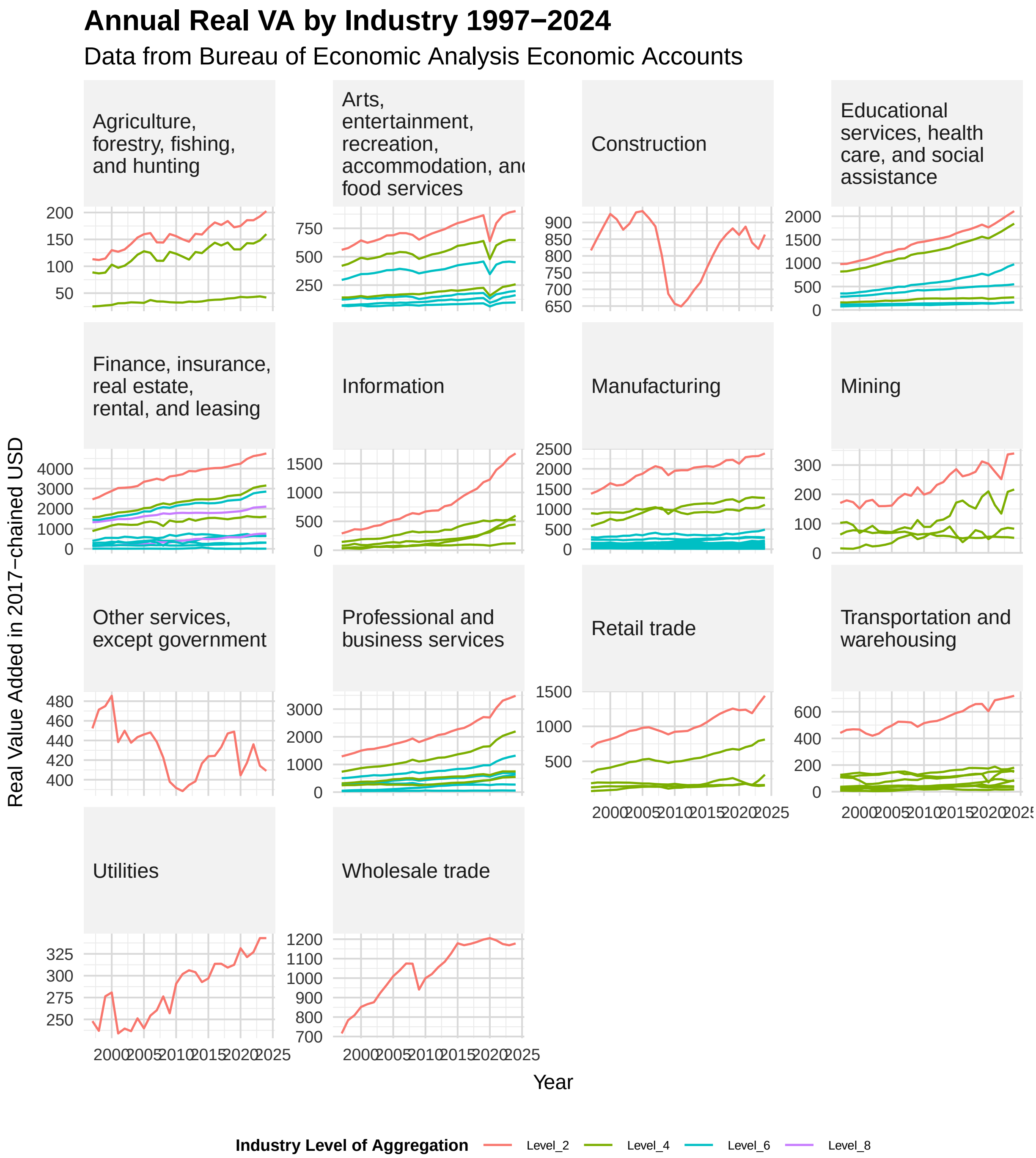
Value Added by Industry







Annual Real VA by Industry 1997−2024
Data from Bureau of Economic Analysis Economic Accounts
Real Value Added in 2017−chained USD
Year
Accommodation and food services
Administrative and waste management services
Agriculture, forestry, fishing, and hunting
Arts, entertainment, and recreation
Construction
Educational services
Finance and insurance
Health care and social assistance
Information
Management of companies and enterprises
Manufacturing
Mining
Other services, except gove
Professional, scientific, and
Real estate and rental and
Retail trade



Annual Real VA by Industry 1997−2024
Data from Bureau of Economic Analysis Economic Accounts
Agriculture, forestry, fishing, and hunting
Arts, entertainment, recreation, accommodation, and food services
Construction
Educational services, health care, and social assistance
Finance, insurance, real estate, rental, and leasing
Information
Manufacturing
Mining
Other services, except government
Professional and business services
Retail trade
Transportation and warehousing
Utilities
Wholesale trade
Real Value Added in 2017−chained USD
Year
2000 2005 2010 2015 2020 2025
Industry Level of Aggregation
Level_2
Level_4
Level_6
Level_8

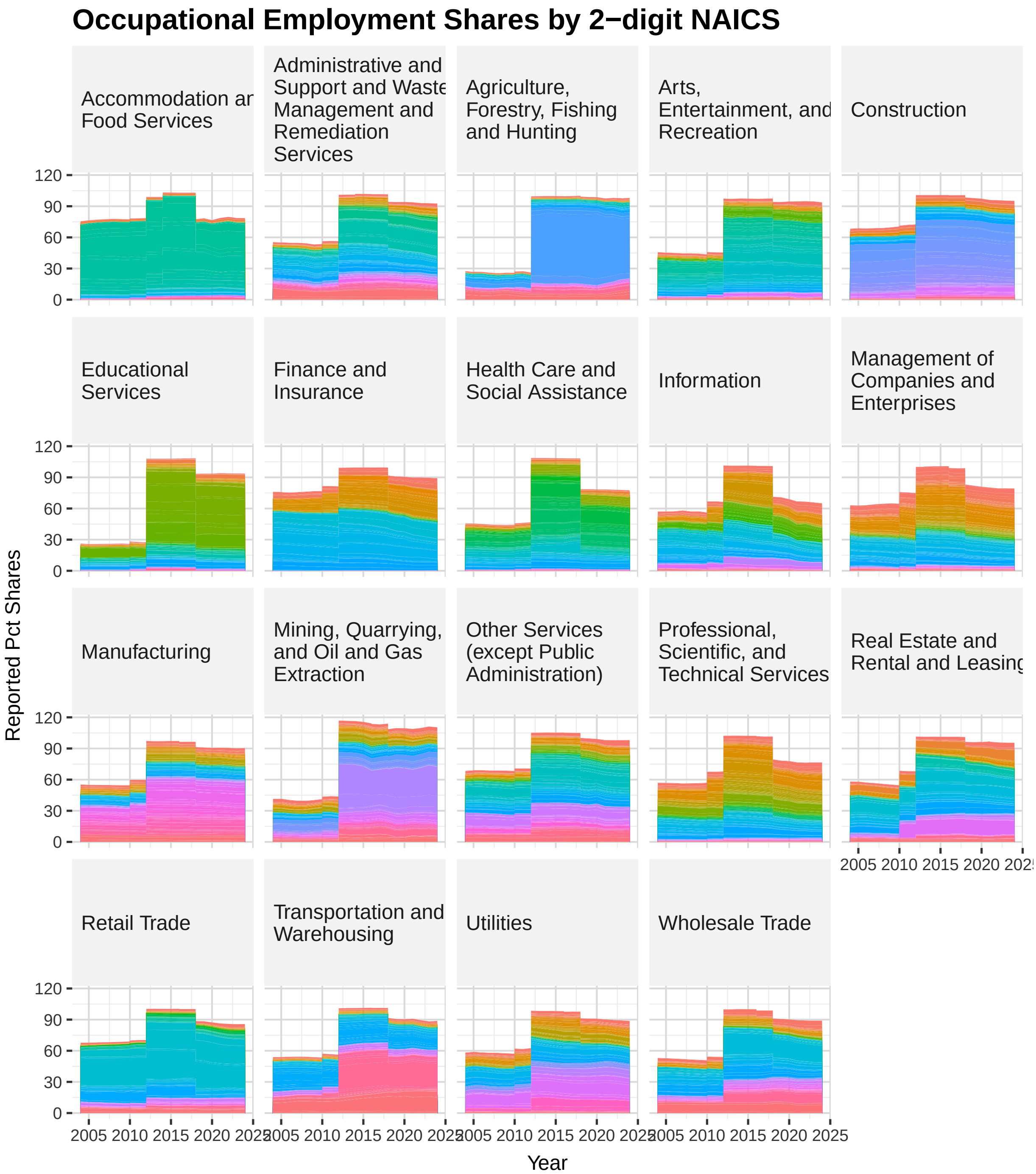
Occupation-shares of industry

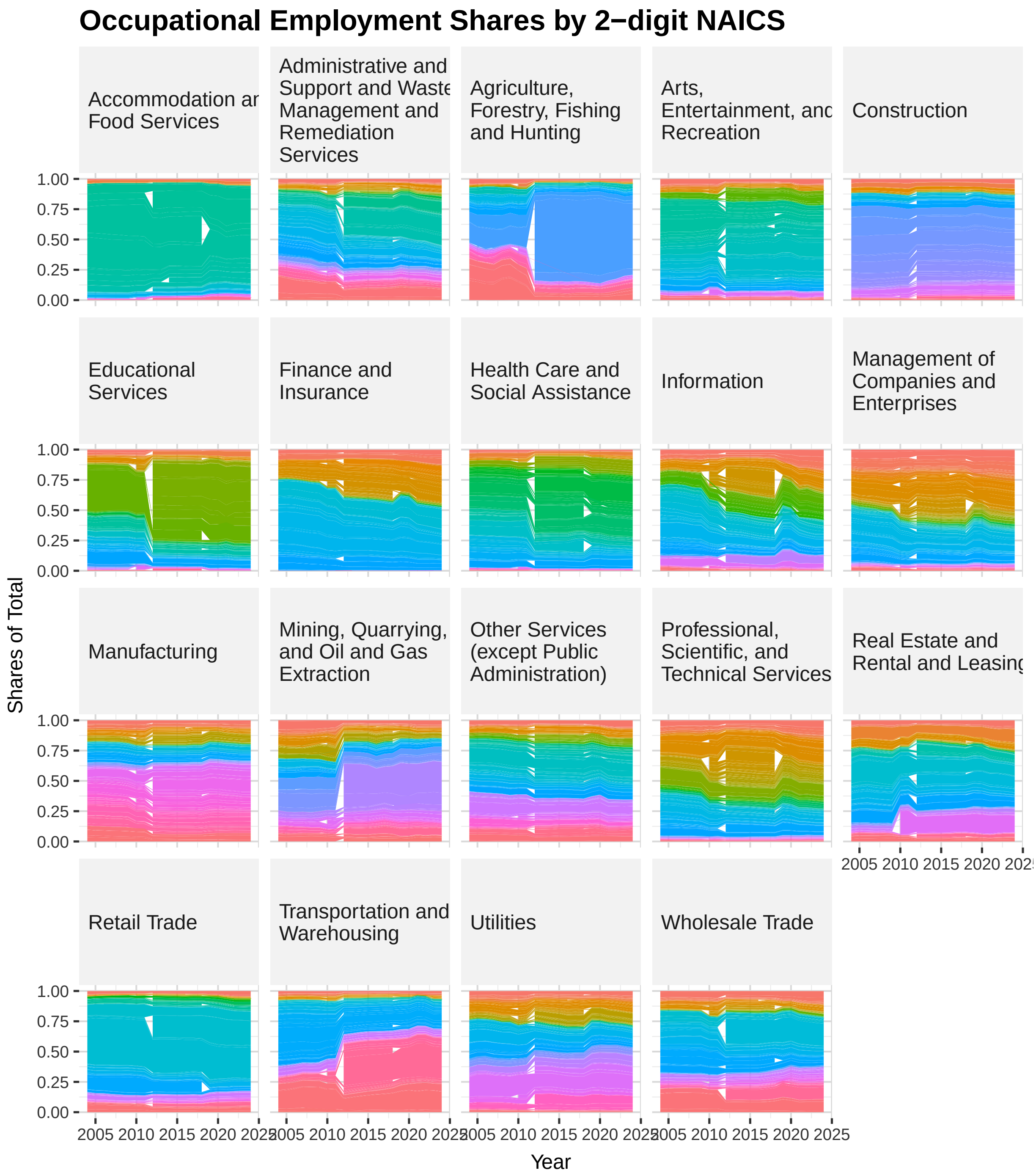
We use annual occupational shares of employment from the Occupational Employment and Wage Statistics database from the US Bureau of Labour Statistics to derive our dij.

Excludes public administration. The first figure shows the "reported percent total" from the OEWS data. The discrepances in reporting is almost certainly due to a reshuffling of occupational codes in 2010 and 2018.

If we look at the shares as a percentage of total reported employment in a particular industry the "shares" are not consistent across the recategorisation - I will need to investigate this again.

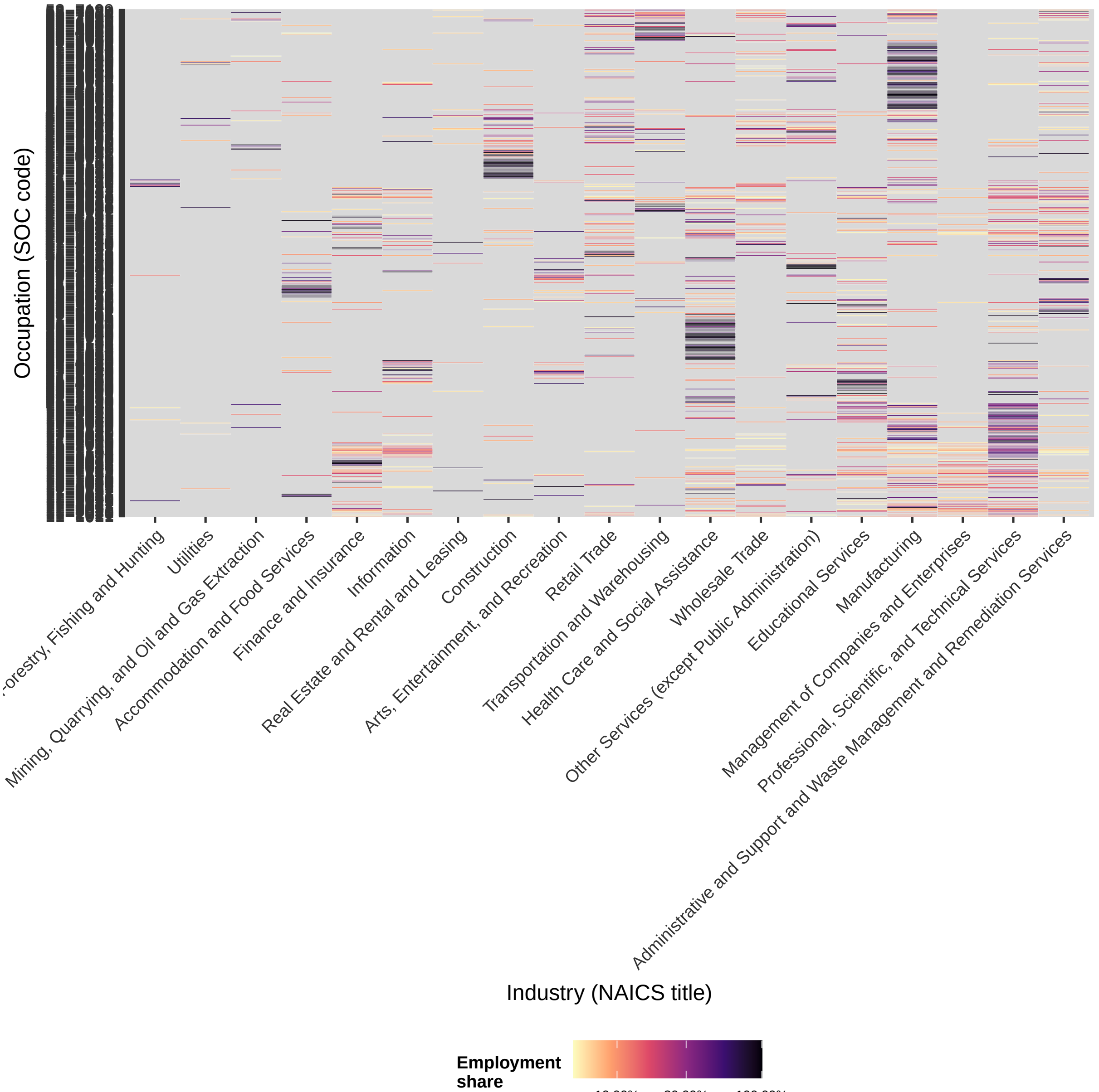
We take the mean industry-share of occupational employment reported in the years where majority (>97%) of our occ codes are present (2012-2018 - after and before SOC reorganisation of 2010 and 2018).




Occupational Employment Shares by 2−digit NAICS
Accommodation and Food Services
Administrative and Support and Waste Management and Remediation Services
Agriculture, Forestry, Fishing and Hunting
Arts, Entertainment, and Recreation
Construction
Educational Services
Finance and Insurance
Health Care and Social Assistance
Information
Management of Companies and Enterprises
Manufacturing
Mining, Quarrying, and Oil and Gas Extraction
Other Services (except Public Administration)
Professional, Scientific, and Technical Services
Real Estate and Rental and Leasing
Retail Trade
Transportation and Warehousing
Utilities
Wholesale Trade
Shares of Total
1.00
0.75
0.50
0.25
0.00
2005 2010 2015 2020 2025
Year

Occupation−Industry Employment Shares

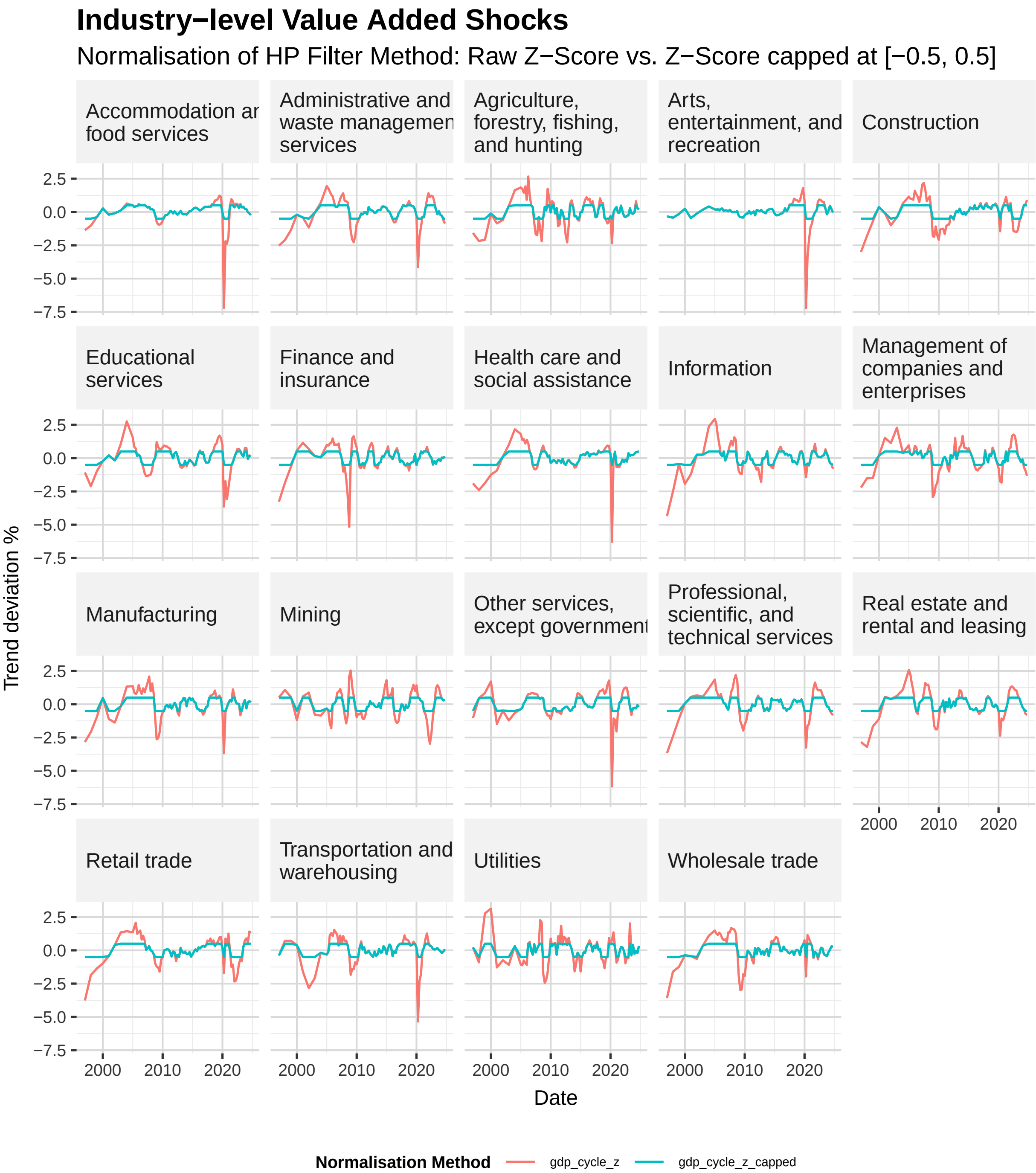
The colors display the share of total occupational employment in each industry.
Industries are ordered by the total number of occupations they employ in ascending c
Display only those occupations whose industrial−level employment share is at least 5

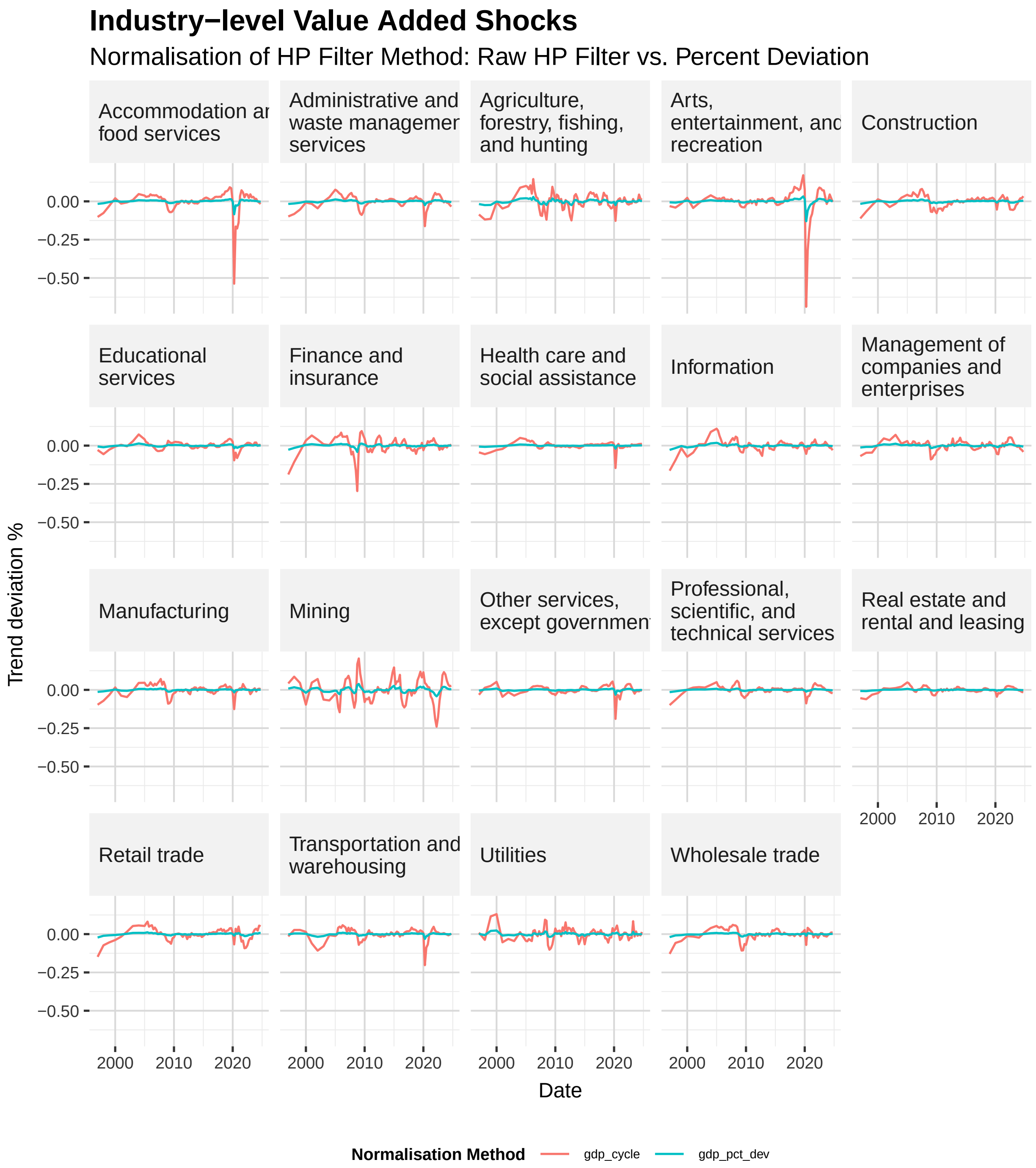


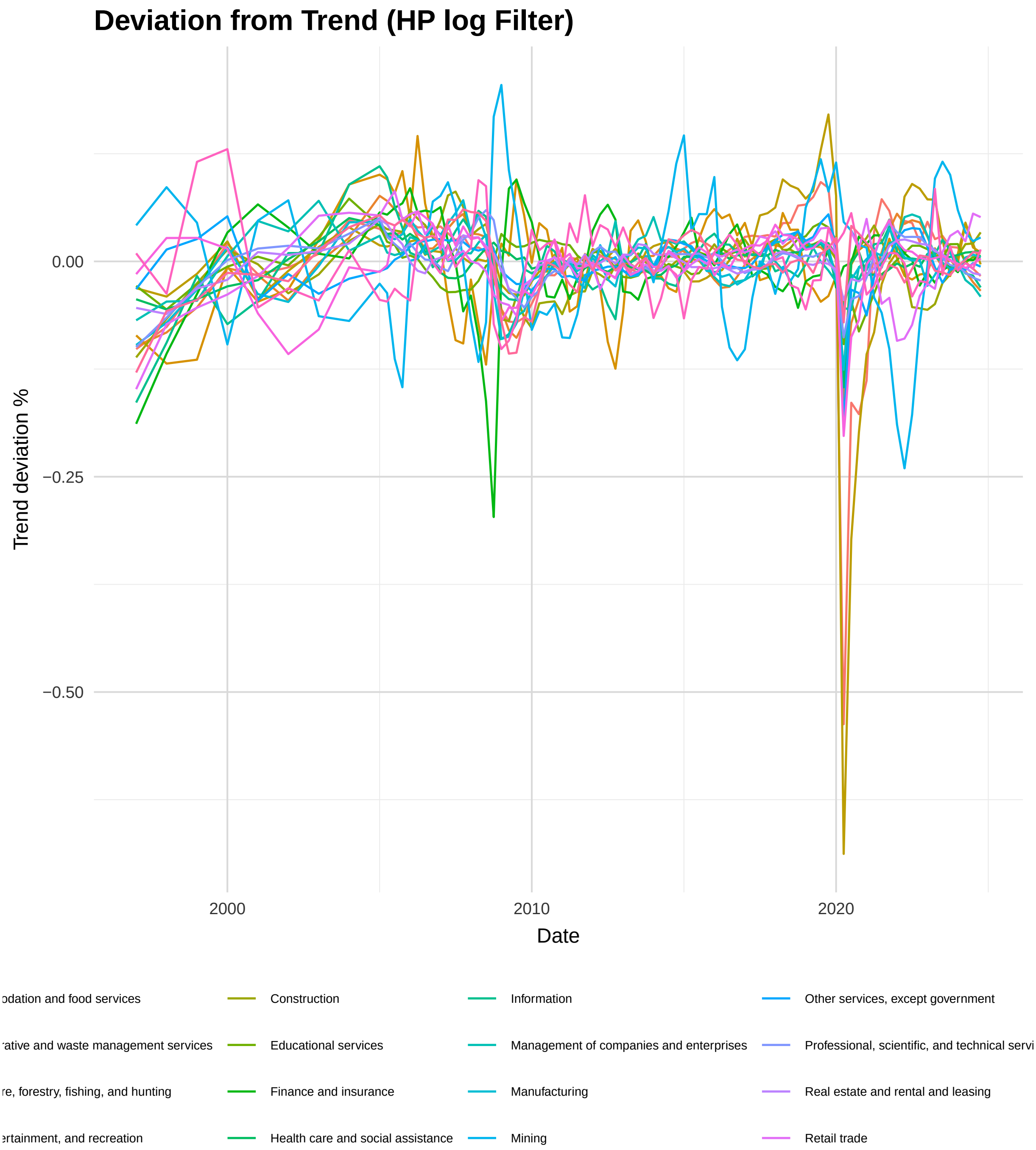
[1] "Two occupational categories have a sum of mean shares > 1.1:"

SOC2010 Occupational Code	Occupational Label	Sum of Mean Shares
45-3011	Fishers and related fishing workers	1.537169
37-2021	Pest control workers	1.135526

Bringing them together




Industry−level Value Added Shocks
Normalisation of HP Filter Method: Raw HP Filter vs. Percent Deviation
Accommodation and food services
Administrative and waste management services
Agriculture, forestry, fishing, and hunting
Arts, entertainment, and recreation
Construction
Educational services
Finance and insurance
Health care and social assistance
Information
Management of companies and enterprises
Manufacturing
Mining
Other services, except government
Professional, scientific, and technical services
Real estate and rental and leasing
Retail trade
Transportation and warehousing
Utilities
Wholesale trade
0.00
−0.25
−0.50
2000
2010
2020
Trend deviation %
Date
Normalisation Method
gdp_cycle
gdp_pct_dev

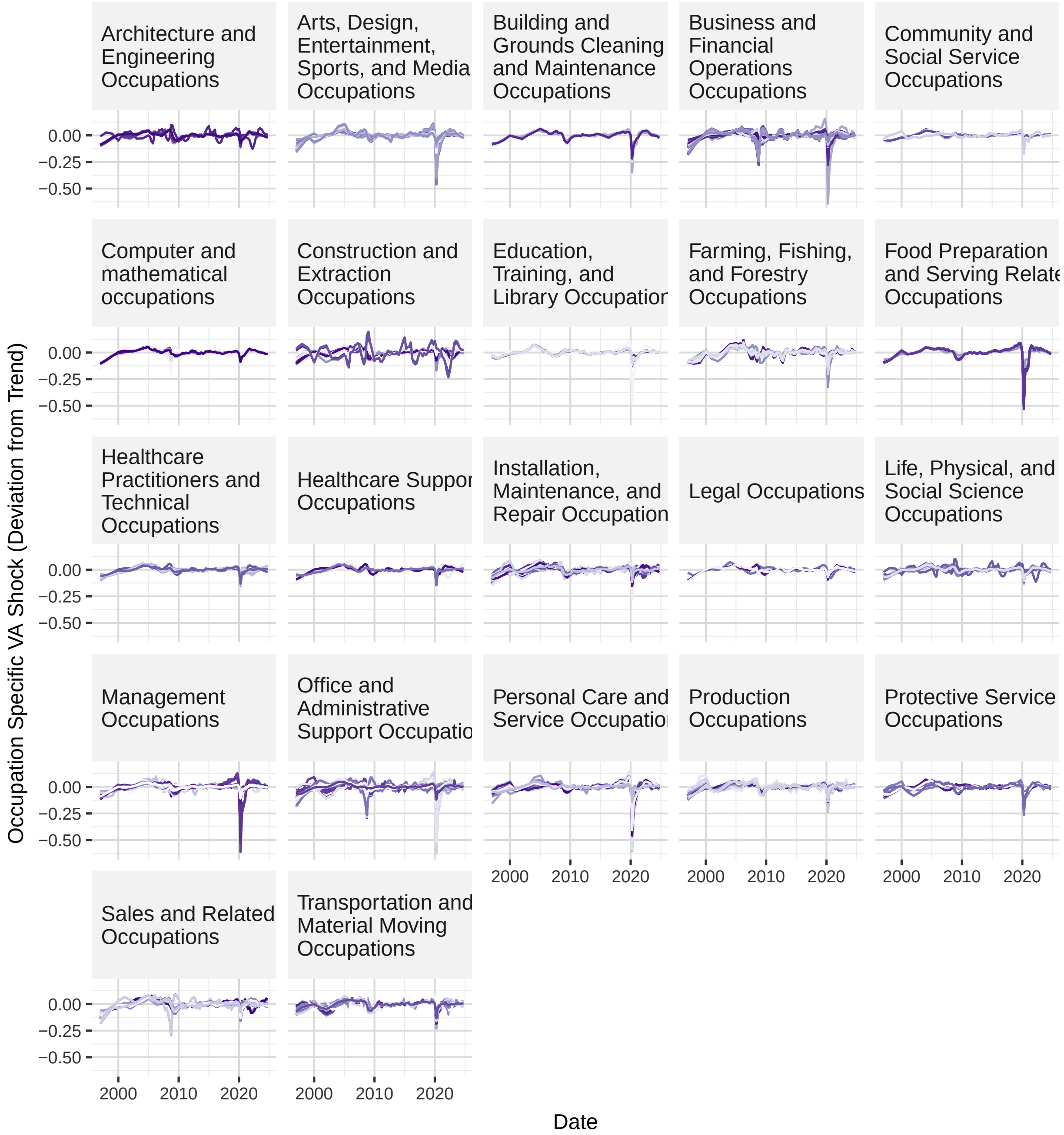


Important future work should aim to accommodate shifts in labor productivity of different industries and/or shifting industry-specific occupational shares to account for additional sources of structural transformation beyond those explored in this work.

Important note is 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, I will use the shocks to 13-2082 as the shocks to 13-2081 though we might consider changing this. For example, we could potentially abstract to say that public administration fluctuations should depend on just GDP fluctuations (ie. we use the HP-filtered GDP series that we were originally using as the direct shock to occupations employed only in public administration).

Occupation Specific Value Added Shock

Composite of Industry VA shocks x Industry Occupational Shares

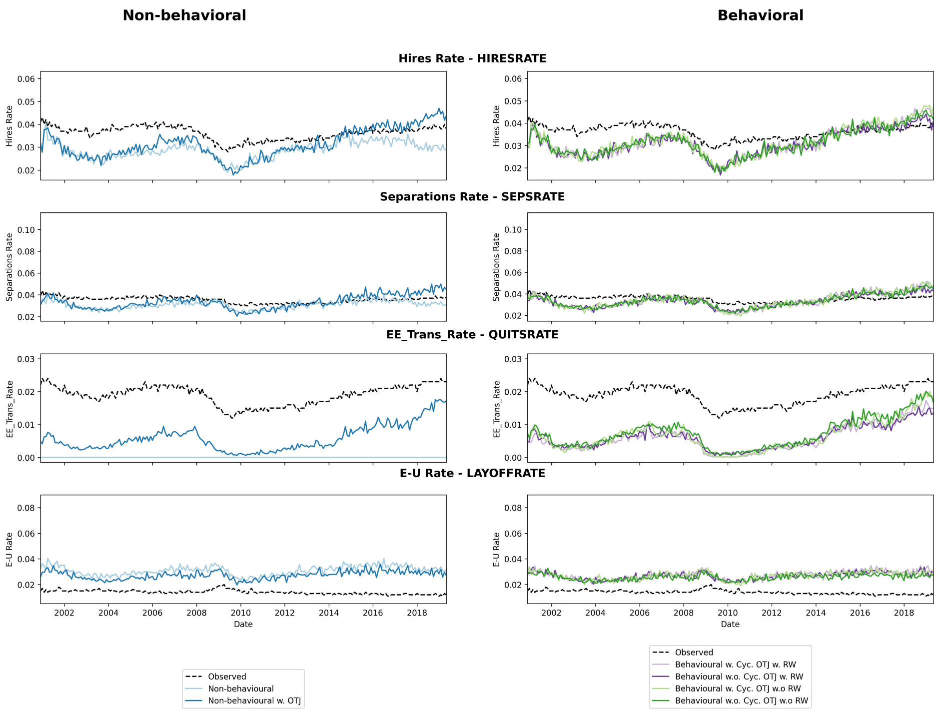


C On the Orthogonality of Wage Preferences and Occupational Mobility

D 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 16 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 16: Simulated vs. Observed Hires and Separations Rates



E Single Node Case

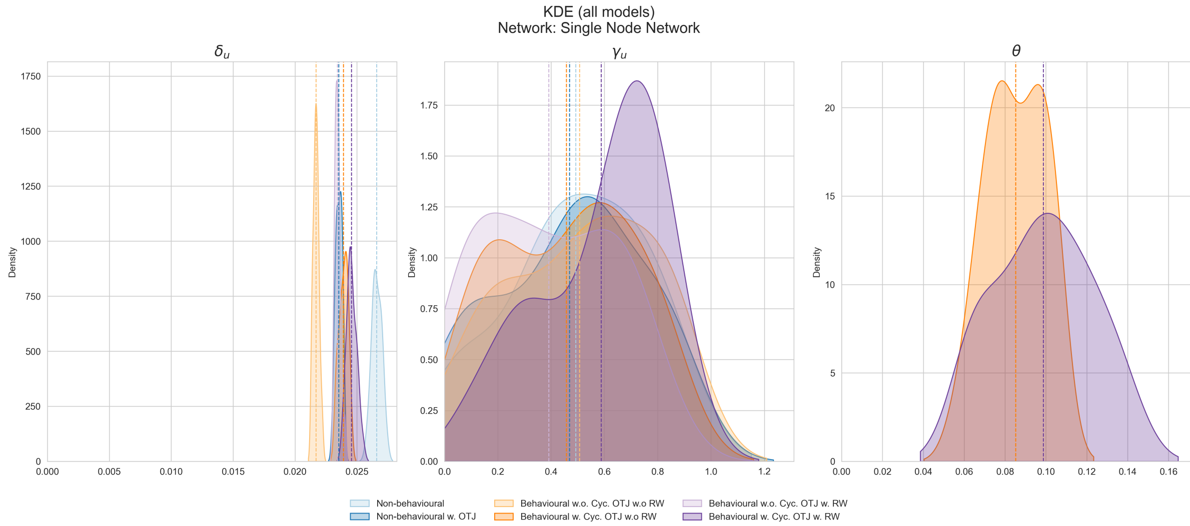
E.1 Model Results

Model Parameters

Parameter	Prior Distribution	Model Category					
		Non-behavioural	Non-behavioural w. OTJ	Behavioural w. Cyc. OTJ w. RW	Behavioural w.o. Cyc. OTJ w. RW	Behavioural w. Cyc. OTJ w.o RW	Behavioural w.o. Cyc. OTJ w.o RW
d_u	$U(0.0001, 0.9)$	0.027	0.024	0.025	0.023	0.024	0.022
gamma_u	$U(0.0001, 0.9)$	0.493	0.47	0.588	0.392	0.457	0.507
theta	$U(0.0001, 0.9)$			0.099		0.085	

Table 4: Prior distribution and parameter estimates for all models. $U(a, b)$ denotes a uniform distribution on $[a, b]$.

Figure 17: ABC Calibration Results: Jointly minimizing unemployment rate loss



Time Series Metrics

Model	Variable	Mean (Sim)	Mean (Obs)	SSE	Correlation
Non-behavioural	Vacancy Rate	0.031	0.031	0.001	0.936
	Unemployment Rate	0.047	0.060	0.120	0.905
	Long-term Unemployment Rate	0.046	0.264	11.416	0.782
	Hires Rate	0.027	0.036	0.023	0.245
	Separations Rate	0.029	0.036	0.013	-0.037
	UE Transition Rate	0.025	0.014	0.035	-0.270
	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	0.940
	Unemployment Rate	0.058	0.060	0.084	0.850
	Long-term Unemployment Rate	0.081	0.264	8.741	0.720
	Hires Rate	0.032	0.036	0.011	0.566
	Separations Rate	0.034	0.036	0.007	0.391
	UE Transition Rate	0.023	0.014	0.021	-0.296
	EE Transition Rate	0.007	0.019	0.038	-0.026
	Application Effort (U)	–	–	–	–
	Seeker Composition	0.563	0.410	7.791	0.596
Behavioural w. Cyc. OTJ w. RW	Vacancy Rate	0.031	0.031	0.001	0.937
	Unemployment Rate	0.062	0.060	0.024	0.871
	Long-term Unemployment Rate	0.065	0.264	9.895	0.684
	Hires Rate	0.028	0.036	0.017	0.535
	Separations Rate	0.030	0.036	0.010	0.372
	UE Transition Rate	0.023	0.014	0.023	-0.229
	EE Transition Rate	0.004	0.019	0.056	-0.018
	Application Effort (U)	–	–	–	0.323
	Seeker Composition	0.365	0.410	6.350	0.658
Behavioural w.o. Cyc. OTJ w. RW	Vacancy Rate	0.031	0.031	0.001	0.941
	Unemployment Rate	0.061	0.060	0.018	0.888
	Long-term Unemployment Rate	0.071	0.264	9.245	0.712
	Hires Rate	0.028	0.036	0.016	0.573
	Separations Rate	0.030	0.036	0.008	0.403
	UE Transition Rate	0.022	0.014	0.018	-0.204
	EE Transition Rate	0.005	0.019	0.047	0.052
	Application Effort (U)	–	–	–	0.280
	Seeker Composition	0.530	0.410	3.933	0.668
Behavioural w. Cyc. OTJ w.o RW	Vacancy Rate	0.031	0.031	0.001	0.945
	Unemployment Rate	0.063	0.060	0.021	0.875
	Long-term Unemployment Rate	0.073	0.264	9.094	0.700
	Hires Rate	0.031	0.036	0.012	0.561
	Separations Rate	0.033	0.036	0.009	0.405
	UE Transition Rate	0.022	0.014	0.020	-0.222
	EE Transition Rate	0.007	0.019	0.040	-0.016
	Application Effort (U)	–	–	–	0.449
	Seeker Composition	0.390	0.410	6.348	0.658
Behavioural w.o. Cyc. OTJ w.o RW	Vacancy Rate	0.031	0.031	0.001	0.942
	Unemployment Rate	0.061	0.060	0.026	0.902
	Long-term Unemployment Rate	0.088	0.264	7.922	0.736
	Hires Rate	0.031	0.036	0.011	0.579
	Separations Rate	0.033	0.036	0.007	0.430
	UE Transition Rate	0.021	0.014	0.014	-0.178
	EE Transition Rate	0.009	0.019	0.030	0.034
	Application Effort (U)	–	–	–	0.371
	Seeker Composition	0.536	0.410	4.600	0.690

Unemployment and Vacancy Rates

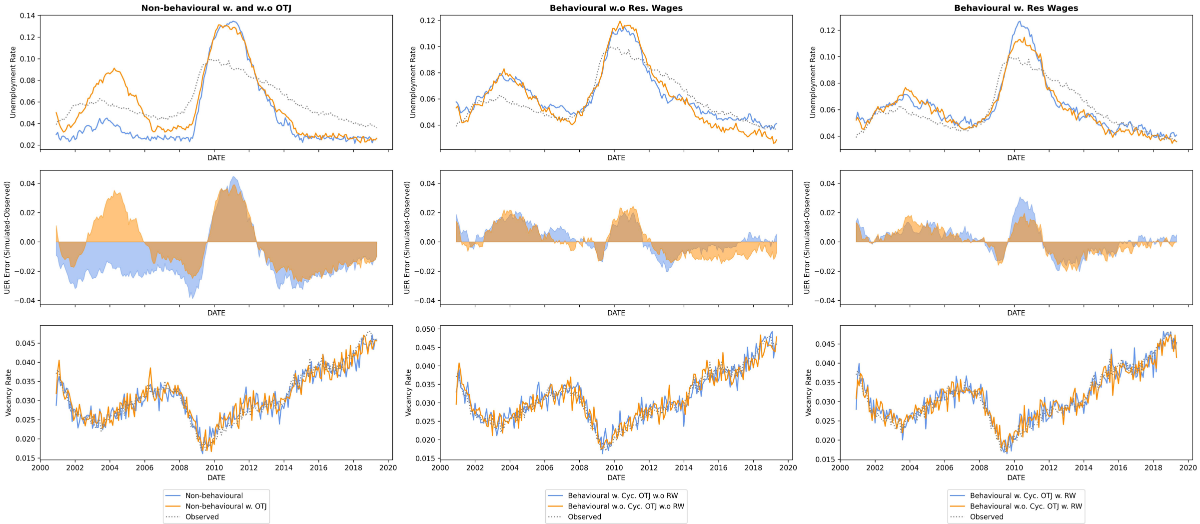


Figure 18: Unemployment and Vacancy Rates

Hires and Separations Rates

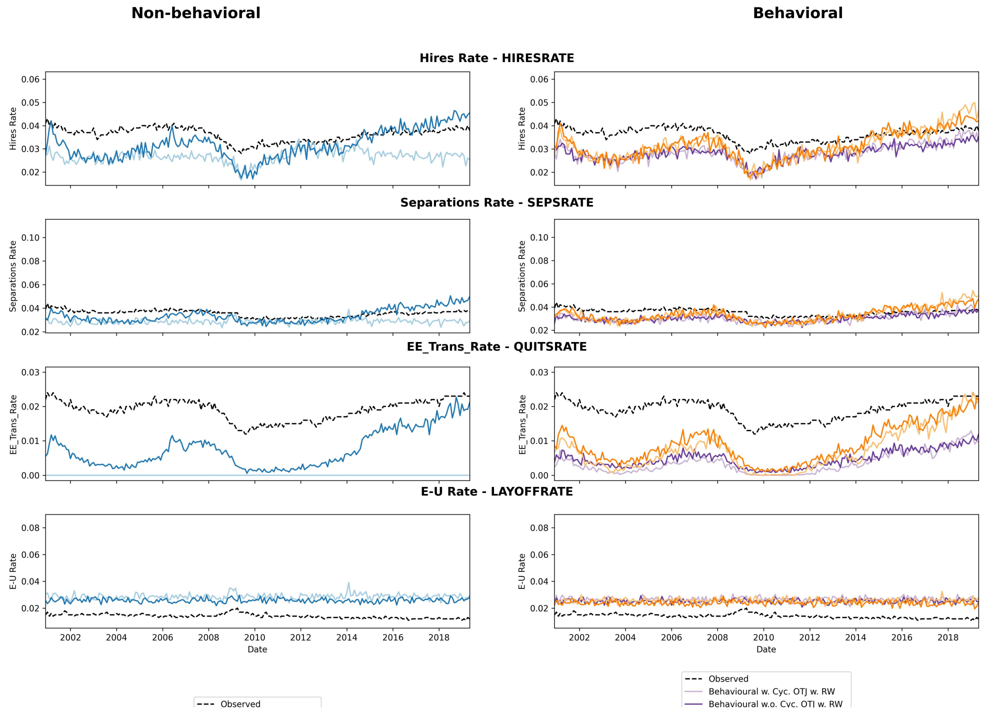


Figure 19: Hires and Separations Rate Grid

Beveridge Curves

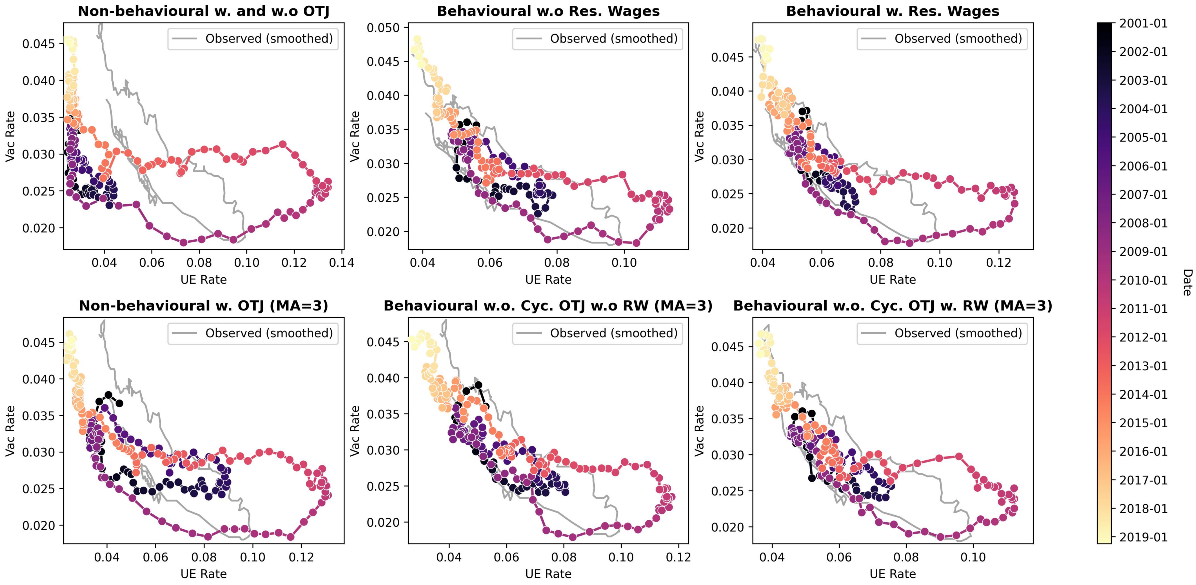


Figure 20: Beveridge Curves

Job Seeker Composition

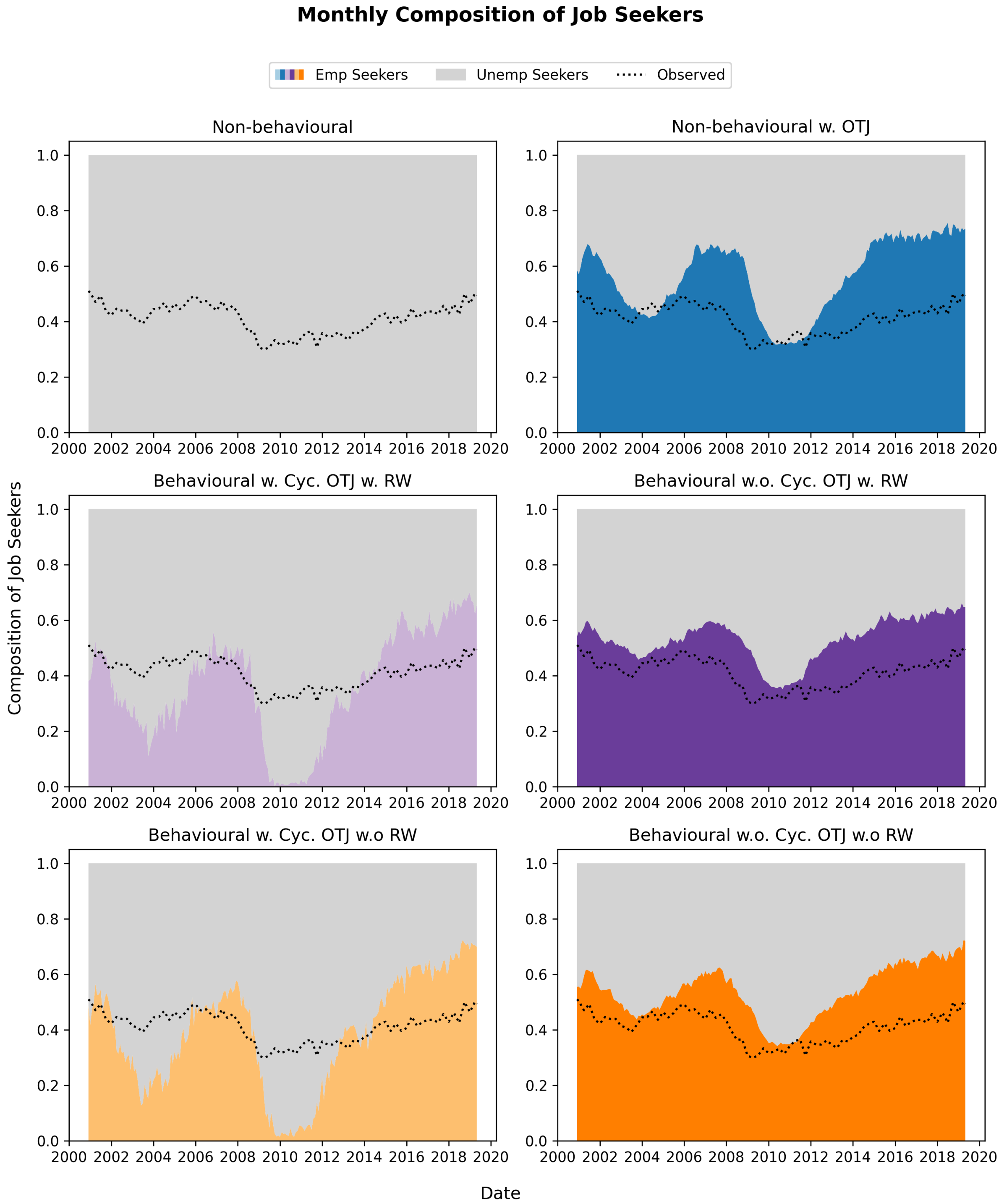


Figure 21: Seeker Composition (Stacked Area)

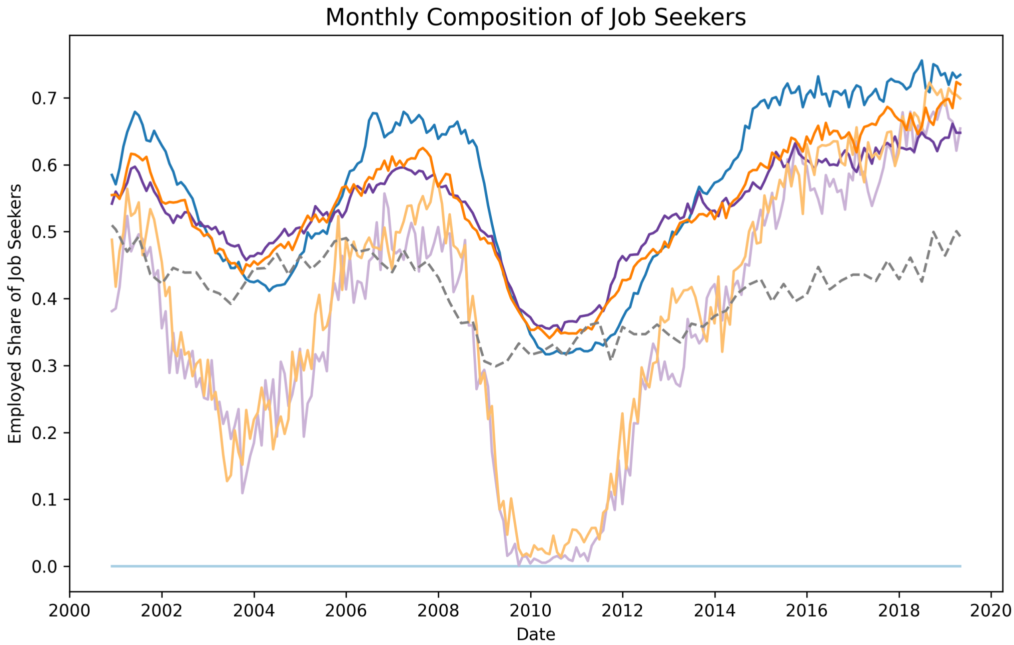


Figure 22: Seeker Composition (Line Plot)

Long-Term Unemployment

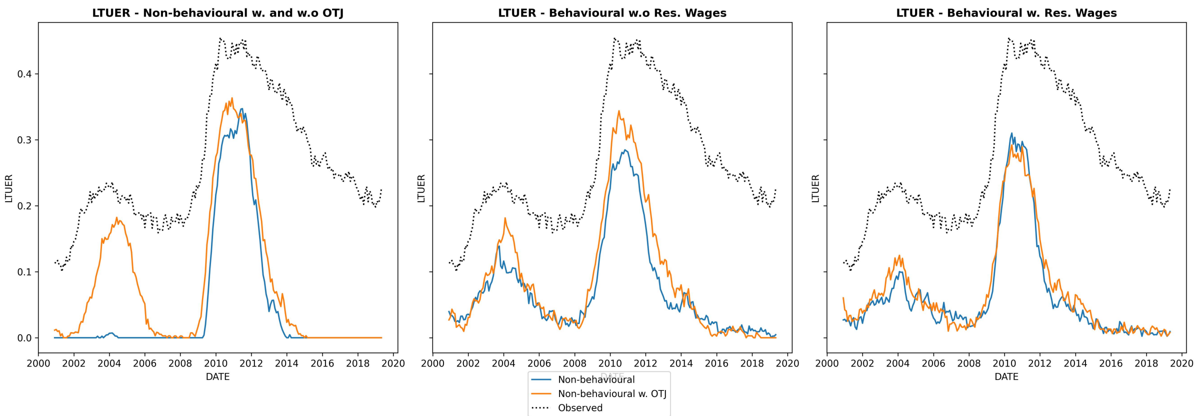


Figure 23: Long-Term Unemployment Rate

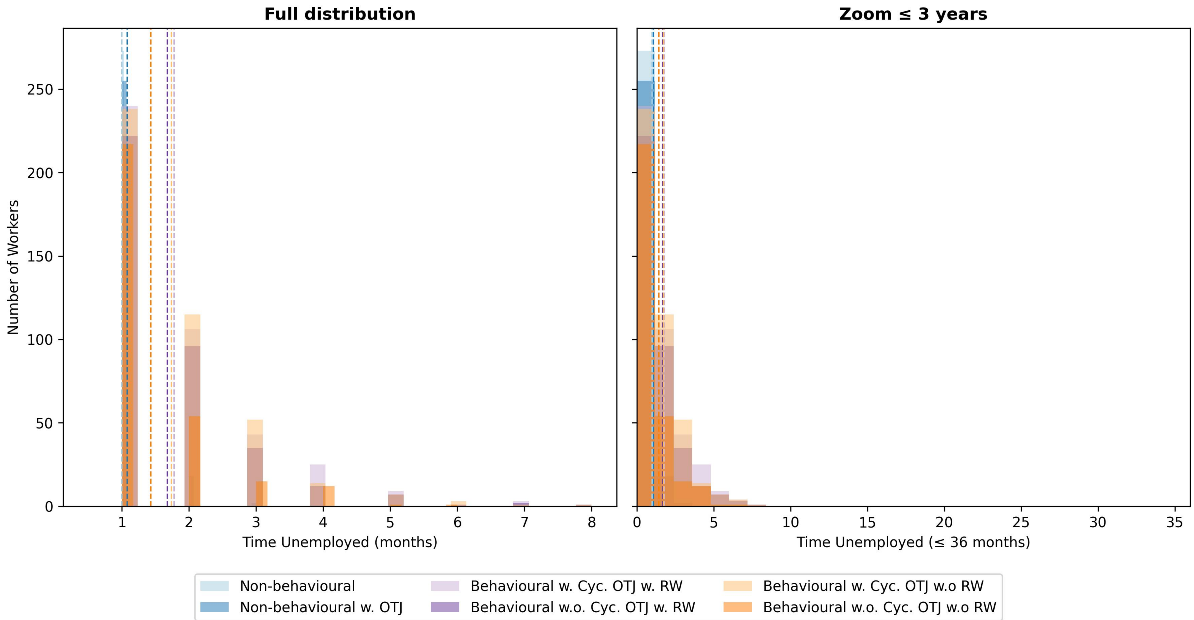


Figure 24: Long-Term Unemployment Distributions

Relative Wages

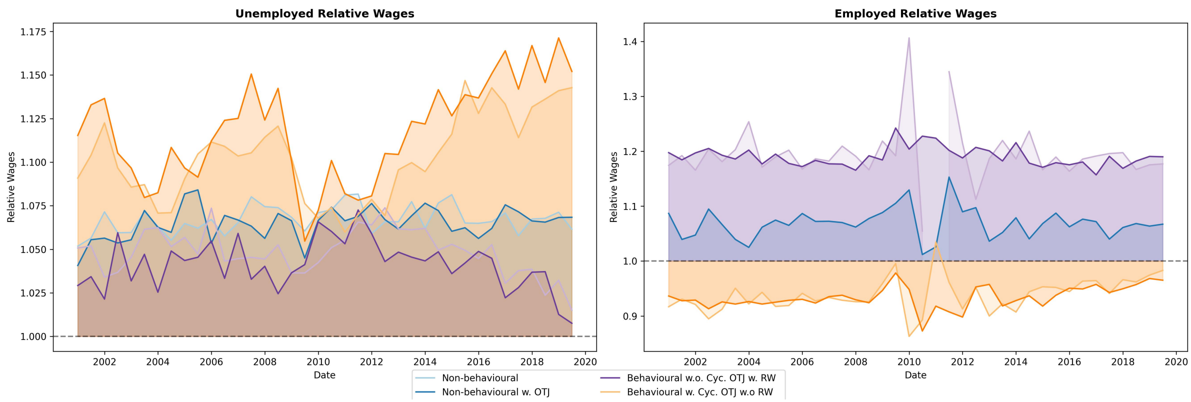


Figure 25: Relative Wages

Transition Rates

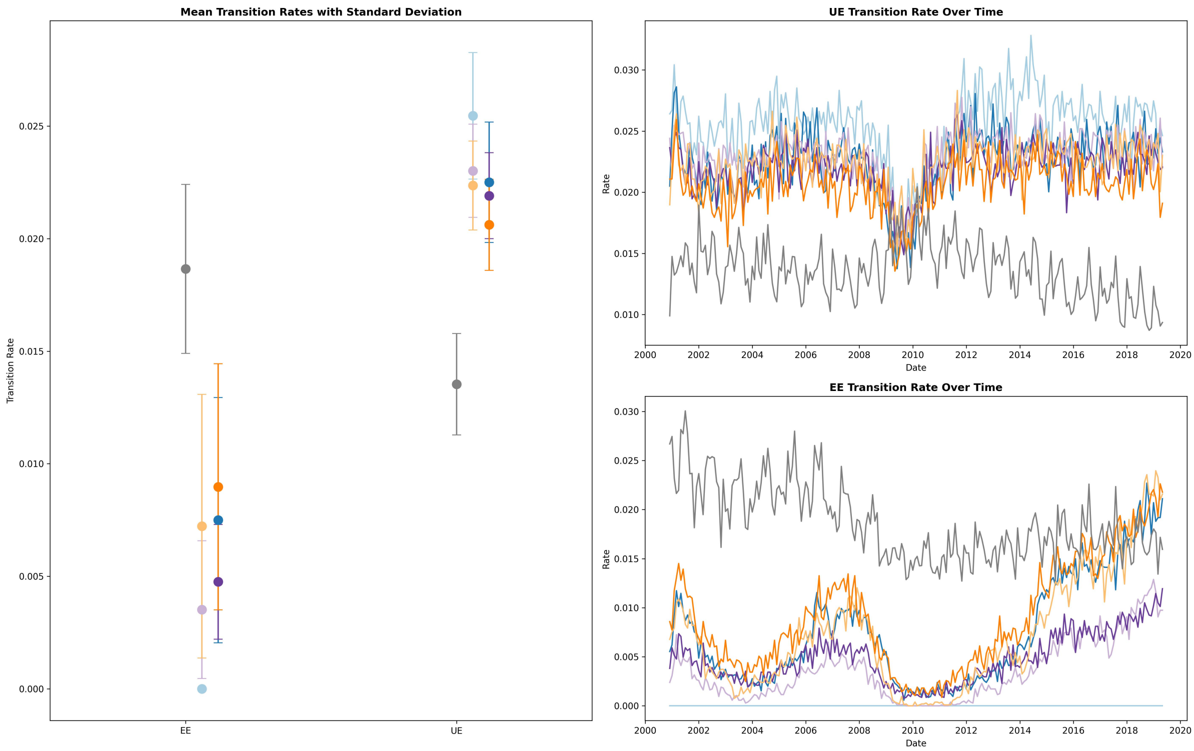


Figure 26: Transition Rates Comparison

Applications per Unemployed Seeker

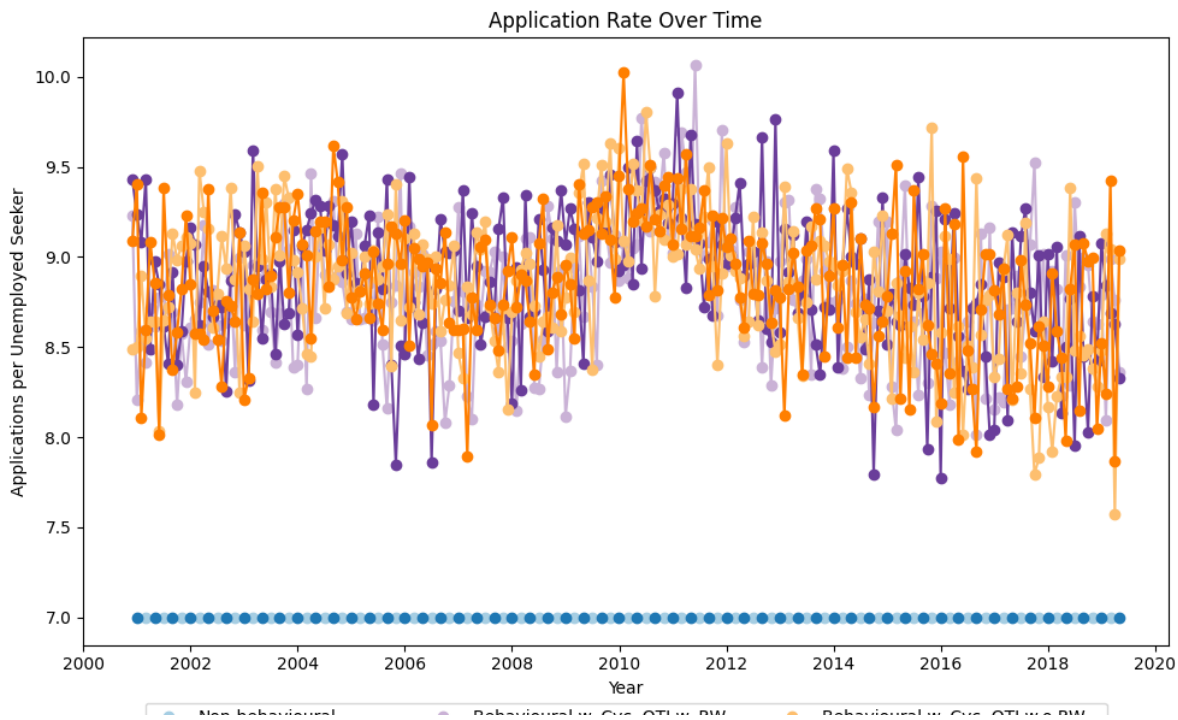


Figure 27: Applications per Unemployed Seeker

Behavioral Regimes - Time to Reemployment

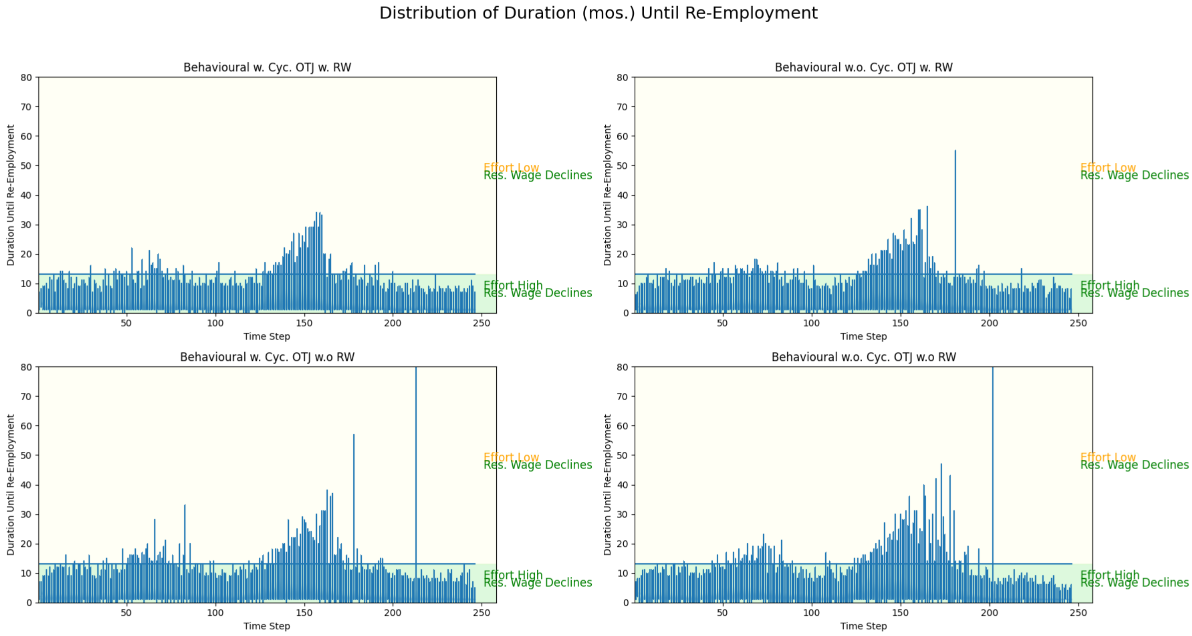


Figure 28: Behavioral Regimes - Time to Reemployment

Current Demand vs Target Demand

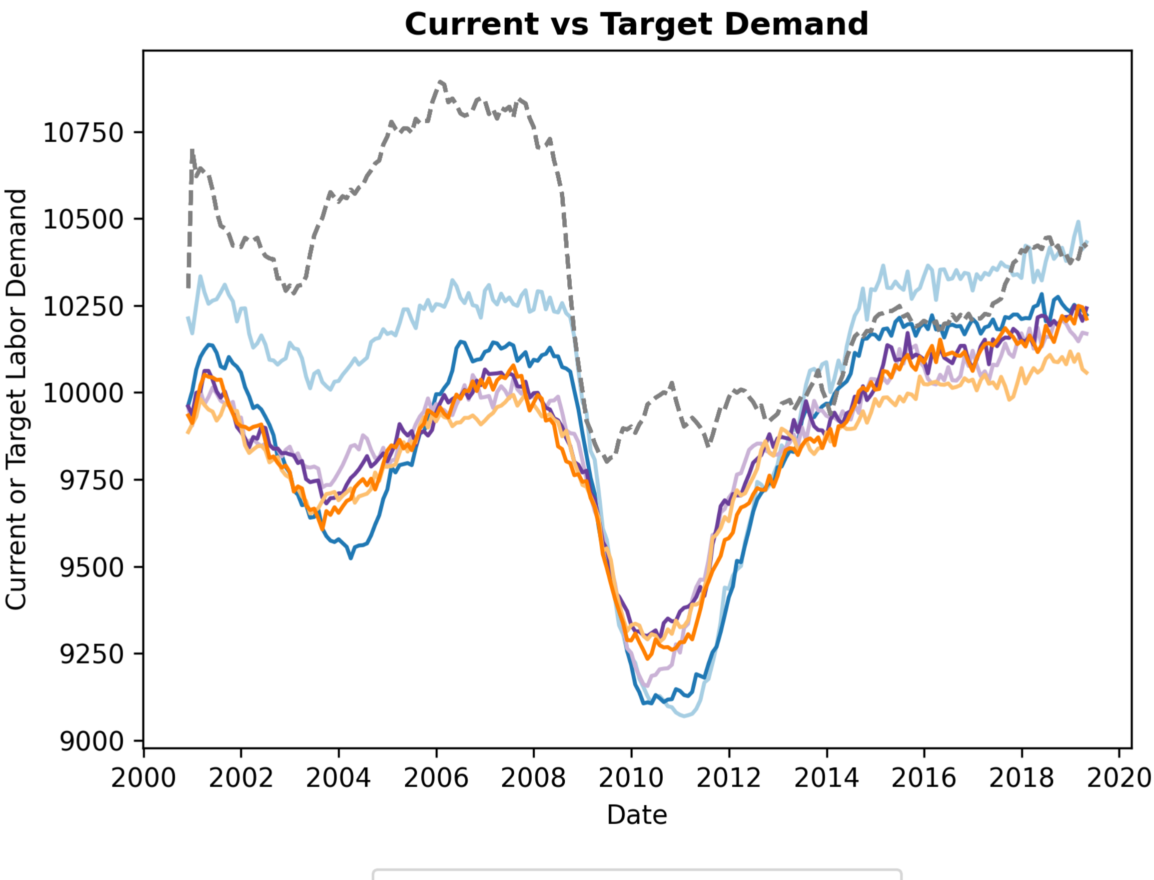


Figure 29: Current Demand vs Target Demand

Gender Wage Gaps

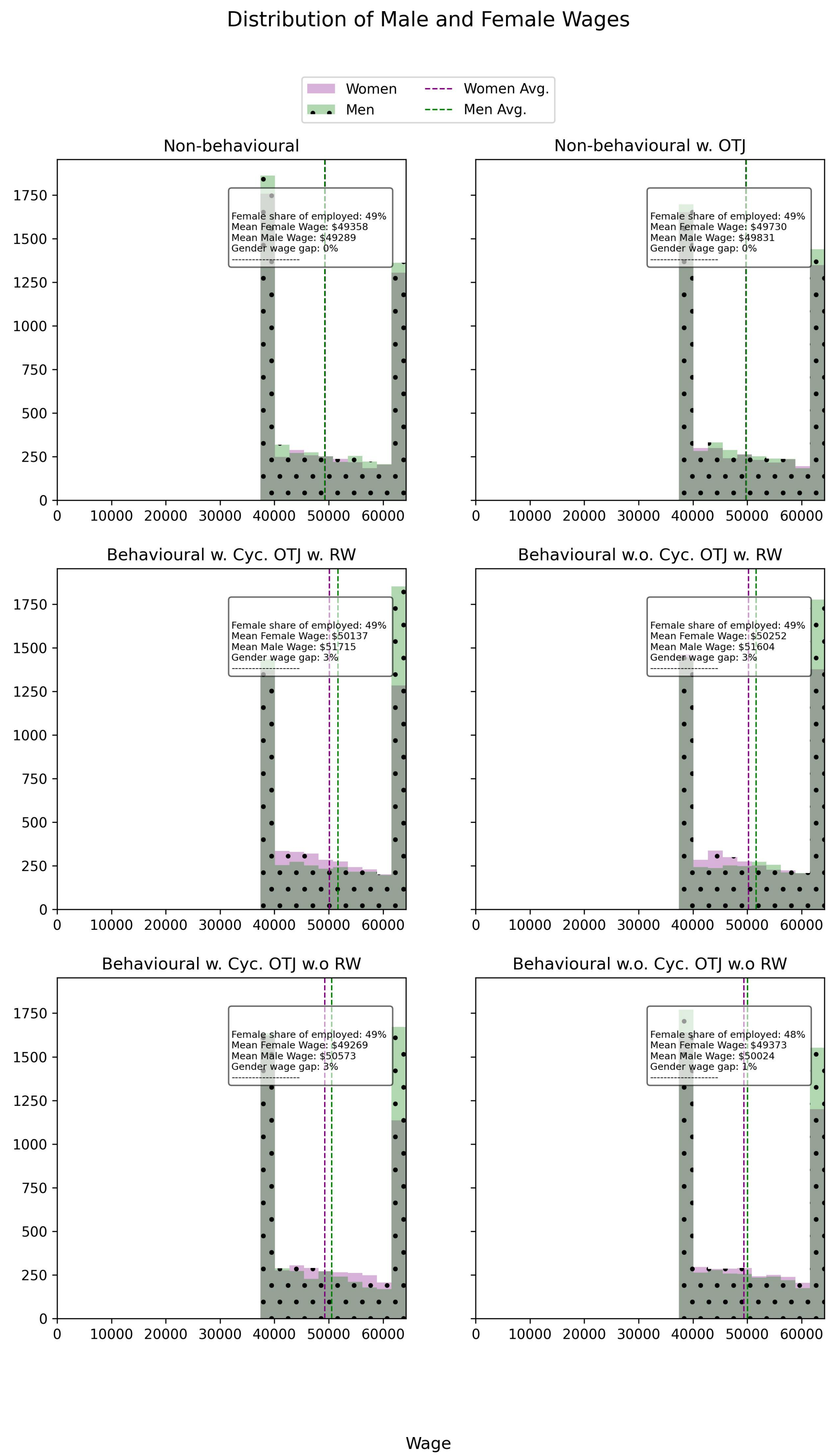


Figure 30: Gender Wage Gaps

F Steady State

F.1 Full Occupational Mobility Network

Figure 31: Unemployment & Vacancy Rate in Steady State

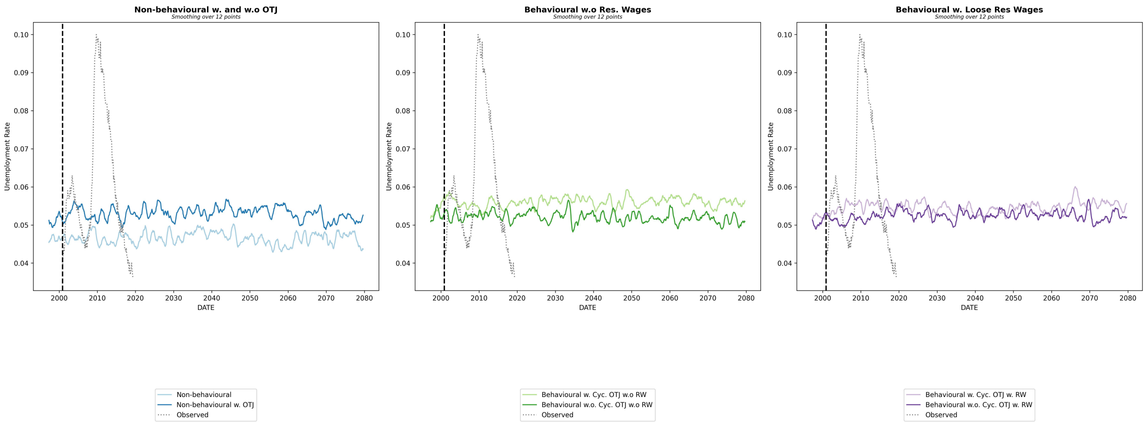
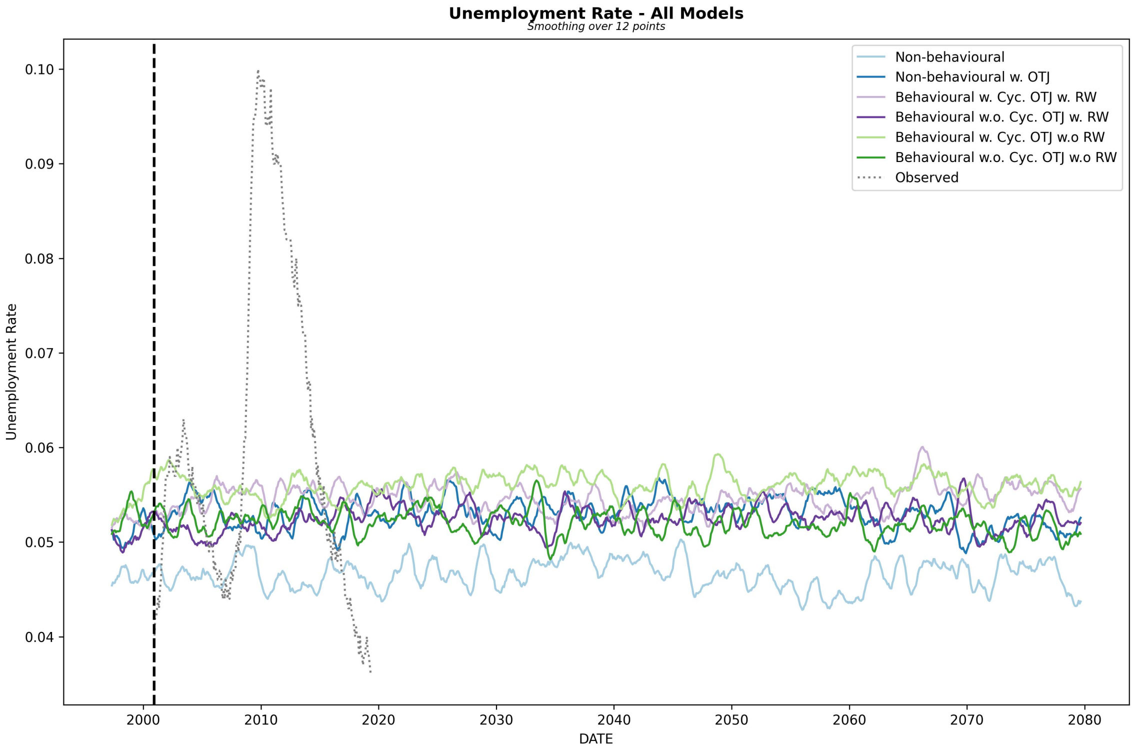


Figure 32: Unemployment & Vacancy Rate in Steady State



F.2 ONET

Figure 33: Unemployment & Vacancy Rate in Steady State

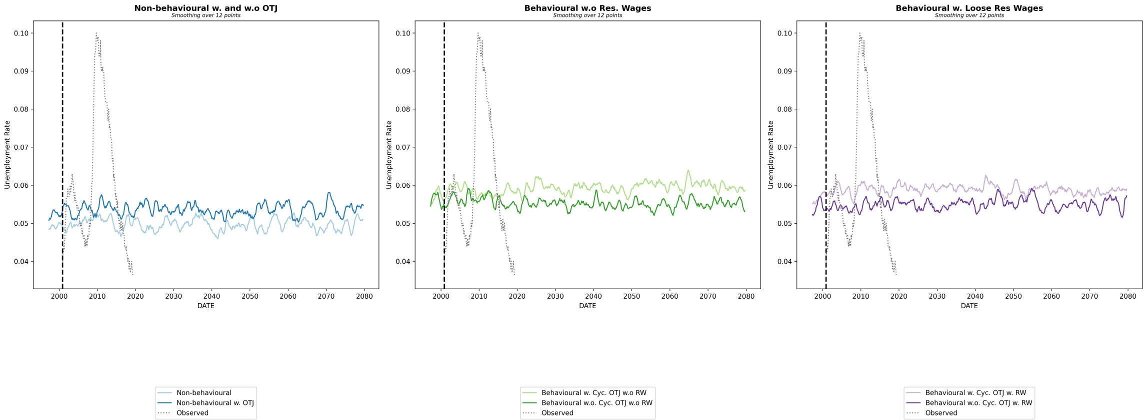
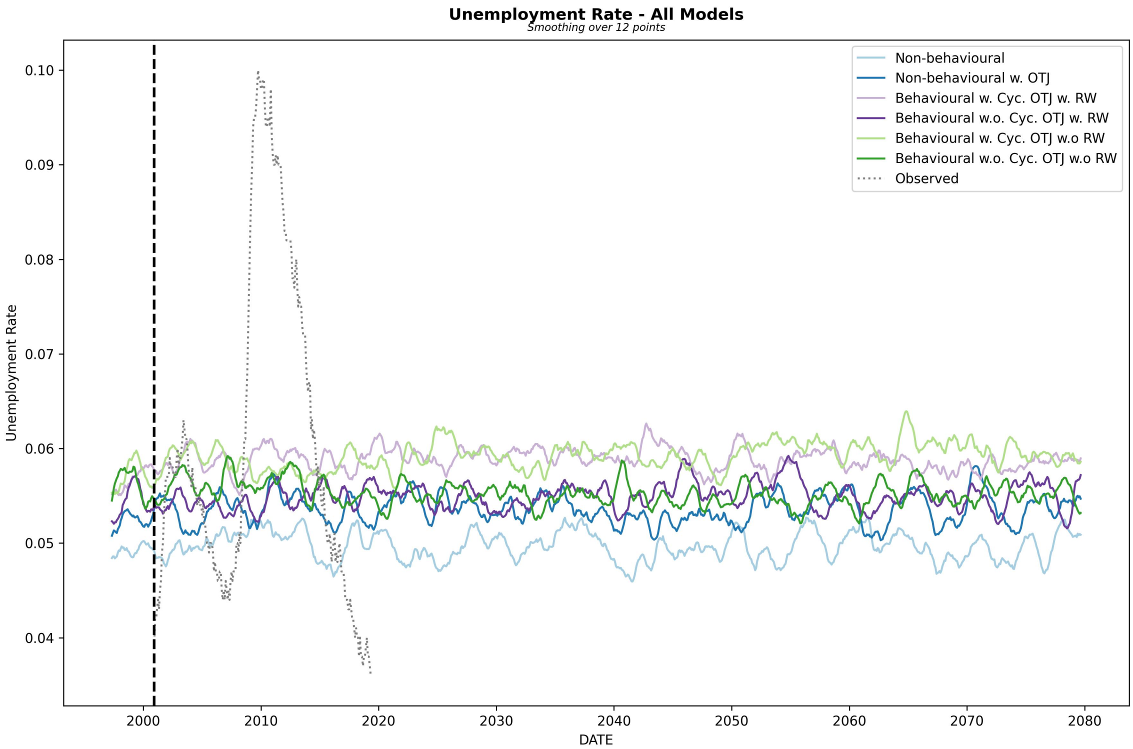


Figure 34: Unemployment & Vacancy Rate in Steady State



F.3 ONET with Wage Asymmetry Correction

Figure 35: Unemployment & Vacancy Rate in Steady State

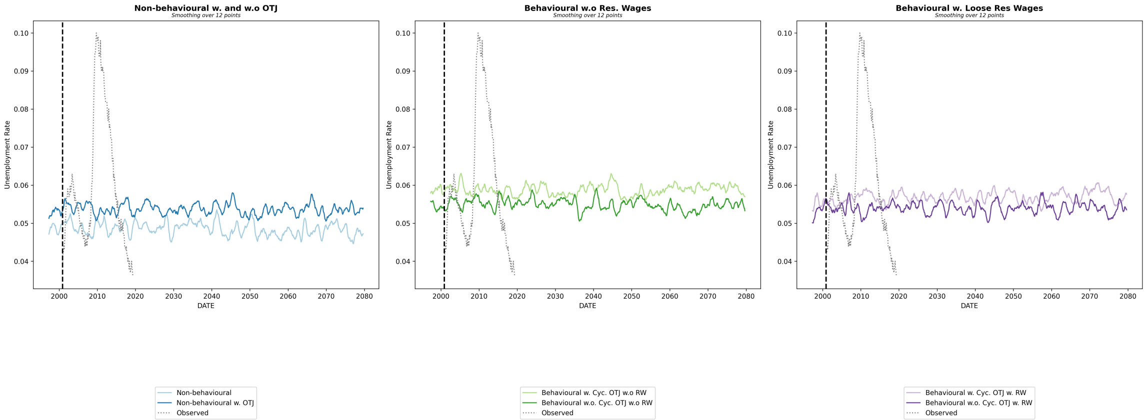
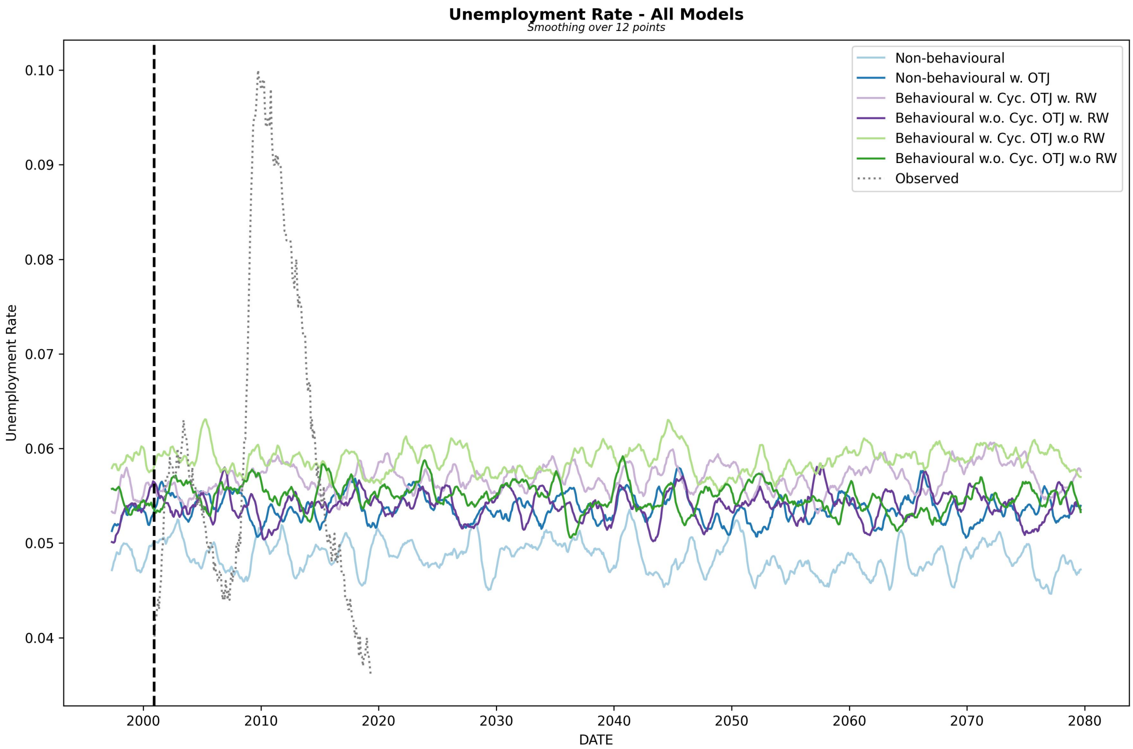


Figure 36: Unemployment & Vacancy Rate in Steady State



F.4 Single Node

Figure 37: Unemployment & Vacancy Rate in Steady State

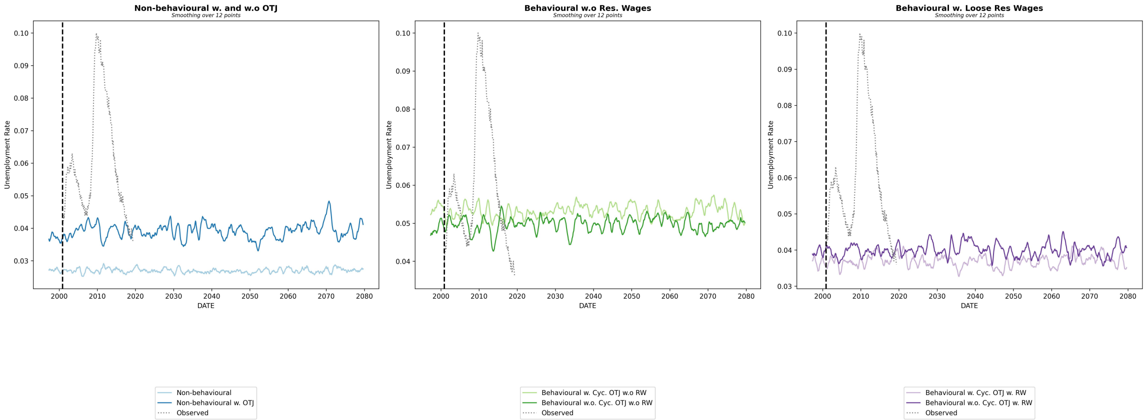
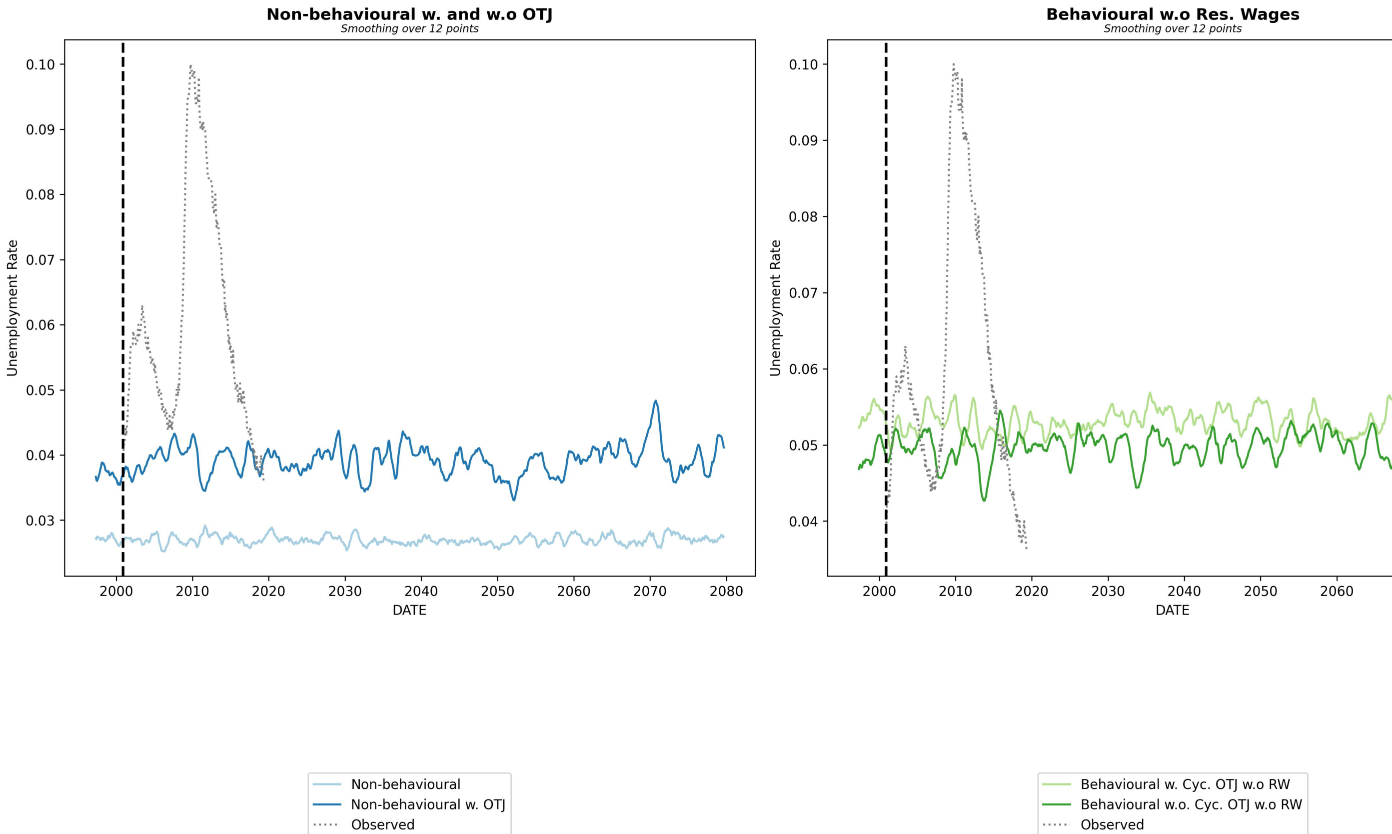


Figure 38: Unemployment & Vacancy Rate in Steady State



The above simulation was run over a period of 1,000 months where target demand across all occupations is 1. Observed unemployment and vacancy rates between 2000-2019 are plotted in relation to the length of this time series. The red line represents the typical "adjustment period" allowed in each simulation whose results are reported in the main text.

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