

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

## Application Effort and Learning Dynamics: Applications Sent

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

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

PRUNEDUR	3	DURATION OF UNEMPLOYMENT FOR LAYOFF AND LOOKING RECORDS	407 - 409
		EDITED UNIVERSE: PEMLR = 3-4	
<b><u>VALID ENTRIES</u></b>			
	0	MIN VALUE	
	119	MAX VALUE	
Topcoded consistent with PELAYDUR or PELKDUR, as appropriate, starting April 2011.			

Figure 1: Survey Question: Unemployment Duration

- A1 Now, we also have a few questions about your experience looking for a new job over the last 2 months. How many jobs (have you/has name) applied for, if any, in the last 2 months?  
 (Do not read the answer choices aloud)
- (0) 1
  - (1) 1 to 10
  - (2) 11 to 20
  - (3) 21 to 80
  - (4) 81 or more

Figure 2: Survey Question: Applications Sent

## Overview of Survey Results

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

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

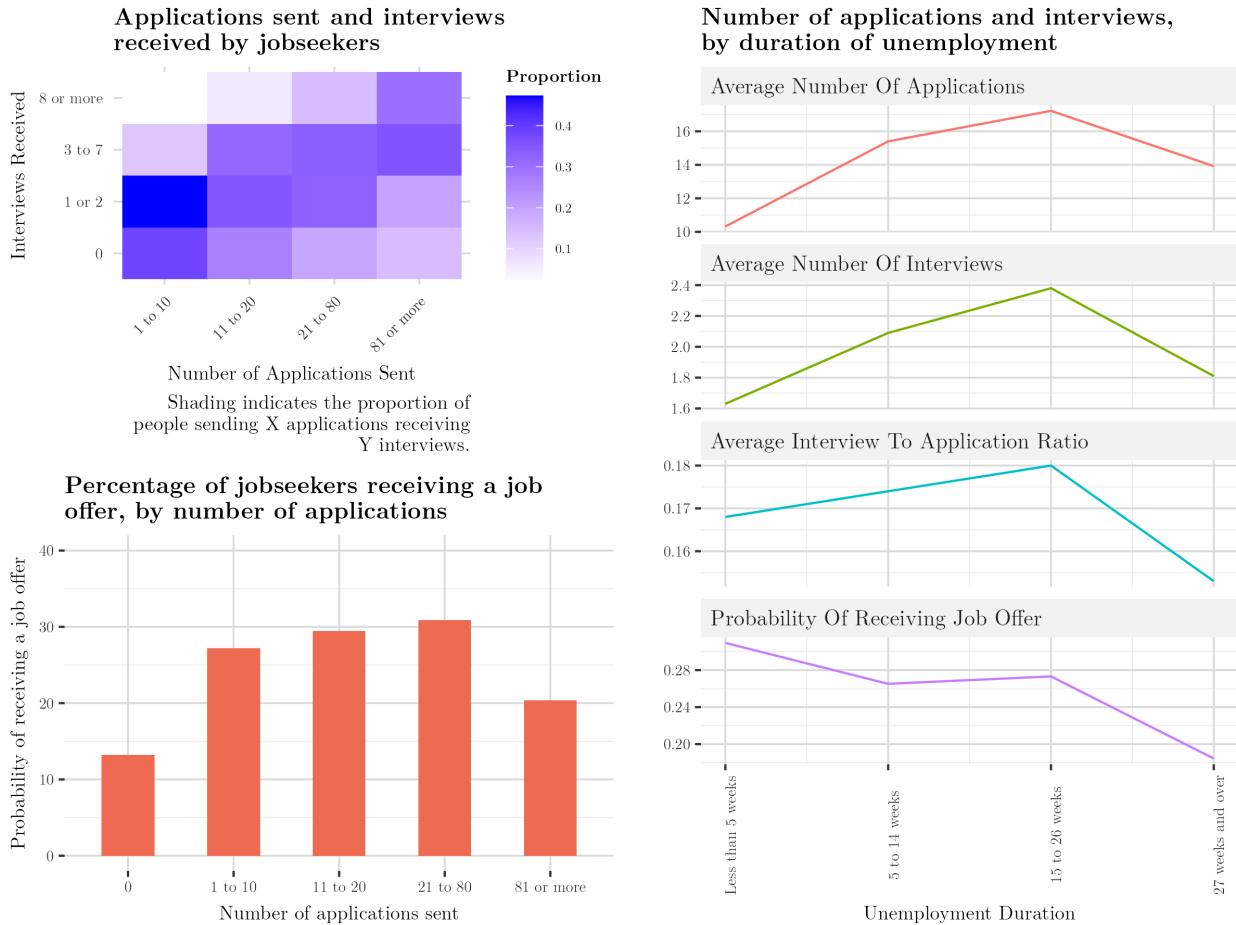
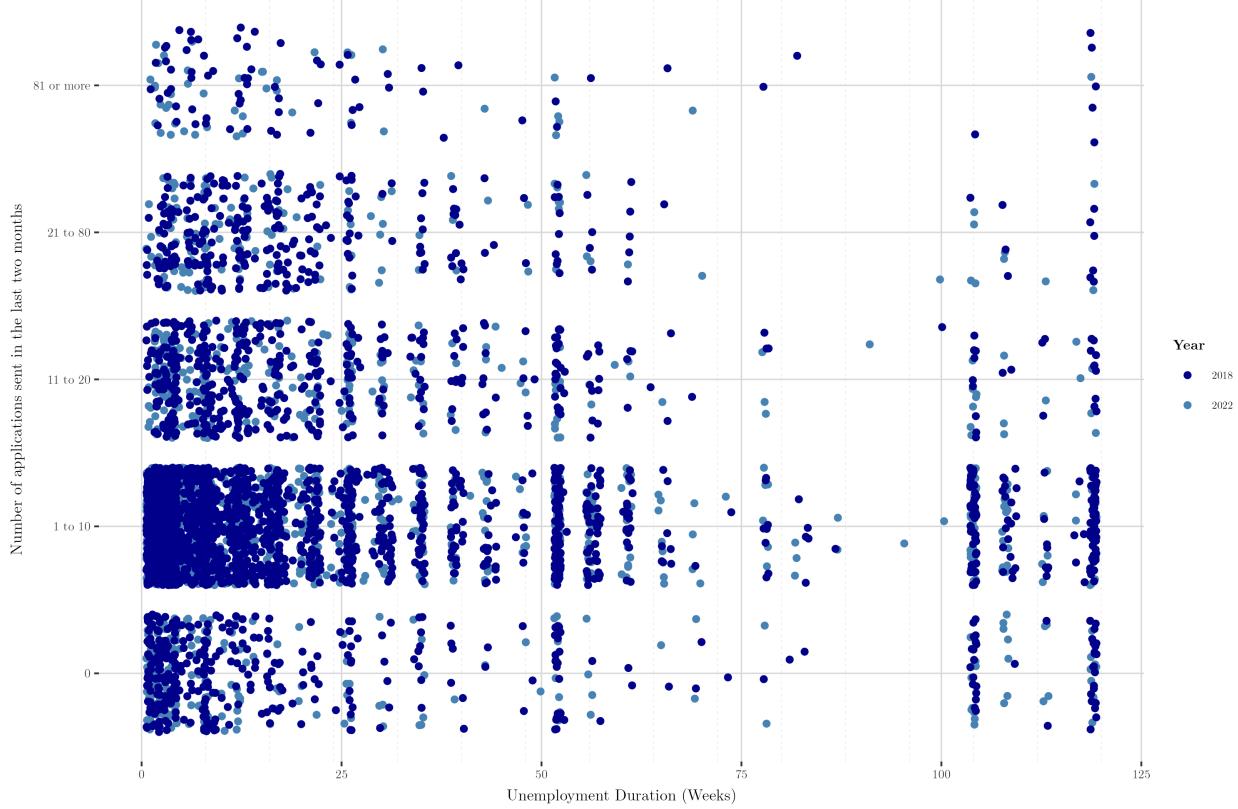


Figure 3: Replication of BLS Analysis

## Econometric Specification Using Raw Data

**Applications sent vs. Time Spent Unemployed: 2022 & 2018**  
 Grey gridlines align with 2-month/8-week intervals. N = 2,896 (2018) & 1,677 (2022)



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

Below, we display the results of an exploration of the probability of reporting a specific number of applications sent (in the bins as in the survey question above) using various specifications of an ordinal logistic regression. We 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,  $\Pr(Y_i \leq j | X_i)$ , is modeled as follows for each link function:

$$\text{Complementary log-log (cloglog): } \Pr(Y_i \leq j | X_i) = 1 - \exp(-\exp(\tau_j - X_i^\top \beta))$$

$$\text{Logistic (logit): } \Pr(Y_i \leq j | X_i) = \frac{1}{1 + \exp(-(\tau_j - X_i^\top \beta))}$$

$$\text{Loglog: } \Pr(Y_i \leq j | X_i) = \exp(-\exp(-(\tau_j - X_i^\top \beta)))$$

$$\text{Probit: } \Pr(Y_i \leq j | X_i) = \Phi(\tau_j - X_i^\top \beta)$$

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

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

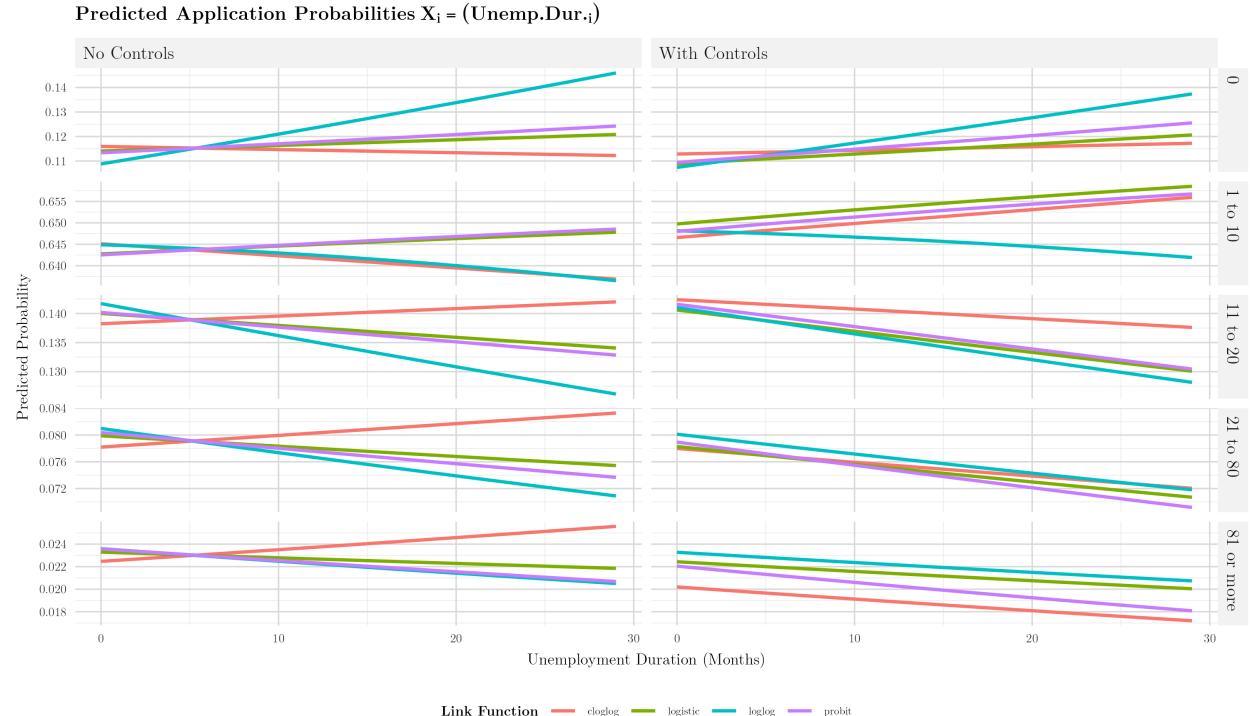
$$X_i = (\text{Unemp.Dur.}_i^2)$$

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

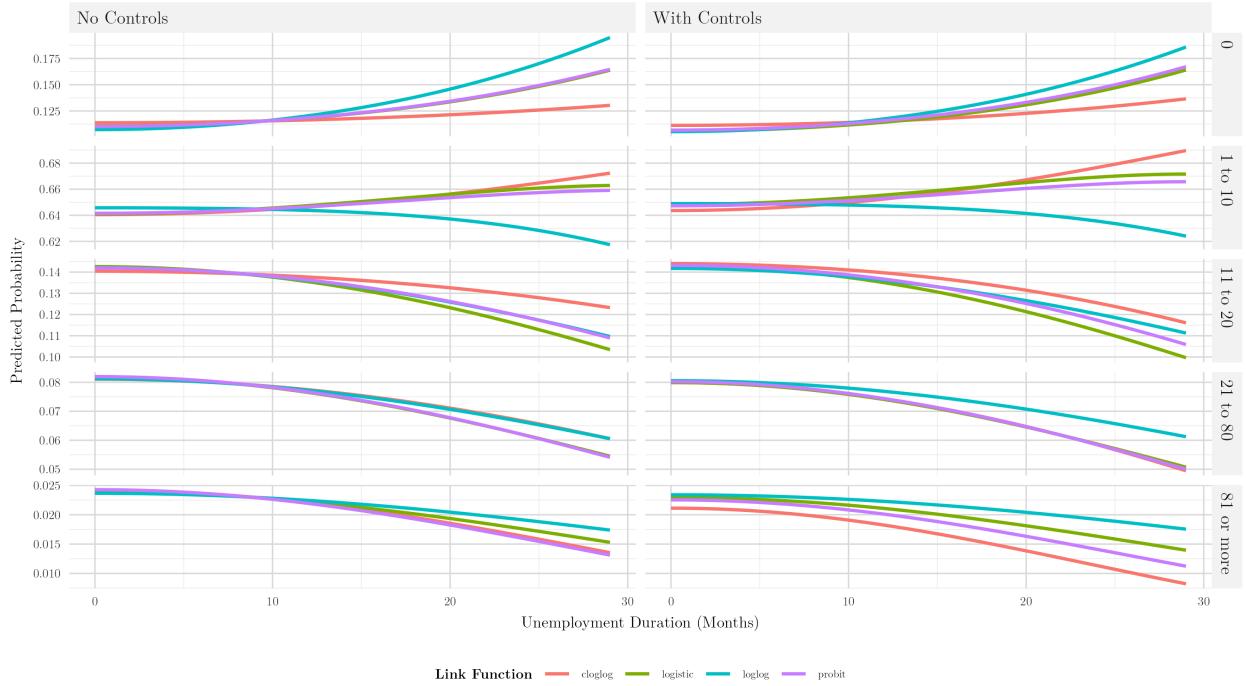
with and without control variables (education, gender, age, family income).

Assumptions about the probability distribution of the errors associated with each link function:

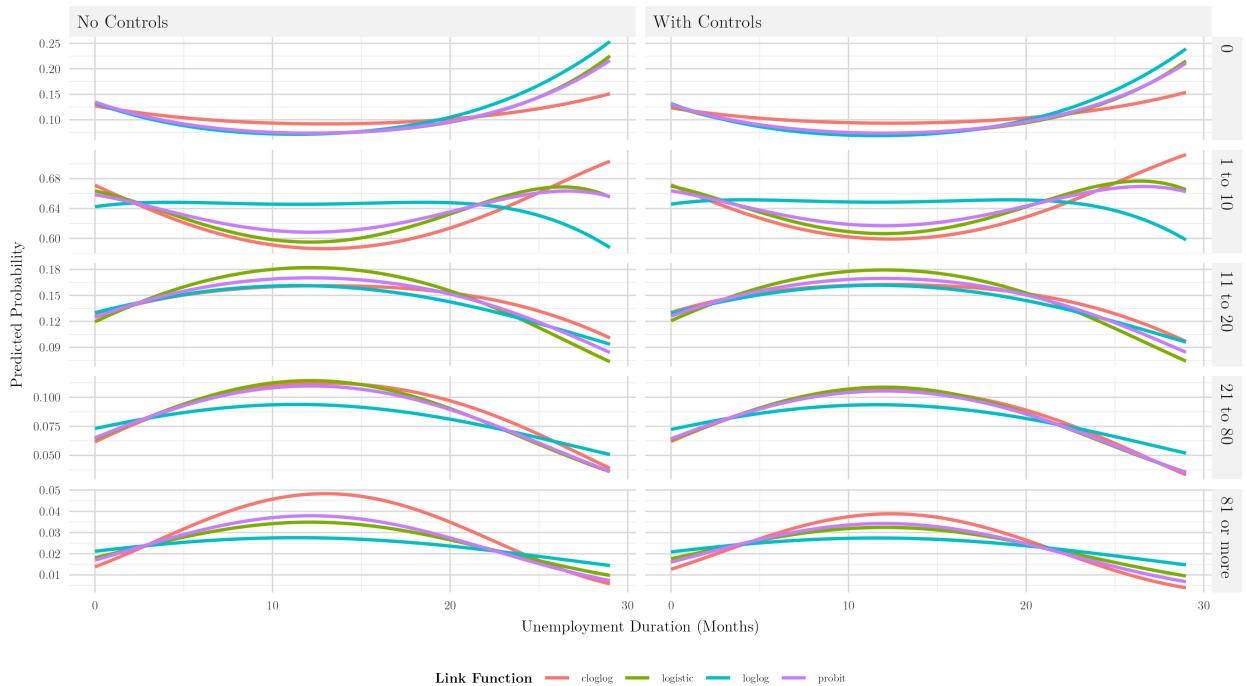
- *Logit*: Useful when responses are evenly distributed across categories.
- *Probit*: Useful when latent variable is assumed to be normally distributed.
- *Complementary log-log*: Useful when higher categories are more probable.
- *Log-log*: When early categories are of more importance or more probable.



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

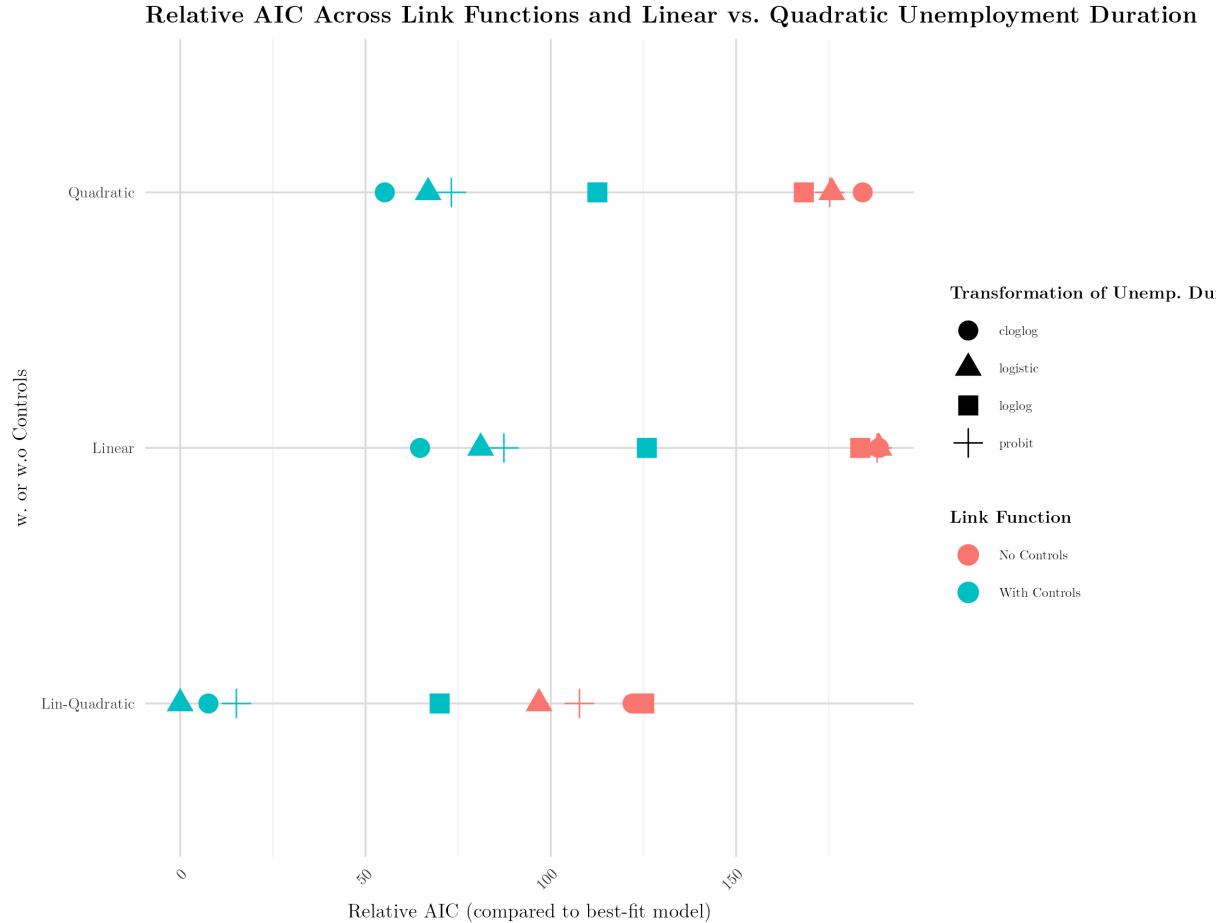


Predicted Application Probabilities  $X_i = (\text{Unemp.Dur.}_i, \text{Unemp.Dur.}_i^2)$



Using an AIC information criterion to compare the fit across all models, clear results emerge. Models including socio-demographic controls consistently outperform unadjusted models (blue versus red dots in the figure below) and the inclusion of a quadratic transformation (labelled “Lin-Quadratic” in the plot below) of unemployment duration better captures the non-linear relationship between unemployment duration and application effort. Among link functions, the complementary log-log specification performs best across model comparisons. Though the logistic link function emerges as slightly superior in the specification incorporating

a linear and quadratic term, we choose to employ the complementary log-log link function to align with the hypothesis that fine-grained resolution is needed among low application effort categories, which dominate the data. Thus, employing a complementary log-log link function, quadratic unemployment duration, and full demographic controls, we generate predicted probabilities over the five application bins for unemployment spells ranging from 0 to 36 months. These fitted probabilities serve as the empirical foundation for modeling job search effort in the agent-based simulation. In our chosen specification, the odds of reporting a lower application bin increase by approximately 0.1% per additional month unemployed, a relationship statistically significant at the 0.1% level. However, the inclusion of a quadratic term allows for a concave shape to emerge, better fitting the non-linearity of this relationship between unemployment duration and applications sent.



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

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

### Predicted Probabilities of Application Effort by Unemployment Duration

N = 5,169

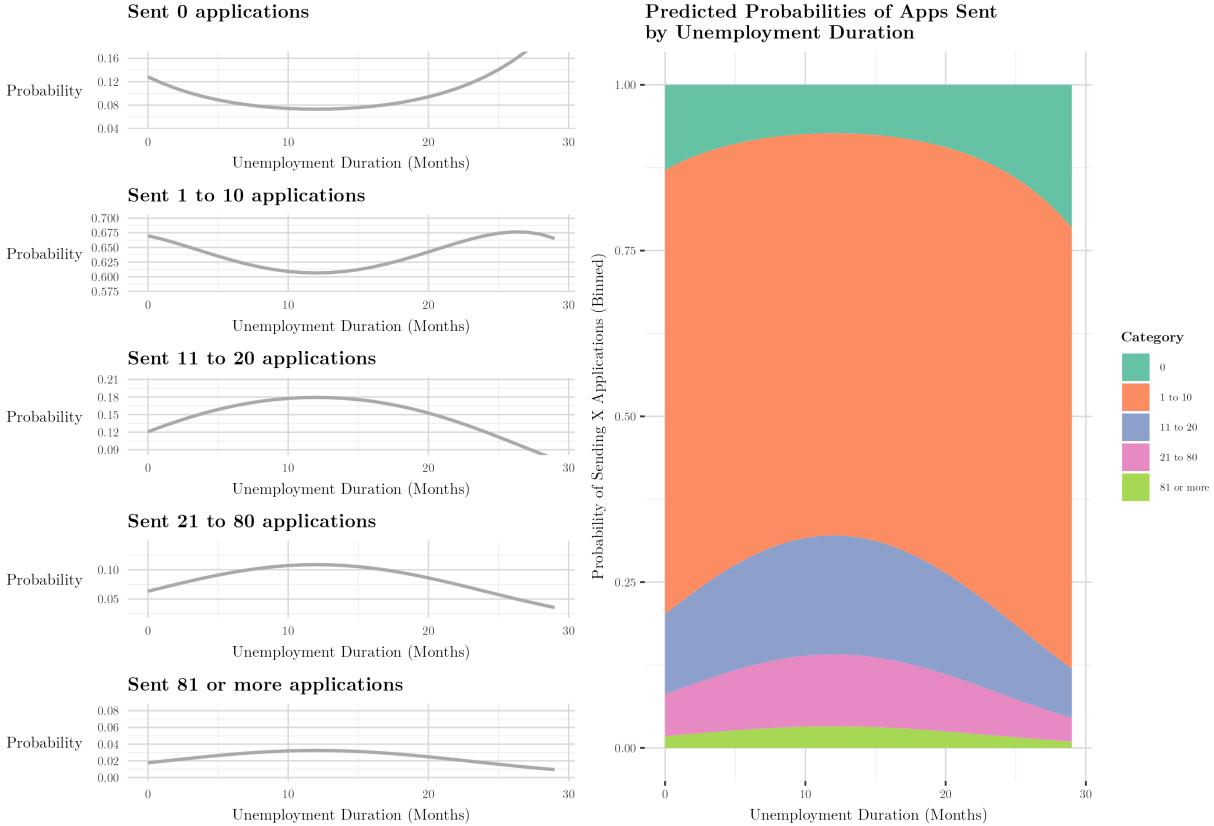
Bureau of Labor Statistics Data reported in 2018 and 2022.

Estimated using an ordinal logistic regression in which the outcome variables are bins of applications sent.

Unemployment duration enters quadratically w. socio-demographic controls.

Controls: Education, Age, Gender, Family Income, Race excluded because of lack of statistical significance.

Link function: Complementary log-log function selected using AIC comparison on 4 alternative link functions.



### Wage Expectations and Satisficing: Reservation Wage Adjustment

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

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

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

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

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

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

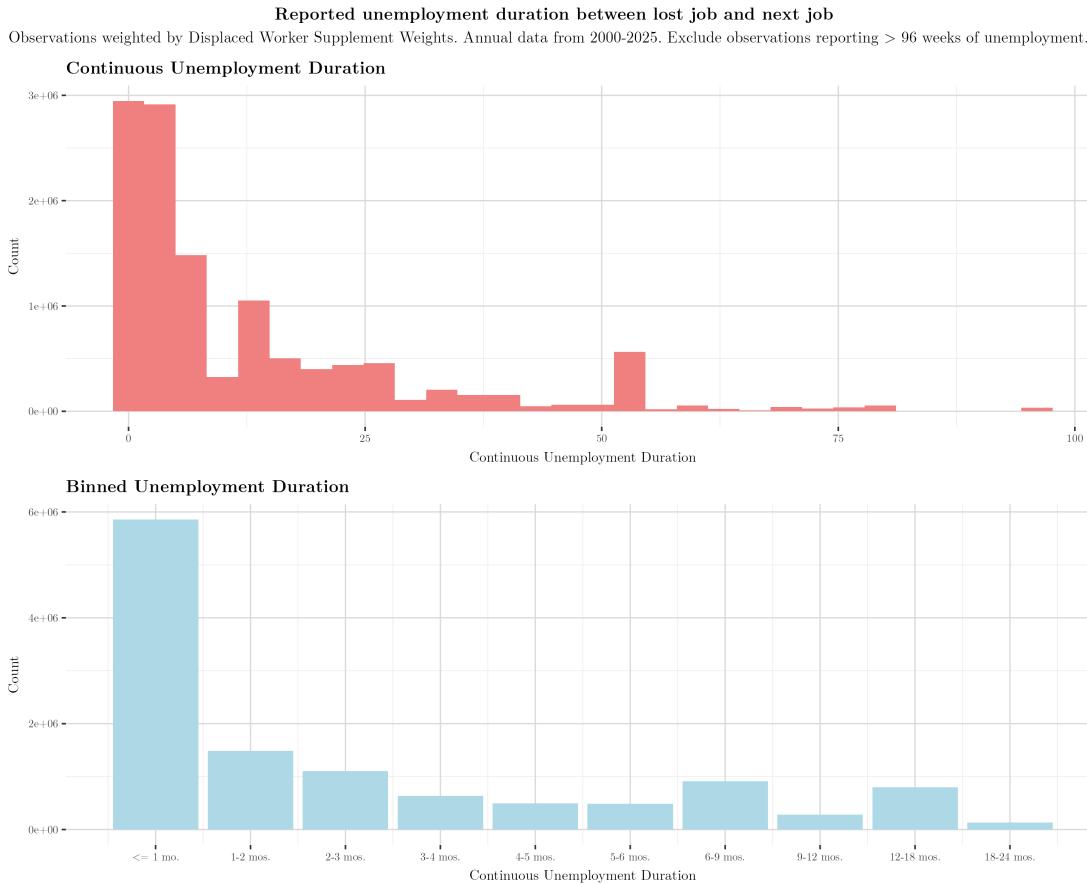
Overall, we find that individuals accept a ~1-percentage point decrease in the wage ratio per additional month of unemployment. Variations using model reweighting, different samples, combinations of control variables, reported hourly and weekly wage ratios do not seem to affect the result. However, the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

#### Potential Limitations:

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

## Descriptives

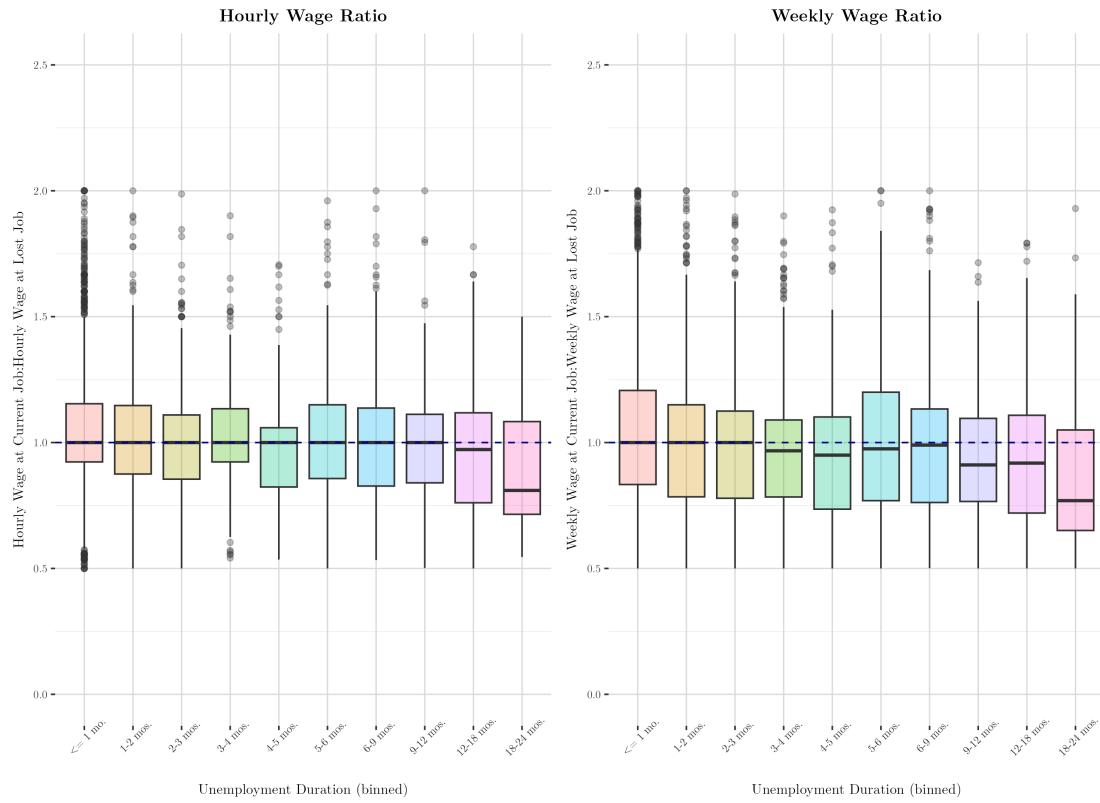
First, we display the distribution of continuous (red) and binned (blue) unemployment duration. The distribution is, as expected, heavily skewed, with more individuals concentrated at low unemployment durations. The binned values in the blue histogram are the binned values later employed as an outcome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



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

**Reported ratio of current wage to lost wage by unemployment duration**

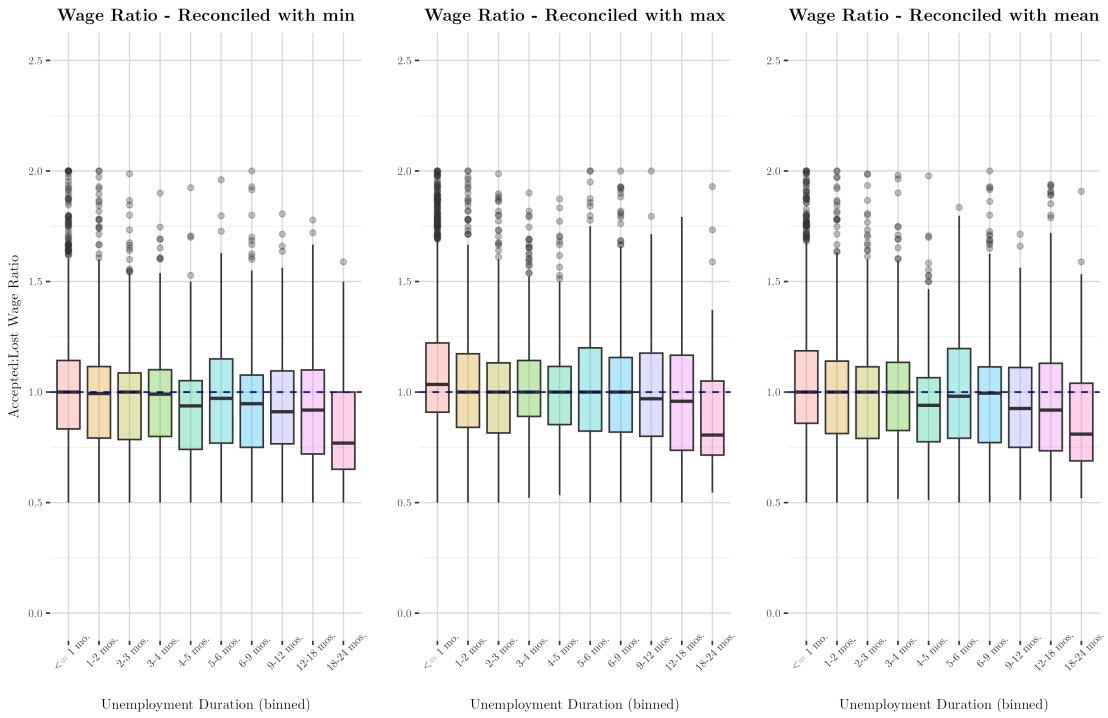
Observations weighted by Displaced Worker Supplement Weights.  
Annual data from 2000-2005.  
Exclude observations reporting > 96 weeks of unemployment.



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

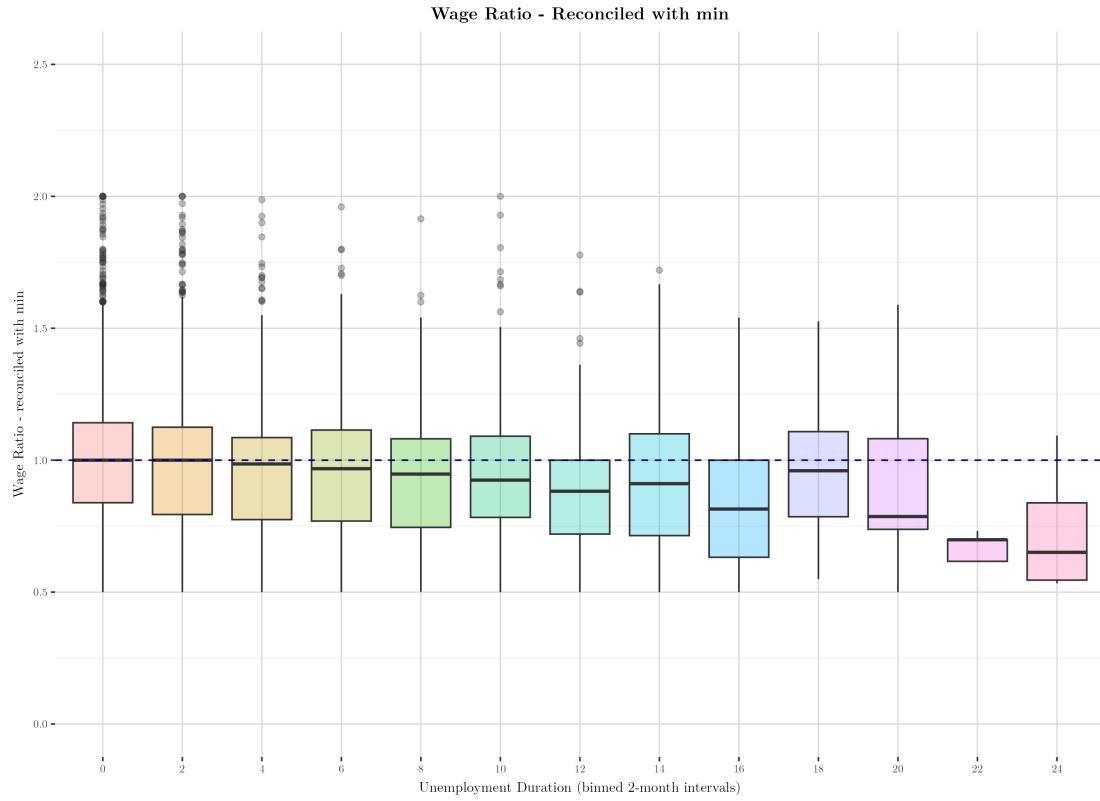
### Reported ratio of current wage to lost wage by unemployment duration

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



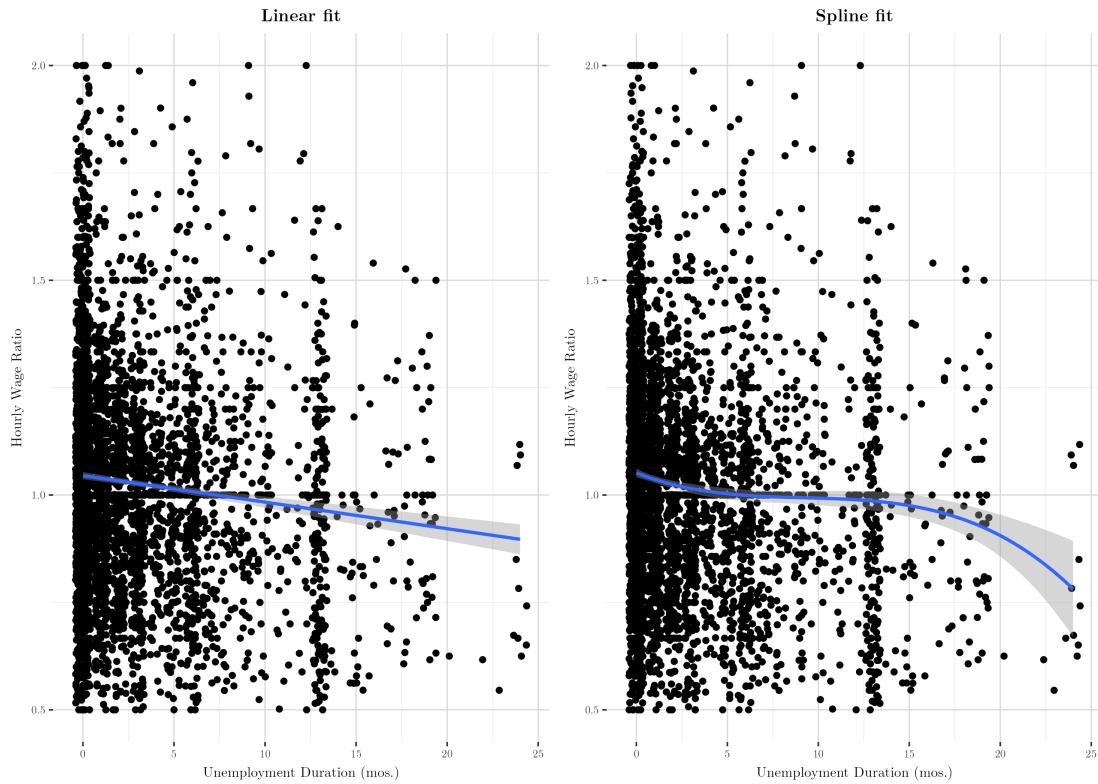
**Reported ratio of current wage to lost wage by unemployment duration**

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



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

**Linear and spline fit to scatter plot of wage ratio vs. unemployment duration in months.**  
 Observations weighted by Displaced Worker Supplement  
 Weights. Annual data from 2000-2025. Exclude observations reporting > 96 weeks of unemployment and wage ratios below 0.5 and above 2.



## Regressions (non-uniform sample)

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

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

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

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

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

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

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

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

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

In each regression table, we include the full set of coefficients to allow for examination of the regression coefficients on the controls as well as the principal variables of interest. In each table, we highlight  $\beta_1$  as this is the main regression coefficient of interest. We employ the *check\_model()* function from the *performance* package in R to display visual checks of various model assumptions.

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

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

## Continuous UE Duration

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

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

	Cont. (clipped)	Cont. w. UI (clipped)	Cont. w. exhausted UI (clipped)	Cont. Sq. w. UI (clipped)	Cont. w. UI & controls (clipped)	Cont. Sq. w. UI & controls (clipped)	Cont. w. UI or controls (clipped)	Cont. Sq. w. UI or controls (clipped)	Cont. w. UI & controls (clipped)	Cont. Sq. w. UI & controls (clipped)	Cont. w. UI or controls (clipped)	Cont. Sq. w. UI or controls (clipped)
Intercept	1.045*** (0.004)	1.045*** (0.004)	1.006*** (0.004)	1.006*** (0.005)	1.006*** (0.005)	1.006*** (0.006)	1.013*** (0.021)	1.013*** (0.021)	1.013*** (0.021)	1.013*** (0.021)	1.013*** (0.021)	1.018*** (0.021)
Unemployment Duration (Months)	-0.012*** (0.001)	-0.012*** (0.001)	-0.012*** (0.001)	-0.012*** (0.002)	-0.012*** (0.002)	-0.012*** (0.002)	-0.012*** (0.003)	-0.012*** (0.003)	-0.012*** (0.003)	-0.012*** (0.003)	-0.012*** (0.003)	-0.012*** (0.002)
Received Unemployment Compensation	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.002)	0.000 (0.002)	0.000 (0.002)	0.000 (0.002)	0.000 (0.002)	0.000 (0.001)
Estimated Unemployment Compensation	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Unemployment Duration (Months) <sup>2</sup>												
Female												
Age												
White												
Black												
Mixed												
Married												
High School												
Associate's Degree												
Bachelor's Degree												
Postgraduate Degree												
Nom.Obs.	664	664	664	664	664	664	644	644	644	644	644	644
R2	0.012	0.012	0.022	0.012	0.012	0.023	0.022	0.022	0.022	0.022	0.022	0.022
R2 Adj.	0.012	0.011	0.022	0.011	0.011	0.022	0.020	0.020	0.020	0.020	0.020	0.020
DIMSE	1.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24

= p < 0.5%, \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

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

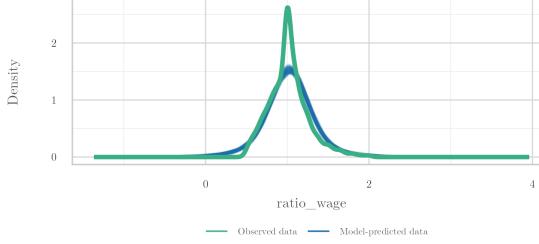
	Cont.	Cont. w. UI	Cont. w. exhausted UI	Cont. Sq	Cont. Sq w. UI	Cont. Sq w. exhausted UI	Cont. w. controls	Cont. w. UI w. controls	Cont. w. exhausted UI w. controls	Cont. Sq w. controls	Cont. Sq w. UI w. controls	Cont. Sq w. exhausted UI w. controls
Intercept	1.053*** (0.006)	1.053*** (0.006)	1.006*** (0.010)	1.055*** (0.007)	1.055*** (0.007)	1.002*** (0.011)	1.180*** (0.031)	1.180*** (0.031)	1.119*** (0.031)	1.180*** (0.031)	1.180*** (0.031)	1.116*** (0.033)
Unemployment Duration (Months)	-0.007*** (0.001)	-0.007*** (0.001)	-0.005*** (0.001)	-0.009*** (0.002)	-0.009*** (0.002)	-0.003 (0.003)	-0.006*** (0.001)	-0.006*** (0.001)	-0.004*** (0.001)	-0.005*** (0.002)	-0.005*** (0.002)	-0.003 (0.003)
Received Unemployment Compensation	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Exhausted Unemployment Compensation		0.001*** (0.000)		0.001*** (0.000)			0.000*** (0.000)		0.000*** (0.000)		0.001*** (0.000)	
Unemployment Duration (Months <sup>2</sup> )		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 (0.011)	0.003 (0.011)	0.003 (0.011)	0.003 (0.011)	0.003 (0.011)	0.003 (0.011)	0.003 (0.011)
Age						-0.003*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)
White						-0.035 (0.023)	-0.035 (0.023)	-0.035 (0.023)	-0.035 (0.023)	-0.035 (0.023)	-0.035 (0.023)	-0.035 (0.023)
Black						-0.048 (0.026)	-0.048 (0.026)	-0.048 (0.026)	-0.048 (0.026)	-0.048 (0.026)	-0.048 (0.026)	-0.048 (0.026)
Mixed						0.014 (0.040)	0.014 (0.040)	0.014 (0.040)	0.014 (0.040)	0.014 (0.040)	0.014 (0.040)	0.014 (0.040)
Married						0.005 (0.011)	0.005 (0.011)	0.005 (0.011)	0.005 (0.011)	0.005 (0.011)	0.005 (0.011)	0.005 (0.011)
High School						0.005 (0.010)	0.005 (0.010)	0.005 (0.010)	0.005 (0.010)	0.005 (0.010)	0.005 (0.010)	0.005 (0.010)
Associate's Degree						0.032 (0.021)	0.032 (0.021)	0.032 (0.021)	0.032 (0.021)	0.032 (0.021)	0.032 (0.021)	0.032 (0.021)
Bachelor's Degree						0.114* (0.045)	0.114* (0.045)	0.122** (0.045)	0.115* (0.045)	0.115* (0.045)	0.115* (0.045)	0.122** (0.045)
Postgraduate Degree												
Numb.Obs.	4870	4870	4870	4870	4870	4870	4870	4870	4870	4870	4870	4870
R2	0.009	0.009	0.017	0.010	0.017	0.025	0.025	0.025	0.025	0.025	0.025	0.025
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

### Continuous U Duration. w. UI Control w. demographic controls (clipped sample)

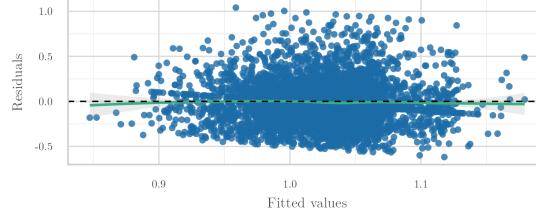
#### Posterior Predictive Check

Model-predicted lines should resemble observed data line



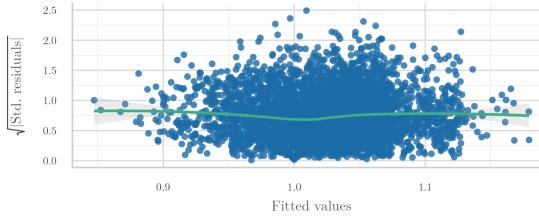
#### Linearity

Reference line should be flat and horizontal



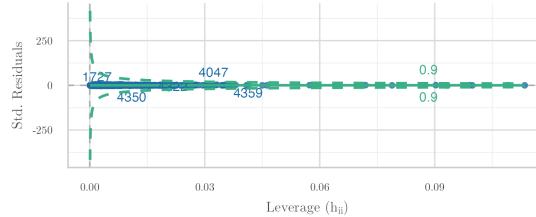
#### Homogeneity of Variance

Reference line should be flat and horizontal



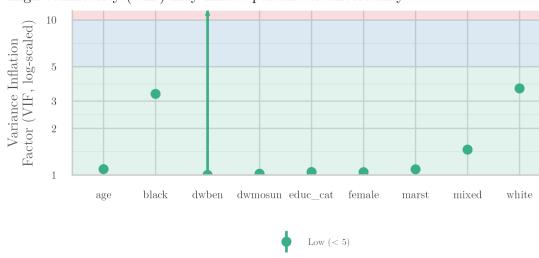
#### Influential Observations

Points should be inside the contour lines



#### Collinearity

High collinearity (VIF) may inflate parameter uncertainty



#### Normality of Residuals

Dots should fall along the line

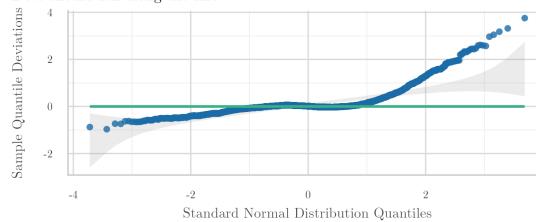


Table 3: Continuous UE Duration w. Wage Level Control (Clipped Sample)

	Cost. (clipped)	Cost. w. UI (clipped)	Cost. w. censored UI (clipped)	Cost. Sq (clipped)	Cost. Sq w. UI (clipped)	Cost. Sq w. censored UI (clipped)	Cost. w. controls (clipped)	Cost. w. censored UI w. controls (clipped)	Cost. Sq w. controls (clipped)	Cost. Sq w. UI w. controls (clipped)	Cost. Sq w. censored UI w. controls (clipped)
Intercept	1.13 <sup>***</sup> (0.001)	1.13 <sup>***</sup> (0.001)	1.09 <sup>***</sup> (0.001)	1.12 <sup>***</sup> (0.001)	1.09 <sup>***</sup> (0.001)	1.12 <sup>***</sup> (0.001)	1.21 <sup>***</sup> (0.001)	1.17 <sup>***</sup> (0.001)	1.21 <sup>***</sup> (0.001)	1.17 <sup>***</sup> (0.001)	1.10 <sup>***</sup> (0.001)
Housy Wage of Lost Job:	-0.000 <sup>**</sup> (0.000)	-0.007 <sup>***</sup> (0.001)	-0.007 <sup>***</sup> (0.001)	-0.007 <sup>***</sup> (0.001)	-0.007 <sup>***</sup> (0.001)	-0.007 <sup>***</sup> (0.001)					
Unemployment Duration (Months)	-0.000 <sup>**</sup> (0.001)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)					
Received Unemployment Compensation	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Estimated Unemployment Compensation		0.000 <sup>**</sup> (0.000)		0.000 <sup>**</sup> (0.000)		0.000 <sup>**</sup> (0.000)		0.000 <sup>**</sup> (0.000)		0.000 <sup>**</sup> (0.000)	
Unemployment Duration (Months) <sup>2</sup>			0.000 (0.000)		0.000 (0.000)						0.000 <sup>**</sup> (0.000)
Female											0.000 (0.000)
Age											0.000 (0.000)
White											0.000 (0.000)
Black											0.000 (0.000)
Mixed											0.000 (0.000)
Married											0.000 (0.000)
High School											0.015 <sup>*</sup> (0.007)
Associate's Degree											0.022 <sup>*</sup> (0.007)
Bachelor's Degree											0.027 <sup>**</sup> (0.007)
Postgraduate Degree											0.030 <sup>**</sup> (0.007)
Num.Obs.	6644	6644	6644	6644	6644	6644	6644	6644	6644	6644	6644
R2	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94
R2 Adj.	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93
R2SE	0.24	0.24	0.24	0.24	0.24	0.24	0.23	0.23	0.23	0.23	0.23

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

### Predicted Wage Ratios by Unemployment Duration

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

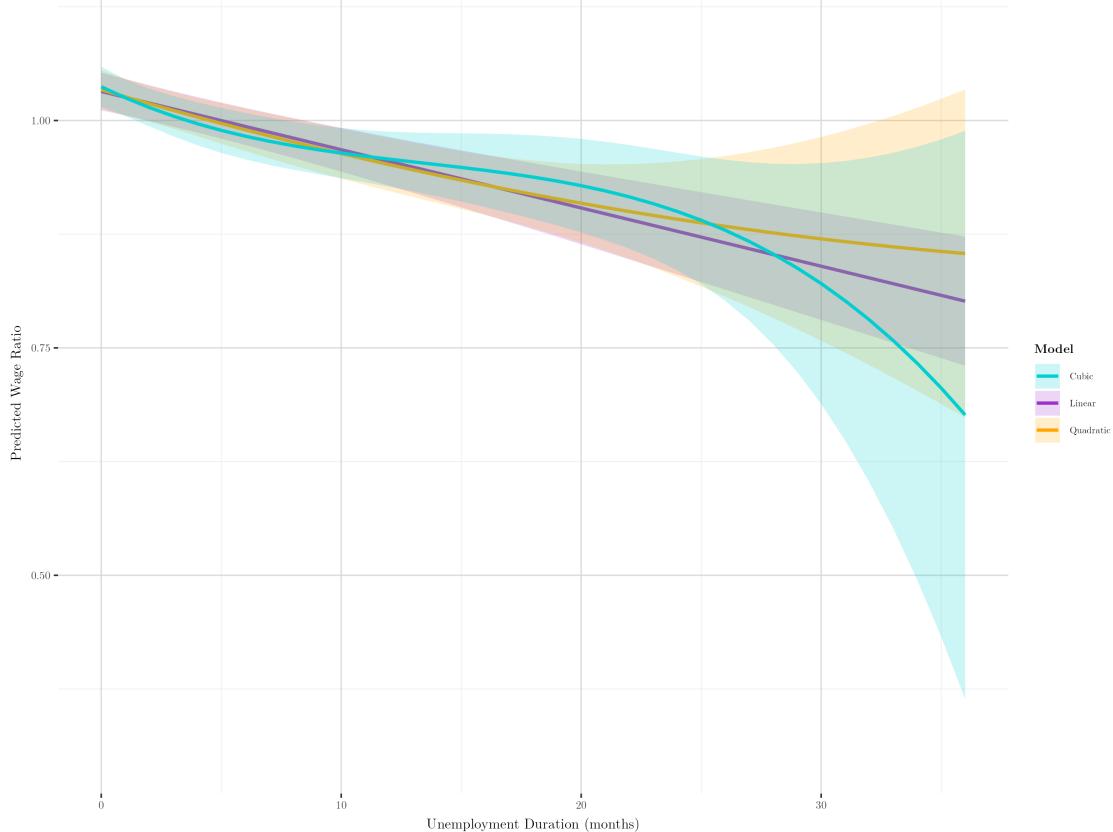


Table 4: Continuous UE Duration w. Wage Level Control (Full Sample)

	Cont.	Cont. w. UI	Cont. w. exhausted UI	Cont. Sq	Cont. Sq w. UI	Cont. Sq w. exhausted UI	Cont. w. controls	Cont. w. UI w. controls	Cont. w. exhausted UI w. controls	Cont. Sq w. controls	Cont. Sq w. UI w. controls	Cont. Sq w. exhausted UI w. controls
Intercept	1.185*** (0.011)	1.186*** (0.011)	1.145*** (0.014)	1.186*** (0.012)	1.187*** (0.012)	1.141*** (0.015)	1.263*** (0.015)	1.263*** (0.031)	1.213*** (0.031)	1.263*** (0.031)	1.263*** (0.031)	1.210*** (0.032)
Hourly Wage of Lost Job	-0.009*** (0.001)	-0.009*** (0.001)	-0.009*** (0.001)	-0.009*** (0.001)	-0.009*** (0.001)	-0.009*** (0.001)	-0.011*** (0.001)	-0.011*** (0.001)	-0.011*** (0.001)	-0.011*** (0.001)	-0.011*** (0.001)	-0.011*** (0.001)
Unemployment Duration (Months)	-0.007*** (0.001)	-0.007*** (0.001)	-0.005*** (0.002)	-0.007** (0.002)	-0.007** (0.003)	-0.003 (0.001)	-0.006*** (0.001)	-0.006*** (0.001)	-0.005*** (0.001)	-0.007** (0.002)	-0.007** (0.002)	-0.003 (0.003)
Received Unemployment Compensation	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Exhausted Unemployment Compensation	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	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 <sup>2</sup> )	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	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** (0.011)	-0.028** (0.011)	-0.028** (0.011)	-0.028** (0.011)	-0.028** (0.011)	-0.028** (0.011)
Age							-0.002*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)
White							-0.013 (0.023)	-0.013 (0.023)	-0.013 (0.023)	-0.013 (0.023)	-0.013 (0.023)	-0.013 (0.023)
Black							-0.058* (0.026)	-0.058* (0.026)	-0.055* (0.026)	-0.057* (0.026)	-0.057* (0.026)	-0.055* (0.026)
Mixed							0.016 (0.039)	0.016 (0.039)	0.016 (0.039)	0.016 (0.039)	0.016 (0.039)	0.016 (0.039)
Married							0.013 (0.010)	0.013 (0.010)	0.013 (0.010)	0.013 (0.010)	0.013 (0.010)	0.014 (0.010)
High School							0.033* (0.015)	0.033* (0.015)	0.037* (0.015)	0.033* (0.015)	0.033* (0.015)	0.037* (0.015)
Associate's Degree							0.084*** (0.021)	0.084*** (0.021)	0.088*** (0.021)	0.084*** (0.021)	0.084*** (0.021)	0.087*** (0.021)
Bachelor's Degree							0.161*** (0.022)	0.161*** (0.022)	0.164*** (0.022)	0.161*** (0.022)	0.161*** (0.022)	0.163*** (0.022)
Postgraduate Degree							0.241*** (0.045)	0.241*** (0.045)	0.241*** (0.045)	0.241*** (0.045)	0.241*** (0.045)	0.246*** (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 <sup>2</sup>	121.551	84.832	88.352	67.07	66.734	66.451	30.310	27.380	29.347	25.363	25.369	28.287
RMSE	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37

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

## Binned UE Duration

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

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

	Disc. (clipped)	Disc. w. UI (clipped)	Disc. w. exhausted UI (clipped)	Disc. w. controls (clipped)	Disc. w. UI w. controls (clipped)	Disc. w. exhausted UI w. controls (clipped)
Intercept	1.055*** (0.005)	1.055*** (0.005)	1.010*** (0.008)	1.170*** (0.021)	1.170*** (0.021)	1.116*** (0.023)
Unemployment Duration (Binned)	-0.009*** (0.001)	-0.009*** (0.001)	-0.005*** (0.001)	-0.008*** (0.001)	-0.008*** (0.001)	-0.005*** (0.001)
Received Unemployment Compensation	0.000 (0.001)				0.000 (0.001)	
Exhausted Unemployment Compensation		0.001*** (0.000)				0.001*** (0.000)
Female			-0.003 (0.007)	-0.003 (0.007)	-0.003 (0.007)	
Age			-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	
White			-0.052** (0.016)	-0.052** (0.016)	-0.052** (0.016)	
Black			-0.056** (0.018)	-0.056** (0.018)	-0.056** (0.018)	
Mixed			-0.070** (0.027)	-0.070** (0.027)	-0.070** (0.027)	-0.068* (0.027)
Married			0.011 (0.007)	0.011 (0.007)	0.011 (0.007)	0.012 (0.007)
High School			0.001 (0.011)	0.001 (0.011)	0.001 (0.011)	0.005 (0.011)
Associate's Degree			-0.009 (0.014)	-0.009 (0.014)	-0.009 (0.014)	-0.005 (0.014)
Bachelor's Degree			0.067*** (0.015)	0.067*** (0.015)	0.067*** (0.015)	0.071*** (0.015)
Postgraduate Degree			0.030 (0.031)	0.030 (0.031)	0.030 (0.031)	0.038 (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*** (0.008)	1.069*** (0.008)	1.016*** (0.012)	1.190*** (0.031)	1.190*** (0.031)	1.127*** (0.034)
Unemployment Duration (Binned)	-0.013*** (0.002)	-0.013*** (0.002)	-0.008*** (0.002)	-0.011*** (0.002)	-0.011*** (0.002)	-0.007*** (0.002)
Received Unemployment Compensation	0.000 (0.001)				0.000 (0.001)	
Exhausted Unemployment Compensation		0.001*** (0.000)				0.001*** (0.000)
Female			0.003 (0.011)	0.003 (0.011)	0.003 (0.011)	
Age			-0.003*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)
White			-0.035 (0.023)	-0.035 (0.023)	-0.035 (0.023)	-0.033 (0.023)
Black			-0.047+ (0.026)	-0.047+ (0.026)	-0.047+ (0.026)	-0.045+ (0.026)
Mixed			0.014 (0.040)	0.014 (0.040)	0.014 (0.040)	0.017 (0.040)
Married			0.004 (0.011)	0.004 (0.011)	0.004 (0.011)	0.005 (0.011)
High School			0.006 (0.016)	0.006 (0.016)	0.006 (0.016)	0.012 (0.016)
Associate's Degree			0.033 (0.021)	0.033 (0.021)	0.033 (0.021)	0.038+ (0.021)
Bachelor's Degree			0.082*** (0.021)	0.082*** (0.021)	0.082*** (0.021)	0.087*** (0.021)
Postgraduate Degree			0.116** (0.045)	0.116** (0.045)	0.116** (0.045)	0.124** (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*** (0.008)	1.139*** (0.008)	1.098*** (0.011)	1.224*** (0.021)	1.224*** (0.021)	1.176*** (0.023)
Hourly Wage of Lost Job	-0.006*** (0.000)	-0.006*** (0.000)	-0.006*** (0.000)	-0.007*** (0.000)	-0.007*** (0.000)	-0.007*** (0.000)
Unemployment Duration (Binned)	-0.009*** (0.001)	-0.009*** (0.001)	-0.005*** (0.001)	-0.008*** (0.001)	-0.006*** (0.001)	-0.005*** (0.001)
Received Unemployment Compensation		0.000 (0.001)		0.000 (0.001)		0.000 (0.001)
Exhausted Unemployment Compensation			0.000*** (0.000)			0.000*** (0.000)
Female				-0.023** (0.007)	-0.023** (0.007)	-0.023** (0.007)
Age				-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
White				-0.050** (0.016)	-0.050** (0.016)	-0.049** (0.016)
Black				-0.061*** (0.018)	-0.061*** (0.018)	-0.059*** (0.018)
Mixed				-0.067* (0.027)	-0.067* (0.027)	-0.065* (0.026)
Married				0.017* (0.007)	0.017* (0.007)	0.018* (0.007)
High School				0.019+ (0.011)	0.019+ (0.011)	0.022* (0.011)
Associate's Degree				0.027+ (0.014)	0.027+ (0.014)	0.030* (0.014)
Bachelor's Degree				0.122*** (0.015)	0.122*** (0.015)	0.124*** (0.015)
Postgraduate Degree				0.120*** (0.031)	0.120*** (0.031)	0.124*** (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*** (0.012)	1.199*** (0.012)	1.154*** (0.016)	1.272*** (0.031)	1.272*** (0.031)	1.220*** (0.034)
Hourly Wage of Lost Job	-0.009*** (0.001)	-0.009*** (0.001)	-0.009*** (0.001)	-0.011*** (0.001)	-0.011*** (0.001)	-0.011*** (0.001)
Unemployment Duration (Binned)	-0.011*** (0.002)	-0.011*** (0.002)	-0.008*** (0.002)	-0.011*** (0.002)	-0.010*** (0.002)	-0.007*** (0.002)
Received Unemployment Compensation		0.000 (0.001)			0.000 (0.001)	
Exhausted Unemployment Compensation			0.000*** (0.000)			0.000*** (0.000)
Female				-0.028** (0.011)	-0.028** (0.011)	-0.028** (0.011)
Age				-0.002*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)
White				-0.034 (0.023)	-0.034 (0.023)	-0.032 (0.023)
Black				-0.057* (0.026)	-0.057* (0.026)	-0.054* (0.026)
Mixed				0.017 (0.039)	0.017 (0.039)	0.019 (0.039)
Married				0.013 (0.010)	0.013 (0.010)	0.013 (0.010)
High School				0.034* (0.015)	0.034* (0.015)	0.038* (0.015)
Associate's Degree				0.085*** (0.021)	0.085*** (0.021)	0.088*** (0.021)
Bachelor's Degree				0.163*** (0.022)	0.163*** (0.022)	0.166*** (0.022)
Postgraduate Degree				0.246*** (0.045)	0.246*** (0.045)	0.250*** (0.045)
Num.Obs.	4870	4870	4870	4870	4870	4870
R2	0.047	0.047	0.051	0.069	0.069	0.072
R2 Adj.	0.047	0.047	0.050	0.067	0.067	0.070
F	120.632	80.422	86.995	30.090	27.774	29.084
RMSE	0.37	0.37	0.37	0.37	0.37	0.37

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

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

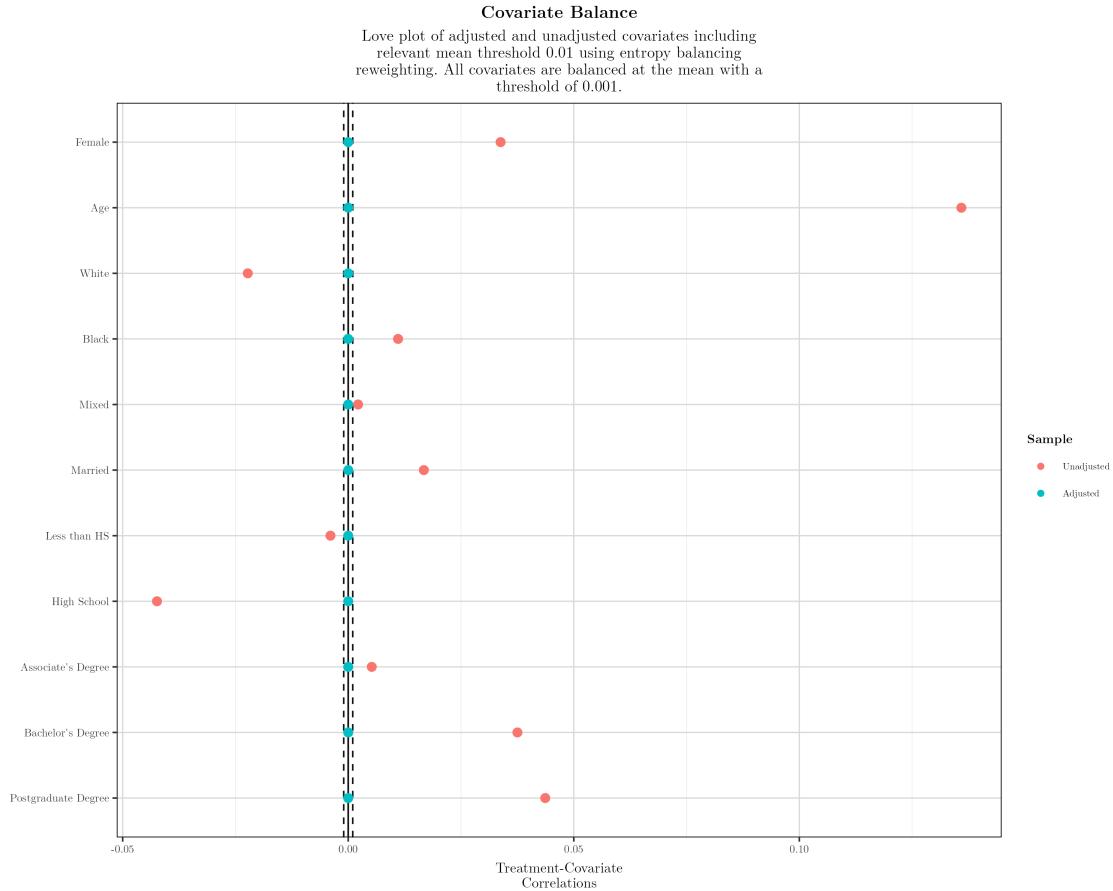
## Regressions with Selection Correction of Non-Random Sample

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

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

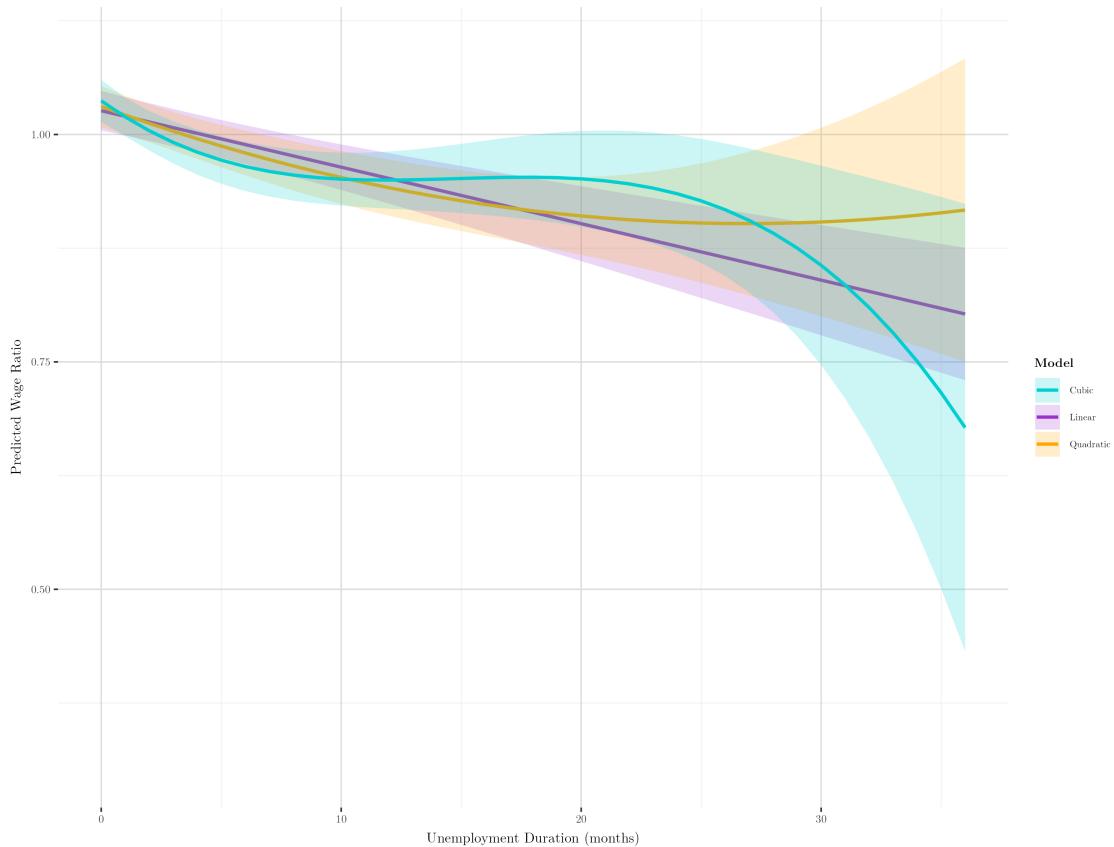
### Entropy Balancing

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

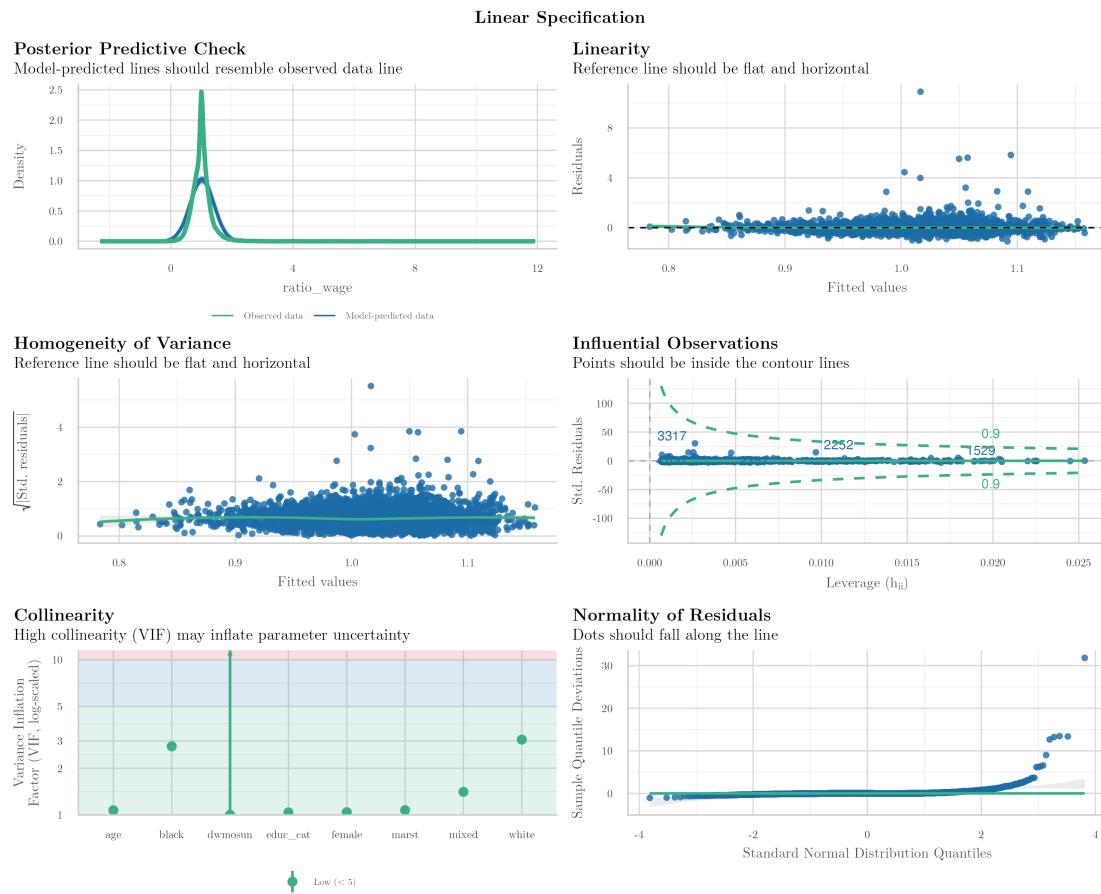


### Predicted Wage Ratios by Unemployment Duration (Entropy Balancing)

From EB-weighted regressions: linear, quadratic, and cubic specifications



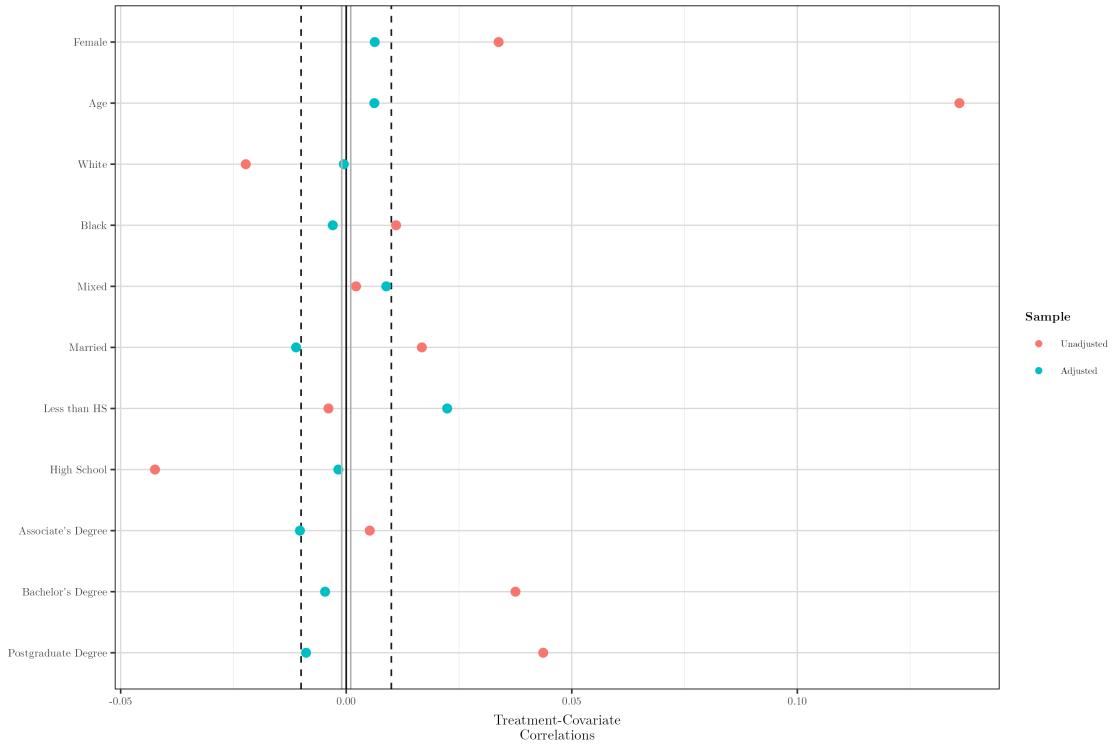
## Diagnostic Tests for Entropy-balanced Reweighted Sample



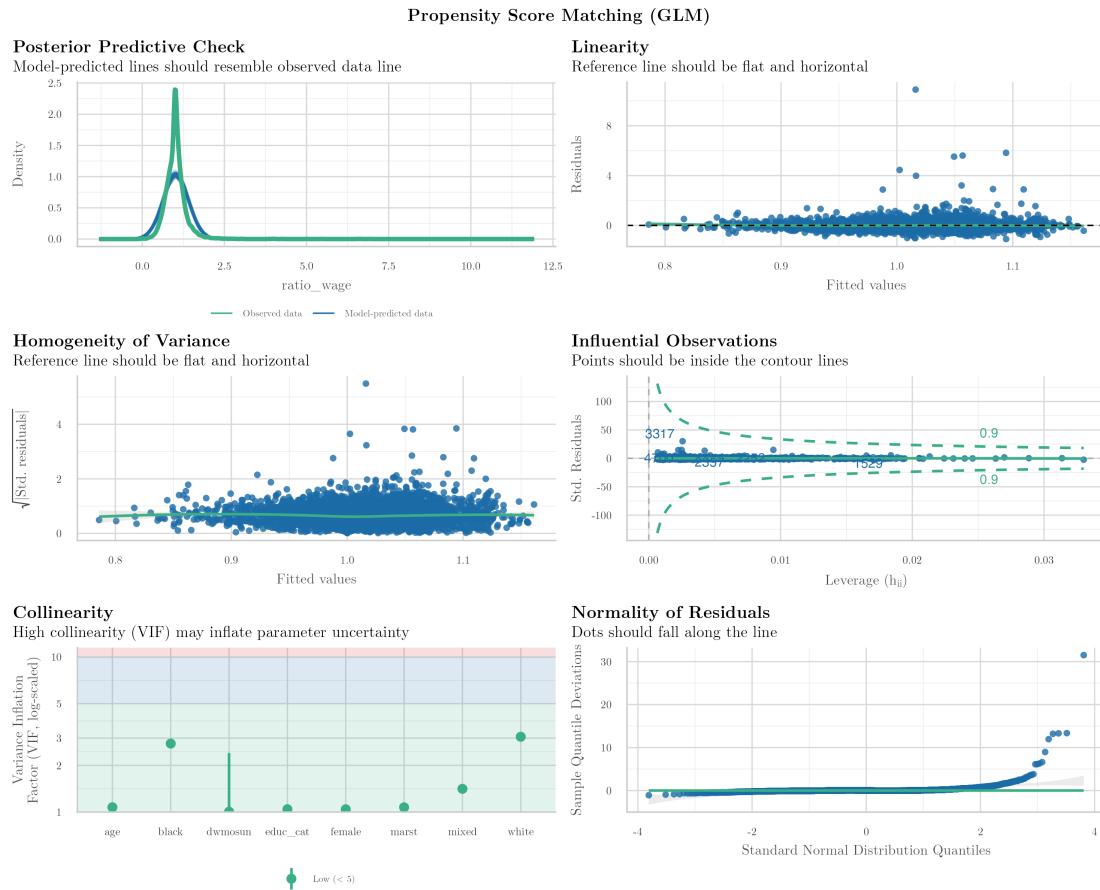
## Propensity Score Weighting with GLM Estimator

### Covariate Balance

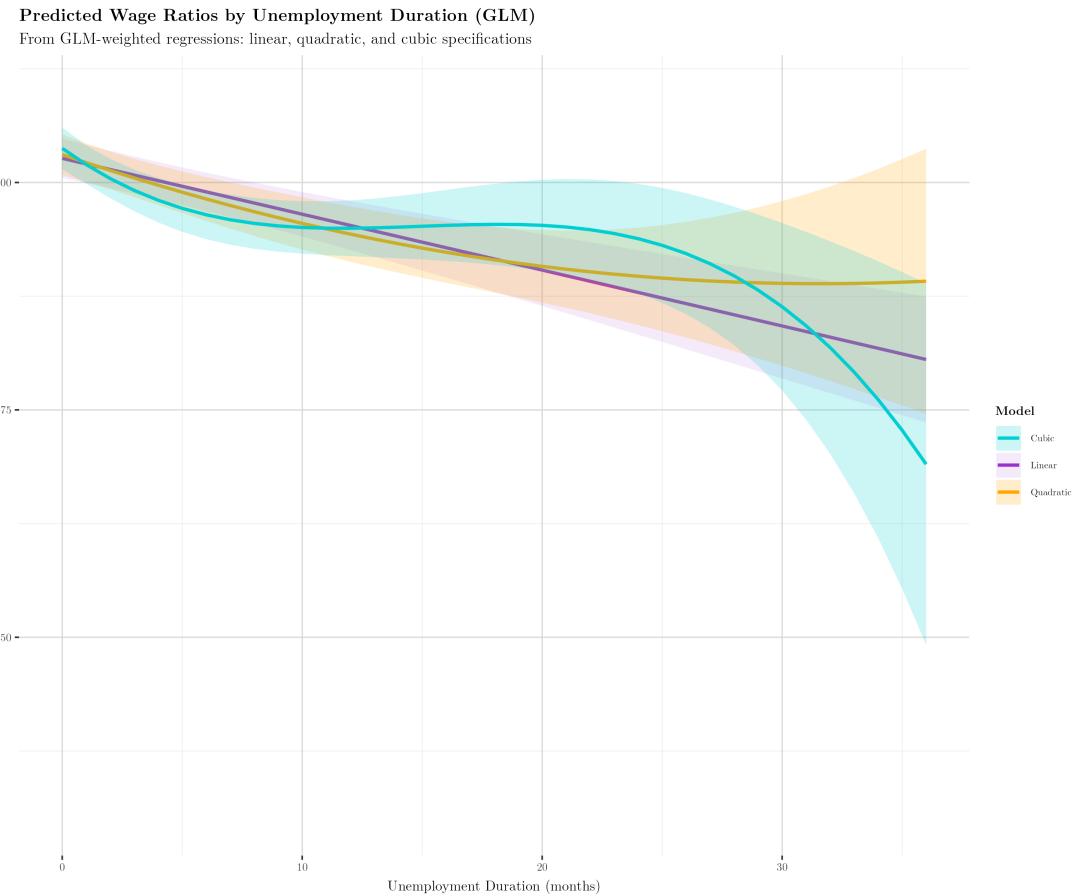
Love plot of adjusted and unadjusted covariates including relevant mean threshold 0.01 using a GLM estimator. All covariates except the binary indicator for having less than a HS degree level of education are balanced at the mean with a threshold of 0.01 (black dashed line) whereas very few variables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



## Diagnostic Tests for Propensity Score Matching (GLM) Reweighted Sample



## Predicted Reservation Wage using GLM Reweighted Sample

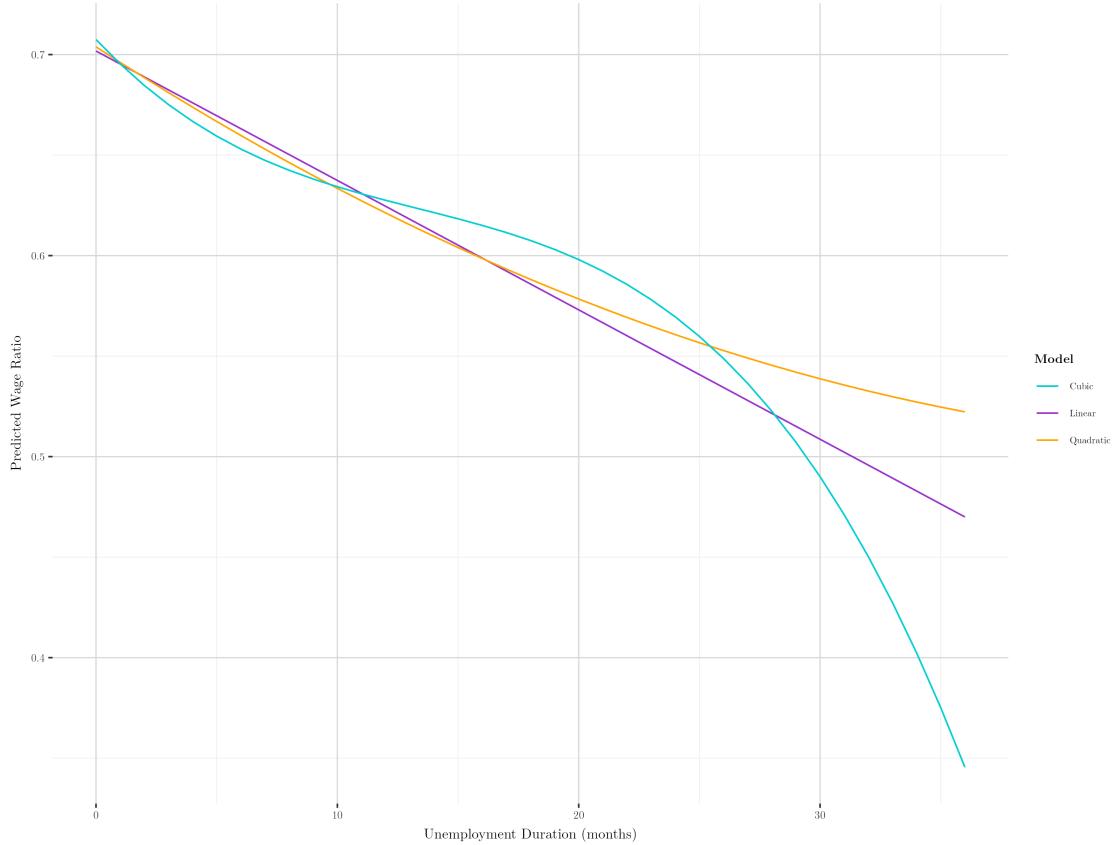


## Heckman Selection

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

**Predicted Wage Ratios by Unemployment Duration (Heckman Selection Correction)**

From Heckman-corrected regressions: linear, quadratic, and cubic specifications



## Regression Results with Sample Reweighting

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

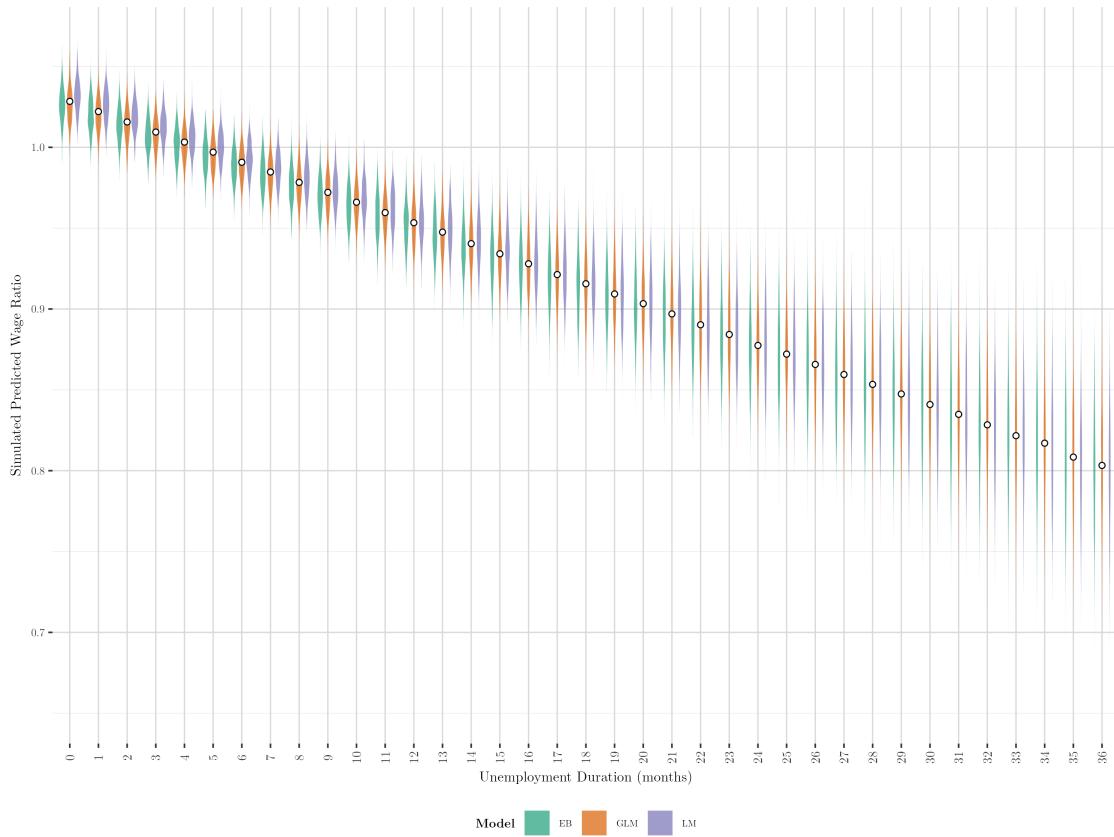
Next, we predict the value of the accepted wage ratio using each of the models, incorporating 95% confidence intervals to allow for stochasticity to enter the behavioral mechanism itself. Essentially, as an agent in our model enters an additional period of unemployment, they will draw their reservation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

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

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

### Simulated Predicted Wage Ratio Distributions by Unemployment Duration

Violin plots from LM, GLM, and EB model predictions



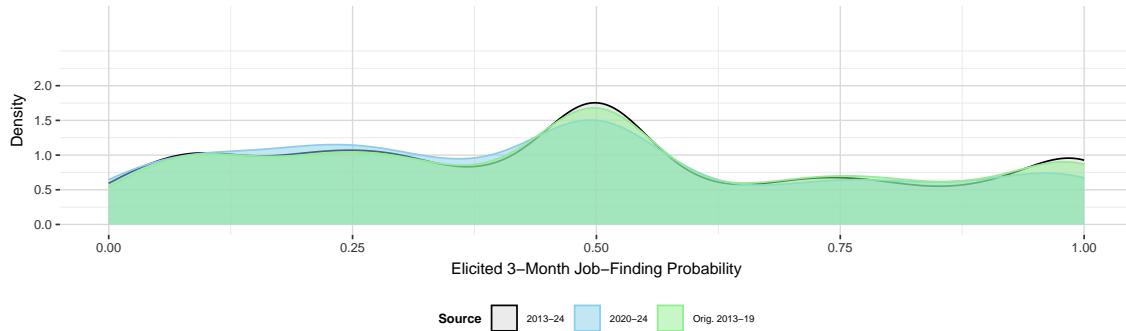
## Additional Considerations

### Job Tenure

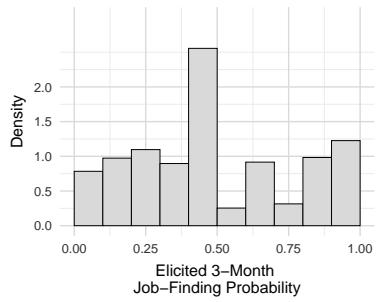
We have information on the tenure spent at the last job which could impact the result. This could speak to the “adaptability” of individuals. Wage ratio seems to decrease (although not sure if meaningfully) with tenure at previous job.

### Density Comparison of Elicited Job-Finding Probabilities

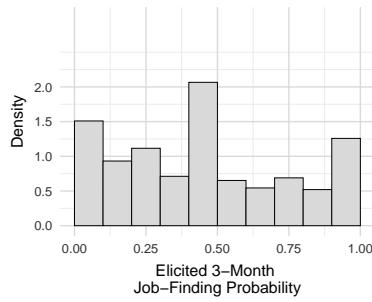
Remarkably consistent beliefs in job-finding probabilities even when including the Covid period.



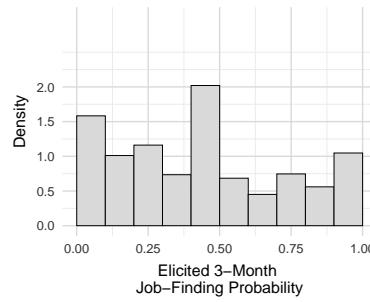
**Orig. 2013–19: Figure 1.**  
Histograms of  
Elicited Job-Finding  
Probabilities –  
Panel A. SCE  
(3-mo horizon)



**2013–24: Figure 1.**  
Histograms of  
Elicited Job-Finding  
Probabilities –  
Panel A. SCE  
(3-mo horizon)



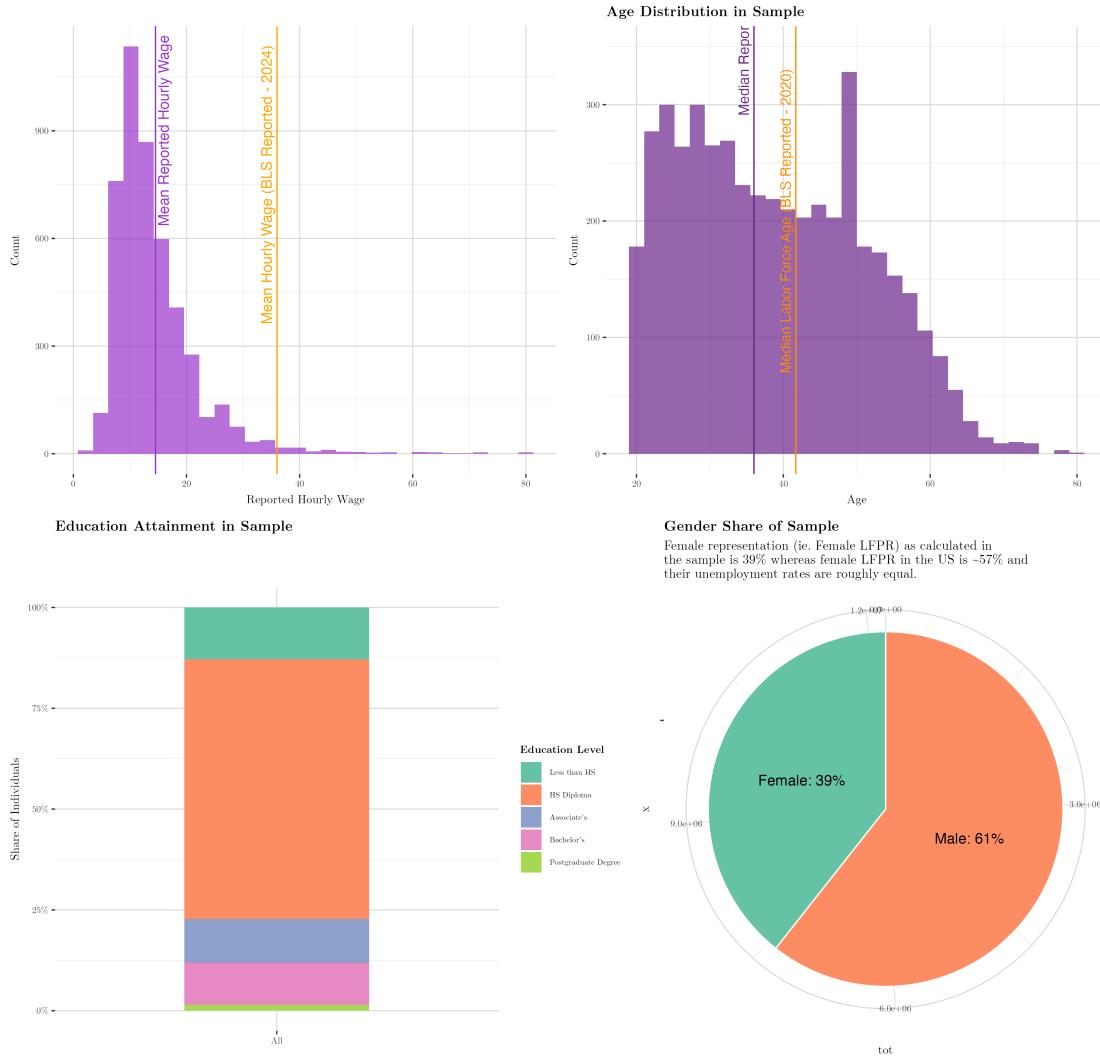
**2020–24: Figure 1.**  
Histograms of  
Elicited Job-Finding  
Probabilities –  
Panel A. SCE  
(3-mo horizon)



## Representation

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

**Sample Composition by Age, Wage, Education, Gender, Occupation**  
 Observations weighted by Displaced Worker Supplement Weights. Annual data from 2000-2025. Exclude observations reporting > 96 weeks of unemployment.



## OTJ Search Propensity

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

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

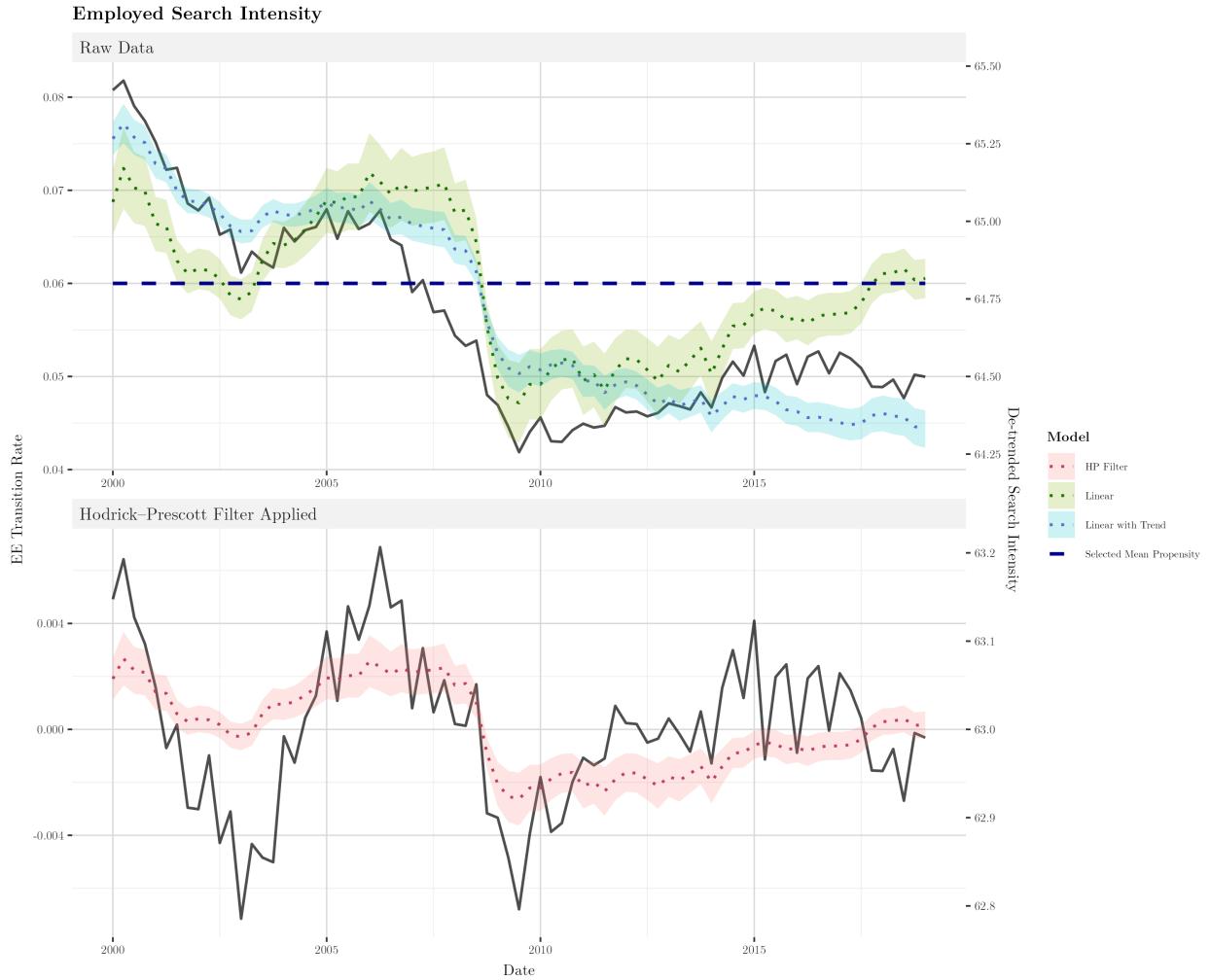


Figure 4: Employed Search Effort Fit

## Supporting Data for Validation

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

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

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

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

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

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

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

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

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

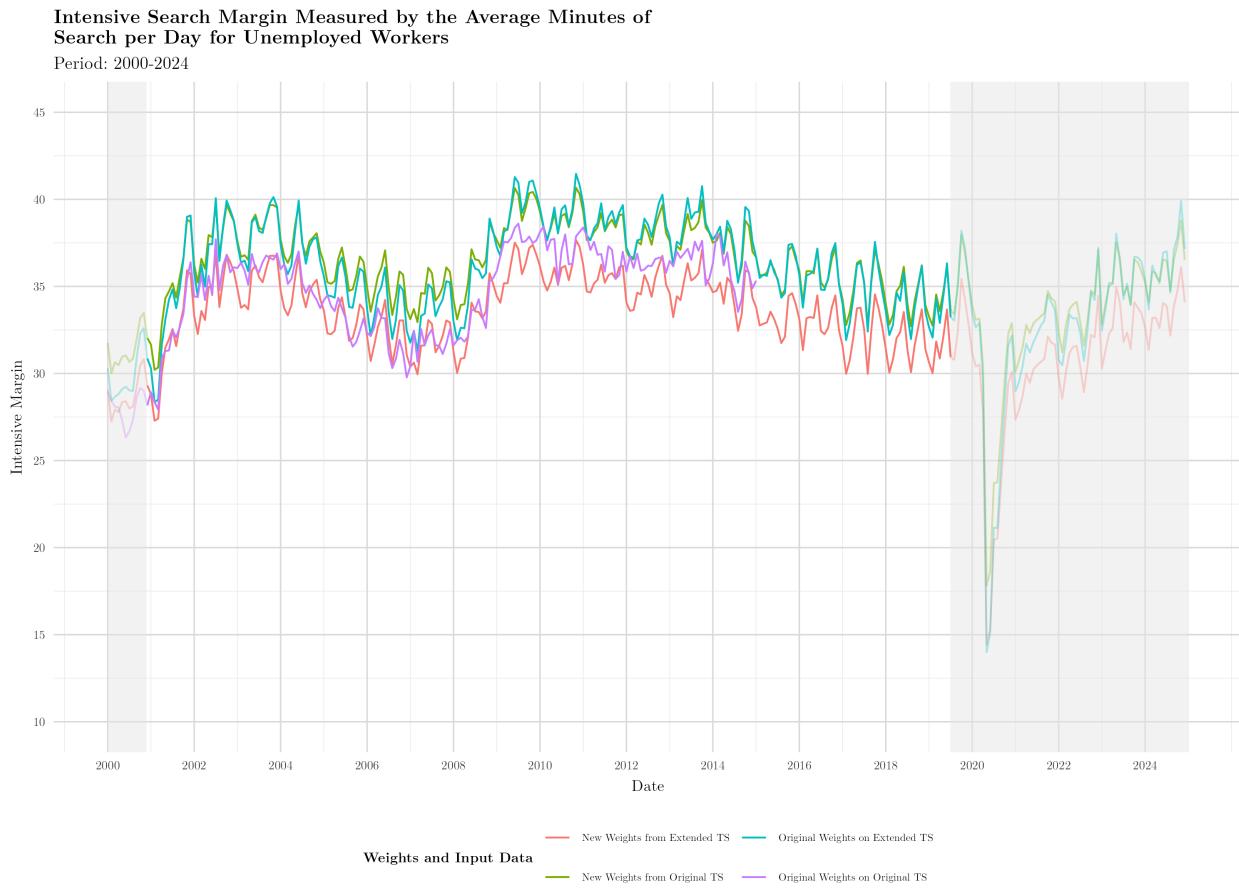


Figure 5: Mukoyama Validation Series

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

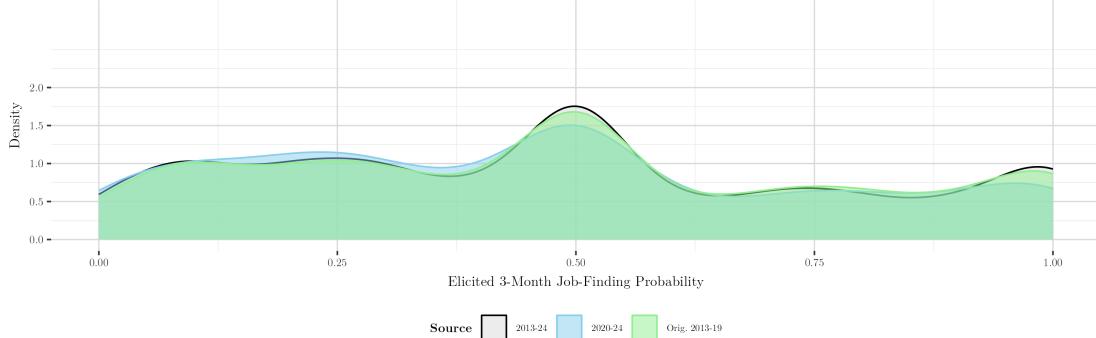
We find that their results are remarkably consistent even when including additional data from 2019-2024. We aim to include this information in our theoretical model of the job search effort as a learning rate (ie. individuals learn about their re-employment probability with repeated failures in the job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

Table 9: Descriptive Statistics (SCE)

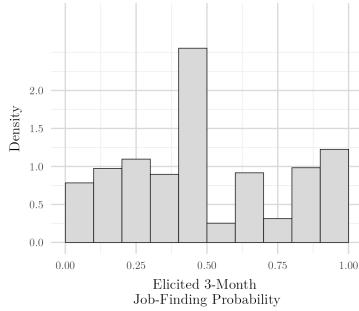
Variable	Orig.	2013-19	2013-24	2020-24
High-School Degree or Less		44.5	40.6	36.9
Some College Education		32.4	34.9	37.6
College Degree or More		23.1	24.6	25.6
Age 20-34		25.4	27.2	30.0
Age 35-49		33.5	33.6	35.3
Age 50-65		41.1	39.2	34.8
Female		59.3	61.2	60.8
Black		19.1	17.9	16.4
Hispanic		12.5	13.0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

### Density Comparison of Elicited Job-Finding Probabilities

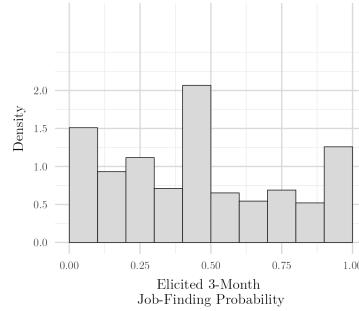
Remarkably consistent beliefs  
in job-finding probabilities even when including the Covid period.



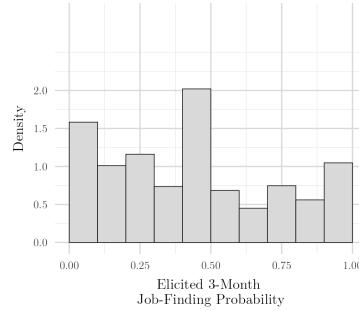
**Orig. 2013-19: Figure 1.**  
Histograms of  
Elicited Job-Finding  
Probabilities -  
Panel A. SCE  
(3-mo horizon)



**2013-24: Figure 1.**  
Histograms of  
Elicited Job-Finding  
Probabilities -  
Panel A. SCE  
(3-mo horizon)



**2020-24: Figure 1.**  
Histograms of  
Elicited Job-Finding  
Probabilities -  
Panel A. SCE  
(3-mo horizon)



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

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

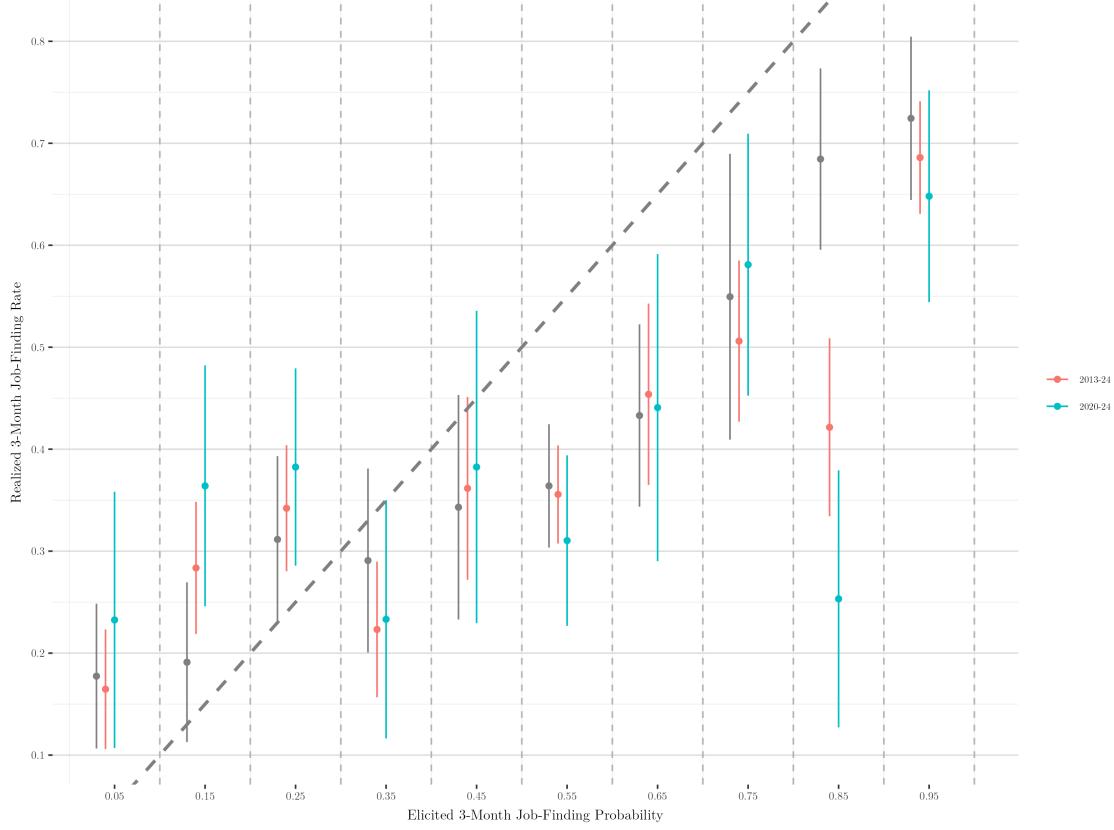


Table 10: Table 2—Regressions of Realized on Elicited 3-Month Job-Finding Probabilities (SCE): Contemporaneous elicitations

Dependent variable:			
	T+3 UE Transitions (3-Months)		
	Orig. 2013-19	2013-24	2020-24
	(1)	(2)	(3)
find_job_3mon	0.464*** (0.045)	0.396*** (0.036)	0.265*** (0.067)
1  userid	-0.104 (0.169)		-0.136 (0.267)
Constant		-0.080 (0.137)	
Observations	1,201	1,911	673
R <sup>2</sup>	0.218	0.139	0.105
Adjusted R <sup>2</sup>	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

	<i>Dependent variable:</i>		
	T+3 UE Transitions (3-Months)		
	Orig. 2013-19	2013-24	2020-24
	(1)	(2)	(3)
find_job_3mon	0.501*** (0.061)	0.418*** (0.051)	0.391*** (0.094)
findjob_3mon_longterm	-0.258*** (0.088)	-0.170** (0.071)	-0.360*** (0.133)
longterm_unemployed	-0.078 (0.051)	-0.127*** (0.041)	-0.043 (0.075)
1  userid			
Constant	-0.062 (0.175)	-0.063 (0.139)	-0.402 (0.266)
Observations	1,201	1,911	673
R <sup>2</sup>	0.259	0.182	0.155
Adjusted R <sup>2</sup>	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

	<i>Dependent variable:</i>		
	T+3 UE Transitions (3-Months)		
	Orig. 2013-19	2013-24	2020-24
	(1)	(2)	(3)
tplus3_percep_3mon	0.332*** (0.067)	0.241*** (0.056)	0.203** (0.102)
1  userid			
Constant	0.304 (0.270)	0.490** (0.207)	0.451 (0.394)
Observations	474	798	300
R <sup>2</sup>	0.168	0.090	0.179
Adjusted R <sup>2</sup>	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

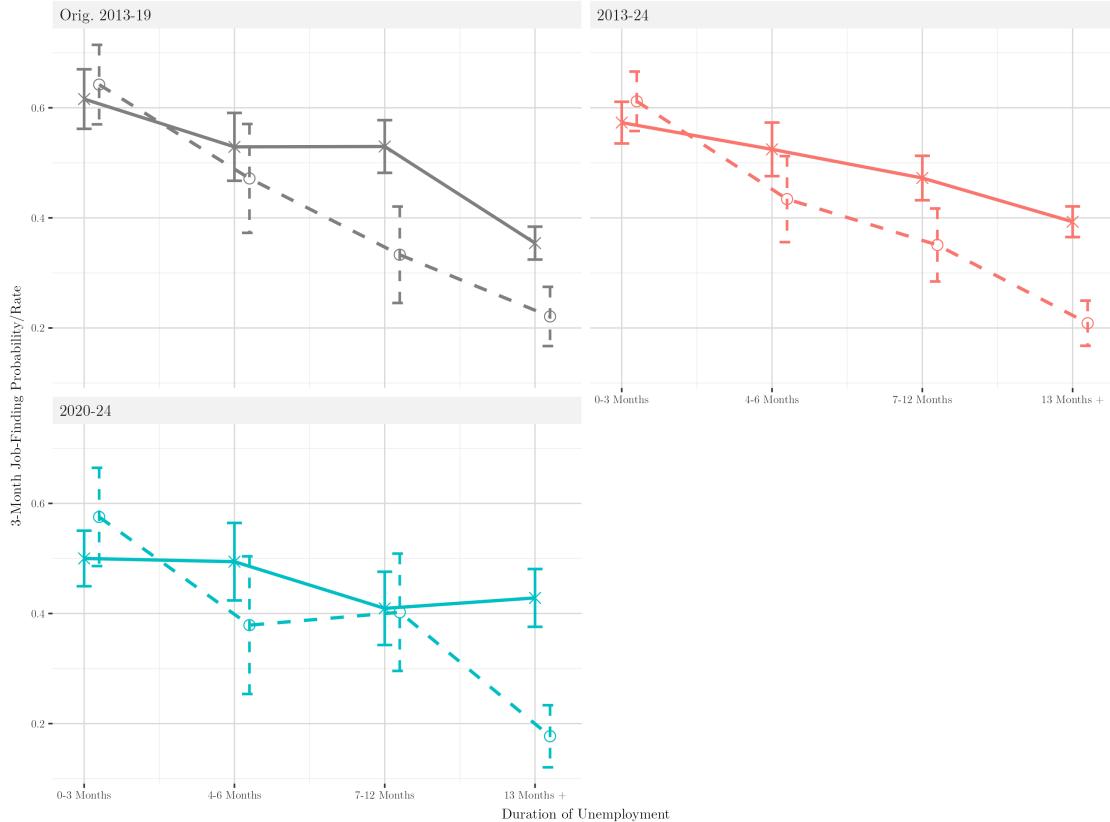
	<i>Dependent variable:</i>		
	T+3 UE Transitions (3-Months)		
	Orig. 2013-19	2013-24	2020-24
	(1)	(2)	(3)
find_job_3mon	0.301*** (0.069)	0.205*** (0.058)	−0.035 (0.110)
1   userid			
Constant	0.201 (0.274)	0.422** (0.207)	0.361 (0.400)
Observations	474	798	300
R <sup>2</sup>	0.159	0.083	0.168
Adjusted R <sup>2</sup>	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

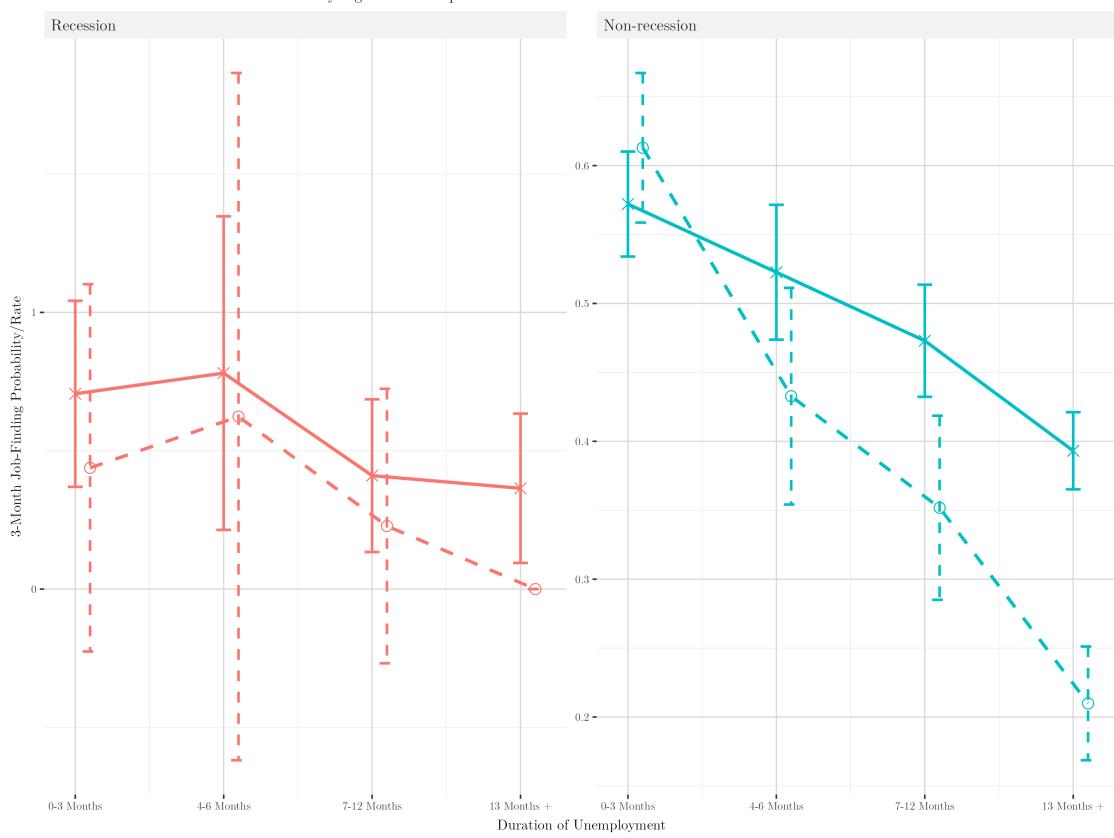
Fig 3. Perceived vs. Realized Job Finding, by Duration of Unemployment

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



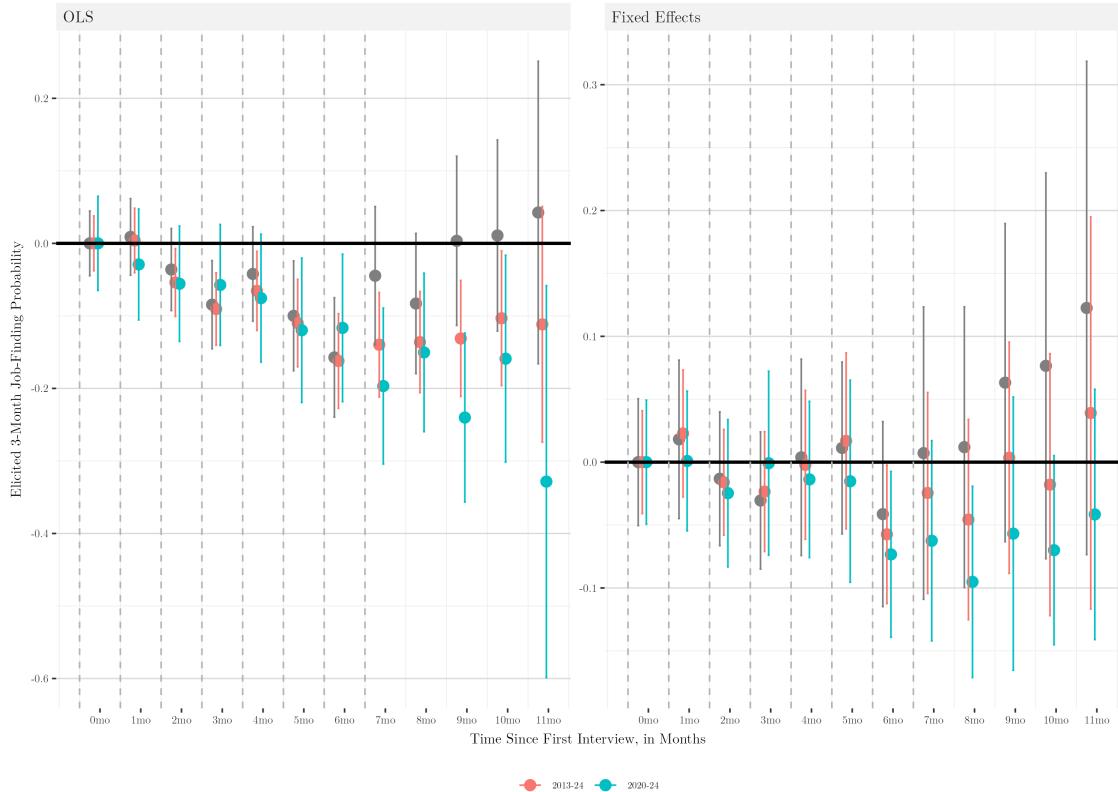
**Fig 3. Perceived vs. Realized Job Finding, by Duration of Unemployment**

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



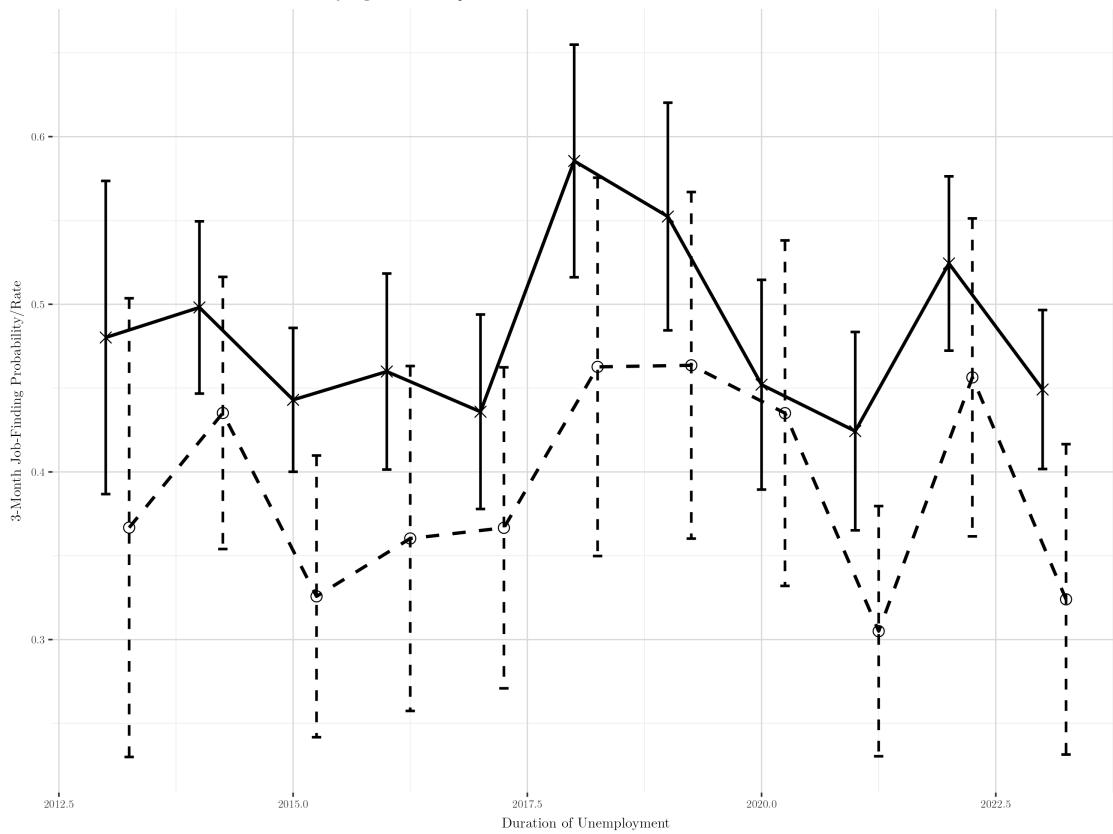
**Fig 4. Changes in Job-Finding Probability Across and Within Spells**

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**

