

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

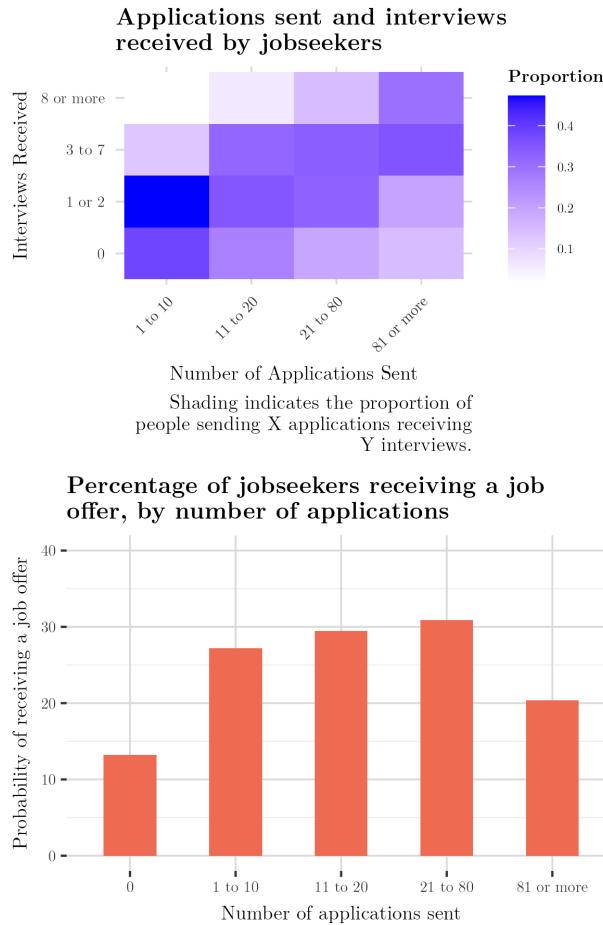
In 2018 (May, September) and 2020 (February, May), the Bureau of Labor Statistics ran the “Unemployment Insurance Nonfilers” supplemental survey to the monthly Current Population Survey run by the US Census Bureau. The survey’s stated intent was to “obtain information on the characteristics of people 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.

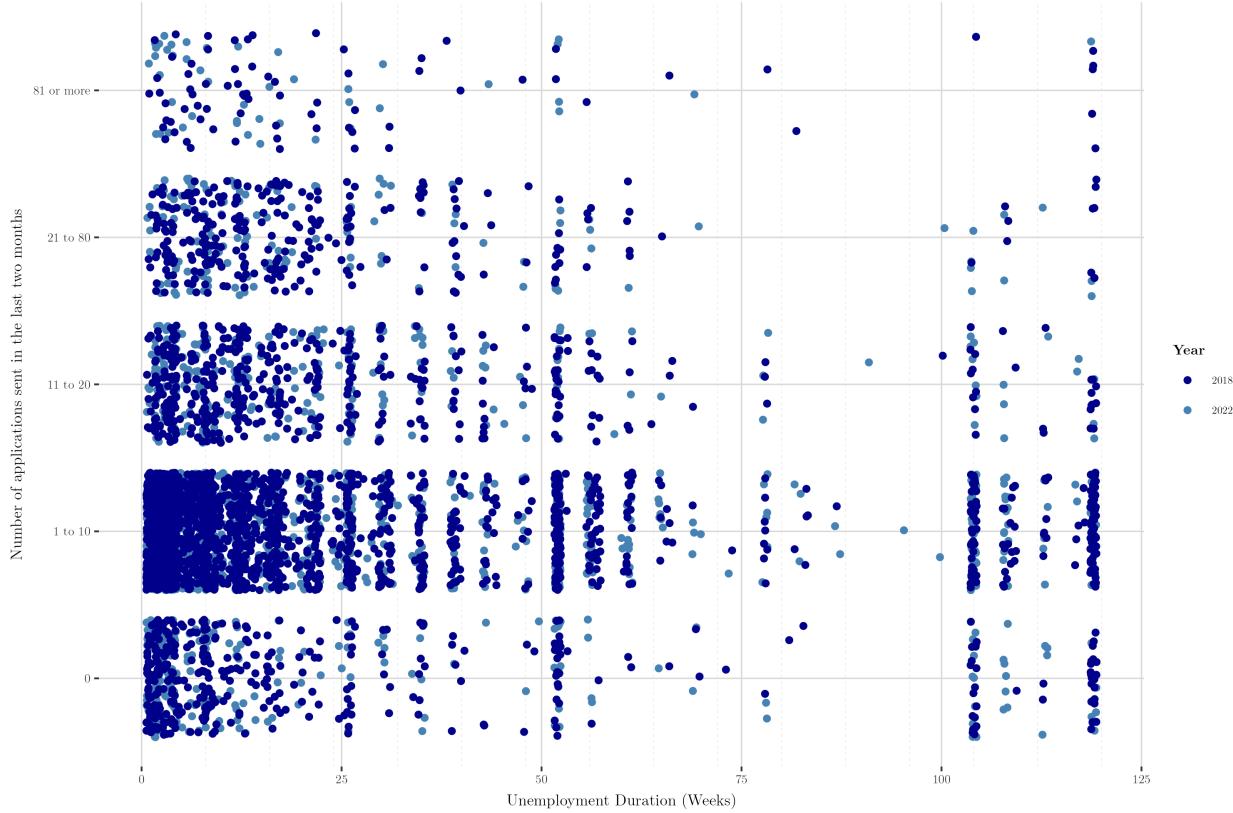
In nearly all cases, the results are “binned” into intervals (ie. number of people sending 81 or more applications or unemployment duration of between 5 and 14 weeks) which means that any line plots (or linear interpretation of the bar graph) should be done carefully. Preliminary results using the raw data are found in the next section.

- Figure 1: 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 Figure 3, the number of interviews received does not necessarily equate to receiving a job offer.
- Figure 2: Demonstrates the number of applications sent (red), interviews received (green), average interview:applicaiton ratio (blue), and probability of receiving a job offer (purple) by individuals in each category of unemployment duration. There is some indication (although, again, interpretation is difficult without the raw data) that both effort and success seems 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: Percentage of jobseekers receiving an offer seems to increase as a function of the number of applications sent, until a certain point.

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## Processing URL: https://www.bls.gov/opub/btn/volume-9/how-do-jobseekers-search-for-jobs.htm#\_edn2
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Applications sent vs. Time Spent Unemployed: 2022 & 2018
 Grey gridlines align with 2-month/8-week intervals. N = 2,896 (2018) & 1,677 (2022)



Below, I 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, $\Pr(Y_i \leq j | X_i)$, is modeled as follows for each link function:

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

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

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

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

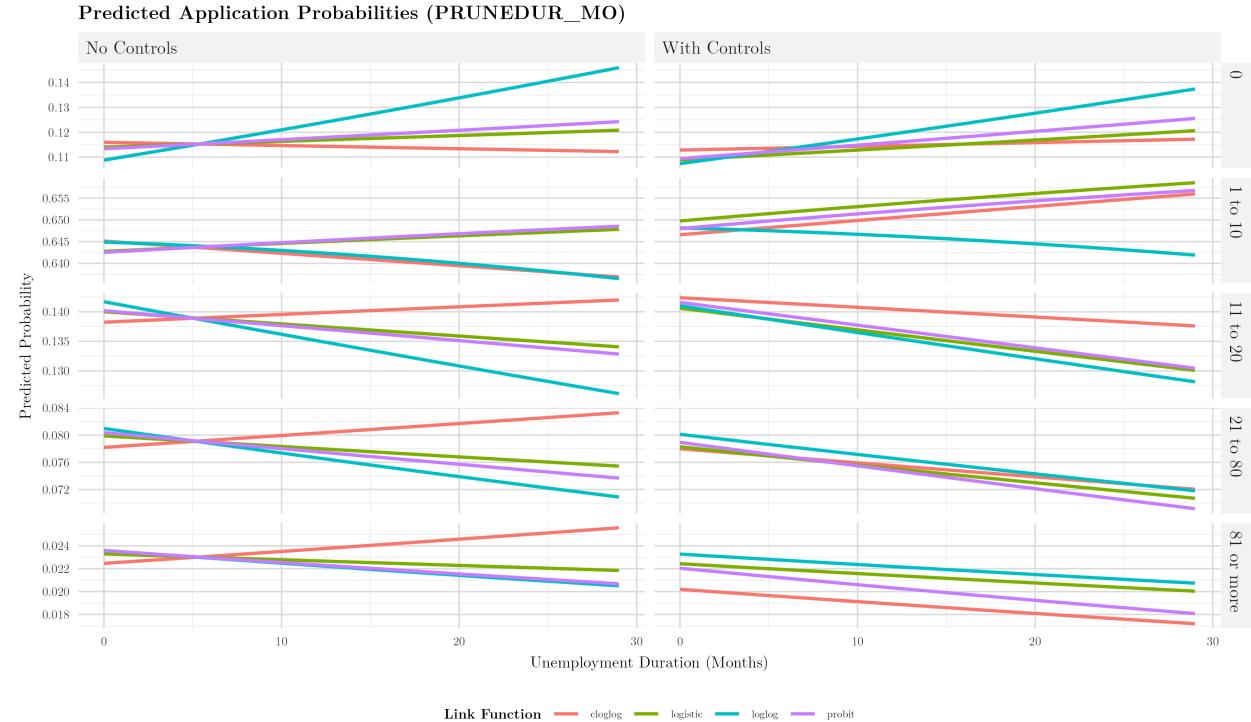
$$X_i = (\text{Unemp.Dur}_{\cdot i}, \text{Unemp.Dur}_{\cdot i}^2)$$

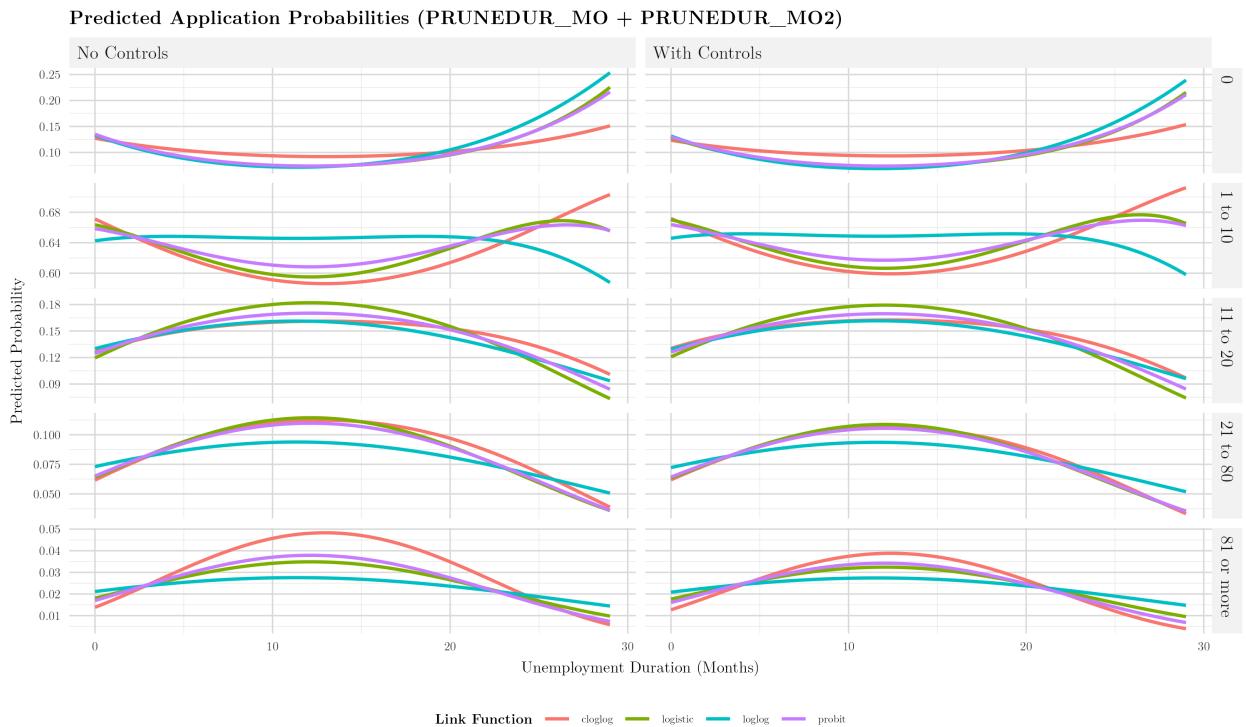
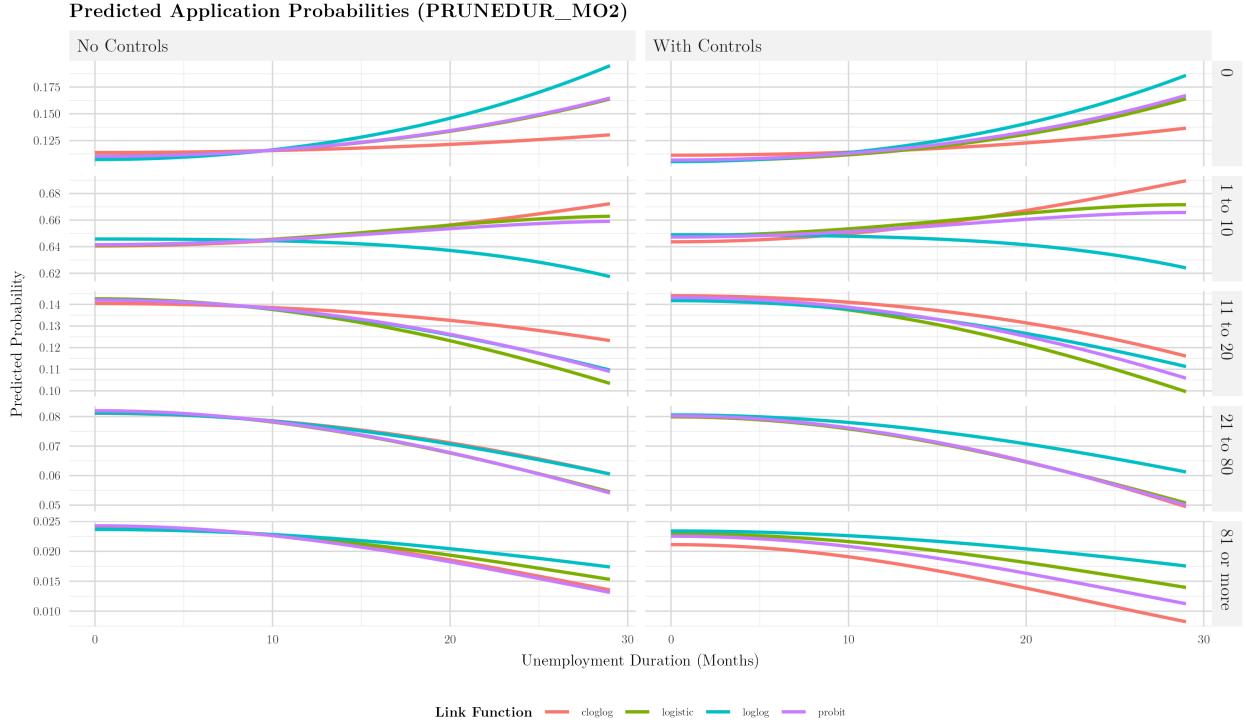
with and without control variables (education, gender, age, family income).

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.

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:

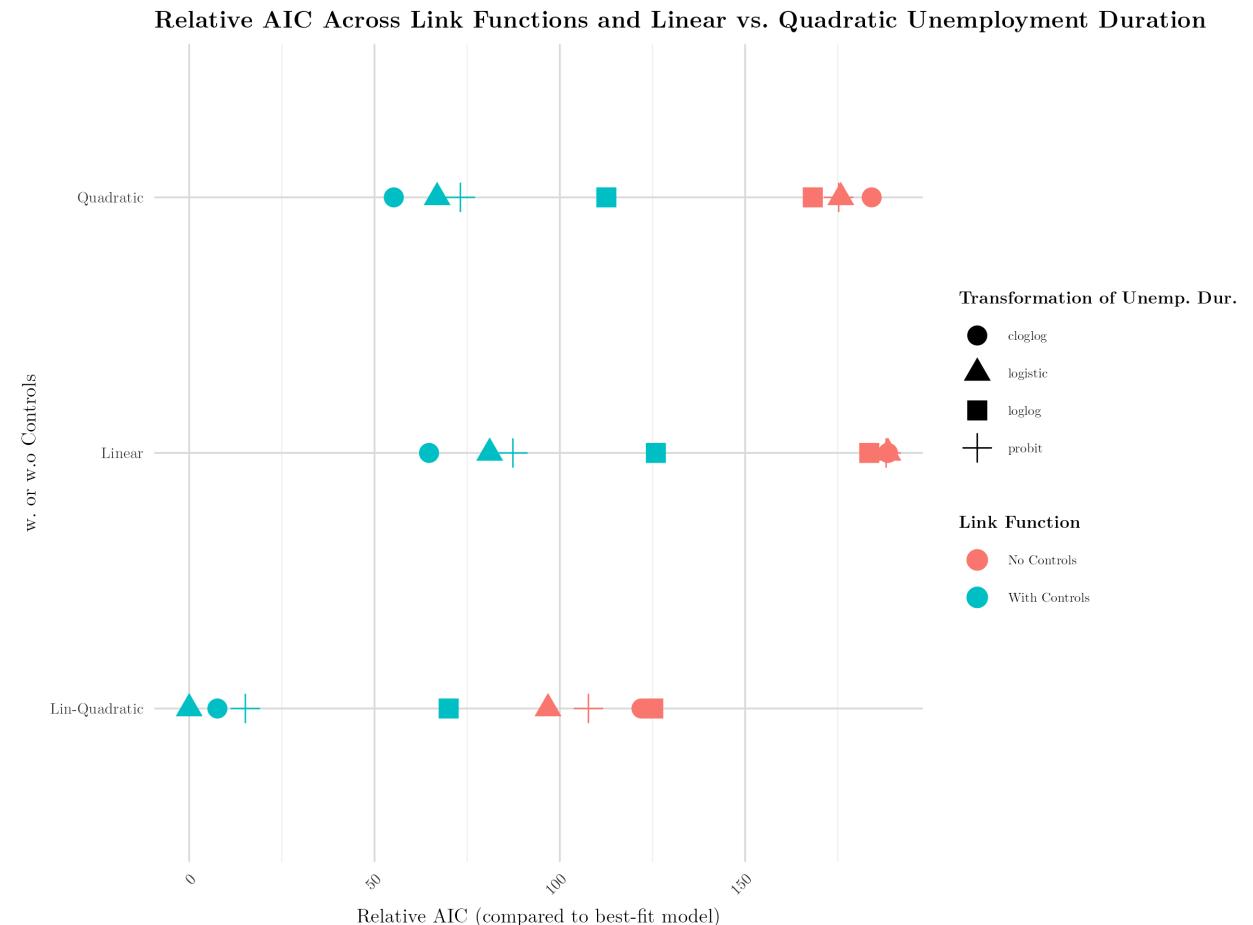
1. Models with control variables consistently perform better than those without.
2. Looking at the plots above, the relationship between unemployment duration and the predicted probability of reporting each application effort bin is very consistent except in the case of the log-log link function (blue 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.



```
## [1] TRUE
## [1] TRUE
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Predicted Probabilities of Application Effort by Unemployment Duration

N = 5,169

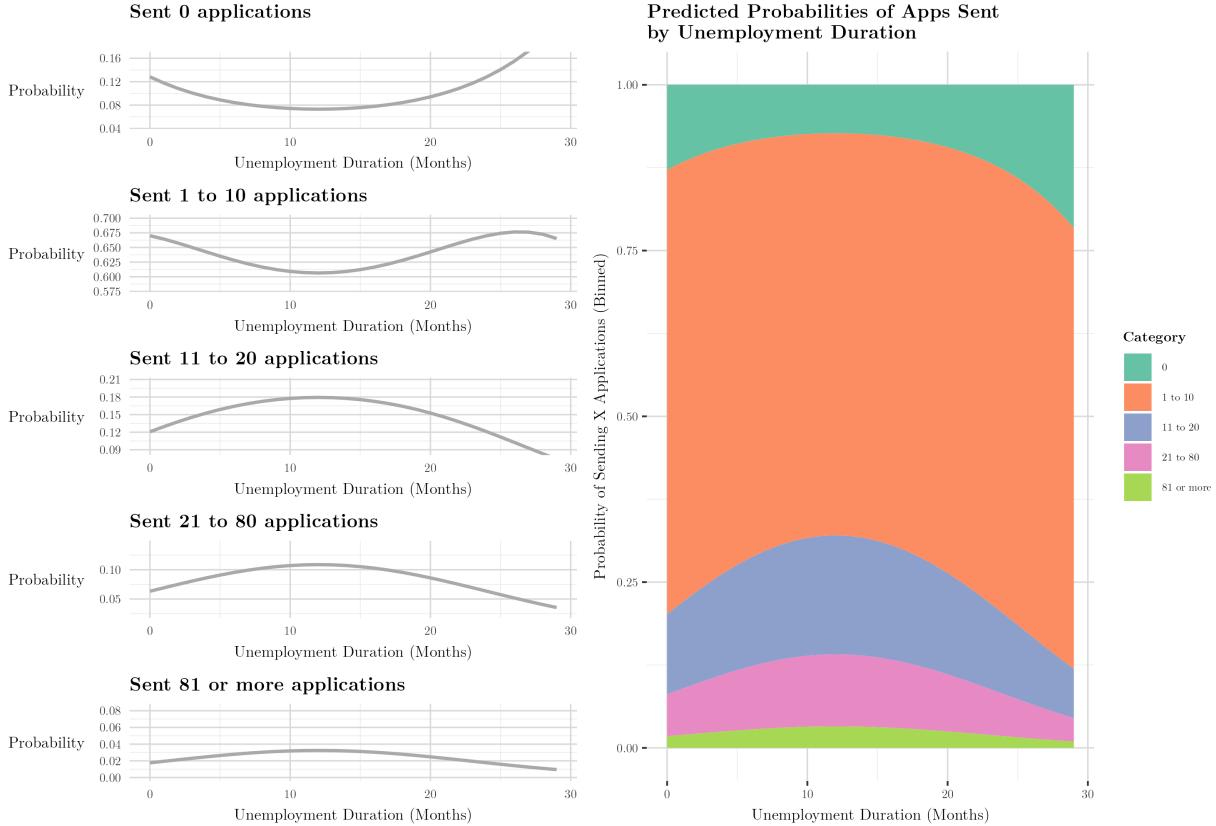
Bureau of Labor Statistics Data reported in 2018 and 2022.

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

Unemployment duration enters quadratically w. sociodemographic 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. 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.

Important Considerations/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.

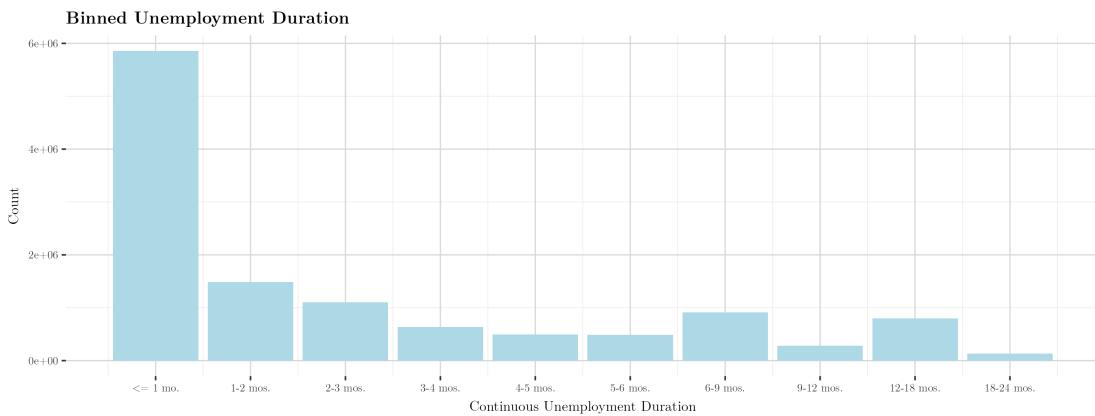
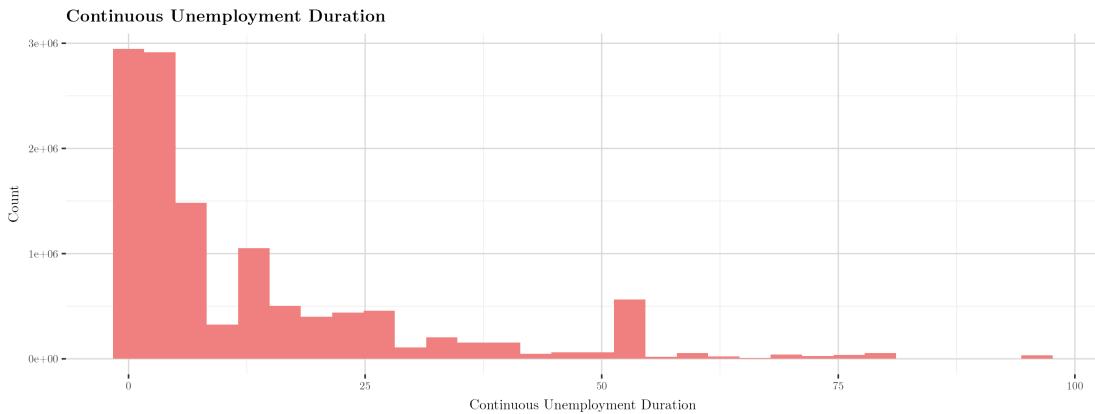
Histogram: sample is skewed (see reweighting alternatives at end of document).

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).

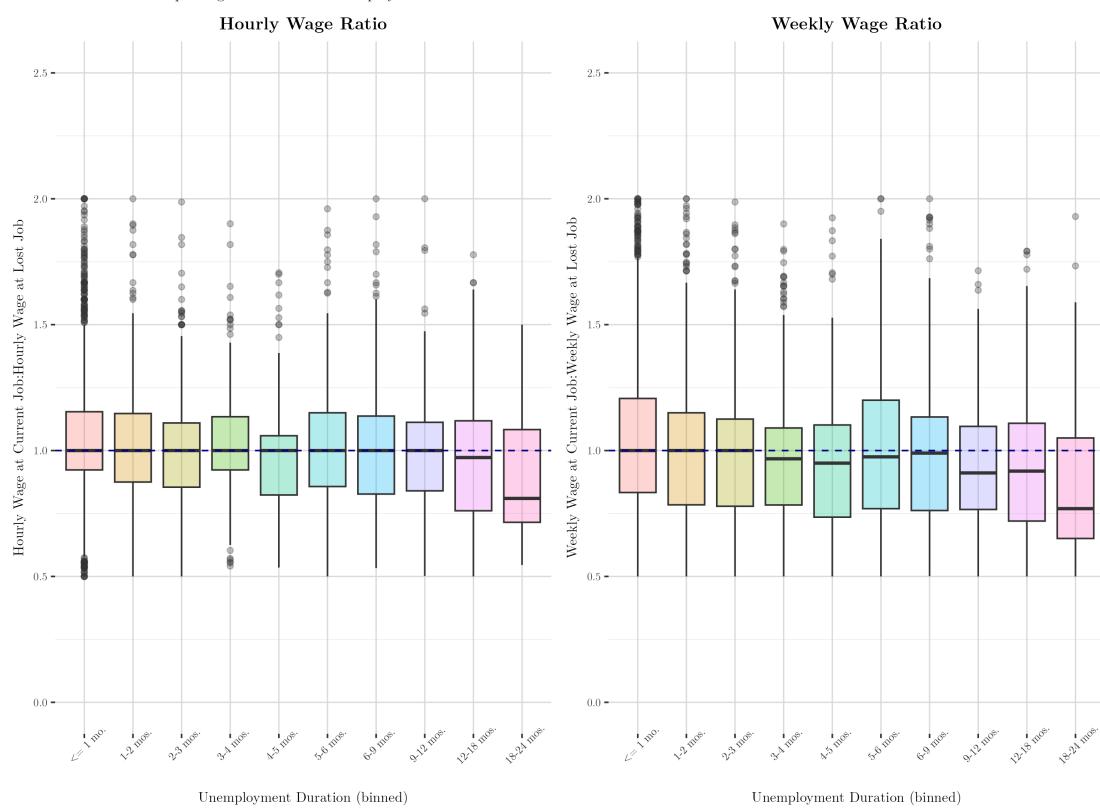
Scatter plot: I fit a linear and spline fit to the scattered plot of the wage ratio to unemployment duration before using the regression. Indicates decline in the wage ratio with unemployment duration that has a potentially non-linear fit.

Reported unemployment duration between lost job and next job
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 2000-2005.
Exclude observations reporting > 96 weeks of unemployment.

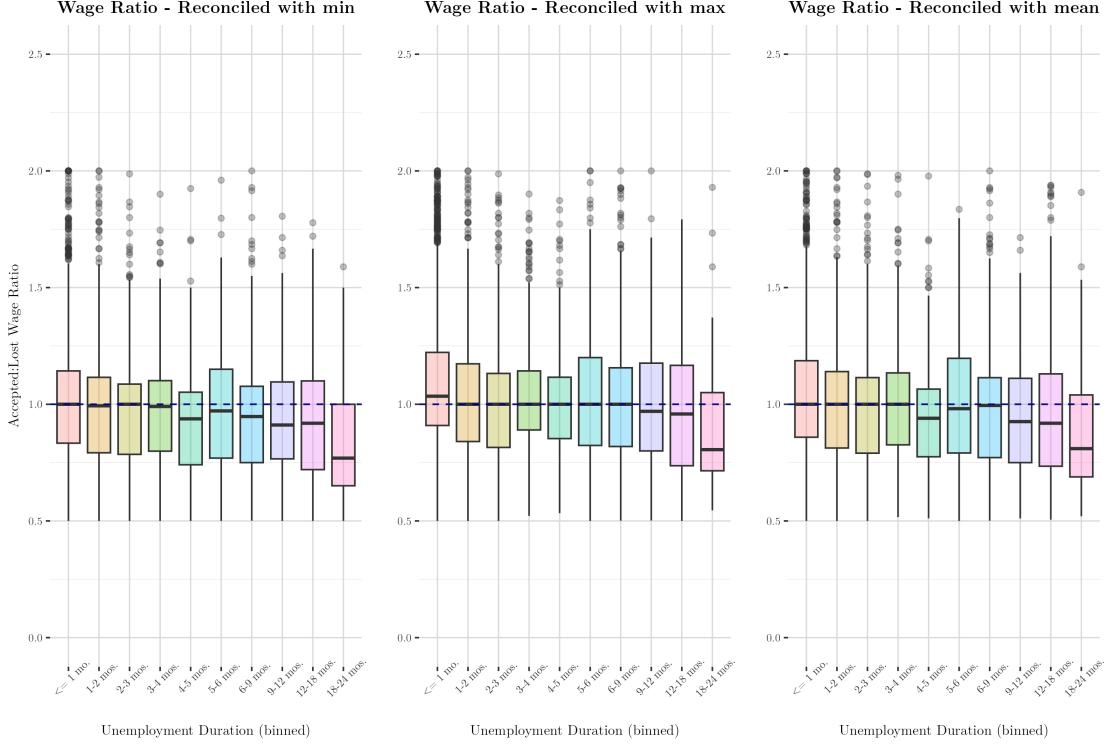


Reported ratio of current wage to lost wage by unemployment duration

Observations weighted by Displaced Worker Supplement Weights.
 Annual data from 2000-2005.

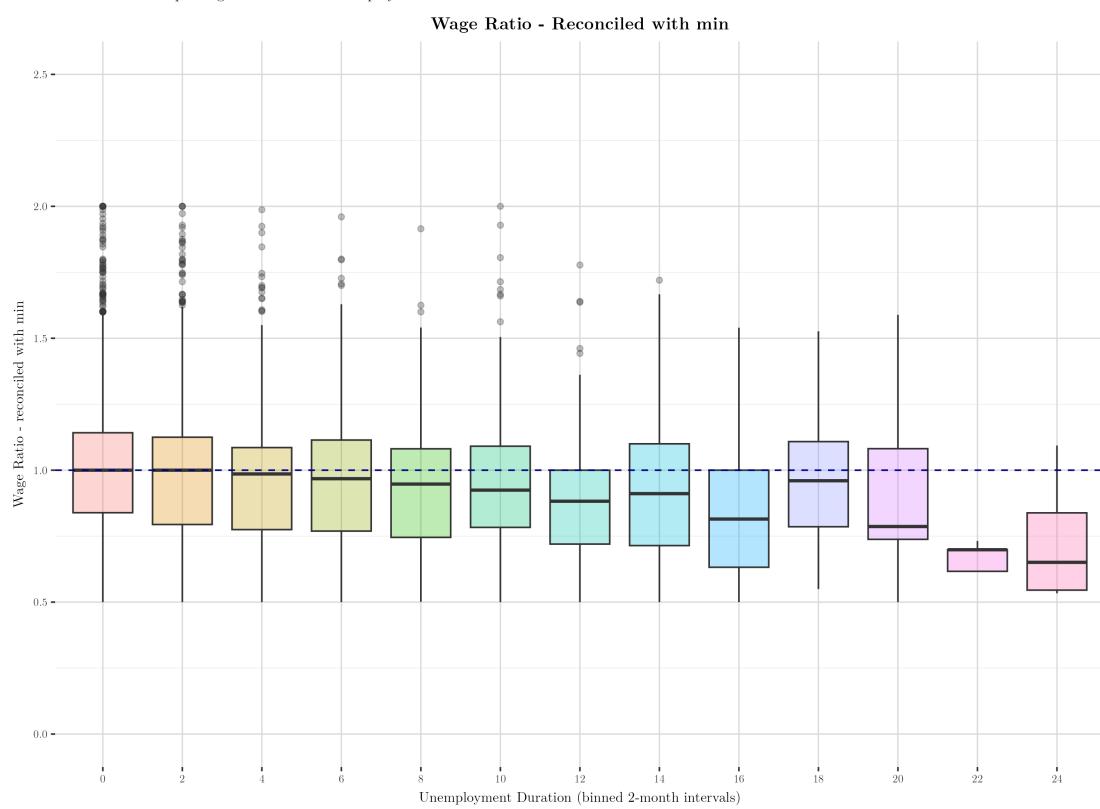
Exclude observations reporting > 96 weeks of unemployment.
 In many cases, only hourly OR weekly wages are reported.

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.



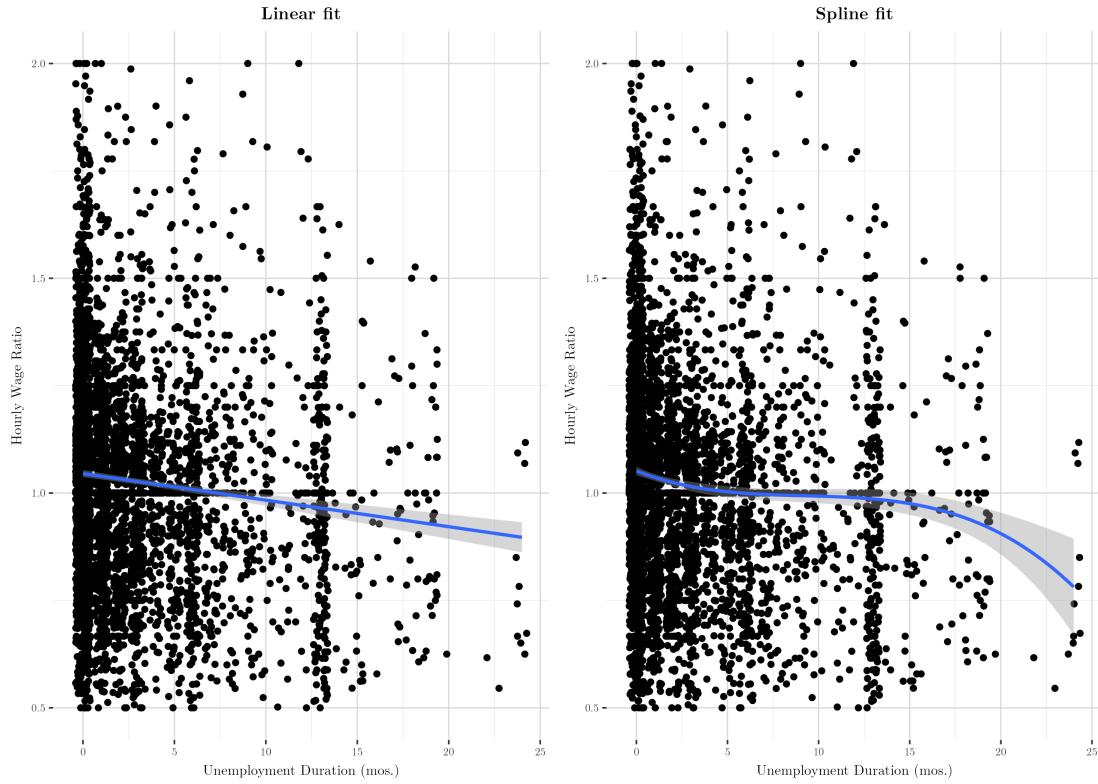
Reported ratio of current wage to lost wage by unemployment duration

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.

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.

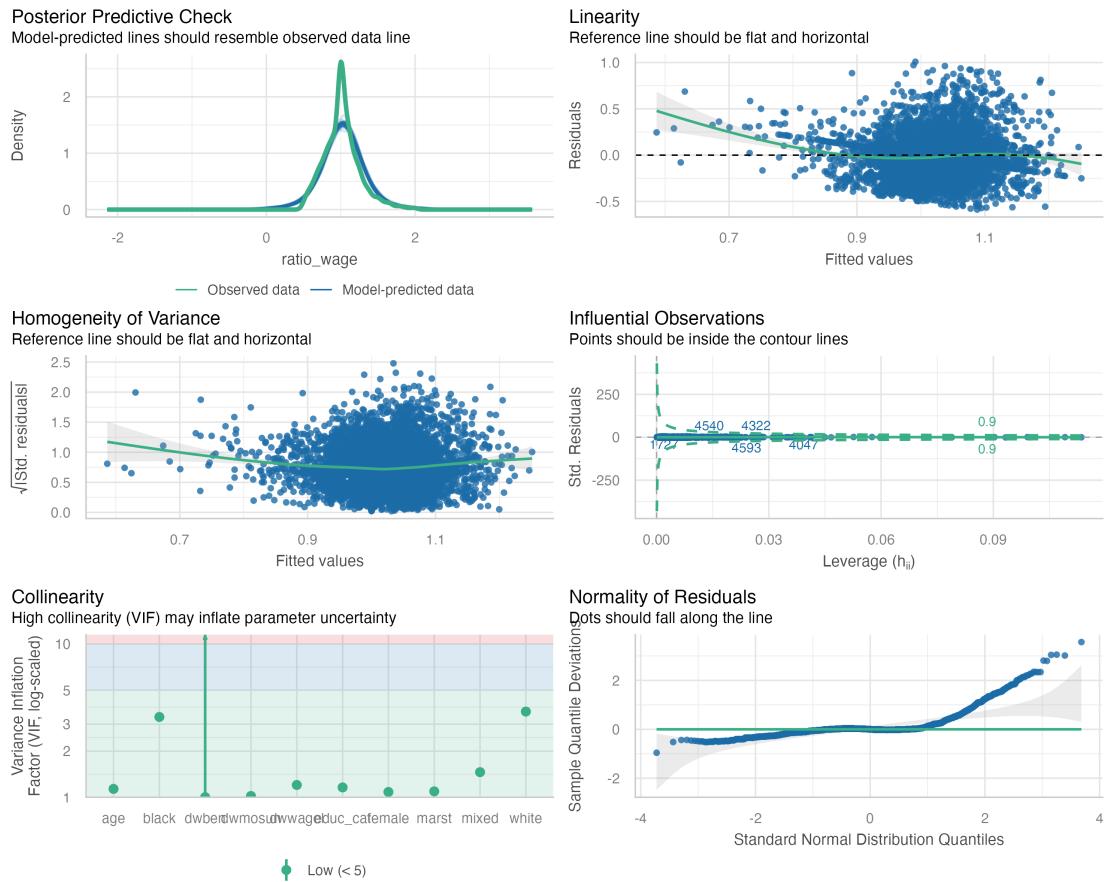
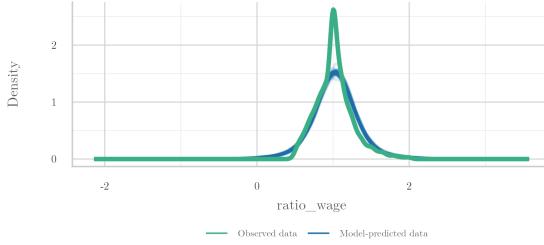


Table 1: Continuous UE Duration w.o Wage Level Control

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

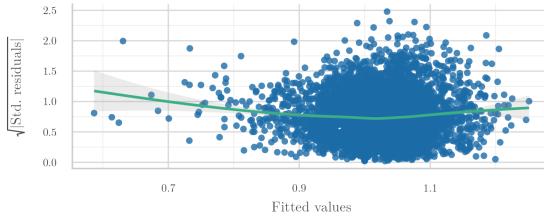
Posterior Predictive Check

Model-predicted lines should resemble observed data lines



Homogeneity of Variance

Reference line should be flat and horizontal



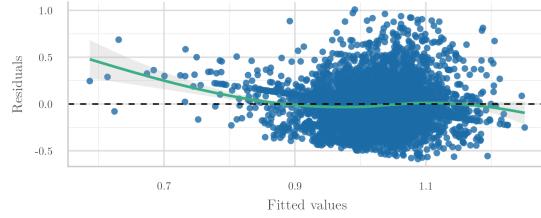
Collinearity

High collinearity (VIF) may inflate parameter uncertainty



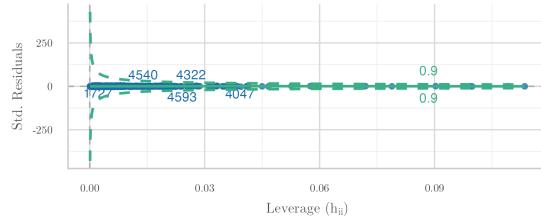
Linearity

Reference line should be flat and horizontal



Influential Observations

Points should be inside the contour lines



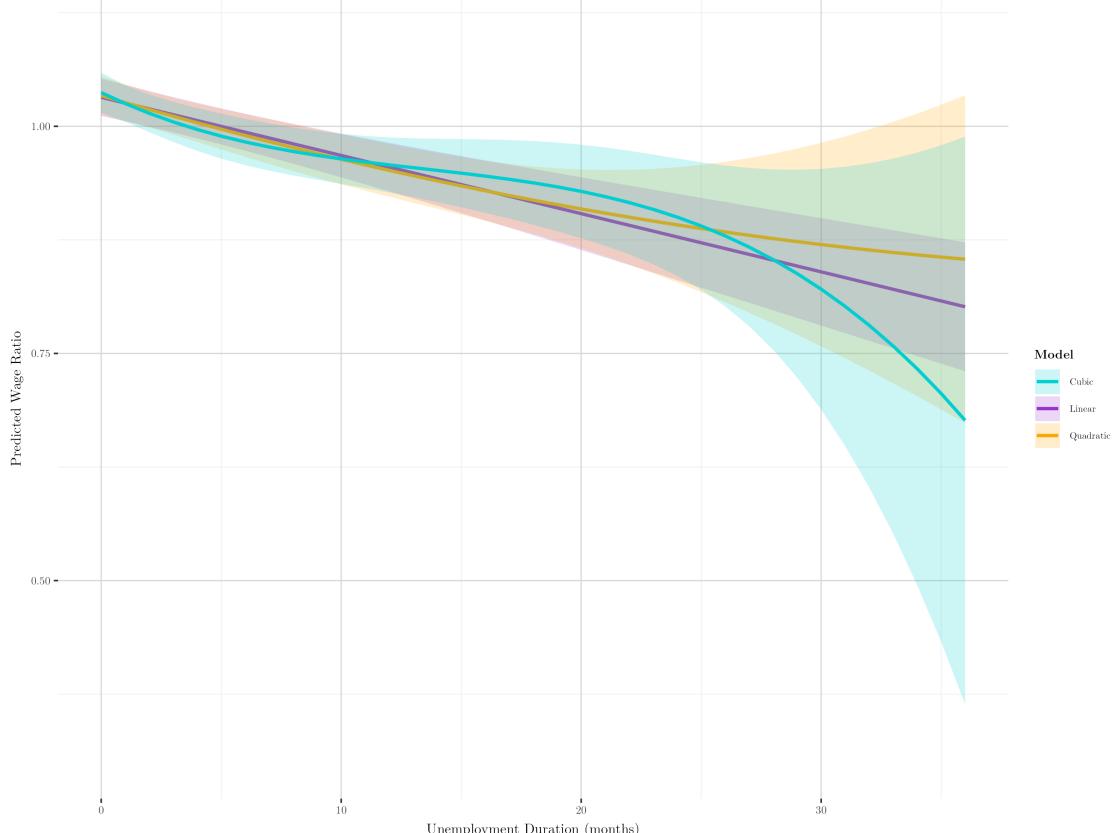
Continuous UE Duration

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

Table 2: Continuous UE Duration w. Wage Level Control

Predicted Wage Ratios by Unemployment Duration

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



Binned UE Duration

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

Additional Considerations

Below J.

1. Show results from some sample reweighting to address the non-uniformity of our cross-sectional data.
 2. Histogram of an additional explanatory variable that might be interesting - the tenure of the lost job. How long (in years) did the individual hold the job they lost.
 3. Additionally, I show some rough graphs/figures about the sample population (age, education, gender, wage distributions). I am still working on an occupational distribution graph to understand the “skills”/occupational distribution of the sample.

Table 3: Binned UE Duration w/o Wage Level Control

	Disc.	Disc. (clipped)	Disc. w. UI	Disc. w. UI (clipped)	Disc. w. exhausted UI	Disc. w. exhausted UI (clipped)	Disc. w. controls	Disc. w. controls (clipped)	Disc. w. UI w. controls	Disc. w. UI w. controls (clipped)	Disc. w. exhausted UI w. controls	Disc. w. exhausted UI w. controls (clipped)
Intercept	1.069*** (0.008)	1.055*** (0.005)	1.069*** (0.008)	1.055*** (0.005)	1.016*** (0.012)	1.010*** (0.008)	1.190*** (0.031)	1.170*** (0.021)	1.190*** (0.031)	1.170*** (0.021)	1.127*** (0.034)	1.126*** (0.023)
Unemployment Duration (Binned)	-0.013*** (0.002)	-0.009*** (0.001)	-0.009*** (0.001)	-0.009*** (0.001)	-0.005*** (0.002)	-0.005*** (0.001)	-0.011*** (0.002)	-0.006*** (0.001)	-0.011*** (0.002)	-0.006*** (0.001)	-0.007*** (0.002)	-0.006*** (0.001)
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)	0.001*** (0.000)
Exhausted Unemployment Compensation					0.003*** (0.000)	0.001*** (0.000)						0.003*** (0.000)
Female					0.003 (0.011)	-0.003 (0.007)	0.003 (0.011)	-0.003 (0.007)	0.003 (0.011)	-0.003 (0.007)	0.003 (0.011)	0.003 (0.007)
Age					-0.003*** (0.006)	-0.002*** (0.005)	-0.003*** (0.006)	-0.002*** (0.005)	-0.002*** (0.006)	-0.002*** (0.005)	-0.002*** (0.006)	-0.002*** (0.005)
White					-0.035 (0.023)	-0.052*** (0.016)	-0.035 (0.023)	-0.052*** (0.016)	-0.035 (0.023)	-0.052*** (0.016)	-0.035 (0.023)	-0.052*** (0.016)
Black					-0.047 (0.026)	-0.047*** (0.018)	-0.047 (0.026)	-0.047*** (0.018)	-0.047 (0.026)	-0.047*** (0.018)	-0.047 (0.026)	-0.047*** (0.018)
Mixed					0.014 (0.040)	-0.079*** (0.047)	0.014 (0.040)	-0.079*** (0.047)	0.014 (0.040)	-0.079*** (0.047)	0.017 (0.040)	-0.068* (0.047)
Married					0.004 (0.011)	0.011 (0.007)	0.004 (0.011)	0.011 (0.007)	0.004 (0.011)	0.011 (0.007)	0.005 (0.011)	0.012 (0.007)
High School					-0.006 (0.016)	0.000 (0.011)	-0.006 (0.016)	0.000 (0.011)	-0.006 (0.016)	0.000 (0.011)	0.005 (0.016)	0.005 (0.011)
educ_catAssociate's					0.033 (0.021)	-0.009 (0.021)	0.033 (0.021)	-0.009 (0.021)	0.033 (0.021)	-0.009 (0.021)	0.038+ (0.021)	-0.005 (0.021)
Bachelor's Degree					0.082*** (0.011)	0.067*** (0.011)	0.082*** (0.011)	0.067*** (0.011)	0.082*** (0.011)	0.067*** (0.011)	0.087*** (0.011)	0.071*** (0.011)
Postgraduate Degree					0.116** (0.045)	0.116** (0.031)	0.116** (0.045)	0.116** (0.031)	0.116** (0.045)	0.116** (0.031)	0.124** (0.045)	0.088 (0.031)
Nun.Obs.	4870	4644	4870	4644	4870	4644	4870	4644	4870	4644	4870	4644
R2	0.040	0.041	0.040	0.041	0.040	0.041	0.040	0.041	0.040	0.041	0.040	0.040
R2 Adj.	0.009	0.011	0.009	0.010	0.016	0.021	0.022	0.023	0.022	0.023	0.022	0.022
F	47.638	23.816	40.199	11.165	10.232	12.314						
RMSE	0.37	0.24	0.37	0.24	0.37	0.24	0.37	0.24	0.37	0.24	0.37	0.24

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

Table 4: Binned UE Duration w. Wage Level Control

	Disc.	Disc. (clipped)	Disc. w. UI	Disc. w. UI (clipped)	Disc. w. exhausted UI	Disc. w. exhausted UI (clipped)	Disc. w. controls	Disc. w. controls (clipped)	Disc. w. UI w. controls	Disc. w. UI w. controls (clipped)	Disc. w. exhausted UI w. controls	Disc. w. exhausted UI w. controls (clipped)
Intercept	1.069*** (0.012)	1.055*** (0.008)	1.069*** (0.012)	1.055*** (0.008)	1.150*** (0.016)	1.168*** (0.016)	1.272*** (0.031)	1.224*** (0.031)	1.224*** (0.031)	1.220*** (0.031)	1.176*** (0.033)	1.176*** (0.033)
Hourly Wage of Lost Job	-0.009*** (0.000)	-0.006*** (0.000)	-0.009*** (0.001)	-0.006*** (0.001)	-0.009*** (0.000)	-0.006*** (0.000)	-0.011*** (0.001)	-0.007*** (0.000)	-0.011*** (0.001)	-0.007*** (0.000)	-0.011*** (0.001)	-0.007*** (0.000)
Unemployment Duration (Binned)	-0.011*** (0.002)	-0.009*** (0.001)	-0.011*** (0.001)	-0.009*** (0.001)	-0.008*** (0.002)	-0.008*** (0.001)	-0.011*** (0.002)	-0.006*** (0.000)	-0.011*** (0.002)	-0.006*** (0.000)	-0.011*** (0.002)	-0.006*** (0.000)
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*** (0.000)
Exhausted Unemployment Compensation					0.003*** (0.000)	0.001*** (0.000)					0.003*** (0.000)	0.003*** (0.000)
Female					-0.028** (0.011)	-0.023** (0.007)	-0.028** (0.011)	-0.023** (0.007)	-0.028** (0.011)	-0.023** (0.007)	-0.028** (0.011)	-0.023** (0.007)
Age					-0.049*** (0.000)	-0.049*** (0.000)	-0.049*** (0.000)	-0.049*** (0.000)	-0.049*** (0.000)	-0.049*** (0.000)	-0.049*** (0.000)	-0.049*** (0.000)
White					-0.034 (0.023)	-0.050*** (0.023)	-0.034 (0.023)	-0.050*** (0.023)	-0.034 (0.023)	-0.050*** (0.023)	-0.032 (0.023)	-0.049*** (0.023)
Black					-0.057* (0.026)	-0.063*** (0.018)	-0.057* (0.026)	-0.063*** (0.018)	-0.057* (0.026)	-0.063*** (0.018)	-0.054* (0.026)	-0.059*** (0.018)
Mixed					0.017 (0.019)	0.017*** (0.027)	0.017 (0.019)	0.017*** (0.027)	0.017 (0.019)	0.017*** (0.027)	0.013 (0.019)	0.018* (0.019)
Married					0.034* (0.015)	0.019** (0.015)	0.034* (0.015)	0.019** (0.015)	0.034* (0.015)	0.019** (0.015)	0.038* (0.015)	0.022* (0.015)
High School					0.002*** (0.012)	0.002*** (0.012)	0.002*** (0.012)	0.002*** (0.012)	0.002*** (0.012)	0.002*** (0.012)	0.002*** (0.012)	0.002*** (0.012)
educ_catAssociate's					0.021 (0.021)	0.017** (0.021)	0.021 (0.021)	0.017** (0.021)	0.021 (0.021)	0.017** (0.021)	0.021 (0.021)	0.018* (0.021)
Bachelor's Degree					0.163*** (0.022)	0.122*** (0.022)	0.163*** (0.022)	0.122*** (0.022)	0.163*** (0.022)	0.122*** (0.022)	0.166*** (0.022)	0.124*** (0.022)
Postgraduate Degree					0.246*** (0.045)	0.120*** (0.031)	0.246*** (0.045)	0.120*** (0.031)	0.246*** (0.045)	0.120*** (0.031)	0.250*** (0.045)	0.124*** (0.031)
Nun.Obs.	4870	4644	4870	4644	4870	4644	4870	4644	4870	4644	4870	4644
R2	0.047	0.045	0.047	0.045	0.051	0.052	0.049	0.052	0.049	0.052	0.049	0.049
R2 Adj.	0.047	0.045	0.047	0.045	0.050	0.051	0.047	0.052	0.047	0.050	0.047	0.047
F	120.632	80.422	86.995	30.190	27.774	29.884						
RMSE	0.37	0.24	0.37	0.24	0.37	0.24	0.37	0.24	0.37	0.24	0.37	0.24

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

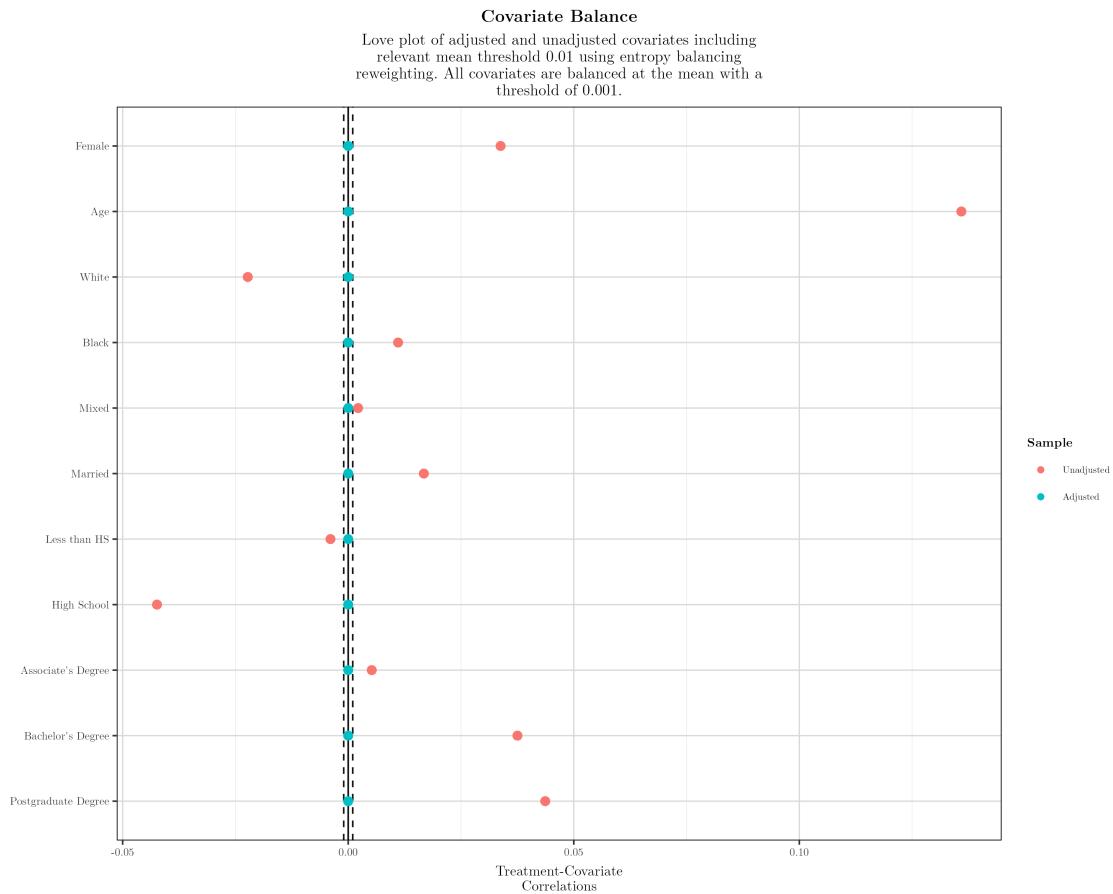
Selection Issues with Non-Random Sample

NOTE: Skip ahead to “Regression Results with Sample Reweighting for Regression Results if you don’t wish to look at the reweighting details below.

One of the challenges with this data is that the sample grows significantly smaller for higher reported of unemployment duration (see scatter plots in Descriptives section). One option is a sample reweighting (beyond the census weights) to ensure population similarity across bins (below I choose GLM propensity score matching & entropy-balancing) or a Heckman Selection. Again, I include the code below (apologies for verbose output), mainly because I am not yet 100% sure of the implementation as I have never implemented such sample correction in a cross-sectional study). Open to suggestions and corrections :)

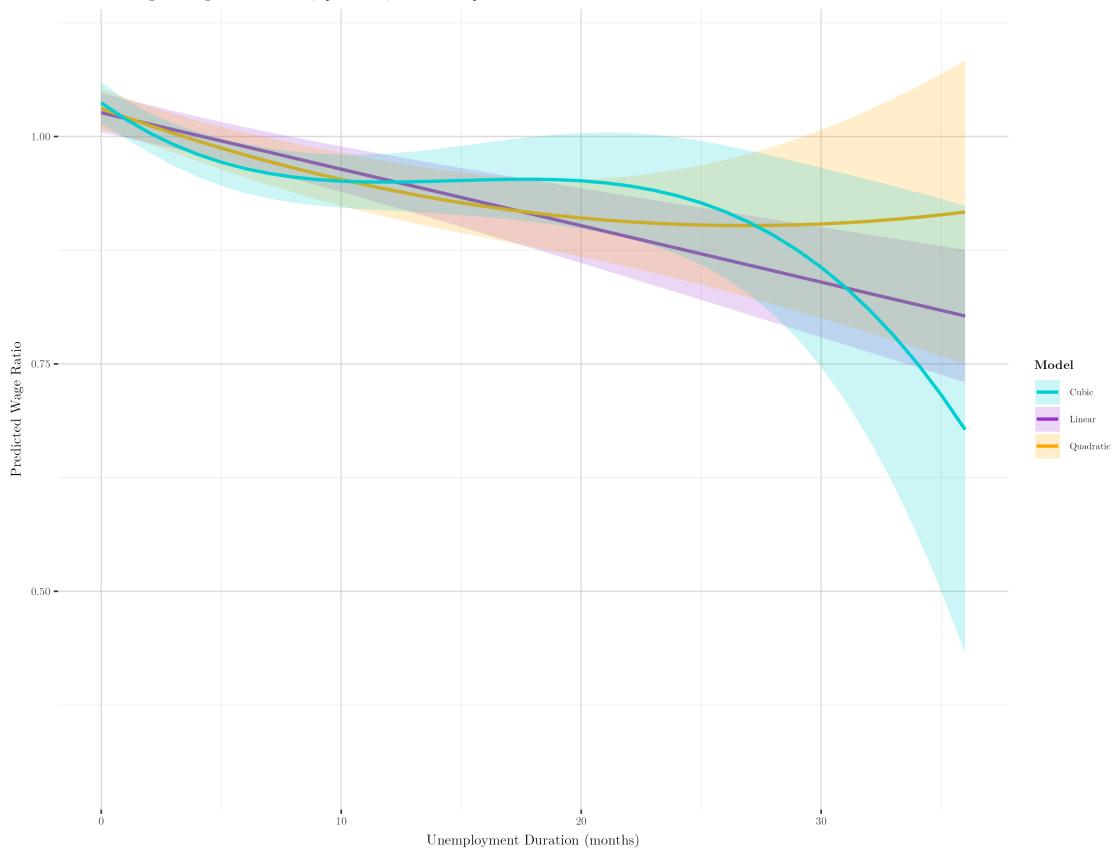
Conclusion: With this implementation (which may very well be wrong for now!), the coefficients on unemployment duration remain stable.

Entropy Balancing Entropy balancing simply reweights observations to ensure population matching across the key dependent variable.

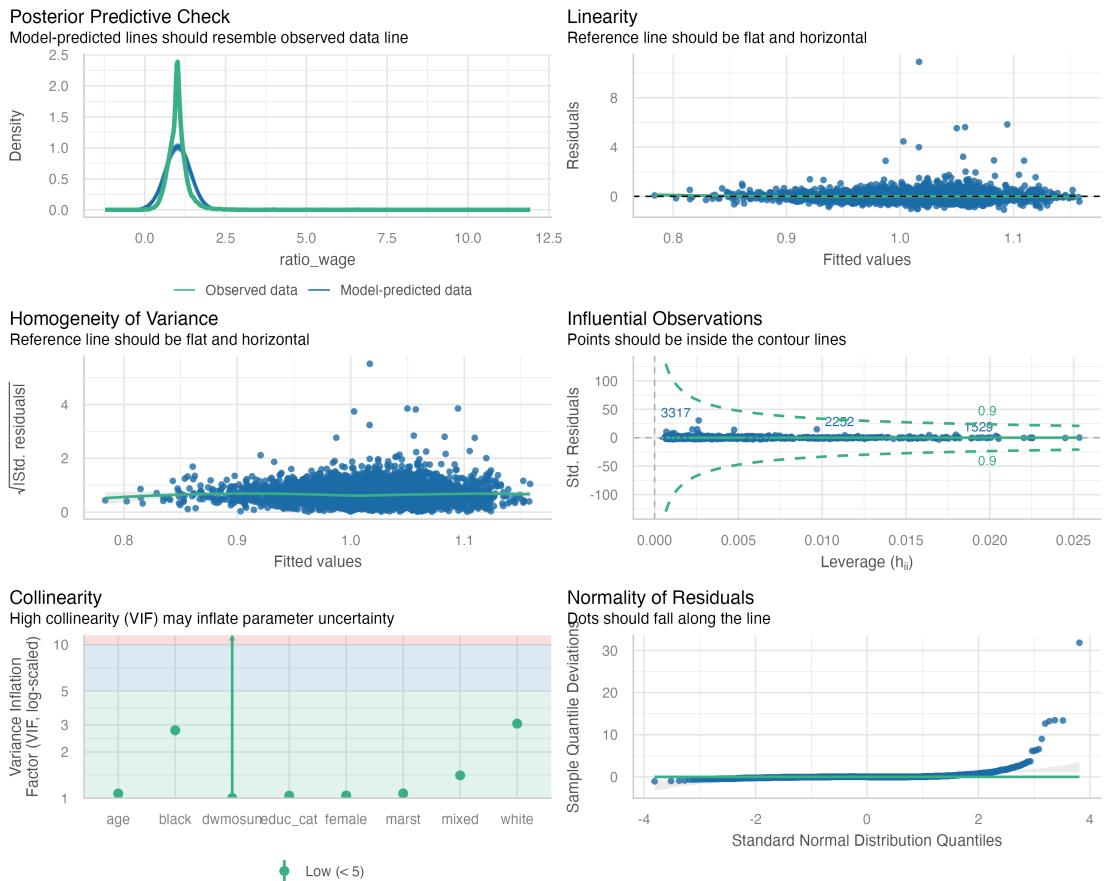


Predicted Wage Ratios by Unemployment Duration (Entropy Balancing)

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



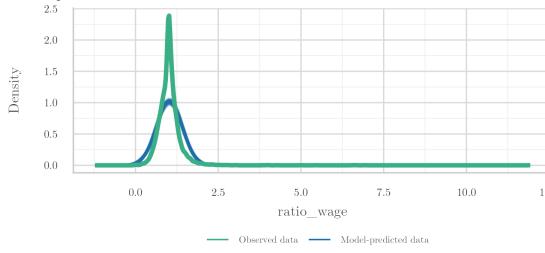
Diagnostic Tests for Entropy-balanced Reweighted Sample



Linear Specification

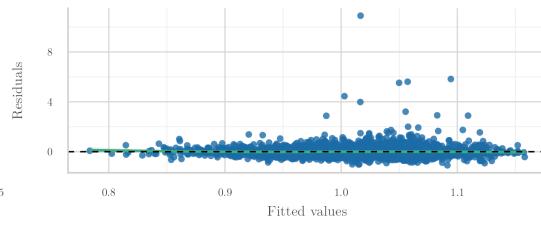
Posterior Predictive Check

Model-predicted lines should resemble observed data line



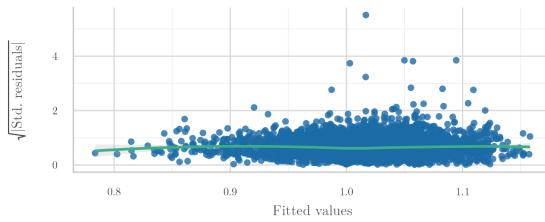
Linearity

Reference line should be flat and horizontal



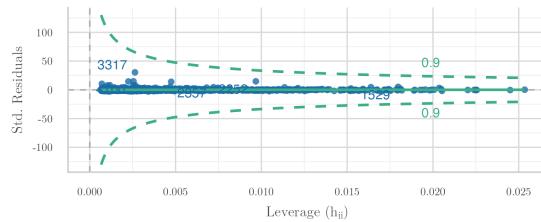
Homogeneity of Variance

Reference line should be flat and horizontal



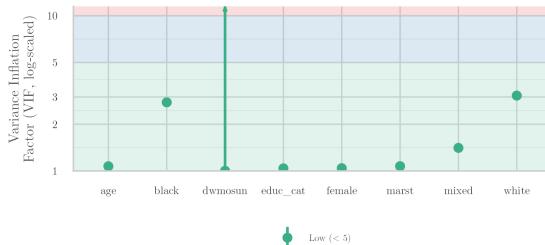
Influential Observations

Points should be inside the contour lines



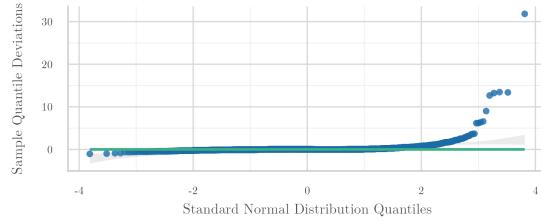
Collinearity

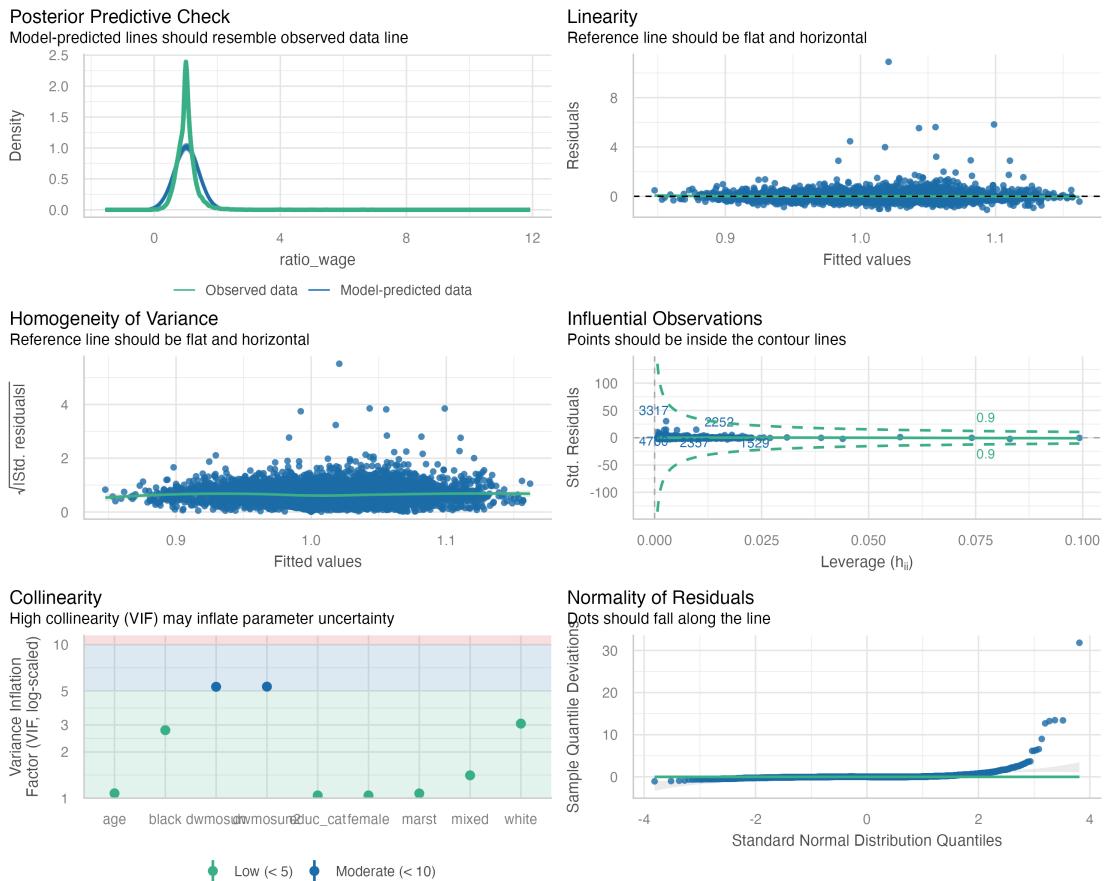
High collinearity (VIF) may inflate parameter uncertainty



Normality of Residuals

Dots should fall along the line

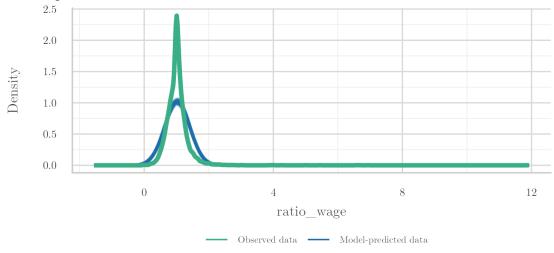




Quadratic Specification

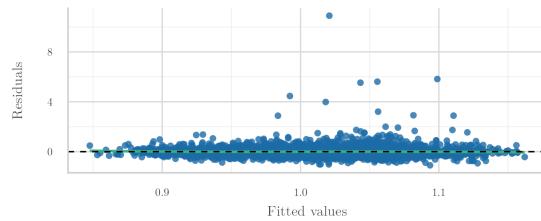
Posterior Predictive Check

Model-predicted lines should resemble observed data line



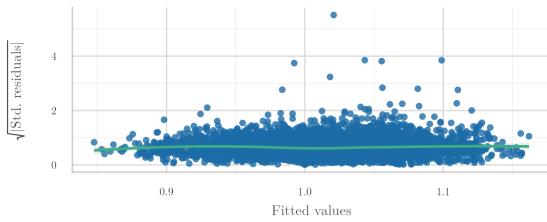
Linearity

Reference line should be flat and horizontal



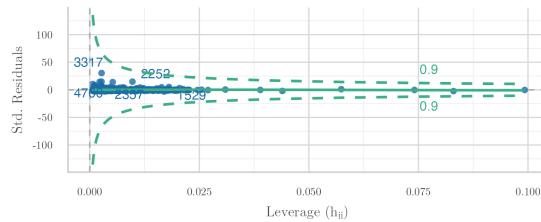
Homogeneity of Variance

Reference line should be flat and horizontal



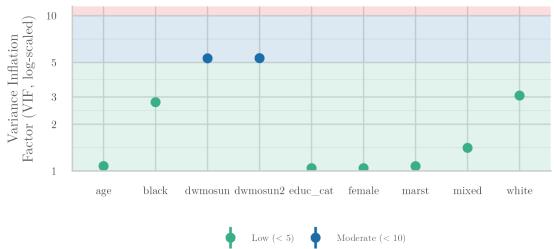
Influential Observations

Points should be inside the contour lines



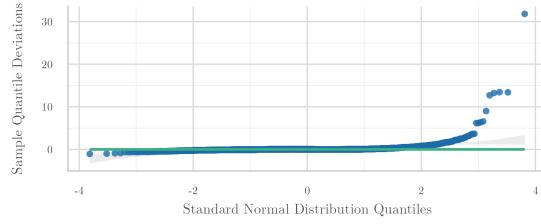
Collinearity

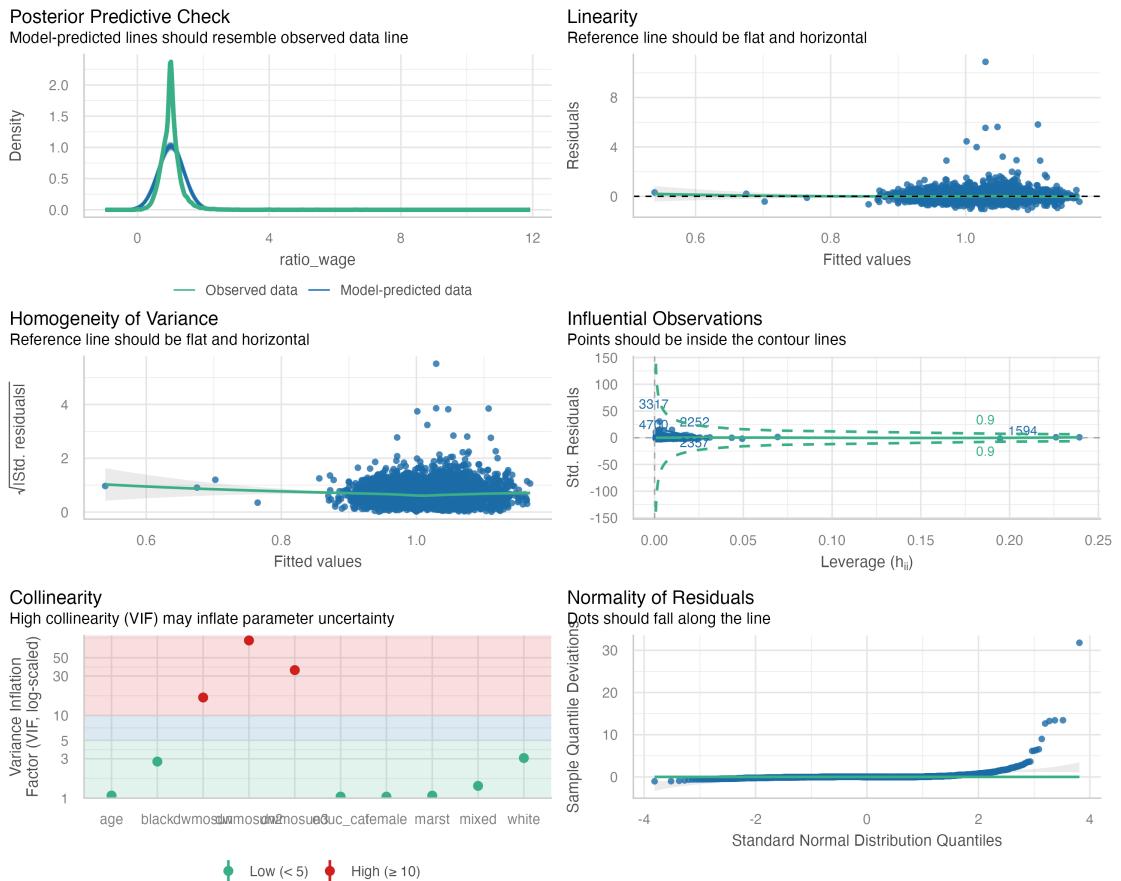
High collinearity (VIF) may inflate parameter uncertainty



Normality of Residuals

Dots should fall along the line

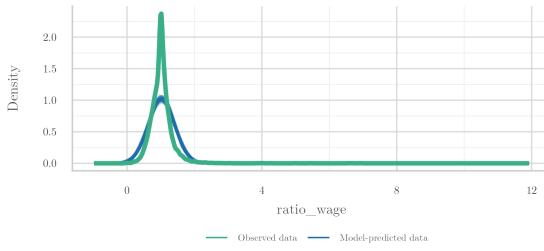




Cubic Specification

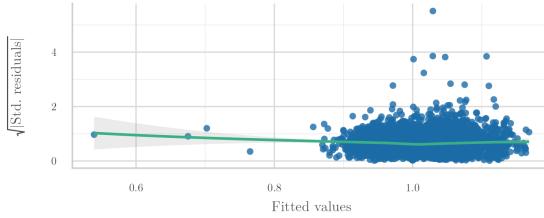
Posterior Predictive Check

Model-predicted lines should resemble observed data line



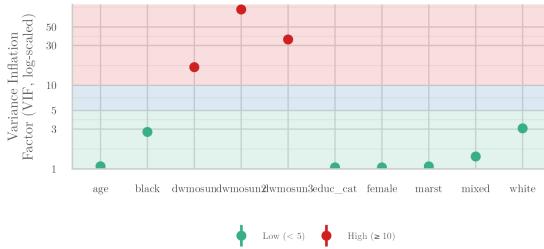
Homogeneity of Variance

Reference line should be flat and horizontal



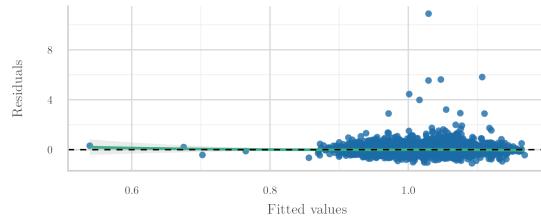
Collinearity

High collinearity (VIF) may inflate parameter uncertainty



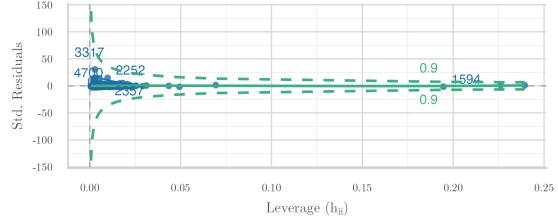
Linearity

Reference line should be flat and horizontal



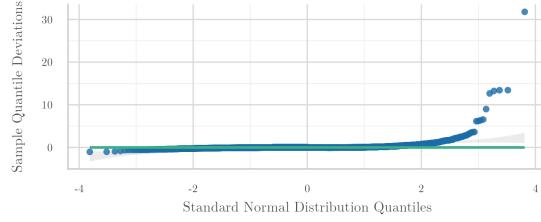
Influential Observations

Points should be inside the contour lines



Normality of Residuals

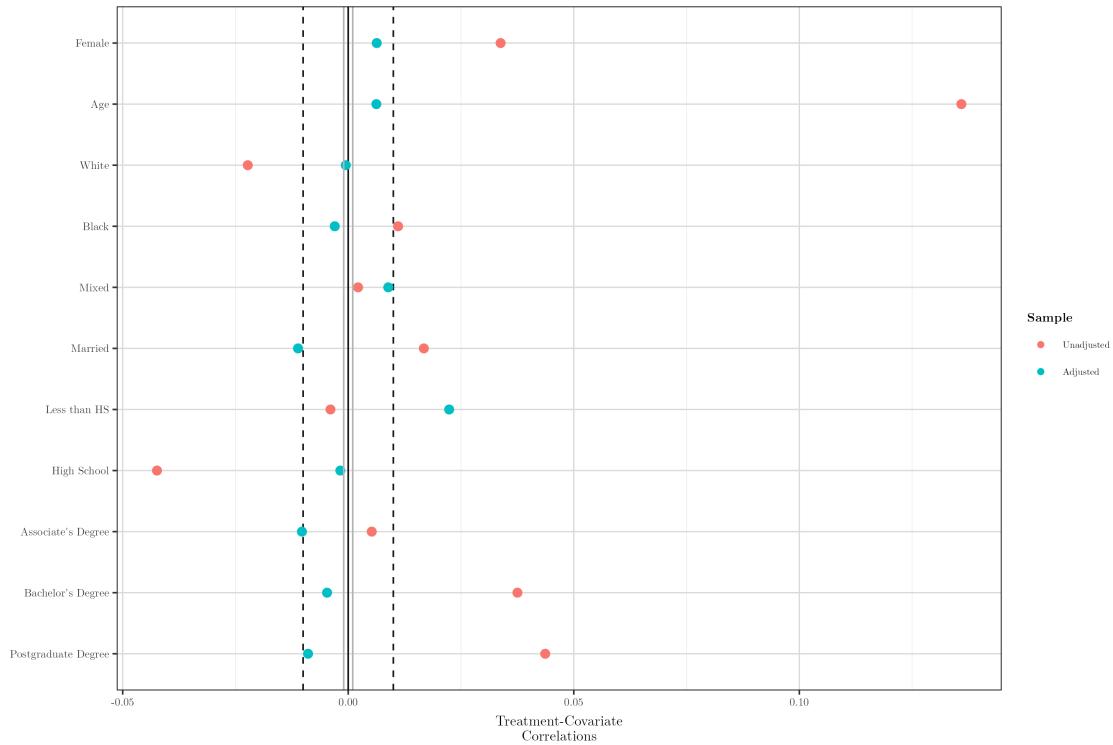
Dots should fall along the line



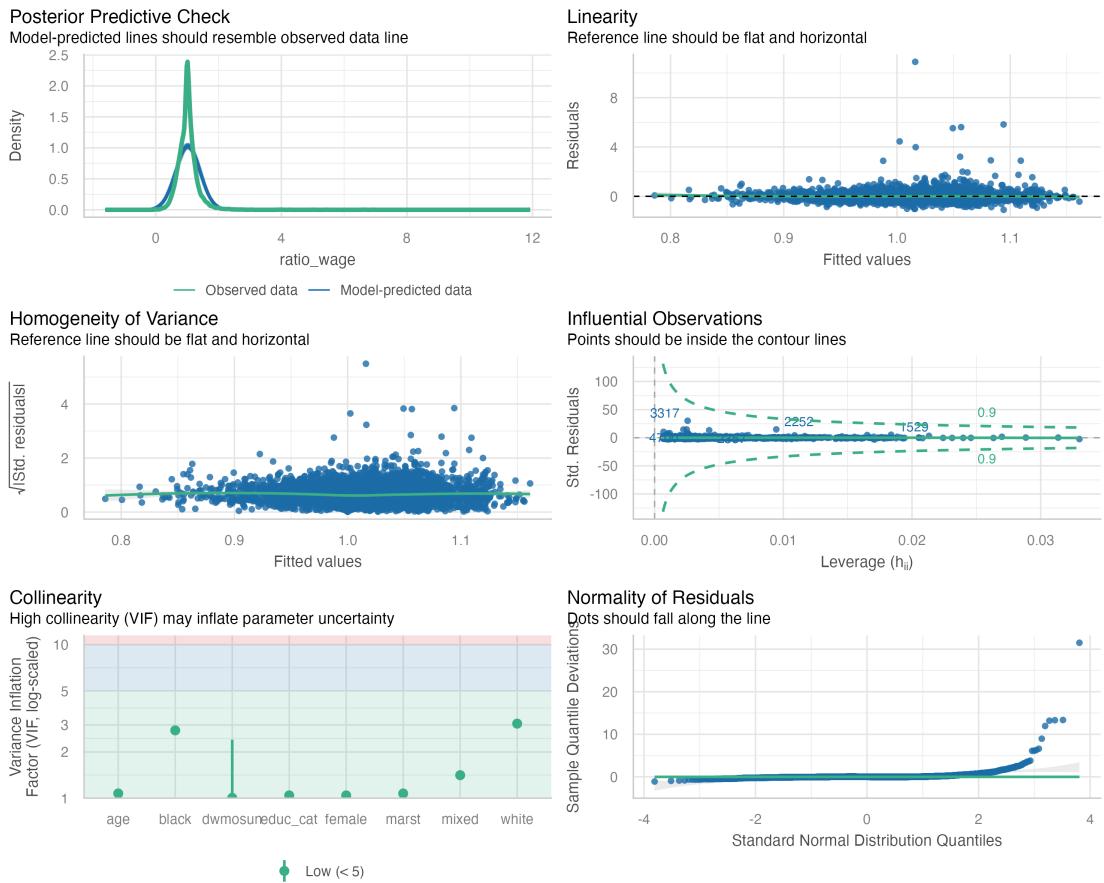
Propensity Score Weighting with GLM Estimator

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.



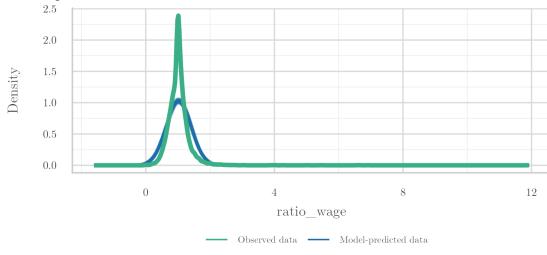
Diagnostic Tests for Propensity Score Matching (GLM) Reweighted Sample



Propensity Score Matching (GLM)

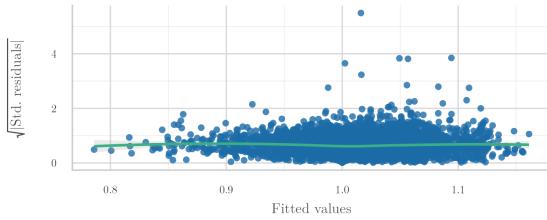
Posterior Predictive Check

Model-predicted lines should resemble observed data line



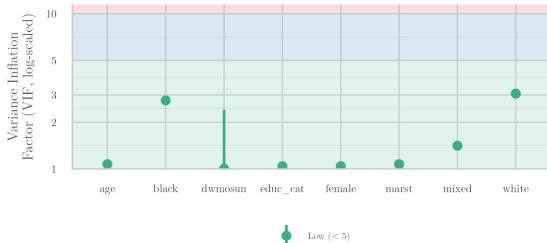
Homogeneity of Variance

Reference line should be flat and horizontal



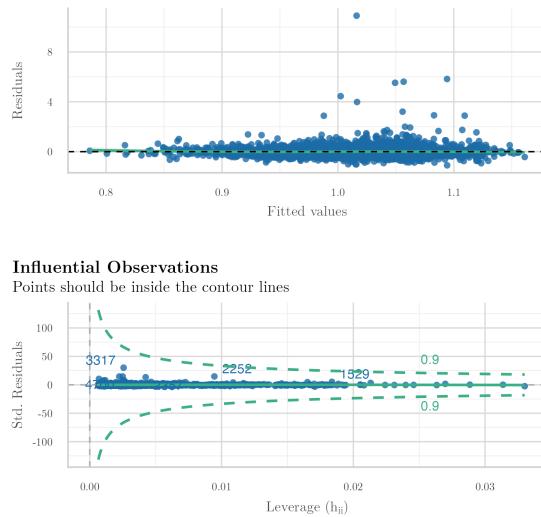
Collinearity

High collinearity (VIF) may inflate parameter uncertainty



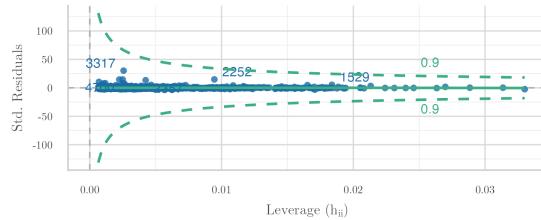
Linearity

Reference line should be flat and horizontal



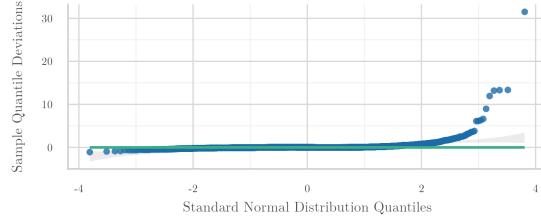
Influential Observations

Points should be inside the contour lines



Normality of Residuals

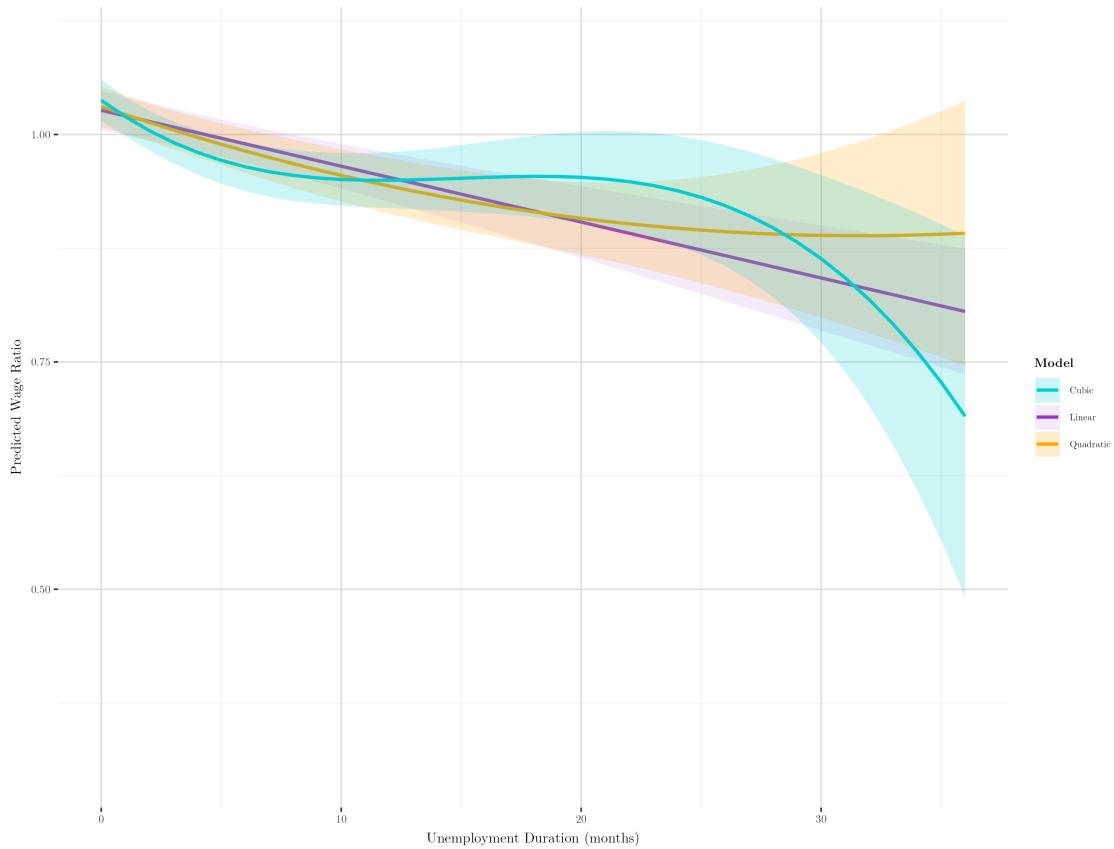
Dots should fall along the line



Predicted Reservation Wage using GLM Reweighted Sample

Predicted Wage Ratios by Unemployment Duration (GLM)

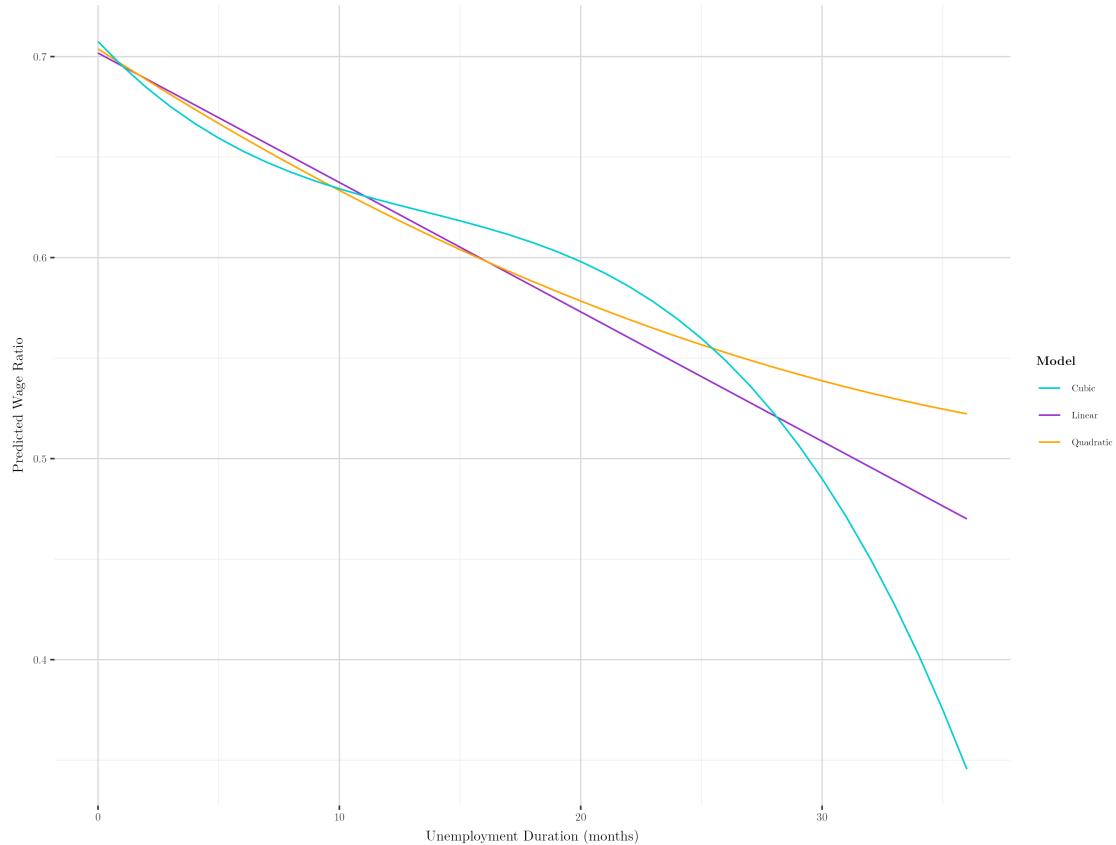
From GLM-weighted regressions: linear, quadratic, and cubic specifications



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)

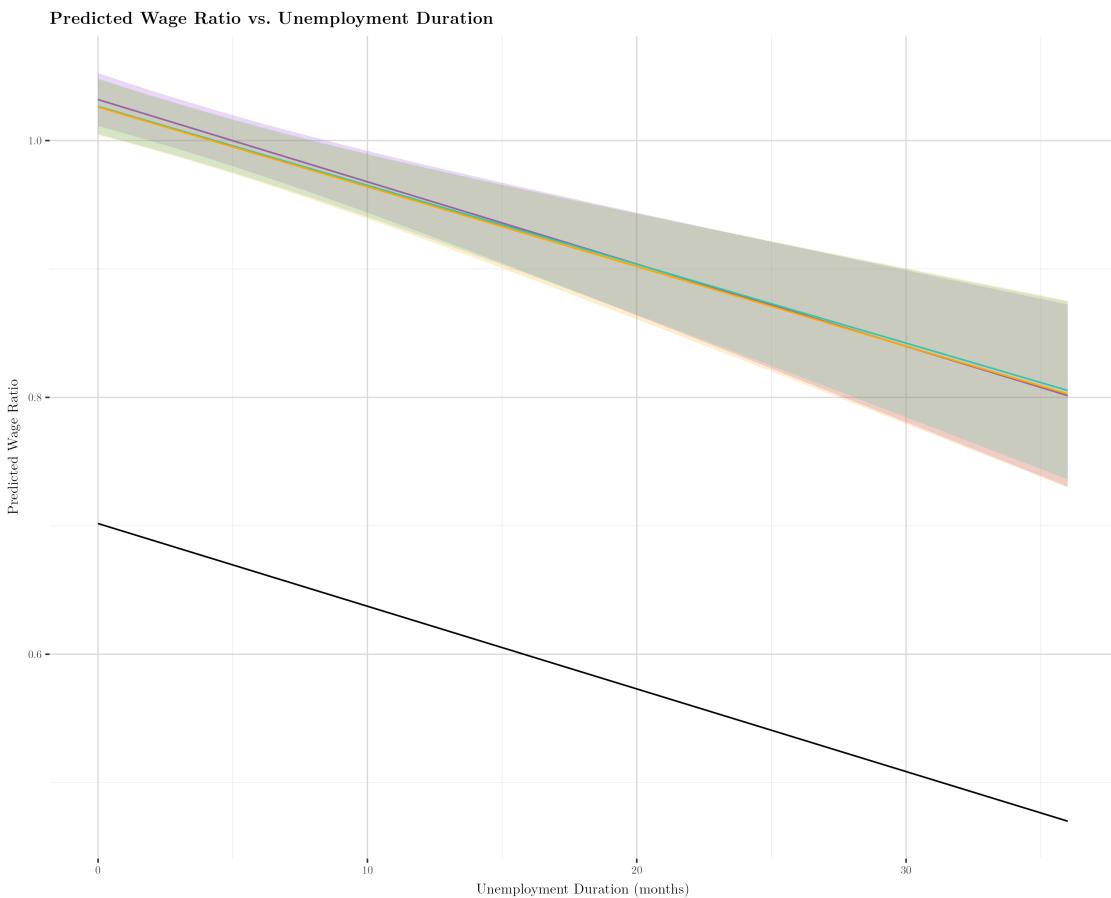
From Heckman-corrected regressions: linear, quadratic, and cubic specifications



Regression Results with Sample Reweighting

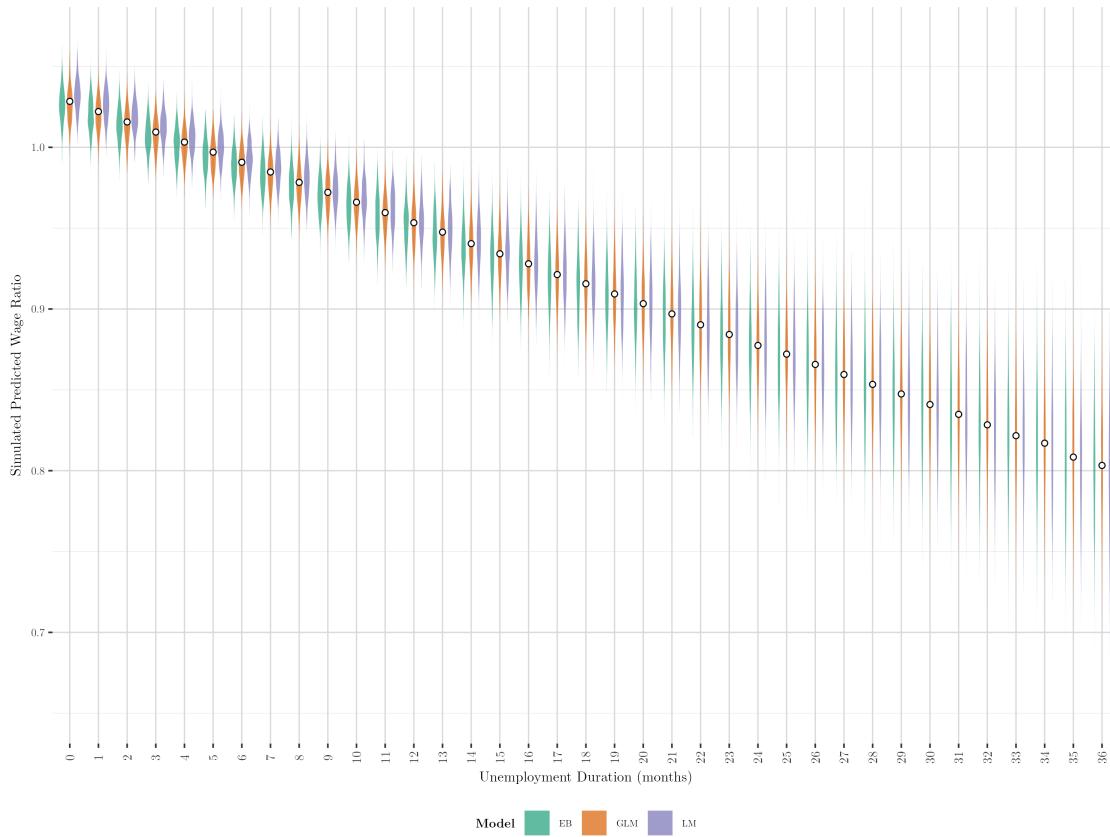
	Heckman Correction	Entropy Balanced Reweight	GLM Reweight
Intercept	1.131*** (0.041)	1.147*** (0.033)	1.143*** (0.033)
Unemployment Duration (Months)	-0.006*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)
Female	0.018 (0.014)	0.001 (0.011)	0.001 (0.011)
Age	-0.007*** (0.002)	-0.002*** (0.000)	-0.002*** (0.000)
White	-0.162* (0.074)	-0.027 (0.025)	-0.023 (0.025)
Black	-0.125* (0.050)	-0.040 (0.030)	-0.036 (0.030)
Mixed	-0.054 (0.055)	0.003 (0.044)	0.007 (0.044)
Married	0.003 (0.011)	0.005 (0.011)	0.004 (0.011)
High School	-0.014 (0.019)	-0.014 (0.017)	-0.014 (0.017)
XOeduc_catAssociate's	-0.078 (0.064)		
Bachelor's Degree	-0.217 (0.165)	0.054* (0.023)	0.054* (0.023)
Postgraduate Degree	-0.479 (0.330)	0.083+ (0.048)	0.086+ (0.047)
Inverse Mills Ratio	0.870+ (0.479)		
educ_catAssociate's		0.007 (0.022)	0.006 (0.022)
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



Simulated Predicted Wage Ratio Distributions by Unemployment Duration

Violin plots from LM, GLM, and EB model predictions



Job Tenure

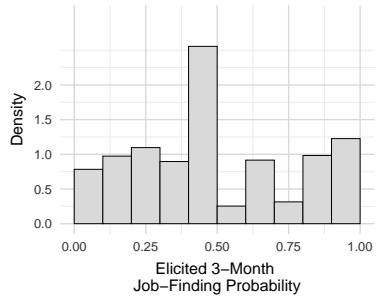
We have information on the tenure spent at the last job which could impact the result. This could speak to the “adaptability” of individuals. Wage ratio seems to decrease (although not sure if meaningfully) with tenure at previous job.

Density Comparison of Elicited Job-Finding Probabilities

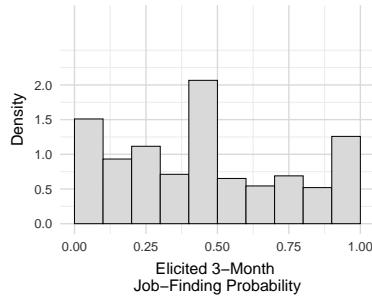
Remarkably consistent beliefs in job-finding probabilities even when including the Covid period.



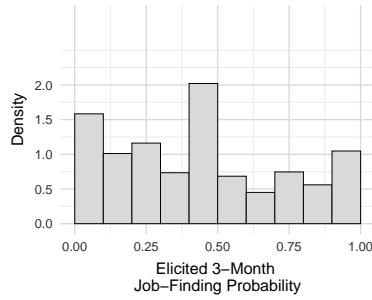
Orig. 2013-19: Figure 1.
Histograms of Elicited Job-Finding Probabilities – Panel A. SCE (3-mo horizon)



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

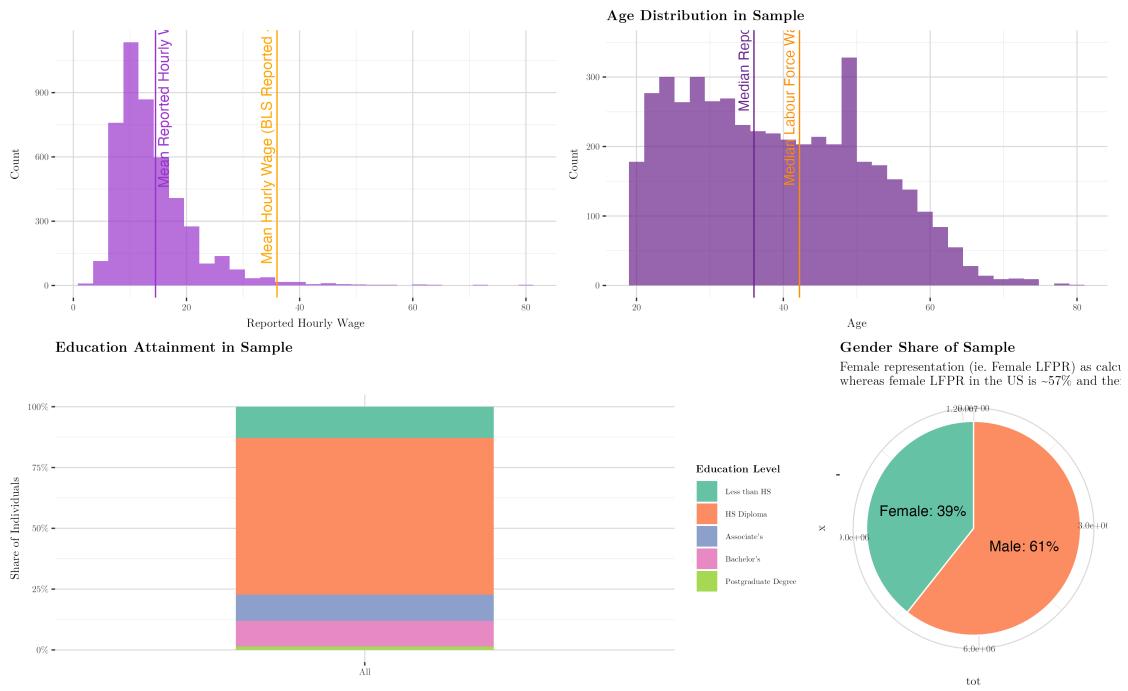
Although the survey does provide sample weights which we use above, it's still likely that those who are laid off might be systematically more susceptible to layoffs (lower-wage, low-skill occupation, male, etc). Below, some (very rough) graphs to indicate what the sample looks like.

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.

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

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).

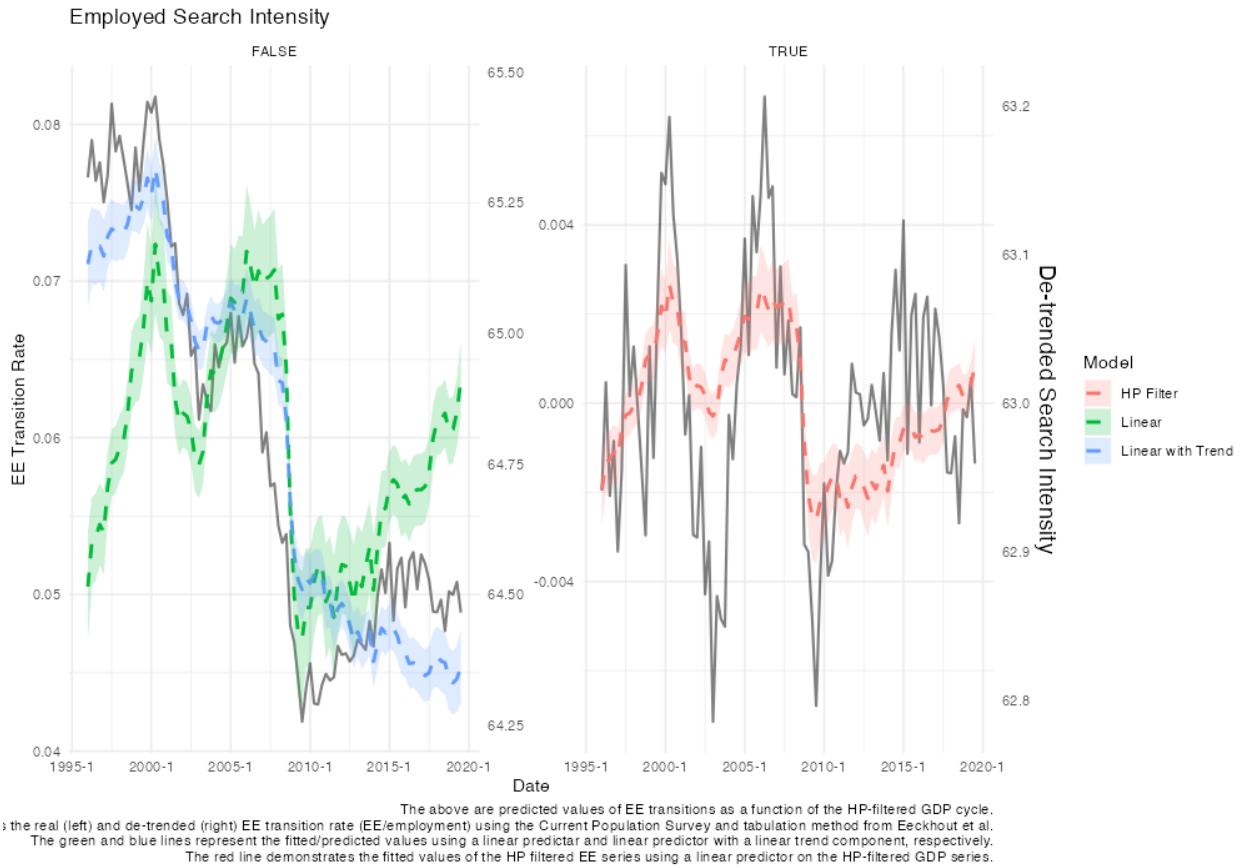
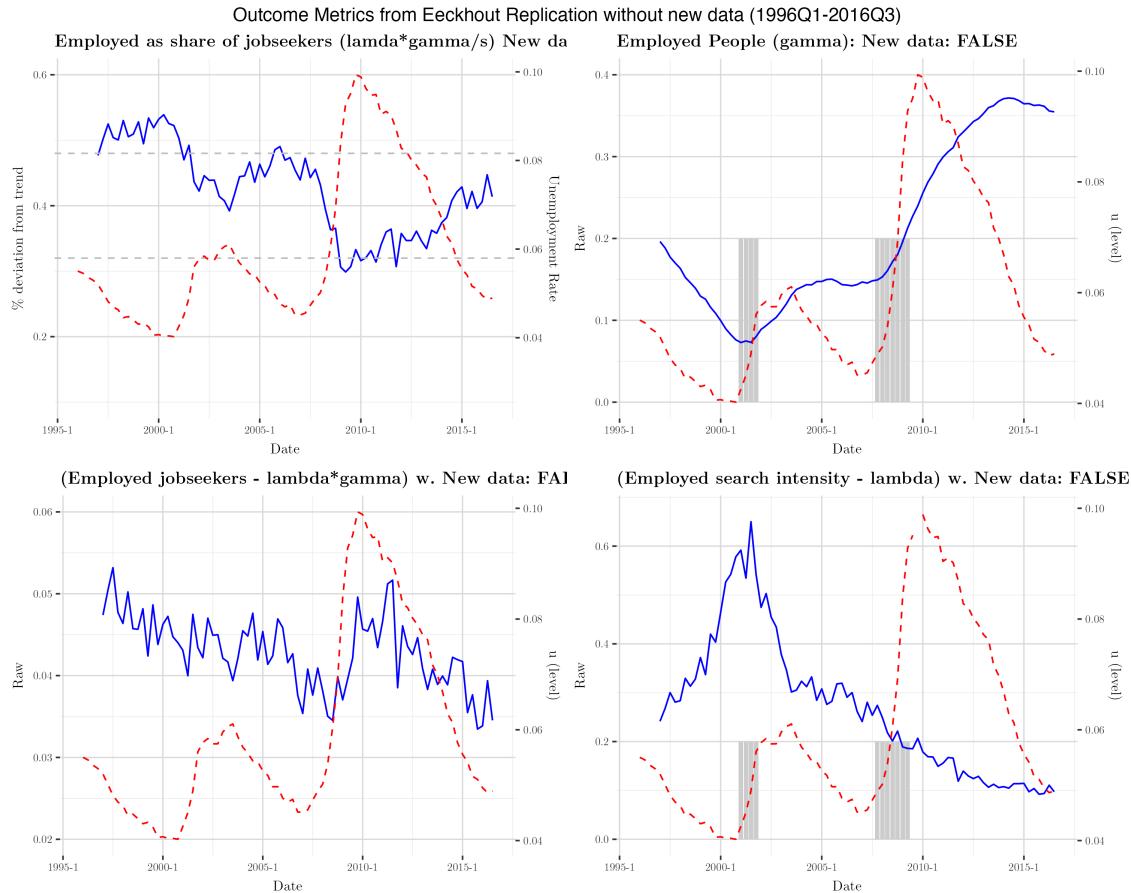


Figure 1: Employed Search Effort Fit

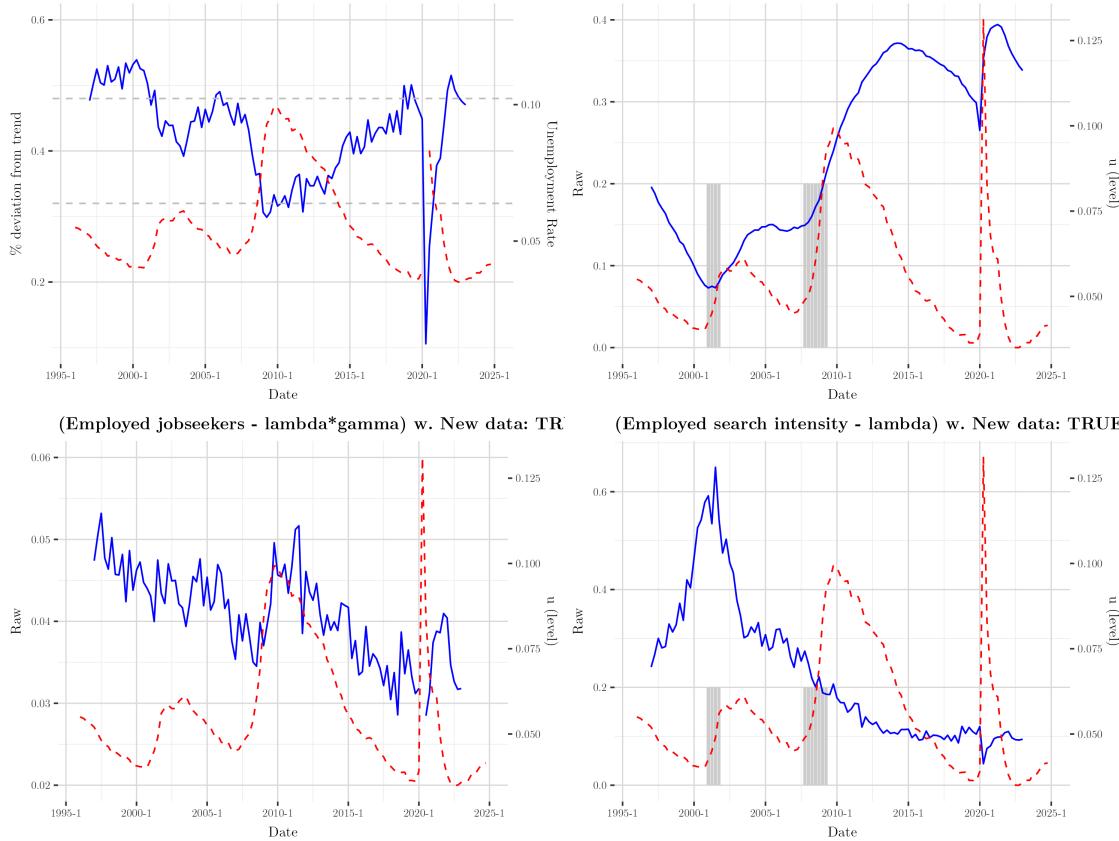
	Linear	Linear with Trend	HP Filter
(Intercept)	-0.174*** (0.035)	-0.053** (0.018)	-0.049*** (0.008)
x	0.233*** (0.035)	0.129*** (0.017)	0.049*** (0.008)
trend		0.000*** (0.000)	
Num.Obs.	95	95	95
R2	0.323	0.854	0.282
R2 Adj.	0.315	0.851	0.275
AIC	-594.7	-738.3	-872.6
BIC	-587.0	-728.1	-865.0
Log.Lik.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

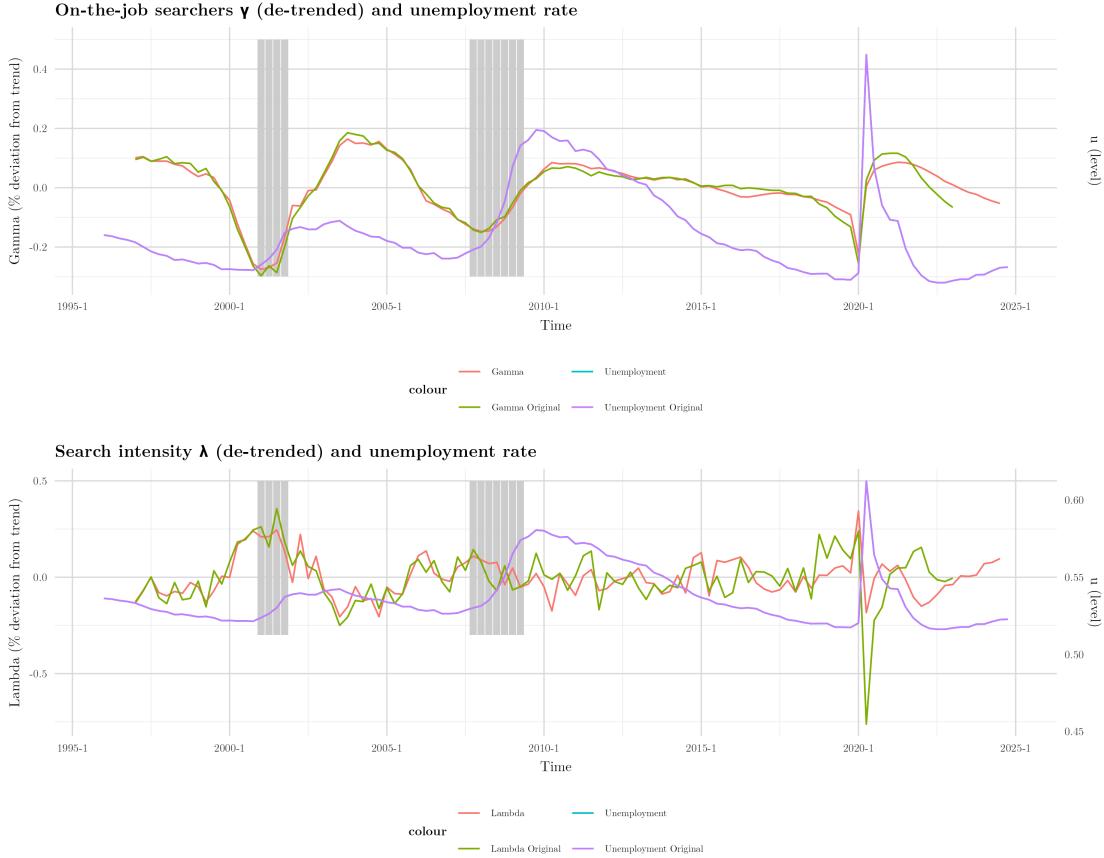
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001



Outcome Metrics from Eeckhout Replication without new data (1996Q1-2024Q4)

Employed as share of jobseekers ($\lambda \gamma / s$) New data Employed People (γ): New data: TRUE





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.

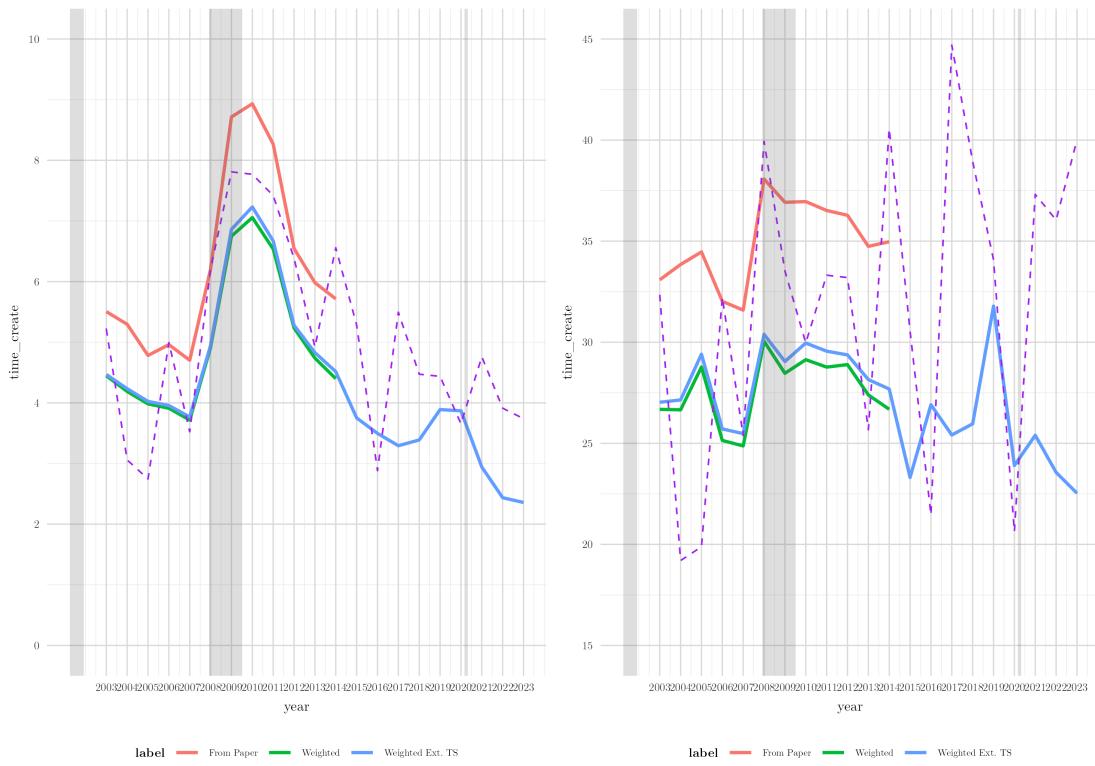
We use evidence from Mukoyama et al regarding the cyclicity of unemployed job search effort to validate the micro behaviour of our agents. I will provide more explanation on this...

(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.

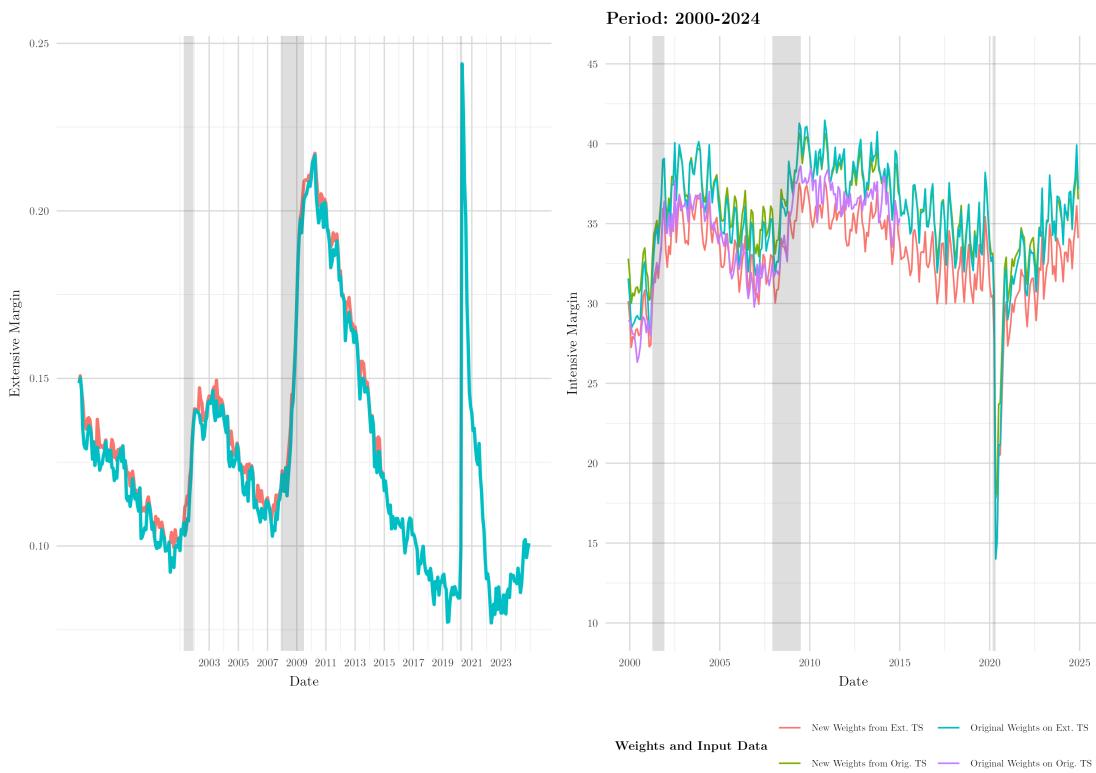
Abstract: We examine the cyclicity of search effort using time-series, cross-state, and individual variation and find that it is countercyclical. We then set up a search and matching model with endogenous search effort and show that search effort does not amplify labor market fluctuations but rather 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. Panels 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



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

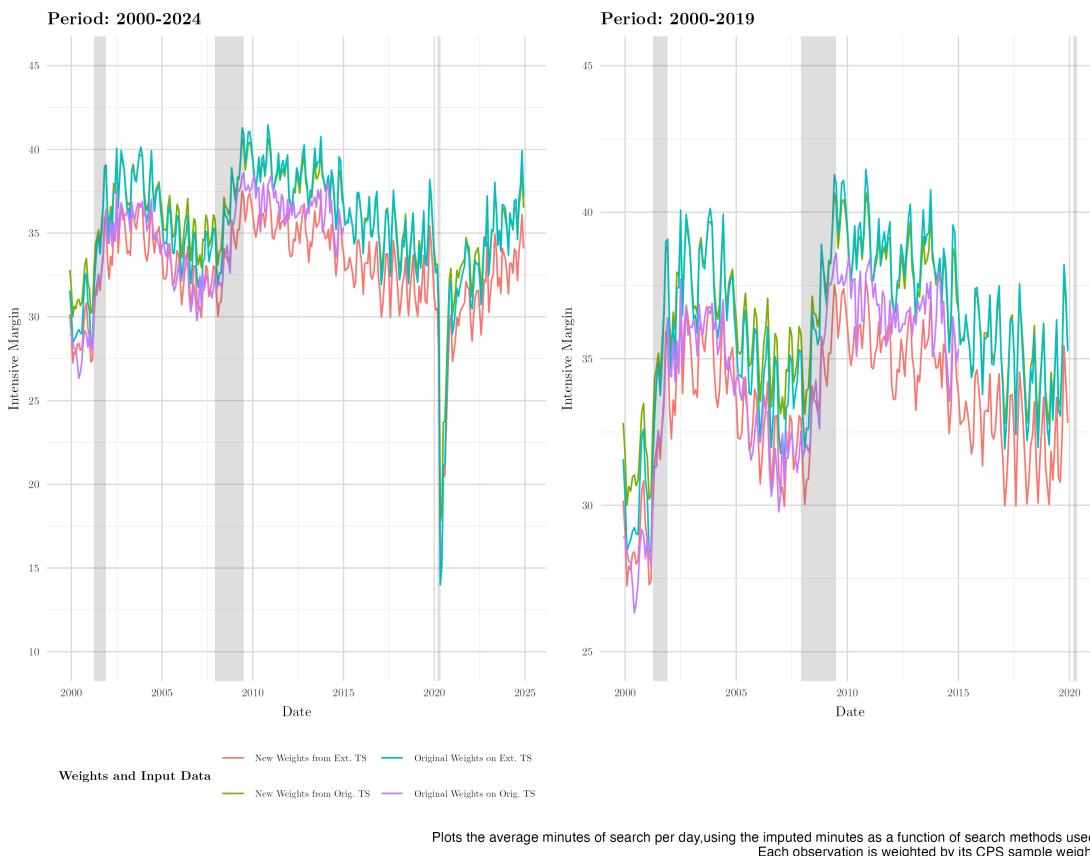
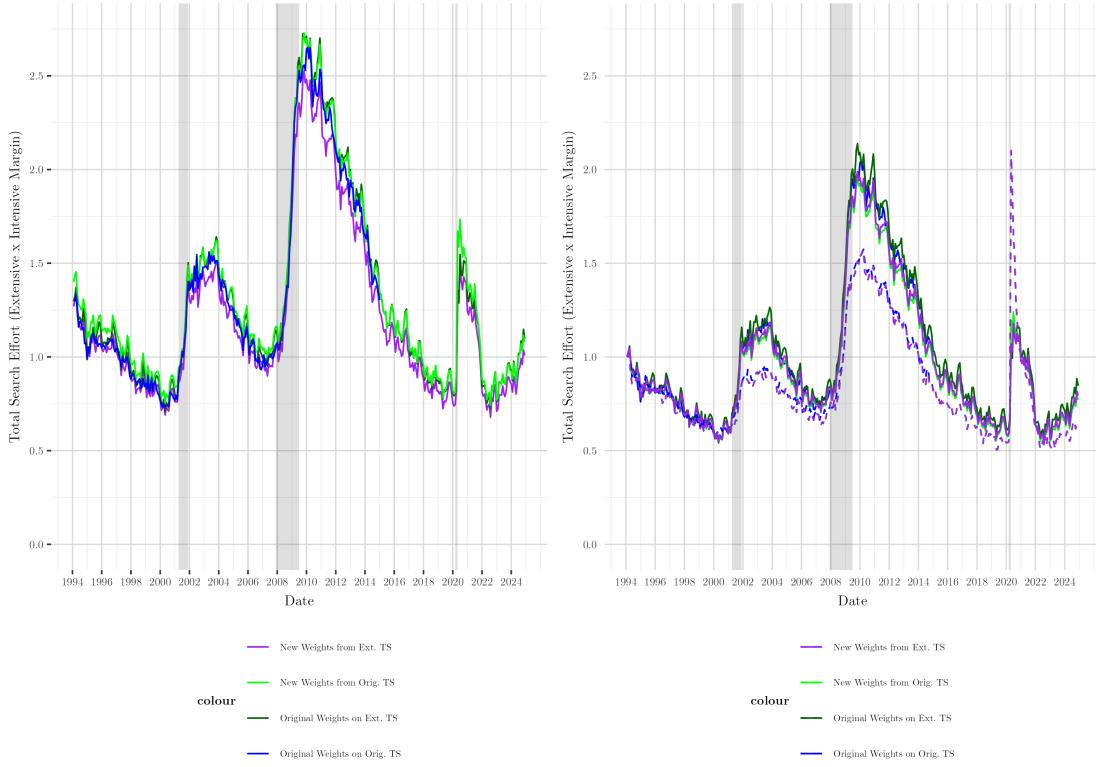


Figure 4. Time Series of (Panel A) Total Search Effort and (Panel B) Total Search Effort Using the Search Time of Unemployed Workers [solid: $(s^*(U/(E + U + N))]$ versus Using the Number of Unemployed Workers [dashed: $U/(E + U + N)$] (panel B)



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 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).

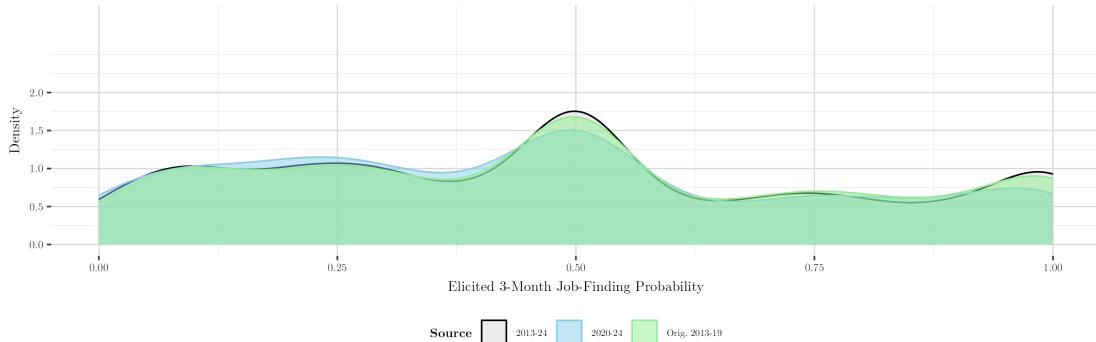
% Table created by stargazer v.5.2.3 by Marek Hlavac, Social Policy Institute. E-mail: marek.hlavac at gmail.com % Date and time: Tue, Jan 06, 2026 - 02:30:52

Table 5: Descriptive Statistics (SCE)

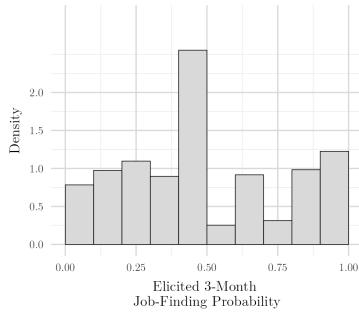
Variable	Orig. 2013-19	2013-24	2020-24
High-School Degree or Less	44.5	40.6	36.9
Some College Education	32.4	34.9	37.6
College Degree or More	23.1	24.6	25.6
Age 20-34	25.4	27.2	30.0
Age 35-49	33.5	33.6	35.3
Age 50-65	41.1	39.2	34.8
Female	59.3	61.2	60.8
Black	19.1	17.9	16.4
Hispanic	12.5	13.0	12.6
UE 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

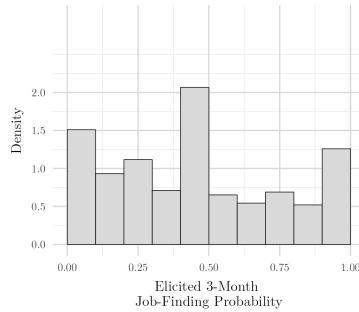
Remarkably consistent beliefs
in job-finding probabilities even when including the Covid period.



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)

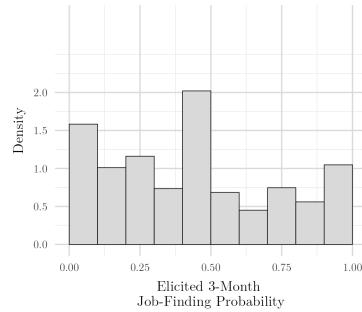
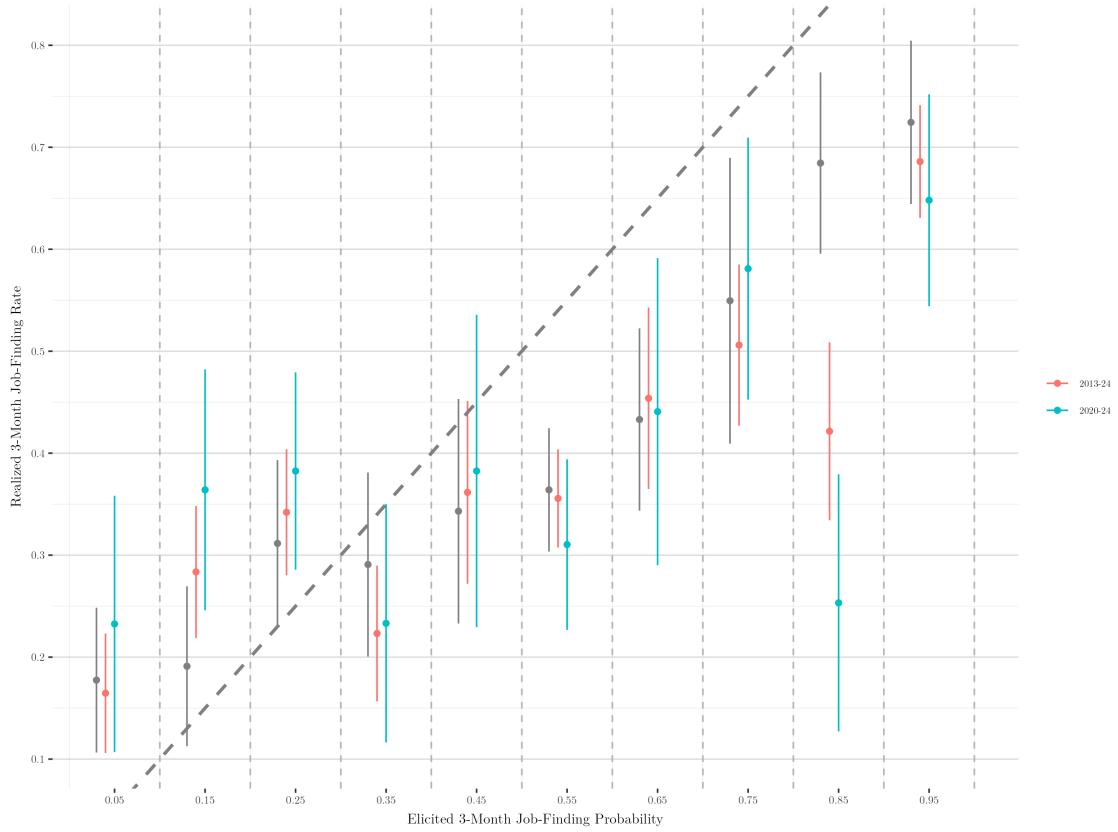


Figure 2: Averages of Realized Job-Finding Rates, by Bins of Elicited Probabilities (SCE)

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



% Table 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 - 02:30:53

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Table 6: 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	0.464*** (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 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 7: 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 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 8: 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 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 9: 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 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.

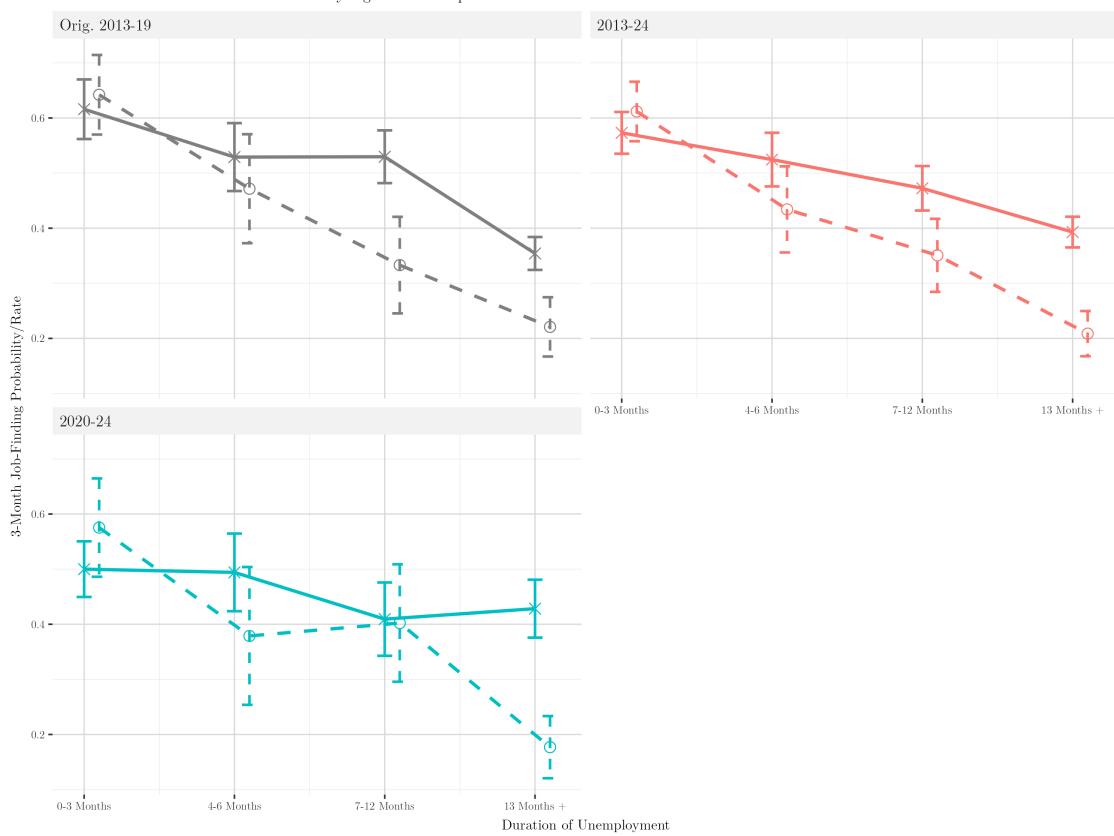


Fig 3. Perceived vs. Realized Job Finding, by Duration of Unemployment

Duration dependence is strongly negative across all samples.
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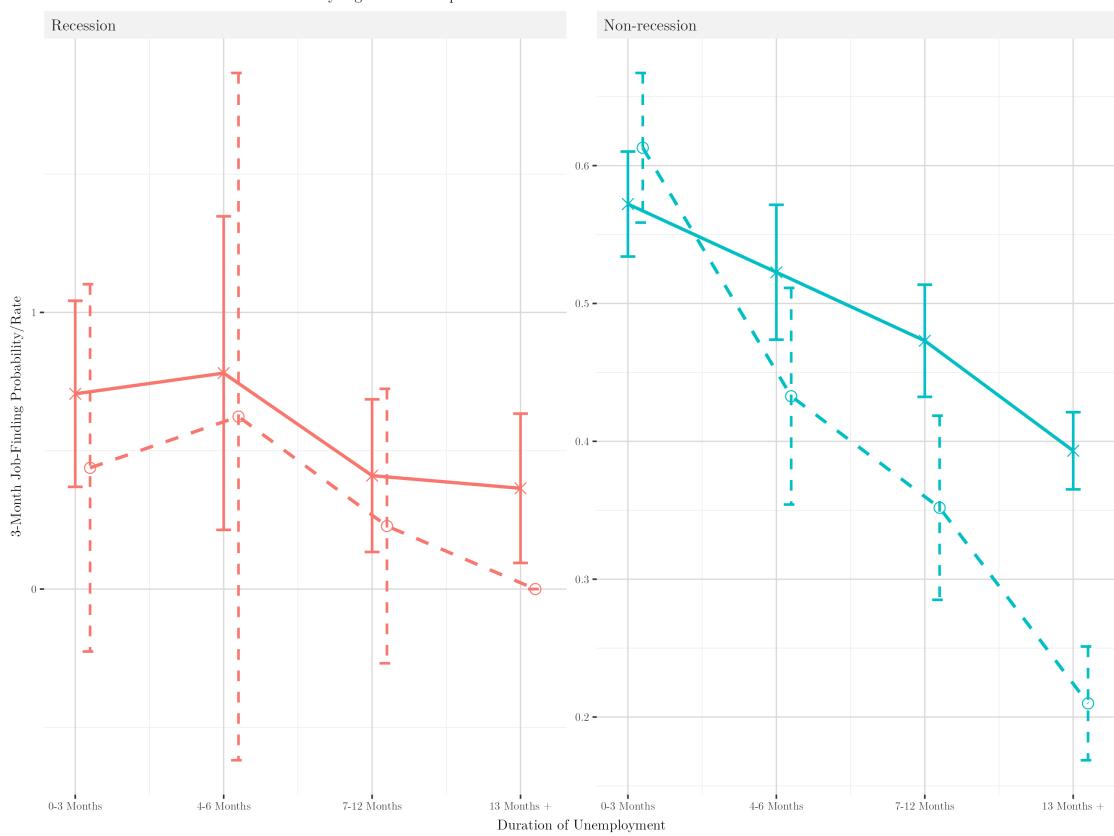


Fig 4. Changes in Job-Finding Probability Across and Within Spells

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.

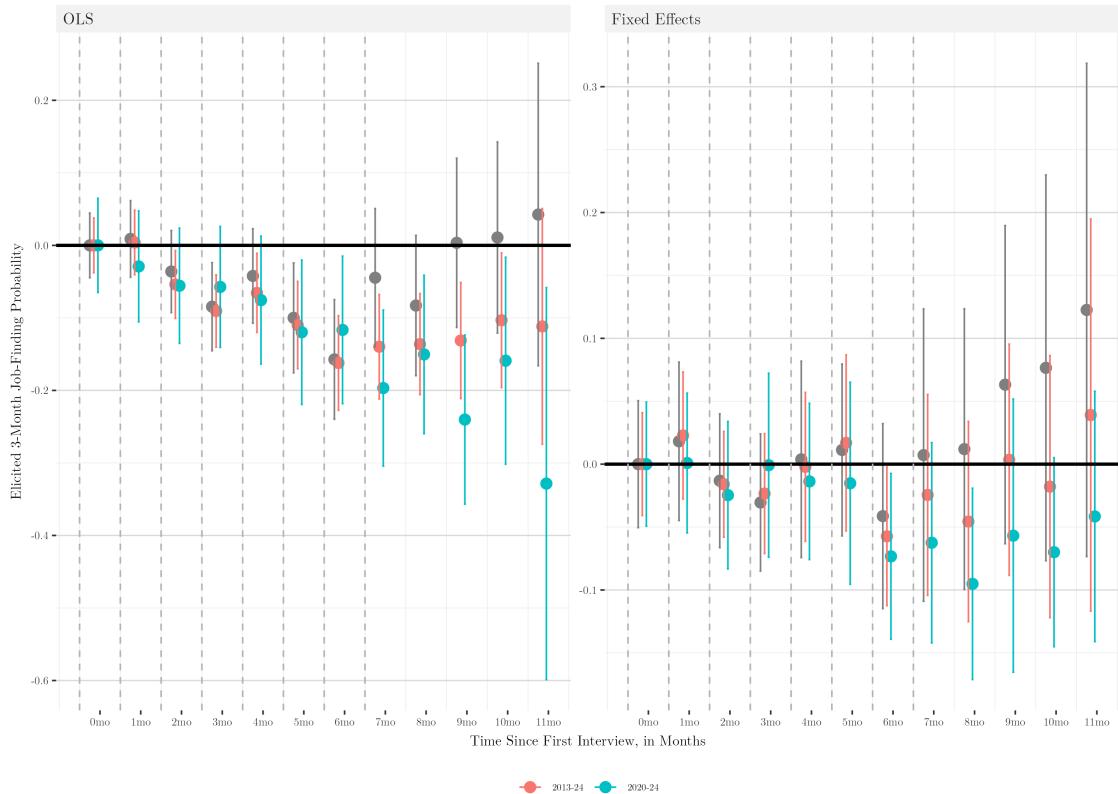


Fig 3. Perceived vs. Realized Job Finding, by Duration of Unemployment

Duration dependence is strongly negative across all samples.
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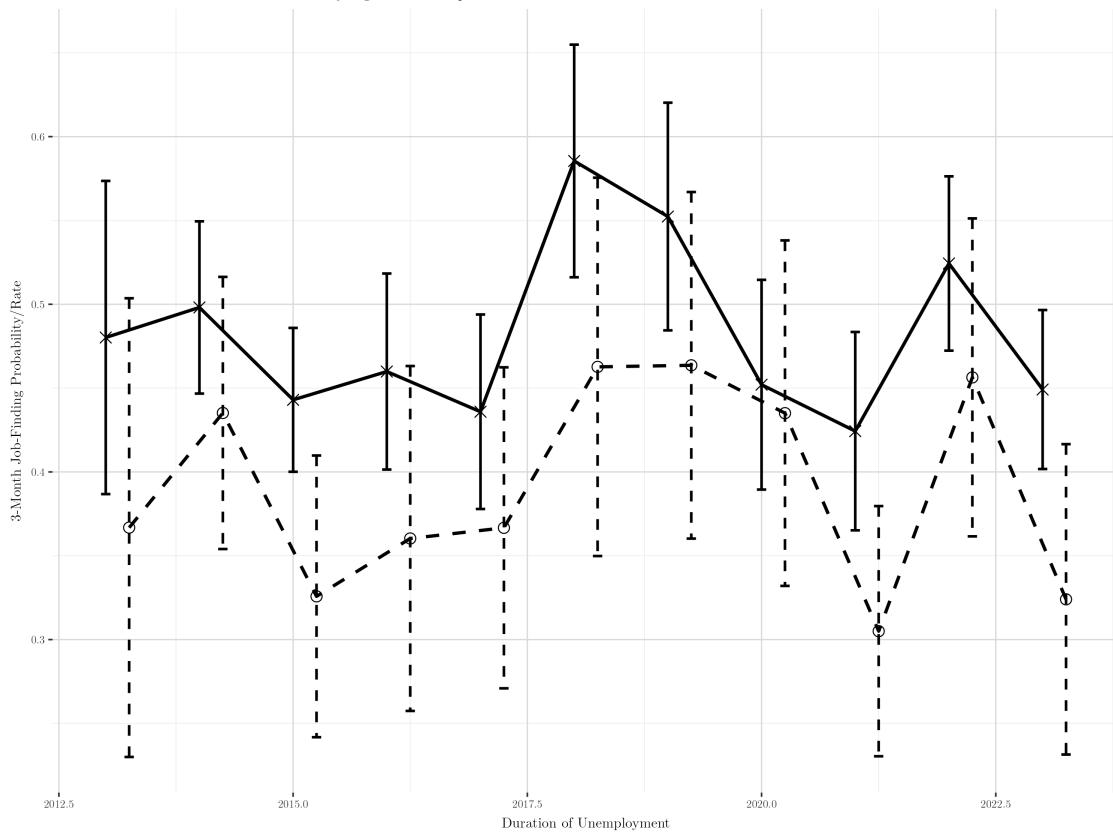
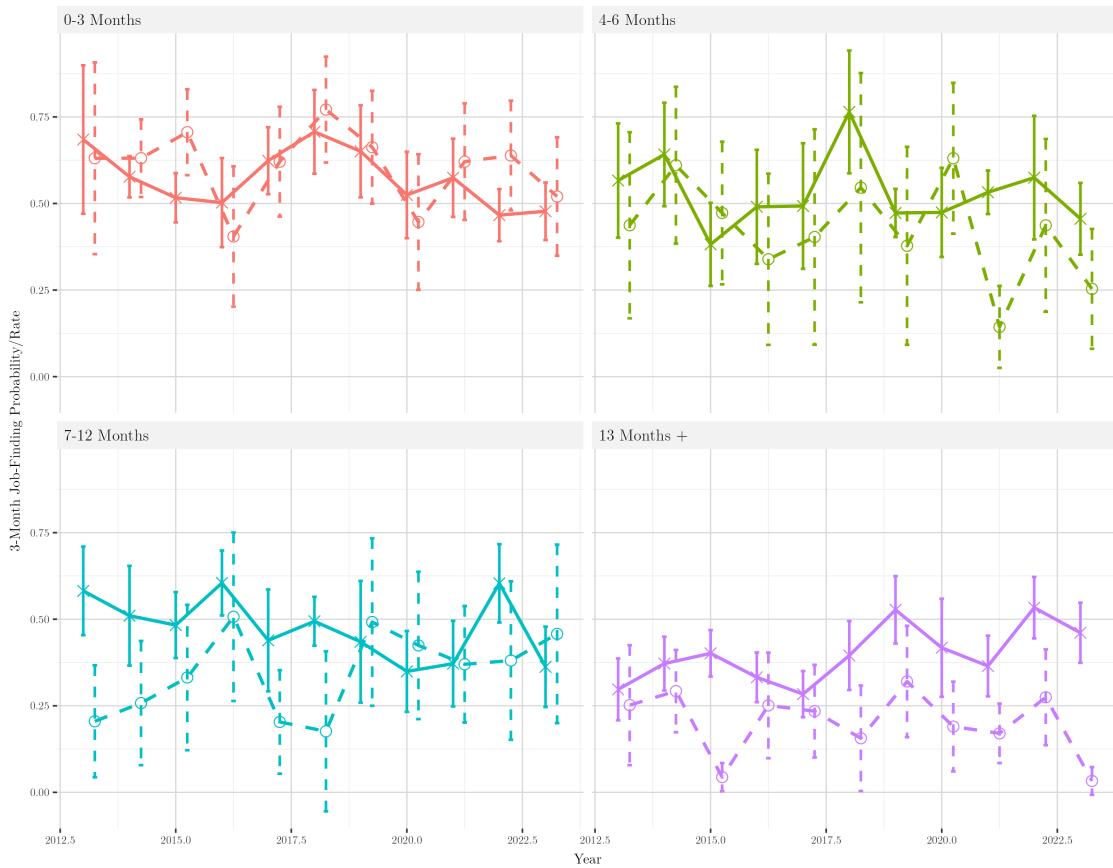


Fig 3. Perceived and Realized Job Finding, by Year



Additional Analyses

SCE Labor Market Survey: Reservation Wages

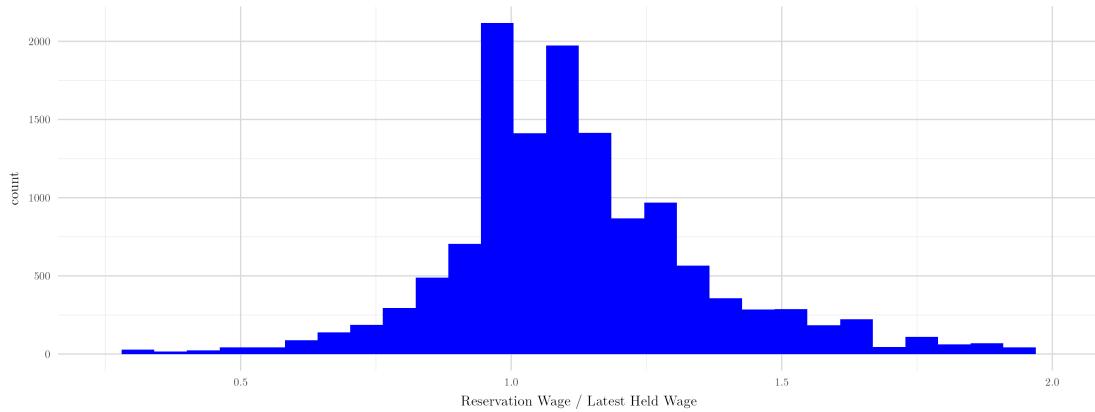
Survey of Consumer Expectations Reservation Wages, Accepted Wages, and Wage Expectations The data is unfortunately sparse and linking outcomes to reservation wages is difficult. However, in a cross-sectional setting we are able to deduce some weak relationships between Unemployment Duration and Absolute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

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

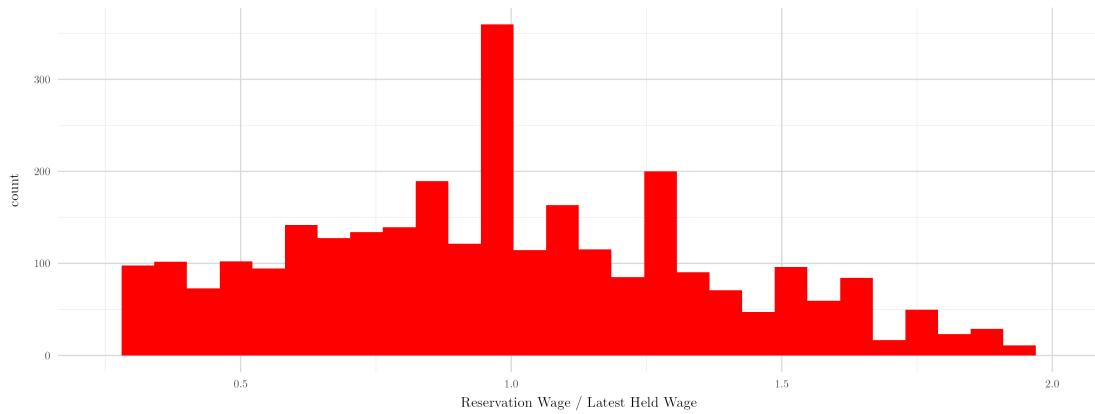
Survey of Consumer Expectations Reservation Wages, Accepted Wages, and Wage Expectations (2014-2022) *The data is unfortunately sparse and linking outcomes to reservation wages is difficult. However, in a cross-sectional setting we are able to deduce some weak relationships between Unemployment Duration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

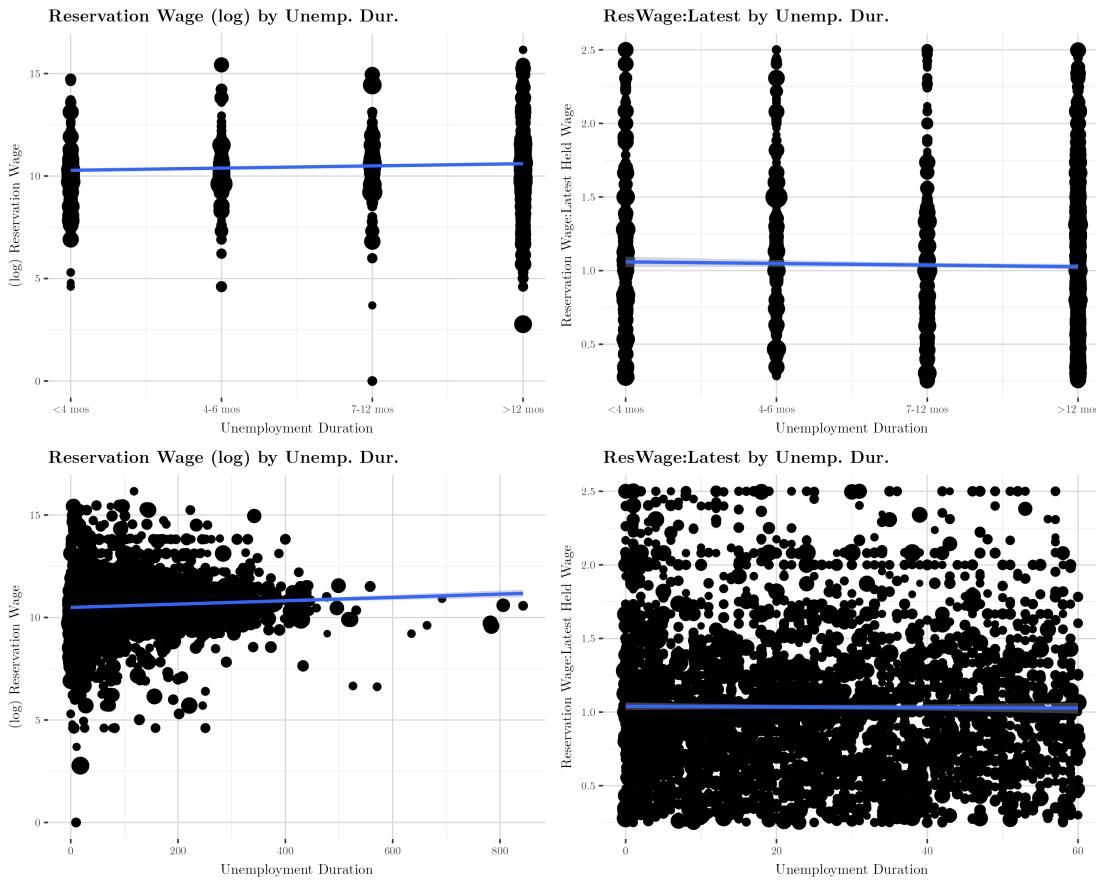
[1] "Plots of RESERVATION WAGE versus latest, current wage"

Reservation Wage as proportion of Current Wage

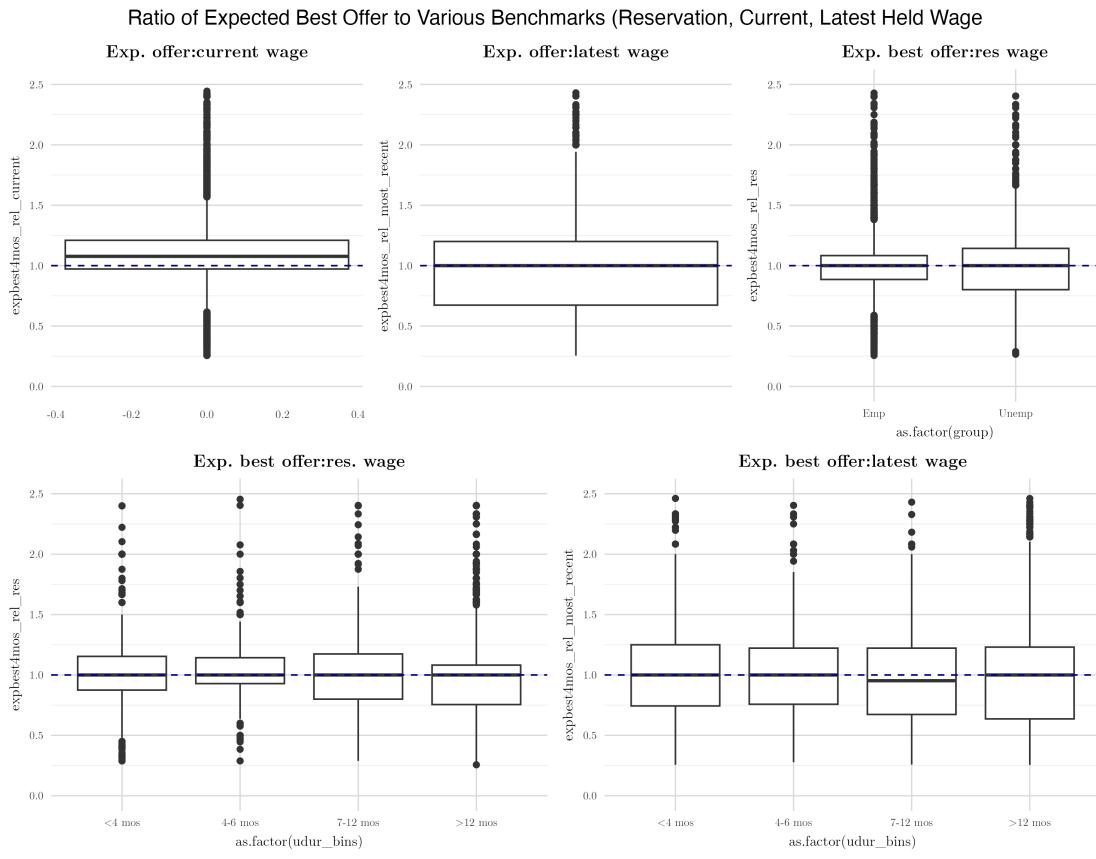


Reservation Wage as proportion of Latest Held Wage





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



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

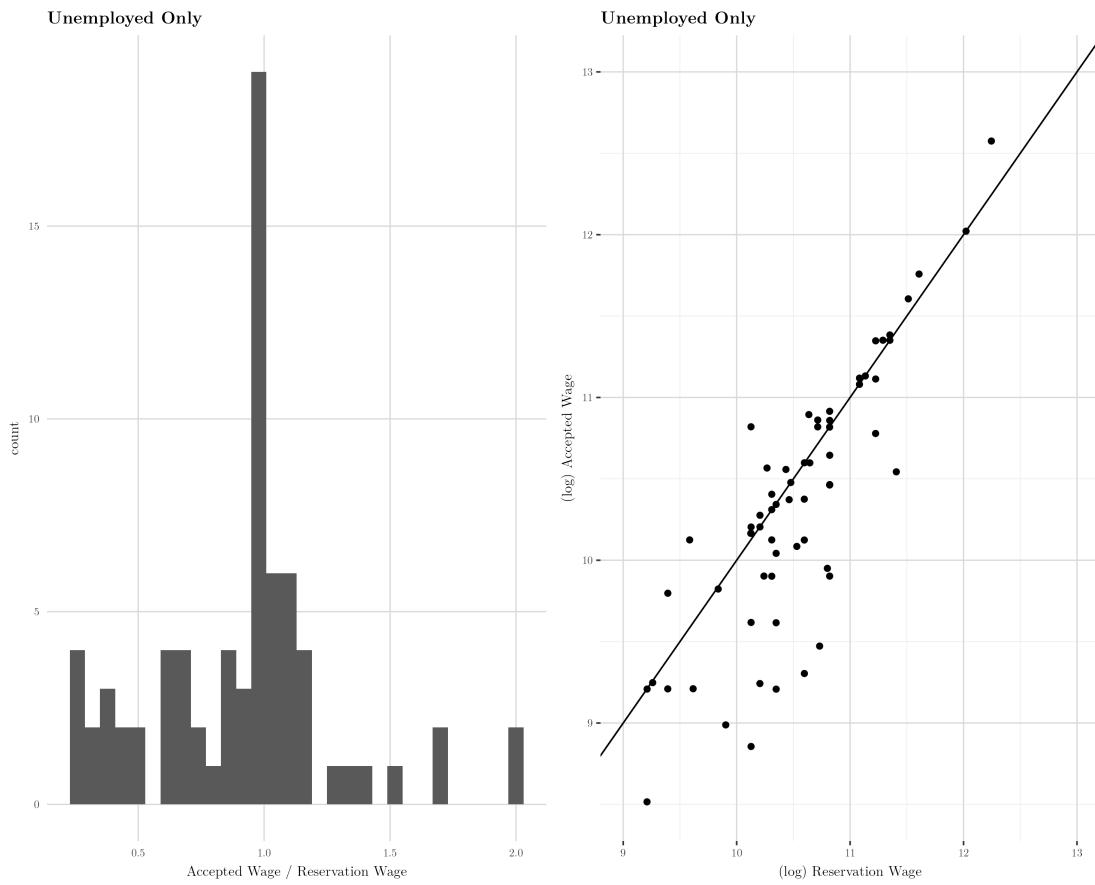
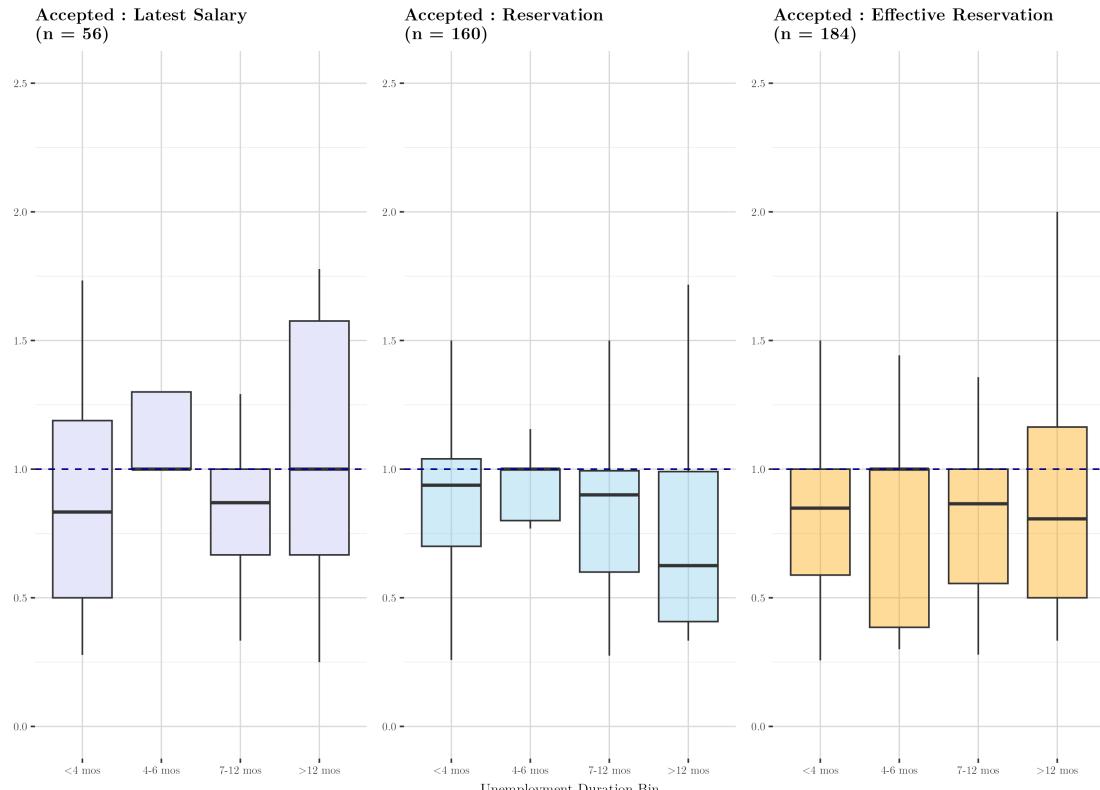


Table 10: Accepted Wages and Unemployment Duration

	Accpt:Latest	AccptWage w.c	Accpt:ResWage	AccptWage:ResWage w.c	Accpt:EffResWage	AccptW
(Intercept)	0.826*** (0.108)	1.743*** (0.260)	0.933*** (0.045)	1.199*** (0.141)	0.826*** (0.051)	
udur_bins	0.050 (0.045)	-0.005 (0.048)	-0.048* (0.019)	-0.053** (0.020)	0.008 (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

Ratio of Accepted Salary to Reservation Wages by Unemployment Duration



Notes: Data from the Survey of Consumer Expectations Labour Market Survey (2014–2022). Only valid responses used. Boxplots are weighted by SCE sample weights.

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 11: Reservation Wages and Unemployment Duration

	ResWage	ResWage w.c.	ResWage/LastWage	ResWage/LastWage w.c.
(Intercept)	10.173*** (0.044)	9.945*** (0.071)	0.825*** (0.022)	0.750*** (0.040)
udur_bins	0.107*** (0.012)	0.083*** (0.011)	0.027*** (0.006)	0.023*** (0.006)
female		-0.275*** (0.022)		0.009 (0.012)
age		0.005*** (0.001)		0.001* (0.000)
hhinc_2		0.230*** (0.026)		-0.008 (0.014)
hhinc_3		0.427*** (0.030)		-0.017 (0.017)
hhinc_4		0.759*** (0.033)		-0.008 (0.019)
education_2		-0.247*** (0.045)		0.050+ (0.026)
education_3		-0.122** (0.047)		0.007 (0.027)
education_4		-0.046 (0.051)		0.052+ (0.029)
education_5		0.027 (0.049)		0.008 (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 12: Accepted Wages and Unemployment Duration

	AccptWage	AccptWage w.c	AccptWage/ResWage	AccptWage/ResWage w.c
(Intercept)	10.568*** (0.106)	11.705*** (0.255)	0.924*** (0.048)	1.303*** (0.132)
udur_bins	-0.006 (0.040)	-0.037 (0.037)	-0.031+ (0.018)	-0.036+ (0.018)
female		-0.164 (0.102)		-0.073 (0.050)
age		-0.008* (0.004)		-0.005** (0.002)
hhinc_2		0.260+ (0.139)		0.043 (0.067)
hhinc_3		0.272+ (0.138)		0.042 (0.069)
hhinc_4		0.377* (0.150)		-0.052 (0.075)
education_2		-0.996*** (0.224)		-0.043 (0.122)
education_3		-0.940*** (0.223)		-0.128 (0.122)
education_4		-1.036*** (0.226)		-0.176 (0.123)
education_5		-0.827*** (0.224)		-0.141 (0.124)
education_6		-0.551* (0.228)		-0.095 (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

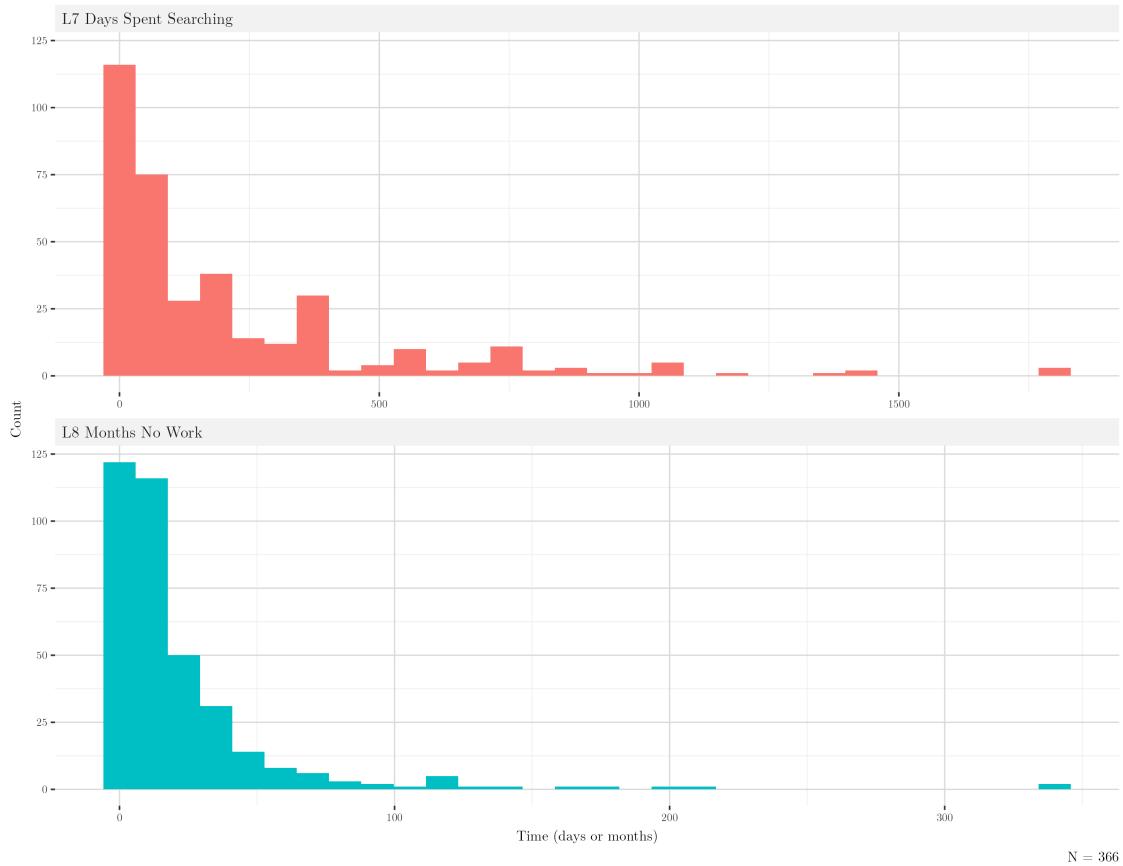
Table 13: Expected Wages and Unemployment Duration

	ExpWage/ResWage	ExpWage/ResWage w.c	ExpWage/LastWage	ExpWage/LastWage w.c
(Intercept)	1.057*** (0.020)	1.226*** (0.040)	1.087*** (0.029)	1.257*** (0.059)
udur_bins	-0.022*** (0.006)	-0.009 (0.006)	-0.024** (0.008)	-0.008 (0.009)
female		-0.022+ (0.013)		0.064*** (0.019)
age		-0.003*** (0.000)		-0.004*** (0.001)
hhinc_2		0.004 (0.016)		-0.038 (0.023)
hhinc_3		0.004 (0.018)		-0.001 (0.026)
hhinc_4		0.000 (0.019)		-0.005 (0.027)
education_2		-0.035 (0.027)		-0.032 (0.040)
education_3		-0.008 (0.028)		-0.056 (0.041)
education_4		0.004 (0.030)		-0.031 (0.044)
education_5		0.011 (0.029)		-0.090* (0.042)
education_6		0.021 (0.032)		0.002 (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

