

Reservation Wages Revisited: Empirics with the Canonical Model*

Steven J. Davis [†] Pawel M. Krolikowski [‡]

27 December 2024

Abstract

We study reservation wages using innovative longitudinal data on unemployment insurance (UI) recipients, guided by canonical search models. Individual-level expectations about the path of own reservation wages are, on average, consistent with realized reservation wage paths. This first result validates a basic premise in many models of job search by the unemployed. Second, we find that individual-level reservation wages fall faster when unemployment benefit durations are shorter, confirming a basic implication of search models. Third, reservation wages elicited early in unemployment spells are more powerful predictors of re-employment wages than are wages on the previous job, confirming the information value of survey-elicited reservation wages. Fourth, unemployed job seekers set their initial reservation wages too high and reduce them too slowly relative to calibrated versions of [Mortensen's](#) (1977) canonical model.

JEL codes: E24, J31, J63, J64.

Keywords: job search, unemployment benefits, survey of job losers, worker expectations

*We thank Andreas Mueller, Ayşegül Şahin, and several colleagues at the Federal Reserve Bank of Cleveland for comments on the paper. Angela Guo provided excellent research assistance. We are grateful to the Booth School of Business, the Becker Friedman Institute at the University of Chicago, and the Federal Reserve Bank of Cleveland for financial support. This study was approved by the University of Chicago Social and Behavioral Sciences Institutional Review Board (Study #IRB18-0871). The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors, the Federal Reserve Bank of Cleveland, or the Federal Reserve System.

[†]StevenD5@Stanford.edu, Hoover Institution and Stanford Institute for Economic Policy Research

[‡]pawel.krolikowski@clev.frb.org, Federal Reserve Bank of Cleveland

1 Introduction

Reservation wages—the lowest wage offer an unemployed worker would accept—play a central role in designing optimal unemployment insurance policy (Shimer and Werning, 2008), in understanding the labor market outcomes of the long-term unemployed (Mueller et al., 2021), and in workhorse models of the labor market (McCall, 1970; Pissarides, 2000). Yet, there exist little longitudinal data on reservation wages to inform labor-market policies and to test the predictions of these models. And, we have no data on how workers expect their reservation wages to evolve over an unemployment spell, even though these beliefs are central to the tradeoffs faced by job seekers (Menzio, 2023; Mueller and Spinnewijn, 2023).

We design and field an innovative, longitudinal survey of unemployment insurance (UI) recipients that fills these gaps. We use these data to document several new facts about reservation wages and to test the implications of a canonical job search model (Mortensen, 1977). First, consistent with the model, we find that reservation wages fall faster when UI benefit durations are shorter. However, workers set their initial reservation wages higher, and adjust them slower, relative to model predictions, as in Krueger and Mueller (2016). Second, workers’ expectations—elicited at the beginning of the unemployment spell—about how their reservation wage will evolve if they remain unemployed are largely congruent with reservation wage realizations, as assumed in the canonical model. Third, our data on expectations and realizations suggest that dynamic selection over the unemployment spell is inconsequential for our results. Fourth, higher wages on workers’ lost jobs, relative to predictions from a Mincerian wage regression, hasten the expected and realized declines in reservation wages over the unemployment spell, consistent with some learning models (similar to Conlon et al., 2021). Finally, reservation wages are a more powerful predictor of re-employment wages than wages on the previous job.

We revisit the conventional wisdom that reservation wages do not fall with unemployment duration (Krueger and Mueller, 2016). Our survey—henceforth, the DK survey—was fielded in the State of Illinois from September 2018 to July 2019, when UI benefit durations were 26 weeks (see Davis and Krolkowski, 2024, for details). The Krueger-Mueller (KM) survey was fielded in the State of New Jersey from October 2009 to April 2010, when maximum UI benefit durations were 99 weeks. We find that reservation wages fall significantly faster in our survey (about 0.3 percent per week) than in the KM survey (about 0.1 percent per week). In both samples, cross-sectional and fixed-effect estimates are similar, suggesting that dynamic selection has limited effects in this context.

We show that the sharper reservation wage decline in our survey is consistent with the predictions of a canonical model. The model predicts that reservation wages should fall more steeply when unemployment benefit durations are shorter because benefit expiration is more

likely. Model calibrations suggest that reservation wages in our survey should fall about three times faster than in the KM survey, largely congruent with our empirical findings. The predictions of the model also account for the sharper reservation wage decline in our survey relative to other work (Addison et al., 2009, 2013; Deschacht and Vansteenkiste, 2021). The model emphasizes that observations on reservation wages throughout the unemployment spell are important for identifying the average effect of unemployment duration on reservation wages because this effect varies with duration before benefit exhaustion. Consistent with these model predictions, Marinescu and Skandalis (2021) find that adjustments to reservation wages occur mostly in the quarter before UI exhaustion. Our survey is well designed in this regard because it provides longitudinal observations on workers throughout their unemployment spell and into new employment.

Nevertheless, workers in our survey set their initial reservation wages higher, and adjust them slower, relative to model implications, as in Krueger and Mueller (2016). The canonical model, calibrated to our sample, implies that job losers set reservation wages at about 25 percent below wages on their lost job and that reservation wages should fall by about 0.6 percent per week. But, observed workers set their initial reservation wages about four percent below their previous wage and reduce them by about 0.3 percent per week, as noted above. The anchoring of initial reservation wages at the previous wage is consistent with several other studies (Feldstein and Poterba, 1984; Drahs et al., 2018; Caliendo et al., 2023; Jäger et al., 2023). Krueger and Mueller (2016) find similar quantitative discrepancies between model and data as we do.

Mean *expected* declines in reservation wages over the unemployment spell are largely congruent with mean *realized* declines in reservation wages among workers in our survey. At the beginning of their unemployment spell, we elicit workers' expectations about how their reservation wages will evolve with unemployment duration. Workers expect their reservation wage to decline by 0.3 to 0.4 percent per week, similar to the actual declines noted above. To our knowledge, we are the first to document these accurate expectations among UI recipients. We find evidence that workers who subsequently remain unemployed expect similar declines in reservation wages than workers who exit unemployment. These results also suggest that dynamic selection is unlikely to be important for our results.

Worker rents reduce initial reservation wages and, together with age, they hasten the decline of reservation wages over the unemployment spell. For example, union coverage on the lost job—one measure of worker rents—reduces initial reservation wages by almost 10 percentage points. This reduction is large given that initial reservation wages are only slightly below wages on the lost job. We also study how wage residuals on the lost job—defined as the wage on the lost job less the prediction from a standard Mincerian wage regression—impact reservation wage declines. We find that an one-standard-deviation increase in the log wage

residual on the last job almost doubles the pace of reservation wage declines over the unemployment spell. This effect is driven by workers with high wage residuals; workers with residuals in the first quartile of the wage residual distribution have no meaningful declines in their reservation wage over their unemployment spell. This result is not driven by proximity to the minimum wage. Older workers reduce their reservation wages faster than younger workers, as in KM.

Worker rents also hasten the declines in expected reservation wages, and workers with the smallest rents over-predict how much their reservation wages will decline. We find that workers in the fourth wage residual quartile expect their reservation wages to decline almost twice as steeply as those in the first quartile. Moreover, even though workers in the first quartile expect their reservation wages to decline by 0.26 percent per week, they have no meaningful changes in their reservation wage over their unemployment spell, as noted above. Older workers expect their reservation wages to decline faster than younger workers at the onset of unemployment, broadly in line with reservation wage realizations.

Finally, we find that initial reservation wages help predict re-employment wages, even controlling for wages on the lost job. Our results are consistent with [Koenig et al. \(2023\)](#), who use UK and German data and fixed-effects specifications to document that higher reported reservation wages imply higher re-employment wages. These results confirm the value of eliciting data on individual reservation wages to understand the outcomes of unemployed workers.

The next section describes related research. Section 3 presents a canonical model and discusses the quantitative implications of two calibrations: one based on the KM sample and one based on our sample. Section 4 describes our survey, reports summary statistics, and presents our empirical strategy. Section 5 studies reservation wages shortly after job loss and how they evolve with unemployment duration. Section 6 studies worker expectations about how their reservation wages will evolve and draws out implications for dynamic selection. Section 7 studies how worker rents on the lost job affect reservation wage levels shortly after job loss, and how they affect the trajectory of reservation wages over the unemployment spell. Section 8 relates reservation wages to re-employment wages. Section 9 concludes.

2 Related Research

Our paper connects with several literatures and contributes to them in at least three ways. First, we contribute to the literature about reservation wages during unemployment, by producing and analyzing new longitudinal survey data. Earlier studies in this literature use cross sectional data on reservation wages (e.g., [Kasper, 1967](#); [Feldstein and Poterba, 1984](#); [Devine and Kiefer, 1991](#)). [Krueger and Mueller \(2016\)](#) highlight that job losers who have

high (low) reservation wages relative to their wage opportunities might be more (less) likely to remain unemployed over time. This selection effect could impart an upward bias to the estimated effect of spell duration on reservation wages in cross-sectional data. As in [Krueger and Mueller \(2016\)](#), we exploit longitudinal data to address this selection issue.¹ We find that these selection effects are likely small in this context.

Second, to our knowledge, we are the first to elicit workers’ expectations about the evolution of their reservation wages if they remain unemployed. In theory, reservation wages respond to workers’ labor market opportunities, as captured by job-offer arrival rates and wage-offer distributions. As such, expectations about reservation wages summarize a worker’s beliefs about how these model primitives, and their other endogenous choices, will evolve over their unemployment spell. These beliefs are central to the tradeoff faced by unemployed workers: whether to accept an offer today or to continue searching for an uncertain offer in the future. Moreover, biases in these beliefs will affect a worker’s “search and acceptance behavior, with important implications for labor market policies such as unemployment insurance and job training programs” ([Mueller and Spinnewijn, 2023](#)). Previous work has documented persistently biased beliefs in this context. For example, [Spinnewijn \(2015\)](#) and [Mueller et al. \(2021\)](#) find that unemployed workers are too optimistic about their job-finding prospects and they resist lowering their expectations.² [Potter \(2021\)](#) finds evidence that “workers are uncertain about the offer arrival process and learn through search.” Similarly, [Kroft et al. \(2013\)](#) and [Bradley and Mann \(2023\)](#) present evidence about duration dependence in call-back rates and expected job-finding probabilities during unemployment spells, respectively. Our expectations data about reservation wages, coupled with our longitudinal data on realized reservation wages, allows us to assess whether expectations differ from realizations over the unemployment spell. We find that expected mean declines in the reservation wages are broadly consistent with realized mean declines in reservation wages. Our findings leave open the possibility that, despite accurate mean expectations about their reservation wage, re-employment wages are below workers’ targeted wages, as in [Drahs et al. \(2018\)](#) and [Caliendo et al. \(2023\)](#).

Third, our results relate to the literature about worker outcomes, unemployment duration, UI benefits, and UI exhaustion (e.g., [DellaVigna and Paserman, 2005](#); [Schmieder and von Wachter, 2016](#); [DellaVigna et al., 2022](#)). For example, our results suggest that in some contexts reservation wages decline with unemployment duration, and that reservation wages help predict re-employment wages. The latter is inconsistent with [Schmieder et al. \(2016\)](#)

¹[Heckman and Singer \(1984\)](#) show that it is impossible, without invoking strong assumptions, to disentangle true duration effects from the effects of unobserved heterogeneity in datasets with one only observation per person.

²[He and Kircher \(2023\)](#) suggest that these stable job-finding expectations among the unemployed could be explained by positive news about aggregate conditions during the 2010s expansion.

who find evidence that reservation wages do not bind. Our results support findings by [Marinescu and Skandalis \(2021\)](#), who find that the predictions of a canonical job search model for search effort and reservation wages are largely born out among French unemployed job seekers. Our results also inform the findings in [Nekoei and Weber \(2017\)](#). They argue that a higher potential benefit duration (PBD) has ambiguous effects on reemployment wages because higher PBD could increase reservation wages, but consequently longer unemployment durations could reduce reservation wages due to negative duration dependence. We provide evidence of significant negative duration dependence in reservation wages.

3 The Canonical Model

In this section, we present the canonical model and discuss the quantitative implications of two calibrations: one based on the KM sample and one based on the DK sample. Additions to the canonical model—like savings or learning—would hasten the decline of reservation wages over the unemployment spell, as discussed in [Krueger and Mueller \(2016\)](#).

3.1 Setup

We study the implications of a canonical job search model with a finite unemployment insurance benefit duration—as in [Mortensen \(1977\)](#) and [Krueger and Mueller \(2016\)](#)—for the behavior of reservation wages while unemployed. The model includes ex-ante identical workers who search over a wage distribution on and off the job. To qualify for unemployment insurance benefits, a worker must be employed for at least \bar{m} periods before job loss. Unemployment insurance benefits are exhausted after T periods. We assume that job loss is exogenous, there are no savings and search effort decisions, and time is discrete. We highlight the implications for reservation wage ratios, defined as the reservation wage divided by the wage on the last job. This focus is consistent with our empirical results in section 5, which also analyze dynamics in the reservation wage ratio to control for individual heterogeneity.

3.2 Bellman Equations

The value of unemployment, $U(t)$, satisfies the following equation:

$$U(t) = u(b(t)) + \beta \left\{ (1 - \lambda) U(t - 1) + \lambda \int \max \{W(x, m = 0), U(t - 1)\} dF(x) \right\}, \quad (1)$$

in which t is the remaining duration of unemployment benefits, β is the discount factor, λ is the job arrival probability for unemployed workers, m is the number of months employed, and $W(x, m = 0)$ is the value of starting an employment spell out of unemployment with wage equal to x . An unemployed worker receives flow utility $u(b(t))$. With probability

$(1 - \lambda)$ the worker remains unemployed next period and has one less period of unemployment benefits. With probability λ the worker receives a wage offer from distribution $F(\cdot)$. The worker accepts the offer only if the value of employment at wage x , $W(x, m = 0)$, exceeds the value of continued unemployment, $U(t - 1)$. Appendix A.1 shows that equation (1) is identical to equation (1) in KM.

The value of employment for a worker who has not qualified for UI benefits ($m < \bar{m}$), satisfies the following equation:

$$W(w, m) = u(w) + \beta \left[\delta U(0) + (1 - \lambda_e)(1 - \delta) W(w, m + 1) + \lambda_e(1 - \delta) \int \max \{W(x, m + 1), W(w, m + 1)\} dF(x) \right]. \quad (2)$$

An employed worker receives flow utility $u(w)$. The following period, exogenous job loss occurs with probability δ . If the shock does not occur, the worker receives no outside job offer with probability $(1 - \lambda_e)$ and remains employed at the current wage. The worker receives an outside offer with probability λ_e and draws a new wage offer from distribution $F(\cdot)$. If the new wage offer exceeds the current wage, the worker switches jobs.

The value of employment for a worker who has qualified for UI benefits ($m \geq \bar{m}$), satisfies the following equation:

$$W(w, \bar{m}) = u(w) + \beta \left[\delta U(T) + (1 - \lambda_e)(1 - \delta) W(w, \bar{m}) + \lambda_e(1 - \delta) \int \max \{W(x, \bar{m}), W(w, \bar{m})\} dF(x) \right]. \quad (3)$$

This equation is similar to equation (2), but the worker qualifies for T periods of unemployment benefits upon job loss.

3.3 Calibrations

We compare model predictions in two calibrations. The first calibration is from Krueger and Mueller (2016), which is consistent with conditions during the KM survey of UI claimants from October 2009 to March 2010. The second calibration more closely resembles conditions from September 2018 to July 2019, when our survey of UI claimants was fielded (Davis and Krolikowski, 2024).

The two calibrations are similar, with three exceptions, as shown in Table 1. First, the KM survey sample was eligible for up to 99 weeks (23 months) of unemployment benefits because of state-level and federal extensions associated with the 2008-2009 recession. Our sample was eligible for maximum of 26 weeks (6 months) of unemployment benefits. Second,

we target a mean unemployment duration of 4 months because KM targeted 6 months and the mean unemployment duration in the Current Population Survey (CPS) fell by about two months between the end of 2009 and the end of 2018. Third, we target a mean employment-to-employment (EE) transition probability that is 0.2 percentage points higher than in the KM calibration, consistent with the increase in EE rates between the KM sample period and our sample period. (We depict the mean unemployment duration in the CPS and the mean EE rate from [Fujita et al., 2020](#), in Figure A1.) We internally calibrate the job-offer arrival probabilities off and on the job (λ and λ_e) to match this mean unemployment duration and this mean EE rate. We externally calibrate the remaining parameters of the model.

Aside from these three differences, we employ the same calibration as in KM to facilitate comparisons. Namely, we assume the same constant relative risk aversion utility function ($\gamma = 2$), the same monthly probability of job loss ($\delta = 0.02$), the same log-normal wage offer distribution ($\mu_w = 1$, $\sigma_w = 0.24$), the same number of months to qualify for UI benefits ($\bar{m} = 6$), and the same flow payoff during unemployment before and after benefit exhaustion ($b = 0.76$, and the drop in consumption at UI exhaustion is 0.313). Appendix A.2 includes some additional details.

3.4 Model Results

In this section we explore the quantitative implications of the two calibrations for the reservation wage ratio over the unemployment spell.

In the KM calibration, agents who enter unemployment have, on average, a reservation wage ratio slightly below 0.75 so that their initial reservation wage is about 25 percent below the wage on their lost job, as shown in Figure 1a. In the first year of unemployment, agents' reservation wage ratio falls only slightly, to about 0.72. Over the next year, the reservation wage ratio falls more sharply, and ends up at about 0.59 at benefit exhaustion. During a 23 month unemployment spell, the (unweighted) mean decline in the reservation wage ratio is 0.23 percent per week, as shown in Figure 1b, row 1, column 2. The (unweighted) average curvature of the reservation wage ratio over this period is -0.0014.³ The reservation wage ratio is flat after benefit exhaustion because the environment becomes stationary.⁴

The DK calibration implies a steeper decline in the reservation wage ratio over the unemployment spell before benefit exhaustion relative to the KM calibration. In the DK

³ The curvature of a function $y = f(x)$ is defined as $\kappa(x) = f''(x) / \left(1 + (f'(x))^2\right)^{3/2}$. Intuitively, curvature measures how fast a curve is changing direction at a given point. As such, the curvature is well approximated by the second derivative of a function if the first derivative is small. We define the average curvature as the mean of the curvature at each point.

⁴Figure 1b also presents weighted statistics that use the distribution of unemployment duration for our sample in section 5.

calibration, agents who enter unemployment have, on average, a reservation wage ratio of slightly below 0.75, similar to the KM calibration. Before benefit exhaustion, the (unweighted) mean decline in the reservation wage ratio in the DK calibration is about 0.58 percent per week, as shown in Figure 1b, row 2, column 1. This decline is about three times as steep as in the KM calibration. Also, the (unweighted) average curvature is higher (in absolute terms) in the DK calibration than in the KM calibration. The wage after benefit exhaustion is lower in the model with longer benefit durations relative to the model with shorter benefit durations because workers need to qualify for benefits by working at least \bar{m} months. As such, more generous UI benefits means workers are willing to accept lower wages to qualify for benefits sooner. Figure A2 shows the trajectory of $100 \times \ln(\text{reservation wage ratio})$, which is the outcome variable in our empirical work in section 5.

Figure 2 explains the steeper decline in the reservation wage ratio in the DK calibration than the KM calibration by presenting comparative statics with respect to UI benefit duration and job offer arrival rates. The steeper decline in the DK calibration is chiefly driven by shorter benefit durations as opposed to higher job offer arrival rates. Figure 2a repeats the reservation wage ratio from the KM calibration. Figure 2b shows how the reservation wage ratio over the unemployment spell changes if we reduce benefit duration (T) from 23 months to 6 months. With shorter benefit duration, workers are less picky at the beginning of the unemployment spell. Also, their reservation wage declines faster than in the model with longer benefit durations because benefit exhaustion is more likely. In particular, in the model with shorter unemployment insurance benefits, the (unweighted) mean decline in the reservation wage ratio is 0.6 percent per week, more than twice as large as in the KM calibration. The average curvature of the reservation wage ratio over the unemployment spell also falls, from -0.0014 to -0.0033, suggesting that the reservation wage ratio is more concave.

Figure 2c shows how the reservation wage ratio over the unemployment spell changes if we double both the off- and on-the-job offer arrival rates simultaneously. On net, workers become pickier throughout their unemployment spell, before and after benefit exhaustion. The mean decline in the reservation wage ratio is similar to Figure 2a. However, agents wait longer to make reductions in their reservation wage and the (unweighted) average curvature rises in absolute value. Increasing the job offer arrival rate for unemployed workers has different effects on the reservation wage ratio than increasing the job offer arrival rate for employed workers, as discussed in appendix A.3 (Figure A3). In short, raising the unemployed job offer arrival rate increases reservation wages, while raising the employed job offer arrival rate lowers reservation wages because workers want to get on the job ladder sooner.

Figure 2d shows the reservation wage ratio when we shorten the UI benefit duration and double both job offer arrival rates. The results is a combination of Figures 2b and 2c.

The (unweighted) mean decline rises to 0.73 percent per week and the function becomes significantly more concave on average, relative to the KM calibration.

In sum, the canonical model has three implications for the reservation wage ratio over the unemployment spell. First, initial reservation wages should be about 25 percent below the wage on the lost job. Second, shorter UI benefit duration and higher job offer arrival rates should hasten the decline of the reservation wage ratio over the unemployment spell. According to the canonical model, the reservation wage ratio should fall by about 0.2 percent per week in the KM sample and by about 0.6 percent per week in the DK sample. Third, the reservation wage ratio should be concave with respect to unemployment duration.

4 Data, Descriptive Statistics, and Empirical Strategy

In this section, we describe the survey data from [Davis and Krolikowski \(2024\)](#) and [Krueger and Mueller \(2016\)](#), as well as our empirical strategy.

4.1 Our Survey of Unemployment Insurance Recipients

Our sample consists of about 2,500 permanently laid off workers in Illinois. These individuals were surveyed at least once in an “Entry Survey” within weeks of their initial UI benefit payment. Individuals responded to at most two Follow-Up surveys, invitations to which were sent out at randomized intervals. These Follow-Up surveys were administered to individuals regardless of their labor market status so that we follow some individuals into new employment. Entry Surveys went to field beginning in September 2018 and the last Follow-Up wave went to field in July 2019. The KM sample consists of about 6,000 UI claimants who were surveyed each week for up to 24 weeks from October 2009 to April 2010. The sample was drawn from the universe of unemployed workers in New Jersey based on unemployment duration.⁵

Both surveys elicited information about reservation wages, search effort, and wage offers, among several other variables. In addition, the DK survey elicits worker expectations about how their reservation wage will evolve over the unemployment spell, it follows workers into employment, and asks them about their preferences over job characteristics at the beginning of the spell. The Entry Surveys for the KM and DK surveys had similar response rates of about 10 percent. We present details about the DK survey in appendix [B.1](#), and details about data cleaning and sample selection in appendix [B.2](#).

The two surveys elicit reservation wages with similar questions. In the DK survey, the reservation wage is elicited with the question, “Suppose someone offered you a job today

⁵KM include temporary layoffs in their baseline sample, whereas we restrict attention to permanent layoffs. But their main results are quantitatively similar if we restrict their sample to permanently laid off workers.

that is suitable in terms of hours, skills, responsibilities and non-wage benefits. What is the lowest wage or salary, before taxes and deductions, you would accept? Please include in this amount any bonuses, overtime pay, tips or commissions that you would expect.” The respondent chooses the pay period (hourly, bi-weekly, twice monthly, monthly, annually), and the dollar per period. The KM survey asks “Suppose someone offered you a job today. What is the lowest wage or salary you would accept (before deductions) for the type of work you are looking for?” These questions are similar to those in the Current Populations Survey and used by [Feldstein and Poterba \(1984\)](#).

4.2 Summary Statistics

Table 2 presents sample summary statistics. Relative to newly unemployed job losers in the CPS, our sample is older, more educated, and tilted to manufacturing. These patterns reflect UI eligibility requirements and higher unionization in manufacturing, plus union efforts to raise UI take-up rates ([Blank and Card, 1991](#)). Relative to the CPS, our sample also tilts toward women, a common survey response pattern ([Curtin et al., 2000](#)). Our sample is similar to the KM sample in many dimensions, including gender, age, race, and ethnicity, although our sample is more educated. Because of the differing survey designs, our sample has a shorter mean unemployment duration during the Entry Survey (5.6 weeks) than the KM sample (47 weeks). Figure 3 shows unemployment duration distributions in the two samples. The two samples also have similar occupational distributions, as shown in Table A1, although our sample has more workers from sales occupations relative to the CPS and KM samples. Relative to the CPS, both samples have fewer construction, extraction, and service occupation workers but more workers from management, office and administrative support, and professional occupations. We will focus on unweighted results below, but our main findings also hold when we re-weight to match the CPS, as discussed in appendix B.3.

4.3 Empirical Strategy

We estimate the following equation:

$$y_{it} = \alpha_i + \zeta d_{it} + \eta X_{it} + \epsilon_{it}, \quad (4)$$

in which y_{it} is an outcome variable, α_i are individual fixed effects, d_{it} is unemployment duration (in weeks), and X_{it} are additional covariates that vary with individual i and time period t . We also estimate equation (4) without individual fixed effects. In this case we include additional covariates in X_{it} , some of which do not vary over time in our sample, like education. We cluster standard errors at the person level.

5 Reservation Wages over the Unemployment Spell

In this section, we compare reservation wage ratio declines over the unemployment spell in the DK and KM samples with the implications from the canonical model in section 3.

5.1 Initial Reservation Wage Ratios

Workers in our sample set their initial reservation wages too high relative to model predictions. Figure A4 shows a binned scatterplot of the reservation wage ratio over unemployment duration after controlling for individual fixed effects. At 5.6 weeks—the mean unemployment duration of respondents during the Entry Survey (Table 2, column 1)—mean reservation wages are about four percent below wages on the lost job. Based on Entry-Survey responses, Column 1 of Table 3 also suggests that the mean reservation wage is about 4 percent below the wage on the lost job. In contrast, the calibrated model in section 3.4 suggests that reservation wages at the beginning of the unemployment spell should be about 25 percent below the previous wage.

This anchoring of reservation wages at the previous wage is consistent with several other studies. For example, [Krueger and Mueller \(2016\)](#) find similar results using the KM sample. [Caliendo et al. \(2023\)](#) find that job seekers’ subjective wage expectations are too narrowly centered about their previous wage when compared to wage changes using administrative data, similar to findings in [Drahs et al. \(2018\)](#). [Feldstein and Poterba \(1984\)](#) find that many recent job losers report reservation wages close to their previous wage. [Jäger et al. \(2023\)](#) find that employed workers appear to anchor their expectations about outside opportunities on their current wage.

We also find that tenure and race have significant effects on reservation wage ratios at the beginning of the unemployment spell, as shown in Table 3, column 1. First, workers with higher tenure report lower reservation wages. For example, workers with more than 5 years of tenure, report reservation wages that are 9.2 percentage points below those of workers with less than 6 months of tenure. This finding aligns well with related evidence that post-displacement earnings losses rise with tenure (e.g., [von Wachter et al., 2009](#)), possibly because displaced workers lose valuable firm-specific human capital ([Carrington and Fallick, 2017](#)). Second, Black job losers report reservation wage ratios that are 5.6 percentage points higher than white job losers. This effect is smaller and insignificant when we allow the coefficient on the previous wage to vary instead of fixing it to one, as shown in Table A2.

Surprisingly, we do not find any significant differences in reservation wage ratios between men and women in Table 3. [Krueger and Mueller \(2016, Table 1\)](#) and [Le Barbanchon et al. \(2019, Table 1\)](#) find that women report lower reservation wage ratios, although the effect size is larger in the former (-8.3pp) and smaller in the latter (-2.9pp). [Caliendo et al. \(2017\)](#)

and [Kim et al. \(2024\)](#) also find that women tend to report lower reservation wages than men. But specifications in these two papers allow the coefficient on the previous wage to differ from one. When we estimate this specification using our sample, we also find that women report lower reservation wages than men, as shown in [Table A2](#).

Finally, we note that the standard deviation of reservation wage ratios is large: about 33 log points. This dispersion suggests substantial heterogeneity in reservation wage ratios across individuals, which is inconsistent with the canonical model. Nevertheless, the R-squared of the model is small (0.07), suggesting that observables account for only a small share of the variation in reservation wage ratios, consistent with the canonical model.

5.2 Declines in Reservation Wage Ratios

We present three results in [Table 4](#). First, estimating equation (4), suggests that reservation wage ratios decline by about 0.28 percent per week in the DK sample, as shown in columns 1 and 2. This effect is highly statistically significant. Whether we account for individual fixed effects or not, the estimated coefficient is similar (0.28 vs. 0.26). Nevertheless, the fixed effect estimate has a considerably smaller standard error (0.055) than the cross sectional estimate (0.107). As such, the fixed effect estimate in column 2 is our preferred estimate.

We also find only weak evidence that selection imposes an upward bias to the estimated effect of spell duration on reservation wages in cross-sectional data. Cross-sectional estimates might be upward biased because job losers who have high (low) reservation wages relative to their wage opportunities are more (less) likely to remain unemployed over time, as discussed in [Krueger and Mueller \(2016\)](#). The difference in the estimated coefficients between columns 1 and 2 in [Table 4](#) includes a combination of a different sample and a different specification. Estimating the pooled cross section specification in column 1 on the longitudinal sample in column 2, yields a coefficient of -0.22 (-0.12) (see [appendix C.1](#) and [Table A3](#) for details). As such, with the same samples, the fixed effects specification yields larger declines in reservation wage ratios than the pooled cross section specification (-0.28 percent per week vs. -0.22 percent per week, respectively). This difference suggests some upward bias in the cross-sectional estimates. Nevertheless, the standard error on the estimate from the pooled cross section specification is large, and we cannot reject the null hypothesis that the two estimates are the same. As a whole, our results suggest only small effects of dynamic selection on our estimates.

The second result in [Table 4](#) is that reductions in the reservation wage ratio over the unemployment spell are significantly faster in the DK sample than the KM sample, consistent with the predictions of the canonical model. The difference between fixed effect estimates in the two samples is economically significant: -0.28 percent per week in the DK sample (column 2) and -0.056 percent per week in the KM sample (column 4). Moreover, we can

reject the null hypothesis that the coefficient on weeks unemployed is the same in the two samples ($p = 0.003$). The canonical model suggests that shorter benefit durations are largely responsible for these faster reservation wage ratio declines in the DK sample than in the KM sample, as discussed in section 3.4. These results are consistent with findings that extensions to UI benefit duration can raise the unemployment rate, especially when initial durations are short (as in [Acosta et al., 2023](#)), because workers raise their reservation wages. The pooled-cross section estimate using the KM sample is within the 95 percent confidence interval of the fixed-effect estimate, suggesting that dynamic selection has only small effects in the KM sample.

The estimated decline in the reservation wage over the unemployment spell is larger than in most other studies, in addition to those in KM, which is consistent with the qualitative predictions of the canonical model. For example, [Deschacht and Vansteenkiste \(2021\)](#) find that reservation wages fall by about 0.1 percent per week in a sample of Belgian workers in 2011. Reservation wages were measured at zero, three, and six months of unemployment in that study. Workers that qualify for UI in Belgium are eligible for at least two years of benefits, and most workers are eligible indefinitely ([Cockx and Ries, 2004](#)). As such, the canonical model suggests that declines in the reservation wage in the first six months of unemployment should likely be smaller in that context than in our context. Another example is [Addison et al. \(2013\)](#), who also find small effects of unemployment duration on reservation wages. But again, their sample is composed of individuals in 15 European Union member states, where potential benefit durations are typically long, and sample individuals are (on average) far from benefit exhaustion. Our estimates are also larger in absolute value than those in [Kim et al. \(2024\)](#) who use cross-sectional data, and [Marinescu and Skandalis \(2021\)](#) and [Fluchtmann et al. \(2023\)](#).

In addition to the importance of benefit duration, the canonical model emphasizes that repeated observations on reservation wages throughout the unemployment spell are important for identifying the average effect of unemployment duration on reservation wages because this effect varies with duration before benefit exhaustion. These various results are also consistent with this implication. For example, [Marinescu and Skandalis \(2021\)](#) find that adjustments to reservation wages occur mostly in the quarter before UI exhaustion. Our survey is well designed in this regard because it provides longitudinal observations on workers throughout their unemployment spell and into new employment.

There are two alternative explanations for why the reservation wage declines in our sample are steeper than in the KM survey. First, if learning is important, unemployed workers may adjust their reservation wages less in slack labor markets than in tight labor markets. When labor markets are slack and aggregate job finding-rates are depressed—as they were during the KM survey—workers may learn little about their individual labor market opportunities if

they experience difficulties finding a new job. In contrast, when labor markets are tight and job-finding rates are high—as they were during the DK survey—workers who have trouble finding new employment may infer that their individual labor-market prospects are poor and adjust downward their reservation wages accordingly. Similarly, employers may take less signal about workers’ ability from unemployment duration during slack labor markets than tight labor markets, as in Kroft et al. (2013). Bradley and Mann (2023) present some evidence about duration dependence in workers’ expected job-finding probabilities during unemployment spells. In future work, we hope to field our survey in different aggregate conditions to test this hypothesis. Second, different survey frequencies could explain our results. In particular, the KM survey was fielded weekly, while our Follow-Up surveys had randomized follow-up intervals, which varied from 2 to 16 weeks. It is possible that higher-frequency elicitation of the reservation wage makes it more likely that workers report their lagged reservation wage, rather than reconsider and introspect again. This behavior would imply stickier reservation wages over unemployment duration in a higher-frequency survey. We are unaware of evidence from survey methodology that tests this hypothesis.

The third result in Table 4 is that the mean reservation wage ratio decline in the DK sample is significantly slower than the decline implied by the calibrated model, similar to the results in KM. We estimate equation (4) using simulated data that are weighted by the unemployment duration distribution in the DK sample.⁶ The model does not include individual fixed effects so we omit these from the estimating equation. We show the resulting coefficient in the last row of Table 4 (columns 1 and 2): -0.685. The 95 percent confidence interval of the empirical counterpart in column 2 does not include this value. Similarly, the fixed effect coefficient using the KM sample (-0.056) implies a significantly slower reduction in the reservation wage ratio with weeks unemployed than the calibrated model (-.202). As such, the canonical model successfully predicts the larger reductions in reservation wages in the DK sample than the KM sample, but in both samples, workers adjust their reservation wages too slowly relative to model predictions.

Point estimates using our sample suggest that the reservation wage ratio is concave with respect to unemployment duration—consistent with the canonical model—but the results are noisy. Appendix C.2 and Table A4 have details.

6 Expectations about Reservation Wages

In this section, we study worker expectations about how their reservation wages will evolve and we draw out implications for dynamic selection. Worker expectations about reservation wages are elicited during the Entry Survey with the following question: “If you don’t find

⁶We use the distribution over the first six months and re-weight uniformly so that this distribution sums to 1, as in in Figure 1b.

suitable work in the next h months, would that change your mind about the lowest wage or salary you would accept?” in which we randomize h over 1, 2, 3, and 6 months. For respondents who answer “no” to this question, we assume that their reservation wage remains unchanged at horizon h . For respondents who answer “yes” to this question, we follow up by asking “In that case, how much would you increase or decrease your lowest acceptable wage or salary?” The respondent specifies whether they would increase or decrease their reservation wage, the pay period (hourly, bi-weekly, twice monthly, monthly, annually), and the dollar per period.

6.1 Determinants of Reservation Wage Ratio Expectations

Observables that are important for determining reservation wage ratios during the Entry Survey (in Table 3) are also important for explaining expectations about future reservation wage ratios, as shown in Table A7. In particular, Blacks tend to report higher reservation wage ratio expectations. And workers who had high tenure on their previous job and who lost jobs covered by a union contract, report lower reservation wage ratio expectations.

6.2 Reservation Wage Ratio Expectations Over the Unemployment Spell

Columns 1 and 2 of Table 5 show how expected reservation wages vary with unemployment duration using a pooled cross section specification and a fixed-effect specification. We assume that the expected reservation wage at horizon $h = 0$ is the reported reservation wage during the Entry Survey. As such, each individual has two expected reservation wage ratio observations: one from the Entry Survey and one from the hypothetical horizon. These two reservation wage observations correspond to unemployment duration at the time of the Entry Survey and unemployment duration at the Entry Survey plus the hypothetical horizon, h .

Expected mean declines in the reservation wage ratio are broadly consistent with realized mean declines in the reservation wage ratio, as in the canonical model. We estimate equation (4). The pooled cross section specification implies that workers expect their reservation wages to fall by about 0.23 percent per week (Table 5, column 1). The fixed-effect specification suggests that this coefficient is -0.34 (Table 5, column 2), which is within the 95 percent confidence interval of the pooled cross section estimate. These magnitudes are comparable to the estimated effect of weeks unemployed on realized reservation wages in Table 4 column 2 (-0.28). As such, worker expectations about how their reservation wage will evolve if they remain unemployed are largely congruent with reservation wage realizations. Figure A5 shows the binned scatterplot of the natural log of the expected reservation wage ratio by unemployment duration after controlling for individual fixed effects.⁷

⁷First difference specifications in which the outcome variable is 100 times the natural log of the ratio of

To our knowledge, we are the first to document that the unemployed, on average, have accurate expectations about their reservation wage trajectories. Our findings contribute to a growing literature on worker beliefs and expectations during job search, as reviewed in [Mueller and Spinnewijn \(2023\)](#). For example, our results complement [Conlon et al. \(2021\)](#), who find that average expected wages among employed workers in the US are only slightly above average actual received wage offers. They also find that workers update beliefs when they receive offers that differ from their expectations. We study how reservation wages, and their declines, vary with worker rents on the lost job in section 7. It’s also worth noting that workers’ re-employment outcomes may differ from their expectations (as in [Drahs et al., 2018](#); [Caliendo et al., 2023](#)), despite our finding that they correctly predict how their reservation wage will evolve with unemployment duration. We discuss reservation wages and re-employment wages in section 8.

6.3 Dynamic Selection

Individuals that expect larger reservation wage declines may be more likely to find employment after the Entry Survey than individuals that expect smaller reservation wage declines. If so, then it may be inappropriate to compare the coefficients in Table 4 column 2, which are based on a sample of workers for whom we observe at least two reservation wage observations, to those in Table 5 column 2, which is based on a sample with at least one reservation wage observation. In particular, the coefficients in Table 5 may be biased down.

To address this concern, we estimate the fixed-effects specification on the expectations data, but restrict to the longitudinal sample. We find that dynamic selection does not meaningfully alter our finding that mean expected declines in reservation wages (in Table 5) are largely congruent with mean realized declines (in Table 4). We present the results in column 3 of Table 5. If anything, those individuals who remain unemployed beyond the Entry Survey expect larger declines in their reservation wage at the beginning of their unemployment spell than those who do not necessarily remain unemployed (-.40 percent per week vs. -.34 percent per week). Nevertheless, these results support the idea that workers who anticipate re-employment difficulties—and subsequently remain unemployed in Follow-Up surveys—expect to reduce their reservation wages faster than those who subsequently find employment, although our results are noisy.

the expected reservation wage at horizon h and the reservation wage at the Entry Survey yield the same results because there are only two expected reservation wage observations.

7 Reservation Wages, and Worker Rents and Age

The canonical model in section 3 predicts that all workers will have the same reservation wages and reservation wage declines over the unemployment spell, regardless of wages on their previous job. In this section, we study whether our data support these predictions. In particular, we study how worker rents on the lost job affect reservation wage ratio levels shortly after job loss, and how they affect the trajectory of reservation wage ratios over the unemployment spell. We also study how worker rents on the lost job affect expectations about the trajectory of reservation wages over the unemployment spell.

7.1 During the Entry Survey

It is natural to hypothesize that initial reservation wage ratios may be lower among UI recipients who enjoyed greater rents on their lost jobs. After job loss, these workers may adjust their wage expectations to better align with their labor market opportunities.

To operationalize this hypothesis, we consider whether union coverage on the lost job—one measure of rents—predicts reservation wages. In our survey we ask workers, “Was the job that ended on [date] covered by a union contract?” This variable is motivated by a large body of evidence that union jobs often pay wages that exceed what union members can earn in other jobs. See, for example, [Freeman and Medoff \(1984\)](#) and [Lewis \(1986\)](#).

Union coverage on the lost job reduces the reservation wage substantially during the Entry Survey. We return to Table 3 and add union coverage on the lost job to our statistical model for the reservation wage ratio in column 2. Previous results continue to hold, and union coverage has material effects on the reservation wage ratio during the Entry Survey. In particular, union coverage reduces the reservation wage ratio by 9.2 percentage points and the coefficient is highly statistically significant. The magnitude is also economically large given that reservation wages are, on average, about 4 percent below wages on the lost job.

7.2 Rents and Reservation Wages Beyond the Entry Survey

We study whether rents on the previous job affect the trajectory of reservation wage ratios beyond the Entry Survey. Job losers may take time to learn about their labor market opportunities, especially because they anchor their initial reservation wages closer to their previous wage than the canonical model predicts (section 5.1). That is, workers with high (low) rents on their previous job might learn about their labor market opportunities during unemployment and revise downward (upward) their reservation wages. In related work, [Conlon et al. \(2021\)](#) find that employed workers revise their wage expectations when they receive outside offers that differ from their ex-ante beliefs.

In this section, we construct a worker-level rent variable using the residual from a standard Mincerian wage regression. Specifically, we obtain the residual from a regression of the lost-job log wage on a quadratic polynomial in potential experience (age minus years of schooling) and dummy variables for four levels of education, sex, six race/ethnicity categories and hourly pay on the lost job. This residual might capture firm-specific skills, among other things. The Mincerian regression yields an R-squared value of 0.31. The standard deviation of the regression residual is 0.52.⁸

We find that higher rents on the previous job imply sharper declines in the reservation wage ratio over the unemployment spell, as shown in Table 6. Column 1 repeats our baseline estimates from Table 4. Column 2 adds an interaction of unemployment duration with the individual's wage residual. The point estimate says that an increase in the log wage residual of one standard deviation hastens the decline of the reservation wage ratio by 0.19 percent per week ($1 \times 0.52 \times 0.356$). This effect is comparable to the baseline effect of weeks unemployed on the reservation wage ratio in this specification (-0.26 percent per week). Moreover, this estimate may understate the true impact of worker-level rents on the willingness to accept job-saving pay cuts, because the simplicity of our wage model may yield a rather noisy measure of rents.⁹ These results are consistent with those in Deschacht and Vansteenkiste (2021, Table 6), who find that workers with higher previous wages reduce their reservation wages faster with unemployment duration.

We find that the effect of rents on the reservation wage is non-linear, as shown in Table 6, column 3. This column interacts weeks unemployed with quartiles of the wage residual distribution, omitting the first quartile. We find that the effect in column 2 is driven by individuals with higher wage residuals, in the upper three quartiles. And, these individuals all have similar declines in the reservation wage ratio over the unemployment spell of about -0.4 percent per week. Individuals in the first wage residual quartile increase their reservation wage ratios by 0.1 percent per week, although this estimate is noisy. Figure A6 shows a binned scatterplot of the log reservation wage ratio by unemployment duration and wage residual quartile on the lost job after controlling for individual fixed effects.

Individuals in the first wage residual quartile have wages that are closer to the minimum wage, on average, than individuals with higher wage residuals. As such, our results may be mechanical because these individuals have less scope for downward adjustments to their reservation wages. In appendix C.4 we show that our results are not driven by the minimum

⁸We do not use this rent variable in section 7.1 because higher wage residuals on the previous job mechanically lower the level of the reservation wage ratio—defined as the reservation wage divided by the previous wage. However, there is no mechanical implication for how these residuals should alter the slope of the reservation wage ratio over the unemployment spell.

⁹We find that union coverage and higher industry premia do not hasten the decline of the reservation wage ratio over the unemployment spell. We discuss these results in appendix C.3. We do not include industry premium as a measure of rents in section 7.1 because that analysis already includes industry fixed effects.

wage. For example, the results are similar when we restrict the sample to individuals whose wages on the lost job were well above Illinois' minimum wage when our survey was in the field.

7.3 Worker Age and Reservation Wages Beyond the Entry Survey

Older workers reduce their reservation wage faster than younger workers, although our estimates are noisy, as shown in Table 6 column 4. Workers younger than 45 years reduce their reservation wage by 0.2 percent per week. Older workers reduce their reservation wage almost twice as quickly as younger workers, although the difference between the two groups is only marginally statistically significant ($p = 0.104$). KM also document a greater willingness of older workers to lower their reservation wage during unemployment. In section 7.5 we find that older workers also expect to reduce their reservation wage faster than younger workers at the onset of unemployment, in line with these realizations.

7.4 Worker Rents and Expected Reservation Wages

Higher rents on the previous job imply sharper expected declines in the reservation wage over the unemployment spell, although this effect is quantitatively less important for reservation wage expectations than realizations. Column 1 of Table 7 repeats our baseline estimates from Table 5, column 2. Column 2 adds an interaction of unemployment duration with the individual's wage residual. The point estimate says that an increase in the log wage residual of one standard deviation hastens the expected decline of reservation wage ratios by 0.07 percent per week ($1 \times 0.52 \times 0.125$). This effect is notably smaller than the effect of the same increase in rents on realized reservation wage ratios (-0.19 percent per week).

Regardless of the magnitude of rents on their previous job, workers expect their reservation wages to decline over their unemployment spell, although workers with higher rents expect sharper declines, as shown in Table 7, column 3. This column interacts weeks unemployed with quartiles of the wage residual distribution, omitting the first quartile. We find that workers with rents in the lowest quartile expect their reservation wage ratio to decline by 0.26 percent per week, somewhat slower than the mean decline of 0.34 percent in column 1. Column 3 also shows that higher rents on the previous job imply sharper declines in the reservation wage ratio. For example, workers in the fourth wage residual quartile expect their reservation wage ratios to fall almost twice as quickly (0.44 percent per week) as those in the first quartile. Figure A7 shows a binned scatterplot of the log expected reservation wage ratio by unemployment duration and wage residual quartile on the lost job after controlling for individual fixed effects.

The smaller impact of worker rents on expected reservation wage declines than on realized

declines is driven by workers with the smallest rents on their previous job. We compare how worker rents affect realized reservation wage declines (in Table 6, column 3) with how they affect expected reservation wage declines in (Table 7, column 3). The realized reductions in reservation wages among workers with wage residuals in the top three quartiles are largely congruent with expected reservation wage declines. For example, workers in the fourth wage residual quartile, expect their reservation wage ratios to decline by 0.44 percent per week (-0.264-0.180) and their realized reservation wage ratios fall by about 0.39 percent per week (0.103-0.493). Workers in the first wage residual quartile, however, expect reductions in their reservation wage ratios of 0.26 percent per week, but their reservation wage ratios actually increase during the unemployment spell by 0.1 percent per week.

7.5 Worker Age and Expected Reservation Wages

Older workers expect to reduce their reservation wages faster than younger workers at the onset of unemployment, as shown in Table 7 column 4. Workers younger than 45 years expect to reduce their reservation wage by 0.3 percent per week, similar to their realized reservation wage declines in Table 6 column 4 (0.2 percent per week). Older workers expect to reduce their reservation wage by 0.3 percent per week, also similar to their realized reservation wage declines (0.4 percent per week). The difference between the reservation wage expectations of younger and older worker are highly statistically significant.

8 Reservation Wages and Worker Outcomes

We find that reservation wages reported at the Entry Survey help predict re-employment wages, even controlling for wages on the lost job, as shown in Table 8. Our Follow-Up surveys elicit wages at the new job if respondents become re-employed. We follow about 400 workers through to new employment. We estimate equation (4) with the natural log of re-employment wage as the outcome variable. Column 1 of Table 8 suggests that the reported reservation wage at the Entry Survey is correlated with the re-employment wage: a 1 percent increase in the reservation wage implies a 0.78 percent increase in the re-employment wage. Column 2 suggests that the previous wage is correlated with the re-employment wage, although the correlation is smaller than with the reservation wage. Column 3 suggests that the correlation between the reservation wage and the re-employment wage persists even if we control for the previous wage, which should control for worker ability. In fact, the previous wage is not significantly correlated with the re-employment wage if we control for the reservation wage and the reservation wage is a much more powerful predictor of the re-employment

wage than the wage on the lost job.¹⁰ Column 4 suggests that the number of weeks spent unemployed before the new job is not correlated with the re-employment wage once we condition for the reservation wage, consistent with the canonical model. Column 5 suggests that the reservation wage continues to be a significant predictor of the re-employment wage even if we control for other observables, like education, race and ethnicity, and gender.

These results confirm the value of eliciting data on individual reservation wages to understand worker outcomes. In results not shown, we find no evidence that expectations about future reservation wages help predict re-employment wages if we control for the reservation wage at the Entry Survey and the previous wage. Also, we find little evidence that reservation wages, or expectations about them, help predict employment outcomes in our sample, as shown in Table A8.¹¹ These results are consistent with our findings that dynamic selection does not seem important for studying reservation wages and reservation wage expectations over the unemployment spell, as discussed in section 6.3. Our findings are also consistent with Koenig et al. (2023), who study employment and wage outcomes in the UK and Germany using fixed-effects specifications, and conclude that “reservation wage data, though undoubtedly noisy, embody meaningful information about job search behaviour. . .”

9 Conclusion

We use survey data from Davis and Krolikowski (2024) to document several new facts about reservation wages and to test the implications of a canonical job search model. Our survey was in the field in 2018-2019 when UI benefit durations were normal (6 months). During this period, we find that reservation wages fell with unemployment duration, by about 0.3 percent per week. In contrast, Krueger and Mueller (2016) find that reservation wages moved little with unemployment duration for workers in New Jersey in 2009-2010 when UI benefit duration was a maximum of 99 weeks. Our results are quantitatively consistent with the implications of a standard job search model and suggest that shorter UI benefit durations hasten reservation wage declines. Nevertheless, workers in our survey set their initial reservation wages higher, and adjust them slower, relative to model implications, as in the KM survey.

Our survey also collects novel information on respondents’ expectations about how their reservation wage will evolve over the unemployment spell. We find that mean *expected* declines in reservation wages over the unemployment spell are largely congruent with mean

¹⁰These results provide *prima facie* evidence that a specification with earnings losses as the dependent variable would be mis-specified because column 3 suggests that the coefficient on the previous wage is significantly less than one.

¹¹Koenig et al. (2023) note that the effect of reservation wages on employment is likely upward biased because more able workers likely have higher reservation wages and are more likely to become employed.

realized declines in reservation wages among workers in our survey. We find that dynamic selection is unlikely to be important for these results.

We show that worker rents on the previous job reduce initial reservation wages and hasten their decline over the unemployment spell. For example, union coverage on the lost job substantially reduces initial reservation wages. And, an one-standard-deviation increase in the log wage residual on the last job almost doubles the pace of reservation wage declines over the unemployment spell. This effect is driven by workers with high wage residuals.

Finally, initial reservation wages help predict re-employment wages, even controlling for wages on the lost job. These results confirm the value of eliciting data on individual reservation wages to understand the outcomes of unemployed workers.

In future work, we plan to explore the importance of learning in determining reservation wages over the unemployment spell, similar to [Conlon et al. \(2021\)](#) for employed workers. Our survey is well designed to study reservation wage dynamics because it provides longitudinal observations on workers throughout their unemployment spell and into new employment. Moreover, our survey asks respondents about their preferences over job characteristics and their received wage offers, which informs workers' amenity values (as in [Bagga et al., 2023](#)) and labor market opportunities.

References

- Acosta, Miguel, Andreas I. Mueller, Emi Nakamura, and Jón Steinsson (2023). “Macroeconomic Effects of UI Extensions at Short and Long Durations.” Available at <https://sites.google.com/view/andreasimueller/research>.
- Addison, John T., Mário Centeno, and Pedro Portugal (2009). “Do Reservation Wages Really Decline? Some International Evidence on the Determinants of Reservtion Wages.” *Journal of Labor Research*, 30, pp. 1–8. doi:[10.1007/s12122-008-9057-y](https://doi.org/10.1007/s12122-008-9057-y).
- Addison, John T., Jose A. F. Machado, and Pedro Portugal (2013). “The Reservation Wage and Unemployment Duration Nexus.” *Oxford Bulletin of Economics and Statistics*, 75(6), pp. 980–987. doi:[10.1111/j.1468-0084.2012.00717.x](https://doi.org/10.1111/j.1468-0084.2012.00717.x).
- Bagga, Sadhika, Lukas Mann, Ayşegül Şahin, and Giovanni L. Violante (2023). “Job Amenity Shocks and Labor Reallocation.” Available at <https://sites.google.com/view/aysegulsahin/home>.
- Blank, Rebecca M. and David E. Card (1991). “Recent Trends in Insured and Uninsured Unemployment: Is There an Explanation?” *Quarterly Journal of Economics*, 106(4), pp. 1157–1189. doi:[10.2307/2937960](https://doi.org/10.2307/2937960).
- Blundell, Richard, Panos Pashardes, and Guglielmo Weber (1993). “What do we learn about consumer demand patterns from micro data?” *The American Economic Review*, 83(3), pp. 570–597.
- Bradley, Jake and Lukas Mann (2023). “Learning about Labor Markets.” Available at <https://jakebradley.webflow.io/>.
- Caliendo, Marco, Wang-Sheng Lee, and Robert Mahlstedt (2017). “The Gender Wage Gap and the Role of Reservation Wages: New evidence for Unemployed Workers.” *Journal of Economic Behavior & Organization*, 136, pp. 161–173. doi:<https://doi.org/10.1016/j.jebo.2017.02.011>.
- Caliendo, Marco, Robertrt Mahlstedt, Aiko Schmeißer, and Sophie Wagner (2023). “The Accuracy of Job Seekers’ Wage Expectations.” doi:[10.48550/arXiv.2309.14044](https://doi.org/10.48550/arXiv.2309.14044). Working Paper.
- Carrington, William J. and Bruce Fallick (2017). “Why Do Earnings Fall with Job Displacement?” *Industrial Relations: A Journal of Economy and Society*, 56(4), pp. 688–722. doi:<https://doi.org/10.1111/irel.12192>.
- Cattaneo, Matias D., Richard K. Crump, Max H. Farrell, and Yingjie Feng (2023). “On Binscatter.” doi:[10.48550/arXiv.1902.09608](https://doi.org/10.48550/arXiv.1902.09608).
- Cockx, Bart and Jean Ries (2004). “The Exhaustion of Unemployment Benefits in Belgium: Does it Enhance the Probability of Employment?” doi:[10.2139/ssrn.561742](https://doi.org/10.2139/ssrn.561742). Available at <https://sites.google.com/site/laurapilososph/>.
- Conlon, John J., Laura Pilososph, Matthew Wiswall, and Basit Zafar (2021). “Labor Market Search with Imperfect Information and Learning.” Available at <https://sites.google.com/site/laurapilososph/>.
- Curtin, Richard, Stanley Presser, and Eleanor Singer (2000). “The Effects of Response Rate Changes on the Index of Consumer Sentiment.” *Public Opinion Quarterly*, 64(4), pp. 413–428. URL <https://www.jstor.org/stable/3078736>.
- Davis, Steven J. and Pawel M. Krolikowski (2024). “Sticky Wages on the Layoff Margin.” Working Paper 31528, National Bureau of Economic Research. doi:[10.3386/w31528](https://doi.org/10.3386/w31528).
- DellaVigna, Stefano, Jörg Heining, Johannes F Schmieder, and Simon Trenkle (2022).

- “Evidence on Job Search Models from a Survey of Unemployed Workers in Germany.” *The Quarterly Journal of Economics*, 137(2), pp. 1181–1232. doi:[10.1093/qje/qjab039](https://doi.org/10.1093/qje/qjab039).
- DellaVigna, Stefano and M. Daniele Paserman (2005). “Job Search and Impatience.” *Journal of Labor Economics*, 23(3), pp. 527–588. doi:[10.1086/430286](https://doi.org/10.1086/430286).
- Deschacht, Nick and Sarah Vansteenkiste (2021). “The Effect of Unemployment Duration on Reservation Wages: Evidence from Belgium.” *Labour Economics*, 71, p. 102,010. doi:<https://doi.org/10.1016/j.labeco.2021.102010>.
- Devine, Theresa J. and Nicholas M. Kiefer (1991). *Empirical Labor Economics: The Search Approach*. New York: Oxford University Press.
- Drahs, Sascha, Luke Haywood, and Amelie Schiprowski (2018). “Job Search with Subjective Wage Expectations.” doi:[10.2139/ssrn.3146764](https://doi.org/10.2139/ssrn.3146764). Working Paper.
- Feldstein, Martin and James Poterba (1984). “Unemployment Insurance and Reservation Wages.” *Journal of Public Economics*, 23(1-2), pp. 141–167. doi:[10.1016/0047-2727\(84\)90070-7](https://doi.org/10.1016/0047-2727(84)90070-7).
- Fluchtmann, Jonas, Anita M. Glenney, Nikolaj Harmon, and Jonas Maibom (2023). “Unemployed Job Search Across People and Over Time: Evidence from Applied-For Jobs.” doi:[10.1086/725165](https://doi.org/10.1086/725165). Forthcoming at the *Journal of Labor Economics*.
- Freeman, Richard and James Medoff (1984). *What Do Unions Do?* Basic Books, N.Y.
- Fujita, Shigeru, Giuseppe Moscarini, and Fabien Postel-Vinay (2020). “Measuring Employer-to-Employer Reallocation.” Working Paper 27525, National Bureau of Economic Research. doi:[10.3386/w27525](https://doi.org/10.3386/w27525).
- Gruber, Jonathan (1997). “The Consumption Smoothing Benefits of Unemployment Insurance.” *American Economic Review*, 87(1), pp. 192–205. URL <http://www.jstor.org/stable/2950862>.
- He, Qiwei and Philipp Kircher (2023). “Updating about Yourself by Learning about the Market: The Dynamics of Beliefs and Expectations in Job Search.” Working Paper 31940, National Bureau of Economic Research. doi:[10.3386/w31940](https://doi.org/10.3386/w31940).
- Heckman, James J. and Burton Singer (1984). “Econometric Duration Analysis.” *Journal of Econometrics*, 24(1-2), pp. 63–132. doi:[10.1016/0304-4076\(84\)90075-7](https://doi.org/10.1016/0304-4076(84)90075-7).
- Jäger, Simon, Christopher Roth, Nina Roussille, and Benjmin Schoeffer (2023). “Worker Beliefs about Outside Options.” doi:[10.3386/w29623](https://doi.org/10.3386/w29623). NBER Working Paper No. 29623, revised.
- Kasper, Herschel (1967). “The Asking Price of Labor and the Duration of Unemployment.” *Review of Economics and Statistics*, 49(2), pp. 165–172. doi:[10.2307/1928224](https://doi.org/10.2307/1928224).
- Kim, Shinyoung, Chad Cotti, and Peter F. Orazem (2024). “The Demographics of Reservation Wages: A Comprehensive Review of Administrative Data.” doi:[10.2139/ssrn.4699053](https://doi.org/10.2139/ssrn.4699053). Working Paper.
- Koenig, Felix, Alan Manning, and Barabara Petrongolo (2023). “Reservation Wages and the Wage Flexibility Puzzle.” Available at <https://www.felixkoenig.com/research>.
- Kroft, Kory, Fabian Lange, and Matthew J. Notowidigdo (2013). “Duration Dependence and Labor Market Conditions: Evidence from a Field Experiment.” *Quarterly Journal of Economics*, 128(3), pp. 1123–1167. doi:[10.1093/qje/qjt015](https://doi.org/10.1093/qje/qjt015).
- Krueger, Alan B. and Andreas I. Mueller (2016). “A Contribution to the Empirics of Reservation Wages.” *American Economic Journal: Economic Policy*, 8(1), pp. 142–179. doi:[10.1257/pol.20140211](https://doi.org/10.1257/pol.20140211).
- Le Barbanchon, Thomas, Roland Rathelot, and Alexandra Roulet (2019). “Unemployment

- Insurance and Reservation Wages: Evidence from Administrative Data.” *Journal of Public Economics*, 171, pp. 1–17. doi:<https://doi.org/10.1016/j.jpubeco.2017.05.002>. Trans-Atlantic Public Economics Seminar 2016.
- Lewis, H. Gregg (1986). *Union Relative Wage Effects: A Survey*. The University of Chicago Press, Chicago.
- Low, Hamish, Costas Meghir, and Luigi Pistaferri (2010). “Wage risk and employment risk over the life cycle.” *American Economic Review*, 100(4), p. 1432–67. doi:[10.1257/aer.100.4.1432](https://doi.org/10.1257/aer.100.4.1432).
- Marinescu, Ioana and Daphné Skandalis (2021). “Unemployment Insurance and Job Search Behavior.” *The Quarterly Journal of Economics*, 136(2), pp. 887–931. doi:[10.1093/qje/qjaa037](https://doi.org/10.1093/qje/qjaa037).
- McCall, J. J. (1970). “Economics of Information and Job Search.” *The Quarterly Journal of Economics*, 84(1), pp. 113–126. doi:[10.2307/1879403](https://doi.org/10.2307/1879403).
- Menzio, Guido (2023). “Stubborn Beliefs in Search Equilibrium.” *NBER Macroeconomics Annual*, 37, pp. 239–297. doi:[10.1086/723582](https://doi.org/10.1086/723582).
- Mortensen, Dale T. (1977). “Unemployment Insurance and Job Search Decisions.” *ILR Review*, 30(4), pp. 505–517. doi:[10.1177/001979397703000410](https://doi.org/10.1177/001979397703000410).
- Mueller, Andreas I. and Johannes Spinnewijn (2023). “Chapter 22 - Expectations Data, Labor Market, and Job Search.” In Rüdiger Bachmann, Giorgio Topa, and Wilbert van der Klaauw, editors, *Handbook of Economic Expectations*, pp. 677–713. Academic Press. doi:<https://doi.org/10.1016/B978-0-12-822927-9.00030-6>.
- Mueller, Andreas I., Johannes Spinnewijn, and Giorgio Topa (2021). “Job Seekers’ Perceptions and Employment Prospects: Heterogeneity, Duration Dependence, and Bias.” *American Economic Review*, 111(1), pp. 324–63. doi:[10.1257/aer.20190808](https://doi.org/10.1257/aer.20190808).
- Nekoei, Arash and Andrea Weber (2017). “Does Extending Unemployment Benefits Improve Job Quality?” *American Economic Review*, 107(2), pp. 527–61. doi:[10.1257/aer.20150528](https://doi.org/10.1257/aer.20150528).
- Pissarides, Christopher A. (2000). *Equilibrium Unemployment Theory*. MIT Press, second edition. URL <https://ideas.repec.org/b/mtpl/titles/0262161877.html>.
- Potter, Tristan (2021). “Learning and job search dynamics during the great recession.” *Journal of Monetary Economics*, 117, pp. 706–722. doi:<https://doi.org/10.1016/j.jmoneco.2020.04.006>.
- Schmieder, Johannes F. and Till von Wachter (2016). “The Effects of Unemployment Insurance Benefits: New Evidence and Interpretation.” *Annual Review of Economics*, 8(Volume 8, 2016), pp. 547–581. doi:[10.1146/annurev-economics-080614-115758](https://doi.org/10.1146/annurev-economics-080614-115758).
- Schmieder, Johannes F., Till von Wachter, and Stefan Bender (2016). “The Effect of Unemployment Benefits and Nonemployment Durations on Wages.” *American Economic Review*, 106(3), pp. 739–77. doi:[10.1257/aer.20141566](https://doi.org/10.1257/aer.20141566).
- Shimer, Robert and Ivan Werning (2008). “Liquidity and Insurance for the Unemployed.” *American Economic Review*, 98(5), pp. 1922–42. doi:[10.1257/aer.98.5.1922](https://doi.org/10.1257/aer.98.5.1922).
- Spinnewijn, Johannes (2015). “Unemployed but Optimistic: Optimal Insurance Design with Biased Beliefs.” *Journal of the European Economic Association*, 13(1), pp. 130–167. doi:[10.1111/jeea.12099](https://doi.org/10.1111/jeea.12099).
- Starr, Evan and Brent Goldfarb (2020). “Binned Scatterplots: A Simple Tool to Make Research Easier and Better.” *Strategic Management Journal*, 41(12), pp. 2261–2274. doi:<https://doi.org/10.1002/smj.3199>.
- von Wachter, Till, Jae Song, and Joyce Manchester (2009). “Long-Term Earnings Losses due

to Mass Layoffs During the 1982 Recession: An Analysis Using Longitudinal Administrative Data from 1974 to 2004.” Available at <http://www.econ.ucla.edu/tvwachter/>.

Table 1: Calibrated model parameters

| Parameter | (1) DK value | (2) Reason | (3) KM value |
|--|--------------------|----------------------------|--------------------|
| <i>Panel A. Externally calibrated parameters in DK</i> | | | |
| UI benefit duration ($T + 1$) | 7 | Actual UI benefit duration | 24 |
| Discount rate (β) | 0.996 | 5% annual interest rate | 0.996 |
| Coefficient of relative risk aversion (γ) | 2 | Same as KM | 2 |
| Exogenous probability of job destruction (δ) | 0.02 | Same as KM | 0.02 |
| Mean of the wage offer distribution (μ_w) | 1 | Normalization | 1 |
| Standard deviation of the wage offer distribution (σ_w) | 0.24 | Same as KM | 0.24 |
| # of months to qualify for UI benefits (\bar{m}) | 6 | Same as KM | 6 |
| Consumption while unemployed before benefits expire | 0.7637 | Same as KM | 0.7637 |
| Drop in consumption at UI exhaustion | 0.313 | Same as KM | 0.313 |
| <i>Panel B. Internally calibrated parameters in DK</i> | | | |
| Job offer arrival rate for the unemployed (λ) | 0.36 | Mean unemployment duration | 0.3 |
| Job offer arrival rate for the employed (λ_e) | 0.105 | Mean <i>EE</i> rates | 0.1 |

Note: Calibrated parameters of the model are at monthly frequency. Mean *EE* rates from [Fujita et al. \(2020\)](#). “DK” stands for Davis and Krolkowski. “KM” stands for [Krueger and Mueller \(2016\)](#). See section 3.3.

Table 2: The Entry Survey analysis sample: Percentage distributions and comparison to the Current Population Survey and to the KM survey

| | (1) | (2) | (3) | (4) |
|--|------------|----------|-------|-------|
| | Unweighted | Weighted | CPS | KM |
| <i>Previous employment data</i> | | | | |
| Previous industry (percent) | | | | |
| Leisure and hospitality | 6.6 | 7.8 | 12.5 | |
| Finance, insurance, real estate | 11.2 | 10.3 | 4.4 | |
| Construction | 4.0 | 5.4 | 14.1 | |
| Education and health care services | 19.6 | 16.2 | 17.5 | |
| Information and other services | 10.4 | 9.8 | 5.9 | |
| Manufacturing | 12.2 | 14.0 | 8.6 | |
| Mining | 0.4 | 0.5 | 0.6 | |
| Prof., technical, business services | 14.2 | 11.2 | 13.5 | |
| Retail and wholesale trade | 11.1 | 13.0 | 11.2 | |
| Transp., warehousing, utilities | 5.1 | 6.4 | 5.8 | |
| Government or military | 1.1 | 1.4 | 2.4 | |
| Agriculture, forestry, fishing | 1.0 | 1.1 | 3.7 | |
| Data missing | 3.1 | 3.0 | 0.0 | |
| <i>Demographic data (percent of total)</i> | | | | |
| Female | 54.2 | 46.0 | 43.1 | 51.9 |
| Age in years | | | | |
| 18-24 | 4.5 | 5.8 | 18.1 | 6.6 |
| 25-34 | 23.6 | 25.4 | 24.1 | 22.8 |
| 35-44 | 23.4 | 25.4 | 19.1 | 22.0 |
| 45-54 | 24.0 | 22.1 | 17.4 | 26.4 |
| 55-64 | 21.2 | 18.2 | 14.3 | 21.2 |
| 65 or older | 3.4 | 3.1 | 6.9 | |
| Race/Ethnicity | | | | |
| White, non-Hispanic | 65.9 | 64.1 | 51.3 | 69.3 |
| White, Hispanic | 4.6 | 4.8 | 21.0 | 9.2 |
| Black | 15.3 | 17.2 | 20.1 | 15.8 |
| Asian | 3.8 | 2.7 | 2.9 | 5.1 |
| Other | 3.8 | 4.2 | 4.6 | 0.6 |
| Data missing | 6.5 | 7.0 | 0.0 | 11.9 |
| Education | | | | |
| High school grad. | 10.7 | 17.6 | 35.4 | 18.2 |
| Technical training/some college | 24.2 | 37.6 | 21.4 | 32.5 |
| Associate's/bachelor's degree | 45.0 | 33.5 | 19.3 | 27.3 |
| Grad. degree or higher | 19.4 | 10.2 | 7.1 | 19.1 |
| <i>Avg. unemployment duration (weeks)</i> | 5.6 | 5.6 | 2.5 | 47.0 |
| No. of observations | 2,070 | 2,070 | 3,820 | 4,444 |

Note: Column 1 reports raw percentages, and Column 2 reports percentages after reweighting the sample to match the CPS distribution of job losers with ongoing unemployment spell durations of less than five weeks for the cross product of two age groups (less than 45 years, or not), two education groups (four-year college degree, or not), and sex. Appendix B.3 explains how we construct the weights. Column 3 reports the corresponding U.S. percentages in the CPS for the period from June 2018 to February 2019, which spans our Entry survey period plus three months on either side. Column 4 reports corresponding percentages from the sample in the first wave of the KM survey. Percentages are missing when the KM survey does not include comparable data. For example, the KM survey does not include industry information. (See Table A1 for occupational distributions in our survey, the CPS, and the KM data.) The KM data do not include an indicator for race being “white.” For this table, we assume that a person is white if they are not Black, Asian, American Indian, or Pacific Islander. This assumption likely overstates the fraction of white individuals in the KM survey. Also, the KM survey does not include more than one race per person, whereas our data and the CPS categorize multi-racial individuals as “Other.” This difference likely explains why the “Other” race category is lower in column 4 than in columns 1 to 3. Education categories sum to less than 100 because not all categories are listed. See section 4.1.

Table 3: How the reservation wage ratio during the Entry Survey varies with observables

Reservation wage question: “Suppose someone offered you a job today that is suitable in terms of hours, skills, responsibilities and non-wage benefits. What is the lowest wage or salary, before taxes and deductions, you would accept? Please include in this amount any bonuses, overtime pay, tips or commissions that you would expect.”

Dependent variable = $100 \times \ln(\text{reservation wage}_{it}/\text{previous wage}_i)$

| | (1) | (2) |
|-----------------------------------|--------------------|--------------------|
| <i>Individual characteristics</i> | | |
| Female | 1.55 (1.61) | 1.38 (1.61) |
| White, Hispanic | 3.90 (3.51) | 3.89 (3.51) |
| Black | 5.55** (2.29) | 5.91*** (2.29) |
| Experience | -0.16 (0.31) | -0.18 (0.31) |
| Experience ² | 0.00 (0.01) | 0.00 (0.01) |
| <i>Tenure on the lost job</i> | | |
| 6mos to 2yrs | -1.98 (2.23) | -2.12 (2.23) |
| 2yrs to 5yrs | -2.65 (2.41) | -2.77 (2.41) |
| More than 5yrs | -9.23*** (2.40) | -9.39*** (2.40) |
| <i>Other variables</i> | | |
| Paid hourly (Yes=1) | -1.52 (2.25) | -1.43 (2.25) |
| Weeks unemployed | -0.24* (0.14) | -0.25* (0.14) |
| <i>Rent variables</i> | | |
| Union job (Yes=1) | | -8.46** (3.43) |
| Dummies for ind. and occ. | x | x |
| Reserv. wage unit dummies | x | x |
| Other controls | x | x |
| Mean of dependent variable | -4.029 | -4.029 |
| Std. dev. of dep. var. | 33.119 | 33.119 |
| R2 | 0.074 | 0.077 |
| Observations | 1,964 | 1,964 |
| Individuals | 1,964 | 1,964 |

Note: Estimated using the Entry Survey sample. Column 1 regresses the reservation wage ratio on observables. Column 2 estimates the same specification on the sample as in column 1 but includes an indicator for union coverage on the previous job. The models include the race/ethnicity and education indicators in Table 2, but we do not show the statistically insignificant ones. The omitted category is a non-Hispanic white man who has at most a high school diploma and who had less than six months of job tenure at layoff. Industry and occupation indicators refer to the lost job. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$) Section 5.1 discusses column 1 and section 7.1 discusses column 2.

Table 4: Reservation wage ratios and unemployment duration: Comparison with Krueger and Mueller and the model

Reservation wage question: “Suppose someone offered you a job today that is suitable in terms of hours, skills, responsibilities and non-wage benefits. What is the lowest wage or salary, before taxes and deductions, you would accept? Please include in this amount any bonuses, overtime pay, tips or commissions that you would expect.”

Dependent variable = $100 \times \ln(\text{reservation wage}_{it}/\text{previous wage}_i)$

| | Davis and Krolikowski (DK) | | Krueger and Mueller (KM) | |
|----------------------------|----------------------------|----------------------|--------------------------|-------------------|
| | (1) | (2) | (3) | (4) |
| | Pooled | Longitudinal | Pooled | Longitudinal |
| | cross section | sample | cross section | sample |
| Weeks unemployed | -0.258** (0.107) | -0.279*** (0.055) | -0.125*** (0.043) | -0.056 (0.056) |
| Individual fixed effects | | x | | x |
| Reserv. wage unit dummies | x | x | x | x |
| Other controls | x | | x | |
| Mean of dependent variable | -5.067 | -5.950 | -11 | -10 |
| Std. dev. of dep. var. | 33.133 | 30.394 | | |
| R2 | 0.074 | 0.877 | 0.52 | 0.964 |
| Observations | 3,330 | 2,150 | 22,701 | 23,396 |
| Individuals | 2,024 | 844 | 4,606 | 3,528 |
| Weeks unemployed (model) | -0.685 | -0.685 | -0.202 | -0.202 |

Note: The reservation wage ratio is defined as the reported reservation wage divided by the wage on the previous job. The table refers to sample data, except for the last row, which we describe below. Columns 1 and 2 use our sample. Column 3 is copied from [Krueger and Mueller \(2016\)](#), Table 3A, column 2. We copy the results, and cannot replicate them, because the disclosed KM data do not include the previous wage. Column 4 is our replication of [Krueger and Mueller \(2016\)](#), Table 3A, column 3, except we copy over the mean of the dependent variable. We can replicate the coefficient in column 4 because the previous wage is a constant for each individual and so does not affect the estimation results when we include individual fixed effects in that specification. In columns 2 and 4, we drop singletons whereas [Krueger and Mueller \(2016\)](#) do not, so the number of observations in column 4 does not match the number in [Krueger and Mueller \(2016\)](#), table 3A, column 3. [Krueger and Mueller \(2016\)](#), Table 3A does not report the standard deviation of the dependent variable so we omit that statistic from those columns. The last row reports the slope coefficient from a linear regression using model data for the DK and KM calibrations (discussed in section 3.3) and weighted by the unemployment durations in the respective samples. The DK coefficient here does not match the weighted mean decline in Figure 1b, column 3 because here we estimate an intercept. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$. See section 5.2.

Table 5: Expected reservation wage ratios, unemployment duration, and dynamic selection

Expected reservation wage questions: 1.) “If you don’t find suitable work in the next h months, would that change your mind about the lowest wage or salary you would accept?” in which $h \in \{1, 2, 3, 6\}$; and if yes, 2) “In that case, how much would you increase or decrease your lowest acceptable wage or salary?”

Dependent variable = $100 \times \ln(\text{expected reservation wage}_{it}/\text{previous wage}_i)$

| | (1) | (2) | (3) |
|----------------------------|----------------------------|----------------------|--|
| | Pooled cross section | Fixed effects | Fixed effect spec. in column 2 using sample with at least two reservation wage ratio obs. |
| Weeks unemployed | -0.231*** (0.053) | -0.344*** (0.017) | -0.402*** (0.025) |
| Individual fixed effects | | x | x |
| Reserv. wage unit dummies | x | x | x |
| Other controls | x | | |
| Mean of dependent variable | -6.163 | -6.163 | -7.550 |
| Std. dev. of dep. var. | 34.810 | 34.810 | 29.118 |
| R2 | 0.080 | 0.966 | 0.965 |
| Observations | 3,990 | 3,990 | 1,644 |
| Individuals | 1,995 | 1,995 | 822 |

Note: Expected reservation wages at all horizons (h) are measured during the Entry Survey. The expected reservation wage at horizon $h = 0$ is equal to the reported reservation wage during the Entry Survey. As such, each individual has two expected reservation wage ratio observations: one from the Entry Survey and one from the hypothetical horizon. Unemployment duration is the unemployment duration at the time of the entry and the unemployment duration at the time of the entry survey plus the hypothetical horizon, which is randomized across individuals. For respondents who answer “no” to the question “If you don’t find suitable work in the next h months, would that change your mind about the lowest wage or salary you would accept?,” we assume that their reservation wage remains unchanged at horizon h . Column 3 estimates the same specification as in column 2, but restricts the sample to the longitudinal sample that has at least two reservation wage observations in Table A3, column 2. (***) $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). See section 6.2.

Table 6: Reservation wage ratios, unemployment duration, wage residuals, and age

Reservation wage question: “Suppose someone offered you a job today that is suitable in terms of hours, skills, responsibilities and non-wage benefits. What is the lowest wage or salary, before taxes and deductions, you would accept? Please include in this amount any bonuses, overtime pay, tips or commissions that you would expect.”

Dependent variable = $100 \times \ln(\text{reservation wage}_{it}/\text{previous wage}_i)$

| | (1) | (2) | (3) | (4) |
|--------------------------------------|--|---|--|-------------------------|
| | Without wage resid. interactions | With linear wage resid. interaction | With wage resid. quartile interactions | With age interaction |
| Weeks unemployed | -0.279*** (0.055) | -0.258*** (0.058) | 0.103 (0.135) | -0.204*** (0.078) |
| Wks. unemp. \times wage resid. | | -0.356** (0.150) | | |
| Wks. unemp. \times Q2 | | | -0.466*** (0.176) | |
| Wks. unemp. \times Q3 | | | -0.505*** (0.169) | |
| Wks. unemp. \times Q4 | | | -0.493*** (0.161) | |
| Wks. unemp. \times (age \geq 45) | | | | -0.184 (0.113) |
| Individual fixed effects | x | x | x | x |
| Reserv. wage unit dummies | x | x | x | x |
| Other controls | | | | |
| Mean of dependent variable | -5.950 | -5.950 | -5.950 | -5.970 |
| Std. dev. of dep. var. | 30.394 | 30.394 | 30.394 | 30.720 |
| R2 | 0.877 | 0.878 | 0.879 | 0.879 |
| Observations | 2,150 | 2,150 | 2,150 | 2,063 |
| Individuals | 844 | 844 | 844 | 812 |

Note: For comparison, Column 1 reproduces our results from Table 4, column 2, in which we estimate a specification with individual fixed effects. Column 2 estimates the same specification on the same sample but includes an interaction between unemployment duration and an individual’s wage residual from their previous job. Column 3 estimates the same specification as in column 1 on the sample sample but includes interactions between unemployment duration and indicators for quartiles of the wage residual distribution. We omit the interaction with the first quartile indicator in this specification. “Q2” denotes the indicator for the second wage residual quartile, and so on. Wage residuals are from a Mincerian wage equation. Standard errors in Columns 2 and 3 are computed by bootstrapping the Mincerian wage estimation and the second-stage estimation with 1,000 replications. Column 4 includes an interaction between unemployment duration and a dummy for age at least 45 years old. The sample is slightly smaller because of missing age and because the analysis restricts to workers no more than 65 years old. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$) See sections 7.2 and 7.3.

Table 7: Expected reservation wage ratios, unemployment duration, wage residuals, and age

Expected reservation wage questions: 1.) “If you don’t find suitable work in the next h months, would that change your mind about the lowest wage or salary you would accept?” in which $h \in \{1, 2, 3, 6\}$; and if yes, 2) “In that case, how much would you increase or decrease your lowest acceptable wage or salary?”

Dependent variable = $100 \times \ln(\text{expected reservation wage}_{it}/\text{previous wage}_i)$

| | (1) | (2) | (3) | (4) |
|--------------------------------------|--|---|--|--------------------------|
| | Without wage resid. interactions | With linear wage resid. interaction | With wage resid. quartile interactions | With age interactions |
| Weeks unemployed | -0.344*** (0.017) | -0.345*** (0.022) | -0.264*** (0.040) | -0.296*** (0.026) |
| Wks. unemp. \times wage resid. | | -0.125** (0.050) | | |
| Wks. unemp. \times Q2 | | | -0.085 (0.053) | |
| Wks. unemp. \times Q3 | | | -0.057 (0.053) | |
| Wks. unemp. \times Q4 | | | -0.180*** (0.056) | |
| Wks. unemp. \times (age \geq 45) | | | | -0.103*** (0.036) |
| Individual fixed effects | x | x | x | x |
| Reserv. wage unit dummies | x | x | x | x |
| Other controls | | | | |
| Mean of dependent variable | -6.163 | -6.163 | -6.163 | -6.105 |
| Std. dev. of dep. var. | 34.810 | 34.810 | 34.810 | 35.081 |
| R2 | 0.966 | 0.966 | 0.966 | 0.966 |
| Observations | 3,990 | 3,990 | 3,990 | 3,856 |
| Individuals | 1,995 | 1,995 | 1,995 | 1,928 |

Note: For comparison, Column 1 reproduces our results from Table 5, column 2, in which we estimate a specification with individual fixed effects. Column 2 estimates the same specification on the same sample but includes an interaction between unemployment duration and an individual’s wage residual from their previous job. Column 3 estimates the same specification as in column 1 on the sample sample but includes interactions between unemployment duration and indicators for quartiles of the wage residual distribution. We omit the interaction with the first quartile indicator in this specification. “Q2” denotes the indicator for the second wage residual quartile, and so on. Wage residuals are from a Mincerian wage equation. Standard errors in Columns 2 and 3 are computed by bootstrapping the Mincerian wage estimation and the second-stage estimation with 1,000 replications. Column 4 includes an interaction between unemployment duration and a dummy for age at least 45 years old. The sample is slightly smaller because of missing age and because the analysis restricts to workers no more than 65 years old. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$) See sections 7.4 and 7.5.

Table 8: Re-employment wages and reservation wages

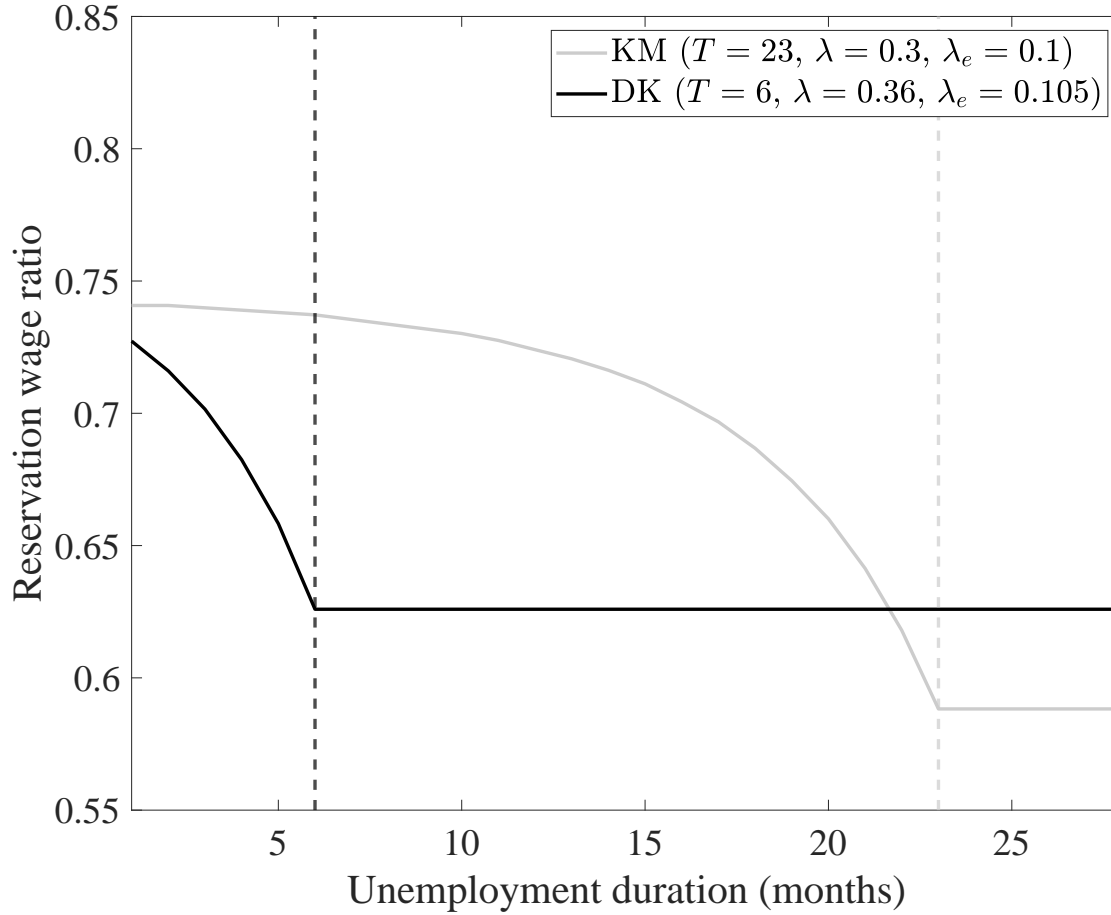
Dependent variable = $\ln(\text{re-employment wage}_{it})$

| | (1) | (2) | (3) | (4) | (5) |
|---|---------------------|---------------------|---------------------|---------------------|---------------------|
| $\ln(\text{res. wage at Entry Survey})$ | 0.778*** (0.048) | | 0.716*** (0.103) | 0.717*** (0.103) | 0.628*** (0.104) |
| $\ln(\text{previous wage})$ | | 0.573*** (0.068) | 0.066 (0.106) | 0.064 (0.105) | 0.127 (0.104) |
| Weeks unemployed | | | | 0.001 (0.001) | 0.002 (0.001) |
| Individual fixed effects | | | | | |
| Dummies for ind. and occ. | | | | | x |
| Reserv. wage unit dummies | x | x | x | x | x |
| Other controls | | | | | x |
| Mean of dependent variable | 3.200 | 3.200 | 3.200 | 3.200 | 3.200 |
| Std. dev. of dep. var. | 0.629 | 0.629 | 0.629 | 0.629 | 0.629 |
| R2 | 0.505 | 0.408 | 0.506 | 0.507 | 0.583 |
| Observations | 395 | 395 | 395 | 395 | 395 |
| Individuals | 395 | 395 | 395 | 395 | 395 |

Note: Sample restricted to workers who were first observed employed for an employer during the first or second Follow-Up survey and were not recalled to their previous employer. The lagged reservation wage is taken from the previous survey. Weeks unemployed refers to the number of weeks between the last day of work at the job before the Entry Survey and the start of the current job. Industry and occupation indicators refer to the last job. (***) $p < 0.01$, ** $p < 0.05$, * $p < 0.1$) See section 8.

Figure 1: Reservation wage ratios in the model

(a) Reservation wage ratios under different calibrations

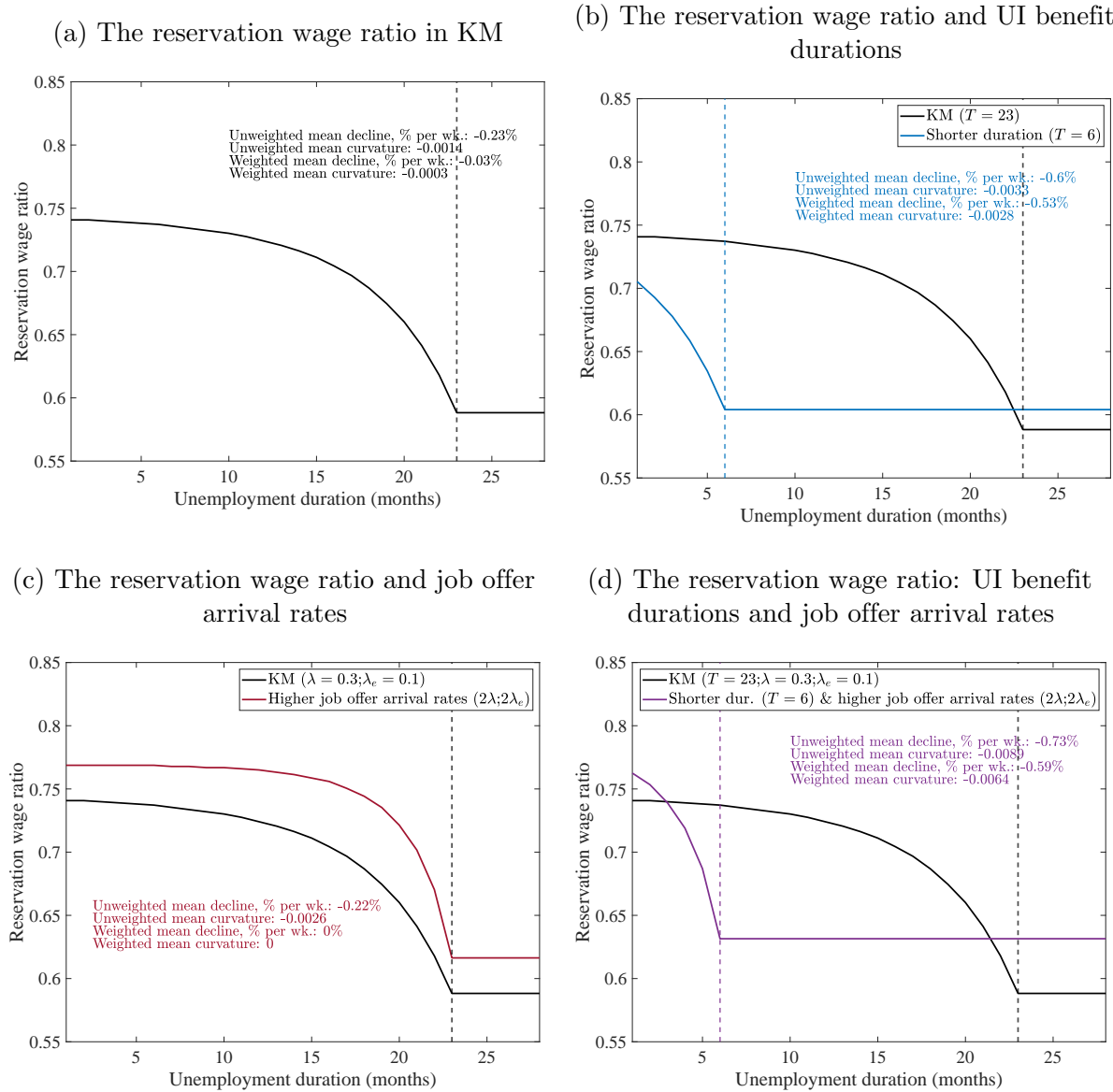


(b) Mean decline and curvature statistics for reservation wage ratios

| | Mean decline (% per week) | | | | Average curvature (1/months) | | | |
|--------------------|---------------------------|---------|----------|---------|------------------------------|---------|----------|---------|
| | Unweighted | | Weighted | | Unweighted | | Weighted | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | [0, 6] | [0, 23] | [0, 6] | [0, 23] | [0, 6] | [0, 23] | [0, 6] | [0, 23] |
| KM ($t \leq 23$) | -0.02 | -0.23 | -0.02 | -0.03 | -0.0002 | -0.0014 | -0.0003 | -0.0003 |
| DK ($t \leq 6$) | -0.58 | | -0.51 | | -0.004 | | -0.0033 | |

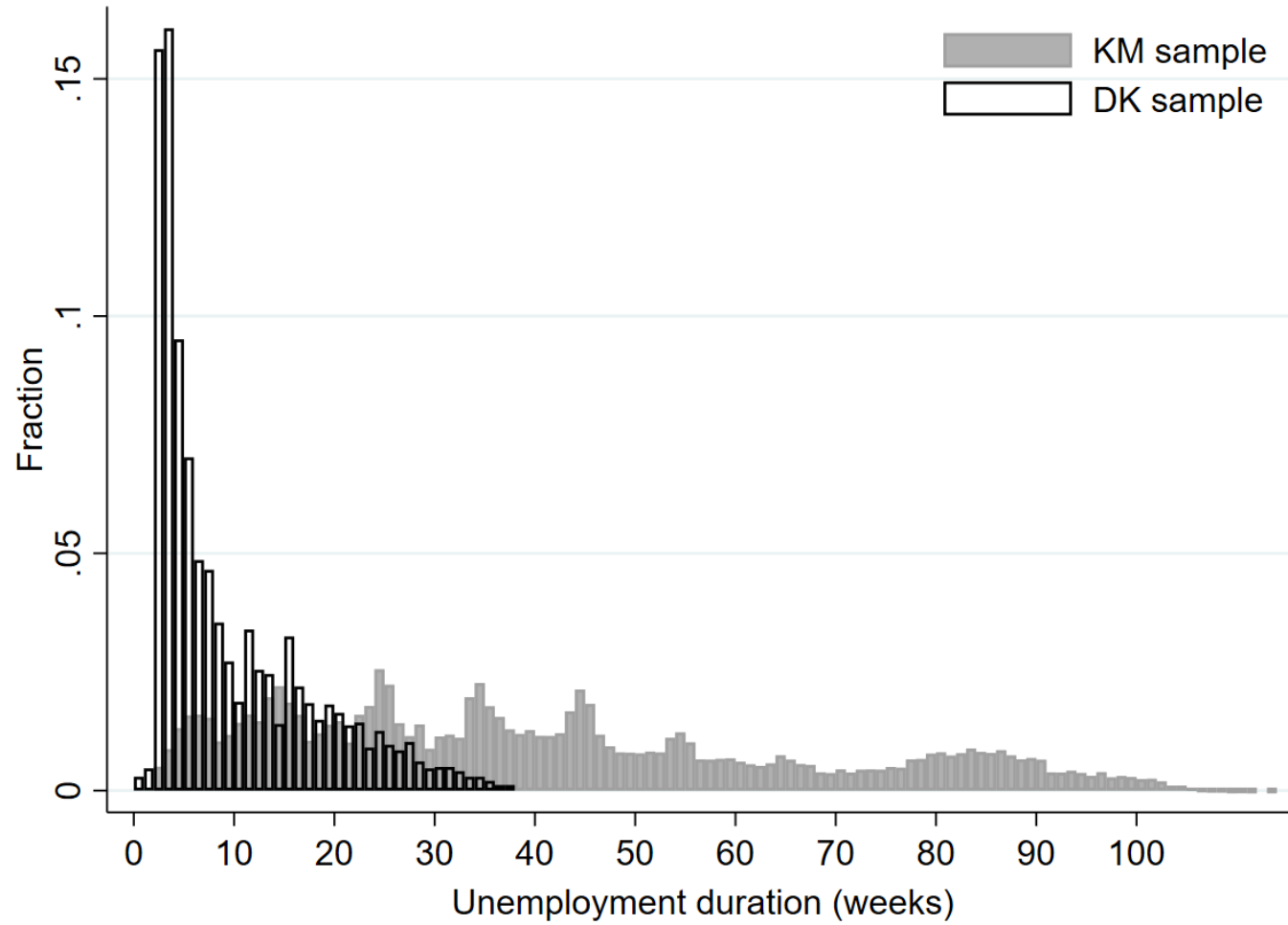
Note: Exhibit 1a depicts the reservation wage ratio in the model calibrated to conditions during our survey (DK) and those during the KM survey (see columns 1 and 3 of Table 1, respectively). T denotes UI benefit duration, λ (λ_e) denotes job offer arrival rates while unemployed (employed), and t denotes unemployment duration in months. Vertical dashed lines denote UI benefit duration. The line denoted “KM” replicates Figure 1 in Krueger and Mueller (2016). Exhibit 1b shows unweighted and weighted mean declines and average curvatures under the DK and KM calibrations over two unemployment durations (0 to 6 months and 0 to 23 months). We define the average curvature as the mean of the curvature at each point. See footnote 3 for the definition of curvature. “Unweighted” statistics use a uniform distribution over unemployment duration. “Weighted” statistics use the distribution of unemployment duration from our sample in section 5, shown in Figure 3. For columns [0, 6], we truncate that distribution at 6 months and re-weight the result so that the new distribution sums to one. We omit the statistics for our calibration for months [0, 23] because after month 6, the reservation wage is flat with $T = 6$. See section 3.4.

Figure 2: Comparative statics with respect to UI benefit duration and job offer arrival rates



Note: The reservation wage ratio in the model and comparative statics with respect to UI benefit duration (T) and job offer arrival rates on (λ_e) and off (λ) the job. Vertical dashed lines denote UI benefit duration. Figure 2a is based on the KM calibration in Table 1, column 3, and replicates Figure 1 in Krueger and Mueller (2016). This figure is copied onto each panel for reference. Figure 2b reduces unemployment duration from 23 months in the KM calibration to 6 months. Figure 2c doubles the job offer arrival rates for unemployed and employed workers from the KM calibration. Figure 2d combines the changes in Figures 2b and 2c. Mean and curvature statistics are computed over unemployment durations that are less than T . We define the average curvature as the mean of the curvature at each point. See footnote 3 for the definition of curvature. “Unweighted” statistics use a uniform distribution over unemployment duration. “Weighted” statistics use the distribution of unemployment duration from our sample in section 5, shown in Figure 3. See section 3.4.

Figure 3: Unemployment duration distribution in the KM sample and our (DK) sample



Note: KM sample uses the weights for the current interview week. DK sample is unweighted. See section 4.2. Bar width is one week.

Appendix Materials

A Model Appendix

A.1 The Value of Unemployment

We show that equation (1) is identical to equation (1) in KM:

$$\begin{aligned}
 U(t) &= u(b(t)) + \beta \left\{ (1 - \lambda) U(t-1) + \lambda \int \max\{W(x, m=0), U(t-1)\} dF(x) \right\} \\
 U(t) &= u(b(t)) + \beta \left\{ U(t-1) - \lambda U(t-1) + \lambda \int_{x < R} U(t-1) dF(x) + \lambda \int_{x \geq R} W(x, m=0) dF(x) \right\} \\
 U(t) &= u(b(t)) + \beta \left\{ U(t-1) - \lambda U(t-1) + \lambda U(t-1) F(R) + \lambda \int_{x \geq R} W(x, m=0) dF(x) \right\} \\
 U(t) &= u(b(t)) + \beta \left\{ U(t-1) + \lambda \int_R (W(x, m=0) - U(t-1)) dF(x) \right\},
 \end{aligned}$$

in which $R(t)$ is the reservation wage with t periods of unemployment benefits left.

A.2 Calibration Details

We discuss monthly parameters of our baseline calibration that are the same as in KM. We set the discount factor, β , to 0.996 to target a an annual discount rate of about 5 percent. We assume the utility function

$$u(c) = \frac{c^{1-\gamma}}{1-\gamma}, \quad (\text{A5})$$

with constant relative risk aversion equal to $\gamma = 2$. Before benefit exhaustion we set $b = 0.7637$ and fix the drop in consumption at UI exhaustion to 31.3 percent. The latter is informed by estimates in [Blundell et al. \(1993\)](#), [Gruber \(1997\)](#), and [Low et al. \(2010\)](#), as discussed in KM.

A.3 Comparative Statics with Job offer Arrival Rates

Increasing the job offer arrival rate for unemployed workers has different effects on the reservation wage ratio than increasing the job offer arrival rate for employed workers, as shown in [Figure A3](#). Doubling the job offer arrival rate for unemployed workers makes workers more picky, as shown in [Figure A3b](#). A higher off-the-job arrival rate means that benefit exhaustion is less likely and agents raise their reservation wages. The (unweighted) mean decline in the reservation wage ratio falls to 0.16 percent per week. Doubling the job offer arrival rate for employed workers makes workers less picky, as shown in [Figure A3c](#). With a higher job offer arrival on the job, workers lower their reservation wages so that they can get on the job ladder sooner. The (unweighted) mean decline in the reservation wage ratio rises to 0.33 percent per week. [Figure A3d](#) shows the reservation wage ratio when we double both the off- and on-the-job arrival rates and replicates [Figure 2c](#).

B Survey Appendix

We describe the details of our survey, which borrows from [Davis and Krolikowski \(2024\)](#).

B.1 Survey Details

Our sample frame covers persons who began collecting UI benefits in the State of Illinois from 10 September to 24 November in 2018, excluding about one-in-ten benefit recipients with no email address on file at the Illinois Department of Employment Security (IDES). All persons in the sample frame received an email invitation to participate in our online Entry Survey, typically one business day after their first UI benefit payment. If the respondent completed the Entry Survey (and permitted further contact), we sent invitations to take part in one or two Follow-Up Surveys.

IDES encourages job losers to file an initial claim for UI benefits in the calendar week after job loss (IDES, 2017). The first full week of unemployment is not eligible for benefits. The second full week is eligible, provided the individual's claim is certified. Certified claimants receive benefit payments the week after each benefits-eligible week. Thus, invitations to our Entry Survey typically arrive 18 to 28 days after job loss, although it can be longer due to delays in claims processing. Respondents received a \$10 Amazon gift card for taking the survey, except during the first week of Entry-Survey invitations (September 10 to 14), during which they received \$5.

Our Entry Survey asks about demographic characteristics, the lost job, willingness to accept pay cuts in lieu of layoff, whether there were discussions about compensation cuts in lieu of layoff, the reasons for employer reluctance to offer such deals, desired attributes in a new job, reservation wages, and more.

Invitations for the first Follow-Up Survey went to field 2, 4, 8, and 12 weeks (randomized) after completing the Entry Survey, and invitations for the second went to field 4, 8, 12 and 16 weeks after completing the first follow up. Respondents received a \$5 Amazon gift card for participating in the first follow up and \$10 for the second. We tailor the follow-up questionnaires based on whether the respondent returned to their prior job, took a new job, was self employed, or still without work. Depending on employment status, the follow-ups probe job search activity, reservation wages, attributes of the current job, compensation on the current job, and more.

The mean completion time for the Entry Survey is 9 minutes, and the median is 8 minutes. The mean (median) completion time for the Follow-Up Surveys is 4 (3) minutes. These short completion times reflect our efforts to design short, highly focused survey instruments to encourage higher response rates and accurate responses.

B.2 Data Cleaning and Sample Selection

We recode reported earnings, reservation wages, and expected reservation wages in two ways. First, if an individual reports making more than \$15,000 per hour, we recode their response to be at the annual frequency. This recode affected 37 gross pay observations. Second, if an individual reports hourly earnings of \$300 or more, but less than \$15,000, we consider their response to be in cents and divided it by 100. This recode affects 78 gross pay observations.

We also recode some expected reservation wage observations if the respondent appeared to misinterpret the question. If the reported expected decline in the reservation wage was more than 100 log points, we interpret the response as the new reservation wage, rather than the expected decline in the reservation wage. 100 log points is at about the 5th percentile of the distribution of expected reservation wage changes. This recode affects 177 expected reservation wage observations. As an example, an individual responds that their current

reservation wage is \$100,000 annually during the Entry Survey. They report that if they don't find work in the next month, they would adjust their reservation wage. When asked "How much would you increase or decrease your lowest acceptable wage or salary," they respond that they would decrease their reservation wage by \$90,000 annually. In this case, we assume that \$90,000 annually is their expected reservation wage rather than the change in their reservation wage. We make the same assumption when reservation wages are expected to rise by over 100 log points. This recode affects 2 expected reservation wage observations.

We trim observations of hourly gross pay, reservation wages, and expected reservation wages below \$2 or above \$200. Sometimes we winsorize changes in gross pay and reservation wage ratios below the 1st and above the 99th percentile. When we apply this winzorization we make note of it in the main text. We also trim reservation wage ratios that were above three and below one-sixth. KM trim observations with reservation wage ratios greater than three or less than one-third, as in [Feldstein and Poterba \(1984\)](#). After careful inspection of our data, we decided that a lower cutoff of one-sixth is more appropriate. To be consistent with KM, we set to missing reservation wages for those who are employed but still looking for other work.

We construct unemployment duration by taking the difference between the survey completion date and the worker's reported last day at their previous job. We top code unemployment durations that are greater than 30 weeks during the Entry Survey because job losers must file a claim within 6 months (26 weeks) of job loss and we allow up to 4 weeks for an individual to receive our Entry Survey.¹² Unemployment duration is set to missing for employed workers. We did not ask about labor force status during the Entry Survey because we were worried that workers, who recently received a UI benefit payment, may not respond truthfully and that such a question would jeopardize truthful responses to the rest of our survey instrument. As such, we assume that all workers are unemployed during the Entry Survey.

We restrict the sample to those who have less than or equal to 38 weeks of unemployment. This restriction is based on the timing of our survey invitations. In particular, we anticipate that individuals should complete the Entry Survey no more than 6 weeks after job loss. The longest follow-up periods for the 1st and 2nd Follow-Up surveys are 12 and 16 weeks, respectively. Allowing for 2 weeks to fill out the Follow-Up surveys yields our 38-week restriction.

We calculate potential experience using a person's age less their years of schooling, derived from their highest level of completed education. We collected individual's ages in brackets (18 to 24, 25 to 34, ..., 65 or older) so we impute a respondent's age to the middle of each age bracket.

Several of our questions offered the option to write in a response, such as the individual's industry and occupation of work and reason for layoff. We hand coded some of these observations to our list of displayed choices and sometimes we created new categories of responses if sufficiently many individuals responded in a similar way. For example, many individuals reported maintenance work and repair at their previous employer as the reason for their temporary layoff. Because this was not one of our original options, we created a new category.

We calculate hourly reservation wages using hours information from the previous job,

¹²Workers with longer unemployment spells typically do not take many days or weeks to respond to our Entry Survey but rather have job loss dates that were a long time ago.

unless the response is in hourly wages. When we ask about reservation wages, we do not elicit expected hours on that job. Instead, we assume that hours on the previous job capture the intended hours on the new job. This assumption implies that we understate the reductions in hourly reservation wages over the unemployment spell if workers also reduce their expectations about how many hours they will work over the unemployment spell. [Krueger and Mueller \(2016\)](#) study weekly reservation wages, although their results are similar with hourly reservation wages.

The percent of workers represented by unions is similar in the KM and DK samples: about 18 percent in NJ in 2010 and about 15 percent in IL in 2019 ([BLS, 2023](#)).

B.3 CPS Weights

Because we lack access to administrative UI records, we cannot re-weight to match Illinois UI benefit claimants. Instead, we use CPS data from June 2018 to February 2019, which were the months when our Entry Survey was fielded with three additional months on each end. We use these data to compute national CPS shares in eight bins defined by: young (less than 45 years old) and old (no less than 45 years old), less (no bachelor's degree) and more educated (bachelor's degree or graduate degree), and male and female. We re-weight each observation in our sample by the share of CPS individuals in each of these bins over the share of our Entry-Survey respondents in each of these bins.

For individuals in our survey that did not reveal their education or age, we impute their response. In particular, we use a multilogit regression with independent variables including gender, temporary layoff status, race, and dummies for previous occupation and industry, to separately predict respondents' age category and educational attainment. We impute a respondent's age and education based on which category is most likely given their observable characteristics. None of our respondents have missing gender.

These weights are little changed if we use CPS individuals who are less than 5 weeks unemployed and not new entrants, who are unlikely to be eligible for UI.

We present our main results using these weights in appendix [C.5](#).

C Empirical Results Appendix

C.1 Individual Heterogeneity and Sample Selection

The difference in the estimated coefficients between columns 1 and 2 in Table [4](#) is a combination of a different sample and a different specification. We find imprecise evidence that neither channel is important for our results, although we find that selection imposes an upward bias to the estimated effect of spell duration on reservation wages in cross-sectional data, as discussed in [Krueger and Mueller \(2016\)](#). Columns 1 and 2 of Table [A3](#) repeat the pooled cross section and fixed effects coefficients from Table [4](#). In column 3 we estimate the pooled cross section specification from column 1 on the longitudinal sample of individuals who have at least two reservation wage ratio observations in column 2. As such, moving from columns 1 to 3 changes only the sample and keeps the specification the same. And moving from columns 3 to 2 changes only the specification and keeps the sample the same.

The coefficient in Table [A3](#), column 3 implies that the reservation wage ratio falls by -0.22 percent per week. This point estimate suggests that the longitudinal sample has smaller declines in the reservation wage ratio than the pooled cross section sample. Nevertheless,

the standard error in column 3 is large and we cannot reject the null hypothesis that this coefficient is the same as the coefficient in column 1. The point estimate in column 2 is more negative than the estimate in column 3, which suggests that accounting for individual, time-invariant heterogeneity hastens the decline in the reservation wage ratio. This change is consistent with the idea that job losers who have high (low) reservation wages relative to their wage opportunities are more (less) likely to remain unemployed over time. But, again, standard errors on the coefficient in column 3 are large and we cannot reject the null hypothesis that the coefficients in columns 2 and 3 are the same.

C.2 Quadratic Specifications

Point estimates using our sample suggest that the reservation wage ratio is concave with respect to unemployment duration—consistent with the canonical model—but the results are noisy, as shown in Table A4. Column 1 repeats our baseline results from Table 4. Column 2 estimates equation (4), but includes linear and quadratic terms in weeks unemployed. The point estimate is negative (-0.001), suggesting concavity, but we cannot reject the null that it is zero. Moreover, estimating the same specification with the KM sample, yields a positive coefficient on the quadratic term.

C.3 Union Coverage, Industry Wage Premia, and Reservation Wage Ratios

Union coverage and industry wage premium on the lost job do not affect the trajectory of the reservation wage ratio over the unemployment spell, as shown in Table A5. Column 1 repeats our results from Table 6, column 3. Column 2 adds interactions between weeks unemployed and union coverage on the lost job and industry wage premia. We interpret industry wage differentials as a measure of rents based on Akerlof (1982), Bulow and Summers (1986) and Krueger and Summers (1988), among others. To quantify industry-level worker rents, we use the wage premiums for eighteen industries that Stansbury and Summers (2020, Figure A8) estimate from CPS micro data. Neither union coverage nor industry premium materially change the trajectory of the reservation wage over the unemployment spell. Column 2 has fewer observations because previous industry is missing sometimes so that the industry wage premium is missing.

C.4 Worker Rents and the Minimum Wage

Workers with previous wages close to the minimum wage do not drive our result that workers rents hasten the decline of the reservation wage in section 7.2. Less than five percent of workers in the first quartile of the wage residual distribution report a reservation wage that is less than or equal to Illinois' minimum wage when our survey was in the field (\$8.25/hr). Moreover, our results are robust to excluding individuals who had previous wages lower than \$10/hr, as shown in Table A6.

C.5 Results with Weights

Our main results are similar when we use the CPS weights discussed in appendix B.3. Table A9 shows that reservation wage ratios fall by about 0.3 percent per week in the pooled cross-section and fixed-effects specifications when we use weights, although the former estimate is

noisier than in Table 4. Table A10 shows that expected declines in reservation wage ratios are similar to the actual declines in reservation wages ratios, similar to findings in Table 5. Table A11 shows that higher wage residuals hasten the decline of the reservation wage ratio over the unemployment spell. And, that this effect is drive by those with higher wages residuals, similar to the results in Table 6. Finally, Table A12 shows that reservation wage reported during the Entry Survey is a more powerful predictor of the re-employment wage than the wage on the last job, similar to the results in Table 8.

Appendix references

- Akerlof, George A. 1982. "Labor Contracts as Partial Gift Exchange." *Quarterly Journal of Economics*, 97(4): 543--569.
- BLS. 2023. "Union Membership." Accessed: 4/24/2024.
- Bulow, Jeremy I., and Lawrence H. Summers. 1986. "A Theory of Dual Labor Markets with Application to Industrial Policy, Discrimination, and Keynesian Unemployment." *Journal of Labor Economics*, 4(3, Part 1): 376--414.
- Davis, Steven J., and Pawel M. Krolikowski. 2024. "Sticky Wages on the Layoff Margin." National Bureau of Economic Research Working Paper 31528.
- Feldstein, Martin, and James Poterba. 1984. "Unemployment Insurance and Reservation Wages." *Journal of Public Economics*, 23(1-2): 141--167.
- IDES. 2017. "Unemployment Insurance Benefits Handbook." Accessed: 11/4/2019.
- Krueger, Alan B., and Andreas I. Mueller. 2016. "A Contribution to the Empirics of Reservation Wages." *American Economic Journal: Economic Policy*, 8(1): 142--179.
- Krueger, Alan B., and Lawrence H. Summers. 1988. "Efficiency Wages and the Inter-Industry Wage Structure." *Econometrica*, 56(2): 259--293.
- Stansbury, Anna, and Lawrence H. Summers. 2020. "The Declining Worker Power Hypothesis: An Explanation for the Recent Evolution of the American Economy." *Brookings Papers on Economic Activity*, Spring(1): 1--96.

Table A1: The Entry Survey analysis sample: Occupational distribution and comparison to the CPS and to the KM survey

| | (1) | (2) | (3) | (4) |
|--|------------|----------|----------|-------|
| | Unweighted | Weighted | CPS (US) | KM |
| Armed forces | 0.2 | 0.3 | 0.0 | 0.0 |
| Construction and extraction occupations | 2.0 | 3.4 | 13.1 | 2.2 |
| Farming, fishing, and forestry occupations | 0.3 | 0.5 | 3.2 | 0.0 |
| Installation, maintenance and repair occupations | 2.0 | 3.5 | 2.3 | 1.1 |
| Management, business and financial occupations | 25.3 | 21.3 | 8.6 | 31.0 |
| Office and administrative support occupations | 16.5 | 17.2 | 10.2 | 15.3 |
| Production occupations | 4.5 | 7.4 | 6.7 | 1.6 |
| Professional and related occupations | 20.1 | 14.8 | 15.6 | 20.3 |
| Sales and related occupations | 16.0 | 15.8 | 8.2 | 8.0 |
| Service occupations | 6.8 | 8.0 | 22.5 | 6.3 |
| Transportation and material moving occupations | 2.6 | 4.0 | 9.5 | 2.8 |
| Data missing | 3.7 | 3.8 | 0.0 | 11.4 |
| No. of observations | 2,070 | 2,070 | 3,820 | 4,444 |

Note: In our survey, occupation in the entry survey is captured with the question “For the job that ended on [job loss date], what was your occupation? That is, what kind of work did you do?” In the CPS, the occupation of the unemployed is based on the last job they held. In the KM survey, occupation is captured with the question “Please describe in a few words the type of work you are looking for,” and then mapped to occupation codes. See section 4.2.

Table A2: How the reservation wage during the Entry Survey varies with observables

Reservation wage question: “Suppose someone offered you a job today that is suitable in terms of hours, skills, responsibilities and non-wage benefits. What is the lowest wage or salary, before taxes and deductions, you would accept? Please include in this amount any bonuses, overtime pay, tips or commissions that you would expect.”

Dependent variable = $\ln(\text{reservation wage}_{it})$

| | (1) |
|--|--------------------|
| Ln (previous wage) | 63.18*** (1.37) |
| <i>Individual characteristics</i> | |
| Technical training/some college | 2.71 (2.34) |
| Associate/bachelor’s degree | 10.72*** (2.31) |
| Grad. degree or higher | 18.80*** (2.78) |
| Female | -2.44* (1.38) |
| White, Hispanic | 2.03 (2.99) |
| Black | 1.52 (1.96) |
| Experience | 0.80*** (0.27) |
| Experience ² | -0.01** (0.00) |
| <i>Tenure on the lost job</i> | |
| 6mos to 2yrs | -1.16 (1.90) |
| 2yrs to 5yrs | -2.22 (2.05) |
| More than 5yrs | -5.13** (2.05) |
| <i>Other variables</i> | |
| Paid hourly (Yes=1) | 0.54 (1.92) |
| Weeks unemployed | -0.17 (0.12) |
| Dummies for ind. and occ. Reserv. wage unit dummies Other controls | |
| Mean of dependent variable Std. dev. of dep. var. | |
| R2 | 0.742 |
| Observations | 1,964 |
| Individuals | 1,964 |

Note: Estimated using the Entry Survey sample. Column 1 regresses the reservation wage on observables. The models include the race/ethnicity and education indicators in Table 2, but we do not show the statistically insignificant ones. The omitted category is a non-Hispanic white man who has at most a high school diploma and who had less than six months of job tenure at layoff. Industry and occupation indicators refer to the lost job. (***) $p < 0.01$, ** $p < 0.05$, * $p < 0.1$) See section 5.1.

Table A3: Reservation wages and unemployment duration: Sample selection vs. individual heterogeneity

Reservation wage question: “Suppose someone offered you a job today that is suitable in terms of hours, skills, responsibilities and non-wage benefits. What is the lowest wage or salary, before taxes and deductions, you would accept? Please include in this amount any bonuses, overtime pay, tips or commissions that you would expect.”

Dependent variable = $100 \times \ln(\text{reservation wage}_{it}/\text{previous wage}_i)$

| | (1) Pooled cross section | (2) Fixed effects | (3) Pooled cross section specification in column 1 using longitudinal sample in column 2 |
|----------------------------|-----------------------------------|-------------------------|--|
| Weeks unemployed | -0.258** (0.107) | -0.279*** (0.055) | -0.218* (0.121) |
| Individual fixed effects | | x | |
| Reserv. wage unit dummies | x | x | x |
| Other controls | x | | x |
| Mean of dependent variable | -5.067 | -5.950 | -5.950 |
| Std. dev. of dep. var. | 33.133 | 30.394 | 30.394 |
| R2 | 0.074 | 0.877 | 0.099 |
| Observations | 3,330 | 2,150 | 2,150 |
| Individuals | 2,024 | 844 | 844 |

Note: For comparison, Columns 1 and 2 reproduce our baseline results from Table 4. Column 3 estimates the pooled cross section specification without individual fixed effects in column 1 but using the longitudinal sample in column 2. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$. See appendix C.1.

Table A4: Reservation wage ratios and unemployment duration: Linear and quadratic specifications

Reservation wage question: “Suppose someone offered you a job today that is suitable in terms of hours, skills, responsibilities and non-wage benefits. What is the lowest wage or salary, before taxes and deductions, you would accept? Please include in this amount any bonuses, overtime pay, tips or commissions that you would expect.”

Dependent variable = $100 \times \ln(\text{reservation wage}_{it}/\text{previous wage}_i)$

| | Davis and Krolikowski (DK) | | Krueger and Mueller (KM) | |
|-------------------------------|----------------------------|-------------------|--------------------------|-------------------|
| | (1) | (2) | (3) | (4) |
| | Linear | Quadratic | Linear | Quadratic |
| Weeks unemployed | -0.279*** (0.055) | -0.257 (0.163) | -0.056 (0.050) | -0.171 (0.120) |
| Weeks unemployed ² | | -0.001 (0.005) | | 0.001 (0.001) |
| Individual fixed effects | x | x | x | x |
| Reserv. wage unit dummies | x | x | x | x |
| Other controls | | | | |
| Mean of dependent variable | -5.950 | -5.950 | -10 | -0.10 |
| Std. dev. of dep. var. | 30.394 | 30.394 | | |
| R2 | 0.877 | 0.877 | 0.964 | 0.964 |
| Observations | 2,150 | 2,150 | 23,396 | 23,396 |
| Individuals | 844 | 844 | 3,528 | 3,528 |

Note: The reservation wage ratio is defined as the reported reservation wage divided by the wage on the previous job. Column 1 repeats Table 4, column 2, and column 3 repeats Table 4, column 4 for reference. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$). See appendix C.2.

Table A5: Reservation wage ratios, unemployment duration, and worker rents

Reservation wage question: “Suppose someone offered you a job today that is suitable in terms of hours, skills, responsibilities and non-wage benefits. What is the lowest wage or salary, before taxes and deductions, you would accept? Please include in this amount any bonuses, overtime pay, tips or commissions that you would expect.”

Dependent variable = $100 \times \ln(\text{reservation wage}_{it}/\text{previous wage}_i)$

| | (1) | (2) |
|---|---|--|
| | Without union and industry wage premium interactions | With union and industry wage premium interactions |
| Weeks unemployed | 0.103 (0.135) | -0.039 (0.168) |
| Weeks unemployed \times Q2 | -0.466*** (0.176) | -0.394 (0.242) |
| Weeks unemployed \times Q3 | -0.505*** (0.169) | -0.444** (0.225) |
| Weeks unemployed \times Q4 | -0.493*** (0.161) | -0.400* (0.224) |
| Weeks unemployed \times Union job | | 0.109 (0.196) |
| Weeks unemployed \times Ind. wage premium | | 0.017 (0.025) |
| Individual fixed effects | x | x |
| Reserv. wage unit dummies | x | x |
| Other controls | | |
| Mean of dependent variable | -5.950 | -6.502 |
| Std. dev. of dep. var. | 30.394 | 31.683 |
| R2 | 0.879 | 0.880 |
| Observations | 2,150 | 1,629 |
| Individuals | 844 | 640 |

Note: For comparison, Column 1 reproduces our results from Table 6, column 3. Column 2 estimates the same specification but includes an interaction between unemployment duration and an indicator for whether the lost job was covered by a union contract and the associated industry wage premium. The sample is smaller in column 2 because previous industry is missing for some respondents so that the industry wage premium is missing. Standard errors are computed by bootstrapping the Mincerian wage estimation and the second-stage estimation with 1,000 replications. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$) See appendix C.3.

Table A6: Reservation wage ratios, unemployment duration, and worker rents

Reservation wage question: “Suppose someone offered you a job today that is suitable in terms of hours, skills, responsibilities and non-wage benefits. What is the lowest wage or salary, before taxes and deductions, you would accept? Please include in this amount any bonuses, overtime pay, tips or commissions that you would expect.”

Dependent variable = $100 \times \ln(\text{reservation wage}_{it}/\text{previous wage}_i)$

| | (1) | (2) |
|----------------------------|----------------------|--|
| | Baseline | Previous wage ≥ \$10/hr. on lost job |
| Weeks unemployed | 0.103 (0.135) | 0.079 (0.151) |
| Weeks unemployed × Q2 | -0.466*** (0.176) | -0.435** (0.190) |
| Weeks unemployed × Q3 | -0.505*** (0.169) | -0.476*** (0.181) |
| Weeks unemployed × Q4 | -0.493*** (0.161) | -0.467*** (0.176) |
| Individual fixed effects | x | x |
| Reserv. wage unit dummies | x | x |
| Other controls | | |
| Mean of dependent variable | -5.950 | -8.739 |
| Std. dev. of dep. var. | 30.394 | 25.638 |
| R2 | 0.879 | 0.834 |
| Observations | 2,150 | 2,058 |
| Individuals | 844 | 806 |

Note: For comparison, Column 1 reproduces our results from Table 6, column 3. Column 2 estimates the same specification but on a sample of workers whose previous wage was above \$10 per hour. Standard errors in Columns 2 and 3 are computed by bootstrapping the Mincerian wage estimation and the second-stage estimation with 1,000 replications. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$. See appendix C.4.

Table A7: How the expected reservation wage ratio during the Entry Survey varies with observables

Expected reservation wage questions: 1.) “If you don’t find suitable work in the next h months, would that change your mind about the lowest wage or salary you would accept?” in which $h \in \{1, 2, 3, 6\}$; and if yes, 2) “In that case, how much would you increase or decrease your lowest acceptable wage or salary?”

Dependent variable = $100 \times \ln(\text{expected reservation wage}_{it}/\text{previous wage}_i)$

| | (1) |
|-----------------------------------|--------------------|
| <i>Individual characteristics</i> | |
| Female | 1.65 (1.76) |
| White, Hispanic | 6.61** (3.10) |
| Black | 10.55*** (2.96) |
| Experience | -0.11 (0.34) |
| Experience ² | 0.00 (0.01) |
| <i>Tenure on the lost job</i> | |
| 6mos to 2yrs | -1.36 (2.66) |
| 2yrs to 5yrs | -2.57 (2.77) |
| More than 5yrs | -9.11*** (2.79) |
| <i>Other variables</i> | |
| Paid hourly (Yes=1) | -2.02 (2.86) |
| Weeks unemployed at horizon h | -0.17* (0.09) |
| <i>Rent variables</i> | |
| Union job (Yes=1) | -9.53** (4.77) |
| Dummies for ind. and occ. | x |
| Reserv. wage unit dummies | x |
| Other controls | x |
| Mean of dependent variable | -8.930 |
| Std. dev. of dep. var. | 36.069 |
| R2 | 0.090 |
| Observations | 1,884 |
| Individuals | 1,884 |

Note: This table estimates the same specification as in Table 5, column 2. Expected reservation wages at all horizons (h) are measured during the Entry Survey. Unemployment duration is the unemployment duration at the time of the Entry Survey plus the hypothetical horizon h (in months), which is randomized across individuals with $h \in \{1, 2, 3, 6\}$. For respondents who answer “no” to the question “If you don’t find suitable work in the next h months, would that change your mind about the lowest wage or salary you would accept?”, we assume that their reservation wage remains unchanged at horizon h . The models include the race/ethnicity and education indicators in Table 2, but we do not show the statistically insignificant ones. The omitted category is a non-Hispanic white man who has at most a high school diploma and who had less than six months of job tenure at layoff. We omit indicators for the horizon h from this specification because they are highly correlated with weeks unemployed at horizon h . (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$) See section 6.1.

Table A8: Re-employment and reservation wages

Dependent variable = Employment_{it} (Yes=1)

| | (1) | (2) | (3) |
|-------------------------------|-------------------|-------------------|-------------------|
| ln(res. wage at Entry Survey) | -0.013 (0.026) | 0.026 (0.045) | 0.022 (0.047) |
| ln(previous wage) | | -0.039 (0.038) | -0.032 (0.039) |
| Individual fixed effects | | | |
| Dummies for ind. and occ. | | | x |
| Reserv. wage unit dummies | x | x | x |
| Other controls | | | x |
| Mean of dependent variable | 0.283 | 0.283 | 0.283 |
| Std. dev. of dep. var. | 0.451 | 0.451 | 0.451 |
| R2 | 0.007 | 0.007 | 0.043 |
| Observations | 1,993 | 1,993 | 1,993 |
| Individuals | 1,118 | 1,118 | 1,118 |

Note: Employment status during the first and second Follow-Up surveys. Linear probability models. Sample restricted to workers who were unemployed or employed for an employer (not self-employed) and not recalled. Industry and occupation indicators refer to the lost job. (***) $p < 0.01$, ** $p < 0.05$, * $p < 0.1$) See section 8.

Table A9: Reservation wage ratios and unemployment duration: Comparison with Krueger and Mueller and the model (weighted)

Reservation wage question: “Suppose someone offered you a job today that is suitable in terms of hours, skills, responsibilities and non-wage benefits. What is the lowest wage or salary, before taxes and deductions, you would accept? Please include in this amount any bonuses, overtime pay, tips or commissions that you would expect.”

Dependent variable = $100 \times \ln(\text{reservation wage}_{it}/\text{previous wage}_i)$

| | (1) | (2) |
|----------------------------|-------------------|----------------------|
| | Pooled | Longitudinal |
| | cross section | sample |
| Weeks unemployed | -0.215 (0.135) | -0.272*** (0.056) |
| Individual fixed effects | | x |
| Reserv. wage unit dummies | x | x |
| Other controls | x | |
| Mean of dependent variable | -3.883 | -4.039 |
| Std. dev. of dep. var. | 33.739 | 30.289 |
| R2 | 0.078 | 0.882 |
| Observations | 3,330 | 2,150 |
| Individuals | 2,024 | 844 |

Note: The reservation wage ratio is defined as the reported reservation wage divided by the wage on the previous job. Similar to Table 4 in the main text, but this table uses the CPS weights described in appendix B.3. (***) $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). See appendix C.5.

Table A10: Expected reservation wage ratios, unemployment duration, and dynamic selection (weighted)

Expected reservation wage questions: 1.) “If you don’t find suitable work in the next h months, would that change your mind about the lowest wage or salary you would accept?” in which $h \in \{1, 2, 3, 6\}$; and if yes, 2) “In that case, how much would you increase or decrease your lowest acceptable wage or salary?”

Dependent variable = $100 \times \ln(\text{expected reservation wage}_{it}/\text{previous wage}_i)$

| | (1) Pooled cross section | (2) Fixed effects |
|----------------------------|-----------------------------------|-------------------------|
| Weeks unemployed | -0.164*** (0.061) | -0.335*** (0.022) |
| Individual fixed effects | | x |
| Reserv. wage unit dummies | x | x |
| Other controls | x | |
| Mean of dependent variable | -5.323 | -5.323 |
| Std. dev. of dep. var. | 35.942 | 35.942 |
| R2 | 0.095 | 0.962 |
| Observations | 3,990 | 3,990 |
| Individuals | 1,995 | 1,995 |

Note: Expected reservation wages at all horizons (h) are measured during the Entry Survey. Similar to Table 5 in the main text, but this table uses the CPS weights described in appendix B.3. (***) $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). See appendix C.5.

Table A11: Reservation wage ratios, unemployment duration, and wage residuals (weighted)

Reservation wage question: “Suppose someone offered you a job today that is suitable in terms of hours, skills, responsibilities and non-wage benefits. What is the lowest wage or salary, before taxes and deductions, you would accept? Please include in this amount any bonuses, overtime pay, tips or commissions that you would expect.”

Dependent variable = $100 \times \ln(\text{reservation wage}_{it}/\text{previous wage}_i)$

| | (1) | (2) | (3) |
|---|--|---|--|
| | Without wage residual interactions | With linear wage residual interaction | With wage residual quartile interactions |
| Weeks unemployed | -0.272*** (0.056) | -0.263*** (0.068) | 0.101 (0.120) |
| Weeks unemployed \times wage residual | | -0.370** (0.145) | |
| Weeks unemployed \times Q2 | | | -0.411** (0.171) |
| Weeks unemployed \times Q3 | | | -0.487*** (0.155) |
| Weeks unemployed \times Q4 | | | -0.532*** (0.157) |
| Individual fixed effects | x | x | x |
| Reserv. wage unit dummies | x | x | x |
| Other controls | | | |
| Mean of dependent variable | -4.039 | -4.039 | -4.039 |
| Std. dev. of dep. var. | 30.289 | 30.289 | 30.289 |
| R2 | 0.882 | 0.883 | 0.883 |
| Observations | 2,150 | 2,150 | 2,150 |
| Individuals | 844 | 844 | 844 |

Note: For comparison, Column 1 reproduces our results from Table A9, column 2, in which we estimate a specification with individual fixed effects. Similar to Table 6 in the main text, but this table uses the CPS weights described in appendix B.3. (***) $p < 0.01$, ** $p < 0.05$, * $p < 0.1$) See appendix C.5.

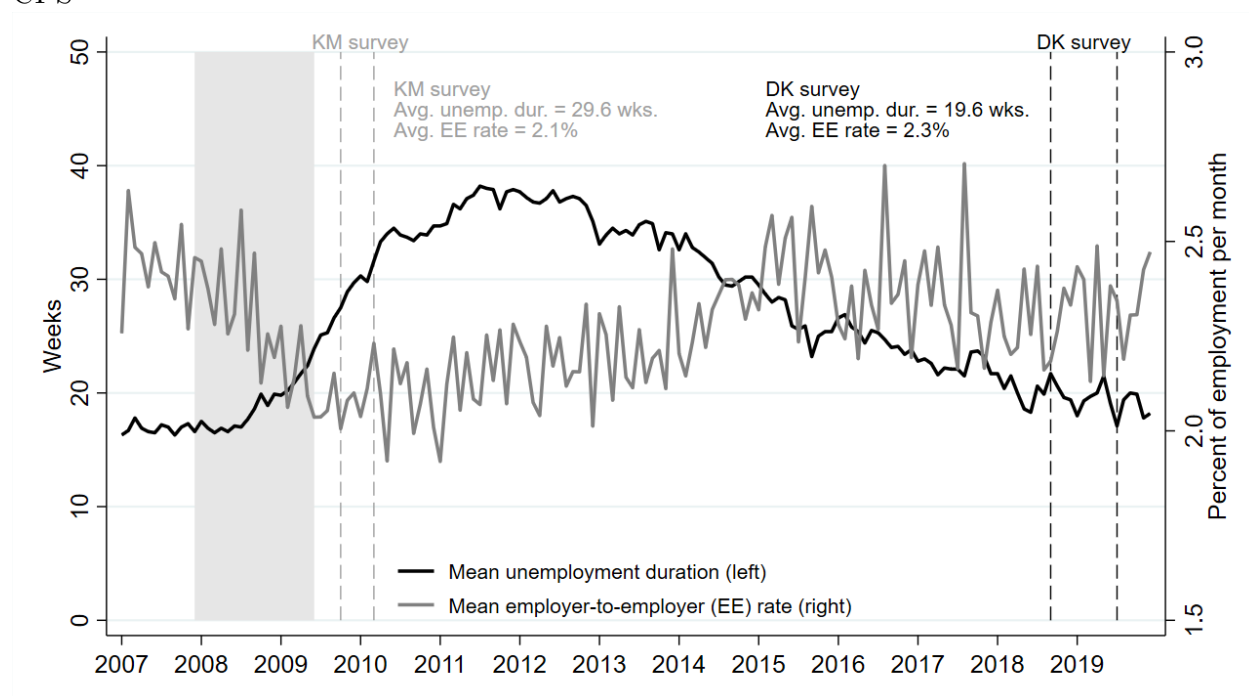
Table A12: Re-employment wages and reservation wages (weighted)

Dependent variable = $\ln(\text{re-employment wage}_{it})$

| | (1) | (2) | (3) | (4) |
|---|---------------------|---------------------|---------------------|---------------------|
| $\ln(\text{res. wage at Entry Survey})$ | 0.741*** (0.047) | 0.650*** (0.137) | 0.649*** (0.138) | 0.581*** (0.128) |
| $\ln(\text{previous wage})$ | | 0.097 (0.127) | 0.097 (0.127) | 0.156 (0.120) |
| Weeks unemployed | | | 0.001 (0.001) | 0.002* (0.001) |
| Individual fixed effects | | | | |
| Dummies for ind. and occ. | | | | x |
| Reserv. wage unit dummies | x | x | x | x |
| Other controls | | | | x |
| Mean of dependent variable | 3.080 | 3.080 | 3.080 | 3.080 |
| Std. dev. of dep. var. | 0.626 | 0.626 | 0.626 | 0.626 |
| R2 | 0.507 | 0.509 | 0.510 | 0.599 |
| Observations | 395 | 395 | 395 | 395 |
| Individuals | 395 | 395 | 395 | 395 |

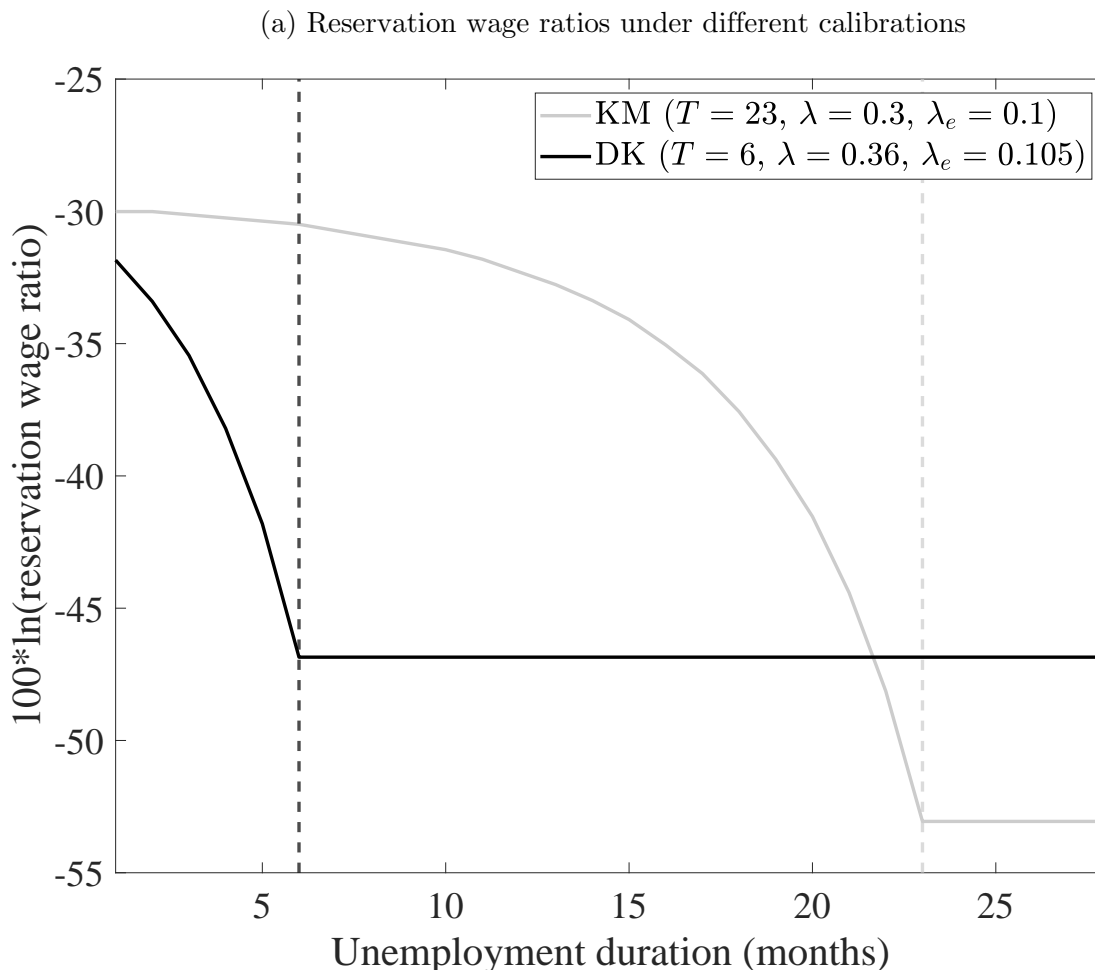
Note: Similar to Table 8 in the main text, but this table uses the CPS weights described in appendix B.3.
 (***) $p < 0.01$, ** $p < 0.05$, * $p < 0.1$) See appendix C.5.

Figure A1: Mean unemployment duration and employer-to-employer switching rates in the CPS



Note: Mean unemployment duration is provided from the Bureau of Labor Statistics (BLS). Mean EE rates are taken from [Fujita et al. \(2020\)](#). The former is seasonally adjusted by the BLS. The latter is seasonally adjusted using X-13-ARIMA-SEATS. As of January 2011, the unemployment duration top code rose from two years to five years. We subtract the difference between the December 2010 and January 2011 observations from all observations after December 2010 to create one series. Gray shading denotes NBER recessions. Vertical dashed lines denote the periods when the KM and DK surveys were in the field. See section 3.3.

Figure A2: The natural logarithm of reservation wage ratios in the model

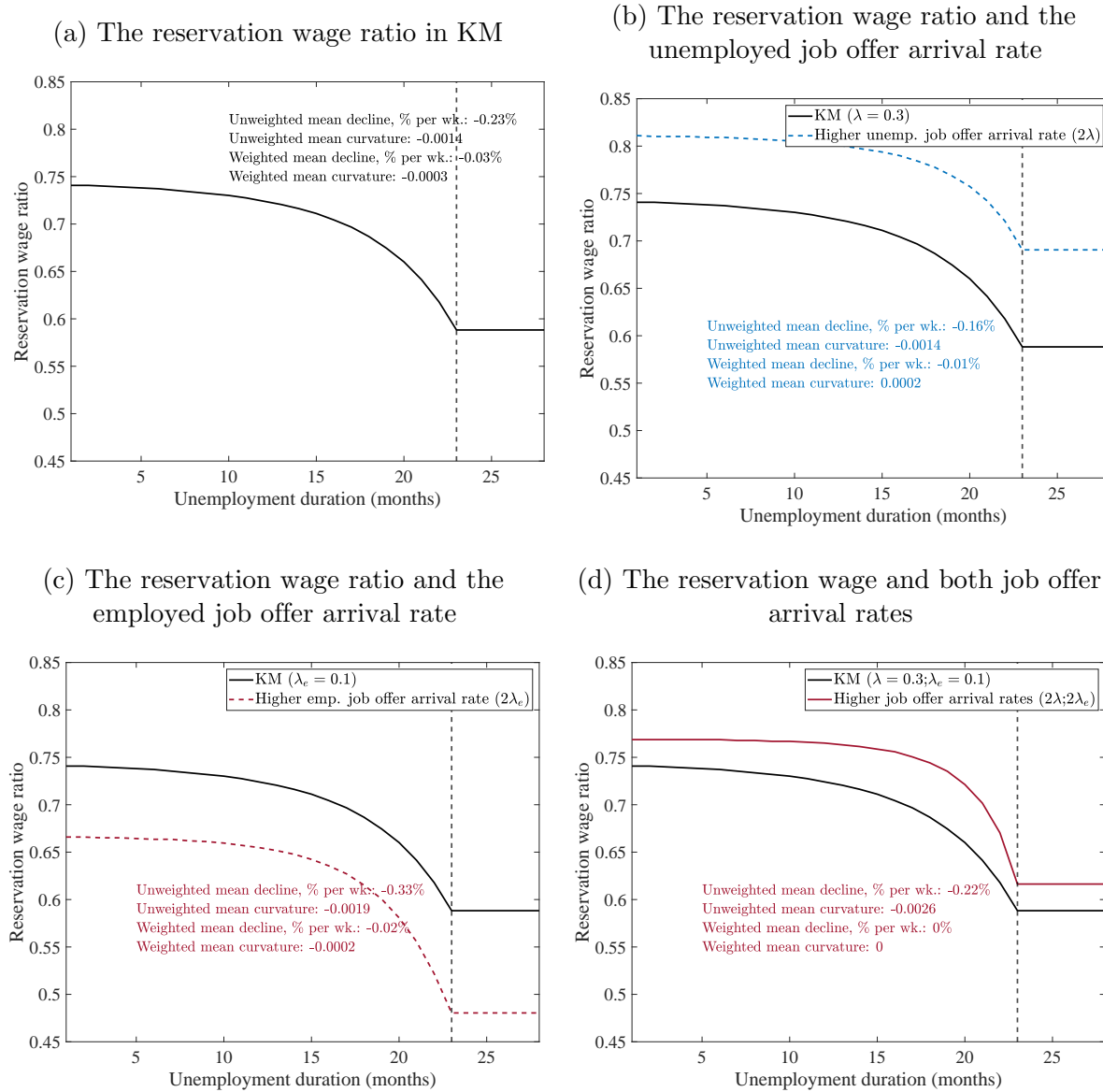


(b) Mean decline and curvature statistics for log reservation wage ratios

| | Mean decline (% per week) | | | | Average curvature (1/months) | | | |
|--------------------|---------------------------|---------|----------|---------|------------------------------|---------|----------|---------|
| | Unweighted | | Weighted | | Unweighted | | Weighted | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | [0, 6] | [0, 23] | [0, 6] | [0, 23] | [0, 6] | [0, 23] | [0, 6] | [0, 23] |
| KM ($t \leq 23$) | -0.02 | -0.23 | -0.02 | -0.03 | -0.0002 | -0.0014 | -0.0003 | -0.0003 |
| DK ($t \leq 6$) | -0.58 | | -0.51 | | -0.004 | | -0.0033 | |

Note: Exhibit A2a depicts 100 times the natural logarithm of the reservation wage ratio in the model calibrated to conditions during our survey (DK) and those during the KM survey (see columns 1 and 3 of Table 1, respectively). T denotes UI benefit duration, λ (λ_e) denotes job offer arrival rates while unemployed (employed), and t denotes unemployment duration in months. Vertical dashed lines denote UI benefit duration. Exhibit A2b shows unweighted and weighted mean declines and average curvatures under the DK and KM calibrations over two unemployment durations (0 to 6 months and 0 to 23 months). “Unweighted” statistics use a uniform distribution over unemployment duration. “Weighted” statistics use the distribution of unemployment duration from our sample in section 5, shown in Figure 3. We omit the statistics for our calibration for months [0, 23] because after month 6, the reservation wage is flat with $T = 6$. See Figure 1 for a figure with reservation wage ratios. See section 3.4.

Figure A3: Comparative statics with respect to job offer arrival rates when unemployed and employed

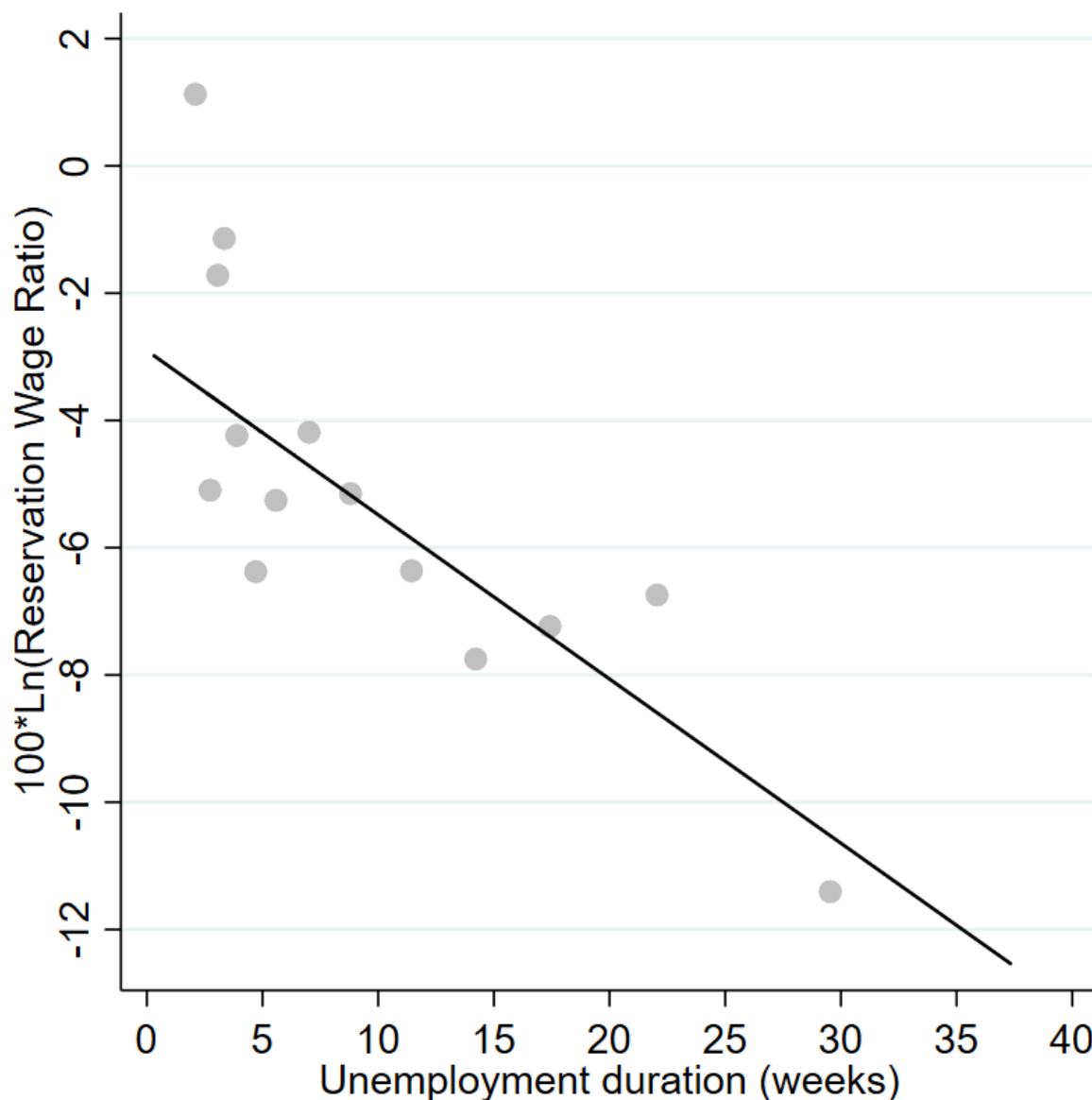


Note: The reservation wage ratio in the model and comparative statics with respect to job offer arrival rates on (λ_e) and off (λ) the job. Vertical dashed lines denote UI benefit duration. Figure A3a is based on the KM calibration in Table 1, column 3, and replicates Figure 1 in Krueger and Mueller (2016). This figure is copied onto each panel for reference. Figure A3b doubles the off-the-job offer arrival rate from 0.3 in the KM calibration. Figure A3c doubles the on-the-job offer arrival rate from 0.1 in the KM calibration. Figure A3d doubles both offer arrival rates and is the same as Figure 2c. Mean and curvature statistics computed over unemployment durations that are less than UI benefit duration (T). We define the average curvature as the mean of the curvature at each point. See footnote 3 for the definition of curvature. “Unweighted” statistics use a uniform distribution over unemployment duration. “Weighted” statistics use the distribution of unemployment duration from our sample in section 5, shown in Figure 3. See section 3.4.

Figure A4: Binned scatterplot of the $\ln(\text{reservation wage ratio})$ by unemployment duration

Reservation wage question: “Suppose someone offered you a job today that is suitable in terms of hours, skills, responsibilities and non-wage benefits. What is the lowest wage or salary, before taxes and deductions, you would accept? Please include in this amount any bonuses, overtime pay, tips or commissions that you would expect.”

Reservation wage ratio = reservation wage/previous wage

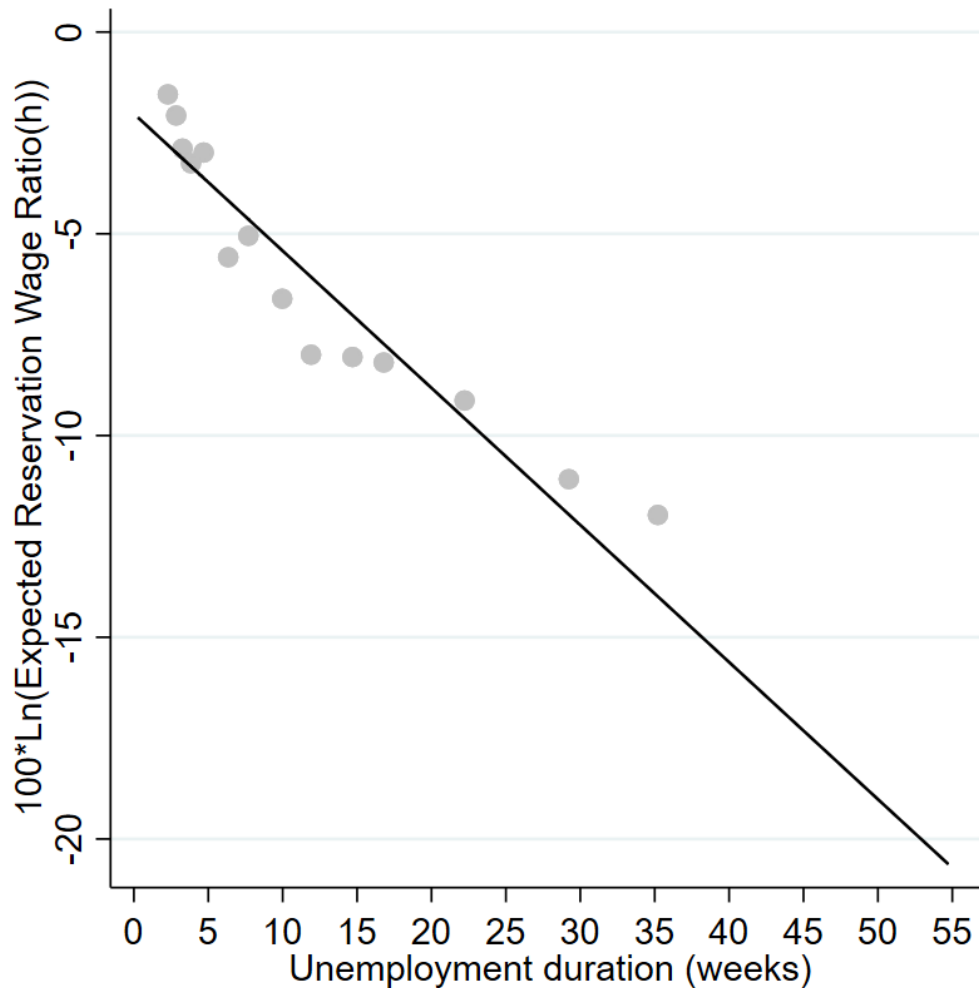


Note: Binned scatterplot of the natural log of the reservation wage ratio by unemployment duration measured at the Entry Survey, the first Follow-up Survey, and the second Follow-up Survey after controlling for individual fixed effects (Starr and Goldfarb, 2020; Cattaneo et al., 2023). Horizontal axis denotes individuals' unemployment duration at the time of their survey response. See section 5.1.

Figure A5: Binned scatterplot of the $\ln(\text{expected reservation wage ratio}(h))$ by unemployment duration

Expected reservation wage questions: 1.) “If you don’t find suitable work in the next h months, would that change your mind about the lowest wage or salary you would accept?”, in which $h \in \{1, 2, 3, 6\}$; and if yes, 2) “In that case, how much would you increase or decrease your lowest acceptable wage or salary?”

Expected reservation wage ratio = expected reservation wage/previous wage

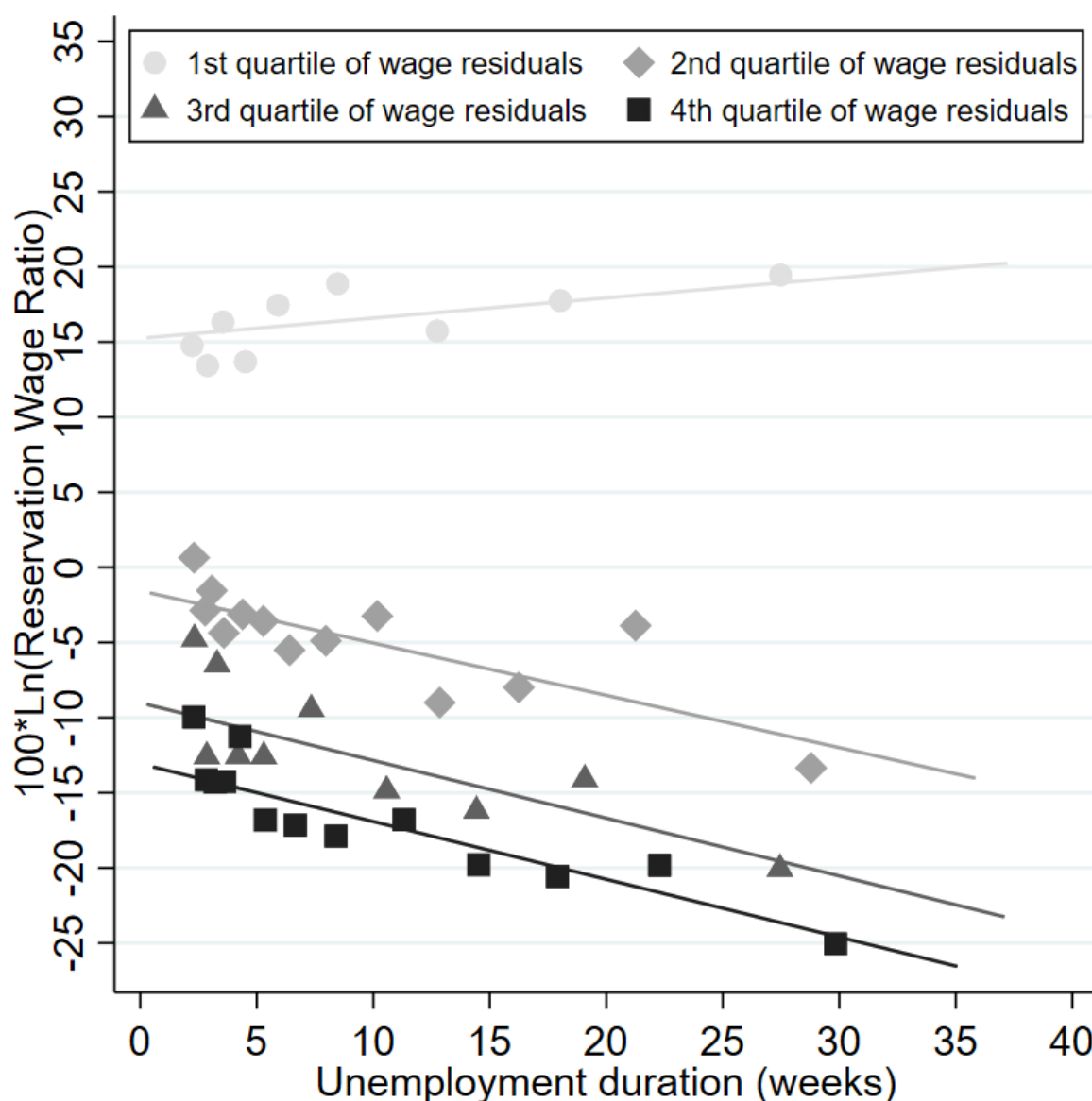


Note: Binned scatterplot of the natural log of the expected reservation wage ratio by unemployment duration after controlling for individual fixed effects (Starr and Goldfarb, 2020; Cattaneo et al., 2023). Expected reservation wages at all horizons (h) are measured during the Entry Survey. Horizontal axis denotes unemployment duration at hypothetical horizon h , which is randomized across individuals with $h \in \{1, 2, 3, 6\}$. The expected reservation wage at horizon $h = 0$ is equal to the reported reservation wage during the Entry Survey. As such, each individual has two expected reservation wage ratio observations: one from the Entry Survey and one from the hypothetical horizon. Unemployment duration is the unemployment duration at the time of the entry and the unemployment duration at the time of the entry survey plus the hypothetical horizon, which is randomized across individuals. For respondents who answer “no” to the question “If you don’t find suitable work in the next h months, would that change your mind about the lowest wage or salary you would accept?”, we assume that their reservation wage remains unchanged at horizon h . See section 6.2.

Figure A6: Binned scatterplot of the $\ln(\text{reservation wage ratio})$ by unemployment duration and wage residual on previous job

Reservation wage question: “Suppose someone offered you a job today that is suitable in terms of hours, skills, responsibilities and non-wage benefits. What is the lowest wage or salary, before taxes and deductions, you would accept? Please include in this amount any bonuses, overtime pay, tips or commissions that you would expect.”

Reservation wage ratio = reservation wage/previous wage

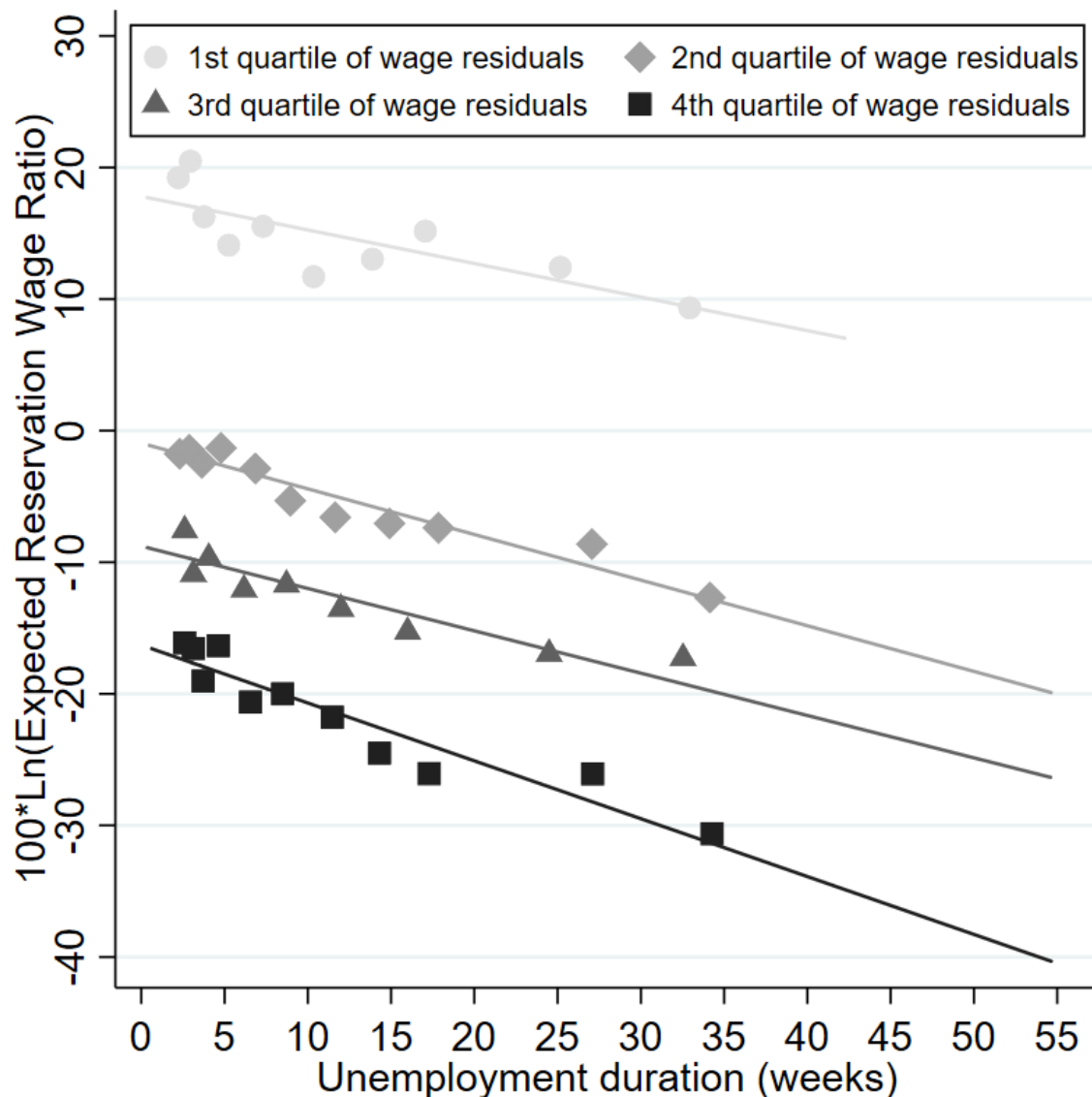


Note: Binned scatterplot of the natural log of the reservation wage ratio by unemployment duration and wage residual on the previous job after controlling for individual fixed effects ([Starr and Goldfarb, 2020](#); [Cattaneo et al., 2023](#)). Wage residuals are from a Mincerian wage equation, as described in the text. See section 7.2.

Figure A7: Binned scatterplot of the $\ln(\text{expected reservation wage ratio } (h))$ by unemployment duration and wage residual on previous job

Expected reservation wage questions: 1.) “If you don’t find suitable work in the next h months, would that change your mind about the lowest wage or salary you would accept?,” in which $h \in \{1, 2, 3, 6\}$; and if yes, 2) “In that case, how much would you increase or decrease your lowest acceptable wage or salary?”

Expected reservation wage ratio = expected reservation wage/previous wage



Note: Binned scatterplot of the natural log of the expected reservation wage ratio by unemployment duration and wage residual on the previous job after controlling for individual fixed effects (Starr and Goldfarb, 2020; Cattaneo et al., 2023). Expected reservation wages at all horizons (h) are measured during the Entry Survey. Horizontal axis denotes unemployment duration at hypothetical horizon h , which is randomized across individuals with $h \in \{1, 2, 3, 6\}$. The expected reservation wage at horizon $h = 0$ is equal to the reported reservation wage during the Entry Survey. As such, each individual has two expected reservation wage ratio observations: one from the Entry Survey and one from the hypothetical horizon. Unemployment duration is the unemployment duration at the time of the entry and the unemployment duration at the time of the entry survey plus the hypothetical horizon, which is randomized across individuals. For respondents who answer “no” to the question “If you don’t find suitable work in the next h months, would that change your mind about the lowest wage or salary you would accept?,” we assume that their reservation wage remains unchanged at horizon h . Wage residuals are from a Mincerian wage equation, as described in the text. See section 7.4.