Duration Dependence and Labor Market Experience*

Arne F. Lyshol[1] — Plamen T. Nenov[1] — Thea Wevelstad[2]

Abstract. We study whether unemployment duration dependence—the negative effect of a current unemployment spell on an individual's employment probability—varies with labor market experience. Using data from the National Longitudinal Survey of Youth and the Current Population Survey, we show that although there is negative duration dependence for experienced workers, it is mostly absent for new entrants to the labor force. This difference suggests that structural forces in addition to *ex ante* heterogeneity in job-finding probabilities and dynamic selection may drive unemployment duration dependence. Our findings are robust to the econometric model used and to a number of demographic controls and time trends, as well as individual fixed effects. We also discuss whether a number of theories of duration dependence can explain our empirical findings.

1. Introduction

The steep and persistent increase in long-term unemployment in many industrialized countries in the aftermath of the Great Recession has renewed research interest in unemployment duration dependence—the negative effect of a current unemployment spell on an individual's job-finding probability. If unemployment duration indeed affects job-finding probabilities, then it would tend to exacerbate individual workers' unemployment spells and lead to persistently elevated long-term unemployment (Kroft *et al.*, 2016). Such persistent negative employment effects would be particularly problematic for younger workers at the start of their careers who, as we show in this paper, face lower job-finding probabilities, as it may adversely impact their whole future career trajectories. On the other hand, if unemployment duration dependence is just a statistical phenomenon due to time-invariant (*ex ante*) heterogeneity in job-finding probabilities and dynamic selection, then a persistent increase in long-term unemployment would be of less concern for labor market performance.

In this paper, we study empirically how duration dependence varies with an individual's labor market experience and, specifically, how it varies between new entrants into the labor force and more experienced workers. Understanding how duration dependence varies with experience is important for two reasons. First, it can shed light on whether unemployment duration can indeed have a structural (causal) effect on job-finding probabilities (the so

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[1]BI Norwegian Business School, Oslo, Norway.
E-mail: arne.f.lyshol@bi.no
[2]Ocean Yield ASA, Lysaker, Norway.

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called 'true' duration dependence) or whether it is purely the outcome of unobserved *ex ante* heterogeneity in job-finding probabilities and dynamic selection out of the pool of unemployed. The reason for this is simple—every worker in the labor market necessarily starts her labor market career as an inexperienced new entrant. Therefore, if unobserved heterogeneity and dynamic selection are the only reasons for observed duration dependence, then one should expect to find duration dependence among both new entrants and experienced workers. Second, the study of duration dependence by experience informs the policy debate on the determinants and consequences of long-term youth unemployment (Scarpetta *et al.*, 2010).

Our main empirical finding is that duration dependence differs between new entrants and experienced workers. Specifically, in our benchmark estimation we find that although there is negative duration dependence for experienced workers, duration dependence is almost completely absent for new entrants into the labor force. This finding therefore suggests that unemployment duration dependence is not just a statistical artifact of *ex ante* heterogeneity and dynamic selection. It also suggests that elevated long-term youth unemployment should not be a major concern to policymakers beyond reflecting lower job-finding probabilities for young inexperienced workers at *any* unemployment duration.

For our main empirical finding, we use data from the U.S. National Longitudinal Survey of Youth 1979 (NLSY) and examine how duration dependence varies with a worker's labor market experience. We follow many of the survey respondents' transition from school to initial employment and through several years of subsequent employment and construct employment histories at weekly frequency. To explore our hypothesis, we estimate a variety of models of unemployment duration dependence. In these models, we look at the interaction effects between new entrant status and unemployment duration.

Our results are as follows. We find that duration dependence is stronger for experienced workers compared with new entrants into the labor force. For example, the weekly (re)employment probability for workers with some labor market experience declines by around 50% after 12–18 weeks of unemployment (from around 0.06 to around 0.03). In contrast, for new entrants into the labor force, the employment probability is roughly constant in the unemployment spell, at slightly <0.02. We show that these results are robust to a number of additional controls and estimation methods. They are also robust to using a non-linear model of duration dependence, such as a discrete-time proportional hazard model or a (log-)logistic model.

We then restrict attention to individuals with at least two unemployment spells, one of which is as a new entrant, and estimate a model with individual fixed effects. Adding individual fixed effects changes the estimated hazards substantially. Specifically, negative duration dependence is weakened substantially for experienced workers. For new entrants, the estimates with individual fixed effects still imply that new entrants have a lower employment probability on average, whereas the estimated hazard becomes upward sloping. Therefore, these results paint a complex picture for the determinants of duration dependence in the data. First, they suggest that unobserved heterogeneity in job-finding probabilities and dynamic selection is a driver of measured duration dependence in cross-sectional or single-spell data. Second, these results suggest that the structural relationship between unemployment duration and job-finding probabilities need not be negative at all durations or for all types of workers.

We further extend our empirical analysis beyond a comparison of new entrants and experienced workers by grouping workers into several experience bins by years of labor market experience and consider the interaction between experience and unemployment duration. We show that workers in the lowest experience group (which include new entrants and workers with up to 1 year of experience) have different employment hazards compared with the other groups, although there is little difference among the other groups. This suggests that our results are not spurious and that there are some underlying structural differences that lead to different employment hazards for workers with little or no labor market experience compared with other workers.

We examine the robustness of our main result by estimating duration dependence models using data from the U.S. Current Population Survey (CPS). Specifically, similar to Shimer (2008) and Rothstein (2011), we exploit the panel aspect of the survey (as the same individuals are interviewed over several consecutive months) to create individual-level indicators for unemployment-to-employment transitions. We obtain results that are very similar to the NLSY sample—there is negative duration dependence but duration dependence is weaker for new entrants into the labor market compared with experienced workers.[1]

Having established that a combination of a structural effect of unemployment duration together with *ex ante* heterogeneity in job-finding probabilities drives the observed employment hazards, we conclude by briefly discussing whether a number of theories of duration dependence proposed in the literature can explain our empirical findings. These include screening theories, models with skill depreciation or discouragement, ranking models, and models with recall. A screening theory of duration dependence (e.g., Fernandez-Blanco and Preugschat, 2018; Lockwood, 1991; Vishwanath, 1989) can be consistent with our findings, provided that new entrants are less efficient at job search compared with experienced workers.[2] Similarly, a skill depreciation or discouragement mechanism (e.g., Acemoglu, 1995; Gonzalez and Shi, 2010; Ljungqvist and Sargent, 1998; Pissarides, 1992), whereby experienced workers lose skills faster or become discouraged faster than new entrants when searching for employment, can also explain our results. We provide suggestive evidence for both of these mechanisms using information on search methods used from the NLSY97. On the other hand, ranking models as in Blanchard and Diamond (1994) cannot be consistent with our results, as ranking of workers is exogenous in those models, and one should expect duration dependence to be independent of labor market experience. Finally, our findings are consistent with models of recall (Fujita and Moscarini, 2017), whereby duration dependence among experienced workers is due to some of these workers being recalled back to their previous job.

1.1. Related literature

There is an extensive empirical literature dealing with unemployment duration dependence (e.g., van den Berg and van Ours, 1996; Dynarski and Sheffrin, 1990; Imbens and Lynch, 2006; Lynch, 1989; Machin and Manning, 1999; Shimer, 2008; Sider, 1985, among others). Similar to us, Imbens and Lynch (2006) also use data from the NLSY79 and find strong support for negative duration dependence. An important limitation of that and other studies, however, is that *ex ante* heterogeneity unobserved by the econometrician but observable to employers may be driving the observed duration dependence in the data. In fact, a large literature argues that duration dependence is mostly due to *ex ante* heterogeneity and dynamic selection effects (see, e.g., Ahn, 2016; Alvarez *et al*., 2016; Hornstein *et al*., 2012).[3] To circumvent this problem, a number of recent papers have relied on audit studies to identify structural duration dependence from unobserved heterogeneity (e.g., Eriksson and Rooth, 2014; Farber *et al*., 2019; Farber *et al*., 2016; Ghayad, 2013; Kroft *et al.*, 2013; Nunley *et al.*, 2017; Nüb, 2018; Oberholzer-Gee, 2008). These studies generally find support for structural duration dependence (in callback rates).[4]

Our study of the effects of unemployment duration by labor market experience, particularly among individuals with unemployment spells both as new entrant and as experienced worker, contributes to this large literature by making direct progress toward addressing the issue of *ex ante* heterogeneity and dynamic selection in measured duration dependence. As already discussed above, our finding of differential unemployment duration effects among new entrants and experienced workers implies that there is a structural link between duration and re-employment probabilities. This is further confirmed in our empirical model with individual fixed effects.[5] Moreover, to limit the issue of *time-varying* individual heterogeneity (e.g., due to differences in quality of the institution granting a college degree), we restrict our analysis to individuals who have a high school diploma, but never enroll in college.

A part of the literature considers the effect of history of labor force status on job-finding rates (e.g., Kudlyak and Lange (2017), and Shibata (2015)). Using the CPS and a new measure of duration of joblessness, Kudlyak and Lange (2017) show that the non-employed with a recent employment spell have higher job-finding rates than those who do not. This paper relates to ours in that new entrants have never had an employment spell, while experienced workers have, predicting that new entrants should have lower job-finding rates than experienced workers. Our paper complements this part of their paper by considering not only level differences, but also potential differences in duration dependence.

Finally, part of the empirical literature on duration dependence considers the interaction of unemployment duration with local or aggregate labor market conditions in an attempt to shed more light on the underlying mechanisms that give rise to duration dependence (Dynarski and Sheffrin, 1990; Vanden Berg and van Ours, 1996; Eubanks and Wiczer, 2016; Imbens and Lynch, 2006; Kroft *et al.*, 2013; Shimer, 2008). For example, Imbens and Lynch (2006) find that duration dependence is weaker for men living in high areas of unemployment. Similarly, Kroft *et al.* (2013) find that duration dependence in callback rates in their audit study is weaker in slacker labor markets. The main proposed explanation for these findings is the combination of employer screening and lower job-contact rates in recessions, which lower the information content of the unemployment spell for worker productivity. As we discuss in Section 6, such a mechanism is also consistent with our findings for weaker duration dependence among new entrants provided that new entrants are less efficient at job search compared with experienced workers.

The rest of the paper is organized as follows. We start by describing the data. Section 3 presents the econometric models we use for our estimation of duration dependence, and Section 4 presents our main results. Section 5 presents some robustness results. Section 6 discusses the theoretical implications of our empirical results. Finally, Section 7 provides brief concluding comments.

2. Data and Sample Selection

The *National Longitudinal Survey of Youth* Cohort 1979 (NLSY79) is a nationally representative sample covering 12,686 individuals who were between 14 and 22 years old when first surveyed in 1979.[6] Up to 1994, these individuals were interviewed annually after which they were interviewed on a biennial basis.

Individual labor force activity is detailed and includes start and stop dates for each job held since the last interview, periods in which individuals are not working but are still with an employer, and labor market status (looking for work, out of the labor force, etc.). The survey also includes information about educational enrollment, military service, family, and demographics. A summary of the variables we use from NLSY is provided in Table 1.

We restrict the sample to only include workers who have completed high school and do not enroll in college throughout the sample period. Considering only high school graduates alleviates potential issues with unobserved heterogeneity, that may be worsened by including individuals that also enroll in college. Thus, we consider individuals that start out in 1979 as high school graduates who are not enrolled in college and stay in that state for the whole sample period or individuals that start out as enrolled in high school and eventually transition to 'not enrolled, high school graduate' and are never enrolled in college. This excludes 1664 individuals that never finished high school and 5885 individuals that eventually enrolled in college. Further, we restrict our sample to only include those who are below 18 years in 1979. This ensures that those who might have graduated from high school already and potentially have been enrolled in college before 1979 or have unreported employment experience are excluded from the sample. A further 2386 individuals are dropped in this step. We drop 41 individuals who have been incarcerated. 187 individuals never report a qualifying unemployment spell. Finally, new entrant status cannot be generated for 18 individuals. Once we have restricted the sample, we are left with a set of individuals that as of 1979 have already finished high school and a set of individuals that as of 1979 are still in high school but eventually finish high school. This leaves a total of 2505 individuals. Table A2 in the Appendix 1 reports summary statistics for both the full and cross-sectional sample only.

We follow these individuals from 1979 to 2014 and create a weekly panel of employment status for each of them (a total of 1930 weeks per individual). Using the individual employment status, we construct an indicator variable rei_{it} for transition from unemployment to employment. Hence, the variable equals 0 if the individual is currently unemployed and stays unemployed in the following week or 1 if the individual is currently unemployed and becomes employed in the following week.[7] In all other cases (e.g., individual is currently employed and stays employed, or individual is currently out of the labor force and stays out of the labor force), the observation is dropped. Furthermore, we consider unemployment spells with a maximum unemployment duration of 2 years or 104 weeks. This leaves us with a total of 230,991 individual-week observations. Out of those, 191,699 are observations in which new entrant status can be determined (see below).

Table 1. Relevant variables in the NLSY79 data set

NLSY79 variable	Description	Possible values
CASEID_1979	Individual identifier	–
AGE_1979	Age of individual	In years
SAMPLE_RACE_1979	Race of individual	Numerical categories
SAMPLE_SEX_1979	Sex of individual	1—male; 2—female
*ENROLLMTREV79_0000**	Education level	Numerical categories
*STATUS_WK_NUM0000****	Employment status	Numerical categories
*JOBSNUM_0000**	Number of unique jobs	Non-negative integer

*Yearly variables.
***Weekly variables.

We create a running count of unemployment spell lengths for unemployed individuals. Next, we create a variable for whether an individual is a new entrant into the labor market in a particular year. To identify which individuals are new entrants and when they enter, we utilize the *JOBSNUM* variable. This variable reports the number of jobs ever held by the individual as of the interview date. An individual is treated as a new entrant for every year where he or she reports having held zero jobs. Hence, a new entrant is a worker without any previous work experience. New entrant status lasts until the week the worker reports finding work. Of the remaining 2505 individuals, 660 are classified as a new entrant for at least one unemployment spell.

Note that some high school graduates may have already accumulated some work experience while enrolled in high school. These are then classified as experienced workers after high school graduation and not as new entrants. Conversely, as individuals are allowed to report employment status while enrolled in high school, workers that are enrolled in high school and have no previous jobs held will be classified as new entrants. Therefore, the spell lengths we compute for new entrants potentially include weeks where the individual was in her last year of high school.

3. Econometric Models

The NLSY survey provides a flow sample of individual unemployment spells. As the NLSY records the employment status of an individual at a weekly frequency, we have a panel data set where the time interval for counting duration is a week. Hence, we will treat the data set as grouped duration data (see Wooldridge (2010)) and estimate discrete-time hazard models.

We estimate the following linear probability model as our baseline specification

$$rei_{it} = \alpha_0 + \alpha_1 n_i + \alpha_2 t + \alpha_3 (n_i \times t) + \varepsilon_{it}, \qquad [1]$$

where rei_{it} is an indicator for whether an individual i who is unemployed for t weeks becomes employed in week $t+1$, or

$$rei_{it} = 1\{\text{unemployed}_{it} \rightarrow \text{employed}_{it+1}\},$$

t denotes the unemployment spell for that individual, n_i is an indicator variable that equals 1 if the individual has started the unemployment spell as a new entrant into the labor force, $n_i \times t$ is an interaction effect, and ε_{it} is a mean zero error term.[8] We choose a linear probability model as our benchmark to alleviate concerns of model misspecification and, in particular, neglected heterogeneity (Wooldridge, 2010). In addition, simple linear models have been used in recent studies of duration dependence (e.g., Kroft *et al.* (2013)). Later on in Section 5.2, we present the results from estimating a group-specific proportional hazard model and a log-logistic hazard model.

In addition to the specification in equation (1), we also estimate specifications with individual controls and with time fixed effects to control for seasonal and cyclical effects in job-finding probabilities. As shown by Imbens and Lynch (2006) for the NLSY, seasonal and cyclical factors are important determinants of individual job-finding probabilities.[9] Finally, we also estimate versions of the model with the log of unemployment duration.

The NLSY follows the same individual over many periods, including possibly over several unemployment spells. For our baseline results, we treat different unemployment spells by the same individual separately. However, to better account for potentially unobserved heterogeneity across individuals with different levels of prior labor market experience, we follow Faberman and Kudlyak (2019) and also estimate a version of equation (1) with individual fixed effects. In that case, we restrict the sample further to individuals for which we observe at least two unemployment spells and at least one of these spells is a new entrant spell.

Finally, rather than classifying workers into new entrants and experienced workers, we also estimate equation (1) with a more detailed classification on labor market experience. Specifically, we group workers into 4 bins based on their labor market experience as of the start of their contemporaneous unemployment spell and estimate the models for each group.

4. Results

4.1. New entrants versus experienced workers

Figure 1 plots the employment hazards for new entrants and experienced workers. It is immediately evident from the figure that there is both a level and a slope difference between the two hazards. Specifically, experienced workers have a higher probability of being (re-)employed at any unemployment duration compared with new entrants. However, although for new entrants the employment hazard is essentially flat, for experienced workers it declines by around 50% in the first 12–18 weeks.

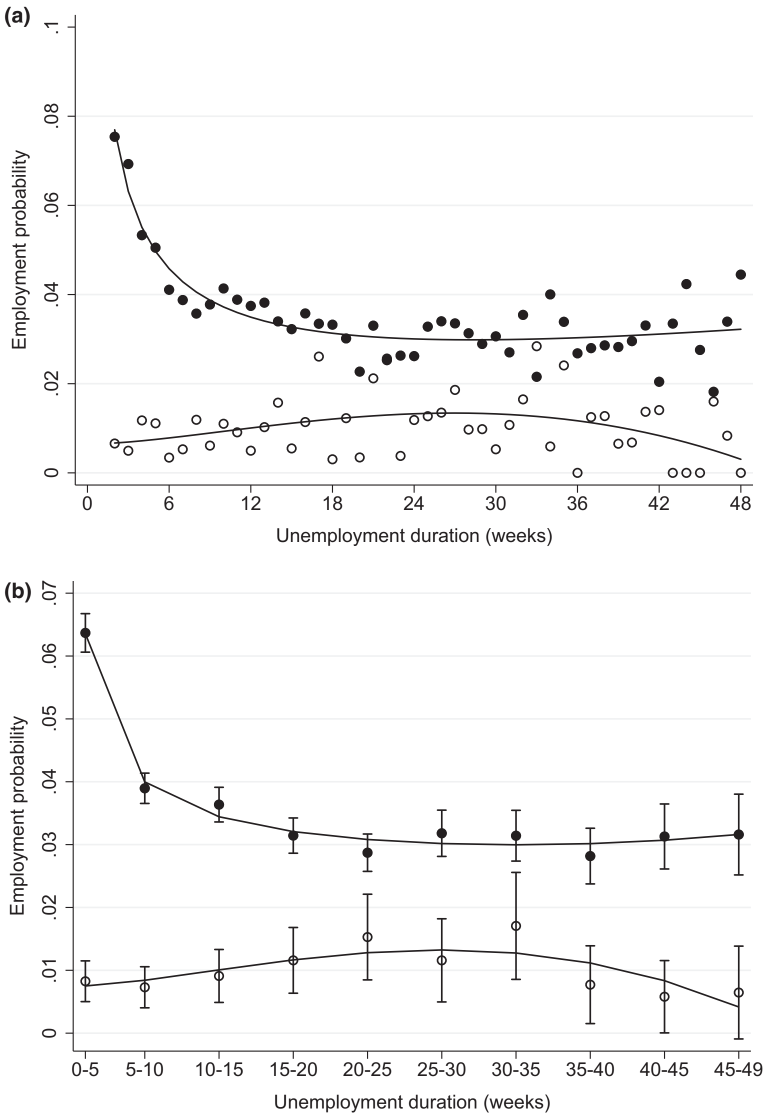
Next, we turn to the estimation results for equation (1), which we present in Table 2. The negative coefficient for the new entrant indicator shows that new entrants have a lower probability of finding a job compared with more experienced workers. Furthermore, the coefficient on the interaction term between the new entrant indicator and unemployment duration is positive and statistically significant and robust to demographic controls and time fixed effects. The time fixed effects are for week by year and therefore a flexible control for labor market seasonality. Most are significant at the 1% level, and some are significant at the 5% level. It is also comparable in magnitude to the estimated coefficient on unemployment duration, indicating that the difference in slopes between the two groups is substantial and that the hazard for new entrants is close to flat.[10]

4.2. Results with individual fixed effects

Table 3 reports the estimation results with individual fixed effects for the restricted sample of individuals with an unemployment spell as new entrant and as experienced worker. This restriction reduces the sample size significantly and could introduce biases due to selection. However, estimating the baseline model (without fixed effects) on this reduced sample yields nearly identical results to the full sample (see Table A7 in the Appendix), suggesting that biases due to selection in sample are likely small. Comparing with the coefficient estimates from Table 2, we see that duration dependence for experienced workers is substantially weaker in this case. The coefficient estimates are close to zero in the specifications where duration dependence is linear in the spell length and are approximately halved

Figure 1. Employment hazard in the NLSY for experienced workers and new entrants (a) and by bins (b) (linear probability model).

Note: Hollow and solid dots are estimated (re-)employment probabilities for new entrants and experienced workers, respectively. A new entrant is an individual reporting having held zero jobs. Unemployment duration is computed by counting the number of consecutive weeks the worker reports being unemployed. Line of fit is a fractional polynomial. 95% confidence internals estimated with individual-level clusters in panel (b)



in magnitude for the specifications with the log of unemployment duration. In contrast, both the level effects of new entrant status and the coefficient estimates for the interaction between unemployment duration and new entrant status remain mostly unchanged.

Figure 2 plots the (re-)employment hazards for the two groups of workers with individual fixed effects, again confirming that duration dependence among experienced workers is

Table 2. Duration dependence: new entrants vs. experienced workers—linear probability model

	(1)	(2)	(3)	(4)	(5)	(6)
New entrant	−0.0423**	−0.0352**	−0.0363**	−0.0612**	−0.0530**	−0.0550**
	(0.0015)	(0.0016)	(0.0017)	(0.0023)	(0.0024)	(0.0026)
Unemployment duration (weeks)	−0.0005**	−0.0004**	−0.0005**			
	(0.0000)	(0.0000)	(0.0000)			
Duration × New Entrant	0.0006**	0.0005**	0.0005**			
	(0.0000)	(0.0000)	(0.0001)			
Log(unempl. duration)				−0.0119**	−0.0105**	−0.0103**
				(0.0005)	(0.0005)	(0.0005)
Log(duration) × New Entrant				0.0125**	0.0117**	0.0125**
				(0.0008)	(0.0008)	(0.0010)
Observations	206,347	206,347	206,347	206,347	206,347	206,347
Individuals	2505	2505	2505	2505	2505	2505
Unemployment spells	15,425	15,425	15,425	15,425	15,425	15,425
New entrant spells	1005	1005	1005	1005	1005	1005
Adjusted R^2	0.005	0.008	0.014	0.007	0.010	0.015
Demographic	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes

Note: The dependent variable is an indicator for whether a worker found a job within a week. New entrant is an indicator for whether an individual reported has held zero jobs. Unemployment duration is computed by counting the number of consecutive weeks the worker reports being unemployed. Demographic controls include age, age-squared, gender, and race. Time fixed effects are for each week in the sample. Standard errors in parenthesis are clustered on individuals.
* and ** indicate significance at the 5% and 1% levels, respectively.

substantially lower once one controls for individual fixed effects. In fact, duration dependence for experienced workers appears to be slightly positive after the first 15 weeks of unemployment. This could be related to the effects of unemployment benefit exhaustion and unemployed workers becoming more willing to accept job offers with lower match quality (Chetty, 2008; Farber et al., 2015; Lyshol, 2020). In contrast, with individual fixed effects the duration dependence of new entrants is no longer flat but rather upward sloping. This could be due to, e.g., new entrants taking some time to increase their search effort as they progress through their unemployment spell.[11]

Therefore, these results suggest that in addition to structural dependence, which may be either negative or *positive*, *ex ante* heterogeneity and dynamic selection are also important for the measured duration dependence in cross-sectional or individual spell data and may obfuscate a more complicated underlying structural dependence relationship.

4.3. Duration dependence by labor market experience

Next, we present coefficient estimates for the linear probability model with multiple experience bins. We separate workers into four bins based on their labor market experience (in years) at the start of their contemporaneous unemployment spell—0–1 years, 1–5 years, 5–10 years, and 10+ years. The estimation results are presented in Figure 3. The figure presents the estimated coefficients (intercept (3) and unemployment duration slope (3)) for each group.

Table 3. Duration dependence: new entrants vs. experienced workers—individual fixed-effects estimation

	(1)	(2)	(3)	(4)	(5)	(6)
New entrant	−0.0447**	−0.0343**	−0.0316**	−0.0622**	−0.0506**	−0.0473**
	(0.0030)	(0.0036)	(0.0040)	(0.0042)	(0.0046)	(0.0047)
Unemployment duration (weeks)	−0.0001*	−0.0000	−0.0000			
	(0.0001)	(0.0001)	(0.0001)			
Duration × New Entrant	0.0005**	0.0004**	0.0004**			
	(0.0001)	(0.0001)	(0.0001)			
Log(unempl. duration)				−0.0050**	−0.0042**	−0.0042**
				(0.0010)	(0.0010)	(0.0010)
Log(duration) × New Entrant				0.0116**	0.0106**	0.0106**
				(0.0015)	(0.0014)	(0.0014)
Observations	59,332	59,332	59,332	59,332	59,332	59,332
Individuals	516	516	516	516	516	516
Unemployment spells	4119	4119	4119	4119	4119	4119
New entrant spells	789	789	789	789	789	789
Adjusted R^2	0.023	0.025	0.025	0.023	0.025	0.026
Demographic	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes

Note: The dependent variable is an indicator for whether a worker found a job within a week. New entrant is an indicator for whether an individual reported has held zero jobs. Unemployment duration is computed by counting the number of consecutive weeks the worker reports being unemployed. Demographic controls include age and age-squared. Time fixed effects are for each year in the sample. Individuals must have had two spells, of which at least one ended with a job. Standard errors in parenthesis are clustered on individuals. * and ** indicate significance at the 5% and 1% levels, respectively.

As is clear from the figures, the lowest experience bin (which includes the new entrants) has a very different employment hazard compared with the other groups, although there is little statistically significant difference between the other groups. This further suggests that our results are not spurious and that there are some underlying differences that lead to different employment hazards for workers with very low or no labor market experience compared with other workers.[12]

5. Robustness

5.1. Results using the CPS

We confirm our main empirical results using data from the Current Population Survey (CPS). To this end, we follow the approach from Shimer (2008) and Kudlyak and Lange (2017) and exploit the panel dimension of the CPS data. One important difference of these data relative to the NLSY is that we observe a cross section of individuals with different initial unemployment spells (stock sampling). We use the reported number of weeks a respondent has been without a job and looking for work as a measure of unemployment duration. A question on reason for unemployment allows us to identify new entrants as those looking for their first ever job. Table 4 compares the sample construction of NLSY79 and CPS. In the Appendix, we provide details on the data and our sample selection. There, we also include some additional results on duration dependence in the CPS, which we omit from the main text for brevity.

Figure 2. Employment probabilities in the NLSY: Experienced workers (solid) and new entrants (hollow) by bins with individual fixed effects.
Note: Hollow and solid dots are estimated (re-)employment probabilities for new entrants and experienced workers, respectively. A new entrant is an individual reporting having held zero jobs. Unemployment duration is computed by counting the number of consecutive weeks the worker reports being unemployed. 95% confidence internals estimated with individual-level clusters. Line of fit is a fractional polynomial

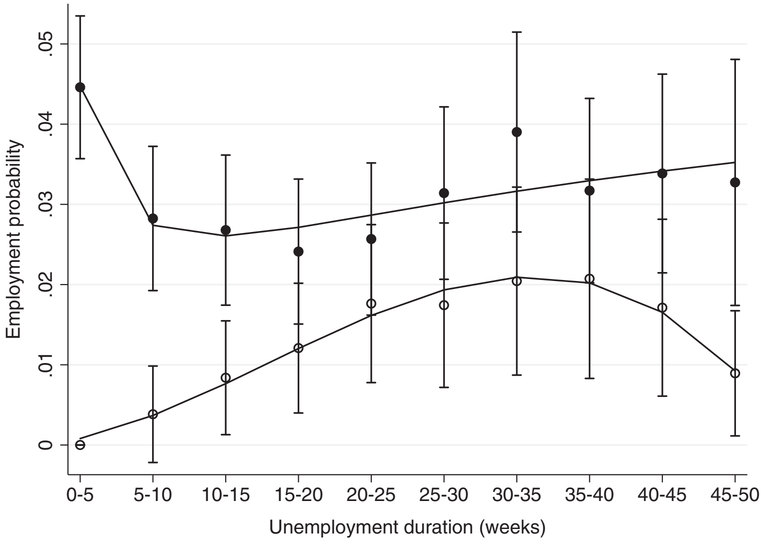


Figure 4 reports the difference in (re-)employment hazards between experienced workers and new entrants in the CPS, where the employment hazards of each group are estimated in a linear regression with demographics and year fixed effects by state. First, we again observe a level difference between the two hazards, indicating that, as in the NLSY, it is in general more difficult for new entrants to find a job compared with experienced workers. The magnitude of the difference (around 0.1) is in line with the difference from the NLSY estimates (cf. Figure 5), considering that the CPS estimates are for monthly employment probabilities and the NLSY estimates are for weekly employment probabilities. Second, there is a difference in slopes, with experienced workers significantly more likely to find a job at short durations (at 12 weeks or less) than new entrants compared with longer durations (12 weeks and more). This indicates that duration dependence is stronger for experienced workers as was the case in the NLSY data.

Tables 5 and 6 present estimation results for a linear probability model and a logit model that provide further support for these observations. The estimates are robust to including demographic controls and state–year fixed effects. All estimates are in line with the estimates from the NLSY and confirm that in the CPS, new entrants also face flatter employment hazards compared with experienced workers.

5.2. Other econometric models

In addition to the linear probability model for the (re-)employment probability, we estimate a group-specific proportional hazard model, which is a standard model used in duration analysis.[13] Specifically, we estimate the following proportional hazard model, for our baseline specification.[14]

Figure 3. Linear probability model estimates—multiple experience bins.
Note: The figures plot the intercept and slope estimates for the equation $\text{rei}_{\text{it}} = \alpha_0 + \alpha_1 t$, where rei_{it} is an indicator for whether the worker found a job in that week, and t is unemployment duration in weeks. Unemployment duration is computed by counting the number of consecutive weeks the worker reports being unemployed. Experience is computed by counting the number of weeks the worker reports working. The model is estimated separately for four different experience groups, and in addition includes controls for demographics (age, age-squared, gender, and race) and year fixed effects. Each estimate includes a 95% confidence interval estimated with individual-level clusters

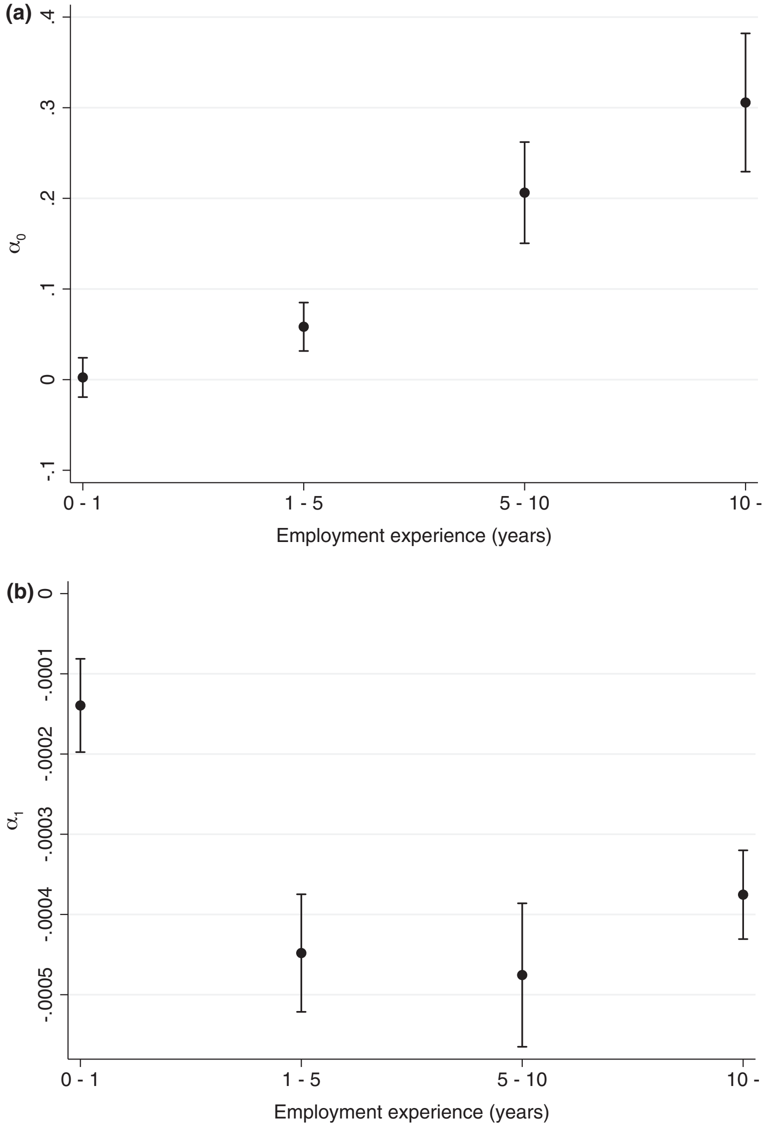
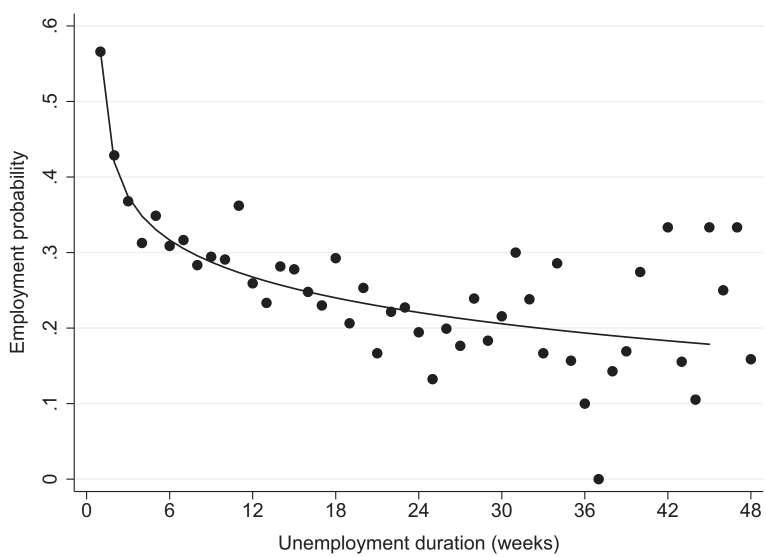


Table 4. Comparison of CPS and NLSY79 sample construction

	NLSY79	**CPS**
Education	High school only	High school only
Years	1979–2014	1994–2018*
Age	Between 14 and 18 in 1979	17–64
Unemployment duration cutoff	104 weeks	104 weeks
Individuals with incarceration history	Discarded	N/A

*We include CPS data from 1979, but poorer labor market activity data in early years limit it to 1994–2018 in the sample selection process.

Figure 4. Difference in employment probabilities between experienced workers and new entrants (CPS).
Note: The figure shows the difference between the employment probabilities of experienced workers and new entrants at each week of duration. A new entrant is an individual reporting being a new entrant to the labor market. Unemployment duration is the number of weeks the survey responded reported being unemployed before finding a job. Line of fit is a fractional polynomial capped at 45 weeks



$$P(rei_{it}=1)=F(\alpha_0+\alpha_1 n_i+\alpha_2 t+\alpha_3(n_i\times t)), \qquad [2]$$

with $F(y)=1-\exp\{-\exp\{y\}\}$. In equation (2), rei_{it} is an indicator variable for whether an individual i who is unemployed for t weeks becomes employed in week $t+1$, n_i is an indicator that equals 1 if the individual has started the unemployment spell as a new entrant into the labor force, and $n_i\times t$ is an interaction effect. We also estimate specifications with individual controls and calendar week indicators, as well as versions of the model with the log of unemployment duration.[15]

Figure 5 plots the estimated employment hazards for experienced workers and new entrants. The estimated hazards are very similar to those in Figure 5—flat for new entrants

Figure 5. Employment hazards in the NLSY: experienced workers (solid) and new entrants (hollow) (proportional hazard model).

Note: Line of fit is a fractional polynomial. A new entrant is an individual reporting being a new entrant to the labor market. Unemployment duration is the number of weeks the survey responded reported being unemployed before finding a job

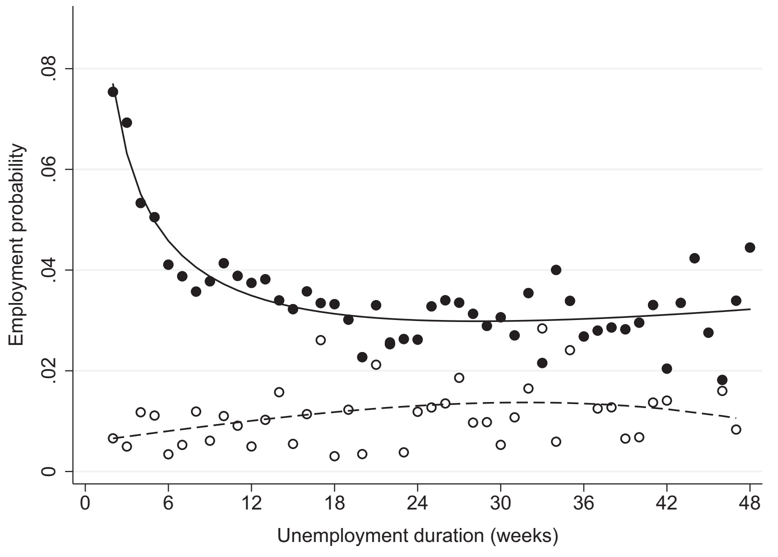


Table 5. Estimation results for CPS – linear probability model

	(1)	(2)	(3)	(4)	(5)	(6)
New entrant	−0.0975**	−0.1073**	−0.0942**	−0.1318**	−0.1346**	−0.1210**
	(0.0128)	(0.0135)	(0.0136)	(0.0206)	(0.0209)	(0.0212)
Unemployment duration	−0.0057**	−0.0054**	−0.0046**			
	(0.0001)	(0.0001)	(0.0001)			
Duration × New Entrant	0.0023**	0.0021**	0.0017**			
	(0.0004)	(0.0004)	(0.0005)			
Log(unempl. duration)				−0.1035**	−0.1002**	−0.0905**
				(0.0019)	(0.0019)	(0.0021)
Log(duration) × New Entrant				0.0359**	0.0347**	0.0311**
				(0.0050)	(0.0074)	(0.0076)
Observations	41,696	41,696	41,696	41,589	41,589	41,589
Individuals	39,919	39,919	39,919	39,813	39,813	39,813
New entrants	2772	2772	2772	2758	2758	2758
Adjusted R^2	0.044	0.049	0.063	0.068	0.072	0.083
Demographic	No	Yes	Yes	No	Yes	Yes
State × Year FE	No	No	Yes	No	No	Yes

Note: The dependent variable is an indicator for whether the worker found a job within a week. New entrant is an indicator for whether the survey respondent reported being a new entrant to the labor market. Unemployment duration is the number of weeks the survey responded reported being unemployed before finding a job. Demographic controls include age, age-squared, gender, and race. Robust standard errors in parenthesis.

**Indicates significance at 1%.

Table 6. Estimation results for CPS— logit model

	(1)	(2)	(3)	(4)	(5)	(6)
New entrant	−.4483**	−.4868**	−.4451**	−.5363**	−.5531**	−.5129**
	(0.0621)	(0.0650)	(0.0673)	(0.0937)	(0.0954)	(0.0999)
Unemployment duration (weeks)	−0.0317**	−0.0305**	−0.0275**			
	(0.0009)	(0.0009)	(0.0009)			
Duration × New Entrant	0.0123**	0.0117**	0.0101**			
	(0.0029)	(0.0029)	(0.0029)			
Log(unempl. duration)				−.4852**	−.4722**	−.4462**
				(0.0097)	(0.0098)	(0.0105)
Log(duration) × New Entrant				0.1385**	0.1343**	0.1263**
				(0.0390)	(0.0391)	(0.0407)
Observations	41,696	41,687	41,626	41,589	41,580	41,519
Individuals	39,919	39,910	39,853	39,813	39,804	39,747
New entrants	2772	2770	2763	2758	2756	2749
Log-likelihood	−25,538	−25,411	−24,494	−25,072	−24,958	−24,068
Demographic	No	Yes	Yes	No	Yes	Yes
State × Year FE	No	No	Yes	No	No	Yes

Note: The dependent variable is an indicator for whether the worker found a job in that week. New entrant is an indicator for whether the survey respondent reported being a new entrant to the labor market. Unemployment duration is the number of weeks the survey responded reported being unemployed before finding a job. Demographic controls include age, age-squared, gender, and race. Standard errors in parenthesis.
**Indicates significance at 1%.

and strongly decreasing up to around 12–18 weeks for experienced workers. Moreover, the estimation results reported in Table 7 again confirm these results even when one controls for demographics or includes a flexible time trend.

6. Theoretical implications

In this section, we briefly discuss different theoretical frameworks, which have been proposed in the literature on duration dependence, and whether they can explain our empirical findings.

6.1. Screening

The informational role of unemployment duration for hiring decisions in an environment with asymmetric information about worker productivity and costly employer screening has been pointed out by Vishwanath (1989) and Lockwood (1991), among others. If workers with higher ability exit from unemployment at a faster rate than workers with low ability, then the resulting dynamic selection implies that a worker's unemployment spell contains information about his ability that firms utilize when making their hiring decisions. Our empirical results are consistent with such a mechanism, provided that new entrants have a lower job search efficiency compared with experienced workers. Under this assumption, new entrants have lower job-finding rates compared with experienced workers. Also, the dynamic selection effect is weaker for new entrants and, so, unemployment duration is less informative about worker ability compared with experienced workers. Consequently, the worker's employment probability decreases less over time.

Table 7. Duration dependence: new entrants vs. experienced workers—proportional hazard model (NLSY)

	(1)	(2)	(3)	(4)	(5)	(6)
New entrant	−1.773**	−1.574**	−1.598**	−2.213**	−20.003**	−20.027**
	(0.1092)	(0.1096)	(0.1113)	(0.1925)	(0.1942)	(0.1968)
Unemployment duration	−0.0174**	−0.0145**	−0.0144**			
	(0.0009)	(0.0009)	(0.0009)			
Duration × New Entrant	0.0200**	0.0178**	0.0184**			
	(0.0035)	(0.0035)	(0.0035)			
Log(unempl. duration)				−0.2810**	−0.2507**	−0.2481**
				(0.0098)	(0.0101)	(0.0102)
Log(duration) × New Entrant				0.3480**	.3294**	.3368**
				(0.0682)	(0.0689)	(0.0693)
Observations	206,347	206,347	206,347	206,347	206,347	206,347
Individuals	2505	2505	2505	2505	2505	2505
Unemployment spells	15,425	15,425	15,425	15,425	15,425	15,425
New entrant spells	1005	1005	1005	1005	1005	1005
Log-likelihood	−33,612	−33,222	−33,175	−33,479	−33,084	−33,041
Demographics	No	Yes	Yes	No	Yes	Yes
Year FE	No	No	Yes	No	No	Yes

Note: The dependent variable is an indicator for whether the worker found a job in that week. New entrant is an indicator for whether an individual reported has held zero jobs. Unemployment duration is computed by counting the number of consecutive weeks the worker reports being unemployed. Demographic controls include age, age-squared, gender, race, and AFQT scores. Standard errors in parenthesis are clustered on individuals.
* and ** indicate significance at the 5% and 1% levels, respectively.

Whether new entrants have lower job contact rates compared with experienced workers is an open question. New entrants enter the labor market with no experience in job search and with a more limited social network of currently employed contacts, which they can utilize to improve their job search outcomes compared with more experienced workers.[16] However, they may partially compensate for that by exerting higher search effort, e.g., by using more search methods compared with experienced workers. Our estimation with individual fixed effects from Section 4.2 showed that for the same individual, new entrant status is associated with a 4 percentage point lower weekly employment probability. This finding is consistent with either lower job search efficiency or lower search effort by new entrants. To provide evidence for search effort and how it varies with unemployment duration and new entrant status, we use information from the NLSY97 on the number of job search methods used by unemployed workers.[17] Table 8 shows these results. New entrants are not statistically different from experienced workers in the number of search methods used and, if anything, actually use more search methods. These observations suggest that the lower employment probability for a new entrant is not due to lower search effort but rather due to lower job search efficiency.

6.2. Skill depreciation and discouragement

Duration dependence may also arise if a worker's reservation wage increases or his search effort decreases with the unemployment spell due to skill depreciation (Acemoglu, 1995; Ljungqvist and Sargent, 1998; Pissarides, 1992). In principle, it is possible for a standard skill depreciation framework to be consistent with our results. Specifically, in such a framework, the differences in employment hazards between new entrants and experienced workers would be attributed to new entrants having lower skills and also losing skills at a lower rate than experienced workers.

Related to the skill depreciation mechanism, unemployed workers may decrease their search effort because they get pessimistic about their job-finding prospects if they have searched unsuccessfully for some time (Gonzalez and Shi, 2010), giving rise to negative duration dependence. Such an explanation for our results would imply that experienced workers become discouraged faster than new entrants when searching for employment. Table 8 provides suggestive evidence for this. Specifically, there is a clear decrease in the number of search methods used as unemployment duration increases, suggesting that a form of discouragement is indeed present in the data and can be a driver of duration dependence.[18] On the other hand, the number of search methods used is flat or mildly increasing in unemployment duration among new entrants, though the effect is not statistically significant. Therefore, a lower skill depreciation rate or lower discouragement among new entrants is a possible driver of our findings.

6.3. Ranking

Duration dependence may arise if firms with multiple applicants rank (for exogenous reasons) prospective employees by their unemployment duration (Blanchard and Diamond, 1994). The main assumption of ranking models is that, for exogenous reasons, job applicants are ranked based on their unemployment spell length. Therefore, ranking models do

Table 8. Search methods used

	(1)	(2)	(3)	(4)
New entrant	0.3190	0.3420	0.2620	0.3370
	(0.2510)	(0.2560)	(0.2880)	(0.2990)
Unemployment duration (weeks)	−0.0124**	−0.0139**		
	(0.0046)	(0.0046)		
Log unemployment duration (weeks)			−0.1460**	−0.1510**
			(0.0494)	(0.0513)
Duration × New Entrant	0.0277	0.0244		
	(0.0211)	(0.0202)		
Log duration × New Entrant			0.2390	0.2080
			(0.1980)	(0.1950)
Observations	84,793	84,481	52,389	52,199
Individuals	1143	1143	1100	1100
Unemployment spells	3745	3726	2175	2165
New entrant spells	1596	1591	811	809
Adjusted R^2	0.014	0.024	0.013	0.019
Demographic	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes

Note: The dependent variable is the number of search methods the worker reported using. New entrant is an indicator for whether an individual reported has held zero jobs. Unemployment duration is computed by counting the number of consecutive weeks the worker reports being unemployed. Demographic controls include age, age-squared, gender, and race. Time fixed effects are for each month in the sample. Standard errors in parenthesis are clustered on individuals.
* and ** indicate significance at the 5% and 1% levels, respectively.

not make predictions about how the ranking on unemployment spell length varies with worker characteristics. Given that the reason for ranking is exogenous in these models, one should expect duration dependence to be independent of labor market experience.

6.4. Recall

Another possible explanation for our findings is related to the possibility that experienced workers can be recalled back to their previous job. As shown recently by Fujita and Moscarini (2017) and suggested earlier by Katz (1986), unemployment duration dependence emerges only for unemployed workers who are eventually recalled to work for their previous employer, with employment hazards flat for workers that find a job with a different employer. In that case, the declining employment hazard is driven by a declining probability of being recalled by the previous employer. Therefore, as new entrants into the labor market cannot be recalled by a previous employer, a declining hazard of being recalled for experienced workers can also explain our empirical findings.

7. Concluding comments

In this paper, we showed using data from the NLSY and the CPS that duration dependence varies with labor market experience. Specifically, although for experienced workers there is strong negative duration dependence, duration dependence is mostly absent for new entrants into the labor market. This finding is important because it suggests that true dependence in addition to *ex ante* heterogeneity and dynamic selection drive the observed employment hazards. Nevertheless, our fixed-effects estimation clearly shows that *ex ante* heterogeneity is important and, moreover, paints a complex picture for the structural effects of unemployment duration with the possibility of both negative and positive structural duration dependence, depending on the spell length.

Our empirical results have important policy implications. The high level of youth unemployment and, in particular, long-term youth unemployment, in the aftermath of the Great Recession, have raised fears of a 'stigma' effects of long-term unemployment among young workers. Our findings suggest that such fears are unwarranted. As the majority of young workers are new entrants into the labor market who are searching for their first job, our estimates suggest that such 'stigma' effects are not likely to be present for young workers. On the other hand, young workers do face a lower employment probability compared with more experienced workers at any unemployment duration, and our results suggest that this is due to low job search efficiency among young inexperienced workers. Such low employment probabilities, and particularly in recessions, could lead to longer-term 'scarring' effects, such as a lower lifetime income due to permanently lower labor market experience (Arulampalam *et al*., 2001; Bell and Blanchflower, 2009; Gregg and Tominey, 2005; Mroz and Savage, 2006). Therefore, policies to tackle youth unemployment should focus not just on the long-term unemployed but on increasing job-finding rates for unemployed youth at any unemployment duration through improved information about jobs and guidance for increasing search efficiency.

Notes

[1]The magnitudes of the effects are also comparable, accounting for the fact that the CPS data give monthly employment probabilities, while the NLSY data give weekly employment probabilities.

[2]Screening models feature time-invariant heterogeneity. However, in that case, since the heterogeneity is unobserved to the employer, unemployment duration has a structural effect on job-finding probabilities due to time-varying adverse selection and the information content of unemployment duration for worker productivity.

[3]Calibrating a structural model using existing estimates of the effect of unemployment duration on callback rates and re-employment wages, Kospentaris et al. (2020) find that unobserved heterogeneity accounts for two thirds of total duration dependence, while skill depreciation accounts for the remainder.

[4]Farber *et al*. (2016) and Nunley *et al*. (2017) are important exceptions, as these authors find no negative duration dependence in their audit study. Without success, Farber *et al*. (2019) attempt to reconcile their results with those of Kroft *et al*. (2013). Also note that negative duration dependence in callbacks may not lead to significant duration dependence in employment probabilities Jarosch and Pilossoph (2016).

[5]As an alternative way to address the unobserved heterogeneity problem, we explore the sensitivity of the association between unemployment duration and past experience to the inclusion of observed job-seeker characteristics. Specifically, we show that our estimates change very little after including individual controls such as age, race, sex, and AFQT score.

[6]For robustness, we also report estimates using only the cross-sectional sample in the Appendix.

[7]Only sequences of unemployed–employed and unemployed–unemployed are therefore considered. Hence, sequences such as unemployed–missing–employed and unemployed–not in labor force–employed are discarded. Results including such sequences are reported in Table A5 in the Appendix. The results in that case are qualitatively similar to our main results.

[8]See Section 2 for a description of how we determine new entrant status.

[9]Restrictions from the Bureau of Labor Statistics prevent us from using NLSY geocodes to control flexibly for local labor market conditions. However, state codes are available in our Current Population Survey robustness sample.

[10]Ahn (2016) shows that there are differences in job-finding rates among workers on temporary layoff, permanent layoff, and new entrants. When controlling for this, we get qualitatively similar results. These results are available upon request.

[11]Table 7 in Section 6 shows suggestive evidence that the number of search methods used by new entrants is increasing in the unemployment spell, which is consistent with new entrants increasing their search effort.

[12]This result is also consistent with the results from Lo Bello and Morchio (2018) who show that the effect of parental network on the job-finding rate of children is only present for the youngest workers (i.e., there are no effects for workers aged 23 or higher).

[13]In the Appendix, we present the results from a log-logistic hazard model.

[14]Strictly speaking, this is not a proportional hazard model given the interaction effect between new entrant status and unemployment duration. Nevertheless, as the model without the interaction effect is a discrete-time proportional hazard model, we use the name 'proportional hazard model' for our specification with an interaction term as well.

[15]As shown by Jenkins (1995), one can estimate the two discrete-time models with a complementary log–log regression, using a panel data set such as our weekly employment status data.

[16]Lo Bello and Morchio (2018) provide indirect evidence for this difference in job search efficiency by looking at the effects of parents' networks on the job-finding rates of their children. Specifically, using data from the British Household Panel Survey, the authors find that workers who choose the occupation of their father tend to find jobs faster, which they interpret as the effect of the father's network on the child's job-finding rate. However, they also find that the effect of the father's occupation on the job-finding rate of the child decreases strongly with the child's age. It is the highest when

the workers are the youngest (aged less than 20) and is not present when the workers are older (aged 23 and higher).

[17]We construct new entrant status in the NLSY97 as close to the NLSY79 as possible. Since NLSY97 does not provide a JOBSNUM variable, we construct new entrant status based on work experience since age 14. We then label individuals who complete high school in a given year and have no more than 20 weeks of labor market experience from age 14 to 18 as new entrants.

[18]Faberman and Kudlyak (2019) also find that job search intensity decreases with unemployment duration, consistent with a discouragement effect. However, they do not examine whether the effect differs between experienced workers and new entrants in a way that can explain our empirical findings. Also, note that the estimated effects could be driven by a combination of heterogeneity in search effort used and dynamic selection, as workers that use more search methods would naturally find employment faster. As with our duration dependence results, however, the fact that the duration effects differ for new entrants differs and experienced workers suggests that a structural effect of duration on search effort is at least partly present.

[19]In this respect, we follow Shimer (2008) and Rothstein (2011), among others.

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Appendix 1

CPS sample details

The *Current Population Survey* (CPS) is designed as a rotating survey: A household is initially interviewed for four consecutive months; then after eight months, the household is interviewed for another four consecutive months. Each month, new households are included in the CPS sample. The design of the survey ensures that interviewed households are equally distributed between all eight-month rotations Drew *et al*. (2014). The variable *hrmis* records the month in sample and thus takes values from one to four in the households' first rotation and five through eight in their second rotation.

The CPS uses unique identifiers for households (*hhid*) and individuals (*individ*) and also records the month in sample, which takes values from one to four in the households' first rotation and five through eight in their second rotation. These aspects of the CPS data allow us to utilize it as a panel data set.[19] The key variable for us is the *empl* variable that records the labor force status of the interviewees. The panel aspect of the data set allows us to identify whether an individual moves from unemployment to employment over two consecutive months in the survey. Formally, we generate an indicator variable (*rei*) for whether an individual becomes (re-)employed in the next month. In addition, a variable *prunedur* records the duration of unemployment in weeks for unemployed individuals. In combination with the *empl* variable, this allows us to calculate (re)employment probabilities for different unemployment durations. Finally, the variable *pruntype*, which gives the reason for unemployment, also allows us to classify a worker as a new entrant into the labor force. Finally, the CPS also registers a set of individual characteristics that are useful as controls. A summary of all available variables is provided in Table 8.

An interesting observation is that the (re-)employment probability for duration of 0 weeks is lower than at duration of 1–6 weeks. A simple two-sided t-test confirms that there is a statistically significant difference between the two employment probabilities. This might be due to, for instance, the natural lag between when one leaves a job, and when one starts looking for a new job.

Table A2 reports estimation results of six various specifications of a linear probability model. Unemployment duration (in both log and levels) has, as expected, a negative sign.

Table A1. Relevant variables in the CPS data

CPS variable	Description	Possible values
month	The month of the interview	1–12
year	The year of the interview	YYYY
hrmis	Month in sample	1–8
state	State of residence of individual	FIPS format
peage	Age of individual	In years
sex	Sex of individual	1—male; 2—female
educ	Highest level of education completed	Numerical categories
perace	Race of individual	Numerical categories
empl	Labor force status of individual	Numerical categories
prunedur	Duration of unemployment	0–119 weeks
pruntype	Reason for unemployment	Numerical categories
hhid	Unique household identifier	–
individ	Unique individual identifier	–

We consider the period 2006–2013. Similar to Shimer (2008), we restrict the sample to only include the unemployed who are job losers; that is, with *empl* 3 or 4, and further restricted to *pruntype* 1, 2, 4, or 6. Unlike Shimer (2008), we also allow for *pruntype* 6, hence including new entrants in our sample. To avoid double counting, we restrict the sample to individuals in either their 1st or 5th month in sample. We consider workers unemployed for up to 104 weeks. After applying these restrictions, we are left with a sample consisting of 41,648 observations. Table A1 presents and compares summary statistics for the NLSY and CPS samples.

Table A2. Summary statistics

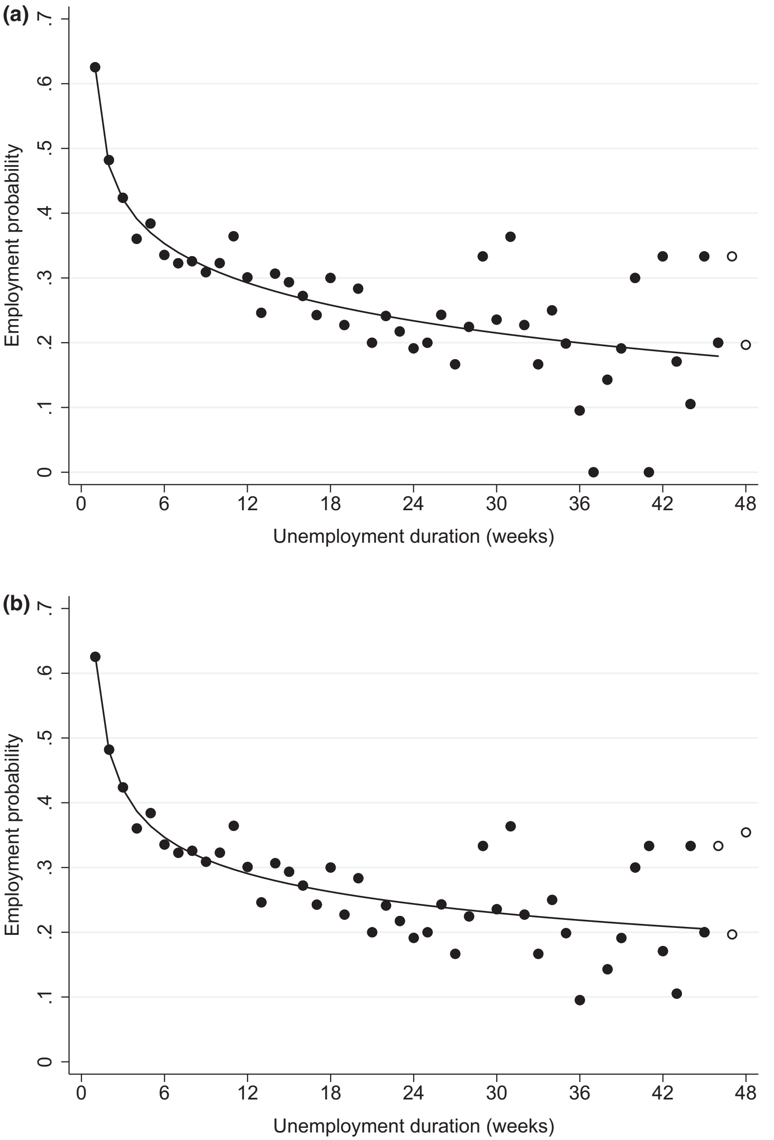
	NLSY79 (full)	NLSY79 (*)	CPS
Avg. spell duration (weeks)	21.7 (22.1)	20.7 (21.6)	16.1 (17.7)
Age	29.1 (10.7)	29.4 (10.9)	36.3 (12.6)
Male	60.4 %	57.1 %	62.6 %
Race			
White	N/A**	N/A**	77.9 %
Black	45.5 %	23.3 %	15.8 %
Hispanic	16.2 %	9.4 %	N/A **
Other	38.4 %	67.3 %	6.3 %

Note: Standard deviations in parenthesis. *Cross-sectional sample only. **Not reported. Included in 'Other' category.

We estimate (re-)employment probabilities using a linear probability model and a logit model. Figure 5 presents the employment hazard estimates for the two models without additional controls. The estimated hazards are in line with the results of Shimer (2008), and there is negative duration dependence. To illustrate this, consider two individuals: The first has been unemployed for just a week, whereas the second has been unemployed for eighteen weeks. From the figures, we can see that the first individual will face a (re-)employment probability of around 50%, whereas the second individual has a (re-)employment probability of just above 15%.

This result is significant at the 1% level for all specifications and remains robust after controlling for both demographic variables and state–year interactions. Similarly, Table A3 reports estimation results of six various specifications estimated via a logit regression. The estimated coefficients are all significant and have the expected signs. Similar to the linear probability model, the results are robust to all demographic controls and state–year interactions.

Figure A1. Employment hazards for the CPS.
Note: Unemployment duration is the number of weeks the survey responded reported being unemployed before finding a job. Solid line is fractional polynomial for durations 1 to 35 (solid dots)



Log-logistic hazard model

As additional robustness, we also estimate a discrete-time log-logistic hazard model. For the discrete-time log-logistic hazard model, our baseline specification is

Table A3. CPS estimation results—linear probability model

	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment duration	−0.0055**	−0.0053**	−0.0046**			
	(0.0001)	(0.0001)	(0.0001)			
Log(unempl. duration)				−0.1017**	−0.0989**	−0.0893**
				(0.0018)	(0.0019)	(0.0020)
Observations	41,696	41,696	41,696	41,589	41,589	41,589
Adjusted R^2	0.043	0.048	0.062	0.067	0.071	0.082
Demographics	No	Yes	Yes	No	Yes	Yes
State–year FE	No	No	Yes	No	No	Yes

Note: The dependent variable is an indicator for whether the worker found a job in that week. Unemployment duration is the number of weeks the survey responded reported being unemployed before finding a job. Demographic controls include age, age-squared, gender, and race. Robust standard errors in parenthesis.
**Indicates significance at the 1% level.

Table A4. CPS estimation results—logit model

	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment duration	−0.0310**	−0.0230**	−0.0270**			
	(0.0008)	(0.0008)	(0.0009)			
Log(unempl. duration)				−.4786**	−.4681**	−.4419**
				(0.0094)	(0.0095)	(0.0102)
Observations	41,696	41,687	41,626	41,589	41,580	41,519
Log-likelihood	−25,566	−25,441	−24,517	−25,094	−24,979	−24,085
Demographics	No	Yes	Yes	No	Yes	Yes
State–year FE	No	No	Yes	No	No	Yes

Note: The dependent variable is an indicator for whether the worker found a job in that week. Unemployment duration is the number of weeks the survey responded reported being unemployed before finding a job. Demographic controls include age, age-squared, gender, and race. Standard errors in parenthesis.
**Indicates significance at the 1% level.

$$P(rei_{it}=1)=G(\alpha_0+\alpha_1 n_i+\alpha_2 \log t+\alpha_3(n_i\times \log t)) \quad [3]$$

where $G(y)$ is the logistic function, rei_{it} is an indicator variable for whether an individual i who is unemployed for t weeks becomes employed in week $t+1$, n_i is an indicator that equals 1 if the individual has started the unemployment spell as a new entrant into the labor force, and $n_{\mathrm{i}}\times t$ is an interaction effect. As with the models in the main text, we also estimate specifications with individual controls and calendar week indicators. Finally, we estimate versions of the models with the level of unemployment duration. As shown by Jenkins (1995), one can estimate the model with a logistic regression, using a panel data set such as our weekly employment status data. Table A4 presents the estimation results confirming the robustness of our main result to the estimation model used.

Table A5. Duration dependence: new entrants vs. experienced workers—(log-)logistic hazard model (NLSY)

	(1)	(2)	(3)	(4)	(5)	(6)
New entrant	−2.246**	−2.035**	−2.060**	−1.795**	−1.593**	−1.618**
	(0.1935)	(0.1952)	(0.1979)	(0.1099)	(0.1103)	(0.1120)
Log(unempl. duration)	−0.2880**	−0.2572**	−0.2546**			
	(0.0101)	(0.0104)	(0.0105)			
Log(duration)× New Entrant	0.3552**	0.3370**	0.3447**			
	(0.0686)	(0.0693)	(0.0698)			
Unemployment duration				−0.0177**	−0.0147**	−0.0146**
				(0.0009)	(0.0009)	(0.0009)
Duration × New Entrant				0.0202**	0.0180**	0.0187**
				(0.0035)	(0.0035)	(0.0035)
Observations	206,347	206,347	206,347	206,347	206,347	206,347
Individuals	2505	2505	2505	2505	2505	2505
Unemployment spells	15,425	15,425	15,425	15,425	15,425	15,425
New entrant spells	1005	1005	1005	1005	1005	1005
Log-likelihood	−33,478	−33,083	−33,041	−33,613	−33,223	−33,176
Demographic	No	Yes	Yes	No	Yes	Yes
Year FE	No	No	Yes	No	No	Yes

Note: The dependent variable is an indicator for whether the worker found a job in that week. New entrant is an indicator for whether an individual reported has held zero jobs. Unemployment duration is computed by counting the number of consecutive weeks the worker reports being unemployed. Demographic controls include age, age-squared, gender, race, and AFQT scores. Standard errors in parenthesis are clustered on individuals. * and ** indicate significance at the 5% and 1% levels, respectively.

Additional Results

Table A6. Duration dependence: new entrants vs. experienced workers—linear probability model (including missing and not-in-labor-force observations) (NLSY)

	(1)	(2)	(3)	(4)	(5)	(6)
New entrant	−0.0236**	−0.0260**	−0.0260**	−0.0636**	−0.0612**	−0.0570**
	(0.0006)	(0.0008)	(0.0008)	(0.0012)	(0.0014)	(0.0017)
Unemployment duration (weeks)	−0.0001**	−0.0001**	−0.0001**			
	(0.0000)	(0.0000)	(0.0000)			
Duration × New Entrant	0.0001**	0.0001**	0.0001**			
	(0.0000)	(0.0000)	(0.0000)			
Log(unempl. duration)				−0.0135**	−0.0126**	−0.0127**
				(0.0002)	(0.0002)	(0.0002)
Log(duration) × New Entrant				0.0123**	0.0121**	0.0114**
				(0.0002)	(0.0003)	(0.0004)
Observations	955,105	955,105	955,105	955,105	955,105	955,105
Individuals	2701	2701	2701	2701	2701	2701
Unemployment spells	14,014	14,014	14,014	14,014	14,014	14,014
New entrant spells	588	588	588	588	588	588
Adjusted R^2	0.007	0.010	0.011	0.020	0.021	0.022
Demographic	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes

Note: The dependent variable is an indicator for whether the worker found a job in that week. New entrant is an indicator for whether an individual reported has held zero jobs. Unemployment duration is computed by counting the number of consecutive weeks the worker reports being unemployed. Demographic controls include age, age-squared, gender, and race. Time fixed effects are for each week in the sample. Standard errors in parenthesis are clustered on individuals.

* and ** indicate significance at the 5% and 1% levels, respectively.

Table A7. Duration dependence: new entrants vs. experienced workers—baseline model on multi-spell sample

	(1)	(2)	(3)	(4)	(5)	(6)
New entrant	−0.0380**	−0.0320**	−0.0345**	−0.0576**	−0.0508**	−0.0545**
	(0.0025)	(0.0028)	(0.0030)	(0.0038)	(0.0038)	(0.0042)
Unemployment duration (weeks)	−0.0004**	−0.0003**	−0.0004**			
	(0.0000)	(0.0000)	(0.0001)			
Duration × New Entrant	0.0005**	0.0005**	0.0006**			
	(0.0001)	(0.0001)	(0.0001)			
Log(unempl. duration)				−0.0110**	−0.0096**	−0.0094**
				(0.0010)	(0.0010)	(0.0010)
Log(duration) × New Entrant				0.0125**	0.0120**	0.0134**
				(0.0012)	(0.0013)	(0.0014)
Observations	59,332	59,332	59,332	59,332	59,332	59,332
Individuals	516	516	516	516	516	516
Unemployment spells	4119	4119	4119	4119	4119	4119
New entrant spells	789	789	789	789	789	789
Adjusted R^2	0.006	0.010	0.015	0.008	0.012	0.017
Demographic	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes

Note: The dependent variable is an indicator for whether a worker found a job within a week. New entrant is an indicator for whether an individual reported has held zero jobs. Unemployment duration is computed by counting the number of consecutive weeks the worker reports being unemployed. Demographic controls include age, age-squared, gender, and race. Time fixed effects are for each week in the sample. Standard errors in parenthesis are clustered on individuals.

* and ** indicate significance at the 5% and 1% levels, respectively.

Table A8. Duration dependence: new entrants vs. experienced workers—proportional hazard model (NLSY, cross-sectional sample)

	(1)	(2)	(3)	(4)	(5)	(6)
New entrant	−1.704**	−1.496**	−1.527**	−2.228**	−2.007**	−2.041**
	(0.1502)	(0.1516)	(0.1550)	(0.2717)	(0.2753)	(0.2799)
Unemployment duration	−0.0186**	−0.0155**	−0.0153**			
	(0.0012)	(0.0012)	(0.0012)			
Duration × New Entrant	0.0221**	0.0200**	0.0207**			
	(0.0052)	(0.0051)	(0.0050)			
Log(unempl. duration)				−0.2814**	−0.2495**	−0.2457**
				(0.0130)	(0.0135)	(0.0137)
Log(duration) × New Entrant				0.3959**	0.3780**	0.3863**
				(0.0997)	(0.0135)	(0.1001)
Observations	96,291	96,291	96,291	96,291	96,291	96,291
Individuals	1286	1286	1286	1286	1286	1286
Unemployment spells	7717	7717	7717	7717	7717	7717
New entrant spells	416	416	416	416	416	416
Log-likelihood	−17,628	−17,417	−17,386	−17,566	−17,350	−17,322
Demographics	No	Yes	Yes	No	Yes	Yes
Year FE	No	No	Yes	No	No	Yes

Note: The dependent variable is an indicator for whether the worker found a job in that week. New entrant is an indicator for whether an individual reported has held zero jobs. Unemployment duration is computed by counting the number of consecutive weeks the worker reports being unemployed. Demographic controls include age, age-squared, gender, race, and AFQT scores. Standard errors in parenthesis are clustered on individuals.
* and **indicate significance at the 5% and 1% levels, respectively.

Table A9. Duration dependence: new entrants vs. experienced workers—(log-)logistic hazard model (NLSY, cross-sectional sample)

	(1)	(2)	(3)	(4)	(5)	(6)
New entrant	−2.267**	−2.042**	−2.076**	−1.729**	−1.517**	−1.549**
	(0.2735)	(0.2773)	(0.2821)	(0.1513)	(0.1529)	(0.1564)
Log(unempl. duration)	−0.2895**	−0.2572**	−0.2534**			
	(0.0135)	(0.0140)	(0.0141)			
Log(duration) × New Entrant	0.4047**	0.3869**	0.3955**			
	(0.1004)	(0.1004)	(0.1008)			
Unemployment duration				−0.0189**	−0.0158**	−0.0156**
				(0.0012)	(0.0012)	(0.0012)
Duration × New Entrant				0.0224**	0.0203**	0.0211**
				(0.0052)	(0.0012)	(0.0051)
Observations	96,291	96,291	96,291	96,291	96,291	96,291
Individuals	1286	1286	1286	1286	1286	1286
Unemployment spells	7717	7717	7717	7717	7717	7717
New entrant spells	416	416	416	416	416	416
Log-likelihood	−17,565	−17,350	−17,322	−17,628	−17,418	−17,386
Demographic	No	Yes	Yes	No	Yes	Yes
Year FE	No	No	Yes	No	No	Yes

Note: The dependent variable is an indicator for whether the worker found a job in that week. New entrant is an indicator for whether an individual reported has held zero jobs. Unemployment duration is computed by counting the number of consecutive weeks the worker reports being unemployed. Demographic controls include age, age-squared, gender, race, and AFQT scores. Standard errors in parenthesis are clustered on individuals.
* and ** indicate significance at the 5% and 1% levels, respectively.