CAHIER DE RECHERCHE 2405E
Département de science économique
Faculté des sciences sociales
Université d'Ottawa

WORKING PAPER 2405E
Department of Economics
Faculty of Social Sciences
University of Ottawa

Why don't firms hire young workers during recessions? A replication of Forsythe (The Economic Journal, 2022)*

Jonathan Créchet†, Jing Cui‡, Barbara Sadaba§, and Antoine Sawyer**

September 2024

* This paper was written as part of the Ottawa replication games organized by the Institute for Replication in May 2023. We thank Abel Brodeur, Anthony Heyes, and the Institute for Replication for organizing and funding this event. This paper is based on the IPUMS-CPS database (Flood et al. (2020)).
† Department of Economics, University of Ottawa, 120 University Private, Ottawa, Ontario, Canada, K1N 6N5; e-mail: jcrechet@uottawa.ca.
‡ Department of Economics, University of Ottawa, 120 University Private, Ottawa, Ontario, Canada, K1N 6N5; e-mail: jcui2@uottawa.ca.
§ Bank of Canada, 234 Wellington St. W, Ottawa, Ontario, Canada, K1A 0G9; e-mail: BSadaba@bank-banque-canada.ca.
** Department of Economics, Queen's University, 94 University Ave, Kingston, Ontario, Canada, K7L 3N6; e-mail: 22as35@queensu.ca.

Abstract

We replicate results of Forsythe (2022) studying the cyclicality of individuals' labor market transitions conditional on their experience. Using Current Population Survey (CPS) data and state-level variations in the unemployment rate, this paper shows that the hiring probability of youths is more sensitive to business-cycle conditions than for experienced individuals. We replicate the main results in this paper by reconstructing the dataset using data from the IPUMS-CPS database (Flood et al. (2020)) and recoding the paper's main regressions from scratch. We also conduct a robustness replicability analysis and show that the paper's main results are robust in terms of statistical significance to (i) extending the sample period from 1994-2014 to 1994-2019 and (ii) using MSA-level unemployment variation instead of state-level variation. These extensions reduce the magnitude of the main effects of interest, but the paper's key conclusions are unaffected.

Key words: *Worker flows, Business cycles, Life cycle.*

JEL Classification: E24, J63, J64.

1 Introduction

We present a replication study of the main empirical results of Forsythe (2022). This article studies the cyclical variations of hiring rates of individuals across groups with different labor market experience—and, more generally, the cyclicality of worker flows across employment, nonemployment, nonparticipation, and across jobs conditional on labor-market experience. It is widely documented that the labor-market costs of recessions are disproportionately borne by young individuals, with low experience. The negative effects of the last two recessions have been felt much harder by young individuals: in the Great Recession of 2008-2009 (e.g., Bell and Blanchflower (2011), Pissarides (2013), and Van Ours (2015)) and the COVID-19 recession (e.g., Beland et al. (2020), Brochu et al. (2020), Lemieux et al. (2020), and Cortes and Forsythe (2023)).

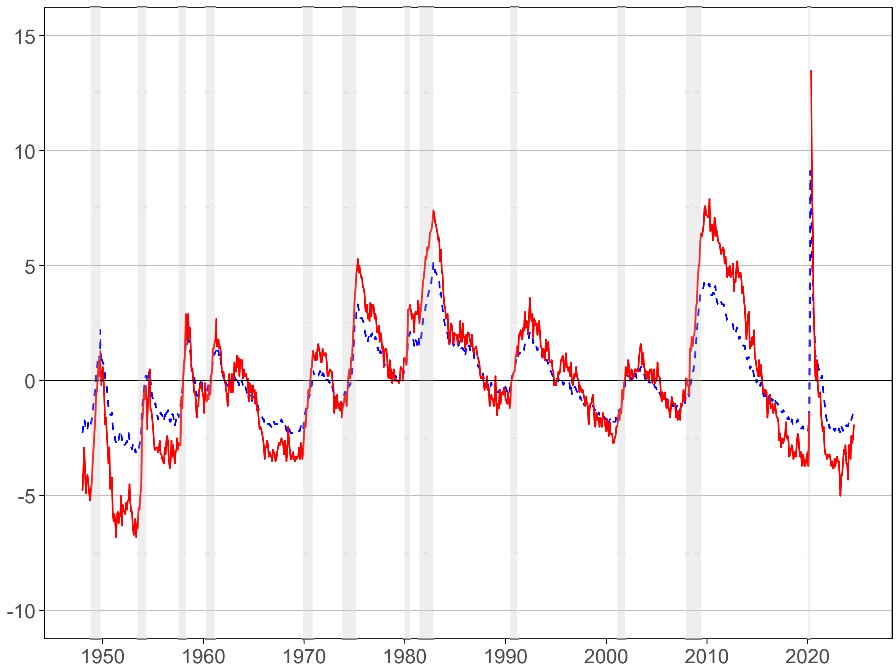


Figure 1: U.S. mean centered unemployment rate (%), youth (age 16-24) and working-age populations

Notes: Solid, red line: unemployment rate for population of age 16 to 24. Dotted, blue line: unemployment rate for the working-age population (16 years and older). Both series are seasonally adjusted and represented in difference from their respective sample averages. The series are retrieved from FRED, Federal Reserve Bank of St. Louis (UNRATE and LNS14024887). The shaded areas show NBER (Business Cycle Dating Committee) recession periods.

In Figure 1 we represent the U.S. unemployment rate from 1948 to 2022 for the working-age (16 years and older) and the youth (16-24) populations, both taken in percentage-point difference from their respective sample averages. In virtually all recessions, the youth unemployment rate increased substantially more, in absolute terms, than for the entire working-age population. The case of the

Great Recession of 2008-2009 illustrates this point: the youth unemployment rate reached a peak about seven and a half percentage points higher than its sample average (equal to 11.7%). In comparison, for the entire population, the same increase was around four percentage points (from a sample average of 5.7%).

Yet, as argued by Forsythe (2022), the mechanisms for the disproportionate impact of recessions on the youths were unclear. In particular, what is the importance of factors related to labor demand in explaining these cyclical patterns? The answer to the latter question has important implications for the design of policies such as unemployment insurance. The contribution of Forsythe (2022) is to provide evidence, which is based on a detailed analysis of worker flows by experience levels and across U.S. states, that shifts in labor demand from firms constitute a major driver of cyclical changes in outcomes for the youths. The key policy recommendation of the paper is an extension of unemployment insurance eligibility for new labor-market entrants, echoing an important body of research studying the design of age-dependant unemployment insurance (e.g., Michelacci and Ruffo (2015)).

More specifically, Forsythe (2022) shows that the hiring rate of youths, defined as individuals' monthly transition rates into a new job from either non-employment or employment (i.e., job to job), is more sensitive to state-specific cyclical labor market conditions relative to experienced individuals.[1] The analysis is based on Current Population Survey (CPS) data from January 1994 to May 2014 (working-age, civilian, non-institutionalized individuals) and exploits state-level variations in the unemployment rate as proxies for local business-cycle activity. Importantly, Forsythe (2022) presents evidence that labor-supply factors can hardly explain these changes in hiring rates. In particular, the paper shows that the effect of recessions on the probability of quitting to unemployment is *less* pronounced for young workers; the same is true for individuals' job-search intensity, measured from CPS questions about job-search activities. Finally, Forsythe (2022) proposes a model of firm optimal cyclical labor demand in the presence of search frictions, with two different types of workers: young (low productivity) and experienced (high productivity). The model is consistent with the documented cyclical hiring patterns and implies that the relative wage of young workers decreases in recessions. The latter is supported by micro-level evidence based on CPS samples with information about earnings.

In practical terms, Forsythe (2022) estimates a linear probability model to gauge the association

[1] Young individuals are defined as having ten years of labor-market experience or less, computed as age − years of education − 6, as usual in the literature.

between variations in the state-level unemployment rate and labor-market outcomes of groups with different labor-market experience levels. The preferred specification includes time, state, and demographic (gender/race/Hispanic origin/education) fixed effects (see equation (1) in the original paper). The following statement from the paper illustrates the key results that we replicate (p. 1772): "*Figure 2 presents the main empirical results, based on the regression in [equation] (1). [...] workers with less than one year of potential experience are approximately half a percentage point less likely to be hired for each additional percentage point of the state unemployment rate. This effect diminishes steadily up until nine years of potential experience, at which point it is statistically indistinguishable from zero. Individuals with above 15 years of potential experience are about 0.05 percentage points more likely to be hired for each additional percentage point of the state unemployment rate, which is significant in each five-year bin at the 0.01% level.*" Hence, individuals with less than ten years of experience face a significantly higher drop in their hiring probability during recessions than experienced individuals. These effects are highly significant, and the magnitude is high: workers with less than ten years of experience face an additional 0.3 percentage-point decrease in their hiring rate in response to a one-percentage-point increase in the state unemployment rate. These results are presented in Figure 2 and Table 2 in the main text (and Table B.2 in the Online Appendix).

The first objective of our study is a direct replication of these main results. Specifically, we replicate Figure 2 and Tables 2 and B.2, which present the paper's results about cyclical changes in the hiring rates by experience. We also replicate Tables 1, 3, and 4, which relatedly estimate the cyclical response of other worker flows (e.g., employment exit). In addition, we replicate Tables 5 and 6, examining the cyclicality of changes in the composition of jobs (occupation, industry) and job searchers (in terms of experience levels) and suggesting that such composition changes cannot explain the observed experience-specific hiring patterns. Finally, we replicate Table 10, analyzing the response to recessions of hiring earnings conditional on experience. Our second objective is to gauge the robustness of the original results. We conduct two pieces of robustness replication analysis, one in which we extend the sample to 1994-2019 and another in which we use MSA-variation in unemployment instead of state-level variation (focusing on Tables 1 and 2 that show the main findings about hiring rates).

Our direct replication study proceeds as follows: (i) we extract data from the IPUMS-CPS database (Flood et al. (2020)) and write Stata code for reconstructing the dataset from the original study (the variable definitions and sample restrictions); (ii) we write a Stata script replicating the main results (Tables 1 to 4) along with Tables B.2, 5, 6 (hiring and labor supply/composition) and Table 10 (wage regressions). These two steps are based on Stata code that we write from scratch. The original data and codes are available at https://doi.org/10.5281/zenodo.5710784. Our dataset is available at https://doi.org/10.5281/zenodo.8095825, and our code is available at https://github.com/jcrechet/replication_forsythe_2022_EJ (on September 12, 2024).

We replicate the original results very closely. Our estimated coefficients for the main regressions have the same sign, significance, and magnitude (Table 1, 2, and B.2). We also find very similar results for the other tables despite minor differences that can be reasonably attributed to our alternative dataset construction procedure.

In addition, the key results hold in our robustness analysis. Extending the sample to 1994-2019 or using MSAs instead of states leaves the significance level of coefficients for the key Tables 1 and 2 unchanged. However, the magnitude of the experience difference is lower. In our extensions, workers with less than ten years of experience face an additional 0.2 percentage-point decline in their hiring rates for each percentage-point increase in local (state or MSA) unemployment (versus 0.3 p.p. in the baseline analysis). In spite of this lower magnitude, the key conclusions from the original study are unchanged in our two extensions.

The next section (2) presents our replication analysis. It is divided into two subsections, presenting (i) our direct replication study (2.1) and (ii) our robustness analysis (2.2). Section 3 concludes.

2 Replication

We conduct direct and robustness replication analysis. The direct replication is based on reconstructing the working dataset using an alternative data source (IPUMS CPS) and recoding the regressions. The robustness analysis has two distinct robustness checks: First, an extension of the sample period (from 1994-2014 to 1994-2019) and second, using MSA- instead of state-level variation in economic conditions (proxied by the unemployment rate).

2.1 Direct replication

Our direct replication analysis relies on the IPUMS-CPS database (Flood et al. (2020)). We write Stata programs from scratch for the dataset construction using this alternative data source and for replicating the results in Section 2 of the original paper that studies the relationship between worker flows by experience and state-level unemployment cycles. In addition, we replicate Tables 5 and 6 of Section 3 (composition of jobs and pools of job searchers) and Table 10 of subsection 4.2 (cyclical response of new hires' earnings). We show our results in Figure 2 and in the tables in Appendix A.1.

The original sample is restricted to the working-age, civilian, and non-institutionalized population from CPS Basic Monthly Samples from 1994 to 2014. Our study applies the same restrictions to the IPUMS database. However, due to differences in data sources and coding decisions, the samples and variables in our dataset present differences from the original described in the following.

- *Longitudinal matching of individuals across CPS monthly samples.* The original paper follows the widely used procedure of Madrian and Lefgren (1999) to longitudinally match individuals across monthly samples, which relies on CPS identification variables (households' and household members' ids) combined with demographic information for gender, age (with a tolerance of a two-year discrepancy), and race (white, black, and other races). Instead of the latter, we use the IPUMS CPS individual ids constructed from a refinement of the procedure in Madrian and Lefgren (1999), as described in Rivera Drew et al. (2014). We also check the consistency of longitudinal ids using gender, race, and age, but we impose tighter constraints: we don't allow for any tolerance for inconsistencies in the age matching and use six race categories (Asian, black, native, pacific, white, and others). As a result, our longitudinally matched sample for 1994-2014 has a smaller size than the original (16,309,862 vs. 16,948,516), indicating tighter constraints on longitudinal matching criteria.

- *IPUMS harmonized CPS variables.* We use IPUMS time harmonized variables for educational attainment, occupations, and industries. In contrast, the original study constructs these variables using the original CPS non-harmonized data, relying on crosswalk schemes that potentially differ from those used by IPUMS to harmonize data over time.

- *Construction of the variable for potential experience.* As a result of the latter point, our potential experience variable constructed by imputing the number of years of education using educational attainment likely presents minor differences from the original. In addition, we impute zero potential experience to observations for which age − education − 6 yields a negative value.

The tables are reported in Appendix A and shows the replication results jointly with those of the original paper. The tables are labeled with numbers matching the original paper. For convenience, we rewrite here the author's preferred specification:

$$D^{\text{hired}}_{ikst} = \alpha_s + \delta_t + \sum_{k=1}^{K} (\beta_k \, D^{\text{PE}}_k + \gamma_k \times D^{\text{PE}}_k \times \text{State Unemp. Rate}_{st}) + \epsilon_{ikst}, \tag{1}$$

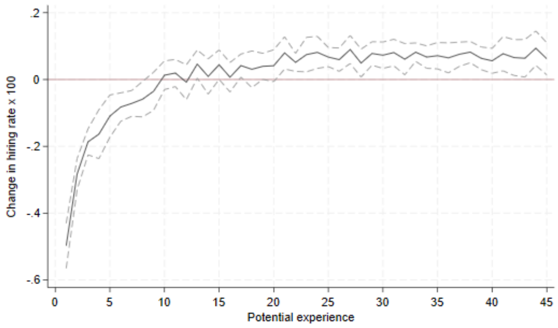
where D^{hired}_{ikst} is an indicator for being hired in month t (rescaled to 100), α_s denote state dummies, δ_t date (month/year) dummies, and D^{PE}_k is an indicator for potential experience group k. This dependent variable is constructed based on the longitudinal monthly matching of individuals in the CPS sample: being hired is defined as starting a new job (i.e., being attached to a new employer). Note that this includes individuals coming from both non-employment and employment in the previous month, job-to-job hiring. Note that the authors' preferred specification includes demographic (gender, race, Hispanic, education) fixed effects and that all estimations have standard errors clustered at the state level.

Worker flows. The main results related to hiring rates are presented in Tables 2, Figure 2 and Table B.2 of the original paper. Table 2 presents estimates of Equation 1 for two broad experience groups, less and more than ten years of experience, and conditioning on the origin labor-force status (employed, unemployed, and NILF). It also reports estimates for the entire sample i.e., unconditional on the origin labor-force status. These regressions include demographic fixed effects. This table shows that the hiring rate of the low-experience groups declines more relative to the high-experience group in recessions as captured by local unemployment rates. This holds across all labor-force statuses, and these differences are significant at the 1% level, as shown by Wald statistics.

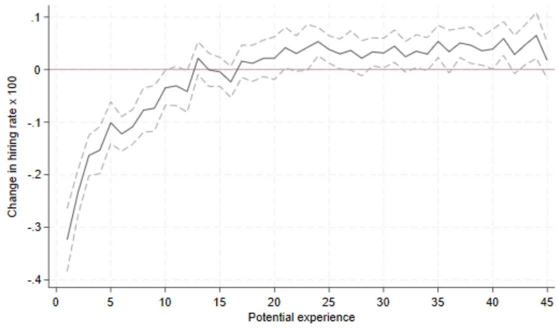
We replicate these key results in Table 2 presented in Appendix A.1. The magnitude and significance of the differences across experience groups are virtually the same across studies, as shown by point estimates and Wald statistics. If anything, we find larger and more significant differences when looking at the nonemployed (unemployed and NILF). The standard errors are very close across studies. In addition, Table 1, which presents results for variations of Equation (1) (i.e., removing interactions and including different sets of fixed effects), replicate closely.

Figure 2 and Table B.2 (in the original paper's Online Appendix) presents similar regressions disaggregated by one- to five-year experience groups. The original table indicates a negative association between the hiring rate and the state unemployment rate, whose magnitude declines with age and tends to fade away as experience increases. This pattern is especially apparent when looking at the sample of employed individuals and less so when looking at the NILF and, foremost, the unemployed, for which the experience effect is much flatter. We find a similar pattern (Figure 2 and Table B.2). The order of magnitude and coefficients' signs are largely consistent across studies. We conclude that the main results from the original paper replicate.

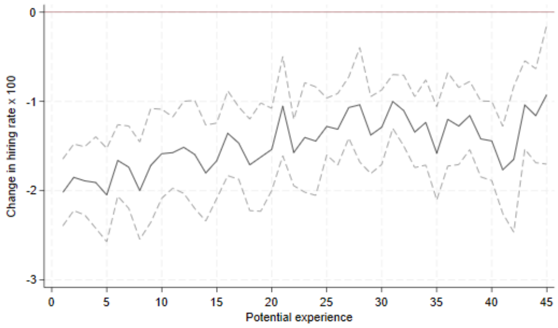
We complement this analysis with Table 3 analyzing the effect of recessions on alternative worker flows (employment exits and flows between unemployment and NILF). The results are very similar both in terms of magnitude and significance. An exception is the transition rate from employment to



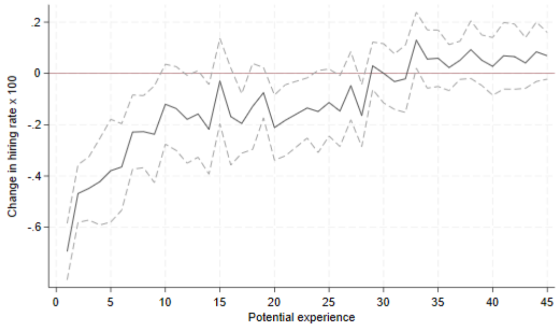
(a) All hires



(b) EE hires



(c) UE hires



(d) NILE hires

Figure 2: Replication of Figure 2 from Forsythe (2022).

Notes: Point estimates and confidence intervals from regressions of hiring rates on one-year experience bins interacted with state-level unemployment rates (Equation (1)). The regressions include state, demographic, and month-year fixed effects and are weighted using the CPS sampling weights. The dashed lines represent 95% confidence intervals based on standard errors clustered at the state level.

NILF, for which we find differences that are *less* significant across experience groups. This result does not affect the author's conclusions and, in fact, reinforces these conclusions. The original table shows that youths' transitions out of employment are much less sensitive (relative to experienced individuals) to the cycle than employer-to-employer transitions. Clearly, our own table points in the same direction. Lastly, we replicate very closely Table 4, showing that the probability of a voluntary employment-to-unemployment transition increases more for the experienced than for the young individuals, indicating that quit behaviors cannot explain the age patterns of cyclical unemployment (as opposed to firms' hiring behaviors).

Composition and labor supply. We turn to results analyzing composition and labor supply as potential explanations for the low hiring probability of youths in recessions. Table 5 of the original paper examines the role of composition. The table shows that including or not industry and occupation fixed effects leaves the relation between the average potential experience of new hires and state unemployment essentially unchanged, ruling out this channel. We find the same result despite differences in the classification of occupations and industries discussed above (Table 5 in Appendix A.1).

Table 6 from the original paper shows that the average experience of all individuals does not change within states and when there is a recession, whereas the average experience of new hires increase, indicating a shift in labor demand rather than a change in labor supply behaviors or composition (Panel A and B). Panel C, showing a positive association between the ratio of the average experience of new hires relative to that in the entire population and the unemployment rate at the state level, corroborates the latter finding. We find the same result; in particular, our point estimates in Panel C of Table 6 are all positive, as in the original table. We do find differences in the degree of significance, which can be presumably traced back to the differences in the construction of the experience variable.[2]

Earnings. In Table 10 in Appendix A, we replicate the original analysis of newly hires' weekly wage response to business cycles. As in the original study, we find (i) a negative (composition-free) association between log earnings and the state unemployment rate (Panel A) and (ii) a higher sensitivity for youths' log earnings to the state-level cycle (Panel B). As in the original regression, the age differences are significant for all groups of hires but the unemployed.

2.2 Robustness replicability

2.2.1 Extending the sample period. We extend the sample period from 1994 to 2014 to 1994 to 2019 and re-run the regressions for Tables 1 and 2 in the original manuscript, which present the main results (and our corresponding tables in Appendix A.1). The results are shown in Tables A.2.1 and A.2.2 in Appendix A.2. Our results are consistent with the baseline analysis, although the magnitude of the age differences of interest is lower. For instance, the baseline sample implies that the hiring rate decreases by an additional 0.30 percentage point for youths (ten years of experience or less) in response to a one p.p. increase in the state unemployment rate. This differential is around 0.20 when we extend the sample period. The lower magnitude is accounted for by the group of individuals hired from employment, for which we find substantial differences from the baseline (0.17 vs. 0.12). The magnitude remains the same for the other populations (unemployment and NILF). The paper's main conclusions are unchanged in the sense that the differences across experience groups remain highly significant (at the 1% level), as shown by the Wald statistics.

[2] Another difference with the original study is that the author restricts the sample of states to those where CPS hires are recorded for all sub-populations (employed, unemployed, and NILF), whereas we do not impose such a restriction.

2.2.2 Using MSA- instead of state-level variation.

We perform an additional and final robustness check using MSA-level instead of state-level variations in unemployment rates (keeping the 1994-2019 sample). We estimate the MSA unemployment rates using our CPS data based on the IPUMS harmonized metropolitan area codes.[3] The results in this subsection must be interpreted with care since estimates for local areas are noisy due to the sample size of small MSAs likely to result in substantial sampling error.[4] Once again, we focus on the main Tables 1 and 2 of the original paper. The results are shown in Tables A.3.1 and A.3.2 in Appendix A.3. With the latter caveat in mind, we find that using the MSA variation leaves the significance of the main effects unchanged. The Wald statistic indicates high (1%) significance. However, the difference across groups in the hiring rate absolute change is now equal to 0.11 p.p., a lower magnitude. The difference in magnitude with the baseline is accounted for by both the NILF individuals (0.29 vs. 0.50 using state variation) and the employed (0.05 vs. 0.12). Of important note, the magnitude of the effects of interest remains the same across the different analyses when looking at the unemployed. Finally, the standard errors are much smaller when using MSAs despite potential noise from sampling error. The main conclusions of the original study are unchanged.

3 Conclusion

We replicate a large subset of the empirical results in Forsythe (2022) from scratch, i.e., using alternative data sources and codes. Despite some differences in the dataset construction, the results closely replicate. We also perform two robustness tests, in which (i) we extend the sample period, and (ii) we use MSA instead of state cyclical unemployment variation. These extensions mildly reduce the magnitude of the main effects of interest, but these remain highly significant, leaving the main conclusions of the original study unchanged.

[3] See https://cps.ipums.org/cps/codes/metfips_2014onward_codes.shtml (consulted on September 12, 2024)

[4] According to the Census Bureau (quoted by IPUMS): "One set of estimates that can be produced from CPS microdata files should be treated with caution. These are estimates for individual metropolitan areas. Although estimates for the larger areas such as New York, Los Angeles, and so forth, should be fairly accurate and valid for a multitude of uses, estimates for the smaller metropolitan areas (those with populations under 500,000) should be used with caution because of the relatively large sampling variability associated with these estimates." See https://cps.ipums.org/cps-action/variables/METFIPS#description_section (consulted on September 12, 2024).

References

Beland, L.-P., Brodeur, A. and Wright, T.: 2020, COVID-19, Stay-At-Home Orders and Employment: Evidence from CPS Data. IZA Discussion Paper Series no. 13282.

Bell, D. N. F. and Blanchflower, D. G.: 2011, Young People and the Great Recession, *Oxford Review of Economic Policy* **27**(2), 241–267.

Brochu, P., Créchet, J. and Deng, Z.: 2020, Labour Market Flows and Worker Trajectories in Canada during COVID-19. CLEF Working Paper no. 32.

Cortes, G. M. and Forsythe, E.: 2023, Heterogeneous Labor Market Impacts of the COVID-19 Pandemic, *ILR Review* **76**(1), 30–55.

Flood, S., King, M., Rodgers, R., Ruggles, S., Warren, J. R. and Michael, W.: 2020, Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [dataset]. Minneapolis, MN: IPUMS. DOI: https://doi.org/10.18128/D030.V8.0.

Forsythe, E.: 2022, Why Don't Firms Hire Young Workers During Recessions?, *The Economic Journal* **132**(645), 1765–1789.

Lemieux, T., Milligan, K., Schirle, T. and Skuterud, M.: 2020, Initial Impacts of the COVID-19 Pandemic on the Canadian labour market, *Canadian Public Policy* **46**(S1), S55–S65.

Madrian, B. C. and Lefgren, L. J.: 1999, A Note on Longitudinally Matching Current Population Survey (CPS) Respondents. NBER Working Paper no. T0247.

Michelacci, C. and Ruffo, H.: 2015, Optimal Life Cycle Unemployment Insurance, *American Economic Review* **105**(2), 816–859.

Pissarides, C. A.: 2013, Unemployment in the Great Recession, *Economica* **80**(319), 385–403.

Rivera Drew, J. A., Flood, S. and Warren, J. R.: 2014, Making Full Use of the Longitudinal Design of the Current Population Survey: Methods for Linking Records across 16 Months, *Journal of Economic and Social Measurement* **39**(3), 121–144.

Van Ours, J. C.: 2015, The Great Recession was not so Great, *Labour Economics* **34**, 1–12.

A Tables

A.1 Direct replication

Table 1: Hiring over the Business Cycle: With and Without Controls

Outcome: Pr(Hired) $\times$ 100	(1)	(2)	(3)	(4)
Panel A: Aggregate effect				
U. rate	-0.119***	-0.146***	-0.140***	-0.0186
	(0.0130)	(0.0089)	(0.00914)	(0.0117)
[original]	-0.119***	-0.149***	-0.149***	-0.0326*
	(0.0150)	(0.0100)	(0.00906)	(0.0132)
R^2	0.000	0.000	0.002	0.003
[original]	0.000	0.000	0.002	0.003
Panel B: Disaggregate by potential experience				
PE $\leq$ 10	5.454***	5.456***	5.350***	5.356***
	(0.118)	(0.121)	(0.118)	(0.118)
[original]	5.039***	5.040***	4.987***	4.988***
	(0.120)	(0.122)	(0.117)	(0.117)
PE $\leq$ 10 $\times$ U. rate	-0.343***	-0.370***	-0.366***	-0.244***
	(0.0171)	(0.0158)	(0.0157)	(0.0163)
[original]	-0.335***	-0.365***	-0.369***	-0.253***
	(0.0203)	(0.0177)	(0.0166)	(0.0185)
PE $>$ 10 $\times$ U. rate	-0.0407**	-0.0664***	-0.0611***	0.0616***
	(0.0122)	(0.00898)	(0.00956)	(0.0126)
[original]	-0.0367**	-0.0656***	-0.0662***	0.0496**
	(0.0131)	(0.00911)	(0.00882)	(0.0142)
R^2	0.008	0.008	0.009	0.010
[original]	0.007	0.007	0.008	0.009
State fixed effect	No	Yes	Yes	Yes
Demographic fixed effect	No	No	Yes	Yes
Month-year fixed effect	No	No	No	Yes
N	16,208,583	16,208,583	16,208,583	16,208,583
[original]	16,948,516	16,948,516	16,948,516	16,948,516

Notes: Replication of Table 1 from Forsythe (2022). The original paper's estimates are displayed below the replication results. The replication sample is constructed using the IPUMS-CPS database (Flood et al. (2020), see discussion in Section 2.1). The dependent variable is a binary variable equal to one if a worker starts a new job (from non-employment or employment) in the next month (rescaled to 100). 'U. rate': state-level unemployment rate; 'PE': potential experience (age − experience − 6). The regressions are weighted using CPS weights. Standard errors, clustered at the state level, are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2: Hiring over the Business Cycle: Young and Experienced

Outcome: Pr(Hired) × 100	(1)	(2)	(3)	(4)
PE ≤ 10	5.356***	2.810***	7.083***	9.815***
	(0.118)	(0.109)	(0.646)	(0.369)
[original]	4.988***	2.662***	6.137***	8.089***
	(0.117)	(0.0960)	(0.660)	(0.316)
PE ≤ 10 × U. rate	-0.244***	-0.167***	-1.887***	-0.578***
	(0.0163)	(0.0162)	(0.157)	(0.0368)
[original]	-0.253***	-0.168***	-1.928***	-0.490***
	(0.0185)	(0.0156)	(0.167)	(0.0332)
PE > 10 × U. rate	0.0616***	0.0291**	-1.395***	0.0329
	(0.0126)	(0.00975)	(0.161)	(0.0371)
[original]	0.0496**	0.0179	-1.505***	0.0148
	(0.0142)	(0.0101)	(0.176)	(0.0364)
Wald test	552.55***	198.71***	58.20***	270.92***
[original]	569.88***	206.51***	38.15***	237.47***
R^2	0.010	0.005	0.035	0.022
[original]	0.009	0.004	0.031	0.018
N	16,208,583	10,584,758	630,938	4,992,887
[original]	16,948,516	10,814,088	653,100	5,481,328
sample	All	Employed	Unemployed	NILF

Notes: Replication of Table 2 from Forsythe (2022). The original paper's estimates are displayed below the replication results. The replication sample is constructed using the IPUMS-CPS database (Flood et al. (2020)). The dependent variable is a binary variable equal to one if a worker starts a new job (from non-employment or employment) in the next month (rescaled to 100). 'U. rate': state-level unemployment rate; 'PE': potential experience (age − experience − 6). The regressions include state, demographic, and month-year fixed effects and are weighted using CPS weights. Standard errors, clustered at the state level, are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The Wald test examines whether the PE ≤ 10 × U. rate and PE > 10 × U. rate coefficients are statistically distinct.

Table 3: Exits and Other Flows

Outcome: Pr(Exit) × 100	(1)	(2)	(3)	(4)	(5)	(6)
PE ≤ 10	5.662***	0.788***	2.665***	2.209***	4.089***	2.631***
	(0.174)	(0.0497)	(0.0888)	(0.131)	(0.209)	(0.489)
[original]	5.950***	0.866***	2.604***	2.479***	3.824***	3.947***
	(0.147)	(0.0590)	(0.0951)	(0.127)	(0.191)	(0.498)
PE ≤ 10 × U. rate	-0.0226	0.149***	-0.177***	0.00545	0.313***	-0.444***
	(0.0255)	(0.00791)	(0.0146)	(0.0187)	(0.0351)	(0.0880)
[original]	-0.0217	0.156***	-0.161***	-0.0165	0.286***	-0.453***
	(0.0274)	(0.00876)	(0.0156)	(0.0198)	(0.0250)	(0.0888)
PE > 10 × U. rate	0.173***	0.134***	0.0133	0.0262	0.280***	-0.965***
	(0.0258)	(0.00642)	(0.0130)	(0.0170)	(0.0167)	(0.102)
[original]	0.187***	0.148***	0.0232	0.0150	0.310***	-0.890***
	(0.0242)	(0.00593)	(0.0116)	(0.0189)	(0.0187)	(0.103)
Wald test	80.10***	3.63	274.89***	1.67	0.61	67.89***
[original]	200.57***	0.65	246.84***	5.87*	0.53	75.79***
R^2	0.017	0.005	0.004	0.013	0.017	0.034
[original]	0.018	0.006	0.004	0.014	0.015	0.037
N	10,584,758	10,584,758	10,584,758	10,584,758	4,992,887	630,938
[original]	10,814,088	10,814,088	10,814,088	10,814,088	5,481,328	653,100
Sample	Employed	Employed	Employed	Employed	NILF	Unemployed
Destination	All	Unemployed	Employed	NILF	Unemployed	NILF

Notes: Replication of Table 3 from Forsythe (2022). The original paper's estimates are displayed below the replication results. The replication sample is constructed using the IPUMS-CPS database (Flood et al. (2020)). The dependent variable in columns 1 to 4 is a binary variable equal to one if a worker ends a job (either transitioning to non-employment or another job) in the next month (rescaled to 100). In columns 5 and 6, the dependent variables are binary variables for transitions between non-participation and unemployment (rescaled to 100). 'U. rate': state-level unemployment rate; 'PE': potential experience (age − experience − 6). The regressions include state, demographic, and month-year fixed effects and are weighted using CPS weights. Standard errors, clustered at the state level, are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The Wald test examines whether the PE ≤ 10 × U. rate and PE > 10 × U. rate coefficients are statistically distinct.

Table 4: Involuntary and Voluntary Separations to Unemployment

	(1) Pr(Involuntary) $\times$ 100	(2) Pr(Voluntary) $\times$ 100
PE $\leq$ 10	0.185***	0.327***
	(0.0419)	(0.0149)
[original]	0.193***	0.322***
	(0.0444)	(0.0157)
PE $\leq$ 10 $\times$ U. rate	0.133***	-0.0117***
	(0.00742)	(0.00270)
[original]	0.140***	-0.0103**
	(0.00671)	(0.00321)
PE $>$ 10 $\times$ U. rate	0.119***	0.00717***
	(0.00674)	(0.00182)
[original]	0.125***	0.00814***
	(0.00559)	(0.00209)
Wald test	3.83	84.43***
[original]	3.29	65.67***
R^2	0.004	0.001
[original]	0.004	0.001
N	10,584,758	10,584,758
[original]	10,814,088	10,814,088

Notes: Replication of Table 4 from Forsythe (2022). The original paper's estimates are displayed below the replication results. The replication sample is constructed using the IPUMS-CPS database (Flood et al. (2020)) and restricted to employed individuals. 'Involuntary' is a binary variable equal to one if a worker separates from a job to unemployment involuntarily (rescaled to 100). 'Voluntary' is a binary variable equal to one if a worker quits a job to become unemployed (rescaled to 100). 'U. rate': state-level unemployment rate; 'PE': potential experience (age $-$ experience $-$ 6). The regressions include state, demographic, and month-year fixed effects and are weighted using CPS weights. Standard errors, clustered at the state level, are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The Wald test examines whether the coefficients for PE $\leq$ 10 $\times$ U. rate and PE $>$ 10 $\times$ U. rate are statistically distinct.

Table 5: Average Potential Experience of Hires

Outcome: average PE of hires	(1)	(2)
U. rate	0.132**	0.113**
	(0.0479)	(0.0409)
[original]	0.138**	0.123**
	(0.0479)	(0.0372)
R^2	0.069	0.182
[original]	0.066	0.187
Occupation fixed effects	No	Yes
Industry fixed effects	No	Yes
N	564,107	564,107
[original]	549,835	549,835

Notes: Replication of Table 5 from Forsythe (2022). The original paper's estimates are displayed below the replication results. The replication sample is constructed using the IPUMS-CPS database (Flood et al. (2020)). The dependent variable is potential experience (age − experience − 6). Negative experience values are imputed values of zero. 'U. rate': state-level unemployment rate. The regressions include state, demographic, and month-year fixed effects and are weighted using CPS weights. Standard errors, clustered at the state level, are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6: Potential Experience within Cells

	(1) All	(2) Employed	(3) Unemployed	(4) NILF
Panel A: Average experience of individuals within cells				
U. rate	-0.0106	0.0364	0.184***	-0.138**
	(0.0283)	(0.0206)	(0.0522)	(0.0467)
[original]	-0.0106	0.0440*	0.174**	-0.142**
	(0.0252)	(0.0174)	(0.0560)	(0.0476)
R^2	0.046	0.040	0.064	0.083
[original]	0.045	0.040	0.064	0.099
N	16,208,583	10,584,758	630,938	4,992,887
[original]	16,948,516	10,814,088	653,100	5,481,328
Panel B: Average experience of newly hired within cells				
U. rate	0.132**	0.171***	0.249***	0.0243
	(0.0479)	(0.0455)	(0.0595)	(0.0961)
[original]	0.138**	0.174***	0.253***	0.0338
	(0.0479)	(0.0474)	(0.0672)	(0.0842)
R^2	0.069	0.059	0.062	0.110
[original]	0.066	0.052	0.058	0.109
N	564,107	211,823	140,188	212,096
[original]	549,835	204,594	138,335	206,906
Panel C: Ratio of average PE of hires to average PE of population in cell				
U. rate	0.00414*	0.00473	0.00839**	0.00215
	(0.00187)	(0.00276)	(0.00289)	(0.00326)
[original]	0.00553**	0.00368	0.00415	0.00515*
	(0.00189)	(0.00265)	(0.00352)	(0.00252)
R^2	0.262	0.160	0.111	0.147
[original]	0.273	0.113	0.045	0.199
N	12,036	12,033	12,021	12,035
[original]	12,214	12,214	12,214	12,214

Notes: Replication of Table 6 from Forsythe (2022). The original paper's estimates are displayed below the replication results. The replication sample is constructed using the IPUMS-CPS database (Flood et al. (2020)). In the first two panels, the dependent variable is potential experience (age − experience − 6). Negative experience values are imputed values of zero. In Panel C, the dependent variable is the ratio of the potential experience of hires to the average potential experience of a given population within the state-month-year cell. 'U. rate': state-level unemployment rate. Regressions are weighted using CPS weights. Standard errors, clustered at the state level, are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 10: Log Wages During Recessions for New Hires

Outcome: log weekly wage	(1)	(2)	(3)	(4)
Panel A: Aggregated hires				
U. rate	-0.0161***	-0.00885	-0.0170***	-0.0221**
	(0.00367)	(0.00441)	(0.00401)	(0.00804)
[original]	-0.0174***	-0.00797*	-0.0173***	-0.0244***
	(0.00287)	(0.00368)	(0.00452)	(0.00658)
R^2	0.407	0.454	0.408	0.336
[original]	0.422	0.467	0.424	0.352
Panel B: Disaggregated by potential experience				
PE $\leq$ 10	-0.121***	-0.172***	-0.151***	-0.0219
	(0.0135)	(0.0221)	(0.0192)	(0.0371)
[original]	-0.138***	-0.178***	-0.176***	-0.0324
	(0.0129)	(0.0225)	(0.0232)	(0.0340)
PE $\leq$ 10 $\times$ U. rate	-0.0250***	-0.0178***	-0.0231***	-0.0318***
	(0.00406)	(0.00485)	(0.00545)	(0.00645)
[original]	-0.0262***	-0.0162***	-0.0217***	-0.0352***
	(0.00360)	(0.00394)	(0.00618)	(0.00568)
PE $>$ 10 $\times$ U. rate	-0.0103*	-0.00453	-0.0161***	-0.0107
	(0.00419)	(0.00474)	(0.00373)	(0.0107)
[original]	-0.0116**	-0.00350	-0.0176***	-0.0103
	(0.00348)	(0.00432)	(0.00415)	(0.00924)
R^2	0.416	0.471	0.418	0.340
[original]	0.433	0.485	0.435	0.358
Wald test	23.97***	17.15***	3.42	9.52**
[original]	23.78***	15.55***	0.81	14.96***
N	118,520	47,243	31,641	39,636
[original]	112,858	44,415	30,387	38,056
sample	All	Employed	Unemployed	NILF

Notes: Replication of Table 10 from Forsythe (2022). The original paper's estimates are displayed below the replication results. The replication sample is constructed using the IPUMS-CPS database (Flood et al. (2020)). The dependent variable is the natural log of weekly non-allocated wages, adjusted for inflation. 'U. rate': state-level unemployment rate; 'PE': potential experience (age − experience − 6). The regressions include state, demographic, month-year, industry, and occupation fixed effects and are weighted using CPS weights. Standard errors, clustered at the state level, are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The Wald test examines whether the PE $\leq$ 10 $\times$ U. rate and PE $>$ 10 $\times$ U. rate coefficients are statistically distinct.

Table B.2: Hiring Over the Business Cycle: Detailed Potential Experience Categories

Outcome: Pr(Hired) × 100	(1)	(2)	(3)	(4)
PE < 0 × U. rate	-0.564***	-0.348***	-1.895***	-0.765***
	(0.0424)	(0.0398)	(0.284)	(0.0715)
[original]	-0.493***	-0.283***	-1.950***	-0.581***
	(0.0241)	(0.0366)	(0.112)	(0.0302)
PE = 0 × U. rate	-0.559***	-0.321***	-2.134***	-0.799***
	(0.0291)	(0.0410)	(0.140)	(0.0485)
[original]	-0.452***	-0.302***	-1.984***	-0.526***
	(0.0371)	(0.0270)	(0.180)	(0.0493)
PE = 1 × U. rate	-0.500***	-0.324***	-2.021***	-0.696***
	(0.0344)	(0.0306)	(0.191)	(0.0563)
[original]	-0.296***	-0.235***	-1.879***	-0.482***
	(0.0256)	(0.0186)	(0.164)	(0.0619)
PE = 2 × U. rate	-0.285***	-0.234***	-1.851***	-0.470***
	(0.0238)	(0.0222)	(0.190)	(0.0574)
[original]	-0.207***	-0.179***	-1.916***	-0.450***
	(0.0294)	(0.0282)	(0.210)	(0.0563)
PE = 3 × U. rate	-0.188***	-0.163***	-1.890***	-0.450***
	(0.0199)	(0.0197)	(0.195)	(0.0631)
[original]	-0.173***	-0.151***	-1.999***	-0.427***
	(0.0347)	(0.0212)	(0.254)	(0.0753)
PE = 4 × U. rate	-0.165***	-0.153***	-1.909***	-0.423***
	(0.0375)	(0.0228)	(0.261)	(0.0860)
[original]	-0.133***	-0.114***	-2.181***	-0.412***
	(0.0337)	(0.0201)	(0.278)	(0.100)
PE = 5 × U. rate	-0.111**	-0.101***	-2.049***	-0.380***
	(0.0322)	(0.0203)	(0.267)	(0.102)
[original]	-0.0858***	-0.124***	-1.643***	-0.339***
	(0.0240)	(0.0192)	(0.201)	(0.0820)
R^2	0.048	0.026	0.246	0.072
[original]	0.011	0.005	0.033	0.025
N	16,208,583	10,584,758	630,938	4,992,887
[original]	16,948,516	10,814,088	653,100	5,481,328
sample	All	Employed	Unemployed	NILF

Table B.2 - continued: Hiring Over the Business Cycle: Detailed Potential Experience Categories

Outcome: Pr(Hired) $\times$ 100	(1)	(2)	(3)	(4)
PE = 6 $\times$ U. rate	-0.0835***	-0.122***	-1.661***	-0.366***
	(0.0218)	(0.0168)	(0.204)	(0.0860)
[original]	-0.0851***	-0.113***	-1.886***	-0.200**
	(0.0184)	(0.0186)	(0.251)	(0.0590)
PE = 7 $\times$ U. rate	-0.0727***	-0.109***	-1.736***	-0.230**
	(0.0197)	(0.0168)	(0.235)	(0.0738)
[original]	-0.0940***	-0.0929***	-2.035***	-0.326***
	(0.0268)	(0.0198)	(0.250)	(0.0901)
PE = 8 $\times$ U. rate	-0.0598*	-0.0771***	-2.000***	-0.228**
	(0.0271)	(0.0215)	(0.279)	(0.0716)
[original]	-0.0370	-0.0668**	-1.712***	-0.223*
	(0.0285)	(0.0208)	(0.289)	(0.0891)
PE = 9 $\times$ U. rate	-0.0363	-0.0735**	-1.717***	-0.238*
	(0.0291)	(0.0221)	(0.326)	(0.0961)
[original]	0.00137	-0.0289	-1.708***	-0.169*
	(0.0211)	(0.0147)	(0.216)	(0.0721)
10 $\leq$ PE < 15 $\times$ U. rate	0.0159	-0.0167	-1.612***	-0.162*
	(0.0192)	(0.0136)	(0.219)	(0.0707)
[original]	0.0242	-0.00495	-1.588***	-0.110*
	(0.0164)	(0.0107)	(0.209)	(0.0466)
15 $\leq$ PE < 19 $\times$ U. rate	0.0318	0.00474	-1.561***	-0.121*
	(0.0163)	(0.0113)	(0.199)	(0.0578)
[original]	0.0484**	0.0261*	-1.474***	-0.182***
	(0.0173)	(0.0111)	(0.204)	(0.0483)
20 $\leq$ PE < 24 $\times$ U. rate	0.0645***	0.0379**	-1.404***	-0.169**
	(0.0161)	(0.0110)	(0.218)	(0.0513)
[original]	0.0534***	0.0186	-1.328***	-0.0801
	(0.0143)	(0.0112)	(0.177)	(0.0405)
R^2	0.048	0.026	0.246	0.072
[original]	0.011	0.005	0.033	0.025
N	16,208,583	10,584,758	630,938	4,992,887
[original]	16,948,516	10,814,088	653,100	5,481,328
sample	All	Employed	Unemployed	NILF

Table B.2 - continued: Hiring Over the Business Cycle: Detailed Potential Experience Categories

Outcome: Pr(Hired) $\times$ 100	(1)	(2)	(3)	(4)
$25 \leq$ PE $< 29 \times$ U. rate	0.0673***	0.0319**	-1.212***	-0.0893
	(0.0135)	(0.0104)	(0.157)	(0.0462)
[original]	0.0546***	0.0236*	-1.287***	-0.000331
	(0.0125)	(0.00983)	(0.139)	(0.0307)
$30 \leq$ PE $< 34 \times$ U. rate	0.0711***	0.0329**	-1.200***	0.0273
	(0.0138)	(0.00979)	(0.138)	(0.0409)
[original]	0.0581***	0.0340**	-1.374***	0.0388
	(0.0133)	(0.0118)	(0.168)	(0.0326)
$35 \leq$ PE $< 39 \times$ U. rate	0.0698***	0.0444***	-1.331***	0.0550
	(0.0138)	(0.0113)	(0.155)	(0.0392)
[original]	0.0552*	0.0382**	-1.455***	0.0317
	(0.0209)	(0.0132)	(0.212)	(0.0490)
$40 \leq$ PE $< 44 \times$ U. rate	0.0689**	0.0468***	-1.443***	0.0573
	(0.0212)	(0.0126)	(0.199)	(0.0549)
[original]	0.0706***	0.0444***	-1.260***	0.0688*
	(0.0110)	(0.0111)	(0.141)	(0.0273)
PE $\geq 45 \times$ U. rate	0.088***	0.050***	-1.089***	0.099**
	(0.0123)	(0.0115)	(0.164)	(0.0336)
[original]	-0.506***	-0.329***	-1.870***	-0.564***
	(0.0322)	(0.0331)	(0.239)	(0.0443)
R^2	0.048	0.026	0.246	0.072
[original]	0.011	0.005	0.033	0.025
N	16,208,583	10,584,758	630,938	4,992,887
[original]	16,948,516	10,814,088	653,100	5,481,328
sample	All	Employed	Unemployed	NILF

Notes: Replication of Table B.2 from Forsythe (2022). The original paper's estimates are displayed below the replication results. The replication sample is constructed using the IPUMS-CPS database (Flood et al. (2020)). The dependent variable is a binary variable equal to one if a worker starts a new job (from non-employment or employment) in the next month (rescaled to 100). 'U. rate': state-level unemployment rate; 'PE': potential experience (age − experience − 6). The regressions include state, demographic, and month-year fixed effects and are weighted using CPS weights. Standard errors, clustered at the state level, are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A.2 Robustness: Sample extended to 1994-2019

Table A.2.1: Hiring over the Business Cycle: With and Without Controls

Outcome: Pr(Hired) × 100	(1)	(2)	(3)	(4)
Panel A: Aggregate effect				
U. rate	-0.0716***	-0.0874***	-0.0866***	-0.0199*
	(0.0106)	(0.00869)	(0.00874)	(0.00965)
R^2	0.000	0.000	0.002	0.003
Panel B: Disaggregate by potential experience				
PE $\leq$ 10	4.736***	4.734***	4.624***	4.629***
	(0.124)	(0.127)	(0.123)	(0.123)
PE $\leq$ 10 × U. rate	-0.235***	-0.250***	-0.250***	-0.183***
	(0.0146)	(0.0155)	(0.0151)	(0.0119)
PE > 10 × U. rate	-0.0159	-0.0308**	-0.0302**	0.0377**
	(0.0106)	(0.00924)	(0.00968)	(0.0119)
R^2	0.007	0.007	0.009	0.009
State fixed effect	No	Yes	Yes	Yes
Demographic fixed effect	No	No	Yes	Yes
Month-year fixed effect	No	No	No	Yes
N	20,597,660	20,597,660	20,597,660	20,597,660

Notes: Robustness check of Table 1 with sample period extended to 1994-2019. The dependent variable is a binary variable equal to one if a worker starts a new job (from non-employment or employment) in the next month (rescaled to 100). 'U. rate': state-level unemployment rate; 'PE': potential experience (age − experience − 6). The regressions are weighted using CPS weights. Standard errors, clustered at the state level, are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.2.2: Hiring over the Business Cycle: Young and Experienced

Outcome: Pr(Hired) × 100	(1)	(2)	(3)	(4)
PE ≤ 10	4.629***	2.303***	6.615***	8.767***
	(0.123)	(0.0970)	(0.563)	(0.393)
PE ≤ 10 × U. rate	-0.183***	-0.123***	-1.790***	-0.506***
	(0.0119)	(0.0143)	(0.176)	(0.0298)
PE > 10 × U. rate	0.0377**	0.0141	-1.346***	-0.0120
	(0.0119)	(0.00854)	(0.181)	(0.0299)
Wald test	220.969***	147.091***	57.594***	141.018***
R^2	0.009	0.004	0.032	0.021
N	20,597,660	13,331,602	756,363	6,509,695
sample	All	Employed	Unemployed	NILF

Notes: Robustness check of Table 2 from Forsythe (2022) with sample period extended to 1994-2019. The dependent variable is a binary variable equal to one if a worker starts a new job (from non-employment or employment) in the next month (rescaled to 100). 'U. rate': state-level unemployment rate; 'PE': potential experience (age − experience − 6). The regressions include state, demographic, and month-year fixed effects and are weighted using CPS weights. Standard errors, clustered at the state level, are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The Wald test examines whether the PE ≤ 10 × U. rate and PE > 10 × U. rate coefficients are statistically distinct.

A.3 Robustness: MSA unemployment variation

Table A.3.1: Hiring over the Business Cycle: With and Without Controls

Outcome: Pr(Hired) × 100	(1)	(2)	(3)	(4)
Panel A: Aggregate effect				
U. rate	-0.0346***	-0.0386***	-0.0416***	-0.0236***
	(0.00518)	(0.00324)	(0.00330)	(0.00314)
R^2	0.000	0.001	0.003	0.003
Panel B: Disaggregate by potential experience				
PE $\leq$ 10	4.051***	4.047***	3.930***	3.932***
	(0.0829)	(0.0828)	(0.0809)	(0.0807)
PE $\leq$ 10 × U. rate	-0.123***	-0.129***	-0.131***	-0.114***
	(0.0101)	(0.00819)	(0.00812)	(0.00711)
PE > 10 × U. rate	-0.00458	-0.00912**	-0.0114**	0.00648
	(0.00457)	(0.00342)	(0.00347)	(0.00400)
R^2	0.007	0.007	0.009	0.009
MSA fixed effect	No	Yes	Yes	Yes
Demographic fixed effect	No	No	Yes	Yes
Month-year fixed effect	No	No	No	Yes
N	14,887,472	14,887,472	14,887,472	14,887,472

Notes: Robustness check of Table 1 from Forsythe (2022) with MSA-level unemployment rates as an explanatory variable (instead of state-level). The dependent variable is a binary variable equal to one if a worker starts a new job (from non-employment or employment) in the next month (rescaled to 100). 'U. rate': MSA-level unemployment rate; 'PE': potential experience (age − experience − 6). The regressions are weighted using CPS weights. Standard errors, clustered at the MSA level, are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.3.2: Hiring over the Business Cycle: Young and Experienced

Outcome: Pr(Hired) × 100	(1)	(2)	(3)	(4)
PE $\leq$ 10	3.932***	1.781***	6.783***	7.463***
	(0.0807)	(0.0590)	(0.375)	(0.212)
PE $\leq$ 10 × U. rate	-0.114***	-0.0432***	-1.658***	-0.293***
	(0.00711)	(0.00605)	(0.0456)	(0.0175)
PE > 10 × U. rate	0.00648	0.0135***	-1.266***	0.00523
	(0.00400)	(0.00289)	(0.0418)	(0.00748)
Wald test	181.357***	74.593***	126.855***	184.624***
R^2	0.009	0.004	0.043	0.021
N	14,887,472	9,712,396	559,554	4,615,522
sample	All	Employed	Unemployed	NILF

Notes: Robustness check of Table 2 from Forsythe (2022) with MSA-level unemployment rates as an explanatory variable (instead of state-level). The dependent variable is a binary variable equal to one if a worker starts a new job (from non-employment or employment) in the next month (rescaled to 100). 'U. rate': MSA-level unemployment rate; 'PE': potential experience (age − experience − 6). The regressions include MSA, demographic, and month-year fixed effects and are weighted using CPS weights. Standard errors, clustered at the MSA level, are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The Wald test examines whether the PE $\leq$ 10 × U. rate and PE > 10 × U. rate coefficients are statistically distinct.