Technical Appendix for Experiences of America’s Promise Participants During the “COVID-19 Recession”: Examining Gender Differences in Labor Market and Training Program Outcomes (Spitzer et al. 2022)

This appendix summarizes the analysis methods for the brief titled *Experiences of America's Promise Participants During the "COVID-19 Recession": Examining Gender Differences in Labor Market and Training Program Outcomes* (Spitzer et al. 2022). Section A describes the data sources used for this study. Section B describes our approach to analyzing employment and earnings. Finally, Section C describes our approach to analyzing program completion and enrollment.

A. Data

Workforce Integrated Performance System (WIPS)

The WIPS is a centralized database that contains quarterly data on participants in workforce programs funded by the U.S. Department of Labor, including America's Promise employment services. It was created in 2016 as a way to have standardized data on all programs and participants. The WIPS data cover participant characteristics, employment and training services received, and training program completion. We obtained program year (PY) 2017–PY 2020 fourth-quarter (Q4) WIPS data for America's Promise participants. These data include Social Security numbers (SSNs), which we used to obtain participants' employment and earnings data from the National Directory of New Hires.

National Directory of New Hires (NDNH)

NDNH data from the Office of Child Support Enforcement at the U.S. Department of Health and Human Services contain information on quarterly earnings and Unemployment Insurance (UI) benefits, submitted from state UI systems and the federal government's employment records (Solomon-Fears 2011). We can obtain NDNH data for America's Promise participants by SSN. For this analysis, we rely on NDNH data on participants in America's Promise PYs 2017 and 2018. For this group, we were able to collect NDNH data covering calendar years 2018–2020. Although some data were available for 2021, the coverage was incomplete, so these data were not used in the analysis. Also, due to incomplete data availability, we excluded all data from participants in Colorado, Indiana, Montana, and North Carolina for the analysis of employment and earnings outcomes. This represented 8.5 percent of participants. We also excluded participants in states with fewer than five participants due to our inability to assess data quality. This additionally excluded participants from Idaho, Maine, Nebraska, Nevada, and South Carolina.

NDNH data cover most wage and salary employment. However, the NDNH has limitations. The NDNH data do not cover all types of jobs and industries. In particular, NDNH data do not cover self-employed workers, railroad employees, workers in service for relatives, most agricultural labor, some domestic service workers, and part-time employees of nonprofit organizations (U.S. Department of Labor et al. 2014). In the past, these sectors have made up about 10 percent of U.S. employment (Kornfeld and Bloom 1999; Hotz and Scholz 2002). NDNH data also exclude workers whose employers do not report their earnings to their UI agency, even in the formal sector, because of the prevalence of flexible staffing arrangements or illegally neglecting to report (Blakemore et al. 1996; Houseman 2001; Hotz and Scholz 2002; Abraham et al. 2018; Katz and Krueger 2019). Additionally, NDNH data do not cover workers who are casually employed, such as day laborers or part-time helpers, and exclude most work that is part of the gig economy (Abraham et al. 2018; Katz and Kruger 2019).

Of the SSNs of America's Promise participants submitted, we received NDNH data on 97 percent of participants in our sample. The remaining unmatched participants may represent inaccurate SSN data or people with no earnings reported. Because we are unable to distinguish between these two scenarios, we dropped all participants from the sample for whom we received no NDNH data from the analyses of employment and earnings. The final sample size for the employment and earnings analysis was 14,373.

B. Analyses of employment and earnings

The analyses on employment and earnings are based on America's Promise participants from PYs 2017 and 2018. This ensures that analyses are limited to people with expected program exits before March 2020. Given that more than 75 percent of participants exit the program within three quarters, this ensures that the analysis is not picking up the impacts of differential program dropout following March 2020.

To assess the regression-adjusted average employment and earnings by gender, we estimate the following regression equation

$$Y_{itz} = \alpha + \beta X_{iz} + \sum_{k=1}^{Z}\sum_{j=1}^{T}\lambda_{jk} 1_{j=t,k=z} + \sum_{j=1}^{T}\delta_j 1_{j=t,\, gender=F} + \varepsilon_{it}$$

where Y_{itz} is the income of person *i* in time period *t* and industry *z*. X_i is a vector of individual characteristics including race, age category, industry, grantee indicators, and program year of entry. λ is a vector of quarter fixed effects for each industry, and ε_{it} is an individual-time specific error. δ is a vector of coefficients on an indicator of being female in each quarter. This coefficient captures the regression-adjusted difference in earnings by quarter, which is not accounted for by differences in individual or grantee characteristics. Standard errors are clustered at the individual level. To address whether gender differences vary by race, age, or training industry, we adjusted the above regression equation to include interactions between each individual characteristic and quarter. We also included separate indicator variables for the interaction between gender and quarter for each characteristic level. Separate models were fit for earnings and employment, although both models were estimated as ordinary least squares regressions. Regression on employment can be interpreted as linear probability models, which produce more interpretable marginal estimates (adjusted employment rate) than logistic regression models (adjusted log odds of employment) and are more computationally efficient (Chatla and Shmueli, 2016).

To assess the magnitude and statistical significance of the differences between the period before and after the onset of COVID-19, we adjusted the above regression equation to remove the indicators for being female in each quarter. We replaced this with two indicators—interactions between being female in the pre-COVID-19 (Q1 2018 – Q1 2020) and post-COVID-19 periods (Q2 2020 – Q4 2020).

C. Analyses of program completion and enrollment

Analyses of program completion and enrollment are based solely on the WIPS data. Program completion analyses are limited to participants who enrolled before the onset of COVID-19, which includes all participants in PY 2017, PY 2018, and PY 2019, Q1–Q3. We consider someone to have completed the program if they completed any training, regardless of whether the person enrolled in more than one training. Program enrollment analyses cover enrollment through PY 2020, Q4.

To assess how program completion differences by gender varied for participants who received services before and after the onset of COVID-19, we first defined two groups of participants based on expected completion date. The two groups represent participants with expected program completion by and following March 2020. To estimate expected program completion for each combination of grantee and industry, we identified the median number of months to program completion among people completing at least one training program over the full period. For each person, we estimated the expected completion date as the month of entrance plus the median months to program completion for their training industry and grantee.

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