Appendices to
"Boomerang Kids In the Pandemic: How High-Income Families Are Their Own Safety Net"
Rachel Widra, André Victor D. Luduvice

Appendix 1: Older Young Adults

To verify that our results are not driven by students who tend to be younger, we run the analysis again with an older group of young adults aged 24 to 30. Some of the figures in the *Commentary* are reproduced below using this older sample. The differences between boomerang kids and young adults not living with their parents persist with even this more restrictive sample.

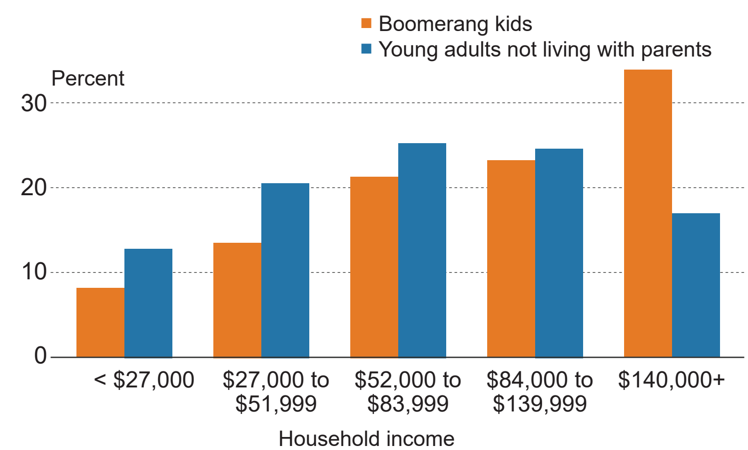
In Figure 5, we observe that the percent of these older young adults living with their parents increases substantially at the start of the pandemic, mirroring what we saw in the 18- to 29-year-old population. The most noticeable difference is that in 2021, this older group saw a larger increase than the group on the whole, and there is a recent upturn in September 2021.

Figure 5: Percent of young adults 24 to 30 who live with at least one parent

Source: Authors' calculations based on the Current Population Survey extracted from IPUMS CPS, University of Minnesota

In Figure 6, the percent of young adults and boomerang kids in each income quintile is similar for the restricted older sample.

Figure 6: Percent of young adults in each income quintile

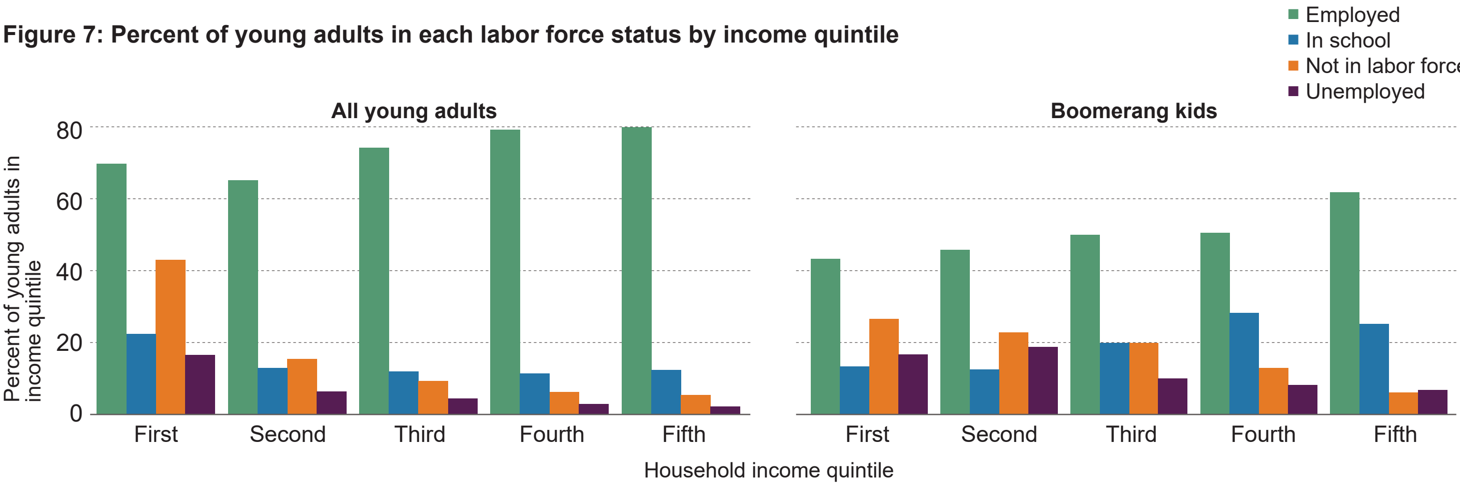


Notes: See text for the methodology used to identify boomerang kids. The sample period spans March 2020 through September 2021. Income quintiles are based on household income in the ASEC. Lower quintile cutoff labels are rounded to the nearest $1,000.

Source: Authors' calculations based on the Current Population Survey extracted from IPUMS CPS, University of Minnesota

Figure 7 shows that older boomerang kids are more likely to be employed and less likely to be students than the group of boomerang kids on the whole, but they are still much less likely to be employed than young adults not living with their parents and more likely to be unemployed at every income level.

Figure 7: Percent of young adults in each labor force status by income quintile

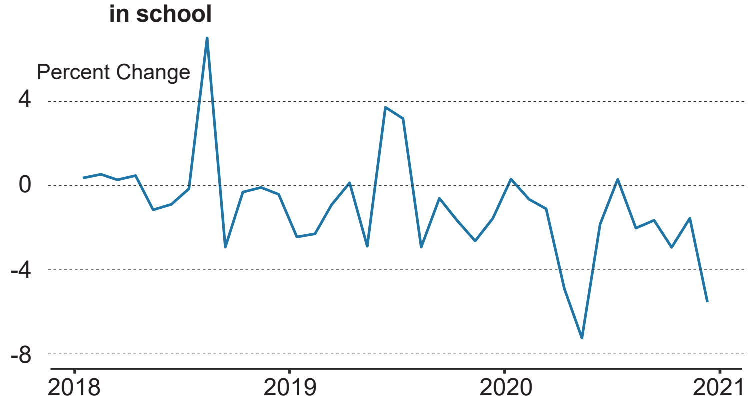


Notes: See text for the methodology used to identify the boomerang kids. The sample period spans from March 2020 through September 2021. Income quintiles are based on household income in the ASEC.

Source: Authors' calculations based on the Current Population Survey extracted from IPUMS CPS, University of Minnesota

Additionally, we graphed the year-over-year percent change of young adults living with their parents who are students. We can observe in Figure 8 a decrease during the initial months of the pandemic and an overall decreasing trend in the most recent months. Most notably, in spring 2020 this percentage is substantially lower than in the same period during 2019. This difference suggests that the influx of young adults to their parents' homes are largely nonstudents. The recent decrease in the percent that are students also points to young adults' leaving their parents' homes to attend universities that have reopened to in-person classes, leaving a smaller percentage of students living at home.

Figure 8: Percent change in young adults living at home that are in school



Source: Authors' calculations based on the Current Population Survey extracted from IPUMS CPS, University of Minnesota

Appendix 2: Construction of the Occupational Risk Index

The occupational risk index is constructed using the methodology laid out in Beland, Brodeur, and Wright (2020). We use survey data on occupation-specific work environments and activities to create an index of how often a worker in each occupation is exposed to hazards or environments that make virus spread more likely.

Data come from two Occupational Information Network (O*NET) surveys, the Work Activities Survey published in August 2018 and the Work Context Survey published in August 2019. Both surveys ask about the importance and frequency of work activities in each of the 974 O*NET-SOC occupations. Respondents were asked to rate on a scale from one to five how important or frequent specific activities or environments are for their jobs, with five being the most important or frequent. Contexts are broken down by interpersonal relationships, physical work conditions, and structural job characteristics. Specific contexts include items such as "Face-to-Face Discussions" and "Exposed to Disease or Infections." The number of respondents that selected each level of importance/frequency are reported for each occupation and context.

To create the occupational risk index, we use four questions from the work context survey that ask how close in proximity workers work, how frequently workers are exposed to viruses or infections, how often workers have face-to-face conversations, and how often workers interact with external customers. We also use one question from the work activities survey on how important caring for others is in each occupation. We use the average response by workers in each occupation to create an index of exposure to each hazard by occupation. For each occupation and each question, we scale the response in an index between 0 and 100.

Index = (Average response by workers in specific occupation -1) / (Maximum response in this category – 1)

We create an index of face-to-face interactions with the public by taking the geometric mean of the face-to-face interactions and deal with external customers indices. The overall occupational risk index is the average of the physical proximity, exposure to disease, face-to-face interaction with external customers, and importance of caring for others indices.

Appendix 3: Construction of the Nonemployment Spell

To define a nonemployment spell and its length, we use the IPUMS CPS variables EMPSTAT, DURUNEMP, CPSIDP, and WNFTLOOK.

We start by ordering our dataset by person ID and date. For each person in each month, we check if the person's labor force status, EMPSTAT, changes in the next month from unemployed to employed. If it does, we flag the end of an unemployment spell. We then look at the person's labor force status in the previous month; if the person was employed in the previous month and is now unemployed or not in the labor force, we flag a new nonemployment spell. If a respondent enters the survey period unemployed, we flag the person's unemployment on the entrance date and use the DURUNEMP variable to determine how long the person was unemployed prior to entering the survey. If we observe a person while the person is not in the labor force (NILF) and then the person becomes unemployed, we add the length of observed time out of the labor force to the length of unemployment to get the nonemployment duration. For people who enter the survey unemployed but are classified as unemployed reentrants, we have no way of determining their length of time out of the labor force before returning. We use their duration of unemployment knowing it is an underestimate. This applies to 5 percent of our classified short-term nonemployment spells.

For people who are not in the labor force, we only count their nonemployment spell and subsequent reemployment if we can measure the length of their nonemployment. If they were previously employed in the survey period, we can observe how long they were out of the labor force, and we include this spell. If they enter the survey unemployed, we can use the DURUNEMP variable to determine how long they were unemployed before they left the labor force, and we use that combined duration as the length of their nonemployment. Only for respondents that enter the survey NILF and then become employed within 26 weeks do we not count their nonemployment spell. For respondents who become employed within 26 weeks of entering the survey but who answer question WNFTLOOK saying they have not been employed in the last 12 months, we count their nonemployment spell but recode it to a spell longer than 26 weeks.

Appendix 4: Occupational Risk before the Pandemic

While there are noticeable differences in occupational risk during the pandemic, we must also examine differences that existed before the pandemic. The differences in length of nonemployment and occupational sorting existed before the pandemic, but they increased for all of our measured categories during the pandemic.

Table 2: Occupational risk and length of nonemployment for young adults before the pandemic

	Live with parents	Do not live with parents	Difference
Percent unemployed who become employed within 26 weeks	64.73%	71.79%	-7.06***
Average duration of nonemployment (weeks)	17.50	14.37	3.13***
Percent of employed young adults working in a high-risk occupation	6.36%	11.81%	-5.45%***
Percent of young adults who changed jobs and switched into a high-risk occupation[11]	6.12%	8.36%	-2.24%***

Notes: The difference in means is tested using t-tests with a significance level of 0.01.

Source: Authors' calculations based on the Current Population Survey extracted from IPUMS CPS, University of Minnesota