Can Online Learning Alter Labor Force Attachment? Evidence from U.S. Labor Markets

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July 2024

Abstract

In 2021, 26% of all postsecondary degree seekers in the U.S. studied exclusively online. Moreover, in 2022, Coursera, an open online course provider, had 19 million U.S. students. In this paper, I seek to answer the following questions: Who is participating in online education, and how does enrollment into online education affect their labor market flows? Using data from the Current Population Survey, I construct occupational exposure to online education and track thousands' of individuals labor market outcomes from 2019 through 2022. First, I find that individuals engaged in online education tend to be more educated, earn higher wages, have higher shares of remote work, and are typically employed in computer- and office-focused occupations. Second, I examine how online education affects labor market flows. I find that, on average, online education increases the probability that individuals keep their job by 3 percentage points and reduces the probability that they exit the labor force by 2 percentage points. When examining heterogeneous treatment effects, I find that women with young children are less likely to retain employment and more likely to exit the labor force compared with women without children. However, my findings reveal that online education has a strong effect on labor market outcomes for women with young children. Online education increases the probability that women with young children keep their job by 8 percentage points and decreases the probability that they exit the labor force by 6 percentage points.

KEYWORDS: Online education, MOOCs, labor force exit, work-from-home, labor market flows
JEL CLASSIFICATION CODES: J24, I21, I26

I would like to thank Kiet Le for his assistance at the beginning of this project. I thank participants at the 2024 Conference on Network Science and Economics, and the 2024 Society of Labor Economists Conference for insightful comments. This paper was previously circulated as "Online Learning in the Face of Unemployment." Any opinions and conclusions expressed herein are those of the author and do not necessarily represent the views of the Board of Governors or its staff. Any errors are my own.

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1 Introduction

Over the past few years, there has been a rise in online learning in the U.S. In 2021, 26% of all postsecondary degree seekers in the U.S. studied exclusively online (Hamilton and Swanston, 2022). In addition, in 2022, Coursera, an open online course provider, had 19 million U.S students (Coursera, 2022). In this paper, I define "online education" to be a range of activities, including the pursuit of online courses, that lead to degrees, certifications, licenses, or job-specific training. The goal of this paper is to answer the following questions: Who is participating in online education, and how does enrollment into online education affect their labor market flows?

In the first part of the paper, using data from the Current Population Survey (CPS), I analyze the distribution of online education across industries and occupations. My findings reveal that individuals enrolled in online education are typically employed in industries that feature computer- and office-focused occupations. In addition, I show that individuals who participate in online education are more educated, which suggests the presence of complementarities between formal education and online education. Moreover, I find that online education is correlated with higher wages and that individuals enrolled in online education possess greater capabilities to work from home. Furthermore, I analyze how online education varies across demographics. I highlight that 27% of the population engages in online education. From this subset, 85% are employed, 2% are unemployed, and 13% are not in the labor force. In addition, I find that online education is concentrated amongst those under the age of 35. Lastly, when compared with their male counterparts, there is a 6% higher share of women enrolled in online education.

In the second part of the paper I answer this question: How does online education affect labor market flows? Specifically, I am interested in how online education affects the probability that individuals keep their job and exit the labor force. Using data from the CPS, I construct occupational exposure to online education and track thousands of individuals' labor market outcomes from 2019 through 2022. Using a linear probability model (LPM) with multiple fixed effects, I find that from 2019 through 2020, on average, online education increases the probability that individuals keep their job by 3 percentage points while reducing the probability they exit the labor force by 2 percentage points. My estimates align closely with previous research examining the effects of online learning within international labor markets (Majerowicz and Zárate, 2024; Novella et al., 2024; Castano-Munoz and Rodrigues, 2021).

I then explore heterogeneous treatment effects (HTEs) for women with young children. My HTE analysis first confirms prior results in the literature that women with young children face hardships of staying in the labor force (Jones and Wilcher, 2024; Katherine Lim, 2021; Luengo-Prado, 2021; Pitts, 2021; Smith and Leigh, 2021; Russell and Sun, 2020). My novel contribution is that online education has a sizeable effect on labor market outcomes for women with young children. From 2019 through 2020, my findings suggest that online education decreases the probability of exiting the labor force for women with children aged 2 to 3 and aged 6 to 11. However, from 2021 through 2022, I find that online education is only beneficial to women with children aged 8 to 14.

I argue that the significant effects disappearing at the lower end of the age distribution can be attributed to the shift in family dynamics during the COVID-19 pandemic. Prior work has shown that childcare disproportionally shifted during the pandemic among couples with children. In fact, in a given week, women provided almost double the amount of childcare hours than their male counterparts (Alon et al., 2020). Moreover, children aged 0 to 8 are classified as newborns and preschoolers, who typically require more supervision. Conversely, middle childhood and teenagers require less supervision. My findings are in line with the idea that during 2021 through 2022, women with middle childhood and teenagers had more flexibility to engage in online education while balancing childcare responsibilities.

Related Literature. First, this paper expands on prior work that has been done on online learning. Mainly, prior work has focused on Massive Open Online Courses (MOOCs) (Picchio and van Ours, 2013; Hällsten, 2012; Banerjee and Duflo, 2014; Ho et al., 2015; Christensen et al., 2014; Castaño-Muñoz et al., 2017; Radford et al., 2014; Castano-Munoz and Rodrigues, 2021; Novella et al., 2024; Majerowicz and Zárate, 2024; Zhenghao et al., 2015). MOOCs are typically an extension of higher education and are modeled as semester-long academic classes (Banerjee and Duflo, 2014).

Work by Zhenghao et al. (2015) examines survey evaluation data from Coursera, revealing that the primary motivation for individuals to enroll in MOOCs is career advancement. Moreover, prior literature, exemplified by Ho et al. (2015), has consistently shown a correlation between MOOC participation and higher levels of formal education. For instance, Ho et al. (2015) analyze HarvardX and MITx online courses from 2012 through 2014, finding that a significant majority of enrolled individuals hold bachelor's degrees or higher, echoing the findings of Christensen et al. (2014) and Zhenghao et al. (2015). Despite this rich descriptive evidence, a notable gap remains in understanding the labor market outcomes of online learning. While studies by Castano-Munoz and Rodrigues (2021), Majerowicz and Zárate (2024), and Hällsten (2012) report positive effects of online learning on employment retention, primarily in European and South American labor market contexts, further research is needed to comprehensively explore this aspect. Thus, while existing literature provides valuable insights into the motivations and educational correlates of MOOC enrollment, additional studies are required to examine the implications for labor market outcomes and employment stability.

The prior work has several limitations. First, work by Zhenghao et al. (2015) and Ho et al. (2015) is mainly descriptive and is subjective to the evaluation of survey respondents (Castaño-Muñoz et al., 2017). Second, work by Zhenghao et al. (2015), Ho et al. (2015), Christensen et al. (2014), Castano-Munoz and Rodrigues (2021), and Hällsten (2012) over-samples highly educated individuals as well as individuals over the age of 30. Third, one overall limitation of MOOCs is that they do not capture individuals who are participating in online job training (Castano-Munoz and

Rodrigues, 2021).

This paper addresses limitations observed in prior research through several key advancements. First, my measure of online education is defined to be taking both online courses and online job training. While direct observation of the specific activity is not feasible, this definition encompasses a wide range of activities, including courses for degrees, certifications, licenses, or job-specific training. To substantiate this assertion, in Section 2, I compare my descriptive findings on online education with previous literature. Second, this study is the first to analyze the effect of online education within the U.S. labor market context. Third, it includes individuals of all age groups enrolled in online education, thereby providing a more comprehensive analysis. Fourth, this paper is the first to analyze the distribution of online education across industries and occupations.

Second, this paper contributes to previous literature that incorporates human capital accumulation in the form of on-the-job training (Acemoglu and Pischke, 1998, 1999; Cairo and Cajner, 2018; Flinn et al., 2017; Becker, 1964; Lentz and Roys, 2024; Shy and Stenbacka, 2023; Dingel and Neiman, 2020). Prior work uses on-the-job training in a general equilibrium framework to draw implications about productivity, wages, and labor market outcomes. Mainly, I highlight that prior literature classifies on-the-job training as informal, in-person, and task-specific learning directly tied to the use of machinery or equipment.

My contribution to this body of literature is that online education is a complement to on-the-job training. I posit that current methodologies for measuring on-the-job training may not adequately capture the extent to which workers engage in online educational activities. As I show in this paper, individuals who are engaged in online education are more educated, earn higher wages, have greater work-from-home ability, and tend to be employed in computer- and office-focused occupations. Consequently, there is a need to consider new dynamics in human capital accumulation that incorporate these digital learning environments.

Third, this paper adds to prior work on women's labor market outcomes (Jones and Wilcher, 2024; Katherine Lim, 2021; Luengo-Prado, 2021; Pitts, 2021; Smith and Leigh, 2021; Russell and Sun, 2020). Specifically, prior work has found that women, particularly with young children, face difficulties in staying in the labor force. For example, Jones and Wilcher (2024) highlight that more than one-fourth of working women leave the labor force when they have a child. In addition, Katherine Lim (2021) find that during 2020 and 2021, there was excess labor force exits for women living with children under the age of 12. In this paper, I find similar results–that women with young children are more likely to exit the labor force. However, I show that online education can help women with young children overcome these labor market challenges.

Fourth, this paper contributes to the rise in remote activities (Barrero et al., 2023, 2021; Gibbs et al., 2023; Dingel and Neiman, 2020; Choudhury et al., 2021). Prior literature has focused on working-from-home, documenting which industries and occupations are well equipped for the shift to remote work. In addition, prior work has studied the effect of working-from-home on wages and productivity. In this paper, I document a positive relationship between working from home and online education at the industry and occupation levels. I find that this relationship is particularly strong in industries that feature computer- and office-focused occupations. Moreover, using job postings data from Lightcast, I show that there is a positive relationship between remote-work job postings and online education. Notably, I find that occupations with higher shares of remote-work job postings have high shares of online education. I interpret these results as suggestive evidence that computer- and office-focused occupations are using online education as a tool to augment their human capital.

The rest of this paper is organized as follows. Section 2 describes the data sources and variable construction used in the study. Section 3 provides descriptive evidence followed by discussion of the model and main empirical results. Section 4 concludes.

2 Data Sources and Measurement

In this section, I describe in detail which data sources and methods are used in the analysis. I begin by discussing the main explanatory variable, *online education*, which is constructed from the Current Population Survey Computer and Internet Use Supplement (CPS-CIS). I show how online education varies by two-digit Standard Occupational Classification system, two-digit North American Industry Classification System (NAICS), and demographic characteristics.

Lastly, I discuss the Current Population Survey Annual Social and Economic Supplement (CPS-ASEC) longitudinal extract, which is a longitudinal dataset that allows me to track labor market flows from 2019 through 2022. Specifically, I use the CPS-ASEC to define the main outcome variables, job keeping and labor force exit.

2.1 Current Population Survey Computer and Internet Use Supplement

The CPS-CIS conducts interviews with approximately 54,000 households for a set of consecutive months during the year and repeats the process for the corresponding period a year later. One advantage of using a CPS source is that it contains detailed information on socioeconomic and demographic variables. Within the CPS-CIS, the question, "Do you participate in online courses or job training?" defines the variable *online education*. This question is collected in November of 2019 and 2021 and refers to activity over the past six months. For the analysis, I narrow the sample to be workers aged 16 to 54.[1]

Given that this topic is understudied I acknowledge certain data limitations. First, the CPS-CIS reported variable for online education does not make it possible to distinguish if the individual is enrolled in online courses or online job training. Second, online classes can encompass a range

[1] I use this range as opposed to prime-age workers aged 25 to 54 because I want to capture any individuals under age 25 who may be using online education as a substitute or complement to formal education.

TABLE 1 – Descriptive Statistics for Online Education (Shares)

Variable	2019	2021	Whole Sample
Online Education	0.25	0.31	0.27
Labor Force Status			
Employed	0.86	0.83	0.85
Unemployed	0.02	0.03	0.02
Not in LF	0.12	0.14	0.13
Age Quintile			
1	0.25	0.27	0.26
2	0.23	0.21	0.22
3	0.18	0.18	0.18
4	0.18	0.18	0.18
5	0.15	0.15	0.15
Race			
White	0.79	0.77	0.78
Black	0.10	0.11	0.10
Asian	0.07	0.08	0.07
Mixed/Other	0.04	0.04	0.04
Female	0.53	0.54	0.53
Observations enrolled in online education	5,684	6,086	11,770
Observations in the whole sample	23,214	19,947	43,161

NOTE: Author's calculations from the CPS-CIS. Individuals aged 16-54.

of activities, including the pursuit of online courses that lead to degrees, certifications, or licenses. In validating my measure, I show that the distribution of online education across age and formal education is similar to that of MOOCs. Third, data for online education are only available for 2019 and 2021. As a result, I will have to take a slightly different empirical approach, which I discuss in more detail in Section 3.

Table 1 shows the shares of online education across demographics. On average, in 2019 and 2021, the share of individuals enrolled in online education is 27%. From this subset, 85% are employed, 2% are unemployed, and 13% are not in the labor force. When looking at age quintiles, I find that online education is concentrated amongst those under age 35. In addition, in appendix Figure A.1, I plot the average distribution of online education across all ages in 2019 and 2021. The average ages for those enrolled in online education in 2019 and 2021 are both 35. My mean estimates for age are similar to those of Castaño-Muñoz et al. (2017), Castano-Munoz and Rodrigues (2021), and Hällsten (2012). Similar to these studies, my sample mean is capturing individuals over the age of 30 enrolled in online education. However, what distinguishes my data from prior studies is the dynamics of online education in the lower end of the age distribution. Notably, between 2019 and 2021, the rise in online education is primarily among individuals under the age of 24, with an average increase of 13%, compared to a 5% increase for those aged 25 to 54. For example, the average enrollment for individuals aged 19, 20, 21, and 22 increased by 19%, 20% , 12%, and 14%,

TABLE 2 – Changes in Online Education by Two-digit Occupation

Major Occupation Group	$Education_{s,2019}$	$Education_{s,2021}$	$\Delta Education_s$
Management	0.27	0.33	0.06
Business and Financial	0.30	0.39	0.09
Computer and Mathematical	0.40	0.42	0.02
Architecture and Engineering	0.35	0.38	0.03
Life, Physical, and Social Science	0.40	0.46	0.06
Community and Social Services	0.34	0.47	0.13
Legal	0.35	0.33	-0.02
Educational Instruction and Library	0.38	0.48	0.10
Arts, Design, Entertainment, Sports, and Media	0.35	0.33	-0.02
Healthcare Practitioners and Technical	0.36	0.41	0.05
Healthcare Support	0.36	0.41	0.05
Protective Service	0.28	0.35	0.07
Food Preparation and Serving Related	0.20	0.28	0.08
Building and Grounds Cleaning and Maintenance	0.14	0.23	0.09
Personal Care and Service	0.22	0.34	0.12
Sales and Related	0.25	0.30	0.05
Office and Administrative Support	0.24	0.32	0.08
Farming, Fishing, and Forestry	0.13	0.16	0.03
Construction and Extraction	0.14	0.18	0.04
Installation, Maintenance, and Repair	0.22	0.24	0.02
Production	0.14	0.16	0.02
Transportation and Material Moving	0.17	0.18	0.01
Average across all occupations	0.27	0.32	0.05

NOTE: Author's calculations from the CPS-CIS. Workers aged 16-54.

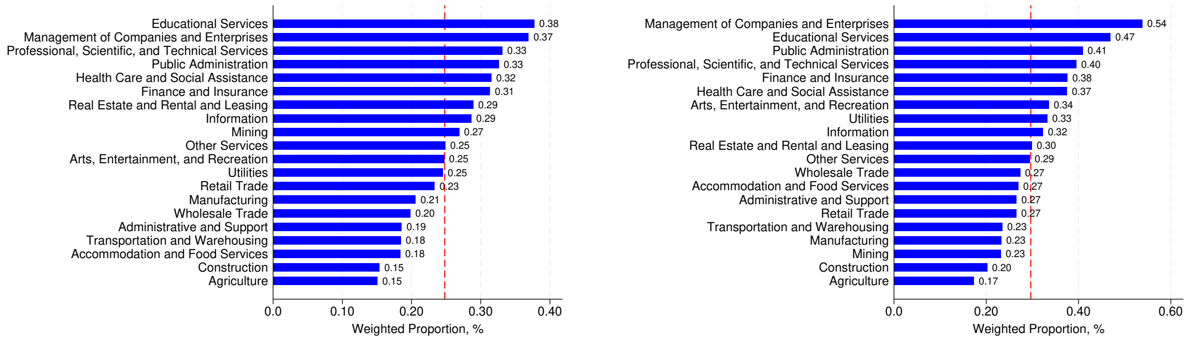
respectively.

In Table 2, I show the distribution of online education across two-digit occupations for 2019 and 2021. The average share of online education for workers increased by 5%, rising from 27% in 2019 to 32% in 2021.[2] Furthermore, Table 2 shows how changes in online education vary across occupations. Occupations with notable increases include Community and Social Services (13%), Personal Care and Service (12%), Educational (10%), Business and Financial (9%), and Office and Administrative Support (8%).

By contrast, occupations with small changes in online education include Construction (4%); Installation, Maintenance, and Repair (2%); and Transportation and Material Moving (1%). I note that some occupations have high levels of online education but small changes between the two periods. For example, in 2021, 42% of workers in Computer and Mathematical occupations engage in online education despite only having a 2% increase from 2019 to 2021. The same relationship

[2] Note that this number is slightly different from what is shown in Table 1, as I do not set employment restrictions for Table 1.

FIGURE 1 – Online Education by Two-digit NAICS



A. 2019 Shares

B. 2021 Shares

NOTE: Authors' calculations from the CPS-CIS. Red line indicates the average across all industries.

holds for Life, Physical, and Social Science occupations, as almost half of workers engage in online education despite having only a 6% increase.

Moreover, in Figure 1, I plot the share of online education across two-digit NAICS. Industries with high shares of online education in 2021 typically feature computer- and office-focused occupations–for example, Management of Companies and Enterprises (54%); Educational Services (47%); Professional, Scientific, and Technical Services (40%); and Finance and Insurance (38%). Industries with low shares of online education, however, include Transportation and Warehousing (23%), Manufacturing (23%), Construction (20%), and Agriculture (17%).

2.2 Current Population Survey Annual Social and Economic Supplement

The CPS-ASEC longitudinal extract (Flood et al., 2023) is a longitudinal dataset that contains employment information and general demographic characteristics. One advantage of the CPS-ASEC is that it ensures that there are two observations per person across a one-year period. Data are collected in March of every year. These data allow me to calculate labor market flows. I am particularly interested in understanding how access to online education affects job keeping and labor force exit.

In my empirical design, I denote labor market flows as: $y_{i,s,j\to l,t}$. Here, I am interested if individual i in occupation s changes labor market status $j \to l$ at time t. For job keeping, $y_{i,s,j\to l,t}$ is equal to 1 if an individual is employed in March of year $t-1$ and employed in March of year t. For labor force exit, it is equal to 1 if an individual is in the labor force in March of year $t-1$ but not in the labor force in March of year t. The reference group for both outcomes contains individuals whose status does not change the following period.

In Table 3, I provide descriptive statistics for those who fall under job keeping and labor force exit. Comparing the two groups, I find that individuals who exit the labor force are younger and

TABLE 3 – Descriptive Statistics for Labor Market Flow Analysis (Means)

Variable	Job Keeping	Labor Force Exit
Age	38.25	33.19
Family size	3.17	3.48
Number of children	1.02	0.78
Age of eldest child	6.64	4.84
Educational attainment	14.00	12.00
Wage ($)	58,000	25,665
Female	0.47	0.57
Married	0.58	0.38
Race (shares)		
White	0.82	0.75
Black	0.08	0.14
Asian	0.06	0.06
Mixed/Other	0.04	0.05
Observations	43,367	3,320

NOTE: Author's calculations from the CPS-ASEC. Sample years 2019-2022. Workers aged 16-54. Wage is CPI adjusted to 2019=100. CPS-ASEC reports educational attainment as a categorical variable. For simplicity, I convert this to years.

have younger children, have lower levels of education, and have lower wages. In addition, across demographics, individuals in this group are mostly women, single, and have higher shares of Black and mixed-race individuals.

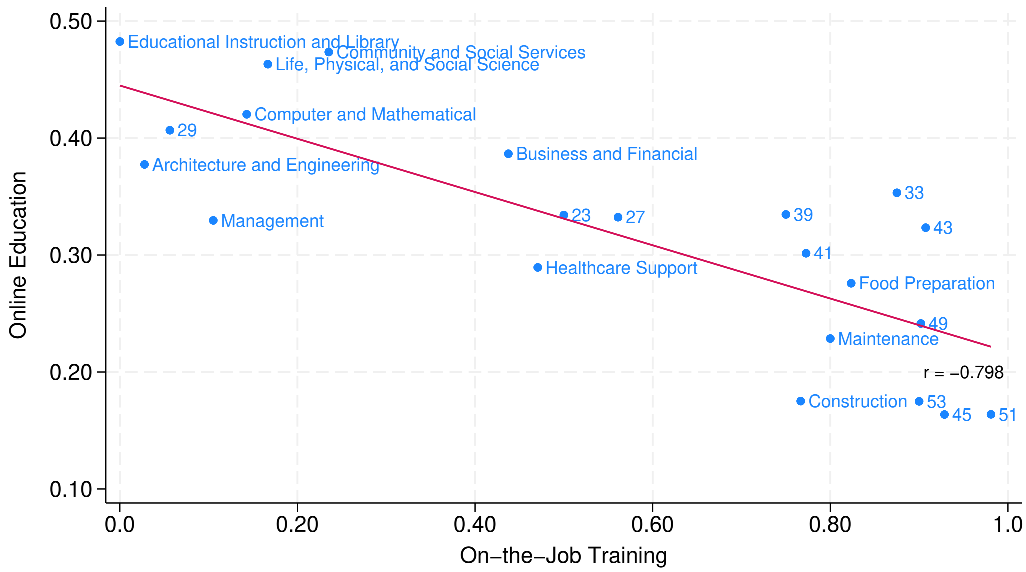
3 Main Results

I now test three empirical specifications to study the relationship between online education and labor market flows. However, before the analysis, I present descriptive evidence in order to have a better understanding of the individuals enrolled in online education. Specifically, I examine the relationship between online education and on-the-job training, formal education, wages, and working from home.

3.1 On-the-Job Training

A large set of literature is dedicated to general equilibrium models that incorporate human capital accumulation in the form of on-the-job training (Acemoglu and Pischke, 1998, 1999; Cairo and Cajner, 2018; Flinn et al., 2017; Becker, 1964; Lentz and Roys, 2024; Shy and Stenbacka, 2023). These models that incorporate on-the-job training have been used to draw implications on wages, productivity, and labor force participation. For example, Cairo and Cajner (2018) use on-the-job training in a search and matching model to explain the lower and less volatile separation rates

FIGURE 2 – Correlation With On-the-Job Training



NOTE: Both expressed as 2021 shares. Online education is calculated from the CPS-CIS. On-the-job training comes from the Employment Projections program, U.S. Bureau of Labor Statistics training assignments by detailed occupation.

between more and less educated workers.

Most important, previous literature classifies on-the-job training to be mainly informal training–for example, learning by observing your manager or colleague. Furthermore, on-the-job training is viewed as traditionally in person and tied to tasks that involve machinery or are equipment specific. In other words, on-the-job training is typically done in person or in hands-on occupations. I posit that current measures of on-the-job training may not be picking up on workers augmenting their human capital via online education.

To test this assumption, I plot the relationship between online education and on-the-job training in Figure 2. As expected, in the top left of the figure, there is a concentration of computer- and office-focused occupations that are assigned very low shares of on-the-job training despite having very high shares of online education.[3] These occupations include Management; Computer and Mathematical; Life, Physical, and Social Science; and Architecture and Engineering. Hence, current measures of on-the-job training are not completely picking up on individuals in these occupations who are augmenting their human capital. As I will show in this section, individuals with high shares of online education are more educated, earn higher wages, and are more likely to work from home. As such, there will be new human capital accumulation dynamics to consider.

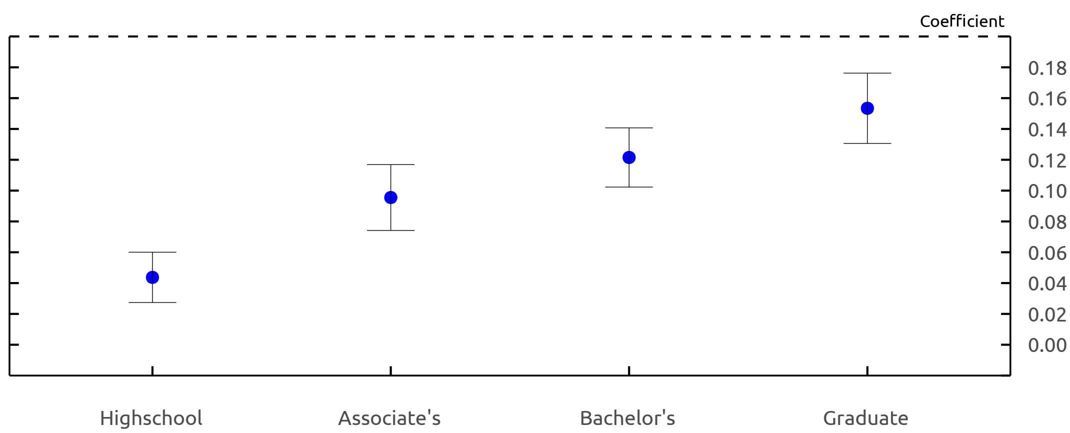
[3]On-the-job training is defined at the two-digit occupational level and refers to training or preparation that is typically needed, once employed in an occupation, to attain competency in the skills needed in that occupation. Training is occupation specific rather than job specific.

I believe that online education can serve as a complement to the on-the-job training literature. Online education will capture a new set of demographics that was not emphasized before.

3.2 Formal Levels of Education

As shown in Figure 3, I plot ordinary least squares (OLS) estimates between online education and formal education. I interpret these results as descriptive and find that there is a positive and significant relationship. In other words, high levels of formal education correspond with high levels of online education. Prior work on MOOCs finds similar results–that the majority of individuals enrolled in MOOCs are highly educated (Ho et al., 2015; Christensen et al., 2014; Castaño-Muñoz et al., 2017; Zhenghao et al., 2015). Similarly, the pattern between formal education and on-the-job training has been documented in prior literature. For example, work by Cairo and Cajner (2018), Bartel (1995), Mincer (1991), and Altonji and Spletzer (1991) suggests the presence of strong complementarities between formal education and on-the-job training. My findings show that there is still a presence of strong complementarities between online education and formal education when online training is included in the measure.

FIGURE 3 – How Online Education Covaries by Educational Attainment



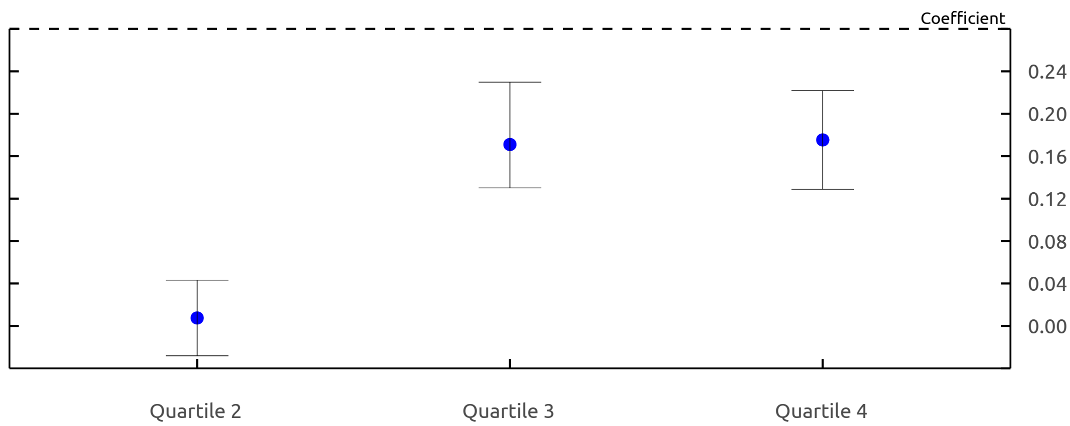
NOTE: Author's calculations from the CPS-CIS. Plots OLS estimates of educational attainment on online education. Reference group are those with less than a high school education. Includes a set of controls and industry-year and state-year fixed effects. All point estimates are significant at the 1% level.

My hypothesized explanation for this pattern is that individuals with higher levels of formal education are likely to be in more advanced occupations that require match-specific skills that cannot be gained through informal training. Hence, in order to gain those match-specific skills, the individuals must enroll in online education. For example, a software engineers may need to enroll into a software-specific course in order to complete tasks for their job. Moreover, marketing specialists may need to enroll into an Adobe Premiere course to learn how to use photoshop for clients. In contrast, individuals with lower levels of formal education will not need such a specific set of skills that must be taught through online education. For example, working as an animal trainer or pesticide handler will typically require a more informal in-person type of training.

3.3 Wages

In Figure 4, I create quartiles of online education to see how log wages covary between them. I interpret these results as descriptive and find a positive significant relationship, indicating that higher quartiles of online education correspond with higher log wages. The estimates suggest that being above the 50th percentile of online education is correlated with a strong premium in log wages. There may be concern that these results are endogenous to levels of formal education. However, these are OLS estimates that control for a set of worker observables and includes formal education.

FIGURE 4 – How Wage Covaries by Quartiles of Online Education



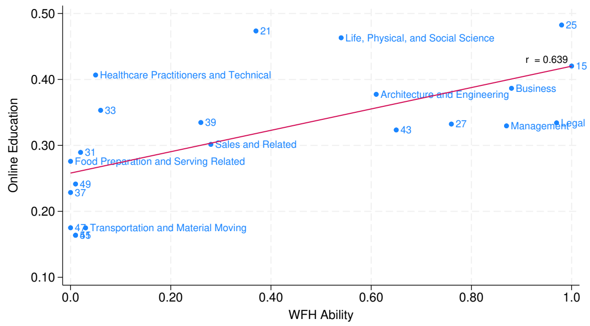
NOTE: Author's calculations from the CPS-ASEC. Plots OLS estimates of quartiles of online education on log wages (CPI adjusted to 2019 = 100). Reference group is quartile 1. Includes a set of controls and industry-year and state-year fixed effects. Point estimate for quartile 1 is insignificant. Point estimates for quartiles 3 and 4 are significant at the 1% level.

3.4 Working from Home

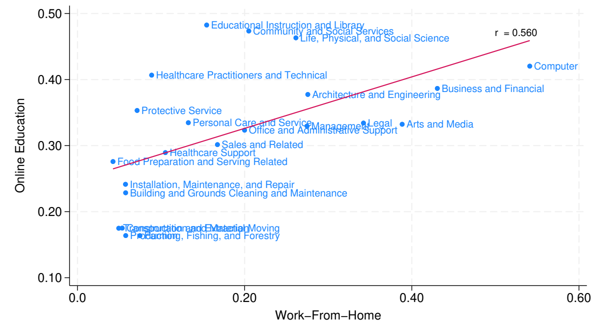
In Figure 5, panel A, I show the relationship between the 2021 share of online education and work-from-home ability at the two-digit occupational level. Notably, I find a positive correlation between the two measures, indicating that higher work-from-home ability corresponds with higher levels of online education. For example, occupations such as Farming, Fishing, and Forestry and Transportation and Material Moving have both low levels of work-from-home ability and online education. By contrast, occupations such as Computer and Mathematical, Business and Financial Operations, and Legal exhibit both high levels of work-from-home ability and online education.

In addition, in Figure 5, panel B, I compare the 2021 shares of online education with actual shares of remote work across two-digit occupations. The correlation is slightly weaker when compared with remote-work-ability. However, these are actual shares of remote work. Actual shares will show a more complete picture of individuals who are engaging in remote work as opposed to just their ability to do so. Notably, high shares of online education and remote work are in more

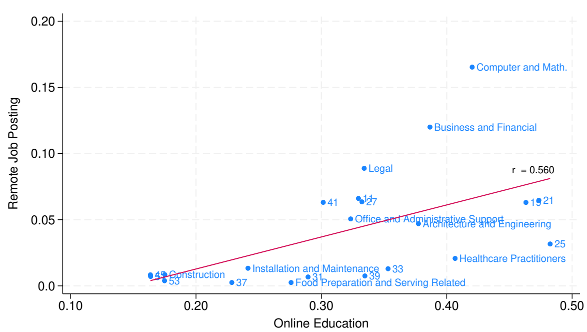
FIGURE 5 – Is Online Education Correlated with Remote Work?



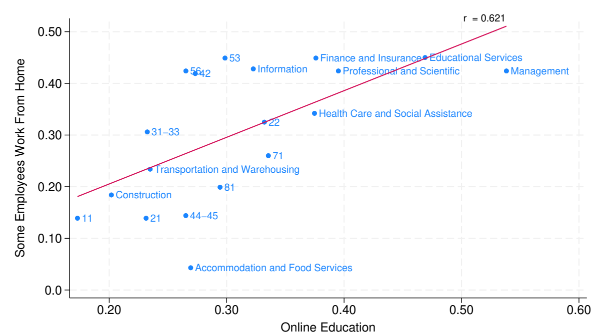
A. Work-from-Home Ability by Two-Digit OCC



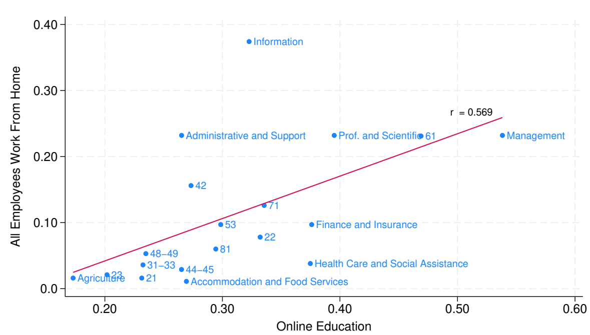
B. Remote Work by Two-Digit OCC



C. Remote Job Postings by Two-Digit OCC



D. Some Work from Home by Two-Digit NAICS



E. All Work from Home by Two-Digit NAICS

NOTE: Author's calculations. All panels report the 2021 share of online education calculated from the CPS-CIS. Panels A, B, and C report the share of Work-from-home ability, actual share of remote work, and remote work job postings by 2-digit occupation, respectively. Data for work from home ability comes from Dingel and Neiman (2020) and is the O*NET-derived classification. Data for shares of remote work is from the 2021 American Community Survey. Data for 2021 remote work job postings is from Lightcast. Panels D and E report the 2021 share of establishments with some of their employees and all of their employees working-from-home by 2-digit NAICS, respectively. This data comes from the Business Response Survey to the Coronavirus Pandemic, 2021.

computer- and office-focused occupations.

For example, roughly 55% of individuals in Computer and Mathematical occupations work from home, which is is associated with a 42% enrollment in online education. Similar to before, occupations with low levels of both variables include Installation, Maintenance, and Repair and Food Preparation and Serving Related.

Moreover, for robustness, in Figure 5, panel C, I show the relationship between online education and remote-work job postings.[4] The correlation is identical to actual shares of remote work from panel B. Moreover, similar to before, I find that higher levels of remote-work job postings and online education tend to be in more computer- and office-focused occupations. For example, Computer and Mathematical occupations have roughly 17% of job postings being remote while having a 42% share of online education. Similarly, Business and Financial Operations occupations have 13% of job postings that are remote while having a 39% share of online education.

Lastly, in Figure 5, panels D and E, I look at the relationship between online education and working from home at the two-digit NAICS industry level. Similar to before, I generally observe higher levels of both variables in industries that feature computer- and office-focused occupations. For example, in Finance and Insurance, 45% of employees who are able to do some work at home and 36% are enrolled in online education. In addition, for Management of Enterprises and Companies, 43% of employees who are able to do some work at home and 54% are enrolled in online education. Moreover, similar to prior results, I observe lower shares in industries that feature occupations that are traditionally in person–that is, Construction, Transportation and Warehousing, and Accommodation and Food Services.

Literature on the rise in remote work, particularly following the COVID-19 pandemic, is well documented (Barrero et al., 2023, 2021; Gibbs et al., 2023; Dingel and Neiman, 2020; Choudhury et al., 2021). While I do not provide rigorous empirical evidence, I believe that this paper sheds light into how online education is playing a role in this shift toward remote work. Specifically, online education may be serving as a tool for human capital accumulation among occupations that have higher shares of remote-work ability.

3.5 Empirical Approach

In the next subsection, I discuss the empirical approach as well as the main results. I seek to answer this question: How does online education affect labor market flows? As defined in Section 2, the outcome variables of interest are job keeping and labor force exit. In constructing the main explanatory variable, I first create sample weighted shares of online education across all two-digit occupations for 2019 and 2021. I then create $\text{Education}_{s,t}$, which is a binary indicator equal to 1 if occupation s is above the 50th percentile of online education at time t, where $t \in [2019, 2021]$. The reference group are those below the 50th percentile.

[4] In unreported results, I repeat this procedure by combing fully remote and hybrid job postings. The correlation is exactly the same as in panel B.

For the analysis, I merge the occupational exposure to online education from the CPS-CIS to the CPS-ASEC by 2-digit occupation codes. This merged dataset allows me to track individuals from 2019 through 2022 while having a rich set of demographic and socioeconomic variables as well as their occupational exposure to online education in 2019 and 2021. All empirical specifications use the CPS-ASEC weight. The CPS sample weight accounts for the following adjustments: failure to obtain an interview; sampling within large sample units; the known distribution of the entire population according to age, sex, and race; over-sampling Hispanic persons; to give husbands and wives the same weight; and an additional step to provide consistency with labor force estimates from the basic survey (Flood et al., 2023).

Recall the variable for online education is only available for 2019 and 2021. Given data limitations, I find it fitting to pool the regressions and estimate the effect of online education on labor market flows in two-year bins. To be precise, I use the 2019 exposure to online education to estimate 2019 to 2020 labor market flows. Similarly, I use the 2021 exposure to online education to estimate 2021 to 2022 labor market flows. In Section B of the appendix, I show the results when estimating all equations year by year.

Empirical Predictions. I have two main empirical predictions for the effect of online education on labor market flows. For my first empirical prediction, I believe that online education is match specific, which will increase the incentive for individuals to keep their job and reduce the incentive to exit the labor force. The idea of match-specific training can be traced back to Becker's theory of human capital accumulation. Becker argues that employees with specific training have less incentive to quit, and firms have less incentive to fire them, than employees with no training or general training (Becker, 1964).[5]

In fact, prior literature shows that one of the main reasons individuals enroll in online learning is to improve in their current job (Castano-Munoz and Rodrigues, 2021; Zhenghao et al., 2015). Hence, it is reasonable to assume that individuals augmenting their human capital through online education are more motivated to remain employed, having invested time in acquiring a specific skill set pertinent to their occupation. Moreover, possessing such skills makes them less inclined to exit the labor force, as they can readily transfer these skills to similar roles. Furthermore, Radford et al. (2014) surveyed 103 employers on their receptivity to using online courses (that is, MOOCs) for recruiting, hiring, and professional development. Their findings revealed that 73% of employers hold a positive view of online courses when making hiring decisions and using them for internal professional development. Therefore, akin to Becker's theory, it is reasonable to assume that when employees are engaged in online education, it gives firms less of an incentive to fire them.

My second empirical prediction is motivated by prior results in the literature suggesting that women with children face labor market challenges. First, Jones and Wilcher (2024) use data between 2000 and 2021 and find that more than one-fourth of women exit the labor force when they

[5] A similar argument is set forth in more recent work by Cairo and Cajner (2018).

have a child. Second, Katherine Lim (2021) show that in 2020 and 2021, there were significant excess labor force exits among women living with children under age 12 relative to women without children. I posit that online education will offer women with young children more opportunities to augment their human capital while balancing childcare responsibilities. As a result, I would expect online education to increase the probability that women with young children keep their job as well as reduce the probability that they exit the labor force.

3.6 Empirical Results

LPMs are widely used in empirical work.[6] To begin, I estimate equation 1 to test the average effect of online education on labor market flows. The outcome variable, $y_{i,s,j\to l,t}$, is a binary indicator equal to 1 if individual i in occupation s changes labor market status $(j \to l)$ at time t. In addition, the main explanatory variable, Education$_{s,t}$ is binary and equal to 1 if occupation s is above the 50th percentile of online education at time t, where $t \in [2019, 2021]$. The reference group are those below the 50th percentile. The main coefficient of interest is α_1, which I interpret as the effect of online education on an individual's labor market status.

$$y_{i,s,j\to l,t} = \alpha_0 + \alpha_1 \text{Education}_{s,t} + \sum_{q=1}^{Q} \beta_{q,t} X_{q,t} + \tau_{k,t} + \gamma_{m,t} + \varepsilon_{i,t}. \tag{1}$$

$X_{q,t}$ is a vector of worker observables that includes gender, age, race, marital status, number of children, income, and formal education at time t. Moreover, I control for remote-work ability as-well as actual shares of remote work at the two-digit occupational level. $\tau_{k,t}$ and $\gamma_{m,t}$ represents industry-by-year and state-by-year fixed effects; $\varepsilon_{i,t}$ is an error term; and I cluster standard errors by occupation-year.

Endogeneity Concerns. In all equations, by including industry-by-year fixed effects, I attempt to address unobservable, time-invariant characteristics unique to each industry k, reducing biases from industry-specific traits that might affect labor market flows. Similarly, including state-by-year fixed effects captures and controls for systematic variations in labor market flows specific to each state m over time. Next, there may be concern of selection into online education. That is, higher exposure to online education may indicate more motivated or higher-skilled individuals. I attempt to control for this skill concern by including worker observables as-well as remote-work activities. Mainly, by controlling for the ability to work from home, I am attempting to capture skills. For example, as I show in Section 3, the ability to work remotely is correlated with occupations that are more computer and office focused, which typically require higher skills. Lastly, I cluster standard errors by occupation-year to address potential serial correlation and unobserved heterogeneity within occupation-year groups.

The results for equation 1 can be found in Table 4. In panel A, I estimate how exposure to online

[6] For example, see Tito (2024) and Chen et al. (2017).

TABLE 4 – ATE: Probability of Job Keeping & LF Exit
(Pooled Regressions: 2019-2020 & 2021-2022)

Regressor	Dependent Variable: Job Keeping	Dependent Variable: Labor Force Exit
A. ***2019-2020***		
$\text{Education}_{s,2019}$	0.021^{***}	-0.013^{**}
	(0.008)	(0.006)
Constant	0.814	0.133
Worker Observables?	✓	✓
State-year FE?	✓	✓
Industry-year FE?	✓	✓
N	25,195	27,246
R^2	0.071	0.051
B. ***2021-2022***		
$\text{Education}_{s,2021}$	0.010	-0.010
	(0.007)	(0.006)
Constant	0.836	0.125
Worker Observables?	✓	✓
State-year FE?	✓	✓
Industry-year FE?	✓	✓
N	22,722	24,528
R^2	0.065	0.046

NOTE: OLS regressions. Estimates from equation 1. $\text{Education}_{s,t}$ is binary and equal to 1 if occupation s is above the 50th percentile of online education at time t. Worker observables include: gender, age, race, marital status, number of children, family size, income quintile, and educational attainment. I also control for remote work ability and actual shares of remote work at the 2-digit occupational level. Workers age 16-54. Standard errors are clustered by occupation-year and are reported in parentheses. * $p < .10$; ** $p < .05$; and *** $p < .01$.

education in 2019 affects labor market flows from 2019 through 2020. I find that being above the 50th percentile of online education increases the probability that individuals keep their job by 2.1 percentage points and lowers the probability that they exit the labor force by 1.3 percentage points. The results are in line with my first empirical prediction that online education is match specific, which will increase the incentive for individuals to keep their job and reduce the incentive to exit the labor force. When comparing my results with previous studies on MOOCs, I find that the magnitudes are similar to studies in Central and South America (Novella et al., 2024; Majerowicz and Zárate, 2024) and slightly lower than the European setting (Castano-Munoz and Rodrigues, 2021; Picchio and van Ours, 2013).[7]

[7] In addition, work by Hällsten (2012) finds positive returns to late tertiary degrees in Sweden. They report an

In panel B, I estimate how exposure to online education in 2021 affects labor market flows from 2021 through 2022. I find similar economic significance–that online education will increase the probability that individuals keep their job and not exit the labor force. However, the estimates fail to be statistically significant.

I suspect that other factors may be at play in 2021 and 2022 that are causing the estimates to be statistically insignificant. So, next, I estimate equation 2 to test if there is a differential impact for women. Here, the outcome, main explanatory variable, controls, and fixed effects are identically defined as in equation 1. The only difference is I am now interested in examining how women fare in the labor market and if online education has any type of effect on their labor market flows.

$$y_{i,s,j\rightarrow l,t} = \alpha_0 + \alpha_1 \text{Education}_{s,t} + \alpha_2 \text{Female}_{i,t} + \underbrace{\alpha_3[\text{Education}_{s,t} * \text{Female}_{i,t}]}_{\text{Impact}} + \sum_{q=1}^{Q} \beta_{q,t} X_{q,t} + \tau_{k,t} + \gamma_{m,t} + \varepsilon_{i,t}. \tag{2}$$

Table 5 shows the HTE for women. The table set-up is identical to the one shown above. Focusing on panel A, I find that from 2019 through 2020, the average effect for online education holds for job keeping and labor force exit. In other words, on average, being above the 50th percentile of online education will increase the probability that individuals keep their job by 1.8 percentage points and reduce the probability of exiting the labor force by 1 percentage point. In addition, I find that women generally face labor market challenges in keeping their job and remaining in the labor force. Women are 3.6 percentage points less likely to keep their job and are 3.2 percentage points more likely to exit the labor force. I observe that the interaction between online education and women is only economically significant and small.

In panel B, I find that from 2021 through 2022, the average effect of online education is not statistically significant and near zero. In addition, it is still the case that women face labor market challenges in keeping their job and remaining in the labor force. When investigating the interaction between online education and women, I note that the estimate is economically significant for labor force exit. Specifically, in 2021 and 2022, women face a 3.2 percentage point higher probability of labor force exit but women above the 50th percentile of online education are 1.4 percentage points less likely to exit. However, the estimate fails to be statistically significant. All together, I interpret the first set of HTE analysis as online education having no differential impact for women.

Up to this point, the estimates from the first two equations confirms there is an average effect of online education that is economically and statistically significant from 2019 through 2020. When testing for underlying gender dynamics, I do not find any evidence of differential impacts for women. However, I suspect that underlying family dynamics are still at play that I am not capturing. I am aware that some of my sample overlaps with the COVID-19 pandemic. Prior work shows that the allocation of household tasks for couples with children changed during this time.

increase in the employment rate by 18 percentage points.

TABLE 5 – HTE: Probability of Job Keeping & LF Exit
(Pooled Regressions: 2019-2020 & 2021-2022)

Regressor	Dependent Variable: Job Keeping	Labor Force Exit
A. ***2019-2020***		
$\text{Education}_{s,2019}$	0.018^{*}	-0.010^{*}
	(0.010)	(0.007)
$\text{Female}_{i,t}$	-0.036^{***}	0.032^{***}
	(0.008)	(0.005)
$\text{Education}_{s,2019} * \text{Female}_{i,t}$	0.006	-0.007
	(0.009)	(0.006)
Constant	0.815	0.132
Worker Observables?	✓	✓
State-year FE?	✓	✓
Industry-year FE?	✓	✓
N	25,195	27,246
R^2	0.071	0.051
B. ***2021-2022***		
$\text{Education}_{s,2021}$	0.004	0.003
	(0.008)	(0.006)
$\text{Female}_{i,t}$	-0.034^{***}	0.032^{***}
	(0.008)	(0.007)
$\text{Education}_{s,2021} * \text{Female}_{i,t}$	0.008	-0.014
	(0.011)	(0.009)
Constant	0.838	0.123
Worker Observables?	✓	✓
State-year FE?	✓	✓
Industry-year FE?	✓	✓
N	22,722	24,528
R^2	0.064	0.046

NOTE: OLS regressions. Estimates from equation 2. $\text{Education}_{s,t}$ is binary and equal to 1 if occupation s is above the 50th percentile of online education at time t. Worker observables include: gender, age, race, marital status, number of children, family size, income quintile, and educational attainment. I also control for remote work ability and actual shares of remote work at the 2-digit occupational level. Workers age 16-54. Standard errors are clustered by occupation-year and are reported in parentheses. * $p < .10$; ** $p < .05$; and *** $p < .01$.

Notably, because of closures of outside services, women increased their childcare responsibilities (Alon et al., 2020).

Furthermore, Alon et al. (2020) use the American Time Use Survey and find that during the pandemic, among all married couples with children, the husbands provide 7.4 hours of childcare per week, on average, versus 13.3 hours for the wives. Moreover, prior work done pre-COVID-19 pandemic shows that, if just restricting the division of childcare responsibilities between men and women to work hours, women provide 70% of childcare during work hours (Alon et al., 2020; Schoonbroodt, 2018). This uneven distribution of childcare is likely to have increased during the COVID-19 pandemic, leading to a disparate impact of excess labor force exits for women with children. To corroborate these findings, prior literature confirms that women with young children exhibit excess labor force exits, and this finding was amplified during the COVID-19 pandemic (Jones and Wilcher, 2024; Katherine Lim, 2021; Luengo-Prado, 2021; Pitts, 2021; Smith and Leigh, 2021; Russell and Sun, 2020).

One unique property of online education is that it tends to be asynchronous (Banerjee and Duflo, 2014; Ho et al., 2015; Novella et al., 2024; Majerowicz and Zárate, 2024). An advantage of this format is that it gives students' more flexibility to complete tasks or modules. Given the structure of online education, I hypothesize that online education will be particularly beneficial for women with young children, offering them more opportunities to augment their human capital while balancing childcare responsibilities. As a result, women with young children will be more likely to keep their job and less likely to exit the labor force. To test my hypothesis, I estimate equation 3.

$$y_{i,s,j\to l,t} = \alpha_0 + \alpha_1 \text{Education}_{s,t} + \underbrace{\alpha_2 [\text{Education}_{s,t} * \text{Female}_{i,t} * \text{Child}_{i,t}]}_{\text{Impact}} + \sum_{q=1}^{Q} \beta_{q,t} X_{q,t} + \tau_{k,t} + \gamma_{m,t} + \varepsilon_{i,t}. \quad (3)$$

Again, the outcome, main explanatory variable, controls, and fixed effects are identically defined as in equation 1. However, I am now interested in the triple interaction between female, child, and online education. This triple interaction involves testing if online education has any differential impact for women with young children. Here, $\text{Child}_{i,t}$ is a binary variable equal to 1 if the woman has a child under the age of 8. The comparison group is women with no children. In addition, I also estimate alternative specifications for each age from 2 to 14, which I discuss towards the end of this section. Because I focus on women with children, the sample size will decrease compared with prior specifications. Table 6 shows the main finding of this paper: Online education serves as a tool that can help women with young children overcome excess labor force exits.

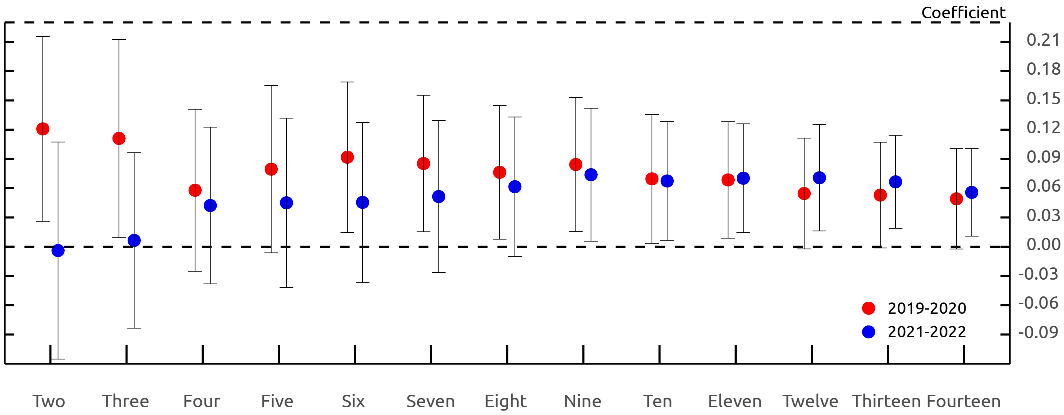
In panel A, I show that from 2019 through 2020, on average, being above the 50th percentile of online education is associated with a 3 percentage point higher probability of job keeping and a 1.8 percentage point lower probability of exiting the labor force. Furthermore, I find evidence that women face labor market challenges in keeping their job and staying in the labor force. In line with prior literature, this effect is amplified for women with young children (Jones and Wilcher, 2024; Katherine Lim, 2021; Luengo-Prado, 2021; Smith and Leigh, 2021; Russell and Sun, 2020). Specifically, women with young children are 12 percentage points less likely to keep their job and 11 percentage points more likely to exit the labor force. However, online education can help

TABLE 6 – HTE: Differential Impact of Having Children Under Eight (Pooled Regressions: 2019-2020 & 2021-2022)

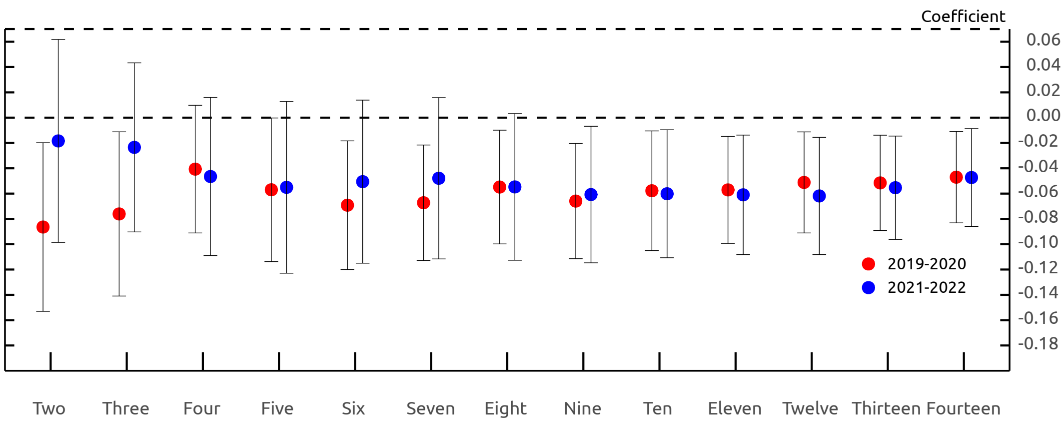
	Dependent Variable:	
Regressor	Job Keeping	Labor Force Exit
A. ***2019-2020***		
$\text{Education}_{s,2019}$	0.029**	−0.018**
	(0.012)	(0.009)
$\text{Female}_{i,t}$	−0.019*	0.020**
	(0.011)	(0.007)
$\text{Child}_{i,t}$	0.073***	−0.054***
	(0.021)	(0.016)
$\text{Female}_{i,t} * \text{Child}_{i,t}$	−0.108***	0.069***
	(0.033)	(0.022)
$\text{Education}_{s,2019} * \text{Female}_{i,t}$	−0.003	−0.004
	(0.014)	(0.009)
$\text{Education}_{s,2019} * \text{Child}_{i,t}$	−0.048**	0.037***
	(0.018)	(0.012)
$\text{Education}_{s,2019} * \text{Female}_{i,t} * \text{Child}_{i,t}$	0.076**	−0.055**
	(0.035)	(0.023)
Constant	0.769	0.160
N	15,759	17,077
R^2	0.084	0.060
B. ***2021-2022***		
$\text{Education}_{s,2021}$	0.015	−0.002
	(0.010)	(0.008)
$\text{Female}_{i,t}$	−0.019**	0.021**
	(0.008)	(0.008)
$\text{Child}_{i,t}$	0.063***	−0.059***
	(0.016)	(0.013)
$\text{Female}_{i,t} * \text{Child}_{i,t}$	−0.104***	0.089***
	(0.030)	(0.025)
$\text{Education}_{s,2021} * \text{Female}_{i,t}$	−0.003	−0.007
	(0.015)	(0.012)
$\text{Education}_{s,2021} * \text{Child}_{i,t}$	−0.030*	0.018
	(0.016)	(0.012)
$\text{Education}_{s,2021} * \text{Female}_{i,t} * \text{Child}_{i,t}$	0.062*	−0.055*
	(0.036)	(0.030)
Constant	0.795	0.157
N	14,361	15,565
R^2	0.078	0.058

NOTE: OLS regressions. Estimates from equation 3. $\text{Education}_{s,t}$ is binary and equal to 1 if occupation s is above the 50th percentile of online education at time t. All specifications include industry-year and state-year fixed effects, as well as worker observables. Worker observables include: gender, age, race, marital status, number of children, family size, income quintile, and educational attainment. I also control for remote work ability and actual shares of remote work at the 2-digit occupational level. Workers age 16-54. Standard errors are clustered by occupation-year and are reported in parentheses. * $p < .10$; ** $p < .05$; and *** $p < .01$.

FIGURE 6 – Differential Impact of Online Education For Women With Children



A. Job Keeping



B. Labor Force Exit

NOTE: Author's calculations. Plots estimates of α_2 from equation 3, changing the criteria for Child$_{i,t}$. The x-axis represents child age. For panel A, 2019-2020, all estimates but age 4 are significant at the 5% level. For panel A, 2021-2022, ages 9-14 are significant at the 5% level and age 8 at the 10% level. For panel B, 2019-2020, ages 2,3, and 6-11 are significant at the 5% level while ages 5, 12-14 are at the 10% level. For panel B, 2021-2022, ages 9-14 are significant at the 5% level while age 8 is at the 10% level.

mitigate this hardship. As shown in the last row of panel A, women with young children who are above the 50th percentile of online education are 8 percentage points more likely to keep their job and 6 percentage points less likely to exit the labor force.

In panel B, from 2021 through 2022, I find a similar story. First, women in general face labor market challenges in keeping their job and remaining in the labor force, and this relationship is amplified for women with young children. Compared with 2019 through 2020, the probability that women with young children exit the labor force increases by roughly 2 percentage points. Nonetheless, online education will increase the probability that women with young children keep their job by 6 percentage points and reduce the probability they labor force exit by 6 percentage points.

In Figure 6, I plot the point estimates across different ages of children. For job keeping, between

2019 and 2020, I find consistent significant effects across ages 2 to 14. Particularly, the probability of job keeping is highest for women with children under the age of 9 at 8 percentage points. In addition, between 2019 and 2020, for labor force exit, I find consistent significant effects across ages 2 to 14. Notably, the strongest effect is for women with children under the age of 2. This group is 9 percentage points less likely to exit the labor force.

Furthermore, in 2021 through 2022, for labor force exit, I find consistent significant effects across ages 8 to 14. Similarly, for job keeping, I find significant affects across ages 8 to 14. Compared to the 2019 through 2020 estimates, the younger end of the distribution becomes insignificant. One possible explanation for the disappearance of significance in the lower end of the age distribution is a shift in the female workload in the family during the pandemic. This shift is primarily due to the suspension of activities and services outside the home (Alon et al., 2020). Ages 0 to 8 can be classified as newborns and preschoolers. Children in this age range will typically require more supervision. As such, online education may not be as effective for women who fall into this group as they may struggle to find the time to augment their human capital. However, middle childhood and teenagers require less supervision. A possible explanation for my findings is that women with middle childhood or teenagers have more flexibility to augment their human capital via online education while balancing childcare responsibilities.

4 Concluding Remarks

In this paper, I seek to answer the following questions: Who is participating in online education and how does enrollment into online education affect their labor market flows?

The main contribution of this paper is that online education has a sizeable effect on helping women with young children stay employed and not exit the labor force, relative to women without children. The importance of this finding is critical, as prior work has established that women with young children are more likely to exit the labor force (Jones and Wilcher, 2024; Katherine Lim, 2021; Luengo-Prado, 2021; Pitts, 2021; Smith and Leigh, 2021; Russell and Sun, 2020).

The second contribution of this paper is adding to the literature on online learning. Prior work has focused on online learning through the lens of MOOCs (Picchio and van Ours, 2013; Hällsten, 2012; Banerjee and Duflo, 2014; Ho et al., 2015; Christensen et al., 2014; Castaño-Muñoz et al., 2017; Radford et al., 2014; Castano-Munoz and Rodrigues, 2021; Novella et al., 2024; Majerowicz and Zárate, 2024; Zhenghao et al., 2015). However, these studies are constrained by several key limitations. First, the focus on MOOCs overlooks the realm of online job training. Second, much of the prior work remains descriptive in nature. And, third, studies assessing labor market outcomes lack representation within the U.S. labor market context. This paper addresses these limitations offering a nuanced definition of online education, encompassing both online courses and online job training. Consequently, it captures a diverse array of activities, including online courses pursued for degrees, certifications, licenses, or job-specific training. Moreover, I am able to study the effect of online education in a U.S. labor market setting.

In addition, I am able to develop an understanding of who is participating in online education. First, my analysis reveals that individuals engaged in online education are more educated, a fact that has been documented in the MOOCs literature (Ho et al., 2015; Christensen et al., 2014; Castaño-Muñoz et al., 2017; Zhenghao et al., 2015). However, I show that there are still strong complementarities between online education and formal education when online training is included in the measure. In addition, I find that being above the 50th percentile of online education is correlated with a strong premium in log wages. Lastly, to my knowledge, this paper is the first to analyze the distribution of online education across industries and occupations. I establish that industries with high shares of online education are those that typically feature computer- and office-focused occupations. For example, Management of Companies and Enterprises (54%); Educational Services (47%); Professional, Scientific, and Technical Services (40%); and Finance and Insurance (38%).

The third contribution of this paper is that online education can serve as a complement to on-the-job training (Acemoglu and Pischke, 1998, 1999; Cairo and Cajner, 2018; Flinn et al., 2017; Becker, 1964; Lentz and Roys, 2024; Shy and Stenbacka, 2023). Mainly, I show that a concentration of computer- and office-focused occupations is assigned very low shares of on-the-job training despite having very high shares of online education. In other words, traditional measures of on-the-job training may not be adequately capturing individuals augmenting their human capital via online education. Furthermore, given that individuals with high shares of online education are more educated, earn higher wages, and have greater work-from-home ability, there will be new human capital accumulation dynamics to consider. Online education will capture a new set of demographics that the on-the-job training literature did not emphasize.

Lastly, this paper contributes to the literature on remote activities (Barrero et al., 2023, 2021; Gibbs et al., 2023; Dingel and Neiman, 2020; Choudhury et al., 2021), particularly working-from-home. I establish that there is a positive relationship between online education and working from home. This finding is robust to alternative measures of work from home at the industry and occupational levels. While I do not present rigorous empirical evidence, I believe that this paper sheds light into how online education may be serving as a tool for human capital accumulation amongst occupations that have more capabilities to work remotely.

This paper leaves several opportunities for additional research. The first is studying the effect of online education on job switches–defined as switching occupations or industries. For example, do workers enroll in online education to switch to another job? If so, how does this affect their wage? Second, additional research should focus on understanding how online education affects employee productivity. Moving forward, understanding of these dynamics becomes crucial for policymakers, educators, and businesses seeking to adapt and foster innovation.

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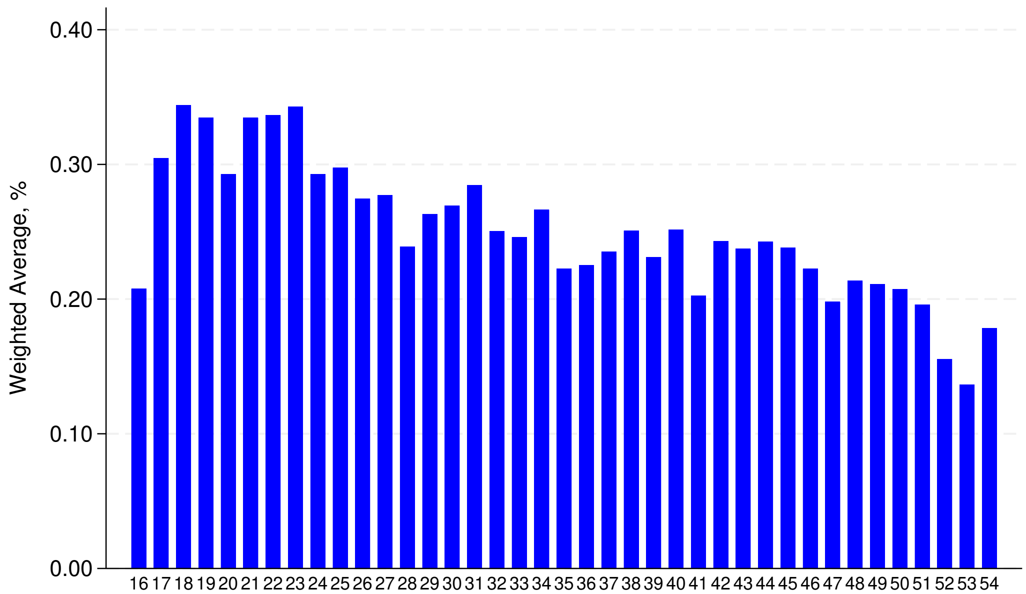
Can Online Learning Alter Labor Force Attachment? Evidence from U.S. Labor Markets

Online Appendix

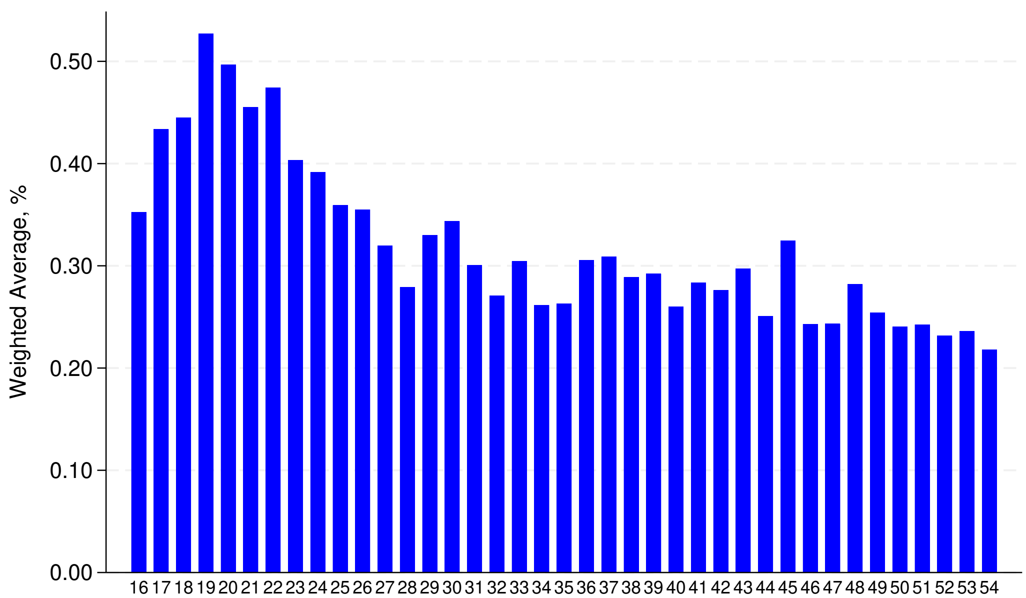
Octavio M. Aguilar

A Appendix: Figures

FIGURE A.1 – Distribution of Online Education by Age



A. 2019



B. 2021

NOTE: Author's calculations from the CPS-CIS.

B Appendix: Tables

TABLE A1 – ATE Probability of Job Keeping & LF Exit
(OLS Regressions: Year by Year)

Regressor	Year Estimated: (2019)	(2020)	(2021)	(2022)
A. **Job Keeping**				
$\text{Education}_{s,t}$	0.020***	0.039***	0.008	0.025***
	(0.007)	(0.008)	(0.007)	(0.007)
Worker Observables?	✓	✓	✓	✓
N	13,308	11,887	11,551	11,211
R^2	0.060	0.057	0.061	0.049
B. **Labor Force Exit**				
$\text{Education}_{s,t}$	−0.011**	−0.025***	−0.004	−0.013**
	(0.005)	(0.006)	(0.006)	(0.006)
Worker Observables?	✓	✓	✓	✓
N	14,373	12,873	12,474	12,074
R^2	0.048	0.038	0.039	0.034

NOTE: Job keeping is a binary outcome equal to one if the individual is employed in March of year t-1 and employed in March of year t. Labor force exit is a binary outcome equal to one if the individual is in the labor force in March of year t-1 and not in the labor force in March of year t. $\text{Education}_{s,t}$ is binary and equal to 1 if occupation s is above the 50th percentile of online education at time $t \in [2019, 2021]$. Worker observables include: gender, age, race, number of children, family size, income quintile, and educational attainment. I also control for remote work ability and actual shares of remote work at the two-digit occupational level. Workers age 16-54. Standard errors are reported in parentheses. * $p < .10$; ** $p < .05$; and *** $p < .01$.

TABLE A2 – HTE Probability of Job Keeping
(OLS Regressions: Year by Year)

Regressor	Dependent Variable: Job Keeping (1)	(2)	(3)
A. ***2019***			
$\text{Education}_{s,2019}$	0.061***	0.020***	0.010
	(0.005)	(0.007)	(0.009)
$\text{Female}_{i,2019}$	−0.034***	−0.029***	−0.036***
	(0.005)	(0.005)	(0.007)
$\text{Education}_{s,2019} * \text{Female}_{i,2019}$			0.017
			(0.011)
N	13,308	13,308	13,308
R^2	0.012	0.060	0.060
B. ***2020***			
$\text{Education}_{s,2019}$	0.083***	0.039***	0.039***
	(0.006)	(0.008)	(0.010)
$\text{Female}_{i,2020}$	−0.045***	−0.040***	−0.040***
	(0.006)	(0.006)	(0.008)
$\text{Education}_{s,2019} * \text{Female}_{i,2020}$			0.001
			(0.011)
N	11,887	11,887	11,887
R^2	0.021	0.057	0.057
C. ***2021***			
$\text{Education}_{s,2021}$	0.071***	0.010	−0.001
	(0.005)	(0.007)	(0.010)
$\text{Female}_{i,2021}$	−0.026***	−0.023***	−0.030***
	(0.005)	(0.005)	(0.007)
$\text{Education}_{s,2021} * \text{Female}_{i,2021}$			0.015
			(0.011)
N	11,511	11,511	11,511
R^2	0.016	0.061	0.062
D. ***2022***			
$\text{Education}_{s,2021}$	0.057***	0.025***	0.021**
	(0.005)	(0.007)	(0.009)
$\text{Female}_{i,2022}$	−0.029***	−0.032***	−0.036***
	(0.005)	(0.005)	(0.008)
$\text{Education}_{s,2021} * \text{Female}_{i,2022}$			0.008
			(0.011)
N	11,211	11,211	11,211
R^2	0.012	0.049	0.049

NOTE: $\text{Education}_{s,t}$ is binary and equal to 1 if occupation s is above the 50th percentile of online education at time $t \in [2019, 2021]$. Column (1) does not include worker observables while columns (2) and (3) add them. Worker observables include: gender, age, race, number of children, family size, income quintile, and educational attainment. I also control for remote work ability and actual shares of remote work at the two-digit occupational level. Workers age 16-54. Standard errors are reported in parentheses. * $p < .10$; ** $p < .05$; and *** $p < .01$.

TABLE A3 – HTE Probability of Labor Force Exit
(OLS Regressions: Year by Year)

Regressor	Dependent Variable: Labor Force Exit (1)	(2)	(3)
A. ***2019***			
$\text{Education}_{s,2019}$	-0.040^{***}	-0.011^{**}	-0.002
	(0.004)	(0.005)	(0.007)
$\text{Female}_{i,2019}$	0.028^{***}	0.026^{***}	0.032^{***}
	(0.004)	(0.004)	(0.006)
$\text{Education}_{s,2019} * \text{Female}_{i,2019}$			-0.015^{*}
			(0.009)
N	14,373	14,373	14,373
R^2	0.010	0.048	0.048
B. ***2020***			
$\text{Education}_{s,2019}$	-0.052^{***}	-0.025^{***}	-0.023^{***}
	(0.004)	(0.006)	(0.008)
$\text{Female}_{i,2020}$	0.039^{***}	0.036^{***}	0.037^{***}
	(0.004)	(0.004)	(0.006)
$\text{Education}_{s,2019} * \text{Female}_{i,2020}$			-0.003
			(0.006)
N	12,873	12,873	12,873
R^2	0.016	0.038	0.038
C. ***2021***			
$\text{Education}_{s,2021}$	-0.050^{***}	-0.004	0.004
	(0.004)	(0.006)	(0.008)
$\text{Female}_{i,2021}$	0.025^{***}	0.025^{***}	0.033^{***}
	(0.004)	(0.004)	(0.006)
$\text{Education}_{s,2021} * \text{Female}_{i,2021}$			-0.016^{*}
			(0.009)
N	12,474	12,474	12,474
R^2	0.012	0.039	0.039
D. ***2022***			
$\text{Education}_{s,2021}$	-0.040^{***}	-0.013^{**}	-0.003
	(0.004)	(0.006)	(0.008)
$\text{Female}_{i,2022}$	0.026^{***}	0.026^{***}	0.034^{***}
	(0.004)	(0.004)	(0.006)
$\text{Education}_{s,2021} * \text{Female}_{i,2022}$			-0.017^{*}
			(0.009)
N	12,074	12,074	12,074
R^2	0.010	0.034	0.035

NOTE: $\text{Education}_{s,t}$ is binary and equal to 1 if occupation s is above the 50th percentile of online education at time $t \in [2019, 2021]$. Column (1) does not include worker observables while columns (2) and (3) add them. Worker observables include: gender, age, race, number of children, family size, income quintile, and educational attainment. I also control for remote work ability and actual shares of remote work at the two-digit occupational level. Workers age 16-54. Standard errors are reported in parentheses. * $p < .10$; ** $p < .05$; and *** $p < .01$.

TABLE A4 – HTE Probability of Job Keeping
(OLS Regressions: Year by Year)

Regressor	Dependent Variable: Job Keeping (2019)	(2020)	(2021)	(2022)
$\text{Education}_{s,t}$	0.016	0.050***	0.010	0.030**
	(0.013)	(0.014)	(0.013)	(0.013)
$\text{Female}_{i,t}$	−0.023**	−0.019*	−0.017	−0.021**
	(0.010)	(0.011)	(0.011)	(0.011)
$\text{Child}_{i,t}$	0.087***	0.058**	0.060**	0.054**
	(0.013)	(0.011)	(0.013)	(0.013)
$\text{Female}_{i,t} * \text{Child}_{i,t}$	−0.093***	−0.119***	−0.094***	−0.103***
	(0.026)	(0.031)	(0.029)	(0.028)
$\text{Education}_{s,t} * \text{Female}_{i,t}$	0.011	−0.012	−0.005	−0.002
	(0.016)	(0.017)	(0.016)	(0.015)
$\text{Education}_{s,t} * \text{Child}_{i,t}$	−0.036	−0.052**	−0.015	−0.042*
	(0.025)	(0.028)	(0.026)	(0.025)
$\text{Education}_{s,t} * \text{Female}_{i,t} * \text{Child}_{i,t}$	0.057	0.090**	0.072*	0.043
	(0.037)	(0.041)	(0.039)	(0.037)
Worker Observables?	✓	✓	✓	✓
N	8,342	7,417	7,250	7,111
R^2	0.072	0.066	0.070	0.060

NOTE: Job keeping is a binary outcome equal to one if the individual is employed in March of year t-1 and employed in March of year t. Labor force exit is a binary outcome equal to one if the individual is in the labor force in March of year t-1 and not in the labor force in March of year t. $\text{Education}_{s,t}$ is binary and equal to 1 if occupation s is above the 50th percentile of online education at time $t \in [2019, 2021]$. Columns one and two use $\text{Education}_{s,2019}$, while columns three and four use $\text{Education}_{s,2021}$. Worker observables include: gender, age, race, number of children, family size, income quintile, and educational attainment. I also control for remote work ability and actual shares of remote work at the two-digit occupational level. Workers age 16-54. Standard errors are reported in parentheses. * $p < .10$; ** $p < .05$; and *** $p < .01$.

TABLE A5 – HTE Probability of Labor Force Exit
(OLS Regressions: Year by Year)

	Dependent Variable: Labor Force Exit			
Regressor	(2019)	(2020)	(2021)	(2022)
$\text{Education}_{s,t}$	-0.002	-0.034^{***}	0.003	-0.007
	(0.010)	(0.011)	(0.011)	(0.010)
$\text{Female}_{i,t}$	0.025^{***}	0.017^{*}	0.021^{**}	0.023^{**}
	(0.008)	(0.009)	(0.009)	(0.009)
$\text{Child}_{i,t}$	-0.076^{***}	-0.035	-0.061^{***}	-0.047^{**}
	(0.011)	(0.011)	(0.011)	(0.011)
$\text{Female}_{i,t} * \text{Child}_{i,t}$	0.070^{***}	0.072^{***}	0.088^{***}	0.081^{***}
	(0.022)	(0.024)	(0.024)	(0.022)
$\text{Education}_{s,t} * \text{Female}_{i,t}$	-0.010	0.015	-0.005	-0.013
	(0.013)	(0.013)	(0.013)	(0.013)
$\text{Education}_{s,t} * \text{Child}_{i,t}$	0.036^{*}	0.037^{*}	0.007	0.025
	(0.021)	(0.022)	(0.022)	(0.020)
$\text{Education}_{s,t} * \text{Female}_{i,t} * \text{Child}_{i,t}$	-0.050^{*}	-0.061^{*}	-0.064^{**}	-0.038
	(0.031)	(0.032)	(0.032)	(0.030)
Worker Observables?	✓	✓	✓	✓
N	9,020	8,057	7,882	7,683
R^2	0.055	0.043	0.047	0.044

NOTE: Job keeping is a binary outcome equal to one if the individual is employed in March of year t-1 and employed in March of year t. Labor force exit is a binary outcome equal to one if the individual is in the labor force in March of year t-1 and not in the labor force in March of year t. $\text{Education}_{s,t}$ is binary and equal to 1 if occupation s is above the 50th percentile of online education at time $t \in [2019, 2021]$. Columns one and two use $\text{Education}_{s,2019}$, while columns three and four use $\text{Education}_{s,2021}$. Worker observables include: gender, age, race, number of children, family size, income quintile, and educational attainment. I also control for remote work ability and actual shares of remote work at the two-digit occupational level. Workers age 16-54. Standard errors are reported in parentheses. * $p < .10$; ** $p < .05$; and *** $p < .01$.