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

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Abstract

Since the COVID-19 pandemic, online learning has surged in the U.S. In this paper, I seek to answer the following questions: Who is participating in online learning, and how does enrollment into online learning affect their labor market flows? Using data from the Current Population Survey, I construct occupational exposure to online learning and track thousands' of individuals labor market outcomes from 2019 through 2022. First, I find that individuals engaged in online learning 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 learning affects labor market flows. I find that, on average, online learning increases employment stability. When examining heterogeneous treatment effects, I find that women with young children are more likely to exit the labor force compared with women without children. However, I show that online learning is associated with a reduction in excess labor force exits for women with young children.

KEYWORDS: Online learning, MOOCs, work from home, labor force participation.
JEL CLASSIFICATION CODES: J24, I21, I26

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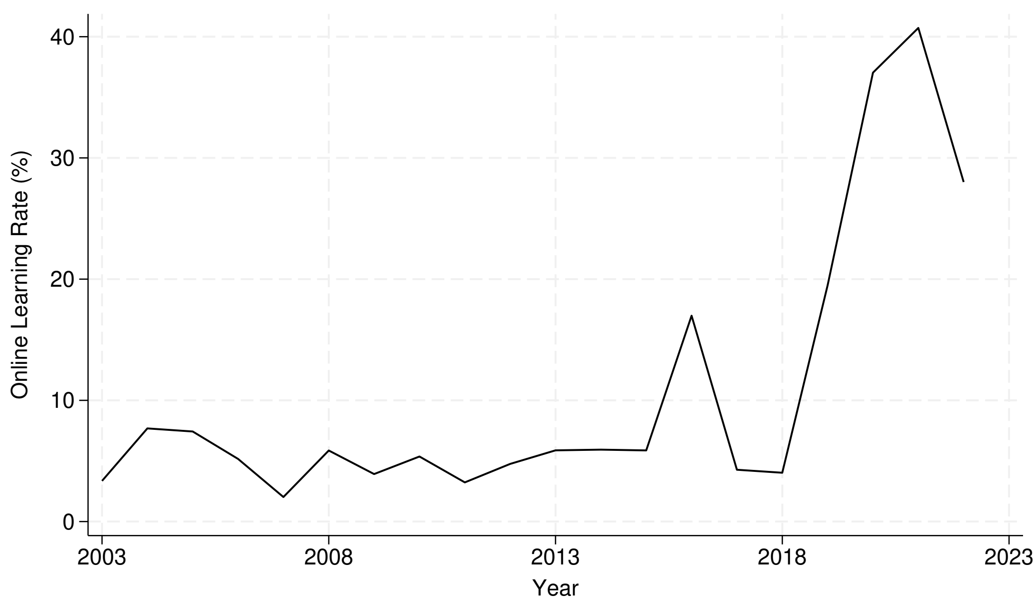
1 Introduction

The COVID-19 pandemic led to an unprecedented surge in online learning. As shown in Figure 7 from 2003 through 2018, the online learning rate, on average, remained below 10%. During the pandemic, in 2020, this rate surged to 37%, rising again in 2021 to 41%. As of 2022, it remains well above pre-pandemic levels, at 28%. Supporting this trend, data from Coursera—a leading provider of massive open online courses—indicate substantial growth. From 2019 to 2021, Coursera reported a 70% increase in U.S. users, from 10 million to 17 million (Coursera, 2019, 2021). Moreover, this was not a temporary shift; Coursera has continued to report year-over-year increases, reaching 28 million U.S. users as of 2024 (Coursera, 2024).

In this paper, I define "online learning" 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 learning, and how does enrollment into online learning affect their labor market flows?

FIGURE 1 – Online Learning Rate Over Time



NOTE: Author's calculations from the American Time Use Survey. The online learning rate is defined as the sum of all days learning at home relative to all learning.

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

In the second part of the paper I answer this question: How does online learning affect labor market flows? Specifically, I am interested in how online learning affects the probability that individuals keep their job and exit the labor force. Using data from the CPS, I construct occupational exposure to online learning 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 learning 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 learning has a sizeable effect on labor market outcomes for women with young children. From 2019 through 2020, my findings suggest that online learning decreases the probability of exiting the labor force for women with children aged 2 to 3 and aged 5 to 14. However, from 2021 through 2022, I find that online learning 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 may 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 may be explained by the fact that during 2021 through 2022, only women with middle childhood and teenagers had flexibility to engage in online learning 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 learning 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 learning with previous literature. Second, this study is the first to analyze the effect of online learning within the U.S. labor market context. Third, it includes individuals of all age groups enrolled in online learning, thereby providing a more comprehensive analysis. Fourth, this paper is the first to analyze the distribution of online learning 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 learning 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 learning. As I show in this paper, individuals who are engaged in online learning 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 learning 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 learning 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 learning. Notably, I find that occupations with higher shares of remote-work job postings have high shares of online learning. I interpret these results as suggestive evidence that computer- and office-focused occupations are using online learning 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 results of the relationship between online learning and on-the-job training, formal education, wages, and work from home. Section 4 discusses the model and empirical results. Section 5 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 learning*, which is constructed from

TABLE 1 – Descriptive Statistics for Online Learning (Shares in %)

Variable	2019	2021	Whole Sample
Online Learning	25	31	27
Labor Force Status			
Employed	86	83	85
Unemployed	2	3	2
Not in LF	12	14	13
Age Quintile			
1	25	27	26
2	23	21	22
3	18	18	18
4	18	18	18
5	15	15	15
Race			
White	79	77	78
Black	10	11	10
Asian	7	8	7
Mixed/Other	4	4	4
Female	53	54	53
Observations enrolled in online learning	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.

the Current Population Survey Computer and Internet Use Supplement (CPS-CIS). I show how online learning 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 (for degree, certifications, licenses) or job training?" defines the variable *online learning*. 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]

[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 learning as a substitute or complement to formal education.

TABLE 2 – Shares (%) and Changes in Online Learning by Two-digit Occupation

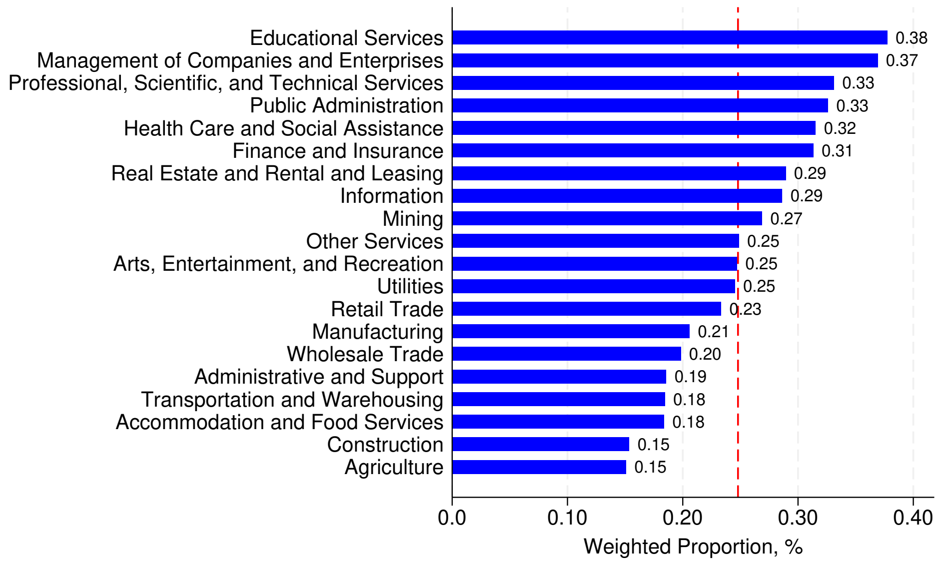
Major Occupation Group	$\text{Learning}^{\text{Remote}}_{s,2019}$	$\text{Learning}^{\text{Remote}}_{s,2021}$	$\Delta\text{Learning}^{\text{Remote}}_{s}$
Management	27	33	6
Business and Financial	30	39	9
Computer and Mathematical	40	42	2
Architecture and Engineering	35	38	3
Life, Physical, and Social Science	40	46	6
Community and Social Services	34	47	13
Legal	35	33	-2
Educational Instruction and Library	38	48	10
Arts, Design, Entertainment, Sports, and Media	35	33	-2
Healthcare Practitioners and Technical	36	41	5
Healthcare Support	36	41	5
Protective Service	28	35	7
Food Preparation and Serving Related	20	28	8
Building and Grounds Cleaning and Maintenance	14	23	9
Personal Care and Service	22	34	12
Sales and Related	25	30	5
Office and Administrative Support	24	32	8
Farming, Fishing, and Forestry	13	16	3
Construction and Extraction	14	18	4
Installation, Maintenance, and Repair	22	24	2
Production	14	16	2
Transportation and Material Moving	17	18	1
Average across all occupations	27	32	5

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

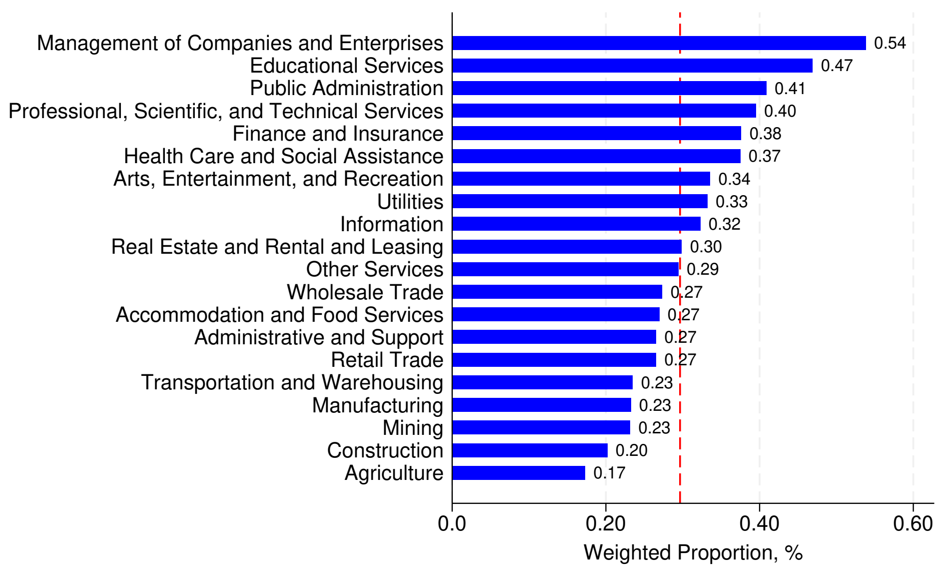
Given that this topic is understudied I acknowledge certain data limitations. First, the CPS-CIS reported variable for online learning does not make it possible to distinguish if the individual is enrolled in online courses or online job training. Second, online classes can encompass a range of activities, including the pursuit of online courses that lead to degrees, certifications, or licenses. In validating my measure, I show that the distribution of online learning across age and formal education is similar to that of MOOCs. Third, data for online learning 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 4.

Table 1 shows the shares of online learning across demographics. On average, in 2019 and 2021, the share of individuals enrolled in online learning 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 learning is concentrated amongst those under age 35. In addition, in appendix Figure A.1, I plot the average distribution of online learning across all ages in 2019 and 2021. The average ages for those enrolled in online learning in 2019 and 2021 are both 35. My mean estimates for

FIGURE 2 – Shares of Online Learning by Industry



A. 2019



B. 2021

NOTE: Authors' calculations from the CPS-CIS. 2-digit NAICS. Red line indicates the average across all industries.

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 learning. However, what distinguishes my data from prior studies is the dynamics of online learning in the lower end of the age distribution. Notably, between 2019 and 2021, the rise in online learning 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%, respectively.

In Table 2, I show the distribution of online learning across two-digit occupations for 2019 and 2021. The average share of online learning for workers increased by 5%, rising from 27% in 2019 to 32% in 2021.[2] Furthermore, Table 2 shows how changes in online learning 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 learning include Construction (4%); Installation, Maintenance, and Repair (2%); and Transportation and Material Moving (1%). I note that some occupations have high levels of online learning but small changes between the two periods. For example, in 2021, 42% of workers in Computer and Mathematical occupations engage in online learning despite only having a 2% increase from 2019 to 2021. The same relationship holds for Life, Physical, and Social Science occupations, as almost half of workers engage in online learning despite having only a 6% increase.

Moreover, in Figure 2, I plot the share of online learning across two-digit NAICS. Industries with high shares of online learning 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 learning, 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 learning affects job keeping, labor force exit, and job switches.

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. First, 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. Second, 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. Lastly, for job switch, it is equal to 1 if an individual is

[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.

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

Variable	Job Keeping	Labor Force Exit	Job Switch
Age	38.25	33.19	37.14
Family size	3.17	3.48	3.16
Number of children	1.02	0.78	0.94
Age of eldest child	6.64	4.84	6.12
Educational attainment	14.00	12.00	14.00
Wage ($)	58,000	25,665	56,232
Female	0.47	0.57	0.46
Married	0.58	0.38	0.53
Race (shares)			
White	0.82	0.75	0.80
Black	0.08	0.14	0.10
Asian	0.06	0.06	0.06
Mixed/Other	0.04	0.05	0.04
Observations	43,367	3,320	22,826

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.

employed in March of year $t-1$ and employed in March of year t, but has a different occupation or industry code in year t. The reference group for all 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, labor force exit, and job switch. Compared to job keepers or job switchers, I find that individuals who exit the labor force are younger, have younger children, have lower levels of education, and have lower wages. In addition, across demographics, individuals who exit the labor force are mostly women, single, and are more likely to be Black or mixed-race.

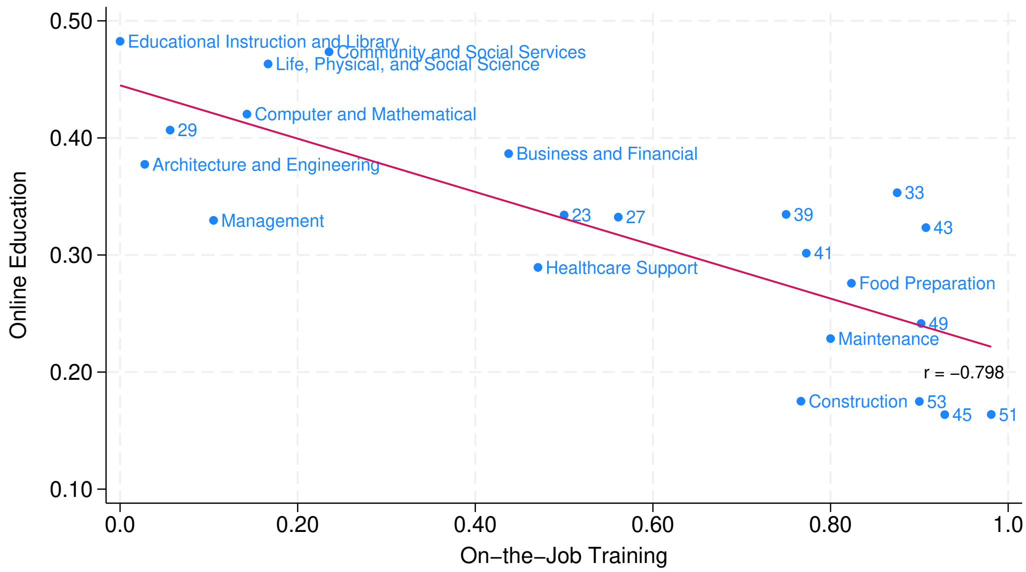
3 Descriptive Results

In this section, I present descriptive evidence in order to have a holistic view of the individuals enrolled in online learning. Specifically, I examine the relationship between online learning and on-the-job training, formal education, wages, and working from home.

3.1 Online Learning vs 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,

FIGURE 3 – Correlation With On-the-Job Training



NOTE: Both expressed as 2021 shares. Online education (learning) 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.

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 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 learning.

To test this assumption, I plot the relationship between online learning and on-the-job training in Figure 3. 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 learning.[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

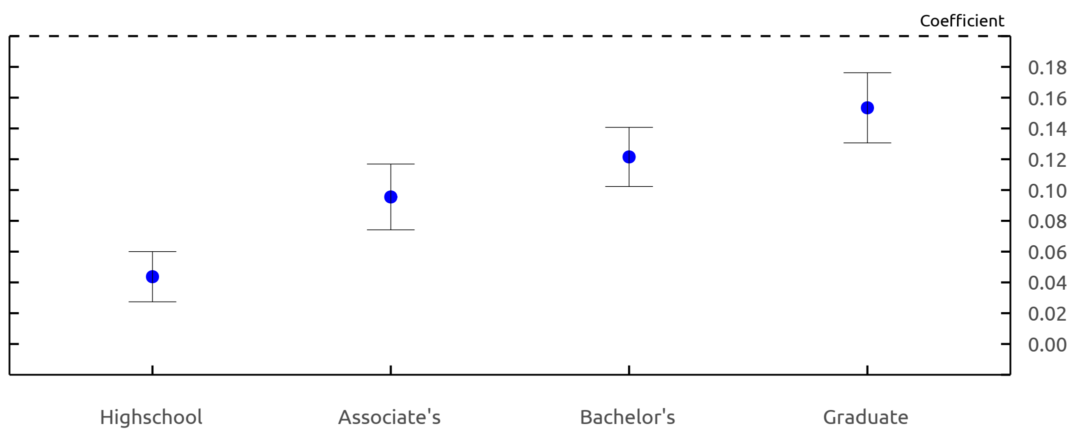
[3] On-the-job training is defined at the two-digit occupational level and refers to training or preparation that is typically needed, once employed in an occupation, to attain competency in the skills needed in that occupation. Training is occupation specific rather than job specific.

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

3.2 Online Learning is a Complement to Formal Education

As shown in Figure 4, I plot ordinary least squares (OLS) estimates between online learning 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 learning. 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 learning and formal education when online training is included in the measure.

FIGURE 4 – How Online Learning Covaries by Educational Attainment

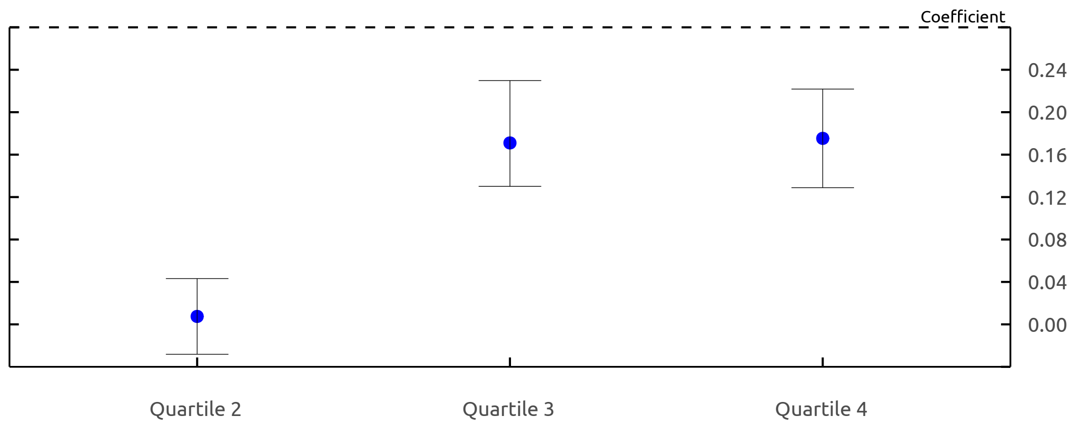


NOTE: Author's calculations from the CPS-CIS. Plots OLS estimates of educational attainment on online learning. Reference group are those with less than a high school education. Includes a set of controls and industry-year and state-year fixed effects. All point estimates are significant at the 1% level.

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 learning. 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 learning. For example, working as an animal trainer or pesticide handler will typically require a more informal in-person type of training.

3.3 Online Learning is Correlated With Higher Wages

FIGURE 5 – How Wage Covaries by Quartiles of Online Learning



NOTE: Author's calculations from the CPS-ASEC. Plots OLS estimates of quartiles of online learning 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.

As an initial check, in Figure 5, I create quartiles of online learning that are pooled from 2019 through 2021 to see how log wages behave when exposure to online learning increases. I interpret these results as descriptive and find a positive significant relationship, indicating that higher quartiles of online learning correspond with higher log wages. The estimates suggest that being above the 50th percentile of online learning 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.

In addition, in Table 4, I show the relationship between online learning and wages when adding controls, fixed effects, and testing for differential impacts across gender. Columns (4) and (5) capture the main interaction of interest. Specifically, column (4) shows that online learning is correlated with higher wages in both the 2019–2020 and 2021–2022 periods. However, in both sample periods, being Female is associated with a negative effect on wages. Interestingly, as shown in column (5), when testing for the interaction of online learning and being Female, the sign on the coefficient flips. In 2019–2020, although not significant, online learning is correlated with a positive effect on wages for Female workers. Moreover, in 2021–2022, there is a similar relationship—online learning is correlated with higher wages for Female workers, and this effect is significant at the 10% level.

TABLE 4 – The Relationship Between Online Learning and Wages

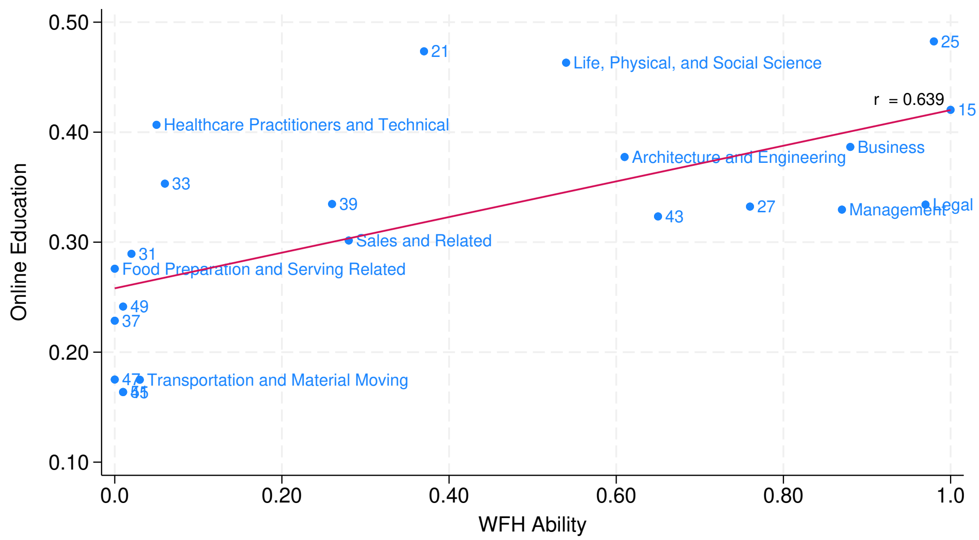
Regressor	Dependent Variable: Log Wages (1)	(2)	(3)	(4)	(5)
A. ***2019-2020***					
$\text{Learning}^{\text{Remote}}_{s,2019}$	0.613***	0.674***	0.139***	0.175***	0.144***
	(0.013)	(0.012)	(0.013)	(0.035)	(0.034)
$\text{Female}_{i,t}$		−0.434***	−0.396***	−0.297***	−0.324***
		(0.012)	(0.010)	(0.017)	(0.027)
$\text{Learning}^{\text{Remote}}_{s,2019} * \text{Female}_{i,t}$					0.055
					(0.037)
Worker Observables?	No	No	✓	✓	✓
Fixed Effects?	No	No	No	✓	✓
N	25,248	25,248	25,248	25,248	25,248
R^2	0.085	0.127	0.452	0.471	0.471
B. ***2021-2022***					
$\text{Learning}^{\text{Remote}}_{s,2021}$	0.705***	0.749***	0.141***	0.174***	0.120*
	(0.013)	(0.013)	(0.015)	(0.041)	(0.048)
$\text{Female}_{i,t}$		−0.375***	−0.345***	−0.260***	−0.307***
		(0.013)	(0.011)	(0.019)	(0.032)
$\text{Learning}^{\text{Remote}}_{s,2021} * \text{Female}_{i,t}$					0.093*
					(0.032)
Worker Observables?	No	No	✓	✓	✓
Fixed Effects?	No	No	No	✓	✓
N	22,731	22,731	22,731	22,731	22,731
R^2	0.114	0.146	0.451	0.479	0.479

NOTE: OLS regressions. Wages are CPI adjusted to 2019 = 100. $\text{Learning}^{\text{Remote}}_{s,t}$ is binary and equal to 1 if occupation s is above the 50th percentile of online learning 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 *** $p < .01$.

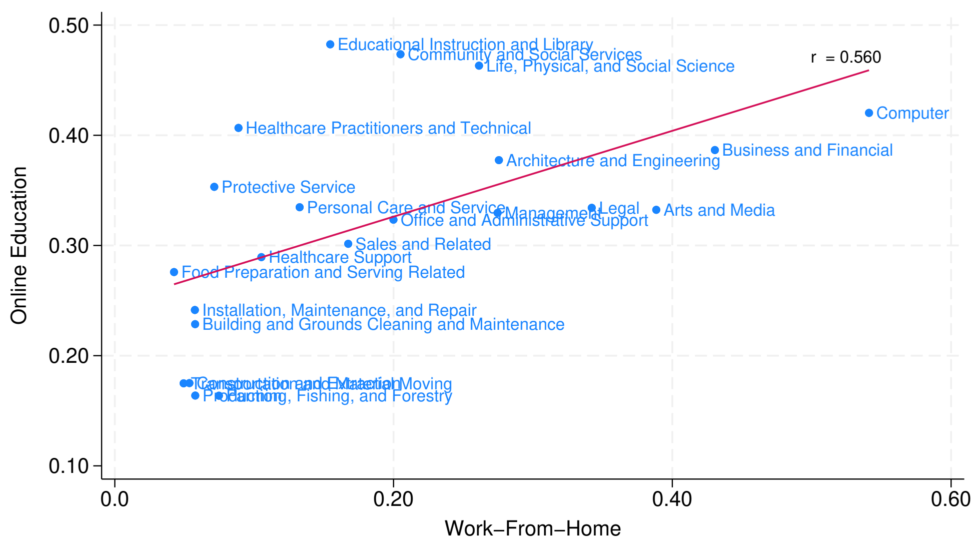
3.4 Online Learning is Higher in More Teleworkable Occupations

In Figure 6, panel A, I show the relationship between the 2021 share of online learning 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 learning. 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 learning. 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 learning.

FIGURE 6 – Online Learning is Positively Correlated with Remote Work



A. Work-from-Home Ability



B. Remote Work

NOTE: Author's calculations. All panels report the 2021 share of online learning calculated from the CPS-CIS. Panel A reports the share of work-from-home ability from Dingel and Neiman (2020) and is the O*NET-derived classification. Panel B reports the actual share of remote work from the 2021 American Community Survey.

In addition, in Figure 6, panel B, I compare the 2021 shares of online learning 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 capture individuals who are engaging in remote work as opposed to just their ability to do so. Notably, high shares of online learning and remote work are in more 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 learning. Similar to before, occupations with low levels of both online learning and remote work include Installation, Maintenance, and Repair and Food Preparation and Serving Related.

Moreover, for robustness, in Appendix Figure A.2, panel A, I show the relationship between online learning and remote-work job postings.[4] The correlation is identical to actual shares of remote work from Figure 6 panel B. Moreover, similar to before, I find that higher levels of remote-work job postings and online learning 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 learning. Similarly, Business and Financial Operations occupations have 13% of job postings that are remote while having a 39% share of online learning.

Lastly, in Figure A.2, panels B and C, I show the relationship between online learning and working from home at the two-digit NAICS industry level. Similar to before, I generally observe higher levels of online learning and work from home 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 learning. 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 learning. 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 my results shed light into how online learning is playing a role in this shift toward remote work. Specifically, my results suggest that online learning may be serving as a tool for human capital accumulation among occupations that are more teleworkable.

4 Empirical Results

4.1 Identification Strategy

In the next subsection, I discuss the empirical approach as well as the main results. I seek to answer this question: How does online learning affect labor market flows? As defined in Section 2, the outcome variables of interest are job keeping, labor force exit, and job switches. In constructing the main explanatory variable, I first create sample weighted shares of online learning across all two-

[4] In unreported results, I combine fully remote and hybrid job postings. The correlation is the same.

digit occupations for 2019 and 2021. I then create $\text{Learning}_{s,t}^{\text{Remote}}$, which is a binary indicator equal to 1 if occupation s is above the 50th percentile of online learning at time t, where $t \in [2019, 2021]$. The reference group are those below the 50th percentile.

For the analysis, I merge the occupational exposure to online learning 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 learning in 2019 and 2021. All empirical specifications use the CPS-ASEC weight. The CPS-ASEC 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 learning is only available for 2019 and 2021. Given data limitations, I find it fitting to pool the regressions and estimate the effect of online learning on labor market flows in two-year bins. To be precise, I use the 2019 exposure to online learning to estimate 2019 to 2020 labor market flows. Similarly, I use the 2021 exposure to online learning to estimate 2021 to 2022 labor market flows. In Section B of the appendix, I show the results when estimating year by year as opposed to two-year bins.

Empirical Predictions. I have two main empirical predictions for the effect of online learning on labor market flows. For my first empirical prediction, I believe that online learning is match specific, which will increase the incentive for individuals to stay at 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 and get promoted(Castano-Munoz and Rodrigues, 2021; Zhenghao et al., 2015). Hence, it is reasonable to assume that individuals augmenting their human capital through online learning are more motivated to remain employed, particularly in the same job, 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

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

learning, 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 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 learning will offer women with young children more opportunities to augment their human capital while balancing childcare responsibilities. As a result, I would expect online learning to increase the probability that women with young children keep their job as well as reduce the probability that they exit the labor force.

4.2 Labor Market Flows: Average Effect

LPMs are widely used in empirical work.[6] To begin, I estimate equation 1 to test the average effect of online learning 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, $\text{Learning}^{\text{Remote}}_{s,t}$ is binary and equal to 1 if occupation s is above the 50th percentile of online learning 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 learning on an individual's labor market status.

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

$X_{q,t}$ 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 learning. That is, higher exposure to online learning 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

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

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

Regressor	Dependent Variable: Job Keeping	Labor Force Exit	Job Switcher
A. ***2019-2020***			
$\text{Learning}^{\text{Remote}}_{s,2019}$	0.021^{***}	-0.013^{**}	-0.117^{***}
	(0.008)	(0.006)	(0.032)
Constant	0.814	0.133	0.535
Worker Observables?	✓	✓	✓
State-year FE?	✓	✓	✓
Industry-year FE?	✓	✓	✓
N	25,195	27,246	25,721
R^2	0.071	0.051	0.061
B. ***2021-2022***			
$\text{Learning}^{\text{Remote}}_{s,2021}$	0.010	-0.010	-0.113^{***}
	(0.007)	(0.006)	(0.018)
Constant	0.836	0.125	0.498
Worker Observables?	✓	✓	✓
State-year FE?	✓	✓	✓
Industry-year FE?	✓	✓	✓
N	22,722	24,528	23,286
R^2	0.065	0.046	0.065

NOTE: OLS regressions. Estimates from equation 1. $\text{Learning}^{\text{Remote}}_{s,t}$ is binary and equal to 1 if occupation s is above the 50th percentile of online learning 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 *** $p < .01$.

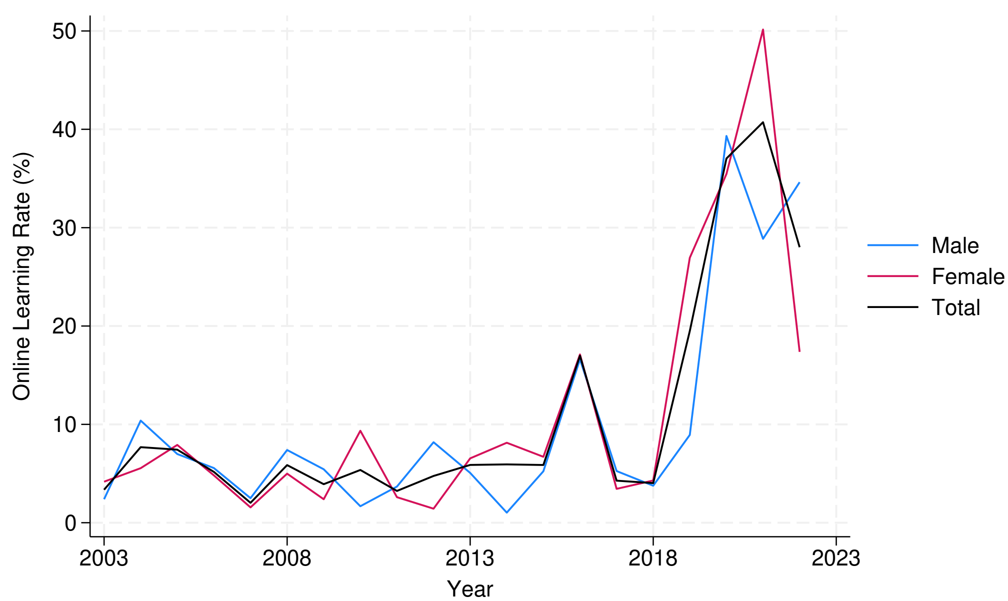
are more computer and office focused, which typically require higher skills. Lastly, I cluster standard errors by occupation-year to address potential serial correlation and unobserved heterogeneity within occupation-year groups.

The results for equation 1 can be found in Table 5. In panel A, I estimate how exposure to online learning in 2019 affects labor market flows from 2019 through 2020. I find that being above the 50th percentile of online learning 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 learning 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] Complementing these results is column 3, which shows that online learning is associated with an 11.7 percentage point reduction in the probability that an individual switches jobs. This suggests that individuals who enroll in online learning are primarily doing so to improve in their current job, most likely seeking promotion, rather than to switch jobs.

In panel B, I estimate how exposure to online learning in 2021 affects labor market flows from 2021 through 2022. Similar to panel A, I find consistent qualitative results—online learning increases the probability that individuals keep their jobs and remain in the labor force. Additionally, the effect of online learning on job switching is nearly identical to that in panel A.

4.3 Heterogeneous Effect for Women

FIGURE 7 – Online Learning Rate by Gender Over Time



NOTE: Author's calculations from the American Time Use Survey. The online learning rate is defined as the sum of all days learning at home relative to all learning.

I will now test if there is any differential impact of online learning for female respondents. Testing for the differential impact of online learning is motivated by Figure 7, which shows the rate of online learning from the American Time Use Survey (ATUS).[8]

[7] In addition, work by Hällsten (2012) finds positive returns to late tertiary degrees in Sweden. They report an increase in the employment rate by 18 percentage points.

[8] The ATUS (Flood et al., 2023) provides information on the minutes per day spent on a diverse set of activities. I focus on the activity labeled "taking a class for degree, certification, license, or personal interest." The ATUS also records the location of this activity. The online learning rate is defined as the sum of all days learning at home relative

TABLE 6 – HTE: Probability of Job Keeping & LF Exit
(Pooled Regressions: 2019-2020 & 2021-2022)

Regressor	Dependent Variable: Job Keeping	Labor Force Exit
A. ***2019-2020***		
$\text{Learning}^{\text{Remote}}_{s,2019}$	0.018^{*}	-0.010^{*}
	(0.010)	(0.007)
$\text{Female}_{i,t}$	-0.036^{***}	0.032^{***}
	(0.008)	(0.005)
$\text{Learning}^{\text{Remote}}_{s,2019} * \text{Female}_{i,t}$	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***		
$\text{Learning}^{\text{Remote}}_{s,2021}$	0.004	0.003
	(0.008)	(0.006)
$\text{Female}_{i,t}$	-0.034^{***}	0.032^{***}
	(0.008)	(0.007)
$\text{Learning}^{\text{Remote}}_{s,2021} * \text{Female}_{i,t}$	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. $\text{Learning}^{\text{Remote}}_{s,t}$ is binary and equal to 1 if occupation s is above the 50th percentile of online learning 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, Figure 7 shows a surge in online learning during the pandemic—reaching a record high in 2020 and remaining above pre-pandemic levels in 2021. When decomposing the rate of online

to all learning.

learning by gender, there is a much higher rate for women relative to men—in 2021, the rate of online learning was 22% higher for women than men. However, this increase in online learning for women exhibits a sharp drop in 2022. 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 learning has any type of effect on their labor market flows.

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

Table 6 shows the HTE for women. The table set-up is identical to Table 5, except now I only focus on the outcomes job keeping and labor force exit. Focusing on panel A, I find that from 2019 through 2020, the average effect for online learning holds for job keeping and labor force exit—that, on average, being above the 50th percentile of online learning 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. The interaction between online learning and women is only economically significant and small. In panel B, I find that from 2021 through 2022, the average effect of online learning 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 learning and women, I find that from 2021 through 2022, women face a 3.2 percentage point higher probability of labor force exit, however, the interaction between online learning and women reveal that there is a 1.4 percentage points reduction in the probability of exiting. However, the estimate on the interaction fails to be statistically significant. All together, I interpret the first set of HTE analysis as online learning having no differential impact for women.

4.4 Heterogeneous Effect for Women With Young Children

Up to this point, the estimates from the first two equations confirms there is an average effect of online learning 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. 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 learning 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 learning, I hypothesize that online learning 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.

$$y_{i,s,j\to l,t} = \alpha_0 + \alpha_1 \text{Learning}^{\text{Remote}}_{s,t} + \underbrace{\alpha_2[\text{Learning}^{\text{Remote}}_{s,t} * \text{Female}_{i,t} * \text{Child}_{i,t}]}_{\text{Effect of interest}} + \sum_{q=1}^{Q} \beta_{q,t} X_{q,t} + \tau_{k,t} + \gamma_{m,t} + \varepsilon_{i,t}. \tag{3}$$

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 learning. This triple interaction involves testing if online learning 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 7 shows the main finding of this paper: online learning serves as a tool that can help women with young children overcome excess labor force exits.

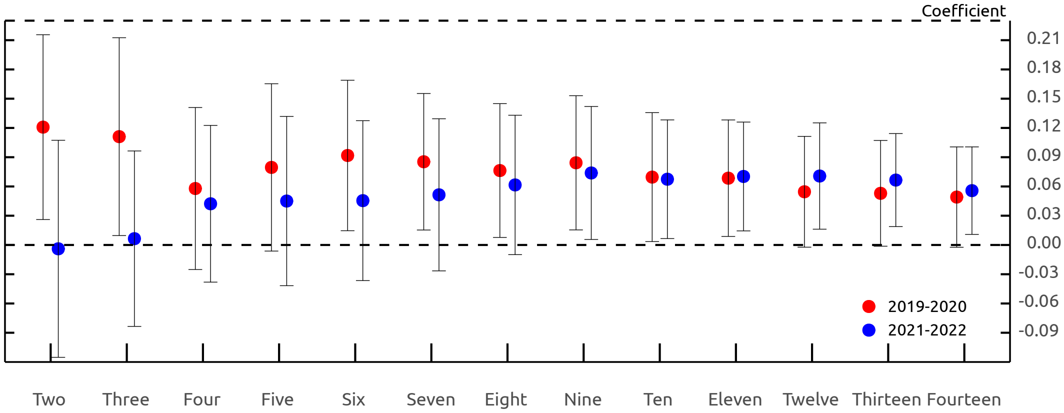
In panel A, I show that from 2019 through 2020, on average, being above the 50th percentile of online learning is associated with a 3 percentage point higher probability of job keeping and a 1.8 percentage point lower probability of exiting the labor force. Furthermore, I find evidence that women face labor market challenges in keeping their job and staying in the labor force.

TABLE 7 – HTE: Differential Impact of Having Children Under Eight (Pooled Regressions: 2019-2020 & 2021-2022)

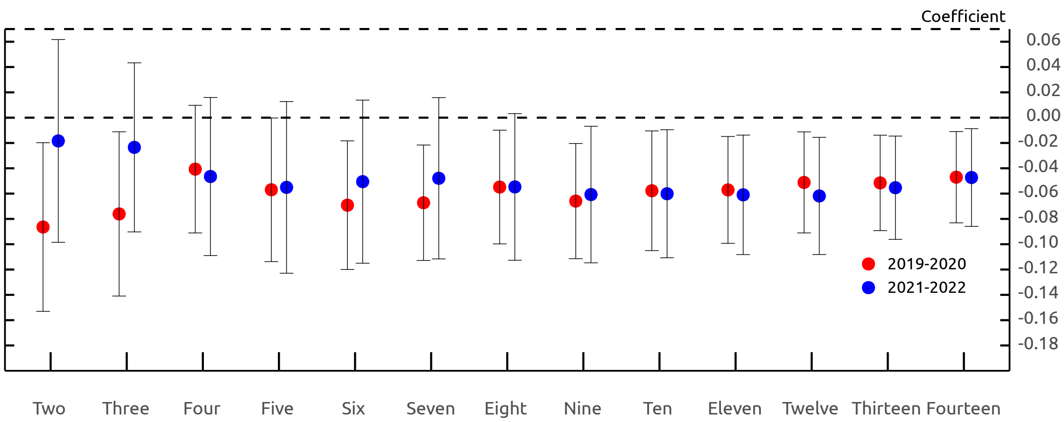
	Dependent Variable:	
Regressor	Job Keeping	Labor Force Exit
A. ***2019-2020***		
$\text{Learning}^{\text{Remote}}_{s,2019}$	0.029^{**}	-0.018^{**}
	(0.012)	(0.009)
$\text{Female}_{i,t}$	-0.019^{*}	0.020^{**}
	(0.011)	(0.007)
$\text{Child}_{i,t}$	0.073^{***}	-0.054^{***}
	(0.021)	(0.016)
$\text{Female}_{i,t} * \text{Child}_{i,t}$	-0.108^{***}	0.069^{***}
	(0.033)	(0.022)
$\text{Learning}^{\text{Remote}}_{s,2019} * \text{Female}_{i,t}$	-0.003	-0.004
	(0.014)	(0.009)
$\text{Learning}^{\text{Remote}}_{s,2019} * \text{Child}_{i,t}$	-0.048^{**}	0.037^{***}
	(0.018)	(0.012)
$\text{Learning}^{\text{Remote}}_{s,2019} * \text{Female}_{i,t} * \text{Child}_{i,t}$	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***		
$\text{Learning}^{\text{Remote}}_{s,2021}$	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)
$\text{Learning}^{\text{Remote}}_{s,2021} * \text{Female}_{i,t}$	-0.003	-0.007
	(0.015)	(0.012)
$\text{Learning}^{\text{Remote}}_{s,2021} * \text{Child}_{i,t}$	-0.030^{*}	0.018
	(0.016)	(0.012)
$\text{Learning}^{\text{Remote}}_{s,2021} * \text{Female}_{i,t} * \text{Child}_{i,t}$	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. $\text{Learning}^{\text{Remote}}_{s,t}$ is binary and equal to 1 if occupation s is above the 50th percentile of online learning 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 8 – Differential Impact of Online Learning 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 $\text{Child}_{i,t}$. 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.

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 learning can help mitigate this hardship. As shown in the last row of panel A, women with young children who are above the 50th percentile of online learning 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 learning 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 8, 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 learning 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 learning while balancing childcare responsibilities.

5 Concluding Remarks

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

The main contribution of this paper is that online learning 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. My results suggest that individuals are more likely to stay with their current employer as opposed to switching jobs, which is consistent with the idea that individuals enroll in online learning to improve in their current job and get promoted. When compared to prior work, the stark contrast is that online learning has been studied 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, with few studies assessing the labor market outcomes of online learning. And, third, studies that do assess labor market outcomes lack representation within the U.S. labor market context. This paper addresses these limitations by offering a nuanced definition of online learning, 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 learning in a U.S. labor market setting.

In addition, I am able to develop an understanding of who is participating in online learning. First, my analysis reveals that individuals engaged in online learning 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 learning and formal education when online training is included in the measure. In addition, I find that being above the 50th percentile of online learning is correlated with a strong premium in log wages. Lastly, to my knowledge, this paper is the first to analyze the distribution of online learning across industries and occupations. I establish that industries with high shares of online learning 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 learning 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 learning. In other words, traditional measures of on-the-job training may not be adequately capturing individuals augmenting their human capital via online learning. Furthermore, given that individuals with high shares of online learning are more educated, earn higher wages, and have greater work-from-home ability, there will be new human capital accumulation dynamics to consider. online learning 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 learning 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 learning may be serving as a tool for human capital accumulation amongst occupations that have more capabilities to work remotely.

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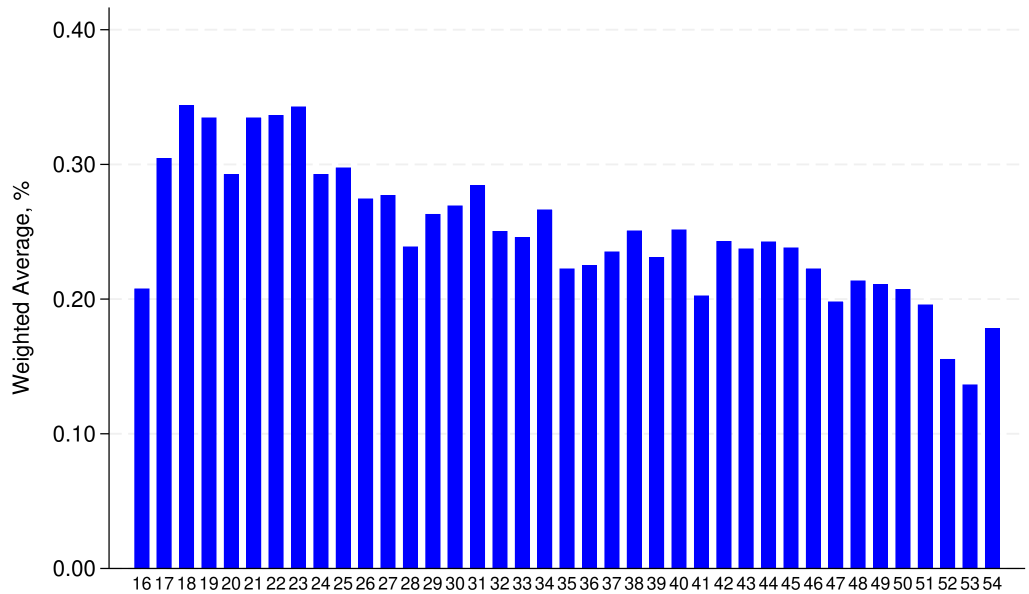
Can Online Learning Alter Labor Force Attachment? Evidence from U.S. Labor Markets

Online Appendix

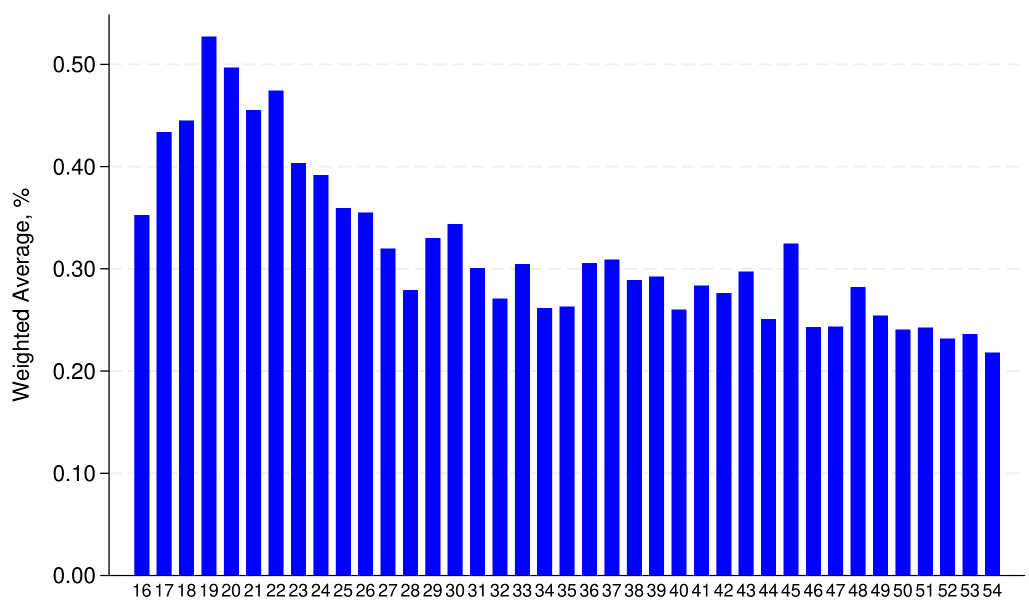
Octavio M. Aguilar

A Appendix: Figures

FIGURE A.1 – Distribution of Online Learning by Age



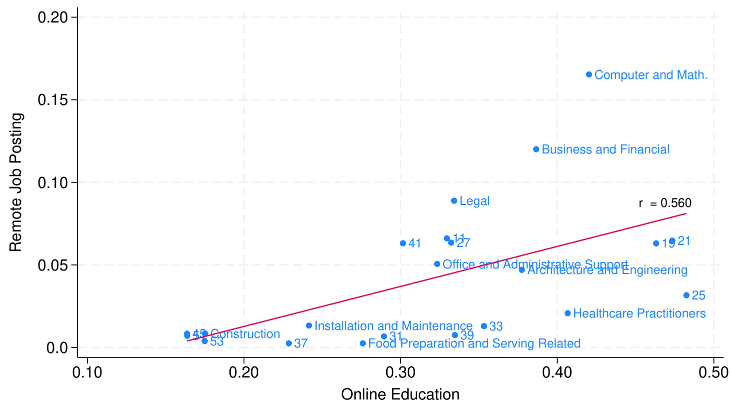
A. 2019



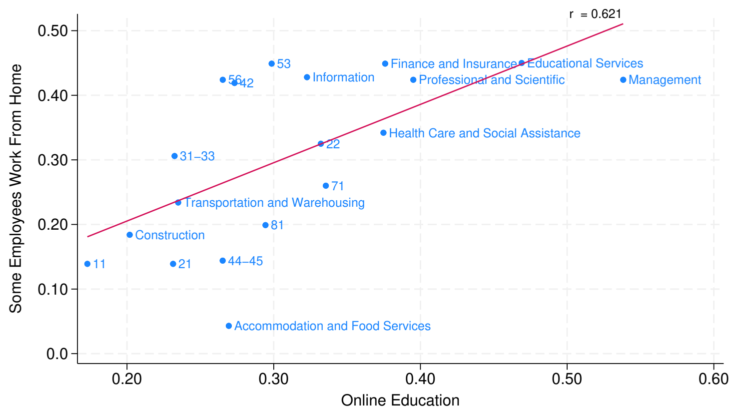
B. 2021

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

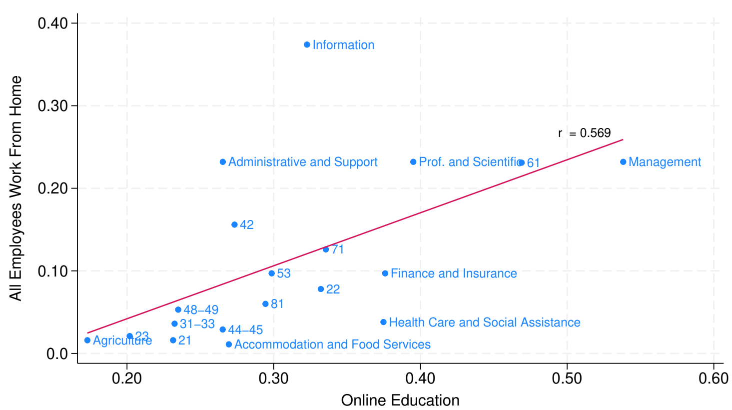
FIGURE A.2 – Is Online Learning Correlated With Other Measures of Remote Work?



A. Remote Job Postings



B. Some Work from Home



C. All Work from Home

NOTE: Panel A reports the share of remote work job postings by 2-digit occupation from Lightcast Technologies. Panels B and C 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.

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**				
$\text{Learning}_{s,t}^{\text{Remote}}$	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**				
$\text{Learning}_{s,t}^{\text{Remote}}$	-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. $\text{Learning}_{s,t}^{\text{Remote}}$ is binary and equal to 1 if occupation s is above the 50th percentile of online learning 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***			
$\text{Learning}^{\text{Remote}}_{s,2019}$	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)
$\text{Learning}^{\text{Remote}}_{s,2019} * \text{Female}_{i,2019}$			0.017
			(0.011)
N	13,308	13,308	13,308
R^2	0.012	0.060	0.060
B. ***2020***			
$\text{Learning}^{\text{Remote}}_{s,2019}$	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)
$\text{Learning}^{\text{Remote}}_{s,2019} * \text{Female}_{i,2020}$			0.001
			(0.011)
N	11,887	11,887	11,887
R^2	0.021	0.057	0.057
C. ***2021***			
$\text{Learning}^{\text{Remote}}_{s,2021}$	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)
$\text{Learning}^{\text{Remote}}_{s,2021} * \text{Female}_{i,2021}$			0.015
			(0.011)
N	11,511	11,511	11,511
R^2	0.016	0.061	0.062
D. ***2022***			
$\text{Learning}^{\text{Remote}}_{s,2021}$	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)
$\text{Learning}^{\text{Remote}}_{s,2021} * \text{Female}_{i,2022}$			0.008
			(0.011)
N	11,211	11,211	11,211
R^2	0.012	0.049	0.049

NOTE: $\text{Learning}^{\text{Remote}}_{s,t}$ is binary and equal to 1 if occupation s is above the 50th percentile of online learning 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***			
$\text{Learning}^{\text{Remote}}_{s,2019}$	-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)
$\text{Learning}^{\text{Remote}}_{s,2019} * \text{Female}_{i,2019}$			-0.015^{*}
			(0.009)
N	14,373	14,373	14,373
R^2	0.010	0.048	0.048
B. ***2020***			
$\text{Learning}^{\text{Remote}}_{s,2019}$	-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)
$\text{Learning}^{\text{Remote}}_{s,2019} * \text{Female}_{i,2020}$			-0.003
			(0.006)
N	12,873	12,873	12,873
R^2	0.016	0.038	0.038
C. ***2021***			
$\text{Learning}^{\text{Remote}}_{s,2021}$	-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)
$\text{Learning}^{\text{Remote}}_{s,2021} * \text{Female}_{i,2021}$			-0.016^{*}
			(0.009)
N	12,474	12,474	12,474
R^2	0.012	0.039	0.039
D. ***2022***			
$\text{Learning}^{\text{Remote}}_{s,2021}$	-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)
$\text{Learning}^{\text{Remote}}_{s,2021} * \text{Female}_{i,2022}$			-0.017^{*}
			(0.009)
N	12,074	12,074	12,074
R^2	0.010	0.034	0.035

NOTE: $\text{Learning}^{\text{Remote}}_{s,t}$ is binary and equal to 1 if occupation s is above the 50th percentile of online learning 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)
$\text{Learning}_{s,t}^{\text{Remote}}$	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)
$\text{Learning}_{s,t}^{\text{Remote}} * \text{Female}_{i,t}$	0.011	−0.012	−0.005	−0.002
	(0.016)	(0.017)	(0.016)	(0.015)
$\text{Learning}_{s,t}^{\text{Remote}} * \text{Child}_{i,t}$	−0.036	−0.052**	−0.015	−0.042*
	(0.025)	(0.028)	(0.026)	(0.025)
$\text{Learning}_{s,t}^{\text{Remote}} * \text{Female}_{i,t} * \text{Child}_{i,t}$	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. $\text{Learning}_{s,t}^{\text{Remote}}$ is binary and equal to 1 if occupation s is above the 50th percentile of online learning at time $t \in [2019, 2021]$. Columns one and two use $\text{Learning}_{s,2019}^{\text{Remote}}$, while columns three and four use $\text{Learning}_{s,2021}^{\text{Remote}}$. 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)

Regressor	Dependent Variable: Labor Force Exit (2019)	(2020)	(2021)	(2022)
$\text{Learning}^{\text{Remote}}_{s,t}$	-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)
$\text{Learning}^{\text{Remote}}_{s,t} * \text{Female}_{i,t}$	-0.010	0.015	-0.005	-0.013
	(0.013)	(0.013)	(0.013)	(0.013)
$\text{Learning}^{\text{Remote}}_{s,t} * \text{Child}_{i,t}$	0.036^{*}	0.037^{*}	0.007	0.025
	(0.021)	(0.022)	(0.022)	(0.020)
$\text{Learning}^{\text{Remote}}_{s,t} * \text{Female}_{i,t} * \text{Child}_{i,t}$	-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. $\text{Learning}^{\text{Remote}}_{s,t}$ is binary and equal to 1 if occupation s is above the 50th percentile of online learning at time $t \in [2019, 2021]$. Columns one and two use $\text{Learning}^{\text{Remote}}_{s,2019}$, while columns three and four use $\text{Learning}^{\text{Remote}}_{s,2021}$. 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 *** $p < .01$.