How Does Online Learning Affect Business Formation, Productivity, and Employment?

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November 18, 2024

Abstract

The surge in online learning since the COVID-19 pandemic has transformed education across the United States, reshaping how individuals acquire skills and how firms operate. While much of the existing research has focused on online learning's individual-level effects, surprisingly little is known about the effects on firm dynamics. In this paper, I use multiple measures of online learning and various U.S. microdatasets to show that: (i) online learning reduces startup entry, establishment entry, and business formation, and (ii) online learning is associated with a reallocation of workers from large, incumbent firms to small, young firms. I show that these shifts contribute to productivity gains, with the reallocation of workers linked to increases in average monthly earnings.

KEYWORDS: Online learning, business formation, employment, productivity
JEL CLASSIFICATION CODES: I20, J24, L25, L26

I thank participants at the 2024 American Causal Inference Conference for insightful comments. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the Board of Governors or its staff. All errors are mine.

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1 Introduction

The COVID-19 pandemic introduced a transformative shift in education and skill development, accelerating the adoption of online learning at an unprecedented rate. While prior research has been devoted to understanding the individual-level effects of this transition—such as impacts on student outcomes, access, and employability—its aggregate implications are lacking. This paper examines how the rise of online learning has effected business formation, employment, wages, and productivity in the U.S.

Using a combination of U.S. industry and firm micro-data from administrative records and surveys, this study finds that online learning is associated with reductions in startup entry, establishment entry, and business formation, particularly among younger and newer firms. At the same time, online learning is associated with a reallocation of workers from large, incumbent firms to smaller, younger firms, contributing to increased wages and productivity. By linking educational trends with macroeconomic outcomes, this research provides evidence into how online learning can shape the future of work in an increasingly digitized economy.

Related Literature This paper contributes to several strands of the literature. First, it builds on prior research related to online learning (Hällsten, 2012; Picchio and van Ours, 2013; Banerjee and Duflo, 2014; Christensen et al., 2014; Radford et al., 2014; Zhenghao et al., 2015; Ho et al., 2015; Castaño-Muñoz et al., 2017; Castano-Munoz and Rodrigues, 2021; Aguilar, 2024; Novella et al., 2024; Majerowicz and Zárate, 2024). Most studies in this area have examined the individual effects of online learning, including why individuals enroll, their basic demographic and socioeconomic characteristics, and the potential impacts on their future employment. In contrast, this paper shifts focus to the aggregate level, investigating the effect that online learning has on industry and firm outcomes.

Second, this paper contributes to the literature on business dynamism during the COVID-19 pandemic and its aftermath (Decker and Haltiwanger, 2024a,b; Sedlacek and Shi, 2024). Previous research has documented a surge in business entry following the pandemic, particularly in high-tech industries. Sedlacek and Shi (2024) examine this trend through the lens of remote work and conclude that more favorable remote work conditions enhance profitability, thereby encouraging firm entry. This paper, however, explores business dynamism during and after the pandemic through the lens of online learning and reaches a contrasting conclusion: digital learning environments are associated with declines in entrepreneurship and business entry.

Third, this paper adds to the growing literature on the rise of remote work and its impact on productivity (Barrero et al., 2021; Battiston et al., 2021; Bloom et al., 2015; Choudhury et al., 2021; Barrero et al., 2023; Emanuel and Harrington, 2023; Gibbs et al., 2023). The literature offers mixed evidence on the overall productivity effects of remote work. While this paper does not directly focus on remote work, Aguilar (2024) shows that online learning and remote work are complementary. Thus, this study examines a closely related channel that exhibits productivity gains.

The rest of the paper is organized as follows. Section 2 describes the data sources, variable construction, and the main empirical results. Section 3 provides a brief discussion of the results, and Section 4 concludes.

2 Empirical Evidence

2.1 Data and Definitions

Online learning. In constructing my first measure of online learning, I use the American Time Use Survey (ATUS), which provides information on the minutes per day spent on a diverse set of activities as well as the location of the activity (Flood et al., 2023). I define online learning to be the activity labeled "taking a class for degree, certification, license, or personal interest." and the location being "at your own home or someone else's home". One advantage of the ATUS is that it provides information starting in 2003 and the sample of households is linked to the Current Population Survey (CPS), allowing me to obtain time allocation data as-well as the industry they work in.[1] In constructing my sample in the ATUS I drop respondents who are flagged by the ATUS for bad data quality, and focus only on respondents who are employed with minimum real annual earnings of $\$20,000$ (counted as 52 times average weekly earnings, deflated by the Personal Consumption Index).

I count learning days of individual j, d_j, as those in which individuals devote more than one hour to learning. Analogously, I define days online learning, d_j^{remote}, as those in which individuals spend at least one hour learning remotely—at home or at someone else's home. Following the methodology of Sedlacek and Shi (2024), I then compute online learning rates at the industry level by complementing information from ATUS with industry classification data from the CPS. I define online learning rates in industry i and

[1] The ATUS samples households which have completed their final month of the CPS. From each of the selected households, a random individual aged 15 and over is chosen to participate in ATUS. The questionnaire asks information about the respondent's previous day and is conducted only once for each individual.

year t as the sum of all days learning remotely by individuals working in industry i relative to the total number of learning days in that industry:

$$\omega_{i,t} = \frac{\sum_{j=1}^{J_{i,t}} d_{j,\tau}^{\text{remote}}}{\sum_{j=1}^{J_{i,t}} d_{j,\tau}},$$

where $J_{i,t}$ is the number of individuals reporting in industry i in year t. In addition, I also construct an analogous measure of online learning rate at the quarterly frequency. Figure 1 shows how the aggregate online learning rate evolved over time. The trend in online learning has been increasing since 2003. In particular, the rate of online learning increased from 7% in 2003 to 36% in 2018. During the COVID-19 pandemic online learning rates increased to 88%, and remain above pre-pandemic levels as of 2022 at 46%. Across sectors, there is variation in online learning rates. For instance, in 2003, in Manufacturing, Professional and Business Services, and Education and Health Services had online learning rates of 5%, 30% and 9%, respectively. Additionally, in 2018, the online learning rates in the same sectors were zero, 50%, and 44%. The COVID-19 pandemic had a strong impact on online learning rates, with all sectors reaching a rate of 80% or higher in 2020. What is clear from Figure 1 is that the pandemic led to a surge in online learning, peaking in 2020. While it has since declined, online learning rates remain significantly higher than pre-pandemic levels.

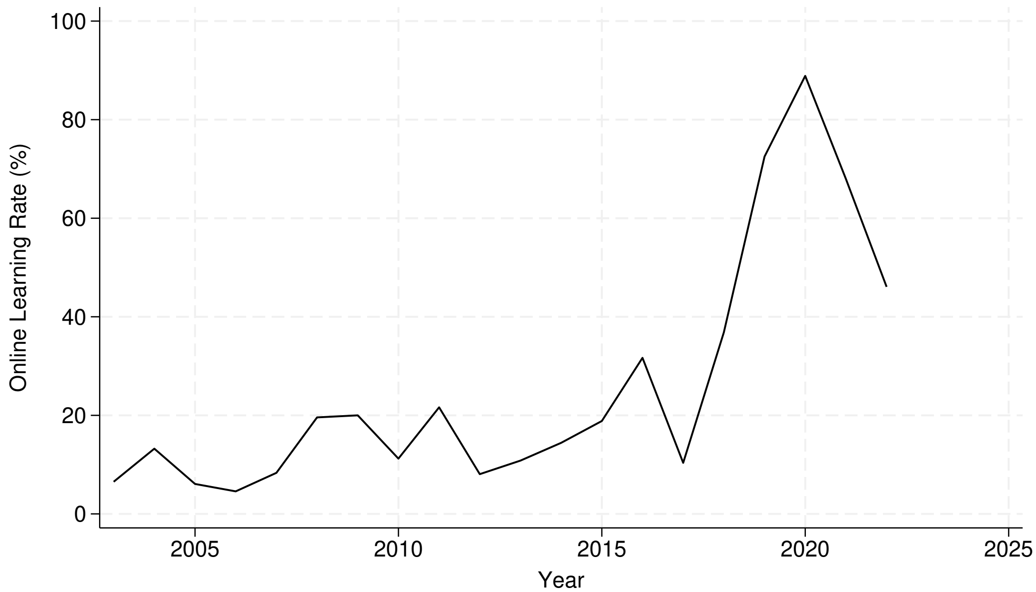
For my second measure of online learning, I construct an exposure instrument of online learning across U.S. industries. I leverage the fact that online learning varies across occupations and that occupations vary in their distribution of industry employment, to create a shift-share variable. The shift-share or "bartik" method was originally proposed by Bartik (1991), and has since taken on different variants.[2] The shift-share method assumes a pooled exposure research design, where the shares measure differential exposure to common shocks. In this design, identification is based on exogeneity of the shares, but is not necessary for the empirical strategy to be valid (Goldsmith-Pinkham et al., 2020).

In constructing my shift-share, for the shift-component, I use the Current Population Survey Computer and Internet Use Supplement (CPS-CIS).[3]

[2]For example see Hershbein and Kahn (2018) and Acemoglu and Restrepo (2021).

[3]The CPS conducts interviews with approximately 54,000 households for a set of consecutive months during the year and repeats the process for the corresponding time period a year later. The CPS-CIS is a subset of the CPS, asking specific questions about respondents computer and internet use. The surveys are released biennial. The CPS-CIS contains reliable industry and occupation data as-well as detailed information on socioeconomic and demographic variables. I impose similar sample restrictions as the ATUS by ensuring the respondent is employed and has reliable industry and occupation information.

FIGURE 1 – Online Learning Rate Over Time



NOTE: The figure plots the online learning rate—computed from the ATUS as described in the main text—over time for the aggregate economy.

The object of interest in the CPS-CIS is the question, "Do you participate in online classes or job training?". This variable is collected in 2019 and 2021 and refers to activity over the last six months. I then calculate changes in online learning,

$$\Delta \text{Learning}_s^{\text{Remote}} = \text{Learning}_{s,2021}^{\text{Remote}} - \text{Learning}_{s,2019}^{\text{Remote}}.$$

Here, $\text{Learning}_{s,2021}$ represents the share of online learning in two-digit occupation s in 2021, and $\text{Learning}_{s,2019}$ denotes the share of online learning in two-digit occupation s in 2019. For the share component, I use the Occupational Employment and Wage Statistics (OEWS), which contains national estimates for cross-industry occupational employment. I use 2019 as my baseline and calculate the employment share of 4-digit industry i in two-digit occupation s. Specifically,

$$\phi_{s,i} = \frac{E_{s,i}}{E_i}.$$

Here, E_i represents total employment in industry i, and $E_{s,i}$ denotes the total employment of occupation s in industry i.

As shown in equation 1, taking the inner product of my shift and share will give me my second measure of online learning, shock_i.[4] Where, ϕ is the 2019 employment share of industry i in occupation s, and $\Delta\text{Learning}_s$ is the change in online learning in occupation s from 2019 to 2021.

$$\text{shock}_i = \sum_{i=1}^{I} \phi_{s,i} * \Delta\text{Learning}_s^{\text{Remote}}, \quad \Delta\text{Learning}_s^{\text{Remote}} = \text{Learning}_{s,2021}^{\text{Remote}} - \text{Learning}_{s,2019}^{\text{Remote}} \tag{1}$$

I interpret shock_i as an industries differential exposure to online learning. One way to interpret this is that high levels of shock_i indicate that the industry was "hit harder" by online learning. In Appendix Figure 8, I show the distribution of shock_i—the calculated values range from 0.01 to 0.10. Industries with high exposure to online learning include Educational Services, Finance and Insurance, Management of Companies and Enterprises, and Accommodation and Food Services.

Business entry, startup entry, and business formation. The first measure of business dynamism is establishment entry and is from the Business Employment Dynamics (BED) dataset generated from the Quarterly Census of Employment and Wages (QCEW) program of the Bureau of Labor Statistics (BLS). The BED calls establishment entry "births", and it is defined as establishments which record positive employment for the first time in a given quarter and do not include reopenings of seasonal businesses. The periodicity of the BED is quarterly and yearly. The BED is only available at the super-sector level, as such, I aggregate online learning rates in the ATUS to the super-sector level in order to examine industry-level patterns of establishment entry. My sample size includes 12 industries from 2003-2022.

The second measure of business dynamism comes from the Business Dynamics Statistics (BDS) of the Census Bureau. The BDS provides measures of establishment entry and startup entry and are available by firm age and size as-well as across different levels of industry aggregations. The BDS is at the annual frequency, as such, I aggregate online learning rates to the annual level. To compare the BDS to the BED, I first construct establishment entry for the 12 super-sectors. I then construct measures of startup entry from the BDS by firm age and size groups at the 4-digit industry level, where I have information for 243 industries from 2013 through 2021.

The third measure of business dynamism comes from the Business Formation Statistics (BFS) of the Census Bureau. The Business Formation Statistics (BFS) provides weekly data on business applications, which includes all applications for an Employer Identifi-

[4] In addition, I also construct shock_i at the 3-digit industry level.

cation Number (EIN)—which is required for all employer businesses in the United States to file payroll taxes. I aggregate the business applications from the weekly to quarterly frequency across 3-digit industries. I then construct deviations in business applications relative to the pre-pandemic mean, calculated within 3-digit industry by quarter cells. My final sample includes 87, 3-digit industries from 2017Q1 through 2022Q4.

Wage and employment information. Information on wages and employment is taken from the Quarterly Workforce Indicators (QWI) which is sourced from the Longitudinal Employer-Household Dynamics (LEHD). The QWI provides local labor market statistics by industry, worker demographics, and firm age and size groups. I use average monthly earnings of employees, averaged to the quarterly frequency as well as quarterly employment across 4-digit industries.[5] I then construct deviations in earnings and the employment share relative to 2019 across all firm size and age groups at the 4-digit industry level.[6]

Industry productivity. The Bureau of Labor Statistics Industry Productivity (BLS-IP) contains annual measures of labor productivity for the U.S. business sector, nonfarm business sector, nonfinancial corporate sector, and manufacturing sector. I use the BLS-IP to construct a panel of industries with information on labor productivity across 286, 4-digit industries from 2011 through 2022.[7]

2.2 Empirical Analysis

2.2.1 Descriptive Evidence of Online learning

Table 1 shows that high levels of online learning tend to be in computer and office-focused occupations. For instance, occupations with the highest shares of online learning in 2021 include: Management (33%); Business and Financial (39%); Computer and Mathematical (42%); Social Science (46%); and Social Services (47%). When looking at the changes in online learning between 2019 and 2021, 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, oc-

[5] I deflate earnings to 2017 = 100 and drop extreme values reported for earnings.

[6] Firm age groups are defined as: 0-1 Years, 2-3 Years, 4-5 Years, 6-10 Years, and 11+ Years. Firm size groups are defined as: 0-19 Employees, 20-49 Employees, 50-249 Employees, 250-499 Employees, 500+ Employees.

[7] As defined by the BLS, labor productivity is a measure of economic performance that compares the amount of goods and services produced (output) with the amount of labor hours worked to produce that output. Therefore, a change in labor productivity reflects the change in output that is not explained by the change in hours worked.

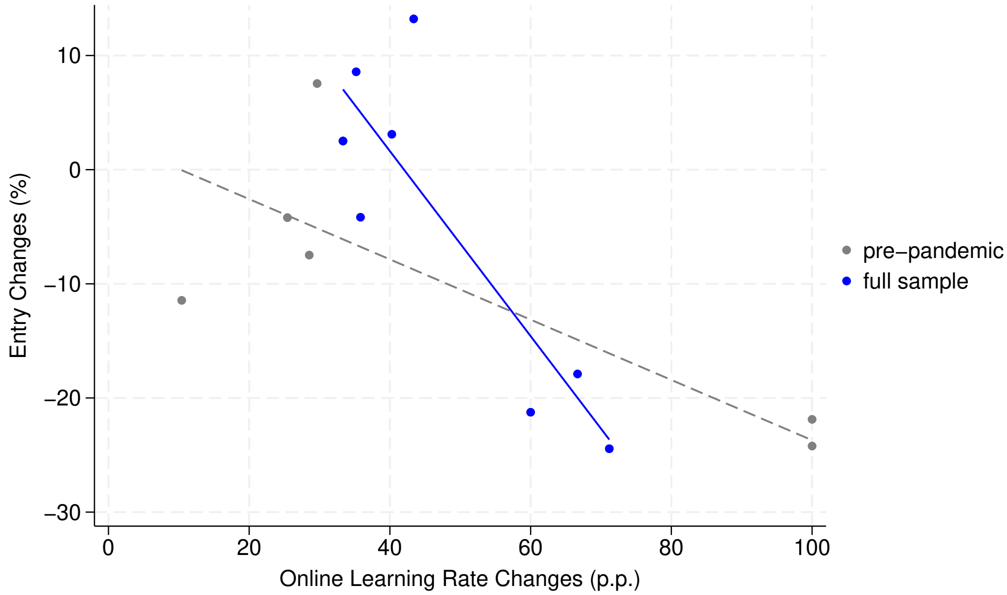
TABLE 1 – Shares (%) and Changes in Online Learning by Two-digit Occupation

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	28	28	0
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.

cupations with small changes in online education include Construction (4%); Installation, Maintenance, and Repair (2%); and Transportation and Material Moving (1%). In other words, lower shares of online learning are in occupations that are traditionally in-person. This descriptive evidence aligns with the idea that online learning is used for human capital accumulation for workers in industries that feature computer and office-focused occupations, and such occupations are inherently more teleworkable. Corroborating this evidence is Aguilar (2024), who shows that online learning is positively correlated with the ability to work remotely and the demand for remote workers.

FIGURE 2 – Changes in Online Learning and Establishment Entry



NOTE: The figure shows super-sector changes in online learning rates and changes in the number of entrants. Online learning rates are estimated from the ATUS as described in the main text. Establishment entry is from the BED. Pre-pandemic sample refers to 2003 through 2019 and the full sample refers to 2003 through 2022.

2.2.2 Online learning and establishment entry: Estimation.

I first begin examining the descriptive relationship between changes in establishment entry and online learning at the super-sector level. Specifically, in Figure 2, the x-axis shows the percentage point changes in super-sector online learning rates, while the y-axis shows the corresponding percent changes in the number of entrants. I examine two samples, the pre-pandemic period, 2003 through 2019, and the full sample period, 2003 through 2022. Mainly, Figure 2 shows that increases in online learning rates are consistently associated with decreases in establishment entry across both the pre-pandemic and full sample periods. Although this relationship existed prior to the pandemic, it appears to have strengthened during the pandemic, as seen by the steeper slope in the full sample.

This suggests that while online learning was already influencing establishment entry, the pandemic may have amplified its impact.

To test the relationship between online learning and establishment entry more formally, I

TABLE 2 – Online Learning Reduces Establishment Entry

	Dependent Variable: Log Entry			
Regressor	BED	BDS All Firms	BDS New	BDS Young
A. ***Pre-pandemic (2003-2019)***				
Online learning rate	-0.032	-0.065^{*}	-0.053^{***}	-0.077^{*}
	(0.028)	(0.037)	(0.019)	(0.043)
N	81	470	94	188
R^2	0.998	0.984	0.999	0.995
B. ***Full Sample (2003-2021)***				
Online learning rate	-0.018	-0.066^{*}	-0.052^{***}	-0.077^{*}
	(0.030)	(0.037)	(0.019)	(0.043)
N	88	490	98	196
R^2	0.998	0.985	0.999	0.995

NOTE: The table reports results from estimating equation 2. Panel A reports estimates using the pre-pandemic period (2003-2019) only, while Panel B report results for the entire sample period (2003-2021). Column 1 panel B is estimated from 2003-2022, since the BED contains 2022 data. Column three is new firms in the BDS, defined to be less than age 1. Column four is young firms in the BDS, defined to be firms aged 1 to 2. All specifications include industry and time fixed effects as well as lagged values of the dependent variable. Standard errors are reported in parenthesis, * $p < .10$; ** $p < .05$; and *** $p < .01$.

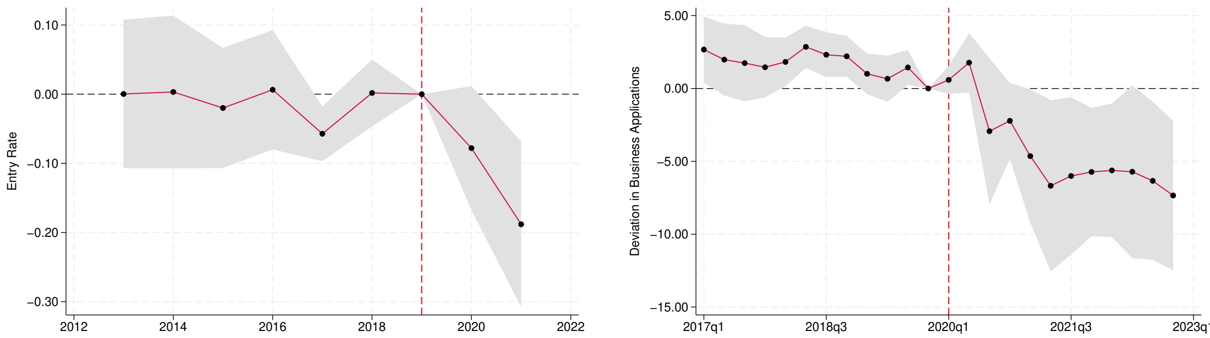
estimate the following panel regression:

$$\text{Entry}_{i,t} = \delta_i + \delta_t + \beta\omega_{i,t} + \Gamma X_{i,t} + \epsilon_{i,t}, \tag{2}$$

where the outcome variable is the log of establishment entry in industry i and period t. δ_i and δ_t are industry and time fixed effects, respectively, and $X_{i,t}$ includes lags of the dependent variable. The main object of interest is coefficient β, which provides the effect of online learning rates, $\omega_{i,t}$, on establishment entry.

Table 2 reports estimates of β from equation 2, examining the relationship between online learning rates and establishment entry. Using BED data, the results suggest a negative relationship between online learning and establishment entry, although BED data do not allow for distinguishing between new or young firms. To address this limitation, I

FIGURE 3 – Online Learning Reduces Startup Entry and Business Formation



A. Startup Entry Rate B. Business Formation

NOTE: The figure reports the estimates from estimating equation 3. Panel A reports estimates for startup entry from the BDS, N = 2174, defined as the number of firms age zero divided by the total number of firms, from 2013 to 2021. Panel B reports results for deviations in business applications relative to the pre-pandemic mean from 2017q1-2022q4. Panel B uses BFS data, N = 1992. All specifications include sector-by-time and industry fixed effects, and standard errors are clustered by industry and year.

also use BDS data, which provides detailed firm age breakdowns. For the pre-pandemic and full sample, across all firms, the BDS confirms a significant negative relationship between online learning rates and establishment entry. Notably, the negative effect is more pronounced for young firms (aged 1 to 2), with coefficients larger in magnitude, and for new firms (age less than 1), where the relationship remains statistically significant. These findings suggest that online learning rates are associated with a reduction in establishment entry, especially among newer and younger firms.

2.2.3 Online learning, startup entry, and business formation: Estimation.

$$\text{outcome}_{i,t} = \alpha_0 + [\text{shock}_i * I^t]\alpha_1 + I^t + \tau_{i,t} + \gamma_t + \varepsilon_{i,t} \tag{3}$$

To estimate the causal effect of online learning on firm entry and business formation, I use a two-way fixed effect event study design. The main regression specification is shown in equation 3. The left-hand side, $\text{outcome}_{i,t}$, represents the firm entry rate and deviation in business applications relative to the pre-pandemic average in industry i at time t. The regression sample includes years both before and after the pandemic. The coefficient of interest is α_1, which is estimated from the interaction of shock_k and a set of time dummies denote by I^t. In other words, α_1 will explain the relationship between online learning and business dynamism before, during, and after the COVID-19 pandemic. I also include I^t as a control to ensure I am not picking up on any time specific trends, $\tau_{i,t}$ represents sector by time fixed effects, γ_t is industry fixed effects, and $\varepsilon_{i,t}$ is an error term. I cluster standard errors by industry and time to address possible serial correlation.

Figure 3 illustrates the effect of online learning on startup entry rates and business formation. In Panel A, a one standard deviation (SD) increase in shock_i is associated with a 7.8% decrease in startup entry rates in 2020 and 18.7% decrease in 2021. In Panel B, a similar pattern emerges for business formation. Despite initial increases in business applications, likely driven by immediate pandemic-related shifts, a one SD increase in shock_i is associated with ten consecutive quarters of negative deviations in business applications relative to the pre-pandemic average. Taken together, the results from panel A and panel B suggest that online learning is associated with a drop in entrepreneurial activity.

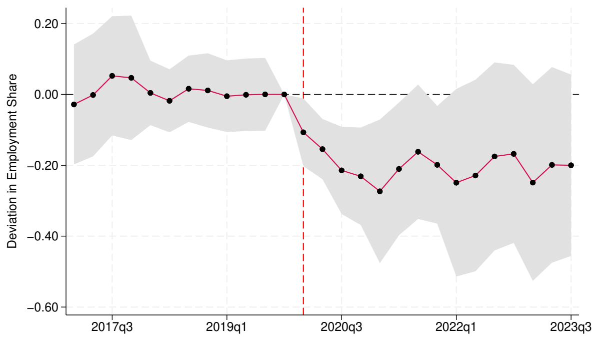
2.2.4 Online learning and employment: Estimation.

$$\text{Employment}_{i,t,f} = \alpha_0 + [\text{shock}_i * I^t]\alpha_1 + I^t + \tau_{i,t} + \gamma_t + \varepsilon_{i,t,f} \tag{4}$$

To estimate the effect of online learning on employment across firm size and age groups, I again use a two-way fixed effect event study design. The regression specification is identically defined as equation 3. However, now the left-hand side, $\text{Employment}_{i,t,f}$, represents the employment share and the deviation in the employment share relative to 2019 in industry i at time t for firm size or age group f. Here, α_1 will explain the relationship between online learning and employment before, during, and after the COVID-19 pandemic. All specifications include year dummies, I^t, sector by time fixed effects, $\tau_{i,t}$, industry fixed effects, γ_t, and when using QWI outcomes, state fixed effects. $\varepsilon_{i,t,f}$ is an error term, and I cluster standard errors by industry and time to address possible serial correlation.

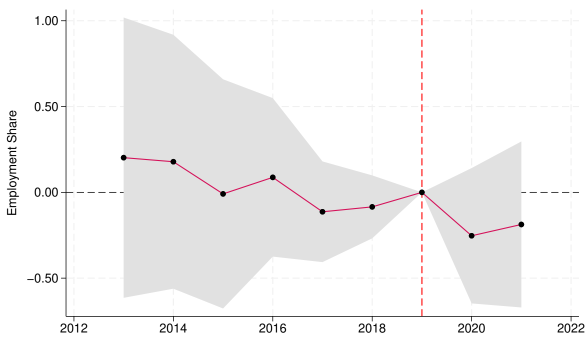
Figure 4 illustrates that online learning reduces employment at large and incumbent firms. In particular, Panel A shows that a one SD increase in shock_i is associated with sharp and persistent drop in the employment share at large firms (500+ employees). The employment share remains approximately 20% below pre-pandemic levels from Q3 2020 through Q3 2023. Similarly, in Panel B, incumbent firms (11+ years) show a sharp decline in employment share relative to 2019, starting in Q1 2020, which remains negative until it gradually recovers to near-zero levels by Q2 2023. To validate these results, I also estimate the effect of online learning on the employment share for large and incumbent firms from the BDS. Specifically, Panel C highlights a that a one SD increase in shock_i is also associated with a sharp and persistent decline in the employment share for firms with over 10,000 employees. Additionally, Panel D shows that incumbent firms (26+ years) exhibit a similar pattern, with a pronounced drop in the employment share in 2020, followed by

FIGURE 4 – Online Learning Reduces Employment at Large and Incumbent Firms

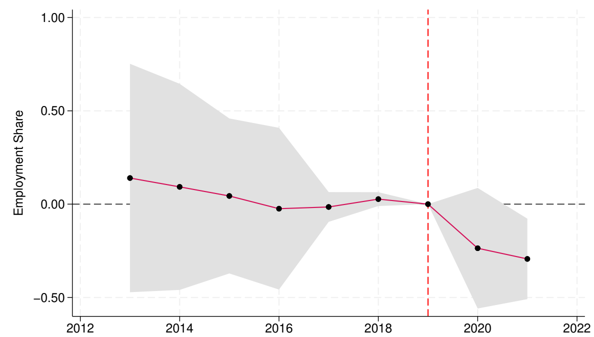


A. 500+ Employees

B. Age 11+



C. 10,000+ Employees



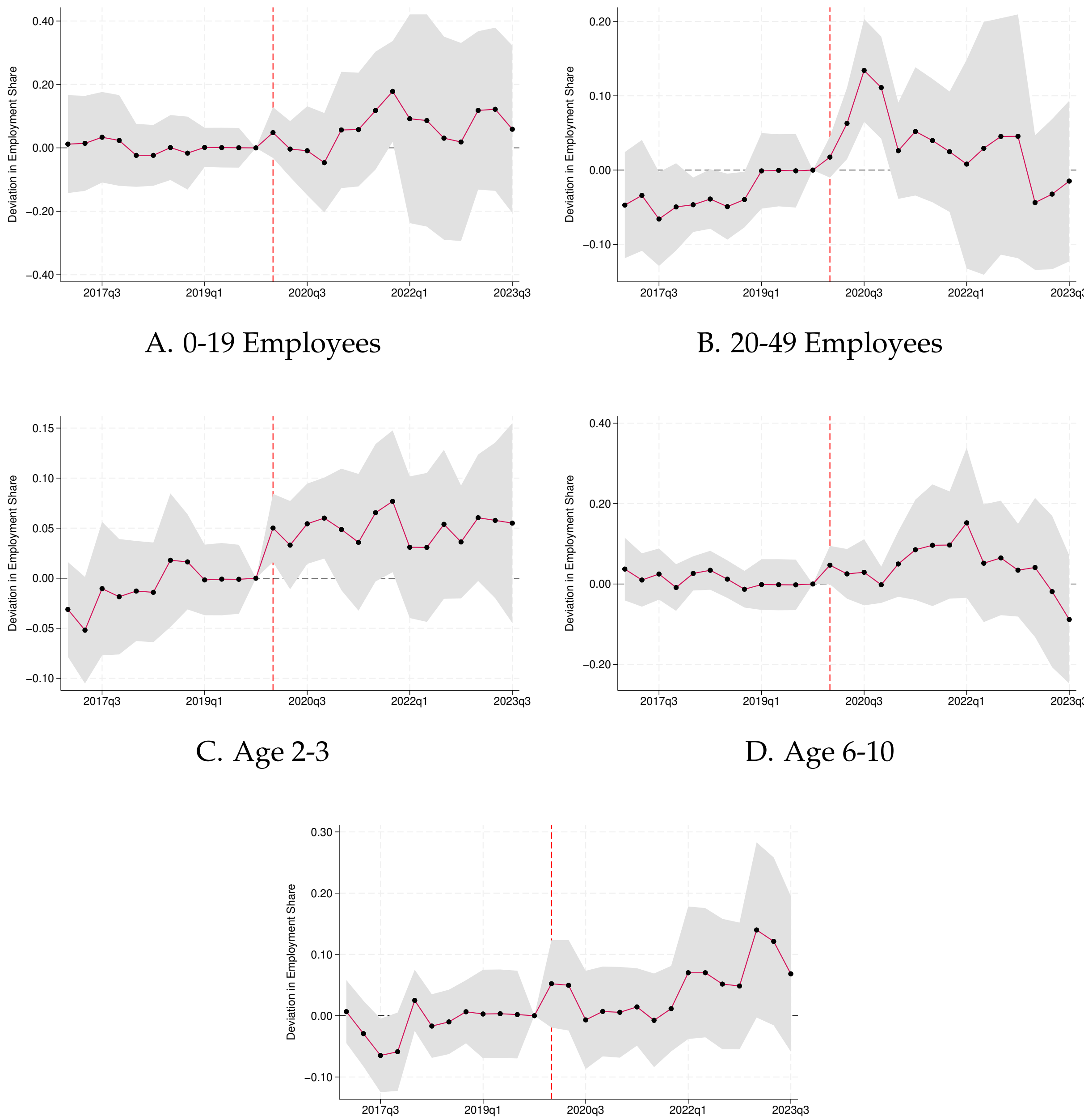
D. Age 26+

NOTE: Panels A and B show the estimate of α_1 from equation 4 for large and incumbent firms in the QWI, estimated from 2017q1 through 2023Q3. Panels C and D show the estimate of α_1 from equation 4 for large and incumbent firms in the BDS, estimated from 2013 through 2021.

another decline in 2021.

On the other hand, in Figure 5 I show that online learning increases employment at small to medium sized firms as-well as young firms. First, Panel A shows that a one SD increase in shock$_i$ is associated with increases in the employment at small firms with 0 to 19 employees. Despite initial declines in 2020, small firms exhibit higher employment relative to 2019, reaching a peak of 18% in Q4 2021. In particular, at the end of the series, Q3 2023, the employment share for firms with 0 to 19 employees remains above pre-pandemic levels by 5.8%. Moreover, in Panel B, for firms with 20-49 employees, a one unit SD increase in shock$_i$ is associated with a rapid increase in the employment share, with the first four quarters of 2020 exhibiting an increase of 1.7%, 6.3%, 13.4%, and 11.1%, respectively. This positive deviation in the employment share for firms with 20-49 employees remains persistent for majority of the sample, however, it begins to decline in 2023.

FIGURE 5 – Online Learning Increases Employment at Small to Medium Sized and Younger Firms



A. 0-19 Employees

B. 20-49 Employees

C. Age 2-3

D. Age 6-10

E. 250-499 Employees

NOTE: Panels A through E show the estimate of α_1 from equation 4. Data is from the QWI. All specifications include sector-year, industry, and state fixed effects. Standard errors are clustered by industry and year.

Contrary to the effect that online learning has on incumbent firms, online learning increases the employment share at younger firms. In Panel C, I show that a one unit SD increase in shock$_i$ increases the employment share for firms aged 2 to 3 across the entire sample period. Specifically, relative to 2019, the employment share remains, on average, 5% higher from Q1 2020 to Q3 2023, with global maximum of 7.7% in Q4 of 2021. Additionally, in Panel D, I show that a one unit SD increase in shock$_i$ increases the employment share for firms aged 6 to 10. From the onset of the pandemic to Q3 of 2023, the average deviation in the employment share relative to 2019 is 4.4%. However, the estimate is negative in the last two quarters of the sample. Lastly, in Panel E, I show that a one unit increase in the SD of online learning is associated with an increase in the employment share for firms with 250 to 499 employees, gradually increasing to 14% in Q1 of 2023, and remains 6.8% higher in Q3 2023, relative to 2019.

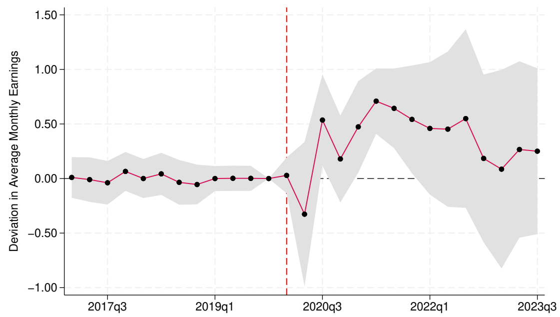
The results from Figure 4 and Figure 5, suggest a reallocation of workers from large and incumbent firms to smaller and younger firms. From the onset of the pandemic, there is an immediate drop in the employment share for firms with 500 plus employees and for the oldest firms, aged 11 plus. On the other hand, from the onset of the pandemic, small firms with 0 to 19 employees, as-well as younger firms aged 2 to 3, experienced a sharp increase in the employment share. Moreover, both medium sized firms with 20-49 employees, and mid-aged firms 6 to 10, experienced positive increases in employment—However, the effect is less pronounced, eventually decreasing towards the end of the sample. Surprisingly, when looking at the employment share of firms with 250-499 employees, there is a positive employment effect. Taken together, these result suggest that online learning leads to a reallocation from the largest and oldest firms to all other firm size and age groups. To understand the mechanism driving this reallocation, in the next section is discuss the relationship between online learning and wages.

2.2.5 Online learning and wages: Estimation.

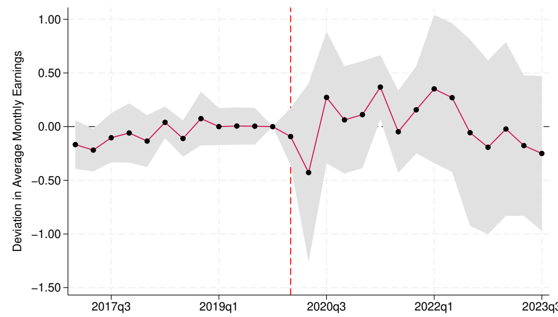
$$\text{Wages}_{i,t,f} = \alpha_0 + [\text{shock}_i * I^t]\alpha_1 + I^t + \delta_m + \tau_{i,t} + \gamma_t + \varepsilon_{i,t,f} \tag{5}$$

I now estimate the effect of online learning on wages across firm size and age groups. The regression specification is identically defined as equations 3 and 4. However, now the left-hand side, Wages$_{i,t,f}$, represents the deviation in average monthly earnings relative to 2019 in industry i at time t for firm size or age group f. Here, α_1 will explain the relationship between online learning and wages before, during, and after the COVID-19 pandemic. All specifications include year dummies, I^t, as well as state, sector by time, and industry fixed effects, denoted by δ_m, $\tau_{i,t}$, and γ_t, respectively. $\varepsilon_{i,t,f}$ is an error term, and I cluster standard errors by industry and time to address possible serial correlation. My employment results suggest a reallocation of workers from large, incumbent firms to smaller, and younger firms. The reallocation of workers may be driven by online

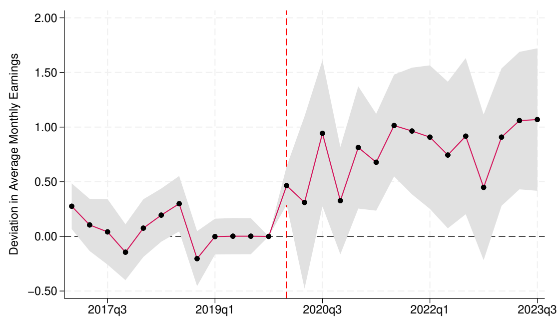
FIGURE 6 – Online Learning Increases Average Earnings Across All Firm Age and Size Groups



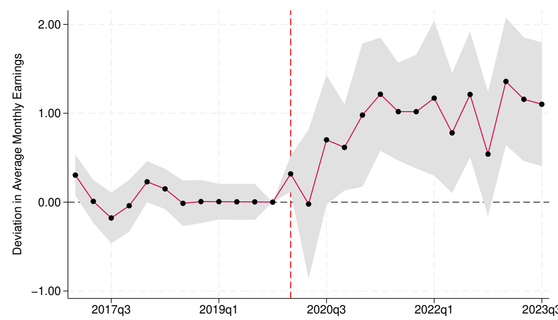
A. 0-19 Employees



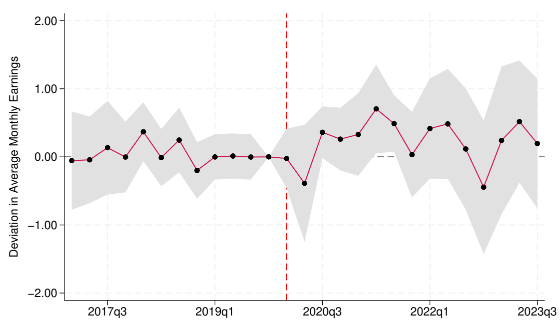
B. 20-49 Employees



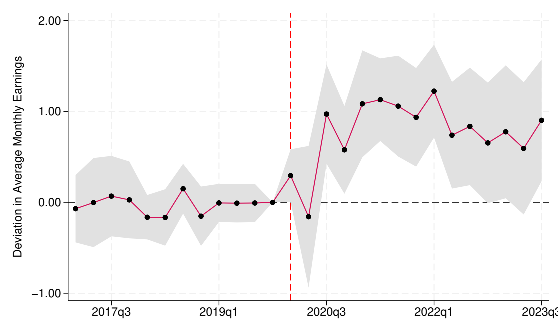
C. 50-249 Employees



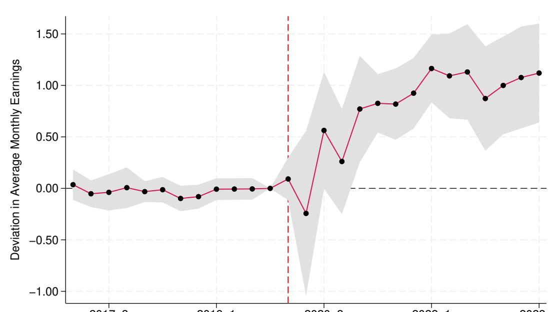
D. 500+ Employees



E. Age 2-3



F. Age 6-10



G. Age 11+

NOTE: Panels A through G show the estimate of α_1 from equation 5. All specifications include sector-year, industry, and state fixed effects. Standard errors are clustered by industry and year.

learning being utilized to gain skills and transition to another job that offers higher wages. If this is true, then I would expect workers who reallocate to receive higher wages. Indeed, In Figure 6, I show that there is a clear increase in wages across firms of all sizes and ages following the onset of the COVID-19 pandemic.

While the general pattern of increasing wages is consistent across all groups, the magnitude and stability of these changes vary depending on firm size and age. For instance, smaller firms (0-19 employees) exhibit a sharp rise in earnings that remains above zero, while firms with 20-49 employees exhibit more volatility in wages. Additionally, medium-sized firms (50-249 employees) show a more gradual and stable earnings increase. Interestingly, despite a decrease in the employment share of large firm with 500+ employees, they experience the most substantial and sustained earnings growth. This evidence suggest that workers who remain at the largest firms experience larger wage gains, relative to those who reallocate to smaller firms.

When considering firm age, younger firms (2-3 years old) display a slight uptick in earnings, but with greater greater volatility relative to older firms. Firms aged 6-10 experience sharp growth from the onset of the pandemic, followed by steady growth, while the oldest firms (11+ years old) exhibit the most consistent and substantial post-pandemic gains. Again, similar to the wage gains observed in the largest firms, workers who stay at incumbent firms experience higher wages gains, relative to those who reallocate to younger firms. The wage results imply that both firm size and age play crucial roles in determining how well firms adapt to the changes brought on by the shift to online learning, with larger and older firms faring better in maintaining and growing their earnings—despite reductions in employment.

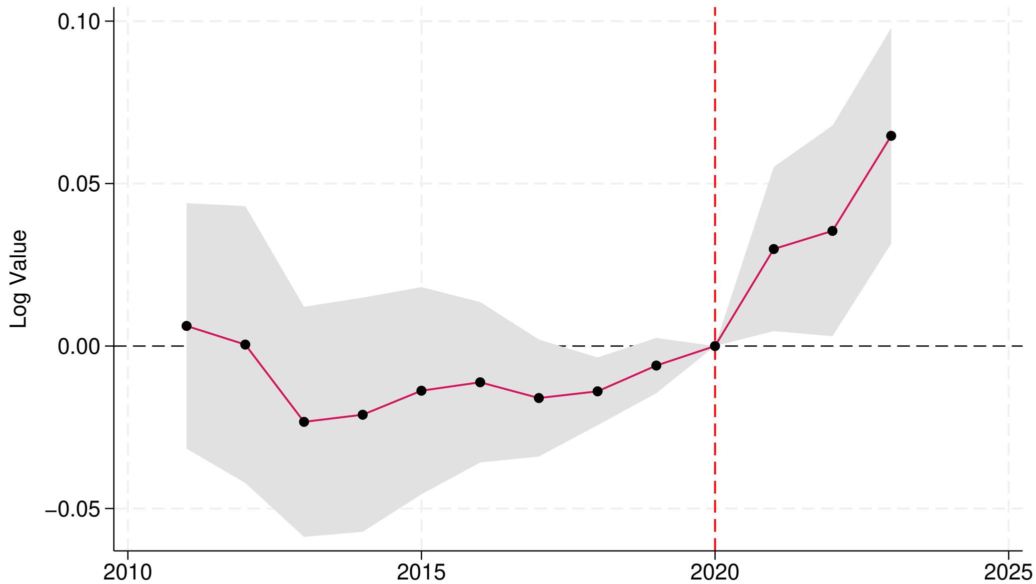
2.2.6 Online learning and labor productivity: Estimation.

$$\text{Productivity}_{i,t} = \alpha_0 + [\text{shock}_i * I^t]\alpha_1 + I^t + \tau_i + \gamma_t + \varepsilon_{i,t} \tag{6}$$

Lastly, I estimate the effect of online learning on labor productivity. In equation 6, the left-hand side, $\text{Productivity}_{i,t}$, is the log of productivity in industry i at time t. The main object of interest is α_1, which will explain the relationship between online learning and changes in labor productivity before, during, and after the COVID-19 pandemic. All specifications include year dummies, I^t, sector fixed effects, τ_i, and industry fixed effects, γ_t. $\varepsilon_{i,t}$ is an error term and I cluster standard errors by industry and year.

Figure 7 shows that prior to the pandemic, productivity remained relatively flat or declined slightly, with no significant deviations from the trend. However, after 2020, the

FIGURE 7 – Online Learning Increases Labor Productivity



NOTE: Estimate of α_1 from equation 6. Includes year, sector, and industry fixed effects. Standard errors are clustered by industry and year.

trend reverses, and productivity begins to increase substantially. The post-pandemic period shows a consistent upward trend, with productivity gains observed in each year following the pandemic. This figure suggests that online learning is associated with a notable improvement in labor productivity after 2020. The implementation of online learning may reflect improved worker skills, and in turn, workers becoming more productive.

3 Discussion

The increase in labor productivity seen in Figure 7 can be understood in light of several key dynamics related to employment, wages, and business formation in the post-pandemic period. First, the rise in wages across firms of all sizes, as depicted in Figure 6, suggests that workers became more valuable, likely due to the skills gained through online learning. As the pandemic accelerated digital adoption, online learning provided workers with the tools to thrive in remote or hybrid environments, thereby increasing their productivity. Higher wages, therefore, reflect firms investing in workers who are more efficient and able to adapt to new technologies, leading to a rise in productivity.

Moreover, the reduction in business dynamism may have further bolstered productivity. Fewer new firms entering the market likely meant that economic activity became more concentrated among established, surviving businesses. These firms, often being more productive and efficient, would have captured a larger share of the market, driving up aggregate productivity. Additionally, during periods of structural change, less productive firms typically exit the market, leaving behind firms that can better leverage technology and adapt to changing conditions. The resulting shift in economic activity toward more productive firms, along with the skill gains from online learning, created an environment where labor productivity could accelerate, despite broader challenges to business formation and employment growth.

Taken together, the combination of enhanced worker skills, higher wages, and the concentration of activity in more productive firms following the reduction in business entry provides a coherent explanation for the observed increase in labor productivity. Online learning played a pivotal role in driving these dynamics by improving labor quality and reinforcing the resilience of established firms. This structural shift, while reducing new firm formation, ultimately led to more efficient resource allocation and higher productivity.

4 Concluding Remarks

Using multiple measures of online learning and various U.S. micro-datasets, I show that online learning has a significant impact on firm dynamics. I conclude that increases in online learning are associated with a declines in establishment entry, especially among younger and newer firms, as well as declines in startup entry and business formation. These results suggest that, although online learning can boost individual capabilities, it may create barriers to entrepreneurship and the entry of new firms into the market. However, my findings also highlight a positive outcome: a reallocation of workers from larger, incumbent firms to smaller, younger firms, which is associated with higher wages and increased productivity. This reallocation points to the potential of online learning to foster a more diversified workforce and contribute to a more efficient allocation of resources in the economy.

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How Does Online Learning Affect Business Formation, Productivity, and Employment?

Online Appendix

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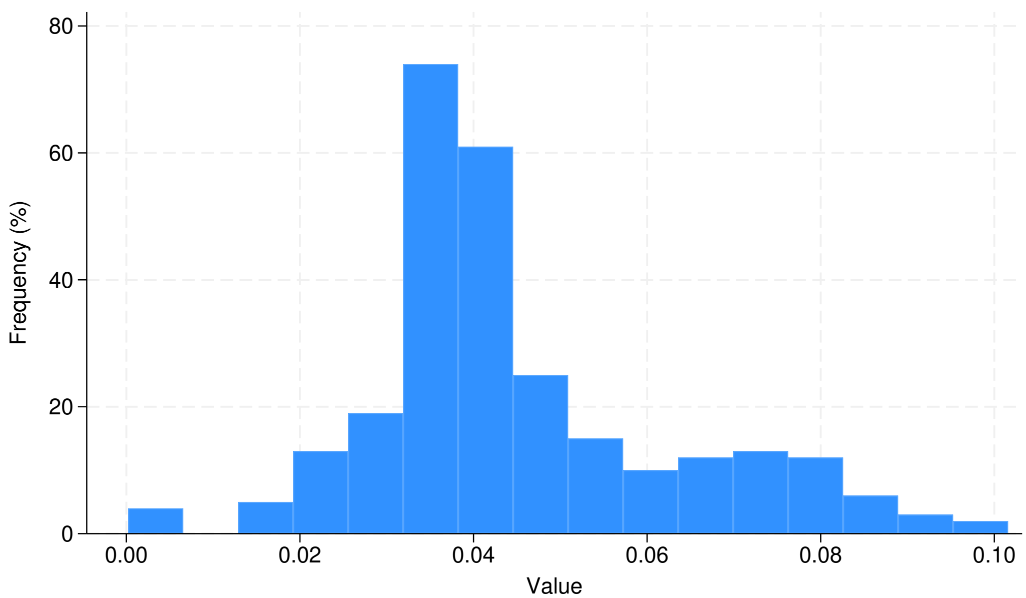
5 Appendix: Figures

FIGURE 8 – Distribution of the Shift-Share Variable



NOTE: Figure shows the distribution of the shift-share variable from equation 1.