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ORIGINAL PAPER

How Did Reskilling During the COVID-19 Pandemic Relate to Entrepreneurship and Optimism? Barriers, Opportunities, and Implications for Equity

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Abstract
With shorter durations and fewer barriers to entry, reskilling programs may serve as vehicles for social mobility and equity, as well as tools for creating a more adaptive workforce and inclusive economy. Nevertheless, much of the limited large-scale research on these types of programs was conducted prior to the COVID-19 pandemic. Thus, given the social and economic disruptions spurred by the pandemic, our ability to understand the impact of these types of programs in recent labor market conditions is limited. We fill this gap by leveraging three waves of a longitudinal household financial survey collected across all 50 US states during the pandemic. Through descriptive and inferential methods, we explore the sociodemographic characteristics related to reskilling and associated motivations, facilitators, and barriers, as well as the relationships between reskilling and measures of social mobility. We find that reskilling is positively related to entrepreneurship and, for Black respondents, to optimism. Moreover, we find that reskilling is not merely a tool for upward social mobility, but also economic stability. However, our results demonstrate that reskilling opportunities are stratified across race/ethnicity, gender, and socioeconomic status through both formal and informal mechanisms. We close with a discussion of implications for policy and practice.

Keywords Reskilling · COVID-19 · Stratification · Entrepreneurship · Optimism

Introduction

During COVID-19, Black and Latinx unemployment soared (EPI, 2021), while many women were pushed out of the workforce (Bateman & Ross, 2020). Yet, at the same time, many sectors struggled to fill jobs (Ferguson, 2022). With the recent wave of resignations—often referred to as the "Great Resignation"—many workers started looking for better employment opportunities (Cook, 2021). However, given recent technological advancements in the labor market, some of these workers—especially those without advanced skills—were unable to find better employment opportunities (Fuller et al., 2021). As traditional education pathways (e.g., 2- and 4-year degrees) are often difficult to enter for many adults—especially those who are low-income, reskilling programs may represent a viable alternative for occupational advancement and social mobility.

In response to the growing demand for advanced skills—both from employers and job-seekers, reskilling programs have rapidly increased in recent years. A recent credential report identified almost 1,000,000 unique credentials (Credential Engine, 2021), and the U.S. Department of Labor has registered over 27,000 apprenticeships (U.S. Department of Labor, 2021). With shorter durations, fewer barriers to entry, increased resources for persistence, and direct connections to employment opportunities, these programs can be seen as vehicles for social mobility and equity, as well as a more adaptive workforce and a more inclusive economy (Jabbari et al., 2022a). Nevertheless, these programs are often examined on a program-by-program basis (Katz et al., 2022), and the limited larger-scale research on these programs was conducted prior to the COVID-19 pandemic (Bettinger & Soliz, 2016; Xu & Trimble, 2016), limiting our ability to understand their impact in more recent labor market conditions.

We fill this gap by leveraging three waves of a longitudinal household financial survey data collected across all 50 U.S. states during the pandemic. Through descriptive methods, we explore the demographic characteristics related to reskilling, motivations for reskilling, and facilitators and barriers

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to reskilling. Through inferential methods, we examine the relationships between reskilling and measures of social mobility. As we approach reskilling from an equity perspective, we note racial/ethnic and gender differences in reskilling, as well as the extent to which families' economic standing, such as income, job loss and other hardships, may hinder reskilling opportunities. We ask the following research questions:

1. Who learned new skills during the pandemic?
2. Why did individuals learn new skills during the pandemic?
3. How did individuals learn new skills during the pandemic?
4. What were the relationships between learning new skills during the pandemic and both objective (i.e., new business ventures) and subjective (i.e., optimism) measures of social mobility?

We find that reskilling is positively associated with entrepreneurial intent and, for Black respondents, associated with a measure of optimism related to thriving and subjective well-being. Moreover, we find that reskilling is not merely a tool for upward social mobility, but also economic stability. However, our results demonstrate that reskilling opportunities are stratified across race/ethnicity, gender, and socioeconomic status through both formal and informal mechanisms. In the following section, we provide a theoretical framework for skills stratification, followed by a review of research connecting reskilling and social mobility, generally, and specifically in the context of the pandemic. After our data, methods, and results sections, we close with a discussion of implications for policy and practice.

Theoretical Perspectives: Stratification in Reskilling and Cumulative Advantage

Labor market stratification research has long shown that people's standing in the labor market is conditioned by their position in the social structure. People in lower socioeconomic strata tend to experience less exposure to resources for social mobility (Ollivier, 2004) and thus tend to experience lower labor market mobility. Here, whether and how people acquire new skills tend to vary by their socioeconomic status. For example, people in higher socioeconomic strata may be more likely to afford formal training, perhaps through advanced degrees, whereas people in lower socioeconomic strata may be more likely to rely on informal learning tools, like free educational materials available via the internet.

Moreover, people in lower socioeconomic strata tend be more vulnerable to labor market adversity like economic downturns caused by the COVID-19 pandemic. For instance, lower socioeconomic status workers are more likely to lose their jobs in time of economic crisis (Kalleberg & Mouw, 2018; le Grand & Tåhlin, 2002). Although workers tend to build human capital over time (e.g., through training and education), which can improve wages and occupational mobility (Kalleberg & Mouw, 2018), cyclical economic shocks are often associated with labor market adversities (e.g., job losses) that can force workers to seek alternative careers or build new skills. In particular, people who have lost their job, or who are vulnerable to job loss, may be more likely to seek new training for improving their labor market standing.

In addition, individual characteristics such as race, ethnicity, and gender may also affect whether and how people reskill for improving their labor market standing (Kalleberg & Mouw, 2018). Employment duration is often associated with increased labor productivity as workers gain more occupation-specific skills. As these skills may be transferable to other occupations, these skills can increase workers' earning and occupational mobility (Gathmann & Schönberg, 2010; Kalleberg & Mouw, 2018). Yet, research has well documented that unemployment rates tend to be higher among Black and Hispanic Americans compared to their White counterparts (Cajner et al., 2017). Indeed, at the onset of the COVID-19 pandemic, Black and Hispanic workers experienced job losses at a significantly higher rate than White Americans, while also experiencing slower job gains as the economy rebounded (Gezici & Ozay, 2020). In this respect, Black and Hispanic Americans would likely have fewer opportunities to learn new skills through an employer compared to their White counterparts, thereby hindering their ability to achieve labor market mobility through new skills acquisition. Labor market segregation (Hellerstein & Neumark, 2008) and discrimination (Brooks & Clunis, 2007) can further exacerbate these inequalities.

It is also important to note that people's standing in the labor market prior to experiencing an economic shock that spurs them to reskill may create cumulative advantages and disadvantages by affecting how people gain new skills. As mentioned above, those in higher socioeconomic strata may be more likely to obtain new skills overall, as well as through more established traditional educational pathways that confer established credentials valued by employers. In contrast, those in lower socioeconomic strata may be less likely to obtain new skills overall, as well as more likely to seek reskilling through non-conventional means lacking the academic credentials valued most by employers (Kalleberg & Mouw, 2018). These differences, in turn, could adversely affect skills disparities, while also limiting the extent to which newly acquired skills by individuals in lower socioeconomic strata could improve their labor market mobility.

Here, it is important to note that the extent to which earning a new education credential is linked to actual skill improvement is often unclear, which can lead to further disparities in the labor market. Indeed, credentialism constitutes a key mechanism underlying social stratification and ensuing disparities in the labor market (Collins, 1979), as credentials are often instilled with elements related to status hierarchy, which can shape access to employment independent of the actual skills associated with the credential (Collins, 1979; Gaddis, 2015). Thus, whether people acquire new skills, how they acquire them, as well as the return people gain from these skills will vary by social groups and individuals' positions in the social status hierarchy. For instance, research found that having credentials from elite universities does not eliminate racial disparities in the labor market, as Black students from elite universities are less likely to receive job interviews and offers compared to their White counterparts with similar educational credentials (Gaddis, 2015; Quillian et al., 2020). Other research finds that job seekers with degrees from for-profit educational institutions are substantially less likely to receive a call back from employers than those with degrees from a not-for-profit institutions (Deming et al., 2016). Yet, Black and lower-income workers are over represented among people attending for-profit educational institutions (Cottom, 2017).

Still, education and the acquisition of new skills, overall, has been argued to increase occupational mobility, including the likelihood of becoming an entrepreneur. For instance, recent research conducted in the U.S., Germany, and France found that educational credentials that are closely linked to workers' occupations tend to improve their labor market mobility (Bol et al., 2019). Thus, as people improve their human capital for career advancement, positive individual attitudes about starting a company may ensue. This may be particularly salient during cyclical labor market changes that spurs reskilling. For instance, while recession, short-term economic shocks, and loss of jobs may push people into self-employment (Biehl et al., 2014; Cahill et al., 2008; Moulton & Scott, 2016), reskilling may affect how people feel about their potential for success as entrepreneurs. Improved human capital through reskilling may also be accompanied by increases in subjective well-being (e.g., life satisfaction and optimism) related to thriving, as individuals anticipate greater returns in the labor market (Cunado & de Gracia, 2012).

Background

Reskilling and Entrepreneurship

Gaining new knowledge and building new skills represent important mechanisms for developing human capital, which leads to increased earnings and greater employment rates (Becker, 1964). Increases in knowledge and skills have also been linked to increased rates of entrepreneurial intentions (Nabi et al., 2011) and subsequent entrepreneurial success (Kolstad & Wiig, 2015). As outlined in resource-based theory, resources can drive innovation, allowing a prospective entrepreneur to identify, exploit, and maintain a competitive advantage (Alvarez & Barney, 2001). Here, some of the most important resources in this process are new knowledge and skills (Grant & Baden-Fuller, 1995).

However, while much of human capital and entrepreneurship research tends to focus on formal education levels, technological and organizational shifts in the labor market, as well as the growing demand for more skilled and multi-skilled workers (Lindbeck & Snower, 2000) suggests the importance of informal skill development as well (De-Grip, 2015). Informal skill development can occur through a variety of channels, such as workplace duties (De Grip, 2008) and peer interactions (De Grip et al., 2011). Moreover, in between formal education levels and informal skill development exists an array of non-degree credentials, which have also been linked to entrepreneurship (Sine et al., 2007). Furthermore, it is not only the type of mechanism for building skills that is important for entrepreneurship, but the format as well. Recent research by Jabbari and his colleagues (2022a; b, c) demonstrate that online learning—representing a more flexible and adaptable tool for human capital development—was significantly related to increased entrepreneurial intent.

Reskilling, Life Satisfaction, and Optimism

Increases in knowledge and skills have also been linked to higher levels of subjective well-being, including life satisfaction and optimism. For example Oreopoulos and Salvanes (2011), found that increases in years of schooling was significantly associated with increases in life satisfaction, even after accounting for increases in income. Nikolaev (2018) demonstrated a similar relationship with increases in education degree levels (e.g., high school diploma, bachelor's degree, graduate degree). In addition, increases in knowledge and skills have been linked to increases in earnings and employment (Cunado & de Gracia, 2012) and expansions of interpersonal networks (Chen, 2012), while providing workers with more independence (Albert & Davia, 2005) and a greater sense of control over their work (Verme, 2009)—all of which can increase life satisfaction.

However, as the act of getting more education and building more skills can be strenuous *in the moment*, it is unsurprising that the relationships among education and subjective well-being can be non-linear, with younger individuals "trading in" some of their current life satisfaction for future life satisfaction as they increase their knowledge and skills (Nikolaev & Rusakov, 2016). While "trading" one's current life satisfaction for future life satisfaction in the pursuit of education and skills is not a direct example of the impact of education and skills on optimism, it can provide some important context for how individuals pursuing education and developing skills perceive their future prospects (Chun et al., 2022). Beyond examinations of education and life expectancy (Puri & Robinson, 2007), few studies have directly examined the relationship between education and optimism. Most notably, Chun and his colleagues (2022) found that individuals who completed a coding and apprenticeship course experienced higher levels of both current life satisfaction and optimism about future life satisfaction. Moreover, it is important to note that life satisfaction and optimism are highly correlated (Bailey et al., 2007) and have been shown to influence each other. For example, greater levels of optimism have been linked to improved life satisfaction among individuals facing adverse circumstances (Carver, et al., 2010).

Education and Reskilling During the Pandemic

Much of the initial attention on education during the pandemic focused on formal post-secondary enrollment, finding that enrollment declines and drops in retention—although observed across both 2- and 4-year institutions—were more substantial in community college contexts (Howell et al., 2021). Given rising costs of traditional education pathways and uncertain labor market conditions, students may have been looking for alternative pathways to employment. Indeed, a nationwide survey administered by the ECMC group in January and February of 2022 to over 1000 high school students found that over half (52%) of respondents believed they could achieve professional success with education programs that lasted under 4 years. Trade skills and on-the-job training were mentioned among these alternative career pathways (2022).

However, reskilling programs were also disrupted during the pandemic. A study conducted by the International Labor Organization (ILO), covering 144 countries, suggests that at the onset of the COVID-19 pandemic, reskilling and upskilling programs were stopped almost completely, and approximately half of surveyed enterprises stopped paying stipends and wages to apprentices and interns/trainees (International Labour Organization, 2021). Nevertheless, as the pandemic persisted, countries have developed rapid new training programs to meet both business needs and the needs of displaced workers (OECD, 2020). Given the growing demand for workers with digital skills and competencies, businesses have also adapted their training opportunities during the pandemic (Chopra-McGowan & Reddy, 2020). For example, the lockdowns led businesses and training organizations to quickly transition to online learning platforms (Callan & Bowman, 2021; International Labour Organization, 2021; White & Rittie, 2022). As the pandemic accelerated the digital transformation of skill-building opportunities (Bennett & McWhorter, 2021), accessibility to these opportunities may have also increased. Unsurprisingly, some countries, such as Australia, have observed record-high rates of vocational qualifications among employers, as well as apprentices and trainees (White & Rittie, 2022).

COVID-19's Effects on Entrepreneurship and Optimism

The COVID-19 pandemic has been characterized in part by sharp changes of circumstances that both inhibited and—in some instances—motivated entrepreneurship. For example, applications for new businesses in the U.S. fell dramatically at the start of the pandemic, but then rose rapidly in the second half of 2020 until May 2021 (Haltiwanger, 2022). While the rise in new business applications was uneven across industries, with more new business applications in industries heavily impacted by the pandemic (Haltiwanger, 2022), the rise in new business applications was also uneven across the demographic characteristics of founders. Data from eight U.S. states[1] suggests that business establishment rates between 2019 and 2020 were greater within neighborhoods with high proportion of Black residents, especially Black neighborhoods with higher incomes (Fazio et al., 2021). The authors suggest that this may reflect federal relief packages, such as those found within the CARES Act (Fazio et al., 2021), which may have been especially salient in contexts where relief was not used to meet basic needs. There is also evidence that the pandemic has changed the way entrepreneurs and start-up businesses work. A qualitative study on a food-tech startup found that online presence was key to success (Varma & Dutta, 2022), which aligns with recent research by Jabbari et al. (2022b) finding that technology experiences in work and learning were associated with increases in entrepreneurial intent. Additionally, using survey data from Russia, Otrachschenko et al. (2022) found that acquiring new skills during the pandemic helped maintain existing businesses, while also starting new businesses.

Finally, several studies have explored different facets of optimism during the COVID-19 pandemic. While generalized optimism has often been explored as a protective factor against mental health problems, such as anxiety and depression (Schug et al., 2021), recent research has also examined differences in optimism related to thriving across demographic characteristics. For instance, Graham and her colleagues (2022) found that life satisfaction and optimism about future optimism was consistently higher among high income respondents, but also among Black respondents and—to a lesser extent—Hispanic respondents throughout the pandemic.

Data and Measures

Data for this study come from the five-wave Socio-Economic Impacts of COVID-19 Survey (Roll et al., 2021), which was administered quarterly from April 2020 to May 2021. The

[1] States include Georgia, Kentucky, New York, Tennessee, Texas, Vermont, Washington, and Florida.

survey includes questions that capture households' demographic, social, and economic characteristics before and during the pandemic. Each wave consists of roughly 5,000 respondents. Respondents from prior waves were invited to subsequent waves, with a re-response rate of roughly 50%, allowing for robust longitudinal analyses. Respondents were recruited into the survey using a quota sampling methodology that ensured national representativeness in terms of race/ethnicity, age, income, and gender. Reskilling and optimism questions were asked in Waves 3 (November–December, 2020), 4 (February–March, 2021), and 5 (May–June, 2021), and entrepreneurship questions were asked only in wave 5[2]. Our total sample consisted of 14,848 respondents. Listwise deletion resulted in a small proportion—roughly 7%—of participants being removed from the sample, resulting in analytic samples across all three waves that ranged from 13,770 to 13,807.

Of note, while the sample of each individual survey wave is representative of the U.S. population across the indicators mentioned above, our longitudinal sample is not constructed to be representative. This is due to differential attrition between waves across several characteristics, including race/ethnicity, the presence of children, educational enrollment and attainment, income, COVID-19-related job loss, and age. While this does not pose an issue for the internal validity of our study, in which we use fixed effects models to examine the relationship between within-person changes in professional skill development and optimism, it does limit our ability to generalize these results.

Our main variable of interest in this study is *reskilling*, which is derived from the following question: "Did you learn any new professional skills during the pandemic?" Respondents could select "No" (61%), "No, but I would like to" (hereafter referred to as "desired to learn new skills") (23%), and "Yes" (16%)[3]. If individuals selected "Yes", then a follow-up question was asked about the reasons for learning a new skill: "Personal fulfillment/Other reason" (36%); "To find a better job/role" (39%); and "To maintain current job/role" (25%). A second follow-up question was asked about the specific *channel* that facilitated their learning of a new skill. As seen in Table 1, respondents could select multiple channels: "Through my employer" (29%); "Through a class or certification program that was entirely online" (14%); "Through a class or certification program offered through a school (e.g., college)" (10%); "Through self-study (e.g., watching videos, reading books)" (27%); "Through job coaching or mentoring" (5%); and "Through job shadowing" (4%). Sociodemographic characteristics by skill learning can be found in Appendix 1.

Life satisfaction and optimism were derived from the Cantril ladder which is a universally applicable (Gallagher et al., 2013), widely used measure for understanding unique aspects of subjective well-being—particularly as it relates to personal striving. The Cantril ladder has been used to examine economic factors, such as earnings and employment (Kahneman & Deaton, 2010), and has also been used to examine circumstances during the COVID-19 pandemic (Graham et al., 2022). Respondents were asked the following: "Please imagine a ladder with steps numbered from zero at the bottom to 10 at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you." For *life satisfaction*, this prompt was followed by: "On which step of the ladder would you say you personally feel you stand currently?" For *optimism*, this prompt was followed by "On which step do you think you will stand about five years from now?" The average score for life satisfaction was 6.70 and the average score for optimism was 7.49.

For *entrepreneurial intent*, we ask "Does anyone in your household plan on starting a business in the next 12 months?" ("No" = 1; "Yes" = 2). Similar formulations of this question have been used in relation to education and skill-building (see for example, Jabbari et al., 2022a; b, c). Moreover, our measure of entrepreneurship at the household level is consistent with the family-embeddedness nature of entrepreneurship—particularly at the early stages of the start-up process. That is, people often identify entrepreneurial opportunities and access resources through the family context (Aldrich & Cliff, 2003; Daspit et al., 2021). For instance, at the beginning of the start-up process, the family context is crucial for mobilizing human and financial resources, as well as providing physical space in the form of family households for the new ventures (Aldrich & Cliff, 2003). Roughly 6% of the sample planned on starting a business in the next 12 months. We also ask about *pre-pandemic entrepreneurial plans*: "Was anyone in your household planning on starting a business before the pandemic?" ("Yes, but the pandemic caused these plans to be cancelled" = 1; "Yes, and business started during the pandemic" = 2; and "No" = 3). Additional sociodemographic characteristics include *age*, *race/ethnicity*, *gender*, *married/partnered status*, *any dependents under the age of 18*, whether *English is the primary language spoken at home*, *urbanicity*, *educational enrollment* and *attainment*, *income* (as a percent of area median income), *employment* and *work-from-home status*, and *household job or income loss due to COVID-19*.

[2] Response rates ranged from 7–14% across the survey waves, which is similar to other household surveys administered during the pandemic, such as the Survey of Household Economics and Decision-making from the Federal Reserve. Response rates were calculated using the RR2 measure from the American Association of Public Opinion Research (AAPOR, 2016).

[3] In order to capture a broad array of skills related to employment, we focused on 'professional' skills in this study. While survey space did not permit us to elucidate further responses on the specific types of professional skills learned, future research should explore this area both quantitatively and qualitatively.

Table 1 Sociodemographic Characteristics of the Study Sample

Wave 3, 4, and 5 Variables (N = 14,848)	%/Mean (S.D.)
Optimism	7.49 (2.07)
Life satisfaction	6.70 (1.98)
Learned any new professional skills during the pandemic	
No	61.04%
No, but would like to	22.92%
Yes	16.03%
Race/Ethnicity	
White	60.24%
Black	12.54%
Asian	6.89%
Hispanic	17.37%
Other	2.95%
Gender: Female	50.77%
Marital status: Married/living with a partner	61.13%
Children under age 18: One or more	29.49%
Primary language is English: Yes	95.76%
Metropolitan area resident: No	11.12%
Age	47.06 (16.85)
Enrolled in an educational program	
Yes, full-time	17.30%
Yes, part-time	5.27%
No	77.43%
Education attainment	
Less than a bachelor's degree	43.90%
Bachelor's degree	30.46%
Greater than bachelor's degree	25.64%
Area median income percent[a]	
ELI, AMI = [0,30%)	15.86%
VLI, AMI = [30,50%)	11.52%
LI, AMI = [50,80%)	18.83%
MOI, AMI = [80,120%)	20.33%
MII, AMI = [120,170%)	15.18%
HI, AMI = [170% +)	18.27%
Employment status	
Full-time; Not from home	25.87%
Full-time; Occasionally from home	9.55%
Full-time; From home	14.77%
Part-time; Not from home	6.41%
Part-time; Occasionally from home	1.95%
Part-time; From home	2.55%
Not working	38.89%
Job/income loss due to COVID-19: Yes	25.55%
Wave	
3	32.92%
4	33.25%
5	33.83%
Wave 5 Variables (N = 5023)	
Planning to start a business in the next 12 months: Yes	6.07%
Planning to start a business before the pandemic	
Yes, but the pandemic caused these plans to be cancelled	5.04%
Yes, and the business was started during the pandemic	2.58%

Table 1 (continued)

Wave 3, 4, and 5 Variables (N = 14,848)	%/Mean (S.D.)
No	92.38%
Learned new skills through my employer: Yes	29.01%
Learned new skills through online class/programs: Yes	13.99%
Learned new skills through a school/college: Yes	10.02%
Learned new skills through self-study: Yes	26.58%
Learned new skills through job coaching or mentoring: Yes	5.40%
Learned new skills through job shadowing: Yes	4.46%
Learned new skills through another channel: Yes	31.60%

Missing values are not included for the calculation of percentages or summary statistics

[a]Area Median Income percent categories are: Extremely Low Income, Very Low Income, Low Income, Moderate Income, Moderate to High Income, and High Income

Methods

Due to survey constraints and the changing nature of the pandemic, not all questions were asked in each wave. Thus, we employ multiple methods to explore reskilling during the pandemic that leverage both cross-sectional and longitudinal designs. In the first stage of our analysis, we explore how sociodemographic characteristics are descriptively related to reskilling during the COVID-19 pandemic using multinomial logit (MNL) regression models. We then explored the reasons for learning new skills among these individuals, again using MNL models. MNL models allowed us to examine dependent variables with more than two (unordered) categories. MNL models in the current study were estimated using a maximum likelihood estimator (ML) of the following general form:

$$L\left(\beta_2, \cdots, \beta_J | y, \boldsymbol{X}\right) = \prod\nolimits_{m=1}^{J} \prod\nolimits_{y_i=m} \frac{exp\left(\boldsymbol{X_i}\beta_m\right)}{\sum_{j=1}^{J-1} exp\left(\boldsymbol{X_i}\beta_j\right) + 1} \tag{1}$$

where $\boldsymbol{X}$ was the vector of predictors, m was one category of the dependent variable, and j indicated the number of categories in the dependent variable. Relative risk ratios (RRR) were reported which demonstrate the risk (or chance) of an event in one group occurring versus the risk of an event occurring in the reference group. Logit regression models were then used to examine the descriptive relationships among channels of learning and sociodemographic characteristics. Here, dummy-coded channels of learning were treated as the dependent variable in a series of logit regression models.

In the second stage of the analysis, logit regression models were used to examine the relationship between learning new skills and entrepreneurial intent. Although entrepreneurial intent was only asked in the final wave of our survey, and thus does not allow for a longitudinal design to be employed, these models do include a control for previous entrepreneurial activities in addition to the sociodemographic characteristics used in other models. Nevertheless, without longitudinal data nor proper instrumentation, these models should be interpreted as correlational and not causal. Logit regression models were estimated using the following general equation:

$$\eta_i = ln\left(\frac{p_i}{1 - p_i}\right) = \beta_0 + \boldsymbol{X_i}\beta_k \tag{2}$$

In the last stage of the analysis, we leveraged a longitudinal design and estimated a set of fixed effects models to examine the impact of learning new skills on optimism when accounting for life-satisfaction. Besides waves, these models only included time-varying covariates, as time-invariant covariates are considered to be fixed within individuals. Specifically, fixed intercepts for each respondent were included in the model instead of assuming a global intercept (Hsiao, 2014) for all respondents:

$$y_{it} = \alpha_i + \beta_1 \text{LearnedSkills}_{it} + \boldsymbol{X_{it}}\beta_k + \epsilon_{it} \tag{3}$$

in which y_{it} represents optimism for respondent i at time t, α_i represented respondent-specific intercepts, β_1 was the estimate of interest that indicated the effect of learning skills on life satisfaction, and $\boldsymbol{X_{it}}$ were time-varying covariates. The use of fixed effects models accounts for unmodeled heterogeneity that was common to all observations within a given respondent (Hsiao, 2014) and allows us to capture changes in the outcome that result from changes in skill learning across the survey waves. Finally, to explore potential cases of heterogeneity, subsample analyses were used to assess the effect of learning new skills on life satisfaction across racial/ethnic groups.

Results

Sample Description

As seen in Table 1, the majority of our respondents were White (60%), were married or lived with a partner (61%),

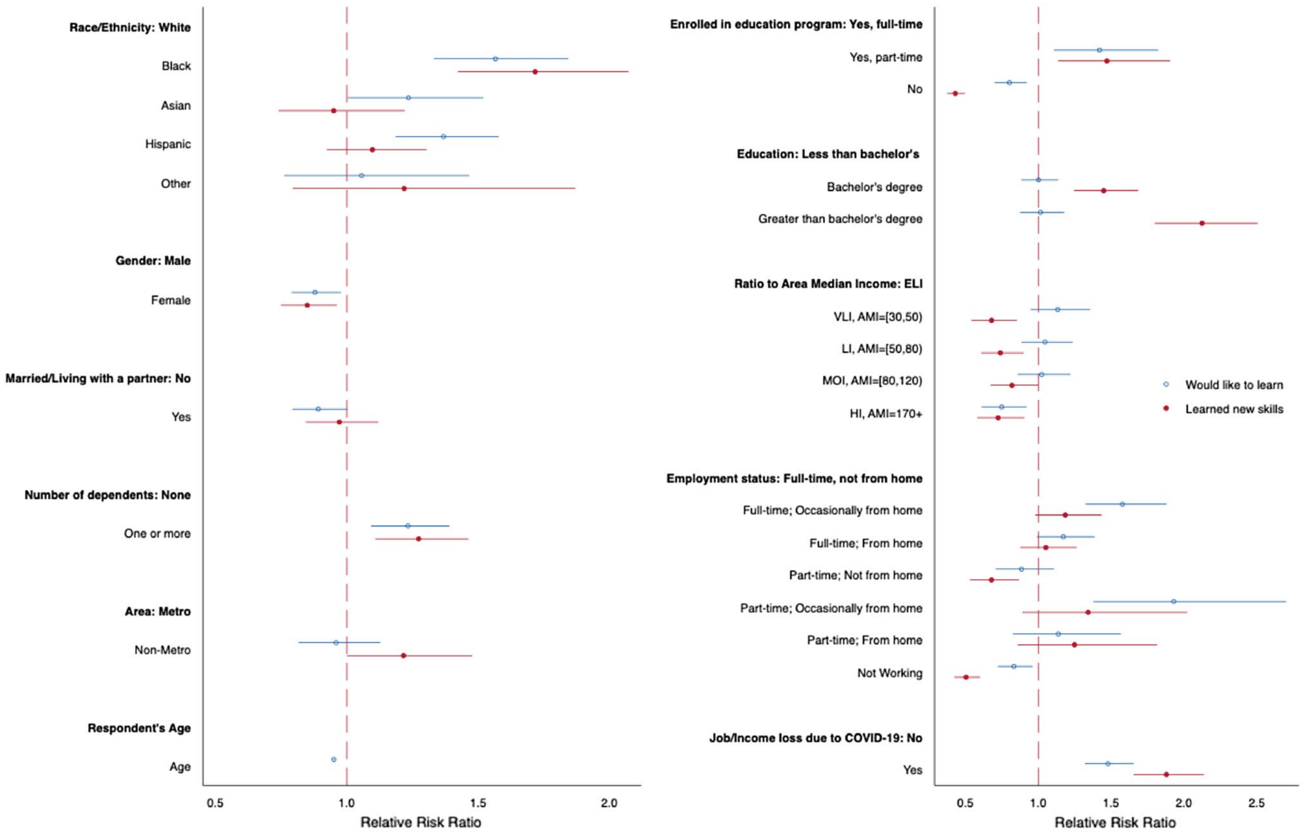

Fig. 1 The Relationship between Sociodemographic Characteristics and Learning a New Skill: Estimates from a Multinomial Logistic Regression Model (Base Category of Outcome: Did Not Learn New Skills. *Notes*. Relative risk ratios presented as coefficient plots. The points on the graph represent the estimated relative risk ratio, while the lines represent the 95 percent confidence intervals. The category following the heading for each variable is the reference category for that variable. N = 13,770

did not have children under the age of 18 (71%), primarily spoke English at home (96%), lived in a metropolitan area (89%), were not enrolled in a formal education program (77%), had a bachelor's degree or above (56%), had moderate to high incomes (54%), were currently working either full-time or part-time (69%), and did not lose a job or income due to COVID-19 (74%).

Who Learned New Skills During the Pandemic?

While only 16% of individuals in our sample learned a new skill during the pandemic, 23% of individuals desired, but were not able, to learn a skill. In our descriptive exploration of sociodemographic characteristics related to skill-learning during the pandemic, we found significant associations with race/ethnicity, gender, household composition, urbanicity, age, educational enrollment and attainment, income, and work and employment status. Specifically, results of the multinomial logistic regression model estimating the relationships between skill learning and sociodemographic characteristics are shown in Fig. 1, which plots the relative risk ratios from our regression model (the full regression table can be found in Appendix 2). The red plots in this figure capture the relative chances of learning a new skill, while the blue plots capture the chances of desiring—but not being able—to learn a new skill. All else being equal, the chances of learning a new skill—relative to not learning new skill—was 72% ($p < 0.001$) higher for Black respondents (when compared to White respondents), 15% ($p < 0.05$) lower for female respondents; 27% ($p < 0.01$) higher for respondents who had one or more children; 22% ($p < 0.05$) higher for respondents living in a non-metropolitan area; 5% ($p < 0.001$) lower for respondents who were a year older; 47% ($p < 0.01$) higher and 57% ($p < 0.001$) lower, respectively, for respondents who were enrolled part-time and not enrolled at all in a formal education program (when compared to respondents that were enrolled full-time in an education program); 45% ($p < 0.001$) and 112% ($p < 0.001$) higher, respectively, for respondents who had a bachelor's degree and greater than a bachelor's degree (when compared to respondents that had less than a bachelor's degree); 32% ($p < 0.01$), 26% ($p < 0.01$), 18% ($p < 0.05$), 22% ($p < 0.05$), and 27% ($p < 0.01$) lower, respectively, for very low income, low income, moderate income, moderate-to-high income, and high income respondents (when compared to extremely low income respondents); 32% ($p < 0.01$) and 50% ($p < 0.001$) lower, respectively, for respondents who worked part-time not from home and for respondents who did not work at all (when compared to respondents who worked full-time on-site); and 88% ($p < 0.001$) higher for respondents who had lost a job or income due to the pandemic.

Alternatively, the chances of desiring to learn a new skill was 57% ($p < 0.001$), 23% ($p < 0.05$), and 37% ($p < 0.001$) higher, respectively, for Black, Asian, and Hispanic respondents; 12% ($p < 0.05$) lower for female respondents; 23% ($p < 0.01$) higher for respondents who had one or more children; 5% ($p < 0.001$) lower for respondents who were a year older; 42% ($p < 0.01$) higher and 20% ($p < 0.01$) lower, respectively, for respondents who were enrolled part-time and not enrolled at all in a formal education program; 23% ($p < 0.01$) and 25% ($p < 0.01$) lower, respectively, for moderate-to-high income and high income respondents; 58% ($p < 0.001$) and 93% ($p < 0.001$) higher, respectively, for full-time and part-time workers who occasionally worked from home, 17% ($p < 0.05$) lower for respondents who did not work at all; and 45% ($p < 0.001$) higher for respondents who had lost a job or income due to the pandemic.

Why Did Individuals Learn New Skills During the Pandemic?

For those that did learn new skills during the pandemic, 36% did it for personal fulfillment or other reasons; 39% did it to find a better job/role; and 25% did it to maintain their current job/role. Similarly, in our descriptive exploration of sociodemographic characteristics related to skill-learning reasons during the pandemic, we found significant associations with race/ethnicity, gender, household composition, urbanicity, age, income, and work and employment status. Specifically, results of the multinomial logistic regression model estimating the relationships between reasons for learning new skills and sociodemographic characteristics are shown in Fig. 2, which plots the relative risk ratios from our regression model (the full regression table can be found in Appendix 3). The red plots in this figure capture the relative chances of learning a new skill to maintain their current job, while the blue plots capture the chances of learning a new skill to find a better job. All else being equal, the chances of learning a new skill to maintain their current job—relative to personal fulfillment/other—was 17% ($p < 0.05$) higher for respondents who had one or more children; 49% ($p < 0.05$) lower for respondents who were not currently enrolled in an educational program (compared to respondents who were enrolled full-time); 28% ($p < 0.001$) lower for respondents who lived in a non-metropolitan area; 23% ($p < 0.05$), 27% ($p < 0.01$), and 23% ($p < 0.05$) lower, respectively, for respondents with very low, low, and moderate incomes (when compared to respondents with extremely low incomes); 28% ($p < 0.01$) higher for respondents who worked full-time occasionally from home and 42% ($p < 0.01$) and 83% ($p < 0.001$) lower, respectively, for respondents who worked part-time occasionally and for respondents who were not working at all (when compared to respondents who worked full-time on-site); and 44% ($p < 0.001$) higher for respondents who lost a job or income due to the pandemic.

Alternatively, the chances of learning a new skill to find a better job was 42% ($p < 0.01$) higher for Asian respondents (when compared to White respondents); 22% ($p < 0.001$) lower for female respondents; 33% ($p < 0.001$) lower for married/partnered respondents; 24% ($p < 0.01$) lower for respondents who lived in a non-metropolitan area; 3% ($p < 0.001$) lower for respondents who were a year older; 23% ($p < 0.01$), 21% ($p < 0.01$), 34% ($p < 0.001$), and 32% ($p < 0.001$) lower, respectively, for low income, moderate income, moderate-to-high income, and high income respondents; 36% ($p < 0.001$), 22% ($p < 0.01$), 53% ($p < 0.001$), 55% ($p < 0.001$), and 55% ($p < 0.001$) lower, respectively, for respondents who worked full-time from home, occasionally from home, part-time occasionally from home, part-time from home, and did not work at all; and 108% ($p < 0.001$) higher for respondents that lost a job or income due to the pandemic.

How did Individuals Learn New Skills During the Pandemic?

Table 2 displays logistic regression estimates of the relationship between demographic/socio-economic characteristics and the channels through which respondents reported learning new skills (e.g., their employers, online, school, self-learning, or some other channel). All else being equal, the odds of learning new skills through employers were 47% ($p < 0.001$) lower for both Black and Hispanic respondents (when compared to White respondents) and 80% ($p < 0.01$), 81% ($p < 0.01$), and 95% ($p < 0.001$) lower, respectively, for respondents who worked part-time occasionally from home, respondents who worked part-time from home, and respondents who did not work at all (when compared to respondents who worked full-time on-site).

The odds of learning new skills online were 30% ($p < 0.05$) lower for respondents who were married or lived with a partner; 50% ($p < 0.05$) higher for respondents who had one or more children (when compared to respondents who did not have any children); 84% ($p < 0.05$) higher for respondents living in a non-metro area; 30% ($p < 0.05$) lower for those who were not enrolled in a formal (e.g. degree-granting) education program (when compared to respondents who were enrolled full-time); 84% ($p < 0.05$) higher for respondents who had greater than a bachelor's degree (when compared to respondents with less than a bachelor's degree); 104% ($p < 0.01$), 89% ($p < 0.05$), and 128% ($p < 0.01$) higher, respectively, for low income, moderate income, and high

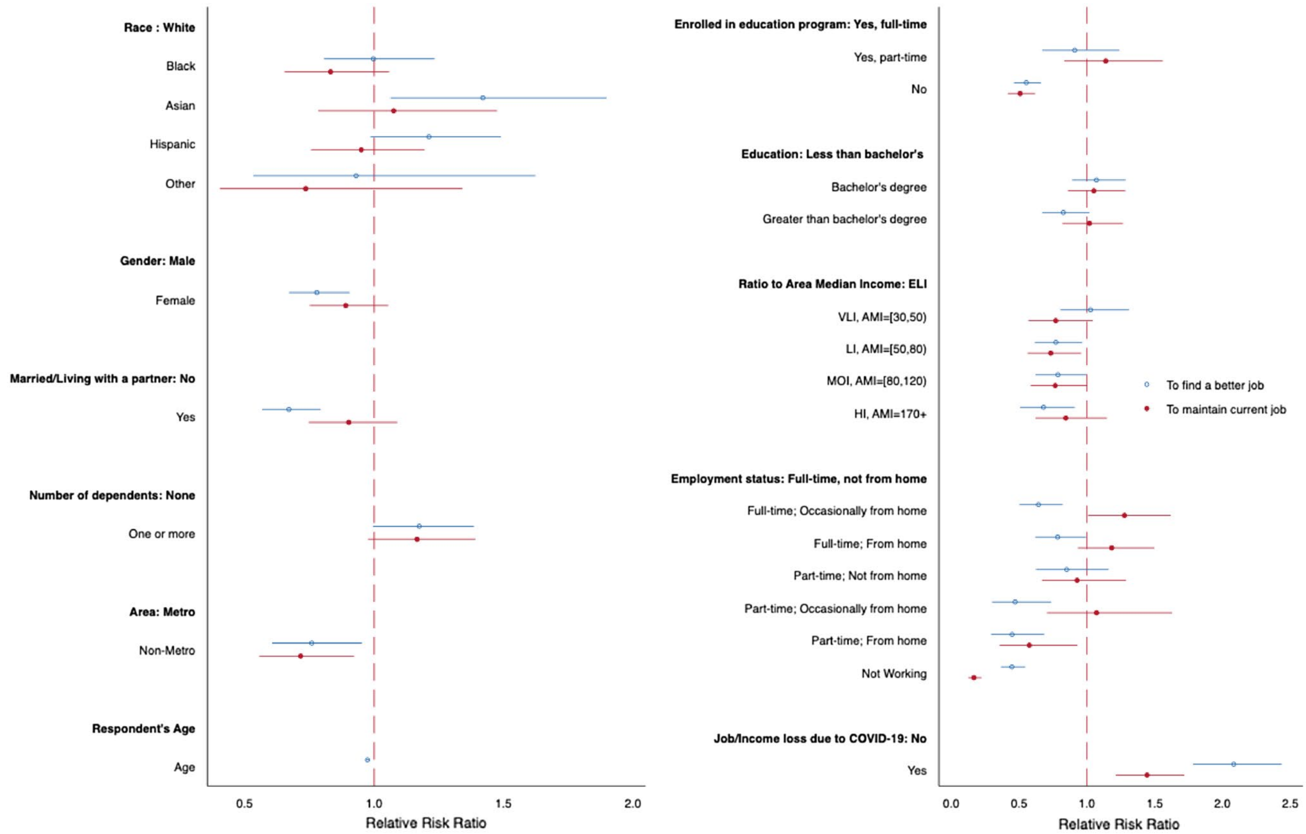

Fig. 2 The Relationship between Sociodemographic Characteristics and Reasons for Learning a New Skill: Estimates from a Multinomial Logistic Regression Model (Base Category of Outcome: Learned New Skills for Personal Fulfillment). Notes: Relative risk ratios presented as coefficient plots. The points on the graph represent the estimated relative risk ratio, while the lines represent the 95 percent confidence intervals. The category following the heading for each variable is the reference category for that variable. N = 5309

income respondents (when compared to extremely low income respondents); and 32% ($p < 0.05$) higher for respondents who lost a job or income due to the pandemic.

The odds of learning new skills through school were 62% ($p < 0.05$) lower for respondents whose home language was English; 70% ($p < 0.05$) lower for respondents who were not enrolled in a formal education program; 74% ($p < 0.05$) higher for respondents who had greater than a bachelor's degree; and the odds of learning new skills through school declined by 4% ($p < 0.001$) for each additional year of age.

Additionally, the odds of self-learning were 70% ($p < 0.05$) higher for Black respondents; 68% ($p < 0.05$) higher for respondents who were not enrolled in a formal education program; 127% ($p < 0.001$), 335% ($p < 0.01$), 655% ($p < 0.001$), and 223% ($p < 0.001$) higher, respectively, for respondents who worked full-time from home, respondents who worked part-time occasionally from home, respondents who worked part-time from home, and respondents who did not work at all; and the odds of self-learning declined by 2% ($p < 0.05$) for each year of age.

Lastly, the odds of learning new skills through other channels were 99% ($p < 0.01$) and 204% ($p < 0.01$) higher, respectively, for respondents who worked part-time on-site and respondents who worked part-time from home.

How Does Learning New Skills Relate to Entrepreneurial Intent?

Table 3 contains logit models of learning new skills on entrepreneurial intent. Compared to respondents who did not learn new skills during the pandemic, those who did learn new skills during the pandemic had 49% ($p < 0.05$) higher odds of intending to start one's own business, holding all other variables constant. Among covariates, having started a business before the pandemic and having business plans cancelled due to the pandemic (when compared to not having business plans before the pandemic), and being older were associated with decreased odds of entrepreneurial intent, while having one or more children, having high income, and identifying as Black were associated with increased odds of entrepreneurial intent.

Table 2 Learning new skills from different channels: estimates from logistic regression models

Variables	Through Employers		Learned Online		Through School		Self-Learning		Other	
	Est. (S.E.)	*OR*	*Est. (S.E.)*	*OR*	*Est. (S.E.)*	*OR*	*Est. (S.E.)*	*OR*	*Est. (S.E.)*	*OR*
Race/ethnicity: black	− 0.63*** (0.22)	0.53	0.05 (0.23)	1.05	0.14 (0.26)	1.15	0.53* (0.21)	1.70	− 0.27 (0.29)	0.76
Race/ethnicity: Asian	− 0.12 (0.31)	0.89	0.27 (0.31)	1.31	0.36 (0.36)	1.43	0.22 (0.29)	1.25	0.09 (0.37)	1.1
Race/ethnicity: hispanic	− 0.64*** (0.20)	0.53	0.27 (0.21)	1.31	0.07 (0.25)	1.07	0.28 (0.20)	1.33	− 0.10 (0.26)	0.91
Race/ethnicity: other	− 0.26 (0.51)	0.77	− 0.79 (0.66)	0.46	0.59 (0.70)	1.81	0.77 (0.49)	2.16	0.05 (0.60)	1.05
Gender: female	− 0.13 (0.15)	0.87	0.25 (0.16)	1.28	− 0.14 (0.19)	0.87	− 0.26 (0.15)	0.77	0.07 (0.20)	1.07
Married/living with a partner	0.24 (0.18)	1.27	− 0.36* (0.18)	0.70	− 0.05 (0.22)	0.96	0.03 (0.17)	1.03	− 0.06 (0.22)	0.94
Has one or more children	− 0.08 (0.17)	0.92	0.41* (0.17)	1.50	− 0.03 (0.20)	0.97	− 0.12 (0.16)	0.89	0.04 (0.21)	1.04
Primary language is English	0.47 (0.47)	1.6	− 0.82 (0.42)	0.44	− 0.96* (0.45)	0.38	0.66 (0.48)	1.94	− 0.59 (0.48)	0.56
Non-metropolitan area resident	− 0.21 (0.25)	0.81	0.61* (0.24)	1.84	0.20 (0.30)	1.22	0.12 (0.24)	1.12	0.02 (0.32)	1.02
Age	< .01 (0.01)	1.00	< -.01 (0.01)	0.99	− 0.04*** (0.01)	0.96	− 0.02* (0.01)	0.98	0.01 (0.01)	1.01
Education enrollment: Yes, Part-time	− 0.47 (0.27)	0.62	0.25 (0.27)	1.28	0.12 (0.28)	1.13	0.44 (0.26)	1.55	− 0.01 (0.32)	0.99
Education enrollment: Not enrolled	< -.01 (0.18)	1.00	− 0.36* (0.18)	0.70	− 1.20*** (0.23)	0.30	0.52* (0.17)	1.68	− 0.24 (0.23)	0.79
Educ. Attainment: Bachelor's degree	0.05 (0.20)	1.05	− 0.047 (0.21)	0.95	0.17 (0.24)	1.19	0.02 (0.19)	1.02	0.28 (0.25)	1.32
Educ. Attainment: > Bachelor's degree	− 0.24 (0.21)	0.79	0.61* (0.21)	1.84	0.56* (0.26)	1.74	0.18 (0.20)	1.20	0.24 (0.27)	1.28
Income: VLI, AMI[a] = [30,50%)	0.46 (0.33)	1.59	0.60 (0.32)	1.81	− 0.58 (0.40)	0.56	− 0.24 (0.30)	0.79	− 0.22 (0.37)	0.8
Income: LI, AMI = [50,80%)	− 0.12 (0.26)	0.89	0.71** (0.26)	2.04	− 0.22 (0.28)	0.8	0.04 (0.25)	1.05	− 0.39 (0.30)	0.67
Income: MOI, AMI = [80,120%)	< − .01 (0.26)	1.00	0.64* (0.27)	1.89	− 0.25 (0.30)	0.78	0.26 (0.25)	1.3	− 0.49 (0.32)	0.61
Income: MII, AMI = [120,170%)	0.02 (0.28)	1.02	0.18 (0.31)	1.2	0.06 (0.32)	1.06	0.40 (0.27)	1.5	− 0.49 (0.35)	0.61
Income: HI, AMI = [170% +)	− 0.07 (0.28)	0.94	0.83** (0.29)	2.28	0.11 (0.32)	1.12	− 0.06 (0.28)	0.94	− 0.53 (0.35)	0.59
Employment: full-time; occasionally from home	− 0.16 (0.21)	0.85	0.30 (0.22)	1.35	− 0.41 (0.28)	0.66	0.41 (0.21)	1.50	0.04 (0.29)	1.04
Employment: full-time; from home	− 0.44 (0.23)	0.64	0.41 (0.25)	1.51	− 0.44 (0.36)	0.64	0.82*** (0.23)	2.27	− 0.04 (0.34)	0.96
Employment: part-time; not from home	− 0.45 (0.28)	0.64	− 0.54 (0.34)	0.58	0.16 (0.34)	1.18	0.36 (0.29)	1.44	0.69** (0.35)	1.99
Employment: part-time; occasionally from home	− 1.60** (0.50)	0.20	0.70 (0.45)	2.01	0.05 (0.54)	1.05	1.47** (0.44)	4.35	0.92 (0.48)	2.51
Employment: part-time; from home	− 1.67** (0.54)	0.19	0.05 (0.51)	1.05	0.85 (0.59)	2.33	2.02*** (0.50)	7.55	1.11** (0.50)	3.04
Employment: not working	− 2.99*** (0.35)	0.05	0.13 (0.25)	1.14	0.14 (0.30)	1.15	1.17*** (0.23)	3.23	0.32 (0.30)	1.37
Lost a job due to COVID-19	0.29 (0.16)	1.34	0.28* (0.16)	1.32	0.20 (0.19)	1.22	− 0.08 (0.16)	0.93	0.19 (0.20)	1.21
Constant	− 0.02 (0.57)	0.98	− 0.81 (0.54)	0.45	1.24* (0.61)	3.46	− 1.32* (0.57)	0.27	− 1.50* (0.63)	0.22
Observations	937		937		937		937		937	
AIC	1158.521		1119.566		860.1656		1214.647		833.3784	
BIC	1289.274		1250.318		990.9181		1345.399		964.1309	

Logit coefficients are provided with standard errors (in parentheses) and odds ratios (to the right). Reference categories are White (Race/Ethnicity), Male (Gender), Was not married/did not live with a partner, Has no children, Primary language was not English, Lives in a metropolitan area, Full-time enrolled in educational programs (Education enrollment), Less than a bachelor's degree (Education attainment), Extremely low income (Income), Full-time on-site employed (Employment), Did not lose job/income due to COVID-19

*p < .05, **p < .01, ***p < .001

[a] Area Median Income ratio categories are: Extremely Low Income, Very Low Income, Low Income, Moderate Income, Moderate to High Income, and High Income

Table 3 The Relationship between Learning New Skills and Entrepreneurial Intent: Estimates from Logistic Regression

Variables	Est. (S.E.)	OR
Learned new professional skills during the pandemic	0.40* (0.27)	1.49
Planning a new business before the pandemic: Yes, and started during the pandemic	– 0.92** (0.11)	0.40
Planning a new business before the pandemic: No	– 3.31*** (0.01)	0.04
Race/Ethnicity: Black	0.82*** (0.53)	2.27
Race/Ethnicity: Asian	– 0.57 (0.22)	0.57
Race/Ethnicity: Hispanic	0.19 (0.28)	1.21
Race/Ethnicity: Other	1.01* (1.31)	2.75
Gender: Female	– 0.053 (0.16)	0.95
Married/Living with a partner	– 0.18 (0.17)	0.84
Has one or more children	0.57** (0.33)	1.77
Primary language is English	– 0.32 (0.31)	0.73
Non-metropolitan area resident	– 0.072 (0.27)	0.93
Age	– 0.038*** (0.01)	0.96
Education enrollment: Part-time	– 0.021 (0.31)	0.98
Education enrollment: Not enrolled	– 0.17 (0.17)	0.84
Education Attainment: Bachelor's degree	– 0.32 (0.16)	0.73
Education Attainment: > Bachelor's degree	– 0.13 (0.21)	0.88
Income: VLI, AMI[a] = [30,50%)	0.047 (0.32)	1.05
Income: LI, AMI = [50,80%)	0.14 (0.31)	1.15
Income: MOI, AMI = [80,120%)	0.11 (0.32)	1.12
Income: MII, AMI = [120,170%)	0.19 (0.41)	1.21
Income: HI, AMI = [170 + %)	0.90** (0.79)	2.45
Employment: Full-time; Occasionally from home	0.13 (0.30)	1.14
Employment: Full-time; From home	0.14 (0.33)	1.15
Employment: Part-time; Not from home	– 0.088 (0.31)	0.92
Employment: Part-time; Occasionally from home	– 0.35 (0.32)	0.7
Employment: Part-time; From home	– 0.15 (0.52)	0.86
Employment: Not Working	0.014 (0.25)	1.01
Lost a job/income due to COVID-19	0.22 (0.23)	1.25
Constant	1.22* (1.99)	3.38
Observations	4070	
AIC	1221.402	
BIC	1410.744	

Logit coefficients are provided with standard errors (in parentheses) and odds ratios (to the right). Reference categories are Did not learn new skills, Plan to start a business but cancelled because of COVID-19, White (Race/Ethnicity), Male (Gender), Was not married/did not live with a partner, Has no children, Primary language was not English, Lives in a metropolitan area, Full-time enrolled in educational programs (Education enrollment), Less than a bachelor's degree (Education attainment), Extremely low income (Income), Full-time on-site employed (Employment), Did not lose job/income due to COVID-19

*p < .05, **p < .01, ***p < .001

[a]Area Median Income ratio categories are: Extremely Low Income, Very Low Income, Low Income, Moderate Income, Moderate to High Income, and High Income

How Does Learning New Skills Relate to Optimism?

Table 4 shows results from fixed effects models estimating the effects of learning new skills on respondents' optimism when controlling for life satisfaction. In the full sample, the effect of learning new skills on optimism was not statistically significant at the $p < 0.05$ level. However, we found a significant effect of learning new skills on optimism in the subsample of Black respondents. Compared to Black respondents who did not learn new skills, those who learned new skills experienced an increase in optimism by 0.32 points ($p < 0.05$), holding all other variables constant. This represents 0.15 standard deviation unit increase, which represents an effect size that is similar to other studies that examine the relationship between education and optimism (see Chun et al., 2022).

Table 4 The Relationship between Learning New Skills and Optimism: Estimates from Fixed Effects Regression Models

Variables	Full sample *Est. (S.E.)*	White *Est. (S.E.)*	Black *Est. (S.E.)*	Asian *Est. (S.E.)*	Hispanic *Est. (S.E.)*
Learned new professional skills during the pandemic	0.08 (0.06)	0.09 (0.08)	0.32* (0.16)	-0.06 (0.21)	0.03 (0.13)
Current life satisfaction	0.47*** (0.02)	0.47*** (0.03)	0.43*** (0.06)	0.54*** (0.06)	0.44*** (0.05)
Education enrollment: Part-time	− 0.04 (0.16)	0.21 (0.19)	0.01 (0.54)	0.25 (0.43)	− 0.58 (0.32)
Education enrollment: Not enrolled	0.23** (0.08)	0.23* (0.11)	0.11 (0.25)	0.22 (0.18)	0.30 (0.17)
Income last month	< .01 (< .01)	< .01 (< .01)	< .01 (< .01)	< .01 (< .01)	< .01 (< .01)
Employment: Full-time; Occasionally from home	− 0.02 (0.09)	− 0.05 (0.12)	0.20 (0.35)	− 0.10 (0.22)	0.06 (0.18)
Employment: Full-time; From home	0.09 (0.10)	0.08 (0.13)	− 0.03 (0.27)	0.05 (0.21)	0.34 (0.20)
Employment: Part-time; Not from home	0.15 (0.15)	− 0.08 (0.21)	0.72* (0.35)	0.26 (0.44)	0.56 (0.44)
Employment: Part-time; Occasionally from home	− 0.11 (0.18)	− 0.13 (0.24)	− 0.02 (0.59)	− 1.07 (0.61)	0.27 (0.34)
Employment: Part-time; From home	0.10 (0.19)	0.09 (0.22)	0.44 (0.63)	− 0.28 (0.38)	0.25 (0.38)
Employment: Not working	0.10 (0.13)	0.08 (0.18)	0.46 (0.45)	0.96** (0.37)	− 0.08 (0.27)
Lost job/income due to COVID-19	− 0.06 (0.06)	− 0.16* (0.08)	0.08 (0.19)	− 0.05 (0.22)	0.08 (0.16)
Wave 4	0.01 (0.03)	0.06 (0.04)	− 0.25** (0.08)	− 0.07 (0.10)	0.04 (0.07)
Wave 5	− 0.06 (0.03)	− 0.04 (0.04)	− 0.32** (0.10)	− 0.01 (0.10)	< 0.01 (0.08)
Constant	4.17*** (0.17)	4.05*** (0.35)	4.75*** (0.45)	3.28*** (0.46)	4.37*** (0.37)
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	13,807	8369	1668	938	2361
R-squared	0.36	0.36	0.33	0.37	0.31
Unique respondents	8743	5398	1053	535	1480

Clustered standard errors are reported in parentheses. Reference categories are Did not learn new skills, Full-time enrolled in educational programs (Education enrollment), Full-time on-site employed (Employment), Did not lose job/income due to COVID-19, and Wave 3

*p < .05, **p < .01, ***p < .001

Discussion

Despite household financial disruptions spurred by the pandemic, changing labor market conditions, and the influx of new reskilling programs, research has yet to explore barriers, facilitators, and outcomes associated with learning new skills during the pandemic. We fill this gap by leveraging three waves of a longitudinal household financial survey collected across all 50 U.S. states during the pandemic. Through multinomial logistic regression models, we explore sociodemographic characteristics related to learning a new skill, motivations for learning a new skill, and barriers and facilitators to learning a new skill. Then, through a logistic regression model in which we account for pre-pandemic entrepreneurial intent, we examine the relationship between learning new skills during the pandemic and current entrepreneurial intent. Finally, through a fixed effects model, we examine the relationships between learning new skills and optimism.

Starting with the overall rates of who learned skills and why, our models demonstrate an unmet need for skill development—the proportion of respondents that wanted to learn a new skill but had not (23%) outweighed the proportion respondents that actually learned new skills during the pandemic (16%). In addition, as a quarter of our respondents reported learning new skills to maintain their current role, our results suggest that reskilling can be necessary for job preservation and may act as an important safeguard against being pushed out of the labor market. While learning new professional skills can be mandatory or voluntary, it is clear that they are not merely a tool for career advancement.

When considering who learned new skills, our results suggest stratified learning opportunities across race/ethnicity, gender, and social class. When compared to White individuals, Black individuals were both more likely to actually learn new skills during the pandemic and more likely to desire to learn new skills during the pandemic; males were also more likely to desire to learn new skills during the pandemic. From an education perspective, when considering that Black individuals, males, and lower-income individuals have lower educational attainment in high school and are less likely to attend traditional 2- and 4-year degree programs (Harper et al., 2009; Bastedo & Jaquette 2011; Reeves, 2022), these findings suggest an accumulation of disadvantages in reskilling opportunities. Conversely, as higher educated individuals were more likely to learn new skills, these findings suggest an accumulation of advantages in this regard. Together, these results may partially explain why the American Dream appears to fading for many groups in the US (Chetty et al., 2014, 2017).

Furthermore, potentially reflecting labor market stratification and racial discrimination in employment settings, Black and

Hispanic workers were less likely to gain new skills through an employer compared to their White counterparts. This finding may reflect broader experiences of workplace discrimination (Wingfield & Chavez, 2020). Moreover, both Black individuals and higher income individuals were more likely to learn new skills from mentors and other supportive individuals, representing the importance of social capital in skill building. Ultimately, these experiences may allow for social capital to be translated into social mobility (Chetty et al., 2022).

Additionally, reflecting labor market disruptions and the influence of human capital development, learning new skills was significantly associated entrepreneurial intentions. Following the "Great Resignation" and the closing of many businesses in the wake of the COVID-19 pandemic, learning new skills may increase employment through entrepreneurial activities. Finally, for Black respondents, learning new skills was significantly associated with optimism during the pandemic. Here, our findings suggest the importance of human capital development through skill building for individuals who have historically been marginalized in traditional education spaces.

Implications

Our results demonstrate the importance of learning new skills for social mobility, while also highlighting the barriers faced by racial minorities, women, and families experiencing hardships. Entrepreneurship not only offers a pathway to employment and wealth-building to individuals, but also offers positive spillover effects (e.g., employment, tax revenue) to communities (Bates, 2006). As cities, which often contain large proportions of racial minorities and low-income individuals, tend to have comparative advantages for business development (Porter, 1995), providing on-ramps to entrepreneurship through reskilling may represent a tool for increasing racial equity—not only at an individual level, but also at the community level. As reskilling is also associated with optimism related to striving, it can be seen as having significant social and emotional value as well. Indeed, as Graham (2011) suggests, in addition ensuring economic stability, public investments should also facilitate the *pursuit* of happiness; the relationship between reskilling and optimism is a prime example of this. Beyond entrepreneurship and optimism, our research suggests that learning new skills is not only necessary for occupational progression, but also necessary for maintaining one's current job. While those who experienced job loss in our study were more likely to learn new skills—often for the purposes of maintaining their current job—they were also more likely to desire to learn new skills, suggesting further need.

Nevertheless, the majority of the $149 billion-dollar federal investment in higher education currently goes to traditional, 2-year, 4-year, and graduate degree-granting programs. Thus, in light of our findings, policy-makers should consider additional investments in reskilling programs and other non-traditional education programs. Moreover, given that Black individuals, males, and parents were more likely to be unable to fulfill their reskilling goals, policy-makers should consider ways to tailor programs to individuals from these groups. Given the pandemic's disproportionate impact on Black communities and workers (EPI, 2021), the record low rates of male college-going (Reeves, 2022), and the rising childcare costs endured by families, tailoring reskilling programs to these and other vulnerable groups is essential for an equitable recovery. In this regard, recent research by Jabbari and his colleagues (2023) demonstrates that free reskilling programs that adopt policies that recruit diverse candidates, support them throughout the program, and directly connect them to employment (e.g. through apprenticeships) can be effective at closing race and gender gaps. Online learning and skill-building opportunities should also be explored, especially when considering their salience in entrepreneurship (2022b), as well as the barriers that persons of color face in learning new skills through employers.

Furthermore, in addition to reskilling programs, access to capital and small business lending should also be explored in this context. Moreover, when considering the role that recent CARES act policies have had on entrepreneurship (Fazio et al., 2021), as well the potential impacts that cash transfers (Roll, et al., 2023) and student debt forgiveness (Jabbari et al., 2022c) can have on starting a new business, these types of policies and programs should be explored as well.

Conclusion

While the COVID-19 pandemic exacerbated inequalities across race/ethnicity, gender, and social class, it has also opened up new pathways to prosperity. One of these pathways is reskilling. With over 1,000,000 unique credentials (Credential Engine, 2021), individuals who may not be able to pursue a traditional 2- and 4-year degree now have the opportunity to build new skills. As technological advances continue shift the future of work, the future of learning must be shifted as well. As our research suggests, life-long learning is no longer a luxury good, but rather a necessity to remain competitive in an ever-evolving labor market. Moreover, with fewer barriers to entry, shorter time commitments, and more flexible learning regimens, many reskilling programs can be seen as tools that can increase occupational mobility and equity, help fill critical skill gaps in the economy, and encourage new businesses that can have positive spillover effects across communities.

Appendix

See Tables 5, 6 and 7

Table 5 Sociodemographic characteristics, by skill learning

Variables	Learned New Skills *Column %/Mean (S.D.)*	Would like to learn *Column %/Mean (S.D.)*	Did not learn new skills *Column %/Mean (S.D.)*
Optimism	7.94 (1.97)	7.47 (2.10)	7.37 (2.08)
Life satisfaction	6.92 (2.01)	6.20 (1.99)	6.83 (1.94)
Race/Ethnicity			
White	57.57%	54.59%	63.18%
Black	15.15%	14.61%	10.99%
Asian	6.38%	7.36%	6.86%
Hispanic	18.64%	21.32%	15.50%
Other	2.26%	2.12%	3.47%
Gender			
Male	51.06%	44.99%	50.34%
Female	48.94%	55.01%	49.66%
Marital status: Married/Living with a partner			
No	37.16%	44.31%	37.35%
Yes	62.84%	55.69%	62.65%
Children under age 18			
None	54.83%	61.24%	78.37%
One or more	45.17%	38.76%	21.63%
Primary language is English			
No	5.08%	5.59%	3.48%
Yes	94.92%	94.41%	96.52%
Metropolitan Area Resident			
Yes	89.01%	89.72%	88.54%
No	10.99%	10.28%	11.46%
Age	37.97 (14.27)	38.30 (13.73)	52.85 (16.02)
Enrolled in an educational program			
Yes, full-time	36.73%	22.32%	9.97%
Yes, part-time	10.92%	8.43%	2.51%
No	52.35%	69.25%	87.52%
Educational Attainment			
Less than a bachelor's degree	34.11%	49.59%	44.29%
Bachelor's degree	34.20%	30.98%	29.31%
Greater than bachelor's degree	31.69%	19.43%	26.40%
Area Median Income percent[a]			
ELI, AMI = [0,30%)	21.90%	20.28%	12.49%
VLI, AMI = [30,50%)	8.66%	15.14%	10.94%
LI, AMI = [50,80%)	17.45%	21.27%	18.30%
MOI, AMI = [80,120%)	20.15%	20.43%	20.36%
MII, AMI = [120,170%)	15.52%	11.08%	16.66%
HI, AMI = [170% +)	16.33%	11.81%	21.25%
Employment Status			
Full-time; Not from home	38.93%	27.86%	21.48%
Full-time; Occasionally from home	13.84%	13.18%	7.09%
Full-time; From home	16.61%	15.77%	13.98%
Part-time; Not from home	7.67%	8.12%	5.43%
Part-time; Occasionally from home	3.15%	3.60%	1.00%
Part-time; From home	3.45%	2.80%	2.25%
Not Working	16.35%	28.66%	48.76%
Job loss due to COVID19			
No	61.36%	67.39%	80.78%

Table 5 (continued)

Variables	Learned New Skills *Column %/Mean (S.D.)*	Would like to learn *Column %/Mean (S.D.)*	Did not learn new skills *Column %/Mean (S.D.)*
Yes	38.64%	32.61%	19.22%
Wave			
3	28.51%	36.01%	33.16%
4	30.28%	36.45%	33.04%
5	41.22%	27.53%	33.80%

Missing values are not included for the calculation of percentages or summary statistics

a Area Median Income ratio categories are: Extremely Low Income, Very Low Income, Low Income, Moderate Income, Moderate to High Income, and High Income

Table 6 The Relationship between Sociodemographic Characteristics and Learning a New Skill: Estimates from a Multinomial Logistic Regression Model (Base Category of Outcome: Did Not Learn New Skills)

Variables	Desired to Learn New Skills		Learned New Skills	
	Est. (S.E.)[1]	*RRR*[2]	*Est. (S.E.)*	*RRR*
Race/Ethnicity: Black	0.45*** (0.08)	1.57	0.54*** (0.10)	1.72
Race/Ethnicity: Asian	0.21* (0.11)	1.23	− 0.051 (0.13)	0.95
Race/Ethnicity: Hispanic	0.31*** (0.07)	1.37	0.093 (0.09)	1.1
Race/Ethnicity: Other	0.055 (0.17)	1.06	0.2 (0.22)	1.22
Gender: Female	− 0.13* (0.05)	0.88	− 0.16* (0.06)	0.85
Married/Living with a partner	− 0.11 (0.06)	0.89	− 0.028 (0.07)	0.97
Has one or more children	0.21** (0.06)	1.23	0.24** (0.07)	1.27
Primary language is English	− 0.2 (0.13)	0.82	− 0.28 (0.15)	0.75
Non-metropolitan area resident	− 0.041 (0.08)	0.96	0.20* (0.10)	1.22
Age	− 0.050*** (0.00)	0.95	− 0.047*** (0.00)	0.95
Education enrollment: Part-time	0.35** (0.13)	1.42	0.39** (0.13)	1.47
Education enrollment: Not enrolled	− 0.22** (0.07)	0.8	− 0.84*** (0.07)	0.43
Education Attainment: Bachelor's degree	0.002 (0.07)	1.00	0.37*** (0.08)	1.45
Education Attainment: > Bachelor's degree	0.015 (0.08)	1.01	0.75*** (0.08)	2.12
Income: VLI, AMI = [30,50%)	0.13 (0.09)	1.13	− 0.39** (0.12)	0.68
Income: LI, AMI = [50,80%)	0.045 (0.09)	1.05	− 0.30** (0.10)	0.74
Income: MOI, AMI = [80,120%)	0.023 (0.09)	1.02	− 0.20* (0.10)	0.82
Income: MII, AMI = [120,170%)	− 0.27** (0.10)	0.77	− 0.24* (0.11)	0.78
Income: HI, AMI = [170 + %)	− 0.29** (0.10)	0.75	− 0.32** (0.11)	0.73
Employment: Full-time; Occasionally from home	0.46*** (0.09)	1.58	0.17 (0.10)	1.19
Employment: Full-time; From home	0.16 (0.09)	1.17	0.05 (0.09)	1.05
Employment: Part-time; Not from home	− 0.12 (0.11)	0.89	− 0.39** (0.13)	0.68
Employment: Part-time; Occasionally from home	0.66*** (0.17)	1.93	0.29 (0.21)	1.34
Employment: Part-time; From home	0.13 (0.16)	1.14	0.22 (0.19)	1.25
Employment: Not Working	− 0.18* (0.07)	0.83	− 0.68*** (0.09)	0.5
Lost a job due to COVID-19	0.39*** (0.06)	1.48	0.63*** (0.07)	1.88
Constant	1.63*** (0.18)	5.11	1.29*** (0.21)	3.64
Observations	13,770			
AIC	21,711.07			
BIC	22,147.83			

Logit coefficients are provided with standard errors (in parentheses) and relative risk ratios (to the right). Reference categories are White (Race/Ethnicity), Male (Gender), Was not married/did not live with a partner, Has no children, Primary language was not English, Lives in a metropolitan area, Full-time enrolled in educational programs (Education enrollment), Less than a bachelor's degree (Education attainment), Extremely low income (Income), Full-time on-site employed (Employment), Did not lose job/income due to COVID-19

*p < .05, **p < .01, ***p < .001. Two-tailed tests

Table 7 The relationship between sociodemographic characteristics and reasons for learning a new skill: estimates from a multinomial logistic regression model (base category of outcome: learned new skills for personal fulfillment)

Variables	To find a better job		To maintain current job	
	Logit (S.E.)	*RRR*	*Logit (S.E.)*	*RRR*
Race/Ethnicity: Black	< -0.01 (0.11)	1.00	− 0.18 (0.12)	0.83
Race/Ethnicity: Asian	0.35** (0.15)	1.42	0.07 (0.16)	1.08
Race/Ethnicity: Hispanic	0.19* (0.11)	1.21	− 0.05 (0.12)	0.95
Race/Ethnicity: Other	− 0.07 (0.28)	0.93	− 0.31 (0.31)	0.74
Gender: Female	− 0.25*** (0.08)	0.78	− 0.12 (0.09)	0.89
Married/Living with a partner	− 0.40*** (0.09)	0.67	− 0.1 (0.10)	0.90
Has one or more children	0.16* (0.08)	1.17	0.15* (0.09)	1.17
Primary language is English	0.30* (0.18)	1.35	0.14 (0.21)	1.15
Non-metropolitan area resident	− 0.28** (0.12)	0.76	− 0.33*** (0.13)	0.72
Age	− 0.03*** (0.00)	0.97	< 0.01 (0.00)	1.00
Education enrollment: Part-time	− 0.09 (0.16)	0.91	0.13 (0.16)	1.14
Education enrollment: Not enrolled	− 0.59*** (0.09)	0.55	− 0.68*** (0.10)	0.51
Education Attainment: Bachelor's degree	0.07 (0.09)	1.07	0.05 (0.10)	1.05
Education Attainment: > Bachelor's degree	− 0.19* (0.11)	0.83	0.02 (0.11)	1.02
Income: VLI, AMI = [30,50%)	0.03 (0.12)	1.03	− 0.26* (0.15)	0.77
Income: LI, AMI = [50,80%)	− 0.26** (0.11)	0.77	− 0.31** (0.14)	0.73
Income: MOI, AMI = [80,120%)	− 0.24** (0.12)	0.79	− 0.27* (0.14)	0.77
Income: MII, AMI = [120,170%)	− 0.42*** (0.14)	0.66	− 0.22 (0.15)	0.81
Income: HI, AMI = [170 + %)	− 0.39*** (0.15)	0.68	− 0.17 (0.16)	0.84
Employment: Full-time; Occasionally from home	− 0.44*** (0.13)	0.64	0.24** (0.12)	1.28
Employment: Full-time; From home	− 0.24** (0.12)	0.78	0.17 (0.12)	1.18
Employment: Part-time; Not from home	− 0.16 (0.16)	0.85	− 0.08 (0.17)	0.93
Employment: Part-time; Occasionally from home	− 0.75*** (0.23)	0.47	0.07 (0.21)	1.07
Employment: Part-time; From home	− 0.80*** (0.22)	0.45	− 0.55** (0.25)	0.58
Employment: Not Working	− 0.81*** (0.10)	0.45	− 1.79*** (0.15)	0.17
Lost a job due to COVID-19	0.73*** (0.08)	2.08	0.37*** (0.09)	1.44
Constant	1.84*** (0.25)	6.28	0.32 (0.28)	1.38
N	5309			
AIC	10,484.44			
BIC	10,865.91			

Logit coefficients are provided with standard errors (in parentheses) and relative risk ratios (to the right). Reference categories are White (Race/Ethnicity), Male (Gender), Was not married/did not live with a partner, Has no children, Primary language was not English, Lives in a metropolitan area, Full-time enrolled in educational programs (Education enrollment), Less than a bachelor's degree (Education attainment), Extremely low income (Income), Full-time on-site employed (Employment), Did not lose job/income due to COVID-19

*p < .05, ** p < .01, *** p < .001. Two-tailed tests

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Declarations

Conflict of interest The authors have no conflicts of interest to declare that are relevant to the content of this article.

Ethical Approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional review board of Washington University in St. Louis (IRB ID: 202004100).

Consent to Participate Survey participants provided their consent to participate in the study in accordance with the ethical standards of the institutional review board of Washington University in St. Louis (IRB ID: 202004100).

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