Cut Me Some Slack!

Slack Resources and Technology-Mediated Human Capital Investments in Entrepreneurship

Jason Jabbari, PhD

Stephen Roll, PhD

Sam Bufe, MA

Yung Chun, PhD

The Social Policy Institute

Washington University in St. Louis

Disclaimer: The authors would like to acknowledge the commitment of Intuit, Inc. and its Tax and Financial Center for making the Refund to Savings Initiative possible. We thank the thousands of taxpayers who consented to participate in the research surveys and shared their personal financial information. The authors would also like to thank Mastercard for its partnership on this paper. The findings and conclusions expressed are solely those of the authors and do not represent the views or opinions of research partners and funders. The authors accept all responsibilities for errors or omissions. Statistical compilations disclosed in this document relate directly to the bona fide research of, and public policy discussions concerning, financial security of individuals and households as it relates to the tax filing process and more generally. Compilations follow Intuit's protocols to help ensure the privacy and confidentiality of

customer tax data. The Washington University in St. Louis Institutional Review Board approved the collection of survey data that were used in this paper.

Abstract: In this paper, we explore the impact that slack resources and technology can have on *individuals*' entrepreneurial aspirations. Focusing on human capital investments that individuals make through education and work that involve both slack resources and technology, we explore the relationship among formal online learning opportunities, informal skill development in the gig economy, and entrepreneurial aspirations. Leveraging a novel dataset that merges administrative tax data with a survey of over 8,528 low and moderate-income households, we use machine learning and propensity score weighting to examine the likelihood that individuals who make these technology-mediated human capital investments will have increased odds of entrepreneurial aspirations when compared to similar individuals who do not make these investments. We find that both partaking in online learning and working in the gig economy are significantly associated with increased odds of entrepreneurial aspirations. Furthermore, through a variety of robustness and mechanism checks, we find that technology-mediation is an important factor in these relationships and that informal skill development and career preparation is one way in which gig employment influences entrepreneurial aspirations. We discuss these findings with implications for both policies and practices around online learning and gig employment.

Keywords: Online Learning; Gig Employment; Slack Resources; Entrepreneurship

If you wanna stick around you gotta cut me some slack

I'm gonna hit the road again and not come back

-- Paul McCartney, Dave Grohl, Krist Novoselic, and Pat Smear, 2012

1 Introduction

Slack resources often consist of the time and money that are needed to meet long-term innovation goals, as opposed to short-term production goals. In the organizational literature, slack resources are associated with the exploration and experimentation of "new ideas, products, strategies, and markets that would otherwise be considered too risky to engage in under a traditional cost-benefit analysis" (Agrawal, Catalini, Goldfarb, & Luo, 2018). Thus, it is unsurprising that many organizations have used slack resources to spur innovation. For example, Google allows employees to use 20% of their paid time on side projects; Gmail, Google Maps, Twitter, Groupon, and, fittingly, the business communication platform *Slack* are all successful ventures that started as side projects.

At the same time, technology has also been used to spur innovation, as it can provide organizations with new knowledge and tools that can help organizations anticipate disruptions, advance products, increase strategic choices, and locate new markets (Bolívar-Ramos, García-Morales, & García-Sánchez, 2012; Martín-Rojas, García-Morales, & Bolívar-Ramos, 2013). For example, over 85% of small and medium-sized businesses in a recent large-scale survey reported that digital business tools have improved their businesses—citing growth in customers, revenues, employees, and innovation (Deloitte, 2017). Moreover, these competitive advantages extend across business sectors: Bartel and her colleagues (Bartel, Ichniowski, & Shaw, 2007) found that information technology increased customization and improved efficiency in manufacturing firms as well.

Technological advances are also making it easier for individuals to invest in their human capital. Thanks to online and mobile learning platforms, a student can now take classes in a wide range of subjects whenever it is convenient to do so. Similarly, an individual can increase their human capital and gain marketable skills while earning money through the gig economy, the segment of the labor market where workers use mobile apps and platforms to find short-term contracts for a wide range of work. Due to the short-term nature of gig employment contracts, a gig worker typically has the flexibility to work when and where it is most convenient.

Nevertheless, despite a wealth of research on the relationships between slack resources and innovation at the firm level (Bourgeois, 1981; Cyart & March, 1963; Levinthal & March, 1981), there is little research on the relationship between slack resources and entrepreneurship at the individual level. The same is true for the relationship between technology and entrepreneurship (Koellinger, 2008). Additionally, there is no current research on the interactions across slack resources and technology and their relationship with entrepreneurship. As technology platforms can create slack resources *and* slack resources can increase technology use, it is likely that both slack resources and technology may work together to increase entrepreneurship.

As we are most interested in the impact that slack resources and technology can have on *individuals*' entrepreneurial aspirations, we focus on human capital investments that individuals make through education and work that involve both slack resources and technology. In this paper, we examine the relationship between entrepreneurial aspirations and two types of technology-facilitated human capital investments: (1) formal online learning opportunities and (2) informal skill development in the gig economy. We explore the extent to which human capital investments in these technology-mediated sources of skill development can increase entrepreneurial aspirations for individuals, as compared to similar individuals not engaged in these activities. We know of no other studies that have tested theories of slack resources and technology in this way.

To address the issue of selection bias in the decision to opt for these technology-mediated human capital investments, we use machine learning and propensity score weighting to balance our treatment group—individuals who engage in either online learning or gig employment—and our comparison group—individuals who do not engage in these activities—on observable characteristics. Leveraging a novel dataset that merges administrative tax data with a survey of over 8,528 low and moderate income households, we find that both partaking in online learning and working in the gig economy are significantly associated with increased odds of entrepreneurial aspirations. Furthermore, through a variety of robustness checks, we find that technology-mediation is an important factor in these relationships, as the point estimates for online learning do not substantially change when we limit our sample only to students, nor does the point estimate for working in the gig economy change when we limit our sample to part-time workers. Moreover, through a series of mechanism checks, we find that informal skill development and career preparation is one way in which gig employment influences entrepreneurial aspirations. These findings have implications for both policies and practices around online learning and gig employment.

These types of human capital investments are increasingly important in a fast-changing and technology-driven economy. As the number of technology-based start-ups grew 47% from 2007-2016 (Wu & Atkinson, 2018), we can assume that both the agility and innovation that come with slack resources and technology will become increasingly associated with entrepreneurial activities (Bradley, Wiklund, & Shepherd, 2011; Nambisan, 2017). Our analyses are focused specifically on low- and moderate-income (LMI) households, a group for whom entrepreneurship plays an important role. Although LMI households tend to have lower levels of entrepreneurial success (Acs & Kallas, 2008), the benefits of entrepreneurship to LMI households can be quite high. Successful entrepreneurship can not only raise the incomes of the entrepreneur, but can have lasting intergenerational effects on the future incomes of family members (Velez-Grajales & Velez-Grajales, 2012). Additionally, one entrepreneurial venture can have spillover effects, increasing the likelihood of others becoming entrepreneurs. As such, entrepreneurial ventures can have a substantial and lasting impact on LMI communities.

2 Conceptual Overview

Technological advances over the past 30 years are allowing people to make better use of their time in ways that would have been difficult to imagine a few decades ago. While some of these advances have focused on entertainment (e.g., smartphones allowing people to binge a TV show on their bus ride to work), others have allowed people to make more productive use of their free time. In this paper, we argue that usage of these productivity-enhancing forms of technology is associated with increases in entrepreneurial aspirations. Specifically, we focus on the relationship between entrepreneurial aspirations and two different productivity-enhancing technological advancements: online education and gig economy platforms.

2.1 Mechanism 1: Human Capital and Skill Development

As noted by Unger and his colleagues (Unger, Rauch, Frese, & Rosenbusch, 2011), human capital (e.g., education, experiences, knowledge, and skills) can help individuals discover and exploit new business ventures (Shane & Venkatraman, 2000), plan and execute venture strategies (Baum, Locke, & Smith, 2016), acquire new resources (Brush, Greene, & Hart, 2002) and locate new markets. Indeed, research on entrepreneurship demonstrates that human capital is most strongly associated with entrepreneurial success when education, experience, knowledge, and skills are directly related to entrepreneurial tasks (Unger et al., 2011).

Technological advances are changing the ways people can invest in human capital. Thanks to smartphones and broad access to the internet, individuals now have the flexibility to invest in their human capital when and where it is convenient. One such example involves investing in online education. Online education refers to any type of educational program in which at least some of the course materials are delivered online. As these platforms have become easier to scale and grown more affordable to students over recent decades, the use of online and mobile learning platforms has grown substantially (U.S. Department of Education, 2016). Today, students can use online education platforms to develop skills in a breadth of subjects ranging from English and history to mathematics and programming.

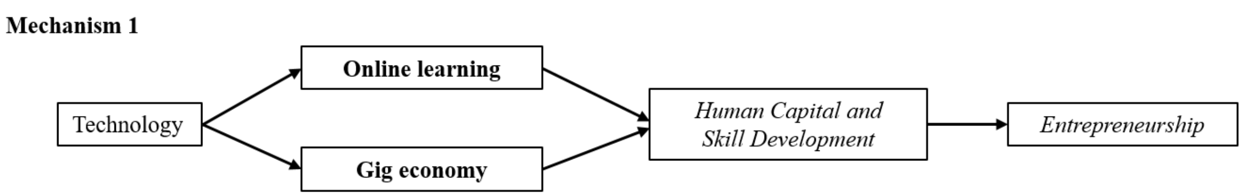
While the efficacy of specific online education programs can vary, there is ample evidence that education delivered online can improve student outcomes. Several studies and meta-analyses have found improved educational outcomes among students receiving online education, with some arguing that education delivered online actually leads to better student outcomes than traditional brick-and-mortar education (Means, Toyama, Murphy, Bakia, & Jones, 2009; Nguyen, 2015). While others argue that the effects of online education are overstated (Jaggars & Bailey, 2010), there is broad consensus that online education programs improve students' skills and knowledge.

Although skill development may not be among their stated goals, gig economy platforms and applications that digitally connect workers with employers through short-term employment contracts, also allow their users to develop important skills. For example, Uber drivers may learn how to pinpoint markets and interact with clients; Etsy workers may learn how to manage an inventory and distribute products; and Airbnb hosts may learn how to market their product and pay employees. On the surface, this may seem like a relatively unimportant reason why workers join the gig economy. However, many gig workers explicitly report seeking out gig employment to build skills that they may want to capitalize on in their future (Broughton et al., 2018; Friedman, 2014).

Both online education and gig platforms allow users to develop skills that increase the likelihood of entrepreneurial success. For example, a student who takes programming classes online will have a marketable skill that potential clients would be willing to pay for. Gig employment can help workers gain the informal skills and knowledge related to starting and running a business, while also acquiring advanced digital literacy skills. Furthermore, a gig worker who learns time management and interpersonal skills by driving for Uber is going to be better equipped to manage themselves when starting a business.

With these entrepreneurially-relevant skills, users of productivity-enhancing technology platforms are more likely to have entrepreneurial success. Accrual of skills and human capital increases the expected value of (and therefore the likelihood of pursuing) an entrepreneurial enterprise. The logic flow for Mechanism 1 is shown in Figure 1.

Figure 1. Human Capital and Skill development (Mechanism 1)



2.2 *Mechanism 2: Slack*

Nevertheless, human capital creation not only requires additional skills, but also additional time needed to execute these skills. Thus, individuals need to invest in education, experiences, knowledge, and skills that can increase entrepreneurial aspirations and abilities *while* also allowing for enough flexibility or "slack" to develop new ventures, strategies, resources, and markets. While slack resources and technology use are typically created through organizational strategies at the firm level, slack resources can be created through human capital investments at the individual level. Similar to organizations, individuals need time to "pay attention, think, and benefit from the knowledge gained" (Lawson, 2001). Some of the human capital investments that are most adept at increasing entrepreneurial aspirations and abilities *while* also allowing for enough slack for individuals to innovate are those that are mediated by technology, as these investment platforms often allow for the greatest degree of flexibility—while also building technology and digital literacy skills.

Thus, another defining characteristic of online education is that it gives students the autonomy to determine where and when their education happens (Allen & Seaman, 2002; Capra, 2011; Chee, Yahaya, Ibrahim, & Noor, 2017). Indeed, online learning is often individualized and self-paced, thus allowing for more flexibility than traditional, in-person courses (Martin & Grudziecki, 2006). Thanks to online education platforms, students can now watch lectures on their bus rides to work and can take practice quizzes while waiting in line at the grocery store. With the ability to study and learn when it is convenient, students may have less of a need to block off time dedicated to their education, creating slack in their schedules.

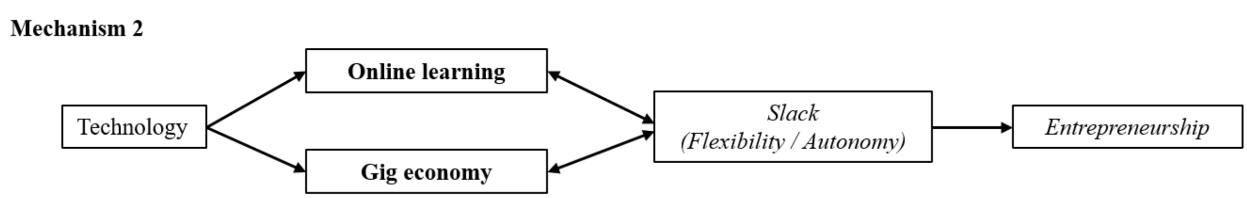
As the flexibility of online education creates slack in students' schedules, the flexibility offered through the gig economy, which consists of technology-enabled peer-to-peer businesses, can also create slack in the schedules of gig workers. Since gig economy platforms offer employment through short-term contracts, gig workers also tend to have a great deal of autonomy over their schedules (Dokko, Mumford, & Schanzenbach, 2015; Lehdonvirta, 2018). An Uber driver, for example, who is not bound by a typical 9 to 5 schedule, has the flexibility to work a few hours on the weekend or at nights. In fact, Hall and his colleague (Hall & Krueger, 2018) found that flexibility was one of the largest sources of attraction for Uber drivers. Their research found that Uber's flexibility was able to help drivers “smooth the transition to other jobs, as driver-partners can take off time to prepare for and search for another job at their discretion” (p. 714). This “smoothing” process may be present for both the transition into other traditional forms of employment and the transition into entrepreneurial activities.

Similarly, someone who earns income selling items on Etsy or renting a property on AirBnB has the scheduling flexibility to work when it is convenient to do so. Here, gig employment offers a considerable amount of slack resources, as the peer-to-peer nature of these businesses offers workers both flexibility and convenience in their employment. These experiences are quite different from those of traditionally employed workers, who are required to be working during certain hours of the day. Even many part-time employees do not know what their schedules are going to look like in a given week, yet have to make themselves available for a full 40-hour workweek regardless. Thus, flexibility creates slack in the schedules of gig workers.

Slack is another important component of entrepreneurial success. If their ventures are going to be successful, individuals need the time, flexibility, and energy to address the issues that their organizations face. Research on the subject has shown that slack can have a positive direct effect on entrepreneurial growth (Bradley et al., 2011). By providing users with additional slack, productivity-enhancing technology, such as gig platforms and online education, increase the likelihood of entrepreneurial success. For example, when compared to traditional college courses, online learning can offer a greater variety of courses, as well as a more cost-effective way of upskilling quickly, which can increase entrepreneurial activities. Massive Online Open Courses—or MOOCs—are one example of online learning where students can choose from a variety of courses at a low cost, take them when convenient, and not have to physically relocate or alter their work schedule.

Finally, it is important to note that technology not only allows for greater degrees of slack, but that slack can also increase technology use. Here, individuals engaged in online learning or gig employment may be more likely use technology for other productive purposes with their slack time. As both online learning and gig employment have the capacity to build technology and digital literacy skills that are related to entrepreneurial activity, the relationship between slack and technology becomes especially important. For example, online learning experiences, which can leverage networking tools that allow for greater personalization, participation, and productivity, can increase creativity, innovation, and entrepreneurship beyond the confines of the course (McLoughlin & Lee, 2008). This logic flow is displayed in Figure 2.

Figure 2. Slack resources (Mechanism 2)



3 Prior Literature

While organizational research has examined a positive relationship between slack resources and exploration activities, such as innovation (Nohria & Gulati, 1996), risk-taking (Singh, 1986), and adaptation (Kraatz & Zajac, 2001), only recently has this been studied at the individual level. In 2018 Agrawal and his colleagues empirically demonstrated a positive relationship between slack resources and entrepreneurial activities. Using data on college breaks and Kickstarter projects in the United States, they observed more project posts on Kickstarter during university breaks. They also observe an increase in higher value projects during the period, which may be linked to the ability of entrepreneurs to put more resources into their ideas.

To-date, there has been no research on the relationship between online learning and entrepreneurship and little research on the relationship between gig employment and entrepreneurship. Concerning the latter, two compelling explanations exist for the relationship between gig employment and entrepreneurship (Burtch, Carnahan, & Greenwood, 2018). On the one hand, the gig economy may discourage entrepreneurial aspirations and activities by providing stable jobs for the unemployed. As many pursue starting their own business in order to resolve unemployment or underemployment—potentially due to the lower opportunity costs of starting a business for those who are unemployed (Block & Koellinger, 2009; Fairlie, 2002; Storey, 1991)—it is possible that gig economy employment may have a negative relationship with entrepreneurship. As the gig economy may provide additional employment opportunities, it is plausible to assume that the gig economy raises individuals' opportunity cost of seeking out new employment opportunities and thus reduces entrepreneurship. Burtch et al. (2018), for example, find a negative association between the gig economy and entrepreneurial activity *at the city level*. Focusing on the entry of Uber X into cities, they found that the Uber X's entry decreases the number of individuals reporting self-employment by 5 percent, as well as a 14 percent decrease in the number of active Kickstarter projects in subject areas.

However, while aggregate gig economy trends may demonstrate lower levels of entrepreneurship at the city-level, a different phenomenon may be taking place at the *individual-level*, especially when considering entrepreneurial *aspirations*. Therefore, on the other hand, we posit that gig economy employment may encourage individuals' entrepreneurial aspirations as it builds human capital and helps individuals secures slack resources. Here, slack resources may encourage a would-be entrepreneur to conceive new business opportunities and ventures (Voss, Sirdeshmukh, & Voss, 2008). Furthermore, a combination of flexible schedules and regular income from the gig economy may resolve both time and monetary constraints that a nascent entrepreneur may confront (Agrawal et al., 2018). Building upon this evidence of a positive association between human capital development, slack resources, and entrepreneurship, we hypothesize that there will be a positive relationship between online learning, gig employment, and individuals' entrepreneurial aspirations.

4 Data and Methods

In this study, we are interested in examining the how technology-mediated human capital investments influence entrepreneurship. Specifically, we explore the relationships among online learning, gig employment, and entrepreneurial aspirations. We do this in multiple steps. First, we examine the relationship between online learning experiences and new gig employment, as well as the relationship between online learning experiences and entrepreneurial aspirations. Next, we explore the relationship between new gig employment and entrepreneurial aspirations. Last, we explore how both online learning and new gig employment are simultaneously related to entrepreneurial aspirations.

Additionally, while we do not have a prior measure of entrepreneurial aspirations, we are able to improve directionality by removing individuals who have previously started a business or non-profit organization, as well as individuals who had worked in the gig economy prior to this year. Finally, while we cannot completely control for the decisions to participate in online learning or work in the gig economy, we are able to balance each group on a variety of demographic and economic measures that are related to selection into these groups, as well as the main outcome measure—entrepreneurial aspirations. We do so by leveraging administrative tax return data and machine learning-based propensity score weighting methods.

4.1 Data

Data for this study come primarily from the 2018 Household Financial Survey (HFS), which gathered detailed information on a variety of measures related to employment, future aspirations, and household finances. The HFS was administered to individuals who consented to participate in the survey following completion of their tax preparation in Intuit's TurboTax Freedom Edition (TTFE) in 2018. As part of the Internal Revenue Service's (IRS) Free File Alliance Program,[1] the TTFE tax-preparation and tax-filing software is free for LMI tax filers who meet certain income and/or military service criteria. In 2018, the qualifying criteria for using TTFE were: (a) claiming the Earned Income Tax Credit, (b) having an adjusted gross income (AGI) less than or equal to $33,000, or (c) being an active duty military serviceperson with an adjusted gross income less than or equal to $66,000. For these analyses, HFS data were merged with administrative tax records for individuals that received a tax refund. By using administrative data, we were able to observe the precise values of household AGI, federal tax refunds, tax filing status, and the

[1] https://freefilealliance.org/

number of dependents in a household. While the unit of observation in this study is a tax household, demographic characteristics (e.g., age, gender, etc.) and self-assessed measures related to online learning, gig employment, entrepreneurial aspirations, and student debt correspond to the tax filer who completed the TTFE on behalf of their tax household.

4.2 Sample

Of the 15,983 households that completed the HFS, we were able to merge in federal tax data for 12,288 households. While these households were restricted to those that did not owe any federal taxes, close examinations of previous HFS surveys reveal that these represent roughly 90% of all LMI tax filers and that there were no systemic differences across individuals that did and did not owe federal taxes. We were then able to merge in urbanicity data from the USDA for 10,141 of these households. We then removed 389 individuals who had already founded a business, as well as 413 individuals who had worked in the gig economy prior to this year. This allows us to isolate the impact of working in the gig economy, while also avoiding the potential "double-measurement" of gig employment and entrepreneurial activities. Additional cases of list-wise deletion resulted in an analytic sample of 8,528 households.

4.3 Measures

4.3.1 Key Dependent and Independent Variables.

We examined the associations among online learning, gig employment, and entrepreneurial aspirations. Our key dependent variable, entrepreneurial aspirations, was based on respondents' answer to the following question: "Are you currently planning to start a business or nonprofit?" (1 = yes; 0 = no). In terms of our key independent variables, a dummy variable for online learning was developed from the question "Are you currently taking classes online?" (1 = yes; 0

= no/not currently enrolled in a part-time or full-time educational program), while a dummy variable for gig employment was developed from the question “In the past year, did you earn any income through services offered through a mobile app or website (sometimes known as the ‘Sharing’ or ‘Gig’ economy)? Examples include ride-sharing services like Uber, home-sharing services like AirBnB, and selling crafts through sites like Etsy” (1 = yes; 0 = no). We also created four binary variables that demonstrate how gig workers view the value of their work (1 = somewhat/strongly agree; 0 = somewhat/strongly disagree): “I value the flexibility this job gives me” (93.67% somewhat/strongly agree); “This job allows me to control my own schedule due to child care, school, or other obligations” (87.71% somewhat/strongly agree); “This job allows me to fill in gaps or fluctuations in my other sources of income” (37.63% somewhat/strongly agree); “This job allows me to gain work experience for future job opportunities” (75.90% somewhat/strongly agree)

4.3.2 Variables in the Propensity Score Estimation Model.

As the decision to participate in online learning and the gig economy is not random and may be systematically related to the outcomes under study, we use propensity score weighting to ensure that individuals participating in online learning and working in the gig economy are comparable to individuals *not* participating in online learning and working in the gig economy. Specifically, we employed a theory-driven approach in our propensity score estimation model, and balanced each group on variables that are theoretically related to online learning, gig employment, and entrepreneurial aspirations. In doing so, the following variables were included the propensity score estimation model: gender (1 = male; 0 = female/other); whether or not individuals lived in an urban area (1 = lives in a metro county; 0 = does not live in a metro county); race/ethnicity—whether individuals identified as White (1 = yes; 0 = no), Black (1 = yes; 0 = no), Hispanic (1 =

yes; 0 = no), Asian (1 = yes; 0 = no); and Other (1 = yes; 0 = no); age quintiles; whether or not an individual has dependents (1 = yes; 0 = no); a tax filing status of single (1 = yes; 0 = no), married filing jointly (1 = yes; 0 = no), and head of household/other (1 = yes; 0 = no); household's AGI; and federal tax refund amount. Variables measuring dependents, tax filing status, household AGI, and the federal tax refund were observed in the administrative tax data; the measure of urbanicity came from the linking USDA data with respondents' zip codes; the remaining measures came from the survey data.

4.3.3 Covariates in Multivariate Response Models

We utilized additional covariates in our multivariate response models to account for other factors that might explain the outcomes. There was some overlap between these covariates and the variables used in the propensity score estimation model, which can provide an added layer of robustness (Bang & Robins, 2005). However, the full set of covariates used in the multivariate response models were substantially different than in the propensity score estimation model, which is also necessary when using propensity score methods (Freedman & Berk, 2008). In addition to gender, urban location, race/ethnicity, household AGI, and federal tax refund amount, age and dependents were also used in the multivariate response models. However, in the multivariate response models it is important to note that continuous measures were used for age and dependents.

Our multivariate response models also included the following covariates: being married or living with a partner (1 = yes; 0 = no); student status (categories: "not a student," "part-time student," and "full-time student"); education level (categories: "high school/less than high school," "certificate/technical degree," "some college," "associate's degree," "college degree," "some graduate school," and "graduate school degree"); employment status (categories: "not working,” “working part-time,” and “ working full-time”); home ownership (1 = yes; 0 = no); car ownership (1 = yes; 0 = no); student debt (1 = yes; 0 = no); unsecured debt—including amounts reported on credit cards, payday loans, and negative balances in checking accounts; liquid assets—including amounts reported in checking accounts, savings accounts, and cash; health insurance (1 = has health insurance; 0 = does not have health insurance); and perceived health. Perceived health was derived from the following question: “How would you rate your general physical health compared to others of your own age?” (1 = much better; 2 somewhat better; 3 about the same; 4 = somewhat worse; 5 = much worse).

In order to censor extreme outliers, age, liquid assets, and unsecured debt variables were winsorized at the upper-bound 99th percentile in the multivariate response models. Additionally, while liquid assets where transformed into quartiles, due a disproportional amount of the sample that had no unsecured debt, this variable was transformed into a categorical variable consisting of 4 categories: (1) no unsecured debt: $0; (2) low unsecured debt: $1-600; (3) moderate unsecured debt: $601-3,000; and (4) high unsecured debt: $3,001-25,000. Notably, individuals with unsecured debt were equally distributed into the latter three categories. Finally, due to variation in the state laws and regulations regarding gig employment, U.S. states were included as a random intercept.

4.4 Analytic Strategy

Propensity scores define the conditional probability of being assigned to a treatment or control group based on a set of observed characteristics (Rosenbaum & Rubin, 1983), but cannot account for unobserved characteristics. As a result, propensity scores can be seen as balancing property: “conditional on the propensity score, the distribution of observed baseline covariates will be similar between treated and untreated subjects” (Austin, 2011). Specifically, propensity score weighting was used in this study, which uses the inverse probability for receiving the treatment (that the subject actually received) to weight these observations from a given sample (Austin, 2011). Stemming from a counterfactual framework, in which treatment participants (individuals that participate in online learning and work in the gig economy) and comparison participants have potential outcomes in the state in which they are observed *and* in the state in which they are not observed (Guo & Fraser, 2014), propensity score weights allow for average treatment effects (ATE) to be estimated, which in this study is the difference in the potential outcomes associated with online learning and gig work for all students. In following Guo's (2014) notation, the ATE weights for cases in the treatment groups are calculated as $w_i = \frac{1}{p(x_i)}$, while the ATE weights for cases in the comparison group are calculated as $w_i = \frac{1}{1-p(x_i)}$. These weights are then applied in logistic regression models as follows:

$$\ln\left(\frac{P(x_i)}{1-P(x_i)}\right) = \beta_0 + \beta_1 Gig_i + \beta_2 Online_i + \mathbf{X}_{\boldsymbol{i}}^{\mathbf{demo}}\boldsymbol{\gamma}_{\mathbf{1}} + \mathbf{X}_{\boldsymbol{i}}^{\mathbf{finance}}\boldsymbol{\gamma}_{\mathbf{2}} + \mathbf{X}_{\boldsymbol{i}}^{\mathbf{health}}\boldsymbol{\gamma}_{\mathbf{3}} + \boldsymbol{\varepsilon}_{\boldsymbol{i}}$$

Here, the dependent variable of each logit model is either binary gig employment or entrepreneurial aspirations indicator. The two key independent variables are gig employment and online learning experiences. In addition to the two key variables, we also control for three sets of covariates as discussed above: demographic characteristics, financial characteristics, and health characteristics. To demonstrate the effect of applying ATE weights, each of our outcome models contains both propensity score weighted and non-propensity score weighted estimates.

Since model misspecification errors have been shown to bias estimates of treatment effects, especially in analyses with binary outcomes (Drake, 1993; Freedman & Berk, 2008), we utilized generalized boosted modeling (GBM) to estimate propensity scores. Nonparametric modeling approaches, such as GBM, have been shown to reduce the chance of these errors

(McCaffrey, Ridgeway, & Morral, 2004). Specifically, GBM utilizes automated, data adaptive modeling algorithms and machine learning techniques to “predict treatment assignment from a large number of pretreatment covariates while also allowing for flexible, non-linear relationships between the covariates and the propensity score” (2004, p. 3). In estimating the propensity score weights, this study utilized the TWANG—Toolkit for Weighting and Analysis of Non-equivalent Groups—package (Ridgeway, Morral, Griffin, & Burgette, 2014) in STATA. As seen in Figures 3 and 4, there was an adequate range of common support.

4.5 Methodological Limitations

As our propensity score method only allows us to balance the groups on observable characteristics, participants may not be balanced on unobservable characteristics related to partaking in online learning or working in the gig economy. As a result, we are unable to make causal inferences. Rather, we use propensity score weighting to balance groups on observables characteristics that are related to our treatments, as well as the outcomes under study. By doing so, we are able to remove some of the bias in our associational estimates.

5 Results

5.1 Sample Description

Table 1 provides a description of the sample. Of the total sample, six percent had entrepreneurial aspirations, six percent worked in the gig economy, and nine percent participated in online learning. There were slightly fewer men than women in our sample (48%), and the majority of the individuals in our sample identified as White (73%) and lived in an urban location (86%). The average age of participants in the sample was 33, and the majority of individuals did not have dependents (83%) and were not married or currently living with a partner (74%).

Unsurprisingly, given the above, the majority of individuals had a “single” tax filing status. The majority of individuals were not students (67%) and had less than a bachelor’s degree (60%). Most individuals were employed (79%), did not own a house (80%), but did own a car (67%). Nearly half (47%) of individuals had student debt, and the average amount of unsecured debt ($3,602) was less than the average amount of liquid assets ($4,679). Additionally, the average AGI was $16,200 a year and individuals received a federal tax refund of $1,501 on average. Finally, most individuals had health insurance (90%) and on average perceived that their health was slightly better than others in their age group (2.72 out of 5).

5.2 Characteristics of Online Learners and Gig Workers

Prior to balancing on observable characteristics through propensity score weighting, there were notable differences between individuals who participate in online learning and those who did not. Most notably, individuals who participate in online learning are less likely to identify as White and more likely to identify as Black or Other. Additionally, individuals who participate in online learning were also more likely to come from both the youngest and oldest age quintiles. Finally, individuals who participate in online learning also had significantly lower levels of adjusted gross income and higher levels of federal tax refunds. Table 2a demonstrates unweighted group means, standardized effect sizes, and p-values for each covariate across individuals who participate in in online learning (treatment) and individuals who do not participate in online learning (control). As seen in model 2b, which demonstrates *propensity score weighted* group means, standardized effect sizes, and p-values for each covariate, these initial differences dissipated.

There were also notable differences between individuals who work in the gig economy and those who did not. Most notably, individuals who work in the gig economy are more likely to live in an urban location, less likely to identify as White and more likely to identify as Black. Additionally, individuals who participate in online learning were also more likely to come from younger (2nd) and middle (3rd) age quintiles, while being less likely to come from the oldest age quintile. Finally, individuals who participate in online learning also had significantly lower levels of adjusted gross income (Table 3a). After weighting on propensity scores, these differences dissipated as well (Table 3b).

5.3 Key Influences of Entrepreneurship: Online Learning and Gig Employment

Before accounting for selection into online learning with propensity score weights (Table 4, Series 1), individuals who participated in online learning had 77% greater odds of working in the gig economy and 76% greater odds of having entrepreneurial aspirations. When accounting for other model covariates (Table 4, Series 2), the influence of online learning increased, suggesting that some of the other model covariates may negatively confound part of the relationship between online learning and the outcomes under study. When accounting for selection into online learning with propensity score weights (Table 4, Series 3), the influence of online learning on gig employment and entrepreneurial aspirations was slightly less than Series 1, suggesting that when selection bias is not limited through propensity score weights, the influence of online learning is upwardly biased. Finally, when accounting for selection into online learning with propensity score weights and accounting for other model covariates (Table 4, Series 4), the influence of online learning on gig employment and entrepreneurial aspirations was slightly larger than Series 3, again suggesting that some of the model covariates may negatively confound the relationship between online learning and the outcomes under study.

The influence of gig employment on entrepreneurial aspirations followed a slightly different pattern. Before accounting for selection into gig employment with propensity score weights, individuals who worked in the gig economy had 213% greater odds of having entrepreneurial aspirations (Series 1). However, unlike online learning, when accounting for other model covariates (Series 2), the influence of gig employment slightly decreased, suggesting that part of the influence of gig employment on entrepreneurial aspirations is positively confounded by some of other the model covariates. Nevertheless, similar to online learning, when accounting for selection into gig employment with propensity score weights (Series 3), the influence of gig employment on entrepreneurial aspirations was slightly less than Series 1, suggesting that when selection bias is not limited through propensity score weights, the influence of gig employment is upwardly biased. Also similar to online learning, when accounting for selection into gig employment with propensity score weights and accounting for other model covariates (Series 4), the influence of gig employment on entrepreneurial aspirations was slightly larger than Series 3, again suggesting that some of the model covariates may negatively confound the relationship between gig employment and entrepreneurial aspirations.

Finally, when both online learning and gig employment predicted entrepreneurial aspirations, online learning lost significance when accounting for selection into gig employment with propensity score weights (Series 3 and 4). This suggests that part of the influence of online learning on entrepreneurial aspirations may be mediated by the balancing of selection effects associated with gig employment. This is to be expected when considering the strong relationships among online learning and gig employment. Together, these findings demonstrates the importance of limiting selection bias through propensity score weights, as well as isolating the influence of online learning by accounting for other—potentially confounding—model covariates.

5.4 Additional Model Covariates

5.4.1 Online Learning and Gig Employment

In addition online learning, identifying as Black or Asian was also associated with increased odds of gig employment when accounting for selection into online learning with propensity score weights (Appendix A, Model 1). We also see that having a certificate/technical degree and having a graduate school degree were both associated with increased odds of working in the gig economy. It is possible that students with high school degrees (or less) may not have the start-up resources (e.g., having a vehicle to work for a ride-share company) to engage in gig employment. Having high levels of unsecured debt were also associated with increased odds of working in the gig economy. Here, individuals may engage in gig work as a means to generate supplemental income in order to pay down debts.

Conversely, age, full-time student status, liquid assets, and adjusted gross income were associated with decreased odds of gig employment. As gig employment is mediated through technology, it is unsurprising that older individuals are less likely to work in the gig economy. As for students, we can assume that college students might be investing in their human capital in other ways. Here, it is important to note that even though our sample is LMI, students might come from higher income backgrounds and thus not need supplemental income. Finally, the relationships among liquid assets and income may suggest that gig employment may represent a consumption smoothing mechanism for individual and families with lower earnings and levels of wealth.

When not accounting for selection into online learning with propensity score weights, there were a few notable differences in the other model covariates (Appendix A, Model 2). First, identifying as Asian was no longer associated with increased odds of gig employment, suggesting that part of the influence of identifying as Asian on entrepreneurial aspirations is activated by the balancing of selection effects associated with online learning in Model 1. Here, it appears that once we balance online learning on observables in the selection model, which includes identifying as Asian as a covariate, its influence on entrepreneurial aspirations increases.

When not accounting for selection into online learning, working part-time and having student debt was now associated with increased odds of gig employment, suggesting that selection into online learning may be driving part of the influence of working part-time and having student debt in Model 2. Considering Model 1, part of the influence of working part-time and having student debt on gig employment may be mediated by the balancing of selection effects associated with online learning. Here it is also important to note that in addition being a full-time student, being a part-time student was now associated with decreased odds of gig employment, suggesting that these influences on gig employment may also be partly driven by driven by selection into online learning.

More subtle changes occurred across student status, education level, unsecured debt levels and liquid assets quartiles. For example, while having a certificate/technical degree (relative to having a high school diploma) was no longer associated with gig employment, all other education levels were now associated with increased odds of gig employment, suggesting that part of the influence of higher levels of education may be mediated by the balancing of selection effects associated with online learning. All levels of unsecured debt were also associated with increased odds of gig employment in Model 2, and while the first quartile of liquid assets was no longer associated with gig employment, the second quartile of liquid assets was now associated with decreased odds of gig employment. In each case, this suggests that part of the influence of unsecured debt and liquid assets on gig employment may be mediated by the balancing of selection effects associated with online learning.

5.4.2 Online Learning and Entrepreneurial Aspirations

In addition to online learning, identifying as Black, Asian or Other, living in an urban location, being married or having a partner, and having a certificate/technical degree were associated with increased odds of entrepreneurial aspirations when accounting for selection into online learning with propensity score weights (Appendix B, Model 3). These findings may be explained by the barriers in formal labor markets for many minority groups, the prevalence of business resources in urban areas, the support of spouses and partners, and the aspirations that are often associated with higher education levels—each of which can contribute to increased entrepreneurial aspirations. Conversely, the number of dependents in a household and being in the highest liquid asset quartile were associated with decreased odds of entrepreneurial aspirations. Here, individuals with greater familial responsibilities may not be able to take on the risk associated with starting a new business or non-profit, while individuals with higher liquid assets may not have the need or desire to take on additional risks. Finally, having worse perceptions of health were associated with a decrease in entrepreneurial aspirations, which may indicate a greater need or desire for stability among individuals with poor health.

When not accounting for selection into online learning with propensity score weights, there were a few notable differences in the other model covariates (Appendix B, Model 4). Being Asian, living in an urban location, being married or having a partner, and number of dependents was no longer associated with increased odds of entrepreneurial aspirations in Model 4, suggesting that part of their influence on entrepreneurial aspirations is activated by the balancing of selection effects associated with online learning in Model 3. Here, it appears that once we balance online learning on observables in the selection model, which either include or are strongly related to these covariates, their influence on entrepreneurial aspirations increases. Additionally, being male and having student debt were associated with increased odds of entrepreneurial aspirations in the unweighted model, while being a full-time student and having health insurance were associated with decreased odds of entrepreneurial aspirations. This suggests that part of their influence occurs through the balancing of selection effects associated with online learning. Finally, more subtle changes occurred across student status and liquid assets quartiles. For example, all education levels were associated with increased odds of entrepreneurial aspirations, while liquid assets quartile three and four were associated with decreased odds of entrepreneurial aspirations, suggesting that part of their influence on entrepreneurial aspirations may be mediated by the balancing of selection effects associated with online learning.

5.4.3 Gig Employment and Entrepreneurial Aspirations

In addition to gig employment, identifying as Black or Other and having a certificate or technical degree were also associated with increased odds of entrepreneurial aspirations when accounting for selection into gig employment with propensity score weights (Appendix C, Model 5). At the same time, higher liquid asset quartiles and having worse perceptions of health were associated with a decrease in entrepreneurial aspirations

When not accounting for selection into online learning with propensity score weights, there were a few notable differences in the other model covariates (Appendix C, Model 6). For example, being male and having student debt were now associated with an increase in the odds of entrepreneurial aspirations, while having health insurance was now associated with a decrease in entrepreneurial aspirations. Moreover, educational attainment beyond a high school diploma was associated with an increase in entrepreneurial aspirations in Model 6.

5.4.4 Gig Employment, Online Learning, and Entrepreneurial Aspirations

When not accounting for selection into gig employment with propensity score weights, being a full-time student was significantly associated with a decrease in entrepreneurial aspirations in Model 8 (Appendix D). All other model covariates in Models 7 and 8 had relationships that were similar to their respective models that did not include online learning (Models 5 and 6).

5.5 Between-State Variation

There was a significant amount of variation left unexplained at the state level in every propensity score-weighted model. This level of between-state variation could due to different regulations concerning gig-employment between states, as well as different business-startup environments in different states. However, it is also important to note that when propensity score weights were not included, there was not a significant amount of variation left unexplained at the state level, which suggests that when we account for individual-level characteristics associated with selection into online learning and gig employment *within* states, the differences *between* states increases. In other words, selection into online learning is negatively correlated with differences in gig employment between states; the same can be said of selection into gig employment and differences in entrepreneurial aspirations between states. One potential explanation is that in states with high levels of gig employment, selection into online learning becomes slightly less important in predicting gig employment, as there may be greater efforts to increase gig employment regardless of individual propensities towards online learning. Here, in states with high proportions of individuals working in the gig economy, there may be slightly fewer individuals with propensities towards online learning than we would expect, which may bring down the average likelihood of individuals working in the gig economy. Thus, these states may appear less extreme. As a result, gig employment would appear more similar across states when not accounting for selection into online learning, which would explain why the overall amount of between-state variation is not significant in models where propensity score weights are not included.

5.6 Robustness Checks

In order to assess the robustness of our results, we run two separate robustness checks (Table 9). First, we limit the sample to all students to see if the influence of online learning is a product of technology-mediated human capital development *or* a product human capital development more broadly. We find that that influence of online learning on gig employment and entrepreneurial aspirations is highly similar to that of the full sample. This suggests that the influence of online learning is not solely a product of human capital investments in education, but rather those human capital investments that are mediated by technology. Through technology, these types of learning programs often offer additional levels of flexibility and variety at a lower cost than traditional college courses and programs. Additionally, digital literacy may be an important factor in entrepreneurial aspirations as well. Next, we limit the sample to part-time workers to see if the influence of gig employment is a product of technology-induced slack time (and other experiences that may prepare individuals for entrepreneurial activities) *or* a slack time more broadly. Again, we find that the influence of gig employment on entrepreneurial aspirations is nearly identical to that of the full sample. This suggests that the influence of gig employment is not solely a product of having “slack” time, but rather experiences that may prepare them for entrepreneurial activities, such as managing their own schedule and income flows. While future research is needed to disentangle the key mechanisms of impact on entrepreneurial aspirations within online learning and gig employment, we do provide some initial mechanism checks for gig employment and entrepreneurial aspirations in the following section.

5.7 Mechanism Checks

In order to better understand the mechanism by which gig employment influences entrepreneurial aspirations, we run four separate models (Table 10) that contain the perceived value of working in the gig economy. In each model we limit the participants to individuals that participate in the gig economy. In the first model, we focus on whether individuals working in the gig economy value the flexibility that gig work provides them, but it was not significantly related to entrepreneurial aspirations. In the second model, we focus on whether individuals working in the gig economy value the control that gig work gives them over their schedule, but it was also not significantly related to entrepreneurial aspirations. In the third model, we focus on whether individuals working in the gig economy value the ability for gig work to fill in income gaps, but, likewise, it was not significantly related to entrepreneurial aspirations. In the final model, we focus on whether individuals working in the gig economy value the ability for gig work to help them gain work experience for future job opportunities, and it *was* significantly related to entrepreneurial aspirations. This suggests that the mechanism by which gig employment influences entrepreneurial aspirations is through informal skill development and job preparation.

6 Discussion

Rapid advances in technology have altered the pathways through which individuals can build their human capital. This is true for both formal skill development opportunities such as the pursuit of certificates or degrees, as well as for informal skill development opportunities, such as the business skills often required to be successful in the gig economy (e.g., schedule management, budgeting, branding, marketing, etc.). These technology-mediated pathways will likely continue to grow in the future. Between 2011 and 2016, the rate of undergraduate students taking any classes online increased from 32% to 43%, and this number may increase further yet as a result of the COVID-19 pandemic making online education a necessity rather than one of several options (U.S. Department of Education, 2016). Though fewer people overall participate in the gig economy than in online education, this type of employment is growing rapidly. By one measure, the rate of gig economy participation in a given quarter increased from 0.3% to 1.6% between 2013 and 2018, with 4.5% of households earning any gig income at all during the year in 2018 (Chase, 2018).

While these technological advances often promise increased economic mobility, there is limited research on the mechanisms by which they may do so. Existing research on the impacts of these tools often concerns evaluating their direct effects, such as the efficacy of online learning relative to traditional classroom settings (e.g., Means, Toyama, Murphy, Bakia, & Jones, 2009; Ngueyen, 2015), or assessing the effect of gig economy access on employment dynamics (Burtch et al., 2018) and household well-being indicators (Daniels & Grinstein-Weiss, 2018). Our work extends this literature by assessing the relationship between these technology-mediated human capital investments and LMI individuals' plans to engage in entrepreneurship, which is one of the ways in which LMI households may become more economically mobile

Specifically, we proposed two primary pathways by which these technology-mediated human capital investments influence entrepreneurial aspirations: Human capital and skill development, and increased slack resources, which we define as the time available to individuals as a result of the flexibility and autonomy inherent in online education and gig work. To test the relationships between gig employment, online learning, and entrepreneurial aspirations, we first employed generalized boosted modeling to estimate and correct for the differential propensity of individuals to select into online learning and gig employment, and then used logistic regression techniques to generate selected-corrected estimates of these relationships.

We found that, individually, both online learning and gig employment were significantly and substantially related to entrepreneurial aspirations. After accounting for differential selection into these technology-mediated human capital investment options, the odds of an individual engaged in online learning having entrepreneurial aspirations were more than double those of someone not engaged in online learning, and the odds of an individual working in the gig economy having entrepreneurial aspirations were more than triple of someone not working in this sector. However, when we included both online learning and gig employment in our model, only gig employment remained significantly associated with entrepreneurial aspirations, potentially indicating that both gig employment and online learning influence entrepreneurial aspirations along similar pathways.

We proposed two distinct mechanisms by which online education and gig employment may affect entrepreneurial aspirations: human capital and skill development (Mechanism 1); and slack resources (Mechanism 2), defined as increased income, time, or flexibility. While this exploratory research is unable to fully disentangle the mechanisms driving the relationships between online education, gig employment, and entrepreneurial aspirations, we were able to leverage our survey data to investigate the relationship between households' motivations for gig employment and gig aspirations. Three of the motivations we explored in the survey—extra income, increased flexibility, and control over schedules—may be seen a desire for different types of slack resources, while doing gig work to gain experience for future job opportunities may be seen as a desire for human capital and skill development. Of the different motivations we assessed, only a desire to gain experience for future job opportunities was significantly associated with entrepreneurial aspirations. These results are reinforced by a robustness analysis in which we restrict our sample to part-time workers—who likely have more free time than full-time workers. In that analysis, we found very similar results to those in the full sample, indicating that slack time *alone* may not be driving entrepreneurial aspirations. These results may indicate that, as far as gig employment is concerned, the development of skills and human capital may be the stronger pathway toward developing entrepreneurial skills and aspirations. As far as online learning is concerned, while we cannot test specific mechanisms within it, we do know from a similar robustness analysis—in which we limit the sample to students—that technology plays an important role in its relationship with entrepreneurship.

We should also note several other limitations in this study. First, we examine entrepreneurial intentions rather than actual entrepreneurship; due to our cross-sectional survey, we cannot directly measure actual rates of business startups *following* online education enrollment or gig employment, which limits our ability to make inferences about future entrepreneurial behaviors. Second, as our data come from a cross-sectional survey, we cannot make any causal inferences about the relationship between engagement with technology-meditated human capital investment platforms and entrepreneurial intentions. In particular, we cannot assess the degree to which unobserved factors may correlate with both the decision to engage in online education or gig employment and with entrepreneurial aspirations, which may bias our results. While we do employ propensity score weighting techniques to reduce selection bias in our estimates, we cannot fully account for the potential role of any unobserved factors.

Finally, our data our drawn from a survey of LMI tax filers administered after tax filing. While the novelty of the measures we use in our analysis justifies the use of this sample, our results should not be interpreted as generalizable to the full U.S. population.

Despite these limitations, this research highlights a relatively unexamined pathway between these technology-mediated human capital investments and economic mobility. While gig employment is often seen as a way to earn income for people who want or need scheduling flexibility and online education is seen as a cheaper and more accessible way to build human capital and increase future earnings, we observe that they also correspond with a desire to engage in entrepreneurship. Thus, these households may see these avenues as a starting point for building a business and meeting their economic needs outside of traditional wage-labor arrangements. Further, we observe that there appears to be something unique to the technological aspect of these arrangements; gig workers have higher rates of entrepreneurial aspirations than non-gig workers, and online students have higher rates of entrepreneurial aspirations than traditional students. This may present an opportunity for schools offering online courses to build an entrepreneurial focus into their curriculum or their career services supports. Similarly, gig platforms may be able to help workers by providing explicit skill development or mentorship opportunities around entrepreneurship.

Future research in this area should further examine the degrees to which technology-mediated human capital investment platforms may attract, encourage, and support aspiring entrepreneurs. For example, the construction of longitudinal datasets that allow for the measurement of the relationships between enrolling in online education or engaging in gig work and subsequent rates of business ownership would allow for the examination of participation in these platforms and actual entrepreneurship, as opposed to the entrepreneurial intentions measured in this paper.

References

Acs, Z. J., & Kallas, K. (2008). State of Literature on Small to Medium-Size Enterprises and Entrepreneurship in Low-Income Communities. In *Entrepreneurship in Emerging Domestic Markets* (pp. xi–xii). https://doi.org/10.1017/cbo9780511805950.001

Agrawal, A., Catalini, C., Goldfarb, A., & Luo, H. (2018). Slack Time and Innovation. *Organization Science*, *29*(6), 1056–1073.

Allen, E., & Seaman, J. (2002). Class differences: Online Education in the United States, 2010. *Babson Survey Research Group*, *16*(18), 21–21. https://doi.org/10.7748/ns.16.18.21.s38

Austin, P. C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behavioral Research*, *46*(3), 399–424. https://doi.org/10.1080/00273171.2011.568786

Bang, H., & Robins, J. M. (2005). Doubly robust estimation in missing data and causal inference models. *Biometrics*, *61*(4), 962–973. https://doi.org/10.1111/j.1541-0420.2005.00377.x

Bartel, A., Ichniowski, C., & Shaw, K. (2007). How does information technology affect productivity? Plant-level comparisons of product innovation, process improvement, and worker skills. *Quarterly Journal of Economics*, *122*(4), 1721–1758. https://doi.org/10.1162/qjec.2007.122.4.1721

Baum, J. R., Locke, E. A., & Smith, K. E. N. G. (2016). A Multidimensional Model of Venture Growth Author (s): J . Robert Baum , Edwin A . Locke and Ken G . Smith Published by : Academy of Management Stable URL : http://www.jstor.org/stable/3069456 REFERENCES Linked references are available on JSTOR for this. *Academy of Management Journal*, *44*(2), 292–303.

Block, J., & Koellinger, P. (2009). I can’t get no satisfaction - Necessity entrepreneurship and procedural utility. *Kyklos*, *62*(2), 191–209. https://doi.org/10.1111/j.1467-6435.2009.00431.x

Bolívar-Ramos, M. T., García-Morales, V. J., & García-Sánchez, E. (2012). Technological distinctive competencies and organizational learning: Effects on organizational innovation to improve firm performance. *Journal of Engineering and Technology Management - JET-M*, *29*(3), 331–357. https://doi.org/10.1016/j.jengtecman.2012.03.006

Bourgeois, L. J. (1981). On the Measurement of Organizational Slack. *Academy of Management Review*, *6*(1), 29–39. https://doi.org/10.5465/amr.1981.4287985

Bradley, S. W., Wiklund, J., & Shepherd, D. A. (2011). Swinging a double-edged sword: The effect of slack on entrepreneurial management and growth. *Journal of Business Venturing*, *26*(5), 537–554. https://doi.org/10.1016/j.jbusvent.2010.03.002

Broughton, A., Gloster, R., Marvell, R., Green, M., Langley, J., & Martin, A. (2018). The experiences of individuals in the gig economy. *Department for Business, Energy & Industrial Strategy (BEIS)*, (February), 108. Retrieved from https://www.gov.uk/government/publications/gig-economy-research

Brush, C. G., Greene, P. G., & Hart, M. M. (2002). From initial idea to unique advantage: The entrepreneurial challenge of constructing a resource base. *IEEE Engineering Management Review*, *30*(1), 86–99. https://doi.org/10.1109/EMR.2002.1022409

Burtch, G., Carnahan, S., & Greenwood, B. N. (2018). Can you gig it? An empirical examination of the gig economy and entrepreneurial activity. *Management Science*, (November 2019), 5497–5520. https://doi.org/10.1287/mnsc.2017.2916

Capra, T. (2011). Online Education: Promise and Problems. *MERLOT Journal of Online Learning and Teaching*, *7*(2).

Chase, J. M. (2018). *The Online Platform Economy in 2018 About the Institute*. (September).

Chee, K. N., Yahaya, N., Ibrahim, N. H., & Noor, M. (2017). Review of Mobile Learning Trends 2010-2015 : A Meta-Analysis. *Journal of Educational Technology & Society*, *20*(2), 113–126.

Cyart, R., & March, J. (1963). *A Behavioral Theory of the Firm*.

Daniels, K., & Grinstein-Weiss, M. (2018). The Impact of the Gig-Economy on Financial Hardship Among Low-Income Families. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3293988

Deloitte. (2017). *Connecting Small Businesses in the US*.

Dokko, J., Mumford, M., & Schanzenbach, D. W. (2015). Workers and the Online Gig Economy. *The Hamilton Project*, 1–8. Retrieved from http://www.hamiltonproject.org/assets/files/workers_and_the_online_gig_economy.pdf

Drake, C. (1993). Effects of Misspecification of the Propensity Score on Estimators of Treatment Effect. *Biometrics*, *49*(4), 1231–1236.

Fairlie, R. W. (2002, July). Drug Dealing and Legitimate Self-Employment. *Journal of Labor Economics*, Vol. 20, pp. 538–567. https://doi.org/10.1086/339610

Freedman, D. A., & Berk, R. A. (2008). Weighting regressions by propensity scores. *Evaluation Review*, *32*(4), 392–409. https://doi.org/10.1177/0193841X08317586

Friedman, G. (2014). Workers without employers: Shadow corporations and the rise of the gig economy. *Review of Keynesian Economics*, *2*(2), 171–188. https://doi.org/10.4337/roke.2014.02.03

Guo, S., & Fraser, M. (2014). *Propensity score analysis: Statistical methods and applications*.

Hall, J. V., & Krueger, A. B. (2018). An Analysis of the Labor Market for Uber's Driver-

Partners in the United States. *ILR Review*, *71*(3), 705–732. https://doi.org/10.1177/0019793917717222

Jaggars, S. S., & Bailey, T. (2010). Effectiveness of fully online courses for college students : Response to a Department of Education meta-analysis. *New York*, (July), 18. https://doi.org/http://dx.doi.org/10.7916/D85M63SM

Koellinger, P. (2008). The relationship between technology, innovation, and firm performance-Empirical evidence from e-business in Europe. *Research Policy*, *37*(8), 1317–1328. https://doi.org/10.1016/j.respol.2008.04.024

Kraatz, M. S., & Zajac, E. J. (2001). How Organizational Resources Affect Strategic Change and Performance in Turbulent Environments: Theory and Evidence. *Organization Science*, *12*(5), 632–657. https://doi.org/10.1287/orsc.12.5.632.10088

Lawson, M. B. (2001). In praise of slack: Time is of the essence. *Academy of Management Perspectives*, *15*(3).

Lehdonvirta, V. (2018). Flexibility in the gig economy: managing time on three online piecework platforms. *New Technology, Work and Employment*, *33*(1), 13–29. https://doi.org/10.1111/ntwe.12102

Levinthal, D., & March, J. G. (1981). A model of adaptive organizational search. *Journal of Economic Behavior and Organization*, *2*(4), 307–333. https://doi.org/10.1016/0167-2681(81)90012-3

Martín-Rojas, R., García-Morales, V. J., & Bolívar-Ramos, M. T. (2013). Influence of technological support, skills and competencies, and learning on corporate entrepreneurship in European technology firms. *Technovation*, *33*(12), 417–430. https://doi.org/10.1016/j.technovation.2013.08.002

Martin, A., & Grudziecki, J. (2006). DigEuLit: Concepts and Tools for Digital Literacy Development. *Innovation in Teaching and Learning in Information and Computer Sciences*, *5*(4), 249–267. https://doi.org/10.11120/ital.2006.05040249

McCaffrey, D. F., Ridgeway, G., & Morral, A. R. (2004). Propensity score estimation with boosted regression for evaluating causal effects in observational studies. *Psychological Methods*, *9*(4), 403–425. https://doi.org/10.1037/1082-989X.9.4.403

McLoughlin, C., & Lee, M. (2008). The Three P's of Pedagogy for the Networked Society: Personalization, Participation, and Productivity. *International Journal of Teaching and Learning in Higher Education*, *20*(1). https://doi.org/10.1017/s1537592709991423

Means, B., Toyama, Y., Murphy, R., Bakia, M., & Jones, K. (2009). Evaluation of Evidence-Based Practices in Online Learning. *Structure*, 66. Retrieved from www.ed.gov/about/offices/list/opepd/ppss/reports.html

Nambisan, S. (2017). Digital Entrepreneurship: Toward a Digital Technology Perspective of Entrepreneurship. *Entrepreneurship: Theory and Practice*, *41*(6), 1029–1055. https://doi.org/10.1111/etap.12254

Nguyen, T. (2015). The Effectiveness of Online Learning: Beyond No Significant Difference and Future Horizons. *MERLOT Journal of Online Learning and Teaching*, *11*(2), 309–319.

Nohria, N., & Gulati, R. (1996). Is slack good or bad for innovation? *Academy of Management Journal*, *39*(5), 1245–1264. https://doi.org/10.2307/256998

Ridgeway, G., Morral, A. R., Griffin, B. A., & Burgette, L. F. (2014). Toolkit for Weighting and Analysis of Nonequivalent Groups (TWANG). *RAND*, 1–31. Retrieved from https://www.rand.org/statistics/twang.html%0Ahttp://www.rand.org/statistics/twang

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1). https://doi.org/10.1017/CBO9780511810725.016

Shane, S., & Venkatraman, S. (2000). The Promise of Entrepreneurship and Economic Growth. *Small Business Economics*, *13*.

Singh, J. V. (1986). Performance, Slack, and Risk Taking in Organizational Decision Making. *Academy of Management Journal*, *29*(3), 562–585. https://doi.org/10.5465/256224

Storey, D. J. (1991, September). The birth of new firms-Does unemployment matter? A review of the evidence. *Small Business Economics*, Vol. 3, pp. 167–178. https://doi.org/10.1007/BF00400022

U.S. Department of Education, N. C. for E. S. (2016). *National Postsecondary Aid Study*.

Unger, J. M., Rauch, A., Frese, M., & Rosenbusch, N. (2011). Human capital and entrepreneurial success: A meta-analytical review. *Journal of Business Venturing*, *26*(3), 341–358. https://doi.org/10.1016/j.jbusvent.2009.09.004

Velez-Grajales, V., & Velez-Grajales, R. (2012). Intergenerational Mobility and Income Effects for Entrepreneurial Activity in Mexico. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2156790

Voss, G. B., Sirdeshmukh, D., & Voss, Z. G. (2008). The Effects of Slack Resources and Environmental Threat on Product Exploration and Exploitation. *The Academy of Management Journal*, *51*(1), 147–164.

Wu, J. J., & Atkinson, R. D. (2018). How Technology-Based Start-Ups Support U.S. Economic Growth. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3079624

Table 1. Sample Characteristics (N = 8,528)

VARIABLES	MEAN	SD	MIN	MAX
Entrepreneurial Aspirations	0.06		0.00	1.00
Gig Employment	0.06		0.00	1.00
Online Learning	0.09		0.00	1.00
Male	0.48		0.00	1.00
Race/Ethnicity				
White	0.73		0.00	1.00
Black	0.06		0.00	1.00
Asian	0.05		0.00	1.00
Hispanic	0.10		0.00	1.00
Other	0.06		0.00	1.00
Urban Location	0.86		0.00	1.00
Age	33.18	14.31	18.00	75.00
Has Dependents	0.17		0.00	1.00
Number of Dependents	0.29	0.70	0.00	3.00
Is Married/Has Partner	0.26		0.00	1.00
Filing Status				
Married Filing Jointly	0.10		0.00	1.00
Other Filing Status	0.11		0.00	1.00
Single Filing Status	0.80		0.00	1.00
Student Status				
Not a Student	0.67		0.00	1.00
Part-Time Student	0.06		0.00	1.00
Full-Time Student	0.26		0.00	1.00
Education Level				
High School (or less)	0.16		0.00	1.00
Certificate/Technical Degree	0.04		0.00	1.00
Some College	0.30		0.00	1.00
Associate's Degree	0.09		0.00	1.00
Bachelor's Degree	0.25		0.00	1.00
Some Graduate School	0.06		0.00	1.00
Graduate School Degree	0.09		0.00	1.00
Employment Status				
Not Currently Working	0.21		0.00	1.00
Working Part-Time	0.34		0.00	1.00
Working Full-Time	0.45		0.00	1.00
Owns Home	0.20		0.00	1.00
Owns Car	0.67		0.00	1.00
Has Student Debt	0.47		0.00	1.00
Unsecured Debt	$3,602	$5,249	$1.00	$25,000
Liquid Assets	$4,679	$10,029	$0.00	$69,500
Adjusted Gross Income	$16,200	$10,510	$0.00	$64,190
Federal Tax Refund	$1,501	$1,852	0.00	$8,937
Has Health Insurance	0.90		0.00	1.00
Perceived Health Score	2.72	1.04	1.00	5.00

Table 2. Propensity Score Estimation Model Variables: Online Learning
Table 2a: Unweighted Variables (N = 8,528)

VARIABLES	Online Learning means (SD)		*No* Online Learning means (SD)		Std. Eff. Size	P-value
Gender: Male	0.447		0.479		-0.064	0.094
Urban Location	0.877		0.861		0.048	0.189
Race/Ethnicity						
White	0.673		0.733		-0.135	0.001
Black	0.083		0.053		0.130	0.004
Hispanic	0.119		0.099		0.065	0.109
Asian	0.044		0.055		-0.05	0.150
Other	0.081		0.059		0.092	0.033
Age						
Quintile 1 (18-22)	0.419		0.213		0.487	0.000
Quintile 2 (23-25)	0.188		0.177		0.028	0.473
Quintile 3 (26-31)	0.196		0.210		-0.035	0.355
Quintile 4 (32-45)	0.144		0.190		-0.119	0.001
Quintile 5 (46-75)	0.053		0.209		-0.393	0.000
Has Dependents	0.167		0.175		-0.023	0.536
Filing Status						
Single	0.811		0.795		0.039	0.295
Married Filing Jointly	0.092		0.099		-0.023	0.543
Head of Household	0.097		0.106		-0.029	0.429
Adjusted Gross Income	$14,900	($10,860)	$16,320	($10,470)	-0.135	0.001
Federal Tax Refund	$1,666	($1,972)	$1,486	($1,839)	0.097	0.016

Note: P-value is based off a t-statistic for continuous variables and a chi-squared statistic for a categorical variable.

Table 2. Propensity Score Estimation Model Variables: Online Learning

Table 2b: Weighted Variables (N = 8,528)

VARIABLES	Online Learning means (SD)		*No* Online Learning means (SD)		Std. Eff. Size	P-value
Gender: Male	0.458		0.477		-0.038	0.443
Urban Location	0.847		0.862		-0.044	0.477
Race/Ethnicity						
White	0.716		0.729		-0.029	0.545
Black	0.057		0.055		0.011	0.775
Hispanic	0.109		0.100		0.029	0.560
Asian	0.060		0.055		0.023	0.700
Other	0.057		0.061		-0.014	0.691
Age						
Quintile 1 (18-22)	0.255		0.230		0.061	0.133
Quintile 2 (23-25)	0.193		0.178		0.040	0.378
Quintile 3 (26-31)	0.222		0.209		0.032	0.509
Quintile 4 (32-45)	0.169		0.187		-0.046	0.334
Quintile 5 (46-75)	0.161		0.197		-0.091	0.197
Has Dependents	0.164		0.175		-0.030	0.538
Filing Status						
Single	0.796		0.796		-0.001	0.984
Married Filing Jointly	0.109		0.098		0.040	0.525
Head of Household	0.095		0.106		-0.037	0.431
Adjusted Gross Income	$15,570	($9,956)	$16,190	($10,490)	-0.059	0.186
Federal Tax Refund	$1,499	($1,888)	$1,499	($1,851)	0.00	0.999

Note: P-value is based off a t-statistic for continuous variables and a chi-squared statistic for a categorical variable.

Table 3. Propensity Score Estimation Model Variables: Gig Employment

Table 3a: Unweighted Variables (N = 8,528)

VARIABLES	Gig Employment means (SD)		*No* Gig Employment means (SD)		Std. Eff. Size	P-value
Gender: Male	0.452		0.477		-0.051	0.278
Urban Location	0.895		0.860		0.101	0.017
Race/Ethnicity						
White	0.672		0.731		-0.133	0.007
Black	0.090		0.053		0.161	0.006
Hispanic	0.120		0.100		0.067	0.187
Asian	0.053		0.055		-0.009	0.849
Other	0.065		0.061		0.017	0.721
Age						
Quintile 1 (18-22)	0.202		0.233		-0.074	0.099
Quintile 2 (23-25)	0.246		0.174		0.187	0.000
Quintile 3 (26-31)	0.265		0.206		0.146	0.004
Quintile 4 (32-45)	0.179		0.187		-0.020	0.660
Quintile 5 (46-75)	0.109		0.201		-0.231	0.000
Has Dependents	0.168		0.175		-0.019	0.690
Filing Status						
Single	0.809		0.796		0.033	0.476
Married Filing Jointly	0.105		0.098		0.025	0.613
Head of Household	0.086		0.107		-0.067	0.123
Adjusted Gross Income	$14,790	($9,878)	$16,280	($10,540)	-0.142	0.001
Federal Tax Refund	$1,457	($1,781)	$1,505	($1,856)	-0.026	0.573

Note: P-value is based off a t-statistic for continuous variables and a chi-squared statistic for a categorical variable.

Table 3. Propensity Score Estimation Model Variables: Gig Employment

Table 3b: Weighted Variables (N = 8,528)

VARIABLES	Gig Employment means (SD)		*No* Gig Employment means (SD)		Std. Eff. Size	P-value
Gender: Male	0.454		0.477		-0.047	0.347
Urban Location	0.884		0.861		0.068	0.159
Race/Ethnicity						
White	0.715		0.730		-0.032	0.515
Black	0.059		0.055		0.017	0.691
Hispanic	0.117		0.100		0.056	0.278
Asian	0.054		0.055		-0.003	0.944
Other	0.055		0.061		-0.025	0.576
Age						
Quintile 1 (18-22)	0.214		0.233		-0.045	0.351
Quintile 2 (23-25)	0.204		0.177		0.070	0.144
Quintile 3 (26-31)	0.231		0.208		0.058	0.241
Quintile 4 (32-45)	0.185		0.186		-0.003	0.951
Quintile 5 (46-75)	0.167		0.197		-0.076	0.164
Has Dependents	0.170		0.175		-0.011	0.833
Filing Status						
Single	0.806		0.796		0.023	0.644
Married Filing Jointly	0.107		0.097		0.034	0.534
Head of Household	0.087		0.106		-0.063	0.181
Adjusted Gross Income	$16,050	($10,090)	$16,220	(10,520)	-0.016	0.744
Federal Tax Refund	$1,488	($1,799)	$1,502	($1,854)	-0.008	0.872

Note: P-value is based off a t-statistic for continuous variables and a chi-squared statistic for a categorical variable.

Table 4. Gig Employment, Online Learning, and their Relationships with Entrepreneurial Aspirations

	GIG EMPLOYMENT	ENTREPRENEURIAL ASPIRATIONS		
		Online Learning Only	Gig Employment Only	Online + Gig
Series 1: Non PS-Weighted (No Controls)				
Gig Employment			3.126***(0.414)	3.035***(0.404)
Online Learning	1.767***(0.243)	1.755***(0.227)		1.665***(0.217)
State Rand. Int. Variance	1.000(0.000)	1.000(0.000)	1.000(0.000)	1.000(0.000)
Pseudo R-Squared	0.01	0.01	0.02	0.03
Observations	8,528	8,528	8,528	8,528
Series 2: Non PS-Weighted (Full Controls)				
Gig Employment			2.800***(0.388)	2.707***(0.377)
Online Learning	2.321***(0.418)	1.998***(0.338)		1.872***(0.320)
State Rand. Int. Variance	1.000(0.000)	1.000(0.000)	1.000(0.000)	1.000(0.000)
Pseudo R-Squared	0.15	0.11	0.11	0.12
Observations	8,528	8,528	8,528	8,528
Series 3: PS-Weighted (No Controls)				
Gig Employment			3.048***(0.464)	3.036***(0.463)
Online Learning	1.669***(0.230)	1.669***(0.243)		1.107(0.310)
State Rand. Int. Variance	1.447**(0.190)	1.496**(0.204)	2.043***(0.350)	2.049***(0.354)
Pseudo R-Squared	0.05	0.06	0.13	0.13
Observations	8,528	8,528	8,528	8,528
Series 4: PS-Weighted (Full Controls)				
Gig Employment			3.343***(0.602)	3.321***(0.594)
Online Learning	2.334***(0.513)	2.144***(0.319)		1.141(0.445)
State Rand. Int. Variance	1.481***(0.153)	1.466**(0.172)	2.053***(0.399)	2.062***(0.405)
Pseudo R-Squared	0.22	0.18	0.24	0.24
Observations	8,528	8,528	8,528	8,528

Notes: Results presented as odds ratios, with robust standard errors in parentheses.
Pseudo R-Squared estimates are based on McKelvey and Zaviona's (1975) formulations.
*** p<0.001, ** p<0.01, * p<0.05

Table 5. Robustness Checks

	GIG EMPLOYMENT		ENTREPRENEURIAL ASPIRATIONS		ENTREPRENEURIAL ASPIRATIONS	
	Full Sample	Students	Full Sample	Students	Full Sample	Part-Time Workers
Online Learning Only						
Odds Ratio	2.334***	2.639***	2.144***	2.106***		
Standard Error	(0.513)	(0.734)	(0.319)	(0.359)		
Controls Included	Yes	Yes	Yes	Yes		
State REs Included	Yes	Yes	Yes	Yes		
PS Weights Included	Yes	Yes	Yes	Yes		
Pseudo R-Squared	0.22	0.35	0.18	0.32		
Observations	8,528	2,807	8,528	2,807		
Gig Employment Only						
Odds Ratio					3.343***	3.307***
Standard Error					(0.602)	(1.072)
Controls Included					Yes	Yes
State REs Included					Yes	Yes
PS Weights Included					Yes	Yes
Pseudo R-Squared					0.24	0.40
Observations					8,528	2,912

Note: Pseudo R-Squared estimates are based on McKelvey and Zaviona's (1975) formulations.

*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table 6. Mechanism Checks: Views on the Value of GIG Work

	ENTREPRENEURIAL ASPIRATIONS	
	Value of GIG: To Have Flexibility	Value of GIG: To Have Control Over Schedule
Odds Ratio	0.479	1.057
Standard Error	(0.238)	(0.457)
Controls Included	Yes	Yes
State REs Included	No	No
PS Weights Included	No	No
Pseudo R-Squared	0.11	0.10
Observations	474	472
	Value of GIG: To Fill In Income Gaps	Value of GIG: To Gain Experience for Future Jobs
Odds Ratio	1.090	2.033*
Standard Error	(0.354)	(0.572)
Controls Included	Yes	Yes
State REs Included	No	No
PS Weights Included	No	No
Pseudo R-Squared	0.10	0.12
Observations	473	473

*** p<0.001, ** p<0.01, * p<0.05

Figure 3. Boxplot of Propensity Scores: Online Learning

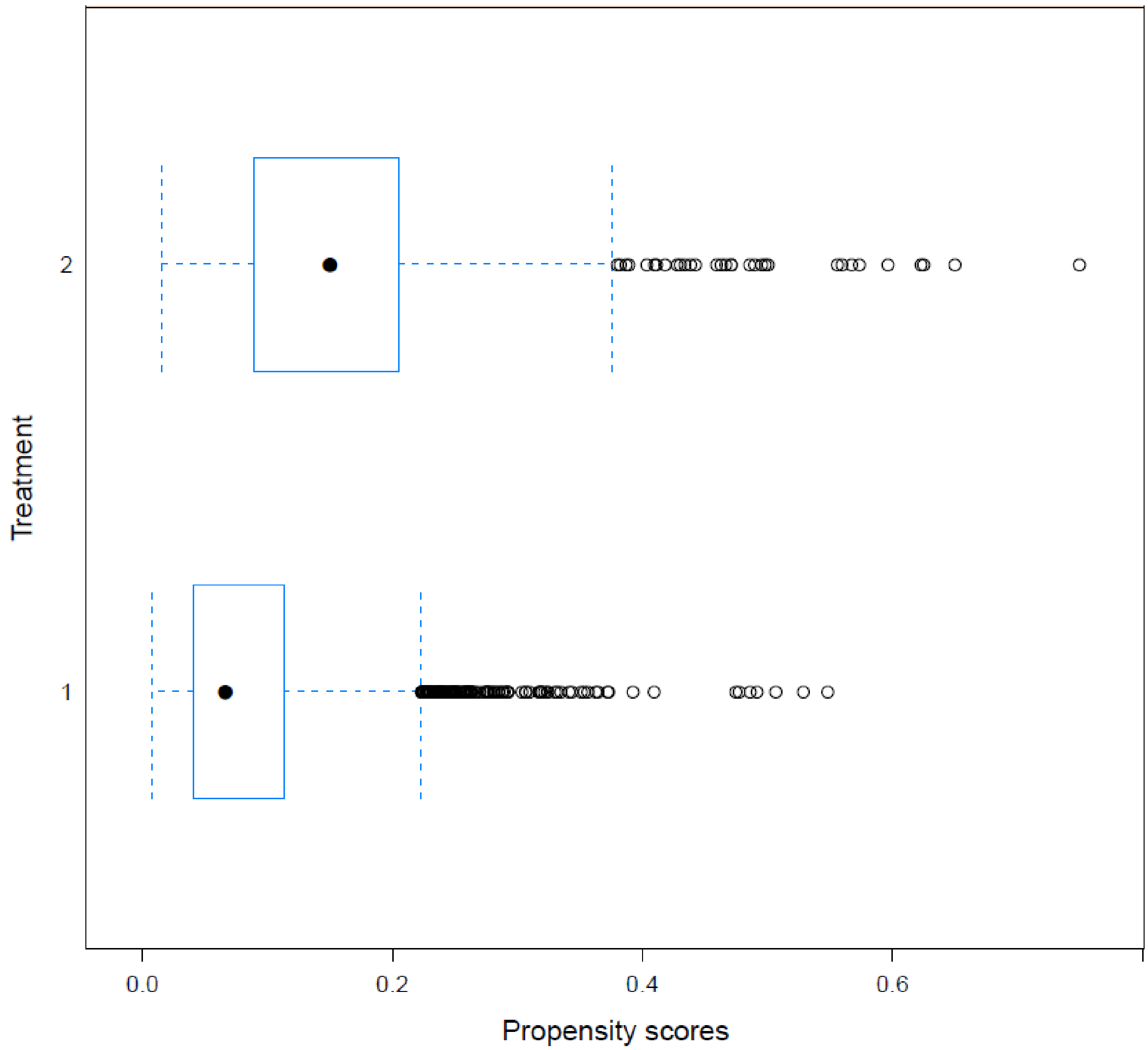
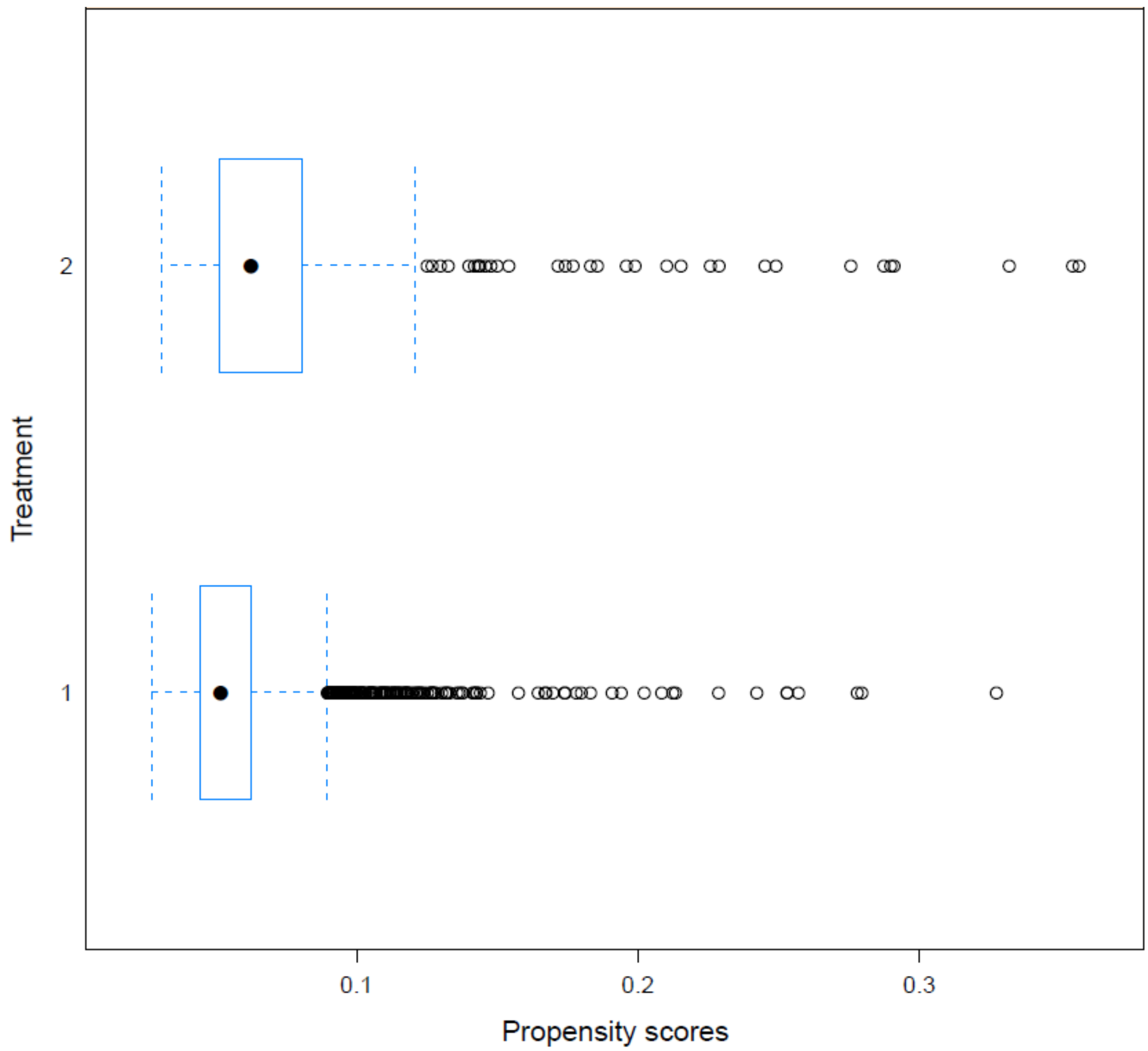


Figure 4. Boxplot of Propensity Scores: Gig Employment



Appendix A

The Relationship among Online Learning and Gig Employment

	MODEL 1: PS-Weighted		MODEL 2: Non PS-Weighted	
VARIABLES	OR	SE	OR	SE
Online Learning	2.334***	(0.513)	2.321***	(0.418)
Male	0.959	(0.160)	1.066	(0.105)
Race/Ethnicity (White)				
Race/Ethnicity: Black	2.376*	(0.950)	1.887***	(0.341)
Race/Ethnicity: Asian	2.172*	(0.829)	0.954	(0.210)
Race/Ethnicity: Other	0.871	(0.243)	1.157	(0.228)
Race/Ethnicity: Hispanic	1.150	(0.301)	1.168	(0.179)
Urban Location	0.795	(0.218)	1.183	(0.188)
Age	0.971**	(0.010)	0.971***	(0.005)
Is Married/Has Partner	1.293	(0.331)	1.248*	(0.139)
Number of Dependents	0.953	(0.185)	1.050	(0.126)
Student Status (Not a Student)				
Part-Time Student	0.614	(0.188)	0.527**	(0.119)
Full-Time Student	0.408***	(0.066)	0.463***	(0.071)
Education Level (High School)				
Certificate/Technical Degree	3.931*	(2.137)	1.403	(0.504)
Some College	1.577	(0.576)	1.744**	(0.351)
Associate's Degree	1.067	(0.411)	2.208***	(0.530)
Bachelor's Degree	1.904	(0.772)	2.694***	(0.562)
Some Graduate School	2.546	(1.299)	2.774***	(0.739)
Graduate School Degree	4.483***	(1.850)	3.876***	(0.923)
Employment Status (Not Working)				
Working Part-Time	1.448	(0.428)	1.379*	(0.193)
Working Full-Time	0.832	(0.239)	0.846	(0.131)
Owns Home	0.976	(0.295)	0.833	(0.123)
Owns Car	0.931	(0.155)	1.128	(0.124)
Has Student Debt	1.347	(0.300)	1.296*	(0.140)
Unsecured Debt (None)				
Low ($1-$600)	1.441	(0.304)	1.537**	(0.208)
Moderate ($601-$3,000)	1.656	(0.475)	1.621***	(0.220)
High ($3,001-$25,000)	2.299**	(0.620)	2.040***	(0.296)
Liquid Assets Quartile (1)				
Quartile 2 ($221-$1,150)	0.560**	(0.125)	0.911	(0.122)
Quartile 3 ($1,151-$4,300)	0.630	(0.178)	0.686*	(0.102)
Quartile 4 ($4,301-$69,500)	0.779	(0.232)	0.882	(0.137)
Adjusted Gross Income/$1k	0.972*	(0.011)	0.979***	(0.006)
Federal Tax Refund	1.000	(0.000)	1.000	(0.000)
Has Health Insurance	0.997	(0.271)	1.147	(0.185)
Perceived Health Score	1.105	(0.084)	1.052	(0.050)
State Random Intercept Variance	1.481***	(0.153)	1.000	(0.000)
Constant	0.084***	(0.054)	0.042***	(0.016)
Observations/Groups	8,528/52		8,528/52	

Appendix B

The Relationship among Online Learning and Entrepreneurial Aspirations

	MODEL 3: PS-Weighted		MODEL 4: Non PS-Weighted	
VARIABLES	OR	SE	OR	SE
Online Learning	2.144***	(0.319)	1.998***	(0.338)
Male	1.212	(0.189)	1.310**	(0.121)
Race/Ethnicity (White)				
Race/Ethnicity: Black	2.990***	(0.639)	2.584***	(0.387)
Race/Ethnicity: Asian	2.197*	(0.834)	0.986	(0.219)
Race/Ethnicity: Other	2.304**	(0.590)	2.181***	(0.330)
Race/Ethnicity: Hispanic	1.655	(0.597)	1.123	(0.168)
Urban Location	1.743*	(0.395)	1.191	(0.170)
Age	0.999	(0.014)	0.992	(0.004)
Is Married/Has Partner	1.517*	(0.266)	1.194	(0.127)
Number of Dependents	0.667*	(0.128)	1.027	(0.107)
Student Status (Not a Student)				
Part-Time Student	0.669	(0.161)	0.827	(0.164)
Full-Time Student	0.605	(0.170)	0.592***	(0.086)
Education Level (High School)				
Certificate/Technical Degree	2.803*	(1.327)	2.747***	(0.679)
Some College	1.359	(0.283)	1.788***	(0.301)
Associate's Degree	1.112	(0.428)	1.973**	(0.410)
Bachelor's Degree	0.936	(0.236)	1.924***	(0.349)
Some Graduate School	1.513	(0.616)	2.450***	(0.583)
Graduate School Degree	0.881	(0.384)	1.851**	(0.414)
Employment Status (Not Working)				
Working Part-Time	0.748	(0.193)	1.013	(0.134)
Working Full-Time	0.688	(0.136)	1.053	(0.146)
Owns Home	0.938	(0.268)	0.916	(0.123)
Owns Car	0.894	(0.148)	0.869	(0.088)
Has Student Debt	1.272	(0.233)	1.297**	(0.130)
Unsecured Debt (None)				
Low ($1-$600)	0.988	(0.193)	0.976	(0.126)
Moderate ($601-$3,000)	1.149	(0.263)	1.121	(0.138)
High ($3,001-$25,000)	0.806	(0.219)	1.107	(0.151)
Liquid Assets Quartile (1)				
Quartile 2 ($221-$1,150)	0.983	(0.190)	0.919	(0.111)
Quartile 3 ($1,151-$4,300)	0.763	(0.154)	0.730*	(0.097)
Quartile 4 ($4,301-$69,500)	0.528*	(0.159)	0.656**	(0.098)
Adjusted Gross Income/$1k	1.009	(0.010)	0.990	(0.006)
Federal Tax Refund	1.000	(0.000)	1.000	(0.000)
Has Health Insurance	0.611	(0.171)	0.593***	(0.073)
Perceived Health Score	0.818**	(0.061)	0.798***	(0.035)
State Random Intercept Variance	1.466**	(0.172)	1.000	(0.000)
Constant	0.072***	(0.050)	0.120***	(0.038)
Observations/Groups	8,528/52		8,528/52	

Appendix C

The Relationship among Gig Employment and Entrepreneurial Aspirations

	MODEL 5: PS-Weighted		MODEL 6: Non PS-Weighted	
VARIABLES	OR	SE	OR	SE
Gig Employment	3.343***	(0.602)	2.800***	(0.388)
Male	1.187	(0.224)	1.293**	(0.120)
Race/Ethnicity (White)				
Race/Ethnicity: Black	2.693*	(1.043)	2.534***	(0.382)
Race/Ethnicity: Asian	0.829	(0.335)	0.970	(0.216)
Race/Ethnicity: Other	2.217*	(0.821)	2.184***	(0.331)
Race/Ethnicity: Hispanic	0.900	(0.272)	1.106	(0.166)
Urban Location	1.002	(0.348)	1.194	(0.171)
Age	0.991	(0.012)	0.994	(0.004)
Is Married/Has Partner	0.950	(0.241)	1.194	(0.127)
Number of Dependents	1.221	(0.244)	1.012	(0.106)
Student Status (Not a Student)				
Part-Time Student	0.878	(0.233)	1.240	(0.208)
Full-Time Student	1.048	(0.155)	0.777	(0.102)
Education Level (High School)				
Certificate/Technical Degree	4.127**	(1.900)	2.774***	(0.687)
Some College	1.855	(0.700)	1.755***	(0.295)
Associate's Degree	1.387	(0.439)	1.935**	(0.403)
Bachelor's Degree	1.711	(0.695)	1.829***	(0.332)
Some Graduate School	1.268	(0.580)	2.151**	(0.512)
Graduate School Degree	1.766	(0.883)	1.678*	(0.376)
Employment Status (Not Working)				
Working Part-Time	0.713	(0.228)	0.969	(0.129)
Working Full-Time	0.657	(0.210)	1.078	(0.150)
Owns Home	0.992	(0.279)	0.944	(0.127)
Owns Car	0.910	(0.154)	0.863	(0.088)
Has Student Debt	1.060	(0.251)	1.276*	(0.128)
Unsecured Debt (None)				
Low ($1-$600)	0.614	(0.205)	0.952	(0.123)
Moderate ($601-$3,000)	0.941	(0.253)	1.094	(0.135)
High ($3,001-$25,000)	0.802	(0.271)	1.051	(0.144)
Liquid Assets Quartile (1)				
Quartile 2 ($221-$1,150)	0.647	(0.187)	0.916	(0.111)
Quartile 3 ($1,151-$4,300)	0.571*	(0.156)	0.741*	(0.099)
Quartile 4 ($4,301-$69,500)	0.409***	(0.104)	0.648**	(0.097)
Adjusted Gross Income/$1k	1.020	(0.012)	0.992	(0.006)
Federal Tax Refund	1.000	(0.000)	1.000	(0.000)
Has Health Insurance	0.631	(0.184)	0.576***	(0.072)
Perceived Health Score	0.690***	(0.069)	0.795***	(0.036)
State Random Intercept Variance	2.053***	(0.399)	1.000	(0.000)
Constant	0.222*	(0.132)	0.107***	(0.034)
Observations/Groups	8,528/52		8,528/52	

Appendix D

Gig Employment, Online Learning, and their Relationships with Entrepreneurial Asp.

	MODEL 7: PS-Weighted		MODEL 8: Non PS-Weighted	
VARIABLES	OR	SE	OR	SE
Gig Employment	3.321***	(0.594)	2.707***	(0.377)
Online Learning	1.141	(0.445)	1.872***	(0.320)
Male	1.191	(0.227)	1.313**	(0.122)
Race/Ethnicity (White)				
Race/Ethnicity: Black	2.685*	(1.050)	2.473***	(0.374)
Race/Ethnicity: Asian	0.841	(0.334)	0.999	(0.223)
Race/Ethnicity: Other	2.227*	(0.827)	2.184***	(0.332)
Race/Ethnicity: Hispanic	0.900	(0.273)	1.107	(0.166)
Urban Location	1.001	(0.347)	1.197	(0.172)
Age	0.990	(0.012)	0.994	(0.004)
Is Married/Has Partner	0.948	(0.243)	1.176	(0.125)
Number of Dependents	1.221	(0.244)	1.021	(0.107)
Student Status (Not a Student)				
Part-Time Student	0.801	(0.307)	0.869	(0.173)
Full-Time Student	0.996	(0.146)	0.628**	(0.092)
Education Level (High School)				
Certificate/Technical Degree	4.094**	(1.917)	2.707***	(0.671)
Some College	1.851	(0.702)	1.733**	(0.292)
Associate's Degree	1.389	(0.440)	1.888**	(0.394)
Bachelor's Degree	1.713	(0.695)	1.816**	(0.330)
Some Graduate School	1.289	(0.578)	2.303***	(0.550)
Graduate School Degree	1.774	(0.879)	1.683*	(0.378)
Employment Status (Not Working)				
Working Part-Time	0.715	(0.229)	0.980	(0.131)
Working Full-Time	0.652	(0.208)	1.062	(0.148)
Owns Home	0.992	(0.278)	0.940	(0.126)
Owns Car	0.913	(0.156)	0.856	(0.087)
Has Student Debt	1.056	(0.248)	1.275*	(0.129)
Unsecured Debt (None)				
Low ($1-$600)	0.613	(0.205)	0.947	(0.123)
Moderate ($601-$3,000)	0.940	(0.252)	1.081	(0.134)
High ($3,001-$25,000)	0.799	(0.270)	1.037	(0.142)
Liquid Assets Quartile (1)				
Quartile 2 ($221-$1,150)	0.652	(0.186)	0.925	(0.112)
Quartile 3 ($1,151-$4,300)	0.572*	(0.156)	0.746*	(0.100)
Quartile 4 ($4,301-$69,500)	0.412***	(0.105)	0.655**	(0.098)
Adjusted Gross Income/$1k	1.020	(0.012)	0.991	(0.006)
Federal Tax Refund	1.000	(0.000)	1.000	(0.000)
Has Health Insurance	0.634	(0.180)	0.582***	(0.072)
Perceived Health Score	0.687***	(0.066)	0.791***	(0.035)
State Random Intercept Variance	2.062***	(0.405)	1.000	(0.000)
Constant	0.226*	(0.133)	0.112***	(0.036)
Observations/Groups	8,528/52		8,528/52	