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Sincerely,

Kelly Gourrier

Hard Work Makes Success? Relationship between Working Hours and Income Growth

By YINHONG ZHAO

Many young people currently want to earn a great future by working longer. This paper examines whether higher income growth in the future is related to longer working hours at present. Empirical data from the Indonesian Family Life Survey indicate a positive relationship between them, but the relationship gradually declines as working hours increase. The correlation is heterogeneous in magnitude but remains positive in most age, gender, education level, and working status cohorts. The relationship found in the study is subject to omitted variable bias, which requires a more sophisticated identification strategy to resolve.

I.INTRODUCTION

"996" has become a popular phenomenon in the labor market of China, which means working from 9 a.m. to 9 p.m., six days a week (Hruby 2018). This adds up to 72 working hours a week, which can be a large burden on employees' physical and mental well-being. On the other hand, many young people find this working manner lucrative after migrating from rural hometowns to metropolises. This practice arouses extensive controversy. The phenomenon of "996" might be local to China, though, as Huberman and Minns (2007, 549) showed that average working hours had been steadily decreasing across the world over the past century.

Can people earn a great future for themselves by working longer at present? This paper aims to study how future income growth relates to present working hours on the individual level, especially in the setting of low- or middle-income countries. Moreover, the paper aims to analyze how this relationship varies in different age, gender, marital status, education level, and working status groups.

Labor economists have been studying the theories of time use for decades on both micro and macro levels. DeSerpa (1971, 828), Barzel (1973, 222–225), and Dickens and Lundberg (1993, 174) proposed theoretical models that consider different aspects of individual decision making, while Boppart and Krusell (2020, 131) provided a framework in macroeconomics to understand labor supply. Empirically, economists have taken advantage of the increasing availability of data to investigate the factors that affect working hours. Alexiou and Kartiyasa (2020, 385) showed that greater income inequality increased working hours, and Bick, Fuchs-Schündeln, and Lagakos (2018, 178) demonstrated that a higher income level is related to lower working hours with cross-country evidence. Boheim and Taylor (2004, 157) showed workers themselves do not have much control over their working hours in the middle of a job; they can only decide their working hours as they switch jobs.

On the other hand, much less literature focuses on how working hours affect other economic factors. It is well known in health sciences that long working hours will damage physical and mental health (Spurgeon, Harrington, and Cooper 1997, 367; Margot 1999, 35). Using instruments from the social security system, Aaronson and French (2004, 341) argued that lower working hours cause personal income to decrease. Not much has been shown on the effect of present working hours on future economic outcomes, especially in the setting of developing countries. It is thus important to study how working hours affect one's future income growth, an important indicator of one's personal development. This paper uses data from the Indonesian Family Life Survey (IFLS) to analyze the relationship between future income growth and present working hours. By comparing cross-wave personal incomes, I acquire the personal income growth rate and apply a regression model with person and wave fixed effects to study the relationship of interest. The model shows that future income growth is positively correlated to present working hours, and the correlation remains robust for most population cohorts. The magnitude of the correlation gradually declines as working hours increase, but it becomes stronger as age increases. The correlation is stronger for females than for males, for the married than for the unmarried, and for wage workers than for self-employed workers. The relationship is reversed for the least educated people. The estimates are subject to omitted variable bias, measurement error, and selective attrition, and a better identification strategy is needed to resolve these problems.

The rest of the paper is organized as follows: Section II provides a brief theoretical framework for understanding how present working hours influence future income growth through capital accumulation. Section III introduces the empirical strategy using fixed effects (FE) regression, and Section IV introduces the data source, the Indonesian Family Life Survey. Section V presents the regression results, and Section VI discusses the interpretations and limitations of the results.

II. THEORETICAL FRAMEWORK

I provide a brief two-period theoretical framework on an individual's income level and allocation of time. I consider a person's economic status at time t and $t + 1$ and model a person's income level at a given time to be dependent on their intangible (human) capital and tangible (physical) capital. Human capital is determined by factors including health conditions and working experiences that are crucial to workers in all sectors, while physical capital is especially important to self-employed workers, including farmers and retailers, because tools and machines significantly improve productivity in these sectors. Hence, I model hourly income in a Cobb-Douglas formula that includes these two factors:

$$I(t) = k_h(t)^{\alpha_h} k_p(t)^{\alpha_p}$$

where $w(t)$ is the hourly income level at time t, k_h and k_p are human and physcal capital, and α_h and α_p are parameters that depend on factors including sector, sex, and education level. I consider the first order logarithm difference of the above formula:

$$\begin{aligned}\ln w(t+1) - \ln w(t) &= \alpha_h(\ln k_h(t+1) - \ln k_h(t)) \\ &+ \alpha_p(\ln k_p(t+1) - \ln k_p(t))\end{aligned}$$

This shows us that the growth in income level depends on the growth in both human and physical capital, i.e.,

$$g_I(t) = \alpha_h g_{k_h}(t) + \alpha_p g_{k_p}(t) \tag{1}$$

where $gx\,(t)$ is the growth rate of variable X at time t.

Now I further link the accumulation of human and physical capital to working hours. Human capital is related to education, previous working experience, health conditions, and other personal characteristics. By working more hours, one can accumulate more working experience. On the other hand, with more leisure time, one can have better health (Margot 1999) and more opportunities to gain education. The total number of hours in each day is fixed at 24 hours, so $H = h(t) + l(t)$, where h is working hours and l is leisure hours. I can therefore model the accumulation of human capital by

$$k_h(t+1) = k_h(t) h(t)^{\beta_h} l(t)^{\beta_l}$$

which gives

(2)

$$g_{k_h}(t) = \beta_h \ln h(t) + \beta_l \ln l(t)$$

Accumulation of physical capital is related to savings, which is related to income in previous periods. I assume that people allocate a fixed proportion, γ, of income to investment (purchase of physical assets) at time *t*. Therefore, the accumulation of physical capital can be modeled as

$$k_p(t+1) = k_p(t) + S(t) = k_p(t) + \gamma h(t)I(t)$$

This gives that

(3)

$$g_{k_p} = \frac{k_p(t+1) - k_p(t)}{k_p(t)} = \gamma \frac{I(t)}{k_p(t)} h(t)$$

Combining (1), (2), and (3), I get

(4)

$$g_I = \alpha_h(\beta_h \ln h(t) + \beta_l \ln l(t)) + \alpha_p \gamma \frac{I(t)}{k_p(t)} h(t)$$

This equation implies that personal income growth depends on the time allocation of the person in the previous period together with a set of other factors including the elasticity of income to human and physical capital allocation (α_h and α_p), the elasticity of human capital accumulation to working and leisure hours (β_h and β_l), the saving rate γ, income level, and asset level. Specifically, by taking the partial derivative of h(t), I observe that

by taking the partial derivative of $h(t)$, I observe that

(5)

$$\frac{\partial g_I}{\partial h} = \frac{\alpha_h \beta_h}{h(t)} - \frac{\alpha_h \beta_l}{H - h(t)} + \alpha_p \gamma \frac{I(t)}{k_p(t)}$$

This equation shows that working hours have a decreasing marginal return to income growth. Also, it predicts that the impact of working hours on income growth is smaller for wealthier people (as their income is a smaller proportion of their original wealth).

Admittedly, many of the factors and parameters in the model are endogenous, but the model succinctly summarizes the relationship between income growth and working hours that I will further analyze empirically in the rest of the paper.

III. EMPIRICAL STRATEGY

To empirically study how future income growth is related to present working hours, I compared an individual's annual average hourly income from year t to year $t + k$ (e.g., 1993 to 1997) in the IFLS panel data and saw how the growth is related to their yearly working hours in year t. The data source itself (IFLS) will be introduced in the next section.

A. Measurement

I calculated the total number of hours each individual worked in a year by multiplying their working hours in an average week and the approximate number of weeks they worked that year. In this way, the problem of seasonality becomes less significant, but respondents' memory about their working hours in the past year might not be exactly accurate.

I computed total yearly income by summing up first-job wage, first-job self-employed income, second-job wage, second-job self-employed income (if existing) in the past year for each respondent. I then divided the total yearly income by working hours to measure the average hourly income for each interviewee. After that, I used the CPI in Indonesia to adjust the hourly income to the price level of 2000. I then calculated the annual real income growth rate using the difference in the logarithm of the real average hourly income from two adjacent waves divided by the gap between two waves of study to adjust for the different time gaps between waves in the IFLS (assuming the income growth rates are largely equal across the years). Mathematically,

$$g_{i,t} = \frac{1}{k}\ln\left(\frac{I_{i,t+k}}{I_{i,t}}\right) = \frac{1}{k}\ln\left(\frac{Y_{i,t+k}/h_{i,t+k}p_{t+k}}{Y_{i,t}/h_{i,t}p_t}\right) = \frac{1}{k}\left(\ln\left(\frac{Y_{i,t+k}}{Y_{i,t}}\right) - \ln\left(\frac{h_{i,t+k}}{h_{i,t}}\right) - \pi_t\right)$$

where I is hourly income, Y is total yearly income, h is working hours, and p is price level. In effect, the growth rate in average real hourly income is measured by the growth in total yearly income subtracted by growth in working hours and inflation.

B. Regression Framework

I estimate the following econometric model with both person and wave fixed effects:

(6)
$$g_{i,t} = \alpha_0 + \alpha_1 I_{i,t} + \alpha_{2,1} h_{i,t} + \alpha_{2,2} h_{i,t}^2 + \alpha \mathbf{X_{i,t}} + \mu_i + \mu_t + \varepsilon_{i,t}$$

where g represents income growth as defined above, I represents average hourly income (in Indonesian Rupees, Rp), h represents yearly working hours (in thousands of hours), and X represents a set of control variables including age, education (no school, elementary school, junior high school, senior high school, and college as a group of dummy variables), working status (self-employed, private, government, etc. as a group of dummy variables), and marital status (married or not). μ_i is the person fixed effect, and μ_t is the wave fixed effect. The quadratic term of working hours is included to account for potential non-linearity.

The coefficients of major concern are $\alpha_{2,1}$ and $\alpha_{2,2}$, which demonstrate the relationship between future income growth *0* and present working hours *h* and so directly answer the research question. Specifically, $\partial g/\partial h = \alpha_{2,1} + 2\alpha_{2,2}h$. Further, the coefficient α_1 shows the relationship between future income growth and current income level and thus serves to test whether income convergence holds on the individual level.

In practice, I applied this econometric model in different subsets of samples to study the heterogeneity of this correlation. Age interaction terms with working hours and the square of working hours were included to study how the relationship differs with age. These terms are not absorbed by the person fixed effect because age differs across time for the same individual. I also ran the model separately for males and females, the married and the unmarried, people in different education groups, and those whose income comes from wages and from self-employed activities. I used the characteristics from the baseline wave ("present") to group the individuals, though characteristics like education level, marital status, and working status may change over time.

IV. DATA

A. Dataset Description

I used all five waves of the Indonesian Family Life Survey Data as my data source. The IFLS is a longitudinal survey that tracks and records household demographics, economic characteristics, consumption behavior, health status, access to community facilities, and social safety nets in Indonesia. The first IFLS sample frame in 1993 stratified the population into 13 major provinces (out of a total of 27 provinces), covering roughly 83% of the population. Households are randomly selected from 321 enumeration areas in the 13 provinces. Household members are interviewed in detail to collect their personal information (Frankenberg and Thomas 2000, 1).

Four follow-up waves of the survey were conducted in 1997, 2000, 2007, and 2014. In each follow-up wave, the goal was to relocate and re-interview all respondents from the past waves, even if the households migrated or split. Each respondent can be tracked across waves with a unique pidlink. The data are available publicly online (Strauss, Witoelar, and Sikoki 2016).

Book 3A Module TK records the employment information of each adult individual in every sampled household. Specifically, respondents were asked about the number of hours they worked in the past week, the number of hours they worked in an average week, and the approximate number of weeks they worked in the past year. Hour information

	Wave 1 1993 Mean/SD/N	Wave 2 1997 Mean/SD/N	Wave 3 2000 Mean/SD/N	Wave 4 2007 Mean/SD/N	Wave 5 2014 Mean/SD/N
yearly working	2.04	2.03	2.04	2.04	2.02
hours (000h)	(1.09)	(1.05)	(1.12)	(1.08)	(1.16)
	7307	9233	13199	15288	18583
average hourly	2602.37	2518.87	2402.80	3297.86	4656.42
income (Rp)	(8851.35)	(4496.37)	(5427.72)	(8839.00)	(13317.39)
	7307	9233	13199	15288	18583
income growth	0.04	-0.03	0.04	0.05	.
	(0.29)	(0.38)	(0.17)	(0.18)	(.)
	4643	6642	7772	9203	0

TABLE 1- SUMMARY STATISTICS OF KEY VARIABLES

was recorded separately for the respondent's first and second jobs (if existing). The same module also records personal income data. Respondents were asked about their income in the past year from their first and second jobs (if existing). The wage income and self-employed income from both first and second jobs were asked separately. Overall, the total income can be computed by summing up income from the first-job wage, first-job self-employed income, second-job wage, and second-job self-employed income (if existing). Other individual-level information can be found in several other modules of the survey: age, sex, marital status, and number of children in Book K Module AR, and education in Book 3 Module DL. Book 3 Module TK also provides information on the respondents' working status (private, government, self-employed, etc.) It is thus possible to evaluate how individual income changes over the waves are related to the hours they worked, controlling for these factors. The summary statistics of the key variables I used are shown in Table 1.

B. Limitations

The issue of attrition due to study design is minor in this study. The attrition rate of the IFLS is much lower than many other longitudinal studies in developing countries because of its efforts in tracking households in migration. The attrition rate of the IFLS between the baseline survey (1993) and the second follow-up survey (2000) is as low as 5%, while the attrition rate of the IFLS between the baseline survey and the fourth follow-up wave (2014) is merely 16.33% (Dartanto 2020, 198). Though Thomas et al. (2012, 111) pointed out that the attrition among adults depends not only on age, education, and the location at baseline but also on characteristics that are associated with other markers of human capital and background, the relatively small portion of attrition should have a limited impact on my results.

attrition	(1) logit	(2) margins
log of real hourly income (Rp)	-0.0161	-0.00374
	(0.00879)	(0.00205)
yearly working hours(000h)	-0.0892***	-0.0208***
	(0.00954)	(0.00222)
age	0.0157***	0.00366***
	(0.000778)	(0.000181)
female (d)	0.512***	0.121***
	(0.0210)	(0.00498)
married (d)	0.575***	-0.138***
	(0.0248)	(0.00604)
self-emoloyed (d)	0.0376	0.00875
	(0.0217)	(0.00504)
Observations	45023	45023

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* p <0.05, ** p <0.01, *** p <0.001

TABLE 2- LOGIT MODEL FOR ATTRITION RATE

Another type of attrition comes with respondents' exit of the labor market, which restricts my scope of analysis. As shown in Table 1, the future income growth rate can only be computed in about two thirds of the samples in each wave except Wave 5. This means that the other one third of respondents either were lost from attrition due to study design or became inactive in the labor market. They might have quit the labor market due to aging, death, unemployment, pregnancy, health conditions, etc.

To see whether attrition of the labor market is selective, I ran a logit regression to study the relationship between data attrition and personal characteristics. An individual is identified as having attrited if the person had positive income in the base wave but zero or missing income in the follow-up wave. Table 2 shows that attrition is negatively related to both hourly income and working hours. This coincides with the economic intuition that people who were originally less involved in the labor market were more likely to quit. Also, older people are more likely to quit as they retire, and the attrition rate of females is 12.1% higher than that of males, possibly due to the heavier burden from the family. In contrast, the attrition rate of married people is 13.8% lower than unmarried people, possibly due to family responsibilities as well.

The problem of attrition is exaggerated as I introduce the person fixed effect into the regression. Using the person fixed effect model, I am in effect studying how the difference in income growth rates relates to the difference in working hours for each respondent. Therefore, at least two income growth rates are needed from the same respondent, which means that they must stay in the labor market and earn positive income in at least three waves of the survey to be included in the regression. This further increases the attrition rate in my study. About half of the sample is eventually included in the fixed effects regression. Nonetheless, I argue that this does not bias my estimates if I restrict my research focus only to the active participants in the labor market.

V. RESULTS

A. Descriptive Analysis

I plotted hourly and total income against working hours in Figure 1 and Figure 2. Figure 1 shows that hourly income levels decrease as working hours increase consistently in all five waves of the IFLS. This supports the theoretical analysis in Section II, and it shows that personal choice and the substitution effect dominate the income effect. This finding is consistent with Bick, Fuchs-Schündeln, and Lagakos's (2018) work that uses cross-country evidence.

Figure 2 shows that total income level has a quadratic relationship with working hours. Specifically, individuals earn more income as they work more, but this relationship is reversed when hours are too high because high working hours usually imply lower hourly income.

B. Main Results

The results of a full-sample regression are displayed in Table 3. In the fixed effects model, the result implies that the future income growth rate increases by 2.39% on average if a person works for an extra 1,000 hours (about 2.74 hours every day) in the present year. This correlation is significant at the 0.1% level. In the ordinary least squares (OLS) model without fixed effects, the correlation is even larger in scale and remains significant. The sample size of the OLS regression is larger than that of the FE regression due to less attrition. Nonetheless, considering that personal characteristics including working ethic and personality can affect both working hours and income growth, the fixed effects model should provide a more accurate estimate of the relationship. The large difference in the regression coefficients between the FE and OLS models implies that personal characteristics (e.g., aspiration) might be very important to income growth, though they are not the primary focus of this paper.

The negative quadratic coefficients in both the FE and OLS models demonstrate that the correlation between future income growth and present working hours declines as present working hours increase. The magnitude of this quadratic relationship is visualized in Figure 3, and the direction is not reversed until working hours reach around 6,000 hours per year (about 16 hours every day). Thus, future income growth is positively correlated with present working hours in almost all cases.

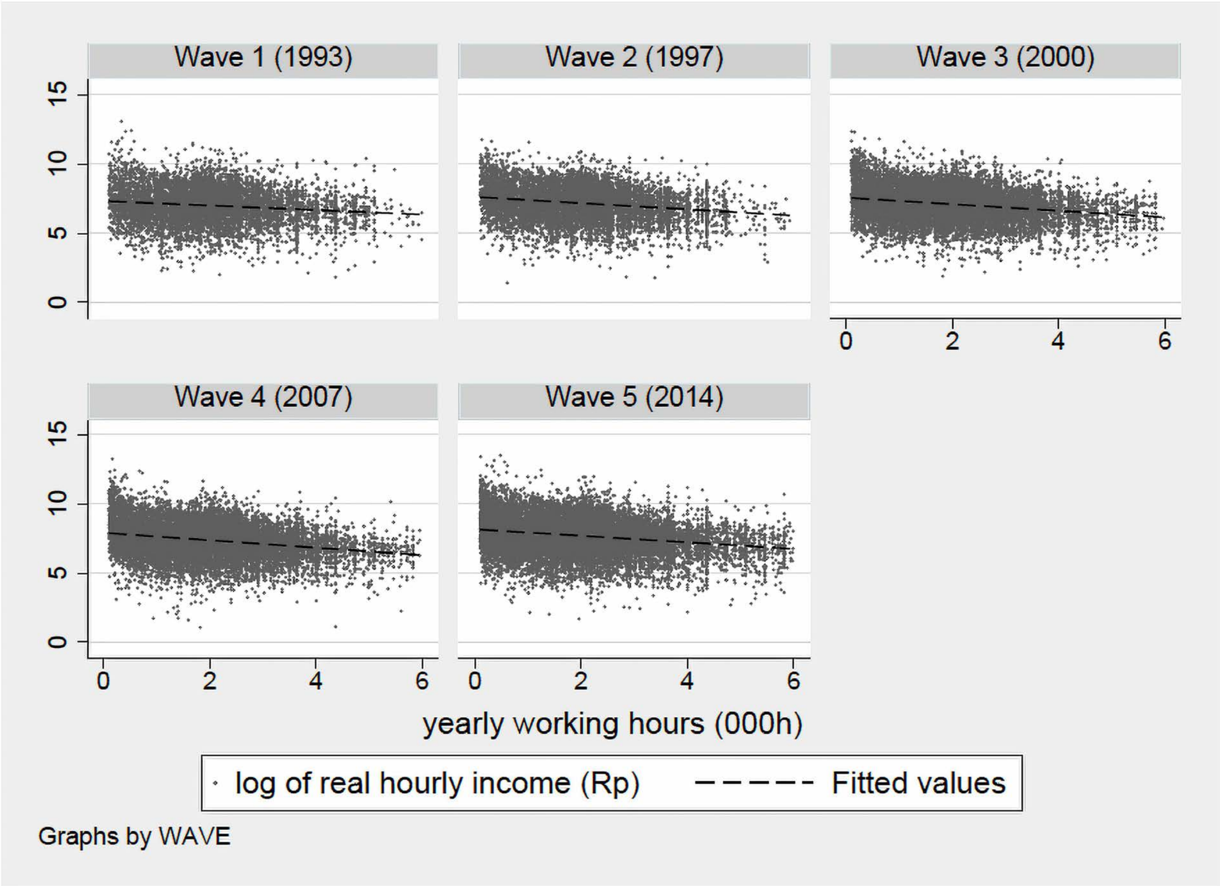

FIGURE 1. HOURLY INCOME AND WORKING HOURS

The coefficients of the logarithm of real hourly income are significantly negative in both the FE and OLS models. This verifies income convergence on the individual level; i.e., richer people see lower income growth rates than poorer people. Income convergence on the country level is an important implication of the Solow growth model (Solow 1956, 65). The regression result shows that if the real present hourly income level increases by 1%, the future income growth rate will drop by 0.275% on average. The third column in Table 3 demonstrates regression results that include age interaction terms. It shows that age significantly affects the relationship between future income growth and present working hours at a 5% significance level. Specifically, the relationship is positive when age is greater than 20. This significant interaction may be related to individual health conditions.

C. Results by Gender and Marital Groups

The relationship between future income growth and present working hours is heterogeneous in different population cohorts. Males and females experience different labor outcomes due to the family structure in Indonesia. Married and unmarried people also see different patterns with their different family responsibilities.

	(1) FE	(2) OLS	(3) FE
log of real hourly income (Rp)	-0.275***	-0.125***	-0.275***
	(0.00312)	(0.00167)	(0.00312)
yearly working hours (000h)^2	0.0239***	0.0618***	-0.0247
	(0.00670)	(0.00435)	(0.0223)
yearly working hours^2 (000h)^2	-0.00400**	-0.00857***	0.00370
	(0.00129)	(0.000854)	(0.00466)
age	0.000315	-0.000828***	-0.00122
	(0.00133)	(0.000139)	(0.00147)
married	0.0208**	0.0245***	0.0216**
	(0.00690)	(0.00356)	(0.00689)
age × yearly working hours			0.00124*
			(0.000573)
age × yearly working hours^2			-0.000195
			(0.000119)
Constant	1.946***	0.808***	2.003***
	(0.0610)	(0.0153)	(0.0649)
Person FE	Yes	No	Yes
Wave FE	Yes	Yes	Yes
Observations	21117	28256	21117

Standard errors in parentheses
using heteroskedasticity robust variances
controlling groups of dummy variables on education and working status
*p<0.05, **p<0.01, **p<0.001

TABLE 3 - FE AND OLS ESTIMATION RESULT FOR ALL SAMPLES

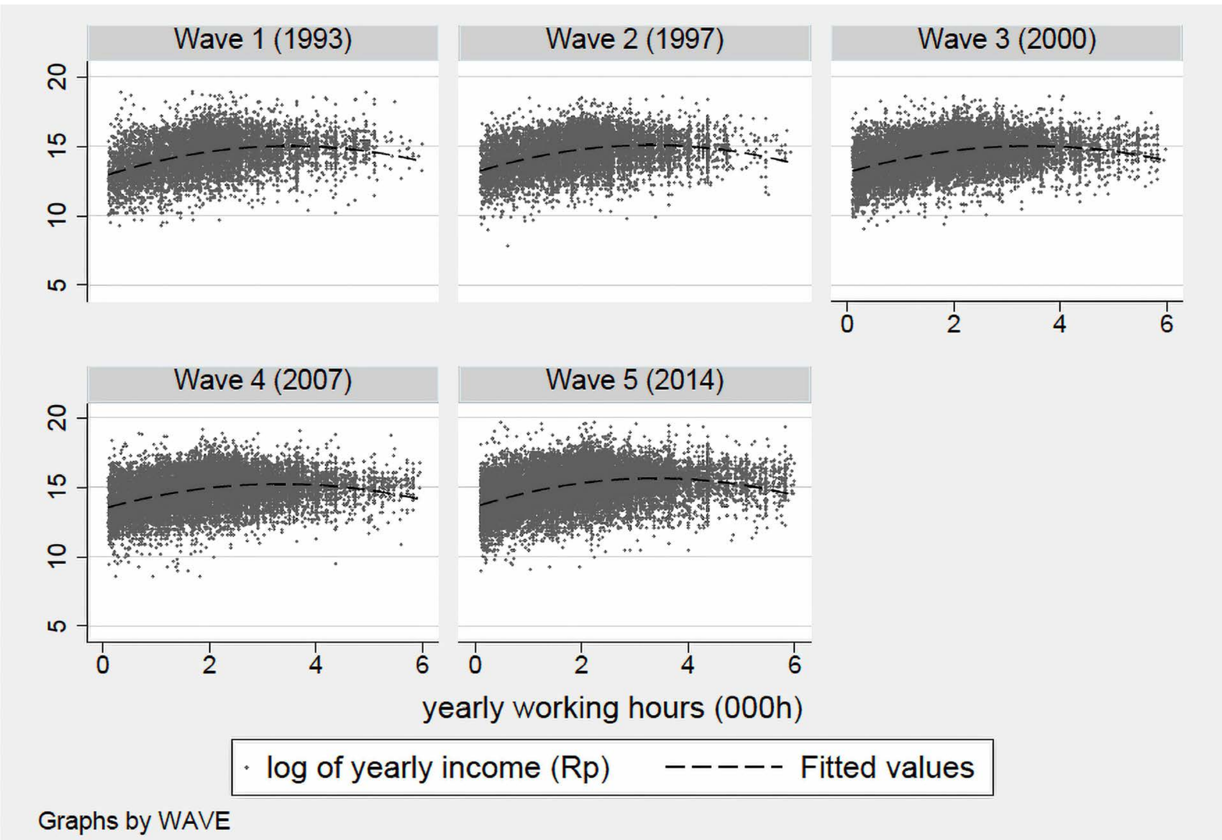

FIGURE 2. TOTAL INCOME AND WORKING HOURS

Table 4 reports the regression coefficients when estimating the model in different gender and marital status groups. The income convergence coefficient does not diverge across gender and marital status groups. However, the relationship between future income growth and present working hours is about 50% larger for females than for males and about twice as large for married people than for unmarried people. Taking the quadratic coefficient into account, I showed the difference in the relationship by gender in Figure 3. The relationship is still stronger for females than for males until yearly working hours reach about 4,400 hours (12 hours a day on average). Therefore, the relationship is stronger for females than for males in most cases. Similarly, the relationship is stronger for the married than for the unmarried until working hours reach about 4,600 per year.

One possible explanation for the differences observed is the difference in consumption and investment preferences between groups. Females who work more are likely to control more income in the household. Previous studies have shown that the consumption preferences of females focus more on the long-term welfare of the family than those of males (Thomas 1990, 642; Rubalcava, Teruel, and Thomas 2009, 520). With more focus on future investment, females may have a larger capital-income elasticity, or the γ I defined in Section II, so the relationship between future income growth and present working hours is stronger for females. A similar mechanism can be argued for married people. Married people

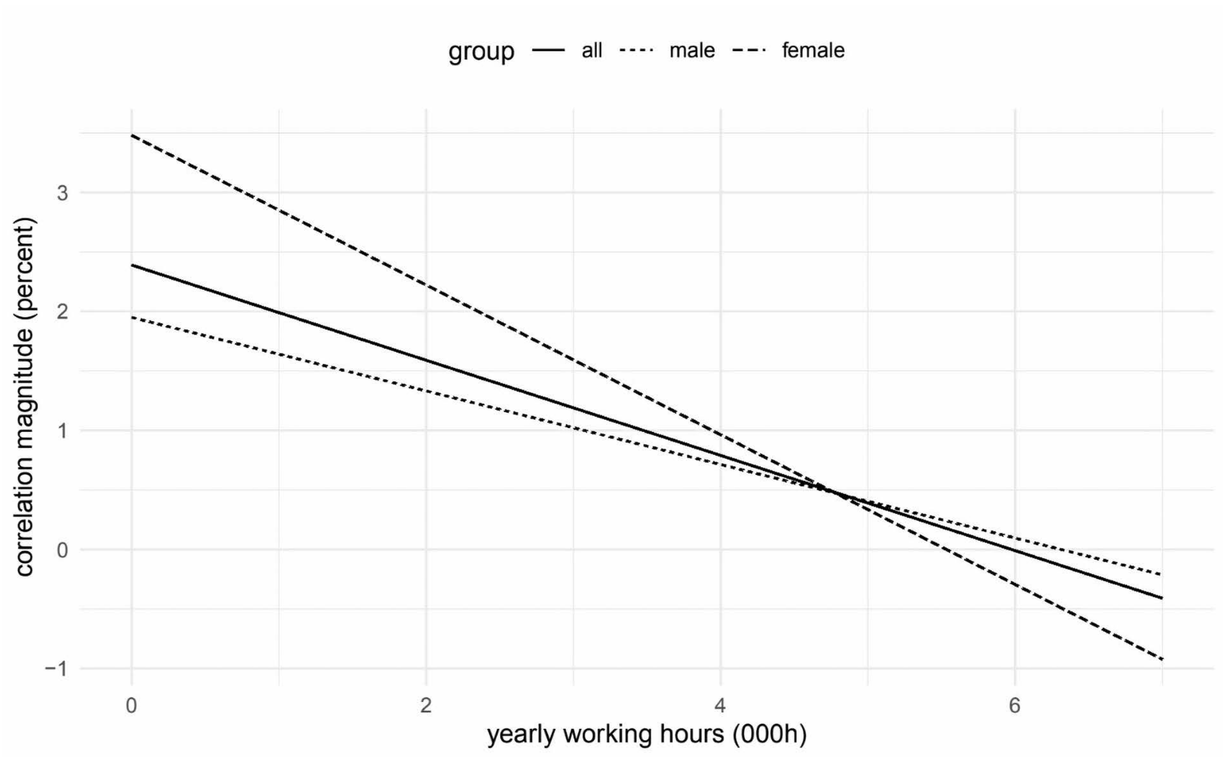

FIGURE 3. $\partial G/\partial H$ DECLINES AS WORKING HOURS INCREASE

are likely to focus more on the long-term welfare of the family and thus input more on investment, increasing γ. It would be interesting, though, to include intra-household allocation of time and income into the model.

D. Results by Education and Working Status Groups

Besides gender and marital status groups, I studied how the relationship between future income growth and present working hours differs by education level and job type.

The positive relationship is reversed in the uneducated cohort, while it remains positive in other education groups. Table 5 shows that the relationships between future income growth and present working hours are all positive and do not vary significantly among the four groups except the "No School" group. For the "No School" group, the relationship is negative, where every 1,000 extra hours of working implies 1.85% less in income growth rate on average. This might be explained by the different labor market structures and consumption preferences of uneducated people.

The relationship is more significant for wage workers than for self-employed workers. Specifically, as shown in Table 6, the regression estimate for wage workers is approximately three times that for self-employed workers, and it is also more significant. Wage workers (including private and government workers) are more deeply involved in the formal labor market compared to self-employed workers (including casual workers, farmers, and micro-enterprise owners), which increases the α_c in Section II. This fact might explain the difference between the two cohorts, and moreover, the level of involvement in the labor market might be one factor that can explain the overall positive relationship that I observe across cohorts.

	Female	Male	Married	Not Married
log of real hourly income (Rp)	-0.276***	-0.275***	-0.279***	-0.292***
	(0.00619)	(0.00361)	(0.00353)	(0.00955)
yearly working hours (000h)	0.0348**	0.0195*	0.0237**	0.0112
	(0.0121)	(0.00807)	(0.00781)	(0.0175)
yearly working hours² (000h)²	-0.00629**	-0.00309*	-0.00389**	-0.00101
	(0.00226)	(0.00156)	(0.00146)	(0.00374)
age	0.00204	-0.000381	0.000327	0.00222
	(0.00244)	(0.00159)	(0.00147)	(0.00449)
married	0.0177	0.0216*		
	(0.0119)	(0.00849)		
Constant	1.858***	1.985***	2.003***	1.961***
	(0.115)	(0.0723)	(0.0691)	(0.182)
Person FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Observations	5997	15115	17229	2238

Standard errors in parentheses
using heteroskedasticity robust variances
controlling groups of dummy variables on education and working status
*p<0.05, **p<0.01, **p<0.001

TABLE 4 - FE ESTIMATION RESULTS BY GENDER AND MARITAL STATUS GROUPS

	No School	Elem. School	Jr. H.S.	Sr. H.S.	College
log of real hourly income	-0.326***	-0.280***	-0.280***	-0.240***	-0.241***
(Rp)	(0.0104)	(0.00470)	(0.00920)	(0.00651)	(0.0144)
yearly working hours	-0.0185	0.0228*	0.0305	0.0208	0.0254
(000h)	(0.0252)	(0.0103)	(0.0196)	(0.0134)	(0.0269)
yearly working hours²	0.00266	-0.00343	-0.00744*	-0.00184	0.00189
(000h)²	(0.00466)	(0.00201)	(0.00357)	(0.00259)	(0.00506)
age	0.00127	0.000934	0.000394	-0.000716	0.00551
	(0.00319)	(0.00189)	(0.00613)	(0.00459)	(0.00347)
married	0.0694*	0.00697	0.0244	0.00663	-0.0196
	(0.0314)	(0.0130)	(0.0197)	(0.0117)	(0.0227)
Constant	1.812***	1.909***	1.994***	1.856***	1.678***
	(0.207)	(0.0895)	(0.238)	(0.168)	(0.197)
Person FE	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes
Observations	1619	9353	2089	4096	1551

Standard errors in parentheses
using heteroskedasticity robust variances
controlling groups of dummy variables on education and working status
*p<0.05, **p<0.01, **p<0.001

TABLE 5 - FE ESTIMATION RESULTS BY EDUCATION LEVELS

	Wage	Self-Employed
log of real hourly income (Rp)	-0.271***	-0.285***
	(0.00536)	(0.00440)
yearly working hours (000h)²	0.0342***	0.0118
	(0.00989)	(0.0109)
yearly working hours² (000h)²	-0.00570**	-0.00201
	(0.00194)	(0.00203)
age	0.0000892	-0.000544
	(0.00228)	(0.00179)
married	0.0161	0.0199
	(0.00832)	(0.0150)
Constant	2.007***	1.997***
	(0.0982)	(0.0919)
Person FE	Yes	Yes
Wave FE	Yes	Yes
Observations	8867	9514

Standard errors in parentheses
using heteroskedasticity robust variances
controlling groups of dummy variables on education and working status
*p<0.05, **p<0.01, **p<0.001

TABLE 6 - FE ESTIMATION RESULT BY WORKING STATUS

VI. INTERPRETATION AND LIMITATIONS

Results from the empirical analysis based on the IFLS data are consistent with the theoretical framework. Overall, I observe a significantly positive correlation between future income growth and present working hours, and this relationship is robust in most population cohorts. The results can be interpreted as causal only if I assume that there is no omitted variable bias and that there is no reverse causation. The latter is likely to hold because income growth that happens in the future cannot influence the working hours at present. However, the empirical model has significant shortcomings that could lead to omitted variable bias.

A. Omitted Variable Bias

While the econometric model I used includes person fixed effects, wave fixed effects, and a set of important control variables, there can still be confounding factors existing in the residual. In this case, the factors that change for an individual person over time and affect both present working hours and future income growth can bias the regression estimates. Several examples of this include income trends, family structure, industry shift, and migration.

Growing income trends can incentivize individuals to work more at present, and individuals might continue to see income growth with the momentum effect. This factor would lead to an upward bias in my estimates. Adding controls about retrospective income might solve this problem. Family structure can play a role as seen in the difference in the relationship across gender and marital status groups. Specifically, having more children may force adults to work for more hours while lowering their income growth (Brander and Dowrick 1994, 11). The income of other members in the household might also affect the present working hours and future income growth. This omitted variable bias might be resolved by controlling for the number of children and whether the respondent was the head of household.

There was a trend of shifting from a first industry to a second and third industry in Indonesia as the country developed into a middle-income country in the late 1990s and early 2000s. On the individual level, those who shift from the agricultural sector to the industrial or service sector might experience a change in working hours and income growth. This effect is complex and can hardly be solved by adding control variables. A similar factor is a migration from rural to urban areas, which may have affected both present working hours and future income growth. These factors, together with many others, are hard to control for due to a lack of data. A better identification strategy is needed to exclude the bias brought by the confounding factors.

B. Measurement Error and Attrition

Besides the omitted variable bias, measurement error and selective attrition might affect my estimates as well, though I argue that the influence is not significant.

There exists classical measurement error in the data. Measurements of both working hours and income levels heavily rely on respondents' memory. For the respondents whose working hours and income level vary hugely within a year, the estimates might not be accurate. While data on seasonal workers are more likely to have such errors the upward or downward direction of the error is not selective, which means that the measurement error is classical and should not bias the regression estimates.

Measurement errors on personal characteristics exist when I group the sample into different population cohorts according to the data in the baseline survey. For example, I would group an individual into the unmarried group if the person was not married in the baseline wave. However, the person might get married between the baseline survey and a follow-up survey, which leads to measurement error. Similarly, an individual's working status might also change between two waves. This weakens my conclusion that the relationship is different in different marital status and working status groups.

The attrition rate is as high as 40% due to both the data collection and the empirical strategy, which restricts my scope of analysis. As mentioned in Section III, the IFLS has a much lower attrition rate than other comparable studies in developing countries, and the attrition rate is also low in absolute value. Beyond that, since I used income growth rate as the dependent variable and included a person fixed effect term in the regression, I needed effective responses from the same individual in at least three waves to include the individual in the sample. This requirement further shrunk the size of the sample. The sample failed to include any individuals who were missing in the data collection or who dropped out from the labor market due to various reasons. As shown in Section III, such attrition was selective in that people who were less involved in the labor market were more likely to quit, so my sample underrepresented the people who were marginally involved in the labor market.

Nonetheless, I argue that attrition does not bias my estimate as long as I restrict my scope of analysis to committed workers. Future income growth is by itself undefined for individuals who quit the labor market in the follow-up wave, so a moderate amount of attrition is natural and justified. The estimates are not biased by the attrition. On the other hand, income growth might not be the best measure for personal success, as it is undefined for a non-trivial group of people.

C. Conclusion

Consistent with economic theory, future income growth has a positive relationship with present working hours in Indonesia, which is observed in IFLS data with fixed effects regression. The relationship becomes weaker as working hours increase, but it becomes stronger as age increases. Females and the married see a larger magnitude in this correlation, while the least educated cohort experiences the opposite. The relationship for wage workers is more significant than for self-employed workers. The relationship is subject to omitted variable bias, measurement error, and selective attrition. A better identification strategy is needed to resolve these problems.

It is worth mentioning that income growth does not necessarily mean success. Long working hours might harm physical and mental well-being. For further study, it would be interesting to see how future health conditions or asset levels relate to present working hours so that a more holistic view of working hours can be formed.

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Pursuing Multiple Majors to Get into STEM Industries? Empirical Evidence from UC Berkeley

By ZAN SONG

This paper investigates the effect of students' number of undergraduate degrees on their probability of working in STEM (science, technology, engineering, and mathematics) industries. The hypothesis is that more majors increase students' likelihood to persist in STEM. After I applied OLS and probit models and checked robustness, I found that more bachelor's degrees do not increase the probability of being in STEM professions and therefore rejected the hypothesis. My paper aims to encourage more discussion of the purposes of pursuing multiple majors. Students may want to think about why they want to pursue multiple majors and how they can contribute to the STEM labor supply effectively.

1. INTRODUCTION

STEM (science, technology, engineering, and mathematics) skills are increasingly regarded as critical to innovation, productivity growth, and competition for the economic growth and prosperity of society (Picot and Hou 2019, 7). In 2012, President Barack Obama's Council of Advisors in Science and Technology (PCAST) announced the need for one million additional STEM workers by 2022. Recognizing the substantial lack of skilled STEM workers and distinctive earning advantages in these industries, students began to show a greater interest in working in STEM. There also exists an increasing trend of pursuing more than one major during undergraduate education. Since simultaneously pursuing multiple majors and maintaining good academic performance requires substantial time and effort, it is worthwhile to investigate the relationship between multiple majors and STEM persistence so that students can make better choices regarding their academic careers.

In this paper, I test whether completing more bachelor's degrees boosts students' competitiveness, measured by the probability of being in STEM-related professions. I want to encourage more discussion on the motivation for students to do multiple majors. If the goal is to increase their likelihood of getting into STEM industries, students should be skeptical of whether devoting efforts to multiple majors can help them reach their goal.

This paper aims to investigate the relationship between multiple majors and the likelihood of entering the STEM industry, and it is organized as follows. Section 2 provides an overview of the current literature and a summary of my contribution, which enriches the literature on students' outcomes of pursuing more than one major. Section 3 presents the data sources, which are the Undergraduate Research Apprentice Program (URAP) and the LiveAlumni database. It also describes the data cleaning process. Section 4 illustrates my empirical methodologies of OLS and probit modeling. Section 5 explains my regression results and robustness check. Section 6 acknowledges my research limitations and further discusses the topic, encouraging undergraduate students to be aware of the outcome of pursuing multiple majors. Section 7 concludes.

2. LITERATURE REVIEW

STEM jobs are a key contributor to economic growth and national competitiveness (Deming and Noray 2018, 1). However, there has been considerable concern this past decade regarding a shortage of STEM workers to meet the demands of the labor market (Xue and Larson 2015, 1). With increased emphasis on encouraging students to pursue degrees in STEM, students tend to improve their labor competitiveness for better professional choices. Even though there h as been a fair amount of research focusing on economic returns to college majors, double majors had been ignored in the economics literature prior to the work of Del Rossi and Hersch (2008). After they conducted their research, more studies on double degrees provided insights into how and why students select a combination of majors. This group of students is not a small portion of undergraduates. Increasing numbers of college students in the United States are accumulating more than one major, with an estimated 25% of college graduates doing two or more (Del Rossi and Hersch 2008, 1). They used the National Survey of College Graduates in 2003 as a data source to argue that double majors have higher earnings than single majors, with the largest gains occurring among those who pursue double majors across different disciplines.

Del Rossi and Hersch (2016) also dived deeper into the private and social benefits of double majors. They found that compared to single STEM majors, double major combinations that include a STEM major are generally more likely to have positive social benefits of more research and development (R&D) and a lower likelihood of a close job match. Del Rossi and Hersch used OLS for the log of earnings and a probit model for R&D activities, job match quality, and job satisfaction. They mainly regressed on different combinations of humanities, business, and STEM. They showed that the business–STEM double major combination is associated with the highest returns to income of around 40%. However, the job match quality for certain major combinations is even lower than that of both of its corresponding single majors.

One thing to notice in this paper is that almost all two-major combinations, especially business and STEM, are associated with a lower likelihood of a job match, and the job satisfaction rate is typically lower compared to students with one major. This mirrors the idea that college major completion may impact whether workers' educations are matched properly to their jobs, which could influence individual earnings, sense of satisfaction, societal productivity, and workplace resource utilization. Even though Pitt and Tepper (2012) state that students report little to no added stress from pursuing a double major, there may still be costs associated with the extra effort. There is substantial literature concentrating on whether workers are mismatched with their jobs, with a big concern on if workers are overeducated (McGuinness 2006). According to this paper, overeducation can lead to higher turnover, lower job satisfaction, as well as a waste of societal resources because education is heavily publicly subsidized.

After the groundbreaking work of Del Rossi and Hersch in 2008, more scholars researched the earnings of STEM-educated employees. Hemelt (2009) showed that on average, students with double majors earn 3.2% more than their single major counterparts. He found that the highest gains of double majoring come from combining majors that are more technical or practical, especially business, computer science, and engineering. The evidence presented is suggestive of a positive earnings benefit from double majoring, but Hemelt also acknowledged that the exact contribution of holding two bachelor's degrees to this higher return is not clear because of intangible personal factors such as motivation and ability. He also mentioned that a fairly limited earning benefit suggests little incentive for students to pursue certain double major combinations such as humanities and STEM.

Recently, Qiong and Liang (2021) investigated the effect of a double major on bachelor's degree recipients' earnings and employment status after college graduation by categorizing high- and low-paying majors. They found that double major graduates are more likely to be employed in the labor market. Their earnings are significantly less than their single major counterparts within one year of graduation, but their earnings become comparable four years after graduation. Further, when there is a large earnings gap between the higher- and lower-paying majors in their double major combination, students might end up with less earnings than those with a single higher-paying major. This is because the earning power of a double-major degree, on average, falls in between the earnings of the two single majors, which suggests a reasonable strategy is to stick to a higher-paying major to develop specialized knowledge.

My research focuses on the relationship between the number of undergraduate majors and STEM persistence, which will drive more discussion on education trends and job match quality. Unlike previous literature that focused on double major student groups, my paper captures students with more than two majors, peaking at four. I use individual-level data of UC Berkeley undergraduates to evaluate the effect of the STEM degree indicator and the number of majors on students' STEM outcomes. Overall, this paper investigates the relationship between pursuing multiple majors and the probability of being in a STEM job, encouraging more comprehensive awareness of multi-major outcomes that may not be optimistic.

The uniqueness of my paper includes the indicator for students' outcomes, which is the probability of being in a STEM career, and the potential influencing variables are the STEM degree indicator, the number of undergraduate degrees, and the interaction term of these two. This angle of measuring students' outcomes has not been used before but is essential because STEM students typically care about whether they can get a decent job immediately after graduation. My research also lays a good foundation for future research on the long-term effect of pursuing multiple majors, such as occupational promotion, job satisfaction, workplace resource allocation, etc. Because of a time limit and difficulty of accessing more data, I collected evidence only from UC Berkeley rather than a national dataset and did not examine earnings consequences associated with multiple majors. Overall, my research helps undergraduate students make better decisions on major selection, and I plan to further develop my research in the near future with more comprehensive and representative data.

3. DATA AND MODEL

3.1 Data Source and Description

The datasets used in this paper come from two main institutions: (1) the Undergraduate Research Apprentice Program, which is an official research program operated by UC Berkeley, and (2) the LiveAlumni database, which is run by a company that systematically collects information from LinkedIn. The URAP office provided the URAP golden dataset and the GPA dataset. The golden dataset contains over 18,000 participants' information for the past 25 years and records students' ID number, gender, ethnicity, year of graduation, degrees, and the time that they joined URAP. The GPA dataset includes students' full name, their GPA when they joined the program, and their class standing (freshman, sophomore, junior, or senior). The dataset from LiveAlumni captures essential employment information on students' job industry, company, and position title.

The reason why I use URAP participants as my target group is because of complete access to all desired variables. Also, since URAP opens research opportunities to all UC Berkeley undergraduates and contains a broad variety of research disciplines, I argue that its participants are representative of the UC Berkeley undergraduate population, and they share similar features such as education quality. However, I acknowledge that my research group might not be representative of a broader population as it only contains observations from a specific program composed of students interested in research. Thus, I controlled for confounding variables such as gender, ethnicity, GPA, transfer status, and class standing in my regression model to minimize bias.

3.2 Data Cleaning

The data I used are cross-sectional because I collected data once, and every single individual is recorded in one row with many features. To clean data, I removed missing values, filtered on certain conditions, and merged separate datasets. I decided to select the time period of 2012–2018 because students' GPA information is only accessible after 2012, and the dependent variable is a binary variable that represents whether the student has a STEM job within two years of graduation. Hence, 2012–2018 is a reasonable time period. The student group that I researched is URAP participants who directly entered industry after receiving their bachelor's degrees, so I excluded those who continued to pursue a master's degree or a Ph.D. Since URAP golden data and LiveAlumni data both have a student ID for each individual, I inner-joined by this primary key to merge these datasets into one. The GPA dataset only contains students' full names to distinguish individuals, so I used students' full names to merge with the previous two datasets and dropped the duplicated names. Removing duplicated full names narrowed my sample size from around 2,000 to 1,704.

The next step is to transform data into a form that can be used in the regression. I first separated students' undergraduate degrees into multiple columns and counted the total number of each individual's bachelor's degrees. Then, I set students' STEM degree indicators to 1 or 0 based on a list of STEM disciplines from the Higher Education Research Institute at UCLA. For the STEM job indicator, I used the Bureau of Labor Statistics listing of STEM jobs as a reference. I subtracted students' graduation year from their first job year to calculate the gap between undergraduate education and career. Then I set 1 to students' STEM outcomes if the individual satisfies the condition that they are in a STEM industry within two years of graduation. Thus, both independent variables and dependent variables are transformed into dummy variables or numeric forms for regression purposes. Below are the summary statistics for the processed data. The classification reference can be found in the appendix.

TABLE 1 SUMMARY STATISTICS

Variable	Gender	Asian	White	Non_W.A	Standing	Transfer	Numdegrees	STEM_ degree	GPA	STEM_job _2Yrs
Count	1704.00	1704.00	1704.00	1704.00	1704.00	1704.00	1704.00	1704.00	1704.00	1704.00
Mean	0.63	0.52	0.35	0.13	2.98	0.18	1.26	0.70	3.55	0.60
std	0.48	0.50	0.48	0.33	0.85	0.39	0.46	0.46	0.34	0.49
min	0.00	0.00	0.00	0.00	1.00	0.00	1.00	0.00	2.09	0.00
max	1.00	1.00	1.00	1.00	4.00	1.00	4.00	1.00	4.00	1.00

Binary variables include: *Gender* (1: Female; 0: Male), *Asian* (1: True; 0: False), *White* (1: True; 0: False), *Non_W/A* (1: Not white or Asian; 0: White or Asian), *Transfer* (1: True; 0: False), *STEM_Degree* (1: True; 0: False), and the outcome variable *STEM_Job_2Yrs* (1: True; 0: False). We can see that females make up the majority of URAP participants; Asian and white ethnicities also dominate. On average, students have 1.26 majors during their undergraduate studies, and around 60% of them secure a STEM job within two years of graduation. For numeric variables, Standing represents students' class standing (1: Freshman; 2: Sophomore; 3: Junior; 4: Senior), and *GPA* is their cumulative GPA when they entered the program.

4. METHODOLOGY AND MODEL

4.1 Intuition and Method

Regarding the main variables of interest, the economic outcome is measured by the likelihood of working in a STEM-related occupation within two years of graduation. Independent variables include the number of bachelor's degrees, the STEM degree indicator, and the interaction of these two terms. I controlled for students' gender, ethnicity (Asian, white, or non-Asian/white), class standing, transfer indicator, and GPA.

It is intuitive that students with at least one STEM major tend to have higher STEM persistence because they are specialized in a STEM field, so I predict the coefficient of the STEM indicator to be significantly positive. What is more interesting is whether pursuing more majors increases STEM students' probability of having a STEM job. To be specific, I want to interpret the coefficient of the cross term of the STEM indicator and the number of undergraduate majors. I hypothesize that students can increase their competitiveness by declaring additional major(s) so that a signaling effect will notify employers that these students have greater ability to manage a large workload. This could explain the trend that the number of multiple-major students is increasing. Thus, my hypothesis is that pursuing more majors will boost STEM students' probability of being in a STEM industry, which approximates the probability of getting into a STEM industry. This outcome is important because STEM undergraduates care about obtaining their first job after graduation. A large proportion of them want to find a high-paying job within a short time to compensate for the opportunity cost of schooling.

I used a linear probability model (OLS) and a probit model for my main analysis. The first model will fit a linear line to the data, and the second will display the marginal effects of independent variables.

4.2 Linear Probability Model (OLS) and Probit Model

My equation for the linear probability model is:

$$STEMjob2Yrs_i = \alpha_0 + \alpha_1 \cdot NumDegree_i + \alpha_2 \cdot STEMdegree_i + \alpha_3 \cdot NumDegree \cdot STEMdegree_i + Controls_i + e_i$$

In this OLS model, *STEM job2Yrs*i is a probability that indicates whether the individual has a STEM job within two years of graduation. *NumDegree* is a numerical variable that represents students' number of majors during their undergraduate studies. *STEMdegree* is a dummy variable indicating whether the student has at least one STEM degree. *NumDegree-STEMdegree* is the cross term between *NumDegree* and *STEMdegree*, which captures the mutual effect of the number of majors and the STEM indicator. I included this term because if a student does a STEM degree, it is more likely that the student will pursue a STEM job. Thus, it is reasonable to look at the mutual effect of the indicator *STEMdegree* and *NumDegree* when analyzing the correlation between the number of bachelor's degrees and entering a STEM profession. For variables in *Control*, I include gender, ethnicity (specifically the Asian and white indicators because of linear independence), class standing, and the transfer indicator. I used the same inputs for my probit model to confirm my regression results.

4.3 Robustness Check

For a robustness check, I examined the economic outcomes of students with different STEM majors by running separate OLS and probit models on students with economics, biology-related, and computer science majors to see if additional majors indicate a higher chance of being in STEM industries for these subjects. Since I only looked at students majoring in these three fields, the STEM degree indicator is 1 for all observations. So, I excluded the STEM degree indicator and the cross term from the regressions. The regression model shown below is the same for all subgroups.

$$STEMjob2Yrs_i = \alpha_0 + \alpha_1 \cdot NumDegree_i + Controls_i + e_i$$

Similar to the equation before, *STEM job2Yrs*i is a binary outcome that represents whether the student obtains a STEM job within two years of graduation. *NumDegree* is students' number of bachelor's degrees, and *Control* includes the same collection of variables as before.

5 REGRESSION RESULTS

5.1 Results of OLS and Probit Models

Table 2 shows the probability estimates of obtaining a STEM job within two years of graduation. Column (1) is the simplest OLS model without any control. Column (2) controls only for students' GPA. Column (3) controls for students' additional characteristics such as gender and ethnicity (either Asian, white, or neither), and column (4) controls for everything mentioned before as well as class standing and transfer status. Column (5) is the probit model with the same inputs as column (4). Other than my control variables, I assume that the observations are comparable in other features.

TABLE 2 REGRESSION RESULT OF STEM JOB WITHIN 2 YEAR OF GRADUATION

	Dependent variable				
	STEM_Job_2Yrs OLS (1)	STEM_Job_2Yrs OLS (2)	STEM_Job_2Yrs OLS (3)	STEM_Job_2Yrs OLS (4)	STEM_Job_2Yrs OLS (5)
Standing				-0.023* (0.014)	-0.068* (0.040)
Transfer				0.067** (0.033)	0.180** (0.092)
Gender			-0.034 (0.024)	-0.033 (0.024)	-0.094 (0.067)
Asian			0.050 (0.037)	0.057 (0.038)	0.157 (0.104)
white			-0.006 (0.038)	0.001 (0.038)	0.004 (0.105)
GPA		-0.124*** (0.034)	-0.128*** (0.035)	-0.148*** (0.036)	-0.148*** (0.101)
NumDegrees	0.064 (0.055)	0.061 (0.055)	0.060 (0.055)	0.076 (0.055)	0.198 (0.149)
STEM_Degrees	0.462*** (0.078)	0.432*** (0.078)	0.415*** (0.078)	0.434*** (0.079)	1.146*** (0.216)
NumDegrees : STEM_Degrees	-0.142** (0.061)	-0.126** (0.061)	-0.131** (0.061)	-0.142** (0.062)	-0.382** (0.167)
Constant	0.327*** (0.068)	0.779*** (0.141)	0.807*** (0.143)	0.906*** (0.157)	1.198*** (0.440)
Observation	1,704	1,704	1,704	1,704	1,704
R2	0.076	0.083	0.087	0.090	
Adjusted R2	0.074	0.081	0.083	0.085	
Log Likelihood					-1,067.295
Akaike Inf. Crit.					2,154.591
Residual Std. Error	0.471 (df=1700)	0.469 (df=1699)	0.469 (df=1696)	0.468 (df=1694)	
F Statistic	46.689***(df=3;1700)	38.593***(df=4;1699)	23.148***(df=7;1696)	18.657***(df=9;1694)	
Note:					*p<0.1; **p<0.05; ***p<0.01

The coefficient term for STEMdegree is statistically significant across all columns. This is within expectations because a STEM degree is assumed to be positively correlated with continuing into a STEM profession. However, it is more valuable to evaluate whether the number of undergraduate majors of a student increases the likelihood of obtaining a STEM job and whether the cross term of the STEM degree indicator and the number of majors is associated with a graduate being in a STEM industry. The regression result shows that while the number of a student's bachelor's degrees has a positive correlation with being in a STEM job within two years of graduation, this association is not significant. Interestingly, the interaction term has a negative correlation with the STEM job outcome at a 0.05 significance level in all four columns of the linear regression. This result indicates that when a student obtains a STEM degree during their undergraduate studies, it is less likely for them to have a STEM job within two years of graduation if they pursue more majors. Specifically, for column (4), we expect a 14.2% decrease in probability if the individual completes one more major during their undergraduate studies given they complete at least one STEM degree. I also checked the marginal effect of the number of degrees and of the cross term using the probit model. The result in column (5) indicates the robustness of the model. I am therefore 95% confident in rejecting the hypothesis that having more majors increases STEM persistence after undergraduate education.

Another noteworthy finding is that the coefficient for GPA is significantly negative under a 0.01 p-value, indicating that an individual is expected to be less likely to persist in a STEM career when they have a higher cumulative GPA. This finding is interesting because people intuitively assume that students who have better academic performances are more competitive in the labor market. Also, according to the last two columns, being a transfer student increases the predicted probability of being in a STEM job after two years of graduation at a 0.05 significance level. Ethnicity and gender do not have significant correlations with the outcome variable.

Now, I want to explore why the regression results seem to support the opposite of the hypothesis that holding more majors will increase students' likelihood of being in STEM industries. Even though the coefficient for the number of degrees is positive, it is not very useful for my interpretation because the effect of the STEM degree indicator might be too large and confound the result. Indeed, we should look at the cross term of the number of degrees and the STEM degree indicator, which has a significantly negative coefficient. Although STEM students with multiple majors can signal to employers that they are able to handle a heavier workload than those who only have one major, which should increase their competitiveness in a job search, they can also do multiple majors out of pure interest. Job matching is not only about employers' preference and selection; it is also about job seekers' interests. Students are likely to choose a second or even a third major based on their passion in those fields, which can expose them to more opportunities and job possibilities. In this sense, STEM students might end up with a non-STEM job when they explore their genuine interest in a second or third major. This likely explains the significant negative coefficient of the cross term between the number of degrees and the STEM degree indicator.

5.2 Robustness Check

So far, the regression results show that the cross term of the number of majors and the STEM degree indicator has a significant negative correlation with the probability of being in a STEM industry two years after graduation. Additionally, the number of bachelor's degrees does not have a significant association with the probability of the outcome. As illustrated before, since economics, biology-related majors, and computer science all belong to STEM, my independent variable in this robustness check is only the number of bachelor's degrees, and the control variables remain the same. In this case, I concentrated on the coefficients of the number of degrees and other control variables.

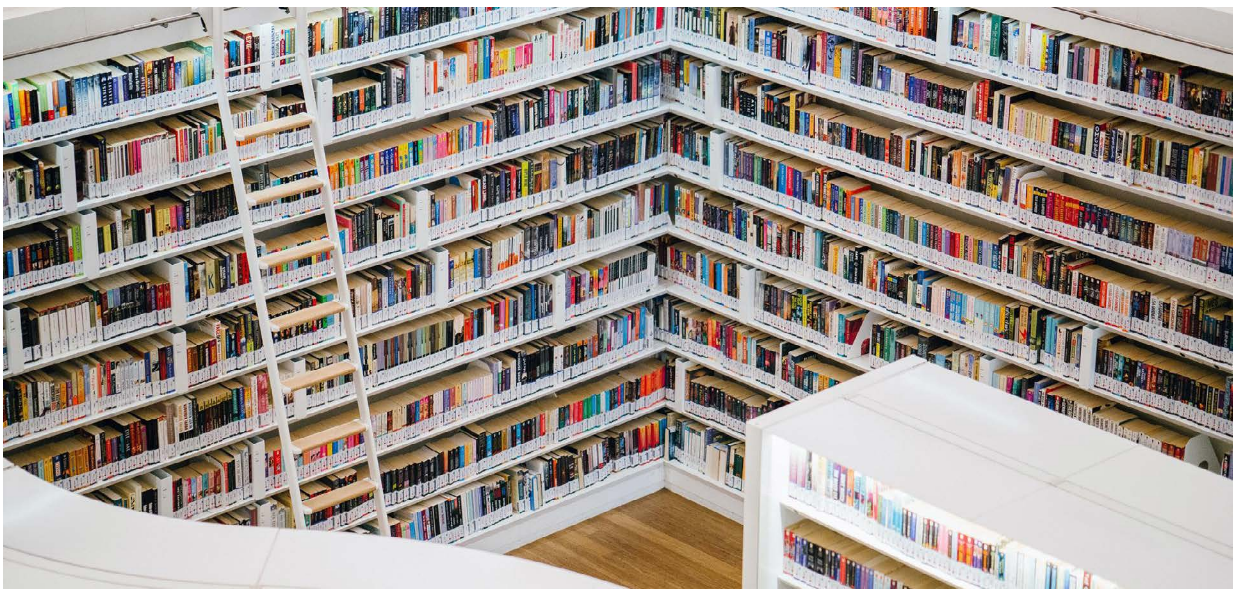

TABLE 3 REGRESSION RESULT OF DIFFERENT STEM MAJORS

	Dependent variable					
	STEM_Job_2Yrs					
	OLS Economics (1)	probit Economics (2)	OLS Bio (3)	probit bio (4)	OLS Computer Sci (5)	probit Computer Sci (6)
Gender	0.044	0.122	-0.006	-0.013	-0.010	0.009
	(0.075)	(0.204)	(0.056)	(0.170)	(0.041)	(0.251)
Asian	-0.061	-0.177	0.132	0.395	0.053	-3.705
	(0.195)	(0.553)	(0.100)	(0.295)	(0.173)	(214.583)
White	0.120	0.325	0.053	0.155	-0.180	-4.282
	(0.205)	(0.586)	(0.108)	(0.316)	(0.177)	(214.583)
Standing	-0.065	-0.188	-0.043	-0.134	-0.032	-0.180
	(0.044)	(0.123)	(0.033)	(0.101)	(0.023)	(0.139)
Transfer	0.246*	0.738*	0.084	0.267	0.078	0.531
	(0.136)	(0.402)	(0.107)	(0.330)	(0.074)	(0.531)
GPA	-0.524***	-1.478***	0.123	-0.391	-0.083	-0.423
	(0.161)	(0.463)	(0.077)	(0.238)	(0.066)	(0.417)
NumDegrees	0.070	0.183	0.014	0.055	-0.068*	-0.349*
	(0.070)	(0.189)	(0.059)	(0.182)	(0.034)	(0.189)
Constant	2.525***	5.749***	1.155***	1.971***	1.455***	7.641
	(0.613)	(1.784)	(0.311)	(0.959)	(0.301)	(214.588)
Observation	168	168	291	291	240	240
R2	0.104		0.023		0.063	
Adjusted R2	0.065		-0.002		-0.034	
Log Likelihood		-105.629		-166.817		-71.323
Akaike Inf. Crit.		227.258		349.634		158.645
Residual Std. Error	0.481(df=160)		0.446(df=283)		0.295(df=232)	
F Statistic	2.656**(df=7;160)		0.934(df=7;283)		2.214**(df=7;232)	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3 displays the OLS and probit regression results for obtaining a STEM job within two years of graduation for students with economics, biology-related, or computer science majors. We can see that the coefficients of the number of degrees for economics and biology students are positive but not significant. For computer science students, one more major is expected to result in a 6.8% decrease in the probability of having a STEM profession at a 0.1 significance level.

6 DISCUSSION

In general, more undergraduate degrees do not increase STEM students' likelihood of persisting in STEM fields. Thus, even when looking at subgroups of URAP participants, pursuing multiple majors does not boost students' post-baccalaureate likelihood of being in a STEM industry. I checked the robustness of these results successfully and confirmed my rejection of the original hypothesis.

One limitation of my research is due to the loss of datasets after merging and filtering. Since students' job information comes from LinkedIn, there exist lots of missing data on students' first job after graduation. It is also possible that certain groups of students have more complete LinkedIn profiles, and therefore they are more likely to be captured by my regressions than other students. For instance, students who major in business could be more likely to have well-organized LinkedIn profiles because they have greater awareness to build their professional networks. This could lead to bias in my result, and it requires additional analysis to determine the direction of the bias.

Another possible bias comes from the classification standard of STEM versus non-STEM jobs. I currently refer to the Bureau of Labor Statistics listing of STEM jobs to distinguish students' professional outcomes. However, I assign 1 and 0 to whether students pursue a STEM job or not based on their company information. For instance, students whose company industry is "biotechnology" or "industrial automation" were labeled as doing a STEM job, and students whose company lies in "alternative dispute resolution" or "executive office" were assigned 0 for the STEM job indicator. These categorical criteria can give us a broad idea of whether students pursue a STEM job or not, but since they are classified based on company industry instead of the individual position, wrong assignments of the STEM job indicator are possible. More specifically, students who do a STEM job within a non-STEM company were not categorized as STEM workers, and students who do a non-STEM job within a STEM company were mistakenly considered STEM workers. I used the classification standard for the company industry because LinkedIn data are self-reported, and the way that different people name their positions could vary. Even though students' specific job titles are recorded in the LiveAlumni dataset, it is hard to properly interpret some of the job positions.

I also cannot assume the generalizability of my findings. The dataset I used contains only students from UC Berkeley, so I can only conclude that there is no valid evidence showing that more undergraduate majors increase students' likelihood of being in STEM industries for UC Berkeley students. Research with more demographics and more diverse academic and racial backgrounds can be done to better understand the relationship between the number of bachelor's degrees and the probability of STEM persistence on a larger scale (such as on a national level). Future research should track students' STEM persistence at several time points to evaluate the long-term effect of multiple undergraduate degrees. Researchers can gather students' salaries and bonuses for their first job as well as job promotion opportunities, helping to define STEM outcomes in a more comprehensive way instead of purely the success of getting into STEM industries. More work can aim to conduct a novel, longitudinal study on the long-term impact of pursuing multiple majors during undergraduate education to uncover more insights into educational outcomes.

To conclude, my paper investigates the relationship between the number of undergraduate majors and STEM career outcomes, and the main conclusion is that there is no significant increase in students' probability of being in STEM industries from holding multiple bachelor's degrees. This is critical to discuss because pursuing multiple majors is not suitable for everyone, and students should be mindful of the tradeoffs between devoting time and effort to more than one major and concentrating on one field.

In Qiong and Liang's 2021 paper, they suggest that having a double major has no significant impact on the likelihood of participating in the labor force, being employed, and enrolling in graduate school within a short time after graduation, but the benefits become salient four years after leaving college. This coincides with the main result of my work, implying that students who strive to be employed in STEM do not necessarily need to take on multiple majors; instead, they can boost their competitiveness through other ways. Also, students might want to consider that more majors can expose them to a more diverse collection of opportunities and possibilities, but deeper knowledge within a single field might make them more competitive in the labor market. Xu (2016) claimed that positive career outcomes, such as better earnings and greater job satisfaction, are associated with individuals having an occupation congruent with their college major. As the pursuit of multiple majors continues to be a trend in undergraduate education, advisors should provide more guidance and insights on major choice and course selection for students who want to pursue multiple majors so that they can obtain an interdisciplinary learning experience while developing specialized knowledge to help them succeed in the labor market.

7. CONCLUSION

My research makes distinctive contributions to the literature examining students' number of bachelor's degrees and STEM career outcomes with trustful empirical data and methods. It argues that pursuing multiple majors does not increase the likelihood of being employed at a STEM company. This encourages students to think about whether they should pursue more degrees for their undergraduate education or dive deeply into a single major based on their goals and expectations. Institutions should provide clear and valuable guidance to students pursuing more than one major such as one-to-one advising on brainstorming career goals. Students should evaluate the suitability of completing multiple majors instead of simply following the crowd. At the same time, students should carefully think about their academic commitment during their undergraduate studies and their professional priorities if they want to lower the attrition rates in STEM during the transition from college to employment and contribute to the STEM labor supply to the best extent.

ACKNOWLEDGMENTS

I am extremely grateful to Professor David Card and Graduate Student Instructor Joaquin Fuenzalida for their continuous guidance and support in ECON 191, Research Topics in Economics, at UC Berkeley. I also thank professor Anita Balaraman and Jill Finlayson for mentoring me and helping me get access to the data. All of the remaining errors are my responsibility.

APPENDIX

[1] Reference for the classification of STEM versus non-STEM majors from the Higher Education Research Institute at UCLA:
https://www.heri.ucla.edu/PDFs/surveyAdmin/fac/Listing-of-STEM-Disciplines.pdf.
[2] Reference for the classification of STEM versus non-STEM industries from the Bureau of Labor Statistics (page 4): https://www.bls.gov/careeroutlook/2014/spring/art01.pdf.

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What's the Hype All About?
Defining the Success Factors of NFT Sellers and Examining Expert Opinions of the Market

By KISHAN GANDHAM, BRYCE GROVE, CALLEIGH SMITH, and EMILY XU

I. OVERVIEW

I(1). Non-Fungible Token Background

A non-fungible token (NFT) is a unit of data stored on a decentralized electronic ledger known as a blockchain that certifies a specific file is unique, something that has previously been impossible for digital files (Clark 2021). By designating files as unique, NFTs are used to develop digital "ownership" of any type of file. While NFTs have represented a drastic change in a variety of electronic spaces, one of their most impressive applications has been in the art world, where billions of dollars of digital art pieces are circulated every year.

While NFTs have only gained popularity in the past year, the technology is already highly realized: by late August 2021, sales volumes on OpenSea, the largest NFT trading platform, reached $1.9 billion, over ten times the sales volume in March ($148 million) (Howcroft 2021).

With each additional transaction, the NFT artist or person who minted the original NFT receives an automatic royalty. Unlike traditional fine art spaces where artists only see profit from their initial sale, NFT utilization presents a strategic opportunity for artists and sellers to capitalize on royalties and repeat profit from sales in secondary and tertiary markets (Clark 2021).

Due to the novelty of NFTs as an asset class, there are currently no official regulations on the buying and selling of NFTs as securities in the United States. Since NFTs have an impressively wide range of characteristics, uses, and formats, they have yet to be classified as a specific asset class and therefore have much more ambiguous regulations than more traditional securities or commodities (Jones Day 2021). In addition, NFTs are typically only bought and sold using decentralized cryptocurrencies (typically Ethereum), which only increases the difficulties in regulating and monitoring this new asset class given the current relationship between cryptocurrencies and governments. Furthermore, NFTs are subject to intellectual property regulations as they contain metadata describing the corresponding assets that they are bound to, making it significantly easier for original artists to profit off all depictions, copies, and displays of their work (Clark 2021).

Unlike other asset classes on which limitations are set by regulatory agencies or third-party rules, NFTs are governed by inherent technological features that are built into how they operate. To truly understand NFTs and the marketplaces where they are bought and sold, it is imperative to develop a fundamental understanding of how a blockchain works and how that allows for NFTs to be transacted.

Theoretically, NFTs sound like the ideal way for artists to eternally profit off of their ideas in a rapidly growing market. However, with high and rapidly increasing minting fees (cost to put an NFT on the market) and gas prices (per transaction cost), can any new or existing artist make profit in the NFT space? As NFTs are fully digital, with no physical product to back them up, much of the surrounding speculative hype lies in the anticipation that a piece of artwork will appreciate in the future (Clark 2021). Thus, it is necessary to examine the relationship between the brand name and social media presence of NFT artists, the success of their artwork, and whether the market share is dominated by an "elite circle."

I(2). Hypothesis and Research Questions

The rise of non-fungible tokens and their digital nature have created a disturbance in the art industry that is relatively understudied, especially with respect to the success factors of NFT sellers. While proponents of NFTs claim the platform has "democratized" the world of fine art by seemingly removing the institutional barriers in conventional fine art markets (Milhado 2021), we believe a detailed analysis of NFT seller profiles, the regulatory environment, and NFT transactions will reveal that much of this "democratization" has been limited to the buyers of NFTs, not the sellers or artists. Much like traditional fine art, we hypothesize that a small number of NFT sellers make a majority of the profits, and the profile of successful mintings will depend on several unique factors (tech, multimedia, blockchain, etc.) that are not applicable to the sale of traditional art.

In our analysis, we will endeavor to answer the following primary question: What quantifiable and qualifiable factors—such as social media following, method of generation, etc.—influence total revenue of a minted NFT, and how do those factors explain the current market share makeup? In the process of investigating this question, we will explore how one's social media following influences the total revenue from an NFT minting; how the involvement of traditional fine art institutions, such as Sotheby's and Christie's, have changed the market for NFTs; and what other quantifiable factors are associated with a successful minting.

II. NFT PEDAGOGY

For all the complexity that exists within the market for NFTs, the underlying technology behind NFTs is perhaps even more complex. It is important to note that a thorough understanding of blockchains, decentralized ledgers, decentralized autonomous organizations (DAOs), cryptocurrency, smart contracts, or cryptowallets is not necessary to participate in the NFT market (websites like OpenSea are designed to be easy to use). However, if we wish to truly understand the markets behind NFTs, developing a deep knowledge of how NFTs work is paramount. Just as traditional art relies on third parties like auction houses or governments to make regulations, facilitate sales, and enforce ownership, NFTs use technology—specifically the blockchain—to accomplish these things (Clark 2021). Trying to understand NFTs without an understanding of what the computers are doing would be like trying to understand traditional art markets without knowing the role auction houses play. This paper hopes to provide that understanding to not only establish that our readers share a similar understanding of NFTs, but also to ensure we incorporate the technological complexities into our analysis.

II(1). Technological Underpinnings

The most important piece of technology that underlies every NFT is a blockchain.

Developed alongside Bitcoin in a 2008 paper *Bitcoin: A Peer-to-Peer Electronic Cash System* by anonymous developer Satoshi Nakamoto, blockchains were created as a way to replace "trust" in online transactions with "proof," which has major implications on the feasibility of conducting commerce in an online setting (Nakamoto 2008, 1). In a transaction with physical cash, "trust" is simple: a seller needs to trust they are not accepting counterfeit currency from a buyer. Once cash is traded between parties, the seller does not need to worry about the buyer retroactively reversing their transaction to receive goods without having to pay because, after all, the seller already has the cash (Nakamoto 2008, 1). Additionally, there is no "double-spending problem" with physical transactions. Once physical cash is spent, there is no possible way to spend that same cash, meaning sellers do not have to worry they are accepting cash that has already been promised to somebody else. It is important to note that "trust" in this setting still comes from a third-party organization—in this case the state—and its ability to enforce counterfeit laws and continue to use and support the currency (Nakamoto 2008, 2).

As transactions move away from physical cash, trust becomes much more complicated. In an online transaction, the seller is not receiving a physical asset but instead a piece of code, meaning many of the issues mentioned above are present. Now, parties have to worry about the transaction being hacked, the money being retracted after the fact, and the received money being spent somewhere else. Before blockchain, this problem required a trusted third party and a single centralized ledger, held by this trusted third party, to solve (Cryptopedia Staff 2021b). This ledger was required to keep a "trusted" record of transactions, to settle disputes, and to ensure people were not spending the same digital cash more than once. By definition, if anybody claimed a series of events that disagreed with the ledger, they were wrong, and their record of accounts was ignored (Cryptopedia Staff 2021a). These trusted third parties, typically banks or other financial institutions, were the sole arbiters of truth in online transactions. While this works in theory, when the "trusted" third party can no longer be fully trusted to provide an objective account of transactions (recent events like the Wells Fargo account scandal suggest our "trusted" third parties can let profits get in the way of the truth), this solution begins to fall apart (Kelly 2020). Since the ledger is read as the correct record of events, if it is incorrect (whether through a mistake or fraud), transactions will not reflect reality, and no other party is able to make a correction without significant work (Acharya, Yerrapati, and Prakash 2019, 79–135). It is clear that even with this centralized ledger, the same issues exist, just one level removed. Blind trust in a third party is still present: this time, there is trust that the organization will provide an accurate ledger. Blockchain represents a significant breakthrough because it uses meticulous cryptographical verification, proof-of-work, and the law of large numbers to create a public record of online transactions that does not require blind trust (Nakamoto 2008, 2–8).

Blockchains were initially created for a very specific and narrow circumstance: to record simple "Person A sends X Bitcoin to Person B" transactions (Nakamoto 2008, 1). Blockchains, however, were quickly adapted into several smarter and more flexible platforms, the most notable of which is Ethereum. Ethereum relies on the same fundamental concept as Bitcoin—blockchain—but was designed to support many other types of code besides basic transactions (Buterin 2014). One type of code which is particularly relevant to NFTs is known as a smart contract ("code that is embedded in a blockchain and run by miners"), which theoretically allows for any program, soft ware, or algorithm to run independently of a centralized server (Chevet 2018, 12). NFTs exist as smart contracts on the Ethereum blockchain which contains information on who has ownership of a digital file, much like an electronic deed. It is important to note that the actual content of a file is typically not stored on the blockchain (files can be stored "on-chain," but this is incredibly expensive and unnecessary) but rather in a separate repository known as an InterPlanetary File System (IPFS). When one purchases an NFT, they are not buying the file but rather a "receipt" that provides a certifiable proof of ownership and authenticity (Mok 2021).

Unlike fungible tokens where there is no effort to differentiate between any two tokens, non-fungible tokens are differentiated. Even if there exist two identical copies of the same file, the differences in their position on the blockchain would designate the two files as distinct, meaning they could still be bought and sold as if they were different (Chevet 2018, 5). The applications of "uniqueness" to digital art are obvious. With a medium as easily cloneable as digital files, it is essential that a potential buyer can distinguish between authentic pieces and forgeries. Much like physical art, distinguishing between authentic pieces and forgeries is incredibly important and can result in millions of dollars in value differences. Unlike physical art, it is easy to see which copy of an NFT one is receiving since only one copy can exist on the blockchain.

Fortunately, purchasing an NFT is much simpler than the technology that creates them. Platforms like OpenSea, NBA TopShot, SuperRare, Rarible, Solana, and many others provide a user interface much like eBay where one can explore different NFT collections and place bids or buy-now offers for NFTs on a specific blockchain. Auctions on these websites work primarily in two formats: an English auction (much like those found at Sotheby's or Christie's), where ascending bids are placed and the piece is sold to the highest bidder within a certain time frame, or an open bid auction, where buyers submit public offers and the piece is sold to whichever offer the buyer choses, often without a fixed time frame (both auction types typically include a "buy now" price which is set by the owner and, if met, will immediately end the auction) (OpenSea Developers 2021).

II(2). Regulatory Environment

There are two primary regulatory spaces regarding NFTs, reflecting their dual nature: copyright laws, which treat NFTs as art (something to be owned for its own sake), and securities laws, which treat NFTs as an asset class (something that is bought and sold for financial gain) (Halfon 2021). Despite dealing with the exact same object, these two spaces have distinct backgrounds and are enforced by different entities. Therefore, they should be investigated separately.

We start by exploring the laws regarding NFTs as art. To learn more about these laws, we interviewed Jesse Halfon, a copyright attorney who specializes in virtual licensing law and assists NFT artists in protecting their creative work. Despite their relationship to cryptocurrencies, which are notoriously separated from government interference, NFTs have a very close and "common-sense" relationship with licensing and copyright law. According to Halfon, with a few notable exceptions, NFTs follow the exact same intellectual property regulations as any other piece of media, including both copyright and licensing laws. Just like one cannot copy or profit off the logos or designs of a traditional brand, most NFT brands have the same protection, at least in theory (Halfon 2021). This often changes, however, from project to project. Depending on the specifics of an NFT's minting and the platform it is purchased on, some projects come with no licensing to the underlying art, some sell a personal use license (permitting personal use of the art for no financial gain) with the piece, while others (notably CrypToadz) sell a complete creative license of the art, meaning the purchaser can use the art as if they created it themself (Halfon 2021).

Interestingly, Halfon says what makes NFTs unique has little to do with any concrete difference in the licensing or fair use laws but rather a pervasive "copy culture" among NFT creators and buyers where laws about fraud, illegal copying, and fair use are actively ignored. For each successful NFT collection, there are likely dozens of illegal copies attempting to make money on the tailwinds of the success of the original.

As mentioned before, NFTs are more than digital art: they represent a significant and growing source of speculative investment in the digital economy. As the amount of money invested in digital art increases, increased attention on NFTs as securities will follow. A security, as defined by the Securities and Exchange Commission (SEC), is any "note, stock… certificate of interest or participation in any profit-sharing agreement, certificate or subscription, or investment contract" (U.S. Congress 1934). This definition is purposefully vague so it can encapsulate any asset which is owned for the primary purpose of generating income or capital gains. Art, both digital and physical, does not cleanly fit into any of the categories that define a security, and as a result, it has a confusing relationship with regulation despite its increasing use as a speculative investment. The digital nature of NFTs only adds another layer of confusion about the current regulatory environment, but there are several concrete characteristics that can eliminate much of the confusion.

According to Halfon, to be regulated as a security by the SEC, an asset needs to satisfy three major characteristics. First, an NFT's status as a security depends on whether or not it is advertised as an investment. It is often thought that most buyers of digital art are primarily interested in the capital gains associated with owning these pieces. To avoid increased scrutiny, creators rarely mention any financial gain, cash flows, or other income associated with owning their pieces even if they exist and are large drivers of demand. Next, if an NFT can be fractionalized and sold on a secondary market, it would likely fit the definition of a security and would be regulated as such. This point has recently garnered some increased attention as websites like fractional.art allow investors to buy, sell, and mint shares of NFTs. Lastly, the increasing presence of "crypto partnerships," hedge funds, and collaborative NFT portfolios could also attract increased attention from regulatory agencies.

Despite the connections to securities law, there has yet to be a single piece of legislation or SEC investigation specifically targeting NFTs or online art even in the face of numerous well-known scams. [Since this article was authored, the SEC has reportedly begun investigating NFTs, particularly fractionalized NFTs, as securities (Chittum 2022)]. The reasons for this are quite simple: art has historically had a lax relationship with securities regulation, and the law has not kept up with the rapidly changing technology (Halfon 2021). While NFTs are now a well-known and lasting feature of the contemporary art scene, they were incredibly niche even just one year ago. Blockchain technology was only developed in 2008, and Quantum, considered by most to be the first NFT, was only minted in 2014. NFTs, which represent a nearly $9.3 billion market as of October 2021, only generated $110 million in total sales in all previous years combined (Portion 2021). With the influx of attention and money entering the NFT space in only the last few months, it is no surprise government regulation has lagged behind. Halfon believes this will quickly change, and NFTs will begin to see regulation more in line with their use as securities in the coming years.

III. QUANTITATIVE ANALYSIS: REGRESSION ON CHARACTERISTICS OF SELLER PROFILES

III(1). Data and Variables

To analyze the success factors of NFT sellers, we constructed an original dataset featuring the characteristics of NFT sellers' profiles. Each observation in our dataset represents an NFT seller on the OpenSea marketplace. According to an October 10, 2021 article published by *The Generalist,* "since its founding in 2017, [OpenSea] has grown to become the undisputed leader in the space with a share that exceeds 97% and volume 12x that of its closest rival" (Gabriele 2021). Thus, a set of sellers exclusively from OpenSea is a sufficiently unbiased sample of prominent NFT sellers. In constructing our dataset, we decided to focus on the top 100 sellers on OpenSea determined by all-time sales volume (measured in Ethereum) as of October 12, 2021 to create a snapshot of the data at that point in time since the NFT world is rapidly changing.

Most of the variables were scraped from the OpenSea website (https://opensea.io/). Our dataset features 14 variables pertaining to each seller: name, biography, ranking, category (e.g., art, collectibles, virtual worlds, utility, sports), year of first sale, number of unique items in the seller's present collection (in thousands), number of unique owners holding at least one NFT from the seller (in thousands), total volume traded (in thousands of Ethereum), lowest floor price at which one can buy an NFT from the seller (in Ethereum), average price (in Ethereum), number of Twitter followers (in thousands), whether the seller uses an algorithm to generate the pieces in their collection, whether the profile features a collaboration of different artists' works, and finally, whether NFTs by the seller have been featured in a traditional art auction such as those held by Sotheby's and Christie's. To obtain dummy variables for whether the seller has been featured in a traditional art auction, collaborates with other artists, or creates their collection pieces algorithmically, we performed web searches and used the resulting information to decide whether a given seller did or did not possess the characteristic in question. When certain sellers were missing data (e.g., floor price, average price), we used imputation of the average to fill in the missing data, as it would not have been appropriate to remove observations altogether. For an in-depth view of the variables used in this analysis, please see the codebook associated with this dataset, which can be located in the following Github repository along with the actual dataset: https://github.com/calleighsmith/NFT_sellers.

III(2). Methodology

Our quantitative analysis features a multiple linear regression model. The benefit of using an ordinary least squares (OLS) model such as this one is that it provides interpretable results. Our goal for this statistical research component is to be able to quantify the relative importance of our variables to identify which factors, if any, contribute to the success of NFT sellers, which we define in terms of economic achievement as total sales volume. Therefore, our regression analysis focuses on inference rather than prediction. Special attention will be devoted to interpreting p-values of the model coefficients, reporting confidence intervals, and ranking the relative magnitudes of the correlations of the independent variables with the response variable, which is sales volume in thousands of Ethereum. In order to fit this model, we used R, the leading statistical programming language.

The model formulation is as follows:

$$\begin{aligned} \textit{sales volume}_i = &\beta_0 + \beta_1 \times \textit{ no. items}_i + \beta_2 \times \textit{no. owners}_i + \beta_3 \times \textit{floor price}_i + \beta_4 \times \textit{average price}_i \\ &+ \beta_5 \times \textit{no. Twitter followers}_i + \beta_6 \times \textit{year first sale}_i + \beta_7 \times \mathbb{1}(\textit{algorithmically generated}_i = \textit{yes}) \\ &+ \beta_8 \times \mathbb{1}(\textit{artist collaboration}_i = \textit{yes}) + \beta_9 \times \mathbb{1}(\textit{featured auction}_i = \textit{yes}) \\ &+ \beta_{10} \times \mathbb{1}(\textit{category}_i = \textit{art}) + \beta_{11} \times \mathbb{1}(\textit{category}_i = \textit{sports}) + \beta_{12} \times \mathbb{1}(\textit{category}_i = \textit{collectibles}) \\ &+ \beta_{13} \times \mathbb{1}(\textit{category}_i = \textit{virtual worlds}_i) + \beta_{14} \times \mathbb{1}(\textit{category}_i = \textit{trading cards}_i) + \beta_{15} \times \mathbb{1}(\textit{category}_i = \textit{utility}_i) \\ &+ \epsilon_i \end{aligned}$$

where i represents an individual seller on OpenSea and $\epsilon_i \overset{i.i.d}{\sim} N(0, \sigma^2)$

We used statistical methods to properly validate our model. These methods include ensuring independence of the sellers in our dataset (our unit of observations), transforming variables if they do not have a linear relationship with the response variable, preventing multicollinearity of seller characteristics (our independent variables), checking that the model residuals are normally distributed, and lastly, empirically measuring homoscedasticity. Upon investigation, these assumptions appeared to be reasonably satisfied.

III(3). Results

The results of our multiple linear regression model can be found on the following page, including coefficient estimates, their 95% confidence intervals, and their p-values. Statistically significant coefficients are those with a p-value of less than 0.05 and are bolded for ease of identification.

TABLE 1 - REGRESSION ANALYSIS RESULTS

Characterristic	Beta	95 % CI[1]	p-value
Category			
art	—	—	—
collectibles	25	-13,64	0.19
new	14	-92,121	0.79
sports	17	-62,96	0.67
trading cards	15	-44,73	0.62
utility	6.2	-45,57	0.81
virtual worlds	-8.2	-60,43	0.75
No. Items	0.00	-0.02,0.01	0.63
No. Owners	0.24	-0.24,0.72	0.32
Floor Price (Ethereum)	-0.44	-0.72,-0.16	0.002
Year of First Sale	-16	-28,-3.2	0.014
Average Price (Ethereum)	3.3	1.6,4.9	<0.001
No. Twitter Followers	-0.05	-0.19,0.08	0.43
Alhorithmically Generated?			
No	—	—	—
Yes	9.9	22,42	0.54
Collaboration to Artist?			
No	—	—	—
Yes	20	-17,57	0.28
Featured in a Treaditiona Auction			
No	—	—	—
Yes	77	42,112	<0.001

[1]CI = Confidence Interval

III(4). DISCUSSION

Based on the model output, the coefficients for several variables are statistically significant, namely *floor price, year first sale, average price,* and *featured auction*. Given that multiple linear regression models are good choices for interpretable results, we can generalize the associations of our model's significant variables with the response, or a seller's total sales volume.

The first significant coefficient is for *floor price*, which is the lowest price for a collection of items. Holding all else constant, for an increase in floor price by 1 Ethereum, we expect the seller's total sales volume to decrease by 0.44 Ethereum. This suggests that there is an inverse relationship between floor price and total sales volume such that collections with cheap NFT offerings tend to generate more total revenue. Perhaps buyers look for inexpensive NFTs because they simply want to be involved in purchasing this new art form, but they are not committed to buying some of the pricier items in a collection.

Moreover, the coefficient for the year of a seller's first sale on OpenSea is statistically significant in our model. Holding all else constant, for an increase in one year, we expect the seller's total sales volume to decrease by 16 Ethereum. This outcome establishes that sellers with a "long-standing" presence on OpenSea—though OpenSea was founded relatively recently, in 2017—have amassed more sales volume over this time. New sellers might generate hype and make sales, but it takes time for their sales volume and community to grow. For NFT sellers, wealth is not generated overnight.

The next significant coefficient in our model is for *average price*. Holding all else constant, for an increase in average price by 1 Ethereum, total sales volume is expected to increase by 3.3 Ethereum. This perhaps is not very surprising, as it makes sense that sellers with pricier collections overall have larger sales volumes.

Whether an NFT seller has had their work featured in a traditional art auction such as Sotheby's or Christie's has a large association with their sales volume. In fact, the coefficient for this variable (77) is both positive and high in magnitude compared to other coefficients in the model. Holding all else constant, compared to an NFT seller who has not been featured in a traditional art auction, one who has been featured is expected to have a total sales volume that is 77 Ethereum higher. For NFT sellers who can get their work to be featured in a physical and reputable art auction, they may very well see elevated sales volumes.

While not statistically significant, the coefficients for the *category* variable reflect a certain hierarchy within our unique dataset such that compared to the baseline category art, the other categories, apart from virtual worlds, have a more positive effect on total sales volume. We inferred this by examining the sign of the coefficients associated with category; positive signs indicate that compared to NFT sellers who categorize their collection as art, sellers in other categories tend to have higher total sales volumes. On the other hand, negative signs indicate that sellers in other categories tend to have lower total sales volumes. This seems to suggest that NFTs that are most akin to traditional art are not as lucrative for sellers as collectible, new, sports, trading card, or utility NFTs are.

IV. QUALITATIVE ANALYSIS

IV.(1) Case Studies

IV.(1).1 Beeple

While much of the existing literature on art markets—including our research—posits that existing players in the art world tend to fare better in terms of pure profit margins and notoriety, the case of Mike Winkelmann, known in the NFT world as "Beeple," presents a stunning alternative to the old-guard model of art sales (Rega 2019, 1–2).

Beeple is a digital artist who makes a living selling the absurd—from comically repulsive images of former presidents to niche references to the inner workings of internet meme culture. Beeple's art is both as hilarious as it is confusing to its loyal core of supporters (Rapkin 2021, 1–2). Regarding supporters, Beeple sports an impressive 2.2 million followers on Instagram alone: even if his work does not appeal to everyone, it clearly strikes a chord with the masses. With this internet cult-style of fame though, Beeple has managed to achieve modern artist stardom in the digital age despite having maintained a low profile most of his career. Winkelmann started his career in website design but quickly focused his attention on creating a piece of artwork every day (Rapkin 2021, 16). He fittingly called his project *Everydays*. While his work initially started off with no significant audience, he quickly began growing his fanbase, eventually receiving attention from creative directors at Louis Vuitton, for example (Rapkin 2021, 18). While his newfound fame excited him, he had not found a way to sell any of his digital artwork let alone a monetization design. Traditional canvas artwork seemed to operate on a different plane than the type of work Beeple was creating

Winkelmann began hearing chatter about the potential of selling digital artwork on platforms directly tied to blockchain technology. He quickly forayed into Nifty Gateway, a website that hosts NFT auctions, and started selling his first pieces for over $60,000. Suddenly, a burgeoning artist who started to find success in some of the stranger parts of the internet had netted a significant profit through the world of cryptocurrency, blockchain, and NFTs. Winkelmann has even diversified; in an attempt to help ground digital art in a physical backing, he has started creating luxury goods that pair with sold digital art and are sent to those who purchase the actual piece (Rapkin 2021, 19–20).

Conceptually, Winkelmann has turned digital art sales into ones based on tried-and-true methods of selling art by creating a physicality to these ethereal online transactions. These days, Winkelmann continues *Everydays* and has recently sold an NFT for $69 million (Moscufo 2021, 1).

While there is something to be said about celebrity status following people to their first art sales on OpenSea or Nifty Gateway, Beeple is a fascinating case study into the so-called democratization effect. While he did have some sizable internet following, his primary profession of digital artmaking is what carried him to fame and netted him enormous returns on his works. Perhaps there is something more to be understood in the world of social media art portfolios, digital images that tilt towards the obscure, and new platforms that help artists reach an audience willing to pay a hefty amount for blockchain-verified proof that they do, in fact, own the newest Beeple.

IV.(1).2. Snoop Dogg and @CozomoMedici

Celebrity status seems to prove advantageous to most burgeoning NFT sellers. While many have forayed into the growing NFT space, it would be fruitful to analyze the NFT story of award-winning entertainer and rapper Snoop Dogg.

In April 2021, Snoop Dogg released his first NFT collection on Crypto.com titled "A Journey with the Dogg." The collection, only available for 48 hours, featured exclusive video and music (PR Newswire 2019, 1). Snoop Dogg tweeted: "108k bid on this piece ! Here we go! 20mins n counting !" (Snoop Dogg 2021). In his first-ever NFT sale, Snoop Dogg managed to sell a piece titled *Death Row* for over $100,000 (Tenenbaum 2021). This is a critical example of how celebrity status often elevates the price and valuation of NFT artwork. While some may speculate on whether the piece of Snoop Dogg on the electric chair (as featured in Death Row) was worth upwards of $100,000, subjective factors related to the maker of the NFT and the significance of the piece in relation to Snoop Dogg caused it to be valued higher.

However, the Snoop Dogg case study presents interesting data on the success of NFT sellers. In late September 2021, Snoop Dogg tweeted: "I am @CozomoMedici." Although seemingly innocuous, this tweet essentially claimed that Snoop Dogg was the identity behind the secretive NFT whale associated with the Twitter account @CozomoMedici (a reference to Cosimo de' Medici, the famed Italian banker and politician) (Morris 2021). Details regarding the veracity of the tweet and whether Snoop Dogg is the NFT whale he proclaims to be are still unclear. Nonetheless, at the time of his tweet, @CozomoMedici had a wallet filled with NFT collectibles valued at over $17 million, and Snoop Dogg's tweet linking himself to this account not only suggested Snoop Dogg is a bigger NFT player than people gave him credit for, but it also highlighted a case study as to how someone—even without big-name celebrity status or any identity known whatsoever—could amass 38,500 Twitter followers and become a big presence in the NFT space (Morris 2021).

Here is what this evidence indicates: while there are some like Beeple, who through consistency and a finger on the pulse of virality on the internet can dominate the NFT space even without pure celebrity status, most rapidly successful NFT sellers had some status prior to their emergence on NFT selling platforms. This is demonstrated by our findings in the regression analysis; the earlier the first sale on OpenSea, the more sales volume the seller is able to garner. By this, we posit that while OpenSea might feature multiple collections by seemingly unknown artists outside of the NFT space, the fastest NFT sellers to obtain high valuations of their artwork or those who experience immediate success are likely drawing upon a social media following and fanbase external to the NFT art world.

That being said, @CozomoMedici presents a notable alternative; while less industry dominant than Beeple, the account was able to boast a valuable NFT wallet and gain a sizeable social media following from NFT work (the account was only created in August 2021; therefore, it gained over 30,000 Twitter followers in under two months). However, the mere association with, first and foremost, a celebrity, and secondarily, a celebrity with a successful history of NFT collection sales was enough to bring @ CozomoMedici's following to over 100,000 Twitter followers just one month later.

IV.(1).3. Bollywood and Knowing Your Market

While the NFT craze might seem distinctly local, the move to NFT auction platforms is distinctly global. This point is underscored most vividly with the example of India, where 15 million of the world's near 100 million cryptocurrency users are located (Pradeep 2021). India is a salient example of NFT valuation and its tie-in to "hype" factors such as celebrity status and following as everyone from famed cricketers to Bollywood stars seem to be moving into the space.

Recently, Bollywood superstar Amitabh Bachchan decided to enter the world of NFTs by launching his first NFT collection in partnership with BeyondLife.club (Raj 2021). Bachchan fills the same niche that American actor Leonardo DiCaprio taps into for American markets. With such a powerful celebrity, it is no surprise that Bachchan's collection auctioned for nearly $1 million as an aggregate—the most valuable auction ever in India. Just a few days after launching his collection, a recording of Bachchan reading his father's poem sold for over $750,000 (Raj 2021).

The inherency of why these collections and pieces go for such sums seems innately clear: Bachchan is famous, and thus, the collectibles that he offers are valuable by proxy of their association with him. However, in a market where 15% of global cryptocurrency users are stationed, for one man to break Indian auction records highlights that the most dominating factor for success could in fact be social media following and celebrity status. In the world of social media, the best barometer of one's fame is their following. Bachchan, with about 29 million followers on Instagram, clearly has that and has evidently used his following as a vehicle to drive up value for his collectibles. Although social media following does not always drive up value—as our regression indicates regarding Twitter following—this highlights how, in exceptional cases like Bachchan's, celebrity status can help with the sale of NFTs.

For NFT sellers, the Bachchan example is clear: know your niche. Most of Bachchan's NFT collection featured old film memorabilia and material goods from his upbringing. The people predominantly purchasing his goods were likely fans who wanted a piece of Bachchan. Therefore, when comparing Bachchan to Beeple, either tap into what fans want or what the internet wants: both are bound to have willing buyers.

IV.2. Expert Opinions on the Market

We conducted multiple rounds of interviews to capture industry-specific insights, fine tune the interpretation of our regression, and take note of potential model improvements. The following section shall dive into recurring major themes across interviews with three main objectives in mind:

1. We would like to determine factors outside our regression model that potentially correlate to sales volume and the covariates. The reason why causal interpretation usually cannot be determined from regres sions in the real world, and why causation is not the same as correlation, is because covariates tend to be indicators of factors out side the model that also affect the dependent variable. The interviews we conducted do a particularly good job of parsing through the extra neous factors that affect the number of followers an NFT artist has.

2. We would also like to determine cases of multicollinearity, or when co variates are highly correlated with each other, which renders it difficult to isolate the effect of each covariate (e.g., social media followers and whether or not an artist has been featured in an auction) on the depen dent variable sales volume.

3. Finally, we would like to distinguish what makes the NFT space unique compared to traditional art markets and add qualitative insights to the future development of this market.

Prior to each interview, we requested and received permission to record. All interviewees have agreed to go on the record. In total, there were six interviewees, including: Jesse Halfon, Beverly McIver, Bill Fick, Nicole Sales, John Caccavale, and Ryan Kuo.

First and foremost, an artist's follower count encompasses multiple different factors that a quantifiable model would find hard to capture precisely, and this holds true for both NFT and traditional artists. For example, follower count is often influenced by unique branding, community (i.e., how engaged a following is with the artist), and whether or not the art style is "first" to the market.

According to Beverly McIver, contemporary artist and Duke Esbenshade Professor of the Practice of Visual Arts, unique branding is important because it makes an artist memorable: "To learn your craft, to perfect it, whether [one is] a painter, photographer, filmmaker, or musician, you're building your brand," she said. "You want to have a voice in your craft that makes you different. Visually, you see it show up in the artwork" (McIver 2021).

Social media, then, exists as a tool for artists to visually link their pieces in a condensed format, network, project their voice, engage with their audience, and establish community.

"I know a lot of artists who have gotten good things to happen through social media," said Bill Fick, printmaker and visual arts professor at Duke University. "I have people who contact me [about my work] … [Social media] doubles as being promotional" (Fick 2021).

These insights hold particular importance because they indicate that the price of artwork is not simply a function of the number of followers but also a function of how well an artist is able to connect with their audience, the artist's online interpersonal skills, and how persuasive the artworks' messages are. This suggests that an artist whose social media primarily consists of bought followers or followers who are not as engaged with the artist would not perform as well in sales as artists whose followers are engaged. It should be noted that soft, qualitative factors such as artist likeability are hard to quantify, and data such as private, direct messages to or from followers are not available in the public domain, which makes it hard to incorporate "engagement" in a regression.

Nevertheless, in the NFT space, similar observations hold true. According to Nicole Sales, business director of digital art sales and NFTs at Christie's Auction House, it is too early to talk about major trends, but in her experience, the best performing NFTs have been characterized by three factors: community, the primary market derived from the artist, and the natively digital aspect of the asset (Sales 2021).

"What we've found in the short period of time that we've done this," said Sales, "is that artists that have existing communities really performed the best. They're the ones that have their own social media following, they have their own brand, their own persona... They're already popular with their audience, and Christie's is just amplifying their voice on its platform" (Sales 2021).

From Sales's quote, we can derive two insights. First, there is a high probability of collinearity between the number of Twitter followers and whether or not an NFT artist has been featured in an auction. Auction houses such as Christie's select for established artists with large followings to feature in auctions, and it is likely that the auction itself brings about even more followers for the artist. This makes it hard to isolate the individual effect of an auction feature versus the effect of the following count. However, it is both plausible and likely that established artists (and potentially new artists) would still benefit greatly from being featured in an auction. Second, “community” seems to be a main factor in the NFT space, and like the traditional art space, this exists outside the model and correlates with artist social media follower count, demand, and the price of an NFT piece.

As for the second insight, it seems that working with the artist in the primary market as opposed to in the secondary market as well as working with artists who can mint under their own name yield more success in terms of price from the perspective of auction houses.

“We've done a few secondary sales for certain projects such as Cryptopunks, but I think when we're working directly with the artist, it makes it more authentic,” Sales said. “I think the most successful artists are the ones who also understand the tech. There are companies that do the minting for artists, but that is less authentic. It's nice when the artists can mint their own piece because then when you're looking at the blockchain, it says it's originally from the artist as opposed to some random company that did it on the artist’s behalf” (Sales 2021).

The digital nature of NFTs makes trust and authenticity even more imperative than before. Buyers need to know that what they are buying is the real version by the artist, and auction houses working directly with said artists is a signal of authenticity.

One factor that contributes to the success of an NFT artist and the price of their works that does not necessarily apply to traditional art markets is the natively digital aspect of an NFT.

“The actual asset is made digitally as opposed to just an NFT pointing to something else that doesn't have to be an NFT,” Sales said. “I think you can't just make an NFT out of anything, and that adds value... The actual asset itself that the NFT is pointing to has to have utility, has to have value, and has to be interesting enough that people want it in and of itself.” (Sales 2021).

Some artists add exclusive club memberships to their NFTs, while others add tangible assets. In some cases, artists also use the blockchain technology within the artwork itself.

“So maybe it's something where the art continuously changes over time based on current events or based on life events,” Sales said. “There's a lot of dynamic attributes that artists can add if they are using blockchain to enhance the actual art that they're creating, and those are the projects that are the most successful, the most interesting, and that are going to make this category unique. You're not just printing out something that you made in Photoshop” (Sales 2021).

Ultimately, the NFT space is still relatively new, but like in any other industry, becoming a successful NFT artist takes strategic work and is not as simple as what conventional media makes it out to be.

“I think it's hard to break in, just like it's hard to break in and become famous and popular in any industry,” Sales said. “In order to be successful, you have to build your own brand, network with the crypto community, and create a project that is immersive

There are creative ways to develop hype, and it's a little bit of marketing and a little bit of artistic talent" (Sales 2021).

However, after an NFT artist breaks into the industry, "price hype" can become a separate factor that influences price. As the price of an NFT art piece increases, speculators may start to believe that the price will go up even further and buy in just to sell in the short term. These speculators then also contribute to an artist's following.

"[If we] talk behavioral finance, I think there's a lot of F.O.M.O. (fear of missing out)," said Professor John Caccavale, executive director of the Duke Financial Economics Center. "Nothing's worse than not being rich than seeing your neighbor get rich" (Caccavale 2021).

So far, we can summarize the covariate social media following as an indicator of several factors, some within the model (i.e., how long the artist has been in the NFT market and whether or not their art has been featured in an auction) and some outside of the model (i.e., unique branding, established community, perceived authenticity, perceived future ability to increase in price, and bragging rights). NFTs's heavy reliance on subjectivity and buyer perception leads many to remain skeptical, including Caccavale.

"I see too many similarities in what's happening in the NFT sphere that remind me of other things [like Pet Rocks]," Caccavale said. "I think, if the market corrects itself, which it will, the people who need money again just like [in the financial crisis of 2008], the start of COVID paranoia in March 2020, 1994 with Mexico, 1997 with Asia, and whenever markets crash [will sell]" (Caccavale 2021).

Therefore, by investing in NFTs, investors may be poised to lose money should the market correct itself. Nevertheless, some view NFTs as a neutral instrument that has pros and cons for all.

"[NFTs] are neither good nor bad," said NFT artist Ryan Kuo. "They are bad because they are a capitalist tool. They are contributing to destructive processes and environments, and they are allowing the investor class to carve out their space on the blockchain… [On the other hand,] many artists [who did not get appreciation via traditional mediums] are finally getting noticed" (Kuo 2021).

V. CONCLUSION

V.1. Limitations

First, due to the fast-changing NFT market, OpenSea rankings change daily. Therefore, our data represent a snapshot of the top 100 sellers at the time that the data were collected (October 12, 2021). Less than a month later, some of the seller rankings and metrics (e.g., number of Twitter followers, number of items, average price) had already changed. Second, missing values were imputed using the mean value, which allowed us to make use of all observations in our dataset and maintain our sample size of the 100 top sellers when creating our model. We believe that this was the best way to deal with missing data in our analysis, but it is necessary to understand that the imputed missing values are, by nature, imprecise. Third, our dataset focuses only on the top 100 NFT seller profiles by volume, which limits the generalizability of our analysis. Our findings from our quantitative analysis can only be applied to high-profile NFT sellers rather than smaller, up-and-coming sellers in the space. Fourth, there is the issue of multicollinearity and the fact that many factors that affect follower count could not be included as covariates due to data restrictions or the infeasibility of measuring subjective factors such as "community." It will be hard to determine the precise magnitudes of the effect of each covariate due to the above limitations.

Qualitatively, our interview sample size was small. While our regression pointed to specific variables, our interviews focused on the notion that social media following and artistic quality are the main determinants of value. Largely, more refined findings should have more interview subjects that span NFT artists, regulators, academics, and economists. Our qualitative findings from interviews and case studies might be more profound with more interviews conducted and use cases researched.

V.2. Future Directions

Our analysis creates many opportunities for further research. First, expanding the data to include more NFT sellers and more variables would be a major undertaking but also one of the first of its kind. Our dataset provides a satisfactory starting point for an NFT quantitative analysis given the resources available to us. As many of the variables in our dataset were collected through search queries, data collection proved to be a time-consuming and tedious process. Given the short-term span of this project (a single academic semester), we needed to construct an accurate, workable dataset with sufficient time to analyze it properly and derive insights.

Additionally, there is concern about reverse causation between NFT fame and sales volume. We have a strong case for bidirectional causality where more followers can cause higher prices, but higher prices can also cause more followers. If we would like to produce a consistent estimate, we would need to produce a model with an instrumental variable. However, this may be infeasible due to the opacity of data collection and the conditions that need to be met to find valid instruments. It would be interesting, however, to see the point in time when the following of each artist increased significantly—that might be an indicator of when price or some other sort of attention-grabbing phenomenon caused an artist's following to explode. However, this might pose difficulties because there are multiple exogenous factors such as press coverage, and it would be hard to pinpoint or define exactly when the "takeoff point" is.

We wish that we had more time to conduct additional interviews and adjust our model based on the interview feedback. While our interviewees were carefully selected to show a diversity of perspectives (artistic, economic, legal, etc.), comparing competing viewpoints could add to the robustness of our analysis. Additionally, the interviews were conducted qualitatively and in conversation, but we considered a quantitative interview approach where interviewees would provide empirical ratings to quantify observations and sentiments. However, we felt that our regression analysis was sufficient for presenting a quantitative approach in our research and preferred the de criptive analyses that our interviewees could provide. Future studies might consider the quantitative interview approach.

Since the technology and regulatory environments for NFTs are ever-changing, it would be wise for future researchers to stay up to date on these disciplines and how they are impacting the NFT space. As Halfon expressed in his interview, it is a matter of time before governmental agencies such as the SEC become more involved in this new asset class, which could have major implications for the market for NFTs.

V.3. Summary and Final Remarks

Given our original research question surrounding the factors that contribute to an NFT's value and its total revenue, our data and findings point to a few different considerations. The data suggest that a low floor price, an early start for an NFT seller on OpenSea, and the piece being featured in a traditional auction are some of the more interesting and significant potential drivers of value. Interviews and case studies present a broad-strokes understanding of NFT value, suggesting that the duality of social media presence and artistic craft are what accelerate NFT works to higher valuations and fame. Perhaps it is a combination: if NFT artists are coming from a different medium and bringing their fans to OpenSea, maybe when they started is not as important. More important to them is leveraging their existing fans to purchase items from their collections. For humble artists trying to get recognized via NFT collections on OpenSea, it is better they foray into the space earlier rather than later and work on refining their artistic craft, community, brand, and social media presence. These, according to various NFT players, are the best drivers of valuation and revenue. Regardless, the world of NFTs is rapidly evolving, deeply convoluted, and tethered to the internet: our findings simply confirm the obvious. At least for now, NFTs are here to stay.

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Extended Pandemic Unemployment Benefits: Effects on Unemployment and Labor Force Participation

By CODY TAYLOR

Policymakers in the US have responded to the last two recessions—the Great Recession and the 2020 pandemic-induced recession—by increasing and extending unemployment benefits, which help smooth consumption for those who have lost their jobs. Is recovery from recession hampered by these benefits because workers are disincentivized to rejoin the workforce? The literature on this question finds mixed results: these benefits do provide an incentive to not rejoin the workforce, but there is evidence that the removal of these benefits restores little of the recession-induced employment losses. I look at the extended unemployment benefits offered during the pandemic through the CARES Act, the American Rescue Plan, and executive order to analyze the same question. Using a difference in means method and linear regressions, I examine the association that extended unemployment benefits had with unemployment levels and labor force participation at both the national and state levels. I found mixed evidence that these benefits hampered economic recovery or were a major factor in the "labor shortage" during recovery.

I. INTRODUCTION

At multiple points during the ongoing COVID-19 pandemic, the federal government extended the availability of unemployment benefits and increased the amount of said benefits beyond their normal levels. The Coronavirus Aid, Relief, and Economic Security (CARES) Act, which was signed into law on March 27, 2020, established three new unemployment insurance programs. The Pandemic Unemployment Assistance (PUA) increased eligibility particularly to gig workers and the self-employed, the Pandemic Emergency Unemployment Compensation (PEUC) extended an additional 13 weeks of unemployment compensation to those who had previously exhausted benefits, and the Federal Pandemic Unemployment Compensation (FPUC) which disbursed an additional $600 in monthly benefits to the unemployed. The FPUC benefits expired on July 26, 2020, but President Donald Trump signed an executive order continuing FPUC payments, reduced to an additional $400, until December 6, 2020. The PUA and PEUC extensions expired on December 31, 2020. Once President Joe Biden came into office, he signed into law the American Rescue Plan, which extended these unemployment programs until September 6, 2021 (117th United States Congress 2021).

Once recovery started from the pandemic recession, conversations about a "labor shortage" started to emerge as companies, predominantly in the service sector, were reporting that they could not find workers to fill their job openings (Ellyatt 2021). State and federal policymakers, especially those who were conservative, began to suggest that the extended unemployment benefits were the root cause of this labor shortage (Skolnik 2021). Their argument was that the benefits were so generous that workers preferred to stay unemployed rather than reenter the workforce. On its face, this argument is intuitive, as sufficiently good benefits combined with relatively relaxed restrictions to receive said benefits could naturally provide a disincentive to work. From this perspective, extended unemployment benefits created an incentive to not work, where too generous of benefits distorted worker's trade-off calculation between leisure time and labor time. However, for this to be the case, the benefits must be sufficiently generous, the administrative barriers to initially receive benefits must be sufficiently low, and the restrictions to receiving continued benefits must be sufficiently low.

I argue that the extended unemployment benefits did not meet all three criteria and cause the labor shortage. Rather, it seems that general macroeconomic trends dictated the extent to which the unemployed reintegrated back into the workforce, most notably a once in generation global pandemic that completely disrupted the economy. It is certainly possible that the benefits were sufficiently generous, as many were receiving more income with the additional $600, $400, and $300 weekly payments than they were at their original jobs (Thomson-DeVeaux 2020). However, this may be more of an indicator that these recipients' previous wages were too low rather than an indicator that benefits were too generous. Especially considering a significant portion of the job loss from the pandemic were lower wage jobs in the service sector. Additionally, while some states initially waived the work search requirements to apply for unemployment during the early stages of the pandemic, there were and still are not only a great deal of initial barriers to receiving benefits, but also barriers to continuing to collect benefits. For example, the state of Alabama, amongst other requirements, asks individuals to continually prove that they have actively sought out that separation from their previous job was no fault of their own (Alabama Department of Labor 2021). Additionally, recipients cannot refuse any suitable employment offer they receive while on benefits. Given these kinds of barriers and the Congressional Budget Office's projection that pre-pandemic employment levels will not return until 2024 (Congressional Budget Office 2021), the "labor shortage issue" seems to be on its face caused by general macroeconomic trends in structural and cyclical unemployment rather than workers being disincentivized to work.

The academic literature surrounding this question gives a mixed answer as to the extent that extended benefits impact employment decisions. One study of the impact of the extended unemployment benefits that were offered during the Great Recession found evidence that extended benefits "slightly reduced the exit rate from unemployment, largely through increased labor force attachment rather than reduced job finding" (Farber, Rothstein, and Valletta Robert 2015, 171). The researchers in this study further qualify this finding by stating that their estimates may have been affected by "historically weak labor market conditions around the Great Recession" (Farber, Rothstein, and Valletta Robert 2015, 171). Another paper conducted a case study of the impacts of benefits on unemployment duration in Missouri from 2003 to 2013 and found that unemployment duration during a recession and the subsequent recovery period is more responsive to benefit levels than pre-recession unemployment duration (Card et al. 2015, 1). A third paper that studied unemployment benefits during the Great Recession found "no evidence of an economically meaningful effect" from the extended unemployment programs passed during the Great Recession on the job search by unemployed individuals (Baker and Fradkin 2017, 1).

Researchers have also addressed this question with respect to the pandemic-induced extended unemployment benefits offered from April 2020 through September 2021. Ganong et al. (2021) found that extended unemployment had a "quantitatively small" disincentive effect on job-finding, estimated that elimination of these benefits "would have restored only a small fraction of overall employment losses," and found that the benefits were not "the key driver of the job-finding rate through April 2021" (Ganong et al. 2021, 1). In a comparison between states, another paper found that ending pandemic unemployment insurance increased employment levels by 4.4% and decreased unemployment recipiency by 35% amongst the unemployed (Coombs et al. 2022, 1). Lastly, in his paper, Professor Arindrajit Dube found evidence that the elimination of the pandemic-extended unemployment benefits had little impact on job gains (Dube 2021, 18).

II. NATIONAL LEVEL ANALYSIS

I analyze the question of whether extended unemployment benefits disincentivized workers from reintegrating into the workforce by looking at the question at both the national and state levels. Using monthly data from the US Bureau of Economic Analysis and the US Bureau of Labor Statistics, I examined the difference in means of labor force participation and total non-farm hires between months of the pandemic where there were extended unemployment benefits and months where there were not. Additionally, I ran three regression models of national labor force participation. Labor force participation "is the percentage of the civilian noninstitutional population 16 years and older that is working or actively looking for work" (US Bureau of Labor Statistics 2016). Receiving unemployment benefits "has no bearing on whether a person is classified as unemployed," and for this reason, any observed changes in the labor participation rate serves as a good indicator of labor force reintegration (U.S. Bureau of Labor Statistics, n.d.). If it is true that the benefits were a disincentive, then the data should show that non-farm hires were greater in months with no extended benefits and that the labor force participation rate was also greater in months with no extended benefits. An initial look at the data as displayed in Table 1 and Table 2 shows that the average civilian labor force participation rate was slightly higher for months where extended benefits were not available, and the average total non-farm hires were lower in months without extended benefits.

TABLE 1. DESCRIPTIVE STATISTICS FOR LABOR FORCE PARTICIPATION AND NON-FARM HIRES FOR MONTHS WITHOUT EXTENDED UNEMPLOYMENT DURING THE PANDEMIC.

	Observations	Mean	Standard Deviation	Minimum	Maximum
Civilian Labor Force Participation Rate	8	62.60%	.81%	61.60%	63.40%
Total Non-Farm Hires (Measured in thousands of jobs)	7	5974.14	465.86	5132	6546

Source: Bureau of Labor Statistics, November 2019 – November 2021

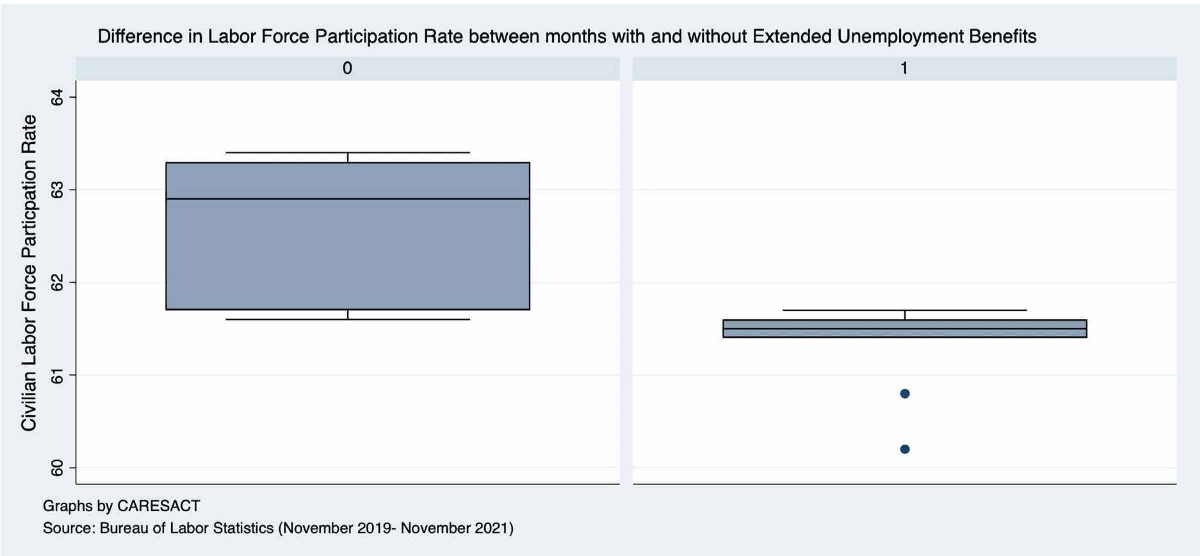
TABLE 2. DESCRIPTIVE STATISTICS FOR LABOR FORCE PARTICIPATION AND NON-FARM HIRES FOR MONTHS WITH EXTENDED UNEMPLOYMENT DURING THE PANDEMIC.

	Observations	Mean	Standard Deviation	Minimum	Maximum
Civilian Labor Force Participation Rate	17	61.42%	.38%	60.20%	61.70%
Total Non-Farm Hires (Measured in thousands of jobs)	17	6197.65	937.00	3942	8272

Source: Bureau of Labor Statistics, November 2019 – November 2021

Figures 1 and 2 would seem to explain this trend in the data as the result of outliers in the data for months with extended benefits. However, to see if this difference between the two groups was statistically significant, I conducted three differences in means hypothesis tests on three outcome variables that should indicate workforce reintegration: labor force participation rate, total non-farm hires, and another variable which measured the number of continued claims for unemployment insurance. The null hypothesis for each test was that there is no difference in the averages of labor force participation, total non-farm hires, or continued claims between the two groups of months. The alternative hypotheses were that months without extended benefits should see a higher average labor participation rate, higher average total non-farm hires, and lower average continued claims than months with extended benefits. The decision rule for each test was that I would reject the null hypothesis if the p-value was equal to or less than 0.05. Prior to these tests, tests for unequal variances were conducted, which revealed that there were unequal variances between the two groups of months for each outcome variable. After adjusting the hypothesis test to account for unequal variances, the tests found that the null hypothesis of equal averages could be rejected for labor force participation and continued claims but could not be rejected for non-farm hires.

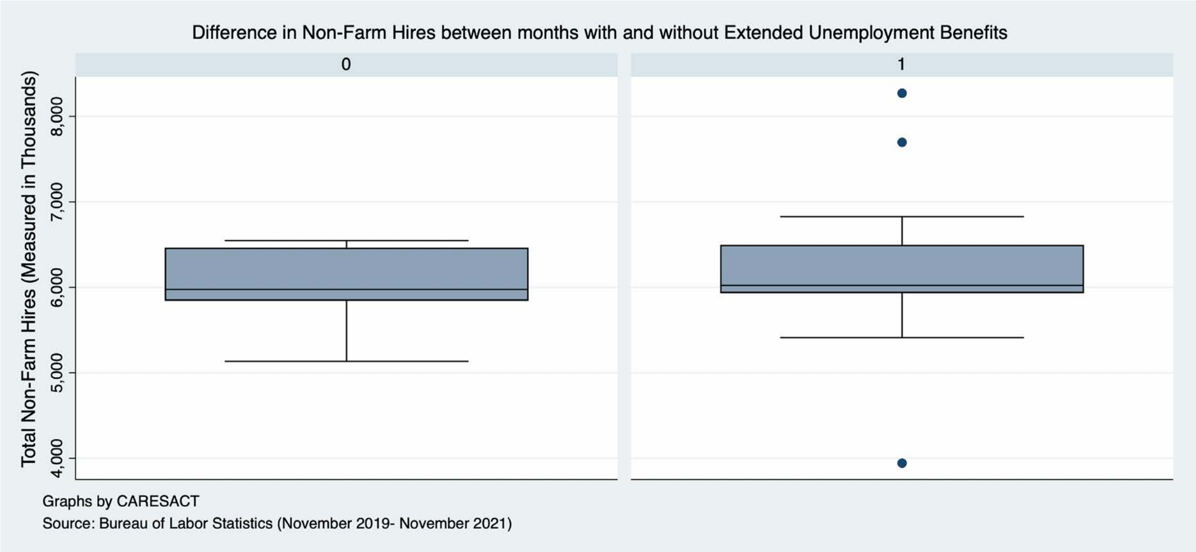
Figure 1.



P-values:

- Labor Force Participation: Probability of seeing difference in average by chance of 0.002
- Continued Claims: Probability of seeing difference in average by chance of 0.0003
- Non-farm hires: Probability of seeing difference in average by chance of 0.2228

Figure 2.



From the hypothesis tests, I constructed three regression models to better understand the extent to which the CARES Act's unemployment benefits affected workforce reintegration. The first model was a simple linear regression of labor force participation on a dummy variable for months which had extended benefits. The second model controlled for the percentage change in the unemployment rate and the total number of non-farm job openings across the months of the pandemic. The last model built on the second model by including the percentage change in real GDP (2012 chained dollars) and continued claims for unemployment. The results of these models are displayed in Table 3.

TABLE 3: NATIONAL LEVEL MODELS

	Labor Force Participation	Labor Force Participation	Labor Force Participation
CARES Act	-1.176*** (-5.00)	-1.269*** (-5.97)	-0.873*** (-4.00)
% Change in Unemployment Rate		-0.00591* (-2.80)	-0.00525* (-2.75)
Total Non-Farm Job Openings		-66.26 (-1.18)	-181.5** (-3.10)
% Change in Real GDP			0.0151 (0.23)
Continued Claims			-6.68e×10^8*** (-3.14)
Constant	62.60*** (322.55)	63.25*** (132.63)	64.30*** (125.21)
Adjusted R2 Value	0.4999	0.6462	0.7530

t statistics in parentheses * p<0.05, ** p<0.01, *** p<0.001

My first model found a highly statistically significant association (at the 0.01% level) between extended benefits and labor force participation rate, with labor force participation on average decreasing by 1.176% in a month with extended benefits. Just the presence of extended benefits in this model accounted for nearly 50% of the variation in the labor force participation rate, as displayed in the adjusted R^2 column in Table 3. When controlling for monthly change in unemployment and non-farm job openings in the second model, the correlation that the CARES Act extended benefits had with labor force participation was amplified, with a month of extended benefits now resulting in an expected decrease of 1.269% in the nation's labor force participation rate, which was also found to be statistically significant at the 0.01% level. Total non-farm openings were found to have no significant association with labor force participation in the second model, but the monthly percentage change in the unemployment rate coincided with a statistically significant (at the 5% level) but non-economically meaningful decrease in labor force participation. The second model accounted for 64% of variation in the labor force participation rate. In the third model, monthly changes in real GDP had no significant association with labor force participation, job openings had a statistically significantly but economically unrealistic association, continued claims and monthly change in the unemployment rate had a statistically significant but non-economically meaningful correlation with labor force participation, and the availability of extended benefits had a slightly smaller influence but still highly significant negative association with workforce reintegration, a -0.873% reduction in the expected labor force participation rate. This last model accounted for 75% of variation in the labor force participation rate.

The inclusion of variables in the national level analysis was based on their suspected use as proxies for general macroeconomic trends that would have impacted employment levels. The logic behind controlling for continued unemployment claims and monthly change in the unemployment rate is that some months during the pandemic saw steeper than normal declines in employment due to sharp decreases in consumption, and this would of course sharply impact the labor force participation rate for that month. Controlling for total non-farm openings and monthly change in real GDP has the opposite logic, that some months saw higher than normal increases in job creation because of a return to normality for consumption spurred by state reopening and expansionary government fiscal policy. A good portion of the previous literature used a difference in differences model but because availability of extended benefits usually coincided with unprecedented expansions in fiscal and monetary policy, I presumed a difference in means model might have suited this analysis better. Ultimately, on a national level the CARES Act extended unemployment benefits did seem to disincentivize workforce reintegration.

III. STATE-LEVEL ANALYSIS

The extended pandemic unemployment programs, PUA, PEUC, and FPUC, were programs that were designed in a way that the states opted into them. Starting in the summer of 2021, states began to withdraw from these programs, many of which cited labor shortage concerns as their primary reason for doing so. In total, 26 states decided to withdraw early from these programs, 25 of which were able to do so because in the State of Indiana, a lawsuit halted the state's withdrawal. So, while I find evidence that on a national level, the extended benefits had a significant association with workforce reintegration, the national-level analysis does not consider the early withdrawal of states from these programs. For this reason, it makes sense to analyze the association of extended benefits with labor force participation and unemployment at the state level, utilizing the difference in means and regression methods again.

Due to a lack of availability of certain monthly state level economic data, specifically median household income and unemployment rates, I instead chose to use the average value of these variables over the 25 months the pandemic has lasted as of December 2021. Using data collected from the US Bureau of Labor Statistics and US Census Bureau, I compiled the average labor force participation rate and average unemployment rate for all 50 states and the District of Columbia for the 25-month pandemic period. I then created two variables for extended benefits for each state and Washington, D.C.: the first was a dummy variable to indicate whether the state was an early withdrawal state, and the second was a variable measuring how many months each state offered extended benefits out of the 17 possible months the benefits were available at the federal level.

Like in the national-level analysis, the same pattern should arise if the extended benefits inhibited workforce reintegration. The data should show states that withdrew early from the benefits having a higher labor participation rate and a lower unemployment rate over the 25-month period. Tables 4 and 5 display descriptive statistics for non-withdrawal and withdrawal states, respectively, and they preliminarily show average unemployment was indeed higher in non-withdrawal states, but average labor participation was lower in withdrawal states.

TABLE 4. DESCRIPTIVE STATISTICS FOR STATES THAT DID NOT WITHDRAW FROM EXTENDED UN EMPLOYMENT BENEFITS.

	Observations	Mean	Standard Deviation	Minimum	Maximum
Average Unemployment Rate	26	5.97%	.74	4.67%	7.60%
Average Labor Force Participation Rate	26	62.88%	3.27	57.29%	70.12%

Source: Bureau of Labor Statistics

TABLE 5. DESCRIPTIVE STATISTICS FOR STATES THAT WITHDREW EARLY FROM EXTENDED UNEMPLOYMENT BENEFITS.

	Observations	Mean	Standard Deviation	Minimum	Maximum
Average Unemployment Rate	25	5.39%	.67	4.43%	6.57%
Average Labor Force Participation Rate	25	62.39%	4.35	55.09%	69.24%

Source: Bureau of Labor Statistics

The hypothesis test I conducted to verify the initial findings of the summary statistics was again a difference in means test between withdrawal and non-withdrawal groups. The null hypothesis was that there was zero difference in the average labor force participation rate between the two groups, and the alternative hypothesis was that the difference between non-withdrawal states and withdrawal states was greater than zero. A variance ratio test confirmed that it could be assumed that the two groups had equal variances, and with a decision rule of a p-value less than or equal to 0.05, the hypothesis test failed to reject the null hypothesis that the difference in average labor force participation was zero.

While there seems to be no significant difference between withdrawal and non-withdrawal group's labor force participation rates, it still may be worthwhile to examine whether an additional month of extended benefits has a significant correlation with workforce reintegration. Table 6 displays three regression models which use the number of months extended benefits were available as its primary independent variable. Model 1 is a simple linear regression of average labor force participation rate on extended benefit availability. Model 2 runs the same regression but holds state median household income and average unemployment rate constant. Lastly, model 3 regresses average unemployment rate on extended benefit availability and state median household income.

TABLE 6. STATE LEVEL MODELS

	Average Labor Force Participation Rate	Average Labor Force Participation Rate	Average Unemployment Rate
CARES Act	-0.0579 (-0.13)	0.228 (0.49)	0.350 (1.37)
Median Household Income		0.0000843 (1.89)	-0.00000992 (-1.08)
Average Unemployment Rate		-2.225**	
Constant	63.56*** (9.06)	65.91*** (10.40)	0.737 (0.17)

t statistics in parentheses * p<0.05, ** p<0.01, *** p<0.001

An additional month of extended unemployment benefits is estimated to have a -0.05% association with the labor force participation in the first model, however this effect is not statistically significant. Its correlation is positive in the second and third models, but again, the association is not statistically significant even when controlling for median household income and the average unemployment rate over the 25-month period. The only variable that seems to have a significant correlation with labor participation rates is the average unemployment rate, which is not that much of a surprise given that the labor force participation rate is calculated in part from the unemployment rate. This significance is why the third model switches to the unemployment rate as the outcome variable, but even after this switch an additional month of extended benefits has no estimated significant effect on the unemployment rate.

The implication of this state analysis is that there seems to be no evidence to suggest that extended benefits inhibited workforce reintegration in any meaningful way or that the early removal of extended benefits increased workforce reintegration. However, there are severe limitations to my state-level analysis, primarily the unavailability of data. State-level median household income was not available for the year 2021 as that data does not get released until the following year. As a result, all state median household income data is just for the year 2020. Quarterly unemployment data also was not available for the year 2021, so the average 2021 unemployment rate for the United States of 6.1% was given to each state for the year 2021, which may very well have changed the results.

IV. Conclusion

In conclusion, there is mixed evidence that the more generous and more accessible unemployment benefits available for most of the pandemic had a negative impact on employment. At the national level, these benefits seem to slow workforce reintegration. This may be the result of lengthening unemployment duration, which is something the academic literature has discovered can occur with increased benefit generosity. However, when one considers the early withdrawal of half of the states from the benefit programs, there is no evidence to suggest the benefits disincentivized employment decisions and that the removal of the benefits induced job search. It simply could be the case that there are structural and cyclical reasons impacting workers' lack of reintegration into the workforce as fast as some companies would like, so further research should be done on this topic. It could be worth studying whether poor wage offers in the service sector, mismatches of workers' skills and businesses' needs, and the possibility of the pandemic causing another jobless recovery from a recession are factors in the labor shortage. Overall, I find mixed results on a complex issue using very limited methods.

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APPENDIX

Figure 3.

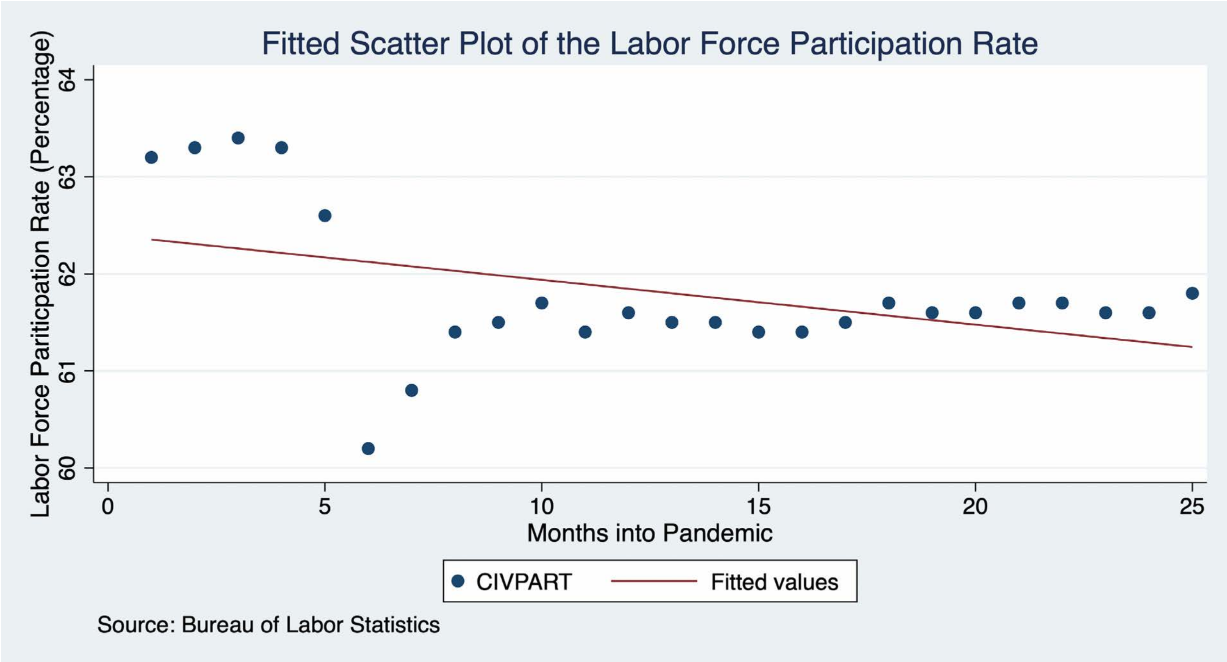

Figure 4.