2017
OKSWP1706

Economics Working Paper Series
Department of Economics

OKLAHOMA STATE UNIVERSITY
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Abstract

This paper uses the American Community Survey to examine the previously overlooked fact that foreign STEM (science, technology, engineering, and mathematics) graduates have much lower self-employment rates than their non-STEM counterparts, with an unconditional difference of 3.3 percentage points. We find empirical support for differing earnings opportunities as a partial explanation for this self-employment gap. High wages in STEM paid-employment combined with reduced earnings in self-employment make self-employment less desirable for STEM graduates. High self-employment rates among other foreign-born workers partially reflect weak paid-employment opportunities. Public policy should encourage efficient use of worker skills rather than low-value business venture creation.

Keywords: self-employment, immigration, foreign-born, college major, STEM, earnings
JEL Classification: F22, J15, J31, L26

The authors thank Mehtabul Azam, Jon Comer, Simon Parker, Dan Rickman, and two anonymous reviewers for helpful suggestions. An Online Only Appendix with additional results is available from the authors' personal webpages at
https://sites.google.com/site/econzhengyu/home/supplementary-materials
https://sites.google.com/site/johnvwinters/supplementary_materials

1. Executive summary

Immigrants to developed countries are generally thought to be especially entrepreneurial (Kerr 2013). In particular, foreign-born workers in the United States have exhibited persistently higher rates of self-employment compared to natives for several decades (Borjas 1986; Yuengert 1995). However, not all foreign-born workers are alike. There are important differences in self-employment rates among immigrant groups. Immigrants groups also differ widely in their level of economic success in host countries, and entrepreneurial spirit is often viewed as a major reason for differing economic outcomes. Immigrant entrepreneurs are often viewed as very valuable for host nations, and many countries have policies to attract and admit immigrants interested in starting new business ventures.

However, narratives do not always perfectly match reality and policies do not always achieve intended goals without adverse side effects. While attracting immigrant entrepreneurs may have some merits, a more salient societal goal may be to attract skilled immigrants with high productivity regardless of whether they are self-employed or paid employees. The level and type of education an individual possesses is among the most important and easily discerned measures of skill. On average, incomes increase with additional education. Furthermore, workers with higher education degrees in science, technology, engineering, and mathematics (STEM) fields on average earn more than comparable workers with degrees in non-STEM fields.

Education level and type can also affect self-employment decisions and outcomes. We uncover large and previously unknown differences in self-employment rates by college major among foreign-born college graduates in the U.S. Specifically, we find that foreign STEM graduates have much lower self-employment rates than foreign graduates educated in non-STEM fields. We examine income differences across college majors as a partial explanation for self-employment differences between STEM and non-STEM. STEM graduates have higher mean earnings in paid employment than non-STEM graduates, and self-employees have lower mean earnings than paid employees among both STEM and non-STEM graduates. Thus, higher earnings in paid employment appear to pull STEM graduates away from self-employment. Earnings penalties in self-employment likely push both STEM and non-STEM graduates away from self-employment, but many non-STEM graduates appear to lack better opportunities in paid employment and likely resort to self-employment somewhat out of necessity.

Better understanding the self-employment decisions of skilled immigrants is important for both researchers and policymakers. Relatively low rates of self-employment for foreign STEM graduates that result from good paid employment opportunities are not a cause for concern or a problem needing a policy solution. STEM graduate employees are well compensated, and their high productivity in paid employment is good for society. Policies that would intentionally encourage high-skilled immigrants to shift from high-paying employment to less lucrative self-employment would likely do more harm than good (Parker 2007; Shane 2009; Acs et al. 2016). More generally, high rates of self-employment among some foreign-born workers without a STEM education partially reflect weak opportunities for paid employment. Policies that attract and encourage immigrants to form low-value business ventures are undesirable. Policies broadly intending to promote economic growth should aim to improve the skills of the workforce and the ability of workers to utilize their skills in the most productive way possible.

2. Introduction

Foreign-born workers make considerable contributions to business venturing and on average have significantly higher self-employment rates than their native counterparts in many countries like the United States (Borjas 1986; Yuengert 1995; Kerr 2013). However, self-employment rates can also differ considerably across immigrant groups, and there is still much that is unknown about the self-employment decisions of skilled foreigners. The current paper uses the 2015 American Community Survey (ACS) to examine the effects of college major on self-employment decisions for foreign-born college graduates working in the U.S.[1] We focus on differences between science, technology, engineering, and mathematics (STEM) graduates and non-STEM graduates.

Immigrants educated in STEM fields are often thought to be especially beneficial for receiving countries because they increase innovation and productivity (Hunt and Gauthier-Loiselle 2010; Winters 2014; Peri et al. 2015). Thus, foreigners educated in STEM and some other high demand fields are often given special consideration in obtaining visas.[2] Furthermore, the strong demand for STEM-educated labor in the U.S. creates good earnings opportunities for international STEM workers and makes the U.S. an attractive destination for them. Not surprisingly, foreign-born residents in the U.S. are more likely than natives to be both educated in and employed in STEM fields. Foreign workers also account for a considerable portion of the growth in U.S. STEM employment in recent years.

[1] College major refers to the major field of study for an individual's first bachelor's degree.
[2] In the U.S., foreign-born STEM graduates can receive a 17-month extension for optional practical training (OPT) after the initial 12-month OPT period available to all foreigners earning degrees in the U.S. STEM fields also comprise the majority of H-1B visas granted (Kerr and Lincoln 2010). H-1B visas are temporary employment visas for skilled foreign workers in the U.S. that can last for up to six years.

Given the high rates of foreigners in both self-employment and in STEM fields and the innovative nature of STEM, there is a common perception that foreign workers in STEM fields have especially high rates of self-employment (Fairlie and Lofstrom 2015). However, Hart and Acs (2011) suggest that “previous studies have overstated the role of immigrants in high-tech entrepreneurship” (p. 116). To our knowledge, there is no prior evidence on foreign-born self-employment differences by college major. In this study, we first document large differences in self-employment rates between foreign-born college graduates educated in STEM and non-STEM fields. We then explore possible causes and suggest major-specific earnings opportunities in paid employment and self-employment as potentially important determinants.

Many researchers have emphasized earnings opportunities as significant factors affecting self-employment decisions for various groups. Higher potential income from self-employment increases the desirability of self-employment, *ceteris paribus*. Paid employment wages are an opportunity cost of being self-employed. The higher the income that could be earned in paid employment, the lower the desirability of self-employment, *ceteris paribus*. Previous research has found self-employment rate differentials across various groups to be positively correlated with the earnings differences between the self-employed and the paid employees (Fairlie and Meyer 1996; Earle and Sakova 2000; Parker 2004). We fill an important gap in the research literature by considering the role of earnings opportunities by college major in explaining foreign-worker self-employment decisions.

Understanding how self-employment decisions vary across immigrant groups and how these are affected by earnings opportunities has important implications for both scholars and policymakers. Entrepreneurship is generally deemed important for economic growth and societal well-being (Audretsch and Keilbach 2004; Audretsch et al. 2006; Bruce et al. 2009; Acs et al.

2012; Glaeser et al. 2015), but self-employed workers are a highly heterogeneous bunch. Some self-employees are innovative entrepreneurs who create new ventures to exploit untapped opportunities and create considerable economic value for themselves and society (Levine and Rubinstein 2016). However, many other self-employees start businesses largely out of necessity because of a lack of good opportunities for paid employment (Acs 2006). Policies intended to attract and encourage additional self-employment should consider which type of self-employees are induced by such policies at the margins and how much additional economic value their ventures create. Shane (2009) argues that "the typical start-up is not innovative, creates few jobs, and generates little wealth" (p. 141). Policies that encourage low-value ventures are unlikely to pass reasonable benefit-cost analysis tests to justify their existence (Parker 2007; Shane 2009; Acs et al. 2016).

The next section provides conceptual background. Section 4 describes our empirical approach and data. Section 5 provides empirical results. Section 6 summarizes our analysis, discusses implications, and concludes this study.

3. Conceptual background

Foreign-born workers have been historically more likely to be self-employed than natives (Borjas 1986; Yuengert 1995). Table 1 illustrates this for the U.S. in 2015. Among all workers ages 25-61, 9.1 percent of natives are self-employed, but 11.5 percent of foreigners are self-employed. Differences in self-employment rates across and within immigrant groups have also received attention from researchers, and numerous factors have been found to affect self-employment decisions.[3] Differences in self-employment can also exist by education level (Fairlie

[3] Researchers have suggested effects of individual risk and time preferences (Cramer et al. 2002; Ekelund et al. 2005; Caliendo et al. 2009), individual resources (Evans and Jovanovic 1989; Blanchflower and Oswald 1998; Parker 2004),

and Meyer 1996; Dunn and Holtz-Eakin 2000; Lofstrom et al. 2014). Table 1 also reports self-employment rates in the U.S. for foreign- and native-born workers separately for those without and with a bachelor's degree or higher. The difference by education for natives is very minimal. For foreigners, however, there is a considerable difference by college education. Among workers ages 25-61, 12.2 percent of foreigners without a college degree are self-employed, while only 10.0 percent of foreign-born college graduates are self-employed. Both rates are still higher than those for natives, but the foreign-native difference in self-employment among college graduates is only moderately large. To some extent, differences in foreign-worker self-employment by education may reflect earning potential in paid employment and self-employment. In particular, a college degree, especially if earned in the U.S., may help resolve asymmetric information issues that make some employers reluctant to hire foreign-born workers.

However, college graduates possess quite heterogeneous knowledge and skills that vary with their major field of study. As such, college major has a substantial effect on earnings, though the literature typically does not differentiate between effects for natives and foreigners (Arcidiacono 2004; Winters and Xu 2014; Eide et al. 2015). STEM majors are often given special attention and typically shown to provide the highest average earnings. Their contributions to innovation also make STEM graduates of considerable interest to policymakers (Winters 2014). College major is also likely to affect self-employment decisions in part by affecting earning prospects in paid employment and self-employment, but the effects of college major on self-employment has received little attention in previous research.

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income tax considerations (Bruce 2000; Bruce and Mohsin 2006), immigrant origin country (Yuengert 1995; Liñán and Fernandez-Serrano 2014; Lassmann and Busch 2015), region of current residence (Mueller 2006; Conroy and Weiler 2015; Liu and Huang 2016), demographic and socioeconomic factors characteristics (Blanchflower 2000; Clark and Drinkwater 2000, 2010; Lofstrom 2004; Djankov et al. 2005, 2006; Patrick et al. 2016), and employer discrimination (Constant and Zimmerman 2006; Fairlie 2006).

Table 1 next reports mean self-employment rates among foreign- and native-born workers ages 25-61 for college graduates with STEM and non-STEM major fields of study.[4] Native STEM graduates are only slightly less likely to be self-employed than native non-STEM college graduates, with rates of 8.8 percent and 9.2 percent, respectively. Combined with the 9.1 percent self-employment rate for native non-graduates, it appears that neither the level of education nor the type of education have much effect on native self-employment rates. For foreign-born workers, however, the story is considerably different. The self-employment rate is 11.3 percent for foreign-born college graduates in non-STEM fields, but only 8.0 percent for foreign-born STEM graduates. Thus, foreign STEM graduates are much less likely to be self-employed than foreign non-STEM graduates; this significantly lower rate for foreign STEM is somewhat surprising and not previously documented to our knowledge. Additionally, the self-employment rate for foreign STEM graduates is moderately lower than the self-employment rate for native STEM graduates. This foreign shortfall in self-employment is unique to STEM graduates. As noted above, for non-college graduates and college graduates in non-STEM fields, foreign workers have higher self-employment rates than natives.

The causes of the self-employment gap between foreign STEM and non-STEM graduates are not immediately clear, and the descriptive nature thus far prevents strong inferences. In our analysis below, we consider two main hypotheses. We first consider whether differences in self-employment persist after controlling for observable individual characteristics. For example, recently arriving foreign-born workers on temporary visas may be reluctant to make entrepreneurial investments that require them to remain in the country to reap the full benefits (Hart and Acs 2011). Foreign STEM graduates are especially likely to initially work in the U.S.

[4] College major is only reported for the field in which an individual earned a bachelor's degree. Our analysis includes all workers with a bachelor's degree or higher and uses the college major of the bachelor's degree for all.

using temporary OPT extensions and H-1B visas.[5] Thus, we will account for naturalized citizenship status, length of time in the U.S., and a number of other observable characteristics.

Hypothesis 1. *A large gap in self-employment rates between foreign STEM and non-STEM graduates persists even after controlling for a large set of individual characteristic variables.*

We suggest that earnings differences across college majors may explain a considerable portion of the self-employment differential between foreign STEM and non-STEM graduates. High earnings in paid employment are expected to reduce self-employment and explain much of the self-employment gap between STEM and non-STEM. Higher relative earnings in self-employment are expected to make self-employment more desirable.

Hypothesis 2. *The self-employment gap between STEM and non-STEM graduates is partially attributable to earnings differences across college majors.*

Hypothesis 1 is straightforward to test. We examine Hypothesis 2 via a number of tests that compare major-specific earnings to major-specific self-employment rates. We also conduct an Oaxaca-Blinder decomposition of the self-employment gap.

[5] Both OPT and H-1B can be used for self-employment (U.S. CIS 2015), but the application processes can be costly and risky (Ruiz et al. 2012). H-1B visa application totals have in recent years exceeded the number of visas that can be awarded and in such cases visas are allocated by lottery. Thus, there is considerable uncertainty about whether an H-1B application will result in receiving an H-1B visa. Similarly, temporary workers are not guaranteed eventual permanent residence and many have very low probabilities depending on their origin country. As such, creating a business and applying for H-1B through that business is a costly process with considerable risk; many will instead seek paid employment and have the employer file an H-1B application. Individuals willing and able to make a considerable investment ($500,000 or more) in a qualifying commercial enterprise can apply for an Immigrant Investor Visa (U.S. DOS 2015), but the substantial financial requirement precludes many potential entrepreneurs.

4. Empirical framework and data

This paper uses a linear probability model (LPM) to examine self-employment differentials across different college majors among foreign-born workers in the U.S. Given that college major appears to play a minimal role for native self-employment in Table 1, we hereafter exclude natives in order to focus the analysis on the more interesting differences by college major for foreign-born graduates. The main model is:

$$Pr(SE_i = 1|\boldsymbol{m}_i, \boldsymbol{X}_i) = \boldsymbol{m}_i'\boldsymbol{\alpha} + \boldsymbol{X}_i\boldsymbol{\beta} \quad (1)$$

where the subscript *i* denotes individual observations, $\boldsymbol{m}_i$ is a vector of dummies for college majors, and $\boldsymbol{X}_i$ is a matrix of individual characteristics. The dependent variable SE_i is a dummy variable indicating whether a worker is self-employed. Our main approach for the vector $\boldsymbol{m}_i$ is to use a single indicator for STEM majors to compare difference in self-employment between STEM college graduates and graduates in all other majors. A secondary approach for $\boldsymbol{m}_i$ uses separate dummies for each of the 45 largest detailed majors.

One concern with this model is that industries could be correlated with self-employment rates and also associated with college majors. Thus, the second specification of our model controls for industry dummy variables. Similarly, to account for local economic conditions, Metropolitan Statistical Area (MSA) dummy variables are also included in the model, which becomes:

$$Pr(SE_{idc} = 1|\boldsymbol{m}_{idc}, \boldsymbol{X}_i) = \boldsymbol{m}_{idc}'\boldsymbol{\alpha} + \boldsymbol{X}_{idc}\boldsymbol{\beta} + \tau_d + \pi_c \quad (2)$$

where subscript *d* indexes industries, *c* denotes MSAs[6], τ_d includes industry dummy variables, and π_c includes MSA dummy variables.

[6] Non-MSA areas are combined into residual categories for each state and treated as separate MSAs. We just refer to them as MSAs for simplicity.

As discussed previously, earnings differentials across different majors for college graduates are expected to play a role in self-employment decisions. Thus, to help understand self-employment differences between STEM and non-STEM graduates, we estimate the following log earnings model:

$$ln(income_{idc}) = \theta SE_{idc} + \delta STEM_{idc} + \rho SE_{idc} \times STEM_{idc} + \boldsymbol{X}_{idc}\boldsymbol{\beta} + \tau_d + \pi_c + \epsilon_{idc} \quad (3)$$

where the dependent variable is the log of total personal earned income in the previous year, which includes self-reported wage and salary income from paid employment and earnings from self-employment. $STEM_{idc}$ is a dummy for STEM college graduates. The STEM dummy will also be generalized to multiple dummies for more detailed majors to compare the earnings differentials among different majors. The θ and δ coefficients represent conditional earnings differences related to self-employment and being a STEM graduate, respectively. The ρ coefficient captures the interactive effects of being a STEM graduate and self-employed.

This paper uses 2015 ACS microdata from IPUMS (Ruggles et al. 2015). The ACS includes a one percent sample of the U.S. population. Our analytic sample only includes foreign-born[7] employed and self-employed workers ages 25-61 with at least a bachelor's degree. All empirical analyses use personal sampling weights to make results representative. The ACS allows us to distinguish between unincorporated and incorporated self-employees, and we look at both with the latter group expected to possess a more entrepreneurial element (Levine and Rubinstein 2016). Definitions for the main variables in our analysis are included in Appendix Table A.1.

[7] We define foreign-born persons using the birthplace variable to include a small number of persons who are born in U.S. outlying areas or territories (American Samoa, Guam, Puerto Rico, U.S. Virgin Islands). However, we discuss a robustness check below that excludes persons born in U.S. outlying areas and territories.

For college graduates the ACS provides information on the undergraduate college major. This includes both the first and second major field for persons earning double majors. Our main definitions only use information from the first major, but we also conduct sensitivity analysis below using information for second majors. STEM graduates are defined based on the STEM list from the U.S. Immigration and Customs Enforcement (ICE).[8]

A standard set of individual characteristics is controlled for in all regressions, including a quartic polynomial of age, dummies for female, married, an interaction of female and married, naturalized citizen, children present in household, and three dummies for educational attainment. Four dummies for English language ability and 13 dummies for national origin group are included as well. These foreign birthplace groups include Canada, Mexico, Rest of Americas, Western Europe, Eastern Europe, China, Japan, Korea, Philippines, India, Rest of Asia, Africa, Oceania, and all other. Four years-in-the-U.S. interval group dummies are also included.[9] Ethnicity and race are excluded from our analysis since they are highly correlated with national origin. We define industry using 14 two-digit groups and include 13 industry dummies in most regressions. Table 2 provides variable means for foreign-born STEM and non-STEM college graduates.

Panel A shows means for the outcome variables. As shown in Table 1, non-STEM foreign-born graduates are more likely to be self-employed than their STEM counterparts. The raw difference is about 0.033 and is statistically significant. The bulk of this difference appears

[8] The ICE list is available at http://www.ice.gov/doclib/sevis/pdf/stem-list.pdf. The list of STEM majors for our study is provided in Appendix Table A.1. The college major coding scheme differs slightly between the ACS and the ICE list, but the differences are negligibly small for practical purposes.

[9] Unfortunately, the ACS does not collect information on visa type for non-citizens, which prevents us from controlling for H-1B or other visa status. Controlling for duration in the U.S. partially accounts for this, and we later examine the robustness of our results to just looking at immigrants in the U.S. for ten years or more. We also do not know specifically when or where college graduates earned their degree, but we do observe when an individual first came to the U.S., and we later examine the robustness of our main results to excluding immigrants arriving before age 18 and before age 22.

attributable to significantly lower rates of STEM graduates in unincorporated self-employment. The raw difference in incorporated self-employed rates between STEM and non-STEM is relatively small. We return to differences in unincorporated and incorporated self-employment later as an extension to the main empirical analysis.

STEM workers on average earn significantly more than non-STEM workers. However, one cannot conclude an association between self-employment rates and annual earnings based on this since the raw means of annual earnings contain information for both the employed and the self-employed and do not control for differences in observable characteristics. More formal tests will be conducted in the following section.

Panel B provides summary statistics for the individual characteristics controls. STEM graduates are on average slightly younger than their non-STEM counterparts. STEM graduates are also more likely to have earned advanced degrees, be male, and be married. Non-STEM fields have higher percentages of native English speakers, but STEM English learners on average report better English skills than their non-STEM counterparts. China, India, and the Rest of Asia are notably the only origin groups with a higher proportion in STEM than in non-STEM fields. STEM graduates are also more likely to be more recent arrivals to the U.S.

5. Empirical results

5.1. Self-employment differentials between foreign STEM and non-STEM fields

Table 3 presents linear regression results for self-employment differentials between STEM and non-STEM college graduates for three specifications.[10] The dependent variable is an

[10] The estimates for detailed controls are available from Online Appendix Table 1. Many of these control variables such as sex, origin country, time in the U.S., and current location are really interesting themselves and could warrant further investigation in future research.

indicator for being self-employed. Column (1) reports estimates for our baseline model without industry or MSA dummy variable controls. The STEM coefficient estimate is statistically significant and large in magnitude. One advantage of LPM is that the coefficient estimates can be directly interpreted as marginal effects. Thus, the coefficient of -0.0375 in Column (1) indicates that the conditional probability of being self-employed for STEM graduates is less than that for non-STEM graduates by 3.75 percentage points, *ceteris paribus,* after controlling for baseline individual characteristics.

Industry dummy variables are added in Column (2). The estimated differential is still large and statistically significant, but the coefficient magnitude decreases in absolute value to -0.0326. Thus, it appears that the nature of different industries varies such that some industries naturally have high self-employed rates, while others have lower rates. Column (3) reports results that also control for MSA dummy variables. The coefficient estimate is now -0.0311, which is still quite large and statistically significant. Thus, including an extensive set of individual characteristic controls still leaves a large self-employment gap between foreign-born college graduates educated in STEM and non-STEM fields.

5.2. Annual earning differentials between STEM and non-STEM graduates

As discussed previously, the difference in self-employment rates between foreign STEM and non-STEM graduates may result from earning differentials across majors in paid employment and self-employment. Table 4 presents regression results for equation (3) above. The dependent variable is log annual earned income. The explanatory variables of interest are indicators for STEM and self-employment and their interaction. The baseline model in Column (1) excludes industry and MSA controls. Industry dummy variables are added in Column (2) and MSA dummy variables are added in Column (3).

The separate effects of self-employment and STEM education are consistently significant in all three columns of Table 4. The interaction term coefficient estimate is close to zero and not statistically significant in all three columns. Results in Column (3) suggest that being a STEM graduate increases log annual earnings by 0.1958, which indicates that STEM graduates out-earn their non-STEM counterparts by roughly 20 percent after controlling for the full set of variables. Self-employed workers experience considerably lower earnings with a coefficient of -0.4006 indicating an earnings penalty of roughly 40 percent. The STEM and self-employed coefficient magnitudes both indicate very large differences, and these earnings gaps might affect decisions to be self-employed for both STEM and non-STEM graduates. Interestingly, the near-zero interaction term suggests that the percentage earnings penalty from self-employment does not differ much between STEM and non-STEM graduates. Both suffer sizable earnings penalties of roughly equal magnitude.

Self-employed foreign-born college graduates have substantially lower earnings than comparable paid employees, which likely pushes graduates away from self-employment. Similarly, STEM graduates have much better earnings prospects in paid employment than non-STEM graduates, which may be especially pulling STEM graduates toward paid employment. Together these could be strong factors affecting the self-employment differences between foreign STEM and non-STEM graduates. We return to this issue later.

5.3. Sensitivity analysis

Table 5 presents results for some sensitivity analysis. The first row replicates the preferred specifications in Column (3) in Table 3 and Column (3) in Table 4 for reference. Rows 2-4 explore alternative variable specifications. In the second row, a broader STEM definition is used that includes all graduates for whom either the first or second major is in STEM; results are very similar. The third row models years in the U.S. as a quartic specification instead of the categorical dummies used in the main specification; results are highly robust. The fourth row includes additional controls for age of immigration to the U.S. with dummy variables for those arriving at ages 5-9, 10-17, 18-20, and 21 and up (ages 0-4 are the excluded group); results are again very similar.

Rows 5-10 of Table 5 experiment with alternative subsamples. The fifth row shows results for full-time workers who usually work more than 35 hours per week. Most results do not change much, though the self-employment earnings penalty is smaller. However, hours worked may be endogenously affected by earning potential, so this is not our preferred specification. The sixth row of Table 5 restricts the sample to foreigners who have been in the U.S. more than 10 years. These long-term immigrants could differ from newcomers with respect to language skills, institutional constraints, time preferences, etc. However, there is no meaningful change in the estimated coefficients relative to the main results in Row (1). The seventh row shows the estimates for the sample of people in the U.S. 10 years or less. Most estimates are similar to Row (1), but the interaction term coefficient becomes negative and statistically significant at the ten percent level, which suggests that newer arriving STEM graduates suffer a particularly large earnings penalty from self-employment, which especially pushes them away from being self-employed. Row (8) excludes people who were born in U.S. outlying areas and territories with results similar to our preferred specification. Row (9) excludes immigrants arriving before age 18 and Row (10) excludes immigrants arriving before age 21; both give similar results to Row (1).

Rows (11) and (12) consider alternative measures of self-employment. Specifically, Row (11) replaces the previous self-employment dummy variable with a dummy variable for being unincorporated self-employed and Row (12) uses a dummy for being incorporated self-employed. Conditional on self-employment, the decision to incorporate is likely endogenous to potential earnings, so these results should be interpreted with caution. We first see that the lower probability of self-employment for STEM graduates is primarily attributable to lower unincorporated self-employment according to the coefficient estimates of -0.0221 and -0.0090 in Rows (11) and (12), respectively. In the log earnings regression, the STEM coefficient is largely unchanged, but indicators for unincorporated and incorporated self-employed have vastly different relationships with a significant coefficient of -0.6620 for unincorporated self-employment and an insignificant virtually-zero coefficient estimate for incorporated self-employment. The interaction term is significant at the ten percent level for unincorporated self-employment but small and insignificant for incorporated self-employment. Thus, Rows (11) and (12) offer two main results. First, more than two-thirds of the lower self-employment for STEM graduates relative to non-STEM graduates is accounted for by unincorporated self-employment. Second, unincorporated self-employment produces a very large earnings penalty. Together these results suggest that the bulk of the business ventures that employee STEM graduates forego are likely to be low income ones.

5.4. Self-employment and log earning differentials for selected detailed majors

Foreign STEM graduates have substantially lower self-employment rates and higher earnings in paid employment than foreign non-STEM graduates. However, self-employment rates and earnings likely vary across detailed majors within both STEM and non-STEM fields. Thus, it is interesting to look at variation among detailed majors.

Column (1) of Table 6 reports the conditional probabilities of being self-employed based on the estimated coefficients for equation (2) for the 45 detailed majors with the largest number of graduates in the sample, which collectively account for 80.71% of all graduates. All other majors form the omitted category and reference group. Estimating separate coefficients for smaller majors would produce noisy estimates. The majors in Table 6 are sorted by their Column (1) self-employment coefficients. The estimates for the top and bottom majors are statistically significant, while many majors with intermediate coefficients are not statistically different from the omitted base group. The pattern of self-employment rates is consistent with previous results for STEM and non-STEM majors. Most STEM majors are toward the bottom of the list for conditional probability of self-employment. Nursing and education majors also have low conditional probabilities of self-employment, which is not surprising given the close ties to specific occupations (nurses and teachers) typically filled as paid employees.

Table 6 also reports log annual earning differences by major similar to equation (3) above but replacing the STEM dummy with dummies for each of the 45 largest majors and replacing the interaction term with interaction terms between each of the 45 largest majors and the self-employment dummy. Results for the dummy variables are reported under the “Level” column heading and estimates for the interactions are under the “Interaction” column. As expected, the “Level” coefficients for detailed STEM fields are typically positive and statistically significant. The level coefficients are also significantly positive and comparable to some STEM fields for a few non-STEM majors such as nursing, finance, economics, and international business. The interaction coefficients do not exhibit an immediately clear pattern.

We previously discussed earnings differentials as a possible partial explanation for why foreign STEM graduates have lower self-employment rates. To provide further support for the earning differentials explanation, we computed correlations between self-employment coefficients and income level and interaction coefficients for the 45 detailed college majors in Table 6. If the earnings push and pull factors are important, then lower self-employment rates should be associated with higher major-specific incomes in paid employment and lower interaction effects. The correlation between the self-employment coefficients and the log annual income level coefficient estimates in Table 6 is -0.535. This suggests that the higher the income for employees, the lower the self-employment rates, consistent with the hypothesis that high wages in paid employment pulls workers into paid employment and reduces self-employment. The correlation between the self-employment coefficients and the log annual income interaction coefficient estimates is 0.133, weakly suggesting that lower relative incomes in self-employment lowers self-employment rates. Thus, we find empirical support that the low self-employment rates for STEM graduates are partially attributable to push and pull factors from earnings differentials, with the effect being most strongly attributable to higher earnings in paid employment for STEM majors.

5.5. Self-employment differentials controlling for major-specific earnings

The regression results in Table 3 show that a large gap in self-employment rates between foreign STEM and non-STEM graduates persists even after controlling for numerous individual characteristics, industry, and MSA dummies. Subsequent results suggest that differing earnings opportunities by college major may explain some of the self-employment differential. We next consider this more systematically by augmenting the linear probability model of self-employment with measures of major-specific earnings differentials. Results are reported in Table 7 with Column (1) reproducing results from Column (3) of Table 3 to ease comparison.

Columns (2)-(4) include additional explanatory variables, Maj_Earn_Lev and Maj_Earn_Int, containing major-specific coefficient estimates from an auxiliary regression with log annual earnings as the dependent variable. The auxiliary regression includes detailed college major dummy variables, a self-employment dummy, and interactions between self-employment and each college major dummy variable along with control variables for the individual characteristics, industry dummies, and MSA dummies similar to the earnings regression in Table 6. It differs slightly from the earnings regression in Table 6 in that dummy variables are included for 173 detailed majors instead of just the 45 largest majors. The Maj_Earn_Lev variable contains “Level” coefficients for the college major dummy variables, and Maj_Earn_Int contains the “Interaction” term coefficients.

Column (2) adds Maj_Earn_Lev to the main model in Column (1). Column (3) instead adds Maj_Earn_Int. Column (4) includes both Maj_Earn_Lev and Maj_Earn_Int simultaneously. Standard errors are now clustered by college major to account for the clustered nature of the major-specific earnings differentials. Clustered standard errors are robust to heteroscedasticity and account for one common problem using regression coefficient estimates as explanatory variables. However, other possible problems related to endogeneity, selection, measurement error, and low statistical power are not easily remedied. Thus, this analysis is suggestive but does not necessarily yield unbiased causal estimates and should be interpreted with some caution.

In Column (2) the STEM coefficient is reduced in magnitude to -0.0172, and Maj_Earn_Lev has a significant negative coefficient of -0.0699. In Column (4), the STEM coefficient is -0.0174, and the Maj_Earn_Lev coefficient estimate is -0.0689. Maj_Earn_Int is small and not statistically significant in both Columns (3) and (4), and the STEM coefficient in column 3 is nearly identical to Column (1). These results are quite interesting. Higher major-specific earnings in paid employment appear to significantly reduce self-employment among foreign-born college graduates according to the results for Maj_Earn_Lev in Columns (2) and (4). Furthermore, the self-employment gap between STEM and non-STEM graduates appears heavily attributable to the higher earnings achievable in paid employment for STEM graduates based on the substantial reduction in the STEM coefficient when including Maj_Earn_Lev. The small coefficient estimates for Maj_Earn_Int appear to suggest that earnings in self-employment are a much less important determinant of self-employment decisions, but the imprecision of Maj_Earn_Int estimates prevents strong conclusions.

5.6. Decomposition analysis of self-employment differentials

We next conduct an Oaxaca-Blinder decomposition for the self-employment differential between foreign-born STEM and non-STEM graduates. Rather than using just the STEM or non-STEM graduate sample for the reference coefficients, we obtain reference coefficients from a pooled model over both groups (that includes a STEM dummy variable) using the pooled option for the oaxaca Stata command discussed in Jann (2008). We also apply the deviation contrast transform to the dummy variables, so that the results of the decomposition are not influenced by the choice of the omitted group. Decomposition results corresponding to regression models in Columns (2)-(4) of Table 7 are reported in Columns (1)-(3) of Table 8. The explained portions for the Maj_Earn variables are reported first. The explained portions for individual characteristic variables are combined into groups for Education level, English ability, Demographics (age, sex, marital status, and parental status), National origin, Citizenship, Years in U.S., Industry, and MSA. The unexplained portion is reported at the bottom of each column. Recall that the self-employment means for STEM and non-STEM graduates are 0.080 and 0.113, respectively, giving a raw difference of 0.033.

The decomposition results for the Maj_Earn variables are consistent with Table 7. Maj_Earn_Lev explains a sizable portion of the observed self-employment gap between STEM and non-STEM graduates. Maj_Earn_Int explains virtually none of the gap. The Maj_Earn_Lev explained portion of 0.014 accounts for roughly 42 percent of the 0.033 raw gap. The explained portion results for individual characteristics are consistent across regressions. Education level, English ability, and Citizenship explain small and statistically insignificant portions of the gap. Demographic and National origin differences actually reduce the gap by 0.0063 and 0.0036, respectively, in Column (3). Years in U.S., Industry, and MSA location differences all increase the gap by 0.0019, 0.0054, and 0.0038, respectively, in Column (3). The unexplained portion is 0.0174 in Column (3). The decomposition analysis suggests that many observable factors partially explain the self-employment gap between foreign STEM and non-STEM graduates, though a sizable portion remains unexplained. Among the explanatory factors, earnings in paid employment plays an especially important role.

6. Discussion and conclusion

6.1. Summary of results

This paper uses American Community Survey microdata to examine differences in self-employment outcomes between foreign-born college graduates with degrees in STEM and non-STEM fields. We begin by documenting the previously unknown result that foreign STEM graduates are much less likely to be self-employed than foreign non-STEM graduates. The raw difference is roughly 3.3 percentage points, which is quite substantial. Using linear regression to control for a large number of individual characteristics including age, sex, national origin, English-language proficiency, length of time in the U.S., industry, and MSA does little to reduce the self-employment gap between foreign graduates educated in STEM and non-STEM fields. We next document that foreign STEM graduates substantially out-earn their counterparts educated in non-STEM fields and self-employed workers have much lower average earnings than comparable paid employees. We suggest that these empirical facts are likely connected, and we go on to explore their relationship in more detail.

We examine self-employment rates and income differences across detailed college majors within STEM and non-STEM fields. We find a strong negative correlation between self-employment rates and major-specific earnings for paid employees, consistent with expectations that higher employee wages pull workers into paid employment and away from self-employment. We also include regression-adjusted major-specific earnings differences in paid employment as an explanatory variable in a linear probability model for self-employment. The results indicate that higher major-specific earnings in paid employment significantly reduce self-employment rates. Thus, the negative relationship between STEM education and self-employment for foreigners appears partially attributable to the higher earnings opportunities in paid employment for STEM graduates. An Oaxaca-Blinder decomposition suggests that major-specific earnings in paid employment explains about 42 percent of the raw gap in self-employment between STEM and non-STEM graduates. Other observable factors also matter to some extent but account for smaller portions than major-specific earnings. A sizable portion of the self-employment gap also remains unexplained.

6.2. Implications for researchers and policymakers

Our study contributes to the research literature documenting self-employment differences across groups and seeking to understand worker decisions regarding self-employment. Previous research has found self-employment differences across various groups to be related to relative earnings in paid employment and self-employment (Fairlie and Meyer 1996; Earle and Sakova 2000; Parker 2004). Our study supports that literature, but also offers new and important insights regarding a specific sub-population of growing importance, skilled immigrants. Skilled immigrants are an increasingly important part of the global workforce, and their behaviors and outcomes warrant increased study in numerous fields (Kerr 2013). Immigrants in general have been an especially notable area of interest for entrepreneurship scholars because of their relatively high-rates of self-employment in developed countries compared to natives (Borjas 1986; Yuengert 1995; Kerr 2013). Various theories for their higher rates of self-employment have been proposed and tested, but a complete explanation has not yet been achieved.

Additionally, the role of education in affecting self-employment outcomes has received some attention in the literature (e.g., Cooper et al. 1994; Dunn and Holtz-Eakin 2000; Davidsson and Honig 2003; Unger et al. 2011; Lofstrom et al. 2014) but likely not as much as its importance warrants. In particular, the role of college major has been heavily overlooked despite important differences in self-employment by college major for foreign-born workers. We document that college major is an important factor for the self-employment decisions of foreign-born college graduates. Our findings of higher earnings and lower self-employment rates for STEM graduates are consistent with STEM graduates generally possessing “hard” skills that are easily recognized by employers and whose values are less dependent on language, culture, etc., while many non-STEM graduates likely possess higher proportions of “soft” skills whose values in paid employment can be greatly reduced by language and cultural barriers for foreign-born workers in host countries. Workers whose skills are not easily authenticated and valued in the market for paid employment are likely especially drawn to self-employment. Though they are not included in our regression analysis, raw self-employment rates for foreign-born workers without a college education are even higher than for non-STEM graduates, suggesting that their skills may be even harder to authenticate. It seems likely that the higher overall self-employment rate for immigrants over natives is partially attributable to greater difficulty for employers in assessing the skills of immigrants.

Immigration policy in developed countries like the U.S. involves numerous tradeoffs. When immigration levels are restricted, various criteria are typically used to ration admissions. The willingness and ability to own a business in the host country is given special consideration in many countries, and some stakeholders argue for expanded policy efforts to attract immigrant entrepreneurs. However, it is unclear if such special considerations for self-employed immigrants have net positive effects on social value domestically or globally (Acs et al. 2016). Pro-entrepreneurship policies are often misguided (Parker 2007; Shane 2009). Many proprietors start small businesses mostly out of necessity because of weak paid employment opportunities (Acs 2006). They typically engage in low-growth ventures with minimal innovation in already competitive industries, and the marginal immigrants admitted via generous pro-entrepreneurship policies are unlikely to be much different.

While immigration policy typically has multiple goals, immigration policies seeking to promote economic growth domestically should seek to admit immigrants with greater skills and higher productivity independent of whether that productivity comes as a paid employee or proprietor. Offered salary is a good measure of productivity for paid employees, but benefits from self-employment are often reaped further into the future making it difficult to justify an income-based admission policy that treats employees and proprietors equally. Education is an important dimension of skills, and foreign-born college graduates educated in STEM fields earn higher average wages in paid employment than graduates in non-STEM fields. STEM graduates also out-earn non-STEM graduates in self-employment. Of course, there is substantial variation in productivity and earning potential across majors and individuals within both STEM and non-

STEM fields with some non-STEM fields (e.g. nursing, finance, and economics) doing especially well. Despite some limitations, education is one of the strongest and easiest to interpret measures of skill, and information on college major can play a useful role in selecting skilled immigrants among both paid employees and proprietors.

6.3. Limitations and directions for future research

The study does have some limitations, and more research on this important topic is clearly warranted. First, a large portion of the self-employment gap between foreign STEM and non-STEM graduates remains unexplained. Second, our data do not allow us to observe the type of visa held by foreign workers, so we cannot draw strong inferences about the potential importance of specific visa programs.

Third, our static analysis uses cross-sectional data that misses important insights that might be revealed by examining flows into and out of self-employment and into and out of the country. In particular, future researchers should use longitudinal data to better assess the causal effects of self-employment on earnings for foreign-born workers entering and leaving self-employment, how immigrant self-employment outcomes evolve over time, and how these vary by education level and field of study.

Finally, our main results and policy implication may be somewhat specific to the particular legal, economic, and cultural environments in the U.S. Other countries with differing immigration policies and differing demands for STEM and non-STEM educated workers may experience very different outcomes. This warrants similar analyses for other countries with large inflows of skilled immigrants.

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Table 1: Self-employment Rates by Nativity and Education

	Foreigners	Natives
All education levels	0.115	0.091
With education less than Bachelor's degree	0.122	0.091
With Bachelor's degree or higher	0.100	0.091
With Bachelor's degree in non-STEM field	0.113	0.092
With Bachelor's degree in STEM field	0.080	0.088

Source: Based on authors' computations from the 2015 American Community Survey. All samples are restricted to individuals ages 25-61 who are employed or self-employed and use sampling weights.

Table 2: Variable Means for Foreign STEM and Non-STEM Graduate Analytical Sample

	Non-STEM	STEM
A. Outcome Variables		
Self-Employed	0.113	0.080
Unincorporated	0.065	0.035
Incorporated Self-Employed	0.048	0.045
Log Annual Earnings	10.636	11.082
B. Individual Control Variables		
Age	42.109	41.323
Bachelor's Degree	0.644	0.463
Master's Degree	0.260	0.336
Professional Degree	0.058	0.079
Doctoral Degree	0.037	0.122
Female	0.604	0.312
Married	0.664	0.739
Has Children	0.525	0.536
Does Not Speak English	0.010	0.005
Speaks only English	0.271	0.205
Speaks English very well	0.512	0.592
Speaks English well	0.153	0.165
Speaks English not well	0.053	0.034
Canada	0.033	0.024
Mexico	0.070	0.041
Rest of Americas	0.224	0.124
Western Europe	0.099	0.073
Eastern Europe	0.085	0.082
China	0.076	0.129
Japan	0.020	0.011
Korea	0.042	0.034
Philippines	0.086	0.043
India	0.095	0.265
Rest of Asia	0.088	0.115
Africa	0.072	0.052
Oceania	0.008	0.006
Other	0.001	0.000
Naturalized citizen	0.542	0.500
Years in U.S. 0-5	0.146	0.211
Years in U.S. 6-10	0.119	0.138
Years in U.S. 11-15	0.144	0.147
Years in U.S. 16-20	0.135	0.142
Years in U.S. 20+	0.456	0.362
Observations	49,449	32,666

Note: Analytical sample includes foreign-born college graduates ages 25-61 who are employed or self-employed. All results use personal sampling weights.

Table 3: Self-Employment Differentials between Foreign-born STEM and Non-STEM College Graduates

	(1)	(2)	(3)
STEM	-0.0375***	-0.0326***	-0.0311***
	(0.0036)	(0.0032)	(0.0030)
Industry dummies	No	Yes	Yes
MSA dummies	No	No	Yes

Notes: The dependent variable is an indicator equal to one if self-employed and zero otherwise. The STEM explanatory variable is a dummy variable for STEM-educated college graduates. The omitted base group includes college graduates with bachelor's degrees in all non-STEM fields. All regressions include individual controls listed in Table 2. Standard errors in parentheses are robust to heteroscedasticity and clustered by MSA.

*** Denotes significance at the 1% level.

Table 4: Log Annual Earning Differentials between Foreign-born STEM and Non-STEM College Graduates

	(1)	(2)	(3)
STEM	0.2451***	0.1954***	0.1958***
	(0.0241)	(0.0181)	(0.0138)
Self-employed	-0.4442***	-0.3994***	-0.4006***
	(0.0348)	(0.0320)	(0.0313)
STEM × Self-employed	-0.0168	0.0189	0.0199
	(0.0421)	(0.0418)	(0.0403)
Industry dummies	No	Yes	Yes
MSA dummies	No	No	Yes

Notes: The dependent variable is log annual earned income. All regressions include individual controls listed in Table 2. Standard errors in parentheses are robust to heteroscedasticity and clustered by MSA.

*** Denotes significance at the 1% level.

Table 5: Sensitivity Analysis

Dependent Variable	Self-Employed	Log Annual Income		
Explanatory Variable	STEM	STEM	Self-Employed	STEM× Self-Employed
(1) STEM preferred definition	-0.0311*** (0.0030)	0.1958*** (0.0138)	-0.4006*** (0.0313)	0.0199 (0.0403)
(2) STEM broader definition	-0.0314*** (0.0032)	0.1948*** (0.0133)	-0.3991*** (0.0314)	0.0160 (0.0396)
(3) Polynomial years in the U.S.	-0.0312*** (0.0030)	0.1976*** (0.0139)	-0.3995*** (0.0315)	0.0196 (0.0406)
(4) Age of immigration	-0.0318*** (0.0031)	0.1945*** (0.0141)	-0.4018*** (0.0314)	0.0203 (0.0405)
(5) Full-time workers	-0.0281*** (0.0031)	0.1733*** (0.0122)	-0.2432*** (0.0328)	0.0102 (0.0490)
(6) More than 10 years in the U.S.	-0.0324*** (0.0036)	0.1690*** (0.0137)	-0.4176*** (0.0319)	0.0609 (0.0469)
(7) 10 years or less in the U.S.	-0.0301*** (0.0046)	0.2217*** (0.0214)	-0.3661*** (0.0621)	-0.1587* (0.0833)
(8) Excluding outlying areas	-0.0316*** (0.0031)	0.1949*** (0.0138)	-0.3885*** (0.0298)	0.0096 (0.0403)
(9) Excluding immigrants arriving before age 18	-0.0349*** (0.0033)	0.2218*** (0.0157)	-0.3525*** (0.0327)	-0.0532 (0.0490)
(10) Excluding immigrants arriving before age 21	-0.0359*** (0.0036)	0.2242*** (0.0157)	-0.3514*** (0.0340)	-0.0575 (0.0523)
(11) Unincorporated self-employed[a]	-0.0221*** (0.0023)	0.1999*** (0.0129)	-0.6620*** (0.0442)	-0.1224* (0.0729)
(12) Incorporated self-employed[a]	-0.0090*** (0.0017)	0.2113*** (0.0139)	0.0041 (0.0239)	-0.0266 (0.0426)

Notes: All regressions include individual controls listed in Table 2, industry dummies, and MSA dummies. Standard errors in parentheses are robust to heteroscedasticity and clustered by MSA.

[a] The self-employed variable is defined as only unincorporated self-employed in Row (11) and as only incorporated self-employed in Row (12).

* Denotes significance at the 10% level; *** significance at the 1% level.

Table 6: Self-Employment and Log Annual Earning Differentials for Selected Detailed Major Categories

	Self-employed		Log Annual Income			
	(1)		(2)		(3)	
			Level		Interaction	
Music	0.1077	(0.0256)***	-0.4706	(0.0581)***	-0.0600	(0.1102)
Fine Arts	0.0940	(0.0147)***	-0.1947	(0.0645)***	0.0938	(0.1285)
Commercial Art and Graphic Design	0.0679	(0.0216)***	-0.0171	(0.0335)	-0.2603	(0.0863)***
Architecture	0.0532	(0.0139)***	-0.0129	(0.0408)	0.2281	(0.1006)**
General Business	0.0293	(0.0079)***	0.0057	(0.0241)	0.0666	(0.0640)
English Language and Literature	0.0261	(0.0092)***	-0.1638	(0.0399)***	-0.0297	(0.1138)
International Business	0.0257	(0.0182)	0.0916	(0.0393)**	-0.0648	(0.1224)
Sociology	0.0243	(0.0152)	-0.1701	(0.0444)***	0.4182	(0.1720)**
Treatment Therapy Professions	0.0215	(0.0129)*	0.2637	(0.0410)***	-0.2801	(0.2209)
Finance	0.0130	(0.0094)	0.1506	(0.0227)***	-0.0733	(0.0954)
Marketing and Marketing Research	0.0116	(0.0117)	0.0621	(0.0396)	-0.0277	(0.1547)
Political Science and Government	0.0113	(0.0114)	-0.0900	(0.0408)**	0.0896	(0.1180)
Communications	0.0072	(0.0124)	-0.0801	(0.0393)**	-0.0381	(0.1454)
Psychology	0.0058	(0.0072)	-0.1294	(0.0277)***	0.0330	(0.1519)
Economics	0.0046	(0.0088)	0.0925	(0.0250)***	-0.0098	(0.0983)
Philosophy and Religious Studies	0.0027	(0.0190)	-0.2031	(0.0649)***	-0.2227	(0.3833)
French, German, Latin and Other Common Foreign Language Studies	0.0023	(0.0162)	-0.0024	(0.0499)	-0.3050	(0.2654)
Biology	-0.0014	(0.0073)	0.1044	(0.0282)***	0.3552	(0.1189)***
Business Management and Administration	-0.0026	(0.0059)	-0.0195	(0.0248)	0.0788	(0.0752)
Accounting	-0.0059	(0.0080)	0.0461	(0.0234)**	0.0943	(0.1101)
Criminal Justice and Fire Protection	-0.0071	(0.0133)	-0.0859	(0.0466)*	-0.1179	(0.1831)
Theology and Religious Vocations	-0.0081	(0.0222)	-0.4515	(0.0566)***	0.2855	(0.2094)
History	-0.0092	(0.0093)	-0.0196	(0.0506)	0.1308	(0.1484)
General Engineering	-0.0115	(0.0104)	0.1845	(0.0321)***	0.0715	(0.0876)
Hospitality Management	-0.0116	(0.0175)	0.0612	(0.0564)	0.3184	(0.1484)**
Liberal Arts	-0.0129	(0.0098)	-0.1999	(0.0506)***	0.1044	(0.1876)
Multi-disciplinary or General	-0.0144	(0.0125)	0.0624	(0.0542)	0.3934	(0.1133)***

Science						
Chemical Engineering	-0.0162	(0.0108)	0.2337	(0.0394)***	0.1734	(0.1300)
Industrial and Manufacturing Engineering	-0.0185	(0.0094)*	0.2049	(0.0606)***	0.0102	(0.2152)
Social Work	-0.0194	(0.0142)	-0.0453	(0.0438)	-0.5727	(0.2665)**
Mechanical Engineering	-0.0198	(0.0085)**	0.2474	(0.0264)***	-0.3563	(0.2185)
Chemistry	-0.0219	(0.0093)**	0.0270	(0.0313)	0.2726	(0.1570)*
Biochemical Sciences	-0.0256	(0.0088)***	0.0914	(0.0476)*	0.1924	(0.1603)
Physics	-0.0295	(0.0086)***	0.1388	(0.0278)***	0.2187	(0.1333)
Civil Engineering	-0.0300	(0.0090)***	0.2008	(0.0348)***	-0.0703	(0.1334)
Pharmacy, Pharmaceutical Sciences, and Administration	-0.0316	(0.0153)**	0.3318	(0.0412)***	0.2330	(0.2302)
Computer and Information Systems	-0.0317	(0.0140)**	0.1461	(0.0468)***	-0.3925	(0.3049)
General Education	-0.0330	(0.0094)***	-0.1463	(0.0290)***	0.0265	(0.1548)
Electrical Engineering	-0.0389	(0.0066)***	0.2768	(0.0253)***	-0.0646	(0.0944)
Computer Engineering	-0.0414	(0.0077)***	0.3538	(0.0343)***	-0.1880	(0.1356)
Computer Science	-0.0419	(0.0064)***	0.2700	(0.0277)***	-0.2926	(0.1046)***
Elementary Education	-0.0423	(0.0083)***	-0.1736	(0.0445)***	-0.6696	(0.2452)***
Mathematics	-0.0427	(0.0093)***	0.0667	(0.0374)*	-0.0429	(0.1616)
Management Information Systems and Statistics	-0.0442	(0.0102)***	0.1681	(0.0464)***	-0.2248	(0.2986)
Nursing	-0.0482	(0.0054)***	0.3842	(0.0231)***	-0.0007	(0.1511)
Self-employed dummy			-0.3953	(0.0467)***		
Industry dummies	Yes		Yes		Yes	
MSA dummies	Yes		Yes		Yes	

Notes: The omitted base group includes college graduates with bachelor's degrees in all other majors not listed. Regressions include individual controls in Table 2. Standard errors in parentheses are robust to heteroscedasticity and clustered by MSA. STEM majors are bold.
* Denotes significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

Table 7: Self-Employment Differentials between STEM and Non-STEM College Graduates Controlling for Major-Specific Earnings

	(1)	(2)	(3)	(4)
STEM	-0.0311***	-0.0172**	-0.0310***	-0.0174**
	(0.0055)	(0.0067)	(0.0053)	(0.0067)
Maj_Earn_Lev		-0.0699***		-0.0689***
		(0.0244)		(0.0252)
Maj_Earn_Int			0.0094	0.0034
			(0.0071)	(0.0078)
Industry dummies	Yes	Yes	Yes	Yes
MSA dummies	Yes	Yes	Yes	Yes

Notes: The dependent variable is an indicator equal to one if self-employed and zero otherwise. All regressions include individual controls listed in Table 2. Standard errors in parentheses are robust to heteroscedasticity and clustered by detailed major.
** Denotes significance at the 5% level; *** significance at the 1% level.

Table 8: Linear Decomposition of Self-Employment Differentials between STEM and Non-STEM College Graduates

	(1)	(2)	(3)
Explained Portion			
Maj_Earn_Lev	0.0142**		0.0140**
	(0.0058)		(0.0059)
Maj_Earn_Int		0.0002	0.0001
		(0.0006)	(0.0003)
Education	0.0004	0.0000	0.0004
	(0.0021)	(0.0022)	(0.0021)
English_ability	0.0003	0.0003	0.0003
	(0.0003)	(0.0003)	(0.0003)
Demographics	-0.0063**	-0.0061**	-0.0063**
	(0.0027)	(0.0027)	(0.0027)
National_origin	-0.0036**	-0.0035*	-0.0036**
	(0.0017)	(0.0018)	(0.0017)
Citizenship	-0.0002	-0.0003	-0.0002
	(0.0002)	(0.0002)	(0.0002)
Years_in_U.S.	0.0019***	0.0020***	0.0019***
	(0.0006)	(0.0006)	(0.0006)
Industry	0.0054*	0.0055*	0.0054*
	(0.0029)	(0.0029)	(0.0029)
MSA	0.0038***	0.0038***	0.0038***
	(0.0008)	(0.0008)	(0.0008)
Total	0.0158**	0.0021	0.0157**
	(0.0075)	(0.0046)	(0.0076)
Unexplained Portion	0.0172***	0.0310***	0.0174***
	(0.0063)	(0.0049)	(0.0063)

Notes: The dependent variable is an indicator equal to one if self-employed and zero otherwise. Standard errors in parentheses are robust to heteroscedasticity and clustered by detailed major.
* Denotes significance at the 10% level; ** significance at the 5% level;
*** significance at the 1% level.

Appendix Table A.1: Definitions for the Main Variables Used in Our Study

Variable	Definition
CLASSWKR	CLASSWKR is an IPUMS variable indicating whether respondents worked for their own enterprise(s) or for someone else as employees. Workers with multiple sources of employment were classified according to the work relationship in which they spent the most time. Incorporated and unincorporated self-employees are distinguished.
INCEARN	INCEARN is an IPUMS variable indicating the self-reported total amount of income earned from paid employment or a person's own business or farm during the past 12 months. Employees report total income from wages, salary, commissions, bonuses, and tips from all jobs. Self-employees report net income after business expenses for all businesses owned.
DEGFIELDD	DEGFIELDD is an IPUMS variable indicating the major field of study for an individual’s first bachelor’s degree for persons whose highest education is a bachelor's degree or higher.
STEM	STEM is an author-constructed dummy variable equal to one for college graduates with DEGFIELDD among the following: 1103, 1104, 1105, 1106, 1300, 1301, 1302, 2001, 2100, 2101, 2102, 2105, 2106, 2107, 2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2499, 2500, 2501, 2502, 2503, 2504, 2599, 3600, 3601, 3602, 3603, 3604, 3605, 3606, 3607, 3608, 3609, 3611, 3699, 3700, 3701, 3702, 3801, 4002, 4003, 4005, 4006, 5000, 5001, 5002, 5003, 5004, 5005, 5006, 5007, 5008, 5098, 5102, 5901, 6106, 6108, 6202, 6212.