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ABSTRACT

Does Education Enhance Entrepreneurship?

Formal education is correlated with entrepreneurial activity and success, but correlation does not indicate causation. Education and entrepreneurship are both influenced by other related factors. The current study estimates causal effects of formal education on entrepreneurship outcomes by instrumenting for an individual's years of schooling using cohort mean years of maternal schooling observed decades prior. We differentiate self-employment by industry employment growth and firm incorporation status. We have multiple important results. Formal schooling significantly increases the probability of self-employment in high-growth industries for both women and men. Education reduces the probability of male self-employment in shrinking industries. Education also increases incorporated self-employment for women and men and reduces unincorporated self-employment among men but not women. The overall probability of self-employment increases with education for women but is unaffected by education for men. The results suggest that formal education enhances entrepreneurship.

JEL Classification: I20, J24, L26

Keywords: entrepreneurship, self-employment, education, human capital

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1. Introduction

Human capital and entrepreneurship are critical and complementary drivers of economic growth and human well-being (Schumpeter 1934; Romer 1990; Mankiw et al. 1992; Gennaioli et al. 2013).[1] Individuals with scarce knowledge and skills are uniquely able to recognize opportunities and develop creative solutions to existing problems (Murphy et al. 1991; Ehrlich et al. 2017). Formal education is an important component of human capital, but the effect of education on entrepreneurship is not well understood. Formal education is correlated with entrepreneurship measures (Robinson and Sexton 1994; Dunn and Holtz-Eakin 2000; Lofstrom et al. 2014), but observed relationships may not be causal (Block et al. 2012, 2013).[2] Educational attainment and entrepreneurship are both influenced by typically unobservable individual characteristics such as ambition and cognitive ability that likely confound observed relationships. The current study seeks to fill an important gap in the literature by estimating causal effects of formal education on entrepreneurial activity. We use a two-stage least squares (2SLS) instrumental variables (IV) strategy that combines large microdata samples from the American Community Survey (ACS) and decennial censuses. More specifically, we instrument for an individual's years of formal schooling using the average years of schooling of mothers from the individual's cohort observed decades prior.

We examine whether and how education affects the probability of self-employment and the type of self-employment. Self-employment can be in response to productive opportunities for firm creation or somewhat out of necessity due to poor prospects for paid employment

[1] On the importance of human capital, see also Glaeser et al. (1995), Simon (1998), Simon and Nardinelli (2002), Moretti (2004, 2013), Shapiro (2006), Hanushek (2013), Winters (2013, 2014, 2018), Hanushek and Woessmann (2015), Hanushek et al. (2017), and Ehrlich et al. (2018). Additional studies on the importance of entrepreneurship include Acs and Storey (2004), Wennekers et al. (2005), Acs (2006), Baumol and Strom (2007), Van Praag and Versloot (2007), Stephens and Partridge (2011), Stephens et al. (2013), and Glaeser et al. (2015).

[2] Surveys of related empirical literature are provided by Le (1999), Van der Sluis et al. (2008), Unger et al. (2011), Marvel et al. (2016), Simoes et al. (2016), Parker (2018), and Hogendoorn et al. (2019).

(Åstebro et al. 2011). Similarly, while some new firms are innovative in their products and processes, others are mostly replicative of existing firms (Hurst and Pugsley 2011). We are interested in the effect of education on entrepreneurship that is innovative and in response to productive opportunities. We differentiate self-employment by industry employment growth. We classify industries as high growth, low to medium growth, and shrinking. We expect that opportunity entrepreneurs are especially likely to own businesses in high growth industries. Furthermore, public policies seeking to promote entrepreneurship often tout the importance of entrepreneurs in creating new jobs, and are thus most interested in high growth entrepreneurship.

We also use firm incorporation status as an additional proxy for opportunity entrepreneurship following Levine and Rubinstein (2017). Levine and Rubinstein (2017) document that the incorporated self-employed are more highly educated and more successful than their unincorporated counterparts. We follow Levine and Rubinstein (2017) and argue that incorporated self-employment better approximates opportunity entrepreneurship than unincorporated self-employment.

We have multiple important results. First, we find that years of formal education significantly increases the probability of self-employment in high-growth industries for both women and men and reduces the probability of self-employment in shrinking industries. Our preferred 2SLS specification indicates that an additional year of schooling increases self-employment in high-growth industries by 1.12 percentage points for women and by 0.88 percentage points for men. Education has relatively small effects on female self-employment in low to medium growth and shrinking industries, resulting in an overall positive effect of schooling on female self-employment of 1.19 percentage points. Thus, education increases female self-employment overall and the increase is driven by increases in high growth industry self-employment. For men a year of additional schooling decreases shrinking industry self-employment by 0.72 percentage points and has no significant effect on low to moderate growth self-employment. Thus, education does not affect the overall probability of self-employment for men but it on average shifts male self-employment from shrinking industries to high-growth industries; of course, it is not necessarily the same men making these shifts. Some may shift from shrinking industry self-employment to paid employment while others shift from paid employment to high-growth self-employment; we can only observe the net effect. Education also increases incorporated self-employment for women and men and reduces unincorporated self-employment among men but increases it for women. These results are qualitatively robust to several alternative specifications.

Few previous studies have used quasi-experimental methods to estimate causal effects of education on the probability of self-employment. Block et al. (2013) is the first study to our knowledge to use instrumental variables to examine the effect of education on self-employment. Block et al. (2013) use as instruments eight dummies for white collar, blue collar, civil servant, and non-employment for each individual's mother and father. They estimate positive effects of education on the overall probability of self-employment. However, their instruments might not be exogenous. For example, white collar parents likely have more income and wealth to help finance their children's education and help fund their business ventures.[3]

A few subsequent studies have used an individual's mother's, father's, and sibling's education as instruments to estimate the effects of education on the overall probability of self-employment (Masakure 2015; Buenstorf et al. 2017; Habibov et al. 2017). Masakure (2015) estimates positive effects of education on the probability of self-employment in Canada.

[3] Additionally, their dataset includes 27 European countries and the USA, so their results may be correct on average but not necessarily representative for a particular country.

Buenstorf et al. (2017) find that the effect of education on self-employment is not statistically significant in Denmark. Habibov et al. (2017) find a negative effect of university education on the probability of self-employment in a dataset of 29 transition countries. Thus, the few IV studies estimating the effects of education on the probability of self-employment yield mixed results.[4] None of these IV studies focus on the USA or differentiate between high-growth industry self-employment and other industry self-employment or between incorporated and unincorporated self-employment. Our analysis uses a novel instrumental variables strategy to provide the first causal estimates for the USA, and we also differentiate the type of self-employment by focusing on high-growth industry self-employment and incorporated self-employment as better measures of opportunity entrepreneurship.

2. Theoretical Framework

Education and entrepreneurship are both investments, and economic theory indicates that they could be complementary or competing investments for individuals (Parker 2004, 2018). Formal educational investments are typically concentrated early in life, while business creation is concentrated later in adulthood. For simplicity, we present a framework for individuals with three life-course periods (1,2,3). In period 1, each individual can either work in paid employment or invest in formal schooling (S). In the second period, individuals can either work in paid employment or start a business venture (V). In the third period, individuals do not work at all, but they can sell their business if started in period 2.

[4] Other studies have used instrumental variables to examine effects of education on measures of entrepreneurial success including entrepreneurial income (Parker and Van Praag 2006; Iversen et al. 2011; Block et al. 2012; Fossen and Buttner 2013; Van Praag et al. 2013; Kolstad and Wiig 2015).

Investment in schooling develops human capital that increases productivity in both paid employment and in owning a business. Paid employment in period 2 pays wage income of W_2 that depends on schooling in period 1; specifically assume $\frac{\partial W_2}{\partial S} > 0$. Starting a business in period 2 requires a capital investment of C and involves an idiosyncratic cost of venturing (θ) but also provides self-employment income in period 2 (B_2) that increases with schooling, i.e., $\frac{\partial B_2}{\partial S} > 0$.[5] The venture equity (π) to sell in period 3 also increases with prior schooling, i.e., $\frac{\partial \pi}{\partial S} > 0$. Specifically, increased human capital allows more educated entrepreneurs to build more valuable businesses and earn greater capital gains when they sell their businesses.

An individual is expected to start a business in period 2 if the net present value is positive. The full opportunity cost of venturing in period 2 is $W_2 + C + \theta$. Individuals discount income in future periods at rate r. The net present value of starting a business venture ($NPVV$) in period 2 is:

$$NPVV = \frac{\pi}{(1+r)} + B_2 - [W_2 + C + \theta] \tag{1}$$

Investment in schooling affects $NPVV$ in competing ways as illustrated by the partial derivative:

$$\frac{\partial NPVV}{\partial S} = \frac{1}{(1+r)}\frac{\partial \pi}{\partial S} + \frac{\partial B_2}{\partial S} - \frac{\partial W_2}{\partial S} \tag{2}$$

First, schooling increases venture equity, so $\frac{1}{(1+r)}\frac{\partial \pi}{\partial S} > 0$. Schooling also increases business income in period 2, so $\frac{\partial B_2}{\partial S} > 0$. Thus, the first two components of equation (2) are positive. However, schooling also increases the opportunity cost of venturing in period 2 and the third

[5] The idiosyncratic cost of venturing depends on a number of factors including personality, risk aversion, access to capital, exposure to other entrepreneurs, developed skills, and innate ability (Blanchflower and Oswald 1998; Lazear 2005; Åstebro and Thompson 2011; Guiso and Schivardi 2011; Wang 2012; Lindquist et al. 2015; Orazem et al. 2015; Levine and Rubinstein 2018; Hamilton et al. 2019; Hvide and Oyer 2019; Guiso et al. 2020).

component of equation (2) is negative, i.e., $\frac{\partial W_2}{\partial S} > 0$ so $-\frac{\partial W_2}{\partial S} < 0$. Schooling increases productivity in starting a business but also increases productivity in paid employment. Thus, the total effect of schooling on the net present value of starting a business is theoretically ambiguous because the partial derivative $\frac{\partial NPVV}{\partial S}$ cannot be signed. This is an important theoretical result that calls for empirical research to examine the effect of education on entrepreneurship. Equation (2) also illustrates that the effect of education on entrepreneurship depends on which of the competing effects dominate. If $\frac{\partial W_2}{\partial S}$ is large relative to $\frac{1}{(1+r)}\frac{\partial \pi}{\partial S} + \frac{\partial B_2}{\partial S}$, then equation (2) will be negative and education will reduce entrepreneurship. However, if $\frac{1}{(1+r)}\frac{\partial \pi}{\partial S} + \frac{\partial B_2}{\partial S}$ is relatively large compared to $\frac{\partial W_2}{\partial S}$, then equation (2) will be positive and education will increase entrepreneurship. This has implications for interpreting empirical research and assessing the value of schooling in skill formation.

If an individual decides to start a business, they also have to choose what industry to enter and whether to incorporate. Industries differ in the expected rewards and in the resources needed to enter and succeed. High-growth industries likely have higher potential rewards for entering entrepreneurs but also more creative destruction and likely require higher skill levels to be successful. Stagnant growth industries have less upside but are likely more accessible for those with lower skills. Thus, we expect increased education to shift some potential entrepreneurs from stagnant industries to high growth industries. Additionally, incorporating provides legal protections for the owner by limiting their personal liability for business debts.[6] However, incorporation typically involves additional paperwork, administrative burden, and

[6] Specifically, the owner's personal assets are not generally recoverable for debts of the corporation, except in cases of fraud or when the owner has explicitly assumed personal responsibility or used personal assets as collateral.

legal fees. Thus, there are both benefits and costs of business incorporation, and a business owner will incorporate if the benefits exceed the costs. An owner with considerable assets outside the business will especially benefit from incorporation and be more likely to do so. Personal wealth likely increases with education, so we expect education to increase the likelihood of business incorporation (Åstebro and Bernhardt 2005; Levine and Rubinstein 2017).

We can also briefly consider the decision to invest in schooling. Employment in period 1 pays wage income of W_1. Assume that formal schooling in period 1 prevents the individual from working in period 1 and requires the individual to pay tuition, fees, and related expenses (T) and incur an idiosyncratic cost of effort (ε). The full opportunity cost of schooling in period 1 is $W_1 + T + \varepsilon$. Individuals will invest in schooling in period 1 if the present value of higher future income from schooling exceeds the opportunity cost of schooling. Notably, idiosyncratic costs influence both schooling (ε) and venturing (θ) decisions. These idiosyncratic costs are influenced by individual characteristics such as intellectual ability, personality, patience, and ambition. A major concern for empirical researchers is that the idiosyncratic costs of schooling and venturing may be correlated and bias observational results. Thus, one needs a credible identification strategy to assess the causal effect of education on entrepreneurship. The next section discusses our data and empirical methods.

3. Data and Methods

Our primary data are individual-level records from the American Community Survey (ACS) and decennial censuses; these data were obtained from IPUMS (Ruggles et al. 2019). We use a pooled cross-section of individual observations from the 2006-2019 ACS. Each year of the ACS includes a one percent random sample of the United States population. The ACS includes individual information on self-employment, industry, education, age, sex, race, ancestry, and birth state that make it an exceptional resource for our analysis. We limit the analytical sample to persons at least age 25 since younger persons are often still in school. We further limit the sample to white, non-Hispanic individuals born in the United States and classify them into 12 ancestry groups based on their self-reported primary ancestry.[7] The 12 groups include Dutch, English, French, German, Irish, Italian, Polish, Scandinavian, Scottish, Other Eastern European, Other Western European, and all other. We use survey year and age at the time of the ACS to define birth year for each individual.

We use birth state, birth year, and ancestry group to measure average parental characteristics from the 1980 and 1990 decennial census five percent microdata samples. This further limits our sample to persons born between 1963 and 1990. Specifically, we use the 1990 census microdata to construct a sample of children born in the USA in years 1973-1990 (ages 0-17 in 1990). We use the 1980 census microdata to construct a sample of children born in the USA in years 1963-1972 (ages 8-17 in 1980). We limit these samples to children under age 18 because we only observe parental characteristics for children who live in the same household as their parents, and 18 is the primary age at which many young people begin to move off for college, military service, work, or other reasons. Some children live with stepparents or adoptive parents. We treat parents, stepparents, and adoptive parents equivalently if they live in the same household as the child.[8]

For each combination of birth state, birth year, and ancestry group, we first use the decennial census samples to define the percentage of children with a mother in the household

[7] These sample restrictions result from our reliance on average parental characteristics discussed below. Missing data, changing composition, and small cell sizes prevent us from computing reliable information on average parental characteristics for other groups.
[8] We have no information on biological parents living outside the child's household.

and the percentage of children with a father in the household. Among children with mothers present, we then define average characteristics of mothers including average years of schooling, average annual income, the percentage that are employed, and the percentage that are self-employed. We also define average years of schooling, average annual income, the percentage that are employed, and the percentage that are self-employed for fathers among children with fathers present. The parental characteristics are all defined by birth state, birth year, and ancestry group combination and then matched to individuals in the ACS with the same combination of birth state, birth year, and ancestry group.[9]

We estimate linear regressions of the form:

$$Y_{isacot} = \beta YearsSchooling_{isacot} + \theta Z_{sac} + \gamma_{sc} + \xi_{ac} + \varphi_o + \delta_t + \varepsilon_{isacot} \quad (3)$$

, where Y_{isacot} measures a self-employment outcome for individual i born in state s with ancestry a birth-cohort-year c and observed at age o in survey year t. The explanatory variable of interest is an individual's years of formal schooling. Z_{sac} includes controls for parental characteristics discussed above, except the parental schooling variables are excluded from the controls. The additional explanatory variables ($\gamma_{sc}, \xi_{ac}, \varphi_o, \delta_t$) comprise an extensive set of dummy variables. ε_{isacot} is a mean zero error term. We estimate separate models for men and women.

Our main dependent variables are binary indicators for various types of self-employment including high-growth industry self-employment, low- and medium-growth industry self-employment, shrinking industry self-employment, incorporated self-employment, unincorporated self-employment, and any self-employment. Persons working in paid employment and persons

[9] The decennial censuses and ACS are independent random samples, so we are generally not observing the same individuals over time. A small percentage of individuals are included multiple times, but we have no way to identify or link them over time. Instead, we construct decennial census cohort averages by birth state, birth year, and ancestry group and link these to individuals in the ACS.

not employed are coded as zero for all the self-employment indicators. Industry growth categories are defined based on industry employment growth during 2006-2019.[10] We define high growth industries as those in the top quartile of employment growth. Industries with positive growth but below the top quartile are defined as low and medium growth. A full list of high growth industries is provided in Appendix Table A1.

We use linear probability models (LPM) instead of non-linear models because our identification strategy leverages a large number of fixed effects, which creates an incidental parameters problem for non-linear models that would lead to biased estimates. We also examine a very large sample of individuals and our preferred estimates utilize instrumental variables, which lend further justification for estimating linear models (Angrist and Pischke 2009). We report standard errors that are clustered by birth state and account for heteroscedasticity. We also compute predicted values based on the regression results and find that only a very small percentage of predicted values are less than zero and none are greater than one.

We include a detailed set of fixed effects that include interactions of birth-state and birth-year (γ_{sc}), interactions of ancestry and birth-year (ξ_{ac}), age at the time of the ACS (φ_o), and ACS year (δ_t). The birth-state×birth-year and ancestry×birth-year interaction dummies are especially important and novel controls that account for unobservable characteristics. With 50 states, 28 birth-years, and 12 ancestry groups, we have nearly 1400 (50×28) birth-state×birth-year fixed effects and nearly 336 (28×12) ancestry×birth-year fixed effects; the exact number is slightly less because a few cells are empty and a few interactions are dropped to avoid perfect collinearity. We use the Stata commands reghdfe and ivreghdfe to estimate our models by absorbing the very large number of fixed effects (Correia 2017, 2018).

[10] We link industries over time using the IND1990 variable in IPUMS. See Appendix Table A1 for more details.

We first estimate equation (3) using ordinary least squares (OLS) regressions, but our preferred estimates are from two-stage least squares (2SLS) regressions that instrument for an individual's years of schooling via the average years of schooling of mothers for the individual's birth-state, birth-year, and ancestry group combination. Our instrument is similar to Winters (2015), who uses average maternal years of schooling by birth state and birth year as an instrument to examine the effects of education on annual wages, hourly wages, and hours worked of employees. Winters (2015) excludes self-employers from the analysis entirely and does not examine outcomes related to self-employment. Furthermore, Winters (2015) does not exploit variation by ancestry group and correspondingly includes a much smaller set of fixed effects. Additional studies have used parental characteristics as instrumental variables in numerous applications, but Winters (2015) is the first to our knowledge to use cohort-level average maternal schooling as an instrument.

Our preferred models do not include average father's schooling, but we examine it as an alternative instrumental variable in sensitivity analysis. We argue that maternal schooling is a better instrument than paternal schooling for our purposes in part because 95.2 percent of children in the 1980 and 1990 samples lived with their mother but only 85.2 percent lived with their father. Furthermore, Gould et al. (2020) find that parent-child transmission of human capital is stronger for parents that spend more time with their kids, and mothers spend more time parenting on average. A valid instrument should be both relevant and exogenous. We can test the relevance criterion via first-stage statistics to confirm that the instrument is a strong predictor of the endogenous explanatory variable. We report first-stage results below.

The exogeneity condition requires that the cohort maternal schooling instrument be uncorrelated with the error term in equation (3). This cannot be tested in exactly identified models, but we do report overidentification tests for 2SLS models that include both average maternal schooling and average paternal schooling as instruments. We also argue that cohort average maternal schooling by birth state, birth year, and ancestry group combination is plausibly exogenous controlling for the extensive set of fixed effects and the additional parental characteristics. Identifying variation for our 2SLS models comes from variation across ancestry groups within birth-state×birth-year cells while controlling for national ancestry×birth-year effects. Intuitively, ancestry groups systematically vary in average education levels, education differences evolve over time, and differences are partially transmitted from parents to their children. Furthermore, these differences manifest among individuals born in the same state and year even after controlling for national ancestry×birth-year effects. The differences in maternal education that underlay our instrument are driven by changing cultural norms and opportunities for female education that differed in timing across ancestry groups within states. These educational differences are then partially transmitted to children and used as instruments for the education of the children decades later. Ours is the first study to our knowledge to leverage birth state, birth year, and ancestry in this way to construct instrumental variables.

Our IV approach using cohort average maternal schooling has important advantages over using individual-level maternal schooling. Most notably, an individual's schooling may be correlated with that of his or her mother due to shared unobservable characteristics such as academic ability, time preferences, and household wealth that may also affect entrepreneurship and related outcomes. Our cohort average approach is driven by observing different individuals with the same birth state, birth year, and ancestry group over time. Unobservable characteristics are largely averaged out at the cohort level and any remaining unobservable factors are accounted for by our very large number of birth-state×birth-year and ancestry×birth-year fixed effects and additional parental characteristic control variables.

Table 1 presents sample means for selected variables by gender. Recall that the sample includes individuals who are self-employed, paid-employed and non-employed. Among women in the sample, 2.4 percent are self-employed in high growth industries, 1.8 percent are self-employed in low and medium growth industries, and 1.4 are self-employed in shrinking industries. Only 1.8 percent of women are incorporated self-employed, while 3.8 percent are unincorporated self-employed. For men, 2.9 percent are in high growth industry self-employment, 2.9 percent are in low and medium growth industry self-employment, and 3.7 percent are in shrinking industry self-employment. 4.1 percent of men are incorporated self-employed and 5.4 percent are unincorporated self-employed. The mean years of schooling for our sample is higher for women than men, but mean paternal schooling exceeds mean maternal schooling, consistent with the gender reversal in education attainment (Goldin and Katz 2009).

4. Empirical Results

4.1 Main Results

Table 2 presents OLS estimates in Panel A and our main 2SLS estimates in Panel B for the effect of years of formal schooling on the probability of high growth industry self-employment, low and medium growth industry self-employment, shrinking industry self-employment and any industry self-employment.[11] We estimate separate regressions by gender. We also present first-stage results for the 2SLS estimates. We report standard errors and first-

[11] Results for the parental characteristic control variables in the 2SLS specification are reported in Appendix Table A2. These are not our focus. Most of these coefficients are not significant. The main results are qualitatively robust to excluding the parental characteristic control variables.

stage F-statistics that account for clustering by birth state. Because we estimate linear models, the coefficients for high growth, low and medium growth, and shrinking industry self-employment sum to equal the coefficient on any industry self-employment for each gender.[12]

The OLS results suggest that years of schooling increases high-growth industry self-employment for both women and men with coefficients statistically significant at the one percent level. OLS results also suggest significant negative effects on shrinking industry self-employment for both genders. The OLS coefficient for the probability of any self-employment is significantly positive for women, but the OLS estimate for men in Column (8) is relatively small and not statistically significant at conventional levels.

Our preferred method is 2SLS. The first-stage results indicate that the instrument has the expected sign and a statistically significant effect on years of schooling. The first-stage F-statistics are quite large, 133.8 in Columns (1) – (4) and 200.7 in Columns (5) – (8), indicating that the instrument is not weak. The second-stage results indicate that years of schooling has a significant positive effect on high growth industry self-employment for both women and men in Columns (1) and (5), respectively. Specifically, an additional year of schooling increases the probability of high growth industry self-employment by 1.12 percentage points for women and by 0.88 percentage points for men. To put this in perspective, recall from Table 1 that 2.4 percent of women and 2.9 percent of men are high growth industry self-employed. Thus, education has a large effect on high growth industry self-employment for both men and women. The 2SLS coefficient estimates for high growth industry self-employment also imply larger point estimates than OLS. We conduct endogeneity tests for years of schooling in OLS, and report the p-values in Table 2. The small p-values indicate that the 2SLS and OLS results are significantly

[12] We also examined predicted values. For all 2SLS models in Table 2, less than two percent of predicted values are below zero and none exceeded one.

different and schooling is endogenous in the OLS specification. In particular, OLS estimates understate the effect of schooling on engaging in high-growth self-employment.

Columns (2) and (6) of Table 2 report the effects of years of schooling on the probability of low and medium growth industry self-employment. The 2SLS estimate is significantly positive for women in Column (2) but not significant for men in Column (6). Columns (3) and (7) report effects on shrinking industry self-employment. The coefficient estimate for women in Column (3) is not significant, while the effect for men in Column (7) is significantly negative and relatively large (-0.0072). Column (4) indicates a significant positive effect (0.0119) on the probability of any self-employment for women, but Column (8) yields a small coefficient that is not statistically significant for the effect of schooling on the probability of any self-employment for men.

The 2SLS results in Table 2 indicate that years of schooling affects self-employment in nuanced ways. Specifically, schooling increases high growth industry, low and medium growth industry, and overall self-employment rates for women, but for men it only increases high growth industry self-employment rates. Schooling instead lowers male shrinking industry self-employment and has no meaningful effect on overall male self-employment rates. Thus, schooling pushes women into multiple types of self-employment and increases the overall number of self-employed women, but it does not meaningfully alter the overall number of self-employed males. It instead, has a net effect shifting male self-employment from shrinking to high growth industries.

Table 3 reports the effects of schooling on incorporated and unincorporated self-employment with OLS results in Panel A and 2SLS results in Panel B. The 2SLS results indicate that an additional year of schooling has significant positive effects on both incorporated (0.0052) and unincorporated self-employment (0.0067) for women. For men, schooling has offsetting positive effects on incorporated (0.0062) and negative effects on unincorporated self-employment (-0.0062). Thus, similar to Table 2, schooling positively affects multiple types of self-employment for women but has offsetting effects on male self-employment. The incorporated self-employed are generally more successful and more aligned with high-impact entrepreneurship (Levine and Rubinstein 2017), so an overall decrease in unincorporated self-employment and similar magnitude increase in incorporated self-employment among males is a positive social outcome.

4.2 Sensitivity Analysis

Table 4 presents results for several sensitivity checks for our preferred 2SLS specification in Table 2. Panel A adds additional dummy control variables for marital status, number of children, and age of the youngest child in the household; these variables are excluded from the main models because they are also outcomes potentially affected by years of schooling and may moderate the effect on self-employment. Controlling for these additional variables yields similar coefficient estimates as Table 2 and does not qualitatively alter the results. Panel B excludes the parental characteristic control variables to check whether results using the maternal schooling instrument are driven by unexpected collinearities with these other parental characteristic variables; results in Panel B of Table 4 are largely similar to the preferred specification. Panel C replaces years of schooling with years of college education; results are similar to the main specification.

Panel D of Table 4 uses cohort mean paternal years of schooling as the instrument, and Panel E simultaneously includes both cohort maternal and paternal schooling as instruments.

Results in Panel D are largely similar to the preferred specification, but the estimates are slightly more negative (e.g. Columns 3 and 6 are now significantly negative). In Panel E, the coefficient estimates are in between those separately using maternal and paternal schooling instruments. Panel E also reports overidentification test p-values; all are well above 0.10 except for Column (7) and (8), both of which exceed 0.05. The maternal schooling variable is our preferred instrument *a priori* for the reasons noted above in Section 3, and it is notable that the results are largely similar using an alternative but less desirable instrument.

Panel F focuses on workers strongly tied to the workforce by limiting the sample to individuals working at least 30 hours per week; this sample selection may be endogenously related to the self-employment decision, so it is not our preferred specification. The results in Panel F are qualitatively similar to the main specification. Panel G restricts the sample to persons age 30 and older since some persons in their 20s are still completing school and have not yet accumulated the financial capital and managerial skills to start a successful business; results are again qualitatively similar to the preferred specification. Finally, Panel H limits the sample to the 2014-2019 ACS years; results are again largely similar to the preferred specification, though coefficient estimates for women are somewhat larger.

Table 5 repeats the sensitivity analyses for incorporated and unincorporated self-employed. On the whole, the results are again qualitatively similar to the preferred 2SLS specification in Table 3.

4.3 Further Extensions

Results in Appendix Tables A4 and A5 also briefly consider additional outcomes as further extensions of our analysis. The specification in Table A4 is the same as our main analysis but the dependent variable in Columns (1) and (3) is an indicator equal to one if the individual works for paid employment and the dependent variable in Columns (2) and (4) is an indicator equal to one if the individual is not working (neither self-employed nor paid-employed). 2SLS results in Table A4 suggest that schooling increases the probability of paid-employment and decreases the probability of non-employment for both women and men. For women, the reduction in non-employment is larger than the increase in paid-employment consistent with the positive effect on any self-employment for women. For men, the increase in paid-employment and the decrease in non-employment are equal magnitudes consistent with no net effect on the probability of self-employment for men.

Table A5 considers the relationship between years of schooling and log annual earnings of the self-employed. This analysis estimates variants of equation (3), but the dependent variable is log annual earnings and the sample is limited to self-employed workers. Because the sample is limited to self-employed workers and we cannot confidently account for endogenous selection into self-employment, the results should be interpreted as descriptive instead of causal estimates. Both OLS and 2SLS coefficient estimates suggest a positive relationship between years of schooling and earnings of the self-employed, and the magnitudes are comparable to previous literature estimates for paid employees (Winters 2015). While not definitive, the results in Table A5 do suggest an important connection between education and entrepreneurial success.

5. Conclusion

Education and entrepreneurship are both important factors for individual well-being and economic growth. However, it is unclear theoretically whether formal education affects an individual’s probability of engaging in entrepreneurship. Despite the importance of this question, there is very limited prior literature using quasi-experimental methods. We fill important gaps in knowledge by using an instrumental variables strategy to estimate causal effects of education on entrepreneurship in the USA. We differentiate between self-employment in a high-growth industry, low- and medium-growth industry, and shrinking industry. High-growth industry self-employment is most closely aligned with entrepreneurship and public policy goals. We also conduct additional analysis that differentiates between incorporated self-employment and unincorporated self-employment.

We find that formal schooling increases self-employment in high-growth industries for both men and women and reduces self-employment in shrinking industries for men. The overall effect of education on any self-employment is positive for women but essentially zero for men. Thus, education pushes more women into self-employment, and the effect is driven by increases in high-growth self-employment. For men, education causes an overall shift from shrinking industry self-employment to high-growth industry self-employment. Additionally, education increases incorporated self-employment for both women and men. Education increases unincorporated self-employment for women but decreases it for men.

Our analysis indicates that education enhances entrepreneurship in the USA. This has important implications for researchers and policymakers. Researchers can better understand what drives individual decisions to start a new business venture and how well they succeed. Human capital is widely accepted as an important factor, but there is debate about what elements of human capital matter, in which direction, and by how much. We focus on formal education, which is often very specialized and could theoretically reduce entrepreneurship. Formal education also provides general knowledge and skills and increases entrepreneurship as measured by high-growth industry self-employment and incorporated self-employment. Also, some scholars posit that the benefits of formal education are driven by credentials and ability signaling. While there may be some truth to that for paid employees, there is much less reason to believe that credentials alone would generate entrepreneurship. The positive effects of education on entrepreneurship provide evidence that schooling confers valuable knowledge and skills.

For policymakers and other stakeholders interested in economic growth and well-being, both entrepreneurship and education are potential mechanisms to target. However, the policy community should always consider possible unintended consequences of policies. A policy push in one dimension can often have adverse effects in another dimension, and the unintended consequences can sometimes be sufficiently large to more than offset the benefits in the intended dimension. In particular, it would be troubling and challenging for the policy community if education had a strong negative effect on entrepreneurship. However, we find that education increases entrepreneurship, so policies that promote education also enhance entrepreneurship, yielding an important yet not fully intended benefit. Furthermore, the policy community also heavily debates the benefits of formal education and concerns about credentialing and signaling. The fact that education increases skills and particularly the skills needed for entrepreneurship is especially encouraging about the overall social benefits of education.

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Table 1: Sample Means for Selected Variables by Gender

	Women	Men
High Growth Industry Self-Employed	0.024	0.029
Low and Medium Growth Industry Self-Employed	0.018	0.029
Shrinking Industry Self-Employed	0.014	0.037
Any Industry Self-Employed	0.056	0.094
Incorporated Self-Employed	0.018	0.041
Unincorporated Self-Employed	0.038	0.054
Years of Schooling	14.25	13.81
Cohort Mean Maternal Years of Schooling	12.57	12.58
Cohort Mean Paternal Years of Schooling	12.99	13.00

Notes: The sample includes white, non-Hispanic individuals born in the USA in years 1963-1990 and observed in the 2006-2019 American Community Survey.

Table 2: OLS and 2SLS Effects of Years of Schooling on Self-Employment and Industry Growth by Gender

	(1) Women High Growth Industry Self-Emp.	(2) Women Low-Med. Growth Industry Self-Emp.	(3) Women Negative Growth Industry Self-Emp.	(4) Women Any Industry Self-Employed	(5) Men High Growth Industry Self-Emp.	(6) Men Low-Med. Growth Industry Self-Emp.	(7) Men Negative Growth Industry Self-Emp.	(8) Men Any Industry Self-Employed
A. OLS								
Years of Schooling	0.0026***	0.0005***	-0.0010***	0.0021***	0.0041***	-6.14e-06	-0.0034***	0.0007
	(0.0001)	(4.01e-05)	(6.89e-05)	(0.0002)	(8.70e-05)	(0.0001)	(0.0002)	(0.0004)
B. 2SLS								
Years of Schooling	0.0112***	0.0022**	-0.0015	0.0119***	0.0088***	-0.0015	-0.0072***	2.24e-05
	(0.0019)	(0.0009)	(0.0009)	(0.0025)	(0.0014)	(0.0010)	(0.0017)	(0.0025)
First-Stage Results								
Cohort Maternal Sch.	0.2989***	0.2989***	0.2989***	0.2989***	0.3479***	0.3479***	0.3479***	0.3479***
	(0.0258)	(0.0258)	(0.0258)	(0.0258)	(0.0246)	(0.0246)	(0.0246)	(0.0246)
F-Statistic	133.8	133.8	133.8	133.8	200.7	200.7	200.7	200.7
Endog. Test P-value	0.0013	0.0526	0.5434	0.0031	0.0025	0.1146	0.0280	0.7972
Observations	4,097,486	4,097,486	4,097,486	4,097,486	4,068,507	4,068,507	4,068,507	4,068,507

Notes: Regressions include cohort parental characteristics control variables and a large number of fixed effects including interactions of birth-state and birth-year, interactions of ancestry group and birth-year, age at the time of the ACS, and ACS year. See the text for more details. Standard errors in parentheses and first-stage F-statistics account for clustering by birth-state. **Significant at 5% level; ***Significant at 1% level.

Table 3: Effects of Schooling on Incorporated and Unincorporated Self-Employment

	(1) Women Incorporated Self-Employed	(2) Women Unincorporated Self-Employed	(3) Men Incorporated Self-Employed	(4) Men Unincorporated Self-Employed
A. OLS				
Years of Schooling	0.0021***	4.63e-05	0.0037***	-0.0030***
	(0.0000)	(0.0001)	(0.0002)	(0.0003)
B. 2SLS				
Years of Schooling	0.0052***	0.0067***	0.0062***	-0.0062***
	(0.0010)	(0.0021)	(0.0012)	(0.0023)
First-Stage Results				
Cohort Maternal Schooling	0.2989***	0.2989***	0.3479***	0.3479***
	(0.0258)	(0.0258)	(0.0246)	(0.0246)
F-Statistic	133.8	133.8	200.7	200.7
Endogeneity Test P-value	0.0049	0.0134	0.0684	0.1522
Observations	4,097,486	4,097,486	4,068,507	4,068,507

Notes: Regressions include cohort parental characteristics control variables and a large number of fixed effects including interactions of birth-state and birth-year, interactions of ancestry group and birth-year, age at the time of the ACS, and ACS year. See the text for more details. Standard errors in parentheses and first-stage F-statistics account for clustering by birth-state. ***Significant at 1% level.

Table 4: Sensitivity Analysis for 2SLS Effects of Schooling on Self-Employment and Industry Growth

	(1) Women High Growth Industry Self-Emp.	(2) Women Low-Med. Growth Industry Self-Emp.	(3) Women Negative Growth Industry Self-Emp.	(4) Women Any Industry Self-Employed	(5) Men High Growth Industry Self-Emp.	(6) Men Low-Med. Growth Industry Self-Emp.	(7) Men Negative Growth Industry Self-Emp.	(8) Men Any Industry Self-Employed
A. Controlling for Marital Status, Number of Children, and Age of Youngest Child								
Years of Schooling	0.0113***	0.0023**	-0.0014	0.0122***	0.0087***	-0.0013	-0.0067***	0.0007
	(0.0018)	(0.0009)	(0.0009)	(0.0024)	(0.0014)	(0.0010)	(0.0016)	(0.0023)
B. Excluding Cohort Parental Controls								
Years of Schooling	0.0109***	0.0021***	-0.0006	0.0125***	0.0098***	-0.0010	-0.0059***	0.0029
	(0.0017)	(0.0006)	(0.0006)	(0.0021)	(0.0012)	(0.0010)	(0.0016)	(0.0029)
C. Estimating Effects of Years of College								
Years of College	0.0155***	0.0021*	-0.0017	0.0159***	0.0127***	-0.0010	-0.0062***	0.0056
	(0.0033)	(0.0012)	(0.0013)	(0.0041)	(0.0025)	(0.0016)	(0.0023)	(0.0046)
D. Using Paternal Schooling IV								
Years of Schooling	0.0109***	0.0014*	-0.0025**	0.0098***	0.0097***	-0.0032***	-0.0099***	-0.0034
	(0.0018)	(0.0008)	(0.0011)	(0.0025)	(0.0014)	(0.0011)	(0.0018)	(0.0024)
E. Using Both Parental Schooling IV								
Years of Schooling	0.0110***	0.0017**	-0.0021**	0.0107***	0.0093***	-0.0025**	-0.0088***	-0.0020
	(0.0018)	(0.0008)	(0.0009)	(0.0024)	(0.0014)	(0.0010)	(0.0017)	(0.0023)
Overid. P-value	0.970	0.467	0.533	0.360	0.517	0.207	0.059	0.088
F. Restricting the Sample to Persons Working 30+ Hours per Week								
Years of Schooling	0.0102***	0.0015	-0.0004	0.0113***	0.0084***	-0.0023**	-0.0093***	-0.0033
	(0.0022)	(0.0012)	(0.0013)	(0.0029)	(0.0015)	(0.0011)	(0.0018)	(0.0027)
G. Restricting the Sample to Persons Ages 30 and Older								
Years of Schooling	0.0126***	0.0027***	-0.0013	0.0139***	0.0102***	-0.0017	-0.0072***	0.0012
	(0.0017)	(0.0010)	(0.0010)	(0.0023)	(0.0014)	(0.0011)	(0.0018)	(0.0024)
H. Restricting the Sample to Years 2014-2019								
Years of Schooling	0.0178***	0.0043***	-0.0019	0.0202***	0.0082***	-0.0009	-0.0064***	0.0010
	(0.0027)	(0.0014)	(0.0016)	(0.0035)	(0.0018)	(0.0015)	(0.0023)	(0.0032)

Notes: Specifications are similar to Table 2 Panel B except as indicated in the panel name. First-stage results are similar to Table 2 and are suppressed to conserve space. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table 5: Sensitivity Analysis for 2SLS Effects on Incorporated and Unincorporated Self-Employment

	(1) Women Incorporated Self-Employed	(2) Women Unincorporated Self-Employed	(3) Men Incorporated Self-Employed	(4) Men Unincorporated Self-Employed
A. Controlling for Marital Status, Number of Children, and Age of Youngest Child				
Years of Schooling	0.0053***	0.0069***	0.0067***	-0.0060***
	(0.0010)	(0.0021)	(0.0012)	(0.0021)
B. Excluding Cohort Parental Controls				
Years of Schooling	0.0058***	0.0067***	0.0077***	-0.0048**
	(0.0008)	(0.0017)	(0.0012)	(0.0022)
C. Estimating Effects of Years of College				
Years of College	0.0075***	0.0084**	0.0098***	-0.0043
	(0.0016)	(0.0032)	(0.0020)	(0.0035)
D. Using Paternal Schooling IV				
Years of Schooling	0.0052***	0.0046**	0.0048***	-0.0082***
	(0.0010)	(0.0020)	(0.0013)	(0.0021)
E. Using Both Parental Schooling IV				
Years of Schooling	0.0041***	0.0036**	0.0057***	-0.0071***
	(0.0009)	(0.0014)	(0.0011)	(0.0021)
Overidentification P-value	0.999	0.232	0.370	0.356
F. Restricting the Sample to Persons Working 30+ Hours per Week				
Years of Schooling	0.0062***	0.0051**	0.0062***	-0.0094***
	(0.0014)	(0.0022)	(0.0013)	(0.0024)
G. Restricting the Sample to Persons Ages 30 and Older				
Years of Schooling	0.0061***	0.0078***	0.0062***	-0.0050**
	(0.0012)	(0.0020)	(0.0016)	(0.0023)
H. Restricting the Sample to Years 2014-2019				
Years of Schooling	0.0079***	0.0123***	0.0057***	-0.0047*
	(0.0017)	(0.0029)	(0.0015)	(0.0027)

Notes: Specifications are similar to Table 3 Panel B except as indicated in the panel name. First-stage results are similar to Table 3 and are suppressed to conserve space. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table A1: List of High-Growth Industries and IPUMS IND1990 Codes

Industry Name	IND1990 Code(s)	Employment Growth %
Social services, not elsewhere classified (n.e.c.)	871	129.9%
Warehousing and storage	411	97.4%
Educational services, n.e.c.	860	82.6%
Health services, n.e.c.	840	73.4%
E-commerce, catalog, and mail order sales	663	72.1%
Computer and data processing services	732	70.9%
Management and public relations services	892	64.9%
Beverage industries manufacturing	120	60.2%
Miscellaneous personal services	791	57.6%
Veterinary services	12	44.5%
Offices and clinics of optometrists	822	41.7%
Business services, n.e.c.	741	38.7%
Alcoholic beverages wholesaling	560	35.3%
Miscellaneous retail stores	682	33.4%
Retail bakeries	610	33.1%
Metal mining	40	32.6%
Misc. and not specified food and kindred products manufacturing	121, 122	32.0%
Residential care facilities, without nursing	870	30.4%
Miscellaneous professional and related services	893	30.3%
Detective and protective services	740	26.4%
Offices and clinics of physicians	812	26.3%
Eating and drinking places	641	25.5%
Liquor stores	650	25.0%
Security, commodity brokerage, and investment companies	710	24.7%
Offices and clinics of dentists	820	23.7%
Lodging places, except hotels and motels	770	23.3%
Landscape and horticultural services	20	23.1%
Offices and clinics of chiropractors	821	22.2%
Oil and gas extraction	42	21.8%
Child day care services	862	21.8%
Miscellaneous entertainment and recreation services	810	21.5%
Bus service and urban transit	401	21.4%
Museums, art galleries, and zoos	872	20.1%
Sanitary services and related utilities	471, 472	20.0%
Services to dwellings and other buildings	722	20.0%
Research, development, and testing services	891	19.3%
Services incidental to transportation	432	18.5%
Direct selling establishments	671	18.2%
Ordnance manufacturing	292	18.2%
Automobile parking and carwashes	750	18.1%
Theaters and motion pictures	800	17.9%
Bakery products manufacturing	111	17.7%

Notes: We define high growth industries as those in the top quartile of employment growth during 2006-2019. We link industries over time using the IND1990 variable in IPUMS along with crosswalks matching IND1990 to NAICS codes. A few IND1990 codes had to be combined; we redefined the industry name and list both IND1990 codes for these cases that are high growth. Our main measure of industry employment growth uses Quarterly Census of Employment and Wages (QCEW) employment data. Two industries (agriculture and barbershops) could not be accurately measured in QCEW data, so we use employment growth in ACS data for these; neither is a high-growth industry. The low-medium growth group includes the following IND1990 codes: 10, 100, 101, 110, 112, 181, 182, 201, 262, 311, 312, 352, 360, 362, 372, 390, 402, 410, 420, 421, 450, 451, 452, 470, 500, 501, 510, 511, 512, 521, 530, 532, 541, 542, 550, 552, 561, 582, 591, 601, 612, 620, 621, 630, 651, 700, 711, 712, 721, 742, 751, 752, 760, 762, 780, 781, 831, 832, 842, 850, 861, 880, 881, 882, 890. All other IND1990 codes are shrinking industries.

Table A2: Parental Characteristic Variable 2SLS Results for Self-Employment and Industry Growth by Gender

	(1) Women High Growth Industry Self-Emp.	(2) Women Low-Med. Growth Industry Self-Emp.	(3) Women Negative Growth Industry Self-Emp.	(4) Women Any Industry Self-Employed	(5) Men High Growth Industry Self-Emp.	(6) Men Low-Med. Growth Industry Self-Emp.	(7) Men Negative Growth Industry Self-Emp.	(8) Men Any Industry Self-Employed
% w/ Mother in House.	-0.0074	0.0016	-0.0005	-0.0063	0.0057	0.0100	0.0085	0.0242*
	(0.0073)	(0.0047)	(0.0054)	(0.0095)	(0.0083)	(0.0060)	(0.0069)	(0.0123)
% w/ Father in House.	-0.0115**	-0.0020	-0.0020	-0.0154**	-0.0098*	0.0038	0.0127**	0.0066
	(0.0057)	(0.0027)	(0.0029)	(0.0065)	(0.0050)	(0.0040)	(0.0054)	(0.0091)
% of Mothers Self-Emp.	0.0092	0.0019	-0.0070*	0.0040	0.0100	0.0018	0.0118*	0.0236**
	(0.0068)	(0.0035)	(0.0037)	(0.0087)	(0.0071)	(0.0053)	(0.0068)	(0.0098)
% of Fathers Self-Emp.	0.0020	0.0024	0.0057**	0.0102	0.0076	0.0157***	0.0151***	0.0384***
	(0.0054)	(0.0022)	(0.0025)	(0.0070)	(0.0062)	(0.0043)	(0.0048)	(0.0106)
% of Mothers Employed	0.0048*	-0.0010	0.0035	0.0073*	0.0008	-0.0022	0.0089**	0.0075
	(0.0027)	(0.0017)	(0.0021)	(0.0040)	(0.0025)	(0.0030)	(0.0042)	(0.0064)
% of Fathers Employed	-0.0130**	0.0023	-0.0013	-0.0121	0.0007	0.0031	0.0032	0.0071
	(0.0060)	(0.0031)	(0.0037)	(0.0074)	(0.0052)	(0.0044)	(0.0063)	(0.0092)
Mean Income of Mothers	5.74e-09	-7.73e-09	2.01e-08	1.81e-08	1.98e-08	-8.95e-09	-1.09e-08	2.79e-12
	(1.73e-08)	(9.11e-09)	(1.43e-08)	(2.42e-08)	(1.60e-08)	(1.31e-08)	(1.77e-08)	(2.36e-08)
Mean Income of Fathers	1.30e-09	2.09e-09	-7.00e-09	-3.61e-09	-1.07e-08	5.97e-09	7.94e-09	3.20e-09
	(1.12e-08)	(5.21e-09)	(5.44e-09)	(1.23e-08)	(9.53e-09)	(1.23e-08)	(1.22e-08)	(2.20e-08)
Observations	4,097,486	4,097,486	4,097,486	4,097,486	4,068,507	4,068,507	4,068,507	4,068,507

Notes: Parental characteristics are measured as cohort level means from the 1980 and 1990 decennial census microdata. Results correspond to the 2SLS specification in Table 2 Panel B. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table A3: Parental Characteristic Variable 2SLS Results for Incorporated and Unincorporated Self-Employment

	(1) Women Incorporated Self-Employed	(2) Women Unincorporated Self-Employed	(3) Men Incorporated Self-Employed	(4) Men Unincorporated Self-Employed
% w/ Mother in Household	1.65e-05	-0.0063	0.0166**	0.0076
	(0.0055)	(0.0075)	(0.0073)	(0.0102)
% w/ Father in Household	-0.0064*	-0.0090*	0.0033	0.0034
	(0.0033)	(0.0050)	(0.0055)	(0.0064)
% of Mothers Self-Employed	0.0066	-0.0025	0.0082	0.0154**
	(0.0043)	(0.0072)	(0.0059)	(0.0071)
% of Fathers Self-Employed	0.0016	0.0085	0.0203***	0.0180***
	(0.0034)	(0.0051)	(0.0072)	(0.0058)
% of Mothers Employed	0.0033	0.0040	0.0028	0.0047
	(0.0026)	(0.0034)	(0.0038)	(0.0050)
% of Fathers Employed	-0.0052	-0.0069	-0.0048	0.0119
	(0.0037)	(0.0063)	(0.0049)	(0.0083)
Mean Income of Mothers	1.58e-08	2.30e-09	1.52e-08	-1.52e-08
	(1.36e-08)	(2.14e-08)	(1.95e-08)	(2.29e-08)
Mean Income of Fathers	-1.19e-09	-2.42e-09	9.77e-09	-6.57e-09
	(5.68e-09)	(1.14e-08)	(1.72e-08)	(1.28e-08)
Observations	4,097,486	4,097,486	4,068,507	4,068,507

Notes: Parental characteristics are measured as cohort level means from the 1980 and 1990 decennial census microdata. Results correspond to the 2SLS specification in Table 3 Panel B. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table A4: Effects of Schooling on Paid and Non-Employment by Gender

	(1) Women Paid-Employed	(2) Women Non-Employed	(3) Men Paid-Employed	(4) Men Non-Employed
A. OLS				
Years of Schooling	0.0356***	-0.0377***	0.0316***	-0.0322***
	(0.0009)	(0.0009)	(0.0006)	(0.0007)
B. 2SLS				
Years of Schooling	0.0125*	-0.0244***	0.0225***	-0.0225***
	(0.0070)	(0.0062)	(0.0053)	(0.0050)
First-Stage Results				
Cohort Maternal Schooling	0.2989***	0.2989***	0.3479***	0.3479***
	(0.0258)	(0.0258)	(0.0246)	(0.0246)
F-Statistic	133.8	133.8	200.7	200.7
Endogeneity Test P-value	0.0100	0.0564	0.0756	0.0413
Observations	4,097,486	4,097,486	4,068,507	4,068,507

Notes: Specifications are similar to Table 2 except the dependent variables differ. The dependent variable in Columns (1) and (3) is an indicator equal to one if the individual works for paid employment. The dependent variable in Columns (2) and (4) is an indicator equal to one if the individual is not working (neither self-employed nor paid-employed). *Significant at 10% level; ***Significant at 1% level.

Table A5: Effects of Schooling on Log Annual Earnings of the Self-Employed

	(1) Women Self-Employed	(2) Men Self-Employed
A. OLS		
Years of Schooling	0.127***	0.130***
	(0.003)	(0.003)
B. 2SLS		
Years of Schooling	0.115***	0.158***
	(0.037)	(0.024)
First-Stage Results		
Cohort Maternal Schooling	0.342***	0.405***
	(0.032)	(0.039)
F-Statistic	114.3	106.7
Endogeneity Test P-value	0.7563	0.2745
Observations	226,685	380,915

Notes: Regressions include cohort parental characteristics control variables and a large number of fixed effects similar to Table 2. Standard errors in parentheses and first-stage F-statistics account for clustering by birth-state. ***Significant at 1% level.