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The impact of entrepreneurship education in high school on long-term entrepreneurial performance

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ABSTRACT

This paper studies the long-term impact of entrepreneurship education and training in high school on entrepreneurial entry, performance, and survival. Using propensity score matching, we compare three Swedish cohorts from Junior Achievement Company Program (JACP) alumni with a matched sample of similar individuals and follow these for up to 16 years after graduation. We find that while JACP participation increases the long-term probability of starting a firm as well as entrepreneurial incomes, there is no effect on firm survival.

1. Introduction

Recent decades have seen a large increase across the globe in entrepreneurship education and training (EET) programs (Fayolle, 2000; Linán, 2004; Kuratko, 2005; O'Connor, 2013; OECD, 2007). The goals of most such efforts are to increase the rate and quality of firms started (Holtz-Eakin, 2000; Fairlie et al., 2014; Inci, 2013; Leibenstein, 1987; Weitzel et al., 2010). Despite growing research interest in these programs, little is known about their long-term effects (Martin et al., 2013). Further, little attention has been paid to EET programs that target students in primary or secondary schools. This lack of knowledge is problematic as these children comprise the vast majority of students enrolled in education worldwide (Rosendahl Huber et al., 2012). It also makes it difficult to infer which skills such programs may foster and to identify mechanisms facilitating the accumulation of entrepreneurial skills. Additionally, it makes resource allocation to such programs highly uncertain.

Studies employing quasi-experimental methods have found that EET often exhibits weak or no effects on short-term outcomes such as entrepreneurial intentions (Oosterbeek et al., 2010; von Graevenitz et al., 2010) but may foster non-cognitive skills relevant for entrepreneurship (Rosendahl Huber et al., 2012; von Graevenitz et al., 2010). To date, few

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studies use rigorous research designs to investigate the impact of EET on actual outcomes such as entrepreneurial entry or performance (Martin et al., 2013). The studies that do consider such outcomes are often limited by small samples, self-selection of participants and short time periods between undergoing EET and subsequent outcomes. Furthermore, few of them consider the effect of EET on entrepreneurial income and firm survival.

In this paper, we try to fill this research gap by investigating the effects of the Junior Achievement Company Program (JACP), a program available to students in Swedish high-schools. We follow three cohorts of students who participated in JACP in the mid-1990s to investigate the long-term effects of the program. To minimize self-selection problems we use propensity score matching (PSM) to match JACP alumni to non-alumni with the same probability of participating in JACP based on a number of background characteristics. While there are limitations to PSM, it does allow us to ask an important hypothetical question: if a student from the mid-1990s was presented with the opportunity to participate in JACP, what were the effects on their entrepreneurial performance in the long term compared to if they had not participated?

We follow individuals up to 16 years after graduation—that is, into their early middle age. The long time period of investigation is important as individuals' probability to start a firm has been shown to be highest during their 30s and early 40s (Delmar and Davidsson, 2000). Our study is also advantageous in terms of sample size. Most experimental studies are limited to samples of perhaps a few hundred treated and non-treated subjects. Ours, by contrast, covers thousands of individuals. Further, we focus on entrepreneurial outcomes rather than entrepreneurial intentions. Specifically, we investigate the effect of JACP participation on (1) the probability of starting a firm, and the previously understudied outcomes (2) entrepreneurial income, and (3) firm survival.

Our results show that JACP participation increases the probability of individuals to engage in entrepreneurship by starting a firm and that their income from the firm will be higher when selection into the program is controlled for. We find no effect of JACP participation on subsequent firm survival, a result in line with earlier studies concerning entrepreneurial opportunity costs (c.f. Amit et al., 1995).

The remainder of the paper is outlined as follows. Section 2 is a summary of our current state of knowledge regarding the relationship between EET and entrepreneurship. In Section 3, we give a background on JACP, describe how we employed datasets from Statistics Sweden (SCB), and our approach of matching students using PSM to correct for student self-selection to JACP. Section 4 shows the results of estimates of the effect of JACP participation on entrepreneurial outcomes up to 16 years later. Finally, Section 5 provides a summary and discussion.

2. Education and training in entrepreneurship

Human capital attributes such as education, relevant experiences and specific knowledge have long been argued to be critical for entrepreneurial success (Iyigun and Owen, 1998; Gimeno et al., 1997). Recent meta-analyses demonstrate that while the relationship between general education and entrepreneurial entry generally is weak, the relationship between education and entrepreneurial performance such as self-employment income, firm survival, profits or growth, is unambiguously positive (Van der Sluis et al., 2008; Unger et al., 2011; see also Van Praag et al., 2013: 376–378).

However, human capital in an entrepreneurial setting means more than formal education. In their meta-analysis, Unger et al. (2011) find that indicators of human capital that are more closely associated to entrepreneurial tasks were more closely related to entrepreneurial success, underscoring the importance of specific human capital. Pointing to Lazear's (2004) suggestion that entrepreneurs are "Jacks of all trades", who need a broad mixture of skills to be successful, Van der Sluis et al. (2008) argue that besides level of education, the choice of school courses or training programs could be an important determinant of entrepreneurship. They add that little is known in the literature about the effect of such specific training on entrepreneurial outcomes.

This said, the more common type of theoretical business educations seem ill suited to represent the economic reality of entrepreneurs (Garavan and O'Cinneide, 1994), a reality characterized by scarce resources, intuitive decision making, and the need to interpret other people's goals and aspirations (Casson, 1982; Sarasvathy, 2001). Many studies show that successful entrepreneurship is more strongly related to previous entrepreneurial experience rather than formal education (Dencker et al., 2009; Folta et al., 2006; Martin et al., 2013; Toft-Kehler et al., 2014). Furthermore, many studies suggest that a broad mixture of skills is more important for entrepreneurial success than a specific education or degree (Lazear, 2004; Leibenstein, 1987; Wagner and Joachim, 2003). Taken together, these points toward the theoretical relevance of practical curriculum that gives familiarity with the daily workings of a firm could increase entrepreneurial success.

Following the rapid spread of EET programs, a literature seeking to evaluate these has emerged. Martin et al. (2013) undertake the first meta-analytic review of the effects of EETs, finding "that there is indeed support for the value" of such programs, as a significant positive relationship can be observed between entrepreneurship-related human capital measures and various entrepreneurship outcomes. Several features stand out in their meta-analysis.

First, the majority of studies focused on the effect of EET on the formation of entrepreneurship-related human capital assets, such as knowledge and skills, positive perceptions of entrepreneurship, and intentions to start a firm. One reason may be that these indicators can be readily measured directly after the program.[2] Among the 42 studies analyzed, 13 investigated

[2] Some of the studies focusing on the effects of EET on entrepreneurial human capital while using a rigorous identification design are summarized below. Peterman and Kennedy (2003) used a pretest–post-test design, finding that EET positively affected entrepreneurial intentions of students in Australian high

actual entrepreneurship outcomes. The outcomes were divided into three components: nascent behavior (1 study), start-up (6 studies), and entrepreneurship performance (9 studies). In the performance component, financial success was examined in 8 studies, while one study examined survival (Chrisman and McMullan, 2004) and one examined personal income from owned firm (Charney and Liebcap, 2000). The positive relationship between EET and entrepreneurial outcomes documented by Martin et al. (2013) is apparent both on the individual level (self-employment) and on the firm level in terms of profits and growth.

The meta-analysis also notes that most prior studies have been based on relatively small samples. In fact, only three studies (Gine and Mansuri, 2014 (previously 2009); Karlan and Valdivia, 2011; Michaelides and Benus, 2010) studying the relationship between EET and entrepreneurial outcomes includes more than 1000 observations. The two studies covering survival (Chrisman and McMullan, 2004) and income (Charney and Liebcap, 2000) cover 141 and 511 subjects, respectively.

Martin et al. (2013) also noted that many prior studies of EET lack methodological rigor. Of 79 studies considered prior to their meta-analysis, 21 were excluded because they did not incorporate either pre-post or treatment-control comparisons, 13 because they did not report data required for creating an r value, and an additional three because they used duplicate samples. Of the 42 studies that met the minimum inclusion criteria, 11 are described as rigorous in that they had at least (i) pre/post and treatment/control group comparisons or (ii) a random assignment of groups. Only six studies had both (i) and (ii). Four of these covered entrepreneurship outcomes (Berge et al., 2009; Gine and Mansuri, 2014; Karlan and Valdivia, 2011; Michaelides and Benus, 2010[3]). Neither of the studies covering survival (Chrisman and McMullan, 2004) and income (Charney and Liebcap, 2000) were deemed rigorous.

Like all studies in the field, ours has its strengths and weaknesses. First, it is based on observational and not experimental data. Experimental data can generate unbiased estimators for causal effects because the randomized design ensures that treated and control groups are equivalently distributed on observed and unobserved characteristics (Li, 2013: 190). Our study is based on a real-life setting where the treatment is a program into which individuals self-select (unlike e.g. the course studied by von Graevenitz et al., 2010, which was compulsory). We try to approximate a random sample by using propensity score matching, a (quasi-experimental) technique that, if used appropriately, can enable causal inference. Nonetheless, our method is sensitive to a number of assumptions, which are discussed in Section 3.3.

In addition, our observational data spans a long time period. This enables us to examine the effect of EET on entrepreneurial performance over the long haul, something which is rarely possible in experimental settings. The ambitious GATE-experiment, for example, at the most covers outcomes five years after treatment (Michaelides and Benus, 2010; Fairlie et al., 2014), whereas Karlan and Valdivia (2011) followed participants for only two years. By contrast, we follow subjects for up to 16 years. The long time period of investigation is important, since most entrepreneurs, particularly successful ones, start their ventures after they have been active in an industry for some time (Klepper, 2001), and the probability to start a firm is highest for individuals in their 30s and early 40s of age (Delmar and Davidsson, 2000).

Furthermore, we contribute to the study of the effect of EET on entrepreneurial outcomes (relatively understudied compared to entrepreneurial human capital assets). Within this field, we focus not only on start-ups, but also on two performance outcomes that as mentioned have scarcely been studied before: survival and entrepreneurial income. Entrepreneurial income is arguably a fundamental performance criterion for individual entrepreneurs (Gimeno et al., 1997). In addition, we focus on a program directed at high-school students. Little attention has been paid to EETs that target students in primary or secondary schools (Oosterbeek et al., 2010), which is problematic since it has been stressed that it might be more efficient to invest in developing children's entrepreneurial skills instead of adolescents' skills (Rosendahl Huber et al., 2012).

schools. DeTienne and Chandler (2004) used a Solomon Four-Group Designed experiment with students from a strategic management course and showed that specific skills training can improve individuals' opportunity identification, notably their ability to generate more ideas and improve the innovativeness of those ideas. Friedrich et al. (2006) studied the effects of a South African program addressing skills and techniques relating to personal initiative, planning, goal setting and innovation. In a pre-test-post-test study of 84 entrepreneurs they found that treated individuals made significantly better progress than the control group. Mentoor and Friedrich (2007) used a pre-test post-test design to test the effect of a first-year university management course in South Africa on 463 students' entrepreneurial orientation, but found small effects of the course on entrepreneurial orientations. Souitaris et al. (2007) used a pretest–post-test quasi-experimental design to test the effect of an EET directed at science and engineering students, finding that participation raised entrepreneurial attitudes and intentions. Oosterbeek et al. (2010) used a difference-in-difference framework to evaluate the effects of a JACP targeted at Dutch junior college students, whose locational choice was used as an exogenous instrument. They did not find any significant effect on students' self-assessed entrepreneurial skills but did find a negative effect on entrepreneurial intentions. Rosendahl Huber et al. (2012) used a randomized field experiment to gauge the effects of the program "Bizworld," which focuses on developing of competencies relevant for future entrepreneurship for children ages 11–12. They found no effect on cognitive competencies such as calculus or reading ability, but a positive effect on non-cognitive competencies, such as persistence, creativity, and forward-looking behavior.

[3] Karlan and Valdivia (2011) used a randomized control trial to measure the marginal impact of adding business training to a Peruvian group lending program for female micro-entrepreneurs. They found little or no evidence of changes in key outcomes such as firm revenue, profits or employment in the primary econometric specification that compared outcome variables. Michaelides and Benus (2010) as well as Fairlie et al. (2014) examined the efficacy of the GATE project, which offered free self-employment training to individuals interested in self-employment. These individuals were similar to the general population of U.S. self-employed in demographic characteristics such as age and education. Both studies found a strong short-run effect on firm ownership for those unemployed when entering the program, but no long-term effects or effects for participants who were employed, self-employed, or not in the labor force at the time of application. Gine and Mansuri (2014) studied the effects of an eight-day business training program in rural Pakistan, in a random field experiment covering 1400 participants. The average age of participants was 38 years and they had an average education of 3.9 years. They find that training increased business knowledge and practices and reduced business failure, but that these benefits were concentrated among male participants.

Table 1
Number of people by cohort, gender, and JACP participation, 1994–1996.

Cohort	Men		Women		Total		Total
	Non-alumni	Alumni	Non-alumni	Alumni	Non-alumni	Alumni	
1994	35,573	1025	31,931	1055	67,504	2080	69,584
1995	29,156	1283	31,429	1330	60,585	2613	63,198
1996	37,560	2676	36,374	2362	73,934	5038	78,972
Total	102,289	4984	99,734	4747	202,023	9731	211,754

Unfortunately, our focus on EET during high school in combination with a focus on outcomes makes it difficult to implement a pre-test/post-test design, simply because Swedish high school students have virtually no entrepreneurial experience. This precludes the usage of e.g. DiD estimation to pinpoint the exact effects of JACP participation, since individuals may differ in their innate entrepreneurial ability (Benz and Frey, 2008; Folta et al., 2006; Van Praag and Cramer, 2001; Patel and Fiet, 2010). Our study has an additional advantage in its sample size. Many previous studies suffer from small samples, and the largest sample involved in a study of entrepreneurial outcomes comprised 2807 (treated and control) individuals (Michaelides and Benus, 2010; Fairlie et al., 2014). Our sample, by contrast, covers thousands of individuals, with a treatment group of close to 10,000 participating in JACP during high school. We will continue with a more detailed description of the data and method we employ.

3. Data and method

3.1. JACP

The stated goal of JACP is to provide high school students with the chance to train and develop entrepreneurial skills. The purpose is to make students experience the whole lifecycle of a company through a “learning-by-doing” approach. Under the guidance of mentors and teachers, students set up and organize a so called JACP company and produce and sell some type of physical product or service, after which balance and results sheets are calculated, and the firm is closed down. The concept of JACP entrepreneurship is today firmly established in more than 550 high schools in Sweden (2010/2011 semester) and every school year, around 20,000 high school students run JACP companies. Since the start of JACP in 1980, around 200,000 people have initiated and managed JACP companies in Sweden. Between 1994 and 1996, the program was established in 278 Swedish high schools.

3.2. Data and descriptive statistics

JACP’s anonymous database consists of all 194,000 persons who have ever run a JACP enterprise. We connect this database to two other databases, with the information necessary to undertake our analysis. First, Statistics Sweden’s (SCB) longitudinal integration database for health insurance and labor market studies (LISA). LISA contains information on all individuals between 16 and 64 years of age residing in Sweden, including occupation, housing, and family characteristics. It also has detailed information on the individual’s education. Secondly, SCB’s company register, which contains all registered firms in Sweden, including incorporated firms, partnerships, and sole proprietorships. The company register is complemented by information from the tax authorities on economic activities, such as firm turnover and salaries/dividends drawn from a firm. The databases are longitudinal in nature. We can therefore follow individuals over time and investigate changes in their occupation and income. For ethical reasons, our data material is anonymous. We can follow individual persons and firms through the data, but we cannot identify them.

SCB’s databases sometimes lack information on individuals that, for example, move abroad, and up until 1986, the database contained only rudimentary information. Therefore, the number of JACP alumni who could be matched to the public databases consists of 166,606 individuals. Our focus lies on the 9731 JACP alumni who were part of three cohorts that finished high school in 1994, 1995, and 1996 when they were between 17 and 19 years of age (the common age of graduation in Sweden). The reason is that we want to consider entrepreneurial outcomes between 11 and 16 years later i.e., between 2005 and 2010. There are several reasons for the choice of a long time span. First, a more short-term investigation would be hampered by the fact that most people aged 18–25 are not at the labor market’s disposal; they generally pursue military service or higher education or travel abroad (Erikson et al., 2007). Second, the long data series permits us to follow individuals all the way into their early middle age, which is important as the probability of someone starting a firm in Sweden tends to peak when the individual is their 30s and early 40s (Delmar and Davidsson, 2000). Third, the long “gap” between when treatment (i.e., JACP participation) occurred and when we measure the outcome variables lessens the risk of endogeneity in terms of simultaneity of individual’s decision to participate in the JACP and their decision to later start a new firm. This could be the case if someone started a new firm directly after participating in the JACP.

The three high-school cohorts from 1994 to 1996 consist of 211,754 individuals in total. Of these, 9731 participated in JACP. Table 1 shows how many are part of each cohort, and JACP participation compartmentalized by gender. We see that

Table 2
Descriptive statistics for cohorts 1994–1996, by JACP participation.

Variables	Alumni	Non-alumni	p-Value*
Variables measured at *t*			
Ln(parents' income)	7.65	7.56	0,00
Woman *(D)*	48.78	49.37	0.13
Second-generation immigrant *(D)*	3.30	3.95	0.00
First-generation immigrant *(D)*	4.34	4.88	0.01
Parent business owner *(D)*	44.13	39.78	0.00
Father university degree *(D)*	13.58	15.91	0.00
Mother university degree *(D)*	11.70	14.59	0.00
Grade (inflation adjusted)	19.30	20.49	0.00
Business administration *(D)*	55.66	11.99	0.00
Cohort 1995 *(D)*	26.85	29.99	0.00
Cohort 1996 *(D)*	51.77	36.60	0.00
Born 1975 *(D)*	22.00	28.62	0.00
Born 1976 *(D)*	33.30	38.95	0.00
Wealthy parish *(D)*	77.45	75.39	0.00
Variables measured at *t + 10*			
Higher education *(D)*	34.89	40.46	0.00
Unemployed *(D)*	14.82	15.8	0.00
Married or cohabitant *(D)*	35.65	36.19	0.14
Variables measured at *t + 11*			
Started new firm *(D)*	1.48	1.19	0.01
Individual observations	9731	202,023	

* Indicates *p*-value from *t*-test. *N* = 211,754.

JACP participation is fairly evenly distributed across gender. In all, 4.6% of men and 4.5% of women in the cohorts were JACP alumni.

The original cohorts are corrected for people who moved abroad or for some other reason disappeared from the register of total population (RTB) during subsequent years. For example, individuals in the 1994 cohort must be found in RTB in 2004 and 2005 in order to be included in the final population. Table 2 shows descriptive statistics for the three cohorts of alumni and non-alumni that remain in the dataset 11 years after graduation (i.e., from 2005 to 2007). The table distinguishes between variables measured a time *t*, i.e. at the time of JACP-participation, and variables measured at $t+10$ and $t+11$.

As almost all the variables are dummy variables that can take either the value 0 or 1, we scale them by 100 in the table below to show the percentage of the groups with the characteristic in question. For example, *Started a new firm (D)* is a dummy variable that takes the value 1 if an individual started a firm 11 years after graduation and 0 if not. Here, we follow SCB's official definition of self-employment as a *full-time labor market activity* in our classification of entrepreneurial entry. This definition is consistent with official registers and is thus replicable by other scholars. This arguably makes our evaluation more conservative than if part-time entrepreneurs had been included (Folta et al., 2010; Elston and Audretsch, 2010). It should be noted however, that even more narrow definitions have been suggested in the previous literature (see e.g. Levine and Rubinstein, 2013; Henrekson and Sanadaji, 2014). As Table 2 reveals, 1.48% of JACP alumni did start a firm at $t+11$, compared to 1.19% of non-alumni. These numbers are consistent with other studies of entrepreneurial entry during the same time period (Folta et al., 2010; Persson, 2008).

The variable *Woman (D)* equals 1 if the individual is a woman. *Ln(parents' income)* measures the combined income of both parents in the household, or the sole breadwinner in case of single-parental households. *First-generation immigrant (D)* is a dummy to denote if the individual is an immigrant, while *Second-generation immigrant (D)* denotes Swedish-born children of immigrants. *Parent business owner (D)* takes the value 1 if at least one of the individual's parents is or has been a firm owner. It is important to include this variable since parental entrepreneurship is one of the strongest determinants of entrepreneurship (e.g. Andersson and Hammarstedt, 2010, 2011; Lindquist et al., 2012). *Father university degree (D)* is a dummy variable taking the value '1' for individuals whose father has a 3-year or longer university degree, and '0' otherwise. *Mother university degree (D)* is a dummy variable taking the value '1' for individuals whose mother has a 3-year or longer university degree, and '0' otherwise. *Grade (inflation adjusted)* is the only variable that is not a dummy variable and is a standardized way to measure high-school grades ranging from 0 to 40. *Business administration (D)* takes the value 1 if the individual attended a business administration program in high-school, the most common educational background for JACP students in the 1990s. *Wealthy parish (D)* is a Dummy variable taking the value '1' for individuals residing in a parish where household annual income is above the national average, and '0' otherwise. *Born 1975 (D)* and *Born 1976 (D)* are dummy variables indicating year of birth among the high school students in the sample. These are included since students who participate in JACP belong to both 2-year and 3-year high school programs and thus may graduate at different ages. The third and omitted baseline category is *Born 1977 (D)*.

Three variables are measured 10 years after the program: *Higher education (D)* takes the value 1 if the individual has a university degree that is 3 years or longer. *Unemployed (D)* equals 1 if the individual has experienced a recent unemployment spell, and *Married or cohabitant (D)* equals 1 if the individual is married or lives with his or her partner in a registered relationship. Finally, as mentioned, the variable *Started a new firm (D)* is measured 11 years after graduation. In all analyses we also control for cohort effects with three dummy variables (educational cohorts 1994, 1995, and 1996, with cohort 1994 as the baseline).[4] All variables are updated annually and lagged one year in all analyses to avoid simultaneity bias.

Table 2 shows that to a greater extent, JACP alumni followed a business administration program in their high-school and have parents who are or were firm owners. The second finding is in line with the existing literature on the intergenerational transmission of an entrepreneurial identity (Hout and Rosen, 2000; Johnson, 2002). We also observe that individuals who graduated from high school before age 21 and native Swedes are more likely to participate in JACP. The only variables without a statistically significant difference at the 5% level between the two groups were Woman (D) and Married or cohabitant (D).

3.3. Matching approach

A central problem of causal inference is how to reconstruct unobserved outcomes, i.e. counterfactuals. Conceptually, either the treatment or the non-treatment is not observed, as it is impossible for an individual to simultaneously receive and not receive the treatment, in our case, JACP during high school. Reconstructing the counterfactuals is crucial to estimate unbiased causal effects. During high-school, someone is either 'treated' with JACP participation or not. Among the treated ($D=1$), we cannot observe the untreated outcome, Y_0, and among those not treated ($D=0$), we cannot observe the treated outcome, Y_1. This is problematic since we want to estimate the 'treatment effect on the treated' (TT):

$$\mathrm{TT} = E(Y_1 \left| D = 1 \right.) - E(Y_0|D = 1)E([Y_1 - Y_0|D = 1]).$$

We can only construct the first term on the right-hand side as the second term is not directly observable. Simply comparing outcomes for the treated and untreated yields:

$$E(Y_1|D = 1) - (Y_0|D = 0) = E(Y_1 - Y_0|D = 1) + \{E([Y_0|D = 1] - E([Y_0|]D = 0))\}.$$

This is the desired TT plus an error term due to self-selection. In an experimental setting, self-selection is circumvented by randomly assigning participants to the treated and control groups, meaning that the TT can be estimated by comparing the mean difference between the two groups. Since this paper relies on longitudinal observational data where individuals have already made the decision to participate in JACP or not, we do not have this option.

We therefore use Propensity Score Matching (PSM) to draw inferences based on reconstruction of counterfactuals using the observational data. PSM does this by reducing two sources of bias in the observational data: bias due to a lack of distribution overlap between treated and control groups and bias due to different density weightings (Heckman et al., 1998). PSM was developed in a series of articles by Rosenbaum and Rubin (1983, 1984, 1985). A 'propensity score' is defined as *the probability of study participants receiving a treatment based on observed characteristics X*. The many potentially confounding covariates in an observational study are hence replaced with a function of these covariates. Adjusting covariates between the treated group and the control group enables the reconstruction of counterfactuals. TT can then be estimated using the propensity score ($P(X)$):

$$E\{E(Y_1|P(X), D = 1) - E(Y_0|P(X), D = 1)|D = 1\}.$$

This allows us to remove difference in the covariates distributions between the treated and the control groups, and the calculated TT should be reasonably close to the TT calculated from experiments (Rubin, 2007). The TT will however only be reliable if the treatment assignment is *strongly ignorable*, meaning that given the propensity scores, the distribution of the covariates between the treated and control groups are the same (Rosenbaum and Rubin, 1983). For a treatment assignment to be strongly ignorable, two conditions must be met.

First, the Conditional Independence Assumption (CIA) requires that variables in need of adjustment be observable. As Criscuolo et al. (2012) point out, CIA is unlikely to hold unless one has access to an unusually rich set of variables. Some studies also find a substantial bias when careful comparisons are made to results of clinical studies (Smith and Todd, 2004; Luellen et al., 2005; Peikes et al., 2008). Hence, selected variables need to be correctly measured and modeled, and be plausible candidates to reduce selection bias (Steiner et al., 2010). Ultimately, the inclusion of variables can only be guided by the causal knowledge of the investigators (Pearl, 2009: 408). In our case, we thus need access to a range of background variables and to include those that are theoretically relevant for selection into entrepreneurship. The LISA database is a high-quality database that provides a host of such relevant variables, presented in Table 2. Our results may nonetheless be affected by unobservable between-subject heterogeneity such as intelligence or some psychological characteristic (Dehejia

[4] Many of our variables are measured in dummy format, which increases the quality of the PSM model (Angrist and Pischke, 2008) and eases interpretation of effects. Inclusion of several dummies in multivariate models may however cause measurement errors or increase risk of multicollinearity. Correlations in the overall sample and the matched sub-samples are generally low to moderate, with the exception of the dummy variables for year of birth and graduation cohort, where correlations range from 0.40 to 0.65. Computed Variance Inflation Factors (VIF) did not indicate risk of multicollinearity, nor did the exclusion of these variables with higher correlation in robustness models (available upon request) affect the results.

and Wahba, 1999: 1061; Patel and Fiet, 2010), which observable characteristics do not fully proxy for.[5] As long as this is a random error—that is, as long as it appears with roughly equal probability in the treated and untreated groups—this should not bias the results. Nonetheless, our results should be carefully interpreted in light of this potential source of bias.

Second, the Common Support Condition (CSA) requires that given X, individuals with the same X-values have a positive and equal opportunity of being assigned to the treated or control group. (Becker and Ichino, 2002). In its strictest sense, this requires some treated and some untreated individuals for all values of $P(X)$. We account for this condition by requiring that all variable means do not deviate more than 10% between the treated and controls.[6]

After estimating the propensity score, we construct the control group using one-to-one nearest-neighbor matching. This matching technique computes the TT by selecting the comparison unit whose propensity score is the nearest to the treated unit in question (Heckman et al., 1997). Since an observation often has several nearest neighbors, a chance algorithm decides which among these are drawn into the control group. Although the estimation of the propensity score is parametric, the matching technique is nonparametric and will hence not suffer from problems prevalent in most parametric models, such as the assumption of distribution (Morgan and Harding, 2006). As robustness tests, we use three other matching techniques—radius matching, kernel matching, and local linear regression matching (Li, 2013: 201–206). The results from these are reported in footnotes 6, 8, and 10.

Besides the aforementioned caveats regarding the assumptions, PSM has other strengths and limitations. First, it simplifies the matching procedure in that we can match our data with a large set of covariates without sacrificing many observations or worrying about computational complexity. Second, it allows us to eliminate bias due to lack of distribution overlap and bias due to different density weightings (Heckman et al., 1998). Third, the nonparametric nature of the matching technique makes it less susceptible to violations of model assumptions (Li, 2013). Like other nonparametric approaches, however, PSM has no test statistics (Imbens, 2004). Further, there currently are no established procedures to investigate whether a treatment assignment is strongly ignorable, and PSM cannot eliminate bias due to unobservable differences across groups (Heckman et al., 1998). Methods like difference-in-difference (DiD) analysis deals with this by eliminating common time and age trends by subtracting the before-after change in nonparticipant outcomes from the before-after change in participant outcomes (Heckman et al., 1997). However, our outcome variable—entrepreneurship in the form of starting a firm as a full-time labor market activity—is virtually nonexistent among high school students due to their youth, precluding the usage of DiD since there is no 'before stage' to exploit. These strengths and limitations should be kept in mind when interpreting the outcomes of the study.

4. Results

The analysis considers three outcomes. First, we investigate the effect of JACP participation on individuals' propensity to start a new firm later in life. Second, we assess the effect of JACP participation on entrepreneurial income provided that the individual started a new firm. Finally, we consider the effect of JACP participation on firm survival.

4.1. The probability of starting a new firm

PSM is a multi-step procedure. In the first step, we regress the treatment variable (JACP participation) on a set of theoretically relevant characteristics to estimate the propensity score. We use all available predictor variables described in Table 2, except for the three dummy variables Higher education (D), Unemployed (D), and Married or cohabitant (D) that are not available for adolescents aged 16–18 in LISA and consequently not logically possible to include in a model predicting JACP participation during adolescence.

The PSM matching process is usually done with some type of discrete choice regression, such as a logit or a probit model. We employ the logit model since a growing empirical literature suggests that it works well in practice (Angrist and Pischke, 2008: 61).

The results from estimating the propensity score are presented in Table 3. As can be seen, a few variables exhibit a strong influence on the probability of participating in JACP, notably Business administration (D). Parent business owner (D) also has a positive influence, which is expected since growing up in an entrepreneurial household is commonly seen as a salient theoretical indicator for entrepreneurial propensity (Benz and Frey, 2008; Folta et al., 2006; Kim et al., 2006). Meanwhile, being a woman or an immigrant lowers the probability of participating in JACP, while individuals from one of the later cohorts or those from a wealthy parish are significantly more likely to participate in JACP. Table A1 in the Appendix shows the means for the matched treated and controls. It also shows that bias is consistently low and never significant, indicating a fair match.

Based on the estimated propensity score, the effect of JACP participation on the probability of starting a firm can be assessed. Table 4 compares the probability of JACP alumni and the (unmatched and matched) control group starting a new

[5] While we cannot observe intelligence as measured by aptitude tests, we do observe high school grades which are known to be strongly correlated with intelligence at or above 0.5.

[6] This is the recommended test in Stata's psmatch2 program with the command "pstest" module, which tests all matching variables against a matched average.

Table 3
Estimating $P(X)$. Logit model of the probability of participating in JACP, high school cohorts 1994–1996.

	Coef.	z-Value
Ln(parents' income)	0.01*	(1.90)
Woman *(D)*	−0.13***	(−5.77)
Second-generation immigrant *(D)*	−0.38***	(−6.24)
First-generation immigrant *(D)*	−0.26***	(−4.64)
Parent business owner *(D)*	0.16***	(7.23)
Father university degree *(D)*	−0.02	(−0.54)
Mother university degree *(D)*	−0.05	(−1.49)
Grade (inflation adjusted)	0.00	(1.22)
Business administration *(D)*	2.57***	(108.37)
Cohort 1995 *(D)*	0.51***	(12.83)
Cohort 1996 *(D)*	1.43***	(27.73)
Born 1975 *(D)*	0.04	(0.69)
Born 1976 *(D)*	−0.07	(−1.62)
Wealthy parish *(D)*	0.12***	(4.54)
Constant	−4.78***	(−60.16)
N		211,754
Prob. > χ^2		0.000
LR $\chi^2(14)$		12977.39
Pseudo R^2		0.164

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 4
Average treatment effect on the treated. Probability of starting a new firm during 2005–2007. Cohorts 1994–1996. Unmatched, $N = 211{,}754$, Matched $N = 19{,}462$.

Variable	Sample	Treated (%)	Controls (%)	Difference (%)	S.E. (%)	Ratio (T/C)	T-stat
New firm	Unmatched	1.48	1.19	0.29	0.11	1.24	2.55
	ATT	1.48	1.13	0.35	0.16	1.30	2.13

firm between 2005 and 2007 in terms of percentage. The average effects between the two groups mean that JACP alumni have a 30% (1.48/1.13 = 1.30) higher probability of starting a firm than comparable non-alumni. Compared to the overall population, JACP alumni have a 24% (1.48/1.19 = 1.24) higher probability of starting a firm. These findings are somewhat surprising since there were reasons to assume that individuals with greater entrepreneurial ability would self-select into JACP. In that case, the results without matching should have an upward bias. The fact that there is a downward bias suggests that selection into JACP is not driven by individuals' entrepreneurial ability but by other factors. In both cases, the differences are significant. In summary, our analysis suggests that JACP participation has a positive effect on the long-term probability of starting a firm, which is as high as 30%.[7]

4.2. *Entrepreneurial income*

Like previous individual-level studies of returns to entrepreneurship, we use yearly earnings from self-employment to measure entrepreneurial income (Inci, 2013; Parker, 2005). Entrepreneurial income can take the form of salary for sole-proprietorship owners or salary and/or owner dividends for those who run incorporated firms. We combine both sources of earnings for entrepreneurs with incorporated firms into a composite measure (Gimeno et al., 1997; Hamilton, 2000). This characteristic is an advantage of our data since many contemporary studies on self-employment do not include those who run incorporated firms (Folta et al., 2010) and is not a risk for systematic bias since owner-managers of incorporated firms have to use a standardized ratio (in Sweden called 'the 3:12 rule') when allocating the pre-tax profits of their firms as dividends or salary (Alstadsæter and Jacob, 2012; Henrekson, 2005). For entrepreneurs who run sole proprietorships or partnerships, their annual earnings amount to the pre-tax profits of their firms—similar to most other nations.

While our analysis of the probability of starting a firm was limited to the entry of new firms, we can in this section consider the *stock* of existing firms run by JACP alumni and a matched control group. This makes for a substantially larger sample and more stable estimates than if we only considered flows. A potential problem with our data is that the FDB database does not say when during 2005 a firm was started because of a change in the way the statistic was collected. Estimates including

[7] Findings were corroborated when we restricted the sample to only those schools where JACP was offered between 1994 and 1996. JACP participation then has a significant 27% effect on the long-term probability of starting a firm (T-stat = 1.95). Findings were also corroborated when alternative matching algorithms were employed, as results from radius matching, kernel matching and local linear regression matching all point to a positive and statistically significant effect from JACP participation. This said, while the t-statistics are slightly larger, the size of the effect is slightly lower and closer to unmatched comparison, suggesting that the downward bias in our main results may be of limited importance.

Table 5
Entrepreneurial income (Swedish Krona) 2006–2007 by gender and JACP participation.

	Obs.	Mean income	Median income	Std. dev.	Min.	Max.
All	17,774	192,632	182,099	191,049	−10,600,000	2,126,000
Total non-JACP	16,793	192,342	181,197	185,608	−10,600,000	1,991,200
Total JACP	981	197,587	200	267,633	−4,557,495	2,126,000
Men non-JACP	12,073	219,881	215	163,266	−3,439,972	1,991,200
Men JACP	721	217,922	234	287,869	−4,557,495	2,126,000
Women non-JACP	472	121,902	100,469	217,934	−10,600,000	1,349,626
Women JACP	260	141,197	120,232	190,554	−1,017,745	1,908,750

Table 6
Estimating *P*(*X*). Logit model of the probability of participating in JACP, subsequent firm owners, 1994–1996.

	Coef.	*z*-Value
Ln(parents' income)	−0.01	−0.38
Woman *(D)*	−0.25***	−3.00
Second-generation immigrant *(D)*	−0.26	−1.43
First-generation immigrant *(D)*	−0.28	−1.58
Parent business owner *(D)*	0.02	0.30
Father university degree *(D)*	0.03	0.23
Mother university degree *(D)*	−0.16	−1.41
Grade (inflation adjusted)	0.01	1.87
Business administration *(D)*	2.42***	29.88
Cohort 1995 *(D)*	0.86***	6.77
Cohort 1996 *(D)*	1.81***	11.43
Born 1975 *(D)*	−0.15	−1.20
Born 1976 *(D)*	0.25	1.60
Wealthy parish *(D)*	−0.01	−0.07
Constant	−4.55***	−18.74
Individual observations		16,664
Prob. > χ^2		0.0000
LR $\chi^2(14)$		1047.59
Pseudo R^2		0.1482

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

individuals who started firms in 2005 are thus at risk of being biased. We therefore exclude the year 2005 from the analysis and study only individuals from the three cohorts who were entrepreneurs in *both* or either of the years 2006 and 2007—in total 981 JACP alumni and 16,793 non-alumni.

We summarize the income from the firms for which individuals prepared tax returns, which means they were owner-managers in incorporated firms, partnerships, or sole proprietorships. Table 5 displays entrepreneurial income by gender and JACP participation. The difference in the mean annual wage between JACP alumni and the control group is about 10,000 Swedish Krona (1 Krona roughly equals USD$0.15). The difference is smaller among men than among women, possibly because women often work shorter hours (Benz and Frey, 2008; Folta et al., 2010).

As can be seen, minimum values are strongly negative—that is, some firm owners sometimes report significant losses from entrepreneurship. In Sweden, losses can be deducted in one to five years against wage income. We therefore treat zero and negative income as censored and estimate the PSM model on logarithmic earning based on an OLS estimator in the second stage, with the first stage being a logit model on JACP participation. Censoring all individuals with negative and zero income from entrepreneurship reduces the sample from 981 JACP alumni and 16,793 non-alumni shown in Table 5 to 911 JACP alumni and 15,753 non-alumni that are included in the new estimation of the propensity score.

Table 6 shows the result from the logit model. The results are very similar to the previous estimation, although Parental firm owner (*D*) is no longer significant.[8] Table A2 in Appendix compares the means of the matched treated and control groups, showing that the bias is again generally small and never significant. Based on the matching, the next step is to examine the effect of JACP participation on entrepreneurial income among those that become entrepreneurs.

Table 7 compares ln(income) of JACP alumni and the (unmatched and matched) non-alumni who ran firms 11 or 12 years after graduation based on an OLS estimator with all control variables equal to those of Table 2.

Based on the differences in ln(income) in Table 7 we see that JACP alumni on average have a 10.2% ($100 \times (\exp(0.097) - 1) = 10.186$) higher entrepreneurial income if they are in entrepreneurship 11–12 years after

[8] For consistency with the first matching model in Table 3, we exclude the three dummy variables Higher education (*D*), Unemployed (*D*), and Married or cohabitant (*D*), from the matching model due to these being unavailable for individual below 18 years of age. In unreported models (available upon request) we included these three predictors in the model to control for the effects of individuals taking a higher educational degree, getting married, or being unemployed before engaging in entrepreneurship in 2006 or 2007. This did not alter the results.

Table 7
Average treatment effect on the treated (ATT) on entrepreneurial ln(income) 2006–2007. Unmatched, N = 16,664, Matched N = 1822.

Sample	Treated ln(income)	Controls ln(income)	Difference ln(income)	S.E. ln(income)	T-stat
Unmatched	11.978	11.881	0.097	0.039	2.51
ATT	11.978	11.880	0.097	0.05	1.95

Table 8
Percentage survival of firms started 2005–2007 by JACP alumni and unmatched non-alumni (N = 139 and N = 2355 respectively).

	2005	2006	2007	2008	2009	2010
JACP alumni	100%	69.1%	56.2%	46.4%	39.7%	34.0%
Non-alumni	100%	66.7%	51.6%	42.2%	36.1%	31.6%

Table 9
Estimating P(X). Logit model of the probability of participating in JACP among firm entrants from the 1994–1996 cohorts.

	Coef.	z-Value
Ln(parents' income)	0.016	0.33
Woman *(D)*	0.023	0.12
Second-generation immigrant *(D)*	−0.163	−0.34
First-generation immigrant *(D)*	−0.159	−0.39
Parent business owner *(D)*	0.094	0.52
Father university degree *(D)*	−0.372	−1.28
Mother university degree *(D)*	−0.043	−0.16
Grade (inflation adjusted)	−0.006	−0.80
Business administration *(D)*	1.338***	7.12
Cohort 1995 *(D)*	0.334	1.08
Cohort 1996 *(D)*	0.518	1.25
Born 1976 *(D)*	−0.491	−1.41
Born 1975 *(D)*	−0.449	−1.08
Wealthy parish *(D)*	−0.002	−0.01
Constant	−3.233***	−5.33
Firm-year observations		2494
Prob. > χ^2		66.28
LR $\chi^2(14)$		0.000
Pseudo R^2		0.618

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

graduation, than a comparable group of non-alumni. In other words, our analysis suggests that JACP participation has a positive effect on subsequent long-term entrepreneurial income, which is as high as 10%.[9]

4.3. *Firm survival*

As a last step in the analysis, we investigate if JACP participation affects firm survival. Table 8 compares the survival of firms started by JACP alumni to that of firms started by non-alumni in the 2005–2007 period. Since survival can only be estimated based on net entry and exit and not cross-sectionally, our analysis of firm survival is based solely on those in the sample (and the control group) that became self-employed by starting a firm between 2005 and 2007. We follow these firms until they disband or until 2011, after which the data is right censored. Right censoring is generally not considered a problem if at least 10% of cases exits during the period of observation (Lancaster, 1979). This condition satisfied in our data since 143 of 278 cases exit during the period.

Table 8 shows that the survival rate for JACP alumni is slightly higher than for non-alumni. For both groups, the survival rate follows a familiar pattern in that it falls fast in the first year and thereafter levels off (Van Praag, 2003).

Since this analysis of firm survival is based solely on those who became self-employed by starting a firm between 2005 and 2007, the PSM is again redone to construct a comparable control group for the 139 JACP alumni entrepreneurs. Table 9 shows the result from a logit model matching these to a comparable sample of individuals in the control group who started companies during the same period. This time, only the variable Business administration (D) has a significant positive effect on JACP participation.

[9] The effect was very similar when we used income instead of ln(income) as dependent variable. Findings were further corroborated when we restricted the sample to only those schools where JACP was offered between 1994 and 1996. JACP participation then increases long-term entrepreneurial income with 13.3% (T-stat = 2.40). In corroborating the results of JACP participation on entrepreneurial income with alternative matching specifications based on radius matching, local linear regression matching, and kernel matching, the magnitude of differences and the t-statistics are somewhat lower than in Table 7, and in all three cases the effect is smaller than for the unmatched sample.

Table 10
Exponential survival model. Dependent variable: firm survival 2005–2010, for firm JACP alumni and matched control groups owners entering entrepreneurship 2005–2006.

	Haz. ratio.	*z*-Value
JACP *(D)*	1.09	0.50
Ln(parents' income)	0.99	−0.16
Woman *(D)*	1.58**	2.48
Second-generation immigrant *(D)*	1.09	0.18
First-generation immigrant *(D)*	0.57	−1.33
Parent business owner *(D)*	0.80	−1.24
Father university degree *(D)*	1.14	0.50
Mother university degree *(D)*	1.05	0.19
Grade (inflation adjusted)	0.99	−1.09
Business administration *(D)*	0.86	−0.84
Cohort 1995 *(D)*	0.66	−1.49
Cohort 1996 *(D)*	0.59	−1.24
Born 1976 *(D)*	1.00	−0.01
Born 1975 *(D)*	1.12	0.25
Wealthy parish *(D)*	0.80	−1.16
Higher education *(D)*	1.67**	2.42
Unemployed *(D)*	3.08***	4.16
Married or cohabitant *(D)*	1.10	0.52
Constant	0.23**	−2.31
Number of subjects		278
Number of failures		143
Time at risk		1009
Log-likelihood test		36.11*
Prob. > χ^2		0.0068

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table A3 in Appendix shows the mean values and bias for the matched sample of JACP alumni and the control group used to investigate differences in firm survival depending on participation in JACP during high school in 1994–1996. The bias is somewhat higher than in previous matching models, which is probably a result of the small sub-sample (Heckman et al., 1997). The bias for all variables is still within the range of ±10%, with parental income as a borderline case with a bias of exactly 10%.[10]

We use the estimated propensity score to undertake the matching. Table 10 shows the results from an exponential survival model, which is suitable for discrete time analysis of survival time (Yamaguchi, 1991). The results are presented in terms of hazard ratios, with ratios above 1 indicating higher likelihood of firm exit, and ratios below 1 indicating lower likelihood of firm exit. We find that JACP participation during high school, captured by the dummy variable *JACP (D)*, does not have any significant effect on subsequent firm survival. This finding is line with research suggesting that firm survival is not an appropriate proxy for entrepreneurial performance, especially for individuals with significant opportunity costs (Amit et al., 1995; Headd, 2003). Significant variables in the exponential survival model are Woman (*D*), Higher Education (*D*), and Unemployed (*D*) which similar to previous studies increase the likelihood of firm exit (Van Praag, 2003). An interesting finding is that the probability of firm exit is about three times higher for firms owned by those recently unemployed compared to the employed. This effect is similar to Carrasco, 1999 analysis of entrepreneur's exit in Spain, and similar but stronger than studies in the UK (Burke et al., 2008) and the US (Van Praag, 2003).[11] As a robustness test we also estimated hazard models using the clog–log specification, with close to identical results as in the exponential model (available upon request).

5. Discussion and conclusions

This paper has examined the effects of entrepreneurship education during high school on long-term entrepreneurial performance. We studied JACP participants from three cohorts in the mid-1990s and considered their long-term entrepreneurial propensity, following recent calls in the literature to focus on entrepreneurial outcomes rather than entrepreneurial intentions. Specifically, we investigated the effect of JACP participation on (1) the probability of starting a firm, (2) entrepreneurial income, and (3) firm survival. The last two outcomes have scarcely been studied in prior evaluations of EET programs (Martin et al., 2013) but have been suggested as more salient proxies for entrepreneurial ability than entry (Gimeno et al., 1997). Our

[10] As a robustness test we exclude this variable from the matching. This did not affect the overall results for the survival analysis (results are available upon request).

[11] Findings were corroborated when we restricted the sample to only those schools where JACP was offered between 1994 and 1996 in that JACP participation has no statistically significant effect on survival. Findings when alternative matching algorithms were employed, i.e. radius matching, kernel matching and local linear regression, are similar to the results presented in Table 10, in that the effect of JACP is not statistically significant.

focus on entrepreneurial income and survival as outcome variables thus follows recent arguments that the typical start-up is "not innovative, creates few jobs, and generates little wealth" (Shane, 2009: 141), and that policy and program evaluations should target the subset of firms with high earnings and growth potential (Autio and Acs, 2010; Holtz-Eakin, 2000; Shane, 2009; Weitzel et al., 2010).

We followed subjects for an extended period of time. This is important since longitudinal studies are the only way to test the link between entrepreneurial intentions and eventual entrepreneurial outcomes (Krueger, 2003; Souitaris et al., 2007). Since we are dealing with observational data, we used PSM to handle self-selection problems by matching JACP alumni to non-alumni who had the same probability of participating in JACP based on a number of background characteristics. While this approach does not ensure causality as strongly as e.g. randomized experiments, it does allow us to use a comprehensive longitudinal data-set that covers thousands of individuals from the general population, whereas most experimental studies have been limited to small samples of perhaps a few hundred treated and non-treated subjects.

Overall, our results show that JACP participation increases the probability that an individual will engage in entrepreneurship by starting a firm and that his or her income from these firms will be higher even when potential self-selection into the program is controlled for. However, JACP participation does not affect firm survival, a result in line with earlier studies considering the opportunity costs for entrepreneurs running low-income firms (Amit et al., 1995; Wennberg et al., 2010).

JACP is a practical program with the stated objective to provide high school students with the chance to train and develop entrepreneurial skills by experiencing the whole lifecycle of a company through a "learning-by-doing" approach. This type of experience is arguably more wide-ranging in terms of skills than more specific EET programs that focus on e.g. firm plan writing or opportunity evaluation (Fayolle et al., 2006). The favorable effect from JACP on entry and income can hence be seen as support of the view of entrepreneurs as jacks-of-all-trades, who benefit from a wide range of skills and experiences (Lazear, 2004; Toft-Kehler et al., 2014).

JACP is furthermore a program that has been running for many years and is widely available in 122 nations. This fact gives our study reasonable claims of external validity. Nevertheless, our findings regarding the positive long-term outcomes of JACP participation during high school stand in contrast to previous research on JACP in vocational colleges indicating that JACP may in fact lower entrepreneurial intentions (Oosterbeek et al., 2010). Further research is necessary to determine if these differences are attributable to differences in timespan, age of participants, or the outcome variables studied (see also Rosendahl Huber et al., 2012).

Our research design also comes with two important limitations. First, the focus on EET during high school makes it difficult to deal with non-observed heterogeneity since high school students cannot start firms before entering JACP. This precludes the usage of e.g. DiD estimation to pinpoint the exact effects of JACP participation, since individuals may differ in their innate entrepreneurial ability (Benz and Frey, 2008; Folta et al., 2006; Van Praag and Cramer, 2001; Patel and Fiet, 2010). In addition, measuring outcomes long after the intervention may result in some measurement issues (Fayolle, 2005). If the self-selection to JACP depends on some unobserved characteristics which we failed to account for, such characteristics may also affect later labor market choices that, in turn, may affect entrepreneurial entry, income or survival. Since we study a whole population of high school students, we do not believe this induces any serious bias. It is still possible, however, that the delay in effects is correlated with some other exogenous shock that occurs after JACP participation, such as the introduction of governmental programs or subsidies aimed at fostering entrepreneurship. If JACP alumni are more receptive to such programs or subsidies this could induce some bias in our study. We are not aware of any such exogenous shock in the time period studied.

In addition, even if we have accounted for unobserved characteristics, it is still possible that program participation increase individuals' subsequent likelihood of selecting into experiences that increase the likelihood of becoming an entrepreneur and subsequent earnings. One may hence ponder whether it is reasonable to attribute all long-term effects on entrepreneurial outcomes on participating in JACP during high school. Nevertheless, if these subsequent choices would not have occurred without JACP participation, the program at least provided the igniting spark for individuals' likelihood of embarking on an entrepreneurial career.

Future studies may further this line of research by conducting more in-depth assessments of what actual pedagogical innovations and processes underlie the positive outcomes of programs like JACP (Weaver et al., 2007). Investigating what specific types of early-stage EET efforts yield long-term effects on entrepreneurship may also help educators to replicating these educational efforts to other settings. Research could also seek to assess the relative competing models of EET such as JACP compared to other programs.

In short, this study demonstrates the long-term effects of entrepreneurship education and training programs during high school on subsequent entrepreneurial performance. Studying the total population of 211,754 Swedish high school students between 1994 and 1996, among which 9731 participated in the Junior Achievement Company Program (JACP), we find that JACP participation increases the long-term probability of starting a firm, as well as entrepreneurial income for those that run a firm. However, there is no effect on firm survival

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Appendix.

Tables A1–A3.

Table A1
Mean values, matched treated and controls, for the probability of starting a new firm.

Variable	Treated	Control	Bias (%)	*t*	*p* > *t*
Ln(parents' income)	7.65	7.62	1.3	0.95	0.341
Woman *(D)*	0.49	0.49	0.4	0.27	0.785
Second-generation immigrant *(D)*	0.03	0.03	0.8	0.57	0.570
First-generation immigrant *(D)*	0.04	0.04	0.0	0.04	0.972
Parent business owner *(D)*	0.44	0.44	−0.6	−0.45	0.655
Father university degree *(D)*	0.14	0.13	1.0	0.69	0.488
Mother university degree *(D)*	0.12	0.11	1.5	1.08	0.280
Grade (inflation adjusted)	19.30	19.37	−0.6	−0.42	0.677
Business administration *(D)*	0.56	0.56	0.0	0.00	1.000
Cohort 1995 *(D)*	0.27	0.27	0.6	0.42	0.674
Cohort 1996 *(D)*	0.52	0.52	0.0	−0.00	1.000
Born 1976 *(D)*	0.33	0.33	0.9	0.66	0.512
Born 1975 *(D)*	0.22	0.22	−1.0	−0.76	0.448
Wealthy parish *(D)*	0.77	0.77	1.0	0.72	0.473

Table A2
Mean values, matched treated and controls, for entrepreneurial income.

Variable	Treated	Control	Bias (%)	*t*	*p* > *t*
Ln(parents' income)	7.47	7.42	2.3	0.49	0.625
Woman *(D)*	0.25	0.26	−2.3	−0.48	0.628
Second-generation immigrant *(D)*	0.04	0.04	2.7	0.59	0.556
First-generation immigrant *(D)*	0.05	0.06	−5.3	−1.10	0.273
Parent business owner *(D)*	0.58	0.57	2.9	0.62	0.538
Father university degree *(D)*	0.15	0.15	−0.3	−0.07	0.948
Mother university degree *(D)*	0.13	0.12	3.5	0.79	0.432
Grade (inflation adjusted)	19.29	19.96	−6.0	−1.31	0.192
Business administration *(D)*	0.48	0.48	0.3	0.05	0.963
Cohort 1995 *(D)*	0.29	0.28	1.0	0.21	0.836
Cohort 1996 *(D)*	0.52	0.52	−0.2	−0.05	0.963
Born 1976 *(D)*	0.33	0.31	3.7	0.80	0.423
Born 1975 *(D)*	0.24	0.24	0.2	0.05	0.956
Wealthy parish *(D)*	0.73	0.73	1.2	0.26	0.792

Table A3
Mean values, unmatched and matched treated and controls, for survival.

Variable	Treated	Control	Bias (%)	*t*	*p* > *t*
Ln(parents' income)	7.54	7.33	10.0	0.85	0.398
Woman *(D)*	0.34	0.38	−9.2	−0.75	0.455
Second-generation immigrant *(D)*	0.04	0.04	−3.8	−0.31	0.759
First-generation immigrant *(D)*	0.06	0.06	−3.1	−0.25	0.803
Parent business owner *(D)*	0.55	0.55	1.4	0.12	0.904
Father university degree *(D)*	0.13	0.14	−2.0	−0.18	0.860
Mother university degree *(D)*	0.15	0.16	−1.9	−0.17	0.869
Grade (inflation adjusted)	19.68	18.92	6.7	0.59	0.558
Business administration *(D)*	0.42	0.43	−3.3	−0.24	0.809
Cohort 1995 *(D)*	0.27	0.27	−1.6	−0.13	0.893
Cohort 1996 *(D)*	0.53	0.53	0.0	0.00	1.000
Born 1976 *(D)*	0.29	0.33	−7.6	−0.64	0.520
Born 1975 *(D)*	0.22	0.22	0.0	−0.00	1.000
Wealthy parish *(D)*	0.75	0.71	8.3	0.67	0.501

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