A growing body of research suggests that early experiences in life play a key role in determining individuals’ college and career choices and behaviors. In particular, prior research indicates that the career-related beliefs, interests and expectations acquired in middle school and even younger grades have profound consequences for the decisions that individuals make in college and beyond (Legewie and DiPrete 2014b; Sadler et al. 2012; Tai et al. 2006). Consistent with this idea, it has been argued that early interventions are needed to address persistent disparities such as the gender gap in STEM (science, technology, engineering, and mathematics) fields (Legewie and DiPrete 2014a; Morgan, Gelbgiser, and Weeden 2013; Tai et al. 2006).

Despite the wide agreement that the beliefs, interests and expectations acquired early in life are highly consequential for later career choices, there is limited clarity regarding the causal pathways between early attitudes and future outcomes. The authors hypothesize that early-acquired attitudes can have a direct effect on future outcomes independent of more recent attitudes. Using a nationally representative sample, the authors implement inverse probability–weighted marginal structural models to estimate the controlled direct effect of math and science identity beliefs in ninth grade on college and career outcomes in science, technology, engineering, and mathematics (STEM). The results suggest that identifying with science or math in school increases the odds of enrolling in a STEM major in college as well expecting to have a STEM career.

Keywords
STEM fields, long-term effects, identity, gender gap

The Long-Lasting Effects of Schooling: Estimating the Effects of Science and Math Identity in High School on College and Career Outcomes in STEM

Rafael Quintana1 and Argun Saatcioglu1

Abstract
A growing body of research suggests that the beliefs, interests, expectations and other attitudes acquired early in life play a critical role in shaping individuals’ career trajectories. Yet the causal pathways connecting early-acquired attitudes and future outcomes are not well understood. In this study, the authors argue that a plausible way to understand this relationship is by postulating a direct effect of early-acquired attitudes on future outcomes that is not mediated by more recent values of these attitudes. This effect is referred to as the controlled direct effect. Using a nationally representative sample, the authors implement inverse probability–weighted marginal structural models to estimate the controlled direct effect of math and science identity beliefs in ninth grade on career and college outcomes in science, technology, engineering, and mathematics (STEM). The results suggest that identifying with science or math in school increases the odds of enrolling in a STEM major in college as well expecting to have a STEM career.

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In this study, we argue for the plausibility of the second hypothesis, namely, that early-acquired attitudes have a direct effect on college and career choices, above and beyond their mediated effect through more recent attitudes. This model contends that early-acquired attitudes can have long-lasting and potentially irreversible effects by affecting future outcomes independent of how these attitudes develop over time.

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methodological difficulties in estimating such effects. We also show how marginal structural models can be used to overcome these difficulties.

To illustrate how early-acquired attitudes can influence career-related outcomes independent of more recent attitudes, we examine the potential effects of science and math identity beliefs in ninth grade on college and career outcomes in STEM. Our hypothesis is that how individuals perceive themselves in ninth grade has a direct effect on outcomes measured in college, even after controlling for the same identity beliefs in college. To estimate these long-lasting direct effects, we used inverse probability–weighted marginal structural models and a nationally representative sample. The results suggest that identity beliefs in ninth grade have a long-lasting influence on future college and career outcomes.

How Schooling Gets under the Skin: Cascades and Critical Periods

The career orientations developed in early childhood and adolescence play a key role in determining individuals’ future decisions to pursue particular careers (Legewie and DiPrete 2014a; Sadler et al. 2012; Tai et al. 2006; Thébaud and Charles 2018). Consequently, it has been argued that to address persistent disparities such as the gender gap in STEM degrees and occupations, one needs to intervene on those early periods in the life course (Legewie and DiPrete 2014a; Morgan et al. 2013; Tai et al. 2006). For example, Legewie and DiPrete (2014a) estimated that the gender gap in STEM degrees would be reduced by as much as 36 percent if women had the same orientations toward STEM than men in eighth grade and by 82 percent if women had the same orientation than men at the end of high school. On the other hand, the authors found that intervening in the years after high school would reduce the gap by only 18 percent, which “challenges the focus on college in much research and policy” (p. 45).

Prior research suggests, then, that early childhood and adolescence plays a critical role in shaping individuals’ future career choices. One way of articulating this claim in a more formal manner is by saying that the attitudes acquired early in life have an effect on college outcomes independent of the individuals’ attitudes after high school. That is, early-acquired attitudes have a direct effect on career outcomes (represented by path 1 in Figure 1), above and beyond the effect mediated by more recent attitudes of the same type (represented by path 2*3).

Theories that highlight the importance of early-life periods can be interpreted as stating that the effect represented by path 1 in Figure 1 is substantial. If path 1 is close to zero, then to modify career-related outcomes one would have to intervene only on the attitudes individuals have at the time of making their decisions (X_C). Yet as described above, prior research suggests that interventions of this kind arrive too late and that meaningful change would only occur if the attitudes acquired earlier in life are modified. This means that there is a substantial effect of early attitudes on career outcomes that is not mediated by more proximal (recent) attitudes.

Stated in this way, there appears to be something counterintuitive or even paradoxical about theories that highlight the importance of early-life periods on adult outcomes. How can intervening on a distal cause be more effective than intervening on a proximal cause? To solve this dilemma, one can hypothesize a more fine grained causal structure such as the one depicted in Figure 2. This figure decomposes the direct and indirect effects of Figure 1 in multiple pathways. In particular, it includes a set of attitudes and behaviors (Z) that mediates the effect of early attitudes on future attitudes as well as career-related outcomes. By identifying the attitudes and behaviors in Z, one will explain some of the mechanisms underlying paths 1, 2, and 3 in Figure 1. That is, one will explain why X_S is connected to X_C and Y_C and why X_C is connected to Y_C. What remains unexplained after including these mechanisms will be contained in paths 1, 4, and 5. In the next section, we exemplify this causal structure with the hypothesized effects of identity beliefs in ninth grade on STEM college and career outcomes. The idea is that individual’s early self-perceptions with respect to science and math affect a series of attitudes (e.g., interest and competence beliefs) and behaviors (e.g., course taking) that affect future identity beliefs (path 2*6) as well as college and career outcomes (paths 2*6*5 and 2*3).

On the basis of this model, early-life attitudes have long-lasting effects because they influence several pathways that

![Figure 1. Causal graph representing the hypothesized effect of an attitude in school X_S on a career-related outcome in college Y_C. X_S has a direct and a mediated effect on Y_C through the same attitude in college (X_C).](image)
both reinforce the same attitudes in the future and determine adult outcomes. As Figure 2 shows, changes in initial conditions ($X_S$) affect a series of factors ($Z$) that produce both reinforcing effects on $Y_C$ (path $2*6$) as well as long-term effects on $Y_C$ (paths $2*3$ and $2*6*5$). This causal process can be described as a “cascade,” which is common in human development (Masten and Cicchetti 2010) as well as other human and natural processes (Ross 2021). The key feature of a cascade is the cumulative and amplifying consequences of the initial trigger (Masten and Cicchetti 2010; Ross 2021). In the present scenario, the amplifying effects occur because changes in $X_S$ affect $Y_C$ through a variety of pathways that cannot be contained by intervening on $X_C$. One can also see how this causal process is related to the notion of a “critical period,” defined as a period with an enhanced plasticity\(^3\) and the potential of generating irreversible changes (Wachs et al. 2014). In the process depicted in Figure 2, the irreversibility arises because intervening on $X_C$ will block the effect of $X_S$ through $X_C$ (paths $4*5$ and $2*6*5$) but will leave open the effect that $X_S$ has on $Y_C$ through $Z$ (path $2*3$). That is, even if a late intervention will have some effect on the outcome (path 5), it will not modify the cascading effects of early events ($X_S$).\(^4\)

The causal structure depicted in Figure 2 clarifies in what sense some life-course periods can be considered critical, and how early-life attitudes and experiences can generate long-lasting effects. In our study, we use this model to examine how the attitudes acquired in school can have enduring consequences for individuals’ adult choices and behaviors. In particular, we explore the extent to which identity beliefs in ninth grade can have an effect on college and career choices in college, above and beyond their identity beliefs at the time of making those choices. That is, we estimate the effect of identity beliefs in ninth grade on college and career outcomes that is not mediated by identity beliefs in college. Before presenting our methodological approach, we explain why we focus on identity beliefs in our empirical analysis.

### Supply-Side Explanations of the Gender Gap in STEM Fields

Even if many researchers agree that the occupational preferences and aspirations developed in middle school and even in earlier years play a determinant role in explaining the gender gap in STEM fields, how those occupational aspirations come about is not well understood (Legewie and DiPrete 2014a; Morgan et al. 2013; Tai et al. 2006). A range of beliefs, interests, goals, expectations, values, perceived opportunities and barriers, and other attitudes might shape occupational preferences and aspirations. Furthermore, these attitudes can be acquired in response to a range of contextual factors such as gender discrimination and cultural stereotypes (Ridgeway and Correll 2004; Thébaud and Charles 2018), peer environments (Breene and Zölitz 2020), high school characteristics (Legewie and DiPrete 2014b), and teacher behaviors (Sansone 2019).

Among the many beliefs, interests, goals, expectations and other attitudes acquired in early life that might influence individuals’ career choices, an increasing number of researchers have focused on the so-called identity beliefs (Hill et al. 2018; Simpson and Bouhafa 2020; Stets et al. 2017). Identity beliefs with respect to a particular field refer to individuals’ self-perceptions and feelings of belonging or alienation with respect to that field (Cribbs et al. 2015). For example, science identity beliefs refer to the extent to which an individual considers himself or herself as a “science kind of person” (Hill et al. 2018). Gaps in STEM identity across gender categories emerges in elementary school and widens in middle school (Archer et al. 2010; DeWitt et al. 2013; Hill et al. 2018).\(^5\) STEM identity beliefs have been found to predict a range of career-related outcomes such as career choice and

\(^3\)The condition of plasticity is met in the process under consideration, as prior research suggests that adolescence is a period of significant physical, emotional, and social change, and a critical moment in the development of individuals’ sense of personal identity (e.g., DeWitt et al. 2013; Erikson 1968).

\(^4\)The irreversibility that characterizes critical periods does not imply that individuals’ career trajectories are completely determined by early-life experiences and decisions. The irreversibility implies instead that those experiences and decisions (e.g., what courses to take) impose constraints on individuals’ trajectories, which complicates the access to some career paths.

\(^5\)Psychological explanations of gender differences often lead to essentialist inferences that perpetuate stereotypes (Quintana 2021). Our argument is not that women naturally identify with certain fields, but rather that early-life experiences can affect women’s self-perceptions, which can have amplifying and long-lasting consequences.
behaviors such as competence beliefs, interest, performance, and ethnic minorities (Ong et al. 2011; Thébaud and Charles 2018). Similar biases and stereotypes arise, individuals tend to change their identity to be more consistent with how they are perceived by others (Stets et al. 2017).

Identity beliefs are considered, then, a key explanatory component in how early experiences and attitudes affect individuals’ career-related choices and behaviors. How individuals perceive themselves reflect a range of relevant experiences, contextual influences and attitudes that predict occupational choices. For instance, identity beliefs with respect to STEM fields are directly linked to cultural stereotypes (Thébaud and Charles 2018), as well as individuals’ achievement (Stets et al. 2017). These beliefs can in turn affect occupational aspirations and other attitudes related to career choice in STEM such as interest and self-concept (Cribbs et al. 2015; Dou and Cian 2022; Hazari et al. 2010; Hill et al. 2018; Stets et al. 2017). Thus, on the basis of prior research we hypothesize that (1) STEM identity beliefs in college have a direct causal effect on college and career choice in STEM, and (2) identity beliefs in ninth grade affect attitudes and behaviors that influence college and career choice in STEM. Put differently, we hypothesize that students’ self-perceptions in school with respect to STEM have enduring and potentially irreversible consequences, as they affect a range of attitudes and behaviors that are consequential for career-related outcomes.

We also hypothesize that identifying with STEM fields in school is more predictive of choosing a STEM occupation for men than for women. Building and maintaining an identity in STEM (or other field) is a social process that depends to a large extent on whether others acknowledge and recognize that identity (Godwin et al. 2016; Stets et al. 2017). When a discrepancy between the self and others’ perceptions arises, individuals tend to change their identity to be more consistent with how they are perceived by others (Stets et al. 2017). This process is thought to reinforce historical inequities, as women are pressured to downgrade their STEM identity and, ultimately, opt out of STEM careers when they encounter cultural stereotypes that associate masculine traits and abilities with STEM disciplines (Cheryan et al. 2017; Thébaud and Charles 2018). Similar biases and stereotypes among peers, parents, and teachers can reduce STEM identities and participation in STEM fields among against racial and ethnic minorities (Ong et al. 2011; Thébaud and Charles 2018).

Negative stereotypes and biases, as well as other experiences affecting individuals’ identities, have cumulative and long-lasting consequences for the career aspirations of women and racial/ethnic minorities (Correll 2001; Hill et al. 2018). These consequences occur because how individuals perceive themselves affect a range of relevant attitudes and behaviors such as competence beliefs, interest, performance, decisions to enroll in certain courses, invest time and effort in certain activities, and so forth (Calabrese Barton et al. 2013; Correll 2001; Goetz et al. 2013; Hazari et al. 2010). That is, how individuals perceive themselves affects a range of attitudes and behaviors that set individuals on specific career paths regardless of how they perceive themselves later in life. The effect of early-life identity beliefs on career-related outcomes that is not mediated by future identity beliefs is defined as the controlled direct effect of early-life identity beliefs. In the next section, we explain the methodological approach we adopt to estimate this controlled direct effect.

Using Marginal Structural Models to Estimate the Controlled Direct Effect of Identity Beliefs on STEM Outcomes

The primary goal of our empirical analysis is to estimate the effect of identity beliefs in ninth grade on college and career outcomes that is not mediated by identity beliefs in college. Our “treatment” variable $T_i$ represents a science or math identity belief in ninth grade for each individual $i (i = 1, \ldots , N)$. We consider identity beliefs as dichotomous, such that individuals with $T_i = 1$ identify with STEM and individuals with $T_i = 0$ do not identify with STEM. We consider two dichotomous outcome variables $Y_i$ representing whether individuals (1) enrolled in STEM majors in college and (2) expect to work in STEM careers at age 30. Thus, $Y_i(1)$ can be defined as the potential outcome if $T_i = 1$ and $Y_i(0)$ as the potential outcome if $T_i = 0$. Finally, identity beliefs in college are considered a mediating variable $M_i$ that can also take two values ($m = 0$ and $m = 1$) corresponding to whether individuals identify with STEM or not in college.

The goal, then, is to examine whether $T$ has an effect on $Y$ after fixing $M$ to a specific level. The effect of $T$ on $Y$ that is not mediated by $M$ is referred to as the “controlled direct effect” (Pearl 2001) and is composed of the effect of $T$ on $Y$ that is not explained by $M$ (path 2*3 in Figure 3) as well as
the unexplained direct effect (path 1). That is, the controlled
direct effect represents the extent to which changes in $T$ will
generate a change in $Y$ while fixing $M$ to a particular value.

In potential outcome notation, controlled direct effects are
defined as $E[Y(t, m) - Y(t^*, m)]$, where $Y(t, m)$ is the potential
outcome when $T = t$ and $M = m$. Given that in the present
setting $M$ can take only two values, we can estimate two con-
trolled direct effects: $E[Y(1, m) - Y(0, m)]$ where $m = 1$ and
$E[Y(1, m) - Y(0, m)]$ where $m = 0$. These effects will differ
in the presence of a treatment-mediator interaction
(VanderWeele 2015).

To identify the controlled direct effect of a treatment on
an outcome, we need to make two assumptions about con-
 founding: we need to assume (1) no unmeasured confound-
ing between the treatment and the outcome and (2) no
unmeasured confounding between the mediator and the out-
come (VanderWeele 2015). These are two strong assump-
tions difficult to meet using observational data. We minimize
these confounding biases by including a wide range of rele-
vant covariates and conducting sensitivity analyses.

The first confounding assumption can be addressed by
controlling for potential causes of the treatment and the out-
come in a regression model (e.g., demographic characteris-
tics, prior achievement, and socioeconomic status). We refer
to these covariates as “pretreatment confounders,” and they
are represented as $C$ in Figure 3. Traditional regression anal-
ysis, however, cannot be used to control for the second kind
of confounders, which we refer to as “posttreatment con-
founders.” As Figure 3 shows, the attitudes and behaviors in
$Z$ not only confound the relationship between $T$ and $M$ but
are in the pathway we are interested in (the path between $T$
on $Y$ that is not mediated by $M$). Thus, controlling for $Z$ will
reduce confounding bias, but it also blocks the effect of inter-
est. Consequently, we need a method different from regres-
sion that allows us to control for observed confounders and
not block the effect of interest.

A well-known method that deals with mediator-outcome
confounders that are affected by treatment is marginal struc-
tural models (Hernán and Robins 2020; Robins, Hernán, and
Brumback 2000). Marginal structural models are models of
the expected value of potential outcomes, which in the pres-
ent scenario take the form of $Y(t, m)$. Marginal structural
models are often estimated using inverse probability weights
(Coffman and Zhong 2012; Hernán and Robins 2020; Robins
et al. 2000). In our empirical analysis we need to create two
weights, corresponding to the two intervention variables $T$
and $M$. Following VanderWeele (2009), we calculate these
weights by

$$w_T^i = \frac{P(T = t_i)}{P(T = t_i|C = c_i)}$$

and

$$w_M^i = \frac{P(M = m_i|T = t_i)}{P(M = m_i|T = t_i, C = c_i, Z = z_i)}.$$  

(1)

The denominator of $w_T^i$ is the probability of receiving the
treatment the individual actually received given the mea-
sured pretreatment covariates. This quantity is generally
referred to as the propensity score (Rosenbaum and Rubin
1983). Thus, the propensity score assigned to individuals in
the treatment group is $1/P(T = 1|C = c_i)$, while the propen-
sity score assigned to individuals in the control group is
$1/[1 - P(T = 1|C = c_i)]$. The probabilities in the numerator
are said to “stabilize” the weight, and are included to reduce
the variability of the weights (Cole and Hernán 2008).
Similarly, the denominator of $w_M^i$ is the probability of hav-
ing the value of the mediator that the individual actually had
given the individual’s treatment status, pretreatment covari-
ates and posttreatment covariates.

The marginal structural model we implement is a weighted
logistic regression of the form

$$\logit \left[ P(Y_i = 1|T_i = t, M_i = m) \right] = \beta_0 + \beta_1 T_i + \beta_2 M_i + \beta_3 M_i T_i,$$

(2)

where $\beta_1$ is the estimated controlled direct effect of $T$ on $Y$.

This model does not condition on any covariates, avoiding
the problem of overcontrol bias described above. The way
this model deals with the two confounding assumptions is by
using an inverse probability weight, $W = w_T^i w_M^i$. The
weight $w_T^i$ adjusts for measured confounding of $T$ and $Y$,
while the weight $w_M^i$ adjusts for measured confounding of $M$
and $Y$. The model includes the possibility of a significant
treatment-mediator interaction $\beta_3$.

In addition to estimating the controlled direct effect of $T$
on $Y$, we tested for potential moderating effects of gender by
including the main effect of gender and the interaction of
treatment and gender in equation 2. We hypothesized that
identifying with STEM has a higher effect on future out-
comes for men than women. This hypothesis is based on
prior research suggesting that (1) STEM identity is more pre-
dictive of career choice for men than women (Godwin et al.
2016), and (2) the gender identity gap might be related to
differences in interest, persistence and other factors that can
affect college and career outcomes and differ across gender
groups (Hill et al. 2018; Stets et al. 2017).

Data

Data Set

The data come from the High School Longitudinal Study of
2009 (HSLS:09) conducted by the National Center for
Education Statistics (Ingels et al. 2011). The study includes
approximately 21,440 students in 9th grade from about 940
schools. In the first step of the sample design, public and
private schools were selected using stratified random sam-
ping at the national level. Subsequently, about 27 students
were randomly sampled from each school. The first round of
data collection took place in the fall of the 2009–2010 school year, and the first follow-up took place in the spring of 2012, when most students were in 11th grade. A second follow-up was done in 2015, when most respondents were three years beyond high school graduation.

HSLS:09 focuses on the transition between secondary and postsecondary education with an emphasis in STEM. For this purpose, HSLS:09 gathered information about a range of factors that might influence individuals’ career-related choices and behaviors. HSLS:09 began by identifying general constructs recognized as relevant in the literature, and then selected the items that could best measure these constructs (see Ingels et al. 2011). Thus, HSLS:09 includes a wide range of beliefs, aspirations, expectations, values, interests, perceived opportunities, barriers and costs that might influence students’ academic and career-related choices.

In the present study, the analytic sample is defined as 13,283 individuals who have a nonzero value in the analytic weight W4W1W2W3STU. This weight accounts for differential nonresponse (which can generate sampling bias in the analysis), and is appropriate for studies using data from the base year as well as the first and second follow-ups.

Identity Beliefs

Identity beliefs were measured using a Likert-type scale item asking respondents whether they agree with the statement “you see yourself as a math person” or “you see yourself as a science person.” Given that identity beliefs are discipline-specific (Bandura et al. 2001), different analyses were conducted for the two items. Prior research has considered this item a good indicator of science, math, and, more generally, STEM identity (Cribbs et al. 2015; Dou and Cian 2022; Hazari et al. 2010; Hill et al. 2018).

The treatment group is defined as individuals who perceive themselves as a science or a math kind of person. Thus, the treatment group is composed of individuals who agree or strongly agree with the statement above, while the control group is composed of individuals who disagree or strongly disagree with the statement. Dichotomizing treatment makes the causal estimand easier to define and interpret. It also facilitates the estimation process, in particular the construction of the inverse probability weights. It is unlikely that we can reliably estimate propensity scores of a multicategorical treatment using a four-level Likert-type scale item as an outcome as well as the observed covariates.

The identity beliefs used to create our treatment indicator were obtained from the base-year student questionnaire (i.e., when individuals were in ninth grade). A mediator measuring whether individuals identify or not with science and math was created in a similar fashion. Measures of the mediator were obtained six years later, from the second follow-up, when most respondents were three years beyond high school graduation.

College and Career Outcomes

We consider two outcomes related to STEM careers, which were obtained from the second follow-up in 2015. The first outcome is an indicator representing whether individuals enrolled in a STEM major in college. Following similar studies (e.g., Legewie and DiPrete 2014b) we define STEM as any science, technology, engineering, or mathematics field, excluding social and behavioral sciences and health work. In our analytic sample, 2,954 individuals (31 percent) enrolled in STEM majors, and 6,442 individuals (69 percent) did not enroll in STEM majors.

The second outcome considered indicates whether an individual’s expected job at age 30 is in a STEM field. This variable is based on a composite included in HSLS:09, which uses the Bureau of Labor Statistics STEM classification on the basis of Standard Occupational Classification codes. In our analytic sample 1,215 individuals (15 percent) expect to work in STEM fields, and 7,112 individuals (85 percent) do not expect to work in STEM fields.

Pretreatment Covariates

Measured potential confounders of the relationship between ninth grade science and math identity beliefs and STEM careers include students’ socioeconomic status, gender, race, school locale, and academic achievement (Hill et al. 2018; Legewie and DiPrete 2014b; Riegle-Crumb, Moore, and Ramos-Wada 2011; Thébaud and Charles 2018). We used a pre–high school measure of academic achievement by including the final grade in ninth graders’ most advanced eighth grade math and science courses. We also included measures for both parents’ most recent occupations (which includes a specific category for STEM fields), as well as students’ parent educational expectations. We control for potential peer effects by including measures of the percentage of students in math course that are unprepared, as reported by science and math teachers. We control for potential teacher effects by including a composite measure of math and science’s expectations of the school’s students, as well as teacher’s emphasis on increasing students’ science and math interest. Finally, we control for potential school effects by including a scale of the school’s administrator’s assessment of the school climate, a sum index based on five STEM-related extracurricular activities, and as a sum index based on the Advanced Placement courses offered at the school (Legewie and DiPrete 2014b). All the pretreatment covariates included were obtained from the first round of data collection.

Posttreatment Covariates

We used different sets of posttreatment covariates to estimate three inverse probability weights, and implemented different marginal structural models for each of these
weights. Differences in the estimated coefficients would indicate sensitivity to potential confounders. It is important to conduct these sensitivity analyses, as the assumption of no unmeasured confounders (the so-called exchangeability assumption) cannot be formally tested (Cole and Hernán 2008). It is worth noting that adding too many confounders when estimating inverse probability weights can be problematic, as it can introduce finite-sample and collider bias as well as yield wide confidence intervals (Cole and Hernán 2008). Thus, we report estimates from the three models that include 4 (set 1), 10 (set 2), and 19 (set 3) potential post-treatment confounders.

**Covariate Set 1.** Supply-side explanations of individuals’ STEM career choices in general, and the gender gap in particular, have highlighted the role of self-assessments of ability or self-efficacy (Correll 2001; Eccles and Wigfield 2002; Ridgeway and Correll 2004) and interest in STEM (Ceci and Williams 2010; Hazari et al. 2010; Sadler et al. 2012; Thébaud and Charles 2018). On the basis of this body of research, we hypothesize that these are the primary mechanisms that mediate early identification with STEM fields and future college and career outcomes. Self-efficacy beliefs and interest are composite variables composed of five and six items, respectively (for details, see Ingels et al., 2011).

**Covariate Set 2.** We conduct an additional analysis by including math and science utility beliefs, academic achievement and course-taking patterns. These attitudes and behaviors have been considered important determinants of academic and career outcomes (e.g., Eccles 2009; Griffith 2010; Wang 2016). Math and science utility beliefs are a composite measures of three items (see Ingels et al. 2011). Academic achievement was measured by students’ grade point averages in STEM courses in high school as well students’ math ability (as measured by HSLS:09). As a measure of course-taking patterns, we include the credits that the student earned in STEM and Advanced Placement courses in high school.

**Covariate Set 3.** Our final model specification adds potentially relevant confounders such as hours spent on math and science homework, mind-set beliefs, educational aspirations and expectations, effort in science and math courses, and beliefs about gender differences in science and math achievement.

Table S1 in the Supplemental Materials lists all the variables used in the empirical analysis.

**Longitudinal Data Structure**

Our definition of pretreatment and posttreatment covariates assumes the temporal and causal ordering depicted in Figure 3. To strengthen these confounding assumptions, all the post-treatment covariates were measured prior to the college and career outcomes as well as the college identity beliefs.

Specifically, the posttreatment covariates were obtained from the first follow-up that took place when most students were in 11th grade. Thus, the posttreatment covariates were measured after treatment and before the outcome and college identity beliefs.

**Missing Data**

The percentage of missing data in the analytic sample among the variables considered ranged from about 1 percent to 45 percent, with an average of 13 percent. Given the number of covariates used in the analysis, the sample size will be reduced considerably with complete case analysis. To preserve the entire sample, we used multiple imputations on the basis of the chained-equations approach (White, Royston, and Wood 2011). To improve the predictive accuracy of the imputation models, we included 49 auxiliary student-, teacher-, and parent-level covariates. We also take into account differential nonresponse patterns by weighting the inverse probability weights estimated using equation 1 by the longitudinal sample weight included in HSLS:09.

**Results**

**Estimates Using Traditional Regression Analysis**

It is useful to compare the results obtained using marginal structural models with the results one would obtain by using traditional regression methods. Thus, we implemented three models using traditional regression analysis. First, we estimated the total effect\(^6\) of science and math identity on college and career outcomes by regressing the outcome on the treatment variable and the pretreatment covariates. Column 1 in Tables 1 and 2 shows that, holding all the pretreatment variables constant, the odds of enrolling in a STEM major are 1.78 times larger (95 percent confidence interval (CI) = 1.56–2.03) for individuals who have a science identity and 1.66 times larger (95 percent CI = 1.44–1.96) for individuals who have a math identity (Table 1). One can also see that the odds of expecting a career in STEM are 1.69 times larger (95 percent CI = 1.43–1.99) for individuals with high science identity and 1.60 times larger (95 percent CI = 1.36–1.89) for individuals with high math identity (Table 2).

Traditionally, the direct effect of a treatment on an outcome (represented by paths 1 and 2*3 in Figure 3) is estimated by regressing the outcome on both the treatment and the mediator (Baron and Kenny 1986). Column 2 in Tables 1 and 2 shows the estimated direct effects obtained using this method.\(^7\) One can see that the estimated direct effects are

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\(^6\)The total effect includes paths 1, 4*5, 2*3, and 2*6*5 in Figure 3.

\(^7\)There was no evidence for a significant interaction between STEM identity in ninth grade and STEM identity in college across different model specifications. Thus, we do not include this interaction term in Tables 1 and 2.
| Regression Adjustment for Pretreatment Covariates | Regression Adjustment for College Identity and Pretreatment Covariates | Regression Adjustment for College Identity, Pretreatment and Posttreatment Covariates | Marginal Structural Model (Covariate Set 1) | Marginal Structural Model (Covariate Set 2) | Marginal Structural Model (Covariate Set 3) |
|-------------------------------------------------|-----------------------------------------------------------------------|-----------------------------------------------------------------|----------------------------------------|----------------------------------------|----------------------------------------|
| (1)                                             | (2)                                                                   | (3)                                                             | (4)                                     | (5)                                     | (6)                                     |
| Science                                        |                                                                       |                                                                  |                                         |                                         |                                         |
| Science identity in ninth grade                | 1.78*** (1.56–2.03)                                                   | 1.25*** (1.08–1.43)                                              | 1.04 (0.89–1.21)                       | 1.25*** (1.09–1.44)                   | 1.25*** (1.09–1.44)                   |
| Science identity in college                    | 5.54*** (4.91–6.24)                                                   | 4.81*** (4.25–5.46)                                              | 4.74*** (4.16–5.40)                   | 4.43*** (3.88–5.06)                   | 4.40*** (3.85–5.04)                   |
| Female                                         | 0.76*** (0.67–0.86)                                                   | 0.81*** (0.71–0.93)                                              | 0.83* (0.72–0.96)                     | 0.90 (0.78–1.03)                     | 0.88 (0.76–1.01)                     |
| Female × science identity in ninth grade       | 0.91 (0.76–1.08)                                                     | 0.90 (0.75–1.08)                                                | 0.98 (0.81–1.19)                     | 0.95 (0.78–1.16)                     | 0.97 (0.80–1.19)                     |
| Math                                           |                                                                       |                                                                  |                                         |                                         |                                         |
| Math identity in ninth grade                   | 1.66*** (1.44–1.92)                                                   | 1.36*** (1.17–1.58)                                              | 1.12 (0.96–1.32)                       | 1.43*** (1.22–1.67)                   | 1.44*** (1.22–1.69)                   |
| Math identity in college                       | 1.79*** (1.61–1.98)                                                   | 1.52*** (1.36–1.70)                                              | 1.59*** (1.41–1.79)                   | 1.54*** (1.36–1.73)                   | 1.54*** (1.36–1.74)                   |
| Female                                         | 0.76*** (0.66–0.89)                                                   | 0.81*** (0.69–0.94)                                              | 0.82* (0.69–0.96)                     | 0.91 (0.78–1.07)                     | 0.89 (0.76–1.05)                     |
| Female × math identity in ninth grade          | 0.90 (0.75–1.09)                                                     | 0.90 (0.75–1.09)                                                | 0.96 (0.79–1.17)                     | 0.92 (0.75–1.12)                     | 0.94 (0.76–1.15)                     |

Note: The table presents odds ratios and 95 percent confidence intervals. All models were estimated using logistic regression. The pretreatment covariates include 18 variables obtained in 2012 (i.e., race, socioeconomic status, school locale, grades in science and math, parental occupation and expectations, school climate, Advanced Placement courses in school and science, technology, engineering, and mathematics [STEM] extracurricular activities, peer academic level, teachers’ expectations and emphasis on students’ interest). The posttreatment covariates include 4 (set 1), 10 (set 2), and 19 (set 3) variables obtained in 2012. The model in column 3 was estimated using covariate set 3 (i.e., science and math self-efficacy, interest, effort and utility, math ability, credits earned in Advanced Placement and STEM courses, grade point average in STEM courses, time spent on science and math homework, mind-set beliefs, aspirations and expectations, and gender beliefs). Math and science identity in college and enrolling in a STEM major were measured in 2015.

*p < .05, **p < .01, ***p < .001.
Table 2. Estimated Effect of Science and Math Identity Beliefs on Expecting a Career in a STEM Field at Age 30 Using Regression Analysis and Marginal Structural Models.

|                      | Regression Adjustment for Pretreatment Covariates | Regression Adjustment for College Identity and Pretreatment Covariates | Regression Adjustment for College Identity and Pretreatment and Posttreatment Covariates | Marginal Structural Model (Covariate Set 1) | Marginal Structural Model (Covariate Set 2) | Marginal Structural Model (Covariate Set 3) |
|----------------------|--------------------------------------------------|------------------------------------------------------------------------|----------------------------------------------------------------------------------------|--------------------------------------------|--------------------------------------------|--------------------------------------------|
|                      | (1)                                              | (2)                                                                    | (3)                                                                                      | (4)                                        | (5)                                        | (6)                                        |
| Science              |                                                  |                                                                        |                                                                                         |                                             |                                             |                                             |
| Science identity in ninth grade | 1.69*** (1.43–1.99)                           | 1.39*** (1.17–1.65)                                                   | 1.21* (1.01–1.46)                                                                      | 1.42*** (1.19–1.69)                        | 1.42*** (1.19–1.70)                        | 1.42*** (1.19–1.70)                        |
| Science identity in college | 2.34*** (1.99–2.74)                            | 2.04*** (1.72–2.41)                                                   | 2.0** (1.61–2.43)                                                                      | 2.20*** (1.85–2.63)                       | 2.1** (1.77–2.51)                         | 2.1** (1.77–2.50)                         |
| Female               | 0.46*** (0.38–0.55)                             | 0.47*** (0.40–0.57)                                                   | 0.50*** (0.41–0.61)                                                                    | 0.53*** (0.44–0.64)                       | 0.52*** (0.43–0.64)                       | 0.53*** (0.43–0.64)                       |
| Female × science identity in ninth grade | 0.78* (0.61–0.98)                             | 0.77* (0.61–0.98)                                                   | 0.82 (0.65–1.05)                                                                       | 0.76* (0.59–0.99)                        | 0.76* (0.59–0.99)                        | 0.76* (0.59–0.98)                        |
| Math                 |                                                  |                                                                        |                                                                                         |                                             |                                             |                                             |
| Math identity in ninth grade | 1.60*** (1.36–1.89)                          | 1.33*** (1.12–1.58)                                                   | 1.07 (0.90–1.28)                                                                       | 1.36*** (1.13–1.64)                       | 1.38** (1.14–1.67)                       | 1.38** (1.14–1.68)                       |
| Math identity in college | 1.70*** (1.47–1.96)                          | 1.38*** (1.19–1.61)                                                   | 1.54*** (1.33–1.79)                                                                    | 1.47*** (1.26–1.72)                       | 1.47*** (1.26–1.71)                       | 1.47*** (1.26–1.71)                       |
| Female               | 0.42*** (0.34–0.51)                             | 0.44*** (0.35–0.54)                                                   | 0.45*** (0.36–0.56)                                                                    | 0.48*** (0.38–0.60)                       | 0.49*** (0.39–0.61)                       | 0.49*** (0.39–0.61)                       |
| Female × math identity in ninth grade | 0.96 (0.74–1.23)                             | 0.96 (0.74–1.24)                                                   | 1.01 (0.78–1.32)                                                                       | 0.99 (0.73–1.34)                         | 0.98 (0.72–1.33)                         |                                             |

Note: The table presents odd ratios and 95 percent confidence intervals. All models were estimated using logistic regression. The pretreatment covariates include 18 variables obtained in 2012 (i.e., race, socioeconomic status, school locale, grades in science and math, parental occupation and expectations, school climate, Advanced Placement courses in school and science, technology, engineering, and mathematics [STEM] extracurricular activities, peer academic level, teachers’ expectations and emphasis on students’ interest). The posttreatment covariates include 4 (set 1), 10 (set 2), and 19 (set 3) variables obtained in 2012. The model in column 3 was estimated using covariate set 3 (i.e., science and math self-efficacy, interest, effort and utility, math ability, credits earned in Advanced Placement and STEM courses, grade point average in STEM courses, time spent on science and math homework, mind-set beliefs, aspirations and expectations, and gender beliefs). Math and science identity in college and expecting a career in a STEM field were measured in 2015.

* p < .05. ** p < .01. *** p < .001.
smaller than the total effects but remain statistically significant. These estimates are unbiased provided that the pretreatment confounders suffice to control for confounding between (1) identity in ninth grade and college and career outcomes and (2) identity in college and college and career outcomes (Nandi et al. 2012; VanderWeele 2016).

One can control for the second kind of confounders (i.e., between identity in college and the outcomes considered) by including posttreatment covariates in a regression model. Column 3 shows that by using this method, the effect of identity beliefs is reduced considerably and, except for the effect of science identity on STEM occupation, is no longer statistically significant. By using this method, we would estimate path 1 in Figure 3. However, as explained above this method blocks part of the effect we are interested in, namely the effect of identity beliefs through the posttreatment covariates that does not go through the mediator (represented by path 2*3). Marginal structural models were used to control for posttreatment covariates without blocking the effect of interest.

Estimates Using Marginal Structural Models

The stabilized weights for the treatment and mediator defined in equation 1 were estimated using logistic regression. Different weights were estimated for the two treatments and the three sets of posttreatment covariates. Weight means far from one indicate potential violations of the positivity assumption or misspecification of the weight model (Cole and Hernán 2008). Table S2 in the Supplemental Materials shows that the mean of all estimated weights is around one. It also presents the standard deviation and minimum and maximum values among the weights.

Inverse probability weights are used to create weighted samples in which the distribution of covariates is similar between treated and control subjects (Austin and Stuart 2015; Hernán and Robins 2020). Thus, researchers recommend generating balance diagnostics to assess whether there are observed systematic differences between treated and control subjects in the weighted and unweighted samples (Austin and Stuart 2015). Table 3 shows that in the unweighted sample there are observed systematic differences between the treated and control subjects among the 36 pretreatment and posttreatment covariates. These differences are consistent with the possibility that these variables confound the relationship between the treatment and the outcome (pretreatment covariates) and the mediator and the outcome (posttreatment covariates). In the weighted sample these differences are largely removed. The largest absolute standardized difference between the two groups in the unweighted sample is 0.55 (science grade), and the largest difference in the weighted sample is 0.13 (science interest).

The difference in science grade between the treatment and control group in the weighted sample is 0.02.

Estimates of the controlled direct effect using marginal structural models are shown in columns 4 to 6 in Tables 1 and 2. On the basis of the most conservative model (column 6), the odds of enrolling in a STEM major for individuals who identify with science or math in school are 1.26 (95 percent CI = 1.09–1.45) and 1.44 (95 percent CI = 1.22–1.69) times larger than for those who do not identify with math and science, respectively. This means that identifying with science or math increases the odds of enrolling in a STEM major by 26 percent and 44 percent, respectively. Similarly, the odds of expecting to have a STEM career for individuals who identify with science and math are 1.42 (95 percent CI = 1.19–1.70 ) and 1.38 (95 percent CI = 1.14–1.68) times larger than for those who do not identify with math and science, respectively. These results show that using regression adjustment can attenuate the controlled direct effect and that marginal structural models can be used to deal with confounders without blocking the effect of interest.

The marginal structural models implemented offer valid estimates provided there is no unmeasured confounding of the treatment-outcome and mediator-outcome relationships (VanderWeele 2009). We minimized this risk by including a wide range of potential pretreatment and posttreatment confounders. Tables 1 and 2 also show that the estimated coefficients remain stable after including different sets of posttreatment covariates (4, 10, and 19 covariates). The results also remain consistent after accounting for differential nonresponse by including longitudinal weights in both the regression and the marginal structural models (see Tables S3 and S4 in the Supplemental Materials).

The estimates in Tables 2 also indicate that, holding all other variables constant, the odds of expecting a career in a STEM field are about 50 percent lower for women compared with men. In addition, Table 2 shows a significant interaction between science identity in school and gender in the models predicting STEM occupation. This interaction implies that identifying with science in ninth grade is more beneficial for men than women (i.e., it increases more the chances of expecting a career in STEM). The interaction term in other models was close to 1 and not statistically significant. Contrary to our hypothesis, these results suggest that identifying with STEM in ninth grade is equally predictive of career outcomes for men and women. Finally, Table 1 shows that the odds of enrolling in a STEM major are about 11 percent lower for women compared with men, but this difference is not statistically significant.

Discussion

A growing body of research suggests that the beliefs, interests, expectations, and other attitudes acquired in early childhood and adolescence play a critical role in shaping individuals’ career trajectories. Yet the causal pathways
Table 3. Pretreatment and Posttreatment Characteristics in Weighted and Unweighted Samples.

| Pretreatment covariates             | Unweighted Sample | Weighted Sample | Standardized Difference | Standardized Difference |
|-------------------------------------|-------------------|-----------------|-------------------------|-------------------------|
|                                     | Untreated (n = 7,246) | Treated (n = 5,988) | Standardized Difference | Untreated (n = 7,291) | Treated (n = 5,946) | Standardized Difference |
| Socioeconomic status                | 0.04 (0.77) | 0.28 (0.82) | −0.31 | 0.14 (0.80) | 0.13 (0.81) | 0.01 |
| Science grade                       | 4.02 (0.95) | 4.48 (0.75) | −0.55 | 4.20 (0.89) | 4.19 (0.96) | 0.02 |
| Math grade                          | 4.05 (0.97) | 4.23 (0.92) | −0.19 | 4.11 (0.95) | 4.10 (0.99) | 0.01 |
| School climate                      | 0.21 (1.00) | 0.26 (1.00) | −0.06 | 0.23 (0.99) | 0.23 (0.99) | 0.01 |
| Peer-level math                     | 3.45 (0.82) | 3.57 (0.75) | −0.15 | 3.51 (0.78) | 3.49 (0.79) | 0.02 |
| Peer-level science                  | 3.51 (0.78) | 3.59 (0.74) | −0.11 | 3.54 (0.76) | 3.54 (0.76) | 0.00 |
| Teachers' math expectations         | 0.14 (0.95) | 0.16 (0.93) | −0.01 | 0.17 (0.95) | 0.15 (0.93) | 0.01 |
| Teachers' science expectations      | 0.11 (0.98) | 0.14 (0.98) | −0.03 | 0.13 (0.97) | 0.11 (1.00) | 0.02 |
| AP courses in school                | 3.70 (2.52) | 3.99 (2.56) | −0.12 | 3.81 (2.54) | 3.79 (2.56) | 0.01 |
| STEM extracurricular                | 9.80 (5.42) | 9.85 (5.33) | −0.01 | 9.79 (5.38) | 9.79 (5.33) | 0.00 |
| Teachers' science interest          | 2.20 (0.66) | 2.25 (0.65) | −0.08 | 2.23 (0.65) | 2.21 (0.66) | 0.03 |
| Teachers' math interest             | 2.44 (0.59) | 2.50 (0.56) | −0.11 | 2.46 (0.58) | 2.47 (0.57) | −0.01 |
| Parental expectations               | 6.74 (3.33) | 8.37 (2.99) | −0.50 | 7.26 (3.43) | 7.54 (3.44) | −0.08 |
| City school                         | 2,050 (28.3%) | 1,822 (30.4%) | −0.05 | 2,134.2 (29.2%) | 1,761.5 (29.6%) | −0.01 |
| Rural school                        | 1,777 (24.5%) | 1,327 (22.2%) | 0.06 | 1,711.9 (23.5%) | 1,381.9 (23.3%) | −0.00 |
| White                               | 4,020 (55.5%) | 3,541 (59.1%) | −0.15 | 4,163.3 (57.1%) | 3,759.5 (56.8%) | 0.01 |
| Black                               | 818 (11.3%) | 499 (8.3%) | 0.10 | 736.3 (10.1%) | 611.7 (10.3%) | −0.01 |
| Hispanic                            | 1,233 (17.0%) | 749 (12.5%) | 0.13 | 1,100.6 (15.1%) | 907.2 (15.3%) | −0.01 |
| Parent 1 in STEM occupation         | 301 (5.1%) | 412 (8.1%) | −0.12 | 373.6 (6.3%) | 315.9 (6.4%) | −0.01 |
| Parent 2 in STEM occupation         | 357 (7.8%) | 507 (12.0%) | −0.14 | 438.6 (9.8%) | 389.8 (9.2%) | −0.02 |

| Posttreatment covariates            |                 |                 |                   |                 |                 |                   |
| Science efficacy                    | −0.12 (0.98) | 0.30 (0.96) | −0.44 | 0.00 (0.98) | 0.10 (1.01) | −0.09 |
| Math efficacy                       | −0.04 (0.98) | 0.21 (1.00) | −0.25 | 0.03 (0.99) | 0.09 (1.01) | −0.06 |
| Science interest                    | −0.17 (0.98) | 0.33 (0.97) | −0.50 | −0.03 (0.99) | 0.10 (1.03) | −0.13 |
| Math interest                       | −0.03 (1.00) | 0.18 (1.01) | −0.21 | 0.00 (1.01) | 0.07 (1.01) | −0.07 |
| Science utility                     | −0.01 (0.07) | 0.02 (0.06) | −0.52 | 0.00 (0.07) | 0.01 (0.07) | −0.12 |
| Math utility                        | −0.04 (0.99) | 0.11 (0.99) | −0.16 | −0.01 (1.02) | 0.03 (1.00) | −0.04 |
| GPA in STEM                         | 2.49 (0.89) | 2.75 (0.86) | −0.29 | 2.59 (0.85) | 2.61 (0.92) | −0.02 |
| Math ability                        | 0.02 (0.91) | 0.38 (0.97) | −0.38 | 0.16 (0.93) | 0.19 (0.98) | −0.03 |
| AP credits                          | 1.00 (1.90) | 1.81 (2.56) | −0.36 | 1.28 (2.17) | 1.38 (2.28) | −0.04 |
| STEM credits                        | 7.61 (2.29) | 8.33 (2.37) | −0.31 | 7.81 (2.16) | 7.93 (2.47) | −0.05 |
| Math homework                       | 3.51 (1.53) | 3.82 (1.59) | −0.20 | 3.61 (1.53) | 3.64 (1.60) | −0.02 |
| Science homework                    | 3.38 (1.51) | 3.82 (1.60) | −0.28 | 3.50 (1.50) | 3.58 (1.60) | −0.05 |
| Mind-set beliefs                    | 2.52 (0.40) | 2.42 (0.40) | 0.25 | 2.49 (0.40) | 2.47 (0.40) | 0.05 |
| Educational aspirations              | 5.65 (1.47) | 6.11 (1.20) | −0.34 | 5.81 (1.36) | 5.85 (1.41) | −0.03 |
| Educational expectations             | 7.90 (2.89) | 8.88 (2.66) | −0.35 | 8.23 (2.70) | 8.32 (2.92) | −0.03 |
| Math effort                         | 0.04 (0.97) | 0.18 (0.91) | −0.15 | 0.07 (0.94) | 0.09 (0.97) | −0.03 |
| Science effort                      | 0.00 (0.96) | 0.21 (0.87) | −0.23 | 0.07 (0.93) | 0.11 (0.94) | −0.04 |
| Gender beliefs in math              | 3.11 (0.89) | 3.18 (0.87) | −0.07 | 3.13 (0.88) | 3.14 (0.89) | −0.01 |
| Gender beliefs in science           | 3.14 (0.80) | 3.17 (0.76) | −0.04 | 3.16 (0.79) | 3.16 (0.78) | 0.00 |

Note: The table reports means and standard deviations for continuous variables and frequencies and percentages for categorical variables. Standardized differences were calculated as described in Austin and Stuart (2015). Balance of the pretreatment covariates is assessed with respect to treatment, and balance of the posttreatment covariates is assessed with respect to the mediator. All weighted estimates were calculated using the weight with all pretreatment and posttreatment covariates. Descriptive statistics were calculated using the raw data, which can contain missing values. For conciseness, the levels of some categorical variables are not included in the table. AP = Advanced Placement; GPA = grade point average; STEM = science, technology, engineering, and mathematics.
connecting early-acquired attitudes and future career choices are not well understood. In this study, we argue that a plausible way to understand this relationship is by postulating a direct effect of early-acquired attitudes on future outcomes that is not mediated by more recent values of these same attitudes. This effect is referred to as the controlled direct effect of early-acquired attitudes.

The existence of a controlled direct effect of early-acquired attitudes on career-related outcomes justifies the idea that early interventions can generate more meaningful changes on adult outcomes (e.g., Legewie and DiPrete 2014a; Morgan et al. 2013; Thébaud and Charles 2018). If early-acquired attitudes affect adult choices and behaviors exclusively through their effect on proximal attitudes, then changing those proximal attitudes would suffice to erase the influence of early-life attitudes and experiences. If, on the other hand, early-acquired attitudes affect future outcomes independently of proximal attitudes, then intervening on the latter will not suffice and early-life interventions would be required.

We used the concepts of developmental cascades and critical periods to justify the existence of controlled direct effects of early-acquired attitudes. Developmental cascades involve cumulative and amplifying consequences of an initial trigger because of the ramification of its causal effects. Critical periods are characterized by the possibility of generating irreversible changes. In the present scenario, the irreversibility is implied by the idea that adult interventions cannot erase the effects of early-life experiences. These concepts explicate in what sense schooling can become ingrained and have long-lasting effects.

We investigated the potential long-lasting effects of early-life experiences on career-related outcomes by hypothesizing a substantial controlled direct effect of math and science identity beliefs in ninth grade on career and college outcomes in STEM. Individuals’ self-perceptions have been considered a determining factor in individuals’ career-related decision-making processes. Science and math identity beliefs have also been considered an important component of the emergence and persistence of the gender gap in STEM fields. Identity beliefs can be consequential in part because individuals’ perceptions as a science (or math) “kind of person” may influence a range of attitudes (e.g., interest, expectations) and behaviors (e.g., course taking, effort) that can ultimately affect their career-related choices. Thus, we hypothesize that individuals’ math and science identity beliefs in ninth grade have an effect on career and college outcomes, above and beyond future values of those identity beliefs.

We used inverse probability–weighted marginal structural models to estimate the controlled direct effect of identity beliefs in school on career-related outcomes. Contrary to traditional regression analysis, marginal structural models allow us to deal with the two confounding assumptions required to estimated direct controlled effects without underestimating the effect of interest. The results suggest that identifying with science or math in ninth grade increases the odds of enrolling in a STEM major by 26 percent and 44 percent, respectively, after holding identity beliefs in college constant. Having these identity beliefs also increase the odds of expecting to have a STEM career by 42 percent and 38 percent, respectively. These results are consistent with the idea that attitudes acquired early in life matter, independently of the attitudes we might develop later on.

These results suggest, then, that individuals’ identity beliefs in ninth grade affect their career choices and behaviors, after controlling for individuals’ identity beliefs at the moment of making their decisions. This controlled direct effect emerges because individuals’ early self-perceptions affect a variety of attitudes and behaviors that influence career-related outcomes through pathways different from subsequent identity beliefs. For example, individuals’ self-perceptions can affect the courses they take, the effort and time they spend on specific subjects, and the interests and aspirations they develop. These attitudes and behaviors can shape individuals career trajectories independently of their future identity beliefs. This ramification of causal effects is what generates the cascading and potentially irreversible consequences of early-life experiences.

The use of inverse probability weights allowed us to control for measured confounders without blocking the effect of interest, but do not address unmeasured confounders. We minimize this problem by including a wide range of relevant pretreatment and posttreatment confounders. In addition, we showed that the estimates remain stable when different potential confounders are used to estimate the inverse probability weights. However, unmeasured confounding remains a possibility. We also assume that the outcome and the identity beliefs in the two measurement occasions were measured without error.

In conclusion, the results of the present study suggest that the way in which individuals perceive themselves with respect to science and math in school affects their future college and career outcomes in STEM, independently of how they perceive themselves in the future. These results are consistent with idea that the attitudes developed early in life, in particular in adolescence, can have long-lasting effects on individuals’ career trajectories.

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Supplemental Material
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