Performance and decisions: immigrant–native gaps in educational transitions in Italy

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Performance and decisions. Immigrant-native gaps in educational transitions in Italy

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Abstract
Following the seminal work of Boudon (1974), sociological research has conceptualized immigrant-native gaps in educational transitions as deriving from children of immigrants' poorer academic performance (primary effects) and from different decision models existing between native and immigrant families (secondary effects). The limited evidence on immigrant-native gaps in Europe indicates that secondary effects are generally positive: children of immigrants tend to make more ambitious educational choices than natives with the same prior performance. In this paper we review the different decomposition methods employed so far in the literature to tackle similar research questions, and extend the existing methodology to allow including interaction effects and taking explanatory variables under control. We apply this method to data coming from a unique Italian administrative dataset. We find that children of immigrants exhibit higher likelihood to opt for vocational training over more generalist and academic programs, even when controlling for socioeconomic background. A large share of the immigrant-native differentials in the probability to attend the different school programs is explained by the different prior performance distribution. However, decision models differ between groups, and, contrary to the evidence on other countries, these differences contribute to widening the existing gaps. If children of immigrants had the same social background and prior performance of their native peers, they still would be more likely to enroll in shorter and less demanding school programs. Interestingly, these results hold true only for boys, while we find no evidence of decision effects for girls.

1. Introduction

A considerable amount of empirical research has pointed out the existence of sizeable immigrant-native gaps in educational outcomes in several European countries. The children of immigrants generally have poorer schooling performance and attain lower educational levels (Heath, Rothon and Kilpi, 2008). Parental socio-economic and cultural background explain the educational disadvantage of migrant children to a significant extent. However, even after accounting for socioeconomic background, a residual disadvantage persists (ibid).

Following the distinction between primary and secondary effects (Boudon 1974) originally applied to social origin differentials (Erikson *et al* 2005; Jackson 2013), a number of recent contributions in the sociological literature have focused on migrant-native gaps in educational transitions to upper secondary school and tertiary education. The aim of these studies is to evaluate to what extent the observed less demanding educational choices of children of immigrants can be ascribed to their poorer school *performance* (primary effects), and to what extent, instead, they are due to different

decisions (secondary effects). If the latter operate, the probability to make a specific educational transition differs between children of immigrants and natives, even when controlling for prior school performance.

The empirical evidence on native-migrants differentials in educational transitions is limited to a few countries. Given prior achievement, students with an immigrant background tend to make more ambitious educational choices. This the case of Turks in Germany, who perform poorly in compulsory education but then show even higher tertiary education enrollment rates than natives, net of previous achievement (Kristen, Reimer, and Kogan 2008). Similar patterns hold for second-generation immigrants in France (Cebolla-Boado 2011), in England and Sweden (Jackson, Jonsson, and Rudolphi, 2012) and in the US (Waters, Heath *et al.* 2013). In Italy, a new immigration country, children of immigrants persistently lag behind natives with regard to transition rates to academic education, while they show a higher propensity to attend vocational educational programs. However, as opposed to the evidence on other countries, children of immigrants' disadvantage in educational transitions appears to persist even after controlling for previous grades (Barban and White, 2011).

Our contribution to the literature is twofold. Firstly, we complement the work of Barban and White (2011) – who use survey data on different areas of the country, but plagued by severe attrition issues – with an analysis of transitions to upper secondary education, by exploiting recent longitudinal administrative school data for the autonomous Province of Trento. This is quite a unique source of information, as Italy still lacks of an integrated official data system on schooling careers. This archive provides very good quality data, and unaffected by sample selection issues. Secondly, our paper aims at offering a methodological contribution. We first review the methods available in the literature to evaluate primary and secondary effects and discuss points of strength and limitations of each. There are basically two competing approaches: the counterfactual approach (Erikson *et al.* 2005; Morgan 2012) and the Breen-Holms-Karlson (BHK) method. The first, as employed in the existing literature, does not allow using control variables, while the second does not allow the inclusion of interaction effects. Yet, both these features may be empirically relevant. Thus, we extend the counterfactual approach in order to allow the inclusion of control variables and apply it to immigrant background differentials in transitions to upper secondary education.

2. Primary and secondary effects in educational transitions

Building on Boudon's (1974) seminal work, social-background inequalities in educational attainment have been recently studied in the sociological literature elaborating on a behavioral

model according to which, first, students achieve some scholastic results, and then, students (and their families) make their educational decisions based on these results and their social positioning. Two distinct mechanisms linking social origin and education have been identified. The first of these mechanisms, called "primary effects", refers to the association between social origins and individuals' educational choices that is mediated by academic performance. The second mechanism, referred as "secondary effects", identifies the differences in educational attainment between social groups that persist given previous performance. These are related to families' decision processes, and are a consequence of socially structured differences in sensitivity and perceptions about costs and benefits of educational investments, as well as in perceived risks associated with the expected probability of children's success (Erikson and Jonsson 1996; Goldthorpe 1996; Breen and Goldthorpe, 1997). Primary effects are measured with the share of the social group differentials explained by different performance, while secondary effects are captured by the residual direct effect of social groups on educational choices.

The distinction between primary and secondary effects is viewed as a policy-relevant issue. Secondary effects are related to institutional features, and considered easier to address with educational policies – for example, interventions providing information on the schooling system and the labor market, or providing incentives to make more ambitious educational choices. Consistently, recent comparative research on social origin inequalities in the transition to upper secondary and tertiary education (Jackson, 2013) shows that primary effects are quite stable across European countries, and that cross-country differences in social origin differentials are mainly driven by differences in secondary effects.

This framework can be extended in order to study educational inequalities related to individuals' immigrant background. Primary and secondary effects should be understood as immigrant background-specific effects, i.e., after controlling for social background. This point is particularly relevant, as immigrant families are often over-represented among the lowest social strata (Heath, Rothon and Kilpi, 2008).

Negative primary effects of immigrant background are related to mastery of the host-country language and cultural differences between native and immigrant families. As children of immigrants might not be as exposed as natives to the culture prevailing in the country, they might encounter difficulties in meeting the demands of teachers and interacting with them (Heath and Brinbaum 2007, Becker 2009). In addition, immigrant parents might lack country specific human capital and access to the type of social networks enhancing their knowledge on the school system of

the host country, and this might reduce their capability of supporting children's schooling since the early years (Kristen 2005).

Information and knowledge of the destination country educational system may contribute to secondary effects of immigrant background. Information is a key resource at educational transition points as knowledge about school curricula, post-school outcomes and relevant regulations can be crucial for making the "right choice". Immigrant parents might lack information about the outcomes of the different educational options, also in terms of labor market returns (Morgan 2005), and this might have detrimental effects on educational investments. Negative secondary effects could also be driven by teachers, who may discriminate against immigrants, by counseling families to enroll their children in short-term educational tracks (Kristen and Granato 2007). Positive secondary effects, instead, may be due to higher aspirations of immigrant families (Kao and Tienda 1995, 1998), and by anticipation of discrimination in the labor market.

Although the application of this analytical framework to migrant-native educational gaps is a rather novel research stream, extant research on selected European countries suggests that children of immigrants' educational attainment disadvantage is entirely driven by their lower previous performance (Cebolla-Boado 2011, Jackson, Jonnsson and Rudolphi 2012, Kristen and Dollmann 2010). According to these studies, when controlling for social background and earlier performance, children of immigrants show even higher propensities to make educational transitions towards higher levels of education and more prestigious educational programs than native children. In other words, there is evidence of positive secondary effects of immigrant background.

3. Decomposition methods in the literature

A recent strand of the empirical literature in sociology of education has focused on quantifying the relative importance of primary and secondary effects in specific educational transitions. Particular attention has been given to the choice of upper secondary school (continuation vs. exit from the schooling system or choice of general vs. vocational educational programs) and to the transition to tertiary education. These methods build on a very simple model. Let us focus on social origin differentials: social origin influences the performance prior to the transition, and prior performance affects educational choices; however, social origin may also have a direct effect on educational choices, given prior performance. The aim is to assess to what extent social origin differentials in the probability to make a specific transition are explained by prior performance, and to what extent they are captured by other mechanisms, related to families' and individuals' decision process.

This issue brings back to the *Blinder-Oaxaca decomposition* (Blinder, 1973 and Oaxaca,1973) that aims at quantifying the degree to which explanatory variables account for the average differential between two groups in linear model for a continuous dependent variable Y. Consider the model: $E(Y_G|z) = \alpha_G + \beta_G z$, where G is the group indicator taking values 1 and 2, and z the relevant explanatory variables. The average sample differential between the two groups can be split as follows:

$$\bar{y}_1 - \bar{y}_2 = (\bar{z}_1 - \bar{z}_2)\hat{\beta}_1 + \left[(\hat{\alpha}_1 - \hat{\alpha}_2) + \bar{z}_2(\hat{\beta}_1 - \hat{\beta}_2)\right] \tag{1}$$

The first term in the right hand side is the component explained by the different distribution of covariates across groups, the second is the unexplained component, which includes the difference in the intercepts and interaction effects between z and G (in economic terms, different returns of z for the two groups). Clearly, there is also an alternative decomposition: $\bar{y}_1 - \bar{y}_2 = (\bar{z}_1 - \bar{z}_2)\hat{\beta}_2 + \left[(\hat{\alpha}_1 - \hat{\alpha}_2) + \bar{z}_1(\hat{\beta}_1 - \hat{\beta}_2)\right]$ that may result in a different share of explained and unexplained effects. If Y is an educational outcome and z is prior performance, there is an evident logical equivalence between primary effects and the explained component on one side, and secondary effects and the unexplained component on the other side. However, this simple decomposition does not apply to non-linear models.

Consider now a *binary response variable Y* taking values 0 and 1. Following the tradition in the stratification literature in the sociological field that focuses on odds-ratios, Erikson *et al.* (2005) propose a method that splits observed odds-ratios into components that involve the computation of so-called "counterfactuals" – connoted in a purely descriptive sense. This term is used to characterize the probabilities of making the educational choice of interest (let us call it "transition probability") that would be observed if individuals of group j (say, low social class) had their own performance distribution, but the transition probabilities given performance z of individuals of group k (high social class). Alternatively, the transition probabilities that would be observed if individuals of group j had their own conditional transition probability function, but the performance distribution of group k. Observed probabilities given social origin can be decomposed as follows:

$$p_{jj} = P(Y = 1| G = j) = \int_z P(Y = 1|z, G = j)P(z|G = j)\,dz \tag{2}$$

Similarly, counterfactuals are defined as:

$$p_{jk} = \int_z P(Y = 1|z, G = j)P(z|G = k)\,dz \tag{3a}$$

$$p_{kj} = \int_z P(Y = 1|z, G = k)P(z|G = j)\,dz \tag{3b}$$

in which the transition probabilities given performance of one class are averaged over the performance distribution of another class.

Typically, transition probabilities are estimated with logit models, either separately for each social origin group, or with interaction effects between social origin and performance, to allow more flexibility and account for the evidence in the literature that children of high family background are less sensitive to performance. Performance distributions, on the other hand, are either approximated by a normal distribution or estimated non-parametrically (Buis 2010).

Once observed and counterfactual probabilities have been computed, the observed odds-ratio can be decomposed as:

$$OR = \frac{p_{jj}/(1-p_{jj})}{p_{kk}/(1-p_{kk})} = \left(\frac{p_{kj}/(1-p_{kj})}{p_{kk}/(1-p_{kk})}\right)\left(\frac{p_{jj}/(1-p_{jj})}{p_{kj}/(1-p_{kj})}\right) = \left(\frac{p_{jj}/(1-p_{jj})}{p_{jk}/(1-p_{jk})}\right)\left(\frac{p_{jk}/(1-p_{jk})}{p_{kk}/(1-p_{kk})}\right) \qquad (4)$$

There are two possible decompositions, according to which counterfactual (p_{jk} or p_{kj}) is considered. First factors capture primary effects, as what changes is the performance distribution, while the transition probability conditional on performance is kept constant. Second factors capture secondary effects, as the performance distribution is fixed while the conditional transition probability changes. The authors apply additive decompositions of $\ln(OR)$, and present as result the average the two relative contributions of primary and secondary effects.

In the same perspective, instead of focusing on *odds-ratios*, Morgan (2012) applies the decomposition to probability *differences*:

$$p_{jj} - p_{kk} = (p_{kj} - p_{kk}) + (p_{jj} - p_{kj}) = (p_{jj} - p_{jk}) + (p_{jk} - p_{kk}) \qquad (5)$$

Once again, there are two alternative decompositions, according to which counterfactual is considered. The first terms in the right hand side represent primary effects (the component explained by different prior performance), while the last represent secondary effects (the direct effect given prior performance). Yet, while Erikson *et al*. (2005) propose to summarize the relative contribution of primary and secondary effects by averaging the two ratios, Morgan argues that both decompositions are informative and suggests considering them separately.

Although not acknowledged in the paper, Morgan's method is basically equivalent to the extension of the Blinder-Oaxaca decomposition to binary response models proposed by Fairlie (2005). Using Fairlie's notation, the decomposition is:

$$\bar{y}_1 - \bar{y}_2 = \left[\sum_{i=1}^{n_1} \frac{F(z_{i1}\hat{\beta}_1)}{n_1} - \sum_{i=1}^{n_2} \frac{F(z_{i2}\hat{\beta}_1)}{n_2}\right] + \left[\sum_{i=1}^{n_2} \frac{F(z_{i2}\hat{\beta}_1)}{n_2} - \sum_{i=1}^{n_2} \frac{F(z_{i2}\hat{\beta}_2)}{n_2}\right] \qquad (6)$$

where $F(z) = P(Y = 1|z)$, $\hat{\beta}_1$ and $\hat{\beta}_2$ the regression coefficient estimates for the two groups, and n are group sample sizes. Note that this formulation is a version of (5) with a fully non-parametric estimate of the distribution of z, obtained by using directly the observed sample values.

The methods described above produce a decomposition of the *probability* difference of a given outcome among groups (Morgan and Fairlie), or the decomposition of the odds-ratio, i.e. a function of these group probabilities (Erikson *et al.*, 2005). A different approach has been offered by Karlson and Holm (2011), Karlson, Holm and Breen (2012), and Breen, Karlson and Holm (2013), who provide a method to decompose *regression coefficients*. Their starting point is the well-known difficulty, due to scaling issues, to compare logit and probit model coefficients of nested models. These scholars propose a method that allows making the comparison, and Karlson and Holm (2011) apply this method to address the substantive issue of estimating primary and secondary effects in educational transitions.

Let us briefly overview the rationale. Consider a linear model for a continuous variable Y such as, for example, wage. Suppose we wish to assess the direct effect of parental social origin and its indirect effect via the person's own educational attainment. Consider two different models: the first, with social origin only, the second, in which we add educational attainment. The coefficient of social origin in the first model is the total effect, while the corresponding coefficient in the second model captures the direct effect of social origin, given educational attainment. The indirect effect of social origin via educational attainment is the difference between these two estimates. Note that this decomposition is equivalent to the Blinder-Oaxaca decomposition, in a model with no interaction between social origin and educational attainment: indirect and direct effects correspond to the explained and unexplained components respectively.

This simple property does not hold for non-linear models. Let us think of regression for binary response variables as a way of modelling outcome Y as the observed counterpart of an unobserved continuous latent variable Y^*, so that when $y^* > 0$, $y = 1$ and when $y^* < 0$, $y = 0$. The latent variable model can be written as: $y^* = \alpha + \beta x + \varepsilon$. To estimate the model we must impose identifiability restrictions and fix the distribution and the variance of the error term. In logit regression, we impose ε to be a standard logistic random variable (with variance $\pi^2/3$). Consequently, when we estimate the logit model for $P(Y = 1|x)$ the estimable parameter is β/σ_ε (Wooldridge 2002). In other words, we standardize the true coefficient β so that residuals have the variance of a standard logistic distribution. When we add a relevant explanatory variable in the regression: $y^* = \alpha + \delta x + \gamma z + \varepsilon'$, the residual variance in the latent model decreases ($\sigma_{\varepsilon'} < \sigma_\varepsilon$).

Yet, to allow identification we must impose a standard logistic distribution for residuals. Hence, we now estimate $\delta/\sigma_{\varepsilon\prime}$, which is not directly comparable to β/σ_ε.

Although this is a well-known issue, many scholars still interpret coefficients in nested models as if they were directly comparable. Karlson and Holm (2011), Karlson, Holm and Breen (2012) and Breen *et al*. (2013) suggest a method (with acronym BHK) to overcome the scaling problem. Instead of comparing the logit regression estimate of the *x* coefficient from the full model (with *x* and *z*), to the estimate from the reduced model (with *x* only), they compare it with the estimate of a reparametrization of the full model (modified full model), which includes *x* and the residual $\tilde{z}$ of the OLS regression of *z* on *x*. Since the residual is by construction uncorrelated with *x*, confounding effects are eliminated. On the other hand, (*x*,*z*) and (*x*,$\tilde{z}$) have the same explanatory power. Thus, these two models share the same error term, solving the problem due to different scaling. In sum, the *x* coefficient of the modified full model captures the total effect of *x*, while the *x* coefficient of the original full model estimates direct effects via *z*. Indirect effects are the difference between the two.

When applied to the study of social origin inequalities in the choice of the upper secondary school track *Y*, *x* is social background (previously indicated by group *G*) and *z* is prior performance. The total effect of social origin is represented by the *x* regression coefficient of the modified full model with *x* and $\tilde{z}$, while the direct effect given prior performance is the regression coefficient of the original full model with *x* and *z*.

4. Accounting for control variables and interaction effects

4.1 Rationale

In Section 3, we described different methods employed in the literature to decompose the effects of a categorical explanatory variable *x* on a binary response variable *y*, into direct effects and indirect effects via another explanatory variable *z*, itself dependent on *x*. These methods follow two different approaches, each having strengths and limitations.

The first approach – proposed by Erikson *et al*. (2005) and developed in Morgan (2012) – allows including interaction effects between the grouping variable (social origin) and the mediating variable (prior performance), but additional explanatory variables cannot be taken under control. In contrast, the BHK method easily allows incorporating control variables by simply including them in the models, but does not allow including interaction effects. However, both issues are potentially relevant when studying migrant-natives differentials in educational transitions. On one side, we would like to analyze the migrant-native gap after having removed the potentially confounding

effect of social origin. On the other side, we would like to allow for interaction effects between immigrant background and prior performance, to account for the fact that the relation between performance and educational choices may differ between migrants and natives. For example, Bernardi and Cebolla-Boado (2013) find empirical evidence of interaction effects between grades and social origin in educational transitions.

In this paper, we exploit the counterfactual approach – naturally incorporating interaction effects – and extend it to allow the inclusion of control variables. Following Morgan (2012), we apply the decomposition to probability differences, which appear to be more easily interpretable than odd-ratios. Our strategy consists in performing the decomposition for each value of the control variables vector, and then averaging over the distribution of control variables for natives.

The variables under study are nativity status (*G=N* or *G=M*), social background (defined by parental occupation and parental education and denoted by *w*), prior performance (*z*) and upper secondary school choices *Y*. We assume the causal path depicted in Figure 1.

Figure 1. **Causal relations among the variables**.
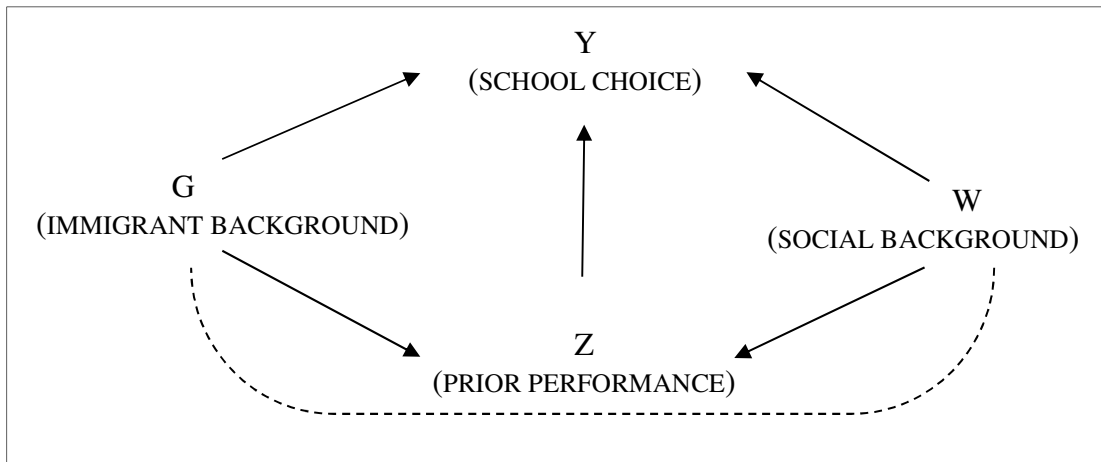
NOTE. Arrows indicate the direction of causal relations (if these relations exist). Dotted curves indicate a generic association.

Consider the probability to make the educational transition given performance *z*, native-immigrant background (*G=N* or *G=M*) and control variables *w*. We can express observable and counterfactual probabilities for each group G, *conditional* on control variables like in (2) and (3).

Observable probabilities are:

$$P(Y = 1|w, G = N) = p_{NN|w} = \int_z P(Y = 1|w, z, G = N)P(z|w, G = N)dz \qquad (7a)$$

$$P(Y = 1|w, G = M) = p_{MM|w} = \int_z P(Y = 1|w, z, G = M)P(z|w, G = M)dz \quad (7b)$$

The corresponding counterfactuals are:

$$p_{NM|w} = \int_z P(Y = 1|w, z, G = N)P(z|w, G = M)dz \tag{8a}$$

$$p_{MN|w} = \int_z P(Y = 1|w, z, G = M)P(z|w, G = N)dz \tag{8b}$$

The first expression corresponds to the probability that immigrant background children would experience if they had the transition probability given grades of natives (or, equivalently, the probability of native children with the performance distribution of children of immigrants). The second expression refers to the transition probability of immigrants' children with the performance distribution of natives.

We apply Morgan's decomposition to each value of social background w, and subsequently average over w, using the control variables distribution of natives. We use the control variables distribution of natives because our substantive interest is in analyzing newcomers' educational participation relatively to the non-migrant student population. Patently, it would also be possible to average over the distribution of children of immigrants. By imposing a specific distribution of social background, we eliminate possible confounding effects due to the different distribution over children of immigrants and natives. Trivially, this procedure is equivalent to first averaging transition probabilities over w and then applying the decomposition.

The "observed" probability for natives is then:

$$p_{NN}^N = P(Y = 1| G = N) = \int_w p_{NN|w} P(w|G = N)dw \tag{9}$$

whereas the corresponding probability for children of immigrants, i.e. the transition probability of children of immigrants had they the social background distribution of natives, is:

$$p_{MM}^N = \int_w p_{MM|w} P(w|G = N)dw \tag{10}$$

Counterfactuals are:

$$p_{MN}^N = \int_w p_{MN|w} P(w|G = N)dw \tag{11a}$$

$$p_{NM}^N = \int_w p_{NM|w} P(w|G = N)dw \tag{11b}$$

The decompositions into primary and secondary effects can be obtained as follows:

$$p_{NN}^N - p_{MM}^N = (p_{NN}^N - p_{NM}^N) + (p_{NM}^N - p_{MM}^N) \tag{12a}$$

$$p_{NN}^N - p_{MM}^N = (p_{MN}^N - p_{MM}^N) + (p_{NN}^N - p_{MN}^N) \tag{12b}$$

The first terms represent primary effects, as we fix the conditional transition probabilities and change the performance distribution; the second terms represent secondary effects, as what changes is the performance distribution, while transition probabilities given performance are fixed. Since we consider more meaningful imagining the children of immigrants having the performance distribution of natives rather that the opposite, our preferred decomposition is (12a).

Note that these decompositions are completely general and that in principle any method – parametric or non-parametric – can be employed to estimate each of the distributions of interest: $P(w|G)$, $P(z|w,G)$, $P(Y|z,w,G)$. These models can also include interaction effects. While the related existing literature generally focuses on binary choices – continuation vs. exit from the schooling system – studies on transitions to upper secondary school may also consider more than two choices if the school systems offers substantially different school-types. If the categorical dependent variable has multiple values, the procedure can be immediately extended to multinomial or ordinal logit estimation. In this case, we would estimate the probabilities $P(Y = j|z,w,G)$ for all j, and apply the decomposition to each value of Y.

Let us go back to Fairlie's decomposition. Equation (6) allows evaluating the contribution of migrant-natives differences in the entire set of independent variables. Yet, Fairlie (2005) also proposed a variant for further splitting the explained component into the separate contributions of each explanatory variable. In a model with two explanatory variables where $P(Y_G = 1) = F(\beta_{1G} z_1 + \beta_{2G} z_2)$, the contribution of z_1 to the differential between the two groups $G=1$ and $G=2$ can be expressed as:

$$\frac{1}{n_2}\sum_{i=1}^{n_2}\left(F\left(z_{1i,G=1}\hat{\beta}_{1,G=2} + z_{2i,G=2}\hat{\beta}_{2,G=2}\right) - F\left(z_{1i,G=2}\hat{\beta}_{1,G=2} + z_{2i,G=2}\hat{\beta}_{2,G=2}\right)\right) \quad (13)$$

The contribution of z_1 to the gap is equal to the change in the average predicted probability from replacing the z_1-distribution of $G=2$ with that of $G=1$, while holding constant the distribution of z_2. Conditional probabilities are averaged over the observed values of explanatory variables. Transition probabilities of group 2 are applied to group 1. To make the calculation, individuals of group 1 and 2 are matched, in order to assign explanatory variable z_1 of an individual of group 1 to an individual of group 2. This is accomplished by drawing random subsamples of equal size from the two groups, and matching them according to predicted probabilities of $Y = 1$.

Despite the similarity, this method and our own differ in the question they address. Consider again migrant-native gaps in educational transitions. Fairlie's procedure may provide an answer to the following question: What share of the migrant-native gap is due the different distribution of prior performance between natives and children of immigrants? What share is due to the different

distribution of social origin? The remaining component of the gap is due to migrant-native differentials in the coefficients, i.e. to the potentially different ways performance and social origin affect the transition probability across the two groups. Prior performance and social origin here are treated symmetrically.

To our research aim, instead, prior performance and social background play different roles (see Figure 1). We are interested in migrant-native differentials arising via prior performance (since prior performance is itself dependent on immigrant background), and given prior performance, when controlling for the confounding effect of social origin. We accomplish this by imposing the same social background distribution – that of natives – to both groups. The quantities we compare – estimated observed and counterfactual probabilities – are consistent with this causal path. Consequently, while in our method primary and secondary effects (or explained and unexplained components) are the averages of the corresponding effects for each social origin level, this is not the case for Fairlie's procedure.

4.2 Implementation of the decomposition

We now summarize how the decomposition is obtained.

The first step is to estimate each of the distributions of interest: $P(w|G)$, $P(z|w,G)$, $P(Y|z,w,G)$. As noted above, this can be done with any method considered appropriate for the specific data and variables involved. In our empirical application, we estimate the distribution of school-type Y and socioeconomic background w with a multinomial logit model, and the distribution of prior performance z with an ordinal logit model.

The second step is to compute all observed and counterfactual probabilities: p_{NN}^N, p_{MM}^N, p_{NM}^N, p_{MN}^N, by averaging the transition probability over the distribution of the appropriate z and w, according to expressions (7)-(12). Since in our case-study all variables of interest are categorical (see Section 5), integrals are substituted by summations (non-parametric techniques similar to that proposed in Buis, 2010 could be employed for continuous z or w).

Finally, we compute decompositions (12a) and/or (12b).

5. Data and empirical results

5.1 Data and the Italian upper secondary schooling system

Regrettably, Italy still lacks of an integrated official data system on schooling careers. Instead, high quality administrative data (AUS-PAT) is collected in the Province of Trento, covering the entire student population enrolled in the educational system. This archive represents a unique source of

high quality longitudinal information in Italy. Key information such as grades and school enrollment are registered on a yearly basis by school offices. In addition, students' demographic information (including country of birth of both students and their parents) are obtained directly from the tax code of both the students and their parents, largely reducing misreporting and measurement error. The data we analyze refer to the school cohort that successfully completed lower secondary school in school year 2009/2010, and making the transition to upper secondary education in the following year. Data comprise 5751 students (732 of which having an immigrant background), leaving from 90 lower secondary schools and enrolling in 52 upper secondary schools or vocational training centers.

We focus on the transition from lower to upper secondary education. School is compulsory up to age 16. At the age of 14 years, upon completion of lower secondary education, students face a choice among four school types: (a) general schools (*licei*), which are academically oriented, and include both scientific as well as classical and socio-pedagogical curricula; (b) technical schools (*istituti tecnici*), which combine general and vocational education and include business and technological paths; (c) vocational schools (*istituti professionali*), providing some general education, but mainly vocationally oriented; and, finally, (d) vocational training courses (*formazione professionale*), providing a fully work-oriented instruction. While the first three options are administered at the national level, vocational training courses are offered by regional authorities. Most importantly, the first three options last five years, after which students face a school-type specific national examination (*esame di maturità*) and eventually attain the upper secondary school diploma. Instead, vocational training courses last three-four years and do not allow a direct transition to tertiary education. However, students of vocational training courses may continue for two additional years and attain the upper secondary diploma. All students with the diploma are eligible for higher education, and there are generally no restrictions based on prior performance. However, transition rates to university vary greatly between tracks, with students from general schools having the highest chances of continuation and those from vocational schools the lowest.

Although the province of Trento enjoys a high degree of autonomy in educational policies, the organizational structure of the education system is the same as the national one and participation rates are similar to those at the national level. However, there is a remarkable difference regarding *vocational training courses*, as the supply of these programs and the share of students enrolled is much higher in the province of Trento than in the rest of the country. This peculiarity turns out to be particularly interesting, as participation to vocational training courses has been continuously

expanding at the national level in the past years (ISFOL, 2012). Hence, despite the local character of the analysis, this case study provides results that are likely to be relevant also at the national level in the upcoming years.

5.2 Variables

To identify students' immigrant background we consider two categories: natives, defined as native-born children with at least one native-born parent, and children of immigrants, defined as foreign-born children with both parents born abroad (first generation students) or native-born children with both foreign-born parents (second generation students).

First generation students represent 76% of the children of immigrants, while 24% are second-generation. Mixed-parentage children account for 8.3% of the native students. The large majority of children of immigrants are of Eastern Europe ancestry (56.8%). We then find students of Northern and sub-Saharan African origins (18%), followed by Latin American students (12%), Asian students (9%) and students from Western countries (4%). Due to small sample size, in the empirical analyses we will not disaggregate the children of immigrants according to generational status or country of origin.

To measure family social origin we use information collected by school offices through students' registration forms. We define parental education as the highest level reached by any of the two parents (dominance criterion), or by the single adult living with the student, according to the categories: tertiary degree, upper secondary education diploma, vocational qualification, and lower secondary education certificate or lower. We apply the dominance criterion also for parental occupation, to classify students into the EGP social class scheme (Erikson, Goldthorpe and Portocarero, 1979) adapted to four categories: large entrepreneurs, professionals and managers; intermediate employees; small employers and self-employed; working class.

Prior performance is measured by the grade obtained on the final exam of lower secondary education. Grades are expressed in numerical form, ranging from six to ten.

Table 1 shows the distribution of the dependent and independent variables employed in the analysis by immigrant status. Immigrant background students make different school choices as compared to natives. In particular, they exhibit a twice as higher probability of enrolling in vocational training courses (.395 vs .206) and a much lower propensity to attend general schools (.260 vs .407). In addition, the children of immigrants display a lower chance of enrolling in technical schools, while there are essentially no differences as regards vocational schools.

Turning to the explanatory variables, the average grade obtained by children of immigrants on the final exam of lower secondary education (6.77) is substantially lower than that of natives (7.50). As for social origins, we find some differences in parental education, but in particular on parental class: the great majority of immigrants' children have parents in the working class (76%, excluding missing values), whereas only 28% of natives belong to this category. Note that missing information on parental education and class variables is substantial and unevenly distributed across the two groups: for this reason, we will include missing cases in the model estimation, by placing them in a separate category. Missing information may be due to families' reluctance to answer and school offices lacking of compliance with data collection or to the greater territorial mobility of migrants (information on family background is usually collected during the first school-year and may be missing if students arrive at a later point in time).

Table 1. Student characteristics by immigrant background

	NATIVE CHILDREN	IMMIGRANTS' CHILDREN
School-type		
Vocational training	.206	.395
Vocational School	.059	.056
Technical School	.328	.290
General School	.407	.260
Lower secondary school final grade (average)	7.50	6.77
Parental education		
University Degree	.149	.150
Upper secondary Diploma	.416	.366
Vocational Qualification	.236	.153
Lower secondary education or below	.200	.331
(Missing)	(.273)	(.385)
Parental class		
Large entrepreneurs, professionals and managers	.136	.029
Intermediate employees	.413	.138
Small employers and self-employed	.171	.073
Working class	.280	.761
(Missing)	(.279)	(.339)
Female	.481	.470
Sample size	5019	732
%	87.3	12.7

5.3 Empirical analyses and results

As a first step, we analyze transition probabilities conditional on migrant background status, social origin, and prior performance. We consider a variety of models: we focus on two binary choices, distinguishing the most and the least academically demanding options: (i) general schools vs. all other options; (ii) vocational training courses vs. all other options. In addition, to account for the entire set of options children face when entering upper secondary education we use ordinal and multinomial logit models; the first, to obtain a more parsimonious specification, the second, to

allow for less stringent assumptions. In the former, the options are ranked from the least to the most demanding in terms of academic targets: vocational training courses, vocational schools, technical schools, general schools. Results on binary and ordinal logit models are shown in Table 2, while those on multinomial estimation are omitted because they do not add much in terms of interpretation.

The statistical significance of the immigrant background coefficients in all models suggests that the decision processes of children of immigrants and natives are to some extent different. Immigrant background students have a higher propensity than natives to attend vocational training courses, even after controlling for social background and prior performance. This is a signal of the existence of negative secondary effects. However, when we examine the choice of general schools vs. others and the ordinal logit model for the entire set of options, the picture is not as clear. Here the immigrant background coefficient is negative, but there is a significant interaction effect with lower secondary school grades: while the poorest performing students exhibit a lower propensity to choose more demanding school-types than natives, the opposite occurs for well performing students.

Table 2. Upper secondary school choices. Estimates of binary logit and ordinal logit models

	General schools vs. others (binary logit coefficients)	Vocational training vs others (binary logit coefficients)	All options (ordinal logit coefficients)
Immigrant background	-0.410**	0.343**	-0.454**
Female	1.097**	-0.208**	0.565**
Parental education (ref 4)			
Missing	-1.415**	1.215**	-1.300**
Parental education 1	-1.343**	1.182**	-1.200**
Parental education 2	-1.362**	0.889*	-1.036**
Parental education 3	-0.880**	0.458*	-0.649**
Parental occupation (ref 4)			
Missing	0.267	0.054	0.141
Parental occupation 1	-0.533**	0.670**	-0.558**
Parental occupation 2	-0.521**	0.486*	-0.450**
Parental occupation 3	-0.356**	0.041	-0.255*
Final mark	0.788**	-1.182**	0.855**
Final mark*immigrant background	0.267**	-0.145	0.315**
Constant	-0.918**	-1.245**	-
cut1	-	-	-0.923
cut2	-	-	0.940
cut3	-	-	1.336
Pseudo R2	*0.253*	*0.255*	*0.168*

*p-value<0.05; **p-value<0.01

NOTES. Parental education: 1: <=lower secondary degree; 2: vocational qualification; 3: upper secondary degree; 4: tertiary degree. Parental occupation: 1: working class; 2: small employers and self-employed; 3: intermediate employees; 4: large entrepreneurs, professionals and managers. Final marks: recoded from 6-10 to 0-4.

The issue now is: do these differences in decision models play a role in explaining observed migrant-native differentials in upper secondary educational choices? If so, do they contribute to raising or reducing the gaps? In this perspective, we now apply the decompositions (12a) and (12b). To this aim, we consider more flexible model specifications than those shown in Table 2. Conditional transition probabilities and performance distributions are estimated separately for children of immigrants and natives: the first with multinomial logit models, to account for the entire set of available options; the second with ordinal logit models. In both cases, we consider all possible interactions between parental education and occupation, including missing data categories. Moreover, since educational decisions differ considerably between males and females, we perform separate analyses by gender. The estimates of observed and counterfactual probabilities are summarized in Table 3.

Table 3. Observed and counterfactual probabilities to upper secondary school, by gender

PANEL (A)		MALES		
SCHOOL TYPE	TRANSITION / PERFORMANCE	Children of immigrants (natives' social origin)	Natives (natives' social origin)	Children of immigrants (own social origin)
General schools	Children of immigrants	0.199	0.207	**0.157**
	Natives	0.293	**0.281**	
Technical schools	Children of immigrants	0.382	0.421	**0.356**
	Natives	0.379	**0.428**	
Vocational Schools	Children of immigrants	0.039	0.054	**0.035**
	Natives	0.034	**0.046**	
Vocational training	Children of immigrants	0.380	0.317	**0.451**
	Natives	0.294	**0.246**	
PANEL (B)		FEMALES		
SCHOOL TYPE	TRANSITION / PERFORMANCE	Children of immigrants (natives' social origin)	Natives (natives' social origin)	Children of immigrants (own social origin)
General schools	Children of immigrants	0.419	0.434	**0.376**
	Natives	0.535	**0.545**	
Technical schools	Children of immigrants	0.232	0.228	**0.206**
	Natives	0.213	**0.221**	
Vocational Schools	Children of immigrants	0.084	0.094	**0.077**
	Natives	0.085	**0.074**	
Vocational training	Children of immigrants	0.265	0.245	**0.342**
	Natives	0.166	**0.160**	

NOTES. Observable quantities are in bold. All other figures represent estimated counterfactuals.
Estimates of transition probabilities conditional on social origin and the lower secondary final examination grade based on separate multinomial models for immigrants' children or native children. Estimates of the distribution of final grades given social origin, based on separate ordinal logit models.

For each school-type, we report the enrollment probability corresponding to the performance distribution of one group (indicated in rows) and the transition probability of another group

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(indicated in columns). In the first two columns we consider natives' social origin distribution, in the last we apply to children of immigrants their own distribution. Consider as an illustrative example the attendance of vocational training courses for males. Our estimates – nearly coincident to the observed proportions – point to 45.1% among immigrants' children and 24.6% among natives. According to our estimates, if children of immigrants had the natives' social background distribution, the share would be 38.0%. Therefore, while the observed gap is 20.5 percentage points, when we account for social origin the gap goes down to 13.4 pp. (see also Table 4). *Ceteris paribus*, if children of immigrants also shared the same performance distribution of natives, the proportion would be 29.4%; if they shared the same decision rules, the proportion would be 31.7%.

In Table 4 we report the overall gap and estimates of primary and secondary effects. The first decomposition – where we look at what would happen if immigrant background children had the performance of distribution of natives – is obtained as follows: $0.246-0.380=(0.294-0.380)+(0.246-0.294)= -0.086-0.048$. The second one – if natives had the performance of distribution of immigrants – is instead: $0.246-0.380= (0.246-0.317)+(0.317-0.380)= -0.072-0.063$. In both cases we find that a substantial part of the gap is not explained by the lower grades of immigrant background children, but is due to different decision rules. As a second example, consider the male transition probabilities to general schools: the gap between natives and immigrant background children is 12.4 pp. When accounting for social origin this differential decreases to 8.2 pp. In this case, according to decomposition (12a), the entire gap is explained by prior performance; secondary effects go in the opposite direction, i.e. children of immigrants make more ambitious choices given prior performance than natives, but this effect is indeed very small. There is very little evidence of a role played by decision rules even in decomposition (12b), where secondary effects account for approximately one tenth of the gap.

Table 4. Decomposition into primary and secondary effects, by gender

PANEL (A)		MALES			
SCHOOL TYPE	Gap net of social origin (*Observed gap*) Natives−Immigrants	Decomposition 1 (12a)		Decomposition 2 (12b)	
		Primary	Secondary	Primary	Secondary
General schools	0.082 (*0.124*)	0.094	-0.012	0.074	0.008
Technical schools	0.046 (*0.071*)	-0.002	0.048	0.006	0.040
Vocational schools	0.006 (*0.010*)	-0.005	0.011	-0.009	0.015
Vocational training	-0.134 (*-0.205*)	-0.086	-0.048	-0.072	-0.063
PANEL (B)		FEMALES			

SCHOOL TYPE	Gap net of social origin (*Observed gap*) Natives–Immigrants	Decomposition 1 (12a)		Decomposition 2 (12b)	
		Primary	Secondary	Primary	Secondary
General schools	0.126 (*0.169*)	0.117	0.009	0.111	0.015
Technical schools	-0.011 (*0.015*)	-0.019	0.008	-0.007	-0.005
Vocational schools	-0.009 (*-0.002*)	0.002	-0.011	-0.019	0.010
Vocational training	-0.105 (*-0.182*)	-0.099	-0.006	-0.084	-0.021

Moving to gender differences, the overall nativity status gap is large for the two extreme options, general schools and vocational training, for both males and females; it is negligible for vocational schools and also for technical schools if we consider girls, while it is fairly large for boys. Are these gaps driven by performance or decision effects? For females, all the observed differentials given social origin are entirely driven by the lower performance of immigrants' children. The picture is more complex for males. While the migrant-native differentials in share of boys attending general schools can be explained by their lower performance, the observed gaps relative to vocational training and technical schools are also due the different decision models between immigrant background and native boys.

6. Summary and discussion

The existence of sizeable immigrant-native gaps in educational outcomes is a quite well-established regularity in several European countries, including Italy. Parental socio-economic and cultural background explain large part of the educational disadvantage of immigrants' children. However, even after accounting for family background, a residual disadvantage persists and children of immigrants still display higher likelihood to engage in shorter and less-demanding school careers.

A recent stream of sociological research on immigrant-native educational gaps attempts to delve deeper into this educational disadvantage taking up the theoretical model initially developed by Boudon (1974) for the explanation of social-background inequality in education. This new strand of research points out that the immigrant-native educational disadvantage is a consequence of the lower academic performance of children of immigrants (primary effects). Secondary effects exist, but go in the opposite direction: if children of immigrants had the same socio-economic background and the same school grades as their native peers, they would show the same, if not an even higher likelihood of choosing more demanding (and rewarding) school careers.

In this paper, we provide evidence on primary and secondary effects of immigrant background for the Italian case, exploiting recent longitudinal administrative school data for the autonomous Province of Trento. With respect to the decomposition methods employed in the literature so far, we propose and apply a novel approach that allows us to include interactions and to take into account other control variables (namely, socio-economic background variables). Our results show that immigrant background students have higher likelihood to opt for vocational education over a more generalist and academic one. The different distribution of social background accounts for approximately one third of the entire gap. Our main result is that when this effect is removed, a large part of the immigrant-native differentials is explained by previous performance, whereas secondary effects play a smaller role. However, sizable secondary effects of immigrant background are found for boys, who show significantly higher transition rates to vocational training courses and a lower likelihood to attend technical schools as compared to natives, even after accounting for their more unfavorable social background and performance distribution. Contrary to the existing evidence on Europe, these results point to different decision rules between children of immigrants and natives, that make the former more likely – given social background and prior performance – to enroll in school careers that prevent them access to tertiary education. Interestingly, secondary effects are not detected for girls, for whom the immigrants' children less ambitious choices are entirely driven by their poorer previous school performance.

Delving into the reasons for this gender difference is beyond the scope of the present work. We advance the hypothesis that it is due to different parenting styles and investments in the education of sons' and daughters' between native and immigrant families, especially when immigrants come from poorer and more traditionalist countries (Dronkers and Kornder, 2014). Traditional gender roles, according to which males are expected to make an early entrance into the labor market in manual and technical professions, might still be prevailing among immigrant families. Alternatively, the result might be related to the higher incidence of early behavioral problems observed among immigrants' sons, which negatively affect their educational expectations and labor market choices (Feliciano and Rumbaut, 2005).

References

Barban, N., and White, M. J. (2011), Immigrants' Children's Transition to Secondary School in Italy, *International Migration Review*, 45: 702-726.

Becker, B. (2009). The Transfer of Cultural Knowledge in the Early Childhood: Social and Ethnic Disparities and the Mediating Role of Familial Activities. *European Sociological Review* 26:17-29.

Bernardi, F. and Cebolla-Boado, H. (2013), Previous School Results and Social Background: Compensation and Imperfect Information in Educational Transitions, *European Sociological Review*, DOI:10.1093/esr/jct029

Blinder, A. S. (1973), Wage Discrimination: Reduced Form and Structural Estimates, *The Journal of Human Resources*, 8: 436–455.

Boudon, R. (1974), *Education, Opportunity and Social Inequality*, New York: Wiley.

Breen, R., Karlson, K B.., and Holm, A. (2013), Total, Direct, and Indirect Effects in Logit and Probit Models. *Sociological Methods & Research* 42, no. 2: 164-191.

Breen, R., and Goldthorpe, J. H. (1997), Explaining Educational Differentials: Towards a Formal Rational Action Theory, *Rationality and Society*, 9, 275-305.

Buis, M. L. (2010), Direct and Indirect Effects in Logit Models, *Stata Journal* 10:11-29.

Cebolla-Boado, H. (2011), Primary and secondary effects in the explanation of disadvantage in education: the children of immigrant families in France*, British Journal of Sociology of Education* 32(3): 407-430.

Dronkers, J. and Kornder, N. (2014), Do migrant girls perform better than migrant boys? Deviant gender differences between the reading scores of 15-year-old children of migrants compared to native pupils, *Educational Research and Evaluation: An International Journal on Theory and Practice*, 20:1, 44-66, DOI: 10.1080/13803611.2013.874298

Erikson, R., Goldthorpe, J. H., and Portocarero, L. (1979), Intergenerational class mobility in three Western European societies: England, France and Sweden, *British Journal of Sociology*, 30: 415-41.

Erikson, R., Goldthorpe, J. H., Jackson, M., Yaish, M. (2005), On class differentials in educational attainment. PNAS, 102: 9730–9733.

Erikson, R., and Jonsson, J. (eds.) (1996), Can Education Be Equalized? The Swedish Case in Comparative Perspective, Oxford: Westview Press.

Feliciano, C., and Rumbaut, R. G. (2005). Gendered paths: Educational and occupational expectations and outcomes among adult children of immigrants. *Ethnic and Racial Studies*, 28, 1087–1118.

Goldthorpe, J. (1996), Class Analysis and the Reorientation of Class Theory: The Case of Persisting Differentials in Educational Attainment, *British Journal of Sociology*, 47: 481-505

Fairlie, R. W. (2005), An Extension of the Blinder-Oaxaca Decomposition Technique to Logit and Probit Models, *Journal of Economic and Social Measurement*, 30: 305-316.

Jackson, M., Jonsson, J. and Rudolphi, F. (2012), Ethnic Inequality in Choice-driven Education Systems: A Longitudinal Study of Performance and Choice in England and Sweden, *Sociology of Education*, 85(2): 158-178

Jackson, M. (Ed.) (2013), *Determined to Succeed? Performance versus Choice in Educational Attainment.* Stanford: Stanford University Press.

Heath, A., and Brinbaum, Y. (2007), Explaining Ethnic Inequalities in Educational Attainment, *Ethnicities*, 7, 291-305.

Heath, A., C. Rothon, e E. Kilpi (2008), The second generation in Western Europe: education, unemployment and occupational attainment, *Annual Review of Sociology* 34: 211-235.

ISFOL (2012), *I percorsi di istruzione e formazione professionale.* Rapporto di monitoraggio delle azioni formative realizzate nell'ambito del diritto-dovere all'istruzione e alla formazione. Roma: Isfol.

Karlson, K. B., and Holm, A. (2011), Decomposing Primary and Secondary Effects: A New Decomposition Method, *Research in Social Stratification and Mobility*, 29: 221-237.

Karlson, K. B., Holm, A., and Breen, R. (2012), Comparing Regression Coefficients between Same-Sample Nested Models Using Logit and Probit a New Method, *Sociological methodology*, 42: 286-313.

Kao, G., and Tienda, M. (1995), Optimism and Achievement: The Educational Performance of Immigrant Youth, *Social Science Quarterly*, 76.

Kao, G., and Tienda, M. (1998), Educational Aspirations of Minority Youth, *American Journal of Education*, 106, 349-384.

Kristen, C. (2005), School Choice and Ethnic School Segregation: Primary School Selection in Germany. Munster, Germany: Waxman

Kristen, C., and Granato, N. (2007), "The Educational Attainment of the Second Generation in Germany. Social Origins and Ethnic Inequality," Ethnicities, 7: 343–366.

Kristen, C., Reimer, D., Kogan, I. (2008) Higher Education Entry of Turkish Immigrant Youth in Germany, *International Journal of Comparative Sociology* 49(2-3): 127–151.

Kristen, C., and Dollmann, J. (2010), "Sekundäre Effekte Der Ethnischen Herkunft: Kinder Aus Türkischen Familien Am Ersten Bildungsübergang," Vom Kindergarten bis zur Hochschule, 117-144.

Morgan, S. L. (2005), On the Edge of Commitment: Educational Attainment and Race in the United States. Stanford, CA: Stanford University Press.

Morgan, S. L. (2012), Models of College Entry in the United States and the Challenges of Estimating Primary and Secondary Effects, *Sociological Methods & Research* 41: 17-56.

Oaxaca, R. (1973), "Male-Female Wage Differentials in Urban Labor Markets," *International Economic Review*, 14: 693–709.

Waters, M. C., Health, A., Tran, Van C. and Boliver V. (2013), Second-Generation Attainment and Inequality: Primary and Secondary Effects on Educational Outcomes in Britain and the U.S. In *The Children of Immigrants at School: A Comparative Look at Integration in the United States and Western Europe*, Richard Alba and Jennifer Holdaway, Eds. New York: New York University Press.

Wooldridge, M.J. (2002), *Econometric Analysis of Cross Section and Panel Data*, The MIT Press, Cambridge, Massachusetts