Integrating Minorities in the Classroom: The Role of Students, Parents and Teachers*

Alexandra de Gendre[†]
University of Melbourne

Krzysztof Karbownik[‡]
Emory University

Nicolas Salamanca[§]
University of Melbourne

Yves Zenou[¶]
Monash University

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Abstract

We develop and empirically test a theory of integration of minorities in the classroom that incorporates endogenous responses of the majority students, their parents, and teachers in these classrooms. Using a unique policy that randomly assigns children to classrooms in Taiwanese middle schools and rich survey data, we show that exposure to Indigenous students lowers the test scores of the majority students. These negative effects are primarily driven by the aforementioned endogenous responses rather than peer effects. Our theory and results highlight the limitations of the reduced-form interpretation of commonly used linear-in-means peer effect models.

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[†]de Gendre: Department of Economics, The University of Melbourne; LCC; IZA. a.degendre@unimelb.edu.au

[‡]Karbownik: Department of Economics, Emory University, CesIfo, IZA, and NBER. krzysztof.karbownik@emory.edu

[§]Salamanca: Melbourne Institute, The University of Melbourne; LCC; IZA. n.salamanca@unimelb.edu.au

[¶]Zenou: Department of Economics, Monash University, CEPR and IZA. yves.zenou@monash.edu

1 Introduction

A minority is defined as any group of people who, because of their physical or cultural characteristics, are singled out from others in the society in which they live for differential and unequal treatment, and who therefore regard themselves as objects of collective discrimination (Wirth, 1945). This definition connotes historical disadvantages, direct discrimination, and general lack of power of certain groups of people in a given society in which they live. There is extensive research in social sciences on how minorities shape societies, as well as how societies might compensate minorities for their historical disadvantage and discrimination (Kymlicka, 1995, 2017, Vasta, 2007). For example, in the 1990s the US Federal Government paid restitutions for the Japanese-American internment (Shoag and Carollo, 2020) while in 2019 the city of Evanston passed the nation's first reparations law for their African-American residents. Specifically related to the population of interest in this paper, Indigenous Peoples, governments in several countries (e.g., Australia, Canada, and Taiwan) are undertaking actions to correct historical injustices. Above and beyond financial compensations, in many cases, the proposed solutions to improve the welfare of minority families revolve around increasing human capital of their children so that they can successfully overcome the disadvantage their parents faced (Coleman, 1968, Heckman, 2000, Alba, Sloan and Sperling, 2011).

One pre-requisite for educational success is access to high quality schools which are often attended by majority populations. This creates a tension between minority and majority students, parents, and teachers, often leading to pushback and increased segregation (e.g., Card and Giuliano, 2013, Geay, McNally and Telhaj, 2013, Cascio and Lewis, 2012, Ohinata and Van Ours, 2013). At the same time, there is surprisingly limited causal evidence on the effects of exposing majority children to ethno-cultural minority peers in the classroom, and we know even less about how such exposure could affect parents and teachers. The predictions from such an exposure are plausibly ambiguous. For example, exposure to minority peers could lead to positive spillovers from increased diversity or more resources dedicated to teaching minority students, but there could be no effect if minority status is not an important input in the school production function. One could likewise envision negative effects, either due to other unfavorable characteristics correlated with minority status or due to adverse behavioral changes of the majority students, their parents, or the teachers.

In this paper, we ask the following research questions: Does exposure to minorities in the classroom affect the achievement of majority students? Are these effects due to the minority status itself or rather due to characteristics correlated with being a minority student (e.g., lower test scores)? And finally, to what extent are these effects driven by peer effects (i.e., changes in behaviors of ethnic majority students) versus investment responses of majority parents and teachers in these classrooms. Answering these questions is essential for understanding the role that minority children could play in the school production function, and for the proper design of

Pareto-improving school mixing policies.

We answer these questions by combining a novel theoretical model with unique data and an institutional feature of the Taiwanese education system where children are randomly assigned to classrooms in junior high school. We propose a theoretical model which generalizes the standard linear-in-means peer effects models and incorporates responses of majority students, their parents and the teachers in classrooms with minority students. We test the predictions from the model using data from the Taiwan Education Panel Survey which collects longitudinal information on the three sets of individuals considered in the model. The random assignment of minorities into classrooms, in our specific application Indigenous Peoples, further allows us to verify the model with causal estimates. This feature, almost non-existent in compulsory school settings in other developed countries, circumvents the endogeneity issues brought on by selection, reflection, or mechanical relationships between own and peer measures that plague other settings (Manski, 1993, 2000, Angrist, 2014).

The theory concerns human capital production in a classroom with a varying share of minority students. We show that, under the assumption that observable characteristics of minority students are lower than those of majority students, the higher the fraction of minority students in a classroom, the lower the study effort of both majority and minority students in the classroom. We verify empirically that Indigenous students indeed have worse observable characteristics and we show additionally that they are perceived as lower ability at baseline by their teachers. The model is then extended to include responses of parents and teachers. We show that under a generalized Cobb-Douglas production function both student's and parent's (or teacher's) efforts and parent's and teacher's efforts are complements in their effects on student test scores. This result suggest that ignoring parents and teachers when considering linear-in-means peer effects models might lead to misinterpreting the reduced-form estimates. The magnitude and importance of these endogenous responses is an empirical question which we bring to the Taiwanese education data.

We show that in classrooms with a one standard deviation (SD) higher share of Indigenous students, test scores of majority students are, on average, lower by 2.4% of a SD. We explore three drivers behind this finding: (1) characteristics correlated with Indigenous status (confounders); (2) student responses (peer effects); and (3) parental and teacher (endogenous) responses. Using Gelbach (2016) decomposition we can attribute 30% of the negative effect to observable characteristics that are perfectly collinear with Indigenous status, and these are partially driven by lower test scores and lower socioeconomic status of Indigenous students. We then show, in line with our theoretical model, that students in the affected classrooms reduce their study effort - descriptively these changes can explain about 17% of the effect. Finally, we also find statistically significant negative responses of parents and teachers which account for about 26% of the effect. Overall, the aforementioned channels account for 73% of the estimated reduced-form relationship. Taking together, our findings suggest that although exposure to Indigenous students has a clear negative effect on the academic achievement of majority students, those classroom externalities are largely

generated by changes in the behavior of teachers and parents—agents in the education production function who are often ignored due to data limitations.

Even though students in our setting are randomly assigned to classrooms, which we verify empirically, we conduct a variety of additional robustness checks. Our estimates are robust to alternative definitions of majority students, to other ways of defining our treatment, or to the addition of a rich set of student-level covariates. Statistical significance is likewise unaffected by randomization inference (Young, 2019). Finally, we conduct two placebo checks using Hakka and synthetic Indigenous students. In neither case, we find sizeable or statistically significant effects on either test scores or other potential mechanisms. This reassures us that the effects are driven by perceptions about Indigenous students and responses to these perceptions.

First, we contribute to the literature on peer effects in education. To the best of our knowledge this is the first paper documenting minority peer effects in compulsory education where children are randomly allocated to their peers and teachers.[1] Prior studies, primarily using data from the United States due to their ethnic-racial history, were forced to rely on cohort-by-school variation due to lack of randomization (Hoxby, 2000, Diette and Oyelere Uwaifo, 2014, Figlio and Özek, 2019, Angrist and Lang, 2004, Geay, McNally and Telhaj, 2013, Setren, 2022). Much prior work also focused on a single (albeit often very heterogeneous) peer group such as immigrants (e.g. Figlio and Özek, 2019, Figlio et al., 2021, Diette and Oyelere Uwaifo, 2014, 2017) or refugees (e.g. Alan et al., 2021, Imberman, Kugler and Sacerdote, 2012, Green and Iversen, 2022, Morales, 2022).[2] One notable exception is Hoxby (2000), who distinguishes between multiple racial groups using data from Texas, and finds negative and statistically significant estimates only for Black peers. This cohort-by-school source of variation is not without issues e.g., Vigdor and Nechyba (2007) show that within-school comparisons are not always valid due to, for example, changes in local school markets affecting peer-composition over time.

Second, to the best of our knowledge, this is one of the first papers investigating potential mechanisms behind the observed reduced-form effects. We show that, in the context of minority peers, a non-trival part of the estimated effect can be attributed to both correlated observable characteristics and endogenous responses of students, parents and teachers. This relates to the literature on the interactions between parents/teachers and kids in education outcomes

1. There are prior studies exploiting random assignment to middle schools in South Korea, and random assignment to classrooms within schools in Chinese middle schools. However, none of those studies have estimated minority peer effects; rather they have focused on estimating the impact of studying with higher-achieving peers, female peers, children of college-educated parents or teacher-student match effects (see e.g., Kang et al., 2007, Fang and Wan, 2020, Chung, 2020, Lim and Meer, 2017, 2020, Feng and Li, 2016). In the United States Antecol, Eren and Ozbeklik (2016) use a small scale RCT based on Mathematica's Teachers Trained Through Different Routes to Certification program to study ability peer effects. They also investigate if a higher share of Black peers increases test scores of other Black students and they don't find any sizeable or statistically significant effects.

2. Some studies on immigrant populations will consider different groups of immigrants (see e.g., Friesen and Krauth, 2011) which is valuable as it reduces within group heterogeneity when defining treatment of interest.

(Agostinelli, 2018, Agostinelli et al., 2020, 2022, Boucher et al., 2023). Along the same lines, Green, Haaland and Vaag Iversen (2022) show that increases in English language skills of Norwegian students are likely due to exposure to English-speaking peers outside the classroom. This means that researchers should exercise caution when interpreting reduced form linear-in-means peer effects models.

Third, our work contributes to the literature on the effects of school racial, ethnic, and linguistic diversity on student achievement that has produced mixed empirical evidence and has been primarily concentrated on the United States. Card and Rothstein (2007) find a strong associations between racial segregation in neighborhoods and schools and the Black-White gap in SAT scores. Angrist and Lang (2004) analyze spillovers generated by school integration policies, and find short-lived, small to null effects on test scores. This null effect is confirmed in recent work by Setren (2022). Hanushek, Kain and Rivkin (2009) estimate the effect of studying in racially diverse schools, keeping school quality constant, and find large negative effects for Blacks, especially higher ability Black students, and small negative effects for White and other non-White minorities. A related but separate strand of literature focusing on ethno-linguistic diversity in schools has also yielded mixed findings (e.g. Cho, 2012, Diette and Oyelere Uwaifo, 2014, 2017, Geay, McNally and Telhaj, 2013, Tonello, 2016, Ohinata and Van Ours, 2013, 2016, Friesen and Krauth, 2011, Gould, Lavy and Daniele Paserman, 2009, Jensen and Rasmussen, 2011, Ahn and Jepsen, 2015, Hunt, 2017). Both strands of the literature share two common limitations: (1) lack of random assignment of students and (2) inability to delve into the mechanisms underlying the findings. On the other hand, three recent small-scale experimental studies focused on the effect of exposure to refugees on pupils' attitudes, prejudice and friendship formation (Boucher et al., 2020, Alan et al., 2021) and on teachers' prejudice (Alan et al., 2020).

We also provide some of the first evidence on educating Indigenous children, a group of people that has largely been omitted from economic research due to data limitations. In related research Friesen and Krauth (2010) study outcomes of Aboriginal students in Canada from exposure to higher share of Aboriginal peers but they do not consider effects on majority students. Studying how Indigenous children can be integrated in ethnic majority schools is important given that Indigenous Peoples face deep and perpetuating disadvantage e.g., they represent about 5% of the global population but as much as 15% of the world's extremely poor (Hall and Patrinos, 2014). Furthermore, they are not evenly distributed within countries; thus, there are regions where effects such as those we document in this paper might be pervasive, leading to starker integration difficulties between minority and majority stakeholders (e.g., in the United States in Alaska 15% of inhabitants are Indigenous, in Taiwan in Hualien County 30% of the population is Indigenous, in British Columbia – Canada's third most populous province – people with Indigenous identity comprise 6% of the population, while in New South Wales – Australia's most populous state – over 4% of people are Aboriginal and Torres Strait Islanders).

Although our focus is on compulsory education and younger children, this paper is also natu-

rally linked to the broader literature on peer effects in education. Considering university-level coursework there are several papers which use random assignment of peers to identify the effects of interest (e.g., Carrell, Fullerton and West (2009), Carrell, Sacerdote and West (2013) in the US, Feld and Zoelitz (2017) in the Netherlands, Garlick (2018) in South Africa, and Brunello, De Paola and Scoppa (2010) in Italy). However, even in this literature, to the best of our knowledge, only Chevalier, Isphording and Lisauskaite (2020) specifically focus on minority status of peers – in their case non-native speakers at a British university – and on the issue of language barriers in the classroom.

Finally, we also contribute to the literature on contact theory from social psychology, which serves as our theoretical guideline and inspiration for why we might find positive peer effects (Pettigrew, 1998, Pettigrew et al., 2011, Rivas-Drake et al., 2019). According to this theory exposing people to other ethnic groups should reduce prejudice and could generate other positive externalities. Our results suggest that consequences of exposing majority students to minority students are more nuanced and may involve reactions of agents other than students themselves. These external agents are for the most part omitted in contact theory.

2 Theory: Peer Effects with Endogenous Responses

2.1 Baseline peer effects model

There are two types of students in each classroom: majority (ethnicity M) and minority (ethnicity m). The number of students is n so that $n^M + n^m = n$. Denote by $q = n^m/n$, the fraction of minority students in a classroom and thus by $1-q = n^M/n$, the fraction of majority students in a classroom.

2.1.1 Utility function

The utility of a student i choosing education effort y_s^i is a function of both a private and a social component. It is given by:

$$U_s^i = b^i y_s^i - \frac{1}{2}\left(y_s^i\right)^2 + \phi y_s^i \bar{y}_s^{-i}, \tag{1}$$

where $\bar{y}_s^{-i}$ is the average student effort in the classroom *leaving out* i, $0 < \phi < 1$ is the intensity of the spillover effects, and b^i is student i's marginal private benefit from education effort. We have $b^i = \mathbf{x}^i\gamma + \varepsilon^i$, where $\mathbf{x}^i$ is a $(1 \times k)$ vector of k observable characteristics, and γ is a $(k \times 1)$ vector, so that $\mathbf{x}^i\gamma = \sum_{l=1}^{k} x^l\gamma^l$; reflects the *ex ante* heterogeneity (observable characteristics, such as gender, ethnicity, etc., and unobservable characteristics, such as talent and motivation) of student i, independently from the influence of other students in the classroom.

This utility function (1) has two terms. The first term, $b^i y_s^i - \frac{1}{2}\left(y_s^i\right)^2$, corresponds to the utility

of exerting y_s^i units of effort when there is *no interaction* with other children. The second term, $\phi y_s^i \bar{y}_s^{-i}$, captures the *spillover effects* that student i experiences from the average effort of classmates. The first-order condition for student i is given by:

$$y_s^i = b^i + \phi \bar{y}_s^{-i} \tag{2}$$

or equivalently

$$y_s^i = \mathbf{x}^i \gamma + \phi \bar{y}_s^{-i} + \varepsilon^i. \tag{3}$$

which is the standard linear-in-means (LIM) model.

2.1.2 Equilibrium

In order to gain additional intuition from the model and derive closed-form solutions to the equilibrium of this game, we assume that all majority students have the same characteristics and all minority students have the same characteristics, that is, $b^i = b^M$ for all majority students and $b^i = b^m$ for all minority students. This will be of course relaxed in the empirical analysis. Under this assumption, there are only two education effort levels: one for each of the n^M majority students, denoted by y_s^M, and one for each of the n^m minority students, denoted by y_s^m. The average education effort in the classroom is then equal to:

$$\bar{y}_s = q y_s^m + (1-q) y_s^M.$$

Equation (2) for student $i = m, M$ can now be written as:

$$y_s^i = b^i + \phi \left[q y_s^m + (1-q) y_s^M - \frac{y_s^i}{n} \right]. \tag{4}$$

Proposition 1 *Consider a peer-effect spillover model with a population of minority and majority students. Then, there is a unique interior equilibrium in which study efforts for each type of students are given by*

$$y_s^{M*} = \frac{(1-\phi q) b^M + \phi q b^m}{1-\phi}, \tag{5}$$

$$y_s^{m*} = \frac{[1-\phi(1-q)] b^m + \phi(1-q) b^M}{1-\phi}. \tag{6}$$

Moreover, if $b^m < b^M$, then the higher is the fraction of minority students in a classroom, the lower is the study effort of both majority and minority students in the classroom, that is,

$$\frac{\partial y_s^{M*}}{\partial q} < 0 \text{ and } \frac{\partial y_s^{m*}}{\partial q} < 0.$$

Indeed, if students from the minority group have lower b^i, that is, they have lower characteristics

(e.g., have lower test scores at baseline and/or their parents are less educated or have lower income), then, for a student i, the higher is the fraction of minority students in her classroom, the lower is the average "quality" $\overline{y}_s^{-i}$ of students in her classroom, and the lower is i's education effort because she obtains less spillovers from other students. Clearly, our results will still hold if we relax the assumption that all minority students have the same b^m and all majority students have the same b^M but, instead, assume that there is a distribution of b^i for each type of students with the average characteristics of minority students being lower than that of majority students.

2.2 Incorporating responses of parents and teachers

The previous model is only concerned with the interactions between the students, however, the teacher and the parents play an important role in shaping education outcomes. Despite that their role, and responses to classroom composition, have been largely ignored in the extant literature. First, to understand how students' study efforts translates into test scores, we need to write the production function of education that gives the test scores of student $i = m, M$. It is given by:

$$S^i = \rho \left(y_s^i\right)^{\alpha_1} \left(y_p^i\right)^{\alpha_2} \left(y_t^i\right)^{\alpha_3}, \tag{7}$$

where $0 < \alpha_1 < 1$, $0 < \alpha_2 < 1$, $0 < \alpha_3 < 1$, with $\alpha_1 + \alpha_2 + \alpha_3 = 1$; $\rho > 0$ is the efficiency of the production function of education, S_i is student i's test score, y_p^i is the effort of student i's *parent* (that is, how much time and resources the parent spends in educating her offspring i) while y_t^i is the *teacher*'s effort in the classroom where i studies (that is, how much time the teacher spends in improving teaching and taking care of her students). Observe that

$$\frac{\partial S^i}{\partial y_s^i \partial y_p^i} = \alpha_1 \alpha_2 \rho \left(y_s^i\right)^{\alpha_1 - 1} \left(y_p^i\right)^{\alpha_2 - 1} \left(y_t^i\right)^{\alpha_3} > 0,$$

$$\frac{\partial S^i}{\partial y_s^i \partial y_t^i} = \alpha_1 \alpha_3 \rho \left(y_s^i\right)^{\alpha_1 - 1} \left(y_p^i\right)^{\alpha_2} \left(y_t^i\right)^{\alpha_3 - 1} > 0.$$

Indeed, the more the parent or the teacher exerts effort, the higher is the impact of the student's effort on her test score. Observe also that

$$\frac{\partial S^i}{\partial y_p^i \partial y_t^i} = \alpha_2 \alpha_3 \rho \left(y_s^i\right)^{\alpha_1} \left(y_p^i\right)^{\alpha_2 - 1} \left(y_t^i\right)^{\alpha_3 - 1} > 0,$$

which means that the higher is the teacher's effort in the classroom, the higher is the impact of parent's effort on her child's test score. This is quite natural since if a student i is in a classroom where the teacher puts a lot of effort, then the effect of parent's effort on test scores is higher.

In summary, student's and parent's (or teacher's) efforts are *complements* and parent's and teacher's efforts are also *complements* in their impact on student's test scores.

The *timing* is as follows. In the first stage, both parents and teachers decide how much effort

to exert. In the second stage, each student decides how much study effort to make. The timing seems natural in this context. Indeed, it is quite natural to think that teachers form their preconceptions about Indigenous students before they are assigned to the classroom and apply those preconceptions as soon as they observe the classroom composition (therefore teachers are first movers). Parents would find out about classroom composition nearly at the same time or only slightly later in this setting, since they are institutionally quite involved (so they can be thought of as first movers). Finally, students would be the last ones since their study effort will be a result of what happens during classroom interactions (i.e., peer effects).

As usual, we solve the model backwards. In the previous section, we already solved the second stage. By plugging the values in equations (5) and (6), we obtain:

$$S^M = \rho\,(1-\phi)^{-\alpha_1}\left[(1-\phi q)\,b^M + \phi q b^m\right]^{\alpha_1}\left(y_p^M\right)^{\alpha_2}\left(y_t^i\right)^{\alpha_3}, \tag{8}$$

and

$$S^m = \rho\,(1-\phi)^{-\alpha_1}\left([1-\phi(1-q)]\,b^m + \phi(1-q)b^M\right)^{\alpha_1}\left(y_p^M\right)^{\alpha_2}\left(y_t^i\right)^{\alpha_3}. \tag{9}$$

2.2.1 Parent's effort choices

The utility of parent $i = m, M$ is given by:[3]

$$U_p^i = S^i - C(y_p^i),$$

where $C(y_p^i) > 0$ is the cost of effort of parent i. Indeed, each parent cares about the test score of her offspring. For tractability, we assume that $C(y_p^i) = y_p^i$, so that

$$U_p^i = S^i - y_p^i. \tag{10}$$

Denote

$$\Delta^M(q) := (1-\phi q)\,b^M + \phi q b^m \text{ and } \Delta^m(q) := [1-\phi(1-q)]\,b^m + \phi(1-q)b^M. \tag{11}$$

Using the optimal efforts of students in equations (5) and (6) and using (11), we obtain:

$$U_p^M = \rho\,(1-\phi)^{-\alpha_1}\left(\Delta^M(q)\right)^{\alpha_1}\left(y_p^M\right)^{\alpha_2}\left(y_t^i\right)^{\alpha_3} - y_p^M. \tag{12}$$

and

$$U_p^m = \rho\,(1-\phi)^{-\alpha_1}\left(\Delta^m(q)\right)^{\alpha_1}\left(y_p^m\right)^{\alpha_2}\left(y_t^i\right)^{\alpha_3} - y_p^m. \tag{13}$$

3. In principle, one could assume that the marginal cost of parental effort is different between the majority and the minority groups. This will just complicate our analysis without changing the main conclusions.

By maximizing these utility functions, we obtain:

$$y_p^{M*}(q) = Z_1^{1/\alpha_2} \left(\Delta^M(q)\right)^{\alpha_1/(1-\alpha_2)} \left(y_t^i\right)^{\alpha_3/(1-\alpha_2)}, \tag{14}$$

and

$$y_p^{m*}(q) = Z_1^{1/\alpha_2} \left(\Delta^m(q)\right)^{\alpha_1/(1-\alpha_2)} \left(y_t^i\right)^{\alpha_3/(1-\alpha_2)}, \tag{15}$$

where

$$Z_1 := (\alpha_2\rho)^{\alpha_2/(1-\alpha_2)} (1-\phi)^{-\alpha_1\alpha_2/(1-\alpha_2)}. \tag{16}$$

2.2.2 Teacher's effort choices

The teacher of student i maximizes the test score of *all* students in her classroom. In the classroom there are $n = n^M + n^m$ students. The utility of teacher i (meaning the teacher in classroom where i belongs to) is given by:

$$U_t^i = \sum_{i=1}^{n} S^i - y_t^i \tag{17}$$

Using equations (8) and (9), we obtain:

$$\begin{aligned} U_t^i &= n^M S^M + n^m S^m - y_t^i \\ &= n^M \rho (1-\phi)^{-\alpha_1} \left(\Delta^M(q)\right)^{a_1} \left(y_p^M\right)^{\alpha_2} \left(y_t^i\right)^{\alpha_3} \\ &\quad + n^m \rho (1-\phi)^{-\alpha_1} \left(\Delta^m(q)\right)^{a_1} \left(y_p^m\right)^{\alpha_2} \left(y_t^i\right)^{\alpha_3} - y_t^i. \end{aligned}$$

By maximizing this utility function, we obtain:

$$y_t^{i*}(q) = (n\alpha_3\rho Z_1)^{(1-\alpha_2)/\alpha_1} (1-\phi)^{-(1-\alpha_2)} \Delta^M(q). \tag{18}$$

2.2.3 Parents' and teacher's effort choices: Equilibrium

We have the following result:

Proposition 2 *Consider a two-stage model when, in the first stage, parents and teachers decide upon their effort while, in the second stage, students decide how much study effort to exert. If $b^m < b^M$, then the higher is the fraction of minority students in a classroom, the lower is the study effort and the test scores of both majority and minority students in the classroom, that is,*

$$\frac{\partial y_s^{M*}}{\partial q} < 0, \ \frac{\partial y_s^{m*}}{\partial q} < 0, \ \frac{\partial S^{M*}}{\partial q} < 0, \text{ and } \frac{\partial S^{m*}}{\partial q} < 0.$$

Moreover, if $b^m < b^M$, then the higher is the fraction of minority students in a classroom, the lower is the parental effort of both majority and minority students as well as the teacher's effort,

that is,

$$\frac{\partial y_p^{M*}(q)}{\partial q} < 0, \frac{\partial y_p^{m*}(q)}{\partial q} < 0 \text{ and } \frac{\partial y_t^{i*}(q)}{\partial q} < 0.$$

Finally, if $b^m = b^M$, then q (the fraction of minority students in the classroom) has no impact on the test scores of all students as well as on the efforts of both parents and teachers.

The intuition of these results is as follows. First, students decide their study effort based on peer effects and thus, on the spillovers they obtain from each other (Proposition 1). Second, observing the study effort of their kids and their peers, parents who maximize their offspring's test score, decide the effort to exert in their interaction with their kids. Since the minority students are disadvantaged in terms of characteristics compared to the majority students, when q, the fraction of minority students in a classroom increases, the average study effort in the classroom goes down, including that of their own kid. This leads to a reduction in parents' effort. Similarly, the teacher who maximizes the sum of the test scores of all students in her classroom, observes first the composition of minority and majority students in her classroom. When q increases, because effort is costly, teachers find it optimal to reduce their effort (their engagement with students) because students make less effort (i.e., study less). Finally, since students' test scores are determined by their own study effort as well as that of their parents and teachers and since all these efforts complement each other, an increase in q reduces students' test scores (Proposition 2).

3 Institutional Setting

3.1 Education in Taiwan

Compulsory education in Taiwan starts with primary school at age 6 and ends with junior high school around age 15, however, approximately 95 percent of students continue their education with either General or Vocational Senior High School or Junior College. Online Appendix Figure C.1 provides a simplified schematic of the Taiwanese education system. The educational curriculum is developed centrally by the Taiwanese Ministry of Education and has no subject specialization during the compulsory stage of education. It is centered around sciences and mathematics which is often credited as the reason why Taiwanese pupils are consistently placed at the top on international educational rankings (e.g., 4^{th} out of 72 countries in PISA 2015; Law (2004)). Since the 1990s, public junior high schools have been managed at the municipal level where, in principle, students can choose their preferred school. If a school is oversubscribed, admission is based on a lottery system. We neither observe this source of random variation in our data nor use it for identification. Rather, we utilize the fact that conditional on admission to a specific junior high school, students are randomly assigned to classrooms. This rule, critical

for our identification strategy, is mandated by the central government.[4] No exceptions to this rule are made based on demographic or socioeconomic characteristics.[5] Classroom assignment is permanent for almost all students in the sense that, net of extraordinary circumstances like moving to a different municipality or (physical) conflict within a classroom, students typically remain with their initially assigned classmates throughout all three years of junior high school. In our data, 98% of students remain in the same school while 88% of students are in the same classroom two years after the beginning of junior high school.[6]

At the end of compulsory education, students take the National Basic Competence Test and its results determine competitive admissions to senior high schools and senior vocational schools. Consequently, students, parents and teachers spend considerable time, money and effort preparing for the exam. For example, schools regularly organize practice exams and other forms of preparation while parents are known to hire private tutors in mathematics, English and sciences. The latter is often facilitated through "cram schools" which are private extra-curricular institutions preparing specifically for high stakes centralized examinations.

3.2 Ethnic Minorities in Taiwan

The population of Taiwan is approximately 23 million, mostly descendants of Han Chinese. According to the 2010 Census, 95% of the population was Han Taiwanese, 4% was Taiwanese Indigenous Peoples, and 1% of individuals were of other ethnicities (mostly immigrants from other Asian countries). At the same time, Han Taiwanese do not constitute a homogeneous group. While the vast majority of those are Hoklo descendants from Fujian (approximately 70%), there is a significant minority of Hakka descendants mostly from eastern Guangdong (approximately 15%).The remaining Han Taiwanese are Waishengren, which defines people who migrated from mainland China to Taiwan between 1945 and 1949 during the relocation of the Republic of China government.

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4. For legislative details see the Implementation Guideline for Class Assignment of Junior High School Students, later superseded by Article 12 of the Primary and Junior High School Act in 2004. Additional information can be found at http://edu.law.moe.gov.tw/EngLawContent.aspx.

5. The random assignment rule also extends to the class' "Dao Shi" who are highly involved homeroom teachers that teach, guide and mentor their students throughout junior high school (see Cobb-Clark, Salamanca and Zhu, 2019). Dao Shi are also expected to get to know each student personally, especially those experiencing disadvantage, and to use this relationship to support their students' academic performance. Finally, Dao Shi are also parents' first port of call for discussing their children's academic performance; they are available for parental phone calls outside of school hours and may visit students at home. Unfortunately, we do not observe teacher ethnicity in our data so we cannot explore potential ethnic complementarities between teachers and students.

6. This means that only 2% of students change schools and only 10% of students change classrooms conditional on remaining in the same school. In our data, Indigenous and Hakka students are no more likely than majority students to change either schools or classrooms. Furthermore, classroom shares of Indigenous and Hakka students at the initial assignment are uncorrelated with the likelihood of ethnic majority students remaining in their assigned classroom. We do find a negative association between share of Indigenous students in a classroom and the likelihood that an ethnic majority child remains in their original school, yet this estimate is of trivial magnitude (0.3 percentage points per 1 SD increase in Indigenous peers).

In the main analysis, we consider all three Han Chinese groups as the ethnic majority, for whom we are interested in measuring outcomes while Indigenous Peoples are the minority group of interest. In a separate placebo analysis, we use Hakka as another minority group that is culturally distinct but observably similar to the other Han Chinese groups as we describe below. We provide a brief cultural and ethnographic sketch for each of the groups below.

Hoklo are primarily descendants of people from southern Fujian who migrated to the island before the start of the Japanese occupation in 1895, with early migrations starting at the beginning of the 17^{th} century. They currently account for about 70% of Taiwanese population. They have the strongest sense of Taiwanese identity among the three Han Taiwanese groups. For example, in 1999, 75% of Hoklo identified as exclusively Taiwanese, while this share was 58% and 32% for Hakka and Waishengren, respectively (Tsai, 2007). Many Hoklo people are bilingual, speaking both Taiwanese Mandarin (the most commonly spoken language in Taiwan) and Taiwanese Hokkien. In our data 91% of Hoklo students are fluent in Mandarin and 45% of those students are additionally fluent in Hokkien.

Hakka are primarily descendants of people who migrated from the Guandong province of China in the mid-17^{th} century, at the end of the Ming dynasty and the beginning of the Qing dynasty. They currently account for about 15% of Taiwanese population. Historically, the Hakka faced discrimination from other Chinese ethnic groups that sometimes turned violent, both in mainland China and in Taiwan. These frictions also led to mass-killings in Hakka villages. The Hakka likewise speak a distinct language and, in our data, we see that 93% of the Hakka children are fluent in Mandarin while 15% of them are fluent in Hakka. In contrast, less than 2% of non-Hakka Taiwanese students declare speaking the language. In our data, Hakka and Hoklo have similar demographic and socioeconomic characteristics and, despite clear cultural differences, the two groups are ethnically closer to one another than to the Indigenous Peoples.[7]

Waishengren are predominantly Han Chinese who arrived from mainland China between the end of World War II in 1945 and the end of Chinese Civil War in 1949. For this reason they are sometimes refereed to as "mainlanders" and we use the two terms interchangeably. They are the smallest of the three Han Chinese groups comprising about 10% of the population of Taiwan. In our data we see that XX% of Waishengren children are fluent in Mandarin while XX, XX, and XX% are fluent in Hokkien, Hakka, and an Indigenous language, respectively. Online Appendix Table X shows that they have similar characteristics to Hokolo and Hakka.

Indigenous Peoples of Taiwan are the minority group of interest in this paper. They are the native inhabitants of the island of Taiwan, and descend from those who lived on the island as far

7. Cultural differences resonate especially in food, architecture, arts and crafts but also in social behaviors and hierarchies. For example, Hakka historically put much emphasis on education making them "perfect bureaucrats" and they are the only Han ethnicity where women never bound their feet.

as 6,000 years ago. Although there are many distinct tribes of Indigenous Peoples, with their own histories and customs, the Taiwanese government officially recognizes 16 distinct ethnic groups within this broader ethnic umbrella. The share of Indigenous students among school-age children is about 4%, but they are not distributed evenly across the country. Online Appendix Figure C.2 presents the fraction of 10 to 14 year old children who are Indigenous by county of residence. The vast majority of those children live in eastern parts of Taiwan, where their concentration is as high as 45%, but there is also a non-trivial share of Indigenous children living in counties surrounding Taipei–the capital. Akin to the two Han Taiwanese groups, the vast majority of Indigenous Peoples are fluent in Mandarin (88%); however, almost 30% speak at least one Indigenous language. On the other hand, our data shows that only 11% of Indigenous children speak Hokkien and only 3% speak Hakka. Conversely, virtually no Hoklo or Hakka child speaks an Indigenous language. As documented in Online Appendix Table C.1 Indigenous students are extremely disadvantaged compared to Han Chinese.

4 Data

We use data from the Taiwanese Education Panel Survey (TEPS), a project jointly funded by the Taiwanese Ministry of Education, the National Science Council, and the Academia Sinica. The TEPS is a nationally representative longitudinal survey of the education system in junior high school, senior high school, vocational senior high school, and junior college. It is a multi-respondent survey, collecting linked information on students, parents, teachers, and school administrators.[8]

We focus on the junior high school sample of the TEPS because it allows us to use measures of student ability and educational inputs paired with random assignment to classrooms in Grade 7. The TEPS junior high school sample includes information on more than 20,000 students, their parents, their teachers and their school administrators over two waves. The first wave was collected in early September 2001 at the very beginning of students' first year of junior high school, and right after their random assignment to classrooms within a school.[9] The second wave was collected in 2003, at the beginning of the students' last year of junior high school.

There are three key features of TEPS that make it the ideal dataset for our study. First, its sampling framework allows us to observe a random sample of classmates in each junior high

8. Although the sample is longitudinal, follow-up of the full panel is only possible at the beginning of the first and the last year of junior high school. Selective attrition and much smaller sample sizes limit the usability of subsequent waves.

9. Although we cannot observe the difference between the admission roster and our post-randomization sample, strictly enforced regulation makes it highly unlikely that students withdraw from school or change classrooms upon learning their assignment, or between admission and randomization. In any case, our balancing tests would capture this type of behavior.

school classroom included in the survey. TEPS follows a stratified nested sampling procedure where first 338 randomly selected junior high schools were sampled (45 percent of all junior high schools in the country at the time), with sampling strata for urban and rural areas as well as public and private schools. In each of these schools an average of three classrooms of first-year junior high school students were then randomly sampled. In each of these classrooms, around 15 students were then randomly sampled. Since the mandated maximum class size at the time was 35 students per class, this generally amounts to approximately observing a random half of the classroom.[10]

Second, students in the TEPS take a standardized test in waves 1 and 2 called the Comprehensive Analytical Ability test. This is a low-stake test constructed for the purpose of the survey, which has no bearing on their subsequent academic careers. It measures students' cognitive ability and analytical reasoning, and was specifically designed to capture gradual learning over time. The test contains 75 multiple-choice questions, covering general reasoning, mathematics, Mandarin and English. These were taken from an extensive set of questions, some of which were adapted from other international standardized tests, and some other which were developed by education and field experts in Taiwan. The Comprehensive Analytical Ability test score, constructed as the sum of all correct answers, provides a measure of academic ability. Importantly, the tests are externally graded and the scores are not disclosed to either students, parents, teachers or school administrators. Their main goal is to have an accurate measure of children's academic achievement in the TEPS. The anonymity and low-stake characteristics of the test limit incentives for teachers, parents, or school administrators to influence the results, and reduce concerns that students might be differently affected by test-taking stress itself. We standardize these test scores to have mean of 0 and standard deviation of 1 in our estimation sample.

Third, beyond test scores, the TEPS provides a wealth of questions measuring student behavior, attitudes and beliefs in and outside the school environment, parent-child interactions and parental investments, as well as detailed information on teachers and school administrators. We construct three indices aggregating measures of student effort, parental investments and teacher effort respectively (see Appendix B for details on the construction of those indices). In addition, teachers are also asked about their subjective assessment of each student's academic achievement, which we use as a contrast to the objective and anonymous measure provided by test scores.

10. This sampling framework is similar to that of the National Longitudinal Study of Adolescent to Adult Health (Add Health), a panel study of middle and high school pupils in the United States. Add Health is unique in collecting friendship ties and in observing multiple cohorts of students in each school, which makes it particularly appealing for peer effect and networks research (see e.g., Calvo-Armengol, Patacchini and Zenou, 2009, Bifulco, Fletcher and Ross, 2011, Card and Giuliano, 2013, Elsner and Isphording, 2017, Patacchini, Rainone and Zenou, 2017, Agostinelli, 2018).

5 Linking Data and Taiwanese Institutional Setting with the Model

Using Propositions 1 and 2, we can now establish the impact of q, the fraction of minority students in a classroom, on S^i, the test score of student $i = m, M$. For that, let us plug the equilibrium values of $y_s^{i*}(q)$ (given by equations (5) and (6)), $y_p^{i*}(q)$ (given by equations (14) and (15)), and $y_t^{i*}(q)$ (given by equation (18)), into equation (7) to obtain $S^{i*}(q) = \rho \left(y_s^{i*}(q)\right)^{\alpha_1} \left(y_p^{i*}(q)\right)^{\alpha_2} \left(y_t^{i*}(q)\right)^{\alpha_3}$, or equivalently

$$S^{i*}(q) = F\left(q, \phi, \alpha_1, \alpha_2, \rho, b^M, b^m\right). \tag{19}$$

Using the results in Propositions 1 and 2 and assuming that $b^m < b^M$, we can show that

$$\frac{\partial S^{i*}(q)}{\partial q} < 0. \tag{20}$$

In other words, due to the (negative) peer effects in study effort among students and to the (negative) reactions of parents and teachers, an increase in q, the fraction of minority students in a classroom, decreases the test scores of all students in this classroom.

Before going to the data analysis, let us explain how this model is relevant for our empirical analysis. First, in the model, the majority group (type M) corresponds to the Han Chinese while the minority group (type m) refers to the Indigenous Peoples of Taiwan (see Section 3). Second, the key assumption to obtain the results in Proposition 1 and 2 is that $b^m < b^M$, that is, minority students have lower characteristics than majority students. This is true in the data. Indeed, Online Appendix Table C.1 shows that the Indigenous Peoples are really disadvantaged compared to the majority students: they have a -0.9 Standard Deviation (SD) lower baseline scores (compared to 0 SD for the majority), they are in the 30% lowest income (compared to 9% for the majority), 80% of them have low parental education (compared to 64% for the majority), and 60% of them have parents who had financial difficulty in the past 10 years (compared to 25% for the majority). Third, as explained in Section 3, in Taiwan, there are two types of minorities: the Hakka and Indigenous Peoples of Taiwan. However, as shown in Online Appendix Table C.1, Hakka and Hoklo have similar demographic and socioeconomic characteristics; thus, the two groups are ethnically closer to one another than to the Indigenous people. Since most of our results are based on the assumption that $b^m < b^M$, we will run a falsification test on the Hakka to see if they have a negative impact on the test scores of the majority students. According to our model, since the Hakka and the majority students have similar characteristics (i.e., $b^m \approx b^M$), we should not find any significant effect.

In the light of this interpretation of the model, we have the following predictions:

(1) The higher is the fraction of Indigenous students in the classroom, the lower are the test scores of both the majority and the minority *students* (Propositions 1 and 2).

(2) The fraction of Hakka students in the classroom has *no* impact on the test scores of both the majority and the minority *students* (Proposition 2).

(3) The higher is the fraction of Indigenous students in the classroom, the lower are the *parents*' effort of both the majority and the minority students (Proposition 2).

(4) The higher is the fraction of Indigenous students in the classroom, the lower are the *teachers*' efforts (Proposition 2).

5.1 Observable differences between the groups

One of the key assumptions in our theoretical model is that minority students have worse observable characteristics compared to majority students; in other words, they are disadvantaged. This disadvantage can be related to any observable characteristic that is predictive of test scores, e.g., socio-economic status, health, parental education and occupation, family composition. Online Appendix Table C.1 compares Indigenous students to their peers from the majority, which comprises students of Han Chinese backgrounds without distinguishing between Hoklo, Hakka, and Waishengren or Mainlander backgrounds.

Indigenous students overall have worse observable characteristics than their peers in the majority. Their average test scores are -0.73 lower at baseline compared to their majority peers, which is a tremendous gap in educational achievement for children entering middle school. Indigenous students have also lower aspirations for higher education (-10 percentage points) and lower subjective expectations (-8 percentage points) that they will be able to.

racial isolation / No racial mixing: indigenous students have indigenous parents but not likely to have Hakka parent.

5.2 Teacher perceptions on student effort

6 Empirical Strategy

6.1 Estimating Equation

In order to evaluate the effects of exposure to minority students in the classroom, following our theoretical model, we bring equation (19) to the data, which expressed in a linear form can be written as:

$$Score_{iscw_2} = \alpha_1 + \alpha_2 \overline{\%Indigenous^{-i}_{iscw_1}} + \delta \mathbf{X}_{iscw_1} + \gamma_{sw_1} + \varepsilon_{iscw_1}, \tag{21}$$

where i stands for student, s for school, c for classroom, w_1 for the start of grade 7 (our baseline) while w_2 stands for the start of grade 9 (when we measure our outcomes). All our models include wave 1 school fixed effects (γ_{sw_1}), which restricts our identifying variation to across-classrooms and within-schools i.e., the level of randomization that the policy imposes. In select specifications, we also include pre-assignment control variables, $\mathbf{X}_{iscw_1}$, which include standard observable characteristics of kids and parents (see Online Appendix Table C.1) as well as students' test scores at the baseline. Thus, our main results have a value-added interpretation, that is, compared to the achievement in grade 7, what is the effect of being exposed to more minority students on test scores in grade 9. Since in the main specifications we run these regressions on a full sample of students, rather than just for the majority students, we also include student's own minority status dummies and its interaction with the share of Indigenous students. We cluster standard errors at the level of the classroom in wave 1, since this is the level at which randomization occurs.[11]

Our coefficient of interest in Equation 21 is α_2 which represent the causal effect of exposure to Indigenous students in the first two grades of junior high school on grade 9 test scores of majority students. To ease interpretation, we scale $\overline{\%Indigenous^{-i}_{iscw_1}}$ by one within-school standard deviation change in the share of Indigenous students in the classroom which is 0.047, or equivalent to having 1.7 more Indigenous children in the classroom. Note that $Score_{iscw_2}$ corresponds to S^i in our theoretical model, $\overline{\%Indigenous^{-i}_{iscw_1}}$ to q and $\mathbf{X}_{iscw_1}$ to b^m and b^M, and thus we predict that α_2 should be negative and statistically significant (Proposition 2).

6.2 Identifying Assumption: Random Assignment to Classrooms

Our identification strategy exploits the random assignment of students to classrooms in Taiwanese junior high schools (see Section 3.1), which implies a randomly allocated exposure of majority students to Indigenous students. This means that the variable $\overline{\%Indigenous^{-i}_{iscw_1}}$ will be conditionally (on school fixed effects) independent of the error term ε_{iscw_1} ($E[\varepsilon_{iscw_1}|\%Indigenous^{-i}_{iscw_1}, \gamma_{sw_1}] = 0$). To support the random assignment assumption, in Table C.3 we show that our treatments of interest—standardized classroom leave-out-means of Indigenous students—is uncorrelated with characteristics of students and parents at the baseline. Each coefficient comes from a separate regression based on modified Equation 21 where we regress the pre-assignment variables on $\overline{\%Indigenous^{-i}_{iscw_1}}$, own Indigenous status, the interactions of these two variables, and school fixed effects, and we exclude all other controls.[12] Panel A presents results for wave 1 tests scores as well as student's gender and birth cohort indicator while panel B shows estimates for parental

11. Our conclusions remain unchanged if we instead cluster at the school-level, allowing correlated errors across classrooms, or if we consider empirical p-values based on randomization inference.

12. We only display coefficients of interest on $\overline{\%Indigenous^{-i}_{iscw_1}}$ but none of the estimates for an Indigenous dummy or the interaction term are statistically significant. The results are similar if we redo the analysis for the majority students only.

education, health, and household's socioeconomic status. Finally, in Panel C we present results for student educational experiences prior to junior high school.

Out of 17 tests only one yields a coefficient statistically significant at 10% level, which is less than what we would expect due to pure chance.[13] Furthermore, the estimates are quantitatively small, never exceeding 2.3% effect size relative to the dependent variable mean. We implement two additional test to ensure that the validity of the identifying assumption. First, we use diagnostics developed by Guryan, Kroft and Notowidigdo (2009) and Jochmans (2022) to detect whether Indigenous students are being sorted into specific classrooms in violation of random assignment. Neither test can reject the null hypothesis of no systematic sorting. Second, we also implement the "left hand side" test of Pei, Pischke and Schwandt (2019) by regressing $\overline{\%Indigenous}^{-i}_{iscw_1}$ on all pre-assignment characteristics and testing the joint significance of all regressors. This test also fail to reject the null of balanced sample with p-value equal to 0.586. Together, we take all these results as evidence of compliance with the mandate of random assignment of students to classrooms within schools in our estimation sample, supporting our identifying assumption.

7 Results

7.1 Effects of classroom exposure to Indigenous students

We first estimate the effects of exposure to Indigenous students on the *test scores*. This is akin to standard linear-in-means models used in the extant peer effects literature augmented with random assignment of minorities to classrooms which to our best knowledge has not been used to date as an identifying variation. The results are presented in Table C.4 where akin to Table C.3 we scale all the coefficients by a one SD increase in classroom share of the Indigenous students. We highlight three main findings from this table.

First, conditional on own test scores measured at the baseline, adding pre-assignment controls does not substantively affect our point estimate of interest (column 2 vs. column 3). This is expected given the balance documented in Table C.3. There is a modest difference in effect sizes between column (1), where we do not control for own test scores, and the subsequent columns where we do. This is likely due to a very strong correlation between test scores in waves 1 and 2 and almost no correlation between share of minorities and wave 1 test scores (as documented in Table C.3). Since the omitted variables bias formula multiples these two correlations, even a small imbalance in baseline test scores (e.g., due to sampling variation) would be magnified by a strong correlation between wave 1 and wave 2 test scores. Overall, we view the point estimates of

13. Sample sizes differ across outcomes due to missing values. Conclusions are unchanged if we force the sample to be stable across outcomes.

-0.018 and -0.023 as qualitatively identical, and more importantly, including baseline test scores meaningfully shrinks the standard errors on our estimates of interest. Second, we find significant negative effects from exposure to Indigenous students on majority students (Proposition X). Third, the interaction terms in the last column of the table show no evidence that increased share of Indigenous students in the classroom helps Indigenous students themselves. This is consistent with Proposition X in the model.

Overall, these results imply that both majority and Indigenous students have about 2.3-2.4 percent of a standard deviation lower test scores per one standard deviation increase in share of Indigenous students in their classroom. Recall that a standard deviation in the classroom share of Indigenous students represents about 1.7 children. In our data 77% of classrooms have no Indigenous children, 15% have just one Indigenous child while 8% have more than one Indigenous child. Thus, adding one Indigenous child to the typical classroom of 35 students would increase the share of Indigenous peers for the vast majority of students by 2.9%, which translates into a negative effect of 1.2% of a standard deviation. Although small, this average effect would apply to the overwhelming majority of students in Taiwanese schools; hence, its aggregate effects should not be understated.

To give context to these estimates, it is worth highlighting that prior results in the literature have been both limited and mixed, and no prior study was able to exploit random assignment of minorities to either schools or classrooms. Neither Angrist and Lang (2004) nor Figlio and Özek (2019) find negative effects on cognitive abilities of native/majority students exposed to racial minorities or immigrants, respectively. Setren (2022) re-examines the METCO program first evaluated by Angrist and Lang (2004) and likewise finds no negative peer effects on academic performance, classroom behavior, and attendance of suburban students. In contrast with our findings, Figlio et al. (2021) find that increasing immigrants in schools from the 10^{th} to the 90^{th} percentile increases native student's test scores in mathematics and reading by 2.8 and 1.7 percent of a standard deviation, respectively. Yet, in line with our findings, Hoxby (2000) documents that a 10 percentage point increase in the share of Black students in a classroom, decreases third grade reading test scores by 0.25, 0.10, and 0.06 points for Black, Hispanics, and Anglo students, respectively.[14] Our Indigenous effect sizes are comparable to Hoxby's estimates for Anglo students, and are much smaller than estimates for Black and Hispanic students. Similarly, Diette and Oyelere Uwaifo (2014), shows that a 10 percentage point increase in students with limited English capacity lowers mathematics and reading scores of native students by about 0.7 percent of a standard deviation.

14. Standard deviation of this test score varies between 2.1 and 2.6 depending on the exact year (Table 2 in Hoxby (2000)), implying re-scaled effect sizes between 2.3 and 11.9 percent of a standard deviation depending on the race and which standard deviation we use.

7.2 Robustness checks

Our main results are robust to a number of alternative specifications.[15] We start our analysis by exploring the stability of our preferred estimates over alternative sample choices. Online Appendix Table **??** presents these results. Column 1 replicates our baseline results from column 4 of Table C.4 while column 2 drops schools where Indigenous students are in the majority and therefore where higher classroom shares of these students do not actually represent increased exposure to minorities. In column 3 we exclude Indigenous and Hakka students from the sample, also dropping ethnic main effects and their interactions with the share of ethnic minority students. In column 4 we drop all private schools, which we worry might be less likely to follow the governmental rules on random assignment to classrooms, or more likely to cater to a more select set of students and parents. Finally, in column 5 we exclude Waishengren students from our definition of what constitutes ethnic majority in schools, as these students are culturally different from Hoklo. Irrespective of the sample we choose, we find very consistent results: negative, statistically significant, and similar magnitude-wise estimates for Indigenous peers and never statistically significant and small coefficients for Hakka peers.[16] Based on these exercises we conclude that our main results are robust to reasonable alternative specifications of the estimation samples.

Next we consider alternative definitions of our treatment variables. Our preferred measure is a standard deviation of minority peers in the classroom, but this might be misspecified. Thus, in Online Appendix Table **??** we present two alternative ways of defining our treatment: the share of specific minority students in a classroom (column 2) and the presence of any student from a specific minority group in a classroom – capturing the extensive margin of the treatment (column 3). The former is a convenient re-scaling that is nonetheless useful for recalculating implied effect sizes; the latter removes intensive margin variation from the estimates and therefore identifies the effects of the mere presence of minorities in the classroom. The results when using the share of students are substantively unchanged, which is to be expected: with both Indigenous and Hakka peer coefficients increasing by a factor of approximately 21. Since the fraction of Indigenous students in the overall Taiwanese population is about 4%, this means that randomly distributing them into classrooms in Taiwan would, on average, reduce test scores by 1.6% of a standard deviation.

Given the relatively small share of Indigenous students in population, it is perhaps more policy

15. In all of the sensitivity analyses we focus on fully saturated model from column 4 of Table C.4 but we only display coefficient on share of Indigenous students.

16. Interestingly, in sample where we exclude Waishengren student (column 5) the coefficient on the interaction between share of Indigenous peers and being Indigenous is positive and marginally statistically significant at 10% level. At 0.7% of a standard deviation it means that negative peer effect for Indigenous students is halved compared with Hoklo majority students.

relevant to ask if having exposure to any Indigenous peer–at the extensive margin–would also generate negative effects. When we use a dummy variable for any Indigenous peer in the classroom we find a negative point estimate of 4.8% of a standard deviation.[17] This effect is about 2.5 times the size of our estimate in column 1, suggesting non-linearity and diminishing penalty over subsequent Indigenous students.[18] Interestingly, on the extensive margin only, we also find a negative and statistically significant penalty from exposure to Hakka peers that is only somewhat smaller than the penalty from exposure to Indigenous peers. Given that our estimates in columns 1 and 2 for Hakka are positive, this suggests that the penalty from Hakka peers might be strongly decreasing in size of this group (which constitutes about 18% of the Taiwanese population). This intuition is confirmed in Figure **??**, where we estimate a penalty of 5.3% of a standard deviation in classrooms with just one Hakka student, yet this penalty declines to 3.4% and a trivial 0.5% of a standard deviation for classrooms with two or three or more Hakka peers, respectively. Our interpretation of these non-linear results are that having a culturally "odd duckling" in a classroom could generate negative externalities, irrespective of the child's ethnicity. It just so happens that, in the Taiwanese context and thanks for the relative prevalence of Indigenous groups, the odd ducklings are much more likely to be Indigenous than Hakka children.

In a final robustness exercise, we check that inference on our estimators is not affected by departures from random assignment to classrooms, or by quantitatively important spillovers across classrooms. To assess this, we perform a series of placebo estimates where we randomly re-assign students to placebo classrooms while keeping school structures intact, and then recalculate "placebo" Indigenous exposure effects. We perform this random re-assignment 1,000 times and obtain normal-looking distributions of both effects centered around zero. Online Appendix Figure C.5 presents these results. These findings are reassuring since, in the presence of unobserved confounders correlated with Indigeneity or quantitatively-important spillovers across classrooms, we would expect skewed distributions for these placebo effects. An additional

17. A important concern here is selection into identification (Miller, Shenhav and Grosz, 2022). Even if students are randomly allocated to classrooms, in any given school with at least one Indigenous or Hakka child in each classroom, there would be no within-school variation in the treatment. Therefore, those schools would not contribute to the identification of the coefficients of interest. If these schools are systematically different from those that do contribute to identification, and in the presence of heterogeneous treatment effects, this can bias our estimates away from Average Treatment Effect of interest. We are less concerned with this phenomenon when it comes to Indigenous children since they constitute only 4% of the sample and is therefore unlikely that all classrooms in any school have at least one Indigenous child. For Hakka students, though, who constitute 18% of the sample, this can become a bigger problem. Out of 307 schools in the sample with at least one Indigenous or Hakka student, 108 schools do not have variation in both treatment variables. These schools are only very slightly more advantaged than schools where variation exists.

18. We have also estimated models with indicators for just one, just two, and three or more Indigenous students in the classroom. The results, presented in Online Appendix Figure **??**, suggest an increasing score penalty with more students, but only up to two students. The point estimate for three or more Indigenous students is smaller but statistically insignificant with a large standard error. This is likely due to very limited set of classrooms that would have more than three Indigenous students. Recall that in our data 77% of classrooms do not have any Indigenous students, 15% have one, 3% have two, and only 5% have three or more such students.

benefit from this exercise is that by comparing actual and placebo effects we can construct exact tests, with a distribution that is independent of sample size or the distribution of the error term (Young, 2019). Indeed, the aforementioned comparisons of placebo and actual effects reaffirms the statistically significance of the negative effect of exposure to Indigenous students in a classroom (with an empirical p-value of 0.005). We present two additional placebo analyses in Section XX, after discussing the mechanisms proposed in our model.

7.3 Alternative explanations and characteristics correlated with Indigeneity

Before exploring changes in student, parent, and teacher behaviors, we first verify to what extent our estimates are driven by characteristics correlated with Indigeneity. Table C.1 makes it clear that Indigenous students have lower ability, are somewhat less fluent in Mandarin, and come from more disadvantaged households. Given the literature on ability peer effects (e.g., Lavy, Silva and Weinhardt, 2012), the importance of language skills in schooling (e.g., Boucher et al., 2020), and the effects of disadvantage in generating peer effects (e.g., Carrell, Hoekstra and Kuka, 2018) we need to ensure that the negative effects documented above are indeed due to the fact that these students are Indigenous rather than due to any other correlated peer characteristics. Note that, in this exercise, we are decomposing the effect of Indigenous students based on other baseline characteristics. Since in our setting students are as good as randomly assigned, this exercise can be viewed as a form of causal decomposition (i.e., identifying the part of the causal effect of Indigenous students that comes through causal effects of other characteristics correlated Indigeneity).

To answer this question we use method proposed in Gelbach (2016), adjusted to utilize only within-school variation, which we need since our randomization is performed at the classroom-level within schools. Importantly, unlike other decomposition methods, this one is not sensitive to ordering of the explanatory variables and takes into account correlations between them. Figure X presents these results and shows that language and investments of Indigenous parents do not contribute to explaining the negative effect on test scores of the majority students. On the other hand, lower test scores and socioeconomic status of Indigenous students explain about one-third of the uncovered negative effect. Overall, we conclude that although characteristics correlated with Indigeneity (or for that matter potentially other minorities status in different settings) need to be accounted for, they are not the predominant factor driving the negative reduced-form effects documented in Table C.4.

7.4 Mechanisms: Student, Parental, and Teacher Behavioral Changes

We now turn to verifying Propositions X and X from our theoretical framework that students, parents, and teachers might alter their investments and behaviors in response to exposure to Indigenous students. In particular, the model predicts that in a classroom with higher share of

minority students, the remaining students (Proposition X) and their parents (Proposition) will lower their investments. Furthermore, teachers in these classrooms are expected to lower their effort (Proposition X). We conduct this analysis in two steps. First, we re-estimate Equation 21 while substituting the dependent variable with measures of student, parents, and teachers inputs described in Appendix B, noticing that higher index values capture better inputs—in the sense that they are positively and significantly correlated with test scores.[19] Second, in a procedure akin to how we decomposed the Indigenous effect by correlated peer characteristics in Section 7.3, we again use the method by Gelbach (2016) to descriptively understand to what extent these changes in student, parent, and teacher inputs could explain our negative estimates.

Table C.5 presents the results for the first part of the analysis.[20] Consistent with our prediction, the inputs of *parents and teachers* appear to drive the negative impact of Indigenous peers on test scores. In classrooms with a higher share of Indigenous students, ethnic majority parents *lower* their productive investments in their children.[21] Why would parents lower their investments in such classrooms? It could be that ethnic majority parents perceive these classrooms as weaker and thus decide to spend their resources elsewhere (perhaps on their other children). Alternatively, parents could be receiving an inflated signal from the teacher about the performance of their child, leading them to believe that they do not need additional time and money investments (we investigate this point below).

We also find negative effects of indigenous peers on *teacher inputs*. There are many potential explanations for this effect, yet a straightforward one could be that teachers perceive their students to be making less progress, which in turn demotivates and disengages them. A related explanation could be that more multicultural classrooms become harder to manage, forcing the teacher to spend more time and effort managing the classroom and less time covering content.[22]

In contrast, we do not find statistically significant effects on either student inputs (with a point estimate several orders of magnitude smaller than those on parental and teacher inputs, yet equally precisely estimated) or on teacher's subjective assessment of student's ability. The former finding rules out that the negative effects are caused by changes in students themselves—a prevalent

19. Pearson correlations of 0.54, 0.35, and 0.38 between test scores and student, parents, and teacher inputs, respectively.

20. We present robustness of the mechanisms to using alternative indices—based on PCA rather than regression analysis–in Online Appendix Table **??**. Our conclusions are substantively unchanged even though the exact magnitudes of estimates differ due to different underlying distributions of the indices.

21. When we investigate specific components of the index we find that the negative effect is driven by *lower spending on private tutoring*, *lower university aspirations*, and *less time spend with their children*. We opt to present the aggregated index results rather than its separate components since considering the many inputs we measure as separate outcomes would require considerable adjustments for multiple hypothesis testing (Clarke, Romano and Wolf, 2020) for which we do not have sufficient power. Thus, we view our analysis of the specific scales in each index as exploratory.

22. There is suggestive evidence in favor of both explanations from separate analyses of the index scale subcomponents. The effects seem to be primarily driven by teachers having lower average assessment of the class performance and reporting that the class is harder to manage.

hypothesis behind the origin of peer effects literature—due to either their characteristics or actions. The latter finding is interesting, since we have shown that the objective performance of majority students has indeed decreased as a result of exposure to Indigenous peers. Yet the teachers do not detect this drop in performance, which means that their subjective assessments of majority students become effectively inflated when there are Indigenous students in the classroom. This is all consistent with the local distortion mechanisms hypothesized above, linking teacher and parent input reactions under one single behavioral model. Unfortunately, we cannot provide a more definitive test of whether teacher's subjective assessment is a causative factor behind changes in parental inputs or if these two phenomena occur in parallel.

We now ask if these changes in student, parent and teacher inputs can explain the negative Indigenous peer effect. Table C.5 presents these results. Since student, parental, and teacher inputs are correlated, and the Gelbach (2016) decomposition accounts for this interdependence, the coefficients change somewhat compared to those from Table C.4. More importantly, the decomposition allows us to include the individual input measures that form the indices separately, rather than forcing us to add the indices themselves. The group-g decomposition proposed by Gelbach (2016, p. 522) takes care of aggregating the separate measures for the purposes of the analysis. This is advantageous, since the indices forcibly lose some information when aggregating input measures; adding all the scales separately rather than the three aggregate indices makes this mediation results robust to all possible constructions of the input indices. Interestingly, Table C.5 shows a slightly positive mediation, albeit statistically insignificant, of student-related inputs. This means that, conditional on parental and teacher input changes, student inputs slightly improve in classrooms with more Indigenous students, potentially offsetting the negative peer effect. In contrast, we consistently find negative and statistically significant mediating effects of parental- and teacher-related inputs, which means that part of the negative peer effect can be explained by the decline in inputs from those two sources. How much of the negative effect do these inputs explain? Table C.5 suggests that almost *two thirds* of the negative peer effects could be due to changes in inputs of students, parents, and teachers. This is about twice the amount that was explained by characteristics correlated with the Indigenous status of peers, as discussed in Section 7.3.

Taken together, these results show the importance of modelling peer effects in schools in the context of a multi-agent production function that involves not only students but also parents and teachers (and perhaps even school administrators, whose behavior we cannot observe in our data). Our results certainly suggest that contextual interactions (in the language of Manski (2000), referring to exogenous peer characteristics correlated with the Indigenous status of peers) explain a rather small part of the effects documented in Section 7.1.

Our final analysis combines the decomposition and mediation results presented in Figures C.4a and C.4b, and asks if we can fully explain away the negative Indigenous peer effect documented in Table C.4 by accounting for correlated student characteristics as well as endogenous responses

of students, parents and teachers. As in Section 7.4, this is a descriptive exercise and Online Appendix Table **??** presents these results. First, it is worth noting again that including pre-assignment controls does not alter the point estimates–comparing columns 1 and 2. Including correlated peer characteristics (column 3) explains 26% of the estimated negative effect, yet the remaining Indigenous peer effect is still sizeable and statistically significant at 10% level. At the same time, including student, parent, and teacher mechanisms (column 4) more than halves the negative Indigenous peer effect and renders it no longer statistically significant. Finally, conditioning of both correlated peer characteristics and endogenous inputs (column 5) explains away almost all of the negative coefficient. Even though this is a descriptive exercise, we conclude that much of the negative peer effect documents in Section 7.1 is due to endogenous responses of parents and teachers (more important) as well as characteristics correlated with peers' indigenous status (less important) which means that correcting these two uncovered mechanisms has a chance to reduce any negative spillovers occurring due to classroom integration to zero.

8 Conclusions

This paper shows that minority peers can have negative effects on cognitive outcomes of the majority children and that these negative externalities can be group-specific even within the context of a single country and education system. We find that classroom exposure to Indigenous peers lowers test scores of ethnic majority students by 1.9% of a standard deviation per one standard deviation increase in number of Indigenous students. We do not find any statistically significant or economically meaningful peer effects from the other minority group we consider - Hakka. Furthermore, we document that a non-trivial share of the negative effect can be explained by changing inputs and investments of majority parents as well as teachers in these classrooms. On the other hand, characteristics correlated with the Indigenous ethnicity can account for a smaller fraction of the estimated coefficient. In that, the negative effect should not be attributed to the ethnicity of students per se but rather to how others react when interacting with ethnic minorities. Thus, successful classroom integration efforts need to better understand and address these endogenous responses of parents and teachers which have largely been ignored in the peer effects literature to date.

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Appendix A Theory

A.1 Size of population n is fixed

Assume that the population n is fixed. The first-order condition (2) can be written as:

$$y^i = b^i + \phi \left[q y^m + (1-q) y^M - \frac{y^i}{n} \right]$$

This implies that

$$y^M = \frac{b^M + \phi\, q y^m}{1 - \phi\,(1-q) + \frac{\phi}{n}}$$

$$y^m = \frac{b^m + \phi(1-q) y^M}{1 - \phi q + \frac{\phi}{n}}$$

By solving these equations, we obtain:

$$y^{M*} = \frac{\left(1 - \phi q + \frac{\phi}{n}\right) b^M + \phi q b^m}{\left(1 - \phi + \frac{\phi}{n}\right)\left(1 + \frac{\phi}{n}\right)}$$

$$y^{m*} = \frac{\left[1 - \phi\,(1-q) + \frac{\phi}{n}\right] b^m + \phi(1-q) b^M}{\left(1 - \phi + \frac{\phi}{n}\right)\left(1 + \frac{\phi}{n}\right)}$$

We have

$$\frac{\partial y^{M*}}{\partial q} = \frac{\phi\left(b^m - b^M\right)}{\left(1 - \phi + \frac{\phi}{n}\right)\left(1 + \frac{\phi}{n}\right)}$$

$$\frac{\partial y^{m*}}{\partial q} = \frac{\phi\left(b^m - b^M\right)}{\left(1 - \phi + \frac{\phi}{n}\right)\left(1 + \frac{\phi}{n}\right)}$$

Clearly, if $b^m < b^M$, then $\frac{\partial y^{M*}}{\partial q} < 0$ and $\frac{\partial y^{m*}}{\partial q} < 0$.

A.2 Proof of Proposition 1

When n is large, $\frac{y_s^i}{n} \to 0$, the first-order condition (2) can be written as:[23]

$$y_s^i = b^i + \phi \left[q y_s^m + (1-q) y_s^M \right]. \tag{A.1}$$

23. Assuming a fixed size of n does not change the results; it just makes the analysis more complicated. See Section A.1 in this Appendix.

This implies that:

$$y_s^{M*} = \frac{b^M + \phi\, q y_s^m}{1-\phi(1-q)} \tag{A.2}$$

$$y_s^{m*} = \frac{b^m + \phi(1-q) y_s^{M*}}{1-\phi q} \tag{A.3}$$

By solving these equations, we obtain:

$$y_s^{M*} = \frac{(1-\phi q)\, b^M + \phi q b^m}{1-\phi} \tag{A.4}$$

$$y_s^{m*} = \frac{[1-\phi(1-q)]\, b^m + \phi(1-q) b^M}{1-\phi} \tag{A.5}$$

We have:

$$\frac{\partial y_s^{M*}}{\partial q} = \frac{\phi\left(b^m - b^M\right)}{1-\phi}, \tag{A.6}$$

$$\frac{\partial y_s^{m*}}{\partial q} = \frac{\phi\left(b^m - b^M\right)}{1-\phi}. \tag{A.7}$$

Thus, if $b^m < b^M$, then $\frac{\partial y^{M*}}{\partial q} < 0$ and $\frac{\partial y^{m*}}{\partial q} < 0$.

A.3 Proof of Proposition 2

A.3.1 Parents' effort choices

Let us solve first the parents' effort choice.

Consider the *majority* parent's utility function (12). The first-order condition is equal to:

$$\frac{\partial U_p^M}{\partial y_p^M} = \alpha_2 \rho\, (1-\phi)^{-\alpha_1} \left(\Delta^M(q)\right)^{\alpha_1} \left(y_p^M\right)^{\alpha_2 - 1} \left(y_t^i\right)^{\alpha_3} - 1 = 0$$

Solving this equation leads to:

$$y_p^{M*} = (\alpha_2 \rho)^{1/(1-\alpha_2)}\, (1-\phi)^{-\alpha_1/(1-\alpha_2)} \left(\Delta^M(q)\right)^{\alpha_1/(1-\alpha_2)} \left(y_t^i\right)^{\alpha_3/(1-\alpha_2)}$$

Thus

$$\left(y_p^{M*}\right)^{\alpha_2} = (\alpha_2 \rho)^{\alpha_2/(1-\alpha_2)}\, (1-\phi)^{-\alpha_1\alpha_2/(1-\alpha_2)} \left(\Delta^M(q)\right)^{\alpha_1\alpha_2/(1-\alpha_2)} \left(y_t^i\right)^{\alpha_3\alpha_2/(1-\alpha_2)}$$

Denote

$$Z_1 := (\alpha_2\rho)^{\alpha_2/(1-\alpha_2)}(1-\phi)^{-\alpha_1\alpha_2/(1-\alpha_2)}$$

We have

$$\left(y_p^M\right)^{\alpha_2} = Z_1\left(\Delta^M(q)\right)^{\alpha_1\alpha_2/(1-\alpha_2)}\left(y_t^i\right)^{\alpha_3\alpha_2/(1-\alpha_2)}$$

and

$$y_p^{M*} = Z_1^{1/\alpha_2}\left(\Delta^M(q)\right)^{\alpha_1/(1-\alpha_2)}\left(y_t^i\right)^{\alpha_3/(1-\alpha_2)}$$

Consider now the *minority* parent's utility function (13). Proceeding as above, we easily obtain:

$$\left(y_p^m\right)^{\alpha_2} = Z_1\left(\Delta^m(q)\right)^{\alpha_1\alpha_2/(1-\alpha_2)}\left(y_t^i\right)^{\alpha_3\alpha_2/(1-\alpha_2)}$$

and

$$y_p^{m*} = Z_1^{1/\alpha_2}\left(\Delta^m(q)\right)^{\alpha_1/(1-\alpha_2)}\left(y_t^i\right)^{\alpha_3/(1-\alpha_2)}$$

A.3.2 Teachers' effort choices

The first-order condition is:

$$\alpha_3 n^M \rho(1-\phi)^{-\alpha_1}\left(\Delta^M(q)\right)^{a_1}\left(y_p^M\right)^{\alpha_2}\left(y_t^i\right)^{\alpha_3-1}$$

$$+\alpha_3 n^m \rho(1-\phi)^{-\alpha_1}\left(\Delta^m(q)\right)^{a_1}\left(y_p^m\right)^{\alpha_2}\left(y_t^i\right)^{\alpha_3-1} = 1$$

which is equivalent to:

$$\frac{c_t(1-\phi)^{\alpha_1}}{n\alpha_3\rho}\left(y_t^i\right)^{1-\alpha_3} = (1-q)\left(\Delta^M(q)\right)^{a_1}\left(y_p^M\right)^{\alpha_2} + q\left(\Delta^m(q)\right)^{a_1}\left(y_p^m\right)^{\alpha_2}.$$

Using the equations above, that is

$$\left(y_p^M\right)^{\alpha_2} = Z_1\left(\Delta^M(q)\right)^{\alpha_1\alpha_2/(1-\alpha_2)}\left(y_t^i\right)^{\alpha_3\alpha_2/(1-\alpha_2)}$$

$$\left(y_p^m\right)^{\alpha_2} = Z_1\left(\Delta^m(q)\right)^{\alpha_1\alpha_2/(1-\alpha_2)}\left(y_t^i\right)^{\alpha_3\alpha_2/(1-\alpha_2)}$$

we have

$$\begin{aligned}\frac{(1-\phi)^{\alpha_1}}{n\alpha_3\rho}\left(y_t^i\right)^{1-\alpha_3} &= (1-q)\left(\Delta^M(q)\right)^{a_1} Z_1\left(\Delta^M(q)\right)^{\alpha_1\alpha_2/(1-\alpha_2)}\left(y_t^i\right)^{\alpha_3\alpha_2/(1-\alpha_2)} \\ &\quad + q\left(\Delta^m(q)\right)^{a_1} Z_1\left(\Delta^m(q)\right)^{\alpha_1\alpha_2/(1-\alpha_2)}\left(y_t^i\right)^{\alpha_3\alpha_2/(1-\alpha_2)}\end{aligned}$$

This is equivalent to:

$$\frac{(1-\phi)^{\alpha_1}}{n\alpha_3\rho Z_1}\left(y_t^i\right)^{\alpha_1/(1-\alpha_2)} = (1-q)\Delta^M(q)^{a_1/(1-\alpha_2)} + q\left(\Delta^m(q)\right)^{a_1/(1-\alpha_2)}$$

$$\Leftrightarrow \frac{(1-\phi)^{\alpha_1}}{n\alpha_3\rho Z_1}\left(y_t^i\right)^{\alpha_1/(1-\alpha_2)} = \Delta^M(q)^{a_1/(1-\alpha_2)}$$

which leads to

$$y_t^{i*}(q) = (n\alpha_3\rho Z_1)^{(1-\alpha_2)/\alpha_1}(1-\phi)^{-(1-\alpha_2)}\Delta^M(q) \tag{A.8}$$

where

$$Z_1 := (\alpha_2\rho)^{\alpha_2/(1-\alpha_2)}(1-\phi)^{-\alpha_1\alpha_2/(1-\alpha_2)}$$

Using this value, we obtain

$$y_t^{i*}(q) = \alpha_2^{\alpha_2/\alpha_1}(n\alpha_3)^{(1-\alpha_2)/\alpha_1}\rho^{1/\alpha_1}(1-\phi)^{-1}\Delta^M(q)$$

Thus

$$\begin{aligned}\frac{\partial y_t^{i*}(q)}{\partial q} &= \alpha_2^{\alpha_2/\alpha_1}(n\alpha_3)^{(1-\alpha_2)/\alpha_1}\rho^{1/\alpha_1}(1-\phi)^{-1}\frac{\partial\Delta^M(q)}{\partial q}\\ &= \frac{\phi}{(1-\phi)}\alpha_2^{\alpha_2/\alpha_1}(n\alpha_3)^{(1-\alpha_2)/\alpha_1}\rho^{1/\alpha_1}\left(b^m-b^M\right)\end{aligned}$$

Thus, if $b^m < b^M$, we have:

$$\frac{\partial y_t^{i*}(q)}{\partial q} < 0$$

A.3.3 Parents's and teachers' effort choices

We have:

$$\begin{aligned}Z_1^{-1/\alpha_2}\frac{\partial y_p^M}{\partial q} &= \frac{\alpha_1}{(1-\alpha_2)}\left(\Delta^M(q)\right)^{-\alpha_3/(1-\alpha_2)}\phi\left(b^m-b^M\right)\left(y_t^{i*}(q)\right)^{\alpha_3/(1-\alpha_2)}\\ &+\left(\Delta^M(q)\right)^{\alpha_1/(1-\alpha_2)}\frac{\alpha_3}{(1-\alpha_2)}\left(y_t^{i*}(q)\right)^{-\alpha_1/(1-\alpha_2)}\frac{\partial y_t^{i*}}{\partial q}\end{aligned}$$

If $b^m < b^M$, we clearly obtain:

$$\frac{\partial y_p^M}{\partial q} < 0$$

Similarly

$$\begin{aligned}Z_1^{-1/\alpha_2}\frac{\partial y_p^m}{\partial q} &= \frac{\alpha_1}{(1-\alpha_2)}\left(\Delta^m(q)\right)^{-\alpha_3/(1-\alpha_2)}\phi\left(b^m-b^M\right)\left(y_t^{i*}(q)\right)^{\alpha_3/(1-\alpha_2)}\\ &+\left(\Delta^m(q)\right)^{\alpha_1/(1-\alpha_2)}\frac{\alpha_3}{(1-\alpha_2)}\left(y_t^{i*}(q)\right)^{-\alpha_1/(1-\alpha_2)}\frac{\partial y_t^{i*}(q)}{\partial q}\end{aligned}$$

If $b^m < b^M$, we also obtain:

$$\frac{\partial y_p^m}{\partial q} < 0$$

Consider now students' test scores, that is,

$$S^{M*} = \rho\,(1-\phi)^{-\alpha_1}\left(\Delta^{M}(q)\right)^{\alpha_1}\left(y_p^{M*}(q)\right)^{\alpha_2}\left(y_t^{i*}(q)\right)^{\alpha_3}$$

and

$$S^{m*} = \rho\,(1-\phi)^{-\alpha_1}\left(\Delta^{m}(q)\right)^{\alpha_1}\left(y_p^{M*}(q)\right)^{\alpha_2}\left(y_t^{i*}(q)\right)^{\alpha_3}$$

Thus

$$\frac{S^{M*}}{S^{m*}} = \left(\frac{\Delta^{M}(q)}{\Delta^{m}(q)}\right)^{\alpha_1}$$

Furthermore

$$\rho\,(1-\phi)^{\alpha_1}\frac{\partial S^{M*}}{\partial q} =$$

$$\begin{aligned}
&\alpha_1\left(\Delta^{M}(q)\right)^{\alpha_1-1}\phi\left(b^{m}-b^{M}\right)\left[\left(y_p^{M*}(q)\right)^{\alpha_2}\left(y_t^{i*}(q)\right)^{\alpha_3}\right]\\
&+\left(\Delta^{M}(q)\right)^{\alpha_1}\left[\alpha_2\left(y_p^{M*}(q)\right)^{\alpha_2-1}\frac{\partial y_p^{M*}(q)}{\partial q}\left(y_t^{i*}(q)\right)^{\alpha_3}\right]\\
&+\left(\Delta^{M}(q)\right)^{\alpha_1}\alpha_3\left(y_p^{M*}(q)\right)^{\alpha_2}\left(y_t^{i*}(q)\right)^{\alpha_3-1}\frac{\partial y_t^{i*}(q)}{\partial q}
\end{aligned}$$

Thus

$$\frac{\partial S^{M*}}{\partial q} < 0$$

With a similar calculation, we obtain

$$\frac{\partial S^{m*}}{\partial q} < 0$$

Appendix B Data and Construction of Summary Indices

Our model predicts changes in student, parent and teacher effort in response to exposure to ethnic minority peers in the classroom. We construct three indices capturing student effort, parental investments and teacher effort respectively.

Since most educational inputs in the TEPS are measured using multiple questions, we first identify blocks of items in the questionnaires that measure related constructs, e.g. students' study hours. We then eliminate badly performing measures of the underlying construct aiming to maximize the informational content and reduce noise. Through Spearman correlations between all items in a block, Cronbach's alpha assessments, and exploratory factor analyses, we remove questions with low correlations to the rest from the block. Once we have narrowed down the list and have verified the performance of each question in a block, we construct a summative scale of all selected questions. This results in a series of scales, some of which measure student-driven inputs into the education production function whereas others measure parent- and teacher-driven inputs.

Finally, to further reduce this still numerous set of scales and ensure we capture the set of inputs most productive in the education production function, we perform three regression-based mappings of indices onto academic achievement: one for student effort, one for parental investments, and one for teacher effort. We refer to these as our aggregate indices, and use them to explore the predictions of our model (Propositions 1 and 2).

For student effort and parental investments, we construct these indices by regressing student test scores in wave 1 on student effort and parental investments in wave 1 (and school fixed effects). The coefficients of these regressions describe the "returns" of each input in the test score production function. We then apply these coefficients to the corresponding scales in wave 2 to generate the "forecasted scores" from student effort and parental investments that are productive for test scores.

For teacher inputs we cannot use the same procedure since teachers are randomly assigned to students at the beginning of junior high school, which means that teacher characteristics in wave 1 are not correlated with student test scores in wave 1. Instead, we construct a measure akin to "predicted teacher value added" to produce a mapping of teacher-related inputs to test scores. We do this by regressing wave 2 test scores on wave 1 teacher effort (and partialling out school-by-baseline-test-score fixed effects to account for baseline class composition).[24] The

24. Our test score measure–a count of the number of correct test answers–has 64 actual points of support. The school-by-baseline-test-score fixed effects means that there is a fixed effect for each student score and school (e.g., everyone who got a 37 questions right in school 3 has a fixed effect, everyone who got a 38 test score in the same school gets a different fixed effect, etc.). Effectively, we absorb 4,572 school-by-baseline-test-score fixed effects with

coefficients from this regression identify the "returns" to teacher-related inputs, which we then apply to the corresponding teacher effort measure in wave 2 to produce predicted scores. Columns (1) in Online Appendix Tables **??** to **??** present the regression-based coefficients–effectively the weights–used to construct each of the student effort, parental investments, and teacher effort indices. In columns (2) we present an alternative approach to constructing these indices using the score of the first component from separate Principal Component Analyses (PCA) of student effort, parental investments, and teacher effort. We use these PCA scores to test the robustness of our findings on mechanisms.[25]

Our index of student effort (which corresponds to y_s^i in the model) combines items capturing study hours. All these measures are, a priori, meaningful contributors to academic achievement and can also be influenced by peers. Study effort is often considered as the main potential mechanism for academic peer effects (see e.g., Feld and Zoelitz, 2017, or Xu, Zhang and Zhou, 2022). Our data allows us to differentiate between study time outside the classroom and time spent in tutoring.

Our index of parental investments (which corresponds to y_p^i in the model) combines three scales of private tutoring, time spent with parents, and parental emotional support. School environment has been shown to affect parental investments and academic achievement (see e.g., Pop-Eleches and Urquiola, 2013, Fredriksson, Öckert and Oosterbeek, 2016), and much of this work hypothesizes peers as a key driver of these effects. Furthermore, parental monetary and time investments are the canonical Beckerian household investments in human capital and can therefore respond as complements or substitutes to school inputs, such as exposure to minorities in classroom. Parental support belongs to a broader set of parenting styles which can also be modelled as parental investments (Cobb-Clark, Salamanca and Zhu, 2019) and thus also react to school inputs for similar reasons. Conceptually parental support is close to warmth and more generally measures parental engagement.

Lastly, our index of teacher effort (which corresponds to y_t^i in the model) combines items capturing teachers' time invested in preparing original material and grading. We also consider a dummy variable for whether they consider the classroom being hard to manage. Both measures proxy for teacher effort that make the classroom productive for learning, and can be affected by the social and cultural diversity. For example, lower-achieving peers such as Indigenous students might increase classroom disruption, making classroom management harder and decreasing teacher effort (Duflo, Dupas and Kremer, 2011). Teachers' effort might also be more productive

this approach, which is a very flexible non-parametric way of controlling for baseline test scores when producing the "predicted value added" for our teacher-related inputs.

25. Other alternative ways to construct aggregate indices of these inputs, such as those proposed by Anderson (2008), Kling, Liebman and Katz (2007) or even simple summative indices, are not suitable for these data. The reason is that these methods implicitly assume that all items measure the same underlying construct. However, by construction, our items measure distinct constructs and so imposing a single-construct assumption when aggregating them is incorrect.

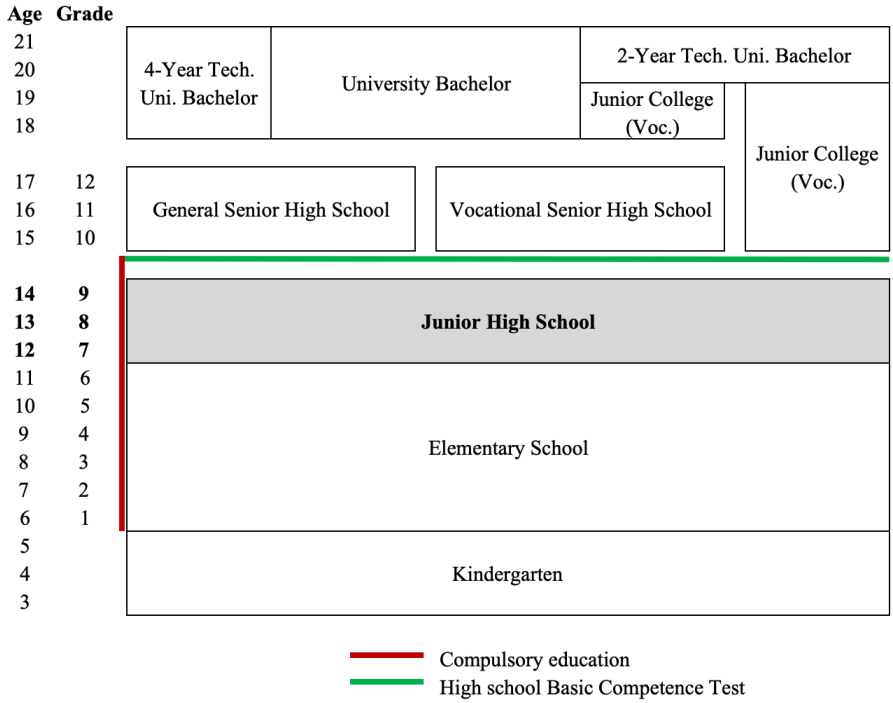
if they feel more motivated and less tired of teaching when working with a more homogeneous classrooms with fewer minority students.

Online Appendix Table C.1 presents basic descriptive statistics for the full TEPS sample (column 1), our estimation sample (column 2), Indigenous students (column 3), and majority students (column 4). The first set of variables presents student characteristics, the second set parental characteristics, and the third set school characteristics. Comparing the first two columns suggests that our estimation sample is very similar to the full data set or, if anything, it is slightly positively selected.[26] Overall, our estimation sample appears to represent the full population of Taiwanese schools well. This table makes it clear that *Indigenous students are much more disadvantaged than majority students*, which confirms the assumption of $b^m < b^M$ in the model. Their baseline test scores are over 90% of a SD lower than those of the majority. Indigenous students also come from larger families (2.4 siblings vs 1.7 for the majority) with less educated parents (80% of parents with at most high school vs. 64% for the majority) who have lower incomes (30% in lowest income bracket vs. 9% for the majority). Schools attended by Indigenous students are worse staffed, about half as likely to have principal with postgraduate degree compared with schools attended by majority students, although years of experience of the principals is comparable across groups. This could reflect the fact that Indigenous Peoples in Taiwan cluster in more rural areas rather than in the largest cities. The main difference across groups is their ability to speak languages other than Mandarin, which we take as a proxy for cultural differences. Almost no majority students are fluent in either Hakka or Indigenous languages, while Indigenous students know Indigenous languages but do not know Hakka. Across both groups about 90% of students are fluent in Mandarin, which is the official language of instruction.

26. The difference between these two columns comes from excluding 341 students of other ethnicities, 284 students attending schools with neither Indigenous nor Hakka students, and 2,085 student with missing test score or ethnicity information. We then drop schools which are likely to be exempt from following random assignment policy (e.g., schools that offer special programs for arts, languages, or for sports-focused students). We identify these schools using a modified version of the fishing algorithm developed by de Gendre and Salamanca (2020). This method identifies and excludes 8 schools for which there is evidence of systematic classroom sorting based on baseline ability, and 11 schools for which there is evidence of sorting in various baseline socioeconomic markers (family income, parental employment, and household financial stability). These exclusions remove additional 1,083 student from our analysis sample.

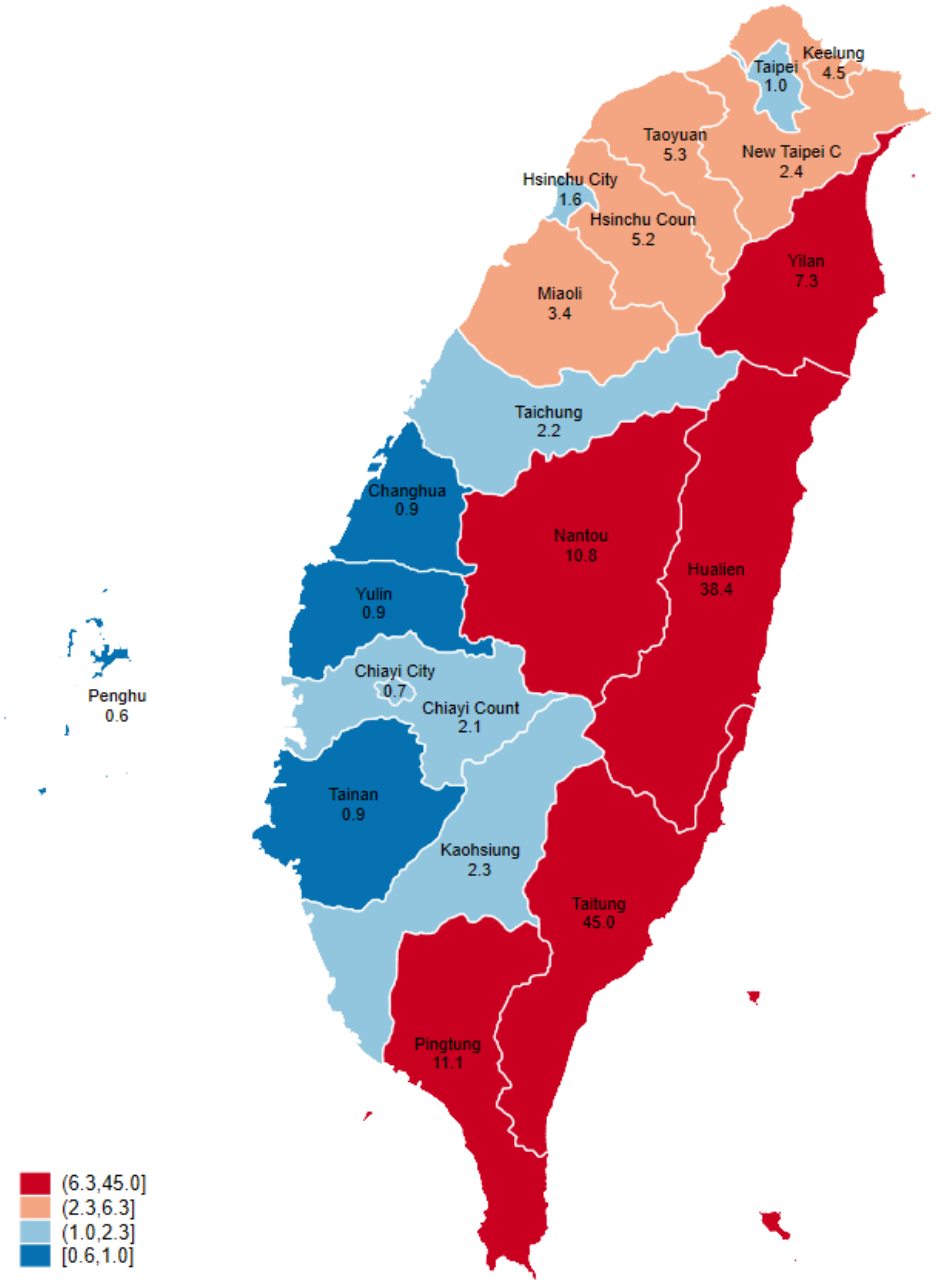
Appendix C Tables and Figures

Figure C.1: *Schematic of Taiwanese Education System*



Note: This graph depicts various levels in Taiwanese education system

Figure C.2: *Fraction of Indigenous Children Among 10 to 14 Year Olds by County*



Note: This figure depicts the share of Indigenous children among 10 to 14 year olds in Taiwan by country of residents based on 2010 Taiwanese Census.

Table C.1: *Descriptive statistics*

	(1)	(2)	(3)	(4)	(5)	
	Mean of characteristics in sample:					
	TEPS	**Estimation**	**Indigenous**	**Majority**	**Diff.**	
Students:						
Indigenous parent(s)	0.04	0.07	1.00	0.00	1.00	
Hakka parent(s)	0.17	0.21	0.06	0.22	-0.16	***
Test scores at baseline [std]	-0.05	-0.19	-0.87	-0.14	-0.73	***
Fluent in Mandarin	0.91	0.92	0.88	0.92	-0.04	***
Fluent in indigenous language	0.02	0.03	0.29	0.01	0.28	***
Fluent in Hakka language	0.04	0.05	0.03	0.05	-0.02	***
Female student	0.50	0.49	0.51	0.49	0.02	
Birth year	1989	1989	1989	1989	0.03	
No. of siblings of student	1.77	1.86	2.36	1.82	0.54	***
Aspires to go to university	0.45	0.43	0.33	0.43	-0.10	***
Expects to go to university	0.35	0.32	0.25	0.33	-0.08	***
Has conflicts with parents	0.24	0.25	0.26	0.25	0.01	
Parents are role models	0.31	0.32	0.36	0.31	0.05	**
Parents:						
Two-parent household	0.89	0.90	0.84	0.90	-0.06	***
Good relationship between them	3.14	3.14	3.10	3.14	-0.04	
Parent(s) education is high school or less	0.65	0.71	0.80	0.71	0.09	***
Employed father	0.89	0.88	0.78	0.88	-0.10	***
Parent(s) in good health	0.59	0.58	0.33	0.60	-0.27	***
Financial difficulties in past 10 yrs	0.27	0.30	0.60	0.28	0.32	***
Household monthly income is						
NT$20,000 or less	0.11	0.12	0.30	0.11	0.19	***
NT$20,000-NT$50,000	0.41	0.46	0.47	0.45	0.02	
NT$50,000-NT$100,000	0.35	0.33	0.20	0.34	-0.14	***
More than NT$100,000	0.14	0.09	0.03	0.09	-0.06	***
Schools:						
Principal has postgraduate degree	0.29	0.24	0.15	0.25	-0.10	***
Principal years of experience	29.1	28.5	28.1	28.5	-0.42	*
Government founded school	0.86	0.94	0.94	0.94	0.00	
School year of foundation	1968	1970	1968	1970	-1.96	***
Observations	20,055	8,517	588	7,929	8,517	

*Note: Summary Stats NOTE. ***, ** and * mark estimates statistically different from zero at the 99, 95 and 90 percent confidence level.*

Table C.2: *Documenting negative perceptions about student ability*

	(1)	(2)	(3)	(4)
Outcome:	**Above-average at problem solving (teacher assessment in W1)**			
	Panel A. Comparison between Indigenous and non-Indigenous students (Mean of Y = 0.30; N schools = 154, N classes = 576, N students = 7,579)			
Indigenous student	-0.121***	-0.153***	-0.049**	-0.086***
	(0.024)	(0.022)	(0.021)	(0.028)
Test scores in W1 [std]			0.234***	0.237***
			(0.005)	(0.006)
Indigenous × Test scores				-0.056***
				(0.021)
	Panel B. Comparison between Hakka and non-Hakka students (Mean of Y = 0.32, N schools = 306, N classes = 1,126, N students = 14,728)			
Hakka student	0.022*	0.021*	0.011	0.011
	(0.011)	(0.012)	(0.011)	(0.010)
Test scores in W1 [std]			0.233***	0.233***
			(0.004)	(0.004)
Hakka × Test scores				-0.001
				(0.009)
	Panel C. Comparison between synthetic Indigenous student and non-Indigenous students (Mean of Y = 0.30, N schools = 154, N classes = 576, N students = 7,579)			
Synthetic Indigenous student	-0.100***	-0.080***	-0.017	-0.029
	(0.023)	(0.024)	(0.020)	(0.032)
Test scores in W1 [std]			0.231***	0.231***
			(0.005)	(0.005)
Synthetic Indigenous × Test scores				-0.018
				(0.024)
School FE	No	Yes	Yes	Yes

*Note: Prejudice note NOTE. ***, ** and * mark estimates statistically different from zero at the 99, 95 and 90 percent confidence level.*

Table C.3: *Balancing*

Treatment:	(1)	(2)	(3)	(4)
		+1SD Indigenous students		
	Mean	Coef.	Std. err.	Obs.
Pre-assignment Outcomes:				
		Panel A. Student characteristics		
Student test scores	Std	0.005	(0.013)	8,517
Female student	0.49	-0.001	(0.006)	8,517
Student born before 1989	0.36	0.004	(0.006)	8,486
		Panel B. Parental characteristics		
Two-parent household	0.90	-0.001	(0.004)	8,505
Household income > NT$50k/mo.	0.42	-0.007	(0.006)	8,472
Stable income for 1+ household member	0.89	-0.001	(0.004)	8,499
Parent(s) education is high school or less	0.71	-0.009	(0.006)	8,517
Employed father	0.88	0.008*	(0.004)	8,210
Parent(s) in good health	0.58	-0.000	(0.006)	8,514
		Panel C. Educational investments/behaviors prior to junior high school		
Prioritized studies since primary school	0.27	0.006	(0.006)	8,467
Reviews lessons since primary school	0.17	0.002	(0.005)	8,460
Likes new things since primary school	0.41	-0.001	(0.007)	8,447
Was truant in primary school	0.35	0.005	(0.005)	8,495
Student had mental health issues in primary school	0.47	-0.002	(0.005)	8,491
Had private tutoring before junior high	0.65	0.005	(0.008)	8,428
Family help with homework before junior high	0.84	0.002	(0.004)	8,125
Student quarreled with parents in primary school	0.66	-0.003	(0.005)	8,503
Guryan et al. (2009) sorting t-statistic		1.1		
Jochmans (2020) sorting t-statistic		1.0		
LHS test of joint balancing (p-value)		0.586		

*Note: This table reports estimates of regressing pre-assignment characteristics in wave 1 on the classroom share of indigenous peers in wave 1. All estimators include school fixed effects and control for own indigenous status. Guryan et al. (2009) and Jochmans (2023) sorting statistics test to sorting tests of whether minority students are more likely to be assigned to classrooms with other indigenous students within schools, and the critical values for these tests are those of the t-distribution. LHS test of joint balancing refers to the F-test of all covariate significance from a regression of indigenous peers on all pre-assignment covariates with school fixed effects, as suggested by Pei at al. (2019). Standard errors clustered at the classroom level in parentheses. ***, ** and * mark estimates statistically different from zero at the 99, 95 and 90 percent confidence level.*

Table C.4: *Main results*

	(1)	(2)	(3)	(4)
	Student test scores in wave 2 (std)			
+1SD Indigenous students	-0.018	-0.023***	-0.024***	-0.024***
	(0.013)	(0.008)	(0.008)	(0.009)
Indigenous students × Indigenous				0.001
				(0.005)
Own test scores	No	Yes	Yes	Yes
Pre-assignment controls	No	No	Yes	Yes
N schools	155	155	155	155
N classes	588	588	588	588
N students	8,517	8,517	8,517	8,517

*Note: This table reports estimates of regressing standardized student test scores in wave 2 on the stnadardized classroom share of indigenous peers, and its interaction with an Indigenous student dummy. All regressions include school fixed effects. Own test scores refer to students' test scores in wave 1. Pre-assignment controls include all variables tested for balancing in Table 1. All controls are interacted with an Indigenous student dummy. Standard errors clustered at the classroom level in parentheses. ***, ** and * mark estimates statistically different from zero at the 99, 95 and 90 percent confidence level.*

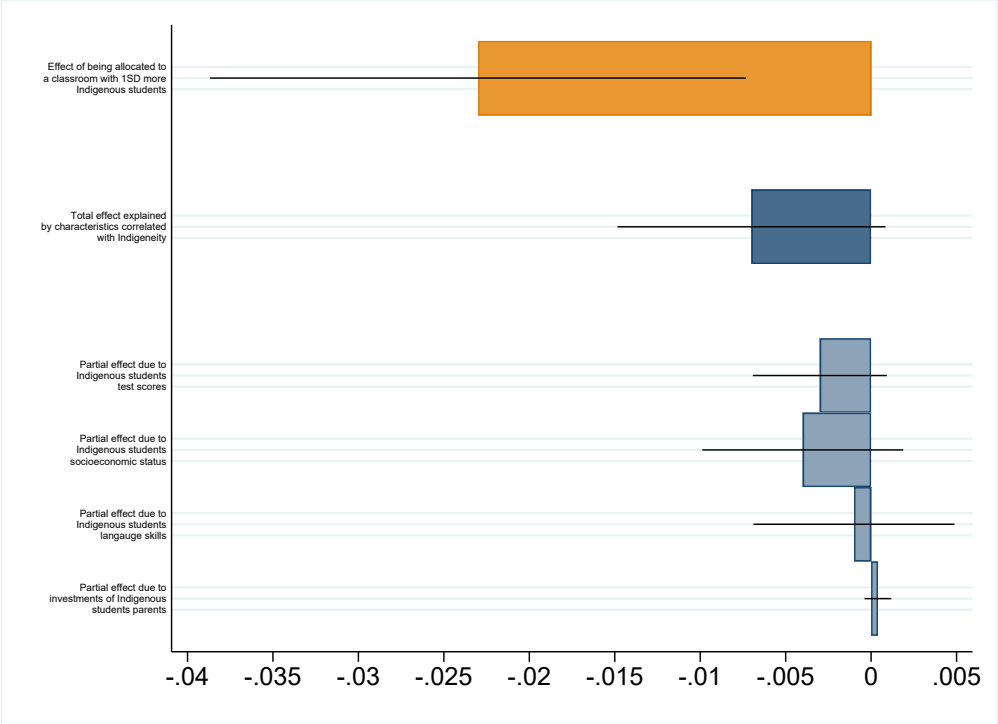
Table C.5: *Mechanisms*

	(1)	(2)	(3)
Outcomes [std]:	**Student behaviors**	**Parental investments**	**Teacher engagement**
+1SD Indigenous students	-0.038**	-0.046***	-0.143***
	(0.018)	(0.014)	(0.040)
Own test scores	Yes	Yes	Yes
Pre-assignment controls	Yes	Yes	Yes
Schools	155	155	155
Classes	588	588	578
Students	8,461	8,416	7,935

*Note: This table reports estimates of regressing standardized aggregate indices of student-related, parent-related, and teacher-related mechanisms in wave 2 on the classroom share of indigenous peers. All regressions include school fixed effects. Own test scores refer to students' test scores in wave 1. Pre-assignment controls include all variables tested for balancing in Table 1. Standard errors clustered at the classroom level in parentheses. ***, ** and * mark estimates statistically different from zero at the 99, 95 and 90 percent confidence level.*

Figure C.3: *Correlated observable characteristics and endogenous responses of students, parents and teachers*

(a) *The role of correlated observable characteristics in explaining the treatment effect: Gelbach's (2016) decomposition*



(b) *Mediation analysis: The role of endogenous responses of students, parents, and teachers*

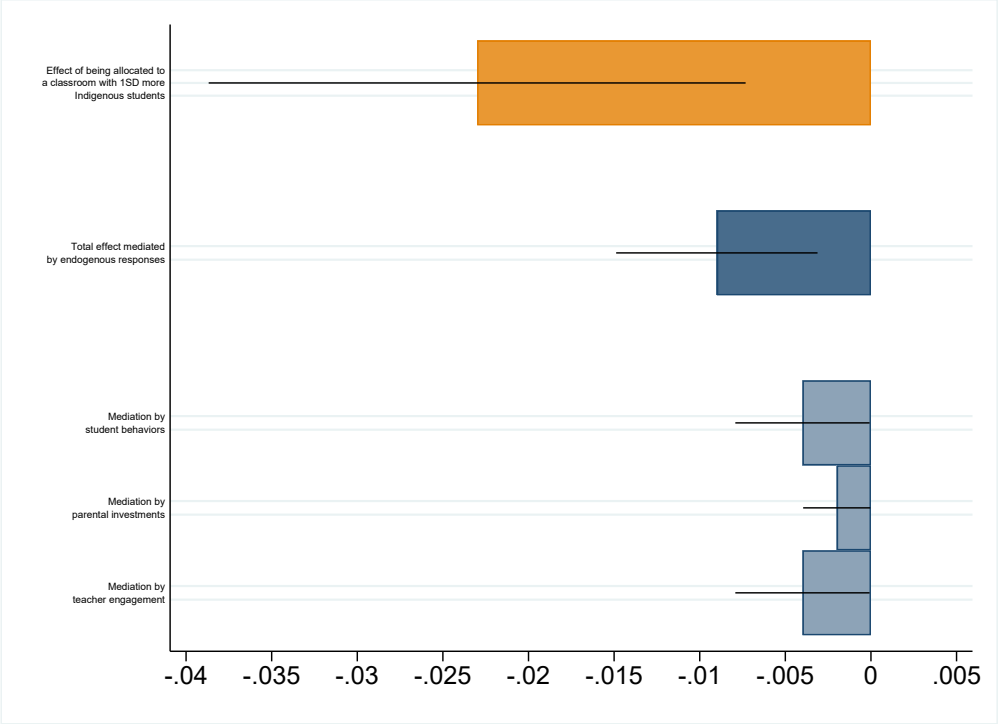
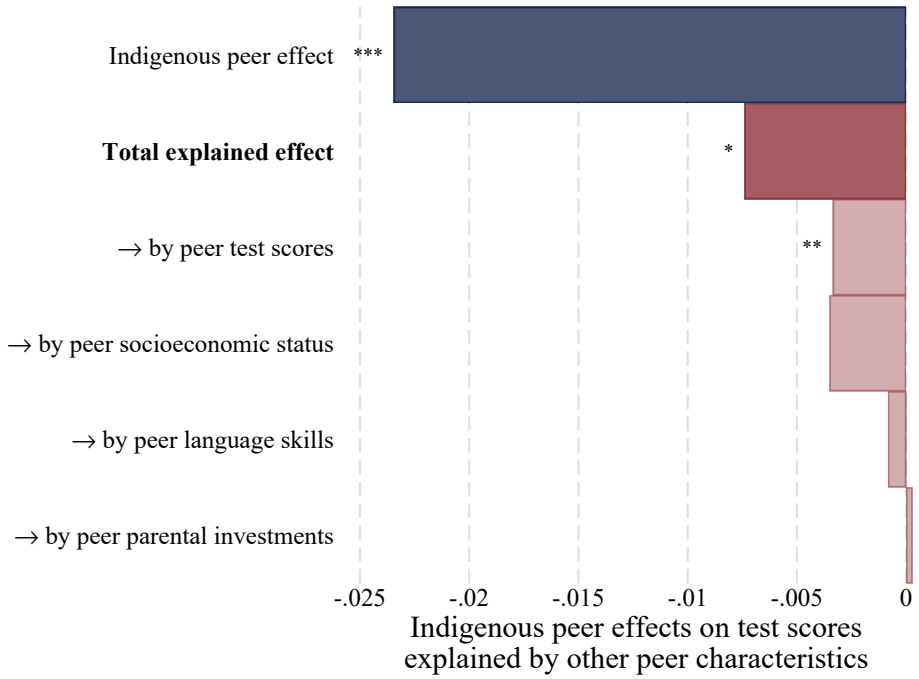


Figure C.4: *Correlated observable characteristics and endogenous responses of students, parents and teachers*

(a) *The role of correlated observable characteristics in explaining the treatment effect: Gelbach's (2016) decomposition*



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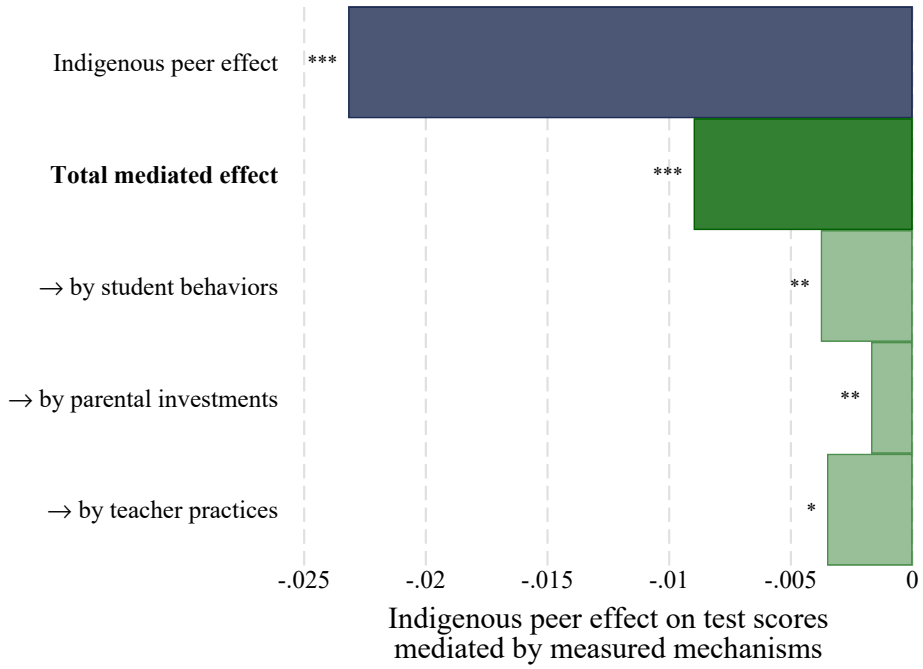
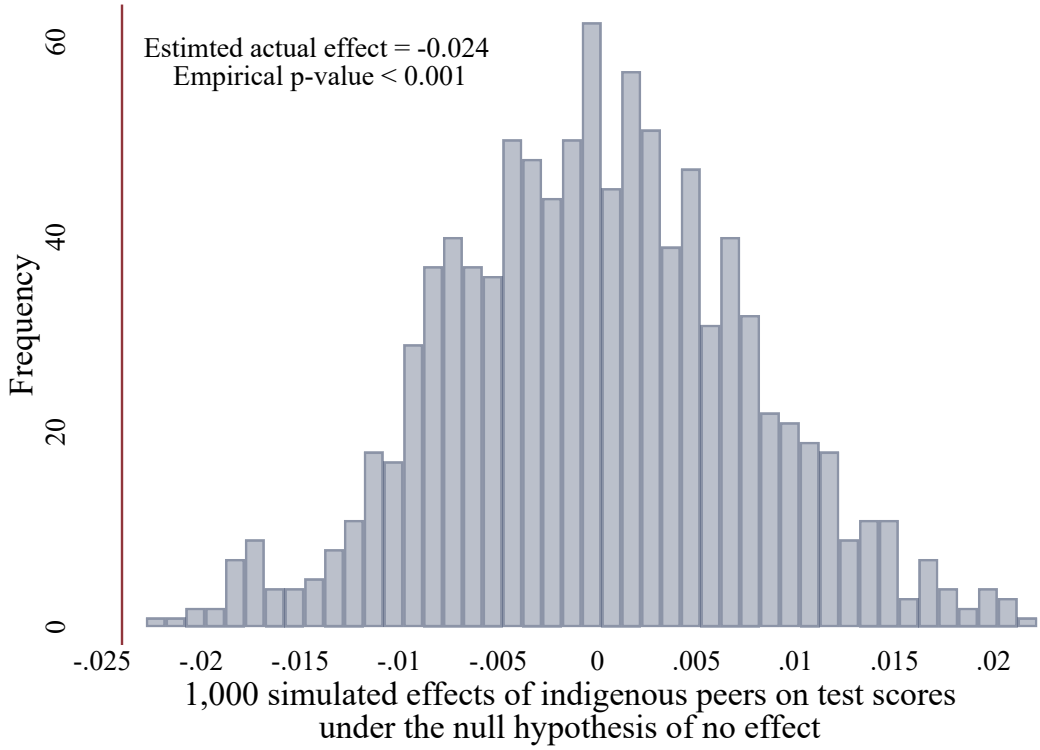


Table C.6: *Falsification test using Hakka and synthetic Indigenous students*

Outcome [std]:	Student test scores	Student behaviors	Parental investments	Teacher engagement
		Panel A. Hakka students		
+1SD Hakka students	0.004	0.015*	0.005	-0.065***
	(0.005)	(0.008)	(0.007)	(0.024)
Schools	307	307	307	307
Classes	1,154	1,154	1,154	1,137
Students	16,262	16,197	16,120	15,039
		Panel B. Synthetic Indigenous students		
+1SD Synthetic Indigenous students	<0.001	0.003	0.035***	-0.025
	(0.007)	(0.013)	(0.011)	(0.029)
Schools	155	155	155	155
Classes	588	588	588	578
Students	8,517	8,461	8,416	7,935
Own test scores	Yes	Yes	Yes	Yes
Pre-assignment controls	Yes	Yes	Yes	Yes

*Note: This table reports estimates of regressing standardized student test scores in wave 2 on the standardized classroom share of Hakka or synthetic indigenous peers, and its interaction with a student dummy for own Hakka (Panel A) or synthetic indigenous (Panel B) status. All regressions include school fixed effects. Own test scores refer to students' test scores in wave 1. Pre-assignment controls include all variables tested for balancing in Table 1. All controls are interacted with a student dummy for own Hakka (Panel A) or synthetic indigenous (Panel B) status. Standard errors clustered at the classroom level in parentheses. ***, ** and * mark estimates statistically different from zero at the 99, 95 and 90 percent confidence level.*

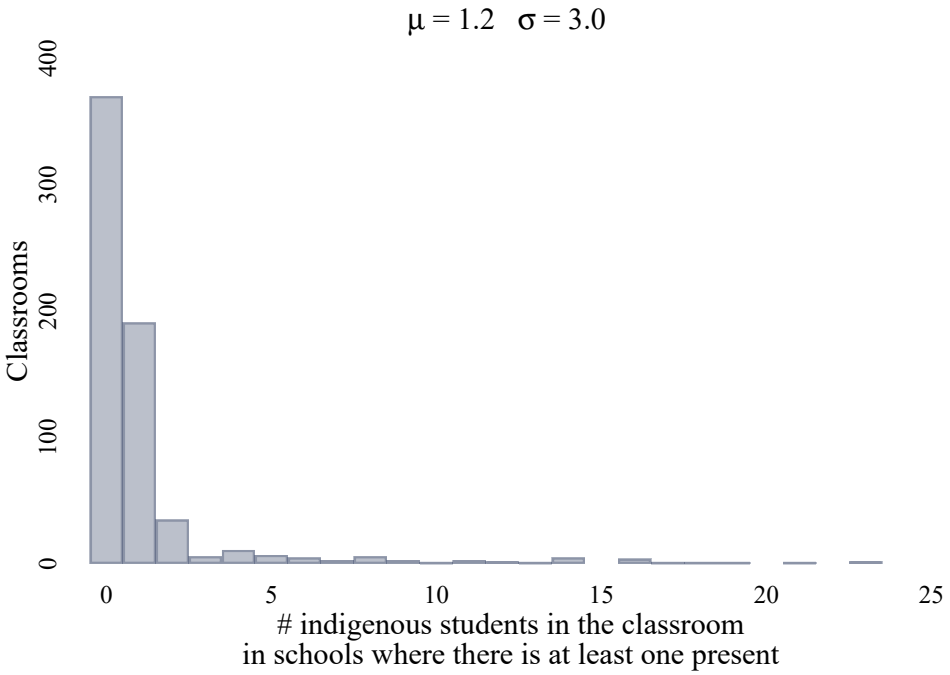
Figure C.5: *Main Results of Exposure to Indigenous Students: Randomization Inference*



Note: These figures present results of a randomization inference computations where the treatment is exposure to Indigenous students. The results are based on estimating Equation 21 where the treatment variables – share Indigenous – is based on re-randomized assignment of students to classrooms rather than the true randomized assigned used in main estimation in C.2. We re-randomize the class structure 1,000 times. Red vertical lines present our point estimates from the preferred specification in column 4 of Table C.2 while the p-values come from computing the location of these point estimates in the simulated distribution.

Figure C.6: *Within-school between-classrooms distance in exposure to indigenous students*

(a) *Distance in number of indigenous students*



(b) *Distance in share of indigenous students*

