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

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Abstract

We develop and empirically test a theory of integrating minorities in schooling 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 majority students. A third of this effect can be attributed to characteristics correlated with Indigeneity while two fifths are due to endogenous responses. Our theory and results highlight the limitations of the reduced-form interpretation of commonly used linear-in-means peer effect models.

JEL: I23, I26, D13
Keywords: minorities, Indigenous Peoples, peer effects, parental investments, teachers

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1 Introduction

A minority can be defined as a person 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 restitution 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 of the pre-requisites for an educational success is access to high quality schools which are often attended by majority students. This creates a tension between minority and majority students, parents, and teachers, often leading to pushback against integration and ultimately 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 minority peers in the classroom, and we know even less about how such exposure could affect parents and teachers. For example, exposure to minority peers could lead to positive spillovers from increased diversity or more resources dedicated to these classrooms, 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, often an argument raised by majority stakeholders, either due to other unfavorable characteristics correlated with minority status or due to adverse behavioral changes of majority students, their parents, or teachers.

In this paper, we ask the following research questions: Does exposure to minority peers 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)? Finally, to what extent are these effects driven by endogenous responses of majority students, their parents, and teachers in these classrooms? Answering these questions is essential for understanding the origins of reduced-form peer effects, the role that minority children could play in the school production function, and ultimately for the proper design of school integration policies that benefit all children.

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. First, we propose a theoretical model that generalizes the standard linear-in-means peer effects model (equivalent to reduced-form regressions commonly run in the literature) and incorporates responses of majority students, their parents and teachers in classrooms with minority peers. We then test the predictions from the model using data from the Taiwan Education Panel Survey which collects longitudinal information on the three types of agents considered in our theory. The random assignment of minorities into classrooms —Indigenous students in our specific application —further allows us to verify the model with causal estimates. This feature, almost non-existent in compulsory school settings in other developed countries, allows us to address the endogeneity issues brought on by selection, reflection, or mechanical relationships between own and peer measures that plague other settings by recasting our estimands as the effects of exposure to pre-determined and exogenously assigned peer characteristics (Manski, 1993, 2000, Angrist, 2014).

Our theory models human capital production in a classroom with a varying share of minority students. We show that, under the assumption that endowments of minority students are lower than those of majority students, the higher the fraction of minority students in a classroom, the lower the effort/investments of students, parents and teachers, and for both majority and minority students in the classroom. First, we verify empirically that Indigenous students in our application are indeed deeply disadvantaged across several dimensions. We also show that indigenous students are likewise perceived as lower ability at baseline by their teachers, even after accounting for differences in actual ability via standardized test scores. The model is then extended to include responses of parents and teachers. We show that under a generalized Cobb-Douglas production function both the efforts of students and their parents (or their teacher) on the one hand, and the effort of parents and teachers on the other hand are complements in their effects on student test scores. This theoretical result suggests that ignoring parents' and teachers' endogenous responses when considering linear-in-means peer effects models could lead to misinterpreting reduced-form estimates. The magnitude and importance of these endogenous responses is an empirical question which we bring to the Taiwanese education data.

Our main result is that in classrooms with a 10 percentage points (pp) higher share of Indigenous students, test scores of majority students decrease by 4.0 % of a SD on average, with little heterogeneity across indigenous and non-indigenous students. We then explain this finding through four drivers: (1) characteristics correlated with Indigenous status; (2) study effort responses of majority students; (3) investment responses of majority parents; and (4) teacher effort in and perception of these classrooms. Using Gelbach (2016) decomposition we can attribute 32% of the negative effect to observable characteristics that are perfectly collinear with Indigenous status, and these are primarily driven by lower test scores and lower socioeconomic status of Indigenous students. We then show that students in the affected classrooms reduce their study effort, in line with our theoretical model. Descriptively these changes can explain about 16% of the reduced-form effect. Finally, we also find statistically significant negative responses of parents and teachers which together account for about 22% of the reduced-form effect. Overall, these four channels add up to about 70% of the estimated negative peer effect; including them in the regressions reduces the peer effect coefficient to 1.2% of a SD which is no longer statistically significant at conventional levels. Taken together, our results suggest that although exposure to Indigenous minorities has a clear negative effect on the academic achievement of majority students, those classroom externalities are to a non-trivial degree caused by endogenous changes in the behavior of majority students, their parents, and teachers in these classrooms —channels that have been scarcely explored in the extant literature.

Even though students in our setting are randomly assigned to classrooms by law, which we also verify empirically, we conduct a variety of additional robustness checks. Our conclusions are invariant 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 test scores.

This paper makes contribution to several strands of literature. First, our findings 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 by law.[1,2] Prior studies primarily used data from the United States due to their ethnic-racial history, but were forced to rely on cohort-by-school variation due to lack of institutionalized randomization in the context of the United States (Hoxby, 2000, Diette and Oyelere Uwaifo, 2014, Figlio and Özek, 2019, Angrist and Lang, 2004, Geay, McNally

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 and none have focused on Indigenous students in particular; 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. Although our focus is on compulsory education and younger children, this paper is also naturally linked to the broader literature on peer effects in education. Considering university-level coursework there are several papers that 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. In a narrower educational setting Rivera (2022) studies minority peer effects at the Chicago Police Academy.

and Telhaj, 2013, Setren, 2022). In addition, most prior studies define minority status based on very heterogeneous peer groups 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).[3] 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 exposure to Black peers. The cohort-by-school source of variation comes with issues; 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 drivers of 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 (Agostinelli, 2018, Agostinelli et al., 2020, 2022, Boucher et al., 2023, de Gendre and Salamanca, 2020). Along the same lines, Green, Haaland and Vaag Iversen (2022) show that Norwegian students have improved English language skills 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 likewise 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 Paserman, 2009, Jensen and Rasmussen, 2011, Ahn and Jepsen, 2015, Hunt, 2017). Both strands of the literature share two common limitations that this paper overcomes: (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

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

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).

Fourth, we contribute to the literature on stereotyping, discrimination and prejudice. Both our theory and empirical evidence support the notion that majority agents react negatively, in terms of both their expectations and investments, to exposure to minority peers. This is consistent with evidence that teacher expectations affect student educational outcome (Papageorge, Gershenson and Kang, 2020), that teacher gender stereotyping could reduce girls' achievement (Rakshit and Sahoo, 2023), or that teacher prejudice could increase peer violence (Alan et al., 2020). In the broader economic context, Glover, Pallais and Pariente (2017) show that manager bias negatively affects minority job performance, Tabellini (2020) shows that immigration to the U.S. in the early 20th century lead to hostile political reactions among the natives while Bazzi et al. (2019) presents evidence that inflow of out-group individuals could lead to intergroup conflict. At the same time, our results contrast the literature on contact theory which posits that exposing majority individuals to minority groups reduces prejudice and can generate positive externalities (Pettigrew, 1998, Pettigrew et al., 2011, Rivas-Drake et al., 2019, Billings, Chyn and Haggag, 2021, Bursztyn et al., 2021, Boucher et al., 2020).

Finally, we also provide some of the first evidence on educating Indigenous children, a group of people that has largely been omitted from research due to data limitations. 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. Barber and Jones (2021) document robust achievement gaps between Indigenous and non-Indigenous students in Canada while Jones (2023) shows that cuts to post-secondary funding for Indigenous students lead to reductions in their educational attainment and labor supply. Studying the potential consequences of integrating Indigenous children into schools attended predominantly by non-Indigenous students is important given that Indigenous Peoples face deep and perpetuating disadvantage. Indigenous Peoples account for 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; there are several regions of the world where effects such as those we document might be pervasive, leading to stronger backlash from majority stakeholders: 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.

We view our results as having three main policy implications. First, the estimated negative peer effects suggest a potential hidden educational cost of policies attempting to integrate minorities in majority dominated schools. Importantly, this negative peer effect is not only driven by worse observable characteristics of these minorities but also to a larger degree by negative endogenous responses of majority students, their parents and teachers. Thus, policy makers might want to proactively consider compensatory interventions to overcome hesitancy towards these interactions. Second, our findings on endogenous responses of majority students, their parents, and teachers in these classrooms suggest how policy makers might counteract these negative educational externalities. In particular, it appears that diversity interventions need to be broad and targeted at all three agents in the education production function while much policy discussion often ignores teachers and especially parents. For example, Alesina et al. (2018) show that making teachers aware of their bias could decreases grading bias while Tumen, Vlassopoulos and Wahaba (2023) show that teacher training programs on diversity awareness improve attendance and academic achievement of refugee students. We are not aware of any research on diversity awareness interventions targeted at parents. Finally, our findings are relevant to a broader policy context, outside of schooling, where peer effects could arise due to endogenous responses of multiple agents. For example, it is plausible that some of the workplace peer effects are generated by the decisions of managers (Cornelissen, Dustmann and Schönber, 2017, Lindquist, Sauermann and Zenou, 2022) or that part of the peer effects found in prisons is due to behaviors of guards or prisoners' visitors (Bayer, Hjalmarsson and Pozen, 2009, Piil Damm and Gorinas, 2020). Understanding *who* is driving the reduced-form effects estimated in the extant literature appears crucial from policy perspective when thinking about effective and efficient interventions.

2 Theory: Peer Effects with Endogenous Responses

2.1 Definitions and baseline peer effects model

There are two types of students in each classroom: majority (M) and minority (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:

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

where $\overline{y}_s^{-i}$ 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, socioeconomic status, 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 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 with respect to effort 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 worse 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 teachers and the parents can play an important role in shaping education outcomes. Despite that their 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 education production function 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 and effort the teacher spends preparing, managing, 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 minority 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 also be thought of as first movers). Furthermore, in smaller schools and outside of big cities, random assignment is done manually by drawing tickets at e.g., school gym while parents and teachers are often witnesses to that process. Finally, students would be the last movers since their study effort will be a result of what happens during classroom interactions.

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:[4]

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

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

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

4. 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 where, 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,*

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

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 observable 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 in turn 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 investments of their parents and teachers and since all these inputs complement each other, an increase in q reduces students' test scores (Proposition 2).

Although our model is very general, it hinges on two critical assumptions that (i) b^i is observable and (ii) that $b^m < b^M$ statistically (e.g., higher poverty rates of minority versus majority students) or in expectations (via e.g., prejudice or discrimination). Therefore, it is most naturally applicable to demographic characteristics used in the extant literature (e.g., race, gender, immigration, language) but not necessarily to ability or disruption (other factors often considered in peer effects research) which are harder to gauge in the short-run. Nonetheless, through repeated interactions and learning the model can be adapted to the latter set of treatments in a medium-run.

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.[5] No exceptions to this rule are allowed based on demographic or socioeconomic characteristics. Some schools, however, may open arts or gifted classrooms; in those schools a small portion of students can be assigned to an arts or gifted class, and the remainder majority of students are randomly assigned to the regular classrooms.[6] 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. By our calculations, 92% of students remain in the same school while 85% of students are in the same school and classroom two years after the beginning of junior high school in our data.[7]

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

5. For legislative details see Article 3 of the Implementation Guideline for Class Assignment of Junior High School Students, which was the relevant legislation for classroom assignment at the time. In particular, Article 3 describes in detail the procedure for forming new classrooms in junior high school (Section 1), the requirement for schools to publicly announce the date and place for the classroom assignment event and the invigilation arrangements made by municipal and county governments (Section 3), and the requirement for classroom assignment rosters to be made publicly available immediately after assignment and for at least 6 months (Section 5). Additional information can be found at http://edu.law.moe.gov.tw/EngLawContent.aspx. This regulation was later superseded by Article 12 of the Primary and Junior High School Act in 2004.

6. The random assignment rule also extends to the class' 'homeroom teacher, or "Dao Shi", as per Article 3, Section 4, of the Implementation Guideline for Class Assignment of Junior High School Students. Dao Shi 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 e.g., they are available for parental phone calls outside of school hours and may visit students at home.

7. This means that at most only 8% of students change schools and at most 15% of students change classrooms conditional on remaining in the same school. In our data, Indigenous students are no more likely than majority students to change either schools or classrooms. Furthermore, classroom share of Indigenous students at the initial assignment is uncorrelated with the likelihood that a majority student remains in their assigned classroom. We do find a positive association between share of Indigenous students in a classroom and the likelihood to change schools, yet this estimate is of trivial magnitude (less than one percentage point per 1 SD increase in Indigenous peers). Furthermore, our identification relies on within-school across-classrooms variation.

preparing specifically for high stakes centralized examinations.

3.2 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 origins (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.

In the main analysis, we consider all three Han Chinese groups as the majority, for whom we are primarily interested in measuring outcomes, while Indigenous Peoples are the minority group of interest. We exclude children of individuals from other countries. In a separate placebo analysis, we use Hakka as another minority group that is culturally distinct but observationally similar to the other Han Chinese groups as we describe 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 the 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 (also called Taiwanese Hoklo). Table C.1 shows that 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 the Taiwanese population. Historically, the Hakka faced discrimination from other Chinese ethnic groups that sometimes led to violence, both in mainland China and in Taiwan. These frictions also led to, for example, mass-killings in Hakka villages. The Hakka likewise speak a distinct language and, in our data, we see that 92% of the Hakka children are fluent in Mandarin while 17% of them are fluent in Hakka and 1% in an Indigenous language. In contrast, less than 2% of non-Hakka Taiwanese students declare speaking the language. Furthermore, Hakka and Hoklo have similar demographic and socioeconomic characteristics and, despite clear cultural differences, the two groups are ethnically close to one another. Cultural differences resonate especially in food, architecture, arts and crafts but also in social behaviors and hierarchies. For example, Hakka historically put much more emphasis on education making them "the perfect bureaucrats" and they are the only Han ethnicity where women never bound their feet.

Waishengren are predominantly Han Chinese descendants of Chiang Kai-shek's retreating army, 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 95% of Waishengren children are fluent in Mandarin while 1% are fluent in an Indigenous language and 4% are fluent in Hakka. They likewise have similar characteristics to Hoklo 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 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 groups within this broader Indigenous umbrella. The share of Indigenous students among school-age children is about 4%, however, 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 the 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, a point that we discuss further in subsequent sections.

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 measure 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 their 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 school classroom included in the survey. TEPS follows a stratified nested sampling procedure where first 333 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 randomly chosen 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 others 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

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, due to funding cuts during the program, limit the usability of subsequent waves.

9. Although we cannot observe the difference between the admission roster and our post-randomization sample, strict enforcement of the regulations 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 selection behavior.

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).

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 a mean of 0 and a standard deviation of 1 in the entire dataset.

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 use this information to construct our student, parent, and teacher responses which proxy for effort, investments, and expectations. Appendix B provide detailed description of the items we use but here we outline the variables for each of the agents considered:

- Student behaviors: number of study hours
- Parental investments: private tutoring, time spent with a child, emotional support
- Teacher engagement: teacher effort, easiness to manage the class

When it comes to students we use just a single variable that proxies best for their effort while for parents and teachers we construct indices aggregating the aforementioned variables.

5 Connecting Institutions and Data 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 diving into the econometric analysis, let us explain how this model matches Taiwanese institutional setting. 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 worse observable characteristics than majority students, which is verifiable with the data. Indeed, Online Appendix Table C.6 shows that the Indigenous students are much more disadvantaged than the majority students: they have a -0.7 Standard Deviation (SD) lower baseline scores, 11 percentage points lower university aspirations and 8 percentage points lower subjective expectations about their ability to go to college. In addition, 30% of them come from families in the lowest income bracket (compared to 11% for the majority), 80% of them have parents with low level of education (compared to 71% for the majority), 60% of them have parents who had financial difficulty in the past 10 years (compared to 28% for the majority), and there is even a 28 percentage points gap in the likelihood that their parents report being in good health. For our main analyses, we consider all other Taiwanese ethnicities as "majorities". We take this approach even though, as explained in Section 3, in Taiwan there are two types of minorities officially recognized by the government: 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;i.e., the two groups are observationally close to one another and therefore the assumption that $b^m < b^M$ does not hold for the difference between Hoklo and Hakka students.[11]

One unnecessary simplification in our model is that $b^m < b^M$ needs to be observed by the students, parents, and teachers. In principle, one could imagine that even teachers cannot know the true ability or socioeconomic status of their assigned pupils early on during the first year of junior high school. Our theory, however, carries forward when these differences hold in expectations, even in the absence of actual differences in student endowments. That is, our models' predictions will hold if minority students are expected, based on taste based or statistical discrimination, to be worse than majority students, even if their actual characteristics are similar.[12]

We argue that systematic differences in how indigenous students are perceived by others are a likely mechanism behind our results. Although in our data we do not observe perceptions of students or parents, we do have information that will allow us to test whether teachers have systematic (and unwarranted) differences in perceptions between Indigenous and non-Indigenous students. In particular, homeroom teachers are asked to rate each student's problem-solving abilities at the beginning of the school year, before having the opportunity to meaningfully interact with them. The survey asks homeroom teachers to evaluate the students' abstract and

11. Since Hakka are observationally similar to Hoklo but still a recognized ethnic minority, their presence in our data will allow us to directly test whether our estimates are driven by ethnic differences in peers absent of observable differences in endowments. See Section 8 for more details.

12. Indigenous Peoples of Taiwan have different physical appearance than Han Chinese. Similarly, in the US context, individuals who identify as African-Americans, Asian or Hispanic are most often physically different from White Americans. These differences would allow students, parents and teachers to ascribe "group-specific expectations" to minority students even if they observe little else about them.

logical thinking ability as “Excellent”, “Above average”, “Average”, “Below average”, ‘Poor”, and “I don’t know”. We combine the first two answering categories to create a discrete measure of whether the homeroom teacher believes a student has an above-average abstract and logical thinking ability. We then use this indicator variable to compare teachers’ subjective expectations about minority and majority students.

To establish if teachers hold systematically biased subjective expectations about Indigenous students, we run a regression of teachers’ subjective assessment of students’ abstract and logical thinking ability on an indicator for Indigenous student without and with additional controls. We present those results in Online Appendix Table C.4. Column 1 implies that, on average, teachers rate Indigenous students 12 percentage points lower than the majority students. This gap only increases when we control for school fixed effects (column 2) and thus leverage the random allocation of students to teachers within a school. In Online Appendix Table C.6 we have documented large “objective” differences in ability and affluence between these two groups of students, and thus it may be that differential perceptions are explained by true differences in ability. Recall, however, that teachers (or students or parents or administrators) were never informed about the performance of the pupils on the baseline (or subsequent) cognitive ability test. Column 3 verifies this and indeed the Indigenous penalty declines by about two-thirds. Nonetheless, the gap at 5 percentage points remains statistically significant at conventional levels. Our non-cognitive ability test is, as expected, positively correlated with teacher perceptions which suggests that teachers can to some degree identify which students will or will not perform well academically. Finally, in column 4, when we include an interaction term between baseline test scores and the Indigenous dummy we find that it is negative and statistically significant and additionally the coefficient on the Indigenous dummy variable becomes more negative. This means that (i) the minority-to-majority gap in expectations is larger at the bottom of the ability distribution and (ii) even high-achieving Indigenous students suffer a penalty when it comes to teacher expectations. Both findings are consistent with teacher’s negative perceptions about Indigenous student’s ability as measured by a blind-test and support the fact that $b^m < b^M$.

One concern could be that teachers discriminate against all minority students (not necessarily only Indigenous) based on e.g., cultural differences, or that we simply have a flawed perceptions measure. To address this concern we show in Online Appendix Table C.5 Panel A that similar bias does not exist for Hakka students. In fact, teachers systematically have more positive perceptions about the problem-solving abilities of Hakka students, whether we ignore school fixed-effects (Column 1) or absorb them (Column 2). Controlling for student academic achievement (Column 3) reduces the favorable expectations to an insignificant 1 percentage point, and additionally controlling for the interaction between Hakka indicator and baseline academic achievement (Column 4) does not alter the conclusions. Results in Online Appendix Table C.5 Panel A therefore indicate that, unlike for Indigenous students, teachers hold accurate perceptions about Hakka students compared to a blind test.

Another concern could be that teachers cannot accurately compare low-achieving students to the blind test because of other correlated markers of disadvantage affecting even early behavior in class. In Online Appendix Table C.5 Panel B we show that teachers also do not hold similarly biased perceptions against majority students with a similar level of disadvantage as Indigenous students. After controlling for school fixed effects (column 2) the penalty in teacher-assessed problem-solving ability is only about half of the penalty reported in panel A, albeit statistically insignificant. It further declines when we control for student test scores and the interaction term (columns 3 and 4). Overall we view these results as supporting the notion that teachers in our sample have biased expectations about the academic potential of Indigenous students; exactly as implied by our theory.

Given the above, we have the following four predictions which we bring to the data:

(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 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).

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

(4) 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).

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:

$$
\begin{aligned}
Score_{iscw_2} = \alpha_1 &+ \alpha_2 \overline{\%Indigenous^{-i}_{iscw_1}} \\
&+ \alpha_3 Indigenous_i + \alpha_4 \overline{\%Indigenous^{-i}_{iscw_1}} \times Indigenous_i \\
&+ \delta \mathbf{X}_{iscw_1} + \gamma_{sw_1} + \varepsilon_{iscw_1},
\end{aligned}
\tag{21}
$$

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.6) as well as students' test scores at the baseline. Thus, our preferred results have a value-added interpretation, that is, compared to the achievement in grade 7, what is the effect of being exposed to more Indigenous 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 Indigenous status dummy 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.[13] Our main 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. Note that $Score_{iscw_2}$ corresponds to S^i in our theoretical model, $\overline{\%Indigenous_{iscw_1}^{-i}}$ 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 $\overline{\%Indigenous_{iscw_1}^{-i}}$ will be conditionally (on school fixed effects) independent of the error term ε_{iscw_1} (i.e., $E[\varepsilon_{iscw_1}|\overline{\%Indigenous_{iscw_1}^{-i}}, \gamma_{sw_1}] = 0$). To support the assumption of random assignment, in Table C.7 we show that our treatment of interest—classroom leave-out-share 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 $\overline{\%Indigenous_{iscw_1}^{-i}}$ and school fixed effects, and we exclude all other controls.[14]

If we run these tests using the entire TEPS data, we do find evidence that Indigenous students are systematically assigned to classrooms with lower-ability peers, with other indigenous students, and generally with students who have somewhat worse observable characteristics. This is, to some extent, not surprising given prior work using the TEPS data. de Gendre and Salamanca (2020) document in detail that some Taiwanese schools systematically assign students to classrooms based on ability, some due to official exemptions (e.g., schools focused on arts) and some in defiance of the national mandate to randomly assign students to classrooms. We suspect similar violations of random assignment are at play when assigning Indigenous students to classrooms.

13. 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 (see Online Appendix Figure C.5).

14. We can augment these tests to allow for differential unbalancing for indigenous and non-indigenous students by regressing baseline characteristics on own Indigenous status, $\overline{\%Indigenous_{iscw_1}^{-i}}$, the interactions of these two variables, and school fixed effects. In these regressions, all but one of the main effects and interaction coefficients are insignificant at conventional levels.

To recover a valid quasi-experiment from these data, we implement a modified version of the "Fishing algorithm" introduced in de Gendre and Salamanca (2020), adapted to detect failures in balancing on Indigenous peers in classrooms within schools. The algorithm helps us identify 19 small schools where Indigenous peers are disproportionately likely to be assigned to peers with low ability and low socioeconomic status.

After excluding these schools, as documented in Table C.7, our balancing tests strongly support the hypothesis that indigenous peers are randomly assigned to classrooms within schools in the remaining data. Out of 17 tests only one yields a coefficient statistically significant at the 10% level, which is less than what we would expect due to pure chance.[15] Furthermore, the estimates are quantitatively small, never exceeding 2.3% effect size relative to the dependent variable mean. We implement two additional tests to ensure the validity of our identifying assumption. First, we use diagnostics developed by Guryan, Kroft and Notowidigdo (2009) and Jochmans (2023) 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 fails to reject the null of balanced sample with p-value equal to 0.586. Taken together, these results imply compliance with the mandate of random assignment of students to classrooms within schools in our estimation sample, and thus support the identifying assumption.

7 Results

7.1 Effects of classroom exposure to Indigenous students on test scores

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 with one exception, to our best knowledge, has not been used in the literature to date. The results are presented in Table C.8 and we want to 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 the point estimate of interest (column 2 versus column 3). This is expected given the balance documented in Table C.7. There is a modest difference in effect sizes between column (1), where we do not control for own test scores, and the subsequent columns

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

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.7). 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 -0.299 and -0.392 as qualitatively similar, and more importantly, including baseline test scores meaningfully shrinks the standard errors on our coefficient of interest.

Second, we find significant negative effects from exposure to Indigenous students on test scores (Equation 20). A 10 percentage point increase in the share of Indigenous students in a classroom reduces test scores of other students by 4.0% of a standard deviation. In our data 60% of classrooms have no Indigenous children, 27% have just one Indigenous child while the remaining 13% have more than one Indigenous child. Figure C.7 shows that we find qualitatively similar effects across classrooms with one, two or three indigenous children in the classroom. Given the maximum mandated class size of 35, adding one Indigenous child would increase the share of Indigenous peers by at least 2.9%, which translates into a negative effect of 1.1% of a standard deviation. Although appearing small, this average effect applies to all the remaining students in the classroom (at most 34), and thus, its aggregate effects should not be understated.

Third, the interaction term in the last column of the table shows no evidence that increased share of Indigenous students in the classroom helps Indigenous students themselves. The coefficient is positive but only about one-twentieth of the negative effect for the majority students. This is consistent with Propositions 1 and 2 in the model which imply that test scores should decline for both the majority and minority students if students, parents, and teachers adjust their behaviors. We note that although one could expect positive concordance effects from one's own group of peers (e.g., Hoxby (2000) finds stronger intra- compared to inter-race peer effects in achievement) this is not guaranteed by our model and indeed we do not find empirical support for this hypothesis.[16]

To give economic context to our estimates, it is worth highlighting that prior results in the literature have been both limited and mixed, and with the exception of Antecol, Eren and Ozbeklik (2016), 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 ability 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

16. It could be that in other contexts concordance induces more student effort through e.g., group studying or help from the peers.

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.[17] Our Indigenous effect sizes are comparable to Hoxby's estimates for Anglo students, and are much smaller than her estimates for Black and Hispanic students. Similarly, Diette and Oyelere Uwaifo (2014), shows that a 10 percentage point increase in students with limited English proficiency lowers mathematics and reading scores of native students by about 0.7 percent of a standard deviation.

7.2 Effects of classroom exposure to Indigenous students on student effort, parental investments, and teacher inputs

We now turn to the important innovation of our paper which is understanding the responses of students, parents, and teachers in classrooms that were randomly allocated Indigenous students compared to those that were not. Recall that Propositions 1 and 2 in our theoretical framework predict that the higher is the fraction of minority students in a classroom, the lower is the effort of students, their parents, and teachers. Although effort is hard to measure, our data contain several variables that appear to be good proxies (i.e., they predict student achievement) for the effort/investments of the three groups in question. For students, our best measure is the number of study hours (based on multiple survey questions), which includes study hours in school, in after-hours tutoring at school, studying and receiving tutoring outside school hours, and time spent on the internet doing homework, and also during summer vacations. Since these are measured at different time intervals we combine them into a single standardized index of student study hours. For parents, we combine into an index expenses on private tutoring, time spent with their children, and emotional support. For teachers, we combine three measures of time spent preparing and grading exams, preparing class lectures and giving one-on-one attention to students for all three main subject matter teachers (in Mathematics, English, and Chinese), as well as the Dao Shi assessment of the easiness to manage the class (which we argue measures the marginal cost of effort of teaching). See Appendix Appendix B for details on the construction of these indices. Online Appendix Table C.8 shows that test scores in wave 1 are strongly correlated to all three indices of student, parent and teacher effort in wave 2. Even after accounting for school fixed effects and other pre-assignment characteristics, student baseline test scores are strongly and statistically significantly correlated to subsequent inputs, which suggests that the indices capture productive skills. Given our theory, we expect negative effects of exposure to minority peers on all three outcomes and we verify this by re-estimating Equation 21 while replacing the

17. 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.

the dependent variable with student, parental and teacher effort proxies.

In Table C.9 we estimate the effects of exposure to Indigenous classroom peers in wave 1 on students, parents and teacher effort. Consistent with our predictions, we find that higher share of Indigenous students in the classroom lowers student's study hours, lowers parental investments, and lowers teacher engagement. A 10 percentage point increase in the share of Indigenous students in a classroom of 35 is expected to decrease study hours of the majority students by 7.5% of a SD, decrease investments of majority parents by 7.1% of a SD, and decrease teacher engagement by 24.7% of a SD. To put these effects in perspective, note that the rural-urban gap in these effort measures is 23% of a SD for study hours and parental investments, and 30% of a SD for teacher engagement. Therefore, the effect of an additional indigenous student in class amounts to a little under a tenth of the rural-urban gap for study hours and parental investment, and over a third of this gap for teacher engagement. Our theory further predicts that the minority students and parents will also negatively adjust their effort but for the two inputs considered here, unlike for test scores, we actually find statistically significant interaction effects. In particular, the negative study hours effects are reduced by two-thirds for indigenous students (rendering it still negative but statistically insignificant), while the negative parental investment effects are actually exacerbated by 40%. Overall, we view these results as consistent with our model suggesting that *all* students will be affected by higher share of minorities assuming that observable characteristics of minorities are worse compared to those of the majority children.

Above and beyond our theoretical model it is worth thinking about *why* students, parents, and teachers could lower their investments in response to exposure to a higher share of minority students. For students the result is mechanical if we assume that peer effects are present. Namely any peer effects multiplier from own effort will be diminished if there is higher share of students with adverse background characteristics that are negatively correlated with their achievement. For parents and teachers, since their effort is complementary to student effort, the model predicts lower investments but it is entirely plausible that those agents might want to compensate the majority students for the "perceived negative" exposure rather than reinforce the differences. As a counter example, we propose two channels that are consistent with our model but not with the compensatory behavior. First, it could be that majority parents perceive these classrooms as weaker and thus decide to spend their resources elsewhere (perhaps on their other children which we do not observe in the data).[18] Alternatively, parents could be receiving an inflated signal from the teachers about the relative performance of their child, leading them to believe that they do not need additional time and money investments. When it comes to teachers we have already documented in Section 5 that they have negative perceptions about the aptitude of Indigenous students; even conditional on their observable characteristics and baseline test scores. This fact is

18. See, for example, literature on sibling spillovers in education by Qureshi (2018), Nicoletti and Rabe (2019), or Karbownik and Özek (forthcoming).

likely correlated with teacher motivation and engagement in classrooms with higher shares of Indigenous students. A related explanation could be that that more heterogeneous classrooms become harder to manage, either forcing the teacher to spend more time and effort managing the classroom and less time covering content or due to weariness from the additional effort.[19]

Our equilibrium result in Equation 20 implies that test scores are affected because student, parental, and teacher responses enter the human capital production function. In other words, it has to be the case that these changes in behavior have explanatory power for our test score result. To address this we use the method of Gelbach (2016) to *descriptively* understand to what extent the changes documented in this section could explain the negative results presented in Table C.8. Table C.11 presents these results.[20] We consistently find negative mediation of our three input categories, which means that part of the negative peer effect can be explained by declines in the inputs of students, parents and teachers. Our results suggest that almost 40% of the negative test score effect documented in Table C.8 could be due to changes in the behavior of students, parents, and teachers —factors that have to date been for the most part ignored in the extant literature on peer effects in education.

7.3 Alternative explanation: Characteristics correlated with Indigenous ethnicity

Results presented in Table C.11 and in Figure C.4 suggest that over 60% of the negative peer effect cannot be explained by the associated changes in behaviors of the three agents we consider in this paper. An obvious factor that we have ignored so far, however, is the fact that Indigeneity itself is correlated with socioeconomic and educational characteristics. In other words, even in a setting with institutionalized random assignment, majority students are not only assigned an Indigenous person but also a person with lower academic achievement and socioeconomic students (see Online Appendix Tables C.6 and C.1). To the extent that these other characteristics, in our setting perfectly collinear with Indigeneity, have causal effects on the majority students achievement, our reduced-form effects captures not only exposure to an Indigenous student but also to their correlated observable and unobservable characteristics, such as lower academic achievement. Given the literature on ability peer effects (e.g., Lavy, Silva and Weinhardt (2012), and in the Taiwanese context de Gendre and Salamanca (2020)), the importance of language

19. For example, Karbownik et al. (2024) document that higher share of lower ability and foreign background students leads to more sick leave and mental health problems among Swedish teachers.

20. 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.8. Furthermore, the method allows us to include the individual input measures rather than forcing us to add the parent and teacher indices themselves i.e., 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 result robust to all possible constructions of the input indices. Finally, unlike other decomposition methods, this one is not sensitive to ordering of the explanatory variables and takes into account correlations between them.

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 again 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. Table C.10 (or equivalently Figure C.3) presents these results and shows that language and investments of Indigenous parents do not contribute meaningfully 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 slightly less than one-third of the uncovered negative effect. 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 matter somewhat less than the changes in behavior documented in Section 7.2.

7.4 Combining correlated characteristics and endogenous responses

Our final analysis combines the decomposition and mediation results presented in Tables C.10 and C.11), and asks if we can fully explain away the negative Indigenous peer effect documented in Table C.8 by accounting for correlated student characteristics as well as endogenous responses of students, parents and teachers. As in Section 7.2, this is a descriptive exercise and Online Appendix Table C.12 presents these results. Recall that results presented in Table C.11) in Section 7.2 suggested explanatory power of 39% while results presented in Table C.10 in Section 7.3 suggested explanatory power of 32%. Therefore, ex ante, we expect that we should be able to explain at most 71% of the reduced form effects from Table C.8. Including only correlated peer characteristics (column 2) explains 31% of the estimated negative effect, yet the remaining Indigenous peer effect is still statistically significant at 10% level. Conversely, including only student, parent, and teacher endogenous responses (column 3) explains 36% of the estimated negative effect, yet again the coefficient remains statistically significant at 10% level. Finally, conditioning on both correlated peer characteristics and endogenous inputs (column 4) explains away 70% of the negative coefficient which is no longer statistically significant at conventional levels - almost matching our prediction above. One reason for this is that due to random assignment to classrooms channels explored in Sections 7.2 and 7.3 are likely independent. Even though this is a descriptive exercise, we conclude that much of the negative peer effect documented in Section 7.1 is due to endogenous responses of parents and teachers (somewhat more important) as well as characteristics correlated with peers' indigenous status (somewhat less important). This finding is important for two reasons. First, much of prior literature does not account for correlated observable characteristics when examining minority peer effects which could lead to distorted conclusions Our final analysis combines the decomposition and mediation results presented in Tables C.10 and C.11), and asks if we can fully explain away the negative Indigenous peer effect documented in Table C.8 by accounting for correlated student characteristics as well as endogenous responses of students, parents and teachers. As in Section 7.2, this is a descriptive exercise and Online Appendix Table C.12 presents these results. Recall that results presented in Table C.11) in Section 7.2 suggested explanatory power of 39% while results presented in Table C.10 in Section 7.3 suggested explanatory power of 32%. Therefore, ex ante, we expect that we should be able to explain at most 71% of the reduced form effects from Table C.8. Including only correlated peer characteristics (column 2) explains 31% of the estimated negative effect, yet the remaining Indigenous peer effect is still statistically significant at 10% level. Conversely, including only student, parent, and teacher endogenous responses (column 3) explains 36% of the estimated negative effect, yet again the coefficient remains statistically significant at 10% level. Finally, conditioning on both correlated peer characteristics and endogenous inputs (column 4) explains away 70% of the negative coefficient which is no longer statistically significant at conventional levels - almost matching our prediction above. One reason for this is that due to random assignment to classrooms channels explored in Sections 7.2 and 7.3 are likely independent. Even though this is a descriptive exercise, we conclude that much of the negative peer effect documented in Section 7.1 is due to endogenous responses of parents and teachers (somewhat more important) as well as characteristics correlated with peers' indigenous status (somewhat less important). This finding is important for two reasons. First, much of prior literature does not account for correlated observable characteristics when examining minority peer effects which could lead to distorted conclusions Second, the fact that over one-third of the effect could be attributed to endogenous responses of students, parents, and teachers leaves hope that resource or information interventions could correct these behaviors such that any negative spillovers occurring due to classroom integration efforts are minimized.

8 Robustness checks

Our main results presented in Tables C.8 and C.9 are robust to a number of alternative specifications.[21] We start our analysis by exploring the stability of our preferred estimates over alternative sample choices. Online Appendix Table C.14 presents these results. Column 1 replicates our baseline results from column 4 of Tables C.8 and C.9 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 both

21. In all of the sensitivity analyses we focus on fully saturated model from column 4 of Table C.8 but we only display coefficient on share of Indigenous students.

schools where Indigenous or Hakka students form a majority. Finally, 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. Irrespective of the sample we choose, we find very consistent results.

In another exercise, instead of dropping specific types of schools, we also consider excluding specific Han Chinese students, who are not from the Hoklo majority. Online Appendix Table C.15 presents these results. Column 1 again replicates our baseline results, column 2 excludes Hakka students, column 3 excludes Waishengren students, and finally column 4 excludes both sets of students. In this case, again, our conclusions remain unchanged.[22] Based on these exercises we conclude that our main results are robust to reasonable alternative specifications of the estimation samples.

Given the relatively small share of Indigenous students in population, it is perhaps more policy 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.[23]

We also 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 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 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-values of at most 0.003).

22. Interestingly, in a sample where we exclude Waishengren student (columns 3 and 4) the coefficient declines by up to one-third which suggests that negative peer effects could be particularly severe for this group of students.

23. 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 child in each classroom, there would be no within-school variation in the treatment. Therefore, these 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. Out of 155 schools in the sample with at least one Indigenous student, 137 schools do not have variation in the extensive margin treatment variables (i.e., they have at most one indigenous student in any one classroom).

Our final robustness exercise involves two sets of placebo tests. Recall that our theoretical model hinges upon the fact that compared to the majority students their Indigenous peers have less favorable observable characteristics ($b^m < b^M$). This means that we should not observe negative peer effects for groups where $b^m \approx b^M$, even if these children come from minority or disadvantage populations. Our first placebo test re-estimates our results from Tables C.8 and C.9 for Hakka students. As mentioned in Section 3.2, Hakka people are likewise an officially recognized ethnic minority by the Taiwanese government, however, as documented in Online Appendix Table C.1 these students have similar observable characteristics to the Hoklo majority. Furthermore, Table C.5 Panel A shows that teachers do not appear to hold prejudiced views against them. Therefore, we do not expect Hakka peers to affect student outcomes, unless prejudice against being a recognized minority group is the primary driver of the results. Online Appendix Table C.13 Panel A shows that Hakka peers do not appear to generate any economically meaningful peer effects, either for the majority students (the level coefficient) or for the other Hakka students (the interaction term). We further note that the negative statistically insignificant at conventional levels coefficient in column 1 is less than one-tenth of the coefficient in column 4 of Table C.8 reported for Indigenous peers. Furthermore, we do not find any endogenous responses of the majority students, their parents, or teachers in classroom with higher share of Hakka students. Two out of three of the coefficients have opposite sign than those reported in Table C.9 and they are all much smaller.

For our second placebo exercise, we construct a group of "synthetic" Indigenous students: majority students that are nearly observationally equivalent to Indigenous students. Specifically, for each Indigenous student in each school we define a synthetic Indigenous student that is a non-Indigenous student most similar to them in terms of baseline test scores and all other pre-assignment characteristics using a propensity score function.[24] We then use these synthetic Indigenous students to construct synthetic Indigenous peers in our placebo regressions. The rationale behind this exercise is to test biased subjective expectations ascribed via Indigeneity as the main mechanisms behind our results. While synthetic Indigenous students are as disadvantaged in terms of observables as actual Indigenous students, others would not have formed expectations about them based on their identify.[25] Therefore, the effect of synthetic Indigenous peers carries with it the treatment of observable disadvantage but without the prejudice—which we argue might be a key mechanisms behind our findings.

Panel B of Online Appendix Table C.13 shows that we indeed find no effects of synthetic Indigenous peers on student test scores. On the other hand, we do find some positive parental responses when we consider this treatment for both the observably better off students (the level

24. Online Appendix Figure C.9 shows there is common support in propensity scores, while Table C.11 shows that synthetic and actual indigenous students are very similar in terms of observable characteristics.

25. Recall that Panel B of Table C.5 confirms that teachers do not hold negative perceptions about the ability of synthetic Indigenous students.

coefficients) and the synthetic students' parents as well (the interaction term). This suggests that absent prejudice parents might actually attempt to compensate for exposure to students with adverse observable characteristics. We do not find any statistically significant estimates for teacher engagement and this coefficient is about one-quarter of the corresponding estimate in Table C.9. Overall, we view these results as strongly suggesting that Indigenous students generate the negative peer effects due to not only their lower observable characteristics ($b^m < b^M$) but also because of prejudice.

9 Conclusions

This paper shows that minority peers can have negative effects on cognitive outcomes of the majority children and that these negative externalities are driven by lower observable characteristics of the minorities as well as prejudice against them. We find that a 10 percentage points increase in classroom exposure to Indigenous peers lowers test scores of the majority students by 4.0% of a standard deviation. Furthermore, we document that over one-third of the negative effect can be explained by endogenous responses of majority students their parents, and teachers in these classrooms. At the same time, adverse characteristics correlated with Indigeneity account for a somewhat smaller fraction of the estimated coefficient. In that, the negative effects should not be attributed to being Indigenous per se but rather to how others react when interacting with Indigenous students as well as to their general disadvantage. In fact, we show no negative or statistically significant effects when considering another minority group recognized by the Taiwanese government – the Hakka – or when we consider a set of majority students who are observationally similar to Indigenous students.

Taken together, our results have several implications for both modelling peer effects in schools as well as classroom integration efforts. First, when estimating peer effects it appears important to consider them in the context of multi-agent production function that involves not only direct interactions between students but also endogenous responses of the majority students, their parents, and teachers in these classrooms. Ignoring those actors could paint a distorted picture on what exactly is driving the reduced form estimates. Second, ignoring the contextual interactions, in the language of Manski (2000) referring to exogenous peer characteristics correlated with the minority status, could lead to biased estimates. Finally, when considering classroom integration policies, it appear important to understand and address the aforementioned endogenous responses of students, parents, and teachers as ignoring those, as has been done to date in majority of the extant literature, could lead to misguided policy interventions.

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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:[26]

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

26. 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' and teachers' effort choices

We have:

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

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

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

Similarly

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

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).[27]

27. 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

The 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 Table C.2 present the regression-based coefficients–effectively the weights–used to construct each of the student effort, parental investments, and teacher effort indices. In column (3) 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 in Online Appendix Table C.3.[28]

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.

28. 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.

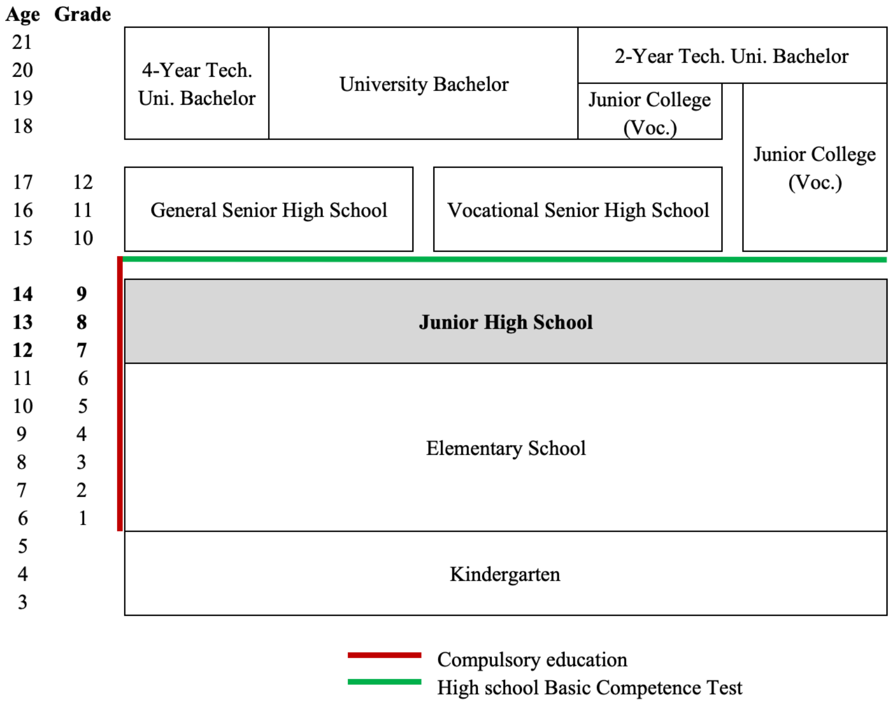
if they feel more motivated and less tired of teaching when working with a more homogeneous classrooms with fewer minority students.

Online Appendix Table C.6 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.[29] 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.

29. 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.

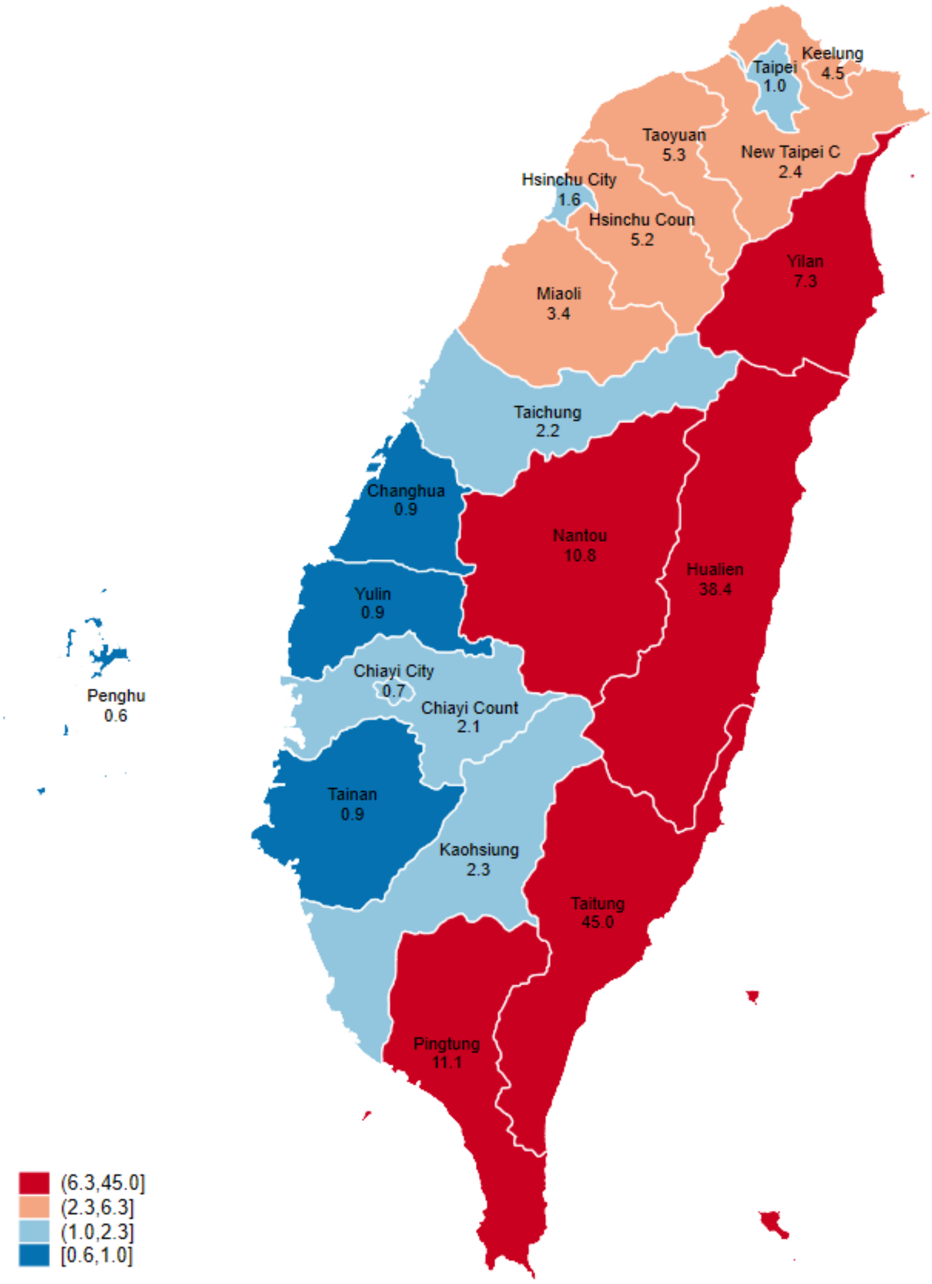
Appendix C Tables and Figures

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*

	Mean of characteristics for:			
	Indigenous	**Hakka**	**Mainlander**	**Hoklo**
Students:				
Indigenous parent(s)	1.00	0.02	0.03	0.02
Hakka parent(s)	0.06	1.00	0.15	0.12
Mainlander parent(s)	0.07	0.11	1.00	0.11
Hoklo parent(s)	0.18	0.47	0.58	1.00
Test scores at baseline [std]	-0.80	-0.12	0.11	-0.09
Fluent in Mandarin	0.88	0.92	0.95	0.92
Fluent in indigenous language	0.29	0.01	0.01	0.01
Fluent in Hakka language	0.03	0.17	0.04	0.02
Female student	0.51	0.49	0.50	0.49
Birth year	1989	1989	1989	1989
No. of siblings of student	2.36	1.89	1.54	1.83
Aspires to go to university	0.33	0.43	0.49	0.43
Expects to go to university	0.25	0.33	0.39	0.33
Has conflicts with parents	0.26	0.24	0.22	0.26
Parents are role models	0.36	0.30	0.32	0.31
Parents:				
Two-parent household	0.84	0.92	0.90	0.91
Good relationship between them	3.10	3.15	3.13	3.14
Parent(s) education is high school or less	0.80	0.71	0.51	0.73
Employed father	0.78	0.88	0.91	0.88
Parent(s) in good health	0.33	0.61	0.58	0.60
Financial difficulties in past 10 yrs	0.60	0.26	0.24	0.29
Household monthly income is				
NT$20,000 or less	0.30	0.12	0.07	0.11
NT$20,000-NT$50,000	0.47	0.43	0.36	0.46
NT$50,000-NT$100,000	0.20	0.36	0.40	0.34
More than NT$100,000	0.03	0.10	0.16	0.09
Schools:				
Principal has postgraduate degree	0.15	0.20	0.29	0.26
Principal years of experience	28.1	29.0	29.2	28.3
Government founded school	0.94	0.91	0.95	0.95
School year of foundation	1968	1969	1971	1971
Observations	588	1,755	1,276	6,846

This table reports means for all key variables in the TEPS data across student ethnicity groups. The bottom row reports the maximum number of observations . Mean estimates might use fewer observations due to missing data points in each case.

Table C.2: *Construction of Parent and Teacher Effort Indices*

	Regression on W1 test scores		PCA 1st comp.
	Coef.	**Std. err.**	**weights**
Student behaviors:			
Study hours	1.164	0.071	-
Parental investments:			
Private tutoring	1.167	0.07	0.56
Time with parents	1.472	0.072	0.38
Parental support	0.738	0.070	0.74
Teacher engagement:			
Teacher effort	-0.018	0.070	0.71
Ease to manage class	0.320	0.061	0.71

Table C.3: *Robustness Checks: Mechanisms using PCA-based Indices of Parent and Teacher Effort*

Outcome [std]:	**First PCA component score of:**		
	Student behaviors	**Parental investments**	**Teacher engagement**
Share of indigenous peers	n/a	-0.624***	-1.866***
		(0.199)	(0.548)
Indigenous peers × Indigenous	n/a	-0.025	0.261
		(0.168)	(0.193)
R^2	n/a	0.22	0.40
Schools	n/a	155	155
Classes	n/a	588	578
Students	n/a	8,416	7,935

*This table reports estimates of regressing wave 2 indices of student-related, parent-related, and teacher-related mechanisms on the share of indigenous peers in the classroom. Indices are constructed as the score of the first component from separate Principal Component Analyses on each set of mechansisms. All regressions include school fixed effects and control for students' own test scores in wave 1 and pre-assignment characteristics, and 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.4: *Documenting negative perceptions about Indigenous students' ability*

Outcome:	**Above-average at problem solving (teacher assessment in W1)**			
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)
School FE		✓	✓	✓
Outcome mean	0.30	0.30	0.30	0.30
R^2	0.00	0.05	0.25	0.25
Schools	154	154	154	154
Classes	576	576	576	576
Students	7,579	7,579	7,579	7,579

*This table reports estimates of regressing a measure of teachers' subjective assessment of student problem-solving ability in wave 1 on an indigenous student dummy, students' test scores in wave 1, and their interaction. 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: *Teacher perceptions about Hakka and Synthetic Indigenous students' ability*

Panel A: Falsification exercise using Hakka students				
Outcome:	**Above-average at problem solving (teacher assessment in W1)**			
Hakka student	0.035**	0.035**	0.013	0.013
	(0.016)	(0.016)	(0.014)	(0.015)
Test scores in W1 [std]			0.235***	0.234***
			(0.005)	(0.006)
Hakka × Test scores				0.001
				(0.012)
School FE		✓	✓	✓
Outcome mean	0.30	0.30	0.30	0.30
R^2	<0.01	0.04	0.25	0.25
Schools	154	154	154	154
Classes	576	576	576	576
Students	7,579	7,579	7,579	7,579

Panel B: Falsification exercise using synthetic Indigenous students				
Outcome:	**Above-average at problem solving (teacher assessment in W1)**			
Synthetic indigenous	0.063**	-0.073	-0.017	-0.029
	(0.026)	(0.065)	(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		✓	✓	✓
Outcome mean	0.30	0.30	0.30	0.30
R2	<0.01	0.04	0.25	0.25
Schools	154	154	154	154
Classes	576	576	576	576
Students	7,579	7,579	7,579	7,579

*This table reports estimates of regressing a measure of teachers' subjective assessment of student problem-solving ability in wave 1 on a Hakka student dummy, students' test scores in wave 1, and their interaction. 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.6: *Descriptive statistics*

	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	***
Mainlander parent(s)	0.18	0.15	0.07	0.16	0.08	***
Hoklo parent(s)	0.82	0.80	0.18	0.85	0.67	***
Test scores at baseline [std]	0.00	-0.14	-0.80	-0.09	0.72	***
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	0.11	***
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	0.00	
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	0.28	***
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	-0.20	***
NT$20,000-NT$50,000	0.41	0.46	0.47	0.45	-0.01	
NT$50,000-NT$100,000	0.35	0.33	0.20	0.34	0.15	***
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	0.01	
School year of foundation	1968	1970	1968	1970	1.96	***
Observations	20,055	8,517	588	7,929	8,517	

*This table reports means for all key variables in the TEPS data. The first column reports means for the entire data. The second column reports means for our estimation sample restricted to schools where there is at least one indigenous student. The third through fifth columns report means for the estimation subsamples of indigenous and majority students, and the difference between both columns. ***, ** and * mark mean differences between indigenous and majority students statistically different from zero at the 99, 95 and 90 percent confidence level, based on two-sample t-tests assuming unequal variances. The bottom row reports the maximum number of observations . Mean estimates might use fewer observations due to missing data points in each case.*

Table C.7: *Balancing Checks: Correlations between Pre-Assignment Characteristics and Exposure to Indigenous Students in the Classroom*

Treatment:		**Share of indigenous peers**		
	Mean	Coef.	Std. err.	Obs.
Pre-assignment Outcomes:				
Student test scores	Std	0.076	(0.220)	8,517
Female student	0.49	-0.022	(0.097)	8,517
Student born before 1989	0.36	0.075	(0.104)	8,486
Two-parent household	0.90	-0.015	(0.063)	8,505
Household income > NT$50k/mo.	0.42	-0.113	(0.103)	8,472
Stable income for 1+ household member	0.89	-0.021	(0.070)	8,499
Parent(s) education is high school or less	0.71	-0.153	(0.102)	8,517
Employed father	0.88	0.134*	(0.073)	8,210
Parent(s) in good health	0.58	-0.008	(0.107)	8,514
Prioritized studies since primary school	0.27	0.107	(0.093)	8,467
Reviews lessons since primary school	0.17	0.038	(0.085)	8,460
Likes new things since primary school	0.41	-0.013	(0.116)	8,447
Was truant in primary school	0.35	0.081	(0.088)	8,495
Student had mental health issues in primary school	0.47	-0.032	(0.087)	8,491
Had private tutoring before junior high	0.65	0.077	(0.127)	8,428
Family help with homework before junior high	0.84	0.037	(0.073)	8,125
Student quarreled with parents in primary school	0.66	-0.053	(0.079)	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		

*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.8: *Main results: The Effects of Exposure to Indigenous Students in the Classroom on Test Scores*

Outcome [std]:	**Student test scores**			
Share of indigenous peers	-0.299	-0.392***	-0.398***	-0.402***
	(0.215)	(0.140)	(0.139)	(0.145)
Indigenous peers × Indigenous				0.020
				(0.090)
Own test scores		✓	✓	✓
Pre-assignment controls			✓	✓
R^2	0.15	0.62	0.63	0.63
Schools	155	155	155	155
Classes	588	588	588	588
Students	8,517	8,517	8,517	8,517

*This table reports estimates of regressing standardized student test scores in wave 2 on the classroom share of indigenous peers in wave 1 (and its interaction with an Indigenous student dummy in the rightmost column). 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.9: *Mechanisms: The Effects of Exposure to Indigenous Students in the Classroom on Student, Parents and Teacher Effort*

Outcomes [std]:	**Student behaviors**	**Parental investments**	**Teacher engagement**
Share of indigenous peers	-0.751***	-0.715***	-2.474***
	(0.282)	(0.224)	(0.660)
Indigenous peers × Indigenous	0.517***	-0.281*	0.351
	(0.187)	(0.165)	(0.266)
R^2	0.19	0.23	0.28
Schools	155	155	155
Classes	588	588	578
Students	8,461	8,416	7,935

*This table reports estimates of regressing standardized aggregate indices of student-related, parent-related, and teacher-related mechanisms in wave 2 on the share of indigenous peers in the classroom. All regressions include school fixed effects and control for students' own test scores in wave 1 and pre-assignment characteristics, and 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.10: *Decomposing the Effect of Exposure to Indigenous Peers by Correlated Observable Characteristics*

Outcome [std]:	**Student test scores**	**Share explained**
Share of indigenous peers	-0.393***	100%
	(0.138)	
Effect explained by other peer characteristics	-0.124*	32%
	(0.072)	
→ by peer test scores	-0.056**	14%
	(0.026)	
→ by peer socioeconomic status	-0.059	15%
	(0.047)	
→ by peer language skills	-0.014	4%
	(0.052)	
→ by peer parental investments	0.005	-1%
	(0.014)	
Students	8,517	

*This table reports the total and mediated effect of the classroom share of indigenous peers on students test scores based on Gelbach's (2016) decomposition. All regressions include school fixed effects and control for students' own test scores in wave 1 and pre-assignment characteristics, and all controls are interacted with an Indigenous student dummy. These estimates are produced using the b1x2 Stata package on a within-school transformation of the data. 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.11: *Mediation Analysis*

Outcome [std]:	Student test scores	Share mediated
Share of indigenous peers	-0.389***	100%
	(0.136)	
Mediated effect	-0.151***	39%
	(0.047)	
→ by student-related mediators	-0.063**	16%
	(0.029)	
→ by parent-related mediators	-0.029**	7%
	(0.013)	
→ by teacher-related mediators	-0.059*	15%
	(0.033)	
Students	8,517	

*This table reports the total and mediated effect of indigenous classroom peers on students test scores based on Gelbach's (2016) decomposition. All regressions include school fixed effects and control for students' own test scores in wave 1 and pre-assignment characteristics, and all controls are interacted with an Indigenous student dummy. These estimates are produced using the b1x2 Stata package on a within-school transformation of the data. 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 in explaining the treatment effect: Gelbach's (2016) decomposition*

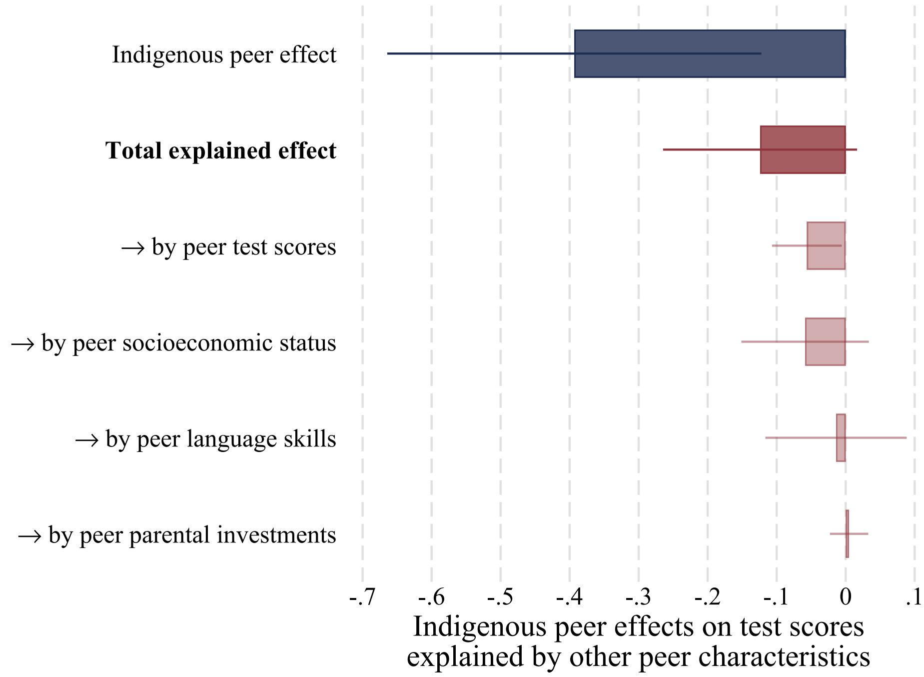


Figure C.4: *Mediation analysis: The role of endogenous responses of students, parents, and teachers*

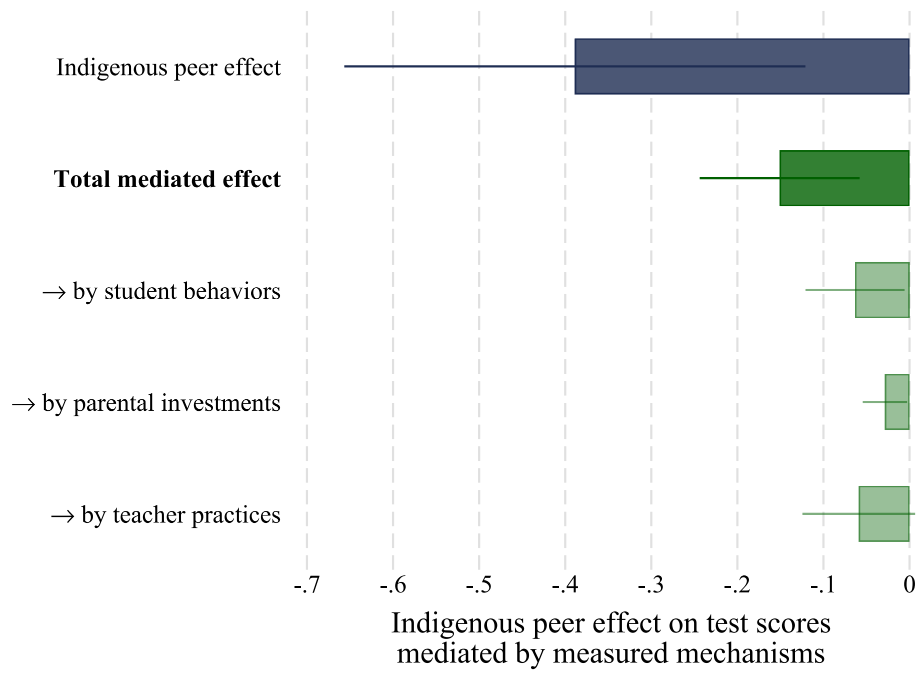


Table C.12: *The Net Effect of Exposure to Indigenous Peers in the Classroom: Correlated Observable Characteristics and Endogenous Responses*

Outcome [std]:	**Student test scores**			
Share of indigenous peers	-0.407***	-0.280*	-0.259*	-0.122
	(0.139)	(0.157)	(0.144)	(0.156)
Other peer characteristics		✓		✓
Mechanisms			✓	✓
Fraction explained	N/A	31%	36%	70%
R^2	0.63	0.64	0.65	0.65
Schools	155	155	155	155
Classes	588	588	588	588
Students	8,517	8,517	8,517	8,517

*This table reports estimates of regressing standardized student test scores in wave 2 on the share of indigenous peers in the classroom. All regressions include school fixed effects and control for students' own test scores in wave 1 and pre-assignment characteristics, and 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.*

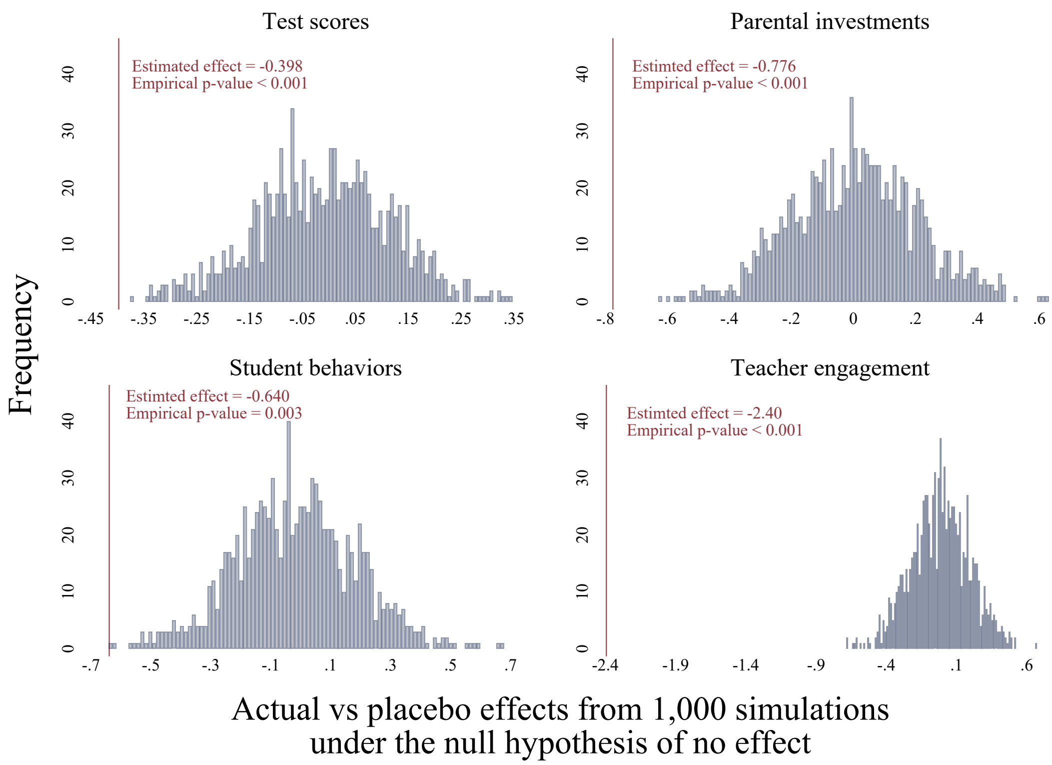
Table C.13: *Falsification test using Hakka and synthetic Indigenous students*

Panel A: Falsification exercise using exposure to Hakka peers				
Outcome [std]:	**Student test scores**	**Student behaviors**	**Parental investments**	**Teacher engagement**
Share of Hakka peers	-0.037	0.225	0.023	-0.169
	(0.097)	(0.161)	(0.137)	(0.414)
Hakka peers × Hakka	0.024	0.157	0.075	0.143
	(0.074)	(0.137)	(0.101)	(0.139)
R^2	0.63	0.19	0.22	0.26
Schools	155	155	155	155
Classes	588	588	588	578
Students	8,517	8,461	8,416	7,935

Panel B: Falsification exercise using exposure to synhetic Indigenous peers				
Outcome [std]:	**Student test scores**	**Student behaviors**	**Parental investments**	**Teacher engagement**
Share of synthetic indigenous peers	-0.022	0.038	0.619***	-0.612
	(0.145)	(0.281)	(0.233)	(0.631)
Synthetic peers × Synthetic indigenous	0.182	0.306	0.971**	0.787*
	(0.201)	(0.421)	(0.442)	(0.458)
R2	0.63	0.19	0.22	0.26
Schools	155	155	155	155
Classes	588	588	588	578
Students	8,517	8,461	8,416	7,935

*Panel A of this table reports estimates of regressing standardized outcomes in wave 2 on the share of Hakka peers in the classroom, and its interaction with a Hakka student dummy. Panel B of this table reports estimates of regressing standardized outcomes in wave 2 on the share of synthetic indigenous peers in the classroom, and its interaction with a synthetic indigenous student dummy. A synthetic indigenous student is defined as the majority student whose observable characteristics are closest to their indigenous peer in school. This proximity is operationalized via propensity scores using test scores and all preassignment characteristics in wave 1. All regressions include school fixed effects and control for students' own test scores in wave 1 and pre-assignment characteristics, and all controls are interacted with a Hakka 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.*

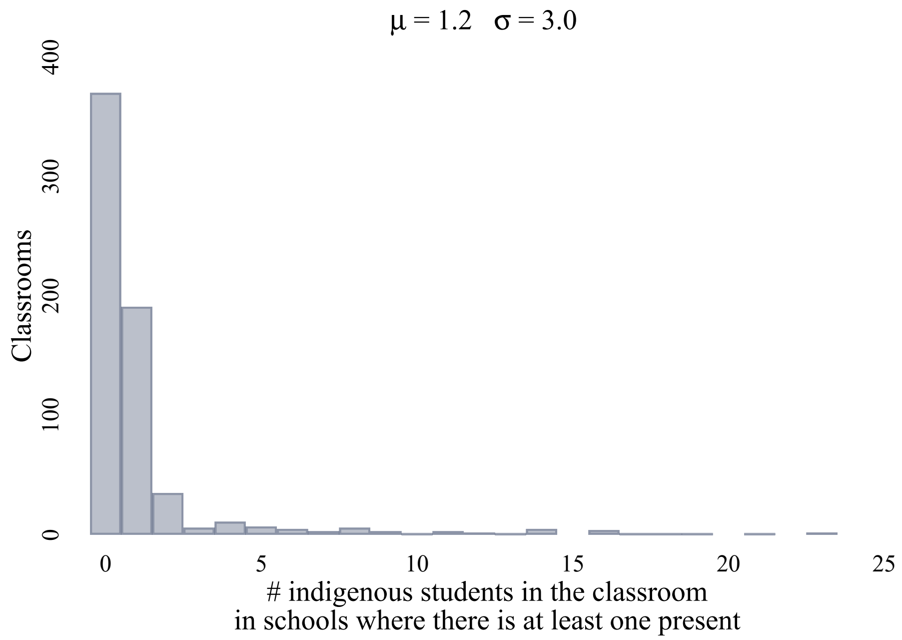
Figure C.5: *Main Results of Exposure to Indigenous Students: Randomization Inference*



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 of Indigenous students in the classroom —is based on re-randomized assignment of students to classrooms rather than the true randomized assigned values used in main estimation in C.8 and C.9. We re-randomize the class structure 1,000 times. Red vertical lines present our point estimates from the preferred specification in column 3 of Table C.8 (and equivalent specification in Table C.9) 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*

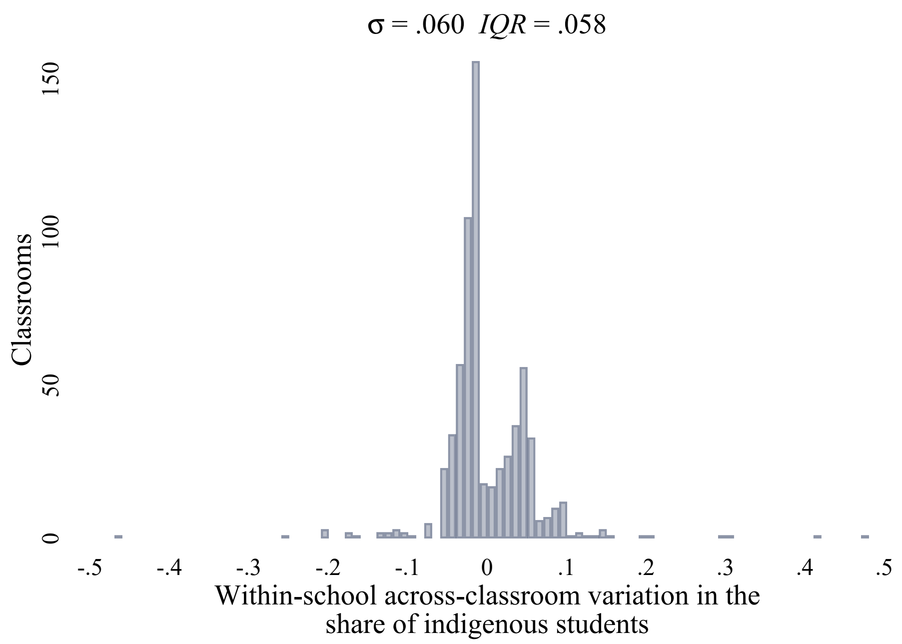


Table C.14: *Robustness Checks: Alternative Samples —Excluding Schools*

Excluded schools:	**None (baseline)**	**Indigenous majority**	**Indig./Hakka majority**	**Private**
Outcome [std]:		**Student test scores**		
Share of indigenous peers	-0.398***	-0.468***	-0.432***	-0.384***
	(0.139)	(0.147)	(0.156)	(0.142)
Students	8,517	8,166	7,286	8,251
Outcome [std]:		**Student behaviors**		
Share of indigenous peers	-0.639**	-0.592*	-0.503	-0.571*
	(0.303)	(0.318)	(0.334)	(0.306)
Students	8,461	8,110	7,231	8,195
Outcome [std]:		**Parental investments**		
Share of indigenous peers	-0.776***	-0.841***	-0.816***	-0.780***
	(0.236)	(0.255)	(0.272)	(0.242)
Students	8,416	8,074	7,200	8,150
Outcome [std]:		**Teacher engagement**		
Share of indigenous peers	-2.393***	-2.301***	-2.659***	-2.499***
	(0.665)	(0.646)	(0.687)	(0.683)
Students	7,935	7,590	6,743	7,686

*This table reports estimates of regressing standardized outcomes in wave 2 on the share of indigenous peers in the classroom. Different columns show estimates that exclude potentially troublesome observation groups from the sample. All regressions include school fixed effects and control for students' own test scores in wave 1 and pre-assignment characteristics, and 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.15: *Robustness Checks: Alternative Samples —Excluding Majority Student Subgroups*

Excluded students:	**None (baseline)**	**Hakka**	**Waishengren**	**Hakka & Waishengren**
Outcome [std]:	**Student test scores**			
Share of indigenous peers	-0.398***	-0.375**	-0.277*	-0.265*
	(0.139)	(0.146)	(0.143)	(0.149)
Students	8,517	6,762	7,241	5,675
Outcome [std]:	**Student behaviors**			
Share of indigenous peers	-0.639**	-0.658*	-0.632**	-0.680*
	(0.303)	(0.348)	(0.302)	(0.354)
Students	8,461	6,713	7,192	5,633
Outcome [std]:	**Parental investments**			
Share of indigenous peers	-0.776***	-0.780***	-0.870***	-0.829***
	(0.236)	(0.255)	(0.233)	(0.251)
Students	8,416	6,680	7,154	5,607
Outcome [std]:	**Teacher engagement**			
Share of indigenous peers	-2.393***	-2.487***	-2.394***	-2.478***
	(0.665)	(0.634)	(0.671)	(0.631)
Students	7,935	6,273	6,738	5,256

*This table reports estimates of regressing standardized outcomes in wave 2 on the share of indigenous peers in the classroom. Different columns show estimates that exclude potentially troublesome observation groups from the sample. All regressions include school fixed effects and control for students' own test scores in wave 1 and pre-assignment characteristics, and 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.*

Figure C.7: *Non-linear Peer Effects on Test Scores*

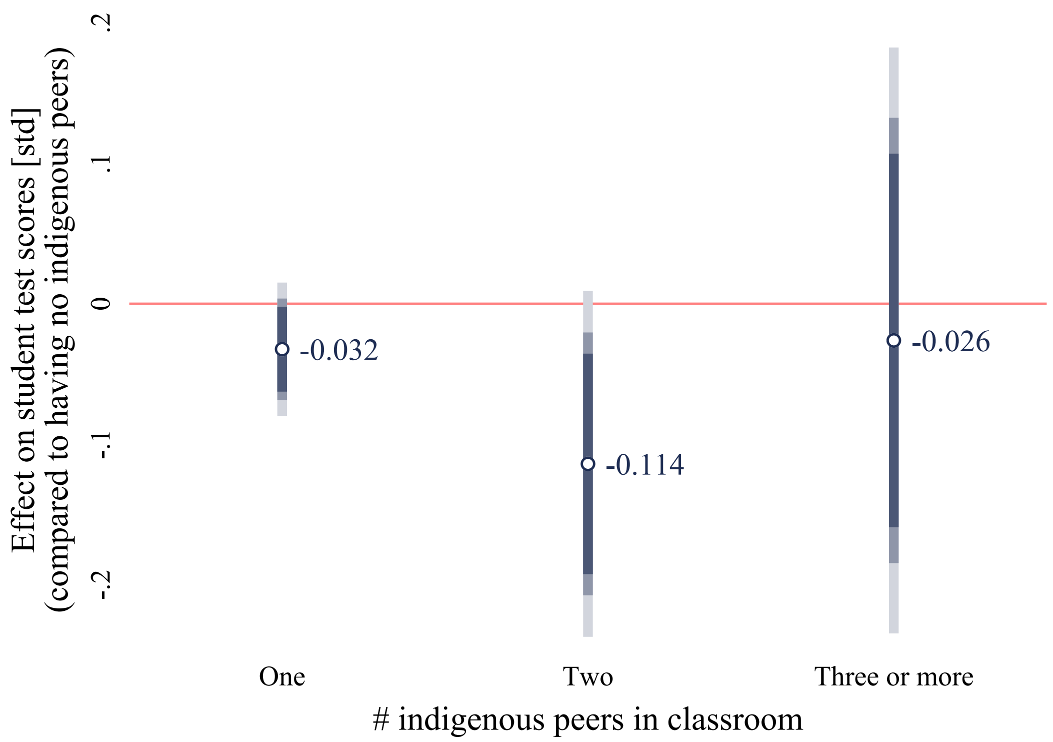


Figure C.8: *Correlation between Test Scores and Student, Parent and Teacher Inputs*

Outcome [std]:	Student behaviors in W2		
Student test score in W1	0.335***	0.312***	0.277***
	(0.014)	(0.014)	(0.015)
School FE		✓	✓
Pre-assignment controls			✓
Students	8,461	8,461	8,461
Outcome [std]:	**Parental investments in W2**		
Student test score in W1	0.204***	0.173***	0.110***
	(0.012)	(0.012)	(0.012)
School FE		✓	✓
Pre-assignment controls			✓
Students	8,416	8,416	8,416
Outcome [std]:	**Teacher engagement in W2**		
Student test score in W1	0.064***	0.085***	0.077***
	(0.022)	(0.016)	(0.016)
School FE		✓	✓
Pre-assignment controls			✓
Students	7,935	7,935	7,935

*This table reports estimates of regressing standardized student behaviors, parental investments, and teacher engagement indices in wave 2 on student test scores in wave 1. Different columns show estimates that additionally control for school fixed effects and pre-assignment student characteristics (including interaction between these and 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.*

Figure C.9: *Falsification Check: Common Support in Propensity-Score Matching of Indigenous and Synthetic Indigenous Students*

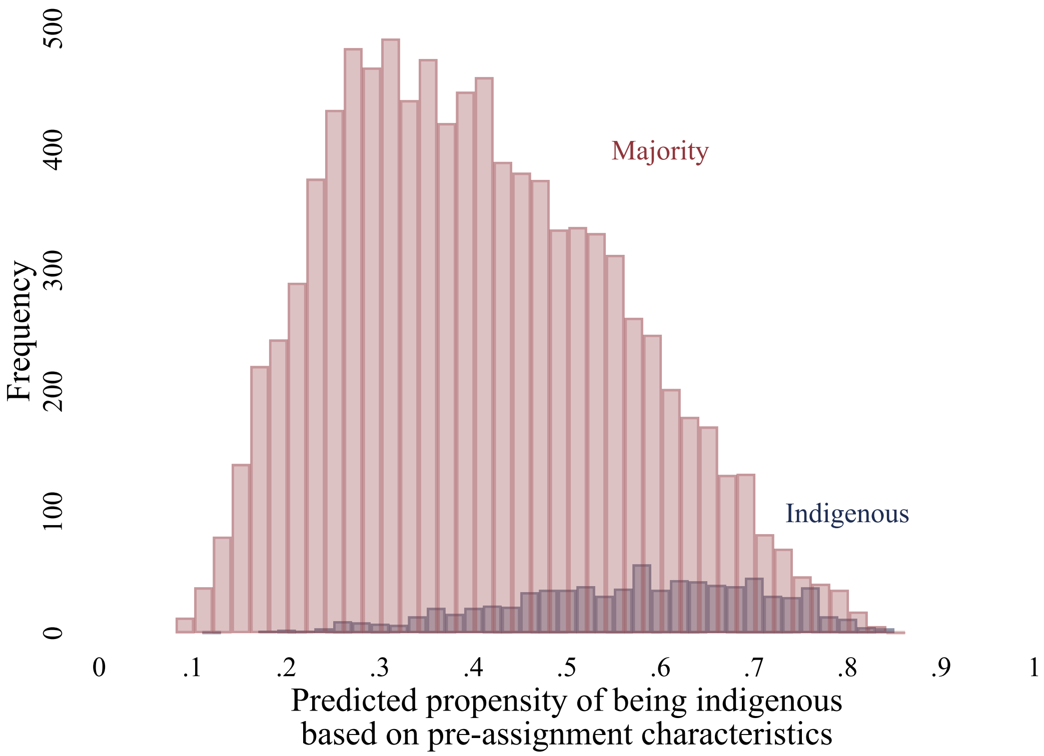


Figure C.10: *Falsification Check: Balancing Tests for Effects of Exposure to Hakka Students*

Treatment:		Share of Hakka peers		
	Mean	**Coef.**	**Std. err.**	**Obs.**
Student test scores	Std	0.212	(0.152)	8,517
Female student	0.49	0.030	(0.055)	8,517
Student born before 1989	0.36	0.010	(0.058)	8,486
Two-parent household	0.90	-0.037	(0.037)	8,505
Household income > NT$50k/mo.	0.42	0.160**	(0.072)	8,472
Stable income for 1+ household member	0.89	-0.015	(0.034)	8,499
Parent(s) education is high school or less	0.71	-0.061	(0.062)	8,517
Employed father	0.88	0.019	(0.037)	8,210
Parent(s) in good health	0.58	0.015	(0.062)	8,514
Prioritized studies since primary school	0.27	-0.008	(0.057)	8,467
Reviews lessons since primary school	0.17	-0.020	(0.052)	8,460
Likes new things since primary school	0.41	0.131**	(0.064)	8,447
Was truant in primary school	0.35	0.002	(0.058)	8,495
Student had mental health issues in primary school	0.47	0.012	(0.054)	8,491
Had private tutoring before junior high	0.65	-0.091	(0.056)	8,428
Family help with homework before junior high	0.84	-0.097**	(0.045)	8,125
Student quarreled with parents in primary school	0.66	0.062	(0.053)	8,503
Guryan et al. (2009) sorting t-statistic		1.0		
Jochmans (2020) sorting t-statistic		0.7		
LHS test of joint balancing (p-value)		0.242		

*This table reports estimates of regressing pre-assignment characteristics in wave 1 on the share of indigenous peers in the classroom. All estimators include school fixed effects. Guryan et al. (2009) and Jochmans (2023) sorting statistics test to sorting tests of whether Hakka students are more likely to be assigned to classrooms with other Hakka 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 Hakka 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.*

Figure C.11: *Falsification Check: Balancing Tests for Effects of Exposure to Synthetic Indigenous Students*

Treatment:		**Share of synthetic indigenous peers**		
	Mean	**Coef.**	**Std. err.**	**Obs.**
Student test scores	0.096	(0.212)	(0.010)	8,517
Female student	0.059	(0.088)	(0.004)	8,517
Student born before 1989	-0.059	(0.111)	(0.005)	8,517
Two-parent household	-0.026	(0.062)	(0.003)	8,517
Household income > NT$50k/mo.	-0.040	(0.103)	(0.005)	8,517
Stable income for 1+ household member	-0.135*	(0.071)	(0.003)	8,517
Parent(s) education is high school or less	0.049	(0.095)	(0.005)	8,517
Employed father	-0.119	(0.082)	(0.004)	8,517
Parent(s) in good health	-0.049	(0.109)	(0.005)	8,517
Prioritized studies since primary school	0.104	(0.107)	(0.005)	8,517
Reviews lessons since primary school	0.056	(0.096)	(0.005)	8,517
Likes new things since primary school	0.233**	(0.106)	(0.005)	8,517
Was truant in primary school	0.079	(0.095)	(0.005)	8,517
Student had mental health issues in primary school	0.076	(0.093)	(0.004)	8,517
Had private tutoring before junior high	0.025	(0.106)	(0.005)	8,517
Family help with homework before junior high	0.043	(0.079)	(0.004)	8,517
Student quarreled with parents in primary school	-0.013	(0.086)	(0.004)	8,517
Guryan et al. (2009) sorting t-statistic		-0.8		
Jochmans (2020) sorting t-statistic		-1.2		
LHS test of joint balancing (p-value)		0.608		

*This table reports estimates of regressing pre-assignment characteristics in wave 1 on the share of synthetic indigenous peers the classroom. A synthetic indigenous student is defined as the majority student whose observable characteristics are closest to their indigenous peer in school. This proximity is operationalized via propensity scores using test scores and all preassignment characteristics in wave 1. All estimators include school fixed effects. Guryan et al. (2009) and Jochmans (2023) sorting statistics test to sorting tests of whether synthetic indigenous students are more likely to be assigned to classrooms with other synthetic 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 synthetic 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.*

Figure C.12: *Robustness Checks: Endogenous Attrition and Changing Classrooms after Random Assignment*

Outcome:	**Changed schools**	**Changed classrooms**
Share of indigenous peers	0.063**	-0.073
	(0.026)	(0.065)
Indigenous student	0.083	0.002
	(0.057)	(0.031)
Outcome mean	0.02	0.04
R^2	0.07	0.18
Schools	155	155
Classes	588	588
Students	8,517	8,388

*This table reports estimates of regressing a dummy for student being in different schools in waves 1 and 2 and, conditional on being on the same school, of being in different classrooms in waves 1 and 2, on the share of indigenous peers in the classroom. All regressions include school fixed effects and control for students' own test scores in wave 1 and pre-assignment characteristics, and 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.*

Figure C.13: *Effects of Exposure to Indigenous Peers: Long-Term Outcomes*

Treatment:		Share of indigenous peers					
	Mean	Coef.	Std. err.	R^2	Schools	Classes	Students
Outcomes:							
Test scores in wave 3 [Std]	-0.46	-0.343	(0.352)	0.66	155	535	1,753
Test scores in wave 4 [Std]	-0.39	-0.353	(0.339)	0.60	155	531	1,705
University in 2009	0.50	0.054	(0.249)	0.43	153	507	1,342
Tertiary vocational education in 2009	0.37	-0.136	(0.281)	0.27	153	507	1,342
University in 2013	0.38	0.105	(0.259)	0.28	153	501	1,300
Postgraduate studies in 2013	0.17	-0.068	(0.220)	0.24	153	501	1,300
Graduated by 2013	0.83	-0.295	(0.241)	0.22	153	501	1,297
Has a full time job in 2013	0.70	-0.431	(0.271)	0.24	153	501	1,294
Earns above-median income in 2013	0.46	-0.517	(0.392)	0.26	148	451	909

*This table reports estimates of regressing student outcomes in senior high school and after graduation for selected students on the share of indigenous peers in the classroom. Selective attrition is accounted for via inverse probability weights. All regressions include school fixed effects and control for students' own test scores in wave 1 and pre-assignment characteristics, and 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.*

Figure C.14: *Heterogeneous Effects of Exposure to Indigenous Peers*

Outcomes [std]:	Effect of share of indigenous peers on: Student test scores	Student behaviors	Parental investments	Teacher engagement
by student gender:				
Boys	-0.449***	-0.618*	-0.826***	-2.420***
	(0.143)	(0.322)	(0.254)	(0.667)
Girls	-0.336**	-0.665**	-0.715***	-2.361***
	(0.147)	(0.303)	(0.239)	(0.669)
by family income:				
Below NT$50k/month	-0.323**	-0.506	-0.888***	-2.500***
	(0.139)	(0.318)	(0.233)	(0.681)
Above NT$50k/month	-0.512***	-0.848***	-0.600**	-2.231***
	(0.162)	(0.308)	(0.283)	(0.655)
by student W1 test scores:				
Below median	-0.264*	-0.415	-0.821***	-2.371***
	(0.135)	(0.308)	(0.243)	(0.670)
Above median	-0.674***	-1.079***	-0.691***	-2.436***
	(0.175)	(0.302)	(0.259)	(0.667)

*This table reports average marginal effects from a separately interacted regressions of wave 2 outcomes on the share of indigenous peers in the classroom, all interacted with each indicators for student gender, family income, and student ability, one at the time. All regressions include school fixed effects and control for students' own test scores in wave 1 and pre-assignment characteristics, and 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.*

Figure C.15: *Selection into Identification: Effect Scaled by Inverse-Probability Weights*

Weights:	None (baseline)	IPW for selection into estimation sample
Outcome [std]:	**Student test scores**	
Share of indigenous peers	-0.398***	-0.596***
	(0.139)	(0.192)
Students	8,517	8,517
Outcome [std]:	**Student behaviors**	
Share of indigenous peers	-0.639**	-0.951***
	(0.303)	(0.298)
Students	8,461	8,461
Outcome [std]:	**Parental investments**	
Share of indigenous peers	-0.776***	-0.686***
	(0.236)	(0.233)
Students	8,416	8,416
Outcome [std]:	**Teacher engagement**	
Share of indigenous peers	-2.393***	-2.137***
	(0.665)	(0.672)
Students	7,935	7,935

*This table reports estimates of regressing standardized outcomes in wave 2 on the share of indigenous peers in the classroom. The rightmost column shows estimates using inverse probability weights (IPW) to account for differences between our main estimation sample and the entire TEPS data. These weights use preassignment student and peer characteristics as predictors, except indigenous students and peers and school fixed effects since this perfectly predicts the outcome by design. We windsorize weights at their 1st and 99th percentile. All regressions include school fixed effects and control for students' own test scores in wave 1 and pre-assignment characteristics, and 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.*