Adjustment Costs of Linguistic Integration: Evidence from Residential School Migrations in India*

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Abstract

Do language transitions impose temporary adjustment costs or persistent human capital losses? We study this question using a large-scale residential school migration program in India that requires approximately 30 percent of Grade IX students to spend one academic year in a linguistically different region. Since participating schools share standardized curricula, assessments, and residential conditions, the program generates plausibly exogenous variation in linguistic exposure while holding institutional inputs constant. Using administrative student level panel data and a difference-in-differences design comparing migrants and non-migrants within schools, we find a short-run decline of approximately 0.14 baseline standard deviations in aggregate test scores during the migration year. The decline is concentrated in cognitively intensive subjects, while performance in language improves. Over time, score differences attenuate and become statistically insignificant, consistent with temporary adjustment costs arising from cognitive reallocation during linguistic transition rather than permanent loss in human capital.

JEL Codes: J24, I21, I24
Keywords: linguistic integration; language transition; learning outcomes; human capital; peer effects

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1 Introduction

In multilingual societies, schooling frequently requires students to learn subject-matter content in a language that is not their primary language. A substantial literature shows that linguistic mismatch in medium of instruction can depress measured learning outcomes, particularly when the language of instruction or assessment changes abruptly (Angrist and Lavy, 1997; Ivlevs and King, 2014; Taylor and von Fintel, 2016; Bernhofer and Tonin, 2022). This problem is further accentuated in linguistically diverse societies, such as India, where more than 1600 spoken languages and 22 constitutionally recognized languages (Jain, 2017) exist. Moreover, roughly 9 million people move between states each year (Government of India, Ministry of Finance, 2017), alongside about 450 million internal migrants as per the 2011 Census (World Bank, 2019). However, little is known about whether these language transitions are primarily short-run adjustment costs, or do they translate into persistent human-capital deficits.

In this paper, we study the academic consequences of linguistic and cultural transitions using a large-scale migration program from residential schools in India. The Jawahar Navodaya Vidyalaya (JNV) system of schools mandates that roughly 30 percent of Grade IX students in a given JNV spend one academic year in a linked JNV located in a different linguistic region, as stipulated in the official migration guidelines of the Navodaya Vidyalaya Samiti (NVS).[1]. Existing studies typically examine medium of instruction reforms or compare migrant and non-migrant populations, settings in which institutional quality, peer composition, and household circumstances often change simultaneously (Angrist and Lavy, 1997; Taylor and von Fintel, 2016). In contrast, the JNV setting holds curriculum, school administration, and residential inputs largely constant, thereby isolating linguistic and peer-cultural exposure as the primary margin of variation. Selection into migration is governed by proportionality rules that frequently require lotteries[2], implying that within a cohort, migrant and

[1] See Online Appendix A.1 (NVS Migration Circular), which specifies the operational framework of inter-Vidyalaya exchange.

[2] See Online Appendix A.1 (NVS Migration Circular), which explicitly prescribes selection by draw of lots

non-migrant students are close to balanced and comparable. This design allows us to get a cleaner interpretation of score changes as adjustment to linguistic transition rather than as changes in schooling quality or family background and similar potential confounds.

We interpret cross-linguistic migration as a cognitive reallocation shock. When students are placed into a new linguistic environment, they must allocate more attention and effort to comprehension, communication, and social adaptation. Under potentially binding constraints on cognitive bandwidth, this reallocation may reduce effective learning capabilities in the short run, particularly in cognitively intensive subjects. In this view, observed short-term test-score responses should reflect transitional adjustment costs. This interpretation is consistent with evidence that taking instruction or examinations in a second language can impose measurable performance penalties and that language skills are a component of human capital formation (Bernhofer and Tonin, 2022; Bleakley and Chin, 2004; Saiz and Zoido, 2005). This is also consistent with an alternate literature focusing on language-switching costs and reduced processing efficiency, thereby potentially affecting learning outcomes (Cunnings, 2017; Grabner et al., 2007; Abutalebi and Clahsen, 2017).[3]

Using administrative panel data tracking the same cohort of students across Grades VIII (pre-migration), IX (migration year), and X (post-migration), we compare test-score changes for migrants and non-migrants within schools. We document a statistically significant decline of at least 0.14 baseline standard deviations in aggregate performance during the migration year, as a lower-bound estimate. Subject-level estimates show that declines are concentrated in Social Science, Science, and Mathematics, while third-language scores actually improve in the migration year. By Grade X, aggregate differences attenuate and become statistically indistinguishable from zero, suggesting a pattern of recovery following a transitory short-term

to maintain proportional representation across gender and social categories.

[3]In cognitive neuroscience, executive control systems are the brain processes that enable goal-directed behaviour: they maintain task goals (working memory), suppress irrelevant responses (inhibitory control), and shift between tasks or rules (cognitive flexibility). These functions are supported primarily by prefrontal and cingulo-parietal networks (Hervais-Adelman et al., 2011; D'Souza and D'Souza, 2016). In bilinguals, executive control selects the target language and suppresses interference from the non-target language, which is why language switching can momentarily reduce processing efficiency (Coderre et al., 2016; Blanco-Elorrieta and Pylkkänen, 2017; Zhu et al., 2020).

shock.

There are two potential explanations for this result. First, Mathematics and Science are cognitively more intensive subjects and despite standardized medium of instruction, operationally, the linguistic environment being different is likely to affect the complementarities of inputs in the learning function. For instance, peer discussion or clarification in local languages may be difficult for students new to this language. Second, students may disproportionately devote more time to learning the new language which crowds out the learning in STEM subjects and reflects high opportunity costs of learning a new language at this stage.

Theoretically, consider that migration across linguistic regions acts as a temporary productivity shock operating through cognitive reallocation. Student achievement in a given subject is a function of effective learning effort and instructional inputs, holding school quality constant. When students are placed in a new linguistic environment, they incur an adaptation requirement that demands cognitive resources for language processing and social integration. Under a fixed cognitive capacity constraint, a share of total effort must be reallocated from content acquisition toward linguistic adjustment. If such linguistic adjustment follows a non-linear learning process such that over time the adjustment effort declines from a high value and converges to zero, one would expect short-run decline in learning achievement levels, particularly in cognitively intensive subjects followed by a recovery when the adjustment effort is no longer costly.

An important feature of the JNV setting is that migration occurs through reciprocal exchanges. As a result, students who do not migrate out of their home school are nonetheless exposed to incoming peers from partner JNVs during the same academic year. This implies that the comparison group is not a pure "no-exposure" control, but rather experiences indirect linguistic and cultural spillovers. Such contamination is likely to attenuate estimated treatment effects toward zero. Consequently, any academic impacts identified in this study should be interpreted as conservative lower-bound estimates of the true effect of linguistic and cultural exposure.

Beyond the education context, our findings speak to a broader literature in labor economics on migrant assimilation and integration dynamics. A large body of work shows that migrants often experience initial earnings penalties that attenuate over time as they acquire host-country language skills and local human capital (Bleakley and Chin, 2004; Saiz and Zoido, 2005). The JNV migration program provides a micro-level analogue of this process during adolescence.

The primary objective of the JNV migration policy is cultural and linguistic integration to foster national unity and enrich social content through lived experience rather than abstract instruction. Our study uses administrative records from thirty-three JNVs under the Jaipur regional office (covering the states of Delhi, Haryana, and Rajasthan). Although each JNV first seeks volunteers to migrate 30% of its Grade IX, the policy requires that the gender and social-category composition of the migrated group match that of the full Grade IX of their school. Accordingly, if volunteers exceed 30% within any category (gender or social), the requisite number in that category is chosen by a lottery; or, if volunteers fall short within any category, all volunteers migrate and the remaining slots are filled by a lottery among non-volunteers.

Our field interactions with the JNV administration indicate that this rule frequently necessitates lotteries and usually the number of volunteers for migrating is negligible. Consequently, the final migrated cohort is effectively randomly selected, or at least balanced and comparable to non-migrants[4] (Navodaya Vidyalaya Samiti, 1998, 2019a). Ideally, given that assignment to migration is plausibly random, we should simply compare the academic scores of migrants and non-migrants. However, we do not have documented empirical evidence along these lines which is why we take a conservative approach and leverage the panel structure of the data to implement a difference-in-differences design around the migration

[4]This pattern is documented in the assessment report of the Navodaya Vidyalaya Samiti by the Programme Evaluation Organisation of NITI Aayog, Government of India and is verified in our data as the pre-migration balance tests show no statistically significant differences between migrant and non-migrant cohorts on observed covariates.

year, supplemented with school fixed effects and student-level controls.

This paper makes three central contributions. First, it provides evidence on the temporal incidence of language-related learning costs, distinguishing between short-run adjustment effects and medium-run outcomes. This complements the existing literature on linguistic mismatch resulting in penalty on exam results and earnings (Bernhofer and Tonin, 2022; Angrist and Lavy, 1997; Ivlevs and King, 2014; Eriksson, 2014)

Second, it documents subject-level heterogeneity consistent with cognitive reallocation mechanisms, consistent with the literature (Cunnings, 2017; Grabner et al., 2007; Abutalebi and Clahsen, 2017). Our analysis dis-aggregates performance by subject and isolates the areas and student types that are vulnerable (or resilient) to linguistic transitions.

Third, by studying a structured and reciprocal exchange program, it highlights how institutional design may mitigate long-run academic losses associated with linguistic integration. This complements studies on bilingual-education programs which show that exposure to more than one language is not necessarily detrimental for academic performance (Admiraal et al., 2006; Chin, 2015; Slavin et al., 2011). In addition, young people exposed to different ethnic regions demonstrate better national-integration outcomes, underscoring broader non-academic gains from such exposure (Okunogbe, 2024), which was one of the apparent motivations to establish the JNV migration programme. Our evidence supports a policy narrative that although migration entails short-term learning costs, the institutional design enables quick recovery.

The rest of the paper is as follows. Section 2 provides the background about the institutional setting and JNV migration policy. In Section 3, the data and sample construction is described. The empirical strategy is described in section 4. The primary findings and heterogeneity are reported under Section 5. In the final section, the policy implications, limitations, and future research directions are outlined.

2 Background and Institutional Context

2.1 The Jawahar Navodaya Vidyalaya System

In 1986, the National Policy on Education established the *Jawahar Navodaya Vidyalaya* (JNV) system as an innovative response to the challenge of providing high-quality education to talented children, especially those from rural areas. Each district of India has at least one JNV. The network operates as an autonomous organisation under the Ministry of Education through the *Navodaya Vidyalaya Samiti* (NVS). NVS is headquartered in New Delhi and governed by a Board of Governors chaired by the Minister of Education (Navodaya Vidyalaya Samiti, 2019b). Below this, eight regional offices supervise groups of schools located across India's districts.

The main aim of the JNV system is to discover and develop children with high academic potential, regardless of socioeconomic status, by offering a fully residential and co-educational learning environment. The admission process begins at Grade VI through the Jawahar Navodaya Vidyalaya Selection Test (JNVST) which is a standardised, grade-neutral examination and it is independent of language proficiency to ensure that rural children are not at a disadvantage while attempting it (Navodaya Vidyalaya Samiti, 2019a). The test is held annually on an All India basis and at block and district levels. A student may take admission only to the JNV of their home district. To ensure equitable access, the 75 percent of seats are reserved for candidates from the rural areas and at least one-third of the overall intake is allocated to girls. The Scheduled Castes and Scheduled Tribes also receive representation in proportion to their population share in the district. After admission, the students are provided with free education, boarding, uniforms, textbooks, and healthcare, with only a nominal development fee, payable only by general-category students.

Because most admitted students would have been previously studied through the medium of mother-tongue/regional language, instruction continues in the same medium up to Grades VII or VIII, during which Hindi and English are taught intensively as language subjects and as co-media to build functional and communicative proficiency. This scaffolding helps students overcome language barriers which would have been present earlier at the entry level (Grades VI). Therefore, the medium of instruction for Hindi-speaking districts is Hindi for all subjects up to Grades VII or VIII; thereafter, English becomes the principal medium for Mathematics and Science, while Social Science continues in Hindi. And, in non-Hindi-speaking districts, the medium is the mother tongue/regional language up to Grades VII or VIII; thereafter, the common medium becomes English for all subjects.

The JNV network's ethos, infrastructure, and selection model make it distinct from other public/private schooling models in India. A combination of a merit-based admission, residential school, and a total state financing creates the atmosphere at JNVs that alleviates socio-economic inequality among students. Moreover, by bringing together children from diverse linguistic and cultural backgrounds, the system explicitly seeks to promote the national integration and social coherence.

2.2 The Migration Policy: Objectives and Design

One of the most distinctive and socially integrative features of the JNV system is its student migration policy. Initially it was envisaged for students from Grade IX to Grade XII, but, later, the policy was reduced to two years (Grade IX and Grade X) in 1991–92 and, eventually, in 1996–97, it was confined to Grade IX (?). So, currently, the NVS mandates that thirty percent of students in Grade IX should migrate for one full academic year to a linked JNV in a different linguistic region, usually a Hindi-speaking school to a non-Hindi-speaking one (Navodaya Vidyalaya Samiti, 1998). This policy is aimed at exposing the students to the diversity of India's languages and cultures and to foster a sense of national unity through lived experience rather than abstract instruction.

The system of linking JNV schools is carefully arranged. Every Hindi-speaking JNV is linked with one or more non Hindi speaking JNVs and vice versa. For example, a school in Haryana can be matched with one in Tamil Nadu, Kerala or Karnataka. During migration, 30 percent of the cohort from Grade IX of each school swaps places to its linked school, living and studying under the same conditions as the host students. Parental consent for participation in the migration programme is obtained ex-ante at the time of admission through a signed undertaking by parents/guardians agreeing to abide by NVS rules, including the migration scheme.[5]

The quasi-random design of the programme is strengthened by its selection mechanism. In every school, administrators must ensure that the gender and social-category ratios of the migrated cohort match those of the entire class. When volunteers exceed 30% within any category (gender or social), the requisite number in that category is chosen by lottery; when volunteers fall short within any category, all volunteers migrate and the remaining slots are filled by lottery among non-volunteers. Lotteries are conducted in the presence of the chairperson of the Vidyalaya Management Committee. Because this proportionality rule often necessitates lotteries, the final migrated cohort is effectively randomly selected, or at least balanced and comparable to non-migrants. Consequently, the resulting migrant and non-migrant cohorts are largely independent of observed and unobserved factors like academic ability or motivation, a feature noted by the Programme Evaluation Organisation of NITI Aayog in its assessment of the Navodaya Vidyalaya Samiti.

The migration programme is in line with broader constitutional values of unity in diversity. Since it enforces mutual exchanges, it fosters inter-regional friendships and learnings of partner languages. Host schools assimilate migrated students in all school activities, be it curricular or co-curricular programs such as national festivals, cultural performances and morning assemblies, thereby promoting informal language learning and cultural assimilation. Academically, all students proceed with the the Central Board of Secondary Education (CBSE) curriculum, with standardized assessments ensuring comparability across schools.

[5]See Online Appendix A.3 (Parent Undertaking/Consent Form), which records ex-ante parental agreement to institutional rules and the migration policy. The governing administrative guidelines further indicate that students selected for migration are expected to participate in the programme, with only limited exemptions under specified circumstances (See Online Appendix A.2 (Medical/No-Excuse Guidelines)). Therefore, under these strict conditions, a student selected for migration is required to participate; otherwise, withdrawal from the school may be required.

To facilitate the migration programme, NVS has adopted a Three–Language Formula in all JNVs under which all students study three languages, and each JNV appoints a third-language teacher responsible for the regional language. These languages are grouped into an ‘A‘-level language and two ‘B‘-level languages, varying by state category, as summarised in Table 1 (Navodaya Vidyalaya Samiti, 2019a). Three languages are taught up to Grade IX. Since CBSE mandates that students study only two languages from Grade X onward, for board appearance NVS prescribes the following: in non-Hindi-speaking states, students appear in the regional language at ‘A‘-level and English at ‘B‘-level; in Hindi-speaking states, in Hindi (‘A‘) and English (‘B‘); and in the North-East, in English (‘A‘) and Hindi (‘B‘).

Table 1: ***Three–Language Formula adopted by NVS***

Category of State	**A Level**	**B Level (1st)**	**B Level (2nd)**
Hindi-speaking	Hindi	English	Regional language
Non-Hindi-speaking (excl. North-East)	Regional language	English	Hindi
North-East States	English	Hindi	Regional language

The Annual Reports of NVS acknowledge both the successes and operational challenges of the migration policy (Navodaya Vidyalaya Samiti, 2019a,b). On the positive side, feedback from principals and regional officers highlights that students returning from migration demonstrate greater adaptability, self-confidence, and linguistic openness. The programme is often cited as one of the most effective institutional mechanisms for promoting national integration among adolescents. At the same time, the reports identify areas requiring continuous attention, including psychological support for migrated students, mitigation of academic disruptions arising from a new language of instruction, coordination of academic schedules, and provision of adequate hostel facilities and infrastructure in host schools.

From a research perspective, the JNV migration programme is a clean setting to examine the impact of linguistic and cultural exposure on the student performance. First, participation is mandatory at the school level and randomized within the cohorts thus reducing the self-selection bias that typically plagues migration or exchange programmes. Second, all JNVs have a common CBSE curriculum meaning that learning outcomes can be compared across regions. Third, since students live in a homogeneous residential setting with uniform facilities and schedules, external confounding factors concerning home environment, parental involvement or private tutoring are substantially reduced.

3 Data

The empirical analysis is based on administrative, student-level data provided by JNVs under the supervision of the Jaipur Regional Office, which oversees schools in Delhi, Haryana, and Rajasthan. These states constitute the western Indian belt and share similar administrative and socio-economic features, which lowers unobserved heterogeneity at the regional level. Data collection was undertaken after obtaining permission from the *Navodaya Vidyalaya Samiti* (NVS) headquarters in New Delhi and the Jaipur Regional Office in Rajasthan.

The dataset contains detailed academic records from thirty-three JNVs in this region, including students' demographic attributes, migration status, annual family income, and aggregate & subject-wise examination scores across three consecutive academic years. In the dataset, each student is tracked over three grades, which include Grade VIII (pre-migration baseline), Grade IX (migration year for the treated group), and Grade X (post-migration year). With this type of panel design, it is possible to construct a within-student measure of academic progress and identification of the consequences of linguistic exposure.

The main outcome variable is the academic performance of the students which is measured in terms of percentages in the annual examinations. The dataset contains both overall (average) scores and subject-specific scores which allows us to capture differential sensitivity to linguistic exposure. The average score is the arithmetic mean of all subject marks in a given academic year. Subject-wise scores are available for Hindi, English, Mathematics, Science, and Social Science (SSC) for all three grades, and for the third-language subject (which varies by state) in Grades VIII and IX only, as it is discontinued in Grade X. The dataset also includes individual characteristics providing demographic and socio-economic information: gender (female = 1, male = 0), area category (rural = 1, urban = 0), social category (General, OBC, SC, ST; encoded numerically), and annual family income (in Indian rupees). These variables are collected at admission and periodically updated through the NVS student information system.

We retain all observations for which background data are available and valid scores exist for all three grades, implying that dropouts and lateral-entry students (who join in Grade IX or later) are excluded from the final dataset. The resulting balanced panel comprises 4,343 student–year observations. Summary statistics are reported in Table 2.

The dataset offers significant advantages, primarily due to its administrative origin and internal consistency. All schools operate under a single authority, NVS, and are affiliated with the Central Board of Secondary Education (CBSE); consequently, curricula, test structures, grading schemes, the weights assigned to evaluation components, examination schedules, and administrative procedures are uniform across all the schools. The presence of unique student identifiers enables precise matching of records across consecutive years which helps to mitigate measurement error in the dependent variable. Moreover, the residential nature of JNVs ensures broadly similar peer and environmental conditions for all schools and this, to a great extent, substantially limiting confounding variation arising from home background.

However, the dataset has significant limitations. There are no direct psychological measures of anxiety, or measures of cultural assimilation (self-reported). Overall, the dataset provides a rich empirical foundation for evaluating how exposure to linguistically diverse peers influences educational outcomes within a standardized institutional setting. Institutional documents including migration circulars, parental undertakings, and administrative guidelines were also consulted to verify programme design, participation rules, and selection procedures (see Online Appendix A.1–A.3). The next section describes the empirical strategy employed to estimate the causal effects of migration on academic performance.

4 Empirical Strategy

The primary objective of the empirical analysis is to estimate the causal effect of exposure to linguistically and culturally diverse peers on the academic performance of the students. The mandatory migration policy of the *Jawahar Navodaya Vidyalaya* system provides a quasi-experimental setting for such inference. Since, for every JNV, approximately 30% of students in each Grade IX cohort are selected for migration in accordance with official NVS administrative guidelines,[6] while the remaining students continue in their home school, we can treat migration status as a plausibly exogenous source of variation.

The administrative provisions of the migration programme require that the gender and social-category composition of the migrating group mirror that of the remaining students, thereby yielding balanced cohorts. This rule frequently necessitates public lotteries conducted in the presence of the Vidyalaya Management Committee[7], rendering selection plausibly independent of unobserved factors and strengthening the exogeneity of migration status.

Because the administrative provisions ensure balance between cohorts, and, our data also demonstrates that migrants and non-migrants are indeed balanced on observables[8], so, we can compare academic scores across groups. But, to be cautious, we leverage the panel

[6]See Online Appendix A.1 (NVS Migration Circular), which specifies the 30% migration quota at the Class IX level.

[7]See Online Appendix A.1 (NVS Migration Circular), which explicitly mandates draw of lots when volunteers exceed the prescribed migration quota.

[8]see Table 2, which reports mean differences and p-values showing no statistically significant imbalance by gender, rurality, or income, consistent with quasi-random assignment

design of our data to implement a difference-in-differences strategy around the migration year, supplemented with school fixed effects and student-level controls. Specifically, to estimate the *during-migration* effect, we compare changes from Grade VIII (pre-migration) to Grade IX (migration year) for migrants versus non-migrants. Moreover, to assess *post-migration* persistence or recovery, we compare changes from Grade VIII (pre-migration) to Grade X (post-migration). This design identifies both the ongoing impact of migration and the subsequent evolution of effects one year after students return to their home schools.

To achieve this, we run the following specification for each student i in Grade g from school s located in district d:

$$\text{Score}_{icsd} = \alpha_s + \beta_1\big(\text{Migrated}_i \times \text{Grade}_g\big) + \beta_2\text{Migrated}_i + \beta_3\text{Grade}_g + \gamma X_i + \varepsilon_{igsd}, \qquad (1)$$

where Score_{igsd} denotes the academic score (either aggregate or subject-wise) of student i in grade g from school s in district d. The term α_s captures school fixed effects to control for unobserved institutional factors such as teacher quality and infrastructure. Migrated_i is a binary indicator equal to 1 if the student migrated in Grade IX and 0 otherwise; Grade_g is a binary indicator taking the value 1 for Grade IX and 0 for Grade VIII. The interaction term ($\text{Migrated}_i \times \text{Grade}_g$) identifies the impact of migration. Specifically, the coefficient on this interaction, β_1, represents the average treatment effect of migration by capturing the differential change in performance between migrants and non-migrants before and during migration. Also, we compute standardized treatment effects by dividing the estimated coefficient β_1 by the standard deviation of the outcome in the pre-treatment period. X_i is a vector of individual covariates including gender, rural/urban background, social category, and family income, as described in Section 3. Standard errors are clustered at the school level.

A potential concern in this design is the presence of within-school spillovers. Because migration operates through reciprocal exchanges, non-migrant students in the home school are exposed to incoming migrant peers from partner JNVs during the migration year. This violates SUTVA assumption[9] and implies that the control group may also experience partial linguistic exposure. Importantly, such spillovers bias estimated treatment effects toward zero rather than generating spurious effects. By comparing changes over time within the same schools and cohorts, our difference-in-differences framework therefore identifies a conservative estimate of the impact of migration-induced linguistic and cultural exposure.

5 Results

5.1 Main Effects

Table 3 presents the estimated coefficients from Equation 1 by comparing the performance of migrated and non-migrated students between Grade VIII and Grade IX. The results show that migrated students face an average decline of 2.2 marks as compared to their non-migrated peers in the year of migration, which is equivalent to a drop of about 0.14 standard deviations relative to baseline variation. This effect is statistically significant at the five percent level.

In the existing literature, similar declines have been recorded in other contexts like Morocco and Latvia when instructional languages were changed abruptly (Angrist and Lavy, 1997; Ivlevs and King, 2014). This trend is consistent with the short-term cognitive adjustment costs predicted by language-switching theories, which posit that learners initially devote more cognitive effort to processing information in a second language, thereby temporarily reducing processing efficiency (Cunnings, 2017; Grabner et al., 2007).

It is worth noting that these estimates likely understate the full academic impact of linguistic exposure. Because non-migrant students are also exposed to incoming migrants within the same school, the estimated effects capture differences between high-intensity and lower-intensity exposure rather than a sharp contrast between exposure and no exposure.

[9] Stable Unit Treatment Value Assumption

The presence of such spillovers implies attenuation bias, suggesting that the true effect of migration-induced linguistic transitions is larger than the estimates reported here.

5.2 Subject-wise Effects

To identify the specific domains most affected by migration, we estimate subject-wise regressions using Equation 1. Results reported in Table 4 show that performance declines are more pronounced in language-intensive subjects. The largest drop is in Social Science (approximately -6.1 marks), then in Science (-4.8 marks), and Mathematics (-4.2 marks), all of which are significant at the one percent level. English performance decreases by roughly -3.3 marks, while Hindi and the Third Language display modest but statistically significant gains.

This heterogeneity reflects differences in the linguistic dependency of content of the subject. Subjects like Social Science and Science require substantial comprehension and written articulation, thus making them more vulnerable to the cognitive burden of learning in a non-native language (Taylor and von Fintel, 2016; Jain, 2017). On the other end, Mathematics is largely based on symbolic reasoning with limited linguistic load, which explains its relatively smaller decline. The rise in Hindi suggests improved performance of migrant students in their mother tongue as assessed by teachers in regions where Hindi is not the first language. The improvement in Third Language aligns with the immersive exposure migrants receive at host schools; an effect comparable to that observed in structured bilingual programmes where second-language proficiency improves (Admiraal et al., 2006; Slavin et al., 2011).

5.3 Heterogeneity by Gender

5.4 Heterogeneity by Baseline Performance

5.5 Evolution of the effect

To assess how the academic effect of migration evolves over time, we re-specify Equation 1 by setting the binary variable $\text{Grade}_g = 1$ for Grade X and 0 for Grade VIII. This adjustment identifies the treatment effect one year after migration using the same benchmark of Grade VIII scores, allowing us to test after 1 year, whether academic losses observed during the migration period persist, attenuate, or reverse once students resume study in their home schools. In this specification, now the interaction coefficient β_1 measures the differential change in academic performance between migrants and non-migrants from Grade VIII to Grade X. All other features of the empirical setup such as school fixed effects, student-level covariates, and clustering of standard errors at the school level remain unchanged.

From the results presented in Table 3, we observe that the negative migration coefficient observed during Grade IX becomes statistically insignificant in Grade X across all specifications which indicates a near-complete recovery in overall and subject-specific performance. In English, the coefficient even turns positive, suggesting modest improvement post-migration, indicating, perhaps, gradual acquisition of english proficiency by continued exposure. These results suggest that the academic costs of exposure are temporary and that the migration experience may enhance long-term adaptability and bilingual competence.

In the existing literature, similar trends have been observed in controlled bilingual learning environments where initial performance decline are typically followed either by a convergence to parity or improvement once students comes back to home environment or internalize the second language as a cognitive medium (Chin, 2015; Admiraal et al., 2006; Bernhofer and Tonin, 2022). In the JNV context, the structured residential environment, uniform curricula, consistent teacher training, and strong peer networks, combined with increased student motivation for the Grade X board examinations and additional teacher support (e.g., extra lectures & revision sessions) would have likely accelerated the performance recovery. Consequently, the migration programme can also seem to satisfy its integrative goals without long-term academic trade-offs impairing it, which is a balance that is rarely reported in large-scale multilingual education systems.

6 Conclusion

Taken together, the evidence in this paper suggests that linguistic integration during adolescence may involve transitional productivity costs without generating permanent academic deficits. Although we do not observe long-run labor market outcomes, the dynamic pattern of initial decline followed by recovery is consistent with broader assimilation trajectories documented in labor economics. If early exposure to linguistic diversity strengthens adaptability and multi-lingual competence, such experiences may yield long run benefits that offset short-term adjustment frictions. More generally, our findings suggest that the design of integration policies matters, i.e., when exposure occurs within a structured and supportive institutional environment, short-run cognitive costs need not translate into durable human capital losses.

Future research could extend this analysis along four directions. First, longitudinal tracking of cohorts into higher education and labor markets would help assess whether early exposure to linguistic diversity influences long-run mobility and occupational outcomes, as suggested by studies linking bilingualism to wage premiums and integration benefits (Saiz and Zoido, 2005; Cappellari and Di Paolo, 2018). In the longer term, exposure to linguistic and cultural diversity may also enhance non-cognitive attributes such as adaptability, openness, and tolerance.

Second, combining quantitative data with qualitative fieldwork could illuminate mechanisms of adaptation that drive recovery, such as peer learning, teacher mediation, or psychological adjustment.

Third, future work exploiting settings with sharper contrasts in linguistic exposure (or designs that more cleanly separate treated students from indirect peer spillovers) could help recover the full magnitude of language-transition effects.

Finally, comparative analyses with other residential school networks or international exchange programs could reveal how institutional design moderates the balance between linguistic costs and social gains.

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7 Tables

Table 2: *Summary Statistics*

Panel 1: Outcomes								
Variables	**Obs**	**Av**	**Hindi**	**Eng**	**Mat**	**Sci**	**SSC**	**3rd Lang**
Grade 8th	2,172	67.194	77.250	62.424	61.992	59.160	67.911	73.989
		(15.831)	(14.415)	(17.098)	(20.036)	(20.202)	(16.936)	(16.041)
Grade 9th	2,375	67.716	78.623	66.075	59.248	56.522	67.755	77.613
		(15.646)	(15.265)	(17.403)	(20.441)	(20.209)	(18.010)	(15.828)
Grade 10th	2,375	77.868	85.262	77.041	74.507	69.387	83.145	–
		(10.776)	(9.691)	(11.957)	(15.386)	(16.071)	(11.986)	–

Panel 2: Explanatory Variables							
Variables	**Description**	**Non-Migrants**		**Migrants**		**Difference**	**p-value**
		Obs	**Mean**	**Obs**	**Mean**		
Gender	Male = 0; Female = 1	5,289	0.401	1,836	0.384	0.017	0.200
			(0.490)		(0.486)		
Area Cat.	Urban = 0; Rural = 1	5,289	0.765	1,836	0.758	0.007	0.543
			(0.424)		(0.428)		
Social Cat.	Gen = 0; Obc = 1	5,289	1.182	1,836	1.252	-0.070	0.005
	Sc = 2; St = 3		(0.884)		(0.963)		
Family Income	Annual Income	5,289	127072.8	1,836	127024.3	48.428	0.991
	(INR)		(149932.1)		(153020.1)		

Notes: Panel 1 shows test scores across grades 8–10. Panel 2 compares explanatory variables between non-migrants and migrants. Standard deviations are reported in parentheses. 'SSC' refers to Social Science. '3rd Lang' refers to the third language subject. Dashes (–) indicate data not available.

Table 3: *Main Results*

	Score From	
	Grade 8 to Grade 9	Grade 8 to Grade 10
	(1)	(2)
Coefficient	-2.205**	0.075
Std. effect	-0.139**	0.005
	(0.975)	(0.834)
R-sq	0.148	0.266
Observations	4,343	4,343

Note: Standardized effects are calculated by normalizing the estimated treatment coefficient by the standard deviation of the outcome in the pre-treatment period. ***, **, * indicate $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

Table 4: *Results by Subject*

Panel A: Score From Grade 8 to Grade 9						
	Hindi	English	Maths	Science	SSC	3rd lang
	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient	1.632*	-3.292***	-4.245***	-4.782***	-6.126***	3.667***
Std. effect	0.113*	-0.192***	-0.212***	-0.236***	-0.362***	0.228***
	(0.932)	(1.043)	(1.271)	(1.264)	(1.047)	(0.946)
R-sq	0.176	0.209	0.137	0.146	0.194	0.210
Observations	4,344	4,344	4,344	4,344	4,344	4,344

Panel B: Score From Grade 8 to Grade 10					
	Hindi	English	Maths	Science	SSC
	(1)	(2)	(3)	(4)	(5)
Coefficient	0.110	1.587*	-0.689	-0.293	-0.383
Std. effect	0.008	0.093*	-0.034	-0.014	-0.023
	(0.763)	(0.890)	(1.113)	(1.136)	(0.866)
R-sq	0.252	0.345	0.237	0.209	0.382
Observations	4,344	4,344	4,344	4,344	4,344

Note: Panel A shows the estimated coefficients for each subject from Grade 8 to Grade 9; Panel B shows them from Grade 8 to Grade 10. Standardized effects are calculated by normalizing the estimated treatment coefficient by the standard deviation of the outcome in the pre-treatment period. ***, **, * indicate $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

Table 5: ***Results by Gender***

Panel A: Boys (From Grade 8 to Grade 9)							
	Average	Hindi	English	Maths	Science	SSC	3rd Lang
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coefficient	-2.405*	1.023	-3.408**	-4.579***	-4.683***	-6.071***	3.381***
Std. effect	-0.150*	0.069	-0.199**	-0.225***	-0.230***	-0.349***	0.206***
	(1.276)	(1.255)	(1.356)	(1.651)	(1.635)	(1.350)	(1.257)
R-sq	0.133	0.149	0.198	0.120	0.142	0.205	0.189
Observations	2,637	2,637	2,637	2,637	2,637	2,637	2,637

Panel B: Girls (From Grade 8 to Grade 9)							
	Average	Hindi	English	Maths	Science	SSC	3rd Lang
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coefficient	-1.920	2.594**	-3.150**	-3.790*	-4.996**	-6.214***	4.086***
Std. effect	-0.129	0.199**	-0.192**	-0.196*	-0.254**	-0.388***	0.285***
	(1.482)	(1.323)	(1.599)	(1.964)	(1.971)	(1.623)	(1.396)
R-sq	0.184	0.206	0.227	0.204	0.198	0.210	0.206
Observations	1,706	1,706	1,706	1,706	1,706	1,706	1,706

Note: Panel A shows estimates for Boys, Panel B for Girls. Each column corresponds to a different subject (including "Average"). Standardized effects are calculated by normalizing the estimated treatment coefficient by the standard deviation of the outcome in the pre-treatment period. ***, **, * indicate $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively..

Table 6: ***Results by Performance Level***

Panel A: High Performers (From Grade 8 to Grade 9)							
	Average	Hindi	English	Maths	Science	SSC	3rd Lang
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coefficient	-0.531	2.701***	-1.626*	-1.479	-3.104***	-4.496***	5.159***
Std. effect	-0.060	0.350***	-0.154*	-0.114	-0.236***	-0.446***	0.547***
	(0.651)	(0.618)	(0.843)	(1.081)	(1.136)	(0.828)	(0.698)
R-sq	0.266	0.296	0.323	0.241	0.242	0.325	0.359
Observations	2,236	2,237	2,237	2,237	2,237	2,237	2,237

Panel B: Low Performers (From Grade 8 to Grade 9)							
	Average	Hindi	English	Maths	Science	SSC	3rd Lang
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coefficient	-1.333	2.482**	-2.428*	-3.558***	-3.267**	-5.342***	4.150***
Std. effect	-0.103	0.180**	-0.164*	-0.221***	-0.213**	-0.340***	0.281***
	(1.043)	(1.235)	(1.244)	(1.370)	(1.302)	(1.264)	(1.208)
R-sq	0.294	0.271	0.345	0.261	0.258	0.341	0.309
Observations	2,107	2,107	2,107	2,107	2,107	2,107	2,107

Note: Panel A shows results for High Performers; Panel B for Low Performers. Standardized effects are calculated by normalizing the estimated treatment coefficient by the standard deviation of the outcome in the pre-treatment period. ***, **, * indicate $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.