Effects of Neighborhoods on Children's Educational Outcomes in Indonesia

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Abstract

There is considerable observed geographic variable in outcomes across space. Neighborhood effects attempt to explain to what extent the place in which an individual grows up impacts their future outcomes. This paper focuses on neighborhood effects on children in Indonesia where there is a large disparity in public and private amenities among different regions. This paper aims to analyze whether and to what extent neighborhoods impact a child's education outcomes and whether there exists a critical age where intervention is most crucial. By restricting my dataset to movers and taking advantage of variation within a family in terms of exposure to different neighborhoods, I find evidence that the duration of time an individual spends in a given neighborhood impacts their outcomes. I also find evidence of a critical age that produces better outcomes, implying that the age at which a child moves matters as well.

JEL classification: I25; H4; H75

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Contents

1 Introduction

Neighborhood effects are important when analyzing to what extent the place in which an individual grows up impacts their future outcomes. Observed geographic variation in outcomes may indicate that neighborhoods have a causal effect on outcomes; in other words, moving a child to a different neighborhood would change their later in-life outcomes. On the other hand, the observed geographic variation may reflect systematic differences in the types of people living in each area. Studies have looked at neighborhood effects at a large scale, tracking movement throughout the US. Using quasi-experimental methods, researchers have found that children's outcomes across neighborhoods are largely due to the causal effects of neighborhood environments with the later incomes of children who move converging at a rate of 4% per year of exposure to the incomes of permanent residents on individuals from ages 9 to 30 (Chetty and Hendren, 2018).

Less research looks at the impact of neighborhood effects in developing countries despite high rates of internal migration and observed geographic variation in opportunities and individuals' outcomes. Many studies that look at internal migration in developing countries focus on the returns to rural-urban migration for adults and find varying gains in income and welfare (Selod and Forhad 2021). These gains in income and welfare suggest urban areas have better labor opportunities compared to rural areas. However, rural and urban areas do not differ in just their labor market opportunities but also in their quality of amenities, such as educational and health services. Thus, one could also expect that a child migrating would impact various outcomes of that child as a result of being exposed to the amenities a particular place offers. Thus, neighborhoods may matter because many public and private goods, such as schools, hospitals, and proximity to jobs, vary in quality across neighborhoods and have direct effects on outcomes. Second, neighborhoods may matter because the habits and behaviors of neighbors and peers may influence key life outcomes. For example, being surrounded by peers and neighbors who are hardworking may motivate a child to do better in school and thus have better educational outcomes.

This paper will focus on the impact of neighborhoods on children's educational outcomes in Indonesia, as measured by National Exam Scores (EBANTAS). In the past four decades, Indonesia has experienced rapid urbanization and economic growth. Alongside this recent economic upsurge, Census data suggest that a substantial share of the population has migrated, with the most popular destinations being metropolitan regions (Selod and Forhad, 2021).

However, migrating to a better neighborhood with more public and private amenities does not guarantee better outcomes because there are many factors that may contribute to a person's development and progress. For example, a child who migrates when they are much older with engrained study habits may find it more difficult to adjust their habits and take advantage of better public schooling and may see no improvement in their education outcomes despite residing in a neighborhood with better schools. Thus, the aim of this paper is to analyze whether and to what extent neighborhoods impact a child's education outcomes and whether there exists a critical age where intervention is most crucial.

By restricting my dataset to movers and taking advantage of variation within a family in terms of exposure to different neighborhoods, I find evidence that the length of exposure to a given neighborhood impacts an individual's outcomes. I also find evidence of a critical age that produces better outcomes, implying that the age at which a child moves matters as well.

2 Background

2.1 Setting

Indonesia is composed of over 17,000 islands with large variations in development. Internal migration in Indonesia has been shaped by the dominant role of Java island, which during the Dutch colonization period (1816-1941), was the center of colonial activity. Today, within Java Island is the economic core region with economic activity being concentrated in Jakarta, the capital, its surrounding provinces, and the northern Java coastal area. This concentration of economic activity has accentuated regional disparities in Indonesia. Consequently, Java Island is the primary destination of migrants and contains over 60% of the population of Indonesia (BPS-Statistics Indonesia, 2020).

Indonesia contains four administrative subdivisions. The first level contains provinces (provinsi), of which there are 38, headed by a governor with its own regional assembly. The second level consists of districts/regencies (kabupaten) and cities (kota), which have their own local governments and legislative bodies. Cities and districts are further divided into subdistricts (kecamatan). These are generally headed by a civil servant who reports to the government of the district. Below subdistricts are villages. In this paper, a neighborhood refers to a subdistrict.

Across Indonesia, there are 7,252 subdistricts as of 2019. In the late 1990s, many reforms aimed to decentralize the government and allow for local governments to take up responsibilities for economic development. These reforms gave greater authority, political power, and financial resources to districts, cities, and subdistricts and transferred a variety of responsibilities in areas such as health, education, public works, environment, agriculture, etc. Thus, there exists substantial variation in terms education quality, jobs, quality of health services, etc. across subdistricts (Evans, 2020).

2.2 Literature Review

In this section, I first present the findings of studies conducted in the US that use various approaches to estimate the causal impact of neighborhoods on children's outcomes. Second, I discuss the literature on neighborhood effects in developing countries.

Neighborhood Effects in Developed Countries

A vast body of economic research aims to investigate the different factors driving children's outcomes later in life, with a focus on education, household income, health, etc. Researchers have taken advantage of various natural experiments, randomized experiments, and utilized quasi-experimental methods to analyze this range of topics to establish the most important factors driving various children's outcomes later in life, such as education attainment, incarceration, adult income, etc. Over the last thirty years, a vast body of literature has been published on neighborhood effects: the idea that where you live shapes your outcomes later in life. Researchers have looked at the impact of neighborhoods on a wide variety of outcomes, ranging from educational achievement, labor opportunities, and mental health. The main challenge in establishing causal effects of neighborhoods is selection bias, which occurs when the selection mechanisms that drive people to locate to a specific neighborhood are correlated with the relevant outcomes (Bergstrom and Ham, 2010). Therefore, direct comparisons between different neighborhoods or between movers and permanent residents cannot be used to establish a causal relationship between neighborhoods and observed outcomes of individuals. Therefore, several studies have focused on randomized experiments and quasi-experimental methods to establish a causal relationship between neighborhood effects and outcomes.

The Gautreaux program was a US housing desegregation program initiated in 1976 by a court order where low-income blacks were assigned randomly to either middle-income white suburbs or low-income black urban areas in Chicago. Rosenbaum (1995) found that suburban movers experienced lower high school dropout rates and higher college attendance compared to urban movers while grades for the two groups were similar.

The Gautreaux program's positive findings helped motivate the Moving to Opportunity Program (MTO), an experimental housing mobility program that took place major in US cities starting in 1994. Interested eligible families applied and some were randomly assigned to one of three program groups: the Experimental group, the Section 8 Comparison group, and the Control group.[1] [2] The MTO experiment allowed researchers to obtain measures of

[1]Families were eligible if they had children and resided in public housing or project-based Section 8 assisted housing in census tracts with a poverty rate of 40 percent or more in 1990.

[2]Families in the Experimental group received a housing voucher that could be used to help pay for rental housing from private landlords in census tracts with under a 10 percent poverty rate and received counseling to help them search for a new neighborhood. The Section 8 Comparison group received a geographically unrestricted housing voucher and no counseling assistance. The Control group received no rental assistance.

the causal impacts of neighborhoods on individual outcomes (Katz et. al. 2001). Several studies have looked at both long-term and short-term outcomes for older children, young adults, and adults of the MTO experiment. Katz et. al. (2001) look at short-term outcomes of the MTO experiment in Boston and find that children in the Experimental and Section 8 Comparison groups exhibit fewer behavior problems and children in the Experimental group have fewer health problems. Leventhal and Brooks-Gunn (2004) look at the impact of the MTO experiment on educational outcomes for children who moved between ages 6-18 and find that moving to low-poverty neighborhoods had positive effects on achievement scores for children aged 11-18. For children aged 6-10, grade repetition significantly decreased while no significant effect was found for achievement test scores.[3] The significant effects can be partially attributed to increased homework time and school safety. Chetty et. al. (2016) look at the long-term impacts of the MTO experiment and find that for younger children, ages 4-12, moving to a better neighborhood increases college attendance and earnings and reduces single parenthood rates while moving when 13-18 years old has slightly negative impacts due to perhaps disruption effects.

Despite the various findings of the MTO experiment, there are still many limitations to its findings. A common theme across studies is that often estimates are statistically significant but small in magnitude.[4] In addition, sample sizes are small, which has made it difficult to obtain precise estimates of critical age effects. [5] The MTO experimental design also cannot be used to determine whether exposure effects exist because the age at which a child moves is perfectly collinear with the amount of time spent in a neighborhood (Chetty et. al., 2016).

Later studies attempt to address some of the MTO experiment's shortcomings. Chyn (2018) takes advantage of the demolition of public housing in Chicago that resulted from unforeseen infrastructure problems.[6] This study finds that children whose households were displaced have higher labor-force participation and earnings in adulthood.[7] Chetty and Hendren (2018a) utilize various quasi-experimental approaches to estimate the causal relationship between neighborhood effects and outcomes later in life using data from tax records spanning from 1996-2012.[8] By exploiting variation in the age of children when families move,

[3]The achievement tests used were the Letter-Word Identification and Applied Problems of the Woodcock-Johnson Tests of Achievement. This is a widely used standardized assessment of subjects learned in school.

[4]For example, in Chetty et.al. (2016), children whose families took up the experimental voucher and moved when they were young experienced an increase in annual earnings in early adulthood of $3447 compared to children whose families did not move.

[5]The percentage of people in the Experimental group and Section 8 Comparison group who used their vouchers is quite low (around 47% for the Experimental group and 63% for the Section 8 Comparison group).

[6]Public housing is government-funded housing established to provide housing for low-income families.

[7]This suggests that the benefits of neighborhoods are not just limited to the type of households that volunteered for the MTO experiment.

[8]They restrict their sample to children who have moved over 100 miles to eliminate moves that do not reflect a true change of location, which contrasts with previous studies that have focused on neighborhood effects within major US cities.

they find that the outcomes of children who move converge at a rate of 4% per year of exposure to permanent residents' outcomes. They present various mechanisms- racial segregation, income inequality, education, family structure, and immigrant population- but the impact of these mechanisms on neighborhood effects is correlational at best due to data and model constraints (Chetty and Hendren, 2018b).

Another branch of the literature on neighborhood effects looks at the impact of location in the context of historical racial segregation and intergenerational mobility measured by income. Andrews et al. (2017) investigate the historical patterns of racial segregation and its relationship with the observed spatial variation in contemptuous economic mobility. They find that racial segregation and the environment that fosters it may diminish upward economic mobility by reducing access to networks, labor and capital markets, and political institutions. Though past literature has shown that childhood location is an important determinant of adult outcomes, the stability of these effects is less understood. Derenoncourt (2022) looks at racial composition shocks during the Great Migration (1940-1970) when millions of African Americans moved from the southern US to the northern US cities. Specifically, this study finds that shifts in the racial composition of northern cities altered the effects locations had on children and turned high-opportunity areas into opportunity deserts.

Neighborhood Effects in Developing Countries

The term neighborhood effects is not widely used in development economics but migration and its impacts are of interest to many researchers. Unlike much of the neighborhood effects literature in the US, the majority of research on the impacts of migration in developing countries looks at outcomes such as consumption, expenditure, income, and welfare. In a randomized control experiment in rural Northern Bangladesh, households were randomly assigned \$8.50 incentive to temporarily out-migrate during the lean season (when rural households are close to starvation). Bryan et. al. (2014) find that migration induced by the intervention caused increases in food intake and expenditures of family members remaining at the origin A study conducted in Tanzania using panel data finds that migration increased consumption growth for movers with those moving out of agricultural regions experiencing the most growth in consumption (Beegle et. al., 2011). Researchers have also found that households who migrate may see little overall change in their socioeconomic situation since when a household moves to a new area, they become the new "poor" in that area. However, this is highly dependent on the dynamic links between migrations and non-migrants and varies depending on context (Sugiyarto et al., 2019). In Indonesia specifically, researchers have looked at migration from a more macro perspective. Bryan and Morten (2018) look at the size of aggregate gains in productivity and wages, taking into account selection and general equilibrium effects. They find a 22% increase in labor productivity when barriers to migration are completely removed but estimate that doubling the share of people who migrate to a particular destination may lead to a 4% decrease in average wages. Thus, there is very little research on the impacts of migration on children, especially education outcomes. This lack of research on the impact of migration can be partly attributed to data constraints that reflect the scarcity of measures of internal migration at national levels.

3 Data

Individual level data is taken from the Indonesian Family and Life Survey (IFLS), a longitudinal survey with five waves: 1993 (IFLS 1), 1997 (IFLS 2), 2000 (IFLS 3), 2007 (IFLS 4), and 2014 (IFLS 5). It contains a survey of households and individuals and a community survey. For individuals and households, detailed information is provided on income, assets, education, health, and household composition. It is drawn from 13 out of the 27 provinces and is representative of 83% of the population.

In the first wave, 7,224 households were interviewed, and individual data was collected for over 22,000 individuals. Due to cost constraints, not all family members were interviewed in surveyed households in wave 1. In the following waves, roughly 94% of the households in the previous wave were recontacted and re-interviewed. In IFLS 2, baseline household members were tracked if they moved out of their household to one of the 13 originally surveyed provinces. In IFLS 3 and later waves, individuals who moved between waves were tracked to all 27 provinces. IFLS surveyors attempt to find every individual who is a panel respondent, including children who were born after 1993, resulting in a 12-fold increase in the sample size between 1993 and 2014. Additionally, baseline re-contact rates in IFLS exceed those observed in other large population representative surveys, with 90.6 percent of surviving baseline respondents being re-interviewed in IFLS 4. From one wave to the next, there is migration within communities, subdistricts, districts, and across provinces, and an effort is made to reinterview each household that relocated.

To create a measure of neighborhood quality, I use both district-level and subdistrict-level data. The data for subdistricts comes from Indonesia's Village Potential Statistics (PODES) dataset, which provides information on all villages in Indonesia. To obtain measures at the subdistrict level, I aggregate data at the village level. This paper uses PODES 2000, 2003, and 2008 datasets which are merged using a crosswalk for villages created in Cassidy (2023) that uses data provided by the Central Bureau of Statistics. Because of human errors in recording the identification codes and names of villages, a series of fuzzy merges, adapted from Cassidy (2023), are used to link villages across survey years. These surveys are filled out by the village head and include information on public goods and services related to health, education, infrastructure, crime, etc. This data is used to create various measures of neighborhood quality specified later in this paper.

District-level data is obtained from the World Bank's Indonesia Database for Policy and Economic Research, which presents measures that aggregate data from PODES and Indonesia's National Socioeconomic Survey (SUSENAS). Measures are presented at the district level, with measures presented either every year, biennially, or triennially, etc. This database contains economic indicators, such as employment, and social and demographic indicators, such as poverty rate, number of schools at different levels (primary, middle, and high school), and measures related to healthcare.

4 Empirical Framework

4.1 Measurement of Neighborhood Quality

To look at neighborhood effects, a measure needs to be established to allow for a comparison between different neighborhoods of different qualities or types. In this paper, the quality of a neighborhood is determined using a combination of the distance a sub-district is from the various metropolitan areas, whether the sub-district is in a rural or urban area, and an index reflecting the quality of the district itself. In Indonesia, there is a wide disparity in living conditions between urban and rural areas. Though there exists variation within districts in terms of living conditions and public amenities and goods, districts often differ from one another on average in terms of public services and goods, employment opportunities, wealth, etc. Therefore, a subdistrict's quality should reflect both the conditions and public amenities of the district and the ruralness of the area.

The index for the quality of a district is created using Principal Components Analysis (PCA) with data from the World Bank's Indonesia Database for Policy and Economic Research. The index is calculated using the following variables for each district in Indonesia: total population, morbidity rate, number of doctors, number of midwives, number of hospitals, number of schools at the elementary, junior, and senior level, number of unemployed, employed, and underemployed individuals, and poverty rate. Then, another index for sub-districts is created with PCA and using data from PODES. This index includes the district's index, whether a sub-district is in a rural or urban area, the distance a sub-district is from that district's metropolitan area, and the distance a sub-district is from the closest municipality's metropolitan area. Therefore, the neighborhood quality of a subdistrict will be expressed in units of standard deviations.

Due to insufficient and missing data across multiple years, data is used from a single year, 2008.[9] It is plausible to assume that over time, conditions in districts may improve or

[9]Data on the number of hospitals is from 2005.

worsen, and thus, the most precise estimates of district quality would require calculating a single index for every year from 1993 to 2014. However, this paper is concerned with the relative quality of districts, and though we may expect conditions in neighborhoods to change over time, change is typically gradual and policies take time to implement. Therefore, even if neighborhoods improve or worsen over time, we may not expect their quality to change much relative to other neighborhoods during this time frame.

4.2 Theoretical Framework

To determine how much a child's outcomes improve on average if they grew up in a better neighborhood, I limit my sample to households of movers. I estimate childhood exposure effects, the impact of spending an additional year in a neighborhood where neighborhood quality is 1 standard deviation, for a child who moved at age m.

Consider a randomized experiment where children are randomly assigned to neighborhoods, n, at different ages, m, at a single point a time for the rest of their childhood. A linear predictor of children's outcomes, y_i (for example, income at age 24) can be written as

$$y_i = \alpha_m + \beta_m Y_n + \Phi_t + \theta_i \tag{1}$$

where θ_i is the error term that captures other determinants of children's outcomes, Y_n is a percentile measure of neighborhood quality, and Φ_t is year fixed effects for the year at which y_i is measured. Random assignment to neighborhoods guarantees that θ_i is uncorrelated with Y_n so β_m represents the mean impact of spending year m onwards in an area where neighborhood quality is one standard deviation higher. Thus, the exposure effect at age m is $\delta_m = \beta_m$ - β_{m+1}.

The exposure effects of neighborhoods, δ_m, can tell us many things about neighborhood effects. It provides insight into the ages at which neighborhood environments matter most and may point to a critical age where impact is largest. $\sum_{m=0}^{j} \delta_m$, where j is the age at which outcomes are measured, represents the impact of growing up in better neighborhoods from birth and provides an estimate of the degree to which the difference in outcomes across geographies is due to neighborhood effects or selection.

When estimating neighborhood exposure effects using observed data, the error term θ_i, is generally correlated with Y_n. For example, families who move to better neighborhoods may be more educated or hard working, which will impact a child's later in life outcomes, y_i. Running equation 1 on observational data would yield an estimate b_m that encompasses both neighborhood effects and selection effects, λ_m, $b_m = \beta_m + \lambda_m$.

To identify exposure effects of neighborhoods, we need to ensure that the age at which people move to better or worse neighborhoods is uncorrelated with a child's potential outcomes. Thus, similar to Chetty and Hendren (2018a), the baseline specification for this paper rests on the assumption that selection effects do not vary with the age at which a child moves; the selection effect λ_m is constant for children who move at different ages, $\lambda_m = \lambda$. Thus, the measurement of the exposure effects of neighborhoods would be represented by $\delta_m = \beta_m - \beta_{m+1} = (\beta_m + \lambda) - (\beta_{m+1} + \lambda)$. This is a very strong assumption that may be violated in several ways. For example, families move to better neighborhoods when their children are younger may invest more in their child's education, which could result in better outcomes. Thus, the validity of this assumption will be examined by a series of additional specifications.

4.3 Empirical Specification

The primary outcome this paper will look at is national examination scores (EBANTAS). In Indonesia, students take national exams at the end of every school level: primary, middle, and high school. Primary school includes 1st to 6th grade, middle school includes 7th to 9th grade, and high school includes 10th to 12th grade. At the primary school level, students are tested in math, Indonesian, and science. At higher school levels, students are tested on more subjects, including narrower topics in science and social studies. To allow for comparison of an individual's exam results over time, only total, math and Indonesian scores will be used in this paper. An advantage of using national exam scores is that their measure is a relatively standard, objective measurement, making it easier to compare individuals and their outcomes, especially across sub-districts.

This paper restricts its sample to individuals who moved either outside their sub-district or moved within a sub-district between rural and urban areas for waves 1-2, 2-3, 3-4, and 4-5. This is to ensure that their migration better reflects a true change in neighborhood. Including individuals who moved within a subdistrict may result in no significant outcomes for children, especially those older. If we assume that peer effects are one channel through with neighborhoods have an effect on outcomes because older children may be less likely to change their established social circles. Restricting the sample to individuals who moved outside their origin subdistrict does not completely eliminate this problem because families may move short distances across subdistrict boundaries, but it minimizes it.

$$\begin{aligned} Y_i = \eta_0 + \sum_{i=1}^{n} \delta_m I(m_i = m)\Delta_{tco} + \beta_m I(m_i = m) + \gamma_0 D_i + \gamma_1 D_i \Delta_{tco} + \\ \theta' X_i + \alpha_y + \alpha_b + \alpha_h + \varepsilon_i \end{aligned} \tag{2}$$

To measure critical age effects, the equation (2) will be used where i = individual, y

= birth year, m = age at move, c = destination neighborhood, o = origin neighborhood, t = year of move. Y_i is the outcome of interest, EBANTAS scores in units of standard deviations. Δ_{tco} is the difference in neighborhood quality (expressed in standard deviations) of destination minus origin neighborhoods at the time of move. $\theta' X_i$ is a vector of individual characteristics (gender, age started school, and whether a child attended kindergarten). $I(m_i = m)$ is an indicator function that is 1 when $m_i = m$ and is 0 otherwise. n is the oldest age at time of migration for individuals included in a given regression, which depends on the specific outcome being observed.

Household fixed effects, α_h, allow for comparisons among siblings. If we assume that a family does not specifically plan their move around a certain child, there exists exogenous variation in the age at which children move within a household. In this instance, our control group should only contain individuals who would have moved if they were given the opportunity to do so. Including permanent residents of households who have not moved introduces omitted variable bias at the individual level because movers are fundamentally different from non-movers. Children born after a family migrates are counted as non-movers of the destination neighborhood while children whose observed education outcome is already completed at the time of move would be counted as non-movers of the origin neighborhood. D_i is an indicator variable that equals one if a child was born in the destination neighborhood and has completed a given outcome and 0 otherwise. D_i is then also interacted with the change in neighborhood quality of the household's migration.

Household fixed effects only account for time invariant aspects of a household. Therefore, household fixed effects would not account for things such as the income of a household when each child is growing up if a family's income changes over time. Parental income can dictate the amount of resources provided for a child when they are growing up, which could be reflected in national exam scores. For example, if a household's income increases over time, a child that is born later may have better nutrition and more academic resources outside of school simply because their parents can afford it. Better nutrition and educational resources could be reflected in their exam scores but would not be a result of neighborhood effects. Therefore, to account for time-varying aspects of a household related to the order in which children are born, birth order fixed effects, α_b, are included. Birth cohort fixed effects are also included to take into account the impact of every year on individuals of a specific age since the same event may effect people differently based on age. In addition, robust standard errors are used to address heteroskedasticity.

Therefore, β_m is the impact of moving at age m. δ_m is interpreted as moving to a neighborhood that is one standard deviation at age m changes an individual's national exam scores by δ_m standard deviations relative to non-movers of the origin neighborhood. γ_0 is the impact of being a non-mover in the destination neighborhood. γ_1 reflects the impact of being a non-mover in a destination neighborhood that is one standard deviation higher. This model is primarily concerned with δ_m, seeing whether the age at which a child moves matters.

$$Y_{it} = \eta_0 + \omega_0 P_{it} + \omega_1 E_{it} + \omega_2 E_{it}\Delta_{tco} + \omega_3 P_{it}\Delta_{tco} + \alpha_i + \alpha_y + \alpha_m + \varepsilon_i \tag{3}$$

To measure exposure effects, spending an additional year in a given neighborhood, equation (3) will be used. The unit of observation is individual, i, by exam taken at time t. In this model, I include all children of households who have moved once: individuals who have completed their exams prior to a move, individuals who moved between exams, and individuals born in destination neighborhoods who have taken exams. Individual fixed effects α_i are added to allow us to compare an individual to itself over time. α_y and α_m are fixed effects for the year and month in which an exam is taken, which would take into account things that vary seasonally and year-by-year.

P_{it} is an indicator variable equal to 1 if an exam was taken after the year an individual moved and 0 otherwise. ω_0 is interpreted as the effect of being in the post-move period, which includes the disruption effect of moving. E_{it} is a measure of the amount of time in years an individual has spent in a given neighborhood. For children that have completed all their exams prior to a move or born after a move, E_{it} is simply the age at which they took a given exam. For children who have experienced a move between exams, E_{it} is equal to the year an exam was taken minus the year that they moved for exams after the move and 0 otherwise. ω_1 can be interpreted as the impact of residing one additional year in the same neighborhood. Like equation (2), $P_{it}\Delta_{tco}$ is a variable representing the change in neighborhood quality from origin to destination neighborhood. For children with full exposure to the origin or destination neighborhood of a household that has moved, $P_{it}\Delta_{tco}$ is equal to 0. For children who experience a move between exams, $P_{it}\Delta_{tco}$ is 0 if an exam was taken before a move and non-zero for exams taken after a move. Interacting E_{it} with Δ_{tco} allows for the exposure effect to vary depending on the change in neighborhood quality between destination and origin neighborhoods and the time spent in a new neighborhood. Thus, the effect of spending one additional year in a neighborhood that is one standard deviation higher is ω_1+ω_2.

5 Results

5.1 Summary Statistics

Table 1 presents summary statistics for individuals of households that have moved. Individuals are separated based on the age in which they moved and whether an individual was born after a household has moved and thus, had exposure to a neighborhood that is equal to their age. Various characteristics regarding the individual's gender, religion, migration details, education outcomes, and IFLS 5 data (2014) measures are presented. Among all groups, the most common migration is from urban to urban. Individuals in all age groups, on average, tend to move within a district or province. As expected, individuals who moved from a rural neighborhood to an urban neighborhood experienced an increase in neighborhood quality while individuals who moved from an urban neighborhood to a rural neighborhood experienced a decrease in neighborhood quality.

As of IFLS 5 (2014), individuals who moved at a younger age are also younger. Most individuals among all age groups that have moved have finished primary school while just nearly over half of individuals born after a household moves had finished elementary school. On average, individuals born after a household move have test scores that are lower compared to individuals who had moved, especially when looking at elementary and middle school.

5.2 Exposure Effects

Table 2 presents estimates of equation (3) run on all individuals in the sample: people with full exposure to the destination neighborhood, people with full exposure to the origin neighborhood, and people who moved between exams. Here, estimates are generally insignificant. For math exam scores, estimated with individual, exam year, and exam month fixed effects, an additional year spent in a neighborhood that is one standard deviation higher in neighborhood quality is associated with a 0.1281 standard deviation decrease in math exam scores.

This model, however, pools together all individuals who have moved, but we should expect heterogeneity in exposure effects based on an individual's origin neighborhood, their change in neighborhood quality, and whether they moved to a better or worse neighborhood (whether the change in neighborhood quality is positive or negative). An individual moving to a neighborhood that is 1 standard deviation higher in the first quartile may experience very different impacts compared to someone in the 3rd quartile who moves to a neighborhood that is 1 standard deviation higher. In addition, an increase in neighborhood quality may not always improve outcomes. If an individual were to move from the first quartile to the last quartile, they may see negative results if they are vastly unprepared for the schooling system in the destination neighborhood. An individual moving from a better neighborhood to a worse neighborhood may not see a decrease in educational outcomes since education and knowledge are gained and accumulated over time. After moving to a worse neighborhood, an individual would still have the foundation from their previous neighborhood that would minimize the negative effects of being in a worse neighborhood.

Table 3 first separates the sample into subgroups based on the quartile of their origin neighborhood.[10] Within each subgroup, individuals are split depending on whether they moved from their origin neighborhood to a worse neighborhood or a better neighborhood.[11]

The impact of an increase in neighborhood quality on Indonesian exam scores is positive and significant for children in the 2nd and 3rd quartiles who moved to a better neighborhood. An additional year of exposure to a neighborhood that is one standard deviation higher results in a 0.2565 standard deviation increase in Indonesian exam scores.

For individuals who moved to worse neighborhoods in quartiles 2 and 3, the estimate for Post is significant and positive at 99 percent confidence. The estimate indicates that moving to a neighborhood and being in the post-move period results in an increase in Indonesian national exam scores by 1.4542 standard deviations. The coefficient for the interaction term, $Post * \Delta_{tco}$ is also significant and positive, indicating a decrease of 0.6487 standard deviations in Indonesian exam scores when an individual moves to a neighborhood that is one standard deviation worse. Here, the impact of a change in neighborhood quality impacts outcomes through the magnitude of the change rather than the amount of time spent in a new neighborhood. Individuals who move to neighborhoods that are lower in quality will tend to see a worse impact on their Indonesian exam scores.

Among individuals living in origin neighborhoods in the 4th quartile, the estimates for the interaction term, $Exposure * \Delta_{tco}$, are significant and negative for total exam scores. When pooling the individuals together, the negative estimate of $Exposure * \Delta_{tco}$ is accompanied by a significant and positive estimate for $Post * \Delta_{tco}$. This shows that a one standard deviation increase in neighborhood quality results in an immediate and lasting increase in total exam scores, 0.7116 standard deviations. As time passes and for larger changes in neighborhood quality, the positive impact of an increase in neighborhood decreases and the net impact may actually be negative. Specifically, an additional year of exposure to a one standard deviation increase in neighborhood quality decreases total exam scores by 0.2227 standard deviations. If we assume that an individual has moved to a neighborhood that is one standard deviation better, after 3 years, the positive impact would fade out. There are many explanations for this pattern. It is possible that as time passes, neighborhoods worsen as a result of various economic or political changes, thus decreasing the initial impact of exposure to a better neighborhood. Another reason could be a change in the attitude of an individual. If we assume that children living in worse neighborhoods are also worse off or more academically unprepared compared to students living in better neighborhoods, the initial increase in total exam scores could result from increased motivation from the child who moved to a better neighborhood. However, over time, because they have a weaker

[10] Quartile 1 is excluded due to low numbers of observations. Quartiles 2 and 3 are pooled.

[11] Moving to a worse neighborhood means $\Delta_{tco}<0$, while moving to a better neighborhood means $\Delta_{tco}>0$

academic foundation compared to their peers, they perform less well and grow unmotivated, resulting in a decrease in their exam scores as time goes on.

The estimate of $Exposure * \Delta_{tco}$ for individuals who moved to a worse neighborhood is significant and negative. In this instance, individuals who moved to a neighborhood that is one standard deviation lower saw a 0.2423 standard deviation increase in total exam scores. A potential reason for this could be a change in the environment that is beneficial to a student but associated with a decrease in neighborhood quality. Better neighborhoods and schools that produce good results may also be stressful compared to lower quality neighborhoods and schools. Moving to a lower quality neighborhood may reduce a child's stress and cause them to perform better.

Table 4 presents another variation of equation (3) where individuals are split into groups depending whether they moved to a neighborhood that was more than one standard deviation worse (Δ_{tco}<-1), less than one standard deviation worse (-1< Δ_{tco}<0), less than one standard deviation better (0 < Δ_{tco}<1), or more than one standard deviation better (Δ_{tco}>1).[12] This allows us to investigate various impacts of a change in neighborhood quality that depend on the size and direction of the change.

Generally, for individuals who move to a neighborhood that is more than one standard deviation worse, moving and exposure to this neighborhood has little impact on their outcomes. This suggests that a student retained the knowledge and skills they acquired from their origin neighborhood before moving to a worse neighborhood and exposure to potentially worse amenities and public services and goods had minimal impact on educational outcomes. The exception is movers from an origin neighborhood in quartiles 2 and 3, where the estimate for $Post$ and $Post * \Delta_{tco}$ are positive for Indonesian exam scores. Here, moving to a neighborhood that is one standard deviation worse results in an immediate increase of 1.3779 standard deviations in Indonesian exam scores as a result of being in the post-move period and a decrease of 0.7724 standard deviations in exam scores as a result of the decrease in neighborhood quality.

Individuals who moved to a neighborhood that is less than one standard deviation better see little change in exam scores in both quartile 2 & 3 and quartile 4. The only value that is significant among the estimates is the coefficient for *Exposure* of individuals in quartile 4 when looking at Indonesian exam scores where the estimate indicates that one additional year of exposure to any neighborhood will result in a decrease of 0.7544 standard deviations in Indonesian exam scores.

For children in quartile 2 or 3, moving to a neighborhood that was more than one standard deviation better produced mixed results. For instance, when looking at Indonesian exam

[12] People whose origin neighborhood was in quartile 4 and had an increase in neighborhood quality that was greater than one standard deviation are excluded due to too few observations.

scores, the estimate for $Exposure * \Delta_{tco}$ indicates that a one standard deviation increase in neighborhood quality results in an increase of 0.3226 for every year spent in that destination neighborhood. On the other hand, for every additional year spent in a neighborhood that is one standard deviation higher, math exam scores decrease by 0.3715 standard deviations.

Several coefficients estimating the impact of individuals moving to a neighborhood that is more than one standard deviation better are significant but their standard error is large, preventing us from attaching real meaning to it due to imprecision.

5.3 Critical Age Effects

Table 5 presents estimates for equation (2) for exams taken at the primary school level. At the end of primary school, all students take the national exam (EBANTAS). Students are typically around 11 or 12 when they take these exams so the relevant critical ages are from 1 to 11. The outcomes included in this table are total exam scores, math scores, and Indonesian scores. Our coefficients of interest are the estimates of the interaction term, $I(m_i = m) * \Delta_{tco}$, which tells us the impact of a one standard deviation increase in neighborhood quality at age m. The estimates for $I(m_i = m)$, separate the effect of moving itself from the effect resulting from a change in neighborhood quality. Without the inclusion of fixed effects, estimates for whether a student attended kindergarten and when a child started school are typically significant. With the addition of fixed effects for the household, birth cohort, birth order, exam year, and exam month, these estimates become insignificantly different from 0.

The coefficients estimated with fixed effects provide evidence of critical age effects, especially at younger ages. For instance, children who are exposed to a one standard deviation increase in neighborhood quality at age 4 have Indonesian exam scores that are 0.0775 standard deviations higher relative to the individuals who had full exposure to the origin neighborhood at the age when they took their primary school exam. Similarly, children exposed to a one standard deviation increase in neighborhood quality at age 3 have math scores that are 0.0848 standard deviations higher and Indonesian schools that are 0.073 standard deviations higher relative to individuals who had full exposure to the origin neighborhood.

The timing of this impact is important because children in Indonesia start compulsory education at 6 years old and prior to that, they can attend kindergarten or preschool. Thus, ages 3 and 4 are when children start interacting with their peers. A neighborhood that is better in terms of public services and goods generally has constituents that are better off and perhaps more educated so interacting with these individuals at an earlier age can improve outcomes by influencing habits, related to studying or impact their outlook on education and motivation. Therefore, seeing that moving at age 3 or 4 has a significantly positive impact on a child's elementary test scores could suggest that peer effects are a mechanism through which neighborhood effects occur.

In addition to the positive and statistically significant estimates we see among children who moved at age 3 and 4, for children who moved at age 11, right before or around the time they take the exam, we also see that there exists a positive impact of moving and exposure to a neighborhood that is 1 standard deviation higher. Here, moving to a neighborhood that is one standard deviation higher than their origin neighborhood results in a total test score that is 0.0609 standard deviations higher relative to that of individuals who had full exposure to the origin neighborhood.

Table 6 presents estimates for equation (2) for middle school exams, which are typically taken when an individual is 14-15. Here, children who are exposed to a one standard deviation increase in neighborhood quality at age 4 have math exam scores that are 0.7249 standard deviations higher relative to the individuals that had full exposure to the origin neighborhood at the age when they took their middle school exam.

The coefficient estimates for the model where the outcome is middle school Indonesian exam scores are large and statistically significant. In addition to having estimates that are large in magnitude, these estimates also have large standard errors. This suggests that these estimates lack precision, likely due to a small sample of movers who are old enough to have completed middle school.

6 Discussion

The results show that moving to better neighborhoods can increase exam scores, particularly Indonesian scores. In addition, moving to worse neighborhoods does not necessarily produce negative results. There exists evidence that critical age effects do exist, typically for children who move when they are younger, around ages 3 or 4.

6.1 Limitations

This paper faces many limitations imposed by the available data. This paper creates a measure of neighborhood quality using Principle Components Analysis with data at the district and sub-district level from a single year and extends this measure to serve as neighborhood quality for all years a household moves. Though this measure may be a good reflection of the relative quality of a neighborhood, an individual's outcomes would be most impacted by the conditions of the neighborhood when they are residing in it. Therefore, a single measure of neighborhood quality may not provide enough precision for us to analyze how neighborhoods impact a person's outcomes because it does not include how a place changes from year to year, which could impact educational outcomes.

There may also be issues related to endogeneity, where the outcomes of interest are partially captured by the explanatory variable. This is because when individuals move to a new neighborhood, they also change the composition of their destination neighborhood. Therefore, a measure such as employment measured after individuals move would capture the impact of new residents on a given neighborhood. This makes it difficult to separate neighborhood effects from selection effects.

In addition, this paper was not able to control for the change in parental income when examining exposure effects where individual fixed effects are used to compare an individual to themselves over time to see how their exam scores change as they move to new neighborhoods of different quality. Oftentimes, households move for employment or job opportunities, and thus, their income would differ before and after a move. As a household's income increases, parents will most likely have more resources to support their children in ways that would improve their education outcomes. Therefore, the increases we see in improvement in exam scores after a move could be partially explained by an increase in household income.

The survey data, IFLS, used in this paper often contains missing data on the relevant outcomes observed in this paper, national exam scores. Since individuals can choose not to respond, there is likely selection bias in those who choose to answer questions about education and exam scores. Therefore, the estimates presented in this paper could either be understated or overstated depending on the direction of the bias.

6.2 Future Research

Future research should aim to investigate the mechanisms behind the critical age effects and exposure effects we see in this paper. Doing so can provide insight into the policies that will benefit children the most. Critical age effects predict that the size of the impact of moving to a new neighborhood changes depending on an individual's age while exposure effects suggest that the amount of time a child spends in a new neighborhood is most important. If critical age effects exist due to social relationships children form with their peers at a young age, we would expect the impact of moving to a new neighborhood to decrease as children move at later ages. In this instance, the amount of time a child spends in an area would not matter since there exists a window of opportunity to form strong connections with peers. If the mechanisms behind such changes are related to the public goods and services offered in a neighborhood such as schools and healthcare, a positive, consistent treatment in each year of childhood, then the duration of time an individual spends in a neighborhood could matter more.

In addition to investigating the mechanisms behind such changes, it would also be important to analyze the impact of neighborhood effects on later-in-life outcomes. This is because education is not always the best predictor for outcomes later in life, such as employment and income. For example, Deming (2009) finds that for disadvantaged children, in particular, the long-term impacts of early childhood intervention programs are large despite a "fadeout" of test score gains. This suggests that exam scores do not completely reflect the positive impacts of an improvement in an individual's surroundings. Thus, not seeing positive and significant results for certain individuals does not necessarily mean that they did not benefit from an increase in neighborhood quality.

7 Conclusion

As a whole, my results do present evidence of critical age effects and exposure effects of neighborhoods. Among students who have taken primary school exams, we see there are ages where moving to a better neighborhood produces better results compared to individuals who had full exposure to the origin neighborhood. In contrast to previous studies that look at the impact of neighborhoods on children's outcomes, I see a window of time where exposure to a new neighborhood could produce the largest improvements. A limitation of prior studies is the lack of data on children who move at young ages. For example, Chetty and Hendren (2018) are limited to observing children who move when they are older than 8 years old. Other papers, such as those that investigate the impact of the MTO experiment are limited in the distance in which an individual moves since the experiment takes place within major US cities. Thus, moving may not result in a very large change in neighborhood. My paper addresses both of these limitations in prior studies by restricting my sample to children who move outside of their subdistrict and extending my analysis to children who move just after they are born, at age 1. In doing so, I have found some evidence suggesting that critical age effects and exposure effects of neighborhoods do exist to some extent.

8 Tables and Figures

Figure 1. Distribution of Neighborhood Quality

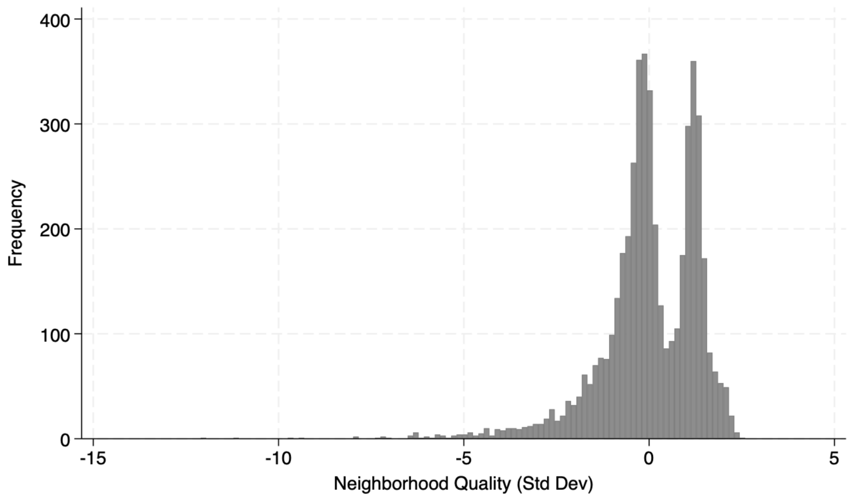

Figure 2. Destination vs Origin Neighborhood Quality

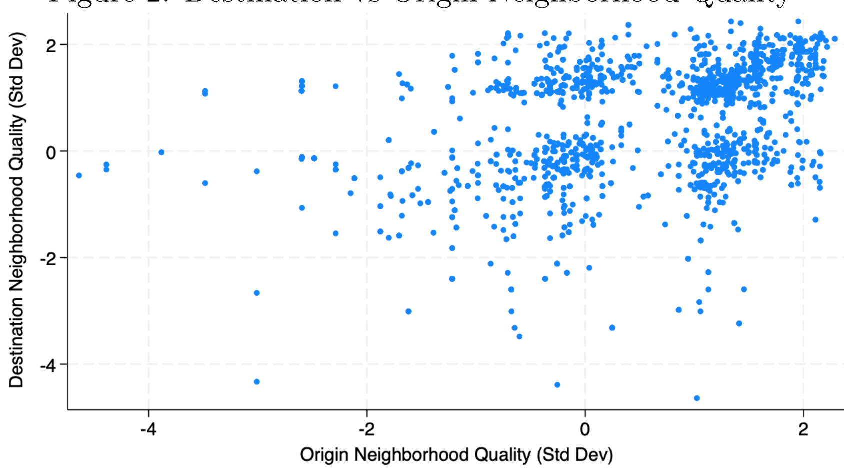

Table 1. Summary Statistics by Age of Migration

	Born After HH Migration	Age 1-5	Age 6-10	Age 11-15	Age 16-20
Male*	0.517	0.553	0.528	0.489	0.392
	(0.500)	(0.498)	(0.500)	(0.501)	(0.489)
Muslim*	0.893	0.904	0.876	0.870	0.888
	(0.309)	(0.295)	(0.330)	(0.337)	(0.316)
Range of Migration[1]	3.641	3.566	3.505	3.487	3.627
	(0.853)	(0.858)	(0.873)	(0.830)	(0.860)
Migration Type*					
Urban to Urban	0.144	0.378	0.407	0.353	0.347
	(0.351)	(0.485)	(0.492)	(0.479)	(0.477)
Rural to Urban	0.052	0.160	0.160	0.210	0.244
	(0.222)	(0.367)	(0.367)	(0.408)	(0.430)
Urban to Rural	0.061	0.218	0.196	0.223	0.167
	(0.240)	(0.413)	(0.398)	(0.417)	(0.374)
Rural to Rural	0.083	0.245	0.236	0.214	0.242
	(0.276)	(0.430)	(0.426)	(0.411)	(0.428)
Change in Neighborhood Quality[2]+					
Urban to Urban	-0.048	-0.072	-0.020	-0.039	0.074
	(0.468)	(0.392)	(0.308)	(0.378)	(0.419)
Rural to Urban	1.506	1.496	1.798	1.914	1.815
	(0.797)	(0.980)	(0.811)	(0.884)	(0.743)
Urban to Rural	-1.616	-1.588	-1.543	-1.541	-1.672
	(0.745)	(0.767)	(0.498)	(0.598)	(0.647)
Rural to Rural	0.129	0.150	-0.060	-0.094	-0.130
	(1.058)	(1.103)	(1.149)	(0.900)	(0.955)
Wave 5 (2014) Measures*					
Age	7.748	15.369	20.535	27.215	31.702
	(4.825)	(4.616)	(4.722)	(4.499)	(3.677)
Worked Last Year	0.020	0.210	0.436	0.647	0.684
	(0.139)	(0.408)	(0.497)	(0.479)	(0.465)
Still in School	0.550	0.622	0.305	0.055	0.002
	(0.498)	(0.485)	(0.461)	(0.228)	(0.046)
Highest Education in Wave 5*					
Grade School	0.390	0.309	0.069	0.147	0.148
	(0.488)	(0.462)	(0.254)	(0.355)	(0.356)
Jr. High	0.110	0.215	0.189	0.122	0.233
	(0.313)	(0.412)	(0.392)	(0.328)	(0.423)
Sr. High	0.053	0.261	0.411	0.332	0.305
	(0.223)	(0.440)	(0.493)	(0.472)	(0.461)
Associates	0.001	0.032	0.036	0.071	0.057
	(0.035)	(0.176)	(0.188)	(0.258)	(0.232)
School Level Completion*					
Elementary School	0.565	0.914	0.897	0.890	0.892
	(0.496)	(0.281)	(0.305)	(0.313)	(0.310)
Middle School	0.172	0.602	0.827	0.737	0.742
	(0.377)	(0.490)	(0.379)	(0.441)	(0.438)
High School	0.061	0.384	0.631	0.601	0.505
	(0.240)	(0.487)	(0.483)	(0.491)	(0.501)
National Exam Scores+					
Primary: Total	-0.091	0.190	0.094	0.175	0.032
	(0.693)	(0.972)	(0.979)	(0.839)	(0.932)
Primary: Math	-0.043	0.097	0.166	0.166	-0.031
	(0.736)	(0.878)	(1.032)	(0.960)	(0.966)
Primary: Indonesian	0.027	0.058	0.127	0.067	0.072
	(0.648)	(0.790)	(0.862)	(1.021)	(0.886)
Middle: Total	-0.035	0.088	0.136	-0.044	0.067
	(1.092)	(0.776)	(1.044)	(0.952)	(0.936)
Middle: Math	0.239	0.244	0.239	-0.048	0.219
	(0.879)	(0.953)	(0.993)	(0.972)	(1.762)
Middle: Indonesian	0.208	0.171	0.119	-0.047	0.168
	(0.944)	(1.037)	(1.161)	(1.218)	(0.944)
High: Total	1.280	0.130	0.154	0.234	0.249
	(1.725)	(0.831)	(0.769)	(0.762)	(1.031)
High: Math	0.613	0.114	0.164	-0.060	0.145
	(0.847)	(1.148)	(0.949)	(0.829)	(1.084)
High: Indonesian	0.406	0.159	0.062	0.194	0.158
	(0.968)	(0.899)	(1.050)	(0.877)	(0.943)
Num of Obs	1614	372	275	238	472

mean coefficients; sd in parentheses

[1] Range of migration is a value from 1-5. Migration within same village (1), same sub-district (2), same district (3), same province (4), to another province (5).

[2] Destination neighborhood - origin neighborhood

* Units: percentage (as decimal)

+ Units: standard deviations

Table 2. Exposure Effects

	Total Scores		Math Scores		Indonesian Scores	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	0.0079	-0.0210	0.0118	-0.0568	-0.0101	-0.0331
	(0.0117)	(0.0670)	(0.0168)	(0.1005)	(0.0124)	(0.0696)
Exposure * Δ_{tco}	-0.0216	-0.0168	-0.0951	-0.1281*	-0.0551	-0.0482
	(0.0423)	(0.0466)	(0.0730)	(0.0750)	(0.0689)	(0.0777)
Post	-0.1989	-0.1884	-0.1385	-0.1797	-0.1708	-0.1840
	(0.1315)	(0.1754)	(0.1776)	(0.2420)	(0.1617)	(0.2363)
Post * Δ_{tco}	0.0447	0.0568	0.2002	0.3108	0.2546	0.2167
	(0.1488)	(0.1440)	(0.2187)	(0.2278)	(0.1928)	(0.2213)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Exam Year FE	No	Yes	No	Yes	No	Yes
Exam Month FE	No	Yes	No	Yes	No	Yes
R-squared	0.6466	0.6684	0.6276	0.6429	0.7117	0.7312
Num. of Obs.	2,034	2,003	1,642	1,640	1,681	1,677

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3. Exposure Effects by Quartile: National Exam Scores

	2nd & 3rd Quartile			4th Quartile		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Total Scores						
Exposure	-0.1381	-0.0489	-0.0885	-0.0964	-0.1155	-0.0360
	(0.1351)	(0.1138)	(0.1483)	(0.1154)	(0.1218)	(0.1604)
Exposure * Δ_{tco}	-0.0953	-0.0843	-0.1538	-0.2227*	-0.2423*	0.0387
	(0.0984)	(0.1278)	(0.2049)	(0.1238)	(0.1355)	(0.6542)
Post	-0.3583	-0.2379	-0.7805	-0.3001	-0.5605	0.1079
	(0.3003)	(0.4287)	(0.5739)	(0.3403)	(0.4525)	(0.5760)
Post * Δ_{tco}	-0.1069	-0.2203	0.5238	0.7116*	0.6093	-0.4813
	(0.1915)	(0.2619)	(0.6434)	(0.3750)	(0.4171)	(4.0957)
R-squared	0.7055	0.7200	0.7122	0.7004	0.7058	0.7331
Num. of Obs.	575	559	559	656	644	613
Panel B: Math Scores						
Exposure	0.0115	-0.0022	0.0142	-0.0218	-0.0273	0.1033
	(0.2158)	(0.2315)	(0.2742)	(0.1515)	(0.1548)	(0.1556)
Exposure * Δ_{tco}	-0.0786	-0.0439	-0.1431	-0.0330	-0.0309	0.5015
	(0.1011)	(0.1177)	(0.2473)	(0.1695)	(0.1664)	(2.2785)
Post	0.0731	0.4768	-0.3729	-0.3985	-0.3198	0.1755
	(0.4203)	(0.6163)	(0.6818)	(0.4351)	(0.5253)	(0.9517)
Post * Δ_{tco}	-0.0476	0.0677	0.3472	-0.2081	-0.1539	-6.0156
	(0.2573)	(0.3583)	(0.9389)	(0.5278)	(0.5651)	(8.2787)
R-squared	0.7860	0.7928	0.7958	0.6958	0.6954	0.7262
Num. of Obs.	452	439	437	483	475	451
Panel C: Indonesian Scores						
Exposure	0.1986	0.2048	0.0332	-0.2962*	-0.2941*	-0.3358
	(0.1759)	(0.1967)	(0.1570)	(0.1726)	(0.1742)	(0.2298)
Exposure * Δ_{tco}	-0.0511	-0.0692	0.2565*	-0.3103	-0.3097	-0.1999
	(0.1065)	(0.0873)	(0.1423)	(0.2988)	(0.2997)	(1.5065)
Post	0.6452	1.4542***	0.0198	-0.5702	-0.5456	0.6931
	(0.4084)	(0.5061)	(0.5887)	(0.3620)	(0.3951)	(0.6936)
Post * Δ_{tco}	0.2366	0.6487**	-0.4030	0.7180	0.7501	-9.9404*
	(0.2637)	(0.2610)	(0.5617)	(0.6992)	(0.6905)	(5.7964)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Exam Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Exam Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.8231	0.8318	0.8304	0.7884	0.7937	0.8176
Num. of Obs.	447	434	432	475	467	445
Restrictions		$\Delta_{tco} < 0$	$\Delta_{tco} > 0$		$\Delta_{tco} < 0$	$\Delta_{tco} > 0$

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Quartile 2 & 3: (1), (2), (3). Quartile 4: (4), (5), (6)

Table 4. Exposure Effects by Quartile with Additional Restrictions: National Exam Scores

	2nd & 3rd Quartile				4th Quartile		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Total Scores							
Exposure	0.0642	-0.2292	0.0377	-0.3567	-0.0622	-0.1893	0.0334
	(0.1189)	(0.2654)	(0.1098)	(0.2706)	(0.1637)	(0.2164)	(0.1679)
Exposure * Δ_{tco}	-0.6405**	-1.0811	0.0350	-0.4562**	-0.9797***	0.0041	-0.1245
	(0.2896)	(1.1165)	(0.0927)	(0.2022)	(0.3517)	(0.6922)	(0.1081)
Post	-0.5722	-0.6907	0.2331	-9.8885**	-0.0866	-0.2301	-0.1809
	(0.7363)	(0.6716)	(0.7029)	(4.2156)	(0.7185)	(0.7066)	(1.1618)
Post * Δ_{tco}	-0.5975	2.3220	-0.3010	7.1482**	3.5040***	0.2526	0.3501
	(2.1058)	(3.0187)	(0.3253)	(3.3602)	(1.2230)	(4.6616)	(0.7331)
R-squared	0.7241	0.7149	0.7261	0.7186	0.7228	0.7367	0.7240
Num. of Obs.	531	535	529	535	611	567	604
Panel B: Math Scores							
Exposure	-0.1396	0.1888	0.0238	0.1444	0.0796	0.1407	-0.1126
	(0.2979)	(0.3015)	(0.3919)	(0.3112)	(0.1733)	(0.2130)	(0.2347)
Exposure * Δ_{tco}	-0.6326	-3.6488	0.0254	-0.3715**	-0.0600	0.5364	-0.0283
	(0.3883)	(2.7960)	(0.1245)	(0.1536)	(0.3939)	(2.3909)	(0.2007)
Post	0.8505	-0.0084	0.3338	-5.8285	-0.0104	0.2517	-0.4171
	(0.8723)	(0.7222)	(1.2570)	(4.2172)	(0.5855)	(0.9686)	(1.9382)
Post * Δ_{tco}	3.8109*	7.2805	-0.1406	4.7927	0.2055	-6.2421	-0.1569
	(2.0054)	(5.1310)	(0.5668)	(2.9962)	(1.7843)	(8.5669)	(1.0916)
R-squared	0.8008	0.7999	0.7954	0.8011	0.7235	0.7107	0.7056
Num. of Obs.	416	415	415	416	452	419	444
Panel C: Indonesian Scores							
Exposure	0.2163	-0.0098	0.1338	0.0226	-0.1367	-0.7544***	0.1034
	(0.2891)	(0.1912)	(0.2484)	(0.2220)	(0.1430)	(0.1524)	(0.1369)
Exposure * Δ_{tco}	0.3203	1.7595	-0.1224	0.3226*	-0.9467**	-0.6914	-0.0358
	(0.2201)	(1.7193)	(0.0801)	(0.1718)	(0.3995)	(1.4399)	(0.2752)
Post	0.8899	-0.1519	1.3779*	1.4226	-0.1597	-0.1153	0.0660
	(0.8900)	(0.6814)	(0.8157)	(2.6383)	(0.6590)	(0.6851)	(1.1236)
Post * Δ_{tco}	-2.6680	-2.9360	0.7724**	-1.5183	3.0661**	-6.8232	-0.0033
	(2.0820)	(3.1879)	(0.3070)	(2.2137)	(1.4351)	(5.4781)	(0.8804)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exam Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exam Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.8319	0.8290	0.8320	0.8285	0.8132	0.8224	0.8108
Num. of Obs.	411	410	410	411	446	413	436
Restrictions	$-1<\Delta_{tco}<0$	$0<\Delta_{tco}<1$	$-1>\Delta_{tco}$	$1<\Delta_{tco}$	$-1<\Delta_{tco}<0$	$0<\Delta_{tco}<1$	$-1>\Delta_{tco}$

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Quartile 2 & 3: (1),(2), (3), (4). Quartile 4: (5), (6), (7)

Table 5. Critical Age Effects: Primary School Exams

	Total Scores			Math Scores			Indonesian Scores		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$I(m_i = m) * \Delta_{tco}$									
Age 1	-0.0108	-0.0112	0.0021	-0.0023	-0.0025	0.0679	0.0163	0.0161	0.0566
	(0.0126)	(0.0126)	(0.0367)	(0.0149)	(0.0149)	(0.0529)	(0.0135)	(0.0135)	(0.0450)
Age 2	-0.0064	-0.0066	-0.0290	-0.0253	-0.0254	0.0002	-0.0001	-0.0002	0.0307
	(0.0124)	(0.0123)	(0.0385)	(0.0160)	(0.0160)	(0.0712)	(0.0127)	(0.0127)	(0.0580)
Age 3	0.0097	0.0100	0.0422	0.0159	0.0161	0.0848*	0.0131	0.0133	0.0730*
	(0.0132)	(0.0132)	(0.0365)	(0.0152)	(0.0152)	(0.0459)	(0.0137)	(0.0137)	(0.0439)
Age 4	0.0121	0.0118	0.0573	-0.0062	-0.0065	0.0699	0.0008	0.0005	0.0775*
	(0.0145)	(0.0144)	(0.0348)	(0.0163)	(0.0163)	(0.0445)	(0.0147)	(0.0147)	(0.0424)
Age 5	-0.0110	-0.0104	0.0358	-0.0135	-0.0130	0.0784	-0.0147	-0.0141	0.0590
	(0.0114)	(0.0114)	(0.0440)	(0.0133)	(0.0133)	(0.0562)	(0.0120)	(0.0120)	(0.0434)
Age 6	0.0117	0.0126	-0.0097	0.0014	0.0021	0.0053	0.0094	0.0103	0.0422
	(0.0110)	(0.0109)	(0.0387)	(0.0123)	(0.0123)	(0.0641)	(0.0122)	(0.0122)	(0.0472)
Age 7	-0.0081	-0.0081	0.0017	0.0003	0.0002	0.0190	-0.0230**	-0.0231**	-0.0211
	(0.0107)	(0.0107)	(0.0374)	(0.0128)	(0.0128)	(0.0886)	(0.0115)	(0.0115)	(0.0472)
Age 8	-0.0080	-0.0089	0.0292	-0.0023	-0.0028	0.0500	0.0054	0.0048	0.0853
	(0.0142)	(0.0142)	(0.0823)	(0.0164)	(0.0164)	(0.0741)	(0.0148)	(0.0148)	(0.0838)
Age 9	0.0275**	0.0272**	0.0666	0.0219	0.0219	0.0685	0.0255	0.0255	0.0806
	(0.0134)	(0.0134)	(0.0429)	(0.0201)	(0.0201)	(0.0508)	(0.0181)	(0.0181)	(0.0538)
Age 10	0.0196	0.0199	0.0237	0.0445**	0.0449**	-0.0060	0.0154	0.0154	0.0562
	(0.0140)	(0.0139)	(0.0302)	(0.0205)	(0.0205)	(0.0805)	(0.0145)	(0.0145)	(0.0518)
Age 11	0.0204*	0.0198*	0.0609*	0.0078	0.0074	0.0539	-0.0043	-0.0048	0.0437
	(0.0120)	(0.0120)	(0.0326)	(0.0137)	(0.0137)	(0.0457)	(0.0123)	(0.0123)	(0.0325)
$I(m_i = m)$									
Age 1	0.0530	-0.0291	0.7181	-0.1313	-0.1970	0.2726	-0.1287	-0.1961	0.4245
	(0.1349)	(0.1382)	(1.1664)	(0.1675)	(0.1732)	(1.3070)	(0.1513)	(0.1563)	(1.1398)
Age 2	0.1947	0.1204	0.8167	0.0632	0.0038	0.6019	-0.0072	-0.0674	-0.4646
	(0.1493)	(0.1515)	(1.1408)	(0.1744)	(0.1789)	(1.5662)	(0.1571)	(0.1609)	(1.3173)
Age 3	0.1486	0.0683	0.7760	0.1810	0.1171	0.1108	0.0574	-0.0077	0.5201
	(0.1372)	(0.1402)	(1.0974)	(0.1606)	(0.1662)	(1.3882)	(0.1449)	(0.1499)	(1.1447)
Age 4	0.0133	-0.0572	0.9136	0.0503	-0.0077	0.9443	-0.0435	-0.1026	0.7353
	(0.1523)	(0.1543)	(0.9465)	(0.1784)	(0.1826)	(1.0833)	(0.1555)	(0.1593)	(0.9167)
Age 5	0.1168	0.0479	0.8093	0.1908	0.1353	-0.1109	0.1152	0.0586	0.3008
	(0.1289)	(0.1312)	(0.9188)	(0.1543)	(0.1588)	(1.1030)	(0.1393)	(0.1432)	(1.0054)
Age 6	-0.0794	-0.1454	0.0133	0.1033	0.0501	0.1803	0.1317	0.0770	0.2716
	(0.1274)	(0.1295)	(0.8686)	(0.1460)	(0.1503)	(1.0562)	(0.1329)	(0.1367)	(0.8631)
Age 7	0.0716	0.0015	0.6312	0.3481**	0.2923*	0.5803	0.1940	0.1371	0.2466
	(0.1272)	(0.1296)	(0.8041)	(0.1505)	(0.1551)	(0.9534)	(0.1359)	(0.1399)	(0.8517)
Age 8	0.1634	0.0932	0.5533	0.3622**	0.3057*	-0.3339	0.0209	-0.0369	-0.1440
	(0.1429)	(0.1449)	(0.8570)	(0.1693)	(0.1735)	(1.0102)	(0.1528)	(0.1565)	(1.0442)
Age 9	0.0612	-0.0073	0.5093	0.0374	-0.0135	0.3168	0.0434	-0.0087	0.8523
	(0.1462)	(0.1480)	(0.7095)	(0.1917)	(0.1947)	(0.7878)	(0.1730)	(0.1756)	(0.7630)
Age 10	-0.0719	-0.1420	0.1741	-0.1160	-0.1721	0.0042	0.0454	-0.0125	0.3282
	(0.1576)	(0.1594)	(0.6354)	(0.1914)	(0.1951)	(0.8512)	(0.1684)	(0.1718)	(0.5848)
Age 11	0.2190	0.1649	0.4680	0.1108	0.0670	0.3980	0.0269	-0.0177	0.4162
	(0.1415)	(0.1425)	(0.4836)	(0.1696)	(0.1721)	(0.7231)	(0.1509)	(0.1531)	(0.5141)
Age Started School	-0.0747**	-0.0899**	-0.1659	-0.0278	-0.0373	-0.0997	-0.0482	-0.0582	-0.0958
	(0.0351)	(0.0354)	(0.1269)	(0.0441)	(0.0446)	(0.2023)	(0.0396)	(0.0401)	(0.1686)
Attended Kindergarten	0.1358**	0.1830***	-0.2772	0.1709**	0.2092***	-0.1154	0.2417***	0.2802***	-0.3225
	(0.0542)	(0.0573)	(0.2488)	(0.0673)	(0.0722)	(0.5260)	(0.0605)	(0.0648)	(0.2980)
Male	0.0466	0.0530	-0.0753	0.0438	0.0459	-0.2053	-0.0897	-0.0874	-0.3095
	(0.0511)	(0.0510)	(0.1991)	(0.0632)	(0.0632)	(0.2793)	(0.0569)	(0.0569)	(0.2347)
D_i		-0.1958***	1.0540		-0.1381	-0.0316		-0.1414*	0.2328
		(0.0754)	(1.3117)		(0.0931)	(1.4692)		(0.0835)	(1.3258)
$D_i * \Delta_{tco}$		0.0041	0.0179		-0.0003	0.0212		0.0002	0.0198
		(0.0041)	(0.0235)		(0.0047)	(0.0333)		(0.0043)	(0.0269)
Household FE	No	No	Yes	No	No	Yes	No	No	Yes
Birth Cohort FE	No	No	Yes	No	No	Yes	No	No	Yes
Birth Order FE	No	No	Yes	No	No	Yes	No	No	Yes
Exam Year FE	No	No	Yes	No	No	Yes	No	No	Yes
Exam Month FE	No	No	Yes	No	No	Yes	No	No	Yes
R-squared	0.0375	0.0454	0.8772	0.0397	0.0423	0.8929	0.0465	0.0499	0.9105
Num. of Obs.	1,004	1,004	983	824	824	817	832	832	825

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Total Scores: (1), (2), (3). Math Scores: (4), (5), (6). Indonesian Scores: (7), (8), (9)

Table 6. Critical Age Effects: Middle School Exams

	Total Scores			Math Scores			Indonesian Scores		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$I(m_i = m) * \Delta_{tco}$									
Age 1	0.0192	0.0191	-0.0584	-0.0308	-0.0308	0.2720	0.0249	0.0250	-89.7943
	(0.0145)	(0.0145)	(0.3011)	(0.0230)	(0.0230)	(0.5771)	(0.0173)	(0.0173)	(60.9296)
Age 2	-0.0039	-0.0039	-0.0203	-0.0066	-0.0066	-0.6474	-0.0018	-0.0018	-206.2121
	(0.0146)	(0.0146)	(0.2395)	(0.0228)	(0.0228)	(1.0654)	(0.0171)	(0.0172)	(137.6160)
Age 3	-0.0092	-0.0095	-0.2523	0.0075	0.0074	1.5945	-0.0220	-0.0222	175.9814
	(0.0270)	(0.0270)	(0.2472)	(0.0422)	(0.0423)	(0.8018)	(0.0317)	(0.0318)	(116.7886)
Age 4	0.0073	0.0068	0.1108	0.0072	0.0071	0.7249^{*}	0.0348	0.0346	9.6996
	(0.0200)	(0.0200)	(0.2783)	(0.0327)	(0.0328)	(0.2741)	(0.0246)	(0.0246)	(5.6243)
Age 5	-0.0244^{*}	-0.0242^{*}	-0.0616	-0.0314	-0.0313	0.5194	-0.0105	-0.0104	-70.4470
	(0.0145)	(0.0145)	(0.2256)	(0.0229)	(0.0230)	(0.3966)	(0.0173)	(0.0173)	(47.4909)
Age 6	0.0139	0.0143	-0.1029	0.0164	0.0165	0.1805	0.0165	0.0166	-20.3843
	(0.0176)	(0.0176)	(0.2142)	(0.0286)	(0.0287)	(0.2053)	(0.0215)	(0.0216)	(13.9065)
Age 7	0.0048	0.0048	-0.0187	-0.0009	-0.0009	0.5153	0.0004	0.0004	71.2244
	(0.0130)	(0.0130)	(0.3363)	(0.0211)	(0.0212)	(0.3452)	(0.0159)	(0.0159)	(46.6320)
Age 8	-0.0001	-0.0007	-0.0189	0.0057	0.0056	-0.1426	-0.0387	-0.0388	-89.7319
	(0.0282)	(0.0282)	(0.3418)	(0.0462)	(0.0463)	(0.7516)	(0.0347)	(0.0348)	(60.8288)
Age 9	0.0003	0.0002	-0.1132	-0.0123	-0.0123	0.5579	0.0105	0.0105	-91.7489
	(0.0181)	(0.0181)	(0.2926)	(0.0310)	(0.0311)	(0.5243)	(0.0233)	(0.0234)	(61.9024)
Age 10	0.0089	0.0090	-0.0711	0.0222	0.0222	0.7231	0.0074	0.0075	41.4524
	(0.0153)	(0.0153)	(0.2985)	(0.0239)	(0.0239)	(0.3659)	(0.0225)	(0.0226)	(27.1006)
Age 11	0.0020	0.0019	-0.1983	-0.0063	-0.0064	0.5336	0.0026	0.0025	-77.5400
	(0.0176)	(0.0176)	(0.2663)	(0.0287)	(0.0288)	(0.5174)	(0.0216)	(0.0216)	(52.4325)
Age 12	-0.0006	-0.0010	-0.1153	0.0004	0.0003	0.0058	0.0157	0.0156	-144.8666
	(0.0236)	(0.0236)	(0.2699)	(0.0374)	(0.0375)	(0.7878)	(0.0281)	(0.0282)	(97.0791)
Age 13	-0.0203	-0.0203	-0.0816	-0.0282	-0.0282	1.2905	-0.0147	-0.0147	107.0338
	(0.0137)	(0.0137)	(0.1494)	(0.0216)	(0.0217)	(0.7076)	(0.0163)	(0.0163)	(70.7582)
$I(m_i = m)$									
Age 1	-0.0119	-0.0495	7.0480	-0.2096	-0.2125	3.4577	0.0087	0.0226	1753.7970
	(0.1905)	(0.1933)	(4.6718)	(0.3162)	(0.3249)	(9.3076)	(0.2374)	(0.2436)	(1172.0534)
Age 2	-0.1070	-0.1411	4.5607	-0.4323	-0.4346	15.4427	-0.1902	-0.1754	1812.3708
	(0.2034)	(0.2055)	(3.8165)	(0.3223)	(0.3299)	(7.7640)	(0.2421)	(0.2474)	(1207.7291)
Age 3	-0.1043	-0.1420	2.5280	-0.1576	-0.1608	18.8445	-0.2032	-0.1905	4164.9236
	(0.2032)	(0.2058)	(4.6943)	(0.3222)	(0.3309)	(18.8602)	(0.2420)	(0.2482)	(2781.3473)
Age 4	-0.0317	-0.0649	5.5036	0.1162	0.1137	9.3439	0.2818	0.2953	2402.0989
	(0.1843)	(0.1865)	(3.6160)	(0.3040)	(0.3116)	(11.9009)	(0.2283)	(0.2337)	(1604.0856)
Age 5	0.0205	-0.0125	2.4600	0.0329	0.0306	11.3857	0.0050	0.0190	1731.0376
	(0.1884)	(0.1906)	(2.5993)	(0.3058)	(0.3131)	(8.9820)	(0.2297)	(0.2349)	(1151.5610)
Age 6	0.2068	0.1752	2.5453	0.1916	0.1897	10.9729	-0.0677	-0.0530	1720.9996
	(0.1721)	(0.1743)	(2.6888)	(0.2874)	(0.2946)	(7.3950)	(0.2160)	(0.2211)	(1149.0601)
Age 7	-0.1405	-0.1758	2.4450	-0.5337^{*}	-0.5362^{*}	5.8659	-0.3040	-0.2901	2036.0557
	(0.1615)	(0.1643)	(2.6460)	(0.2723)	(0.2811)	(9.5464)	(0.2044)	(0.2107)	(1361.3753)
Age 8	0.2681	0.2354	2.7110	0.3209	0.3188	3.5640	0.3575	0.3729	1197.4866
	(0.2076)	(0.2096)	(2.7795)	(0.3445)	(0.3514)	(4.9033)	(0.2589)	(0.2638)	(803.5102)
Age 9	-0.0713	-0.1051	3.0037	-0.3166	-0.3187	7.3327	0.0755	0.0902	730.3431
	(0.1936)	(0.1959)	(2.4244)	(0.3203)	(0.3275)	(3.8759)	(0.2408)	(0.2459)	(485.2520)
Age 10	-0.2914	-0.3249^{*}	0.9393	-0.2673	-0.2697	5.0831	-0.0800	-0.0663	392.0707
	(0.1845)	(0.1868)	(2.3473)	(0.2980)	(0.3058)	(2.5404)	(0.2393)	(0.2445)	(262.8950)
Age 11	-0.0517	-0.0795	0.5063	-0.4652	-0.4665	10.4801	-0.3907	-0.3741	1409.5988
	(0.2106)	(0.2121)	(2.4006)	(0.3805)	(0.3861)	(5.9729)	(0.2861)	(0.2899)	(941.7537)
Age 12	-0.0663	-0.0998	1.8196	0.0159	0.0139	4.2447	-0.0716	-0.0570	-757.5475
	(0.2213)	(0.2232)	(2.3087)	(0.3726)	(0.3788)	(7.2073)	(0.2723)	(0.2769)	(505.5964)
Age 13	-0.6010^{***}	-0.6322^{***}	2.2905	-0.9562^{***}	-0.9579^{***}	11.0782	-0.5065^{**}	-0.4903^{*}	1001.6583
	(0.2033)	(0.2052)	(2.2575)	(0.3378)	(0.3443)	(6.6167)	(0.2539)	(0.2585)	(662.7009)
Age Started School	-0.0585	-0.0614	0.7027	-0.0922	-0.0923	-3.6237	-0.1170^{*}	-0.1161^{*}	-270.8723
	(0.0522)	(0.0523)	(1.0528)	(0.0928)	(0.0931)	(1.8754)	(0.0695)	(0.0697)	(181.0948)
Attended Kindergarten	0.1151	0.1340^{*}	-1.0229	0.0633	0.0666	6.2194	0.2035^{**}	0.2078^{**}	1196.7681
	(0.0752)	(0.0774)	(1.1301)	(0.1308)	(0.1359)	(6.5865)	(0.0979)	(0.1015)	(796.9632)
Male	-0.0413	-0.0404	-0.4736	0.1215	0.1203	-2.9709	-0.2033^{**}	-0.2097^{**}	-229.6973
	(0.0734)	(0.0738)	(0.7784)	(0.1276)	(0.1285)	(1.6092)	(0.0957)	(0.0963)	(150.7687)
D_i		-0.1572	5.3223		-0.0103	15.3252		0.0373	3694.1978
		(0.1327)	(5.4597)		(0.2219)	(16.1302)		(0.1650)	(2468.5877)
$D_i * \Delta_{tco}$		-0.0014	0.0188		-0.0014	-0.2100		-0.0060	-157.8465
		(0.0076)	(0.3004)		(0.0120)	(0.6901)		(0.0090)	(106.0030)
Household FE	No	No	Yes	No	No	Yes	No	No	Yes
Birth Cohort FE	No	No	Yes	No	No	Yes	No	No	Yes
Birth Order FE	No	No	Yes	No	No	Yes	No	No	Yes
Exam Year FE	No	No	Yes	No	No	Yes	No	No	Yes
Exam Month FE	No	No	Yes	No	No	Yes	No	No	Yes
R-squared	0.0488	0.0513	0.9838	0.0552	0.0552	1.0000	0.0704	0.0716	0.9977
Num. of Obs.	570	570	562	460	460	458	463	463	460

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Total Scores: (1), (2), (3). Math Scores: (4), (5), (6). Indonesian Scores: (7), (8), (9).

Table 7. Average Exam Scores: Complete Exposure to Origin Neighborhood

	Primary School	Middle School	High School
Total Score	0.026	0.084	0.158
	(0.918)	(0.975)	(1.177)
Math Score	0.028	0.260	-0.046
	(0.944)	(1.755)	(0.975)
Indonesian Score	0.048	0.198	0.218
	(0.895)	(0.969)	(1.017)
Num of Obs	515	277	63

mean coefficients; sd in parentheses

Table 8. Average Exam Scores: Complete Exposure to Destination Neighborhood

	Primary School	Middle School	High School
Total Score	-0.083	-0.023	0.823
	(0.762)	(1.085)	(1.974)
Math Score	-0.041	0.338	0.175
	(0.722)	(0.863)	(1.109)
Indonesian Score	-0.033	0.216	0.103
	(0.724)	(0.967)	(1.064)
Num of Obs	220	56	11

mean coefficients; sd in parentheses

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