Title

For the sake of the children? A longitudinal analysis of residential relocations and academic performance of Australian children.

Authors

Sergi Vidal and Janeen Baxter (Life Course Centre, University of Queensland)

Abstract

The family and residential environments are critical to children's wellbeing and, hence, moving home can affect children's developmental outcomes. In this research, we study the associations between residential relocations and academic performance in the Australian context using longitudinal data of a representative sample of 3,481 children born in the late 1990's from the Longitudinal Study of Australian Children (LSAC). We examine the impact of residential relocations from infancy to middle childhood and pay special attention to the distance, frequency and developmental age-stage of relocations on academic test scores from the National Assessment Program – Literacy and Numeracy (NAPLAN) of 3rd, 5th and 7th graders. We use hybrid models and random coefficients models. Our results confirm findings of modest associations from previous research in the US context. Frequent residential mobility relates to poor academic performance, but the association is largely due to family and home circumstances. After controlling for a number of predictors, we find that moderate levels of residential mobility, particularly relocations to a different local area, are associated with improvements in academic performance over time. Further, our multivariate results show a modest negative effect of relocations around the time of school entry (i.e. ages 4/5 to 6/7). We conclude that the associations between residential change and cognitive development are nuanced by the circumstances and contexts of childhood relocations.

Keywords

Residential relocations, academic performance, longitudinal data, LSAC, Australia

Introduction

In recent years, there has been an increasing interest in understanding developmental outcomes of children's residential relocations. An underlying concern is that the home and residential environments are critical for children's wellbeing and hence, moving home may affect their development and have impacts on outcomes later in life (Ackerman et al., 1999; Adam & Chase-Lansdale, 2002; Anderson et al., 2014). Previous literature has been devoted to the study of relocation impacts on cognitive ability and school performance. Research concurred in finding moderate and weak associations, with children who move home performing worse in school than children who stay in the same house. Despite consistency in findings across studies, empirical evidence is ambiguous about *when* relocations have larger impacts, and whether these impacts are short-lived or persist in further developmental stages. Moreover, it remains unclear whether the negative associations are due to direct impacts of relocations, or due to pre-existing poor cognitive development among children who relocate.

We argue here that home relocations, which are standard experiences in childhood, are complex processes with important intersections between individual biographies (i.e. how often, how far, during what developmental stages, and why children moved) and the family and social contexts in which children are embedded. Recently, there have been a few efforts to investigate more thoroughly the processes that regulate the potential adverse and beneficial impacts of relocations on cognitive development (e.g. Joshi et al. 2015; Gasper et al., 2010). Largely focused on the US context, these studies have capitalized on recent collections of longitudinal data rich in information on the contexts and circumstances of childhood relocations and the use of adequate methods to make better causal assessments of the associations.

In this article, we investigate the implications of residential relocations from infancy to middle childhood for school performance in the Australian context using longitudinal data and methods. Despite similarities with the US in some economic and cultural aspects, Australia's institutional setting provides higher equality of opportunity through education. For instance, access to high-quality early education and care in Australia is less dependent on family income than in the US (Coley et al., 2013). As far as we know, no longitudinal analysis has been published for the Australian case, despite two in three Australian children moving home by age 10 (Maguire et al., 2012). We examine representative data of Australian children born in the late 1990's on life-time residential relocations and academic test scores of 3rd, 5th, and 7th graders from the Growing Up in Australia: The Longitudinal Study of Australian Children (LSAC). We deploy methods for panel data analysis, which acknowledge the nested structure of the data, to examine the impacts of residential relocations (i.e. occurrence, distance, frequency) on children's performance and to assess the importance of the developmental age-stage of relocations in shaping school performance trajectories.

Residential relocations and children's educational outcomes

Residential mobility is a common experience during childhood. The family and residential environments are key factors shaping children's cognitive development (Bronfenbrenner & Morris, 2006), and, hence, moving home can affect children's outcomes. Previous studies revealed moderate negative associations, with home relocations entailing poor school performance (Haveman et al., 1991; Ingersoll et al., 1989; Pribesh & Downey, 1999; Wood et al., 1993), repeating a school grade (Wood et al., 1993), school drop-outs (Crowder & South, 2003; Crowder & Teachman, 2004; Rumberger & Lim, 2008) and lower educational attainment (Astone & McLanahan, 1994; Haveman et al., 1991). Common mechanisms proposed to explain these associations emphasized the downsides of relocations, such as changes in social relationships and support networks, lack of engagement with the school as well as changes in household routines of parents and children that produce stress and directly impact school performance (Astone & McLanahan, 1994; Evans & Wachs, 2010; South & Haynie, 2004). Concurrently, other research evidence revealed that children in relocation-prone families were already performing poorly in school before the relocation (Pribesh & Downey, 1999). These were often children from low-income families who moved house frequently or who reported unfavourable relocation motivations (e.g. eviction, divorce). Thus, the direct effects of residential relocations on academic performance might be rather weak or inexistent once accounting for family structures, particularly those that concentrate multiple sources of disadvantage such as lone parents often do (Adam & Chase-Lansdale, 2002; Anderson et al., 2014; Astone & McLanahan, 1994; Ersing et al., 2009; Herbers et al., 2012; Pettit & McLanahan, 2003; Pribesh & Downey, 1999; Scanlon & Devine, 2001).

Although the importance of previous research for understanding and potentially supporting equality of opportunity is indisputable, we believe that *whether* and *how* relocations affect cognitive development remains unclear. One major drawback is that the bulk of the existing evidence is derived from studies that deployed cross-sectional designs. These studies relied on the examination of one single observation of cognitive ability at a given age stage, and treated residential mobility as a cumulative measure of all prior life relocations. In our view, such research designs cast little light on whether relocations induce or reproduce school performance because the studied associations conflate the immediate impacts of contemporary relocations, the lagged impacts of past relocations, and pre-existing differences in school performance. The lack of repeated observations of children also hampers ability to compare and contrast the stages when relocations have more relevant impacts on academic performance, or whether these impacts accumulate over time. Developmental psychologists posit that age when exposure to an impacting event occurs is not trivial, particularly at stages of noteworthy developmental expansion such as early childhood (Bradley & Corwyn, 2002). Additionally, life course theory posits that the effects of events earlier in life accumulate and shape later development (Moen et al,. 1995).

Leveraging growing sources of longitudinal data, recent research investigated the impacts of relocations occurring at different developmental stages on academic performance, and whether these impacts persist over time (Anderson et al., 2014). Sophisticated analyses deployed growth curve models to assess children’s cognitive evolution and showed that developmental stage matters (Anderson et al., 2014; Fowler et al., 2014; Rumbold et al., 2012), though there is no agreement on when relocation impacts are more relevant. Typically, families with pre-school children move more often than families with school children, because moves during school age are believed to have negative impacts on schooling (Mehana & Reynolds, 2004). Along these lines, Lawrence et al. (2016) also found that infants and pre-school age children often move to better neighbourhoods than children who move at later stages. Schmitt and Lipscomb (2016) examined cognitive abilities of low-income pre-school children, and found that residential mobility by age four had only modest negative impacts on cognitive abilities by the end of pre-kindergarten. No cumulative effects were observed since the negative impacts of early relocations levelled off by kindergarten and 1st grade. Voight et al. (2012) also found negative effects of early childhood relocation on reading and math skills in 3rd grade, which persisted for reading in later grades. In contrast, Coley & Kull (forthcoming) found that early childhood mobility had no effect on cognitive skills during 5th and 8th grade.

We note that inconsistencies in findings across studies can be due to the uneven interests in the aspects of relocations that were examined. For example, the focus of much research has been limited to the negative impact of highly frequent mobility on cognitive development, often using samples of low income families. Using a nationally representative sample for the US context, Kull & Coley (forthcoming) highlighted a linear relationship between relocation frequency and children's development, and concluded that even a single move may have modest negative effects on the functioning of children. Despite this result, a few recent studies have revealed that, under certain conditions, moving homes has no negative consequences on children's cognitive development (Joshi et al., 2015). For instance, Ziol-Guest and McKenna (2014) find that children from middle income families were not susceptible to negative cognitive development if they move house.

In addition, other aspects of relocations such as the distance moved have received little attention, despite the potential disrupting impacts of long-distance relocations with regards to relevant contexts such as friends, support networks and changing school. Among non-intact families, children's long-distance relocations can potentially reduce the amount of physical contact with the parent who stays behind. However, research is inconclusive on the associations between cognitive development and contact with non-resident parents (Rasmussen & Stratton, 2012). Moreover, long-distance moves are often motivated by positive triggers such as parents' careers progress (Huinink et al., 2014), deriving in improvements in household living standards and neighbourhood quality (Clark & Maas, 2016), which could benefit children, cancelling out the negative consequences of relocating to a new context.

Finally, prior studies often neglected that substandard performance among children who relocate can be due to selective factors or traits. If omitted factors are relevant to cognitive development, the estimated associations are likely to be biased, leading to inaccurate causal interpretations. For instance, certain personality traits of parents leading to instability that are difficult to measure might limit parental provision of cognitive stimulation to children. Such personality traits might enhance household relocation propensities as well. While it is methodologically complex to account for selectivity in cross-sectional analyses, panel regression methods for longitudinal data reduces these potential biases. Based on the exploitation of within-individual variation from repeated observations of the same individuals, some research has improved the causal assessments of the associations under investigation using longitudinal data. Coley et al. (2013) used hierarchical models with a three-level structure and assessed between- and within-individual effects of housing features and house relocations on child's functioning measures. Coley & Kull (forthcoming) and Gasper et al. (2010) examined similar associations using, respectively, fixed-effects regression models and hybrid regression model, which combines virtues of random- and fixed effects models. These studies modelled within-individual estimators to predict children's development over time, assessing the impacts of changes in covariates and controlling for time-constant unobserved heterogeneity.

The current research makes an original contribution by investigating the associations between residential relocations and children's academic performance in the Australian context. Compared to the US, Australia provides more financial support to families (including self-care of infants and access to high-quality early education). Australian children are also less likely to suffer poverty. Only 18 percent of children were living under the poverty line in 2012 (Australian Council of Social Service, 2014). Furthermore, Australian mothers of young children display lower levels of employment. In 2011, less than 50 percent of Australian mothers of children under 6 were employed, being this one of the lowest rates among OECD countries (OECD 2014). We expect associations to be less negative than the ones found in previous US studies. We set several research objectives. First, we examine patterns in the associations between age-specific relocations (since infancy until middle schools) and school performance. Second, we analyse other relevant aspects of relocations such as frequency and distance. Third, we assess whether relocations induce changes in academic performance or reproduce pre-existing performance levels. To this end we exploit the longitudinal aspect of the data to assess between-group effects – i.e. differences in school performance between children who relocate and those who do not relocate – and within-group effects – i.e. differences in individual school performance over time (e.g. before and after relocation). Finally, we identify factors that influence average differences and alterations in school performance of children who relocate.

Method

Data

To gather adequate evidence of children's residential trajectories and academic performance over time, we rely on data from the study 'Growing Up in Australia: The Longitudinal Study of Australian Children' (LSAC). The LSAC is an on-going longitudinal study with a biannual panel design that started in 2004 and is administered by the Australian Federal Department of Social Services (Gray & Sanson, 2005). The study collects data on parenting, family relationships, childhood education, non-parental child care, and health of children born in the late 1990s and early 2000s. In 2004, 10,090 families were interviewed, being representative of Australian children aged 0-1 (cohort 'B') and 4-5 (cohort 'K') living in non-remote areas.

We use longitudinal information from the LSAC cohort 'K' study (LSAC-K) between 2004 and 2010 (waves 1 to 4), which enables the study of academic performance through the pre-adolescence stage, up to 7th grade. We disregard respondents from cohort 'B' from our analyses since academic tests scores were only available in one wave at the time the analyses were done.

To assess complete histories of residence and academic performance in middle childhood, we restrict the analytical sample to respondents who participated in the first four survey waves. The original sample size (wave 1) of LSAC-K was n=4,983 children, and by 2010 (wave 4) the sample of respondents who provided a response was n= 4,163. Sample attrition after four waves of the study involved less than 20 percent of original respondents; hence attrition rates in LSAC-K are not higher than those of comparable national household panel studies. Regarding sources of attrition, Sipthorp and Misson (2009) found that sample attrition is related to length of residence, but these and other variables associated with residential mobility have been integrated for the computation of longitudinal weights in LSAC that we use in the analysis.

To assess longitudinal associations, we additionally restrict the sample to children who participated in more than one survey wave, and to children's observations with non-missing information on academic performance items collected in 3rd, 5th, and 7th grade. Missing data in academic performance involves 29 percent of 3rd graders, and about 10 percent of 5th and 7th graders. Since the administration of academic performance tests available in LSAC (see more detail below) started in 2008, approximately 23 percent of respondents of LSAC-K who did 3rd grade in 2007 have no available information on academic performance because no test was administered to them. Remaining sources of missingness are test absences related to illness or other accepted reasons, non-consent of parents to access the data, or lack of data match by the state/territory jurisdiction. In sensitivity analyses (available under request) of multivariate models, we contrasted results of the analysis presented in the results section with an alternative analysis that included only children with no missing observations. We did not find substantively different results. The analytical sample contains 3,481 children and 8,609 observations.

The inspection of model covariates revealed trivial levels of missing data. To minimize observation loss we imputed missing information of model covariates applying multiple imputations for chained equations to create 20 imputed datasets using the mice command in Stata 14.0 (Royston & White, 2011).

Measures

<u>NAPLAN test scores</u>

To assess school performance we use measures of academic skills in literacy and numeracy for children of different ages. This includes tests scores from The National Assessment Program—Literacy and Numeracy (NAPLAN), which is a national test conducted annually since 2008 and administered to nearly all Australian students[1] in school grades 3, 5, 7 and 9 in -1- reading, -2- writing, -3- spelling, -4- grammar and punctuation and -5- numeracy (Daraganova et al., 2013). NAPLAN test scores are reported using single scales to enable comparisons of results across Year levels and over time. Test scores in each of the five domains of NAPLAN range from 0 to 1000 with a mean score of 500, but results are not comparable across domains.

For the analysis we use information on school grade 3, 5 and 7 NAPLAN tests. Since predictors must be measured prior to responses, we note some limitations in the analysis of linked NAPLAN data in LSAC. First, while NAPLAN test are administered nationwide, every year, in the second full week in May, LSAC main interviews take place from March to December every two years. Second, LSAC respondents of the same study cohort may sit the same school grade NAPLAN test in different calendar years. For instance, LSAC-K respondents may sit in school grade 5 NAPLAN tests in 2009, 2010 and 2011, while LSAC data collection takes place in 2008, 2010 and 2012.

---

[1] Students with significant intellectual disabilities and those with a language background other than English who arrived in Australia less than one year ago may be exempted from testing.

To enable the longitudinal analysis of the determinants of school performance, information on the time of testing, test repeating[2], and age at time of testing are available in the linked NAPLAN data files. To ensure that predictors are measured prior to NAPLAN testing, we have assigned NAPLAN test scores to predictors of the most immediate survey wave prior to the test. As a result, test scores in year 2008[3] have been matched to predictors of wave 2 (2006), tests scores in years 2008[4], 2009 and 2010[5] have been matched to predictors of wave 3 (2008), and test scores in year 2010[6], 2011 and 2012 have been matched to predictors of wave 4 (2010). The time gap in months between the LSAC main survey time and the NAPLAN test ranges from 1 month to 25 months. In the analyses, NAPLAN tests scores of school grade 3, 5 and 7 are assigned to information collected in LSAC-K that correspond to children around average ages 6/7, 8/9 and 10/11, respectively. To assess the effect of different time gaps, we included in preliminary multivariate models a control variable for the calendar year of administration of NAPLAN test, but results remained unchanged.

We reduce the number of outcomes by means of factor analysis because scores on the five NAPLAN tests display high common correlation (overall Cronbach alpha = .936). The results of the factor analysis with varimax rotation indicate that only one factor captures common variation among the five scores (eigenvalue=3.708). The standardized factor – NAPLAN score – ranges from -3.33 to 3.01 and has a mean value approximate to 0 and a standard deviation approximate to 1. Thus, the NAPLAN score takes negative values for scores below the grand mean and positive values for scores above the grand mean across grade 3, 5 and 7 NAPLAN tests[7].

Residential relocations

The LSAC collects relevant measures for building detailed residential histories of children at each wave, with information since last interview (or since birth in wave 1) on relocation occurrence, region of residence, recency of latest relocation before interview date, and number of life-time relocations. To address the impact of frequent mobility, we construct an indicator of cumulative frequency of life time relocations (coded 1 if child did 3+ moves, coded 0 otherwise). Relocation distance is measured in two cumulative indicators for short-distance relocations (coded 1 if moved within Local Government Areas[8], coded 0 otherwise) and for long-distance relocations (coded 1 if moved across Local Government Areas, coded 0 otherwise). Relocation age-stage consist of four indicators coded 1 if occurring before school age (i.e. before age 4/5), by school start (i.e. between age 4/5 and age 6/7), between

[2] Since only the most recent NAPLAN scores are available for children repeating a school grade and siting NAPLAN tests for a second time, we tested a dummy variable that takes value one for children repeating school grade (0 otherwise) in multivariate models, but results were largely small and statistically insignificant.
[3] If interview in Wave 3 (2008) was in May or afterwards.
[4] If interview in Wave 3 (2008) was before May.
[5] If interview in Wave 4 (2010) was in May or afterwards.
[6] If interview in Wave 4 (2010) was before May.
[7] Only selected results of domain specific tests scores are presented in the text. Full results are available upon request.
[8] Local government in Australia (LGA) is the lowest tier of government in Australia administered under the states and territories which in turn are beneath the federal tier. There are currently 565 LGAs in Australia.

age 6/7 and age 8/9, and between age 8/9 and age 10/11).[9] It is worth noting that most children in our sample moved home by age 10/11. About 26 percent did not move home, 31 percent moved home before reaching school age and 43 percent moved home during school age.

Covariates

We include a number of covariates that are known correlates of residential relocations and academic performance. We divide them among those that stem from the family and home environments, those from the residential environment, and those from the school context. Family covariates include family structure indicators (for one biological parent and step parents; *ref.* two biological parents), number of under-age children in household (for two or three children, and four or more children; *ref.* only one child), maternal age in years, maternal education indicator (coded 1 if completed secondary education by the first interview, coded 0 otherwise), parental unemployment indicator (coded 1 if at least one parent is unemployed, coded 0 otherwise), poor household indicator (coded 1 if household income is less than fifty percent of median household income, coded 0 otherwise). An unclean and crowded home restricts cognitive development and for that reason home environment covariates include an indicator of household crowding (number of residents divided by number of bedrooms in the dwelling), the interviewer observations of the internal condition of the dwelling (coded 1 if all visible rooms of the household were NOT reasonably uncluttered, coded 0 otherwise). To address the impacts of the residential environment, we include as covariates the Socio-Economic Index For Areas (SEIFA[10]) score divided by 100, an indicator for the parent's perception of whether the neighbourhood is a good place to bring up children (coded 1 if yes, coded 0 if no), and an indicator of residence in an urban area (coded 1 if yes, coded 0 if no). Characteristics of the school environment include an indicator of whether the child meets friends often (coded 1 if yes, coded 0 if no), an indicator of whether the child has attended more than one school (coded 1 if yes, coded 0 if no), an indicator of frequent school absences (coded 1 if yes, coded 0 if no), and an indicator of teacher's opinion about whether parents are involved with the school (coded 1 if yes, coded 0 if no). We also include additional demographic and (pre-school) child characteristics. These covariates included child's birthweight percentile, child's age in months, child's gender, child's country of birth (indicator coded 1 if Australian born, coded 0 otherwise), child's indigenous background (indicator coded 1 if indigenous background, coded 0 otherwise). Table A1 in the on-line appendix presents summary statistics for all model covariates.

Analytical Strategy

After the description of NAPLAN test score averages by school grade and relocation circumstance (Table 1), our analytical strategy combines two types of panel data methods to

[9] We disregard moves that occur between age 10/11 and age 12/13 because we do not know with certainty if a move has occurred before NAPLAN test administration for seventh graders, the last observation of school performance we observe.

[10] The SEIFA index combines different aspects of socio-economic advantage/disadvantage in the neighbourhood, including income, education, employment, and housing stress.

address longitudinal, multivariate associations: hybrid regression and random coefficient regression models.

First we estimate hybrid panel regression models (Allison, 2009) to address the question of whether relocations (i.e. occurrence, distance, and frequency) *impact* children's school performance (Table 2). The hybrid panel model is an extension of multivariate regression models that leverage the longitudinal structure of the data by partitioning the overall variation of the association under study in between- and within-subject variation.[11] By between-subject variation we refer to *average differences* in school performance across children. The between-subject analysis enables conclusions on whether school performance is associated with group-differences in the family home and residential environments of those who move and those who stay. By within-subject variation we refer to *changes within* children in school performance before and after the relocation. The within-subject analysis allows conclusions about the *impacts* of relocations by comparing the average school performance in periods before and after relocations. An additional advantage of hybrid panel regression models is that time-invariant selective factors or traits of children are cancelled out in the model specification, as in fixed-effects models.

Second, we estimate random coefficient regression models to address the question of the contemporaneous and cumulative impacts of age-specific relocations on progress in school performance (Table 3). Random coefficients models are extensions of multivariate regression models that, leveraging the longitudinal structure of the data, relax the assumption that all study subjects follow the same average trajectory, e.g. a steady increase in academic performance (Bliese & Ployhart, 2002). To relax this assumption, we define a model with a random intercept and a random coefficient for age. This model resembles a basic growth model, where each child's school performance may start at a different level and depart from the average progress. The cumulative impact of age-specific relocation is captured by three indicators that predict whether the individual experienced relocation before school age, at age 6/7, or at age 8/9 (coded 0 if no relocation within the age-group occurred and when the study subject has not yet attained the age group). Age-specific relocations representing contemporaneous effects of moves was also included in the model as four indicators flagging (i.e. coded 1 for) relocations occurring at age 4/5, age 6/7, age 8/9 and age 10/11 (coded 0 otherwise). Significant associations of the cumulative age-specific indicators will shed light on the relocation ages that have sustained or later impacts in academic progress. Significant associations of the contemporaneous age-specific indicators will shed light on the relocation ages with immediate impacts on academic progress.

To identify factors that influence the above-mentioned associations, we estimate several models where we add other covariates to model specifications in a sequential fashion. In a first model specification, we only control for demographic variables and children's infancy indicators. In the second model we add to the first model specification controls for family structure and socio-economic status. In the third model we add to the first model

---

[11] In brief, the method proposed by Allison (2005) consists of the estimation of random-effects regression models adding group-mean deviated variables of time-varying covariates in the models. By adding group-mean deviated variables of the covariates in the model, the assumption in random-effects models that the random term is uncorrelated with the covariates is relaxed. Additionally, the coefficients of the group-mean deviated variables can be interpreted as within-effects, and the coefficients of the original variables can be interpreted as between-effects.

specification controls for the residential environments, including characteristics of the peer-, neighbourhood-, and school-context. In the fourth model we include all sets of control variables. Variations in the significance and the strength of the relocation coefficients can be used as an indication of the type of factors that more likely affect the association between relocations and school performance.

Results

Table 1 presents weighted means of standardized NAPLAN test scores by school grade and a number of characteristics of children's lifetime relocation experiences – children's age, distance and frequency. Detailed mean test scores for subject-specific tests can be consulted in Table A2 in the on-line appendices. We show results for school grades 3, 5, and 7 as well as the progression between school grade 3 and 7. Note that the average standardized test score increases across school grades because test results are reported in single scales.

Results according to relocation characteristics in Table 1 suggest certain association patterns that repeat across school grades. First, we find that children with early relocation experiences, since infancy up to pre-school (i.e. before age 4/5), have statistically significant worse average scores in all school grades than children who do not move in early stages. The consistent pattern across school grades hints at a possible sustainability of the impact of children's early experiences in later cognitive development. Test scores are slightly worse for children who move at later stages, between ages 4/5 to 8/9, but the statistical significance of the association is largely marginal. The average lower residential mobility of families with school-age children may partly explain lower significance levels when the average differences are actually larger. Second, mean test scores for children who relocated over short distances are slightly better than those who relocated over long distances, and even higher than the school-grade average for grades 3 and 7. Despite this, no statistically significant differences in test scores by distance are found. Third, the largest mean differences in school performance observed in Table 1 are those related to the frequency of relocation. Compared to grade-specific average test performance, children who relocate once or twice perform better, while children who relocate three or more times perform much worse. These mean differences are highly significant and suggest a non-linear association between relocation frequency and school performance as found in previous American research (Coley?).

Regarding performance progress in NAPLAN tests from grade 3 to 7, we find very small and largely insignificant differences in Table 1. This result is a preliminary indication that school performance trajectories are not importantly altered by relocation events. If the performance growth rate is the same despite differences in initial levels, then, relocations might be leading towards neither convergence nor divergence in school performance. Our next step is to test whether these associations remain in a multivariate setting.

– TABLE 1 about here –

Within- and between-subject effects of relocation distance and frequency

Table 2 displays selected results (and Table A3 in the on-line appendix displays full results) of the hybrid regression models that address the multivariate associations of relocation distance and frequency with differences in school performance across children who move and who stay (*between-subject effects*) and changes in school performance before and after a relocation (*within-subject effects*). Model 1 in Table 2 included relocation variables (i.e. frequency and distance) and, additionally, controlled for age and other characteristics of children. Results from Model 1 indicate that some relocation characteristics are only related to average performance differences between children, only related to changes in school performance after relocations, or unrelated with school performance. More specifically, we find a significant between-effect of relocation frequency (*b= -.198, p>.001*) where children moving three or more times perform worse than children who move less or who do not move. We also find a positive within-effect of long-distance relocations (*b= .098, p>.01*), where children do improve their academic performance after moving across regional boundaries. We find no significant between- or within-effect for short distance relocations on school performance. Overall, the size of the effects in Model 1 is modest, below .2 standard deviations. In contrast, other model variables such as age or indigenous origin have larger effects that exceed 2 or .5 standard deviations, respectively.

In Models 2, 3 and 4 of Table 2, we add to Model 1 characteristics of the family and home environment, the residential environment, and the school environment, respectively. Comparing results of these models to those of Model 1, we observe a few changes in coefficients' size and significance. First, the significant negative between-effect of relocation frequency vanishes after controlling for characteristics of the family and home environment. This change might have been induced by the inclusion of indicators of household structure such as lone parent or step-family, which are negatively correlated with school performance but positively correlated with frequent relocations. Second, we find marginal positive statistical significance for a between-effect of short distance moves after controlling for characteristics of the family and home environments, and for those of school environments. The inclusion of characteristics associated with relocations and school performance – particularly those with relevant size effects such as absenteeism, parents' school involvement, and household structure – might suggest that average performance of children is better among those who relocate, not frequently, over short distances compared to otherwise. In model 5 of Table 2, we add to Model 1 all additional covariates of models 2, 3 and 4, and thus, it is a fully specified model. Results of Model 5 are similar to those of prior models, and thus, interpretations of the impacts of relocations on school performance remain unchanged.

– TABLE 2 about here –

Effect of age-specific relocations

Selected results of the random coefficients models are presented in Table 3 (full results are available in Table A4 in the on-line appendix). The pattern of results were very similar across model specifications, and for that reason we only show Model 1, with the baseline specification, and Model 5, the fully specified model. Overall, we find neither substantive nor very significant effects of the age stage when relocations occur on school performance trajectories. In Model 1, which additionally controls for children's characteristics, only relocations occurring at the time of school entry (i.e. between age 4/5 and age 6/7) have marginally significant and small immediate impacts (*b= -.036, p>.05*), and cumulative impacts (*b= -.048, p>.1*) on school performance. In the fully-specified Model 5, the modest immediate impact of relocations occurring at the time of school entry remains unchanged, while the cumulative impact vanishes. Controlling for age and age squared in the model renders insignificant and small coefficients not only for age-at-relocation variables, but also for the random coefficient of age, which suggests that children follow similar patterns of higher scores in NAPLAN tests overtime. Overall, these results suggest that developmental stage at relocation has little effect on school performance trajectories measured as repeated participations in NAPLAN tests.

– TABLE 3 about here –

Discussion

In this study, we have examined for the first time in Australia the longitudinal associations between relocations, from infancy to middle childhood, and school performance in school grades 3, 5 and 7 using recent data from the Longitudinal Study of Australian Children. We are also one of the few studies to use longitudinal data that enables disentanglement of whether any observed negative associations are the result of relocations, or due to pre-existing characteristic of children who relocate. We have argued that the associations between childhood relocations and school performance are complex and highly dependent on the intersections between relocation biographies (e.g. frequency, distance, and developmental age-stage) and the proximal contexts where children are embedded (e.g. family, home, and school).

Some key findings arise from our study. First, our bivariate and multivariate analyses confirm for the Australian case that, under certain conditions, residential relocations are associated with school performance. In line with studies from the US context, the associations we find can be considered *modest*, since differences among those who relocate and those who do not are around 0.1 - 0.2 standard deviations. To put this in perspective, we find that differences among children who experience changes in family structure across survey waves are around 0.3 - 0.6 standard deviations.

Second, we have some evidence of a non-linear association between relocation frequency and school performance. Bivariate analyses showed that children who relocate three or more times during childhood display lower-than-average school performance persistently through school grades 3, 5 and 7. In contrast, children that relocated one or two times performed better in school, particularly at later school grades, than children who stayed in the same location. The multivariate analyses showed that very frequent relocations (i.e. three or more) did not induce a worsening in school performance over time, but the initial performance level was lower than average and remained lower across school grades. Hybrid panel regression models allowed partitioning the effect of relocations in differences in school performance between subjects (between-effects) and changes in school performance within subjects (within-effects), which was particularly useful to show that some associations were due to impacts of relocation and some were due to pre-existing differences between children who relocate and those who do not. Additionally, results from multivariate analyses showed that the negative associations between frequent relocations and school performance vanished after controlling for characteristics of the family and home environment. These results can be taken as evidence of family situations that lead to frequent relocations as the determinants of poor school performance. On the one hand, children who relocate moderately may be found in family and home contexts that provide opportunities, while on the other hand, children who relocate frequently may be found in contexts with high concentrations of disadvantage, with residential insecurity one possible source.

Third, our multivariate results show that long distance relocations were modestly associated with better school performance after the relocation (within-effect). The result is contrary to the idea that relocations over longer distances break proximal environments and preclude children from benefiting from enduring connections with peers, the community, and the school environment. However, long distance relocations are often motivated by positive changes, such as parental careers or neighbourhood improvements that derive in better situations and contexts for children's cognitive development. Additionally, results from models controlling for a number of predictors showed that children who relocated over short distances have better average school performance than children who remained in the same housing location (between-effect). This result can be also interpreted as evidence of inequality structures in household relocations, where individuals that do not move during childhood are in families that are trapped in situations and contexts of disadvantage.

Last, extending extant research, we examined the associations between the relocation age-patterns and school performance trajectories. We found that the negative bivariate association between childhood relocations and school performance is slightly stronger at the outset of primary school, and effects of earlier relocations endure through time. Multivariate results from random coefficient models showed no relevant impacts of the age-at-relocation on performance trajectories. Nevertheless, a modest effect of relocations at about school start (ages 4/5 to 6/7) remained significant in models controlling for a number of predictors, suggesting that changes in proximal contexts occurring at critical moments in children's lives, such as school entry, can be detrimental to their academic performance development.

In conclusion, our findings suggest that the associations of relocations with cognitive ability and development are imbued in the biographical and social context of childhood relocations. A key question that arises from our research is how best to prepare and equip children for navigating through school and mitigating academic underperformance when they face residential relocations. Since family relocations are often a necessary feature of contemporary housing and labour markets, interventions are needed to buffer the potential negative impacts of relocations on children's cognitive development and overall wellbeing. For instance, policies aimed at supporting disadvantaged families, which reduce situations of residential instability, may benefit children's cognitive development. Policy should also tackle the direct impacts of relocations through general campaigns and case-specific counselling on relocation preparations. It has been found in other contexts (e.g. Martin, 1999) that relocation preparations can explicitly reduce problems that arise when moving home and that may negatively impact households, particularly children.

Our study is embedded in an emerging body of research, largely focussed on the US context, and contributes by examining the relevant longitudinal associations in the Australian context. We did not find the associations to differ much to those of US based research, despite the relatively more equal chances to access high-quality early education and lower poverty levels among Australian children. Our study also makes a contribution by furthering the diachronic assessment of the associations between academic performance and residential histories, using analytical models and measures that acknowledge the biographical aspects of the association, as well as potential sources of time-constant unobserved heterogeneity.

Despite the contributions, we note several analytical limitations in our study. First, despite the number of sensitivity tests we performed, our results may not be completely accurate due to the different calendars of data collection of LSAC (every two years, from March to December) and NAPLAN tests (each year, May). Second, we note that there is a lower number of relocation events during school-age than before school-age, which reflect the lower tendency of families with school-age children to move, but which may also have rendered lower statistical power to assess the associations between school-age relocations and school performance. Last, we did not have information on the motivations for household relocations, the assessment of which can be critical to understand the eventual impact of relocations on school performance, and to offer more adequate solutions for policy intervention in the field.

Acknowledgements

This paper uses unit record data from Growing Up in Australia, the Longitudinal Study of Australian Children (LSAC) Survey. The study is conducted in partnership between the Department of Social Services (DSS), the Australian Institute of Family Studies (AIFS) and the Australian Bureau of Statistics (ABS). The views expressed in this report are those of the authors alone and do not represent those of DSS, AIFS, the ABS or DEEWR.

References

Ackerman, B. P., Kogos, J., Youngstrom, E., Schoff, K., & Izard, C. (1999). Family instability and the problem behaviors of children from economically disadvantaged families. *Developmental psychology*, 35(1), 258-268.

Adam, E. K., & Chase-Lansdale, P. L. (2002). Home sweet home (s): parental separations, residential moves, and adjustment problems in low-income adolescent girls. *Developmental psychology*, 38(5), 792-805.

Allison, P. D. (2009). *Fixed-Effects Regression Models*. Thousand Oaks, CA: Sage Publications.

Anderson, S., Leventhal, T., Newman, S., & Dupéré, V. (2014). Residential Mobility Among Children: A Framework for Child and Family Policy. *Cityscape*, 16(1), 5-36.

Astone, N. M., & McLanahan, S. S. (1994). Family structure, residential mobility, and school dropout: A research note. *Demography*, 31(4), 575-584.

Australian Council of Social Service (2014). The Poverty Report 2014.

Bliese, P. D., & Ployhart, R. E. (2002). Growth modeling using random coefficient models: Model building, testing, and illustrations. *Organizational Research Methods*, 5(4), 362-387.

Bradley, R. H., & Corwyn, R. F. (2002). Socioeconomic status and child development. *Annual review of psychology*, 53(1), 371-399.

Bronfenbrenner, U., & Morris, P. A. (2006). The bioecological model of human development. In R. M. Lerner and W. Damon (Eds.), *Handbook of child psychology Vol 1* (pp. 793-828). Hoboken, NJ: John Wiley & Sons, Inc.

Clark, W., & Maas, R. (2016). Spatial mobility and opportunity in Australia: Residential selection and neighbourhood connections. *Urban Studies*, 53(6), 1317-1331.

Coley, R. L., Leventhal, T., Lynch, A. D., & Kull, M. (2013). Relations between housing characteristics and the well-being of low-income children and adolescents. *Developmental psychology*, 49(9), 1775.

Coley, R. L., & Kull, M. (forthcoming). Cumulative, Timing-Specific, and Interactive Models of Residential Mobility and Children's Cognitive and Psychosocial Skills. Child Development.

Crowder, K., & South, S. J. (2003). Neighborhood distress and school dropout: The variable significance of community context. *Social Science Research*, 32(4), 659-698.

Crowder, K., & Teachman, J. (2004). Do residential conditions explain the relationship between living arrangements and adolescent behavior?. *Journal of Marriage and Family*, 66(3), 721-738.

Daraganova, G., Edwards, B., & Sipthorp, M. (2013). *Using National Assessment Program Literacy and Numeracy (NAPLAN) Data in the Longitudinal Study of Australian Children (LSAC)*. Department of Families, Housing, Community Services and Indigenous Affairs.

Dockery, A. M., Kendall, G., Li, J., Mahendran, A., Ong, R., & Strazdins, L. (2010). Housing and children's development and wellbeing: a scoping study. *Melbourne: Australian Housing and Urban Research Institute*.

Ersing, R. L., Sutphen, R., & Loeffler, D. N. (2009). Exploring the impact and implications of residential mobility: From the neighborhood to the school. *Advances in Social Work*, 10(1), 1-18.

Evans, G. W., & Wachs, T. D. (2010). Chaos and its influence on children's development. Washington, DC: American Psychological Association.

Fowler, P. J., Henry, D. B., Schoeny, M., Taylor, J., & Chavira, D. (2014). Developmental timing of housing mobility: Longitudinal effects on externalizing behaviors among at-risk youth. *Journal of the American Academy of Child & Adolescent Psychiatry*, 53(2), 199-208.

Gasper, J., DeLuca, S., & Estacion, A. (2010). Coming and going: Explaining the effects of residential and school mobility on adolescent delinquency. *Social Science Research*, 39(3), 459-476.

Gray, M., & Sanson, A. (2005). Growing up in Australia: the longitudinal study of Australian children. *Family Matters*, (72), 4.

Hansen, K. (2014), Moving house for education in the pre-school years. *British Educational Research Journal*, 40: 483–500. doi: 10.1002/berj.3092

Haveman, R., Wolfe, B., & Spaulding, J. (1991). Childhood events and circumstances influencing high school completion. *Demography*, 28(1), 133-157.

Herbers, J. E., Cutuli, J. J., Supkoff, L. M., Heistad, D., Chan, C. K., Hinz, E., & Masten, A. S. (2012). Early reading skills and academic achievement trajectories of students facing poverty, homelessness, and high residential mobility. *Educational Researcher*, *41*(9), 366-374.

Huinink, J., Vidal, S., & Kley, S. (2014). Individuals' openness to migrate and job mobility. *Social science research*, *44*, 1-14.

Ingersoll, G. M., Scamman, J. P., & Eckerling, W. D. (1989). Geographic mobility and student achievement in an urban setting. *Educational Evaluation and Policy Analysis*, 11(2), 143-149.

Joshi, H., Gambaro, L., Mostafa, T., Lupton, R., Lennon, M.C., Buttaro, A., & Beck, B. (2015). 'Moving home in the early years: Family and child outcomes in the UK and US.' Centre for Longitudinal Studies.

Kull, M. & Coley, R. L (forthcoming). Operationalizing Residential Mobility:How is Mobility Associated with Child Functioning?

Lawrence, E., Root, E. D., & Mollborn, S. (2015). Residential mobility in early childhood: Household and neighborhood characteristics of movers and non-movers. *Demographic research*, *33*, 939.

Maguire, B., Edwards, B., & Soloff, C. (2012). Housing characteristics and changes across waves. *Annual statistical report 2011*, 67-77.

Martin, R. (1999). Adjusting to job relocation: Relocation preparation can reduce relocation stress. *Journal of Occupational and Organizational Psychology*, *72*(2), 231-235.

Mehana, M., & Reynolds, A. J. (2004). School mobility and achievement: A meta-analysis. *Children and Youth Services Review*, *26*(1), 93-119.

Moen, P. E., Elder Jr, G. H., & Lüscher, K. E. (1995). *Examining lives in context: Perspectives on the ecology of human development*. Washington, DC, US: American Psychological Association.

Pettit, B., & McLanahan, S. (2003). Residential Mobility and Children's Social Capital: Evidence from an Experiment. *Social Science Quarterly*, 84(3), 632-649.

Pribesh, S., & Downey, D. B. (1999). Why are residential and school moves associated with poor school performance?. *Demography*, 36(4), 521-534.

Rasmussen, A. W., & Stratton, L. S. (2012). How distance to a non-residential parent relates to child outcomes. IZA Discussion Paper No. 6965. Available at SSRN: http://ssrn.com/abstract=2170653

Royston, P., & White, I. R. (2011). Multiple imputation by chained equations (MICE): implementation in Stata. *Journal of Statistical Software*, *45*(4), 1-20.

Rumberger, R., & Lim, S. A. (2008). *Why students drop out of school: A review of 25 years of research*. (Vol. 15, pp. 1-130). California Dropout Research Project Report.

Rumbold, A. R., Giles, L. C., Whitrow, M. J., Steele, E. J., Davies, C. E., Davies, M. J., & Moore, V. M. (2012). The effects of house moves during early childhood on child mental health at age 9 years. *BMC public health*, 12(1), 583-594.

Scanlon, E., & Devine, K. (2001). Residential mobility and youth well-being: Research, policy, and practice issues. *J. Soc. & Soc. Welfare*, 28, 119-138.

Schmitt, S. A., & Lipscomb, S. T. (2016). Longitudinal associations between residential mobility and early academic skills among low-income children. *Early Childhood Research Quarterly*, 36, 190-200.

Sipthorp, M., & Misson, S. (2009). *Wave 3 weighting and non-response*. Australian Institute of Family Studies.

South, S. J., & Haynie, D. L. (2004). Friendship networks of mobile adolescents. *Social Forces*, *83*(1), 315-350.

Swanson, C. B., & Schneider, B. (1999). Students on the move: Residential and educational mobility in America's schools. *Sociology of Education*, 54-67.

Voight, A., Shinn, M., & Nation, M. (2012). The longitudinal effects of residential mobility on the academic achievement of urban elementary and middle school students. *Educational Researcher*, 41, 385–392.

Wood, D., Halfon, N., Scarlata, D., Newacheck, P., & Nessim, S. (1993). Impact of family relocation on children's growth, development, school function, and behavior. *JAMA*, 270(11), 1334-1338.

Ziol-Guest, K. M., & McKenna, C. C. (2014). Early childhood housing instability and school readiness. *Child development*, 85(1), 103-113.

Table 1. Means of standardized NAPLAN test scores by school grade and relocation characteristics

	Grade 3		Grade 5		Grade 7		Grade 7-Grade 3	
Average	-0.85		0.05		0.63		1.50	
Age at relocation								
before 4/5	-0.89	**	0.03	**	0.61	*	1.50	
4/5 to 6/7	-0.92	**	0.02	(*)	0.60	(*)	1.51	
6/7 to 8/9	-1.02		0.01		0.59	(*)	1.50	
8/9 to 10/11			0.03		0.6		1.52	
Relocation distance								
short distance	-0.87		0.06		0.64		1.51	
long distance	-0.89		0.03		0.62		1.52	
Relocation frequency								
1 to 2	-0.84		0.08	(*)	0.68	**	1.52	(*)
3 or more	-0.98	***	-0.01	*	0.55	***	1.49	

Source: LSAC-K (2004-2012). Significance tests for mean differences between relocation characteristics and their absence. (*) = p<0.1; * = p<0.05; ** = p<0.01; *** = p<0.001.

Table 2. Between- and within-subject differences in school performance

	Model 1 Baseline controls	**Model 2** Family/home controls	**Model 3** Residential controls	**Model 4** School controls	**Model 5** All controls
Differences *between* individuals					
No relocation	*ref.*	*ref.*	*ref.*	*ref.*	*ref.*
Short-distance relocations	0.041	0.077**	0.027	0.066*	0.069*
	[0.03]	*[0.03]*	*[0.03]*	*[0.03]*	*[0.03]*
Long-distance relocations	-0.006	0.027	0.009	0.026	0.048
	[0.04]	*[0.04]*	*[0.04]*	*[0.04]*	*[0.04]*
Frequent relocations (three +)	-0.198***	-0.066	-0.156**	-0.149**	-0.053
	[0.05]	*[0.05]*	*[0.05]*	*[0.05]*	*[0.05]*
Differences *within* individuals					
No relocation	*ref.*	*ref.*	*ref.*	*ref.*	*ref.*
Short-distance relocation	0.014	0.01	0.016	0.011	0.011
	[0.02]	*[0.02]*	*[0.02]*	*[0.02]*	*[0.02]*
Long-distance relocation	0.098**	0.093**	0.104**	0.095**	0.096**
	[0.03]	*[0.03]*	*[0.03]*	*[0.03]*	*[0.03]*
Frequent relocations (three +)	-0.001	-0.001	-0.002	-0.001	-0.002
	[0.02]	*[0.02]*	*[0.02]*	*[0.02]*	*[0.02]*
Subjects	3,481	3,481	3,481	3,481	3,481
Subject-observations	8,609	8,609	8,609	8,609	8,609

Notes: **Hybrid panel regression models**. Coefficients can be interpreted as standard deviation change. Standard errors in square brackets under coefficients. Control variables – All models include children's gender, age in months, age-squared, indigenous background, non-Australian born, birth weight percentile. Model 2 includes one biological parent, step-family, two or three / four or more under-age children in household, maternal age, mother completed secondary education, at least one parent is unemployed, and poor household. Model 3 includes house crowding indicator, house cluttered, SEIFA index, bad neighborhood perception, and urban area. Model 4 includes school change, absenteeism, and regular contact with friends. Model 5 includes all covariates mentioned before. (*) = p<0.1; * = p<0.05; ** = p<0.01; *** = p<0.001.

Table 3. Effects of age-specific relocations on school performance trajectories

	Model 1	**Model 5**
Relocation age-stage (contemporaneous)		
Before age 4/5	-0.001	-0.001
	[0.01]	*[0.01]*
Ages 4/5 to 6/7	-0.036*	-0.035*
	[0.02]	*[0.02]*
Ages 6/7 to 8/9	0.014	0.01
	[0.02]	*[0.02]*
Ages 8/9 to 10/11	-0.002	-0.002
	[0.02]	*[0.02]*
Relocation age-stage (cumulative)		
Before age 4/5	-0.038	-0.007
	[0.03]	*[0.02]*
Ages 4/5 to 6/7	-0.048(*)	0.008
	[0.03]	*[0.03]*
Ages 6/7 to 8/9	-0.014	0.004
	[0.02]	*[0.02]*
Subjects	3,481	3,481
Subject-observations	8,609	8,609

Notes: **Random-coefficient regression models**. Coefficients can be interpreted as standard deviation change. Standard errors in square brackets under coefficients. Control variables – All models include children's gender, age in months, age-squared, indigenous background, non-Australian born, birth weight percentile. Model 5 additionally includes one biological parent, step-family, two or three / four or more under-age children in household, maternal age, mother completed secondary education, at least one parent is unemployed, poor household, house crowding indicator, house cluttered, SEIFA index, bad neighborhood perception, urban area, school change, absenteeism, and regular contact with friends. (*) = p<0.1; * = p<0.05; ** = p<0.01; *** = p<0.001.

On-line appendix

Table A1. Univariate summary statistics

	Mean	SD	Min.	Max.
Test score: Reading	504.312	94.177	0	842
Test score: Writing	492.548	83.73	89	807.2
Test score: Spelling	494.501	88.003	180	751.9
Test score: Grammar	509.891	97.267	62	839
Test score: Numeracy	499.606	90.211	0	848.4
Standardized score	0.073	0.948	-3.332	3.01
Short-distance relocations	0.619	0.486	0	1
Long-distance relocations	0.177	0.381	0	1
1 or 2 relocations	0.507	0.5	0	1
3 or more relocations	0.193	0.395	0	1
Relocated before age 4/5	0.589	0.492	0	1
Relocated ages 4/5 to 6/7	0.257	0.437	0	1
Relocated ages 6/7 to 8/9	0.145	0.352	0	1
Relocated ages 8/9 to 10/11	0.064	0.245	0	1
Female	0.493	0.5	0	1
Age	8.807	1.655	6.25	11.667
Non-australian born	0.035	0.185	0	1
Indigenous	0.024	0.154	0	1
Birthweight	49.897	28.739	0.001	100
Two biological parents	0.816	0.388	0	1
Lone parent	0.129	0.335	0	1
Step family	0.056	0.229	0	1
One child	0.107	0.31	0	1
2 - 3 childre	0.783	0.413	0	1
4 or more children	0.11	0.313	0	1
Poor household	0.165	0.371	0	1
Maternal education	0.82	0.384	0	1
Unemployed parent	0.266	0.442	0	1
Maternal age	39.004	5.214	22	58
House crowding	1.287	0.392	0.4	5
House cluttered	0.053	0.225	0	1
SEIFA index	10.128	0.746	5.9	12.1
Bad neighbourhood	0.092	0.289	0	1
Urban area	0.852	0.355	0	1
Absentism	0.041	0.198	0	1
Regular friend's contact	0.46	0.498	0	1
School change	0.123	0.329	0	1
Parent' school involvement	0.89	0.312	0	1

Source: LSAC-K (2004-2010).

Table A2. Means of standardized NAPLAN test scores and subject-specific test scores by school grade and relocation characteristics

	SD score		Reading		Writing		Spelling		Grammar		Numeracy	
						Grade 3						
Average	-0.85		419.72		427.15		417.61		426.68		415.83	
Age at relocation												
before 4/5	-0.89	**	415.44	**	424.57	*	413.42	**	422.53	**	413.17	*
4/5 to 6/7	-0.92	**	413.55	*	422.86	(*)	408.86	***	418.80	**	411.57	(*)
6/7 to 8/9	-1.02		415.16		401.44	*	404.20		409.84		397.39	(*)
Relocation distance												
short distance	-0.87		417.58		426.22		415.42		425.27		414.52	
long distance	-0.89		418.98		423.23		412.42		421.52		414.81	
Relocation frequency												
1 to 2	-0.84		420.37		427.33		418.69		427.05		417.02	
3 or more	-0.98	***	408.09	**	418.33	*	403.09	***	414.94	**	405.73	**
						Grade 5						
Average	0.05		500.97		491.39		492.41		510.27		497.36	
Age at relocation												
before 4/5	0.03	**	498.56	*	488.22	**	491.07		506.67	**	494.55	**
4/5 to 6/7	0.02	(*)	498.75		486.83	*	488.48	(*)	509.17		492.99	*
6/7 to 8/9	0.01		498.51		487.73		489.11		505.10	(*)	490.55	**
8/9 to 10/11	0.03		511.45		473.58		486.98		502.46		506.63	
Relocation distance												
short distance	0.06		501.53		490.89		493.46		511.08		497.82	
long distance	0.03		500.81		490.26		488.70		507.74		492.23	(*)
Relocation frequency												
1 to 2	0.08	(*)	502.92		493.37	*	495.06	*	512.27		498.58	
3 or more	-0.01	*	497.28		483.43	***	486.47	*	504.31	*	491.76	*
						Grade 7						

Average	0.63		553.51		531.23		548.39		555.13		550.72	
Age at relocation												
before 4/5	0.61	*	551.85		528.58	*	546.90		552.51	*	547.50	**
4/5 to 6/7	0.60	(*)	550.87		523.74		547.10		551.93	(*)	546.91	(*)
6/7 to 8/9	0.59	(*)	550.81		529.98		544.86		550.08	*	543.77	**
8/9 to 10/11	0.60		551.86		530.82		547.74		549.77	(*)	544.19	*
Relocation distance												
short distance	0.64		554.21		530.71		549.35		555.27		549.5	
long distance	0.62		553.36		529.32		544.98		552.93		549.97	
Relocation frequency												
1 to 2	0.68	**	557.18	**	533.74	*	551.86	**	559.65	**	553.21	(*)
3 or more	0.55	***	547.54	**	524.67	**	543.38	*	546.83	***	542.57	***
Grade 7 - Grade 3												
Average	1.50		136.04		102.39		133.01		133.40		134.88	
Age at relocation												
before 4/5	1.50		137.29		100.78		133.92		132.98		132.98	(*)
4/5 to 6/7	1.51		137.72		94.43	**	136.58	*	134.79		134.77	
6/7 to 8/9	1.50		137.59		104.95		133.24		129.16		132.9	
8/9 to 10/11	1.52		140.57	(*)	104.21		135.48		131.64		133.6	
Relocation distance												
short distance	1.51		138.04	*	101		135.25	**	133.48		134.54	
long distance	1.52		137.16		102.28		131.87		135.86		136.58	
Relocation frequency												
1 to 2	1.52	(*)	137.49		104.22		134.61		135.69		135.14	
3 or more	1.49		137.69		96.88	*	135.06		130.5		132.34	

Source: LSAC-K (2004-2010). Significance tests for mean differences between relocation characteristics and their absence. (*) = $p<0.1$; * = $p<0.05$; ** = $p<0.01$; *** = $p<0.001$.

Table A3. Between- and within-subject differences in school performance (full models)

	Model 1	Model 2	Model 3	Model 4	Model 5
Differences *between* individuals					
Short-distance relocations	0.041	0.077**	0.027	0.066*	0.069*
	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]
Long-distance relocations	-0.006	0.027	0.009	0.026	0.048
	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]
Frequent relocations (three +)	-0.198***	-0.066	-0.156**	-0.149**	-0.053
	[0.05]	[0.05]	[0.05]	[0.05]	[0.05]
Differences *within* individuals					
Short-distance relocations	0.014	0.01	0.016	0.011	0.011
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
Long-distance relocations	0.098**	0.093**	0.104**	0.095**	0.096**
	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]
Frequent relocations (three +)	-0.001	-0.001	-0.002	-0.001	-0.002
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
Other model covariates					
Female (between-effect)	0.198***	0.207***	0.204***	0.196***	0.207***
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
age (between-effect)	2.873***	2.373***	2.114***	2.684***	1.834**
	[0.65]	[0.63]	[0.63]	[0.64]	[0.61]
age2 (between-effect)	-0.163***	-0.132***	-0.116**	-0.151***	-0.098*
	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]
Non-australian born (between-effect)	0.397***	0.322***	0.320***	0.400***	0.287***
	[0.07]	[0.06]	[0.06]	[0.06]	[0.06]
Indigenous (between-effect)	-0.640***	-0.460***	-0.517***	-0.540***	-0.370***
	[0.08]	[0.08]	[0.08]	[0.08]	[0.07]
Birthweight (between-effect)	0.001	0	0	0	0
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
age (within-effect)	1.135***	1.059***	1.136***	1.131***	1.054***
	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]
age2 (within-effect)	-0.043***	-0.043***	-0.043***	-0.043***	-0.042***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Lone parent (between-effect)		-0.180***			-0.127*
		[0.05]			[0.05]
Step family (between-effect)		-0.183**			-0.157*
		[0.07]			[0.07]
2 - 3 children (between-effect)		-0.061			-0.067(*)
		[0.04]			[0.04]
4 + children (between-effect)		-0.227***			-0.151**
		[0.05]			[0.05]
Lone parent (within-effect)		-0.01			-0.012
		[0.03]			[0.03]
Step family (within-effect)		0.027			0.023
		[0.04]			[0.04]

Poor household (between-effect)		-0.172**			-0.091(*)
		[0.05]			[0.05]
Maternal education (between-effect)		0.268***			0.195***
		[0.03]			[0.03]
Unemployed parent (between-effect)		0.037			0.054
		[0.04]			[0.04]
Maternal age (between-effect)		0.018***			0.010***
		[0.00]			[0.00]
Poor household (within-effect)		-0.005			-0.004
		[0.02]			[0.02]
Unemployed parent (within-effect)		0.029*			0.028*
		[0.01]			[0.01]
Maternal age (within-effect)		0.065***			0.066***
		[0.02]			[0.02]
House crowding (between-effect)		-0.021			-0.01
		[0.02]			[0.02]
House cluttered (between-effect)		-0.016			-0.013
		[0.02]			[0.02]
SEIFA index (between-effect)			0.260***		0.192***
			[0.02]		[0.02]
Bad neighbourhood (between-effect)			-0.118**		-0.070(*)
			[0.04]		[0.04]
Urban area (between-effect)			0.054		0.065(*)
			[0.04]		[0.04]
Bad neighbourhood (within-effect)			-0.018		-0.019
			[0.02]		[0.02]
Urban area (within-effect)			0.064*		0.066*
			[0.03]		[0.03]
Absentism (between-effect)				-0.478***	-0.328**
				[0.11]	[0.11]
Regular friend's contact (between-effect)				-0.151***	-0.124***
				[0.03]	[0.03]
School change (between-effect)				-0.063	-0.067
				[0.08]	[0.08]
Parent' school involvement (between-effect)				0.705***	0.471***
				[0.06]	[0.06]
Absentism (within-effect)				-0.027	-0.029
				[0.03]	[0.03]
Regular friend's contact (within-effect)				0.012	0.013
				[0.01]	[0.01]
School change (within-effect)				0.011	0.009
				[0.01]	[0.01]
Parent' school involvement (within-effect)				-0.002	-0.006
				[0.01]	[0.01]
Constant term	-12.29***	-11.27***	-12.19***	-11.98***	-11.21***
	[2.44]	[2.36]	[2.35]	[2.38]	[2.28]

Subjects	3,481	3,481	3,481	3,481	3,481
Subject-observations	8,609	8,609	8,609	8,609	8,609

Notes: **Hybrid panel regression models**. Coefficients can be interpreted as standard deviation change. Standard errors in square brackets under coefficients. (*) = p<0.1; * = p<0.05; ** = p<0.01; *** = p<0.001.

Table A4. Effects of age-specific relocations on school performance trajectories (full models)

	Model 1	Model 2	Model 3	Model 4	Model 5
Relocation age-stage (contemporaneous)					
Before age 4/5	0	0.003	-0.004	0	-0.001
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Ages 4/5 to 6/7	-0.036*	-0.033(*)	-0.034*	-0.039*	-0.035*
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
Ages 6/7 to 8/9	0.014	0.016	0.013	0.009	0.01
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
Ages 8/9 to 10/11	-0.002	0.006	-0.008	-0.004	-0.002
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
Relocation age-stage (cumulative)					
Before age 4/5	-0.038	0.003	-0.042(*)	-0.037	-0.007
	[0.03]	[0.03]	[0.02]	[0.03]	[0.02]
Ages 4/5 to 6/7	-0.048(*)	0.006	-0.035	-0.047(*)	0.008
	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]
Ages 6/7 to 8/9	-0.014	-0.004	-0.005	-0.013	0.004
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
Other model covariates					
female	0.201***	0.208***	0.203***	0.201***	0.209***
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
age	1.118***	1.096***	1.110***	1.114***	1.093***
	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]
age2	-0.042***	-0.042***	-0.042***	-0.042***	-0.042***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Non-Australian born	0.396***	0.336***	0.354***	0.394***	0.309***
	[0.07]	[0.06]	[0.06]	[0.07]	[0.06]
Indigenous	-0.644***	-0.494***	-0.562***	-0.636***	-0.448***
	[0.08]	[0.08]	[0.08]	[0.08]	[0.08]
Birthweight	0.001	0	0	0.001	0
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Lone parent		-0.082***			-0.079***
		[0.02]			[0.02]
Step family		-0.075*			-0.069*
		[0.03]			[0.03]
2 - 3 children		-0.026			-0.034
		[0.04]			[0.04]
4 + children		-0.201***			-0.180***
		[0.05]			[0.05]
Poor household		-0.024(*)			-0.021
		[0.01]			[0.01]
Maternal age		0.291***			0.259***
		[0.03]			[0.03]
Unemployed parent		0.026*			0.027*

		[0.01]			[0.01]
Maternal age		0.021***			0.017***
		[0.00]			[0.00]
House crowding		-0.023			-0.017
		[0.02]			[0.02]
House cluttered		-0.013			-0.013
		[0.02]			[0.02]
SEIFA index			0.133***		0.101***
			[0.01]		[0.01]
Bad neighbourhood			-0.146***		-0.110**
			[0.04]		[0.04]
Urban area			0.079***		0.079***
			[0.02]		[0.02]
Absentism				-0.052*	-0.045(*)
				[0.02]	[0.02]
Regular friend's contact				0.001	0.004
				[0.01]	[0.01]
School change				0.014	0.013
				[0.01]	[0.01]
Parent' school involvement				0.025(*)	0.013
				[0.01]	[0.01]
Intercept	-6.57	-7.410***	-7.935***	-6.576***	-8.322***
	[0.15]	[0.18]	[0.20]	[0.15]	[0.21]
Random part					
Age	-22.812***	-17.801	-17.115	-18.528	-20.927
	[0.41]	[169.78]	[220.85]	[229.87]	[484.82]
Intercept	-0.373***	-0.410***	-0.404***	-0.375***	-0.429***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Subjects	3,481	3,481	3,481	3,481	3,481
Subject-observations	8,609	8,609	8,609	8,609	8,609

Notes: **Random-coefficients regression models**. Coefficients can be interpreted as standard deviation change. Standard errors in square brackets under coefficients. (*) = p<0.1; * = p<0.05; ** = p<0.01; *** = p<0.001.