Time-Varying Effects of Changes in Parental Jobs, Partnership Statuses, and Residence On Children's Educational Attainment

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Abstract

Changes in socioeconomic status, household composition, and residence affect children's educational outcomes. However, event timing in childhood matters. I address variation in experience of disruptive events by analyzing high school completion, college attendance, and college completion; I divide childhood into ages 0-5, 6-11, and 12-17 and look at models across all child ages from 0 to 17 years to see if effects vary depending on timing. I find that events occur in substantial numbers at all times in children's lives, though all events are more likely in the youngest age range. The effects of job changes become more salient as the child grows older, whereas the effects of family changes decrease in negative effect over time. Residential moves become increasingly detrimental to educational outcomes as the child ages. When events combine, effects worsen, though the pattern of effects can be masked by the combination: e.g., when children experience a parental partner loss and a residential move, the effect increases in size over time because of the move; those who do not move in conjunction with the partner loss see effects diminishing over time. Finally, the analysis shows differences between mothers and fathers: mothers' job losses in early childhood are actually beneficial to children's educational outcomes in sharp contrast to fathers' job losses which are always detrimental to children's outcomes, and fathers' partner gains become insignificant as time goes on, whereas mothers' partner gains have negative effects on children's educational outcomes.

Introduction

Disruptive events in parents' lives have adverse effects on their children's educational attainment, as other work shows (Simon Thomas 2015a). However, this work focused on events occurring when children were between 0 and 17 years old. This paper aims to address variation in the experience of disruptive events by asking: *do educational outcomes vary depending on the time in the child's life when these events occurred?* On the one hand, educational milestones such as high school graduation are closer to later childhood in time; on the other hand, children at younger ages are more vulnerable to parent influence, and indeed, they rely on their parents significantly more, compared to older children who have access to other adults such as peers and teachers and are more independent in their daily activities.

This paper uses these trigger events: partner loss, partner gain, job loss, job gain, entry into self-employment, and residential moves, following DiPrete and McManus (2000). Entry into self-employment does not happen frequently enough to have a useable sample size for each age category, however, so I limit the analysis to the other five events instead. I also look briefly at the experience of event combinations and how those vary over time, particularly as compared to time-varying trends of single events.

Responses to treatments, in this case the trigger events, can vary systematically over time (Brand & Simon Thomas 2014; Voight, Shinn & Nation 2012). Also, the risk of experiencing these events, from the parents' perspective, varies over the life course (Esping-Anderson 1999). Haveman, Wolfe, and Spaulding (1991) found that the effect on high school completion of income and residential changes varied depending on the age of the child at the time of the event. Brand and Simon Thomas (2014) found differences in the effects of parental displacement depending on when in childhood the displacement occurred; Voight, Shinn, and Nation (2012) found differences in math and reading achievement for children who moved at various times. However, in an earlier study Alwin and Thornton (1984) did not find differences in educational achievement when comparing results from factors in early childhood versus late adolescence. Thus, the events I will be examining could show different effects at different times in the child's life course, or they could affect children similarly regardless of their timing in childhood. Additionally, some events may show differences in outcomes while others may not vary over time.

As Brand and Simon Thomas (2014) did, childhood is divided into ages 0-5, 6-11, and 12-17. That creates categories corresponding to infant and preschool years, elementary/middle school years, and high school years. I also look at trends over the childhood years by analyzing models for each child age, year by year. I then compare those two approaches to see how disruptive event effects vary over time. The outcomes remain children's high school completion, college attendance, and college completion (at ages 19, 21, and 25, respectively).

Literature

It is not just the event(s) but also the timing of the event(s) that matters. Indeed, there is a lot of research focused on determining when in a child's life interventions are most effective, and research in various fields has found that early childhood is the most crucial time to affect change (The Carnegie Corporation of New York 2002; Ermisch, Peter & Spiess 2012; Rhodes & Hoey 1994; Werner & Smith 1992). However, I am interested in outcomes that are part of the transition to adulthood, not elementary or middle school, which means that if the events occurred well before these transitions, the mechanisms by which children are impacted are likely to be different. Additionally, effects may have waned by the time the educational transition becomes relevant in the child's life. The question then becomes whether or not a shock in early childhood lasts until decisions about high school completion or college attendance are made. This paper focuses on both three different times in childhood (early, middle, late; or toddler/preschool, school age, adolescence) as well as looking at trends with models for each child age from 1 to 17, thereby expanding knowledge of how parents' disruptive events affect children.

Brand and Simon Thomas (2014) found time-varying effects based on the age of child when a maternal job displacement occurred: the older the child was when the event happened, the greater the effect on the child's educational attainment and psychological wellbeing. In an earlier study, Alwin and Thornton (1984) did not find differences when contrasting results from factors in early childhood versus late adolescence, though those authors only look at two discrete time points. Kowaleski-Jones and Duncan (1999) find that shocks affect achievement, providing a potential mechanism for being pushed "off track" to certain levels of educational attainment while also implying that shocks during school ages will affect educational attainment more than shocks during infant, toddler, and preschool ages. On the other hand, Crosnoe and coauthors (2014) find that shocks in early childhood lead to changes in child care situations, and this affects educational attainment.

Another potential mechanism is that disruptive events affect income, and research has found income shocks to affect younger children more heavily, though starting socioeconomic status mitigates these effects (Page, Stevens, & Lindo 2009). When previous income is taken into account, Hardy (2014) finds that "the negative association between [income] volatility exposure and educational attainment is largest for young adults from moderate-income families" (1641). The causality of income effects on child outcomes is also debated, given that there can be various pathways by which income and income shocks can affect children (McLanahan &

Percheski 2008). Lastly, another mechanism is simply instability having negative effects on child outcomes, underscoring findings that consistency and predictability are crucial to early child development (Brown 2010; Levine Coley & McPherran Lombardi 2012).

There is also the possibility of positive effects. Hsin and Felfe (2014) find that maternal employment is negatively associated with child wellbeing, meaning that shocks that cause mothers to be in the home with their children more often may actually lead to an unexpected positive effect. Brand and Simon Thomas (2014) indeed found this positive effect when job loss occurred among mothers of children young enough to not yet be in school full-time. However, Hsin and Felfe (2014) underscore that unstructured time does not aid children, meaning that mothers would need to use the extra time with their children in more educational ways to reap benefits.

Looking at birth through 5 years old, economists Almond and Currie (2011) find that shocks during that time can indeed persist as "permanent damage," yet there is also a surprising resilience to children. In other words, the effects could remain or fade over time. They focus mostly on health-related shocks (e.g., nutrition, pollution), however, as well as maltreatment. Though the latter could potentially be an outcome of the events on which I focus, job changes, family status changes, and residential moves are generally less catastrophic. It is nonetheless important to note that even for such large-scale and potentially biological shocks, the change in effects over time is unclear and varied.

Data

This analysis uses data from the Panel Study of Income Dynamics (PSID). The PSID began in 1968 and the most recent wave occurred in 2011, which makes it ideal for intergenerational studies. Having grown from 18,000 individuals in 5,000 families, the study currently contains data from more than 80,000 individuals.

The trigger events outlined by DiPrete and McManus (348, 2000) provide a blueprint for the disruptive events which I examine in this study. The employment events are: (1) work to no work, (2) entry into self-employment, or (3) no work to work, the relationship events are: (1) add partner, and (2) lose partner, and I also include moving to a new residence as another event. This gives me a total of six events. However, initial analysis shows that sample sizes for entry into self-employment, once divided into different times in childhood, are too small for further analysis.[1] Thus, I eliminate this event and use the other five events as parental disruptive events in this paper. I also use parental disruptive event combinations in this paper, which juxtapose experiencing no events, only one event, or two events concurrently (within the same two years).

I measure educational outcomes for children following Brand and Simon Thomas (2014) as high school completion by age 19, college attendance by age 21, and college completion by age 25. I look at mothers' and fathers' events separately, since the chances of differences between mothers' and fathers' influences, particularly in early childhood, are high. For one set of models, I do combine mothers and fathers, however, to increase sample size.

Methods

In this paper, my goal is to answer the question: *do children's educational outcomes vary depending on the time in the child's life when disruptive events occurred in their parents' lives?*

[1] The rate of entry into self-employment for mothers when children are between 0 and 5 years old is 0.15%, between 6 and 11 years old is 0.11%, between 12 and 17 years old is 0.17%; for fathers, these numbers are 0.15%, 0.07%, and 0.12%, respectively. Even given a sample size of over 15,000 respondents, this simply is not a high enough number of cases with which to run models, even if mothers and fathers are combined.

I take two approaches to address this: first, I divide the childhood years, from ages 0 to 17, into three subsets of time; second, I look at trends across those subdivisions. Childhood years are naturally subdivided by education: at 0-5 years of age, children are not yet in a formal schooling environment; at 6-11 years of age, children attend elementary schools; at 12-17 years of age, children attend secondary schools, generally speaking. I look at the influence of parental disruptive events on children's educational attainment within each subgroup of ages to see how the effects differ. Then, I look at the effect within each year of age to see if there are any trends from age 0 to 17. I do this by running separate models for each year and also by including each year within one model. By looking at the outcomes for separate and inclusive models, I can determine how events are connected.

Beyond descriptive analyses, all models in this paper are logistic regression models, where the outcome signifies the odds ratio of graduating from high school, attending college, or graduating from college, for children. Logistic models looking at outcomes due to events occurring during three groups or single years of child age are structured as follows:

(1)

where p is the probability of reaching an educational milestone (completing high school, attending college, or completing college; expressed as odds ratios), is the set of covariates being examined in this model, is the constant, and the other coefficients evaluate covariates. The event variables are dichotomous and added in to the models as . Each educational outcome is a separate model. Each event is considered in a separate model, including events at different times in children's lives; in other words, I create different variables for event occurrence during 0-5, 6-11 and 12-17 years old as well as during each year of child age, and each of these timed events is considered in a separate model as well. I analyze mothers' and fathers' events in separate models to be able to examine potential differences in parental influence, with one exception (which will be discussed in greater detail) in which mothers' and fathers' events are combined due to sample size constraints.

Models with interactions between child age and event variables, to determine time trend significance, take the form of:

(2)

Covariates for all controlled models include the child's sex and race, whether the child was born in the South, and mothers' and fathers' education (high school and college completion). For the models with mothers' events, I include a covariate signifying if mother was married when child was born; for models with fathers' events, I use a similar covariate for fathers. For the models that include the events of job loss or job gain, I use covariates signifying if the parent in question worked in manufacturing or trade in the year their child was born. I use a clustering correction (by mother, father, or family ID, depending on the model) to correct for families with more than one child in the survey.

Results: Descriptive Statistics

Table 1a shows that the frequency of all five disruptive events decreases over time. Particularly residential moves are less common when children are 12-17 years old, though all events occur more frequently when children are 0-5 years old. Fathers are more likely to experience employment events, especially when children are 0-5 years old, which makes sense given that they are likely younger workers with less stable careers.

Table 1b reports the frequency of event occurrence during specific times in childhood, given the fact that an event occurred. For example, for those children whose mothers ever experienced a job loss when they were 0-17 years old, nearly 38% of those children experienced a job loss between the ages of 0 and 5 years. Gaining a partner for mothers is by far most common in those early childhood years, as are all disruptive events for fathers. Again, the prevalence of disruptive events decreases as children get older, though they never become rare occurrences. As other work also shows (Simon Thomas 2015a), residential moves are quite common at all ages.

Results: Single Events

The first analysis I perform shows the effects on children's educational attainment at ages 0-5, 6-11, and 12-17. Table 2a reports results without control variables. Overall, it looks as though being of school age has a protective effect on children's educational attainment: effects are more highly negative in the 0-5 years old group compared to the other two age groups. For high school graduation and college attendance, effects of all events are even positive. A notable exception is job loss and job gain, which are insignificant or significantly positive for mothers but significantly negative for fathers. This exception will arise again in other results and be discussed in detail at that point.

For children who are between 0 and 5 years of age when the parental disruptive event occurs, gaining a partner has large negative effects on their future educational attainment, whereas residential moves only negatively affect their chances of high school graduation. For children who are between 6 and 11 years old when the event occurs, all events show insignificant or positive effects on high school graduation and college attendance for mothers and fathers, but effects on college graduation are significantly and highly negative. Especially for residential moves, given that these models do not control for other socioeconomic factors, this is likely catching the families who are "moving up," to better neighborhoods and schools, as salaries increase. For children who are between 12 and 17 years old when the event occurs, the same gradient of positive to negative can be seen between high school to college completion.

Table 2b shows results for models that include controls for the child's gender and race, parents' education, and being born in the South; these results look quite different. Job loss is not significant in early childhood, though values are closer to no effect for mothers versus fathers; fathers' job loss becomes significantly negative for children aged 6-11 and 12-17. Partner loss has significantly more of a negative effect in early childhood compared to school-aged children. Partner gain has a similarly negative effect on college attendance and graduation across age groups, though for high school completion, there are no significant effects for school-aged children. Residential moves become worse as child age increases for the chances of college graduation, but the negative effect stays similar for high school graduation and college attendance.

These tables show that there are differences across childhood, and there are also differences in how high school graduation is affected compared to college completion; college attendance often falls in between these two outcomes in terms of effects. Partner changes affect children in early childhood more negatively, whereas residential moves affect children in adolescence more negatively. This makes intuitive sense – changing partners in those early childhood years is stressful and can affect income significantly, changing schools in later years is disruptive to the college application process.

Next, I run a separate model for each child age from 1 to 17 years. Figures 1 to 5 show results for each event, broken down by high school graduation, college attendance, and college completion, with a trend line added to show how effects change over time.[2] Figure 1 shows that there seems to be a downward trend for the effect of a parental job loss on the chances of child's college graduation, but there is no evident trend on high school completion. Figure 2 shows a similar downward trend for the effect of a parental job gain on college attendance. Figure 3, on the other hand, shows an upward trend for the effect of a parental partner loss on all children's educational outcomes considered. Figure 5 shows a dramatic downward trend of residential moves on all outcomes, particularly on college completion.

In most graphs in Figures 1 through 5, mothers' and fathers' events do not show differences in outcomes. The notable exception here is partner gain, which becomes increasingly negative for mothers but positive (for high school graduation) or flat (for college attendance) for fathers. Due to this difference, I first run logistic regression models looking at the significance of time trends for mothers and fathers separately (results are shown in Appendix A). For partner gain, the main effect does not differ between mothers and fathers for college attendance and completion, but the trend over child age shows a significant worsening for mothers but not for fathers. For job loss, this difference also exists: though the main effect is worse for fathers for college attendance and completion, it significantly worsens for mothers over child age for college attendance and it worsens for fathers over child age for college completion. These results also confirm the significant downward trend of the effect of residential moves.

Despite those differences, the majority of results are similar for mothers and fathers, and so I next combine mothers and fathers (into "parents," where the event variable takes a value of 1

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[2] Though a quadratic trend line can be used in these graphs, it becomes highly linear in most graphs. In other words, the linear trend line is an equally good fit, so it is used for simplicity.

if the event occurred to either the mother or the father, and 0 otherwise) and run models of the effects of an event for either parent. Doing so allows me to have a larger sample of those who experience events at each age; since I am subdividing the sample by 17 ages, keeping mothers and fathers separate can lead to unstable coefficient estimates. Combining mothers and fathers lets me find out more about the trend over child ages by giving me more events in each model at each age. Table 3 shows the results for these models.

The combined models show that parental job loss has a significantly negative effect on high school graduation, which does not alter significantly as the child gets older. However, parental job loss shows an insignificant (and not as strong) effect on college attendance and graduation, but effects grow significantly worse as the child ages. For college graduation, the effect of a parental job loss grows, on average, 3.1% more negative for each year of child age. This leads to a substantial difference by the time the child is 17 years old and getting ready to transition to college. Job gain shows a significantly negative trend over child age for the effect on college attendance.

On the other hand, parental partner loss shows a significantly positive age trend on high school graduation; though not significant, the age trend of partner loss on college attendance and college graduation are also in the positive direction. Though the main effect of partner loss is negative, the effect seems to get better over time, reflecting the results from the previous analysis. Partner gain does not show a trend from child ages 0 to 17.

The effect of moving becomes significantly more negative as the child grows older. Given that the main effect of moving is negative on all educational outcomes, this increasing negativity follows the trend line that the individual models by age showed as well (in Figure 5). It is worth noting that residential moves include all moves; in other words, I do not differentiate between local moves and interstate moves, for example, and I also do not distinguish planned from unplanned moves. There is a possibility that there are differences in effects depending on distances, reasons, and perhaps other differences in migration.

Results: Event Combinations

When events combine in the same year, the effect on children's educational attainment is magnified (Simon Thomas 2015b). The question for this paper, then, is if this magnification upholds across all child ages. The challenge here is sample size: breaking down the sample into mothers and fathers, events versus event combinations in each year, and 17 child ages creates group sizes that are not sustainable for analysis in many cases (e.g., 12 cases of mothers who experience a job loss and a partner loss in the same year). Thus, in this paper, given the age divisions, I discard event combinations in which one of the combined events is not a residential move. Residential moves are much more likely to combine with job or partner changes than job and partner changes are to combine with each other; the latter type of combination does not run stable models and has extreme outliers that drive potential trends. To avoid the small number of cases, I look only at the combinations of job changes (loss or gain) and residential moves, and partner changes (loss or gain) and residential moves.

One way to increase sample size would be to combine mothers and fathers to create "parent" variables, as I did earlier in this paper for single events. However, that obfuscates possible differences between the effects of mothers' and fathers' events (which exist, as I will show next); it also confuses what combined events mean. Job losses are inherently individual events which affect the family, usually adversely, but residential moves are generally family events. Partner losses affect both mothers and fathers at the same time. In other words, it becomes difficult to disentangle individual and group events and consequences when parents are combined into one variable. For single events, using a clustering correction for families can help methodologically. For combined events, however, individual events such as job losses or gains can happen to both parents in a year, whereas moving stays a single event per year for the family. This makes the categories of, for example, job loss only versus move only versus job loss and move for one year less mutually exclusive. Though possible and a partial (though by no means complete) solution to the sample size problem, since I am interested in broad trends, and since the trends of mothers versus fathers here have interesting connotations, I keep mothers and fathers separated for the analysis of event combinations.

Figures 6 through 10 show trends for event combinations in which each child age is a separate model. Thus, this is a similar idea to Figures 1 through 5 for single events, though I show mothers and fathers on separate graphs in this case for clarity's sake, since each graph already contains three time trend lines, one for each event or event combination. I also use a quadratic trend line for these figures because the exceptions on which I will next focus are illuminated via these trend lines but get lost in linear fit lines. For the most part, Figures 6 through 10 show that event combinations do lead to slightly worse effects than single events at all ages. However, there are indeed notable exceptions of changes across child ages.

The main exception is in the time trends for effects on children's college attendance and graduation given a mother's job loss compared to a father's job loss (in Figure 6). Just losing a job, without being combined with a residential move, actually increases a child's odds of college attendance and completion in early childhood. The trend for college attendance turns upward again at later ages as well. By contrast, for college attendance, the combination of a maternal job loss and a residential move has an increasingly negative effect through adolescence. For fathers, this pattern does not exist. This does not per se run counter to the finding that stable maternal labor market success is beneficial for children (e.g., Levine Coley & McPherran Lombardi 2012) but rather means that younger children of mothers who lost their jobs for a variety of possible reasons seem to see a benefit on future educational attainment. Though models control for the parents being married when the child was born and for both parents' educational attainment, it is possible that this is showing a socioeconomic difference, where mothers who can afford to leave work, do leave work, possibly in order to spend higher quality time with their children (Hsin & Felfe 2015). However, Brand and Simon Thomas (2014) found that these advantages are present even when single mothers lose their jobs, suggesting that there is something beneficial about mothers being at home, at least for a short period of time (but likely longer given how long unemployment can last post-job loss, see Simon Thomas 2015), in early childhood. This could be a positive effect via the mother or a counterpoint to negative effects of child care. I return to this discussion with estimates of time trend coefficients after discussion of the second anomaly in these graphs.

The second exception to the general time trends appears in Figure 8. Here it can be seen that the effects of losing a partner improve as the child gets older, whereas the effects of losing a partner and moving worsen (following the trend for moving only). This divergence is particularly pronounced for college attendance and college graduation. Especially for fathers as compared to mothers, the effect of losing a partner only wanes to practically no effect at all at age 17; for mothers, the effect for this category improves but actually decreases slightly again at the end of the childhood time span. Finally, gaining a partner combining with a residential move (Figure 9) shows some diverging trends for women and child college completion, though that trend looks to be roughly estimated.

In order to find out more about the significance of time trends for event combinations compared to single events, I next estimate models with all ages included in one model for each event combination. The full table of outcomes for these models is shown in Appendix B; most of the time trend appears to be driven by residential moves, as the moving only category shows the vast majority of the significant coefficients. All significant coefficients on the time trend of residential moves show decreases in the chances of children's educational attainment as they get older.

The benefit of the event combination models, besides being able to see that combinations of events are worse in their main effects, is that we can speculate what the effect of job and partner changes are when they are not combined with residential moves. For example, we can see that a parent gaining a job does not significantly affect educational outcomes for children, unless this job gain is coupled with a residential move, in which case effects become significantly negative; for mothers, this negative value increases over child age. We can also see that the effects of losing a partner abate over child age, when it is not concurrent with a residential move.

Of particular interest are the outcomes for job loss over time. In previous models, I showed that there is a vastly different dynamic over time for mothers' job loss as compared to fathers' job loss, and this is illuminated in the event combination models. The pattern of effects for child's high school graduation does not differ when we compare mothers and fathers. However, for college attendance, the combination of losing a job and moving is highly negative for fathers across child age; it does not change significantly as the child ages. For mothers, the story is quite different: the main effect is insignificant, but the time trend shows a significant decline in the chances of college attendance. Thus, for children aged 1, the chances of college attendance are not affected by a mother's job loss and move, whereas they are significantly affected if they are older when this combination of events occurs. For college graduation, a similar pattern emerges with job loss only: the main effect for mothers' job loss is positive (though not significant) but the time trend is significantly negative. Interestingly, losing a job and moving at the same time does not show a significant trend over child age for mothers. It is possible that this is driven by selectivity, where parents who lose jobs and move with older children are disadvantaged in some other way compared to those who lose their jobs but do not move. This selectivity would reflect the assessment that the effects of mothers' employment vary by mother characteristics such as educational attainment (Hsin & Felfe 2015).

As mentioned previously, I speculate that differences between mothers and fathers could occur because of differences in the nature of the job loss: whether the worker quit, was laid off, or was fired. Also, when the job loss is concurrent with a move, it is possible that this means that the parent who lost the job was the main income producer, though we cannot be sure about this possibility.

Discussion

Parental disruptive events are more likely to occur when children are younger, in fact, before they are school-aged. Yet there are also differences in how events affect those younger children as compared to the effects when children are older. Though it might seem that disruptive event effects would be more salient at ages closer to the educational outcomes being explored in this paper, this is not always the case.

When dividing children into three age groups (0-5, 6-11, 12-17 years), it becomes clear that partner changes affect educational outcomes most when they occur in early childhood (0-5 years old). This is an interesting finding, given that this means that an event that occurs 13-18 years prior to high school graduation has a larger effect than the same event occurring fewer years prior. This could mean that particularly partner loss sets children on a path of perpetual disadvantage. It could also mean that parents who are likely to get divorced or break up that soon after the birth of a child provide a more unstable home generally. I do not distinguish based on factors that occur after the event, though other work did show that repeated events are not an unlikely occurrence (Simon Thomas 2015a). On the other hand, job changes affect educational outcomes most when they occur to school-aged children (6-11 and 12-17 years old). This supports an economic hypothesis: job loss leads to income loss which means that children might need to go to work themselves rather than focus on education, or it could mean that savings for college are no longer available, for example. Residential moves are always detrimental to educational outcomes, but they are worse for older children than for younger children. This makes sense: changing schools is likely not conducive to increased educational performance, and moving that at time in a child's life could signify a childhood with more upheaval compared to children who do not experience a move at that time.

Looking at children's age trends within age categories and across ages confirms the previous findings but adds more detail to the analysis. Parental job loss becomes increasingly more detrimental to the chances of college attendance and graduation with each year of the child's age. Job gain similarly affects college attendance. This confirms that temporal proximity to the outcome matters for parental job changes. Partner loss, on the other hand, decreases in its negative effect over time, which again confirms the prior results. Partner gain shows no changes over time. This means that a stable union is most crucial before children start Kindergarten, which is not surprising per se; however, the outcomes are closer to later ages so it is interesting that instability at earlier ages, in terms of marital or cohabiting partners, proves to be worse for educational outcomes at ages 19, 21, and 25.

The negative effect of residential moves increases over the child ages considered. It is plausible that this means that moving directly prior to high school graduation, when college applications are likely due, matters more than moving in early childhood. However, this could also be signaling a more unstable childhood in general. It is also possible that moves later in childhood are disproportionately unplanned and therefore lead to worse educational outcomes. This analysis does not take distance into account – a residential move could be within the same county or even neighborhood or it could be an interstate move; it is possible that this plays a role in determining the effect as well.

Given the toll that residential moves take, it is important to separate partner and job changes from residential moves. Event combinations are generally worse than single events, as shown generally in other work (Simon Thomas 2015a) and this trend is upheld across all child ages. Analysis shows that much of the change in effect over time for job losses is due to concurrent residential moves. For partner changes, the effect actually improves over time for those who do not also move.

At a general level, this paper shows that disruptions can occur at any time in childhood, but the effect can vary substantially. Additionally, age variation does not necessarily follow the same pattern for different disruptions, so although instability is rarely, if ever, beneficial for children's educational outcomes, the cause of the instability matters in how children of different ages are affected. Finally, when events combine, the effect of those events on children's educational attainment is often exacerbated at all ages.

There are important limitations to this analysis. First of all, I define events as moving from one state to another (e.g., employed to unemployed) and do not differentiate between reasons for event occurrences. There is a possibility that trends are being driven by specific reasons behind events or masking other patterns for other motivations. Secondly, repeated events could cause families with more instability to be overrepresented in my data. Based on analyses of multiple events (Simon Thomas 2015b), I do not believe this strongly affects the analyses in this paper, but it is possible that there is unobserved heterogeneity. Finally, it is possible that some of the dynamics I see when comparing mothers and fathers have changed in recent years, but since I look at an average effect from 1968 through 2011, it is possible that those updated labor market and childrearing changes will not be reflected in this analysis.

The findings in this paper have policy implications. Most importantly, if partner loss at early ages is driving later childhood inequality in terms of educational outcomes, it is important to figure out if this is due to income loss or other factors. Secondly, if parental job loss is indeed affecting educational outcomes when they happen closer to those outcomes, this likely means that children of parents who experience disruptive events are disproportionately pushed to choose work over school completion. This underscores the need for policies such as those which give tuition assistance. Finally, residential moves are by far the most likely event in respondents' lives, and their negative impact increases over childhood, a fact of which schools should be aware and with which they could be assisting their students. By understanding the different impact at different times in childhood, we can better plan how to help those children affected and keep them on the path to high school and college completion.

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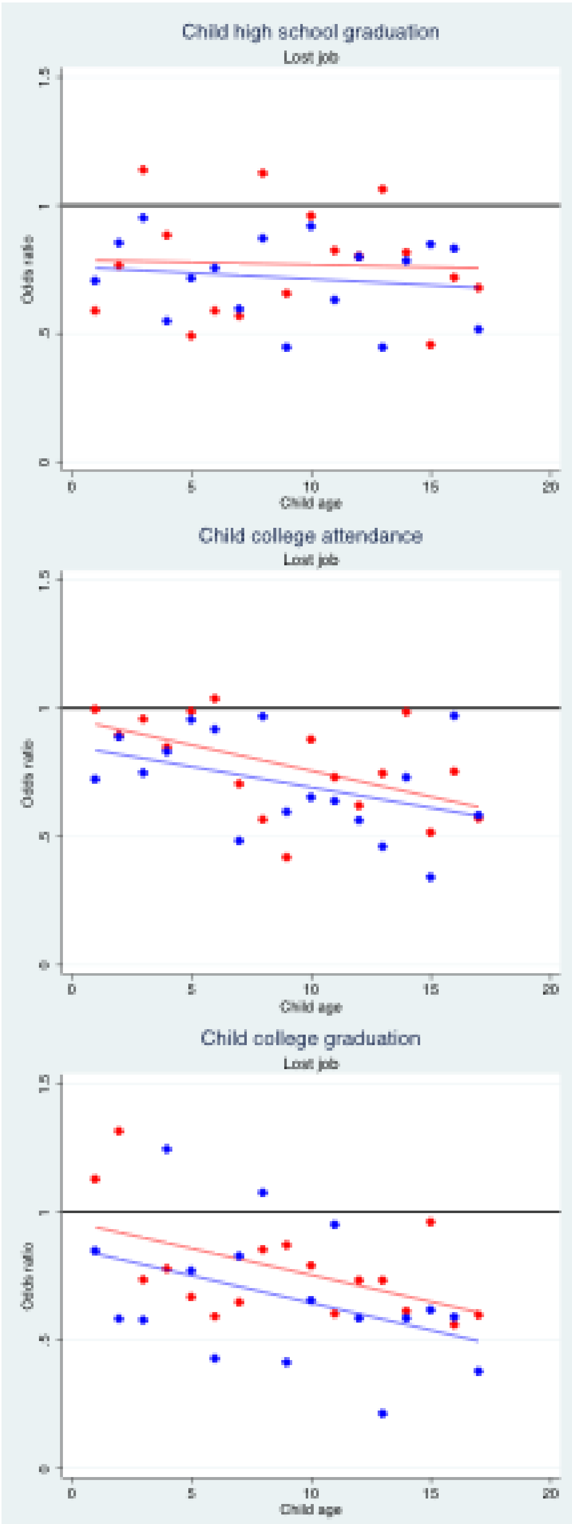
Figure 1.



Child high school graduation
Lost job
Odds ratio
Child age
Child college attendance
Lost job
Odds ratio
Child age
Child college graduation
Lost job
Odds ratio
Child age

Figure 2

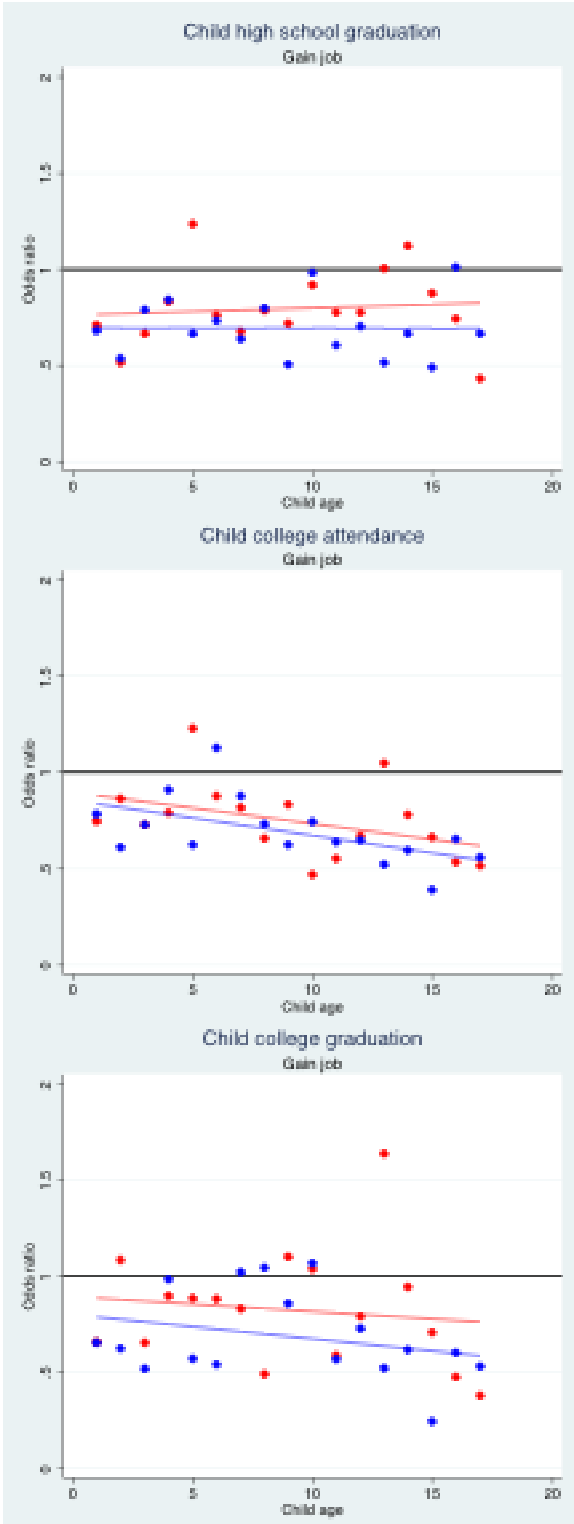

Child high school graduation
Gain job
Odds ratio
Child age
Child college attendance
Gain job
Odds ratio
Child age
Child college graduation
Gain job
Odds ratio
Child age

Figure 3

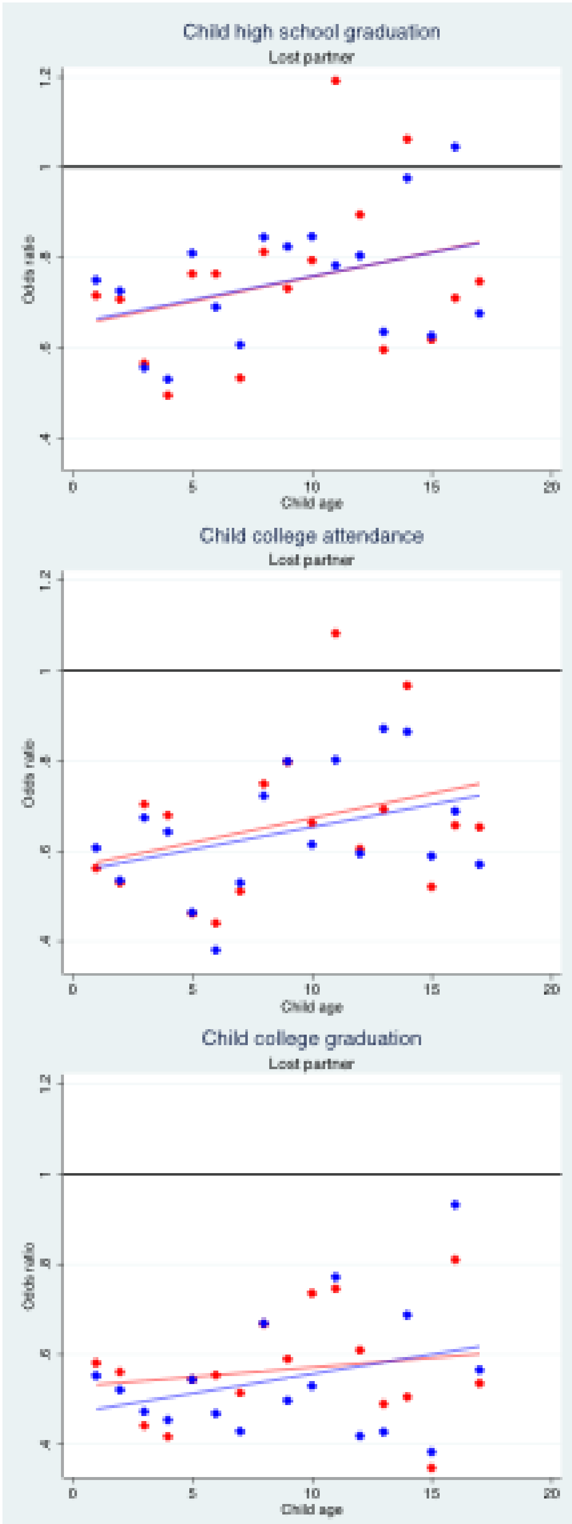
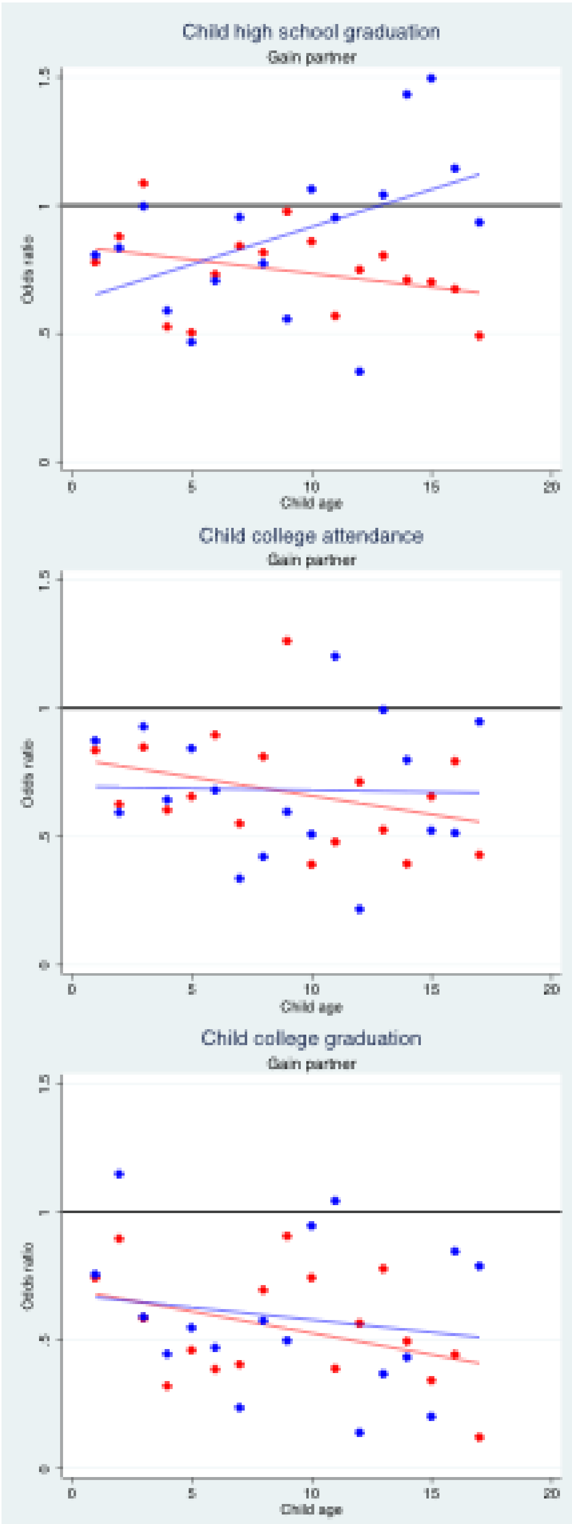

Child high school graduation
Lost partner
Odds ratio
Child age
Child college attendance
Lost partner
Odds ratio
Child age
Child college graduation
Lost partner
Odds ratio
Child age

Figure 4



Child high school graduation
Gain partner
Odds ratio
Child age
Child college attendance
Gain partner
Odds ratio
Child age
Child college graduation
Gain partner
Odds ratio
Child age

Figure 5

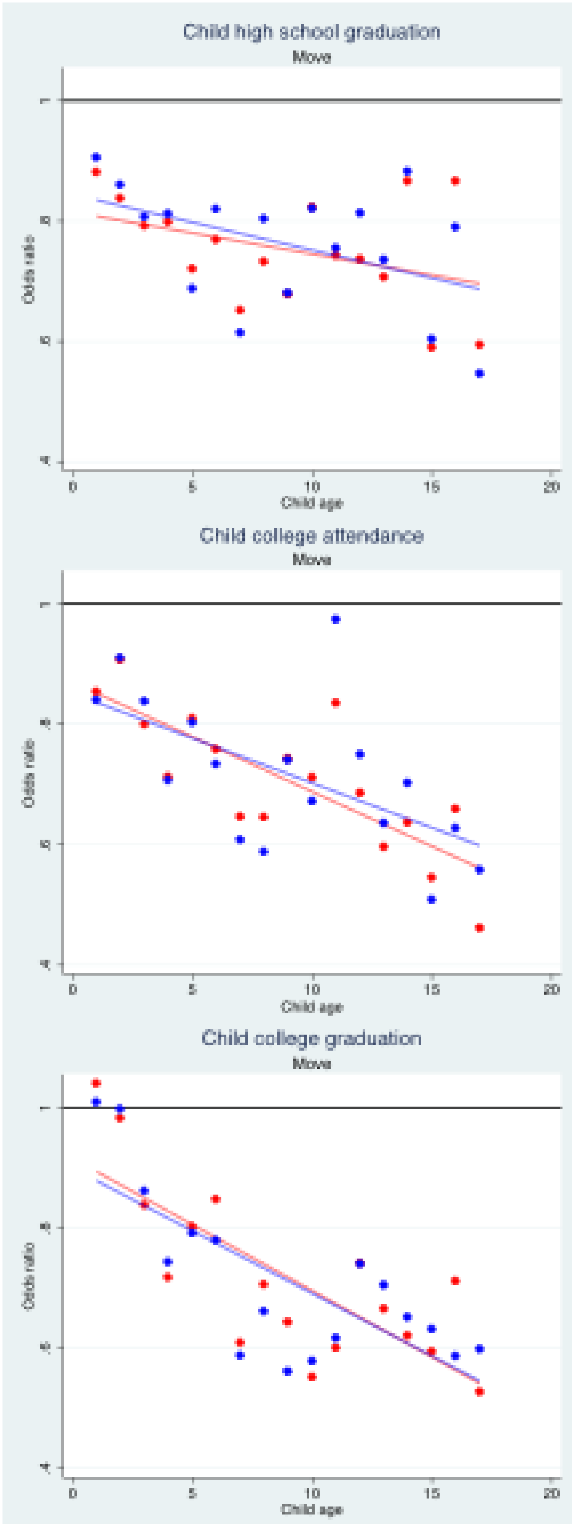
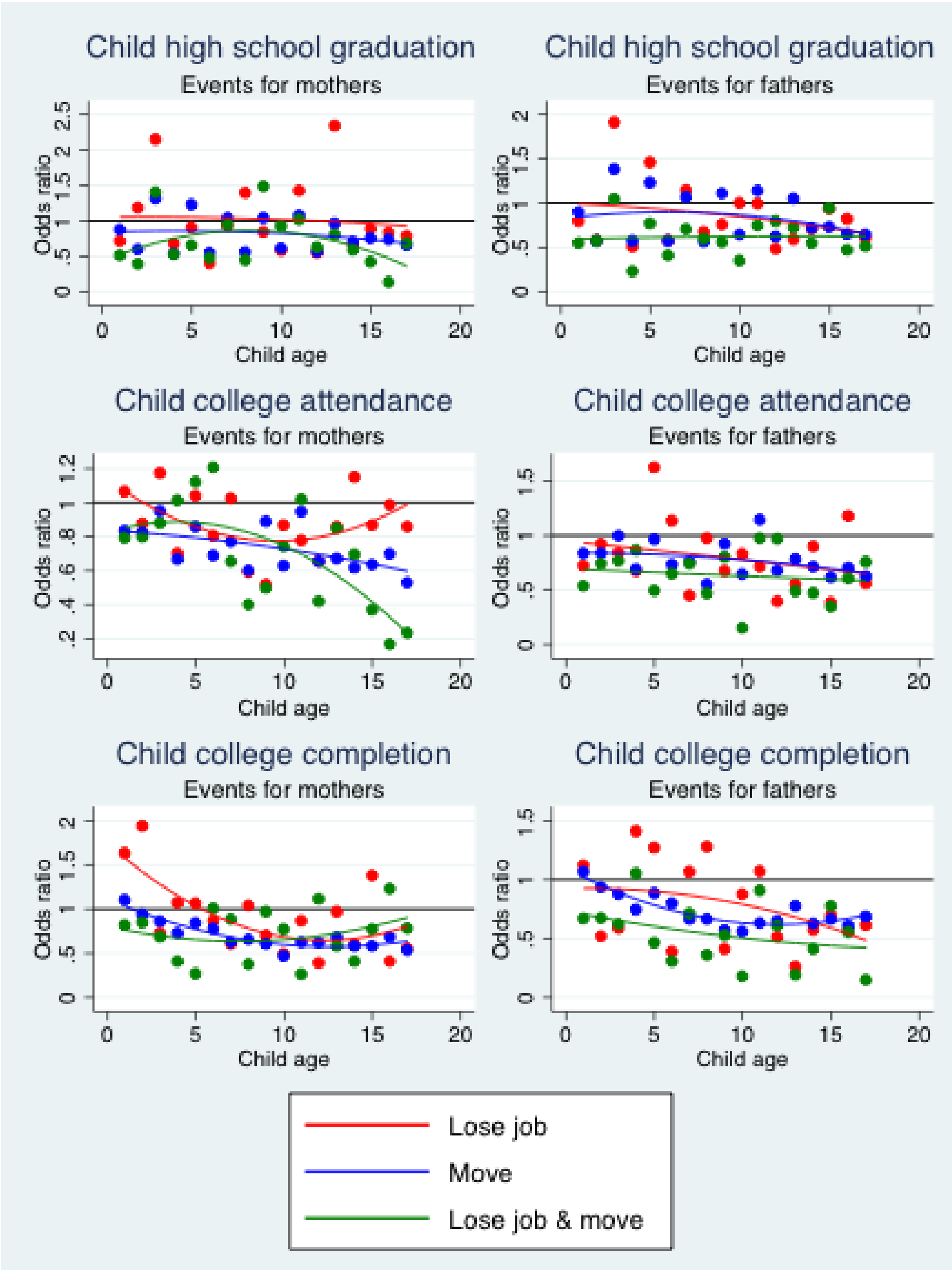
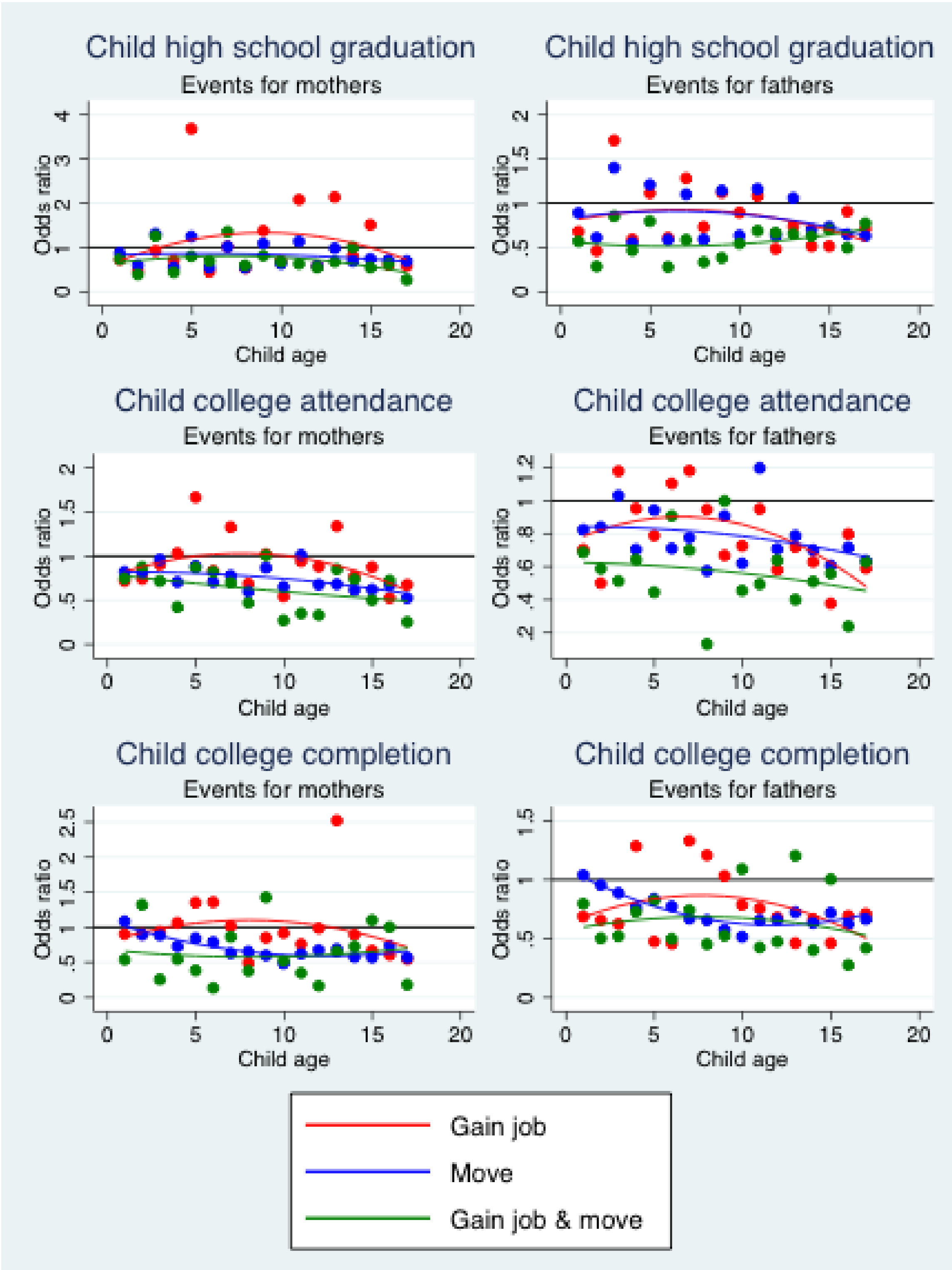

Child high school graduation
Move
Odds ratio
Child age
Child college attendance
Move
Odds ratio
Child age
Child college graduation
Move
Odds ratio
Child age

Figure 6



Child high school graduation
Events for mothers
Odds ratio
Child age
Child high school graduation
Events for fathers
Odds ratio
Child age
Child college attendance
Events for mothers
Odds ratio
Child age
Child college attendance
Events for fathers
Odds ratio
Child age
Child college completion
Events for mothers
Odds ratio
Child age
Child college completion
Events for fathers
Odds ratio
Child age
Lose job
Move
Lose job & move

Figure 7



Child high school graduation
Events for mothers
Child high school graduation
Events for fathers
Child college attendance
Events for mothers
Child college attendance
Events for fathers
Child college completion
Events for mothers
Child college completion
Events for fathers
Odds ratio
Child age
Gain job
Move
Gain job & move

Figure 8

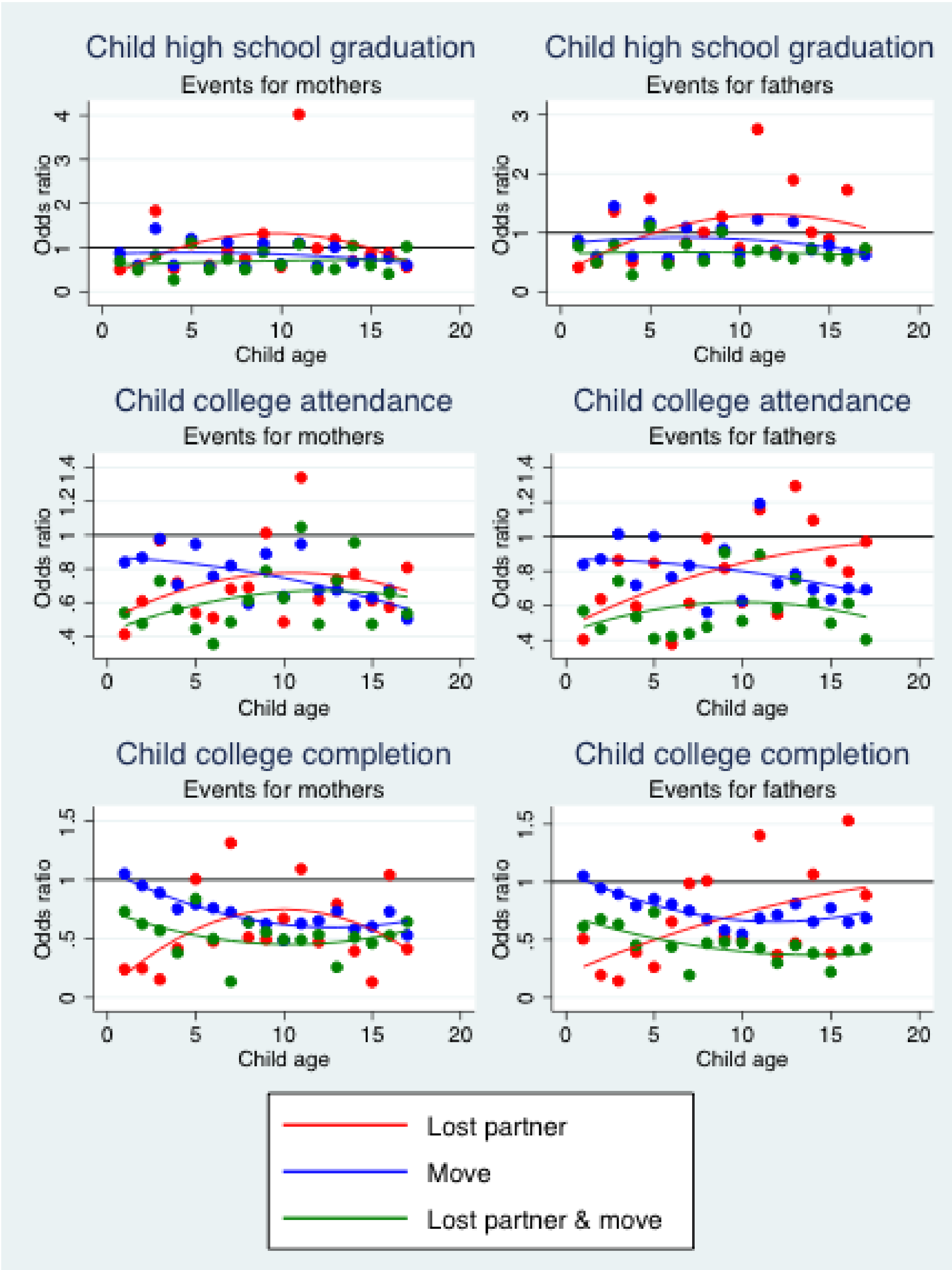
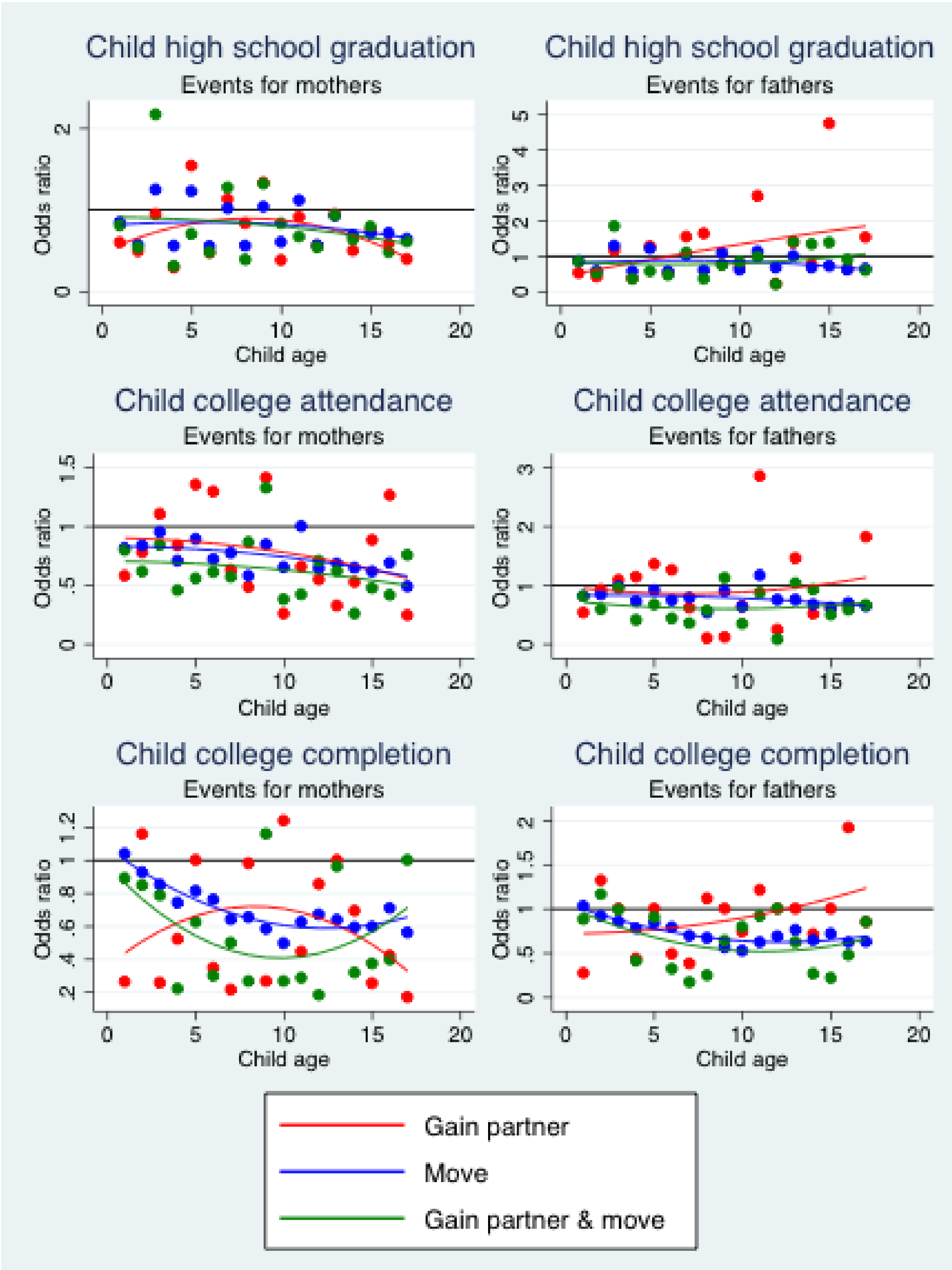

Child high school graduation
Events for mothers
Odds ratio
0
1
2
3
4
0
5
10
15
20
Child age
Child high school graduation
Events for fathers
Odds ratio
0
1
2
3
0
5
10
15
20
Child age
Child college attendance
Events for mothers
Odds ratio
.4
.6
.8
1
1.2
1.4
0
5
10
15
20
Child age
Child college attendance
Events for fathers
Odds ratio
.4
.6
.8
1
1.2
1.4
0
5
10
15
20
Child age
Child college completion
Events for mothers
Odds ratio
0
.5
1
1.5
0
5
10
15
20
Child age
Child college completion
Events for fathers
Odds ratio
0
.5
1
1.5
0
5
10
15
20
Child age
Lost partner
Move
Lost partner & move

Figure 9



Child high school graduation
Events for mothers
Odds ratio
Child age
Child high school graduation
Events for fathers
Odds ratio
Child age
Child college attendance
Events for mothers
Odds ratio
Child age
Child college attendance
Events for fathers
Odds ratio
Child age
Child college completion
Events for mothers
Odds ratio
Child age
Child college completion
Events for fathers
Odds ratio
Child age
Gain partner
Move
Gain partner & move

Table 1a: Frequency of event occurrence

This table reports the frequency of events ever occurring during the survey time (1968-2011). It only includes mothers/fathers whose children were 0-17 years old when the event occurred. It is also limited to respondents who were at least 17 years old at the last survey wave (in 2011). (N = 15,792)

Child was 0-5 years old when event occurred		
	Frequency	
Event	*Mother*	*Father*
Lost job	5.62%	7.81%
Gained job	5.61%	7.21%
Lost partner	8.58%	8.51%
Gained partner	8.96%	8.70%
Moved	35.64%	35.45%
Child was 6-11 years old when event occurred		
	Frequency	
Event	*Mother*	*Father*
Lost job	4.67%	6.37%
Gained job	4.48%	5.93%
Lost partner	7.96%	7.69%
Gained partner	4.31%	3.49%
Moved	26.50%	25.22%
Child was 12-17 years old when event occurred		
	Frequency	
Event	*Mother*	*Father*
Lost job	4.38%	5.58%
Gained job	4.25%	4.91%
Lost partner	6.42%	6.27%
Gained partner	3.57%	3.07%
Moved	21.47%	19.55%

Table 1b: Frequency of event occurrence

This table reports the frequency of events occurring during the survey time (1968-2011), during specific times in childhood, given that the event occurred when the child was 0-17 years old. It is limited to respondents who were at least 17 years old at the last survey wave (in 2011). (N = 15,792)

Child was 0-5 years old when event occurred		
	Frequency	
Event	*Mother*	*Father*
Lost job	37.78%	43.49%
Gained job	38.37%	43.19%
Lost partner	37.79%	37.93%
Gained partner	53.06%	54.76%
Moved	59.81%	59.99%
Child was 6-11 years old when event occurred		
	Frequency	
Event	*Mother*	*Father*
Lost job	31.43%	35.49%
Gained job	30.69%	35.54%
Lost partner	35.06%	34.27%
Gained partner	25.53%	21.93%
Moved	44.48%	42.67%
Child was 12-17 years old when event occurred		
	Frequency	
Event	*Mother*	*Father*
Lost job	29.44%	31.09%
Gained job	29.07%	29.45%
Lost partner	28.29%	27.95%
Gained partner	21.16%	19.33%
Moved	36.02%	33.08%

Table 2a: Logistic regression of the effect of events on children's educational outcomes
(No controls; child age refers to age range during which event occurred. Sample size is 15,792.)

	Child graduated high school by age 19				*Child attended college by age 21*				*Child graduated college by age 25*			
Events	Mother event		Father event		Mother event		Father event		Mother event		Father event	
Child age 0-5												
Lost job	0.975		0.743	***	1.223	*	0.752	**	1.147		0.617	***
	(0.077)		(0.053)		(0.110)		(0.069)		(0.138)		(0.080)	
Gained job	0.924		0.669	***	1.073		0.697	***	0.970		0.564	***
	(0.072)		(0.050)		(0.101)		(0.065)		(0.123)		(0.076)	
Lost partner	0.550	***	0.564	***	0.485	***	0.489	***	0.305	***	0.315	***
	(0.038)		(0.038)		(0.044)		(0.045)		(0.047)		(0.047)	
Gained partner	0.575	***	0.572	***	0.577	***	0.587	***	0.366	***	0.379	***
	(0.037)		(0.037)		(0.047)		(0.048)		(0.049)		(0.052)	
Moved	0.884	**	0.877	**	1.030		1.035		0.932		0.947	
	(0.035)		(0.034)		(0.048)		(0.048)		(0.058)		(0.059)	
Child age 6-11												
Lost job	1.241	*	1.101		1.145		1.044		0.729	*	0.669	**
	(0.105)		(0.082)		(0.111)		(0.097)		(0.107)		(0.092)	
Gained job	1.358	***	1.140	†	1.191	†	1.122		0.974		0.783	†
	(0.117)		(0.089)		(0.119)		(0.103)		(0.147)		(0.107)	
Lost partner	1.024		1.024		0.934		0.920		0.573	***	0.587	***
	(0.066)		(0.067)		(0.074)		(0.074)		(0.076)		(0.078)	
Gained partner	1.051		1.048		0.938		0.870		0.491	***	0.586	**
	(0.089)		(0.099)		(0.098)		(0.105)		(0.091)		(0.110)	
Moved	1.355	***	1.364	***	1.271	***	1.287	***	0.895		0.982	
	(0.056)		(0.057)		(0.062)		(0.064)		(0.060)		(0.066)	
Child age 12-17												
Lost job	2.198	***	1.835	***	1.353	**	1.170	†	1.034		0.721	*
	(0.185)		(0.141)		(0.127)		(0.107)		(0.138)		(0.103)	
Gained job	1.981	***	1.712	***	1.229	*	1.096		1.004		0.794	
	(0.171)		(0.140)		(0.124)		(0.106)		(0.148)		(0.118)	
Lost partner	1.522	***	1.598	***	1.215	*	1.255	**	0.724	*	0.786	†
	(0.107)		(0.115)		(0.099)		(0.103)		(0.094)		(0.098)	
Gained partner	1.764	***	1.813	***	1.082		1.209	†	0.729	†	0.800	
	(0.165)		(0.183)		(0.117)		(0.138)		(0.127)		(0.139)	
Moved	1.892	***	1.811	***	1.325	***	1.434	***	1.067		1.199	*
	(0.084)		(0.083)		(0.068)		(0.075)		(0.076)		(0.086)	

† p<.10   * p <.05   ** p < .01   *** p < .001   (two-tailed tests)

Table 2b: Logistic regression of the effect of events on children's educational outcomes, with control variables (Child age refers to age range during which event occurred. Sample size is 15,792.)

	Child graduated high school by age 19				*Child attended college by age 21*				*Child graduated college by age 25*			
Events	Mother event		Father event		Mother event		Father event		Mother event		Father event	
Child age 0-5												
Lost job	0.871		0.849		1.076		0.843		0.973		0.884	
	(0.098)		(0.088)		(0.118)		(0.095)		(0.136)		(0.127)	
Gained job	0.812	†	0.703	**	0.910		0.766	*	0.830		0.801	
	(0.087)		(0.074)		(0.103)		(0.086)		(0.123)		(0.118)	
Lost partner	0.728	**	0.752	**	0.560	***	0.575	***	0.464	***	0.484	***
	(0.071)		(0.073)		(0.060)		(0.062)		(0.079)		(0.082)	
Gained partner	0.780	*	0.758	**	0.756	**	0.757	*	0.624	**	0.649	**
	(0.082)		(0.079)		(0.081)		(0.082)		(0.101)		(0.107)	
Moved	0.860	*	0.849	*	0.830	**	0.845	*	0.874		0.897	
	(0.061)		(0.060)		(0.058)		(0.059)		(0.077)		(0.079)	
Child age 6-11												
Lost job	0.899		0.740	**	0.840		0.765	*	0.691	*	0.670	*
	(0.119)		(0.084)		(0.108)		(0.091)		(0.126)		(0.118)	
Gained job	0.862		0.701	**	0.785	†	0.822	†	0.877		0.807	
	(0.112)		(0.081)		(0.099)		(0.097)		(0.149)		(0.137)	
Lost partner	0.930		0.908		0.802	*	0.776	*	0.648	**	0.675	**
	(0.087)		(0.087)		(0.081)		(0.081)		(0.097)		(0.102)	
Gained partner	0.907		0.982		0.762	*	0.750	†	0.534	**	0.743	
	(0.109)		(0.129)		(0.099)		(0.113)		(0.112)		(0.156)	
Moved	0.881	†	0.912		0.807	**	0.828	**	0.706	***	0.785	**
	(0.061)		(0.063)		(0.056)		(0.058)		(0.063)		(0.070)	
Child age 12-17												
Lost job	0.823		0.841		0.801		0.726	*	0.822		0.609	*
	(0.114)		(0.112)		(0.122)		(0.102)		(0.175)		(0.122)	
Gained job	0.906		0.798	†	0.774		0.682	**	0.815		0.630	*
	(0.121)		(0.108)		(0.113)		(0.100)		(0.159)		(0.128)	
Lost partner	0.929		0.973		0.785	*	0.837	†	0.691	*	0.689	*
	(0.096)		(0.101)		(0.085)		(0.089)		(0.108)		(0.105)	
Gained partner	0.926		1.193		0.704	*	0.776	†	0.605	*	0.530	**
	(0.118)		(0.172)		(0.099)		(0.109)		(0.125)		(0.118)	
Moved	0.917		0.876	†	0.719	***	0.802	**	0.776	**	0.841	†
	(0.066)		(0.065)		(0.052)		(0.060)		(0.073)		(0.081)	

† p<.10   * p <.05   ** p < .01   *** p < .001   (two-tailed tests)

Table 3: Logistic regression of the effect of events for either parent on children's educational outcomes (results shown are interaction effects of child ages and event; models include controls; each event is a separate model; N=15,792)						
Events	*Child graduated high school by 19*		*Child attended college by 21*		*Child graduated college by 25*	
Lost job	0.743	***	0.894		0.934	
	(0.057)		(0.070)		(0.096)	
Lost job x child age	1.002		0.979	**	0.969	**
	(0.008)		(0.008)		(0.010)	
Gained job	0.684	***	0.846	*	0.803	*
	(0.053)		(0.067)		(0.084)	
Gained job x child age	1.010		0.982	*	0.992	
	(0.008)		(0.008)		(0.011)	
Lost partner	0.650	***	0.572	***	0.454	***
	(0.061)		(0.059)		(0.074)	
Lost partner x child age	1.015	†	1.014		1.021	
	(0.009)		(0.010)		(0.016)	
Gained partner	0.682	***	0.684	***	0.566	***
	(0.056)		(0.063)		(0.078)	
Gained partner x child age	1.014		0.994		0.996	
	(0.009)		(0.010)		(0.016)	
Moved	0.833	***	0.822	***	0.890	†
	(0.044)		(0.042)		(0.056)	
Moved x child age	0.988	*	0.978	***	0.970	***
	(0.005)		(0.005)		(0.006)	
† p<.10 * p <.05 ** p < .01 *** p < .001 (two-tailed tests)						

Appendix A: Logistic regression of the effect of event counts on children's educational outcomes (models include controls; each event is a separate model; N=15,792)												
Events	*Child graduated high school by age 19*				*Child attended college by age 21*				*Child graduated college by age 25*			
	Mother		*Father*		*Mother*		*Father*		*Mother*		*Father*	
Lost job	0.671	***	0.764	**	0.953		0.827		0.963		0.837	
	(0.074)		(0.079)		(0.106)		(0.096)		(0.146)		(0.124)	
Lost job x child age	1.014		0.994		0.976	*	0.983		0.973		0.974	†
	(0.012)		(0.011)		(0.012)		(0.011)		(0.017)		(0.015)	
Gained job	0.663	***	0.663	***	0.842		0.814	†	0.815		0.761	†
	(0.070)		(0.071)		(0.095)		(0.092)		(0.120)		(0.109)	
Gained job x child age	1.019		1.006		0.982		0.983		0.996		0.992	
	(0.012)		(0.011)		(0.012)		(0.011)		(0.017)		(0.015)	
Lost partner	0.698	***	0.698	***	0.603	***	0.590	***	0.514	***	0.508	***
	(0.070)		(0.070)		(0.067)		(0.068)		(0.090)		(0.090)	
Lost partner x child age	1.013		1.014		1.016		1.015		1.019		1.017	
	(0.010)		(0.010)		(0.011)		(0.011)		(0.017)		(0.017)	
Gained partner	0.858	†	0.786	**	0.863	†	0.813	†	0.802	†	0.825	
	(0.069)		(0.064)		(0.076)		(0.073)		(0.106)		(0.114)	
Gained partner x child age	0.992		1.015		0.978	†	0.986		0.967	†	0.971	
	(0.010)		(0.011)		(0.011)		(0.012)		(0.017)		(0.018)	
Moved	0.857	**	0.880	*	0.869	*	0.856	**	0.949		0.939	
	(0.048)		(0.050)		(0.048)		(0.050)		(0.064)		(0.065)	
Moved x child age	0.988	*	0.986	*	0.977	***	0.982	**	0.968	***	0.973	***
	(0.005)		(0.006)		(0.005)		(0.006)		(0.007)		(0.007)	
† p<.10 * p <.05 ** p < .01 *** p < .001 (two-tailed tests)												

Appendix B: Logistic regression of the effect of combinations of events on children's educational outcomes interacted with child age, with control variables, 3 regressors (for single events and event combination)
(events occur in the same survey year, order of events does not matter; N=15,792)

Events	Child graduated high school by age 19				Child attended college by age 21				Child graduated college by age 25			
	Mother		Father		Mother		Father		Mother		Father	
Lost job & Moved												
Lost job & Moved	0.629	***	0.616	***	0.937		0.670	*	0.571	*	0.730	
	(0.095)		(0.084)		(0.145)		(0.113)		(0.140)		(0.181)	
Lost job & Moved x child age	0.998		0.994		0.957	*	0.995		1.005		0.960	
	(0.017)		(0.016)		(0.017)		(0.018)		(0.028)		(0.035)	
Moved	0.868	**	0.900	*	0.862	**	0.864	**	0.962		0.937	
	(0.040)		(0.043)		(0.040)		(0.040)		(0.056)		(0.056)	
Moved x child age	0.987	*	0.987	*	0.981	***	0.987	*	0.963	***	0.974	***
	(0.005)		(0.006)		(0.005)		(0.006)		(0.006)		(0.007)	
Lost job	0.856		0.934		0.933		0.936		1.321		0.966	
	(0.129)		(0.133)		(0.138)		(0.138)		(0.243)		(0.182)	
Lost job x child age	1.005		0.987		0.993		0.979		0.947	*	0.972	
	(0.015)		(0.014)		(0.015)		(0.014)		(0.020)		(0.017)	
Gained job & Moved												
Gained job & Moved	0.729	*	0.529	***	0.785		0.652	**	0.628	**	0.738	
	(0.108)		(0.074)		(0.126)		(0.106)		(0.141)		(0.149)	
Gained job & Moved x child age	0.992		1.008		0.963	†	0.987		0.975		0.969	
	(0.018)		(0.016)		(0.020)		(0.019)		(0.028)		(0.026)	
Moved	0.858	**	0.910	*	0.870	**	0.867	**	0.952		0.934	
	(0.040)		(0.043)		(0.040)		(0.040)		(0.055)		(0.056)	
Moved x child age	0.988	*	0.986	*	0.981	***	0.987	*	0.965	***	0.974	***
	(0.005)		(0.005)		(0.005)		(0.006)		(0.006)		(0.007)	
Gained job	0.751	*	0.862		0.926		0.963		0.979		0.809	
	(0.108)		(0.128)		(0.139)		(0.142)		(0.182)		(0.160)	
Gained job x child age	1.017		0.993		0.990		0.979		0.990		0.995	
	(0.015)		(0.015)		(0.015)		(0.015)		(0.020)		(0.019)	
Lost partner & Moved												
Lost partner & Moved	0.640	***	0.685	**	0.561	***	0.578	***	0.651	*	0.705	†
	(0.075)		(0.080)		(0.075)		(0.077)		(0.130)		(0.142)	
Lost partner & Moved x child age	1.024	†	1.016		1.020		1.014		0.997		0.979	
	(0.013)		(0.012)		(0.014)		(0.014)		(0.021)		(0.021)	
Moved	0.917	†	0.926		0.934		0.916	†	1.007		0.995	
	(0.042)		(0.044)		(0.043)		(0.043)		(0.058)		(0.059)	
Moved x child age	1.000		1.001		0.984	**	0.992		0.974	***	0.985	*
	(0.005)		(0.005)		(0.005)		(0.006)		(0.006)		(0.007)	
Lost partner	0.861		0.726	†	0.689	†	0.629	*	0.312	***	0.306	***
	(0.158)		(0.135)		(0.138)		(0.131)		(0.094)		(0.091)	
Lost partner x child age	1.022		1.047	*	1.022		1.039	†	1.074	**	1.098	***
	(0.018)		(0.020)		(0.019)		(0.020)		(0.028)		(0.028)	
Gained partner & Moved												
Gained partner & Moved	0.889		0.839	†	0.819	†	0.792	*	0.876		0.940	
	(0.087)		(0.082)		(0.086)		(0.085)		(0.136)		(0.146)	
Gained partner & Moved x child age	0.997		1.014		0.982		0.992		0.963		0.970	
	(0.013)		(0.014)		(0.014)		(0.005)		(0.023)		(0.023)	
Moved	0.882	**	0.905	*	0.907	*	0.896	*	0.993		0.981	
	(0.041)		(0.043)		(0.042)		(0.042)		(0.057)		(0.057)	
Moved x child age	1.002		1.001		0.986	**	0.992		0.975	***	0.983	*
	(0.005)		(0.005)		(0.005)		(0.005)		(0.006)		(0.007)	
Gained partner	0.704	*	0.604	**	0.844		0.725		0.489	*	0.401	*
	(0.119)		(0.109)		(0.162)		(0.146)		(0.159)		(0.150)	
Gained partner x child age	1.025		1.066	**	0.994		1.011		1.013		1.032	
	(0.019)		(0.022)		(0.020)		(0.023)		(0.031)		(0.037)	

† p<.10 * p <.05 ** p < .01 *** p < .001 (two-tailed tests)