Vulnerability, Risk, and the Transition to Adulthood

Daniel Kuehn, Michael Pergamit, and Tracy Vericker

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Growing up poor strongly predicts poverty and poor adult outcomes later in life. Evidence of declines in economic mobility (Isaacs, Sawhill, and Haskins 2008) and increases in inequality (Goldin and Katz 2008) have focused policymakers' attention on breaking this vicious cycle of poverty. Recently, a great amount of effort has revolved around making work pay by giving low-income families incentives to work rather than relying on transfer payments (Acs and Turner 2008). Other initiatives have focused on promoting marriage, with the understanding that single mothers have fewer resources at their disposal than two-parent families (Martinson and Nightingale 2008).

Although policies directed at addressing vulnerabilities like low income levels and single parenthood may be useful, they can ignore how poverty and single parenthood influence adult outcomes for vulnerable youth. This study explores two primary reasons poverty may persist across generations. First, family poverty and single parenthood may make a youth more likely to engage in risk behaviors (including substance abuse, risky sexual activity, and crime), which in turn increase the likelihood of poor economic outcomes in early adulthood. Second, family poverty and single parenthood may make a youth more likely to drop out of school, which in turn increases the likelihood of poor outcomes. As indirect effects of family poverty and single parenthood, these mechanisms operate through the impact of those factors on risk behavior and dropping out. If these mechanisms contribute substantially to poor performance in young adulthood, then it may be advisable to supplement traditional antipoverty policies with strategies to prevent risky behavior and dropping out among vulnerable youth.

We estimate the direct and indirect effects of adolescent vulnerability (family poverty and single parenthood) on economic performance in young adulthood using the National Longitudinal Survey of

Youth 1997 (NLSY97) with a two-stage recursive model similar to the mediation models used in psychology (R. Baron and Kenny 1986) and the path analysis models used in sociology. This framework first estimates the effect of family poverty and single parenthood on risk behavior and dropping out. It then predicts our outcome variable, youth connection to school and the labor market, using single parenthood, risk behavior, dropping out, and various control variables. Our dependent variable in the second stage is developed using group-based trajectory analysis, a method for identifying patterns in longitudinal data, to characterize youth connectedness to school and the labor market in early adulthood.

Vulnerability and Poor Outcomes

Understanding vulnerable youth is a complicated task. The definition of vulnerable youth varies, and the term is often used interchangeably with other terms like "at-risk youth." In this study, we further clarify distinctions between risk factors and vulnerabilities by separating exogenous characteristics of the youth from the endogenous behaviors of youth that put them at risk. For example, factors that are exogenous to youth, but make them vulnerable, include having a physical or mental health disability, growing up in a low-income family, or living in a distressed neighborhood. Endogenous risk behaviors include drug or alcohol use, dropping out of school, or delinquency. Our framework allows us to separate the direct and indirect relationship between being vulnerable and attaining positive adult outcomes.

The term vulnerable youth is also frequently associated with youth who are disconnected during early adulthood. The term "disconnected youth" has many definitions, but typically refers to youth age 16 to 24 that are out of school and out of work (Besharov 1999; Sum et al. 2003). Estimates of the share of disconnected youth in the United States range from 15 to 37 percent, depending on the definition of disconnectedness. In this paper, we define connectedness as being employed or enrolled in school, and identify four common trajectories of youth connectedness from age 18 to 24.

A long literature spanning multiple disciplinary fields has established an empirical link between the vulnerabilities youth experience in their childhood and their connection to school and the labor market as young adults (Aaronson and Mazumder 2008; Musick and Mare 2006). Even in societies that pride themselves on economic mobility, such as the United States, a substantial amount of variation in earnings, education, and employment in young adulthood can be accounted for by the earnings, education, and employment experiences of a youth's family. While some evidence suggests that the intergenerational correlation of earnings is lower than it has been in the past (Solon 1992), it remains substantial. Children from low-income families and high-income families have the lowest chances of reaching a higher economic position than their parents. Children from middle-income families have the highest levels of intergenerational mobility. While most youth experience absolute mobility (earning more in real terms than their parents), relative mobility is stagnant (Isaacs et al. 2008).

While a direct, monetized relationship between a family's income and youth employment and earnings is possible through parental assistance, transfers, and inheritance, much of the correlation may also be indirect and nonpecuniary. For example, family income provides access to resources that make youth more successful, such as higher education. The share of the total effect of parental income accounted for by these indirect effects can be quite large. Hertz (2006) concludes that only 0.5 percent of the intergenerational correlation of income is explained directly by inheritances, compared with 29.7 percent of the variation explained by education.

Risk Behavior as a Mediator of Vulnerability

While Hertz (2006) and others make a clear case that family income influences youth income primarily through the access it provides to important resources and human capital investments, family income may also operate through a mediating behavioral mechanism. Youth coming from vulnerable families may be more likely to engage in risky behaviors in adolescence, putting them at a disadvantage in the labor market in young adulthood. Bowles, Gintis, and Osborne (2001) suggest that noncognitive behavioral inheritances facilitate the intergenerational transmission of labor market performance, complementing the roles played by education, inheritance, and intelligence. These noncognitive behavioral traits include personality and expectations along with characteristics such as aggressiveness that play an important role in risk taking. Crosnoe, Mistry, and Elder (2002) highlight the importance of parental optimism and proactive parenting as a behavioral link between family poverty and youth enrollment in higher education. Baron, Cobb-Clark, and Erkal (2008) find evidence consistent with transmission of attitudes toward work and welfare across generations, another possible cognitive mechanism driving the correlation between parental economic performance and the performance of youth in young adulthood. Finally, Dohmen and colleagues (2006) find that willingness to take risks on financial, health, and career matters is carried over from parents to children.

Burt, Zweig, and Roman (2002) suggest that modeling these behavioral mechanisms through which family poverty affects adult outcomes for youth is essential to understanding the long-term costs of adolescent vulnerability. They propose a research framework very similar to the one implemented in this paper: identifying adolescent vulnerabilities and estimating their effect on adult outcomes both directly and indirectly through increased risk behavior. Burt, Zweig, and Roman's most salient point is that researchers often fail to understand the economic context of these behaviors as intermediaries between poverty as an adolescent and the reproduction of that poverty as a young adult. This paper reframes risk behavior in this intermediary role and provides evidence on the mechanisms driving the intergenerational transmission of poverty. While previous research has investigated the economic antecedents of risk behavior and the economic consequences of risk behavior, we combine these strands of research by investigating whether risk behavior is a mechanism for the persistence of poverty across generations.

Theoretical Framework

This paper uses a two-stage recursive framework to model the mechanisms through which poverty and single parenthood affect youth connections to school and the labor market. We model the direct effect of income and single parenthood on connectedness, as well as two indirect mechanisms: the effect of these vulnerabilities on connectedness through an increased or decreased probability of committing risk behaviors, and through an increased or decreased probability of dropping out. The first stage expresses risk behavior and dropping out as a function of family income and single parenthood, and a vector of controls. The second stage presents membership in one of four youth connectedness groups[1] as a function of family income, single parenthood, risk behavior, and dropping out.

Identification of the indirect effects of income and single parenthood relies on the fact that risk behavior and dropping out are themselves functions of income and single parenthood. This model is recursive in that the dependent variables in the first stage (predicting risk behavior and dropping out) occur chronologically before the outcome of connectedness is measured in the second stage. Rather than relying on the partial derivative of connectedness with respect to income and single parenthood in the second-stage equation to quantify the effect of these vulnerabilities, this model allows us to use the first-stage estimates in combination with the direct effects of risk and dropping out on connectedness in the second-stage models to identify the total derivative of connectedness with respect to income and single parenthood. This total effect can then be decomposed into direct and indirect effects as:

$$\frac{dC_j}{dI} = \frac{\partial C_j}{\partial I} + \left(\frac{\partial C_j}{\partial R}\right)\left(\frac{\partial R}{\partial I}\right) + \left(\frac{\partial C_j}{\partial D}\right)\left(\frac{\partial D}{\partial I}\right) \text{ and } \frac{dC_j}{dS} = \frac{\partial C_j}{\partial S} + \left(\frac{\partial C_j}{\partial R}\right)\left(\frac{\partial R}{\partial S}\right) + \left(\frac{\partial C_j}{\partial D}\right)\left(\frac{\partial D}{\partial S}\right)$$

where C_j are the j connectedness groups, I is family income, R is the measure of risk behavior, D is dropping out, and S is growing up in a single-parent family. To calculate the statistical significance of these indirect effects, we use Sobel's method, described by R. Baron and Kenny (1986). If the two parameters being multiplied to form the indirect effect are a and b, and the standard errors associated with those parameters are s_a and s_b, then the standard error of the product, ab, is:

$$\sqrt{b^2 s_a^2 + a^2 s_b^2 + s_a^2 s_b^2}$$

The product of the standard errors of the parameters is generally very small and is often omitted from the calculation (R. Baron and Kenny 1986). We include this third term to provide the most conservative estimate of the standard error of the direct effect.

Data

This study employs data from the NLSY97, which is sponsored by the U.S. Bureau of Labor Statistics (BLS) and consists of a nationally representative sample of approximately 9,000 youth who were 12 to 16 years old as of December 31, 1996. The first round of the survey took place in 1997–98. In that round, age-eligible youth and one of their parents received hour-long personal interviews. The youth have been reinterviewed annually with high sample retention rates. The NLSY97 focuses on labor market participation and behaviors and activities thought to influence, or be influenced by, labor market participation. Of relevance to this study, the survey captures a nearly complete weekly employment history as well as monthly educational histories of participating youth. These histories are combined in this analysis to form a history of connectedness to either work or school in a particular week.

Many factors that influence connectedness are measured in the NLSY97, including engagement in risk behaviors and dropping out. Most other control data needed for the analyses are available in the public-use data file. Measures of neighborhood characteristics are not available from the public-use dataset. Access to local-level geography (e.g., census tracts) of youth is confidential and only available on site at the BLS. We accessed these data in order to include additional measures of the neighborhood environment.

Our sample consists of 2,041 youth who were age 15 and 16 in 1997, were age 24 at the ninth round (the wave of data available at the time our study was conducted), and had no missing values on our variables of interest.[2] We applied complex sampling weights to adjust to population totals to be representative of youth nationally. We include the youth's family income, expressed as a ratio to the federal poverty level. We use parents' earnings and other income in 1996 (collected in the 1997 wave of the NLSY97), household size, and the 1996 poverty thresholds to create these income-to-poverty ratios for each family. Because we did not include income from other members of the household, our measure is of parental income instead of household income. We included a dummy variable for youth where family income was missing to control for any observed differences in these cases. A limitation of the family income variable is that it was measured for only one year, 1996 (or 1997 if 1996 data were missing). This limited observation period ignores the fact that income, particularly for low-income households, is significantly transitory, with many families moving in and out of poverty.

We created four family structure types: two biological parents, one biological parent and one non-biological parent, a single biological parent, and all other family structures. Our analysis focuses on youth living in single-parent households; we use youth from families with two biological parents as the reference group in our models.

Thirteen risk behaviors are included in the analysis: consumed alcohol by age 13, used marijuana by age 16, ever used other drugs, engaged in sex by age 16, ever attacked someone and/or got into a fight, ever been a member of a gang, ever sold drugs, ever destroyed property, ever stole something worth less than $50, ever stole something worth more than $50, ever committed another type of property crime (i.e., vandalism), ever carried a gun, and ever ran away from home. Originally, we posited a latent propensity to engage in risk behaviors. We conducted a factor analysis, creating one composite factor score, which allowed each risk behavior to have a different weight. The weakness of a factor score is that it is difficult to interpret in a regression context. We thus considered a cumulative risk measure (Sameroff et al. 1993) as an alternative. This measure sums the number of risky behaviors in which the youth engages, ranging from zero to thirteen. The weakness of a cumulative measure is that it implicitly weights all risks equally. However, in our case, the correlation between the factor score and the cumulative risk measure was very high (0.98), suggesting that the cumulative measure of risk captures different levels of propensity to engage in risk behaviors.

We created a dummy variable to capture dropping out of high school. This measure captures those individuals who do not have a high school diploma by the ninth round of data collection. Some of these individuals may have obtained a G.E.D., but we did not count this as high school completion because having a G.E.D. differs little from dropping out in terms of labor market success (Cameron and Heckman 1993).

All analyses also control for the role of individual characteristics (race, gender, cognitive ability,[3] mental health,[4] percentage of weeks employed between ages 16 and 18, had a child during adolescence), family characteristics (parents' education,[5] any parent working full time, family structure, household size, receipt of any government assistance in the past five years,[6] and the youth's report of parental "supportiveness"), and neighborhood characteristics (family lives in a distressed neighborhood).[7] Table 1 presents the characteristics of the population.

Trajectory Analysis of Youth Connectedness

Youth connectedness was described above as a youth's attachment to either school or a job in a particular week. Connections to institutions such as school and the labor market are essential to a successful transition into adulthood. Stable youth employment helps develop job tenure, and postsecondary education is an important human capital investment. Strong connectedness during the transition to adulthood is therefore instrumental in laying a foundation for future employment stability as an adult. In addition, school and employment are both potential sources of health insurance.

In this study, a youth is considered connected at a given point in time if that youth is either employed or enrolled in school. This variable is constructed weekly from age 18 to age 24. While this longitudinal, dichotomous series of connectedness can be used directly as a longitudinal dependent variable,

TABLE 1. Descriptive Statistics

Characteristic	Mean or percent	Standard deviation
Income-to-poverty ratio	2.88	2.90
Cumulative risk score	3.27	2.98
Dropout	16.67%	37.28%
Individual characteristics		
Black	14.51%	35.23%
Female	48.63%	49.99%
Cognitive ability score	44.28	32.71
Cognitive ability score is missing	15.39%	36.09%
Mental health score	15.24	2.48
Percent of weeks employed, age 16–18	38.65%	32.34%
Had child during adolescence (females only)	3.53%	18.47%
Family characteristics		
Parent is not high school graduate[a]	11.50%	31.91%
Parent's highest degree is high school diploma[a]	42.92%	49.50%
Any parent is employed full time	83.26%	37.33%
Two parents (only one biological parent)	15.01%	35.73%
One biological parent	27.65%	44.74%
Other household structure[b]	4.06%	19.76%
Household size (number)	4.38	1.42
Received any governmental assistance, past 5 years	39.05%	48.79%
Parent is supportive	66.21%	47.30%
Neighborhood characteristics		
Family lives in a distressed community	7.30%	26.02%
No. of observations	2,041	—

Sources: Authors' calculations from the National Longitudinal Survey of Youth 1997; Census 2000.

Note: All means are weighted.

a. Parent's highest degree is college degree or some college is the reference category.

b. Two biological parents is the reference category.

we find this simple expression of youth connectedness unsatisfactory. A substantial amount of research has investigated population-wide trends in the rate of youth connection to the labor market, school, or both, but little work has identified distinct patterns of youth connectedness during the transition to adulthood. Some research, such as Klerman and Karoly's (1994) work with the NLSY79, has highlighted the heterogeneity of the transition to stable employment in early adulthood, but even this work does not try to identify or verify any underlying patterns of connectedness.

Recent studies by Macomber and colleagues (2008) and Hynes and Clarkberg (2005) have used group-based trajectory analysis to identify and express employment patterns. Trajectory analysis was developed to identify subgroup patterns in youth delinquency for developmental psychology literature (Nagin 1999). This method was presented as an alternative to the aggregated delinquency statistics that were more routinely available. The application of this method to diverse employment patterns is more recent. This study expands that strategy for the identification of connectedness patterns.

Trajectory analysis uses data on a longitudinal series of outcomes of a variable y for an individual i in trajectory group j, over T timespans. In this study, y_{it} is 1 when a youth is either enrolled in school or employed, and 0 otherwise. The probability of a specific y_{it} outcome, conditional on group membership, is specified as:

$$p^j\left(y_{it}\right) = e^{\left(\beta_j^0+\beta_j^1 age_{it}+\beta_j^2 age_{it}^2\right)} \Big/ 1+e^{\left(\beta_j^0+\beta_j^1 age_{it}+\beta_j^2 age_{it}^2\right)}$$

This is a logit equation with the age of individual *i* at time *t* and age squared as arguments. The product of these instantaneous probabilities is the probability of a unique sequence of connectedness outcomes for individual *i*. The sum of all such unique sequence probabilities multiplied by π^j, the proportion of the sample in each trajectory group, produces the unconditional probability of a specific sequence of outcomes for y_{it}:

$$P\left(Y_i\right) = \sum_{j=1}^{J}\left[\pi^j * \prod_{t=1}^{T} p^j\left(y_{it}\right)\right]$$

The product of all possible $P(Y_i)$s is then maximized to produce estimates of π^j, which determines the proportion of the sample in each trajectory group, and the βs, which determine the shape of each trajectory. Once the shape of the trajectories is estimated, the probability that an individual *i* is a member of a specific group is easily calculated (Nagin 2005). Researchers can estimate any number of trajectory groups. A Bayesian information criterion (BIC) is used to arbitrate between different sets of trajectories to determine which provides the best fit for the data (Nagin 2005). Insights from the BIC as well as the judgment of the researcher are used to determine the appropriate number of trajectory groups. We elected to use the trajectories produced by a four-group model. While the BIC suggested that we could justify the inclusion of additional trajectory groups, estimation of more than four trajectory groups produced redundant patterns, differing only slightly from the first four patterns. All these calculations are made with the PROC TRAJ SAS command (Jones and Nagin 2007).

Figure 1 presents the patterns of connectedness produced by the trajectory analysis. The estimated probability of being connected in a particular week is presented on the vertical axis of the graph. Age is presented

FIGURE 1. Estimated Youth Connectedness Trajectories

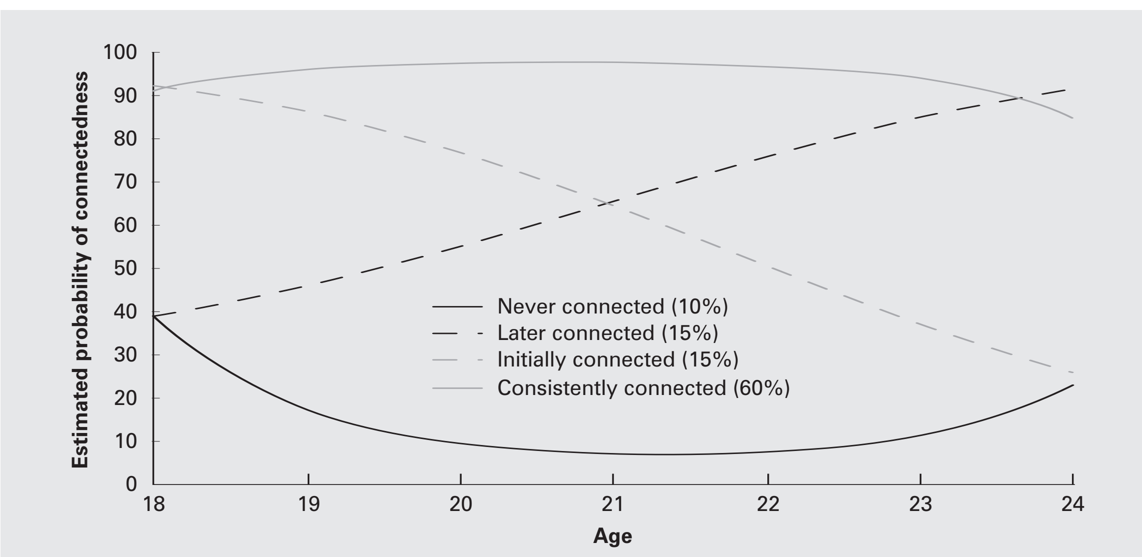

TABLE 2. Parameter Estimates of the Trajectory Analysis

	Never connected	Later connected	Initially connected	Consistently connected
Constant	–0.46803	–0.44596	2.47627	2.34289
Age coefficient	–0.24502	0.04837	–0.12684	0.18623
Age^2 coefficient	0.00705	0.00131	0.00047	–0.00656
Sample share	10.20%	15.44%	14.67%	59.69%

Source: Authors' calculations from the National Longitudinal Survey of Youth-1997.

on the horizontal axis. Each youth in the sample is assigned to a group, depending on which trajectory best approximates his or her own connectedness pattern. The parameter estimates defining the shape of each trajectory are presented in table 2.

We labeled the four different trajectory groups: youth who were never connected, later connected, initially connected, and consistently connected. Never-connected youth performed the worst of all youth. At age 18, these youth had a predicted probability of being connected of less than 40 percent, although this probability quickly declined to less than 10 percent. For most of the study period, these youth continued to have a very low probability of connectedness, despite a slight increase as they entered their mid-twenties. Initially connected youth start out with a very high predicted probability of connection to school or a job; almost 90 percent at age 18. However, as these youth get older, their chances of being connected diminish considerably. By age 24, their predicted probability of being connected is below 30 percent. Later-connected youth start out with predicted probabilities of connection very similar to never-connected youth, around 40 percent. As they transition into adulthood they make very strong connections to school and the labor market. Later-connected youth achieve a predicted probability of connection of over 90 percent by age 24. Most youth, however, are consistently connected to school or work. This group of youth forms strong initial connections (over 90 percent predicted probability of connectedness) and maintains that level of connectedness throughout their transition to adulthood.

Average rates of connectedness, school enrollment, and employment for each of the four trajectory groups confirms the characterization of the groups provided above. Never-connected youth have an average connectedness rate of 14 percent over the six-year study period. Later- and initially connected youth have average connectedness rates of 65 and 64 percent, respectively, while consistently connected youth have an average connectedness rate of 95 percent. Never-connected youth have an average employment rate of 11 percent over the study period and a school enrollment rate of 4 percent, while consistently connected youth have an employment rate of 83 percent and an enrollment rate of 41 percent, predictably higher in both categories than never-connected youth. However, later- and initially connected youth show different profiles of enrollment and employment. Later-connected youth are more likely than initially connected youth to be employed during the study period (58 percent versus 50 percent), but they are less likely to be enrolled in school (14 percent versus 22 percent).

Clearly, being consistently connected is the ideal outcome, although youth who are later connected also seem to perform well in the labor market as young adults. The two unambiguously negative groups are youth who are never connected and youth who are initially connected. Both these groups enter their mid-twenties with very little connection to either school or work. An especially discouraging facet of the initially connected is that because these youth perform comparatively well in their late teens, they may not be identified as needing assistance while they are still in school or being supported by their families.

Model Specification

We implemented the direct and indirect effect estimation described above using two modeling stages. The first stage predicts the cumulative risk score using a negative binomial model. Although the risk score is a count variable, it does not conform to the assumptions of a Poisson model, which requires the mean of the dependent variable to be equal to the variance of the variable. Under these conditions, the negative binomial model is the appropriate model to use.[8] In an additional first-stage model, we predict dropping out using a linear probability model. Robust standard errors were calculated by clustering on a family identification variable to account for siblings in the data.

In addition to the income-to-poverty ratio and single parenthood, a vector of control variables (***X***) described earlier is used to predict risk behavior and dropping out. One variable, teen childbirth, is excluded from the model predicting risk behavior, but it is included in the dropout model. The causal role of teen childbirth is much less ambiguous in the decision to drop out than in the commission of risk behaviors because teen childbirth is frequently the reason young girls drop out of school. However, because sexual activity before age 16 is one risk behavior we investigate, it is less clear whether teen childbirth causes risky behavior or whether risky behavior causes teen childbirth. Rashad and Kaestner (2004) find a similar confused causal link between drug and alcohol use and teenage sexual activity.

$$D = \alpha_0 + \alpha_1 I + \alpha_2 I^2 + \alpha_3 S + \alpha_5 \boldsymbol{X} + u$$

$$R = \beta_0 + \beta_1 I + \beta_2 I^2 + \beta_3 S + \beta_4 \boldsymbol{X} + v$$

The second-stage model predicts the four connectedness trajectories with the income-to-poverty ratio and single parenthood, as well as risk behavior, dropping out, and a vector of control variables. This second-stage equation was estimated using a multinomial logit model. The parameter estimates were translated into marginal effects, to make them comparable to the parameters in the first-stage models.

$$C_j = \gamma_0 + \gamma_1 I + \gamma_2 I^2 + \gamma_3 S + \gamma_4 R + \gamma_5 D + \gamma_8 \boldsymbol{X} + \varepsilon$$

Normally in two-stage models, we are used to seeing the inclusion of predicted values produced from the first stage. In these types of models, identification is ensured by the use of an instrumental variable that is included in the first stage but excluded from the second stage. Usually, this strategy is used to identify a parameter in an endogenous system or solve an expected omitted variable bias problem (e.g., Angrist and Krueger 1991). Although we present a two-stage model, we do not use the instrumental variable strategy here because we assume that both stages are sufficiently identified on their own.[9] We are able to include many variables at both stages that normally elude researchers, including a youth's ability level (captured in the standardized ASVAB score), neighborhood quality (captured by a census block–level poverty variable from the Census), and parenting style. Therefore, most of the omitted variable bias that typically *motivates* an instrumental variable strategy is already accounted for in this model. In addition, we maintain a very strict time-ordering in our models to prevent confusion about causality due to feedback loops or simultaneity. While most two-stage models are used to improve estimates of the direct effect of an independent variable on the dependent variable, this paper uses the two-stage model to differentiate between the direct effect of poverty and single parenthood and their indirect effects, operating through youth behavior and decisionmaking. This recursive framework is algebraically equivalent to the mediating model used in psychology literature (R. Baron and Kenny 1986).

The effect of income on youth connectedness in early adulthood presented in the equations above can be decomposed into direct and indirect effects that sum to form the total derivative of connectedness for income:

$$\frac{dC}{dI} = \gamma_1 + (2\gamma_2)I + \gamma_4\beta_1 + (2\gamma_4\beta_2)I + \gamma_5\alpha_1 + (2\gamma_5\alpha_2)I$$

In this decomposition, $\gamma_1 + (2\gamma_2)I$ is the direct effect of an increase in family income as a percentage of the federal poverty level on youth connectedness, holding all else constant. The indirect effect of family income on youth connectedness, operating through risk behavior, is $\gamma_4\beta_1 + (2\gamma_4\beta_2)I$. This effect is the product of the marginal effect of risk behavior on youth connectedness and the marginal effect of income on risk behavior. While most analyses would hold risk behavior constant in the second stage when evaluating the effect of family income on youth connectedness, this indirect effect estimate holds all control variables constant but allows risk behavior to vary in response to variation in family income. The indirect effect of income operating through risk is therefore the expected change in youth connectedness in response to the variation in risk behavior caused by a unit change in family income. The indirect effect of income on youth connectedness, operating through dropping out, is $\gamma_5\alpha_1 + (2\gamma_5\alpha_2)I$, and it has an analogous interpretation. This is the expected change in youth connectedness as a result of the variation in dropping out caused by a unit change in family income. A similar decomposition of the total effect of growing up in a single-parent family on youth connectedness is possible:

$$\frac{dC}{dS} = \gamma_3 S + \gamma_4\beta_3 S + \gamma_5\alpha_3 S$$

Here, the total effect of growing up in a single-parent family (the reference group is growing up in a family with two biological parents) is γ_3. The indirect effect of single parenthood acting through an increased (or decreased) likelihood of committing risk behaviors is $\gamma_4\beta_3$, and the indirect effect operating through an increased (or decreased) likelihood of dropping out is $\gamma_5\alpha_3$.

Results: Direct Effects

Table 3 presents both the first- and second-stage models. The second-stage model indicates strong direct effects of risk behavior, dropping out, and income on at least one of the four connectedness trajectories. Income is a significant predictor of being never connected. If a youth growing up in a household with income that was 100 percent of the federal poverty level experienced an increase to 200 percent of the federal poverty level, this would reduce the probability of being never connected by 2 percent. While this effect is not inordinately large, it remains significant even after controlling for family structure, welfare dependence, cognitive ability, risk behavior, and dropping out. A youth's family income level is not a statistically significant predictor of any of the other connectedness groups.

Risk behavior and dropping out are also statistically significant predictors of being in the never-connected group in early adulthood. Each additional risk behavior increases the probability of being never-connected by 0.54 percent. The average youth committed three to four risk behaviors, so an intervention that prevented youth from engaging in risk behaviors entirely could be expected to reduce the probability of being never-connected by 1.62 to 2.16 percent, on average. Risk behavior has almost twice as great an

TABLE 3. First- and Second-Stage Multivariate Models

	First Stage—Risk Behaviors		Second Stage—Employment Trajectory Outcomes			
Dependent variable	Cumulative risk	Dropout	Never connected	Later connected	Initially connected	Consistently connected
Sample size	2,041	2,041	2,041	2,041	2,041	2,041
Model fit (R^2 for dropout, Wald χ^2 for all others)	430.24	0.2301	440.38	440.38	440.38	440.38
Constant	—	0.4598***	—	—	—	—
Income as a percent of FPL	–0.0835	–0.0133*	–0.0188***	–0.0137	0.0143	0.0181
Income as a percent of FPL, squared	0.0046	0.0007*	0.0006**	0.0004	–0.0007	–0.0004
Income missing (dummy)	0.1241	–0.0258	–0.0266**	–0.0421	0.0177	0.0510
Cumulative risk	—	—	0.0054***	0.0091***	0.0076**	–0.0222***
Dropout	—	—	0.0508***	0.0942***	0.0800**	–0.2251***
Female	–1.3727***	–0.0620***	0.0004	–0.0345*	0.0477**	–0.0136
African American	–0.6390***	–0.0579**	0.0002	0.0538*	–0.0076	–0.0464
Hispanic	–0.2984	–0.0632**	0.0016	0.0069	0.0300	–0.0386
Ability percentile	–0.0151***	–0.0027***	–0.0013***	–0.0012***	–0.0006	0.0033***
Ability missing (dummy)	–0.6968***	–0.0247	–0.0432***	–0.0691***	0.0014	0.1109***
Mental health score	–0.1070***	–0.0107***	–0.0006	–0.0074**	–0.0041	0.0122**
Teen childbirth	—	0.3204***	0.0199	0.0025	–0.0657*	0.0432
Percent of time employed, age 16–18	—	—	–0.0106	–0.0821***	–0.0534*	0.1463***
Parent educ. less than high school[a]	0.0846	0.2427***	–0.0055	0.0136	–0.0059	–0.0022
Parent educ. high school degree[a]	–0.1665	0.0320*	0.0047	0.0333	–0.0144	–0.0235
At least one parent has full-time job	0.3159*	–0.0296	–0.0157	–0.0239	–0.0220	0.0617
Two parents, one biological[b]	0.6356***	0.0512*	0.0321	–0.0068	0.0024	–0.0278
One biological parent[b]	1.0920***	0.0867***	0.0369**	–0.0445**	0.0506*	–0.0430
Other family structure[b]	0.8792**	0.1582***	0.0683*	–0.0255	–0.0132	–0.0296
Household size	–0.0940*	–0.0010	0.0029	–0.0088	0.0167***	–0.0108
Received government support	0.3124**	0.0713***	–0.0051	0.0297	0.0293	–0.0539*
Supportive parent	–1.2744***	–0.0290	–0.0021	–0.0011	0.0110	–0.0076
North central region	–0.3438*	0.0132	–0.0022	0.0147	–0.0091	–0.0033
South region	–0.3967**	0.0304	0.0394**	0.0037	0.0325	–0.0757*
West region	–0.1989	–0.0028	0.0002	0.0709**	–0.0084	–0.0627
Rural	–0.4732***	–0.0257	0.0109	–0.0454**	0.0150	0.0194
Distressed neighborhood	–0.5553***	–0.0026	0.0149	–0.0005	0.0598*	–0.0742*

Source: Authors' calculations from the National Longitudinal Survey of Youth-1997.

Notes: Estimates for the negative binomial and multinomial logit models are marginal effects calculated at the mean.

a. Parent's highest degree is college degree or some college is the reference category.

b. Two biological parents is the reference category.

*p = 0.10; **p = 0.05; ***p = 0.01

impact on the probability of being later-connected as it has on the probability of being never-connected (0.91 percent). This may suggest that low connectedness in the early twenties (when connectedness levels are low for later connectors) may be largely attributable to youthful indiscretions that make it difficult to stay focused in school or on a job. These youth may be perfectly capable of connecting to school or work but are simply distracted in early adulthood. Engaging in an additional risky behavior increases the likelihood of being initially connected by 0.76 percent, also a statistically significant magnitude.

Risk behavior is also a negative predictor of consistent connectedness. One additional risk behavior decreases the probability of being consistently connected by 2.22 percent. The negative effect on consistent connectedness is over twice the effect of risk behaviors on later connection and four times the effect of risk behaviors on being never-connected. In other words, youth who engage in risk behaviors have a greatly reduced likelihood of being consistently connected, but they do not seem to be decisively tracked into one of the other three groups. The effect of dropping out manifests a very similar pattern. Dropouts are much less likely (22.5 percent) to be consistently connected than youth who graduate from high school. Dropping out of high school has a statistically significant impact on membership in the other connectedness groups, raising the probability that a youth would be never-connected (5.0 percent increased probability), later-connected (9.4 percent), or initially connected (8.0 percent).

This suggests an important interpretation of the role of risk behavior and dropping out in the employment patterns of young adults. Youth who engage in risk behavior and who drop out are much less likely to be consistently connected to school or the labor market. However, the paths they do take are substantially diverse. Some remain disconnected through age 24, while others rally in their early twenties and achieve connectedness rates comparable to consistently connected youth.

Single parenthood also affects the likelihood of membership in most of the connectedness outcomes, although it had no statistically significant impact on the likelihood of being consistently connected. Growing up in a single-parent family increases the probability of being never-connected by 3.6 percent and of being initially connected by 5.0 percent. Growing up in a single-parent family decreases the likelihood of being later-connected by 4.4 percent.

A particularly strong control variable in the second-stage models that is worth noting in addition to the independent variables of interest is our cognitive ability score, measured by the NLSY97's reproduction of the ASVAB test. A 10 percentile point increase in this ability measure lowers the probability of being never-connected by 1.3 percent and the probability of being later-connected by 1.2 percent; it also increases the probability of being consistently connected by 3.3 percent. The standard deviation of the distribution of ASVAB scores is 32.7 percentiles, suggesting that cognitive ability is a potentially important factor in explaining connectedness outcomes.

Results: Indirect Effects

Risk behavior stands out as statistically significant and an important determinant of connectedness, although a statistically insignificant mechanism for facilitating the effect of income on connectedness (table 4). Risk behavior does, however, act as a statistically significant mediator for the effect of growing up in a single-parent family on connectedness in early adulthood (table 5).

First, we will discuss the role of risk behavior in mediating the effect of income. Growing up in a household with higher income has no statistically significant effect on the likelihood of engaging in risks

TABLE 4. Decomposition of the Effect of Income on Connectedness

	Never connected	Later connected	Initially connected	Consistently connected
Components of the effect of income on employment trajectories				
Estimated direct effect	−0.01882*** + (Income) × (0.00138)**	−0.013732 + (Income) × (0.000964)	0.014396 + (Income) × (0.00146)	0.018162 + (Income) × (−0.00044)
Computed indirect effect, acting through risk behavior	−0.000451 + (Income) × (0.000050)	−0.000760 + (Income) × (0.000084)	−0.000635 + (Income) × (0.000070)	0.001854 + (Income) × (−0.000204)
Computed indirect effect, acting through dropping out	−0.000676 + (Income) × (0.000072)	−0.001253 + (Income) × (0.000132)	−0.001065 + (Income) × (0.000112)	−0.002994* + (Income) × (−0.000316)

*$p = 0.10$; **$p = 0.05$; ***$p = 0.01$

TABLE 5. Decomposition of the Effect of Single Parenthood on Connectedness

	Never connected	Later connected	Initially connected	Consistently connected
Components of the effect of single parenthood on employment trajectories				
Estimated direct effect	0.0360**	−0.0445**	0.0506*	−0.0430
Computed indirect effect, acting through risk behavior	0.005897***	0.00993***	0.00829**	−0.024242***
Computed indirect effect, acting through dropping out	0.004404**	0.008167***	0.00694**	−0.019516***

*$p = 0.10$; **$p = 0.05$; ***$p = 0.01$

behaviors, relative to growing up in a poorer household. However, as discussed earlier, engaging in risk behaviors predisposes a youth toward being never-, later-, or initially connected and against being consistently connected. The insignificant relationship between family income and risk behavior anticipates the statistical insignificance of the indirect effect of income acting through risk behavior on connectedness during the transition to adulthood, despite the significant direct effect that risk behavior has on connectedness. When the indirect effect is calculated, this turns out to be the case; the increased likelihood of engaging in risk behaviors does not act as a mechanism through which household poverty influences connectedness in the transition to adulthood (table 4).

Risk behavior emerges as a statistically significant mediator of the effect of growing up in a single-parent family on all four connectedness groups. Growing up in a single-parent family increases the likelihood of being never-connected by 0.58 percent through its impact on risk behavior (table 5). This indirect effect of single parenthood on the likelihood of being never-connected is independent of the 3.6 percent direct effect of single parenthood mentioned above. Similarly, living in a single-parent family during adolescence increases the likelihood of being later-connected by 0.99 percent, and the probability of being initially connected by 0.82 percent, through the impact of single parenthood on risk behavior. Growing up in a single-parent family indirectly decreases the likelihood of being consistently connected by 2.4 percent, by virtue of its impact on risk behavior. This finding is especially notable since the direct effect of growing up in a single-parent family on the likelihood of being consistently connected is not statistically significant.

Dropping out of high school is very similar to risk behavior in the role it plays in mediating the impact of vulnerability on connectedness. It does not play a statistically significant role in mediating the relationship between family income during adolescence and the likelihood of being never-, later-, or initially connected during the transition to adulthood. However, unlike risk behavior, it is a weak mediator of family income's influence on the likelihood of being consistently connected. It is not surprising that income does not affect connectedness through the mediator of risk behavior, and only weakly affects connectedness through the probability of dropping out, because income was not a notable factor in predicting risk behavior in the first-stage models, and was a very weak predictor of dropping out, after controlling for other variables.

The indirect effects of single parenthood on the probability of membership in the four connectedness groups, acting through dropping out, are statistically significant just as the indirect effects through risk behavior are. Moreover, the effect of growing up in a single-parent family that is mediated through dropping out is comparable in magnitude to the effect mediated through risk behavior. Growing up in a single-parent family increases the likelihood of being never-connected by 0.44 percent through its impact on the likelihood of dropping out (table 5). Living in a single-parent family increases the likelihood of being later-connected by 0.81 percent, and the probability of being initially connected by 0.69 percent, through the impact of single parenthood on dropping out. Growing up in a single-parent family indirectly decreases the likelihood of being consistently connected by 1.95 percent, by virtue of its impact on dropping out.[10]

The general conclusion of the models is that very little of the impact of parental income on youth connectedness is mediated through factors such as risk behavior and dropping out. However, a great deal of the effect of growing up in a single-parent family on connectedness is translated indirectly through these intervening variables. Single parenthood makes both youth risk behavior and dropping out more probable, and these factors in turn influence youth connectedness during the transition to adulthood.

Conclusions

In this paper, we explored youth risk behavior and dropping out as a potential indirect mechanism through which income and single parenthood influence youth connectedness during the transition to adulthood. This was accomplished in a two-stage framework that first predicted risk behavior and dropping out using parental income and single parenthood, then predicted youth connectedness with risk behavior, dropping out, parental income, and single parenthood. The product of the estimated effects of the first-stage predictors and the estimated effects of risk behavior and dropping out in the second stage produced an estimate of these indirect pathways.

This study also introduced a relatively new method for identifying longitudinal patterns in youth connection to school and the labor market called group-based trajectory analysis. The trajectory analysis identified four groups: youth who were never-connected, later-connected, initially connected, and consistently connected. Our models predicted membership in these four groups, rather than point estimates of connectedness at a specific age.

A few general patterns emerged from the analyses that could inform policy on poverty, risk behavior, and the transition to adulthood. The most notable result was that the indirect effects of family income, acting through risk behavior and dropping out, were largely insignificant. This suggests that the best way to break the cycle of poverty is probably to address poverty directly, rather than targeting the causal mechanisms through which poverty may be thought to operate (such as risk behavior or dropping out). Income did not strongly predict risk behavior or dropping out after controlling for other family and neighborhood characteristics, and therefore the impact of risk-taking and dropping out on connectedness was not able to magnify the impact of income. Single parenthood, on the other hand, had significant indirect effects. Risk behavior and dropping out were both important vehicles through which single parenthood exercised an indirect effect on connectedness in the full sample. In the case of the likelihood of being consistently connected, roughly half of the impact of growing up in a single-parent family was translated through the indirect effects of growing up in a single-parent family.

A more complicated policy strategy emerges for children of single parents compared with growing up in a low-income family. Single parenthood's impact operates, in part, through youth risk-taking behavior and dropping out. Policies directed at preventing risk behavior and promoting high school graduation specifically for children from single-parent families may be an appropriate method of breaking the link between single parenthood and poor economic outcomes. This suggests a balanced policy approach, recognizing the varying mechanisms influencing youth connectedness.

NOTES

1. We identified these groups with group-based trajectory analysis, discussed in more detail on pages 6–7.
2. Two exceptions are cases with missing values on family income and missing values on the cognitive ability score. We created a dummy variable to identify these missing cases and assigned their family income or cognitive ability score as zero.
3. In the baseline year of the NLSY97, respondents were asked to take a standardized test the military uses to determine enlistment acceptability, the Armed Services Vocational Aptitude Battery (ASVAB), consisting of 10 subtests. Four of these subtests measure verbal and math ability and, when combined, provide a measure that correlates highly with standard IQ tests. The ASVAB was administered at a central location, and not all respondents chose to take it. Thus, ability scores are available for approximately 79 percent of the 15- to 16-year-olds. We included a dummy variable to capture observed information for respondents who chose not to take the ASVAB.
4. Mental health problems are measured using the Mental Health Inventory-5 (MHI-5). The MHI-5, administered to NLSY97 respondents in 2000, 2002, and 2004, uses five questions to assess degrees of depression and anxiety. The MHI-5 has been used in numerous studies and has proved a valid measure of depression and anxiety among adolescents and adults (Berwick et al. 1991; Ostroff et al. 1996). To assess mental health as close to adolescence as possible, we used the mental health score from 2000. If the mental health score is missing in 2000, the score from the 2002 survey is used. Although the mental health measure will come from a period technically outside adolescence, the scale is intended to measure chronic conditions.
5. The parent with the higher degree attained is used to construct parent education variables.
6. Types of assistance include Aid to Families with Dependent Children (AFDC), Food Stamps, WIC, Medicaid, and Supplemental Security Income.
7. Distressed neighborhoods are defined as census tracts in which 30 percent or more of the households live at or below the federal poverty level.
8. We also estimated a Poisson model. Although it failed the goodness of fit test, most likely as a result of overdispersion in the data, the results were comparable in significance and magnitude to the results of the negative binomial reported in the paper.

9. Any unaccounted-for omitted variable bias may still not be large enough to justify an instrumental variable approach if the available instruments are not strong (Bound, Jaeger, and Baker 1995).
10. When the indirect effect of single parenthood acting through risk behavior (−2.42 percent) is combined with the indirect effect of single parenthood acting through dropping out (−1.95 percent), they exceed the direct effect of single parenthood on the likelihood of being consistently connected (−4.30 percent).

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ABOUT THE AUTHORS

Daniel Kuehn is a research associate in the Center on Labor, Human Services, and Population, and a doctoral candidate in economics at American University.

Michael Pergamit is a senior research associate in the Center on Labor, Human Services, and Population.

Tracy Vericker is a research associate in the Center on Labor, Human Services, and Population.