Vulnerability, Risk, and the Transition to Adulthood

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Introduction

Growing up poor is a strong predictor of poverty later in life. Evidence of declines in economic mobility (Isaacs, Sawhill, and Haskins 2008), and increases in inequality (Goldin and Katz 2008) have focused policy makers' attention on breaking the "vicious cycle" of vulnerability and poverty. A variety of policy levers are available to break this causal chain. Recently, a great amount of effort has revolved around "making work pay," by focusing on incentivizing low income families to work, rather than relying on transfer payments (Acs and Turner 2008). Other initiatives have focused on fatherhood and promoting marriage, with the understanding that single mothers have far less resources at their disposal than two parent families do (Martinson and Nightingale 2008).

We suggest that while policies directed at addressing vulnerabilities like low income levels and single parenthood may be useful, they can ignore the mechanisms through which poverty and single parenthood influence poor adult outcomes for vulnerable youth. Two primary mechanisms for the intergenerational transmission of poor economic performance are explored in this paper. First, family poverty and single parenthood may make a youth more likely to commit risky behaviors, like substance abuse, risky sexual activity, and crime, which in turn

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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 high school, which in turn also increases the likelihood of poor outcomes. These causal mechanisms represent an “indirect” effect of family poverty and single parenthood, which operates through risk behavior and dropping out. If these indirect mechanisms are a substantial contributor to poor performance in young adulthood, then policy might need to be redirected towards risk behavior and drop-out prevention for targeted groups of vulnerable youth, as a preferable anti-poverty strategy.

We estimate the direct and indirect effects of vulnerability (family poverty and single parenthood) on economic performance in young adulthood using the 1997 National Longitudinal Survey of Youth. A two stage model is used that is similar to the mediation models used in psychology (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 in the second stage with income, single parenthood, risk behavior, dropping out, and a variety of control variables. We use a new method of identifying patterns in longitudinal data, group based trajectory analysis, to measure youth connectedness to school and the labor market in early adulthood, which is our dependent variable.

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.” Some youth who may be categorized as “vulnerable,” include youth in the mental health, foster care, or juvenile justice systems; youth reentering the community from the criminal justice system; youth in special education; youth with physical disabilities and chronic illness; and runaway and homeless youth (Osgood et al., 2005). Other vulnerable youth may include pregnant or parenting youth, youth with mental health problems, youth who come from low-income families, youth who are from single parent families, and youth with limited English proficiency. Estimates for the number of vulnerable youth in the United States vary by the definition used and data source. The Department of Labor estimates that the population of "youth at risk" is about 7.5 million youth (U.S. Department of Labor, 2002).

In this study, we further clarify distinctions between risk factors and vulnerabilities by separating those characteristics that are exogenous to the youth that may make them vulnerable and the actual behaviors of youth that put them at risk. For example, factors that are exogenous to youth, but make them vulnerable would include having a physical or mental health disability, growing up in a low-income family, or living in a distressed neighborhood. Risk behaviors would include drug or alcohol use, dropping out of school, or delinquency. The advantage of this framework is that it allows us to separate out the direct and indirect relationship between being vulnerable and attaining positive adult outcomes. While vulnerable youth are more likely to engage in certain risk behaviors than non-vulnerable youth, not all will engage in these behaviors. Likewise, some non-vulnerable youth will engage in at-risk behaviors.

Vulnerable youth are also frequently associated with what are called "disconnected youth." The term disconnected youth has many definitions, but typically refers to youth ages 16 to 24 who are out of school and out of work (Sum, Pond, Trubskyy, Fogg, and Palma, 2003). Besharov (1999) defines disconnectedness by four factors: not enrolled in school, not employed, not in the military, and not married. Estimates of the number of disconnected youth in the United States range from 15 to 37 percent of all youth ages 16 to 24, depending on the length of disconnectedness. In this paper, we identify four common patterns of youth connectedness from age 18 to 24, and explore the relationship between these connectedness patterns and vulnerability.

A long literature, spanning multiple disciplinary fields, has established an empirical link between the vulnerabilities experienced by youth 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 recent evidence suggests that the intergenerational correlation of earnings is lower than past estimates (Solon 1992), the correlation is still substantial. Children from low income families and high income families have the lowest chance of changing their economic position from the level experienced by their parents. Those children who come from middle income families have the highest levels of intergenerational mobility (Isaacs 2008). Isaacs (2008) highlights that while most youth experience absolute mobility (earning more in real terms than their parents) relative mobility has stagnated.

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. For example, family income may provide access to resources that make youth more successful, such as higher education. In this situation, it is not family income that is directly making youth more successful as adults, rather, family income provides youth with a human capital investment, which in turn leads to higher earnings. 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 which is 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 that it provides to important resources and human capital investments, another avenue of research is that family income may be operating through a 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 non-cognitive behavioral inheritances may play a major role in facilitating the intergenerational transmission of labor market performance, complementing the role played by education, inheritance, and intelligence. These non-cognitive behavioral traits include personality and expectations, as well as characteristics such as aggressiveness, which may 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 that is consistent with an intergenerational transmission of attitudes toward work and welfare, another possible cognitive mechanism driving the correlation between parental economic performance and the performance of youth in young adulthood. Finally, Dohmen, Falk, Huffman, and Sunde (2006) find that willingness to take risks on financial, health, and career matters is transmitted from parents to children.

Burt, Zweig, and Roman (2001) 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 (2001) most salient point is that researchers who focus on youth often concentrate on very specific risk behaviors, such as smoking, gang activity, or dropping out. Research often fails 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 seeks to reframe risk behavior in this intermediary role, thereby enhancing our understanding of the economics of risky behavior, as well as providing evidence on the causal 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, this paper will combine these strands of research by investigating the extent to which risk behavior is a mechanism for the intergenerational transmission of poverty.

Theoretical Framework

This paper uses a two stage 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 poverty on connectedness, as well as two indirect mechanisms: the effect of these vulnerabilities on connectedness through an increased or decreased probability of committing risky behaviors, and through an increased or decreased probability of dropping out. The first stage expresses risk behavior and dropping out as a function of poverty and single parenthood, and a variety of controls.

Risk = R(Income, Single Parent, X)

Drop Out = D(Income, Single Parent, X)

The second stage presents membership in one of four youth connectedness groups[2] as a function of income, single parenthood, risk behavior, and dropping out.

$Connectedness_j$ *= C(Income, Single Parent, Risk, Drop Out, X)*

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.

$Connectedness_j$ *= C(Income, Single Parent, R(Income, Single Parent), D(Income, Single Parent), X)*

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 paper uses 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

[2] We identified these four connectedness groups with group based trajectory analysis, which will be discussed in more detail below.

direct and indirect effects. The indirect effect that we identify is the product of the direct effect of income (single parenthood) on risk (dropping out) in the first stage equation and the direct effect of risk (dropping out) on connectedness in the second stage equation.

$$\frac{dConnectedness_j}{dIncome} = \frac{\partial C}{\partial Income} + \left(\frac{\partial C}{\partial R}\right)\left(\frac{\partial R}{\partial Income}\right) + \left(\frac{\partial C}{\partial D}\right)\left(\frac{\partial D}{\partial Income}\right)$$

and:

$$\frac{dConnectedness_j}{dSingleParenthood} = \frac{\partial C}{\partial SingleParenthood} + \left(\frac{\partial C}{\partial R}\right)\left(\frac{\partial R}{\partial SingleParenthood}\right) + \left(\frac{\partial C}{\partial D}\right)\left(\frac{\partial D}{\partial SingleParenthood}\right)$$

To calculate the statistical significance of these indirect effects, we use Sobel's method, described by Baron and Kenney (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 (Barron and Kenney 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 National Longitudinal Survey of Youth—1997 cohort (NLSY97). The NLSY97 was designed specifically to examine the transition to adulthood. The NLSY97 consists of a nationally representative sample of approximately 9,000 youths who were

12 to 16 years old as of December 31, 1996. The NLSY97 over-samples blacks and Hispanics. Round 1 of the survey took place in 1997. In that round, both the eligible youth and one of that youth's parents received hour-long personal interviews. The NLSY97 is currently in its eleventh round of data collection. 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 during a youth's transition to adulthood.

Many factors that influence these outcomes are also measured, including engagement in risky behaviors and dropping out. These measures are used as dependent variables in the first stage models, and independent variables in our second stage models, and are integral to our calculation of the direct and indirect effects of income and single parenthood on connectedness.

Most data needed for the analyses are available in the public-use data file. Only measures of neighborhood characteristics are not available from the NLSY97 public-use dataset. Access to local level geography (e.g., zip codes and census tracts) of youth is confidential and available at the Bureau of Labor Statistics only. We accessed this data in order to include measures of the neighborhood environment that are not available on the public use dataset.

Because we are only interested in outcomes from 2005, our sample consists of all youth who responded to the survey in the ninth wave. Specifically, we present findings on a sample of youth who were ages 15 and 16 in 1997 and are age 24 in the most recent wave of data, resulting in a sample of 2,041 after excluding cases that had missing values on our variables of interest[3]. This sample was used for a series of research briefs and fact sheets for ASPE and the Urban

[3] 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 to zero.

Institute's Low Income Working Families group. This paper only analyzes data on black and white youth, reducing the sample to 1,554. We used complex sampling weights to adjust to population totals to be representative of youth nationally.

The first independent variable of interest is 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. Since we did not include income from other members of the household, our measure is a parental income measure instead of a household measure. Two types of missing data require adjustments in the creation of parental income variable. In the survey, one parent responds for the family. In some cases, the responding parent does not report the other parent's earnings or one or more components of other income. Furthermore, about 10 percent of youth do not have any parent report so that all family income information is missing. To deal with these missing data issues, we used 1997 earnings and other family income reported by the parents in 1998 (deflated to 1996 dollars using the CPI). We replaced cases with any missing 1996 income data with 1997 income data if it was complete. If income data was not complete for either 1996 or 1997 it remained missing in our analyses. This approach eliminated most of the missing values problem. We also included a dummy variable for youth where no report of family income was included to control for any observed differences in these cases. Another important limitation of the income variable is that family income will be measured for only one year, 1996 (or 1997 if 1996 data is missing). This limited observation period is a liability because there is a significant transitory element to income, particularly for low-income households, with many families moving in and out of poverty.

The second independent variable of interest is the youth's family structure, specifically youth who grew up in a single parent family. The NLSY97 identifies four different types of family structure: youth from families with two biological parents, one biological parent and one non-biological parent, a single biological parent, and all other family structures. We use youth from families with two biological parents as the family structure reference group in our models.

Risk behaviors are captured by a cumulative risk score incorporating thirteen possible risk behaviors: consumed alcohol by age 13, used marijuana by age 16, 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. Possible values for this cumulative risk behavior score range from zero to thirteen. This measure does not weight any risk behavior. To check the reliability of this measure, we also conducted a confirmatory factor analysis, creating one composite factor score, which allowed each risk behavior to have a different weight. These weights did not vary substantially across risk behaviors. The correlation between the factor score and the cumulative risk measure was very high (0.98), suggesting that the cumulative measure of risk does indeed capture different levels of propensity to engage in risk behaviors. We also created a dummy variable for youth who dropped 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.

All analyses also control for the role of individual characteristics (race, gender, cognitive ability[4], mental health[5], percent of weeks employed between ages 16 and 18, had a child during adolescence), family characteristics (parent has less than a high school education[6], parent has high school education, any parent works full-time, family structure, household size, receipt of any government assistance in the last five years[7], and parent "supportiveness," which is rated by the youth), and neighborhood characteristics (family lives in a distressed neighborhood[8]). Table 1 presents the characteristics of the population.

<u>Trajectory Analysis of Youth Connectedness</u>

Youth connectedness was described above as the attachment of a youth to either school or a job in a particular week. Connection to institutions such as school and the labor market are essential to a successful transition into adulthood. Stable youth employment helps to develop job tenure, and post-secondary education is an important human capital investment. Strong connectedness during the transition to adulthood is therefore instrumental in laying a foundation

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[4] Cognitive ability is measured in the baseline year of the NLSY97. Respondents were asked to take a standardized test used by the military for determining enlistment acceptability, the Armed Services Vocational Aptitude Battery (ASVAB), consisting of ten 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.

[5] 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, is a set of five questions used to assess degrees of depression and anxiety. The MHI-5 has been used in a number of studies and has been shown to be a valid measure of depression and anxiety among adolescents and adults (Ostroff et al. 1996; Berwick et al. 1991). 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.

[6] Parent with the highest degree attained is used to construct parent education variables.

[7] Types of assistance include Aid to Families with Dependent Children (AFDC), Food Stamps, WIC, Medicaid, and Supplemental Security Income.

[8] Distressed neighborhoods are defined as census tracts in which 30 percent or more of the households are at or below the federal poverty level.

for future employment stability as an adult. School and employment are also both potential sources of health insurance.

In this study, a youth will be 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 dependent variable, 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 been done to identify 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 et al. (2008) and Hynes and Clarkberg (2005) have used an alternative method for identifying and expressing employment patterns. Trajectory analysis was developed by Nagin (1999) and his colleagues to identify sub-group patterns in youth delinquency in the developmental psychology literature. 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, and 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 time periods. 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:

$$p^j(y_{it}) = \frac{e^{(\beta_j^0 + \beta_j^1 age_{it} + \beta_j^2 age_{it}^2)}}{1 + e^{(\beta_j^0 + \beta_j^1 age_{it} + \beta_j^2 age_{it}^2)}}$$

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}:

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

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 β's, 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 (described in Nagin, 2005). These calculations are made using the PROC TRAJ command in SAS (Jones and Nagin 2007).

The predicted patterns of connectedness produced by the trajectory analysis are presented in Figure 1. The estimated probability of being connected in a particular week is presented on the vertical axis of the graph. Age is presented on the horizontal axis. This procedure uses maximum likelihood estimation to identify the patterns that were most likely to have produced the observed trends. Each youth in the sample is assigned to one of the groups, depending on which trajectory best approximates their own connectedness pattern. The table of parameter estimates defining the shape of each trajectory is presented in Table 2.

We identified 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 20 percent.

Later connected youth start out with predicted probabilities of connection very similar to never connected youth, around 50 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.

Rather than predict average rates of connectedness for the entire sample in the second stage model, we predict the probability of membership in these four employment trajectory groups. 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 of these youth enter their mid-twenties with very little connection to either school or work. An especially discouraging facet of the initially connected group is that because these youth perform comparatively well in their late teens, they may not be identified as being in need of assistance while they are still in school or being supported by their families.

Model Specification

We operationalize the direct and indirect effect estimation described in the *Theoretical Framework* using two modeling stages. The first stage predicts the cumulative risk score using a negative binomial model. Alough 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 standard deviation of that variable. Under these conditions, the negative binomial model is the appropriate model to use. In an additional first stage model, we predict dropping out using a linear probability model. Marginal effects are calculated from the parameters estimated in the negative binomial model, to make them comparable to the parameter estimates in the linear probability model. Both of these first stage models provide robust standard errors by clustering on a family identification variable (many NLSY97 respondents were siblings).

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

$$Drop\ Out = \alpha_0 + \alpha_1 Income + \alpha_2 Income^2 + \alpha_3 SingleParenthood + \alpha_4 TeenChild + \alpha_5 X + u$$

$$Risk = \beta_0 + \beta_1 Income + \beta_2 Income^2 + \beta_3 SingleParenthood + \beta_4 X + v$$

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. Teen childbirth is included in the second stage model, as well as the percent of weeks between ages sixteen and eighteen that a youth was employed. 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.

$$Connectedness_j = \gamma_0 + \gamma_1 Income + \gamma_2 Income^2 + \gamma_3 SingleParenthood + \gamma_4 Employment16\text{-}18 + \gamma_5 TeenChild + \gamma_6 Risk + \gamma_7 DropOut + \gamma_8 X + u$$

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. For example, Angrist and Krueger (1991) use this method to identify an (instrumented) effect of schooling on wages that is uncorrelated with the unobserved error term. In traditional estimates of a supply function or a demand function, the inclusion of a predicted value is necessary for estimating a system of simultaneously determined price and quantity equations, by identifying shocks to either supply or demand (P.G. Wright 1928, Angrist and Krueger 2001).

Although we present a two-stage model, we do not us the instrumental variable strategy here because we assume that both stages, on their own, are sufficiently identified[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. The two stage model is used here, not to produce predicted values from an instrumental variable, but to sketch out reasonable indirect effects of poverty and single parenthood on youth connectedness. 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, as well as their indirect effects, operating through youth behavior and decision making.

This framework is therefore much more similar to the path analysis models of sociologists or a recursive analysis in economics than it is to the familiar micro-econometric instrumental variable model. The effect of income on youth connectedness in early adulthood presented in the equations above can be decomposed into direct and indirect effects which sum to form the total derivative of connectedness with respect to income:

[9] Any unaccounted for omitted variable bias may still not be large enough to justify an IV approach if the available instruments are not strong (Bound, Jaeger, and Baker 1995).

$$\frac{dConnectedness}{dIncome} = \gamma_1 + (2\gamma_2)Income + \gamma_6\beta_1 + (2\gamma_6\beta_2)Income + \gamma_7\alpha_1 + (2\gamma_7\alpha_2)Income$$

$$= \frac{\partial Connectedness}{\partial Income} + \left(\frac{\partial Connectedness}{\partial Risk}\right)\left(\frac{\partial Risk}{\partial Income}\right) + \left(\frac{\partial Connectedness}{\partial DroppingOut}\right)\left(\frac{\partial DroppingOut}{\partial Income}\right)$$

In this decomposition, "$\gamma_1 + (2\gamma_2)Income$" is the direct effect of an increase in family income as a percent of the federal poverty level on youth connectedness, holding all else constant. This is the traditional marginal effect in the second stage equation associated with manipulations of the independent variable of interest (marginal effects are computed from the odds ratios in the multinomial logit model). The indirect effect of family income on youth connectedness, operating through risk behavior is "$\gamma_6\beta_1 + (2\gamma_6\beta_2)Income$". 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 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 "$\gamma_7\alpha_1 + (2\gamma_7\alpha_2)Income$", 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:

$$\frac{dConnectedness}{dSingleParenthood} = \gamma_3 SingleParenthood + \gamma_6\beta_3 SingleParenthood + \gamma_7\alpha_3 SingleParenthood$$

$$= \frac{\partial Connectedness}{\partial SingleParenthood} + \left(\frac{\partial Connectedness}{\partial Risk}\right)\left(\frac{\partial Risk}{\partial SingleParenthood}\right) + \left(\frac{\partial Connectedness}{\partial DroppingOut}\right)\left(\frac{\partial DroppingOut}{\partial SingleParenthood}\right)$$

Here, the total effect of growing up in a single 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 "$\gamma_6\beta_3$", and the indirect effect operating through an increased (or decreased) likelihood of dropping out is "$\gamma_7\alpha_3$".

Results: Direct Effects

The full sample, 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 highly significant predictor of being never connected. If a youth who grew up in a household that was 100 percent of the federal poverty level experienced an increase to 200 percent of the federal poverty level, this would result in a 2.2 percent reduction in the probability of being never connected. While this effect is not inordinately high, it remains strongly significant even after controlling for family structure, welfare dependence, cognitive ability, risk behavior, and dropping out. A youth's family income level was also a significant predictor of being consistently connected. Moving from a household income of 100 percent of the federal poverty level to 200 percent of the federal poverty level increases the probability of being consistently connected by 2.85 percent.

Risk behavior and dropping out were also significant predictors of being in the never connected group in early adulthood. Each additional risk behavior increased the probability of being never connected by 0.46 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 1.38 to 1.84 percent, on average. Risk behavior had over twice as great an impact on the probability of being later connected as it had on the probability of being never connected. 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.

Risk behavior is also a negative predictor of consistent connectedness. One additional risk behavior decreases the probability of being consistently connected by 2.04 percent. The negative effect on consistent connectedness is 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 do not seem to be decisively tracked into one of the other three groups.

The effect of dropping out manifested a similar pattern. While drop outs were extremely less likely (24.2 percent) to be consistently connected than youth who graduated from high school, they were almost equally likely to be in each of the other three connectedness groups.

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

Single parenthood had a surprisingly weak direct effect on employment outcomes, in contrast to the strong influence it exercised in predicting risk and dropping out in the two first stage models. Growing up in a single parent family increased the probability of being never connected by 3.9 percent and being initially connected by 5.17 percent, although these effects were only weakly statistically significant.

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 percentage point increase in this ability measured lowered the probability of being never connected by 1.1 percent, but increased the probability of being consistently connected by 2.8 percent.

<u>Results: Indirect Effects</u>

Risk behavior stood out as statistically important, although a substantively weak mechanism for facilitating the effect of income (Table 6.) and single parenthood (Table 7.) on connectedness in early adulthood. Youth from households with higher income were less likely to engage in risky behaviors than poor youth, and refraining from risk behaviors in turn made youth with higher family incomes more likely to be consistently connected and less likely to be never connected or initially connected. This finding is important because it quantifies one mechanism through which income affects connectedness. However, this particular causal mechanism is somewhat weak. When income as a percent of the federal poverty level increases by 100 percentage points, the probability of being consistently connected increases by about 0.22 percent. The negative indirect relationship between income, risk, and being never connected or initially connected is even smaller than that. While these three indirect effects were statistically significant, none of them were substantively significant. The majority of the total effect of income on youth connectedness is therefore primarily attributable to the direct effect of income.

Income does not seem to impact connectedness through the mechanism of increasing the likelihood of dropping out, either. None of these indirect effects were statistically significant. It is not surprising at all that income only weakly affected connectedness through risk, and did not affect connectedness at all through dropping out. Income was not a notable factor in predicting either risk or dropping out in the first stage models, after controlling for other variables.

Single parenthood operated through much stronger indirect mechanisms than income (Table 7). The total effect of single parenthood on the probability of being later or consistently connected was due largely to its indirect effect, operating through risk behavior and dropping out[10]. The probability of being never connected and initially connected also increased as a result of single parenthood, operating indirectly through risk. Unlike the indirect effect of *income* on connectedness, the indirect effects of *single parenthood* are more substantial. For example, youth who grow up in single parent families are 2.58 percent less likely to be consistently connected than youth who grow up with two biological parents, as a result of the impact that single parenthood has on youth risk taking behavior. Single parenthood is a strong first-stage predictor of risk behavior (youth from single parent families engage in 1.26 more risk behaviors than youth from families with two biological parents), and this impact on risk behavior in turn influences youth connectedness.

The indirect effects of single parenthood on the probability of membership in the four connectedness groups through the mechanism of dropping out of high school were statistically and substantively significant for the total sample. The individual indirect effects of each group

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[10] The direct effect of single parenthood on connectedness was statistically insignificant.

are comparable in magnitude and sign to the estimated indirect effect of single parenthood, operating through risk behavior. Dropping out therefore mediates at positive relationship between single parenthood and being never, initially, or later connected to school or the labor force, but it mediates a negative relationship between single parenthood and being consistently connected.

The general conclusion of the full sample models is that very little of the impact of parental income on youth connectedness is mediated through factors such as risky 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.

Findings from the Race Sub-Sample Analysis

One concern about using the full sample models to understand the role of risk behavior in transmitting the effect of parental income and family structure on youth connectedness trajectories is that different sub-groups in the sample may experience substantively different direct and indirect effects of parental income, single parenthood, risky behavior, and dropping out. To account for this possibility, we ran all models on black youth and white youth separately.

The results of the first stage models predicting risk behavior and dropping out for black and white youth are comparable to the full sample models, in terms of the predictive power of income. Income is a very weak predictor of both risk behavior and dropping out for both black youth and white youth.

A more complicated story emerges around the role of single parenthood in predicting risk behavior and dropping out. White youth have estimated effects of single parenthood that are very similar to the full sample model. Single parenthood is a strong and significant predictor of risk behavior for these youth. White youth who grow up in single parent families are also 8.5 percent more likely to drop out of high school than youth who grow up with two biological parents. Single parenthood plays a much different role in the risk taking behavior of black youth. The effect of single parenthood on risk taking behavior is half the magnitude that it is for white youth (0.71 additional risk behaviors are associated with growing up in a single parent family, compared to 1.42 additional risk behaviors for white youth). Single parenthood has no significant effect on dropping out for black youth. Therefore, while policies promoting marriage and fatherhood should improve outcomes for all youth, such policies are likely to make greater progress in reducing risky behavior for white youth than they are for black youth.

Black youth also had second stage model effects that diverged from those of white youth. Although parental income was a strong predictor of being never connected for white youth, it had no effect on being never connected for black youth[11]. Single parenthood also held more direct predictive power for being never connected or initially connected in the white youth sample, although it had no statistically significant impact in the models run on the black youth sub-sample.

In contrast, the direct effect of risk behavior and dropping out on the never and consistently connected groups for black youth was much more pronounced in terms of effect magnitude and statistical significance than it was for white youth (although these effects were also significant for white youth). This suggests that risk behavior plays a much larger role in

[11] Although it was a weak predictor of being initially connected.

predicting connectedness patterns during the transition to adulthood for black youth than it does for white youth, while white youth's connectedness patterns are more strongly predicted by the direct effects of income and family structure. However, being initially or later connected was more strongly predicted by risk behavior and dropping out for white youth than for black youth.

The indirect effects of income and single parenthood on connectedness also diverged by racial group. White youth generally mirrored the findings of the full sample for the indirect effect of single parenthood, operating through risk behavior. While the indirect effect of single parenthood on the probability of being never connected became insignificant (the effect was statistically significant for the full sample), the indirect effect of single parenthood on being later connected and consistently connected operating through risk behavior was very similar to those found in the full sample models. Growing up in a single parent family made a white youth more likely to be later connected, and less likely to be consistently connected, relative to growing up in a family with two biological parents.

White youth also reproduced most of the results from the full sample regarding the indirect effect of single parenthood, operating through dropping out. While dropping out of high school mediated the effect of single parenthood on all connectedness groups for the full sample, this indirect pathway remained significant for white youth only for the never connected and consistently connected outcomes. The magnitude, significance, and sign of these effects were very comparable to the full sample models: single parenthood operating through dropping out made a youth more likely to be never connected, but less likely to be consistently connected.

The strong indirect pathway tracing single parenthood to connectedness, through dropping out, was not apparent in the sub-sample of black youth. While this effect was significant in the full sample and white youth, no such indirect effect exists for black youth.

However, single parenthood does influence the connectedness of black youth during the transition to adulthood through its effect on risk taking behavior. Black youth who grow up in single parent families are more likely to be never connected and less likely to be consistently connected as a result of the increased likelihood of these youth to commit risk taking behavior.

No indirect effects of income operating through either risk behavior or dropping out were statistically and substantively significant for either sub-group. This is not particularly surprising, because these indirect effects were very weak for the full sample models. The sub-group analyses confirms that while both income and single parenthood exercise some direct effect on youth connectedness, only single parenthood expresses itself indirectly through risk behavior and dropping out.

Conclusions

Economists generally explore causality in terms of the marginal effect of an independent variable on a dependent variable, holding all other factors constant (*ceteris paribus*). In the real world, other factors are not held constant, and a significant portion of the effect of an independent variable of interest may be channeled indirectly through other variables that are thought of simply as "controls" in a regression analysis. In this paper, we explored youth risk behavior and dropping out as a potential indirect mechanism through which income and single parenthood impacts 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, and 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 a "back of the envelope" 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 have the potential to inform policy on poverty, risk behavior, and the transition to adulthood. The most notable result was that direct effects, rather than indirect effects, of income dominated the total effect of income on youth connectedness for the full sample, as well as both race sub-groups. This suggests that the best way to break the vicious cycle of poverty is probably to address poverty directly, rather than targeting the causal mechanisms through which poverty operates (such as risk behavior or dropping out). Generally speaking, income did not operate indirectly through risk behavior. Income was not a strong predictor of risk behavior or dropping out after controlling for other family and neighborhood characteristics, and therefore the impact that risk taking and dropping out did have on connectedness was not able to magnify the impact of income.

Single parenthood, on the other hand, did have significant indirect effects, which in many cases were even stronger predictors of connectedness than the direct effects. Risk behavior and dropping out were both important vehicle through which single parenthood exercised an indirect effect on connectedness in the full sample. However, when the sample was divided by race, a different pattern emerged. White youth still experienced an indirect effect of single parenthood operating through risk behavior and dropping out. However, black youth felt the effect of single parenthood as a result of increases in the probability of risky behavior only, which in turn increased the likelihood of being never connected and decreased the likelihood of being consistently connected.

The policy implication of the direct and indirect effect of poverty was relatively straightforward: policy makers should focus directly on raising family income, rather than on its indirect effect through risk or dropping out.

A much more complicated strategy emerges for children of single parents. Single parenthood operates, in part, through youth risk taking behavior and dropping out, so 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. However, the emphasis of such policies may influence youth differently. White youth are more likely to benefit from campaigns that seek to break the indirect operation of single parenthood through dropping out than black youth. If policy makers focus more exclusively on high school graduation, black youth may therefore experience lower benefits. However, addressing the relationship between single parenthood and risk taking behavior would pay dividends for both black and white youth. It would therefore be advisable to provide a balanced policy approach, and for policy makers concerned with youth from single parent families to be cognizant of the varying mechanisms influencing youth connectedness. While policies addressing risk taking behavior and dropping out will improve economic outcomes for all youth, dropping out only emerges as a mediator of youth vulnerabilities for white youth.

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
Drop out	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 between ages 16 and 18	38.65%	32.34%
Had child during adolescence (females only)	3.53%	18.4%
Family characteristics		
Parent is not high school graduate[2]	11.50%	31.91%
Parent's highest degree is high school diploma[2]	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[1]	4.06%	19.76%
Household size (number)	4.38	1.42
Received any governmental assistance, last 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	1,554	--

All means are weighted.
Sources: National Longitudinal Survey of Youth-1997; Census 2000
[1] Two biological parents is the reference category.
[2] Parent's highest degree is college degree or some college is the reference category.

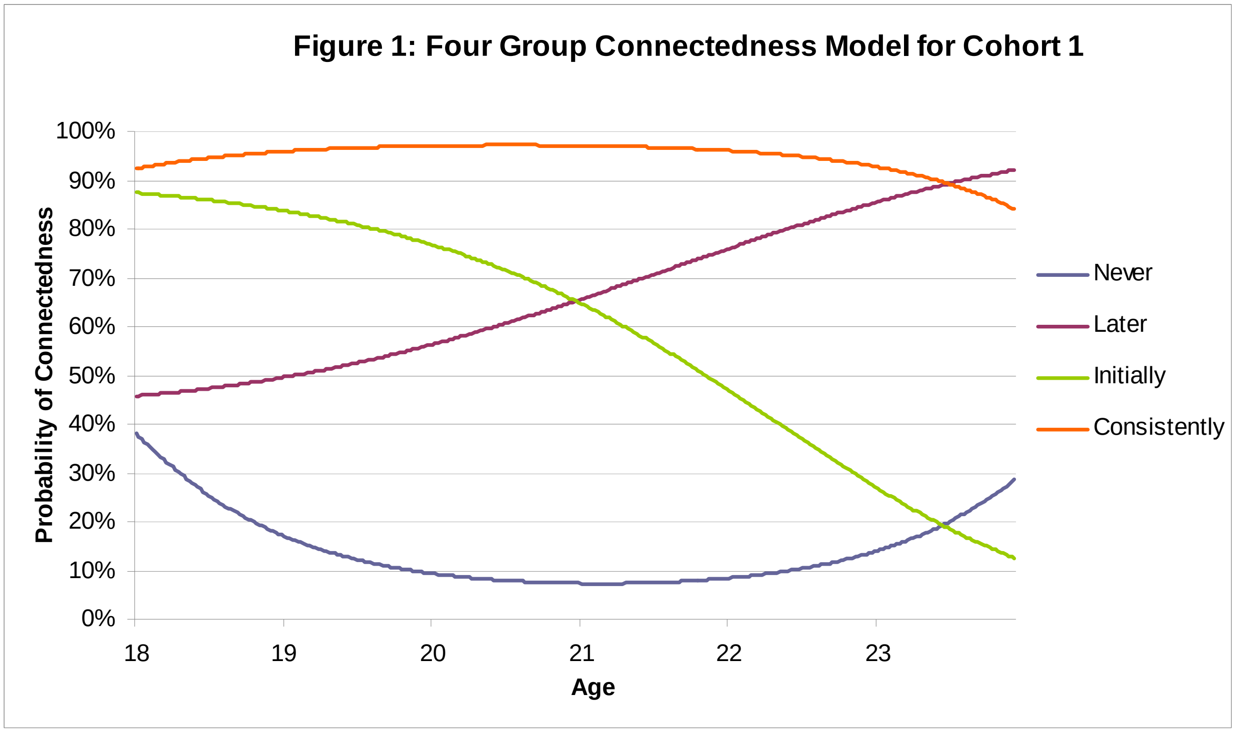

Table 2. Parameter estimates of the trajectory analysis

	Never Connected	Later Connected	Initially Connected	Consistently Connected
Constant	-0.48431	-0.16866	1.93883	2.49319
Age Coefficient	-0.24702	0.01785	-0.04316	0.15623
Age^2 Coefficient	0.00743	0.0021	-0.00256	-0.00582
Sample Share	10.10%	15.41%	12.23%	62.26%

Table 3: Results for All Black and White Youth	First Stage - Risk Behaviors		Second Stage - Employment Trajectory Outcomes			
Dependent Variable	**Cumulative Risk**	**Dropping Out**	**Never Connected**	**Later Connected**	**Initially Connected**	**Consistently Connected**
Sample Size	1554	1554	1554	1554	1554	1554
Model Fit (Wald χ^2 for Cumulative Risk and Connectedness, R^2 for Drop Out)	355.16	0.2448	369.68			
Constant	--	0.4241***	--	--	--	--
Income as a Percent of FPL	-0.1191	-0.0110	-0.0212***	-0.0103	0.0030	0.0285*
Income as a Percent of FPL, Squared	0.0068	0.0005	0.0008***	0.0003	-0.0002	-0.0009
Income Missing (dummy)	0.0224	-0.0130	-0.0226	-0.0461	0.0011	0.0676
Cumulative Risk	--	--	0.0046**	0.0100**	0.0056	-0.0204***
Drop Out	--	--	0.0722***	0.0888**	0.0917**	-0.2429***
Female	-1.3500***	-0.0564***	0.0021	-0.0221	0.0456**	-0.0256
African American	-0.7780***	-0.0603**	0.0142	0.0502	0.0104	-0.0749*
Ability Percentile	-0.0158***	-0.0027***	-0.0011***	‡	-0.0006	0.0028***
Ability Missing (dummy)	-0.6782***	-0.0324	-0.0378***	-0.0400	-0.0099	0.0878*
Mental Health Score	-0.1194***	-0.0112**	-0.0016	-0.0077	-0.0054	0.0147**
Teen Childbirth	--	0.2786***	0.0185	0.0468	-0.0761**	0.0107
Percent of Time Employed, Age 16-18	--	--	-0.0013	-0.0945***	-0.0487	0.1446***
Parent Education - Less than High School †	0.1485	0.2979	0.0085	0.0292	0.0114	-0.0492
Parent Education -High School Degree †	-0.2138	0.0314*	0.0109	0.0327	-0.0045	-0.0391
At Least One Parent Has FT Job	0.2714	-0.0341	-0.0098	-0.0161	-0.0186	0.0446
Two Parents, One Biological ††	0.7549***	0.0480*	0.0183	-0.0167	0.0101	-0.0118
One Biological Parent ††	1.2664***	0.0830***	0.0396*	-0.0314	0.0517*	-0.0598
Other Family Structure ††	0.9000	0.1634***	0.0589	-0.0182	0.0041	-0.0447
Household Size	-0.0619	0.0055	0.0029	-0.0082	0.0156**	-0.0103
Received Government Support	0.2394	0.0664***	-0.0039	0.0341	0.0004	-0.0306
Supportive Parent	-1.4331***	-0.0194	-0.0054	0.0084	-0.0073	0.0043
North Central Region	-0.3919*	0.0184	-0.0139	0.0377	-0.0029	-0.0208
South Region	-0.4333**	0.0403	0.0341	0.0214	0.0235	-0.0791*
West Region	0.0819	0.0374	0.0359	0.1344***	-0.0181	-0.1522***
Rural	-0.5405***	-0.0321*	0.0187	-0.0268	0.0102	-0.0021
Distressed Neighborhood	-0.3327	0.0021	-0.0016	0.0444	-0.0270	-0.0157

Note: Authors' calculations from the NLSY97. Estimates for the negative binomial and multinomial logit models are marginal effects calculated at the mean.
† - College, Reference; †† - Two Biological Parents, Reference; ‡ - Marginal effect could not be computed

Table 4: Results for Black Youth

Dependent Variable	First Stage - Risk Behaviors		Second Stage - Employment Trajectory Outcomes			
	Cumulative Risk	**Dropping Out**	**Never Connected**	**Later Connected**	**Initially Connected**	**Consistently Connected**
Sample Size	557	557	557	557	557	557
Model Fit (Wald χ^2 for Cumulative Risk and Connectedness, R^2 for Drop Out)	113.73	0.2423	168.02			
Constant	--	0.5041***	--	--	--	--
Income as a Percent of FPL	0.2247	-0.0222	-0.0059	-0.0086	-0.0663*	0.0809
Income as a Percent of FPL, Squared	-0.0481**	0.0020	0.0003	-0.0025	0.0081*	-0.0059
Income Missing (dummy)	-0.1543	-0.0989	-0.0505	-0.0263	-0.1102**	0.1872**
Cumulative Risk	--	--	0.0289***	0.0194**	0.0064	-0.0548***
Drop Out	--	--	0.1488**	0.0900	0.0721	-0.3110***
Female	-1.4203***	-0.1425***	0.0221	0.0634*	0.0563	-0.1420***
African American	--	--	--	--	--	--
Ability Percentile	-0.0089*	-0.0034***	-0.0008	-0.0020**	-0.0007	0.0036***
Ability Missing (dummy)	-0.2004	-0.0883	-0.0143	-0.0736*	0.0328	0.0552
Mental Health Score	-0.0690*	-0.0145**	-0.0084	-0.0078	-0.0080	0.0242**
Teen Childbirth	--	0.2445***	-0.0116	0.0489	-0.1152***	0.0779
Percent of Time Employed, Age 16-18	--	--	-0.0496	-0.0435	-0.0416	0.1348
Parent Education - Less than High School †	0.2626	0.4113***	0.0366	-0.0418	-0.0379	0.0431
Parent Education -High School Degree †	0.0465	0.1594***	0.0390	-0.0108	0.0101	-0.0383
At Least One Parent Has FT Job	0.1805	-0.0582	-0.0200	-0.0294	0.0792**	-0.0297
Two Parents, One Biological ††	0.4660	0.0371	-0.0063	0.0577	0.1414*	-0.1929**
One Biological Parent ††	0.7116**	0.0247	0.0605	0.0112	0.0133	-0.0850
Other Family Structure ††	0.4076	0.0207	0.0904	-0.0588	0.0090	-0.0406
Household Size	-0.0481	0.0145	0.0149	-0.0220*	0.0229**	-0.0158
Received Government Support	0.1543	-0.0203	-0.0082	-0.0283	-0.0615	0.0981
Supportive Parent	-0.7716***	0.0066	-0.0280	0.0357	0.0611	-0.0689
North Central Region	0.4659	-0.0045	-0.0464	0.0329	-0.0929	0.1064
South Region	0.0673	0.0286	-0.0433	-0.0345	-0.0939*	0.1717*
West Region	1.2637*	0.0158	-0.0699	0.1054	-0.1203*	0.0848
Rural	-0.6993***	-0.0980*	0.0524	0.0766	0.0427	-0.1718**
Distressed Neighborhood	-0.1596	0.0039	0.0168	0.0484	-0.0042	-0.0610

Note: Authors' calculations from the NLSY97. Estimates for the negative binomial and multinomial logit models are marginal effects calculated at the mean.
† - College, Reference; †† - Two Biological Parents, Reference

Table 5: Results for White Youth	First Stage - Risk Behaviors		Second Stage - Employment Trajectory Outcomes			
Dependent Variable	**Cumulative Risk**	**Dropping Out**	**Never Connected**	**Later Connected**	**Initially Connected**	**Consistently Connected**
Sample Size	997	997	997	997	997	997
Model Fit (Wald χ^2 for Cumulative Risk and Connectedness, R^2 for Drop Out)	310.64	0.2533	251.43			
Constant	--	0.4135***	--	--	--	--
Income as a Percent of FPL	-0.1179	-0.0096	-0.0226***	-0.0093	0.0091	0.0228
Income as a Percent of FPL, Squared	0.0073	0.0004	0.0009***	0.0003	-0.0006	-0.0006
Income Missing (dummy)	0.2245	0.0097	-0.0167	-0.0631	0.0421	0.0377
Cumulative Risk	--	--	0.0008	0.0100**	0.0058	-0.0166***
Drop Out	--	--	0.0649**	0.0754	0.0764*	-0.2168***
Female	-1.2951***	-0.0413**	0.0017	-0.0377	0.0470**	-0.0110
African American	--	--	--	--	--	--
Ability Percentile	-0.0176***	-0.0025***	-0.0013***	-0.0007	-0.0006	0.0026***
Ability Missing (dummy)	-0.8685***	-0.0078	-0.0477***	-0.0176	-0.0103	0.0757
Mental Health Score	-0.1267***	-0.0110**	0.0000	-0.0077	-0.0051	0.0129*
Teen Childbirth	--	0.3200***	0.1000	-0.0378	-0.0446	-0.0175
Percent of Time Employed, Age 16-18	--	--	0.0107	-0.1029***	-0.0495	0.1417***
Parent Education - Less than High School †	0.1836	0.02873***	0.0027	0.0456	0.0381	-0.0866
Parent Education -High School Degree †	-0.2541	0.0099	0.0080	0.0424	-0.0059	-0.0445
At Least One Parent Has FT Job	0.2495	-0.0215	-0.0126	0.0008	-0.0425	0.0542
Two Parents, One Biological ††	0.7512***	0.0461	0.0157	-0.0257	-0.0064	0.0164
One Biological Parent ††	1.4225***	0.0859***	0.0429*	-0.0468	0.0663*	-0.0623
Other Family Structure ††	0.9209	0.2266***	0.0351	0.0385	-0.0019	-0.0717
Household Size	-0.0245	-0.0014	0.0028	-0.0072	0.0146	-0.0101
Received Government Support	0.2529	0.0897***	-0.0050	0.0530	0.0104	-0.0584
Supportive Parent	-1.5688***	-0.0244	0.0032	-0.0005	-0.0207	0.0180
North Central Region	-0.5339**	0.0219	-0.0113	0.0364	0.0108	-0.0360
South Region	-0.4700*	0.0388	0.0577**	0.0267	0.0403	-0.1248**
West Region	0.0588	0.0411	0.0541	0.1284**	-0.0048	-0.1776***
Rural	-0.5131***	-0.0269	0.0220	-0.0381	0.0114	0.0046
Distressed Neighborhood	-0.4160	-0.0439	-0.0288	0.0674	-0.0733	0.0346

Note: Authors' calculations from the NLSY97. Estimates for the negative binomial and multinomial logit models are marginal effects calculated at the mean.
† - College, Reference; †† - Two Biological Parents, Reference

Table 6. Decomposition of the effect of income on connectedness: Full Sample

	Never Connected	Later Connected	Initially Connected	Consistently Connected
Components of the Effect of Income on Employment Trajectories				
Estimated Direct Effect	**-0.0212*** + (Income)x(0.0016)*** **	-0.0103 + (Income)x(0.0006)	0.0030 + (Income)x(-0.0004)	**0.0285*** + (Income)x(-0.0018)
Computed Indirect Effect, Acting Through Risk Behavior	**-0.000548** + (Income)x(0.000062**)**	**-0.001191** + (Income)x(0.000068**)**	-0.000667 + (Income)x(0.000076)	**0.002430*** + (Income)x(-0.00027***)**
Computed Indirect Effect, Acting Through Dropping Out	-0.000794 + (Income)x(0.000072)	-0.000977 + (Income)x(0.000088)	-0.000899 + (Income)x(0.000082)	0.002672 + (Income)x(-0.000242)

Table 7. Decomposition of the effect of single parenthood on connectedness: Full Sample

	Never Connected	Later Connected	Initially Connected	Consistently Connected
Components of the Effect of Single Parenthood on Employment Trajectories				
Estimated Direct Effect	0.0396*	-0.0314	**0.0517***	-0.0598
Computed Indirect Effect, Acting Through Risk Behavior	**0.0058*****	**0.0127****	0.0071	**-0.0258*****
Computed Indirect Effect, Acting Through Dropping Out	**0.0060*****	**0.0074***	**0.0068***	**-0.0202*****

Table 8. Decomposition of the effect of income on connectedness: Black Youth	**Never Connected**	**Later Connected**	**Initially Connected**	**Consistently Connected**
Components of the Effect of Income on Employment Trajectories				
Estimated Direct Effect	-0.0059 + (Income)x(0.0006)	-0.0086 + (Income)x(-0.0050)	**-0.06633* + (Income)x(0.01622)***	0.0809 + (Income)x**(0.002639)***
Computed Indirect Effect, Acting Through Risk Behavior	0.006501 + (Income)x(-0.00278)	0.004374 + (Income)x(-0.00187)	0.001454 + (Income)x(-0.00062)	-0.012329 + (Income)x**(0.005278)***
Computed Indirect Effect, Acting Through Dropping Out	-0.003275 + (Income)x(0.000596)	-0.001981 + (Income)x(0.000360)	-0.001588 + (Income)x(0.000288)	0.006843 + (Income)x(-0.001244)

Table 9. Decomposition of the effect of single parenthood on connectedness: Black Youth	**Never Connected**	**Later Connected**	**Initially Connected**	**Consistently Connected**
Components of the Effect of Single Parenthood on Employment Trajectories				
Estimated Direct Effect	0.0605	0.0112	0.0133	-0.0850
Computed Indirect Effect, Acting Through Risk Behavior	**0.0206***	0.0139	0.0046	**-0.0390***
Computed Indirect Effect, Acting Through Dropping Out	0.0037	0.0022	0.0018	-0.0077

Table 10. Decomposition of the effect of income on connectedness: White Youth	**Never Connected**	**Later Connected**	**Initially Connected**	**Consistently Connected**
Components of the Effect of Income on Employment Trajectories				
Estimated Direct Effect	**-0.0226*** + (Income)x(0.0018)*** **	-0.0093 + (Income)x(0.0006)	0.0091 + (Income)x(-0.0012)	0.0228 + (Income)x(-0.0012)
Computed Indirect Effect, Acting Through Risk Behavior	-0.00095 + (Income)x(0.000012)	-0.001181 + (Income)x(0.000146)	-0.000690 + (Income)x(0.000086)	0.001965 + (Income)x(0.000244)
Computed Indirect Effect, Acting Through Dropping Out	-0.000625 + (Income)x(0.000058)	-0.000726 + (Income)x(0.000066)	-0.000736 + (Income)x(0.000068)	0.002087 + (Income)x(-0.000096)

Table 11. Decomposition of the effect of single parenthood on connectedness: White Youth	**Never Connected**	**Later Connected**	**Initially Connected**	**Consistently Connected**
Components of the Effect of Single Parenthood on Employment Trajectories				
Estimated Direct Effect	**0.0429***	-0.0468	**0.0663***	-0.0623
Computed Indirect Effect, Acting Through Risk Behavior	0.0011	**0.0142***	0.0083	**-0.0237****
Computed Indirect Effect, Acting Through Dropping Out	**0.0056***	0.0065	0.0066	**-0.0186*****

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