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Family Socio-Economic Status, Childhood Life-Events and the Dynamics of Depression from Adolescence to Early Adulthood*

Paul Contoyannis[†] **and Jinhu Li**[‡]

[†] **Department of Economics and Centre for Health Economics and Policy Analysis, McMaster University**

[‡] **Melbourne Institute of Applied Economic and Social Research, The University of Melbourne**

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Melbourne Institute of Applied Economic and Social Research

The University of Melbourne

Victoria 3010 Australia

Telephone **(03) 8344 2100**

Fax **(03) 8344 2111**

Email **melb-inst@unimelb.edu.au**

WWW Address **http://www.melbourneinstitute.com**

Abstract

This paper employs a conditional quantile regression approach to examine the roles of family SES, early childhood life-events, unobserved heterogeneity and pure state dependence in explaining the distribution of depression among adolescents and young adults using data on the children of the US National Longitudinal Survey of Youth 79 cohort (CNLSY79). Our study also extends previous work by explicitly modelling depression dynamics during adolescence. To estimate dynamic models we integrate the 'jittering' approach for estimating conditional quantile models for count data with a recently-developed instrumental variable approach for the estimation of dynamic quantile regression models with fixed effects.

JEL classification: I12, C22, C23

Keywords: Health dynamics, dynamic quantile regression models, instrumental variable approach, depression, adolescence

1. Introduction

This study was motivated by three observations. First observation is the prevalence of child and adolescent mental health problems. The MECA Study (Methodology for Epidemiology of Mental Disorders in Children and Adolescents) found that approximately 20% of children and adolescents in the U.S. exhibit some impairment from a mental or behavioural disorder, with 1.1 percent having significant functional impairments and 5% suffering extreme functional impairment (David Shaffer et al. 1996; U.S. DHHS 1999). Depression is one of the most common mental health problems in the transition period of adolescence to early adulthood (Asarnow et al. 2009), with 15% to 20% of youth estimated to suffer from depressive disorders by the age of 18 (Lewinsohn 2002). In the United States, 28.3% of high school students report periods of depression during the past year that interfered with usual activities and lasted at least for 2 weeks (Centers for Disease Control 2002).

Secondly, evidence has shown that poor health in childhood is related to various negative consequences on future outcomes. The critical role of child physical health in subsequent health and economic outcomes has been reported by a number of authors (Case et al. 2002; Case et al. 2005; Smith 2009; Currie et al. 2010; Contoyannis and Dooley 2010). Recently the importance of child/adolescent mental health and behavioural problems has been increasingly investigated particularly using longitudinal data (see Currie and Stabile 2006; Contoyannis and Dooley 2010; Currie et al 2010; Smith and Smith 2010; and Goodman et al 2011). Moreover, some descriptive studies have specifically focused on depression during adolescence and documented the association between adolescent depression and adverse short-term and long-term outcomes. During adolescence, depression is associated with poor health and behavioral outcomes, poor academic performance and poorer peer relationships (Saluja et al. 2004; Roeser et al. 1998; Kessler et al. 1995; McLeod and Kaiser 2004). In the long-run, depression in adolescence is associated with lower economic status, poorer labour market outcomes, drug and alcohol abuse, and suicidal behaviors at adulthood ages (Gregg and Machin 2000; Fergusson et al. 2007; Fergusson and Woodward 2002).

Thirdly, as described in Heckman's persuasive skill formation framework which represents the dynamic causal pathways for the development of human capital, health is a "capacity" that affects the production of a wide range of future capacities including itself (Heckman 2007). Furthermore, Cunha and Heckman discuss the ways that both "cognitive" ability and "non-cognitive" abilities such as perseverance, motivation, time preference and self-control have direct effects on wages, schooling, smoking, crime and many other aspects of social and economic life (Cunha and Heckman 2007; Heckman 2007). We would therefore expect some of these abilities to be strongly related to measures of mental health in childhood and for these mental health measures to be somewhat persistent, even after taking account of observed and time invariant unobserved characteristics.

Our study examines the roles of family SES, early childhood life-events, unobserved heterogeneity and pure state dependence in explaining the distribution of depression among adolescents and young adults using data on the children of the US National Longitudinal Survey of Youth 79 cohort (CNLSY79). We employ a conditional quantile regression framework to approach this important question. Compared with conditional mean estimation models, which have been predominated in this literature, conditional quantile regression allows us to examine the differential effects of characteristics of interest at different parts of the depression distribution. This provides a more complete view of the links between these factors and youth depression. As will be described further in the next section, some studies have found statistically significant associations between family SES and youth depression while others have not. These discrepancies might be due to the heterogeneity of the effects of these characteristics over the conditional distribution of youth depression. In particular if the effects of these factors vary over the conditional distribution of youth depression, using an estimator appropriate for a conditional mean model will average over these heterogeneous effects. This implies that conditional mean estimates will vary, sometimes dramatically, depending on the distribution of the regressors in the sample. In addition, conditional mean regression is often strongly affected by the behaviour of outliers. This lack of robustness is another potential reason for the variability of estimates across studies which use different data sets. In light of this we begin our analysis by estimating a set of static conditional mean and conditional quantile models. By comparing the results from conditional mean models and conditional quantile models, we investigate whether the effects of key family SES conditions and the effects of early childhood life-events vary across different quantiles.

Our study also expands on previous work by explicitly modelling depression dynamics during adolescence and early adulthood. It is important to quantify both the mobility and persistence of depression as it aids understanding an important aspect of the health and human capital accumulation process early in the life course, including the protective effects of certain family SES factors in this dynamic process. To estimate dynamic models we integrate the 'jittering' approach suggested for estimating conditional quantile models for count data in a cross-sectional context (Machado and Santos Silva 2005) with a newly-developed instrumental variable approach suggested by Galvao (2011) for the estimation of dynamic quantile regression models with fixed effects. This estimator not only allows us to control for individual-specific heterogeneity via fixed effects in the dynamic panel data framework, but also effectively reduces the dynamic bias generated by conventional dynamic fixed-effects estimation of the quantile regression models.

The results from our static conditional mean models suggest that gender, race, birth order, maternal smoking behaviour during pregnancy, and maternal education play important roles in youth depression, while there is no consistently significant effect of maternal drinking during pregnancy, family income, poverty status, maternal unemployment duration and psychological consultations for stressful life-events during childhood. Our conditional quantile regression results indicate heterogeneous effects of some of these factors across the distribution of depression outcome: the estimated effects of psychological consultations for stressful life-events during childhood are statistically significant for some but not all quantiles of the depression distribution; the effects of family SES factors, in particular maternal education and family income, vary substantially across quantiles of the depression distribution. The fact that we observe these heterogeneous effects across quantiles provides a possible explanation of why some studies observe the link between family socio-economic status, stressful life events and youth depression while others do not. Results from our dynamic conditional quantile regression models suggest that the pure state dependence in youth depression is very low and the observed positive association between previous depression and current depression is mainly due to time-invariant unobserved individual heterogeneity.

This paper proceeds as follows. Section 2 describes some previous literature. Section 3 describes the data set we used for the study and presents some descriptive analysis of the data. Section 4 introduces the empirical methods of the study. In Section 5, the regression results are reported and analyzed. In Section 6 some conclusions are provided.

2. Previous Literature

There is an increasing recognition in the psychology literature that the presence of depressive disorders often starts in the period of childhood and adolescence (Chang 2009), and depression during this transition period often persists into adulthood (Colman et al. 2007). Adolescents who experience depression often struggle with depression throughout their lives (Lewinsohn et al. 1999), and in many cases, early onset of depression predicts more severe depression during adulthood (Weissman et al. 1999). Detection and effective treatment of early-onset major depressive disorders can be more important than for late-onset depressive symptoms. Greden (2001) documented that early-onset depression (before the age of 21 or 22) is associated with longer first episodes, higher rates of recurrence of major depression, higher overall rates of comorbid personality disorders, and longer hospitalizations. Berndt et al. (2000) found that early-onset depression can lead to reduced educational attainment and other human capital loss, particularly for women; a randomly selected 21-year-old woman with early-onset major depressive disorder in 1995 could expect future annual earnings that were 12%-18% lower than those of a randomly selected 21-year-old woman whose onset of major depressive disorder occurred after age 21 or not at all.

Literature in psychology points out that family socio-economic status can affect the outcome of depression among adolescents: low family SES can lead to depression in adolescence transmitted by parent-child interaction patterns while high family SES can serve as a protective factor that improves resilience in youth (see Lee and Eden 2009). However, there are few empirical studies that attempt to examine the relationship between family or individual SES and depression in adolescents or young adults, and these have produced mixed results[1]. Graetz (1993) showed that there is an association between unemployment and depression among Australian young men and women. Using data from the National Longitudinal Study of Adolescent Health (Add Health), Goodman et al. (2003) examined the socioeconomic status (SES) gradient on adolescents' mental health and found that the effect of income and education on depression were large. Using data from the Child Supplement of the National Longitudinal Study of Youth (NLSY79), Strohschein (2005) employed a growth curve analysis to examine the effect of initial family income level and changes in family income over time on depression and antisocial behavior outcomes for children aged 4 to 14. The results showed that low

[1] Some empirical literature in health economics has documented a link between socio-economic status and depression in adults. Depression has been shown to be associated with income in a wide variety of settings (Bruce et al. 1991; Dohrenwend et al. 1992; Murphy et al. 1991). Using an instrumental variables approach, Ettner (1996) found evidence that the association between income and depressive symptoms is causal. Moreover, unemployment has been shown to lead to depression (Rice and Miller 1995; Hamilton et al. 1997). Zimmerman and Katon (2005) found that while income loses much of its relationship to depression when other variables are controlled, employment status and financial strain are more robust predictors of depression.

household income is associated with higher levels of child depression and subsequent improvements in household income reduce child depression levels, while the effect of initial household income on rate of change in child depression attenuates as children grow older. However, some empirical studies have found "no relationship" between depression among adolescents and socioeconomic status. Waschbusch et al. (2003) examined the relationship between depression and SES measured by the Hollingshead Four-Factor Index (Hollingshead 1975) in a sample of adolescents and found no association. In the examination of the trajectories of depressive symptoms among a sample of African-American youth aged 14 to 17, Repetto et al. (2004) found that depressive symptoms were not related to parental occupation. Using the National Longitudinal Study of Adolescent Health (AddHealth) data, Rushton et al. (2002) examined factors associated with persistent depressive symptoms among 13,568 adolescents who completed the initial survey in 1995 and were followed up 1 year later. They found that socioeconomic status did not predict persistent depressive symptoms. Other studies have attempted to draw causal inferences regarding the SES-depression gradient among adolescents. The analysis of depression from Miech et al. (1999) found no support for either causation or selection processes, suggesting that SES and depression have little influence on each other before age 21. In the Great Smoky Mountains Study, Costello et al. (2003) examined the effect of family income on children's mental health by exploiting a natural experiment involving the opening of a casino on an Indian reservation. They found that family income (especially moving out of poverty) had a positive effect on the health conditions of conduct and oppositional disorders for the children, but there was no such effect on anxiety and depression.

In summary, the psychology literature has pointed out depression during adolescence may persist over time, and that the dynamics of depression among young people may be fundamentally different from that among adults. Only a few empirical studies in the economics literature have focused on depression in adolescents and examined the effects of family or individual SES and stressful life events. Moreover, the existing evidence is unclear on the effects of most socio-economic variables including parental employment status and occupation class, parental education, family income and family poverty status.

3. Data and Sample

3.1 Data Source

This study uses data on the children of the US National Longitudinal Survey of Youth 79 (CNLSY79). The NLSY79 child sample is an ongoing biennial panel survey that began in 1986 and which interviewed the children born to the female respondents of the 1979 cohorts of the NLSY. Data is currently available through the thirteenth wave (2010 collection). The assessments measure cognitive ability, temperament, motor and social development, behavior problems, and self-competence of the children as well as the quality of their home environment (see NLSY79 Child &Young Adult Data Users Guide 2008 cycle[2]). Starting in 1994, children who reach the age of 15 by the end of the survey year are no longer assessed but instead were given the Young Adult survey akin to that given to their mothers during late adolescence and

[2] The most recent NLSY79 Child &Young Adult Data Users Guide is the 2008 version, but the data is available for use till the 2010 collection.

into adulthood. This Young Adult questionnaire focuses on the transition to adulthood, with detailed questions on education, employment, training, health, family experiences, attitudes, interactions with family members, substance use, sexual activity, non-normative activities, computer use, health problems, and pro-social behaviors. According to the 2008 NLSY79 Child and Young Adult data user's guide, in 1994 a total of 7,089 children who were born to the original 6,283 NLSY79 female respondents were interviewed, and among these, 6,109 were under age 15 and 980 were 15 years or older. In 2008, a total of 7,660 children, including young adults, were interviewed. Of these, 1,354 were under age 15 and 6,306 were interviewed as young adults.

These "young adults" constitute the main study sample in our analyses. From the Young Adult Survey, we constructed the repeated measures of depression of these older children and other relevant variables that are potential determining factors for depression in young adulthood. Drawing on the extensive information in the Child Survey, we constructed variables representing important life-course characteristics of the young adults in the period of childhood. In addition, we constructed family-level variables by using the information contained in the main NLSY79 survey, which provides more information on the mothers of the young adults. Information from the Child Survey, the Young Adult Survey and the main NLSY79 survey can be linked by the unique identifiers of the child and the mother.

3.2 Study Sample and Variables

3.2.1 Variable Definitions

The outcome variable is a scale of depression-- the Center for Epidemiological Studies Depression Scale (CES-D) developed by Radloff (Radloff 1977)[3]. In the Young Adults Survey, the respondents completed a 7-item, reduced version of the CES-D questionnaire in all the cycles from 1994 to 2010. A set of seven questions was administered with skip patterns based on age and interview status. Specifically, the CES-D scale was administered to all eligible young adults in 1994 through 1998, and 2004 through 2010. But in 2000, it was administered only to the eligible young adults who were not interviewed in 1998, and in 2002 it was administered only to the eligible young adults who were not interviewed in 2000. As in the full-version of CES-D questionnaire[4], the answers to these 7 questions were coded on a scale from 0 to 3 with 0 representing "rarely/none of the time" and 3 representing "most/all of the time". Our study employs the 7-item composite CES-D score (ranging from 0 to 21) as our dependent variable in the analyses. From this point on, we use "the CES-D score" to represent the composite score of the 7-item questions.

[3] The CES-D has been used in a large body of studies on depression and has been shown to have very good validity and reliability in the general population and in a wide variety of specific ethnic and socioeconomic sub-populations (Beekman et al. 1997; Prescott et al.1998; Thomas et al.2001; Weissman et al.1977). Furthermore, the CES-D has been proved to have high internal consistency reliability and high degree of stability over time for the population of adolescence and young adults (Radloff 1991; Roberts et al 1990). The examination of the screening efficacy for the CES-D shows that the concurrent validity (i.e. the degree of congruence between the screener and the diagnosis of depression) of the CES-D is reasonably high and consistent across different sub-populations (Lewinsohn et al 1997).

[4] The full-version of CES-D includes 20 questions related to symptoms of depression. Examples of such questions include: "In the last week I felt that I couldn't shake off the blues, even with help from my family and friends", and "In the last week I felt that everything I did was an effort." Responses are coded on a scale from 0 to 3, with 0 representing "rarely/none of the time" and 3 representing "most/all of the time". Accordingly, the composite CES-D score ranges from 0 to 60.

In explaining the dynamics of youth depression our study focuses on family and own socio-economic environment, prenatal or biological factors, and stressful life-events in childhood. A set of demographic variables for the young adults is constructed, including age, gender, race, and birth order. In order to allow for flexible birth order effects on depression, we include a set of dummies representing the first born, the second born, the third born, the fourth or higher birth orders. Variables representing living environment are also included, such as, whether the youth lives in an urban or rural area, and whether the youth lives in a Standard Metropolitan Statistical Area (SMSA). In order to capture the effect of health care utilization, we include two variables in the Youth Survey: whether the youth received help for emotional problem, and whether the youth take any medicine or prescription drugs to control behavior in the past year. We include variables for biological factors including age of mother at the birth of the child, mother's drinking, smoking and substance use one year prior to the birth of the child.

In the psychology literature, previous experience of traumatic life-events has been identified as one of the most important risk factors associated with elevated risk of depression (Lee and Eden 2009). In the Child Survey, a question was asked about whether the child had a psychological consultation in the previous 12 months; if the answer is "Yes", the respondent was asked the reason for the consultation. We use two variables to capture traumatic life experiences during childhood: whether a child consulted a psychiatrist in the previous 12 months due to emotional trauma, molestation or abuse (referred to as "trauma" in the rest of the paper), and whether the child consulted a psychiatrist in the previous 12 months because of loss of parents/siblings or divorce of parents (referred to as "family events" in the rest of the paper).

As we observe repeated measures of these two variables over multiple cycles, we constructed two variables measuring the number of times in the past that a child consulted a psychiatrist because of these two problems. We appreciate that any estimated effect of these variables captures the effect of consultations/treatment for these events relative to outcomes for a composite baseline group consisting of those who experienced the relevant life-event but went untreated and those who didn't experience the relevant life event. Ideally we would want to separate the effects of life-events and prior treatment, but we do not observe whether these life events were experienced unless they were also treated.

To capture family socio-economic factors we include maternal education measured as the highest grade completed by the mother. We include maternal employment status measured as the number of weeks unemployed in the past calendar year. We constructed a parental income measure as the total net family income in the family of the mother, which is included in the Main NLSY79 Survey. This measure is adjusted to 2010 dollar equivalents and CPI inflated according to the specific interview year of the survey. We don't adjust the income measure for family size nor use any income-to-needs ratio measures because the literature has shown that adjusting income for family size wrongly combines effects that operate differently on child outcomes (Blau 1999; Duncan et al. 1998)[5]. This variable will be missing if the young adult was living in the father's or another relative's household at the time of the Young Adult Interview.[6]

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[5] The inclusion of birth order dummies which capture the effects of household position on depression outcomes partially accounts for the effect of family size in a flexible way.

[6] Since 2000 a question has been included in the Young Adult Interview asking the total family income of the respondents, which refers to the sum of income from all sources over all family members. We don't use this family income measure as this measure does not exist previous cycles.

We also include the variable of maternal family poverty status because living under the poverty line may contribute to youth depression over and above the effect from the absolute family income level. In addition to their family SES, we also consider the young adults' own SES, focusing on their employment status. The only employment measures of the youth administered consistently in the Young Adults Interview relate to a young adult's "significant job" defined as the last job lasting two weeks or more in the last year[7].

3.2.2 Sample Definition

There are in total 7,612 individuals who ever completed a Young Adult Survey during the survey years of 1994-2010. We used several criteria to select our sample. First, we only kept the individuals in the Youth Survey who had at least one CES-D score during the survey years of 1994-2010. Imposing this criterion reduces the available sample to 7,598 individuals. Second, we dropped the observations for which an individual was aged 26 or above in any wave of the Young Adults Interview. This leads to a further reduction of the sample to 7,541 individuals. Third, we dropped individuals with fewer than three consecutive waves of observation of the CES-D score, because we need to include the first lag of the CES-D score to estimate a dynamic model and the second lag of the dependent variable as the instrumental variable for the IV approach we employ for estimating conditional quantile models (We describe this in section 4.2.6). After applying this criterion, we have 4,275 individuals with 17,584 observations in the

[7] We also considered other family and youth SES factors, including highest grade completed by the father, paternal unemployment status, young adults' own education variables such as year of school currently enrolled in, highest grade of regular school completed, and whether the respondent ever repeated or skipped grade, and young adults' own income. But due to a large proportion of missing values, these variables are dropped from our estimation analyses.

sample. Lastly, we dropped observations with missing values on our main regressors described above; this leaves 3,812 individuals with 11,238 observations in total as our study sample.

3.2.3 Descriptive Statistics of the Study Sample

In Table 1, we list the summary statistics of the variables we use for the estimation models across all individuals in our study sample and over all waves. In this sample about half of the individuals are male with the mean age over all observations around 19. Around 2% of the sample reported at least one psychiatric consultation for trauma and 6% of the sample reported it for family events during the period of childhood. The CES-D depression score has a mean of 4.5 and a standard deviation of 3.68. About 12.1% of the observations have CES-D scores of zero. Figure A.1 in the Appendix presents a histogram of the CES-D score for our sample. The distribution of the CES-D score has a long right tail with about 95% of the values under 12.

Table 2 presents the transition matrix for the CES-D score classified into five categories: 0, 1-3, 4-6, 7-11 and 12 and above[8]. The rows of the transition matrix indicate the depression level in the previous period, while the columns indicate the depression level in the current period. The transition matrix shows that the majority of the transitions among different levels of depression appear on the diagonal or one cell off the diagonal. This indicates that substantial persistence exists in the dynamics of depression for the young adults, with the most persistence is observed for those with CES-D scores of 1-3 or 4-6. This is suggestive of a benefit from using quantile regression models for depression dynamics.

[8] The categories are chosen to contain relatively equal proportions of the sample and are not based on clinical classifications.

4. Empirical Methods

We first estimate static conditional mean and conditional quantile models to examine the roles of family SES, childhood stressful life-events, prenatal and biological factors in explaining the distribution of youth depression. We then estimate dynamic conditional mean and conditional quantile models to examine the dynamics of depression during adolescence to young adulthood, and to explore the roles of these factors marginal to prior depression. We control for previous depression by including the first lag of the depression score as a covariate, in addition to all the covariates in the static models. As the static models are nested in the dynamic models we need only outline the methodological issues and the empirical specifications for the dynamic models in the following discussion.

4.1 Quantile Regression Dynamic Panel Instrumental Variable Model with Fixed Effects

We employ an instrumental variable approach suggested in Galvao (2011) for a dynamic quantile regression panel data model with fixed effects. This model and associated estimator provides us several advantages for the analysis of depression dynamics. Firstly, exploring heterogeneous covariate effects within the quantile regression framework offers a more flexible approach than the classical Gaussian fixed- and random-effects estimators (Galvao 2011). Secondly, it is important to separate individual-specific heterogeneity from state dependence in the context of studying the persistence of health outcomes (see e.g. Contoyannis 2004a, 2004b); this estimator allows the control of individual-specific effects via fixed effects in the dynamic panel data framework. Thirdly, the quantile regression model has a significant advantage over models based on the conditional mean, since it will be less sensitive to observations in the tail of the underlying random variables, and consequently will be less sensitive to outliers. This approach can provide robust estimates that do not rely on specific assumptions of the outcome distributions. Fourth, this IV-estimator reduces the bias relative to conventional fixed-effects estimation of the dynamic quantile regression model. Specifically, Galvao (2011) shows that under some mild regularity conditions (notably with T $\rightarrow \infty$ as N$\rightarrow \infty$ and $N^{\alpha}/T \rightarrow 0$, for some a>0), the estimator is consistent and asymptotically normal, while Monte Carlo experiments showed that even in short panels such as ours this instrumental-variable estimator can substantially reduce bias.

In a dynamic panel data model with individual fixed effects, the τth conditional quantile function of the outcome variable of the *t*th observation on the *i*th individual y_{it} can be represented as

$$Q_{yit}(\tau |\, y_{it-1}, x_{it}, z_i) = \alpha(\tau) y_{it-1} + x'_{it}\beta(\tau) + z_i \eta \,, \qquad (1)$$

where y_{it} is the outcome of interest, y_{it-1} is the first lag of the variable of interest, x_{it} are a set of exogenous variables, z_i is an individual identifier, and η represents the *Nx1* vector of individual-specific effects. Since it is difficult to estimate a τ-dependent individual effect in a short panel of large cross-sections (large N and modest T), Galvao (2011) restricts the individual-specific effects to be independent of τ. In other words, only the effects of the covariates (y_{it-1}, x_{it}) are allowed to depend on the quantile τ of interest in the above model. Koenker (2004) introduced a general approach to the estimation of quantile regression panel data models with fixed effects but without dynamics. Application of the approach suggested by Koenker (2004) to (1) would lead to an estimator for the parameters of (1) based on the solution of:

$$(\hat{\eta}, \hat{\alpha}, \hat{\beta}) = \min_{\eta,\alpha,\beta} \sum_{k=1}^{K} \sum_{i=1}^{N} \sum_{t=1}^{T} \upsilon_k \rho_\tau \left(y_{it} - \alpha(\tau_k) y_{it-1} - x'_{it}\beta(\tau_k) - z_i\eta\right), \qquad (2)$$

where $\rho_\tau(u) \coloneqq u(\tau - I(u < 0))$ as in Koenker and Bassett (1978), and υ_k are the weights that control the relative influence of the *K* quantiles $\{\tau_1, \ldots, \tau_K\}$ for estimating the quantile invariant parameters η_i.

However, Galvao (2011) notes that the estimator defined by (2) suffers from bias in the presence of lagged dependent variables as regressors when T is moderate even as N goes to infinity. Using a rationale analogous to that of Anderson and Hsiao (1981, 1982) and Arellano and Bond (1991), Galvao (2011) suggests that valid instruments for consistently estimating (1) are available within the model. Specifically, because the lagged regressors (or functions of them) are correlated with the included regressors but are uncorrelated with the error term, they can be used as instruments. Following Chernozhukov and Hansen (2006, 2008), Galvao (2011) then proposed an IV estimator for the state dependence parameter.

The implementation of the IV procedure proposed by Galvao (2011) in the context of (1) requires the minimization of:

$$Q_{NT}(\tau, \eta_i, \alpha, \beta, \gamma) := \sum_{k=1}^{K} \sum_{i=1}^{N} \sum_{t=1}^{T} \upsilon_k \rho_\tau\left(y_{it} - \alpha(\tau_k) y_{it-1} - x'_{it}\beta(\tau_k) - z_i\eta - \omega'_{it}\gamma(\tau_k)\right), \qquad (3)$$

In addition to the variables in (2), ω_{it} is a *dim(* γ *)*-vector of instruments such that $dim(\gamma) >= dim(\alpha)$. Specifically, the instruments may include values of *y* lagged two periods or more and/or lags of the exogenous variable *x* which affect lagged y but are independent of *u*. The estimator should minimize the effect of ω_{it}. The intuition is that imposing this restriction is valid when (1) is the true model and the instruments ω_{it} are valid as ω_{it} should be uncorrelated with the error term and should therefore have a zero coefficient at the true values of the parameters.

A complication in our context is that the outcome variable is an ordered discrete response—the CES-D score. In this case, estimation of the conditional quantile regression model (developed for continuous outcome variables) is problematic because the cumulative distribution function of the CES-D score is discontinuous with discrete jumps between flat sections, so the quantiles are not unique[9]. As noted by Machado and Santos Silva (2005), the main problem with estimating conditional quantiles for discrete responses (e.g. count data) stems from the conjunction of a non-differentiable sample objective function with a discrete dependent variable. To extend the conditional quantile regression to count data, Machado and Santos Silva (2005) proposed an approach which adds artificial smoothness to the data using a form of "jittering process". Specifically, the artificial smoothing is achieved by adding uniformly distributed noise to the count variable. They are therefore able to construct a continuous variable with conditional quantiles that have a one-to-one relationship with the conditional quantiles of the original counts, and use this artificially constructed continuous variable as a base for inference. Machado and Santos Silva (2005) show that "jittering" allows inference to be performed using standard quantile regression techniques. However, jittering increases the variance relative to using the observed data. To reduce this effect, the parameters of the model are estimated repeatedly using K independent jittered samples, and the multiple

[9] Conventionally, the lower boundary of the relevant section defines the quantile in the case of a single distribution.

estimated coefficients and confidence intervals are averaged over the K jittered replications. We implemented the jittering process suggested by Machado and Santos Silva (2005) prior to the estimation of the quantile regression models, and then estimated the above instrumental variable with fixed-effects model with the jittered data.

4.2 Empirical Specifications and Estimation Methods

We examine the level of state dependence of the CES-D score and the inter-temporal roles of family SES, childhood stressful life-events, prenatal and biological factors in explaining the distribution of youth depression using both conditional mean and conditional quantile models. The empirical specifications of these dynamic panel data models are described in the sub-sections below.

4.2.1 Pooled dynamic conditional mean regression models

For a conditional mean estimation without considering individual heterogeneity, we consider the following specification:

$$E(y_{it}|y_{it-1}, x_{it}) = \alpha y_{it-1} + x_{it}'\beta, \qquad (4)$$

where y_{it} is the CES-D score, y_{it-1} is the first lag of the CES-D score, x_{it} is a vector of explanatory variables. First, we estimate a linear model (treating the CES-D score as a continuous variable) using OLS ignoring the possible dependence across observations (we call this pooled OLS). To account for the integer nature of the CES-D score, we then estimate the conditional mean of the dependent variable with a Poisson model, again pooling the data. It is worth noting that for the

Poisson model the conditional mean is not as specified in equation (4), but follows the standard parameterization of $E(y|\boldsymbol{x})=\exp(\boldsymbol{x'\beta})$.

4.2.2 Dynamic conditional mean regression models with individual-specific effects

To separate pure state dependence from unobserved individual heterogeneity, we consider the following specification:

$$E(y_{it}|y_{it-1}, x_{it}, z_i) = \alpha y_{it-1} + x'_{it}\beta + z_i\eta, \qquad (5)$$

where η denote the individual fixed effects. We first estimate the linear random-effects and fixed-effects models[10], and then estimate the Poisson model with random-effects and fixed-effects specifications. Again for the Poisson estimation the conditional mean is not as specified in equation (5), but follows the standard parameterization of $E(y|x)=\exp(x'\beta)$.

4.2.3 Pooled dynamic quantile regression model

We consider a dynamic model for the τth conditional quantile function of the outcome variable with the following specification:

$$Q_{y_{it}}(\tau|y_{it-1}, x_{it}) = \alpha(\tau)y_{it-1} + x'_{it}\beta(\tau), \qquad (6)$$

where y_{it} is the CES-D score, $y_{it-1}$is the first lag of the CES-D score, x_{it} is vector of explanatory

[10] Both random-effects and fixed effects estimators are inconsistent due to the inclusion of lagged dependent variable as a regressor. For consistent estimation of the lagged dependent variable coefficient we can estimate a first-difference (FD) with IV model, in which dependent variable lagged for two periods (or the first-difference of this) is used as the instrument variable for the lagged dependent variable (Anderson-Hsiao levels and difference estimators). An alternative is to estimate the Arellano-Bond estimator but it is not preferable due to the very short T of our sample. However, since our focus is to provide comparators for the quantile regression models which include the individual fixed-effects explicitly, we don’t discuss in length these FD with IV estimators for the dynamic conditional mean regression models here. As an additional check for the state dependence estimate from the within estimator though, we conducted the Anderson-Hsiao levels estimator for comparison—see results section 5.3.

variables. The parameter α captures the state dependence level of the CES-D scores. It should be noted that all the parameters α and β in this model are allowed to vary over quantiles.

4.2.4 Pooled Dynamic quantile regression model with jittering

As noted above, standard conditional quantile estimation for continuous data may be problematic in our context. Following Machado and Santos Silva (2005), we first add randomness to our dependent variable by "jittering" the CES-D score, and then estimate dynamic conditional quantile models to the jittered data. Specifically, we replace the discrete CES-D score y_{it} with a continuous variable $J_{it}= h(y_{it})$, where $h(.)$ is a smooth continuous transformation. The transformation used is

$$J_{it}= y_{it} +u, \quad (7)$$

where u~ U(0, 1) is a random draw from the uniform distribution on (0, 1). The conditional quantile of $Q_J(\tau|X)$ is specified to be

$$Q_J(\tau|X) = \tau + exp\big(X'\beta(\tau)\big), \quad (8)$$

where X represents the design matrix in the specification of y_{it} considered in (6). The additional term τ appears in the equation because $Q_J(\tau|X)$ is bounded from below by τ. To estimate the parameters of a quantile model in the usual linear form, a log transformation is applied so that $ln(J- \tau)$ is modeled, with the adjustment that if $J- \tau <0$, then $ln(\varepsilon)$ is used, where ε is a small positive number[11]. To reduce the effect of noise due to jittering, the parameters of the model

[11] The log transformation with the adjustment is justified by the property that quantiles are equivariant to monotonic transformation and the property that quantiles above the censoring point are not affected by censoring from below (details see Cameron and Trivedi (2009)). Note that this specification does not take into account the upper-bound of the original CES-D score but this is unlikely to be a problem in this particular application.

need to be estimated multiple times based on multiple jittered replications. We use 500 replications to derive the estimates for the quantile regression models[12].

4.2.5 Dynamic quantile regression model with fixed effects

To account for potential unobserved individual heterogeneity, we consider a dynamic panel quantile regression with individual fixed-effects:

$$Q_{y_{it}}(\tau|y_{it-1}, x_{it}, z_i) = \alpha(\tau)y_{it-1} + x'_{it}\beta(\tau) + z_i\eta, \quad (9)$$

where z_i identifies the individual fixed effects. The estimation of the above model is implemented by a regularization method developed by Koenker (2004)[13]. We use bootstrap techniques to obtain the standard errors and confidence intervals.

4.2.6 Dynamic panel instrumental variable quantile regression with fixed effects

As noted above, the instrumental variable approach suggested by Galvao (2011) can reduce bias when estimating the dynamic quantile regression model with fixed effects. We use the values of CES-D score lagged two periods as our instrument[14]. The estimates of the parameters are

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[12] We experimented with the number of replications, including 50, 100, 500 and 1,000 jittered samples. We chose 500 jittered samples because results change at only the 3rd decimal place when increasing from 500 to 1000, but the calculation time doubles.

[13] As in Koenker 2004, fixed effects are assumed invariant across quantiles. However, we include an intercept that varies with different quantiles in the fixed effects model by setting for a very small shrinkage parameter (i.e. 1e-6) in Koenker's penalized fixed effects model. Koenker (2004) notes that as the shrinkage parameter approaches 0 we obtain the FE estimator, while as the shrinkage parameter approaches to infinity the estimates of FEs approach 0 and we obtain an estimate of the pooled model. Therefore, our estimate represents a very close approximation of the FE estimator.

[14] We use y_{it-2} as the instrument because it is structurally correlated with y_{it-1}; and it is a valid instrument when we assume the error term is serially uncorrelated conditional on the individual fixed effects. In the case of dynamic conditional mean regression models, the assumption of no serial correlation after controlling for fixed effects is testable if we implement the Arellano-Bond type of estimator which employs additional lags of the dependent variables as instruments and therefore can offer an opportunity to implement an overidentifying restrictions test on

obtained by minimizing the objective function (3).

We perform bootstrap-based inference in this context. Specifically, we construct the bootstrap samples by resampling from the cross-sectional units (individual persons in our case) with replacement[15]. We used 499 bootstrap replications with a pair-wise resampling technique to construct the empirical distribution of the estimator and construct the bootstrap standard errors. We also used a percentile bootstrap procedure to construct 95% confidence intervals for the parameters of interest.

4.2.7 Dynamic instrumental variable quantile regression model estimation with jittering and fixed effects

To account for the problems arising with quantile regression when the dependent variable takes integer values, we apply the IV approach described in Section 4.1 to jittered data. We use the same process to construct the jittered data as for the dynamic panel quantile estimation described in Section 4.2.4. We then implement the IV estimator with the artificially smoothed CES-D score as the dependent variable[16]. We use 500 jittered samples again in this model.

As the jittering process involves a non-linear transformation from the original CES-D

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the validity of the instruments (see Arellano and Bond 1991). In the case of dynamic conditional quantile estimation, we are unaware of such tests to test this assumption. In any event, this is not possible in our case because we can only use y_{it-2} as the single instrument in the model, due to the very short panel of our data.

[15] Monte Carlo simulations suggest that cross-sectional bootstrapping has the best performance among three alternative bootstrapping procedures in this context (Galvao and Montes-Rojas 2009; Kato, Galvao and Montes-Rojas 2010).

[16] It is worth noting that when we estimate the quantile models with jittering (as in Sections 4.2.4 and 4.2.7), we are estimating marginal effects for a different specification (the conditional quantile function is an exponential function of X) than when assuming continuity (as in Sections 4.2.3, 4.2.5 and 4.2.6), where the conditional quantile function is specified as a linear function of X.

score to a smoothed variable, the marginal effect (ME) estimates are different from the coefficient estimates. We use the marginal effects at the mean (MEM) convention to calculate the MEs. According to Equation (8), the MEs for any continuous regressor x_j are estimated by $exp(\overline{\boldsymbol{X}}'\widehat{\boldsymbol{\beta}})\hat{\beta}_j$, with all the regressors evaluated at their mean values. For any dummy variable x_j, we calculate the MEs with respect to a change in this dummy variable from 0 to 1, using the difference of the corresponding predicted values: $exp(\overline{\boldsymbol{X_1}}'\widehat{\boldsymbol{\beta}}) - exp(\overline{\boldsymbol{X_0}}'\widehat{\boldsymbol{\beta}})$, where $\overline{\boldsymbol{X_1}}$ represents the design matrix evaluated at 1 for this dummy variable x_j and at the means for all the other regressors, while $\overline{\boldsymbol{X_0}}$ represents the design matrix evaluated at 0 for this dummy variable x_j and at the means for all the other regressors[17].

5. Estimation Results

5.1 Results for Static Conditional Mean Regression Models

Table 3 presents results for the conditional mean estimation for the CES-D score based on static linear panel data models. Columns (1) and (2) present marginal effects and standard errors for the pooled linear model; columns (3) and (4) present the results for the random-effects model; and columns (5) and (6) present the results for the fixed-effects model. Several patterns can be observed from the results. First, as indicated in the current literature on youth depression, demographic characteristics are important in explaining the variability of depression. Females

[17] Care is needed in interpreting the results because the quantiles of y_{it} are step-functions. In particular since y_{it} is a step function, when the ME is > 1 for the model for J_{it} there will be an effect on the quantile of y_{it}; when the ME is <1 for J_{it} it is not necessarily true that there is an effect on the quantile of y_{it}. The paper reports partial effects (evaluated at the mean) on the quantiles of J_{it}, not y_{it}. Practically note that observing an effect for the jittered sample does not necessarily translate to an impact on the CES-D score. We are grateful to Joao Santos Silva for this point.

and blacks have higher CES-D scores as do those with older siblings. As expected there is a statistically significant and large positive correlation between health care utilization and higher CES-D score. Perhaps surprisingly, the pooled model suggests that psychiatric consultations for family events and emotional trauma during childhood do not explain the variability of youth depression. However the likelihood of unobserved heterogeneity driving these results precludes causal inference, particularly in static models[18]. Prenatal factors including the age of mother at birth of the child and maternal smoking behaviour are statistically significant in the model: children who were born to younger mothers and those born to mothers who smoked during pregnancy are likely to have higher depression scores. Maternal alcohol consumption during pregnancy is not statistically significant. Having a job as a youth is associated with higher depression scores, while living in an urban or rural area appears unimportant. Lastly, among the set of family SES factors, maternal education and maternal unemployment duration are important in explaining the variability of youth depression: lower maternal education and longer maternal unemployment are associated with higher CES-D scores. Surprisingly, total family income and maternal poverty status are not associated with youth depression.

A linear specification might not be appropriate to model the conditional mean of the CES-D score with our data because the CES-D score exhibits skewness and discreteness as described by the descriptive statistics and the histogram of the CES-D scores. Table 4 summarizes the results for the pooled model, the random-effects model and the fixed-effects

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[18] Interestingly the results based on the random effects model show that after taking account of individual heterogeneity (which is assumed uncorrelated with included regressors), variables measuring prior psychiatric consultations for both types of stressful life events (family events or emotional trauma) become statistically significant at the 10% level.

model using Poisson specifications. The reported standard errors for the random- and fixed-effects models are based on bootstrapping for 499 replications. Most of the patterns found in the linear model regressions are preserved and the sizes of the estimated marginal effects are generally comparable. However, a few exceptions are worth noting. First, both the pooled model and random effects model suggest that psychiatric consultations for family events is statistically significant while psychiatric consultations for trauma is statistically insignificant in explaining the variability of youth depression. Second, the random effects model with Poisson specification indicates that higher family income is associated with lower CES-D scores while maternal unemployment duration is not important.

5.2 Results for Static Conditional Quantile Regression Models

Table 5 presents the pooled static conditional quantile regression model without jittering. Columns (1) and (2) list the marginal effects and the standard errors for the estimation of the 0.25 conditional quantile of the CSE-D score; Columns (3) and (4) list the results for the estimation of the 0.5 conditional quantile of the CSE-D score; Columns (5) and (6) present the results for the estimation of the 0.75 conditional quantile of the CSE-D score. Table 6 presents the pooled static conditional quantile regression model based on 500 jittered replications. The estimates appear to be insensitive to the use of jittering and the signs of statistically significant marginal effects are generally consistent with those based on the pooled static conditional mean model. The magnitudes of the marginal effects in general vary across different quantiles and for some of the variables a clear gradient is observed. First, gender differences are larger at the 0.75

quantile of CES-D scores, with males reporting lower scores. Second, the positive association between emotional problem consultation or drug use for behaviour problem and CES-D scores is stronger at the higher end of the distribution. Third, prenatal and biological factors appear to play different roles at different points of the depression distribution. In particular, the protective role of higher maternal age at birth of child is stronger at the higher end of the CES-D distribution, as are the adverse effects of the pre-natal maternal alcohol and tobacco consumption[19]. Interestingly, experience of trauma or family events during childhood are statistically significant only at some of the quantiles and the effects of childhood consultations due to different types of events play different roles across quantiles. Psychological consultations for family events during childhood plays a more important role at the 0.75 quantile of the CES-D distribution, while psychological consultations for trauma during childhood only contributes to the variability of depression at the 0.25 quantile of the CES-D distribution.[20] Finally, the roles of family SES characteristics differ across different quantiles of the CES-D distribution. The link between higher depression scores and lower family SES, i.e. lower maternal education and lower family income, is stronger at the 0.75 quantile, highlighting the critical role of these factors for individuals who have higher CES-D levels. Again higher family income is only statistically significant at the 0.75 quantile of the distribution, providing a possible explanation

[19] Specifically, the estimated effect of pre-natal maternal alcohol consumption is only statistically significant at the 0.75 quantile of the CES-D distribution, which might explain why we don't observe any effect of maternal drinking during pregnancy in the conditional mean models.

[20] This raises the question whether different types of early-life events have differential impacts on youth depression because different types of events trigger different responses from the children themselves and from their parents, or whether treatment effectiveness varies with the putative presenting cause. Unfortunately we cannot answer this question with our data, while conditional mean approaches may be misleading.

for the lack of an effect of family income in the pooled static conditional mean models.

5.3 Results for Dynamic Conditional Mean Regression Models

Table 7 presents results for the dynamic linear conditional mean regression models. Columns (1) and (2) present marginal effects and standard errors for the pooled linear model; columns (3) and (4) present the results for the random-effects model; and columns (5) and (6) present the results for the fixed-effects model. The estimated marginal effect of the first lag of CES-D score captures the pure state dependence of youth depression conditional on other covariates. Estimates for the pooled and random-effects models indicate strong positive state dependence. However, the state dependence parameter estimate in the fixed-effects model is negative *and* statistically significant. This "regression to the mean" finding suggests that conditional on all other variables and individual fixed effects, a negative serial correlation in depression scores remains. This may be due to negative serial correlation in the errors or negative state dependence. It is worth noting that the magnitude of the estimated persistence level based on the fixed effects model is surprisingly large, but this estimate is subject to bias and thus needs to be interpreted with caution[21]. The intra-class correlation coefficient (ICC) estimate reported in the random-effects model suggests that about 13.1% of the latent error variance is attributable to

[21] As a robustness check on the fixed-effects estimator we also estimated a first-difference (FD) with IV model (Anderson-Hsiao estimator), in which dependent variable lagged for two periods is used as the instrument variable for the lagged dependent variable. This estimator provides consistent estimate of the state dependence parameter under the assumption that there is no serial correlation after controlling for individual fixed effects. Results are not shown but available upon request. The estimated state dependence is 0.0489 and is only statistically significant at 7.5% level. This is a more reliable estimate than that from the fixed-effects model, indicating a less statistically significant positive state dependence with a much smaller scale.

unobserved individual heterogeneity. The ICC estimate reported in the fixed-effects model indicates that about 65.0% of the total variance in the dependent variable is due to the variation across individuals.

Table 8 presents the results from the pooled model, the random-effects model and the fixed-effects model using a dynamic Poisson specification. The reported standard errors for the random- and fixed- effects models are based on 499 bootstrap samples. Table 8 shows that the estimate of state dependence is substantially different in the Poisson specification models: the state dependence parameter is negative but statistically insignificant in the random-effects model; the estimate in the fixed effects model remains negative but much closer to zero.

Several patterns are observed in both Table 7 and Table 8 about the inter-temporal effects of other covariates on youth depression. First, the signs of the marginal effects are the same as those from the static models, except for youth having a job and living in SMSA but these variables are not statistically significant in the dynamic modes. This indicates that the associations between the factors of interest and youth depression exist both in the long run and during the inter-temporal transitions process. The dynamic model results are in line with the static models in a number of other ways. First, the pooled model and random-effects model results indicate that youth depression varies substantially with demographic characteristics: females and blacks are more likely to report higher CES-D scores. Second, there is a positive correlation between psychological health care utilization and the presence of depression. Young adults who utilize consultations for emotional or behaviour problems, or who take prescription drugs to control their activity level or behaviour tend to have higher CES-D scores. Third, higher maternal education is associated with lower CES-D scores. It can also be observed that estimated marginal effects for the dynamic models are in general smaller than those in the static models based on pooled and random-effects specifications. This is not surprising as the dynamic models only capture the inter-temporal effects of these factors conditional on the previous CES-D score rather than long-run effects. The exceptions are maternal education and family income: the estimates from the dynamic models become statistically significant for family income and the magnitudes are slightly larger for maternal education than those from the static models. This means that the protective effects of higher maternal education and higher family income are no smaller in the short-run than in the long-run.

5.4 Results for Conditional Quantile Estimation with Dynamic Models

Table 9 presents the dynamic conditional quantile estimation results for the pooled model without individual-specific effects. Columns (1) and (2) list the marginal effects and the standard errors for the estimation of the 0.25 conditional quantile of the CSE-D score; Columns (3) and (4) list the results for the estimation of the 0.5 conditional quantile of the CSE-D score; Columns (5) and (6) present the results for the estimation of the 0.75 conditional quantile of the CSE-D score. Table 10 presents the conditional quantile estimation results for the pooled model based on 500 jittered samples. Both sets of dynamic quantile regression models show that the estimated persistence level is stronger at the higher ends of the CES-D distribution with the magnitudes of the estimates based on jittered sample slightly smaller. The positive state dependence is stronger at the 0.75 quantile of the conditional CES-D distribution, suggesting high persistence of relatively high severity of depression. With or without jittering, the inter-temporal effects of some covariates vary across quantiles of the CES-D score. Consistent with the results in the static models, the effect of gender on CES-D scores is larger at the 0.75 quantile, while racial differences in CES-D scores are smaller at the 0.75 quantile. Psychological consultations for family events or trauma during childhood are relevant only at the 0.25 quantile. These findings differ from those from static models, which suggested that psychological consultations for family events during childhood played a more important role at the 0.75 quantile of the CES-D distribution. Similarly, maternal tobacco consumption only adversely affects the 0.25 quantile in the dynamic models. Finally, the roles of family SES characteristics differ across quantiles of the CES-D score. The protective effects of higher maternal education and higher family income are larger at the 0.75 quantile. Compared with the results from the static models, the dynamic model results highlight the importance of the inter-temporal effects of total family income on youth depression.

In order to illustrate graphically the differences in the marginal effects across different quantiles, we display the marginal effect estimates and their respective confidence intervals in Figure A.2 in the Appendix. In each graph, the horizontal dashed lines are the pooled OLS estimates of the point estimate and the 95% confidence interval (corresponding to the estimates presented in columns 1 and 2 of Table 7). The green solid lines and the shaded areas represent the quantile regression estimates of the marginal effects and the 95% confidence intervals (corresponding to estimates presented in Table 9). The first graph clearly shows that estimated state dependence varies dramatically at different quantiles of the CES-D score distribution: the persistence level of depression increases from the 0.25 to the 0.75 quantile.

Table 11 summarizes the results for the conditional quantile estimation with individual fixed effects[22]. The reported standard errors are based on 499 bootstrap replications. As for the conditional mean models with individual fixed effects (as shown in Table 7 and Table 8), the estimated marginal effects for the lag of the CES-D score are statistically significant and negative for all three quantiles. Given that the state dependence estimates from the conditional quantile models without individual fixed effects are statistically significant and positive, this again suggests that much of the positive estimated state dependence effect is due to individual fixed effects and that conditional on all the other variables and individual fixed effects, a negative serial correlation in depression scores remains. The absolute value of the estimated state dependence effect is smaller at higher quantiles of the CES-D distribution. It is worth noting that these estimates of state dependence are likely to suffer from small T bias. Some different patterns are also observed for other regressors compared to the pooled dynamic quantile regression model results. Consultations for emotional problems and the use of drugs for activity or behaviour problems are still positively associated with higher CES-D scores, but less statistically significant after controlling for individual fixed effects. Interestingly, after controlling for the individual fixed effects, both maternal education and family income become statistically insignificant even at the 0.75 quantile.

Table 12 presents the results for the dynamic conditional quantile regression models:

[22] As in conditional mean models with fixed effects, we cannot separately identify fixed effects and time-invariant variables without adding some structure, in particular a penalty term as suggested in Koenker 2004. We experimented including time-invariant variables in the fixed effects model without penalty and the convergence is problematic.

instrumental variable approach with individual fixed effects and without jittering. The estimation is based on the original CES-D score without the jittering process. The reported standard errors are based on 499 bootstrap replications. After instrumenting the first lag of CES-D score, the estimates for the persistence level change dramatically across all estimated quantiles. Compared to the fixed effects model without instrumenting (Table 11 where negative estimates were found), the estimated state dependence parameter becomes positive but statistically insignificant for all quantiles. Since the IV estimator should have lower bias, these estimates should be preferred on these grounds to those without instrumenting. It is worth noting that instrumenting the first lag of CES-D score with the second lag of the CES-D score leads to a loss of 3,053 observations. This, in conjunction with the use of instrumental variables, increases the standard errors dramatically: for some of the covariates the bootstrapped standard errors are at least twice those based on individual fixed effects without instrumenting (as in Table 11).

Table 13 presents the results for the instrumental variable approach to estimating dynamic conditional quantile regression models with individual fixed effects and jittering. The point estimates of the marginal effects are based on 500 jittered samples. The reported standard errors are based on 499 bootstrap replications. Consistent with the results without jittering in Table 12 the estimated state dependence parameter is positive but statistically insignificant across all estimated quantiles. However the magnitudes of the estimates are smaller based on the jittered sample. Again, because we have fewer time periods to estimate the model, only a few factors remain statistically significant in this model. The patterns with regard to the effect of the other variables are similar with those observed in the IV estimator without the jittering process (as in Table 12).

6. Discussion and Conclusion

Our study examines the roles of family SES, early childhood life-events, unobserved heterogeneity and pure state dependence in explaining the distribution of depression among adolescents and young adults. We employ a conditional quantile regression framework to address this question and to explore potential heterogeneity in the effects of these factors across different quantiles of the CES-D (depression) score. This is important because these factors of interest may not only affect the location of the conditional distribution of youth depression, but also affect the scale or other aspect of the distribution. If the underlying mechanism that links these factors with youth depression does differ at different parts of the depression distribution, using a conditional mean estimation will neglect this and provide quite different policy implications. Using US data on the children of the NLSY79 cohort, we first estimated a set of static conditional mean models. The results highlight the important roles of gender, race, birth order, maternal smoking behaviour during pregnancy, and maternal education. This is in line with the majority of the literature. On the other hand, our pooled conditional mean estimation model results suggest that there is no consistent significant effect of maternal drinking during pregnancy, family income, poverty status, maternal unemployment duration and psychological consultations for stressful life-events including divorce or family bereavement or trauma during childhood. Note that the existing literature is contradictory on the effects of most socio-economic variables such as parental employment status, occupation class, parental education, family income and family poverty status. We then estimated a set of static conditional quantile regression models. Our conditional quantile regression results provide us with insights into the heterogeneous effects of covariates across the distribution of CES-D scores. For example, the pooled conditional quantile estimation model results show that the estimated effects of psychological consultations for stressful life-events during childhood are statistically significant for some but not all quantiles. Furthermore, different types of life-events seemingly have different roles across different quantiles of the depression score: psychiatric consultations for the incidence of family events during childhood plays a more important role at the 0.75 quantile of the distribution, while psychiatric consultations for trauma during childhood plays a more important role at the 0.25 quantile. Moreover, the family SES-youth depression gradient varies substantially across quantiles of the depression distribution. Specifically, maternal education and family income are more important at the median and 0.75 quantile; family income is only statistically significant at the 0.75 quantile of the depression distribution. These heterogeneous effects are masked by conditional mean estimation, providing a possible explanation of why some studies observe the adverse effect of low family socio-economics status and stressful life events on youth depression while others do not.

Our study also explicitly models the dynamics of depression during adolescence to early adulthood. A methodological contribution of our study is that in addition to standard dynamic quantile regression models, we employ a newly-developed instrumental variable quantile regression for dynamic panel with fixed-effects model (Galvao (2011) combined with 'jittering' as suggested by Machado and Santos Silva in another context (Machado and Santos Silva 2005). This approach provides us with a small-T bias-corrected estimate of the pure state dependence parameter taking account of the unobserved heterogeneity relative to 'brute force' fixed effects. The dynamic conditional quantile regression models revealed the importance of taking into account time-invariant unobserved heterogeneity when examining the dynamics of youth depression. After taking into account the individual fixed effects, the persistence level of CES-D scores becomes very close to zero across all estimated quantiles. This finding, in conjunction with the positive estimates obtained from the pooled models, suggests that the pure state dependence in youth CES-D scores is very low and the observed positive association between previous depression and current depression is mainly due to time-invariant unobserved individual heterogeneity. Furthermore, the estimates from the dynamic quantile regression models show heterogeneous inter-temporal effects of psychological consultations for stressful life events and family SES factors across quantiles. Consultations for family events or trauma during childhood have the largest effects at the 0.25 quantile. The family SES-youth depression gradient is steeper at the 0.75 quantile.

This study can be improved in a number of ways. Firstly, we would like to estimate these models for more extreme quantiles at the high end of the CES-D distribution, because these quantiles would capture the individuals who have clinically diagnosed depression symptoms. More data would help in making any findings sufficiently precise. Secondly, we would like to employ more sophisticated dynamic models to capture the evolving process of youth depression. In particular, if additional waves of data become available we can use multiple lags of the dependent variable and lags of some exogenous covariates for the estimation of dynamic IV models and employ tests of overidentifying restrictions. We could also employ other outside covariates as instruments if we are able to obtain data on environmental factors that directly affect outcomes of the parents but not the adolescents themselves, e.g. potentially socio-economic status of the grandparents of our study sample. Lastly, if data becomes available for both childhood life-events and the treatment they receive due to these events, we could then model the effect of stressful life-events and the effect of treatment separately. This is very important for further investigation given a lot of people remain untreated for these problems for a variety of reasons. Our current results regarding the effects of life-events are hard to interpret because we do not observe whether these life events were experienced unless the individuals were also treated for experiencing these events. This imposes a limitation on our study for making policy implications in this respect due to potential selection issues.

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Table 1. Descriptive statistics of variables used for estimation

Variables	Mean	Std. dev.	Median
Youth CES-D depression score	4.496	3.679	4
Youth CES-D=0	12.14%		
Youth Sex (Male)	49.00%		
Youth race			
Hispanic	22.84%		
Black	34.40%		
Non-Hispanic, non-black	42.76%		
Birth order of youth			
First	39.93%		
Second	34.65%		
Third	16.99%		
Fourth and above	8.42%		
Youth live in urban area (0-1)	0.780	0.414	1
Youth live in SMSA (0-1)	0.888	0.315	1
Youth has a CPS job[23] (0-1)	0.711	0.453	1
Youth emotional problem in last year (0-1)	0.072	0.259	0
Youth prescription drug for behavior problem (0-1)	0.039	0.194	0
Psychiatric consultations during childhood (in all Child Survey years) due to:			
Emotional trauma, molestation, abuse	0.020	0.177	0
Loss of parents/siblings, divorce	0.059	0.280	0
Age of mother at birth of child	24.567	3.752	25
Mother drinking alcohol during pregnancy (0-1)	0.431	0.495	0
Mother smoking during pregnancy (0-1)	0.307	0.461	0
Highest grade completed by mother	12.710	2.567	12
Maternal # of weeks unemployed in past calendar year	2.254	8.657	0
Total real annual family income (in 2010 dollars)	65,528.6	67,661.62	50,479.29
Poverty status of mother's family in past calendar year (0-1)	0.212	0.408	0

[23]A CPS job is a job type within the classification used in the Current Population Survey (CPS).

Table 2. Transition matrix for the CES-D score over all waves (5 categories)

	0	1-3	4-6	7-11	12-21	Total
0	29.42	**41.63**	19.59	7.53	1.82	100
1-3	15.18	**43.4**	27.54	11.66	2.22	100
4-6	8.36	34.03	**34.64**	19.59	3.39	100
7-11	5.41	21.82	**31.85**	30.1	10.82	100
12-21	4.55	15.86	21.51	**34.54**	23.55	100
Total						100

Note: the cells represent the unconditional transition probabilities in percentages. The bold cell shows the biggest cell in each row.

Table 3. Conditional mean estimation for CES-D score—Linear model

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled linear model		Linear model, random-effects specification		Linear model, fixed-effects specification	
	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.
Youth Gender: male	-0.6803***	0.0872	-0.7116***	0.0883		
Race: black	0.3725***	0.1245	0.4121***	0.1240		
Race: non-Hispanic & non-black	-0.0416	0.1221	-0.0440	0.1244		
Birth order2	0.1835*	0.1044	0.2058**	0.1046		
Birth order3	0.2832**	0.1342	0.2861**	0.1359		
Birth order4	0.4629**	0.1959	0.4064**	0.1838		
Emotional problem consultation last year	1.9138***	0.1790	1.3374***	0.1301	0.6205***	0.1483
Drug use for behavior problem last year	1.7146***	0.2386	1.3380***	0.1796	0.7167***	0.2199
Youth has a CPS job	0.1404*	0.0796	0.1419**	0.0724	0.1513*	0.0828
Psychiatric consultations during childhood due to family events	0.2807	0.1716	0.3147*	0.1627		
Psychiatric consultations during childhood due to trauma	0.4210	0.2940	0.4518*	0.2480		
Age of mother at birth of child	-0.0537***	0.0138	-0.0504***	0.0133		
Mother drinking during pregnancy	0.1315	0.0967	0.1121	0.0944		
Mother smoking during pregnancy	0.4576***	0.1064	0.5032***	0.1019		
Youth living in urban	0.0617	0.1032	0.0104	0.0947	-0.0582	0.1253
Youth living in SMSA	0.0042	0.1350	0.0825	0.1263	0.1994	0.1791
Maternal highest grade completed	-0.0431**	0.0199	-0.0396**	0.0189	-0.0351	0.0416
Maternal # of weeks unemployed last year	0.0061	0.0046	0.0067*	0.0039	0.0050	0.0045
Maternal total family income*	-9.62E-04	6.28E-04	-9.56E-03	6.06E-04	-8.11E-04	8.46E-04
Maternal family poverty status	0.1491	0.1158	0.0744	0.1010	-0.0921	0.1353
Constant	5.8815***	0.3881	5.7896***	0.3730	4.6860***	0.5560
sigma_u			2.0356		2.8858	
sigma_e			2.9216		2.9216	
ICC (rho)			0.3268		0.4938	

1. * Maternal family income is CPI inflated according to the interview year and the value is in 1000 US dollars.
2. The reported standard errors are robust to cluster effects for the pooled specification.
3. *** denotes statistical significance at 1% level, ** denotes statistical significance at 5% level, * denotes statistical significance at 10% level.
4. ICC is the intra-class correlation coefficient, $(\sigma_u^2 / (1+ \sigma_u^2))$.
5. The time-invariant regressors are automatically dropped from the fixed-effects model.

Table 4. Conditional mean estimation for CES-D score—Poisson model

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled model		Poisson model, random-effects specification		Poisson model, fixed-effects specification	
	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.
Youth Gender: male	-0.6757***	0.0861	-0.6980***	0.0833		
Race: black	0.3574***	0.1250	0.4272***	0.1213		
Race: non-Hispanic & non-black	-0.0452	0.1235	-0.0546	0.1198		
Birth order2	0.1796*	0.1049	0.2113**	0.1079		
Birth order3	0.2775**	0.1363	0.2699**	0.1317		
Birth order4	0.4601**	0.1976	0.4029**	0.1941		
Emotional problem consultation last year	1.7846***	0.1724	0.8246***	0.1355	0.1045***	0.0352
Drug use for behavior problem last year	1.4984***	0.2193	0.8405***	0.1924	0.1099**	0.0489
Youth has a CPS job	0.1446*	0.0778	0.1558**	0.0748	0.0339*	0.0191
Psychiatric consultations during childhood due to family events	0.2484*	0.1450	0.3297**	0.1508		
Psychiatric consultations during childhood due to trauma	0.2929	0.2047	0.3905	0.2444		
Age of mother at birth of child	-0.0512***	0.0134	-0.0461***	0.0134		
Mother drinking during pregnancy	0.1242	0.0949	0.1002	0.0961		
Mother smoking during pregnancy	0.4418***	0.1033	0.5145***	0.1054		
Youth living in urban	0.0572	0.1031	-0.0180	0.1050	-0.0136	0.0277
Youth living in SMSA	0.0042	0.1336	0.1310	0.1309	0.0448	0.0389
Maternal highest grade completed	-0.0439**	0.0200	-0.0405**	0.0201	-0.0077	0.0087
Maternal # of weeks unemployed last year	0.0054	0.0040	0.0055	0.0040	0.0010	0.0010
Maternal total family income*	-1.16E-03	0.00071	-9.80E-04*	0.00060	-1.57E-04	0.00017
Maternal family poverty status	0.1203	0.1087	0.0125	0.1014	-0.0160	0.0296

1. * Maternal family income is CPI inflated according to the interview year and the value is in 1000 US dollars.
2. For the pooled specification, the reported standard errors are robust to cluster effects; for the random-effects and fixed-effects models, the reported standard errors are based on bootstrapping for 400 replications.
3. *** denotes statistical significance at 1% level, ** denotes statistical significance at 5% level, * denotes statistical significance at 10% level.
4. The time-invariant regressors are automatically dropped from the fixed-effects model.

Table 5. Pooled Static Conditional Quantile Models: No jittering process

	(1)	(2)	(3)	(4)	(5)	(6)
	0.25 Quantile regression		0.50 Quantile regression		0.75 Quantile regression	
	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.
Youth Gender: male	-0.3085***	0.0696	-0.5917***	0.0732	-0.9967***	0.1076
Race: black	0.2872***	0.0984	0.3130***	0.1035	0.3332**	0.1522
Race: non-Hispanic & non-black	-0.0082	0.0992	0.0783	0.1043	0.0114	0.1534
Birth order2	0.2753***	0.0821	0.0878	0.0863	0.1999	0.1269
Birth order3	0.3427***	0.1069	0.1828	0.1124	0.4167**	0.1652
Birth order4	0.5016***	0.1457	0.2075	0.1532	0.6655***	0.2252
Emotional problem consultation last year	1.2620***	0.1417	1.7017***	0.1490	2.5103***	0.2190
Drug use for behavior problem last year	1.0910***	0.1871	1.7955***	0.1967	2.4996***	0.2893
Youth has a CPS job	0.1034	0.0790	0.0578	0.0830	0.2090*	0.1221
Psychiatric consultations during childhood due to family events	0.1598	0.1285	0.3456**	0.1351	0.5159***	0.1987
Psychiatric consultations during childhood due to trauma	0.4456**	0.1958	0.3437*	0.2058	0.2329	0.3027
Age of mother at birth of child	-0.0340***	0.0109	-0.0442***	0.0114	-0.0921***	0.0168
Mother drinking during pregnancy	-0.0294	0.0742	0.0940	0.0780	0.3136***	0.1147
Mother smoking during pregnancy	0.2435***	0.0807	0.4072***	0.0848	0.7101***	0.1247
Youth living in urban	0.0200	0.0934	0.1177	0.0982	0.2345	0.1444
Youth living in SMSA	0.0527	0.1218	-0.0784	0.1281	-0.1666	0.1883
Maternal highest grade completed	-0.0289*	0.0162	-0.0440***	0.0170	-0.0638**	0.0250
Maternal # of weeks unemployed last year	0.0018	0.0042	0.0055	0.0044	0.0045	0.0065
Maternal total family income*	-8.12E-04	5.82E-04	-7.72E-04	6.12E-04	-1.20E-03	9.00E-04
Maternal family poverty status	0.0568	0.0993	0.1746*	0.1044	0.1480	0.1535
Constant	2.7304***	0.3195	5.0717***	0.3359	8.7942***	0.4939

1. * Maternal family income is CPI inflated according to the interview year and the value is in 1000 US dollars.
2. The reported standard errors are robust to cluster effects for the pooled specification.
3. *** denotes statistical significance at 1% level, ** denotes statistical significance at 5% level, * denotes statistical significance at 10% level.

Table 6. Pooled Static Conditional Quantile Regression with jittering

	(1)	(2)	(3)	(4)	(5)	(6)
	0.25 Quantile regression		0.50 Quantile regression		0.75 Quantile regression	
	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.
Youth Gender: male	-0.2993***	0.0667	-0.5998***	0.0691	-1.0044***	0.1047
Race: black	0.3194***	0.0947	0.3366***	0.0984	0.2917**	0.1456
Race: non-Hispanic & non-black	-0.0090	0.0982	0.0471	0.0983	-0.0472	0.1456
Birth order2	0.2274***	0.0817	0.1026	0.0813	0.1638	0.1244
Birth order3	0.2833***	0.1103	0.2238**	0.1057	0.4217**	0.1652
Birth order4	0.4438***	0.1495	0.2453	0.1602	0.6273***	0.2345
Emotional problem consultation last year	1.2050***	0.1261	1.6027***	0.1703	2.2703***	0.2406
Drug use for behavior problem last year	0.9818***	0.1695	1.6616***	0.2253	2.1132***	0.2619
Youth has a CPS job	0.1095	0.0741	0.0777	0.0760	0.2232**	0.1124
Psychiatric consultations during childhood due to family events	0.1315	0.1090	0.3348***	0.1177	0.4707***	0.1807
Psychiatric consultations during childhood due to trauma	0.3359**	0.1375	0.2395	0.1747	0.0901	0.2506
Age of mother at birth of child	-0.0284***	0.0107	-0.0452***	0.0103	-0.0890***	0.0171
Mother drinking during pregnancy	-0.0595	0.0716	0.0659	0.0735	0.3330***	0.1121
Mother smoking during pregnancy	0.2804***	0.0795	0.3965***	0.0862	0.6634***	0.1191
Youth living in urban	0.0238	0.0951	0.1200	0.0931	0.2036	0.1323
Youth living in SMSA	0.0165	0.1239	-0.0611	0.1202	-0.1839	0.1672
Maternal highest grade completed	-0.0300**	0.0152	-0.0400***	0.0151	-0.0592**	0.0254
Maternal # of weeks unemployed last year	0.0026	0.0037	0.0061	0.0039	0.0046	0.0054
Maternal total family income*	-8.88E-04	6.69E-04	-8.89E-04	7.17E-04	-1.58E-03**	6.90E-04
Maternal family poverty status	0.0541	0.0893	0.1345	0.1041	0.1277	0.1375

1. * Maternal family income is CPI inflated according to the interview year and the value is in 1000 US dollars.
2. All the estimates are based on 500 jittering replications.
3. The marginal effects are calculated based on the jittered sample.
4. *** denotes statistical significance at 1% level, ** denotes statistical significance at 5% level, * denotes statistical significance at 10% level.

Table 7. Dynamic conditional mean regression models—Linear Specification

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled linear model		Linear model, random-effects specification		Linear model, fixed-effects specification	
	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.
CESDlag (t-1)	0.3422***	0.0132	0.2625***	0.0105	-0.2994***	0.0140
Youth Gender: male	-0.3727***	0.0738	-0.4381***	0.0817		
Race: black	0.3155***	0.1045	0.3431***	0.1145		
Race: non-Hispanic & non-black	-0.0322	0.1038	-0.0289	0.1152		
Birth order2	0.1419	0.0879	0.1590*	0.0962		
Birth order3	0.1541	0.1141	0.1651	0.1247		
Birth order4	0.1763	0.1544	0.1926	0.1682		
Emotional problem consultation last year	1.2034***	0.1906	1.1933***	0.1543	0.5300***	0.1833
Drug use for behavior problem last year	1.3377***	0.2610	1.3702***	0.2128	0.9858***	0.2781
Youth has a CPS job	-0.0718	0.0932	-0.0587	0.0957	0.1250	0.1173
Psychiatric consultations during childhood due to family events	0.2236*	0.1311	0.2700*	0.1513		
Psychiatric consultations during childhood due to trauma	0.4034*	0.2191	0.4384*	0.2292		
Age of mother at birth of child	-0.0275**	0.0117	-0.0320**	0.0126		
Mother drinking during pregnancy	0.1259	0.0811	0.1277	0.0867		
Mother smoking during pregnancy	0.2878***	0.0900	0.3274***	0.0945		
Youth living in urban	0.0536	0.0986	0.0512	0.1032	0.0586	0.1511
Youth living in SMSA	-0.0147	0.1368	-0.0015	0.1494	0.4476	0.2825
Maternal highest grade completed	-0.0444**	0.0174	-0.0457**	0.0186	-0.0521	0.0489
Maternal # of weeks unemployed last year	0.0009	0.0048	0.0018	0.0044	0.0066	0.0053
Maternal total family income*	-1.06E-03**	5.35E-04	-1.10E-03*	6.40E-04	-4.72E-04	1.00E-03
Maternal family poverty status	0.1500	0.1077	0.1489	0.1093	-0.0718	0.1688
Constant	3.9237***	0.3538	4.3923***	0.3760	5.9211***	0.6844
sigma_u			1.0646		3.7355	
sigma_e			2.7404		2.7404	
ICC (rho)			0.1311		0.6501	

1. *Maternal family income is CPI inflated according to the interview year and the value is in 1000 US dollars.
2. The reported standard errors are robust to cluster effects for the pooled specification.
3. *** denotes statistical significance at 1% level, ** denotes statistical significance at 5% level, * denotes statistical significance at 10% level.
4. ICC is the intra-class correlation coefficient, ($\sigma_u^2 / (1+ \sigma_u^2)$).
5. The time-invariant regressors are automatically dropped from the fixed-effects model.

Table 8. Dynamic conditional mean regression models-- Poisson Specification

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled model		Poisson model, random-effects specification		Poisson model, fixed-effects specification	
	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.
CESDlag (t-1)	0.2739***	0.0091	-0.0157	0.0135	-0.0438***	0.0092
Youth Gender: male	-0.3574***	0.0733	-0.6734***	0.0945		
Race: black	0.2932***	0.1031	0.4531***	0.1295		
Race: non-Hispanic & non-black	-0.0352	0.1044	-0.0307	0.1335		
Birth order2	0.1320	0.0872	0.2419**	0.1138		
Birth order3	0.1368	0.1117	0.2098	0.1427		
Birth order4	0.1707	0.1456	0.3164	0.2146		
Emotional problem consultation last year	0.9846***	0.1678	0.8282***	0.1760	0.0780*	0.0416
Drug use for behavior problem last year	0.9909***	0.2196	1.0657***	0.2627	0.1440**	0.0652
Youth has a CPS job	-0.0346	0.0892	0.0266	0.0986	0.0327	0.0256
Psychiatric consultations during childhood due to family events	0.1878*	0.1065	0.4095***	0.1599		
Psychiatric consultations during childhood due to trauma	0.2511*	0.1448	0.4930*	0.2571		
Age of mother at birth of child	-0.0250**	0.0112	-0.0433***	0.0145		
Mother drinking during pregnancy	0.1185	0.0780	0.1393	0.1035		
Mother smoking during pregnancy	0.2555***	0.0843	0.4780***	0.1187		
Youth living in urban	0.0642	0.0975	0.0539	0.1104	0.0076	0.0298
Youth living in SMSA	-0.0495	0.1346	0.1145	0.1705	0.1115*	0.0670
Maternal highest grade completed	-0.0443***	0.0170	-0.0515**	0.0237	-0.0053	0.0119
Maternal # of weeks unemployed last year	0.0005	0.0043	0.0032	0.0051	0.0012	0.0012
Maternal total family income*	-1.22E-03**	0.00061	-1.24E-03*	0.00072	-1.16E-04	0.0002
Maternal family poverty status	0.1055	0.0977	0.0855	0.1285	-0.0133	0.0339

1. * Maternal family income is CPI inflated according to the interview year and the value is in 1000 US dollars.
2. For the pooled specification, the reported standard errors are robust to cluster effects; for the random-effects and fixed-effects models, the reported standard errors are based on bootstrapping for 499 replications.
3. *** denotes statistical significance at 1% level, ** denotes statistical significance at 5% level, * denotes statistical significance at 10% level.
4. The time-invariant regressors are automatically dropped from the fixed-effects model.

Table 9. Pooled Dynamic conditional quantile regression without Jittering

	(1)	(2)	(3)	(4)	(5)	(6)
	0.25 Quantile regression		0.50 Quantile regression		0.75 Quantile regression	
	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.
CESDlag (t-1)	0.2851***	0.0119	0.3669***	0.0112	0.4636***	0.0156
Youth Gender: male	-0.1152	0.0862	-0.3156***	0.0814	-0.5472***	0.1133
Race: black	0.4012***	0.1210	0.2830**	0.1142	0.3455**	0.1589
Race: non-Hispanic & non-black	0.1030	0.1219	0.0110	0.1151	0.0841	0.1601
Birth order2	0.1108	0.1013	0.1063	0.0956	0.1602	0.1330
Birth order3	0.1709	0.1313	-0.0055	0.1240	0.2520	0.1725
Birth order4	0.1481	0.1773	-0.0091	0.1675	0.3425	0.2330
Emotional problem consultation last year	0.8915***	0.1784	1.0449***	0.1684	1.4287***	0.2343
Drug use for behavior problem last year	0.9197***	0.2425	1.3544***	0.2290	1.5449***	0.3185
Youth has a CPS job	0.0445	0.1099	-0.1594	0.1038	-0.0353	0.1444
Psychiatric consultations during childhood due to family events	0.2740*	0.1601	0.1676	0.1512	0.0456	0.2104
Psychiatric consultations during childhood due to trauma	0.4346*	0.2414	0.4054*	0.2280	0.2432	0.3172
Age of mother at birth of child	-0.0199	0.0134	-0.0216*	0.0127	-0.0430**	0.0177
Mother drinking during pregnancy	-0.2135**	0.0913	-0.0096	0.0862	0.3042**	0.1199
Mother smoking during pregnancy	0.3689***	0.0997	0.2945***	0.0941	0.2071	0.1310
Youth living in urban	0.1057	0.1152	0.0199	0.1088	0.2138	0.1514
Youth living in SMSA	-0.1226	0.1642	-0.0486	0.1551	-0.1524	0.2157
Maternal highest grade completed	-0.0259	0.0200	-0.0480**	0.0188	-0.0576**	0.0262
Maternal # of weeks unemployed last year	-0.0082	0.0051	0.0022	0.0048	0.0065	0.0067
Maternal total family income*	-2.79E-04	7.09E-04	-7.10E-04	6.70E-04	-1.75E-03*	9.31E-04
Maternal family poverty status	0.0989	0.1218	0.1272	0.1150	0.1885	0.1600
Constant	1.2882***	0.4080	3.3955***	0.3853	5.5983***	0.5360

1. * Maternal family income is CPI inflated according to the interview year and the value is in 1000 US dollars.
2. The reported standard errors are robust to cluster effects for the pooled specification.
3. *** denotes statistical significance at 1% level, ** denotes statistical significance at 5% level, * denotes statistical significance at 10% level.

Table 10. Pooled Dynamic Conditional Quantile regression models with jittering

	(1)	(2)	(3)	(4)	(5)	(6)
	0.25 Quantile regression		0.50 Quantile regression		0.75 Quantile regression	
	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.
CESDlag (t-1)	0.2059***	0.0087	0.2979***	0.0093	0.3908***	0.0158
Youth Gender: male	-0.1126	0.0825	-0.2936***	0.0725	-0.5604***	0.1210
Race: black	0.3353***	0.1214	0.3380***	0.1066	0.2725*	0.1621
Race: non-Hispanic & non-black	0.0389	0.1212	0.0580	0.1082	0.0098	0.1564
Birth order2	0.1678*	0.1005	0.1162	0.0855	0.1083	0.1284
Birth order3	0.2420**	0.1217	0.0483	0.1195	0.2488	0.1798
Birth order4	0.1406	0.1714	0.0348	0.1473	0.3448	0.2832
Emotional problem consultation last year	0.7091***	0.1559	0.9216***	0.1877	1.0836***	0.2964
Drug use for behavior problem last year	0.7033***	0.1899	0.9421***	0.2103	1.1978***	0.4440
Youth has a CPS job	0.0689	0.1030	-0.1102	0.0909	-0.0011	0.1642
Psychiatric consultations during childhood due to family events	0.1166	0.1439	0.1562	0.1540	0.0905	0.1478
Psychiatric consultations during childhood due to trauma	0.2653*	0.1525	0.3366*	0.1728	0.0910	0.1798
Age of mother at birth of child	-0.0145	0.0124	-0.0178	0.0114	-0.0394**	0.0177
Mother drinking during pregnancy	-0.2191***	0.0836	-0.0038	0.0794	0.3244***	0.1203
Mother smoking during pregnancy	0.3039***	0.0972	0.2595***	0.0855	0.1987	0.1342
Youth living in urban	0.0997	0.1062	0.0185	0.1013	0.2221	0.1367
Youth living in SMSA	-0.0943	0.1389	-0.0555	0.1434	-0.2785	0.2191
Maternal highest grade completed	-0.0284	0.0193	-0.0475***	0.0176	-0.0642**	0.0255
Maternal # of weeks unemployed last year	-0.0069	0.0053	0.0011	0.0048	0.0079	0.0085
Maternal total family income*	-8.99E-04	6.94E-04	-9.88E-04	6.52E-04	-2.24E-03***	7.90E-04
Maternal family poverty status	0.0560	0.1071	0.1067	0.1080	0.1294	0.1498

1. * Maternal family income is CPI inflated according to the interview year and the value is in 1000 US dollars.
2. All the estimates are based on 500 jittering replications.
3. The marginal effects are calculated based on the jittered sample.
4. *** denotes statistical significance at 1% level, ** denotes statistical significance at 5% level, * denotes statistical significance at 10% level.

Table 11. Dynamic conditional quantile regression models with individual fixed effects and without jittering

	(1)	(2)	(3)	(4)	(5)	(6)
	0.25 Quantile regression		0.50 Quantile regression		0.75 Quantile regression	
	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.
CESDlag (t-1)	-0.3909***	0.0215	-0.2921***	0.0191	-0.2136***	0.0200
Youth Gender: male						
Race: black						
Race: non-Hispanic & non-black						
Birth order2						
Birth order3						
Birth order4						
Emotional problem consultation last year	0.2975	0.2186	0.4008*	0.2051	0.4593	0.2821
Drug use for behavior problem last year	0.7568**	0.3151	0.5944*	0.3043	0.4744	0.4478
Youth has a CPS job	0.0551	0.1342	-0.0050	0.0842	0.0289	0.1242
Psychiatric consultations during childhood due to family events						
Psychiatric consultations during childhood due to trauma						
Age of mother at birth of child						
Mother drinking during pregnancy						
Mother smoking during pregnancy						
Youth living in urban	-0.0056	0.1379	0.0050	0.1379	-0.0050	0.1536
Youth living in SMSA	0.1317	0.2943	0.1469	0.3031	0.4804	0.3045
Maternal highest grade completed	-0.0321	0.0509	-0.0440	0.0476	-0.0374	0.0490
Maternal # of weeks unemployed last year	0.0011	0.0072	0.0003	0.0065	0.0051	0.0074
Maternal total family income*	-0.0004	0.0011	0.0000	0.0010	-0.0005	0.0010
Maternal family poverty status	0.0517	0.2036	0.0094	0.1737	-0.0309	0.1907
Constant	4.8661***	0.6962	5.4252***	0.6768	5.6509***	0.7146

1. * Maternal family income is CPI inflated according to the interview year and the value is in 1000 US dollars.
2. The reported standard errors are based on 499 bootstrapping replications.
3. *** denotes statistical significance at 1% level, ** denotes statistical significance at 5% level, * denotes statistical significance at 10% level.
4. The time-invariant regressors are dropped from the fixed-effects model.

Table 12. Dynamic conditional quantile regression models: instrumental variable approach with individual fixed effects and without jittering

	(1)	(2)	(3)	(4)	(5)	(6)
	0.25 Quantile regression		0.50 Quantile regression		0.75 Quantile regression	
	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.
CESDlag (t-1)	0.0199	0.2239	0.0824	0.1580	0.1238	0.1451
Youth Gender: male						
Race: black						
Race: non-Hispanic & non-black						
Birth order2						
Birth order3						
Birth order4						
Emotional problem consultation last year	0.0437	0.2940	0.0101	0.2789	0.0737	0.3015
Drug use for behavior problem last year	1.1650*	0.6114	1.0831*	0.6178	0.9365	0.6114
Youth has a CPS job	-0.1879	0.2139	-0.1630	0.2119	-0.0911	0.2224
Psychiatric consultations during childhood due to family events						
Psychiatric consultations during childhood due to trauma						
Age of mother at birth of child						
Mother drinking during pregnancy						
Mother smoking during pregnancy						
Youth living in urban	0.0841	0.2733	0.0888	0.2743	0.1110	0.2825
Youth living in SMSA	-0.9255	0.6472	-0.8949	0.6478	-0.8153	0.6500
Maternal highest grade completed	0.0093	0.0659	0.0118	0.0643	0.0366	0.0663
Maternal # of weeks unemployed last year	-0.0049	0.0101	-0.0049	0.0099	-0.0058	0.0100
Maternal total family income*	-0.0026	0.0021	-0.0012	0.0019	-0.0006	0.0018
Maternal family poverty status	-0.2797	0.3045	-0.2452	0.2981	-0.2746	0.3040
Constant	4.2106***	1.4456	4.0959***	1.4298	3.7708***	1.4486

1. * Maternal family income is CPI inflated according to the interview year and the value is in 1000 US dollars.
2. The reported standard errors are based on 499 bootstrapping replications.
3. *** denotes statistical significance at 1% level, ** denotes statistical significance at 5% level, * denotes statistical significance at 10% level.
4. The time-invariant regressors are dropped from the fixed-effects model.

Table 13. Dynamic conditional quantile regression models: instrumental variable approach with individual fixed effects and jittering

	(1)	(2)	(3)	(4)	(5)	(6)
	0.25 Quantile regression		0.50 Quantile regression		0.75 Quantile regression	
	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.
CESDlag (t-1)	0.0169	0.0163	0.0403	0.0358	0.0568	0.0591
Youth Gender: male						
Race: black						
Race: non-Hispanic & non-black						
Birth order2						
Birth order3						
Birth order4						
Emotional problem consultation last year	0.0185	0.0593	0.0300	0.1370	0.0110	0.1457
Drug use for behavior problem last year	0.1624	0.1148	0.3265	0.2558	0.3149	0.2922
Youth has a CPS job	-0.0633	0.0549	-0.1059	0.1107	-0.1056	0.1127
Psychiatric consultations during childhood due to family events						
Psychiatric consultations during childhood due to trauma						
Age of mother at birth of child						
Mother drinking during pregnancy						
Mother smoking during pregnancy						
Youth living in urban	0.0043	0.0589	0.0155	0.1318	-0.0714	0.1619
Youth living in SMSA	-0.1434	0.1677	-0.4452	0.3694	-0.2521	0.3572
Maternal highest grade completed	-0.0091	0.0168	-0.0059	0.0343	-0.0218	0.0464
Maternal # of weeks unemployed last year	-0.0005	0.0027	-0.0042	0.0058	-0.0036	0.0058
Maternal total family income*	-0.0004	0.0005	-0.0005	0.0011	-0.0002	0.0009
Maternal family poverty status	-0.0297	0.0668	-0.0935	0.1344	-0.1711	0.1299
Constant	0.9386***	0.2909	2.3555***	0.5798	2.5120***	0.7104

1. * Maternal family income is CPI inflated according to the interview year and the value is in 1000 US dollars.
2. The point estimates of the marginal effects are based on 500 jittering replications.
3. The reported standard errors are based on 499 bootstrapping replications.
4. *** denotes statistical significance at 1% level, ** denotes statistical significance at 5% level, * denotes statistical significance at 10% level.
5. The time-invariant regressors are dropped from the fixed-effects model.

Appendix

Figure A.1. Histogram of youth CES-D depression score

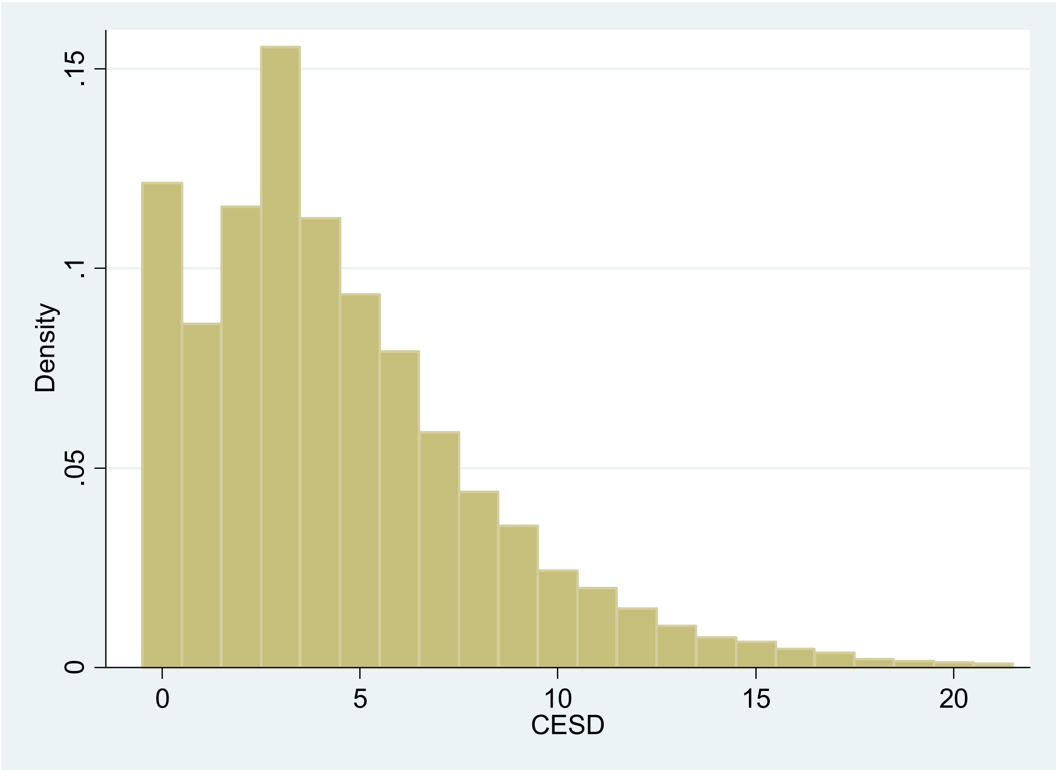

Figure A. 2. Dynamic quantile regression pooled estimates of marginal effects and 95% confidence intervals by quantiles

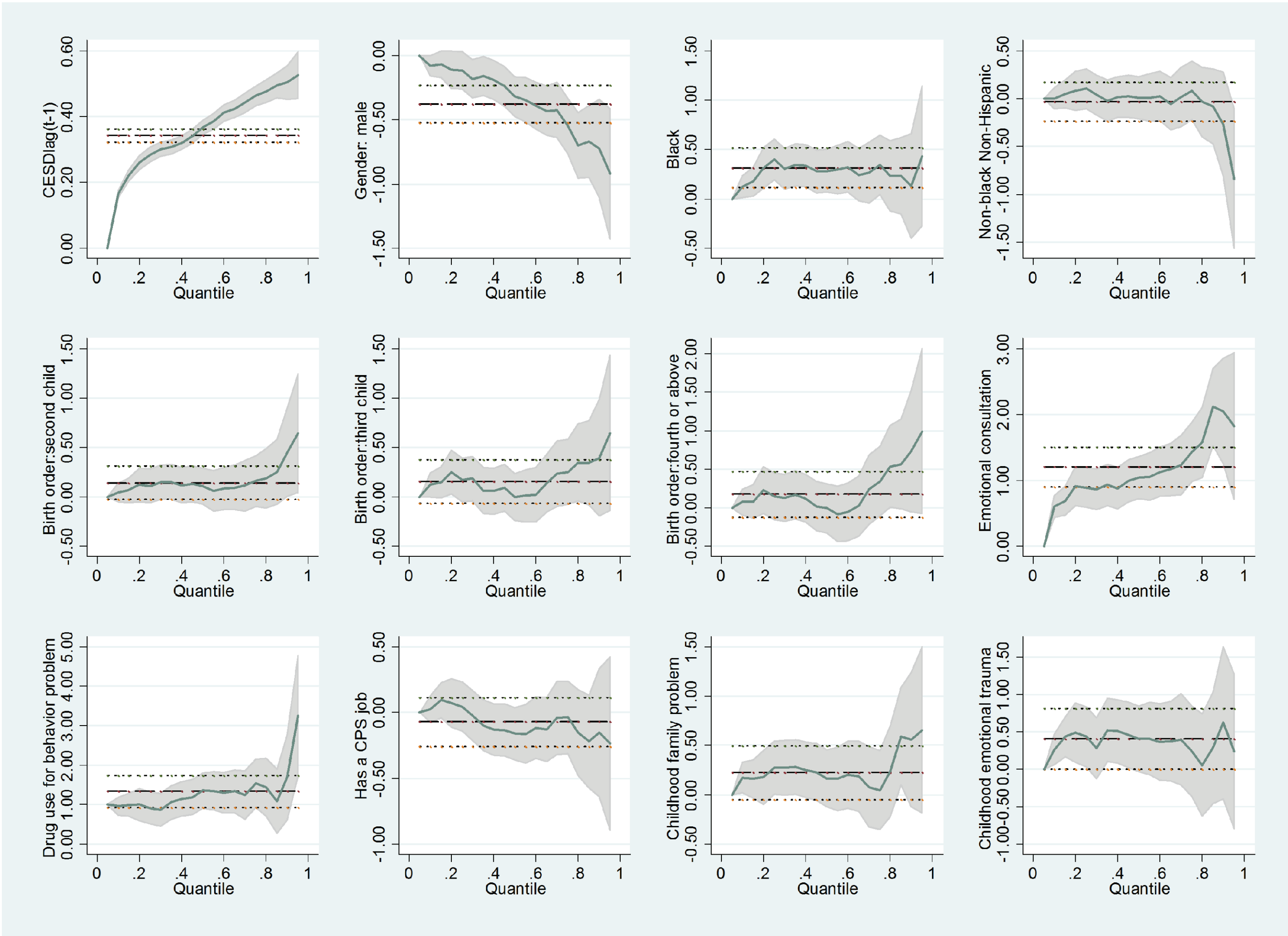

Figure A.2. Dynamic quantile regression pooled estimates of marginal effects and 95% confidence intervals by quantiles (Continued)