Online Appendix

Technical note:

For comparison with our main model, we also estimate a set of dynamic conditional mean regression models, pooled dynamic quantile regression model, and dynamic quantile regression model with fixed effects (but without IV). Details of these models are described below in section 1.1, section 1.2.1 and section 1.2.2. In the main text of the paper we only describe our proposed method in detail. Our proposed model is also briefly described in section 1.2.3 below, including some additional technical details that are not included in the main text of the paper.

1.1 Dynamic conditional mean regression models

A common modelling approach for health dynamics is to employ dynamic conditional mean estimation models. In our case, the following specification is considered:

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

where y_{it} is the CES-D score for individual i at time period t, y_{it-1} is the first lag of the CES-D score, x_{it} is a vector of explanatory variables, and η denote the individual effects. The parameter α captures the state dependence level of the CES-D scores. To account for the integer nature of the CES-D score, we estimate the conditional mean of the dependent variable with a Poisson specification.

We first estimate a pooled model, ignoring the fixed effects (effectively setting η to zero) and other possible causes for dependence in the error term across observations. To separate true state dependence from unobserved individual heterogeneity, we then estimate the Poisson specification with random-effects and fixed-effects models (see Cameron and Trivedi 2013). In addition we estimated a first-difference (FD) with IV model (Anderson-

Hsiao estimator) based on a linear specification, in which the dependent variable lagged for two periods is used as the instrument for the first difference of the lagged dependent variable.

1.2 Dynamic conditional quantile regression models

1.2.1 Pooled dynamic quantile regression model

We first consider a dynamic model for the τth conditional quantile function of the outcome variable without individual effects using the following specification:

$$Q_{y_{it}}(\tau|y_{it-1}, x_{it}) = \alpha(\tau)y_{it-1} + x'_{it}\beta(\tau) \qquad (2)$$

where y_{it} is the outcome of interest, y_{it-1} is the first lag of the outcome variable, x_{it} are a set of exogenous variables. The parameter α captures the state dependence level of the CES-D scores.

A complication in our context is that the outcome variable is an ordered discrete response. 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 and the sample objective function is non-differentiable. To address this problem we estimate the model suggested by Machado and Santos Silva (2005) that is used for quantile regressions with count data. Essentially, their model first adds randomness to the dependent variable by “jittering” the original count data, and then estimates conditional quantile models to the jittered data. Specifically, the discrete outcome variable y_{it} is replaced with a continuous variable $J_{it}= h(y_{it})$, where $h(.)$ is a smooth continuous transformation. The transformation is

$$J_{it}= y_{it} +u, \qquad (3)$$

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

$$Q_J(\tau|X) = \tau + exp\big(X'\beta(\tau)\big), \quad (4)$$

where X represents the design matrix in the specification of y_{it} considered in (2). 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. 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 (for details see Cameron and Trivedi 2013). 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. To reduce the effect of noise due to jittering, the parameters of the model need to be estimated multiple times based on multiple jittered replications and the final estimate takes the average of these multiple estimates. We use 500 jittered replications for this estimation.

1.2.2 Dynamic quantile regression with fixed effects model

We now consider a dynamic panel quantile regression model with individual fixed-effects. The τth conditional quantile function of the outcome variable of the tth observation on the ith individual y_{it} can be represented as:

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

Where z_i is the individual indicator and η represents the $Nx1$ vector of individual-specific effects.

As a comparison we estimate the above fixed effects model by using the penalized fixed effects model developed by Koenker (2004). In order to allow for some flexibility in the effect of any time-invariant observables, 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). Koenker (2004) notes that as the shrinkage parameter in this penalized fixed effects model 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 estimator represents a very close approximation of the FE estimator.

1.2.3 Dynamic quantile regression IV model with fixed effects

Galvao (2011) proposed an IV estimator to reduce bias for the state dependence parameter in the above dynamic quantile regression with fixed effects model developed by Koenker (2004). We use this estimator as our main empirical approach. The implementation of this IV procedure minimizes the following objective function R_{NT}

$$R_{NT}(\tau, \eta_i, \alpha, \beta, \gamma) := \sum_{k=1}^{K} \sum_{i=1}^{N} \sum_{t=1}^{T} \upsilon_k \rho_\tau \big(y_{it} - \alpha(\tau_k) y_{it-1} - x'_{it}\beta(\tau_k) - z_i\eta - \omega'_{it}\gamma(\tau_k) \big), \qquad (6)$$

where $\rho_\tau(u) \coloneqq u(\tau - I(u < 0))$ as in Koenker and Bassett (1978), 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, and ω_{it} is a $dim(\gamma)$-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. More details are described in the main text of the paper.

We use the values of CES-D score lagged two periods as our IV, because y_{it-2} is structurally correlated with y_{it-1} and this IV is valid under the assumption that the error term is serially uncorrelated conditional on the individual fixed effects.

References

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Koenker, R., (2004) ‘Quantile regression for longitudinal data,’ *Journal of Multivariate Analysis*, Elsevier, 91(1), 74-89.Lewinsohn PM, and Essau CA, (2002) ‘Depression in adolescents.’ Guilford Press

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Additional regression results

Table A1. Dynamic conditional mean regression models based on linear specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled linear model		Linear model, random-effects specification		Linear model, fixed-effects specification		Linear model, Anderson-Hsiao estimator	
	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.	Marg. Eff.	St. Err.
CESDlag (t-1)	0.3433***	0.0132	0.2642***	0.0105	-0.2970***	0.0140	0.0516*	0.0275
Youth Gender: male	-0.3777***	0.0737	-0.4430***	0.0817				
Race: black	0.2959***	0.1041	0.3207***	0.1142				
Race: non-Hispanic & non-black	-0.0261	0.1038	-0.0212	0.1151				
Birth order2	0.1460*	0.0880	0.1628*	0.0962				
Birth order3	0.1569	0.1139	0.1681	0.1246				
Birth order4	0.1793	0.1540	0.1956	0.1682				
Emotional problem consultation last year	1.2160***	0.1914	1.2083***	0.1542	0.5663***	0.1832	0.3999**	0.2017
Drug use for behavior problem last year	1.3761***	0.2600	1.4091***	0.2124	0.9737***	0.2784	0.8913***	0.3199
Youth has a job	-0.0616	0.0930	-0.0499	0.0956	0.1179	0.1174	0.1395	0.1388
Age of mother at birth of child	-0.0279**	0.0117	-0.0326***	0.0126				
Mother drinking during pregnancy	0.1339*	0.0810	0.1373	0.0866				
Mother smoking during pregnancy	0.2958***	0.0900	0.3358***	0.0943				
Youth living in urban	0.0618	0.0985	0.0604	0.1031	0.0599	0.1512	0.1011	0.1723
Youth living in SMSA	-0.0148	0.1365	-0.0011	0.1494	0.4481	0.2828	0.8482**	0.3581
Maternal highest grade completed	-0.0412**	0.0173	-0.0423**	0.0185	-0.0549	0.0490	0.0174	0.0579
Maternal # of weeks unemployed last year	0.0012	0.0048	0.0022	0.0044	0.0076	0.0053	-0.0004	0.0061
Maternal total family income*	-0.0012**	0.0005	-0.0012*	0.0006	-0.0005	0.0010	-0.0007	0.0011
Maternal family poverty status	0.1590	0.1075	0.1576	0.1093	-0.0744	0.1690	-0.0204	0.1880
Constant	3.8966***	0.3537	4.3647***	0.3759	5.9475***	0.6851	-0.2455***	0.0648
sigma_u			1.0621		3.7274			
sigma_e			2.7435		2.7435			
ICC (rho)			0.1303		0.6486			

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 A2. 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 job	-0.1879	0.2139	-0.1630	0.2119	-0.0911	0.2224
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.
5. The time-invariant regressors are automatically dropped from the fixed-effects model.